Geotechnical Engineering Journal of SEAGS & AGSSEA

https://ph01.tci-thaijo.org/index.php/seags_agssea_journal

The Uplift Capacity Prediction for Regular and Enlarged Piles in Sandy Soils Using Artificial Neural Networks

Shaymaa T. Kadhim[1], Mustafa M. Khattab[1], Ahmed S. Abdulrasool[1], and Humam Hussein Mohammed Al-Ghabawi[1]
[1]College of Civil Engineering, University of Technology-Iraq, Baghdad, Iraq
E-mail: shaymaa.t.kadhim@uotechnology.edu.iq

ABSTRACT: The uplift capacity of piles is considered as a crucial aspect in practice for a geotechnical engineer. Nowadays, artificial machine learning techniques have emerged as a powerful tool in engineering for prediction and estimation with reasonable accuracy. This paper investigates the uplift capacity of two types of single piles: regular and enlarged piles installed in sand using an artificial neural network (ANN). Different activation functions were used, and the ANN results were compared with those of other algorithms. The results showed that one unified machine learning model has proven its efficiency in giving reasonable and accurate estimates of the uplift capacity of regular and enlarged piles. The ANN algorithm had the best results compared with other algorithms (Random forests, XGBoost, and Adaboost) with a coefficient of determination R^2 equal to 0.970151 and 0.96924 for training and testing data, respectively, while other algorithms showed a sign of over-fitting. Finally, the ANN model was compared to well-known theoretical models and the ANN had better results.

KEYWORDS: Piles, Uplift Capacity, Sand, and Artificial Neural Networks.

1. INTRODUCTION

Pile foundations transmit massive loads coming from high-rise structures such as transmission towers, tall chimneys, underground tanks, and even offshore structures to a desirable deeper, stronger stratum. Therefore, piles that support these kinds of structures are susceptible to different types of loading: axial, lateral, overturning moments, and uplift loads. The combination of these types of loading can occur concurrently on the pile (Mosquera et al., 2015; Milad et al., 2015). Piles need to transmit the generated uplift load to deep soil layers by means of soil-pile interaction along the pile shaft (i.e., skin friction), which is associated with the lateral effective stress experienced during failure. The typical failure modes of regular piles (i.e., piles with constant cross-sectional area along their depth) under uplift forces are inverted-truncated cone-shaped shear failure, the shear failure formed along pile-soil interface periphery, and compound shear failure. Whereas the shear failure generated along the pile-soil boundary is found to be the most common failure mode of regular piles embedded in sand and subjected to uplift loading (He et al., 2015).

Enlarged piles, also known as under-reamed piles or belled piles, have proven their effectiveness in increasing the uplift capacity as compared with regular piles. Enlarged piles are characterized by a bell-shaped or inverted-cone base that offers an enlarged area to enhance the uplift resistance (Harris & Madabhushi, 2015). These piles are usually manufactured from concrete. The enlarged base can contribute to the uplift capacity of the pile due to the mobilization of a passive wedge of soil as a result of the weight of soil located above the base thus forcing the failure to occur and enhancing the end-bearing capacity (Harris & Madabhushi, 2015).

Various research work is available in the literature regarding the uplift capacity of regular piles embedded in sand soil (Al-Mhidib & Edil, 1999; Dash & Pise, 2003; Bose & Krishnan, 2009; Basha & Azzam, 2018; Emirler et al., 2021) and enlarged piles (Vanitha et al., 2007; Verma & Joshi, 2010; Honda et al., 2011; Niroumand et al., 2012; Nazir et al., 2015; Kotal & Khan, 2015). In addition, the uplift capacity of piles was investigated numerically using finite element and finite difference methods (Honda et al., 2011; Faizi et al., 2015; Emirler et al., 2019; Liu et al., 2020; Kumar et al., 2022).

Dash and Pise (2003) investigated the influence of compressive load on the uplift capacity of regular single steel pipe piles embedded in the sand. Bose and Krishnan (2009) reported that the uplift capacity of regular piles was found to be significantly increased as pile diameter (D) and slenderness ratio (L/D) increased. Basha and Azzam (2018) conducted a series of laboratory model tests to evaluate the importance of water table rising on the uplift capacity of regular piles considering various slenderness ratios, sand densities, and pile installation methods. It was concluded that the uplift capacity of the pile declined when the submerged length ratio of the pile (i.e., the ratio of the height of water to the length of the pile) increased. Liu et al. (2020) studied the uplift capacity and failure mechanism of regular piles with the effect of different factors using numerical analysis through FLAC 3D software. It was concluded that the slenderness ratio (L/D), the friction angle at the interface between soil and pile, the pile cross-section, and the pile location in the group have a great influence in enhancing the uplift capacity of regular piles.

Extensive research has been conducted to investigate the failure mechanism of enlarged piles under uplift loading. The ultimate uplift capacity of the enlarged pile is based on the mobilized shearing resistance along the failure wedge as well as the weight of soil mass above the enlarged pile base (i.e., the soil surrounded by the failure wedge). Different methods were proposed to analyse the uplift capacity of enlarged piles in homogeneous strata, for instance: Meyerhof & Adams (1968), Chattopadhyay & Pise (1986), and Rao & Kumar (1994). Patra & Pise (2003) proposed a method to analyse the uplift capacity of enlarged piles installed in multi-layer strata. Vanitha et al. (2007) performed an experimental study on a single and group of enlarged piles of 2 × 2 configuration in dry sand subjected to uplift loading. In addition, an analytical model was proposed using the limit equilibrium method to estimate the uplift capacity of the enlarged pile group. Verma and Joshi (2010) studied the effect of pile material on the uplift capacity of single and group of regular piles as well as enlarged piles with enlarged base to diameter ratios of 2 and 3 made of different pile materials (i.e., concrete, PVC, and Galvanised Iron). The results showed that the galvanized iron pipe pile delivered the highest uplift capacity compared to other piles materials in the case of a regular single pile. Furthermore, enlarged piles enhanced the uplift capacity to a further extent as compared to regular piles, and increasing the enlarged base-to-diameter ratio

https://doi.org/10.14456/seagj.2025.2 Published on 17 July 2025

increased the uplift capacity of the piles significantly. Honda et al. (2011) performed a 2D finite element analysis to estimate the uplift capacity of single-belled and multi-belled piles installed in dense sand. Nazir et al. (2015) investigated various factors that may affect the performance of enlarged piles under uplift loading using large-scale model tests. The uplift capacity of the enlarged pile was significantly influenced by the pile shaft diameter (D), the diameter of the enlarged base (D_b), the embedment ratio (L/D_b), the base inclination angle (α), and the soil relative density. Kumar et al. (2022) conducted a 2D finite element analysis to evaluate the uplift capacity of regular and enlarged piles installed in sand.

