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Original Research Article

STRENGTH PREDICTION OF FIBER-REINFORCED CLAY SOILS STABILIZED WITH LIME USING XGBOOST MACHINE LEARNING

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Abstract

This article proposes a predictive model for the compressive strength (UCS) of lime-stabilized clay soils reinforced with polypropylene fibers (PPF) using the extreme gradient boosting (XGBoost) algorithm. The research indicates that the developed model is highly effective and can serve as a reliable tool for anticipating the UCS of these specific soils. A comparison between experimental data and model predictions suggests that it can effectively elucidate the impact of the combined effect of lime and PPF on the compressive strength of clay soils, thus avoiding the need for new experiments to formulate new compositions. Furthermore, a parametric analysis reveals the benefits of fiber incorporation, particularly at an optimum lime content of 6% dosage. The results also show that an optimal fiber content of 1.25% and a length of 18 mm are essential for achieving satisfactory results. These findings have significant implications for the planning and implementing fibre treatments, allowing for considerably enhancing soil strength. They provide a solid foundation for more precise and effective interventions in the lime stabilization of clay soils, thus paving the way for more efficient practices in this area of research.

Keywords: clayey soils, lime, polypropylene fibers, unconfined compressive strength (UCS), XGBoost algorithm

1. INTRODUCTION

Chemical stabilization involves adding binders like lime or cement to enhance the mechanical properties of fine soils [1-3]. However, excessive use of lime can make the soil brittle and cause cracks, compromising the geotechnical and environmental performance [4-6]. The addition of discrete fibers in the soil is proposed to address this issue. Introducing fibers in a random pattern promotes more uniform blending and diminishes the occurrence of weak zones, concurrently enhancing soil properties such as tensile strength, thermal conductivity, resilience, and reducing overall soil weight [1,7,8]. Polypropylene fibers (PPF) have become popular for soil reinforcement due to their high tensile strength, durability,

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and corrosion resistance [9, 10]. The incorporation of PPF creates a three-dimensional matrix, bolstering soil strength and stability while shifting its properties from brittle to ductile [10,11].This reinforcement technique not only mitigates erosion risks but also fortifies resistance against cracks, shrinkage, settlements, ensuring prolonged durability according to various sources [1,7,12-14]. Furthermore, it helps enhance shear strength and reduce the compressibility of lime-treated soil [15]. Increasing soil strength, evaluated through unconfined compressive strength, is crucial in geotechnical design to ensure safety and stability of constructions [16, 19]. Soil reinforcement with fibers improves UCS, thus enabling higher load-carrying capacity and increased stability of foundations, slopes, and retaining structures [17, 20].

The effect of fibers on the strength of stabilized clay soils is a significant area of interest in geotechnical engineering. Fibers, such as polypropylene, have been extensively studied for their ability to enhance the strength and stability of clay soils when introduced into the mixture. Several research studies have explored how adding fibers to stabilized clay soils enhances their mechanical properties, particularly the unconfined compressive strength. Findings reveal that fibers reinforce soil structure, diminish cracking, and enhance ductility, resulting in a considerable boost in soil strength overall. Furthermore, the effect of fibers on the strength of stabilized clay soils depends on several factors, including the type of fibers used, their concentration, the method of incorporation into the soil, as well as environmental conditions such as moisture and temperature. For example, studies have shown that PPF and basalt fibers are among the most effective types of fibers for enhancing the strength of stabilized clay soils. Additionally, the addition of fibers in combination with stabilizing agents such as lime or cement can result in significant improvements in soil strength. However, it is important to note that the effectiveness of fibers may vary depending on the specific characteristics of the soil and site conditions, underscoring the importance of conducting thorough studies to assess their impact before their use in engineering projects.

In this context, several studies have investigated the effects of polypropylene fibers on the UCS of the soil [1,2,4,21]. Cai et al. [2] conducted a study to examine how a blend of polypropylene fiber and lime impacted the engineering characteristics of clay soil. They prepared nine groups of treated soil samples with varying percentages of fiber and lime and subjected them to various tests. The results indicated that increasing the fiber content, lime content, and curing duration all had notable effects on the characteristics of the treated soil. Augmenting the lime content decreased swelling and shrinkage potential, albeit with a minor adverse impact strength. An increase in fiber content increased strength and shrinkage potential but decreased swelling potential. The use of lime produced a chemical reaction with the soil, while the presence of fiber contributed to physical interaction between fiber and soil. Boz et al.[23] conducted an experimental investigation to evaluate how various types of fibers impact the strength of lime-stabilized clay. Unconfined compressive strength tests were conducted on specimens that included basalt and polypropylene fibers, each with different lengths, contents, and lime concentrations. Results indicated that both basalt and polypropylene fibres enhanced the strength when used with lime, with the strength of polypropylene fibre-reinforced specimens surpassing that of basalt fibre in lime-stabilized clay. The most significant enhancement in strength resulted from the utilization of 0.75% basalt fiber measuring 19 mm in length in conjunction with lime content of 9% after a 90-day curing period. The effectiveness of incorporating fibers was influenced by the dosage of lime content. In addition, Abdi et al. [1] examined how the presence of lime and PPF impacted the compressive and shear strength (of clay samples reinforced with fibers). Kaolinite underwent treatment with 1%, 3%, and 5% lime and blended with 0.1% monovalent PPF. Subsequently, the samples underwent testing through uniaxial and triaxial compression tests after being cured at 35°C for durations of 1, 7, and 28 days. The results demonstrated that adding PPF to clay/lime mixtures increased compressive and shear strengths and ductility. The most influential factors were the lime content and the curing period. Scanning electron microscope analysis revealed that the addition of lime and cementitious compounds enhanced the interactions between soil and fibers at the interface, resulting in improved shear strength. Similarly, Akbari et al. [4] explored a new method to stabilize soft soil using lime, nano-zeolite, and polypropylene fibers. They prepared samples containing different proportions of lime, lime-nano-zeolite, and lime-nano-zeolite-fiber and exposed them to wet-dry cycles. The outcomes indicated that the sample containing 15% lime-nano-zeolite-fiber (LZF) exhibited remarkable resistance to environmental conditions and showed notable strength enhancements. Specifically, the unconfined compressive strength increased by 39% before wet-dry cycles and 16% after. These findings suggest that using the LZF modifier is an effective approach to lime-based stabilization in areas prone to wet-dry cycles. These findings suggest that employing the lime-nano-zeolite-fiber modifier effectively enhances lime-based stabilization in regions susceptible to alternating wet and dry conditions. In summary, the studies examined suggest that polypropylene fibers enhance the UCS of soil, especially when employed alongside lime. The optimal proportion of fibers and lime fluctuates based on the particular soil variety and intended purpose. Nevertheless, the research indicates that PPF are a viable option for enhancing the mechanical characteristics of soil, especially in construction applications where high strength and durability are required. In conclusion, the studies above demonstrate the importance of unconfined compressive strength in soil-based structures' design, construction, and long-term stability. However, laboratory testing often presents significant challenges in obtaining representative samples and requires substantial time and labor. In this regard, advancements in estimation techniques for evaluating soil UCS provide effective means for expeditiously and proficiently performing laboratory examinations. Therefore, it is essential to develop mathematical models that link the increase in compressive strength to the responsible variables to optimize its use and incorporate various modifications. This will simplify laboratory testing, save time, and facilitate decision-making in designing and constructing robust, long-lasting structures. In this context, this article presents a predictive model for the compression resistance of lime-stabilized clay soils reinforced with polypropylene fibers. The XGBoost algorithm, a supervised learning technique, is used to develop this model.

