Journal of Soft Computing in Civil Engineering 4-2 (2020) 85-102

Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

# Neural Models for Unconfined Compressive Strength of Kaolin Clay Mixed with Pond Ash, Rice Husk Ash and Cement

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https://doi.org/10.22115/SCCE.2020.223774.1189

## ARTICLE INFO

Article history:
Received: 16 March 2020
Revised: 12 May 2020
Accepted: 28 May 2020

Keywords:
Kaolin clay;
Artificial neural network;
Pond ash;
Rice husk ash;
Cement and unconfined compressive strength.

## ABSTRACT

In this study an Artificial Neural Network (ANN) model was used to predict the Unconfined Compressive Strength (UCS) of Kaolin clay mixed with pond ash, rice husk ash and cement content model under different curing period. The input parameters included percentages of admixtures added along with clay content and curing period. The curing Period range was 7, 14 and 28 days considered in neural model. The feedforward back propagated neural model with Levenberg Marqaurdt gradient descent with momentum constant was used to predict the UCS and optimized topology of 5-10-1 was obtained. The sensitivity analysis based on weights of neural model indicated that all admixtures contributed 70% to the UCS of Kaolin clay. The comparison of ANN model with Multiple Regression Analysis (MRA) model indicated that ANN models were performing better than MRA model with values of r as $R^2$ as 0.98 and 0.97 respectively in testing phase of neural model and for MRA model r was 0.94 and $R^2$ as 0.88.

## 1. Introduction

The strength of soil plays an important role in long-term stability of structures over soil. To accomplish this in many cases, soil improvement using admixtures is done and is termed as soil

How to cite this article: Priyadarshee A, Chandra, S, Gupta D, Kumar V. Neural models for unconfined compressive strength of kaolin clay mixed with pond ash, rice husk ash and cement. J Soft Comput Civ Eng 2020;4(2):85–102. https://doi.org/10.22115/scce.2020.223774.1189.

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improvement. Addition of admixture to soil is one of the soil improvement techniques widely used and is economical and if admixtures are such that waste utilization is done then it is also an environment friendly way. To improve the engineering behavior of soil, different cementing and non-cementing materials are available. Lime, cement etc. are the example of cementing material, while fly ash, pond ash, rice husk ash etc. are the examples of non-cementing materials which are by-products of other processes and also a better waste management option. Many researchers have studied the behavior soil mixed with different admixtures like lime, cement, fibers, fly ash etc. [1–10]. All such studies have shown that these materials have potential to improve the strength behavior of soil. These materials can be used in construction of different geotechnical structures like road subgrade, embankment, retaining wall etc.[11–16].

Utilization of the wastes like pond ash and rice husk ash, which are industrial wastes and agricultural wastes respectively, the proper disposal and utilization is of utmost important so that circularity in products along with environment sustainability can be achieved. Pond ash is an industrial waste generated from the thermal power plants after burning of coal. Pond ash is low density material, which is normally not an active pollutant. But due to bulk production, it creates environmental problem. Researchers like [17,18] through laboratory tests have found that pond ash as admixture can improve the soil behavior. Similar to pond ash, rice husk ash is also a waste product, which is produced due to the burning of the rice husk. It can also be used for different geotechnical constructions [19,20]. Potential of rice husk ash as admixture for the improvement of the behavior of soil through laboratory investigation is considered by different researchers [21–24].

The strength values of such soils can be measured directly or indirectly but laboratory tests are time taking and cost intensive, therefore development of estimation model is of prime importance to have simulation before and decide series of experiments [25]. Based upon the laboratory results many prediction models using multiple regression analysis are developed to estimate the strength behavior of soil-admixture mix [10] These models have to be fitted with variable polynomial functions and type of polynomial which is time consuming and yields results which cannot capture non-linearity [25]. In fact, getting a proper model is a time consuming as well as crucial task for any human and automated system. Most of the time, one has to rely upon analytical and hit and trial things. To avoid such bottle necks and limitations, many researchers have recommended use of Artificial Neural Networks (ANN's) [26]. These have been used for prediction of unconfined compressive strength of geopolymer stabilized clayey soil[27], prediction of soil behaviour [28], prediction of maximum dry density [29] and also for prediction of unconfined compressive strength of soft rocks [30]. It can be used in many civil engineering problems like prediction of ultimate bearing capacity of skirted footing [31], free swell index for expansive soils [32] and also be used for the prediction of the strength behavior of the mix [26,33,34]. From the literature study, it was identified that ANN models have not been used for soils like clay stabilized with waste material like pond ash and rice husk ash in combination with cement. Therefore, this study uses ANN model to predict the Unconfined Compressive Strength (UCS) of Kaolin clay mixed with admixtures for stabilization.

## 2. Materials and methods

In this study, Kaolin clay mixed with pond ash and rice husk ash was tested for its unconfined compressive strength [35]. As per Unified Soil Classification System (USCS) soil is classified as CL (Clay with low plasticity) with specific gravity (G) as 2.7, Liquid Limit (LL) as 43.3% and Plastic Limit (PL) as 19.5% along with Plasticity Index ($I_p$) as 23.8. The optimum moisture content (OMC) obtained was 18.3% and Maximum dry density was 17.5 kN/m$^3$.

Pond ash used as an admixture is the waste product produced due to the burning of coal in thermal power plant. As per ASTM C 618-1992, pond ash used in the study was classified as F type. The pond ash used was rounded and sub-rounded with light grey color and specific gravity (G) as 2.10 and was non-plastic. The silt and clay proportion in ash was 41.6% while fine sand was 44.6%.

Rice husk ash is basically a waste material produced from processing of rice. 20-25% of rice husk get generated during processing of rice from paddy. About 25% of rice husk ash gets produced after burning of the rice husk. The properties of the rice husk ash depend upon the burning temperature. The ash was basically non-plastic in nature and major chemical constituents were $SiO_2$, $Fe_2O_3$ and $Al_2O_3$.

