Comparing the reliability of classical statistics and data mining techniques in unit energy prediction in circular stone cutting

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Abstract

Energy efficiency is one of the critical parameters affecting production in the natural stone sector, as it is in every industrial sector. High energy consumption negatively affects production costs, especially in stone cutting and surface treatments. Nowadays, it is crucial to predetermine energy consumption with reliable predictive techniques to produce with the lowest energy possible and sustain sectorial competition. This study conducted stone cutting tests with a computer-assisted circular cutting machine at different peripheral speeds (PSs) and advance rates (ARs). Unit energy (UE) consumptions were measured in stone cuttings. UE was evaluated regarding the circular stone cutting machine's (CSCM's) operating parameters, some stone characteristics, vibration amplitude (VA), and sound level (SL) measured during cutting. Classical statistics (CS) and data mining (DM) techniques were used to predict UE. 287 and 24 cutting data sets were selected as training and testing data for CS and DM techniques, respectively. These techniques were also compared and provided more significant and reliable results of DM techniques than CS. DM techniques predicted the UE with high correlation coefficients obtained in the range of R^2=0.963 and 0.973. DM models for UE prediction before stone cutting have been introduced for stone processing researchers and those interested.

Keywords: Natural stone cutting; unit energy prediction; data mining; classical statistics; prediction reliability.

1. Introduction

The size of the global natural stone market increases steadily, according to researches and reports worldwide. Increasing construction according to the growing population, renovation of old buildings, increasing demand for outdoor social areas accelerate the use of natural stones worldwide. Besides, sectorial competition among producers increases to take a share from the growing natural stone market. Therefore, producers need to produce natural stone products as low a cost as possible to be at the forefront of this competition. For this, producers should reduce their cost items whenever possible.

Energy consumption is an essential cost item in the natural stone industry, especially in stone cutting. Several machines, such as CSCM, frame cutting/sawing machines, wire cutting/sawing machines, etc., can be used to cut natural stone processing plants. CSCMs are broadly used due to being more economical and more flexible.

It is necessary to determine the optimum cutting parameters for the efficient usage of CSCMs. CSCMs should be operated at a minimum UE and maximum AR conditions for low-cost production. UE consumed during cutting can be measured with a unique energy analyzer to be placed in the CSCM. Besides, machine operating parameters (PS and AR) and some stone properties can be an effective solution for predetermining this UE. It is necessary to investigate the effects of machine operating parameters and stone properties on UE consumption.

Some researchers have studied circular stone cutting performance parameters. In some of these studies, cutting performance and cutting forces, cutting parameters, and stone properties have been related [1-14]. The relationships between specific energy and energy consumption with cutting performance have been investigated in some studies [15-20]. Also, the performance of the cooling medium used for the cutting tool was studied for the reduction of the consumed energy [21, 22]. Conventional statistical techniques defined as hard computing have been used in the studies mentioned above generally.

On the other hand, except the artificial neural networks (ANN), DM techniques have not been widely used in circular stone cutting. DM techniques, such as fuzzy logic, genetic algorithms, neural networks, machine learning, and expert systems deal with approximate models and offer solutions to more complex problems. There are a limited number of studies in the literature on circular stone cutting using DM techniques. Yurdakul et al. [23] developed specific cutting energy prediction models with adaptive hybrid intelligence techniques. Mikaeil et al. [24] tried to predict a circular cutting machines' hourly production rate with meta-heuristic algorithms and fuzzy clustering techniques. Guney [25] estimated circular cutting machines' hourly areal slab productions during marble blocks' dimensioning with ANN and regression methods. Akhyani et al. [26] predicted the circular diamond saw wear by combining the fuzzy rock engineering system (Fuzzy RES) and genetic algorithm (GA). Ataei et al. [27] evaluated the energy consumption and vibration of cutting machine by incorporating a combination of multi-layered perceptron ANN and genetic algorithm (GANN-BP) and the support vector regression method and Cuckoo optimization algorithm (COA-SVR). Hosseini et al. [28] investigated the effect of cooling and lubricant fluid on the cutting performance (as a maximum electrical current) with ANN and the hybrid genetic algorithm - artificial neural networks (hybrid GA-ANN). Sadjad et al. [29] developed predictive models depends on machine vibration and physical-mechanical properties of stones using statistical and soft computing methods. Mikaeil et al. [30] proposed new prediction models for determining the vibration of circular sawing machine using machine learning.

