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Estimation of Compression Index using Genetic Algorithm Approach

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Abstract: *Genetic algorithm was employed to create a tool for estimating the compression index of clayey soils. Data collection was done in some areas in the Eastern part of the National Capital Region (NCR) of the Philippines were plastic soils are known to be present. The collected data separated into two categories namely, training data (70%) and validation data (30%). The objective function used in this study is an empirical equation that is dependent on the initial void ratio, natural water content, and liquid limit. It has a Pearson's Coefficient of Correlation value of 0.86 which was used as the target criteria for the training data. By comparing the validation data to the empirical equation of Rendon-Herrero (1983), a minimum R value of 0.8590 was obtained. Based on the results, the genetic algorithm program developed were determined to be comparable to the empirical equation by statistical analyses.*

Keywords: Genetic Algorithm; Compression Index; Compressibility

1. INTRODUCTION

In geotechnical practices, settlement estimation is usually being carried out by theoretical and experimental approach. The common method in settlement estimation is by correlation of data from in-situ tests such as piezocone test and seismic dilatometer test [1-2]. These addresses the challenges in obtaining undisturbed samples for ex situ testing to be able to determine compressibility parameters under a target stress and strain history [2]. Studies with regards to comparative analysis of available traditional methods showed inconsistent estimation of magnitude of settlement [3-4]. The coefficient of compression, or compression index, is a key parameter in the estimation and evaluation of settlement in soils [5]. This parameter is usually obtained in performing ex-situ test.

A promising method to determine this parameter is by utilizing machine learning algorithms. These approaches have already been implemented in different geotechnical applications such as data classification techniques to bridge the gap of traditional methods and improve validity of existing theories [6-9]. Nevertheless, the use of neural networks algorithms, evolutionary-based approaches, and computer-based software are amongst the most used numerical methods to estimate soil settlement behaviors [10-13]. Genetic algorithm (GA) was considered a reliable tool to estimate properties or settlement in various kinds of soils because of its capability to model complex soil behavior that often arises in engineering practice. The genetic model can directly produce the data necessary without the use of calibrations and normalization [14]. Unlike other approaches, the GA approach involved a population of a large magnitude [15].

With this, it is the objective of the study to develop a GA program that incorporates specific gravity (G_s), natural water content (w%), liquid limit (LL), unit weight of water (γ_w), and unit weight of soil (γ) as independent variables. Since they are deemed to be affecting the compressibility behavior of plastic soils. The final output of the study is the estimated value of compression index, C_c, of compressible soils.

2. METHODOLOGY

2.1 Case Study

As shown in Figure 1 are the location of the borehole (BH) data collected for this study. The chosen area where the data was at the Eastern part of the National Capital Region (NCR) of the Philippines. This area is known to have plastic soils [7].

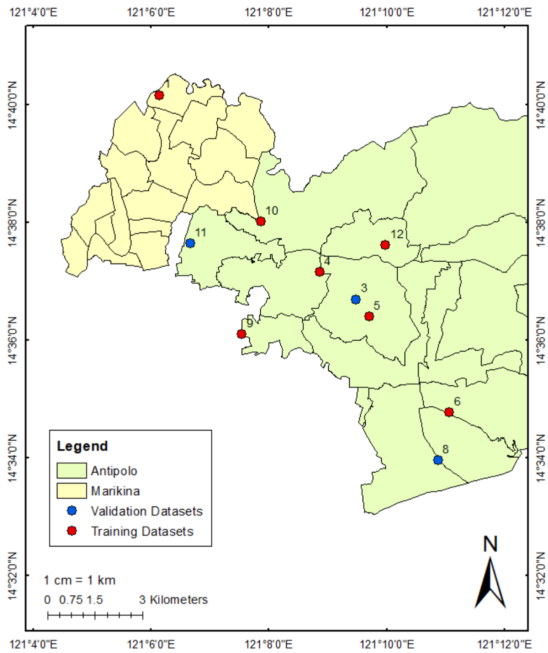

Fig. 1. Collected Data in Eastern NCR.

2.2 Data Cleansing

A total of 13 borehole data was collected. It was divided into 70% training data (7 borehole data) and 30% (3 borehole data) validation data. In order to eliminate erroneous information, data cleansing was first performed. One borehole log per square kilometer was considered [16]. If the location of the borehole data were located less than one kilometer apart, it will be considered as a validation data. The division of the data is tabulated in Table 1.

