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Estimating Uniaxial Compressive Strength of Pyroclastic Rocks using Soft Computing Techniques

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Abstract

In this study, several soft computing analyses are performed to build some predictive models to estimate the uniaxial compressive strength (UCS) of the pyroclastic rocks from central Anatolia, Turkey. For this purpose, a series of laboratory studies are conducted to reveal physico-mechanical rock properties such as dry density (ρd), effective porosity (ne), pulse wave velocity (Vp), and UCS. In soft computing analyses, ρd, ne, and Vp are adopted as the input parameters since they are practical and cost-effective non-destructive rock properties. As a result of the soft computing analyses based on the classification and regression trees (CART), multiple adaptive regression spline (MARS), adaptive neuro-fuzzy inference system (ANFIS), artificial neural networks (ANN), and gene expression programming (GEP), five robust predictive models are proposed in this study. The performance of the proposed predictive models is evaluated by some statistical indicators, and it is found that the correlation of determination (R2) value for the models varies between 0.82 – 0.88. Based on these statistical indicators, the proposed predictive models can be reliably used to estimate the UCS of the pyroclastic rocks.

1. Introduction

Physico-mechanical rock properties are significant inputs to evaluate the stability of surface and underground rock structures. For example, uniaxial compressive strength (UCS) is one of the most critical input parameters in rock engineering projects. Due to its applicability in rock engineering, it has been adopted in rock failure criteria such as Mohr-Coulomb and Hoek-Brown [1, 2]. It is also a significant input in most rock mass classification systems such as RMR, Q, SMR, and RMI [3–6]. However, preparing rock samples and running experiments are costly and time-consuming in some situations [7, 8]. More profoundly, it can be difficult to obtain high-quality core or cubical rock samples from certain types of rocks that are weak, highly fractured, thinly bedded, foliated or have a block-in-matrix (BIM) structure [9, 10].

In these cases, the researchers have postulated various predictive models to estimate the UCS of rocks. In the literature, many empirical formulas are used to predict the UCS of rocks. However, most of them are based on simple or multiple regression analyses. Regression-based predictive models often fail to capture gaps and uncertainties in the dataset despite being an easy and practical way to estimate any mechanical rock property. Due to this reason, most regression models are site-specific and valid only for a particular area of interest [11].

On the other hand, artificial intelligence methods such as adaptive neuro-fuzzy inference systems (ANFIS), artificial neural networks (ANN), multivariate adaptive regression splines (MARS), support vector machine (SVR), and gene expression programming (GEP) are relatively more sensitive to large datasets, and

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provide better results than the classical regression analyses [12, 13]. For over a decade, the implementation of soft computing methods for predicting the UCS of rocks has gained popularity due to the above statement. Based on numerous soft computing methods, several predictive models to estimate the UCS of different rock types are listed in Table 1.

Table 1. Some predictive models to estimate the UCS of rocks based on different soft computing methods.

Input parameters	Method	Rock type	R2	n	Reference
V_p, w_a, ρ_d, ρ_s	LGP, MEP, GEP	Limestone	0.60 – 0.88	106	[14]
ρ_d, SHV, n_e, V_p, I_{d4}	ANN	Travertine Limestone	0.61 – 0.90	54	[15]
V_p, ρ_d, n_e	ANN	Sandstone	0.96	133	[16]
SHV, ρ_d, n_e	ANN	Limestone Sandstone Dolomite Granite Gabbro	0.96	93	[17]
n_e, I_{d4}, V_p	ANN	Limestone Marl	0.86	55	[18]
V_p, SHV, SHRV	ANN	Marble Limestone Travertine	0.82 – 0.96	37	[19]
V_p, ρ_d, n_e	GEP	Limestone Dolomite	0.76	72	[20]
V_p, BTS, PLS, BPI	ANN ANFIS	Granite Granodiorite	0.40 – 0.69	75	[21]
BTS, PLS, V_p	PSO-ANN	Sandstone Limestone Schist	0.83 – 0.97	160	[22]
BPI, PLS, SHV, V_p	ANFIS, FIS, ANN	Granite, Schist, sandstone	0.92 – 0.98	44	[23]
ρ_d, V_p, SHV, PLS	PSO-ANN	Limestone Granite	0.98	66	[24]
V_p, ρ_d, n_e	ANN	Limestone	0.95	105	[25]
SHV with different applications	SVR ABC ANFIS-SCM	Basalt Metabasalt	0.72 – 0.84	47	[26]
V_p, n_e, ρ_d	ANFIS	Limestone Sandstone	0.66 – 0.91	45	[27]
V_p, n_e, PLS, SHV	RF	Travertine	0.93	30	[28]
SHV, V_p	LSSVM	Limestone Marble Dolomite	0.78	90	[29]
n_e, I_{d4},	LSSVM MPRM ELM	Andesite Tuff Basalt Dacite	0.90 – 0.96	47	[30]
n_e, ρ_d, ρ_s, V_p, SHV	EPR-MOGA	Limestone	0.85 – 0.93	104	[31]

Explanations: n_e: Effective porosity, ρ_d: Dry density, ρ_s: Saturated density, V_p: Pulse wave velocity, SHV: Schmidt hammer value, BPI: Block punch index, w_a: Water absorption by weight, SHRV: Shore hardness value, PLS: Point load strength, I_{d4}: Slake durability index after four-cycle, BTS: Brazilian tensile strength, EPR-MOGA: Advanced evolutionary polynomial regression analysis, ANFIS: Adaptive neuro-fuzzy inference system, FIS: Fuzzy inference system, ANN: Artificial neural networks, LGP: Linear genetic programming, MEP: Multi expression programming, GEP: Gene expression programming, PSO-ANN: Particle swarm optimization-based artificial neural networks, SVR: Support vector machine, ABC: artificial bee colony algorithm, ANFIS-SCM: Adaptive neuro-fuzzy inference system-subtractive clustering method, LSSVM: Least square support vector machine, MPMR: Minimax probability machine regression, ELM: Extreme Learning Machine, RF: Random forest.

