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Strength Prediction Of Cement Stabilized Clay Using Artificial Neural Networks

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Abstract—**Stabilization of clay soils is necessary in many civil engineering projects in order to increase strength, reduce settlement and also for other special purposes, especially when weak soils do exist. Soil treatment with cement is one of the most commonly used method, it is proved to be an efficient and effective chemical stabilization method due to its economic advantages and ease of use. In this research, Test data sets with a wide range of parameters were implemented in an Artificial Neural Networks (ANN) program in order to evaluate the unconfined compressive strength of cementations clay soils. The data were collected from the selected published laboratory experimental investigations conducted by many researchers to study the effect of various parameters on the strength improvement of cement treated clay. The selected data were chosen to represent a wide range of clayey soils obtained from different places around the world. The predictive model was developed using the artificial neural network tools in MATLAB software. The artificial neural network (ANN) technique was applied using the Levenberg-Marquardt algorithm to develop a model that predicts the unconfined compressive strength of cement treated clayey soils. The number of data sets for this study were (429) collected from (15) previous research studies. Eight input parameters were chosen as follows: Liquid limit (LL)%, Plasticity index (PI)%, Clay fraction (CF)%, Sand (S)%, silt (M)%, water content (Wc) % , curing time (Tm) in days and cement content (Cc)% The unconfined compressive strength (UCS) was chosen as one output parameter, then the data was normalized using the min-max method. In order to evaluate the performance of the predictive model developed in this study, the statistical analysis of the model was performed using regression (R2), mean square error (MSE), root mean square error (RMSE), and coefficient of efficiency (CE). Good correlation was obtained with regression (R2) of 0.897. Sensitivity analysis indicate that the cement content is mostly affecting the resulting soil strength (UCS) followed by water content, curing time and liquid limit. The rest of the variables show relatively lower impact.**

Index Terms—**Artificial Neural Networks (ANN), cement stabilization, unconfined compressive strength, clay soil.**

I. Introduction

Fine grained soils especially Soft clay is considered as one of the problematic soils that requires attention during construction of any civil engineering project. This type of soils is commonly associated with a change in water content that leads to a reduction in shear strength and hence low bearing capacity. The behaviour usually associated with a volume change that causes swelling, shrinkage and settlement which can cause severe damage to buildings and infrastructures [1]. Most of the constructions especially of buildings and roads are preferably build on the soil that is strong and stable. Nevertheless, in practice, it sometimes difficult to find natural soil that provided the desired strength and acceptable stiffness. Such less competent soils need a kind of treatment in order to improve their strength and stiffness. However, several types of soil stabilization have been widely practiced [2]. Soil stabilization is a method of improving soil properties and engineering performance by adding special cementing material, or other chemicals to natural soil to improve one or more of its geotechnical properties such as compressibility, strength, permeability, and durability [3]. The stabilization techniques that have been used over the years for soil remediation include physical, mechanical and chemical stabilization processes. Chemical stabilization is the process of soil stabilization by improving the engineering properties of the soil by adding a chemical additive to the soil, which changes the physical and chemical properties of the soil to be stabilized [4, 5]. Cement is one of the oldest bonding agents used since the invention of the soil stabilization technique, which is the bonding of soil particles resulting from the interaction of cement particles with water, and they grow into crystals that can intervene with each other, which gives a high compressive strength [6]. There exist in the research literature large amount of experimental work previously conducted to improve the strength of clay soils by adding cement as a stabilizing agent. The results of many researches have demonstrated that the cement stabilization technique is improving the resulting strength of clay soils [7,8,9,10,11,12,13,14,15,16,17,18,19,20-21]. Their work covers a wide range of fine grained soils (i.e. silt and clay) from different places around the world using ordinary Portland cement (OPC). It is aimed in this study to apply a reliable technique in order to investigate the link between the several parameters which have a significant effect on the resulting strength of cement treated clayey soils generated from the large amount of data in the literature. Artificial neural network (ANN) is a form of artificial intelligence that is a machine learning technology that can simulate the mechanism of the human brain. ANNs have been successfully applied to almost all aspects of geotechnical engineering problems and have shown predictive ability when compared to traditional methods [8]. The ANN technique is therefore applied to develop a strength prediction model in terms of the unconfined compressive strength (UCS) for different data samples collected from several previous studies involved the stabilization of clay soils using ordinary Portland cement,

