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PREDICTION OF ULTIMATE BEARING CAPACITY OF BORED PILES WITHIN THE NIGERIAN PORTS ATHORITY, INDUSTRIAL AREA APAPA LAGOS USING ARTIFICIAL NEURAL NETWORK

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Abstract—In this study, Feed Forward Neural Network (FFNN) was used to predict the ultimate bearing capacity of bored piles. For the verification of applicability of Neural Networks, Meyerhof's formula was used to estimate the bearing capacities of piles and results were compared to ANN model predictions. One hundred and eleven (111) sets of data were used for the study, which are representative of over one thousand two hundred installed bored piles of diameter ranging from 450mm to 900mm and depth of 16m to 22m within the Nigeria Ports Authority Industrial Area, Apapa Lagos. The ANN model had five input parameters namely, Penetration depth ratio (**l/d**), Average standard penetration test number, N-value along the pile shaft ($\mathbf{N_{sa}}$) Average N-value near the pile end ($\mathbf{N_b}$) Effective vertical pressure at pile base ($\boldsymbol{\delta_v}$) Coefficient of earth pressure at rest ($\boldsymbol{k_o}$) and one single output, ultimate capacity ($\mathbf{Q_u}$). 70% of the data sets were used for the training of the ANN model while the remaining 30% was used for validation of the model. Twenty nine (29) data sets randomly selected from the results of training and validation were used in testing the ANN model. The results showed the existence of a strong correlation between the ANN model predictions and the targeted output, there was a correlation between the ANN model and Meyerhof's estimates. The ANN model developed had a correlation coefficient (R) of *0.965* and root mean square error (*RMSE*) of 228*kN.* The study shows that the ANN models gave good predictions of the ultimate bearing capacity of the bored piles.

Index Terms— Artificial Neural Network, Bored piles, Ultimate bearing capacity.

1 INTRODUCTION

Piles have been used for many years as a type of structural foundation. However, prediction of bearing capacity has been a difficult task because of various factors affecting the capacity and their uncertainties. Recent advances in soil mechanics and foundation engineering have provided useful information regarding the factors that affects bearing capacity, but the introduction of these factors to analysis and design is impractical, therefore most theoritical approaches have mainly been based on simplifications and assumptions [1].

Because of these difficulties, it has been commonly accepted that pile load testing is the best way to provide accurate bearing capacity predictions. Since pile load tests have been restricted by time and expense inspite of their reliability, engineers have developed a corelation between the results of pile load tests and insitu tests such as the standard penetration test (SPT) and cone penetration test (CPT). In recent times, artificial neural networks (ANN) have been applied to many geotechnical engineering tasks and have demonstrated some degree of success [2[, [3].

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Since pile load tests have been restricted by time and expense inspite of their reliability, engineers have developed a correlation between the results of pile load tests and in-situ tests such as the standard penetration test (SPT) and Cone Penetration Test (CPT). Most of the researches in piles bearing capacity prediction are based on driving data, soil properties and piles geometry for driven piles, not much work has been conducted on the areas of bored piles. This study therefore, investigateds the feasibility of using artificial neural networks in the predicting the bearing capacity of bored piles.

Maizir *et al.* [4] presented the development of ANN model for prediction of axial capacity of a driven pile based on Pile Driving Analyzer (PDA) test data. As many as three hundred (300) sets of high quality test data from dynamic load test performed at several construction projects in Indonesia and Malaysia were selected for this study. Inputs considered in the modeling are pile characteristics (diameter, length as well as compression and tension capacity), pile set, and hammer characteristics (ram weight, drop height, and energy transferred). An ANN model was developed in this study using a computerized intelligent system for predicting the total pile capacity as well as shaft resistance and end bearing capacity for various pile and hammer characteristics. The results show that the ANN serves as a reliable prediction tool to predict the resistance of the driven pile with coefficient of correlation (R) values close to 0.9 and mean squared error (MSE) less than 1% after ABOUT fifteen thousand (15,000) number of iteration process.

