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Evaluation of the Uniaxial Compressive Strength of Gneiss from Southern Togo from Non-Destructive Tests

Ezouwè Kessie[1], Irina Pachoukova[1], Abalo P'kla[1]

[1]Laboratoire de Recherche en Sciences de l'Ingénieur (LARSI), École Polytechnique de Lomé (EPL), University of Lome, 01 BP 1515, Lomé (TOGO)

Correspondance author : Ezouwè Kessie

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ABSTRACT

The mechanical and physical characteristics of rocks hold significant importance across various realms of research and engineering, particularly in the field of Civil Engineering. The utilization of rocks as construction materials hinges on several of their mechanical traits (Los Angeles, Micro Deval under water presence, Young's Modulus, Compression Strength) as well as physical attributes (homogeneity, porosity, etc.). Tests for determining certain of these characteristics are expensive, challenging, and time-consuming. Among these attributes, mention can be made of determining compression strength, which necessitates substantial equipment for proper sample preparation. This renders the process very costly, laborious, and leads to the complete destruction of samples during experimental measurements.

Our objective in this study is to assess the uniaxial compression strength of gneiss from southern Togo using non-destructive testing. This would help mitigate the relatively high costs associated with this test. To address this issue, the development of new methods for determining this test using non-destructive testing approaches is necessary. Among the most commonly used reference techniques for characterizing materials and determining their physical and mechanical properties are non-destructive evaluation techniques based on ultrasonic wave propagation and rebound hammer testing.

The adopted methodological approach involves the collection of rock samples (amphibole and biotite gneiss) from 33 sites in southern Togo, their proper sampling, and the execution of various tests on the obtained samples. The obtained results have facilitated the examination of several approaches, notably the ANFIS model (Adaptive Neuro-Fuzzy Inference System) and the MLR model (Multiple Linear Regression), for predicting the uniaxial compression strength value based on the sclerometer index and the ultrasonic wave propagation velocity (in parallel or perpendicular orientation to the foliations).

It emerges from the ANFIS model, combining ultrasonic waves in the perpendicular orientation to the foliations and the sclerometer index, that the uniaxial compression strength can be predicted with an R^2 of 0.9884, an RMSE of 2.9271, a MAPE of 1.160, and a VAF of 98.83. In comparison, the MLR model yields an R^2 of 0.9832, an RMSE of 3.686, a MAPE of 1.402, and a VAF of 98.22. The derived ANFIS models can be utilized to estimate the uniaxial compression strength of gneiss in Togo and beyond.

Keywords: Gneiss, Non-destructive Testing, Sclerometer Index, Ultrasonic, Compression Strength.

Acronyms: ANFIS: Adaptive Neuro-Fuzzy Inference System; RMSE: Root Mean Square Error; VAF: Variance Account For; MLR: Multiple Linear Regression; MAPE: Mean Absolute Percentage Error; RPE: Relative Percentage Error.

1. INTRODUCTION

During the execution of Civil Engineering projects (dams, power plants, buildings, bridges, pavements), technical specifications necessitate the use of high-quality materials (aggregates). For certain specialized tasks, the primary specification for aggregate usage pertains to their uniaxial compression strength. The current method for determining the uniaxial compression strength of rocks involves substantial equipment for proper sample preparation, rendering it expensive, challenging, and time-consuming.

The goal of this study is to assess the uniaxial compression strength of gneiss from southern Togo using non-destructive testing methods. This could lead to a reduction in the relatively high costs associated with this test. To address this issue, the development of new methods for determining this test using non-destructive techniques becomes necessary. Among the most widely employed benchmark techniques for characterizing materials and ascertaining their physical and mechanical properties, non-destructive evaluation techniques predicated on the propagation of ultrasonic waves and rebound sclerometer testing are prominent.

The principle of the sclerometer is based on measuring the rebound height of a mass after impacting the surface under testing. The rebound value (sclerometer index: SI) is higher when the surface hardness is greater. Ultrasonic tests are highly regarded for their inspection quality and ease of implementation. These techniques require relatively lightweight and user-safe equipment. They also fulfill demands for enhanced performance in terms of characterization (non-destructive, rapid, cost-effective, reliable, accurate, etc.). The sclerometer index combined with the ultrasonic wave propagation velocity (in parallel or perpendicular orientation to the foliations) will then determine the rock's compression strength.

Several approaches will be examined, notably the ANFIS model (Adaptive Neuro-Fuzzy Influence System), where inputs will include values of the Sclerometer Index (SI) and ultrasonic wave propagation velocity (in parallel or perpendicular orientation to the foliations) obtained during tests conducted on the rocks. These inputs will yield the uniaxial compression strength (UCS) of the rock. Leveraging the ANFIS approach as used by Gokceoglu et al. [1] for predicting rock mechanical properties, Aali et al. [2] for estimating soil saturation coefficient, and Singh et al. [3] for predicting rock deformation modulus, we propose that rock mechanical properties, such as uniaxial compression strength, can be predicted using the ANFIS approach. ANFIS combines the advantages of a neural network [4] and fuzzy logic [5].

In this study, we utilized the ANFIS approach and compared it to a multiple linear regression-based approach [6] for predicting rock compression strength based on sound propagation velocity and the sclerometer index. The non-destructive sclerometer test [9] and ultrasonic wave propagation velocity [7] enable the determination of the rock's uniaxial compression strength [8].

2. MATERIAL AND METHOD

The adopted methodological approach involves the collection of rock samples (gneiss) from various sites in southern Togo, followed by proper sampling and conducting different tests on the obtained samples. Based on the obtained results, several approaches will be examined to predict the uniaxial compression strength value based on the sclerometer index and the ultrasonic wave propagation velocity (in parallel or perpendicular orientation to the foliations)

2.1 Dataset

The ANFIS approach and the MLR method are utilized to predict the uniaxial compressive strength of gneiss based on the sclerometric index and the propagation of ultrasound waves (following either the parallel or perpendicular direction of the foliations), which serve as input data for the models. These results are derived from tests conducted on rock samples collected from gneiss formations in southern Togo. Indeed, the most widely used aggregates in civil engineering projects in Togo predominantly stem from gneiss sources. To achieve our objectives, our focus was directed towards gneiss within the structural unit of the Benin-Togo plain, originating from the West African Croton geological formation [10]. We conducted sampling at thirty-three (33) sites, with four (04) test samples per site for the sclerometric index and ultrasound wave propagation tests, yielding a total of one hundred and thirty-two (132) test samples. Additionally, for the uniaxial compressive strength determination tests, three (03) test samples were taken from each site, resulting in a total of ninety-nine (99) test samples.