In recent years, the Artificial Neural Network (ANN) technique has emerged as a promising technology for solving various complex geotechnical engineering problems with high accuracy, offering an alternative to numerical modelling (Das & Basudhar, 2008). The complexity of modelling the interaction between piles and surrounding soils has limited the effectiveness of traditional methods (i.e., experimental, numerical, and analytical methods) in predicting pile behavior (Fatehnia & Amirinia, 2018). Numerous attempts have been made to predict the uplift capacity of different types of piles using various machine learning techniques (Jebur et al., 2018; Moayedi & Rezaei, 2019; Tien Bui et al., 2019; Dadhich et al., 2022). Studies in the literature have investigated the performance of regular and enlarged piles separately under the influence of uplift loading. This paper aims to simulate both types of piles in a single general model using artificial neural network machine learning techniques. A large dataset was collected from the literature for both regular and enlarged piles to accurately predict their uplift capacity in the sand.

2. MACHINE LEARNING TECHNIQUES IN PREDICTING BEHAVIOUR

Machine learning is the capacity of a machine to mimic intelligent human behavior. In other words, the capability of the computer to learn without human intervention. Machine learning can be divided into three main categories: supervised, unsupervised, and reinforced learning. Each one of the learning types follows different techniques and has its own algorithms and each type can be applied to certain problems. However, the most popular type for engineering applications is supervised machine learning, where it can be used in regression and classification problems. Supervised machine learning is data dependent, providing labels of each feature or independent and labelling the target or the dependent. Many algorithms could be used in supervised learning for regression or classification, such as linear regression, logistic regression, neural networks, etc. In this study, a supervised learning neural network algorithm will be used to predict the uplift ultimate capacity of regular and enlarged piles with data collected from the literature. Many researchers have studied pile behavior using different machine-learning techniques.

Pham et al. (2020) studied the prediction of axial bearing capacity for piles using artificial neural networks (ANN) and random forest machine learning algorithms, using 2314 datasets of driven piles, taking into consideration many features, including the SPT. In their study, the Random Forest performed better than the artificial neural network for the prediction of the pile-bearing capacity. However, both algorithms had better results compared to classical known models of pile bearing capacity predictions. Jebur et al. (2022) used the Levenberg–Marquardt training neural network algorithm to predict the uplift settlement of concrete piles using 274 experimentally tested piles. The proposed model showed good results with great prediction accuracy. The R^2 for the training and the testing data were 0.99088 and 0.98436 respectively.

Prayogo and Susanto (2018) used a self-tuning least squares support vector machine (STLSSVM), a novel hybrid prediction technique presented in this study, to precisely predict the friction capacity of driven piles in cohesive soil. This thorough assessment proved that this approach could accurately simulate the friction capacity of driven piles in clay; however, very few data points were used in their study. Muduli et al. (2013) used extreme machine learning, a type of supervised learning, to predict the lateral capacity of piles with good accuracy.

Benbouras et al. (2021) used deep neural networks for the prediction of the bearing capacity of driven piles and compared the results with other algorithms such as lasso regression, Random Forests and SVR etc. Although most algorithms had great accuracy in predicting the bearing capacity, Deep Neural Networks had the best accuracy of all. Amjad et al. (2022) used the extreme boosting algorithm XGBoost for the prediction of piles' bearing capacity. Two hundred driven piles, in total, under static load were used for the learning process of the XGBoost. The results were compared with other algorithms as well, such as Random Forests, Adaboost, and SVR. All the models had great accuracy, but XGBoost scored the best. Pham et al. (2020) developed a deep neural network architecture to estimate the bearing capacity of piles. The deep neural network was able to predict the bearing capacity of piles with great accuracy for all training, testing, and validation data.

In summary, most of the studied algorithms were able to capture the behavior of piles. From the literature, Artificial Neural Networks, extreme learning, and Random Forests have been able to predict different pile characteristics with great accuracy. In this study, ANN will be used to predict the uplift capacity of piles embedded in sand and the model will be compared with different algorithms.

3. DATA

The data used in this study were collected from several previous studies (Rao & Venkatesh, (1985); Shooshpasha et al., (2009); Al-Mhidib & Edil, (1999); Alawneh et al., (1999); Shanker et al., (2007); Krabbenhoft et al., (2008); Shelke & Patra, (2009); Gaaver, (2013); Nasr, (2013); Faizi et al., (2015); Nazir et al., (2015); Ali et al., (2017); Narayanan et al., (2017); Basha & Azzam, (2018); Bajaj et al., (2019); Emirler et al., (2019) and (2021); Agarwal et al., (2021); Abdul-Hussein & Hamadi, (2021); Hussein et al., (2021)). A total of 764 datasets were collected for both regular and enlarged base piles under axial uplift load. The considered features in this study are diameter of the shaft (D_s), length of the shaft (L), the embedded length (L_{embed}), base diameter (D_b), base height (L_b) base angle(α), the ratios of the length to diameter for both the shaft and the base (L/D) and (L_b/D_b) as the pile properties. For the soil properties, only the friction angle (ϕ) and the relative densities (Dr) were taken into consideration. The target is only the maximum uplift axial load of the pile, denoted as Q_u, measured in (kN). Besides the numerical data collected from the papers, several categorical data have been collected such as the pile section, pile material, pile type and the method of installation. Tables 1 and 2 show some statistics of the collected data.