Tajdar [5], worked on "Prediction of ultimate pile bearing capacity using artificial neural networks" the researcher was guided by the similarity between pile and cone penetration test (CPT), he used the CPT results in predicting the piles bearing capacity. He used artificial neural networks to study the relation between cone tip and sleeve friction strength obtained from cone penetration test and ultimate pile bearing capacity, obtained from static pile load test. By comparing predicted ultimate pile bearing capacity by utilizing ANN with the numbers which are predicted by five (5) common traditional methods, the researcher found that using of artificial neural networks is a suitable method for predicting ultimate pile bearing capacity, compared to common traditional methods.

Shahin [6], worked on intelligent computing for modeling axial capacity of pile foundations. The researcher developed an artificial neural network using data collected from the literature which comprises eighty (80) driven pile and ninety four (94) drilled-shaft load tests, as well as CPT results. The predictions from the ANN models are compared with those obtained from the most commonly used available CPT-based methods, and statistical analyses were carried out to rank and evaluate the performance of the ANN models and CPT methods. To facilitate the use of the developed ANN models, they were translated into simple design equations suitable for hand calculations. The cone penetration test (CPT)-based models have been shown to give better predictions in many situations. This can be attributed to the fact that CPT-based methods have been developed in accordance with the CPT results, which have been found to yield more reliable soil properties; hence, more accurate axial pile capacity predictions.

Alkroosh [7], worked on modeling pile capacity and load-settlement behavior of piles embedded in sand & mixed soils using artificial intelligence. The study developed three ANN models: a model for bored piles and two models for driven piles (a model for steel and a model for concrete piles). The predictive ability of the models was verified by comparing their predictions in training and validation sets with experimental data. Statistical measures including the coefficient of correlation and the mean square error were used to assess the performance of the ANN models in training and validation sets. The results revealed that the predicted load-settlement curves by ANN models were in agreement with experimental data for both of training and validation sets. The results also indicate that the ANN models have achieved high coefficient of correlation and low mean values. This also indicates that the ANN models can predict the load-settlement of the piles accurately.

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2 METHODOLOGY

The ultimate bearing capacity of the pile foundations considered in this study were first estimated using the conventional capacity estimation method from data obtained from piling contractors that are actively involved in piling activities in the industrial area of the Nigerian Ports Authority, Lagos, Nigeria. An Artificial Neural Network (ANN) model was developed using the same set of data to predict the ultimate bearing capacity of the pile foundations. Statistical methods were used to compare the results of the conventional capacity estimation method and that predicted by the ANN model.

2.1 Pile Capacity Estimation by Conventional Method

Meyerhof [8] has correlated the shaft and base resistance of a pile with results of standard penetration test (SPT). For displacement piles in saturated sand, the ultimate load in U.S tons, is given for driven piles as:

$$Q_u = 4N_p \,.A_p + \frac{(N_{sa}\ A_s)}{50} \qquad (1)$$

N_p= standard penetration number N at pile base
N_{sa} = average value of N along pile shaft.

For small displacement piles e.g (bored piles and steel H piles)

$$Q_u = 1.2N_p \,.A_p + \frac{(N_{sa}\ A_s)}{100} \qquad (2)$$

Meyerhof's equation is further simplified into

$$Q_u\ (Mpa) = 0.4N_b + 0.002N_{sa} \qquad (3)$$

Equation three (3) is frequently used in practical design for routine check [2].

2.2 Artificial Neural Network (ANN) Model

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It was observed that Back-propagation neural networks (BPNN) and feed forward neural networks have a high capability of data mapping [9] and have been applied to a wide range of areas including classification, estimation, prediction, and functions synthesis [10]. Multi-layered Feed Forward neural network (FFNN) was adopted in this study.

