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Influential Parameters in Estimating Soil Properties from Cone Penetrating Test: An Artificial Neural Network Study

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***Abstract*—**The Cone Penetration Test (CPT) is a common in-situ test which generally investigates a much greater volume of soil more quickly than possible from sampling and laboratory tests. Therefore, it has the potential to realize both cost savings and assessment of soil properties rapidly and continuously. The principle objective of this paper is to demonstrate the feasibility and efficiency of using artificial neural networks (ANNs) to predict the soil angle of internal friction (Φ) and the soil modulus of elasticity (E) from CPT results considering the uncertainties and non-linearities of the soil. In addition, ANNs are used to study the influence of different parameters and recommend which parameters should be included as input parameters to improve the prediction. Neural networks discover relationships in the input data sets through the iterative presentation of the data and intrinsic mapping characteristics of neural topologies. General Regression Neural Network (GRNN) is one of the powerful neural network architectures which is utilized in this study. A large amount of field and experimental data including CPT results, plate load tests, direct shear box, grain size distribution and calculated data of overburden pressure was obtained from a large project in the United Arab Emirates. This data was used for the training and the validation of the neural network. A comparison was made between the obtained results from the ANN's approach, and some common traditional correlations that predict Φ and E from CPT results with respect to the actual results of the collected data. The results show that the ANN is a very powerful tool. Very good agreement was obtained between estimated results from ANN and actual measured results with comparison to other correlations available in the literature. The study recommends some easily available parameters that should be included in the estimation of the soil properties to improve the prediction models. It is shown that the use of friction ration in the estimation of Φ and the use of fines content in the estimation of E considerable improve the prediction models.

***Keywords*—**Angle of internal friction, Cone penetrating test, General regression neural network, Soil modulus of elasticity.

I. Introduction

THE Cone Penetration Test (CPT) is becoming progressively popular for its high ability to delineate stratigraphy of soil and assess soil properties rapidly and continuously. Many soil properties can be obtained from the CPT results including angle of internal friction, soil modulus of elasticity, seismic assessment, and relative density [1]-[5]. The current study focuses on the prediction of the angle of internal friction (*Φ*) and the soil modulus of elasticity (E) from CPT results which are important in bearing capacity and settlement calculations. Over the years, many correlations were developed to estimate Φ and E from CPT results [1]-[4].

The correlations mostly considered the value of qc (cone penetration resistance) only which is obtained from CPT results. The study investigates the influence of other parameters on the correlations. These parameters are easily obtained from laboratory tests such as grain size distribution analysis or are readily available from CPT results such as Fr (Friction ratio defined as the ratio between the sleeve and tip resistanc). The current paper studies the feasibility and efficiency of using artificial neural networks (ANNs) to estimate the soil properties (Φ and E) from CPT results and to investigate 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 [6]-[17]. It has been applied to estimate many soil and material properties [18], [19] and it proved to be a powerful tool that can have a superiority over other correlation techniques such as regression analysis [5], [20]-[24]. It has been shown that ANNs are capable of mapping nonlinear and complex relationships in nature. The neural network technology mimics the brain's own problem-solving process. An ANN is composed of a large number of connected neurons which act like simple processors. Generally, ANNs offer viable solutions when a large volume of data is available for training. When a problem is complex or difficult to formulate analytically, a neural network solution could be appropriate to use.

A large amount of field and experimental data including CPT results, plate load tests, direct shear box, grain size distribution was obtained, filtered and processed from a large-scale project that covers the United Arab Emirates (UAE). The soil in UAE is mostly cohessionless soil and the country is witnessing a lot of development and many construction projects. It is believed that developed soil relations that can be applied to such active areas in construction would be of benefit to engineers in this area specifically and to geotechnical engineers in general.

The database used and the neural network modeling are first presented. For estimating both Φ and E, different ANN models are then developed with different input parameters 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.

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Conclusions highlighting the efficiency of the ANNs and the parameters that have the greatest and least impact on the properties' estimation are finally presented.

II. Available Data

The data for this study was collected from the results of geotechnical investigation work that has been done for a large-scale project which extended all over United Arab Emirates UAE (Fig. 1). The soil in that area is cohessionless soil.

