

Statistical and neural network assessment of the compression index of clay-bearing soils

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Abstract The compression index is used to estimate the consolidation settlement of clay-bearing soils. As the determination of compression index from oedometer tests is relatively time-consuming, empirical equations based on index properties can be useful. In this study the performance of widely used single and multi-variable empirical equations was evaluated using a database consisting of 135 test data. New empirical equations were developed utilizing least square regression analysis. In addition, an artificial neural network (ANN) with eight input variables was also developed to estimate the compression index. It was concluded that ANN provides the best results.

Keywords Artificial neural networks · Clay soils · Compression index · Regression analysis

Résumé L'indice de compression est utilisé pour estimer le tassement de consolidation des sols argileux. Comme la détermination de cet indice à partir des essais oedométriques prend quelque temps, des équations empiriques basées sur des indices géotechniques peuvent être utiles. Dans cette étude, l'intérêt d'équations empiriques à une ou plusieurs variables a été évalué à partir d'une base de données comportant 135 résultats d'essais. De nouvelles équations empiriques ont été développées à partir d'une analyse de

régression par la méthode des moindres carrés. De plus, un réseau de neurones artificiel (ANN) avec huit variables d'entrée a été développé pour estimer l'indice de compression. La conclusion est que l'ANN donne les meilleurs résultats.

Mots clés Réseaux de neurones artificiels · Sols argileux · Indice de compression · Analyse de régression

Introduction

The compression index represents the slope of the curve of void ratio versus logarithm of effective pressure and is conventionally determined by oedometer tests. Used for the calculation of consolidation settlement of clayey soils, this parameter directly affects the type and dimensions of the foundation system hence the cost of the construction.

The amount of consolidation settlement of fine grained soils depends on the fabric of the soil, the water absorption capacity of the clay sized particles, the existing stress state, the pre-consolidation pressure of the soil sample, and to some extent the compressibility of the soil grains. Therefore, it would be assumed that any direct or indirect parameters which define these conditions should be related to the compression index. Atterberg limits reflect the relative amount of clay sized particles and their mineralogy; the initial void ratio of the soil is an indication of the existing stress state and the pre-consolidation pressure; the natural water content is a measure of the water attracted to the clay particles and free water present within the voids; and dry unit weight may to some degree be an indication of the compressibility of soil grains. Other weight–volume relationship parameters, such as specific gravity and natural unit weight, are physically related to dry unit weight,

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natural water content and the void ratio of the soil. For this reason, it seems logical to estimate the compression index from the above mentioned parameters.

As the oedometer test is relatively time-consuming compared with standard index tests, various attempts have been made to estimate the compression index from tests more easily carried out. Empirical equations relating various parameters to the compression index have been presented by many researchers, e.g. for local clays (Helehelund 1951; Cozzolino 1961; Bowles 1989; Yin 1999; Yoon et al. 2004); organic soils (Bowles 1989); low plasticity clays (Sowers 1970; Nakase et al. 1988); and remolded soils (Skempton 1944; Wroth and Wood 1978; Carrier 1985; Nagaraj and Murthy 1986; Sridharan and Nagaraj 2000; Giasi et al. 2003). In addition to these particular conditions, a large number of empirical equations have been published which are applicable to all clays.

Many researchers have used single parameter models for the estimation of compression index, such as liquid limit, natural water content or in-situ void ratio, although others recommend multiple soil parameter models for the estimation of the compression index.

Some widely used equations for the estimation of compression index which are valid for all clays are presented in Table 1. It should be noted that the majority of these equations are linear in form.

This study compares the performance of some widely used empirical compression index equations applicable to

all clays. New empirical equations relating the compression index with other parameters of fine grained soil are proposed using the least squares regression technique. In addition to empirical equations, a neural network model is also developed for the estimation of compression index.

Database compilation

The data includes tests undertaken specifically for this research (77) and 58 results from Herrero (1980). In addition to the oedometer tests, natural water content (w_n), initial void ratio (e_o), liquid limit (w_L), plastic limit (w_p), plasticity index (I_p), specific gravity of soil particles (G_s), dry unit weight (γ_d) and natural unit weight (γ_n) were used. Whilst the new results are from different parts of Turkey, those from Herrero (1980) were obtained on undisturbed soil samples from different parts of America. Although Herrero (1980) presented results from 90 samples, as some physical-index properties were not reported, only 58 were used in this study. The conventional oedometer tests in both studies were undertaken following ASTM D 2435 (1996) and the other tests according to the relevant ASTM standards.