2. METHODS OF ESTIMATING THE UCS OF SOIL

Unconfined compressive strength plays a significant role in the design and evaluation of geotechnical structures such as embankments, foundations, and tunnels. Several previous studies have established empirical relationships to predict the UCS of soils (clay, sand, gravel), rocks, and mortars, whether they are improved or not [16-18, 20, 22-26]. In contemporary times, artificial intelligence (AI) techniques are progressively harnessed as potent instruments for predicting the UCS of soils and tackling optimization challenges within intricate geotechnical applications.

Numerous studies have indicated that various AI methodologies have been employed in soil UCS prediction. For instance, Narendra et al. [27] used artificial intelligence techniques to create a mathematical model of soil resistance development. They compared the performance of multilayer perceptron (MLP), radial basis function (RBF), genetic programming (GP), and an existing empirical model on three types of inland soils with varying water and cement content and curing periods. MLP performed the best, followed by GP, RBF, and the existing empirical model. Motamedi et al. [28] employed an adaptive neuro-fuzzy computing method, known as ANFIS, to to predict the UCS of a blend comprising pulverized fuel ash, cement, and sand. Unlike other mathematical models, the ANFIS technique was useful for estimating the strength with suitable learning and estimation abilities. The root mean square error (RMSE) for the ANFIS method was found to be 0.0617, indicating good accuracy. The study by Mozumder and Laskar[29] aimed to predict the unconfined compressive strength of geopolymer-stabilized clay soil using an artificial neural network (ANN) model. They investigated the effects of factors on UCS and tested various source materials for geo-polymerization. The study created a predictive model based on 283 stabilized samples and compared its performance with a multi-variable regression (MVR) analysis. This study found that the ANN model was more efficient than the MVR model in predicting UCS due to its flexibility and adaptability. Soleimani et al [30] developed new models using multi-gene programming (MGGP) to predict the unconfined compressive strength of geopolymer stabilized clay soils. The models included various parameters and were shown to accurately evaluate UCS through sensitivity analysis. Al-Bared et al. [31] studied marine clay treated with recycled tiles to determine its properties, including unconfined compressive strength. The team employed two hybrid intelligent systems, "neuro-swarm" and "neuro-imperialism". These systems enhanced the performance of the artificial neural network (ANN) by utilizing both particle swarm optimization (PSO) and the imperialism competitive algorithm (ICA). The best predictive model was neuro-swarm, which was more accurate in predicting UCS. Both models can be used to predict UCS values for geotechnical structure design. Saadat and Bayat [32] conducted a study involving 150 stabilized soil samples to investigate the influence of stabilizer content, curing time, and water content on unconfined compressive strength. They identified the presence of an optimal quantity for lime or cement content, with its dependency on moisture content. Additionally, the research revealed a positive correlation between curing time and UCS, while moisture content showed a negative correlation. ANFIS with fuzzy logic and non-linear regression (NLR) were utilized to predict UCS, with ANFIS being more accurate. Cement and moisture content have the most significant positive and negative impacts, respectively, on UCS values. Some other studies have also focused on predicting the unconfined compressive strength of soils using AI techniques[33-35].

In summary, predicting the strength of stabilized soil is a critical undertaking in geotechnical engineering practice. While empirical relationships are used to make predictions in the past, AI techniques are now becoming increasingly popular. Compared to empirical relationships, AI techniques provide numerous benefits, and the accuracy of predictions depends on the quality and quantity of data utilized for training the models. AI techniques offer various advantages, and the precision of predictions relies on the caliber and quantity of data employed in training the models. As a result, AI techniques are projected to enhance the accuracy of predicting the UCS of stabilized soil in the future. The scientific literature on lime-stabilized clay soils contains numerous studies on the effect of polypropylene fibers on their unconfined compressive strength. Nevertheless, proposing a predictive model for the compressive strength of lime-stabilized soils reinforced with fibers offers significant advantages in terms of mix optimization, structural safety, cost and time savings, adaptability to site conditions, technological advancements and innovation, reduced environmental impact, and standardization of construction practices.

However, despite this abundance of research, no study aims to propose a predictive model of the compressive strength of cementitious stabilized clay soils reinforced with fibers. Therefore, this article aims to fill this gap by proposing a prediction model of the compressive strength of lime-stabilized clay soils reinforced with polypropylene fibers, using the XGBoost algorithm, a supervised learning technique. To achieve this objective, the authors collected and evaluated 341 test data from 14 experimental studies available in the literature. These data were then used to train and test the proposed model.

3. SUPERVISED LEARNING TECHNIQUES

Supervised learning is a technique that utilizes labeled data to train algorithms for precise data classification or outcome prediction. During training, the model adjusts its weights by processing input data until it fits appropriately. To prevent over fitting or under fitting, the model undergoes cross-validation.

Different techniques, including neural networks, naive Bayes, linear regression, logistic regression, random forest, the XGBoost Algorithm, the support vector machine (SVM), and more, are frequently utilized in supervised learning [36,37].

