Prediction of Unconfined Compressive Strength in Stabilized Clay Soil Using Artificial Neural Networks

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Abstract. Expansive clay is a problematic type of soil because it has large shrinkage properties. One action that can be taken to improve problematic soil is to stabilize it with additives such as lime, cement, RHA, fly ash, and GGBS. The results of stabilization using additives like this can increase the strength value of clay soil. Artificial Neural Networks (ANN) have been introduced in the geotechnical field to predict different soil properties. This research develops an artificial neural networks model to predict the Unconfined Compressive Strength (UCS) value of soil that has been stabilized, this is because the artificial neural networks model can show superior prediction results due to its flexibility and adaptability in generating data. The amount of data in this test was 420 and was divided into 336 training data and 84 testing data. In carrying out the training phase, 13 inputs were used in the form of granulometric test results, and in the testing phase, data from soil-free compression tests in the laboratory were used. The result of this research is that the use of the artificial neural networks model can predict the soil unconfined compressive strength value accurately because it gets a coefficient of determination value of 0.99229 which is almost close to number one. **Keywords.** Unconfined compressive strength, Prediction, Artificial neural networks, Stabilization

1 Introduction

Expansive clay soil is a problematic type of soil because it has large shrinkage properties. When soil is wetted and dried, it expands and shrinks, causing major damage to the structures built on it. When expansive soil is moistened and drained, the magnitude of swelling and shrinkage results in uneven deformation [1]. One of the actions that can be taken to improve problematic soils is to make modifications through stabilization of the soil to produce new materials that can meet the requirements [2]. Some researchers have developed various

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stabilization methods to reduce the effects of swelling. The stabilization method is in the form of chemical and mechanical stabilization. Chemical stabilization involves adding additives to the soil, such as fly ash, cement, and lime. So that the material produces a chemical reaction that can reduce swelling [3].

Research has been conducted by several researchers by mixing additives into expansive soil, among others, in cement [4]-[5] stabilization of expansive clay soil using cement experienced a very significant reduction in swelling pressure, in lime [5] and [6] increasing the amount of lime in expansive soil can increase soil strength significantly, in fly ash [7]-[8] adding fly ash to organic soil led to a decrease in Maximum Dry Density (MDD) and an increase in Optimum Moisture Content (OMC). Specimens treated with geopolymer showed a substantial increase in soil strength along with increasing fly ash content in the geopolymer, as well as on Ground Granulate Blast-furnace Slag (GGBS) [9]-[10] the use of GGBS in expansive soil stabilization reduces expansion by reducing the plasticity value and increasing the mechanical properties, which are mostly effective in increasing soil strength and reducing swelling.

The strength and stability of clay soil volume increases with the increase of calcium-containing chemical stabilizers. The proportion of stabilizers, clay mineralogy, soil type, soil matrix pH, pickling time, pickling temperature and the presence of harmful compounds (such as sulfates and organic matter) are factors affecting the stabilization process [2]. To assess the effect of various stabilizers on soil behavior, it is usually necessary to conduct experimental investigations that take a long time. Therefore, [11] introduced intelligence-based methods such as neural networks or supporting vector machines that can be used to measure soil strength and stiffness, namely Adaptive Neuro Fuzzy Inference System (ANFIS) and artificial neural networks methods. Both methods can be used to predict the unconfined compressive strength of compacted soil based on the results of a single test, such as granulometry, without requiring additional testing on the soil. [12] have predicted maximum dry density values and unconfined compressive strength values with the Multivariate Adaptive Regression Splines (MARS) model. [13] it suggests that Artificial Neural Networks (ANNs) perform better in estimating unconfined compressive strength than traditional regression models or statistical models. This is due to its adaptability and flexibility in generalizing data. Cement stabilized soil maximum dry density and unconfined compressive strength values can be predicted with effective artificial neural networks and Support Vector Machine (SVM) models using inputs such as cement content, moisture content, grain size, and soil plasticity [14].

