Development Models of Artificial Neural Network and Multiple Linear Regression for Predicting Compression Index and Compression Ratio for Soil Compressibility of Ramadi City

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Abstract

Artificial neural networks (ANN) as new techniques employed for the development of predictive models to estimate the needed parameters in geotechnical engineering to be used for comparison with laboratory and field tests and consequently reduce the cost, time, and effort. Flexible computing techniques are using an alternative statistical tool to analyze and evaluate experimental data from 102 consolidation tests on a variety of undisturbed soils from Ramadi city. The regression equations are developed to estimate the compression index and the compression ratio from index data. Multi-Layer Perceptron (MLP) network model is used to calculate compression index and a compression ratio of soils and comparing with the multiple linear regression statistical model MLR. It is found that the MLP showed a higher performance than MLR in predicting C_c and C_r and model accuracy between 0.81 to 16 percent. This will provide a good method for minimizing the potential inconsistency of correlations.

Keywords: Compression index, consolidation test, MLP, ANN, compression ratio.

1. Introduction

Application of load either by a structure or fill will lead to a deformation of soil layers. The magnitude of this deformation is known as settlement [1,2]. In general, the consolidation settlement, S_c, for consolidated clay could be stated as

$$S_c = \frac{C_c}{1+e_o} H \log \frac{\sigma'_o + \Delta\sigma}{\sigma'_o} \tag{1}$$

where
H = Thickness of layer
e_o = Void ratio
C_c = compression index
σ'_o= Effective overburden pressure, and
$\Delta\sigma$ = induced stress

Where as the slope of the " virgin compression" portion of the e-log σ'_o curve determined by a standard one-dimensional consolidation test on an undisturbed sample is C_c. However, the cost of consolidation tests is expensive and in many cases, they may be disproportionate to the total engineering costs for a given project [1,2].

This study aims to predict the compression index, C_c and the compression ratio, C_r (defined as $C_c/[1+e_o]$) of soils by using multiple regression and artificial neural network model to predict and compare the models with the experimentally measured data capabilities. Data from the 102 consolidation tests collected to establish predictive models.

2. Previous Correlations

The properties of different soil have been used to calculate the compression index and the compression ratio by several investigators, but most of these examined only simple linear models to correlate C_c with different properties, such as the initial void ratio, e_o (Nishida, 1956; Hough, 1957; Cozzolino, 1961; Sowers, 1970; Azzouz et al., 1976) [3,4,5,6,1], the natural water content, w_n (Peck and Reed, 1954; Osterberg, 1972) [7,8], and the liquid limit, LL (Skempton, 1944; Terzaghi and Peck, 1967; Azzouz et al., 1976) [9,10,1]. Multiple linear regression models, in which Cc is considered to be a function of both LL and e_o, was reported by Cozzolino (1961) [5]. Another correlation involving multiple soil parameters for C_c, was obtained by Nagaraj and Murty (1985) [11]. Yoon et al. (2004)[12] proposed a set of equations correlating various index properties of marine clay from the east, south, and west coasts of Korea with the multiple regression analysis based on data from 1200 consolidation tests. Peak and Reed (1954) [7] expressed the variation of C_c with w_n by a second-degree polynomial. The compression ratio, C_r, was shown to be highly correlated with both e_o and w_n (Peck and Reed, 1954; Elnaggar and Krizek, 1970)[7,13]. Al-Busoda, B. S., and Al-Taie, A. J., (2010)[14] estimated C_c and C_r of Baghdad cohesive soil from other soil properties. It was concluded that the better values of C_c and C_r of Baghdad soil can be obtained when more than one index property is used in the regression analysis. Summary of many existing regression equations for the prediction of both C_c and C_r as described in Table 1. These equations were proposed or established by many different authors from various places. It should be noted that there have been continuous attempts to develop simple methods, to predict C_c and C_r of soils from simple soil index parameters.

Table 1: Existing statistical equations for calculation of C_c and C_r.

Regression Equation	Regions of Applicability	Reference
C_c=0.007(LL-7)	Remolded clays	Skempton, 1944[8]
C_r=0.208e_o+0.0083	Chicago clays	Peck and Reed, 1954[6]
C_c=17.66x10^{-5} w_n^2 +5.93x10^{-3} w_n -1.35x10^{-1}	Chicago clays	Peck and Reed, 1954[6]
C_c=1.15(e_o-0.35)	All clays	Nishida, 1956[2]
C_c=0.30(e_o-0.27)	Inorganic, cohesive soil; silt; some clay	Hough, 1957[3]
C_c=0.256+0.43(e_o-0.84)	Brazilian clays	Cozzolino, 1961[4]
C_c=0.0046(LL-9)	Brazilian clays	Cozzolino, 1961[4]
C_c=1.21+1.055(e_o-1.87)	Motley clays from Sao Paulo city	Cozzolino, 1961[4]
C_c=0.00186(LL-30)	Motley clays from Sao Paulo city	Cozzolino, 1961[4]
C_c=0.009(LL-10)	Normally consolidated clays	Terzaghi and Peck, 1967[9]
C_c=0.075(e_o-0.50)	Soils of very low plasticity	Sowers, 1970[5]
C_r=0.156 e_o+0.0107	All clays	Elnaggar and Krizek, 1971[12]
C_c=0.01 w_n	Chicago clays	Osterberg, 1972[7]
C_c=0.208 e_o+0.0083	Chicago clays	Azzouz et. al., 1976[1]
C_c=0.006(LL-9)	All clays	Azzouz et. al., 1976[1]
C_c=0.2343(LL/100)G_s	All clays	Nagaraj and Murty,1985[10]
C_c= -0.0003 w_n+ 0.538 e_o+0.002 LL-0.3	South Coast	Yoon et al. (2004)[11]
C_c=0.0098 LL+0.194 e_o-0.0025 PI-0.256	East Coast	Yoon et al. (2004)[11]
C_c= 0.0038 w_n+0.12 e_o+0.0065 LL-0.248	West Coast	Yoon et al. (2004)[11]
C_c= -0.0405+0.3018 e_o +0.0001γ_d +0.00044P_o	Baghdad Cohesive soil	Al-Busoda, B. S., and Al-Taie, A. J., (2010)[14]