In 2016, Chen and Guestrin introduced the XGBoost algorithm, utilizing the gradient boosting decision trees (GBDT) framework, which has gained widespread recognition due to its exceptional performance in Kaggle's ML competitions [37]. Unlike GBDT, XGBoost incorporates a regularization term in its objective function to prevent overfitting. The primary objective function can be defined as follows:

$$O = \sum_{i=1}^{n} L\big(y_i, F(x_i)\big) + \sum_{k=1}^{t} R(f_k) + C \tag{3.1}$$

The regularization term at iteration k is denoted by $R(f_k)$, where C is a constant that can be selectively removed and $L\big(y_i, F(x_i)\big)$ represents the loss function, quantifying the error between the actual value y_i and the model prediction $F(x_i)$ for the i-th example. The expression for the regularization term $R(f_k)$ is given as:

$$R(f_k) = \alpha H + \frac{1}{2}\eta \sum_{j=1}^{H} \omega_j^2 \tag{3.2}$$

Where α is the complexity of leaves, H represents the number of leaves, η is the penalty variable, and ω_j indicates the output results for each leaf node. Leaves denote the expected categories based on the classification criteria, while the leaf node refers to the unsplit tree node. In contrast to GBDT, XGBoost utilizes a second-order Taylor series of primary functions rather than the first-order derivative. When the mean square error (MSE) is used as the loss function, the primary function can be expressed as follows:

$$O = \sum_{i=1}^{n} \left[p_i \omega_{q(x_i)} + \frac{1}{2}\left(q_i \omega_{q(x_i)}^2\right)\right] + \alpha H + \frac{1}{2}\eta \sum_{j=1}^{H} \omega_j^2 \tag{3.3}$$

The function $q(x_i)$ maps data points to leaves and the total loss value is obtained by summing up all the individual loss values. Since each sample in the decision tree (DT) corresponds to a node that is a leaf, the overall loss value can be computed by aggregating the loss values of all the leaf nodes. Consequently, the primary function can be expressed as follows: The function $q(x_i)$ maps data points to leaves and the total loss value is obtained by summing up all the individual loss values.

Since each sample in the DT corresponds to a node that is a leaf, the overall loss value can be computed by aggregating the loss values of all the leaf nodes. Consequently, the primary function can be expressed as follows:

$$O = \sum_{j=1}^{T} \left[P_j \omega_j + \frac{1}{2}\left(Q_j + \eta\right)\omega_j^2\right] + \alpha H \tag{3.4}$$

wherePj $= \Sigma_{i \epsilon I_j} p_i$, Qj $= \Sigma_{i \epsilon I_j} q_{i,}$ and Ij are the total number of samples in leaf node j.

In summary, identifying the minimum of a quadratic function is the key to optimizing the main function. XGBoost's ability to prevent overfitting is enhanced by including regularization techniques. Figure 1 displays the structure of XGBoost [37].

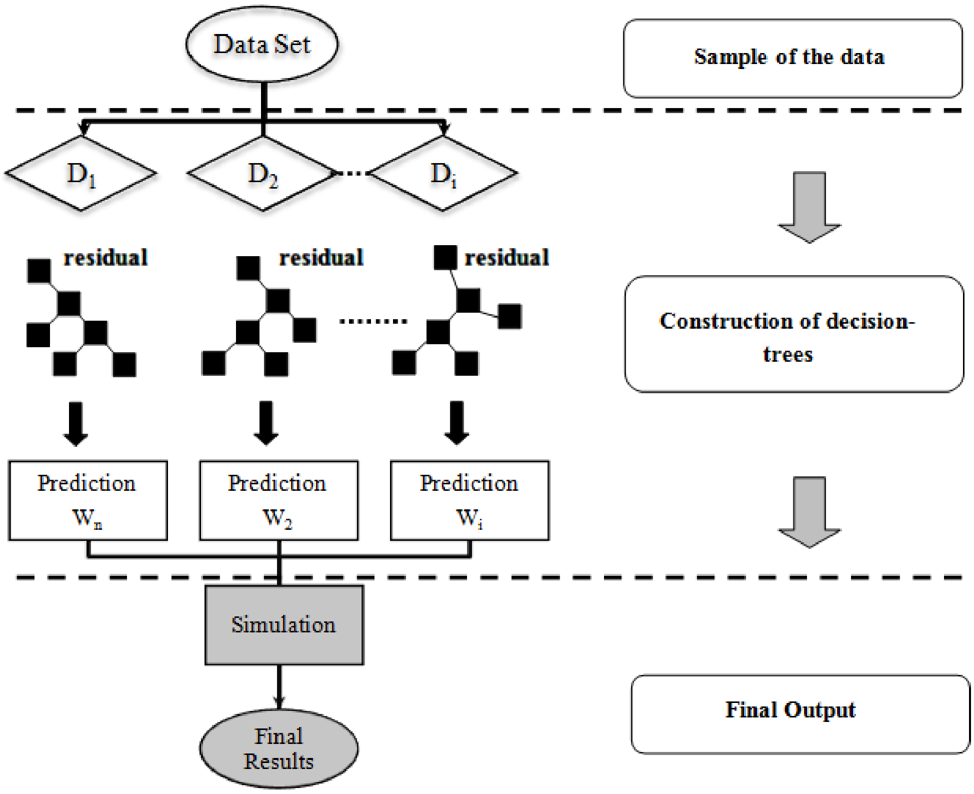

Fig. 1. Architecture of the XGBoost Algorithm [37]

4. EVALUATION OF PREDICTION ACCURACY

The model's ability to predict accurately was evaluated through the use of different assessment metrics, including the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE), and mean absolute percentage error (MAPE) on both the training and independent test sets[11]. These metrics help to determine theeffectiveness of the model's predictive power and its ability to accurately predict outcomes. The evaluation results can provide valuable insights into the model's strengths and limitations, helping to improve its performance. The degree to which a statistical model can predict an outcome, represented by the model's dependent variable, is measured by the coefficient of determination (R^2). This parameter is given by equations (4.1-4.4) as follows:

$$R^2 = \left(\frac{\sum_{i=1}^{n} (x_i - \bar{x})\,(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}} \right)^2 \tag{4.1}$$

The MAE unit, denoting the average absolute deviation between predicted and actual values, is congruent to the measurement unit:

$$MAE = \frac{\sum_{i=1}^{n}|x_i - y_i|}{n} \tag{4.2}$$

The accuracy of a prediction model can also be determined by the extent of errors' spread, which is referred to as the Mean Squared Error (MSE), as shown in the following equation:

$$MSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \tag{4.3}$$

The MAPE index is commonly utilized for assessing the precision of prediction models, whereby a lower value signifies better prediction results. A MAPE value of less than 10% indicates that the model is highly effective and accurate in its performance.

$$MAPE = \frac{1}{n}\left(\sum_{i=1}^{n}\left|\frac{x_i - y_i}{x_i}\right| \times 100\right) \tag{4.4}$$

5. DATABASE

Several researchers have highlighted the benefits of integrating lime stabilization and polypropylene fiber reinforcement techniques for soil stabilization. These advantages encompass enhancements in clayey soil properties, heightened durability, cost-effectiveness, and environmental advantages [1,2]. In this context, this study collected high quality data regarding unconfined compressive strength tests conducted on lime-stabilized clayey soils reinforced with polypropylene fibers. The data used in this study was sourced from the literature from 2003 to 2021[1, 2, 4, 9, 21, 38-46].This data collection step is significant as it aims to create a relevant database. Several parameters were considered during this phase, including soil classification and the types of lime and fibers used. In this context, numerous data points were extracted from previous research. However, only data related to soils classified as having high or medium plasticity and stabilized with either hydrated lime ($Ca(OH)_2$) or quicklime (CaO), while being reinforced with polypropylene fibers, were included in this study to form the database.

