IOP Conference Series: Earth and Environmental Science

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

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

E Köken[1*], P Strzałkowski[2] and U Kaźmierczak[2]

[1]Abdullah Gul University, Nanotechnology Engineering Department, 38100, Kayseri – Turkey

[2]Wroclaw University of Science and Technology, Faculty of Geoengineering, Mining and Geology, Department of Mining, Wybrzeże Wyspiańskiego 27, 50-370 Wrocław – Poland

*Corresponding author e-mail: ekin.koken@agu.edu.tr

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.

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

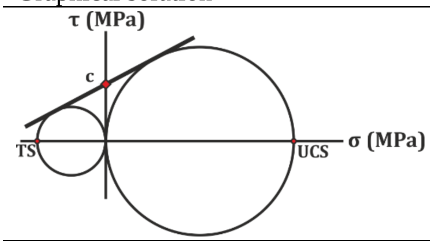
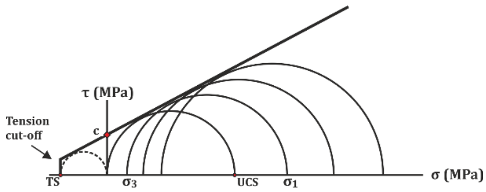
where a and s are 0.5 and 1 for intact rock materials (GSI = 100), respectively. For general purposes, σ_{3n} equals to $\frac{7.5}{UCS}$ [15,16]. The Hoek-Brown m_i parameter can be estimated from Eq. 2 [16].

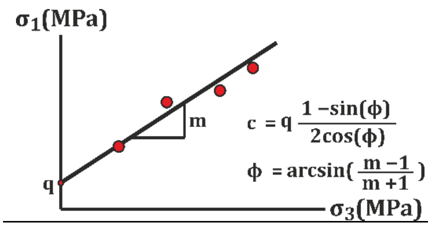
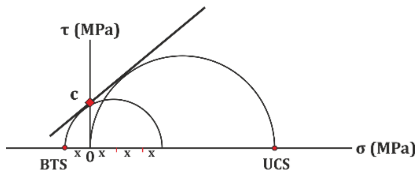
$$\frac{UCS}{TS} = 0.81m_i + 7 \tag{2}$$

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.

<table>
<tr><th>Graphical solution</th><th>Reference</th></tr>
<tr><td>
</td><td>Wuerker [17]</td></tr>
<tr><td>


</td><td>Mohr [18]
Labus and Zang [19]</td></tr>
<tr><td>
</td><td>Sulukcu and Ulusay [20]
Gercek [21]</td></tr>
</table>

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 physicomechanical 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, Andesinte, Sandstone, Marl, Schist.	11	0.86	[23]
$c = 57.868{n_e}^{-0.859}$	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	
$c = 5.12BTS^{0.75}Vp^{-0.53}$ **			0.88	
$c = 12.42648{w_a}^{-1.40075}$	Basalt	7	0.98	[26]
$c = 55.97656{w_a}^{-0.91036}$		8	0.93	
$c = 3.427 + 0.17UCS$	Basalt, Metabasalt, Dacite, Limestone,	37	0.90	[27]
$c = 7.255 + 0.85BTS$			0.85	
$c = 0.0038V_p + 3.357$ *	Limestone	63	0.80	[28]
$c = 0.699UCS^{0.696}$			0.79	
$c = 3.494BTS^{0.630}$			0.72	
$c = 3.00{n_e}^{-0.80}$	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 physicomechanical 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 (R2) 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 75.2	44.4 16.6	−3.97 4.52	62	0.26
M2	$c=12.58+0.866BTS$	12.58 0.866	1.33 0.12	9.46 7.22	123	0.31
M3	$c=3.66+0.1862UCS$	3.66 0.1862	1.07 0.011	3.42 16.93	134	0.68

