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Evaluation of the compression index of soils using an artificial neural network

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A B S T R A C T

The compression index is a one of the important soil parameters that is essential to geotechnical designs. As the determination of the compression index from consolidation tests is relatively time-consuming, empirical formulas based on soil parameters can be useful. Over the decades, a number of empirical formulas have been proposed to relate the compressibility to other soil parameters, such as the natural water content, liquid limit, plasticity index, specific gravity, and others. Each of the existing empirical formulas yields good results for a particular test set, but cannot accurately or reliably predict the compression index from various test sets. In this study, an alternative approach, an artificial neural network (ANN) model, is proposed to estimate the compression index with numerous consolidation test sets. The compression index was modeled as a function of seven variables including the natural water content, liquid limit, plastic index, specific gravity, and soil types. Nine hundred and forty-seven consolidation tests for soils sampled at 67 construction sites in the Republic of Korea were used for the training and testing of the ANN model. The predicted results showed that the neural network could provide a better performance than the empirical formulas.

1. Introduction

Stress increments in soil strata due to various civil engineering structures are accompanied by settlements (consolidation, compression). It is the geotechnical engineer's responsibility to calculate the amount of the possible settlements as precisely as possible for the safety of the projects. The volume change characteristics of soils can be determined by means of oedometer tests in the laboratory. It is a conventional test, which is assumed to simulate the zero lateral strain condition on the specimen. As a result of the test, a change of the void ratio against the corresponding effective stress can be observed. Compressibility parameters, such as the compression index (C_c), which are related to the changeability of the global void ratio under applied stresses, can be determined. The compression index represents the slope of the curve of the void ratio versus the logarithm of the effective pressure and is conventionally determined by oedometer tests. Used for the calculation of the consolidation settlement of clayey soils, this parameter directly affects the type and dimensions of the foundation system and hence the cost of the construction. 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 formulas relating various parameters to the compression index have been presented by many researchers [2–5,8,21,22,26,28,30–32]. Most researchers have used single- or dual-parameter models, such as the liquid limit, natural water content, void ratio, and others, for the estimation of the compression index. The main criticism of these methods is that they oversimplify the complicated mechanism of the consolidation characteristic, and the various soil parameters are not properly taken into account. When multiple variables are considered to improve the predictability of the empirical formula for the estimation of the compression index, the variables used in the regression formula are likely to be correlated and this leads to complex multicollinearity problems. Therefore, a formula that is capable of resolving the complexities between the compression index and the related soil parameters is required.

This paper describes the application of an artificial neural network (ANN) to overcome the limitation of empirical formulas obtained from regression analysis using few variables. The advantage of the ANN is that it is very useful in learning complex relationships between multi-dimensional data. Recently, owing to their simplicity and robustness, ANNs have been employed to model complex relationships between input and output datasets in geotechnical engineering [6,12–16,24]. In this study, we propose a simple method of predicting the compression index of Korean soils from several basic soil parameters using an ANN without carrying out consolidation tests for the determination of the compression index. The authors collected the data for 947 consolidation

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tests for soils sampled at 67 construction sites in Korea and classified the soil parameters according to the water content, liquid limit, plastic index, specific gravity, and soil types. The developed ANN model can be used to predict the compression index and a neural interpretation diagram is proposed here relating the parameters affecting the compression index. We selected nine empirical formulas to compare their predictability with our developed ANN model: the best fit line for the predicted compression index and laboratory test value, the mean and standard deviation of the ratio, and a boxplot which is often used for statistical analysis.

2. Artificial neural network (ANN)

An artificial neural network (ANN) is a computational procedure which is able to acquire, represent, and compute a mapping from one multivariate space of information to another with a set of data representing that mapping. ANNs can handle imperfect or incomplete data and can capture nonlinear and complex relationships among variables of a system. The artificial neural network is emerging as a powerful tool for modeling with these abilities.

In a feed forward network, the nodes are generally arranged in layers, starting from a first input layer and ending at the final output layer. There can be several hidden layers, with each layer having one or more nodes. Information passes from the input to the output side. In most networks, the input layer receives the input variables for the problem at hand. This consists of all the quantities that can influence the output. The input layer is, thus, transparent and is a means of providing information to the network. The output layer consists of values predicted by the network and, thus, represents the nodal output. The number of hidden layers and the number of nodes in each hidden layer are usually determined by a trial-and error procedure. An ANN consists of a number of interconnected neurons. Each neuron/node is an independent computational unit, which works as per the following formula:

$$y_j = f\left(\sum w_{ij}x_i + \theta_j\right) \tag{1}$$

where y_j = the transformed output by the jth hidden or output neuron, x_i = the input of the ith neuron in the previous layer, w_{ij} = the weight of the connection joining the jth neuron in a layer with the ith neuron in the previous layer, θ_j = the bias at the jth neuron, and f = the transfer or activation function which controls the output of a neuron or squashes it to a finite range $(-1, 1)$. The weight indicates the strength of the connection while the bias increases the net input to the activation function, leading to an increase in the error convergence.