Fig. 1 : Core rock sample for uniaxial compression testing

Fig. 2 : Rock samples taken from sites

Fig. 3 : Sample of rock cut byx non-destructive testing (Sclerometer and ultrasound)

2.2 Multiple linear regression

The multiple linear regression model [6, 11] for two regresses x_1 *and* x_2 is provided in equation (1),

$$y = a_0 + a_1x_1 + a_2x_2 + \varepsilon \qquad (1)$$

where y represents the response,a_0, a_1 *et* a_2 are referred to as regression coefficients, and ε is a random error term.

2.3 The adaptive neuro-fuzzy ANFIS

The neuro-fuzzy system is a hybrid system that combines the techniques of fuzzy logic and neural networks [5, 6, and 12].

There are two main families of fuzzy systems [13]: Mamdani and Takagi-Sugeno. Neuro-fuzzy systems are divided into two major categories: Mamdani neuro-fuzzy system and Takagi-Sugeno neuro-fuzzy system. Among these, the Takagi-Sugeno neuro-fuzzy systems are more commonly used [14] due to their universal approximation properties and the fact that they do not require a defuzzification module, as is the case with Mamdani fuzzy systems.

One of the commonly used tools based on the Takagi-Sugeno neuro-fuzzy system is ANFIS (Adaptive Neuro-Fuzzy Inference System). ANFIS is an adaptive neuro-fuzzy inference system consisting of a five-layer neural network, with each layer corresponding to a step in a Takagi-Sugeno-type fuzzy inference system.

For simplification, let's assume the fuzzy inference system has two inputs x and y, and one output z. Let's also assume that the rule base contains two Takagi-Sugeno fuzzy rules (relations (2) and (3)).

Rule 1:

if x is A1 and y is B1

then $Z1 = p1x + q1y + r1$ (2)

Règle 2:

if x is A2 and y is B2

then $Z2 = p2x + q2y + r2$ (3)

The ANFIS has an architecture composed of five layers, as depicted in Figure 4 [14]:

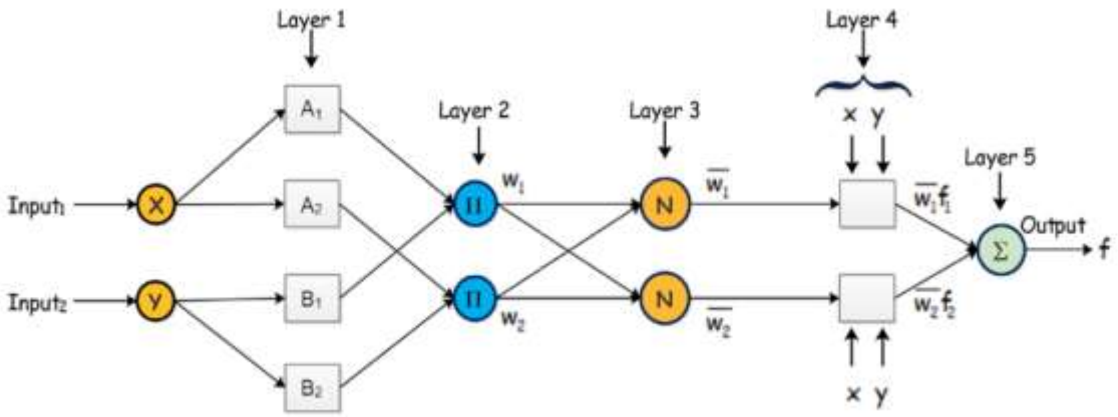


Fig. 4 : Architecture ANFIS

Layer 1: This layer enables the fuzzification of the inputs X and Y. Each neuron in this layer corresponds to a linguistic variable. The inputs X and Y are fuzzified using the membership functions of the linguistic variables Ai and Bj (typically triangular, trapezoidal, or Gaussian in shape). For instance, equations (4) and (5) define the Gaussian membership function:

$$\mu_{A_i}(x) = \exp\left[-\frac{1}{2}\frac{(x-\bar{x}_i)^2}{\sigma_{x_i}{}^2}\right] \quad (4)$$

$$\mu_{B_j}(y) = \exp\left[-\frac{1}{2}\frac{(y-\bar{y}_i)^2}{\sigma_{y_j}{}^2}\right] \quad (5)$$

where, **i, j = 1.2**; are the centers, and **σ** is the width of the membership function.

The outputs of the first layer are given by equations (6) and (7):

$$x_{1,i} = \mu_{A_i(x)} \quad (6)$$

$$y_{1,j} = \mu_{B_j (y)} \quad (7)$$

So, the values and $\mu_{A_i}(x)$, μ_{B_j}(y) respectively represent the degree of membership of the value x to the set A and y to the set B.

Layer 2: each node corresponds to a fuzzy T-standard (the T-standard operator provides the equivalent of a Boolean "AND"). It receives the output from the fuzzification nodes and calculates its output value using the product operator (although the product operator is commonly used, others like max, min, etc., can also be used).

The activation function of neurons i-th neuron in the first layer is expressed by equation (8) [5]:

$$w_i = min \{ \mu_{A_i}(x), \mu_{B_j}(y)\}, \text{ i = 1,2; j = 1,2} \quad (8)$$

Layer 3: This layer normalizes the results provided by the previous layer based on the relation (9). The obtained results represent the degree of implication of value in the final result [16]. The output of this layer can be written according to equation (9).

$$\overline{w}_i = \frac{w_i}{\sum_{i=1}^{2} w_i} \quad (9)$$

The outputs of this layer are referred to as normalized weights.

