Scientific Research and Essays Vol. 7(31), pp. 2835-2848, 9 August, 2012
Available online at http://www.academicjournals.org/SRE
DOI: 10.5897/SRE12.297
ISSN 1992-2248

Full Length Research Paper

Prediction of compression index using artificial neural network

Farzin Kalantary[1] and Afshin Kordnaeij[2]*

[1]Department of Geotechnical Engineering, Faculty of Civil Engineering, K. N. Toosi University of Technology, Tehran, Iran.
[2]Faculty of Engineering, Institute of Higher Education Allameh Mohaddes Noori, Noor, Mazandaran, Iran.

Accepted 6 June, 2012

Over the decades, a number of empirical correlations have been proposed to relate the Compression Index of normally consolidated soils to other soil parameters, such as the natural water content, liquid limit, plasticity index and void ratio. In this article too it has been attempted to establish a correlation between compression index and physical properties for the clayey soils of Mazandaran region. Due to the multiple effects of various parameters, Artificial Neural Network (ANN) has been adapted for predicting the compression index from more simply determined index properties. In order to develop the ANN model, four hundred consolidation tests for soils sampled at 125 construction sites in the province of Mazandaran, in the north of Iran were collected and 90% of these were used to train the prediction model and the other 10% were used to test it. A comparison was carried out between the experimentally measured compression indexes with the predictions. Furthermore, the predictions of a number of previously proposed empirical correlations were obtained using the available data and it has been shown that an improvement of 1 - 4% with respect to the other correlations has been achieved.

Key words: Compression index, consolidation, settlement, artificial neural network, regression analysis.

INTRODUCTION

Settlement prediction is an important task in geotechnical engineering. Several researchers have predicted settlement by considering different uncertainty parameters, probabilistic measurements, analytical methods, regression analysis and simplified methods (Wakita, 1993; Du and Zhang, 2001; Fenton et al., 1996; Hornig, 2010).

An increase in stress caused by the construction of foundations or other loads compresses the soil layers. The compression is caused by (a) deformation of soil particles, (b) relocation of soil particles, and (c) expulsion of water or air from the void spaces. In general, the soil settlement caused by loads may be divided into three broad categories:

1. Immediately settlement, which is caused by the elastic deformation.
2. Primary consolidation settlement.
3. Secondary consolidation settlement (Das, 2004).

To calculate settlement in clayey soil layers, laboratory consolidation tests which depict one-dimensional compression behavior need to be performed on samples taken from representative layers (Terzaghi, 1925; Lambe, 1967).

One of the manners for settlement calculation of normally consolidated fine soil is by using the compression index from the conventional oedometer test (ASTM, 1998). Using the calculated values of Cc, the settlement (S_c) due to an increase in load ($\Delta\sigma_v$) can be determined from the following equation:

$$S_c = \frac{C_c H}{1+e_0} \log \left(\frac{\sigma'_{v0}+\Delta\sigma_v}{\sigma'_{v0}}\right) \quad (1)$$

Where, S_c = Settlement due to primary consolidation

*Corresponding author. E-mail: afshin_geotec@yahoo.com. Tel: +989111133765.

caused by an increase in load; C_c = Compression Index; H = Initial thickness of the in situ cohesive soil layer; e_0 = Initial void ratio of the in situ saturated cohesive soil layer; σ'_{v0} = Initial vertical effective stress of the in situ soil; and $\Delta\sigma_v$ = load increment.

As the oedometer test in laboratory takes a much longer time than simpler index property tests various attempts have been made to estimate this index to obtain an initial estimate and also to cross check the results of the consolidation test. Empirical formulas relating various parameters to the compression index have been presented by many researchers (Azzouz et al., 1976; Koppula, 1981; Herrero, 1983a,b; Park and Lee, 2011; Nishida, 1956; Cozzolino, 1961; Sower, 1970; Bowles, 1989; Ahadiyan et al., 2008; Hough, 1957; Gunduz and Arman, 2007; Mayne, 1980; Terzaghi and Peck, 1967; Nagaraj and Murty, 1985; Al-Khafaji and Andersland, 1992; Yoon and Kim, 2006; Ozer et al., 2008).

However, due to fact that the index is affected by multiple parameters, simple regression analysis does not suffice and thus multiple regression techniques or better known Artificial Neural Network (ANN) is needed. ANN is potentially useful, where the underlying physical process relationships are not fully understood and well-suited in modeling such systems. Therefore it is proposed to be used here for predicting the compressibility characteristics of soils. The advantage of the ANN is that it is very useful in learning complex relationships between multi-dimensional data.

ANNs have been applied in a number of geotechnical problems where mathematical models sustain simplifycations, lack of robustness or are not available at all.

The authors have collected the data from four hundred consolidation tests for soils sampled at 125 construction sites in province of Mazandaran, Iran and classified the soil parameters according to the void ratio, natural water content, liquid limit, plastic index and specific gravity.

Artificial Neural Network (ANN)

The concept of an artificial ANN was inspired by the complex architecture of the human brain, regarded as a highly non-linear, parallel operating system (Haykin, 1999).

An ANN is developed for a specific application, such as pattern recognition or data classification, through a learning process. There are various types of ANN which differ in their operations, such as data prediction, data classification, data association, data conceptualization, and data filtering. The common type of ANN consists of three interconnected layers: input, hidden and output.

Multi-layer network use a variety of learning techniques; the most popular is back-propagation. Back-propagation networks are probably the most well-known and widely applied of the neural networks today. The feed-forward, multi-layer perception's ANNs have become the most popular ones in geotechnical engineering.

ANNs do not have any prior knowledge about the existing problem. Therefore, training is required to make the network more intelligent. Training a neural network is conducted by presenting a series of example patterns for associated input and bases are set to random values. The performance of ANN model is measured in terms of an error criterion between the target output and the calculated output.

The most important step in designing an ANN is the determination of the ANN architecture and the selection of a training algorithm. An optimal architecture is able to obtain good performance with minimal resulting error. The number of hidden layers and the number of nodes in each hidden layer are usually determined by a trial-and error procedure (Kolay et al., 2008).

At the end of the training phase, the neural network represents model able to predict a target value when given the input value.

Recently ANNs have been employed to model complex relationships between input and output datasets in geotechnical engineering (Sinan, 2009; Ozer et al., 2008; Park et al., 2009; Cho, 2009; Park, 2010; Park and Cho, 2010; Park and Lee, 2011; Park and Kim, 2010; Mollahasani et al., 2011; Goktepe et al., 2010).

Database compilation

Following the previous trend of studies, in the present study the compression index of the soils was assumed to be affected by the void ratio (e_o), natural water content (ω_n), liquid limit (*LL*), plastic index (*PI*), and specific gravity (*Gs*). The data was produced by the Technical and Soil Laboratory of Mazandaran Province which is one of the most experienced consultants in the country (appendix 1). The samples were all collected using a standard procedure and tests were carried out using ASTM D 2435-96. Table 1 display the descriptive statistics of each variable.

