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Predicting the Cutting Rate of Circular Saws in Stone Cutting Plants Using Random Tree Algorithm

Keywords

Circular saw
Cutting rate
Random tree algorithm
Multiple linear regression
Stone cutting plant

Abstract

Circular saws are the most widely used tools in stone cutting plants for slicing slabs into desired dimensions. Their cutting rate is governed by several factors, including the physical and mechanical properties of the stone, saw design parameters, and operational conditions. Accurate prediction of the cutting rate is essential not only for enhancing productivity but also for reducing costs and optimizing production scheduling. In this study, the Random Tree (RT) algorithm was applied to predict the cutting rate of circular saws in stone cutting operations. Four key variables were used for model development: Uniaxial Compressive Strength (UCS), Brazilian Tensile Strength (BTS), Cerchar Abrasivity Index (CAI), and Rotation Speed of Saw (RSS). The RT model achieved coefficients of determination (R^2) of 0.975 for training data and 0.923 for testing data, outperforming multiple linear regression, which yielded an R^2 of 0.77. Similarly, the Root Mean Square Error (RMSE) was 0.6167 for training and 0.9221 for testing. These results demonstrate the superior predictive accuracy of the RT algorithm, underscoring its potential to significantly improve productivity and scheduling efficiency in stone cutting plants.

1- Introduction

Dimensional stones are widely utilized as construction and decorative materials across the world. In recent years, advances in technology and the growing adoption of innovative architectural and interior design concepts have significantly increased their demand. Consequently, optimizing the processes involved in the production and supply of dimensional stones has become a critical requirement [1].

Circular saws are among the most commonly used machines in stone cutting plants for slicing stone blocks into slabs of varying dimensions (Figure 1). This method is effective for producing slabs with smooth surfaces that typically require minimal additional finishing. High cutting efficiency, accuracy, and production capacity are the primary reasons for the widespread adoption of circular saws in the stone industry [2, 3]. Moreover, their cost-effectiveness compared to other cutting technologies has made them the preferred choice for cutting stone blocks and large slabs across a wide hardness and abrasivity spectrum, ranging from soft to hard, and non-abrasive to highly abrasive materials [4].

The performance of circular saws is primarily assessed through two indicators: cutting rate and wear rate. The main objective of cutting tool manufacturers is to optimize these parameters to maximize efficiency and durability [5]. Factors influencing cutting performance are categorized into three categories: stone properties, tool properties, and machine capacity [6].

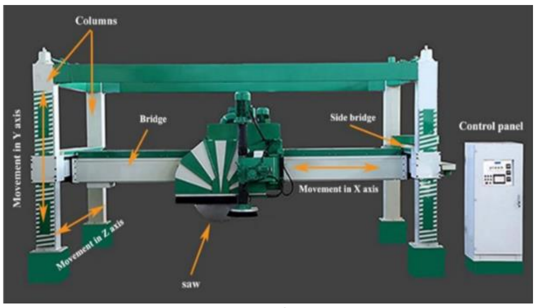

Figure 1. Major components of a circular saw machine [1]

Since stone properties are intrinsic and cannot be altered, understanding the stone's response to cutting and the associated influencing parameters is critical when selecting an appropriate tool [7]. Conversely, once the tool is chosen, operational parameters can still be optimized to enhance cutting performance [8]. In this study, a Random Tree (RT) algorithm was employed to develop a predictive model for estimating the cutting rate of circular saws, using key stone properties along with the saw rotational speed as input variables.

2- Literature Review

Optimal selection and accurate performance evaluation of circular saws are critical for reducing operational costs and enhancing productivity in stone cutting plants. The

performance of these machines is influenced by the physical and mechanical properties of the stone, operational conditions, and the technical specifications of the equipment. Previous studies have primarily focused on estimating parameters such as cuttability, production rate, and specific energy, for which various predictive models have been proposed [1].
Table 1 summarizes the existing models developed to estimate cutting performance, categorized by stone type and the number of influencing parameters considered. As shown, Uniaxial Compressive Strength (UCS) and Brazilian Tensile Strength (BTS) are among the most frequently employed parameters in these models. A notable limitation, however, is the small number of rock samples used, typically ranging from 5 to 25.
To date, no study has applied the RT method for predicting the cutting rate of circular saws. Furthermore, most existing studies have been restricted to a single category of rock—igneous, sedimentary, or metamorphic. To address these gaps, this study develops an RT-based predictive model for circular saw cutting rates, utilizing a comprehensive database encompassing a wide range of building stones.

