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ANFIS Prediction Model for the Mechanical Properties of Soil and Activated Rice Husk Ash Blend for Sustainable Construction

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Abstract
Adaptive neuro-fuzzy inference system (ANFIS), which integrates both Takagi-Sugeno fuzzy logic and neural network principles and also captures their benefits in a single framework was deployed for the modelling of the mechanical strength behaviour of expansive clayey soil treated with hydrated-lime activated rice husk ash (HARHA). The compaction properties, consistency limits and the activated ash (HARHA) were the predictors while CBR and UCS were the targets in this evolutionary model. The advantages of artificial intelligence techniques deployment in geotechnical research is to deal with the complex challenges associated with effectiveness in construction materials’ utilization so as to achieve optimal assessment of geotechnical materials’ behaviour and sustainable engineering design. ANFIS model development were carried out with 35 data sets derived from the experimental responses with respect to varying proportions of HARHA treatment from 0% to 12%. 25 and 10 datasets were used for training and testing the network respectively. The California bearing ratio (CBR) and unconfined compressive strength (UCS) were the target response while the HARHA replacement ratio, compaction and consistency limits properties were the input variables of the developed model. The model evaluation results obtained using statistical tools showed mean absolute error (MAE) of 0.582 and 0.7196, root mean square error (RMSE) of 0.6198 and 0.9004, mean square error (MSE) of 0.384 and 0.811, and coefficient of determination (CoD) value of 0.9973 and 0.9992 for CBR and UCS response parameters respectively. The results obtained indicates a very good performance in terms of prediction accuracy. This shows that ANFIS provides the flexibility in achieving sustainable geotechnical materials integration in civil works.

Keywords: Soft Computing; Unconfined Compressive Strength (UCS); California Bearing Ratio (CBR); Soil Stabilization; Hydrated-lime; ANFIS; Soil Strength Properties.

1. Introduction
Various kinds of soil are used for geotechnical engineered construction works. Most commonly used soil deposits in their natural form support civil structures effectively without treatment while others require treatment in order to be suitable for construction works such as expansive clayey soil. These soils are expected to be removed and replaced with materials with better properties to avoid failure, or by the modification of its mechanical and swelling properties in order to improve its performance [1-2]. Expansive soil tends to produce serious challenge when utilized for civil foundation works due to poor mechanical behaviour of the clay minerals composition, which makes them possess and display shrink-swell properties during drying and wetting cycles [3]. It tends to suddenly expand and swell when in contact with water and shrink when it losses moisture due to its physicochemical properties. The presence of clay minerals, over-consolidation of soil, intrinsic stresses emission and hydration of cations on the clay surface generally influences the soil’s swelling properties; while on drying through desiccation, the volume of the soil reduces followed by built up of internal stresses in the shrunken or dried soil mass resulting to cracks, which appear in weakness planes within the expansive soil [4-5].

Several treatment methods are utilized, which include chemical modification through blending with chemical additives as a stabilizing agent and humidity control. However, stabilization of expansive soil using lime-alumina-silicates combination is achieved through agglomeration, cation exchange and pozzolanic reactions [6-9]. The problematic soil’s properties are improved by significantly increasing the cohesion, CBR and internal friction angle properties while decreasing its swelling potentials characteristics [10].

The utilization of industrial waste for expansive soil stabilization has been a subject of research by material engineers and scientists so as to achieve sustainable, eco-friendly and eco-efficient construction materials for infrastructural development. Rice husk ash (RHA) is gotten from rice milling process as a by-product from the industrial unit; they are classified as pozzolanic material because they possess alumina-silicates with little or no binding properties. But, they chemically react with lime in the presence of water to obtain cementitious products which enable mechanical properties improvement of the problematic soil through enhancement of its deformation properties such as compression index, swelling potentials, swelling pressure and consistency indices [11-14]. Several stabilization techniques were used for the mechanical properties modification of the expansive soil which undergo large volumetric change when the water content is altered for civil construction works. These soil pose heavy threat to geotechnical and civil construction works leading to foundation failure due to its
physicochemical properties [15-16]. Ahmed et al. [17], investigated the swell-strength characteristics of expansive clay-sand mixture prepared artificially stabilized using two additives namely; dolomitic limestone and hydrated lime. The testing program carried out includes modified proctor test, Atterberg limit test, CBR, free swell, chemical analysis and pH test. The strength and expansivity of the treated soil were then assessed based on Egyptian code and relationships proposed by relevant literatures.

