Arab J Sci Eng (2015) 40:2003–2012
DOI 10.1007/s13369-015-1589-x

RESEARCH ARTICLE - EARTH SCIENCES

Performance Prediction of Diamond Sawblades Using Artificial Neural Network and Regression Analysis

Gokhan Aydin · Izzet Karakurt · Coskun Hamzacebi

Received: 24 September 2014 / Accepted: 19 January 2015 / Published online: 31 January 2015

Abstract This paper is concerned with the application of artificial neural networks (ANNs) and regression analysis for the performance prediction of diamond sawblades in rock sawing. A particular hard rock (granitic) is sawn by diamond sawblades, and specific energy (SE) is considered as a performance criterion. Operating variables namely peripheral speed (V_p), traverse speed (V_c) and cutting depth (d) are varied at four levels for obtaining different results for the SE. Using the experimental results, the SE is modeled using ANN and regression analysis based on the operating variables. The developed models are then tested and compared using a test data set which is not utilized during construction of models. The regression model is also validated using various statistical approaches. The results reveal that both modeling approaches are capable of giving adequate prediction for the SE with an acceptable accuracy level. Additionally, the compared results show that the corresponding ANN model is more reliable than the regression model for the prediction of the SE.

Keywords Diamond sawblades · Granite · Specific energy · Artificial neural networks · Regression analysis

G. Aydin · I. Karakurt (✉)
Mining Engineering Department, Faculty of Engineering, Karadeniz Technical University, 61080 Trabzon, Turkey
e-mail: karakurt@ktu.edu.tr

C. Hamzacebi
Industrial Engineering Department, Faculty of Engineering, Karadeniz Technical University, 61080 Trabzon, Turkey

List of symbols

F_h	Horizontal force (N)
F_v	Vertical force (N)
F_z	Axial force (N)
F_n	Normal force (N)
F_t	Tangential force (N)
F_c	Cutting force (N)
D_s	Disc diameter (mm)
W	Width of the sawblade segments
d	Cutting depth (mm)
V_c	Traverse speed (m/s)
V_p	Peripheral speed (m/s)
Q_f	Flow rate of cooling fluid (ml/s)
φ	The total included angle of the contact zone (degrees) and
$k\varphi$	The angle showing the location of the resultant force (degrees)
F_c	Cutting force (N)
SE	Specific energy (kN/mm^3)
RM	Regression models
MRA	Multiple linear regression analysis
ANNs	Artificial neural networks

1 Introduction

As a constructional material, the use of granites has dramatically increased recently owing to their excellent features such as beautiful colors, high durability, and resistance to the environmental conditions [1]. This increase has resulted in improving the performance of machining and processing technologies for the granite production. Circular diamond sawblades have extensive applications in granite production. Since they have been widely used as a machining technology, many documents investigating the cutting performance of these technology have been reported in the published literature [2–21].

For the natural stone industry, predictive models could provide opportunity to evaluate the machining performance without conducting complex test procedures. Therefore, various modeling techniques have been recently employed in recent studies aiming at modeling the cutting performance of circular diamond sawblades. Yurdakul and Akdaş [22]; Yasitli et al. [23]; Aydin et al. [24]; Karakurt et al. [25]; Aydin et al. [26]; Aydin et al. [27]; Karakurt et al. [28]; Karakurt [29] are the recent studies using different modeling techniques. Among different modeling techniques, simple and multiple regression techniques have been mostly employed for the modeling purposes in the several fields of geosciences. This is because (1) they are appropriate techniques when the research problem includes one dependent variable that is related to two or more independent variables and (2) they can easily be used for determining the linear and/or nonlinear relationship between dependent predictive and independent criterion variables. On the other hand, Artificial Intelligent (AI)-based models have recently gained attention for conventional and nonconventional machining technologies. As one of the AI based models, the ANN approach has been mostly preferred for modeling the rock material behavior [30]. The main reasons for this preference can be listed as (1) the capability for learning and generalizing interactions among many variables; (2) more successful when compared to conventional approaches, in terms of capacity to learn from examples, especially when the existing of nonlinear relationship between the dependent and independent variables; (3) a multidisciplinary nature providing popularities among researchers, planners, and designers; (4) showing a good performance in the solving of nonlinear multivariable problems; (5) continuously re-train the new data meaning that it can conveniently be applied to new data; and (6) no need of any assumption for the degree of nonlinearity among the variables [31].

