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Comparative Modelling of Strength Properties of Hydrated-Lime Activated Rice-Husk-Ash (HARHA) Modified Soft Soil for Pavement Construction Purposes by Artificial Neural Network (ANN) and Fuzzy Logic (FL)

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ABSTRACT

Artificial neural network and fuzzy logic based model soft-computing techniques were adapted in the research study for the evaluation of the expansive clay soil-HARHA mixture's consistency limit, compressibility and mechanical strength properties. The problematic clay soil was stabilized with varying proportions of HARHA (stabilizing agent) which is an agricultural waste derivative from the milling of rice ranging from 0% to 12%; the utilization of the alkaline activated wastes encourages its recycling and re-use to obtain sustainable, eco-efficient and eco-friendly engineered infrastructure for use in the construction industry with economic benefits also. The obtained laboratory and experimental responses were taken as the system database for the ANN and fuzzy logic model development; the soil-HARHA proportions with their corresponding compaction and consistency limit characteristics were feed to the network as the model input variables while the mechanical strength (California-bearing-ratio (CBR), unconfined-compressive-strength (UCS) and Resistance value (R-values)) responses of the blended soil mixture were the model target variables. For the ANN model, feed forward back propagation and Levernberg Marquardt training algorithm were utilized for the model development with the optimized network architecture of 8-6-3 derived based on MSE performance criteria; while for the fuzzy logic model, the mamdani FIS with both triangular and trapezoidal membership function with both models formulated, simulated and computed using MATLAB toolbox. The models were compared in terms of accuracy of prediction using MAE, RMSE and coefficient of determination and from the computed results, 0.2750, 0.4154 and 0.9983 respectively for ANN model while 0.3737, 0.6654 and 0.9894 respectively was obtained for fuzzy logic model. The two models displayed robust characteristics and performed satisfactorily enabling the optimization of the solid waste derivatives utilization for soil mechanical properties improvement for engineering purposes.

Keywords: California bearing ratio (CBR); Unconfined compressive strength (UCS); Resistance value (R-V); Activated rice-husk-ash; Soil stabilization; Fuzzy logic (FL); Artificial neural networks (ANN); hydrated-lime; soil strength properties

INTRODUCTION

A conventional way of soil stabilization for flexible pavements with expansive soil involves the provision of stiffer load bearing characteristic material base over the soft expansive subgrade. From in situ CBR and shear strength assessment, the required base materials thickness is determined; for soft expansive soil subgrade the required thickness of the base materials often goes so high (Miao and Liu 2001). In such case, chemical stabilization method is utilized which result in substantial base thickness reduction using mixture combination and optimization techniques that will result in performance improvement of the subgrade in terms of strength properties of the stabilized soil (Louafi et al. 2015). Several mineral additives/admixtures utilized to achieve this chemical soil modification mostly are materials possessing alumina-silicate content which have pozzolanic behaviour and tend to improve its binding ability to obtain better strength performance of the soil mixture (K. C. Onyelowe et al. 2019).

Optimum moisture content (OMC) and maximum dry density (MDD) of the soil are very vital in compaction and compressibility property of the modified soil. Soil compaction involves the densification process of the soil by reduction or elimination of pore air spaces through mechanical energy application to achieve better bulk density characteristics (Bui Van and Onyelowe 2018). Addition of water in the process of compaction helps to ease soil particle movement towards closed packing arrangement so as to eject air voids and free water content in the soil. This enables the particles of the soil to slips and slid over each other while relocating to achieve more densely packed settings (Shahin 2013). As the water content is increased during compaction, the corresponding dry density characteristics also increases; but as the water added is increased gradually and compaction effort remains constant, the soil's weight per unit volume increases gradually until it gets to the optimum moisture content OMC value at a corresponding maximum dry density of the soil. Beyond this limit further increase in water content would result into decrease in the soil's density value obtained (Salahudeen et al. 2018). The CBR test provides one of the essential strength performance test carried out to evaluate the quality of soil's subgrade and base/sub-base suitability for flexible pavement construction. The CBR test was carried out in an attempt to deal with several deficiencies and anomalies in field loading test so as to provide a convenient method for achieving suitable sub-base and base materials for the subgrade reinforcement to achieve durable flexible pavement performance under serviceability conditions (Khan et al. 2016). The CBR is computed as force over area needed to penetrate into a given mass of soil using circular 50mm diameter plunger at 1.25mm per minute rate. It is also an indirect computation of soil's shear resistance under specified moisture and density conditions (Franco and Lee 2012). The maximum load that can be transmitted to the subsoil by a foundation depends upon the resistance of that underlying soil preceding deformation and compressibility characteristics. The actual load is applied at a constant rate of strain without any lateral support to the soil specimen and increased until failure occurs. The compressive load per unit area required to fail the soil specimen under such conditions is called unconfined compressive strength of the soil which is mostly applicable for cohesive soils (A. S. Rao et al. 2004).

Development of smart systems which has the capability to learn from historical or experimental data so as to estimate complex system behaviour with higher degree of accuracy and to deal with the challenges of conventional methods of mixture experiments previously utilized for chemical stabilization and modification of expansive soil's mechanical strength characteristics which consume more time and resources through series of trial and error involved (Zhu et al. 1998). The utilization of this soft-computing methodology provides a robust and flexible approach to mixture design experiments of expansive soil so as to optimize chemical additives or stabilizing agent utilization and to derive the optimal combination level of these mixture ingredients (T. Munakata 1998). This method of optimization incorporates human brain reasoning system as an advantage which tackles complex perceptual issues with high degree of speed and accuracy; this smart system also processes and stores basic information through experience by re-adjustment and modification of the network architecture to execute complex, non-linear and parallel system computations (Park and Lee, 2011).

The utilization of intelligent systems applications for data analysis, generalization and estimation has increased; ANN and FL provide suitable extensive applicability to produced improved performance by achieving human reasoning behaviour-like data processing (Alaneme and Mbadike, 2019). FL and ANN possesses the capability to learn and improve its performance from the environment; several researchers have investigated the comparative study of smart systems applications as a useful tool for material properties optimization for civil engineering works. Sevda and Yusuf (2020); in their research on the comparative analysis of ANN, Adaptive Neuron Fuzzy inference system (ANFIS) and MLR models for the estimation of permanent wilting point (PWP) and field capacity (FC) of Bafra plain soils. From the correlation analysis carried out on the model results; sand, clay content, $CaCO_3$, organic matter and cation exchange use statistical significant with PWP and FC. ANN produced the best performance validation results with lowest RMSE and MAE while producing the highest coefficient of determination value.

Akkurt et al. (2004); in their research study, compressive strength of cement was modelled using fuzzy logic and ANN at 28days drying period Balanic, SO_3, alkaline and C3S content of the mixture were feed to the network as the input variables with the strength properties designed as the network output. 2.69% was obtained for average MAPE levels which indicate a better performance for the developed ANN and fuzzy model.

Malagavelli and Manalel (2014); in their work, the compressive strength of soft computing concrete mixed with admixture was predicted using both ANN and FL soft computing techniques at 28days hydration period. The estimated results were validated by comparison with experimental results using correlation coefficient, RMSE, MAPE and mean relative error.

In this research study, laboratory procedures were carried out to determine the material soil properties and those treated with the additives and the obtained experimental results were utilized as the system knowledge base for the model formulation; which helps to predict the soil-additive blend mechanical strength properties and also to optimize the material utilization so as to derive better strength performance for flexible pavement construction using artificial neural network and fuzzy logic based model.

FUZZY LOGIC

The fuzzy logic (FL) concept introduced by Zadeh and Kacprzyk (1992); essentially for substituting the Boolean logic which possesses two sharp and definite boundaries that is 1 (true) or 0 (false). FL avails an analytical framework to address vague and imprecision challenges related with attribute description through the introduction of unclear defined criteria. In this case, unclear and uncertainty does not represent probabilistic, arbitrary and stochastic variations (Adoko and Wu 2011). FL is a precise methodology of problem solving which deals simultaneously with linguistic variables and numerical data computation in order to facilitate a complex system control without much involvement of intricate mathematical description but requires practical system behaviour understanding (Alaneme et al. 2020a). This is very important due to the fact that conventional logic system is unable to manipulate complicated system represented by vague or subjective ideas; so FL aid computers to calculate distinctions of data similar to reasoning process of the human brain by recognizing not only black and white or clear cut alternatives but also the infinite set of gradations between them. FL assign numbers or values to these gradations thereby eliminating the vagueness which exists in crisp logic and these numeric values helps in the computation of exact solutions of complex system (Zimmerman 2001).

Fuzzy method carries out numerical calculations by use of linguistic variables. These variables are appropriately linked with their corresponding membership functions and simulated using fuzzy Inference System (FIS) to evaluate complex input – output data relationships. The major idea of FL is the ability to deal with partial belongingness of elements of different subsets with respect to the universe of discourse. The degree of belongingness is described using membership functions which help to derive the response parameters of intermediate range of values to properly analyse complex system behaviour. The membership functions help in the characterization of fuzziness degree in a fuzzy set whether the elements of the set are continuous or discrete (Z. Sen 1998).

PROCESS OF FUZZY INFERENCE SYSTEM

FUZZIFICATION

Fuzzification helps in the transformation of crisp input values into fuzzy truth values. These input values are mapped to values ranging from 0 to 1 using set of membership functions. It involves appropriate mapping of each input data element to the associated membership degree. In this step the numerical values are transformed into fuzzy number through related membership functions (Mamdani 1975).

FUZZY RULE BASE

Fuzzy rule base consists of rule-base based on the input-output data relationships using logic functions formulated based on expert knowledge, relevant literatures and by proper assessment of the system data base. It involves rule evaluation which helps in the computation and evaluation of the corresponding output truth values; the rules are formulated with the set of if-then control rules using logical operators. Here the input variables are applied to a set of if-then rules while the outcomes of these rules are aggregated to generate set of fuzzy outputs (Demir 2005).

DEFUZZIFICATION

Defuzzification helps in the transformation of the fuzzy truth values into crisp output results.

ARTIFICIAL NEURAL NETWORK

Based on the biological functioning process of the human brain, artificial neural network (ANN) is utilized to model its essential features of pattern recognition, decision making and correlation of complex system input-output data relationships (Turk et al. 2001). ANN consists of network structure of several elements which are the neurons or perceptron; operating in very broad and parallel interconnections to process data through training, validation and testing steps of the model development to be able to determine the appropriate network architecture for better data generalization. Information are processed in the system through cross-weighted function interconnections which derive the signal strength of each of the network input variable to obtain the required output signal through non-linear transformation or activation function compared with the threshold value (Ikizler et al. 2010).

