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Prediction of Pile Bearing Capacity Using Artificial Neural Networks

تقدير قدرة تحمل الخازوق بأستخدام الشبكات العصبيه الذكيه

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ملخص البحث

من المعروف أن المخ البشري له ميزة التعامل مع تصنيف و ترتيب البيانات بكفاءة .
وعلى هذا الأساس، قد وضعت نظرية الشبكات العصبية الذكيه وتم تطبيقها على مختلف المجالات العلمية بنجاح.
في هذه الدراسة، تم أستخدام طريقة الخطأ المستدرك للشبكات العصبية الذكيه للتنبؤ بقدرة تحمل الخازوق التشغيلية.
باضافة نتائج اختبارات تحميل الخوازيق التي اجريت خصيصا إلى النتائج التي تم الحصول عليها لأختبارات تحميل أخرى و استخدامها للتحقق من قدرة نموذج الشبكات العصبية الذكية.
وأظهرت النتائج أن الحد الأقصى لخطأ التنبؤ لم يتجاوز ٢٥٪. و لهذا فأن استخدام الشبكات العصبية للتنبؤ بقدرة تحمل الخوازيق يبدو مناسبا لغرض عملي.

ABSTRACT

It is well known that the human brain has the advantage of handling disperse and parallel distributed data efficiently. On the basis of this fact, artificial neural networks theory was developed and has been applied to various fields of science successfully.

In this study, error back propagation neural networks were utilized to predict the working bearing capacity of piles.

The data of performed pile load tests are used to verify the applicability of the presented neural network procedure.

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The results showed that the maximum error of prediction did not exceed 25%. Thus, the use of Neural Networks to predict pile capacity seems to be feasible for practical purpose.

INTRODUCTION

Piles have been used for many years as a type of structural foundation. However, prediction of their bearing capacity has been a difficult task because of various factors. Recent advances in soil mechanics and foundation engineering have provided useful information regarding the factors that affect bearing capacity; however the introduction of all these factors to analysis and design is impractical. Therefore, most theoretical approaches have mainly been based on simplifications and assumptions. Because of these difficulties, it has been commonly accepted that pile load testing is the best way to provide accurate bearing capacity predictions. Pile load test costs a lot of money, time and effort. Artificial Neural Network (ANN) is one of the new techniques that can be used to determine the bearing capacity of piles.

Since the early 1990s, artificial neural networks (ANNs) have been applied to almost every problem in geotechnical engineering. Among these, blasting ([22]); dams ([18]); earth retaining structures ([10,11,12,19]); environment geotechnics ([28]); ground anchors ([25,26,27]); liquefaction ([2,3,9,13,15,16,17,18,30,31]).

The prediction of the load capacity has been examined by several ANN researches. ([8,11]) presented a neural network to predict the friction capacity of piles in clays. The model inputs were considered to be the pile length, the pile diameter, the mean effective stress and the undrained shear strength. The results obtained by utilizing the neural network were compared with the results obtained by the method of Semple and Rigden ([24]) and the method of Burland ([5]).

In this work, error back propagation neural networks were utilized to predict pile bearing capacity. For the verification of applicability of this approach, both the results of a model pile load test using a calibration chamber and those of *in-situ* pile load tests obtained from a literature survey are used.

ERROR BACK PROPAGATION NEURAL NETOWRKS

It is well known that the human brain has the advantage of handling a lot of disperse and parallel distributed data, and also has the ability to learn. On the basis of these facts, artificial neural networks theory introduced and has been applied to various fields of science successfully. Artificial neural networks include the two working phases of learning and recall. Learning is the weight structure of the network via learning algorithms. During the learning phase, known data sets are commonly used as training signals in the input and output layers. After the learning phase is completed, thus allowing for the prediction of new input data sets, the recall phase is performed by one pass using the weight obtained in the learning phase. That is to say, artificial neural networks are a means for the mapping of data from the space of *N*-dimension to that of *M*-dimension.