A. Factors Affecting the Clay Stabilization with Cement

The purpose of chemical stabilization is to enhance soil stability by increasing the grain size of the soil material, reducing the plasticity index, swelling and shrinking potential, and provide cementation [22].The type of stabilizer used depends on the type of soil to be treated mainly; plasticity, particle size distribution, clay content and minerals. However, properties of the soil required to be often improved; strength, compressibility and durability, and environmental conditions [10]. Cement is one of the commonly used binders for soil stabilization since the invention of soil stabilization techniques in the sixties of the last century [2]. The strength of the soil increases when it is fixed with cement due to the occurrence of the same pozzolanic reaction. Cement soil stabilization process can be affected by several factors, including water-cement ratio, curing conditions [23, 21, 15, and 24]. In order to obtain a good bond, the cement particles should cover most of the soil particles to provide good contact between the cement particles and the soil and thus stabilize the soil effectively. The soil-cement mixture becomes a solid and strong substance when the cement is hydrated as the cement reacts with water and becomes hard [25, 26]. Other factors also important such as the sample preparation method used for the cement treated clay which reflects the initial condition of the material to be stabilized and their water content. [15, 24].

B. *Artificial Neural Networks (ANN)*

Artificial neural networks provide a way to describe artificial neurons to solve complex problems in the same way as the human brain [27]. In multilayer artificial neural networks, there are neurons that are laid out in a manner similar to human brain cells. Where each neuron is connected to other neurons with certain parameters, during the training process, information is distributed to these connection points so that the network can be recognized [28]. In artificial neural networks, the learning process is an important behavior for network training. The learning process is a technique for introducing network experience in this field to help them acquire decision-making skills based on real data and the knowledge gained. Thus, the artificial neural network will build a predictive model that can solve a specific problem by taking advantage of the learning ability it has previously acquired [29]. A multi-layer artificial neural network consists of three layers known as input, output, and hidden layers. The transmission of the signal from the input units to the output units. The intermediate layer between the input and output layers is the hidden layer in which all computations are performed during the network training process [30]. Using weights, the nodes are connected to each other, and the size of the weight determines the effect of the input variables on the output values [31]. Recently, the use of artificial neural networks (ANNs) has increased widely in many fields of engineering, especially geotechnical engineering [32]. Classification and prediction are the most common applications of supervised learning artificial neural networks. In supervised learning, both the actual input and output values are provided. After completing the training process, the output of the model will be compared with the desired output to reduce the difference between them. The classification focuses on determining which group the data belongs to, while prediction attempts to estimate a specific value based on the real data [30]. Juwaied (2018) [33] stated that Neural networks have a number of important properties for modeling a complex mechanical behavior: good generalization capability, universal function approximation capability, resistance to noisy or missing data, and accommodation of multiple nonlinear variables for unknown interactions. The ANN technique was applied in the field of geotechnical engineering for modelling problems related to Site characterization, Soil properties and behavior, foundations, slope stability, Earth retaining structures, soil liquefaction and other geotechnical engineering applications [34]. It is also stated that the use of ANN model may work as a simple and reliable predictive tool for deriving many geotechnical parameters of soil at the site without the need for excessive field tests [35]. Furthermore, it was concluded that the ANN model allows the development of a highly efficient predictive model by reducing the costs and time required to conduct laboratory or field tests [36]. Moreover, it was demonstrated that using the GMDH-type NN is an efficient method in obtaining a new empirical mathematical model to provide a reliable prediction of the strength parameters of soils [37]. Das et.al (2010) [38] has developed an artificial neural network model to predict the unconfined compressive strength (UCS) of cement-stabilized soils. The input parameters were liquid limit (LL), plasticity index (PI), clay fraction (CF)%, sand (S)%, gravel Gr (%), moisture content (MC), cement content (Ce), and compressive strength value unconfined compressive strength as an output parameter. The value of the correlation coefficient was (R2) = 0.851, while the value of coefficient of efficiency CE = 0.73. Pham et al [39] developed an ANN model to predict compressive strength in cement-treated sandy soil. The results of the statistical analysis showed that the proposed model developed in this study is accurate and reliable with a high correlation coefficient and low root mean square errors. It also demonstrated that the UCS prediction model met external criteria well; hence it demonstrates the great potential of the predictive ability of ANN technique for geotechnical parameters.

