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Evaluation of ANFIS and Regression Techniques in Estimating Soil Compression Index for Cohesive soils

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ABSTRACT

Generally, direct measurement of soil compression index (Cc) is expensive and time-consuming. To save time and effort, indirect methods to obtain Cc may be an inexpensive option. Usually, the indirect methods are based on a correlation between some easier measuring descriptive variables such as liquid limit, soil density, and natural water content. This study used the ANFIS and regression methods to obtain Cc indirectly. To achieve the aim of this investigation, 177 undisturbed samples were collected from the cohesive soil in Sulaymaniyah Governorate in Iraq. Results of this study indicated that ANFIS models over-performed the Regression method in estimating Cc with R^2 of 0.66 and 0.48 for both ANFIS and Regression models, respectively. This work is an effort to practice the advantages of machine learning techniques to build a robust and cost-effective model for Cc estimation by designers, decision makers, and stakeholders.

Keywords: ANFIS, Regression, Cohesive Soils, Compression Index

تقييم ANFIS وتقنيات الانحدار في تقدير مؤشر ضغط التربة للتربة المتماسكة

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الخلاصة

يعد القياس المباشر لمؤشر ضغط التربة (Cc) عمومًا مكلفًا ويستغرق وقتًا طويلاً، ولتوفير الوقت والجهود فان الطرق غير المباشرة للحصول على النسخة يكون خيارًا غير مكلفا. عادةً ما تعتمد الطرق غير المباشرة على الارتباط بين بعض المتغيرات الوصفية التي يسهل قياسها مثل حد السائل وكثافة التربة ومحتوى الماء الطبيعي. في هذه الدراسة تم استخدام أساليب ANFIS والانحدار للحصول على نسخة غير مباشرة. لتحقيق هدف هذه الدراسة فقد تم جمع 177 عينة غير مضطربة من التربة المتماسكة في محافظة السليمانية في العراق. أشارت نتائج هذه الدراسة إلى أن نماذج ANFIS تجاوزت طريقة الانحدار في تقدير Cc بـ 0.66 R^2 و 0.48 لكل من نموذج ANFIS والانحدار على التوالي. ان هذا العمل هو محاولة لممارسة مزايا تقنيات التعلم الآلي لبناء نموذج قوي وفعال من حيث التكلفة لتقدير نسخة من قبل المصممين وصناع القرار وأصحاب المصلحة.

الكلمات الرئيسية: ANFIS ، الانحدار ، التربة المتماسكة ، معامل الانضغاط

1. INTRODUCTION

The compression index (Cc) is a very significant parameter that can be used to obtain the consolidation settlement of the foundation of buildings on cohesive soils. Cc can be obtained from the Odometer test in the laboratory. To conduct this test, undisturbed samples are needed, and the test duration is about seven days which is more expensive and requires more time and effort. Therefore, attempts have been made to develop empirical models to predict Cc from simple indices such as liquid limit (LL), plastic limit (PL), plasticity index (PI), water content (WC), and dry density (DD). Often, the simple regression method was used to develop such equations (**Skempton, 1944; Terzaghi and Peck, 1967; Bowles, 1979; Sridharan and Nagaraj, 2000).**

Normally direct measurement of Cc using undisturbed samples is the most precise and consistent method, but it requires intensive laboratory and fieldwork, which is time-consuming and very expensive. Therefore, modeling can be an inexpensive and swift method to measure Cc with an acceptable accuracy range. Modeling can be in different approaches, such as physical-based models and data-driven models. The latter, data-driven model maps the relation between independent variables with the dependent variable. However, regular tools such as multilinear regression methods cannot define the mapping properly in nonlinear relations between dependent and independent variables. Subsequently, computer development raised robust artificial intelligence (AI) methods to predict dependent variables accurately with more confidence, such as artificial neural networks (ANN) and fuzzy logic systems (**Hamaamin, 2014**).

Engineering correlations between various soil parameters can be achieved using different approaches, such as artificial neural networks (ANN). In many studies, ANN is successfully used to model soil properties and behavior **(Shahin et al., 2001; Al-Busoda and Al-Taie, 2010; Al-Taie et al., 2017).**

Artificial Intelligence (AI) involves the approximate method of solving complex nonlinear systems through linking input to output variables using internal functions. These methods have been observed to provide reliable results using less time and calculation efforts, for instance, ANFIS, a hybrid of ANN with fuzzy logic (**Rai and Mathur, 2008; Kisi et al., 2009**).

