# Compression Index and Compression Ratio Prediction by Artificial Neural Networks

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## ABSTRACT

Information about soil consolidation is essential in geotechnical design. Because of the time and expense involved in performing consolidation tests, equations are required to estimate compression index from soil index properties. Although many empirical equations concerning soil properties have been proposed, such equations may not be appropriate for local situations. The aim of this study is to investigate the consolidation and physical properties of the cohesive soil. Artificial Neural Network (ANN) has been adapted in this investigation to predict the compression index and compression ratio using basic index properties. One hundred and ninety five consolidation results for soils tested at different construction sites in Baghdad city were used. 70% of these results were used to train the prediction ANN models and the rest were equally divided to test and validate the ANN models. The performance of the developed models was examined using the correlation coefficient R. The final models have demonstrated that the ANN has capability for acceptable prediction of compression index and compression ratio. Two equations were proposed to estimate compression index using the connecting weights algorithm, and good agreements with test results were achieved.

**Key words:** compression index, compression ratio, index properties, artificial neural network.

# التنبؤ بمؤشر ونسبة الانضغاط بواسطة الشبكات العصبية الاصطناعية

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## الخلاصة

ان معرفة خصائص الانضمام للتربة مهم في التصميم الجيوتقني. نظرا للوقت والنفقات المتضمنة في إجراء اختبارات الانضمام، فإن المعادلات التجريبية التي تتضمن مؤشرات خصائص التربة مطلوبة لتقدير مؤشر الانضغاط. وعلى الرغم من اقتراح العديد من المعادلات التجريبية المتعلقة بخصائص التربة، فإن هذه المعادلات قد لا تكون مناسبة للحالات المحلية. الهدف من هذه الدراسة هو إقامة علاقة ارتباط بين خصائص الانضمام والخصائص الفيزيائية للتربة المتماسكة. وقد تم استخدام الشبكة العصبية الاصطناعية (ANN) للتنبؤ بمؤشر ونسبة الانضغاط من الخصائص لأكثر بساطة. تم استخدام مئة وخمسة وتسعين نتيجة اختبار انضمام للتربة التي تم أخذ عيناتها من مواقع البناء المختلفة في مدينة بغداد. استخدمت 70٪ من هذه النتائج لتدريب نماذج الـ(ANN) وباقي النتائج قسمت بالتساوي للاختبار والتحقق من صحة نماذج الـ(ANN). تم فحص أداء النماذج الرياضية المطورة باستخدام معامل الارتباط R. وقد أظهرت النماذج النهائية قدرة الـ(ANN) على التنبؤ باؤشر الانضغاط ونسبة الانضغاط بشكل مقبول. تم اقتراح معادلتين لتقدير مؤشر الانضغاط باستخدام خوارزمية أوزان الربط (connecting weights algorithm)، وتم التوصل إلى تقارب جيد مع نتائج الاختبار.

## 1. INTRODUCTION

Consolidation properties of soil at a particular site would require a detailed and expensive testing program, well beyond the scope of most projects budgets. Therefore, most geotechnical engineers must depend on empirical equations derived from simple soil properties.

Developing engineering correlations between various soil parameters can be achieved using different approaches such as artificial neural network (ANN). In many studies, ANN is successfully used for modeling properties and behavior of soil**, Shahin et. al., 2001.** In this study, artificial neural network (ANN) has been utilized to propose efficient models for predicting the compression index (Cc) and compression ratio (CR) of cohesive soil.

## 2. DATABASE

Database used in this study were collected mainly from geotechnical data compiled by **Al-Taie and Al-Busoda 2013**. It consists of consolidation and physical properties results of cohesive soil obtained from standard tests in accordance with ASTM D 2435. The cohesive soil used in this study has low to intermediate degree of compressibility and has low to high consistency. The results used were collected from various geotechnical investigations located in Baghdad city that were conducted by public agencies and private geotechnical companies. The data consisted of one hundred ninety five sets that were included seven soil parameters. Parameters are natural water content ($w_n$), initial void ratio ($e_o$), total unit weight ($\gamma_t$), dry unit weight ($\gamma_d$), effective overburden pressure ($P_o$), compression index (Cc), and compression ratio (CR). Table 1 presents the statistical properties of the abovementioned parameters, while, the frequency histogram for each of these parameter is presented in **Fig. 1.** It can be inferred from this figure that the chosen data is distributed widely, and hence, it can be used in the ANN investigation.

