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Predictive models of volumetric stability (durability) and erodibility of lateritic soil treated with different nanotextured bio-ashes with application of loss of strength on immersion; GP, ANN and EPR performance study

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ABSTRACT

Volumetric stability and erodibility are important soil properties influenced by moisture through raindrops and eventual runoff and the rise in water tables during wet seasons. Compacted subgrade materials made of clay respond to water ingress through swelling and shrinking in turn during drying and this poses a problem for foundation structures. Supplementary cementitious materials have been used to treat soils, in a cleaner procedure to improve the mechanical properties and to overcome undesirable behavior during changes in seasons. However, design and construction of foundation structures exposed to these problems become necessary and common, which requires constant visits to the laboratory and equipment needs. In order to overcome this, machine learning-based predictive models have been proposed in this work for the estimation of durability (Sv) via loss of strength on immersion technique and erodibility (Er) of agro-based ashes. Genetic programming (GP) (six levels of complexity), artificial neural network (ANN) (sigmoid activation function), evolutionary polynomial regression (EPR) (GA optimized PLR method) techniques have been used to conduct this intelligent prediction exercise. The performance of the models was conducted using the sum of squared errors (SSE) and coefficient of determination (R^2) indices. The results show that EPR's Er and Sv prediction with SSE of 5.1% and 2.7% respectively and R^2 of 97.2% and 92.9% respectively outclassed GP and ANN. However, both GP and ANN showed minimal error and acceptable R^2 above 0.85, which showed their ability to predict with good performance accuracy.

1. Introduction

Preamble

Various geotechnical engineering structures, such as pavements, subgrades and footings are exposed to various severe environmental phenomena such as rain and wind, which cause their total or partial degradation. Understanding, analyzing and predicting this degradation which can occur in terms of heightened soil loss and/or reduced durability of soil has been of critical attention to geotechnical engineers. Whereas soil erodibility entails the removal of surface layers of soil, which involves a process of both particle detachment and particle transport by the disturbing agencies; soil durability defines its property that reflects its performance under freeze–thaw and wetting–drying cycles. Expansion of water in the pore space due to water ingress into the soil matrix or matric suction occasioned by repeated freezing and thawing as well as other seasonality factors cause the compacted soil surface to heave, leading to changes in microstructure, strength loss and increased erosion susceptibility (Shen and Akky, 1974; Saarenketo, 2000). This phenomenon weakens the bond strength between cementing particles and consequently reduces the soil's erosion resistance. It is also known that under different matric suction actions, porosity of the soils reduces gradually with the increase of matric suction and the matric suction action frequency (Zhang et al., 2020).

Basically, less severe ground movements and soil loss usually occur during transient rainfall infiltration and under partially saturated conditions. Hence, fluctuations in soil matric suction among others remain fundamental variables determining soil degradation (Bittelli et al., 2012; Carman, 1997). As soon as geotechnical and structural engineers

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Nomenclature

Notations

A	Proportion of Agro-waste Ashes
I_P	Plasticity Index
U_O	Unconfined compressive strength of soil air-cured for 28 days
Er	Erodibility
S_V	Volumetric Stability (Durability)
GP	Genetic Programming
ANN	Artificial Neural Network
EPR	Evolutionary Polynomial Regression
GA	Genetic Algorithm
PLR	Polynomial Linear Regression
R^2	Coefficient of Determination
SSE	Sum of Squared Errors
AWA	Agro-Waste Ashes
NWPA	Nanotextured Waste Paper Ash
NPBA	Nanotextured Palm Bunch Ash
NSSA	Nanotextured Snail Shell Ash
NQD	Nanotextured Quarry Dust
NPSA	Nanotextured Palm-kernel Shell Ash

understood and reported the effectiveness and suitability of cement and other cementitious materials in improving the engineering properties such as durability, erodibility, consistency and shear strength of a wide variety of soils, cement-treated or cement-stabilized soils were being employed in pavement, base, subbase, and subgrade construction since the earlier part of the 20th century. In practice, depending on the intended use, cement-treated soils are mostly blended with low cement such as nono-ash dosages with or without a targeted strength (Baghdadi and Shihata, 1999; Barbu and McManis, 2004). It is also known that untreated and cement-treated or stabilized materials with less free moisture generally perform better in the long term than those with freer moisture, provided all other influencing variables are neglected (Zhang and Tao, 2008). The addition of stabilization agents such as cementing materials like various bio-ash does not only enhance the soil's durability when used as a foundation or construction material, but fortifies soil to resist weathering and subsequent erosion (Syed et al., 2003; Shen and Akky, 1974; Stavridakis, 2006). In fact, Shen and Akky (1974) had earlier concluded that it was possible to relate soil–cement erodibility to durability test results using the rotating cylinder apparatus; maintaining that whereas a steady state of erosion loss could be achieved in samples of higher cement contents, resistance to weathering and subsequent erosion of cement-stabilized soil increases as cement content in the soil samples increases. Hence, their result posited that a strong connection exists between erodibility and durability of soils (Onyelowe and Duc, 2018). The plasticity index, defined as the range of moisture contents over which the soil deforms plastically, is also being regarded as a critical influencer of soil erodibility and durability (Keller and Dexter, 2012). Also, the degree of saturation, water content, dry density, unconfined compressive strength and percentage of the nano-ash being used affect the erodibility and durability of sands treated with various nano-ashes such as: Nanotextured Waste Paper Ash (NWPA), Nanotextured Palm Bunch Ash (NPBA), Nanotextured Snail Shell Ash (NSSA), Nanotextured Quarry Dust (NQD) and Nanotextured Palm-kernel Shell Ash (NPSA) (Onyelowe and Duc, 2018; K. C. Onyelowe, 2019; Onyelowe, 2017a; Onyelowe, 2017b). As earlier advanced, the durability and erodibility of cement-treated or stabilized soils remains a concern for the mix design of cement stabilization under wetting drying or/and freezing-thawing cycles. First, there is non-linear and complex interactions within the stabilized soil matrix owing to various variables influencing these parameters like moisture ingress, bonding architecture, and so on, as well as challenges of longer testing time, and dynamic behaviours during extreme loading exposures (Syed et al., 2000; Scullion and Saarenketo, 1997; Zhang and Tao, 2008; Cui et al., 2008; and so on). The use of evolutionary computational techniques therefore proves to be a promising option to predict the erodibility and durability state of nanotextured bio-ashes.