In geotechnical engineering, ANFIS has been used to predict compression index and shear strength parameters. **(Mokhtari et al., 2014)** used ANFIS and ANN models to predict the Cc of municipal solid waste (MSW) based on data from the literature. They concluded that AI models could precisely predict the Cc of MSW. **(Pham et al., 2019)** used ANFIS to predict the Cc of soft clay and their results agreed with the real measured data of Cc. In Vietnam, **(Saadat and Bayat, 2022)** used ANFIS and Non-Linear Regression (NLR) models to predict Unconfined Compressive Strength (UCS) of clay soil stabilized by cement and lime. They concluded that the accuracy of ANFIS in predicting UCS is better than the NLR model. **(Srokosz and Bagińska, 2020)** studied the possibility of using the ANFIS technique to find the soil's mechanical properties. They concluded that using the ANFIS method is very successful in geotechnical engineering.

(Alzabeebee et al., 2021) conducted a research to predict the Cc of fine-grained soils of Sulaymaniyah Province through soil property variables of void ratio, moisture content, liquid limit, plasticity index, and dry density using multi-objective genetic algorithm evolutionary polynomial regression analysis. Using five predictor variables, they found good agreement (R^2=0.67) with laboratory measured values of Cc.

According to the knowledge of the authors of this research, the ANFIS technique has not been used to predict the Cc of cohesive soil in the Sulaimani region using undisturbed samples. This study aims to analyze, compare and test the performance of ANFIS and multilinear regression (MLR) modeling techniques to estimate compression index Cc for cohesive soils in Sulaymaniyah governorate using undisturbed soil samples. This study attempts to improve modeling systems in the geotechnical field through cost-effective modeling approaches, subsequently saving time and effort for future simulations and estimations of Cc by using a lower number of predictor variables (DD, WC, and PI) by geotechnical designers and stakeholders.

2. MATERIALS AND METHODS

2.1 Study Area and Data Measurement

Fig. 1 shows the study area which is located in Sulaimaniyah province in the Kurdistan Region of Iraq. The area is in a high folded zone, and the resulting fine-grained soils are of quaternary age. The depth of this fine-grained soil layer varies between 0 m and 20m. In this study, 177 undisturbed soil samples were obtained from different locations and depths (1.0m to 5.0m) within the study area. The following soil property variables were also measured: void ratio, moisture content, liquid limit, plasticity index, and dry density (**Alzabeebee et al., 2021**).

For the current study, three predictor variables (DD, WC, and PI) were selected depending on their better performance among all available five predictor variables (void ratio, moisture content, liquid limit, plasticity index, and dry density) to estimate the Cc.

To conduct the odeometer test the following tests must be conducted: soil density, specific gravity, water content, Atterberq Limits (LL and PL), and consolidation tests. **Table 1** presents the standards that usually are utilized to conduct laboratory works.

Table 1. Utilized Standards in this study

Laboratory test	Standard
Soil density	ASTM D7263
Specific Gravity	ASTM D854
Water content	ASTM D2216
Atterberg limits	ASTM D4318
Consolidation test	ASTM D2435