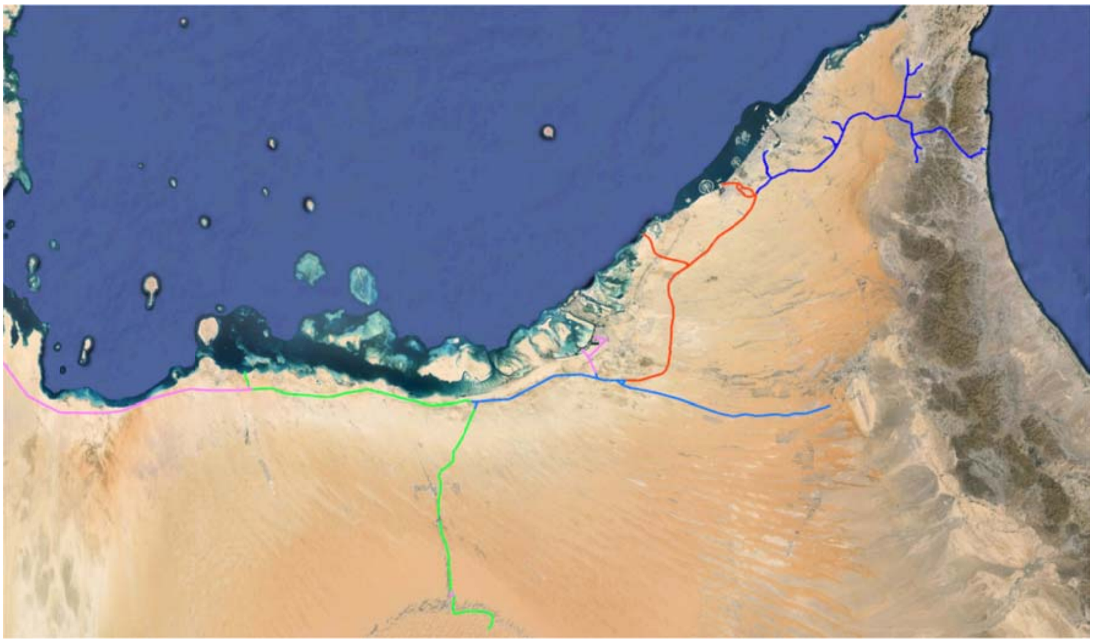

Fig. 1 The colored lines (Magenta, Red, Green, Blue) illustrate the locations of the available site investigations along UAE

The project has about 820 boreholes with variable depths and with SPT for each borehole along the project alignment as shown in Fig. 1 and about 400 CPT are executed beside the boreholes. Moreover, there are about 630 test pits with maximum depth 3.0m along the project alignment with 260 plate loading test to determine the modulus of soil elasticity and 606 CBR test. In addition, other lab tests are performed on the soil sample for classifications such as, Grain size distribution tests (Sieve analysis and Hydrometer), and lab tests for determining the shear strength parameters such as direct shear box.

III. Neural Network Modeling

A. Background

There are two main types of neural networks; supervised networks and unsupervised networks. In the supervised network, a large number of correct predictions are given to the model from which it can learn. Examples of supervised networks are backpropagation networks (BPN), general regression networks (GRNN) and probabilistic neural networks (PNN). Unsupervised networks, on the other hand, can classify a set of patterns into a specified number of categories without learning from previous correct patterns. An example of an unsupervised network is the Kohonen networks [25].

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 while 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 [26]. The neurons in the input layer, hidden layer(s) and output layer are interconnected; each of which is connected to the neurons in the next layer. 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 [27]-[29]. These outputs are then weighted by the connections between the hidden and output layer. The output layer produces the desired results.

There are two basic phases in neural network operation. The first phase is the training phase and the second phase 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 subsequently be used to make predictions for a given set of previously unseen input patterns where the output values are unknown.

B. ANN Models Developed in the Study

The neural networks used in the current study were developed using the neural network program Neuroshell 2. This program implements several different neural network algorithms. The general regression neural network (GRNN) is used in the current study. GRNNs are known for their ability to train quickly on sparse data sets [30]. In addition, GRNNs were preferred over feed-forward back propagation algorithm-based neural networks because there is no problem of local minimums in GRNNs [19].

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 and the number of neurons in the output layer is equal to the number of outputs, while 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. The smoothing factor determines how tightly the network matches its predictions to the data in the training patterns. Higher smoothing factors cause more relaxed surface fits through the data. In general, it is recommended to allow the network to choose a smoothing factor through Calibration.

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

IV. Estimating Φ from CPT Results

A. Output/Input Variables of ANN Analysis

For estimating Φ from CPT results, the CPT results, direct shear test and grain size analysis were used from the available date. The readings of the CPT test were filtered to be at the same elevation of the lab tests. A total of 82 data points were prepared. The parameters that were investigated as input parameters to be included in the GRNN models developed were q_c and F_r (obtained from CPT results), Fc (fines content) and D_{50}, D_{30}, D_{10} (defined as grain diameter corresponding to 50%, 30% and 10%, respectively, of the material being smaller) obtained from grain size analysis and δ_{eff} (the effective overburden pressure) calculated at the same level of the CPT 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 is tan Φ which was both measured (obtained from direct shear box) and estimated by the GRNN models developed. Seven 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.

