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ORIGINAL PAPER

Sensitivity analysis and prediction of erodibility of treated unsaturated soil modified with nanostructured fines of quarry dust using novel artificial neural network

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Abstract

Sensitivity and error analyses and machine-based prediction have been conducted on the erodibility response of erodible unsaturated soil (degree of saturation 60%) treated with local cement and modified with nanostructured quarry fines. The machine-based exercise has become necessary because of the incessant washing away of soil on erosion watersheds causing devastating gullies around the developing world and the need to propose model equations to study, design and proffer future solutions to this environmental problem. Also, in order to overcome complex experimental setup needed to repeatedly study erosion problems, there is also need to forecast model equations by employing variables that can easily be determined as predictors of the model. This work was aimed at the prediction of erodibility and generating a model equation using the ANN learning technique. The erodible soil was collected and classified as poorly graded, highly plastic and as an A–7–6 group. 121 datasets were generated from multiple experiments for the input parameters and deployed in model training and testing in the ratio of 70 to 30%, respectively. The model performance was validated and error analysis was conducted using R^2, MAE, MSE, RMSE and MAPE indices. The performance showed that the model has R^2 of more than 0.95 in both training and testing between the predicted and measured values. Also, the error indices showed significantly small values, which showed good performance. Finally, the sensitivity analysis outcome showed that the liquid limit was the most influential on the erodibility model results. Generally, ANN technique has shown to be very flexible in forecasting civil engineering problems and fundamentally in proposing model equations.

Keywords Sensitivity analysis · Erodibility · Erodible soil · Artificial neural network · Nanostructured quarry fines · Error analysis · Agiel neural network software

Notations

E_r (K)	Erodibility
$[E_r]_{max}$	Maximum values of predicted erodibility
$[E_r]_{min}$	Minimum values of predicted erodibility
ANN	Artificial neural network
GP	Genetic programming
GEP	Gene expression programming
EPR	Evolutionary polynomial regression
ANFIS	Adaptive neuro-fuzzy inference system
NQF	Nanostructured quarry fines
ANNS	Agile neural network software
SA	Sensitivity analysis
EA	Error analysis
r	Correlation coefficient
R2	Coefficient of determination
MSE	Mean square error
MAE	Mean absolute error
RMSE	Root mean square error

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MAPE	Mean absolute percentage error
MATLAB	Matrix laboratory
MFNN	Multilayer feed-forward neural network
CDW	Construction and demolition waste
HC	Hybrid cement
CL	Clay content
A_c	Clay activity
C_c	Coefficient of curvature
C_u	Coefficient of uniformity
δ_{max}	Maximum dry density
W_{max}	Optimum moisture content
δ_{part}	Partial maximum dry density
W_L	Liquid limit
I_p	Plasticity index
N_c	Cohesion
$\varnothing^{\circ}$	Frictional angle
γ_{unsat}	Unsaturated unit weight
D_{oc}	Degree of compaction

Introduction

Soil detachment and transport of the detached particles are responsible for most environmental issues affecting pavement foundations and erosion sites across the world [1, 2]. The combined effect of the two watershed phenomena has disastrous effect on environmental and transportation geotechnics [1, 2]. The intrinsic susceptibility of the soil to detachment and transport by raindrop and runoff, respectively, is known as erodibility (Er/K) [1–3]. In erosion models and designs for earthwork practices to solve erosion problems, the higher the Er/K value, the higher the susceptibility of the watershed or foundation materials (compacted subgrade) to erosion [1, 2]. The developing world suffers the effect of these parameters, the solution of which has been a hugely costly project. In Nigeria, for example, huge sums of funds are spent annually through the Ministry of Environment and its adhoc agency. The Nigeria Erosion and Watershed Management Project (NEWMAP), which is a world bank assisted project agency in charge of environment management in the country [1–3]. With the rate at which our environment is being depleted by erosion, researches have been conducted on different fronts to solve erosion problems across the developing world [1–3]. Most of these works are focused on the modification/treatment and stabilization (compaction) of erosion sites and subgrade materials in order to reduce erodible soil's susceptibility to the erosion menace [1–3]. No research until this moment has actually tried to forecast erosion parameters like the erodibility using intelligent learning techniques. Among other things, this work is aimed at forecasting the susceptibility factor of unsaturated erodible soil treated with hybrid cement made from rice husk ash activated with hydrated lime and modified with nanostructured quarry fines using the ANN learning technique and considering some selected geotechnical and mechanical properties of soil as independent parameters. These parameters are such that can be derived through simple experimental procedures, which include clay content, clay activity, coefficient of curvature, coefficient of uniformity, maximum dry density, optimum moisture content, partial maximum dry density, liquid limit, plasticity index, cohesion, frictional angle, unsaturated unit weight and degree of compaction.

Artificial neural networks

Artificial neural network (ANN) is a prediction simulated algorithm that replicate the function of the human brain with the help of neural networks. The focus on the ANN has majorly increased from the past decades in geotechnical engineering [4–7] due to its ability to mimic natural intelligence in its learning from experience. A typical arrangement of the ANN consists of input layer (with different input parameters), output layer and hidden layers with different number of neurons between them [8]. ANNs are used to find the relationship between the input and output variables. Unlike conventional method, ANN has capability to predict the acceptable results instantly and without providing any rules and assumptions. Several researches have been conducted to predict various properties and parameters in civil engineering,

