APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO PREDICT SOIL RECOMPRESSION INDEX AND RECOMPRESSION RATIO

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ABSTRACT

Overconsolidated soils are widely encountered in practice where settlement calculations are crucial. The recompression index (Cr) and the recompression ratio (Crε) are considered as one of the most important parameters used in settlement calculations. To achieve this purpose, expensive and time-consuming laboratory tests are usually conducted using undisturbed specimens to obtain the values of these parameters. Various equations derived from regression analysis were proposed to predict consolidation parameters from the physical properties of a soil. In this paper, however, an artificial neural network model (ANN) is proposed to predict Cr and Crε using natural water content, initial void ratio, total unit weight and effective overburden pressure. The proposed ANN model achieved good agreement with the results of one hundred seventy-nine standard one-dimensional consolidation tests collected from previous geotechnical investigations in Baghdad.

1. INTRODUCTION

The settlement of low permeability fine grained soils is mostly due to the time dependent consolidation processes. Consolidation settlement of these soils must be considered in the design of foundations of structures. These soils may be normally consolidated or overconsolidated depending on the effective overburden pressure, stress increments, and preconsolidation pressure. Holtz et al., (2010) mentioned that overconsolidated soils are encountered more than the normally consolidated soils. When the effective vertical stress increases due to the applied load, $\Delta\sigma_v$, the consolidation settlement, s_c, can be calculated from the following equation, (Das, 2011):

$$s_c = C_r \frac{H_o}{1+e_o} log \frac{\sigma'_{vo}+\Delta\sigma_v}{\sigma'_{vo}}$$

1

When the overconsolidated soils subjected to increase in effective stress exceeding the overconsolidation pressure, the consolidation settlement s_c can be calculated from the following equation, (Das, 2011).

$$s_c = C_r \frac{H_o}{1+e_o} log \frac{\sigma'_p}{\sigma'_{vo}} + C_c \frac{H_o}{1+e_o} log \frac{\sigma'_{vo}+\Delta\sigma_v}{\sigma'_p}$$

2

Where *eo*, *Ho*, *Cc* and *Cr* are initial void ratio, thickness of soil layer, compression index and recompresion inedx respectively. In 1940, California soil mechanics practice used the term 'modified' for compressibility indices at which *Cc* and *Cr* replaced by compression ratio (*Ccε = Cc/(1+eo)*) and recompresion ratio (*Crε = Cr/(1+eo)*) respectively. Accordingly, the settlement equations can be rewritten as shown below:
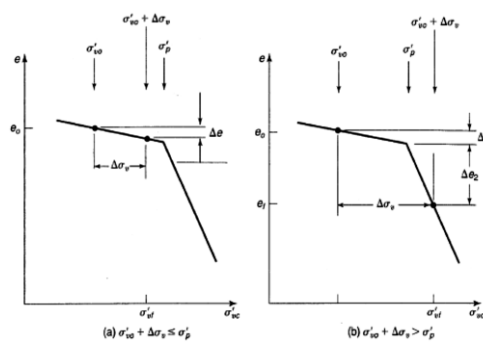

Fig. 1. Settllement of overconsolidated soil (Perloff and Baron, 1976).

$$s_c = C_{r\varepsilon} H_o log \frac{\sigma'_{vo}+\Delta\sigma_v}{\sigma'_{vo}}$$

3

$$s_c = C_{r\varepsilon} H_o log \frac{\sigma'_p}{\sigma'_{vo}} + C_{c\varepsilon} H_o log \frac{\sigma'_{vo}+\Delta\sigma_v}{\sigma'_p}$$

4

Terzaghi et al., (1996) stated that due to the geological unloading or aging, natural soil deposits have a preconsolidation pressure, as such, it is expected that the increase of effective vertical stress is in the range of recompression in compression curve presented as void ratio, e, versus logarithm of effective vertical pressure, log σ plot. According to this statement, an estimation of Cr is required for calculation of settlement in many engineering practices. Typical e-log σ plot is shown in Fig. 2. According to this plot, Cr is the slope of recompresion part.