B. Results of Neural Networks

Fig. 2 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. From Fig. 2, it is observed that Fr has a great influence on the prediction model. This can be observed by comparing GRNN2 with GRNN7 where the value of r^2 is more than doubled by including Fr. GRNN2 includes only the input parameters commonly used in correlations in the literature which are qc and δ_{eff}. The combination of inputs in GRNN7 yielded the best model for estimation of Φ.

Table I presents the data used in GRNN7 as input and the measured and predicted tan Φ. The comparison between the predicted tan Φ from GRNN and the actual measured values is presented in Fig. 3. It shows very good agreement between predicted and measured results with r^2=0.95.

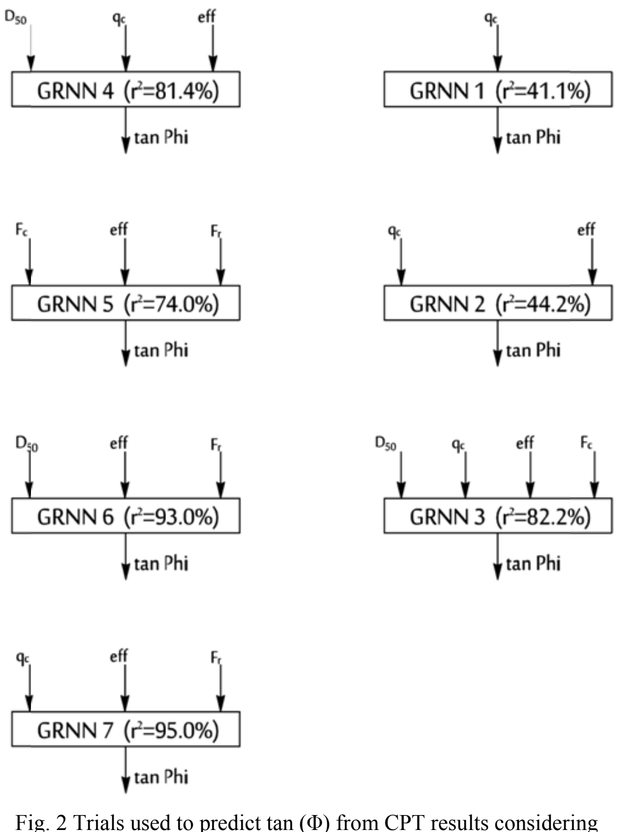

Fig. 2 Trials used to predict tan (Φ) from CPT results considering different input parameters with r^2 coefficient (%)

For GRNN7, 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. 4. It is concluded from Fig. 4 that (δ_{eff}) is the first input variable that influences the network, the friction ratio (F_r) is the second one and q_c is the last one.

C. Comparison between Neural Networks and a Set of Traditional Methods

Table II shows some of the correlations used for estimation of Φ from CPT results available in the literature. The table includes the values of r^2 calculated by comparing the actual Φ (measured from shear box test) and the predicted Φ values from the correlations. When applying the available data it is clear that the available correlations in the literature poorly predict Φ. This might be attributed to not including the value of Fr in the estimation of Φ in the literature correlations.

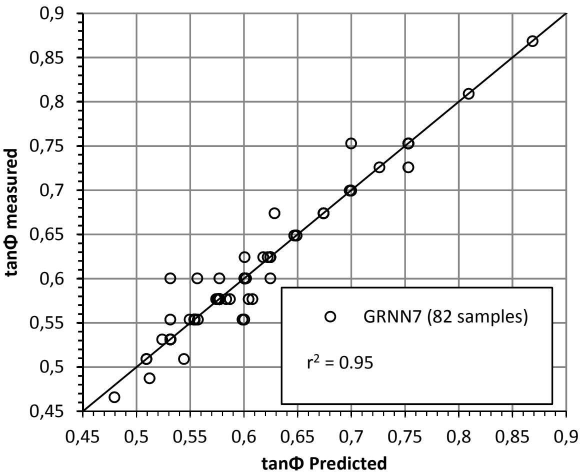

Fig. 3 Comparison between predicted and measured tan (Φ) from CPT results with r^2% coefficient

TABLE I
THE USED DATA FOR ESTIMATION OF Φ (GRNN7)

