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Prediction of specific cutting energy in natural stone cutting processes using the neuro-fuzzy methodology

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ABSTRACT

Specific cutting energy (SE_{cut}) values are used for the determination of energy requirements of the stone cutting process and are thus useful in predicting the cost and production schedule. In this study, adaptive hybrid intelligence (AHI) techniques were employed to develop SE_{cut} prediction models based on 40 different natural building stones in nineteen different stone processing plants. The feed rate, depth of cut, which are cutting process working parameters, and uniaxial compressive strength, bending strength and point load strength of the rock to be cut which constitute rock physico-mechanical properties were used as the input parameters in the development of SE_{cut} prediction models. The AHI techniques included Adaptive Neuro-Fuzzy Inference System (ANFIS), Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS), and Evolving Fuzzy Neural Networks (EFuNN). Among the AHI techniques, ANFIS gave the best SE_{cut} prediction accuracy. The results also showed that it is possible to predict specific cutting energy of natural stone cutting operations with higher accuracy ($R^2 = 0.95$) with the developed ANFIS prediction models using depth of cut, feed rate and uniaxial compressive strength values of natural building stones.

1. Introduction

Developments in artificial intelligence and computer sciences make it possible to model the problems in earth science research with increasing reliability and accuracy. Evaluation of the behaviors observed in nature together with the modeling results has strengthened the empirical approaches. This explains why the applications of artificial intelligence (expert systems, artificial neural networks, etc.) are preferred today [1]. Artificial intelligence (AI) based models are a form of systematic human thought adapted to the machines. One of the most important features of AI based models is that the model has the ability to make inference for different situations with the experience gained through analyzing the information introduced to them. Thus, artificial intelligence based models can be adapted to different situations easily and quickly. Because of these capabilities, along with rapid developments in computer technology, the AI based models are widely used in stone cutting processes and other areas related to rock engineering [2–12].

There are several studies reported in the literature on the investigation of the natural stone cutting process. In most of these studies, the modeling of the actual cutting process is directed by the laboratory-scale studies. The natural stone sawing process is a complex system influenced by a variety of factors [13]. Sawing mechanism and structural properties of diamond impregnated circular saws were investigated by Büttner [14] and Konstanty [15] in their earlier studies. They evaluated the factors that affect the cutting process and explained the mechanism involved. Saw blade performance was studied by Jennigs and Wright [16] determined the optimum choice of diamond sawblades with respect to various factors that affect the saw blade performance. In summary, the mode of cutting, peripheral speed, machine conditions, properties of the rock being cut, and operator skills are among the most important factors that affect the performance and therefore the service life of the sawblade.

Ersoy and Atici [17] in their laboratory-scale study examined the effects of operating and the rock parameters on the performance of the diamond saws. They described the relationships among the cutting variables. Their results indicated that the diamond circular saw performances were significantly affected by the cutting variables. They emphasized that the specific cutting energy was a very significant measure of cutting performance because it indicated the amount of energy required to cut the rock. Regression models for the prediction of slab production of carbonate rocks were studied by Kahraman et al. [18], and they

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investigated, in particular, the models developed for large diameter circular saws. Models that take into account the Schmidt Hammer value, point load strength, impact strength, and *P*-wave velocity were favored according to their study with respect to rapid estimation of the sawability of carbonate rocks. In another study by Ersoy and Atici [19], a theoretical model for the explanation of the relationship between the SE_{cut} of the sawblade operating parameters and rock properties was proposed. It was supported by the laboratory tests that were conducted on three groups of rocks with the help of three types of diamond disk saws with various feed rates and cutting depths at constant peripheral speed. They used bending strength, Schmidt rebound hardness, and wear factor as their model parameters.

The SE_{cut} is an important factor for specifying the mechanical performance of a machine and its basic indicator of the cutting efficiency and performance. It indicates the amount of energy required to cut the unit volume of rock. Cutting energy is often used as a parameter for monitoring the stone cutting process [20–22].

Thus, in almost all the studies reported in the literature focusing on natural stone cutting processes, the data were obtained from laboratory tests. However, in this study the data is obtained from in-situ cutting conditions. Also, there is no study using adaptive hybrid intelligence (AHI) techniques such as DENFIS, EFuNN concerning the natural stone cutting process in the current literature. In this study AHI based models were used for estimating the values of SE_{cut} based on optimal set of inputs.

2. Specific cutting energy in natural stone sawing process: theory

Specific cutting energy is defined as the energy required to remove a specific volume of workpiece material [23]. Generally, mechanical efficiency is at a maximum when specific energy is at a minimum [24]. Specific cutting energy values are affected by several parameters. Generally, specific cutting energy is a function of the machine working parameters, the properties of the blade used, and the mineralogical–petrographical and physico-mechanical properties of the rock being cut. The specific cutting energy can be calculated using

$$SE_{cut} = E_t/Q \qquad (1)$$

where SE_{cut} is the specific cutting energy (J/mm^3), E_t is the total energy consumed during cutting (Ws), and Q is the volume of the channel cut in the stone by the saw during cutting (mm^3).

The SE_{cut} value for each cut can be calculated as the amount of the energy found divided by the volume of the channel cut by the sawblade on the stone:

$$SE_{cut} = Pt/V_f t\, dw \qquad (2)$$

where P is the average power consumption during cutting (W), t is the cutting time (s), V_f is the feed rate (m/min), d is depth of cut (mm), and w is the average width of cutting zone (mm).

