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Nonlinear regression methods and genetic algorithms for estimation of compression index of clays using toughness limit

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Abstract. Measurement or prediction of compression index (C_c) of soils is essential for assessment of total and differential settlement of structures. It is a well-known fact that this parameter is controlled by several index identifiers of soil including initial void ratio, Atterberg limits, overconsolidation ratio, specific gravity, etc. Many studies in the past proposed relationships for prediction of C_c based on different index properties. Therefore, this study aims to present a comparison of previously proposed equations for estimation of C_c. Data from literature was compiled, and a total of 90 and 623 test results on remolded and undisturbed specimens were used to question the validity of previously proposed equations. Nevertheless, the modeling ability of 7 and 12 equations for estimation of C_c of remolded and undisturbed soils were questioned by use of compiled data. Moreover, new empirical relationships based on initial void ratio and toughness limit for prediction of C_c was proposed by use of nonlinear multivariable regression and evolutionary based regression analyses. The results are promising-the performances of models established are quite acceptable, which are verified by statistical analyses.

Keywords: compression index; fine-grained soils; toughness limit

1. Introduction

It is well-known that a comprehensive geotechnical analysis involves laboratory and field testing. Disturbed samples obtained from field can be used to determine index properties in the laboratory, and a basic laboratory testing procedure is composed of determination of grain size distribution, Atterberg limits, specific gravity, unit weight, water content and several other parameters derived from these index properties. On the other hand, strength, compression and permeability characteristics of soils can be identified using tests on undisturbed specimens. Evaluation of amount of compression necessitates determination of compression indices: this is a time-consuming experimental process, particularly when several clay layers are encountered within efficient depth. However, a specimen is never completely undisturbed, during removal of overburden pressure, sampling, transport of specimens to laboratory, a non-negligible disturbance occurs. In this regard, use of correlations for estimation of several geotechnical parameters can save time and money. Besides, simple correlations can also be used for verification purposes.

In fact, apart from basic index parameters, many factors control the compressibility of soils. The use of liquid limit (*LL*) for estimation of compression parameters was questioned by several researchers in the past (Cherubini 1991, Al-Khafaji and Andersland 1992). Tsuchida (1999) found that, when soils were consolidated under stresses greater than preconsolidation stress, a reasonable correlation between the liquid limit and compressibility was observed. Sridharan and Nagaraj (2000) stressed that soils of same liquid limits, but different shrinkage and plastic limits (*SL*, *PL*) could show different compressional behaviors. Therefore, the authors advocate that liquid limit cannot be a single parameter used in prediction of compression characteristics, similar studies incorporating different independent parameters should be performed. Giasi *et al*. (2003) underlined that apart from the intrinsic compressional characteristics of soils, relationships taking the geological history and/or the initial void ratio (e_0) of the soil into account was somewhat better capable of representing the compressional potential of a soil. Cherubini and Giasi (2000) emphasize that independent variables should be considered to establish predictive relationships for compression index (C_c). It is proposed that the combination of e_0 and *LL* has a potential in estimation of C_c (Giasi *et al.* 2003).

Two features defining the compression properties of a soil are compression index and the precompression pressure, and these parameters are indicators of compressibility and stress history, respectively. Gregory *et al.* (2006) tries to evaluate different ways of estimating these parameters based on laboratory test data. The accuracy of preconsolidation pressure estimation and the magnitude of C_c generally increased with increasing clay content. Estimates of C_c based on sigmoidal curves were not remarkably different from the linear regression estimates. On the other hand, previous studies based on

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correlations between C_c and e_0 yielded good results (Gunduz and Arman 2007, Ahadiyan *et al.* 2008, Park and Lee 2011). Onyejekwe *et al*. (2015) assessed the validity of 18 empirical equations proposed in the literature used in estimation of C_c in terms of accuracy and precision for Missouri fine-grained soils. They found out that the equation proposed by Azzouz *et al.* (1976) based on *LL* and natural water content (w_n) was the best correlation with the least mean square error.

The large number of correlations applied to the same parameters is an indication of the variability inherent to the use of these correlations. Therefore, the use of these correlations in varying soil and in-situ conditions could lead to inefficient and cost-ineffective results (Onyejekwe *et al.* 2015, 2016). Besides, these approaches depend on simplified assumptions such as a linear behavior or production heuristics. This decreases the effectiveness of traditional regression methods when used in simulation of the complex heterogeneous behavior of soil (Shahin *et al*. 2009, Alavi and Gandomi 2011, Park and Lee 2011, Cai *et al*. 2015, Shahin 2015).

On the other hand, to overcome the limitations of traditional regression methods in geotechnical engineering, use of artificial neural network (ANN) models has shown a rapid progressive increase since the early nineties. ANN has an unprecedented capacity to learn from input–output training datasets and complex relationships between multidimensional data (Park and Cho 2010). Among the most important studies dealing with C_c, Kurnaz *et al*. (2016) used a one hidden layer ANN model with selected input parameters, including water content (w_n), *LL*, e_0, and plasticity index (*PI*), and two output parameters, i.e., C_c and recompression index (C_r) for fine-grained soils. They found out that the (4×20×2) ANN model can successfully predict the C_c with a reasonable accuracy. Alam *et al*. (2014) developed an ANN model to predict C_c of clay from a database consisting of 125 samples, using w_n, *LL*, e_0, and *PI* as inputs. Performance of a proposed 4×4×1 ANN model was much better than multiple regression analysis (MRA) models. Kumar and Rani (2011) established an ANN model of 5 inputs, a hidden layer with 8 neurons and a single output (C_c). They used 41 test results with inputs fines content (*FC*), *LL*, *PI*, maximum dry density (*MDD*), and optimum water content (*OWC*). Lastly, Benbouras et al. (2019) tried to propose a novel approach for an accurate estimation of C_c. To test the approach, they adopted a K-fold cross-validation technique based on several multilayer neural network models, genetic programming and multiple regression analysis. 373 oedometer test results were used to estimate the C_c from several physical parameters of soils. The results indicate that the performance of ANN with two hidden layers (7×14×4×1) was the best, compared with other models and the relationships suggested by previous studies.