The main objective of this study is to create an inference model to predict the unconfined compressive strength of soil that has been stabilized with various types of stabilizers and assess the performance of the artificial neural networks model in predicting soil unconfined compressive strength based on the composition of its stabilizers such as cement, lime, fly ash, ground granulate blast-furnace slag and Rice Husk Ash (RHA). The study utilized an artificial neural networks-based unconfined compressive strength predictive model due to its superior predictive efficacy and adaptability in data generation. Based on laboratory testing conducted by [15], [16], [17] the test result data is used for training and testing. The granulometry test produces data in the form of input while the soil unconfined compressive strength produces output data. The expected result of this research is accuracy in predicting the unconfined compressive strength value against the unconfined compressive strength value from laboratory testing using the artificial neural networks method. So that this artificial neural networks method can be used to predict much larger datasets.

2 Materials and methods

2.1 Testing materials

Using the data base from previous studies, this study tested two types of soil originating from the Matang Kerat Telunjuk and Nibong Tebal areas in Malaysia, namely silty sand (SM) and high plasticity silt (MH) [16], with soil properties that have been tested based on American Standar Testing Material (ASTM) guidelines, as well as three types of soil originating from the city of Silchar in India, namely inorganic clays of high plasticity (CH) and inorganic clays of low to medium plasticity (CL) [17], all three soil properties are tested against the guidelines of the Indian standard code of practice.

In this study, hydrated lime high in calcium (Ca (OH)2), regular Portland cement and 90% silica-containing rice husk ash were used which shows the exact pozzolan characteristics of this type of additive. Sodium Hydroxide and Sodium Silicate were combined in this study to produce variations in several test variables. The sodium silicate used has a specific gravity of 1.5 and a purity of 97% and a molecular weight of 212.

2.2 Database

Soft commutation techniques such as Artificial Neural Networks (ANN) are utilized to maintain the strength of stabilized soil specimens under diverse conditions. A total of 420 soil specimens underwent unconfined compressive strength testing to provide the data needed to predict stabilized soil unconfined compressive strength values. A total of 336 were used for training data which was 80% of the total specimens used and 84 specimens were testing data, which is 20% of the total data. Some examples of training data used in this study are shown in Table 1 and examples of test data can be seen in Table 2.

Table 1. Training data example

No	1	2	3	4	5
Type soil	SM1	SM2	SM3	MH	SM
LL	116	82.2	38	0	0
PI	88.46	56.46	14.07	0	0
ɤd	0	0	0	14	17
%S	25	50	4	0	0
%FA	0	0	8	0	0
C%	0	0	0	3.75	2.50
L%	0	0	0	7.50	5
R%	0	0	0	3.75	2.50
M	12	12	4	0	0
A/B	0.45	0.45	0.45	0	0
Na/Al	0.93	0.93	0.39	0	0
Si/Al	1.49	1.49	1.49	0	0
Curing time	28	28	28	60	7
UCS (MPa)	5012	18530	30.1	482	1300

Table 2. Test data example

No	**1**	**2**	**3**	**4**	**5**
Type soil	SM1	SM2	SM3	MH	SM
LL	116	82.2	38	0	0
PI	88.46	56.46	14.07	0	0
ɤd	0	0	0	13	17
%S	16	50	0	0	0
%FA	0	0	8	0	0
C%	0	0	0	2.5	1.25
L%	0	0	0	5	2.5
R%	0	0	0	2.5	1.25
M	12	12	12	0	0
A/B	0.45	0.45	0.85	0	0
Na/Al	0.93	0.93	1.55	0	0
Si/Al	1.49	1.49	2.49	0	0
Curing time	28	28	28	60	7
UCS (MPa)	1519.8	18.53	155.5	249	879

2.3 ANN model

Deep learning involves training a neural network to match input and output to minimize the difference between predicted values and outputs that are known to be true. In this case it often requires large data sets that are prosessed manually and can be subject to various errors. Important parameters in neural networks include hidden layers, neurons, training points, activation function selection, and minimization algorithm choice [18]. Artificial neural network (ANN) is a processing system where a neuron is the fundamental processing element. It consists of a large number of nodes connected by links, performing simple operations on data. The output at each node is known as its activation or node value. Feedforward and feedback are two types of artificial neural networks topologies [15].