## 3. APPLICATIONS OF ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) has been employed to model complex problems in geotechnical engineering such as pile capacity prediction ,**Lee and Lee 1996; Park and Cho 2010; Momeni et. al. 2015**, ultimate bearing capacity of shallow foundations **, Kalinli et. al., 2011**,settlement of structures ,**Rezania and Javadi 2007; Kim and Kim 2008**. modeling soil behavior (**Ellis et. al., 1995**), site characterization ,**Basheer et al., 1996**. earth retaining structures **Goh et. al., 1995**, slope stability **,Gordan et. al. 2016**. design of tunnels and underground openings **Yoo and Kim, 2007**. liquefaction ,**Farrokhzad et. al., 2012**. soil permeability and hydraulic conductivity ,**Yusuf et. al., 2009**. soil compaction ,**Sinha and Wang, 2008**. soil swelling ,**Yilmaz and Kaynar, 2011**. strength parameters ,**Ceryan et. al., 2013**. and classification of soils ,**Cal, 1995**.
The compression index of soil was also investigated using ANN technique. For example, **Ozer et al., 2008** were applied ANN to predict the of compression index of clayey soils with the help of eight input variables of one hundred thirty five test data. They concluded that ANN provided a better prediction than those of regression equations.

**Kumar and Rani, 2011**, also applied ANN technique to predict compression index (Cc) of compacted soil using sixty eight soils test data, in which, good agreements with tests were achieved. It is important to note that the input data used in their investigation were fine fraction, liquid limit, plasticity index, maximum dry density, and optimum moisture content.

**Park and Lee, 2011** implemented the ANN technique to predict the compression index using nine hundred and forty-seven results collected from geotechnical investigations of various construction

sites in Republic of Korea. The input data were the natural water content, liquid limit, plasticity index, specific gravity, and soil types. They achieved good agreements with the test results.
**Kalantary and Kordnaeij, 2012, Alam et. al., 2014, Kashefipour and Daryaee 2014, Kurnaz et al., 2016** also applied ANN technique to predict the compression index using results collected from geotechnical investigations of construction sites in various countries. These researchers concluded that the ANN technique provided good predictions with the help of simple physical properties of soil.

From the previous studies presented above, and as summarized in **Table 2**, the following conclusions are drawn:

1. The ANN technique has been used widely to study different aspects in geotechnical engineering.
2. There are several published works concerning the utilization of artificial neural network technique for predicting compression index of soil.
3. In general, the compression index was predicted using five input variables including the initial void ratio, natural water content, liquid limit, plasticity index, and specific gravity.
4. Investigations using ANN technique were limited to study the effect of input parameters and no equations were derived.
5. There is no literature employing the application of ANN technique in studying the compressibility characteristics of soil under consideration.

Therefore, there is a need to investigate consolidation properties and aid the understanding of the physical properties of the studied cohesive soil in Baghdad city using ANN technique from which, to develop relevant prediction equations.

## 4. ANN MODEL DEVELOPMENT

Artificial neural networks (ANN) are becoming widely popular due to their abilities in developing complex nonlinear models and solving various mathematical tasks. Neural Network is computational tool developed for information processing in a way similar to that of biological neural system in terms of architectural structures, learning, and operating, **Demuth and Beale, 2002**.

The architecture of neural networks generally consists of an input layer, one or more hidden layers, and an output layer. The input layer usually consists of number of neurons that represents the independent test variables, in addition to a neuron having a value of one called bias. The number of hidden layers and the number neurons in these layers are usually found from trial and error to provide best predictions while keeping the network generalized **,Demuth and Beale, 2002**. The neural networks used in this paper are designed to predict Cc and CR. They consisted of one input layer, one hidden layer, and one output layer. The input layer consist three neurons. The hidden layer consists of 10 neurons (see **Fig. 2**). The output layer was to predict Cc or CR. It is important to note that the use of higher number of neurons would limit the generalization of the network and does not improve the prediction, **Demuth and Beale, 2002**.

