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Original Research Article

Predictive Model for Flood – Induced Collapse Phenomenon in Residual Soils of Northern Edo, Nigeria

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Abstract

Residual soils are in the category of questionable soils which have been experienced in the arid and semi-arid climatic zones of the world. The conditions in these zones favour the development of most unsafe collapsible soils. At their dry natural state, they possess awesome stiffness and high apparent shear strength, however upon flooding, may demonstrate a remarkable reduction in volume, consequently deteriorate in strength and collapse. In this research, the collapse phenomenon of residual soil collected from three locations in Auchi, Northern Edo, Nigeria has been investigated on undisturbed specimens by utilizing single Oedometer test. The results obtained from Oedometer tests were utilized to form the database to develop the Artificial Neural Network model for the prediction of collapse potential induced by flood. The influences of flood, flooding pressure, void ratio, dry density and porosity on soil collapse have been investigated. Six input parameters (i.e. Flooding Pressure, Initial void ratio, Initial water content, Initial dry density, Liquid limit and Initial porosity) are considered to have the most noteworthy influences on the degree of collapse and have been utilized as the model's inputs while the model output will be the equivalent collapse potential. The proposed network was developed using Microsoft Visual Studio 2010 and the MS.NET Framework 4.0 and source codes were written in C-Sharp (C#). A supervised learning was utilized to train the Back Propagation feed forward multi-layer ANN algorithm with the momentum coefficient and learning rate as its parameters. The prediction performance of the Artificial Neural Network model was assessed by utilizing the primary statistical criterion proposed by Shahin, *et al.*, [1] such as the coefficient of correlation, R2, and the root mean square error, RMSE. The model outcomes demonstrated that it has the aptitude to predict the collapse potential from single Oedometer test in residual soil samples with a good degree of precision with coefficient of correlation, R2 = 0.856 and root mean square error, RMSE = 166.199.

Keyword: Artificial Neural Networks, Collapse Phenomenon, Collapse Potential, Residual Soils.

INTRODUCTION

Collapsible soils are commonly distributed in various parts of the world, primarily in arid and semi-arid climatic zones. The conditions in these zones support the development of most unsafe collapsible soils. Collapsible soils are sensitive to moisture, such that rise in water content is the main activating mechanism accountable for their volume reduction. These misleading soils stance potential threat to structures engineered on/in or with them when they are flooded. One amongst the first vital issues regarding collapsible soils is instability and substantial settlement attributed to slight changes in the water content which may cause notable harm to overlying structures.

At their dry state of nature, they have awesome robustness and high apparent shear strength. However, upon flooding, may show a remarkable reduction in volume; consequently deteriorate in strength and collapse. Previously, much attention was not paid to thorough studies and investigation of soils at risk of collapse in the study location since structures engineered on these soils tended to be cheap and of little size.

Additionally, the pattern of water consumption was fairly not quite the same as those of these days. In any case, the late progression of human advancement in the arid regions of Nigeria (e.g. Northern Edo) accompanied by the utilization of huge quantity of water for watering system, industrial and local capacities near the structures cause extreme harm to such structures founded on collapsible soil. Also, framework improvements in all parts of life have brought about the development of contemporary urban areas and substantial structures in zones of collapsible residual soils. This clearly warrants an extensive investigation of the issue of collapsing in collapsible soils. A safe, reliable and cost-effective technique for predicting areas of likely soil subsidence is seriously necessary. In this research, detailed examination will be carried out to ascertain the collapse potential of residual soil induced by flood, examine the impacts of basic index properties and other factors on soil collapsibility and finally to predict a relevant model for a reliable estimation of the collapse phenomenon.

The engineering properties of soil and rock display various and uncertain behaviour because of the intricate nature coupled with the setting up of these materials. This does not concur with most other civil engineering materials, for example concrete, timber and steel which show far more noteworthy homogeneity and Isotropy. In any case, to adjust to the multifaceted nature of geotechnical behaviour, and the spatial variability of these materials, conventional methods of engineering design models are reasonably improved with the utilization of Artificial Neural Network (ANNs).

Location of Study Area

The study area for this research work is Auchi, the Administrative headquarter of Etsako West Local Government area of Edo State, Nigeria. It lies between Latitudes $7^0 14^1$ North and $7^0 34^1$ North of the equator and Longitudes $6^0 14^1$ East and $6^0 43^1$ East of the Greenwich Meridian. Auchi is surrounded by Iyuku to the North, Aviele to the South, Jatu to the East, and Warrake to the West. It is a transit town which lies along Benin–Okene–Abuja highway. It is a simple access for those in the Eastern and Southern section of Nigeria setting out toward the North.