Nanotechnology and application for erodibility and durability enhancement of unsaturated soil: potentials of the use of nanotextured materials for environmental and energy sustainability

As materials possessing, at minimum, one external dimension measuring 1–100 nm; occupying within 0.5–5% of the medium matrix, the use of nanotextured materials have swept across various fields of research and implementation, including medicine and pharmaceuticals (Bajwa et al., 2017), agriculture (Marchiol, 2018; Marchiol et al., 2016; Adetunji et al., 2020), aviation (Alsharef et al., 2016; Amadi, 2014), engineering (Kadivar et al., 2011; Almurshedi et al., 2020, Baziar et al., 2018; and many more), as well as in other fields. The uncontrolled deposition of agro-industrial wastes, which can be converted to useable nanomaterials can pose serious problems to health and environment (Onyelowe and Okafor, 2015). Many energy policy interventions, which can make a major contribution to the sustainable economic, environmental, and social development of Africa's most populated country, Nigeria, have been initiated of which one of the major routes is the sustainable utilization of green composites and nano-ashes to improve soil properties (Oyedepo, 2012). Sustainable engineering practice should encompass energy exploitation and promotion of renewable energy resources, energy efficiency practices, as well as the application of energy conservation measures in various sectors such as in the construction of industrial, residential, roads, and office buildings, in transportation and agriculture. Fundamentally, the enhancement of soils using nanocomposites and bio-ashes nanomaterials is critical for obtaining a smart and ecological and environment-friendly construction and foundation work.

Within the last few decades, various studies have been carried out to analyse and predict the influence of adding nanotextured materials on the durability and erodibility of soils. Zhang and Tao (2008) evaluated three testing methods for predicting the durability of cement-stabilized soils, viz: the tube suction (TS), 7-day unconfined compression strength (UCS), and wetting–drying durability tests, for a problematic low plastic silt clay. Their study indicated that the water-cement ratio of cement-stabilized soil had the dominant influence on the maximum dielectric value (DV), 7-day UCS, and durability of stabilized samples tested, although they discovered that the dry unit weight of cement-stabilized soil could cause the variation of the results. Their study confirms that TS, 7-day UCS, and wetting–drying durability tests were equivalent in predicting durability, and derived tentative charts ensured the durability of cement-stabilized low plasticity soils were developed using their 7-day UCS or the maximum DV values. Pham et al. (2016) evaluated the durability of cement treated soil exposed to synthetic sea water via uniaxial compression and needle penetration testing. Recently, Wang et al. (2021) investigated the effects of granular rubber on the erosion resistance of cement soils by performing erosion test, permeability test and crystallization test. They further concluded their findings by giving three reasons for increasing of erosion resistance of rubber-cement treated soils, which included: blocking of capillary action, elastomer action and prevention of crack propagation action triggered by the stabilization materials.

Menaa et al. (2009) evaluated the performance of rigid surface structures such as concrete pavements and slabs-on-grade supported by a deteriorate subgrade and experiencing local contact loss experimentally and numerically. They constructed a laboratory setup to enable the simulation of subsurface erosion and to measure the changes in contact pressure at selected locations under a slab-on-grade supported on granular material. Their finding suggested that the presence of erosion voids under a slab-on-grade can lead to rapid increase in the contact pressure in the immediate vicinity of the void in addition to an inducement of significant tensile stresses at the outermost fibers of the slab. Meguid and Kamel (2014) employed elasto-plastic finite element analyses to investigate the three-dimensional effects of erosion voids developing behind the walls of an existing sewer pipe on the earth pressure distribution around the pipe and the stresses in the pipe wall. Their findings confirmed that the presence of erosion voids can have a significant impact on the earth pressure distribution around an existing pipe as well as on the pipe wall stresses, thereby affecting its durability or longevity of usage. Moreover, in their own study, Gidday and Mittal (2020) attempted to enhance road sub-grade durability by stabilizing dispersive soil with lime. Their evaluation provided more acceptable index properties, reduces dispersivity, increases unconfined compression strength, and California Bearing Ratio value with an increasing lime quantity and curing at varying test conditions. From their research, they stated optimum lime content to be 7% to 9 % of dry soil weight, maintaining that such blend gave high strength and quality of subgrade pavement rating. It has also been confirmed that carbon nanomaterials (CNMs) made with small amounts (0.05, 0.075, 0.1, and 0.2%) of nanocarbons, that is, carbon nanotube (multiwall carbon nanotube (MWCNTs)) and carbon nanofibers (CNFs), had striking effects on the Atterberg limits, optimum water content, maximum dry density, specific gravity, pH, and hydraulic conductivity. Some evaluated the effects of common soil additives incorporating lime, cement, and sand on the shrinkage and hydraulic conductivity of compacted clay soils which is employed in clay liner constructions. Onyelowe (2018) confirmed the potential of the use of nanostructured kaolin as an additive in the stabilization of lateritic soils while enhancing the durability and general performance of such stabilized soil as a sub-base material.

1.3. Evolutionary computational techniques for predicting soil erodibility and durability

The use of stochastic algorithms whose search methods model some natural phenomena such as genetic inheritance and Darwinian strive for survival, in making engineering predictions is gaining strong attention among researchers and engineering solution seekers. Owing to the non-linearity and complexity of the interaction of the stabilized soil particles within the soil matrix, the introduction of an initial set of candidate solutions produced by stochastically removing less desired solutions, and introducing small random changes generated and iteratively updated for the formation of each new generation. Evolutionary computation techniques can yield super optimized solutions across a large domain, making them suitable in performing many predictions and analytical functions. Various evolutionary computational techniques, otherwise known as machine learning techniques, such as artificial neural networks (ANN), support vector machines (SVM), genetic programming (GP), genetic algorithm (GA), and many more, have been developed to capture the solutions of various non-linear problems within a complex domain. An elaborate study of evolutionary computation in the context of structural design has been done in the Information Technology and Engineering School at George Mason by Kicinger and his colleagues (Kicinger et al., 2005). They provided a comprehensive review and sequential classification of the applications of evolutionary computation in structural design. Arciszewski and Jong (2001) gave a description of the evolving evolutionary computation analysis, including an analysis in the context of complex adaptive systems and based on the visualization of the gene pool and of the fitness function.

The use of genetic programming (GP), artificial neural networks (ANN) and artificial neural network optimized genetic algorithm, otherwise known as evolutionary regression polynomial (ERP) has gained deeper applications in engineering applications, and in geotechnical predictions in particular. Not only has the application of GP, a heuristic search technique which searches for an optimal or suitable program among the space of all programs been astronomical, it's potential and performance has been phenomenal. Onyelowe et al. (2021a) successfully predicted the compression index of multiple-binder treated weak and highly plastic soil by GP techniques.

Similarly, artificial neural network (ANN), an assembly of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain with each connection, like the synapses in a biological brain transmitting a signal to other neurons, have become a rampantly used method (Onyelowe et al., 2021b). This is owing to it's potential to give more efficient and accurate results to regression based statistical equations when it comes to modelling non-linear and complex systems. Kurnaz et al. (2016) proposed an artificial neural network (ANN) model for prediction of compression index and recompression index from basic soil properties using the input parameters of natural water content, initial void ratio, liquid limit and plasticity index. Le et al. (2020) evaluated soil durability by predicting the unconfined compressive strength of some soil samples using ANN model. Their findings suggested that plasticity index was a key factor that influences soil durability. Kouchami-Sardoo et al. (2020) developed a Multi-Layer Perception (MLP) neural network to predict erodibility changes in response to spatial variation of the selected features. Their developed MLP-model provided a strong basis for the prediction of soil erodibility. Anjita et al. (2017) predicted maximum dry density of soil using genetic Algorithm (GA), a process of natural selection where the fittest individuals are selected from the generation for reproduction in order to produce offspring (solutions) of the next generation (subsequent results).