Table 1. Borehole data for training and validation.

Training Data	Validation Data
BH-1, BH-4, BH-5, BH-6, BH-9, BH-10, BH-12	BH-3, BH-8, BH-11

In the process of data cleansing, independent variables such as liquid limit was the focus. Since, this parameter is known to contribute to the compressibility of a soil. Information on the liquid limit of the soil were taken from the collected borehole logs. Moreover, Table 2 was used as a guide in the projected depth of the soil layer that was considered. Since the parameter to be desired in this research is the compression index, C_c, the table above classified up to which layer of soil was compressible. With this, the depth to be considered were classified and analyzed correspondingly.

Table 2. The conditions of the soil layer as determined by Atterberg's limits [16, 17]

If natural water content (w%) is approximately close to Liquid Limit (LL)	Soil is normally consolidated
If the natural water content (w%) is approximately close to Plastic Limit (PL)	Soil is some to heavy overconsolidated
If natural water content is intermediate	Soil is somewhat overconsolidated
If natural water content (w%) is larger than Liquid Limit (LL)	Soil is on the verge of being viscous liquid

The natural water content was determined from the borehole data collected. The specific gravity was assumed based on the established values for silt and clay. The unit weight of soil values obtained using Eq. 1. The correlations using SPT-N values established by Prasad, Puri, and Jain (2017) for cohesive soils. Equation 1 is applicable for SPT-N value ranging from 1 to 50 and its R-squared is 0.97.

$$\rho_b = 0.0080N + 1.7202 \quad (1)$$

In order to validate the estimated unit weight, the typical unit weight values of Coduto, Kitch, and Yeung (2016) was used as a reference.

2.3 Objective Function

The compression index (C_c) was defined as the parameter which describes the factor in which soils will settle when subjected to change in stress [17]. This parameter reflects on the compressibility characteristics of soil which is significant in the calculation of the primary consolidation. Values of C_c that are high correlates to the soil being highly compressible while a low value will correlate to the soil being slightly compressible.

The objective function requires a fitness function to serve as a guide in creating the optimal fitness equation which could lead to accurate results. The fitness function shown in Eq. 2 was based on Azzouz, Krizek, & Corotis (1976). In their study, it was proposed to use common soil index properties such as plastic limit and liquid limit, and initial void ratio to compute for the compression index, C_c, with the utilization of regression analysis. Based on their study, the Pearson's Coefficient of Correlation (R) value of Eq. 2 resulted in a relatively high correlation of 0.86 [18].

$$C_c = 0.37(e_o + 0.003LL + 0.0004w - 0.34) \quad (2)$$

where, C_c is the actual compression index, e_o is the initial void ratio, w is the natural water content, and LL is the liquid limit.

This objective function is limited to clayey soils only and it is not recommended to be used for granular soils. Equation 2 could also generate an R value greater than 0.70. Hence, it was determined that this formula was best suited for this study, as well as the type of soil under consideration. Moreover, the Pearson's Coefficient of Correlation value of 0.86 was the basis of whether criteria has been met by the developed program.

The independent variables that can be directly obtained from a borehole data are liquid limit and water content. In order to determine initial void ratio (e_o), weight volume relationships between e_o and unit weight (γ) were considered to estimate these parameters. The level of groundwater table must be noted as it corresponds to the soil layer having a dry unit weight or a saturated unit weight. The formulated equations used are shown below.

$$\gamma_d = \frac{G_s \gamma_w}{1+e_o} \quad (3)$$

$$\gamma_{sat} = \frac{(G_s+e_o)\gamma_w}{1+e_o} \quad (4)$$

Equation 3 and 4 were simplified to establish equations for e_o as shown below. Equation 5 is for a dry soil while Eq.6 is for a soil submerged in water.

$$e_o = \frac{G_s\,\gamma_w}{\gamma_d} - 1 \quad (5)$$

$$e_o = \frac{\gamma_{sat} - G_s\,\gamma_w}{\gamma_w - \gamma_{sat}} \quad (6)$$

The objective function was improved to incorporate equations for e_o. Equation 5 and 6 where substituted to Equation 2. This resulted to two equations as shown below. Equation 7 is for a dry soil while Eq. 8 is for a soil submerged in water.

