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Original Research Article

DEVELOPMENT OF SOFT COMPUTING-BASED PREDICTIVE TOOLS FOR ESTIMATING THE YOUNG MODULUS OF WEAK ROCKS

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Abstract

The deformation characteristics of rocks are of vital importance in addressing most geomechanical issues as they are one of the most critical input parameters in rock engineering analyses. For this reason, robust forecasting models are required when analysing the stability of tunnels, slopes, mine galleries, and other underground excavations. In this research, novel predictive models are proposed to estimate the tangential Young modulus (E_{ti}) of weak rocks. To achieve this, an extensive literature review is performed to obtain a comprehensive database including critical physico-mechanical properties of various weak rocks. Thanks to the advantages of soft computing methods such as genetic algorithm (GA), adaptive neuro-fuzzy inference system (ANFIS), artificial neural networks (ANN) and multivariate adaptive regression splines (MARS), novel predictive models are established. The effectiveness of the developed predictive models is investigated using various statistical measures and it is concluded that empirical models utilizing ANN and ANFIS methodologies are the most effective tools for estimating the E_{ti} of weak rocks. In addition, a practical design chart is also developed for assessing the E_{ti} of weak rocks.

Keywords: weak rocks, soft computing, mathematical modelling, deformation modulus

1. INTRODUCTION

The deformation modulus of intact rock is an essential rock property frequently used as an input parameter for estimating the elastic modulus of rock masses [1−10]. It is also utilized to analyze the behaviour of various rock masses [11–17]. However, determining the deformation properties of intact rocks in the laboratory necessitates specialized equipment like strain gauges, linear variable differential transformers (LVDTs) and high-precision stiff-loading machines [18].

Furthermore, obtaining high-quality core samples with consistent geometry, a critical requirement for determining the deformation properties of rocks, can be difficult, especially when dealing with weak,

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fractured or foliated rocks [19, 20]. Additionally, drilling operations in rock formations linked to complex underground mines can also be difficult. Consequently, researchers have developed numerous predictive models to estimate critical rock properties. However, most predictive models in rock engineering literature are based on traditional regression analysis results. While regression-based predictive models are straightforward to implement, they often fall short in addressing certain gaps and uncertainties in the dataset [21–23]. Thanks to the developments in computer-aided analysis methods, several soft computing methodologies have recently been adopted to estimate some rock properties (i.e., deformation properties and shear strength parameters of intact rocks, etc.) that are costly and difficult to determine in the laboratory. Table 1 shows several predictive models based on various soft computing methods for estimating the Eti of different rock types.

Table 1. Several predictive models for estimating the Eti of different intact rocks using various soft computing methods

Researcher	Independent variable	Methodology	Number of datasets	R^2
Aboutaleb et al. [24]	E_d, ν_d	ANN	482	0.92
Bejarbaneh et al. [25]	SHV, V_p	ANFIS	96	0.67
		ANN		0.81
Köken [26]	n_e, Q, S_c, V_p	ANN	32	0.95
Shahani et al. [27]	ρ_{wet}, ρ_d, BTS	ANFIS	132	0.94
		ANN		0.70
Köken and Kadakçı Koca [28]	ρ_d, n_e, V_p, UCS	ANFIS	147	0.93
		GA		0.84
		ANN		0.94
Khosravi et al. [29]	ρ_d, V_p, w_a	ANN	80	0.69
Jin et al. [30]	n_e, SHV, I_s, V_p	SVR	101	0.87
		ELM		0.88
		GW		0.89
Armaghani et al. [31]	ρ_d, V_p, Q, Plg	ANN	45	0.99
		ANFIS		0.98
Abdi et al. [32]	n_e, ρ_d, V_p, Id_2	RF	90	0.94
		AB		0.93
		XGB		0.91
		CATB		0.93
Matin et al. [33]	Vp, ne, SHV, Is	RF	30	0.90

