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Prediction of the compression index of saturated clays (C_c) using polynomial models

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Abstract. Settlement-based design for shallow foundation realizing consolidation aspect is a major task of geotechnical engineer. Compression index (C_c) from the oedometer test is used to estimate the consolidation settlement of clays. Since the determination of C_c from oedometer tests is relatively time-consuming, empirical equations, based on index properties, can be useful for settlement estimation. Empirical correlations have been proposed to relate C_c of clay deposits to other soil parameters. New polynomial models are proposed for correlation. In order to assess the merits of the proposed approach, a database containing 352 data points has been compiled from case histories via geotechnical investigation sites in the province of Mazandaran, along southern shoreline of the Caspian Sea, Iran. We compare our results, involving polynomial fitting with earlier results of statistical correlation relations, with other geotechnical soil properties. The predicted values using our model are checked with the measured ones to evaluate the performance of the polynomial model. The results suggest that the newly proposed approach of correlation provides a means for recognizing, more efficiently, the patterns in the data and predicting the C_c, reliably.

1. Introduction

Geomaterials are extremely complex in terms of their stress-strain-time dependent behavior. It is due to the non-linear stress-strain relationships of soil, time dependent response to loading, elasto-plastic performance under loading and unloading situation, and effects of stress history (pre-consolidation) [1-3]. For any earthen structure, a transition element is used to carry the loads from super-structure to substructure or naturally deposited materials [4-6]. Bearing capacity, settlement, and structural design are major aspects for foundation engineering practice. Among three common occurrence settlement components, i.e. immediate, creep, and consolidation time dependents, the latter plays an important role in geotechnical engineering [7-9].

Settlement prediction, especially of the time-dependent one, called consolidation in saturated clays, is an important issue in geotechnical engineering. Several researchers have predicted settlement by probabilistic measurements, analytical methods, regression analysis, and simplified methods [10].

To calculate settlement for clays, laboratory consolidation tests, which depict one-dimensional compression behavior, need to be performed on samples taken from representative locations [11].

In settlement calculation for clays, in case of Normally Consolidated (NC) condition, only the compression index (C_c) from the conventional oedometer test is required. If Over-Consolidated (OC), then, both compression and recompression (C_r) indices are necessary. C_r must be obtained to compute the level

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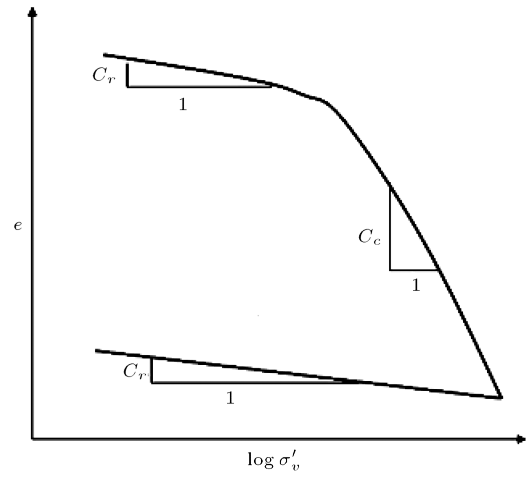

Figure 1. Definition of C_c and C_r indices.

of settlement for OC clays as opposed to NC clays (Figure 1).

For NC clay deposit, the settlement due to an increase in load can be determined from the following equation:

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

In over-consolidated if $\sigma'_{v0}+\Delta\sigma_v \le \sigma'_c$, then:

$$S_c = \frac{C_r H}{1+e_0} \log\left(\frac{\sigma'_{v0}+\Delta\sigma_v}{\sigma'_{v0}}\right), \tag{2}$$

and if $\sigma'_{v0}+\Delta\sigma_v > \sigma'_c$, then:

$$S_c = \frac{C_r H}{1+e_0} \log\left(\frac{\sigma'_c}{\sigma'_{v0}}\right) + \frac{C_c H}{1+e_0} \log\left(\frac{\sigma'_{v0}+\Delta\sigma_v}{\sigma'_c}\right), \tag{3}$$

where:

e_0	Initial void ratio;
$\Delta\sigma_v$	Stress increment;
σ'_c	Pre-consolidation pressure;
σ'_{v0}	Initial vertical effective stress;
C_c	Compression index;
C_r	Recompression index.