Moreover, the utilization of statistical approach for derivation of the soil-additives blend behaviour proved to provide required performance in recent times. However, development and use of expert intelligent systems for the modelling of the consistency limits and swelling potentials properties of treated or stabilized soil is essential for better robust performance and enhancing sustainable development [18-19]. Keshavarz et al. [20] in their research study, ANFIS and ANN were adapted for modelling of concrete’s compressive strength property. 150 different concrete mixes of ingredients namely, gravel, cement, water, fine aggregates and Silica. The results generated shows that ANN and ANFIS models developed can accurately predict the concrete compressive strength characteristics. Also, Behfarnia et al. [21] performed concrete compressive strength property prediction using ANFIS and ANN. 160 different mix designs were cast after 28-day hydration period. The results obtained indicates that ANFIS and ANN model were suitable for estimating the concrete mechanical properties. Furthermore, Kurtener et al. [22] carried out assessment on soil disturbance using ANFIS to study the relationship between the soil disturbances indicators namely; disturbance factor complex (DFC) and disturbance factor simple (DFS), soil depth values and also relationship between (DFS) indicators and the combined soil disturbance indicator.

Adaptive network based fuzzy inference system (ANFIS) is a multi-layer feed forward network which uses ANN learning algorithms and Fuzzy logic theory to map sets of input space to an output space. It combines the benefits of FIS and ANN system to solve different kinds of complex and non-linear challenges effectively by the interpretation of linguistic and numerical knowledge from Fuzzy logic and ANN’s capability of data generalization, classification and pattern recognition makes Fuzzy logic and ANN less relying on expert knowledge and systematic. The research idea is to evaluate the swelling and compaction properties of the expansive clayey soil treated with lime activated rice husk ash through development of expert artificial intelligent systems using ANFIS. This research will contribute to scientific knowledge on adaptation of soft-computing techniques
for the modelling of treated expansive clayey soil to ensure good judgement in utilization of solid waste derivatives as a stabilizing agent to improve its general engineering properties [23-24].

2. Adaptive Network Based Fuzzy Inference System (ANFIS)

ANFIS modelling system is the learning and training of the network where the associated membership degrees are automatically adjusted using Neural Network (NN) capability, which removes the burden of manual adjustment of the membership function parameters. ANFIS is an artificial intelligence (AI) or soft computing modelling tool, which has become attractive and desirable due to a combination of linguistic variables transparency from the Fuzzy logic method and leaning capability of ANN techniques [25]. Through the utilization of the ANN’s learning and generalization capability to update and process Takagi-Sugeno fuzzy inference System (FIS) type provides ANFIS with the learning ability similar to ANN through data training, it is able to process and model behaviour of complex system such as mixture experiments optimization. The results generated can therefore be mapped into FIS described in linguistic labels. Thus, the hidden layer and learning processing parameters are determined by FIS in the ANFIS network which removes the conventional challenges faced in ANN-modelling for the determination of hidden layer parameters and also the determination of membership function parameters and Fuzzy if-then rule generation in Fuzzy logic modelling. Its major advantages are Complex mathematical model computations is not involved, it is rather robust, adaptive and perform data generation faster with higher efficiency [26].

2.1 ANFIS Architecture

The architecture as shown in Fig. 1 possess five layers for the model development where each layer has several nodes are utilized in the description of the model function. Adaptive nodes that are denoted by square shape represent sets of parameter which are adjustable or modifiable within the nodes while fixed nodes which are un-adjustable parameters are presented in circles [27]. The simplest ANFIS structure possesses two input variables \( I_1 \) and \( I_2 \) and one output (F: response function) which are explained below;
Layer 1: the first layer receives the input, converts it to Fuzzy set using suitable membership function parameters. Fuzzification of the Crisp numerical input takes place here which possesses adaptive nodes whose node functions are described as presented in Eqs. 1-2.

$$O_{1,j} = \mu_{A_j}(I_1) \text{ for } j = 1,2$$  \hspace{1cm} (1)

$$O_{1,j} = \mu_{B_{j-2}}(I_2) \text{ for } j = 3,4$$  \hspace{1cm} (2)

Where $I_1$ and $I_2$ are the input nodes, j, A and B are linguistic variables associated with the nodes $\mu(I_1)$ and $\mu(I_2)$ are membership with values ranging from 0 →1 [28].