As seen in Table 1, different soft computing methods with varying input combinations are used to estimate the UCS for different rocks. Herein, numerous rock properties such as effective porosity (n_e), dry density (ρ_d), point load strength (PLS), and pulse wave velocity (V_p) are adopted as the input parameters.

Nevertheless, apart from a few studies [14, 21, 26, 30], the performances of different soft computing methods in estimating the UCS of rocks have not been compared in a detailed manner. In addition to the contributions to the applicability of soft computing methods in rock engineering, the present study introduces several predictive models to estimate the UCS of pyroclastic rocks from central Anatolia – Turkey based on five widely used soft computing methods (i.e. ANFIS, ANN, GEP, multivariate adaptive regression splines (MARS), and CART decision trees).

For this purpose, detailed laboratory studies were conducted to build a comprehensive database to implement the above-mentioned methods. During laboratory studies, non-destructive rock properties such as dry density (ρ_d), effective porosity (n_e), and pulse wave velocity (V_p) were determined for each rock sample. Since these rock properties are routinely measured in many rock engineering projects, it is possible to claim that there is considerable potential for building some predictive models by using these cost-effective testing methods. In addition, when considering the relative suitability of pyroclastic rocks for different applications such as earthwork, decorative and masonry purposes, predictive models based on soft computing techniques can be a deterministic and holistic approach to selecting proper rock types for special engineering applications. In this way, international readers find some critical notes on implementing some soft computing methods for evaluating the UCS of pyroclastic rocks.

2. Materials and methods

To perform the experimental studies, representative rock blocks were obtained from several locations in central Anatolia, Turkey. In other words, a total of 131 rock blocks were collected during field sampling. The sampling locations are given in Figure 1. Firstly, the size of the rock blocks was reduced by using an industrial rock saw, and then cubical rock samples (70 x 70 x 70 cm) were prepared for each rock block (Figure 2a, 2b). Using these cubical rock samples, ρ_d, n_e, V_p, and UCS values were determined individually. The laboratory studies were performed under oven-dried conditions.

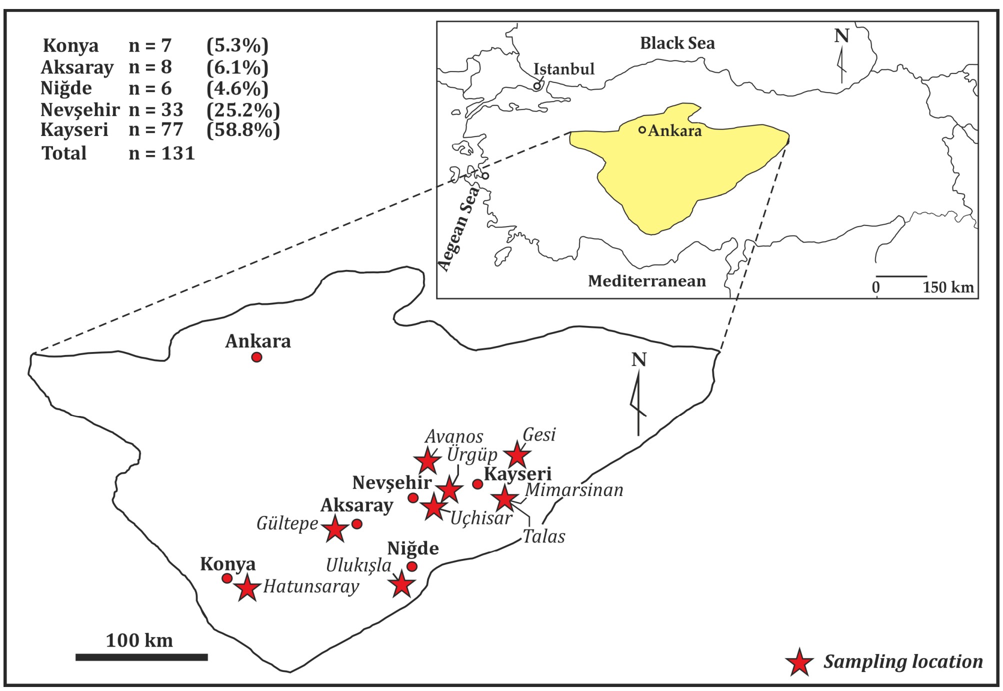

Figure 1. Sampling location map.