$$C_c = 0.37\left(\frac{G_s\,\gamma_w}{\gamma_d} + 0.003LL + 0.0004w - 1.34\right) \quad (7)$$

$$C_c = 0.37\left(\frac{\gamma_{sat} - G_s\,\gamma_w}{\gamma_w - \gamma_{sat}} + 0.003LL + 0.0004w - 0.34\right) \quad (8)$$

where:

G_s = specific gravity
γ_w = unit weight of water
γ_d = dry unit weight
γ_{sat} = saturated unit weight
LL = liquid limit
w = natural water content

2.4 Machine Learning Model

Genetic Algorithm is a machine learning model that implements the concept of natural selection based on

Darwin's principle [9]. Natural selection was aimed to determine the optimal solution for a specific problem. In the early stage of the natural selection process, the algorithm would produce one population of chromosomes. These are defined as the independent variables. These variables would be optimized to create a new population through a natural selection process [9]. They contain a group of numbers that relay a solution for its objective function. Specifically, the input parameters were quantified and evaluated on how fit a solution is such that the C_c values formulated were based on their best fit of the input parameters to Eq. 7 and 8.

To evaluate the goodness of fit to the objective function, a minimum target Pearson's R value of 0.86 was used. It was based on the Pearson's R value of the equation Azzouz, Krizek, & Corotis (1976) in estimating C_c. This value was considered since the objective function used in this study was based on this equation as shown in Eq. 7 and 8.

The chosen chromosomes in the natural selection would then be crossed over and mutated to form a new offspring that possess the best fit for the objective function. From there, the Genetic Algorithm were based on the criteria to be met to ensure accurate results. During the optimization process, the selection operator would choose which chromosome to be utilized to reproduce offspring that best fits the conditions set by the objective function. The choice or selection depend on the ranking of chromosomes according to their "genes" or best fit. This allows for the perseverance of good solutions and the elimination of bad unfit chromosomes while keeping the population constant. Nevertheless, main processes of GA such as selection, crossover, and mutation were further discussed in this section.

In order to apply GA in this study, a flowchart was designed to systematically create the program. The flowchart is shown in Figure 2. It starts with extracting from the borehole data some independent variables such as natural water content (w%) and liquid limit (LL). Other independent variables are estimated using Eq. 5 and 6. The initial population was based on the collected and estimated independent variables and it was first introduced to the objective function (Eq. 7 and 8) [18]. When the criteria was satisfied the estimated C_c was considered. However, when the criteria were not met, selection, crossover and mutation would be performed. This would be performed until the set criteria was met.

2.5 Validation

As the final output of the developed Genetic Algorithm program would be the compression index C_c, the value of the compression index was utilized in the equation for primary settlement and the final value of settlement was calculated. However, in order to verify its accuracy, the research incorporated comparisons from established empirical equations. The reason for this was because C_c was an important parameter for soil settlement as it dictates the characteristics of soil under compression. Hence, evaluating accuracy of values obtained was indeed significant. The empirical equations shown in were utilized as these depicts all types of clays; hence, were to be used for comparisons.

Skempton (1944):

$$C_c = 0.009(LL(\%) - 10) \tag{9}$$

Nagaraj and Murthy (1985):

$$C_c = 0.2343[LL(\%)/100]G_s \tag{10}$$

Rendon-Herrero (1983):

$$C_c = 0.141.\, {G_s}^{1.2}\left(\frac{1+e_o}{G_s}\right)^{2.38} \tag{11}$$

The accuracy of the data was calculated by determining the Pearson's R value. The coefficient of correlation was a measurement of the percentage of the variance between the two variables. The coefficient was computed using Eq. 12.

$$R = \frac{[\Sigma(S_{empirical} - \underline{S_{empirical}})(S_{predicted} - \underline{S_{predicted}})]}{\sqrt{\Sigma(S_{empirical} - \underline{S_{empirical}})^2 \Sigma(S_{predicted} - \underline{S_{predicted}})^2]}} \tag{12}$$

where:

$S_{empirical}$ = C_c obtained from the empirical equations considered using validation datasets

$\underline{S_{empirical}}$ = C_c obtained from empirical equations considered at a given point

$S_{predicted}$ = C_c from the testing dataset of GA model

$\underline{S_{predicted}}$ = C_c obtained from the testing dataset of GA model.

