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Estimation of cohesion for intact rock materials using regression and soft computing analyses

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Abstract Shear strength parameters such as cohesion (c) and internal friction angle (ϕ) are among the most critical rock properties used in the geotechnical design of most engineering projects. However, the determination of these properties is laboring and requires special equipment. Therefore, this study introduces several predictive models based on regression and artificial intelligence methods to estimate the c of different rock types. For this purpose, a comprehensive literature survey is carried out to collect quantitative data on the shear strength properties of different rock types. Then, regression and soft computing analyses are performed to establish several predictive models based on the collected data. As a result of these analyses, five different predictive models (M1–M5) were established. Based on the performance of the established predictive models, the artificial neural network-based predictive model (model 5, M5) was the most suitable choice for evaluating the c for different rock types. In addition, mathematical expressions behind the M5 model are also presented in this study to allow users to implement it more efficiently. In this regard, the present study can be declared a case study showing the applicability of regression and soft computing analyses to evaluate the c of different rock types. However, the number of datasets used in this study should be increased to get more comprehensive predictive models in future studies.

Keywords: cohesion, intact rock material, regression, soft computing

1. Introduction

Adopting rock strength criteria is the fundamental basis for designing and evaluating the stability of engineering structures in rock mechanics [1,2]. In general, the physical and mechanical properties of rocks are principal input parameters in rock mass stability models. These physical and mechanical properties depend on rock type and origin, regional tectonism, porosity, water content, grain size, and binder properties [3].

Rocks become damaged under the domination of high-stress and progressive rock weathering conditions [4]. Intact rock strength, in this context, is one of the fundamental properties in geomechanics and geoengineering [5,6]. For example, the shear strength properties (cohesion (c) and internal friction angle (ϕ)) of rocks are among the most critical phenomena that are widely used in mining, civil, and engineering geological projects [7–9]. However, referring to the c and ϕ of rocks may have two meanings or be evaluated differently. In other words, the c and ϕ can be assessed for intact rocks and rock discontinuities [10].

The c and ϕ are determined using the shear box testing apparatus for rock discontinuities. On the other hand, they are determined mainly for intact rock materials using Hoek cells. It should be noted that the shear strength properties of rock discontinuities are of prime importance in rock slope stability analyses [11,12]. In addition, the c and ϕ of intact rocks are mainly considered in underground excavation analyses or numerical modeling of rock masses [13,14]. Based on the Hoek–Brown failure criterion [15], the c of intact rock materials can be determined using Eq. 1.



$$c = \frac{UCS[(1+2a)s + (1-a)m_i\sigma_{3n}](s + m_i\sigma_{3n})^{a-1}}{(1+a)(2+a)\sqrt{1 + \frac{6am_i(s + m_i\sigma_{3n})^{a-1}}{(1+a)(2+a)}}} \tag{1}$$

where a and s are 0.5 and 1 for intact rock materials (GSI = 100), respectively. For general purposes, σ_{3n} equals to $\frac{7.5}{UCS}$ [15,16]. The Hoek-Brown m_i parameter can be estimated from Eq. 2 [16].

$$\frac{UCS}{TS} = 0.81m_i + 7 \tag{2}$$

where UCS is the uniaxial compressive strength, and TS is the direct tensile strength of rocks.

However, determining shear strength parameters for intact rock materials is labouring and requires special equipment such as confining pressure units, Hoek cells, and stiff loading machines. Therefore, several theories or relationships have been postulated to estimate these properties. These theories are mainly divided into two different groups. The graphic solutions to calculate c of intact rocks are listed in Table 1.

Table 1. Table 1. Graphical solution methods to estimate the c of intact rocks.

Graphical solution	Reference
	Wuerker [17]
	Mohr [18] Labus and Zang [19]
$c = q \frac{1 - \sin(\phi)}{2 \cos(\phi)}$ $\phi = \arcsin\left(\frac{m-1}{m+1}\right)$	
	Sulukcu and Ulusay [20] Gercek [21]

In the context of the graphical solutions, the one based on the Mohr-Coulomb failure criterion requires triaxial compressive tests. However, the others (e.g., Wuerker's method and Gercek's method) depend upon uniaxial compressive strength (UCS), direct tensile strength (TS), and Brazilian tensile strength (BTS) tests. Apart from the graphical solutions, several empirical relationships to estimate the c of intact rocks are also given in Table 2.