Layer 2: all the nodes in the layer are fixed and un-adjustable with a label (M). The incoming input signal is multiplied in this layer where the products of all the incoming signals is the output from the node. The node function is presented in Eq. 3.

$$O_{2,j} = w_j = \mu_{A_j}(I_1) \ast \mu_{B_{j-2}}(I_2) \text{ for } j = 1,2$$  \hspace{1cm} (3)

Where $O_{2,j}$ is layer 2 output and the output signal weight denoted by $w_j$ signals the nodes forming strength depending on the received input signal [29].
Layer 3: in this layer, the nodes are fixed and un-adjustable with circle shape marked by label (N). The node function here normalizes the firing strength obtained from layer 2 by calculating the ratio of $j^{th}$ node firing strength to the sum of all networks firing strength due to the renewed input signal in Eq. 4.

$$O_{3,j} = \bar{w} = \frac{w_j}{w_1 + w_2}, \text{ for } j = 1,2$$

(4)

Where $O_{3,j}$ is the layers output, $\bar{w}$ is the computed normalized firing strength [30].

Layer 4: all the nodes in this layer are adjustable and are thus marked in a square shape where the output from this layer is the product of the normalized firing strength $\left( \bar{w} \right)$ and first order polynomial for Sugeno model [31]. The fuzzy if-then rules are added to the output in this layer with the node function shown in Eq. 5.

$$O_{4,j} = \bar{w} \times f_j, \text{ for } j = 1,2$$

(5)

$F_1$ and $F_2$ denotes the fuzzy if then rules as follows.

Rule 1: if $I_1$ is $x_1$ and $I_2$ is $y_1$, then $f_1 = P_1I_1 + q_1I_2 + r_1$

Rule 2: if $I_1$ is $x_2$ and $I_2$ is $y_2$, then $f_2 = P_2I_1 + q_2I_2 + r_2$

Where $q_i$, $P_i$ and $r_i$ are the parameters referred to as the consequent parameters for the fuzzy if-the rules formulation.

Layer 5: the nodes in the layer is un-adjustable and fixed as they are marked by a circle and performs overall summation of the node output function of ANFIS presented in Eq. 6.

$$O_{5,j} = \sum_j \bar{w} \times f_j = \frac{\sum_j w_j f_j}{w_j}$$

(6)

ANFIS utilizes back-propagation learning rule which calculates recursively, errors from output layer 5 and backwards to the layer one of the ANFIS Architecture which is the same as BPA used in feed-forward artificial neural networks [32]. Other learning can techniques such as genetic algorithm (GA) and hybrid-learning algorithms be adopted for ANFIS network training. Hybrid-
learning algorithms (HCA) which integrate the least squares method and the gradient descent method to optimum generalization of data as a result shows better ANFIS model performance [33].

3. Materials and Methods

3.1 Test Materials

The clayey soil material was obtained through method of disturbed sampling from 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. It was observed as smaller fragments in broken form, it was thus air dried, pulverised and as well sieved with BS sieve No. 4 (4.75mm aperture). The representative soil was prepared in accordance with British Standard International BS1377 [34] and stored for the laboratory work at room temperature. And the treated soil was prepared in accordance with British Standard International BS1924 [35].

Rice husk ash utilized as the stabilizing agent was gotten by the direct combustion of rice husk collected from rice mills in Abakaliki, Nigeria in a controlled incineration system to avoid air pollution. The ash samples obtained according to relevant literature, satisfies the requirements of a pozzolanic material in accordance with British Standard International BS 8615-1 (2019) [36] and American Standard for Testing and Materials ASTM C618 [37] due to the presence of Al₂O₃, SiO₂ and Fe₂O₃ in its chemical oxides’ composition. The release of alumina-silica from the activated rice husk ash enables pozzolanic reaction in the clayey soil adsorbed complex interface through calcination and hydration to achieve stabilization of the problematic soil [38].

