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# PREDICTION OF SOIL BEARING CAPACITY USING SOFT COMPUTING TECHNIQUES

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## ABSTRACT

*The nature and manner in which structures are collapsing in Nigeria are alarming. It creates a room in which structural engineers, the building industry, government, estate developers, building consultants and other relevant stakeholders in the department building industry ask many questions about how and what is behind the sudden collapse of structures. Therefore, this research aimed to predict the ultimate bearing capacity of the square, strip and circular footing from shearing strength parameters using ANN and ANFIS. This paper, 200 data sets were used to develop the model; 75% were used for training and 25% for testing the model. ANN and ANFIS learning algorithms were employed in developing the models under various foundation types. Eventually, Various error measures, such as coefficient of determination (R2), root mean square error (RMSE), mean absolute error (MAE), and correlation coefficient (R), were employed to compare the efficiency of the models. The performance comparison findings indicated that the soft-computing system is an efficient instrument for risk reduction in soil engineering projects. The models were validated using external data and the correlation prediction capacity of the models where ANN-STRIP (89%), ANN-SQUARE (83%), ANN-CIRCULAR (89%), ANFIS-STRIP (86%), ANFIS-SQUARE (79%) and ANFIS-CIRCULAR (96%). All the models have shown a quite good and reliable prediction capacity, with ANFIS-CIRCULAR having 96% prediction accuracy of soil bearing capacity.*

**Keywords:** *Neural network, neuro-fuzzy, cohesion, angle of internal friction*

## INTRODUCTION

Many ways of doing regression analysis have been developed. A vast variety of literature on linear regression methods, including ordinary least square regression as a parametric approach, has been reviewed by several academics. The nonparametric regression technique allows the correlation component to be included in a unified collection of functions [1]. Multiple regression analysis is a well-known statistical method for depicting the interlinkages between a combination of dependent and independent variables, according to Ul-Saufie et al. [2]. MLRA is a well-known method that illustrates the link that exists between a group of dependent and independent variables in their research utilizing statistical methodologies [2].

All engineering structures are supported by soil. Several researchers have classified soil properties into three (3) categories: physical (color, porosity, structure, texture); chemical (PH, salinity, cation exchange capacity (CEC), organic material, C - N ratio (carbon, nitrogen); and mechanical (bearing capacity, permeability, seepage, shear strength, lateral earth pressure) [1],[3]. Another of the various tactics and techniques used in researching soil properties is modeling techniques. Multiple linear regressions are one of the modeling tools used to investigate the connection between a dependent variable and numerous independent variables [4]-[6]. It is a more sophisticated variant of the basic linear regression model. He continues by stating that in multiple linear regression models, an error term is assumed to be normally distributed with mean and variance (which are constant), soil mechanics and foundation engineering are used to identify soil properties adsorption using statistical analysis and regression step-by-step using Microsoft Excel [7]-[8].

Many researchers have used machine learning to investigate and predict the bearing capacity of soil; for an instant, Namdarvand et al. [9] used an Artificial Neural Network (ANN) and several linear regressions to compare the predictions of soil pore size distribution. As per the researchers, multiple-linear regression models are also effective for estimating microbial load in a drinking water source. Multiple-linear regression is a statistical technique used to describe data and the relationship between one dependent variable and two or more independent variables [10]. For instance, thoroughly investigated the generic structure of regression models as an error. This technique makes a linear connection that fully reflects all data points. In contrast, MLRA is a statistical approach that predicts a response variable's outcome by integrating many explanatory factors. MLRs are used to simulate the association between the variables and response variables.

The superiority of using soft computing techniques stems from their capacity for storing, learning, and capturing the intricate relationships between many variables without any prior assumptions on the bearing capacity ratio. As a result, this study employed two approaches for soft computing, namely Artificial Neural Network (ANN), and Adaptive Neuro-Fuzzy Inference System (ANFIS), to predict the bearing capacity of the strip, square and circular footing.

## METHODOLOGY

### Data Collection

Secondary data sources included Bayero University Kano, the Kano State Ministry of Works, the Kano University of Science and Technology Wudil's department of civil engineering library, and previous research. The data includes shear strength properties such as cohesion and angle of internal friction (c), as well as ultimate bearing capacity. We acquired 45 sets of data from KUST Wudil, 115 sets of data from BUK Kano, 15 sets of data from Kano State's Ministry of Works, and 25 sets of data from previous research. Out of 200 datasets, 175 were used for modeling and 25 for model validation.