Fig. 1.1: Map of Nigeria and Auchi Location

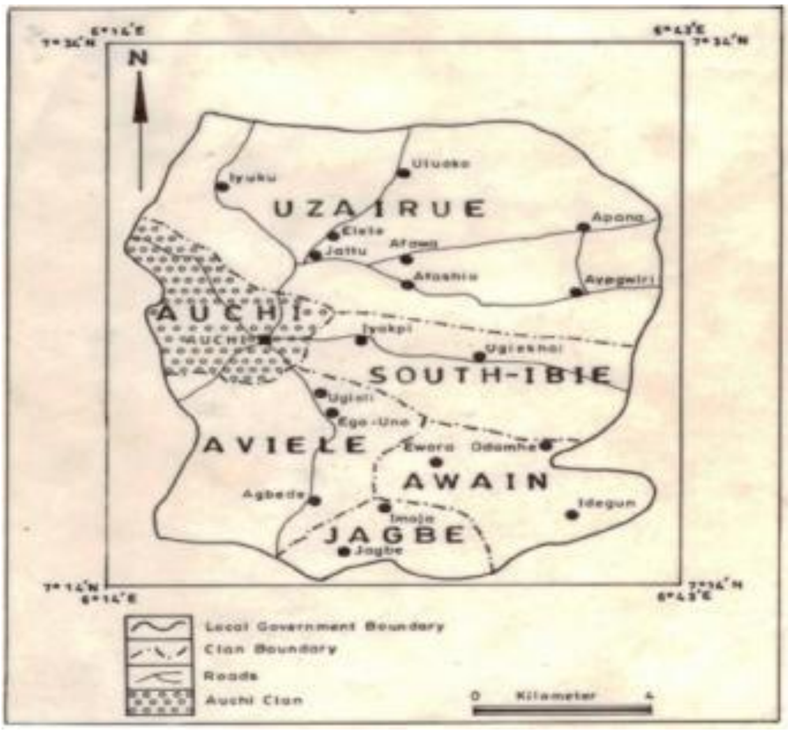

Fig. 1.2: Map of Edo North

MATERIALS AND METHODS

An experimental program has been considered to study the collapse phenomenon of the collapsible soil that is prevalent in Northern Edo, Nigeria. Representative undisturbed soil samples were collected and analyzed in an effort to ascertain their collapse phenomenon during flooding and the impact of index properties on the collapse Phenomenon.

Data Collection/Sampling Method

Different undisturbed block samples of soils were collected from three test pits at different locations within the same geologic formation. Undisturbed block samples were collected from excavated pits of each site locations with the help of a spade and hand tools at various depths of 0.6 – 1.2 metres. Plastic sacks were utilized to seal each sample securely, and were taken care of mindfully when conveying them to the laboratory so as to keep the block samples from crumbling and in addition saving the natural water content. The size of the undisturbed natural block samples cut in the field varied, subject to the material features and the simplicity with which a complete block of material could be cut and emptied without breaking. Lastly, each sample was named and stamped appropriately, keeping in mind the end goal to show the location, depth, sample description, observed colour and date of sampling. The recovered blocks of undisturbed materials were adequate that one quantity of undisturbed Oedometer ring specimen was cut from each to use in the consolidometer, while six quantities were cut for engineering properties and classification tests. The site locations and information are shown in Table 2.1.

Table 2.1: Sampling Information

SITE LOCATION	DEPTH OF SAMPLE(m)	SAMPLE DESCRIPTION	VISUAL COLOR OBSERVED	SAMPLE DATE
EGELESSOR	0.6	S_1	REDDISH	7/5/2015
EGUNOR	1.0	S_2	DARKISH RED	7/5/2015
JATTU	1.2	S_3	DARKISH RED	7/6/2015

Specimen Preparation and Laboratory Testing

The standard Oedometer test specimens were gotten from the natural soil obtained from excavated pits at Auchi as appeared in Table 2.1. The tests were done on a cylinder-shaped specimen of undisturbed soils with the dimensions of 50mm diameter and 20mm thick. Prior to every test, the consolidation ring and glass plate were weighed independently and recorded. At that point, inside diameter of the ring was greased with petroleum jelly. After the application of grease, the height and diameter of the ring were measured using the Vernier caliper and the area ‘A’ was calculated in mm2.

The cutting ring was then pushed downwards into the soil sample until its upper most rim was just beneath the soil sample. Excess soil trimmed off carefully from the consolidation ring with the help of a palette knife. A sample of the excess soil trimmed was utilized to decide the moisture content for each specimen as per BS 1377-5:1990. The height of the ring was used as the initial height of the soil sample. With the aim of preventing the sample from squeezing, soil pieces were utilized to cautiously fill the Voids. After this, the soil sample encased in the consolidation ring was positioned on a porous stone and filter papers were integrated between the soil and the porous stone, and a loading cap was put on top of the fitter paper. The sample was then mounted in the consolidation cell and the loading unit. A total of three natural undisturbed specimens were obtained from different levels at the three sites locations for the Oedometer and six specimens for the Index tests.

Single Oedometer Test

One dimensional Oedometer consolidation test was performed on the undisturbed specimens of natural soil using an Oedometer according to BS 1377 (1990): P 5.3.

A seating load of 2kg was placed on the top pan of the weight hanger to give a little positive descending load on the specimen in the consolidation ring. The beam ratio was set to 10:1, then the seating load was removed and the sample was flooded by water at room temperature. At that point, vertical loads were applied to the specimen incrementally and permitting the specimen to come to equilibrium under the applied pressure in accordance with British Standard (BS 1377, 1990, P.5.0 SECTION 3.5.1) and the corresponding deformation recorded. The change in the thickness of the sample against time was recorded during each loading increment. Once equilibrium was reached for a loading step, the next load increment was applied. For each test, six incremental loads were applied, the load was duplicated at every addition until the most extreme load was attained e.g. 0.5kg, 1kg, 2kg, 4kg, 8kg, and 16kg, then deformation induced by the addition of water divided by the height of the specimen before flooding, is expressed as a percentage, describes the collapse potential CP(%). So as to complete the test, the sample was weighed, then oven-dried and weighed again to determine the final moisture content of the sample.

Calculation of mass (m) or equivalent mass (in kg) supported by the specimen is given as:

$$\sigma'v = \frac{9.810 * m * a}{A} \text{ kPa } (2.1)$$

Where;

σ’v - is the vertical stress applied to the specimen (kPa),
m - is the mass or equivalent mass, supported by the specimen (kg),
a - is the lever arm ratio (10:1), A is the area of the specimen in (mm)

Table 2.2: Loading Scheduling

LOADING(kg)	FLOODING PRESSURE(kPa)
0.5	25
1.0	50
2.0	100
4.0	200
8.0	400
16.0	800

Moisture Content

The moisture content test is detailed in BS1377 (1990): Part 2.3.2 to decide the moisture content W, of a soil sample. The initial moisture content or the moisture content of the material as it were in its ordinary state can be calculated as the ratio of the weight of water in a given volume of soil to the weight of water in the same volume. It is attained utilizing any bit of material left over the consolidometer sample preparation process. The part of material is positioned in a tin container of a known weight then the material and the container together place in the scale to obtain the weight, then placed in the oven at 1050C and left for overnight (24hrs). After 24hrs, the material with the tin container is weighed again and the variation in the weight noted. Any change in weight of the total sample is assumed to be the result of a change in the moisture content. The moisture content is expressed in percentage as demonstrated in (2.2) below:

$$W = \frac{W_w}{W_s} * 100 \ (2.2)$$

Where;

W is the moisture content (%).
W_w is the weight of the water which is equal to the difference in weight of the material before and after oven drying (g);
Ws is the weight of the solids, which is equal to the total weight of the material after oven drying (g).