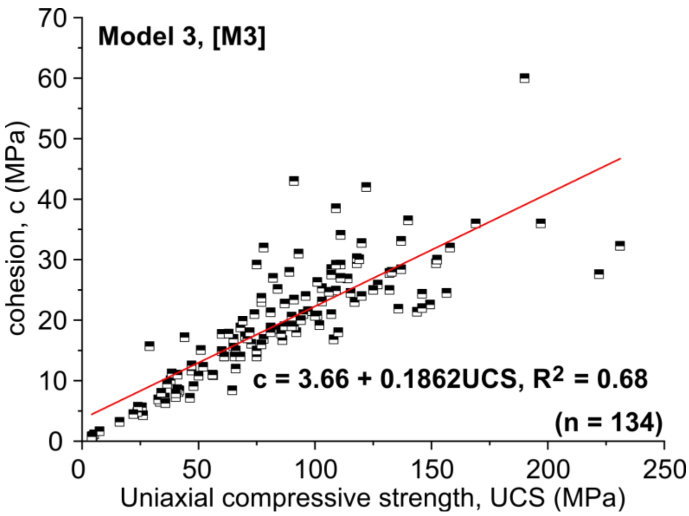


Fig 1. Scatter plot of Model 3 (M3).

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.

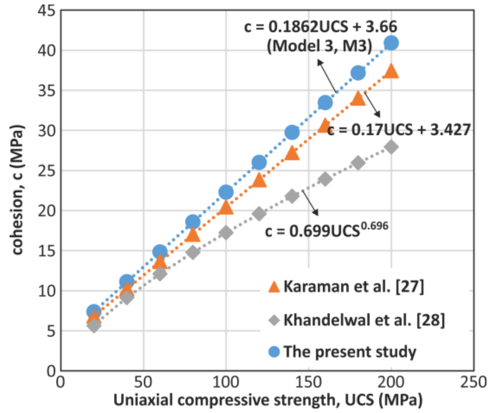


Fig 2. Comparison of some predictive models as a function of UCS.

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.

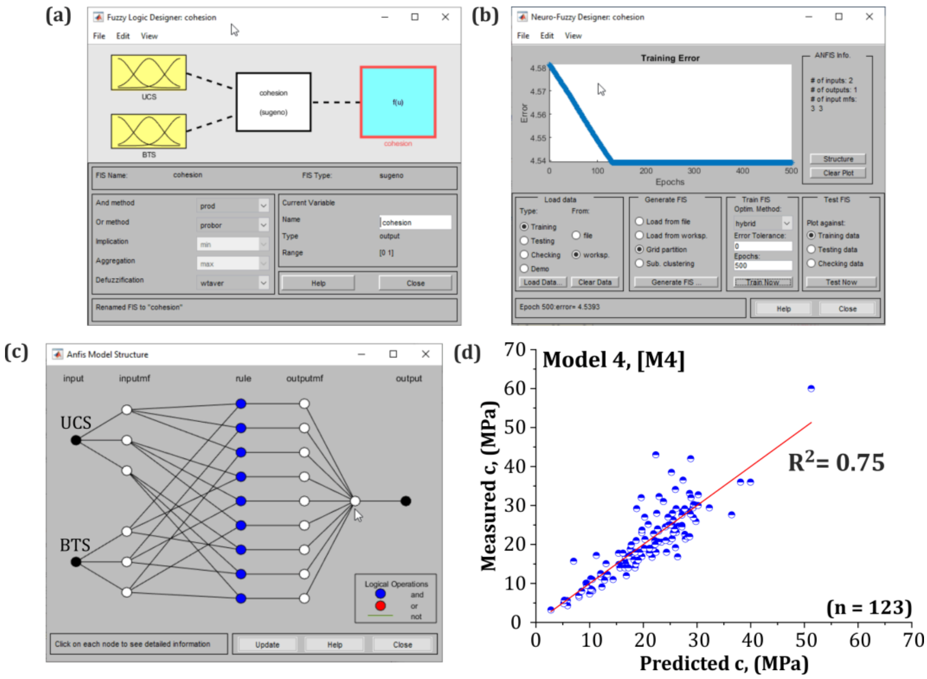


Fig 3. Illustrations of the established ANFIS model in the MATLAB environment a) Input parameters b) Training process c) ANFIS structure d) Predicted and measured c values for the established ANFIS Model.