### Artificial Neural Network (ANNs)

Artificial Neural Network (ANN) applies the model structure of a neural network, which is a very effective computational technique for modeling complicated non-linear interactions, particularly when the explicit form of the relationship between the variables involved is unclear [11]. ANNs are generally computational models that integrate a human-like cognitive process [12]. This algorithm is a cornerstone of artificial intelligence (AI) and is frequently used to solve curve fitting problems [13]. Nearly every field has approximation challenges, however, it is possible to design and build an ANN to model complicated systems. Numerous interconnected layers comprise its multilayer structure packed with neurons. The three basic components of this method are a shifting function, a network topology, and a learning algorithm. Recurrent neural networks and feed-forward (FF) neural networks are the two main subclasses of ANNs. The implementation of FF is possible even in the absence of time-dependent components because its behavior is not time-dependent. Three layers make up the multilayer perceptron (MLP) that makes up an ANN: one input layer, one or more hidden layers, and one output layer. Instead of being composed of computational neurons or microprocessors, as are the hidden and output layers, Non-computational neurons make up the input layer, which gathers data from the outside world [12]-[14] energy, and cost and also provide information about scheduling for construction and framework removal. In this study, Artificial Neural Network (ANN). Another node that can be found in the hidden and output layers is biased. Through connections known as weights, neurons in the input, hidden, and output layers are successively connected to one another. Figure 1 shows an ANN's structure as well as the computations carried out by each computation.

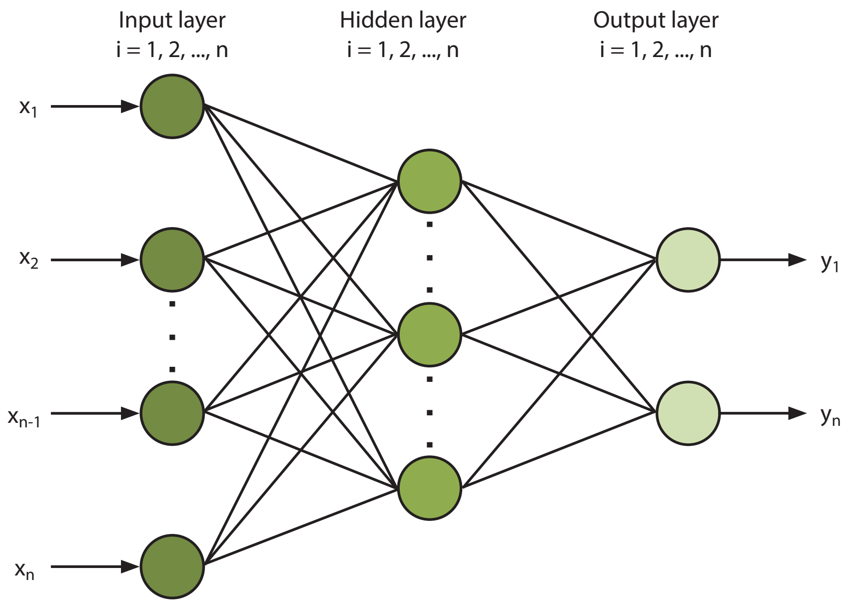


**Figure 1** Architecture of a typical feed forward ANN [15]

## Adaptive Neuro-Fuzzy Inference System (ANFIS)

### *ANFIS Architecture*

Jang initially unveiled the Adaptive Neuro-Fuzzy Inference System technology in 1993 [16]. ANFIS is a straightforward data learning approach that uses Fuzzy Logic to turn supplied inputs into desired outputs using highly linked Neural Network processing units and weighted information connections that map numerical inputs to outputs [5]. In other words, Jang created ANFIS in 1993, which combines the benefits of two machine learning algorithms (fuzzy logic and neural networks) [13]. An ANFIS tunes the parameters of a Fuzzy Inference System utilizing Neural Network learning techniques (FIS). There are several traits present. The following variables contribute to ANFIS's success.

1. It improves fuzzy IF-THEN rules to explain the behavior of a complex system.
2. It requires no prior human ability and is simple to use.
3. It allows for quick and precise learning.

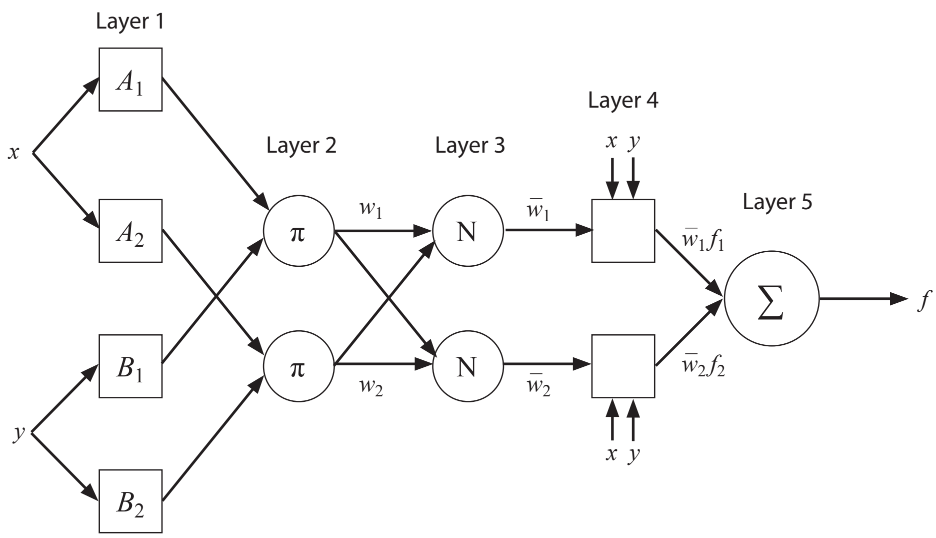


**Figure 2** ANFIS architecture

4. It provides the necessary data collection; a larger selection of membership functions to apply; powerful generalization capabilities; outstanding explanation capabilities via fuzzy rules; and;
5. It is simple to use both language and numerical expertise to problem solving [5]-[17].