Once the initial or natural moisture content of the material is known, and the dry weight of material in the consolidometer ring gotten, the increase in moisture content with the addition of water can be determined.

This is accomplished utilizing the dry unit weight of the material in the ring after drying overnight in the oven at 1050C and then obtaining the sample weight as well as the weight of the water in the sample at the start of the test.

In this research work, the speedy moisture tester from Ashworth instrumentation was used to measure the initial moisture content of the soil samples. The Speedy moisture tester is a handy instrument that consists of a receptacle that has an essential pressure gauged, a weighing scale and a carry case. A small sample of the soil (26g) was prepared, weighed and placed into the vessel. A reagent (calcium carbide) was then added and the vessel was sealed and shaken to mix the reagent with the sample. Water reacts with calcium carbide in the sample to produce acetylene gas which activated a pressure gauge that is calibrated to read as percent moisture.

Particle Size Distribution

Soil particles might comprise of sizes ranges from boulders to fine-sized clay. Grain size analysis is utilized to decide the actual diameter of the soil particles that constitute and explicitly strongly impact the homogeneity features of the soil mass. In other word, the primary goal of this test is to group soil particles into separate range sizes and choose relative properties by dry /wet weight of each size range. A particle size distribution analysis is an essential index test for soils, specifically coarse soils in that it displays the relative amount of different sizes of particles. From the particles, it is less difficult to say if the soil comprises primarily of gravel, sand, silt or clay sizes and to what degree the variable size of the particles is likely to dominate the engineering properties.

In this research work, the wet sieving procedure was implemented in accordance with BS 1377 (1990) Part 2.9.2 [3].

Atterberg Limits

Atterberg limits tests were carried out on the air-dried samples after first sieving the soil on a 425µm test sieve. 300g of the material passing through this sieve was used for these tests. The air-dried samples were prepared by spreading the material out in trays in the laboratory and leaving it to the air for 5 days at room temperature of 260C. Before testing commences, each sample was mixed thoroughly with water and stored in an airtight plastic bag overnight. Then liquid limits of the selected samples were determined using the cone penetrometer method. Plastic limits were also performed by the rolling thread method. The Liquid limits, Plastic limits and Plasticity index methods are described in BS 1377 (1990) part 2.4.3, 2.5.3 & 2.5.4 [3].

Specific Gravity

Specific gravity test of the samples was performed by the pyknometer method in accordance with the British standard as mentioned in BS 1377 (1990) Part 2.8.3 [3].

Figure 2.1: Set-Up of Oedometer Apparatus

Figure 2.2: Weighing of Specimen

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section presents the results and the initial conditions of various soils collected at Auchi, Northern Edo, Nigeria. Tables 3.1 to 3.3 summarize the consolidation test results of Egelessor, Egunor and Jattu respectively; Table 3.4 displays the specific gravities of the representative soils, Tables 3.5 to 3.7 show the grain size distributions for the Egellesor, Egunor and Jattu soils. Figs. 3.1 to 3.3 show the grain size distribution curves of the soil in the study area. Figs. 3.1a, 3.1b and 3.1c illustrate the collapse behavior of Egelessor, Egunor & Jattu soils.

Every Figure presents the behaviour at flooding pressure of 0, 25, 50, 100, 200, 400 and 800 kPa.

Table 3.1: Summary of Consolidation (Oedometer) Test Results of Egelessor

Depth	Initial moisture	Initial dry density	Flooding Pressure	Initial void ratio	Collapse Potential	Initial Porosity
m	w_0(%)	γ_d(Mg/m^{3})	P(kPa)	e_0	CP(%)	n(%)
0.6	12.1	1.075	0	1.484	0.000	59.750
	12.1	1.083	25	1.466	0.750	59.450
	12.1	1.100	50	1.427	1.550	58.800
	12.1	1.125	100	1.374	2.150	57.875
	12.1	1.161	200	1.299	3.000	56.510
	12.1	1.209	400	1.209	3.650	54.724
	12.1	1.266	800	1.109	4.000	52.591

Table 3.2: Summary of Consolidation (Oedometer) Test Results of Egunor

Depth	Initial moisture	Initial dry density	Flooding Pressure	Initial void ratio	Collapse Potential	Initial Porosity
m	w_0(%)	γ_d(Mg/m$^{3)}$	P(kPa)	e_0	CP(%)	n(%)
1.0	10.3	1.112	0	1.410	0.000	58.500
	10.3	1.126	25	1.371	1.600	57.825
	10.3	1.152	50	1.317	2.250	56.838
	10.3	1.190	100	1.245	3.000	55.448
	10.3	1.233	200	1.166	3.250	53.838
	10.3	1.296	400	1.060	4.400	51.462
	10.3	1.373	800	0.945	4.800	48.575

Table 3.3: Summary of Consolidation (Oedometer) Test Results of Jattu

Depth	Initial moisture	Initial dry density	Flooding Pressure	Initial void ratio	Collapse Potential	Initial Porosity
m	w_0(%)	γ_d(Mg/m$^{3)}$	P(kPa)	e_0	CP(%)	n(%)
1.2	7.7	1.021	0	1.614	0.000	61.750
	7.7	1.048	25	1.549	2.500	60.769
	7.7	1.085	50	1.460	3.400	59.352
	7.7	1.133	100	1.357	3.950	57.571
	7.7	1.190	200	1.244	4.300	55.446
	7.7	1.257	400	1.124	4.600	52.923
	7.7	1.340	800	0.992	5.050	49.803

Table 3.4: Summary of the Specific Gravity Values of Soils Collected at Various Locations