Comparison of existing equations

As the oedometer test is relatively time-consuming test compared with standard index tests, various attempts have been made to estimate the compression index from tests more easily carried out. Many researchers have used single parameter models for the estimation of the compression index, that is,, liquid limit, natural water content or in-situ void ratio. However, others recommend multiple soil parameter models for the estimation of this index. Several of these empirical correlations (one and multi–variable equations) are presented in Table 2.

Absolute fraction of variance (R^2), root mean squared error (RMSE), mean absolute percent error (MAPE) and

Table 1. Descriptive statistics of variables.

Variable	Minimum	Maximum	Mean
e_0	0.357	1.882	0.767
ω_n	10.2	70	28.62
LL	24	81	39.8
PI	3	50	18.58
G_s	2.43	2.8	2.64
C_c	0.05	0.628	0.206

ω_n= natural water content (%), e_0= initial void ratio, *LL*= liquid limit (%), *PI*= plastic index (%), G_s= specific gravity of soil particles, C_c= compression index.

mean absolute deviation (MAD) were used to evaluate the performance of the proposed equations and models, which are defined as follows (Abedimahzoon et al., 2010):

$$R^2 = 1 - \left[\frac{\sum_1^n (C_{mi} - C_{pi})^2}{\sum_1^n (C_{mi})^2}\right] \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_1^n (C_{mi} - C_{pi})^2} \quad (3)$$

$$MAPE = \frac{\sum_1^n |C_{mi} - C_{pi}|}{\sum_1^n C_{mi}} \times 100 \quad (4)$$

$$MAD = \frac{\sum_1^n |C_{mi} - C_{pi}|}{n} \quad (5)$$

Where, n is the number of data points, C_{mi} and C_{pi} are respectively the actual measured and predicted output value from the i^{th} output. The lower the RMSE, MAPE and MAD values, the better the model performance. Under ideal conditions an accurate and precise method gives R^2 of 1.0, RMSE, MAPE and MAD of 0. In Table 3, the RMSE, MAPE, MAD and R^2 of empirical equations are compared for all data sets collected in this study (400 data sets).

It can be seen that the multi variable equation proposed by Azzouz et al. (1976) using e_0, ω_n and LL as predictor variables gave the lowest RMSE value (0.0428), the lowest MAPE value (16.51), the lowest MAD value (0.0339) and the highest R^2 value (0.97) (Equation 26 in Table 3).

Among the single variable equations, the equation with the lowest RMSE value (0.0445), the lowest MAPE value (17.32), the lowest MAD value (0.0356) and the highest R^2 value (0.96) was that proposed by Azzouz et al. (1976) using e_0 as predictor variable. (Equation 9 in Table 3)

Development of new empirical equations

K-fold cross validation was used to obtain the best prediction using single variable as well as multiple parameters. The formulas using single parameters of the void ratio and natural water content show better performance than other types of formulas using the single parameter. The developed equations and their R^2, RMSE, MAPE and MAD indices are shown in Table 4.

It can be seen that the proposed equation 3 using e_0, ω_n, G_s and LL as predictor variables gave the lowest RMSE value (0.0385), MAPE value (14.86), MAD value (0.0306) and the highest absolute fraction of variance (R^2= 0.97) (Equation 3 in Table 4 and Figure 3.).

Also the single variable equation with e_0 as variable parameter has the least error toward the single variable relations in the past. (RMSE=0.044, MAPE=17.12, MAD=0.0352 and R^2= 0.96)(Equation 2 in Table 4 and Figure 2.

(Figures 1 and 2 show the relationship between output targets and predicted values obtained from the proposed relationships (R, Coefficient of Correlation). It can be seen that the proposed equation results in points more closely located around the 1:1 line.

Development of the ANN model

In order to develop the artificial neural network (ANN) model, it is common practice to divide the available data into two subsets: training set to construct the ANN model and an independent validation set to estimate model performance.

We divided the data set randomly into two separate data sets—the training data set (90% of the total data set) and the testing data set (10% of the total data set).

In this study, among 400 data sets, 40 randomly collected data sets were used in the testing stage and 360 data sets were used in the training stage. The five parameters, ω_n, e_0, *LL*, *PI* and G_s were included in the input layer of all ANN models (Table 5). The network uses the default Levenberg-Marquardt algorithm for training. In the training stage the application randomly

Table 2. Some widely used compression index equations.

Independent variable	Equation	Reference
	Single variable equation	
ω_n	$C_c = 0.01\omega_n - 0.05$	Azzouz et al. (1976)
	$C_c = 0.01\omega_n$	Koppula (1981)
	$C_c = 0.01\omega_n - 0.075$	Herrero (1983b)
	$C_c = 0.013\omega_n - 0.115$	Park and Lee (2011)
e_0	$C_c = 0.54e_0 - 0.19$	Nishida (1956)
	$C_c = 0.43e_0 - 0.11$	Cozzolino (1961)
	$C_c = 0.75e_0 - 0.38$	Sower (1970)
	$C_c = 0.49e_0 - 0.11$	Park and Lee (2011)
	$C_c = 0.4(e_0 - 0.25)$	Azzouz et al. (1976)
	$C_c = 0.15e_0 + 0.01077$	Bowles (1989)
	$C_c = 0.287e_0 - 0.015$	Ahadiyan et al. (2008)
	$C_c = 0.3(e_0 - 0.27)$	Hough (1957)
	$C_c = 1.02 - 0.95e_0$	Gunduz and Arman (2007)
LL	$C_c = 0.006(LL - 9)$	Azzouz et al. (1976)
	$C_c = (LL - 13)/109$	Mayne (1980)
	$C_c = 0.009(LL - 10)$	Terzaghi and Peck (1967)
	$C_c = 0.014LL - 0.168$	Park and Lee (2011)
	$C_c = 0.0046(LL - 9)$	Bowles (1989)
	Multi-variable equation	
LL, G_s	$C_c = 0.2343\left(\frac{LL}{100}\right).G_s$	Nagaraj and Murthy (1985)
	$C_c = 0.2926\left(\frac{LL}{100}\right).G_s$	Park and Lee (2011)
ω_n, LL	$C_c = 0.009\omega_n + 0.005LL$	Koppula (1981)
	$C_c = 0.009\omega_n + 0.002LL - 0.1$	Azzouz et al. (1976)
e_0, ω_n	$C_c = 0.4(e_0 + 0.001\omega_n - 0.25)$	(Azzouz et al. 1976)
e_0, LL	$C_c = -0.156 + 0.411e_0 + 0.00058LL$	Al-Khafaji and Andersland (1992)
	$C_c = -0.023 + 0.271e_0 + 0.001LL$	Ahadiyan et al. (2008)
e_0, ω_n, LL	$C_c = 0.37(e_0 + 0.003LL + 0.0004\omega_n - 0.34)$	Azzouz et al. (1976)
	$C_c = -0.404 + 0.341e_0 + 0.006\omega_n + 0.004LL$	Yoon and Kim (2006)
G_s, e_0	$C_c = 0.141G_s^{1.2}[(1 + e_0)/G_s]^{2.38}$	Herrero (1983a)
ω_n, LL, e_0, γ_d	$C_c = 0.1597(\omega_n^{-0.0187})(1 + e_0)^{1.592}(LL^{-0.0638})(\gamma_d^{-0.8276})$	Ozer et al. (2008)
	$C_c = 0.151 + 0.001225\omega_n + 0.193e_0 - 0.000258LL - 0.0699\gamma_d$	Ozer et al. (2008)

divides input vectors and target vectors into three sets as follows:

1. 60% are used for training.
2. 20% are used to validate that the network is generalizing and to stop training before over fitting.
3. The last 20% are used as a completely independent test of network generalization.