The oedometer test requires undisturbed soil samples. Clearly, some degree of disturbance is unavoidable, which causes deviation on the e -log p plot. Schmertmann (1953) described a procedure to obtain the equivalent of a field

Table 1 Some widely used compression index equations applicable to all clays

Independent variable	Equation	Reference
Single variable equations		
w_n	$C_c = 0.01 (w_n - 5)$	Azzouz et al. (1976)
	$C_c = 0.01w_n$	Koppula (1981)
	$C_c = 0.01 (w_n - 7.549)$	Herrero (1983b)
e_o	$C_c = 0.40 (e_o - 0.25)$	Azzouz et al. (1976)
	$C_c = 0.30 (e_o - 0.27)$	Hough (1957)
	$C_c = 0.54 (e_o - 0.35)$	Nishida (1956)
w_L	$C_c = 0.006 (w_L - 9)$	Azzouz et al. (1976)
	$C_c = (w_L - 13)/109$	Mayne (1980)
	$C_c = 0.009 (w_L - 10)^a$	Terzaghi and Peck (1967)
Multi-variable equations		
	$C_c = 0.40 (e_o + 0.001w_n - 0.25)$	Azzouz et al. 1 (1976)
	$C_c = 0.37 (e_o + 0.003w_L - 0.34)$	Azzouz et al. 2 (1976)
	$C_c = 0.37 (e_o + 0.003w_L + 0.0004w_n - 0.34)$	Azzouz et al. 3 (1976)
	$C_c = 0.009w_n + 0.002w_L - 0.10$	Azzouz et al. 4 (1976)
	$C_c = 0.141 G_s^{1.2} [(1 + e_o)/G_s]^{2.38}$	Herrero 1 (1983a)
	$C_c = 0.185[G_s (\gamma_w/\gamma_d)^2 - 0.144]$	Herrero 2 (1983b)
	$C_c = 0.141 G_s (\gamma_w/\gamma_d)^{12/5}$	Herrero 3 (1983b)
	$C_c = -0.156 + 0.411e_o + 0.00058w_L$	Al-Khafaji and Andersland (1992)
	$C_c = 0.2343(w_L/100) G_s$	Nagaraj and Murty (1985)
	$C_c = 0.009w_n + 0.005w_L$	Koppula (1981)

C_c compression index, w_n natural water content (%), e_o initial void ratio, w_L liquid limit (%), G_s specific gravity of soil particles, γ_w unit weight of water (g/cm^3), γ_d dry unit weight (g/cm^3)

^a This equation originally suggested by Skempton (1944) as $C_c = 0.007 (w_L - 10)$ for remoulded soils. Terzaghi and Peck (1967) extended the applicability of this equation for undisturbed normally loaded clays

(virgin) consolidation curve from the laboratory consolidation curve. This was followed in both the present study and by Herrero (1980).

Table 2 Descriptive statistics of variables used in the database

Variable	Minimum	Maximum	Mean	Standard deviation
w_n	12.0	62.0	27.7	10.2
e_o	0.365	1.780	0.806	0.276
w_L	23.9	112.9	52.3	18.9
w_p	0 (N.P.)	45.3	23.7	6.8
I_p	0 (N.P.)	82.4	28.7	14.3
G_s	2.51	2.82	2.68	0.063
γ_d	1.105	2.025	1.557	0.207
γ_n	1.593	2.650	1.970	0.148
C_c	0.041	0.567	0.218	0.101

w_n natural water content (%), e_o initial void ratio, w_L liquid limit (%), w_p plastic limit (%), I_p plasticity index (%), G_s specific gravity of soil particles, γ_d dry unit weight (g/cm^3), γ_n natural unit weight (g/cm^3), C_c compression index

In order to obtain an empirical equation which is valid for all clays, the database must include a sufficiently wide range of data. In order to assess the adequacy of the database, descriptive statistics and the frequency distribution of each data set were determined. Table 2 displays the descriptive statistics and Fig. 1 represents the histogram of each variable.

Comparison of existing equations

In order to evaluate the performance of empirical equations, root mean square error (RMSE) indices (Eq. 1) was used, following for example Alvarez Grima and Babuska 1999; Finol et al. 2001; Gokceoglu 2002; Yılmaz 2006).

