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Enhancing Energy Efficiency in Stone Cutting: Utilizing Rock Engineering System Method for Precise Maximum Energy Consumption Prediction

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Abstract

The maximum energy consumption of stone cutting machines is one of the important cost factors during the process of cutting construction stones. Accurately predicting and estimating the maximum energy consumption performance of the cutting machine, along with estimating the cutting costs, can help approach the optimal cutting operating conditions to reduce energy consumption and minimize machine depreciation. However, due to the uncertainty and complexity of building stone textures and properties, determining the maximum energy consumption of the device is a difficult and challenging task. Therefore, this paper employs the rock engineering system method to solve the aforementioned problem. To this end, 120 test samples were collected from a marble factory in the Mahalat region of Iran, representing 12 types of carbonate rocks. The input parameters considered for the analysis were the Mohs hardness, uniaxial compressive strength, Young's modulus, production rate, and Schimazek's F-abrasiveness factors. In the study, 80% of the collected data, equivalent to 96 data points, were utilized to construct the model using the rock engineering system-based method. The obtained results were then compared with other regression methods including linear, power, exponential, polynomial, and multiple logarithmic regression methods. Finally, the remaining 20 percent of the data, comprising 24 data points, were used to evaluate the accuracy of the models. Based on the statistical indicators, namely root mean square error, mean square error, and coefficient of determination, it was found that the rock engineering system-based method outperformed other regression methods in terms of accuracy and efficiency when estimating the maximum energy consumption.

1. Introduction

Decorative stones play a significant role as mineral reserves, contributing to a country's non-oil exports and generating substantial income. Cutting building stones using gang saw machines poses a significant challenge in the industry. Accurate prediction and estimation of cutting capabilities based on physical and mechanical characteristics are crucial for cost estimation and designing stone processing plants. A comprehensive understanding of cutting equipment capabilities allows the production planners to enhance processing speed and increase production. To meet the demand for high-quality and competitive products in global markets, the industry requires advanced technology and tools for stone extraction and processing. Proper utilization of equipment and a thorough understanding of their performance can greatly improve efficiency. Saw cutting equipment with high production capacity and competitive cutting quality is commonly used in processing plants [1-13]. Considering the maximum energy consumption (MEC) of cutting devices in processing factories, the energy consumption depends not only on the type of device and equipment but also on the type of stone. Stones

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with higher quartz content and greater hardness require more energy for cutting. Therefore, predicting and estimating the MEC for various types of stones is crucial for cost reduction and optimizing production capacity in stone processing factories [14-27].

Limited research has been conducted in the field of gang saw cutting. Early studies by Lons (1970) examined cutting and expanding forces of diamond segments in saw machines, establishing a loose correlation between cutting pressures and diamond wear [28]. Mancini *et al*. (1992) analyzed the parameters influencing stone cutting machine performance by simulating saw cutting in the laboratory and comparing the results with field performance [29,30]. Kapur *et al*. (2011) conducted field and laboratory tests on carbonate stones to investigate the relationship between their mechanical and physical characteristics and the specific energy of the saw machine. Their research work provided valuable insights, especially regarding the uniaxial compressive strength (UCS) and Brazilian tensile strength as predictive parameters [31,32]. Neves *et al*. (2016) studied the prediction of cutting efficiency using multi-blade saws through multiple regression methods [33]. Bayram (2013) predicted stone cutting ability based on the stone characteristics index, considering parameters such as tensile strength, UCS, hardness coefficient, and brittleness [34]. Mikaeil *et al*. (2014) used multiple regression analysis to predict gang saw machine vibration based on operating characteristics and rock fragility indices [35]. Korman *et al*. (2015) studied the relationship between specific cutting energy and cutting speed of the gang saw machine, observing a direct relationship between specific energy and saw speed reduction [36]. Dormishi *et al*. (2018) studied rock engineering characteristics (texture coefficient) on 14 different carbonate rock samples to predict gang saw energy consumption using regression methods [37]. Ziaei *et al*. (2020) utilized regression analysis to estimate wear in andesite stone sawing operations, correcting the F-Schimazek abrasive factor [38]. Mikael *et al*. (2021) predicted energy consumption of construction stone cutting machines through laboratory and statistical studies on 12 different types of soft and hard stones [39]. Shaffiee haghshenas *et al*. (2022) predicted and measured the amperage of the gang saw machine using laboratory tests and statistical studies on 12 different types of stones [40].

While laboratory, field, and regression methods provide satisfactory accuracy, the varying and uncertain input values of stone parameters limit their precision. Additionally, these methods often require significant time and financial resources. Hence, the use of smart methods and algorithms to predict gang saw performance has gained prominence, addressing the limitations associated with experimental, analytical, numerical, regression, laboratory, and field methods [41-52].

The primary focus of this article lies in utilizing the RES method, a cost-effective and efficient approach capable of accommodating uncertainties in rock parameter values. This method also allows for the simultaneous analysis of multiple variables influencing gang saw maximum energy consumption, ensuring highly accurate performance evaluations of stone cutters. Consequently, the RES method has been extensively applied in various engineering challenges, particularly within the domains of rock and mining mechanics. These applications span risk and vulnerability assessment following the Songun copper mine explosion [53], predicting TBM drilling machine's underground penetration rate [54], estimating rock fragmentation and explosion outcomes in mines across Chile and Canada [55], enhancing rock mass conditions in subterranean passageways, dams, and foundations through material injection [56], quantitative analysis of gas and explosion risks in coal mines [57], predicting maximum ground surface settlement due to tunneling using earth pressure balance shield tunneling (TBM-EPB) [58], assessing risks associated with rock-embedded pile shafts [59], generating landslip estimation maps for Sallekular in the Jama River Gorge [60], fire risk prognosis in coal mine strata [61], anticipating fragmentation and rock tossing threats resulting from explosions in the Sarcheshme copper mine [62], estimating and predicting rock mass deformation modulus [63], exploring coal mine methane gas drainage potential [64], and conducting safety factor assessments and risk evaluations for circular failures [65].

As previously mentioned, aside from the type of cutting machine employed, the machine's energy consumption is of paramount importance. However, it's essential to recognize that the energy consumption of the machine is significantly influenced by the characteristics of the stone, encompassing factors like texture and strength. Thus a meticulous examination of the stones regarding their strength and texture is imperative at the initial stage. Given that stone parameters exhibit variations at each location and harbor numerous uncertainties, one must delve into the inherent characteristics of the stone at each specific point. This inherent variability in stone attributes translates to divergent energy requirements for cutting the stone at different points. If the energy consumption remains uniform across all stones, it not only accelerates machine depreciation but also runs the risk of device failure, ultimately leading to reduced production in the processing plant. Given the heightened sensitivity of this matter, the use of conventional methods such as experimental, analytical, and numerical techniques, which fail to account for the inherent uncertainties and complexities within the stone, proves insufficient in addressing these challenges. Moreover, the multitude of parameters influencing the machine's energy consumption cannot be collectively considered, often yielding models that lack generality and are applicable only to specific contexts. Direct approaches including field and laboratory tests are likewise unsuitable due to their impracticality stemming from time, cost, and repetitive testing requirements. Therefore, in resolving these multifaceted challenges, the utilization of the rock engineering system method emerges as a potent solution. This method offers the capacity to obtain precise energy consumption estimations for stone cutting machines at any given point with minimal time and cost outlays, alongside a high degree of accuracy and minimal margin of error. In essence, this research work endeavors to introduce and elucidate a formidable tool for engineers and researchers operating in the realm of rock engineering. With this method at their disposal, engineers and researchers can adeptly anticipate energy consumption for stone cutting machines at any specific stone location, ensuring optimal operations with minimal errors. Embracing this methodology holds the potential to boost the production of building stones within processing facilities. Simultaneously, by optimizing the energy consumption of cutting machines, the extent of wear and tear on the machinery is curtailed, leading to minimized cutting costs.