In the literature review shown above, there is no DM study related to predicting the UE in circular stone cutting using the machine operating parameters (PS, AR), stone characteristics, VA and SL measured during cutting as a prediction data. Besides, there is no study comparing CS methods and DM techniques in UE prediction. The much better, more effective, and more reliable results have been obtained with DM techniques used in this study according to the hard computing techniques (such as CS) used in literature. DM techniques are very successful in evaluating such complex cutting data. The UE prediction models obtained in this study offer an approach that natural stone researchers can use in cost and performance estimates.

2. Methodology of Study

This study for unit energy prediction includes experimental studies and the evaluation of data collected. Figure 1 shows the methodology of the study. Experimental studies were conducted in two stages. In the first stage, rock mechanics tests were carried out to determine the stone properties cut in CSCM. The cutting experiments were performed in CSCM at different PSs and ARs in the second stage. Then, the obtained data were evaluated with different techniques.

Figure 1. Methodology of study

2.1. Stone Characteristics

Limestone (sedimentary rock) and real marble (metamorphic rock) samples were used in this study. The physical and mechanical properties [unit volume weight (UVW), uniaxial compressive strength (UCS), tensile strength (TS), bending strength (BS), impact strength (IS), Shore hardness (SH), and Bohme surface abrasion (BAR)] of stone samples were determined according to International Society for Rock Mechanics and Rock Engineering (ISRM) [31] and Turkish Standards Institution (TSE) [32] standards. Table 1 shows some rock characteristics of the stone samples.

Table 1. Some rock characteristics of the samples

2.2. Stone Cutting Experiments

Stone cutting experiments were carried out with the computerized CSCM for this study. This machine is a specially manufactured cutting machine to control operating parameters with a computer (Figure 2). Limestone and real marble samples were used in the cutting studies. The experimental samples were prepared in 200x300x500 mm mini blocks. The cutting operations were carried out at a 60 mm constant depth and 24 conditions which are the combination of four PSs (at a range of 40-70 m/s) and six ARs (at a range of 400-900 mm/min). The cutting operations were repeated five times for each condition.

Figure 2. Computerized CSCM

2.2.1. Measurements of UE

A microprocessor network analyzer installed on the control panel was used to measure all electrical network parameters in CSCM. The measured parameters can be monitored with five different indicators, and at the same time, the measured parameters can be transferred to the computer with serial communication. The instantaneous energy consumed during the cutting operations within this study’s scope was measured, and the related data were transferred to the computer with this analyzer. Table 2 shows the measured UE after cutting operations.

2.2.2. Measurements of VA and SL

SL of cutting operation was measured by a RadioShack digital sound level meter. The net SLs of cutting conditions were determined around the cutting blade by removing the background sounds. A vibration sensor manufactured by Wilcoxon was used to measure the lateral vibration on the circular saw blade during cutting. VAs were determined as the average amplitude of lateral vibration measured while the saw blade was in the rock. Table 2 shows the measured average VA and net SLs after cutting operations.

Table 2. The measured UE, average VA, and net SL after cutting operations

2.3. CS Assessments for Determining UE

The dependent variable (UE) and independent variables (stone cutting parameters, stone characteristics and VA, and SLs of cutting operations) were determined in the first stage of statistical assessment. The descriptive statistics of the dependent and independent variables were investigated (Table 3). Skewness and kurtosis coefficients were within normal limits (±3), thus satisfying the normal distribution.

Table 3. Descriptive statistics for variables

The ideal variables for the multiple regression model were selected using the best subsets regression, which is an automatic process that defines the optimal regression models using independent variables. The basic approach in this process is to choose the smallest subset of independent variables that can fully satisfy statistical criteria. The adjusted coefficient of determination (adjusted R^2) and Mallows' C_p statistics are commonly used to select the ideal model to be developed the best subsets regression. The higher the adjusted R^2, the more appropriate the model, while the lower the Mallows' C_p, the more suitable the model. Table 4 shows the results of the best subsets regression.

Table 4. Best subsets regression results

The 287-cutting data of different limestone and real marble samples as training data were used to develop the regression model. The data mentioned above were analyzed using Minitab 17 statistical software. Model 7 (in Table 4) has the most suitable conditions; the highest adjusted R^2 (91.0%), low Mallows' C_p (7.0).

Table 5 shows the results of the multiple regression model for UE. The coefficient of determination (R^2) of the UE regression equation was 0.9122.