The same return classifier cannot be shared by several rules. The number of rules must be equal to the number of classifiers. Two fuzzy IF-THEN rules based on a first order Sugeno model are used to show the ANFIS architecture [13]:

Rule $_{(1)}$: IF $x$ is A1 AND $y$ is B1, THEN

$$f1 = p1x + q1y + r1$$

Rule $_{(2)}$: IF $x$ is A2 AND $y$ is B2, THEN

$$f2 = p2x + q2y + r2$$

where, $x$ and $y$ are the inputs, A1 and B1 are the fuzzy sets, $f1$ are the outputs inside the fuzzy area defined by the fuzzy rule and the design parameters $p1$, $q1$, and $r1$ are determined throughout the training procedure.

Figure 2 depicts the reasoning method for the Sugeno model, which is the foundation for the ANFIS model. The ANFIS architecture utilized to implement these two rules. In this diagram, a circle represents a fixed node, whereas a square represents an adaptable node. ANFIS is built on a five-layer design.

All of the nodes in layer 1 are adaptive nodes. Layer 1 produces the fuzzy membership grade of the inputs, which is determined by the following expression:

$$O_{i,i} = \mu_{Ai}(x),\ i = 1,2 \tag{1}$$

$$O_{1,i} = \mu_{Bi} - 2(y),\ i = 3,4 \tag{2}$$

where, the inputs to node I are $x$ and $y$, and the linguistic labels (high, low, etc.) associated with this node function are $Ai$ and $Bi$. Any fuzzy membership function can be used by $\_Ai(x)$ and $\_Bi\text{-}2(y)$. If the bell-shaped membership function is used, for example, $\_Ai(x)$ is provided by,

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right] b_i} \tag{3}$$

Or Gaussian membership function by:

$$\mu_{Ai} = \exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \tag{4}$$

where, $a_i$, $b_i$, and $c_i$ are the membership function parameters.

The nodes in Layer 2 are fixed nodes. This layer employs fuzzy operators, namely the AND operator, to fuzzify the inputs. They are marked with it to indicate that they function as a basic multiplier. This gradient output may be expressed as:

$$O_{2,i} = w_i = \mu_{Ai}(x) {*}\ \mu_{Bi}(y)\ ,\ i = 1,2 \tag{5}$$

These are the rules' so-called firing strengths. In Layer 3, the nodes are likewise fixed nodes labeled with N, indicating that they provide a leveling role to the prior layer's firing strengths. This layer's output may be expressed as:

$$O_{3,i} = \tilde{\omega}_i = \frac{w_i}{w_1 + w_2},\ i = 1,2 \tag{6}$$

This layer's outputs are referred to as standardized firing strengths. The nodes in Layer 4 are adaptive. Each node in this layer's output is just the product of normalized firing strength and a first order polynomial (for a first order Sugeno model). This layer's output is expressed as,

$$O_{4,i} = \tilde{\omega}_i f_i = \tilde{\omega}_i\ (p_i x + q_i y + r_i),\ i = 1,2 \tag{7}$$

where $\tilde{\omega}_i$ is the output of Layer 3, and $p_i$, $q_i$, and $r_i$ are the consequent parameters.

Only one fixed node is labeled with P in Layer 5. This node computes the total of all incoming signals. The model's aggregate output is given by:

$$O_{5,i} = \textstyle\sum_i \tilde{\omega} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \tag{8}$$

**Model Validation**

Once the model's training segment has been successfully finished, the trained model's performance should be verified. The purpose of the model validation step is to confirm that the model can simplify within the limits of the training data. Erroneous criteria such as the coefficient of correlation (R), the root mean squared error (RMSE), and the mean absolute error (MAE) are frequently used to evaluate model performance (MAE). The correlation coefficient is a measure of the relative correlation and goodness-of-fit between calculated and observed data.

**Performance Efficiency Criteria**

Upon successfully completing the model's training segment, the trained model's performance should be validated and presented in Tables 3 and 4. The calibration and validation phase's purpose is to guarantee that the model can simplify while adhering to the limitations given by the training data. Error measures such as the coefficient of correlation (R), the root mean squared error (RMSE), the mean square error (MSE), and the coefficient of determination are widely used to evaluate model performance (R2). The Pearson correlation is a statistic for measuring the relative correlation and goodness-of-fit between predicted and observed data. The RMSE is the most often used error metric since it is capable of identifying big mistakes than minor flaws. Yet, RMSE cannot always ensure optimal model performance. On the other hand, the value of R should be between 0 and 1 as well as there are 45 rules for determining the model's success. If |R| 0.8, there is a high correlation; if |R| 0.2, there is a correlation; and if |R| 0.2, there is a weak connection. When the value of |R| is larger than 0.9, the variables have a very strong association. Table 4 reveals that the values of |R| are larger than 0.9, indicating a very strong relationship between observed and projected values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_p - y)^2} \quad (9)$$