## 3. Methodology

### 3.1. Artificial neural network

The science of Artificial Neural Networks (ANN's) is based on the biological neuron, and the architecture is designed according to the elements of a neuron. On the basis of biological neuron, the first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. Neurons are the fundamental component of the central nervous system and it consists of the nucleus, dendrites, cell body, and axon. The dendrites gather signals coming from the neighboring neurons and then transmit it to the cell body. The cell body consists of the nucleus of the neuron. If the sum of the received signal is greater than the threshold value, then the neuron send an electrical pulse along the axon to the next neuron. Based on this biological working, ANN processes the incoming information in a similar way. The network is composed of large, highly interconnected processing elements (neurons) working in parallel to perform a particular task. Neural networks can learn through the example and provide an approximate solution. Fig.1. shows the elementary model of artificial neural network. It is a one form of artificial intelligence and unlike standard statistical prediction model, it is a class driven nonlinear approach.

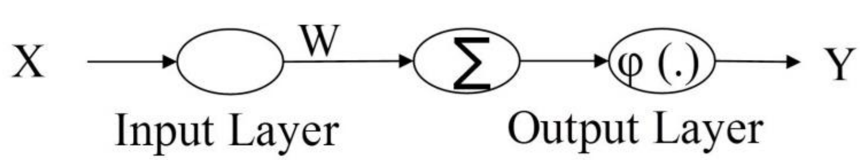


**Fig. 1.** Elementary model of Artificial Neural Network.

3.1.1. Neural architecture

In artificial neural networks there are mainly two broad types of architecture - feedforward networks and feedback networks. Feedforward or multi-layer networks have been extensively used while making neural model. In such models, it may consist of several layers as hidden layer and one output layer as shown in Fig. 2. In most of the applications where neural network is used one or two hidden layers are kept in the architecture. The detailed working of these multi-layer networks also known as multilayer perceptron is presented in Annexure-I.

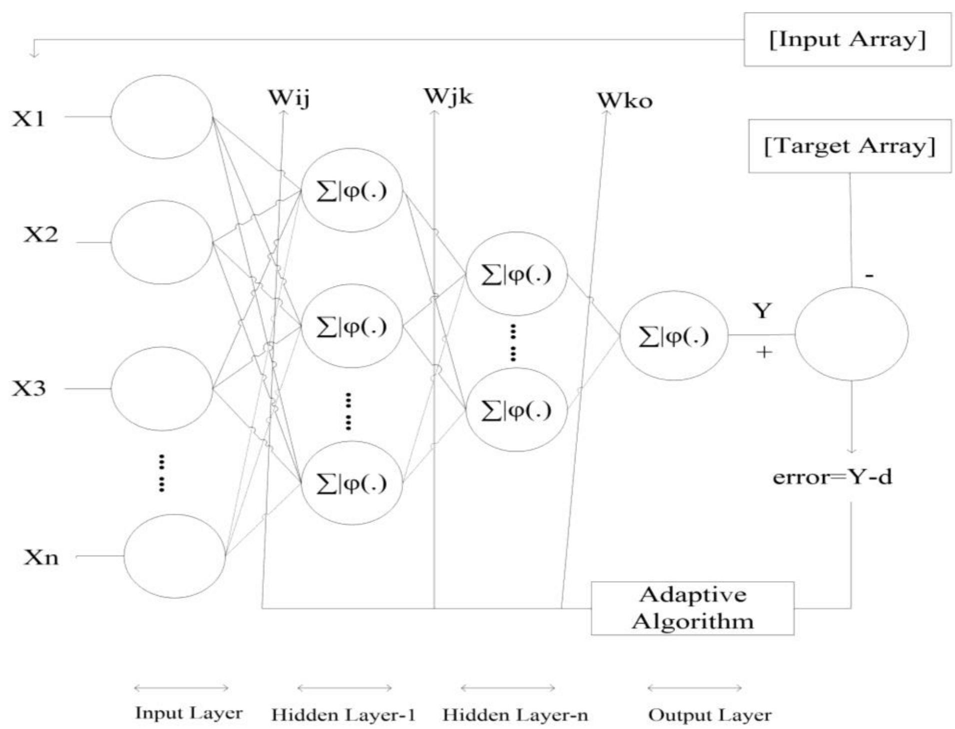


**Fig. 2**. Architecture of multilayer perceptron.

In Fig.2., $X$ is input of the neural network and each input is multiplied by weight $W$. Similarly, $\varphi(.)$ and Y are the activation function and the output of the neural network model respectively.

The number of neurons in each hidden layer can be fixed by trial and error process and also depending upon the complexity of process to be modeled. ANN's comprises numerous interconnected networks which help to form a relationship between historical sets of inputs and corresponding output. This is achieved by repeatedly providing input/output data to an ANN network and the model output as well as target value are compared to find out the error which is further utilized for adjusting the model coefficients i.e. neural network weights. This process assist to minimize an error function of any ANN based model. The activation function $\varphi(.)$ is needed to introduce nonlinearities into the network. The activation function is chosen to satisfy some specification of the problem that neuron is attempting to solve. There are 3 main types of activation function, i.e., tan-sigmoid, log-sigmoid and linear. Broadly, the activation function may be sigmoid or hyperbolic tangent type. Fig.3. depicts the graphical representation of three different activation functions.