3. Laboratory Studies

3.1. Determination of physical and acoustic properties

The physical properties consist of ρ_d and n_e in this study. These properties were determined by considering the standard of TS EN 1936 [32]. Each test was performed at least five times, and average values are considered in soft computing analyses. Under atmospheric conditions, the n_e was determined by saturating the cubical samples in a water tank for 24 hours (Figure 2c). After the saturation, the saturated weight (W_s) of the sample was measured using a precise balance (Figure 2d). Then the samples were placed in a drying oven at 105 ± 2 °C for another 24 hours. Following the drying process of the rock samples, the dry weight (W_d) of the sample was also measured. Finally, the ρ_d and n_e values were calculated using Equation 1 and 2, respectively.

$$\rho_d = \frac{W_d}{V} \qquad (1)$$

$$n_e = \frac{W_s - W_d}{V} \times 100 \qquad (2)$$

where W_d is the dry weight of the sample, W_s is the saturated weight of the sample, and V is the total volume of the dry sample.

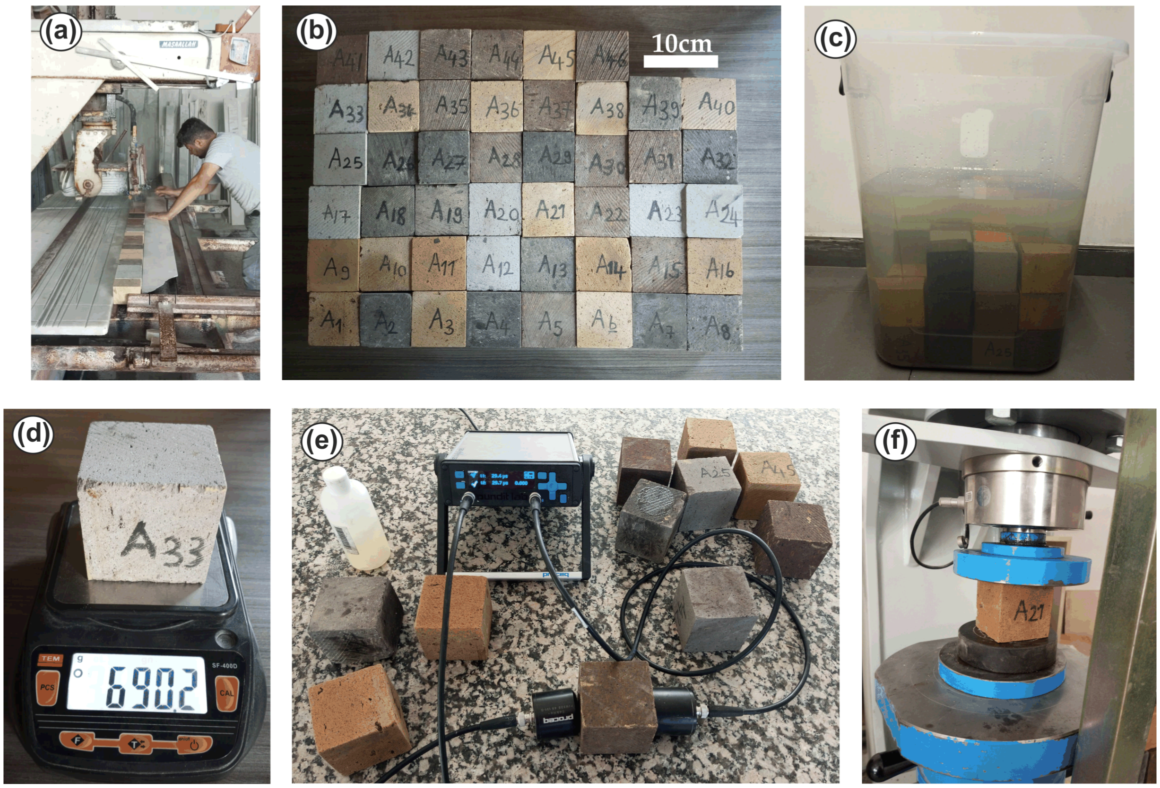

Figure 2. Laboratory studies a) Preparation of the cubical rock samples b) Some of the prepared rock samples c) Saturation of the rock samples under atmospheric conditions d) Weighing the rock samples e) Pulse wave velocity measurement f) UCS test.

A standard Pundit plus testing apparatus was used to measure the pulse wave velocity (V_p) (Figure 2e). The V_p and UCS tests were performed by following the procedures suggested by the International Society of Rock Mechanics [33]. The frequency of the probes during the pulse wave measurement was about 54 kHz, and 20 measurements were conducted from different cross-sections. The average pulse wave velocity was recorded for each sample. In the last part of the laboratory studies, the UCS tests were performed using a stiff loading machine (Figure 2f) whose stress rate was within the limits of 0.5 – 1.0 MPa/s [33].

4. Soft Computing Methods

4.1. Classification and regression tree (CART) algorithms

Decision trees are characterized by a series of questions that divide the learning sample into smaller and smaller parts [34]. A regression tree is similar to a classification tree, except that the dependent variable takes ordered values, and a regression model is fitted to each node, giving some outputs [35].

For several decades, the CART methodology has been utilized across various mining engineering disciplines [36–38]. In this study, several CART analyses were performed using the input parameters of ρ_d, n_e, and V_p.

4.2. Multivariate adaptive regression spline (MARS)

The MARS method proposed by Friedman [39] is a hybrid linear model used for nonparametric regression. This methodology has mainly been adopted for prediction and optimization problems [40–46]. There are two essential components in a typical MARS model. Two passes are involved in this process: the forward pass and the backward pass. In MARS models, constant terms called basis functions (BFs) initiate the forward pass. In the backward pass, the BFs are connected to linear regression models. The MARS analyses were performed using the R software, and a feasible predictive model is proposed based on the MARS methodology.