During training, the weighted function of the network are adjusted with respect to the system data base generalization using mean square error (MSE) and the coefficient of determination as performance criteria while the stages involved in training a neural network is the learning rule. Through learning process, appropriate biases and weights are assigned to the input variables of the neural network so as to suit the desired response. This training process is done repeatedly until the desired result is obtained when the performances ceases to improve and each training set is called Epoch (Alaneme et al. 2020b).

After the summation or transfer function which involves the linear combination of the input variables and the respective weights and biases b_0, and activation function which are the non-linear transformation are utilized to better generalize the data sets from the complex system. ANN helps to generalize input-output relationships and interdependencies based on the training data possessing so as to achieve reasonable agreement with the corresponding testing data. These learnable parameters of the neural network are randomly assigned (Kolay et al. 2008).

The sum function evaluates the linear combination of the synaptic weights, input parameters and the bias is the network shown in Eqn. 1 and the non-linear activation function in Eqn. 2

$$net = b_0 + W_1 x_1 + W_2 x_2 + ... + W_n x_n = b_0 + \sum_{i=0}^{n} W_i x_i \qquad (1)$$

$$y = f\left(net\right) \qquad (2)$$

MATERIALS AND METHODS

MATERIALS

HYDRATED LIME

Hydrated lime ($Ca\ (OH)_2$) is the quicklime combined chemically in water with 33% to 34% magnesium oxide (MgO), 46% to 48% of CaO and 15% to 17% chemically combined water. It is a crystal, nonflammable, odorless inorganic powder, which is soluble in water at ambient temperature. It has a melting point of 580°C, boiling point of 2850°C and density of 2.21g/cm^3. Its density is less than that of quicklime (3.34g/cm^3) due to its more aqueous condition that created pores in the structure of the solid. It is caustic with a pH of 12.8 and possesses pozzolanic characteristics, which makes it a good supplementary or alternative binder in civil engineering and earth works. It dissociates into the ions of calcium and hydroxyl as presented in Eqn. 3 and this property enhances its ability to calcinate the dipole minerals of clayey soils in a stabilization procedure by pozzolanic reaction. It was obtained from the chemical store and kept under room temperature for use in this research work. It meets the standard conditions stipulated in the appropriate design codes (Onyelowe et al. 2020a and 2020b).

$$Ca\ (OH)_2 \quad \rightarrow \quad Ca^{2+} + OH^- \qquad (3)$$

THE RICE HUSK ASH

The rice husk ash (RHA) was derived from the direct combustion of rice husk collected from rice mills in Abakaliki, Nigeria. The ash according to studies satisfies the requirements of a pozzolanic material in accordance with British Standard International BS 8615-1 (2019) and American Standard for Testing and Materials ASTM C618 (1998) due to the presence of Al_2O_3, SiO_2 and Fe_2O_3 in its chemical oxides' composition. The release of silica and alumina from the activated rice husk ash triggers pozzolanic reaction in the clayey soil adsorbed complex interface through hydration and calcination, the stabilization points. The active compounds of RHA in aqueous condition yields the following dipole compounds presented in Eqns. (4 – 5);

$$Al_2O_3 \quad \rightarrow \quad Al^{3+} + O^{2-} \qquad (4)$$

$$SiO_2 \quad \rightarrow \quad Si^{4+} + O^{2-} \qquad (5)$$

Following the activation of the RHA by calcination and hydration reactions, compounds responsible for strength gain through the formation of flocs when mixed soil are formed; thus as shown in Eqn. 6;

$$Al^{3+} + O^{2-} + Si^{4+} + Ca^{2+} + OH^- \rightarrow CAH + CSH\ (CASH) \qquad (6)$$

Calcium aluminate hydrate (CAH) and calcium silicate hydrate (CSH) or calcium aluminate silicate hydrate (CASH) are very important end points of the activation process, which are achieved by calcination and hydration reactions (Onyelowe et al. 2020b).

THE CLAYEY SOIL

The clayey soil used as a representative soil for this experimental work was collected from a depth of 1 meter from a borrow pit located at Ndoro Oboro, Abia State. The representative soil was prepared in accordance with British Standard International BS1377 (1990) and stored for the laboratory work at room temperature. And the treated soil was prepared in accordance with British Standard International BS1924 (1990).

METHODS

Basic laboratory experiments were conducted as follows; particle size analysis of soil and rice husk ash, Atterberg limits test, compaction test, specific gravity of soil test, unconfined compression, resistance value (modified compression) and California bearing ratio test to enable the characterization of the representative soil and the rice husk ash. These basic tests were conducted under laboratory conditions in accordance with the British Standard International BS1377 (1990). The rice husk ash was activated using hydrated lime in accordance with the requirements of Davidovits (2004). The activated rice husk ash activated with caustic binder of $Ca(OH)_2$ (5% by weight of RHA), was utilized in the proportions of 0% (the reference test), 0.5%, 1%, 1.5%, 2%, 2.5%, 3%, 3.5%, 4%, 4.5%, 5%, 5.5%, 6%, 6.5%, 7%, 7.5%, 8%, 8.5%, 9%, 9.5%, 10%. 10.5%, 11%, 11.5% and 12% by weight of dry soil to modify the clayey soil in the stabilization process. Compaction test was conducted on the treated soil in accordance with appropriate standards (BS1924, 1990). Atterberg limits (liquid limit (w_L) and plastic limit (w_P)) behavior of the hydrated lime activated RHA modified clayey soil were observed by experimentation using the Casagrande apparatus in accordance with design standard (BS1924, 1990). From the observed test results, the plasticity index (I_P) was computed from Eqn. 7, activity of clay, was also computed from Eqn. 8.

$$I_P = w_L - w_P \tag{7}$$

$$A_C = \frac{I_P}{C} \tag{8}$$

Where, I_P = plasticity index, w/W_N. = initial water content of soil as a percentage of dry mass (NMC), w_L. = liquid limit, w_P. = plastic limit, A_c. = clay activity, c = % passing 2μm sieve.

DATA UTILIZED FOR THE MODEL DEVELOPMENT USING FUZZY LOGIC AND ANN

Through relevant literatures, laboratory methodology and expert knowledge; the information derived from this process which consist of the expansive soil-HARHA mixture's plasticity, compaction and strength responses with respect to varying proportional concentrations of the mixture ingredients were utilized as the system data base for t development. The soil-HARHA mixture formulations, compaction and consistency limits characteristics were fed to the network as the input parameters of the model while the blended expansive soil's mechanical strength responses such as unconfined compressive strength UCS, R-values and California bearing ratio CBR were the output or dependent variables of the network (Alaneme et al. 2020). These input and output datasets are presented in a bar chart shown in Figures 1 and 2

DATA PROCESSING TECHNIQUE

Fuzzy logic model and artificial neural network were both utilized for the modelling process for the estimation of the expansive clay soil-HARHA mechanical strength characteristics using the mixture constituents, plasticity and compaction properties as the independent variables of the model. For the ANN model development, the MATLAB neural network input-output and curve fitting application (nftool) was adapted through which mapping between a dataset from the system database of the numerical inputs and a set of numerical outputs. This application toolbox will help to select the datasets, create and train the given network and also to assess the model performance using R-value and MSE. By so doing a feed-forward two layer network with sigmoid activation function for the hidden neuron and linear target neurons for better generalization of data to fit multi-dimensional mapping problems; using Levenberg Marquardt back propagation algorithm (trainlm) which has the advantage of precision and speed but expends much memory in the search for the best performance criteria. 70%, 15% and 15% of the total datasets will be divided randomly for the training, validation and testing of the network while the training is halted once the generalization performance stops improving (Das and Sivakugan 2010).

For the fuzzy logic based model development, fuzzy logic toolbox in MATLAB software were utilized for the designing, analysing and simulation of the formulated model which helps to deal with complex system behaviours using fuzzy rules which are created through expert judgement by relevant literature and with respect to the trends of the system data base using logic operators after which the mamdani fuzzy inference system (FIS) method which is essentially utilized for crisp output results were utilized in the aggregation, implementation and simulation of the formulated fuzzy rules. The fuzzy logic model processing parameters includes; trapezoidal and triangular membership functions were used to measure and associate degrees of membership or belongingness of the fuzzy variables for better data generalization. The processing parameters for the FIS are Or-method: max; And-method: min; Aggregation-method: max; Implication-method: min and Defuzzification method: centroid (Alaneme et al. 2010).

MODEL PERFORMANCE EVALUATION

The developed model performance was assessed in order to affirm that it possesses a proven ability of predicting or estimating the target parameters with acceptable degree of accuracy. Based on related literatures, several performance criteria used are statistical measures such as the R-values and the less function parameters MAE and RMSE with the formula presented in Equations 9 and 10.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(E_i - M_i\right)^2}{n}} \tag{9}$$