In the present study feed forward with back-propagation neural network is utilized for data. MATLAB 7.6 is used in training and simulation of data. Various numbers of

Table 3. Statistical results for conventional empirical formulas (C_c).

Equation No	Equation	R^2	MAPE	RMSE	MAD
1	$C_c = 0.01\omega_n - 0.05$	0.918	25.17	0.0629	0.0517
2	$C_c = 0.01\omega_n$	0.80	41.83	0.0975	0.086
3	$C_c = 0.01\omega_n - 0.075$	0.937	21.26	0.0553	0.0437
4	$C_c = 0.013\omega_n - 0.115$	0.85	33.79	0.0845	0.0695
5	$C_c = 0.54e_0 - 0.19$	0.93	21.27	0.0572	0.0437
6	$C_c = 0.43e_0 - 0.11$	0.95	18.63	0.0478	0.0383
7	$C_c = 0.75e_0 - 0.38$	0.86	29	0.0820	0.0596
8	$C_c = 0.49e_0 - 0.11$	0.87	31.46	0.0781	0.0647
9	$C_c = 0.4(e_0 - 0.25)$	0.96	17.32	0.0445	0.0356
10	$C_c = 0.15e_0 + 0.01077$	0.80	39.31	0.0983	0.0808
11	$C_c = 0.287e_0 - 0.015$	0.957	17.5	0.0458	0.036
12	$C_c = 0.3(e_0 - 0.27)$	0.89	28.72	0.0723	0.059
13	$C_c = 1.02 - 0.95e_0$	0.30	95.38	0.2499	0.196
14	$C_c = 0.006(LL - 9)$	0.87	29.45	0.0792	0.0605
15	$C_c = (LL - 13)/109$	0.79	37.41	0.1012	0.0769
16	$C_c = 0.009(LL - 10)$	0.74	41.96	0.1111	0.0863
17	$C_c = 0.014LL - 0.168$	0.045	91.4	0.2244	0.188
18	$C_c = 0.0046(LL - 9)$	0.81	36.81	0.0965	0.0757
19	$C_c = 0.2343\left(\frac{LL}{100}\right).G_s$	0.84	33.42	0.0867	0.0687
20	$C_c = 0.2926\left(\frac{LL}{100}\right).G_s$	0.6426	53.98	0.1313	0.111
21	$C_c = 0.009\omega_n + 0.005LL$	0.3984	122.09	0.2597	0.251
22	$C_c = 0.009\omega_n + 0.002LL - 0.1$	0.92	24.87	0.0621	0.0511
23	$C_c = 0.4(e_0 + 0.001\omega_n - 0.25)$	0.95	18.326	0.0468	0.0377
24	$C_c = -0.156 + 0.411e_0 + 0.00058LL$	0.95	19.17	0.0498	0.0394
25	$C_c = -0.023 + 0.271e_0 + 0.001LL$	0.95	17.7851	0.0492	0.0366
26	$C_c = 0.37(e_0 + 0.003LL + 0.0004\omega_n - 0.34)$	0.97	16.51	0.0428	0.0339
27	$C_c = -0.404 + 0.341e_0 + 0.006\omega_n + 0.004LL$	0.88	29.45	0.0766	0.0605
28	$C_c = 0.141G_s^{1.2}[(1 + e_0)/G_s]^{2.38}$	0.94	19.39	0.0538	0.0398
29	$C_c = 0.1597(\omega_n^{-0.0187})(1 + e_0)^{1.592}(LL^{-0.0638})(\gamma_d^{-0.8276})$	0.96	18.03	0.0455	0.0371
30	$C_c = 0.151 + 0.001225\omega_n + 0.193e_0 - 0.000258LL - 0.0699\gamma_d$	0.95	18.89	0.0475	0.0389

Table 4. Suggested empirical equations and statistical results.

Equation No	Equation	R^2	MAPE	RMSE	MAD
1	$C_c = 0.0074\omega_n - 0.007$	0.95	19.48	0.0513	0.04
2	$C_c = 0.3608e_0 - 0.0713$	0.96	17.12	0.044	0.0352
3	$C_c = 0.7331 + 0.4152e_0 - 0.00134\omega_n - 0.3167G_s + 0.0007LL$	0.97	14.86	0.0385	0.0306

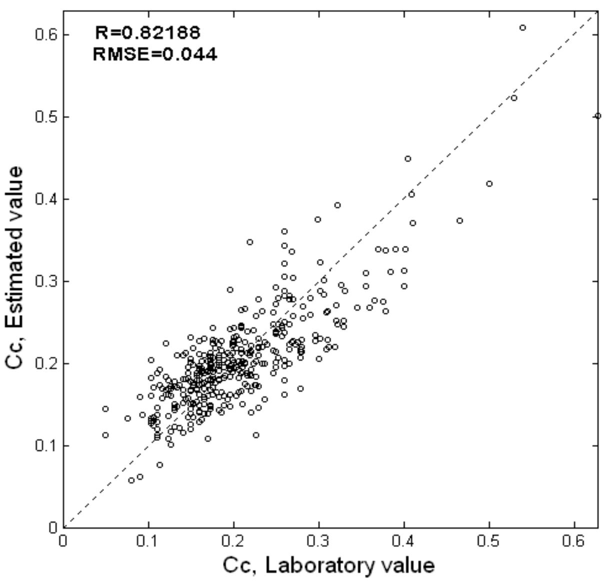

Figure 1. The measured compression indexes obtained from the consolidation test versus the suggested equation estimated compression indexes (Equation 2, Table 4).

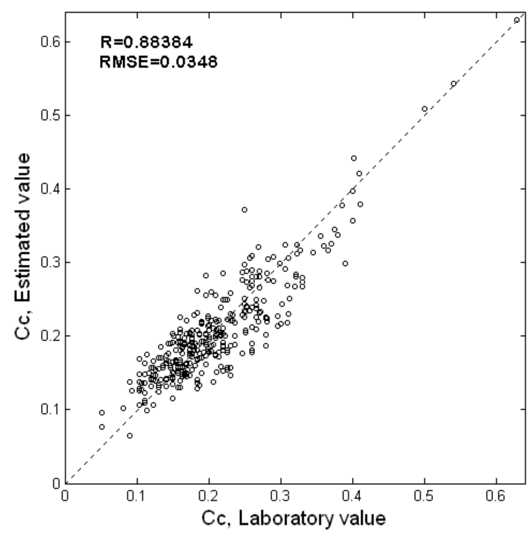

Figure 3. The measured compression indexes obtained from the consolidation test versus the ANN estimated compression indexes (result of training process).