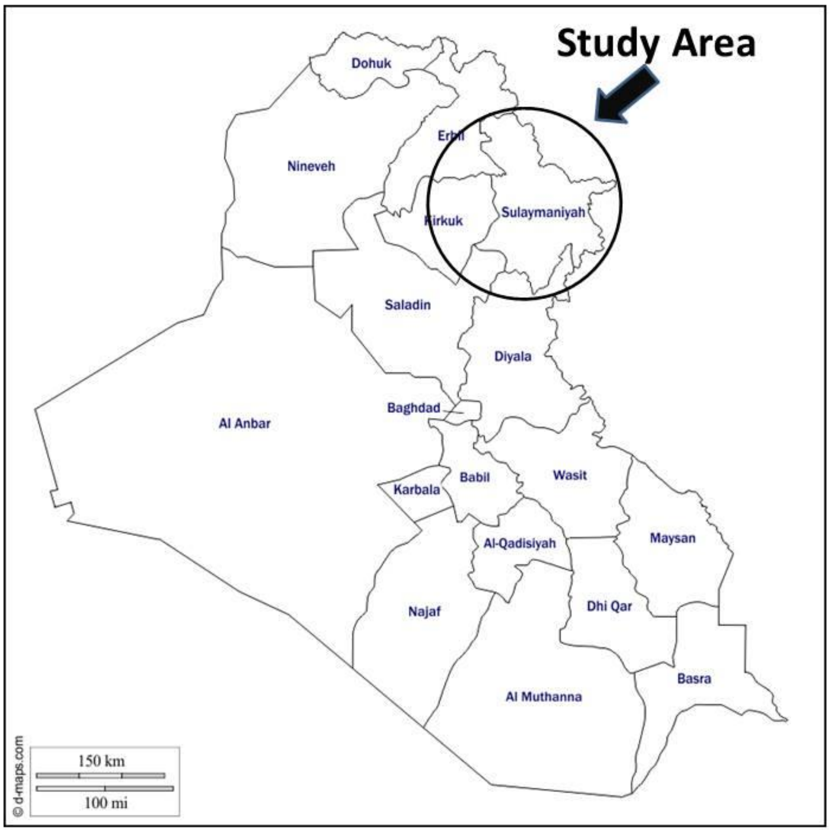

Figure 1. Location of the study area (d-maps.com).

In this study, for the purpose of modeling compression index Cc, three predictor variables (DD, WC, and PI) were selected. The descriptive statistics of the measured data sets is shown in **Table 2.**

Table 2. Descriptive statistics of measure variables (Cc, moisture content, soil density and PI).

Variable	Mean	Std Error of Mean	Median	StdDev	Minimum	Maximum	Skewness	Kurtosis
WC (g)	20.579	0.555	19.275	7.361	6.100	70.880	3.75	21.44
DD (g/cm^3)	1.6974	0.0113	1.7075	0.1505	1.1604	2.0534	-0.64	1.03
PI (%)	26.297	0.294	25.950	3.907	13.500	40.400	0.27	1.01
Cc	0.16318	0.0051	0.14695	0.0678	0.05700	0.5867	2.08	8.56

3. ANFIS METHOD

3.1 ANFIS Modeling Technique

ANFIS as a hybrid method combines ANN learning ability to draw fuzzy rules in a fuzzy logic system. ANFIS can perform all required steps in a fuzzy logic system, such as fuzzification, inference, and defuzzification of the data set with the help of ANN mapping ability (**Thipparat, 2012**). ANFIS system uses ANN learning algorithms (gradient descent backpropagation and/or least square methods to update assumed values of modeling parameters until an acceptable error level is reached (**Jang, 1993; and Cobaner, 2011**). The number of trials to estimate system parameters can be defined previously before the calibration (training) process. Each iteration consists of two passes of calculations, forward and backward. The forward pass fixes the predecessor parameters, and the consequential parameters are determined as the least square estimation of parameters. In the backward pass, the consequential parameters are fixed, and the errors from the difference between the two parameters are propagated back to update the antecedent parameters, which lowers the error in the estimation process (**Rai and Mathur, 2008; Kisi et al., 2009**). To prevent overfitting during the model calibration process, the iteration can be terminated when the error is at a minimum (**Bianconi et al., 2010; Thipparat, 2012**).

3.2 Fuzzy Subsets

The two well-known membership function (MF) generation methods are grid partitioning and clustering. ANFIS modeling depends on the fuzzy logic technique, which starts with dividing the input and output measured data subsets using a Sugeno-type fuzzy inference system, either grid partitioning method or clustering method. The grid partitioning method was found to be more useful for a relatively small number of data sets, as used in this study (**Hamaamin, 2014**). Therefore, for this paper, the grid partitioning method is known in MATLAB as genfis1 MFs. The function genfis1 generates Fuzzy Rules by counting all possible combinations of MFs depending on the number of partitions of each variable. The number of rules depends on the number of variables and partitions of each variable (**MathWorks, 2018**).

For the ANFIS modeling toolbox in MATLAB, two sets of data can be loaded, training and testing data sets. The software will generate the model using the training data set and test the performance of the model using the testing data set (**MathWorks, 2018**).

3.3 Variables Fuzzy Subsets

For a successful modeling process, the created model should be validated to test its performance on new data points. Therefore, the collected data points were divided into calibration data and validation data sets. In this study, the available 177 data points were randomly divided into two portions, 75% (133 points) for calibrating the model, while the remained 25% (44 points) were used to validate the calibrated model. During the model calibrations in MATLAB (R2015a), all available MFs (triangular, trapezoidal, Gaussian, Pi, and sigmoidal) were tested on the input and output variables. The best function was triangular MF for the input variables, while linear MF was the best for the output MFs.

