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Modeling the compression index for fine soils using an intelligent method

Seyed Mahmood Kashefipour, Mehdi Daryaee*

Hydraulic Structures Department, Water Sciences Engineering Faculty, Shahid Chamran University Ahwaz, Iran

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Abstract

Construction of buildings and different structures leads to soil consolidation, hence, causes soil settlement. Soil settlement depends on numerous factors, for instance, pressure deformation, depletion of pore water, and so forth. One way to calculate soil settlement, is utilizing compression index, which is obtained through consolidation test. Obtaining this index through consolidation test is too time-consuming; thus, researchers have attempted to relate compression index to soil physical parameters such as plasticity limit, liquid limit, void ratio, and relative density, which all could be simply measured; therefore, there is great deal of empirical relations in this regard. In this study, the correlation coefficients between the physical characteristics of fine soil and compression index were investigated using the Artificial Neural Network (ANN). A few but common empirical equations describing the relationship of compression index with other soil properties were evaluated along with the developed ANN model in this study. The results have indicated that among the considered empirical relations, the Rendon-Herrero formula performed better in calculating the compression index. By comparison, the ANN calculates the compression index more accurately and with less error than the Rendon-Herrero formula.

***Corresponding Author:** Mehdi Daryaee ✉ Mehdi.Daryaee@yahoo.com

Introduction

Due to the importance of soil settlement in the stability of structures, before constructing structures, determination and prediction of the soil settlement resulted from the administered pressure on soil from a structure is essential. One way to determine soil settlement is use of the compression index based on the consolidation test. Since soil settlement may cause damage to a project, utilizing accurate prediction in structure designing along with setting designing criterion based on the estimated settlement, can prevent this kind of damage. Compression index may depend on several soil properties, including the primary of soil water content at liquid limit, water content at plasticity limit, plasticity index, and relative density. Because consolidation test is very time-consuming; thus, researchers have attempted to relate compression index to the aforementioned soil physical parameters, consequently, numerous empirical relations have been presented. The point that has to be taken seriously is each of these relations is calculated for a special zone, and if the circumstances of the project location are not in harmony with the empirical formula, the accuracy of estimated results could not be valid and reliable. Having said these, it is crucial to select the formula or a special method to be suitable for each region, in addition, research and investigation in this regard is recommended to halt any potential damages.

(Skempton, 1944) proposed the following formula that was obtained through consolidation test on some intact clay:

$$C_C = 0.007(w_L - 10) \qquad (1)$$

where, C_C stands for compression index and w_L (%) for liquid limit. (Nishida, 1956) based on a theoretical formula could find a relation between compression index and the primary void ratio of soil for adhesive soil as follows:

$$C_C = 0.15(e_0 - 0.35) \qquad (2)$$

where, e_0 is the primary void ratio. According to the (Terzaghi and Peck, 1968) this equation is suitable for consolidated clay with minimum sensitivity. They formulated the following equation based on their experimental results through statistical analysis:

$$C_C = 0.009(w_L - 10) \qquad (3)$$

(Rendon-Herrero, 1980) proposed the following worldwide equation for compression index:

$$C_C = \frac{1}{2}\left(\frac{1+e_0}{G_S}\right)^{2.4} \qquad (4)$$

In this equation G_s stands for relative density (ρ_S / ρ). (Nagaraj and Murty, 1985) presented the following relationship between compression index and soil physical parameters:

$$C_C = 0.2243 w_L . G_S \qquad (5)$$

The following formula was proposed for calculating compression index by Park and Koumoto (2004) after obtaining the results of eighty-three consolidation tests on intact clay samples:

$$C_C = \frac{n_0}{371.747 - 4.27 n_0} \qquad (6)$$

where, n_0 indicates the primary porosity of soil.