In this study, the uncertainty associated with input parameters was addressed by utilizing 120 data points from a stone processing plant in the Mahalat region of Iran. These data points represented 12 different types of carbonate rocks. The aim of this research work was to develop a model based on the RES method, considering five crucial and interconnected factors that significantly influence the evaluation of gang saw performance. Subsequently, the effectiveness of the RES technique was assessed by employing statistical indicators such as root mean square error (RMSE), mean square error (MSE), and coefficient of determination (R^2). These indicators were used to evaluate the accuracy and predictive power of the non-linear and complex model generated by the RES method. Furthermore, for comparative analysis, multiple regression methods were also applied to the same input parameters and data. This allowed for a comparison of the performance of the RES method with that of traditional regression approaches.

2. Gang Saw Apparatus

The gang saw machine is commonly used for sawing building stones. Among its crucial factors, the MEC holds great significance, which is influenced by various parameters including rock hardness, rock texture (such as shape and size of stone grains), porosity, density, modulus of elasticity, wear, UCS, and tensile strength. The hardness of the stone also plays a significant role. Figure 1 illustrates the functioning of the gang saw machine employed in this study [66]. Additionally, Table 1 provides an overview of the specifications and features of the gang saw machine used in the studied area.

Figure 1. Illustration of the gang saw machine used in this paper [66].

Table 1. Operational characteristics of the gang saw machine [66].

Characteristic	Value
Cutting length	3300 mm
Cutting width	1440 mm
Main engine power	55 Kw
Cutting height	1950 mm
Max. No. of blades	50 n
Total weight of machine	47 ton
Blade length	4400 mm
Blade run	750 mm

3. Model Dataset

To evaluate the performance of MEC in the gang saw machine, this research work focused on the marble factories located in the Mahalat region of Iran. Twelve different carbonate stones were examined, and rock blocks were collected from these factories for laboratory testing purposes. The objective was to obtain rock samples of sufficient size that would yield all the required test specimens from a single piece of a particular rock type. Each block sample underwent a meticulous examination to ensure the absence of macroscopic flaws, fractures, partings or alteration zones. Table 2 presents information on the locations, names of the analyzed rocks, and their corresponding MEC in the studied area.

Table 2. Names of rocks, MEC values, and locations for the analyzed rocks [66].

Commercial name	Name of quarry	Average of MEC (Ampere)
Kerman Marble	Mirzaei	105.5
Darebokhari Travertine	Kohbar	96.1
Abbas Abad Travertine	Abbas Abad	97
Chocolate Travertine	Kashan	86.9
Takab Travertine	Takab	93.7
Harsin Marble	Harsin	110.3
Laybid Marble	Laybid	105.5
Ghorveh Marble	Ghorveh	104
Atashkoh Travertine	Atashkoh	104
Khalkhal Travertine	Khalkhal	85.5
Hajiabad Travertine	Hajiabad	98.3
Azarshahr Travertine	Azarshahr	88.1

In order to evaluate the performance of the gang saw, a total of 120 tests were conducted on 12 types of carbonate rocks. The selection of input parameters is crucial as it significantly impacts the output. In this article, the following input parameters were considered: Mohs hardness (Mh), UCS, Young's modulus (YM), production rate (V), and Schimazek’s F-abrasiveness factors (SF-a). The output parameter was the MEC. Table 3 presents some of the input parameters along with their corresponding MEC values.

Table 3. Part of input and output data for modeling [66].

Inputs					Output
SF-a (N/mm)	UCS (MPa)	YM (GPa)	V	Mh	MEC (Ampere)
0.0361088	61.5	21	17	2.9	97
0.0361088	61.5	21	37	2.9	102
0.0361088	61.5	21	14	2.9	96
0.0361088	61.5	21	27	2.9	100
0.0361088	61.5	21	23	2.9	100
0.0361088	61.5	21	20	2.9	99

Furthermore, Table 4 provides statistical features of the input and output data including minimum, maximum, average, and standard deviation values, offering a summary of the dataset used in the analysis.

Table 4. Description of input and output dataset statistics.

Statistical index	Mh	YM (GPa)	UCS (MPa)	V	SF-a (N/mm)	MEC (Ampere)
Minimum	2.2	14.5	50.50	8	0.02	81
Maximum	4.3	32	72	37	0.17	118
Mean	3.13	22.22	62.02	21.975	0.0637	97.88
Standard deviation	0.64	4.98	6.49	9.21	0.0446	8.39
Range	2.1	17.5	21.50	29	0.15	37

To gain a better understanding of the data distribution, Figure 2 illustrates the distribution functions of the input and output data. The histogram was generated using the SPSS statistical software [67].