3- Methodology

3-1- Input Data

In this study, data from three previous investigations were utilized [1, 4, 25]. Four key parameters were selected for model development: two strength-related rock properties—UCS and BTS; the Cerchar Abrasivity Index (CAI), representing rock hardness; and the Rotational Speed of Saw (RSS), an operational parameter affecting cutting performance. Table 2 presents the data used for model training, while Table 3 provides the testing data for the RT model.
UCS is defined as the maximum compressive stress a specimen can withstand before failure. Tests were conducted in accordance with the International Society for Rock Mechanics (ISRM) guidelines [34] on cylindrical specimens with a length-to-diameter ratio of 2–2.5, under a controlled loading rate of 0.5–1.0 MPa/s.
The Brazilian test is an indirect method for determining rock tensile strength. A disk-shaped specimen with a height-to-diameter ratio of ~1 is loaded along its diameter, inducing tensile failure perpendicular to the applied load.

Table 1. Summary of recent studies on circular saw performance prediction

Source	Year	Parameters	Method	Sample size	Objective
[9]	2024	SHH, BTS, Vp ,WA, UCS, E, PLSI	RF, MLR	9	CR,WR
[7]	2022	KH, BTS, BS, CAI	SLR, MLR	13	WR
[10]	2022	UCS, E	MLR	12	SE
[11]	2021	SH, BTS, UCS, Pv, P	SLR, MLR, Non-linear Reg	8	WR
[12]	2019	UCS, BTS	SLR, MLR	28	CR
[5]	2019	MH, UCS	SLR	7	CR
[1]	2018	UCS, BTS, CAI, SHH, SSH, GS	MLR, Non-linear Reg	25	CR
[13]	2017	UCS, MH, E, BTS, EQC, GS	ABC	14	WR, SE
[14]	2017	UCS, SH, SHH, Bohme surface abrasion	GEP	23	SE
[15]	2017	Knoop hardness	SLR	10	WR
[16]	2016	BTS, EQc, Gs, UCS, E, MH	ICA, fuzzy clustering	12	CR
[17]	2016	UCS, BTS, EQc, Gs, E, MH	ANN	7	SE
[18]	2016	UCS, BTS, CAI	ANN	11	CR
[19]	2013	WA, P, SH, UCS, TS	SLR, MLR	7	SE
[20]	2013	UCS, BTS	SLR, MLR, Non-linear Reg	17	CR
[21]	2013	UCS, BS, MH, CAI, SH, MH, WA, Vp, SHH	MLR	9	WR
[22]	2013	UCS, BTS, SHH, SSH, LA, Pv, BS	SLR	12	SE
[23]	2013	SH, CI, BA, Brittleness	MLR	6	WR
[24]	2012	UCS, BS, BTS, PLSI, SH, SHH, Pv, WA	MLR	6	SE
[25]	2011	MH, Vickers Hardness, Rosiwal number	SLR, MLR	9	WR
[8]	2011	SH, SHH, Gs	SLR, MLR	5	CR
[26]	2011	UCS, BTS, SHH, LA	MLR, Non-linear Reg	10	CR
[4]	2011	UCS, BTS, SH, Density, WA, Porosity, Qc, Gs	MLR	9	WR
[27]	2008	Indentation Hardness (based on PLSI)	SLR	8	CR
[28]	2007	UCS, BTS, SHH, PLSI, IS, LA, Vp	SLR	8	CR
[29]	2007	UCS, BTS, SH, PLSI, IS, LA, Pv	Multifactorial fuzzy approach	8	CR
[30]	2006	SS	ANN	13	CR
[31]	2005	UCS, BS, Abrasivity	SLR	14	WR
[32]	2004	UCS, BTS, IS	SLR, MLR, Non-linear Reg	8	CR
[33]	2004	UCS, TS, SH, IS, LA, PLSI, Pv	SLR, MLR, Non-linear Reg	13	CR
[6]	2004	UCS, BTS, Abrasivity	SLR, MLR	14	CR