3. Machine studies

Block cutters are widely used in natural stone processing plants because of low initial investment costs and the opportunity to cut relatively small size and irregular-shaped blocks of natural stones. Knowing the sawability properties of natural stones (cut by block-cutters) is very important in terms of planning the production and estimating the cost of the natural stone cutting process.

This study was carried out on 40 different natural stones in nineteen different stone processing plants and was focused on the sawability of carbonate rocks (cut with the use of large-diameter circular diamond saws in the block cutter) marketed in Turkey and around the world.

The data collection phase of the study in the stone processing plants included two parts: the electrical data obtained from the electrical panel of the block cutter and the time measurement and the data obtained from the block during and at the end of sawing.

To determine the amount of energy consumed during the cutting, electrical data from the cutting process is needed. To do this a digital power meter is located on the power line that transfers electricity to the block cutter vertical sawing disc in the block cutter electrical panel. During the time that the block cutter cut along the block, the data was obtained through clamp sensors and voltage test leads. The cuts were repeated four times. The electrical parameters in the cutting process, such as the active power, apparent power, reactive energy, power factor, current and voltage that passed through each cut were recorded for analysis by the computer with the digital mobile power meter.

The cutting depth, cutting length, the cutting channel width cut on the block by the sawblade (a total of 40 measurements at the beginning, in the middle and at the end of the cutting), and the time spent on each cutting were measured and recorded. Based on the collected data, basic descriptive statistics of the SE_{cut} values calculated via the cutting depths and the feed rates measured are provided in Table 1.

4. Laboratory studies

In order to keep the range wide in choosing natural building stone to be analyzed in terms of sawability, it was important to choose rocks with different mineralogical, petrographical, and physico-mechanical properties. The mineralogical, petrographical, and physico-mechanical properties of the stone samples chosen for this purpose were determined through laboratory investigation and were intended to be associated with the sawability properties.

The mineralogical and petrographical definitions of the stones among thin section samples prepared for each stone sample were provided based on the known trade names in this study. Folk's [25] classification was taken as the reference in classifying the stones during the application of the modal analysis method.

4.1. Uniaxial compressive strength tests

Uniaxial compression tests were performed on cubic samples, which had a dimension of 70 mm at a 0.6 MPa/s constant loading rate. Tests were carried out according to Turkish standard TS EN 1936 [26].

Table 1
Basic descriptive statistics of the all data.

	UCS (MPa)	*BS (MPa)*	*PLI (MPa)*	*SH (MPa)*	*BTS (MPa)*	N_R	*P-Wave (m/s)*	Water Ab. (%)	Density (g/cm^3)	Porosity (%)	SE_{cut} (J/mm^3)
Min	24.50	9.12	3.79	28.15	2.55	54.20	3235.98	0.01	2.35	0.03	0.56
Max	192.98	22.71	11.45	65.80	8.06	71.00	6224.58	3.35	2.73	7.88	3.32
Mean	89.44	15.47	6.81	48.20	4.50	64.75	5293.11	0.71	2.62	1.77	1.43
St. deviation	38.33	3.74	1.68	10.60	1.12	4.35	604.66	0.81	0.12	1.94	0.58

4.2. Brazilian tensile strength

A 50-kN maximum load capacity mechanical testing device was used for the determination of the Brazilian tensile strength tests. Core samples had a diameter ratio of 0.5. The tests were carried out according to TS 699 Standards [27] with the 0.20 MPa/s loading rate.

4.3. Point load strength

The point load strength test is intended as an index test for the strength classification of rock materials. Specimens used for point load strength are NX size drill core samples in 1:2 length/diameter ratios. The tests were carried out according to Franklin [28].

4.4. Bending strength

Bending strength tests were carried out according to the TS EN 12372 Turkish Standard [29]. 10 specimens were prepared with the dimensions of 25 × 75 × 150 mm. The loading rate applied was 0.25 MPa/s. Bending strength of each sample were calculated as

$$\mathrm{BS} = 3\mathrm{FL}/2bh^2 \tag{3}$$

where BS is the bending strength (MPa), F is the failure load (N), L is distance between the centers of the supports (mm), b is the width of the specimen (mm), and h is the height of the specimen (mm).

4.5. Shore hardness

The C-2 model Shore hardness test device was used in order to determine shore hardness values (SH) of rock samples. The tests were carried out according to the ISRM standard [30]. The hardness value was recorded thirty times in a way to have at least 5 mm between the measurement points, and the mean of the hardness values was calculated for each sample.

4.6. Schmidt hammer hardness

Schmidt hammer rebound tests were applied on the rock blocks having different dimensions varying between 2–6 m^3. The tests were performed with an N-type hammer with impact energy of 2.207 J. The ISRM recommendations [31] were applied for each rock type. ISRM suggested that 20 rebound values from single impact separated by at least a plunger diameter should be recorded, and the mean of the highest 10 values were recorded as the Schmidt hammer hardness value (N_R).

4.7. Ultrasonic pulse (P-wave) velocity

The mean values of the ultrasonic pulse velocity were obtained by averaging three measurements of the transit time recorded during the test. After measuring the sample length, the values of the velocity were calculated. The mean values of the ultrasonic pulse velocity of the cubic specimens with the dimensions of 70 × 70 × 70 mm^3 were measured. Ultrasonic pulse velocity values were calculated according to ASTM D2845 [32]:

$$\mathrm{SV} = L_p/T_p \tag{4}$$

where SV is the ultrasonic pulse velocity (m/s), L_p is the pulse travel distance (m), and t is effective pulse travel time (s).