For each of the used three input variables (DD, WC, and PI), two triangular MFs were used, which concludes in 8 Fuzzy Rules according to Eq. (1), while for the output, eight linear MFs were used corresponding to each Fuzzy Rule.

$$\text{Number of Fuzzy Rules} = (\text{number of MFs})\ n \qquad (1)$$

Where n is the number of input variables.

4. REGRESSION METHOD

In this study, a multiple linear regression was executed through a stepwise process using three predictor variables (moisture content, soil density, and PI) to estimate the Cc. For the calibration data set, the following regression model, Eq. (2), was obtained:

$$Cc = 0.5127 + 0.0027\ WC - 0.2175\ DD - 0.0013\ PI \qquad (2)$$

4.1 Methods Evaluation Criteria

In this study, the predictive accuracy of the ANFIS and Regression models was evaluated using the coefficient of determination (R^2), root mean square of errors (RMSE), and percent bias (P-bias).

1- The coefficient of determination is the square of the Pearson product-moment correlation coefficient known as R^2, Eq. (3). When comparing two sets of data which are usually a model output and the measured data, this R^2 shows the degree to which two variables are related. The expected value of R^2 changes from zero to one. When $R^2 = 1$ for a plot between modeled and measured data sets, the model performed best, while $R^2 = 0$ means worst performance (**Lyman and Longnecker, 2010**). While $R^2 > 0.5$ represents satisfactory model performance (**Arnold et al., 2012)**.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \hat{\bar{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 (\hat{y}_i - \hat{\bar{y}})^2}} \right]^2 \quad (3)$$

Where: y_i and $\bar{y}$ are measured and modeled data points, respectively, with n number of data points. $\bar{y}_i$ and $\hat{\bar{y}}$ are averages of measured and modeled data points, respectively.

2- Root mean square of error measures average error in predicting a set of measured data which is the goodness of a model relevant to measured data, Eq. (4).

3-

$$RMSE = \sqrt{\frac{1}{n}(y_i - \hat{y}_i)^2} \quad (4)$$

The best performance of a model can be described with a value of RMSE = 0 (**Lyman and Longnecker, 2010; Nayak and Jain, 2011)**.

4- Percent bias measures the average deviation of the estimated data from measured data points, Eq. (5). The best value of PBIAS is zero, positive values indicate underestimation bias, and negative values indicate model overestimation bias. (**Moriasi et al., 2007**).

$$PBIAS = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)\times 100}{\sum_{i=1}^{n}(y_i)} \quad (5)$$

5. RESULTS AND DISCUSSIONS

In this study, two different techniques, Regression and ANFIS, were used to estimate Cc through moisture content, density, and plasticity index predictor variables. The available data is divided into the calibration part (to create the model) and the validation part (to validate the model). ANFIS and Regression models were calibrated using 133 data points, then the calibrated models were used to estimate the values of compression index (Cc) for the validation data set of 44 points. The calibration and validation results of the ANFIS model and Regression models are shown in **Table 3**.

Table 3. Calibration and validation results for ANFIS and regression models.

Model	Calibration			Validation		
	R^2	RMSE	P-bias	R^2	RMSE	P-bias
ANFIS	0.66	0.041632	4.12E-06	0.61	0.035755	-1.13131
Regression	0.48	0.051683	8.97E-14	0.51	0.039038	-4.27387

It can be observed from **Table 3** results that the R^2=0.66 for the ANFIS model is higher than the R^2 =0.48 for the regression model. Also, RMSE for the ANFIS model is less than RMSE for the regression model, which confirms a better prediction of the ANFIS model than the regression model. Another evaluation measure is P-bias, which is smaller for ANFIS than the regression. The performance of each model was evaluated using the previously mentioned evaluation criteria of R^2, RMSE, and P-bias. **Figs 2 and** 3 show a plot of Cc measured data versus results of Cc data points calibration outputs from ANFIS and Regression models, respectively. To test the performance of the created models, both ANFIS and Regression models were tested against validation data points. Results from **Table 3** and **Figs 4 and 5** confirm that the prediction of the ANFIS model is better than the regression model for validation data sets. The value of R2 for ANFIS model validation is 0.61, while R^2 = 0.51 for Regression model validation result. Also, the RMSE and P-bias of the ANFIS model are lower than the regression model for the validation data set, as shown in **Table 3**. Although the value of P-bias for both methods is in the acceptable range, the ANFIS method has lower P-bias values for both calibration and validation sets compared to P-bias values for the Regression method, **Table 3.**