Index	qc	Fr	Effective pressure	Measured tan(ϕ)	Predicted tan(ϕ) (GRNN7)
	Mpa	%	KN		
1	45.110	1.160	29	0.8687	0.8687
2	44.150	1.250	38	0.8092	0.8092
3	37.500	0.630	51	0.7530	0.7530
4	36.900	0.190	73	0.7530	0.6997
5	46.900	0.400	45	0.7530	0.7530
6	34.250	0.271	81	0.7530	0.7530
7	42.500	0.350	58	0.7530	0.7530
8	36.950	0.360	58	0.7261	0.7261
9	38.400	0.349	43.5	0.7261	0.7530
10	24.150	0.560	59.2	0.6997	0.6997
11	13.300	0.400	66	0.6997	0.6997
12	34.350	0.175	76	0.6997	0.6984
13	25.350	0.460	35	0.6741	0.6741
14	22.250	0.575	29	0.6741	0.6284
15	13.900	1.032	77	0.6741	0.6741
16	33.400	0.540	65	0.6741	0.6741
17	12.070	0.360	28	0.6490	0.6489
18	20.500	0.560	29	0.6490	0.6468
19	2.330	0.477	34.5	0.6490	0.6490
20	48.100	0.440	57.5	0.6245	0.6245
21	40.310	0.154	29	0.6245	0.6005
22	22.500	0.430	29	0.6245	0.6221
23	35.820	0.504	52	0.6245	0.6245
24	28.120	0.060	22.5	0.6245	0.6245
25	13.950	0.420	43.5	0.6245	0.6245
26	27.627	0.522	43	0.6245	0.6179
27	45.100	0.410	28	0.6005	0.6005
28	11.610	0.777	26	0.6005	0.6005
29	33.820	0.520	76	0.6005	0.6018
30	11.900	0.316	43.5	0.6005	0.6245
31	24.770	0.430	25	0.6005	0.6005
32	13.120	0.420	25.5	0.6005	0.6003
33	32.000	0.065	55	0.6005	0.6005
34	30.700	0.680	44.5	0.6005	0.5314
35	35.700	0.430	28.5	0.6005	0.6005
36	31.000	0.360	33	0.6005	0.5770
37	22.500	0.320	68	0.6005	0.6005
38	16.500	0.590	29	0.6005	0.5565
39	6.820	1.230	40.5	0.6005	0.6005
40	14.000	1.000	29.5	0.6005	0.6005
41	22.840	0.570	29.5	0.5770	0.6042
42	22.600	0.280	52	0.5770	0.5770
43	14.200	0.360	24	0.5770	0.5773
44	9.300	0.440	32	0.5770	0.5770
45	14.950	0.730	50	0.5770	0.5770
46	27.460	0.290	43.5	0.5770	0.5834
47	16.450	0.360	27	0.5770	0.5769
48	22.060	0.550	30	0.5770	0.6079
49	13.250	0.434	30.5	0.5770	0.5770
50	26.100	0.652	62	0.5770	0.5770
51	23.000	0.434	81	0.5770	0.5868
52	8.600	0.270	36	0.5770	0.5770
53	44.500	0.415	89	0.5770	0.5770
54	24.028	0.531	42	0.5770	0.5770
55	29.000	0.380	41	0.5770	0.5770
56	9.500	0.900	27	0.5770	0.5740
57	10.000	0.730	29	0.5770	0.5756
58	5.830	0.800	42	0.5540	0.5986
59	5.500	0.500	33	0.5540	0.5314
60	10.410	0.300	35	0.5540	0.5536
61	4.370	0.240	14.85	0.5540	0.5540
62	19.400	0.500	28	0.5540	0.5493
63	54.200	0.360	61	0.5540	0.6002
64	29.250	0.520	60	0.5540	0.5540
65	17.100	0.704	30	0.5540	0.5540
66	4.500	1.100	39	0.5540	0.5540
67	22.000	0.700	61	0.5540	0.5540
68	12.000	0.900	21	0.5540	0.5540
69	9.300	0.700	26	0.5540	0.5570
70	10.000	0.720	37.3	0.5314	0.5314
71	26.000	0.380	43	0.5314	0.5316
72	31.000	0.380	43	0.5314	0.5314
73	14.000	0.600	47.01	0.5314	0.5314
74	6.500	0.950	36	0.5314	0.5314
75	18.000	0.420	26	0.5314	0.5238
76	29.000	0.380	47	0.5314	0.5314
77	12.400	0.850	38	0.5314	0.5314
78	16.500	0.850	45	0.5092	0.5441
79	19.500	0.780	49	0.5092	0.5092
80	9.500	0.950	48.07	0.5092	0.5092
81	21.000	0.550	50	0.4874	0.5120
82	18.440	0.500	27.5	0.4660	0.4793

The comparison between the GRNN model developed (GRNN7) and the other correlations in the literature (Table II) are given in Fig. 5. The predicted values by the GRNN are in very good agreement with measured values compared to available correlations in the literature. Thus ANN is shown to be a powerful tool in the prediction of Φ and highlights the importance of inclusion of Fr, which is easily available from CPT test, in the estimation of Φ.

