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DEVELOPMENT OF A CONSTITUTIVE MODEL FOR EVALUATION OF BEARING CAPACITY FROM CPT AND THEORETICAL ANALYSIS USING ANN TECHNIQUES

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ABSTRACT: Bearing capacity is significant value in pile design. Various approaches have been introduced to estimate the axial pile capacity. These approaches have restrictions and accordingly did not implement uniform and precise estimation of axial pile capacity. To add a value of the effort to achieve a proper and accurate relationship of a cone penetration test, including axial pile capacity, the Artificial Neural Networks (ANN) method is employed in this paper, which can be applied in cases where the relationship between the input parameters is unknown. In this paper, ANN was used to predict the bearing capacity of bored and driven piles. The present study uses the neural network approach to develop a model that can be adopted to predict bearing capacity values using ANN Techniques and can comfortably accommodate new data as this becomes available. ANN was used to predict the bearing capacity of bored and driven piles. The data, which is used as inputs accompanied by CPT. Furthermore, three artificial neural network models were generated. All models show that ANN provides a more accurate result by comparing it with the available CPT method.

Keywords: Bearing Capacity, ANN, CPT

1. INTRODUCTION

Pile foundations are widely utilized to carry different buildings constructed on weak soil. However, shallow foundations would encounter extreme shear bearing capacity failure and settlements. Moreover, weak soil layers cannot resist the load from superstructures. Then a pile footing is required to move the load from superstructure from the weak layer to a strong layer. The primary purpose of piles is to transfer structural loads from weak layers through material or stratum to another one that is sufficiently able to support the applied loads. Thus, the design of deep foundation mainly depends on real pile capacity, which directly affected by the complex response of piles in soil, pile load transfer mechanism, and soil disruption and due to pile placing (Kiefa 1998). Static or dynamic load tests and in situ tests such as SPT and CPT can be used to measure piles capacity. Many studies have shown that one of the important issues in driven piles is a variety of pile bearing capacity with time behind the original time of pile installation [1]. This variation depends on the soil type, the increment of pile capacity called Soil Setup while the decrease of it called Relaxation. Simply, installed the piles disturbs the surrounding soils and generates excess pore water pressures which will be dissipation and leads to increase pile capacity with the time. However, the time to dissipate excess pore pressure depends on the soil type, the square of the horizontal pile dimensions, effective stress at the tip, and the horizontal coefficient of consolidation of the soil [2]. In addition to the high cost of deep foundations which may reach 30% relative to the structure costs, the stability of the foundation and overall structure mainly depends on the accurate estimation of the pile capacity.

Studies presented several empirical equations and formulas of bearing capacity for different piles installed in similar geotechnical settings [3]. On the other hand, these formulas have limited success because of the uncertain relation between piles and soil. Subsequently, genetic programming and linear regression with different parameters are used to develop many models to evaluate accurate values of soil setup so more economical pile design can be used. This study developed the Gene Expression Programming model for pipe pile using for 104 dynamic load test experiments from previous literature. Seven variables were selected as input data: pipe pile length, soil properties, effective stress, diameter, time after installation, soil type, the original pile axial capacity, the axial pile capacity at time (t) after driving, and the effective vertical stress at the pile tip [4,5]used neural network modeling method to estimate axial pile capacity using the dataset for 94 driven piles records in cohesionless soil, an arbitrarily chosen specimen of 59 data was utilized for training and the other data was utilized for testing the model. Elastic modulus of the pile, pile cross-sectional area, pile length, pile set, pile weight, pile hammer drop, hammer type, and hammer weight were used as model inputs. [6] analyzed the axile pile capacity of a pile using the Artificial Neural Networks method.

The model was selected from the full-scale pile load test and a standard penetration test was used. [3] developed a method using a flap number for predicting the ultimate pile capacity of concrete and steel piles. Artificial Neural Network was utilized as the first method of this research, the second method used Genetic Programming. Finally, was done by utilizing the Linear Regression approach to obtain the best linear fit to predict the pile capacity. [7] used both Artificial Neural Networks and Multiple Linear Regression to estimate pile setup for three types of pile pipe, H-pile, and concrete. Dataset for 169 from CAPWAP and dynamic test obtained from the published literature was used. The selected data consisted of seven inputs: driven length, time after installation, pile diameter, soil classification, and effective vertical stress at pile tip, initial axial capacity, and the axial capacity at time (t) after driving.