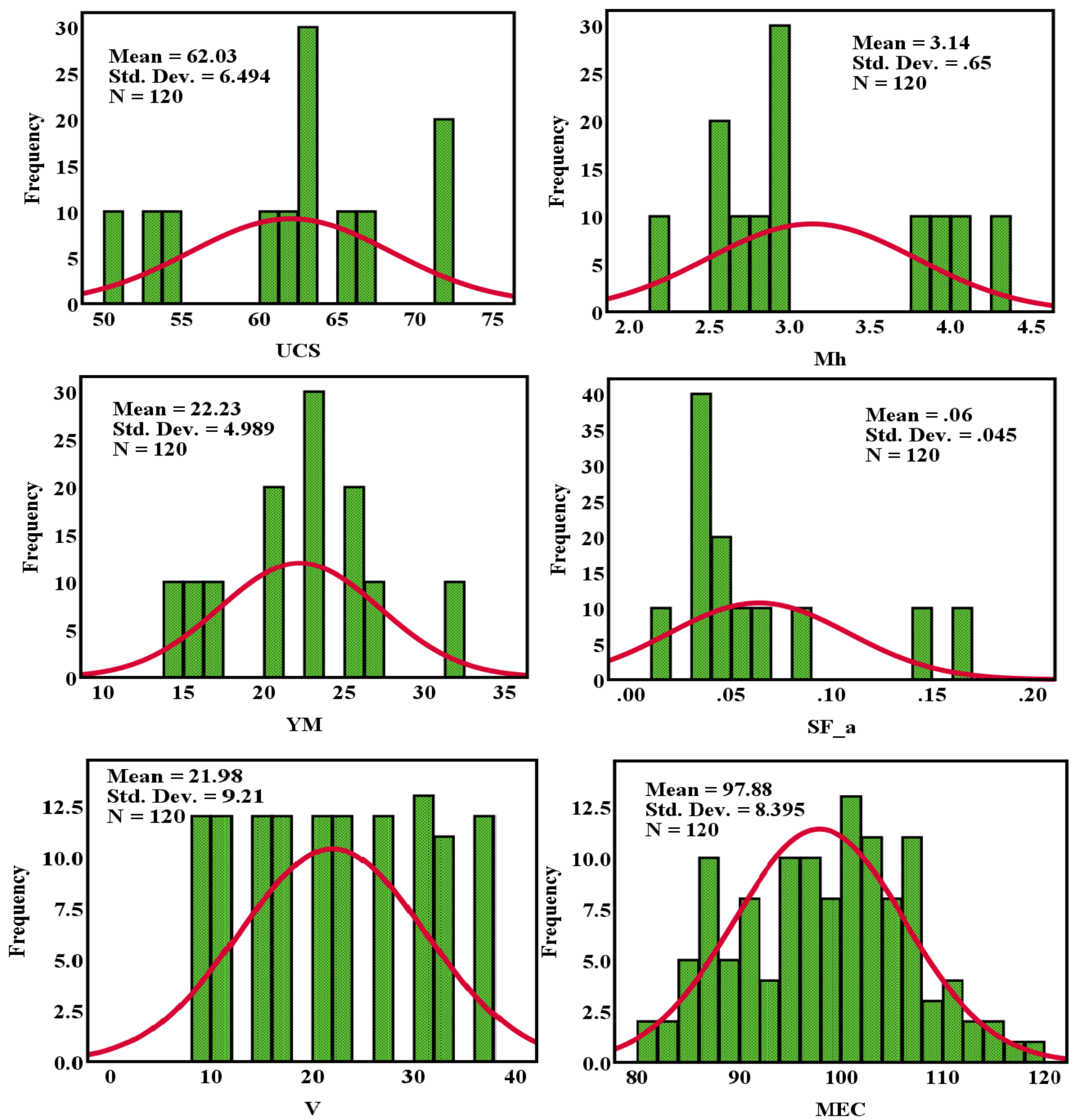

Figure 2. Distribution functions of input and output data.

Figure 3 presents the correlation scatter matrix between the input and output data. Positive correlation indicates a direct relationship, while negative correlation suggests an inverse relation between the output and input data.

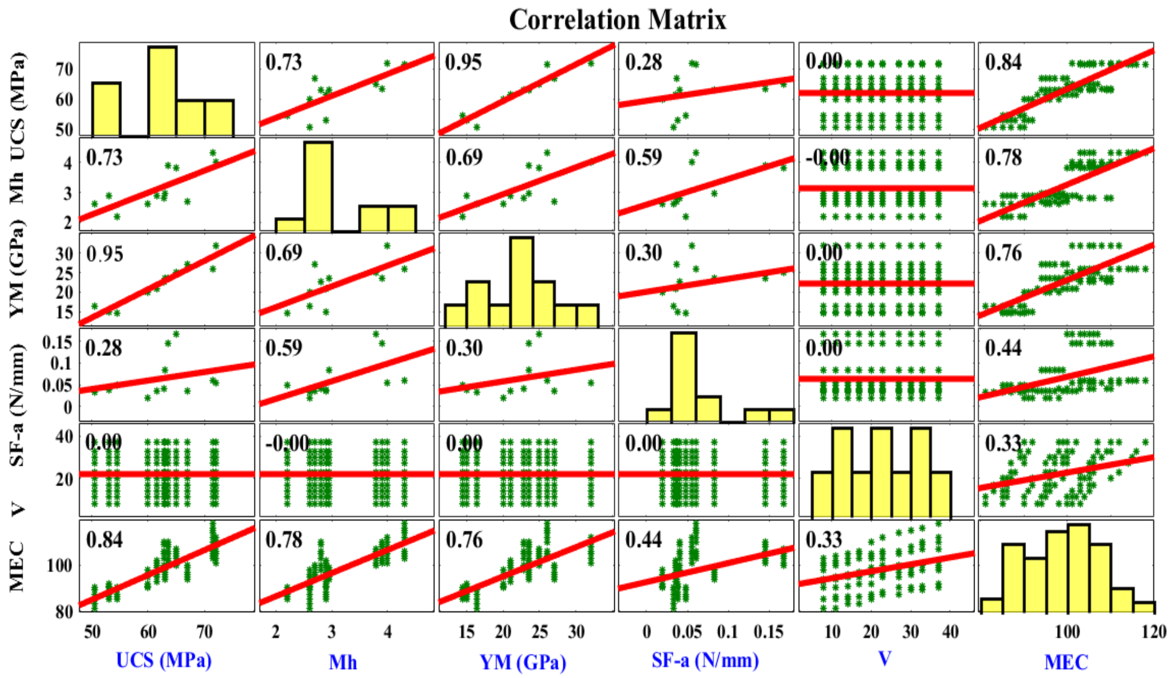

Figure 3. Correlation scatter matrix for input and output data.

4. Statistical Modeling

4.1. Multiple linear regression (MLR) Analysis

When there is a linear relationship between the dependent variable (output parameter) and multiple independent variables (input parameters), it can be represented by a mathematical equation. In this case, the mathematical equation for multiple regression is as follows:

$$y = C_1 + C_2x_2 + C_3x_3 + \ldots C_nx_n + e \quad (1)$$

In Equation (1), y represents the dependent parameter, x denotes the independent parameters, e is the relationship error, and $C_1, C_2, C_3, \ldots C_n$ represent unknown regression coefficients that need to be determined. A smaller deviation between the points on the regression line indicates better prediction accuracy, while a higher dispersion and deviation around the regression line decrease the model's predictive quality.

In this study, a multiple linear regression analysis was performed using the statistical software SPSS. The dependent variable was MEC, and the independent variables were Mh, UCS (MPa), SF-a (N/mm), YM (GPa), and V. The resulting predicted model is as follows:

$$MEC = 13.941 + 1.387UCS(MPa) + 2.001Mh - 0.755YM(GPa) + 29.768SF - a(N/mm) + 0.317V \quad (2)$$

To assess multicollinearity, an evaluation was conducted to determine if there were any significant correlations among the independent variables. Multicollinearity can lead to incorrect conclusions due to duplicated data from the independent variables. The variance inflation factor (VIF), which ranges from 1 to ∞, is commonly used to assess the strength of the linear relationship. If VIF > 10, it indicates potential issues with the established relationship [68]. In this article, according to Table 5, the VIF values for the independent variables in Equation (2) were determined.

Table 5. Collinearity and MLR coefficients for Equation (2).

