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Determination bearing capacity of driven piles in sandy soils usingArtificial Neural Networks (ANNs)

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Abstract:*Due to some effective factors such as inhomogeneity of soil environment surrounded one pile, implementation of pile, pile material and its shape, correct estimation of pile load carrying capacity is difficult. However, pile load test with a high accuracy can be used as a reliable method in different steps of design and analysis, it is costly and its implementation takes long time in civil projects. This imposed some limitation on using this test. In contrast, modeling by artificial neural networks is a method which doesn't require simplification and use of high reliability coefficients and is based on pervious data and information.*
In this paper, artificial neural network is applied for prediction of load carrying capacity of open ended metal piles pounded in sandy soils. Four parameters of pile length, its diameter, soil elastic modulus and soil internal friction angle are used as input and pile load carrying capacity is applied as output. How to designa network and effective factors for its behavior are studied in the related topic. Finally, the effects of four input parameters on network output are discussed using sensitivity analysis of introduced optimized structure.
Key words:*pile load test, load carrying capacity determination device, artificial neural networks, Multi-Layer Perceptron, sensitivity analysis.*

I. Introduction

In the design of pile foundations a good estimation of the pile bearing capacity is one of the major concerns. Bearing capacity designs are carried out by determining the allowed pile load, which is obtained by dividing the ultimate pile load by an assumed factor of safety. There are several static and dynamic load test based approaches to specify the pile capacity, But due to practical problems and the financial considerations, researchers are forced to look into the alternate numerical methods to determine the pile capacities.One of the alternate ways to reduce the time and costs are using soft computing techniques includes Artificial Neural Networks (ANN) and Fuzzy Systems (FS), which can be used to predict the load bearing capacity of piles using both static and dynamic data sets. (Chan et al., 1995 ; Lee et al., 1996 ; Das et al., 2006 ; Padmini et al., 2008).
Fuzzy logic set theoretic models try to imitate human reasoning and the capability of handling uncertainty whereas neural network models attempt to emulate architecture and information representation scheme of human brain (Jang and Sun 1998). Hence neuro fuzzy computing acts as more intelligent systems. Artificial neural network is used for learning and adaptation whereas fuzzy systems are used to supplement its application domain. (Nasira et al., 2008). Back-propagation neural network (BPNN) , developed by Ramelhart et al. (1986), is one of the most frequentlyused algorithms in artificial neural networks. Tak Kim et al. (2001) used BPNN to predict the lateral behavior of single and group piles. Padmini et al. (2008) used Adaptive NeuroFuzzy Inference System (ANFIS) to undertake a comparative study with ANNs and fuzzy inference system (FIS) in predicting the ultimate bearing capacity of shallow foundations. The results indicate that the ANFIS model was able to yield a sufficient prediction of the ultimate bearing capacity of shallow foundations and remarkably outperforms the ANN and FIS models although all three models comes more efficientthan the theoretical methods.In recent years there were number of studies using ANNs to predict the lateral and axial bearing capacities of pile foundations in compression or uplift, including driven piles and drilled shafts (Shahin and Jaksa 2006; Pal 2006; Ahmad et al.,2007; Ardalanetal., 2009; Shahin, 2010; Alkrooshand and Nikraz, 2011; Tarawneh, 2013 ; Fatehnia et al 2014 ; Goh et al., 2005; Shahin, 2010).Multilayer perceptrons (MLPs) which have been used in the present study is an algorithmtodetermine the driven piles bearing capacity. MLP is a feedforward artificial neural network model consists a number of processing elements or nodes that are arranged in layers: an input layer, an output layer, and one or more inter-mediate layers called hidden layers.Ornek et al. (2012) used MLP and multilinear regression (MLR) to predict bearing capacity of a circular footing over clay soil. They research states ANNs as a simple and reliable tool for the bearing capacity of circular footings clay soil and the results produced high coefficients of correlation for the training and testing data. camparison of the results obtained from both mothods indicated that MLP produced more accurate results than the MLR technique.M.A. Shahin (2014) modeled Load-settlement for axially loaded driven piles using recurrent neural networks (RNNs) developed for any soil type. RNNs has been proposed by Jordan (1986) imply an extension of the MLPs with current-state units, which are processing elements that remember past activity. Based on this study RNN model

can capture the highly non-linearload-settlement response of steel driven piles reasonably well.This study will present use of artificial neural networks (ANNs) and the Multi-Layer Perceptron model (MLP) to predictbearing capacities of steel driven piles in sandy soils. The data used to run the network models have been obtained from several in-situ full-scale pile load testsandgeotechnical investigations in Hormozgandockyard. An MLP distinguishes itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called the hidden neurons of hidden units.In this study one hidden layer MLPs is applied.

II. Artificial Neural Networks

Artificial neural network is a set of simple interconnected computational elements called neuron whose unique learning capability enables this system to learn very complicated relations. These computational units are connected to many interconnections in which all the knowledge from environment is stored. First neuron model which is known as basis of present neural networks was introduced by Piths and McCulloch (1943) (Figure 1).
Three main elements are observed in this model:
- Set of synapses or connections which are determined by weight values or resistance. One $x_j$signal (j th input) which is connected to kth neuron is multiplied by w_{kj} weigh. Suffix k and j represent the number of considered neuron and input connection, respectively.
- One adder sums inputs of a neuron ($w_{kj}x_j$) with a bias value. This action is called linear combination.
- One activation function is applied for limiting neuron output to an appropriate range. Activation function or simulator can be linear or nonlinear. The most common simulator functions arelinear function, Log-Sigmoid Transfer Function, two-valued symmetric threshold function and Hyperbolic Tangent Sigmoid Transfer Function.

