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Investigating the durability and sustainability of soilcrete containing metakaolin using adaptive neuro–fuzzy inference system

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Abstract. Recent years have witnessed a burgeoning interest in sustainable, eco-friendly, and cost-effective construction materials for civil engineering projects. Soilcrete, an innovative blend of soil and cement, has gained significant acclaim for its versatility and effectiveness. It serves not only as grout for soil stabilization in corrosive environments like landfills and coastal regions but also as a reliable material for constructing structural elements. Understanding the mechanical properties of soilcrete is crucial, yet traditional laboratory tests are prohibitively expensive, time-consuming, and often imprecise. Machine learning (ML) algorithms present a superior alternative, offering efficiency and accuracy. This research focuses on the application of the adaptive neuro-fuzzy inference system (ANFIS) algorithm to predict the uniaxial compressive strength (UCS) of soilcrete. A total of 300 soilcrete specimens, crafted from two types of soil (clay and limestone) and enhanced with metakaolin as a pozzolanic additive, were meticulously prepared and tested. The dataset was divided, with 80% used for training and 20% for testing the model. Eight parameters were identified as key determinants of soilcrete's UCS: soil type, metakaolin content, superplasticizer content, shrinkage, water-to-binder ratio, binder type, ultrasonic velocity, and density. The analysis demonstrated that the ANFIS algorithm could predict the UCS of soilcrete with remarkable accuracy. By combining laboratory results with ANFIS model predictions, the study identified the optimal conditions for maximizing soilcrete's UCS: 11% metakaolin content, a 0.45 water-to-binder ratio, and 1% superplasticizer content.

Keywords: adaptive neuro-fuzzy inference system; compressive strength; laboratory test; soilcrete

1. Introduction

In recent years, there has been an intensifying focus on the development and implementation of sustainable and environmentally benign construction materials within the domain of civil engineering. This shift is driven by the need to reduce environmental impact and promote cost-effective solutions without compromising on structural integrity. Among various innovative materials, soilcrete has emerged as a highly valued option. Soilcrete, an amalgam of soil and cement, offers several advantages that make it an attractive choice for a wide range of construction applications:

- Soilcrete utilizes locally available soil, reducing the need for transporting materials over long distances. This not only cuts down on transportation costs but also minimizes the carbon footprint associated with construction projects.
- The use of soil as a primary component significantly lowers the overall material costs compared to traditional concrete. This makes soilcrete an economical alternative for large-scale construction projects.
- Soilcrete can be tailored to suit various engineering requirements by adjusting the proportions of soil, cement, and additives. This flexibility allows for its use in diverse applications, including soil stabilization, landfill cover systems, and structural elements.
- Soilcrete demonstrates resilience in harsh environments such as coastal regions and landfills, where traditional materials might degrade more rapidly. Its resistance to chemical attack and ability to stabilize soils make it ideal for such settings (Helson *et al.* 2017).

Despite its potential, traditional laboratory testing of soilcrete poses challenges. These tests require extensive sample preparation, involve complex and time-consuming procedures, and incur substantial costs. The inherent variability in soil and cement properties further complicates the process, introducing uncertainties in test results that can undermine the precision of engineering designs and

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construction practices. To address these challenges, advancements in testing methodologies and technologies are being explored. Innovations such as in-situ testing, non-destructive evaluation techniques, and computational modeling are being developed to streamline the testing process, reduce costs, and enhance the accuracy and reliability of soilcrete assessments. These advancements not only promise to improve the efficiency of soilcrete utilization in construction but also aim to enhance the overall safety and durability of the structures that rely on this innovative material.

Today, machine learning (ML) methods have provided a remarkable ability to estimate and predict the engineering problems (Abdelmawla *et al.* 2023, Lawal *et al*. 2023, Mahmoodzadeh *et al.* 2022). Harnessing ML techniques to assess the mechanical properties of soilcrete offers substantial advantages. ML algorithms can significantly cut down the time and financial costs linked to traditional lab testing (Naugler and Church 2019). Instead of conducting labor-intensive and costly tests on numerous samples, engineers can utilize trained models to accurately predict soilcrete's mechanical properties. This leads to more efficient decision-making during design and construction, resulting in cost savings and improved project timelines (Kakasor Ismael Jaf *et al*. 2023).