Explanations: ρ_d: Dry density, V_p: Pulse wave velocity, n_e: Effective porosity, UCS: Uniaxial compressive strength, ρ_{wet}: Saturated density, BTS: Brazilian tensile strength, E_d: Dynamic Young modulus, ν_d: Dynamic Poisson's ratio, SHV: Schmidt hammer rebounding value, I_s: Point load strength, Q: Quartz content, Sc: Sorting coefficient, w_a: Water absorption by weight, Plg: Plagioclase content, I_{d2}: Second slake durability index value, ANFIS: Adaptive fuzzy logic inference system, ANN: Artificial neural networks, SVR: Support vector regression, GA: Genetic algorithm, ELM: Extreme learning machine network, GW: Grey wolf optimization algorithm, RF: Random forest, XGB: extreme gradient boosting, AB: AdaBoost, CATB: CatBoost, R^2: Correlation of determination value.

More profoundly, Sonmez et al. [7] adopted artificial neural networks (ANN) to assess the E_{ti} of intact rocks. Their analyses considered input parameters of dry unit weight (γ_d) and uniaxial compressive strength (σ_{ci} or UCS). Aboutaleb et al. [24] also adopted ANN as a research tool, and they considered dynamic Poisson's ratio (ν_d) and dynamic elastic modulus (E_d) for estimating the E_{ti}. Bejarbaneh et al. [25] used an adaptive neuro-fuzzy inference system (ANFIS), and they considered Schmidt hammer value (SHV), pulse wave velocity (Vp), and point load strength (Is) as input parameters in their soft computing analyses. Focusing on the variations in E_{ti} values for different sandstones, Köken [26] succeeded in estimating the E_{ti} of sandstones from Turkey by considering the rock properties of effective porosity (ne), quartz content (Q), sorting coefficient (Sc), and Vp.

Shahani et al. [27] adopted both ANN and ANFIS, and they used saturated density (ρ_{wet}), dry density (ρ_d), and Brazilian tensile strength (BTS) in their analyses. In recent years, Köken and Kadakçı Koca [28] collected a comprehensive database to estimate the E_{ti} for various rock types. Their investigations considered ANN as a primary research tool where ρd, Vp, ne, and UCS values were adopted as input parameters. Based on the ANN methodology, Khosravi et al. [29] modelled the E_{ti} based on the rock parameters of ρd, Vp, and water absorption by weight (wa). Jin et al. [30] adopted relatively new soft computing methods like extreme learning machine network (ELM) and support vector regression (SVR) for estimating the E_{ti} of rocks. In their analyses, ne, SHV, Is, and Vp were used as input parameters. To assess the E_{ti} of granitic rocks, Armaghani et al. [31] adopted both ANN and ANFIS methods. The ρd, Vp, Q, and plagioclase content (Plg) were used as input parameters in their soft computing analyses. Recently, Abdi et al. [32] also adopted relatively new soft computing algorithms such as AdaBoost (AB), random forest (RF), extreme gradient boosting (XGB), and CatBoost (CATB) for the assessment of E_{ti} for weak rocks. Their analysis results indicated that the predictive model found on RF provides promising results in estimating the E_{ti} of weak rocks. Last but not least, Matin et al. [33] performed RF methodology for estimating the E_{ti} of travertine samples.

Nevertheless, it can be claimed that limited studies (e.g., Abdi et al. [32]) directly focus on the estimation of E_{ti} for weak rocks. Due to this reason, comprehensive predictive models are necessary to assess the E_{ti} of these rock types. To achieve this, an extensive literature review is conducted to gather quantitative datasets on weak rocks. As a result of soft computing analyses, several predictive models are developed in this study. The performance of the developed predictive models is compared by considering the statistical indices of root means squared error (RMSE), correlation of determination (R2), and variance accounted for (VAF). The details and robust mathematical expressions of the developed predictive models can be found in this research paper. In addition, in this study, a design chart for the assessment of E_{ti} of weak rocks was also developed. The predictive models obtained in this work, as well as the chart for the assessment of the E_{ti} of weak rocks, can contribute to estimating the E_{ti} of weak rocks based on non-destructive testing methods.

