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GENERAL REGRESSION NEURAL NETWORK MODELING OF SOIL CHARACTERISTICS FROM FIELD TESTS

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ABSTRACT: The Standard Penetrating Test (SPT) can be considered as one of the most common in-situ popular and economic tests for subsurface investigation. Therefore, many empirical correlations have been developed between the SPT N-value, and other properties of soil. The principle objective of the current study is to demonstrate the feasibility and efficiency of using artificial neural networks (ANNs) to predict the soil angle of internal friction (Φ), the soil modulus of elasticity (E) and tip resistance (q_c) of cone penetration test (CPT) results from SPT results considering the uncertainty and non-linearity of the soil. In addition, ANNs are used to study the influence of different input parameters that can be used to improve the prediction. A large amount of field and experimental data including SPT/CPT results, plate load tests, direct shear box, grain size distribution was obtained from a project in the United Arab Emirates to be used in the training and the validation of the ANNs. The ANN results are compared with some common traditional correlations. The results show that the developed ANNs can efficiently predict the aimed parameters from the SPT results. The predicted parameters from ANN are in very good agreement with the measured results compared to the predicted values from available traditional correlations.

Keywords: Angle of Internal Friction; Cone Penetrating Test; General Regression Neural Network; Soil Modulus of Elasticity, Standard Penetrating Test.

1. INTRODUCTION

The Standard Penetration Test (SPT) is one of the most commonly used in-situ tests for site investigation and foundation design. Many empirical correlations have been developed between the SPT N-value, and other engineering properties of soil. Despite the fact that this test has disadvantages such as discrete strength measurement and dependence on operator and apparatus, it is still the most popular and economic mean for subsurface investigation.

The current paper studies the feasibility and efficiency of using artificial neural networks (ANNs) to estimate the soil properties Φ (angle of internal friction), E (modulus of elasticity) and q_c (tip resistance of cone penetration test (CPT)) [1]-[5] from SPT results. In addition, the study investigates which parameters should be included in the soil property estimation to improve the prediction models.

Artificial neural networks have been intensively studied and applied to many geotechnical engineering problems. In addition, It has been applied to estimate many soil and material properties and it is proved to be a powerful tool that can have superiority over other correlation techniques [6] - [10]. The idea of neural network technology is similar to the brain's own problem-solving process. An ANN is composed of a large number of connected neurons which act like simple processors. Generally, when a large volume of data is available for training, ANNs offer viable solutions. It has been shown that ANNs are capable of mapping nonlinear and complex relationships in nature and are very beneficial when a problem is difficult to formulate analytically.

To train and test a neural network a large amount of data is needed. In the current study, field and experimental data including SPT/ CPT results, plate load tests, direct shear box, grain size distribution were obtained then filtered and processed from a large-scale project that covers the United Arab Emirates (UAE). The soil in UAE is mostly cohessionless soil. UAE is witnessing a lot of development and many construction projects. It is believed that using data from such active areas in construction for prediction of soil properties would be of benefit to engineers in this area specifically and to geotechnical engineers in general.

The available data used for estimating Φ (Direct shear box), E (plate loading test) and q_c (CPT results) from N (SPT results), is first presented. The different ANN models are then developed. Different input parameters were considered to study the influence of the input parameters on the ANN models. The predictions from ANN are compared to predictions from other correlations available in the literature. Conclusions highlighting the efficiency of the ANNs are finally presented.

2. AVAILABLE DATA

The data for this study was collected from the results of geotechnical investigation work that had been done for a large-scale project. The project extends all over United Arab Emirates (UAE) where the soil is mainly cohessionless soil.

The project had about 820 boreholes with variable depths including standard penetration tests (SPT) for each borehole along the project alignment. Additionally, 400 cone penetration tests (CPT) were executed beside the boreholes. Moreover, there were 630 test-pits with maximum depth of 3.0m with 260 plate loading tests to determine the modulus of soil elasticity and 606 California Bearing Ratio tests (CBR). Lab tests were performed on the soil samples for classification (grain size distribution tests; sieve analysis and hydrometer) and for determining the shear strength parameters (direct shear box).

3. NEURAL NETWORK MODELING

The current study uses a supervised ANN. In a supervised network, a large number of correct predictions are given to the model from which it can learn. Examples of supervised networks are back propagation networks (BPN), general regression neural networks (GRNN) and probabilistic neural networks (PNN) [11], [12].