Gs: Grain Size of mineral, P: Porosity, Qc: Quartz Content, TS: Tensile Strength, UCS: Uniaxial Compressive Strength, BTS: Brazilian Tensile Strength, E: Elastic modulus, PLSI: Point Load Strength Index, IS: Impact Strength, BS: Bending Strength, SS: Shear Strength, EQC: Quartz Equivalent Content, SHH: Schmidt Hammer rebound number Hardness, SH: Shore Hardness, CI: Cone Indenter Hardness, MH: Mohs Hardness number, CAI: Cerchar Abrasivity Index, LA: Los Angeles Abrasion, WA: Water Absorption, Pv: P-wave velocity, ANN: Artificial Neural Networks, SLR: Simple Linear Regression, MLR: Multiple Linear Regression, RF: Random Forests, GEP: Gene Expression Programming, ABC: Artificial Bee Colony Algorithm, ICA: Imperialist Competitive Algorithm, CR: Cutting Rate, WR: Wear Rate, SE: Special Energy.

Table 2 – Training Data for RT Model [1, 4, 11]

Sample number	UCS (MPa)	BTS (MPa)	CAI (μm)	RSS (rpm)	CR (m^2/h)
1	88.6	4.9	2.94	2322	7.3
2	65.3	3.4	2	2214	15.4
3	70.4	4.1	2.05	2245	16.3
4	63.8	4.6	1.04	2276	11.9
5	108	7.9	1.01	2300	7.1
6	81.3	3.9	3.7	2400	10
7	139.6	8.1	2.9	2245	6.9
8	70.2	6.4	2	2400	11.5
9	79.3	6.4	3.4	2450	9.9
10	70.8	5.8	2.63	2350	14.3
11	89	5.3	2.44	2348	12.4
12	55.3	4.9	2.1	2220	20.2
13	45.1	4	0.6	2600	12.3
14	11	4.4	0.4	2610	20
15	50.5	4.8	0.7	2550	14
16	70.2	4.7	1.32	2420	13.4
17	77.8	5.1	1.11	2300	12.3
18	91.7	5.9	4.8	2630	8.9
19	120.3	9.4	1.3	2310	6.1
20	81.3	5.1	3.05	2440	11.3
21	88.6	6	3.5	2322	7.3
22	70.4	4.1	2.15	2245	16.3
23	97.3	7.1	2.99	2614	8.7

Table 3 – Testing Data for RT Model [1, 4, 11]

Sample number	UCS (MPa)	BTS (MPa)	CAI (μm)	RSS (rpm)	CR (m^2/h)
1	97.3	6.4	3.46	2614	8.7
2	91.3	5.1	3.1	2365	13
3	63.8	4.6	1	2400	12.8
4	112.3	4.3	1.4	2215	7
5	83.1	5.1	3.05	2440	11.3
6	111.9	6.9	1.9	2220	6.8
7	70.8	5.4	1.86	2350	14.3
8	65.3	3.9	2	2214	15.4

Following ISRM guidelines, the load is applied at a uniform rate to ensure failure occurs within 1–10 minutes. BTS is calculated as [34]:

$$\sigma_t = \frac{2P}{\pi DL} \tag{1}$$

where P is the failure load, D is the specimen diameter, and L is the specimen length.

CAI is an empirical measure of rock abrasiveness widely used in mining, drilling, and tunneling. It estimates the scratchability of rock surfaces against steel tools, influencing equipment selection. In standard CAI testing, a hardened steel conical stylus is drawn across a smoothed rock surface under a constant vertical 70 N load over a distance of 10 mm. The reduction in tip diameter is measured, and the CAI is obtained as the average over multiple repetitions [35].

The RSS is a critical operational parameter affecting cutting rate. Cutting rate measurements were recorded using machines with motor powers of 110, 132, 135, 160, and 190 kW and saw blade diameters of 1200, 1400, and 1600 mm.

