Empirical Formulas to Predict the Axial Capacity of Driven Piles Using in-Situ Dynamic Load Testing Data

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Abstract—**Accurate estimation of the axial capacity of driven piles is crucial and leads to more economical design. In this research, Artificial neural networks (ANNs) and regression analysis (RA) have been used to develop empirical formulas to estimate piles' axial capacity using experimental dynamic load testing data. The RA model was further improved using a nonlinear fitting software "Eureqa", based on artificial programming. Three input variables were used to build the formulas; these variables are pile cross-sectional area, friction angle at pile tip, and effective stress at pile tip. Simplified mathematical expressions are presented to be used as empirical formulas to estimate piles' axial capacity. An optimize formula was developed using ANNs; it has a coefficient of determination (R^2) of 0.92, root mean square error (RMSE) of 478.11, and mean absolute error (MAE) of 366.67. On the other hand, the improved RA formula has R2 of 0.86, RMSE of 450.1, and MAE of 416.91. The results indicated that the predictions of ANNs formula are in close agreement with the experimental data.**

Index Terms—**Axial capacity, driven piles, neural network, regression.**

I. INTRODUCTION

Piles are structural members that are made of steel, concrete, or timber. They are more expensive than shallow foundations. In spite of their cost, utilizing piles is often necessary to meet structural loading conditions. Piles are used to transfer surface loads to lower levels in the soil mass. The load transfer mechanism may be a vertical distribution of the load along the pile or a direct application of pressure to a deeper layer through the pile point. A vertical distribution of the load is made using a friction pile, and a direct load is made by a point, or end bearing pile.

Most piles carry the load as a mixture of side resistance and end-bearing with the exception when the pile penetrates a significantly soft soil to a solid base. Vertical distribution of the load is made using a

Estimation of the pile's load carrying capacity is a significant factor in the design and construction of driven piles. It is essential to calculate the required cross-section and length of the pile based on the loading of the superstructure, allowable stress of the pile material, and the in-situ soil parameters. Analytical and empirical estimation of axial capacity of piles based on soil properties has improved significantly. However, the results are still questionable because of many issues such as soil profile inconsistency, interpretation of geotechnical exploration data, and various assumptions used in the calculation methods in addition to disturbance during the driven pile installation.

Static load test (STL) is considered the best available method to estimate the ultimate capacity of piles. However, the SLT is not preferred by geotechnical engineers because of its high cost and time-consuming. In some circumstances such as a very soft soil near the surface and marine environment, the test is uncontrollable due to the large pile setup.

Dynamic formulas were introduced to estimate the capacity of driven piles. However, the methods are inexact due to the simplicity in representing the driving system, soil-pile-structure interaction, and the distribution of soil friction along the pile. Therefore, most design codes require many SLT, as required by the ASTM-D5780-10, to be implemented during the pile driving production phase to guarantee the actual capacity of the piles.

High strain dynamic pile test (HSDPT) was formed to produce data on strain or force and acceleration of a driven shaft when subjected to impact load. The collected data is employed to estimate the bearing capacity and the structural integrity of the driven pile as well as hammer performance, pile stresses and soil properties such as damping coefficients and quake values. The procedure is regulated in the ASTM-D4945-08.

When determining the axial capacity, geotechnical engineers have been using Pile Driving Analyzer (PDA) combined with Case Pile Wave Analysis Program (CAPWAP) software which is the most widely used method for HSDPT because it is simple and can quickly handle data.

Likins *et al.* [1] concluded that, if performed and interpreted correctly, the high strain dynamic restrike testing with CAPWAP analysis can provide agreement with the results of SLT regarding design capacity.

Many researchers have utilized artificial neural networks (ANNs) and regression analysis (RA) as tools to develop predictive models for various geotechnical engineering problems. Tarawneh [2] employed ANNs to estimate the N-value of the standard penetration test (SPT) using the cone penetration test (CPT) results. Tarawneh [3] used ANNs to forecast post installation setup of pipe piles. Tarawneh and Imam [4] employed ANNs and RA to estimate pile setup for three-pile types (pipe, concrete, and H-pile).

