Estimating the wear rate of diamond cutting wire segment in building stone cutting using SVR and GA_MLP system

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Research Article

Keywords: Diamond Cutting Wire, Building Stones, SVR, GA-MLP, Savitzky-Golay

Posted Date: April 20th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-435024/v1>

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Abstract

As the cutting stone is a wear process, performing this process with diamond pieces' aid can be considered the wear of stone particles bypassing diamond grains on its surface. To better understand this process as well as the conditions governing the cutting diamond grain, it is necessary to familiar with the cutting mechanism along with the affecting parameters. In this matter, predicting the amount of segment consumption plays a prominent role to estimate the production cost as well as to schematize the building stone mines. This paper utilized the data obtained from Carbonate and Granite stones to estimate the amount of consumption of diamond cutting wire segments. To do so, two methods, namely support vector regression (SVR) and genetic algorithm + Multilayer perceptron (GA-MLP) were chosen using the MATLAB software toolboxes in order to estimate the segment erosion. In each of the above algorithms, a lowpass smoothing filter, called Savitzky-Golay was employed on the data. For this purpose, three rock properties including uniaxial compressive strength, Shimazk friction factor, and Young's modulus, were also employed as the model's input. After that, twelve models were constructed and then the segment erosion was estimated as well. Ultimately, the accuracy of the above models was assessed using the coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), mean value absolute error (MAD), mean absolute percentage error (MAPE), and variance of factor analysis (VFA). According to the obtained results, it can be concluded that the SVR approach and the Savitzky-Golay filter with Polynomial Kernel could better estimate the wear rate of the diamond cutting wire segment.

Introduction

Employing a diamond cutting wire is the most common approach to extract building stones. This method has attracted considerable attention around the world. Since 1997, it has gradually become the primary selection for miners as the efficiency and accuracy of diamond cutting wire . This indicated that diamond cutting wire is a sufficiently advanced method. Fig. 1 shows the cutting method in the floor and walls of mines, and Fig. 2 depicts the components of a diamond cutting (Özçelik 2005).

When using the diamond cutting wire, two holes are first drilled perpendicular to each other to meet at one point. Next, the diamond cutting wire passes through the holes and cuts the surface. Through this method, a stone can be trimmed both horizontally and vertically (Atai 2009). Up to now, the performance of the diamond cutting wire has been successfully explored by researchers. Some studies have been performed on the cutting ability of building stone to present the relationships between the characteristics of the stone and the amount of its wear, energy consumption, and cutting speed. For example, using 36 different experiments, Jain and Rathore (2011) demonstrated that factors, such as the speed of the cutting tool, the adhesion coefficient of stone, and the thrust of the cutting machine could significantly impact the cutting rate as well as the wear rate of diamond cutting wire segments. They also defined the wear rate of the diamond cutting wire segment as a function of variables, such as adhesion, ambient speed, and the amount of device's trust. Then, using ANN and multivariate regression models, their

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js tion of the variability of adhesion, ambient

speed, and the amount of device trust was analyzed. They finally concluded that ANN models have more predictive power than the regression models (Jain and Rathore 2011).

Ataei et al. (2012) studied 14 Carbonate building stones in Iran and examined the relationship between the cut-rate of diamond wire and some stone parameters including uniaxial compressive strength, tensile strength, Los Angeles abrasion, and Schmidt hammer hardness. They concluded that the production rate slightly increases with increasing Los Angeles abrasion (weak positive correlation), while it strongly increases when the compressive strength, Brazilian tensile strength, and Schmidt hammer decrease strong negative correlation (Ataei et al. 2012). Moreover, Bagherpour et al. (2014) proved that one of the most important parameters in cutting building stones is the number of diamond cutting wire segments per unit length. Accordingly, they also showed that the optimum number of diamond cutting wire segment in Travertine stones is 31 per unit length so that by decreasing their number, the production rate decreases. Further, Bagherpour et al. (2014) argued that increasing the number of nuts, depending on the height of stone, had either no impact or a negative impact on the production rate (Bagherpour et al. 2014). Furthermore, Yilmazkaya et al. (2016) investigated the relationship between the performance parameters in cutting (unit energy and unit erosion) and some physical and mechanical properties of samples (Yilmazkaya et al. 2016). Similarly, Almasi et al. (2017) predicted the amount of diamond grains erosion as one of the main performance criteria in building stone mines through studying 11 types of igneous stones in the laboratory (steady conditions). The results showed that in abrasive stones, the diamond cutting wire segment had highly eroded for low production. Therefore, in such conditions, production should be increased as much as (Almasi et al. 2017).