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 R2 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.

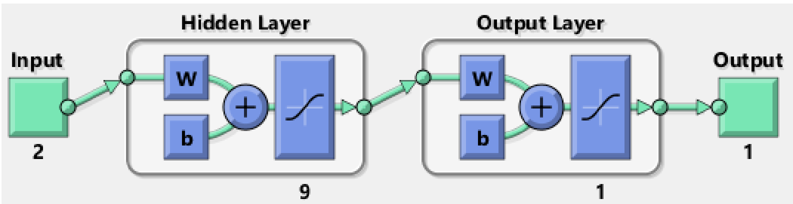


Fig 4. ANN architecture adopted in this study.

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].

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

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.

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

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.

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

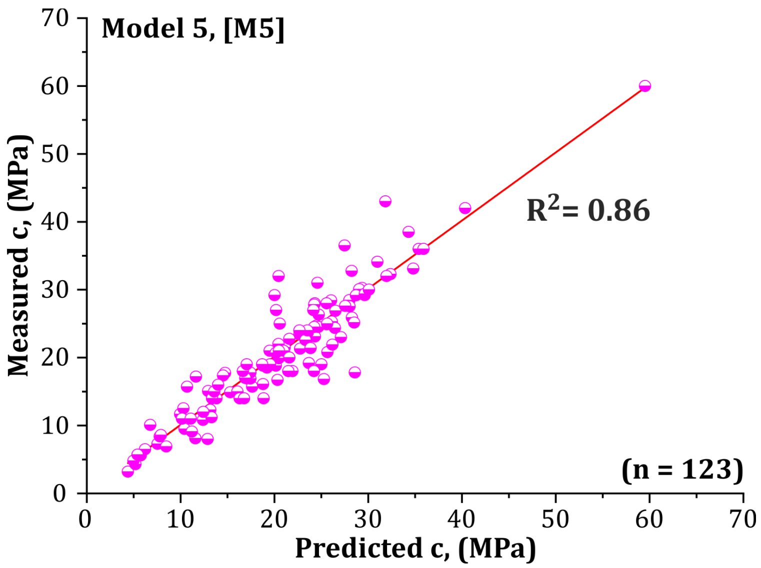


Fig 5. Predicted and measured c values of the proposed model.

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.

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

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

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

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
	M1	0.26	7.568	25.39	62
Regression	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 R2 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.

Acknowledgments

The authors are indebted to Abiodun Ismail Lawal (Federal University of Technology, Akure) for his valuable help in the ANN analyses.