II. Material and Methods

A. *Soil Data Collection*

Submit your manuscript electronically for review. This study uses the Levenberg-Marquardt algorithm (LMNN) to develop a predictive model for unconfined compressive strength (UCS). Prior to the development of this model, data for this study were collected from previous scientific research on clay soil samples treated in the laboratory with cement, as shown in Table 1. Where the number of samples reached 429 samples from 15 scientific researches for several varieties of clay soil taken from several regions around the world. Soil parameters that are expected to have the greatest effect on unconfined compressive strength were identified as observed from the literature review. The collected data from previous studies were also meant to cover wider ranges of the parameters that influencing the resulting unconfined compressive strength of cement treated clay were included and as shown in Table 2. The range of water content is generally ranges from 11 to 250 % although the majority of the used data are below 150 % as seen in Figure 1a. Also the range of cement content is generally ranges from 1 to 33.3% while the majority of the used data are below 16 % as seen in Figure 1b. The curing time range is from 1 to 95 days while most of the data were cured up to 28 days. The referenced researches also adopting deference procedures for sample preparation and curing methods. It should be noted that some data sets were excluding from that used for modeling process which were considered not practical for example high cement content exceeding 35 % or those considered as overestimated values for example the resulting unconfined compressive strength exceeding 2000 kPa.

Table 1. Sources of research studies from which data were collected.

Reference	Study area	Soil Classification
Uddin K. et.al (1997) [7]	Bangkok	Soft clay CH
Eskisar T. (2015) [8]	Turkey	Soft clay CL
Jafer H. M. et.al (2016) [9]	UK	Silty clay ML
Chew S. H. et al (2004) [10]	Singapore	Marine clay CH
Obaid Q. J. et al (2019) [11]	India	Silty soil ML
Majeed Q. G. et.al (2021) [12]	Iraq	Soft clay CL
Yan-Jun Du et.al (2013) [13]	China	Kaolin clay ML
Preetham H. K. and Nayak S. (2019) [14]	India.	Marine clay CH
Rahman M. M. et al (2012) [15]	Bangladesh	Silty clay CH, CL
Al-Jabban W. et al (2019) [16]	Sweden.	Sandy clayey silt ML
Mohammed O. A. et al (2017) [17]	(USA)	Silty clay CH
Narendra B.S. et al (2006) [18]	India	Silty sand SM, Clay CH
Alkiki I. M. et al (2021) [19]	Iraq	Silty clay CL
Verástegui Flores R. D. and Emidio Di G. (2010) [20]	U K	Kaolin clay CH
Lorenzo G. A. and Bergado D. T (2004) [21]	Bangkok	Silty clay MH

B. Datasets

The unconfined compressive strength (UCS) is the output Parameters required to be predicted in this study using artificial neural networks, and to obtain good and accurate prediction results, the input parameters must be chosen correctly and closely related to the output parameter. This study was conducted using the results of UCS considered as an output parameter. 8 input parameters were selected, liquid limit (LL)% , plasticity index (PI)% , clay fraction (CF)%, sand (S)%, silt (M) %, water content (Wc) % , curing time (Tm) in days and cement content (Cc)% . In Table 3, a statistical description of the data parameters of this study is presented. Statistical analysis can be performed by various methods to measure and evaluate the performance of prediction models. In this study, the value of regression (R2), mean squared error (MSE), root mean squared error (RMSE), and coefficient of efficiency (CE) of the predicted parameters were calculated in evaluating the performance of regression models.