Onwuka and Awodiji [9] demonstrated the applicability of artificial neural network (ANN) to the design of concrete of required modulus of rupture. The concrete was made of different mix proportions of cement, sand, granite chippings and water. A total of 400 data were used for training and 67 data were used for verifying and testing, respectively. The ultimate network to predict the modulus of rupture was the feed-forward back-propagation neural network, in which the training and transmission function were TRAINGDM and TANSIG, respectively. Their research findings revealed that the outcome results of the created ANN were close to the results of the experimental effort. In a study carried out by Khan et al. [10], the predictive model of compressive strength for plain concrete confined with ferro-cement was developed by using MATLAB Artificial Neural Network (ANN) simulation. Out of 55, 19 experimental results were selected for training of multilayer feed-forward neural network. Comparative analysis of the results showed that compressive strength estimated by ANN predictive model was very close to the experimental results than existing theoretical models. Das et al. [11] demonstrated in their research that ANN technique can be used effectively for predicting concrete mix proportions. Predicted mix proportions using the developed ANN model showed maximum percentage error of 0.7281%. The comparison of output results between

ANN model and regression analysis showed that prediction of fine and coarse aggregate quantity is more difficult as compared to prediction of cement content and water content. In their study, the ANN model was found to be more efficient than regression analysis. The application of artificial neural networks for predicting the compressive strength of masonry was investigated by Panagiotis et al. [12]. Specifically, back-propagation neural network models were used for predicting the compressive strength of masonry prism based on experimental data available in the literature. The comparison of the derived results with the experimental findings demonstrated the ability of artificial neural networks to approximate the compressive strength of masonry walls in a reliable and robust manner. Rama and Rao [13] demonstrated in their research that artificial neural network can be effectively adopted for predicting the compressive strength of fly ash concrete, with different aggregate binder ratio. The cement content was replaced by 30, 40 and 50% of class C fly ash. The aggregate binder ratio was varied 1.50, 1.75 and 2.00 and the water binder ratio was varied 0.35, 0.40, 0.45 and 0.50. MATLAB software was used to predict the results using ANN. ANN was trained with about 70% of the total data sets and tested with about 30% of the total data sets. The results revealed that the predicted values of maximum load, facture energy, and critical stress intensity factor were in good agreement with those of the experimental values. A study carried out by Ogbodo and Dumde [14] showed the prediction of concrete mix ratio using artificial neural network (ANN). Based on the findings of this investigation, it was observed that the model performed quite well in predicting, not only the output parameters used in the training process, but also those of test mixtures that were unfamiliar to the neural network. A 3-layered feed-forward neural network model with a back-propagation algorithm was adopted. Input layer comprises of 4 nodes representing the fineness modulus, coarse aggregate ratio, water cement ratio, and maximum aggregate size and five output parameters which are compressive strength, water content, fine aggregate content, coarse aggregate content and cement contents all in (grams) which are the expected output. The results obtained from the developed artificial neural network model were compared with results from experimental studies and were considered adequate. The absolute error between the output from conversional mix design and the artificial neural network predicted data was 0.00083. The results indicate the utility, reliability and usefulness of the artificial neural network for accurately predicting concrete mix ratio. Chandan et al. [15] investigated the design of reinforced concrete structures using neural networks. Predicted values from the artificial neural network (ANN) for the design of reinforced concrete columns, beams were very close to those obtained from conventional design using IS: 456–2000. In the predicted values, the errors were quite low. The maximum values of base shear, nodal displacements and moments from the analysis were compared with those from the predicted values using artificial neural network. The two were very close to one another. They concluded that such a well-trained artificial neural network can be used to perform design. A method to predict 28-day high compressive strength of concrete by training multilayer feed-forward neural network (MFNN) using concrete mix design data compiled from a technical literature was proposed by Noorzaei et al. [16]. Cement, water, silica fume, super-plasticizer, fine aggregate and coarse aggregates were the inputs to the neural networks, while 28-day concrete strength formed the neural network output. The study revealed that trained ANN can recognize the concrete strength with a confidence level of about 95%, which denotes significant accuracy of the network. Dantas et al. [17] investigated the prediction of the compressive strength at the age of 3, 7, 28 and 91 days of concrete containing construction and demolition waste (CDW), using ANN. A total of 1178 data were used to model compressive strength using ANN having 17 input parameters and one output parameter. The principal component analysis (PCA) was performed to separate out the 17 parameters into four groups consisting of variables catering to mix design proportions, CDW composition, physical characteristics and age of sample, respectively. An empirical equation was established between the variables of four groups and compressive strength of concrete, using ANN. The study revealed that ANN predicted values were in close agreement with that of experimental values. Also, the study showed that the equation derived using ANN provided a simplified approach of predicting the compressive strength of concrete based on the parameters included in the four important groups. According to Krishna and Rao [18], artificial neural network (ANN) is an effective soft computing tool to predict the strength variation that may occur due to the variation in concentration of geopolymer solution. In their study, ANN was used to predict the strength of geopolymer concrete with molar concentration variation. A good fit was found between experimental and predicted values.