2. DATA DOCUMENTATION AND DATA ANALYSIS METHODS

The dataset was obtained from scientific publications and the total number of data was 173 in this study. These data include basic properties (ρ_d, n_e, V_p and E_{ti}) of weak rocks with relatively high porosity. The database adopted is listed in Table 2. The soft computing methods of ANFIS, ANN, GA, and multiple adaptive regression spline (MARS) were considered in this paper. ANFIS and ANN analyses were conducted in the MATLAB environment. On the other hand, GA and MARS methods were implemented using GeneXpro tools and R programming language, respectively.

Table 2. Database employed in soft computing analyses

Rock type	n_e (%)	ρ_d (g/cm^3)	V_p (km/s)	E_{ti} (GPa)	n	Reference
Claystone, Siltstone, Marl, Limestone	5.44−56.55	1.88−2.62	1.01−3.25	1.12−5.32	61	Abdi et al. [32]
Dolomite Limestone	6.22–10.36	2.57–2.73	3.30–4.87	2.7–6.1	5	Pappalardo [34]
Sandstone	9.96–14.51	2.15–2.38	1.35–2.62	2.9–7.2	2	Abdi et al. [35]
Carbonate Rocks	1.09–18.66	2.00–2.53	2.20–5.00	5.2–6.9	13	Madhubabu et al. [36]
Limestone (Caliche)	16.23–32.49	1.77–2.34	0.44–1.58	0.18–1.4	18	Dinçer et al. [37]
Andesite Trachyte	8.72–24.58	2.60–2.72	3.26–4.08	2.60–3.36	4	Herşat [38]
Travertine Limestone	0.15 – 7.75	2.24 – 2.63	3.76–5.34	2.17–8.03	70	Fereidooni et al. [39]
Explanations: n_e: Effective porosity ρ_d: Dry density, V_p: Pulse wave velocity, E_{ti}: Tangential Young modulus, n: number of samples				Total	173	

3. SOFT COMPUTING ANALYSES

3.1. MARS analyses

Friedman [40] was the pioneer of MARS analysis, which is based on a nonparametric regression method. Typical MARS models consist of two main components: the forward pass, where basis functions (BFs) are introduced as constants, and the backward pass, where these BFs are combined with linear regression techniques. This research introduced a robust MARS model specifically for estimating the E_{ti} of weak rocks. Based on soft computing analyses, Table 3 lists the most accurate predictive model along with its BFs.

Table 3. Proposed MARS model its BFs

Empirical formula
$E_{ti} = 3.64 - 2.075BF2 + 4.92BF3 + 0.059BF6 - 13.98BF8$
$BF1 = \max\left(0; V_p - 2.20\right)$ $BF4 = \max\left(0; 4.57 - V_p\right)$ $BF2 = \max\left(0; 2.20 - V_p\right)$ $BF6 = \max\left(0; 17.71 - n_e\right) \times BF4$ $BF3 = \max\left(0; V_p - 4.57\right)$ $BF8 = \max\left(0; 2.11 - \rho_d\right) \times BF1$

3.2. GEP analyses

Various GEP applications were conducted to construct a robust predictive model for evaluating the E_{ti} of weak rocks. GeneXproTools software was utilized to implement a range of GEP models for this purpose. As a result of GEP analyses, the E_{ti} of weak rocks can be estimated using the equations listed in Table 4.