The ANN model was design to received five (5) inputs and predicts one (1) output. The input parameters were Penetration depth/pile diameter ratio (l/d), Average standard pene-

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tration number; N-value along the pile shaft (N_{sa}), Average N-value near the pile end (N_b), Effective vertical pressure at pile base (δ_v) and the Coefficient of earth pressure at rest (k_o), while the output is the Ultimate Bearing Capacity (Q_U) as shown in figure 1.

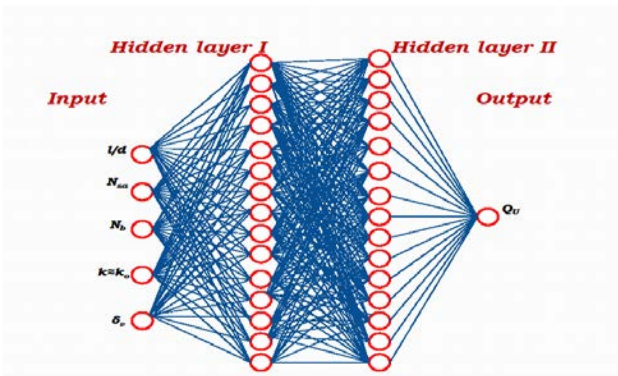

Fig. 1. Schematic Diagram for the Neural Network Model Adopted in the Study.

2.3 Study Area

The study area is Nigerian Ports Authority (NPA) industrial area, Apapa Lagos, Nigeria. Lagos is the commercial capital of Nigeria. It houses most of the major ports in Nigeria because of its boundary with the atlantic oceon. Most of the buildings at the vercinity of Apapa port are founded on pile foundation. Figure 2 shows the map of the study area.

Fig. 2. Study Area

One hundred and eleven (111) set of field data were used as representative samples of over one thousand two hundred installed piles obtained from piling contractors that are actively involved in piling activities in the industrial area of the Nigerian Ports Authority. The data set was randomly divided into three sets; A training set, used in determining the network weights; A validation set, used in estimating the network performance and decide when to stop training; and A prediction (or test) set, used in verifying the effectiveness of the stopping criterion and to estimate the expected performance in the future.

2.4 Statistical Analysis

The performance of the trained model after evaluation was measured using two statistical tools [11], namely Root Mean Squared Error (RMSE) and Correlation Coefficient (r^2). The coefficient of correlation showed the relative correlation between the ANN predicted values and that due to Meyerhof's for both the training and evaluation data set. A higher number means a better model, with a value of one (1) indicating a perfect statistical correlation and a value of zero (0) indicating there is no correlation. The RMSE is a measure of the differences between values predicted by a model and the values actually observed from the phenomenon being modeled or estimated. Since the RMSE is a good measure of accuracy, it is ideal if it is small.

3 ANALYSIS OF RESULTS

Table 1 shows a sample of data obtained from piling contractors working at the study area. The data showed the pile parameters and the measured ultimate bearing capacities. Table 2 shows some sample results of the predicted bearing capacitu from the ANN model, calculated bearing capacity using Meyerhof's equation and the targeted bearing capacitiy. Table 3 shows comparism using coefficient of correlation and root mean square error.

