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Applied Genetic Programming for Predicting Specific Cutting Energy for Cutting Natural Stones

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ABSTRACT
In the processing of marbles and other natural stones, the major cost involved in sawing with circular diamond sawblades is the energy cost. This paper reports a new and efficient approach to the formulation of SE_{cut} using gene expression programming (GEP) based on not only rock characteristics but also design and operating parameters. Twenty-three rock types classified into four groups were cut using three types of circular diamond saws at different feed rates, depths of cut, and peripheral speeds. The input parameters used to develop the GEP-based SE_{cut} prediction model were as follows: physico-mechanical rock characteristics (uniaxial compressive strength, Shore scleroscope hardness, Schmidt rebound hardness, and Bohme surface abrasion), operating parameters (feed rate, depth of cut, and peripheral speed), and a design variable (diamond concentration in the sawblade). The performance of the model was comprehensively evaluated on the basis of statistical criteria such as R^2 (0.95).

Introduction

With the growing global demand for natural stones, the production of natural stones is becoming increasingly efficient to improve productivity and reduce cost. Block cutting machines are generally classified into frame sawing machines and stripper-trimmer (ST) machines. Circular diamond saws have been widely used in principal industrial applications because they cut fast, are flexible, and economical, and are easy to operate with high accuracy of the cut surface. Rock blocks can be split into slabs by the reciprocating movement and vertical downfeed of the diamond sawblades.

The prediction of rock sawability is important in the cost estimation and planning of stone plants. Accurate estimation of rock sawability facilitates efficient planning of rock sawing projects. Rock sawability depends on non-controlled parameters related to rock characteristics and controlled parameters related to the properties of cutting tools and equipment (Mikaeil, Mohammad, and Reza 2011). One of the major goals of natural-stone cutting

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processes is to minimize the production cost of the final product. Therefore, it is critical to determine the costs involved and to understand and control the energy-consumption mechanisms throughout the cutting process (Yurdakul and Akdas 2014). Stone processing cost is controlled to a large extent by the cutting rate of the saws. A saw is a complex system whose performance is influenced by a variety of factors. The principal factors that require consideration in predicting cutting rates, particularly for stone applications, are the rock characteristics and the design and operating parameters of the saw.

The specific cutting energy (SE_{cut}) is one of the most important performance indicators in sawing processes with circular diamond sawblades. It is derived from the amount of energy required to remove a given volume of rock and has been successfully used for the performance evaluation of circular diamond sawblades in the rock sawing and diamond tool industry (Buyuksagis and Goktan 2005; Sengun 2009; Ersoy and Atici 2004). The specific energy is the most widely used parameter to measure the efficiency of a rock cutting system. A smaller value of specific energy indicates higher sawability.

Many studies have investigated the sawing performance and mechanism of the circular diamond saw (Buyuksagis 2007; Buyuksagis and Goktan 2005; Ersoy and Atici 2004, 2007; Fener, Kahraman, and Ozder 2007; Luo and Liao 1995; Theodoridou, Dagrain, and Ioannou 2015; Turchetta, Polini, and Buyuksagis 2009; Ucun et al. 2012; Wright and Cassapi 1985; Wright and Jennings 1989; Yurdakul 2015; Yurdakul and Akdas 2014). Most of these studies are related to a single rock type, especially granite.

The various modeling techniques, simple and multiple regression techniques have been widely employed in several fields of geoscience. This is because they are appropriate techniques when the research problem includes one dependent variable that is related to two or more independent variables, and they can easily be used for determining the linear and/or nonlinear relationship between dependent predictive and independent criterion variables (Aydin et al., 2015). Many studies have used regression analysis to predict the SE_{cut} and performance of a circular diamond saw (Ersoy and Atici 2005; Kahraman, Fener, and Gunaydin 2004; Sengun and Altindag 2013; Aydin et al. 2013; Velchev et al. 2014; Yurdakul and Akdas 2012). Most of these studies are related to rock characteristics for estimating SE_{cut}; operating parameters have not been used. In addition to rock characteristics, Kahraman, Fener, and Gunaydin (2004) used operating parameters such as traverse speed (V_c), depth of cut (h_c), and saw diameter to predict the sawing rate for 13 different carbonate rocks. Aydin et al. (2013) carried out an experimental study to determine SE_{cut} using rock characteristics and operating parameters for nine granitic rocks. These researchers have suggested 11 and 9 different models including rock properties and operating parameters, respectively. However, the aforementioned studies did not suggest a single model including operating and design parameters. Yurdakul and Akdas (2012) presented a theoretical model to explain the estimation of SE_{cut} based on the relationship between the sawblade operating parameters and the rock properties using 13 values collected from 7 different types of block cutters and 6 different carbonate rocks.