4.8. Water absorption at atmospheric pressure

The water absorption at atmospheric pressure (A_b) tests was determined following TS EN 13755 [33] recommendations, and the tests were carried out on cube shaped samples having a side length of 70 mm prepared by sawing from large blocks.

4.9. Apparent density and open porosity

Apparent density ρ_b and open porosity ρ_o of the rocks were determined according to the specifications outlined by the TS EN 1926 [34].

Basic descriptive statistics related to the physico-mechanical properties of the stones are given in Table 1.

The main objective of this paper is to develop efficient AHI models for predicting specific cutting energy, based on a minimal (optimal) set of available inputs. The results from the in-situ cutting conditions were utilized in developing the AHI based models. The full set of possible model inputs are: depth of cut (D), feed rate (F), uniaxial compressive strength (UCS), bending strength (BS), point load strength (PLI), shore hardness (SH), Brazilian tensile strength (BTS), Schmidt hammer hardness (N_R), seismic velocity (SV), water absorption at atmospheric pressure (A_b), apparent density (ρ_b) and open porosity (ρ_o).

5. Adaptive hybrid intelligence (AHI) techniques

5.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

One of the most important and promising research fields in recent years has been Nature-Inspired Heuristics, an area utilizing some analogies with natural or social systems for deriving non-deterministic heuristic methods to obtain better results in combinatorial optimization problems. Fuzzy logic approach (FLA) is one such heuristic method [35]. In contrast to classical set theory, where membership of the elements are assessed in binary terms (an element either belongs to or does not belong to the set), fuzzy sets are sets whose elements have degrees of membership. The fuzzy set theory permits the gradual assessment of the membership of elements in a set with the aid of a membership function valued in the real unit interval [0, 1].

Fuzzy inference systems (FIS) are powerful tools for the simulation of nonlinear behaviors utilizing fuzzy logic and linguistic fuzzy rules (if-then role). In the literature, there are several inference techniques developed for fuzzy rule-based systems, such as Mamdani and Sugeno [36]. In the Mamdani fuzzy inference methodology, inputs and outputs are represented by fuzzy relational equations in canonical rule-based form. In Sugeno FIS, output of the fuzzy rule is characterized by a crisp function with linear or constant and it was developed to generate fuzzy rules from a given input-output data set. Neuro-fuzzy systems are multi-layer feed forward adaptive networks that realize the basic elements and functions of traditional fuzzy logic systems. Since it has been shown that fuzzy logic systems are universal approximators, neuro-fuzzy control systems, which are isomorphic to traditional fuzzy logic control systems in terms of their functions, are also universal approximators.

ANFIS is an extension of the Sugeno fuzzy model. In general, ANFIS is much more complicated than FIS. The ANFIS allows the fuzzy systems to learn the parameters of a membership function using adaptive back propagation learning algorithm. Note that typical back propagation ANN learns the weights assigned to input vectors to minimize the error of inputs and outputs.

The architecture of an ANFIS framework of two inputs with two rules for each input is shown in Fig. 1. The complete activity of each layer from Jang et al. can be summarized as follows [37].

Layer 1: each input (x and y) obtains the degree to which they belong to each of the appropriate fuzzy sets through membership

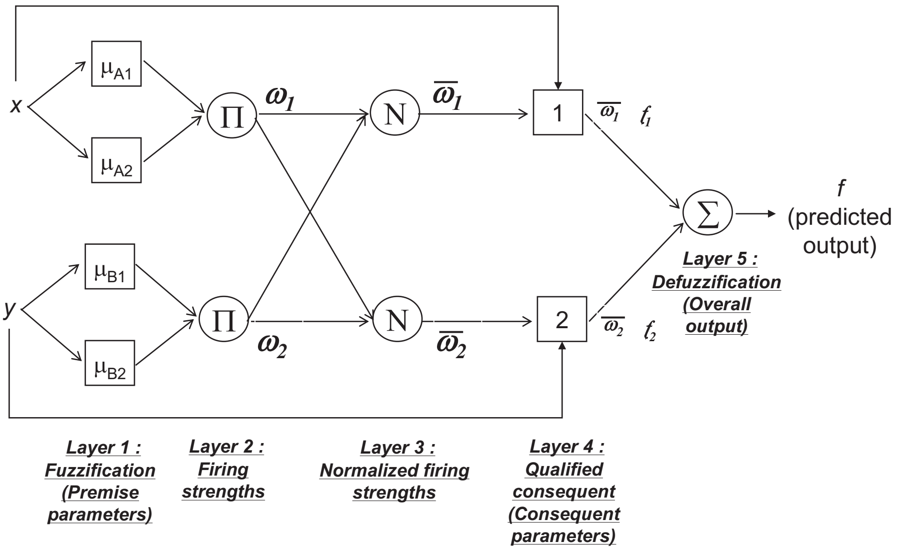

Fig. 1. The typical structure of ANFIS.