Table 4. Proposed GEP model

Empirical formula
$E_{ti} = 0.84\left(x_1 + x_2\right) + 0.65$
$x_1 = a\tan\left(\left(a\tan\left(V_p^{\,2}\right) - \frac{2.48}{3.37}\right) + \frac{\left(-\frac{1}{2.48}\right)}{\left(\frac{V_p - 3.05}{2}\right)}\right)^2$ $x_2 = \max\left(V_p; \left(\frac{2.74}{\max\left(\frac{1.98}{V_p}; \max\left(-2.32; n_e\right)\right)} - n_e\right)\right)$

3.3. ANN analyses

In this paper, detailed ANN analyses were performed in the MATLAB environment. Before conducting the ANN analyses, the dataset was normalized between –1 and 1 to mitigate overfitting issues. Different ANN architectures were attempted in the analyses and the optimal one can be identified as 3-6-1, which includes three input parameters (ρ_d, n_e, and V_p), six hidden layers, and one output (E_{ti}). The equations for estimating the E_{ti} of weak rocks are detailed in Table 5.

Table 5. Proposed ANN model

Empirical formula
$E_{ti} = 3.925\tanh\left(\sum_{i=1}^{6} x_i - 0.778\right) + 4.105$
$x_1 = 0.50031\tanh\left(-1.2068\,{}^n\rho_d + 9.1231\,{}^n n_e + 14.6189\,{}^n V_p - 4.0375\right)$
$x_2 = -0.52767\tanh\left(9.2297\,{}^n\rho_d + 2.7982\,{}^n n_e + 18.4459\,{}^n V_p - 4.6571\right)$
$x_3 = -0.88387\tanh\left(-1.2363\,{}^n\rho_d + 0.83018\,{}^n n_e + 0.39926\,{}^n V_p + 0.22588\right)$
$x_4 = -0.5704\tanh\left(4.0979\,{}^n\rho_d - 2.5028\,{}^n n_e - 9.1738\,{}^n V_p - 4.3992\right)$
$x_5 = 0.59728\tanh\left(-2.7437\,{}^n\rho_d - 9.5452\,{}^n n_e - 5.1678\,{}^n V_p + 0.51952\right)$
$x_6 = 0.29147\tanh\left(-2.974\,{}^n\rho_d + 11.127\,{}^n n_e + 14.4403\,{}^n V_p + 2.2854\right)$
Normalization functions
${}^n\rho_d = 2.083\rho_d - 4.687$ ${}^n n_e = 0.0355 n_e - 1.0053$ ${}^n V_p = 0.4076 V_p - 1.1793$

3.4. ANFIS analyses

The MATLAB environment was also used to perform the ANFIS analyses. Each input parameter (n_e, ρ_d and V_p) was represented by six Gaussian membership functions. These membership functions activated six if-then rules governing the ANFIS model. The analysis continued until achieving minimal root means square error (RMSE) values. Figure 1 in MATLAB illustrates some examples of the proposed ANFIS model.