Ahadian (2004), found out that there is a significant relationship between compression index and void ratio.The following relationship was presented between these parameters:

$$C_C = 0.0681 e^{1.405 e_0} \qquad (7)$$

Compression index is generally an important parameter for the fine soils especially clay soils and from the geotechnical and consolidation view points its value is predominant in constructive projects such as hydraulic structures, dams and so on. In contaminated clay soils this parameter may be changed. For instance, an empirical equation has been presented by Di Matteo *et al.,* (2011) showing the effect of contaminated Kaolinitic clay soil with ethanol-gasoline blends on the liquid limit and compression index. This equation states that by increasing the percentage of ethanol-gasoline to the soil this index decreases. Hong *et al.,* (2012) have shown that adding zeolite to the bentonite clay soil in order to amend its properties and to enhance sorption capacity, causes the compression index to be slightly decreased, from 0.24 to about 0.21.

The effect of dielectric constant of fluid on the permeability and consolidation characteristics of Na-montmorillonite swelling clay soil was investigated by (Amarasinghe *et al.,* 2012). They found that the clay-fluid molecular interactions (for polar and non-polar fluids) may significantly affect the mobility of fluid molecules and as a result increase the permeability. They also showed that the compression index significantly decreases for the polar fluids.

Today, the Artificial Neural Network, henceforth called, ANN, has vast usage in various areas (Karimi Madahi and Hassani, 2012). This method has also been used widely in water and soil; for example, to determine the geotechnical characteristics of soil and to calculate the level of accuracy of ANN, Shahin *et al.,* (2001) performed some experiments. Kashefipour *et al.,* (2005) used ANN to model the caliform bacteria concentration levels in the west of Scotland Sea. Sarangi and Bhattacharya (2005), applied the ANN and regression models to predict the sediment loss from watershed and postulated that the ANN model has had the maximum accuracy. Tareghian and Kashefipour (2007), used ANN and fuzzy logic methods to model the flood hydrographs at the upstream of Dez reservoir dam, Iran.

There are plenty of research studies, which are recently published in the literature showing the application of ANN method for simulation of different phenomena in soil and water. For example, Erzin *et al.,* (2009) modeled the hydraulic conductivity of compacted fine grained soils using ANN. Soil solution electrical conductivity was modeled using ANN by (Namdar-Khojasteh *et al.,* 2010). Xiong and Li (2011), applied ANN model for prediction of deformation of deep foundation pit. Gautam *et al.,* (2011) developed a new algorithm for ANN model to predict soil hydraulic parameters with minimizing the bias error.

The idea of using the ANN method is not a new concept. The practical usage of the ANN was initiated by (Sverdrup, 1946). he used this method in his thesis to predict weather. This method was not successful, due to the lack of calculation and computer usage.

The ANN is formed regularly in multi layers. The first layer that hosts inputs and data is the input layer. The medial layers are hidden layers and the final layer that supplies the outputs is the output layer. The Multi-Layer perceptron along with supervisor are the simplest and the commonest ANNs that are used in both the current study and numerous engineering fields. In this network, the number of input layer is equal to the elements of input vector and also the number of output layer is equal to the elements of output vectors. The accurate and factual analysis of the number of neurons in the medial layers is complex. It could be declared that the number of the medial layers is a function of the number of input vector and the maximum of surrounding of input areas that are inseparable; therefore, the number of the hidden layers is empirically selected. Each neuron is connected via its output to the neurons of the other layers; however, it has no connection to the neurons of its layer. The ending of each neuron is calculated via the following formula:

$$a = f\left(\sum_{i=1}^{n} p_i w_{j,i} + b_j\right) \qquad (8)$$

In this formula $w_{j,i}$ indicates the weight of the connection between the j^{th} of the current neuron and the i^{th} neuron of the previous layer. The amount of this weight implies the importance of the connection between the two consecutive neurons. b_j indicates the biased weight of the j^{th} neuron, p_i shows the output amount of i^{th} neuron of the previous layer, a is the output amount of j^{th} neuron, and f is a transfer function of the j^{th} neuron. There are various functions that might be used in digits transfer from one layer to the other layers; for example, Zeigmoid function, etc., but Zeigmoid function has the most usage in engineering issues. This function is defined as follows:

$$f(z) = \frac{1}{1+\exp(-z)} \qquad (9)$$

The ANN model mainly comprises of two patterns. The first one is network training pattern, which is usually carried out using about 70% of the whole available data. The second pattern which is usually uses about 20-30% of the other available data is validation pattern. In this stage of the model development the rate and algorithm of training pattern is controlled by comparing the amount of accuracy of model predictions. In many ANN modeling for different engineering cases, depending on the input variables and their relationship with the desired parameter to be modeled, approximately 10% of the data is used for model testing and evaluation, also for critical points assessment, for instance, reference point, and maximum and minimum levels in a series of data. It should be noticed that the data used for each pattern including: training, verification and test must be different.

In this study an ANN model is developed based on the available measured data for prediction of compression index, which is an important physical characteristic of soil, and the capability of this model is then evaluated by comparing it with the other existing empirical equations.

Materials and methods

The compression indexes and the other related soil characteristics data, which were measured in different parts of the Khuzestan province in south-west of Iran, were collected for this research study. The physical characteristics include void ratio, water content at liquid limit and plasticity limit, relative density. Sampling from numerous areas in different depths was performed to complete the data. The experiments were implemented at the laboratory of Water Sciences Engineering Faculty in Shahid Chamran University. In total 137 data sets were collected for developing the ANN model.

As it was mentioned the effects of physical parameters of soil such as the primary void ratio, water content at liquid limit and plasticity limit on the compression index have been considered by many scientists. In this study the five main physical parameters, which are easily and readily measured in a laboratory, were considered as the effective factors on compression index, in other words, the compression index can be written as a function of these physical parameters, as:

$$C_C = f(e_0, w_i, LL, PI, G_s) \qquad (10)$$

where, e_0 indicates the void ratio, w_i is the primary soil water content, LL stands for the water content at liquid limit, PI is the water content at plasticity index, and G_s is the relative density. Concerning the dependent and independent variables, the ANN must have five neurons in the input layer and one in the output one. In The proposed ANN structure is shown to clarify the point (Fig. 1).

Ninety sets out of the 137 measured sets of data were used for model training, 32 sets of them for model verification, and the rest were used for the final testing of the model. Only one hidden layer with five nodes on it was considered for the network architecture to avoid model localization and achieve more accurate simulation. It should be mentioned that this network structure was adapted after too many runs of model and having the minimum error. With about 45000 iterations in training pattern the minimum errors was obtained for training, verification and test patterns. The transfer function for model implementation was Zeigmoid function.

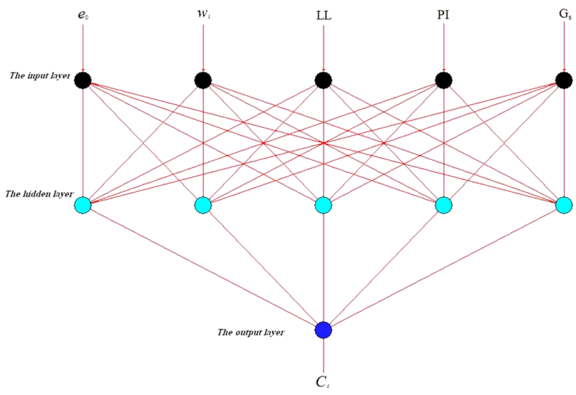

Fig. 1. Interface of the ANN.

Results and discussion

The following statistical parameters were used for evaluation and comparison of the predicted compression indexes by the ANN and empirical models with the corresponding measured values:

-The slope (α) of a line, which is drawn between C_{Cm} and C_{Cp} with the corresponding determination coefficient, R^2. It is obvious whatever α and R^2 are closer to unity, the model predictions are more accurate.