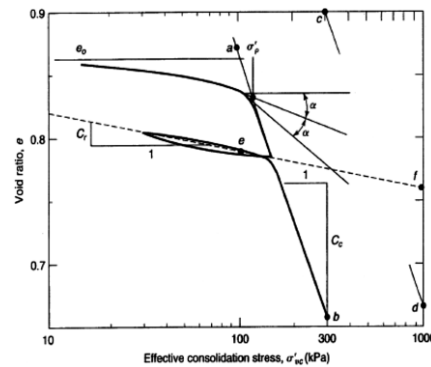**Fig. 2. e-log σ plot (Hoitz et al, 2010).**

According to the results of standard one-dimensional consolidation test, e-log σ plot can be attained. Unforentuatly, this test required high quality undisturbed specimens and take long time of period with relatively high cost. For these reasons most, geotechnical engineers must depend on empirical equations developed using different approaches such as artificial neural network (ANN). In the present work, such goal was investigates using artificial neural network models for predicting the Cr and Crε.

2. APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Many geotechnical engineering problems were modeled by using artificial neural networks (ANNs). ANNs have been employed to model various problems in soil mechanics and foundation engineering. In soil mechanics the modeled problems includes soil behavior (Ellis et al, 1995), classification, physical properties and soil compaction (Cal, 1995; Shetu and Masum, 2015; Ismeik and Al-Rawi, 2014; Sinha and Wang, 2008), soil permeability and hydraulic conductivity (Yusuf et al, 2009), geotechnical properties (Yang and Rosenbaum 2002; Bahmed et al., 2017), site characterization and field test (Basheer et al., 1996; Agan and Algin, 2014), and liquefaction and swelling (Farrokhzad et al, 2012; Tahasildar et al., 2016). In foundation engineering and design, ANNs used to calculate bearing capacity and settlement of shallow footing (Kalinli et al., 2011; Kanayama et al., 2014) and deep foundation (Nejad et

al., 2009; Momeni et al., 2015). ANNs applications extended to earth retaining structures and slope stability (Goh et al, 1995; Gordan et al., 2016).

Regarding to consolidation parameters, ANNs technique was used to investigate the possibility to predict compression index from other simple soil properties such as: Atterberg limits, compaction parameters, specific gravity, void ratio, and water content (Ozer et al., 2008; Park and Lee, 2011; Kalantary and Kordnaeij 2012; Al-Taie et al., 2017). It was found that ANNs provided good predictions to labs results. Kordnaeij et al., (2015) stated that the Atterberg limits, water content, void ratio, dry unit weight and specific gravity of soil can be used as input parameters of to predict Cr via ANN with the help of lab results of soil collected from various places in Iran. They found that ANN provided more accurate predictions than other methods. In 2016, Kurnaz et al. proposed ANN model to predict Cc and Cr using natural water content, liquid limit, plasticity index, and initial void ratio of soil from Turkey. Although their ANN model accurately estimated Cc, the predictions of Cr were not accurate.

Based on the above, it can be seen that although ANNs technique has been used widely to study different aspects in geotechnical engineering, there is limited studies concerning the utilization of this technique for predicting recompression index and recompression ratio of soil. In this study, both response variables (Cr and Crε) was estimated from ANNs model using natural water content, initial void ratio, unit weight and effective overburden pressure as input variables.

3. THE DATA DESCRIPTION

A total of one hundred seventy-nine test results of standard one-dimensional consolidation test and physical tests are used in this research. All tests were conducted according to ASTM standards. The data originally compiled by Albusoda and Al-Taie (2010) and Al-Taie and Albusoda (2013) from various geotechnical investigations located in Baghdad-Iraq. The investigations were conducted by public agencies and private companies.

It should be mentioned that the selected soil properties to estimate recompression index (Cr), and recompression ratio (Crε) are based on the parameters that affect the soil compressibility i.e. in-situ state parameters. Soil sedimentation, stress history, environments of soil deposition, and natural conditions of soil are among these parameters, Kurnaz et al., (2016). Therefore, the following properties were used in the data sets: natural water content (wn), initial void ratio (eo), total unit weight (γt), and effective overburden pressure σ'_{vo}. However, the investigated soils are cohesive fine grained with low to intermediate degree of compressibility and low to

high plasticity. These soils are a part of the quaternary deposits of Mesopotamian Plain which were resulted from depositional of Euphrates and Tigris rivers Al-Taie (2015). Table 1 presents statistics information of the database and Fig. 3 presents histogram and residual probability plots of the soil properties. As can be seen in Fig. 3, the database, in general, satisfies the condition of normal distribution.