The approaches summarized in Tables 1 and 2 provide a solid basis for quantifying the c of intact rocks. It is worth noting that both graphical solutions, except for the one based on the Mohr-Coulomb failure criterion and empirical relationships, depend upon the physico-mechanical properties of rocks. However, most empirical relationships with higher prediction accuracy to estimate the c of intact rocks are valid for small-scale datasets. Therefore, they may also have limitations when dealing with broader datasets with different rock lithologies.

As Mehranpour and Kulatilake [22] pointed out, choosing the best method to estimate rock strength properties can reduce the risk and cost of rock engineering projects. From this point of view, there is a need to establish more comprehensive approaches to evaluate the c of rocks. In this manner, soft computing methods would be declared feasible tools to develop more comprehensive relationships to evaluate the c of rocks.

Table 2. Some empirical formulae to estimate the c of intact rocks.

Empirical formula	Rock type	n	R ²	Reference
$c = 1.207BPI$	Andesite, Mudstone, Diabase, Granodiorite, Sandstone, Tuff, Marble	200	N.R	[20]
$c = 0.83BPI$	Limestone, Travertine, Andesite, Sandstone, Marl, Schist.	11	0.86	[23]
$c = 57.868n_e^{-0.859}$	Shale	13	0.85	[24]
$c = \frac{54.94BTS}{7.82V_p + BTS}^{**}$	Tuff, Travertine, Andesite, Conglomerate, Shale, Marl, Sandstone, Siltstone, claystone	13	0.85	[25]
$c = 0.16UCS + 0.37BTS$			0.82	
$c = 5.12BTS^{0.75}V_p^{-0.53}^{**}$			0.88	
$c = 12.42648w_a^{-1.40075}$	Basalt	7	0.98	[26]
$c = 55.97656w_a^{-0.91036}$		8	0.93	
$c = 3.427 + 0.17UCS$	Basalt, Metabasalt, Dacite, Limestone,	37	0.90	[27]
$c = 7.255 + 0.85BTS$			0.85	
$c = 0.0038V_p + 3.357^*$			0.80	
$c = 0.699UCS^{0.696}$	Limestone	63	0.79	[28]
$c = 3.494BTS^{0.630}$			0.72	
$c = 3.00n_e^{-0.80}$	Andesite, Dacite, Basalt, Trachyandesite	12	0.51	[29]
$c = 3.66 + 0.1862UCS$	Various rock types	123	0.68	The present study

Explanations: V_p : P-wave velocity (*m/s, **km/s), UCS: Uniaxial compressive strength (MPa), BTS: Brazilian tensile strength (MPa), BPI: Block punch index (MPa), n_e : Effective porosity (%), w_a : Water absorption by weight (%), n: Number of datasets, N.R.: Not reported.

For example, Khandelwal et al. [28] proposed a robust model to estimate the c of limestones based upon artificial neural networks (ANN). However, the implementation of soft computing tools to establish such predictive models used to estimate the c of rocks is quite limited. Focusing on this problematic issue, in this study, comprehensive predictive models are introduced to estimate the c of different rock types based on regression and soft computing analyses.

2. Data documentation

A comprehensive literature survey was carried out to establish several predictive models to estimate the c of intact rocks. Accordingly, the datasets considered in this study are summarized in Table 3. Unfortunately, a significant number of previous studies could not have been considered due to a lack of information about the physico-mechanical properties of rocks, which are to be used as input parameters.

Table 3. Datasets considered for regression and soft computing analyses in this study.

Rock type	ρ_d (g/cm ³)	BTS (MPa)	UCS (MPa)	c (MPa)	ϕ (°)	n	Reference
Limestone, Andesite, Travertine, Marl, Schist	N.R	N.R	4.1 – 64.5	0.78 – 10.9	N.R	11	[23]
Travertine, Tuff, Andesite, Shale, Mudstone, Sandstone, Limestone	N.R	0.7 – 6.3	16.1 – 47.9	3.2 – 9.5	32 – 50.4	13	[25]
Basalt, Metabasalt, Dacite, Limestone, Volcanic breccia	N.R	4.4 – 34.4	34 – 197	8 – 36	37 – 56	37	[27]
Sandstone, Siltstone, claystone, conglomerate, shale	2.56 – 2.79	2.4 – 12.9	29 – 146	10.09 – 36.51	26 – 51	54	[30]
Sandstone, siltstone	N.R	6.5 – 11	38.5 – 156.5	11.2 – 24.5	35.8 – 56.1	8	[31]
Granite, Granodiorite, Tonalite,	N.R	11 – 16	152 – 231	27.6 – 32.3	47 – 60	3	[32]
Marble, Schist, dolomite, Quartzite, Phyllite	2.73 – 2.87	6.4 – 23.2	78 – 190	27 – 60	26 – 41	8	[33]