References

[1] Kaiser, P. K., Kim, B., Bewick, R. P., & Valley, B. (2011). Rock mass strength at depth and implications for pillar design. Mining Technology, 120(3), 170-179.
[2] Lan, H., Chen, J., & Macciotta, R. (2019). Universal confined tensile strength of intact rock. Scientific Reports, 9(1), 6170.
[3] Siegmund, M. (2021). Selected technologies for the destruction of rocks cohesion by using their tensile strength properties. Mining Machines, https://doi.org/10.32056/KOMAG2021.1.1
[4] Zhang, H. Q., Tannant, D. D., Jing, H. W., Nunoo, S., Niu, S. J., & Wang, S. Y. (2015). Evolution of cohesion and friction angle during microfracture accumulation in rock. Natural Hazards, 77(1), 497-510.
[5] Ewy, R. T. (1999). Wellbore-stability predictions by use of a modified Lade criterion. SPE Drilling & Completion, 14(02), 85-91.
[6] Mehranpour, M. H., & Kulatilake, P. H. (2016). Comparison of six major intact rock failure criteria using a particle flow approach under true-triaxial stress condition. Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 2(4), 203-229.
[7] Singh, M., Raj, A., & Singh, B. (2011). Modified Mohr–Coulomb criterion for non-linear triaxial and polyaxial strength of intact rocks. International Journal of Rock Mechanics and Mining Sciences, 48(4), 546-555.
[8] Komurlu, E., & Demir, A. D. (2018). Determination of Cohesion values of Rock Materials using Double Shear Jaws. Periodica Polytechnica. Civil Engineering, 62(4), 881.
[9] Shen, B., Shi, J., & Barton, N. (2018). An approximate nonlinear modified Mohr-Coulomb shear strength criterion with critical state for intact rocks. Journal of Rock Mechanics and Geotechnical Engineering, 10(4), 645-652.
[10] ISRM: (2007) The complete ISRM suggested methods for rock characterization, testing and monitoring: 1974–2006. In: Ulusay R, Hudson JA (eds) Suggested methods prepared by the commission on testing methods. Int. Soc. Rock Mech. (ISRM), Ankara, Turkey
[11] Hencher, S. R., & Richards, L. R. (2015). Assessing the shear strength of rock discontinuities at laboratory and field scales. Rock Mechanics and Rock Engineering, 48(3), 883-905.

[12] Sanei, M., Faramarzi, L., Fahimifar, A., Goli, S., Mehinrad, A., & Rahmati, A. (2015). Shear strength of discontinuities in sedimentary rock masses based on direct shear tests. International Journal of Rock Mechanics and Mining Sciences, 75, 119-131.
[13] Nasehi, M. J., & Mortazavi, A. (2013). Effects of in-situ stress regime and intact rock strength parameters on the hydraulic fracturing. Journal of Petroleum Science and Engineering, 108, 211-221.
[14] Deng, J., Li, S., Jiang, Q., & Chen, B. (2021). Probabilistic analysis of shear strength of intact rock in triaxial compression: a case study of Jinping II project. Tunnelling and Underground Space Technology, 111, 103833.
[15] Hoek, E., Carranza-Torres, C., & Corkum, B. (2002). Hoek-Brown failure criterion-2002 edition. Proceedings of NARMS-Tac, 1(1), 267-273.
[16] Hoek, E., & Brown, E. T. (2019). The Hoek–Brown failure criterion and GSI–2018 edition. Journal of Rock Mechanics and Geotechnical Engineering, 11(3), 445-463.
[17] Wuerker, R. G. (1959). Influence of stress rate and other factors on strength and elastic properties of rocks. In The 3rd US Symposium on Rock Mechanics (USRMS).
[18] Mohr O (1900) Welche Umsta¨nde bedingen die Elastizita¨tsgrenze und den Bruch eines Materials? Zeit des Ver Deut Ing 44:1524–1530
[19] Labuz, J. F., & Zang, A. (2012). Mohr–Coulomb failure criterion. Rock mechanics and Rock Engineering, 45(6), 975-979.
[20] Sulukcu, S., & Ulusay, R. (2001). Evaluation of the block punch index test with particular reference to the size effect, failure mechanism, and its effectiveness in predicting rock strength. International Journal of Rock Mechanics and Mining Sciences, 38(8), 1091-1111.
[21] Gercek H. (2013) Rock mechanics lecture notes (unpublished), Zonguldak Bulent Ecevit University, Zonguldak, Turkey.
[22] Mehranpour, M. H., & Kulatilake, P. H. (2016). Comparison of six major intact rock failure criteria using a particle flow approach under true-triaxial stress condition. Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 2(4), 203-229.
[23] Sonmez, H., & Tunusluoglu, C. (2008). New considerations on the use of block punch index for predicting the uniaxial compressive strength of rock material. International Journal of Rock Mechanics and Mining Sciences, 6(45), 1007-1014.
[24] Cuisiat, F. (2011). Cap rock fracturing criteria for assessment of CO2 storage capacity, Technical report, NGI.
[25] Köken E. (2013) Zayıf kayaçlarda kohezyonun dolaylı olarak tahmini, 23rd International Mining Congress & Exhibition of Turkey, 537 – 547 (in Turkish).
[26] Yang, S. B. (2015). Cohesion and Internal Friction Angle of Basalts in Jeju Island, Journal of the Korean Geotechnical Society, 31(11): 33 – 40.
[27] Karaman, K. A. D. İ. R., Cihangir, F. E. R. D. İ., Ercikdi, B. A. Y. R. A. M., Kesimal, A. Y. H. A. N., & Demirel, S. (2015). Utilization of the Brazilian test for estimating the uniaxial compressive strength and shear strength parameters. Journal of the Southern African Institute of Mining and Metallurgy, 115(3), 185-192.
[28] Khandelwal, M., Marto, A., Fatemi, S. A., Ghoroqi, M., Armaghani, D. J., Singh, T. N., & Tabrizi, O. (2018). Implementing an ANN model optimized by genetic algorithm for estimating cohesion of limestone samples. Engineering with Computers, 34(2), 307-317.
[29] Villeneuve, M. C., & Heap, M. J. (2021). Calculating the cohesion and internal friction angle of volcanic rocks and rock masses. Volcanica, 4(2), 279-293.
[30] Muftuoglu Y.V., Didari V. & Gercek H. (1994) Establishment of an industrial support centre in Zonguldak, Zonguldak Indistrial Support Centre (ZEDEM), final report (NATO-TU 848), 104 pp, Zonguldak, Turkey
[31] Colak K. (1998) A study on the strength and deformation anisotropy of coal measure rocks at Zonguldak Basin, Dissertation, Zonguldak Karaelmas University, 214 pp, Zonguldak, Turkey
[32] Glamheden R. & Fredriksson A., Röshoff K., Karlsson J., Hakami H., Christiansson R. (2007) Rock Mechanics Forsmark, Site descriptive modelling: Forsmark stage 2.2, Swedish Nuclear Fuel and Waste Management Co, Technical Report (R-07-31), 265 pp, Stockholm
[33] Panthee S., Khanal M. & Singh T.N. (2016) Geotechnical and geomechanical characteristics of the rocks along tunnel of Kulekhani III Hydro-electric Project, Journal of Nepal Geological Society, 50: 39–50.