Furthermore, most UCS test results were obtained following the guidelines outlined by ASTM. D2166 standards (72%), it is also worth noting that the soils considered in this study as part of the database were reinforced by adding polypropylene fibers combined with either hydrated lime (57%) or quicklime (43%). After taking into account the significant factors that affect the unconfined compressive strength of reinforced soils, as reported in the literature [2, 21, 39].Table 1 presents the parameters analyzed in this study. The table provides a thorough overview of the topic, incorporating a compiled database of 341 test results from stabilized clay soils reinforced with PPF. Several researchers have reported that the unconfined compressive strength of fiber-reinforced lime-stabilized clay soils is influenced by several factors, including the percentages of fiber and lime and the curing time [1,2,4, 9].The addition of fibers and lime can improve the strength of clay soils, while longer curing times can result in further strength development [47].However, the optimal fiber and lime percentages and curing time may vary depending on the soil's specific characteristics and the stabilized soil's intended application. Careful consideration and testing are necessary to determine the most suitable combination of these factors for achieving the desired strength and durability of the stabilized soil. Figure 2 displays scatter plots representing the distributions of the selected variables in the UCS-model.

Table 1. Database Compiled from Experiments on Lime-Treated Clayey Soils, Including Fiber Reinforcement

References (Years)	Data points	Fiber parameters		Lime parameters	Time parameters	Soil parameters			
		Lf(mm)	*Xf(%)*	*Lc(%)*	*t (days)*	*LL(%)*	*PI(%)*	*Class*	*UCS(kPa)*
[**38**] (2003)	28	19.0	0.15-0.3	8.0	3.0-14.0	69.0-70.6	41.4-45.0	CH	140.0-1560.0
[2](2006)	32	12.0	0.05-0.25	2.0-8.0	7.0-28.0	34.5	17.6	CL	90.0-880.0
[39] (2013)	5	12.0	0.28-0.8	2.0-8.0	28.0	95.1	43.2	CH	210.0-740.0
[40](2015)	19	12.0	0.0-1.0	0.0-9.0	0.0-28.0	76.0	50.0	CH	111.2-1412.1
[41] (2017)	14	6.0-12.0	0.0-0.6	0.0-6.0	28.0	66.0	34.0	CH	598.1-1810.5
[9](2018)	6	12.0	0.5-1.0	0.0-3.0	28.0	56.0	26.0	CH	74.0-550.0
[21](2018)	102	6.0-19.0	0.0-1.0	0.0-3.0	1.0-90.0	56.0	26.0	CH	97.0-1174.9
[42](2018)	15	7.0	0.5	9.0	0.0-120.0	50.0	21.2	CH-CL	163.4-304.0
[43](2018)	26	6.0-31.0	0.1-0.3	8.0	28.0	32.6	15.8	CL	149.0-362.3
[44](2019)	26	6.0	0.0-2.0	0.0-9.0	7.0-28.0	316.2	266.0	CH	238.4-1427.3
[1] (2021)	19	6.0	0.0-0.1	1.0-5.0	1.0-28.0	51.0	25.0	CH	188.3-1161.0
[4] (2021)	5	12.0	1.0	5.0-10.0	28.0	39.4	20.1	CL	188.0-2078.1
[45] (2021)	19	6.0-12.0	0.2-0.6	6.0	60.0-360.0	66.0	34.0	CH	598.1-3171.0
[46] (2021)	25	10.0	0.0-2.0	2.5-10.0	60.0-360.0	51.0	33.0	CH	139.7-553.7
Total	**341**								

The dataset contains six variables: lime content (Lc), fiber content (*X*f), fiber length (Lf), curing time (t), unconfined compressive strength of untreated soil (UCS_0), and improved soil unconfined compressive strength (UCS). Lc, Lf, *X*f, t, and UCS are categorical variables, while UCS_0 is a continuous variable. The scatter histograms provide a visual representation of the distribution for each variable. The lime content ranges from 0 to 10%, with most values falling between 5 and 10%. The fiber content is a categorical variable with varying frequencies, showing a right-skewed trend. Values between 0 and 0.4% have higher frequencies compared to other values. The fiber length ranges from 0 to 31 mm, with the most common lengths being 6 and 12 mm. Curing time is an important categorical variable, with values ranging from 0 to 360 days. The 28-day value has a higher frequency compared to others. UCS_0 is a continuous variable ranging from 74 to 598.1 kPa, with the majority falling between 100 and 250 kPa. UCS, the improved soil unconfined compressive strength, ranges from 74 to 3171 kPa and shows a right-skewed distribution. Most values are located between 200 and 800 kPa.

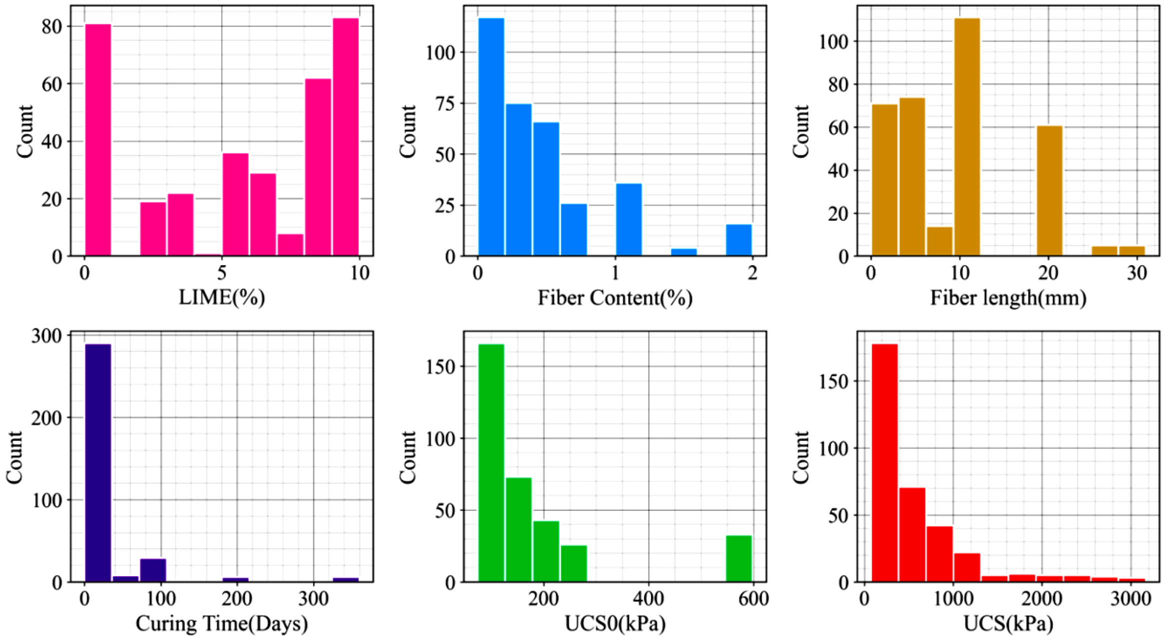

Fig. 2. Data distribution

In summary, the analyzed data consist of a combination of categorical and continuous variables. Each variable has a distinct distribution, emphasizing the diversity of the data and the importance of considering these variations when interpreting the results. Table 2 summarises the input and output parameters considered in constructing the model.