The architecture of a supervised ANN, generally, consists of an input layer, an output layer and one or more hidden layers. The input layer contains the input variables. The output layer contains the target output vector. At least one hidden layer that contains the artificial neurons (processing units) is used between the input and output to assist in the learning process. The neurons in the different layers are interconnected. Each connection has a 'weight' associated with it. Input values in the first layer are weighted and passed on to the hidden layer. Neurons in the hidden layer produce outputs by applying an activation function to the sum of the weighted input values [11], [12]. These outputs are then weighted by the connections between the hidden and output layer. The output layer produces the desired results.

Two main phases are included in neural network operation. The first is the training phase and the second is the testing phase. In the first phase the data is repeatedly presented to the network while the weights of the data are updated to obtain the desired output. In the second phase the trained network with the frozen weights is applied to data it has never seen. A properly trained network can model the unknown function that relates the input variables to the output variables. It can then be used to make predictions for a given set of previously unseen input patterns where the output values are unknown.

The neural networks used in the current study were developed using the neural network program Neuroshell 2 [13]. This program implements several different neural network algorithms. The general regression neural network (GRNN) was used in the current study. GRNNs are known for their ability to train quickly on sparse data sets [10].

The GRNN models developed were three-layer networks (input layer, output layer and one hidden layer). The number of neurons in the input layer is equal to the number of inputs while the number of neurons in the output layer is equal to the number of outputs. The number of neurons in the hidden layer is usually equal to the number of correct patterns given to the model to learn from.

The inputs were scaled using a linear scale function [0,1]. The GRNN used was genetic adaptive; i.e. it uses a genetic algorithm to find an input smoothing factor adjustment. The genetic breeding pool size of 100 was used in the developed GRNN. An initial smoothing factor was taken as 0.3. The smoothing factor is an important parameter in the GRNN which determines how tightly the network matches its predictions to the data in the training patterns.

For each of the data sets prepared to estimate Φ, E and q_c from N, 20% of the data was randomly extracted. This 20% was used as a testing set while the rest of the data was used as a training set**.**

4. ESTIMATING Φ FROM SPT RESULTS

4.1 Output/Input Variables of ANN Analysis

For estimating Φ from SPT results, the SPT results (N values), direct shear test and grain size analysis were used from the available data. The readings of the SPT test were filtered to be at the same elevation of the lab tests. A total of 84 data points were prepared. The parameters that were investigated as input parameters to be included in the GRNN models developed were N (obtained from SPT results), F_c (fines content), D_{50} (defined as grain diameter corresponding to 50% of the material being smaller) obtained from grain size analysis and σ_{eff} (the effective overburden pressure) calculated at the same level of the SPT test. The calculation of effective overburden pressure was based on a unit weight of soil of 18 KN/m^3 and the unit weight of water of 10 KN/m^3 taking into consideration the effect of ground water level.

The output of the GRNN models considered was tan Φ which was both measured (obtained from direct shear box) and estimated by the GRNN models developed. Five different GRNN models were developed with different input parameters to study the influence of the input parameters on the obtained tan Φ. To evaluate the efficiency of the GRNN models developed, the coefficient of correlation (r^2) was used. r^2 is a statistical measure of the strength of the relationship between the actual versus predicted outputs. r^2 value of 1 indicates a perfect fit, while that of 0 indicates no relationship.

4.2 Results of Neural Networks

Fig. 1 shows 5 different GRNN models developed (GRNN1 to GRNN5) with 5 different input combinations and the corresponding r^2 (for all data points) obtained for each Network. GRNN2 with inputs (N, σ_{eff}) was the best model to represent the correlation of predicting (tanΦ) from SPT results and effective overburden with a high value of r^2 of 97.55%.

Table 1 presents the data used in GRNN2 as input and the measured tan Φ. The comparison between the predicted tan Φ from GRNN and the actual measured values is presented in Fig. 2.

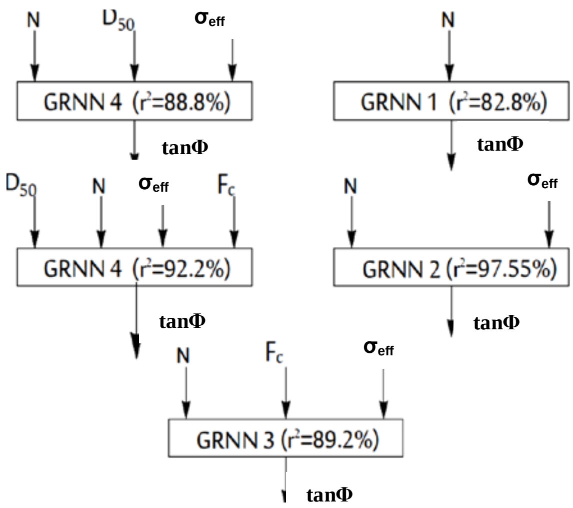

Fig. 1 Trials used to predict tan (Φ) from SPT results considering different input parameters with r^2 coefficient (%)