ML methodologies also effectively manage the natural variability in soil and cement characteristics by considering a broad range of input parameters. By analyzing multiple factors simultaneously, ML models capture complex relationships and provide more precise predictions of mechanical properties. This enhances the reliability and predictability of soilcrete performance, allowing engineers to design structures with greater confidence.

Moreover, ML techniques offer opportunities for continuous monitoring and real-time evaluation of soilcrete properties. By integrating sensor data from construction sites or existing structures, ML models can constantly update and refine their predictions, enabling proactive maintenance and ensuring the long-term stability and safety of infrastructure.

Despite these promising benefits, the application of ML methods in estimating soilcrete properties is still relatively uncommon. A notable study by Asteris *et al*. (2017) used artificial neural networks (ANN) to estimate the mechanical characteristics of soilcrete materials, utilizing 134 data categories. This study highlighted the high accuracy of the ANN method. However, further developments in this field have been limited, particularly in exploring the performance of various ML models in predicting soilcrete's mechanical properties. To advance this area, future research should focus on investigating the potential of other ML models to determine their effectiveness in predicting soilcrete characteristics. Additionally, creating extensive, high-quality datasets for training and validating these models is crucial for improving their accuracy and generalizability.

This article aims to rigorously investigate the capability of the adaptive neuro-fuzzy inference system (ANFIS) to accurately estimate the uniaxial compressive strength (UCS) of soilcrete materials. The choice of the ANFIS algorithm over other ML algorithms in this study is driven by its superior handling of complex, uncertain data, its adaptive learning capabilities, and its interpretability, all of which contribute to a more accurate and reliable estimation of the UCS of soilcrete materials.

Numerous soilcrete specimens are carefully prepared for UCS testing, resulting in multiple data points. The creation of these soilcrete samples utilizes two different soil types: natural clay ground soil (CGS) and crushed quarry limestone sand (CQLS), with metakaolin serving as a mineral additive. Moreover, several unseen datasets are used to assess the generalization capability of the machine learning models.

The contributions of this study are as follows:

- The study explores the performance of ANFIS algorithm to estimate the UCS of soilcrete materials.
- Employing a comprehensive dataset.
- Generalization capability evaluation of the ANFIS algorithm.
- Optimizing the parameter values of the concrete mixture.

2. ANFIS algorithm

The ANFIS algorithm is a hybrid computational model that integrates the principles of neural networks and fuzzy logic. It was developed to combine the learning capabilities of neural networks with the human-like reasoning style of fuzzy logic systems (Jang 1993).

Here's a brief overview of how ANFIS works:

- Fuzzification: In the first stage, crisp input values are converted into fuzzy values using linguistic variables and membership functions. This step helps in representing uncertain or imprecise input data.
- Rule Evaluation: ANFIS uses a set of fuzzy IF-THEN rules that define the relationship between input and output variables. Each rule combines fuzzy sets from input variables to produce a fuzzy output.
- Rule Combination: In this stage, the outputs of individual rules are combined to produce a single crisp output. This can be done using methods like weighted average or centroid defuzzification.
- Parameter Optimization: The parameters of the membership functions and the rule strengths are adjusted using a learning algorithm, typically a variation of gradient descent. This step is crucial for fine-tuning the model to fit the training data.
- Training: ANFIS learns from examples by adjusting its parameters iteratively using a training dataset. The goal is to minimize the error between the actual outputs and the predicted outputs.
- Testing and Validation: Once trained, the ANFIS model can be tested and validated using a separate dataset to evaluate its performance and generalization ability.