Error back propagation (EBP) algorithm is a particular learning technique of muti-layer networks, classified as "supervised learning" because the networks are adjusted by comparing the actual output with desired output. A gradient descending procedure, called delta rule is applied in order to minimize the sum of squared errors of the actual and the desired output. This procedure is a forward process and is achieved by moving along the path of the steepest descent in weight space (1-4).

Many civil engineers have investigated the applications of neural networks. ([10,14]), soon after, developed another neural network to estimate the ultimate load capacity of driven piles in cohesionless soils. In this study, the data used were derived from the results of actual load tests on timber, precast concrete and steel piles driven into sandy soils. The inputs to the ANN model that were found to be more significant are the hammer weight, the hammer drop, the pile length, the pile weight, the pile cross sectional area, the pile set, the pile modulus of elasticity and the hammer type while the model output is taken to be the pile load capacity.

([6]) developed a neural network as an alternative to pile driving formulae. The network was trained with the same input parameters listed in the simplified Hiley formula ([4]), including the elastic compression of the pile and soil, the pile set and the driving energy delivered to the pile. The model output considered was the pile capacity. The desired output value of the pile capacity that was used in the training process was estimated by using a commercial computer code called CAPWAP ([23]) or the CASE method ([7]).

([21]) utilized neural networks to predict the ultimate bearing capacity of piles. The problem was simulated using data obtained from model pile load tests using a calibration chamber and results of in-situ pile load tests. For the simulation using the model pile load test data, the model inputs were the penetration depth ratio (i.e. penetration depth of pile/pile diameter), the mean normal stress of the calibration chamber and the number of blows. The ultimate bearing capacity was the model output.

([1]) introduced three neural network models (referred to GRNNM1, GRNNM2 and GRNNM3) to predict the capacity of driven piles in cohesionless soils. The first model was developed to estimate the total pile capacity. The second model was employed to estimate the tip pile capacity, whereas the final model was used to estimate the shaft pile capacity.

([29]) proposed a neural network for estimating the static pile capacity determined from dynamic stress-wave data for precast reinforced concrete piles with a square section. The networks were trained to associate the input stress-wave data with capacities derived from the commercial computer code CAPWAP ([23]).

APPLICATIONS

Model pile load tests, were performed in order to examine the possibility of predicting ultimate bearing capacity of pile by utilizing neural networks theory. The error back propagation neural network used had four layers: input layer, two hidden layers, and output layer.

IN-SITU LOAD TEST

The possibility of ultimate bearing capacity prediction using artificial neural networks was examined under actual ground conditions. Since the data of *in situ* pile load tests were obtained from a literature survey, it was difficult to find detailed reports of site investigations. These published data are summarized in Table 1. In this study, it was assumed that ultimate bearing capacities were affected by the following factors:

- Penetration depth (L)
- Pile diameter (D)
- Geological section
- Ultimate pile load

Table 1: Pile load test data for piles in El-Daqahliya governorate.

School Code	Section	Diameter cm	Length m
47	DKD	60.00	32.00
77	DKD	60.00	27.60
38	DKD	60.00	14.75
66	DKD	50.00	19.00
60	DKD	60.00	34.00
17	DKD	50.00	32.00
18	DKD	50.00	31.00
32	DKD	50.00	25.00
67	DKD	60.00	18.00
68	DKD	60.00	30.00
69	DKD	60.00	28.00
71	DKD	60.00	25.00
74	DKD	60.00	22.00
10	DKB	50.00	21.00
16	DKB	60.00	24.00
41	DKB	60.00	32.00
73	DKB	60.00	22.50
70	DKB	50.00	16.00
64	DKB	60.00	30.00
65	DKB	60.00	24.00
49	DKB	60.00	20.80
4	DKC	60.00	21.00
62	DKC	60.00	31.00
78	DKE	60.00	16.36
56	DKA	50.00	21.00
52	DKA	60.00	33.00
6	DKA	60.00	12.00
12	DKA	60.00	24.00
13	DKA	60.00	15.00
80	DKA	50.00	23.00
72	DKA	50.00	27.00
1	DKA	60.00	15.00
61	DKA	60.00	19.80
63	DKA	60.00	26.00
27	DKA	60.00	20.00
34	DKA	60.00	21.00
43	DKA	60.00	24.70
23	DKA	60.00	27.00
5	DKA	50.00	25.00
53	DKD	50.00	30.00
8	DKD	50.00	25.00
42	DKD	60.00	28.00
3	DKD	60.00	30.00
37	DKD	60.00	36.00
79	DKD	60.00	27.80
81	DKD	60.00	30.00
44	DKD	50.00	24.65