Layer 4: Each node in this layer is connected to the initial inputs. The result is calculated based on its input and a first-order linear combination of the initial inputs (Takagi-Sugeno approach). The output of this layer is expressed by equation (10):

$$f_i^4 = y_i = \overline{w}_i \, x \, (p_i x_1 + q_i x_2 + r_i) \quad (10)$$

where: yi is the output of the third layer; and $\boldsymbol{p_i}, \boldsymbol{q_i}, \boldsymbol{r_i}$ are the set of parameters referred to as "consequent".

Layer 5: it consists of a single neuron that calculates the sum of signals from the previous layer as per equation (11):

$$y = \sum_{1=1}^{2} y_i \quad (11)$$

ANFIS employs a hybrid learning process to estimate the premises and the resulting parameters [1]. This hybrid algorithm divides the learning process into two (02) independent stages: the first stage involves adapting the learning weights, and the second stage deals with adapting the non-linear membership functions. This approach can reduce the algorithm's complexity while simultaneously increasing the learning time [16].

2.4 Statistical indicators used for performance evaluation

To assess the model's performance, various statistical parameters were employed within this study. These parameters include the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Coefficient of Determination (R2), Variance

Accounted For (VAF), and Relative Percentage Error (RPE). A concise description of the statistical metrics under consideration is provided below.

2.4.1. *Relative Percentage Error*

The RPE indicates the percentage difference between the predicted values *xi* and the value obtained from the measured values *yi*, and its values typically fall withing the range of -10% to +10%, which is generally considered acceptable. The RPE is defined as follows:

$$\text{RPE}(\%) = 100.\left(\frac{y_i - x_i}{y_i}\right) \quad (12)$$

2.4.2. *Mean Absolute Percentage Error*

The MAPE depicts the average absolute percentage difference between the predicted values and the values achieved through measurements. The MAPE is calculated as follows [3, 4]:

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - x_i}{y_i}\right|.100 \quad (13)$$

2.4.3. *Root Mean Square Error*

The RMSE assesses the accuracy of the model by comparing the difference between the values obtained from the predicted values and those of the measured data. The RMSE always has a positive value and is calculated using equation (14) [4]:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2} \quad (14)$$

2.4.4. *Correlation coefficient*

The R^2 coefficient, which indicates the strength of the linear relationship between the predicted values and the measured values, is given by [4]:

$$R^2 = \frac{\sum_{i=1}^{N}(x_i - \bar{x}_i)(y_i - \bar{y}_i)}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x}_i)^2\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}} \quad (15)$$

2.4.5. *Variance Account For*

The variance account for (VAF) was calculated using equation (16):

$$\text{VAF}(\%) = 100.\left(1 - \frac{Var(y_i - x_i)}{Var(x_i)}\right) \quad (16)$$

with the variance (Var) given by equation (17).

$$\text{Var}(y) = \frac{1}{n}\sum_{i=1}^{n}(y_i - y)^2 \quad (17)$$

3. RESULTS AND DISCUSSION

A comparison between the MLR and ANFIS models for predicting the uniaxial compressive strength (UCS) of Gneiss is performed. Two variables, namely the sclerometric index and the propagation velocity of ultrasonic waves (following the parallel or perpendicular direction of foliations), are used as input variables. The results of the tests are utilized to determine the model parameters. Each data point in Figures 5 and 6 has the following coordinates: (VPerpFoliations, IS, UCS) or (VFoliations, IS, UCS).

To ensure prediction, we calculated the five indicators whose formulas are presented in Section 2.4 of this article. For example, plus R^2 is close to 1, the better the prediction and RPE values between -10% and +10% are considered acceptable.

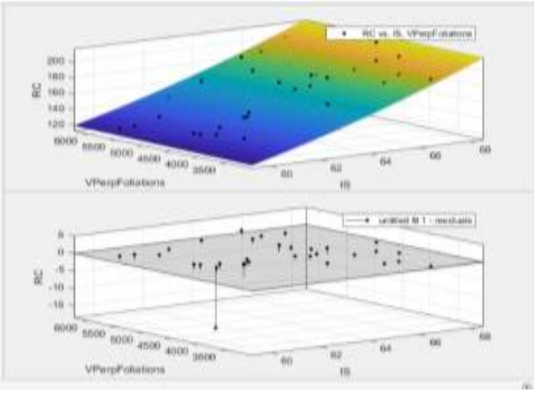


Fig. 6 : Results 1 of the RC prediction model using MLR (perpendicular direction of

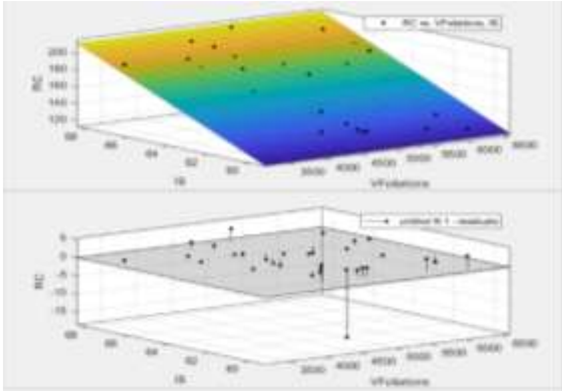


Fig. 5 : Results 1 of the RC prediction model using MLR (parallel foliation direction)

Figures 5 and respectively depict the plane corresponding to the equation (18) of the MLR model for the predicting UCS with an R^2 of 0,9832 and the plane corresponding to the equation (19) of the MLR model for the predicting of UCS obtained with an R^2 of 0,9833.

RC = - 507,1 + 0,0003868*VPerpFoliations + 10,48*IS (18)

RC = - 508,3 + 0,0004952*VFoliations + 10,48*IS (19)

Additionally, by extending the same model to quadratic polynomial analysis, each data point in Figures 7 and 8 reveals the respective plane corresponding to the equations (20) of the MLR model for predicting UCS with an R^2 of 0,9835 and the plane corresponding to the equation (21) of the MLR model for the predicting UCS obtained with an R^2 of 0,9836.