Independent variables	Unstandardized coefficients		Standardized coefficients	95.0% Confidence interval for *B*		Collinearity statistics		t values	R^2	Standard error of estimate
	B	Std. error	*β*	Lower bound	Upper bound	Tolerance	VIF			
Constant	13.941	4.889		4.227	23.654			2.851	0.947	2.87
UCS (MPa)	1.387	0.152	1.076	-1.690	-1.085	0.11	9.09	9.118		
Mh	2.001	0.864	0.146	0.284	3.718	0.286	3.496	2.315		
YM (GPa)	-0.755	0.188	-0.428	0.382	1.127	0.101	9.885	-4.021		
SF-a (N/mm)	29.768	7.995	0.165	-45.652	-13.884	0.586	1.706	3.723		
V	0.317	0.032	0.337	-0.381	-0.254	0.992	1.008	9.927		

Table 6 presents the regression results and analysis of variance (ANOVA) for Equation (2). The F model value and significance (Sig.) are used to evaluate the significance of the model. In this study, the F value is 156.750, and the Sig. value is 0.000, which is less than the significance level of 0.05. This indicates that the null hypothesis can be rejected, suggesting that the independent variables have a significant effect on the MEC.

Table 6. Variance analysis for Eq. (2).

	Sum of squares	*df*	Mean square	*F*	Sig.
Regression	6461.947	5	1292.389	156.750	0.000
Residual	742.042	90	8.245		
Total	7203.990	95			

4.2 Multivariate regression models

To further evaluate the performance of the gang saw as the dependent variable, multivariate regression analysis was conducted using various models, including exponential, power, polynomial, and logarithmic models, with the same dataset and independent variables. The mathematical formulas for each model and their corresponding R2 values are provided:

The power model (with $R^2 = 0.7946$) is:

$$MEC = 5.481(UCS(MPa))^{0.795}(Mh)^{0.067}(YM(GPa))^{-0.134}(SF - a(\frac{N}{mm}))^{0.0999}(V)^{0.061} \tag{3}$$

The exponential model (with $R^2 = 0.7644$) is:

$$MEC = exp(\,2.991 + 0.025UCS(MPa) + 0.014Mh - 0.001YM(GPa) + 0.248SF - a(\frac{N}{mm}) + 0.0001V) \tag{4}$$

The polynomial model (with $R^2 = 0.8719$) is:

$$MEC = 18.379 - (-1.251UCS(MPa)) - (-0.517Mh^2) - (0.0001YM(GPa)^3) + (3092.244SF - a(\frac{N}{mm})^4) + (0.00000001V^5) \tag{5}$$

The logarithmic model (with $R^2 = 0.845$) is:

$$MEC = -210.361 + 72.608\,ln(UCS(MPa)) + 8.523\,ln(Mh) - 11.409\,ln(YM(GPa)) + 1.715\,ln(SF - a(\frac{N}{mm})) + 12.016\,ln(V) \tag{6}$$

5. Rock Engineering Systems (RESs)

Considering that rock engineering projects including geotechnics and rock mechanics involve numerous uncertainties and complexities, existing conventional methods such as experimental, numerical, and analytical approaches may not encompass all the factors affecting a specific issue and often have limitations. Therefore, an alternative method that can account for the complexities and all the influential factors in the system is needed. The RES approach serves as a suitable solution. This approach was first introduced by Hudson in 1992, and has since been widely used to tackle problems with multiple complex parameters [69]. RES is an engineering strategy that comprehensively considers the primary and secondary objectives of an issue, providing a confident evaluation that can be applied to engineering projects with diverse goals. By considering the problem as a real system and utilizing system thinking, RES offers a novel solution to complex engineering problems [70].

In the RES approach, the interactions between factors within the system are also taken into account, in addition to considering all the individual factors. These interactions can be systematically examined by organizing them into an interaction matrix. As shown in Figure 4, an interaction matrix is a square matrix where the effective and influential parameters are placed along the main diagonal, and the interactions between the parameters are located in the non-diagonal regions. Figure 4 illustrates a hypothetical system with two parameters, A and B, where parameter A is positioned in the upper left section and parameter B is positioned in the lower right section. The upper right section indicates the effect of A on B, and the lower left section represents the effect of B on A.

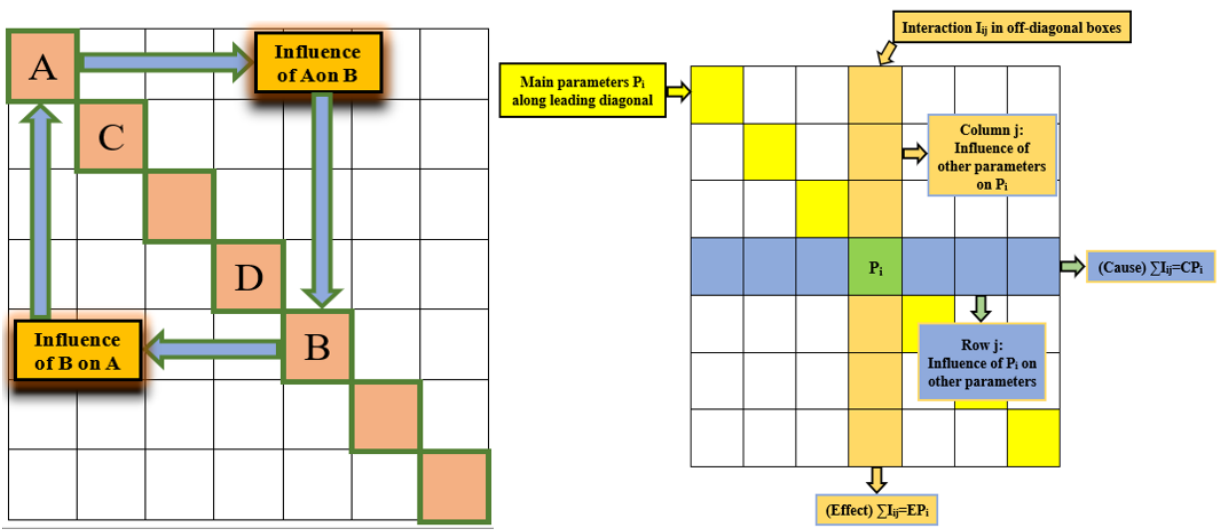

Figure 4. Concept of interaction matrix in RES [69].

To assess the severity of parameter influences on the system, the interaction matrix needs to be coded. Hudson has provided five different coding methods for the interaction matrix: explicit method, probabilistic expert semi-quantitative (PESQ) method, continuous quantitative coding (CQC) [71], binary method, and expert semi-quantitative (ESQ) method [69]. Among these methods, the ESQ method is often preferred due to its simplicity and high accuracy [54]. Table 7 demonstrates that the coding is performed using five levels ranging from 0 to 4. According to expert opinions, a score of 4 indicates a significant dependence and connection between two parameters, while a score of 0 implies no effect between the two parameters.

