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Prediction of Pile Bearing Capacity Using Artificial Neural Networks

In-Mo Lee[a] & Jeong-Hark Lee[b]

[a]Department of Civil Engineering, [b]The Institute of Industrial Technology, Korea University, Seoul 136-701, Korea

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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 ultlmate bearing capacity of piles. For the verification of applicability of neural networks, results of model pile load tests performed by the authors were simulated. In addition, the results of in situ *pile load tests obtained from a literature survey were also used. The results showed that the maximum error of prediction did not exceed 25%, except for some bias data. These limited results indicated the feasibility of utilizing neural networks for pile capacity prediction problems. Copyright © 1996 Elsevier Science Ltd.*

INTRODUCTION

Piles have been used for many years as a type of structural foundation. However, prediction of bearing capacity has been a difficult task because of various factors affecting the capacity and their uncertainties. Recent advances in soil mechanics and foundation engineering have provided useful information regarding the factors that affect bearing capacity, but 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. Since pile load tests have been restricted by time and expense in spite of their reliability, engineers have developed a correlation between the results of pile load tests and *in situ* tests, such as the standard penetration test (SPT).

In this paper, 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 were used.

ERROR BACK PROPAGATION NEURAL NETWORKS

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 was 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 process in which the information between input and output is captured in 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 multi-layer networks, classified as "supervised learning" because the networks are adjusted by comparing the actual output with the 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. Using neural networks, Ghaboussi *et al.* [5] reported on the behaviors of concrete in a state of plane stress under monotonic biaxial loading and compressive uniaxial cyclic loading. Ghaboussi *et al.* [6] also showed that neural networks were powerful tools for the mathematical constitutive modeling of geomechanics. Goh [7] demonstrated that neural networks could model the complex relationship beween seismic soil parameters and liquefaction potential using actual field records. Robert [8] applied neural networks to the interpretation of the CAPWAP analysis. Zhou and Wu [9] investigated the estimation of rockhead elevations using this theory. However, to the authors' knowledge, few studies were applied to the pile bearing capacity prediction problem.

APPLICATIONS

Model pile load tests, using a calibration chamber, were performed in order to examine the possibility of predicting ultimate bearing capacity of pile by utilizing neural networks theory. In addition, results of *in situ* pile load tests obtained from a literature survey were also applied for the feasibility study of artificial neural networks in pile bearing capacity prediction. The error back propagation neural network used had four layers: input layer, two hidden layers, and output layer.

Model pile load test

A closed-end model pile was fabricated using a 40 mm diameter steel tube with a wall thickness of 1.5 mm. Total length of the test pile was 500 mm and the tip angle was 60°. A calibration chamber, in which field stress conditions could be simulated, was designed (Fig. 1). The structural parts of the chamber consisted of a steel cylinder and two steel plates. The height of the chamber was 1000 mm and the internal diameter of the steel cylinder was 760 mm. In the top plate, a hole for the model pile was drilled for pile driving. A tubular side membrane was attached to the inner surface of the steel cylinder and a flat membrane was located at the bottom plate. These served as the

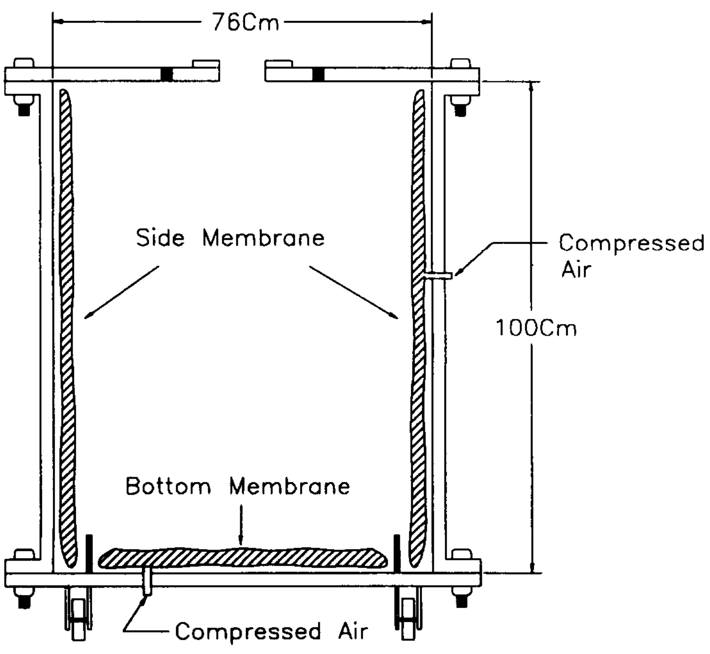


Fig. 1. Calibration chamber.

lateral and vertical pressure membranes, respectively. Pressure was independently applied to each membrane by compressed air, controlled by regulators.