On the other hand, Careddu et al. (2019) examined the amount of segment erosion in cutting Basalt stone and compared it with that of Granite stone cutting. They totally measured 15 beads (one bead in each meter of diamond cutting wire) (Careddu et al. 2019). Yilmazkaya et al. (2018) utilized the artificial neural and regression models to predict performance parameters, i.e., unit erosion values on diamond wire and unit energy values in single-layer cutting wire in marble and limestone samples. The performance of these generated models was assessed and compared in terms of predicting unit abrasion and unit energy values. They finally concluded that the artificial neural network (ANN) models with shear velocity (CS) inputs, uniaxial compressive strength (UCS), perimeter speed (PS), abrasion output, and the energy of cutting wire are the best predictors for the energy consumption and segments erosion (Yilmazkaya et al. 2018). Mikhael et al. (2018) predicted the friction scale in the diamond cutting wire. Mikhael et al. (2018) they conducted a study on 38 types of building stones. In this study, they used an adaptive neural-fuzzy inference system (ANFIS) to estimate the amount of diamond wire wear in unspecified processes.

Predictions were made based on four effective stone properties, such as salinity hardness, Shimazk friction factor, uniaxial compressive strength, and Young's modulus. They finally claimed that ANFIS-SCM is a valid modeling method for predicting the erosion rate of diamond cutting wire and could be used for effective prediction of wear rate of diamond cutting wire segment (Mikhael et al. 2018). In addition, Jalil and Raza (2019) conducted a study to estimate the cost of cutting with diamond cutting wire in a Granite

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d, the consumption cost was about a quarter,

and the labor cost (the cost of non-repairable items, such as wires and fittings, etc.) was about one-fifth of the total cost spent in the cutting phase of stone mines performed through diamond cutting wire (Jalil and Raza 2019). Likewise, Zhang et al. (2019) conducted a series of shear tests to investigate the effect of operating parameters on the friction properties of diamond. Micromorphology was utilized to investigate the wear mechanism of the diamond. The analyses showed that the friction mechanisms of metal matrix of diamond piece could mainly be attributed to abrasive wear and erosion due to friction and liquid (Zhang et al. 2019).

Recently, apart from the existing traditional approaches, artificial intelligence methods and machine training for modeling and prediction have been successfully employed. Hence, in the present study, we presented two methods (SVR and GA-MLP). In each of the above methods, the allocation of data was done through three methods: Random, Filter + (Random), and separate file. Moreover, in this study, noise reduction was performed using a Savitzky-Golay filter (SG). One of the primary benefits of using the smoothing filter is to eliminate fluctuations and errors in measuring data and subsequently obtaining more desirable results. We also used three-stone properties, such as uniaxial compressive strength, Shimazk friction factor, and Young's modulus as input to the models, while considering the abrasion on the diamond segments as an output to predict the cutting performance of the diamond cutting wire. In the end, the accuracy of the mentioned models was investigated using the coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), mean value absolute error (MAD), mean absolute percentage error (MAPE), and variance of factor analysis (VFA). Indeed, the present research work was conducted to investigate the application and efficiency of the mentioned methods for evaluating the performance of diamond segments through cutting.

Support Vector Regression (Svr)

Support vector machines (SVM) have been a popular model since it was developed at the AT&T Bell Laboratories by Vapnik and colleagues (Burges et al. 1998; Smola and Schölkopf 2004; Zhong and Carr 2016). The SVMs used for classification problems are called SVCs, while those used for modeling and forecasting are called SVRs (Burges 1998; Smola and Schölkopf 2004). The simple structure of an SVR network can be seen in Fig. 3. According to this structure, the inputs first enter the middle layer (kernel functions). Next, the output of these functions is multiplied by a weight value and penetrates the final layer or the aggregate layer. Then, in the aggregation layer, all the previous layers' weighted output is added and multiplied by weight to give us the final output. Moreover, Kernel functions transferred data from a primary to a secondary space, where the data are linearly separable. The three well-known kernel functions include the Gaussian, polynomial, and linear functions, whose relationships are presented in Table 1 (Zhong and Carr 2016).

Table 1. Famous kernel functions used in SVR

Name kernel	Formula
Linear	$K(x_i, x_j) = x_i^T x_j$
RBF	$K(x_i, x_j) =$
Polynomial	$K(x_i, x_j) = (1)^d$

After applying the kernel functions, the relevant calculations were performed to obtain the model error and minimize it through an optimization algorithm. The model's error rate was determined by an error function based on the data deviation from the defined range. The following attempted to reduce this error through the social media optimization (SMO) optimization algorithm. Indeed, we decreased this error by changing the model parameters (kernel parameters, network weights, and biases).