In the relevant literature, the effects of operating variables and material properties on the performance of the circular diamond sawblades have been investigated in detail. Additionally, some studies have provided predictive models based on the rock properties for performance prediction of circular diamond sawblades. Therefore, differing from other studies documented, the current study only focused on the operating variables of diamond sawblades for modeling of the SE using ANNs and RA. In this regard, the study will be the first attempt for modeling the sawblade performance as a function of operating variables using ANNs.

2 Experimental Study

2.1 Experimental Setup

Sawing tests were performed on an experimental cutting machine with a high precision (see Fig. 1). The sawing machine consists of three major sub-systems: a sawing unit, instrumentation, and a personal computer (PC). The diamond sawblade used in the tests was of 40 cm diameter having 28 impregnated diamond segments (circumferential length 40 mm, width 3.5 mm, and height 10 mm). The diamonds were sized at 40/50 US mesh with a concentration of 30, which is commercially recommended for the sawing of hard materials.

Disc movements forward–backward in the horizontal plane and up–down in the vertical plane were driven with two 0.75 kW motors, while the rotation of the disc was provided by a 4 kW motor. Moreover, 0.75 kW motor was used to move the wagon in the cutting line. Operating variables were measured using sensors, load cells, transducers, and an encoder in the monitoring system. All movements of the sawing machine were controlled by the PC and industrial electronic control cards.

2.2 Material Characteristics

In this study, a particular granitic rock was sampled and dimensioned according to the requirements of the study (a length of 30 cm and 10 cm × 3 cm sections). The physical properties of the rock which is traditionally known as Balaban Green are presented in Table 1. The specific mass (grams per cubic centimeter), water absorption by volume (percent), porosity (percent), ultrasonic velocity (meters per second), Schmidt hammer hardness, and Shore hardness are determined according to methods suggested by the International Society for Rock Mechanics [32], while the microhardness of the sample was measured by a Vickers Microhardness meter as recommended by Xie and Tamaki [33]. A similar procedure with the determination of microhardness was followed for the determination of Mohs' hardness of the rock sample. For Cerchar abrasiveness index testing, a pointed steel pin having 610 ± 5 Vickers hardness, 200 kg/mm^2 tensile strength, and a cone angle of 90° was applied to the surface of the rock samples for approximately one second under a static load of 68.646 N to scratch a 10 mm long groove.

This procedure was repeated five times in various directions using a fresh pin for each repetition. The abrasiveness of the rock was determined by the resultant wear flat generated at the point of the stylus, which was measured in 0.1 mm units under a microscope. The unit of abrasiveness was defined as a wear flat of 0.1 mm which is equal to 1 Cerchar abrasivity index, ranging from 0 to 6. Thin section of the rock was also examined under a petrographical microscope for deter-

Fig. 1 Experimental setup

Table 1 Physical properties of rock used in the sawing tests

Rock properties	
Specific weight (kN/m^3)	26.6
Water absorption by volume (%)	0.19
Porosity (%)	2.20
Ultrasonic velocity (m/s)	4,849
Cerchar abrasion index	4.356
Schmidt hammer hardness	55
Microhardness (HV)	559.03
Shore hardness	75.15
Mohs' hardness	6.0

mining the mineral type and content (see Fig. 2). Moreover, the point count method was employed for the modal analyses. These examinations mainly included the determination of modal compositions and grain size distributions of the sampled rock. The mineralogical composition of the sampled rock is given in Table 2 along with its textural and granular description. As can be followed from the Table, alkali feldspar, quartz, plagioclase, and amphibole are the main rock-forming minerals in the sample, varying in their percentage contents. Additionally, grain sizes of the rock-forming minerals were also determined using a digital image processing software of Dewinter Material Plus 4.1, and the mean grain size of the sampled rock was then calculated.