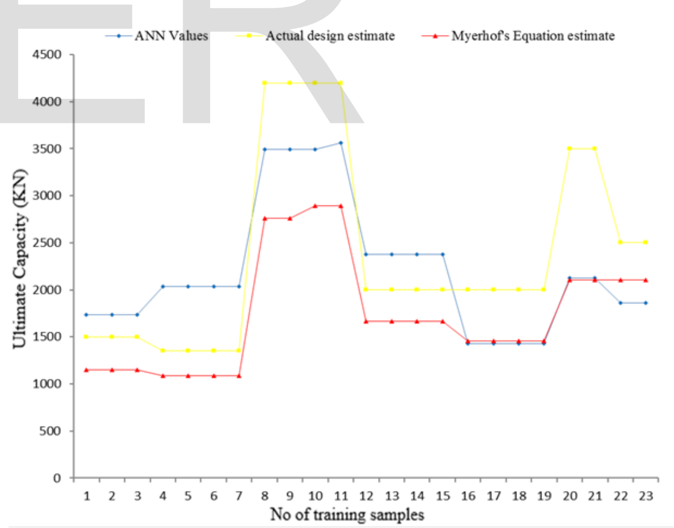

Fig. 3. ANN Predictions, Meyerhof's Estimates & Actual Estimates

The results illustrates that using ANN model, ultimate bearing capacity of piles (Q_U) can be better predicted than applying other methods such as the Meyerhof's equation, because the ANN predictions match closer to the targeted values as shown in fig. 3. This is confirmed by a high regression coefficient and lower value of RMS error, as well as insignificant scatter of results around the y = x diagonal line as shown in Table 3 and fig. 4.

Table 1: Samples of p*ile data used for training of ANNmodel*

			INPUTS					*TARGET*	
Case no	*D (mm)*	*L (m)*	*l/d*	N_{sa}	N_b	(k_s)	(δ_v) *KN/m*^{2}	(Q_U) *KN*	(Q_m) *KN*
1	*600*	*22*	*36.7*	*15*	*20*	*0.577*	*190.8*	*1139*	*1373*
2	*600*	*22*	*36.7*	*15*	*20*	*0.577*	*190.8*	*1139*	*1373*
3	*600*	*22*	*36.7*	*15*	*20*	*0.577*	*190.8*	*1139*	*1373*
4	*600*	*22*	*36.7*	*15*	*20*	*0.577*	*190.8*	*1139*	*1373*
5	*600*	*22*	*36.7*	*18*	*20*	*0.617*	*170*	*1563*	*1588*

Table 2: ***ANN results for validation model***

S/n	*ANN Model Predicted capacity*	*Targeted Capacity* (Q_U) *KN*	*Meyerhof 's capacity* (Q_m) *KN*	*Error (R) (Meyerhof 's)*	R^2 *(Meyerhof 's)*	*Error (R) (ANN model)*	R^2 *(ANN model)*
1	*1736.689*	*1500*	*1150*	*350*	*122500*	*-155.925855*	*24312.87*
2	*1736.689*	*1500*	*1150*	*350*	*122500*	*-155.925855*	*24312.87*
3	*1736.689*	*1500*	*1150*	*350*	*122500*	*-155.925855*	*24312.87*
4	*2032.768*	*1350*	*1086*	*264*	*69696*	*-376.496882*	*141749.9*
5	*2032.768*	*1350*	*1086*	*264*	*69696*	*-376.496882*	*141749.9*

Table 3: Correlation Coefficient and RMSE Comparison

Correlation coefficient		**Root mean square error**	
Model	Meyerhof's	Model	Meyerhof's
0.965	0.858	227.9	770.0