Table 1 Data statistics

Name	Mean	Median	Dispersion	Min.	Max.	Missing
L_{embed} (mm)	427.828	282.679	2.19921	0	14994.3	0 (0%)
D_b (mm)	63.78	75	0.93	0	150	0 (0%)
L_b (mm)	22.6707	14.4338	1.19643	0	103.923	0 (0%)
L (mm)	853.84	500	1.45969	0	14994.3	0 (0%)
D_s (mm)	52.0362	40	1.96908	10	1200	0 (0%)
hw/L	0.0593	0	3.4114	0	1	88 (12%)
ϕ	38.3929	38	0.1184	28.9	48	6 (1%)
D_r%	59.21	60	0.426	9	95	71 (9%)
Q_u (kN)	8.07402	0.2	8.43983	0	1537.6	0 (0%)

Table 2 Categorical data statistics

Name	Most frequent	Missing
Pile material	Steel	24(3%)
Method of installation	Non-displacement	42(6%)
Pile type	Solid	33 (4%)

4. METHODOLOGY

Every supervised machine learning algorithm follows the general procedure of gathering and analysing input data, training the algorithm, testing the algorithm, and producing output/outputs. Before the data gathering process, a consideration of what factors may influence the prediction target should be thoroughly investigated. Since the studies in literature have tested different types, ranges and considered different factors, a unification process should be done before applying the learning algorithms. Moreover, many missing data could result hence the different factors studied for each work. In this study, the main challenge was the unification of data for both regular and belled or enlarged piles since the regular pile does not have the enlarged part and its properties represented in base diameter (D_b), base height (L_b) and base angle (α) as shown in Figure 1. The authors have decided to apply zeros for the enlarged part parameters when collecting data for the regular pile. Pre-processing of the collected data was carried out to account for missing data, that include data imputations and filling missing data based on some techniques for until best results were reached. In this study, missing data for a particular feature was replaced with the average of the observed data for that feature. Moreover, feature selection was carried out until best contributing features were selected.

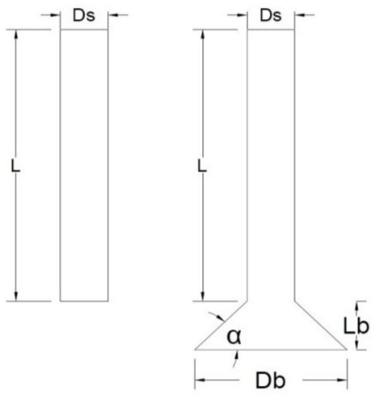

Figure 1 Regular and enlarged pile

The authors of this study have used python 3 and its open-source libraries to clean and impute the data as well as applying the artificial neural network for the learning process and the testing metrics. Many libraries such as Pandas, NumPy, Matplotlib and learn have been used. Multi-layer Perceptron (MLP) back propagation neural network from sci-kit that is used for supervised learning, both regression and classification, have been implemented for the learning and prediction of the ultimate uplift capacity of the pile. This library does not support GPU for faster learning; however, the data used does not require such implementation. Usually, an artificial neural network consists of neurons distributed in several layers. Each layer, have a several number of neurons that can be defined by the user. The layers can be divided into three types of layers: input layer, output layer and layers between them that are called hidden layer. Figure 2 shows a typical artificial neural network with only one hidden layer. Each layer is connected to the layer next to it by weights and each neuron could contain what is called an activation function for modelling non-linear problems. The sci-kit learn provides several activation functions; ReLu, Sigmoid and Tanh function as well as Identity which is the same as having no activation function in the neurons. The number of hidden layers, number of neurons in each layer and the activation functions should be changed until best accuracy has been reached.

Besides Artificial Neural Networks, Ensemble methods in machine learning are being used in this study for the purpose of comparison. Ensemble methods combine different models to enhance the system's overall predictive performance. The premise behind ensemble approaches is that by combining the results of several models, the errors and biases of each model can be eliminated or decreased, resulting in predictions that are more reliable and accurate.

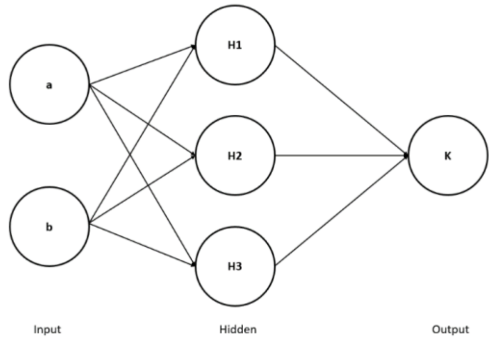

Figure 2 An artificial neural network

There are many different kinds of ensemble methods, but a few of the most popular ones are as follows: Bagging (Bootstrap Aggregating) is a technique that entails training numerous different models on arbitrary selections of the training data before averaging the results. Bagging is frequently utilized with decision tree algorithms. Boosting: This approach includes successively training models on the same data, with each model aiming to fix the flaws of the one before it. Combining all of the models' predictions yields the ultimate prediction. This research investigates the use of one bagging technique represented in the Random Forest Algorithm and two boosting algorithms: the XGBoost and the Adaboost algorithms.

5. RESULTS

This section looks at the predictions of the uplift ultimate capacity of piles using artificial neural network machine learning model. The data utilized in each model was divided into training and testing data at ratios of 80% and 20% of the total data. Following the completion of the learning process, various assessment metrics were calculated for both training and testing data to measure the model's prediction accuracy. The assessment metrics are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2), which can be calculated as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y°_i)^2 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y°_i)^2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - y°_i| \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - y°_i)^2}{\sum_{i=1}^{N}(y_i - y^{\wedge})^2} \tag{4}$$

where: N= Number of data points,
y_i = Actual observed value,
$\mathring{y}_i$ = Predicted value,
$y^{\wedge}$ = Mean of the observed value (y_i).

For each selected activation function and number of neurons, these assessment metrics were calculated until best accuracy was reached. Moreover, the results of the ANN were compared with different algorithms, selected based on the literature, to determine which algorithm can best predict uplift capacity. Every algorithm has its own properties that were changed until the highest R^2 and lowest

MSE, RMSE and MAE were reached. As a result, three hidden layers were chosen; the first hidden layer contains 64 neurons, the second layer contains 128 neurons, and the third layer contains 64 neurons. The size of batch was set to 32 and the number of epochs for this analysis was set to 100. In Table 3, the results of four algorithms can be seen.