The connection weights and bias values are initially selected as random numbers and are then fixed as a result of a training process. As such, each node multiplies every input by its interconnection weight, sums the product, and then passes the sum through a transfer function to produce its result. Many different training schemes for an ANN are available in the literature. The Bayesian Regularization was applied to a back-propagation neural network for prediction [17]. This approach minimizes the over-fitting problem by taking into account the goodness-of-fit as well as the net-

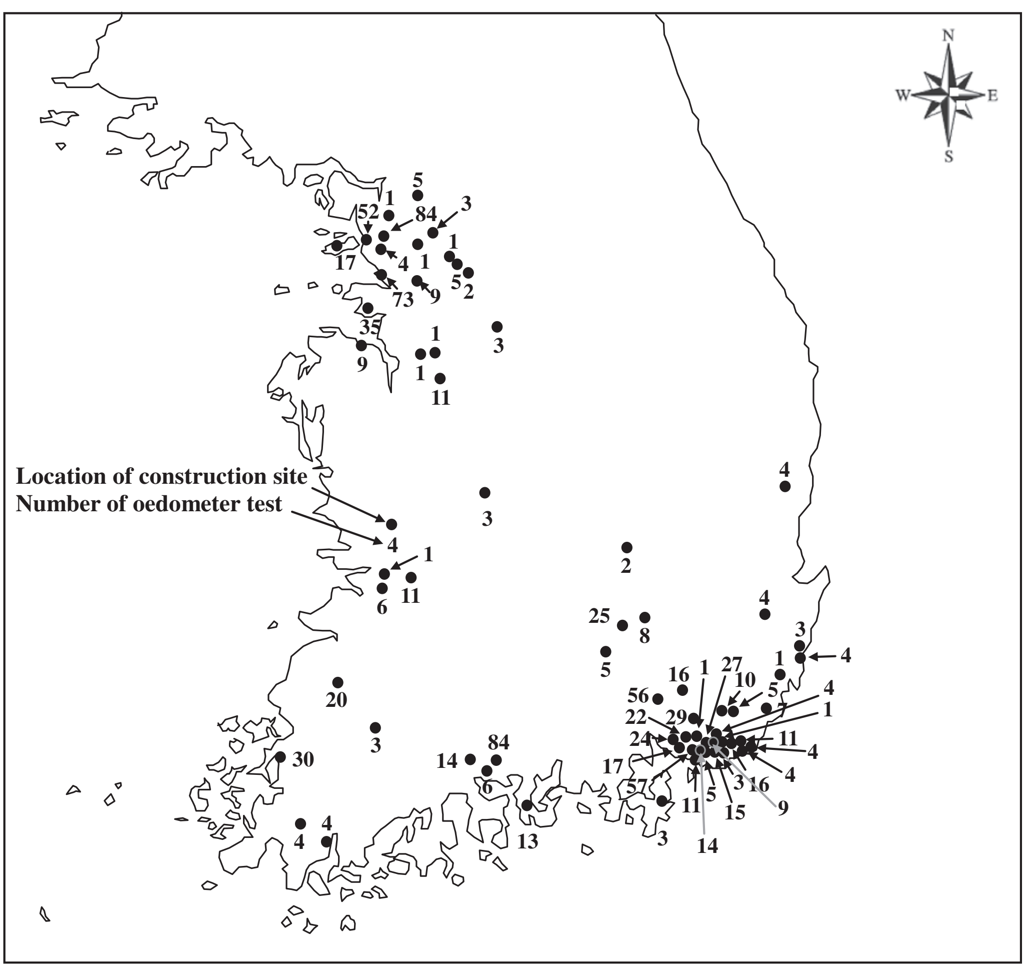

Fig. 1. Map showing the location of construction sites in Korea.

work architecture. As learning rate varies according to the terrain of performance surface, it is known as adaptive learning rate back-propagation method. The following is the short description about the Bayesian regularization. Typically, the training aims to reduce objective function, F such as the mean sum of squared network errors (E_d). The Bayesian Regularization approach involves modifying the usually used objective function. The objective function, F is expanded with the addition of a term, E_w which is the sum of squares of the network weights; i.e. the objective function becomes $F = \beta E_d + \alpha E_w$. The α and β are parameters which are to be optimized in Bayesian framework of MacKay [17], MacKay [18] The relative size of the objective function parameters dictates the emphasis for training. If $\alpha \ll \beta$, then the training algorithm will drive the errors smaller. If $\alpha \gg \beta$, training will emphasize weight size reduction at the expense of network errors, thus producing a smoother network response.

At the end of the training phase, the neural network represents a model able to predict a target value when given the input value. An algorithm called back-propagation is then used to adjust the weights and biases until the mean-squared error is minimized. The network is trained by repeating this process several times. Once the ANN is trained, the prediction mode simply consists of

Table 1
Detailed information for the compression index and soil.

	w_n	e_o	LL	PI	G_s	W_{sand}	W_{silt}	W_{clay}	C_c
Range	11–157	0.27–3.94	6.9–144	0–95	2.46–2.9	0–99	0–100	0–71	0.1–2.25

*w_n = natural water content (%), e_o = void ratio, LL = liquid limit (%), PI = plastic index, G_s = specific gravity, W_{sand} = weight percentage of grain size larger than 0.075 mm, W_{silt} = weight percentage of grain size between sieve 0.075 mm and 0.005 mm, W_{clay} = weight percentage of grain size less than 0.005 mm, C_c = compression index.