3-2- Multiple Linear Regression

Multiple Linear Regression (MLR) is a statistical method for modeling the relationship between several independent variables and a dependent variable [36, 37]. It assumes linearity and can be expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \tag{2}$$

where y is the dependent variable, β_0 is the intercept, $x_1, x_2, \dots, x_n$ are the independent variables, and $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients of the independent variables representing the effect of each independent variable on the dependent variable. The term ε is a random error representing the discrepancy between the model prediction and the actual value [38].

3-3- Random Tree Algorithm

The RT algorithm is a machine learning method based on decision trees, suitable for classification and regression tasks. It recursively partitions the training data into smaller subsets, maximizing purity according to a criterion such as minimizing variance or maximizing the coefficient of determination. A key feature of RT is the random selection of a subset of features at each node, which reduces the likelihood of overfitting and improves generalization [39].

For regression, RT uses Mean Squared Error (MSE) to evaluate node purity:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_p)^2 \tag{3}$$

$$y_p = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{4}$$

where y_i represents the actual value, y_p is the mean of node outputs, and n is the number of samples in the node.

The RT algorithm computes an estimate that minimizes the MSE in the resulting subsets. This process organizes the data such that each subset contains samples with relatively homogeneous outputs.

The tree is grown recursively until subsets are pure or constraints such as minimum samples per node or maximum depth are met. These properties allow the RT to naturally balance model complexity and accuracy without the need for pruning. When a split results in a leaf node, the predicted value for new data is determined by the mean of the output values in the corresponding leaf node.

3-4- Model Validation

Validation assesses the model performance using unseen data, ensuring accuracy while avoiding overfitting or underfitting [39]. For regression, common evaluation metrics include:

I) Coefficient of Determination (R^2):

R^2 measures the strength of the relationship between predicted and observed values. This index provides a measure of the correlation between two random variables, based on the deviation of each variable's values from its mean [40, 41]:

$$R^2 = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - m_x)\left(y_i - m_y\right)}{\sigma_x \sigma_y} \tag{5}$$

where n is the number of data points; x_i represents the values of the first variable; m_x is the mean of the first variable; and σ_x is its standard deviation. Similarly, y_i denotes the values of the second variable; m_y is the mean of the second variable; and σ_y is its standard deviation. The range of R^2 values lies between 0 and 1, with higher values indicating stronger correlation [42].

II) Mean Absolute Error (MAE):

Error evaluation methods in machine learning and regression analysis are statistical tools used to measure the discrepancy between actual and predicted values. These evaluations help assess the accuracy, efficiency, and the degree of fit, while preventing overfitting or underfitting. MAE quantifies the average magnitude of errors without considering direction [39]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (6)$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of data points [39].

III) Root Mean Squared Error (RMSE):

RMSE calculates the square root of the mean of the squared errors. Due to the squaring of errors, it is more sensitive to outliers. It emphasizes larger errors due to squaring, making it suitable when large deviations are critical [39]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (7)$$

4- Discussion and Results

4-1- Multivariate Linear Regression

The relationship between the Cutting Rate (CR) and the independent variables of UCS, BTS, CAI, and RSS was analyzed using MLR in SPSS software. The resulting regression equation is expressed as:

$$CR = 46.166 - 0.158\,UCS + 0.169\,BTS + 0.496\,CAI - 0.010\,RSS \qquad (9)$$

The correlation between predicted and actual values is shown in Figure 2, where R^2 was found to be 0.77.