Table 3 MSE, RMSE, MAE, and R^2 scores for the different algorithms used in this study

	MSE		RMSE		MAE		R^2	
Model	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
Random Forest	4.22689	24.8621	2.05594	4.98619	0.38394	0.82717	0.98763	0.93415
Neural Network	10.20053	11.61393	3.19383	3.40792	0.65567	0.82718	0.97015	0.96924
XGBoost	1.40285	35.16158	1.18442	5.92972	0.19347	0.84675	0.99590	0.90687
AdaBoost	1.26106	33.85551	1.12297	5.81855	0.09016	0.76256	0.99631	0.91033

MSE calculates the average of the squared differences between the predicted and actual values of the target variable. A lower MSE score suggests that the model is performing better. In Table 3, it can be seen that for the training dataset, the Adaptive boosting algorithm (AdaBoost) outperforms the other algorithm in terms of the MSE, followed by XGBoost, Random Forests, and Neural Networks. The Root Mean Squared Error (RMSE) represents the average difference between the predicted and actual values. Considering that RMSE is the square root of the MSE, it has the same trend as that of MSE for the training data for all the algorithms. A lower RMSE value denotes improved model performance. MAE measures the average absolute difference between predicted and actual values. Model performance improves as MAE decreases. In Table 3, the AdaBoost has the lowest MAE among all the used algorithms. The same can be seen in the results of R^2, where AdaBoost scored the highest value of R^2, followed by XGBoost, then Random forests, and ANN. R^2 is a measure of how much of the target variable's variance can be attributed to the independent variables. An R^2 value that is nearer 1 suggests that the model fits the data more accurately.

For the testing data set, however, a different scenario was observed whereby the performance of the algorithms was different concerning the parameters being measured. The MSE and RMSE were the lowest for the ANN model, the second was the Random Forest, and the third was AdaBoost, while the largest was on the XGBoost. This proves that ANN gave the higher performance of the testing set in terms of MSE and RMSE, where the lowest values are preferred. While AdaBoost seemed to have the lowest MAE, suggesting that it made fewer large errors, it was still outperformed by ANN based on MSE and RMSE. For the R^2, the ANN algorithm had the highest score and the same order algorithm can be observed. Looking at the results of both training and testing data, it can be seen that there are differences between the evaluation metrics of training and testing sets. For example, the MSE results of the XGBoost algorithm for training and testing datasets are 1.4 and 35.16, respectively, and the R^2 are 0.996 and 0.91, respectively. This suggests that overfitting phenomena are observed for some models. When a model learns the noise in the training set while doing poorly on the test set, it is said to be overfit. A comparison between the models' performance on the training and test sets of data was made to see if there is overfitting. The model may be overfitting if its performance on training data is noticeably better than on test data.

The XGBoost method has much lower MSE and RMSE scores on the training data compared to the test data, which raises the possibility that it may be overfitting to the training data based on the evaluation metrics in the table above. As seen by a lower MSE and RMSE score on the training data compared to the test data, the Adaboost method also exhibits some overfitting characteristics. The Neural Networks method, in comparison, exhibits comparable performance on the training and test sets of data with almost the same values, with a little lower MSE and RMSE score on the training sets but still with a respectable level of performance on the test sets. Moreover, the Random Forest algorithm performs similarly on both training and test data but with a larger difference between training and testing results. Therefore, it can be safely said that the ANN does not have overfitting with reasonably good MSE, RMSE, MAE, and R^2. Therefore, ANN was chosen as the main model for this study.

An ANN model training and validation for 100 epochs are presented on the learning curve in Figure 3 in terms of MSE. It is evident that the training and validation error are quite similar, and the model has stop overfitting entirely.

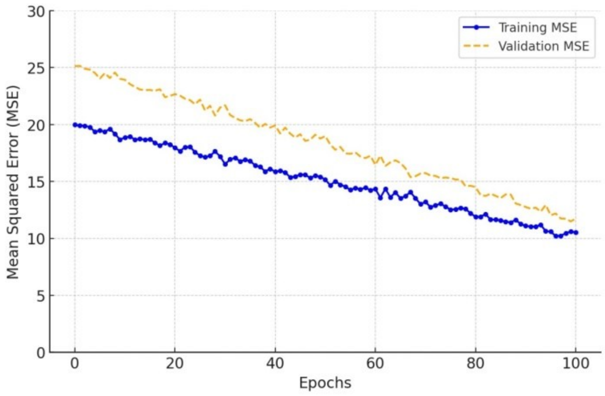

Figure 3 Learning curve presenting training and validation MSE for ANN

Different activation functions have been used for the ANN. The results for each algorithm are shown in Table 4 below. The choice of activation function has a direct impact on the accuracy of the predicted uplift-bearing capacity of piles in sand employing an ANN. The best performance of the tested models is characterized by ReLU since it provides the least errors and the highest R^2 in all experiments, proving high predictive potential and model generalization. It provides a sufficient measure of the complicated relationship that exists in the data. Sigmoid and Tanh give reasonable performances but have the maximum absolute error, making them less effective to ReLU and displaying signs of overfitting. Identity has the highest error and the worst fit, which can indicate that it may be the very model that is least suitable for the formulation of the complexities of the non-linear relationships, which are necessary for making accurate predictions. Thus, ReLU is the most appropriate activation function for estimating uplift-bearing capacity in sand owing to the highest accuracy and generalization.

Moreover, an analysis of the importance of the permutation feature was carried out. The model score declines when one feature value is randomly shuffled, whichis known as the importance of the permutation. As a result, the model score drops, demonstrating how dependent it is on the feature. This method breaks the correlation between the feature and the target. With different permutations of the feature, this technique can be used repeatedly and is independent of models. Figure 4 below shows the effects of feature permutation on the MAE, MSE, RMSE, and R^2, respectively. In all the results, the most important feature that affects the model accuracy is the pile material, and the second is the pile length, while other features had lower effects on the model accuracy metrics.

