

Prediction of Cutting Performance of Diamond Wire Saw Machine in Quarrying of Marble: A Neural Network Approach

S. C. Jain · S. S. Rathore

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1 Introduction

In Global competitive era, the ultimate objective of any marble mine operator is to produce good quality blocks at optimum cost with maximum recovery. To reduce the cutting cost with diamond wire saw machine, it is necessary to get optimum cutting performance from the machine. Performance prediction of diamond wire saw machine is important in the cost estimation and planning of quarries. Performance of diamond wire saw machine also depends on the implementation of automatic setting device for real time control of pull-back force and of peripheral velocity.

All researchers have so far focused on evaluating and modeling of the large diameter circular saws cutting process, but no serious study has been made on diamond wire saws performance prediction in marble quarries. Gunaydin et al. (2004) investigated the correlation between sawability and different brittleness using regression analysis. They concluded that sawability of carbonate rocks can be predicted from the rock brittleness, which is half the product of compressive strength and tensile strength. Kahraman et al. (2004) developed alternative multiple

curvilinear regression models for the prediction of slab production of carbonate rocks with large diameter circular saws. With impregnated tools, continuous and efficient cutting can only be facilitated by compatible wear of the diamond particles and their bonding matrix (Wright et al. 2000; Wright and Engels 2003). The cutting rate in marble stone quarrying is a function of both the peripheral diamond wire velocity and the distribution of normal forces exerted on the rock by individual beads (Bortolussi et al. 1994).

Recently applications of artificial neural networks (ANN) have been introduced in the several fields of rock engineering (Yonghun and Chungin 2002). ANN system reduces the error by adjusting the interconnections between layers. Kahraman et al. (2005) derived artificial neural networks models for the sawability prediction of carbonate rocks with large diameter circular saws from shear strength parameters and compared it with simple and multiple regression models.

Graphical user interface (GUI) module used ANN tool of MATLAB 6.0 for predictability of the cutting performance of diamond wire saw and compared it with the multivariate regression analysis. Performance parameters cutting rate (Y_1) and diamond beads wear rate (Y_2) were predicted based on the shear strength parameter cohesion (c), peripheral velocity of diamond wire (n) and thrust on wire (t). Shear strength parameter was determined in laboratory by ISRM methods. The statistical evaluation was carried out using the SYSTAT 8.0 packet programs.

S. C. Jain (✉) · S. S. Rathore
Department of Mining Engineering, College of Technology and Engineering, Maharana Pratap University of Agriculture and Technology, Udaipur 313001, Rajasthan, India
e-mail: scjain44@rediffmail.com

S. S. Rathore
e-mail: ssrathore58@yahoo.co.in

2 Field Studies

Experiments were conducted on soft, medium-hard and hard dolomitic marble quarries to measure cutting

performance with variable speed diamond wire saw machine by varying peripheral speed and thrust parameters. Soft dolomitic marble has coarse-grained texture of calcite with subhedral grains of quartz, augite, pyroxene and muscovite; and has compressive strength 48.2 MPa. Medium-hard dolomitic marble has medium to coarse-grained texture of calcite with small grains of quartz and fibrous tremolite as mineral impurities; and has compressive strength of 58.4 MPa. Hard dolomitic marble has fine to medium grained texture of calcite with high amount of quartz grains; and has compressive strength 72.6 MPa.

Operational parameters of variable speed diamond wire saw machine used in the study are given in Table 1. The cutting operations in the quarry were performed on bench (10 m height \times 30 m width) for cut size 15 m length and 10 m height. Cutting rates (m^2/h) were calculated by dividing cut area of bench with time elapsed for cutting and wear rates ($\mu\text{m}/\text{m}^2$) calculated by dividing diameter reduced of beads with cut area of bench which are given in Table 2.