Table 1 The used data for estimation of φ (GRNN2)

Index	Effective stress(KPa)	N (SPT)	Tan (Φ)
1	38.0	27	0.809213
2	29.0	68	0.86865
3	39.0	7	0.553974
4	21.5	16	0.624476
5	28.0	11	0.600487
6	35.0	22	0.674071
7	58.0	33	0.726056
8	43.5	20	0.726056
9	29.5	9	0.576996
10	52.0	10	0.576996
11	59.2	22	0.699746
12	26.0	11	0.600487
13	24.0	9	0.576996
14	32.0	7	0.576996
15	42.0	7	0.553974
16	33.0	5	0.553974
17	35.0	5	0.553974
18	14.9	5	0.553974
19	52.0	8	0.576996
20	50.0	27	0.576996
21	76.0	11	0.600487
22	27.5	2	0.466038
23	43.5	6	0.576996
24	28.0	5	0.553974
25	27.0	10	0.576996
26	55.0	13	0.600487
27	44.5	9	0.600487
28	30.0	10	0.576996
29	29.0	15	0.624476
30	61.0	6	0.553974
31	28.0	8	0.576996
32	60.0	8	0.553974
33	29.0	24	0.674071
34	29.0	10	0.600487
35	77.0	23	0.674071
36	28.0	16	0.648993
37	52.0	15	0.624476
38	29.0	20	0.648993
39	65.0	16	0.674071
40	22.5	16	0.624476
41	81.5	19	0.648993
42	28.5	16	0.600487
43	30.5	16	0.576996
44	30.0	6	0.553974
45	62.0	7	0.576996
46	33.0	12	0.600487
47	81.0	8	0.576996
48	51.0	13	0.753041
49	73.0	14	0.753041
50	68.0	10	0.600487
51	36.0	6	0.576996
52	76.0	26	0.699746
53	45.0	15	0.753041
54	89.0	7	0.576996
55	43.5	19	0.624476
56	29.0	10	0.600487
57	81.0	38	0.753041
58	34.5	20	0.648993
59	58.0	14	0.753041
60	40.5	11	0.600487
61	42.0	12	0.576996
62	58.0	23	0.648993
63	43.0	20	0.624476
64	37.3	1	0.531392
65	39.0	11	0.553974
66	43.0	4	0.531392
67	51.0	7	0.531392
68	45.0	5	0.509225
69	50.0	1	0.487448
70	43.0	8	0.531392
71	47.0	6	0.531392
72	61.0	9	0.553974
73	41.0	9	0.576996
74	21.0	6	0.553974
75	36.0	8	0.531392
76	49.0	3	0.509225
77	26.0	3	0.531392
78	47.0	9	0.531392
79	38.0	5	0.531392
80	48.1	4	0.509225
81	27.0	12	0.576996
82	29.0	12	0.576996
83	29.5	14	0.600487
84	26.0	13	0.553974

For GRNN2, the weight (influence) of each input parameter on the relation is reflected by the individual smoothing factor of each input parameter. The individual smoothing factors for each input are shown in Fig. 2. It is concluded from Fig. 2 that (σ_{eff}) is the second input variable that influences the network and N- value (SPT result) is the first one.

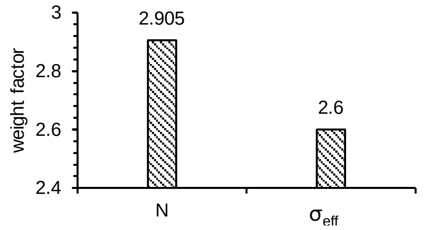

Fig.2 The weight factors for the correlation between angle of internal friction and SPT results (GRNN2)

4.3 Comparison between Neural Networks and a Set of Traditional Methods

Table 2 shows some of the correlations used for the estimation of Φ from SPT results available in the literature. The available data is applied to the available correlations in the literature and are plotted in Fig. 3 along with the results from the ANN model developed.