ANFIS model output points, for calibration data points, have less spread around the best fit line compared to Regression model output points which have a higher spread around the line. This confirms the better performance of the ANFIS model versus the Regression model, **Fig. 2 and Fig.3.** Also, for the validation output points, better performance of the ANFIS model is obvious compared to the output data points for the Regression model, **Figs 4 and 5**. This confirms the robustness of the ANFIS model even with a low number of input variables, which are only three predictor variables (water content, soil density, and PI). In addition, Identical R^2 (0.66) for the same data that is used in this study was obtained by **(Alzabeebee et al., 2021)** with a higher number of variables which were five predictor variables (water content, void ratio, liquid Limit, plastic limit and soil density) by using the multi-objective genetic algorithm evolutionary polynomial regression analysis (EPR-MOGA).

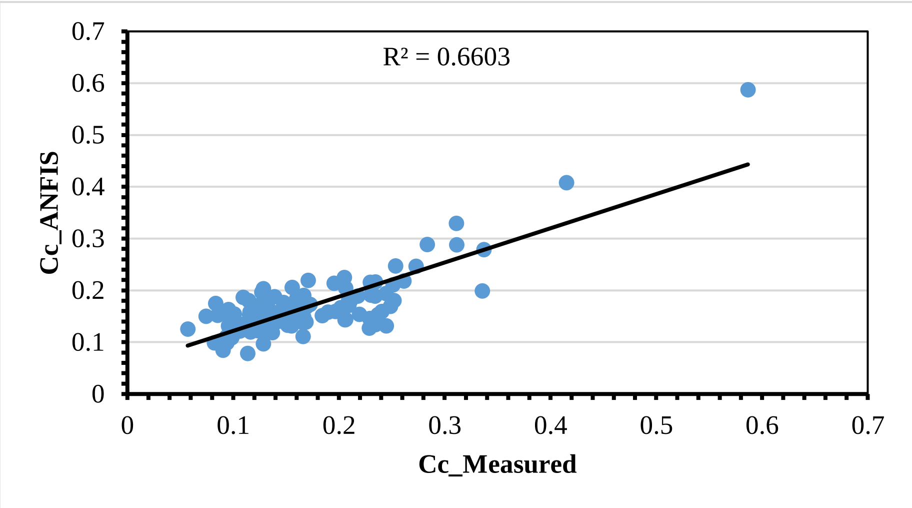

Figure 2. Calibration results for the ANFIS model.

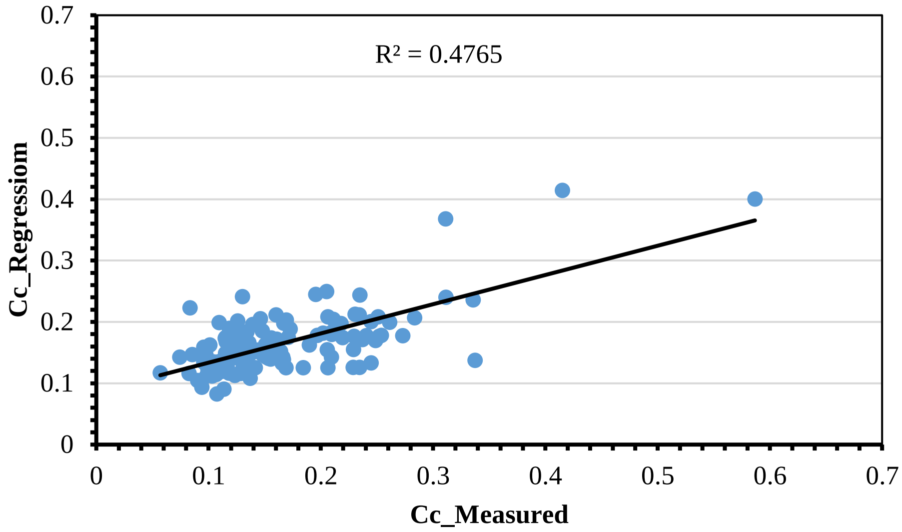

Figure 3. Calibration results for the Regression model.