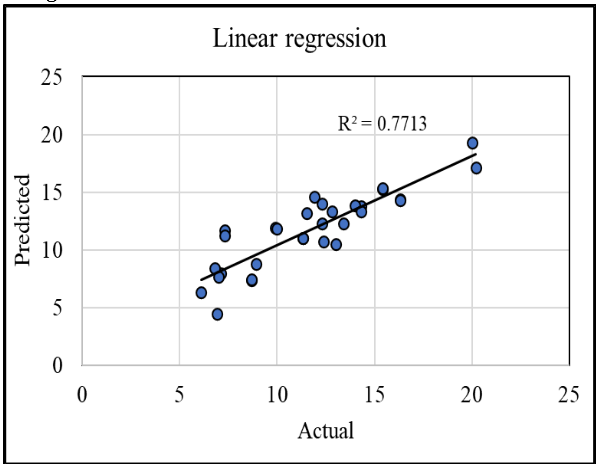

Figure 2. Correlation between actual and predicted values in MLR

4-2- Selection of Training and Test Data

The predictor variables in this study included UCS, BTS, CAI, and RSS, with CR serving as the dependent variable. Statistical analysis (minimum, maximum, and mean values) was performed to evaluate the dispersion and representativeness of the training and test datasets.

According to the rock strength classification [43], UCS values ranged from very weak (11 MPa) to hard rock (139.6 MPa). Based on ASTM abrasiveness classification [44], CAI values ranged from very low (0.4) to very high (8.4). This wide variability provided a reliable basis for model development.

Since the RT algorithm predicts CR based on the mean values within decision tree leaves, extrapolation beyond the training data range could result in large errors. Therefore, ensuring proper coverage and dispersion of the test dataset is essential. Table 4 summarizes the statistical indices of training and test data. The close similarity of mean, minimum, and maximum values between training and test data confirms appropriate dataset partitioning.

Additionally, the datasets were stratified to maintain proportional representation of machine motor power ratings and saw blade diameters. Their distributions are illustrated in Figures 3 and 4.

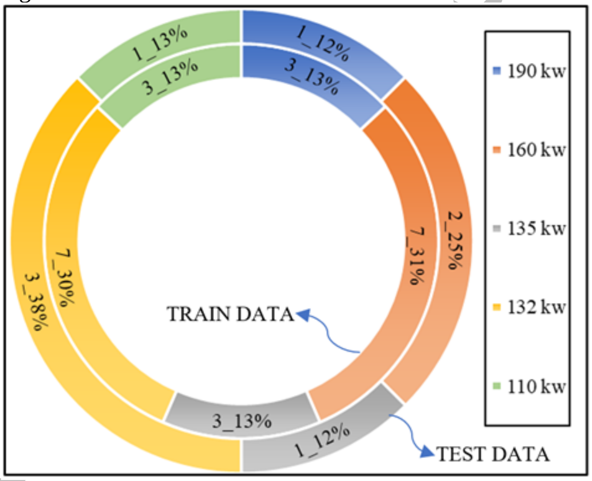

Figure 3. Relative frequency and number of samples by machine power (training: inner chart; testing: outer chart)

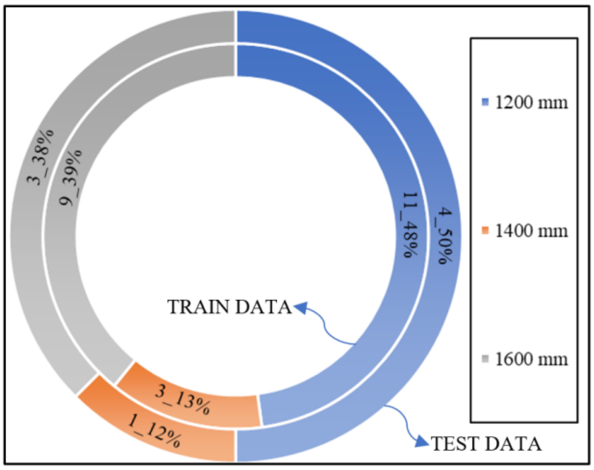

Figure 4. Relative frequency and number of samples by saw blade diameter (training: inner chart; testing: outer chart)

Table 4- Statistical indices of independent and dependent variables

Statistical index / Parameter	Mean			Min			Max		
	All	Training	Test	All	Training	Test	All	Training	Test
UCS (MPa)	82.41	83.81	78.57	11	45.1	50.5	139.6	139.6	111.9
BTS (MPa)	5.42	5.50	5.18	3.4	3.4	3.9	9.4	9.4	6.9
CAI (µm)	2.19	2.21	2.12	0.4	0.4	0.6	4.8	4.8	3.46
RSS (rpm)	2375	2366	2400	2214	2214	2214	2630	2630	2614
CR (m²/h)	11.71	11.67	11.83	6.1	6.1	6.8	20.2	20.2	15.4