Test data is divided randomly into 3 parts, namely training, validation, and testing. In neural networks, the training phase is the most important thing. Training is a continuous simulation process to modify connection weights and neural network biases in order to reduce the error function. The dataset used for training undergoes a model training process using the artificial neural network algorithm, so that each dataset will undergo this process [19]. The validation set monitors error performance, determines the optimal network, and stops training if overlearning occurs. Validation is carried out using the previous input, then repetition occurs based on the number of folds used and exchange of test data and training data occurs at each iteration [20].

This research uses a feed forward artificial neural network model, where 80% of the lab test data is used randomly for training and 20% is used to test the model used. In general, overfitting of a model can be prevented by using two techniques, namely by increasing the amount of data used for training the model or by reducing network complexity. This research avoids the problem of overfitting by providing a large enough input sample, using an early stopping method in artificial intelligence. The overfitting problem is illustrated by a neural network error that stops decreasing when the number of epochs increases beyond a certain point [15]. Once the network design process is complete, the test set provides an evaluation of network performance. To assess the accuracy and performance of the prediction model, various performance metrics were calculated on the test data [21]. In modeling, artificial neural network performance is tested by evaluating the coefficient of determination (R^2) and Root mean square error (RMSE). This coefficient is used to measure the degree of closeness of the match. A perfect fit will produce an R^2 value ≈1, a very good fit if it is close to 1, and a poor fit if it is close to 0 [11, 22]

In this study, the artificial neural network model used is a feed forward backpropagation neural network. In this model, dry unit weight, liquid limit, plasticity index, molar concentration, alkali ratio (A/B), Na/Al, Si/Al, curing age, as well as cement, RHA, lime, fly ash, GGBS content as parameters input and unconfined compressive strength values are used as output. Artificial neural networks modeling was implemented in MATLAB R2021a software with the neural network toolbox.

3 Results and discussion

The development of the artificial neural networks model to predict unconfined compressive strength values used laboratory test data of 336 specimens for training and 84 specimens for testing. 336 test results and unconfined compressive strength values were used to train the artificial neural networks model. To demonstrate its ability to characterize unseen data and correctly estimate unconfined compressive strength values, 84 separate tests were conducted. Table 2 summarizes the statistical performance of the artificial neural networks models used. The artificial neural networks model evaluates the Mean Square Error (MSE) and R-squared values for the training and test data of 2.27, 0.99637 and 4.99, 0.99229, respectively.

Table 2. Artificial neural networks model performance

Model	Dataset	Statistical Parameter	
		R	MSE
Artificial Neural Networks	Training data	0.99637	2.27
	Testing data	0.99229	4.99

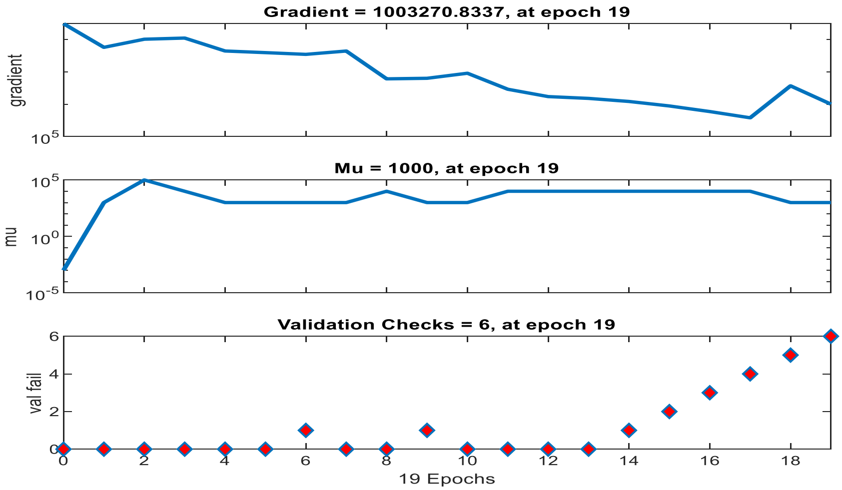

Fig. 1. Plot training state.