As the oedometer test in laboratory takes a much longer time than simpler index property tests, various attempts have been made to estimate the C_c from other geotechnical tests, which are carried out more easily. Many researchers have used single-parameter models for estimation of the compression and recompression indices; i.e. liquid limit (LL %), natural water content (ω_n%), or in-situ void ratio (e_0) [12-19]. However, others recommend multiple soil-parameter models [12-14, 20-24] for the estimation of C_c.

As presented in Table 1, several types of empirical correlations (one- and multi-variable equations) are selected. Moreover, easily obtainable fundamental characteristics of soils, which are of the same origin and/or from the same area, can be used to find the C_c indices of fine grained soils by these formulae.

The aim of this study is to propose and test a polynomial model for the prediction of C_c from the measured geotechnical soil parameters, w_n, LL, e_0, G_s, and γ_d. In this paper, first, current method is discussed briefly, then, a field database and the suggested polynomial model are presented and followed by a validation of this model on the field database.

2. Modelling using a polynomial function

The basic assumption is that a pair of input parameters can be connected through a polynomial function to outputs. The task is to find a function $\hat{f}$ that can be proximate to an observed function f in order to produce the value of the output $\hat{y}$ for a given value of the input vector, $X=(x_1,x_2,x_3,...,x_n)$, such that the difference between $\hat{y}$ and y is minimum. Therefore, for a given M observations of multi-input, single output data pairs are:

$$y_i = f(x_{i1},x_{i2},x_{i3},...,x_{in}), \tag{4}$$

where, $i=1,2,...,M$. It is possible to use a polynomial function to predict the output value ($\widehat{y_l}$) for any given input vector, $X=(x_{i1},x_{i2},x_{i3},...,x_{in})$, such that:

$$\widehat{y_l} = \hat{f}(x_{i1},x_{i2},x_{i3},...,x_{in}), \tag{5}$$

where, $i=1,2,...,M$. The challenge is to define a polynomial function such that the square of the differences between the observed output and the predicted one is minimum:

$$\sum_{i=1}^{M}\left[\hat{f}(x_{i1},x_{i2},x_{i3},...,x_i)-y_i\right]^2 \rightarrow \min. \tag{6}$$

The general connection between input and output variables can be expressed by a discrete form of the Volterra functional series, known as Kolmogorov-Gabor polynomial (Ivakhnenko, A.G., 1971 "Polynomial theory of complex systems", *IEEE Trans. Syst. Man Cybern*, **4**, pp. 364-378). Hence:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + ... \tag{7}$$

This mathematical description can be represented by a

Table 1. Some widely used compression index equations.

	Independent variable	Equation	References
Single-variable equations	ω_n	$C_c = 0.01\omega_n - 0.05$	Azzouz et al. [13]
		$C_c = 0.01\omega_n$	Koppula [14]
		$C_c = 0.01\omega_n - 0.075$	Herrero [15]
		$C_c = 0.013\omega_n - 0.115$	Park and Lee [12]
	e_0	$C_c = 0.49e_0 - 0.11$	Park and Lee [12]
		$C_c = 0.4(e_0 - 0.25)$	Azzouz et al. [13]
		$C_c = 0.287e_0 - 0.015$	Ahadiyan et al. [16]
		$C_c = 1.02 - 0.95e_0$	Gunduz et al. [17]
	LL	$C_c = 0.006(\text{LL} - 9)$	Azzouz et al. [13]
		$C_c = (\text{LL} - 13)/109$	Mayne [18]
		$C_c = 0.009(\text{LL} - 10)$	Terzaghi and Peck [19]
		$C_c = 0.014\text{LL} - 0.168$	Park and Lee [12]
Multi-variable equations	LL, G_s	$C_c = 0.2926(\frac{\text{LL}}{100}).G_s$	Park and Lee [12]
	ω_n, LL	$C_c = 0.009\omega_n + 0.005\text{LL}$	Koppula [14]
		$C_c = 0.009\omega_n + 0.002\text{LL} - 0.1$	Azzouz et al. [13]
	e_0, ω_n	$C_c = 0.4(e_0 + 0.001\omega_n - 0.25)$	Azzouz et al. [13]
	e_0, LL	$C_c = -0.156 + 0.411e_0 + 0.00058\text{LL}$	Andersland [20]
		$C_c = -0.023 + 0.271e_0 + 0.001\text{L}$	Mitchell and Gardner[21]
	e_0, ω_n, LL	$C_c = 0.37(e_0 + 0.003\text{LL} + 0.0004\omega_n - 0.34)$	Azzouz et al. [13]
		$C_c = -0.404 + 0.341e_0 + 0.006\omega_n + 0.004\text{LL}$	Yoon and Kim [22]
	G_s, e_0	$C_c = 0.141G_s^{1.2}[(1 + e_0)/G_s]^{2.38}$	Hornig [23]
	$\omega_n, \text{LL}, e_0, \gamma_d$	$C_c = 0.1597(\omega_n^{-0.0187})(1 + e_0)^{1.592}(\text{LL}^{-0.0638})(\gamma_d^{-0.8276})$	Ozer [24]
		$C_c = 0.151 + 0.001225\omega_n + 0.193e_0 - 0.000258\text{LL} - 0.0699\gamma_d$	Ozer [24]