To obtain the ultimate bearing capacity of the model pile, a uniform sand layer was composed. Test sand was dried in air below 2% of water content. It was poorly graded, clean, fine sand, classified as SP by the USCS (unified soil classification system). The grain size distribution is shown in Fig. 2. The maximum dry density was 16 kN/m^3. The angle of internal friction, ϕ, of 40° was obtained from a direct shear test.

Sand was deposited using the "raining method". In this method, streams of sand were dropped through still air at a controlled, constant height to form a uniform sand deposit of a known relative density. A series of stress conditions of the calibration chamber is summarized in Table 1. Since the coefficient of lateral earth pressure, the K_0 value, was reasonably assumed to be 0.4 in actual field conditions, each stress level was controlled to maintain this value.

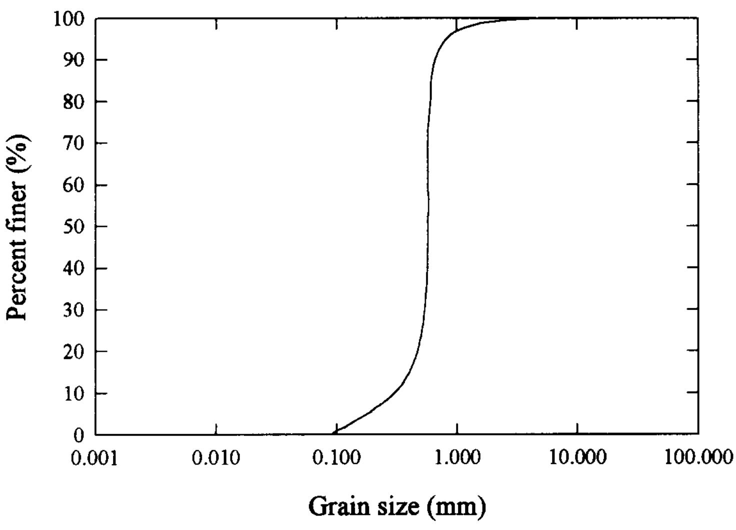


Fig. 2. Grain size distribution of test sand.

TABLE 1
Stress conditions in laboratory model tests

Step	1	2	3	4	5	6
σ_v(kPa)	25	50	75	100	150	200
σ_h(kPa)	10	20	30	40	60	80

After the consolidation process, lasting 24 h, the model pile was driven into the specimen using the model laboratory hammer. The hammer consisted of a ram weighing 43 N, a steel guide rod that ran through the center hole of the ram and an anvil that fitted into the head of the pile. The compresive load was applied by the oil jack, which had a maximum capacity of 50 kN. Loads were measured through a proving ring, the allowable capacity of which was 30 kN. Results of the model pile load test are summarized in Table 2. Ultimate bearing capacities of the model pile were assumed to be affected by the penetration depth ratio of the model pile, the mean normal stress and the number of blows, as shown in Table 2.

TABLE 2
Results of model pile tests

Case No.	*Penetration depth ratio* (l/d)	*Chamber pressure (kPa)* *Vertical* (σ_1)	*Horizontal* (σ_3)	*Mean normal stress* (σ_m)[a]	*No. of blows*	*Ultimate capacity* (kN)
1	3.75	75	30	45	64	279
2	4.00	75	30	45	96	368
3	6.25	75	30	45	147	440
4	7.50	75	30	45	195	497
5	8.75	75	30	45	248	387
6	10.00	75	30	45	297	535
7	11.25	75	30	45	349	499
8	3.75	100	40	60	71	205
9	4.00	100	40	60	105	340
10	6.25	100	40	60	161	375
11	7.50	100	40	60	213	403
12	8.75	100	40	60	266	419
13	10.00	100	40	60	321	502
14	11.25	100	40	60	377	615
15	3.75	150	60	90	100	341
16	4.00	150	60	90	144	436
17	6.25	150	60	90	202	589
18	7.50	150	60	90	254	540
19	8.75	150	60	90	308	600
20	10.00	150	60	90	358	595
21	11.25	150	60	90	414	819
22	3.75	200	80	120	101	450
23	4.00	200	80	120	156	530
24	6.25	200	80	120	211	642
25	7.50	200	80	120	258	765
26	8.75	200	80	120	310	670
27	10.00	200	80	120	358	724
28	11.25	200	80	120	404	774

[a] $\sigma_m = (\sigma_1 + 2\sigma_3)/3$.