3. Characteristics of the Used Data

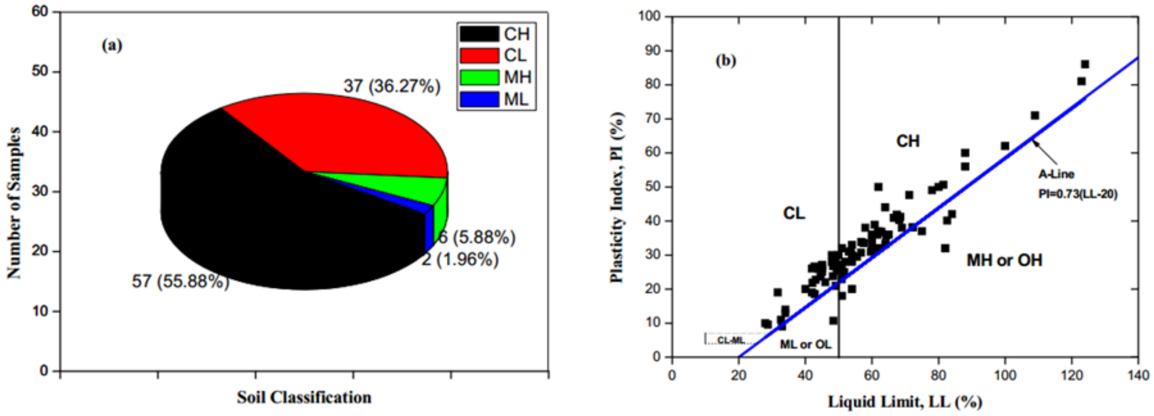
Most Soils in Ramadi city consist of 2 to 4 meter silty sand to sand with gravel in the top layers and then gradient with 16 to 30 meters depth to become silt, lean clay, and fat clay. The collected available data were obtained from wide spread field investigations accompanied by laboratory testing (including standard one-dimensional consolidation) for various places in Ramadi city. In particular, data were collected from Andrea Engineering Testing Laboratory, the National Centre for Construction Laboratories and Research (NCCLR), Engineering Consulting Bureau at University of Anbar. A reliable predictive model is required to construct an adequate number of data having high quality; that is why only 102 out of 150 data sets included in the analyses. In order to determine the compression index and compression ratio of the soil samples, standard one-dimensional consolidation tests were carried out by ASTM D 2435. The specimen, kept under water during each test.

The Unified Soil Classification System were used for classification of soil samples. The pie chart in Fig. 1a shows the percentages of each soil type used is this study. The *LL* and *PI* data of the whole soil samples, Fig. 1b, indicated that the majority of the soil samples is inorganic clay of either low plasticity or high plasticity.

The statistical parameters of the soil properties are given in Table 2 which calculated by the software SPSS Version 20 (2011) package [15]. In Fig. 2, the independent value shows approximately normal distribution. It can be seen that the skewness and kurtosis values of 0.239 and 0.474 respectively are very low. In conclusion, it was evident that the analyses will work well in case[16].

4. Data Processing and Analyses

Most of the correlations were summarized in Table 1 were obtained solely from experience and have neither a theoretical nor a statistical basis. In this study, the first stage of the 102 consolidation test was performed by regression analysis, and reasonably reliable equations were obtained to describe most of the variation in both C_c and C_r. The independent variables in the regression equations were chosen according to their correlation coefficients with the dependent variables C_c or C_r.



Figures 1a and 1b: The classification of soil and number of samples.