The mean absolute error (MAE) is a measure of the difference in error between two observations reflecting the same phenomena. The mean absolute error is calculated as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_p - y| \quad (10)$$

The coefficient of correlation (R) value represents the linear connection between the predicted and actual values. The following formula is used to compute the R value.

$$R = \frac{n(\sum y.y_p) - (\sum y)(\sum y_p)}{\sqrt{\left[n\sum y^2 - (\sum y)^2\right]\left[n\sum y_p^2 - (\sum y_p)^2\right]}} \quad (11)$$

$$\text{Mean of the observed data} = \bar{y} = \frac{1}{n}\sum(y_i) \quad (12)$$

$$\text{Total sum of square} = \sum_{i=1}^{n}(y_p - \bar{y})^2 \quad (13)$$

$$\text{Residual sum of square} = \sum_{i=1}^{n}(y_p - y_p)^2 \quad (14)$$

$$\text{Coefficient of determination } R^2 = 1 - \frac{\textit{Total sum of residual}}{\textit{Total sum of square}} \quad (15)$$

where $y$ and $y_p$ are the actual and anticipated values, respectively, and p represents the average of the actual and anticipated values, respectively. The sample size is denoted by n.

**Table 3** Performance criteria between observed and predicted values using models

| Performance Criteria | | | | |
|---|---|---|---|---|
| **ANN** | | | | |
| **Foundation Type** | **R2** | **MAE** | **RMSE** | **R** |
| Strip | 0.898 | 19.555 | 132.612 | 0.948 |
| Square | 0.838 | 89.487 | 198.281 | 0.916 |
| Circular | 0.894 | 34.620 | 153.762 | 0.946 |
| **ANFIS** | | | | |
| | **R2** | **MAE** | **RMSE** | **R** |
| Strip | 0.868 | 61.075 | 151.320 | 0.932 |
| Square | 0.794 | 133.988 | 224.098 | 0.891 |
| Circular | 0.966 | 93.567 | 195.757 | 0.983 |

**Table 4** Correlation coefficient (R) between observed and predicted values

| Foundation Type | Model | |
|---|---|---|
| | ANN | ANFIS |
| Strip | 0.967 | 0.963 |
| Square | 0.985 | 0.992 |
| Circular | 0.968 | 0.952 |

## RESULT AND DISCUSSION

### Validation of Soil Bearing Models

The bearing capacity of the models and the estimated bearing capacity are shown in the tables below. Figures 3 to 8, which are plots of model bearing capacity vs estimated bearing capacity, were utilized to assess the model's quality further. The charts demonstrate a good link between the model bearing capacity and the estimated bearing capacity since both have $R^2$ values larger than 0.75 (75 percent).