4.3. Adaptive neuro-fuzzy inference system (ANFIS)

The researchers have used ANFIS to develop predictive models for most geoengineering problems [21, 47–50]. The ANFIS uses a hybrid learning process to estimate premise and consequent parameters [51]. In most ANFIS models, the Sugeno fuzzy reasoning algorithm is used based on various membership functions and if-then rules. Several ANFIS models were developed in the MATLAB environment for this study.

4.4. Artificial neural networks (ANN)

ANN can analyze the data and save the experience-based knowledge for future predictions [52–54]. This algorithm can be used in various social and applied sciences. Although artificial neural networks (ANNs) can reveal input-output relationships, they are primarily black-box models, which limits their broader usage [55]. In this study, various ANN analyses were conducted using the toolbox (nntool) in the MATLAB environment. The present study introduced a novel predictive model based on the ANN methodology. The model was formulated using specific mathematical equations derived from the weights and biases in the ANN model.

4.5. Gene expression programming (GEP)

Using an evolutionary approach, the GEP algorithm generates an explicit mathematical formula for the relationship between dependent and independent variables. The GEP was first developed by Ferreira [56], and has gained popularity among the researchers in different geoengineering disciplines [57–60]. The main goal of GEP is to develop empirical formulas using specific sub-expression trees (Sub-ETs). The algorithm tries to estimate the dependent variable by combining the Sub-ETs with some numerical operators (addition, multiplication, etc.). In this study, GEP analyses were performed using GeneXpro tools (v. 5) software. After attempting various numbers of chromosomes, head sizes, and numerical operators, a GEP-based predictive model was developed.

5. Results and Discussion

Based on the laboratory studies, the descriptive statistics of the rock properties are given in Figure 3. Accordingly, it was found that the UCS of pyroclastic rocks varied between 3.14 and 83.39 MPa. In this regard, the pyroclastic rocks were defined from very low to medium strength, according to Deere and Miller [61]. Soft computing analyses were performed using the specified database.

5.1. Proposed CART model

CART decision trees are based on if-then rules, and are easy to understand when dealing with modest datasets. However, it doesn't seem very easy for larger datasets due to repeated outputs and larger standard deviations in the dataset. Several computational algorithms are used to perform CART analyses. In this study, CART analyses were performed using the Salford predictive modeler (v. 8) software. During the analyses, the ensemble method was assigned to bagging, and the number of trees and nodes was 10 and 24, respectively.

There were no restrictions, constraints or penalties in the dataset. Based on this information, the simplified CART decision tree to estimate the UCS of rocks is given in Figure 4. The ρ_d, V_p, and n_e were effectively used during the CART analyses. For specific conditions, UCS values can be easily estimated by implementing decision three in Figure 4.

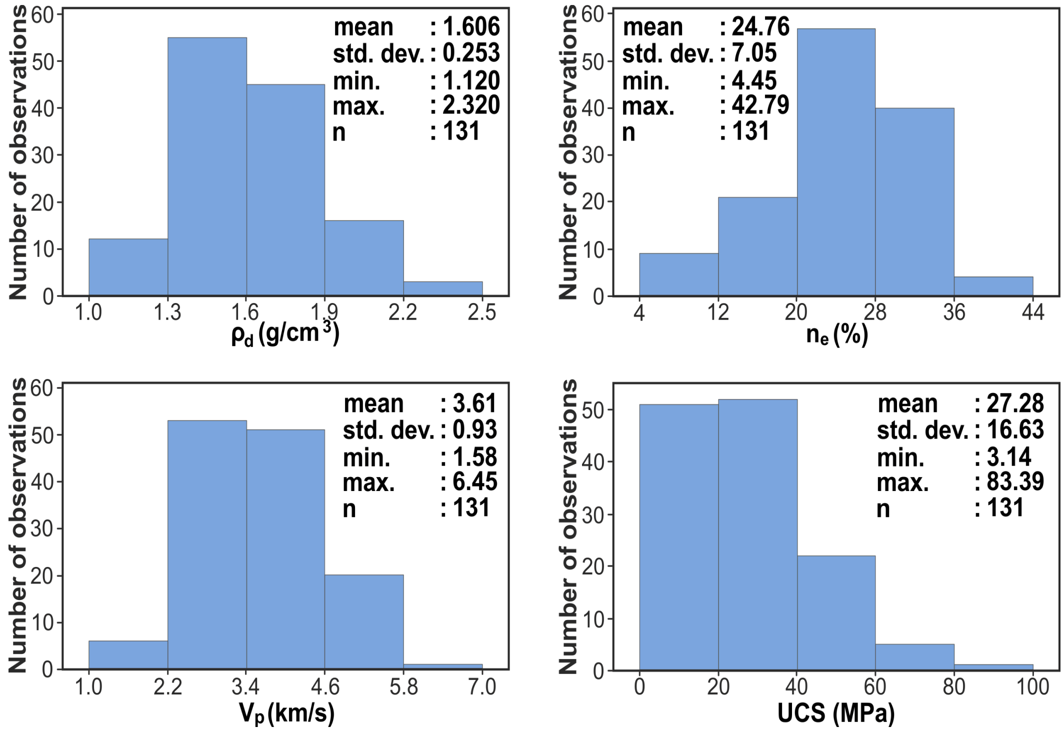

Figure 3. Histograms and descriptive statistics of the laboratory test results.