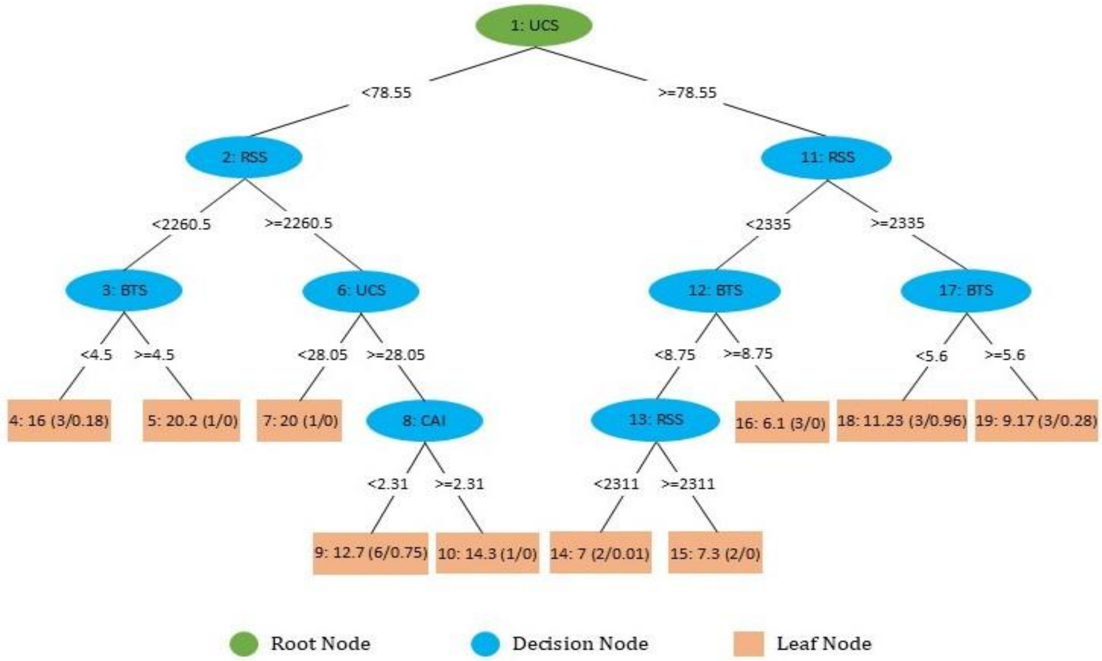

Figure 5. Decision tree developed using the RT algorithm

4-3- Development of the Random Tree Model

The RT model developed in this study consisted of 19 nodes with a maximum depth of 4, representing a balance between accuracy and complexity. The root node used UCS as the primary splitting parameter with a threshold of 55.78 MPa. If the UCS value is below this threshold, the data are directed to the left branch; otherwise, they are sent to the right branch. Subsequent splits involved RSS, BTS, and CAI. Terminal nodes (leaves) contained four numerical values: the leaf number, the predicted CR values, number of assigned samples, and associated prediction errors. A graphical representation of the decision tree is shown in Figure 5, illustrating the decision-making structure and data partitioning.

The correlation between the actual and predicted values for the training and test data is shown in Figure 6. Model performance was evaluated using both training and test datasets. For the training set, a strong correlation of 0.9874 was obtained between actual and predicted values (Figure 6a). For the test set (8 samples), the correlation was 0.9606 (Figure 6b). As observed, the RT model, despite encountering unseen data, was able to accurately capture the existing patterns and provide high-precision predictions.

The error metrics also confirmed the model's accuracy. For training data, MAE was 0.429 and RMSE was 0.6167. For test data, MAE increased slightly to 0.6333 and RMSE to 0.9221. The differences between actual and predicted values are illustrated in Figure 7.

Based on the results, the RT algorithm demonstrated reasonably good performance in predicting CR for the test data. However, notable discrepancies were observed for data points 2 and 7. These deviations can be attributed to the inherent mechanism of the RT algorithm, in which the predicted value for each terminal leaf is the average of all data points assigned to that leaf.