Table 2. Overview of Parameters Examined in This Study

Type of variable	Category	Parameter	Minimum	Maximum
Input variable	Fiber	Fiber length *Lf (mm)*	6.0	31.0
		Fiber content *Xf(%)*	0.0	2.0
	Lime	Lime content *Lc (%)*	0.0	10.0
	Time	Curing time *t (days)*	0.0	360.0
	Soil	Unconfined compressive strength of natural soil UCS_0 *(kPa)*	74.0	598.1
Output variable	lime stabilized fiber-reinforced soil strength	Unconfined compressive strength of lime stabilized fiber-reinforced soil *UCS (kPa)*	74.0	3171.0

6. DEVELOPMENT OF UCS-MODEL

To assess the impact of each parameter on UCS, we created a correlation matrix (Fig. 3). The correlation matrix shows the pairwise correlations between all variables. The correlation coefficient (r) spans from

-1 to 1. A positive figure signifies a positive correlation, whereas a negative figure signifies a negative correlation. A value of 0 signifies the absence of correlation. Here are some observations from the correlation matrix: The variable UCS which represents the unconfined compressive strength of the improved soils is highly correlated with the variables UCS_0 and t which represent the strength of the natural soil (r=0.70) and the curing time (r=0.63) respectively. Lime content has a moderate positive correlation with UCS (correlation coefficient of 0.29). There is no strong linear correlation between UCS and the other variables. Figure 3 presents the model's performance analysis results on the training dataset. The statistical indicators of the model show that it achieves a high level of accuracy in predicting the unconfined compressive strength of stabilized and reinforced clayey soils with PPF. It is worth noting that these statistical measures play a crucial role in evaluating the developed model, as they offer valuable insights into prediction accuracy and precision, thereby aiding decision-making processes.

Figure 4 shows the performance of the proposed model on the training dataset. The R^2 score of 0.97 implies that the model accounts for 97% of the variance in UCS. The MAE (Mean Absolute Error) of 46.59 indicates that, on average, the model predictions are shifted by 46.59 (kPa). The RMSE (Root Mean Square Error) of 92.71 suggests that the model predictions have an average deviation of 92.71 (kPa) from the true values. Finally, the MAPE (Mean Absolute Percentage Error) of 9.34 indicates that, on average, the model predictions have a relative error of 9.34% compared to the true values of UCS. These indicators suggest that the model has good performance and is likely to provide accurate predictions. A similar analysis has been developed for the test set (Fig. 5) . The R^2 value signifies a robust correlation between the predicted and observed values, with the model accounting for 91% of the data's variability. The MAE and RMSE values show that the predicted values are on average 95.44 and 155.16 kPa off from the actual values, respectively. The MAPE value indicates that the average percentage difference between the predicted and actual values is 22.45%.

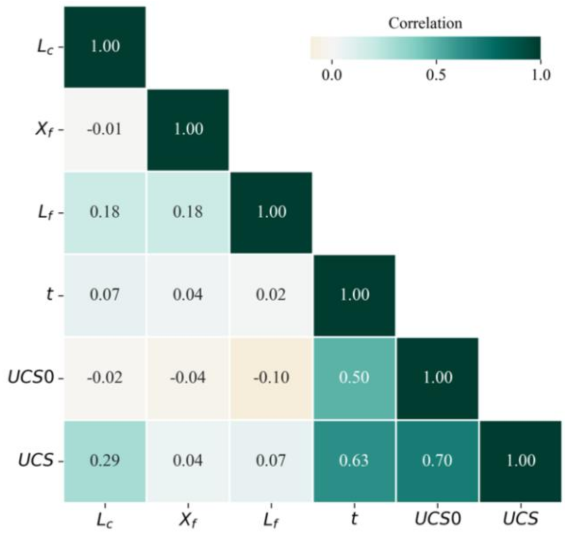

Fig. 3.Correlation matrix of UCS

The plot depicting the comparison of UCS predicted values to the actual values reveals a robust

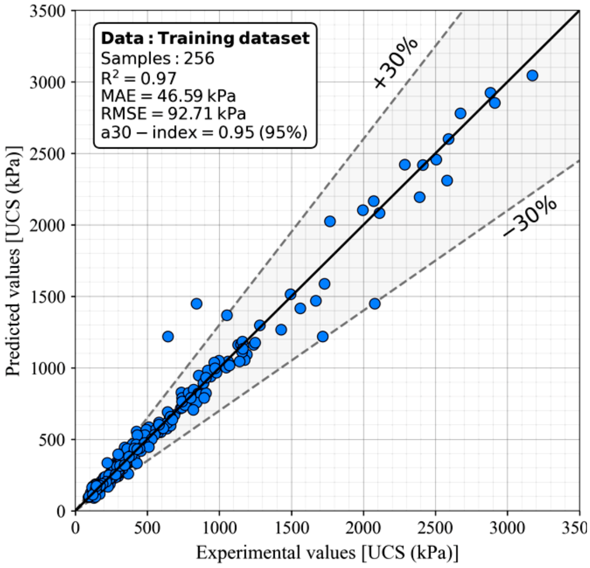

Fig. 4. Model performance for the training set

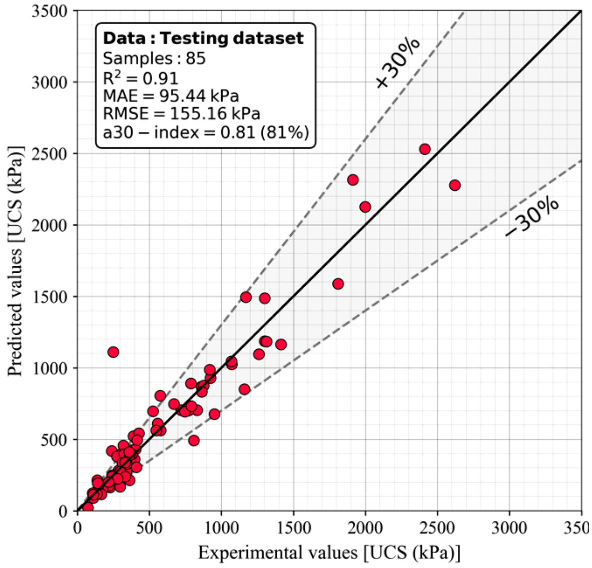

Fig. 5. Model performance for the test set

linear correlation, with most predicted values closely aligning with the diagonal line, signifying a strong agreement between the predicted and actual values. The graphical representations of the training and test data comparisons are presented in Figures 6 and 7, respectively. These figures unequivocally showcase the exceptional accuracy achieved by the UCS model developed in this study