Relationships of variables with each other were analyzed, and it was investigated whether there is multicollinearity between independent variables for regression analysis. As a rule of thumb, the variance inflation factor (VIF) should be less than 10 to indicate no multicollinearity among independent variables. It was determined in the VIF analysis that there was no multicollinearity between the variables.

Table 5. Results of multiple regression model for UE

The statistical validity of the UE regression model was evaluated with analysis of variance, also called ANOVA. Table 6 shows the ANOVA results. The model is statistically highly significant according to the P-value.

Table 6. The ANOVA results for the UE regression model

2.4. DM Assessments for Determining UE

The DM techniques in this study were performed using Weka software version 3.8.3, approved widely, and one of the complete tools in DM applications. In this study, DM assessments are intended to test the performance of DM techniques to predict UE from some machine parameters, stone characteristics and VA, and SL measured during cutting. The 287-cutting data consisted of seven limestone samples, and six marble samples were used as training data. The DM techniques used in this study were the ANN, k-nearest neighbor (k-NN), M5' model tree (M5P), and random forest (RF). All model algorithms were optimized to represent training data in the optimum condition and predict test data most reliably.

The ANN technique depends on the human brain's structure and is contained with simple processing units, artificial neurons, and their interconnections, etc. The multilayer perceptron structure was adopted in this study [33]. In ANN analysis, back-propagation neural networks were used to determine the relationships between UE and stone cutting parameters (machine parameters, stone characteristics, VA, and SL). For ANN analysis to be efficient, it is necessary to modify the ANN model and parameters. Hidden layers and nodes per hidden layer were tested systematically. Three hidden layers were constructed with the 9, 5, 5 nodes, respectively. These network parameters can also be monitored and modified during data training. Figure 3 shows the ANN networks.

Figure 3. ANN network for UE

The k-NN is used both in classification and regression analyses. The nearest neighbor method is one of the most straightforward techniques in statistical discrimination. It is a nonparametric method. A new observation is placed into the observation class from the training data closest to this observation concerning covariates. In the k-NN process, the classification and value of an object are influenced by its nearest neighbors. The parameter k is the number of neighbors in the analysis. The value of the object is a weighted mean of k-nearest neighbors' values in regression analysis [34, 35]. In k-NN analysis, the number of neighbors used in the model was 5 for the best result.

The M5P technique is a system for machine learning models that predicts the data. M5' model tree splits the data space into subspaces and constructs a linear regression equation for each subspace. M5P constructs a regression or model tree by reiterative separation based on treating the standard deviation of the class values. Regression and model trees are effective for big data. However, model trees generally have a smaller size than regression trees, and their prediction integrity is better [36]. The stone cutting parameters were classed with the M5P algorithm to predict UE. M5P algorithm generated a decision tree using this classification and derived a localized linear regression equation (LM) instead of the class label in all leaves of the model tree. UE was predicted using these LMs more effectively. Figure 4 shows this model tree.

Figure 4. M5P model tree for UE

As shown in Figure 4, the M5P classed the data set into some subclass based on the AR and UCS values and constructed LMs for each class using the more related parameters. These models allowed a more accurate prediction of the UE in stone cutting.

One of the practical tools in prediction is the RF technique. RFs are a combination of tree predictors. Each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. A RF is a tree-structured classifier {h(x, Θk), k = 1} where the {Θk} is independent identically distributed random vectors, and each tree casts a unit vote for the most popular class at input x [37]. In RF analysis, 100 iterations were performed.

The coefficient of determination (R^2) and cross-validation metrics such as the mean absolute error (MAE) and the root mean square error (RMSE) were used to determine and compare the performance of models. Table 7 shows the global statistical metrics (R^2, MAE, and RMSE) for the correlations between measured and predicted UE.

Table 7. The global statistical metrics for applied DM techniques

As shown in Table 7, all applied DM models have acceptable reliability for predicting UE values. The coefficients of determination for the results obtained with DM techniques are pretty high. This situation shows that the independent variables used in the study explain the dependent variable in a more meaningful way thanks to the DM algorithms.

3. Discussion

In the study, using different methods and algorithms, five different prediction models were developed and optimized with CS methods (best subsets regression and multiple regression) and DM techniques (ANN, k-NN, M5P and RF). After developing prediction models based on CS and DM techniques, the performance of the prediction models on the same test data was investigated.

The UE regression model developed with CS was tested with the 24-cutting data of a marble sample not used in statistical modeling. Figure 5 shows the relationship between the measured and predicted UE values for testing data according to the CS regression model. The predicted UE values meet the measured UE values by 89.9%.