After completing the coding of the interaction matrix, it is possible to create a cause-effect diagram. The cause-effect diagram represents the relationship between parameters and the system. The "cause" (C) of a parameter on the system is determined by the sum of the numerical values in each row, which is obtained by adding the algebraic sums of each row and column. Similarly, the "effect" (E) of the system on the parameter is the algebraic sum of the values in each column. The cause and effect values of each parameter are plotted on the horizontal and vertical axes, respectively, creating a cause-effect diagram (Figure 4). The location of each point in the diagram represents the interaction state of the parameter. A higher numerical value of the sum of cause and effect values (C + E) indicates a greater intensity of interaction with the system. Conversely, a higher numerical value of cause and effect subtraction (C - E) indicates lower dominance of that factor on the system. The sum of cause and effect values (C + E) is used to obtain the weight (a_i) of each parameter, as shown in Equation (7) [72].

Table 7. The ESQ method [69].

Code number	Concept
0	No interaction
1	Low interaction
2	Moderate interaction
3	High interaction
4	Intense interaction

$$a_i = \frac{(C_i + E_i)}{(\sum_{i=1}^{n} C_i + \sum_{i=1}^{n} E_i)} \times 100 \qquad (7)$$

Benardos & Kaliampakos [72] proposed the vulnerability index (VI) to assess the risk of collapse in loose areas of underground structures excavated using TBM. The vulnerability index is calculated using Equation (8):

$$VI = 100 - \sum_{i=1} a_i \frac{Q_i}{Q_{\max}} \qquad (8)$$

where a_i represents the weight of the i^{th} parameter obtained from Equation (8), Q_{max} denotes the maximum value (rating) of the parameters, and Q_i represents the value of each parameter. Table 8 provides the classification of the vulnerability index, where higher values indicate greater project risk, and values approaching zero indicate lower project risk [72]. In this research work, the vulnerability index is used to create a model for predicting the performance evaluation of the gang saw.

Table 8. Classification of the VI [72].

Risk description	Low-medium	Medium-high	High-very high
VI	0-33	33-66	66-100
Category	I	II	III

5.1 Parameters affecting MEC

The MEC model is constructed based on the RES method, using the essential parameters listed in Table 9 as input variables.

Table 9. Input variables used to build the RES-based model.

	Parameter	Symbol
P_1	Uniaxial compressive strength	UCS (MPa)
P_2	Mohs hardness	Mh
P_3	Young modulus	YM (GPa)
P_4	Schimazek's F-abrasiveness factors	SF-a (N/mm)
P_5	Production rate	V

5.2 Interaction matrix

To create the interaction matrix, five effective factors on gang saw performance evaluation were identified, and a 5*5 matrix was created. The matrix was scored by the experts and engineers in the field of rock mechanics and geotechnical engineering using the ESQ method, as shown in Table 10.

Using the cause and effect values from the interaction matrix, a cause-effect diagram is generated (Figure 5). The geometric location C = E represents the main diameter. Parameters located in the lower right corner of the diagram dominate the system, while parameters placed in the upper left part are influenced by the system. In this study, parameter 1 (UCS) is completely under the effect of the system, while parameters 4 and 5 (SF-a and V) have the greatest impact on the system.

Table 10. Effect of input parameters on MEC in the interaction matrix.

P_1	4	3	3	4
0	P_2	0	2	4
1	0	P_3	1	4
0	0	0	P_4	1
0	0	0	0	P_5

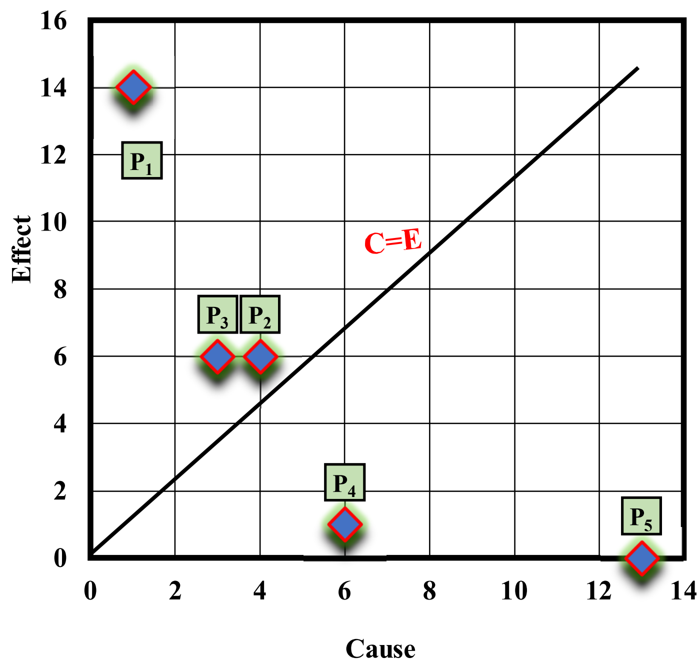

Figure 5. Cause-effect plot for principal parameters of MEC.

Table 11 provides the weight (a_i), effect (E), dominance (C-E), cause (C), and interactive intensity (C+E) of each parameter.

With the presence of C + E, the histogram of the intensity of interaction of the system can be drawn according to Figure 6. In general, the higher the interaction intensity of a system, the more potentially unstable the system is because there is a greater chance that a small change in that parameter will significantly affect the behavior of the system. According to Figure 6, which shows that parameters 1 and 4, i.e. UCS and SF-a, have the highest intensity of interaction, it is clear that a small change in these two parameters will significantly affect the behavior of the system.

Table 11. Weighting of the key variables MEC.

Main factor	C	E	C-E	C+E	a_i (%)
UCS (MPa)	14	1	13	15	27.77
Mh	6	4	2	10	18.51
YM (GPa)	6	3	3	9	16.66
SF-a (N/mm)	1	6	-5	7	12.96
V	0	13	-13	13	24.07
Total	27	27	0	54	100

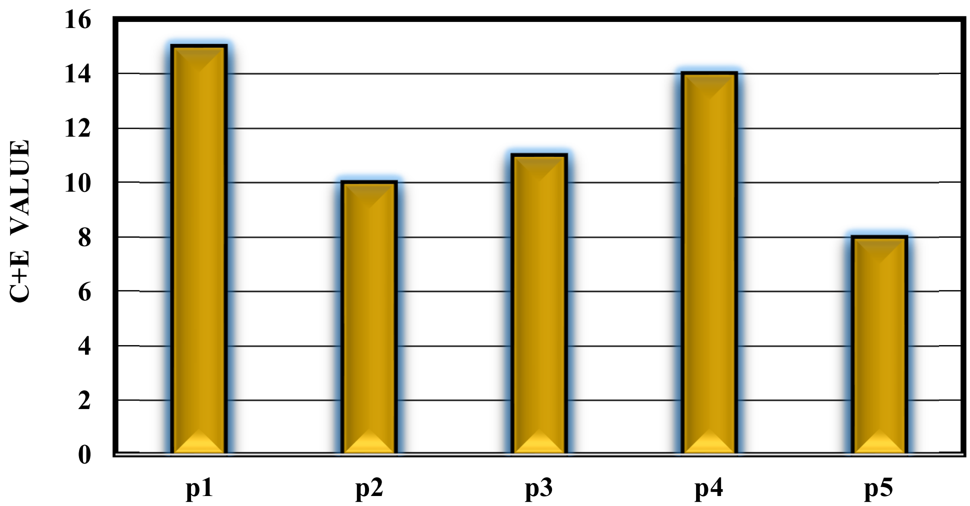

Figure 6. Cause-effect values for principal parameters of MEC.