The natural-stone sawing process is a complex process influenced by a variety factors such as rock characteristics, operating and machine parameters, and circular diamond disk design parameters. To make the right decision regarding the power consumption of rock cutting, all known criteria related to the problem should be analyzed. Although an increase in the number of related criteria complicates the problem and makes it more difficult to reach a solution, it may increase the correctness of the decision based on such criteria. Owing to the increasing complexity of the decision process, many conventional methods such as regression analysis are able to consider limited criteria and may be generally deficient. Therefore, it is obvious that assessing all the known criteria related to the power consumption is extremely important for the decision-making process (Mikaeil, Mohammad, and Reza 2011).

Developments in various fields of computer science such as artificial intelligence (AI), artificial neural networks, adaptive neurofuzzy inference systems, and fuzzy logic methods are commonly adopted in many engineering applications. They facilitate modeling of problems with high reliability and accuracy; moreover, such models can be adapted to different situations easily and quickly. Because of these capabilities, along with the rapid developments in computer technology, AI-based models are widely used in stone cutting processes (Kahraman et al. 2006; Mikaeil et al. 2013; Yurdakul and Akdas 2014; Aydin et al. 2015; Tutmez, Kahraman, and Gunaydin 2007). A major disadvantage of such systems is that they are not capable of providing practical prediction equations. To overcome these limitations, genetic programming (GP) and its variants, such as linear genetic programming and gene expression programming (GEP), have been successfully adopted in engineering applications in recent years.

Owing to the complexly of the cutting process, SE_{cut} cannot be predicted accurately by a classical model including operating and design parameters as well as rock properties. The main objective of the present study is to investigate the use of GEP in predicting SE_{cut} for a circular diamond saw on the basis of rock properties (uniaxial compressive strength (f_c), Shore scleroscope hardness number (SHN), Schmidt rebound hardness (RH), and Bohme surface abrasion strength (BSA)), operating parameters (feed rate (V_f), depth of cut (h_c), and peripheral speed (V_p)), and a design parameter of the circular diamond disk (diamond concentration in the sawblade ($D_{\%}$)). To build the model, SE_{cut} values of 535 specimens were used in training, testing, and validation; the datasets were obtained from an experimental study. In this regard, the present study is the first attempt at using a single model for modeling sawblade performance as a function of rock properties, operating parameters, and design variables using GEP.

In the present study, 23 rock types (6 limestones, 3 andesites, 7 granites, and 7 travertines) were cut with 3 different types of circular diamond saws on a fully instrumented laboratory-cutting rig at different feed rates and depths. The objective of this paper is to examine the influence of the cutting variables and cut rock properties on the performance characteristics of circular diamond saws using GEP.

Experimental procedures

Cutting rig

Circular sawing tests were performed on a high-precision fully instrumented experimental side-cutting machine specially designed for this study. It consists of three major sub-systems: a cutting unit, an instrumentation unit, and a personal computer. Sawing tests were performed with a maximum spindle motor power of 4 kW; the spindle speed could be adjusted between 0 and 5000 rpm. The cutting unit was placed on the columns of the machine with a sledge. The saw movements (forward–backward in the horizontal plane, and up–down in the vertical plane) were driven by two 0.75 kW AC motors, which were located in the beginning and end sections of the cutting unit.

During the study, data were collected by a PC. Cutting parameters such as feed rate or cutting speed, depth of cut, peripheral speed, specific removal rate, and vertical and horizontal axial forces were measured using sensors, load cells, transducers, and an encoder in the monitoring system. The power consumed during a sawing test was measured using a digital measuring instrument. All aspects of the cutting machine (such as motors, sensors, transducers, inverters, load cells, and changes in cutting parameters) were controlled by the computer with specially developed software. One set of data for each test was recorded in 1 s. Complete details of the sawing experiments can be found elsewhere (Ersoy and Atici 2004).