The multilayer feed-forward network was used by Iyeke et al. [19] to demonstrate the feasibility of ANNs in order to predict the shear strength parameters for lateritic soils in some areas of Delta State. The ranges of the angle of internal friction and cohesion used were 2 to 43° and 3 to 82 kN/m^2, respectively. The optimum architecture for the ANN network for cohesion was found to be 3–9–1, i.e., three inputs, nine hidden layer nodes, and one output node with a learning rate of 0.2. While the angle of friction had an optimal ANN geometry of 3–11–1, that is, three inputs, eleven hidden layer nodes and learning rate of 0.4. The results between the predicted and measured shear strength parameters obtained by utilizing ANNs were compared with three traditional methods. The results obtained demonstrated that the ANN method outperforms the empirical methods considered. According to Sharmila et al. [20], the advantage of using the artificial neural network comes mainly from saving calculation time of the parameters and the ultimate bearing capacity. In their study, artificial neural network (ANN) with feed-forward back-propagation network with supervised learning technique was used to estimate the ultimate bearing capacity of the soil. Also, other soil characteristics such as specific gravity, cohesion, angle of internal friction, type of soil were estimated. The results showed that using ANN gave a very high correlation factor associated with the results obtained from Terzaghi's equation within the least time and in a cost effective manner. Sharad et al. [21] have analyzed soil water retention data using artificial neural networks. The ANN approach was found to produce equally or more accurate descriptions of the retention data as compared to several analytical retention functions popularly used in the vadose zone hydrology literature. Given sufficient input data, the ANN approach was also found to closely describe the hysteretic behavior of a soil, including observed scanning wetting and drying curves. In a study carried out by Sarmadian and Mehrjardi [22], MLR, ANFIS and ANN models were employed to develop a pedo-transfer function for predicting soil parameters using easily measurable characteristics of clay, silt, organic carbon, etc. The performance of models was evaluated using RMSE. Results showed that the neuro-fuzzy model gives better estimation than the other techniques for all characteristics. After neuro-fuzzy model, artificial neural network had better accuracy than multivariate regression. An artificial neural network model with 5–8–1 architecture with a feed-forward back-propagation using algorithm log sigmoid activation function was developed by Kumar and Rani [23] to predict compression index (cc) using basic soil properties, fine fraction; FF (%), liquid limit; W_L (%), plasticity index; I_P (%), maximum dry density (MDD) and optimum moisture content (OMC) as input parameters. The network was trained with 41 soils test data. The performance of the modal was verified for 27 soils test data. The proposed neural network model was found to be quite satisfactory in predicting desired output. Kuo et al. [24] studied ANN-based model for predicting the bearing capacity of strip footing on multilayered cohesive soil. Predictions of bearing capacity from the developed multiple regression models and MLP in tractable equations form were obtained and compared with the value predicted using traditional methods. The results indicate that ANNs were able to predict accurately the bearing capacity of strip footing and outperform the existing methods. In a study carried out by Kurnaz et al. [25], an artificial neural network (ANN) model was used for prediction of compressibility parameters from basic soil properties. The input parameters selected were the natural water content, initial void ratio, liquid limit and plasticity index. In this model, two output parameters, including compression index and recompression index, were predicted in a combined network structure. The result of the study showed that ANN model was successful for the prediction of the compression index.

From the foregoing, it can be observed that in recent years, there has been an increasing number of studies and applications of intelligent systems in civil engineering. These included expert systems, neural networks, fuzzy logic, genetic algorithms, rough sets, etc. Compared to traditional methods, soft computing has shown high predictive ability and as a result of this, it has become widely usable as has been shown in modeling the complex behavior of most civil engineering systems. From the findings in previous works, it has been observed that ANN has been used to predict problems with flexibility and accuracy, however, none as able to generate and propose model equations that enables future application in design and construction. Obviously, the focus in this work is mainly on the application of artificial neural networks (ANNs) to predict the erodibility of a modified erodible soil under unsaturated condition and fundamentally to generate model equations governing the erosion environment.

Materials and methods

Materials

The soil was collected from Amuzukwu erosion site located in Umuahia North Local Government of Abia State, Nigeria as presented in Fig. 1, which has suffered the menace of erosion for a long time. The soil was prepared by removing lumps and sundried for three days in open air.

Conversely, the rice husk was collected from Abakaliki, Nigeria where the main occupation is rice farming and the husk, a solid waste disposed indiscriminately for lack adequate disposal management program. The husk was combusted to generate RHA in a controlled incinerator to check the emission of CO_2 as a result in order to achieve environmentally friendly procedure [26]. Furthermore, the rice husk ash was activated by blending 5% of hydrated lime by weight of the ash in order to generate the composite binder called the hybrid cement (HC). Note, "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 with water. It is a crystal, non-flammable, odorless inorganic powder, which is soluble in water at ambient temperature. It has a melting point of 580 °C, a boiling point of 2850 °C, and a density of 2.21 g/cm^3. Its density is less than that of quicklime (3.34 g/cm^3) due to its more aqueous condition that creates pores in the structure of the solid. It is caustic with a pH of 12.8 and