School Code	Section	Diameter cm	Length m
36	DKE	60.00	18.00
54	DKE	50.00	16.00

DATA COLLECTION

The results of 94 pile load tests were obtained from the General Authority of Educational Buildings (GAEB). The tests were performed for piles of school buildings in Delta region, especially El-Daqahliya and Damietta governorate. Each governorate is divided into zones, each of which has almost the same in geological properties.

El-Daqahliya region is divided into five sectors as followings:

- Fill or agriculture silty clay with depth about 0.50 to 1.50 m.
- Medium silty clay with depth about 3.00 to 6.00 m with average 4.00 m.
- Organic silty clay with depth about 1.00 to 2.00 m.
- Soft clay with depth a bout 9.00 to 16.00 m.

3. DKC:

1. DKA:

It contains Talkha, Bane-Ebad, Mansoura and Nabroha cities. The soil profile in this section is as followings:

- Fill or agriculture silty clay with depth about 0.50 to 1.50 m.
- Medium silty clay with depth about 4.00 to 14.00 m with average 9.00 m.
- Organic silty clay with depth about 1.00 to 2.00 m.
- Soft clay with depth a bout 5.00 to 13.00 m.

2. DKB:

It contains Dekrns and Manyt Elnasr cities. The soil profile in this section is as followings:

It contains Elgamalyia and Manzla cities. The soil profile in this section is as followings:

- Fill or agriculture silty clay with depth about 0.50 to 1.50 m.
- Medium silty clay with depth about 1.00 to 6.00 m with average 2.00 m.
- Soft clay with depth a bout 14.00 to 18.00 m with average 17.00 m.

4. DKD:

It contains Sherbin and Belkaas cities. The soil profile in this section is as followings:

- Fill or agriculture silty clay with depth about 0.50 to 1.50 m.
- Medium to hard silty clay with depth about 3.00 to 10.00 m with average 6.00 m.
- Soft clay with depth a bout 10.00 to 16.00 m with average 13.00 m.

5. DKE:

It contains Met-Ghamr and Elsenblwaen cities. The soil profile in this section is as followings:

- Fill or agriculture silty clay with depth about 0.50 to 1.50 m.
- Hard to very hard silty clay with depth about 4.00 to 17.00 m with average 10.00 m.
- Medium sand various graded with depth a bout 1.00 to 4.00 m.

Table (1) shows the result of 71 pile load test data which performed in El-Daqahliya governorate, pile diameter and pile length,.

SIMULATION USING MODEL PILE LOAD TEST DATA

Parameters used to perform the neural networks with *in situ* load test results were decided by trial and error. These included the number of hidden layers, number of processing elements in hidden layers, initial values of weights, learning rate and momentum term. These values used in this study are as follows:

- Number of hidden layers: 2
- Number of processing elements of first hidden layer: 30
- Number of processing elements of second hidden layer: 10
- Initial values of weights: random values between -1.0 and 1.0
- Learning rate: 0.2
- Momentum term: 0.9.