Lacation	Sample no	Depth (m)	Specific gravity
Egelessor	1S1	0.60	2.62
	1S2		2.65
	1S3		2.64
	1S4		2.61
	1S5		2.66
	1S6		2.64
Egunor	2S1	1.00	2.61
	2S2		2.67
	2S3		2.62
	2S4		2.63
	2S5		2.65
	2S6		2.67
Jattu	3S1	1.20	2.64
	3S2		2.63
	3S3		2.67
	3S4		2.65
	3S5		2.61
	3S6		2.66

Where; P = Flooding Pressure (kPa), H = Height at the end of consolidation (mm), e = Void ratio, w_0 = Initial moisture content (%), Δe = Change in void ratio, γ_d = Initial dry density (Mg/m^3), Sr = Initial degree of saturation (%), n = Porosity (%), CP = Collapse Potential (%)

Table 3.5: Grain Size Distribution for Egellesor Soils

Sieve Sizes(mm)	% Passing
50	100
37.5	94.86
25	89.1
13	85.98
6.3	75.39
3.35	38.63
1.18	19.94
0.6	13.4
0.15	8.1
0.063	4.83

Table 3.6: Grain Size Distribution for Egunor Soils

Sieve Sizes(mm)	% Passing
6.3	100
2	97
0.6	88
0.212	66
0.063	38
0.02	20
0.006	11
0.002	4