5.3 Rating of parameters

To obtain the vulnerability index, it is necessary to rank the parameters affecting the evaluation of the performance of the gang saw. The ranking of parameters is based on the judgment of experts and engineers in the field of stone engineering in five classes from 0 to 4. In this case, if a parameter gets a rank of 0, it indicates the worst or most unfavorable state, and if a parameter gets a rank of 4, it indicates the best or most favorable state. Table 12 shows the ranking range of parameters affecting the gang saw performance.

Table 12. Suggested ratings and ranges.

Number	Parameters	Values and ratings					
1	UCS (MPa)	Value	< 55	55-60	60-65	65-70	> 70
		Rating	0	1	2	3	4
2	Mh	Value	< 2.71	2.71-2.79	2.79-3.8	3.8-3.89	> 3.89
		Rating	0	1	2	3	4
3	YM (GPa)	Value	< 16.5	16.5-20	20-27	27-31	> 31
		Rating	0	1	2	3	4
4	SF-a (N/mm)	Value	< 0.036	0.036-0.039	0.039-0.0831	0.0831-0.09	> 0.09
		Rating	0	1	2	3	4
5	V	Value	< 14.6	14.6-21	21-29	29-34	> 34
		Rating	0	1	2	3	4

5.4 Risk analysis and performance evaluation of gang saw

This study used 120 data points to evaluate the gang saw performance. Among the 120 data, 80% of the data, i.e. 96 data, were used to calculate the vulnerability index (VI) in order to build a relationship using the RES-based method, and the remaining 20%, i.e. 24 data, were used to evaluate the built relationship. To better understand this issue, Table 13 provides an example calculation of the vulnerability index for dataset number 1.

Table 13. Values, ratings, and vulnerability indices for dataset number 1.

Parameters	YM (GPa)	Mh	V	SF-a (N/mm)	UCS (MPa)
Value or description	21	2.9	8	0.0361088	61.5
Value rating (Q_i)	2	2	0	1	2
Weighting (% a_i)	16.66	18.51	24.07	12.96	27.77
VI			62.27		

Furthermore, the variations of VI for the 96 data points are displayed in Figure 7. The average VI, which is 53.18, indicates the presence of the second group of risks (medium to high).

As mentioned, after obtaining the VI values for the 120 data points, regression analysis can be performed based on the RES method. As clear from Figure 8, polynomial regression analysis was performed with a coefficient of determination of 0.9116 to build a relationship with the 96 data points. Since the developed relationship has a high coefficient of determination, it can be concluded that the developed model (Eq. (9)) has good accuracy for performance evaluation of the gang saw in the training stage.

$$MEC = -0.0002VI^2 - 0.3438VI + 117.84 \tag{9}$$

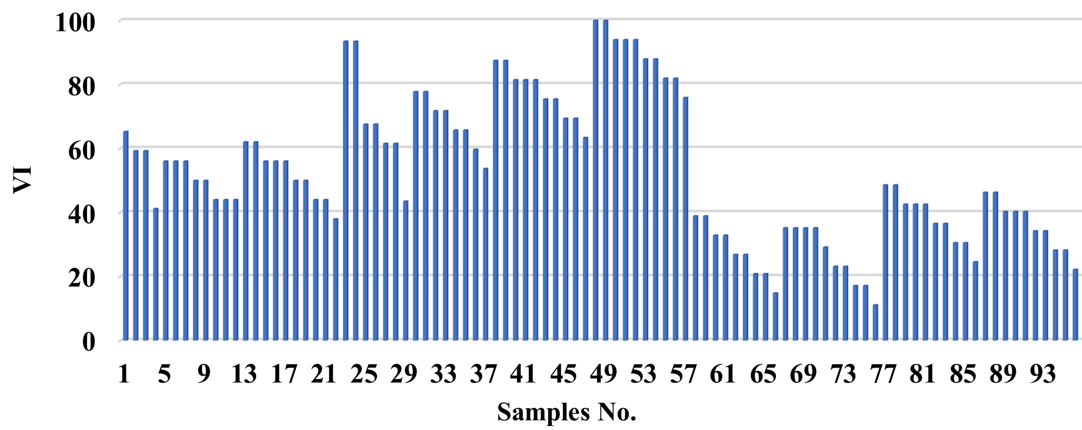

Figure 7. VI for the sample of data points.

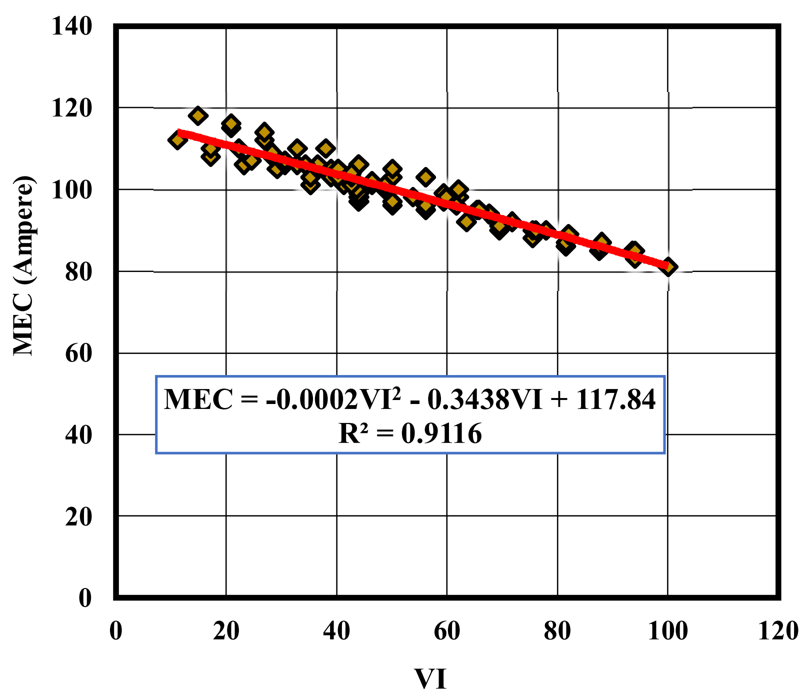

Figure 8. MEC-VI prediction model.

6. Results and Evaluation of Model Performance

As explained, 24 data out of 120 data were used to evaluate the built models. Table 14 shows some of the predicted values of linear, power, exponential, polynomial, logarithmic, and RES-based relationships with real values for the 24 data points.

Table 14. Comparison of the values obtained from the built and measured models of MEC.