The circular diamond sawblade used in the tests had a diameter of 400 mm with a steel core having a thickness of 4 mm; 28 pieces of diamond-impregnated segments (40 × 7 × 4 mm) were brazed to the periphery of the circular steel core with a standard narrow radial slot. Three different sawblades were used in the study for 16 types of rocks. The sawblade specifications are listed in Table 1. The grit (US mesh) sizes of the diamond were approximately 50/60, 40/50, and 30/40 at concentrations of 35, 34, and 28 (1.54, 1.50, and 1.23 carat/cm^3), respectively.

Table 1. Specification of the diamond segments.

Sawblade	US mesh of diamond	$D_{\%}$	Bond composition	Stone groups
A	50/60	30–40	Co–Bronze–Sn	Granite, syenite, and gabbro
B	40/50	30–38	Co–Bronze	Andesite, basalt, tuff, and dacite
C	30/40	25–30	Co–Bronze	Limestone and marble

$D_{\%}$, diamond concentration in the sawblade (%).

Blade A is used for granite, syenite, and gabbro stones, which are generally fine-grained and high-strength stones that are very hard and abrasive and contain no visible cracks or fractures. Blade B is used for andesite, basalt, tuff, and dacite stones, which are abrasive, medium hard, and porous. Blade C is used for limestones and marbles, which are non-abrasive, medium hard, and generally medium- to coarse-grained.

Operating parameters

The saw operating parameters involved in the sawing trials are as follows: rotational (peripheral) speed, cutting speed or feed rate, depth of cut, specific removal rate, cutting (horizontal, vertical, and axial) forces, power, and SE_{cut}. These were monitored on a computer-controlled logging system (except for SE_{cut}). Water was used as the flushing and cooling medium, at a flow rate of 15–20 L/min.

The circular sawing experiments were performed in the down-cutting mode. Each rock was sawn using each saw (A, B, C types; Table 1) with a particular feed rate (0.2, 0.4, 0.6, 0.8, and 1.0 m/min) and depth of cut (10, 30, 50, 70, and 90 mm) at five peripheral speeds (60, 65, 70, 75, and 80 m/s). Thus, for each saw and each rock, a set of sawing data was obtained depending on the depth of cut and feed rate adopted at a constant peripheral speed. Thus, 280 sawing tests were completed with a total sawn area of approximately 70,000 cm^2.

Rock characteristics

The sawing trials were conducted on 23 rock samples that have substantial market demand. The mechanical tests were performed according to related Brown (1981) recommendations and testing procedures of the used instruments. The physico-mechanical properties of the tested rocks are summarized as statistical values in Table 2.

Specific cutting energy

The specific cutting energy (SE_{cut}) is derived from the amount of energy required to remove a given volume of rock and has been successfully used in the diamond tool industry. The significance of SE_{cut} as a fundamental

Table 2. Mechanical and physical properties of rocks used in the experiments.

	Minimum	Maximum	Mean	Standard deviation
f_c (MPa)	30.7	292	77.36	45.6
SHN	9.0	80.5	42.22	6.44
RN	41.3	62.8	51.87	6.44
BSA (cm^3/50 cm^2)	1.4	43.43	16.63	9.91

f_c, uniaxial compressive strength (MPa); SHN, Shore scleroscope hardness number; RN, Schmidt rebound hardness; BSA, Bohme surface abrasion strength (cm^3/50 cm^2).

parameter derives from the fact that any proposed machining mechanism must be able to account for the magnitude of SE_{cut} and its dependence on the rock characteristics and operating parameters. In particular, the magnitude of SE_{cut} is useful for estimating the power requirements of a cutting operation. Thus, studying SE_{cut} provides a very good indication as to how well a saw is performing for a particular rock formation.