3. Data preparation and analysis

300 cylindrical soilcrete specimens, each with a height-

	W/B	MK	B	SP	Sh	D	UV	UCS
W/B	----	0.005	0.003	0.08	0.13	0.28	0.09	0.48
MK	0.005	----	0.09	0.01	0.02	0.02	0.03	0.34
B	0.003	0.09	----	0.07	0.03	0.08	0.07	0.27
SP	0.08	0.01	0.07	----	0.02	0.15	0.04	0.29
Sh	0.13	0.02	0.03	0.02	----	0.09	0.07	0.23
D	0.28	0.02	0.08	0.15	0.09	----	0.35	0.45
UV	0.09	0.03	0.07	0.04	0.07	0.35	----	0.24
UCS	0.48	0.34	0.27	0.29	0.23	0.45	0.24	----

Fig. 1 Correlation matrix

to-diameter ratio of 2, were subjected to rigorous testing procedures to analyze their properties comprehensively. These soilcrete samples, meticulously crafted, comprised diverse combinations of natural clay ground soil (CGS) and crushed quarry limestone sand (CQLS), with the latter replacing the traditional aggregate phase. To enhance the performance characteristics of the soilcrete, a mineral additive called metakaolin (MK) was meticulously introduced into the conventional Portland cement-based binder and water mixture, employing varying water/binder (W/B) ratio values.

The core objective of this extensive investigation revolved around evaluating the 28-day uniaxial compressive strength (UCS) of the soilcrete specimens, a crucial parameter indicative of their structural integrity and load-bearing capacity. This evaluation process involved a meticulous exploration of distinct groups of binders (B), where differing percentages of CEM I 42.5 N Portland cement (PC) were blended with MK. Achieving homogeneity across the binder categories necessitated the meticulous blending of MK and PC in a laboratory swing mill for an extended duration. Moreover, the crafting of soilcrete batches involved the utilization of two distinct soil materials: CGS and CQLS. The clay-based soilcrete formulations stemmed from the meticulous blending of CGS with the binder at various W/B ratio values, while the sand-based soilcrete formulations emerged from the meticulous combination of CQLS with the binder at different W/B ratio values. This approach ensured a comprehensive exploration of the effects of soil type and W/B ratio on the resultant soilcrete's mechanical properties.

In the process, a vast dataset comprising 300 entries was meticulously compiled, incorporating a total of eight predictor variables: W/B ratio, soil type (ST), MK content, shrinkage (Sh), superplasticizer content (SP), binder type (B), ultrasonic velocity (UV), and density (D). The eight predictor variables were chosen based on their significant influence on the UCS of soilcrete, as established by existing literature and preliminary experiments. Here is a detailed rationale for each variable:

- W/B Ratio: This ratio is a critical determinant of the workability and strength of cementitious materials. It directly influences the hydration process and, consequently, the mechanical properties of soilcrete.
- ST: Different STs have distinct physical and chemical properties that affect the interaction with cement and additives, impacting the overall strength and durability of the soilcrete.
- MK content: MK is a pozzolanic additive known to enhance the mechanical properties and durability of cementitious materials by improving the microstructure and reducing porosity.
- Sh: Sh is an important factor affecting the dimensional stability and crack resistance of soilcrete. Measuring shrinkage helps in understanding how the material will behave under drying and curing conditions.
- SP content: This parameter are used to improve the workability of soilcrete without increasing the water content, thereby maintaining or enhancing strength.
- B: Different types of binders can significantly influence the hydration process and the resulting mechanical properties of soilcrete. The binder type is crucial for determining the material's final performance.
- UV: UV is an indirect measure of the material's density and homogeneity, providing insights into the internal structure and potential flaws within the soilcrete.
- D: This parameter is a fundamental property that affects the strength, durability, and overall performance of soilcrete. Higher density typically correlates with better mechanical properties.

One of the main challenges encountered was the inherent variability in soil properties. To mitigate this, soils were thoroughly characterized for their physical and chemical properties before use. Additionally, the experiments were conducted under controlled environmental conditions to minimize external influences.