Beginning with Skempton and Jones (1944), to date, many correlations were proposed for prediction of compression, strength and permeability characteristics of different types of soils, and some of these are concentrated on estimation of compression index (Table 1). These correlations are based on use of *LL, PL, PI,* e_0, void ratio at liquid limit (e_L), water content ratio ($WCR=w_n/LL$), initial porosity (n_0), consistency index (*CI*), specific gravity (G_s) and w_n as well as their combinations as independent parameters. Analyzing the enlisted equations in Table 1, it is understood that many relationships have high correlation coefficients which is the proof of strong relationships among above-mentioned parameters, however, it is evident that these relationships are produced for specific soil types and conditions, which raises questions about the common use of these equations. Besides, several relationships are obtained using local data, which causes a number of question marks about the applicability of the equations to data obtained from many parts of the world.

According to considerations of past researchers which a few are enlisted above, use of different parameters for estimation of C_c should be questioned. In this regard, following empirical equation suggested by Vinod and Sreelekshmy Pillai (2017) defines toughness limit (w_T) based on results of experiments performed using Barnes apparatus (Barnes 2013, Vinod and Sreelekshmy Pillai 2017)

$$w_T=PL + 0.42 \times PI \tag{1}$$

where *PI* is the difference between *LL* and *PL*. The empirical approach is based on measurement of applied loads on soil threads. Nevertheless, the thread diameter, nominal stresses and strains were determined for each rolling application, and the stress-strain variation of thread and toughness of the soil is determined with reducing diameter. The "toughness limit" is calculated as the water content at zero toughness level. In fact, toughness limit is simply the water content which behavior of fine-grained soils evolves from an adhesive-plastic like behavior to tough-plastic (Shimobe *et al.* 2023). As can be seen from Eq. (1), toughness limit is based on Atterberg limits, and is a reasonable way to numerically identify the workability of the soil. Shimobe *et al.* (2023a, b) list several studies in literature, revealing the usefulness of toughness limit in evaluation of geotechnical aspects of fine-grained soils, i.e. index, compression and even compaction identifiers.

Therefore, in this study, after an analysis of the validity of proposed equations for estimation of C_c, nonlinear multivariable regression and evolutionary based regression methods were employed to establish possible and plausible relationships for estimation of C_c, based on e_0 and w_T.

2. Compilation of database

Inspired from previous studies, it was considered that C_c of soils was affected by e_0, w_n, *LL*, *PI* and G_s. In addition, this study introduced w_T and combined parameter, *SSI* (the product of e_0 and w_T) named 'soil state index'. In this scope, data from various parts of the world concerning oedometer tests on undisturbed and remolded specimens were compiled. In this regard, results of 51 tests on remolded specimens from India (Kumar *et al*. 2016; Vinod and Bindu 2010),18 from Bangladesh (Anik 2019), 21 from China (Du *et al.* 2017) were used to constitute a database. In addition to seven empirical equations proposed in the past, two

Table 1 Previously published and proposed empirical equations for estimation of compression index (C_c) of normally consolidated (NC) clays