In all of the published researches, different genetic programming used many different parameters and tests. The results for the same case are not similar in all methods in addition to the inaccuracy in it. Recently, the methods that use CPT results have become favorable that because of the ability of the CPT test to conduct on cohesion-less soil which cannot transport to the laboratory without the need to furnish intermediate parameters [8,9]. On the other side, several trials have been made to use Artificial Neural Networks (ANNs) for developing pile capacity models to generate a nonlinear and complex relationship between the bearing capacity and factors affecting it. In this paper, ANN used to predict the axial capacity of pile foundations driven into cohesive soils based in Cone Penetration Test (CPT) and to perform sensitivity analysis to study the effect of the inputs on the output. To improve the versatility of the pile model as well as for more naturally accommodate future expected expansions of the dataset as additional information becomes available the paper was re-formulated as artificial neural network. Furthermore, ANN used to predict the resilient modulus for stabilized soil and this provides a strong statement that ANN is a useful tool that can be used in geotechnical engineering applications [10].

1.1 Data Collected

The data employed to propose the ANN models were collected from the previous studies and involves load test experiments organized by[11]. The collected experimental data used to generate the ANN models are gathered from the previous studies published by [12,8] the experiments were conducted on driven and bored piles that were installed in cohesionless soil. Moreover, experimental testing composed a set of in-situ bored and driven pile load tests as well as CPT results. Comparable pile embedment length (L), weighted average cone point resistance over pile tip pressure (qc_tip), pile diameter (D), weighted average sleeve friction along shaft (fs), weighted average cone point resistance over shaft length (qc_shaft); pile elastic modulus and pile type were used as model inputs. However, the same dataset was used in this research divided into 3 cases; 50 bored piles, 30 steel driven piles and 28 concrete driven piles. The datasets employed are presented in Table 1 for the bored piles and Tables 2 driven concrete piles and 3 for driven steel piles.
1996. The bored piles have several dimensions, with diameters varying from 0.32 to 1.8 m and bored piles length from six to twenty-seven m. The driven piles further include various pile dimensions with diameters varying from 0.25 to 0.66 m and driven piles lengths from eight to thirty-six m. regarding the piles have a different range of pile diameter, there is the attention that piles with a large diameter may exhibit a distinctive response when compared with pile with a small diameter. Therefore, the piles are classified into small-diameter piles [13].

2. METHODOLOGY

Artificial Neural Networks (ANN_S) utilized to estimate the pile's axial capacity based on CPT experimental data. ANN_S is a set of massively parallel processes to develop a computational model by the saved information that is taken from the dataset, it was first used by McCulloch and Pitts in 1943. Depending on the system of the human brain, ANN_S represent complex relationships between inputs and one or more output. Commonly, it includes several arranged layers; the first one has the input parameter(s) and the last layer contain the target of the network. Between it is one or more hidden layers which are for estimate complex networks between inputs and outputs. Furthermore, the successful performance of ANN_S of modeling nonlinear mathematical problems offering faster and more accurate calculations compared with other mathematical methods. ANN_S is an important approach for modeling many different soil behaviors and properties such as dry density[14], soil moisture variability[15], soil deformation[16], liquefaction resistance of sands [17], stress-strain modeling of sands[18]. Figure1 presents the arrangement of the artificial neural model, as depicted in Fig.1 several amounts of input data on the left side. by alternating the hidden layer numbers and achieve the most suitable model.

2.1 Development of ANN Models to Predict Pile Axial Capacity

In this study, Matlab software was used to create three neural network models and the data was divided automatically by Matlab toolbox into three sets of samples.