Table 3.7: Grain Size Distribution for Jattu Soils

Sieve Sizes(mm)	% Passing
0.425	97.73
0.3	93.18
0.2	81.21
0.15	54.24
0.063	16.36

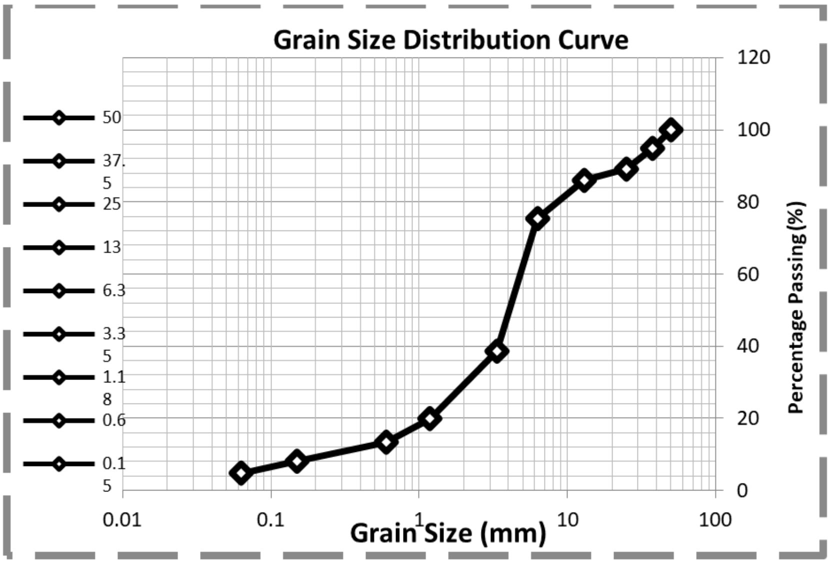

Fig. 3.1: Grain Size Distribution Curve for Egellesor Soil

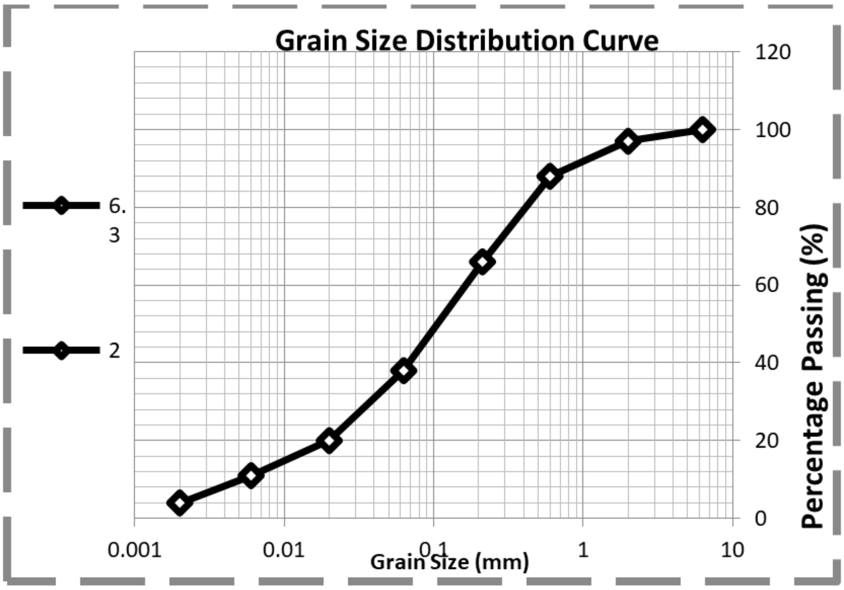

Fig. 3.2: Grain Size Distribution Curve for Egunor Soil

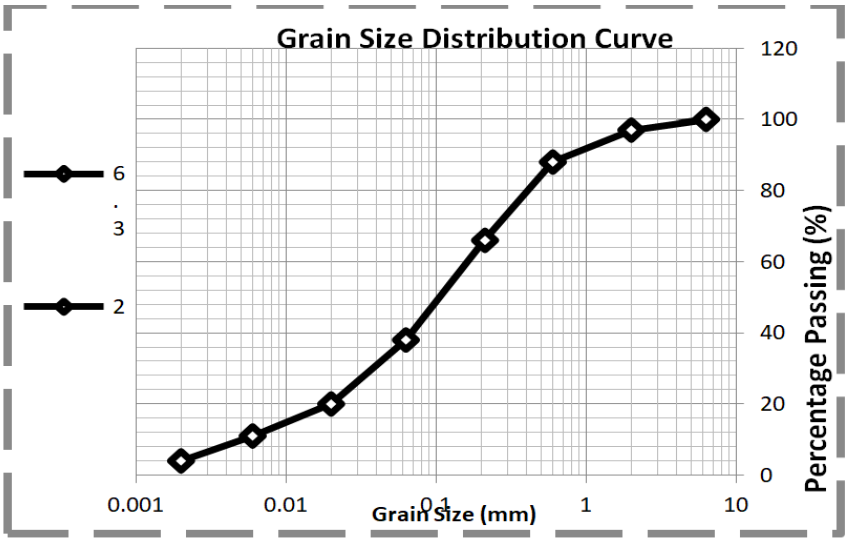

Fig. 3.3: Grain Size Distribution Curve for Jattu Soi

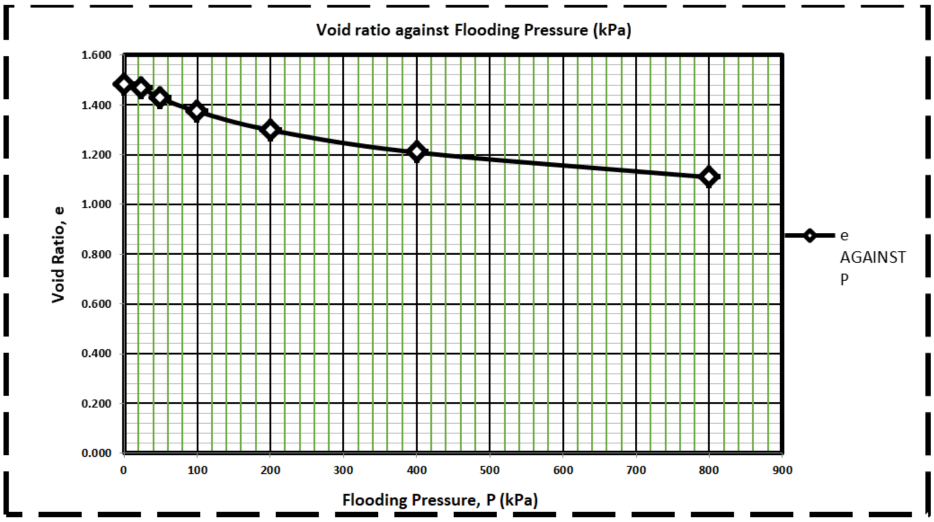

Fig. 3.1a: Collapse behaviour of Egellesor Soil

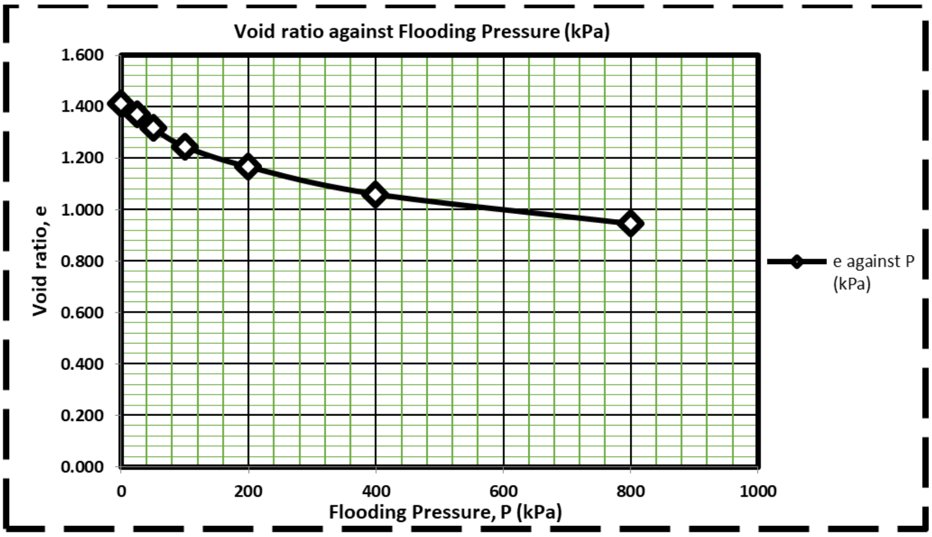

Fig. 3.1b: Collapse behaviour of Egunor Soil

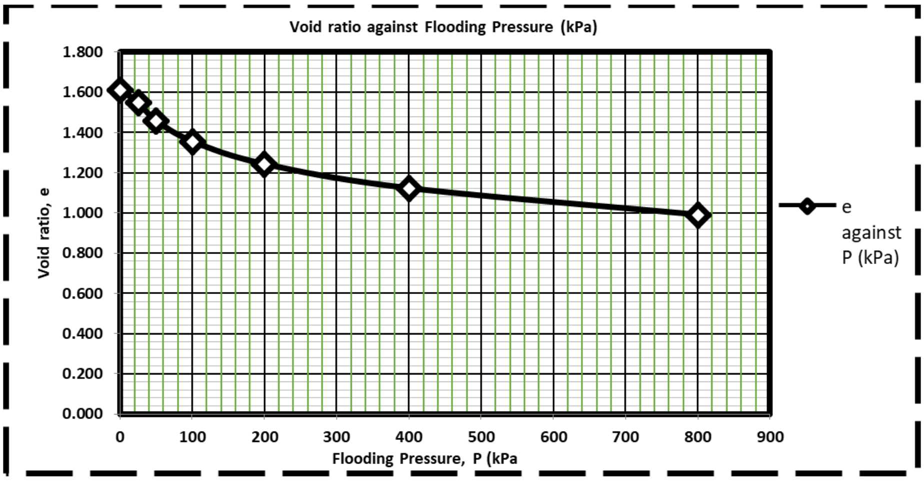

Fig. 3.1c: Collapse behaviour of Jattu Soil

IV. DEVELOPMENT OF NEURAL NETWORK MODEL

The proposed neural network model was developed using Microsoft Visual Studio 2010 and the MS .NET Framework 4.0 and source codes were written in C#. The model encompasses a training engine that can be fed with input data, learning rate, neurons, sigmoid function, momentum coefficient, and maximum iteration. A sample data file consisting of test results from consolidation and index tests is attached to the user document directory named prediction data. The Input data is formatted as an Excel sheet which can be imported to the system utilizing the imported data command. The necessary steps (i.e. data collection, model input selection, data division, model architecture, model optimization, and model validation) utilized to develop the model are described subsequently.