A common practice is the use of variants of various evolutionary computational techniques or their combinations for optimized output to predict soil behavior such as erodibility and durability responses. For instance, Alavi et al. (2011), utilized the variants of genetic programming, namely linear genetic programming (LGP), and a hybrid search algorithm coupling LGP and simulated annealing (SA), called LGP/SA, to predict the performance characteristics of stabilized soil. They reported that LGP and LGP/SA- based models related to unconfined compressive strength (UCS), maximum dry density (MDD) and optimum moisture content (OMC) of the stabilized soil to the properties of natural soil and type and quantity of stabilizing additives. They stated that soil texture and particle size fractions (PSFs) were critical characteristic of soil that influence most physical, chemical, and biological response of soil; furthermore, reliable spatial predictions of PSFs are crucial for agro-ecological modeling. Taghizadeh-Mehrjardi et al. (2021) developed a series of hybridized artificial neural network (ANN) models with bio-inspired metaheuristic optimization algorithms such as a genetic algorithm (EPR), particle swarm optimization (PSO-ANN), bat (BAT-ANN), and monarch butterfly optimization (MBO-ANN) algorithms, for predicting the soil texture and particle fraction for the Mazandaran Province of northern Iran. Their result confirmed that the hybridized ANN methods (such as ERP) were far superior to the reference approach using ANN with a backpropagation training algorithm (BP-ANN).

Despite the numerous studies performed using various evolutionary computations techniques, no attention has been directed to the combined prediction of erodibility and durability of various bio-ash stabilized lateritic soils, nor has any focus being paid to their predictions using GP, ANN and ERP while employing multiple influencing parameters. Consequently, the present study reports the volumetric stability (durability) and erodibility of unsaturated lateritic soils treated with various nanotextured bio-ashes namely: Nanotextured Waste Paper Ash (NWPA), Nanotextured Palm Bunch Ash (NPBA), Nanotextured Snail Shell Ash (NSSA), Nanotextured Quarry Dust (NQD) and Nanotextured Palm-kernel Shell Ash (NPSA), predicted and compared using GP, ANN and EPR techniques from the predictor variables namely: plasticity index (Ip), bio-ash proportions (A) and unconfined compressive strength of soil-air cured at 14 days and immersed at 14 days (U_1) and unconfined compressive strength of soil-air cured at 28 days (U_0).

2. Methodology

2.1. Background

The data collection method applied in this work was the literature search and data collation method where the outcome of soil stabilization exercise conducted by Onyelowe and Duc (2018) on the behavior of durability by loss of strength on immersion technique and erodibility of A-2–7 soil treated with different dosages (2.5%, 5%, 7.5%, 10%, 12.5% and 15% by weight of dry soil), of agro-based nanotextured ashes was collected for intelligent predictive model work. The selected nanotextured agro-based ashes, which included; nanotextured waste paper ash (NWPA), nanotextured palm bunch ash (NPBA), nanotextured snail shell ash (NSSA), nanotextured quarry dust (NQD) and nanotextured palm-kernel shell ash (NPSA) were studied with Xray Fluorescence (XRF) test to determine the spread of the pozzolanic oxides composition, which showed that all tested ash materials were highly pozzolanic with the total percentage of Al_2O_3, SiO_2 and Fe_2O_3 above 70%, which satisfied the requirements of pozzolanic materials standard (ASTM C618, 1978), which is utilized as cleaner cementing materials with zero carbon footprint. The increased pozzolanic index of above 70% was due to the increased reactive and nucleating surface because of increased fineness by nanosization. The results obtained have been deployed in the machine learning-based predictive models for durability and erodibility of ash treated soil.

2.2. Collected database and statistical analysis of input and output parameters

31 soil samples were tested to determine the following physical and mechanical proprieties

- Ash Proportion (A) %,
- Plasticity index (Ip) %,
- Unconfined compressive strength of soil air-cured for 28 days (Uo) MPa;
- Erodibility (Er) g/sec,
- Volumetric Stability (Sv) %

The measured records were divided into training set (21 records; 68%) and validation set (10 records; 32%). Table 1 includes the complete dataset, while Tables 2, 3 summarizes their statistical characteristics and the Pearson correlation matrix. Finally, Fig. 1 shows the histograms for both inputs and outputs.

2.3. Research program of predictive models

Three different Artificial Intelligent (AI) techniques were used to predict the shear strength parameters of the tested soil samples. These

Table 1
The used database.

A	Ip	Uo	Er	Sv
–	–	MPa	g/sec	–
Training set				
0.150	0.161	0.233	0.088	0.937
0.075	0.223	0.276	0.078	0.726
0.025	0.231	0.395	0.090	0.952
0.025	0.239	0.346	0.088	0.827
0.075	0.213	0.390	0.063	0.909
0.150	0.110	0.465	0.030	0.893
0.025	0.227	0.387	0.088	0.921
0.000	0.219	0.219	0.112	0.761
0.025	0.232	0.228	0.090	0.594
0.125	0.153	0.290	0.073	0.827
0.075	0.218	0.417	0.055	0.868
0.100	0.201	0.425	0.040	0.909
0.100	0.149	0.256	0.088	0.825
0.150	0.140	0.412	0.040	0.973
0.100	0.207	0.411	0.057	0.953
0.125	0.132	0.243	0.087	0.884
0.100	0.173	0.400	0.058	0.939
0.050	0.272	0.220	0.087	0.662
0.050	0.243	0.401	0.068	0.890
0.050	0.289	0.200	0.102	0.825
0.125	0.179	0.438	0.037	0.913
Validation set				
0.025	0.228	0.204	0.105	0.815
0.100	0.176	0.296	0.077	0.831
0.150	0.140	0.413	0.035	0.970
0.150	0.143	0.301	0.070	0.787
0.050	0.237	0.395	0.068	0.857
0.050	0.220	0.401	0.068	0.931
0.125	0.154	0.404	0.048	0.941
0.125	0.163	0.409	0.047	0.978
0.075	0.210	0.401	0.062	0.953
0.075	0.271	0.236	0.092	0.767

Table 2
Statistical analysis of collected database.

Stat Indices	A (%)	Ip (%)	Uo (MPa)	Er (g/sec)	Sv
Training set					
Max.	0.00	0.11	0.20	0.03	0.59
Min	0.15	0.29	0.47	0.11	0.97
Avg	0.08	0.20	0.34	0.07	0.86
SD	0.05	0.05	0.09	0.02	0.10
Var	0.56	0.23	0.26	0.31	0.11
Validation set					
Max.	0.03	0.14	0.20	0.04	0.77
Min	0.15	0.27	0.41	0.11	0.98
Avg	0.09	0.19	0.35	0.07	0.88
SD	0.04	0.04	0.08	0.02	0.08
Var	0.45	0.22	0.22	0.30	0.09

Table 3
Pearson correlation matrix.