Explanations: ρ_d : Dry density, BTS: Brazilian tensile strength, UCS: Uniaxial compressive strength, c : cohesion of intact rock, ϕ : Internal friction angle of intact rock, n: Number of samples, N.R: Not reported.

Before performing the regression and soft computing analyses, simple correlations between the considered rock properties (i.e., dry density (ρ_d), UCS, and BTS) and c were revealed through Pearson's correlation coefficient (r) and Spearman's rho values (Table 4). Accordingly, the ρ_d , BTS, and UCS are associated with the c . Of these parameters, UCS is the most influential parameter for evaluating c .

Table 4. Correlation matrix of the variables considered in this study.

Parameter	ρ_d	BTS	UCS
r	0.504	0.556	0.824
Spearman's rho	0.438	0.584	0.885
n	62	123	134

3. Data analysis methods

3.1. Regression analyses

Linear and nonlinear regression analyses were performed in this section. Based on these analyses, it was determined that the single linear regression analyses as a function of ρ_d and BTS provide undulating results in estimating the c of rocks (Table 5). On the other hand, the linear regression model as a function of UCS could be used to estimate the c of rocks. The correlation of determination value (R^2) for this model (Model 3, M3) is 0.68 for 134 datasets (Fig 1).

Table 5. Simple regression analysis results.

Model No	Empirical formula	Estimate	Std. Error	t value	n	R^2
M1	$c = -176.2 + 75.2\rho_d$	-176.2	44.4	-3.97	62	0.26
		75.2	16.6	4.52		
M2	$c = 12.58 + 0.866BTS$	12.58	1.33	9.46	123	0.31
		0.866	0.12	7.22		
M3	$c = 3.66 + 0.1862UCS$	3.66	1.07	3.42	134	0.68
		0.1862	0.011	16.93		

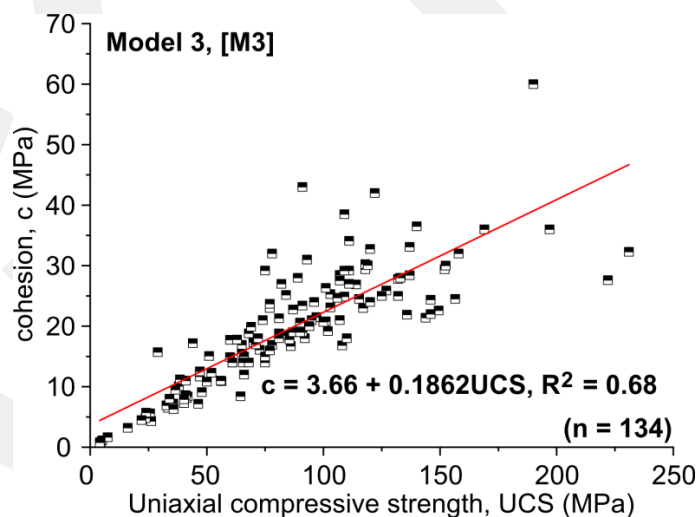


Fig 1. Scatter plot of Model 3 (M3).

Fig 2 shows some predictive models to estimate the c of rocks as function of UCS. Accordingly, the M3 model provided higher cohesion values than the other models of Karaman et al. [27] and Khandelwal et al. [28]. However, the m3 Model seems limited when considering high-strength rock types (Fig 2). Therefore, soft computing tools were attempted to build more comprehensive models to estimate the c of rocks.