Figure 5. Performance of CS regression model for testing data

Prediction models developed with 287-cutting data (training data) using DM techniques were tested with the same data set used in testing the UE regression model. Figure 6 shows the performance of DM models for testing data. It can see from the figure that the predicted values for DM models reflect the measured values very well at a range of R^2=0.963 and 0.973.

Figure 6. Performance of DM models for testing data

According to the above evaluations, DM techniques outperformed CS methods in UE prediction. Although similar results were obtained in DM techniques, the RF algorithm was given the best results.

4. Conclusions

Fourteen different stones, including limestone (sedimentary rock) and real marble (metamorphic rock), were cut with a computerized CSCM in this study. The UE consumed during cutting was tried to predict with DM techniques and CS methods from some stone characteristics, machine operating parameters, VA and SL.

DM techniques have a better ability to predict according to CS methods. The prediction of UE in stone cutting should be obtained more accurately with DM techniques. In this study, the coefficient of determination for CS methods (best subsets and multiple regression) was determined by 0.896 in predicting testing data. The developed DM models (ANN, k-NN, M5P and RF) were tested with testing data and provided a higher coefficient of determination in the range of 0.963 and 0.973. Among the DM techniques, the RF algorithm gave the best results (R^2=0.973).

This study contains beneficial results for stone processing researchers. The UE can be determined accurately and reliably before stone cutting with DM techniques. DM algorithms give more successful outcomes than CS methods in analysis with such complex data.

Acknowledgments

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Declaration of Conflicting Interests

The author has no conflicts of interest to declare that they are relevant to the content of this article.

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Author’s biography

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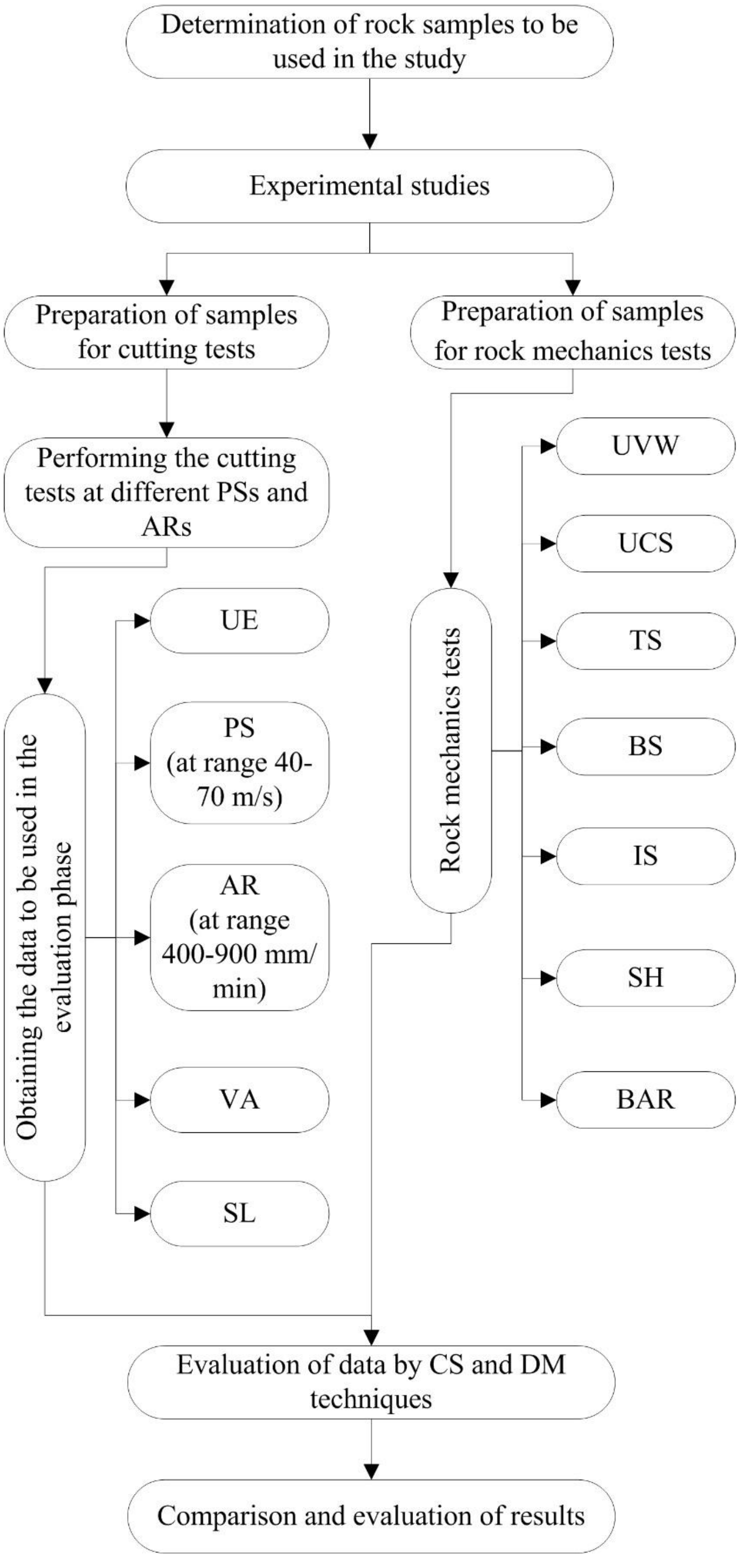