Gene expression programming

The major disadvantage of classical modeling methods is that they are not capable of providing practical prediction equations for complex cases such as SE_{cut} estimation. To overcome this limitation, new approaches such as GP and GEP (a variant of GP) have been proposed. They generate simplified prediction equations without assuming prior form of the existing relationship. GEP is a new and powerful evolutionary AI-based method developed by Ferreira (2001). Its evaluation system for any kind of knowledge mirrors that of biological evaluation, and it is encoded as a computer program with linear chromosomes of fixed length. In this approach, a mathematical function defined as a chromosome with multiple genes is developed using the data presented to it. Although GEP mainly executes symbolic regression via most of the genetic operators of genetic algorithms (GA) and GP, there are some differences between GA, GP, and GEP. While any mathematical expression is adopted as symbolic strings of fixed length (chromosomes) in GA, GP represents it as nonlinear entities of different sizes and shapes (parse trees). However, in GEP it is encoded as simple strings of fixed length, which are subsequently expressed as expression trees of different sizes and shapes (Cevik 2007; Kayadelen 2011). Further details have been provided by Ferreira (2001; 2006).

GEP model

The GEP model developed herein mainly aims to generate mathematical functions for predicting SE_{cut} based on rock properties, design variables, and operating parameters. The first step is the selection of rock properties (f_c, SHN, RH, and BSA), operating parameters (V_f, h_c, and V_p), and a design parameter of the circular diamond disk ($D_{\%}$). The correlation matrix for SE_{cut} and other parameters is presented in Table 3. The correlation between

Table 3. Statistical correlation matrix of rock properties and SE_{cut}.

	$D_{\%}$	f_c	SHN	RN	BSA	V_p	V_f	h_c	SE_{cut}
$D_{\%}$	1.000	0.442	0.153	−0.351	0.126	−0.192	−0.117	−0.069	−0.018
f_c	0.442	1.000	0.732	0.523	−0.563	−0.165	−0.084	−0.457	0.300
SHN	0.153	0.732	1.000	0.771	−0.676	−0.248	−0.017	−0.458	0.411
RN	−0.351	0.523	0.771	1.000	−0.574	−0.061	0.061	−0.449	0.433
BSA	0.126	−0.563	−0.676	−0.574	1.000	0.153	0.020	0.329	−0.175
V_p	−0.192	−0.165	−0.248	−0.061	0.153	1.000	0.029	0.051	−0.047
V_f	−0.117	−0.084	−0.017	0.061	0.020	0.029	1.000	0.043	−0.036
h_c	−0.069	−0.457	−0.458	−0.449	0.329	0.051	0.043	1.000	−0.667
SE_{cut}	−0.018	0.300	0.411	0.433	−0.175	−0.047	−0.036	−0.667	1.000

Significance at 95% confidence level. $D_{\%}$, diamond concentration in the sawblade (%); f_c, uniaxial compressive strength (MPa); SHN, Shore scleroscope hardness number; RN, Schmidt rebound hardness; BSA, Bohme surface abrasion strength ($cm^3/50\ cm^2$); V_p, peripheral speed (m/s); V_f, feed rate (m/min); h_c, depth of cut (mm); SE_{cut}, specific cutting energy (MJ/m^3, J/mm^3).

SHN and f_c and RN is 0.732 and 0.771, respectively. A strong correlation between independent variables, known as multicollinearity, leads to problems in the analysis. For example, the variables do not contribute sufficiently to the model. Figure 1 shows the effects of the independent variables on the first created model. The contribution of V_f is shown to be quite low. Because of multicollinearity and low contribution, SHN and V_f were excluded from the model, and then, the GEP model was developed using datasets of 535 rock specimens obtained from an experimental study. When training and testing the GEP model, f_c, RH, BSA, V_f, h_c, and $D_{\%}$ were entered as input variables, while the SE_{cut} value was the output variable. The training and testing data were randomly selected. The numbers of experimental datasets used for training and testing/validating this model were 401 and 134, respectively.