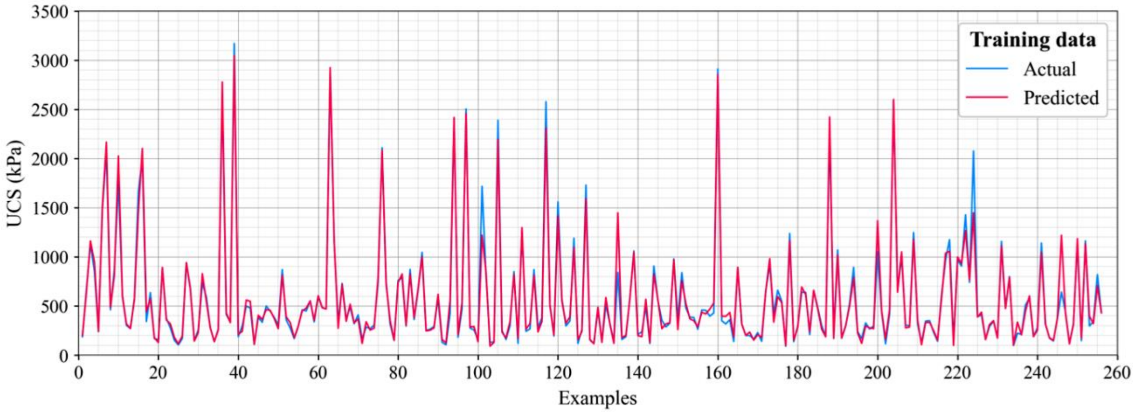

Fig. 6.Train predictions vs actual training data

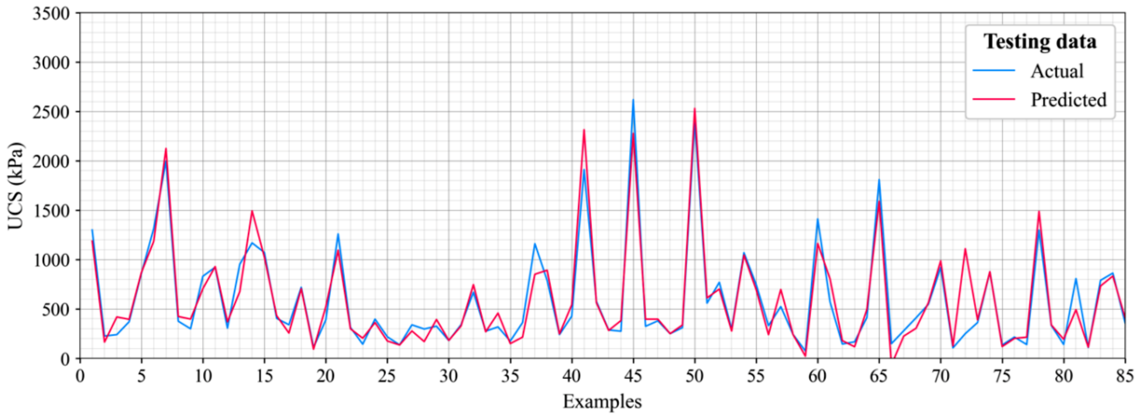

Fig. 7. Test predictions vs actual test data

7. PARAMETRIC STUDY

This section aims to evaluate how well a created model performs in predicting the UCS of lime-stabilized clay soilsreinforced with fibers. Moreover, the research examines how various input parameters impact this characteristic. To accomplish this, the model's predicted values are juxtaposed with a range of previously published UCS data for these soils.Additionally, a parametric analysis is conducted to verify whether the model can accurately evaluate the impact of lime and Polypropylene fiber on the UCS of improved clayey soils.

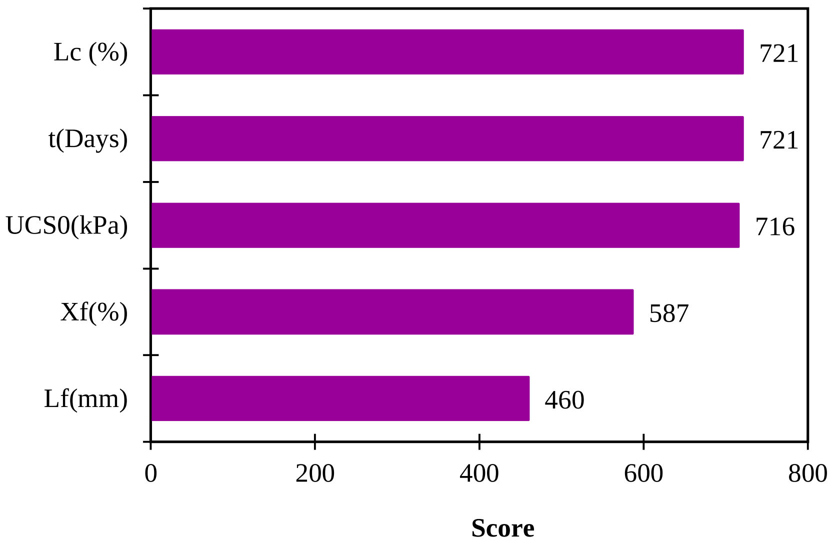

Fig. 8. Feature importance

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Figure 8 illustrates the analysis of the prediction model for unconfined compressive strength of clayey soils stabilized with lime and reinforced with polypropylene fibers. The scores assigned to the features indicate their influence on the prediction. Several characteristics are evaluated: fiber length (Lf), fiber content (xf), natural soil strength (UCS_0), curing duration (t), and lime content (Lc). The results show that natural soil strength, curing time, lime content, and, notably, fiber content significantly impact the strength prediction, yielding high scores.

The fiber content might show low linear correlation with UCS (as shown in Figure 3) but high feature importance (score = 587), (as shown in Figure 8) due to its ability to capture non-linear relationships, interactions with other variables, local importance variations, feature engineering effects, and regularization effects that linear correlation cannot detect, which XGBoost algorithm can identify.