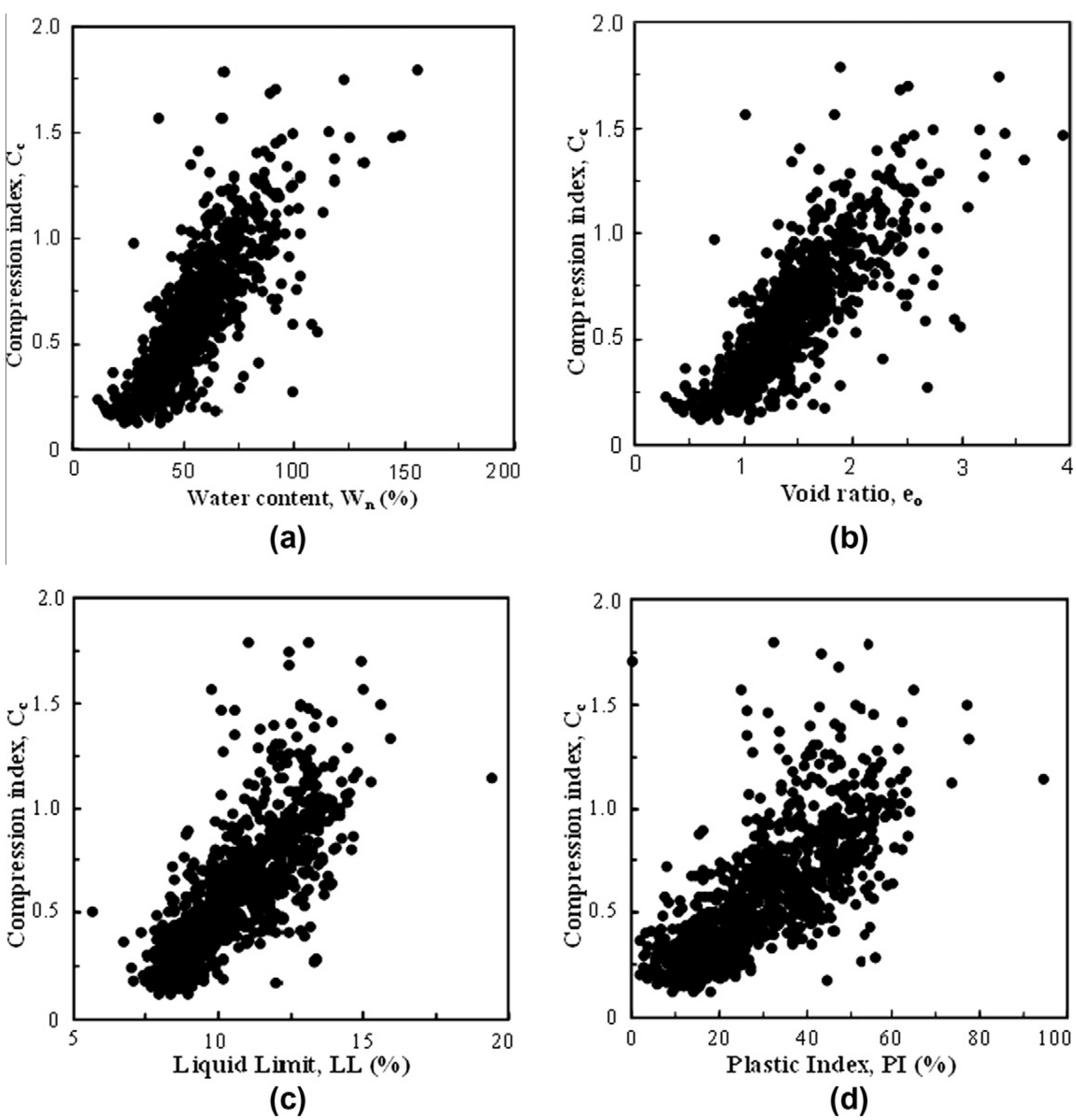

Fig. 2. Relationship between the compression index and soil parameters.

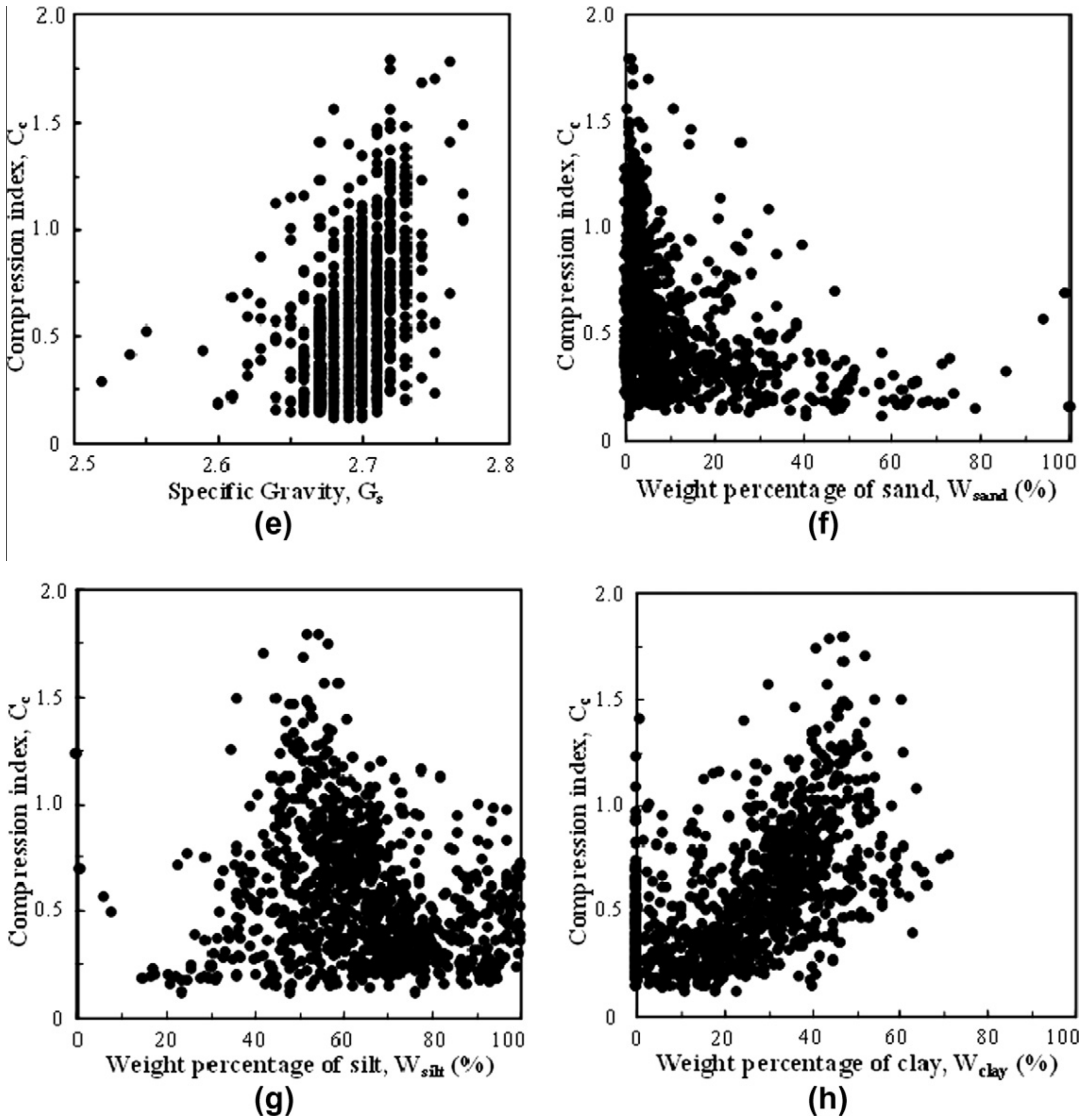

Fig. 2 (*continued*)

propagating the data through the network, yielding immediate results.