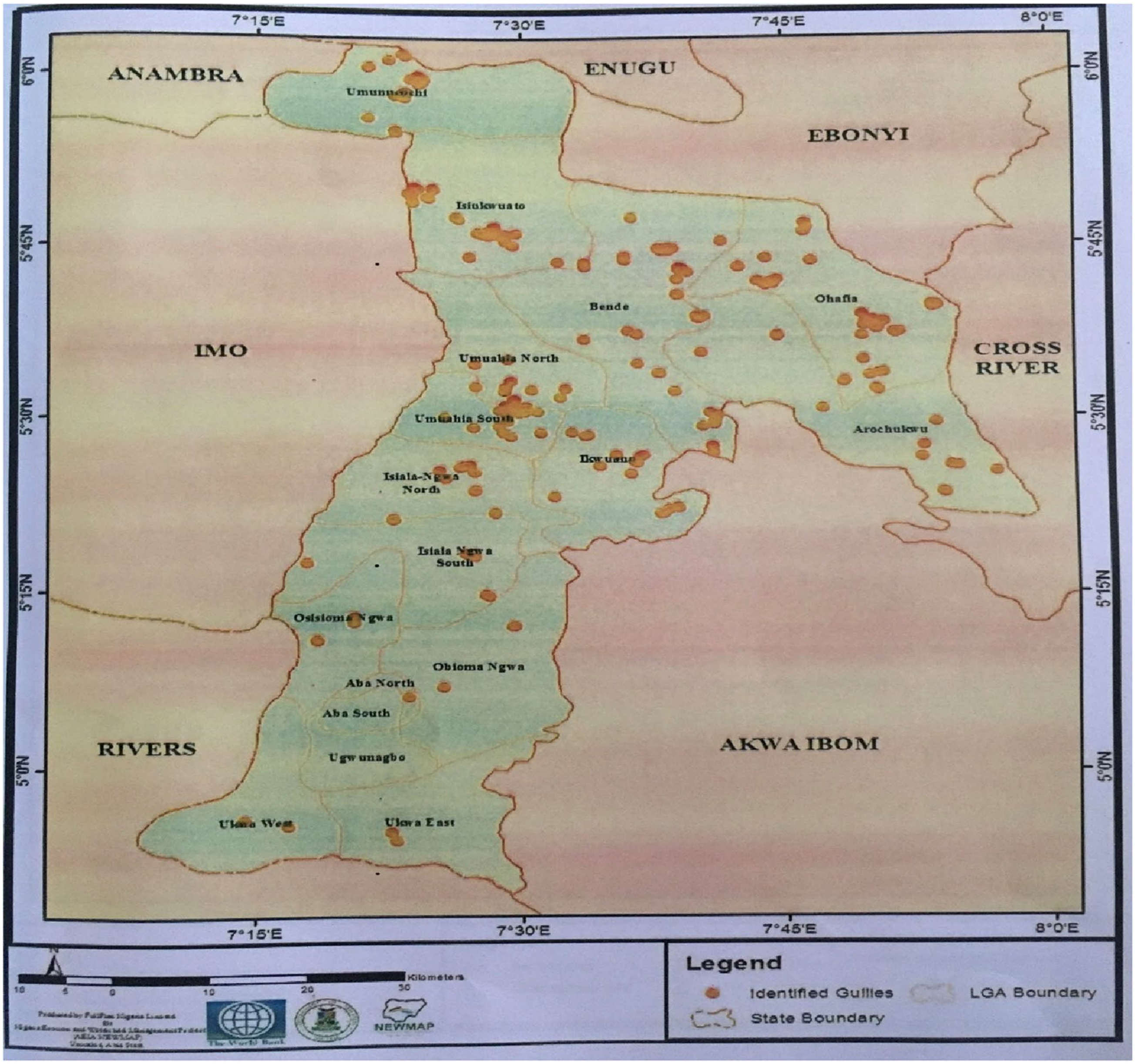

Fig. 1 Gully erosion sites spread in Abia State, Nigeria

possesses pozzolanic characteristics, which makes it a good supplementary or alternative binder in civil engineering and earthworks". In addition, quarry dust (QD) was also collected from rock blasting site at Amasiri, Nigeria where aggregates are produced for construction works. The QD was completely crushed to fineness and sieved through a 200 nm sieve to generate the nanostructured quarry fines used as a second binder in the stabilization process. These binding materials, HC and NQF, were observed to meet the requirements for materials to be classified as pozzolanas [27].

Methods

Experimental study

The design conditions of the British Standard International (BSI) [28] were observed in carrying out the general tests on the materials for the purpose of materials characterization and classification; thus, the particle size analysis, compaction, Atterberg limits, specific gravity, and the angle of internal friction were conducted on the natural soil. In order to determine the oxides composition of the binder materials (RHA, HC and NQF), the XRF was carried out in accordance with the ASTM E1621-13 [29]. Also, in order to achieve reliable and precise results in the stabilization and treatment process, the samples were prepared and mixed to high homogeneity and the results were observed and recorded. Further, the treatment exercise was conducted in accordance with the requirements of the BS1924 [30] and multiple data were generated for varying percentages of HC and NQF between 0 and 12%.

Data handling

A total of 121 numbers of data set was developed from the extensive laboratory experimentation to predict the erodibility (E_r) of the soil. Generated data for both training and testing were applied in the ratio of 70 to 30%, respectively. Further, the erodibility of the soil was considered to depend on the input parameters; hybrid cement (HC), nanostructured quarry fines (NQF), clay content (CL), clay activity (A_c), coefficient of curvature (C_c), coefficient of uniformity (C_u), maximum dry density (δ_{max}), optimum moisture content (W_{max}), partial maximum dry density (δ_{part}), liquid limit (W_L), plasticity index (I_p), cohesion (N_c), frictional angle (∅°), unsaturated unit weight (γ_{unsat}) and degree of compaction (D_{oc}). Therefore, a model was developed considering all the fifteen variables as input, whereas the output was the erodibility.

Neural network modeling

To develop the ANNs model architectures, the training data were used to generate the connection weights of the network. Further, the statistical parameters such as the coefficient of determination (R^2) and the mean square error (MSE) were used to fix the number of hidden layer neurons in the architecture of the ANNs model. A variation of the number of neurons in the hidden layer and the MSE is shown in Fig. 2.

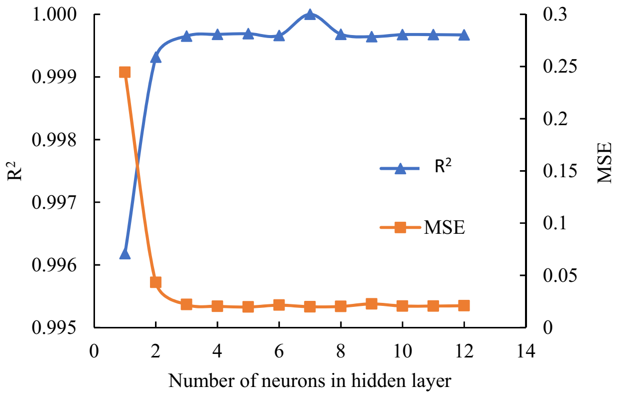

Fig. 2 Variation between RMSE, R^2 and number of neurons in hidden layer

This figure reveals that at 7 numbers of neurons in the hidden layer, the least value of the MSE and the highest value of R^2 were observed. Keeping this in view, the neural network structure was finalized using 15 input parameters–1 hidden layer (with 7 hidden layer neuron)–1 (output layer). ANN architecture through the diagram is shown in Fig. 3.