Type of equatio	Equation	Applicability	Reference
$C_c=f\,(LL)$	$C_c\,(C_c')=0.007\,(LL-7)$; $C_c\,(C_c')=0.007\,(LL-10)$	Remolded (Reconstituted) clays,	Skempton and Jones (1944) , Terzaghi and Peck (1967)
	$C_c=0.009\,(LL-10)$	Undisturbed (Intact) low to medium sensitive clays	Terzaghi and Peck (1967)
	$C_c=0.006\,(LL-9)$	Undisturbed all clays with LL＜100%	Azzouz *et al.* (1976)
	$C_c=0.015\,(LL-19)$	Undisturbed marine clays	Ogawa and Matsumoto (1978)
	$C_c=(LL-13)/109=0.0092\,(LL-12.9)$	Undisturbed all clays	Mayne (1980)
	$C_c=0.016\,(LL-14)$	Undisturbed marine clays	Liu *et al.* (2011)
$Cc=f\,(G_s, LL)$	$C_c=0.234\,G_s\,LL$	Remolded (Reconstituted) clays	Nagaraj and Miura (2001)
$C_c=f\,(LL, PL)$	$C_c=0.0173\,LL-0.0216\,PL\ (=0.666e_L-0.830e_P)$	Remolded (Reconstituted) clays	Habibbeygi *et al.* (2017)
$C_c=f\,(LL, PI)$	$C_c=0.002\,LL+0.0025\,PI-0.005$	Undisturbed clays	Singh and Noor (2012)
$C_c=f\,(LL, CI)$	$C_c=\{0.535\,(LL/100)-0.119\}\cdot CI^{-\{0.904-0.33\,(LL/100)\}}$	Undisturbed cohesive soils	Dey and Chattopadhay (2021b)
$C_c=f\,(PI)$	$C_c=PI/0.81$	Remolded (Reconstituted) clays	Biarez and Favre (1975)
	$C_c=(PI+26)/138$	Undisturbed all clays	Mayne (1980)
	$C_c=0.046+0.0104\,PI$	Remolded (Reconstituted) clays	Nakase *et al.* (1988)
	$C_c=PI/74=0.0135\,PI$	Remolded all soils	Kulhawy and Mayne (1990)
$C_c=f\,(G_s, PI)$	$C_c\,(C_c')=PIG_s/2\simeq1.35\,PI$	Remolded structureless clays	Wood (1990), Sharma and Bora (2015)
$C_c=f\,(w_n)$	$C_c=0.01\,(w_n-5)$	Undisturbed all clays	Azzouz, Krizek and Corotis (1976)
	$C_c=0.01w_n$	Undisturbed all clays	Koppula (1981)
	$C_c=0.0103w_n$	Undisturbed clays in uncemented condition	Nagaraj and Miura (2001)
	$C_c=0.0112w_n-0.0686$	Undisturbed clays	Gao *et al.* (2017)
$C_c=f\,(w_n, LL)$	$C_c=0.009\,w_n+0.002\,LL-0.10$	Undisturbed all clays	Azzouz *et al.* (1976)
$C_c=f\,(w_n, e_0)$	$C_c=0.40\,(e_0+0.001\,w_n-0.25)$	Undisturbed all clays	Azzouz *et al.* (1976)
	$C_c=-0.12459+0.00241\,w_n+0.34887\,e_0$	Undisturbed fine-grained soils	Dagdeviren *et al.* (2018)
$C_c=f\,(e_L)$	$C_c=0.234\,e_L$	Remolded (Reconstituted) clays	Nagaraj and Miura (2001)
	$C_c^{*}=0.257\,e_L-0.04$	Remolded (Reconstituted) clays	Burland (1990)
$C_c=f\,(e_0)$	$C_c=0.54\,(e_0-0.35)$	Undisturbed natural soils (S_t＜1.5)	Nishida (1956)
	$C_c=0.35\,(e_0-0.50)$	Undisturbed organic soils	Hough (1957)
	$C_c=0.75\,(e_0-0.50)$	Undisturbed soils with low plasticity	Sowers (1970), Bowles (1979)
	$C_c=0.40\,(e_0-0.25)$	Undisturbed all clays	Azzouz *et al.* (1976)
$C_c=f\,(e_0, LL)$	$C_c=-0.07+0.21\,e_0+0.00341\,LL$	Undisturbed clays	Sengupta (1974)
	$C_c=0.37\,(e_0+0.003\,LL-0.34)$	Undisturbed clays	Azzouz *et al.* (1976)
	$C_c=-0.156+0.411\,e_0+0.00058\,LL$	Undisturbed clays	Al-Khafaji and Andersland (1992)
$C_c=f\,(e_0, G_s)$	$C_c=0.141\,G_s^{1.2}\{(1+e_0)/G_s\}^{2.38}$	All clays	Rendon-Herrero (1983)
$C_c=f\,(e_0, e_L)$	$C_c=-0.064+0.153\,e_0+0.11\,e_L-0.006\,e_0^2$	Remolded (Reconstituted) clays	Zeng *et al.* (2015)
$C_c=f\,(n_0)$	$C_c=0.00269\,n_0/(1-0.0115\,n_0)$	Undisturbed clays	Park and Koumoto (2004)
	$C_c=0.0018\,n_0/(1-0.0109\,n_0)$	Remolded (Reconstituted) clays	Park and Koumoto (2004)
	$C_c=1.0584\,(n_0/100)^2+0.0885\,(n_0/100)$	Remolded (Reconstituted) clays	Tiwari and Ajmera (2012)
$C_c=f\,(e_0\times LL)$	$C_c=0.1576\,e_0\,(LL/100)+0.193$	Remolded (Reconstituted) clays	Jin and Yin (2020)
$C_c=f\,(e_0, w_T)$	$C_c=0.92669\,(e_0)^{1.384}(w_T)^{-0.306}$	Undisturbed clays	This study-based on NLR
	$C_c=0.00204\,(e_0)^{-0.095}(w_T)^{1.369}$	Remolded (Reconstituted) clays	ditto
$C_c=f\,(e_0, w_T)$	$C_c=0.548803\,(e_0)^{1.371}\,(w_T)^{-0.172}$	Undisturbed clays	This study-based on GA
	$C_c=0.002027\,(e_0)^{-0.096}\,(w_T)^{1.371}$	Remolded (Reconstituted) clays	ditto
$C_c=f\,(LL, WCR)$	$C_c=0.91\,(LL/100)+0.25\,WCR-0.461$	Remolded (Reconstituted) clays; WCR＝0.7-2.0	Yin and Miao (2013)
$C_c=f\,(e_0, w_n, LL)$	$C_c=0.37\,(e_0+0.003\,LL+0.0004\,w_n-0.34)$	Undisturbed clays	Azzouz *et al.* (1976)

equations were proposed in this study. Based on a total of results of 90 tests on remolded specimens, the scatterplots among the predicted and measured C_c values were comparatively analyzed. Similarly, results of tests on undisturbed specimens were also compiled. In this scope, results of 26, 85, 20, 17, 391 tests on soils from Iraq, India, Indonesia, U.S.A. and Iran were tabulated (Widodo and Ibrahim 2012, Kalantary and Kordnaeij 2012, Nam *et al.* 2019, Mandhour 2020, Dey and Chattopadhay 2021a). Results of 539 tests above were combined with results of 84 tests on miscellaneous soils from Dey and Chattopadhay (2021b). Using a total of 623 data, twelve empirical approaches from past studies and one proposed in current study were comparatively analyzed in terms of their prediction capability.

3. Estimation of compression index (C_c) using different empirical equations

As tabulated in Table 1, many empirical equations were proposed in literature for estimation of C_c parameter. In the scope of this study, the performance of models used for prediction of C_c were comparatively analyzed, based on

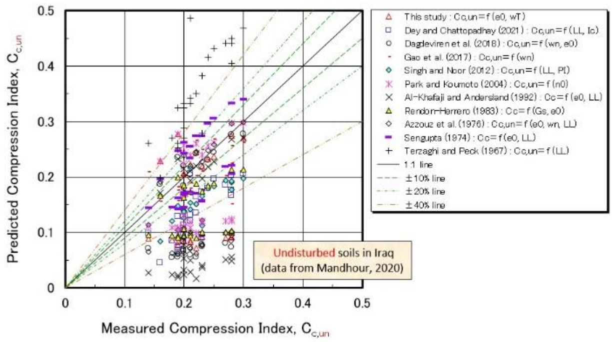


Fig. 1 Prediction of C_c of undisturbed soils in Iraq (data from Mandhour 2020)

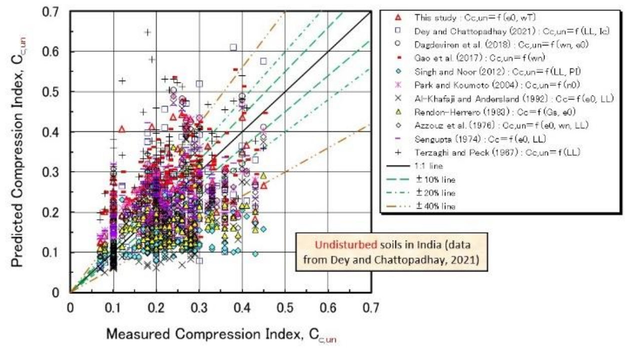


Fig. 2 Prediction of C_c of undisturbed soils in India (data from Dey and Chattopadhay 2021a, b)

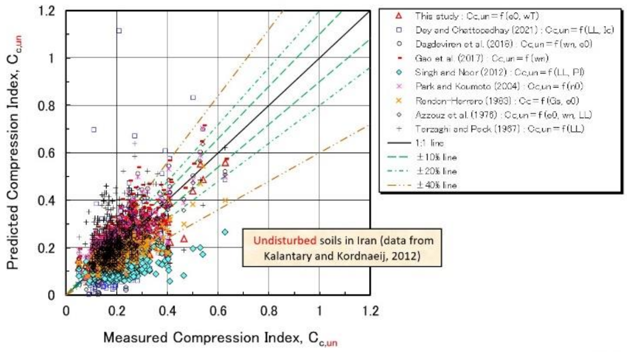


Fig. 3 Prediction of C_c of undisturbed soils in Iran (data from Kalantary and Kordnaeij 2012)

above-mentioned data for remolded and undisturbed soils. The figures below include data from various parts of the world along with equations for prediction of C_c, which is particular to data in hand.