Table 1. Descriptive statistics of data.

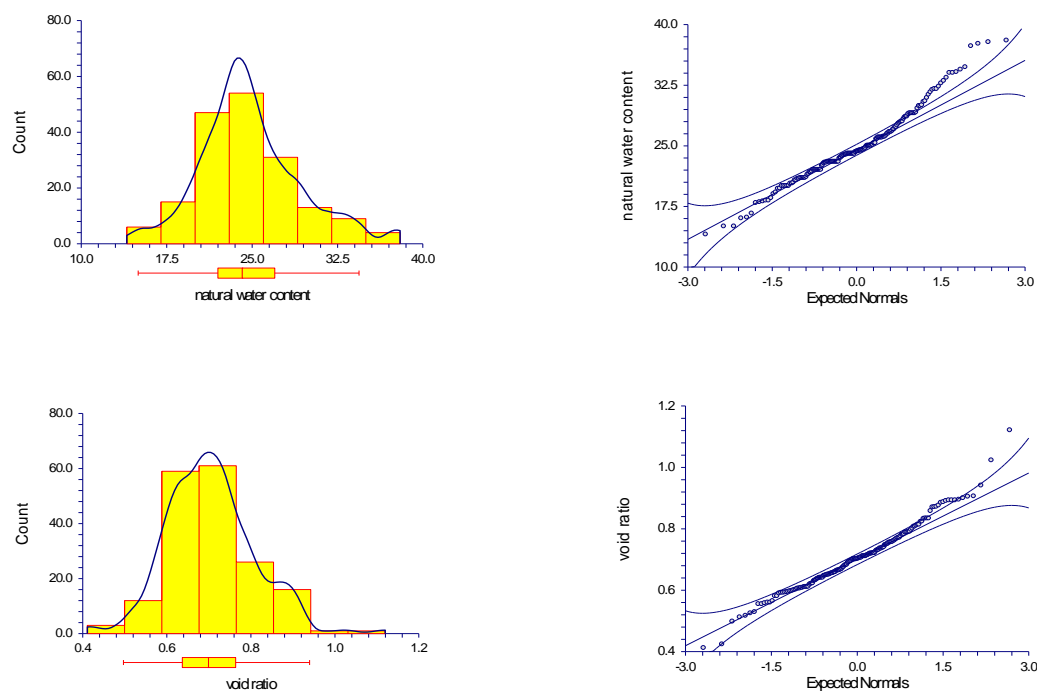| Variables	Number	Minimum	Maximum	Mean	Standard Deviation	Standard Error
wn (%)	179	14.0	38.0	24.850	4.473	0.334
eo	179	0.411	1.120	0.7048	0.1051	0.008
γ_t, (kN/m^3)	179	17.0	21.3	19.485	0.796	0.059
σ'_{vo}, (kPa)	179	14.0	384	114.20	83.58	6.246
Cr	179	0.017	0.099	0.0491	0.0136	0.0010
Crε	179	0.0111	0.0525	0.0281	0.0067	0.0005