2-1 Multi-Layer Perceptron neural network

One of the most common neural networks is Multi-Layer Perceptron neural network or briefly MLP network. This network has an input layer, one output layer and several hidden layers. In this network which for the first time was presented by Widrow and Rosenblatt neurons in each layer are fully connected toall neurons in previous and next layers and there is no reversible connection in the network [1]. MPL neural network having a hidden layer is able to describe every nonlinear relation between input and output patterns [1]. Therefore, a neural network withone hidden layer is used in this study.

2-1-2 Determining the number of intermediate neurons

Intermediate neurons act as pattern recognizers [2] and let network learn nonlinear mappings well. It has been shown that MLP networks having a hidden layer will be able to approximate all functions with alldegrees of approximation by takingderivative of transfer functions in intermediate and output layers provided that there are enough neurons in hidden layer [3]. In another words, if there is a mapping, one MLP network having one hidden layer can be determined to approximate this mapping.

Determining the number of neurons in hidden layer has a significant effect on network behavior. If the number of neurons is few, neural network can’t reflex nonlinear mapping between input and output accurately (under fitting). On the other hand, if the number of neurons is more than required number, network learns training data well (memorizing) by producing complex nonlinear mapping but new data don’t have an appropriate performance and indeed network lose its generalization capability (over fitting). The number of neurons in hidden layer is usually obtained experimentally [4].

2-1-3 Training and testing network

The purpose of training in MLP network is adjusting network free parameters (weights) in order to receive appropriate responses from it. Therefore, in training process, inputs from some parts of information bank (training set) are presented to network. Output values are calculated and are compared with target values and then weights are corrected based on the errors. Each presentation of inputs and weights adjustment is called training cycle. Training cycles continues until the error becomes an acceptable value. After training, weight values are stored and network is testedby other parts of data that has not been used in training process. In this study, method of standard error back propagation with momentum is used. In addition to increasing training speed this method also prevents network instability.

III. Field tests

Training artificial neural networks needs using results of tests taken on real pile samples. For this aim and regarding accurate pile load tests and their acceptable results, results of 21 pile compressive load tests which were taken for complementary geotechnical studies of dry poolbyPazhooheshOmranRahvar consulting engineers in ship building complex of Hormozgan region, are used. Iran Ship Building and Offshore Industries Complex is located 40 km west of Bandarabas. According to division of sedimentary-building units of Iran, the considered area is situated in Zagros folded zone.

According to geotechnical studies that performed in 1995, general situation of soil layers in the location of project is as following:

- Green mixture of silty sand and silty clay with a thickness of ~ 3 m (approximately to depth of 3m)
- Alternation of green silty sand layer with thickness of ~4 m (depth of ~3 to 7 m)
- Stone layer with average thickness of 20 cm (depth of ~7 m)
- Green silty sand layer (some gritty) with thickness of ~2 m (depth of ~7 to 9 m)
- Silty clay layer with mudhaving a thickness of ~8 m (depth of 9 to 17 m)
- Red silty sand to the end of boreholes (گمانه)(depth more than 17 m)

Figure 2 shows one cross-section of considered area.

3-1 Replacing clay by sand

As it is seen in Figure 2, it is obvious that soil of the region has fine-grained soil layers. Fine-grained layers are as two separate clayey-sandy silt and silty clay whose average SPT values are from 18 to 22 and the situation of soil from density aspect is estimated to be stiff to very stiff.

Mentioned clay layer influences tested piles in the region and some part of pile load carrying capacity is influenced by this layer. On the other hand, laboratory pile were tested in sandy beds. Therefore, in order to make condition of laboratory tests and field tests similar, it is required to replace clay layers of the region by sandy layers which have the same density as clay layer and produce a capacity equivalent to clay layer capacity. For this purpose, firstly it is essential to calculate the amount of load which clay layer can bear.

Since tips of all piles pounded in the region, is placed in underneath coarse-grained soil, clay layer produces a frictional capacity in all piles.

Considering clay layer thickness and other related characteristics, frictional resistance value due to clay layer was calculated for all piles using three methods of β .λ and α and their average value was considered as frictional resistance of clay layer.

After determining the amount of clay layer contribution to overall load carrying capacity of pile, the purpose of next step is finding sand that firstly has the same density as clay layer and secondly shows a resistance equivalent to clay layer resistance. In this part different sand with various internal friction angles were considered and finally sandy soil with density of 1.75 T/m^3 and internal friction angle of 34° selected for alternative sand.

It must be mentioned that some errors occurs in obtained resultsbecause of replacing soil for which experimental equations are used. Regarding the fact that most of resulting capacity in in-situ experiments is related to load carrying capacity of pile tip which means thatobtained frictional resistance of clay layerforms a small percent of overall capacity, obtained error is small and ignorable.

IV. Laboratory experiments

4-1 Pile load test

Since the number of taken real tests was limited and on the other hand training the network required many data, it was required to take several tests in laboratory. In this study for determining load carrying capacity of vertical piles under axial load, pile load carrying capacity determination testsweretaken using a large scale load carrying device which was made in soil and foundation laboratory of TarbiatModares University.

Mentioned device consists of three main sections. These three sections includes: sample making tank (100 cm length ×100 cm wide × 85 cm height), force applicationsection and force and settlementmeasurement section. Figure 3 shows total view of load carrying capacity device.