Results discussion

Materials characterization and classification

From Fig. 4, it can be observed that the soil is poorly graded with coefficients of curvature and uniformity as 0.84 and 2.05, respectively, and classified as an A-7–6 group soil according to AASHTO classification method. The soil was also found to be highly plastic with high clay content. The angle of internal friction was 15°, with clay content and clay activity of 23.02% and 2, respectively (see online Appendix). It can be read from Table 1 that the RHA, HC and NQF showed pozzolanic properties with the combined oxide compositions of SiO_2, Al_2O_3 and Fe_2O_3 as more than 70% [27]. This cementing characteristics were important in the stabilization operation where these materials in single and composite forms were blended with soil to trigger hydration, pozzolanic, calcination, and cation exchange reactions culminating to the behavioral changes observed in the treated soil with respected to the measured

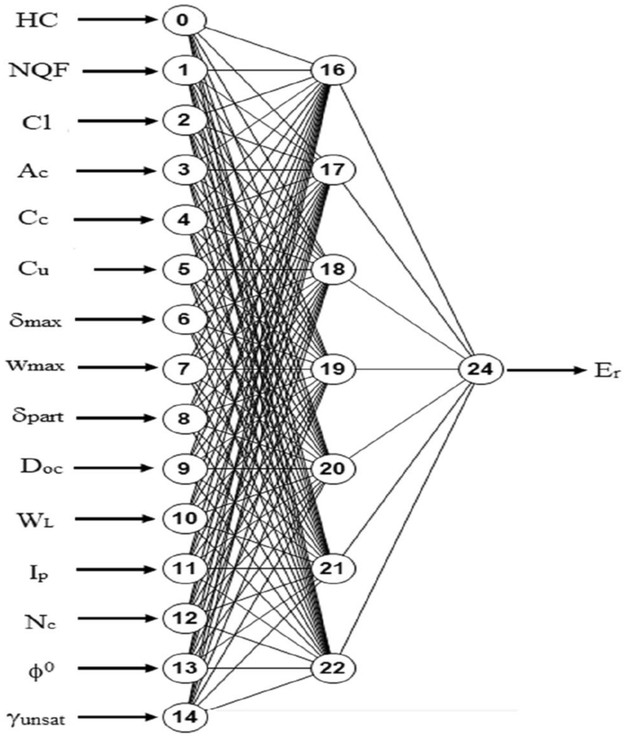

Fig. 3 ANNs model architecture for erodibility

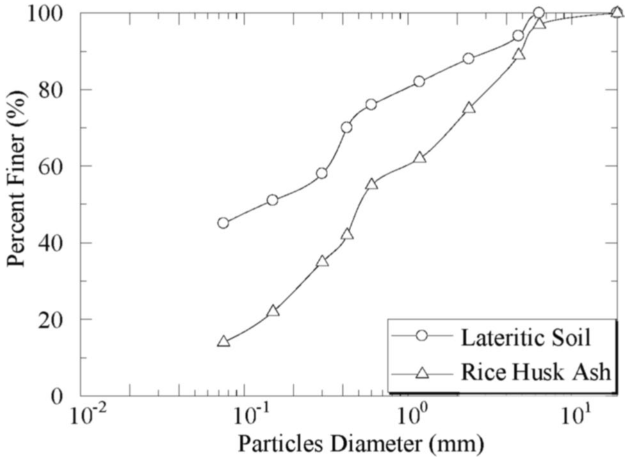

Fig. 4 Particle size distribution curve of clayey soil and rice husk ash

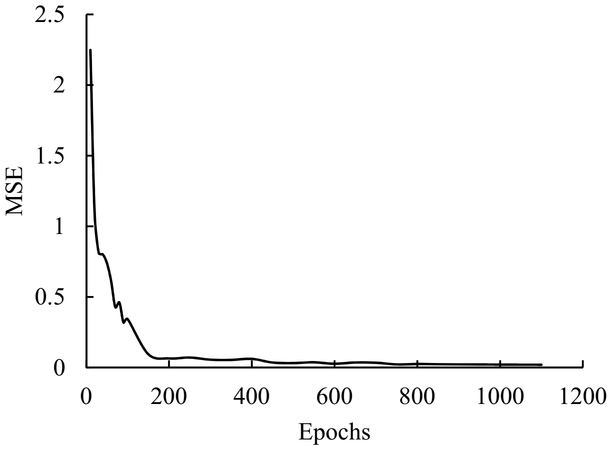

Fig. 5 Variation of mean square error with number of epochs

parameters. Also, from the tabulated results in the supplementary material, it can be observed that the addition of the nonconventional waste-based nanotextured binders substantially improved the erodibility of the treated unsaturated erodible soil. This is in line with the use of nanotextured materials as supplementary cementing materials (SCM) [27].

Model performance analysis and validation

The mean square error and coefficient of determination expressions are reported in [6]. The next step in the ANN is to fix the number of optimum iterations. For this, the MSE was calculated for each lift (containing 10 iterations) and continued up to 1100 numbers of iterations and the same was presented in Fig. 5. The study of Fig. 5 reveals that at about 1000 numbers of iterations/epochs, there is not much change in the MSE and the plot becomes parallel to a horizontal axis. Hence, 1000 numbers of iterations were considered optimum for modeling. Where in the ANNs modeling, inbuilt sigmoid activation function was used and the whole modeling was done in the open sources *Agiel neural network* software. The erodibility obtained from the neural network was compared with the actual erodibility to verify the prediction accuracy of the ANN model.