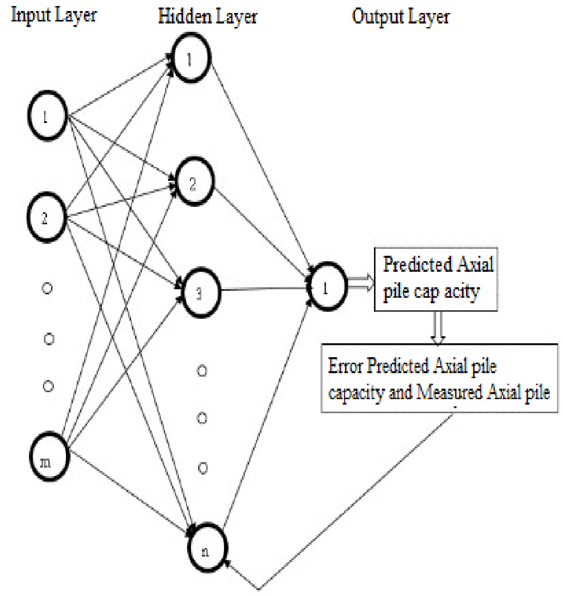

Fig.1 Arrangement of backpropagation artificial neural network

Seventy percent of the data were used as training data to find the weight of the parameters and train the network with minimum values of error. Furthermore, fifteen percent of the data were selected for validation. This set of data measures network generalization and the error in a test set. The last fifteen percent were used to perform testing for the neural network. Testing means evaluating the performance of the selected model with the optimum weights found during training. However, these sets were randomly selected from the total dataset and to measure the success of ANN models; The Coefficient of Determination (R^2) was checked. This coefficient is an indicator of how well the model fits the data and its value is often between 0 and 100%. If the value close to 0 that indicates a random relationship and if the value close to 1 indicates that the model fits the dataset. On the other hand, the mean squared error (MSE) also evaluated. It is the average squared difference between outputs and targets.

2.2 Model 1 for Bored Piles

The data for bored 50 piles were used to predict the capacity for them. Moreover; pile diameter, pile embedment length, weighted average cone point resistance over pile tip failure zone, and weighted average cone point resistance over shaft length were selected as inputs and the only output was the predicted bearing capacity. Several trails with different hidden layers were conducted to get the optimum model with the highest value of R^2, validation, and testing sets shown in (Table 1). Furthermore, the correlation between predicted and measured capacity for the total dataset shown in Fig.2.

Table 1 Data of driven steel piles model

Test	D	L	q_{ctip}	q_{cshaft}	Q_m	Q_p
1	1,100	13	16.2	4	2,624	2,771
2	421	5.8	22.9	11.8	912	685
3	320	10.2	22	7.2	712	924
4	457	15.2	1.6	8.1	1,423	1,471
5	393	6.5	10.1	12.8	738	794
6	410	5.6	16.7	15.8	560	701
7	320	10.2	14.6	4.5	832	717
8	320	7.7	8.3	2.6	445	445
9	403	9.2	13.1	10.3	1,352	1,034
10	814	24.2	6.5	9.6	5,872	4,966
11	320	10.2	21.9	7.1	818	921
12	671	13	25.6	17.2	4,270	3,745
13	1,000	9.5	29.3	5.1	2,358	2,587
14	1,000	9	35.9	8.5	3,692	3,105
15	840	24.4	47.9	9.2	9,653	8,169
16	600	7.2	10.9	7.6	1,437	1,199
17	1,100	9	15.4	5.4	3,247	2,464
18	500	10.2	8.9	2.2	1,005	800
19	329	6.2	20.7	10.6	605	511
20	408	5.8	17.6	8.2	765	648
21	521	8.2	12.9	9.6	1,334	1,235
22	1,800	11.5	36.6	7.6	7,651	6,767
23	405	8.4	33.4	11.5	1,019	1,121
24	405	10.4	8.9	11.3	1,019	1,186
25	399	7.8	12.8	4.4	667	687
26	671	10.2	13.7	20.1	4,697	3,190
27	430	8.7	31.7	14.5	516	1,248
28	320	7.7	7.9	2.6	356	442
29	399	10	24.6	12.7	756	1,291
30	600	12	21.4	10.8	2,687	2,315
31	600	12	21.3	11.1	2,406	2,345
32	1,100	27	7	9.4	8,207	7,727
33	320	7.7	8.2	2.6	391	446
34	400	9.4	2.4	1.4	480	469
35	1,085	25.1	32	9	7,695	8,639
36	350	15.8	5.1	5.5	840	907
37	500	10.2	14.7	3.2	1,299	1,006
38	405	7.9	6.2	12.8	792	1,025
39	1,100	6	21	7.8	2,469	2,264
40	631	18.3	30	11.7	1,770	4,249
41	521	8.2	12.8	9.5	1,263	1,230
42	405	7	17.8	14.3	1,294	867
43	399	7.8	13.1	4.1	578	682
44	1,500	6	10.4	8.5	2,669	3,339
45	400	7.8	10.6	3.6	543	635
46	320	7.7	8.5	2.6	409	449
47	762	16.8	5.9	5.2	3,425	2,244
48	430	8.7	26.8	11.7	627	1,188
49	329	6.3	25.9	15.6	756	441
50	1,078	13	31	19	8,825	7,218