Figure 1. Methodology of study

Figure 2. Computerized CSCM

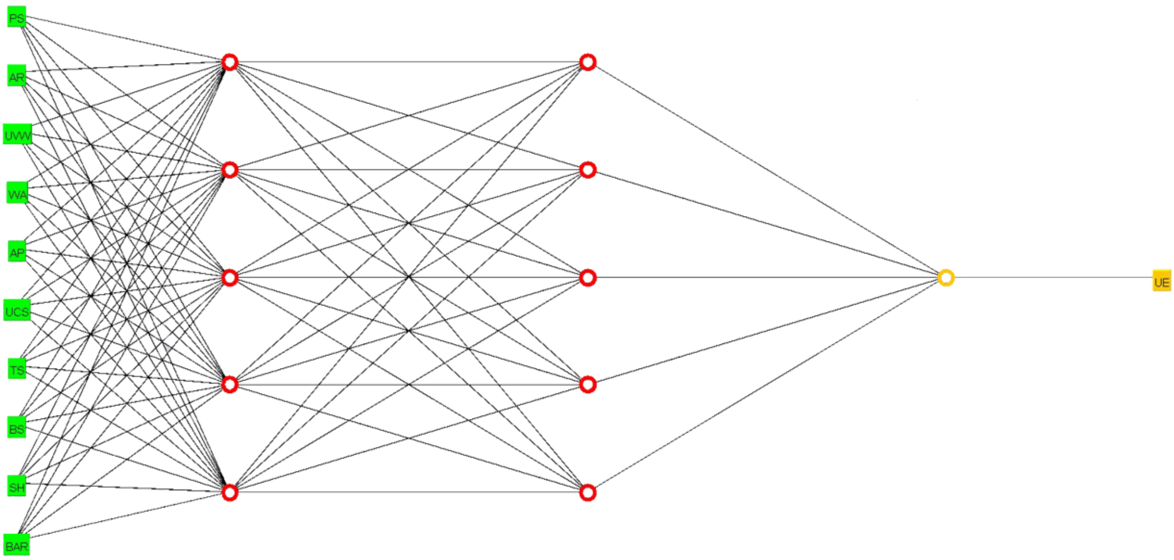

Figure 3. ANN network for UE

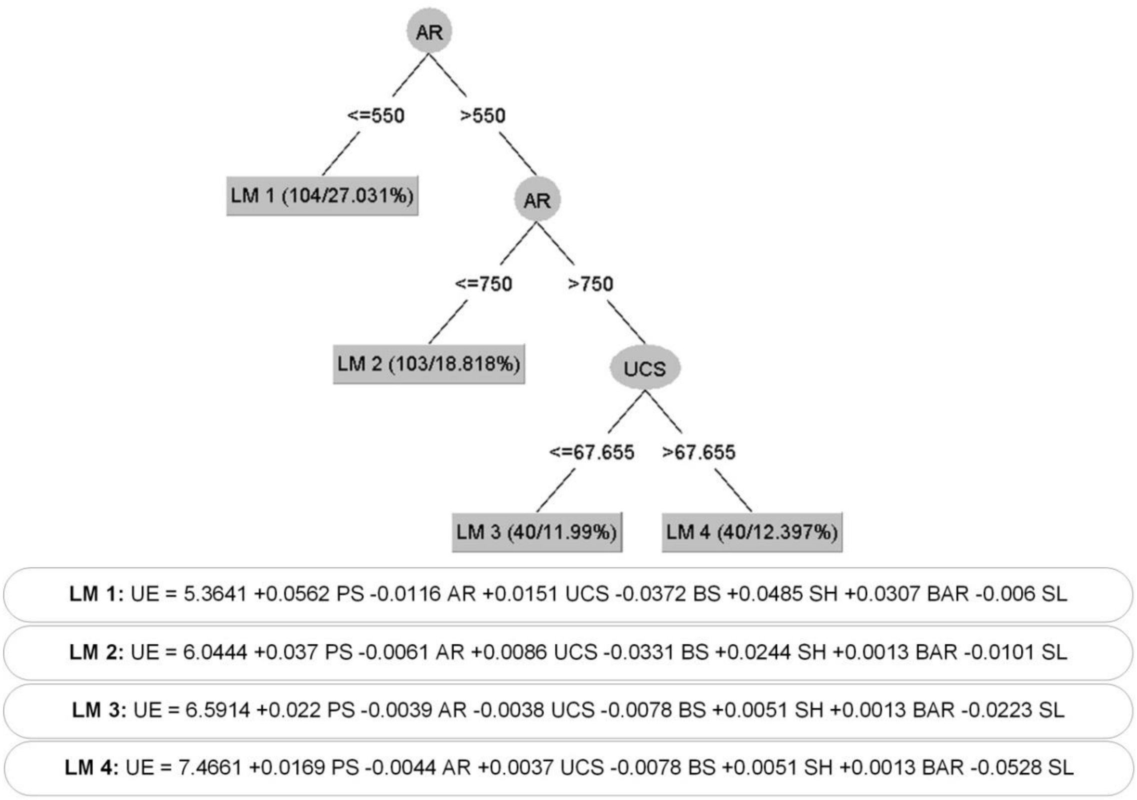

Figure 4. M5P model tree for UE

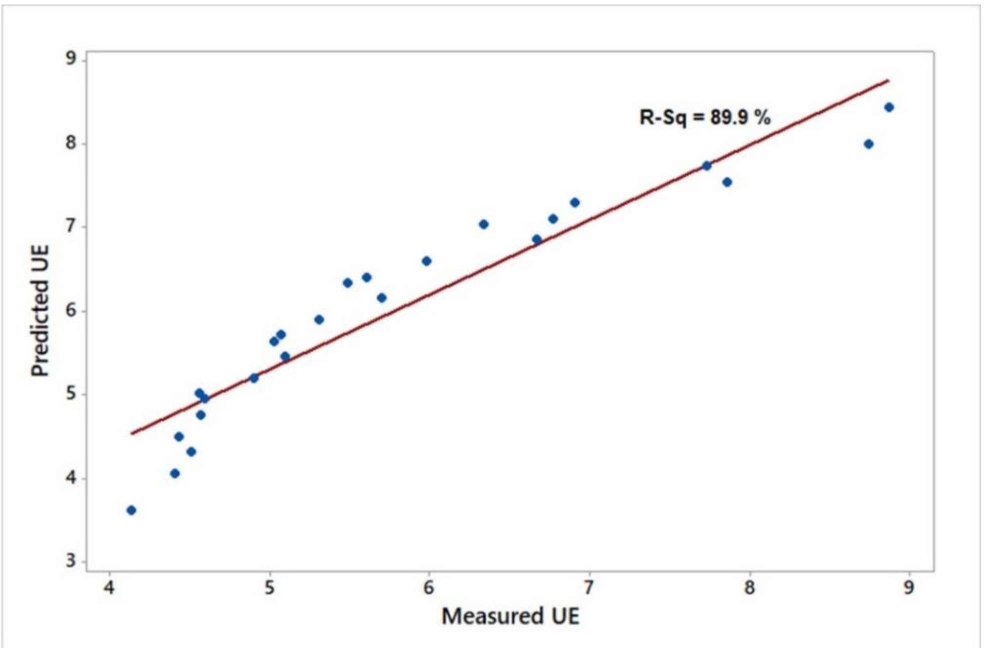

Figure 5. Performance of CS regression model for testing data

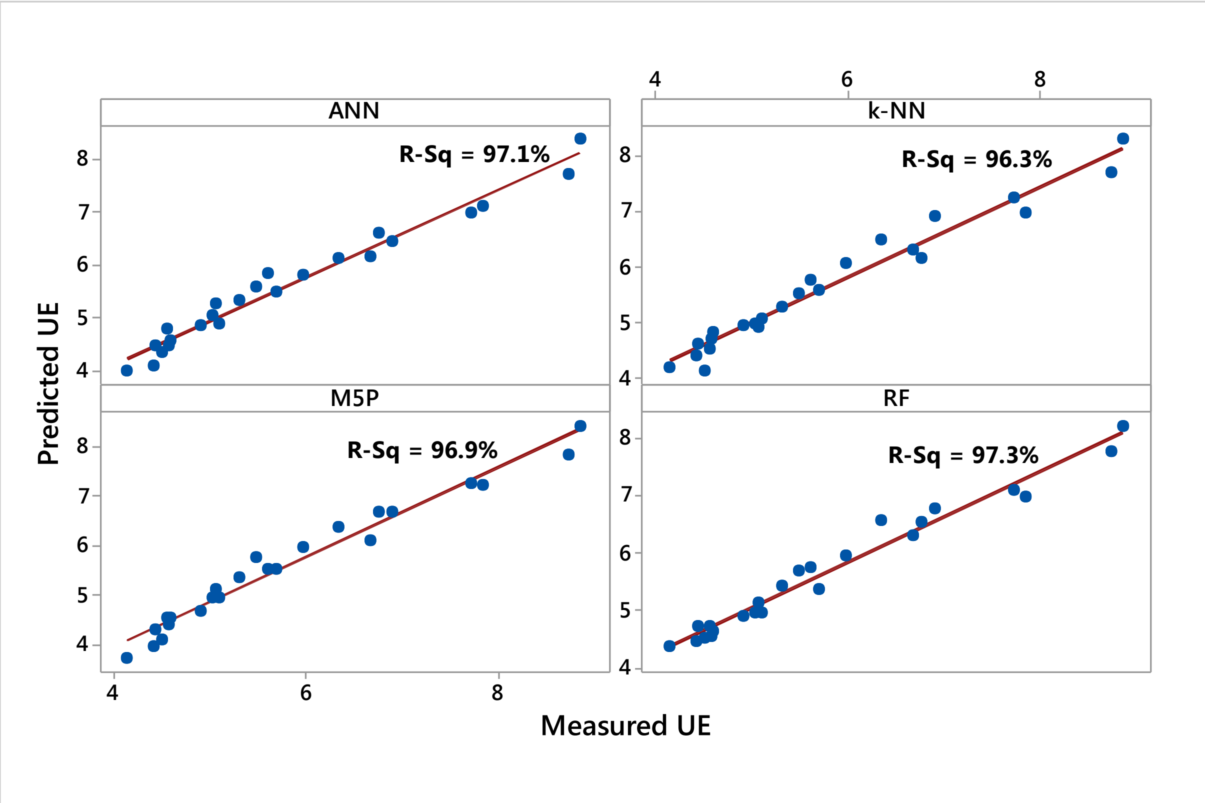

Figure 6. Performance of DM models for testing data