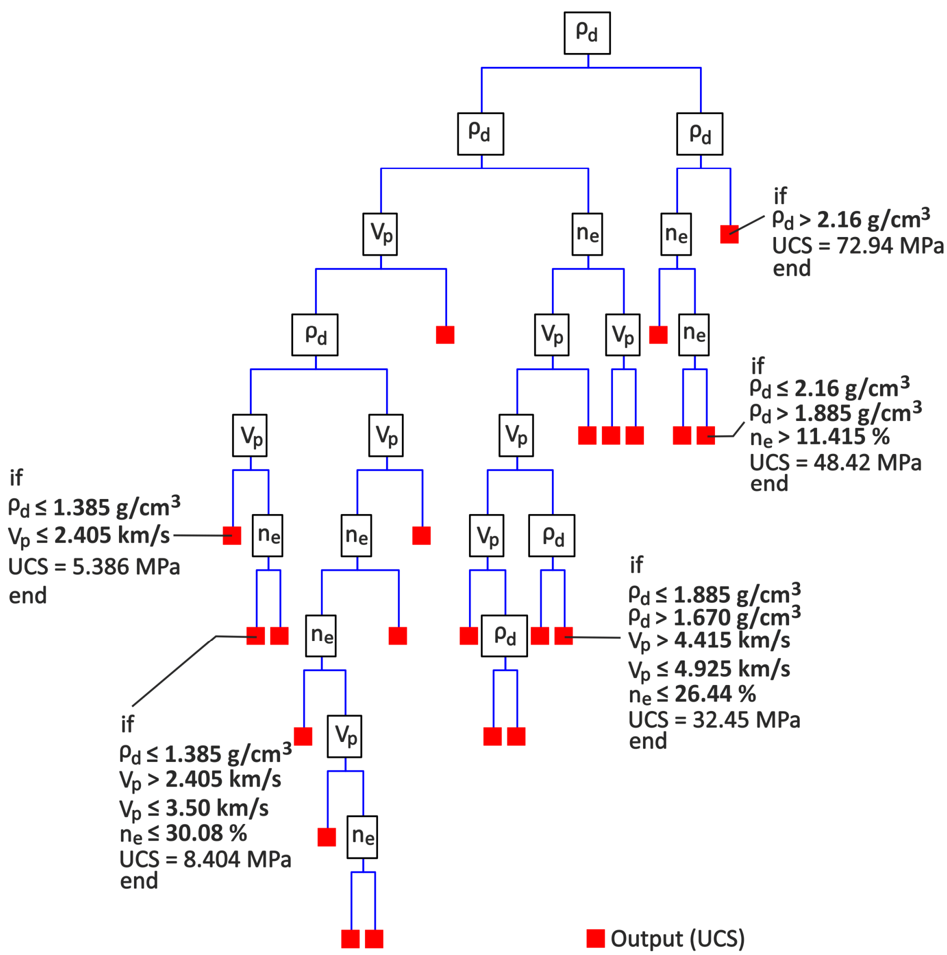

Figure 4. Illustration of a simplified CART decision tree (node: 22).

5.2. Proposed MARS model

Various MARS analyses were conducted using the software R. Before performing the analyses, the dataset was randomly divided into training (70/100) and testing (30/100) parts. Maximum BFs and interactions were assigned to 10 and 2, respectively. Based on these configurations, the proposed MARS model is given by Eq 3. The BFs are also listed in Table 2.

$$UCS = 25.21 + 54.32BF1 + 26.85BF3 - 6.78BF4 - 16.41BF5 + 3.04BF8 \quad (3)$$

Table 2. BFs for the proposed MARS model.

$BF1 = \max(0; \rho_d - 1.37)$
$BF3 = \max(0; V_p - 4.98)$
$BF4 = \max(0; 4.98 - V_p)$
$BF5 = \max(0; V_p - 3.47) \otimes BF1$
$BF8 = \max(12.97 - n_e) \otimes BF1$

5.3. Proposed ANFIS model

ANFIS analyses were performed in the MATLAB environment. The error metric during the analyses was root means square error (RMSE). The ANFIS model was developed using eight Gaussian membership functions that represented each input parameter (ρ_d, n_e, V_p). Depending upon these membership functions, eight if-then rules activated the ANFIS model. The ANFIS analysis was carried out until the minimum RMSE values were achieved. Some illustrations of the proposed ANFIS model in the MATLAB environment are given in Figure 5.

5.4. Proposed ANN model

In this study, neural network toolbox (nntool) was used to perform various ANN analyses in the MATLAB environment. A novel ANN-based predictive model was presented using precise mathematical formulas derived from the weights and biases. Before performing ANN analyses, the dataset was normalized between −1 and 1 to overcome overfitting problems. Based on many ANN analyses with different architectures, the best ANN architecture was found to be 3–8–1 in this study.