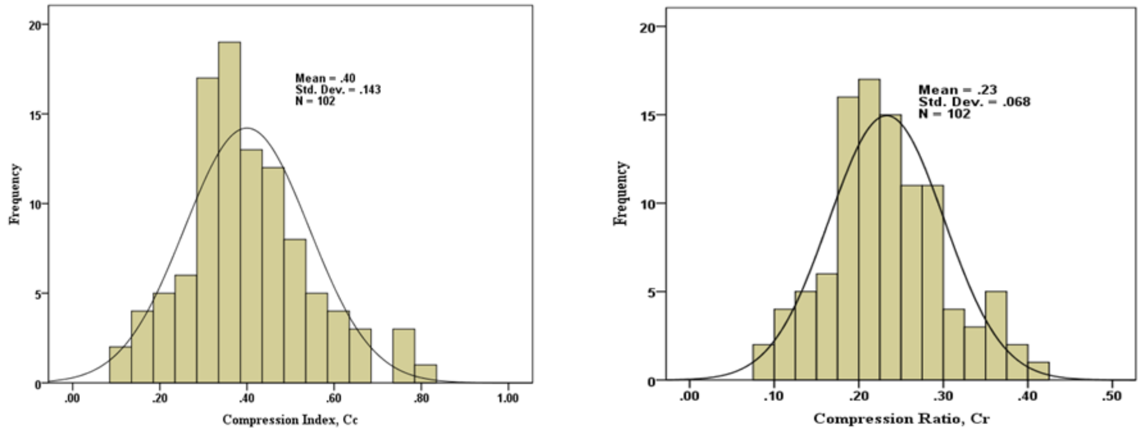


Figure 2: Histogram chart shows data of frequencies of C_c and C_r values of samples

Table 2: Statistical parameters of different soil properties for all samples.

Statistics	W_n (%)	LL (%)	PL (%)	PI (%)	Pc (kN/m^2)	C_c	C_r	G_s	γ_d (kN/m^3)	e_o
N	102	102	102	102	102	102	102	102	102	102
Mean	24.5465	58.40	25.84	32.56	189.4111	0.3998	0.233	2.6809	15.4225	0.6846
Std. Error of Mean	0.62122	1.902	0.681	1.463	3.63293	0.01417	0.00674	.00688	.13548	0.01149
Median	23.6550	54.00	24.41	30.81	184.9150	0.3750	0.2259	2.6650	15.4500	0.6700
Mode	20.00	62	20	26	120.45	0.32	0.22	2.60	14.70	0.62
Std. Deviation	6.27398	19.209	6.875	14.780	36.69075	0.14315	0.06803	0.06945	1.36823	0.11605
Variance	39.363	369.001	47.260	218.462	1346.211	0.020	0.005	0.005	1.872	0.013
Skewness	0.357	1.293	0.978	1.214	0.200	0.604	0.228	0.198	-0.007	0.643
Std. Error of Skewness	0.239	.239	0.239	0.239	0.239	0.239	0.239	0.239	0.239	0.239
Kurtosis	0.671	2.076	1.140	2.309	-0.621	0.450	0.026	-1.670	-0.541	0.812
Std. Error of Kurtosis	0.474	0.474	0.474	0.474	0.474	0.474	0.474	0.474	0.474	0.474
Range	34.39	96	38	77	151.11	0.70	0.33	0.18	5.70	0.58
Minimum	5.61	28	12	9	120.45	0.11	0.08	2.60	12.50	0.45
Maximum	40.00	124	50	86	271.56	0.81	0.41	2.78	18.20	1.03
Sum	2503.74	5957	2636	3321	19319.93	40.78	23.76	273.45	1573.10	69.83

The correlation coefficient (R) between -0.5 and +0.5 were considered, for all practical purposes, to indicate an insignificant linear correlation and consequently R^2 have very low[1]. Table 3 presents the general correlation matrix for the soil samples taking into consideration all the available properties. It has shown from this matrix that both C_c and C_r are highly correlated with e_o, LL, and PI while there is no correlation with other variables. Therefore, these three variable will be utilized in different regression equations to obtain the best regression model for the determination of both parameters as in Table 4.

The plot of C_c and C_r versus the liquid limit, *LL*, the plasticity index, *PI*, and the initial void ratio, e_o, respectively as shown in Fig. 3 and Fig. 4. It has shown that the relationship in each case justifies the use of a linear model.

4.1 Multiple Linear Regression Model

The multiple regression is worked to account the variance of interval dependent and independent variables based on linear combinations. The typical form of the multiple linear regression model is as follow [2]:

$$y = b_1x_1 + b_2x_2 + \ldots + b_nx_n + c \tag{2}$$

where
$b_1, b_2, \ldots, b_n$ =The regression coefficients, and
c = A constant.

The analyses of multiple linear regression were approved to determine of C_c and C_r regarding more than one predictor are presented and evaluated in Table 5 and Table 6. During this analysis, all possible relationships were tried; however, naturally in some of these relationships, the correlation coefficients were low. The equations given in Table 5 is the ones which had the highest correlation coefficient(R ± 0.5). The relationships between measured and predicted values were obtained from the MLR models for C_c and C_r with excellent correlation coefficients as shown in Fig. 5 and 6. The values account for (*VAF*) and root mean square error (*RMSE*) represent a frequency used measurement of the defferences between pridicted and measured values were calculated (in Table 6 and 7) to control the performance of the prediction capacity of predictive model as informed by Alvarez and Babuska (1999)[17]:

$$VAF = \left[1 - \frac{var(y-y')}{var(y)}\right] \times 100 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y-y')^2} \tag{4}$$

where
y = The measured value, and
y' = The predicted value.

It has been using the mean absolute percentage error (MAPE), which is installed in the accuracy of the statistics series also to compare the predictive performance models scale value[16]. *MAPE* usually expresses as

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y-y'}{y}\right| \times 100 \tag{5}$$

The values of *RMSE*, *VAF*, and *MAPE* used to measure the quality and the predictability power of the model as shown in Table 7 and 8.