Table 4 MSE, RMSE, MAE, and R^2 scores for the different algorithms used in this study

	MSE		RMSE		MAE		R^2	
Model	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
Random Forest	4.22689	24.8621	2.05594	4.98619	0.38394	0.82717	0.98763	0.93415
Neural Network	10.20053	11.61393	3.19383	3.40792	0.65567	0.82718	0.97015	0.96924
XGBoost	1.40285	35.16158	1.18442	5.92972	0.19347	0.84675	0.99590	0.90687
AdaBoost	1.26106	33.85551	1.12297	5.81855	0.09016	0.76256	0.99631	0.91033

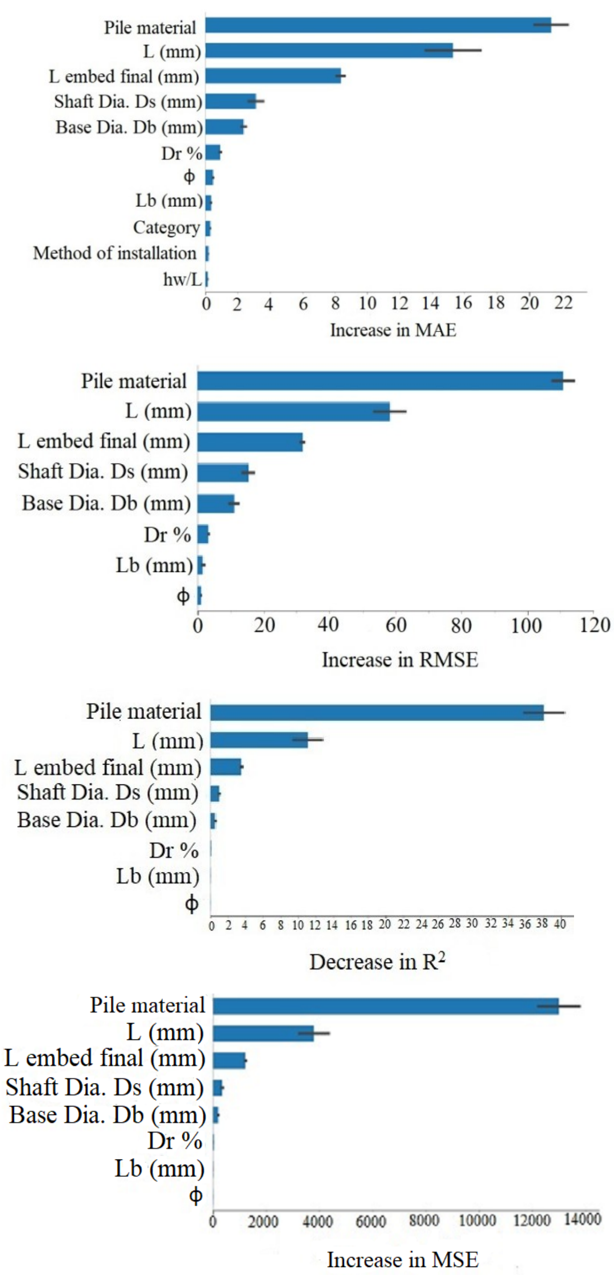

Figure 4 Feature importance of the ANN model

6. MODEL VERIFICATION

A comparative study was made between different analytical theories proposed in literature to predict the uplift capacity of piles inserted in sand and the results obtained from artificial neural network (ANN) with respect to the measured uplift capacity (Q_u). Three theoretical models were used in this study for comparison: Meyerhof (1973), Das (1983), and Shanker et al. (2007), the theoretical equations of these models were illustrated in Table 5. Experimental data of (22) large-scale pile tests from Al-Mhaidib and Edil (1995) were chosen to perform this comparison. Circular piles of 0.089 m in diameter and with different (L/D) ranging from 17 to 19 were installed in loose and dense sand soil. Loose sand with (D_r=9%) has an angle of internal friction of 30.5° and a unit weight of 15.69 kN/m^3, while dense sand with (D_r=85%) has an angle of internal friction of 39° and a unit weight of 17.45 kN/m^3. The properties of pile and sand for proposed data points like: pile diameter (D) and length (L), relative density (D_r), unit weight of sand (γ), angle of internal friction (ϕ) and soil-pile interface friction angle (δ) were the main parameters used for prediction of (Q_u) from theoretical models. Since the angle of soil-pile interface (δ) should be estimated carefully; therefore, for a conservative prediction, it was assumed to be ($\delta = 0.4\ \phi$) for very loose sand (i.e., D_r = 9%) and ($\delta = \phi$) for dense sand (i.e., D_r = 85%) (Das et al., 1977). Figure 5 depicts the measured versus predicted uplift capacity of pile in sand for the selected data points. Table 6 summarizes the results of predicted (Q_u) from theoretical models and ANN as compared to the measured (Q_u) in (kN). The predicted uplift capacity from ANN compared very well with respect to measured data among the predicted (Q_u) derived from the theoretical methods adopted in this study.

Table 5 A summary of theoretical equations for the model used to this study

Models	**Theoretical Equations**
Meyerhof (1973)	$Q_u = \frac{\pi}{2} K_u\, D\, \gamma\, L^2 \tan\delta$ K_u= uplift coefficient
Das (1983)	$Q_u = \frac{\pi}{2} K_u D \gamma L^2 \tan\delta$ for $\frac{L}{D} \leq \left(\frac{L}{D}\right)_{cr}$ $Q_u = \frac{\pi}{2} K_u D \gamma L_{cr}^2 \tan\delta + \pi K_u D \gamma L_{cr}(L - L_{cr}) \tan\delta$ for $\frac{L}{D} > \left(\frac{L}{D}\right)_{cr}$ For $D_r \leq 70\%$ $\left(\frac{L}{D}\right)_{cr} = 0.156 D_r + 3.58$ For $D_r > 70\%$ $\left(\frac{L}{D}\right)_{cr} = 14.5$
Shanker et al. (2007)	$Q_u = \pi\gamma\left(\frac{DL^2}{2} + \frac{L^3}{3\tan\theta}\right)\left(\frac{1}{\tan\theta} + (\cos\theta + K\sin\theta)\tan\phi\right) - \frac{\pi}{4}\gamma L D^2$ $K = (1 - \sin\phi)\left(\frac{\tan\delta}{\tan\phi}\right)$ and $\theta = \frac{\pi}{2} - \frac{\phi}{4}$