Hydrated-Lime (Ca(OH)₂) is quicklime chemically combined with 33-34% magnesium oxide (MgO), 46-48% (CaO), and 15-17% chemically combined water. It is an odorless inorganic powder, crystal and nonflammable, which is soluble in water at room temperature. It has a boiling point of 2850°C, density of 2.21g/cm³ and melting point of 580°C. Its density is less than that of quicklime at 3.34g/cm³ because it’s in more aqueous condition which created pores in the structure of the solid; and also caustic possessing a pH of 12.8 and pozzolanic behaviour, which makes it a good supplementary or alternative binder for earth works construction. It dissociates into the ions of hydroxyl from water and calcium ion from lime as presented in Eqn. 7 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 [39].
\[ \text{Ca (OH)}_2 \rightarrow \text{Ca}^{2+} + \text{OH}^- \]

(7)

By mixing 5% of hydrated lime by weight of RHA with the ash under laboratory conditions, the hydrated rice husk ash (HARHA) used for the stabilization process was achieved. Through calcination reaction of the pozzolanic solid waste ash compounds, calcium silicate and aluminate were formed, which are responsible for strength properties improvement [40].

3.2 Methods

Laboratory experiments were carried out on the collected test material samples so as to derive its general engineering behavior namely; sieve analysis test, compaction test, Atterberg limits test, California bearing ratio and specific gravity of soil test to enable the characterization of the representative RHA and problematic soil. Following the required laboratory conditions in accordance with the British Standard International BS1377 [34], these basic tests were conducted. RHA was then activated with the three compounds of calcium in accordance with the requirements of Davidovits [41]. The rice husk ash mixture was thus activated with caustic solution of Ca(OH)$_2$ (5% by weight of RHA), it was then used in blending with ratios of 0% (the control test), to 12% by weight of soil to improve the expansive clayey soil mechanical, swelling and compaction behavior. Atterberg limits (plastic limit and liquid limit) behavior of problematic clayey soil blended with quicklime activated RHA were observed by experimentation using the Casagrande apparatus in accordance with design standard. From the observed test results, the plasticity index ($I_P$) and activity of clay was computed using the formula in Eqns. 8 - 9.

\[
I_P = w_L - w_P
\]

(8)

\[
A_C = \frac{I_P}{c}
\]

(9)

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 2\(\mu\)m sieve.

3.2.1 California bearing ratio (CBR)

CBR test is an indicator of soil mechanical strength behaviour parameter, it was carried out in the laboratory to evaluate the effects of varying proportions of HARHA-soil blend according to the guidelines in BS 1377 [34] and BS 1924 [35]. The tests were carried out for soil materials compacted based on British Standard Light (BSL) compaction energy. The soil mixture specimens
were compacted in three layers using a 2.5 kg rammer, 62 number of blows were applied for each of the three layers. The compacted soil specimens during the CBR tests were then cured for seven days. Thereafter, the cured specimens were subjected to a static loading system by the CBR machine until failure took place [42].

3.2.2 Unconfined compressive strength (UCS)
UCS test involves a cylinder of soil without lateral support is tested to determine failure stress in axial compression, at a constant rate of stream. The compressive force per unit cross-sectional area which is required to fail the test soil specimen is called unconfirmed compressive strength of the soil in accordance with B.S.1377 [34]. The test was also carried out with respect to varying proportions of HARHA-soil blend from 0% to 12% and the test soil mixture were compacted using BSL and cured for seven days. The test soil specimens were then placed inside the loading frame of the UCS testing machine after the curing exercise [43].