From Fig. 3, it is clear that the ANN model predicted values of angle of internal friction are very close to the measured values compared to the other available correlations. Therefore, it is a good indication for the applicability of using this model in comparison with other correlations

Table 2 Different correlations for predicting (tanφ)

Researcher	Correlation
Kulhawy and Mayne, (1990)	$\phi = tan^{-1}(N/(12.25 + 20.35\delta_{vo}/pa)^{0.34}$
Wolff, (1989).	$\phi = 27.1 + 0.30N - .00054N^2$
Shioi and Fukui (1982)	$\phi = 4.5\,N + 20$
Hatanaka and Uchida, (1996)	$\phi = \sqrt{18\,N_1} + 20$ Where, $N_1 = \sqrt{\frac{98}{\sigma_{vo}}}\,N$ & σ_{vo} *in KPa* *where* σ_{vo} *is effective earth pressure*

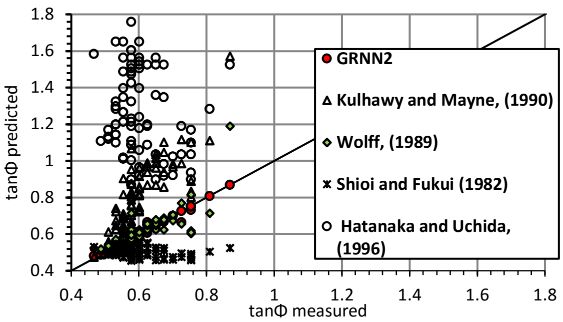

Fig. 3 Comparison between actual (measured) and predicted (tanΦ) from SPT.

5. ESTIMATING E FROM SPT RESULTS

5.1 Output/Input Variables of ANN Analysis

For estimating E from SPT results, the SPT results (N values), plate loading test and grain size analysis were used from the available data. The readings of the SPT test were filtered to be at the same elevation of the lab tests and at the zone of 120 cm below plate loading test (influence zone while the plate width is 60cm). Thirty-four data points were prepared. The parameters that were investigated as input parameters to be included in the GRNN models developed were N (obtained from SPT results), F_c (fines content), D_{50} and depth of water below the plate loading test.

5.2 Results of Neural Networks

Fig. 4 shows 7 different GRNN models developed (GRNN1 to GRNN7) with 7 different input combinations and the corresponding r^2 (for all data points) obtained for each Network. GRNN2 with inputs (N, D_{50}) was the best model to represent the correlation of predicting (E) from SPT results with a high value of r^2 of 95.46%. Fig. 5 shows the influence/weight factors for every input.

Table 3 presents the data used as input and the measured E. Fig. 6 shows the comparison between the predicted E from GRNN2 and the actual measured values.

Table 3 The used data for the estimation of E

Index	N SPT	F_c (%)	D_{50} (mm)	Water Depth below PLT (m)	E (MPa)
1	7	12.7	0.121	0.406	54.35
2	6	6.6	0.144	0.4	31.6
3	14	9.4	0.1539	0.945	23.89
4	2	10.1	0.1318	1.2	42.78
5	14	1	0.1678	50	27.51
6	24	1	0.2159	50	19.2
7	20	1.4	0.1875	50	10.09
8	15	1.9	0.1382	50	33.78
9	15	1.5	0.1541	2.7	73.05
10	28	1.5	0.2149	50	20.13
11	28	1.6	0.1889	50	37.63
12	53	1.7	0.183	50	27.85
13	30	7.8	0.178	1.1	41.98
14	2	10	0.155	1.1	19.07
15	10	8.6	0.135	1.2	18.88
16	3	8.4	0.148	1.1	19.07
17	3	8.7	0.136	1.2	13.46
18	14	7.7	0.186	1.3	13.36
19	3	8.8	0.122	1.2	22.06
20	4	8.9	0.143	1.3	24.56
21	4	10	0.1227	1.3	9.9
22	7	9.1	0.152	1.2	22.1
23	4	9.9	0.157	1.3	22.1
24	7	10	0.143	1.5	31.16
25	7	9.3	0.1426	1.7	33.38
26	13	12	0.135	2.2	33.58
27	10	12.5	0.131	1.7	29.15
28	18	11.7	0.132	1.8	29.61

Table 3 (continued)

Index	N SPT	F_c (%)	D_{50} (mm)	Water Depth below PLT (m)	E (Mpa)
29	38	12.7	0.137	50	37.63
30	3	13.5	0.163	1.3	11.28
31	2	29	0.187	1.1	54.35
32	5	68	0.206	2.5	25.74
33	2	7.8	0.1563	2.7	40.76
34	2	9	0.15	2.6	43.44