	A	Ip	Uo	Er	Sv
A	1				
Ip	−0.82504	1			
Uo	0.294081	−0.30654	1		
Er	−0.66775	0.546439	−0.8398	1	
Sv	0.427541	−0.42439	0.714568	−0.57236	1

techniques are Genetic programming (GP), artificial neural network (ANN) and polynomial linear regression optimized using genetic algorithm (GA-PLR), which is known as evolutionary polynomial regression (EPR). All the three developed models were used to predict the values of both erodibility (Er) and volumetric stability (Sv) using the measured ash proportion (A), plasticity index (Ip) and unconfined compressive strength of soil air-cured for 28 days (Uo) in mathematical functional relationships as follows;

Er = f (A, I_P, U_O) (1)

Sv = f (A, I_P, U_O, Er) (2)

Each model on the three developed models was based on different approach; evolutionary approach for GP, mimicking biological neurons for ANN and optimized mathematical regression technique for EPR. However, for all developed models, prediction accuracy was evaluated in terms of Sum of Squared Errors (SSE).

The following section discusses the results of each model. The accuracies of developed models were evaluated by comparing the (SSE) between predicted and calculated shear strength parameters values. The results of all developed models are summarized in Table 4.

3. Results and analysis

3.1. Preliminary study

According the literature, the soil used in the examination was collected from Olokoro, Nigeria located on latitude of 05°28′36.700″ North and longitude 07°32′23.170″ East from a depth of 1.5 m, a distance of 5 km off Ubakala road from the Ishi Court junction, Umuahia, Abia state capital, Nigeria (Onyelowe and Duc, 2018). The soil was an A-2-7 group soil according to AASHTO method of soil classification and was treated with 5%, 10% and 15% by weight of dry soil of selected nanotextured agro-based ashes and tests results showed that the addition of these ashes improved the properties of the soil (Onyelowe and Duc, 2018). The basic treated soil parameters which included durability obtained by method of loss of strength on immersion and erodibility were substantially improved with the addition of the selected ashes (Onyelowe and Duc, 2018; Onyelowe, 2017a; Onyelowe, 2017b and K. C. Onyelowe, 2019).

3.2. Prediction of erodibility and Volumetric Stability (Durability) of Agro-waste Ashes-Treated soil

3.2.1. Model (1) – Using (GP) technique:

The developed GP model started with the one level of complexity and settled at six levels of complexity. The population size, survivor size and number of generations were 100 000, 30 000 and 200 respectively. Eq. (3) & (4) present the output formulas for (Er) & (Sv) respectively, while Figs. 3(a) & 4(a) show their fitness respectively. The average error % of total set for (Er) & (Sv) are (6.3%) & (2.8%) respectively, while the (R^2) values are (0.958) & (0.926) respectively, which agrees with the findings of Onyelowe et al. (2021a).

$$\mathrm{Er} = \frac{(0.33\mathrm{Ip})^{\mathrm{Ip}*\mathrm{Uo}}}{49^{(7*\mathrm{A}*\mathrm{Uo}^2)(1+\mathrm{Uo})}(5*\mathrm{Ip}+\mathrm{Uo}+7)} \tag{3}$$

$$\mathrm{Sv} = (33\mathrm{Er})^3(\mathrm{A}+9\mathrm{Er}^2) + 360\mathrm{Er}.\mathrm{Uo}^2(9\mathrm{Uo}-11\mathrm{Uo}^2-1)+9/8 \tag{4}$$

3.2.2. Model (2) – Using (ANN) technique:

A back propagation ANN with one hidden layer and nonlinear activation function (Sigmoid) was used to predict both Erodibility (Er) and Volumetric Stability (Sv) after preliminary trials showed that sigmoid nonlinear activation function performed better than hyper-tanh nonlinear activation function. The used ANN sigmoid network layouts and their connation weights are illustrated in Fig. 2. Eq. (5) & (10) present the equivalent functions of the developed ANN models for Er and Sv supported by substitution by Eq. (6)–(9) and Eq. (11)–(14) respectively. The average error % of the total dataset for these equations are (7.3%) & (3.6%) and the (R^2) values are (0.939) & (0.852) respectively, which agrees with the results of Onyelowe et al. (2021b). The relations between calculated and predicted values are shown in Figs. 3 (b) & 4(b).