3.3 ANFIS Modelling Algorithm Flow Chart
After derivation of results from the laboratory, the data generated are logically sorted so as to obtain the model variables. The data base for the model development are divided into two parts for training and testing of the ANFIS network with 70% and 30% allotted respectively. The research study flowchart is presented in Fig. 2. showing the sequential flow of events, training, testing and ANFIS model validation using statistical computational technique. The loss function parameters namely; Root mean square error (RMSE), mean square error (MSE) and coefficient of determination (R^2) were utilized for performance evaluation of the ANFIS model [44].
3.4 Data Base for ANFIS Model Development

The data generated from experimental laboratory results, relevant literature and expert knowledge, from which investigates the compaction, consistency limits and mechanical strength properties of treated expansive clayey soil with respect to varying ratio of replacement partially by HARHA from 0 % to 12 % [45]. The ANFIS network’s input parameters constitute the replacement ratio by HARHA, the Atterberg limits and compaction properties of the soil mixture combinations, while the output variables of the network are the mechanical strength characteristics of the stabilized soil as presented in Figs. 3 and 4;
The descriptive statistics of the experimental results generated from the laboratory tests which was further utilized for ANFIS model development are presented in Table 1.
Table 1. Descriptive Statistical of data sets used for training and testing the ANFIS Network

| Variables | Mean  | Standard Error | Standard Deviation | Sample Variance | Range | Minimum | Maximum |
|-----------|-------|----------------|--------------------|-----------------|-------|---------|---------|
| Soil (%)  | 94.000| 0.736          | 3.680              | 13.542          | 12    | 88      | 100     |
| HARHA (%) | 6.000 | 0.736          | 3.680              | 13.542          | 12    | 0       | 12      |
| WL (%)    | 47.900| 2.419          | 12.097             | 146.333         | 39    | 27      | 66      |
| WP (%)    | 17.160| 0.512          | 2.561              | 6.557           | 8     | 13      | 21      |
| OMC (%)   | 17.964| 0.171          | 0.853              | 0.728           | 3     | 16      | 19      |
| MDD (g/cm³)| 1.683 | 0.050         | 0.252              | 0.064           | 0.74  | 1.25    | 1.99    |
| CBR (%)   | 24.068| 2.421          | 12.105             | 146.526         | 36    | 8       | 44      |
| UCS (kN/m²)| 172.720| 6.535        | 32.677             | 1067.793        | 105   | 125     | 230     |

4. ANFIS Model Development and Result Discussion

4.1 Materials characterization

The general engineering properties of the problematic soft clayey soil and its particle size distribution test rest results were shown in Table 2 and Fig. 5. From the presented results, it can be deduced that the clays soil samples possess 45% of its particles passing sieve size 0.075mm, with a natural moisture content of 14% and liquid limit of 66%. Based on the derived experimental results, the soil specimen was further classified using AASHTO classification as A-7-6 soil and poorly graded with high clay content (CH) according to USC system. Furthermore, the plasticity index of 45% indicates a highly plastic soil which breaks easily upon the load application and that the representative clayey soil also has a swelling potential property, with a plastic limit of 21% and this means that the soil is highly expansive. The maximum dry density of the soil was observed to be 1.25g/cm³ derived at an optimum moisture content value of 16%. These properties have characterized the clayey soil as a high expansive and problematic soil which is very unsuitable for civil construction works [46-47].
| Property Description of Clayey Soil and Units | Value |
|-----------------------------------------------|-------|
| % passing sieve, no. 200 (0.075mm) [25]        | 45    |
| $w_N$ (%)                                      | 14    |
| $w_L$ (%)                                      | 66    |
| $w_P$ (%)                                      | 21    |
| $I_P$ (%) = $w_L - w_P$                        | 45    |
| $w_S$ (%) = 0.00216 * $I_P^{2.44}$ [30]       | 23.35 |
| Degree of expansion [30]                      | high  |
| $G_s$                                          | 1.43  |
| AASHTO classification [33]                     | A-7-6 |
| Universal soil classification system           | GP (20), CH |
| $\delta_{max}$ (g/cm$^3$)                     | 1.25  |
| $\omega$ (%)                                   | 16    |
| CBR (%)                                        | 8     |
| Color                                          | reddish |

---

**Fig. 5:** Sieve Analysis Plot of the Clayey Soil and Rice Husk Ash
The chemical oxides composition of the representative test clayey soil and the rice husk ash were also presented in Table 4. The results indicate that the soil has high oxide composition (34.33%) of Na$_2$O, 18.09% of Al$_2$O$_3$ and 12.45% of SiO$_2$ by the test soil sample’s weight. These elemental oxides contribute to the expansive condition of the soil. The ferrite composition shows its rich in the red color of the clayey soil and plays active role during pozzolanic reaction. This property supports the high swelling potential of the clayey soil. However, RHA has high of the alumina-silicates content, which fulfills the minimum requirements of pozzolanic materials in accordance with specified design standards [48].