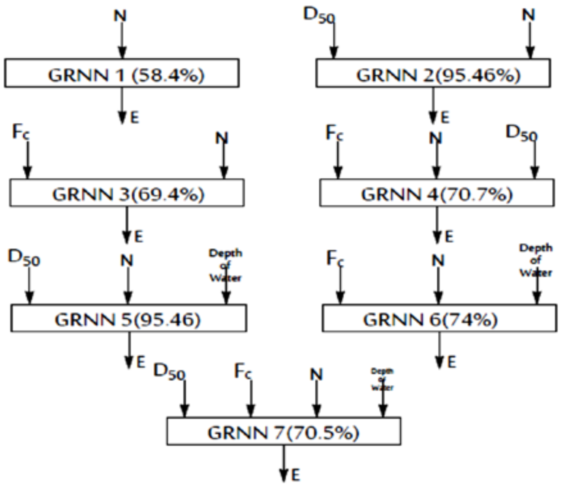

Fig. 4 Trials used to predict E from SPT results considering different input parameters with r^2 coefficient (%).

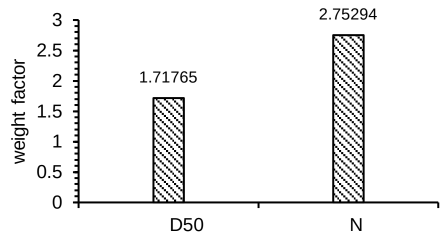

Fig. 5 The weight factors for the correlation between angle of internal friction and SPT results (GRNN2)

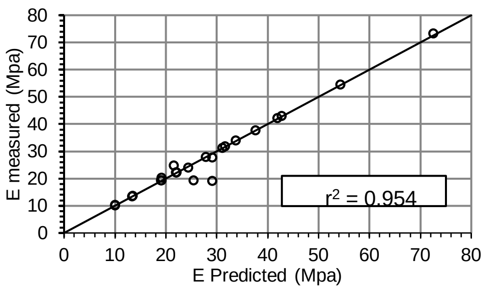

Fig. 6 Comparison between predicted and measured E

5.3 Comparison between Neural Networks and a Set of Traditional Methods

Table 4 and Fig. 7 show some of the correlations used for estimation of E from SPT results available in the literature. From Fig. 7, it is shown that the ANN model (GRNN2) was in very good agreement with measured values of E compared to the other available correlations in the literature.

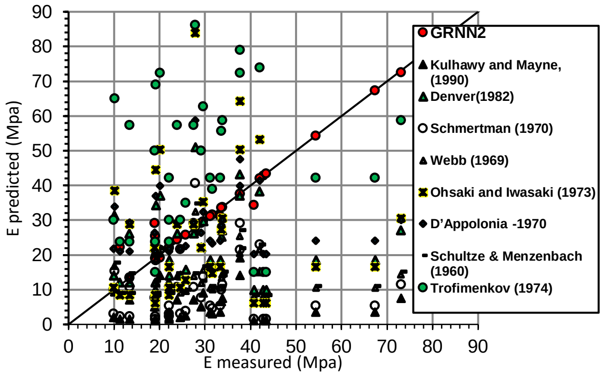

Fig. 7 Comparison between actual (measured) and predicted (E) from SPT.

Table 4 Different correlations for predicting (E) from SPT results

Researcher	Correlation
Kulhawy and Mayne, (1990)	$5N = E/P_a$
Schmertman(1970)	$E(KPa) = 766N$
Denver(1982)	$E(MPa) = 7\sqrt{N}$
Webb (1969)	$E(Kg/cm2) = 7.17 + 0.478N$
Ohsaki and Iwasaki (1973)	$E(MPa) = 3.5 * N\,0.8$
D'Appolonia (1970)	$E(MPa) = 18.75 + 0.756N$
Schultze & Menzenbach (1960)	$E(MPa)$= 7.46+0.517N
Trofimenkov (1974)	$E(Kg/cm2)$= 500 $\log_{10}(N)$

6. ESTIMATING (q_c) FROM SPT RESULTS

6.1 Output/Input Variables of ANN Analysis

For estimating q_c from SPT results, the SPT results (N values), results of grain size analysis (F_c, D_{50}, D_{30}, D_{10}) and effective overburden pressure (σ_{eff}) were used from the available data. The readings of the CPT tests were filtered to be at the same elevation of the lab tests and N-value of SPT. A total of 93 data points were prepared.

