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RESEARCH ARTICLE

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Prediction of Unconfined Compressive Strength of Lime Treated Soils Using an Artificial Neural Network

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Abstract. Robust model based on Artificial-Neural-Network was proposed to predict the Unconfined Compressive Strength (UCS) of lime treated soils. In total, an experimental database using 1120 test specimens was created. Critical examination of the collected experimental data suggested that there are eight key parameters that govern the attained strength gain. These input parameters are; liquid limit, plastic limit, dry unit weight, water content, fine content, lime content, curing temperature and curing time whereas the only output dependent parameter is the UCS. The parameters of the proposed model including weights, biases and transfer functions were successfully converted to an explicit mathematical model relating the UCS with the key input parameters. Based on the results of the statistical evaluation, it was shown that a three-layered Artificial-Neural-Network model with 19 hidden neurons was capable to predict the UCS of lime treated soils with a high degree of accuracy. A coupling effect of the input parameters and weights analysis were conducted for the developed Artificial-Neural-Network-model to assess the importance of the key parameters.

Keywords: unconfined compressive strength; lime stabilisation; artificial neural network.

1 Introduction

Increasing populations and scarcity of land for construction led to an increasing demand for construction on poor grounds that may overly expansive soils. Expansive soils undergo drying-wetting cycles due to seasonal fluctuations of ground water and irregular rainstorms which inevitably result in changes in the moisture content. Stabilisation of soils by lime is considered by far the most known method due to abundant availability of lime at low cost and the potential to achieve high treatment efficiency. Lime stabilisation was, therefore, the subject of numerous studies in the last few decades [1-6]. A consensus was reached that when lime reacted with clay minerals, a noticeable improvement was achieved from reduced elasticity and potential swell and increased workability and strength. Distinctive reactions including i. cation exchange, ii. flocculation and agglomeration, iii. pozzolanic reaction and iv. lime carbonation are responsible for the mechanisms that lead to the observed improvement in behaviour. In order for a cost effective and safe structures to be built, the ground must achieve a particular strength to avoid overstressing the ground and/or resulting in excessive settlement.

In most of the structures i.e. road pavements, foundations, retaining walls and earth dams, Unconfined Compressive Strength (UCS) is an important engineering property and used extensively to indicate the quality of stabilised materials. It is noteworthy that despite the fact that abundant data is available in the technical literature for measured UCS of lime stabilised soils, differences in the material composition, testing conditions, etc. require attention and care when being analysed. Development of innovative mathematical and predictive models are therefore encouraged for meaningful correlations to be made. These predictive models would assist to minimise the need for laborious and time-consuming extensive laboratory tests. Nevertheless, it is essential that predictive models are capable to estimate the evolution of strength of lime treated soils at various curing time duration whilst reflecting the key input parameters that might affect strength gain.

Careful inspection of the technical literature review indicated that there are eight key parameters that govern the behaviour of lime stabilised soils and strength gain. Many researchers have stated that the index features such as liquid and plastic limits, water content and unit weight which are easily measurable in the laboratory, have significant effects on compressive strength of stabilised soil [7-9]. To develop a deep understanding of the evolution of UCS of treated soils, it is essential that all the aforementioned factors must be considered. Nevertheless, there seems that no single study is conducted to assess all the key parameters influencing the evolution of strength of lime treated soils. Hence, the development of predictive model would be beneficial providing an engineering tool for prediction of strength without the need to carry out extensive and costly experimental programs since ample data exist.

In the recent decades, the use of artificial intelligence is receiving an increasing interest in the geotechnical engineering field. In particular, Machine Learning algorithms are found very capable to explore nonlinear relationships with high precision [10]. Utilisation of Artificial-Neural-Networks (ANNs) was widely used in several ground studies as an estimation tool [11-20]. According to the aforementioned studies, it was concluded that the estimated values obtained based on ANN models were close to the experimentally attained data and these properties can be predicted in ANNs without the attempt to carry out experiments. Until recently, the prediction of UCS of lime treated soils and a general equation between UCS and eight engineering properties of soil is not yet available. The primary objectives of this study are to i. collate available data in the technical literature alongside with data attained in this current study in order to consider all pertinent parameters that significantly affect the strength gain of lime treated soils, ii. develop an ANN predictive model based on the collated laboratory data, and iii. evaluate the performance of the proposed model using weights and biases.

2 Methods

2.1 Data collection

A detailed literature review was conducted to ensure the collection of diverse data for the UCS on different types of soil stabilised with lime under different conditions. In this study, a database is generated based on the results from twenty-four studies published between 1966 to 2020. Table 1 reports the research studies utilised in the present study and number of data points. In total 1120 experimental data points generated from both the current study and gathered from the literature were considered for the development of the predictive models. Careful inspection of the gathered data illustrated that the key input parameters consist of liquid limit (LL, %), plastic limit (PL, %), dry unit weight (ɤ, kN/m^3), water content (WC, %), fine content (FC, %), temperature (C), lime content (LC, %) and curing time (h). The UCS (kPa) was taken as the only output parameter for building the UCS predictive models. Of note, there were specimens shared similar parametric values such as material properties, but the experimentally measured UCS were different due to discrepancy treatment conditions. The range of values for individual parameters that are used in the present study are illustrated in Table 2.