The comparison between the erodibility estimated from the ANN, and the actual erodibility for the training and the testing data are presented in Figs. 6 and 7, respectively. Study of Figs. 6 and 7 reveals that the calculated values of the coefficient of determination (R^2) were found to be 0.995 and 0.991, respectively, for the training and the testing data. Further, the accuracy of the developed model was assessed with other statistical parameters (correlation coefficient (r), MSE, RMSE, MAE and MAPE) for the training and the testing data which were tabulated in Table 2.

The prediction accuracy of the developed ANNs model will be assessed by the statistical parameters, the detailed explanation about these parameters was discussed in Dutta et al. [5]. Table 2 reveals that all the statistical parameters were within the permissible range based on the findings of Dutta et al. [5]. After simulating the model for the optimal conditions, a matrix of the connection weights between the input layers to hidden layer, hidden layer to the output layer, input bias were presented in Table 3.

Model equation

After obtaining the final weights from the successful completion of training and testing, a model equation was proposed

Table 1 Chemical oxide 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	2.3	10.66	4.89	12.1	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	–	–	–	–
HC	59.12	25.3	6.3	4.23	2.5	1.21	–	1.34	–	–	–	–	–
NQF	62.48	18.72	4.83	6.54	2.56	3.18	–	0.29	1.01	–	–	–	–

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

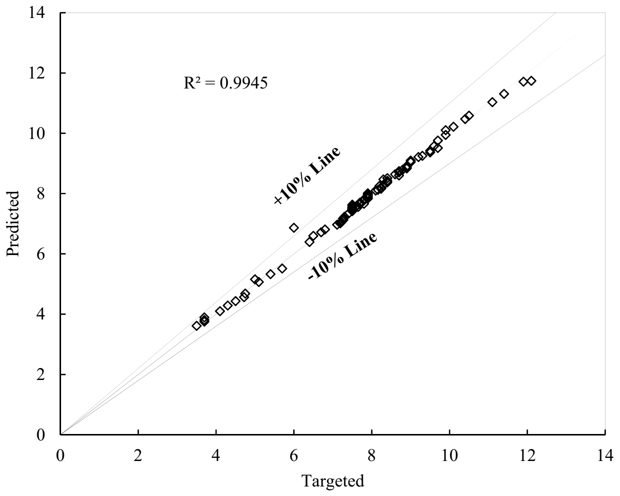

Fig. 6 Comparison between experimental erodibility versus predicted erodibility of soil for training

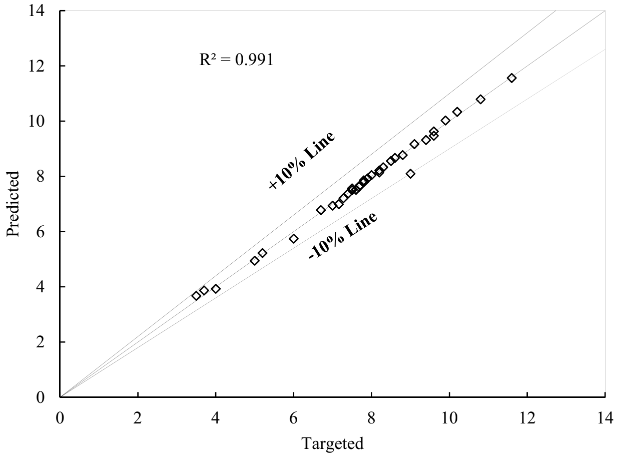

Fig. 7 Comparison between experimental erodibility versus predicted erodibility of soil for testing

in this section. Taking into account the weights and biases from the Table 3, the ANN model takes the following form:

$$E_r(g/\min) = f_n\left\{ z_0 + \sum_{i=1}^{h}\left[y_{\mathrm{jk}} f_n\left(\sum_{i=1}^{n} x_{\mathrm{ji}} E_i \right)\right]\right\} \tag{1}$$

where h = number of neurons in a hidden layer which is equal to 7 in this case, E_i = normalized inputs in the range of 0 to 1. f_n = Activation function, n = number of input variables, x_{ji} = weight between jth neuron of the hidden layer and ith neuron in the input layer; y_{jk} = weight between the kth layer of output neuron and jth neuron in the hidden layer; z_j = jth neuron of the hidden layer bias, z_0 = output layer bias.

The following Table 3 Eqs. 2–10 were developed as ANNs model equation. The final expression obtained was as per Eq. (10). This Eq. (10) provides a normalized erodibility (g/min). Equation (11) provides the output erodibility (g/min) in de-normalized form.

$$\begin{aligned} A = {} & y + i \times \mathrm{HC} + j \times \mathrm{NQF} + k \times \mathrm{Cl} \\ & + l \times A_c + m \times C_c + n \times C_u + o \times \delta_{\max} \\ & + p \times W_{\max} + q \times \delta_{\mathrm{part}} + r \times W_L + s \times I_P \\ & + t \times N_c + u \times \phi + v \times \gamma_{\mathrm{unsat}} + w \times D_{\mathrm{oc}} \end{aligned} \tag{2}$$

$$\begin{aligned} B = {} & y + i \times \mathrm{HC} + j \times \mathrm{NQF} + k \times \mathrm{Cl} \\ & + l \times A_c + m \times C_c + n \times C_u + o \times \delta_{\max} \\ & + p \times W_{\max} + q \times \delta_{\mathrm{part}} + r \times W_L + s \times I_P \\ & + t \times N_c + u \times \phi + v \times \gamma_{\mathrm{unsat}} + w \times D_{\mathrm{oc}} \end{aligned} \tag{3}$$