4.2 ANN Model

The neural networks can be used as a direct replacement for automatic correlation, multivariate regression, linear regression, trigonometric and statistical analysis techniques (Singh, Kanchan, Verma, & Singh, 2003) [18,17]. Neural networks can be used to extract patterns and detect trends that are more complicated than that observed by humans or computer techniques (Singh, Kanchan, Verma, & Singh, 2003) [18]. A trained neural network can be thought of as an ''expert'' in the kind of information it has been given to analyze. It used to provide projections given new situations of interest (Simpson, 1990) [19]. When analyzing the data flow using the neural network, it is possible to detect significant predictive patterns that have never clear to non-experts. Thus, the neural network can act as an expert (Simpson, 1990)[19]. The particular network can be defined by three fundamental components: transfer function, network architecture and learning law [17]. It is essential to define these components, to solve the problem satisfactorily. Neural networks consist of a large class of different architectures. To solve the problem, it is crucial to define a Multi-Layer Perceptron (MLP) as the one of the most widely used neural network architecture in literature for classification or regression problems (Cohen & Intrator, 2002, 2003; Kenneth, Wernter, & MacInyre, 2001; Loh & Tim, 2000) [20, 21, 22, 23]. It is good in the problems of classification pattern. It works with a strong ability to generalize to input data is inaccurate. MLP and distributed more approach is the production output by linear combinations of the contract hidden layer output which each neuron maps weighted average of inputs through the sigmoid function.

All data normalization first and is divided into three data sets, such as: training (70% of all data), and test (15% of all data), verification (15% of all data). In this study, Matlab 7.1 (2005) [24] software was used in neural network analyses having a three-layer feed-forward network that consists of an input layer (eight neurons), one hidden layers (9 neurons for MLP) and one output layer (Fig. 7). In the analysis, it has been appointed network parameters of the learning rate and momentum to 0.01 and 0.9, respectively. The use of multiple learning rate with momentum for networking, job training and tansig as activation function for all layers[17].

4.3 ANN-MLP Model

Multi-layer perceptron (MLP) popular network models used in most research applications such as medicine, engineering, mathematical modeling, etc. in the MLP, it is likely that the input agrees term bias to the activation level through the transfer function of the amount of production output. The modules are arranged in nutrition classes forward topology called feed forward neural network (Venkatesan & Anitha, 2006) [25]. MLP networks consist of a layer of inputs,one or more hidden layers, and a layer of output.The MLP transforms *n* inputs to *l* outputs through some nonlinear functions. The output of the network is determined by the activation of the units in the output layer as follows[17]:

$$X_o = f(\sum_h X_h W_{ho}) \tag{6}$$

where
$f(\,)$ = A activation function
X_h = Activation of *h*th hidden layer node, and
W_{ho} = The interconnection between *h*th hidden layer node and *o*th output layer node.

The sigmoid activation function is mostly used, and it given as follows[17]:

$$X_o = \frac{1}{1+e^{(-\sum X_h W_{ho})}} \tag{7}$$

In a similar manner, the level of nods activation in the hidden layer can be determined. There is an error between the target value and the calculated output which can be defined as follows[17]:

$$E = \frac{1}{2}\sum_s^N \sum_o^L \left(t_o^{(s)} X_o^{(s)}\right)^2 \tag{8}$$

where
N = The number of patterns in the data set, and
L = The number of output nodes.

The objective is to reduce the error by adjusting the bonding between the layers. The weights are adjusted using the gradient descent backpropagation (BP) algorithm. The algorithm requires a training data that consists of a set of corresponding input and target pattern values t_o. During the training process, MLP starts with a random set of initial weights and then training continues to set of W_{ih} and that of W_{ho} are optimized so that a predefined error threshold is met between X_o and t_o [17]. According to the BP algorithm, each interconnection between the nodes are adjusted by the amount of the weight update value as follows:

$$\Delta W_{ho} = \eta \frac{\delta E}{\delta W_{ho}} = \eta \delta_o X_h \tag{9}$$

$$\Delta W_{ih} = \eta \frac{\delta E}{\delta W_{ih}} = \eta \delta_h X_i \tag{10}$$

where
E = The error cost function given in Equation (8),
$\delta_o = X_o' (t_o - X_o)$
$\delta_h = X_h' = \sum_o \delta_o W_{ho}$
$X_o' = X_o (1 - X_o)$, and
$X_h' = X_h (1 - X_h)$

The relations between the observed and predicted values as shown in Fig. 8 and Fig .9 pointed out that the ANN model of MLP very acceptable to expect C_c and C_r as shown in Tables 6 and 7 which presented the values of *RMSE*, *VAF*, *MAPE* and R^2.

5. Discussion of Results

The multiple linear regression (MLR) and ANN-MLP model were used for the prediction of compression index, and a compression ratio of compressibility soils in Ramadi City. In this study, based on results of simple regression analyses, there are statistically relationships between C_c and C_r with a liquid limit, plasticity index, and initial void ratio. It is shown that both C_c and C_r are best expressed regarding the initial void ratio using simple linear regression models.