To facilitate robust model development and validation, the dataset was divided into two subsets: 80% (240 data points) for training purposes and 20% (60 data points) for

Table 1 General specification of numerical datasets

		W/B	MK (% w/w in the dry mix)	B (% w/w in the dry mix)	SP (% w/w of the cementitious materials)	Sh (%)	D (kg/m^3)	UV (m/s)	UCS (Mpa)
raining data	count	240	240	240	240	240	240	240	240
	mean	0.81	5.21	35.28	1.17	8.52	1814.42	2722.58	33.76
	std	0.26	4.38	9.11	1.14	6.49	163.96	594.674	10.74
	min	0.35	0.00	20.00	0.00	0.00	1438.03	1518.70	15.46
	25%	0.65	6.21	27.64	0.53	2.69	1712.63	2910.39	31.85
	50%	0.88	10.08	32.28	1.36	7.22	1862.20	3251.21	34.97
	75%	1.08	14.19	46.55	2.76	13.90	1982.27	3414.63	44.11
	max	1.30	20.00	50.00	3.00	25.00	2077.61	4000.98	72.16
Testing data	count	60	60	60	60	60.00	60	60	60
	mean	0.50	6.41	34.96	1.34	10.49	1783.25	2531.64	49.77
	std	0.11	3.94	10.37	1.25	6.11	153.98	731.86	8.27
	min	0.28	0.00	20.00	0.00	0.00	1488.41	1688.37	33.21
	25%	0.46	3.80	27.49	0.71	6.75	1618.35	2816.22	42.53
	50%	0.51	7.12	33.04	1.38	10.06	1727.27	3180.01	48.21
	75%	0.64	10.44	44.86	2.12	15.41	1979.28	3881.43	55.18
	max	0.74	17.00	47.00	3.00	25.00	2005.17	3982.84	69.88

Table 2 General specification of datasets regarding the nominal parameters

Parameter		Count	Class	Vector	Frequency [%]
ST	Training data	240	CGS	[1 0]	45
			CQLS	[0 1]	55
	Test data	60	CGS	[1 0]	70
			CQLS	[0 1]	30

testing and validation. The selection of data for the testing subset was conducted randomly, ensuring the representative nature of the test dataset. The attributes of both the training and testing datasets, encompassing numerical and nominal parameters, were meticulously documented and presented in Tables 1 and 2, providing valuable insights into the dataset's composition and structure. This meticulous approach to data collection and analysis laid a solid foundation for the subsequent modeling and predictive analysis endeavors.

In Fig. 1, depicted is a Pearson correlation matrix demonstrating the linkage between input and output parameters. The matrix reveals a feeble correlation among the input parameters and their association with the output parameter (UCS). Consequently, a conspicuous absence of a straightforward linear relationship among these parameters is observed, rendering linear methodologies inappropriate for pattern recognition. Clearly, the association between inputs and output transcends linearity, necessitating the application of sophisticated non-linear ML algorithms to unravel this intricate interconnection.

4. Performance evaluation of the ML models

The following metrics have been utilized to assess the performance of the ML models in predicting the UCS of soilcrete in this study. These metrics are crucial for evaluating the ML models' effectiveness in estimating the UCS of soilcrete. Each metric provides distinct insights into the models' accuracy and effectiveness.

Coefficient of determination (R^2): This gauges the fraction of the variation in the response variable that can be accounted for by the predictor variable(s). Put differently, it shows how well the predictor variables clarify the variation in the response variable. R^2 figures span from 0 to 1, with 1 indicating a perfect alignment (Eq. (1)).

Mean Absolute Percentage Error (MAPE): MAPE assesses the forecast precision of a prediction technique in statistics, especially in chronological data analysis. It calculates the mean of the absolute percentage discrepancies between actual and forecasted values, represented as a percentage of the actual values (Eq. (2)).

Root Mean Squared Error (RMSE): RMSE is a widely used gauge for measuring the disparities between forecasted and observed values. It is the square root of the mean of the squared discrepancies between forecasted and actual values. RMSE is responsive to substantial errors and is extensively used in disciplines such as engineering, physics, and finance (Eq. (3)).