Namely, there were three inputs (ρ_d, n_e, V_p), eight hidden layers, and one output (UCS). Based on this ANN architecture, the UCS can be estimated by using the following equations:

$$UCS = 37.681\tanh\left(\sum_{i=1}^{8} A_i - 6.5027\right) + 42.668 \quad (4)$$

$$A_1 = 9.763\tanh\left(1.4459^n\rho_d - 7.4547^n n_e - 0.56841^n V_p + 7.1724\right) \quad (5)$$

$$A_2 = -0.12835\tanh\left(-11.6869^n\rho_d + 12.1313^n n_e + 13.3238^n V_p + 2.068\right) \quad (6)$$

$$A_3 = -2.19\tanh\left(2.8138^n\rho_d + 1.0284^n n_e - 0.12619^n V_p - 1.8146\right) \quad (7)$$

$$A_4 = 5.1288\tanh\left(4.7725^n\rho_d + 7.1211^n n_e - 1.4178^n V_p - 6.4978\right) \quad (8)$$

$$A_5 = -5.3601\tanh\left(-0.09958^n\rho_d + 0.37379^n n_e - 0.38504^n V_p - 0.14732\right) \quad (9)$$

$$A_6 = -1.3518\tanh\left(-5.8291^n\rho_d - 0.54172^n n_e - 3.7685^n V_p + 6.9331\right) \quad (10)$$

$$A_7 = 1.5735\tanh\left(0.61871^n\rho_d + 1.6029^n n_e - 1.2735^n V_p + 0.18185\right) \quad (11)$$

$$A_8 = -0.05804\tanh\left(-3.11^n\rho_d - 14.6143^n n_e - 4.0258^n V_p - 1.219\right) \quad (12)$$

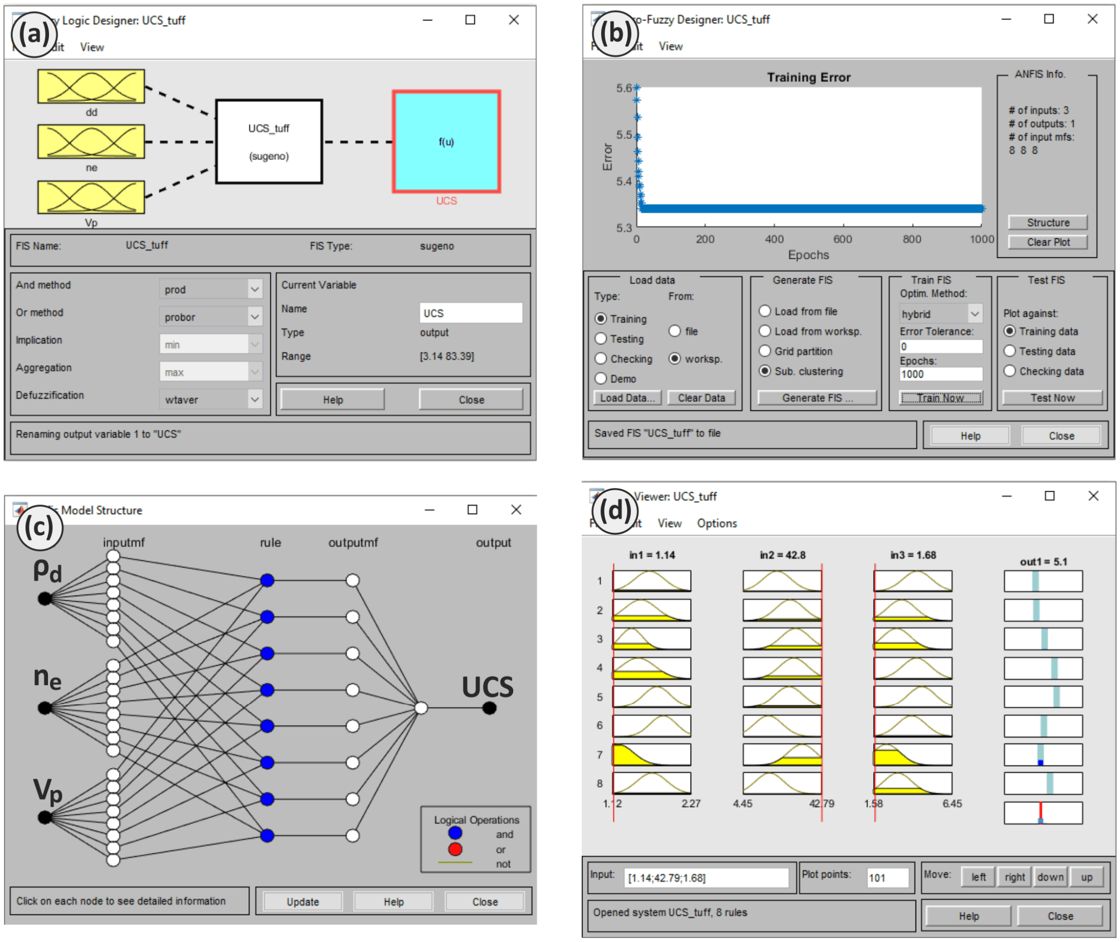

Figure 5. ANFIS outputs a) Input parameters b) Training process c) ANFIS model structure d) Rule viewer.

Normalization functions:

$$^{n}\rho_{n} = 1.6667\rho_{d} - 2.8667 \qquad (13)$$

$$^{n}n_{e} = 0.0522n_{e} - 1.2321 \qquad (14)$$

$$^{n}V_{p} = 0.4107V_{p} - 1.6489 \qquad (15)$$

5.6. Proposed GEP model

Numerous GEP applications were performed to build a predictive model for the assessment of UCS. For this purpose, the GeneXproTools software was used to implement various GEP models. The configuration of the developed model is listed in Table 3. The Sub-ETs of the proposed GEP model are given in Figure 6. The mathematical expressions of the Sub-ETs are also provided by Equations 16 – 18. Consequently, the UCS of pyroclastic rocks can be estimated using Equation 19.

Table 3. Configuration of the proposed GEP model.