C. Pre-Processing

In machine learning systems, data quality is often a major concern. In order to build a decent and widely applicable prediction model as possible, the independent variables must be normalized and unified within a certain range, in addition to eliminating the dependence of the variables on unity [38]. Therefore, normalization is performed, which is the method of transforming the data and limiting it within a certain range, and it is especially useful in neural networks, where once the data is normalized, the type of unit used will not affect the result [39]. Normalization is done using the min – max method in normalizing variables, due to its ability to ensure that all features are scaled in the same range and receive equal attention while training the artificial neural network. All data values are independent of their units [39].

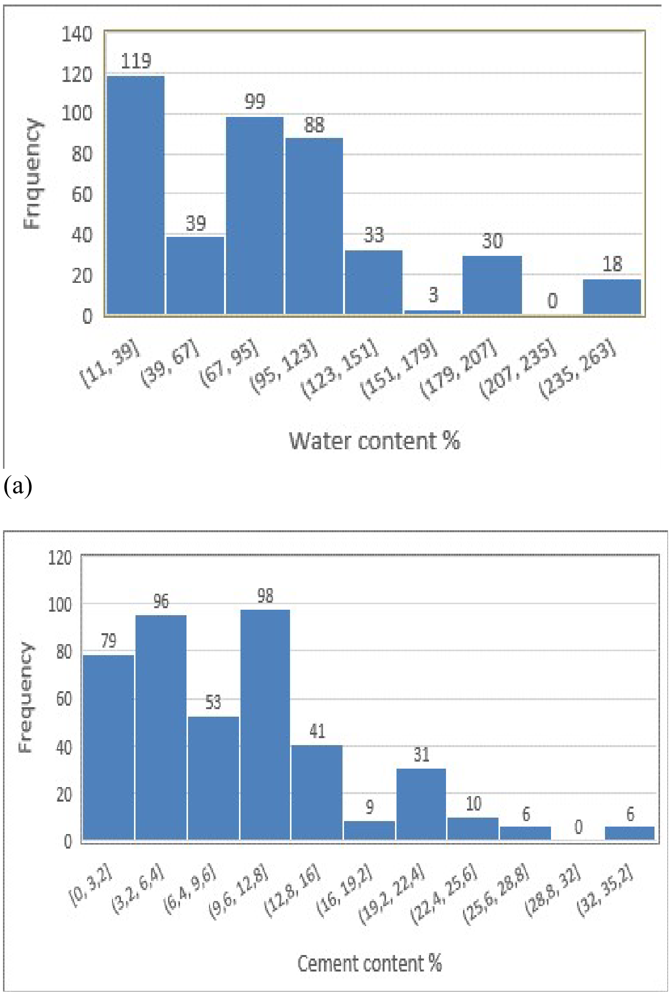

Fig. 1. Ranges of collected data a) water content b) Cement content

Table 2. Summary of the samples test conditions in each of the collected reference research study.