Fiber length also has a significant impact, albeit less pronounced than the other factors. This assessment reveals that the initial soil strength, curing time, lime and fiber quantities are the predominant elements in strength prediction, providing crucial insights for optimizing the soil stabilization.

The results obtained by plotting the results provided by the proposed model are shown in Figure 9 in relation to the curing time for UCS gain. Parametric analysis was based on a natural soil's UCS_0 value of 200 (kPa) and curing time (1, 7, 14, and 28 days), with lime taken at 1%, 3%, 6%, and 9%. For fibers, theoretical values were taken equal to 0%. Figure 9 demonstrates that UCS of clayey soils experiences an increase as the lime percentage and curing time rise.

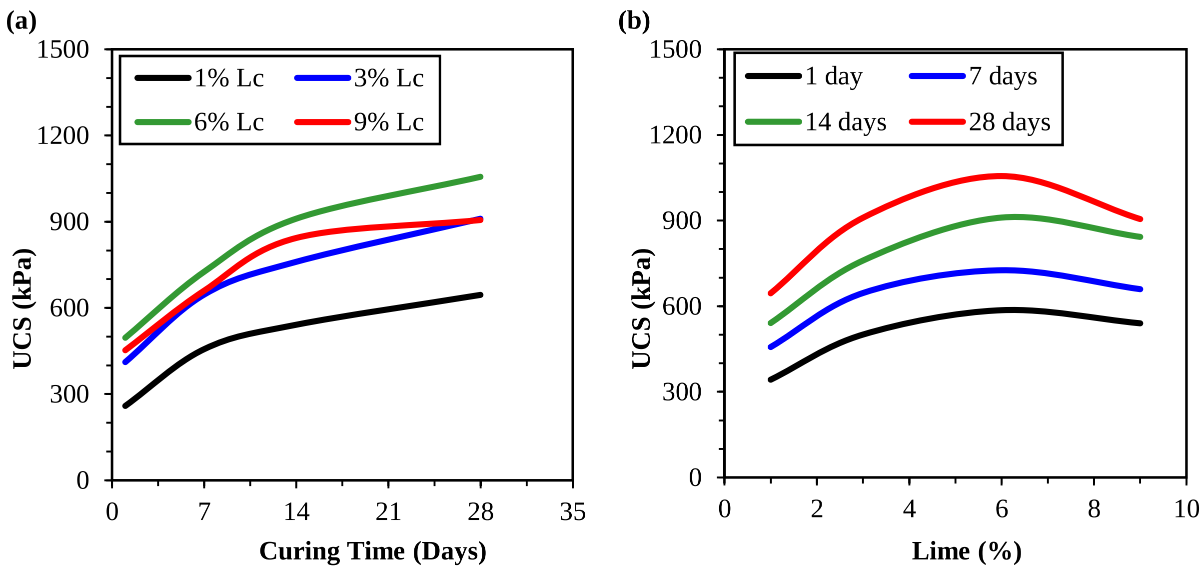

Fig. 9.Influence of lime on the UCS of stabilized clayey soils at various curing durations:
(a) Influence of Curing Duration (b) Impact of Lime Content

This trend is evident because the UCS values increase as the lime percentage increases for a given curing time [48, 49]. Likewise, with a fixed lime percentage, the UCS values rise as the curing time extends. For example, for 7 days curing time, the UCS–model anticipates a 263% augmentation in the UCS value with 6% lime (as shown in Figure 9). Conversely, with a 28-day curing period, the UCS–model predicts substantial increases in UCS values: 222% for 1% lime, 355% for 3% lime, and 428% for 6% lime, as illustrated in Figure 9. When comparing, it becomes evident that the strength gain attributed to lime addition is notably less than that attributable to the curing time in all instances. Notably, the highest strength for all lime concentration levels is consistently observed with longer curing durations. This is because lime serves as a stabilizing agent that enhances the engineering characteristics of soils by boosting their strength and diminishing their compressibility [20, 50, 51].Etim et al. [52] pointed out that the rise in UCS values mainly resulted from alterations in the microstructure and the

creation of cementitious compounds: calcium silicate hydrate (C–S–H) and calcium aluminate hydrate (C–A–H) due to pozzolanic reactions [53], which play a crucial role in strength development, particularly throughout the curing period.
Additionally, the curing time permits the lime and clay particles to engage in chemical reactions, leading to the enhanced soil consolidation.

Therefore, the results indicate that utilizing lime as a stabilizing agent in clay-rich soils can notably enhance their strength, and the duration of the curing process is a crucial element that should be taken into account in soil stabilization endeavors. The UCS of clayey soil can potentially be influenced when lime is added, a common practice in soil stabilization. Lime works by raising the pH level of the soil, leading to improvements in the soil's engineering properties, including its strength [54, 55]. Several researchers have reported similar findings when comparing their experimental data to the predicted values from the UCS model. For instance, Dunlap et al. [56].noted that the UCS of clayey soil increased significantly from 202 to 842 kPa after 7 days of curing with 6% lime, and it further increased to 1045 kPa after 28 days of curing. This represents a remarkable increase of 261% and 418% in UCS with the same lime content over the respective curing periods. Additionally, Saride et al. [57] noticed that, following 28 days of curing, the UCS of clayey soil rose from 205 to 900 kPa when treated with 3% lime, while Lockett and Moore [58] found an increase from 200 to 1070 kPa with 6% lime. These findings indicate a significant boost in UCS values of 339% and 435%, respectively, for 3% and 6% lime content. Several other researchers[55, 59-62], have consistently reported this trend. Figure 9 also illustrates that the resistance of soils treated with lime tends to rise until it peaks at a lime content of 6%. Afterward, it declines as the lime content continues to increase. This suggests that there is an optimal lime content associated with the highest strength for various curing durations. Similar obervations have been made by other researchers [59, 63, 64].