3 Laboratory Studies

In laboratory studies, shear strength parameter cohesion was determined. For this, marble cube blocks were collected from the studied quarries. Each block sample was inspected for macroscopic defects so that it would provide test specimens free from fractures, partings or alteration zones. Then standard test samples were prepared from these block samples. Triaxial compression tests were carried out on smooth core samples which had a diameter of 54 mm and a length-to-diameter ration of 2. The stress rate was applied within the limits of 0.5–1.0 MPa/s. Shear strength parameter cohesion was measured in accordance with the International Society of Rock Mechanics (ISRM 1981) methods given in Table 2.

Table 1 Operational parameters of the diamond wire saw machine

Parameters	Description
No. of beads/meter	30
Power of machine	
Main motor (ac)	44.7 kW
Feed motor (dc)	0.75 kW
Diamond wire peripheral speed	26–30 m/s
Voltage	440 V
Pulley diameter	800 mm
Pull-back force (thrust)	850/930/1010 N
Diamond beads	Sintered type (0.63 carat/bead)

4 Neural Network Models

The prediction of cutting performance of diamond wire saw machine is performed using ANN model. Multi-layered perception neural network structure is implemented in the MATLAB environment. The structure of the ANN models is given below:

Network type	Multi-layer feed forward backdrop
Adaptive Learning function	Gradient descent method
Training algorithm	Levenberg–Marquardt
Transfer function	Sigmoid
No. of input neurons	03
No. of output neurons	02
No. of hidden layers	01
No. of hidden neurons	06
No. of training epochs	500
No. of datasets	36

The constructed model established a non-linear relation between the input parameters—shear strength parameter cohesion (c), peripheral velocity (n) and thrust (t) with cutting performance of diamond wire saw. This is as follows:

$$P_h = f(c, n, t)$$

where P_h is cutting performance measured in the form of cutting rate (m^2/h) and beads wear rate ($\mu\text{m}/\text{m}^2$). Result obtained from the neural network model is given in Table 2. Performance observed was 0.001329 and 1.08 e–06 by ANN models for prediction of cutting rate and wear rate, respectively.

5 Multiple Regression Models

Multiple regression models were developed based on same input independent variables and output-dependent variables as used in the neural network model. This resulted in the following equations:

$$Y_1 = -4.9260 - 0.1268 c + 0.0345 n + 0.0134 t \quad (1)$$

$$Y_2 = -0.8059 + 0.0395 c + 0.0139 n + 0.0007 t \quad (2)$$

where Y_1 = cutting rate (m^2/h), Y_2 = beads wear rate ($\mu\text{m}/\text{m}^2$), c = cohesion (MPa), n = peripheral velocity (m/s), t = thrust (N).

The correlation coefficient for the predicted and observed values for cutting rate and wear rate are 0.896 and 0.967, respectively. Above equations indicate that peripheral speed and thrust parameters have positive constant values, which imply that both have positive impact on both cutting rate and beads wear rate. The equations also indicate that cohesion

Table 2 Results of field and laboratory studies and predicted values by ANN and regression models