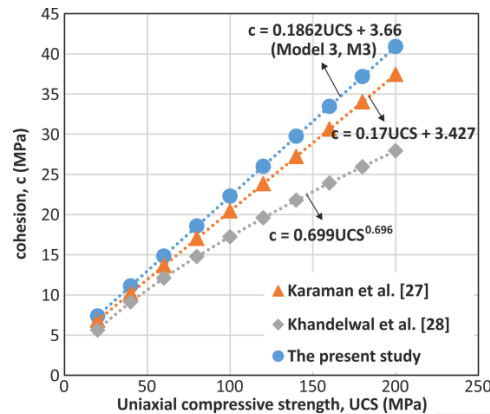


Fig 2. Comparison of some predictive models as a function of UCS.

3.2. Adaptive-neuro fuzzy inference system (ANFIS)

Considering many advantages, researchers have used ANFIS to build predictive models in many engineering geological problems [34–36]. The advantage of the ANFIS is that it practices a hybrid learning process to estimate the premise and consequent parameters [37]. In this context, the Sugeno fuzzy reasoning algorithm based on numerous membership functions is primarily adopted in most ANFIS models.

From this approach, several ANFIS models were created in the MATLAB environment in this study. Some illustrations of the established ANFIS model (Model 4, M4) are given in Fig 3. Accordingly, the UCS and BTS of rocks were used in this model (Fig 3a). For each input parameter, three triangular membership functions were identified.

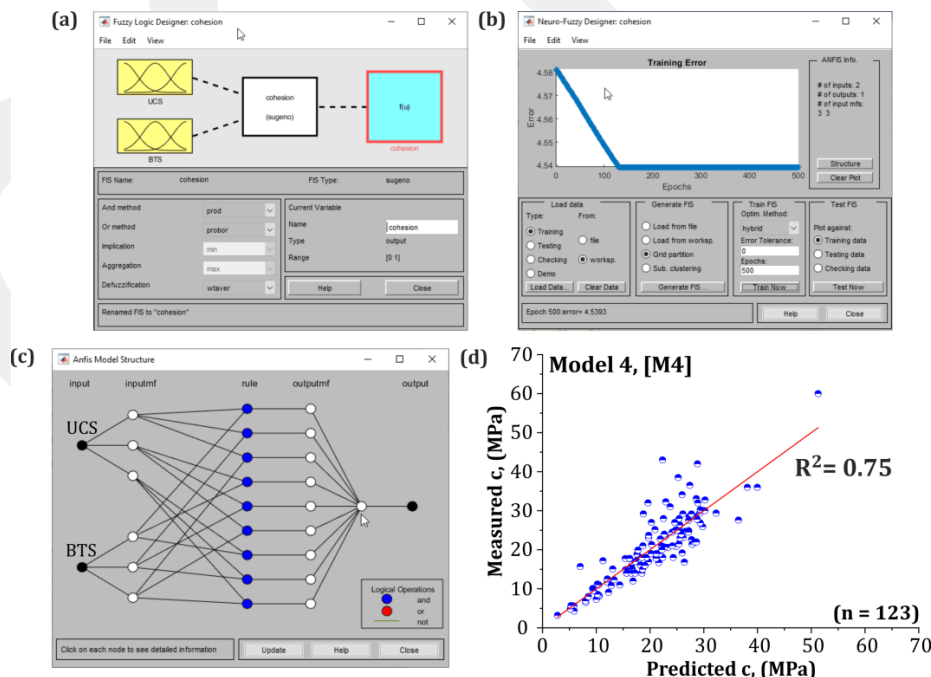


Fig 3. Illustrations of the established ANFIS model in the MATLAB environment a) Input parameters b) Training process c) ANFIS structure d) Predicted and measured c values for the established ANFIS Model.

The training of the ANFIS model was based upon the Sugeno fuzzy reasoning algorithm, and root mean square error (RMSE) was adopted to minimize the relative errors in the training process (Fig 3b). Based on the ANFIS structure, nine different if-then rules were described (Fig 3c). The predicted and measured c values for the M4 model are also plotted (Fig 3d). Accordingly, the R^2 value for the M4 model was found to be 0.75 based on 123 datasets.

3.3. Artificial neural networks (ANN)

The artificial neural network (ANN) has been widely adopted to predict several dependent variables based on complex datasets. It is a well-accepted method in most engineering geological problems. The ability of ANN is that complex datasets can be modeled using such ANN methodologies [38]. In practical ANN applications, neural networks have been trained by a feedforward backpropagation algorithm [39] to establish empirical formulae based on the weights and biases extracted from neural network analyses.