Variance Accounted For (VAF): VAF is another way of expressing the goodness of fit of a model. It represents the percentage of variance explained by the model relative to the total variance observed in the data (Eq. (4)).

a20–index: The a20–index functions as a distinct performance measure for assessing the precision of the models within a set tolerance range. It measures the proportion of forecasted values within ±20% of the target parameter values. A higher a20–index signifies a superior ability of the models to deliver accurate estimates within the defined tolerance range (Eq. (5)).

$$R^2 = \left(\frac{\sum_{i=1}^{n}(f(x_i) - \bar{f}(x))(f^*(x_i) - \overline{f^*}(x))}{\sqrt{\sum_{i=1}^{n}(f(x_i) - \bar{f}(x))^2 \sum_{i=1}^{n}(f^*(x_i) - \overline{f^*}(x))^2}}\right)^2 \quad (1)$$

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{f(x_i) - f^*(x_i)}{f(x_i)}\right| \quad (2)$$

$$\mathrm{RMSE} = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(f(x_i) - f^*(x_i))^2} \quad (3)$$

$$\mathrm{VAF} = 1 - \left[\frac{var(f(x_i) - f^*(x_i))}{var(f(x_i))}\right] \times 100\% \quad (4)$$

$$a20 - inxex = \frac{n - number\ of\ points\ between\ x = 1.20y\ and\ x = 0.80y}{n} \quad (5)$$

Where $f(x_i)$ and $f^*(x_i)$ are the actual and forecasted values of parameter x for i^{th} dataset, respectively. n is the total number of test datasets.

5. Results analysis and comparison

In Fig. 2, we contrast the values estimated using the ANFIS algorithm to the measured UCS values. This juxtaposition is accomplished using a graph that utilizes the a20–index measure. The majority of the points lie within the x=1.20y and x=0.80y lines, indicating the high precision of the predictions made by the ANFIS algorithm. Based on this measure, we can infer that the ANFIS algorithm is appropriate and precise for estimating the UCS of soilcrete. Other assessment criteria results are presented in Table 3. The computed values for each assessment standard illustrate the high precision of the ANFIS algorithm.

Now, we investigate the effectiveness of the trained ANFIS algorithm when applied to fresh datasets. To accomplish this, we will alter the values or type of a parameter within its specified range while keeping the other input parameters unchanged. The primary goal is to determine how the ANFIS model forecasts the UCS of soilcrete when encountering a modified parameter. An exceptionally proficient algorithm should display acute sensitivity to these parameter variations.

Initially, the value of the MK parameter is adjusted within its designated range of 0 to 205, with the other parameters remaining constant. For laboratory testing, a total of 20 soilcrete specimens were created, each adhering to the specifications detailed in Table 4. The outcomes of these laboratory tests are presented in Table 4. These 20 datasets form the foundation for assessing the performance of the ANFIS model. The results generated by each ANFIS model on this new dataset are compared to the experimental findings shown in Fig. 3. From the laboratory experiments, it was observed that increasing the MK content in soilcrete specimens from 0 to 11% led to a rise in UCS values, from 27.81 MPa to 61.25 MPa. However, further increasing the MK content from 11% to 20% resulted in a decrease in UCS value to 47.42 MPa. These findings indicate that the optimal MK content for maximizing UCS in soilcrete specimens is 12%. Moreover, the ANFIS model exhibited excellent correlation and close agreement with the laboratory measurements, underscoring its accuracy and reliability in predicting UCS based on varying MK content.