Equations Required to Optimize the Artificial Neural Network Algorithm

(4.1) below is required to calculate the local gradients (d) for the neurons in the network while Equation 4.3 is required to calculate the neurons output signals. Assume that the activation function in all the three neurons is sigmoid functions represented by the equation below:

$$\varphi(A) = \frac{1}{1 + \exp(-A)} \tag{4.1}$$

$$\varphi'(A) = \varphi(A)[1 - \varphi(A)] \tag{4.2}$$

$$\varphi'(A) = \frac{1}{1 + \exp(-A)}\left[1 - \frac{1}{1 + \exp(-A)}\right] \tag{4.3}$$

Refer to (4.4) to adjust the weights of the network using the learning rule:
w(n+1)=w(n)+α*w(n-1)+η*δ(n)*y (4.4)

Refer to (4.5) to adjust the bias of the network using the learning rule:
b(n+1)=b(n)+α*b(n-1) +η*δ(n)*y (4.5)

Where, φ = activation function, φ' = differential of activation function φ, w = connection weight, b = bias, D = local gradient:
α = momentum constant,

η = learning rate,
y = output neuron,
A = input neuron,
w (n+1) = new weight,
w (n) = previous weight

Model Architecture

Another essential and difficult task in the development of ANN models is to determine the model architecture. The proposed ANN is a three layers ''6-2-1'' network composed of an input, hidden and an output layer. The input layer is made up of six input source nodes (Pf, w0, e0, yd, n0 and LL) represented by X1, X2,.X6, with six corresponding neurons which are fed to the network. The hidden layer is made up of two neurons (n1 & n2) which receive input signal from the input layer and multiply them by the values of certain weights (Wij) to become the input values A1 & A2 going into the hidden neurons. The input values A1 and A2 to the hidden neurons are fed to an activation function to produce the output values y1 & y2 from the hidden neurons. The output values y1 and y2 are equally combined with certain weights to produce the input value A3 to the output layer neuron (n3). The input value A3 is further fed to an activation function to produce the output value y3 from the neuron of the output layer. Note that the output value y3 from the neuron of the output layer is called the predicted output from the network. In fact, the hidden layer is the layer where the entire computation is done. The weights represent the interconnection between the different neurons of the network. The output layer is made up of a single neuron which provides the output of the work. The network uses sigmoid activation function of 1.0 for both the hidden and the output neurons. Moreover, the model employs a supervised learning style utilizing the back-propagation algorithm to train the network. The algorithm comprises of two passes: A forward pass which transfers the input data in the forward direction from the input layer to output layer of the network. The pass finally closes behind by producing an output value as well compute an error value while leaving the weights intact. Basically, the error is computed by subtracting the desired (predicted) output from the targeted output produced. If the error is within acceptable range, then the network is trained with new set of input data; otherwise, a backward pass is executed. The backward pass is a reverse pass which propagates the error signal backward through the network layers in order to update the weights of the network using the local gradient values. Fig. 4.1 below shows the diagrammatic representation of the network architecture while (4.6) to (4.12) below show the mathematical calculations required for the network development and training.

Mathematical Calculations Required for the Network Development and Training

STEP 1: Calculate the local gradients (d0, dh1, and dh2) for the neurons in the network.

Assume that the activation function in all the three neurons have same sigmoid function as given in (4.3).
Learning rate η = 0.10, Momentum constant = 0.0, Activation function = 1.0, d3 = targeted output (experimented)
Let n1, n2, & n3 be the neurons in the network,
Let d0, dh1, and dh2 be the local gradients for the neurons in the network
Let A1, A2, & A3 be the inputs to the neurons n1, n2, & n3, Let y1, y2, & y3 be the output from the neurons n1, n2 & n3
But note that: y3 = actual (predicted) output of the network
(d3-y3)2 = error

Compute the Input and Output Signals to & from Neurons N1, N2 & N3 as:

Input signal to neuron n1
A1=X1*w11+X2*w12+X3*w13+X4*w14+X5*w15+X6*w16
Output signal from neuron n1
y1=φ(A1)= 1/(1+exp(-A1))
Input signal to neuron n2
A2=X1*w21+X2*w22+X3*w23+X4*w24+X5*w25+X6*w26
Output signal from neuron n2
y2=φ(A2)= 1/(1+exp(-A2))
Input signal to neuron n3
A3 = y1*w31+y2*w32
Output signal from neuron n3

$$y3 = \varphi(A3) = \frac{1}{1+\exp(-A3)}$$

Compute the Local Gradients for the Neurons

d0=φ' (y1*w31+y2*w32)*(d3-y3) (4.6)
dh1=φ'(X1*w11+X2*w12+X3*w13+X4*w14+X5*w15+X6*w16)(δo*w31) (4.7)
dh2=φ'(X1*w21+X2*w22+X3*w23+X4*w24+X5*w25+X6*w26)(δo*w32) (4.8)
Equations 4.6, 4.7 & 4.8 above can be re-written as:
d0=φ'(A3)*(d3-y3) (4.6')
dh1=φ'(A1)(δo*w31) (4.7')
dh2=φ'(A2)(δo*w32) (4.8')

But recall that:

$$\varphi' (A) = \frac{1}{1+\exp(-A)} [1 - \frac{1}{1+\exp(-A)}]$$

STEP 2: Adjust the weights of the network using the learning rule
Recalling (4.4) to update the weights during training process
w(n+1)=w(n)+α*w(n-1)+η*δ(n)*y
The meaning of each parameter remains the same as described above.
Using (4.4) above, the new weights of the back propagation can be estimated. If you have a certain weight during the forward pass, a new weight can be obtained by simply adding up the value of the previous weight using (4.3) during backward pass. For instance,

let's consider a new weight for weight w31, w32, w11…. wn in Fig. 4.1

w31(n+1)=w31(n)+α*w31(1-n)+η*δo(n)*y1 (4.9)

w32(n+1)=w32(n)+α*w32(1-n)+η*δo(n)*y2 (4.10)

w11(n+1)=w11(n)+α*w11(1-n)+η*δh1(n)*X1 (4.11)

w26(n+1)=w26(n)+α*w26(1-n)+η*δH2(n)*X6 (4.12)