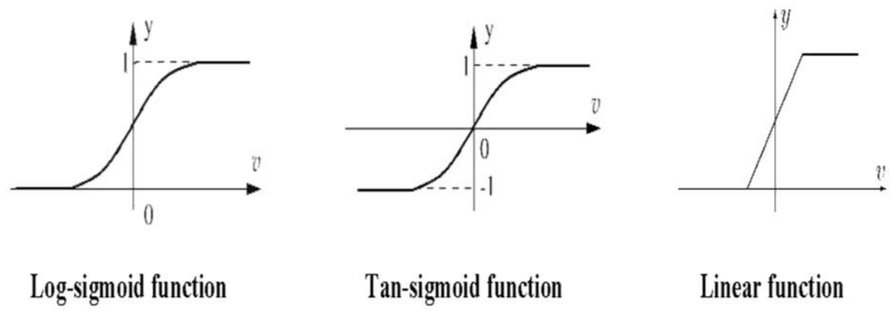


**Fig. 3.** Activation functions used in neural model**.**

3.1.2. Data for neural model, pre-processing and data division

In this study, the outcomes of experiments conducted over Kaolin clay mixed with different admixtures were used for database development for neural model. All the series of tests were collated and total 129 data points were obtained to develop neural model for prediction of unconfined compressive strength (UCS). The dataset was collated and randomized in order to avoid network from just memorizing while making models. Once the dataset is finalized, it is processed, randomized and normalized as it has to pass through activation function. The normalization can be done in any range from [-1,1] or [0,1] but in this study it has been taken in range [0.1,0.9] to avoid saturation in dataset [36]. Once collated the data was randomly divided into two set of data. One set of the data known as training set was used for training of neural network with 70% (91 points) randomly selected data points. This set of the data helps to develop the neural network model. Other set of data known as testing set with 15% samples included 19 points and validation also with 15% includes 19 points. These were used for validation and testing of the trained neural model [37]. The test data is one which is not presented to the network while training and was not seen by model before. The neural interpretation figure (NIF) used in the study is shown in Fig. 4.

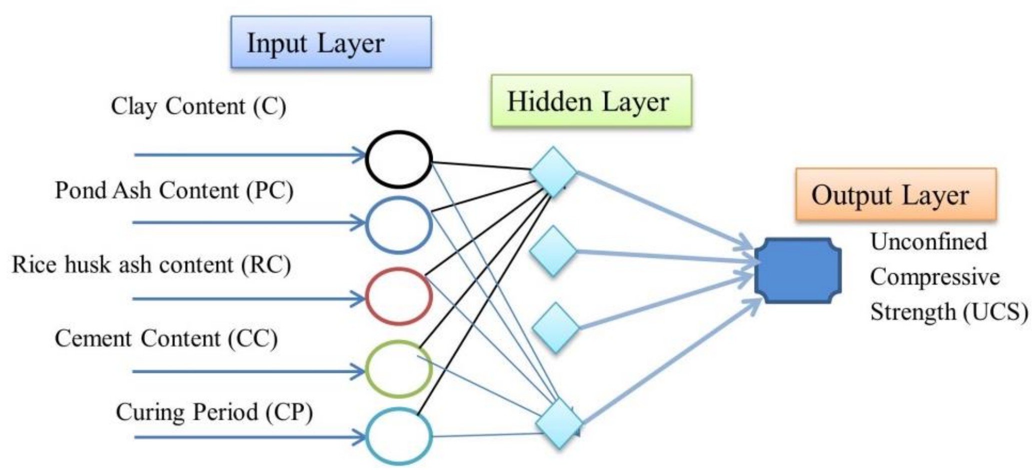


**Fig. 4.** Neural Interpretation Figure for ANN used in the study.

The Simulation task was implemented in Matlab® 2015 software, using PC with hardware specification of 4 Gb installed memory, Intel Core i3 CPU @ 1.70 GHz processor and Microsoft Windows 8 operating system.

### 3.1.3. Model input and output

The experiments conducted on Kaolin clay for its unconfined compressive strength had variable parameters such as clay content (C), Pond ash (PC), Rice husk ash content (RC), Cement content (CC) and Curing Period (CP). Therefore, these variable parameters were used as input data during the development of the model. Unconfined compressive strength (UCS) was considered as target data or output data. The range of the values of input data is presented in Table 1.

**Table 1**
Range of input values used for development of the ANN model.

| S. No. | Variable parameter | Values |
|---|---|---|
| 1 | Clay content (C) | 46-100 % |
| 2 | Pond ash content (PC) | 10-50 % |
| 3 | Rice husk ash content (RC) | 5-20 % |
| 4 | Cement content (CC) | 2%, 4% |
| 5 | Curing period (CP) | 7, 14, 28 days |

The statistics of data used for development of neural models for prediction of UCS using neural model is presented in Table 2.

**Table 2**
Statistical Parameters for all inputs and output used in neural model.

| Variable | Clay Content (C) (%) | Pond Ash Cement (PC) (%) | Rice husk ash content (RC) (%) | Cement Content (CC) (%) | Curing Period (CP) (days) | Unconfined Compressive Strength (UCS) (kN/m$^2$) |
|---|---|---|---|---|---|---|
| Parameter | | | | | | |
| Min | 46.00 | 0.00 | 0.00 | 0.00 | 7 | 118.00 |
| Max | 100.00 | 50.00 | 20.00 | 4.00 | 28 | 512.00 |
| Average | 69.43 | 21.51 | 7.14 | 2.00 | 16.33 | 258.69 |
| SD | 18.63 | 18.60 | 7.49 | 1.63 | 8.73 | 80.38 |

## 3.2. Multiple regression analysis

In this study, apart from ANN model multiple regression analysis was also done to predict UCS of Kaolin clay. The UCS was taken as dependent variable and C, PC, RC, CC and CP as independent variable. After various combinations, the equation obtained after regression analysis is given below.

$$\frac{UCS_m}{UCS_{C7}} = -1.003 + 1.568 * \left[\frac{CC}{100}\right]^2 + 2.477 * [\frac{PC}{100}]^{0.5} + 2.287 * \left[\frac{RC}{100}\right]^{0.5} + 6.731 * [\frac{C}{100}]^{0.5} + 0.017 * CP \quad (1)$$

where, $UCS_m$ is Unconfined Compressive Strength of mix and $UCS_{C7}$ is unconfined compressive strength of clay alone at 7 days curing period. Using Equation (1) the coefficient of determination ($R^2$) was 0.88 for prediction of UCS and the results obtained from regression and actual values were plotted and a close-fit was obtained (Fig. 5).