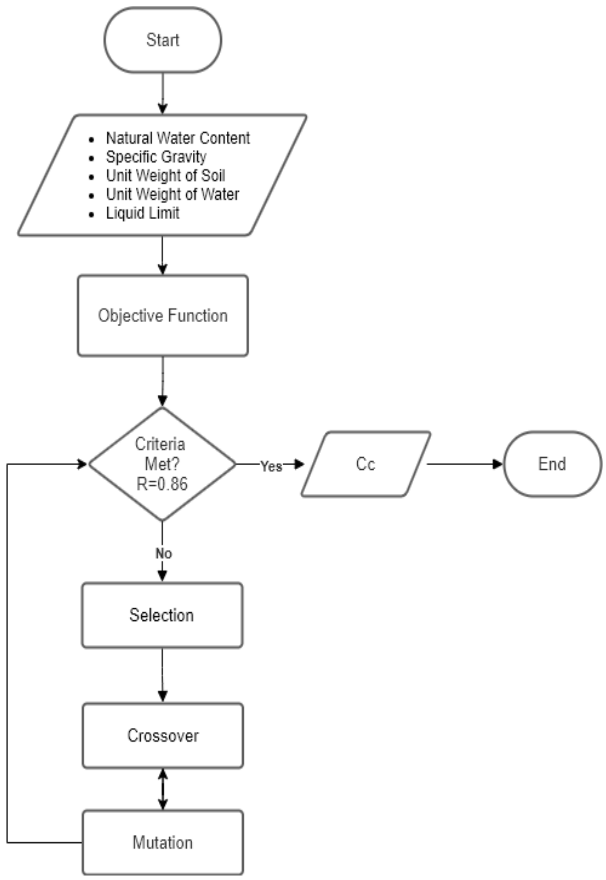

Fig. 2. Genetic Algorithm Flow Chart [16].

Sensitivity analysis was utilized to assess the impact and importance of input variables to the output variable, C_c. The concept of sensitivity analysis method performed by Prasanth (2015) was applied in this study wherein one input variable was fixed to its mean value while other variables remained to its original values. Subsequently, the analysis was done per elevation based from the mean sea level. In addition, error and weight calculation of Mrzyglod, Haeryluk, Janik, and Olejarczyk-Wozenska

(2020) was also incorporated in the study to be able to quantify and classify the relevance of input variables by order of importance. With this, error and weight of input parameters were calculated based on the equations shown below.

$$Error = \frac{1}{n}\sum_{i=1}^{n} \quad (y_i - \widehat{y_{i-GA}})^2 \quad (13)$$

where, y_i is the empirical C_c values, $\widehat{y_{i-GA}}$ is the estimated C_c values from GA program, and n the number of datasets.

$$Error_i = \frac{1}{n}\sum_{i=1}^{n} \quad (y_i - \widehat{y_{i-mean}})^2 \quad (14)$$

where, y_i is the empirical C_c values, $\widehat{y_{i-mean}}$ is the estimated C_c values from GA program using mean values, and n the number of datasets.

$$W = Error_i / \, Error \quad (15)$$

where, $Error$ is the obtained error for a dataset with original variables while $Error_i$ is the obtained error for a dataset with input parameters changed to its mean.

3. RESULTS AND DISCUSSION

The soil type per soil layer in corresponding borehole logs is tabulated in Table 3. Specifically, the soil type per depth was identified to determine the types of soils commonly present in some parts of Marikina and Antipolo City. Since, the research would be focusing on settlement at 4-meter below the foundation, soil layer up to 6-meter depth for the ground level were investigated. Based on the summarized soil types, the general soil type of each layer consists of mostly clays specially in the first few depths from the ground, some silt, and some sands in the lower depths.

Table 3. Soil type per layer depth [16]

BH	Depth from the ground (m)					
	1-m	2-m	3-m	4-m	5-m	6-m
1	clay	clay	clay	silt	clay	clay
3	clay	clay	clay	clay	clay	clay
4	clay	clay	clay	clay	sand	sand
5	clay	clay	sand	sand	sand	sand
6	clay	clay	clay	clay	sand	sand
8	clay	clay	clay	clay	sand	sand
9	clay	clay	clay	clay	clay	clay
10	clay	clay	clay	clay	sand	sand
11	clay	clay	clay	clay	clay	clay
12	clay	clay	sand	sand	sand	sand

Based on the gathered data, some parts of Marikina and Antipolo City are abundantly clayey soils. However, it was found that loose sands are present at 5-m to 6-m depths of soils in Antipolo. In general, some parts of Marikina and Antipolo city is predominantly underlain by soft clays coupled with few layers of loose sands.