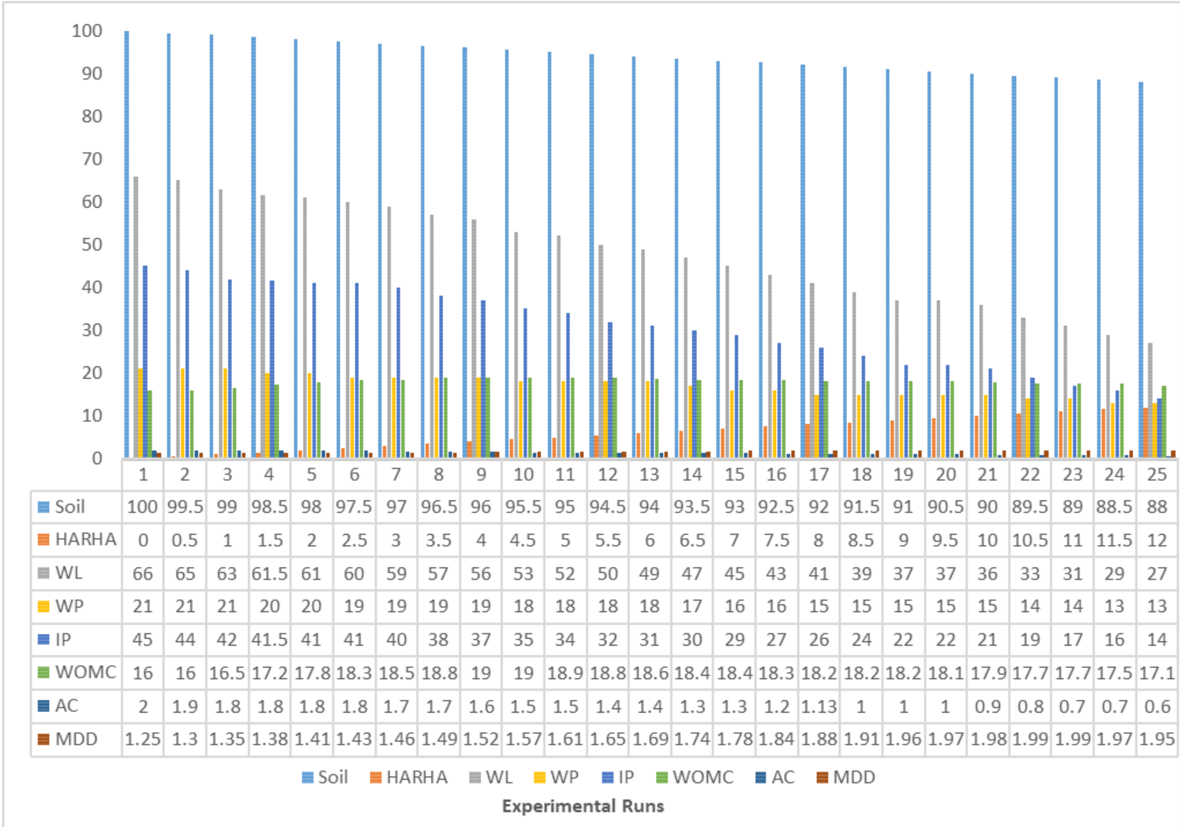
$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|E_i - M_i\right| \tag{10}$$

Where n is the size of the data points under investigation, E_i is the experimental or actual values while M_i is the model predicted results (Colin and Windmeijer 1997).

RESULTS AND DISCUSSION

MATERIALS CHARACTERIZATION

The basic characteristic features of the representative clayey soil are presented in Tables 1, 2 and Figure 3. From the basic test results, it can be deduced that the soil has 45% of its particles passing sieve size 0.075mm, liquid limit of 66% and with a natural moisture content of 14%. The above properties show that the soil is an A-7-6 soil group according to AASHTO classification (Onyelowe et al. 2018; 2019) and poorly graded with poorly graded clay CP according to USC system. Further, the plasticity index of the soil of 45% shows



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Soil	100	99.5	99	98.5	98	97.5	97	96.5	96	95.5	95	94.5	94	93.5	93	92.5	92	91.5	91	90.5	90	89.5	89	88.5	88
HARHA	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10	10.5	11	11.5	12
WL	66	65	63	61.5	61	60	59	57	56	53	52	50	49	47	45	43	41	39	37	37	36	33	31	29	27
WP	21	21	21	20	20	19	19	19	19	18	18	18	18	17	16	16	15	15	15	15	15	14	14	13	13
IP	45	44	42	41.5	41	41	40	38	37	35	34	32	31	30	29	27	26	24	22	22	21	19	17	16	14
WOMC	16	16	16.5	17.2	17.8	18.3	18.5	18.8	19	19	18.9	18.8	18.6	18.4	18.4	18.3	18.2	18.2	18.2	18.1	17.9	17.7	17.7	17.5	17.1
AC	2	1.9	1.8	1.8	1.8	1.8	1.7	1.7	1.6	1.5	1.5	1.4	1.4	1.3	1.3	1.2	1.13	1	1	1	0.9	0.8	0.7	0.7	0.6
MDD	1.25	1.3	1.35	1.38	1.41	1.43	1.46	1.49	1.52	1.57	1.61	1.65	1.69	1.74	1.78	1.84	1.88	1.91	1.96	1.97	1.98	1.99	1.99	1.97	1.95

FIGURE 1, Input Variables of the Model

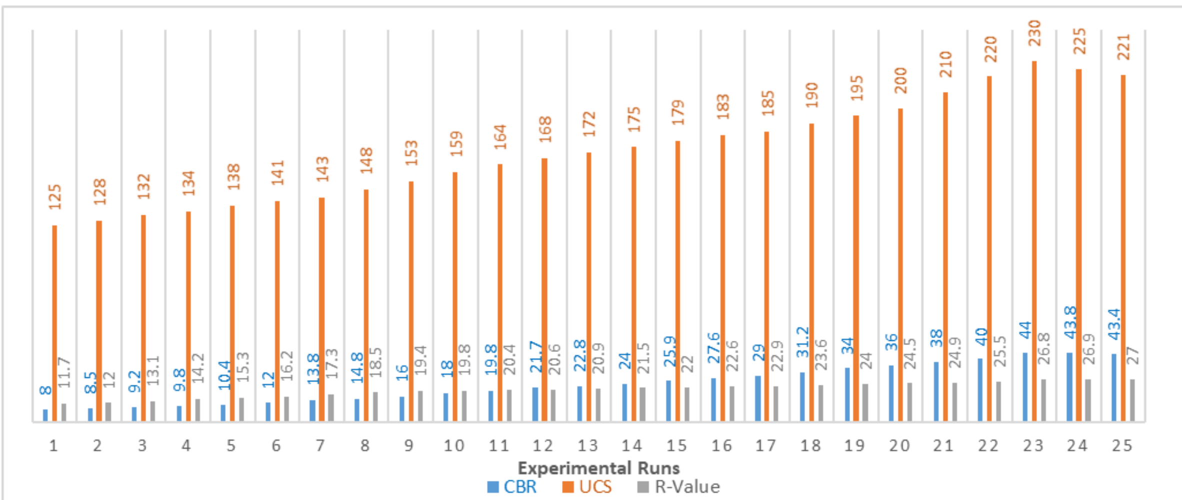


FIGURE 2, Output Variables of the Model

that the soil is highly plastic and breaks upon the application of load. The representative clayey soil also has a swelling potential, which is a function of plasticity of 23.35% and this means that the soil is highly expansive (Kayadelen, 2008). The MDD of the soil was observed to be 1.25g/cm^3, obtained at an OMC of 16%. This shows that soil is very porous agreeing with its swelling potential and expansive condition. These properties have characterized the soil as a problematic and high expansive soil very unsuitable for earth works.

Table 3 presents the chemical oxides composition of the representative soil and the rice husk ash. The results show that the soil has Na_2O with the high oxide composition by weight of the soil. This oxide contributes to the expansive condition of the soil. The ferrite composition is rich in the red color of the clayey soil and contributes to the pozzolanic reaction during stabilization works (Herve et al. 2009). This property supports the high swelling potential of the clayey soil. Conversely, the rice husk ash has high of the alumina-silicates, which fulfills the minimum requirements of a

TABLE 1, Characterization Properties of Clayey Soil

property description of clayey soil and units	value
% passing sieve, no. 200 (0.075mm) (Ikizler et al. 2010)	45
w_{N}. (%)	14
w_{L}. (%)	66
w_{P} (%)	21
I_{P} (%) = w_{L} - w_{P}	45
w_{S} (%) = 0.00216 * $I_{P}^{2.44}$ (Herve et al. 2009)	23.35
degree of expansion (Herve et al. 2009)	high
G_{S}.	1.43
AASHTO classification (AASHTO, 1993)	A-7-6
iversal soil classification system	CP (20),
δ_{max}. (g/cm^3)	1.25
(%)	16
CBR (%)	8
Color	reddish

TABLE 2, particle size distribution (PSD) of test materials

materials	% passing sieve (mm)										
	19	6.35	4.75	2.36	1.18	0.6	0.425	0.3	0.15	0.075	Pan
clay soil	100	100	94	88	82	76	70	58	51	45	0
rice husk ash	100	97	89	75	62	55	42	35	22	14	0

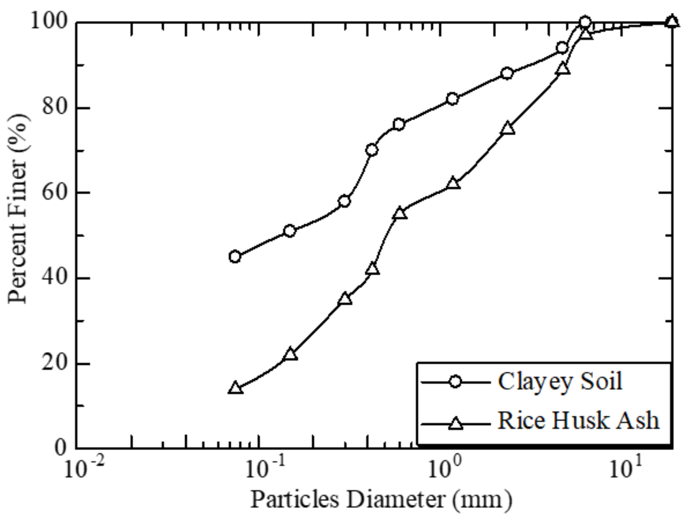


FIGURE 3. Particle size distribution curve of the clayey soil and rice husk ash

pozzolana in accordance with appropriate design standards (Herve et al. 2009).