Table 1. Collected data points and source studies

Source	Data points
[21]	27
[22]	181
[23]	40
[24]	63
[25]	75
[26]	87
[27]	10
[2]	6
[28]	10
[29]	18
[30]	11
[31]	26
[32]	8
[1]	318
[33]	4
[34]	14
[35]	40
[4]	8
[36]	18
[37]	13
[38]	4
[3]	5
[39]	14
[40]	13
Current study	107
Total	1120

Table 2. Range of values of the key used variables

Parameter	LL (%)	PL (%)	ɤ (kN/m^3)	WC (%)	FC (%)	T (C)	LC (%)	CT (h)	UCS (kPa)
Max	330	67	24.21	80	100	50	25	6360	11290.93
Min	24	12	8.34	10	46.3	5	0	0	50.04

LL = Liquid Limit, PL = Plastic Limit, ɤ = Dry unit weight, WC = Water content, FC = Fine content, T = Temperature, LC = Lime content and CT = Curing time.

In the current study, the Neural Network Fitting Tool (nftool) available in MATLAB R2020a was utilised to develop an ANN model. The entire experimental data that was gathered in this study was randomly split into three sub-groups for training, testing and validation of the proposed models where 70% of the data were utilised for training phase, 20% of the total data points were used for testing and the remaining 10% of the data points were utilised for validation. It should be noted that the training phase is three stages including: i. using input data to calculate the outputs, ii. comparing the estimated outputs against those measured, and iii. adjusting the weights for each node to close the gap between estimated and measured values [19]. The testing phase is for assessing the network employing test specimens from the database, which should be used once only after training stage is complete. The main purpose of the validation phase is to assess training when generalisation stops improving. The frequency distribution of each variable element used in this study is shown in Table 3. The aim of the frequency distribution is to ascertain the range for each variable that is thoroughly covered in order to avoid anomalous and those with a limited number of specimens which could affect the ability of the model to accurately extrapolate out of the used range.

Table 3. Frequency distribution of the key variables and the output

Input parameters																Output parameter	
LL (%)		PL (%)		γ (kN/m^3)		WC (%)		FC (%)		T (ºC)		LC (%)		CT (h)		UCS (kPa)	
Range	Freq	Range	Freq	Range	Freq	Range	Freq	Range	Freq	Range	Freq	Range	Freq	Range	Freq	Range	Freq
24-58	346	12-17	108	8.34-10.34	110	10-20	184	46.3-55.3	86	5-10	49	0-5	420	0-672	1009	50-800	546
58-92	346	17-22	7	10.34-12.34	199	20-30	444	55.3-64.3	3	10-15	0	5-10	529	672-1344	17	800-1550	311
92-126	70	22-27	265	12.34-14.34	407	30-40	371	64.3-73.3	142	15-20	748	10-15	120	1344-2016	19	1550-2300	134
126-160	22	27-32	220	14.34-16.34	271	40-50	47	73.3-82.3	148	20-25	0	15-20	18	2016-2688	65	2300-3050	43
160-194	60	37-37	50	16.34-18-34	108	50-60	33	82.3-91.3	38	25-30	48	20-25	35	2688-3360	10	3050-3800	29
194-228	0	37-42	126	18.34-20-34	21	60-70	25	91.3-100	705	30-35	0			3360-4032	0	3800-4550	23
228-262	0	42-47	299	20.34-22.34	0	70-80	18			35-40	214			4032-4704	0	4550-5300	17
262-296	4	47-52	6	22.34-24.34	5					40-45	0			4704-5376	0	5300-6050	6
296-330	274	52-57	23							45-50	63			5376-6048	0	6050-6800	6
		57-62	0											6048-6720	2	6800-7550	3
		62-67	18													7550-8300	0
																8300-9050	1
																9050-9800	1
																9800-10550	0
																10550-11300	2

2.2 Construction of ANN Predictive model

Artificial-Neural-Networks were widely used in the field of Civil Engineering and proved to be as a powerful predicting tool comparing with the numerical or statistical methods [41]. Moreover, though ANNs provide very powerful tools for the prediction of engineering behaviour, utilised algorithms operate as a “black box” where calculations are completed using hidden layers [42]. ANN is utilised to relate a set of inputs to another set as output in order to arrive at solutions, which could save both time and money. An ANN is comprised of several simple but highly interconnected processing elements similar to the brain cells of human neural networks. Each network contains input and output layers and one or more hidden layers. Neurons transmit the sum of the weighted inputs and bias to all neurons of the next layer using a transfer function called activation function. This process is formulated in Equation 1:

$$Y = b_2 + \left[\sum_{k=1}^{n} W_2 * \mathrm{tansig}\left(\sum_{i=1}^{m} W_1 * X_i + b_1\right)\right] \tag{1}$$

where; Y is the output variable, X_i is the input variables (X_1 to X_n), k is the neuron of hidden layer, n is the number of neurons, i is the neuron of input variable, m stands for the number of input variables, W_1 and W_2 stand for the weight of hidden layer and output layer respectively, and b_1 and b_2 are the bias of the hidden layer and output layer respectively. As suggested by Khanlari, Heidari [43], the linear and tan-sigmoid functions are the most commonly used transfer functions.

The number of neurons in the ANN layers plays a significant role on the network performance. However, explicit rules do not exist to calculate the number of hidden neurons or hidden layers [44]. The number of hidden neurons or layers is determined by trial and improvement until convergence is reached in the mean sum of squared errors. Shaikh and Sawlani [45] stated that the mean squared error (MSE) decreases with increasing the number of neurons. Employing a few hidden neurons could lead to large errors during training and testing stages which could be attributed to under-fitting and/or high statistical bias. Contrary, using several hidden neurons could reduce training errors but it may result in experiencing high testing errors due to over-fitting and/or high variance [46].