Table 4. Chemical Oxides Composition of the Additive Materials

| Materials | SiO$_2$ | Al$_2$O$_3$ | CaO | Fe$_2$O$_3$ | MgO | K$_2$O | Na$_2$O | TiO$_2$ | LOI | P$_2$O$_5$ | 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      | -      | -  | -        |
| RHA       | 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,

4.2 Experimental Responses of Clayey Soil Modified with Calcined Rice Husk Ash

The incorporation of chemical additive (HARHA) for mechanical properties modification of problematic expansive clayey soil were evaluated in this study to improve its engineering performance for civil construction purposes. From the obtained laboratory results presented in Fig. 6, the soil’s Atterberg limits properties reduced with higher percentage addition of HARHA. Moreover, for the compaction test of the, the OMC for the control mix is 16% and the moisture content result increased to maximum limit of 19% at 4% replacement while the OMC results decreased subsequently, slightly at further addition of HARHA to 17% at 12% replacement by HARHA. However, MDD results increased linearly as HARHA addition increased from 1.25g/cm$^3$ for the control to maximum value of 1.95g/cm$^3$ at 12% replacement by HARHA. Moreover, from the mechanical strength properties of the blended soil namely; California bearing ratio (CBR) and unconfined compressive test (UCS) increased from 8% and 125kN/m$^2$ respectively at control mix to 40% and 230kN/m$^2$ for CBR and UCS respectively at 11%
replacement. This mechanical strength improvement is achieved due to binding effect of the hydrated lime and alumina-silicates from the blended rice husk ash [49-50].

4.3 ANFIS Model Development

Data obtained from relevant literatures and expert judgement were utilized for appropriate model input-output pattern structure formulation; the input parameters of the ANFIS network were the soils’ replacement ratio by HARHA, compaction and consistency limits characteristics while the output variables were the mechanical strength properties of the blended soil samples (CBR and UCS). The network architecture is presented in Fig. 7. showing the model variables and processing parameters of the network [51].

Using ANFIS toolbox in MATLAB software for the model simulation, testing training and validation, the data sets was loaded from the workspace, and using Sub. clustering method of fuzzy inference system (FIS) generation which is very suitable for multiple inputs complex systems. Furthermore, hybrid optimization method was utilized for training of FIS at 100 epochs. For Sub. clustering membership function generation, the following parameters were selected as presented in Table 5.

---

**Fig. 6: Graphical Plot of Experimental Results**
### Table 5. ANFIS Network Parameter

| ANFIS Network Parameter | Settings       |
|-------------------------|----------------|
| FIS type                | Sub clustering|
| Range of influence      | 0.5            |
| Squash factor           | 1.25           |
| Accept ratio            | 0.5            |
| Reject ratio            | 0.15           |
| Optimization method     | Hybrid         |
| Error tolerance         | 0              |
| Epochs                  | 100            |
| Membership functions    | 7              |
| Number of fuzzy rules   | 7              |
| Membership functions    | Gauss MF       |
| Implication method      | Minimum        |
| Or Method               | Probor         |
| And Method              | Prod           |
| Aggregation | Maximum |
|-------------|---------|
| Defuzzification | Wtaver |

### 4.3.1 Training and testing of the ANFIS network

As the ANFIS network is fed the datasets, appropriate FIS parameters and hybrid training methods were then selected. The loaded datasets for the ANFIS network training which possess 25 index number in the x-axis plotted against output variables at y-axis for CBR and UCS response respectively is shown in Fig. 8.