There were 36 data sets for this study. As shown in Table 2, three input nodes, representing the penetration depth, the pile diameter and the geological section, are chosen as the input vectors to predict the ultimate bearing capacity of a model pile in the output. The schematic diagram for the neural network model is shown in Fig. 1. As a first step, the available data were partitioned into four cases based on the number of learning samples. Each case had a different number of learning data sets, and the remaining data sets (not used as the learning data sets) are applied to test the predictive ability of the trained network. The number of learning samples is listed in Table 2.

Figure 2 illustrates the error plots during training in each case. The convergence criterion considered in this study is the root mean squared error of less than 0.001. Iterations less than 30,000 were required in Cases 1, 2 and 3 (training 14 or less samples), but more than 70,000 iterations were required in Case 4. Figure 3 shows the plots of estimated vs measured values for ultimate bearing capacities of model piles. For cases of training more than14 samples (Cases 2, 3 and 4), the maximum error of prediction did not exceed 20% and the average summed square error was less than 15%.However, the results of training 9 samples (Case 1) showed widely scattered plots. The maximum error of prediction exceed 65% in this case and the average summed square error is more than 40%. Therefore, it could be concluded that a certain number of training data sets was needed to obtain reasonable predictions.

Table 2. Number of learning samples

Case	*No. of learning samples*
Case 1	9
Case 2	14
Case 3	14
Case 4	21

CONCLUSIONS

The applications of artificial neural networks for predicting ultimate pile bearing capacity was investigated in this study.

In this work, the prediction utilizing the neural networks theory is successful because all major affecting factors were taken into consideration. Since both the data and information of *in situ* pile load tests were insufficient, predictions of *in situ* pile load tests showed a wider scattering than the former; however, except for some bias data, the maximum error of prediction did not exceed 20%. This indicates that predictions from the neural networks model were much better than other bearing capacity methods. It is expected that with enough information better predictions can be achieved. These limited results illustrated the possibility of utilizing neural networks for pile capacity prediction problems.

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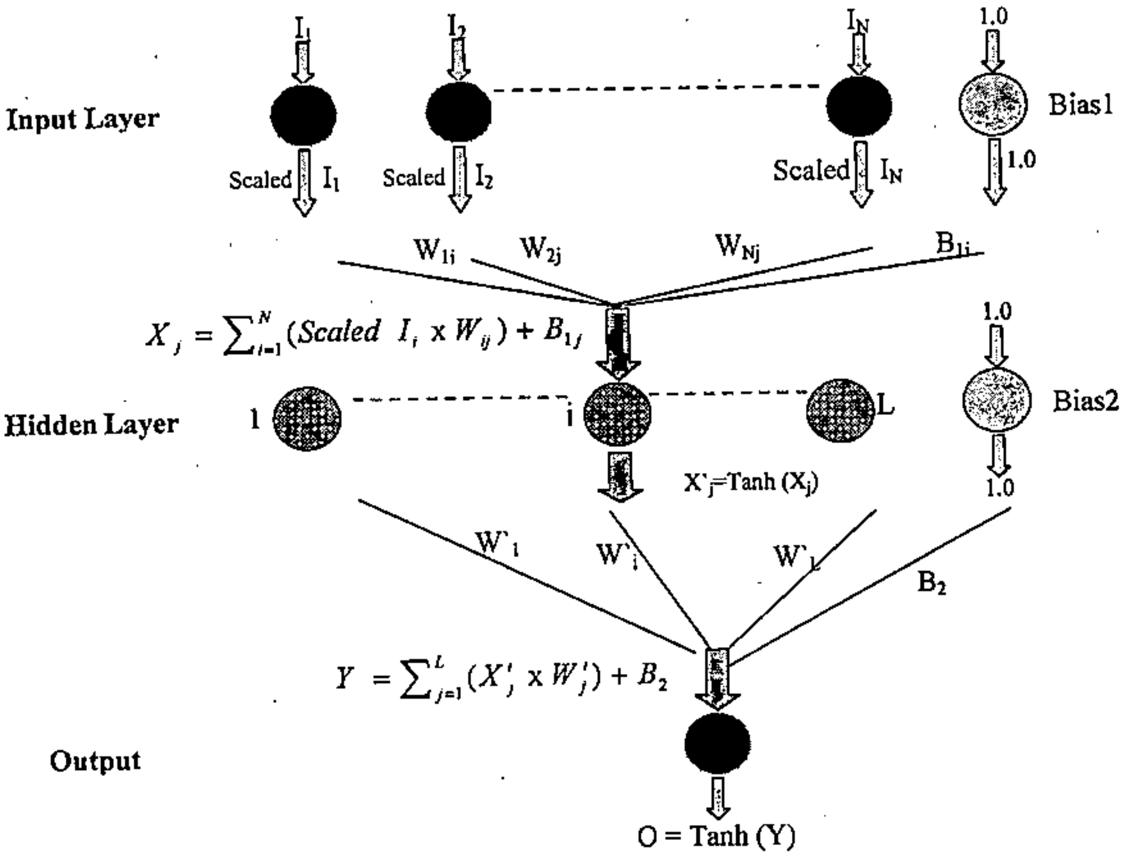