functions (μ) on premise part (if-part) of fuzzy rule. The several types of membership functions that can be used include piece-wise linear functions, the Gaussian distribution function, and the sigmoid curve function. The parameters of "μ" in this layer are called as premise parameter and this step often called fuzzification.
Layer 2: the membership values obtained from layer 1 are multiplied to get firing strength (weight) of each rule. The "ω_i" are the products of membership values as follows:

$$\omega_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \quad i = 1,2 \tag{5}$$

Layer 3: the firing strengths from layer 2 are normalized as follows:

$$\overline{\varpi}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1,2 \tag{6}$$

Layer 4: the qualified consequents ($\overline{\varpi}_i f_i$) are generated by multiplying the normalized fire strengths ($\overline{\varpi}_i$) and the output (f_i) on consequent part (then-part) of fuzzy rule. The "f_i" is output functions if Mamdani reasoning is applied or a constant or linear function if Sugeno reasoning is applied [32]. The parameters of "f_i" in this layer are called as consequent parameters.
Layer 5: a predicted output (f) are generated, namely defuzziffiction, by aggregating the qualified consequents ($\overline{\varpi}_i f_i$) as following the center of gravity method:

$$f = \sum_i \overline{\varpi} f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}, \quad i = 1,2 \tag{7}$$

In summary, a FIS in ANFIS can be considered to be a parameterized non-linear map or a crisp function in a consequence called "f", namely

$$f(x) = \frac{\sum_{l=1}^{m} \left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i) \right) f_l}{\sum_{l=1}^{m} \left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i) \right)} = \frac{\sum_{l=1}^{m} \omega_l f_l}{\sum_{l=1}^{m} \omega_l} = \sum_{l=1}^{m} \overline{\varpi}_l f_l \tag{8}$$

where the output f_i on consequent part of rule is output functions if Mamdani reasoning is applied or a constant or linear function if Sugeno reasoning is applied [36]; the membership function $\mu_{A_i^l}(x_i)$ corresponds to the input $x = [x_1, \ldots, x_i, \ldots, x_n]$ of the rule "l, m" is the number of fuzzy rules and n is the number of inputs. For the ith input predictor variable, "x_i" is the real data (for example, the measured FWD deflection) in one point from the set of observed values. The output values, $f(x_i)$ are the estimated values (for example, the critical structural responses) of simulation function within the range of input set.

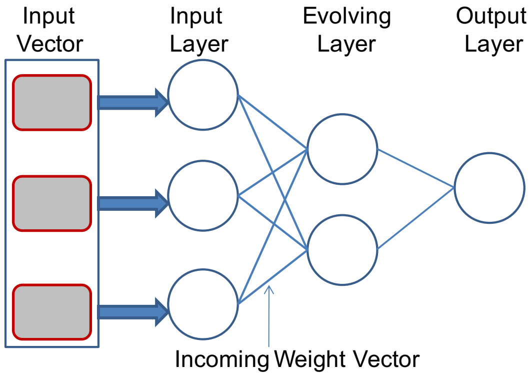

Fig. 2. Schematic of a general ECoS (DENFIS and EFuNN) architecture.

The "Learning" process in ANFIS methodology, namely adaptation of membership functions to emulate the training data, is commonly performed by two techniques: back propagation and hybrid learning algorithms. The hybrid optimization method is a combination of the Least Squares Error (LSE) and back propagation (BP) descent method. In the hybrid learning algorithm, consequent parameters (parameters in output layers) are identified in forward computation by LSE algorithm, and premise parameters (parameters in hidden layers) are adjusted in backward computation using the back propagation algorithm.

5.2. Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS)

Evolving Connectionist Systems (ECOS) can be considered as open architecture artificial neural networks (ANN) in which the neurons are added to their structures and the connection weights are modified as the system evolves based on a continuous input data stream in an adaptive, life-long, modular way [38,39]. A schematic of general ECOS architecture is shown in Fig. 2. Two ECOS networks proposed by Kasabov and his colleagues were

Table 2
Definitions and ranges of values for input and output parameters used in development of AHI models.

Parameter	Range		Mean	Std. dev
	Min	Max		
Operational properties				
Depth of cut (*D*), *cm*	200	650	404.54	126.35
Feed Rate (*F*), *m/min*	0.32	2.07	0.89	0.40
Rock physico-mechanical properties				
UCS (*MPa*)	24.50	192.98	89.44	38.3
BS (*MPa*)	9.12	22.71	15.47	3.74
PLI (*MPa*)	3.79	11.45	6.81	1.68
Output parameter				
SE_{cut} (J/mm^3)	0.56	3.32	1.43	0.59