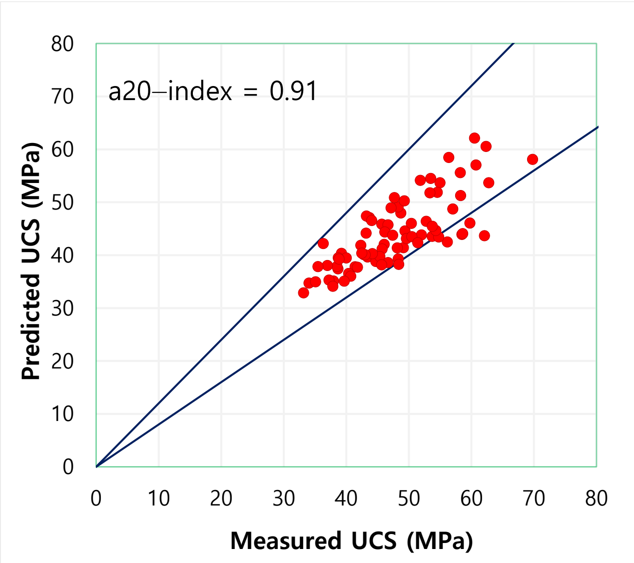

Fig. 2 Measured UCSs versus predicted ones

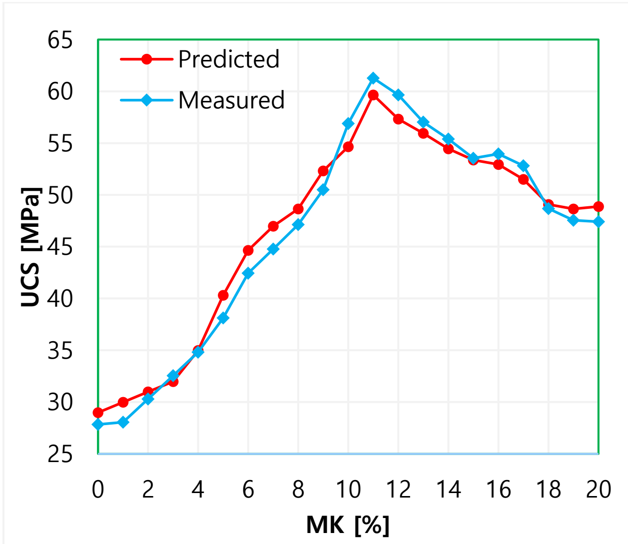

Fig. 3 Contrasting the effectiveness of the ANFIS model for soilcrete's UCS prediction by modifying the value of the MK parameter while keeping the other parameters fixed

Table 3 Statistical metrics results

R^2	MAPE	RMSE	VAF [%]	a20–index
0.90	0.03	2.39	95.8	0.91

Table 4 An assessment dataset to verify the efficacy of the trained ANFIS model for soilcrete's UCS prediction by altering the value of the MK parameter while maintaining the other parameters unchanged

ST	W/B	MK (% w/w in the dry mix)	B (% w/w in the dry mix)	SP (% w/w of cementitious materials)	Sh (%)	D (kg/m^3)	UV (m/s)	UCS (MPa)
CQLS	0.75	0	33	1	8	1800	2700	27.81
CQLS	0.75	1	33	1	8	1800	2700	28.06
CQLS	0.75	2	33	1	8	1800	2700	30.29
CQLS	0.75	3	33	1	8	1800	2700	32.54
CQLS	0.75	4	33	1	8	1800	2700	34.82
CQLS	0.75	5	33	1	8	1800	2700	38.12
CQLS	0.75	6	33	1	8	1800	2700	42.44
CQLS	0.75	7	33	1	8	1800	2700	44.78
CQLS	0.75	8	33	1	8	1800	2700	47.13
CQLS	0.75	9	33	1	8	1800	2700	50.51
CQLS	0.75	10	33	1	8	1800	2700	56.89
CQLS	0.75	11	33	1	8	1800	2700	61.25
CQLS	0.75	12	33	1	8	1800	2700	59.66
CQLS	0.75	13	33	1	8	1800	2700	57.04
CQLS	0.75	14	33	1	8	1800	2700	55.39
CQLS	0.75	15	33	1	8	1800	2700	53.54
CQLS	0.75	16	33	1	8	1800	2700	53.96
CQLS	0.75	17	33	1	8	1800	2700	52.82
CQLS	0.75	18	33	1	8	1800	2700	48.69
CQLS	0.75	19	33	1	8	1800	2700	47.55
CQLS	0.75	20	33	1	8	1800	2700	47.42