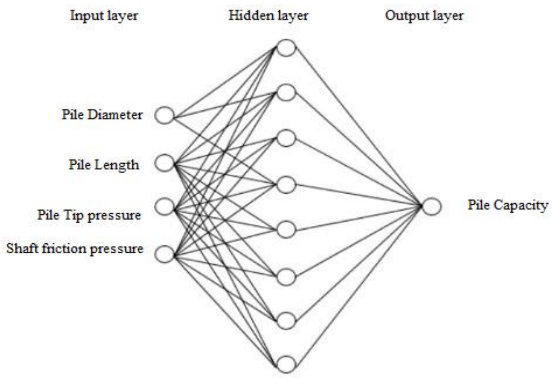

Fig.2 The structure of ANN used for the first model

2.3 Model 2 for Driven Concrete Piles

The data employed for generating the ANN model are assembled from different previous studies and include a result of 28 driven concrete pile load tests. The sources utilized to organize the dataset are presented in Table 1.

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The data employed for generating the ANN model are assembled from different previous studies and include a result of 28 driven concrete pile load tests. The sources utilized to organize the dataset are presented in Table 1.

Fig.3 shows the neural network model shows a strong estimation and provides R^2 value for training as 0.96.

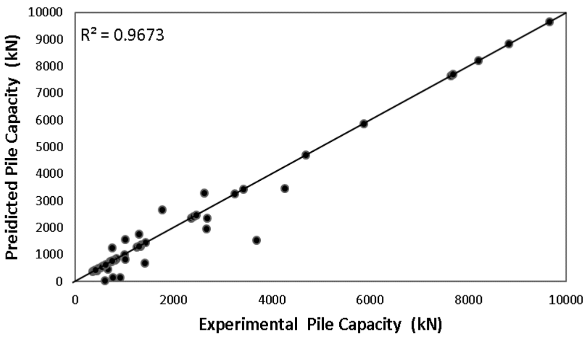

Fig.3 Comparison of ANN predictions and measured pile bearing capacity

Table 2 shows a report of the conclusive weights and bias between the input and the output parameter.

Table 2 Weight and bias parameters for ANN model 1

F	`Weight						
	Hidden layers (F=8, G=4) IW (F,G)				Output layer OL (s,l)	Bias	
	pile Diameter (G=1)	pile Length (G=2)	pile Tip Pressure (G=3)	Shaft Friction Pressure (G=4)	Om	b1	b2
W_{1i}	-2.19	-0.13	1.26	-0.18	0.14	2.13	-0.74
W_{2i}	-0.12	0.92	1.76	-1.41	1.23	-2.11	
W_{3i}	-1.33	-0.53	0.26	-2.18	-0.23	1.20	
W_{4i}	1.52	1.18	-2.49	-0.18	-1.13	0.16	
W_{5i}	1.24	0.06	1.52	-0.53	-0.71	0.66	
W_{6i}	2.91	0.11	0.23	-0.71	0.88	1.18	
W_{7i}	-1.24	1.03	0.89	-0.09	-1.58	-0.98	
W_{8i}	-0.16	-1.541	-0.57	-1.21	-0.91	-3.09	

The gathered dataset composed the pile diameter, pile length, weighted average cone point resistance, weighted average sleeve friction over shaft length, weighted average cone point resistance along pile shaft, measured axial capacity. Equivalent pile diameter, pile embedment length, weighted average cone point resistance over pile tip failure zone, weighted average sleeve friction along the shaft, weighted average cone point resistance over shaft length, pile elastic modulus and pile type were used as inputs to predict the pile capacity of concrete piles and the output was piles capacity. (6) hidden layers were chosen. However, more details showed in Table 2 and Fig.4.