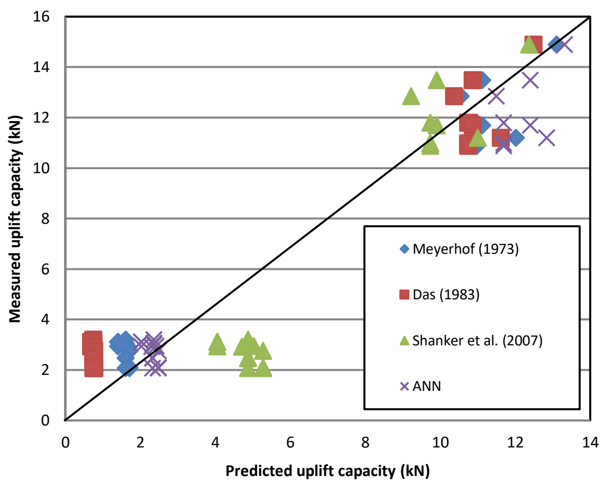

Figure 5 Predicted versus measured uplift capacity of pile in sand

Table 6 Predicted versus measured uplift capacity of 0.089 m piles in size embedded in sand for data collected from Al-Mhaidib and Edil (1995)

Point	L (m)	D_r (%)	γ (kN/m³)	ϕ (Deg.)	δ (Deg.)	Uplift capacity of pile (Q_u) in (kN)				
						Measured	Meyerhof (1973)	Das (1983)	Shanker et al. (2007)	ANN
1	1.54	9	15.69	30.5	12.2	2.94	1.41	0.69	4.05	2.03
2	1.65	9	15.69	30.5	12.2	3.06	1.61	0.75	4.87	2.36
3	1.65	9	15.69	30.5	12.2	3.01	1.61	0.75	4.87	2.36
4	1.67	9	15.69	30.5	12.2	2.95	1.65	0.76	5.03	2.42
5	1.54	9	15.69	30.5	12.2	3.11	1.41	0.69	4.05	2.03
6	1.65	9	15.69	30.5	12.2	3.21	1.61	0.75	4.87	2.36
7	1.54	9	15.69	30.5	12.2	3.11	1.41	0.69	4.05	2.03
8	1.63	9	15.69	30.5	12.2	2.92	1.58	0.74	4.72	2.30
9	1.51	85	17.45	39	39	10.88	10.98	10.75	9.74	11.70
10	1.51	85	17.45	39	39	10.98	10.98	10.75	9.74	11.70
11	1.51	85	17.45	39	39	11.8	10.98	10.75	9.74	11.70
12	1.48	85	17.45	39	39	12.85	10.55	10.37	9.23	11.50
13	1.7	9	15.69	30.5	12.2	2.76	1.71	0.78	5.28	2.49
14	1.65	9	15.69	30.5	12.2	2.47	1.61	0.75	4.87	2.33
15	1.65	9	15.69	30.5	12.2	2.48	1.61	0.75	4.87	2.33
16	1.7	9	15.69	30.5	12.2	2.1	1.71	0.78	5.28	2.49
17	1.7	9	15.69	30.5	12.2	2.07	1.71	0.78	5.28	2.49
18	1.65	9	15.69	30.5	12.2	2.08	1.61	0.75	4.87	2.33
19	1.58	85	17.45	39	39	11.2	12.02	11.62	11.0	12.84
20	1.52	85	17.45	39	39	11.7	11.13	10.87	9.91	12.41
21	1.65	85	17.45	39	39	14.9	13.11	12.49	12.37	13.32
22	1.52	85	17.45	39	39	13.48	11.13	10.87	9.91	12.41

7. CONCLUSIONS

This paper focuses on the application of an artificial neural network (ANN) to predict the uplift capacity of both regular and enlarged piles embedded in sand. Based on the research findings from this study, several conclusions can be drawn:

The prediction of the uplift behavior of two types of piles (i.e., regular and enlarged piles) embedded in sand soil using one unified machine learning model has proven its efficiency in giving reasonable and accurate estimates compared to the measured data.

Four different algorithms implemented in this study were able to give good predictions of the uplift capacity of piles in sand.

Artificial neural network (ANN) performed better over the different algorithms used in this study in predicting piles' uplift capacity in the sand since it does not show overfitting on training and test data sets.

For the artificial neural network, the Relu activation function had the best results compared to other activation functions that were considered in this study.

The accuracy and reliability of the prediction of piles' uplift capacity in sand using an artificial neural network could be enhanced significantly by increasing the quantity and quality of training data.

The ANN model was more accurate than other theoretical models in prediction the uplift capacity of piles.

8. REFERENCES

Abdul-Husain, H. A., and Hamadi, H. S. (2021). "Regression of Pullout Capacity for Model Open-Ended Pile Embedded in Cohesionless Soil." *Journal of Engineering Science and Technology*, Special Issue on DMPCE2021, 82-92.

Agarwal, A., Irtaza, H., and Khan, M. A. (2021). "Experimental Study of Pulling-Out Capacity of Foundation for Solar Array Mounting Frames." *Indian Geotechnical Journal*, *Springer*, 51, 414-420, doi: 10.1007/s40098-020-00456-w.

Alawneh, A. S., Malkawi, A. I. H., and Al-Deeky, H. (1999). "Tension Tests on Smooth and Rough Model Piles in Dry Sand." *Canadian geotechnical journal*, 36(4), 746-753, doi: 10.1139/t98-104.

Ali, F., Khatun, S., and Lincoln, A. (2017). "An Experimental and Numerical Investigation of Uplift Capacity of Single Piles and Group Piles in Cohesion-less Soil." In Proc., Indian Geotechnical Conference GeoNEst, 8-11, 14-16 December, IIT Guwahati, India.

Al-Mhidib, A., and Edil, B. (1999). "Effect of Pile Installation Method on Uplift Capacity of Piles in Sand." In Proc., 4th Saudi Engineering Conference, 73-79, Jeddah.

Amjad, M., Ahmad, I., Ahmad, M., Wróblewski, P., Kamiński, P., and Amjad, U. (2022). "Prediction of Pile Bearing Capacity Using XGBoost Algorithm: Modeling and Performance Evaluation." *Applied Sciences,* 12(4), 2126, doi: 10.3390/app12042126.

Bajaj, P., Yadu, L., and Chouksey, S. K. (2019). "Behavior of Vertical and Batter Piles under Lateral, Uplift and Combined Loads in Non-Cohesive Soil." *Innovative Infrastructure Solutions*, *Springer*, 4(55), 1-17, doi: 10.1007/s41062-019-0242-z.