Tests on thin wall tubular piles with lengths of 35, 40, 45 and 50 cm, diameters of 20, 25 and 32 mm and thickness of 0.9 mm were taken in sandy beds having relative densities of 50, 60, 70, 75 and 80 percent. The total number of tests was 60 tests.

Standard sand called Firouzkouhbroken silica sand which is briefly named standard sand 161 was used. This type of sand has a golden yellowish color and based on unified soil classification it is classified in SP category (poorly grained sand). Graining curve for considered sand is shown in Figure 4.

Other characteristics of this sand include:

Grains density $2.66=G_S$

Soil void ratio in the stiffest condition $e_{max} = 0.928$

Soil void ration in the densest condition $e_{min}= 0.583$

Diameter of particles than which half of particles are finer $D_{50} =0.26$

Percentagepassing sieve No. 200 F (%)= 0

Uniformity coefficient $C_u = D_{60}/D_{10} = 1.8$

Coefficient of Gradation or Curvature $C_c = D_{30}^2/(D_{60})(D_{10}) = 1.19$

Sandy beds samples were made in load carrying capacity tank. In order to make sandy samples having desired relative densities, specific weight of sand was poured in load carrying capacity tank and each layer was pounded to the height of 10 cm.

After preparing sandy beds for pounding pile,one guide tube which was connected to adjacent column of device by a metal arm was used in order to minimize load eccentricity so as piles are placed inside guide tube and they are pounded.

For applying force, one hydraulic jack having capacity of 5 tons was used. Mentioned hydraulic jack ends intest plate (which is situated on pile) from bottom and a movable column (made by a 100 mm box) which is connected to a crane from top. Loading in these tests was done by standard loading method according to ASTM standard.

Force and settlement measurement section consists of a force meter ring and 3 electrical strain gauges. For measuring applied force by hydraulic jack, one 6 tons capacity force gauge ring having a strain gauge indicator timer with accuracy of 0.002 mm was used. The amount of pile's strain was calculated by three electrical strain gauges with accuracy of 0.01 mm. these strains are shown as vertexes of one equilateral triangle on the monitor.

Finally after finishing tests and plotting force-displacement diagrams for each pile, load carrying capacities were calculated by Chin's method for all piles. Based on Chin's method, firstly displacement values are divided by their equivalent forces and then diagram of displacement versus this value (division quotient of displacement by force) is plotted. If the obtained results by this method lie on a straight line, the slope of this line represents load carrying capacity of pile tip. But in most cases obtained results lie on two straight lines, therefore the slope of first line determines wall load carrying capacity and the second slop represents total pile load carrying capacity (Figure 5).

4-2 Plate load Test- PLT

Since soil elastic modulus is considered as one input of neural network, some load tests were taken to obtain these parameters. One circular solid plate with diameter of 20 cm was used. System for application of compressive loading is similar to that of pile loading tests and three stain gauges were used for determining the amount of plate settlement due to applied load. In Figure 6, load carrying capacity device is shown while plate is tested. Force-displacement diagrams were also plotted in these tests and elastic moduli for different densities were calculated using equation 1.

$$\mathrm{E} = \frac{\mathrm{Q}}{\delta \mathrm{D}}(1-\mu^2) * \mathrm{I}$$

δ= produced settlement (strain) due to load Q
D = solid plate diameter
μ = Poisson's coefficient
Q = applied load
I = correction factor related to test condition and arrangement

V. Applied Neural Network in this study

5-1 Information bank

In this study, results of 21 pile compressive load tests were used.

As mentioned previously, 60 compressive load tests were taken in TarbiatModares University using a large scale load carrying capacity device.

Totally there were 81 data for training, evaluating and testing the network. 51 data were used for training, 15 data were used for evaluating and 15 data were used for testing.

5-2 input and output parameters

Based on effective factorsforpile load carrying capacity, parameters which are considered as input of models include:

- Soil properties: in this study, internal friction angle, ø, was used for modeling and determining soil resistive properties. Also due to importance of soil elastic modulus in load carrying capacity, this parameter is considered as input parameter.
- Properties of tested pile: since pile dimensions influence on its load carrying capacity, two parameters of pile diameter (D) and pile length (L) are also considered as inputs of the network.

It must be mentioned that because laboratory tests were taken in very smaller dimensions than real dimensions, centrifuge scale rule was used for compensating the effect of scale. Based on this method, different parameters are change according to Table 1 [8]. N is scale number and since selection of 45 for scale number caused laboratory tests data to approach in-situ tests data, 45 was selected for N. For example, based on Table 1 and selection of 45 as scale number, laboratory piles lengths are multiplied by 45 (N) in order to have real dimensions.

For example, applied inputs and outputs of the network before multiplication by scale for apile with diameter of 32 mm, length of 45 cm in different sand densities are listed in Table 2.These numbers must be multiplied by scales mentioned in Table 1 before beingused in MLP network. Since input and output variables varies in a wide range, it is better to transfer them to [0 , 1] interval or [-1, 1] interval. The most important purpose of this transfer is correcting distribution of input and output variable so that network modeling error reduces [2]. Linear transfer is the most common transfer in neural networks. Therefore, in this study input and output variables were normalized respect to their maximum and minimum values by a linear relation (equation 2).

$$NP = \frac{UB - LB}{MaxP - MinP} \times (SP - MinP) + LB$$

5-3 Evaluation indexes

For comparing models and their evaluation, some indexes, which can judge models performance for predicting load carrying capacity of piles, are required. Therefore, below indexes were considered in this study:

- Coefficient of correlation (R): this index shows degree of connection between two variables. Cofficient of correlation for two x and y variables is defined as following [6]:

$$R = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}}$$

In which $\bar{x}$ and $\bar{y}$ are average values of x and y, respectively. great R values indicate strong connection between variables in two data sets. In contrast, small R values shows poor or no connection between two sets [6].