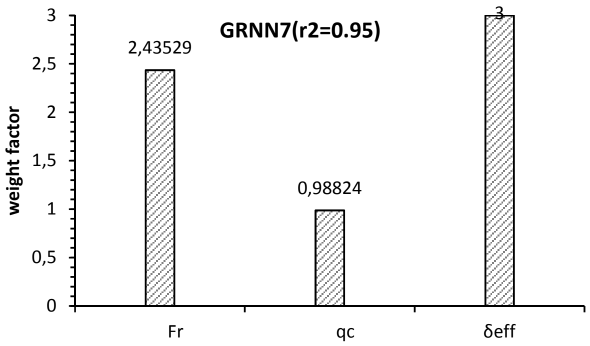

Fig. 4 The weight factors for the correlation between angle of internal friction and CPT results

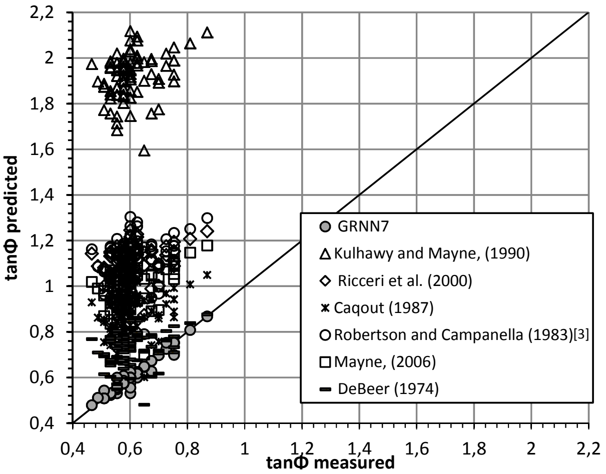

Fig. 5 Comparison between actual (measured) and predicting (tanΦ) from CPT [3]

TABLE II
THE VARIABLES CORRELATIONS FOR PREDICTING (TANΦ) FROM CPT WITH (**R^2**) [3]

Researcher	Correlation	R^2
Robertson and Campanella (1983)	$tan\phi = \frac{1}{2.68}\,(log\frac{q_c}{\sigma_v} + 0.29)$	0.094
Mayne, (2006)	$\phi = 17.60^0 + 11\,log\frac{q_c - \sigma_0}{\sqrt{\sigma_0 * p_a}}$	0.091
Kulhawy and Mayne (1990)	$tan\phi = 0.90 + 0.38\,log\frac{q_c}{\sigma_0}$	0.11
Ricceri et al. (2002)	$tan\phi = 0.38 + 0.27\,log\frac{q_c}{\sigma_0}$	0.092
Lee et al. (2004)	$\phi = 15.575 + (\frac{q_c}{\sigma_0})^{0.1714}$	0.161
DeBeer (1974)	$\phi = 1.3e^{2\pi\tan\varphi} * tan^2(45 + \frac{\varphi}{2})$	0.095

V. ESTIMATING E FROM CPT RESULTS

A. Output/Input Variables of ANN Analysis

For estimating E from CPT results, the CPT results, plate load tests and grain size analysis were used from the available date. The readings of the CPT test were filtered to be at the same elevation of the lab tests. A total of 55 data points were prepared. The parameters that were investigated as input parameters to be included in the GRNN models developed were q_c, Fc, D_{50} and depth of water table below plate level (DWT). The depth of water was considered as 50m (influence ignored) for depths of water at level greater than twice the plate width B (B=60cm). The output of the GRNN models considered is E which was both measured (obtained from plate load test) and estimated by the GRNN models developed. Seven different GRNN models were developed with different input parameters to study the influence of the input parameters on the obtained E. To evaluate the efficiency of the GRNN models developed, r^2 was used.

B. Results of Neural Networks

Fig. 6 shows the different GRNN models developed and the corresponding r^2 obtained for each network. From Fig. 6, it is observed that Fc has a great influence on the prediction model after q_c. This can be observed by comparing GRNN1 with GRNN3 where the value of r^2 is almost tripled by including Fc. Also the values of r^2 increase significantly in the models that include Fc as an input (GRNN3, GRNN4, GRNN6, GRNN7).