$$\begin{aligned} C = {} & y + i \times \mathrm{HC} + j \times \mathrm{NQF} + k \times \mathrm{Cl} \\ & + l \times A_c + m \times C_c + n \times C_u + o \times \delta_{\max} \\ & + p \times W_{\max} + q \times \delta_{\mathrm{part}} + r \times W_L + s \times I_P \\ & + t \times N_c + u \times \phi + v \times \gamma_{\mathrm{unsat}} + w \times D_{\mathrm{oc}} \end{aligned} \tag{4}$$

$$\begin{aligned} D = {} & y + i \times \mathrm{HC} + j \times \mathrm{NQF} + k \times \mathrm{Cl} \\ & + l \times A_c + m \times C_c + n \times C_u + o \times \delta_{\max} \\ & + p \times W_{\max} + q \times \delta_{\mathrm{part}} + r \times W_L + s \times I_P \\ & + t \times N_c + u \times \phi + v \times \gamma_{\mathrm{unsat}} + w \times D_{\mathrm{oc}} \end{aligned} \tag{5}$$

$$\begin{aligned} E = {} & y + i \times \mathrm{HC} + j \times \mathrm{NQF} + k \times \mathrm{Cl} \\ & + l \times A_c + m \times C_c + n \times C_u + o \times \delta_{\max} \\ & + p \times W_{\max} + q \times \delta_{\mathrm{part}} + r \times W_L + s \times I_P \\ & + t \times N_c + u \times \phi + v \times \gamma_{\mathrm{unsat}} + w \times D_{\mathrm{oc}} \end{aligned} \tag{6}$$

$$\begin{aligned} F = {} & y + i \times \mathrm{HC} + j \times \mathrm{NQF} + k \times \mathrm{Cl} \\ & + l \times A_c + m \times C_c + n \times C_u + o \times \delta_{\max} \\ & + p \times W_{\max} + q \times \delta_{\mathrm{part}} + r \times W_L + s \times I_P \\ & + t \times N_c + u \times \phi + v \times \gamma_{\mathrm{unsat}} + w \times D_{\mathrm{oc}} \end{aligned} \tag{7}$$

Table 2 Performance measures of developed ANN model with help of sigmoid activation function

Performance measures	r	R^2	MSE	RMSE	MAE	MAPE
Training	0.99	0.99	0.02	0.14	0.09	1.22
Testing	0.99	0.99	0.03	0.17	0.09	1.34

Table 3 Final weight and biases between the input and the hidden neuron as well as the hidden neuron and the output neuron respectively

Equations	Weights																	
	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z
A	0.21	0.25	0.13	−0.24	0.16	0.06	−0.02	0.07	0.21	1.11	−0.10	−0.04	0.35	−0.60	0.42	−1.14	0.06	0.56
B	0.14	0.16	0.03	−0.18	0.27	−0.02	0.10	0.22	0.45	1.29	−0.06	0.08	0.57	−0.38	0.48	−1.33	0.07	
C	−0.78	−0.74	−0.46	0.58	−0.94	−0.05	−1.08	−1.52	−1.39	−2.64	−0.01	0.18	−1.48	−0.55	−0.56	3.55	−0.64	
D	−0.04	0.05	0.13	−0.58	0.01	−0.09	−0.47	−0.34	−0.33	−0.04	−0.73	−0.60	0.32	−0.42	0.33	−0.98	−0.61	
E	−0.19	−0.17	−0.33	0.89	−0.11	−0.14	0.50	0.90	0.35	0.27	0.92	0.96	−0.57	0.17	−0.74	1.80	0.77	
F	0.48	0.63	0.85	−2.40	0.55	0.46	−0.64	−2.60	−0.65	−0.78	−2.52	−2.55	1.28	1.46	−1.92	−4.42	−1.92	
G	−0.05	−0.04	−0.12	−0.21	−0.06	−0.10	−0.22	0.02	−0.11	0.14	−0.18	−0.10	0.05	−0.24	−0.07	−0.06	−0.28	

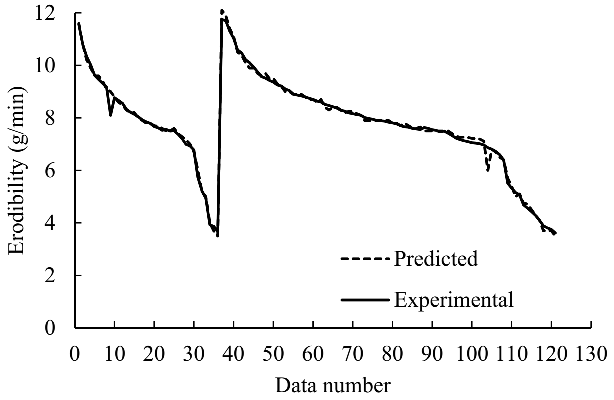

Fig. 8 The performance of the ANN-based predictive model for total data in predicting erodibility

$$
\begin{aligned}
G = y + i \times \mathrm{HC} + j \times \mathrm{NQF} + k \times \mathrm{Cl} \\
+ l \times A_c + m \times C_c + n \times C_u + o \times \delta_{\max} \\
+ p \times W_{\max} + q \times \delta_{\text{part}} + r \times W_L + s \times I_P \\
+ t \times N_c + u \times \phi + v \times \gamma_{\text{unsat}} + w \times D_{\text{oc}}
\end{aligned} \tag{8}
$$

For example, the development of Eq. 2 is from the Table 3 and row as represented with *A*. Corresponding to the row *A*, the *i* to *w* values were taken to develop the Eq. 2. The similar procedure was followed for preparing remaining Eqs. 3–8.