3. Data base

A site investigation including various laboratory tests must be performed before a construction project can be approved in Korea. The Ministry of Homeland and Maritime Affairs has been building a database including in situ tests and laboratory test results since 2001. They also furnish good quality data on the website (http://www.geoinfo.or.kr) so that civil engineers easily put the data to practical use. As shown in Fig. 1, we collected 947 consolidation tests at 67 construction sites in Korea through the website. The results of the liquid limit test, plastic limit test, specific gravity test and grain distribution test were classified with the consolidation tests and are illustrated in Table 1. The settlement associated with load increments is generally determined directly using the $e - \log p$ curve or the compression index C_c determined from the $e - \log p$ curve, where e is the void ratio and p is the normal overburden pressure. For a layer of normally consolidated soil of thickness H, initial void ratio e_o, compression index C_c, and effective overburden pressure p'_o, the total settlement S_t under an applied load Δp can be expressed as

$$S_t = \frac{C_c}{1 + e_o} H \log \frac{p'_o + \Delta p}{p'_o} \tag{2}$$

where C_c is the slope of the virgin compression portion of the $e - \log p$ curve determined from a standard consolidation test on an undisturbed sample.

The compression index of the soils was assumed to be affected by water content (w_n), the void ratio (e_o), the liquid limit (LL), the plastic index (PI), the specific gravity (G_s), the weight percentage of the sand (W_{sand}), silt (W_{silt}), and clay (W_{clay}), as shown in Table 1. The consolidation tests were undertaken following KSF 2316 and the other tests according to the relevant KSF standards. The relationships between the compression index and soil parameters are shown in Fig. 2. The water content, void ratio, liquid limit, plastic index, and the weight percentage of clay have relatively linear correlations with the compression index.

To statistically estimate the relationship between the compression index and soil properties, a partial rank correlation coefficient (PRCC) was calculated [10]. Rank regression is preferred over usual regression when poor linear fits are caused by nonlinear data [7]. The Spearman rank correlation coefficient was chosen for comparisons between the compression index and soil parameters. It is based on the ranking of the variables. The ranks are numbered from 1 to 947, which is the number of data sets. These ranks replace the original data provided by the detector. The non-parametric correlation coefficient, r_s is expressed in the following form:

$$r_s = \frac{\sum(B_i - \bar{B})(B_i - \bar{B}')}{\left(\sum(B_i - \bar{B})^2(B_i - \bar{B}')^2\right)^{1/2}} = \frac{BB'}{((BB)(B'B'))^{1/2}}, \tag{3}$$

where B_i is the rank corresponding to the values of the original input and $B_i'$is the rank corresponding to the output values. The closer B_i is to +1 or −1, the stronger the likely correlation. A perfect positive correlation is +1 and a perfect negative correlation is −1.

The coefficient, r_s for the eight soil parameters, w_n, e_o, LL, PI, G_s, W_{sand}, W_{silt}, W_{clay} are shown in Fig. 3. For the present problem, the most linearly correlated variable is e_o followed in order by w_n, LL, PI, W_{clay}, G_s, W_{sand}, W_{silt}. The r_s value of w_n, e_o, LL, and PI are 0.844, 0.847, 0.820, and 0.794, respectively. These values imply a fairly strong positive linear relationship, which indicates that an increase in these parameters tends to proportionally increase the compression index. The values of W_{sand} and W_{silt} are negative r_s values, −0.435 and −0.254. These parameters have a nonlinear negative relationship which indicates that these variables tend to nonlinearly decrease the compression index. This means that the parameters w_n, e_o, LL, and PI are parameters to obtain a linear correlation with the compression index in comparison with G_s, W_{sand}, W_{silt}, and W_{clay} which are supposed to have a complex nonlinear relationship with the compression index.

4. Comparison of the empirical formula

As shown in Table 2, five types of empirical formulas are selected to test performances of formulas based on laboratory experiments [1,9,11,19,20,29]. In Table 2, the authors obtained new formulas for each type of empirical formulas through the regression analysis of the data set collected in this study. Fig. 4 shows scattergrams for the predicted compression from the application of the formulas and the measured value from the consolidation test. The R^2 value reflects how much the errors are reduced when predicting the compression index obtained using the empirical formulas. The R^2 value shows poor performances ranged from 0.534 to 0.712. Figs. 4a and b shows that the four formulas of type 1 utilizing w_n and the four formulas of type 2 utilizing e_o give better prediction for Korean soil. On the other hand, the formulas using LL, PI, and G_s give a considerable over- or under-estimation for Korean soil, as shown in Fig. 4c–e, because the water content and the void ratio are more simple soil parameters to measure and also less sensitive to the experimental code of each nation or the skill of experimental technicians in comparison to the liquid limit, plastic index, and specific gravity. Therefore, when an engineer has to estimate the compression index without the consolidation test result, the formulas using the natural water content, w_n or the void ratio e_o are likely to give a reliable prediction.