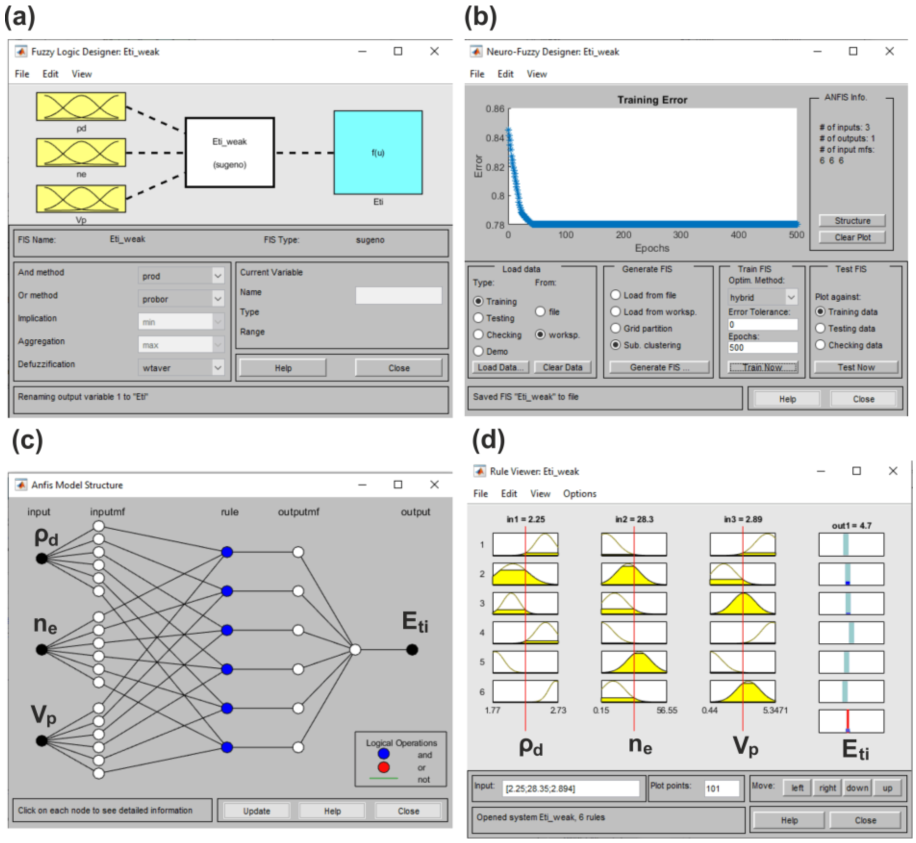

Fig. 1. ANFIS analyses and processes: a) identification of input parameters, b) training process, c) The structure of the optimal ANFIS model, d) ANFIS rule viewer

4. RESULTS AND DISCUSSION

Based on the collected data (Table 2), four robust predictive models were developed to evaluate the E_{ti} of weak rocks. The performance of the proposed predictive models is first revealed by scatter plots, and then through some statistical indicators such as the correlation of determination (R2) and root means square error (RMSE). Accordingly, the predictive models that yield the best results are based on the ANN and ANFIS methodologies. The R2 and RMSE values for these models are between 0.65 – 0.85 and 1.006 – 1.574 GPa, respectively (Fig 2).