3.1 An empirical equation for estimation of C_c-test results on undisturbed specimens

Mandhour (2020) used results of soil investigations from five sites in Al-Nasiriya city, the center of Thi-Qar governorate, Iraq. The averages of liquid limit (*LL*), plastic limit (*PL*) and plasticity index (*PI*) were 46.42%, 26% and 20.57%, respectively while the average natural water content (w_n) was about 25.79% (Fig. 1). The average amounts of clay, silt and sand were 29%, 50% and 21%, respectively. A total of 26 soil samples were collected and analyzed (Fig. 1). The soils can be classified as inorganic clays of medium to high plasticity since most of the plotted samples lie above or on the A-line in Casagrande's plasticity chart. Fig. 1, which includes data from Mandhour (2020) is modeled using equations of various researchers based on different parameters. Fig. 1 also includes line of equality (black line), relative error ±10%, 20% and 40% lines, which are boundary lines for "better estimation". Besides, about the introduction of the ±40% lines, authors referred the recent research results for C_c predictions (e.g., Hong *et al.* 2013, Mohammadzadeh *et al*. 2014, 2016, 2019). It is evident that the equation proposed in this study, Sengupta (1974), Gao *et al*. (2017) and Dagdeviren *et al*. (2018) reasonably predicts C_c, however, the number of data points falling beyond ±40% lines cannot be discarded. Taking the scatterplots beyond ±20% lines, it is understood that the equations of Rendon-Herrero (1983), Al-Khafaji and Andersland (1992), Singh and Noor (2012), Dey and Chattopadhay (2021b) mostly underestimate the C_c parameter. On the other hand, the equation of Terzaghi and Peck (1967), which only considers *LL* as independent parameter, overestimates C_c. It was observed that w_n and e_0 are viable parameters that can be used in prediction of C_c, however, use of these parameters alone should be avoided.

In Fig. 2, analyses of 170 tests on undisturbed soils by Dey and Chattopadhay (2021a, b) were given. Aiming to validate previously proposed equations, the study presents the results of experiments including consolidation tests on undisturbed alluvial soils by river Hooghly around Kolkata, West Bengal, India. Investigating the index properties of soils, it was found that the *LL*, *PL*, *PI* and w_n values range among 30%-80%, 14%-50% and 5%-57%, 55.7%-185%, respectively. Furthermore, measured and predicted C_c values ranged among 0.070-0.450 and 0.051-0.648, respectively. The proposed equation in this study is a reasonable predictor for C_c: most of the predictions were within ±40%. Similar comments can be made for Dey and Chattopadhay (2021)'s study, proving that *LL* and *CI* are good predictors of C_c. Singh and Noor (2012) formulation based on *LL* and *PI* underestimated the C_c values; measured and predicted C_c values were between 0.113-0.197 and 0.084-0.216, respectively. Equations proposed by Sengupta (1974) and Al-Khafaji and Andersland (1992) based on e_0, and *LL* also underestimate the C_c parameter. Similarly, predictions by Rendon-Herrero (1983)'s equation depending on e_0 and G_s were also lower than measured values (see also Fig. 1). Contrary to these, Gao *et al*. (2017)'s predictions were above +40% line. Dağdeviren *et al.* (2018) used w_n and e_0 parameters for prediction of C_c, it is clear that the method underestimates the C_c values. Surprisingly, one of the oldest equations by Azzouz *et al.* (1976) based on independent parameter e_0, w_n and *LL* is a good predictor of C_c parameter: of all 170 data, 16 are underestimated and 26 are overestimated. Predictions by Terzaghi and Peck (1976) were way too beyond +40% line, ratio of predicted and measured values rise up to 3.6.

Kalantary and Kordnaeij (2012) constituted a database concerning e_0, w_n, *LL*, *PL*, *PI*, G_s and C_c tests on 391

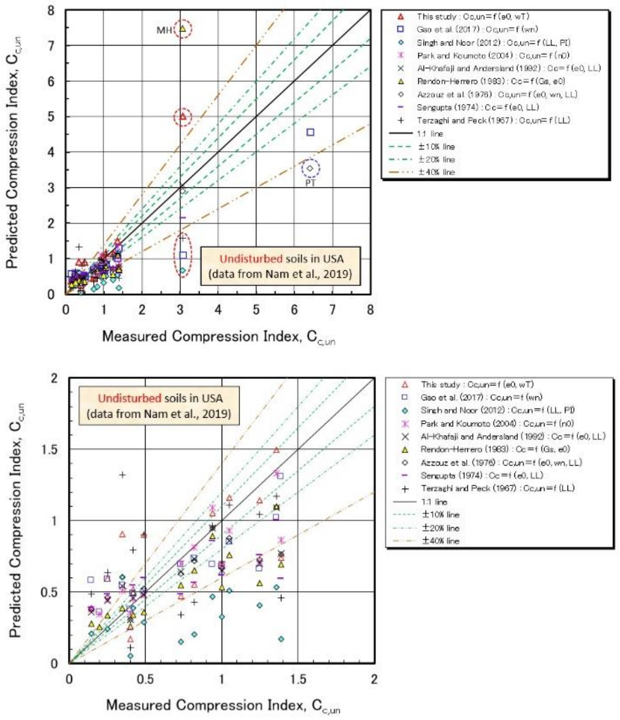


Fig. 4 Prediction of C_c of undisturbed soils in U.S.A.-Plots inside dashed red and blue polygons show test results on highly plastic silts (MH) and peat (PT), respectively (data from Nam *et al.* 2019)