Figure 1. Architecture of the neural networks model.

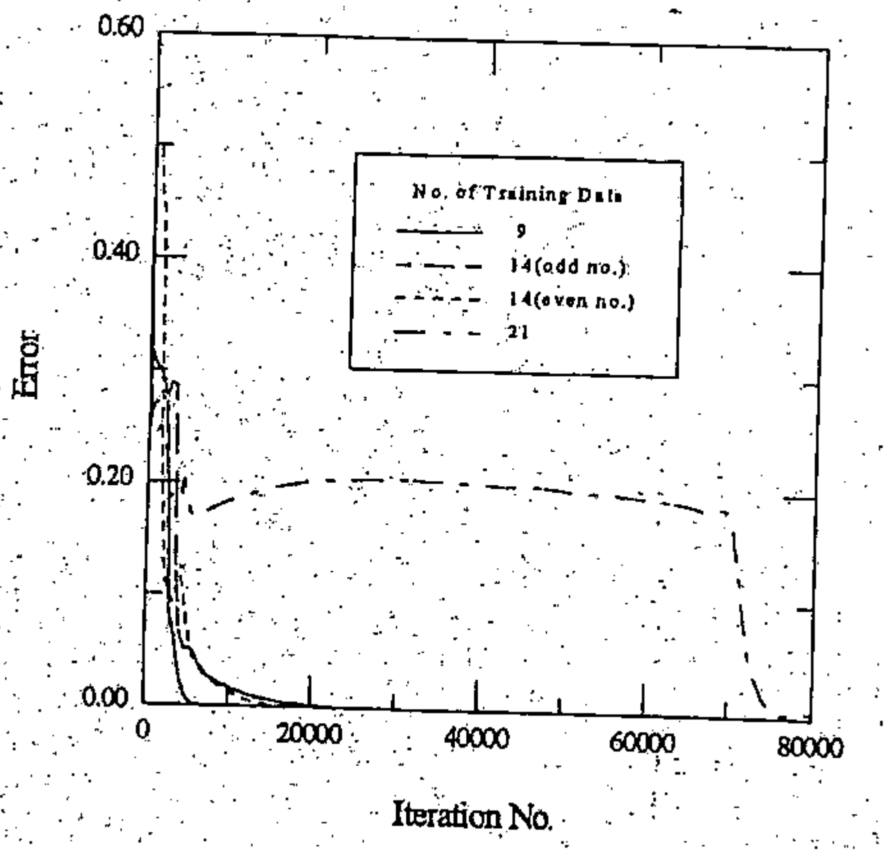
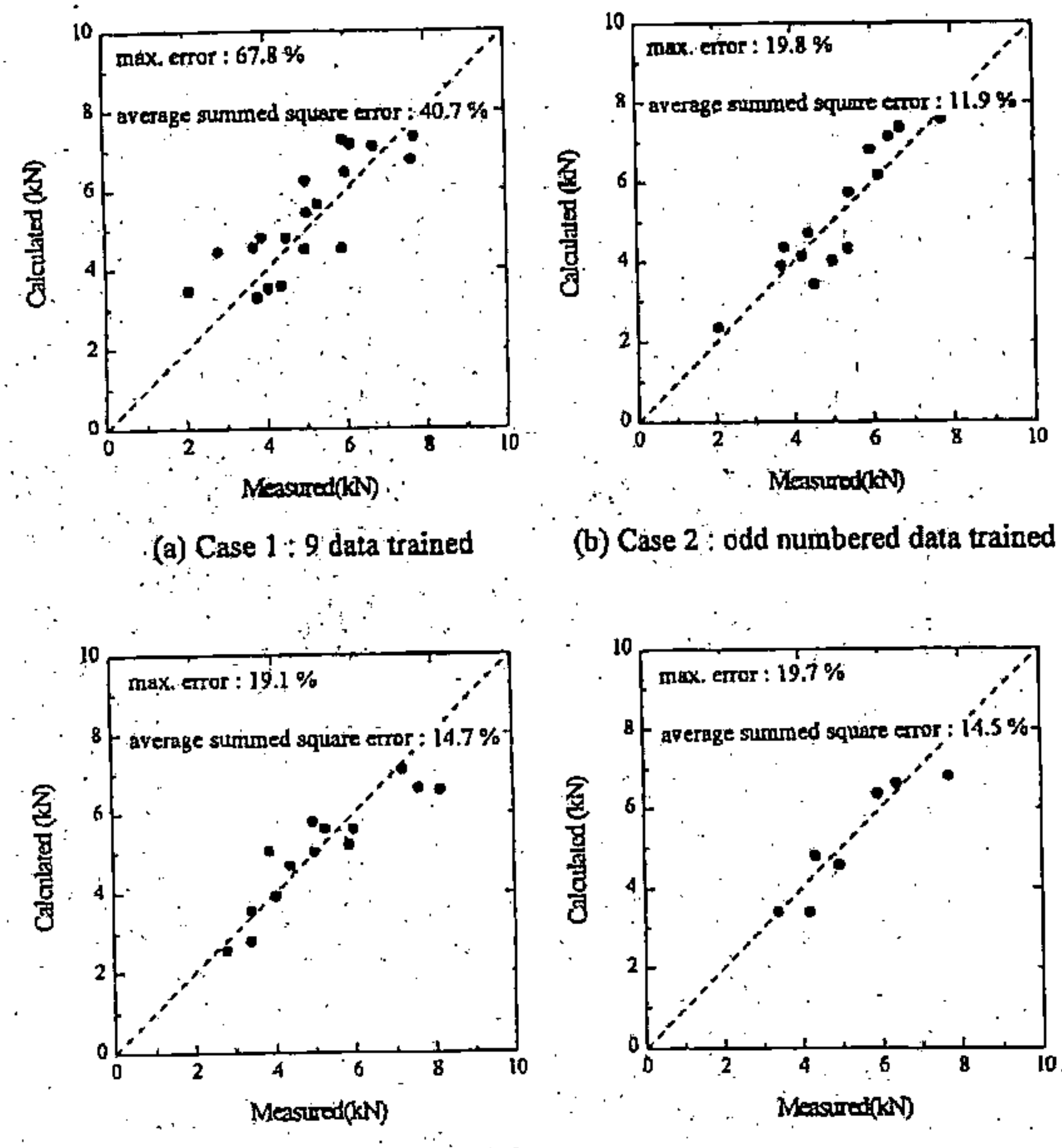


Figure 2. Variation of error with the number of training samples.



(a) Case 1 : 9 data trained

(b) Case 2 : odd numbered data trained

(c) Case 3 : even numbered data trained

(d) Case 4 : 21 data trained

Figure 3. Testing results of estimated vs. measured pile bearing capacity from model pile load test.