$$\mathrm{Er} = 0.03 + \frac{0.082}{1+e^{-Y1}} \tag{5}$$

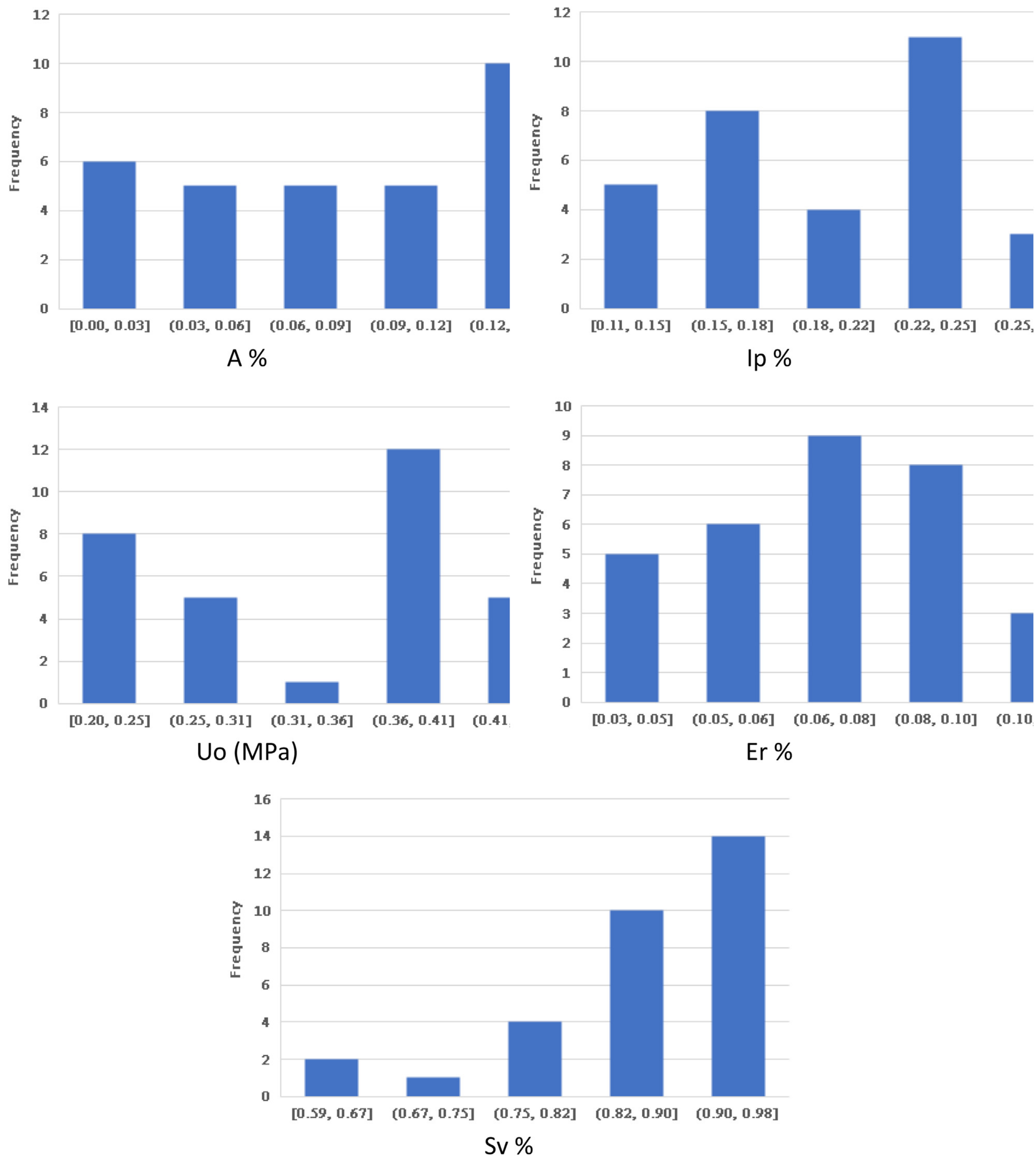


Fig. 1. Distribution histograms for inputs and outputs.

$$Y1 = 4.92 - \frac{4.40}{1 + e^{-X1}} - \frac{6.36}{1 + e^{-X2}} \tag{6}$$

$$X1 = -0.82 + 1.76A' + 1.34Ip' + 7.46Uo' \tag{7}$$

$$X2 = -7.69 + 3.68A' + 1.21Ip' + 4.45Uo' \tag{8}$$

$$A' = \frac{Hc}{0.15}; Ip' = \frac{Ip - 0.11}{0.18}; Uo' = \frac{Uo - 0.20}{0.27} \tag{9}$$

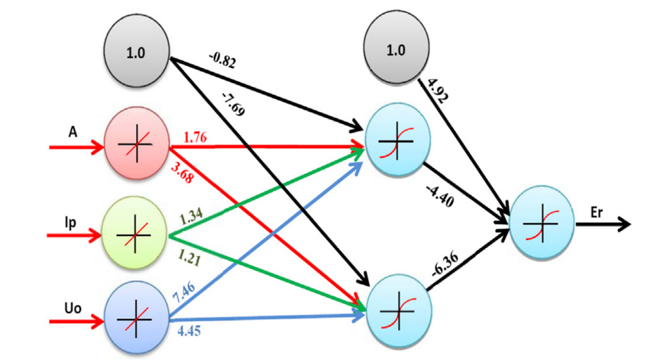
$$Sv = 0.594 + \frac{0.384}{1 + e^{-Y1}} \tag{10}$$

$$Y1 = 1.16 - \frac{5.70}{1 + e^{-X1}} + \frac{7.49}{1 + e^{-X2}} \tag{11}$$

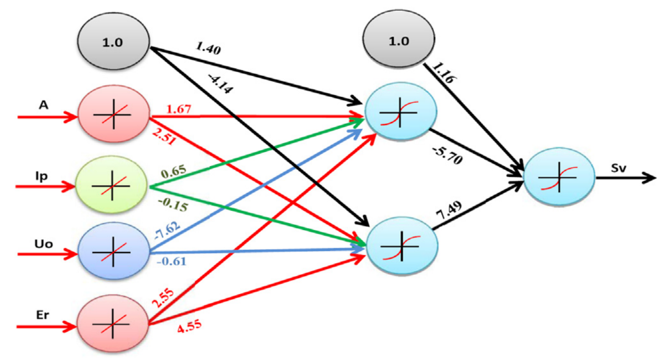
$$X1 = 1.40 + 1.67A' + 0.65Ip' - 7.62Uo' + 2.55Er' \tag{12}$$

$$X2 = -4.14 + 2.51A' - 0.15Ip' - 0.61Uo' + 4.55Er' \tag{13}$$

$$A' = \frac{Hc}{0.15}; Ip' = \frac{Ip - 0.11}{0.18}; Uo' = \frac{Uo - 0.20}{0.27}; Er' = \frac{Er - 0.03}{0.08} \tag{14}$$



a) ANN for (Er)



b) ANN for (Sv)

Fig. 2. Layout for the developed ANN models and their connection weights.

3.2.3. Model (3) – Using (EPR) technique:

Finally, the developed EPR model was limited to quadratic level, for four inputs, there are 86 possible terms $(\sum_{i=1}^{i=4} X_i + \sum_{i=1}^{i=4}\sum_{j=1}^{j=4}\sum_{k=1}^{k=4} X_i.X_j.X_k + C)$. GA technique was applied on these 86 terms to select the most effective 7 terms to predict the values of (Er) & (Sv). The outputs are illustrated in Eq. (15) & (16) and their fitness are shown in Figs. 3(c) & 4(c). The average error% and (R^2) values were improved to (5.1%) -(0.972) & (2.7%) -(0.929) for the total datasets respectively, which agrees with the findings of Onyelowe and Shakeri (2021).

$$\mathrm{Er} = 0.512 - 2.5\mathrm{A} + 9.67\mathrm{A}*\mathrm{Ip} - 1.85\mathrm{A}*\mathrm{Uo} + 5.4\mathrm{A}^2 - 2.9\mathrm{Ip} + 4.96\mathrm{Ip}^2 \tag{15}$$

$$\mathrm{Sv} = 3.4 + 3022\mathrm{A}*\mathrm{Er}^3 - 26.94\mathrm{Ip}*\mathrm{Uo}*\mathrm{Er} - 31.0\mathrm{Uo} + 106.7\mathrm{Uo}^2 - 111.0\mathrm{Uo}^3 + 2122\mathrm{Er}^4 \tag{16}$$

4. Conclusions

This research presents three models using three (AI) techniques (GP, ANN and EPR) to predict values of both Erodibility (Er) and Volumetric Stability (Sv) using the measured Ash Proportion (A), Plasticity index (Ip) and Unconfined compressive strength of soil air-cured for 28 days (Uo). The results of comparing the accuracies of the developed models could be concluded in the following points:

- Prediction accuracies of (Er) for all models are so close (between 92.7% and 94.9%) which gives an advantage to the simplest model (EPR model), while the prediction accuracies of (Sv) are ranged between 97.3% and 96.4% and the simplest model is the (GP) model.
- The three developed models illustrated that (Sv) value is mainly governed by (Uo) and (Er). On the other hand, the (GP) model showed that the impact of (Ip) is neglected.
- Although the ANN model had very simple configurations (one hidden layer with two neurons & sigmoid activation function) but it was still able to capture the relations between the inputs and the outputs accurately. It almost shared the same accuracy level with (GP) models.