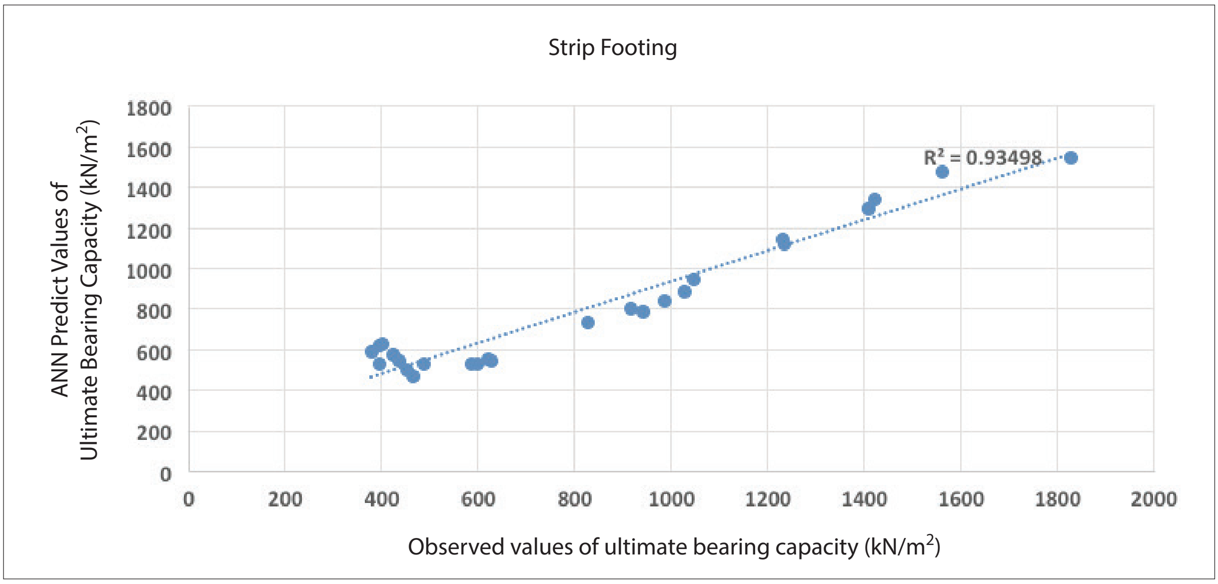


**Figure 3** Model versus calculated ultimate bearing capacity for strip foundation

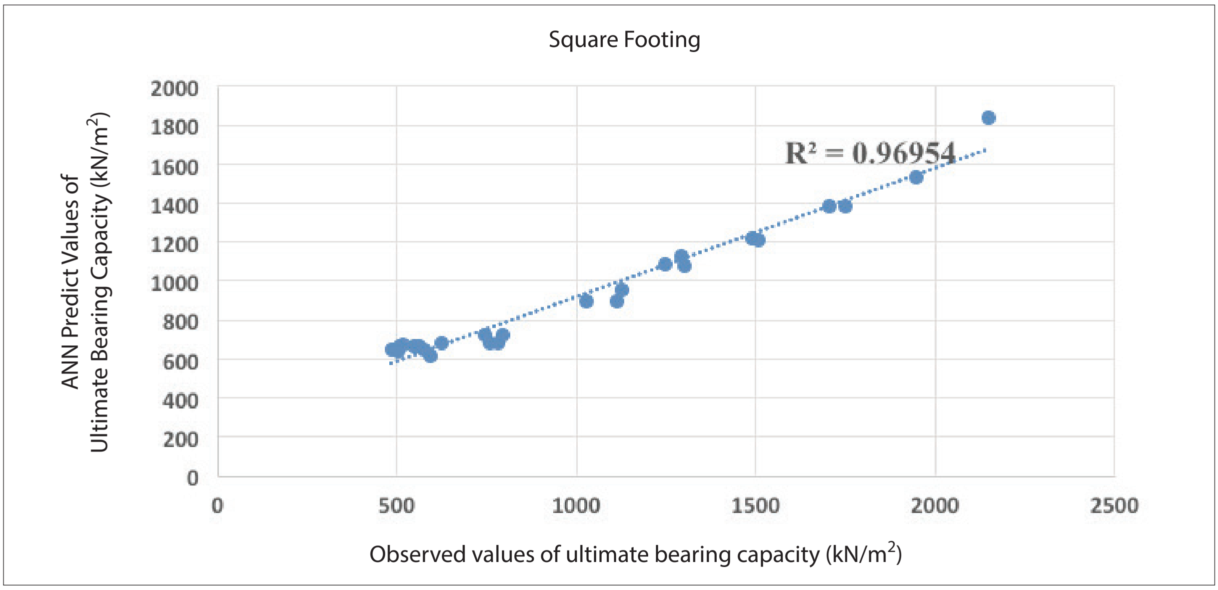


**Figure 4** Model versus calculated ultimate bearing capacity for square foundation

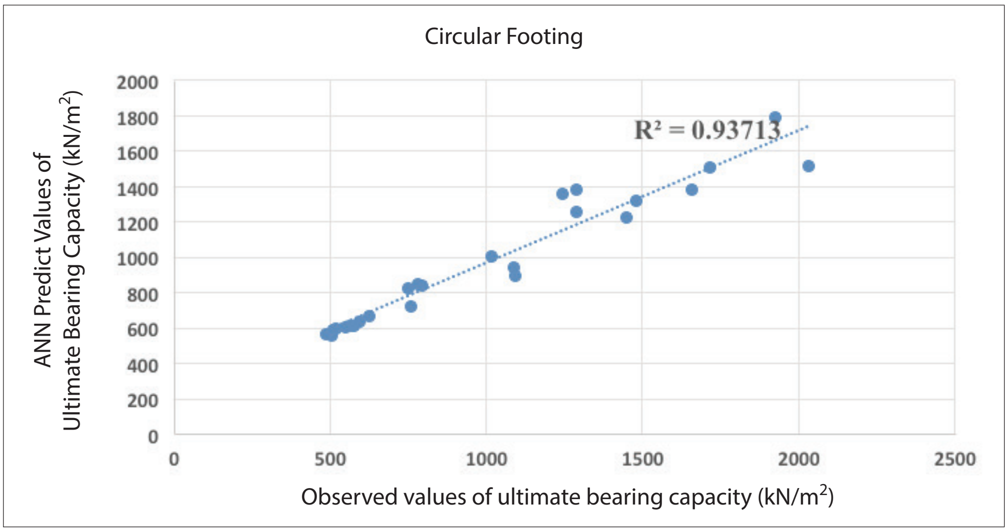


**Figure 5** Model versus calculated ultimate bearing capacity for circular foundation

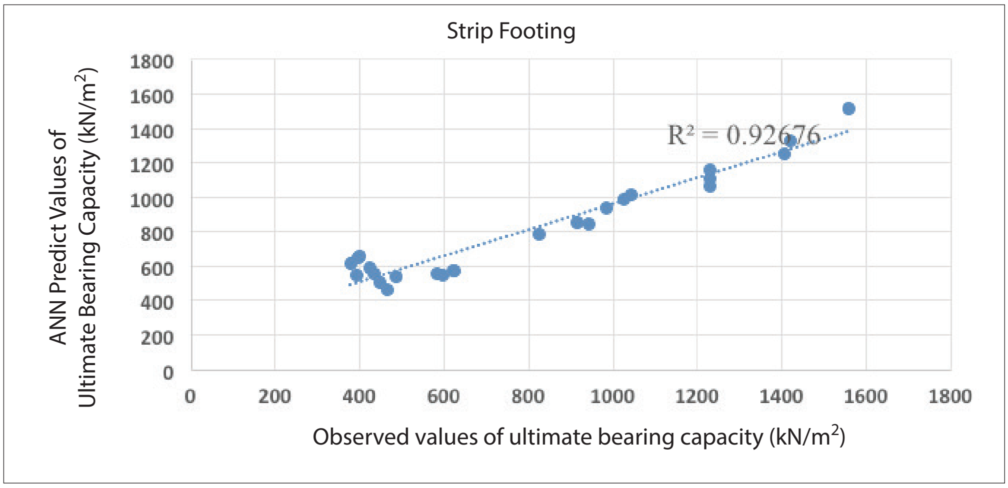


**Figure 6** Model versus calculated ultimate bearing capacity for strip foundation

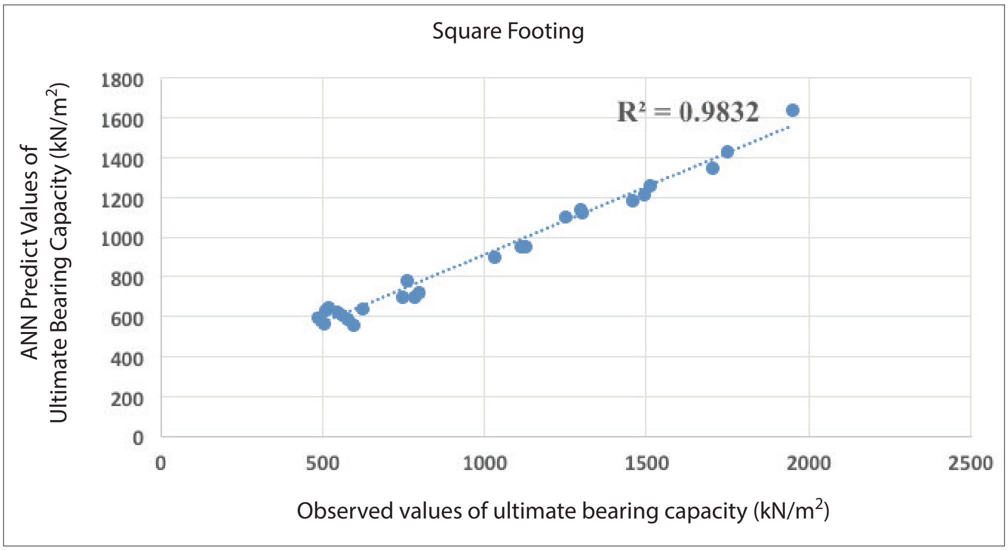


**Figure 7** Model versus calculated ultimate bearing capacity for square foundation

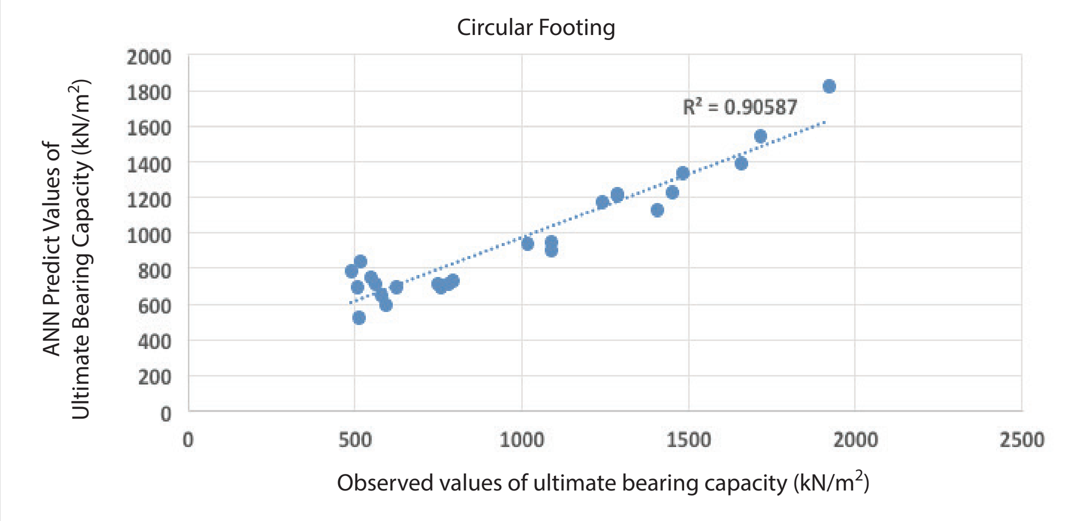


**Figure 8** Model versus calculated ultimate bearing capacity for circular foundation

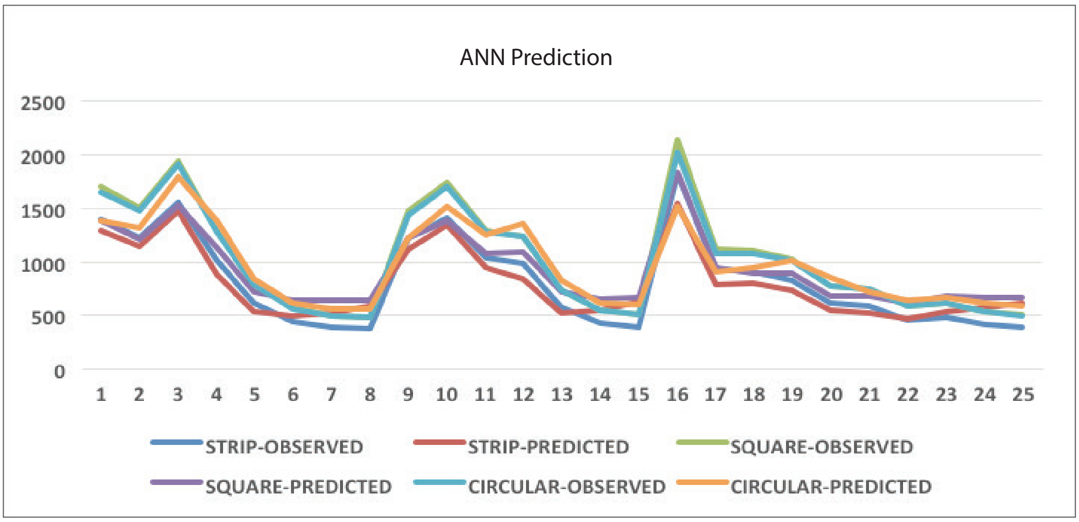