Data points 2 and 7 were assigned to leaves 9 and 18, respectively. Examination of these leaves revealed that their value ranges were relatively wide and the data were not concentrated within a narrow interval. As a result, the computed mean did not closely approximate the actual values of these specific points. As illustrated in Figure 5, leaf 9 contained 6 data points, while leaf 18 contained only 3. Further analysis showed deviations from the mean of 0.75 and 0.96, respectively, indicating that the data within these leaves were more dispersed compared to other nodes. This dispersion explains the higher prediction errors associated with these cases. To address this limitation, a larger dataset and the development of a tree with finer-grained partitioning would be necessary, enabling the model to capture local variations more effectively and reduce prediction errors in sparse or widely distributed data regions.

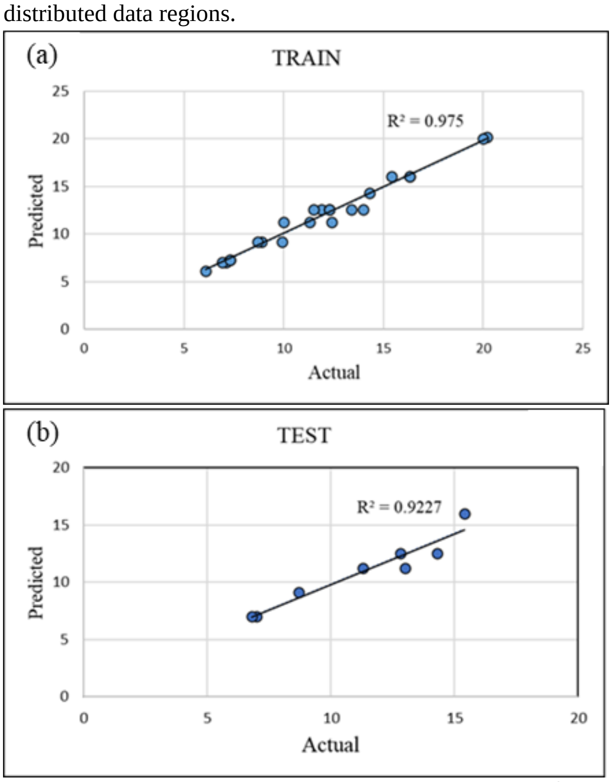

Figure 6. Correlation between actual and predicted values of the RT algorithm: (a) training data; (b) test data

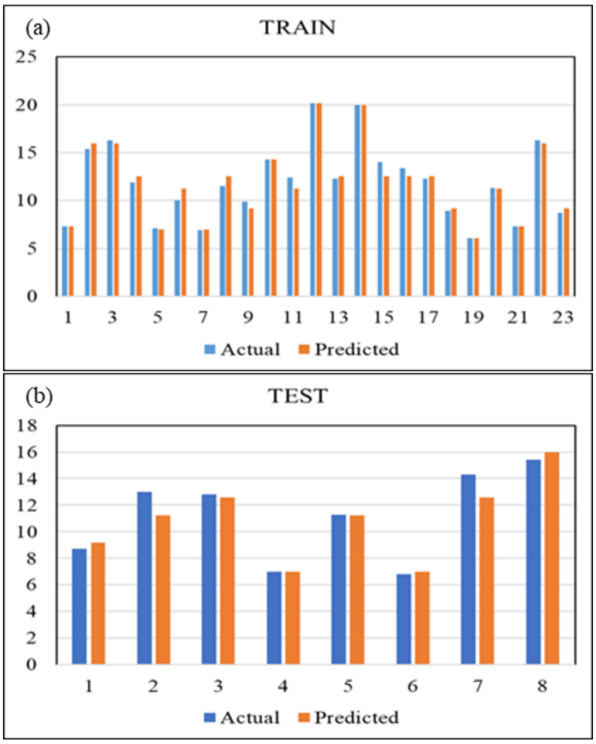

Figure 7. Differences between actual and predicted values using the RT algorithm: (a) training data; (b) test data

Figure 8 compares the absolute prediction errors obtained from both MLR and RT models. The vertical axis indicates error magnitude, while the horizontal axis corresponds to the data numbers listed in Tables 2 and 3. As shown, the RT algorithm consistently outperforms MLR and provides relatively accurate predictions of the cutting rate of circular saws within the studied parameter ranges. This improved performance can be attributed to its ability to capture complex relationships among variables while reducing the risk of overfitting.