![Fig. 8: ANFIS Training Datasets Plot](image)

The ANFIS network were further trained after loading the datasets and setting the appropriate training and testing parameters. For the CBR response, $2.0315 \times 10^{-5}$ was the obtained training error while UCS response produced $4.649 \times 10^{-3}$ as shown in Fig. 9.

![Fig. 9: ANFIS Training Error Plot](image)
After training the network with the sorted datasets, the indexed points which were initially open circle now has a red asterisk inside the circle to show that the ANFIS network is trained with given sets of data as shown in Fig. 10.

![Training Data Plots](image1)

Fig. 10: Training Data Plots

The testing data sets are then loaded from the workspace after end of ANFIS data training. 30% of the system data base is allotted for this stage as the remaining 70% were utilized for training of the network. The loaded testing datasets were plotted with the trained data sets in blue dotted color with 10 index points as shown in Fig. 11. for the CBR and UCS response respectively [52].

![ANFIS Training and Testing Datasets Plots](image2)

Fig. 11: ANFIS Training and Testing Datasets Plots

The network is further tested with the loaded testing datasets using the initially prescribed training and FIS parameters to ensure better model prediction performance. A testing error of $2.8947 \times 10^{-5}$ for the CBR response while $5.322 \times 10^{-5}$ was obtained for UCS response as shown in Fig. 12.
4.3.2 Developed ANFIS Network architecture

The developed ANFIS architecture after training and testing with the datasets fed to the network is shown in Fig. 13. Showing the complex connections of the input variables, the fuzzification node, the inputs weight signals aggregations, network firing strength normalization, fuzzy if-then rule automatic generation and output nodes overall summation function. The architecture clearly shows that we have six input variables namely effective soil proportion (%), HARHA replacement ratio (%), liquid limit (%), plastic limit (%), optimum moisture content (%) and maximum dry density (g/cm$^3$) with one output parameter for the CBR (%). The input variables were further fed to the ANFIS network with UCS (kN/m$^3$) as the output parameter for the second stage of the modelling process [53].
4.3.2 ANFIS Network Membership Function

After training and testing of the ANFIS network with the system database, the network variables develops the appropriate membership function criteria which would enhance better data generalization. The model membership function plot is shown in Fig. 14. The plot shows the data range for each input parameter on the x-axis against the universe of discourse ranging from 0 to 1 on the y-axis [54].
4.3.3 Graphical Expression of ANFIS Model Variables Relationships

The ANFIS network learns the generalization of data sets fed to it using hybrid learning method, and is able to map a given input space with the corresponding output response. The network variables’ relationships can be assessed through 3D-surface plot after testing and training of the ANFIS network as shown in Fig. 15. The effects of clayey soil replacement by HARHA, its atterberg limits and compaction properties in respect to CBR and UCS response were observed [55].
Fig. 15: ANFIS Model Variables’ Surface Plots
4.3.4 Model Validation

For optimization of the given laboratory response values, the training and testing datasets were fed into the ANFIS model for mechanical behavior prediction of the soil-additive blend. After development of the model, the experimental or actual results were statistically compared with the ANFIS model results using loss function parameters RMSE, MSE, MAE, and also coefficient of determination so as to rate the prediction accuracy performance of the developed ANFIS model. The statistical computation was carried out with Microsoft Excel software and the results are presented in Tables 6-7. The obtained statistical results indicate existence of no significant difference between the actual values and the ANFIS model results with MAE of 0.582 and 0.7196, RMSE of 0.6198 and 0.9004, MSE of 0.384 and 0.811, and coefficient of determination value of 0.9973 and 0.9992 for CBR and UCS response parameters respectively [56-57].