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 3. In this study, it was assumed that ultimate bearing capacities were affected by the following factors:

- Penetration depth ratio(l/d): penetration depth of pile(l)/pile diameter (d)
- Average standard penetration number, N-value along the pile shaft (N_{sa})
- Average N-value near the pile end(N_b)
- Pile set(s)—final penetration depth (mm)/blow
- Hammer energy(E)

TABLE 3
Results of *in situ* pile load tests

Case No.	l/d	N_{sa}	N_b	s (mm/blow)	E (kJ)	*Ultimate Capacity* (MPa)	*Authors*	
1	119.75	10	64	1.20	40.1	49.7	Bozozuk *et al.*	[10]
2	129.92	10	64	2.15	40.1	41.4	Bozozuk *et al.*	[10]
3	97.84	10	10	5.35	40.1	21.2	Bozozuk *et al.*	[10]
4	103.35	10	10	9.80	40.1	16.7	Bozozuk *et al.*	[10]
5	107.47	11	21	2.12	49.7	24.2	Brieley *et al.*	[11]
6	16.32	78	187	1.27	49.7	20.2	Brieley *et al.*	[11]
7	66.05	10	247	0.89	33.2	26.2	Thompson	[12]
8	65.74	10	247	0.60	33.2	23.0	Thompson	[12]
9	98.77	10	247	0.63	33.2	21.6	Thompson	[12]
10	75.31	10	247	0.14	33.2	27.4	Thompson	[12]
11	75.31	10	247	0.19	53.9	33.0	Thompson	[12]
12	75.31	10	247	0.51	53.9	27.9	Thompson	[12]
13	75.31	10	247	0.57	33.2	23.6	Thompson	[12]
14	49.02	30	70	2.34	128.2	16.3	Gurtowski and Wu	[13]
15	41.97	37	55	2.34	128.2	13.7	Gurtowski and Wu	[13]
16	44.44	17	150	17.00	71.2	12.0	Likins *et al.*	[14]
17	51.11	17	150	7.30	71.2	16.8	Likins *et al.*	[14]
18	33.33	17	150	9.00	71.2	8.7	Likins *et al.*	[14]
19	33.33	17	150	4.00	71.2	11.1	Likins *et al.*	[14]
20	24.44	17	150	3.30	210.8	6.6	Likins *et al.*	[14]
21	46.00	17	10	7.30	186.9	8.5	Matsumoto *et al.*	[15]
22	31.67	15	50	2.00	186.9	7.4	Matsumoto *et al.*	[15]
23	94.12	8	14	19.05	27.0	12.7	Darragh and Bell	[16]
24	115.11	8	93	1.80	27.0	21.9	Darragh and Bell	[16]

Simulation using model pile load test data

Parameters used to perform the neural networks simulation 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. Those values used in this study were 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 28 data sets for this study. As shown in Table 2, three input nodes, representing the penetration depth ratio, the mean normal stress of the calibration chamber and the number of blows, were chosen as the input vectors to predict the ultimte bearing capacity of a model pile in the output. The schematic diagram for the neural network model is shown in Fig. 3. 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

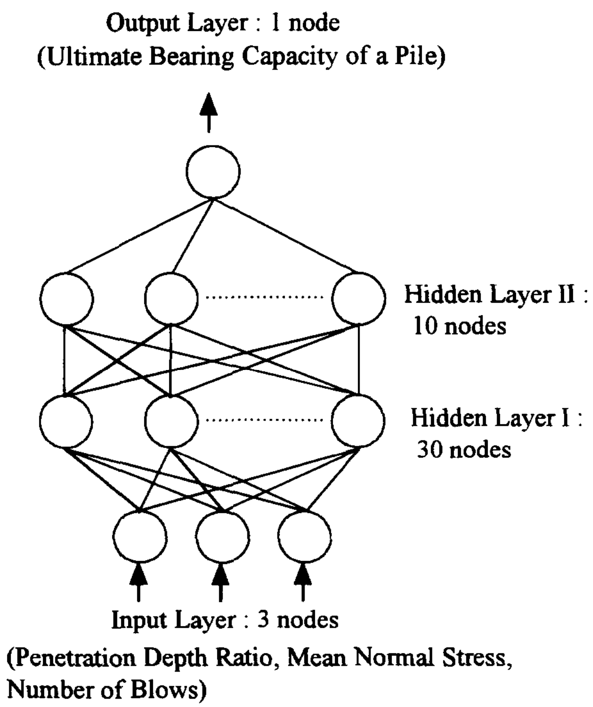


Fig. 3. Architecture of the neural networks model.