2.3 Experimental Procedure

In the study, SE is considered as a performance criterion. The SE has been successfully used for the performance evaluation of circular diamond sawblades in granite sawing. It is derived from the amount of energy required to remove a given volume of rock. The lower value of SE indicates that the sawing is performed more efficiently [19]. In order to determine the levels of the operating variables for the study, preliminary sawing tests were conducted by considering instructions of diamond disc manufacturers and related studies. The levels for operating variables of peripheral speed (V_p), traverse speed (V_c), and cutting depth (d) were selected as given in Table 3 and each varied at four levels. A factorial design requiring 64 trials was followed for the sawing tests. Each trial was repeated four times to increase the accuracy of results obtained. The sawing experiments were conducted in the down-cutting mode, and the dimensioned samples were cut through their lengths. The horizontal (F_h) and vertical (F_v) force components acting on the disk were measured using load cells. The tangential (F_t) force and normal (F_n) force were derived from the Eqs. (1–11) considering the geometrical relations presented in Fig. 3 [34]. Finally, the SE was calculated through the Eq. (12).

$$\cos\delta = \frac{F_v}{F_c} \tag{1}$$

$$\sin\delta = \frac{F_h}{F_c} \tag{2}$$

$$F_n = F_c\cos[(k\varphi) - \delta] \tag{3}$$

$$F_n = F_c\left[\cos(k\varphi)\frac{F_v}{F_c} + \sin(k\varphi)\frac{F_h}{F_c}\right] \tag{4}$$

$$F_n = F_v\cos(k\varphi) + F_h\sin(k\varphi) \tag{5}$$

$$F_t = F_c\sin[(k\varphi) - \delta] \tag{6}$$

$$F_t = F_c\left[\sin(k\varphi)\frac{F_v}{F_c} - \cos(k\varphi)\frac{F_h}{F_c}\right] \tag{7}$$

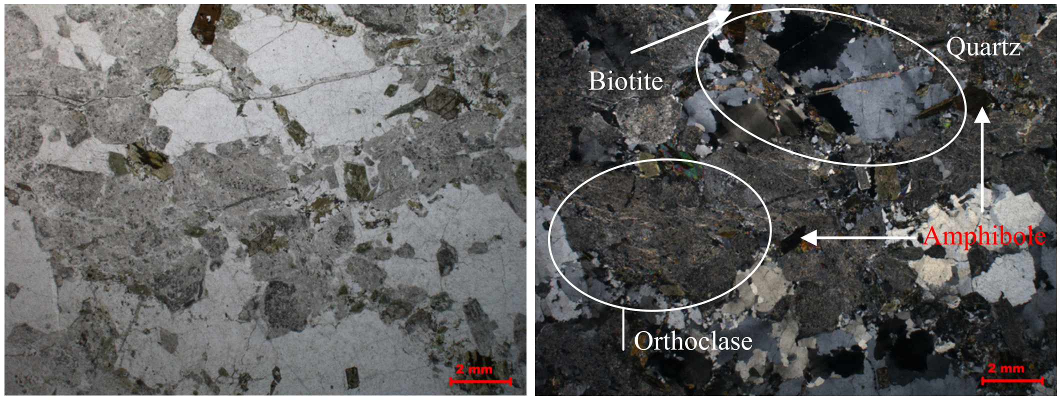

Fig. 2 Photographs of the thin section of the rock tested

Table 2 Mineralogical properties of the rock sawn

Mineral	Grain Size (mm)			Prop. (%)	Summary of petrographic description (texture, grain size)
	Min.	Max.	Mean		
Alkali feldspar (orthoclase. mikroklin)	0.80	6.80	2.1	38	Hypidiomorphic, coarse-grained, grains between 0.08 and 6.80 mm
Quartz	0.16	5.60	2.7	25	
Plagioclase	0.96	5.20	2.2	14	
Amphibole	0.24	1.20	0.4	10	
Epidot	0.08	0.40	0.1	6	
Biotite	0.48	3.20	0.7	4	
Other and secondary components (mica, titanit, zircon, opaque)	0.16	0.96		3	

Table 3 Operating variables and their levels

Operating variables	Level			
V_p (m/s)	25	30	35	40
V_c (cm/min)	50	60	70	80
d (cm)	0.5	1.0	1.5	2.0
Q_f (ml/s)	150 (kept constant)			

$$F_t = F_v \sin(k\varphi) - F_h \cos(k\varphi) \tag{8}$$

$$F_c = \sqrt{F_n^2 + F_t^2} \tag{9}$$

where F_h is horizontal force (N), F_v vertical force (N), F_z axial force (N), F_n normal force (N), F_t tangential force (N), F_c resultant cutting force (N), D_s disc diameter (mm), d cutting depth (mm), V_c traverse speed (m/s), V_p peripheral speed (m/s), φ the total included angle of the contact zone (degrees), and $k\varphi$ is the angle showing the location of the resultant force (degrees). The total included angle of the contact zone (φ) and the angle ($k\varphi$) indicating the location of the resultant force can be calculated by the following formulas:

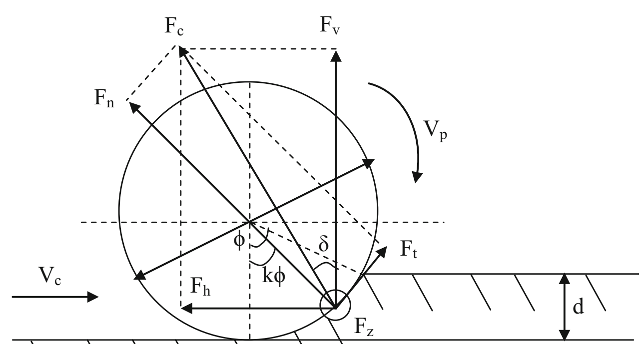

Fig. 3 The kinematics of cutting process for the down-cutting model

$$\varphi = \cos^{-1}\left(1 - \frac{2d}{D_s}\right) \tag{10}$$

$$k\varphi = 0.7\varphi \tag{11}$$

Specific energy was calculated as:

$$\mathrm{SE} = \frac{F_t V_p}{d W V_c} \tag{12}$$

where W is the width of the sawblade segments.

3 Modeling Studies

3.1 Artificial Neural Networks (ANNs)

ANNs which are a branch of artificial intelligence (AI) attempt to imitate the brain functions and learn from sample data presented to them with the purpose of capturing the relationship among data. ANNs are considered as a type of intelligent tool for solving complex problems. In each neuron of ANNs consisting of densely interconnected simple processing units referred as neurons, the input data are processed and a single output is obtained [35]. In the presented study, a Multi-Layer Perception (MLP) type of ANNs has been used for prediction of SE. A MLP network is the most commonly employed ANN architecture. A typical MLP structure is shown in Fig. 4. A MLP has three types of layers: the input, output, and the hidden layers. Each neuron on the input layer is assigned to an attribute in data and produces an output which is equal to the scaled value of the corresponding attribute. The hidden layers, usually numbering one or two, are intermediate between the input and output layers [36]. The mathematical expression of the output of the MLPs as shown in Fig. 4 is presented below.

$$Y = f\left(\beta + \sum_{j=1}^{m} v_j \left[\sum_{i=1}^{n} g(w_{ij}X_i + \theta_j)\right]\right) \tag{13}$$

where Y is the prediction value of dependent variable; X_i is the input value of ith independent variable; w_{ij} is the weight of connection between the ith input neuron and jth hidden neuron; θ_j is the bias value of the jth hidden neuron; v_j is the weight of connection between the jth hidden neuron and output neuron; β is the bias value of output neuron; and $f(.)$ and $g(.)$ are the activation functions of output and hidden neurons respectively.

Training is a very important procedure for a MLP to accomplish a required task. Training of a MLP means to determine the best weights of connections between the neurons in order to obtain minimum difference between actual and predicted value of dependent variable. Back propagation is a most widely used training algorithm. On the other hand, some factors such as number of input neurons, hidden neurons, output neurons, and activation function affect the ANNs performance. In a prediction problem based on cause and effect relationship, the number of input neurons is equal to the number of independent variables, and the number of output neurons is equal to the number of dependent variables. In order to determine the number of hidden neurons, heuristic approaches may be used or experimental design may be done [37]. Although there are some proposed approaches [38–42] in the literature to determine the number of hidden neurons, they are not valid for all the problems [43].