The above described neural networks used feed-forward back propagation algorithm. The TRAINLM training function available in MATLAB R2013b was used to train the networks in association with the LERNGDM adoption learning function. Early stopping was used to improve the generalization of the networks and to avoid over-fitting **Demuth and Beale, 2002**. That is, the data set was divided into three subsets: training, validation, and testing. The training set consists of 70% of the total input date, and the rest equally divided between validation and testing sets.

Three parameters were considered in this study (i.e. $\gamma_t$, $e_o$, and $P_o$). These parameters attested by statistical analysis to have strong influence on Cc and CR **Al-Busoda and Al-Taie, 2010 A**. Good agreements were achieved between ANN predications (training, validation, and testing) subsets with lab tests. The correlation coefficient (R) between predicted Cc and lab results was 0.93 (see **Fig. 3**), and the correlation coefficient (R) between predicted CR and lab results was 0.90 (see **Fig. 4**).

## 5. PROPOSED EQUATIONS TO PREDICT Cc AND CR

The following equations are proposed to predict Cc and CR. The function relationship between the independent variables and the contribution of each of these variables were determined using the connecting weight algorithm **,Garson, 1991**. Both equations were made function of $\gamma_t$, $e_o$, and $P_o$. These parameters were found to provide best predictions for Cc and CR, **Al-Busoda and Al-Taie, 2010 B.** The proposed equations are given by:

$$C_c = 0.033\,{\gamma_t}^{0.19}\,{e_o}^{0.47}\,{p_o}^{0.33} \quad (1)$$

$$CR = 0.017\,{\gamma_t}^{0.2}\,{e_o}^{0.45}\,{p_o}^{0.35} \quad (2)$$

The accuracy of the proposed equations was examined using the existing lab results. The proposed equations showed good agreements between the predictions and test results. The mean ratio of prediction to test using Eq. (1) was 1.00 with a standard deviation of 0.15 (see **Fig. 5**). The mean ratio of prediction to test using Eq. (2) was 1.00 with a standard deviation of 0.16 (see **Fig. 6**).

## 6. CONCLUSIONS

In this paper, two equations were proposed to help the geotechnical engineer to estimate the compression index (Cc) and compression ratio (CR) of cohesive soils. The proposed equations are function of the total unit weight ($\gamma_t$), initial void ratio ($e_o$), and effective overburden pressure ($P_o$). These equations were derived from ANN analysis using connecting weight algorithm. A database of 195 test results collected from geotechnical investigations by local public agencies and private geotechnical companies was used to train the neural networks. The later were applied to predict the compression index (Cc) and compression ratio (CR). The one hundred ninety five of lab test results were used to train, test, and validate the neural network models. In which, 70% of the database were used for training, 15% were used for testing, and the rest were used for validation. The proposed equations yielded good agreements with the test results. The mean ratio of prediction to test using equation (1) was 1.00 with a standard deviation of 0.15. The mean ratio of prediction to test using equation (2) was 1.00 with a standard deviation of 0.16.

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**NOMENCLATURE**

$e_o$: initial void ratio

$P_o$ : effective overburden pressure

R : Correlation Coefficient

$W_n$: natural moisture content

$\gamma_d$ :dry unit weights

$\gamma_t$: total unit weight

**Table 1.** Database statistics descriptive**.**

| Variables | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|
| $w_n$ (%) | 14.0 | 38.0 | 25.3 | 4.1 |
| $e_o$ | 0.411 | 1.120 | 0.709 | 0.109 |
| $\gamma_{t,}$ (kN/m$^3$) | 17.00 | 21.30 | 19.48 | 0.80 |
| $\gamma_d$, (kN/m$^3$) | 12.68 | 17.90 | 15.57 | 0.99 |
| $P_o$, (kPa) | 14.0 | 384.0 | 115.6 | 83.2 |
| Cc | 0.11 | 0.48 | 0.23 | 0.07 |
| CR | 0.067 | 0.270 | 0.131 | 0.033 |