Table 1. Some rock characteristics of the samples

Natural Stones	UVW (g/cm^3)	UCS (MPa)	TS (MPa)	BS (MPa)	IS (MPa)	SH	BAR ($cm^3/50\ cm^2$)
Afyon Violet	2.72	73.94	5.49	10.98	3.0	42	33.85
Afyon Grey	2.70	49.65	6.53	10.95	2.5	51	36.35
Afyon Pink	2.73	46.71	6.32	11.76	2.5	58	23.09
Afyon Tigerskin	2.71	40.95	7.80	13.97	2.5	56	35.73
Afyon White	2.70	51.45	6.22	12.93	3.0	49	37.09
Mugla White	2.70	65.31	4.77	15.02	3.0	42	30.85
Kutahya Violet	2.69	63.50	6.80	11.00	3.6	50	28.75
Rosalia Beige	2.68	91.95	5.94	6.78	1.6	55	18.59
Hazar Pink	2.67	100.28	8.13	21.60	2.0	51	20.79
Rustic Green	2.69	70.47	7.77	13.64	3.0	63	15.28
Amasya Beige	2.70	105.40	6.92	22.50	3.0	60	14.15
Burdur Cream Creama	2.69	79.40	6.39	6.49	1.6	51	24.65
Sivrihisar Beige	2.70	70.00	7.05	15.50	2.5	62	14.20
Mustafakemalpasa Beige	2.70	110.75	7.50	23.80	3.6	64	14.25