Figure 10 illustrates the impact of polypropylene fibers (PPF) on the compressive strength of lime-stabilized clay soils, showcasing the proposed model's analysis results. The parametric analysis is based on an initial value of the UCS_0 (unconfined compressive strength of the natural soil) of 200 kPa, with a curing time of 28 days and a lime content of 6%. As for the PPF, theoretical rates of 0.25%, 0.75%, 1.25%, and 1.75% were considered, as well as equivalent fiber lengths of 6 mm, 12 mm, 18 mm, and 24 mm. Figure 10 highlights that the unconfined compressive strength of clay soils increases proportionally with the increase in percentage and length of fibers. Considering a 28-day treatment period and a lime concentration of 6%, the UCS model anticipates a 428% increase in the UCS value for the soil unreinforced by PPF (see Figure 10). In contrast, when reinforced with a 1.25% percentage of 18mm long fibers, and with the same treatment duration and lime concentration, the UCS model predicts a 579% increase in strength, as shown in Figure 10. Comparing these data, it becomes evident that the beneficial effect of adding fibers to the strength is exceptional. Several researchers have reported similar findings when comparing their experimental data to the predicted values from the UCS model [2, 37, 41, 43, 65]. Figure 10 also reveals information regarding lime-treated soils and their strength as a function of fiber content. Firstly, it is clear that this strength progressively increases until it reaches a peak when the fiber proportion reaches 1.25%, as illustrated in Figure 10-a. However, beyond this point, the strength decreases as the fiber concentration increases. This observation highlights optimal fiber content, corresponding to maximum strength in lime-treated reinforced soil. Furthermore, Figure 10-b also informs us about the significance of the optimal fiber length, established at 18 mm. These results are of great significance to effectively guide the planning and implementation of fiber treatments, to optimize soil strength improvement.

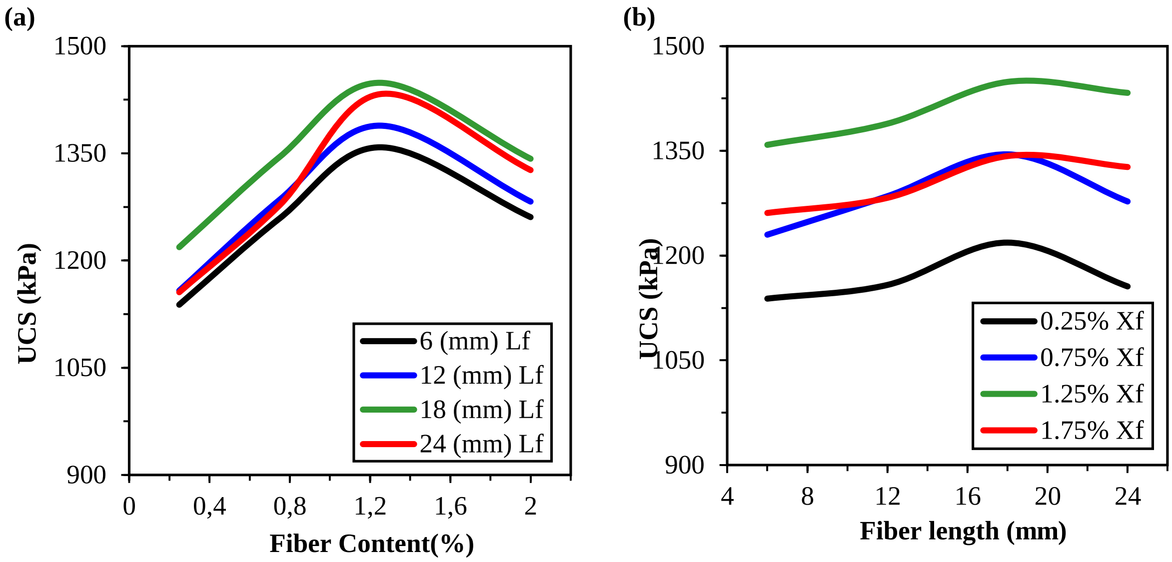

Fig. 10. Effect of PPF fibers on UCS of lime-stabilized clayey soils:
Influence of (a) fiber content (b) fiber lenght

Adding lime to clayey soil reinforced with fibers has proven to be an effective method for increasing its unconfined compression strength, provided that the appropriate proportions are adhered to. This improvement arises from a specific chemical reaction between lime and the clay minerals present in the soil [9]. This reaction is not instantaneous but rather a long-term process. The strength of the stabilized soil increases with the curing duration [2, 21]. However, it is crucial to note that there is a close relationship between the amount of lime to be used and the clay content of the soil. The existing literature indicates that this quantity should not exceed the optimal content (6% in the present study) [2,48,49,66]. An excess of lime could lead to undesirable reactions without significant improvements in the strength of the clayey soil [2]. Other researchers suggested that this phenomenon is mainly due to the additional water needed to achieve the optimal water content of the soil with a higher lime content. Adding lime to the soil requires a certain amount of water to activate its chemical properties, but a higher lime content may require even more water. Excess water could then excessively saturate the soil, thereby compromising its stability and strength [67].

This chemical reaction between lime and the soil also plays a crucial role in creating a stronger interface between the fibers and the composite material, enhancing their mutual adhesion. However, the success of this method relies on maintaining the appropriate proportions. The complex interaction between fibers, soil, lime, and by-products is critical for soil consolidation, governing the displacement and deformation of clay particles while significantly improving the mixture's strength [21]. Increasing the quantity of fibers enhances the strength of the stabilized soil by increasing the contact surface area between the fibers and soil particles, promoting increased friction that reinforces resistance to applied forces.

Furthermore, fibers play a major role in preventing the formation of cracks, thereby improving the toughness of the stabilized soil. However, it is essential not to exceed the optimal quantity of fibers, as this could lead to their agglomeration, limiting their effectiveness [2].The length of the fibers is also a crucial factor. Short fibers promote the development of secondary stresses that cause the sliding of surrounding soil particles. In contrast, using long fibers can reduce the tensile, flexural, and torsional strength of the fibers themselves [21].In conclusion, soil reinforcement by adding fibers and lime holds significant potential in civil engineering. However, it is imperative to have a deep understanding of the interactions between the components to optimize performance in various applications.

8. CONCLUSION

This work proposes a predictive model for the unconfined compressive strength of lime-stabilized clay soils reinforced with polypropylene fibers (PPF). The following conclusions are drawn from the study:

- The proposed UCS model successfully underwent training and testing process, making it suitable for evaluating the UCS of lime-stabilized clay soils reinforced with PPF.
- The results demonstrated that the statistical analysis of geotechnical data can be an appropriate approach for developing new statistical models to deepen our understanding of the behavior of problematic soils.
- The comparison between experimental data and predictions suggests that the developed model can be effectively used to understand the influence of the combination of lime and polypropylene fibers on the unconfined compressive strength of clay soils. It also allows for formulating new compositions without the need for additional experiments.
- The parametric study conducted by analyzing the results from the proposed model reveals the positive effect of fiber incorporation on the strength of lime-stabilized clay soils. This improvement is particularly significant when the lime content reaches an optimum of 6%.
- The obtained data also indicate an optimal fiber content of 1.25%. Going further, we discover that the optimal fiber length, established at 18 mm, plays a crucial role in achieving satisfactory results.
- These conclusions are highly relevant for effectively guiding the planning and implementation of fiber treatments, enabling significant optimization of soil strength. They provide a solid foundation for more precise and efficient interventions in lime stabilization of clay soils.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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