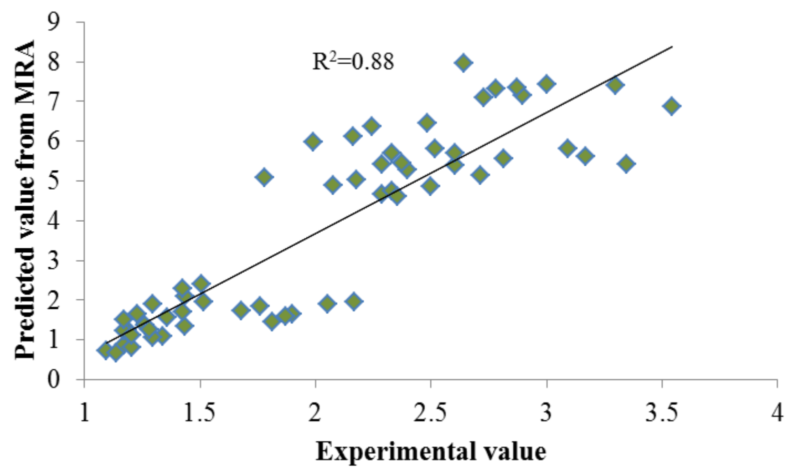


**Fig. 5.** Comparison between Regression model and experimental values.

## 4. Results and discussion

### 4.1. Neural architecture

The number of neurons plays an important role in the performance of the proposed neural network based strength predictive model and it is essential to select the appropriate number of neurons for optimizing the performance level. Different numbers of neurons were adopted to evaluate the efficiency level of the proposed network. The comparison of the performance of the neural network with different numbers of neurons was done in terms of mean square error (MSE) as in Eq.(1) and is shown in Fig. 6 [38].

$$MSE = \left[\frac{\sum_{i=1}^{N}\left(Value_m - Value_p\right)^2}{N}\right] \quad (2)$$

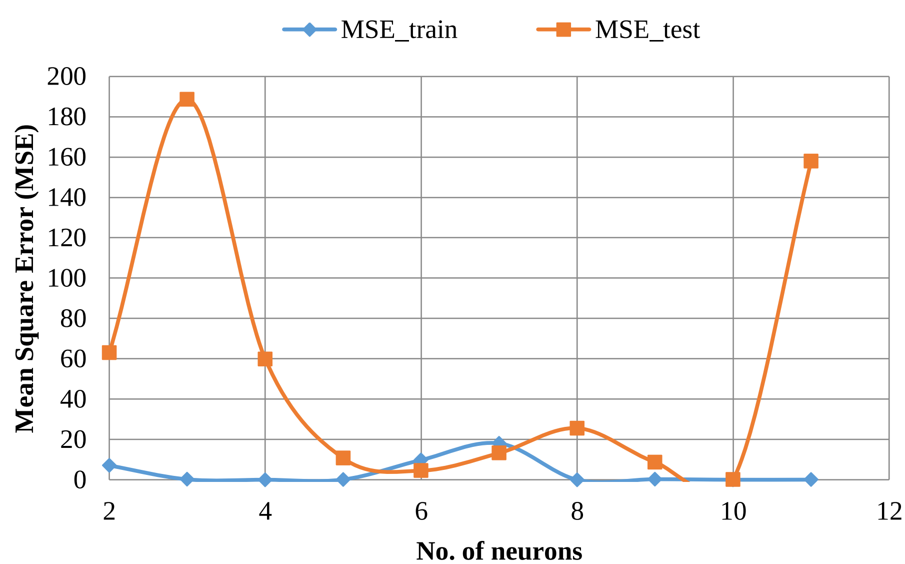


**Fig. 6.** Variation in MSE with number of neurons.

The number of neurons was varied from 2 to 11 in hidden layer with tan-sigmoid activation function between input and hidden layer and purelin as transfer function between hidden layer and output layer. During this process, it was observed that at neurons 10, the testing and training error was less and model has better predictive power. Therefore, the optimized topology for prediction of UCS of Kaolin clay mixed with PC, RC and CC was 5-10-1. The performance of model at optimized topology is shown in Fig.7.

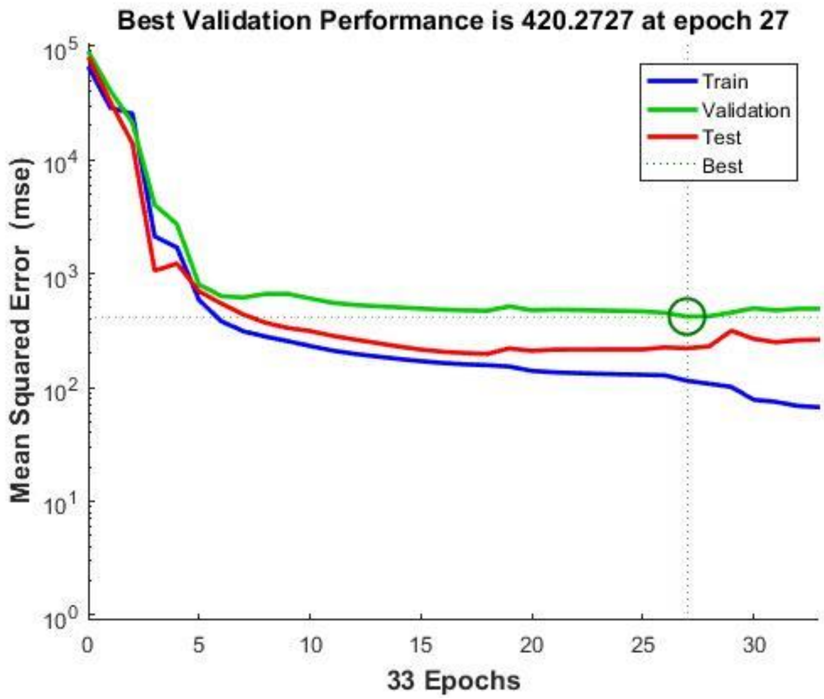


**Fig. 7.** Plot between MSE and epoch at neuron 10.

Fig.6. shows the performance of model when 5-10-1 trained architecture was used for prediction of UCS. It can be seen that at after epoch 27 the training error was reducing but testing error was increasing, therefore the model after 5 more epochs got terminated and optimized performance was achieved at 27 epochs. With 10 neurons in hidden layer, the model has better predictive power which is the main objective of constructing and optimizing the neural model.

## 4.2. Performance of model

The obtained neural model with 5-10-1 architecture was trained with Levenberg-Marquardt algorithm with gradient descent and momentum back-propagation. The parameters fixed for the model are given in Table 3.