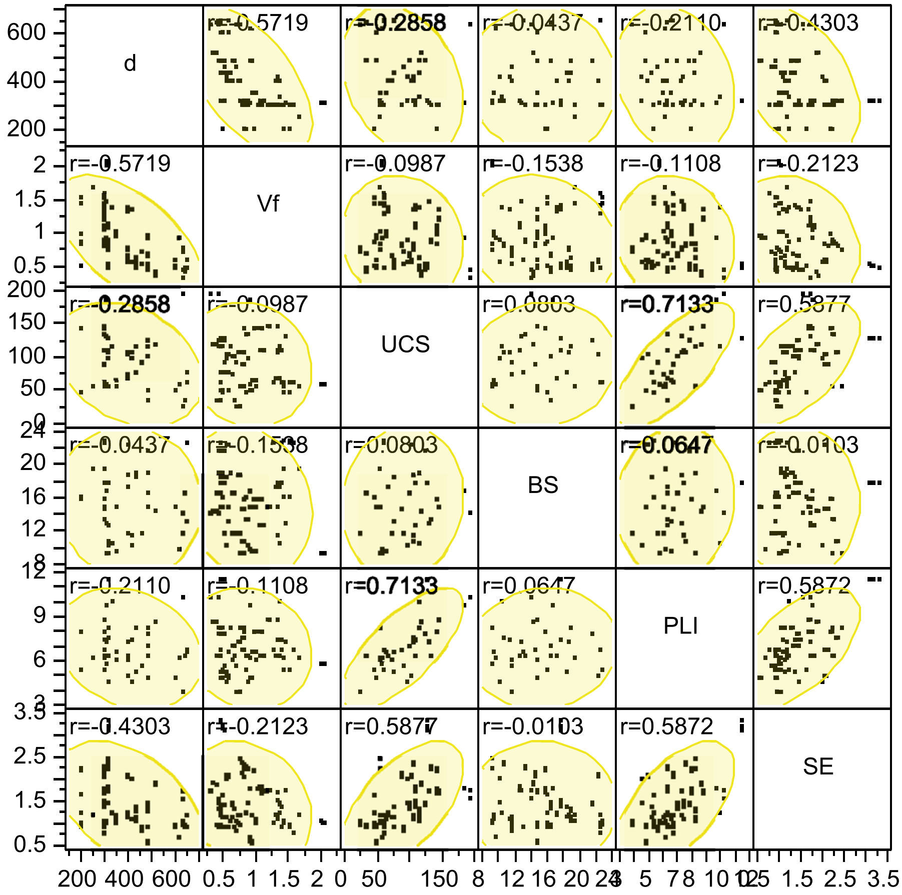

Fig. 3. Scatterplot matrices of variables used in developing AHI prediction models.

employed to study this problem: DENFIS and EFuNN, which are explained in this and in the next section.

DENFIS is a Takagi-Sugeno type of Fuzzy Inference System (FIS) with a backpropagation (BP) algorithm developed for both on-line and off-line learning [39]. The DENFIS model forms a FIS dynamically for calculating the output depending on the input vector position in the input space. The dynamically formed FIS is based on fuzzy rules created during the past learning process. The DENFIS model for offline learning in batch mode was used in this paper in attempting to develop an effective tool for rubblized pavement layer moduli backcalculation. Two DENFIS models for offline learning were developed by Kasabov and Song [39]: Model I is linear model, and model II is multi-layer perceptron (MLP) based model. A first-order Takagi-Sugeno type fuzzy inference engine is employed in model I while model II employs an extended high-order Takagi-Sugeno fuzzy inference engine. In model II, several small-size, two-layer (the hidden layer consists of two or three neurons) MLPs are used to realize the function in the consequent part of each fuzzy rule instead of using a predefined function.

5.3. Evolving Fuzzy Neural Networks (EFuNN)

The seminal ECOS network proposed by Kasabov [40] and Watts [41], EFuNN, contains fuzzy logic elements that transform the input variables into "fuzzy" representations, which then maps these fuzzy input values to the target fuzzy output values.

6. Development of AHI-based specific cutting energy prediction models

6.1. Data preparation

The data were divided randomly into two different subsets of the training data subset and the testing data subset in such a way that they are representative of same statistical population. Of the total 107 data points, 87 data points were used for training and the rest 20 data points were used for testing. In accordance with the following equation (Eq. 9), both datasets were normalized within the range of 0.1–0.9 to prevent training network saturation, which could impede the model performance.

$$x_{normalized} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \times 0.8 + 0.1 \tag{9}$$

where $x_{normalized}$ is the normalized value of each parameter, x_i is the actual value of each parameter, x_{min} and x_{max} are minimum and maximum values of each parameter. Tables 1 and 2 present the description and ranges of values for all input and output parameters used in the AHI models.

A grid of scatterplot matrices between pairs of variables used in AHI modeling is displayed in Fig. 3. These scatterplot matrices present comparisons among many variables visually by presenting orderly collections of bivariate graphs. A 95% bivariate normal density ellipse is imposed on each scatterplot and the variables are uncorrelated if the ellipse is fairly round and is not diagonally oriented. As seen in Fig. 3, the output variable SE_{cut} is more strongly correlated to UCS and PLI which confirms findings reported in the literature.

The objective of this study was to develop SE_{cut} prediction models based on optimal set of inputs. Based on principal component analysis (PCA), the depth of cut (D), feed rate (F), unconfined compressive strength (UCS), bending strength (BS) and point load strength (PLI) were found to be the dominant set of inputs. Therefore, three sets of prediction models using each of the AHI approaches were attempted. Inputs for Set 1 consisted of D, F, and UCS. Inputs for Set 2 were D, F, UCS, and BS and inputs for set 3 were D, F, UCS, BS, and PLI.

6.2. ANFIS approach

The input parameters were partitioned using a *subtractive clustering* technique and Gaussian membership functions were used. First order Sugeno FIS with linear output function was selected as the inference system. ANFIS structure was completed by the selection of hybrid learning algorithm and a batch learning scheme was used. In this learning algorithm, the BP algorithm is applied to the learning of premise parameters, while the LSE algorithm is applied to the learning of consequent parameters. In the rulebase, fuzzy variables were connected with T-norm (fuzzy AND) operators and rules were associated using max-min decomposition technique. The output part of each rule uses a linear defuzzifier formula; the total output of ANFIS is the weighting average of the output of each rule. The ANFIS based approach was implemented in MATLAB® using the built-in toolbox. The architectural details of the ANFIS SE_{cut} prediction models are captured in Fig. 4.