The MLR and the ANN-MLP models have been created to predict of C_c and C_r using seven inputs and one output expressed as follow:

a. A higher prediction performance was found on MLR models.
b. The best improvement in the value of R can be reached when *PI* and G_s is included in addition to e_o for C_c and C_r in multiple linear regression analysis as shown in Tables 5 and 6.
c. The relationships proposed to predict the C_c and C_r of Ramadi soils are similar to equations shown in Table 1.
d. ANN-MLP revealed a more reliable prediction compared with the multiple linear regression model.

As a result, compared to the *VAF*, *RMSE* and *MAPE* indicators and correlation coefficient (R^2) to predict C_c and C_r shown in Tables 7 and 8, it obtained that the performance prediction model ANN-MLP is higher than The multiple linear regression.

Table 3: The correlation matrix for the different properties of the soil for all samples

Soil Property	W_n (%)	LL (%)	PL (%)	PI (%)	P_o (kN/m^2)	P_c (kN/m^2)	C_c	G_s	γ_d (kN/m^3)	e_o	C_r
Water Content, W_n (%)	1	0.494	0.514	0.403	-0.221	-0.451	0.403	-0.285	-0.759	0.422	0.363
Liquid Limit, LL (%)	0.494	1	0.749	0.951	-0.006	-0.111	0.912	0.269	-0.374	0.902	0.880
Plastic Limit, PL(%)	0.514	0.749	1	0.508	-0.067	-0.177	0.613	0.121	-0.412	0.616	0.585
Plasticity Index, PI (%)	0.403	0.951	0.508	1	0.024	-0.061	0.900	0.293	-0.295	0.886	0.871
Overburden Pressure, P_o (kN/m^2)	-0.221	-0.006	-0.067	0.024	1	0.869	-0.003	0.035	0.351	0.036	0.007
Preconsolidation Pressure, P_c (kN/m^2)	-0.451	-0.111	-0.177	-0.061	0.869	1	-0.079	0.287	0.683	-0.060	-0.057
Compression Index, C_c	0.403	0.912	0.613	0.900	-0.003	-0.079	1	0.351	-0.295	0.967	0.993
Specific Gravity, G_s	-0.285	0.269	0.121	0.293	0.035	0.287	0.351	1	0.478	0.286	0.382
Dry Unit Weight, γ_d (kN/m^3)	-0.759	-0.374	-0.412	-0.295	0.351	0.683	-0.295	0.478	1	-0.326	-0.258
Initial Void Ratio, e_o	0.422	0.902	0.616	0.886	0.036	-0.060	0.967	0.286	-0.326	1	0.942
Compression Ratio, C_r	0.363	0.880	0.585	0.871	0.007	-0.057	0.993	0.382	-0.258	0.942	1

Table 4: Linear regression equations used to calculate C_c, and C_r

Dependent Variable	Independent Variables	R	R^2	Std. Error of the Estimate	Statistical Equation	Sample Numbers
C_c	$LL\%$	0.912	0.831	0.05912	$C_c=0.007\ LL\% + 0.003$	102
	$PI\%$	0.900	0.810	0.06274	$C_c=0.009\ PI\% + 0.116$	102
	e_o	0.967	0.934	0.03685	$C_c=1.192\ e_o - 0.417$	102
C_r	LL (%)	0.880	0.774	0.03253	$C_r=0.003\ LL\% + 0.051$	102
	PI (%)	0.871	0.759	0.03359	$C_r=0.004\ PI\% + 0.102$	102
	e_o	0.942	0.888	0.02293	$C_r=0.552\ e_o - 0.145$	102

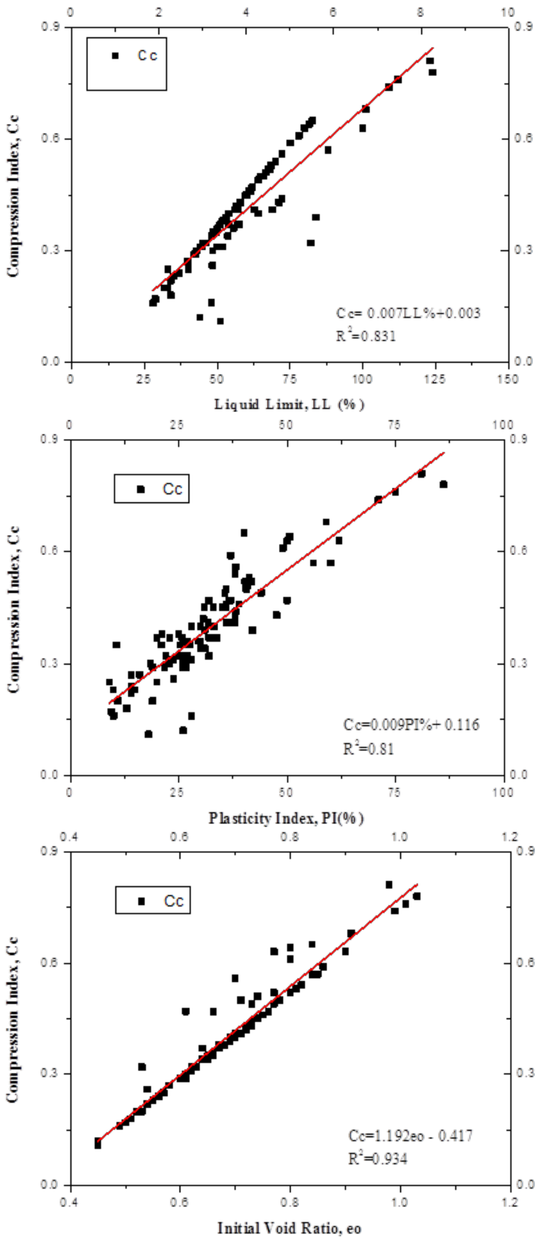


Figure 3: Compression index various *LL*, *PI* and e_o.