The performance of model with number of neurons varied from 2 to 11 in hidden layer was assessed using Mean Square Error (MSE) and correlation coefficient (r) and results obtained are shown in Table 4. Value of 'r' can be calculated using Equation (3) [39].

$$r = \frac{\sum_{i=1}^{N}(Value_p - \overline{Value_p})(Value_m - \overline{Value_m})}{\sqrt{\sum_{i=1}^{N}(Value_p - \overline{Value_p})^2}\sqrt{\sum_{i=1}^{N}(Value_m - \overline{Value_m})^2}} \quad (3)$$

where, $Value_m$ is result obtained from experiments ,$Value_p$ is result predicted by model, $\overline{Value_m}$ is mean of results from experiment and $Value_p$ is mean of results from model.

**Table 3**
Parameters fixed for Neural model.

| S. No. | Neural Network Parameters | Adopted Parameters |
|---|---|---|
| 1 | Training Function | Trainlm(.) |
| 2 | Learning Function | Learngdm(.) |
| 3 | Performance Function | MSE(.) |
| 4 | Number of neurons | 10 |
| 5 | Activation Function | tansig(.) |
| 6 | epoch | 1000 |
| 7 | min_grad | $1e^{-07}$ |
| 8 | max_fail | 1000 |

**Table 4**
Performance parameters of trained artificial neural model.

| Neurons | Structure | | MSE | r |
|---|---|---|---|---|
| 2 | 5-2-1 | Training | 7.1036 | 0.8373 |
| | | Testing | 62.9299 | 0.4876 |
| 3 | 5-3-1 | Training | 0.2125 | 0.9568 |
| | | Testing | 188.537 | 0.9404 |
| 4 | 5-4-1 | Training | 0.0279 | 0.9026 |
| | | Testing | 59.8785 | 0.9075 |
| 5 | 5-5-1 | Training | 0.1271 | 0.9795 |
| | | Testing | 10.6892 | 0.9188 |
| 6 | 5-6-1 | Training | 9.8292 | 0.9451 |
| | | Testing | 4.5469 | 0.8858 |
| 7 | 5-7-1 | Training | 18.0555 | 0.9638 |
| | | Testing | 13.2486 | 0.9051 |
| 8 | 5-8-1 | Training | 0.0136 | 0.9882 |
| | | Testing | 25.595 | 0.9409 |
| 9 | 5-9-1 | Training | 0.3004 | 0.9698 |
| | | Testing | 8.7589 | 0.9554 |
| 10 | 5-10-1 | Training | 0.0395 | 0.9906 |
| | | Testing | 51.34 | 0.9856 |
| 11 | 5-11-1 | Training | 0.0704 | 0.9794 |
| | | Testing | 157.97 | 0.9466 |

From Table 4 it can be seen that error during testing significantly reduces when number of neurons were kept at 10 in hidden layer and correlation coefficient during training and testing was high. Once the model was trained, it was tested on unseen data and also was validated. The performance of model during training, testing and validation is shown in Fig. 8.

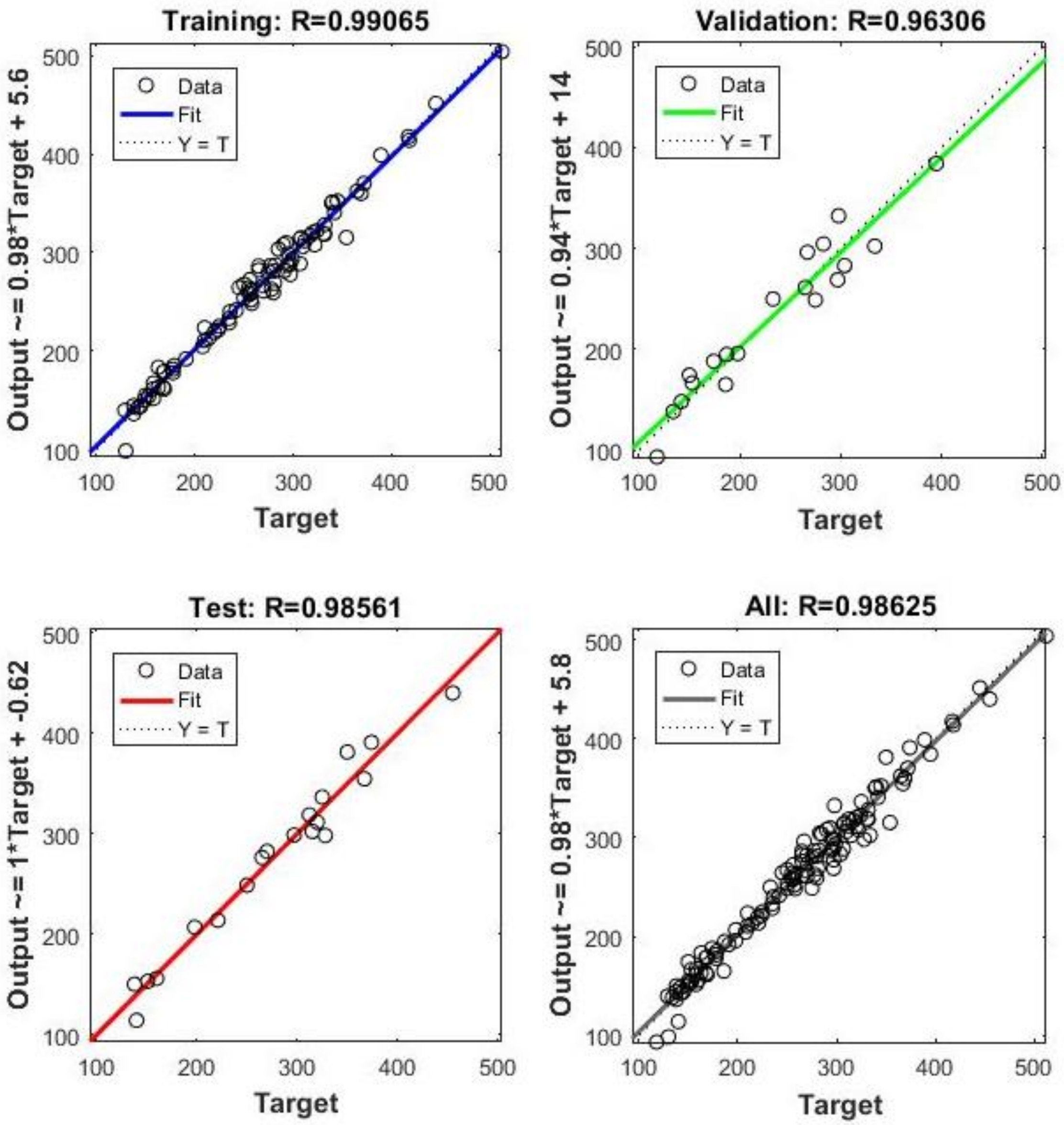


**Fig. 8.** Performance of optimized ANN for UCS.

From Fig. 7. it can be seen that optimized model has higher values of correlation coefficient during training, testing and validation, which means that model was able to predict values closer to actual values of UCS and hence this model indicates that well optimized ANN can be used to predict UCS of Kaolin clay mixed with CC, PC and RC under varying ranges.