VI	Measured MEC	Predicted MEC					
		Linear	Power	Exponential	Polynomial	Logarithmic	RES
65.27	93	92.8	84.29	95.72	98.74	84.84	94.54
59.25	96	94.7	87.22	95.78	98.79	95.41	96.76
53.24	100	97.55	98.89	99.83	99.38	98.80	98.96
53.24	100	98.82	99.86	99.87	100.17	100.92	98.96
47.22	100	99.82	100.51	95.93	101.17	98.22	101.15
41.22	102	101.99	101.8	99.97	105.67	105.08	103.33
62.037	94	94.49	92.09	100.83	100.54	94.38	95.74
62.037	94	95.44	93.9	100.86	97.96	93.97	95.74
87.5	85	88.85	84.07	80.46	88.82	82.64	86.22
81.48	87	91.7	86.66	83.54	89.41	88.61	88.49

The correctness of the constructed models has been assessed using three statistical indices: MSE, RMSE, and R^2. In this evaluation, if the MSE and RMSE statistical indicators tend to zero and the R^2 value tends to 1, it indicates that the built models are highly accurate and the predicted values for evaluating the performance of the gang saw are closer to the true values [73-76]. The equations for these criteria are as follows:

$$\mathrm{MSE}=\frac{1}{n}\sum_{k=1}^{n}\left(t_k-\widehat{t}_k\right)^2 \tag{10}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(t_k-\widehat{t}_k\right)^2} \tag{11}$$

$$R^2=1-\frac{\sum_{k=1}^{n}\left(t_k-\widehat{t}_k\right)^2}{\sum_{k=1}^{n}t_k^2\frac{\sum_{i=1}^{n}\widehat{t}^2}{n}} \tag{12}$$

In the above equations, n represents the number of samples, t_k represents the real amount, and t_n represents the prediction value for the k^{th} observation. Table 15 presents the statistical index values of the models built for 24 data points using linear, power, exponential, polynomial, logarithmic, and RES method. From the results, it is evident that the model developed using the RES-based method has higher accuracy compared to other models, with statistical indices MSE = 0.03, RMSE = 0.175, and R^2 = 0.9791, for evaluating the gang saw performance.

Table 15. Performance results of different constructed models.

Models	MSE	RMSE	R^2	Observations
Linear	0.0481	0.219	0.8224	24
Power	0.0541	0.232	0.7946	24
Exponential	0.06	0.246	0.7644	24
Polynomial	0.0394	0.198	0.8719	24
Logarithmic	0.042	0.205	0.8451	24
RES	0.030	0.175	0.9791	24

Additionally, Figure 9 illustrates the accuracy radar chart for the models built using different methods: linear, power, exponential, polynomial, logarithmic, and RES method. The chart assesses the MSE and R^2 statistical performance of each model.

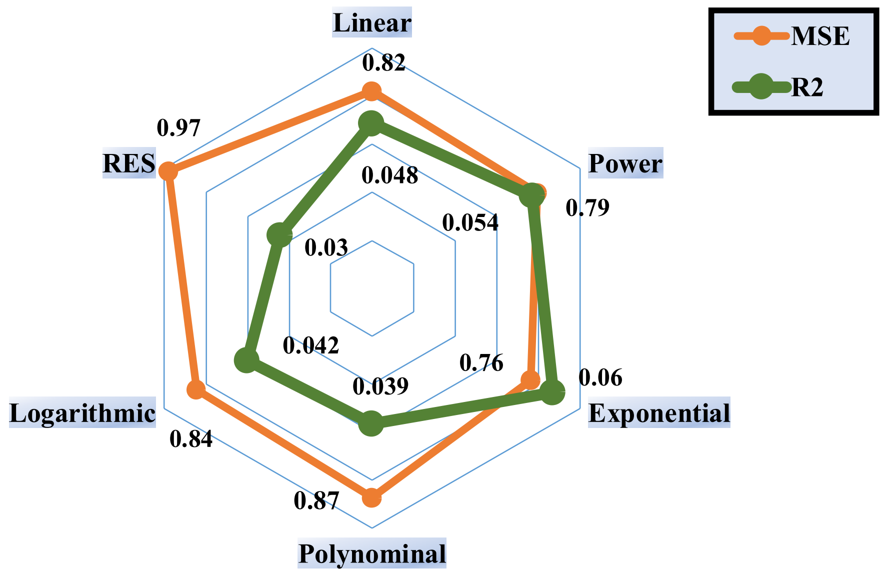

Figure 9. Comparing the outcomes and assessing the MSE and R^2 statistical performance for all built models.

To better understand and compare the values obtained from the models built in Table 14, a comparison between the RES-based model and other regression methods can be drawn for 24 data points, as shown in Figure 10.

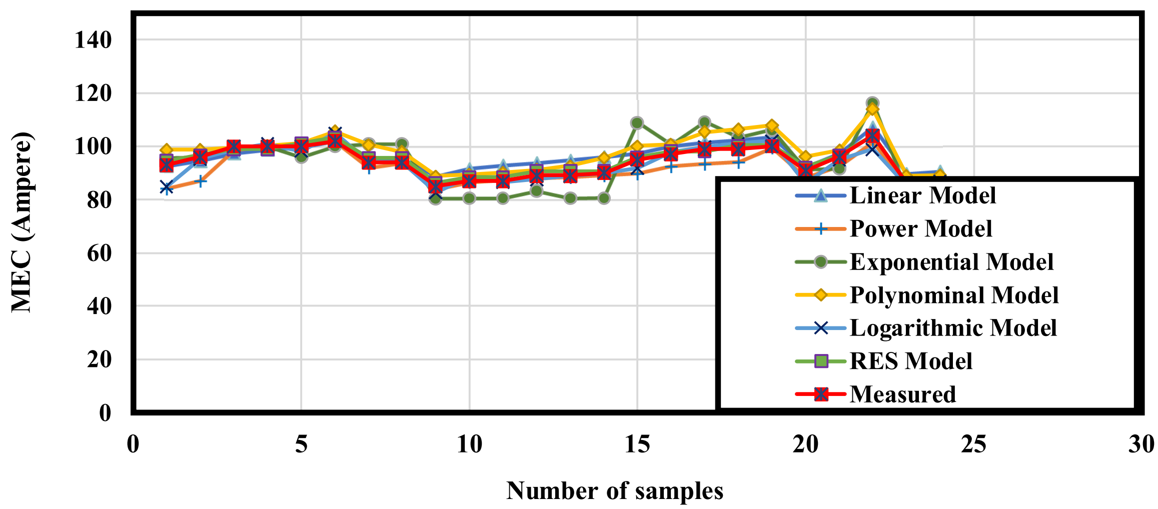

Figure 10. Comparison of measured and predicted MEC using polynomial model, exponential model, logarithmic model, power model, and RES-based model.

The results of this paper indicate that the actual gang saw performance values closely match the predicted values obtained from the RES-based method, compared to other regression methods. This high accuracy of the built model suggests its reliability. Considering the consideration of uncertainty in the developed model, the relationship established by the RES method can be utilized in other projects (case studies). Furthermore, for better visualization, Figure 11 demonstrates the alignment of the actual values with the predicted values of the gang saw performance, representing the superior performance of the RES-based model.