In the current study, back propagation was selected which is usually used to train a network since being known as the most powerful technique. The Levenberg– Marquardt algorithm was utilised as the training algorithm where according to Das, Samui [15], in geotechnical engineering Levenberg– Marquardt algorithm application is the most widely used algorithm. To attain some desired outputs, weights were adjusted using several training inputs and the corresponding target values weights which signify the strength of connection between neurons and biases. A backward approach was applied to generate the network error from the output layer to the input layer to recalculate the weights and biases of the network. The adjusting process continues until an achieved network error falls within an acceptable level of accuracy [47].

To establish an optimum network architecture and its parameters, the trial and improvement method was applied. In this process, the number of neurons was varied until reaching the optimum ANN model architecture. An ANN model based on three hidden layers with 19 neurons produced the lowest MSE value (0.0039) and the highest linear correlation coefficient (R) value on the average (0.958) for the prediction of UCS. The ANN model was characterised by 19 neurons in each hidden layer with tan-sigmoid (hyperbolic tangent) transfer function and a pure linear transfer function at output layer. The architecture of the proposed ANN model based on three hidden layers for prediction of UCS is presented in Fig. 1. It was referred as ANN 8-19-1 as it consisted of 8 input parameters, 19 neurons and 1 output dependent parameter. The eight input independent parameters are liquid limit (LL), plastic limit (Pl), dry unit weight (ɤ, kN/m3), water content (WC, %), fine content (FC, %), temperature (T, ºC), lime content (LC, %) and curing time (CT, h), whilst the UCS in kPa is the output dependent parameter.

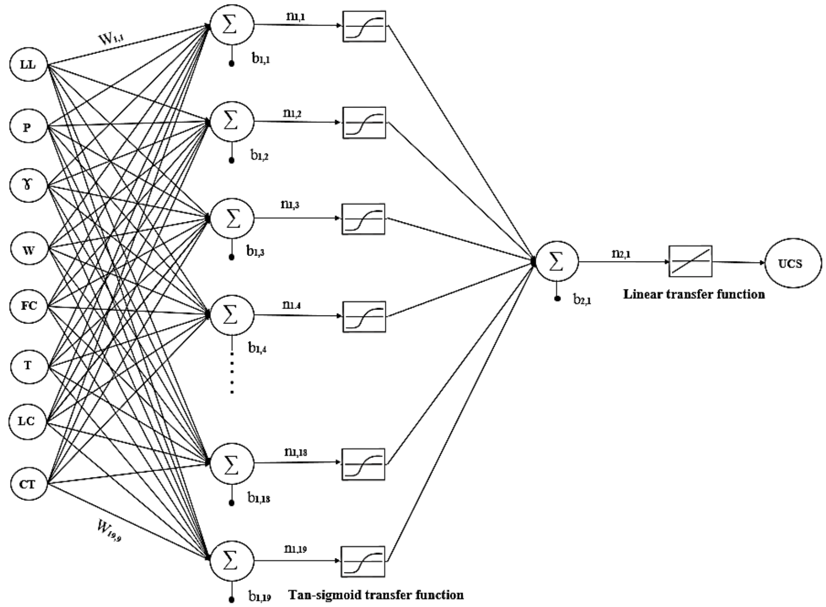


Fig. 1. Architecture of the ANN 8-19-1 prediction model

2.3 Performance evaluation

The robustness of the ANN model was evaluated based on assessment values of several statistical parameters including mean squared error (MSE), mean absolute error (MAE), correlation coefficient (R), mean (M), standard deviation (SD), coefficients of determination (R^2) and coefficient of variation (COV). These parameters were employed to examine the validity of the proposed predictive models. The model that provides relatively accurate prediction values was chosen. As part of pre-processing, all of numeric variables ought to be normalised to equalise the importance of variables. Hence, training, testing and validation data sets were normalised relative to their minimum and maximum values to be within a range of [-1, 1] because of using the hyperbolic tangent sigmoid function in the model. The normalisation was performed using the Equation 2:

$$I_n = 2 \times \frac{I - I_{min}}{I_{max} - I_{min}} - 1 \tag{2}$$

where; I_n is the normalised input variable, I stands for the variable value to be normalised, and I_{min} and I_{max} are the minimum and maximum values respectively that were reported in the training set for a specific parameter [48]. It should be noted that the corresponding predicted values should be reverted to the original scale using reverse normalisation process to evaluate the results. Normalisation helps in preserving the relationship between the actual data values [45].

2.4 Laboratory studies

A laboratory testing programme was performed to generate experimental data relating the strength gain with the soil properties. Measured data for liquid limit, plastic limit, dry unit weight, water content and unconfined compressive strength were measured on a highly plastic clay (bentonite). The testing methods are described below:

Soil index testing. Table 4 presents the measured values for the plasticity limits which were determined as prescribed in BS1377-2 [49]. To obtain the dry unit weight and the OWC, specimens were compacted using a specially designed mould and hammer that is capable of preparing specimens with the same compactive energy as that applied in a Standard Proctor test [50].