Basha, A., and Azzam, W. R. (2018). "Uplift Capacity of Single Pile Embedded in Partially Submerged Sand." *KSCE Journal of Civil Engineering*, *Springer*, 22(12), 4882-4890, doi: 10.1007/s12205-017-1715-2.

Benbouras, M. A., Petrişor, A. I., Zedira, H., Ghelani, L., and Lefilef, L. (2021). "Forecasting the Bearing Capacity of the Driven Piles using Advanced Machine-Learning Techniques." *Applied Sciences (Switzerland)*, 11(22), 10908, doi: 10.3390/app112210908.

Bose, K. K., and Krishnan, A. (2009). "Pullout Capacity of Model Piles in Sand." *Indian Geotechnical Society Chennai Chapter*, *Student Competition Paper*, 49-54.

Chattopadhyay, B. C., and Pise, P. J. (1986). "Uplift Capacity of Piles in Sand." *Journal of Geotechnical Engineering*, *ASCE*, 112(9), 888–904, doi: 10.1061/(ASCE)0733-9410(1986)112:9(888).

Dadhich, S., Sharma, J. K., and Madhira, M. (2022). "Estimation of the Uplift Resistance for an Under-Reamed Pile in Dry Sand Using Machine Learning." *Slovak Journal of Civil Engineering*, 30(3), 17-26.

Das, B. M., Seeley, G. R., and Pfeifle, T. W. (1977). "Pullout Resistance of Rough Rigid Piles in Granular Soil."

Soils and Foundations, *Elsevier*, 17(3), 72-77, doi: 10.3208/sandf1972.17.3_72.

Das, S. K. and Basudhar, P. K. (2008). "Prediction of Residual Friction Angle of Clays using Artificial Neural Network." *Engineering Geology, Elsevier*, 100(3-4), 142–145.

Dash, B. K., and Pise, P. J. (2003). "Effect of Compressive Load on Uplift Capacity of Model Piles." *Journal of Geotechnical and Geoenvironmental Engineering*, *ASCE*, 129(11), 987-992, doi: 10.1061/(ASCE)1090-0241(2003)129:11(987).

Emirler, B., Tolun, M., and Yildiz, A. (2019). "3D Numerical Response of a Single Pile under Uplift Loading Embedded in Sand." *Geotechnical and Geological Engineering*, *Springer*, 37(5), 4351-4363, doi: 10.1007/s10706-019-00913-1.

Emirler, B., Tolun, M., and Yildiz, A. (2021). "An Experimental Study of Rough Single Pile and Pile Group under Uplift Loading in Sand." *European Journal of Environmental and Civil Engineering*, *Taylor & Francis Group*, 25(3), 557-574, doi: 10.1080/19648189.2019.1642242.

Faizi, K., Kalatehjari, R., Nazir, R., and Rashid, A. S. A. (2015). "Determination of Pile Failure Mechanism under Pullout Test in Loose Sand." *Journal of Central South University*, *Springer*, 22(4), 1490-1501, doi: 10.1007/s11771-015-2666-8.

Faizi, K., Armaghani, D. J., Sohaei, H., Rashid, A. S. A., and Nazir, R. (2015). "Deformation Model of Sand around Short Piles under Pullout Test." *Measurement*, *Elsevier*, 63, 110-119, doi: 10.1016/j.measurement.2014.11.028.

Fatehnia, M., and Amirinia, G. (2018). "A Review of Genetic Programming and Artificial Neural Network Applications in Pile Foundations." *International Journal of Geo-Engineering*, *Springer*, 9(1), 2.

Gaaver, K. E. (2013). "Uplift Capacity of Single Piles and Pile Groups Embedded in Cohesionless Soil." *Alexandria Engineering Journal*, *Elsevier*, 52(3), 365-372, doi: 10.1016/j.aej.2013.01.003.

Harris, D. E., and Madabhushi, G. S. P. (2015). "Uplift Capacity of an Under-Reamed Pile Foundation." In Proc., Institution of Civil Engineers Geotechnical Engineering, 168(6), 526-538, doi: 10.1680/jgeen.14.00154.

He, H. N., Dai, G. L., and Gong, W. M. (2015). "Review of Computational Models and Methods for Predicting Ultimate Capacity of Uplift Piles with Uniform Cross Section." *Journal of Highway and Transportation Research and Development (English Edition)*, *ASCE*, 9(2), 69-76, doi: 10.1061/JHTRCQ.0000443.

Honda, T., Hirai, Y., and Sato, E. (2011). "Uplift Capacity of Belled and Multi-Belled Piles in Dense Sand." *Soils and Foundations*, *Elsevier*, 51(3), 483-496, doi: 10.3208/sandf.51.483.

Hussein, H. N. A., Shafiqu, Q. S. M., and Khaled, Z. S. (2021). "Seismic Effect on Uplift Bearing Capacity of Pile Embedded in Dry Sand." *Journal of Physics: Conference Series*, 1895(1), 012019, doi: 10.1088/1742-6596/1895/1/012019.

Jebur, A., Atherton, W., Al Khaddar, R., Loffill, E., and Al-Jumeily, D. (2018). "An Enhanced Neural Network Scheme to Model Pile Load-Deformation under Uplift Loading." 11th International Conference on Developments in eSystems Engineering (DeSE), 129-133, Cambridge: IEEE

Jebur, A. A., Atherton, W., Alattar, Z. I., and Al Khaddar, R. M. (2022). "A New Approach for Modelling Pile Settlement of Concrete Piles under Uplift Loading using an Evolutionary LM Training Algorithm." *Ships and Offshore Structures*, *Taylor & Francis Group*, 17(6), 1413–1425, doi: 10.1080/17445302.2021.1926658.

Kotal, A., and Khan, A. K. (2015). "Pullout Capacity of Model Pile Group Anchors Embedded in Cohesionless Soil." In Proc., 50th Indian Geotechnical Conference, 17th – 19th December, Pune, Maharashtra, India.

Krabbenhoft, S., Andersen, A., and Damkilde, L. (2008). "The Tensile Capacity of Bored Piles in Frictional Soils." *Canadian Geotechnical Journal*, 45(12), 1715-1722, doi: 10.1139/T08-086.