RC = -539,6 + 0,005162*VPerpFoliations + 11,16*IS + 0,0000005113*VPerpFoliation² - 0,0001506*IS*VPerpfoliations (20)

RC = - 579,9 + 0,01368*VFoliations + 11,66*IS + 0,0000001616*Vfoliations² - 0,0002296*Vfoliations*IS (21)

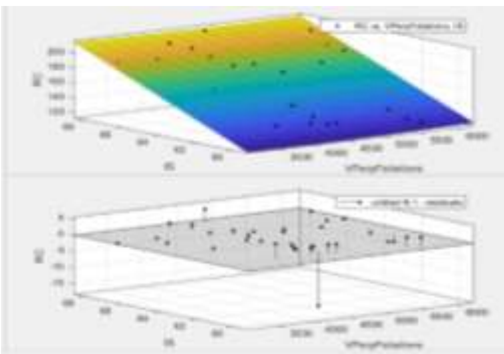


Fig. 8 : Results 2 of the RC prediction model using MLR (perpendicular direction of foliations)

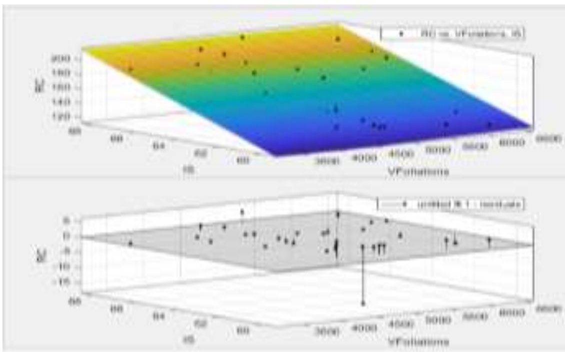


Fig. 7 : Results 2 of the RC prediction model using MLR (parallel foliation direction)

The obtained results demonstrate a strong correlation between the uniaxial compressive strength (UCS) and the propagation velocity of ultrasonic waves (following the parallel or perpendicular direction of foliations).

The ANFIS models for estimating uniaxial compressive strength are constructed according to the structure shown in Figure 9.

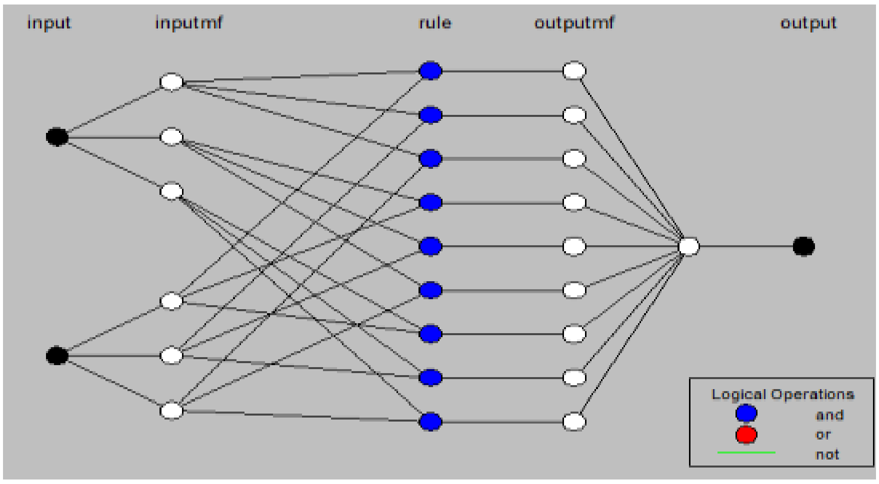
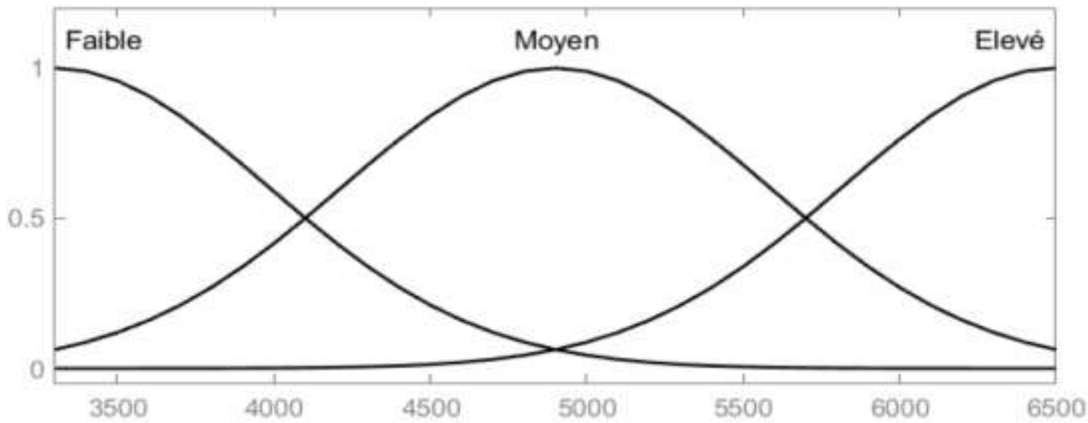


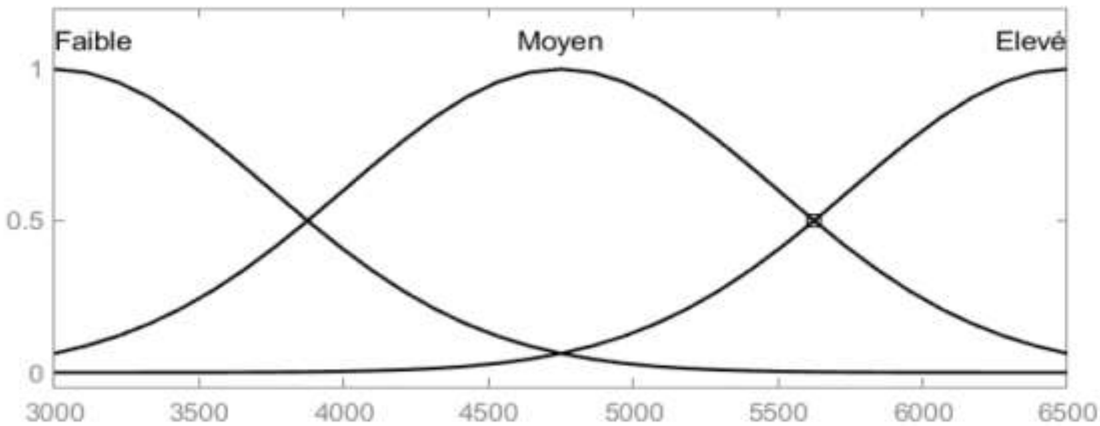
Fig. 9 : Structure of the ANFIS model for the prediction of uniaxial compressive strength

To perform fuzzy inputs, two membership functions (Gaussian and Bell) often referenced in the literature [3] are employed.