EXPERIMENTAL RESPONSES OF CLAYEY SOIL MODIFIED WITH CALCINED RICE HUSK ASH

The addition of HARHA chemical additive for stabilizing expansive clay soil which was evaluated in this study resulted to mechanical strength characteristics improvement of the test soil. From the experimental responses presented in Figure 4; the soil's consistency limit properties decreased with increased percentage addition of HARHA. For the compaction characteristics of the blended soil samples, the OMC obtained at the control mix (0% replacement of the additive) is 16% and the result increased to the observed maximum limit of 19% at 4% replacement while the obtained OMC results subsequently decreased slightly at further addition of HARHA to 17% at 12% replacement by HARHA. The maximum dry density (MDD) results appreciated as HARHA addition increased from 1.25g/cm^3 to maximum value of 1.95g/cm^3 at 12% replacement by HARHA. Similarly, from the mechanical strength characteristics of the blended soil sample; the CBR, UCS and R-values increases from 8%, 125kN/m^2 and 11.7 respectively at control mix (0% replacement of the additive) to 40% and 230kN/m^2 for CBR and UCS respectively at

TABLE 3. chemical oxides composition of the additive materials

Materials	Oxides composition (content by weight, %)												
	SiO_2	Al_2O_3	CaO	Fe_2O_3	MgO	K_2O	Na_2O	TiO_2	LOI	P_2O_5	SO_3	IR	free CaO
clay soil	12.45	18.09	2.30	10.66	4.89	12.10	34.33	0.07	-	5.11	-	-	-
rice husk ash	56.48	22.72	5.56	3.77	4.65	2.76	0.01	3.17	0.88	-	-	-	-

**IR* is insoluble residue, LOI is loss on ignition,

11% replacement while the obtained maximum result of 27 for the R-values were at 12% replacement. This behaviour occurred due to binding effect of the alumina-silicates and hydrated lime from the blended rice husk ash. Calcination reaction and subsequently pozzolanic reaction due to ion exchange and hydration reactions made this improvement in the plasticity of the HARHA treated soil possible (Onyelowe et al. 2020a).

MODEL DEVELOPMENT PROCESSES

From the generation of experimental data utilized for the evaluation of the plasticity, compaction and mechanical strength properties of the stabilized expansive clay soil with HARHA, the model development commences using ANN and Fuzzy logic based intelligent systems for better data generalization to ensure optimization of the material utilization saving less time and deriving the required level of combination of the soil and chemical additives. The system data base descriptive statistics is presented in Table 4, which constitutes the input-output variables of the developed model.

ANN MODELLING

Using the system data base and from relevant literatures, the model input-output pattern was structured as appropriate with the input variables the mixture constituents' proportion, consistency limits, and compaction characteristics of the expansive soil-HARHA mixture while the output variables the mechanical strength responses of the blended soil samples. The network architecture is presented in Figure 5 showing the variables and processing parameters of the network.

ANN TRAINING STATE

The training state presents the graphical details of the network training, testing and validation performance of the model development. The performance continues to improve with repeated iteration of the network through adjustments of its learnable parameters known as Epoch. The training state for this network development is presented in Figure 6, which shows the performance gradient as it improves with respect to the repeated number of epochs while the improvement is monitored until it ceases to improve further. From the plot, at gradient of 0.15758 with respect to epoch 21 produced the best obtainable performance at which the validation checks fails at 6 which is shown in the vertical axis of the training state plot.

MODEL VALIDATION PERFORMANCE OF THE ANN

Network performance validation of the ANN which was evaluated using loss function parameter, MSE is presented in the performance validation plot of epoch on the x-axis against MSE on the y-axis. The training, validation, testing and best performance result details of the developed ANN model were traced in the plot and from the plotted results; the best performance of 0.80428 was obtained at epoch 15 with respect to the validation performance of the trained network shown in Figure 7.

ANN ERROR HISTOGRAM

The error histogram of the ANN with 20 bins for the training, testing and validation of the model presented in Figure 8 shows the zero error point which signifies the point of best performance indicated with the yellow slim line through the coloured bar chart. From the histogram chart of the ANN; 16, 18 and 21 instances were obtained for training, testing and validation respectively.

ANN REGRESSION PLOT

The regression plot of the ANN which represents the relationship which exists between the experimental or actual datasets and the model predicted results which is measured through the use of statistical parameters; coefficient of determination with respect to the training, testing and validation sets of the network shown in Figure 9. The plot displays the experimental results in the x-axis and the model predicted values in the y-axis and the R-values obtained indicates a very good prediction accuracy performance of the developed model.

OPTIMIZED NETWORK FOR THE ANN MODEL

Based on the developed network architecture of the ANN, which structured the input-output of the model with respect to appropriate processing parameters. 8 inputs-n-3outputs network architecture was derived with the n variable representing the number of neurons for the hidden layers; however, varying number of the neurons for the hidden layers enables a reliable choice of the neuron number to be selected based on R-values and MSE criteria. In order to obtain the optimized network processing parameters, 0 to 15 numbers of neurons for the hidden layers were assessed with the best performance selected at number of neurons of 6 providing an optimized network of 8-6-3 as shown in

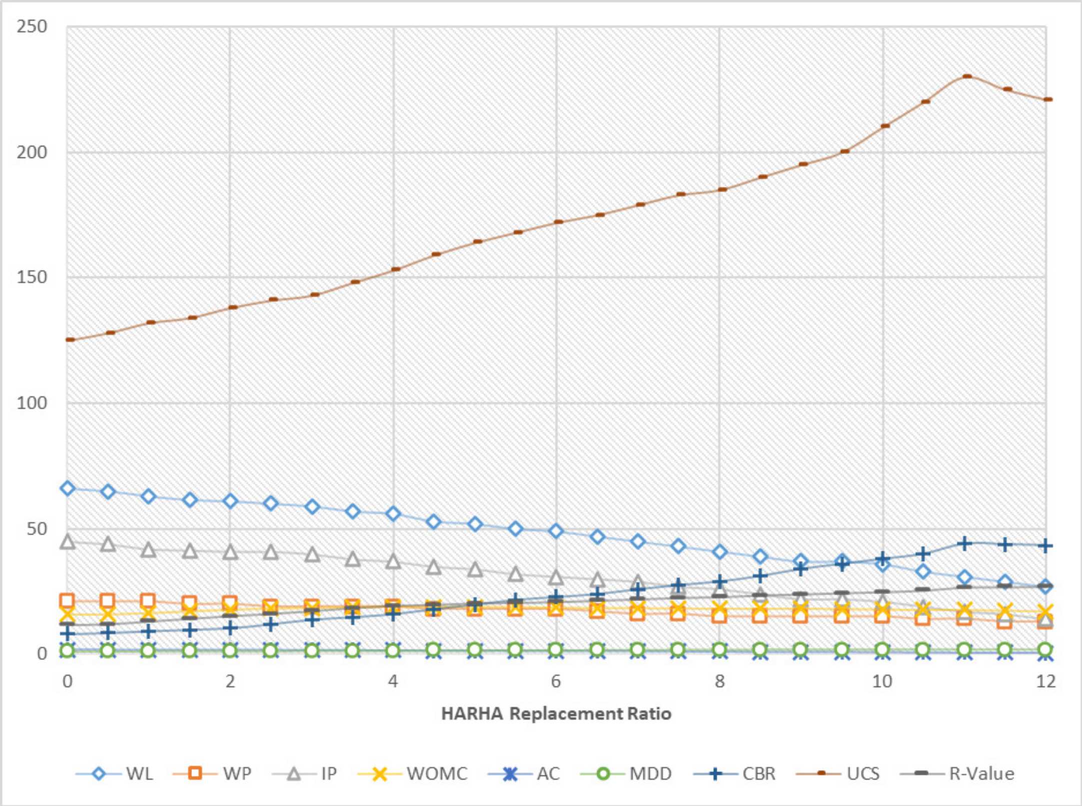


FIGURE 4, Experimental results graphical details

TABLE 4. Descriptive statistics of data sets used for the Model Development

Input-Output Variables	Mean	Standard Error	Standard Deviation	Sample Variance	Range	Minimum	Maximum
Soil	94	0.74	3.68	13.54	12	88	100
HARHA	6	0.74	3.68	13.54	12	0	12
WL	47.9	2.42	12.10	146.33	39	27	66
WP	17.16	0.51	2.56	6.56	8	13	21
IP	30.74	1.91	9.57	91.57	31	14	45
WOMC	17.964	0.17	0.85	0.73	3	16	19
AC	1.3412	0.08	0.42	0.18	1.4	0.6	2
MDD	1.6828	0.05	0.25	0.06	0.74	1.25	1.99
CBR	24.068	2.42	12.10	146.53	36	8	44
UCS	172.72	6.54	32.68	1067.79	105	125	230
R-Value	20.464	0.93	4.67	21.85	15.3	11.7	27

Figures 10 and 11 with respect to training, validation and testing of the network.

FUZZY LOGIC MODELLING

Based on the established input-output structure initially derived from the system database through the experimental data, the fuzzy logic variables were determined as appropriate for the accurate estimation of the blended expansive soil-HARHA mechanical strength characteristics. The fuzzy input-output variables connections and links are presented in Figure 12.

FUZZY VARIABLES MEMBERSHIP FUNCTIONS

The input-output variables utilized for the fuzzy logic developed were designed and structured for the model development using appropriate degree of belongingness know as membership function which helps to fuzzify the crisp input numeric data for better data generation. For this research study, the triangular and trapezoidal membership functions were utilized and the fuzzy variables assigned expertly with the aid of the data base derived from experimental methodology. Five membership function types were carefully assigned to each of the variables namely;