-The percentage of error, $\%E$, is calculated via the following formula:

$$\%E = \frac{\sum_{i=1}^{N} \left| C_{Cmi} - C_{Cpi} \right|}{\sum_{i=1}^{N} C_{Cmi}} \times 100 \qquad (11)$$

-The root mean square error (RMSE) is computed on the basis of the formula below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (C_{Cmi} - C_{Cpi})^2}{N}} \qquad (12)$$

In these equations, N shows the total number of data, C_{Cm} and C_{Cp} are the measured and predicted compression indexes, respectively.

The above mentioned statistical parameters were calculated for the predicted compression indexes by the ANN model for training, verification and test patterns and are summarized (Table 1). As it is noticeable from this table the results for the test pattern was even better than the other two patterns. This shows that the ANN model was able to accurately predict the compression index.

The determination coefficient (R^2) is not very close to unity and this could be due to complexity of the phenomenon and the other variables that are difficult to be quantified (Table 1). The determination coefficients for the other considered empirical relations in this study are by far less than the corresponding value that is calculated for the ANN model (Table 2). Comparison of the predicted compression index by the developed ANN model in this research study for test pattern and the corresponding measured values is shown in (Fig. 2). As can be seen in this fig. the ANN model was able to accurately predict this very complex soil characteristic.

Table 1. Statistical parameters' results for the ANN model.

Pattern	*RMSE*	$\%E$	α	R^2
Training	0.03	14.44	1.00	0.67
Verification	0.03	16.00	0.97	0.55
Test	0.02	10.93	1.03	0.70

Table 2. Comparison of the ANN and other empirical relations for prediction of the compression index based on statistical methods.

Model	*RMSE*	$\%E$	α	R^2
Rendon-Herrero	0.04	16.80	1.04	0.48
Ahadiyan	0.02	20.88	0.88	0.47
Park and Koumoto	0.06	32.75	0.77	0.46
Nishida	0.12	68.40	0.31	0.44
Nagaraj and Murty	0.05	22.60	1.11	0.18
Terzaghi and Peck	0.11	53.40	0.88	0.23
Skempton	0.07	34.34	0.74	0.21
ANN(present study)	0.02	10.93	1.03	0.70

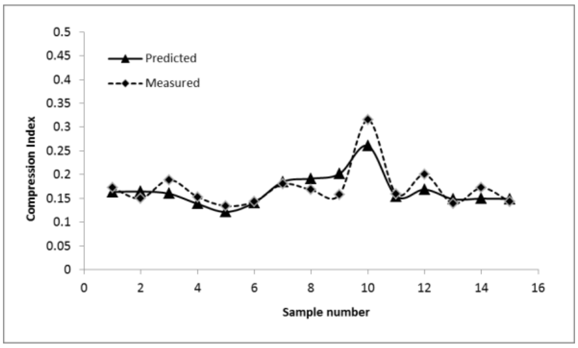

Fig. 2. Comparison of the measured and predicted compression index by the ANN model for the test pattern.

The level of the importance of each soil physical parameter considered for developing the ANN model is introduced as the percentage of its contribution in model production and is shown in (Fig. 3). This fig. shows that e_0 or the void ratio with a value about 30% of contribution is the most effective and important physical parameter in compression index. All existing empirical equations, which were reviewed in this research study, prove this fact. It seems that the other parameters with slight differences have had relatively the same contributions in model creation, which confirm the similarity between the levels of significance of these physical parameters on the soil compression index. According to (Fig. 3.), specific gravity, G_s, has had the minimum level of significance among the other physical parameters; however, it has been appeared in some empirical models. Anyway it is difficult to judge decisively, since in various places soils behave different.

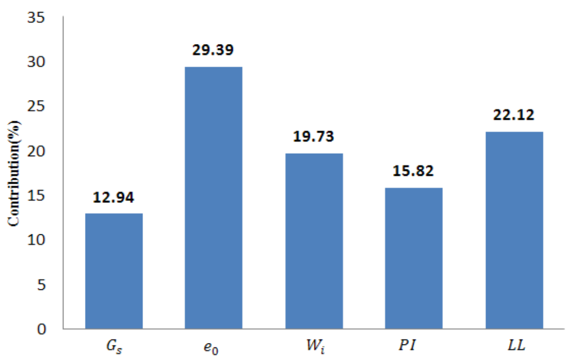

Fig. 3. Comparison of the significance of the studied physical parameters in compression index.