6.2 Results of Neural Networks

Fig. 8 shows 10 different GRNN models developed (GRNN1 to GRNN10) with 10 different input combinations and the corresponding r^2 (for all data points) obtained for each Network. GRNN7 with inputs (N, F_c, D_{50}, D_{30}, D_{10}, σ_{eff}) was the best model to represent the correlation of predicting (q_c) from SPT results, effective overburden and results of grain size distribution tests with a high value of r^2 of 90%.

Fig. 9 shows the influence factors for every input for GRNN3, GRNN4, GRNN7, GRNN8 that have r^2 >90%, however, GRNN7 is considered the strong correlation between q_c (CPT result) and N-value of SPT result because N-value has a high influence factor of 2.77 and is considered the last factor in the other correlations (GRNN3, GRNN4, GRNN8). In addition, D_{50} is the last factor that has no effect on output results for GRNN7.

Table 5 presents the data used in GRNN7 as input and the measured q_c. Fig. 10 shows the comparison between the predicted q_c from GRNN7 and the actual measured values.

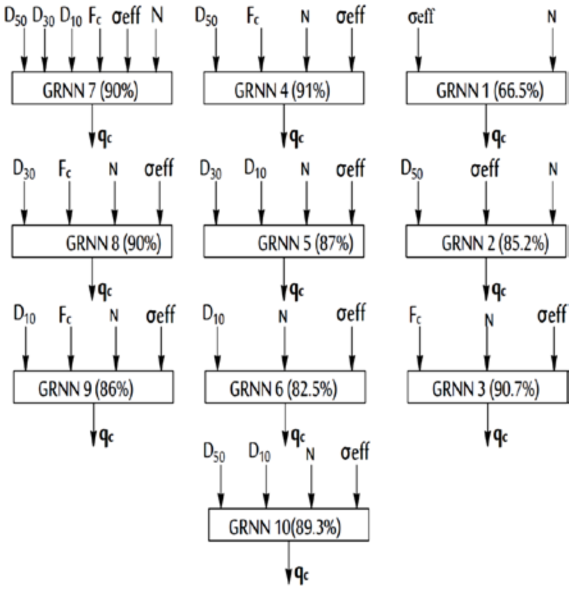

Fig. 8 Trials used to predict q_c from SPT results with r^2 coefficient (%).

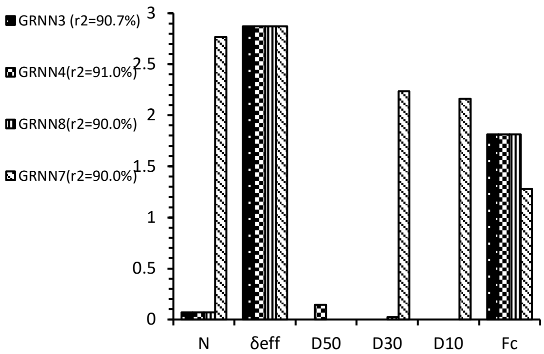

Fig. 9 The weight factors for the correlation between q_c (CPT result) and N (SPT result).

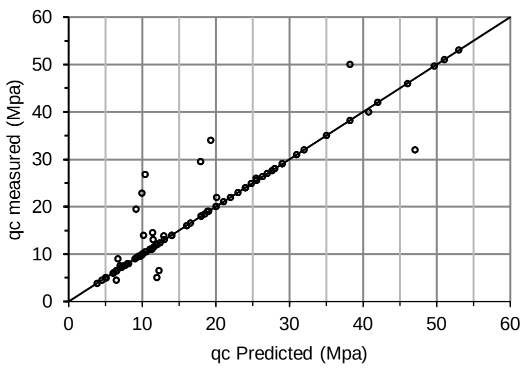

Fig. 10 Comparison between predicted and measured q_c for GRNN7.

6.3 Comparison between Neural Networks and a Set of Traditional Methods

Table 6 and Fig. 11 show some of the correlations used for estimation of q_c from SPT results available in the literature. It is clear from the figure that the ANN model yields better prediction of q_c.

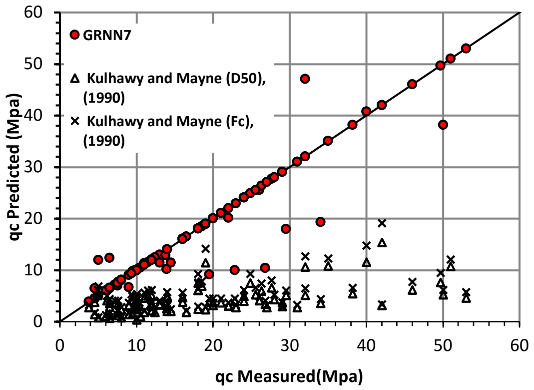

Fig. 11 Comparison between actual (measured) and predicted (q_c) from SPT.