The Predicted values and experimental values for all data points are presented in Table 5.

**Table 5**
Comparison of experimental and predicted values of unconfined compression tests.

| Conditions | | | | | | UCS ($kN/m^2$) | |
|---|---|---|---|---|---|---|---|
| Test. No | Clay (%) | Pond Ash (%) | Rice Husk Ash (%) | Cement (%) | Curing Period (Days) | Experimental | Predicted |
| 1 | 100 | 0 | 0 | 0 | 7 | 118 | 120 |
| 2 | 100 | 0 | 0 | 0 | 14 | 130 | 122 |
| 3 | 100 | 0 | 0 | 0 | 28 | 140 | 131 |
| 4 | 98 | 0 | 0 | 2 | 7 | 163 | 151 |
| 5 | 98 | 0 | 0 | 2 | 14 | 187 | 161 |
| 6 | 98 | 0 | 0 | 2 | 28 | 210 | 212 |
| 7 | 96 | 0 | 0 | 4 | 7 | 174 | 174 |
| 8 | 96 | 0 | 0 | 4 | 14 | 191 | 205 |
| 9 | 96 | 0 | 0 | 4 | 28 | 225 | 226 |
| 10 | 95 | 0 | 5 | 0 | 7 | 129 | 138 |
| 11 | 95 | 0 | 5 | 0 | 14 | 138 | 144 |
| 12 | 95 | 0 | 5 | 0 | 28 | 150 | 164 |
| 13 | 93 | 0 | 5 | 2 | 7 | 250 | 258 |
| 14 | 93 | 0 | 5 | 2 | 14 | 270 | 262 |
| 15 | 93 | 0 | 5 | 2 | 28 | 295 | 297 |
| 16 | 91 | 0 | 5 | 4 | 7 | 265 | 262 |
| 17 | 91 | 0 | 5 | 4 | 14 | 291 | 292 |
| 18 | 91 | 0 | 5 | 4 | 28 | 312 | 307 |
| 19 | 90 | 0 | 10 | 0 | 7 | 150 | 166 |
| 20 | 90 | 0 | 10 | 0 | 14 | 158 | 164 |
| 21 | 90 | 0 | 10 | 0 | 28 | 169 | 174 |
| 22 | 88 | 0 | 10 | 2 | 7 | 275 | 308 |
| 23 | 88 | 0 | 10 | 2 | 14 | 297 | 295 |
| 24 | 88 | 0 | 10 | 2 | 28 | 320 | 317 |
| 25 | 86 | 0 | 10 | 4 | 7 | 293 | 295 |
| 26 | 86 | 0 | 10 | 4 | 14 | 317 | 323 |
| 27 | 86 | 0 | 10 | 4 | 28 | 340 | 357 |
| 28 | 85 | 0 | 15 | 0 | 7 | 138 | 152 |
| 29 | 85 | 0 | 15 | 0 | 14 | 149 | 149 |
| 30 | 85 | 0 | 15 | 0 | 28 | 158 | 166 |
| 31 | 83 | 0 | 15 | 2 | 7 | 257 | 264 |
| 32 | 83 | 0 | 15 | 2 | 14 | 280 | 260 |
| 33 | 83 | 0 | 15 | 2 | 28 | 307 | 290 |
| 34 | 81 | 0 | 15 | 4 | 7 | 281 | 273 |
| 35 | 81 | 0 | 15 | 4 | 14 | 304 | 301 |
| 36 | 81 | 0 | 15 | 4 | 28 | 324 | 328 |
| 37 | 80 | 0 | 20 | 0 | 7 | 138 | 149 |
| 38 | 80 | 0 | 20 | 0 | 14 | 145 | 155 |
| 39 | 80 | 0 | 20 | 0 | 28 | 153 | 196 |
| 40 | 78 | 0 | 20 | 2 | 7 | 233 | 248 |
| 41 | 78 | 0 | 20 | 2 | 14 | 255 | 265 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 42 | 78 | 0 | 20 | 2 | 28 | 282 | 289 |
| 43 | 76 | 0 | 20 | 4 | 7 | 250 | 246 |
| 44 | 76 | 0 | 20 | 4 | 14 | 277 | 268 |
| 45 | 76 | 0 | 20 | 4 | 28 | 298 | 284 |
| 46 | 90 | 10 | 0 | 0 | 7 | 134 | 136 |
| 47 | 90 | 10 | 0 | 0 | 14 | 142 | 137 |
| 48 | 90 | 10 | 0 | 0 | 28 | 153 | 149 |
| 49 | 88 | 10 | 0 | 2 | 7 | 258 | 254 |
| 50 | 88 | 10 | 0 | 2 | 14 | 278 | 263 |
| 51 | 88 | 10 | 0 | 2 | 28 | 295 | 278 |
| 52 | 86 | 10 | 0 | 4 | 7 | 250 | 256 |
| 53 | 86 | 10 | 0 | 4 | 14 | 270 | 280 |
| 56 | 86 | 10 | 0 | 4 | 28 | 315 | 296 |
| 57 | 80 | 20 | 0 | 0 | 7 | 142 | 153 |
| 58 | 80 | 20 | 0 | 0 | 14 | 151 | 148 |
| 59 | 80 | 20 | 0 | 0 | 28 | 163 | 155 |
| 60 | 78 | 20 | 0 | 2 | 7 | 245 | 282 |
| 61 | 78 | 20 | 0 | 2 | 14 | 256 | 294 |
| 62 | 78 | 20 | 0 | 2 | 28 | 283 | 309 |
| 63 | 76 | 20 | 0 | 4 | 7 | 265 | 269 |
| 64 | 76 | 20 | 0 | 4 | 14 | 297 | 298 |
| 65 | 76 | 20 | 0 | 4 | 28 | 325 | 329 |
| 66 | 70 | 30 | 0 | 0 | 7 | 160 | 160 |
| 67 | 70 | 30 | 0 | 0 | 14 | 168 | 158 |
| 68 | 70 | 30 | 0 | 0 | 28 | 179 | 163 |
| 69 | 68 | 30 | 0 | 2 | 7 | 257 | 278 |
| 70 | 68 | 30 | 0 | 2 | 14 | 280 | 303 |
| 71 | 68 | 30 | 0 | 2 | 28 | 307 | 320 |