Number of chromosomes	30
Head size	7
Number of genes	3
Linking function	Addition
Fitness function	RMSE
Numerical operators	+, –, x, Ln, Avg2, Min2.

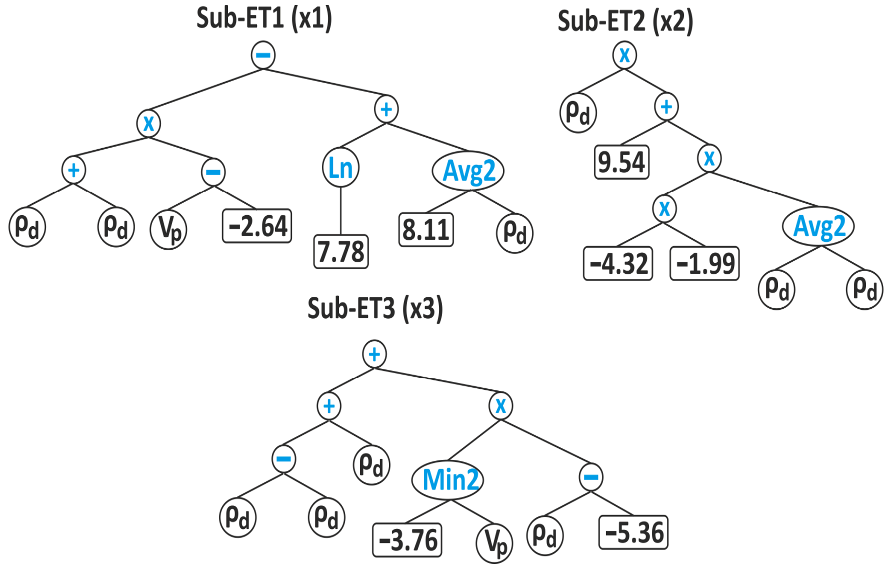

Figure 6. Sub-ETs of the proposed GEP model.

$$x_1 = 2\rho_d \otimes \left(V_p + 2.64\right) - 2.052 + \frac{8.11 + \rho_d}{2} \quad (16)$$

$$x_2 = \rho_d \otimes \left(9.54 + 8.59\rho_d\right) \quad (17)$$

$$x_3 = \rho_d + \min\left(-3.76, V_p\right) \otimes \left(\rho_d + 5.36\right) \quad (18)$$

$$UCS = 1.16\sum_{i=1}^{3} x_i - 0.153 \quad (19)$$

5.7. Evaluation of proposed models

The scatter plots of the proposed models are given in Figure 7. Accordingly, the prediction models have correlation of determination (R^2) values ranging from 0.821 to 0.878. In addition, the RMSE values were found to be between 5.78 – 7.03 MPa. When considering the R^2 and RMSE values, it can be claimed that the models based on CART, ANFIS, and ANN methodologies have a better prediction performance than the ones found on MARS and GEP. Nevertheless, these models seem to have no superiority over one another.

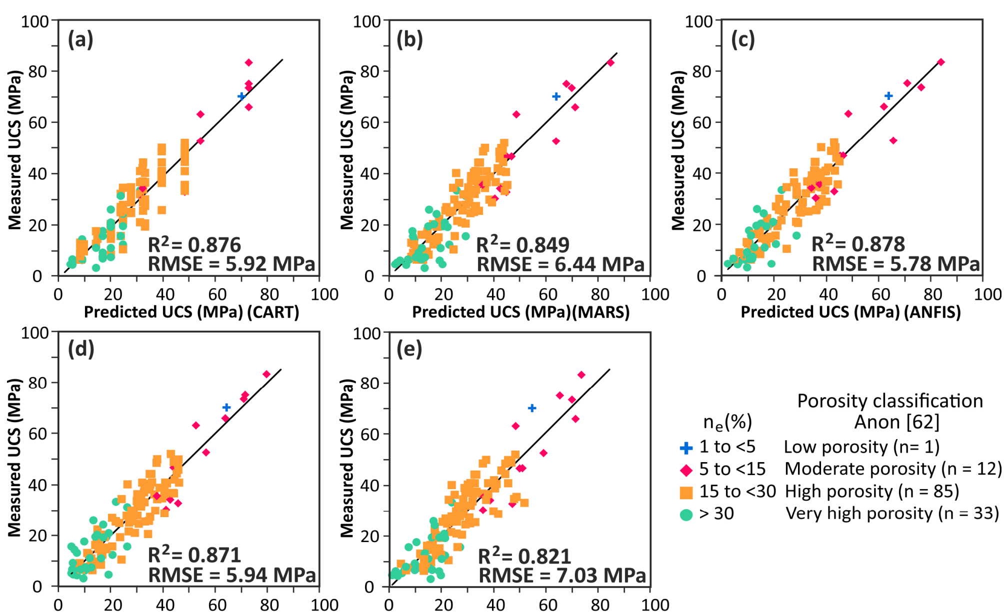

Figure 7. Scatter plots of the proposed models a) CART b) MARS c) ANFIS d) ANN e) GEP.

The input parameters (ρ_d, n_e and V_p) used in this study were also adopted by different researchers [16, 20, 25, 27], and robust predictive models were obtained by using them effectively.