Table 4
Performance accuracies of developed models.

Soil Property	Intelligent Technique	Developed Eq.	Performance Indices	
			SSE %	R^2
Er	GP	Eq. (3)	6.3	0.958
	ANN	Eq. (5)	7.3	0.939
	EPR	Eq. (15)	5.1	0.972
Sv	GP	Eq. (4)	2.8	0.926
	ANN	Eq. (10)	3.6	0.852
	EPR	Eq. (16)	2.7	0.929

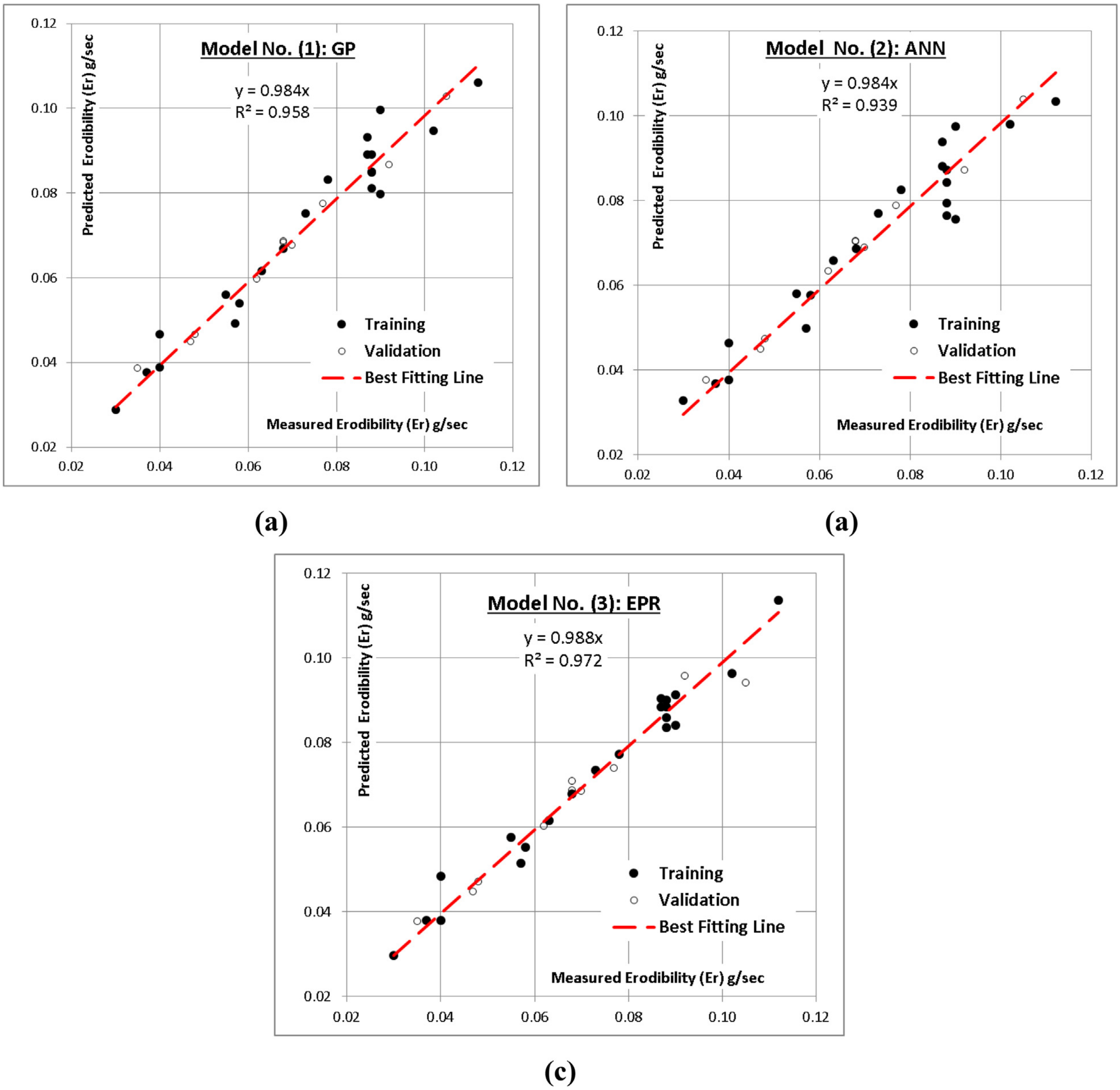


Fig. 3. Relation between predicted and calculated (Er) values using the developed models.

- Regardless of the complexity of models, (EPR) models showed better level of accuracy than both GP and ANN models.
- GA technique successfully reduced the 86 terms of conventional PLR quadratic formula to only 7 terms without significant impact on its accuracy.
- Like any other regression technique, the generated formulas are valid within the considered range of parameter values, beyond this range; the prediction accuracy should be verified.

Data availability statement

This data supporting this work has been reported in the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clema.2021.100006.