To investigate the compressibility of soils, the plasticity index per depth of soils was used as an indicator to verify if the soil is indeed compressible or not. Along with this, Table 4 indicates the fines content of cohesive soils.

Table 4. Percent of fines passing in no. 200 sieve at depths

BH	Depth from the ground (m)					
	1-m	2-m	3-m	4-m	5-m	6-m
1	88	95	95	96	55	92
3	62.7	62.6	65.9	59	3.2	1.1

As seen in Table 5, soil depths that possess clay layers exhibit high plasticity index ranging from 19% to 47%. This can be attributed to the fines content that the clay layers possess. For certain borehole logs, high plasticity values are often found in depths ranging from 0 to 4-m depth as clay layers are usually present at these depths. It can be observed that soils in some parts of Marikina and Antipolo City exhibit high plastic characteristics which can lead to soils being more compressible.

Table 5. Plasticity index values per depth of soil [16]

BH	Depth from the ground (m)					
	1-m	2-m	3-m	4-m	5-m	6-m
1	45	48	43	48	18	47
3	30	30	29	32	32	32
4	18	15	12	12	0	0
5	18	17	0	0	0	0
6	19	12	22	22	0	0
8	19	18	22	22	0	0
9	32	38	48	30	22	30
10	20	17	16	16	0	0
11	20	17	23	15	15	11
12	19	16	0	0	0	0

Based on the USCS soil classification chart, soils are classified as fine grained if more than half of its material passes through the no. 200 sieve. As observed in Table 3, all soils in that specific layer have more than 50% of fines passed through the no. 200 sieve indicating that the soil was indeed cohesive. Also, if the percent of fines passing goes above 50% of its weight, it can be implicated that the soil is cohesive and exhibits significant plasticity. Only two borehole logs, BH-1 situated in Marikina and BH-3 in Antipolo, were presented in the percent of passing fines. This is because only two borehole logs were able to show percent of passing fines per depth. Although other borehole logs did not show this test, it can still be inferred that soils are cohesive due to its high plasticity index values present.

The training datasets are tabulated in Table 1 were considered in creating the GA program. In the training stage, C_c was determined until 6-meter depth with an interval at every meter. The percent difference of the calculated values from the GA program and the objective function were determined per depth. Observably, a maximum percent difference of 35.25% was obtained in BH-4, located 2 m below the ground surface. While a zero percent was observed as the minimum percent difference determined from BH-1, BH-9, BH-10, and BH-12. Nevertheless, the objective function and the genetic algorithm results were deemed to have minimal difference and maximum difference of 35.25%.

The objective function utilized was suitable for calculating the compression index of clayey soils. As

such, layers composed of sandy and silty soils were not considered. The remaining 3 borehole logs, as shown in Table 1, were designated to be part of the validation set. The Pearson's R value was computed for each iteration. The GA program yielded Pearson's R value with a maximum value of 1.0 and a maximum value of 0.8604. The results imply that there is a positive linear relationship from the estimation of C_c from the GA program between the objective function used. Consequently, high Pearson's R value indicates that the GA program resulted to satisfactory results due to the strong correlation present.
The Pearson's R values were also compared with Skempton (1944), Nagaraj and Murthy (1985) and Rendon-Herrero (1983). It was observed that for Skempton (1944) and Nagaraj and Murthy (1985) resulted to inconsistent results. It had a low to high correlation as shown in Table 5. When compare to Rendon-Herrero (1983), it was observed that there was a high correlation. Its minimum value of 0.8590 and a maximum value of 1.0.

Table 5 Comparison of Pearson's R value of the empirical equations. [16]

Depth (m)	Objective Function	Skempton (1944)	Nagaraj and Murthy (1985)	Rendon-Herrero (1983)
1	0.8604	-0.2017	-0.2017	0.8598
2	0.8614	0.5013	0.5013	0.8680
3	0.8802	-0.5473	-0.5473	0.8590
4	0.9252	0.3310	0.3310	0.9284
5	1.0000	0.9930	0.9955	1.0000
6	0.9999	0.7440	0.7640	0.9490