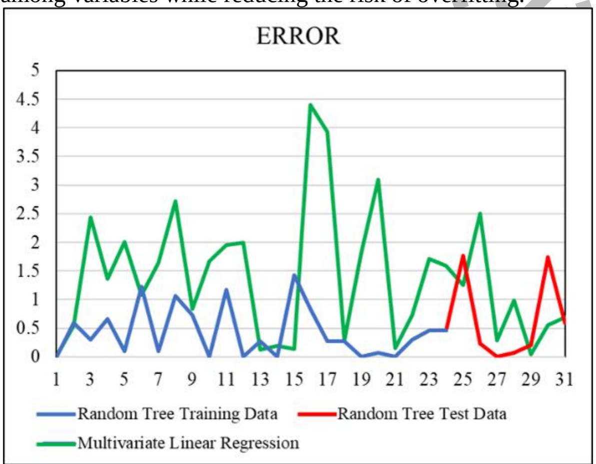

Figure 8. Absolute prediction errors of MLR and RT methods

Nonetheless, the reliability of the developed model is contingent upon unseen data falling within the parameter ranges represented in the training dataset. Its reliability is limited to conditions similar to those represented in the training dataset. Moreover, operational factors such as machine motor power and saw blade diameter should be comparable to those used in model development. These constraints may limit the applicability of the model to entirely different operating conditions or machines. To enhance robustness and ensure broader applicability, periodic retraining of the model with new datasets is recommended, thereby improving its generalizability and predictive accuracy under diverse conditions.

5- Conclusion

Determining the optimal operational parameters and accurately estimating the cutting rate of circular saws are essential for enhancing productivity, reducing operating costs, and optimizing production scheduling in stone cutting plants. In this study, a predictive model based on the RT algorithm was developed and validated for various types of building stones spanning a wide range of strength and hardness values. The results showed that the model achieved R^2 of 97.50% and 92.28% for the training and test datasets, respectively; substantially outperforming the MLR approach, which achieved an R^2 of 0.77. Similarly, the RMSE values for the training and test datasets were 0.6167 and 0.9221, respectively, confirming the model's robustness and reliability. These findings highlight the ability of the RT algorithm to effectively capture nonlinear and complex interactions among rock properties and operational parameters, despite its relatively simple structure. The developed model thus provides a practical and accurate tool for predicting cutting performance, enabling stone cutting plants to optimize operational planning, select suitable equipment configurations, and minimize production uncertainties. However, its predictive reliability is contingent on input data falling within the ranges represented in the training dataset. To extend its applicability to different operational conditions and machine types, retraining with updated datasets is recommended. Overall, the RT-based predictive framework can serve as a valuable decision-support tool in stone cutting industries and could be further enhanced by integrating additional machine learning techniques or hybrid models for broader applicability in mining and construction operations.

6- List of Symbols

RT	Random Tree
Gs	Grain size of mineral
P	Porosity
Qc	Quartz content
TS	Tensile Strength
UCS	Uniaxial Compressive Strength
BTS	Brazilian Tensile Strength
E	Elastic Modulus
PLSI	Point Load Strength Index
IS	Impact Strength
BS	Bending Strength
SS	Shear Strength
EQC	Equivalent Quartz Content
SHH	Schmidt Hammer rebound number Hardness
SH	Shore Hardness
CI	Cone Indenter hardness
MH	Mohs Hardness number
CAI	Cerchar Abrasivity Index
LA	Los Angeles Abrasion
WA	Water Absorption
Pv	P-wave velocity
ANN	Artificial Neural Networks
SLR	Simple Linear Regression
MLR	Multiple Linear Regression
RF	Random Forests
GEP	Gene Expression Programming
ABC	Artificial Bee Colony Algorithm
ICA	Imperialist Competitive Algorithm

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