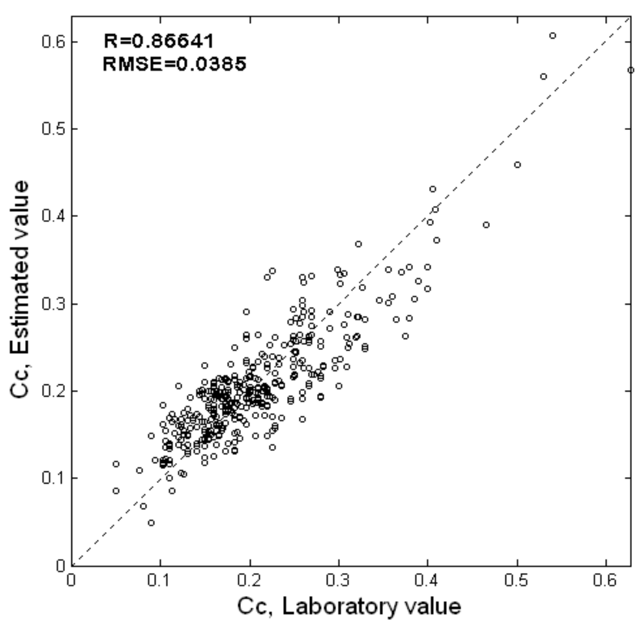

Figure 2. The measured compression indexes obtained from the consolidation test versus the suggested equation estimated compression indexes (Equation 3, Table 4).

neuron in the hidden layer and the combinations of transfer functions were tested to find the optimal structure for the ANN model. The value of the minimum mean squared error, mean absolute percent error and mean absolute deviation were varied based on the correlation coefficient (R^2) for the testing results.

The combination of two hidden layers gives better results than single hidden layer and also the combination of transfer functions composed of log-sigmoid, tan-sigmoid and linear function gives good results. The ANN model with five neurons in the input layer, nine neurons in the first hidden layer, three neurons in the second hidden layer, and one node in the output layer gives the best results. Figures 3 and 4 shows the relationship between output targets and predicted values obtained through the training and testing process.

The model shows very good correlation for both the training and testing data compared with the conventional empirical formulas and the suggested formulas.

In Table 6, the predictability of the ANN model is statistically compared with the empirical formulas. The value of RMSE, MAPE and MAD are found to be minimum for the ANN model in both training and testing stage. Therefore, the developed ANN model is more efficient than the existing and proposed empirical formulas and by using it we can accurately estimate the consolidation settlement of this aria.

Conclusion

In this study, the performances of widely used single and multi-variable empirical equations for the estimation of the compression index were evaluated using a database consisting of 400 wide-ranging samples from the Province of Mazandaran, Iran. Using the same database, new single and multi-variable empirical equations were developed. Furthermore, an attempt has been made to predict this index by using neural network simulation. The

Table 5. Descriptive statistics of variables used in the ANN.

Variable		Test (40 data set)			Train (360 data set)		
		Mean	**maximum**	**minimum**	**mean**	**Maximum**	**minimum**
Input	e_0	0.357	1.882	0.767	0.476	1.647	0.769
	ω_n	10.2	70	28.51	14.5	64.1	29.47
	LL	24	81	39.9	27	64	39.15
	PI	3	50	18.68	7	35	17.85
	G_s	2.43	2.8	2.64	2.44	2.74	2.62
Output	C_c	0.05	0.628	0.2054	0.076	0.53	0.2067

ω_n= natural water content (%), e_0= initial void ratio, *LL*= liquid limit (%), *PI*= plastic index (%), G_s= specific gravity of soil particles, C_c= compression index.

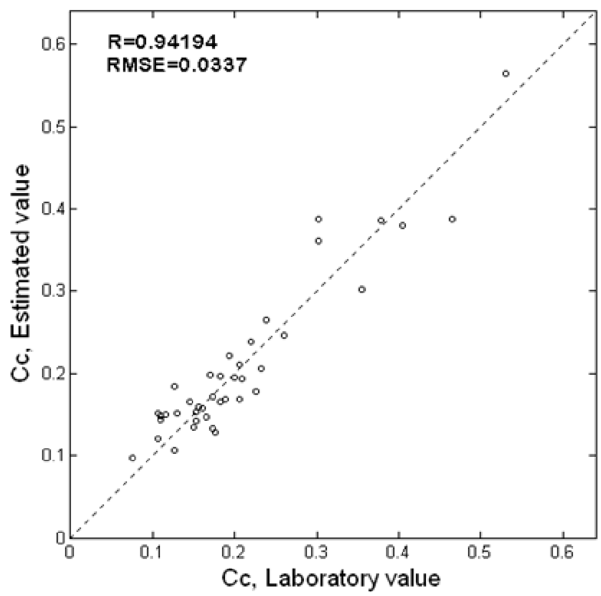

Figure 4. The measured compression indexes obtained from the consolidation test versus the ANN estimated compression indexes (result of testing process).

Table 6. Statistical results for the best empirical formulas and ANN.

Equation No	Equation	R^2	MAPE	RMSE	MAD
1	$C_c = 0.01\omega_n - 0.075$, Herrero (1983) [12]	0.937	21.26	0.0553	0.0437
2	$C_c = 0.0074\omega_n - 0.007$, in this study	0.95	19.48	0.0513	0.04
3	$C_c = 0.4(e_0 - 0.25)$, Azzouz et al. (1976) [10]	0.96	17.32	0.0445	0.0356
4	$C_c = 0.3608e_0 - 0.0713$, in this study	0.96	17.12	0.044	0.0352
5	$C_c = 0.37(e_0 + 0.003LL + 0.0004\omega_n - 0.34)$, Azzouz et al. (1976) [10]	0.97	16.51	0.0428	0.0339
6	$C_c = 0.7331 + 0.4152e_0 - 0.00134\omega_n - 0.3167G_s + 0.0007LL$, in this study	0.97	14.86	0.0385	0.0306
7	C_c, ANN model (training)	0.975	13.34	0.0348	0.0274
8	C_c, ANN model (testing)	0.978	13.17	0.0337	0.0272

results indicate that:

1. Among the single variable equations, the equation proposed by Azzouz et al. (1976) (Equation 9 in Table 3), utilizing initial void ratio as the variable, has the lowest error.
2. Among the multi variable equations, the equation proposed by Azzouz et al. (1976) (Equation 26 in Table 3) gave the best performance using initial void ratio, natural water content and liquid limit of soil as predictor variables.
3. Based on the regression analysis, the formulas using single parameters of the void ratio and natural water content show better performance than other types of formulas using the single parameter.
4. The proposed equation using void ratio shows the lowest RMSE, MAPE, MAD and the highest regression coefficient which is better than the existing single variable equations.
5. Among the suggested equations, the equation $C_c = 0.7331 + 0.4152\,e_0 - 0.00134\omega_n - 0.3167\,G_s + 0.0007LL$ shows the lowest RMSE value (0.0385), MAPE value (14.86), MAD value (0.0306) and the highest regression coefficient for the compression index.
6. The predictions of artificial neural network model agreed well with the measured compression index of the consolidation tests. Therefore, reliable predicting capabilities were obtained.
7. The developed ANN model is more efficient than the existing and proposed empirical formulas and by using it we can accurately estimate the consolidation settlement of this aria.