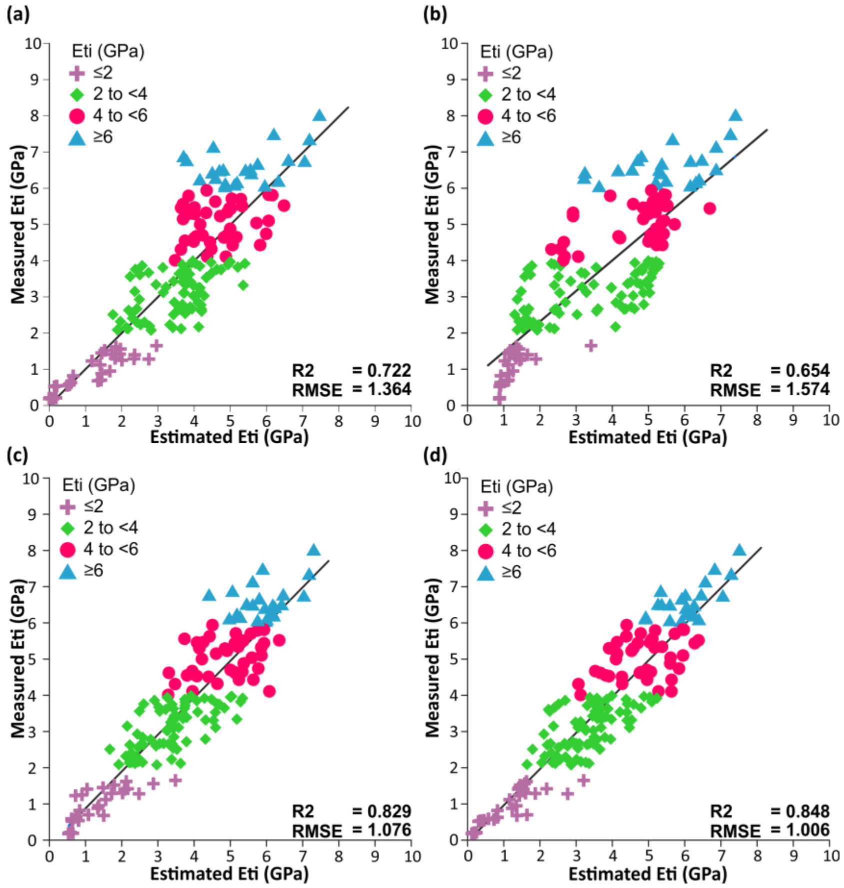

Fig. 2. Performance evaluation of each predictive model: a) MARS, b) GEP, c) ANN, d) ANFIS

In these models, non-destructive testing methods (ρd, ne and Vp) were used effectively. For this reason, the proposed methods based on ANN and ANFIS methodologies can be effectively used to estimate the E_{ti} of weak rocks. The validity of the ANN and ANFIS methods to estimate the E_{ti} of various rocks has also been confirmed in other publications [7, 24, 26].

The previous studies also confirmed that soft computing methods are more effective than conventional regression analyses for estimating the deformation modulus of rocks [41–45]. Nevertheless, when it comes to the performance of other introduced models, the ones found on GEP and MARS methods should be improved by increasing the number of datasets and/or input parameters.

The relative errors of the predictive models found on the ANN and ANFIS methodologies are also listed in Fig 3 for different subclusters of E_{ti}. Accordingly, when the E_{ti} values are below 2 GPa, the average relative error (ARE) is at the highest degree (ARE = 32–67%). On the other hand, for other E_{ti} classes described in Fig 3, The predictive models based on ANN and ANFIS can be reliably used to estimate the E_{ti} of weak rocks. The overall ARE values for these models are between 19–25%, which is statistically acceptable.

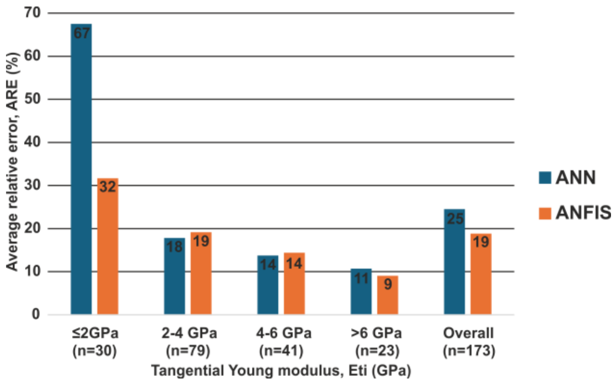

Fig. 3. Average relative errors of the proposed predictive models based on different E_{ti} subclusters

When it comes to comparing the performance of the proposed predictive models with the ones of previous predictive models in the literature, the predictive models found on the ANN and ANFIS methodologies outperform the ones provided by Fereidooni et al. [39]. On the other hand, the predictive models by Abdi et al. [32] seem to have a better prediction performance than the models highlighted in this study. The underlying reason can be attributed to the fact that Abdi et al. [32] considered only sedimentary rock types such as claystone, siltstone, marl and limestone in their soft computing analyses. In this regard, the highlighted predictive models (ANN and ANFIS models) can be considered as comprehensive predictive tools for estimating the E_{ti} of a wide range of weak rocks.

To facilitate the practical implementation of the proposed ANFIS method, a novel design chart is established to evaluate the E_{ti} of weak rocks. Design charts or graphical design tools offer several advantages in rock engineering [46]. For example, they allow for rapid comparisons between different input parameters, helping in quick decision-making. The main motivation in the preparation of the design chart is to reveal common E_{ti} values required for the analysis of rock structures practically and safely.