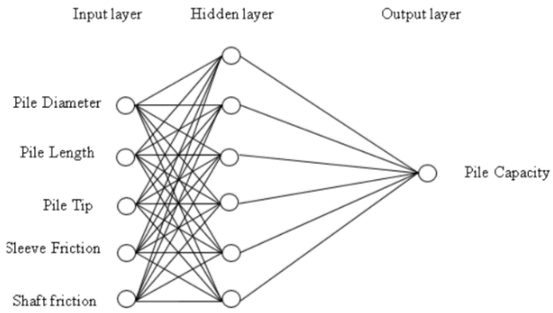

Fig.4 The structure of ANN used for the first model

Fig.5 shows, the neural network model shows a strong estimation and provides R^2 value for training as0.94

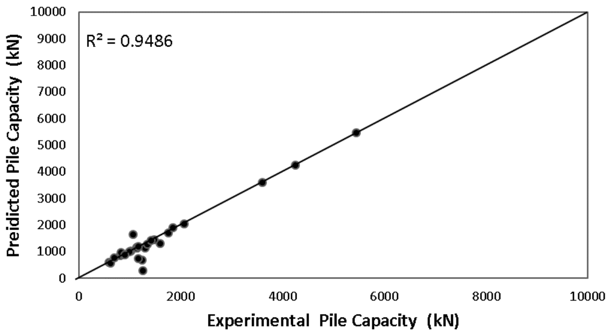

Fig.5 Comparison of ANN predictions and measured pile bearing capacity.

Table 5 shows a report of the conclusive weights and bias between the input and the output parameter

Table 5 Weight and bias parameters for ANN model 2

F	`Weight						
	Hidden layers (F=8, G=4) IW (F,G)				Output layer OL (s,l)	Bias	
	pile Diameter (G=1)	pile Length (G=2)	pile Tip Pressure (G=3)	Shaft Friction Pressure (G=4)	Om	b1	b2
W_{1i}	-2.19	-0.13	1.26	-0.18	0.14	2.13	-0.74
W_{2i}	-0.12	0.92	1.76	-1.41	1.23	-2.11	
W_{3i}	-1.33	-0.53	0.26	-2.18	-0.23	1.20	
W_{4i}	1.52	1.18	-2.49	-0.18	-1.13	0.16	
W_{5i}	1.24	0.06	1.52	-0.53	-0.71	0.66	
W_{6i}	2.91	0.11	0.23	-0.71	0.88	1.18	
W_{7i}	-1.24	1.03	0.89	-0.09	-1.58	-0.98	
W_{8i}	-0.16	-1.541	-0.57	-1.21	-0.91	-3.09	

2.4 Model 3 for Driven Steel Piles

The data employed for generating the ANN model are assembled from different previous studies and include a result of 31 driven concrete pile load tests. The sources utilized to organize the dataset are presented in Table I. The gathered dataset composed the pile diameter, pile length, weighted average cone point resistance, weighted average sleeve friction over shaft length, weighted average cone point resistance along pile shaft, measured axial capacity.

Table 6 Data of driven steel piles model

Test	D	L	qctip	fs	qcshaft	Om	Op
1	300	11	0	66	15.2	560	901
2	455	12	0	65	15.9	1,170	934
3	455	11.3	0	67	15.8	870	916
4	273	22.5	23.9	46	8.1	1,620	1,877
5	660	18.2	10.2	46	9.5	3,650	3,966
6	609	34.3	13.3	48	9.5	4,460	4,461
7	330	10	2.3	38	3	625	651
8	300	28.4	1.3	24	3.2	1,240	1,078
9	273	22.5	0	27	2.1	765	1,077
10	455	16.2	0	67	9.8	1,170	1,081
11	300	16.2	20	64	16.9	1,310	1,140
12	450	15.2	0.5	50	6.2	1,020	960
13	455	16.8	0	66	17.5	1,260	1,095
14	350	14.4	21.6	72	17.6	1,300	1,105
15	400	14.6	20	74	17	1,800	2,064
16	400	14.6	0	50	15.5	945	962
17	273	9.2	6.5	18	5.4	490	833
18	273	15.2	5.4	36	6.4	675	998
19	455	16.2	15.5	89	9.7	3,600	2,704
20	392	36.3	14	131	11.7	2,130	2,240
21	490	14	15.6	32	11.2	3,500	2,977
22	385	19	2.8	82	2	1,370	1,196
23	385	12.4	1.8	48	1.7	520	859
24	455	15.2	0.3	55	6.1	1,010	975
25	321	8.5	5	70	1.5	590	671
26	350	31.1	5.6	19	1.4	1,710	1,013
27	609	34.3	8.7	33	4.5	4,330	3,223
28	455	11.3	0	65	15.5	817	908
29	350	11.1	0	60	15.5	630	882
30	300	31.4	1.2	35	3.1	1,690	1,187
31	660	36.3	23.9	131	17.6	4460	4461