Table 4. Artificial Neural Network Input and Output Statistics

Model variables/ data sets	No of data	Statistical parameters				
		Mean	SD	Min	Max	Range
Penetration / diameter ratio (L/B)						
450mm	4	38.9	3.30	35.6	42.2	6.6
600mm	55	32.5	4.00	26.7	36.7	10.0
750mm	28	25.9	1.39	25.3	29.3	4.0
800mm	12	24.2	2.73	22.5	27.5	5.0
900mm	12	22.9	2.07	20.0	24.4	4.4
N-value along the pile shaft (Nsa)						
450mm						
600mm	4	17.0	2.23	16.0	18.0	2.0
750mm	55	17.3	2.12	15.0	20.0	5.0
800mm	28	16.7	1.45	15.0	20.0	5.0
900mm	12	18.3	2.87	15.0	22.0	7.0
	12	19.5	1.19	18.0	22.0	4.0
N-value at the pile base (N_b)						
450mm	4	17.0	2.23	16.0	18.0	2.0
600mm	55	17.3	2.12	15.0	20.0	5.0
750mm	28	16.7	1.45	15.0	20.0	5.0
800mm	12	18.3	2.87	15.0	22.0	7.0
900mm	12	19.5	1.19	18.0	22.0	4.0
Effective vertical pressure at pile base (δ_v)	4	151.0	12.73	142.0	160.0	18.0
450mm	55	174.0	18.91	140.0	200.0	60.0
600mm	28	171.4	15.78	155.0	200.0	40.0
750mm	12	173.3	12.47	160.0	170.0	10.0
800mm	12	176.7	17.32	160.0	200.0	40.0
900mm						
Coefficient of earth pressure at rest (k_o)						
450mm						
600mm	4	0.597	0.02	0.577	0.617	0.040
750mm	55	0.628	0.07	0.500	0.658	0.158
800mm	28	0.594	0.04	0.500	0.658	0.158
900mm	12	0.605	0.07	0.500	0.658	0.158
	12	0.605	0.07	0.500	0.658	0.158
Ultimate Bearing Capacity (Q_u)						
450mm	4	1125.0	125.0	1000.0	1250.0	250.0
600mm	55	1625.1	232.2	1139.0	2000.0	861.0
750mm	28	3057.1	258.3	2500.0	3500.0	1000.0
800mm	12	2833.3	235.6	2500.0	3000.0	500.0
900mm	12	3983.3	184.1	3750.0	4200.0	450.0

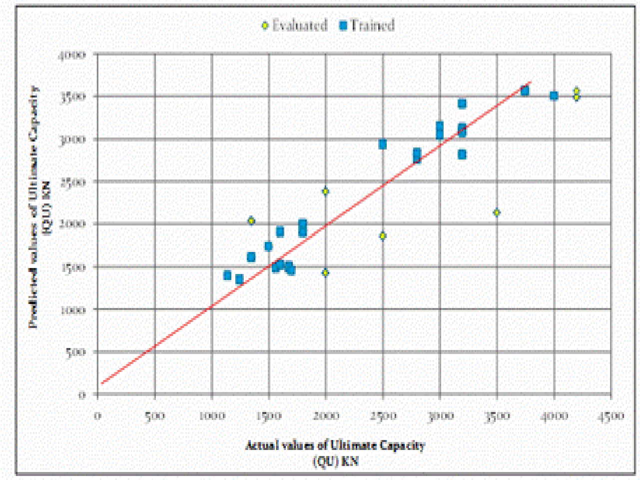

Figure 4: Cross plot ANN model prediction versus Targeted values

The ANN model designed has the ability to predict bearing capacity of bored piles with an acceptable degree of accuracy (r^2 =0.965 and RMSE=228KN) for predicted bearing capacity ranging from 1391 to 3561KN. The optimum network geometry was found to be 5-2-1 (i.e. five inputs, two hidden layer nodes and one output node). Artificial neural network have the advantage of being used as an accurate and quick tool for estimating the bearing capacity without the need to perform any manual work such as using tables or charts. Like all empirical models, the range of applicability of ANN is constrained by the data used in the model calibration phase and ANN should thus be recalibrated as new set of data becomes available. Despite the aforementioned limitations, the results of this study indicate that ANN has a number of significant benefits that makes it a powerful and practical tool for predicting the ultimate capacity of bored pile.

3 CONCLUSION

The suitability of the ANN technique in predicting the ultimate capacity of bored piles was investigated. An ANN model was trained, tested and validated in predicting the ultimate capacity of bored piles. The developed ANN model has the capability of making predictions with a fairly reasonable degree of accuracy; the model predictions are more accurate than Meyerhof's estimate. It can be used for routine checks for piles instead of pile load test which is expensive and time consuming. Based on the results of the study, it is evident that ANN perform well in terms bearing capacity prediction of bored piles in most of the data sets with a correlation coefficient of 0.896 and an RMSE of 100kN, it can be deduced that, the model results are at 90% of design values. The model is also limited to piles of sizes 450mm to 900mm diameter and lengths varying from 16m to 22m.

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