Table 4. Physical properties of the utilized clay

Property	Value
Water content, %	10.6
Liquid limit, %	330
Plastic Limit, %	43
Plasticity index, %	287
Maximum dry unit weight, kN/m^3	12.16
Optimum moisture content, %	40

Unconfined Compression Strength tests: UCS tests were carried out in compliance with British standards [51]. Specimens of pure clay and lime treated clay were prepared with two different dry unit weights of 12.16 and 8.34 kN/m^3. In total 88 specimens were compacted with 40% water content and prepared at dry unit weight of 12.16 kN/m^3. In addition, 19 specimens were prepared with moisture content of 50%, 60%, 70% and 80% at a dry unit weight of 8.34 kN/m3. The UCS results of these specimens were added to the database and used to develop the model. The specimens were then stored in sealed plastic bags and left in an environmental cupboard at controlled temperature of 20^{O}C or 40^{O}C and 90% humidity for a curing period of 3, 6, 12, 24, 72, 168 and 672 h. Cured specimens were then subjected to a progressively increasing compression load in the triaxial test rig until failing. All specimens were loaded to failure at an axial movement rate of 1 mm per minute.

3 Results and discussion

3.1 Data analysis and description

To develop robust predictive model, availability of high quality measurements and sisable data set are essential. Two statistical parameters namely, mean squared error (MSE) and linear correlation coefficient (R) were utilised to examine the performance of the proposed ANN model. The training of the ANN 8-19-1 model was stopped after 58 epochs where the lowest MSE values (0.0033) and the highest R (0.967) were reached. The model was examined using a different data set that was used previously during the training stage. The lowest MSE and highest R values for testing and validation data of ANN 8-19-1 were 0038, 0.93, 0.0063 and 0.92, respectively. These values suggested that the proposed ANN model can predict the data with high accuracy.

The performance criteria values used to assess the performance of the ANN model in the prediction of UCS values are presented in Table 5. Based on the statistical observations, ANN 8-19-1 model has showed high degree of fitness to the actual values which proved that the proposed ANN model can be used to predict UCS without the need for conducting comprehensive experimental studies.

Table 5. Statistical evaluations of proposed models

Model	MSE	MAE	R	R^2	SD	M	COV
ANN 8-19-1	0.0039	0.037	0.958	0.92	0.54	1.03	0.52

The relationship between the experimental and predicted values obtained using the proposed model is shown in Fig. 2. According to data the figure, R^2 values for training, testing and validation stages by the proposed ANN 8-19-1 are 0.97, 0.93 and 0.92, respectively. This indicates that the proposed ANN model is capable of explaining at least 97% for the training phase, 93% for the validation phase and 92% for the testing phase of the experimental data. Additionally, the relationship between measured and predicted values for all data is presented in Fig. 3.

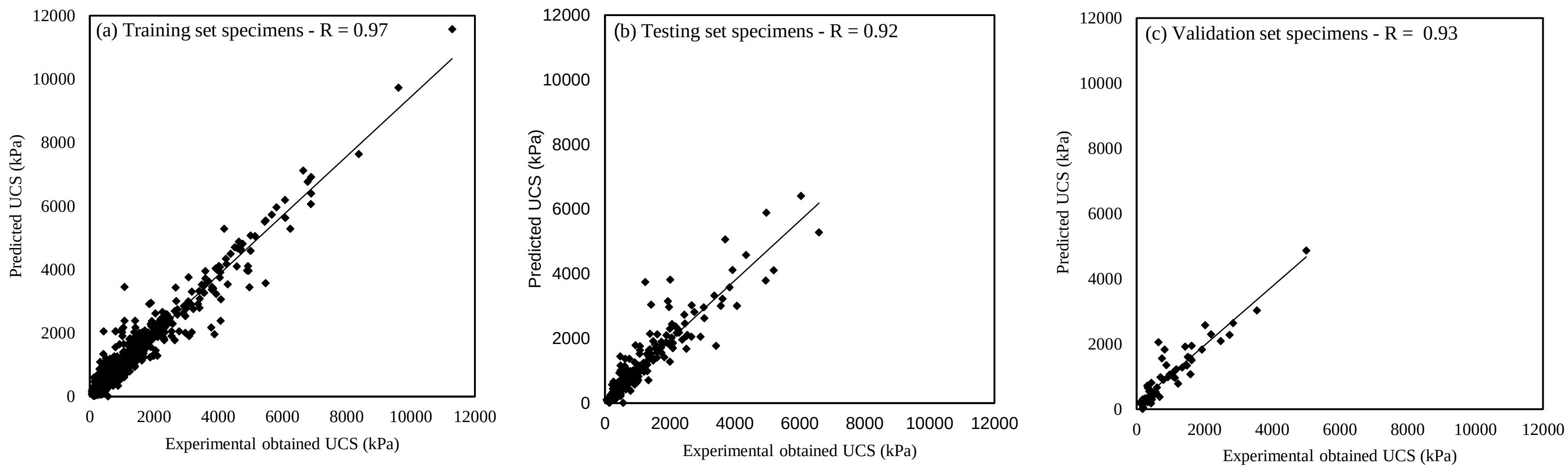


Fig. 2. Plots for measured values against predicted values of UCS by ANN during (a) training, (b) testing and (c) validation stages