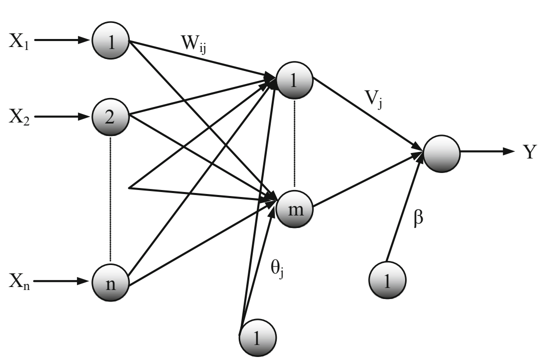

Fig. 4 A typical MLP structure of ANNs

3.2 Regression Analysis

Regression analysis (RA) was performed for the prediction of SE from operating variables in the presented study. As one of the traditional statistical methods is used for proposing an indirect estimation by empirical equations, RA is widely used for modelling and analyzing the experimental results. RA focuses on learning more about the relationship between several predict or variables and a dependent. The performance of the model depends on a large number of factors that act and interact in a complex manner [44,45]. Simple RA can show how a single dependent variable is affected by the values of one independent variable. This method only involves the X_i variable as a predictor and the Y variable as an outcome. Therefore, simple RA has mainly two anomalies. One is related to the number of predictors, and the other is related to the prediction of most significant X variable among independent variables. Because if two or more predictors are used for the simple RA, each predictor can separately show an individual relationship with the outcome variable and it cannot predict the most significant X variable among independent variables [46]. On the other hand, multiple regression analysis (MRA) is a powerful modeling technique and can be useful in those cases where complex relations are involved. Additionally, MRA can be the right method where more than one variable affects a material property as pointed out by Karakus et al. [47]. A multiple linear regression model is generally expressed by the relationship between a single outcome variable (Y) and some explanatory variables (X_i) given as:

$$Y = a + b_1X_1 + b_2X_2 + \cdots + b_nX_n \tag{14}$$

where the term Y is the outcome variable (estimated from X_i), a is the constant, and b_i are the partial regression coefficients.

Following the regression model establishing, goodness of fit of the models and the statistical significance of the estimated variables is generally confirmed by various statistical approaches. F test is used to determine the overall signifi-