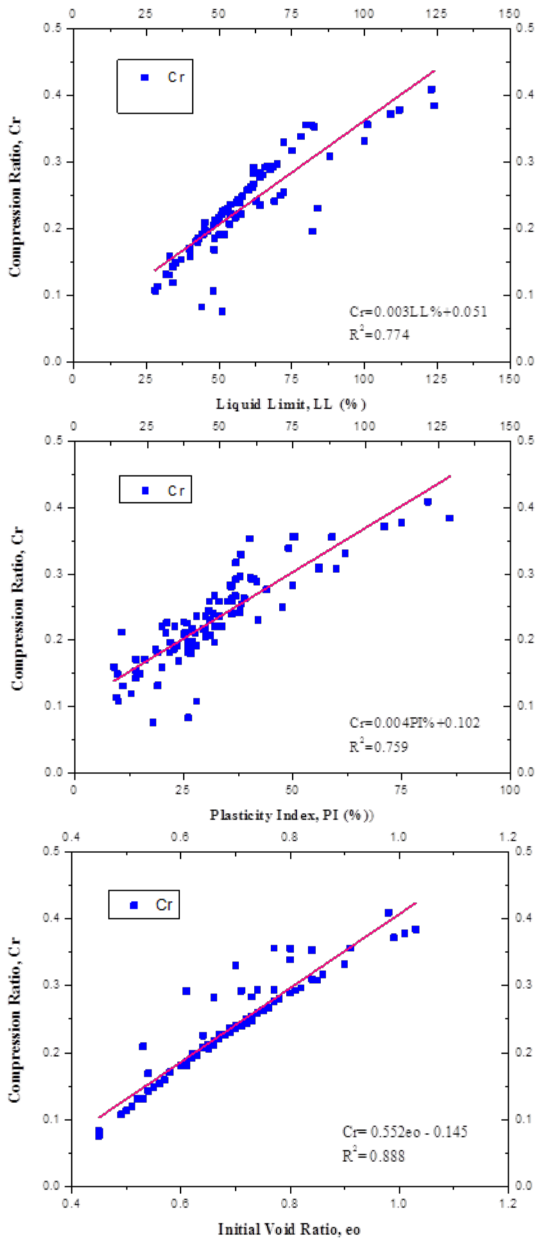


Figure 4: The Compression ratio various *LL*, *PI* and e_o.

Table 5: Multiple linear regression equations used to calculate, C_c

Dependent Variable	Independent Variables	R	R^2	Std. Error of the Estimate	Regression Equation	NO. of Samples
C_c	e_o and $LL\%$	0.971	0.943	0.03460	$C_c=0.957\ e_o + 0.002LL\% - 0.347$	102
	e_o and $PI\%$	0.971	0.943	0.03448	$C_c=0.972\ e_o + 0.002PI\% - 0.329$	102
	e_o, $W_n\%$ and $LL\%$	0.972	0.944	0.03444	$C_c=0.95\ e_o + 0.002LL\% - 0.001\ W_n\% - 0.332$	102
	e_o, $PI\%$ and G_s	0.974	0.948	0.03314	$C_c=0.961\ e_o + 0.002PI\% + 0.151G_s - 0.721$	102
	$W_n\%^*$, $LL\%$, $PL\%$, PI^{**}, G_s, e_o, γ_d, Pc^*	0.965	0.932	0.03288	$C_c= 0.927\ e_o + 0.002LL\% + 0.163G_s + 0.003\gamma_d - 0.001PL\% - 0.764$	102

* Considering the values of *Wn%* and *Pc* equal to zero. ** *PI* value excluded from multiple linear regression analysis.

Table 6: Multiple linear regression equations used to calculate, C_r.

Dependent Variable	Independent Variables	R	R^2	Std. Error of the Estimate	Regression Equation	NO. of Samples
C_r	e_o and $LL\%$	0.945	0.892	0.02256	$C_r=0.468e_o + 0.001LL\% - 0.121$	102
	e_o and $PI\%$	0.945	0.894	0.02241	$C_r=0.465e_o + 0.001PI\% - 0.110$	102

	e_o, $W_n\%$ and $LL\%$	0.946	0.896	0.02229	C_r=0.463e_o + 0.001LL% – 0.001 W_n% – 0.107	102
	e_o, $PI\%$ and G_s	0.952	0.906	0.02118	C_r=0.456e_o + 0.001PI% + 0.114G_s – 0.407	102
	$W_n\%^*$, $LL\%$, $PL\%$, G_s, PI^{**}, e_o, γ_d, Pc	0.933	0.871	0.02143	C_r= 0.448e_o + 0.001LL% + 0.119G_s +0.001γ_d –9.635×10^{-5}W_n% – 8.269×10^{-5}Pc – 0.448	102