Genetic Algorithm (Ga)

The first ideas of using genetic algorithms date back to the 1960s, so that there is voluminous research literature on this subject. This algorithm's main concepts presented in the current study can be found in Holland's book, which is based on natural evolution (Holland 1991). The genetic algorithm has three main operators performing the relevant calculations. These operators are described below:

- 1- Selection operator: is responsible for selecting the best answer.
- 2- Intersection operator: is responsible for combining answers to achieve a better solution.
- 3- Mutation operator: is responsible for changing the initial answers into new answers

Multilayer Perceptron Neural Networks (Mlpnns)

A multilayer perceptron artificial neural network (**MLPNN**) is a neural network with parallel processing capability that can either learn the known cases of a problem or predict or solve unknown cases of a problem. It is commonly used to solve problems with nonlinear distribution. An artificial neuron, which is very similar to biological neurons, acts as a basic unit in neural networks. Fig. 4 shows a model of an artificial neuron. According to this figure, a neural network structure consists of some inputs entering the network and several weights assigned to each of these input links. Each input link is multiplied by the corresponding weight, and the result enters the collector section. Then, all the multiplied inputs are added together to enter the Activation function (the activation function that decides whether to open or delay the signal to some neurons). Each activation function has a threshold value that decides whether to move the signal to the next layer or wait for it. The sum of the calculated inputs must be greater than this threshold. If this is the case, the signal will be transmitted to output; otherwise, the signal will be slower. In the above figure X_1, X_2 and X_n are the inputs fed to the neurons, While W_1, W_2 , and W_N are related to the

weight of input junction's neurons. Because inputs pass through neurons to produce output, this system is called a feeder (Kumar and Suresh 2016). Below, we listed different types of neural network structures:

- 1. Feed neural networks
- 2. Multilayer feed neural networks
- 3. Restoring Neural Networks

Savitzky-golay Filter

In this research, the Savitzky-Golay filter was selected because it can decrease noises as they can deform and irregulate data during the picking operation of data. Indeed, the superiority of the Savitzky-Golay filter in maintaining statistical distribution has made it a reasonable choice among all the smoothing filters. Moreover, a Savitzky-Golay is a digital filter that can be applied to a set of digital data points to irregulate the data, whose function is to increase the data's accuracy without distorting the signal orientation. This process is done particularly as the summation because Savitzky-Golay filter tends to be generated by placing consecutive subsets of adjacent data points with low-order polynomials utilizing the linear least-squares method. When the data points have equal space, there is a definite probability that an analytical solution to the least-squares equations can be obtained in the form of a single set of "cochlear coefficients" that can be applied to all data subsets (More information about the Savitzky-Golay filter are stated in (Luo et al. 2005; Savitzky and Golay 1964).

Study Areas And Laboratory Studies

In this study, 23 types of carbonate rocks from Mikaeil et al. (2018) article and 33 data from 11 different granite rocks from the diamond treatise were used (Mikaeil et al. 2018; Almasi et al 2017). In all the samples, the diamond segment's wear values were measured after a series of cutting experiments in each type of studied rock using digital micrometers in five different directions, as shown in Fig. 5. The difference between the values of the diamond cutting wire segment diameter before and after the cutting operation shows the average amount of wear on the diamond beads. The wear rate of each diamond segment was also calculated from this mean wear. The characteristics of the studied rocks, such as Shimazak wear factor, uniaxial compressive strength, and Young's modulus, and the amount of segment wear are given in Table 2.

Table 2. Diamond cutting wire Segment abrasion rate and characteristics of the studied (Mikaeil et al. 2018; Almasi et al 2017)

Sample number	WR ($\mu\text{m}/\text{dm}^2$)	UCS (MPa)	YM (GPa)	SFa (N/mm)
Granite	0.175	147	80.1	22.20
1	0.194	147	80.1	22.20
2	0.183	147	80.1	22.20
3	0.345	145	36.5	24.22
4	0.421	145	36.5	24.22
5	0.515	145	36.5	24.22
6	0.024	103	30.0	5.28
7	0.051	103	30.0	5.28
8	0.045	103	30.0	5.28
9	0.230	128	65.9	22.03
10	0.280	128	65.9	22.03
11	0.297	128	65.9	22.03
12	0.042	91	20.0	10.47
13	0.081	91	20.0	10.47
14	0.069	91	20.0	10.47
15	0.167	113	39.8	9.75
16	0.155	113	39.8	9.75
17	0.167	113	39.8	9.75
18	0.277	147	81.4	25.88
19	0.217	147	81.4	25.88
20	0.259	147	81.4	25.88
21	0.166	193	89.4	28.16
22	0.200	193	89.4	28.16
23	0.279	193	89.4	28.16
24	0.057	124	59.1	21.43
25	0.131	124	59.1	21.43
26	0.097	124	59.1	21.43
27	0.037	105	45.3	13.47
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js			45.3	13.47