6.3. Evolving Connectionist System (ECoS) Models: DENFIS and EFuNN

The *NeuCom*© *v*0.919 software developed at the Knowledge Engineering and Discovery Research Institute (KEDRI), Auckland University of Technology, New Zealand was used for developing, training, and testing the DENFIS and EFuNN models for specific cutting energy predictions. *NeuCom*© is self-programmable, learning and reasoning computer environment based on connectionist modules. The software has user-ready options to develop DENFIS and EfuNN ECOS models.

The parameters to be optimized in the DENFIS model include: Dthr – Distance Threshold which determines the maximum radius of the rule nodes in this network; *M-of-N*-this determines the number of nodes which are referenced to estimate the output of the current sample; and Epoch – the number of epochs (a single step in the training process of ANFIS where each vector in the training dataset is presented once to the network) used to train or retrain the network originally. To estimate the accuracy of predictions, the DENFIS model outputs three result parameters: NumRn – number of Rule Nodes (RNs) in the network; NDEI – Non-Dimensional Error Index; and RMSE – Root Mean Squared Error. In addition, the system also outputs the CPU time (seconds) taken for training the network.

In the case of EFuNN, there are several model parameters to be optimized: sensitivity threshold – represents the maximum radius of clusters (rule nodes); error threshold – the level of error tolerance for the output; number of membership functions used in the fuzzy inference system; learning rate for the weights of first layer (W1); learning rate for the weights of second layer (W2); pruning – whether or not to prune old nodes; node age – if pruning is enabled, when should the old nodes be removed; aggregation–whether or not to allow similar nodes to be merged; max field - the maximum radius for clusters in self-tuning mode (only applied in self-tuning mode); number of activity rule nodes to derive the output; EFuNN version – standard or self-tuning; and recurrent connections – whether or not to allow recurrent connections.

7. Discussion of results

7.1. ECOS-based models

In order to identify the best-performance ECOS-based prediction models, parametric sensitivity analyses were conducted for both DENFIS and EFuNN for determination of optimal model parameter settings. It is true that most machine learning techniques require fine tuning of model parameter settings, especially in solving highly non-linear, ill-posed problems. However, in this particular case, it was found, after conducting parametric sensitivity analyses, that the best-performance DENFIS and EFuNN models were achieved using values in the vicinity of default parameter settings.

The best-performance DENFIS prediction models and best-performance EFuNN prediction models are reported in Tables 3 and 4, respectively. In general, the EFuNN prediction models have higher accuracies compared to the counterpart DENFIS prediction models.

7.2. ANFIS

The best-performance ANFIS prediction models are reported in Table 5. In general, the ANFIS prediction models have higher accuracies compared to both DENFIS and EFuNN prediction models. The predictive performances of the AHI techniques were evaluated in terms of goodness-of-fit statistical indicators such as coefficient of determination (R^2) with reference to the line of equality and Root Mean Squared Error (RMSE) values. The R^2 is a measure of correlation between the predicted and the measured values and therefore, determines accuracy of the prediction model (higher R^2 equates to higher accuracy). The RMSE indicates the relative improvement in accuracy and thus a smaller value is