$$RMSE = \sqrt{\frac{1}{n} \sum_1^n (C_{c_{est}} - C_{c_{lab}})^2} \tag{1}$$

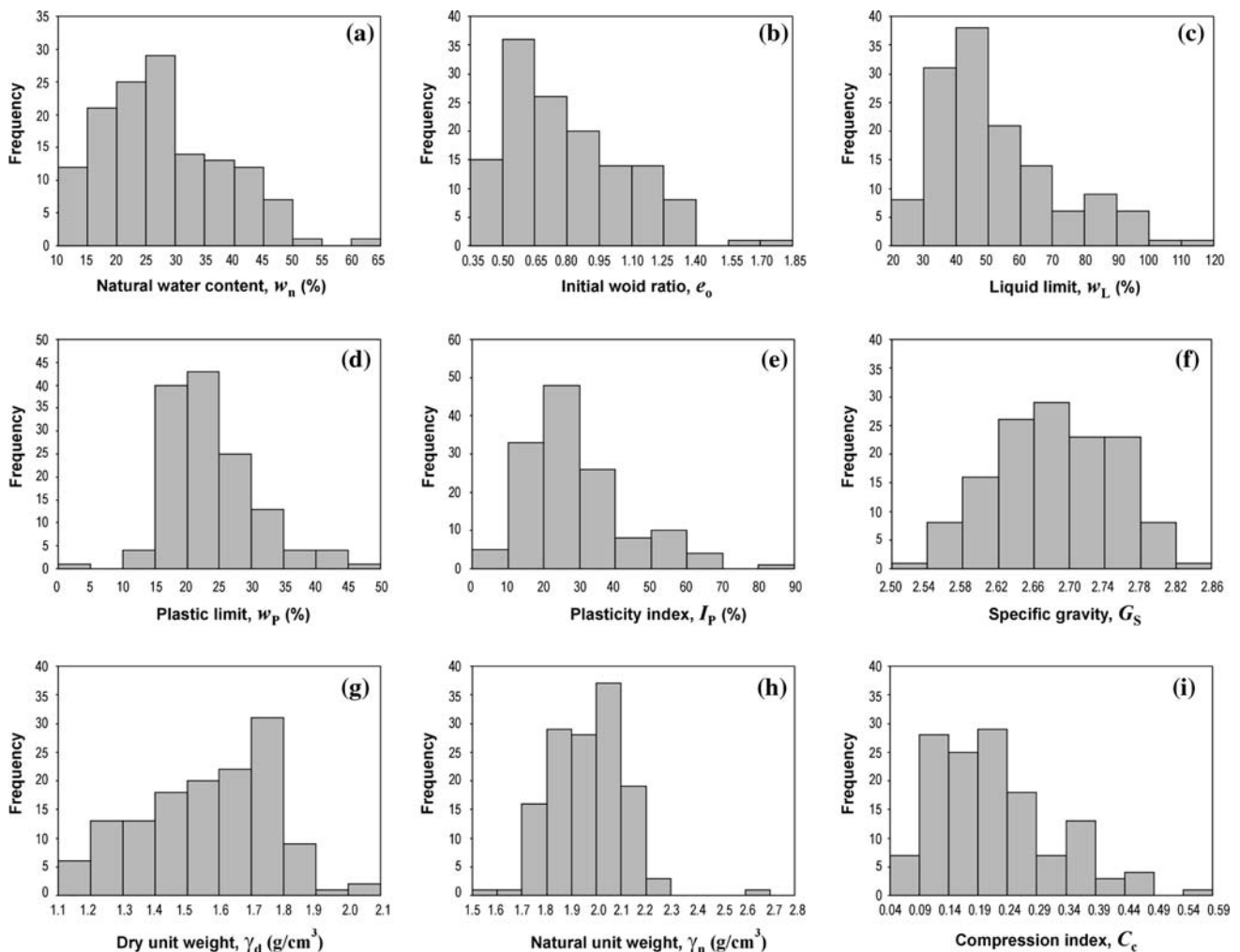


Fig. 1 Histograms of **a** natural water content, **b** initial void ratio, **c** liquid limit, **d** plastic limit, **e** plasticity index, **f** specific gravity of soil particles, **g** dry unit weight, **h** natural unit weight and **i** compression index

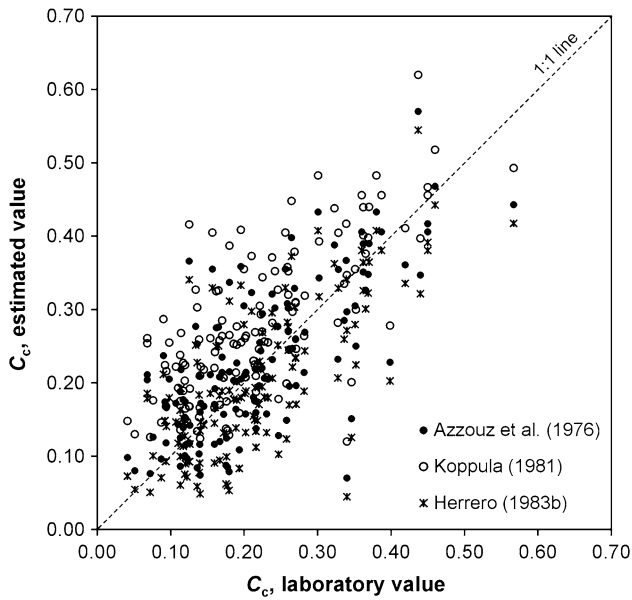


Fig 2 Comparison of single variable equations dependent on w_n

Where, n is the number of data points, Cc_{est} is the compression index estimated from empirical equations, Cc_{lab} is the compression index determined in laboratory. The lower the RMSE value, the better the model performance.

Figures 2, 3, 4 illustrate the performance of the single variable equations listed in Table 1; the RMSE are presented in Table 3. It can be seen that the performance of the three equations utilizing w_n as the predictor is very similar (Fig. 2). The equation with the lowest RMSE value (0.077) was that proposed by Azzouz et al. (1976) (Eq. 1 in Table 3). Nevertheless, as can be seen from Fig. 2, it still results in a considerable under-estimate of the compression index for some of the soil samples.