Tatari *et al.* [5] employed ANNs to evaluate the existing conditions of culverts using inventory data presented by [6], [7], [8]. Tarawneh and Nazzal [9] employed RA and ANNs to optimize the prediction of subgrade resilient modulus design input from falling weight deflectometer test results. Ornek *et al.* [10] presented a study to describe the

application of artificial neural networks (ANNs), and the multi-linear regression model (MLR) to determine the bearing capacity of shallow circular foundation carried by layers of compacted granular fill over natural clay soil. Nejad *et al.* [11] developed an ANN model to predict pile settlement based on standard penetration test data. Abu-Kiefa [12] introduced three neural network models to predict the capacity of driven piles in granular soils.

In this research, ANNs and RA are applied to predict the axial capacity of driven piles. The purposes of the study are to:

- Compile driven piles' axial capacity dynamic load test data from the published literature.
- Develop formulas to predict driven pile's axial capacity using ANNs RA.
- Provide a simplified mathematical expression of the developed formulas.

II. DATASET

A dataset was assembled from the results of 162 driven pile dynamic load tests. The data were collected from the published literature. The references used to compile the database are shown in Table I. The collected data included the axial capacity of driven pile in kN (Q), pile length in meter (L), pile cross-sectional area in m^2 (A), friction angle along the pile in degrees (ϕ_s), friction angle at pile tip in degrees (ϕ_t) , and effective stress at pile tip in kN/m^2 (σ').

TABLE I: DATABASE REFERENCES

Reference	No. of Testing
Tarawneh [3]	44
Khan and Decapite [13]	20
Thompson *et al.* [14]	58
Komurka [15]	6
Dover and Howard [16]	11
Holloway and Beddard [17]	5
Antorena and McDaniel [18]	4
Goble *et al.* [19]	6
Tavenas [20]	8

The friction angle of the soil along the pile shaft and near the pile tip provides information about the shear strength of the surrounding and supporting soils. Effective stress at the tip of the pile has a significant role in calculating the pile capacity. Pile length and the cross-sectional area provides the necessary information about pile dimensions.

III. ANNs AND REGRESSION INPUTS, OUTPUT, AND PERFORMANCE CRITERIA

To achieve accurate pile axial capacity predictions, a thorough understanding of the factors affecting axial capacity is needed. Most of the traditional pile axial capacity methods include the following fundamental parameters: pile geometry, effective stress at pile tip, and soil properties.

To evaluate the developed formula, a performance criterion was established using the mean absolute error (MAE), root-mean-square error (RMSE), and the coefficient of determination (R^2). The aim is to develop a formula with higher R^2 value and least MAE and RMSE. The equations of these performance criteria are given in equation (1) and (2) below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}e_i^2} \qquad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}e_i^2}{\sum_i^n (Q_i - \overline{Q})^2} \qquad (3)$$

where n is the total number of collected data points, e_i is differences between measured s and predicted values. Q_i is actual axial capacity values, and $\overline{Q}$ is the average of the measured values.

IV. DIVISION AND PRE-PROCESSING OF THE DATA

In this research, the data were randomly split into two statistically consistent sets(training and testing). 80% of the data were used for training, and 20% were employed for testing the developed model. The training data is used to train the model. The test data is used to measure the performance of the chosen ANNs and RA formulas. The data employed for training and testing should represent the corresponding population [21]. The statistical properties (e.g., range, mean, and standard deviation) of the training and testing data should be alike [22].