Kumar, A., Khatri, V. N., and Gupta, S. K. (2022). "Numerical and Analytical Study on Uplift Capacity of Under-Reamed Piles in Sand." *Marine Georesources & Geotechnology*, *Taylor & Francis Group*, 40(1), 104-124, doi: 10.1080/1064119X.2021.1871689.

Liu, B., Li, H., and Liu, S. (2020). "Influencing Factors of Load Carrying Capacity and Cooperative Work Laws of Metro Uplift Piles." *Structural Durability & Health Monitoring*, 14(3), 249-264 , doi: 10.32604/sdhm.2020.06482.

Meyerhof, G. G., and Adams, J. I. (1968). "The Ultimate Uplift Capacity of Foundations." *Canadian Geotechnical Journal*, Ottawa, 5(4), 225–244, doi: 10.1139/t68-024.

Milad, F., Kamal, T., Nader, H., Erman, O. E. (2015). "New Method for Predicting the Ultimate Bearing Capacity of Driven Piles by using Flap Number." *KSCE Journal of Civil Engineering*, *Springer*, 19(3), 611-620.

Moayedi, H., and Rezaei, A. (2019). "An Artificial Neural Network Approach for Under-Reamed Piles Subjected to Uplift Forces in Dry Sand." *Neural Computing and Applications, Springer*, 31(2), 327-336.

Mosquera, Z. S., Tsuha, C. D. H., Schiavon, J. A., and Thorel, L. (2015). "Discussion of Field Investigation of the Axial Resistance of Helical Piles in Dense Sand." *Canadian Geotechnical Journal*, 52(8), 1190-1194, doi: 10.1139/cgj-2015-0212.

Muduli, P. K., Das, S. K., and Das, M. R. (2013). "Prediction of Lateral Load Capacity of Piles using Extreme Learning Machine." *International Journal of Geotechnical Engineering*, *Taylor & Francis Group*, 7(4), 388-394, doi: 10.1179/1938636213Z.00000000041.

Narayanan, P. S., Faris, M., and Sivameenakshi, M. P. (2017). "Model Tests to Determine Uplift Capacity of Mono Piles Embedded in Sandy Soil." *Electronic Journal of Geotechnical Engineering*, 22(2), 749-756.

Nasr, A. M. (2013). "Uplift Behavior of Vertical Piles Embedded in Oil-Contaminated Sand." *Journal of Geotechnical and Geoenvironmental Engineering*, *ASCE*, 139(1), 162-174, doi: 10.1061/(ASCE)GT.1943-5606.0000739.

Nazir, R., Moayedi, H., Pratikso, A., and Mosallanezhad, M. (2015). "The Uplift Load Capacity of an Enlarged Base Pier Embedded in Dry Sand." *Arabian Journal of Geosciences*, *Springer*, 8(9), 7285-7296, doi: 10.1007/s12517-014-1721-3.

Niroumand, H., Kassim, K. A., Ghafooripour, A., and Nazir, R. (2012). "Uplift Capacity of Enlarged Base Piles in Sand." *Electronic Journal of Geotechnical Engineering*, 17, 2721-2737.

Patra, N. R., and Pise, P. J. (2003). "Uplift Capacity of Pile Groups in Sand." *Electronic Journal of Geotechnical Engineering*, 8, 1.

Prayogo, D., and Susanto, Y. T. T. (2018). "Optimizing the Prediction Accuracy of Friction Capacity of Driven Piles in Cohesive Soil using a Novel Self-Tuning Least Squares Support Vector Machine." *Advances in Civil Engineering*, vol. 2018, doi: 10.1155/2018/6490169.

Pham, T. A., Ly, H. B., Tran, V. Q., Giap, L. V., Vu, H. L. T., and Duong, H. A. T. (2020). "Prediction of Pile Axial Bearing Capacity using Artificial Neural Network and Random Forest." *Applied Sciences (Switzerland)*, 10(5), doi: 10.3390/app10051871.

Pham, T. A., Tran, V. Q., Vu, H. L. T., and Ly, H. B. (2020). "Design Deep Neural Network Architecture using a Genetic Algorithm for Estimation of Pile Bearing Capacity." *PLoS One*, 15(12), doi: 10.1371/journal.pone.0243030.

Rao, K. S. S., and Venkatesh, K. H. (1985). "Uplift Behavior of Short Piles in Uniform Sand." *Soils and Foundations*, *Elsevier*, 25(4), 1-7, doi: 10.3208/sandf1972.25.4_1.

Rao, K.S., and Kumar, J. (1994). "Vertical Uplift Capacity of Horizontal Anchors." *Journal of Geotechnical Engineering Division, ASCE*, 120(7), 1134-1147, doi: 10.1061/(ASCE)0733-9410(1994)120:7(1134).

Shanker, K., Basudhar, P. K., and Patra, N. R. (2007). "Uplift Capacity of Single Piles: Predictions and Performance." *Geotechnical and Geological Engineering*, *Springer*, 25, 151-161, doi: 10.1007/s10706-006-9000-z.

Shelke, A., and Patra, N. R. (2009). "Effect of Arching on Uplift Capacity of Single Piles." *Geotechnical and Geological Engineering*, *Springer*, 27, 365-377, doi: 10.1007/s10706-008-9236-x.

Shooshpasha, I., Kiakojoori, M., and Mirzagoltabar, R. A. (2009). "Evaluation of Tension Capacity of Pile (Case Study in Sandy

Soil).” *International Journal of Geological and Environmental Engineering*, 3(10), 343-350.

Tien Bui, D., Moayedi, H., Abdullahi, M. A. M., Safuan A Rashid, A., and Nguyen, H. (2019). “Prediction of Pullout Behavior of Belled Piles through Various Machine Learning Modelling Techniques.” *Sensors*, 19(17), 3678.

Vanitha, L., Patra, N. R., and Chandra, S. (2007). “Uplift Capacity of Pile Group Anchors.” *Geotechnical and Geological Engineering*, *Springer*, 25(3), 339-347, doi: 10.1007/s10706-006-9114-3.

Verma, A. K., and Joshi, R. K. (2010). “Uplift Load Carrying Capacity of Piles in Sand.” *Indian Geotechnical Conference,* 857-860, 16th -18th Dec, India.