S. Nr.	Reference	Water content %	Cement content %	Sample preparation	Curing time (days)	Curing method
1	K.Uddin et.al (1997)	84	5, 7.5, 10, 12.5, 15, 20	Compaction at water content 84%	7,14,28,42 & 56	The prepared sample was placed in a humid room for curing.
2	Tugba Eskisar (2015)	30	5, 10	Compaction at water content 30%.	7 & 28	The samples were wrapped and placed in a moisture room (at 25 ◦C and humidity 97%)
3	Hassnen M. Jafer et.al (2016)	36.8	1.5, 3, 6, 9, 12	Compaction at OMC	1,3,7,14 & 28	The samples were stored in humidity cabinet for curing under 20 ±2°C in temperature and 100% humidity.
4	S. H. Chew , et.al (2004)	70, 120	5,10,20, 30	Slurry at high water content	7 & 28	The samples were wrapped and kept submerged in water during the entire curing period.
5	Obaid Qadir Jan and Sandeep Raj (2019)	19%	5% , 7.5% , 10% ,12.5% & 15%	Compaction at OMC	7	---
6	Qutaiba G. Majeed, et.al (2021)	17.45%	10%	Compaction at the OMC	7 & 28	The specimens were cured at 25 ± 3° C
7	Yan-Jun Du, et.al (2013)	59%	8% , 12% , 15% & 18%	Slurry at water content 59%.	7 & 28	Specimens were cured under controlled ambient conditions (22 °C and relative humidity of 95%)
8	H. K. Preetham and Sitaram Nayak (2019)	27%	2% , 4% , 6% , 8% & 10%	Compaction at the OMC.	7 & 28	The samples are cured for 7 days and 28 days. After curing, samples are fully saturated.
9	M. M. Rahman, et al (2012)	120%,150 %,200% & 250 %	Range from 8% to 33.3%	Slurry at high water content .	28 & 84	The samples were wrapped and stored in a room of approximate constant temperature (25 ± 2 °C)
10	Wathiq Al-Jabban et.al (2019)	12%	1% , 2% , 4% & 7%	Compaction at the OMC.	7,14,28,60 & 90	Cured for 7, 14, 28, 60 and 90 days at 20° C before testing.
11	Mohammed O. A. Bazne, et al (2017)	100%	2.5% , 5% & 10%	Compaction at the OMC.	9 & 95	Specimens were stored in a curing room with 100 % relative humidity at approximately 22°C.
12	B.S. Narendra et al (2006)	Range from 38% to 194%	Range from 3% to 24%	Slurry at high water content	7, 14, 28 & 56	The specimens are cured in desiccators at 100% humidity,
13	Ibrahim M. Alkiki, et al (2020)	11%	2%, 4% & 6%	Compaction statically at the OMC	3, 10, 30, 60 & 90	Specimens were left at room temperature of 20 C° for different periods of 3, 10, 30, 60 and 90 days to be cured.
14	R. D. Verástegui Flores et al (2010)	115%	5%, 10% & 20%	Slurry at high water content	7, 14, 28, 42 & 56	Specimens were sealed and stored in an air-conditioned room at 18°C and they were allowed to cure
15	Glen A. Lorenzo and Dennes T. Bergado (2004)	103%, 206%	5, 10, 15, & 20%.	Slurry at high water content	7, 14, & 28	The specimens were placed for curing inside the humidity room having a maintained ambient temperature of 25 °C and humidity of 97%.

Data were normalized using the following formula;

$$X_{norm} = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

Where x and Xnorm represent data value and normalized data, respectively.

III. NEURAL NETWORK MODEL DEVELOPMENT

A. Data Division

The data were divided after normalization into two determined using the trial and error method in this work. The best ratio was chosen based on the performance of the resulting neural network, where the ratio that gives the lowest value of the mean squared error (MSE) and the highest correlation coefficient R2 in addition to the highest equivalence coefficient CE was taken as the best ratio for training neural networks. It was found that the ratio of 75% (320 data sets) and 25% (109 data sets) is the best ratio for training and testing, respectively.

B. Define Neural Network Architecture

A two-layer feed-forward network structure was used, one hidden layer of 10 neurons and one output layer. The input layer is not calculated because no calculations are performed in this layer. In a frontal neural network, there is no backward transmission of information, information is transmitted only in the forward pathway to the neurons of the next layer.