ACKNOWLEDGEMENTS

Authors are thankful to engineers Afshin Khatami, Mohsen Taheri and Hadi Shirsavar for their help. Authors also thank the Technical and Soil Laboratory of Mazandaran Province for collecting the borehole data.

REFERENCES

Abedimahzoon N, Molaabasi H, Lashtehneshaei MA, Biklaryan M (2010). Investigation of undertow in reflective beaches using a GMDH-type neural network. Turk. J. Eng. Environ. Sci. 34:201-213.
Ahadiyan J, Ebne JR, Bajestan MS (2008). Prediction Determination of Soil Compression Index, Cc, in Ahwaz Region (In Persian). J. Faculty Eng. 35(3):75-80.
Al-Khafaji AWN, Andersland OB (1992). Equations for compression index approximation. J. Geotech. Eng. ASCE. 118(1):148-153.
ASTM D 2435-96 (1998). Standard Test Method for One-dimensional Consolidation Properties of Soils, Annual Book of ASTM standards. Vol. 04.08, Soil and Rock (I). Standard. Pennsylvania pp.207-216.
Azzouz AS, Krizek RJ, Corotis RB (1976). Regression Analysis of Soil Compressibility. Soils Found. 16(2):19-29.
Bowles JE (1989). Physical and Geotechnical Properties of Soils. McGraw-Hill Book Company Inc. New York, pp. 442-448.
Cho SE (2009). Probabilistic stability analyses of slopes using the ANN-based response surface. Comput. Geotech. 36:787-797.
Cozzolino VM (1961). Statistical forecasting of compression index. In: Proceedings of the fifth international conference on soil mechanics and foundation engineering. Paris pp.51-53.
Das BM (2009). Principles of geotechnical engineering. 7nd edition. Thomson Engineering p. 294.
Du JC, Zhang LM (2001). Simplified Procedure for Estimating Ground Settlement under Embankments. In: Third International Conference on Soft Soil Engineeringc. Hong Kong pp.193-198.
Fenton GA, Paice GM, Griffiths DV (1996). Probabilistic Analysis of Foundation Settlement. Proceedings of the ASCE Uncertainty. 96 Conference. Madison. Wisconsin. Aug. ASCE Geotechnical Special Publication 58(1):657-665.
Goktepe F, Arman H, Pala M (2010). A new approach for classification of clayey soil: A case study for Adapazari region, Turkey. Sci. Res. Essays 5(15):2037-2043.
Gunduz Z, Arman H (2007). Possible Relationships between Compression and Recompression Indices of a Low–Plasticity Clayey Soil. Arab. J. Sci. Eng. 32(2B):179-189.
Haykin S (1999). Neural Networks. A Comprehensive Foundation (2nd edn). Prentice-Hall: Upper Saddle River. New Jersey.
Herrero OR (1983a). Universal compression index equation. Discussion. J. Geotech. Eng. Div. ASCE. 109(10):1179-1200.
Herrero OR (1983b). Universal compression index equation. Closure. J. Geotech. Eng. Div. ASCE. 109(5):755-761.
Hornig ED (2010). Field and Laboratory Tests Investigating Settlements of Foundations on Weathered Keuper Marl. Geotech. Geol. Eng. 28:233-240.
Hough BK (1957). Basic Soils Engineering. The Ronald Press Company. New York pp.114-115.
Kolay PK, Rosmina AB, Ling NW (2008). Settlement Prediction of Tropical Soft Soil by Artificial Neural Network (ANN). The 12th International Conference of International Association for Computer Methods and Advances in Geomechanics (IACMAG) pp.1843-1848.
Koppula SD (1981). Statistical estimation of compression index. Geotech. Test. J. 4(2):68-73.
Lambe TW (1976). Stress Path Method. JSMFD. ASCE. (SM6) 93:309-331.
Mayne PW (1980). Cam-clay predictions of undrained strength. J. Geotech. Eng. Div. ASCE. 106(11):1219-1242.
Mollahasani A, Alavi AH, Gandomi AH, Rashed A (2011). Nonlinear Neural-Based Modeling of Soil Cohesion Intercept. KSCE. J. Civ. Eng. 15(5):831-840.
Nagaraj TS, Murty BRS (1985). Prediction of the preconsolidation pressure and recompression index of soils. Geotech. Test. J. 8(4):199-202.
Nishida Y (1956). A brief note on compression index of soils. J. SMFE. Div. ASCE. 82(3):1-14.
Ozer M, Isik NS, Orhan M (2008). Statistical and neural network assessment of the compression index of clay-bearing soils. Bull. Eng. Geol. Environ. 67(4):537-545.
Park HI (2010). Development of neural network model to estimate the permeability coefficient of soils. Marine Geosourc. Geotechnol. 29(4):267-278.
Park HI, Cho CH (2010). Neural Network Model for Predicting the Resistance of Driven Piles. Marine Geosources and Geotechnol. 28(4):324-344.
Park HI, Keon GC, Lee SR (2009). Prediction of Resilient Modulus of Granular Subgrade Soils and Subbase Materials Based on Artificial Neural Network. Road Mater. Pavement Design. 10(3):647- 665.
Park HI, Kim YT (2010). Prediction of Strength of Reinforced Lightweight Soil Using an Artificial Neural Network. Int. J. Computer-Aided Eng. 28(5):600-615.
Park HI, Lee SR (2011). Evaluation of the compression index of soils using an artificial neural network. Comput. Geotech. 38(4):472-481.
Sinan N (2009). Estimation of swell index of fine grained soils using regression equations and artificial neural networks. Sci. Res. Essays 4(10):1047-1056.
Sower GB (1970). Introductory soil mechanics and foundation. 3rd ed. London: The Macmillan Company of Collier-Macmillan Ltd. p.102.
Terzaghi K (1925). Erdbaumechanik auf bodenphysikalischer Grundlage F. Deuticke.
Terzaghi K, Peck RB (1967). Soil mechanics in engineering practice. 2nd ed. New York: Wiley p. 73.
Wakita E (1993). Settlement Prediction Using Observed Data and Its

Feedback to Original Design. Proc. of the Intl. Conf. on Soft Soil Engineering. Edited by Cheung YK, Yuan JX, Lu PY, Tsui Y, Cao H. Guangzhou. China. Nov. Recent Adv. Soft Soil Eng. pp.92-97.