TABLE II: DATABASE STATISTICS

Variable	Mean	Standard Deviation	Min.	Max.	Range
Pile cross sectional area in m^2, A	0.156	0.12	0.00613	0.666	0.66
Pile length in m, L	18.33	8.05	2.987	47.213	44.226
Friction angle at pile tip, ϕ_t	36	2.44	29	41	12
Friction angle along the pile, ϕ_s	34.4	2.36	28	39	11
Effective stress (kN/m^2), σ'	175.5	82.23	38	475	437
Axial capacity of the pile (kN), Q	2154.15	1191.38	75.18	5604.31	5529.13

Also, developed formulas perform best when they do not extrapolate beyond the range of their training data [23], [24]. Therefore, to develop the finest possible model, all patterns that are contained in the data need to be included in the training set. To accomplish this, several random combinations of the training and testing sets were used until a statistically consistent data set was obtained. The statistical parameters examined include the mean, standard deviation, minimum, maximum and range, as suggested by [25] are shown in Table II. In general, the statistics are in good agreement, and the dataset can be used to represent the same population.

V. REGRESSION ANALYSIS (RA)

A complete statistical analysis was carried out to develop a regression model that better the axial pile capacity. RA is a collection of statistical methods for predicting the relations

between variables. It involves many procedures for modeling and investigating several variables to find the correlation between a dependent and one or more independent variables. RA helps in understanding how the value of the dependent variable varies when any of the independent variables is varied, while the other independent variables are kept fixed. Q is used as the dependent variable. L, A, ϕ_s, ϕ_t, and σ' were used as the independent variables.

A multivariable linear stepwise RA was conducted to find the relevant independent variables that influence forecasting pile's axial capacity. The stepwise technique was applied to the collected data. In this method, independent variables elimination is based on two statistical tests(t-test and F-test) results. Forward and backward procedures are blended in the process.

Stepwise technique fits all possible linear models and selects the one with the highest F-test statistic value. During the process, at every step, a variable is excluded if its significance level drops lesser than the defined criteria. Excluding insignificant independent variables yields a more precise prediction [26]. The process is stopped when no more independent variables outside the model have the needed level of significance to enter the model.

However, at each stage of the procedure, the deletion of early selected independent variables is permitted. To eliminate the insignificant variables, the regression statistics used are significance level (P value less than 0.05).

A. Regression Analysis Results

TABLE III: REGRESSION ANALYSIS OUTPUT

No.	Model	Coefficient	P-value (Significance)	R^2	MAE	RMSE
1	Constant	1304.67	0.0001	0.29	799.8	995.7
	A	5459.15	0.0001			
2	Constant	-7194.60	0.0001	0.53	631.5	814.87
	A	5512.58	0.0001			
	ϕ_t	236.06	0.0001			
3	Constant	-7901.70	0.0001	0.7	504.2	660
	A	5843.69	0.0001			
	ϕ_t	225.59	0.0001			
	σ'	5.88	0.0001			

The results of the stepwise linear multivariable RA are provided in Table III. The Coefficients represent the weights used for the independent variables in the prediction model. RMSE, MAE, and R^2 values are provided for each model. It can be noted that model 3 has the highest R^2 value 0.7, the least MAE (504.18) and RMSE (660). Model 3 is considered the best one among the developed models. As summarized in Table III, Model 3 is presented in equation (4) as shown below:

$$Q = -7901.7 + 5843.69A + 22.59\phi_t + 5.88\sigma'$$ (4)

The linear multivariable RA results showed that only three independent variables (A, ϕ_t, and σ') are statically significant ($P < 0.05$). However, two independent variables (L and ϕ_s) are eliminated because they are insignificant ($P > 0.05$). It should be noted that ϕ_s is considered a soil parameter along the pile depth and L represents the pile length. However, σ' which represents the effective stress at pile tip is a significant independent variable which is

calculated by multiplying the pile length by the submerged unit weight of the soil. So, the pile length is included in the effective stress calculations. On the other hand, the submerged unit weight of the soil is highly correlated with ϕ_s along the pile depth ($R^2 = 0.65$). Therefore, σ' appeared as a significant variable because it includes L and ϕ_s indirectly.