C. Neural Network Training

The MATLAB neural network toolkit was used to build the prediction model. One hidden layer was used as it gives better results, as shown in Figure 2. In addition to the feeding network, the standard Evenberg-Marquardt backpropagation algorithm was used to adjust the weights and bias, thus reducing the potential error. ' Trainlm ' is often used as the fastest back propagation algorithm and is suggested as a first choice learning algorithm. As a first step both the corresponding input and output values were provided while training the neural network. Although this training function is more memory consuming than other methods, it was chosen because of its fast computing power. For the transfer function we used the tangential sigmoid transfer function (TANSIG), which is the most common function.

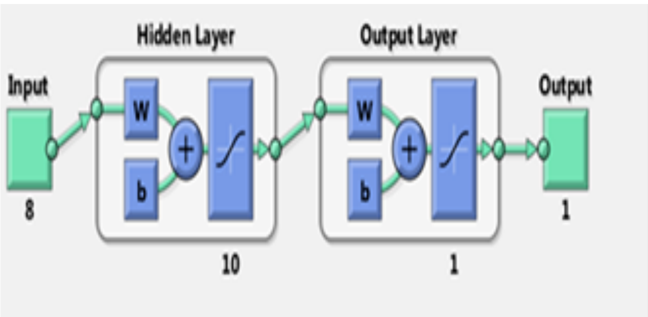

Fig. 2. Implementation of FFBP ANN Model using MATLAB

D. Model Performance Evaluation

To evaluate the performance of the artificial neural network model developed in this study, the values of regression (R2), mean squared error (MSE), root mean squared error (RMSE), and coefficient of efficiency (CE) were calculated for the estimated and actual target parameters in evaluating the performance of the regression models. Where the values of (R2), (MSE), (RMSE), and (CE) are mathematically calculated as follows:.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{mea} - y_{pre}\right)^2}{\sum_{i=1}^{N}(y_{mea} - y_m)^2} \quad (2)$$

$$MSE = \frac{\sum_{i=1}^{N}\left(y - y_{pre}\right)^2}{N} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y - y_{pre}\right)^2}{N}} \quad (4)$$

$$CE = 1 - \frac{\sum_{i=1}^{N}\left(y_m - y_{pre}\right)^2}{\sum_{i=1}^{N}\left(y_{pre} - y_{mea}\right)^2} \quad (5)$$

Where:

y_m : actual output value .

y_{pre} : estimated output value .

y_{mea} : the average of actual output value .

N : represents the total number of data.

IV. RESULTS AND DISCUSSIONS

The lowest prediction error and maximum correlation coefficient was obtained from the network with 10 hidden layer nodes. Figure 2 shows predictive capability of developed ANN model by plot of measured against predicted normalized unconfined compressive strength UCS, for the testing data sets. As seen, most of the predicted UCS are around the middle, showing good distribution of the results, indicating that the model has R2 of 0.897, MSE of 0.0024, RMSE of 0.049 and CE of 0.887 values. However, the predictive study model can be considered highly efficient after obtaining these values for the statistical analysis of the performance of the model, as the mean square error MSE value was low. Furthermore, values of R2 and CE indicates a highly efficient model. A minor deviation from the line of perfect equality shown in Figure 3 is an indication of a good relationship between the actual and predicted values of unconfined compressive strength UCS. The adopted method of sensitivity analysis of the input variable is implemented based on the method described by Mrzygłód et al (2020) [40] after the network training process is completed and the network error is determined.