system of quadratic polynomials consisting of only two variables in the form of:

$$\hat{y} = G(x_i, x_j) = a_0 + a_1x_i + a_2x_j + a_3x_ix_j + a_4x_i^2 + a_5x_j^2. \quad (8)$$

The coefficients, a_i, in Eq. (5) are calculated using regression analysis so that the difference between the observed output y and the calculated one, $\hat{y}$, for each pair of x_i and x_j as input variables is minimum:

$$E = \frac{1}{M}\sum_{i=1}^{M}(y_i - G_i)^2 \rightarrow \min. \quad (9)$$

Using the quadratic expression in Eq. (5) for each of the M rows, the following matrix can be obtained:

$$Aa = Y, \quad (10)$$

where a is the vector of unknown coefficients for the quadratic polynomial function in Eq. (5) and Y is the vector of output values from observation. Then, A takes the form:

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ . & . & . & . & . & . \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{bmatrix}_{M\times 6} \quad (11)$$

A least-squares optimization approach for multiple regression analysis leads to the solution of the normal equations:

$$a = (A^TA)^{-1}A^TY. \quad (12)$$

This gives the vector of the best-fit coefficients for Eq. (5) for the whole set of M data triplets.

3. Database compilation

Databases have collected the data from 352 consolidation tests for soils sampled at 95 construction sites in province of Mazandaran, Iran [25]. Following the previous trend of studies, in this study, C_c 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 (G_s). The compiled database contains 352 records produced by the Technical and Soil Laboratory of Mazandaran Province of Iran, which is one of the most experienced consultants in the country, as summarized in Figures 2 and 3. The samples were all collected using a standard procedure and tests were carried out using ASTM D 2435-96.

The samples were all collected using a standard procedure and tests were carried out using ASTM D 2435-96.

4. Modelling compression index using a polynomial function

Based on Table 1, which shows previous efforts in predicting C_c, and using the polynomial model, 8 functions are introduced as follows:

$$\text{Function 1}: \; C_c = a_1 + a_2 w_n + a_3\mathrm{LL} + a_4 w_{n_2} + a_5\mathrm{LL}_2 + a_6 w_n\mathrm{LL},$$

$$\text{Function 2}: \; C_c = a_1 + a_2 G_s + a_3\mathrm{LL} + a_4 G_{s_2} + a_5\mathrm{LL}_2 + a_6 G_s\mathrm{LL},$$

$$\text{Function 3}: \; C_c = a_1 + a_2 e_0 + a_3\mathrm{LL} + a_4 e_{0_2} + a_5\mathrm{LL}_2 + a_6 e_0\mathrm{LL},$$

$$\text{Function 4}: \; C_c = a_1 + a_2\mathrm{LL} + a_3 e_0 + a_4\mathrm{LL}_2 + a_5 e_{0_2} + a_6 e_0\mathrm{LL}w_n + a_7 w_n + a_8 w_{n_2},$$

$$\text{Function 5}: \; C_c = a_1 + a_2 G_s + a_3 e_0 + a_4 G_{s_2} + a_5 e_{0_2} + a_6 e_0 G_s w_n + a_7 w_n + a_8 w_{n_2},$$

$$\text{Function 6}: \; C_c = a_1 + a_2\gamma_d + a_3\mathrm{LL} + a_4\gamma_{d_2} + a_5\mathrm{LL}_2 + a_6\gamma_d\mathrm{LL},$$