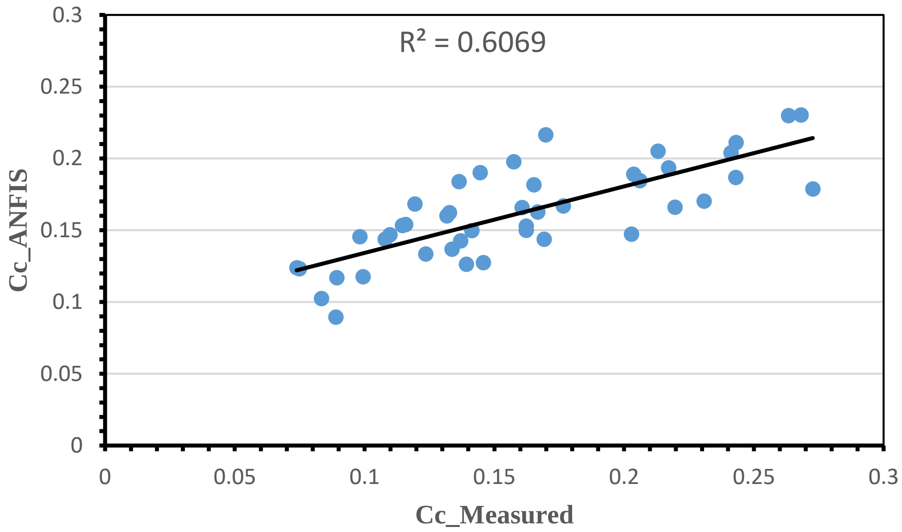

Figure 4. Validation results for the ANFIS model.

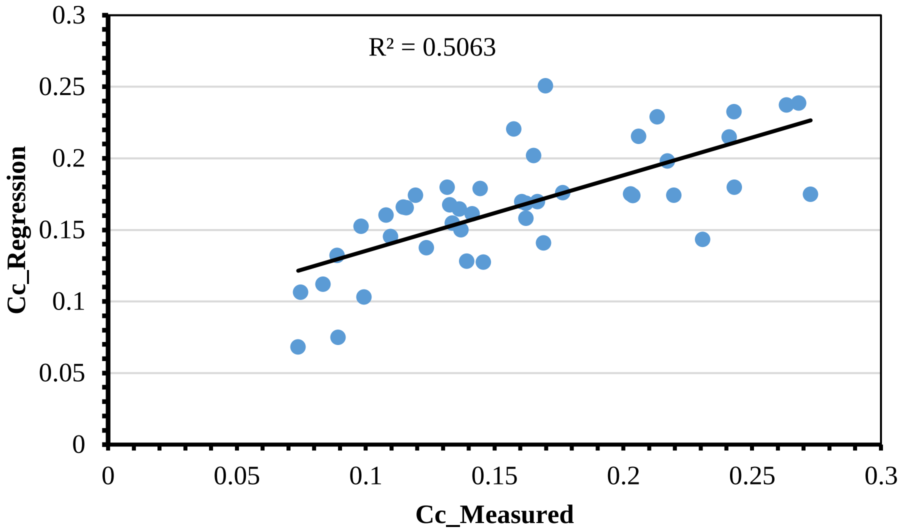

Figure 5. Validation results for the Regression model**.**

To further analyze the results from both methods, for validation data set, Cc outputs values from both models are plotted against measured Cc data points, **Fig. 6**. It can be observed better replication of the real measured data from the ANFIS model compared to the Regression model. As it is known for the Regression model, it is more affected by extreme data points, while the ANFIS performance is less effective to extreme data points, as shown in **Fig. 6**.