GRNN1 includes only the input parameter commonly used in correlations in the literature which is qc. The combination of inputs in GRNN7 yielded the best model for estimation of E.

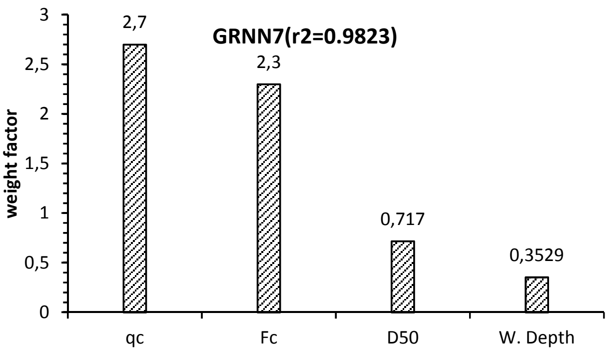

Fig. 6 The variable GRNNs used to predict E (with r^2)

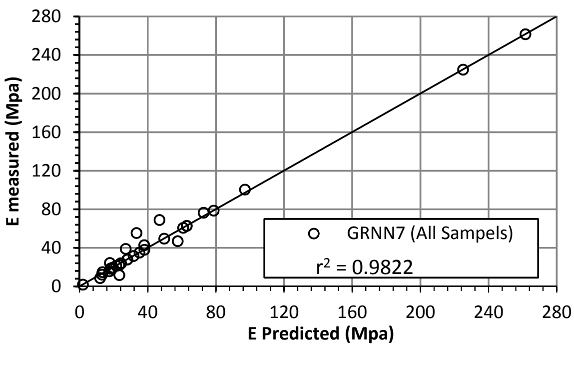

Fig. 7 Comparison between predicted and measured E

Table III presents the data used in GRNN7 as input and the measured and predicted E. The comparison between the predicted E from GRNN7 and the actual measured values is presented in Fig. 7. It shows very good agreement between predicted and measured results with r^2=0.98.

For GRNN7, the individual smoothing factors for each input are shown in Fig. 8. It is concluded from Fig. 7 that qc is the first input variable that influences the network, Fc is the second followed by D50 then DWT is the last one.

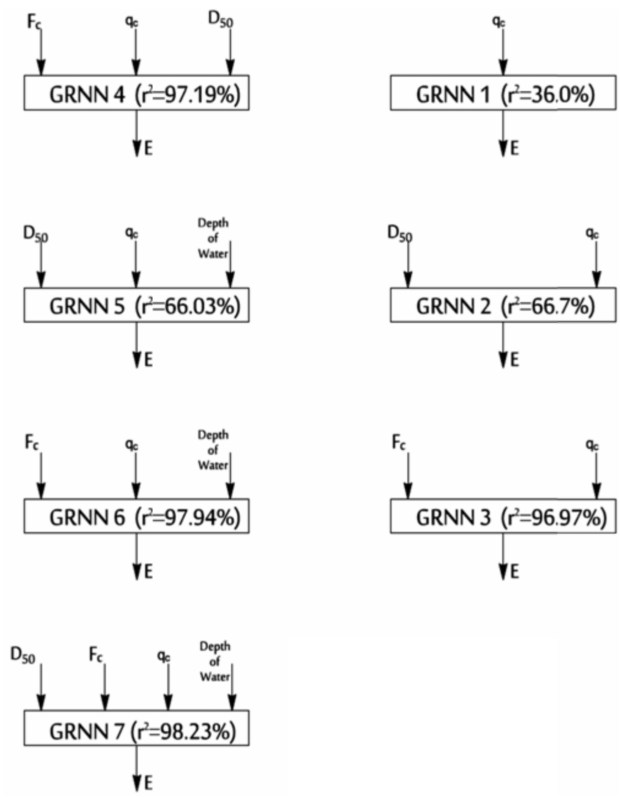

Fig. 8 The variable GRNNs used to predict E (with r2%)

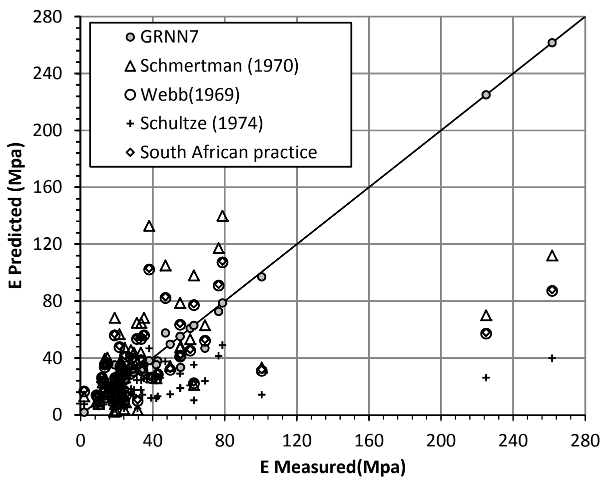

Fig. 9 Comparison between actual (measured) and predicting (E) from CPT [5]