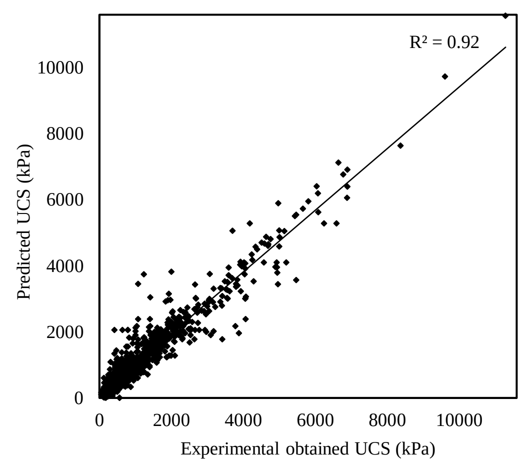


Fig. 3. Plots for measured values against predicted values of UCS by ANN 8-19-1 model

3.2 Artificial-Neural-Network model equation

A mathematical equation correlating the UCS as the dependent output parameter with the input variables can be given by Equation 3. It should be noted that weights that were determined for ANN training were used as the model parameters.

$$UCS_n = b_2 + [\sum_{k=1}^{n} W_2 * tansig(\sum_{i=1}^{m} W_1 * X_i + b_1)] \quad (3)$$

where; UCS_n is the normalised UCS value in the range of [-1, 1], X is the normalised input variables (LL, PL, ɤ, WC, FC, T, LC and CT), n stands for the number of neurons, m stands for the number of input variables, W_1 and W_2 refer to the weight of hidden layer and output layer respectively, and b_1 and b_2 are the bias of the hidden layer and output layer respectively. Equations 4 and 5 are written to correlate UCS values with the eight key input parameters based on the values of the weights and biases that were determined from ANN training and presented in in Table 6.

A1 = 8.162 - 0.6503LL + 0.221PL - 1.0792ɤ - 0.2009WC + 0.0426FC - 0.7701T - 0.3743LC + 6.9601CT
A2 = 2.6065 - 0.7041LL - 0.8302PL - 1.1967ɤ - 0.2524WC + 1.1914FC - 1.3405T-0.2826LC + 1.8491CT
.
.
A19 = -2.2368 - 1.1542LL + 4.0939PL - 2.0991ɤ + 1.3327WC - 0.4714FC - 0.5379T - 1.2501LC -2.3635CT

$$B1 = 5.1652 \times \frac{e^{A_1} - e^{-A_1}}{e^{A_1} + e^{-A_1}}$$

$$B2 = -1.8805 \times \frac{e^{A_2} - e^{-A_2}}{e^{A_2} + e^{-A_2}}$$

.
.

$$B19 = 0.5502 \times \frac{e^{A_{19}} - e^{-A_{19}}}{e^{A_{19}} + e^{-A_{19}}}$$

C1 = -0.95606 + B1 + B2 + B3 + B4 + B5 + B6 + B7 + B8 + B9 + B10 + B11 + B12 + B13 + B14 + B15 + B16 + B17 + B18 + B19

$$UCS_n = \frac{e^{C_1} - e^{-C_1}}{e^{C_1} + e^{-C_1}} \quad (4)$$

The UCS value acquired from equation 5 is in the range [-1, 1] which requires to be denormalised as given by Equation 6.

$$UCS = \frac{(UCS_n + 1) \times (UCS_{max} - UCS_{min})}{2 + UCS_{min}} \quad (5)$$

where; the maximum and minimum values of UCS in the datasets are represented by UCSmax and UCSmin.

Table 6. Weights and biases for UCS of lime treated soil

Neurons	Input Layer (Weight Matrix)								Hidden Layer (Weight Vector)	Input and Output Layers (Bias Vectors)	
	W_1								W_2	b_1	b_2
	LL	PL	ɤ	WC	FC	T	LC	CT	UCS		
Hidden neuron 1 (k = 1)	-0.65	0.22	-1.08	-0.20	0.04	-0.77	-0.37	6.96	5.17	8.16	-0.96
Hidden neuron 2 (k = 2)	-0.70	-0.83	-1.20	-0.25	1.19	-1.34	-0.28	1.85	-1.88	2.61	
Hidden neuron 3 (k = 3)	-0.78	2.04	1.58	0.68	-0.59	-0.01	-0.86	0.29	-2.18	2.36	
Hidden neuron 4 (k = 4)	-0.50	-0.10	1.14	1.24	1.09	0.88	-0.58	-0.85	0.42	1.20	
Hidden neuron 5 (k = 5)	-2.95	-1.67	-0.57	0.19	-0.02	1.13	0.40	2.45	3.46	0.11	
Hidden neuron 6 (k = 6)	2.38	-0.14	0.87	0.33	-0.51	-1.04	-0.37	0.40	2.39	-0.85	
Hidden neuron 7 (k = 7)	1.41	0.28	-2.53	1.80	0.37	-0.92	-0.86	-1.30	0.99	-0.19	
Hidden neuron 8 (k = 8)	-0.31	-1.00	-1.16	0.40	0.56	-0.28	0.01	-1.55	-1.68	0.37	
Hidden neuron 9 (k = 9)	-1.06	1.34	-2.13	1.93	0.51	-0.37	-0.60	-0.71	-1.55	-0.77	
Hidden neuron 10 (k = 10)	3.84	-2.55	-0.58	-0.22	-0.52	-1.43	-0.26	2.21	-2.32	-0.61	
Hidden neuron 11 (k = 11)	-3.91	-1.20	-1.35	0.37	0.30	1.01	0.53	1.74	-2.55	-1.14	
Hidden neuron 12 (k = 12)	-1.72	-2.41	-0.05	-0.11	-0.24	1.38	0.09	3.17	-1.20	1.24	
Hidden neuron 13 (k = 13)	-0.16	1.48	1.32	0.61	-0.48	0.36	-1.08	0.38	1.20	1.82	
Hidden neuron 14 (k = 14)	-0.48	1.64	-0.18	0.02	2.13	-0.20	-0.75	-1.65	-1.16	0.42	
Hidden neuron 15 (k = 15)	-1.62	1.28	0.00	-2.60	-1.00	0.37	0.18	0.55	-1.82	-2.85	
Hidden neuron 16 (k = 16)	-1.24	-0.48	-0.69	-0.37	-0.03	-0.19	-0.15	0.81	-2.27	-0.64	
Hidden neuron 17 (k = 17)	-1.29	-1.34	0.09	-0.35	1.06	0.27	0.38	0.37	1.83	-1.40	
Hidden neuron 18 (k = 18)	2.48	-0.38	1.61	-0.06	0.44	0.25	-0.05	-0.77	-2.29	1.40	
Hidden neuron 19 (k = 19)	-1.15	4.09	-2.10	1.33	-0.47	-0.54	-1.25	-2.36	0.55	-2.24	