B. Improved Regression Model

Further improvement to the regression analysis is carried out using a nonlinear fitting software "Eureqa," based on artificial programming. The software was used to find a general function using the significant independent variables (A, ϕ_t, and σ') to predict the pile's axial capacity (Q). The software searches for a formula by combining mathematical building-blocks (e.g., addition, subtraction, multiplication, division, exponential, and power). As mentioned earlier, 80% of the data was used to build the function and 20% to test it. The software does not require a predefined formula for variables fitting. Instead, the software fitting tool creates generations of equations. A review of artificial programming techniques can be obtained from [27], [28].

TABLE IV: EUREQA SOFTWARE OUTPUT

No.	Model	R^2	MAE	RMSE
1	$Q = 1822.45 + 1904.57A + 0.553\phi_t + 0.068\ \sigma' - 6645.98A^2$	0.86	416.91	450.11
2	$Q = 2057.18 - 0.4\sigma' - 0.78\ \phi_t A$	0.84	456.75	514.78

The results of the developed models using Eureqa software are shown in Table IV. The output of the software led to two models that outperformed the RA based on the performance criteria (R^2, MAE, RMSE). Formula 1 has the highest R^2 value of 0.86, the lowest MAE and RMSE of 416.91 and 450.11, respectively. It can be seen that the results of Eureqa pointed improvement to the developed linear regression model.

VI. ARTIFICIAL NEURAL NETWORKS (ANNS)

ANNs are neurons linked with connections defined by their weights. The distinctiveness of artificial networks is that they are not programmed but trained. To create the ANNs model, two data sets are needed. The first set is for training and the second one is a testing set which is required to establish the efficiency of the trained model. An essential aspect of neural network modeling is the determination of weights applied during network training. There are several methods of training. One of the regularly used methods is a generalized delta rule or error back-propagation algorithm which is reported in detail by [29].

The back-propagation algorithm is used for optimizing the connection weights in this study, whereas the Levenberg- Marquardt (LM) algorithm was used as a learning rule. LM is one of the best higher-order adaptive algorithms recognized for reducing the error of a neural network [30].

A typical ANN is shown in Fig. 1. Neuron u_i is linked with a few neurons which send their output signal ($o_{k,j,1}$) to the neuron (u_i). Output signals are multiplied by weights

(w_{ij}). A signal (b_i) is added to the sum of weighted signals. This gives the value of the signal of the neuron (u_i). Then the produced function (f) copies the value to the output signal (o_i) of the neuron (u_i). Connections between neurons and the output function may be synchronized in advance [31].
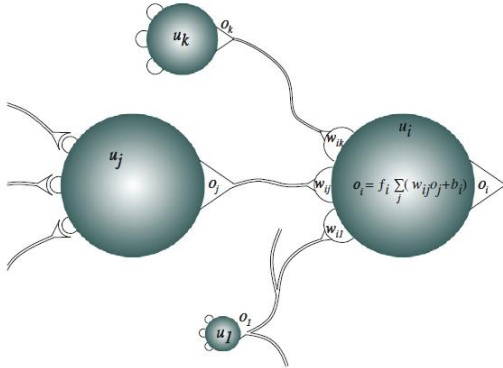

Fig. 1. Scheme of ANNs [31].

The symbols in Fig. 1 have the following definitions:
u_i value of neuron i,
u_j value of neuron j,
u_k value of neuron k,
u_l value of neuron l,
w_{ij} weight of interaction between neurons i and j,
w_{ik} weight of interaction between neurons i and k,
w_{il} weight of interaction between neurons i and l,
b_i threshold of neuron i,
f_i output function,
o_i output signal of neuron i,
o_j output signal of neuron j,
o_k output signal of neuron k,
o_l output signal of neuron l.