It should be noted that D50 and DWT have a minor influence. Accordingly, GRNN3 which includes only qc and Fc can be adequately used yielding a high r^2 as well (r^2=0.97). The weight of the different input parameters for the 4 GRNN models with high r^2 values (GRNN3, GRNN4, GRNN6, GRNN7) are presented in Fig. 9 that confirms the importance of the inclusion of Fc in the estimation of E.

C. Comparison between Neural Networks and a Set of Traditional Methods

TABLE III
THE USED DATA FOR ANALYSIS

Index	Depth of Water Below PLT	FC	D50	qc	E (Actual values)	E (GRNN values)
	m	%	mm	Mpa	Mpa	Mpa
1	1.00	5.10	0.14	10.30	28.05	28.05
2	1.13	6.10	0.18	15.20	60.80	60.80
3	50.00	5.30	0.15	13.80	55.42	33.38
4	50.00	9.70	0.14	10.20	22.15	23.17
5	0.70	9.70	0.16	5.45	18.50	18.07
6	0.60	7.10	0.15	2.64	8.78	11.99
7	0.40	41.80	0.08	1.15	24.09	24.09
8	0.40	6.60	0.14	1.05	31.60	31.60
9	0.60	9.70	0.13	2.20	19.00	19.00
10	0.80	9.50	0.16	4.70	15.82	17.37
11	0.70	3.90	0.14	16.20	21.51	21.51
12	0.60	6.30	0.14	7.50	39.06	27.03
13	1.00	23.30	0.12	9.80	49.65	49.65
14	0.90	3.80	0.15	33.50	76.53	72.72
15	1.00	5.70	0.12	6.50	12.18	13.09
16	0.70	7.20	0.16	28.00	62.85	62.85
17	50.00	7.40	0.15	40.00	78.67	78.67
18	50.00	11.40	0.20	38.00	38.01	38.01
19	50.00	3.70	22.00	0.75	19.57	19.57
20	50.00	5.00	0.19	11.50	14.86	13.36
21	0.95	9.40	0.15	9.50	23.89	24.32
22	0.80	7.00	0.14	19.50	35.16	35.16
23	50.00	11.40	0.14	30.00	47.07	57.54
24	50.00	19.50	0.12	32.00	261.63	261.63
25	50.00	11.00	0.14	9.50	100.45	97.01
26	1.10	23.90	0.12	6.00	62.85	62.85
27	1.10	5.60	0.19	3.70	1.88	1.88
28	1.20	10.10	0.13	8.50	42.78	37.89
29	1.30	14.30	0.12	13.00	27.92	27.92
30	1.10	13.40	0.12	18.00	69.02	46.82
31	0.90	5.90	0.13	7.60	11.82	23.32
32	50.00	1.70	0.19	0.65	18.35	18.35
33	50.00	1.00	0.24	20.00	225.00	225.00
34	50.00	1.00	0.28	13.50	24.40	17.75
35	50.00	1.20	0.18	2.50	25.00	24.30
36	50.00	1.00	0.16	3.50	12.81	13.51
37	1.10	10.50	0.14	22.50	55.15	55.15
38	1.20	7.70	0.19	13.50	55.15	55.15
39	1.10	7.80	0.18	7.35	41.98	35.27
40	1.10	10.00	0.16	7.50	19.07	20.52
41	1.20	8.60	0.14	19.50	18.88	35.16
42	1.10	8.40	0.15	4.50	19.07	19.86
43	1.20	8.70	0.14	11.30	13.46	24.07
44	50.00	7.70	0.19	10.50	13.36	13.38
45	1.20	8.80	0.12	4.20	22.06	20.28
46	50.00	8.90	0.14	7.50	24.56	24.56
47	50.00	10.00	0.12	2.20	9.90	9.90
48	1.20	9.10	0.15	8.50	22.10	25.48
49	50.00	9.90	0.16	10.80	22.10	22.20
50	1.10	12.70	0.14	9.50	34.30	34.30
51	50.00	10.00	0.14	18.50	31.16	31.16
52	50.00	9.30	0.14	12.50	33.38	33.38
53	50.00	12.00	0.14	18.50	33.58	31.16
54	50.00	12.50	0.13	9.50	29.15	31.16
55	50.00	11.70	0.13	12.50	29.61	29.61

Table IV shows some of the correlations available in the literature used for estimation of E from CPT results. The table includes the values of r^2 calculated by comparing the actual E (measured from Plat loading test) and the predicted E values from the correlations. When applying the available data it is clear that the available correlations in the literature poorly predicts E. This might be attributed to not including the value of Fc in the estimation of E in the literature correlations. The comparison between the GRNN model developed (GRNN7) and the other correlations in the literature are given in Fig. 10. The predicted values by the GRNN are in very good agreement with measured values compared to available correlations in the literature. Thus ANN highlights the importance of inclusion of Fc, which is easily available from grain size analysis, in the estimation of E.