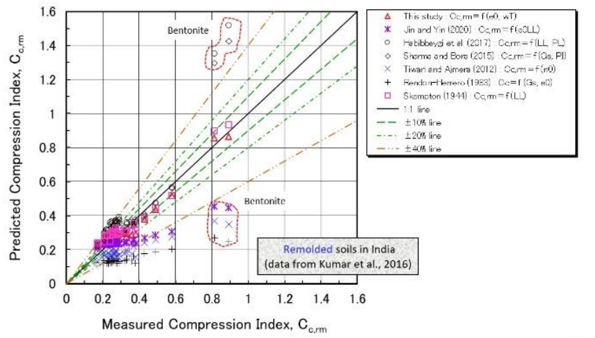


Fig. 5 Prediction of C_c of remolded soils in India-Plots inside dashed red polygons show test results on bentonite (data from Kumar *et al*. 2016)

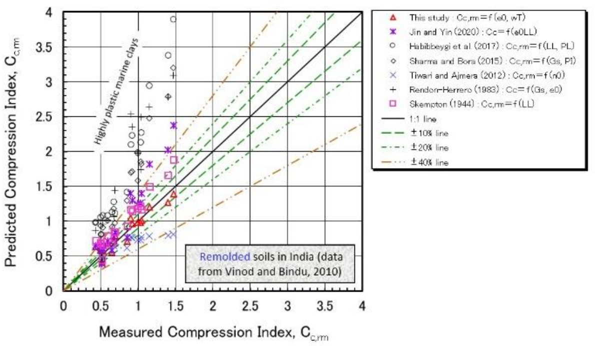


Fig. 6 Prediction of C_c of remolded soils in India (data from Vinod and Bindu 2010)

undisturbed soil specimens. The ranges of e_0, w_n, *LL*, *PL*, *PI*, G_s are 0.267-1.876, 10.20%-70%, 24%-81%, 10%-34%, 3%-50%, 2.43-2.80 g/cm^3, respectively (Fig. 3). The equation based on the e_0 and w_T parameters proposed in this study is a good estimator of C_c parameter, the errors in estimations are below ±40%. Dey and Chattopadhay (2021b)'s predictions were mostly below -40% line. The lowest measured and predicted values of C_c are 0.05 and 0.0027. Dağdeviren *et al*. (2018) and Gao *et al*. (2017) used w_n as the common parameter in their formulations, however, it is observed that Dagdeviren *et al*. (2018)'s additional selection of e_0 creates a difference, the plots between measured against predicted values are scattered in the vicinity of 1:1 line. On the other hand, Gao *et al.* (2017)'s formulation overestimates C_c values. Park and Koumoto (2004)'s estimations are based on initial porosity (n_0), the predictions of C_c are generally close to or slightly higher than the measured values. Singh and Noor (2012)'s predictions based on *LL* and *PI* generally underestimates C_c. On the contrary, the equation proposed by Terzaghi and Peck (1967) based on *LL* overestimates this parameter.

Vinod and Bindu (2010) tested eighteen types of soils from Kuttanad region in the State of Kerala, India (Fig. 6). Soils encountered in the region are soft black or grey marine clay. Plastic and shrinkage limit of soils range between 29.5%-50.9% and 14.9%-28.7% respectively, and the *LL* values are extremely high, which are measured to be between 70.8% to 276.3 %. Mostly classified as clay of high plasticity, the best predictors of C_c values obtained by Vinod and Bindu (2010) are *SSI* parameter and Skempton and Jones (1944)'s equation based on *LL*. Apart from these, C_c predictions of Jin and Yin (2020), Habibbeygi *et al.* (2017), Sharma and Bora (2015) and Rendon-Herrero (1983) are remarkably high. On the contrary, Tiwari and Ajmera (2012)'s equation based on n_0 underestimates C_c values up to maximum -40% line.

Klai and Bouassida (2009) performed tests on Tunis soft clay (5 undisturbed core samples and 2 reconstituted samples). w_n, *LL* and *PI* values of clays were between 56.5-67.5%, 80-84%, and 49-50%, respectively. These values for undisturbed soils ranged among 40-60%, 46-79% and 5-29%, respectively (Fig. 7). It should be noted that, predictions by authors falls within ±20% for undisturbed core samples. However, C_c values of reconstituted specimens were underestimated by e_0 and w_T. The predictions by relationships proposed by Sengupta (1974), Azzouz *et al.* (1976), Rendon-Herrero (1983), Al-Khafaji and Andersland (1992), Park and Koumoto (2004), Gao *et al.* (2017), Dagdeviren *et al.* (2018) and Dey and Chattopadhay (2021b) as well as those by Terzaghi and Peck (1967) are reasonable and mostly bounded by ±40% lines. However, C_c estimations (0.121-0.384) by Singh and Noor (2012) based on *LL* and *PI* parameters are significantly lower than the measured values (0.35-0.485). For reference, their proposed model is based on 23 undisturbed soil samples in India (soil type: CL and CH) and the statistical accuracy of model in terms of the root mean squared error (*RMSE*) was 0.035, whereas for the

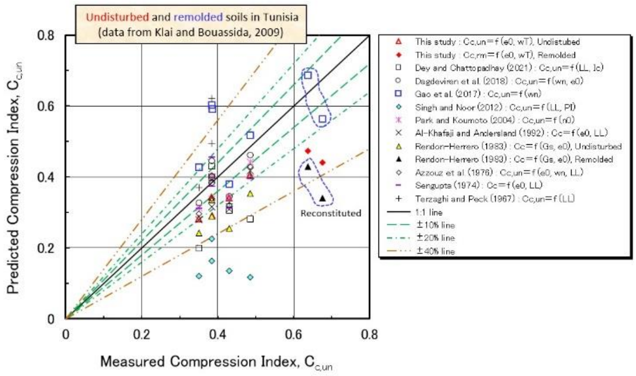
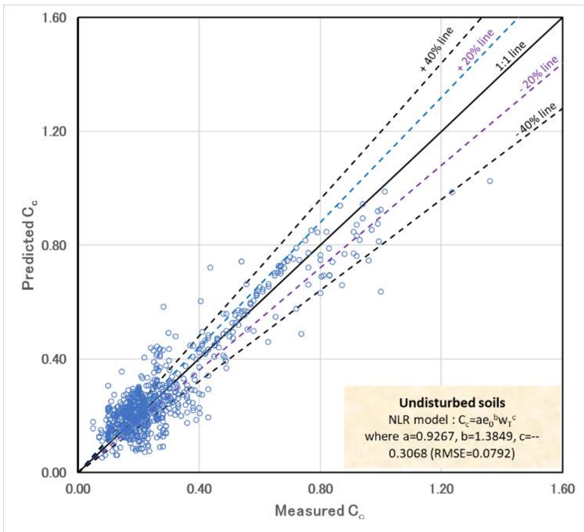