The generalized delta rule [29] which is the error back-propagation is summarized in the equation (5) and (6). alteration in weights is relative to the derivative of the error of neuron which is assessed in a different way for the output and the hidden layers of neurons. The learning stage of ANNs is influenced by several parameters, such as the maximum number of iterations, learning step size, an output function, maximum permitted error geometry of the network and data.

$$\Delta p w_{ji} = \eta \delta_{pj}\, o_{pi} \qquad (5)$$

δ_{pj}
$\begin{cases} f_j^{'}\left(net_{pj}\right)\left(t_{pj} - O_{pj}\right); \text{ weights for output neurons,} \\ f_j^{'}\left(net_{pj}\right) \sum_k \delta_{pk} w_{kj} \text{ ; weight for neurons on hidden layers} \end{cases}$

$$(6)$$

Feed-forward neural networks with error back-propagation learning algorithm have been used to estimate pile's axial capacity. The learning stage of the ANNs depends on several parameters, such as learning step size, the maximum number of iterations, geometry of the network and, most importantly, the data. Taking into account the geometry of the ANNs, it cannot be accurately defined which one corresponds to the exact data. Therefore, it was decided to use different network geometries as shown in the next section of this paper.

A. Development of the ANN Model

To build an ANN model, it is required to determine the model inputs and outputs, division and pre-processing of the existing data, optimization of a network, model validations, and stopping criteria. Neuro-Solutions 6.0 Software was employed in developing the neural network model. This software combines a modular design interface with advanced learning procedures, giving the strength and adaptability required to design the neural network that produces the best solution.

The data used to develop and validate the neural network model were obtained from both published literature. Suitable case studies were those having pile load tests and information regarding the piles and soil. The database contains a total of 162 cases of pile dynamic load tests. The references used to compile the database are presented in Table I.

B. ANN Model Architecture

Choosing the network architecture is a crucial and challenging task in ANN model development [32]. It needs the selection of the optimum number of hidden layers and the number of nodes in each layer. There is no theory to determine the best ANN architecture [33]. The number of nodes in the input and output layers is constrained by the number of model inputs and outputs. A total of three input variables are included in developing the ANN model, namely, pile cross-sectional area (A), friction angle at pile tip (ϕ_t), and effective stress at pile tip(σ'). Only three variables are used because they are statistically significant. The output layer possesses a single node which is the measured value of the axial capacity of the pile.

Numerous network structures with different numbers of hidden layers and nodes in the hidden layer were trained and tested. This method was selected to find the optimal network architecture from various trials. It has been proved that a network with one hidden layer can approximate any continuous function [34].

In this paper, one hidden layer was employed. To achieve the best network geometry, ANNs with a single hidden layer and a varying number of elements, in the hidden layer, are trained using sigmoidal (Sig.) and hyperbolic tangent (tanh) transfer functions for the hidden and output layers. Combinations of numbers of nodes in the hidden layer and various types of the transfer function that produced the best forecasts of pile's axial capacity are displayed in Table V.

The training set is utilized to modify the connection weights, while the testing set checks the capability of the model to generalize. The performance of the model is examined at several stages during the training process, and training is stopped when the error of the testing set starts to increase [25].

The performance of the trained ANN model should be validated using data sets that have not been used as part of the learning process. This dataset is known as the testing set. The goal of the model validation phase is to ensure that the model can generalize within limits robustly placed by the training data [25]. Table 6 shows the RMSE, MAE, and R values for the developed ANN models. It is clear that model 4 has the highest R-value and the lowest RMSE and MAE.

TABLE V: ANNs MODELS STRUCTURE

Model No.	Model name	Input nodes	No. of elements in the hidden layer	No. of elements in the output layer	Transfer function
1	*Ann-5-2-1-Sig*	5	2	1	*Sig.*
2	*Ann-5-2-1-tanh*	5	2	1	*tanh*
3	*Ann-5-3-1-Sig*	5	3	1	*Sig*
4	*Ann-5-3-1-tanh*	5	3	1	*tanh*
5	*Ann-5-4-1-Sig.*	5	4	1	*Sig.*
6	*Ann-5-4-1-tanh*	5	4	1	*tanh*
7	*Ann-5-5-1-Sig.*	5	5	1	*Sig*
8	*Ann-5-5-1-tanh*	5	5	1	*tanh*