- Mean Absolute Error (MAE): represents average value of error in considered set. This index is expressed by below equation:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |E_i|$$

- Mean Square Error (MAE): this index also shows average value of error, the difference between obtained results by tests and those by models with this difference that it focuses more on greater errors [7].

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (E_i)^2$$

- Maximum Absolute Error (MAXAE): this index indicates maximum error occurred in considered set. This index is defined by following equation:

$$MAXAE = Max(|E_i|)$$

- Standard Deviation of Absolute Error (SDAE): this index determines variation degree of absolute error around MAE. It is obvious that the smaller is this index, the nearer is error of model in overall set to average value and the more stable is model.

5-4 Implementing network – training and stopping training

For implementing training and testing networks, neural network toolbar Matlab R2009b was used and networks were trained using LonbergMarca (ML) method. In order to increase generalization capability of network, cross-validation method was used for stopping training. Since the number of intermediate neurons influence on networks behavior, one study was performed about their performance with different numbers of intermediate neurons as following:

Evaluation set as one part of not experimented data which are used for controlling training process, can simultaneously show network simulation capability (against experimented training data) and network prediction capability (against not experimented test and evaluation data) in initial analyses. Therefore, firstly performance of trained networks with different intermediate neurons against these data is evaluated based on error indexes. (In this stage, coefficient of correlation is calculated for training and test sets). For more accurate selection, networks that have a good performance against evaluation data are also studied against training and test data. Finally a network having best performance in simulation (against training data) and in prediction (against test and evaluation sets) is selected as a network having optimized number of neurons.

In this study, different sets with 4, 6, 8, 10, 12, 14, 16, 18, 20, 22 and 24 intermediate neurons were evaluated. Coefficient of correlation and mean square error index of evaluation data are shown in Table 3 for MLP network having different neurons. For this aim, each network having constant number of neurons was tested 20 times and finally a network having minimum error was stored.

As it is obvious in Table 3, four networks with 6, 8, 10 and 14 neurons in hidden layer that had better performance than other networks, were selected and were evaluated against training and test data (Table 4). According to obtained results, the best condition for considered network is use of 6 neurons in hidden layer because a network with 6 neurons in hidden layer has minimum error values for network evaluation and test data.

Diagrams of neural network outputsversus target values for training, evaluation and test dataare shown in Figures 7,8 and 9, respectively. It must be mentioned that considered network in these diagrams has 6 intermediate neurons in hidden layer.

5-5- Effect of different transfer functions on performance

For evaluating performance of different transfer (activation) functions, networks with different transfer functions in their intermediate and output layers were studied. 6 intermediate neurons were considered for these networks in hidden layer and other network parameters were the same. In this study, three activation functions including linear function (pureline), simulator sigmoid function (logsig) and tangent hyperbolic function (tansig) were considered. It must be mentioned that based on recommendations of experienced people in neural networks, purelin transfer function was not used in hidden layer [6]. Totally 6 networks with different transfer functions and other similar parameters can be formed using mentioned activation functions. These networks and their transfer functions are listed in Table 5. For evaluating performance of these networks, firstly they were compared using evaluation data.

As it is seen in Table 5, among these 6 networks, two networks whose transfer functions are tansig in intermediate layer andpureline and tansigin output layer had better performance. Therefore, these two networks were compared for training and test data using error parameters. Based on error indexes in Table 6, it is observed that the network whose transfer function are tansig in hidden layer and purelin in output layer has the best performance.

VI. Sensitivity Analysis

Studying how uncertainties in output model are attributed to different uncertainties sources in input model is called sensitivity analysis [. Some advantages of sensitivity analysis are informing model creatorof its technical errors and determining critical areas in inputs space.

6-1 Results analysis and sensitivity analysis

In this study, sensitivity analysis was performed on three inputs including pile length, pile diameter, sand internal friction angle and sand elastic modulus.

Relative derivatives of output respect to four inputs were separately calculated for each point of data set which has its relative input. Statistical properties of relative derivative values are listed in Table 7. As it is expected, relative derivatives of outputs respect to each input in inputs space have different values.

Average value of sensitivities can be considered as resultant of input effect on output. Indeed, changes in output values due to changes in inputs is influenced by resultant of output changes respect to one variable unite in inputs or in another word output sensitivity respect to input to each point of input changes route (from one initial value to a secondary value). Of course, average comparison similar to sensitivity values must be considered relatively to be comparable with other average input values.

Based on mentioned facts and variability of sensitivity values, one method is required for sensitivity analysis that simultaneously shows scattering and possibility of different output sensitivity values respect to one input in input space. For this purpose, one statistical method of relative sensitivity values which was used by Luo et al. (2001) was applied [10]. In this method, five statistical percentages (D10, D25, D50, D75, D90) of outputs relative sensitivity values respect to considered input are calculated. Based on random samples effect of an increase or decrease in each input on outputs and dominant general trend in overall input spacearedetermined by this method. Explanation and interpretation of obtained results will be discussed in the following paragraphs.
D10: represents a value for relative sensitivity than which 90% of values are greater and 10% of values are smaller. Therefore, if this value becomes positive, it shows that the possibility for positive relative sensitivity values is greater than 90% or in another word, the possibility for increasing output with increasing considered input is greater than 90%.