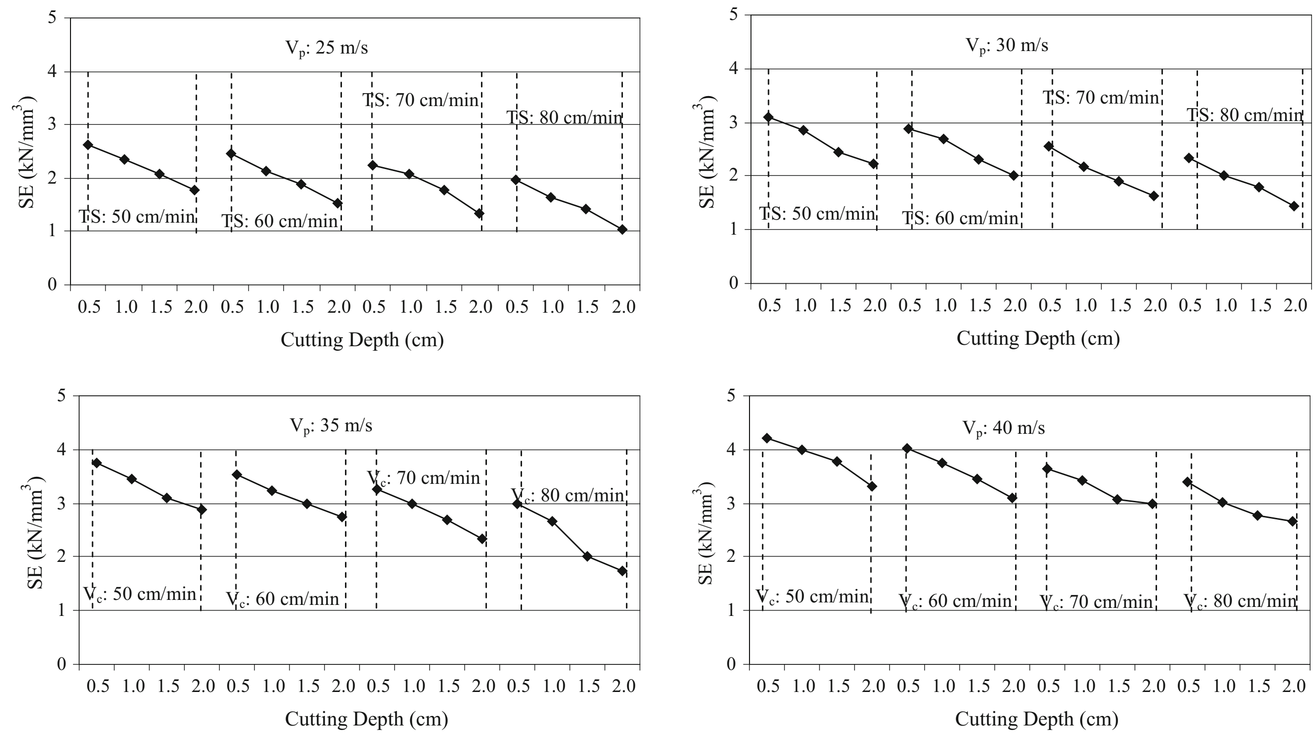

Fig. 5 Experimental results

cance, i.e., whether there is a significant relationship between the response and the set of all the predictors. If the F test shows an overall significance, then separated t test is conducted to determine the individual significance, i.e., whether each of the predictors is significant or not. If the calculated F- and t-ratios are greater than the tabulated F- and t-ratios (obtained from F and t distribution Tables), the validation of model is confirmed [48].

4 Results and Discussion

Experimental results are presented in Fig. 5 in graphical form. As can be understood, the independent variables (operating variables) are highly correlated with the dependent variable, SE, and therefore, they are seemed to be significant for using them in the models that will be developed for the prediction of SE. A better model that has high correlation coefficient has not been produced by discarding one or two independent variables. Therefore, it was decided to include these three variables in the model. Using 64 trials' results, the developed regression model is given below. As seen, the dependent variable, the SE, is a linear function of three independent variables.

$$\mathrm{SE} = (1.784) + (0.103)V_\mathrm{p} - (0.027)V_\mathrm{c} - (0.598)d \qquad (15)$$

where SE is the specific energy (Nm/mm^3), V_p is the peripheral speed (m/s), V_c is the traverse speed (cm/mm), and d is the cutting depth (cm).

The statistical results of confirmation tests for the developed model validation are given in Table 4. As seen, the determination coefficient of the model is 0.98 indicating a high degree of relationship between the operating variables and SE. This value implies that 0.02 % of the variation in the SE is due to all causes other than the predictors as they appear in the expression. Similarly, it can be stated that 0.02 % variation in the SE remains unexplained.

Additionally, it can be also concluded that the calculated F- and t-ratios are greater than the tabulated F- and t-ratios confirming the correctness of the whole model and individual variables involved in the model, respectively. Consequently, it can be concluded that the validation of the developed model has statistically confirmed and the SE may be modeled in this way.

To develop model for the SE by ANNs, inputs and output of the model were determined. While peripheral speed, traverse speed, and cutting depth are the inputs, the SE is the output of the model. After preparation of the data belonging to the inputs and output, the network was trained. The training was carried out by making attempts to establish different ANN models with different network architecture and learning parameters. The models were tested using a test data set which was not utilized for the training processes in order to test the performance of networks. Thus, ANN models given the most sensitive results were targeted. As a result, the ANN models produced the closest values to the actual values were chosen as the prediction models. ANN models

Table 4 Statistical results of the MRA

Independent variables	Coefficient	Standard error	Standard error of estimate	t value	Tabulated t value	F ratio	Tabulated F ratio	Determination coefficient (R^2)
C	1.784	0.116	0.108	15.361	2.388	981.732	4.968	0.98
V_p	0.103	0.002		42.710				
V_c	−0.027	0.001		−22.589				
d	−0.598	0.024		−24.715				

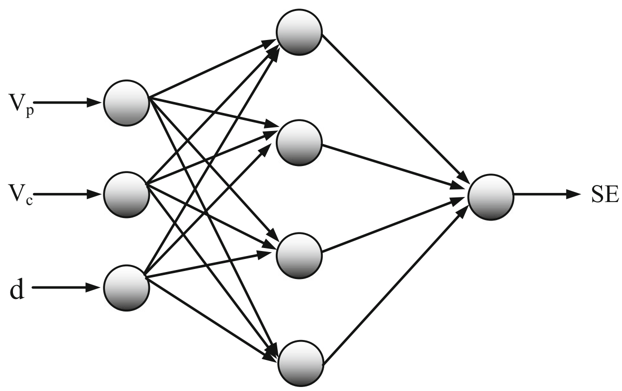

Fig. 6 ANN model for SE

consisting of one input layer, one hidden layer, and one output layer selected as the prediction models are shown in the Fig. 6 for the SE. The number of neurons in the hidden layer was determined by trying various networks. The number of hidden layer neurons was changed from 2 to 8, and finally the best number of hidden layer neurons was found as 4. Hyperbolic tangent was preferred as the activation function and linear transfer function in the hidden and output layers, respectively.