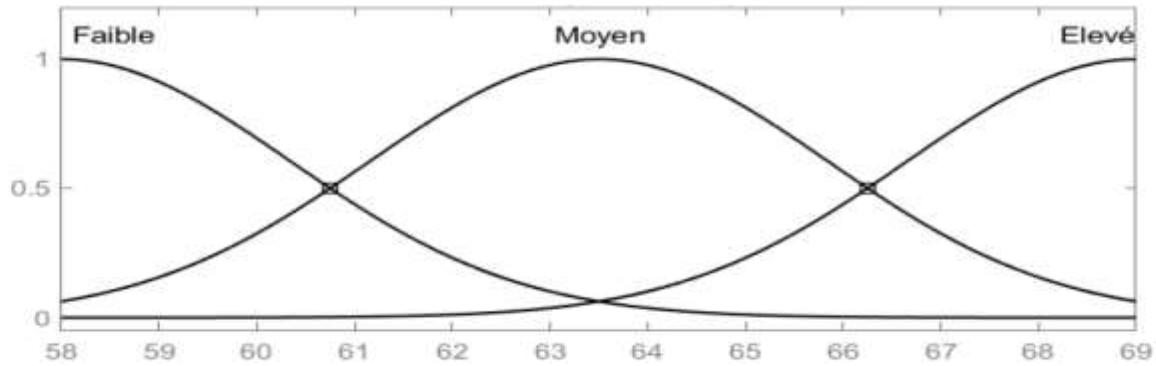
Figures 10 and 11 respectively illustrate the input variables of the ANFIS models with Gaussian and Bell membership functions.



a) Gaussian membership function diagram for VFoliations input

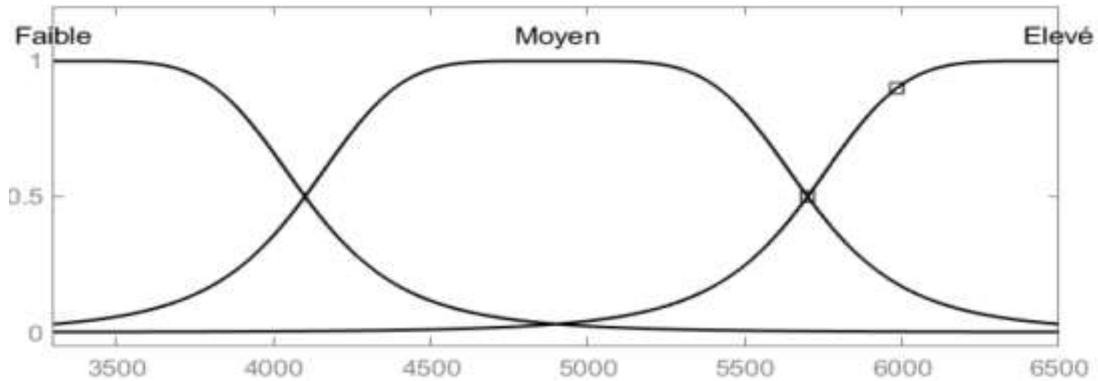


b) Gaussian membership function diagram for VPerpFoliations entry

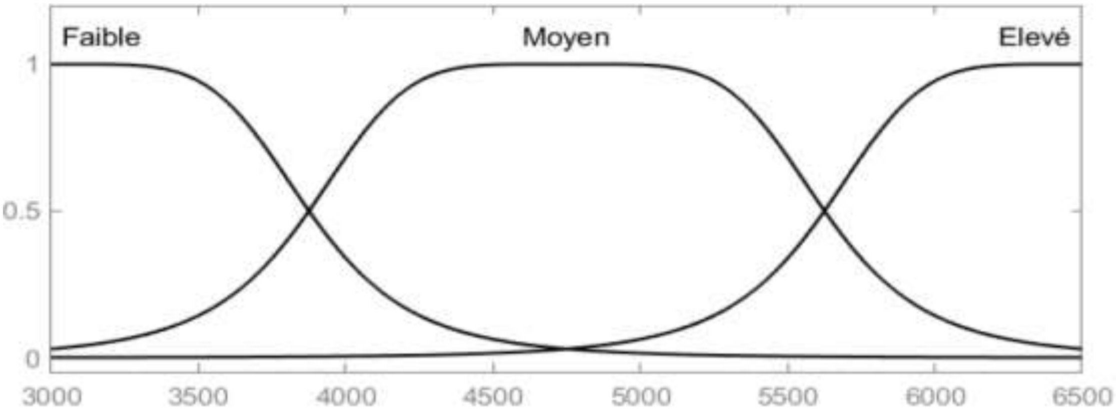


c) Gaussian membership function diagram for IS input

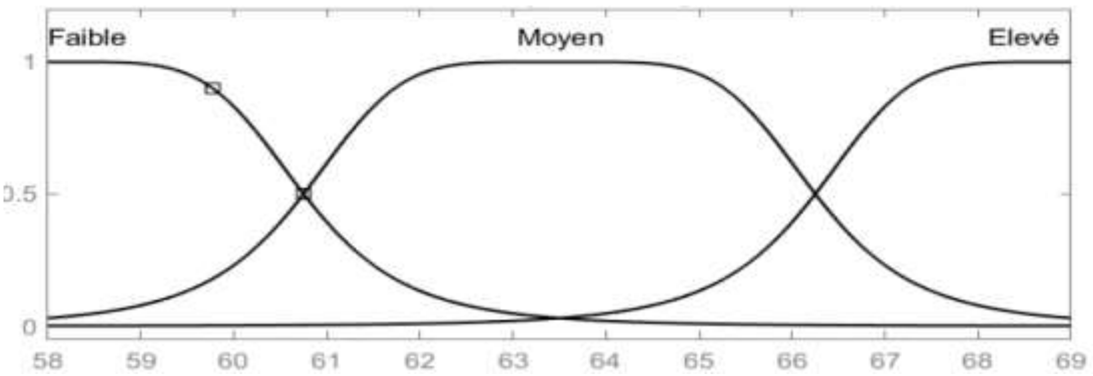
Fig. 10 : Gaussian membership function diagram for entries (a) " VFoliations" (b) "VPerpFoliations and (c) "IS")



a) Bell membership function diagram for VFoliations input



b) Bell membership function diagram for VPerpFoliations entry



c) Bell membership function diagram for IS input

Fig. 11 : Bell membership function diagram for entries (a) " VFoliations" (b) "VPerpFoliations and (c) "IS")