**Figure 9** Comparing observed and predicted values of ultimate bearing capacity

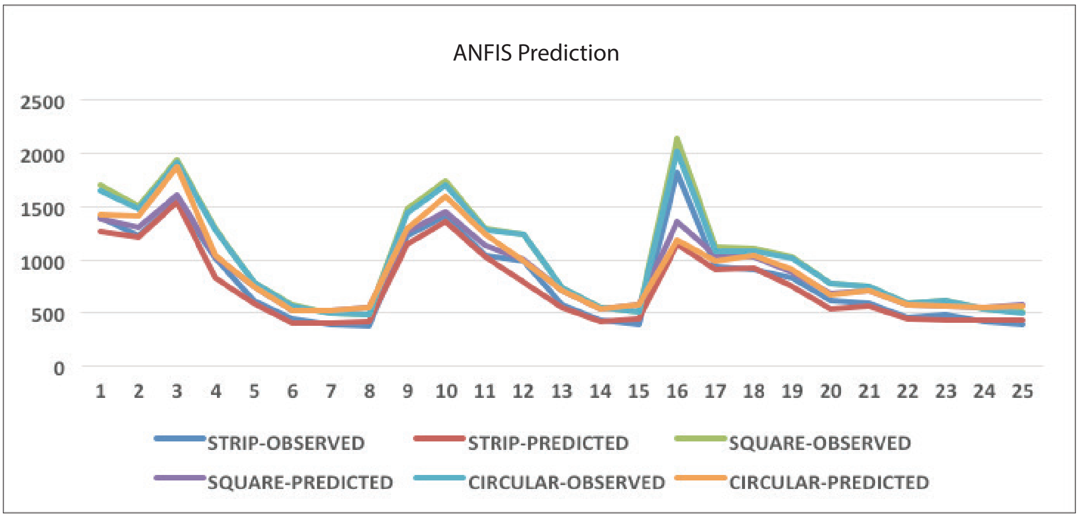


**Figure 10** Comparing observed and predicted values of ultimate bearing capacity

## CONCLUSIONS

The main aim of this paper was to develop a model using shear strength parameters; the ultimate bearing capacity of square, strip and circular footings were predicted by different artificial intelligence models (ANN and ANFIS). A database comprising cohesion, angle of internal friction, and ultimate bearing capacity of strip, square, and circular footing was a total data set of 200. The ANN and ANFIS models were used to calculate the ultimate bearing capacity of strip, square, and circular foundations. To assess the models, this study used a total of 25 external sets of data. The observed and predicted ultimate bearing capacity of the strip, circular, and square footings are close to the correlation coefficients reported in Table 4. ANN is somewhat better than in strip and square footing prediction, whilst ANFIS is marginally better than ANN in circular footing prediction.

## RECOMMENDATIONS

As per the findings of this study, machine learning is a very potent tool for modeling the relationship between shear strength parameters and the ultimate bearing capacity of shallow foundations. Other evolutionary computation technologies should be explored while developing models of soil ultimate bearing capacity. Future research should look at deep foundations and alternative bearing capacity equations in addition to Terzaghi's.