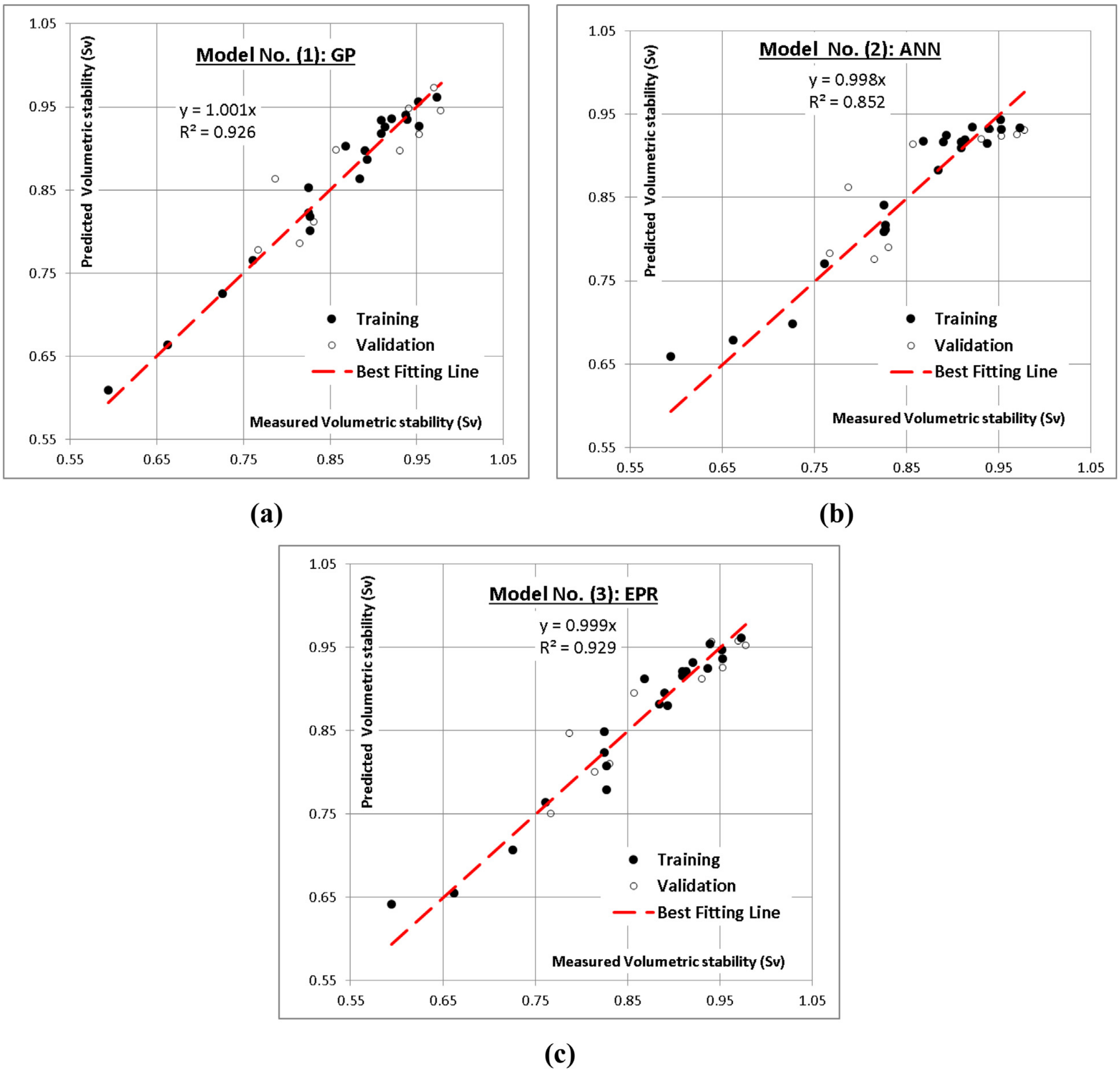


Fig. 4. Relation between predicted and calculated (Sv) values using the developed models.

References

Adetunji, C., Kadiri, O., Islam, S., Nwankwo, W., Thangadurai, D., Anthony, A., Makinde, A. Sangeetha, J., Adetunji, J., 2020. Potential agri-food applications of novel and sustainable nanomaterials: an ecofriendly approach. 10.1007/978-3-030-11155-7_45-1.

Alavi, A., Gandomi, A., Mollahasani, A., 2011. A genetic programming-based approach for performance characteristics assessment of stabilized soil. https://doi.org/10.1007/978-3-642-23424-8_11.

Almurshedi, A., Thijeel, J., Al-Awad, K., 2020. Mitigation of collapse of marshes soil by nano silica fume. IOP Conf. Ser.: Mater. Sci. Eng. 737, 012110. https://doi.org/10.1088/1757-899X/737/1/012110.

Alsharef, M.A., Taha, M.R., Firoozi, A.A., Govindasamy, P., 2016. Potential of using nanocarbons to stabilize weak soils. Appl. Environ. Soil Sci. 1–9. Article ID 5060531. 10.1155/2016/5060531.

Amadi, A.A., 2014. Enhancing durability of quarry fines modified black cotton soil subgrade with cement kiln dust stabilization. Transp. Geotech. 2014 (1), 55–61. https://doi.org/10.1016/j.trgeo.2014.02.002.

Anjita, A., George, C., Krishnankutty, S., 2017. Prediction of maximum dry density of soil using genetic algorithm. Int. J. Eng. Res. 6. 10.17577/IJERTV6IS030517.

Arciszewski, T., De Jong, K., 2001. Evolutionary computation in civil engineering: research frontiers. 161–184.

ASTM C618, 1978. Specification for fly ash and raw or calcined natural pozzolan for use as a mineral admixture in Portland Cement Concrete. American Standard of Testing and Materials, Washington, DC.

Baghdadi, Z., Shihata, S., 1999. On the durability and strength of soil-cement. Ground Improvement 31, 1–6. https://doi.org/10.1680/gi.1999.030101.

Bajwa, S.Z., Munawar, A., Khan, W.S., 2017. Nanotechnology in medicine: innovation to market. Comment. Pharmaceut. Bioprocess. 5(2).

Barbu, B., McManis, K., 2004. Study of problematic silt stabilization. Transportation Research Board, Washington, D.C..

Baziar, Mohammad Hassan, Saeidaskari, Javad, Alibolandi, Mahdi, 2018. Effects of nanoclay on the treatment of core material in earth dams. J. Mater. Civ. Eng. 30 (10), 04018250. https://doi.org/10.1061/(ASCE)MT.1943-5533.0002415.

Bittelli, M., Valentino, R., Salvatorelli, F., Pisa, P.R., 2012. Monitoring soil-water and displacement conditions leading to landslide occurrence in partially saturated clays. Geomorphology 173, 161–173. https://doi.org/10.1016/j.geomorph.2012.06.006.

Carman, P.C., 1997. Fluid flow through granular beds. Chem. Eng. Res. Des. 75, S32–S48. https://doi.org/10.1016/S0263-8762(97)80003-2.

Cui, Y.J., Tang, A.M., Loiseau, C., Delage, P., 2008. Determining the unsaturated hydraulic conductivity of a compacted sandâ bentonite mixture under constant-volume and free-swell conditions. Phys. Chem. Earth Parts A/B/C. https://doi.org/10.1016/j.pce.2008.10.017.

Gidday, B.G., Mittal, S., 2020. Improving the characteristics of dispersive subgrade soils using lime. Heliyon, 14 Feb 2020, 6(2), e03384. 10.1016/j.heliyon.2020.e03384

Onyelowe, K.C., 2019. Nanosized palm bunch ash (NPBA) stabilisation of lateritic soil for construction purposes. Int. J. Geotech. Eng. 13 (1), 83–91. https://doi.org/10.1080/19386362.2017.1322797.

Kadivar, M., Barkhordari, K., Kadivar, Mehdi, 2011. Nanotechnology in geotechnical engineering. Adv. Mater.Res. 261–263, 524–528. https://doi.org/10.4028/www.scientific.net/AMR.261-263.524.

Keller, Thomas, Dexter, Anthony R., 2012. Plastic limits of agricultural soils as functions of soil texture and organic matter content. Soil Res. 50 (1), 7. https://doi.org/10.1071/SR11174.

Kicinger, Rafal, Arciszewski, Tomasz, Jong, Kenneth De, 2005. Evolutionary computation and structural design: a survey of the state-of-the-art. Comput. Struct. 83 (23-24), 1943–1978. https://doi.org/10.1016/j.compstruc.2005.03.002.

Kouchami-Sardoo, I., Shirani, H., Esfandiarpour-Boroujeni, I., Besalatpour, A.A., Hajabbasi, M.A., 2020. Prediction of soil wind erodibility using a hybrid Genetic algorithm and artificial neural network method. CATENA 187. https://doi.org/10.1016/j.catena.2019.104315.