For each type of membership function (Bell or Gaussian), the hybrid algorithm is applied, which combines the backpropagation method and the least squares method to obtain the optimal parameters of the ANFIS model. To execute this hybrid algorithm, the number of iterations is set to 100.

To assess the performance of each developed model in this article, we calculated the five indicators, the formulas of which are presented in Section 2.4 of this article. Figures 12 and 13 respectively illustrate the performances of the ANFIS prediction models for uniaxial compressive strength (UCS) using a Bell-type membership function and a Gaussian membership function. These figures demonstrate that:

a- Following the perpendicular direction of the foliations

The prediction model of uniaxial compressive strength (UCS) using the ANFIS approach with a Bell-type membership function achieved an R^2 of 0,9898, an RMSE of 2,7441, a MAPE of 1,024, and a VAF of 98,97. In comparison, the ANFIS approach with a Gaussian membership function resulted in an R^2 of 0,9884, an RMSE of 2,9271, a MAPE of 1,160 and a VAF of 98,83.

b- According to the direction of the foliations

The prediction model of uniaxial compressive strength (UCS) using the ANFIS approach with a Bell-type membership function achieved an R^2 of 0,9878, an RMSE of 3,0027, a MAPE of 1,228, and a VAF of 98,76. In comparison, the ANFIS approach with a Gaussian membership function resulted in an R^2 of 0,9880, an RMSE of 2,9676, a MAPE of 1,1604 and a VAF of 98,79.

It's also worth noting that the MLR approach using equation (18) allowed for the prediction of uniaxial compressive strength (UCS) with an an R^2 of 0,9832, an RMSE of 3,686, a MAPE of 1,402 and a VAF of 98,22. The approach using equation (19) enabled the prediction of UCS with an R^2 of 0,9833, an RMSE of 3,678, a MAPE of 1,359 and a VAF of 98,34.

Based on the results presented in Figures 12 and 13, we can conclude that the suitable model for estimating the compressive strength of Gneiss in southern Togo is the ANFIS model using the Gaussian-type membership function. To evaluate the appropriate model among ANFIS (BELL and GAUSS) and MLR, Tables 1 and 2 show, for each validation data, the prediction error (RPE) from the 33 sites of the ANFIS model predicting uniaxial compressive strength along the perpendicular direction of foliations, with a maximum RPE of 11.055% for the ANFIS model compared to a maximum RPE of 24.438% for the GAUSS model and 10.714% for the BELL model, versus 14.390% for the MLR model. Similarly, for the parallel direction of foliations, the ANFIS model has a maximum RPE of 11.055% compared to a maximum RPE of 12.332% for the GAUSS model and 11.909% for the BELL model, while the MLR model has a maximum RPE of 14.862%. Thus, the ANFIS model with Gaussian-type input variable membership function is the most suitable for estimating the compressive strength of Gneiss in southern Togo.

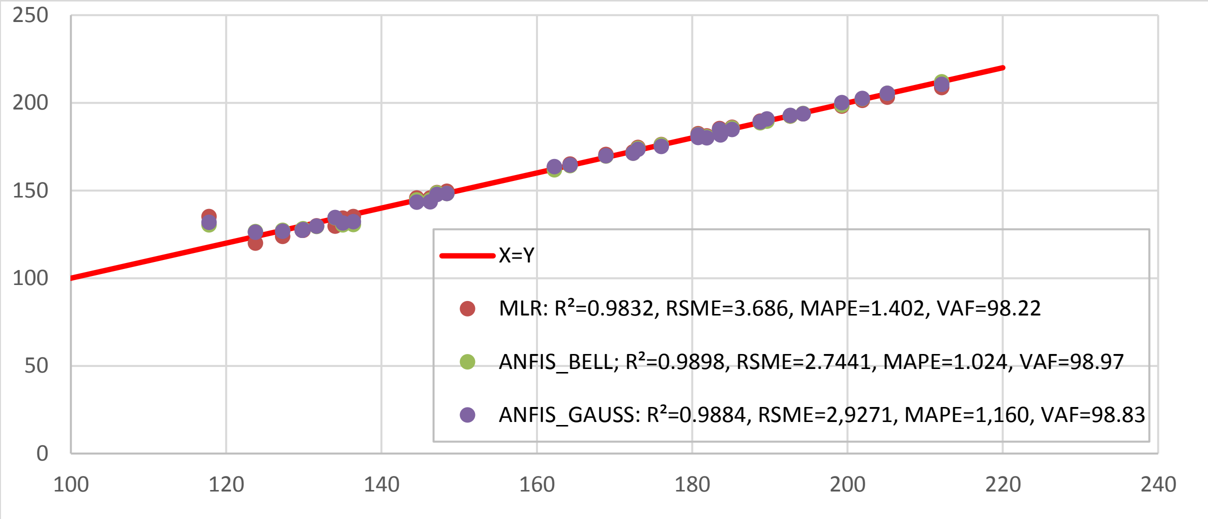


Fig. 12 : Quality adjustment between actual and predicted CR values (Perpendicular direction of foliations)