Among the single variable empirical equations utilizing e_o as the predictor, Azzouz et al. (1976)'s equation (Eq. 4 in Table 3) again shows the best performance with the lowest RMSE index. It is clear from Fig. 3 that the Hough (1957) equation generally under-estimates the compression index, while Nishida's (1956) equation generally gives an over-estimate.

As can be seen from Fig. 4, the general performance of single variable equations based on w_L are not as good as those based on w_n and e_o . All the w_L based single variable equations over-estimate the compression index.

As noted above, some researchers recommended multiple soil parameter models for the estimation of the compression index. This is very logical as a number of different factors control the amount of consolidation settlement of fine grained soils. The performance of the multi-variable equations proposed by Azzouz et al. (1976) are presented in Fig. 5, those proposed by Herrero (1983a, b) in Fig. 6 and those by Al-Khafaji and Andersland

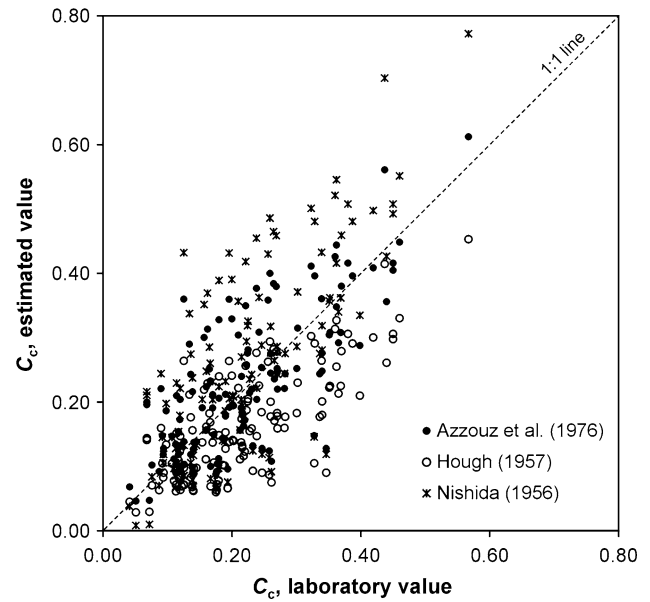


Fig 3 Comparison of single variable equations dependent on e_o

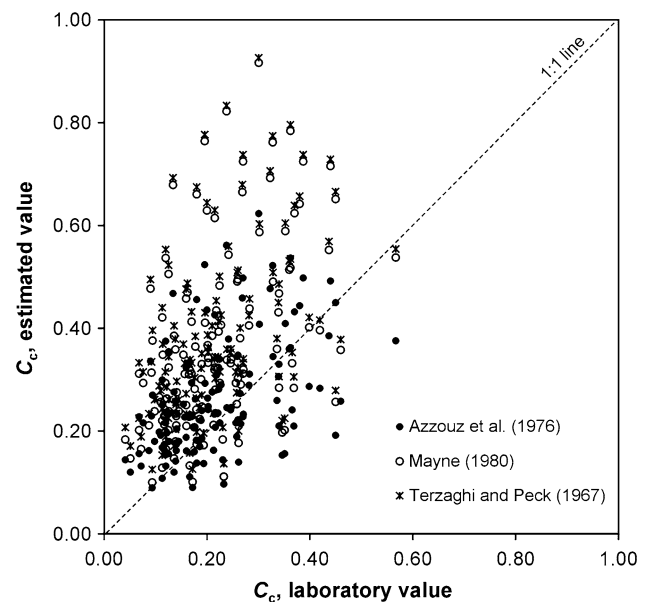


Fig 4 Comparison of single variable equations dependent on w_L

(1992), Nagaraj and Murty (1985), and Koppula (1981) in Fig. 7.

All the multi-variable equations proposed by Azzouz et al. (1976) gave good results (Fig. 5); the best using e_o and w_n (Eq. 10 in Table 3). This is consistent with the results obtained using their single variable equation, when that using w_L was found to be less accurate than those using e_o and w_n .

Figure 6 shows that the Herrero 2 (1983b) and Herrero 3 (1983b) equations generally under-estimate the compression index, with the lowest RMSE recorded for Herrero 1 (1983a).