3.3 Effect of input parameters (Parametric study)

Lime-soil pozzolanic reaction is affected by many factors. Therefore, a given lime-soil mixture can display a wide variation in the gained strength depending upon prevailing conditions. In order to quantify the coupling effect of the parameters on the UCS of lime treated soil, individual parameter was varied whilst all other parameters were kept fixed according to the database frequency (LL = 58%, PL = 45%, ɤ = 13.34 kN/m^3, WC = 25%, FC = 95.8%, T = 20^OC, LC = 7.5% and CT = 672 h). Careful inspection of Table 3 suggested that data was not distributed due which may affect the ability of the model to accurately extrapolate beyond this frequency range. For instance, specimens with a liquid limit of 262-296 % was only tested four times and specimens with a plastic limit of 47-52 % was only tested six times. Therefore, a narrow range was considered in this parametric study. The regression equation can be presented graphically by 3D surfaces. Many matrices were developed by MATLAB to simulate a wide range of input parameters using the developed ANN model to study the behaviour of materials under different conditions. This gave an idea of how the output (UCS) was altered in response to the input variables.

Effect of consistency limits. Fig. 4 illustrates the effect of consistency limits on the UCS values of lime treated soils. The figure reveals that the UCS of soil with a low plastic limit and a high liquid limit (up to 135%) improved substantially with the addition of 7% lime. In contrast, a reduction in UCS was experienced on soils with higher plastic limits and low liquid limits. It is noteworthy to state here that changes in LL and PL lead to a remarkable change on recorded UCS. To understand the role of the plasticity index, Hosseini, Mojtahedi [52]'s results indicated that soils with low plasticity index (PI) can influence adversely the strength gain where they can adsorb less water and therefore influence the curing process. Conversely, soils with higher PIs experienced high degree of improvement due to their capabilities in holding water. This is in agreement with the current study and Ali and Mohamed [1]'s findings as shown in Fig. 5.

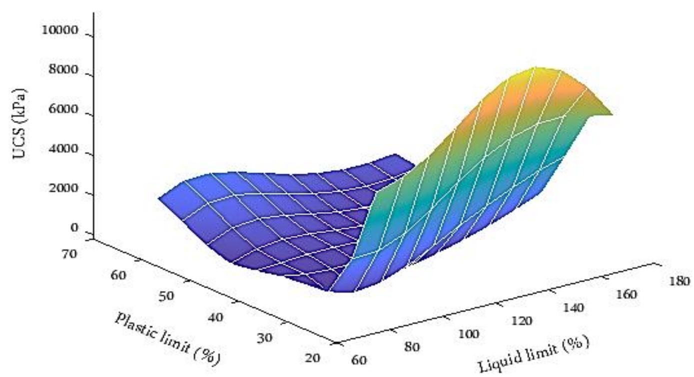


Fig. 4. 3-D representation of variations in UCS against liquid limit and plastic limit

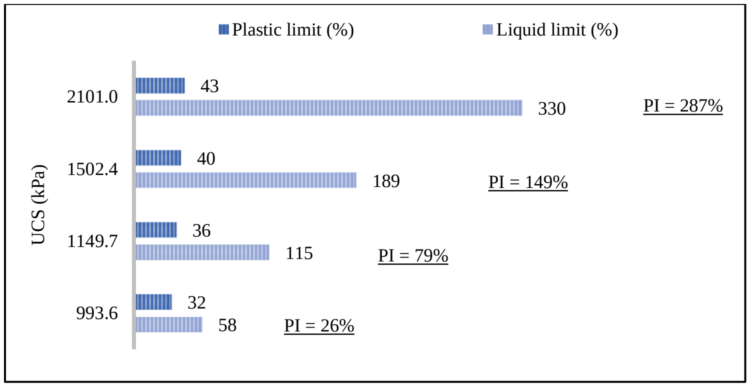


Fig. 5. Effect of consistency limits on the UCS of lime stabilised soil [1]

Effect of compaction properties. Fig. 6 presents a 3D plot for the UCS predicted using the ANN model as a function of water content and dry unit weight. Inspection of the figure illustrated that UCS increased with increasing water content. In other words, increasing water content has a favourable effect on the strength gain of stabilised soil even though its unit weight was low. However, the results suggested that denser soils might respond different to variation in water content. The results attained in the present study as well as those from Bell [22]'s study showed that dense soils required less water to be prepared and resulted in achieving high compressive strength (Fig. 7). Morel, Pkla [53] stated that compressive strength is strongly related to the unit weight achieved in compaction. It consistently increases as dry unit weight increases. In lime-soil stabilisation, water is an essential component for the pozzolanic reaction to produce cementitious compounds which significantly contribute to long-term strength gain. It exerts controlling effect on most of the physical and chemical processes that occur in soil [54]. However, the influence of the water content is completely depending on the unit weight of the lime stabilised clay specimens which may explain the variation in the UCS values. The contribution of the precipitation of cementitious compounds is likely to be significant on specimens prepared at low density due to the large pores space [55]. The availability of water improves the ion migration which enabled the development of the cementing compounds which bridge the space between particles instead of the water [56].