Yoon GL, Kim BT (2006). Regression Analysis of Compression Index for Kwangyang Marine Clay. KSCE. J. Civ. Eng. 10(6):415-418.

Appendix 1

ω_n	LL	PI	e_0	Gs	Cc
33.6	33	13	0.789	2.6	0.28
26.2	46	24	0.666	2.7	0.126
30.5	37	18	0.853	2.67	0.26
19.2	34	15	0.706	2.5	0.196
32.5	40	20	0.793	2.65	0.186
30.2	41	22	0.777	2.68	0.219
39.1	67	43	0.939	2.55	0.36
55.7	60	32	1.357	2.54	0.5
34.5	75	47	0.828	2.58	0.27
36.5	62	34	0.959	2.72	0.375
36.2	58	33	0.894	2.63	0.32
22.5	25	5	0.595	2.64	0.183
12.7	31	10	0.63	2.62	0.236
22.4	27	8	1	2.67	0.196
20.8	30	10	0.508	2.69	0.05
24.5	31	12	0.748	2.61	0.266
25.7	46	23	0.722	2.63	0.199
26.6	27	7	0.766	2.66	0.149
44.4	42	20	1.148	2.7	0.26
40.3	42	19	1.04	2.73	0.27
48.1	40	19	1.286	2.72	0.322
32.7	44	22	0.859	2.64	0.216
26.7	40	19	0.669	2.67	0.133
27.7	36	14	0.677	2.63	0.136
28.6	41	17	0.702	2.58	0.146
47.6	42	21	1.135	2.63	0.37
27.4	27	6	0.68	2.66	0.163
18.7	34	13	0.711	2.66	0.22
39.1	49	24	0.948	2.6	0.32
25.9	36	13	0.762	2.7	0.103
27.6	37	16	0.748	2.61	0.236
24.4	38	14	0.613	2.53	0.13
28.6	35	14	0.764	2.62	0.3
31.1	30	10	0.856	2.68	0.25
21.6	39	21	0.552	2.6	0.11
28.8	36	17	0.759	2.64	0.21
20	36	20	0.562	2.61	0.163
21.3	27	17	0.547	2.64	0.103
25.2	42	20	0.645	2.6	0.159
22.1	34	13	0.66	2.6	0.173
22.4	58	32	0.685	2.61	0.153
20	40	19	0.605	2.6	0.196
17.2	43	21	0.73	2.7	0.206
19.4	44	21	0.576	2.7	0.11
31.2	50	29	0.74	2.52	0.259
23.7	40	21	0.585	2.6	0.22

Appendix 1. Contd.

ω_n	LL	PI	e_0	Gs	Cc
37.5	47	24	0.915	2.6	0.29
29.7	36	14	0.753	2.63	0.2
25.9	31	11	0.736	2.63	0.21
24.1	27	8	0.675	2.67	0.126
21.6	34	12	0.83	2.59	0.28
25.3	34	13	0.734	2.61	0.2
27.1	37	14	0.72	2.65	0.176
31.4	29	7	0.839	2.68	0.15
30.8	35	13	0.825	2.71	0.2
30.8	25	5	0.869	2.69	0.2
22.4	53	28	0.583	2.6	0.169
19.5	52	28	0.517	2.61	0.14
27.1	45	22	0.652	2.6	0.18
28.9	52	28	0.806	2.55	0.28
39	53	29	0.98	2.63	0.26
25.3	35	14	0.675	2.7	0.13
25.2	40	18	0.588	2.6	0.16
26.7	29	8	0.663	2.67	0.12
29.7	30	10	0.718	2.66	0.11
22.6	33	10	0.632	2.64	0.116
36.5	49	28	0.97	2.62	0.29
29.4	52	28	0.731	2.62	0.22
27.1	45	22	0.809	2.72	0.22
24.7	29	11	0.71	2.63	0.19
24.4	40	22	0.695	2.7	0.123
48.7	25	5	1.222	2.59	0.41
36.9	56	28	0.909	2.57	0.27
22.6	56	34	0.612	2.68	0.15
31.9	39	17	0.837	2.68	0.2
27.2	33	14	0.677	2.66	0.17
24.7	34	13	0.745	2.67	0.18
25.3	27	8	0.661	2.66	0.156
26	37	17	0.723	2.59	0.21
26.9	42	20	0.716	2.58	0.216
21.8	38	17	0.563	2.67	0.103
32	51	32	0.829	2.59	0.31
40.9	37	10	0.928	2.53	0.31
23.5	35	15	0.507	2.52	0.11
57.4	79	45	1.587	2.53	0.628
31.1	43	22	0.964	2.65	0.365
32.2	30	10	0.782	2.62	0.159
38.1	42	20	0.87	2.51	0.256
29.8	47	27	0.736	2.57	0.25
27.5	34	15	0.739	2.72	0.146
22.1	34	14	0.573	2.59	0.123
31.8	37	16	0.776	2.65	0.166

Appendix 1. Contd.

ω_n	LL	PI	e_0	Gs	Cc
27.3	37	18	0.802	2.74	0.179
27.4	36	14	0.777	2.63	0.229
27.2	31	11	0.769	2.65	0.176
28.1	34	12	0.824	2.66	0.269
22.1	43	21	0.643	2.56	0.203
24.5	39	19	0.761	2.62	0.183
29.6	37	15	0.761	2.66	0.173
11.5	45	22	0.537	2.63	0.13
17.6	52	28	0.615	2.56	0.21
18.5	46	23	0.611	2.62	0.173
19.2	51	25	0.586	2.63	0.186
13.6	46	22	0.407	2.62	0.113
35.3	35	13	0.841	2.61	0.256
32.1	49	29	0.805	2.61	0.233
32.4	48	28	0.85	2.65	0.249
32.8	49	28	0.797	2.61	0.309
30.5	38	17	0.79	2.62	0.249
30.3	42	20	0.755	2.63	0.193
31.4	41	22	0.816	2.68	0.266
34	33	16	0.894	2.62	0.329
28.5	39	19	0.725	2.64	0.183
25.6	35	16	0.803	2.62	0.203
28.3	37	17	0.734	2.64	0.159
30.8	32	14	0.813	2.63	0.272
26.7	44	22	0.667	2.67	0.123
24.8	26	6	0.704	2.7	0.226
22	24	4	0.558	2.64	0.103
27.6	37	15	0.873	2.64	0.329
41.1	39	17	0.993	2.63	0.259
49.2	60	36	1.008	2.63	0.249
34.8	51	27	0.854	2.57	0.249
27.2	36	19	0.678	2.66	0.153
37.8	44	24	0.965	2.69	0.229
38.4	62	44	1.014	2.61	0.326
35.3	41	20	0.909	2.69	0.226
28	37	17	0.721	2.71	0.163
29	39	19	0.77	2.68	0.279
38.7	53	30	0.833	2.61	0.302
29.8	54	31	0.755	2.57	0.149
34	58	36	0.867	2.61	0.196
26.5	36	17	0.676	2.62	0.159
25.1	43	25	0.708	2.6	0.156
30.3	46	25	0.775	2.63	0.173
19.4	38	17	0.529	2.64	0.11
22.5	36	16	0.599	2.63	0.149
20.3	30	8	0.546	2.64	0.149

Appendix 1. Contd.