For GEP formulation, the fitness f_i of an individual program i is measured by

$$\mathrm{f}_i = \sum_{j=1}^{C_t} \left(M - \left| C_{ij} - T_j \right| \right), \tag{1}$$

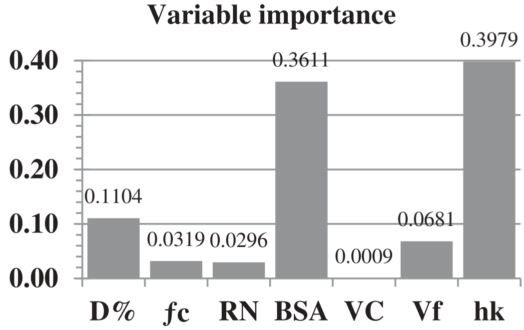

Figure 1. Effect of independent variables in the first model.

where M is the range of selection, C_{ij} is the value returned by the individual chromosome i for fitness case j (out of C_t fitness cases), and T_j is the target value for fitness case j. If $|C_{ij} - T_j|$ (the precision) is less than or equal to 0.01, then the precision is equal to zero, and $f_i = f_{max} = C_t M$. In this case, $M = 100$ was used; therefore, $f_{max} = 1000$. The advantage of this kind of fitness function is that the system can find the optimal solution by itself (Ferreira 2006). Then, the set of terminals 'T' and the set of functions 'F' used to create the chromosomes were chosen, that is, T = {f_c, RH, BSA, V_f, h_k, $D_{\%}$}, and four basic arithmetic operators (+, −, *, /) and some basic mathematical functions (Sqrt, cubic root, 4Rt, Sub3, Exp, x^3, $1/x$, Ln) were used.

For choosing the chromosomal tree, that is, the length of the head and the number of genes, the GEP model initially used a single gene and two lengths of heads, and increased the number of genes and heads, one after another, during each run, while monitoring the training and testing performance of each model. After several trials, the numbers of genes and lengths of heads were found to be 6 and 8, respectively, in order to obtain the best results. The sub-ETs (genes) were linked by addition.

Finally, a combination of all genetic operators (mutation, transposition, and crossover) was used as the set of genetic operators. The parameters for training the GEP model are listed in Table 4. Chromosome 30 was observed to be the best generation of individuals in predicting SE_{cut}. The explicit formulation based on the GEP model for SE_{cut} is given by

$$\begin{aligned}
SE_{cut} = {} & e^{\left[\frac{7.95-\left(4.63d_4^3*\left(3d_3+d_5\right)\right)}{d_3}\right]} + \left(\frac{12.26+d_2}{d_5+d_0}\right)^3 + \left[1-\left(\frac{d_2-20.38}{d_1}\right)\right] \\
& + \sqrt[2]{e^{\left[\left(\frac{(d_2-d_3)+\sqrt[2]{d_5}}{2}\right)-\left(\frac{5.15+d_1}{2}\right)\right]^3}} + e^{\left[\left[\frac{4(0.66-d_3)}{(-12.63+d_4)}\right]-\left(\frac{d_0-d_4}{2}\right)\right]^3} \\
& + \left[\frac{1.03d_3*(9-d_3)}{(d_1-d_2-d_0-d_3)}\right]^{\left(\frac{10}{3}\right)} \\
& + \frac{2}{\sqrt[5]{e^{d_3}*d_3*d_2^2*(-9.86)}-52.91}
\end{aligned} \tag{2}$$

The expression tree of the formulation is shown in Figure 2, where d_0, d_1, d_2, d_3, d_4, and d_5 refer to $D_{\%}$, f_c, RH, BSA, V_f, and h_c, respectively. The constants used in the formulation are listed in Table 5.

Results and discussion

This section presents the analysis results of the developed model and presents a quantitative assessment of the predictive abilities of the model. In evaluating the model, it is important to define the criteria,

Table 4. GEP parameters used for the developed model.

Parameter definition	GEP model
Program size	94
Literals	30
Fitness function	RMSE
Number of generations	1999
Arithmetic operators	+, −, *, /
Mathematical functions	Inv, sgrt, 3Rt, 4Rt, 5Rt, X^2, X^3, X^4, X^5
Number of chromosomes	30
Head size	8
Number of genes	6
Linking function	Addition
Mutation rate	0.00138
Inversion rate	0.00546
One-point recombination rate	0.00277
Two-point recombination rate	0.00277
Gene recombination rate	0.00277
Gene transposition rate	0.00277

RMS, root mean square error.

namely, the performance of the model and prediction accuracy. Of the 535 datasets, 401 were used for training the model and the remaining 134 were used for testing the model. The performance of the developed model was evaluated on the basis of the following parameters: fitness, mean squared error (MSE), which measures the average of the squares of the errors, that is, the difference between the observed and predicted values, root mean square error (RMSE), which represents the sample standard deviation between the observed and predicted values, and mean absolute percentage error (MAE), which is a measure of prediction accuracy of a forecasting method in statistics, for example, in trend estimation, and it usually expresses accuracy as a percentage. The coefficient of determination (R^2) and calculation errors were used as criteria for assessing the agreement between the experimental and predicted values. The statistical performance of the developed model is summarized in Table 6.