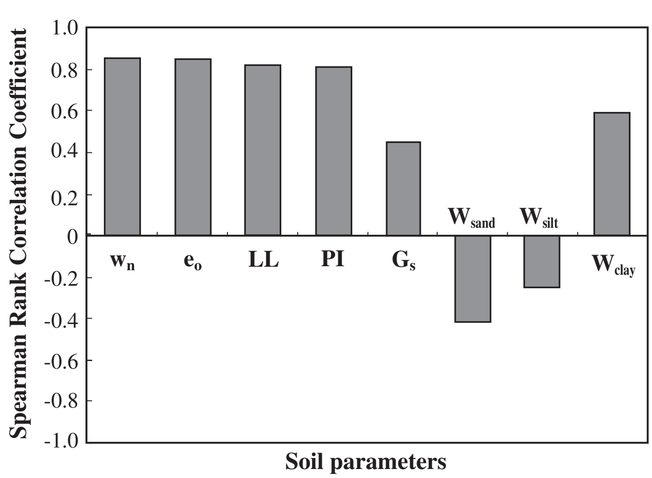

Fig. 3. Spearman rank correlation coefficients of soil parameters.

5. Development of the ANN model

In order to develop the artificial neural network (ANN) model, it is common practice to divide the available data into two subsets: a training set to construct the ANN model and an independent validation set to estimate model performance. The data set was divided randomly into two separate data sets—the training data set (90% of the total data set) and the testing data set (10% of the total data set). Among 947 data sets, 852 randomly collected data sets were used in the training stage and the remaining 95 data sets were used in the test stage. Feed-forward neural networks with back-propagation algorithms are the most widely used method [25]. Therefore, in this study a back-propagation algorithm was used during training. The training data set was used to train the ANN model with the help of a suitable algorithm and the testing data were used for testing the generalization capability of the ANN model.

Determination of a network structure involves the selection of an input parameters input layer, the number of hidden layer nodes and also a combination of transfer functions between the layers. In order to find an appropriate input combination of ANN model for evaluating the compression index, we trained ANN models composed of various combinations of input parameters given in Table 3. The basic methodology used is to exclude parameters in the input layer of ANN model and then perform the same analysis again. The four parameters, w_n, e_o, LL, and PI was included in the input layer of all ANN models because of strong linear correlations with the compression index shown in Fig. 3. The model II shows best correlation for the training and testing data in comparison of other ANN models in Table 3. The natural water content (w_n), void ratio (e_o), liquid limit (LL), plastic index (PI), weight percentage of sand (W_{sand}), weight percentage of sand (W_{silt}), weight percentage of sand (W_{clay}) made up the input layer. In Table 4, various

Table 2
Some widely used compression index equations.

Function type		Equation	References
1	$C_c = a \cdot w_n + b$	$C_c = 0.01w_n - 0.05$	Azzouz et al. [1]
		$C_c = 0.01w_n$	Koppula [9]
		$C_c = 0.01w_n - 0.075$	Herrero [11]
		$C_c = 0.013w_n - 0.115$	In this study
2	$C_c = a \cdot e_o + b$	$C_c = 0.54e_o - 0.19$	Nishida [23]
		$C_c = 0.43e_o - 0.11$	Cozzolino [4]
		$C_c = 0.75e_o - 0.38$	Sowers [27]
		$C_c = 0.49e_o - 0.11$	In this study
3	$C_c = a \cdot w_L + b$	$C_c = 0.006\ (w_L - 9)$	Azzouz et al. [1]
		$C_c = (w_L - 13)/109$	Mayne [19]
		$C_c = 0.009\ (w_L - 10)$	Terzaghi and Peck [29]
		$C_c = 0.014 \cdot w_L - 0.168$	In this study
4	$C_c = a \cdot \frac{w_L}{G_s}$	$C_c = 0.2343\ (w_L/100)\ G_s$	Nagaraj and Murty [20]
		$C_c = 2.926\ (w_L/100)\ G_s$	In this study
5	$C_c = a \cdot w_n + b \cdot w_L + c$	$C_c = 0.009w_n + 0.005w_L$	Koppula [9]
		$C_c = 0.013w_n + 0.0w_L + 0.168$	In this study

∗Parameter, a and b is evaluated by a regression analysis of the data set.