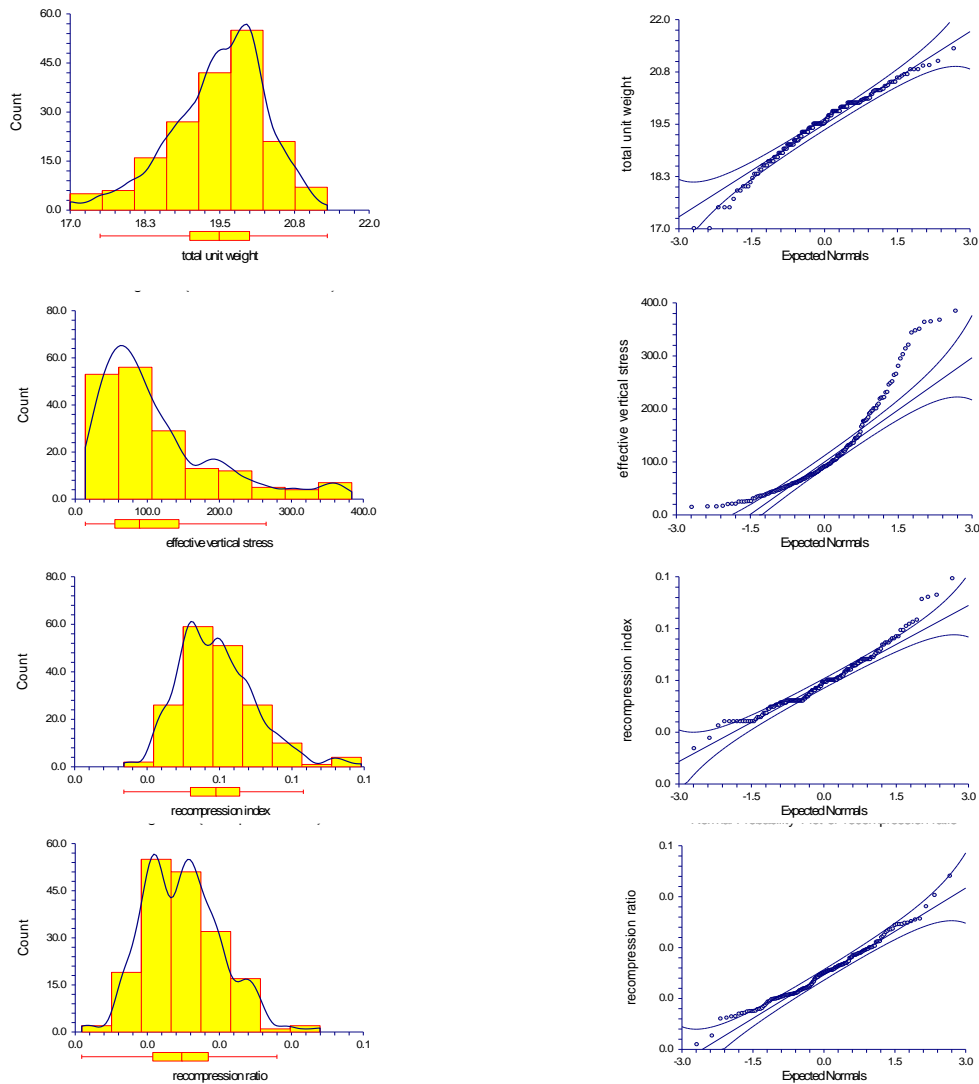**Fig. 3. Histograms and normal probability plots of data.**

Fig. 3. (continoue)

4. NEURAL NETWORKS MODEL

The artificial neural network (ANN) is powerful computing technique that perform in a manner similar to that of biological neural networks. This technique is able to solve complex problems without reasonable engineering solutions by learning and generalizing from large test results. After satisfactory training and testing, the ANN is able to predict the required output(s) using independent input(s). The computation process is carried out using simple connections called neurons. These neurons are connected together via links. Each of these links have certain weights, through them complicated problems are solved.

A typical multi-layered ANN consists of input layer, hidden layer(s), and output layer. The number of neurons in the input layer usually represents the parameters of the problem in hand, while, the number of neurons in the hidden layer(s) is usually decided to improve the predictions

by keeping the network generalized and minimizing the errors between the measured output and that of the ANN (Demuth et al., 2009).

In this paper, a feed forward back propagation neural network model is built to predict the recompression index (Cr) and recompression ratio (Crε). The architecture of this model involves of one input layer, one hidden layer, and one output layer. The input layer consists of four neurons representing the independent parameters (natural water content, initial void ratio, unit weight and effective overburden pressure) plus bias. The latter has a value of one. The hidden layer consists of fifty neurons. The output layer is the recompression index (Cr) and recompression ratio (Crε), see Fig. 4.
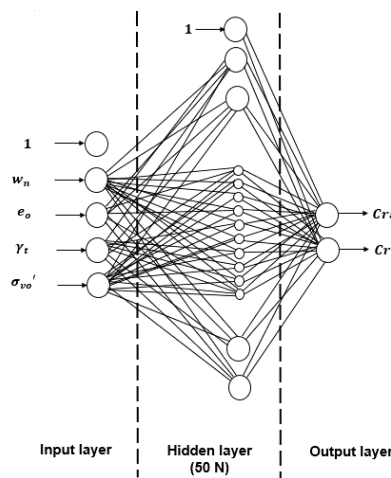