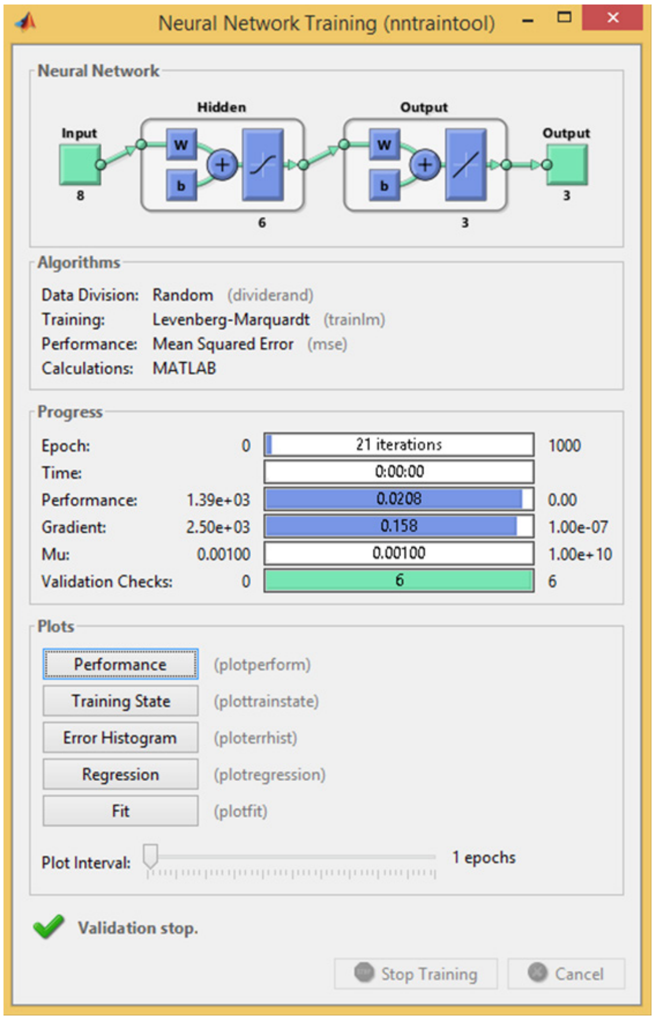


FIGURE 5. ANN Network Architecture

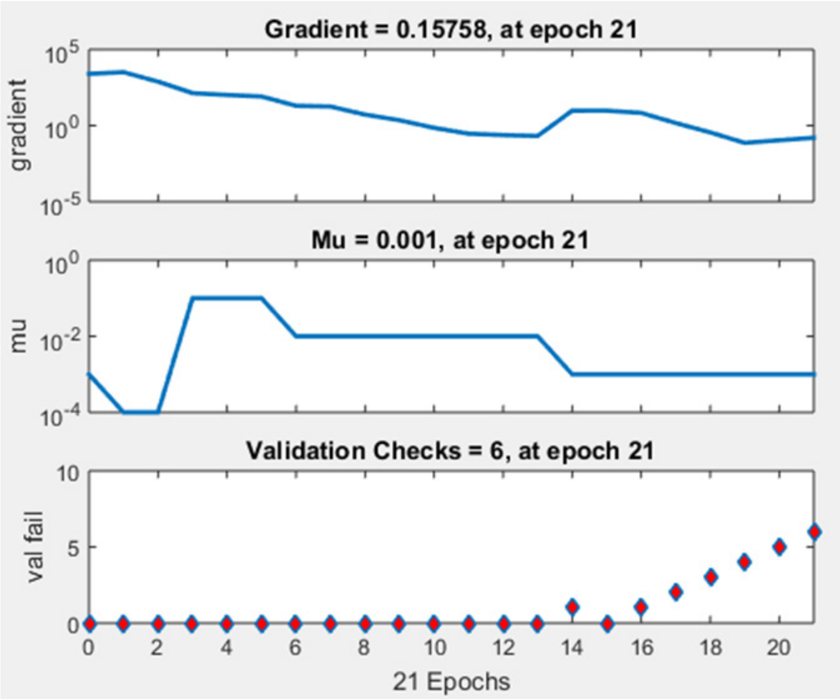


FIGURE 6, Network Training State

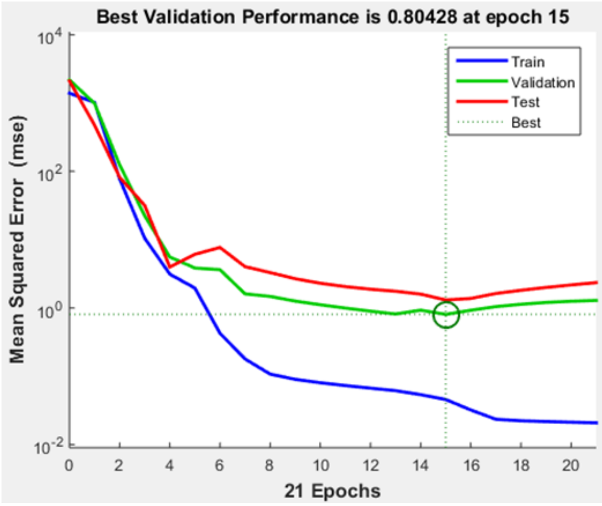


FIGURE 7, Best Validation Performance of ANN

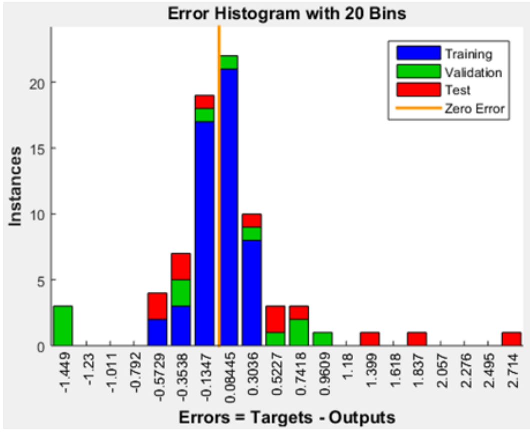


FIGURE 8, Error Histogram of the Network

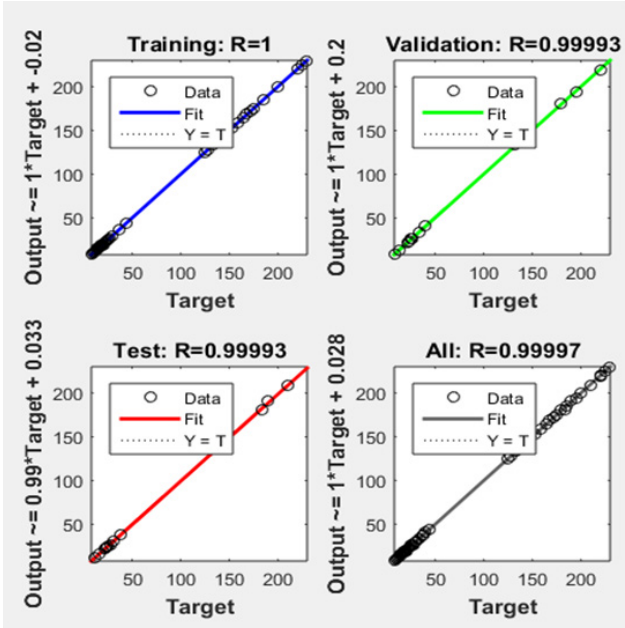


FIGURE 9. ANN Regression Plot

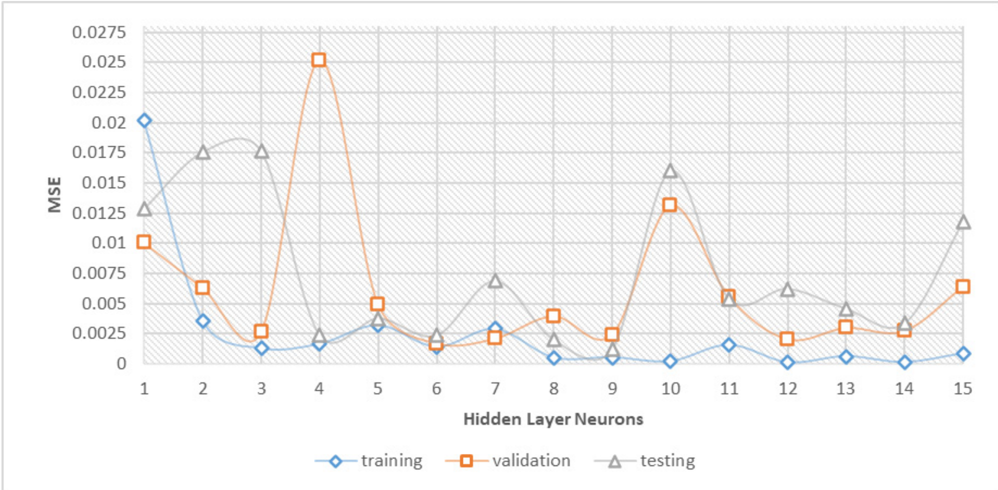


FIGURE 10. MSE for Varying Number of Hidden Layer Neuron

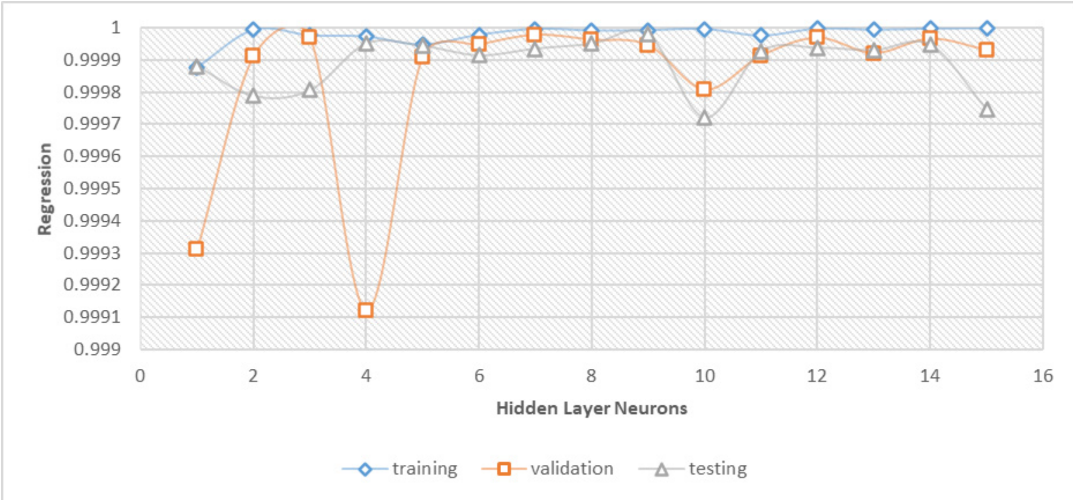


FIGURE 11. Regression values for Varying Number of Hidden Layer Neuron

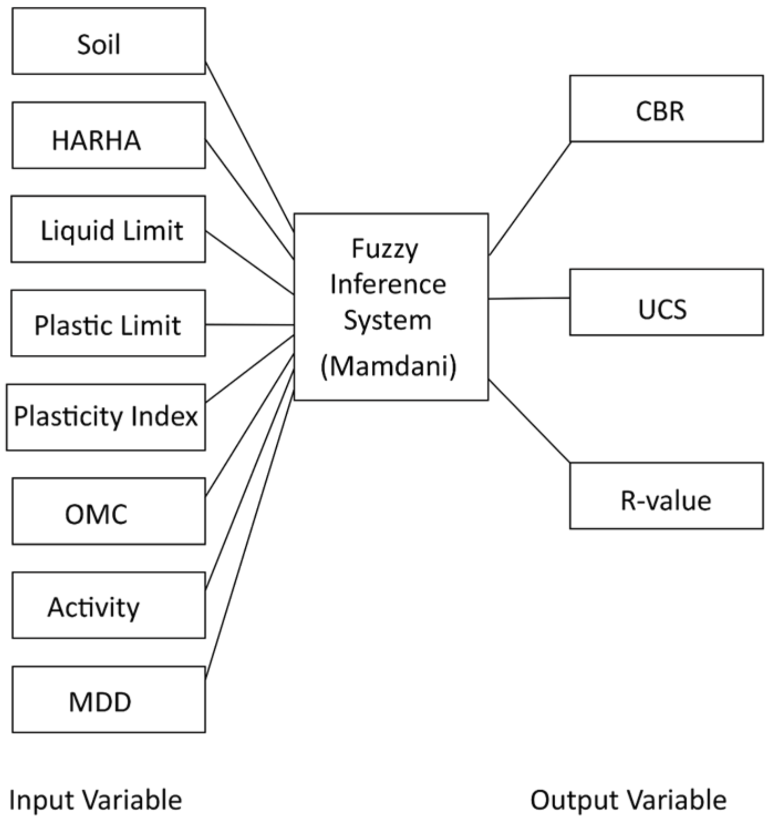


FIGURE 12. Fuzzy Variables Connections

very low (VL), low (L), medium (M), high (H) and very high (VH). The membership function plot is presented graphically in Figure 13 and also the MATLAB script for the computation process is presented in Table 5; to present more details of the points associated with each of the membership function types used for each of the variables.