To investigate on the different trends on the Pearson's R value a sensitivity analysis was performed. Five input parameters that was used to estimate the compression index, C_c, are moisture content, liquid limit, unit weight, unit weight of water, and specific gravity. The aim of the sensitivity analysis was to analyze the effect of the independent parameters. The sensitivity analysis was performed in referenced to the depth from the ground level. This parametric study significantly aided to determine which independent variable gave the most impact and most relevance to the result. The unit weight of water was not considered since it is a constant value.
Correspondingly, representative depths for boreholes in Marikina and Antipolo regions were utilized to perform the sensitivity analysis as these were the depths that have the greatest number of soil layer data which can be examined. With this, depths 1-m and 2-m from the ground were analyzed. Results of sensitivity analysis in calculating for the weights were summarized in Table 6, summarized results were also illustrated in Figure 3.
From the sensitivity analysis in Table 6, it was observed that among the independent variables such as the moisture content, liquid limit, unit weight, and specific gravity, the unit weight resulted to have a significant effect in determining compression index of soils. Both results shown in Figure 3 from the 1-m and 2-m depths in the city of Marikina and Antipolo have shown that unit weight was the most significant parameter that pose a great relevance in the computation of compression index. Such that, it can be deemed that the unit weight parameter has the greatest effect in the resulting output parameter.

It is known that the unit weight is dependent on the soil type, how susceptible a soil is to compaction, and how resistant it is to compression. In addition, the correlation of unit weight with soil type is relevant as the specific weight of soil incorporates its deformation capacities which corresponds to the compression tendencies of the studied layer. For cohesive soils, unit weight of soils has a huge effect as fine particles when compressed will incur high deformation characteristics.
The equation of Rendon-Herrero (1983) exhibited the highest correlation due to the fact that unit weight had the most significant effect. The initial void ratio in this equation was computed considering the unit weight of soil. For Skempton (1944) and Nagaraj and Murthy (1985), their equation is dependent on LL and specific gravity which only has a minimal significance based on the sensitivity analysis.

Table 6 Input parameter weights

Depth (m)	w%	LL	γ	G_s
1	79.18	3854.20	6455.51	191.66
2	86.08	102.03	2844.96	1072.65

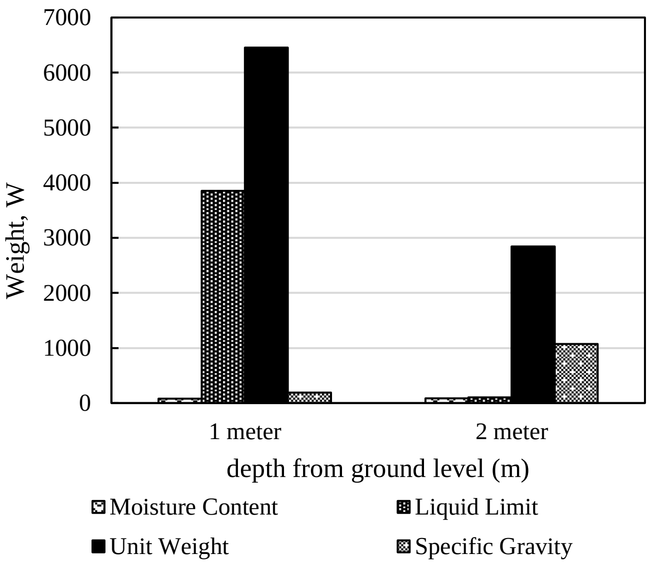

Fig. 3. Input parameter weights at varying depths.

4. CONCLUSIONS

Genetic algorithm was implemented as a tool to estimate the compression index of a clayey soil in some areas in the Eastern part of the National Capital Region (NCR) of the Philippines. The estimation was done until 6-meter for every 1-meter interval. The accuracy of the developed GA program was evaluated by setting a criterion based on Pearson's Correlation R. A value of 0.86 was implemented in this study. Based on the results, the GA program developed was able to satisfy the required criteria. To further investigate the accuracy of the program, the results were also compared to other empirical equations in estimating C_c.
The empirical equations from Skempton (1944) and Nagaraj and Murthy (1985) demonstrated a low to high correlation with the results from the GA program. This can be attributed to the few similar input parameters that were employed such as liquid limit and specific gravity. On the other hand, Rendon-Herrero (1983) demonstrated a high correlation. It resulted to a minimum R value of 0.8590. This is due to the fact that the objective function and Rendon-Herrero share similar input parameters,

specifically the initial void ratio and specific gravity. Another factor is that the initial void ratio was determined using unit weight of soil, unit weight of water and specific gravity. Based on the sensitivity analysis, unit weight had the largest impact on the estimation of the C_c.

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