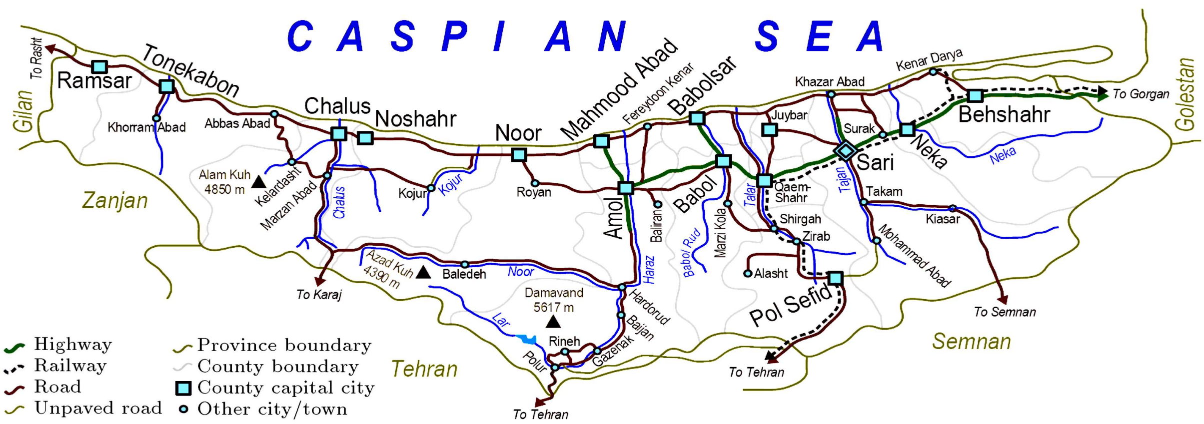

Figure 2. Location of descriptive data collection.

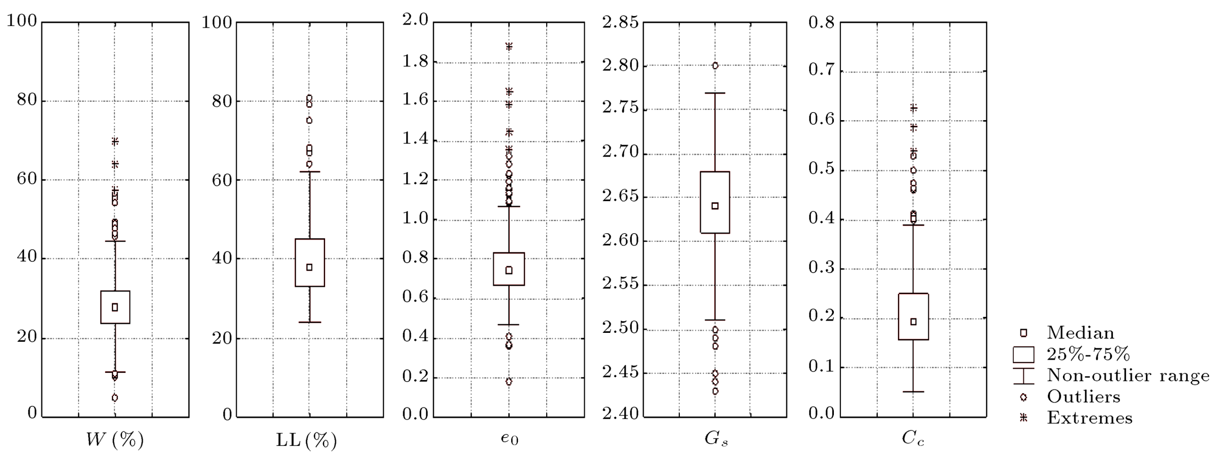

Figure 3. Descriptive statistics of variables.

Table 2. Coefficients of different functions.

a_i	Function 1	2	3	4	5	6	7	8
a_1	0.124401	-1.53507	-0.021526	-0.106924	2.801158	1.286989	1.183080	-4.16759
a_2	-0.001284	1.51988	0.233135	0.001286	-0.003871	-0.119995	-0.095982	0.41618
a_3	-0.000616	-0.00854	-0.000644	0.584375	-0.414050	0.006046	0.011880	4.61053
a_4	0.000045	-0.32568	-0.050804	-0.000015	-0.000009	0.002985	0.002083	-0.00998
a_5	-0.000015	0.00006	-0.000017	-0.195431	0.024656	-0.000007	-0.000050	-0.82259
a_6	0.000111	0.00222	0.004298	0.000054	0.000460	-0.000312	-0.000724	-0.23311
a_7	-	-	-	-0.004482	-0.242307	-	-	-
a_8	-	-	-	0.000040	0.005753	-	-	-

$$\text{Function 7}: \; C_c = a_1 + a_2\gamma_d + a_3 w_n + a_4\gamma_{d_2} + a_5 w_{n_2} + a_6 w_n\gamma_d w_n,$$

$$\text{Function 8}: \; C_c = a_1 + a_2\gamma_d + a_3 e_0 + a_4\gamma_{d_2} + a_5 e_{0_2} + a_6\gamma_d e_0,$$

where a_i are constant coefficients. The corresponding coefficients are shown in Table 2 for different combinations of soil condition.