The number of errors accumulated in the estimated value is used to evaluate the efficiency of the network. The model with the fewest errors is the most trained. Since the network is trained for 1000 epochs, it can iterate up to 1000 rounds to guarantee model fit. Training has ended at the 19th epoch with a validation set value of 6, as shown in Figures 1 and 2, which show the training state plot and network training performance graph. Based on Figure 2, it can be seen that when the validation set shows an MSE value, each model will converge. According to [23] the validation set stops training and the network converges immediately to prevent overfitting if the MSE in the current iteration is higher than the error in the previous iteration.

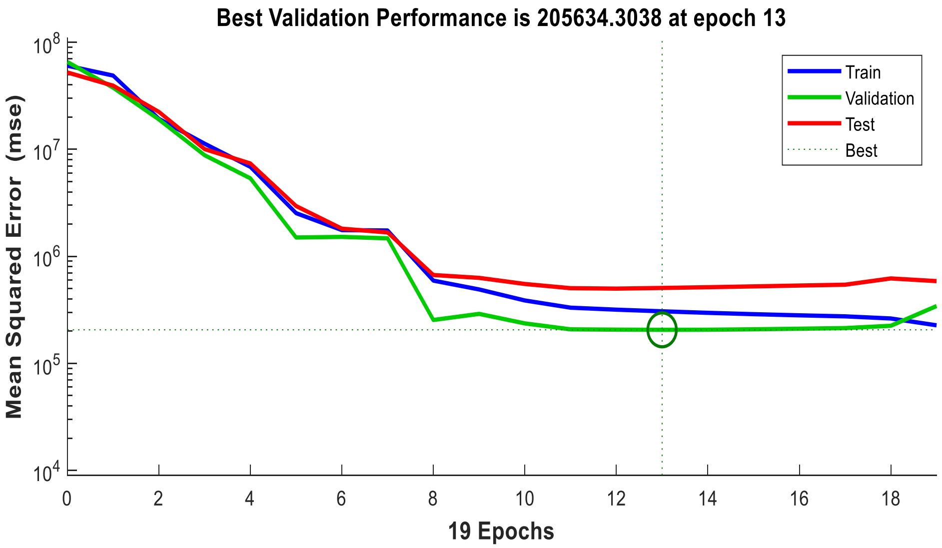

Fig. 2. Plot training performance.

Figure 3 displays a graph of the training results in the artificial neural network model simulation in relation to the experimental results. The target unconfined compressive strength value obtained from the free compression test in Figure 4 is compared with the output, namely the unconfined compressive strength value predicted by the artificial neural network model. As shown in Figures 3 and 4, the data points are distributed around the equivalence line, which shows that there is no significant difference between the unconfined compressive strength values of the experimental results and the unconfined compressive strength values predicted with the artificial neural networks model. The correlation between experimental unconfined compressive strength values and predicted unconfined compressive strength values reached R^2 values of 0.99637 and 0.99229, respectively, indicating good performance despite no input parameter limitations. The artificial neural networks model, with an error close to zero, accurately predicts large output values within an acceptable margin of error [24]. According to [17] the artificial neural network model outperforms the MVR model in unconfined compressive strength prediction because of its flexibility and adaptability in generalizing data.