FUZZY RULE BASE FORMULATION

After careful assignment of the membership functions which describe the degree of belongingness of the fuzzy variables with respect to the system data base, the fuzzy rule were formulated with the designed membership functions using appropriate logical operators ('OR', 'AND') linking up the fuzzy input variables with their corresponding target variables. These rule base formulation would be carefully carried out so as to model the complex behaviours and interdependencies of the system under investigation using linguistic variables. Series of rules are developed to deal with vagueness which exists in between fixed boundaries of the datasets in order to ensure full optimization of the system objective function with respect to the defined constraints.

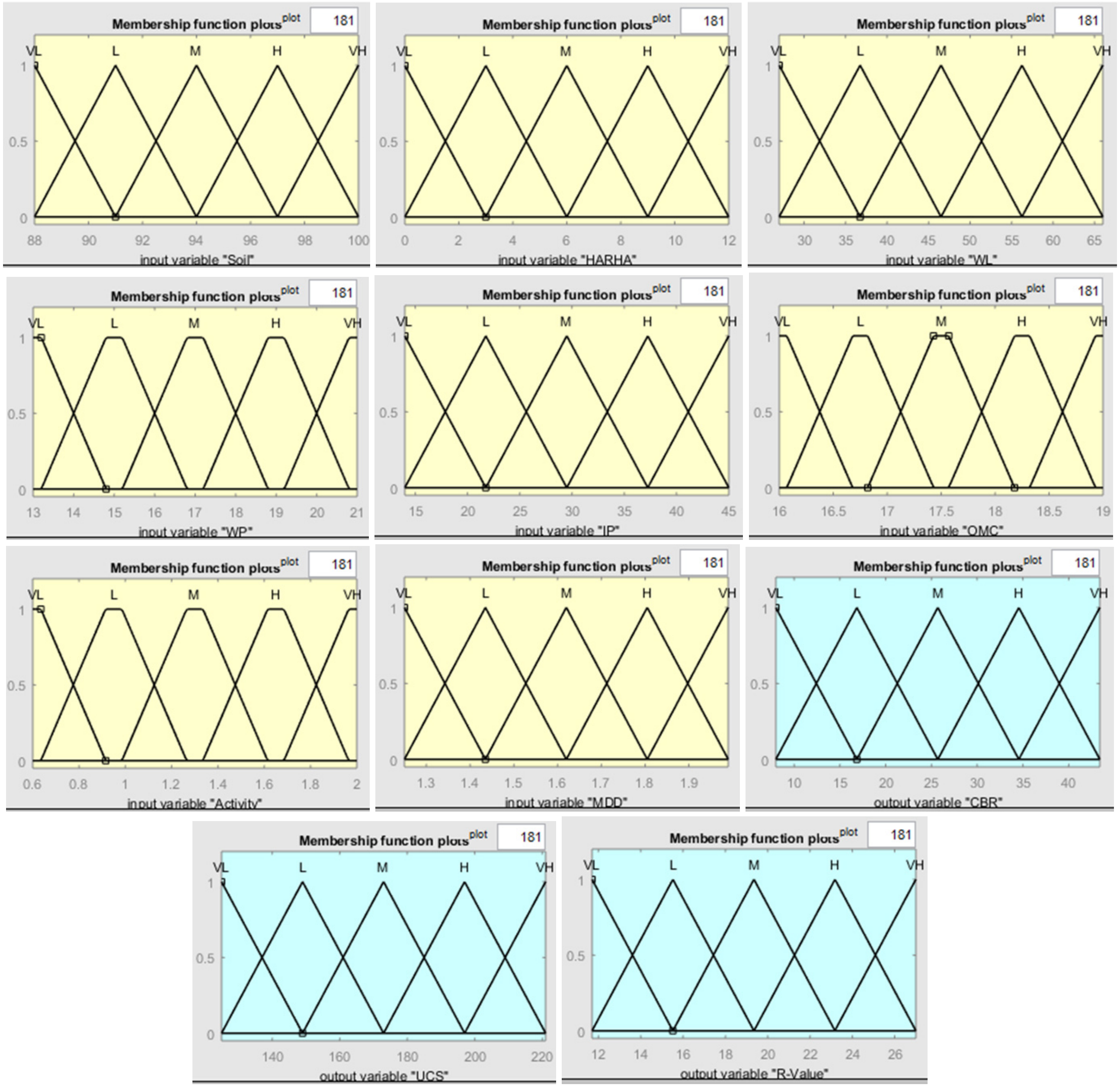


FIGURE 13. Membership Function Plots

TABLE 5. MATLAB script of Fuzzy variables membership functions

[Input1]	[Input7]
Name='Soil'	Name='Activity'
Range=[88 100]	Range=[0.6 2]
NumMFs=5	NumMFs=5
MF1='VL':'trimf',[85 88 91]	MF1='VL':'trapmf',[0.285 0.565 0.635 0.915]
MF2='L':'trimf',[88 91 94]	MF2='L':'trapmf',[0.635 0.915 0.985 1.265]
MF3='M':'trimf',[91 94 97]	MF3='M':'trapmf',[0.985 1.265 1.335 1.615]
MF4='H':'trimf',[94 97 100]	MF4='H':'trapmf',[1.335 1.615 1.685 1.965]
MF5='VH':'trimf',[97 100 103]	MF5='VH':'trapmf',[1.685 1.965 2.035 2.315]

[Input2]	[Input8]
Name='HARHA'	Name='MDD'
Range=[0 12]	Range=[1.25 1.99]
NumMFs=5	NumMFs=5
MF1='VL':'trimf',[-3 5.551e-17 3]	MF1='VL':'trimf',[1.065 1.25 1.435]
MF2='L':'trimf',[0 3 6]	MF2='L':'trimf',[1.25 1.435 1.62]
MF3='M':'trimf',[3 6 9]	MF3='M':'trimf',[1.435 1.62 1.805]
MF4='H':'trimf',[6 9 12]	MF4='H':'trimf',[1.62 1.805 1.99]
MF5='VH':'trimf',[9 12 15]	MF5='VH':'trimf',[1.805 1.99 2.175]
[Input3]	[Output1]
Name='WL'	Name='CBR'
Range=[27 66]	Range=[8 43.4]
NumMFs=5	NumMFs=5
MF1='VL':'trimf',[17.25 27 36.75]	MF1='VL':'trimf',[-0.85 8 16.85]
MF2='L':'trimf',[27 36.75 46.5]	MF2='L':'trimf',[8 16.85 25.7]
MF3='M':'trimf',[36.75 46.5 56.25]	MF3='M':'trimf',[16.85 25.7 34.55]
MF4='H':'trimf',[46.5 56.25 66]	MF4='H':'trimf',[25.7 34.55 43.4]
MF5='VH':'trimf',[56.25 66 75.75]	MF5='VH':'trimf',[34.55 43.4 52.25]
[Input4]	[Output2]
Name='WP'	Name='UCS'
Range=[13 21]	Range=[125 221]
NumMFs=5	NumMFs=5
MF1='VL':'trapmf',[11.2 12.8 13.2 14.8]	MF1='VL':'trimf',[101 125 149]
MF2='L':'trapmf',[13.2 14.8 15.2 16.8]	MF2='L':'trimf',[125 149 173]
MF3='M':'trapmf',[15.2 16.8 17.2 18.8]	MF3='M':'trimf',[149 173 197]
MF4='H':'trapmf',[17.2 18.8 19.2 20.8]	MF4='H':'trimf',[173 197 221]
MF5='VH':'trapmf',[19.2 20.8 21.2 22.8]	MF5='VH':'trimf',[197 221 245]
[Input5]	[Output3]
Name='IP'	Name='R-Value'
Range=[14 45]	Range=[11.7 27]
NumMFs=5	NumMFs=5
MF1='VL':'trimf',[6.25 14 21.75]	MF1='VL':'trimf',[7.875 11.7 15.52]
MF2='L':'trimf',[14 21.75 29.5]	MF2='L':'trimf',[11.7 15.52 19.35]
MF3='M':'trimf',[21.75 29.5 37.25]	MF3='M':'trimf',[15.52 19.35 23.18]
MF4='H':'trimf',[29.5 37.25 45]	MF4='H':'trimf',[19.35 23.18 27]
MF5='VH':'trimf',[37.25 45 52.75]	MF5='VH':'trimf',[23.17 27 30.83]
[Input6]	
Name='OMC'	
Range=[16 19]	
NumMFs=5	
MF1='VL':'trapmf',[15.32 15.93 16.07 16.68]	
MF2='L':'trapmf',[16.07 16.68 16.82 17.43]	
MF3='M':'trapmf',[16.82 17.43 17.57 18.18]	
MF4='H':'trapmf',[17.57 18.18 18.32 18.93]	
MF5='VH':'trapmf',[18.32 18.93 19.07 19.68]	

SIMULATION OF THE FUZZY SYSTEM

After fuzzy rule base formulation, the set of rules were simulated using Mamdani fuzzy inference system to aggregate the rules and application of implication methods which helps to derive crisp numeric output from the model making use of multiple input and multiple output (MIMO) system. Fuzzy rule evaluation is essentially executed in this stage to ensure the evaluation and computation of the corresponding fuzzy output truth values through the aggregation of the formulated rule base.