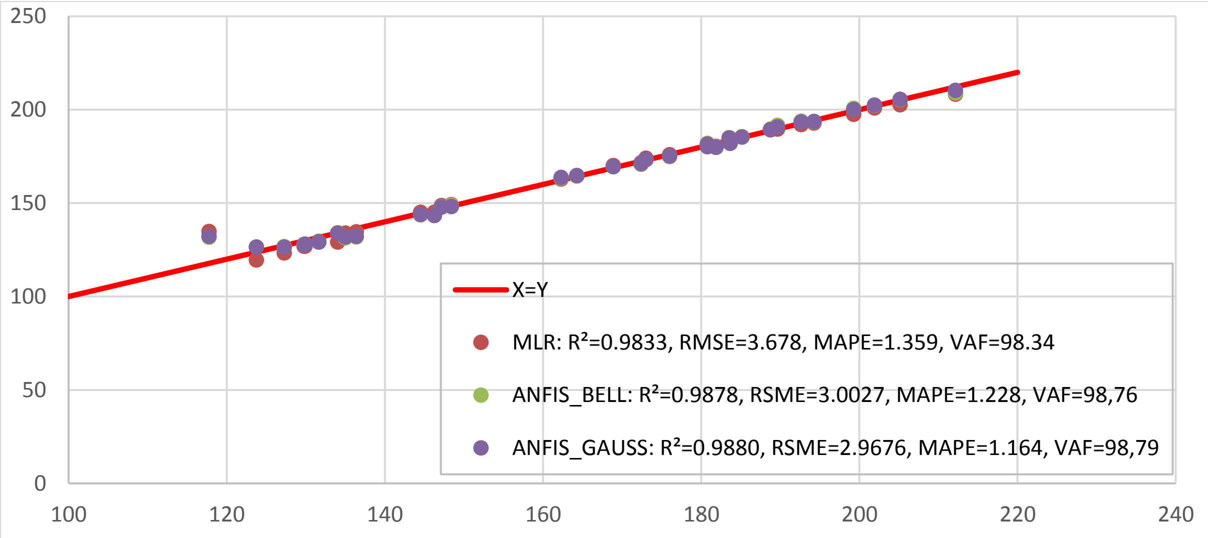


Fig 13 : Quality adjustment between actual and predicted CR values (Perpendicular direction of foliations)

The tables below present the actual and predicted values of the compressive strength (RC) of Gneiss in southern Togo using the ANFIS and MLR models along with the corresponding RPE values.

Table 1. Actual and predicted CR values from ANFIS (GAUSS and BELL) and MLR models with RPE (foliation direction)

Sample numbers	IS	Wave velocity in the direction of the Foliations (m/s)	CR Measured (MPa)	CR Predicted by MLR (MPa)	RPE By MRL (%)	CR Predicted ANFIS (MPa)		RPE by ANFIS (%)	
						BELL	GAUSS	BELL	GAUSS
1	65,63	4992,5	180,75	182,48	0,959	181,83	181,58	0,595	0,461
2	67,63	4505,1	205,13	203,21	0,932	205,34	205,52	0,105	0,193
3	65,88	5726,0	183,50	185,33	0,996	184,99	184,77	0,815	0,693
4	68,13	5209,3	212,13	208,70	1,614	208,94	210,30	1,502	0,859
5	62,13	4775,5	146,25	145,68	0,387	143,33	143,37	1,998	1,973
6	64,50	4871,5	168,88	170,65	1,050	169,34	169,61	0,273	0,434
7	65,63	6448,5	183,63	183,01	0,334	181,91	182,02	0,936	0,875
8	60,38	4861,3	129,88	127,37	1,931	128,11	127,96	1,362	1,473
9	61,00	6072,5	135,00	134,31	0,509	131,39	131,78	2,672	2,384
10	67,38	6291,3	201,88	201,35	0,261	202,25	202,39	0,185	0,255
11	60,00	5659,8	127,25	123,83	2,686	126,70	126,43	0,434	0,644
12	60,63	4857,5	131,63	129,92	1,298	129,06	129,07	1,946	1,939
13	63,75	6102,8	162,25	163,31	0,656	163,47	163,67	0,751	0,873
14	64,00	4346,3	164,25	165,10	0,515	164,49	164,82	0,146	0,346
15	64,63	5313,4	172,38	172,09	0,163	170,78	171,09	0,927	0,744
16	65,50	4625,0	181,88	181,08	0,438	180,02	179,87	1,020	1,103

17	65,50	5205,0	180,75	181,19	0,243	180,28	180,15	0,259	0,333
18	64,88	4880,3	173,00	174,54	0,890	173,18	173,33	0,103	0,189
19	61,13	4849,5	136,38	135,22	0,846	131,79	132,29	3,361	2,994
20	59,63	6132,3	123,75	119,94	3,077	126,62	126,41	2,317	2,147
21	60,38	4924,8	129,75	127,41	1,801	127,89	127,72	1,436	1,567
22	62,50	4867,5	148,38	149,66	0,869	148,84	148,09	0,310	0,193
23	61,13	4855,0	117,75	135,25	14,862	131,77	132,27	11,909	12,332
24	66,00	4180,0	185,13	186,00	0,475	185,40	185,31	0,148	0,101
25	66,25	6419,9	188,75	189,53	0,413	189,58	189,24	0,437	0,262
26	65,00	5953,9	176,00	176,27	0,155	174,91	175,23	0,619	0,440
27	66,38	4758,4	189,63	190,21	0,308	191,63	190,79	1,056	0,615
28	67,13	4683,8	199,25	198,05	0,604	200,81	200,12	0,781	0,437
29	66,63	4174,3	192,63	192,56	0,033	193,84	193,29	0,633	0,344
30	62,38	6454,0	147,13	148,89	1,203	147,95	147,73	0,561	0,409
31	66,75	3306,6	194,25	193,67	0,299	193,54	193,74	0,365	0,262
32	60,63	4351,4	134,00	129,72	3,191	134,02	133,93	0,016	0,050
33	62,13	4647,5	144,50	145,71	0,836	143,73	143,81	0,536	0,476

Table 2. Observed and predicted CR values from ANFIS (GAUSS and BELL) and MLR models with RPE (perpendicular foliation direction)