The performances of polynomial models are shown in Figure 4.

The goodness of the fit between observation and model is evaluated thorough estimation of the variance (R^2), Root-Mean-Square Error (RMSE), Mean-Square-Error (MSE), and Mean Absolute Deviation (MAD):

$$R^2 = 1 - \left[\frac{\sum_1^M (C_{mi} - C_{pi})^2}{\sum_1^M (C_{mi})^2}\right], \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum_1^M (C_{mi} - C_{pi})^2}, \tag{14}$$

$$\text{MAPE} = \frac{\sum_1^M |C_{mi} - C_{pi}|}{\sum_1^M C_{mi}} \times 100, \tag{15}$$

$$\text{MAD} = \frac{\sum_1^M |C_{mi} - C_{pi}|}{M}. \tag{16}$$

The accuracy of the proposed models (see Table 3) for predicting C_c is compared with correlations presented earlier in [12-22] (see Table 1), which are shown in Table 4.

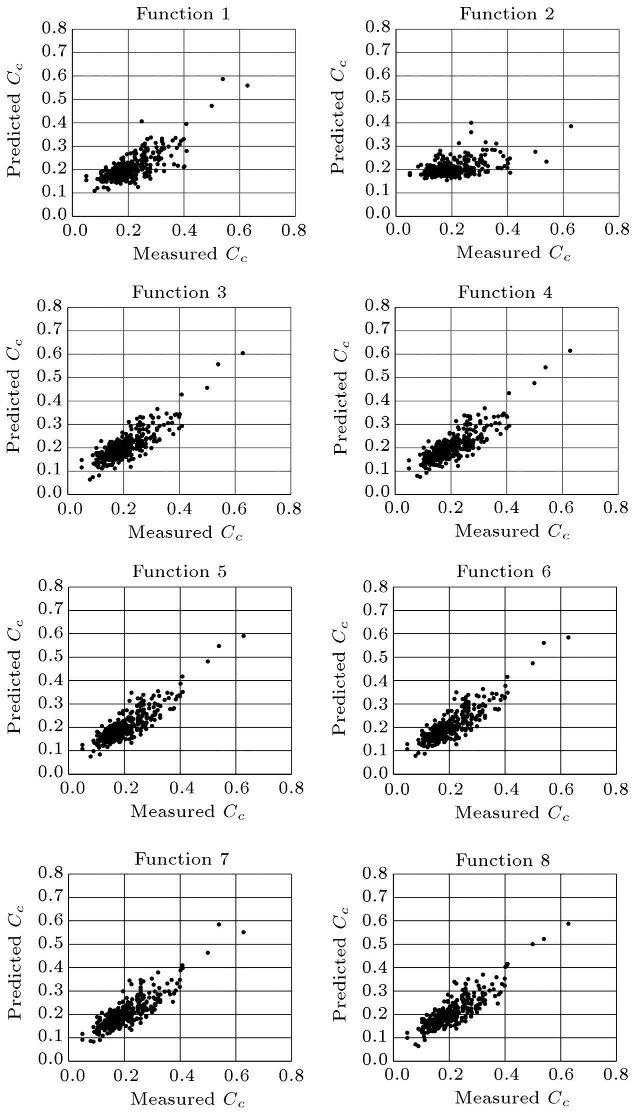

Figure 4. The performance of the functions in this study.

5. Conclusions

Relatively accurate prediction of time-dependent settlement has been a challenge in geotechnical engineering. To achieve this important purpose, considering different soil parameters, compiled in a database, can improve the process instead of relying solely on a couple of mini-scale and relatively disturbed odeometer test outputs.

We have proposed a new approach for correlation of C_c and geotechnical soil parameters, viz., w_n, LL, e_0,

Table 3. Statistical information for the polynomial model for predicting C_c.

	Function							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
R^2	0.949792	0.905944	0.962176	0.962372	0.968529	0.967752	0.96691	0.967406
RMSE	0.04895	0.066998	0.042486	0.042376	0.038755	0.03923	0.039739	0.03944
MSE	0.002396	0.004489	0.001805	0.001796	0.001502	0.001539	0.001579	0.001555
MAD	0.038256	0.051587	0.03405	0.033769	0.031158	0.031258	0.031306	0.031198

Table 4. Statistical information for the previous models for predicting C_c.