Table 3 RMSE indices of the assessed equations

Eq. No.	Equation	Reference	RMSE
One variable equations			
1	$C_c = 0.01 (w_n - 5)$	Azzouz et al. (1976)	0.0777
2	$C_c = 0.01w_n$	Koppula (1981)	0.0972
3	$C_c = 0.01 (w_n - 7.549)$	Herrero (1983b)	0.0788
4	$C_c = 0.40 (e_o - 0.25)$	Azzouz et al. (1976)	0.0768
5	$C_c = 0.30 (e_o - 0.27)$	Hough (1957)	0.0888
6	$C_c = 0.54 (e_o - 0.35)$	Nishida (1956)	0.1046
7	$C_c = 0.006 (w_L - 9)$	Azzouz et al. (1976)	0.1187
8	$C_c = (w_L - 13)/109$	Mayne (1980)	0.2104
9	$C_c = 0.009 (w_L - 10)$	Terzaghi and Peck (1967)	0.2228
Multi-variable equations			
10	$C_c = 0.40(e_o + 0.001w_n - 0.25)$	Azzouz et al. 1 (1976)	0.0799
11	$C_c = 0.37(e_o + 0.003w_L - 0.34)$	Azzouz et al. 2 (1976)	0.0822
12	$C_c = 0.37(e_o + 0.003w_L + 0.0004w_n - 0.34)$	Azzouz et al. 3 (1976)	0.0837
13	$C_c = 0.009w_n + 0.002w_L - 0.10$	Azzouz et al. 4 (1976)	0.0956
14	$C_c = 0.141 G_s^{1.2} [(1 + e_o)/G_s]^{2.38}$	Herrero 1 (1983a)	0.0740
15	$C_c = 0.185[G_s (\gamma_w/\gamma_d)^2 - 0.144]$	Herrero 2 (1983b)	0.0756
16	$C_c = 0.141 G_s (\gamma_w/\gamma_d)^{12/5}$	Herrero 3 (1983b)	0.1058
17	$C_c = -0.156 + 0.411e_o + 0.00058w_L$	Al-Khafaji and Andersland (1992)	0.0833
18	$C_c = 0.2343(w_L/100) G_s$	Nagaraj and Murty (1985)	0.1583
19	$C_c = 0.009w_n + 0.005w_L$	Koppula (1981)	0.3204

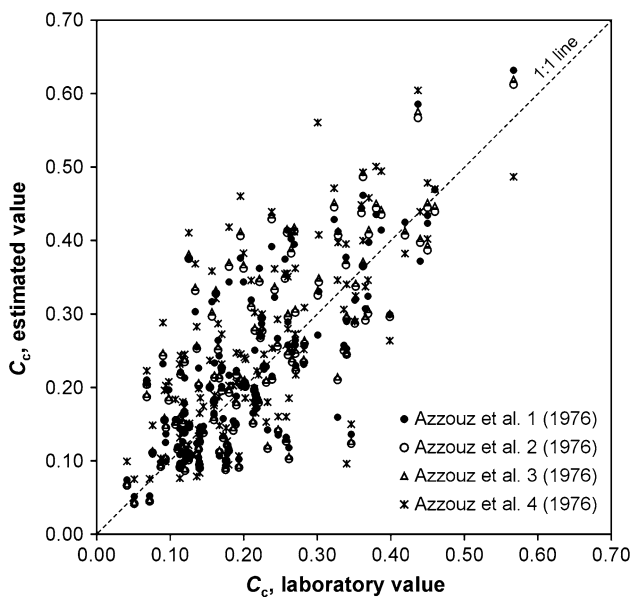


Fig. 5 Comparison of multi-variable equations proposed by Azzouz et al. (1976)

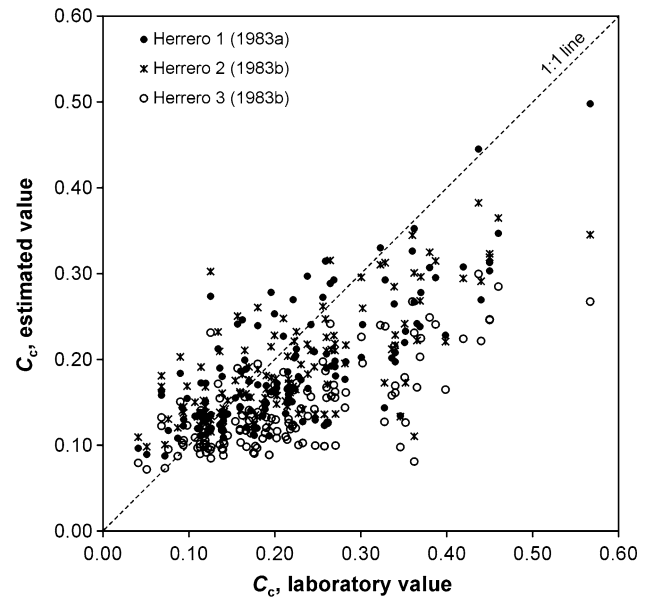


Fig. 6 Comparison of multi-variable equations proposed by Herrero (1983a, b)

Figure 7 clearly demonstrates that the Koppula (1981) and Nagaraj and Murty (1985) multi-variable equations significantly over-estimate the compression index, with relatively high RMSE indices (Table 3). The equation from Al-Khafaji and Andersland (1992) gives a relatively lower RMSE.