Fig. 7 Prediction of C_c of undisturbed and remolded soils in Tunisia- *p*lots inside dashed blue polygons show test results on reconstituted samples (data from Klai and Bouassida 2009)

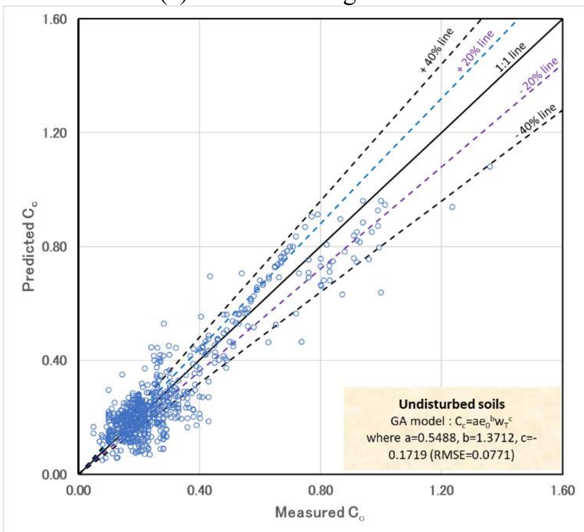
well-known Skempton's and Terzaghi and Peck's models were 0.131 and 0.211, respectively. Therefore, they concluded that the model was in good agreement with the measured values and much accurate compared with other ones. Thus, the geotechnical engineers especially need to pay attention to the applicability of various empirical correlations to different soil origin and type.

3.3 A comparison of nonlinear and genetic algorithm-based regression for coefficient estimates

Firstly, instructed by Holland (1975), genetic algorithm (GA) is a stochastic search and optimization algorithm which mimic principles of natural evolution (Holland 1975). GA-based regression techniques are subject of many papers in geotechnical engineering based on their ease of use (Deb *et al*. 1999, Cui and Sheng 2005, Levasseur *et al*. 2007, 2009, Cabalar *et al*. 2009, Adarsh and Jangareddy 2010, Alavi and Gandomi 2011, Gandomi and Alavi 2013, Garg *et al.* 2014, Shahin 2015 Islam and Rokonuzzaman, 2018). In essence, any population-based algorithms utilizing selection, crossover, and mutation over chromosomes for reaching to an optimal solution is the definition of GA. In essence, a binary or real valued string defines members of the populations, i.e., chromosome/genotype. A typical GA problem is constituted of initialization, selection, generation, which the process is terminated by a stopping criteria (Keshanichi *et al*. 2017). At first, genotypes are generated in a randomized manner in the scope of an objective function-but constrained Generation of initial chromosomes in step 0 (genotypes) is the first step in GA algorithm. Later, an operator is defined to population in hand. Later, implementation of crossover-mutation operators to the results obtained in previous phase comes up with subsequent population. In essence, crossing over is simply the formation of a chromosome from two parent chromosomes, by the operator. On the other hand, minor modifications in parent chromosome may cause formation of a new chromosome-which is also identified as mutation (Goldberg 1989). A well-designed algorithm necessitates a composition of reasonable identification of the model, evaluation of real-life results and experience.



(a) NLR based regression



(b) GA based regression

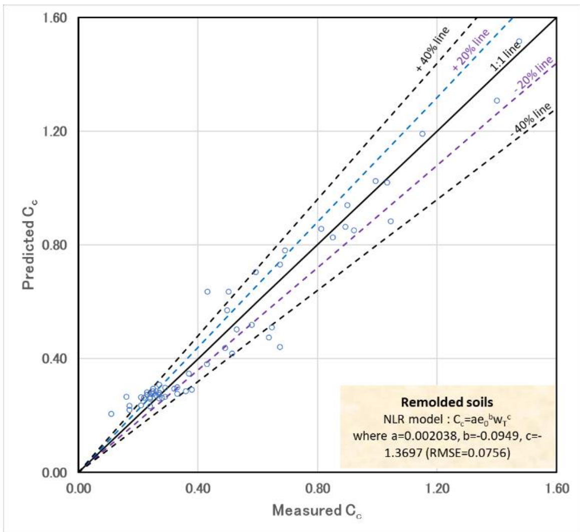
Fig. 8 Scatterplots of predicted and measured C_c values of undisturbed specimens

Statistically speaking, nonlinear regression (NLR) is an advanced form of regression analyses. In essence, the dependent parameter in NLR is nonlinearly modeled by one or more independent parameters, in which a goodness of fit is expected after successive approximations. The nonlinear model relies on a nonlinear least-squares (NLS) estimator which aims to minimize the sum of squared errors. A local minimum is seldom encountered in solution, which makes it compulsory to start with different parameters for obtaining similar parameter estimates. As can be remembered from Table 1, the nonlinear regression-based equations in this study are in the following form (the product with power of e_0 and w_T, i.e., a kind of *SSI* parameter):

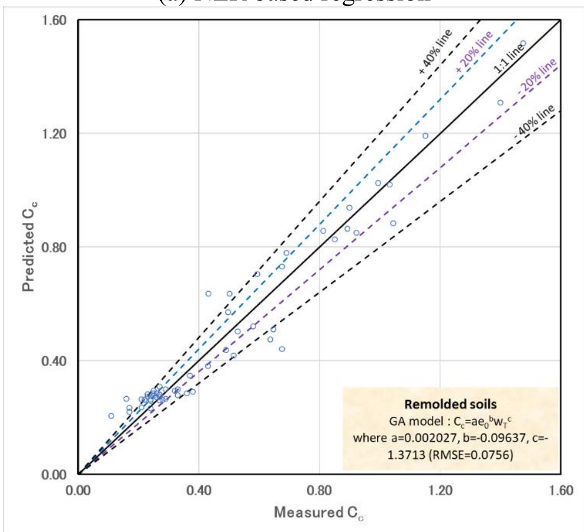
$$C_c = ae_0^b\omega_T^c \tag{2}$$

where a, b and c are the coefficients obtained by the NLR model above or GA model below.