- D25, D75 and D90 have the same explanations as D10.

One input with scattered relative sensitivity percentages values around a base line, has minimum effect on output comparing with one input whose relative sensitivity percentages are scattered far from a base line.

Therefore, based on statistical percentages values and their distance from base line, influence degree of each variable on output can be studied and compared with other variables [10].

Statistical percentages values pertaining to relative sensitivities of load carrying capacity values were calculated for four input parameters of MLP network having 8 neurons in hidden layer and they are shown in Table 8.

As it is seen in Figure 10, all parameters have positive relative sensitivity value which indicates increasing effect of these parameters on load carrying capacity, however based on sensitivity values and their distances from base line, effects of these parameters are different. For example, because of greater values of relative sensitivity than internal friction angle and their larger distance from base line it can be concluded that maximum increasing effect on load carrying capacity occurs due to increasing sand internal friction angle.

Generally, based on distances of statistical categories from base line, percentages values and relative average values, it can be stated that soil internal friction angle, soil elastic modulus, pile diameter and pile length respectively have maximum increasing effect on piles load carrying capacity

VII. Conclusion

In this study, MLP neural network was used as an alternative method for predicting load carrying capacity of metal piles pounded in sandy soils. Obtained results revealed that neural network with minimum error, high speed and learning capacity, has very high efficiency inpredicting load carrying capacity of metal piles. Specially MLP network having one hidden layer, 6 intermediate neurons,tansig transfer function in hidden layer and purelintransfer function in output layerhas the best performance. Also based on performed sensitivity analysis on the best obtained network, all parameters have an increasing effect onload carrying capacity and according to sensitivity values and their distances from base line, it is concluded that soil internal friction angle, soil elastic modulus, pile diameter and pile length respectively have maximum effect on load carrying capacity of piles.

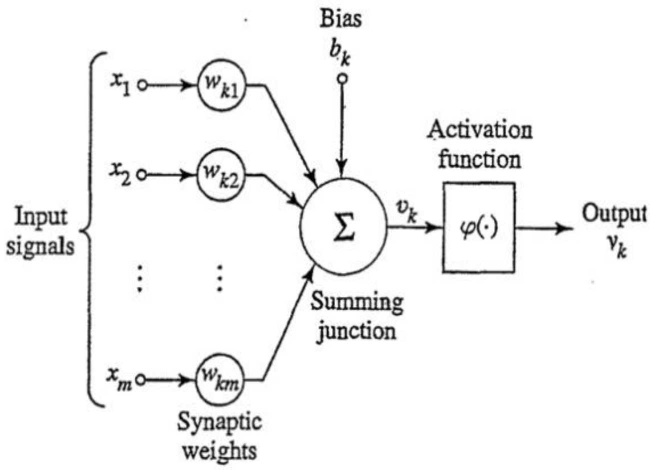
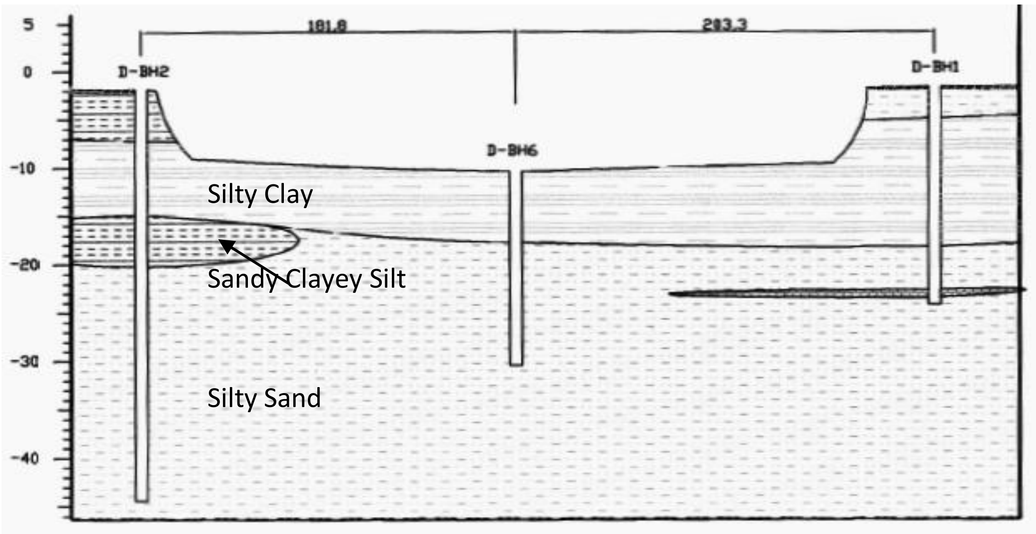


Figure 1- Neuron mathematics model.