Development of new empirical equations

Using the same database, a correlation matrix was generated (Table 4) to identify the relationship between the parameters. This indicates a strong positive relationship between w_n , e_o , w_L and C_c , and a strong negative

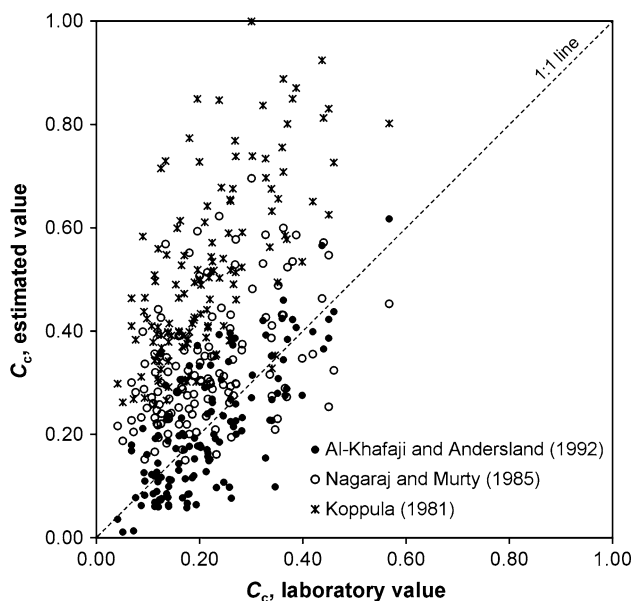


Fig. 7 Comparison of multi-variable equations proposed by Koppula (1981), Nagaraj and Murty (1985), and Al-Khafaji and Andersland (1992)

relationship between γ_d , γ_n and C_c . Both multiple linear and multiple non-linear regression analyses were performed utilizing the variables with good correlation with the compression index. After trying numerous combinations with all parameters, one linear and one non-linear equation with the highest regression coefficient and lowest RMSE index were determined. These equations and their RMSE indices are given in Table 5 and their performance compared in Fig. 8.

It can be seen that the proposed non-linear equation (Eq. 1) is slightly better than the linear one. However, the RMSE indices of both are lower than those achieved using

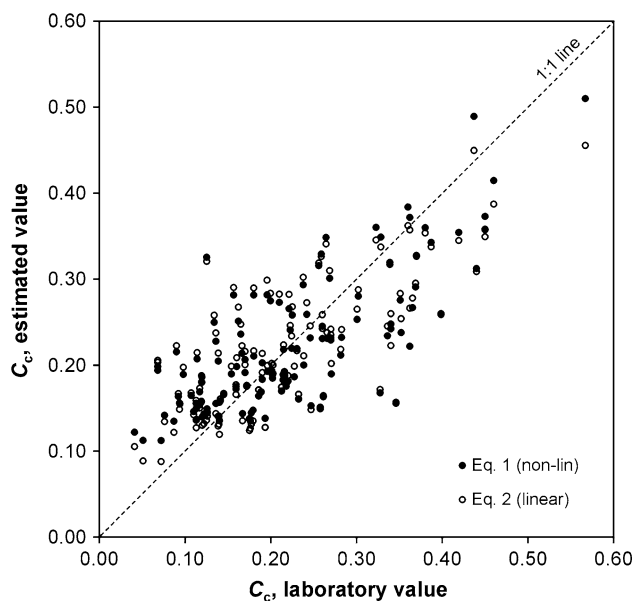


Fig. 8 Comparison of new suggested empirical equations

the single and multi-variable equations previously proposed. The non-linear equation developed in this study is compared with the equations proposed by Herrero 1 (1983a) and Azzouz et al. 1 (1976) in Fig. 9, where it can be seen that the proposed non-linear equation results in points more closely located around the 1:1 line.

Artificial neural network-based compression index estimation

In recent times, artificial neural networks (ANNs) have been applied to many geotechnical engineering tasks and

Table 4 Correlation matrix of parameters

Parameters	w_n	e_o	w_L	w_p	I_p	G_s	γ_d	γ_n	C_c
w_n	1.00	0.93	0.65	0.31	0.52	-0.04	-0.89	-0.60	0.71
e_o	0.93	1.00	0.65	0.37	0.50	-0.05	-0.89	-0.67	0.74
w_L	0.65	0.65	1.00	0.47	0.81	-0.14	-0.63	-0.45	0.47
w_p	0.31	0.37	0.47	1.00	0.64	-0.22	-0.31	-0.24	0.16
I_p	0.52	0.50	0.81	0.64	1.00	0.00	-0.50	-0.37	0.37
G_s	-0.04	-0.05	-0.14	-0.22	0.00	1.00	0.11	0.13	-0.08
γ_d	-0.89	-0.89	-0.63	-0.31	-0.50	0.11	1.00	0.89	-0.70
γ_n	-0.60	-0.67	-0.45	-0.24	-0.37	0.13	0.89	1.00	-0.54
C_c	0.71	0.74	0.47	0.16	0.37	-0.08	-0.70	-0.54	1.00