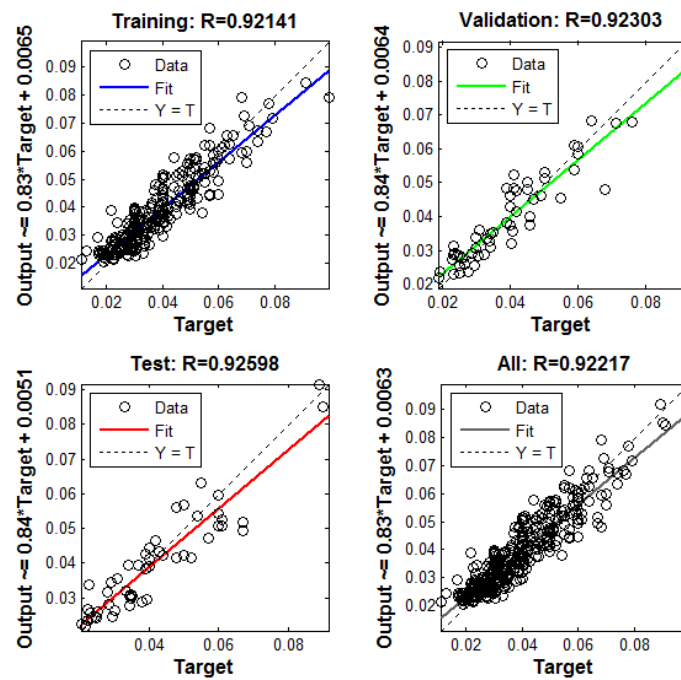**Fig. 4. Architecutre of the ANN model.**

Fig. 5. Correlation coefficient of the ANN model.

It is important to note that the current architecture has been chosen to provide best predictions after carrying out several attempts using various architectures of hidden layers and neurons. The modelling was conducted onto 179 test results of standard one-dimensional consolidation test and physical tests of soil using MATLAB R2013b, where the TRAINLM and LERNGDM functions were adopted for training and learning, respectively. The data were divided into three subsets: 70% used for training the model, 15% for testing the generality of the model, and 15% for validating the model (Demuth et al., 2009). The performance of the model was evaluated by means of the correlation coefficient, R. As can be seen from Fig. 5, the correlation coefficient, R, between the predicted Cr and Crε and lab results was 0.922. Which, gave confidence in the propose model. Fig. 6 compares between the correlations of the predicted Cr and Crε and lab results. The mean of predicted Cr and Crε to lab results were 1.01 and 1.03, respectively. The corresponding standard deviation was 0.16 and 0.18, respectively. Comparisons between these figures indicate that the predications of recompression index were better than that of recompression ratio. Fig. 7 examines the errors between the predicted Cr and Crε and the lab results. As can be inferred from this figure, the errors were lower between the predicted Cr and the lab results than those between the predicted Crε and the lab results.
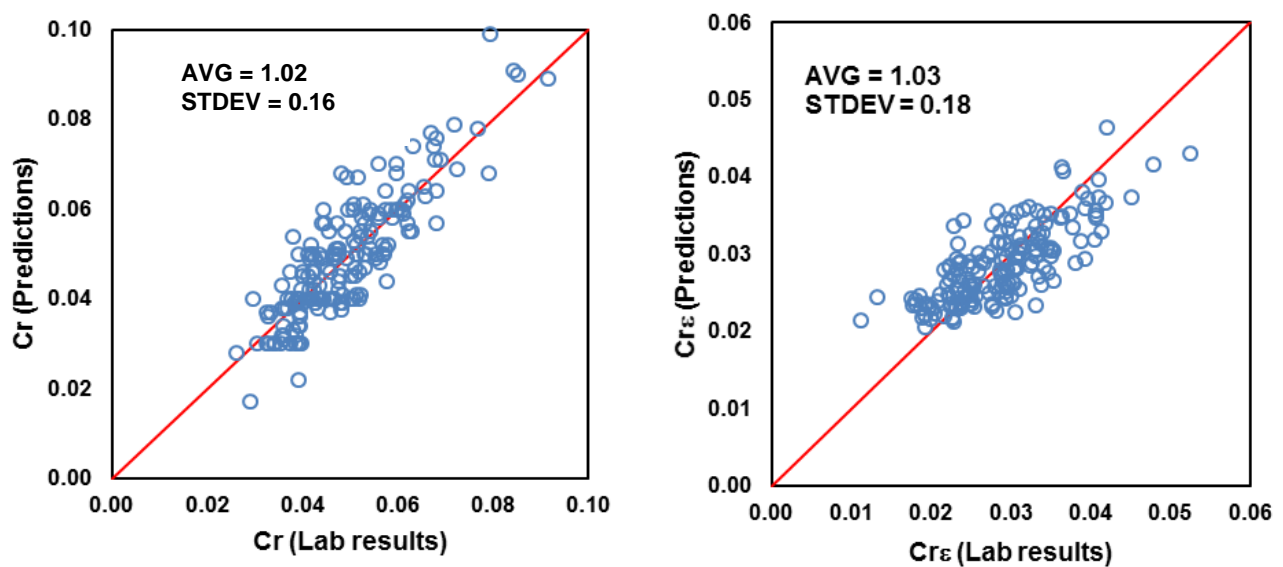