Sample numbers	**IS**	**Wave velocity in the perpendicular direction of the Foliations (m/s)**	**CR Measured (MPa)**	**CR Predicted by MLR (MPa)**	**RPE by MRL (%)**	**CR predicted ANFIS (MPa)**		**RPE by ANFIS (%)**	
						BELL	**GAUSS**	**BELL**	**GAUSS**
1	65,63	4741,3	180,75	181,92	0,649	181,82	181,74	0,590	0,547
2	67,63	4146,5	205,13	202,64	1,211	205,45	205,47	0,160	0,170
3	65,88	5319,3	183,50	184,91	0,766	184,57	184,76	0,584	0,685
4	68,13	4784,3	212,13	208,23	1,836	211,93	210,55	0,093	0,742
5	62,13	4433,0	146,25	145,13	0,763	144,68	143,52	1,075	1,868
6	64,50	4625,1	168,88	170,07	0,709	169,70	169,86	0,490	0,580
7	65,63	6104,3	183,63	182,64	0,535	182,53	181,79	0,595	0,997
8	60,38	4492,5	129,88	126,84	2,339	128,21	127,69	1,284	1,683
9	61,00	5512,5	135,00	133,99	0,750	130,34	131,45	3,453	2,628
10	67,38	6096,5	201,88	200,91	0,480	202,33	202,46	0,226	0,288
11	60,00	5512,8	127,25	123,30	3,102	127,40	126,75	0,117	0,394
12	60,63	4310,0	131,63	129,46	1,648	129,60	129,73	1,537	1,443
13	63,75	5984,8	162,25	162,82	0,353	161,86	163,67	0,239	0,876
14	64,00	3815,0	164,25	164,57	0,196	164,20	164,62	0,032	0,225
15	64,63	4972,4	172,38	171,60	0,449	171,28	171,22	0,634	0,671
16	65,50	4494,5	181,88	180,43	0,794	180,53	180,11	0,739	0,969
17	65,50	4782,5	180,75	180,72	0,018	180,53	180,24	0,120	0,282
18	64,88	4522,0	173,00	174,01	0,582	174,06	173,47	0,612	0,273
19	61,13	4476,8	136,38	134,69	1,234	130,54	132,16	4,279	3,088
20	59,63	5615,4	123,75	119,61	3,348	126,68	126,18	2,364	1,964
21	60,38	4608,8	129,75	126,87	2,221	127,93	127,33	1,405	1,866
22	62,50	4562,5	148,38	149,11	0,496	148,37	148,40	0,003	0,018
23	61,13	4551,3	117,75	134,69	14,390	130,37	131,94	10,714	12,055
24	66,00	3682,5	185,13	185,45	0,176	185,75	184,87	0,339	0,139
25	66,25	6023,5	188,75	189,18	0,227	188,65	189,13	0,052	0,202
26	65,00	5619,1	176,00	175,85	0,086	176,06	175,06	0,032	0,536
27	66,38	4392,6	189,63	189,67	0,022	189,49	190,86	0,069	0,650
28	67,13	4336,8	199,25	197,49	0,884	198,66	200,18	0,296	0,469
29	66,63	3702,5	192,63	192,00	0,326	192,50	192,88	0,067	0,132
30	62,38	5958,2	147,13	148,59	0,993	148,64	147,81	1,027	0,463
31	66,75	3176,8	194,25	192,88	0,707	193,97	193,84	0,144	0,211
32	60,63	3809,8	134,00	129,20	3,579	134,45	134,56	0,334	0,415
33	62,13	4495,0	144,50	145,07	0,395	144,63	143,40	0,092	0,758

CONCLUSIONS

Our study aimed to predict the uniaxial compression strength of gneiss from southern Togo using the ANFIS model based on non-destructive testing. By leveraging simple and cost-effective tests such as the rebound hammer and ultrasonic wave measurements, we sought to reduce the expenses and time associated with traditional laboratory tests.

1. The comparison between the ANFIS model and the Multiple Linear Regression (MLR) model revealed that the ANFIS model outperforms the MLR model in terms of predictive accuracy. The ANFIS model exhibited superior results, particularly when utilizing ultrasonic wave measurements in the perpendicular direction to the foliations

of the gneiss samples. This approach yielded higher R^2 values, lower RMSE, MAPE, and higher VAF, indicating a more accurate prediction of uniaxial compression strength (For instance, when using the ANFIS model with ultrasonic waves in the perpendicular direction to the foliations, the uniaxial compression strength is predicted with an R^2 of 0.9884, an RMSE of 2.9271, a MAPE of 1.160, and a VAF of 98.83. In contrast, the MLR model yields an R^2 of 0.9832, an RMSE of 3.686, a MAPE of 1.402, and a VAF of 98.22).

2. The unique advantage of the ANFIS model lies in its hybrid nature, combining both neural and logical approaches. The hybrid algorithm effectively optimized the model's parameters, resulting in improved performance. The ANFIS models developed in this study can serve as reliable tools for estimating uniaxial compression strength in gneiss not only in Togo but also in various geological contexts worldwide.
3. Overall, our research highlights the potential of utilizing ANFIS models with non-destructive testing to enhance the efficiency and cost-effectiveness of assessing rock properties for engineering applications. This approach contributes to more informed decision-making in civil engineering projects, facilitating safer and more economically viable construction practices.

List of Symbols

ANFIS: Adaptive Neuro-Fuzzy Influence System; IS: Sclerometric Index; MLR: Multiple Linear Regression; MAPE: Mean Absolute Percentage Error; RMSE: Root Mean Error Square; RPE: Relative Percentage Error; RMSE: Root Mean Square Error; VAF: Variance Account For; CR: Compressive strength.

Authors' contributions

EK contributed to the conduct of the tests, the analysis of the test results and drafted the article. IP contributed to the design of the article and its revision. AP and YMDA helped revise the article thoroughly. All authors have read and approved the final article.

Availability of data and materials

All data generated or analyzed during this study are included in this published article.

Authors information

Ezouwè Kessie is a PhD student at École Polytechnique de Lomé (EPL).
Irina Pachoukova is a Mining Engineer, Associate Professor in Civil engineer, Civil engineering department, École Polytechnique de Lomé (EPL).
Abalo P’kla is a Civil engineer, Associate Professor in civil engineering, civil engineering department, École Polytechnique de Lomé (EPL).

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