Bayesian regularization training function (trainbr in MATLAB coding) was chosen as training algorithm. The data set was splitted into two separate parts for learning and validation purposes. Data belong to the 69 trials (five of them is the test data set which was not utilized for the training processes) were used for training (32 data set, 46.4 % of total trials), validating (32 data set, 46.4 % of total trials), and testing (5 data set, 7.2 % of total trials) of ANNs. In order to evaluate the performance of the ANNs in training phase, root-mean-square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) measures were preferred as their equations are given below.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{16}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\left|\frac{e_i}{y_i}\right|\right) \times 100 \tag{17}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{18}$$

where n is the total number of measurements, e_i is differences between actual (measured) and predicted values, and y_i is actual values. Finally, three input neurons, four hidden neurons, and one output neuron were determined for the best ANN model. By using this model, the obtained performance measures for training data are as 0.078, 2.225, and 0.056 for the RMSE, MAPE, and MAE, respectively. Accordingly, the determination coefficient (R^2) of the ANN model was obtained as 0.994.

5 Comparison and Evaluation of Regression and ANN Models

In this part of the study, the performances of developed models by RA and ANNs were compared and evaluated. To compare both models' performances, RMSE, MAPE, and MAE performance measures were used. The accuracy of prediction is evaluated based on the estimation of error, thus the smaller the value of RMSE, MAPE, and MAE, the better the prediction is. Herein, the criterion of MAPE is the decisive factor as it is expressed in easy generic percentage term.

The criteria of MAPE for model evaluation indicated by Lewis [49] and the compared results for the models developed by ANNs and RA are given in Tables 5 and 6, respectively. As seen, the MAPE values were determined as 3.064 and 5.34 % for ANN and regression models, respectively. Similarly, the RMSE values were determined as 0.088 and 0.113, while the MAE values were determined as 0.068 and 0.121 for ANN and regression and models, respectively. Additionally, the determination coefficients of the ANN and

Table 5 Typical MAPE values for model evaluation

MAPE (%)	Evaluation
MAPE ≤ 10 %	High accuracy prediction
10 % < MAPE ≤ 20 %	Good prediction
20 % < MAPE ≤ 50 %	Reasonable prediction
MAPE > 50 %	Inaccurate prediction