7. CONCLUSION

The paper studied the feasibility and efficiency of applying artificial neural networks (ANN) to predict ϕ (angle of internal friction), E (modulus of elasticity) and q_c (CPT result) from SPT results (N values) which is one of the most commonly used in-situ tests. A large amount of data for cohesionless soil was used that was collected from a project covering most of UAE. The effect of different input parameters was investigated and ANN results were compared with other available correlations. The following can be concluded:

- The results of the ANN models developed for predicting ϕ, E and q_c from N gave a very good agreement with actual results compared to some of the traditional methods available in the literature.
- ANN model (GRNN2) with coefficient of correlation (r^2= 97.6%) and inputs (N, σ_{eff}) was the best model to represent the correlation of predicting (tanΦ) from SPT results (N) and effective overburden pressure (σ_{eff}).
- ANN model (GRNN2) with r^2= 95.6% and inputs (N, D_{50}) was the best model to represent the correlation of predicting (E) from SPT results and grain size distribution.
- ANN model (GRNN7) with coefficient of correlation (r^2= 90%) and inputs (N, σ_{eff}, F_c, D_{10}, D_{30}, and D_{50}) was the best model to represent the correlation of predicting (q_c) from SPT results**,** effective overburden pressure and results of grain

size distribution tests.

Table 5 The used data for estimation of q_c (GRNN7)

No.	D_{50} (mm)	D_{30} (mm)	D_{10} (mm)	F_c %	N -SPT	q_C (Mpa)	EFFECTIVE PRESSURE (σ_{eff}) (KPa)
1	0.192	0.141	0.071	7.80	19	18.5	22.0
2	0.141	0.104	0.065	9.00	10	26.8	26.0
3	0.142	0.102	0.064	9.50	12	24.0	42.0
4	0.150	0.108	0.066	8.50	16	38.2	58.0
5	0.186	0.119	0.066	8.90	11	22.8	22.0
6	0.150	0.108	0.067	8.00	12	26.0	26.0
7	0.129	0.094	0.052	12.30	23	24.8	34.0
8	0.139	0.102	0.065	9.00	18	26.3	42.0
9	0.140	0.104	0.068	7.10	23	49.7	58.0
10	0.177	0.127	0.067	8.70	7	13.9	23.0
11	0.131	0.096	0.062	10.70	10	11.9	27.0
12	0.137	0.099	0.061	11.30	20	27.6	43.0
13	0.129	0.097	0.065	8.90	16	25.6	59.0
14	0.187	0.133	0.064	9.60	4	6.5	25.3
15	0.178	0.114	0.065	9.20	2	5.0	29.3
16	0.123	0.093	0.064	9.60	1	10.0	37.3
17	0.157	0.113	0.069	7.30	12	6.1	53.3
18	0.137	0.101	0.065	8.80	14	53.0	77.3
19	0.154	0.109	0.065	8.90	15	5.0	27.0
20	0.177	0.126	0.068	8.30	10	7.2	31.0
21	0.149	0.108	0.068	7.70	11	4.5	39.0
22	0.135	0.098	0.061	11.20	6	14.5	55.0
23	0.171	0.116	0.065	9.20	14	14.0	87.0
24	0.163	0.113	0.064	9.60	5	11.0	23.0
25	0.150	0.106	0.062	10.30	2	6.5	27.0
26	0.153	0.108	0.063	9.80	11	16.0	59.0
27	0.126	0.094	0.061	11.10	19	46.0	75.0
28	0.160	0.113	0.068	7.80	13	10.0	23.0
29	0.152	0.109	0.065	9.00	10	9.8	27.0
30	0.163	0.116	0.066	8.60	7	18.0	51.0
31	0.145	0.103	0.061	10.80	15	11.5	59.0
32	0.062	0.025	0.003	52.10	40	51.0	75.0
33	0.149	0.106	0.062	10.40	3	6.0	25.0
34	0.149	0.109	0.069	7.20	4	4.5	29.0
35	0.190	0.135	0.069	8.10	5	16.5	45.0
36	0.123	0.093	0.062	10.60	9	12.0	61.0
37	0.053	0.025	0.004	62.10	12	42.0	85.0
38	0.212	0.130	0.069	7.90	3	7.5	27.0
39	0.158	0.112	0.065	9.10	31	32.0	66.0
40	0.126	0.095	0.065	8.80	36	40.0	82.0
41	0.150	0.106	0.062	10.40	8	23.0	23.0
42	0.147	0.106	0.065	9.00	8	31.0	43.0
43	0.167	0.117	0.065	9.30	10	7.6	27.0
44	0.158	0.114	0.067	8.30	11	19.5	31.0
45	0.133	0.098	0.064	9.50	6	14.0	47.0
46	0.163	0.113	0.064	9.60	9	9.0	25.0
47	0.150	0.106	0.062	10.30	8	3.8	29.0
48	0.183	0.139	0.064	9.80	9	13.0	45.0
49	0.153	0.108	0.063	9.80	9	22.0	61.0
50	0.126	0.094	0.061	11.10	16	32.0	77.0
51	0.161	0.111	0.066	8.80	7	9.8	21.0
52	0.134	0.099	0.064	9.30	7	19.0	25.0
53	0.135	0.101	0.067	7.90	9	29.0	41.0
54	0.165	0.116	0.063	10.10	6	12.0	21.0
55	0.135	0.099	0.064	9.60	11	20.0	33.0
56	0.143	0.103	0.063	10.00	11	21.0	49.0
57	0.135	0.097	0.059	12.10	13	28.0	73.0
58	0.132	0.097	0.063	10.30	17	5.0	27.0
59	0.166	0.118	0.066	8.70	8	6.5	36.0
60	0.169	0.122	0.064	9.70	9	20.0	53.0
61	0.156	0.110	0.063	10.10	9	10.4	69.0
62	0.184	0.131	0.063	9.90	2	8.0	27.0
63	0.127	0.096	0.064	9.40	3	10.5	33.0
64	0.151	0.107	0.062	10.30	15	29.5	65.0
65	0.165	0.119	0.065	9.20	15	50.0	58.0
66	0.166	0.114	0.067	8.20	4	9.0	27.0
67	0.131	0.097	0.064	9.50	8	10.0	31.0
68	0.152	0.108	0.064	9.70	9	22.0	39.0
69	0.300	0.025	0.005	46.50	9	29.0	47.0
70	0.150	0.107	0.065	9.20	5	7.5	26.0
71	0.167	0.116	0.062	10.20	5	12.4	38.0