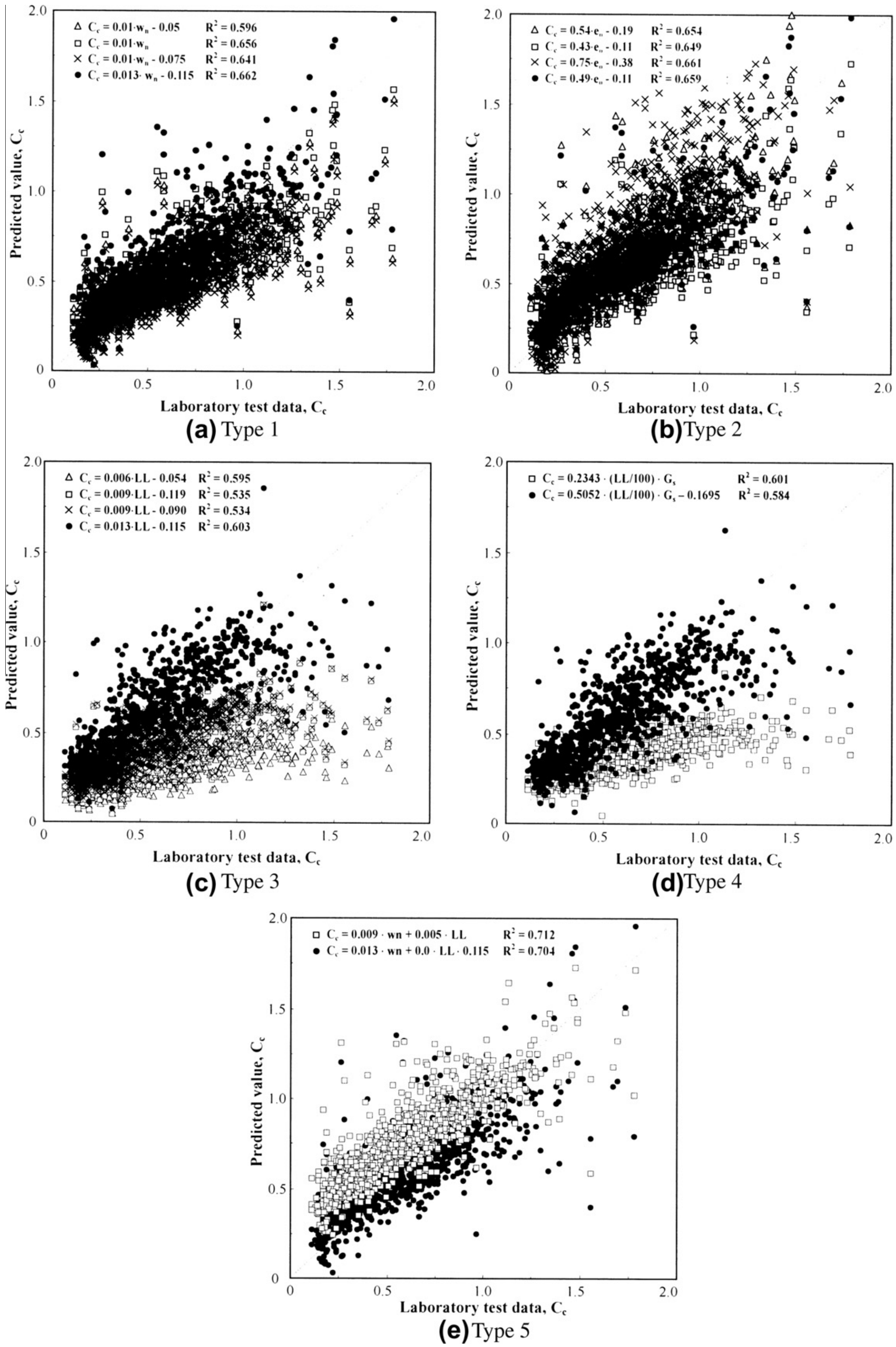

Fig. 4. Comparison between the measured compression index obtained from a consolidation test and the computed compression index using empirical formulas. Comparison between the measured compression index obtained from a consolidation test and the computed compression index using empirical formulas.

numbers of neuron in the hidden layer and the combinations of transfer functions were tested to find the optimal structure for the ANN model. The value of the minimum sum-squared error goal was varied based on the coefficient of the determination of R^2 for the testing results. The R^2 value reflects the contribution of input information in predicting the target value, which means by how much the errors are reduced when predicting the compression index by using the provided input information. Table 4 shows the variation in R^2 with different numbers of hidden nodes. In general, the R^2 value for the training data set was larger than for the testing set, i.e., the neural network made better predictions for the training data sets than the testing data sets. The combination of two hidden layers gives better results than single hidden layer and also the combination of transfer functions composed of tan-sigmoid, log-sigmoid and linear function gives good results. Fig. 5 shows the selected structure of the ANN model applied to predict the compression index of soil. The ANN model has seven neurons in the input layer, ten neurons in first hidden layer, seven neurons in second hidden layer, and one node in the output layer. The transfer functions in the input layer-the first hidden layer, the

Table 3
Various ANN models used to select an appropriate combination of input parameters.

Parameter	Input variable of ANN								
	I	II	III	IV	V	VI	VII	VIII	
w_n	O	O	O	O	O	O	O	O	O
e_o	O	O	O	O	O	O	O	O	O
w_L	O	O	O	O	O	O	O	O	O
PI	O	O	O	O	O	O	O	O	O
G_s	O		O	O	O	O			O
W_{sand}	O	O		O	O	O	O		
W_{silt}	O	O	O		O		O	O	
W_{clay}	O	O	O	O				O	O
R^2 (Training)	0.816	0.818	0.809	0.806	0.733	0.714	0.739	0.741	0.778
R^2 (Testing)	0.820	0.824	0.799	0.780	0.763	0.698	0.765	0.764	0.821

Table 4
Summary of the results for various structures of ANN model.

No. of HL	No of neuron in each HL		Transfer function	R^2 value	
	First HL	Second HL		Training	Testing
1	8		Log-sigmoid, linear	0.707	0.693
	9		Log-sigmoid, linear	0.712	0.700
	10		Log-sigmoid, linear	0.720	0.712
	11		Log-sigmoid, linear	0.744	0.752
	12		Log-sigmoid, linear	0.756	0.749
	13		Log-sigmoid, linear	0.783	0.787
	8		Log-sigmoid, tan-sigmoid	0.799	0.785
	9		Log-sigmoid, tan-sigmoid	0.818	0.824
	10		Log-sigmoid, tan-sigmoid	0.829	0.835
	11		Log-sigmoid, tan-sigmoid	0.831	0.818
	12		Log-sigmoid, tan-sigmoid	0.868	0.831
	13		Log-sigmoid, tan-sigmoid	0.872	0.829
2	9	4	Log-sigmoid, tan-sigmoid, linear	0.817	0.826
	9	5	Log-sigmoid, tan-sigmoid, linear	0.822	0.814
	9	6	Log-sigmoid, tan-sigmoid, linear	0.843	0.835
	9	7	Log-sigmoid, tan-sigmoid, linear	0.846	0.829
	9	8	Log-sigmoid, tan-sigmoid, linear	0.853	0.841
	9	9	Log-sigmoid, tan-sigmoid, linear	0.869	0.847
	9	10	Log-sigmoid, tan-sigmoid, linear	0.865	0.833
	9	4	Tan-sigmoid, log-sigmoid, linear	0.830	0.809
	9	5	Tan-sigmoid, log-sigmoid, linear	0.844	0.818
	9	6	Tan-sigmoid, log-sigmoid, linear	0.854	0.834
	9	7	Tan-sigmoid, log-sigmoid, linear	0.862	0.851
	9	8	Tan-sigmoid, log-sigmoid, linear	0.864	0.857
	9	9	Tan-sigmoid, log-sigmoid, linear	0.877	0.860
	9	10	Tan-sigmoid, log-sigmoid, linear	0.881	0.864
	10	4	Log-sigmoid, tan-sigmoid, linear	0.833	0.825
	10	5	Log-sigmoid, tan-sigmoid, linear	0.845	0.847
	10	6	Log-sigmoid, tan-sigmoid, linear	0.841	0.856
	10	7	Log-sigmoid, tan-sigmoid, linear	0.860	0.863
	10	8	Log-sigmoid, tan-sigmoid, linear	0.864	0.849
	10	9	Log-sigmoid, tan-sigmoid, linear	0.865	0.847
	10	10	Log-sigmoid, tan-sigmoid, linear	0.857	0.851
	10	4	Tan-sigmoid, log-sigmoid, linear	0.869	0.841
	10	5	Tan-sigmoid, log-sigmoid, linear	0.874	0.859
	10	6	Tan-sigmoid, log-sigmoid, linear	0.890	0.882
	10	**7**	**Tan-sigmoid, log-sigmoid, linear**	**0.896**	**0.885**
	10	8	Tan-sigmoid, log-sigmoid, linear	0.901	0.873
	10	9	Tan-sigmoid, log-sigmoid, linear	0.905	0.872
	10	10	Tan-sigmoid, log-sigmoid, linear	0.904	0.865