In this study, the neural network toolbox (nntool) was used to develop several neural networks in the MATLAB environment. For this purpose, the database (Table 3) was randomly divided into training (70/100) and testing/validating (30/100) parts. Various ANN network architectures, hidden layers, and neurons were attempted to determine the most suitable and practical structural combination. The ANN architecture adopted in this study is illustrated in Fig 4. The input parameters in the developed ANN model were the BTS and UCS of rocks. The number of hidden layers was nine, and the output was the c in this model.

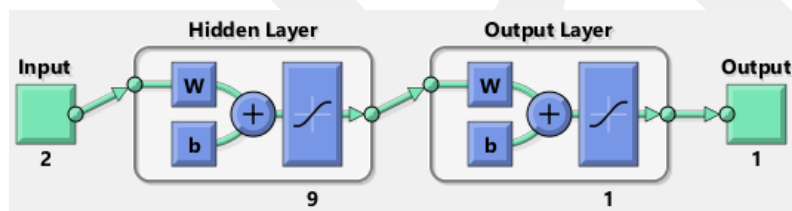


Fig 4. ANN architecture adopted in this study.

Before performing the ANN analyses, the database was normalized between -1 and 1 using Eq 3. Then, the normalized database was loaded into the MATLAB environment to implement such ANN analyses. As a result, a robust predictive model was developed to estimate the c . The mathematical expressions of the developed model were revealed by adopting the deterministic approach previously described by Das [40].

$$V_N = 2 \times \left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \right) - 1 \quad (3)$$

where x_i is the relevant parameter to be normalized, x_{\min} , and x_{\max} are the minimum and maximum values in the database.

Based on the ANN analysis results, the c of rocks can be estimated by model 5 (M5), which is given as Eq 4. The sub-equation systems for Eq 4 are also listed in Table 6. The ANN-based predictive model (M5) can be easily implemented by coding into any programming language, such as MATLAB. The predicted and measured c values are also plotted in Fig 5. Accordingly, the predicted c values are in good harmony with the measured ones.

$$E_{ii} = 28.4 \tanh\left(\sum_{i=1}^9 x_i + 0.015895\right) + 31.6, R^2 = 0.86 \quad (4)$$

The R^2 value of the M5 model is 0.86, showing its relative success. The number of datasets for this model is 123, notably more than the other models in Table 2, excluding the study of Sulukcu and Ulusay [20].

Table 6. Sub-equation systems of the proposed ANN model.

$x_1 = -7.50113 \tanh(1.30448 {}^n UCS + 15.10103 {}^n BTS - 8.69797)$
$x_2 = 0.117562 \tanh(51.54395 {}^n UCS - 23.7149 {}^n BTS - 6.61701)$
$x_3 = 9.316223 \tanh(-4.75824 {}^n UCS + 14.26506 {}^n BTS + 5.49345)$
$x_4 = 20.39267 \tanh(0.562242 {}^n UCS + 3.16274 {}^n BTS - 1.46243)$
$x_5 = 1.35 \tanh(5.421795 {}^n UCS - 4.78142 {}^n BTS - 0.15684)$
$x_6 = 13.89389 \tanh(0.042961 {}^n UCS + 6.762281 {}^n BTS - 1.32204)$
$x_7 = 11.82495 \tanh(4.179516 {}^n UCS - 12.0153 {}^n BTS - 4.54595)$
$x_8 = 26.27324 \tanh(-0.51763 {}^n UCS - 4.95209 {}^n BTS + 1.220302)$
$x_9 = 3.760835 \tanh(-3.20586 {}^n UCS + 6.076658 {}^n BTS + 1.844983)$
Normalization functions
${}^n UCS = 0.0093 UCS - 1.1498$ ${}^n BTS = 0.0593 BTS - 1.0415$