[34] Yesiloglu-Gultekin N, Gokceoglu C, Sezer EA (2013) Prediction of uniaxial compressive strength of granitic rocks by various nonlinear tools and comparison of their performances, Int. J. Rock Mech. Min. Sci. 62: 113–122, https://doi.org/10.1016/j.ijrmms.2013.05.005
[35] Sharma LK, Vishal V, Singh TN (2017) Developing novel models using neural networks and fuzzy systems for the prediction of strength of rocks from key geomechanical properties, Measurement, 102: 158–169, https://doi.org/10.1016/j.measurement.2017.01.043
[36] Roy DH, Singh TN (2020) Predicting deformational properties of Indian coal: soft computing and regression analysis approach Measurement, 149: 106975 https://doi.org/10.1016/j.measurement.2019.106975
[37] Jang JSR (1992) Neuro-fuzzy modeling: architecture, analyses and applications, Dissertation, Department of Electrical Engineering and Computer Science, University of California, Berkeley, CA 94720
[38] Mayorga, R.V., Arriaga, M., 2007. Non-linear global optimization via parameterization and inverse function approximation: An artificial neural networks approach. International Journal of Neural Systems. 17(5), 353-368.
[39] Saravanan, K., Sasithra, S., 2014. Review on classification based on artificial neural networks. Int. J. Ambient Syst. Appl. 2(4), 11-18. https://doi.org/10.5121/ijasa.2014.2402.
[40] Das, S.K., 2013. Artificial neural networks in geotechnical engineering: modeling and application issues. Metaheuristics in Water Geotech. Transp. Eng. 5, 231-267.