**Table 2.** A summary of research developed for application of ANN in predicting Cc**.**

| Reference | Soil Data | Parameters |
|---|---|---|
| Ozer et al. (2008) | 135 test data | - |
| Park and Lee (2011) | 947 soil test data from Republic of Korea | wn, LL, PI, $G_s$, and soil types |
| Kumar and Rani (2011) | 68 soil test data Compacted Soil | LL, PI, $\gamma_{dmax}$, , optimum moisture content (OMC) and fine fraction. |
| Kalantary and Kordnaeij (2012) | 400 test data, North of Iran | - |
| Kashefipour and Daryaee (2014) | 137 data sets south-west of Iran | $e_o$, $w_n$, LL, PI, and $G_s$ |
| Alam et. al. (2014) | 391 experimental results | $e_o$, $w_n$, LL, and PI. |
| Kurnaz et al. (2016) | test data, Turkey | $e_o$, $w_n$, LL, and PI. |

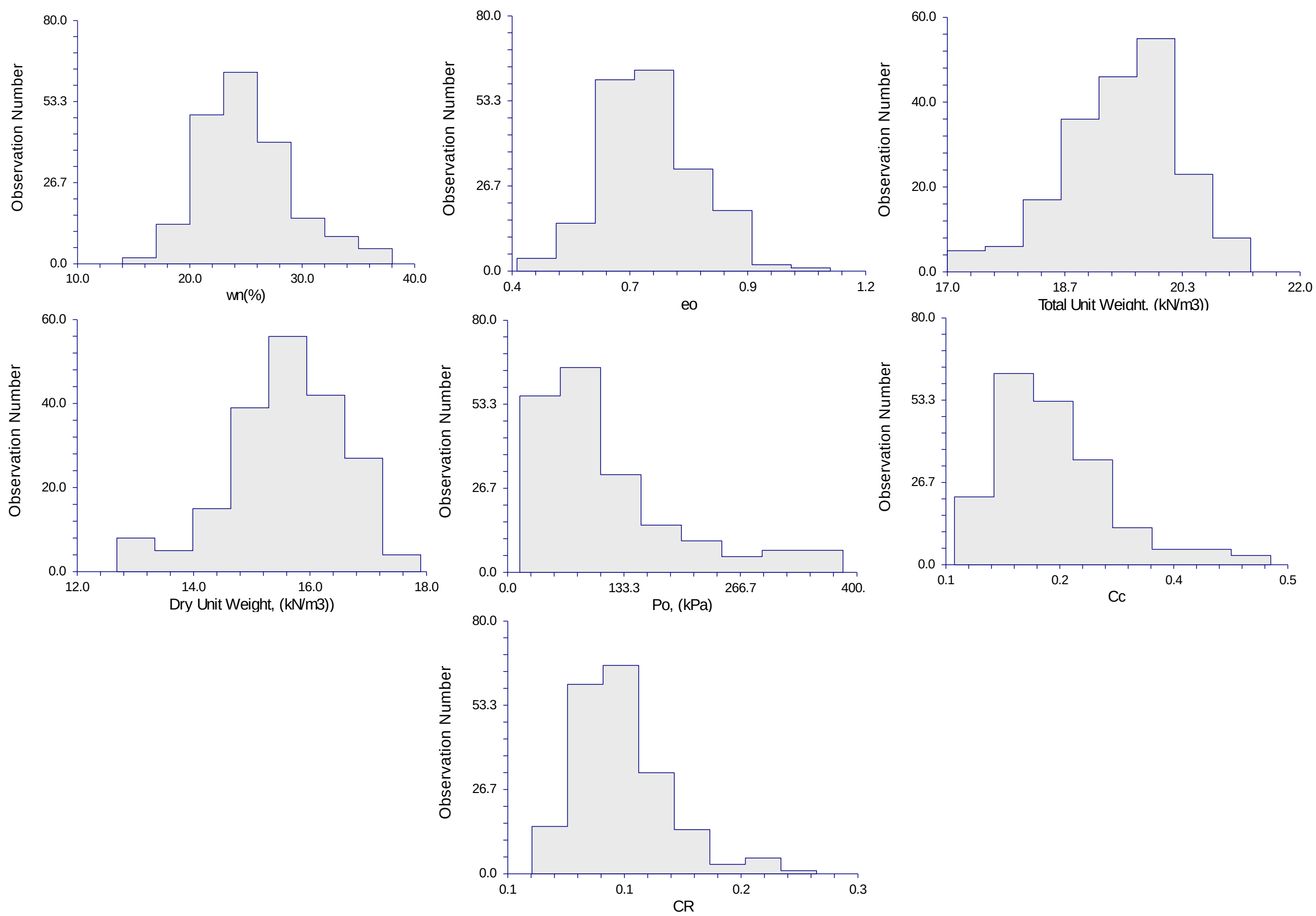


**Figure 1.** Histograms for soil properties**.**

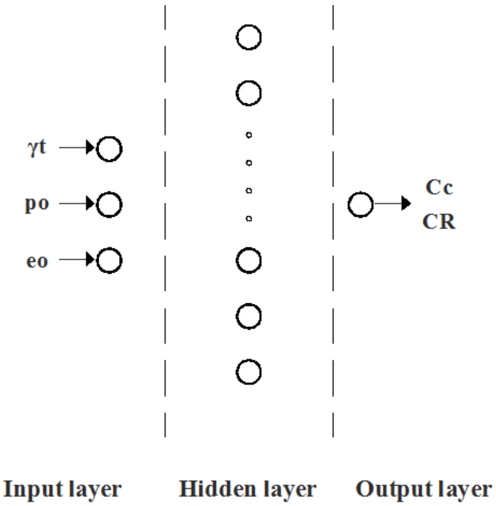


**Figure 2.** Architecture of Neural Network.

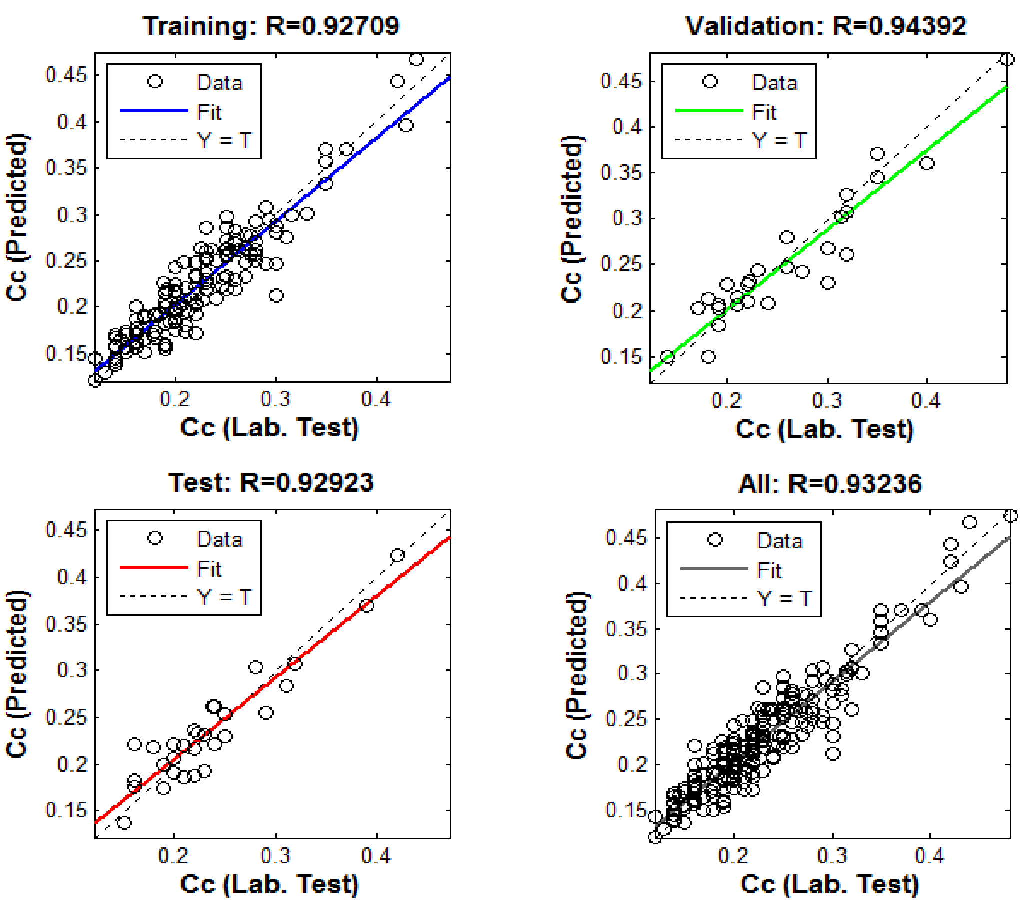