The equation obtained by nonlinear regression-individually for undisturbed and remolded test data- based on Eq. (2) was given in Table 2, respectively. Later, genetic



(a) NLR based regression



(b) GA based regression

Fig. 9 Scatterplots of predicted and measured C_c values of remolded specimens

algorithms were employed to modify the coefficients a, b and c. Although the coefficients seem to be remarkably different from those proposed in Table 2, it is evident that the performance of the model was not significantly improved. The scatterplots in Figs. 8 and 9 for evaluation of data obtained from tests on undisturbed and remolded specimens revealed that the predictions of NLR and GA-based equations are almost the same.

In order to compare the performances of the models, several parameters should be introduced. The root mean square error (*RMSE*) parameter can be defined as

$$RMSE = \left(\frac{\sum_{i=1}^{n}(y_i - p_i)^2}{n}\right)^{0.5} \tag{3}$$

In this equation, y_i and p_i are measured and predicted values and n is the number of data. If this parameter equals to zero, if the model is perfectly fit to data in hand. Another parameter for assessment of relevance between predicted and measured values of C_c can be demonstrated by

Table 2 A comparative analysis of the performance of the models (1: NLR-based (undisturbed) 2: NLR-based (remolded), 3: GA-based (undisturbed), 4: GA-based (remolded)

Model	Coefficients			RMSE	PCC	F/F$_{cr}$
	a	b	c			
1	0.926686	1.38486	-0.30675	0.07915	0.9164	1.131/1.158
2	0.002038	-0.09494	1.36973	0.07556	0.9721	1.072/1.564
3	0.548803	1.37122	-0.17186	0.07702	0.9212	1.101/1.131
4	0.002027	-0.096370	1.37125	0.07555	0.9721	1.071/1.564

Pearson's coefficient of correlation (*PCC*), which is computed in the following way

$$PCC = \frac{\sum_{i=1}^{n}(p_i - \bar{p})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(p_i - \bar{p})^2}} \tag{4}$$

where, $\bar{y}$ and $\bar{p}$ are means of measured and predicted values, respectively. *PCC* values range between -1 and 1, where a value of 1 and -1 show a perfect direct proportional and inverse proportional relationships, respectively. On the other hand, Fisher's F test is a viable tool in evaluation of model performance, which is formulated as

$$F = \frac{\sum_{i=1}^{n}(p_i - \bar{p})^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2} \times \frac{m-1}{n-1} \tag{5}$$

where m and n are numbers of data in p and y data sets. The F value gives an idea about the equality of the variances of two different data.

The performances of the models were comparatively analyzed in Table 2. It should be emphasized that, GA-based methods cannot outperform NLR models, the *RMSE* values are insignificantly different from each other. *PCC* values are very close to 1, which show a strong relevance among predicted and measured values. Despite the uncertainties in testing, data obtained from different parts of the world show a reasonable correlation. A comparison of the critical values and F_{cr} values in the table reveals that the variances of predicted and measured data are equal, at a statistical significance level of 0.05.

3.4 Verifications of NLR and GA models for remolded and undisturbed soils

Here on the verification of four models proposed in this study, judging comprehensively from *RMSE* and *PCC* values in Table 2, authors selected the NLR model for remolded soils and the GA model for undisturbed soils, respectively. The verification results using another reference datasets including authors' data are shown in Figs. 10 and 11. Besides, the legend "This study" in these figures stand for the experimental data for 11 natural and artificial cohesive soils obtained by authors and their results are presented in Table 3. According to these figures, the NLR and GA predictive models selected can explain approximately these local C_c data around the world within maximum ±40% relative error.

In Table 2, C_c values obtained by Eq. (2) and corresponding a, b, c coefficients for undisturbed and

Table 3 Physical properties and C_c values of cohesive soils used in this study (Authors' data)

No.	Soils (USCS)	e_0	LL (%)	PL (%)	PI (%)	C_c Remolded	C_c Undisturbed	w_T (%)	e_0w_T (%)	Remarks
1	Kaolin clay 100% (CH)	1.8	75.1	25.2	49.9	0.45		46.2	83.1	Kaolin-sand mixtures
2	Kaolin clay 70% (CH)	1.1	52.2	20.2	32.0	0.28		33.6	37.0	
3	Kaolin clay 50% (CL)	0.9	37.7	16.3	21.4	0.21		25.3	22.8	
4	Silty clay (MH)	1.2	50.1	30.4	19.7		0.25	38.7	46.4	
5	Organic clay (OH)	3.634	127.5	51.7	75.8		1.48	83.5	303.6	Organic soil
6	Silty clay (MH)	3.102	118.8	49.3	69.5		1.38	78.5	243.5	
7	Blue clay-1 (CH)	1.538	59.02	25.06	33.96		0.56	39.3	60.5	2 soil specimens
8	Blue clay-2 (CH)	1.554	59.02	25.06	33.96		0.52	39.3	61.1	
9	Clayey silt (CH)	1.073	52.8	24.6	28.2		0.32	36.4	39.1	
10	Silty clay (MH)	2.774	80.4	44.4	36.0		1.24	59.5	165.1	
11	Sandy silt (CL)	1.119	48.8	25.1	23.7		0.47	35.1	39.2	