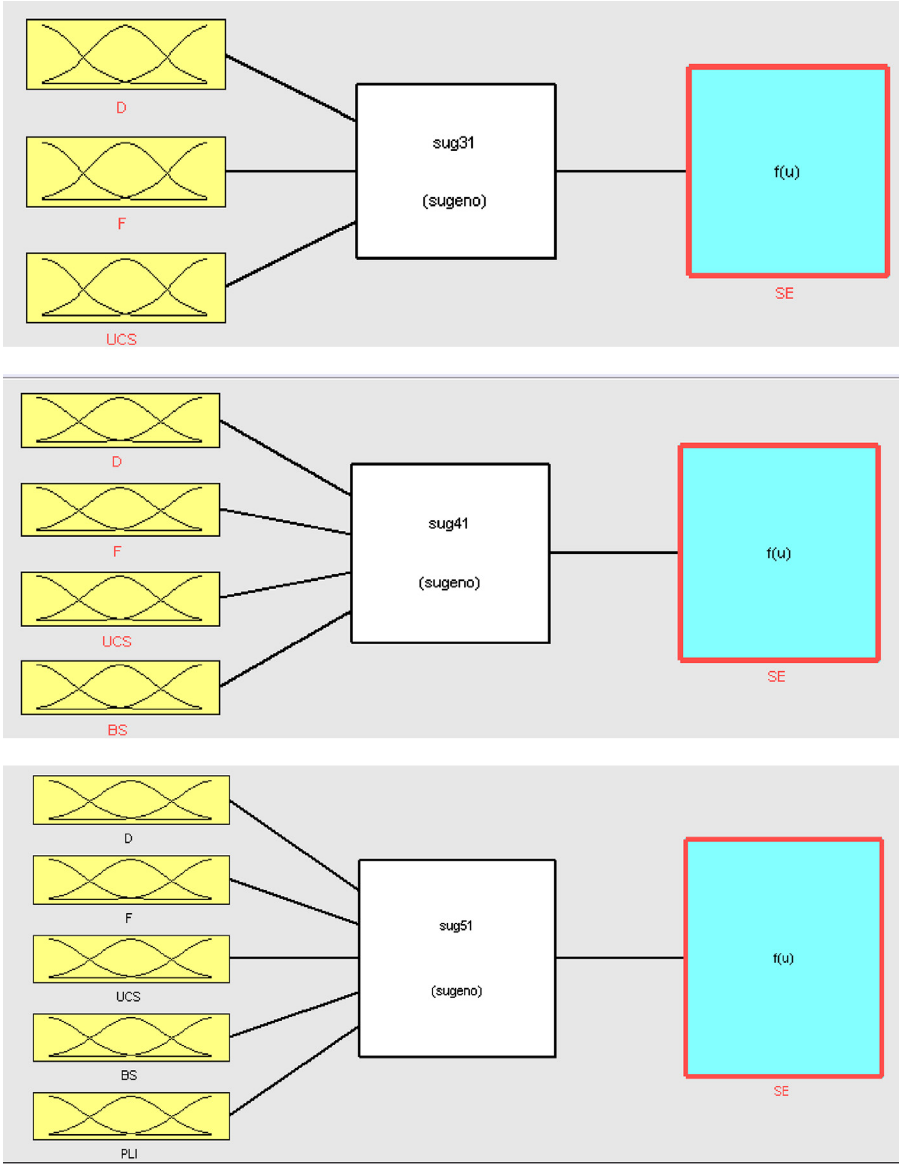

Fig.4. ANFIS architectures for SE_{cut} prediction models.

Table 3
Summary of DENFIS-based SE_{cut} prediction models.

Inputs	Output	Epochs	Fuzzy rules	Testing NDEI	Testing *RMSE*	R^2
D, *F*, *UCS*	SE_{cut}	2	23	0.6676	0.0753	0.73
D, *F*, *UCS*	SE_{cut}	10	23	0.6708	0.0756	0.73
D, *F*, *UCS*	SE_{cut}	20	23	0.6770	0.0763	0.72
D, *F*, *UCS*, *BS*	SE_{cut}	2	30	1.1677	0.1316	0.61
D, *F*, *UCS*, *BS*, *PLI*	SE_{cut}	2	34	1.162	0.1309	0.65

Table 4
Summary of EFuNN-based SE_{cut} prediction models.

Inputs	Output	Epochs	Fuzzy rules	Testing NDEI	Testing RMSE	R^2
D, *F*, *UCS*	SE_{cut}	2	43	0.3414	0.0385	0.93
D, *F*, *UCS*, *BS*	SE_{cut}	2	47	0.8507	0.0959	0.88
D, *F*, *UCS*, *BS*, *PLI*	SE_{cut}	2	46	0.8061	0.0909	0.89

Table 5
Summary of ANFIS-based SE_{cut} prediction models.

Inputs	Output	Epochs	*r*	Testing RMSE	R^2
D, *F*, *UCS*	SE_{cut}	20	0.5	0.1130	0.78
D, *F*, *UCS*	SE_{cut}	20	0.1	0.0985	0.95
D, *F*, *UCS*	SE_{cut}	20	0.05	0.0987	0.95
D, *F*, *UCS*, *BS*	SE_{cut}	20	0.5	0.1137	0.97
D, *F*, *UCS*, *BS*	SE_{cut}	20	0.1	0.1330	0.68
D, *F*, *UCS*, *BS*	SE_{cut}	20	0.05	0.0697	0.91
D, *F*, *UCS*, *BS*, *PLI*	SE_{cut}	20	0.5	0.1326	0.70
D, *F*, *UCS*, *BS*, *PLI*	SE_{cut}	20	0.1	0.0812	0.96
D, *F*, *UCS*, *BS*, *PLI*	SE_{cut}	20	0.05	0.0812	0.96

indicative of better accuracy. Based on this quantitative multi-criteria assessment using the test vectors, it was deemed that all three AHI techniques showed satisfactory predictive performance. Fig. 5 displays the ANFIS predicted SE_{cut} response surface as a function of *D*, *F*, UCS, and PLI. In Fig. 5, a continuous surrogate response surface model is fitted to the ANFIS predictions of SE_{cut} values at random discrete locations. The colors of the response surfaces are auto-generated by the MATLAB ANFIS toolbox and they correspond to specific ranges of values between 0 and 1 (i.e., similar colors on the surfaces correspond to similar values). As opposed to a traditional multivariate linear regression response surface model that estimates the linear functional trends between model outputs and inputs, the ANFIS response surfaces provide a “function-free” numerical approximation of the nonlinear relationship between SE_{cut} values and model inputs. From Fig. 5 (a), it is seen that SE_{cut} predictions are generally inversely proportional to depth of cut (*D*) and feed rate (*F*). In other words, lower values of *D* and *F* tend to result in higher SE_{cut} values. The response surfaces depicted in Fig. 5 (a–c) are based on the available datasets. In Fig. 5 (b), it is seen that some areas of the response surfaces are not well defined, especially at higher *D* values and lower UCS values. This could be due to the fact that there are not enough training data points in that space such that smoothly interpolated predictions could be made. These nonlinear response surfaces could be used to estimate point estimates of sensitivities (such as a point-normalized sensitivity index) across the problem domain. For instance, the local percentage in model output, SE_{cut}, caused by a given percentage change in the model input at a specific location in the problem domain could be estimated through these response surfaces.