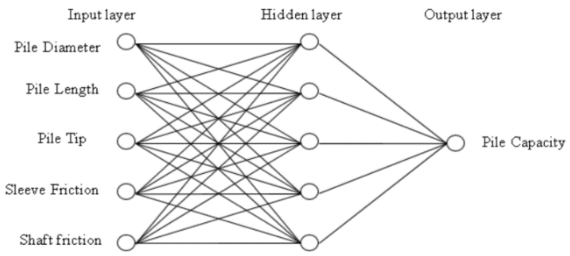

Fig.6 The structure of ANN used for the first model

For steel pile; the same parameters in model 2 were used here. Performance measurements for (5) hidden layers showed in Table 3, Figs.5 and 6. Details about the number of hidden layers, inputs, and targets have been shown in Figs. 6 and 7 show, the neural network model shows a strong estimation and provides R^2 value for training as 0.96

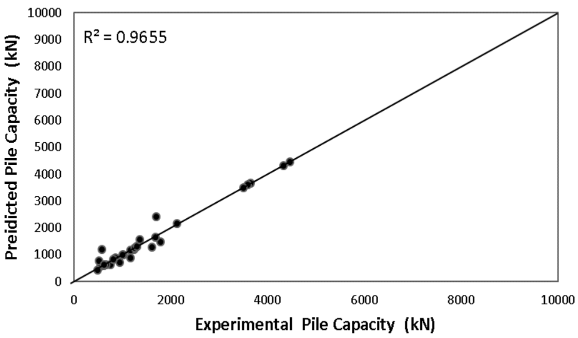

Fig.7 Comparison of ANN predictions and measured pile bearing capacity

Table 7 shows a report of the conclusive weights and bias between the input and the output parameter

Table 7 Weight and bias parameters for ANN model 2

F	'Weight							
	Hidden layers (F=5, G=5) IW (F,G)					Output layer OL (s,l)	Bias	
	Pile Diameter (G=1)	Pile Length (G=2)	Pile Tip Pressure (G=3)	Sleeve Friction (G=4)	Shaft Friction Pressure (G=5)	Q_m	b1	b2
W_{1i}	-0.38	-1.12	0.81	-1.27	-0.38	0.19	2.03	-0.01
W_{2i}	0.01	0.95	-0.25	-0.92	1.31	0.88	-0.61	
W_{3i}	-0.37	1.34	0.90	-2.11	0.08	0.60	-0.76	
W_{4i}	-1.90	0.47	-0.69	-1.13	-0.88	-1.10	-0.72	
W_{5i}	-0.54	-1.10	0.026	-0.53	1.54	-0.09	-1.57	

3. ANN_S MODELS RESULT

For the first model, the values of sleeve friction were not available, this not affect the previous process because the measurements of sleeve friction are less reliable than those of the cone point resistance [19]. Generally, the values of R^2 were between 0.94 and 0.96 with the highest value for the third model. The relationship between the number of hidden layers and the value of R^2 is not linear. On the other side excess, data can give more accurate models.

4. SENSITIVITY ANALYSIS

One of the necessary issues to discuss soil setup is to determine the importance of each parameter which can affect the value of pile bearing capacity. Some analysts can be achieved to find the contribution of each input. [20] conduct SA for the ultimate axial load-bearing capacity of piles based on varying each parameter from its minimum to maximum value, which calculated by change one input and fixed other inputs at their mean then find the new output. Several types of research conduct analysis by different methods in a way to study the variation of the pile capacity depending on many parameters. In the present paper, simulation analysis has been done by studying virtual cases developed by fixed the inputs except for one which has many changes and the value of predicted piles capacity was found by $ANN_{S.}$ The results in Fig.8 show the comparisons between the average value for the origin ANN_S predicted piles capacity and average ANN_S predicted piles capacity after multiplied each parameter by several values ranges from -15% to 15%.

5. FIRST MODEL FOR BORED PILES

At Fig.7, present pile diameter, pile embedment length, weighted average cone point resistance over pile tip failure zone, and weighted average cone point resistance over shaft length respectively.

6. SECOND MODEL FOR CONCRETE PILES

The gathered dataset composed the pile diameter, pile length, weighted average cone point resistance, weighted average sleeve friction over shaft length, weighted average cone point resistance along pile shaft represent the inputs which used in model 2 as shown in Fig.9.