DEFUZZIFICATION

This is the final stage of the fuzzy logic model development at which the fuzzy truth values obtained from the fuzzy inference engine and fuzzy rule evaluation is transformed into crisp numeric values corresponding to the appropriate output membership function. The centroid of area method is the defuzzification method utilized to execute this operation with the mathematical expression presented in Equation 11

$$C.A = \frac{\sum_i \mu(M_i) \times O_i}{\sum_i \mu(M_i)} \tag{11}$$

Where $C.A$ is the centroid of area de-fuzzified output result, $\mu(M_i)$is the membership value for the output results in the i^{th} subset and O_i is the output results in the i^{th} subset.

VALIDATION OF THE DEVELOPED ANN AND FUZZY LOGIC MODEL PERFORMANCE

After development of the model using fuzzy logic and ANN soft-computing techniques, the generated models were validated using loss function parameters (K-values, MAE and RMSE), which provides a suitable criterion for prediction accuracy performance evaluation where the model results are compared with the corresponding experimental or actual values. The calculations for the validation assessments are presented in Tables 6 and 7.

From the statistical results computations, the ANN model produced a better performance when compared with fuzzy logic performance evaluation results; average R-values, MAE and RMSE of 0.9983, 0.2750 and 0.4154 respectively was derived for the ANN model while 0.9894, 0.3737 and 0.6654 respectively was obtained for fuzzy logic model. Although the overall performance of both models produced robust and satisfactory results which are basically acceptable based on prescribed evaluation criteria.

The K-values which is the slope or gradient of the regression line for the fitted plot utilized in the evaluation of the error function of the developed model. This value helps to assess the strength of the relationship between the actual or experimental results and the corresponding model predicted results. The lines of fit plots with respect to the response parameters for the ANN model are shown in Figures 14-16. While the line of fit plot for the fuzzy logic results are presented in Figures 17-19.

This line of fit plots present a regression line which best approximates the datasets under investigation which is determined accurately through the least square method and the equation of the line which best approximates the solution result for the generated models are presented in Eqns. 12-14 for the ANN model while Eqns. 15-17 represents the case of fuzzy logic model.

$$y = 0.9916x + 0.1681 \tag{12}$$

$$y = 1.0019x - 0.208 \tag{13}$$

$$y = 1.0067x - 0.1144 \tag{14}$$

$$y = 0.9684x + 0.9853 \tag{15}$$

$$y = 0.9844x + 1.6641 \tag{16}$$

$$y = 0.887x + 1.6295 \tag{17}$$

TABLE 7. Performance Measure for ANN-Model

Target Variables	Loss Function Parameter	Specification	Calculated Values	Remarks
CBR	MAE	close to 0	0.2987	Very Good
	RMSE	close to 0	0.4346	Satisfactory
	K	close to 1	0.9987	Better performance
UCS	MAE	close to 0	0.3230	Good
	RMSE	close to 0	0.557	Satisfactory
	K	close to 1	0.9992	Excellent
R-values	MAE	close to 0	0.2033	Very Good
	RMSE	close to 0	0.2545	Better performance
	K	close to 1	0.9970	Good

TABLE 8. Performance Measure for Fuzzy Logic Model

		Fuzzy		
Target Variables	Loss Function Parameter	Specification	Calculated Values	Remarks
CBR	MAE	close to 0	0.3213	Good
	RMSE	close to 0	0.5561	Satisfactory
	K	close to 1	0.9921	Better performance
UCS	MAE	close to 0	0.3145	Very Good
	RMSE	close to 0	0.8152	Satisfactory
	K	close to 1	0.9981	Excellent
R-values	MAE	close to 0	0.4852	Very Good
	RMSE	close to 0	0.6251	Good
	K	close to 1	0.981	Better performance