| 72 | 66 | 30 | 0 | 4 | 7 | 299 | 282 |
| 73 | 66 | 30 | 0 | 4 | 14 | 322 | 308 |
| 74 | 66 | 30 | 0 | 4 | 28 | 339 | 342 |
| 75 | 60 | 40 | 0 | 0 | 7 | 158 | 166 |
| 76 | 60 | 40 | 0 | 0 | 14 | 169 | 170 |
| 77 | 60 | 40 | 0 | 0 | 28 | 178 | 171 |
| 78 | 58 | 40 | 0 | 2 | 7 | 275 | 266 |
| 79 | 58 | 40 | 0 | 2 | 14 | 297 | 286 |
| 80 | 58 | 40 | 0 | 2 | 28 | 320 | 306 |
| 81 | 56 | 40 | 0 | 4 | 7 | 328 | 288 |
| 82 | 56 | 40 | 0 | 4 | 14 | 354 | 309 |
| 84 | 56 | 40 | 0 | 4 | 28 | 369 | 349 |
| 85 | 50 | 50 | 0 | 0 | 7 | 168 | 171 |
| 86 | 50 | 50 | 0 | 0 | 14 | 178 | 175 |
| 87 | 50 | 50 | 0 | 0 | 28 | 186 | 182 |
| 88 | 48 | 50 | 0 | 2 | 7 | 235 | 234 |
| 89 | 48 | 50 | 0 | 2 | 14 | 255 | 251 |
| 90 | 48 | 50 | 0 | 2 | 28 | 265 | 278 |
| 91 | 46 | 50 | 0 | 4 | 7 | 265 | 288 |
| 92 | 46 | 50 | 0 | 4 | 14 | 285 | 308 |
| 93 | 46 | 50 | 0 | 4 | 28 | 312 | 355 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 94 | 50 | 45 | 5 | 0 | 7 | 198 | 192 |
| 95 | 50 | 45 | 5 | 0 | 14 | 208 | 204 |
| 96 | 50 | 45 | 5 | 0 | 28 | 220 | 223 |
| 97 | 48 | 45 | 5 | 2 | 7 | 270 | 298 |
| 98 | 48 | 45 | 5 | 2 | 14 | 332 | 318 |
| 99 | 48 | 45 | 5 | 2 | 28 | 365 | 370 |
| 100 | 46 | 45 | 5 | 4 | 7 | 308 | 319 |
| 101 | 46 | 45 | 5 | 4 | 14 | 342 | 358 |
| 102 | 46 | 45 | 5 | 4 | 28 | 389 | 427 |
| 103 | 50 | 40 | 10 | 0 | 7 | 221 | 215 |
| 104 | 50 | 40 | 10 | 0 | 14 | 235 | 228 |
| 105 | 50 | 40 | 10 | 0 | 28 | 256 | 262 |
| 106 | 48 | 40 | 10 | 2 | 7 | 345 | 331 |
| 107 | 48 | 40 | 10 | 2 | 14 | 395 | 359 |
| 108 | 48 | 40 | 10 | 2 | 28 | 445 | 427 |
| 109 | 46 | 40 | 10 | 4 | 7 | 418 | 349 |
| 110 | 46 | 40 | 10 | 4 | 14 | 455 | 408 |
| 111 | 46 | 40 | 10 | 4 | 28 | 512 | 466 |
| 112 | 50 | 35 | 15 | 0 | 7 | 210 | 206 |
| 113 | 50 | 35 | 15 | 0 | 14 | 224 | 216 |
| 114 | 50 | 35 | 15 | 0 | 28 | 242 | 244 |
| 115 | 48 | 35 | 15 | 2 | 7 | 290 | 316 |
| 116 | 48 | 35 | 15 | 2 | 14 | 331 | 342 |
| 117 | 48 | 35 | 15 | 2 | 28 | 374 | 408 |
| 118 | 46 | 35 | 15 | 4 | 7 | 332 | 342 |
| 119 | 46 | 35 | 15 | 4 | 14 | 367 | 400 |
| 120 | 46 | 35 | 15 | 4 | 28 | 417 | 443 |
| 121 | 50 | 35 | 20 | 0 | 7 | 198 | 182 |
| 122 | 50 | 35 | 20 | 0 | 14 | 214 | 202 |
| 123 | 50 | 30 | 20 | 0 | 28 | 236 | 252 |
| 124 | 48 | 30 | 20 | 2 | 7 | 267 | 290 |
| 125 | 48 | 30 | 20 | 2 | 14 | 310 | 315 |
| 126 | 48 | 30 | 20 | 2 | 28 | 350 | 352 |
| 127 | 46 | 30 | 20 | 4 | 7 | 297 | 284 |
| 128 | 46 | 30 | 20 | 4 | 14 | 334 | 317 |
| 129 | 46 | 30 | 20 | 4 | 28 | 372 | 361 |

## 4.3. Sensitivity analysis

For understanding the effect of all inputs on UCS of Kaolin clay, the sensitivity analysis was done by using the weights obtained from optimized neural model for input to hidden layer and hidden layer to output layer. It was carried out as per the methodology suggested in [40] [40] and is represented in Fig.9. The analysis helped to identify the effect of different admixtures along with curing period on UCS of Kaolin clay. The analysis revealed that, Rice husk ash content (RC) contributed most to the UCS of clay with 26% followed by Pond ash content (PC) with 24%. It was also revealed that all the parameters selected for constructing the neural model were contributing minimum to 10%. It can also be said that admixtures are affecting the UCS by 70% and rest is curing period and clay content.