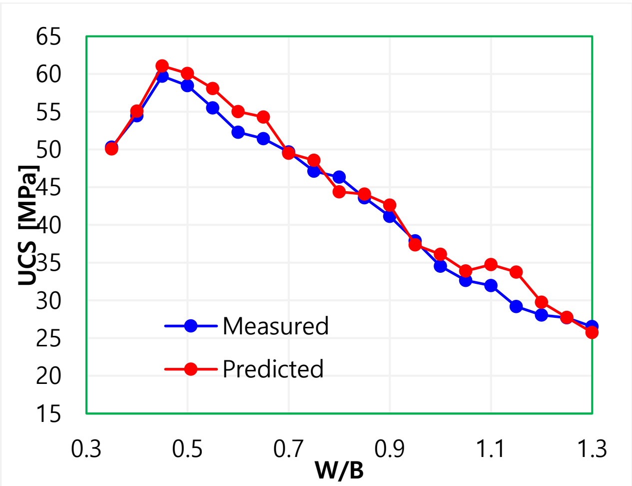

Fig. 4 Contrasting the effectiveness of the ANFIS model for soilcrete's UCS prediction by modifying the value of the W/B ratio while keeping the other parameters fixed

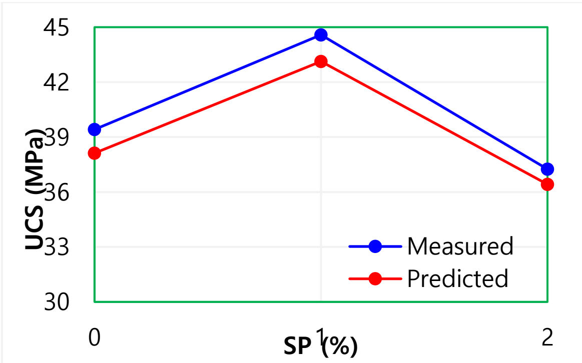

Fig. 5 Contrasting the effectiveness of the ANFIS model for soilcrete's UCS prediction by modifying the value of the SP while keeping the other parameters fixed

We now turn our attention to modulating the W/B ratio within the precise interval of 0.35 to 1.3, while maintaining all other variables invariant. For the purpose of rigorous laboratory evaluation, twenty soilcrete specimens were meticulously fabricated, adhering scrupulously to the parameters delineated in Table 5. The extensive data derived from these laboratory trials are systematically presented in the corresponding table.

These twenty datasets constituted the foundational basis for appraising the performance of the ANFIS model. The calibrated ANFIS model was subsequently employed to forecast the UCS of soilcrete utilizing this dataset. The outcomes procured from the ANFIS model were then rigorously juxtaposed with the empirical findings, yielding profound insights that are graphically elucidated in Fig. 4. The empirical investigations disclosed that augmenting the W/B ratio of soilcrete specimens from 0.35 to 0.45 engendered an increment in the UCS value from 50.31 MPa to 59.72 MPa. Conversely, with the escalation of the W/B ratio from 0.45 to 1.3, a decrement in UCS value to 26.52 MPa was observed. These results elucidate that the optimal W/B ratio for attaining maximal UCS in soilcrete specimens is 0.45.

Table 5 An assessment dataset to verify the effectiveness of the trained ANFIS model for soilcrete's UCS estimation by altering the value of the W/B ratio and maintaining other parameters constant

ST	W/B	MK (% w/w in the dry mix)	B (% w/w in the dry mix)	SP (% w/w of cementitious materials)	Sh (%)	D (kg/m^3)	UV (m/s)	UCS (MPa)
CQLS	0.35	8	33	1	8	1800	2700	50.31
CQLS	0.4	8	33	1	8	1800	2700	54.46
CQLS	0.45	8	33	1	8	1800	2700	59.72
CQLS	0.5	8	33	1	8	1800	2700	58.45
CQLS	0.55	8	33	1	8	1800	2700	55.51
CQLS	0.6	8	33	1	8	1800	2700	52.28
CQLS	0.65	8	33	1	8	1800	2700	51.43
CQLS	0.7	8	33	1	8	1800	2700	49.66
CQLS	0.75	8	33	1	8	1800	2700	47.13
CQLS	0.8	8	33	1	8	1800	2700	46.33
CQLS	0.85	8	33	1	8	1800	2700	43.60
CQLS	0.9	8	33	1	8	1800	2700	41.14
CQLS	0.95	8	33	1	8	1800	2700	37.90
CQLS	1	8	33	1	8	1800	2700	34.53
CQLS	1.05	8	33	1	8	1800	2700	32.64
CQLS	1.1	8	33	1	8	1800	2700	31.96
CQLS	1.15	8	33	1	8	1800	2700	29.19
CQLS	1.2	8	33	1	8	1800	2700	28.06
CQLS	1.25	8	33	1	8	1800	2700	27.70
CQLS	1.3	8	33	1	8	1800	2700	26.52