Bold values indicates relatively high correlations

Table 5 Suggested empirical equations for the estimation of compression index

Equation No.	Equation	Correlation coefficient, r	RMSE
1	$C_c = 0.1597 (w_n^{-0.0187}) (1 + e_o)^{1.592} (w_L^{-0.0638}) (\gamma_d^{-0.8276})$	0.754	0.0661
2	$C_c = 0.151 + (0.001225 w_n) + (0.193 e_o) - (0.000258 w_L) - (0.0699 \gamma_d)$	0.746	0.0671

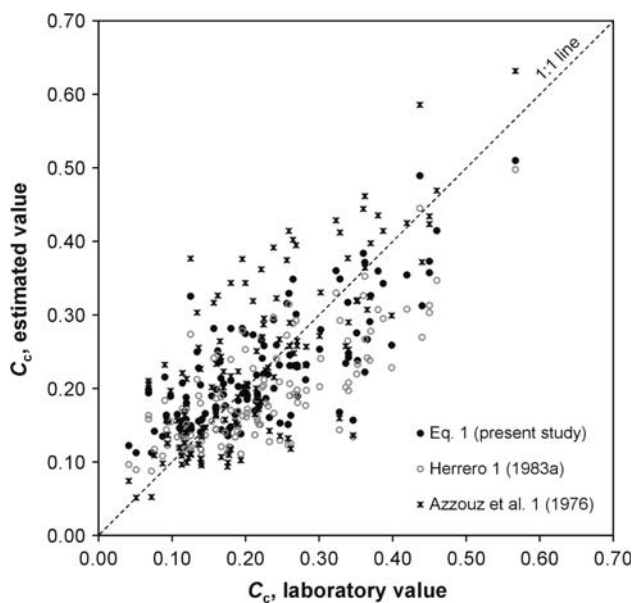


Fig. 9 Comparison of new suggested empirical equation and previously proposed multi-variable equation showing the best performance

have demonstrated some degree of success (Shahin et al. 2002). They are a form of artificial intelligence which tries to simulate the human brain in a very crude way. The purpose of ANNs is to set a relationship between model inputs and outputs by continuously updating connection weights according to inputs–outputs. The main advantage of ANNs is that they are very flexible, and complex relationships between inputs and outputs can be discovered by changing the model structure and connection weights. In addition, a previously developed (trained) network can easily be updated when new datasets become available. However, ANNs have an important disadvantage in not being transparent as a closed form equation.

Neural network model development involves six main stages: determination of input and output variables; grouping of database as training and validating datasets; determination of network structure; optimization of connection weights, stopping criteria; and validation of the neural network. In order to obtain good predictions from an ANN, a large set of data is needed which must be diverse as ANNs are unable to extrapolate beyond the range of the training data. As described previously the database used in this study covered a wide range. All the available parameters (w_n , e_o , w_L , w_p , I_p , G_s , γ_d , γ_n) were used as input variables, scaled between 0 and 1 as recommended by Masters (1993).

It is common practice to divide the available data into two subsets; a training set to construct the neural network model and an independent validation set to estimate model performance (Twomey and Smith 1997). Approximately 80% of the data were used for training and 20% for

validation. The validation data were selected to cover a wide range of compression index values.

Determination of a network structure involves the selection of the number of hidden layer nodes. Hornik et al. (1989) showed that a network with one hidden layer can approximate any continuous function provided that sufficient connection weights are used; therefore, in this study a network with one hidden layer is used and the number of hidden layer nodes was increased until a good model was achieved. During the training stage (i.e. optimization of connection weights) the aim is to find a global solution to what is typically a highly non-linear optimization problem (Shahin et al. 2002). Feed-forward neural networks with back propagation algorithms are the most widely used method (Rumelhart et al. 1986). Therefore, in this study a back propagation algorithm was used during training with a 0.6 momentum and 0.8 learning rate. Stopping criteria are used to decide whether to stop the training process or not; in this study the training process was stopped when the average error was below 0.02.

Figure 10 displays the architecture of the neural network for prediction of the compression index and the relative connection weights. Figure 11 shows the laboratory-determined scaled compression index values versus the ANN estimated scaled compression index values of training data. The RMSE of the validation data was calculated as 0.051, which is considerably better than the RMSE of 0.0661 (Eq. 1 in Table 5) achieved by the best empirical equation. In addition to the lower RMSE of the ANN estimations, laboratory determined versus ANN estimated compression index values are more closely spread around the 1:1 line (Fig. 11).

Summary and conclusions

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 135 wide-ranging test data. The results indicate that the single variable model of Azzouz et al. (1976), utilizing initial void ratio as the predictor, has the lowest RMSE index while for the multi-variable models, Herrero's (1983a) equation gave the best performance (RMSE 0.0740) using initial void ratio and specific gravity of soil particles as predictor variables.