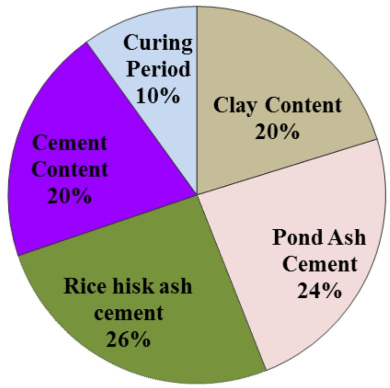


**Fig. 9.** Relative importance of different parameters affecting UCS.

## 4.4. Comparison of MRA and ANN

In this study, MRA and ANN models were developed to predict the UCS of Kaolin clay and the comparison for both the models is presented in Table 6.

**Table 6**
Comparison of MRA and ANN.

| | Prediction models | | |
|---|---|---|---|
| | ANN | | MRA |
| Performance measures | Training | Testing | |
| r | 0.9906 | 0.9856 | 0.9418 |
| $R^2$ | 0.9813 | 0.9714 | 0.8870 |
| MSE | 0.0395 | 51.34 | 68.7603 |
| RMSE | 0.1987 | 7.1651 | 8.2921 |

From Table 6, it can be inferred that ANN models compared to MRA models have better predictive power for predicting the UCS of Kaolin clay. This is evident as correlation coefficient (r) and coefficient of determination ($R^2$) for optimized neural model is more compared to MRA model. The error obtained from neural model is less compared to MRA model hence ANN model with 5-10-1 topology in this study is a better predicting model.

# 5. Conclusion

In this study, multilayer perceptron was used to predict the Unconfined Compressive Strength (UCS) of Kaolin clay mixed with pond ash and rice husk ash along with cement. It was found that neural model with 5-10-1 architecture was the best performing model and it has performed better than the regression model. The LM algorithm with gradient descent and momentum constant back-propagation was used to predict UCS values and tansigmoid activation function was used with purelin transfer function. The sensitivity analysis showed that admixtures used in the study contributed 70% to the UCS of Kaolin clay. The r and $R^2$ values for ANN were 0.98

and 0.97 for testing phase while MRA had lower r and $R^2$ as 0.94 and 0.88 respectively. It was also inferred that ANN model had better performance when compared to regression models.

## Funding

This research received no external funding.

## Conflicts of interest

The authors declare no conflict of interest.

## Authors contribution statement

AP, VK: Conceptualization, Methodology, original draft DG: Data Collection and Experimental work, Resources, SC: ANN Modelling, Validation, Visualization, review and editing

## Appendix 1

### Methodology of strength prediction based on multilayer perceptron

The multilayer perceptron (MLP) comprises of several layers i.e., an input, hidden and output layers. It consists of more than one hidden layer where nodes of each layers are usually interconnected through a pre-initialized set of normal distributed random weights.

For the training, the experimental data need to arrange into inputs (features) and output (desired/target) arrays. The inputs of MLP network i.e., $\{X1, X2, \cdots, Xn\}$ are obtained from the input array. The network output '$Y_n$' is obtained by the sum of their weighted inputs which can be expressed mathematically as Eq. (A1).

$$Y_n = \left[\left(\sum_i X_{ij} \times W_{ij}\right) - b_n\right] \tag{A1}$$

Then, apply the outcome to a nonlinear activation/threshold function '$\varphi(.)$' and the predictive model output is obtained by the Eq. (A2)

$$Y = [\varphi(.) \times Y_n] \tag{A2}$$

Where, $W_{ij}$ is the synaptic weight coefficient and $b_n$ is the bias respectively. Similarly, '$d$' is the desired value which is chosen from the target array and it is utilized in finding network error by comparing network output. (dtail abou strength). The error '$e$' expressed as,

$$error: e(n) = Y - d(n) \tag{A3}$$

Typically, the MLP based network errors are used to adjust network interconnection weights through a backpropagation (BP) algorithm. It is a gradient search based algorithm which helps to select the optimum set of weights of MLP by minimizing error repeatedly. Rest equation of this section highlight the functionality of BP and the instant error energy in the output layer is,

$$\xi(n) = \frac{1}{2}\sum_{i=}^{n} e_l^2(n) \tag{A4}$$

The weights are updated in different layers according to,

$$w_{kl}(n+1) = w_{kl}(n) + \Delta w_{kl}(n) \tag{A5}$$

$$w_{jk}(n+1) = w_{jk}(n) + \Delta w j_k(n) \tag{A6}$$

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) \tag{A7}$$

Where, $\Delta w_{kl}(n)$, $\Delta w j_k(n)$ and $\Delta w_{ij}(n)$ are the change in the weights of the second hidden layer-to-output layer, first hidden layer-to-second hidden layer and input layer-to-first hidden layer respectively. That is,

$$\Delta w_{kl}(n) = -2\mu \frac{d\xi(n)}{dw_{kl}} = 2\mu \frac{dy_l(n)}{dw_{kl}} = 2\mu e(n)\varphi_l'[w_{kl} f_k + \alpha_l] \tag{A8}$$

The threshold of each layer can be updated in a similar manner, i.e.,

$$\alpha_l(n+1) = \alpha_l(n) + \Delta\alpha_l(n) \tag{A9}$$

$$\alpha_k(n+1) = \alpha_k(n) + \Delta\alpha_k(n) \tag{A10}$$

$$\alpha_j(n+1) = \alpha_j(n) + \Delta\alpha_j(n) \tag{A11}$$

Similarly, the change in threshold is represented as,

$$\Delta\alpha_l(n) = 2\mu e(n)\varphi_l'[w_{kl} f_k + \alpha_l] \tag{A12}$$

By attaining the minimum error, training will over and then proposed model get tuned with the best set of weight which can be utilized in predicting strength of any unknown input data.

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