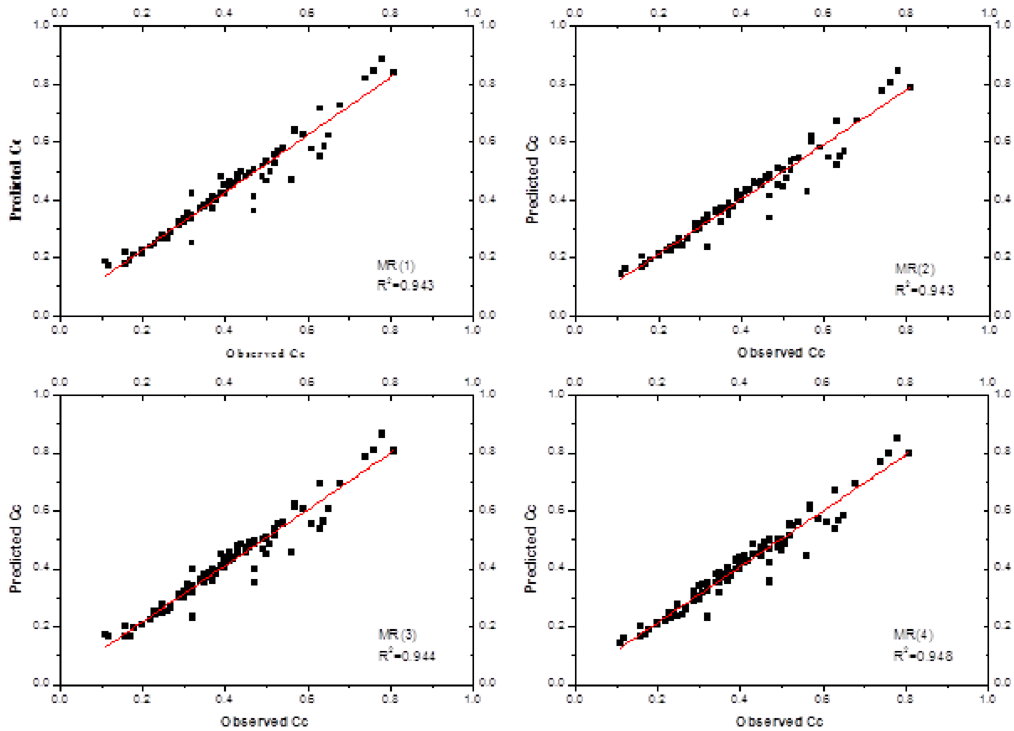
*Considering the value of *PL%* equal to zero.
** *PI* value excluded from multiple linear regression analysis.

Table 7: *RMSE*, *MAPE*, *VAF* and R^2 values used to predict C_c.

Type	Predictive Model	RMSE	MAPE%	VAF%	R^2
MR(1)	Cc=0.957 eo + 0.002LL% – 0.347	0.043	10.13	93.95	0.943
ANN-MLP(1)		0.021	2.50	97.94	0.979
MR(2)	Cc=0.972 eo + 0.002PI% – 0.329	0.034	5.81	94.31	0.943
ANN-MLP(2)		0.027	5.38	96.50	0.965
MR(3)	Cc=0.95 eo + 0.002LL% – 0.001 Wn% – 0.332	0.036	7.04	94.29	0.944
ANN-MLP(3)		0.024	5.11	97.32	0.973
MR(4)	Cc=0.961 eo + 0.002PI% + 0.151Gs – 0.721	0.034	6.39	94.77	0.948
ANN-MLP(4)		0.038	4.26	93.66	0.938
MR(5)	C_c= 0.927 e_o + 0.002LL% + 0.163G_s +0.003γ_d – 0.001PL% –0.764	0.056	12.41	93.15	0.932
ANN-MLP(5)		0.0037	0.34	99.88	0.998

Table 8:. *RMSE*, *MAPE*, *VAF* and R^2 values used to predict C_r .

Type	Predictive Model	RMSE	MAPE%	VAF%	R^2
MR(1)	C_r=0.468e_o + 0.001LL% – 0.121	0.0344	14.14	87.70	0.892
ANN-MLP(1)		0.0074	1.04	98.87	0.989
MR(2)	C_r=0.465e_o + 0.001PI% – 0.110	0.0237	8.21	89.12	0.894
ANN-MLP(2)		0.0221	7.18	89.93	0.900
MR(3)	C_r=0.463e_o + 0.001LL% – 0.001 W_n% – 0.107	0.0249	8.92	89.05	0.896
ANN-MLP(3)		0.0182	7.01	93.46	0.935
MR(4)	C_r=0.456e_o + 0.001PI% + 0.114G_s – 0.407	0.0237	8.41	90.11	0.906
ANN-MLP(4)		0.0136	4.29	96.17	0.962
MR(5)	C_r= 0.448e_o + 0.001LL% + 0.119G_s +0.001γ_d – 9.635×10^{-5}W_n% – 8.269×10^{-5}Pc – 0.448	0.0439	15.88	83.78	0.871
ANN-MLP(5)		0.0025	0.42	99.78	0.997



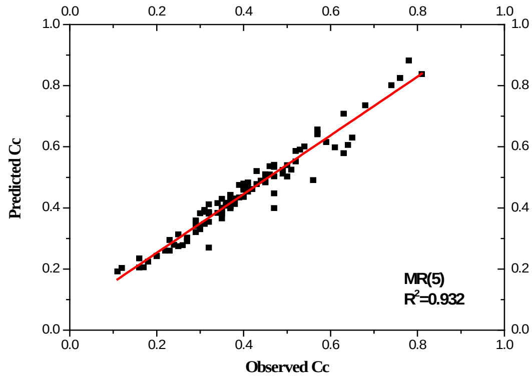


Fig.ure 5: Relations between observed and predicted values of C_c for MLR models.