Using the same database, new multi-variable empirical equations (both linear and non-linear) were developed using least square regression analysis. In these equations natural water content, initial void ratio, liquid limit and dry unit weight were used as the predictor variables as a correlation matrix indicated these have a strong relationship with compression index. The new equations gave a slightly

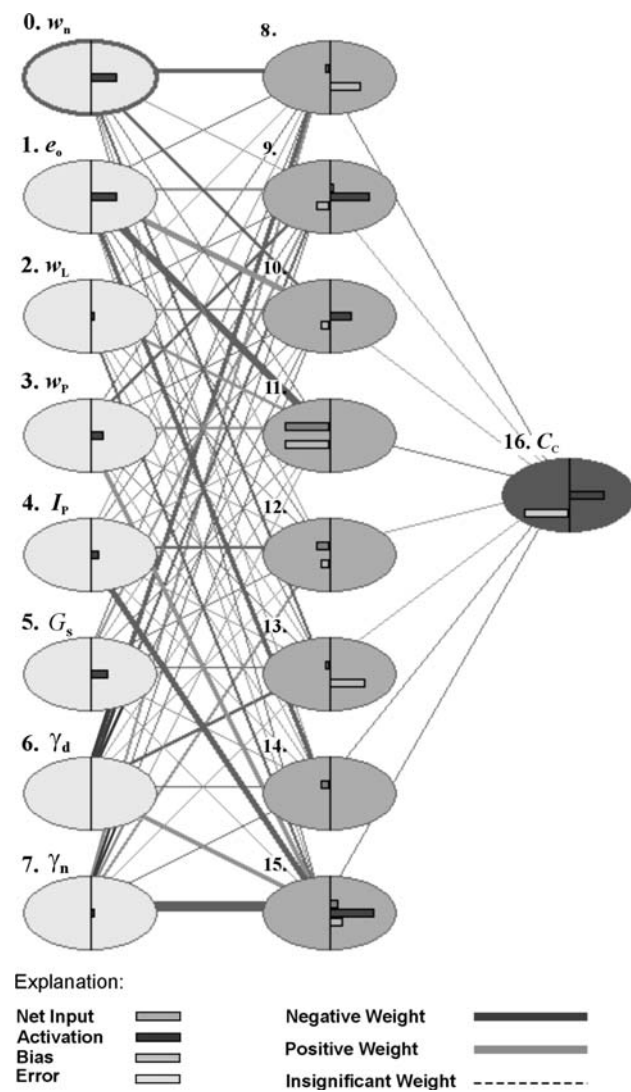


Fig. 10 Architecture of the neural network and relative connection weights

lower RMSE index than the existing single or multi-variable empirical equations.

In addition, an ANN was developed using all the parameters in the compiled database as predictor variables. The network had one hidden layer and eight hidden layer nodes. Back propagation algorithm was used to train the network. Approximately 80% of the data were used for training and 20% for validation. The RMSE of the validation data was calculated as 0.051, which is significantly lower than that for of the empirical equations obtained from regression analysis.

It should always be kept in mind that some environmental factors such as fabric and cementation could not be considered in any of the empirical equations. In view of this, it must be pointed out that these equations may be useful only for the preliminary estimation of the compression index. In order to improve the usefulness of the

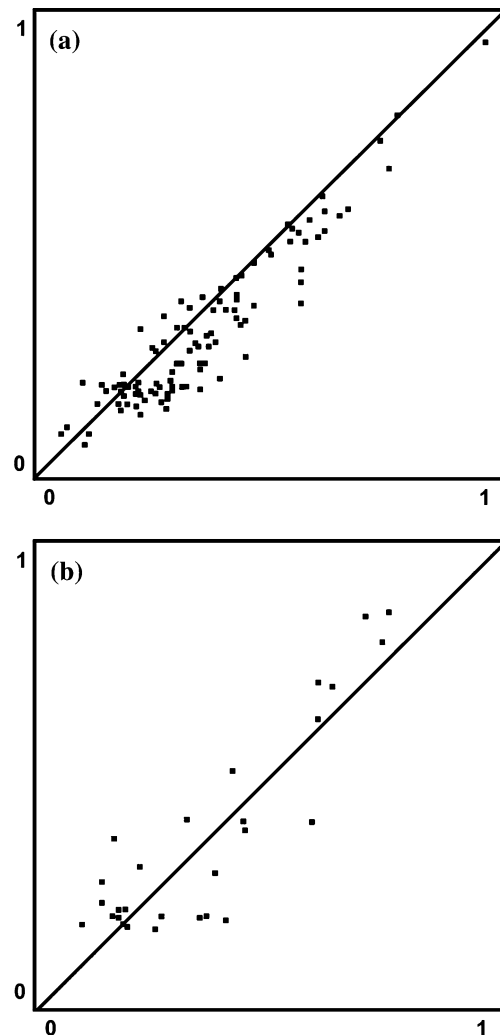


Fig. 11 Laboratory determined scaled compression index values versus ANN estimated scaled compression index values, **a** result of training process, **b** result of validating process

equations, the procedure suggested by Bowles (1996) can be applied, i.e. at least one oedometer test should be performed on a sample taken from the area of interest and an empirical equation which gives the closest estimate selected.

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