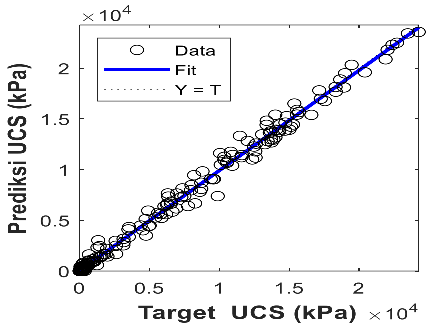

Fig. 3. UCS dataset training

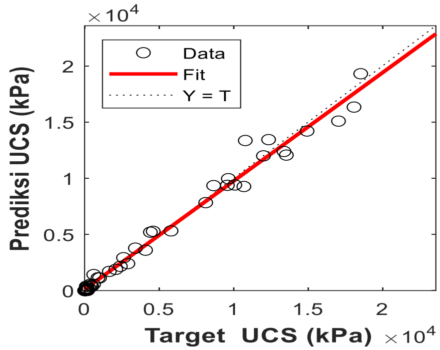

Fig. 4. UCS dataset prediction performance

4 Conclusion

This study evaluated the strength of stabilized clay soils. The results showed that soil stabilized additives such as lime, cement, rice husk ash, *fly ash* and ground granulate blast-furnace slag can increase the compressive strength value of the soil. Then, the use of the artificial neural networks model used in this study has advantages in predicting unconfined compressive strength values because of its flexibility and adaptability in generalizing data. And artificial neural networks model performance can simulate data training well and effectively predict data. So that in this study, the value of the coefficient of determination in the unconfined compressive strength prediction was 0.99229. This study recommends that future research should concentrate on improving pre-processing techniques to achieve greater accuracy results. And further increasing research focusing on unconfined compressive strength predictions using artificial neural networks models especially for stabilized clay soils.

References

[1] W. S. Abdullah and A. S. Alsharqi, "Rehabilitation of medium expansive soil using cement treatment," *Jordan Journal of Civil Engineering*, vol. 5, pp. 343-356, 01/01 2011.

[2] D. Barman and S. K. Dash, "Stabilization of expansive soils using chemical additives: A review," *Journal of Rock Mechanics and Geotechnical Engineering*, vol. 14, no. 4, pp. 1319-1342, 2022/08/01/ 2022, doi: https://doi.org/10.1016/j.jrmge.2022.02.011.

[3] A. R. Estabragh, H. Rafatjo, and A. Javadi, "Treatment of an expansive soil by mechanical and chemical techniques," *Geosynthetics International*, vol. 21, pp. 233-243, 06/01 2014, doi: 10.1680/gein.14.00011.

[4] A. Sorsa, "Engineering Properties of Cement Stabilized Expansive Clay Soil," *Civil and Environmental Engineering*, vol. 18, no. 1, pp. 332-339, 2022, doi: https://doi.org/10.2478/cee-2022-0031.

[5] A. S. A. Al-Gharbawi, A. M. Najemalden, and M. Y. Fattah, "Expansive Soil Stabilization with Lime, Cement, and Silica Fume," *Applied Sciences*, vol. 13, no. 1, p. 436, 2023, doi: https://doi.org/10.3390/app13010436.

[6] N. Malathi, D. N. Komala, S. Shabeena, and V. C. Jaya Saahithya, "Stabilization of Expansive Soil by Using Lime and Reinforcement With Geo-Textile," *IOP Conference Series: Materials Science and Engineering*, vol. 1112, no. 1, p. 012023, 2021/04/01 2021, doi: 10.1088/1757-899X/1112/1/012023.

[7] N. Varma, T. Kumar, and V. Nagaraju, "Compressive Strength of High Plastic Clay Stabilized with Fly Ash-Based Geopolymer and Its Synthesis Parameters," Singapore, 2021: Springer