29	0.043	105	45.3	13.47
30	0.136	126	46.4	17.85
31	0.188	126	46.4	17.85
32	0.176	126	46.4	17.85
33	0.00370	69.00	12.20	0.021
Real marble	0.00280	42.00	12.10	0.034
1	0.00260	55.00	11.00	0.154
2	0.00300	64.00	11.80	0.014
3	0.00820	52.26	17.02	0.004
4	0.00980	79.00	17.50	0.004
5	0.00820	63.49	21.14	0.004
6	0.00650	74.19	21.43	0.003
7	0.00490	51.84	15.96	0.003
8	0.00440	49.02	13.07	0.004
9	0.00440	45.57	15.72	0.003
10	0.00290	28.68	12.74	0.003
11	0.00150	30.00	9.86	0.002
12	0.00310	70.50	9.90	0.014
13	0.00370	72.00	12.50	0.014
Limestone	0.00380	70.00	13.20	0.013
1	0.00390	68.00	12.20	0.012
2	0.00610	55.30	22.83	0.061
3	0.00850	65.80	25.24	0.104
4	0.00710	59.77	17.43	0.122
5	0.00820	56.75	20.35	0.370
6	0.01990	105.48	20.25	0.122
7	0.01573	110.77	17.94	0.121
8				
9				
10				

Predicting The Amount Of Wear Using The Svr Model

In the current study, to generate an optimal MLP model, MLP neural networks' basic structure was first created. This structure consisted of an input layer, one or more hidden layers, and an output layer. Moreover, the multilayer perceptron algorithm was combined with the genetic algorithm, and the GA_MLP model was developed. After several analyses, the most appropriate control parameters were obtained. The control parameters considered to estimate the wear of the diamond cutting wire segment are the maximum number of 10 neurons, the number of layers 5, and the number of repetitions is 500. Data were assigned to the model through three methods: Random, Filter + (Random), and separate. The data allocation for training and testing of the models was 80 to 20 so that in the random method, the assignment was randomly done by the model. In contrast, in the separate file, the training and testing data sets were called directly. (We introduced 80% of the data to the model as training and 20% of them as testing). Moreover, in this study, the noise was reduced using a Savitzky-Golay (SG) filter. Three models were constructed, which are summarized in the evaluation results and the prediction of the data obtained to estimate the wear of the diamond cutting wire segment is shown in Table 5. The results presented in this table show that the SVR + filter (random) Poly method based on R², RMSE, MSE, MAD, VFA, and MAPE values is superior to the GA_MLP model.

Table 5. Results of estimation of wear of diamond cutting wire segment in cutting building stones

VFA%	MAPE%	MAD	RMSE	MSE	R ²	Model
91	41.99	0.03	0.05	0.002	0.85	GA-MLP (random)
91	17.52	0.03	0.04	0.002	0.81	GA-MLP+ filter (random)
99	4.93	0.01	0.07	0.005	0.60	GA-MLP (separate file)

Conclusion

In the present research work, the data related to Granite and Carbonate stones were used. Some models were also illustrated using the support vector regression (SVR) method and combining genetic algorithm and artificial neural network of multilayer perceptron (GA-MLP) with a lowpass smoothing filter Savitzky-Golay to predict the amount of segment abrasion for diamond cutting wire performance. According to the obtained results, the SVR + Filter (Random) technique with the polynomial Kernel was a reliable modeling method for predicting the abrasion rate of a diamond cutting wire segment. The determination coefficient (R²) with a value of 0.93, mean square error (MSE) of 0.000, root mean square error (RMSE) of 0.02, mean absolute value of error (MAD) of 0.01, mean absolute percentage error (MAPE) of 10.06, and variance of factor analysis (VFA) of 99.6 demonstrated the validity of the proposed model. Therefore, the SVR + Filter (Random) method with polynomial Kernel could be effectively used for the prediction of diamond wire cutting segment wear. It should be also mentioned that this study provided a good starting point for

further discussion and research; hence, more research could be conducted with more data and clustering methods to obtain better and more accurate results.

Declarations

Funding: There is no funding for this paper.

Conflicts of interest/Competing interests: The authors declare that they have no conflict of interest.

Availability of data and material: Not applicable

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Figures

Figure 1

Schematic presentation of a diamond wire-cutting layout (Özçelik 2005)

(a) Diagram of the wire sawing machine

(b) Structure of the diamond wire

(c) Contact curve

(d) Bead(diamond)/workpiece interface

Figure 2

Diamond cutting wire structure (Huang and Xu 2013)

Figure 3

A simple structure of an SVR network

Figure 4

Schematic of the structure of the artificial neuron in neural networks

Figure 5

Measuring device and measuring points to determine the scale of diamond cutting wire Segment (Mikaeil et al. 2018; Almasi 2017)

Figure 6

Comparison of actual and estimated values for training, test and total data sets

Figure 7

Regression diagram for training, test and total data sets