Table 5 (continued)

No.	D_{50} (mm)	D_{30} (mm)	D_{10} (mm)	F_c %	N -SPT	q_C (Mpa)	EFFECTIVE PRESSURE (σ_{eff}) (KPa)
72	0.144	0.101	0.058	12.40	10	13.8	62.0
73	0.142	0.099	0.057	12.80	8	27.0	78.0
74	0.135	0.098	0.061	11.20	7	8.0	27.0
75	0.146	0.103	0.061	11.00	4	9.5	48.1
76	0.147	0.107	0.066	8.30	18	18.0	64.1
77	0.159	0.115	0.066	8.90	12	9.5	27.0
78	0.139	0.099	0.059	11.80	14	11.0	36.0
79	0.131	0.095	0.053	12.40	19	18.0	56.0
80	0.141	0.103	0.065	8.80	15	12.0	25.0
81	0.126	0.093	0.061	11.40	12	10.0	29.0
82	0.132	0.097	0.062	10.60	35	19.0	37.0
83	0.030	0.013	0.002	65.10	34	18.0	45.0
84	0.153	0.105	0.057	12.60	12	10.0	25.5
85	0.136	0.101	0.067	7.80	14	14.0	29.5
86	0.143	0.102	0.061	11.00	14	16.0	45.5
87	0.135	0.097	0.025	24.50	33	35.0	61.5
88	0.136	0.100	0.064	9.30	47	42.0	77.5
89	0.146	0.106	0.066	8.70	10	13.0	25.0
90	0.122	0.091	0.059	12.60	11	6.5	22.0
91	0.129	0.097	0.065	9.00	13	9.3	26.0
92	0.129	0.094	0.059	12.30	11	34.0	34.0
93	0.135	0.100	0.065	8.70	15	24.0	50.0

Table 6 Different correlations for predicting (q_c) from SPT results

Researcher	Correlation
Kulhawy and Mayne, (1990)	$(^{qc}/_{pa})/N = 4.25 - \frac{F_c}{41.3}$
	$(^{qc}/_{pa})/N = 5.44\ D_{50}^{0.26}$

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