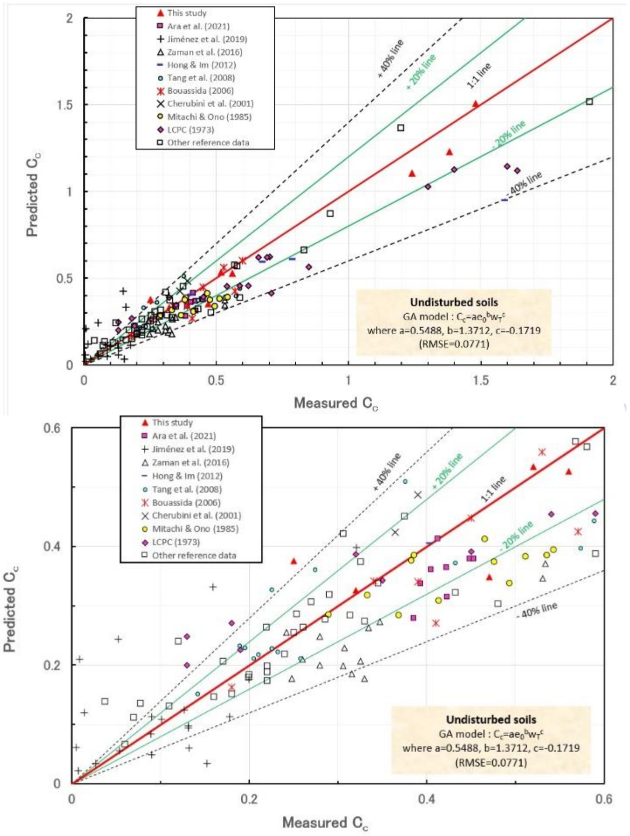


Fig. 10 Comparison of predicted and measured C_c values of undisturbed specimens based on GA regression

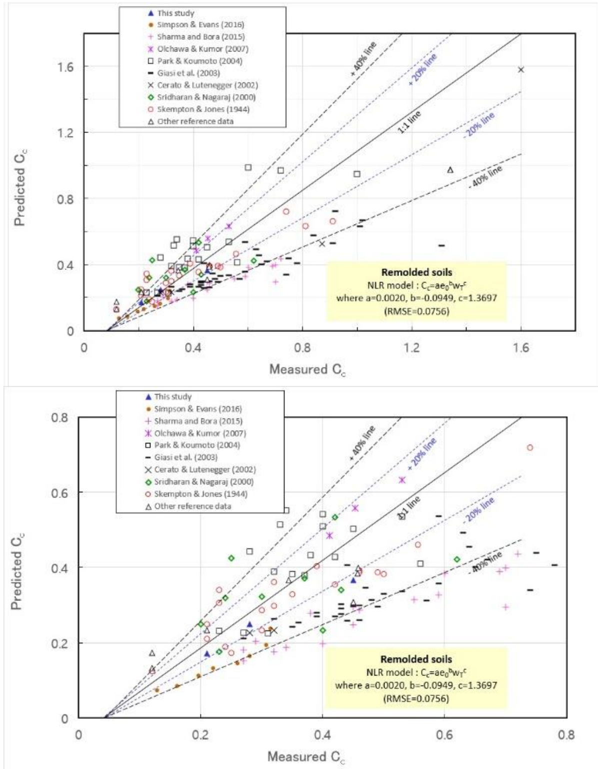


Fig. 11 Scatterplots of predicted and measured C_c values of remolded specimens based on NLR regression

remolded soils were given. In this manner, the coefficients for Eq. (2) obtained by GA method were used to predict C_c values of undisturbed soils, based on previously published data (LCPC 1973, Mitachi and Ono 1985, Cherubini *et al*. 2001, Klai and Bouassida 2006, Tang *et al*. 2009, Hong and Im 2012, Zaman *et al*. 2015, Jimenéz *et al*. 2019, Ara *et al*. 2021, Other reference data: Ortigão 2020, Işık 2009, Boone 2010, Ishida *et al*. 2011, Mohammadzadeh *et al*. 2014, Fakharian and Mehdizadeh 2015, Kurnaz *et al*. 2016, Mohammadzadeh *et al*. 2016, Hashemi *et al*. 2017, Alkroosh *et al*. 2020, Hameedi *et al*. 2020, Jiang *et al*. 2020, Alzabeebee *et al*. 2021, Sun 2021, He *et al*. 2022, Mohammed *et al*. 2022). The results from GA-based model are promising, an *RMSE* value of 0.077 was obtained for undisturbed soils. On the other hand, Fig. 11 shows the plot of predictions of NLR-based model against measured values of C_c for remolded soils.

For remolded soils, the predictive performance of the NLR model in Eq. (2) using initial void ratio and toughness limit as independent variables based on previously published data was presented (Skempton and Jones 1944, Sridharan and Nagaraj 2000, Cerato and Lutenegger 2004, Giasi *et al*. 2003, Park and Koumoto 2004, Olchawa and Kumor 2007, Sharma and Bora 2015, Simpson and Evans

2016, Other reference data: Farias and Llano-Serna 2016, Liu *et al.* 2020). Similarly, the *RMSE* for the relationship between predicted and measured C_c values of remolded soils is 0.075 (see Table 2), which is an acceptable value.

4. Conclusions

In the scope of this study, a database composed of index and consolidation test results on undisturbed and remolded soil samples was compiled. A total of 90 test results on remolded soil samples from literature were used to question the modeling ability of 9 relationships proposed in the past and in this study. Later, results of 623 tests on undisturbed specimens were used to evaluate the performance of 14 empirical equations for estimation of C_c – either proposed in the literature and in this study. Comparative analyses based on scatter plots and statistical analyses were made. Generally speaking, estimations using equations proposed in this study, based on initial void ratio and toughness limit were acceptable. For highly plastic remolded marine clays, C_c predictions of Habibbeygi *et al.* (2017), Sharma and Bora (2015), Rendon-Herrero (1983) were 2.5 times greater than measured values. The equation of Terzaghi and Peck (1967) based on *LL* overestimated C_c values for undisturbed soils. The predictions by Dağdeviren *et al.* (2018), Al-Khafaji and Andersland (1992) and Azzouz *et al*. (1976) depending on e_0, *LL* and w_n underestimated C_c values for half of the data. The equation of Singh and Noor (2012) based on *LL* and *PI* underestimates C_c, the scatterplots were below -40% line. Moreover, the C_c of organic soils are underestimated by nearly all approaches.

Genetic algorithms were used to improve the strength of the empirical relationships proposed. Despite the changes in control parameters of GA, the performance of GA equations was slightly better than that of nonlinear regression equations. Comparison of the coefficients as well as the performance of the models were presented.

Last but not the least, the validity of the NLR and GA model equations proposed in this study should be questioned by future studies. Nonetheless, it is observed that toughness limit has a great potential in prediction of compression index of soils, either at undisturbed or remolded states.

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