Figure 2- plotted geological cross-section



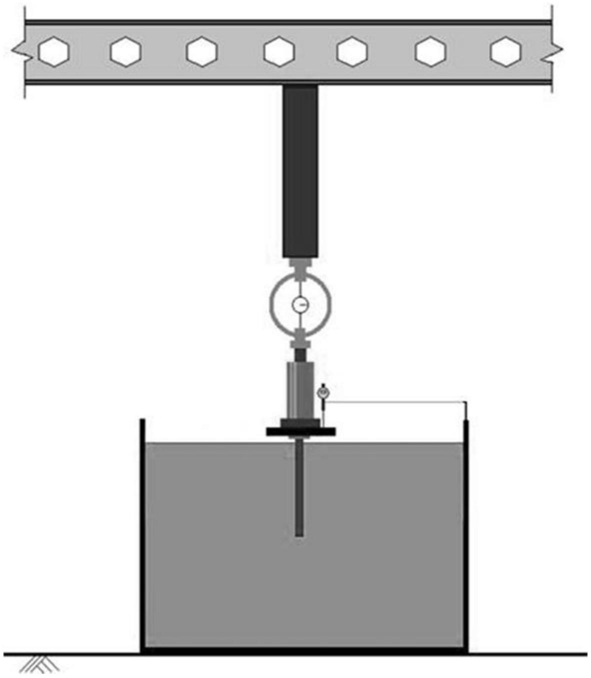


Figure 3. device of pile bearing capacity

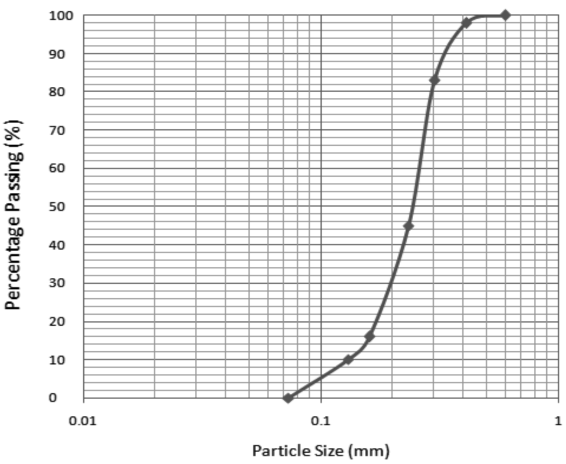


Figure 4. Graining curve of tested sand

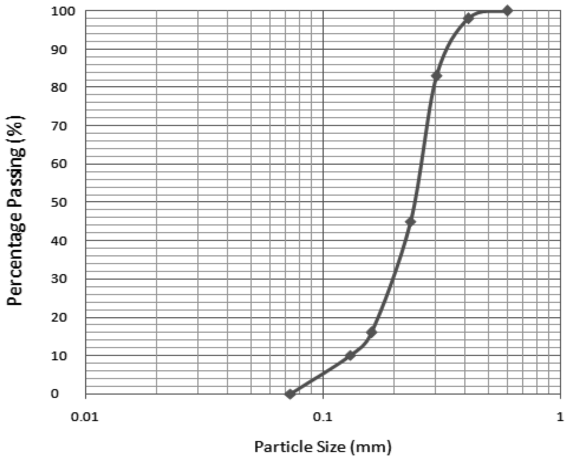


Figure 5- One example of pile force –displacement curve presented by Chin

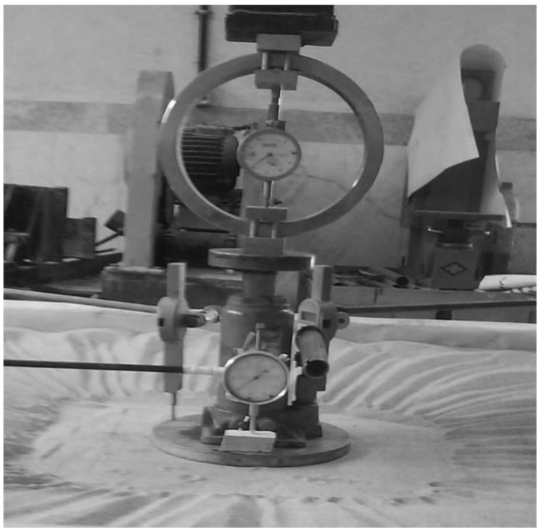


Figure 5- plate load test

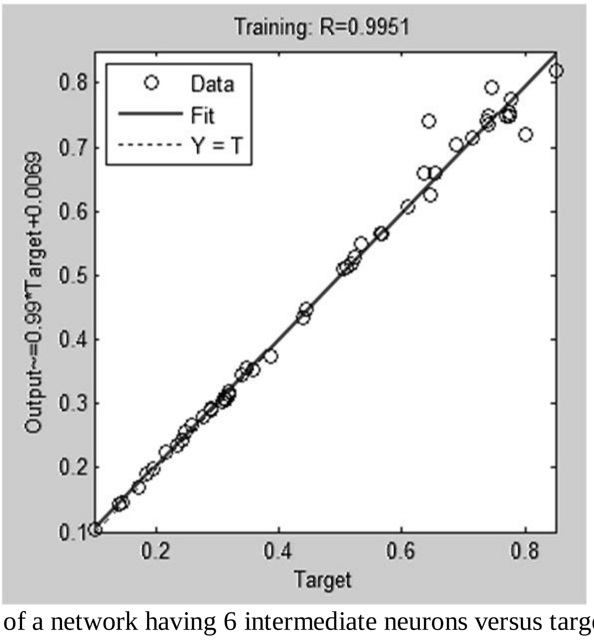


Figure 7- obtained outputs of a network having 6 intermediate neurons versus target values for training data.