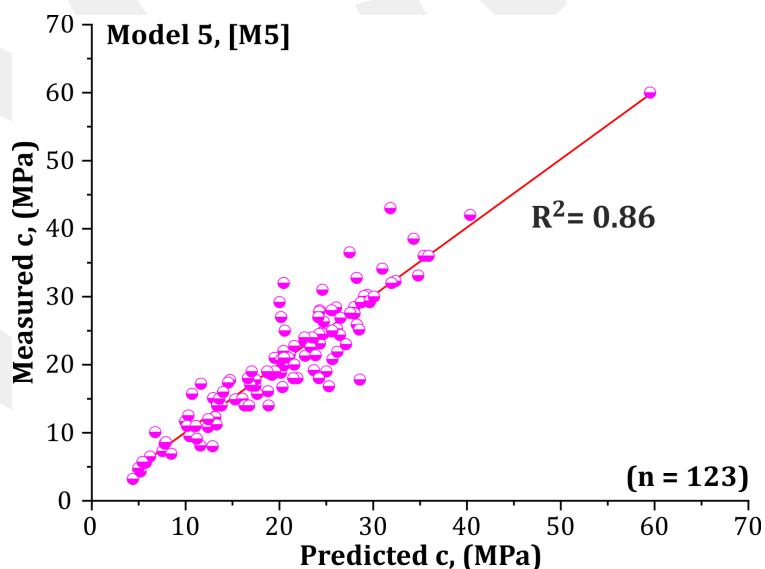


Fig 5. Predicted and measured c values of the proposed model.

4. Results and Discussion

Several statistical indicators such as R^2 , RMSE, and variance accounted for (VAF) were adopted to evaluate the performance of the predictive models established in this study. These error metrics target different requirements depending on data sets; hence, they can be used together to evaluate the errors from different aspects. The mathematical expressions of these statistical performance indicators are given in Eqs. 5–7.

$$R^2 = \left(\frac{n \sum xy - \sum x \sum y}{\sqrt{n \sum x^2 - (\sum x)^2} \sqrt{n \sum y^2 - (\sum y)^2}} \right)^2 \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - x_i)^2}{n}} \quad (6)$$

$$VAF = \left(1 - \frac{\text{var}(y_i - x_i)}{\text{var}(y_i)} \right) \times 100 \quad (7)$$

where x is the dependent variable, y is the independent variable, and n is the number of datasets.

Accordingly, the performance evaluations of the models are listed in Table 6. Theoretically, a predictive model having the R^2 value of 1, RMSE of 0, and VAF of 100 is assumed to have the perfect prediction performance. In this regard, the model based on ANN was the most reliable tool for evaluating c for different rock types. The R^2 , RMSE, and VAF values of M5 were found to be 0.86, 3.43, and 85.69, respectively (Table 7).

Table 7. Performance evaluation of the established models.

Method of analysis	Model No	R2	RMSE	VAF	n
Regression	M1	0.26	7.568	25.39	62
	M2	0.31	7.508	30.93	123
	M3	0.68	5.510	67.92	134
ANFIS	M4	0.75	4.539	74.75	123
ANN	M5	0.86	3.430	85.69	123

On the other hand, it should be mentioned that the performance of the ANN model proposed by Khandelwal et al. [28] is better than the M5 model. The R^2 value of Khandelwal's model is 0.96. However, this model was based upon only limestones with 63 datasets. The M5 model is more comprehensive than Khandelwal's model and can save time in estimating the c of intact rocks using the rock properties of UCS and BTS. This model can reliably estimate the c of intact rocks without performing triaxial compressive tests.

This model can be used in practical evaluations when the c is desired in engineering designs. Since the UCS and BTS tests are occasionally performed in most engineering geological projects, they can simultaneously be used to estimate the c of rocks. However, the performance of the M5 model should be cross-checked by using other test results in future studies. In this way, this model can be improved by adding new test results to the database.

5. Conclusion

The present study aims to establish several predictive models for evaluating the c of different rock types. For this purpose, a comprehensive literature survey was conducted to collect such datasets (Table 3) for regression and soft computing analyses. Based on these analysis results, several predictive models (M1-M5) were established based on the ρ_d , BTS, and UCS of rocks. Accordingly, the M5 model with an R^2 of 0.86 was found to have the best prediction performance in estimating the c of different rock types (Fig 5).

Furthermore, the mathematical expressions behind the M5 model were also introduced to let users implement this model more efficiently. However, the M5 model should be improved using additional laboratory test results in future studies. Last but not least, it should be remembered that mathematical analyses of laboratory test results and applications of soft computing models are required in mining and civil engineering projects. In this manner, advanced methodologies allow one to analyze a large number of datasets that can save time and provide practical information on the desired rock parameters. Therefore, the present study can be declared a case study on modeling the cohesion of intact rock materials as a function of UCS and BTS of rocks.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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