$$
\begin{aligned}
H = z - \frac{1.14}{1+e^{-A}} - \frac{1.33}{1+e^{-B}} + \frac{3.55}{1+e^{-c}} - \frac{0.98}{1+e^{-D}} \\
+ \frac{1.79}{1+e^{-E}} - \frac{4.42}{1+e^{-F}} - \frac{0.06}{1+e^{-G}}
\end{aligned} \tag{9}
$$

where *z* is the bias from the Table 3. Furthermore,

$$
E_r = \frac{1}{1+e^{-H}} \tag{10}
$$

The E_r value as obtained from Eq. (10) have been in the range of [− 1, 1] and this needs to be de-normalized as

$$
E_r(g/\min) = 0.5\left(E_r + 1\right)\left(\left[E_r\right]_{\max} - \left[E_r\right]_{\min}\right) + \left[E_r\right]_{\min} \tag{11}
$$

where $[E_r]_{\max}$ and $[E_r]_{\min}$ are the maximum and the minimum values of predicted erodibility in g/min., respectively.

Finally, the comparison was made between predicted and experimental data of erodibility in terms of data number vs erodibility as shown in the Fig. 8. It reveals that the prediction of the erodibility from the ANNs model reasonably acceptable.

Sensitivity Analysis

This part of the study discusses the contribution of the individual variables on the erodibility (output) by performing the sensitivity analysis. For this purpose, the methods (based on weight configuration) reported by Garson [31] and Olden and Jackson [32] were used. In the first method [31], the connection weights of each of the hidden neurons in the hidden layer were divided into components and this supported by the work of Onyelowe et al. [8]. These components were associated with each input neuron. In the second method of Olden and Jackson [32], the sum of the product of the final weights of the connections (input neuron to hidden neurons and hidden neurons to output) for all the input neurons is calculated [33]. The contribution of the individual variable corresponding to a given input is computed by following the procedure presented in the literature of Garson [31] and Olden and Jackson [32]. The obtained results are presented in the Fig. 9. From the Fig. 9, it can be observed that the major influencing parameter is liquid limit (W_L) followed by clay activity (A_c), frictional angle (∅°), plasticity index (I_p), degree of compaction (D_{oc}), unsaturated unit weight (γ_{unsat}), optimum moisture content (W_{max}), cohesion (N_c), partial maximum dry density (δ_{part}), maximum dry density (δ_{max}), clay content (CL), coefficient of curvature (C_c), nanostructured quarry fines (NQF), hybrid cement (HC) and coefficient of uniformity (C_u) based on the findings of Olden and Jackson [32]. Similarly, based on the work of Garson [31], the significance influencing parameter is liquid limit (W_L), due to its affinity with erodible soils on exposure to raindrops, followed by the clay activity (A_c), plasticity index (I_p), optimum moisture content (W_{max}), cohesion (N_c), degree of compaction (D_{oc}), frictional angle (∅°), unsaturated unit weight (γ_{unsat}), partial maximum dry density (δ_{part}), maximum dry density (δ_{max}), clay content (CL), nanostructured quarry fines (NQF), coefficient of curvature (C_c), hybrid cement (HC) and coefficient of uniformity (C_u). From the above discussion, marginal difference was observed between the two methods. The initial two major influence parameters were same by the both the methods.

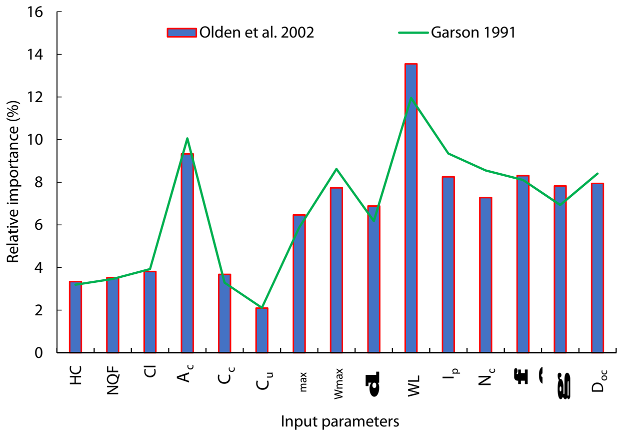

Fig. 9 Sensitivity analysis (relative importance of individual variable) of the erodibility

Conclusions

The behavior of erodibility of erodible soil under unsaturated condition stabilized with the combined effects of hybrid cement and nanostructured quarry fines has been studied by using the novel artificial neural network (ANN) with the ability to propose model equation. From the foregoing, the following can be concluded;

- Erodible soil was collected from an erosion watershed, characterized and classified as highly plastic, poorly graded, and high clay content soil. Further, it was classified according to the AASHTO method as A-7–6 group soil.
- Multiple experiments were conducted to determine the values of the input parameters and 121 datasets were generated. It was observed that the HC and NQF inclusion improved the erodibility of the treated soil.
- The datasets were deployed in the ANN learning technique to predict erodibility using multiple parameters.
- The performance of the model was evaluated using the error analysis indices and this showed great performance in terms of MAE, MSE, RMSE and MAPE.
- The validation of the predicted model showed great consistency more than 0.95 with the measured values.
- Finally, the sensitivity analysis showed that liquid limit had the greatest influence on the model performance.
- It is generally recommended for other learning techniques like EPR, GP, GEP, ANFIS, etc., to be employed in predicting this environmental problem and also to increase the data points to 300 and above.

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Data availability The data supporting the results of this research work have been presented in the manuscript.

Declarations

Conflict of interests The authors have no conflicting interests to report in this work.

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