Singapore, in Transportation, Water and Environmental Geotechnics, pp. 25-37, doi: https://doi.org/10.1007/978-981-16-2260-1_3.
[8] S. Ameen, A. Abdulkareem, and N. Mahmood, "Shear strength behavior of organic soils treated with fly ash and fly ash-based geopolymer," *Journal of the Mechanical Behavior of Materials,* vol. 32, 05/03 2023, doi: 10.1515/jmbm-2022-0264.
[9] A. Mircea, L. S. Irina, and S. Anghel, "Effects of Eco-cement (GGBS) on the Expansive Soil Strength," 2014.
[10] W. Mila Kusuma, K. S. Putu Tantri, and R. Mafrita, "The Performance of Ca(OH)2 to Reduce the Plasticity Index and Increase the Shear Strength Parameter for Expansive Soil," *Journal of the Civil Engineering Forum,* vol. 8, no. 3, 07/28 2022, doi: https://doi.org/10.22146/jcef.3455.
[11] E. Kalkan, S. Akbulut, A. Tortum, and S. Çelik, "Prediction of the unconfined compressive strength of compacted granular soils by using inference systems," *Environmental Geology,* vol. 58, pp. 1429-1440, 10/01 2008, doi: 10.1007/s00254-008-1645-x.
[12] S. Suman, M. Mahamaya, and S. K. Das, "Prediction of Maximum Dry Density and Unconfined Compressive Strength of Cement Stabilised Soil Using Artificial Intelligence Techniques," *International Journal of Geosynthetics and Ground Engineering,* vol. 2, no. 2, p. 11, 2016/04/08 2016, doi: https://doi.org/10.1007/s40891-016-0051-9.
[13] O. Gunaydin, A. Gokoglu, and M. Fener, "Prediction of artificial soil's unconfined compression strength test using statistical analyses and artificial neural networks," *Advances in Engineering Software,* vol. 41, no. 9, pp. 1115-1123, 2010/09/01/ 2010, doi: https://doi.org/10.1016/j.advengsoft.2010.06.008.
[14] S. K. Das, P. Samui, and A. K. Sabat, "Application of Artificial Intelligence to Maximum Dry Density and Unconfined Compressive Strength of Cement Stabilized Soil," *Geotechnical and Geological Engineering,* vol. 29, no. 3, pp. 329-342, 2011/05/01 2011, doi: https://doi.org/10.1007/s10706-010-9379-4.
[15] A. Tabarsa, N. Latifi, A. Osouli, and Y. Bagheri, "Unconfined compressive strength prediction of soils stabilized using artificial neural networks and support vector machines," *Frontiers of Structural and Civil Engineering,* vol. 15, no. 2, pp. 520-536, 2021/04/01 2021, doi: https://doi.org/10.1007/s11709-021-0689-9.
[16] Y. Bagheri, F. Ahmad, and M. A. M. Ismail, "Strength and mechanical behavior of soil–cement–lime–rice husk ash (soil–CLR) mixture," *Materials and Structures,* vol. 47, no. 1, pp. 55-66, 2014/01/01 2014, doi: https://doi.org/10.1617/s11527-013-0044-2.
[17] R. A. Mozumder and A. I. Laskar, "Prediction of unconfined compressive strength of geopolymer stabilized clayey soil using Artificial Neural Network," *Computers and Geotechnics,* vol. 69, pp. 291-300, 2015/09/01/ 2015, doi: https://doi.org/10.1016/j.compgeo.2015.05.021.
[18] C. Anitescu, E. Atroshchenko, N. Alajlan, and T. Rabczuk, "Artificial neural network methods for the solution of second order boundary value problems," *Computers, Materials & Continua,* vol. 59, no. 1, pp. 345-359, 2019.
[19] Y. Jusman, M. Sakatri, and A. Zaki, "Machine Learning for Cracks Level Classification on Concrete Surfaces Using Histogram Oriented Gradient Features," in *2023 International Conference on Information Technology Research and Innovation (ICITRI)*, 2023: IEEE, pp. 49-53.
[20] S. Riyadi and H. A. Ashari, "Prediction of TOEFL Completion Exam Using Support Vector Machine (SVM)," in *2023 International Conference on Information Technology and Computing (ICITCOM)*, 2023: IEEE, pp. 29-33.
[21] S. Riyadi, A. D. Andriyani, A. M. Masyhur, C. Damarjati, and M. I. Solihin, "Detection of Indonesian Hate Speech on Twitter Using Hybrid CNN-RNN," in *2023 International Conference on Information Technology and Computing (ICITCOM)*, 2023: IEEE, pp. 352-356.
[22] B. T. Pham, S. K. Singhº, and H.-B. Ly, "Using Artificial Neural Network (ANN) for prediction of soil," *Vietnam Journal of Earth Sciences,* vol. 42, no. 4, pp. 311-319, 2020.
[23] A. Ajiboye, R. Abdullah-Arshah, H. Qin, and H. Isah-Kebbe, "Evaluating the effect of dataset size on predictive model using supervised learning technique," *Int. J. Comput. Syst. Softw. Eng,* vol. 1, no. 1, pp. 75-84, 2015.
[24] D. R. Goutham and A. Krishnaiah, "Prediction of Unconfined Compressive Strength of Expansive Soil Amended with Bagasse Ash and Lime Using Artificial Neural Network," 2023.