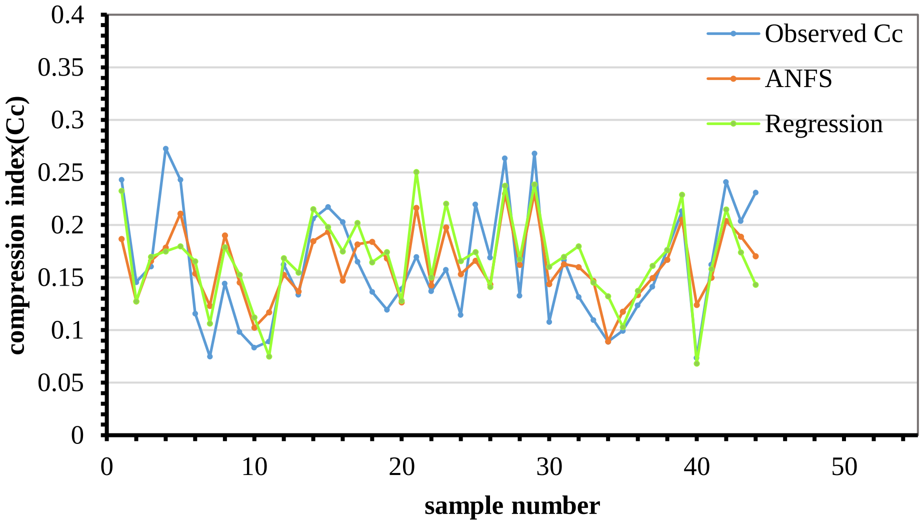

Figure 6. Comparison of performance for the ANFIS and the Regression models for the validation data set.

Finally, to test if there are any extreme data points (outliers) from model predictions, **Fig. 7** shows box- plots for the validation set were plotted for both ANFIS and Regression models outputs compared to the measured Cc values. From **Fig.7**, one can detect four outlier points for the regression box-plot, while there is no outlier for the ANFIS model, this confirms the robustness of the ANFIS modeling technique compared to the Regression model. Also, the data distribution of the ANFIS model outputs looks better, where the median line has less deviation from the center of the box compared to the line for the Regression outputs box, **Fig.7**.

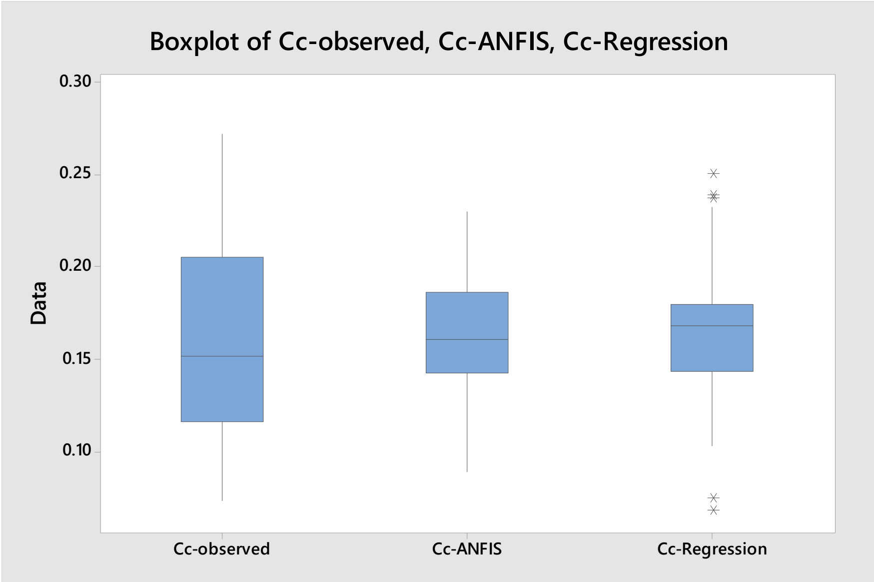

Figure 7. Performance comparison for the ANFIS and the Regression model.

6. CONCLUSIONS

An effective and low-cost predicting model to estimate compression index (Cc) can save time and effort compared to a more complex laboratory-based finding of soil Cc values. ANFIS model was found to be more effective in predicting soil Cc values than the Regression model. ANFIS model can perform the same as genetic algorithm evolutionary polynomial regression with a lower number of predictor variables (three against five). Results of this study confirmed that triangular MFs perform best among other types of MFs in estimating Cc values from moisture content, soil density, and PI input variables. This work is an effort to use the advantages of new techniques (ANFIS) to build a cost-effective model to be used by Sulaymaniyah governorate stakeholders and geotechnical designers to successfully estimate Cc values with a lesser amount of cost and time.

List of Abbreviations
AI = artificial intelligence
ANFIS = Adaptive neuro-fuzzy inference system
ANN = Artificial Neural Network
ASTM = American Society for Testing and Materials
Cc = Compression Index
DD = Dry Density

LL = Liquid Limit
MF = Membership Function
MLR = Multi-Linear Regression
MSW = Municipal Solid Waste
NLR = Non-Linear Regression
PI = Plasticity Index
PL = Plastic Limit
RMSE = Root mean Square Error
UCS = Unconfined Compressive Strength
USCS = Unified Soil Classification System
WC = Water Content

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