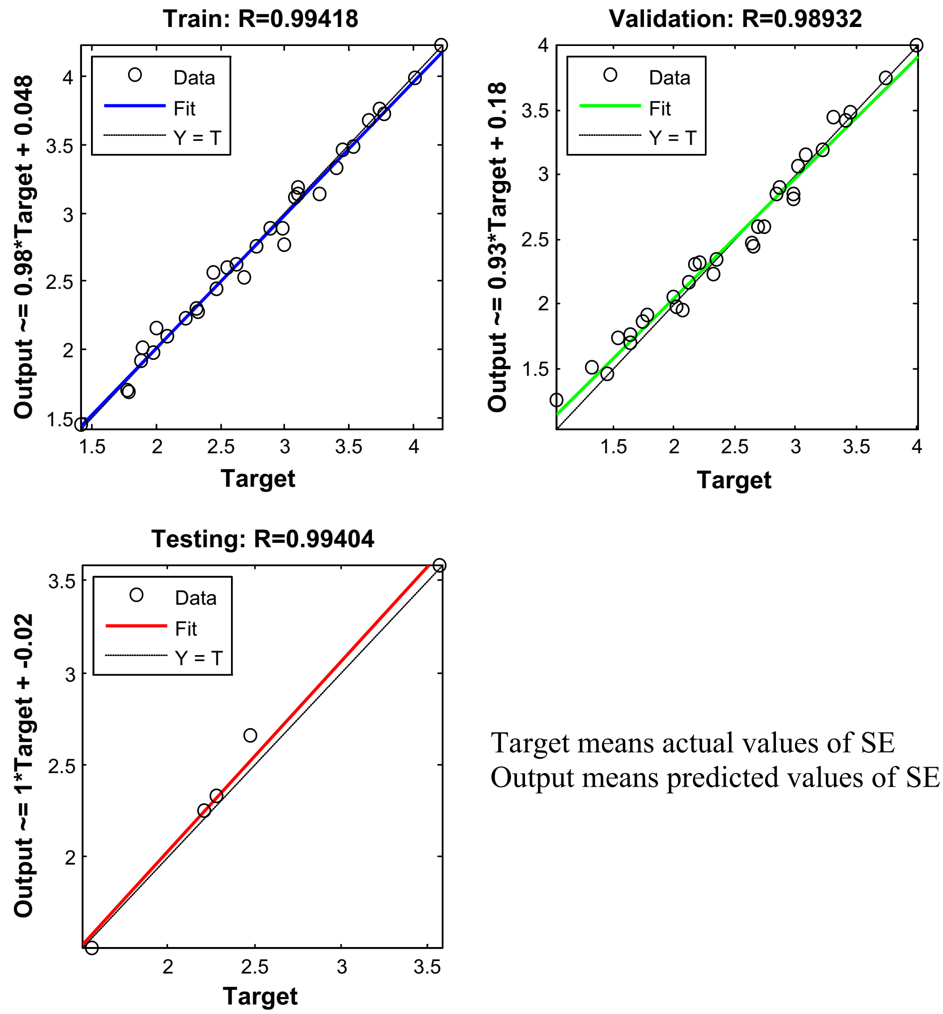

Fig. 7 Plots of training, validating and testing data for the ANN model

Table 6 Compared results for ANNs and RA models

Model type	Experimental	Prediction	MAPE (%)	RMSE	MAE	R^2
ANNs	2.21	2.24	3.06	0.08	0.06	0.99
	1.56	1.49				
	2.28	2.28				
	2.48	2.64				
	3.57	3.60				
RA	2.21	2.29	5.34	0.113	0.121	0.98
	1.56	1.51				
	2.28	2.36				
	2.48	2.67				
	3.57	3.50				

regression models were found as 0.99 and 0.98, respectively as shown in Fig. 7. The compared results revealed that both models can give adequate prediction for the SE with a high accuracy prediction because their MAPE are in the ranges of $\leq 10\,\%$ (see Table 5). However, it can be stated that the corresponding ANN model is more reliable than the regression model for the prediction of SE as this model has the lower MAPE of 3.064 %.

Furthermore, focused on the predicted SE values, the evaluation of the developed regression and ANN models is given as follows as reported by Mohd Zain et al. [50]:

1. Experimental data versus regression
   The minimum SE value (since minimum SE is desired in sawing applications) among the experimental trials (Table 6) was obtained as 1.56 kN/mm^3. Therefore, with the predicted minimum SE of 1.51 kN/mm^3 (Table 6), it can be stated that the regression model has given a minimum value of the SE compared to experimental data by about 0.05 kN/mm^3.
2. Experimental data versus ANN
   With the predicted minimum SE $=$ 1.49 kN/mm^3 for ANN and SE $=$ 1.56 kN/mm^3 for experimental data, it

can be stated that the ANN model has given a minimum value of the SE compared to experimental data by about 0.07 kN/mm^3.

3. Regression versus ANN
With SE = 1.51 kN/mm^3 for regression and SE = 1.49 kN/mm^3 for ANN models, it can be stated that the ANN model has given a minimum value of the SE compared to regression model by about 0.02 kN/mm^3.

As it is seen, the ANN and RA techniques are capable of giving minimum value of SE compared to experimental data in rock sawing applications by diamond sawblades.

6 Conclusions

A modeling study using ANN and regression techniques on the SE in sawing of granitic rock was presented in the current study. Models' performances were measured, compared, and evaluated for showing the accuracy levels in prediction of SE. Results of both modeling techniques showed that the form of the models was generally feasible and consistent with the experimental trends. The statistical criteria for validation also confirmed the correctness of the developed models that provide promising potential for future applications. Although both approaches present better results, the compared results revealed that the corresponding ANN model is reliable than the regression model for the prediction of SE. In other words, the compared results demonstrated the superiority of the ANN model over regression model. As a consequence, the present work indicated that the ANNs and regression analysis can be effectively used for predicting the rock sawing performance of diamond sawblades. Therefore, it is highly recommended that in addition to the SE, other performance indicators (especially wear rate of sawblade elements and surface quality of the cut surface) should be modeled by ANNs and other artificial intelligent methods since such studies will enable the natural stone producers to sustain their productions in a planned scale.

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