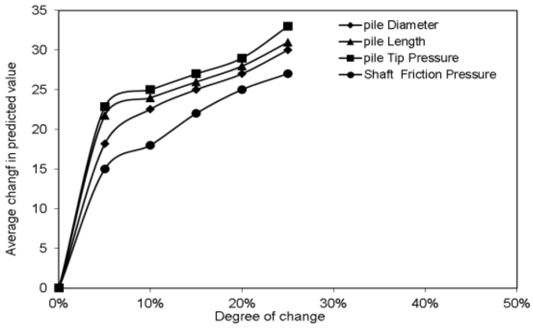

Fig.8 The values of predicted pile capacity at different changes in each parameter

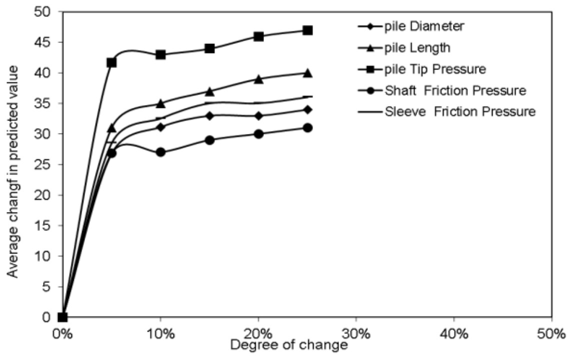

Fig.9 the values of predicted pile capacity at different changes in each parameter

7. THIRD MODEL FOR STEEL PILES

The gathered dataset composed the pile diameter, pile length, weighted average cone point resistance, weighted average sleeve friction over shaft length, weighted average cone point resistance along pile shaft the inputs which used in model 3 as shown in Fig.10.

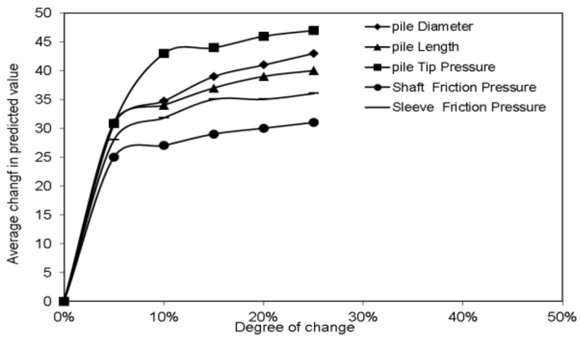

Fig.10 the values of predicted pile capacity at different changes in each parameter

8. SENSITIVITY ANALYSIS RESULTS

Depending on the maximum drop in the charts and the maximum error and difference between the origin and modified values of predicted piles capacity; the most effective parameters have been determined. Results showed that the weighted average cone point resistance over pile tip failure zone has the largest effect on the pile bearing capacity in bored and concrete driving piles but in steel driven piles the pile diameter affects the most. However; the pile's diameter has high importance in the three models. On the other side, the pile's length has approximately less importance and effect in the three models[21].

9. SUMMARY AND CONCLUSION

An Artificial Neural Network (ANN) is an information process system that is inspired by the way the human brain processes information for solving one of the most critical problems in geotechnical engineering. One of the most critical problems in estimating the ultimate bearing capacity of bored and driven piles into cohesive soils based on sets of data collected from published researches conduct from CPT.
The selected data include information about the dimension of the piles, material types, and the resistance of the tip, sleeve, and the shaft of the piles. However, several trials have been done and studied to have the optimum models depends on the values of The Coefficient of Determination (R^2) and Mean Squared Error (MSE). Moreover, the values of R^2 which vary from 0.94 to 0.96 indicate that ANN_S has high accuracy in prediction and estimating the piles bearing capacity and solves the geotechnical problems.

Much existing literature developed empirical equations, which can be used in the same geotechnical conditions to estimate the pile's capacity. On the other side; the disadvantage of ANN_S is its weakness in generating equations so hand calculation is needed[20]. Furthermore, the sensitivity analysis showed that the weighted average cone point resistance over the pile tip failure zone and the pile diameter have a large importance in estimating piles capacity. The accuracy of the numerical models highly depends on the data and information used. To generate more accurate equations and predictions; new models should be developed by using other variables and piles types into different soil types.

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