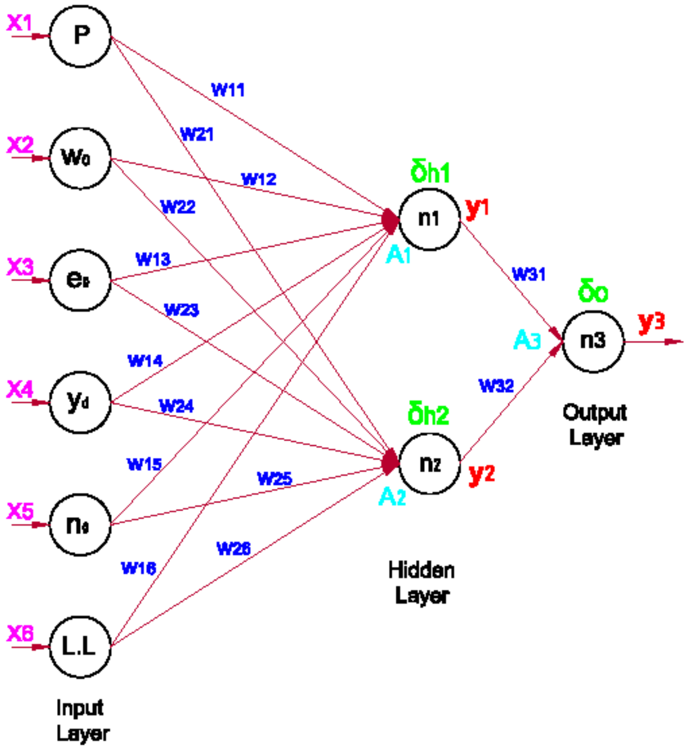

Fig 4.1: Back-propagation neural networks (BPNN) Architecture

D. Model Input Selection

An important step in developing the artificial neural network model is to select an appropriate set of input variables that have the most significant influence on the model performance. When selecting input variables, it is important to know that the number of variables will need to be as small as possible because:

i. The inclusion of variables that are not relevant, whose contribution to the output is smaller than the contribution of disturbances will lead to modelling errors.
ii. The inclusion of new input variables will require the addition of more parameters which can lead to the increase in the number of hidden neurons. Consequently, the processing speed decreases and network efficiency reduces (Lachtermacher and Fuller 1994) [4].

There are so many input selection strategies, but the one used in this research work was the trial and error approach. In this approach, many attempts are carried out using various combinations of input variables to train the ANN. The set of variables that produces the best performing output was selected to be the model input.

E. Data Division

The next step in the development of the ANN model is how to divide the data. The division of the available data into subdivisions is a vital segment in modeling with artificial neural networks. The major reason for this step is to check that the model is not over fitted which could happen during the training phase. The capacity of the model to commit to memory rather than oversimplify the form of the relationship between input and output data is called over fitting. The ANNs model have high tendency towards over fitting, particularly if training data is noisy. Hence, in order to develop a model that has the ability of generalization, the data are randomly divided into two sets: validation sets and training set. The model parameters are adjusted using the training data so as to reduce the error between the model output and the corresponding targeted output. The validation data are independent data that are not included in the training phase used to test the generalization ability of the model and verify its performance in the real world. Sometimes, when sufficient data are available, it can be divided into training, testing and validation. The training set is used for model parameter adjustment. The testing set is used to monitor the performance of the model during training stages and specify when to stop training in order to avoid over fitting. This option has advantage as it puts the performance of the developed model under serious scrutiny making it more dependable (Stone, 1974) [5]. The main aim of this step is to use the available data to obtain a model that is able to generalize the solution. To achieve this, the available data were divided into two statistically consistent sets: a training set, to construct the neural network model and an independent validation sets to estimate model performance in the deployed environment. However, recent studies have established that the way the data are divided can have a significant impact on the obtained results (Shahin, *et al.*, 2004) [6]. In total, 14 cases are used for training, 4 cases for validation. For good model prediction, the two sets of data, for each input and output variable are selected in such a way that they are statistically consistent and hence represent the same population. The statistical consistency of the data sets is achieved by applying the method discussed by Shahin *et al.*, (2004) [6]. In this method, the data are divided using 20% for validation set and 80% for the training set and the statistical parameters used are mean, standard deviation, maximum, minimum, median and variance, as shown in Tables 4.1, 4.2 & 4.3.

F. Model Validation

To assess the reliability of the ANN model and guarantees it's considered to be robust, the following criteria are used to evaluate the prediction performance as outlined by Shahin (2008) [1] and Smith (1986) [7]. These criteria include: coefficient of correlation, (R^2), and the root mean square error, (RMSE). Table 4.4 shows the computed values of coefficient of correlation, R^2, and RMSE for the built BPNN algorithm considering different network arrangements. A total of three network architectures were developed by varying the number of neurons in the hidden layers. The outcomes obtained indicate that model BPNN-2 (6-2-1), performs better, as it has higher coefficient of correlation and lowest RMSE value that shows a good agreement between observed and predicted values. The coefficient of correlation in the same way falls within the guide suggested by Smith (1986) [7].

Table 4.1: ANN Model Input and Output Statistics of Egelessor

Parameter Name/Symbol	Mean	Min.	Max.	Median	Variance	Standard Deviation
P_f (kPa)	225.00	0.00	800.00	100.00	71250.00	266.93
w_0 (%)	10.77	8.90	12.10	11.20	1.76	1.33
e_0	1.34	1.11	1.48	1.37	0.02	0.13
y_d (Mg/m3)	1.15	1.08	1.27	1.13	0.00	0.07
n_0 (%)	57.10	52.59	59.75	57.88	6.05	2.46
LL (%)	32.39	29.00	34.17	33.00	2.72	1.65
CP (%)	2.16	0.00	4.00	2.15	1.91	1.38

Table 4.2: ANN Model Input and Output Statistics of Egunor.