Kurnaz, T.F., Dagdeviren, U., Yildiz, M., Oskan, O., 2016. Prediction of compressibility parameters of the soils using artificial neural network. Springer Plus 5, 1801. https://doi.org/10.1186/s40064-016-3494-5.

Le, H., Nguyen, T., Nguyen, D., Prakash, I., 2020. Prediction of soil unconfined compressive strength using artificial neural network model. Vietnam J. Earth Sci. 42, 255–264. https://doi.org/10.5625/0866-7187/42/3/15342.

Marchiol, L., 2018. Nanotechnology in Agriculture: New Opportunities and Perspectives. https://doi.org/10.5772/intechopen.74425.

Marchiol, Luca, Mattiello, Alessandro, Pošćić, Filip, Fellet, Guido, Zavalloni, Costanza, Carlino, Elvio, Musetti, Rita, 2016. Changes in Physiological and Agronomical Parameters of Barley (Hordeum vulgare) Exposed to Cerium and Titanium Dioxide Nanoparticles. Int. J. Environ. Res. Public Health 13 (3), 332. https://doi.org/10.3390/ijerph13030332.

Meguid, M., Kamel, S., 2014. A three-dimensional analysis of the effects of erosion voids on rigid pipes. Tunnell. Underground Space Technol. 43, 276–289. https://doi.org/10.1016/j.tust.2014.05.019.

Menaa, M., Meguid, M.A., Assaf, G., 2009. On the effects of subgrade erosion on the contact pressure distribution under rigid surface structures. J. Geotech. Geoenviron. Eng. 135 (10), 1538–1542. https://doi.org/10.1061/(ASCE)GT.1943-5606.0000097.

Onyelowe, K.C., 2018. Kaolin Soil and its Stabilization Potentials as Nanostructured Cementitious Admixture for Environmental Geotechnics Purposes. Int. J. Pavement Res. Technol.. https://doi.org/10.1016/j.ijprt.2018.03.001.

Onyelowe, K.C., Duc, B.V., 2018. Durability of nanostructured biomasses ash (NBA) stabilized expansive soils for pavement foundation. Int. J. Geotech. Eng.. https://doi.org/10.1080/19386362.2017.1422909.

Onyelowe, K.C., 2017a. Local Nanostructured Ashes Synthesized by Incineration, Pulverization and Spectrophotometric Characterization of Solid Wastes Ashes for Use as Admixtures in Soil Stabilization. Int. J. Sustain. Constr. Eng. Technol. 7 (2), 50–64 (ISSN 2180–3242).

Onyelowe, K.C., 2017b. Nanostructured waste paper ash stabilization of lateritic soils for pavement base construction purposes. Electron. J. Geotech. Eng. 2017 (22.09), 3633–3647.

Onyelowe, K.C., Okafor, F.O., 2015. Review of the Synthesis of Nano-Sized Ash from Local Waste for Use as Admixture or Filler in Engineering Soil Stabilization and Concrete Production. J. Environ. Nanotechnol. 4(4), 23–27. 10.13074/jent.2015.12.154167

Onyelowe, Kennedy C., Ebid, Ahmed M., Nwobia, Light, Dao-Phuc, Lam, 2021a. Prediction and performance analysis of compression index of multiple-binder treated soil by genetic programming approach. Nanotechnol. Environ. Eng. 6 (2). https://doi.org/10.1007/s41204-021-00123-2.

Onyelowe, K.C., Gnananandarao, T., Nwa-David, C., 2021b. Sensitivity analysis and prediction of erodibility of treated unsaturated soil modified with nanostructured fines of quarry dust using novel artificial neural network. Nanotechnol. Environ. Eng. 6. https://doi.org/10.1007/s41204-021-00131-2.

Onyelowe, K.C., Shakeri, J., 2021. Intelligent prediction of coefficients of curvature and uniformity of hybrid cement modified unsaturated soil with NQF inclusion. Clean. Eng. Technol. 4 (2021). 10.1016/j.clet.2021.100152.

Oyedepo, Sunday Olayinka, 2012. Energy and sustainable development in Nigeria: The way forward. Energy Sustain. Soc. 2 (1). https://doi.org/10.1186/2192-0567-2-15.

Pham, V., Turner, B., Huang, J., Kelly, R., 2016. Experimental study on the durability of soil-cement columns in coastal areas. The 19th Southeast Asian Geotechnical Conference & 2nd AGSSEA Conference.

Saarenketo, T., 2000. Tube suction test-results of round robin tests on unbound aggregates. Finnish National Road Administration, Lapland Road Region, Rovaniemi, Finland.

Scullion, T., Saarenketo, T., 1997. Using suction and dielectrical measurements as performance indicator for aggregate base materials. Transp. Res. Rec. 1577, 37–44.

Shen, C.K., Akky, M.R., 1974. Erodibility and durability of cement-stabilized loam soil (abridgment). Transp. Res. Board http://onlinepubs.trb.org/Onlinepubs/trr/1974/501/501-006.pdf.

Stavridakis, Evangelos I., 2006. A solution to the problem of predicting the suitability of silty-clayey materials for cement-stabilization. Geotech. Geol. Eng. 24 (2), 379–398. https://doi.org/10.1007/s10706-004-7934-6.

Syed, I., Scullion, T., Randolph, R., 2000. Use of tube suction test for evaluation of aggregate base materials in frost/moisture susceptible environment. Transp. Res. Rec. 1709, 78–90.

Syed, I., Scullion, T., Smith, R., 2003. Recent developments in characterizing durability of stabilized materials. The 82nd TRB Annual Meeting CD-ROM, Washington, D.C.

Taghizadeh-Mehrjardi, Ruhollah, Emadi, Mostafa, Cherati, Ali, Heung, Brandon, Mosavi, Amir, Scholten, Thomas, 2021. Bio-Inspired Hybridization of Artificial Neural Networks: An application for mapping the spatial distribution of soil texture fractions. Remote Sensing 13 (5), 1025. https://doi.org/10.3390/rs13051025.

Wang, Fengchi, Zhao, Hengliang, Ma, Jie, Kang, Tianbei, 2021. Experimental study on the erosion resistance of rubberized cement-soil. Soils Found. 61 (3), 734–751. https://doi.org/10.1016/j.sandf.2021.02.003.

Zhang, J., Zhang, S., Xu, T., 2020. Individual Effect of Matric Suction on Soil Microstructure and Hydraulic Conductivity. KSCE J. Civ. Eng. 24, 1448–1459. 10.1007/s12205-020-1381-7

Zhang, Zhongjie, Tao, Mingjiang, 2008. Durability of cement stabilized low plasticity soils. J. Geotech. Geoenviron. Eng. 134 (2), 203–213. https://doi.org/10.1061/(ASCE)1090-0241(2008)134:2(203).