**Figure 3.** Regression during training process for Cc.

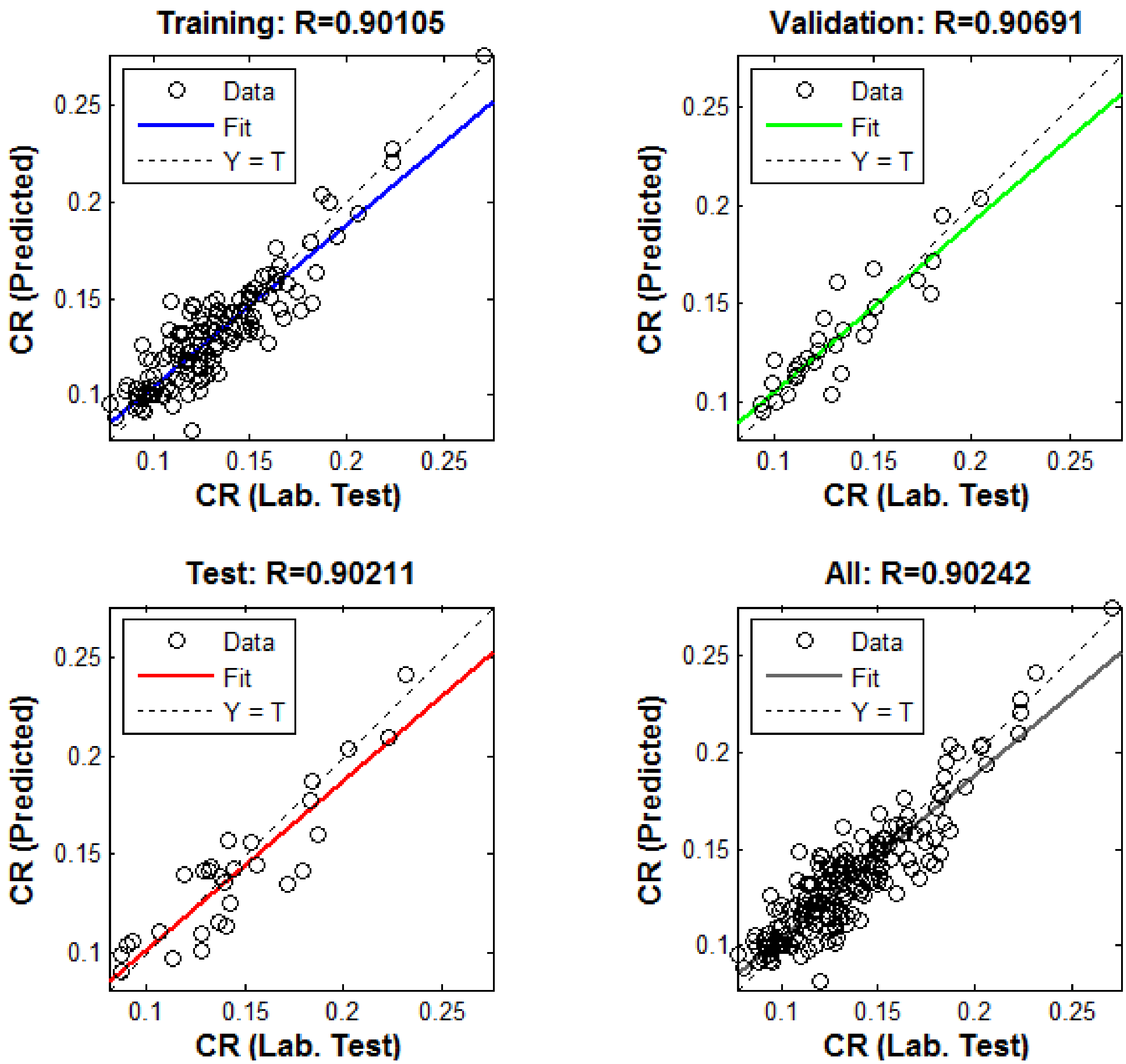


**Figure 4.** Regression during training process for CR.

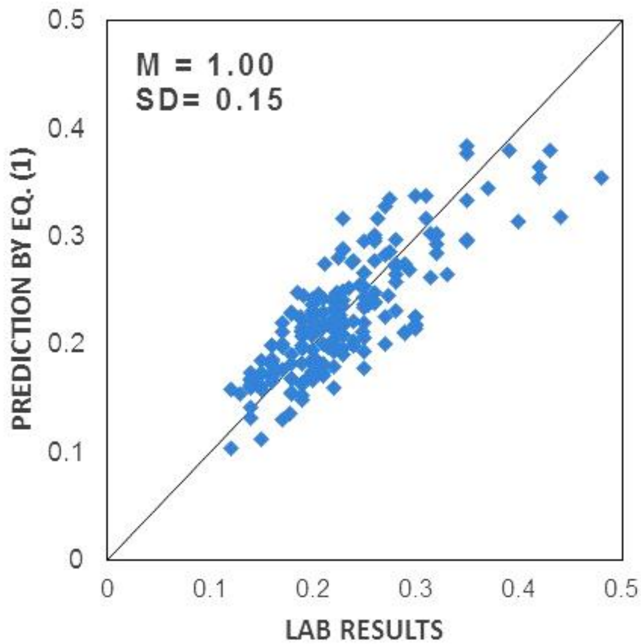


**Figure 5**. Lab and predicted Cc using Eq. (1).

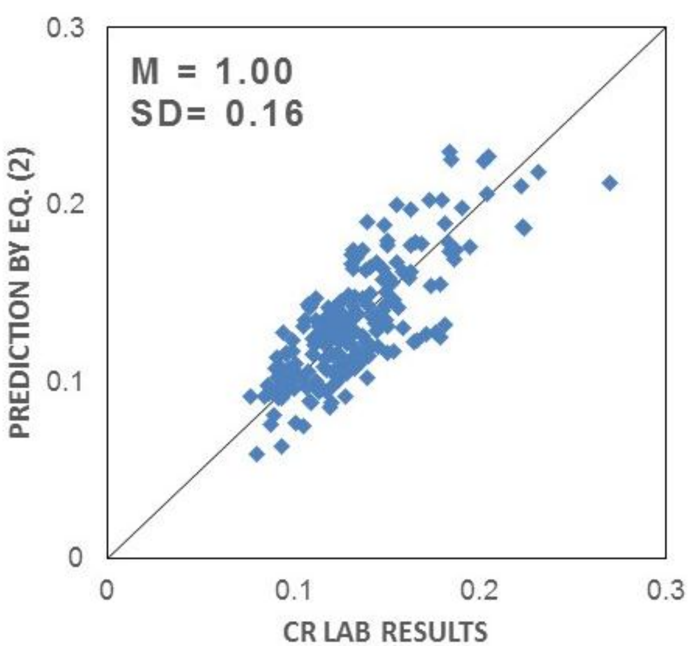


**Figure 6.** Lab and predicted CR using Eq. (2).