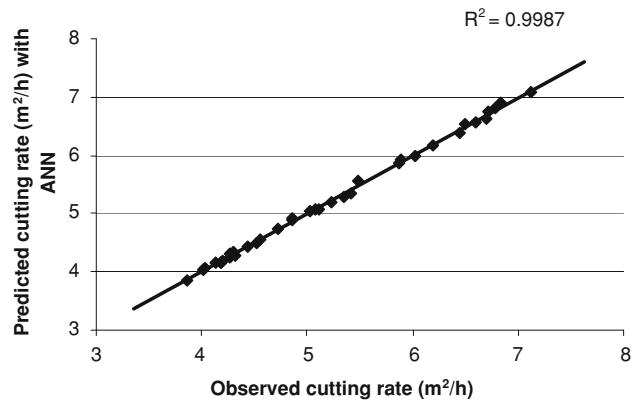
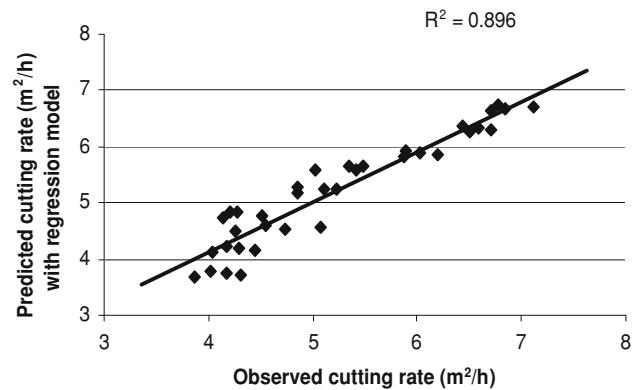
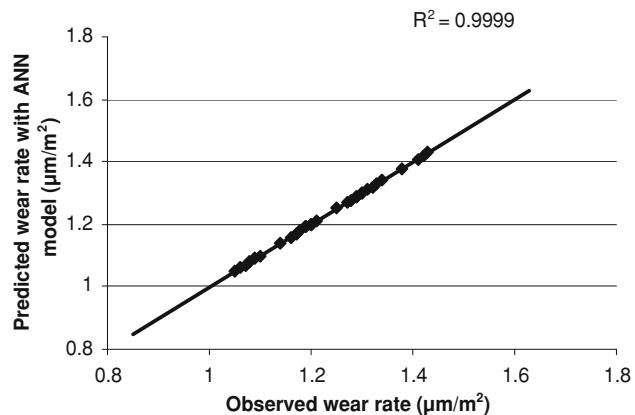
S. no	Shear strength parameters (confining pressure range: 3–15 MPa and compressive strength: 56.7–119.2 MPa) based on five specimen	Peripheral speed [(n) m/s]	Thrust/pull-back force [(t) N]	Cutting performance measured in field	Predicted cutting performance by ANN model		Predicted cutting performance by Regression model
					Cutting rate [(Y_1) m ² /h]	Diamond beads wear rate [(Y_2) $\mu\text{m}/\text{m}^2$]	
1	22.80	18	27	850	4.26	1.05	4.25
2	22.80	18	28	850	4.73	1.07	4.74
3	22.80	18	29	850	5.08	1.08	5.06
4	22.80	18	30	850	4.55	1.09	4.55
5	22.80	18	27	930	5.03	1.06	5.03
6	22.80	18	28	930	5.41	1.08	5.36
7	22.80	18	29	930	5.48	1.09	5.55
8	22.80	18	30	930	5.34	1.10	5.30
9	22.80	18	27	1,010	6.70	1.14	6.63
10	22.80	18	28	1,010	6.84	1.17	6.90
11	22.80	18	29	1,010	7.12	1.19	7.08
12	22.80	18	30	1,010	6.78	1.20	6.82
13	25.80	22	27	850	4.03	1.16	4.08
14	25.80	22	28	850	4.44	1.18	4.42
15	25.80	22	29	850	4.30	1.19	4.33
16	25.80	22	30	850	4.18	1.20	4.15
17	25.80	22	27	930	4.86	1.17	4.91
18	25.80	22	28	930	5.23	1.19	5.20
19	25.80	22	29	930	5.11	1.20	5.08
20	25.80	22	30	930	4.86	1.21	4.90
21	25.80	22	27	1,010	6.50	1.25	6.53
22	25.80	22	28	1,010	6.71	1.28	6.75
23	25.80	22	29	1,010	6.59	1.29	6.58
24	25.80	22	30	1,010	6.44	1.30	6.38
25	29.00	25	27	850	3.86	1.27	3.85
26	29.00	25	28	850	4.31	1.29	4.27
27	29.00	25	29	850	4.18	1.30	4.16
28	29.00	25	29	850	4.02	1.31	4.05
29	29.00	25	26	930	4.14	1.29	4.17
30	29.00	25	27	930	4.52	1.32	4.48
31	29.00	25	28	930	4.27	1.33	4.30