## REFERENCES


[1] J. G. Egbe, D. E. Ewa, S. E. Ubi, G. B. Ikwa, & O. O. Tumenayo, "Application of multilinear regression analysis in modeling of soil properties for geotechnical civil engineering works in Calabar South", *Nigerian Journal of Technology*, 36, 4, pp. 1059, 2018, doi: https://doi.org/10.4314/njt.v36i4.10

[2] A Z. Ul-Saufie, A. S. Yahya, & N. A. Ramli, "Improving multiple linear regression model using principal component analysis for predicting PM 10 concentration in Seberang Prai , Pulau Pinang", *International Journal of Environmental Science*, 2, 2, pp. 403–410, 2011.

[3] A. Y. Abdulfatah, M. Umar, & A. Idris, "Modelling and Prediction of Compaction Parameters Based on Atterberg Limits and Clay Content", *Journal of Engineering and Technology (JET)*, 9, 2, pp. 24–27, 2014.

[4] S. I. Abba, S. J. Hadi, & J. Abdullahi, "River water modelling prediction using multi-linear regression, artificial neural network, and adaptive neuro-fuzzy inference system techniques", *Procedia Computer Science*, 120, pp. 75–82, 2017, doi: https://doi.org/10.1016/j.procs.2017.11.212

[5] S. I. Malami, F. H. Anwar, S. Abdulrahman, S. I. Haruna, S. I. A. Ali, & S. I. Abba, "Implementation of hybrid neuro-fuzzy and self-turning predictive model for the prediction of concrete carbonation depth: A soft computing technique", *Results in Engineering*, 10, p. 100228, 2021, doi: https://doi.org/10.1016/j.rineng.2021.100228

[6] F. Khademi, M. Akbari, S. M. Jamal, & M. Nikoo, "Multiple linear regression, artificial neural network, and fuzzy logic prediction of 28 days compressive strength of concrete", *Frontiers of Structural and Civil Engineering*, 11, 1, pp. 90–99, 2017, doi: https://doi.org/10.1007/s11709-016-0363-9

[7] Y. L. Kuo, M. B. Jaksa, A. V. Lyamin, & W. S. Kaggwa, "ANN-based model for predicting the bearing capacity of strip footing on multi-layered cohesive soil", *Computers and Geotechnics*, 36, 3, pp. 503–516, 2009, doi: https://doi.org/10.1016/j.compgeo.2008.07.002

[8] E. Momeni, D. J. Armaghani, S. A. Fatemi, & R. Nazir, "Prediction of bearing capacity of thin-walled foundation: a simulation approach", *Engineering with Computers*, 34, 2, pp. 319–327, 2018, doi: https://doi.org/10.1007/s00366-017-0542-x

[9] F. Namdarvand, A. Jafarnejadi, & G. Sayyad, "Estimation of Soil Compression Coefficient Using Artificial Neural Network and Multiple Regressions", I*nt Res J Appl Basic Sci* 4, 10, pp. 3232–3236, 2013.

[10] F. E. Eregno, V. Nilsen, R. Grøndahl-Rosado, R. Seidu, M. Myrmel, & A. Heistad, "Multiple Linear Regression Models for Estimating Microbial Load in the Drinking Water Source Case from Glomma River , Norway", *Vann*, 44, 2013.

[11] A. J. Tenza-Abril, Y. Villacampa, A. M. Solak, & F. Baeza-Brotons, "Prediction and sensitivity analysis of compressive strength in segregated lightweight concrete based on artificial neural network using ultrasonic pulse velocity", *Construction and Building Materials*, 189, pp. 1173–1183, 2018, doi: https://doi.org/10.1016/j.conbuildmat.2018.09.096

[12] A. Hammoudi, K. Moussaceb, C. Belebchouche, & F. Dahmoune, "Comparison of artificial neural network (ANN) and response surface methodology (RSM) prediction in compressive strength of recycled concrete aggregates", *Construction and Building Materials*, 209, pp. 425–436, 2019, doi: https://doi.org/10.1016/j.conbuildmat.2019.03.119

[13] E. M. Golafshani, A. Behnood, & M. Arashpour, "Predicting the compressive strength of normal and High-Performance Concretes using ANN and ANFIS hybridized with Grey Wolf Optimizer", *Construction and Building Materials*, 232, p. 117266, 2020, doi: https://doi.org/10.1016/j.conbuildmat.2019.117266

[14] X. Zhang, M. Z. Akber, & W. Zheng, "Prediction of seven-day compressive strength of field concrete", *Construction and Building Materials*, 305, p. 124604, 2021, doi: https://doi.org/10.1016/j.conbuildmat.2021.124604

[15] A. Idris & A. Y. Abdulfatah, "Predicting shear strength parameters from compaction parameters of soil using an artificial neural network", *Civil-Comp Proceedings*, 92, pp.1–10, 2009, doi: https://doi.org/10.4203/ccp.103.36

[16] J. R. Jang, "ANFIS: Adap tive-Ne twork-Based Fuzzy Inference System", *IEEE transactions on systems, man, and cybernetics* 23, 3, pp. 665-685, 1993.

[17] D. Karaboga & E. Kaya, Adaptive network based fuzzy inference system (ANFIS) training approaches: a comprehensive survey", *Artificial Intelligence Review*, 52, 4, pp. 2263–2293, 2019, doi: https://doi.org/10.1007/s10462-017-9610-2