In light of the analysis depicted in Fig. 4, it is manifest that the ANFIS model demonstrated exceptional predictive accuracy in this phase. Its forecasts exhibited remarkable concordance with the laboratory measurements, underscoring its elevated precision. Thus, the ANFIS model once again has been corroborated as a reliable instrument for predicting UCS values in novel datasets.

In accordance with the preceding methodologies, the performance of the ANFIS model was further evaluated using three additional novel data points, wherein the SP parameter was treated as a variable (0%, 1%, 2%), while other parameters were held invariant. As the SP content in the soilcrete specimens augmented from 0% to 1%, the UCS value concomitantly increased, ascending from 39.41 MPa to 44.58 MPa. Conversely, upon further increment of the SP content from 1% to 2%, the UCS value exhibited a decrement, descending to 37.25 MPa. These findings elucidate that the optimal SP content for maximizing UCS in soilcrete specimens is 1%.

A deeper examination of the analysis, as depicted in Fig. 5, demonstrates that the ANFIS estimations exhibited a high degree of concordance with the empirical laboratory measurements, underscoring its exceptional precision. Consequently, the ANFIS model has been substantiated as a dependable instrument for predicting UCS values in novel datasets.

6. Limitations and suggestions

This investigation is constrained by several limitations that merit careful consideration, alongside valuable recommendations for prospective research to surmount these limitations:

- Future research endeavors could concentrate on amassing a more extensive dataset to bolster the robustness and reliability of the models.
- To further augment the precision and applicability of the models, it would be advantageous to investigate the incorporation of supplementary parameters or diverse combinations thereof.
- The present study predominantly centered on the performance assessment of the ANFIS algorithm. To furnish a more holistic evaluation of disparate machine learning (ML) algorithms for the prediction of the unconfined compressive strength (UCS) of soilcrete, subsequent research could broaden the comparative scope to encompass a wider array of ML models.
- For the validation of these models in real-world contexts, it is advisable for future research to apply the models to actual engineering projects and juxtapose the predicted UCS values with empirically observed values.
- The current study did not emphasize the interpretability of the ML models. Future investigations could explore methodologies that enhance the interpretability of ML models, thereby enabling engineers to discern the underlying factors that influence UCS predictions.

By addressing these limitations and integrating the proposed avenues for future research, the study can significantly advance the accuracy, reliability, and practical utility of ML models in predicting the UCS of soilcrete.

7. Conclusions

This research focused on the application of the ANFIS algorithm to predict the UCS of soilcrete. A total of 300 soilcrete specimens, crafted from two types of soil (clay and limestone) and enhanced with metakaolin as a pozzolanic additive, were meticulously prepared and tested. The dataset was divided, with 80% used for training and 20% for testing the model. Eight parameters including ST, MK content, SP content, Sh, W/B ratio, BT, UV, and D were identified as key determinants of soilcrete's UCS. Five statistical indicators were used to explore the prediction performance of the ANFIS model in the prediction of soilcrete's UCS. The salient findings of this study are as follows:

- The ANFIS algorithm delineated in this research demonstrates substantial potential in estimating the UCS of soilcrete.
- Empirical data from the laboratory experiments revealed that the optimal MK, W/B ratio, and SP content for maximizing the UCS of soilcrete specimens are approximately 11%, 0.45, and 1%, respectively. These optimal parameters were also successfully identified by the ANFIS model.
- It is imperative not to exclusively rely on the performance metrics of ML algorithms on training and test datasets, as these metrics might reflect artificially high accuracy due to phenomena such as overfitting. The generalization capability of algorithms must be evaluated using novel and unseen data to ascertain their efficacy in responding to new inputs.
- The ANFIS algorithm exhibited commendable performance in this investigation and is advocated for the estimation of UCS in soilcrete applications.

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