Table 3. Descriptive statistics of parameters

Variable	Min.	Max.	Mean	Stand. Dev.
Liquid limit (L.L)%	33	105	65 .7	**25.1**
plasticity index (PI)%	8	62	37.6	**18.1**
Water content (Wc) %	11	250	90.7	**59.8**
clay fraction (CF)%	12	73	48.0	**16.2**
Silt (M) %	11	85	38.6	**13.1**
Sand (S) %	0	40	13.2	**11.5**
curing time (Tm) days	0	90	30.2	**27.3**
cement content (Cc)%	0	33.3	9.3	**6.8**
Unconfined Compressive Strength (UCS) (kPa)	5	1842	300.7	**310.6**

The level of significance of input variables can be assessed by a way of eliminating them one at the time from the network input, re-implementing the training process and determining a new network error Ei. However, when a certain amount of data is rejected, an increase in the network error should be expected. Therefore, the basic measure of network sensitivity is the quotient W of the error obtained at the network startup for a data set without one variable Ei and the error obtained for a dataset with all the variables E.

$$W = E_i / E \qquad (6)$$

The quotient W is considered to represent the significant of each parameter as presented in Figure 4. It is clearly seen that the cement content Cc, have the a highly significant effect on the predicted UCS with a value equals to 43.73 followed by the effect of water content Wc of 12.71, curing time Tm of 9.49 and liquid limit LL of 7.96. The other variables PI, CF, M & S have relatively low effects ranging between 4.41 To 6.27 It is also seen that none of the implemented variables can be considered as completely insignificant.

V. Conclusion

A back-propagation neural network was used to demonstrate the feasibility of ANN to predict the unconfined compressive strength UCS of a cement treated clay based on 429 collected datasets from the literature used for development of the model.

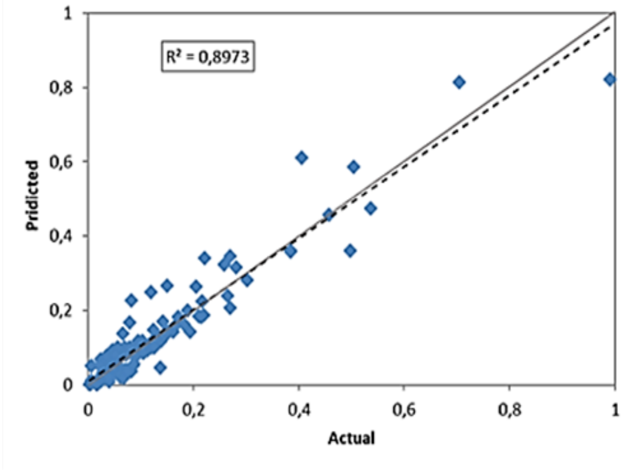

Fig. 3. Regression relationship between the actual and predicted UCS data.

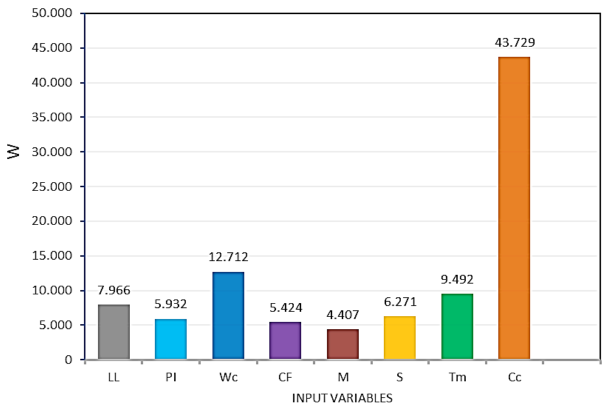

Fig. 4. Results of sensitivity analysis presenting the relative importance of input variables

A feed-forward network with the Levenberg-Marquardt algorithm was used in the training stage. The optimal network was found to be 8 inputs, one hidden layer of 10 neurons, and one output. The results obtained in this study indicate that the model has ability to predict the unconfined compressive strength UCS with a highly acceptable degree of accuracy ($R2 = 0.897$). A sensitivity analysis was also carried out to study the relative importance of the factors, affecting the unconfined compressive strength of cement stabilized clay. The sensitivity analysis indicates that the cement content is the most significant factor affecting the predicted UCS while water content and curing time have respectively moderate effect and the other factors have relatively lower impact but none of them can be considered as completely insignificant**.**

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