The fitness values ranged from 0 to 1000, with 1000 corresponding to ideal fitness. For this model, the fitness values were in a good range. For both training and validation cases, MSE, RMSE, and MAE were very close to 0. The R^2 value relating the experimental and predicted data from the GEP model was 0.96, implying that 96% of the variation in the data could be explained by the model, which showed good performance. The total errors between the experimental and predicted values were evaluated on the basis of the MAE. The SE_{cut} values predicted by the GEP model in the training and testing phases are graphically compared with their experimental counterparts in Figures 3 and 4, respectively. As can be seen from these figures, the actual values are close to the predicted values.

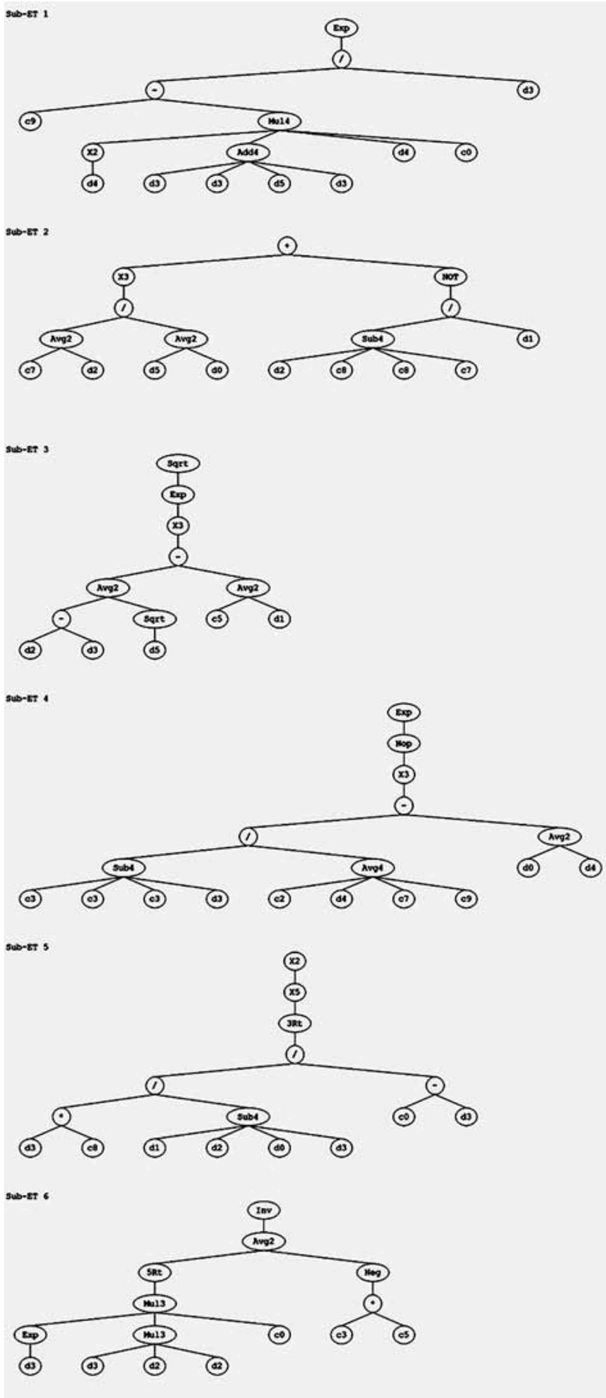

Figure 2. Expression tree for the GEP model.

Table 5. Constants in the GEP model.