TABLE VI: R, RMSE AND MAE FOR THE ANN MODELS

Model No.	Model name	Testing data set		
		RMSE	MAE	R^2
1	*Ann-5-2-1-Sig*	684.16	510.03	0.49
2	*Ann-5-2-1-tanh*	646.39	592.65	0.52
3	*Ann-5-3-1-Sig*	1011.2	791.21	0.34
4	*Ann-5-3-1-tanh*	478.11	366.47	0.92
5	*Ann-5-4-1-Sig.*	1437.77	937.5	0.44
6	*Ann-5-4-1-tanh*	1180.57	856.78	0.38
7	*Ann-5-5-1-Sig.*	769.57	587.4	0.46
8	*Ann-5-5-1-tanh*	581.0	442.22	0.71

C. ANN Results

Table III and Table IV show the structure and results of the developed ANN best performing models. The results showed that the RMSE values were between 478.11 and 1437.77, the MAE values were between 366.47 and 937.5, and the coefficient of determination, R^2, values were between 0.34 and 0.92 for the testing data set. It is remarked that model 4, which used three nodes in the hidden layer and tanh as the transfer function for both hidden and output layer was the best model based on the performance criteria (R^2, MAE, RMSE). It has the highest R^2 value (0.92), the lowest RMSE (478.11) and MAE values (366.47) for the testing data set. The mathematical expression of the developed ANN model 4 algorithm is presented below in equations (7), (8), (9), and (10):

$$Q = 2739.73 \ [\tanh(-10.643X_1 + 6.767X_2 + 0.027X_3 + 5.309) + 0.9275] \quad (7)$$

where X_1, X_2, and X_3 can be calculated using the equations below:

$$X_1 = \tanh(0.0695\phi_t + 0.0024\sigma' - 0.1728A + 3.0824) \quad (8)$$

$$X_2 = \tanh(0.0594\phi_t + 0.004\sigma' + 0.4236A + 1.8013) \quad (9)$$

$$X_3 = \tanh(-0.9471\phi_t + 0.0217\sigma' + 7.4745A + 70.927) \quad (10)$$

The results of the ANNs showed that there is a strong correlation between the actual and ANNs predicted axial capacity. It is clear that the value of R^2 represents an excellent fit.

VII. SUMMARY AND CONCLUSIONS

In this study, RA and ANNs were used to develop formulas to predict the axial capacity of driven piles. The RA model was further improved using a nonlinear fitting software "Eureqa," based on artificial programming. A database was assembled from the results of 162 driven pile dynamic load tests. The data were obtained from the published literature.

Five input variables were investigated, however, three of them were used to develop the formulas because they are statistically significant. Those variables are pile cross-sectional area (A), friction angle at pile tip (ϕ_t), and effective stress at pile tip(σ'). To evaluate the generated models, a performance criterion was established using RMSE, MAE and the R^2. The goal was to develop a formula with higher R^2 value and least RMSE and MAE. Several models were produced as shown in Tables III, IV, V, and VI.

ANN model 4 has the highest R^2 value and the lowest RMSE and MAE. The mathematical expression of the best performing ANN algorithm is presented in equations (7) through (10). Based on the available data and result, this formula can be recommended to predict the pile's axial capacity. The suggested ANNs method uses feed-forward neural networks with the error back-propagation algorithm. It should be noted that the ANN modeling is based on experimental data and is appropriate for use in an interpolative method. Similar to all empirical formulas, the range of applicability of the ANN-based equation is limited by the data used to build and calibrate the model. To improve the model and enhance its accuracy, it is important to include additional data so that the model can be re-trained. The outcomes of this research show that ANNs have several advantages that make them a powerful tool to predict the pile's axial capacity.

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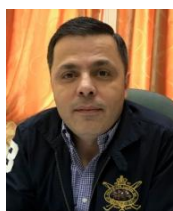
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