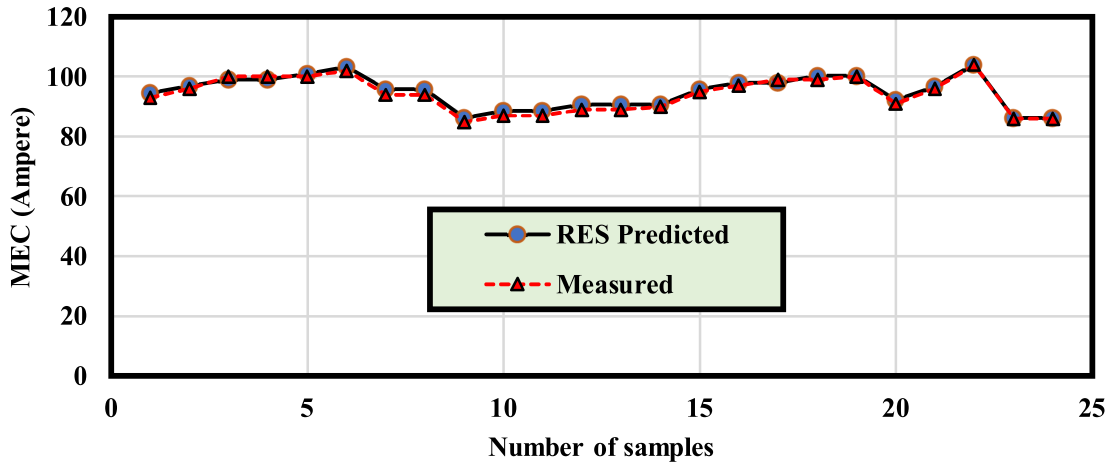

Figure 11. Comparison of measured and predicted MEC for the RES-based model.

7. Conclusions

In today's stone processing factories, achieving precise stone cutting is essential to minimize costs and time. Accurately estimating the MEC of stone cutting machines is crucial in approaching optimal cutting conditions, reducing energy consumption, and minimizing machine depreciation. However, due to the complexity and uncertainty of building stone textures and properties, determining the MEC of the machine is challenging. Traditional methods such as regression, experimental, analytical, laboratory, and field methods have limitations in accuracy, simplifying the problem and disregarding uncertainties.

To address these challenges, this study proposed a novel approach based on the RES to evaluate the performance of gang saw machines in mining engineering. The RES method considers the nonlinearity and complexity of soil and rock behavior and incorporates the influence of key parameters on gang saw performance estimation. By developing a comprehensive and non-linear model, the RES method enables more accurate and reliable predictions of gang saw behavior.

To validate the effectiveness of the RES-based approach, data from 120 test samples representing 12 types of carbonate rocks were collected from a marble factory in the Mahalat region of Iran. Five influential parameters including UCS, Mh, YM, SF-a, and V were considered for estimating the MEC of gang saw machines.

The results of this study demonstrated that the RES-based method outperformed other regression methods in estimating the MEC of gang saw machines. The statistical indicators including MSE, RMSE, and R^2 indicated the superior accuracy and efficiency of the RES-based method. The RES approach considers uncertainties, avoids simplifications, and accounts for critical factors, providing mining engineers and rock mechanics specialists with a robust tool to tackle challenges related to rock behavior.

The implications of this study are significant for the engineers and researchers involved in mining and geotechnical operations. Accurate assessment of the maximum gang saw energy in mining and stone projects enables improved design, increased production, reduced costs, and shorter processing time in stone factories, leading to enhanced overall productivity. The RES-based method offers valuable insights and supports decision-making processes, empowering engineers to make informed judgments regarding gang saw machines.

In conclusion, the RES approach presented in this study represents a powerful tool to enhance the accuracy of estimating the MEC of gang saw machines in mining applications. The findings illustrate how the RES method can help engineers overcome challenges and advance gang saw rock cutting, ultimately boosting productivity and efficiency in mining and geotechnical operations. The application of the RES approach has the potential to revolutionize the fields of mining engineering and rock mechanics, contributing to sustainable and efficient stone processing in the industry. Further research and implementation of the RES method in various mining projects can lead to significant advancements and improvements in energy efficiency and cost-effectiveness. By embracing the RES approach, mining engineers and rock mechanics specialists can drive innovation and achieve optimal results in stone cutting processes, paving the way for a more sustainable and productive future in the mining industry.

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افزایش کارآیی انرژی در برش سنگ: استفاده از روش سیستم مهندسی سنگ برای پیش‌بینی دقیق حداکثر مصرف انرژی

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چکیده:

مصرف حداکثر انرژی در ماشین‌های برش سنگ یکی از عوامل مهم هزینه‌ای در فرآیند برش سنگ‌های ساختمانی است. پیش‌بینی دقیق و تخمین عملکرد مصرف انرژی حداکثر دستگاه برش، به همراه تخمین هزینه‌های برش، می‌تواند به تعیین شرایط بهره‌برداری بهینه برای کاهش مصرف انرژی و کاهش فرسایش دستگاه کمک کند. اما به دلیل عدم قطعیت و پیچیدگی ساختار و خصوصیات سنگ‌های ساختمانی، تعیین مصرف انرژی حداکثر دستگاه وظیفه دشوار و چالشی است. بنابراین، این مقاله از روش سیستم مهندسی سنگ برای حل مشکل فوق استفاده می‌کند. به این منظور، ۱۲۰ نمونه آزمایشی از یک کارخانه مرمر در منطقه محلات ایران جمع‌آوری شد که ۱۲ نوع سنگ کربناتی را شامل می‌شود. پارامترهای ورودی مورد نظر برای تحلیل شامل سختی موهس، مقاومت فشاری تک‌محوره، مدول یانگ، نرخ تولید و فاکتور سایش شیمازک بود. در این مطالعه، ۸۰٪ از داده‌های جمع‌آوری شده که معادل ۹۶ نقطه داده هستند، برای ساخت مدل با استفاده از روش مبتنی بر سیستم مهندسی سنگ استفاده شدند. سپس نتایج به دست آمده با سایر روش‌های رگرسیون از جمله رگرسیون خطی، توانی، انفجاری، چندجمله‌ای و لگاریتمی چندگانه مقایسه شدند. در نهایت، ۲۰ درصد باقی‌مانده از داده‌ها که شامل ۲۴ نقطه داده هستند، برای ارزیابی دقت مدل‌ها استفاده شدند. بر اساس شاخص‌های آماری، به عبارت دقیقی میانگین مربعات خطا، مربع متوسط خطا و ضریب تعیین، مشخص شد که روش مبتنی بر سیستم مهندسی سنگ نسبت به سایر روش‌های رگرسیون از نظر دقت و کارآیی در تخمین مصرف انرژی حداکثر بهتر عمل می‌کند.

کلمات کلیدی: مصرف انرژی حداکثر، سیستم مهندسی سنگ، شاخص‌های آماری، روش‌های رگرسیون، سنگ ساختمانی.