TABLE 4.
Number of learning samples

Case	*No. of learning samples*	*Remarks*
Case 1	9	the multiples of 3-numbered samples
Case 2	14	odd-numbered samples
Case 3	14	even-numbered samples
Case 4	21	remainders except the multiples of 4-numbered samples

data sets, and the remaining data sets (not used as the learning data sets) were applied to test the predictive ability of the trained network. The number of learning samples is listed in Table 4.

Figure 4 shows the error plots during training in each case. The convergence criterion considered in this study was 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 5 shows the plots of estimated vs measured values for ultimate bearing capacities of model piles. For cases of training more than 14 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

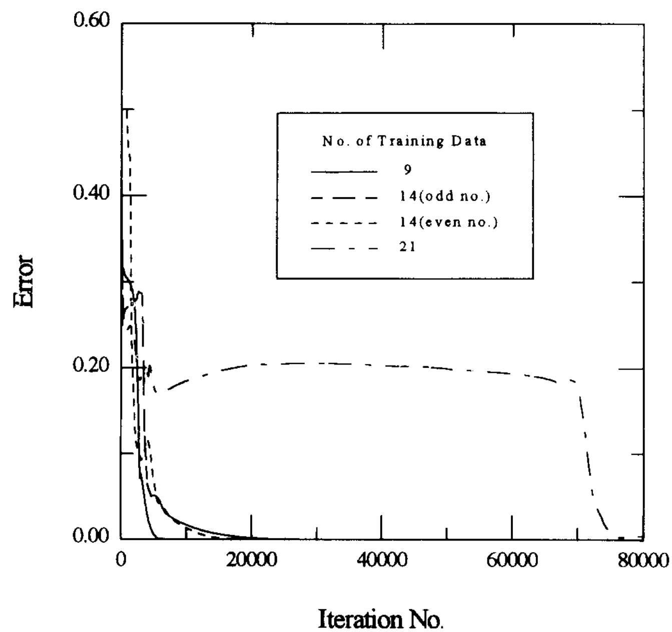
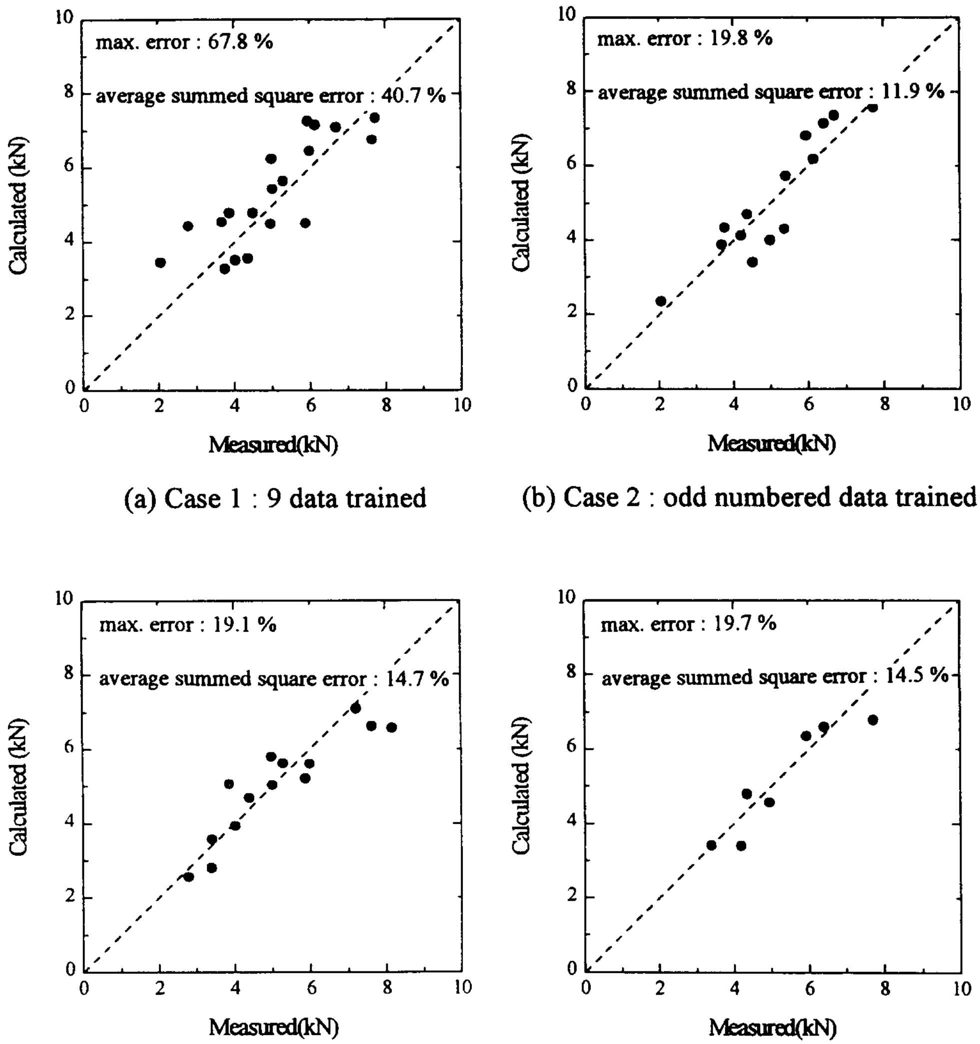