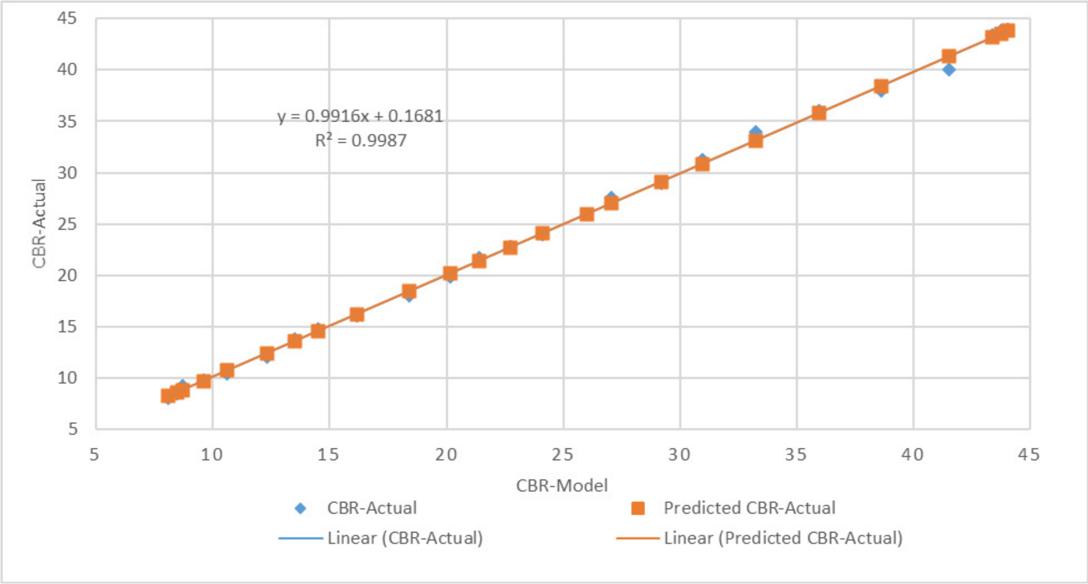


FIGURE 14. ANN Line of Fit Plots-CBR

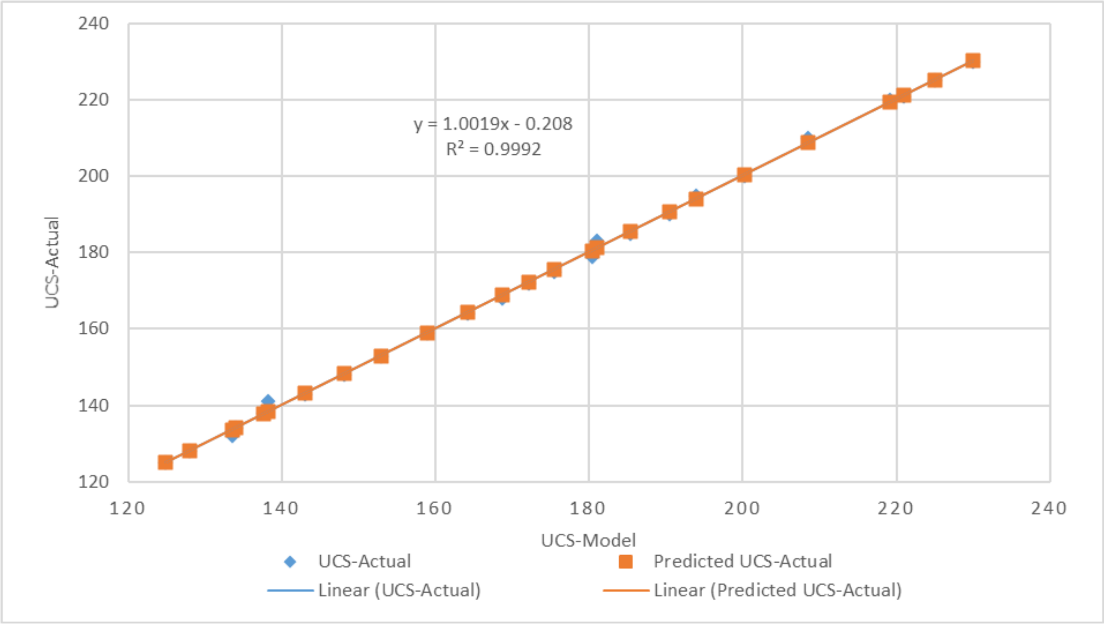


FIGURE 15. ANN Line of Fit Plots-UCS

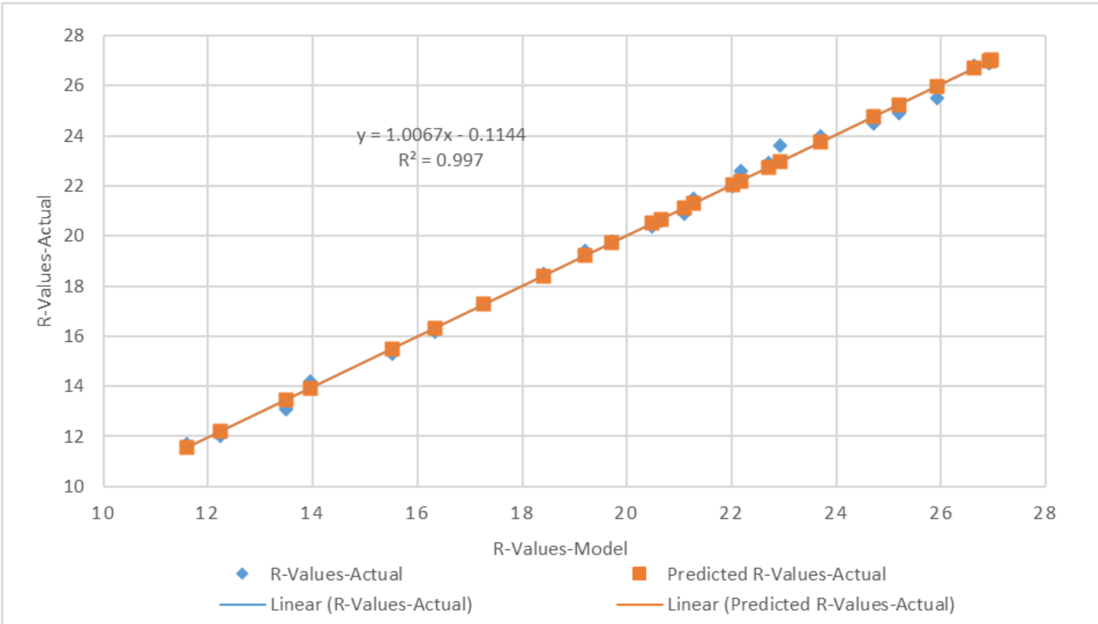


FIGURE 16. ANN Line of Fit Plots-R-values

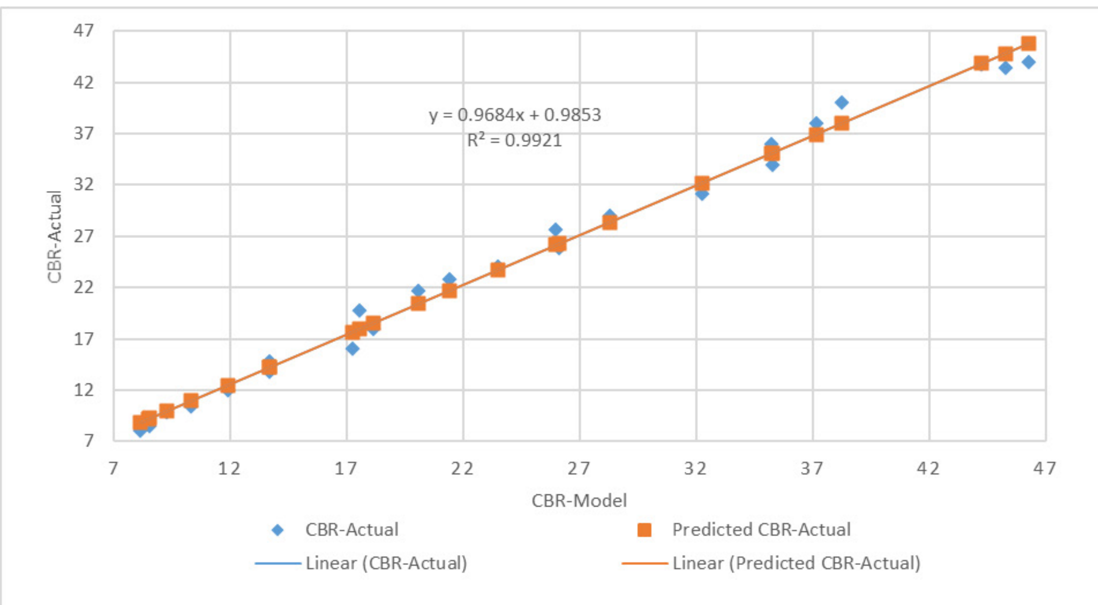


FIGURE 17. Fuzzy Model Line of Fit Plot-CBR

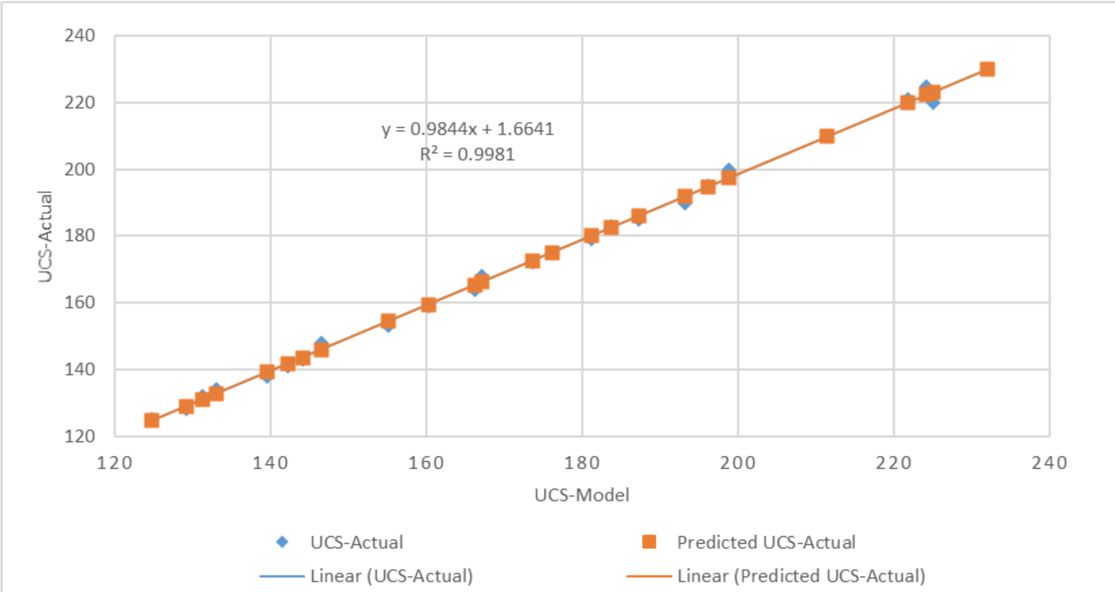


FIGURE 18. Fuzzy Model Line of Fit Plot-UCS

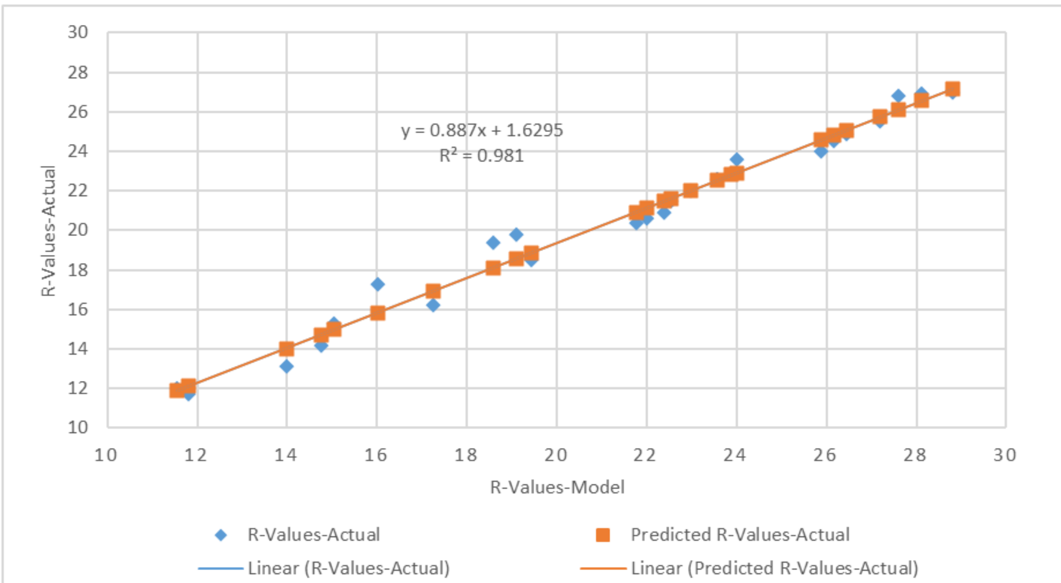


FIGURE 19. Fuzzy Model Line of Fit Plot-R-values

CONCLUSIONS

Varying ratios of expansive clay-HARHA mixture were analysed in order to evaluate the consistency limits, compaction and mechanical strength (CBR, UCS and R-values) characteristic behaviour of the blended soil mixture ranging from 0% (control mix) to 12% modified soil by HARHA.

The addition of chemical additive (stabilizing agent) resulted to significant improvement in the expansive soil's consistency properties and activity with the plastic limit, liquid limit and clay activity decreasing from 21%, 66% and 2% respectively for the control mix to 13%, 27% and 0.6% respectively for the soil sample modified with 12% by weight HARHA of dry soil. These mixture variations impacted significantly on the compaction properties of the blended soil samples with MDD increasing from 1.25g/cm^3 for the control mix to 1.95g/cm^3 at 12% modification by HARHA while the OMC increased from 16% for the control mix to the maximum achievable value of OMC at 19% for 4-4.5% modification by HARHA while this value decreased further to 17.1% with more addition of HARHA to 12% addition.

The expansive soil preliminary tests results which presents the general engineering behaviour of the soil reveals that it is poorly graded and have high clay content (CH) according to unified soil classification system (USCS). The chemical oxides composition summary of the expansive clay soil and chemical additives shows that the soil possesses high content of Na_2O which eventually contributed to its expansive behaviour while the (RHA) possesses high content of Fe_2O_3, Al_2O_3 and SiO_2 totalling 82.97% which signifies a better pozzolanic activity behaviour. This pozzolanic activity causes significant improvement in the mechanical properties and binding abilities of the blended soil-HARHA mixture.

ANN and fuzzy logic based model were adapted for the prediction of the soil mechanical strength characteristics (CBR, UCS and R-values) with the soil-HARHA ratio, consistency limit and compaction characteristics as the input variables of the developed model. For the ANN model development, Levernberg Marquardt training algorithm and 8-6-3 optimized network architecture were derived using MSE as the performance criteria with feed-forward back propagation as the processing parameters while for the fuzzy logic model development, the Mamdani fuzzy inference system which is essentially utilized for multiple input multiple output systems (MIMOS) architecture to derive crisp numeric output results.

The developed ANN and fuzzy logic model performance were further evaluated in terms of accuracy of prediction using loss function parameters (MAE, RMSE and R-values) which presents a significant yardstick and criteria for performance evaluation. These statistical results were used as a base for comparison between the developed ANN and fuzzy logic model; from the results, ANN model produced average MAE, RMSE and R-values of 0.2750, 0.4154 and 0.9983 respectively while fuzzy logic model produced 0.3737, 0.6654 and 0.9894 respectively. These results showed that ANN model performed better than the fuzzy logic model even though the overall performances of both models were satisfactory.

From this research study, the mechanical strength properties of the expansive soil-HARHA blended mixture were evaluated and modelled using fuzzy logic model and ANN soft-computing techniques which enables the optimization of the materials utilized in the stabilization process taking into consideration the non-linear relationships in the input-output of a complex system and at the same time saving time and cost expended in series of trial tests.

ABBREVIATIONS

1. ANN-Artificial Neural Network
2. FL-Fuzzy logic
3. HARHA-Hydrated Lime Activated Rice Husk Ash
4. MSE-Mean Square Error
5. RMSE-Root Mean Square Error
6. LMA- Levenberg Marquardt Optimization Algorithm
7. MLR- Multiple Linear Regression
8. BP-Back Propagation Algorithm
9. W_L = Liquid Limit
10. W_P = Plastic Limit
11. I_P = Plasticity Index
12. MAE = Mean Absolute Error

DECLARATION OF COMPETING INTEREST

None.

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