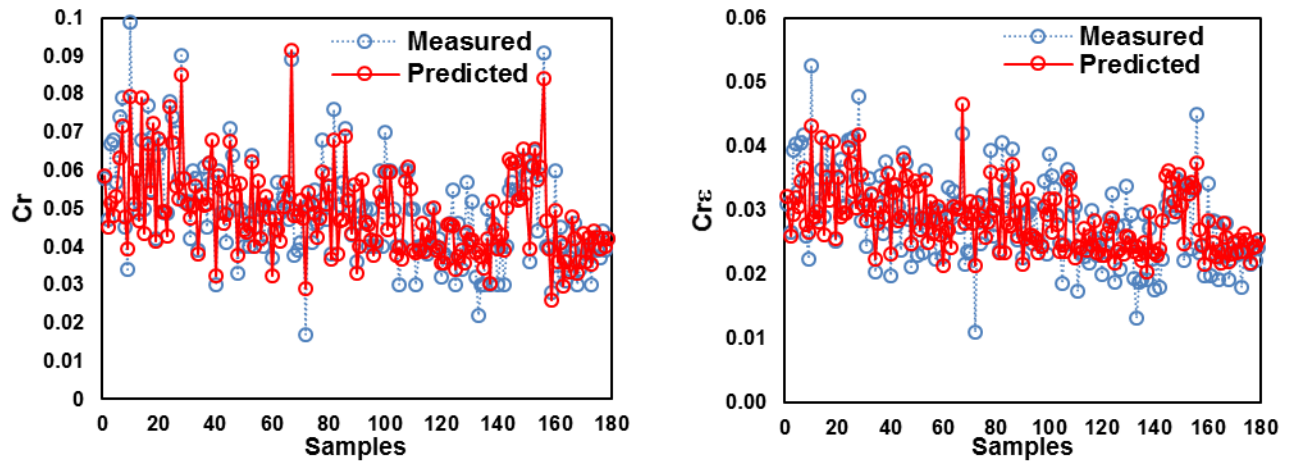**Fig. 6. Predictions vs. lab results.**

Fig.7. Comparison between predictions and lab results.

5. CONCLUSIONS

The current research was conducted to predict the recompression index (Cr) and the recompression ratio (Crε) of cohesive fine-grained soil with low to high plasticity using artificial neural network analysis. The latter was conducted using the test results of one hundred seventy-nine of one-dimensional consolidation tests collected from previous geotechnical investigations in Baghdad-Iraq. Predictions were carried out using natural water content (wn), initial void ratio (eo), total unit weight (γt), and effective overburden pressure σ'_{vo}. The advantages of the current ANN models over those reported in the literature that the same input was used to predict two different outputs. The proposed model achieved good agreements with the lab results. The correlation coefficient, R, between the predicted Cr and Crε and lab results was 0.922. Therefore, it can be concluded the performance of ANN's prediction reflects a good functional relation.

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