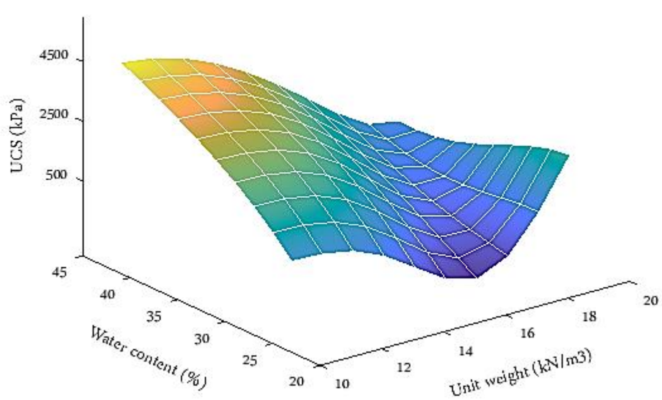


Fig. 6. 3-D representation of variations in UCS against unit weight and water content

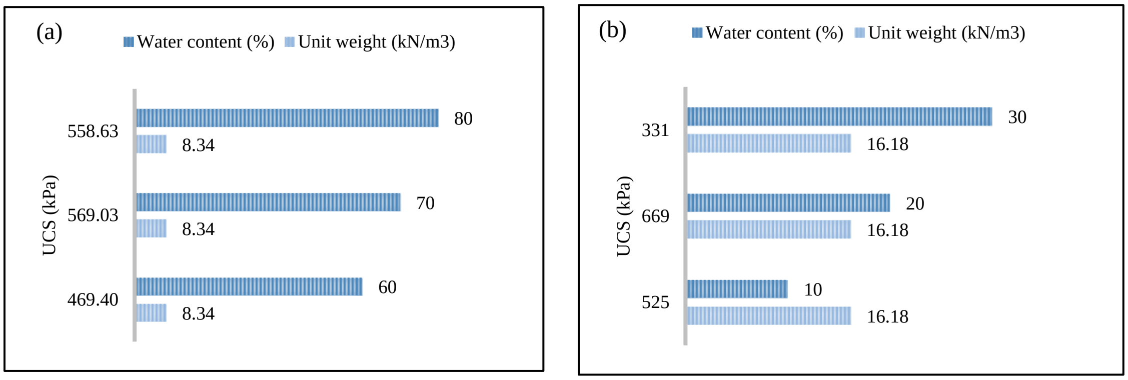


Fig. 7. Effect of water content and dry unit weight on the UCS of lime stabilised soil (a) Current study and (b) [22]

Effect of fine and lime contents. The relationship between fine and lime contents as the two input variables and UCS as the output variable is shown Fig. 8. The response surface plotted using the ANN model shows that higher fine content and lower lime content up to 11% led to the achievement of high UCS. The strength increased substantially with increasing the fine content whereas increasing lime content caused a slight increase in strength gain up to a peak value. The results attained using the ANN model indicated that UCS values is linearly proportional to the fine content. Fine particles are required to provide adequate silica and/or alumina sources for the pozzolanic reaction. Ingles and Metcalf [57] stated that lime content should ideally be linked with the content of clay mineral which is needed for reaction. It was further recommended that 1% of lime content (by weight of dry soil) is required for each 10% content of the clay in soil. The better reactivity of fine particles can be due to the smaller particle sise and higher specific surface area [58]. The loss of strength with increasing lime content could result from excessive use of lime which might not react with the clay minerals and remains as a soft material within the matrix of stabilised soil reducing the overall strength of lime-soil stabilised [3]. The effect is also proven by the experimental work of Ali and Mohamed [59] and the current study which are presented in Fig. 9.

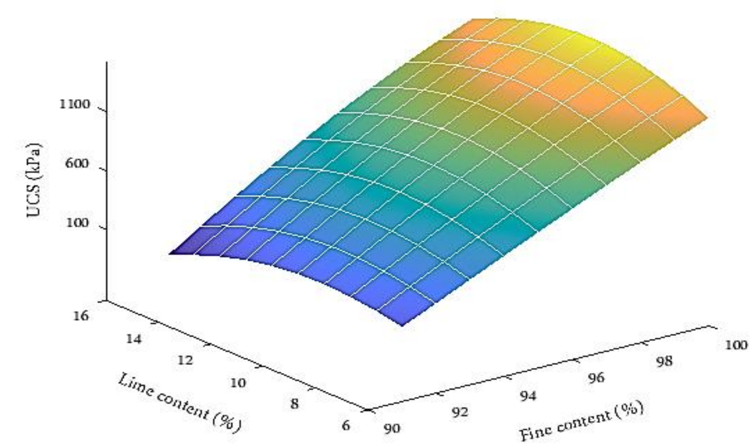
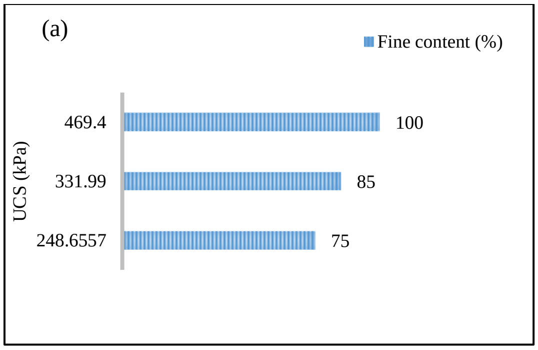