Fig. 4. Variation of error with the number of training samples.



(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

Fig. 5. Testing results of estimated vs measured pile bearing capacity from model pile load test.

error of prediction exceeded 65% in this case and the average summed square error was more than 40%. Therefore, it could be concluded that a certain number of training data sets was needed to obtain reasonable predictions.

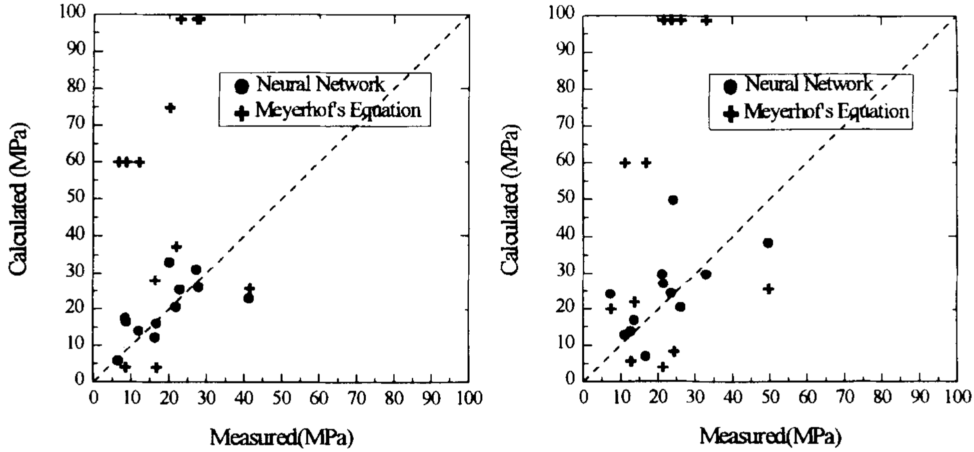
Simulation using *in situ* pile load test data

In order to train the network with the *in situ* load test results shown in Table 3, the same network parameters used in the previous section were adopted.

The *in situ* pile load test data, however, had a somewhat different form from the model test. The input layer had five nodes and 24 data sets were available. To investigate the feasibility of bearing capacity prediction, the data sets were arbitrarily partitioned into two parts, odd and even numbered sets. First, all odd numbered samples were used for training and the even numbered data sets were used for predicting the bearing capacities. Then the roles were reversed, with the even numbered samples being used for training and the odd numbered data sets being used for predicting. Figure 6 shows the plots of estimated vs measured values for *in situ* pile bearing capacities. Since Meyerhof's equation based on the SPT-N value,

$$q_u(\mathrm{MPa}) = 0.4N_b + 0.002N_{sa} ,$$

is frequently used in practical design, calculated results using this equation are also shown in the same plot. The results demonstrated somewhat broader predictions; however, the error of prediction was less than 25%, except for four data points in both cases. Moreover, it was clear that the calculated values utilizing the neural networks theory matched the measured values much better than those using Meyerhof's equation. Since the *in situ* data concerning the ultimate bearing capacity in this study were insufficient for prediction, the networks showed widely dispersed predictions; however, it was believed that with enough data sets, a better correlation could be expected.



(a) odd numbered data trained (b) even numbered data trained

Fig. 6. Testing results of estimated vs measured pile bearing capacity from *in situ* pile load test.

CONCLUSIONS

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

In the case of model pile load tests, the prediction utilizing the neural networks theory was 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 25%. Moreover, predictions from the neural networks model were much better than from Meyerhof's bearing capacity equation correlated from the SPT-N value. 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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