Equation	R^2	**RMSE**	**MSE**	**MAD**
$C_c = 0.01\omega_n - 0.05$	0.914504	0.063876	0.00408	0.05223
$C_c = 0.01\omega_n$	0.799978	0.097703	0.009546	0.085753
$C_c = 0.01\omega_n - 0.075$	0.932479	0.056766	0.003222	0.044957
$C_c = 0.013\omega_n - 0.115$	0.849831	0.084656	0.007167	0.069448
$C_c = 0.49e_0 - 0.11$	0.870633	0.078574	0.006174	0.065142
$C_c = 0.4(e_0 - 0.25)$	0.956251	0.045693	0.002088	0.03666
$C_c = 0.287e_0 - 0.015$	0.954599	0.046548	0.002167	0.036931
$C_c = 1.02 - 0.95e_0$	0.17737	0.237041	0.056189	0.186696
$C_c = 0.006(\text{LL} - 9)$	0.876973	0.076625	0.005871	0.059162
$C_c = (\text{LL} - 13)/109$	0.789435	0.100245	0.010049	0.07632
$C_c = 0.009(\text{LL} - 10)$	0.744839	0.110351	0.012177	0.085795
$C_c = 0.014\text{LL} - 0.168$	0.788907	0.10037	0.010074	0.076895
$C_c = 0.2926(\text{LL}/100).G_s$	0.641566	0.130789	0.017106	0.110119
$C_c = 0.009\omega_n + 0.005\text{LL}$	0.4116	0.259551	0.067367	0.250593
$C_c = 0.009\omega_n + 0.002\text{LL} - 0.1$	0.91727	0.062835	0.003948	0.051422
$C_c = 0.4(e_0 + 0.001\omega_n - 0.25)$	0.951911	0.047906	0.002295	0.038758
$C_c = -0.156 + 0.411e_0 + 0.00058\text{LL}$	0.946186	0.050678	0.002568	0.040067
$C_c = -0.023 + 0.271e_0 + 0.001L$	0.950249	0.048727	0.002374	0.040886
$C_c = 0.37(e_0 + 0.003\text{LL} + 0.0004\omega_n - 0.34)$	0.959833	0.043783	0.001917	0.034929
$C_c = -0.404 + 0.341e_0 + 0.006\omega_n + 0.004\text{LL}$	0.878516	0.076143	0.005798	0.060311
$C_c = 0.141G_s^{1.2}[(1 + e_0)/G_s]^{2.38}$	0.924811	0.059902	0.003588	0.044856
$C_c = 0.1597(\omega_n^{-0.0187})(1 + e_0)^{1.592}(\text{LL}^{-0.0638})(\gamma_d^{-0.8276})$	0.270614	0.186572	0.034809	0.173611
$C_c = 0.151 + 0.001225\omega_n + 0.193e_0 - 0.000258\text{LL} - 0.0699\gamma_d$	17.3718	0.936361	0.876772	0.933046

G_s, and γ_d. We have assessed the performance of this approach in prediction of C_c. A polynomial function has been used to predict C_c based on geotechnical soil properties. A database, consisting of 352 consolidation tests, from the southern part of the Caspian Sea in Iran was compiled and used to evaluate the performance of the new approach. The polynomial model that we have proposed represents such mix of parameters. The proposed models for all combinations of parameters, except Function 2 (combination of G_s and LL), show good performance in predicting C_c. As seen in Tables 3 and 4, in comparison with the previous studies, this study operates well and the performance of the polynomial model is acceptable for each combination of soil parameters.

Results of this study confirm the conclusion reached by many earlier studies, that an empirical correlation between C_c and geotechnical parameters should only be used in a site-specific sense.

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Nomenclature

C_c	Compression index
C_r	Recompression index

e	Void ratio
e_0	Initial void ratio
G_s	Specific gravity of soil particles
H	Initial thickness of the soil layer
LL	Liquid limit (%)
PI	Plastic index (%)
ω_n	Natural water content (%)
$\Delta\sigma_v$	Stress increment
S_c	Primary consolidation settlement
σ'_c	Pre-consolidation pressure
σ'_{v0}	Initial vertical effective stress
σ'_v	Vertical effective stress
a_i	Constant of empirical equation
RMSE	Root mean square error
MAD	Mean absolute deviation
MAPE	Mean absolute percent error
R^2	Absolute fraction of variance
M	Total number of datasets
C_m	The measured C_c by the seismic measurements
C_p	The calculated C_c by empirical correlations

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