Table 2 continued

S. no	Shear strength parameters (confining pressure range: 3–15 MPa and compressive strength: 56.7–119.2 MPa) based on five specimen	Peripheral speed [m/s]	Thrust/pull-back force [(t) N]	Cutting performance measured in field	Predicted cutting performance by ANN model	Predicted cutting performance by Regression model
Cohesion [c] MPa	Internal friction angle [Φ] degree]			Cutting rate [(Y_1) m ² /h]	Diamond beads wear rate [(Y_2) $\mu\text{m}/\text{m}^2$]	Cutting rate (m ² /h) beads wear rate ($\mu\text{m}/\text{m}^2$)
32	29.00	25	29	930	4.20	1.34
33	29.00	25	26	1,010	5.87	1.38
34	29.00	25	27	1,010	6.20	1.41
35	29.00	25	28	1,010	6.02	1.42
36	29.00	25	29	1,010	5.89	1.43

Table 3 Standard error of estimates

Models	Standard error of estimate
ANN (cutting rate)	0.00133
Regression (cutting rate)	0.339
ANN (wear rate)	1.08 e–006
Regression (wear rate)	0.02

**Fig. 1** Predicted versus measured cutting rates by ANN model**Fig. 2** Predicted versus measured cutting rates by regression model**Fig. 3** Predicted versus measured wear rates by ANN model

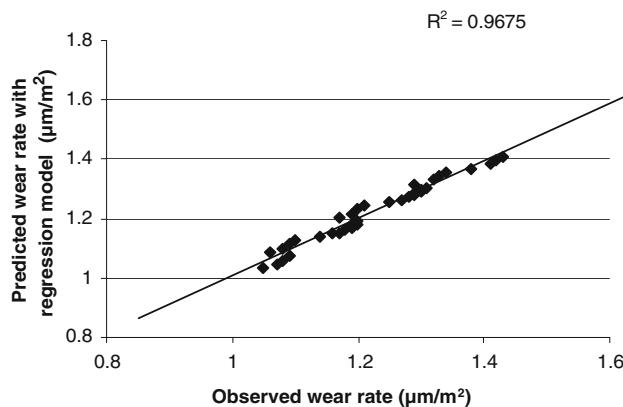


Fig. 4 Predicted versus measured wear rates by regression model

has positive impact on beads wear rate and negative impact on cutting rate.

6 Discussion

The determination coefficients obtained were 0.998 and 0.999 from ANN models and 0.896 and 0.967 from regression models for cutting rate and wear rate, respectively. Thus, according to the determination coefficient, ANN has a better performance compared to the multivariate regression analysis. However, determination coefficient does not necessarily identify the most appropriate models. Standard errors of estimates are shown in Table 3. It shows that standard errors of estimate for the ANN models are much lower than that of the regression models. Finally, the models were compared according to the plots of observed and predicted cutting and wear rate values. Estimated cutting rates were plotted against the observed cutting rates for ANN and regression models which are shown in Figs. 1 and 2, respectively. Similarly, estimated wear rates were plotted against the observed wear rates for ANN and regression models and are shown in Figs. 3 and 4, respectively. Points lying on the line indicate an exact estimation. Prediction capability of the ANN model is much better than that of the regression model.

On the basis of above discussion, it was concluded that ANN models give much better prediction than regression models.

7 Conclusions

Mine operators wish to know the cutting performance of diamond wire saw for the planning of production of marble

blocks and cost estimation. An accurate estimation of cutting performance helps to plan a marble quarry more efficiently and reduces the bench cutting cost. For this reason, ANN models were developed for the prediction of cutting performance from shear strength parameter cohesion and machine parameters peripheral speed and thrust, and the results were compared with multiple regression models. It was concluded that applicability of ANN for cutting performance prediction of diamond wire saw machine in dolomitic marble is more reliable than the regression models. The determination coefficients for the predicted and observed values for ANN and regression models were for cutting rate 0.998 and 0.896 and for wear rate 0.999 and 0.967, respectively. Also standard errors of estimates for ANN and regression models were for cutting rate 0.00133 and 0.339 and for wear rate 1.08 e–006 and 0.02, respectively. The peripheral speed and thrust parameters have positive impact on both cutting rate and beads wear rate. Cohesion has positive impact on beads wear rate and negative impact on cutting rate.

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