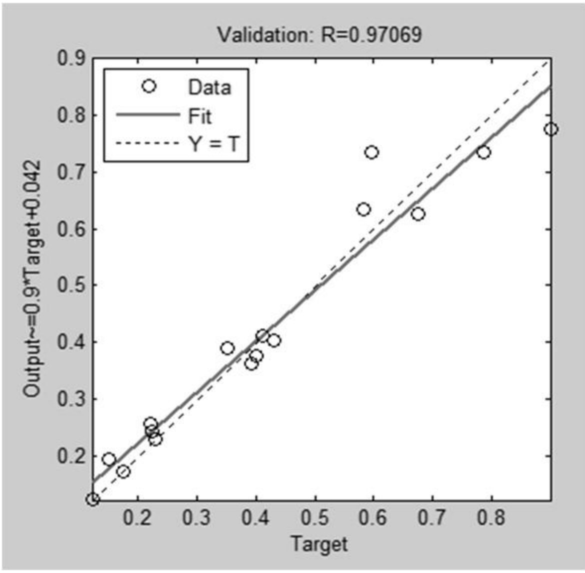


Figure 8- obtained outputs of a network having 6 intermediate neurons versus target values for evaluation data.

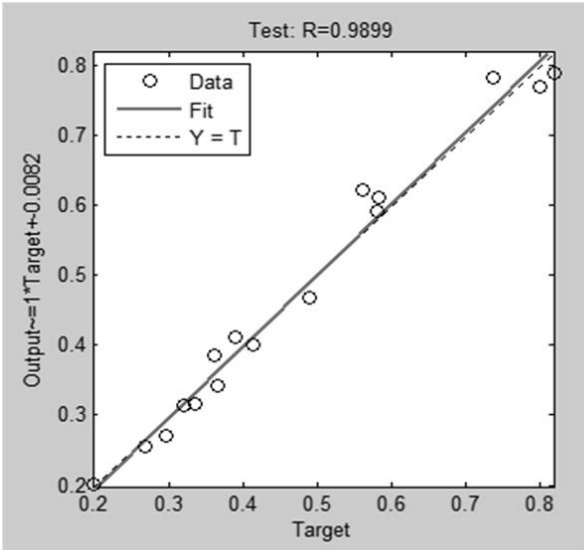


Figure 9- obtained outputs of a network having 6 intermediate neurons versus target values for test data with 6 intermediate neurons.

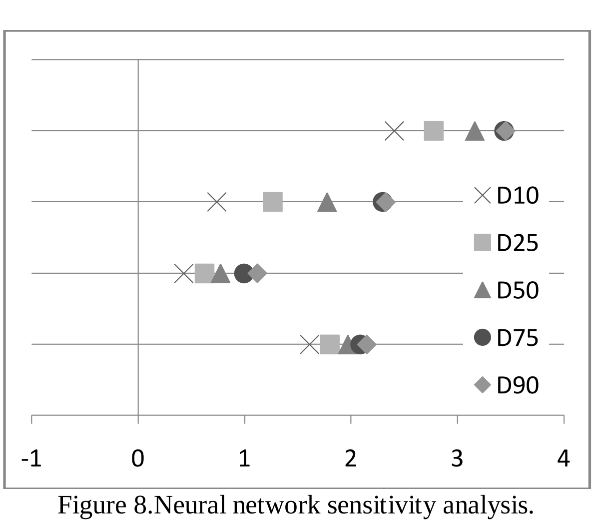


Figure 8.Neural network sensitivity analysis.

Table 1- Scale factor for different parameters.

Quantity	Scale Factor
	for static events
Length, L	1/N
Force, F	$1/N^2$
Modul, E	1
Friction Angle, φ	1

Table 2- input and output parameters for a pile with diameter of 32 mm and length of 45 cm before multiplication by scales.

	Input				Output
Dr %	L (mm)	D (mm)	E(Kpa)	φ	Qu (Kg)
50	32	450	53	37	247.9
60	32	450	83	38	360.3
70	32	450	130	39	448.6
75	32	450	160	39.5	552.7
80	32	450	198	40	591.5

Table 3.Comparing errors of networks having different numbers of neurons in hidden layer for evaluation data.

N.ofH.Neurons	Error or Validation Subset	
	R	MSE
4	0.9624	0.0036
6	0.9706	0.0023
8	0.9733	0.0018
10	0.9810	0.0015
12	0.9675	0.0029
14	0.9754	0.0027
16	0.9576	0.0047
18	0.9612	0.0034
20	0.9567	0.0054
22	0.9418	0.0075
24	0.9544	0.0061

Table 4. Comparing errors of networks having different numbers of neurons in hidden layer for training and test sets.

N.of H. Neurons	Error or Training Subset				
	R	MSE	MAE	MAXAE	SDAE
6	0.9951	0.0006	0.014	0.099	0.02
8	0.9854	0.0015	0.025	0.127	0.03
10	0.992	0.00073	0.0167	0.1149	0.021
14	0.9962	0.001	0.021	0.1236	0.023
	Error or Testing Subset				
6	0.9899	0.0008	0.017	0.1277	0.024
8	0.9895	0.0016	0.027	0.1351	0.029
10	0.9824	0.0023	0.029	0.139	0.031
14	0.9851	0.0021	0.023	0.1349	0.025

Table 5.Effect of different transfer functions on network error for evaluation data.

Transfer Functions		Testing Subset	
Hid.Layer	Out.Layer	R	MSE
Ttansig	Tansig	0.9711	0.0022
Tansig	Logsig	0.8835	0.032
Tansig	Purelin	0.9706	0.0023
Logsig	Tansig	0.9514	0.0068
Logsig	Logsig	0.9317	0.012
Logsig	Purelin	0.9594	0.0045

Table 6.effect of different transfer functions on network error for training ant test data.