ω_n	LL	PI	e_0	Gs	Cc
21.7	42	22	0.658	2.6	0.22
19.4	40	19	0.528	2.53	0.149
22.9	31	12	0.628	2.57	0.143
25.3	31	11	0.723	2.62	0.169
28.4	36	16	0.732	2.63	0.176
23.7	34	15	0.761	2.66	0.189
29.1	34	13	0.748	2.66	0.213
39.8	53	27	0.97	2.64	0.252
28.6	46	22	0.801	2.77	0.153
24.9	33	14	0.69	2.77	0.13
27.2	34	13	0.759	2.76	0.163
20.9	30	13	0.601	2.76	0.11
21	25	9	0.643	2.74	0.103
25	36	15	0.697	2.72	0.183
29.8	43	19	0.828	2.72	0.186
31.1	30	10	0.874	2.72	0.209
26.3	60	30	0.733	2.72	0.196
25.1	37	16	0.738	2.67	0.203
25.8	39	17	0.73	2.64	0.196
30.1	39	19	1.012	2.52	0.4
26.9	43	20	0.732	2.63	0.163
23.9	30	8	0.605	2.53	0.133
28.9	26	8	0.824	2.74	0.199
28.5	39	20	0.653	2.53	0.186
27	44	24	0.629	2.51	0.166
29.7	32	11	0.822	2.76	0.213
24.3	42	24	0.809	2.76	0.199
28.4	29	9	0.777	2.73	0.14
24.4	31	15	0.711	2.66	0.159
25.1	29	11	0.658	2.7	0.149
26.4	31	14	0.619	2.64	0.14
26.2	30	15	0.746	2.8	0.183
22.6	30	10	0.602	2.67	0.13
27.5	31	7	0.738	2.66	0.173
28	33	12	0.703	2.68	0.103
25.7	32	10	0.718	2.71	0.166
23.2	35	13	0.652	2.68	0.206
23.1	31	11	0.635	2.66	0.146
27	32	10	0.644	2.44	0.196
22.4	27	6	0.643	2.66	0.189
32.7	57	35	0.904	2.76	0.282
28.8	56	36	0.793	2.75	0.246
29.8	31	11	0.831	2.72	0.176
29	43	22	0.798	2.74	0.209
27.3	58	35	0.807	2.72	0.229
18.6	32	13	0.645	2.72	0.14

Appendix 1. Contd.

ω_n	LL	PI	e_0	Gs	Cc
25.6	48	25	0.724	2.64	0.163
31.2	54	30	0.776	2.63	0.183
29.8	47	26	0.785	2.64	0.173
25.2	35	16	0.663	2.65	0.14
26.4	39	19	0.667	2.55	0.279
20	27	9	0.63	2.59	0.193
22.7	29	7	0.637	2.7	0.183
31.4	33	10	0.768	2.45	0.252
25.2	34	12	0.675	2.67	0.229
29.5	33	9	0.784	2.66	0.143
29.3	29	7	0.795	2.71	0.186
30.8	28	5	0.751	2.62	0.173
29.8	54	31	0.755	2.57	0.149
34	58	36	0.867	2.6	0.196
26.5	36	17	0.676	2.62	0.159
30.3	46	25	0.775	2.63	0.173
23.9	31	12	0.621	2.61	0.156
26.9	43	20	0.732	2.63	0.163
23.9	30	8	0.605	2.53	0.133
28.9	26	8	0.824	2.74	0.199
33.6	33	13	0.789	2.6	0.279
26.2	46	24	0.666	2.7	0.126
11.1	27	5	0.519	2.58	0.126
20.5	29	8	0.717	2.71	0.146
24.1	34	12	0.668	2.71	0.106
31.4	47	29	0.826	2.64	0.179
36.6	35	15	0.883	2.59	0.246
32.1	29	7	0.753	2.6	0.213
28.9	47	26	0.717	2.64	0.246
34.4	49	28	0.864	2.61	0.223
19.9	52	31	0.582	2.59	0.166
20.2	56	36	0.498	2.43	0.169
23.1	53	35	0.642	2.53	0.169
16.6	37	21	0.507	2.56	0.226
23.2	61	37	0.586	2.55	0.159
22	34	13	0.675	2.54	0.216
35.4	38	19	0.859	2.56	0.249
36.2	39	17	0.881	2.63	0.252
31.9	33	12	0.705	2.67	0.12
27.6	40	18	0.666	2.67	0.156
28.9	36	15	0.711	2.66	0.216
28.1	43	20	0.719	2.67	0.156
29.8	34	14	0.753	2.66	0.183
28.3	58	35	0.692	2.57	0.159
35	57	34	0.88	2.61	0.256
23.8	39	16	0.828	2.72	0.159

Appendix 1. Contd.

ω_n	LL	PI	e_0	Gs	Cc
21.3	36	12	0.502	2.52	0.11
20.6	26	9	0.551	2.61	0.159
18.5	36	15	0.567	2.63	0.106
10.6	24	3	0.368	2.65	0.09
26.1	31	12	0.778	2.64	0.189
20.1	49	25	0.638	2.7	0.09
19.7	45	22	0.661	2.7	0.149
21.9	51	26	0.694	2.71	0.156
28.8	44	22	0.75	2.67	0.209
33.7	36	14	0.844	2.64	0.203
28.7	40	20	0.755	2.55	0.249
28.2	40	18	0.757	2.6	0.169
30.1	29	10	0.75	2.62	0.223
27.6	34	16	0.738	2.7	0.189
30.8	37	15	0.784	2.61	0.199
26.5	29	8	0.637	2.63	0.166
21.3	41	20	0.699	2.68	0.14
26.3	24	4	0.695	2.68	0.169
20.4	32	11	0.699	2.7	0.173
26.1	30	11	0.752	2.71	0.183
19.5	28	9	0.73	2.7	0.113
19	40	19	0.715	2.63	0.219
18.4	37	17	0.682	2.62	0.213
18.4	34	15	0.613	2.63	0.153
49.6	55	28	1.322	2.67	0.409
40.6	37	16	1.088	2.69	0.259
39	58	35	1.059	2.7	0.385
31.2	34	14	0.871	2.73	0.176
36.1	56	34	0.983	2.7	0.306
33	37	15	0.88	2.67	0.209
32.7	62	36	1.054	2.62	0.355
34.4	62	36	0.806	2.56	0.312
30.9	40	21	0.926	2.59	0.379
37.4	55	30	0.921	2.6	0.246
27.1	59	36	0.693	2.61	0.259
33.6	46	24	0.847	2.64	0.296
31.4	41	22	0.804	2.63	0.229
29	39	20	0.748	2.59	0.233
25.6	48	25	0.724	2.64	0.163
31.2	54	30	0.776	2.63	0.183
25.3	39	21	0.647	2.61	0.259
23.3	25	6	0.579	2.65	0.093
25.3	30	9	0.702	2.53	0.189
25.3	39	21	0.647	2.61	0.259
29	39	20	0.748	2.59	0.233
35.3	44	23	0.815	2.54	0.183

Appendix 1. Contd.