Table 6. ANFIS Model and Experimental Results -7

| % Replacement of HARHA | CBR (%) | CBR-ANFIS Model | UCS (kN/m²) | UCS-ANFIS Model |
|------------------------|---------|-----------------|-------------|-----------------|
| 0                      | 8       | 7.35            | 125         | 124.52          |
| 0.5                    | 8.5     | 9.06            | 128         | 128.63          |
| 1                      | 9.2     | 9.82            | 132         | 133.04          |
| 1.5                    | 9.8     | 10.22           | 134         | 133.49          |
| 2                      | 10.4    | 10.91           | 138         | 137.69          |
| 2.5                    | 12      | 11.59           | 141         | 142.41          |
| 3                      | 13.8    | 13.33           | 143         | 142.37          |
| 3.5                    | 14.8    | 14.25           | 148         | 147.65          |
| 4                      | 16      | 16.34           | 153         | 152.42          |
| 4.5                    | 18      | 17.66           | 159         | 156.46          |
| 5                      | 19.8    | 19.35           | 164         | 164.54          |
| 5.5                    | 21.7    | 21.06           | 168         | 167.58          |
| 6                      | 22.8    | 22.19           | 172         | 171.34          |
| 6.5                    | 24      | 24.62           | 175         | 174.63          |
| 7                      | 25.9    | 26.39           | 179         | 178.69          |
From the computed results which provides sufficient assessment of the developed ANFIS model performance showing satisfactory results as compared with model performance result obtained by [58-59]. The slope of the regression line of ANFIS model results vs. actual results is presented in Figs. 16-17. The plot shows the steepness of the line of fit which is the straight line that best predicts the provided sets of data. The line of fit equations for the output variables namely, CBR and UCS are presented in Eqs. 10-11.
\[ y = 0.996x + 0.0452 \]  
\[ y = 0.9939x + 1.0999 \]

Fig. 16: CBR-ANFIS Model Line of Fitness Plot

\[ y = 0.996x + 0.0452 \]
\[ R^2 = 0.9973 \]

Fig. 17: UCS-ANFIS Model Line of Fitness Plot

\[ y = 0.9939x + 1.0999 \]
\[ R^2 = 0.9992 \]

Where \( y \) is the CBR/UCS and \( x \) is the varying proportions of HARHA.
5. Conclusion

Soft computing technique method known as ANFIS was adapted for the modelling of the compaction, consistency limits and mechanical properties of expansive clay soil treated with HARHA from 0 % to 12 % replacement ratio. The following conclusions can be drawn from the research study;

The preliminary soil’s test indicated a poorly graded, expansive clayey soil, which is classified as CH according to unified soil classification system; these properties fall off the required specification as a construction material. However, the incorporation of HARHA enhanced the problematic soil’s mechanical behavior making it suitable for engineering purposes.

Moreover, the obtained experimental responses were utilized as the system data base for ANFIS model development which provides a better assessment of the problematic clayey soil-HARHA blend deformation and mechanical strength behavior. In order to achieve testing and training of the ANFIS network, the system datasets were divided into two with the former and later receiving 30% and 70% respectively.

Furthermore, the developed ANFIS model performance in terms of accuracy of prediction were evaluated using loss function parameters RMSE, MSE, MAE, and also coefficient of determination ($R^2$). The ANFIS model evaluation results indicate MAE of 0.582 and 0.7196, RMSE of 0.6198 and 0.9004, MSE of 0.384 and 0.811, and coefficient of determination value of 0.9973 and 0.9992 for CBR and UCS response parameters respectively.

Finally, the deformation behavior of expansive clayey soil treated with HARHA were evaluated through model development using ANFIS soft computing method which has the capacity to deal with complex relationships among variables and predict the output parameters with good accuracy. The results obtained from this research shows clearly the flexibility of ANFIS method application in soil-additive blend engineering behavior modelling for sustainable development.
Abbreviations

- ANFIS- Adaptive neuro-fuzzy inference system
- HARHA-Hydrated Lime Activated Rice Husk Ash
- MSE-Mean Square Error
- RMSE-Root Mean Square Error
- MAE = Mean Absolute Error
- WL = Liquid Limit
- WP = Plastic Limit
- IP = Plasticity Index

Conflict of Interests

There are no recorded conflicts of interests in this research work. We also affirm that the content of this work is original and has followed the journal template. Compliance with Ethical Standards was strictly observed.

Declaration

The authors declare that this work is original.

Ethical Approval and Consent

The authors declare that all ethical conducts have been adhered in preparing this manuscript

Consent for Publication

The authors give their consent to publish this paper if accepted

Availability of Supporting Document

The data supporting this work has been reported in this manuscript

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