The compression index was calculated based on the available set of data for the test pattern using the ANN model and the other considered empirical models in this study. The statistical parameters were than computed with the calculated results for the practical comparisons of the ANN and the other models being illustrated in (Table 2). It is clear that the ANN model has been more successful to predict the compression index more precise than any other empirical model. It should be noticed that five physical soil parameters were used to develop the ANN model; whereas, merely two parameters are used in the other empirical models. Despite the vast number of the required parameters in the ANN, the usable parameters are measurable in less time and without any burden; however, direct measurement of compression index in soils demands a great deal of time.

(Table 2) reveals that the Rendon-Herrero relation (Equation 4) has been the best empirical method for the available data than any other considered empirical models.

In (Table 3) another comparison has been carried out between the developed ANN model and the other existing empirical relations for the level of accuracy in predicting the compression index, especially in view of over and/or underestimating of this parameter. In order to achieve this object all the predicted results by different models and their error estimation were classified in three categories including: $(C_{Cp} < 0.8C_{Cm})$, $0.8 \le C_{Cp} / C_{Cm} \le 1.2$, and $(C_{Cp} > 1.2C_{Cm})$, which states $\pm 20\,\%$ error estimation in predicted compression indexes. The percentage of the predicted results for each category and for each model was calculated and summarized in Table 3. A precise inspection of this table shows that some models like Nishida equation generally underestimates this index, whereas some of them such as Park and Koumoto, and Terzaghi and Peck models overestimate the compression index. Among the studied models, the ANN and the Rendon-

Herrero with over 70% of the predicted values within the range of $0.8 \le C_{Cp}/C_{Cm} \le 1.2$, signify that they are the most suitable models for C_C level prediction.

Table 3. Percentage of the predicted C_C by the studied models in the borderline of $\pm 20\%$ level of error.

Models	$C_{Cp}/C_{Cm} > 1.2$	$0.8 \le C_{Cp}/C_{Cm} \le 1.2$	$C_{Cp}/C_{Cm} < 0.8$
Rendon-Herrero	18.26	70.07	11.67
Ahadiyan	37.23	58.39	4.38
Park and Koumoto	67.16	29.92	2.92
Nishida	0.00	0.00	100.00
Nagaraj and Murty	16.80	51.09	32.11
Terzaghi and Peck	68.62	27.00	4.38
Skempton	43.08	36.49	20.43
ANN (present study)	16.05	73.00	10.59

C_{Cm} = **Measured data**, C_{Cp} = **Predicted value**

It may be said that according to the importance of compression index for design of buildings, hydraulic structures, and so on, it is better to directly measure this parameter. It is recommended to do this for very important engineering projects however, due to the complexity and variability of soils from one point to another one, to have a better understanding from compression index, it is useful to utilize either relatively precise empirical equations or to apply ANN model to predict this parameter.

Conclusions

In this study, the compression index which is among the most important parameters and soil characteristics and measuring it demands a great deal of time, has been investigated. For quick and accurate estimation of the compression index values, an ANN model was developed based on some soil physical characteristics that are easily and quickly measured in laboratory or filed. This model was then compared with the results obtained from the related and very famous or recent empirical equations in the literature using existing measured data. The main conclusions drawn from this study are:

- The ANN model estimates the compression index with higher accuracy than any other empirical relation.

- Among the studied empirical methods, the Rendon-Herrero has the highest degree of accuracy for determination of the compression index.

- The ANN model showed that the primary void ratio is the most effective physical properties affecting the compression index. Most of the existing related empirical formulas in the literature prove this fact. The models, which excluded this parameter, have had less degree of accuracy.

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