However, when considering the physico-mechanical rock properties, pyroclastic rocks exhibit considerable heterogeneity in the dataset. The heterogeneity in pyroclastic rocks can easily be observed when considering the variations in the n_e values in Figure 7. In most cases, pyroclastic rocks bearing micro-fissures tend to have higher n_e values [63–65]. Eventually, the pyroclastic rocks have inherent micro-fissures due to a rapid cooling regime during their solidification. Apart from the presence of micro-fissures, silicified rock surfaces also impact the n_e for pyroclastic rocks [66]. These two phenomena (micro-fissures and silicified surfaces) are commonly observed in/on the rock blocks obtained. For these reasons, the dataset handled in this study can be declared complicated.

The present study also includes sensitivity analyses to investigate the effectiveness of the input parameters used in the proposed models. In this study, the cosine amplitude method (CAM) was adopted to assess the sensitivity degree of each input parameter. The correlation degree (rij) for the sensitivity analyses was calculated using Equation 20.

$$rij = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2 \otimes \sum_{i=1}^{n} y_i^2}} \tag{20}$$

where x_i is the input parameter, y_i is the estimated output, and n is the number of samples (n = 131 in this study).

It is important to note that as the value of r_{ij} increases, the impact of the related input parameter becomes greater. Based on the sensitivity analysis results (Table 4), r_{ij} values were found to be between 0.69 and 0.96. In this regard, the most important input parameters for the proposed models are ρ_d and V_p. These parameters are easy to determine in the laboratory, and thus they can be reliably used to estimate the UCS of pyroclastic rocks. However, due to the heterogeneity of the pyroclastic rocks, additional parameters such as mineralogical features and packing density would be beneficial to improve the proposed models. It is recommended to include such variables in future studies.

Table 4. Sensitivity analyses results.

Methodology	Input parameter		
	ρ_d	n_e	V_p
CART	0.94	0.74	0.95
MARS	0.92	0.72	0.96
ANFIS	0.93	0.72	0.95
ANN	0.90	0.69	0.85
GEP	0.90	–	0.88

6. Conclusions

In this study, a series of laboratory studies are conducted to reveal common physico-mechanical properties (ρ_d, n_e, V_p, and UCS) of pyroclastic rocks from central Anatolia, Turkey. Based on the laboratory test results including 131 datasets, several soft computing analyses are performed to build some predictive models used to estimate the UCS of the rocks. Accordingly, five different predictive models are proposed. The performance of the proposed predictive models is revealed by two important statistical indicators (i.e. R^2 and RMSE), and it is found that the R^2 values are approximately between 0.82 and 0.88, indicating their relative success. When comparing the performance of the models, the models based on CART, ANFIS, and ANN provide better results than the ones based on MARS and GEP. Therefore, these three models can be reliably used to estimate the UCS of the pyroclastic rocks. In addition, sensitivity analysis results indicate that the ρ_d and V_p become prominent in assessing the UCS of the rocks for all models.

The present study is believed to show the applicability of some soft computing algorithms for evaluating the UCS of pyroclastic rocks. Another critical finding obtained from the present study is that the performance of soft computing methods relies on the quality of the dataset and its deviation. The presence of heterogeneity in the pyroclastic rocks delimitates the success of the soft computing tools to some extent. When trying to improve the proposed predictive models, it would be beneficial to use additional input parameters such as mineralogical features and packing density in future studies. Last but not least, the proposed predictive models can be considered when comparing the initial performance of the pyroclastic rocks based on the UCS. In this manner, the proposed methods should be evaluated together to obtain a holistic approach to the quality of pyroclastic rocks for different engineering applications.

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برآورد مقاومت فشاری تک محوری سنگ‌های آذرآواری با استفاده از تکنیک‌های محاسباتی نرم

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چکیده:

در این مطالعه، چندین تحلیل محاسباتی نرم برای ساخت برخی مدل‌های پیش‌بینی برای تخمین مقاومت فشاری تک محوری (UCS) سنگ‌های آذرآواری از آناتولی مرکزی، ترکیه انجام می‌شود. برای این منظور، یک سری مطالعات آزمایشگاهی برای آشکار کردن خواص فیزیکی و مکانیکی سنگ مانند چگالی خشک (ρd)، تخلخل موثر (ne)، سرعت موج پالس (Vp) و UCS انجام می‌شود. در تحلیل‌های محاسباتی نرم، ρd، ne و Vp به‌عنوان پارامترهای ورودی استفاده می‌شوند، زیرا آنها ویژگی‌های سنگ غیرمخرب عملی و مقرون‌به‌صرفه هستند. در نتیجه تحلیل‌های محاسباتی نرم بر اساس درخت‌های طبقه‌بندی و رگرسیون (CART)، خطوط رگرسیون تطبیقی چندگانه (MARS)، سیستم استنتاج عصبی فازی تطبیقی (ANFIS)، شبکه‌های عصبی مصنوعی (ANN) و برنامه‌ریزی بیان ژن (GEP))، پنج مدل پیش بینی قوی در این مطالعه پیشنهاد شده است. عملکرد مدل‌های پیش‌بینی‌شده توسط برخی شاخص‌های آماری ارزیابی می‌شود و مشخص می‌شود که همبستگی مقدار تعیین (R^2) برای مدل‌ها بین ۰.۸۲ - ۰.۸۸ متغیر است. بر اساس این شاخص های آماری، مدل های پیش بینی پیشنهادی را می‌توان به طور قابل اعتماد برای تخمین UCS سنگ‌های آذرآواری مورد استفاده قرار داد.

کلمات کلیدی: سنگ‌های آذرآواری، مقاومت فشاری تک محوری، ویژگی سنگ، محاسبات نرم.