Parameter Name/Symbol	Mean	Min.	Max.	Median	Variance	Standard Deviation
P_f (kPa)	225.00	0.00	800.00	100.00	71250.00	266.93
w_0 (%)	10.16	8.40	11.80	10.30	1.25	1.12
e_0	1.22	0.95	1.41	1.25	0.03	0.16
y_d (Mg/m3)	1.21	1.11	1.37	1.19	0.01	0.09
n_0 (%)	54.64	48.58	58.50	55.45	11.15	3.34
LL (%)	39.04	33.00	43.33	39.33	13.11	3.62
CP (%)	2.76	0.00	4.80	3.00	2.34	1.53

Table 4.3: ANN Model Input and Output Statistics of Jattu

Parameter Name/Symbol	Mean	Min.	Max.	Median	Variance	Standard Deviation
P_f (kPa)	225.00	0.00	800.00	100.00	71250.00	266.93
w_0 (%)	9.19	7.70	11.50	9.20	2.20	1.48
e_0	1.33	0.99	1.61	1.36	0.04	0.21
γ_d (Mg/m3)	1.15	1.02	1.34			
n_0 (%)	56.80	49.80	61.75	57.57	16.17	4.02
LL (%)	35.12	33.80	36.20	34.65	0.84	0.92
CP (%)	3.40	0.00	5.05	3.95	2.52	1.59

Table 4.4: Performance of the Neural Network Model

Model	Network arrangeme	No. of hidden	R^2	RMSE
BPNN-1	6-1-1	1	0.852	166.646
BPNN-2	**6-2-1**	**2**	**0.856**	**166.199**
BPNN-3	6-3-1	3	0.796	165.955

RESULTS ANALYSIS AND INTERPRETATION

The analysis and interpretation of data is based on all the outcomes and observations available during the testing process of the collapsible soils. This section presents the discussions and observations of the influence of various parameters on soil collapsibility.

Influence of Flooding on Collapsibility of Soil

The values of void ratios of the representative soils are summarized in Table 3.1 to 3.3. While Figs. 3.1a, 3.1b & 3.1c display typical void ratio plots for all the soils. The results from single Oedometer test demonstrate that the residual soil from Northern Edo has high void ratios ranging from 0.945 to 1.614 and low initial dry densities from 1.021 to 1.373Mg/m3. These high values of void ratios can be ascribed to weathering which leads to a porous structure as a consequence of leaching of minerals from the soil. Generally, high void ratios and low initial dry densities are the most fundamental elements of residual soil. It was observed that when the specimens were flooded at any level of stress, they exhibited collapse and experienced incredible loss of particle strength. This loss of shear strength could be due to the reduction of the void volume as a result of the softening and breaking of the inter-particle bonds (matric suction) as well as reduction in the particle contacts. After this, the new profiles of the soil particles tried to reorganize themselves and densify into another structure with smaller volume.

Summary

Once the new weights of the network are known, a second forward pass can then be carried out to train the algorithm. If the computed error from the second pass is within acceptable range, the network will be trained with new set of input data; otherwise, a backward pass will be executed. This process continues until the error becomes very small or falls within acceptable range. In this research work, the process was carried out 1000 times before the acceptable error range was achieved. This iterative learning process helps the network to learn by adjusting the weights so as to be able to predict the correct output value to be closer to the target value.

VI. CONCLUSION

1. The collapse potential of the soil in the study area increases from 0.0% to 4.0% for Egelessor soil, 0.0% to 4.8% for Egunor soil and 0.0% to 5.05% for Jattu soil as the flooding pressure increases upon flooding. The collapse potential is an indication of the degree of volume change the soil exhibits due to the combined effects of load and flood. Hence, the soil from Egelessor and Egunor exhibited behavior of moderate trouble soil while that of Jattu indicates that of trouble soil as per Jennings and Knight, 1975 [2] classification.
2. The experimental outcomes indicated that when the soil in the study area would be flooded under various vertical pressures, it will experience noteworthy loss of particle strength

thus exhibiting unstable behaviour and collapse. This unstable nature could be that as the soil become flooded, the residual bond between the soil particles turns out to be weak as their voids appeared to become smaller, hence rearranged themselves in a denser formation.

3. It was witnessed that the collapse potential increases from 0.0% to 4.0% as initial void ratio decreases from 1.484 to 1.109 for Egelessor soil, correspondingly from 0.0% to 4.8% as void ratio decreases from 1.410 to 0.945 for the Egunor soil while that of Jattu has its collapse potential increasing from 0.0% to 5.05% with a corresponding decrease in void ratio from 1.614 to 0.992.
4. Based on Jennings and Knight (1975) [2] classification of collapse potential severity table, the potential severity of collapse for both Egelessor and Egunor soils have moderate trouble with collapse potential range of 0-4% and 0-4.8% while that of Jattu soil fall under trouble soil with collapse potential range of 0 to 5.05%.
5. The higher the initial dry density upon flooding, the higher the collapse potential that occurs.
6. This research only covered shallow depth of 0.6m to 1.2m of the residual soil of Northern Edo and the representative undisturbed soil samples were collected at locations where collapse phenomenon is prevalent. The ratio of the final change in volume of soil resulted from the single Oedometer test to the initial thickness of the sample is denoted as collapse potential, which depends on the flooding pressure, initial void ratio, initial dry density, initial porosity, Liquid limit and initial moisture content.
7. Based on the obtained experimental data, a feed-forward back-propagation neural network was developed to predict the soil collapse potential induced by flood. The outcomes show that model BPNN-2 (6-2-1), which utilized six input neurons in the input layer, two neurons in the hidden layer and one neuron in the output layer has the highest value of coefficient of correlation (R2) of 0.856 and the lowest value of RMSE of 166.199, hence, has the ability to predict the collapse potential of the residual soil of Northern Edo, Nigeria with an acceptable degree of accuracy.

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