8. Summary and conclusions

The specific cutting energy is a basic indicator of the cutting efficiency and mechanical performance of a machine employed in natural stone cutting and processing plants. It is generally a function of machine working parameters, the properties of the blade used, and the mineralogical–petrographical and physico-mechanical properties of the rock being cut. Previous studies that have examined and developed relationships between different variables involved in the natural stone cutting processes have primarily focused on laboratory test data. The study reported in this paper is unique in that it used data obtained from industrial cutting conditions in natural stone processing plants. Similarly, this is the first time Adaptive Hybrid Intelligence (AHI) techniques such as Adaptive Neuro-Fuzzy Inference System (ANFIS), Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS), and Evolving Fuzzy Neural Networks (EFuNN) are used in modeling the natural stone cutting process.

Based on principal component analysis (PCA), the depth of cut (*D*), feed rate (*F*), unconfined compressive strength (UCS), bending strength (BS) and point load strength (PLI) were found to be the dominant set of inputs used in developing the AHI-based prediction models. Both ANFIS and DENFIS require few parameters and settings that need to be optimized in developing best-performance models, while, EFuNN requires fine-tuning of relatively large number of parameters. Preliminary parametric sensitivity studies revealed that the default DENFIS and EFuNN model parameter settings represent the best performance model parameter settings.

In general, the EFuNN prediction models have higher accuracies compared to the counterpart DENFIS prediction models. The ANFIS prediction models have higher accuracies compared to both DENFIS and EFuNN prediction models. Thus, although all three AHI techniques showed satisfactory performance in fulfilling objectives of the study, the ANFIS based models are recommended for predicting specific cutting energy.

The developed techniques and the results from this study are useful from multiple perspectives. This includes benefits such as more efficient and economical stone cutting process, improved equipment designs for cutting-tool manufacturers and proper selection of equipment and more accurate planning of production schedules by engineers. Accurate determination of SE_{cut} values will lead to reduction in costly errors and increased accuracy in the determination of energy requirements of the stone cutting process and as well as cost and production schedule. Also, as demonstrated by the study, the depth of cut, feed rate and uniaxial compressive strength values of natural building stones alone are sufficient to predict the SE_{cut} values with good accuracy. Thus, by developing a database of values for different natural building stones and stone processing plants, the sensitivity of SE_{cut} values and other critical parameters to a range of inputs as well as their synergistic relationships could be unearthed through advanced data mining and knowledge discovery methods in conjunction with adaptive hybrid intelligence techniques. This could lead to newer insights into the underlying science and mechanisms behind stone cutting processes and rock properties.

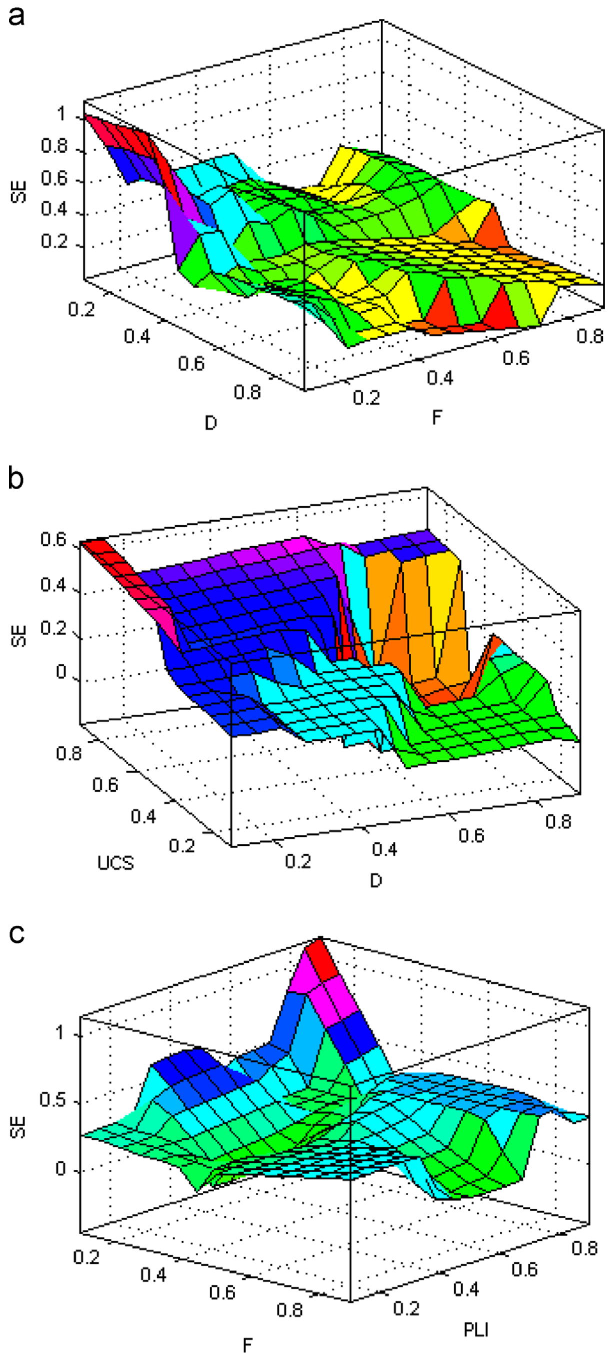

Fig. 5. ANFIS-based SE_{cut} response surfaces.

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