Table 2. The measured UE, average VA, and net SL after cutting operations

Stone Class	Natural Stones	UE (kWh/m^2)		Average VA (Hz)		Net SL (dB)	
		Min	Max	Min	Max	Min	Max
Real Marble	Afyon Violet	4.078	8.720	7.8	27	6	13
	Afyon Grey	4.078	9.267	9	23.6	4	14
	Afyon Pink	4.141	8.870	9	20	4	17
	Afyon Tigerskin	3.933	8.432	9	20.75	3	11
	Afyon White	3.748	9.053	12.25	23.8	3	14
	Mugla White	3.701	7.800	9.75	21	3	13
	Kutahya Violet	3.663	7.922	9.75	20	4	14
Limestone	Rosalia Beige	4.507	8.573	12.5	24.75	6	14
	Hazar Pink	4.442	8.734	12	28.4	3	17
	Rustic Green	4.652	8.883	10.5	24.6	2	16
	Amasya Beige	4.606	8.935	11	24.5	2	11
	Burdur Cream Creama	4.762	9.413	11.5	32	4	14
	Sivrihisar Beige	4.611	9.057	10.5	31.75	2	11
	Mustafakemalpasa Beige	4.427	8.459	9.5	35	4	14

Table 3. Descriptive statistics for variables

Variables	Data	Mean	Standard deviation	Skewness	Kurtosis
PS	287	55.854	11.152	-0.12	-1.34
AR	287	632.06	165.83	0.12	-1.18
UVW	287	2.6967	0.0122	-0.31	0.27
UCA	287	73.63	21.15	0.29	-0.98
TS	287	6.6959	0.9503	-0.37	-0.61
BS	287	14.243	5.133	0.50	-0.62
IS	287	2.7101	0.609	-0.41	-0.63
SH	287	53.199	7.059	-0.03	-1.00
BAR	287	25.561	8.921	-0.07	-1.64
VA	287	15.190	4.643	1.24	1.67
SL	287	8.645	3.121	0.09	-0.65
UE	287	5.8418	1.3121	0.60	-0.36

Table 4. Best subsets regression results

Model No	Adjusted R^2	Mallows' C_p	Mean square error	PS	AR	UVW	UCS	TS	BS	IS	SH	BAR	VA	SL
1	73.4	555.0	0.67614		X									
2	88.4	85.1	0.44770	X	X									
3	89.4	54.3	0.42796	X	X						X			
4	90.2	30	0.41144	X	X					X	X			
5	90.5	20.7	0.40448	X	X	X				X		X		
6	90.9	10.0	0.39646	X	X	X	X			X	X			
7	**91.0**	**7.0**	**0.39358**	**X**	**X**	**X**	**X**		**X**	**X**	**X**			
8	91.0	7.8	0.39343	X	X	X	X		X	X	X			X
9	91.0	8.2	0.39300	X	X	X	X		X	X	X	X		X
10	91.0	10.1	0.39365	X	X	X	X	X	X	X	X	X		X
11	91.0	12.0	0.39432	X	X	X	X	X	X	X	X	X	X	X

Table 5. Results of multiple regression model for UE

Predictors	Coefficient	Standard Error of Coefficient	T-value	P-value	VIF
Constant	-20.72	6.36	-3.26	0.001	
PS	0.04413	0.00211	20.95	0.000	1.02
AR	-0.00696	0.000142	-49.00	0.000	1.02
UVW	10.28	2.36	4.36	0.000	1.53
UCS	0.00654	0.00149	4.39	0.000	1.84
BS	-0.01473	0.00652	-2.26	0.025	2.07
IS	-0.2278	0.0486	-4.69	0.000	1.61
SH	0.02089	0.00372	5.62	0.000	1.27

Table 6. The ANOVA results for the UE regression model

Source	Degree of Freedom	Adjusted Sum of Squares	Adjusted Mean Square	F value	P (probability)
Regression	7	449.162	64.166	414.22	0.000
PS	1	68.005	68.005	439.01	0.000
AR	1	371.876	371.876	2400.64	0.000
UVW	1	2.949	2.949	19.04	0.000
UCS	1	2.980	2.980	19.24	0.000
BS	1	0.791	0.791	5.10	0.025
IS	1	3.410	3.410	22.01	0.000
SH	1	4.895	4.895	31.60	0.000
Error	279	43.219	0.155		
Total	286	492.381			

Table 7. The global statistical metrics for applied DM techniques

Statistical Metrics	DM Techniques			
	k-NN	**RF**	**M5P**	**ANN**
MAE	0.2455	0.2458	0.2605	0.2755
RMSE	0.3706	0.3598	0.3443	0.3767
R^2	0.9629	0.9730	0.9688	0.9710