Accordingly, the common E_{ti} values based on varying rock parameters can be estimated by using the design chart given in Fig 4. Nevertheless, it should be mentioned that although the prepared design chart is suitable to estimate the E_{ti} of weak rocks, it is not recommended to use this chart for the condition of E_{ti} < 2 GPA due to having relatively higher ARE values (Fig 3). Fig 4 also illustrates four examples of implementing the proposed design chart. As observed from the examples, it is confirmed that each coupling variable (ne-ρd, Vp-ρd and Vp-ne) provides promising results in estimating the E_{ti} of weak rocks.

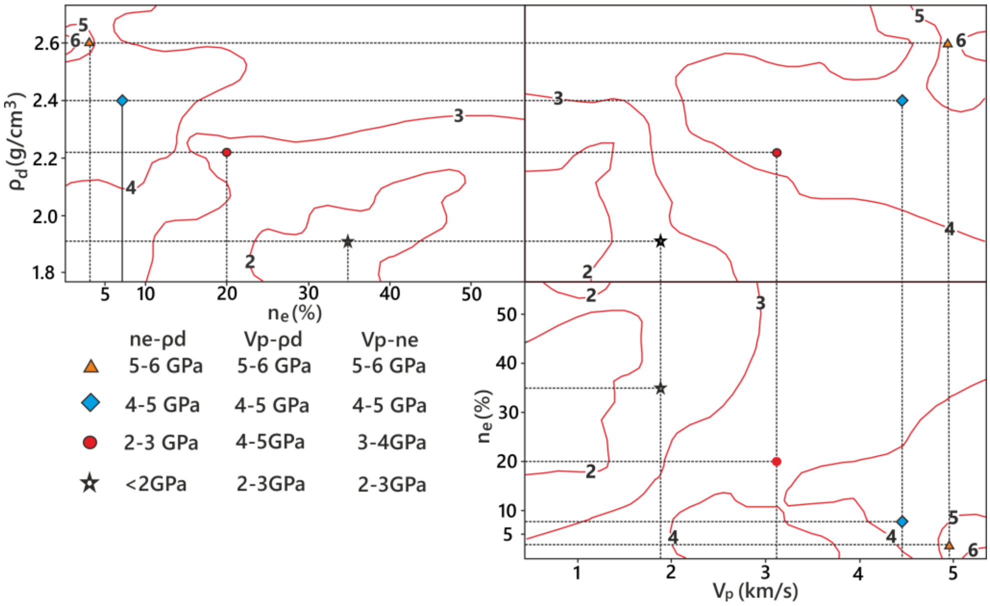

Fig. 4. Proposed design chart based on the ANFIS methodology

5. CONCLUSIONS

Since dealing with weak rocks in the laboratory is a labour-intensive issue, researchers have postulated several theories to assess some rock properties that are relatively hard to obtain. In this study, the E_{ti} of weak rocks are investigated based on four soft computing algorithms.

The performance of the proposed predictive models is assessed using scatter plots and various statistical metrics such as R2 and RMSE. Consequently, it is found that the models based on the ANN and ANFIS methodologies outperform the other models. The R^2 values for these models are found to be greater than 0.82, showing their relative success. Additionally, by adopting the ANFIS method, a novel design chart is also prepared to easily estimate the E_{ti} of weak rocks. The design chart can be regarded to reveal the E_{ti} of weak rocks when E_{ti} tests are not possible or easy to implement. However, the use of the proposed design chart is not recommended for the conditions of $E_{ti} \leq 2$ GPa. Further research and analysis should be conducted in this area.

Keep in mind that laboratory tests become crucial when analysing any rock structure. However, predictive models and/or design charts may help provide practical information on rock properties that are both necessary and hard to determine in the laboratory. In this regard, the present study can be declared as a novel research tool by providing comprehensive forecasting models to assess the E_{ti} of weak rocks. However, further studies may be beneficial by dividing analysed datasets into different parts that enable one to analyse the E_{ti} of weak rocks more precisely.

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