Fig. 8 . 3-D representation of variations in UCS against fine content and lime content



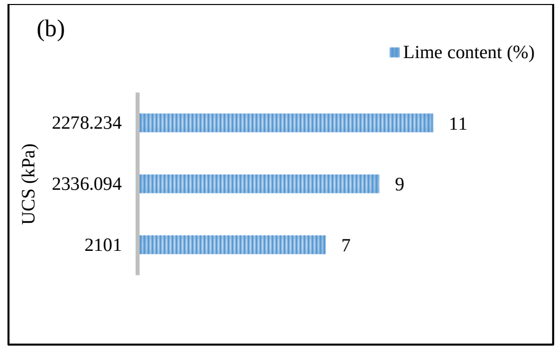


Fig. 9. Effect of the fine and lime contents on the UCS of lime stabilised soil (a) Current study and (b) [59]

Effect of curing time and temperature. The effects of increasing curing temperature and time is depicted in Fig. 10. The UCS increased linearly with increasing the curing period and temperature, which indicated that the ANN model predicted the effects adequately. Curing at high temperatures and extending the curing duration is depicted to be essential in lime-clay reactions to achieve higher strength. The chemical reactions are accelerated when curing is carried out at higher temperatures since it increased the solubility of the silicates and aluminates that exist in the soil and resulted in higher strength gain which could be attributed to the completion of the chemical reactions and accelerating the ion migration [34, 60]. In the current study, the results showed similar evidence for the effect of curing conditions as presented in Fig. 11.

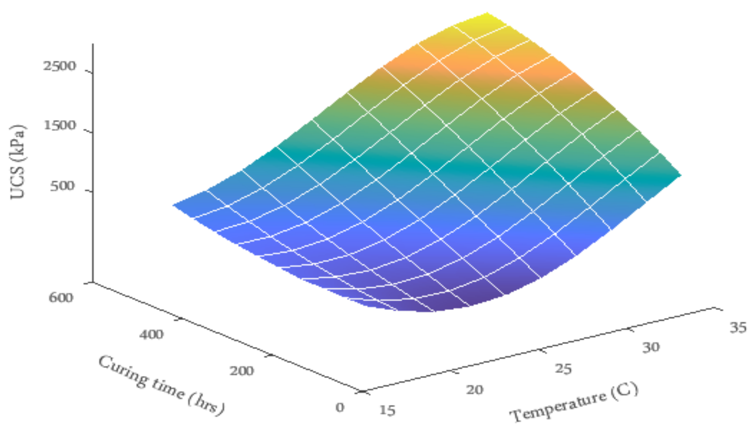


Fig. 10. representation of variations in UCS against temperature and curing time

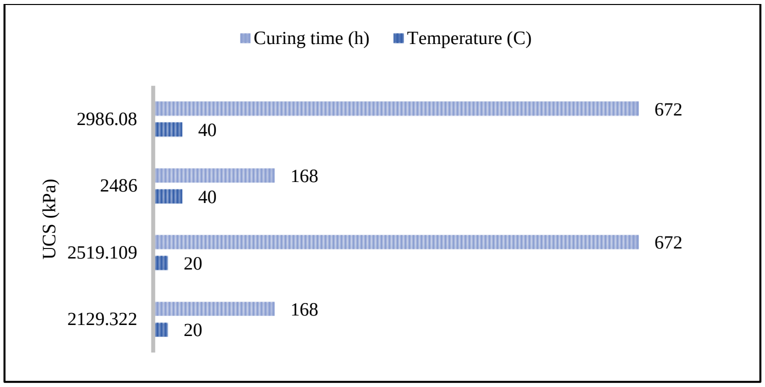


Fig. 11. Effect of the curing conditions on the UCS of lime stabilised soil

4 Conclusions

In this study ANN model was proposed to estimate the Unconfined Compressive Strength of lime treated soils. Based on the results and discussion the following conclusions are drawn:

- ANN model is developed for the prediction of the UCS values of lime treated soils based on eight key variables which are; LL, PL, ɤ, WC, FC, T, LC and CT as independent input parameters.
- Based on the statistical performances, the developed ANN 8-19-1 model was found to be efficient for prediction of attained strength of lime stabilised clays.
- Equations were presented for the prediction of UCS which were developed based on the trained parameters resulted from ANN analysis.
- The trained ANN 8-19-1 was applied to quantify the coupling effect of input parameters. The UCS at low plastic limit and high liquid limit improved significantly. On the contrary, a decrease in UCS at higher plastic limit and low liquid limit was observed. Increasing the water content has a positive effect on the soil strength that its unit weights are low. Noticeably, the strength increased with increasing the fine content. On the other hand, the strength increased slightly as lime content increased. However, with increasing the content, the UCS decreased. Temperature and curing time are both linearly proportional to the UCS.

Conflict of Interest

The authors declare no conflict of interest.

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