ω_n	LL	PI	e_0	Gs	Cc
24.6	34	14	0.676	2.63	0.225
29	40	19	0.8	2.64	0.279
25.8	34	12	0.692	2.63	0.173
27.8	33	10	0.707	2.63	0.176
26.7	38	18	0.684	2.62	0.179
54.3	30	10	0.943	2.67	0.282
28.3	34	13	0.778	2.68	0.133
29.5	32	14	0.744	2.65	0.173
27.7	35	15	0.73	2.68	0.159
20.5	42	21	0.601	2.6	0.229
23.4	45	21	0.697	2.67	0.176
21.6	42	23	0.664	2.58	0.156
21.9	44	24	0.686	2.59	0.166
20.5	47	22	0.742	2.56	0.196
25.3	55	27	0.719	2.63	0.209
20	46	25	0.671	2.61	0.176
70	52	29	1.882	2.68	0.54
37.8	81	50	0.966	2.67	0.27
37.1	27	6	0.951	2.69	0.25
10.2	44	23	0.357	2.62	0.08
44	47	23	1.137	2.69	0.39
40.1	46	23	0.996	2.66	0.33
43	53	31	1.062	2.64	0.4
27.2	33	8	0.881	2.61	0.266
37.2	62	34	0.937	2.56	0.345
27.9	35	15	0.745	2.67	0.153
34.4	68	46	0.909	2.44	0.226
24.4	32	14	0.824	2.66	0.276
37	40	19	0.923	2.63	0.309
28.2	47	24	0.814	2.717	0.2
39.6	49	25	0.891	2.611	0.26
27.1	41	18	0.666	2.633	0.116
28.5	27	7	0.735	2.67	0.173
23	53	28	0.608	2.55	0.16
25.1	39	16	0.672	2.65	0.13
27.4	33	12	0.727	2.62	0.17
20.5	34	13	0.565	2.7	0.076
29.8	43	24	0.789	2.59	0.22
21.4	38	21	0.583	2.68	0.15
22.2	50	27	0.614	2.62	0.166
43.4	44	21	0.994	2.51	0.302
21.6	39	21	0.552	2.6	0.11
28.8	36	17	0.759	2.64	0.206
24.5	39	19	0.644	2.7	0.176
56.9	36	15	1.442	2.68	0.405
22.2	42	21	0.568	2.6	0.153

Appendix 1. Contd.

ω_n	LL	PI	e_0	Gs	Cc
31.8	36	16	0.831	2.67	0.206
29.6	25	6	0.834	2.74	0.229
31	32	11	0.786	2.64	0.216
33.3	39	20	0.868	2.62	0.252
42.2	34	13	1.161	2.69	0.219
38.2	31	11	0.967	2.68	0.266
26.1	29	9	0.786	2.67	0.209
24.7	29	8	0.763	2.67	0.259
22.4	57	33	0.697	2.64	0.143
22.2	42	19	0.534	2.49	0.136
16.4	41	24	0.605	2.61	0.173
19.4	29	11	0.495	2.61	0.123
25	29	9	0.691	2.66	0.149
29.7	29	11	0.778	2.67	0.196
32.1	39	20	0.823	2.69	0.236
30.2	40	22	0.787	2.59	0.219
25.4	30	10	0.644	2.68	0.12
23.6	38	19	0.592	2.6	0.13
17.7	32	12	0.74	2.65	0.159
41.5	31	11	1.195	2.73	0.259
47.6	36	17	1.237	2.74	0.299
46.6	43	22	1.127	2.64	0.269
36.5	33	12	0.934	2.69	0.213
25.9	33	12	0.8	2.61	0.266
33.5	50	26	0.827	2.65	0.296
23.5	37	16	0.596	2.71	0.05
33.7	36	15	0.835	2.67	0.166
21.6	32	12	0.665	2.69	0.166
30.6	41	17	0.727	2.6	0.173
32.1	44	26	0.761	2.57	0.199
28.7	43	16	0.82	2.71	0.12
40.7	40	18	1.045	2.66	0.259
33.1	50	27	0.771	2.66	0.176
29.9	48	25	0.756	2.65	0.163
38.5	68	42	0.884	2.56	0.322
28	42	24	0.657	2.54	0.209
39.3	40	17	0.931	2.62	0.209
39.4	32	8	0.979	2.67	0.266
28.9	27	6	0.817	2.66	0.176
28.9	57	35	1.031	2.61	0.306
28.9	47	25	1.137	2.54	0.402
20.1	26	8	0.676	2.65	0.113
23.8	46	25	0.647	2.63	0.123
28	33	12	0.703	2.68	0.103
34.5	45	26	0.808	2.5	0.319
25.2	30	11	0.681	2.63	0.163

Appendix 1. Contd.

ω_n	LL	PI	e_0	Gs	Cc
20	34	13	0.693	2.64	0.183
19.5	34	12	0.609	2.57	0.189
31.2	37	16	0.87	2.73	0.209
23.9	31	12	0.621	2.61	0.156
34.2	44	25	0.816	2.54	0.239
21.6	39	21	0.552	2.61	0.11
28.8	32	11	0.703	2.64	0.206
25.5	29	9	0.643	2.56	0.126
45.7	52	31	1.132	2.64	0.379
42.1	34	10	1.013	2.59	0.355
39.2	57	34	1.091	2.65	0.302
35	37	14	0.928	2.71	0.233
24.6	34	14	0.676	2.63	0.226
64.1	64	31	1.647	2.57	0.53
31	33	15	0.786	2.63	0.193
25.2	56	35	0.569	2.44	0.146
14.5	44	21	0.476	2.64	0.126
22.6	28	7	0.598	2.65	0.173
27.2	29	10	0.77	2.74	0.183
23	37	16	0.541	2.52	0.106
20.5	32	11	0.557	2.64	0.106
22.8	28	7	0.619	2.63	0.153
46.4	31	10	1.232	2.57	0.465

ω_n= natural water content (%), e_0= initial void ratio, *LL*= liquid limit (%), *PI*= plastic index (%), G_s= specific gravity of soil particles, C_c= compression index.