Hidden Layer	Output Layer	Error or Training Subset				
		R	MSE	MAE	MAXAE	SDAE
Tansig	Tansig	0.9872	0.0025	0.023	0.1131	0.027
Tansig	Purelin	0.9951	0.0006	0.014	0.099	0.02
		Error or Testing Subset				
Tansig	Tansig	0.9863	0.0018	0.019	0.1245	0.024
Tansig	Purelin	0.9899	0.0008	0.017	0.1277	0.024

Table 7.Statistical properties of absolute sensitivity with respect to inputs.

Input	Max.	Min.	Mean.	Std. Deviation
D	2.1719	1.2495	1.9196	0.2122
L	1.2194	0.1694	0.7792	0.2588
E	2.5505	0.2309	1.7070	0.6054
ϕ	3.4732	1.8365	3.0514	0.4204

Table 8. Statistical percentages values of relative sensitivity for each input.

	D	L	E	ϕ
D10	1.6117	0.4279	0.7408	2.4068
D25	1.8002	0.6216	1.2619	2.7728
D50	1.9682	0.7721	1.7728	3.1608
D75	2.0862	0.9952	2.2941	3.436
D90	2.1464	1.1185	2.3248	3.4513

Reference

[1] Haykin, s,; “Neural Networks, a Comprehensive foundation”, Prentice Hall, 1999.

[2] Fausett, L. V. (1994). Fundamentals neural networks: Architecture, algorithms, and applications, Prentice-Hall, Inc., Englewood Cliffs, New Jersey.

[3] Knowels, P., “Predicting Labor Productivity using neural networks”, MSc thesis, University of Alberta, Edmonth, Canada.

[4] Smith, G.N., Probably and statistics in civil engineering, Collins, 1986.

[5] The, C. I., Wong, K. S., Goh, A. T. C., and Jaritngam, s. (1997). “Prediction of pile capacity using neural network.”.

[6] B. H. Fellenius; “ What Capacity Value to Choose from the Results a static Loading Test”: Winter 2001.

[7] Lu, M., Abourizk, S.M. & Hermann, U.H., Sensitivity Analisys of neural networks in spool fabrication productivity studies, j. comp. in civil engineerings, Vol. 15, No.4

[8] Chan, W. T., Chow, Y. K., and Liu, I. F. 1995. “Neural networks:An alternative to the pile driving formulas.” Comput. Geotech., 17(2),135–156.

[9] Lee, I.M., Lee, J.H., 1996. “Prediction of pile bearing capacity using artificial neural networks.” Comput. Geotech. 18(3),189–200.

[10] Das, S.K.,Basudhar,P.K.,2006. “Undrainedlateralloadcapacityofpilesin clay usingartificial neural network.” Comput.Geotech.33(8),454–459.

[11] Padmini, D., Ilamparuthi, K., Sudheer, K.P., 2008 “Ultimate bearing capacity prediction of shallow foundations on cohesionless soils using neurofuzzy models.” Comput.Geotech. 35 33–46

[12] J.Jang, C. Sun, E. Mizutani, 1998 “Neuro Fuzzy and Soft Computing”, Prentice Hall, 35-68

[13] Nasira, G. M.,Ashok Kumar, S., SweetyKiruba, M.,2008.“A comparative study of fuzzy logic with artificial neural networks algorithms in clustering”J. of Comput.Applicat. 1(4), 6-8

[14] Shahin, M.A., Jaksa, M.B., 2006. “Pull out capacity of small ground anchors by direct conepenetration test methods and neural networks.”Can.Geotech. J. 43(6),626-637.

[15] Pal, M., 2006. “Support vector machines-based modelling of seismic liquefaction potential”Int. J. Numer. Anal. Methods Geomech.30(10),983–996.

[16] Ahmad, I., ElNaggar, H., Kahn, A.N., 2007. “Artificial neural network application to estimate kinematicsoilpileinteractionresponseparameters.”Soil Dyn.Earthq.Eng.27(9),892-905

[17] Ardalan, H., Eslami, A., Nariman-Zadeh, N., 2009. “Piles shaft capacity from CPT and CPTU data by polynomial neural networks and genetic algorithms.” Comput. Geotech. 36(4), 616-625.

[18] Alkroosh, I., Nikraz, H., 2011. “Simulating pile load-settlement behavior from CPT data using intelligent computing.” Cent. Eur. J. Eng. 1(3),295-305

[19] Tarawneh, B., 2013. “Pipe pile setup: data base and prediction model using artificial neuralnetwork.” Soils Found. 53(4), 607-615.

[20] Fatehnia, M., Tawfiq, K., Hataf, N., Ozguven, E.E., 2014. “New Method for Predicting the Ultimate Bearing Capacity of Driven Piles by using Flap Number”KSCE J. Civil. Eng.Pp 1-10

[21] Goh, A.T.C.,Kulhawy, F.H., Chua, C.G., 2005. “Bayesian neural network analysis of undrained side resistance of drilled shafts.” J. Geotech. Geoenviron. Eng. 131(1), 84-93.

[22] Shahin, M.A.,2010.“Intelligentcomputingformodelingaxialcapacityofpile foundations.” Can. Geotech. J.47(2),230-243.

[23] M.A., Shahin.,2014.“Load–settlement modeling of axially loaded steel driven piles using CPT-based recurrent neural networks.”Soils Found.54(3),515-522

[24] Jordan, M.I., 1986. “Attractor dynamics and parallelism in a connectionist sequential machine.” In:Proceedings of the 8th Annual Conference of the Cognitive Science Society. Amherst, MA,531-546.