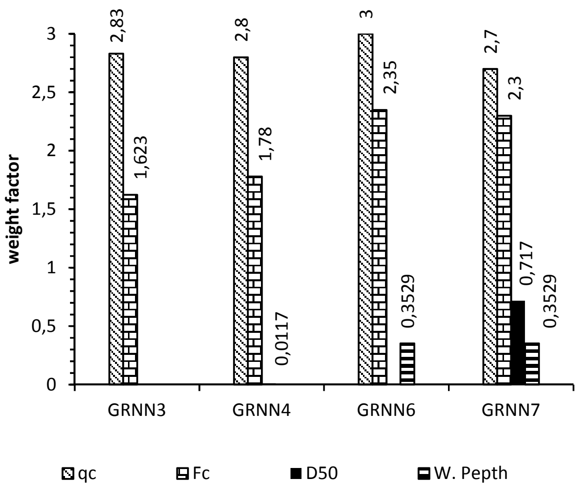

Fig. 10 The weight factors for every GRNN models

TABLE IV
CORRELATIONS FOR PREDICTING (E) IN LITERATURE [5]

Researcher	Correlation	R^2
Schmertman (1970)	E=3.5qc	0.252
Webb (1969)	$E(t/ft^2) = 2.5qc + 75$	0.260
Schultze (1974)	E (Kg/cm^2) = 1.141q_c + 33.129.	0.2552
South African practice	Es = 2.5 (q_c + 3200) kN / m^2	0.270

VI. SUMMARY AND CONCLUSIONS

A large amount of field and experimental data from the United Arab Emirates (UAE) was used to develop artificial neural networks (ANNs) that can estimate the angle of internal friction (Φ) and the soil modulus of elasticity (E) from CPT results. The general regression neural network (GRNN) architecture was utilized in the study. Most f the correlations available in the literature use the value of qc only or qc and sigma eff to estimate Φ or E. Seven different GRNN models were developed for each of Φ and E to study the influence of other easily available-parameters that can affect the prediction of the soil properties from CPT results. The predicted soil properties by GRNN models were compared to other correlations available from the literature. The following conclusions can be withdrawn:

A. For Estimating Φ from CPT Results:

1) The inclusion of Friction ration (Fr) in the estimation of Φ improved the predicted Φ values considerably.
2) The best GRNN model was the model that included qc, Fr and sigma eff as input parameters to the model.
3) The individual smoothing factors reflecting the weight of each input parameter for that GRNN model were compared (qc=0.988, δeff=3.00 and Fr=2.43). Therefore, (δeff) is the first input variable that influences the network, the friction ratio (Fr) is the second one and qc is the last one.
4) When compared to other predictions from the literature, the obtained results from GRNN were in very good agreement with actual measured values of Φ (r^2=0.9).

B. For Estimating E from CPT Results:

1) The inclusion of fines content (Fc) in the estimation improved the predicted E values considerably.
2) The best GRNN model was the model GRNN7 that included qc, Fc, D50 and Depth of water table below plate (DWT) as input parameters (with r^2=0.98). However, the influence of D50 and DWT were minor. Therefore, another GRNN (GRNN3) that includes only qc and Fc can be used in the estimation (with r^2=0.96).
3) For GRNN7, the first input variable that influences the network is qc followed by Fc then D50 then DWT (with factors for qc=2.7, Fc=2.3, D50=0.71 and GWT=0.35). For GRNN3, the first input variable that influences the model is qc followed by Fc (with factors for qc=2.8 and Fc=1.6).
4) The obtained results from GRNN were in very good agreement with actual values of Φ (r^2=0.9) compared to other predictions from the literature.

The paper demonstrated the efficiency of the use of ANN in the estimation of Φ and E. ANN was proved to be a very powerful tool that could include other easily available influential parameters on the Φ and E estimation. It highlighted the importance of including Fr in the Φ prediction and Fc in the E prediction. It is believed that the developed prediction models will be of benefit to engineers in UAE specifically and geotechnical engineers in general.

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