$*$, HL = hidden layer.

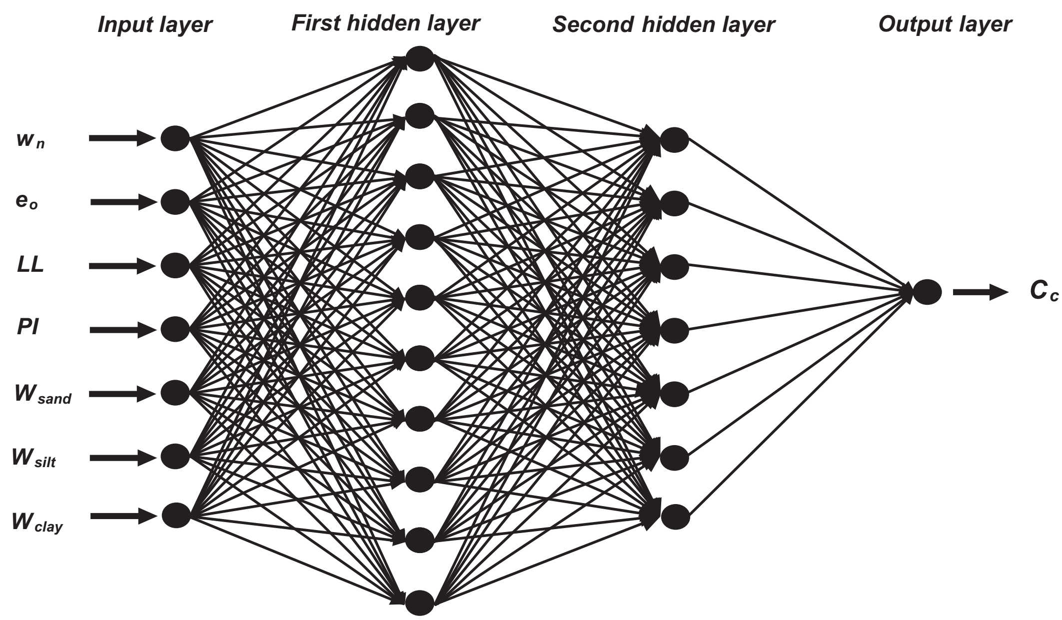

Fig. 5. Structure of the ANN model to predict the compression index.

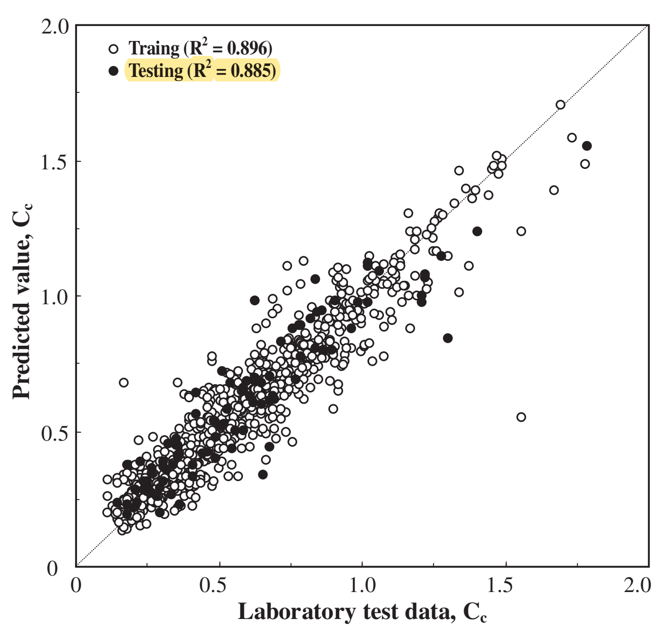

Fig. 6. Comparison between the measured compression index obtained from the consolidation test and the computed compression index using the ANN model.

Table 5
Statistical results for conventional empirical formulas.