Constant	Sub-ET 1	Sub-ET 2	Sub-ET 3	Sub-ET 4	Sub-ET 5	Sub-ET 6
c0	4.63	1.12	−9.25	9.81	9.00	−9.86
c1	−9.31	2.48	−5.27	−9.16	6.97	2.29
c2	1.08	6.12	6.50	−1.38	7.31	−8.48
c3	8.57	−3.16	−226.89	−0.66	2.08	−11.00
c4	6.72	0.55	−3.96	−1.05	−10.90	3.03
c5	2.58	−0.81	5.17	0.13	9.83	4.81
c6	−5.41	2.20	2.66	−1.90	−2.08	7.15
c7	−7.36	12.26	1.88	−7.67	8.65	−6.55
c8	1.27	4.06	−2.19	9.21	1.03	5.18
c9	7.95	−7.68	−5.79	−3.58	−4.55	−5.71

Table 6. Performance statistics of the model.

	Training	Validation
Fitness	742.06	722.95
MSE	0.121	0.147
RMSE	0.348	0,383
MAE	0.235	0.237
R^2	0.956	0.959
Calculation errors	0	0

MSE, mean squared error; RMS, root mean square error; MAE, mean absolute percentage error; R^2, coefficient of determination.

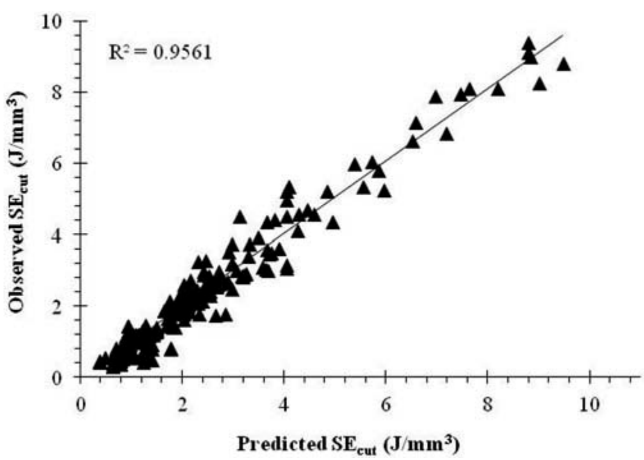

Figure 3. Measured versus predicted SE_{cut} for data used to train the GEP model.

Conclusions

This paper reported a new and efficient GEP-based approach to the formulation of SE_{cut} for natural rock cutting using a circular diamond saw. This is the first such report in the literature. Unlike previous studies, this study developed a single model for more than one rock type. The proposed model is empirical and based on experimental results. Data for the development of the model

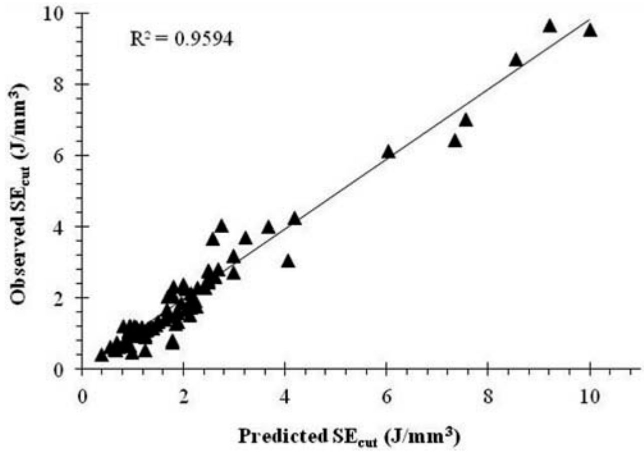

Figure 4. Measured versus predicted SE_{cut} for data used to validate the GEP model.

were obtained from an experimental study. The proposed GEP-based equation is sufficiently simple to be used by those who are not familiar with GEP.

The validity of the GEP model was verified by the statistical performance criteria used for evaluating the model. Furthermore, the model yielded a high R^2 value (0.96) and low MSE, RMSE, and MAE values (0.121, 0.348, and 0.235, respectively). In addition, it resulted in a highly nonlinear relationship between SE_{cut} and the cutting process, with high accuracy and relatively low error.

This paper presented not only a mathematical model of GEP but also software models in different computer languages such as MATLAB, Excel, and C++. Using such software, researches and producers can easily predict SE_{cut} and the cutting efficiency. The overall GEP evaluation results obtained in this study revealed that GEP is a promising approach for modeling natural stone cutting, which is a complex process influenced by a variety of factors.

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