Type	Equation	Average, μ	Standard deviation, σ
1	$C_c = 0.01w_n - 0.05$	0.92	0.353
	$C_c = 0.01w_n$	1.04	0.404
	$C_c = 0.01w_n - 0.075$	0.86	0.330
	$C_c = 0.013w_n - 0.115$	1.08	0.415
2	$C_c = 0.54e_o - 0.19$	1.07	0.420
	$C_c = 0.43e_o - 0.11$	0.95	0.362
	$C_c = 0.75e_o - 0.38$	1.21	0.538
	$C_c = 0.49e_o - 0.11$	1.12	0.425
3	$C_c = 0.006w_L - 0.054$	0.54	0.201
	$C_c = 0.009w_L - 0.119$	0.74	0.273
	$C_c = 0.009w_L - 0.090$	0.79	0.293
	$C_c = 0.014w_L - 0.168$	1.17	0.428
4	$C_c = 0.2343\ (w_L/100)\ G_s$	0.70	0.272
	$C_c = 2.926\ (w_L/100)\ G_s$	1.12	0.407
5	$C_c = 0.009w_n + 0.005w_L$	1.49	0.553
	$C_c = 0.013w_n + 0.0w_L + 0.168$	1.12	0.411
6	ANN model	1.05 (Training) 1.07 (Testing)	0.216 (Training) 0.223 (Testing)

first hidden layer- the second hidden layer, and the second hidden layer-the output layer are a tan-sigmoid function($1/(1+e^{-n})$), log-sigmoid function ($2/(1+e^{-2n})-1$), and linear function respectively. Fig. 6 shows the relationship between output targets and predicted values obtained through the training and testing process. The model shows very good correlation for both the training ($R^2 = 0.896$) and testing data ($R^2 = 0.885$) compared with the conventional empirical formulas.

In Table 5, the predictability of the ANN model is statistically compared with the empirical formulas, the mean and standard deviation of the ratio $C_{c,\text{pred}}/C_{c,\text{mea}}$ and a boxplot, which is often used for statistical analysis. The mean (μ) and standard deviation (σ) of $C_{c,\text{pred}}/C_{c,\text{mea}}$ are important indicators of the accuracy and precision of the prediction method. Under ideal conditions an accurate and precise method gives a mean value of 1.0 and a standard deviation of 0. A μ value greater than 1.0 indicates overestimation and under-estimation, otherwise. The best model is represented by a μ value close to 1.0 and σ close to 0. Based on the μ value, the ANN model shows a good prediction followed by the formulas of type 1 using the soil parameter, w_n. Other empirical formulas yield a μ value in the range of 0.54–1.49. This means that they considerably underestimate or overestimate the compression index on average. The value of σ is also found to be minimum for the ANN model. Other formulas yield σ values in the range of 0.201–0.553. Similarly, the boxplots of $C_{c,\text{pred}/Cc,\text{mea}}$ in Fig. 7 can be used to visually assess the reliability of the ANN model and empirical formulas. This means that most formulas considerably underestimate or overestimate the compression index and also show a great deal of scattering. ANN model shows almost same results in training and testing stage, regardless of whether the data

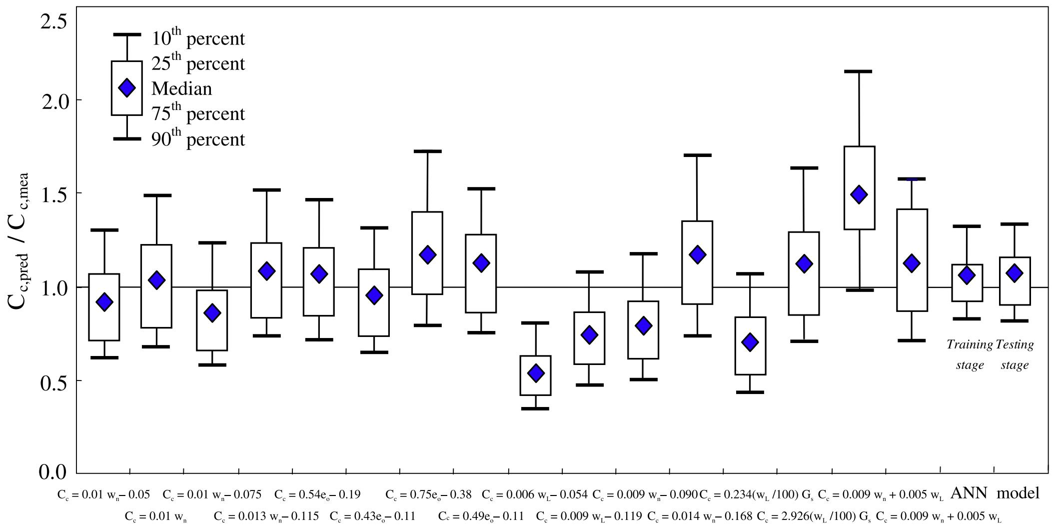

Fig. 7. Box plot of the ratio $C_{c,\mathrm{pred}}/C_{c,\mathrm{mea}}$ by empirical formulas and the ANN model.

sets used in the train stage or not. It represents the best prediction, close to 1.0, followed by the formulas of type 1 and also a short box, which means little scattering of the prediction of the compression index.

6. Conclusions

The following conclusions can be drawn from the above study:

1. The performances of empirical formulas were tested with the best fit lines for the predicted compression index and measured compression index of consolidation tests. Nine hundred and forty-seven consolidation test sets collected from 67 construction sites in Korea were used in this study. It can be seen that the formulas using the natural water content, w_n show better performance among the four types of formulas using the parameter, natural water content, void ratio, liquid limit, and specific gravity.
2. An artificial neural network model was developed to predict the compression index based on seven soil parameters including the natural water content, void ratio, liquid limit, plastic index, specific gravity, and others. The predictions of this model agreed well with the measured compression index of the consolidation tests. We concluded that reliable predicting capabilities were obtained.
3. Three criteria were selected to compare the performances of the developed ANN model with the conventional empirical formulas: the best fit line analysis comparing the predicted compression index with the measured compression index of the consolidation test, the mean and standard deviation of the ratio, $C_{c,\mathrm{pred}}/C_{c,\mathrm{mea}}$ and a boxplot of $C_{c,\mathrm{pred}}/C_{c,\mathrm{mea}}$. These showed that the developed ANN model is more efficient than the empirical formulas.

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