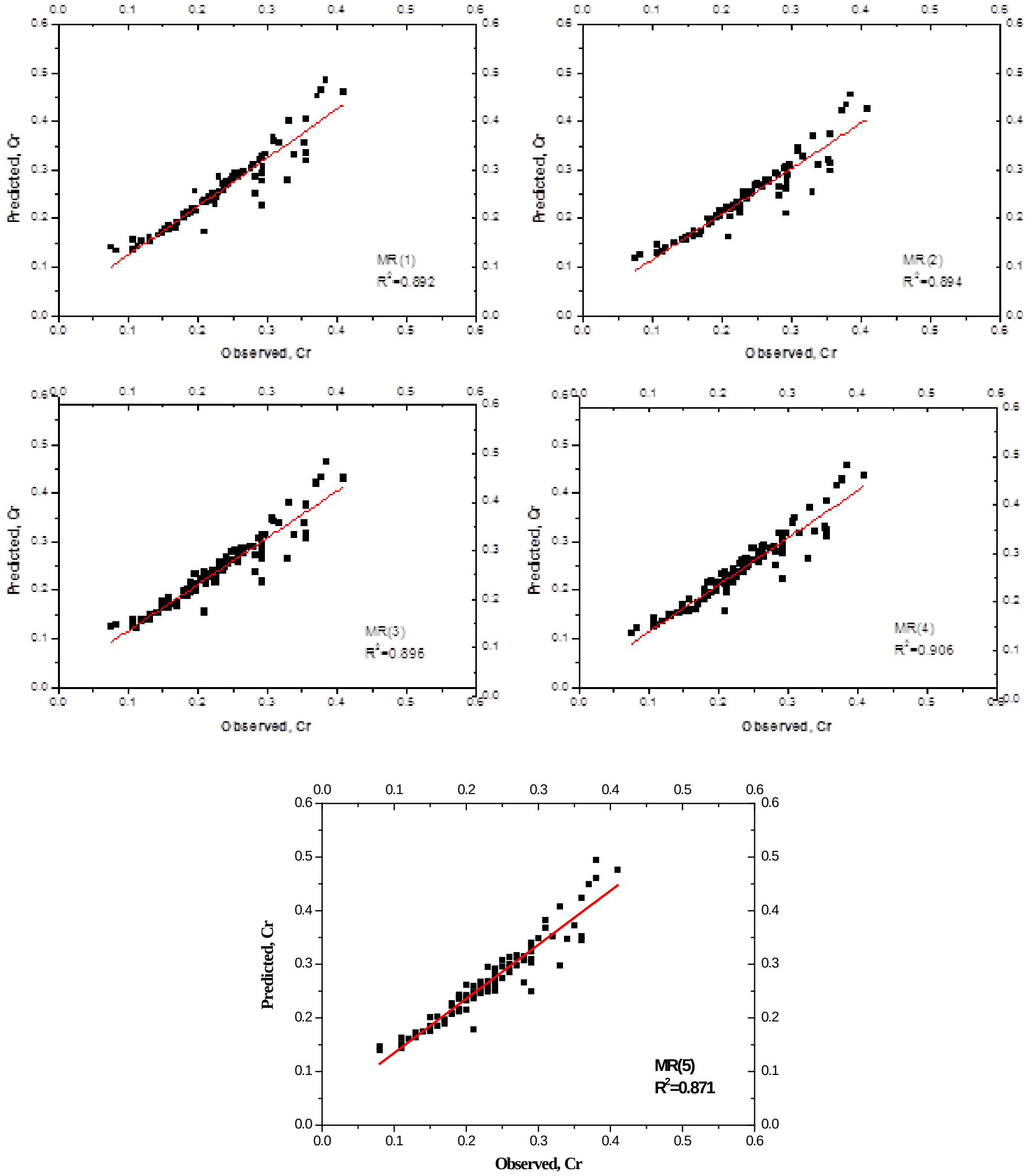


Figure 6: Relations between observed and predicted values of C_r for MLR models.

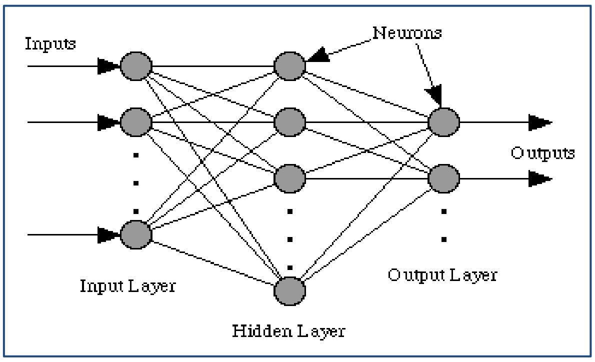


Figure 7: A model of MLP artifical neural network[26].

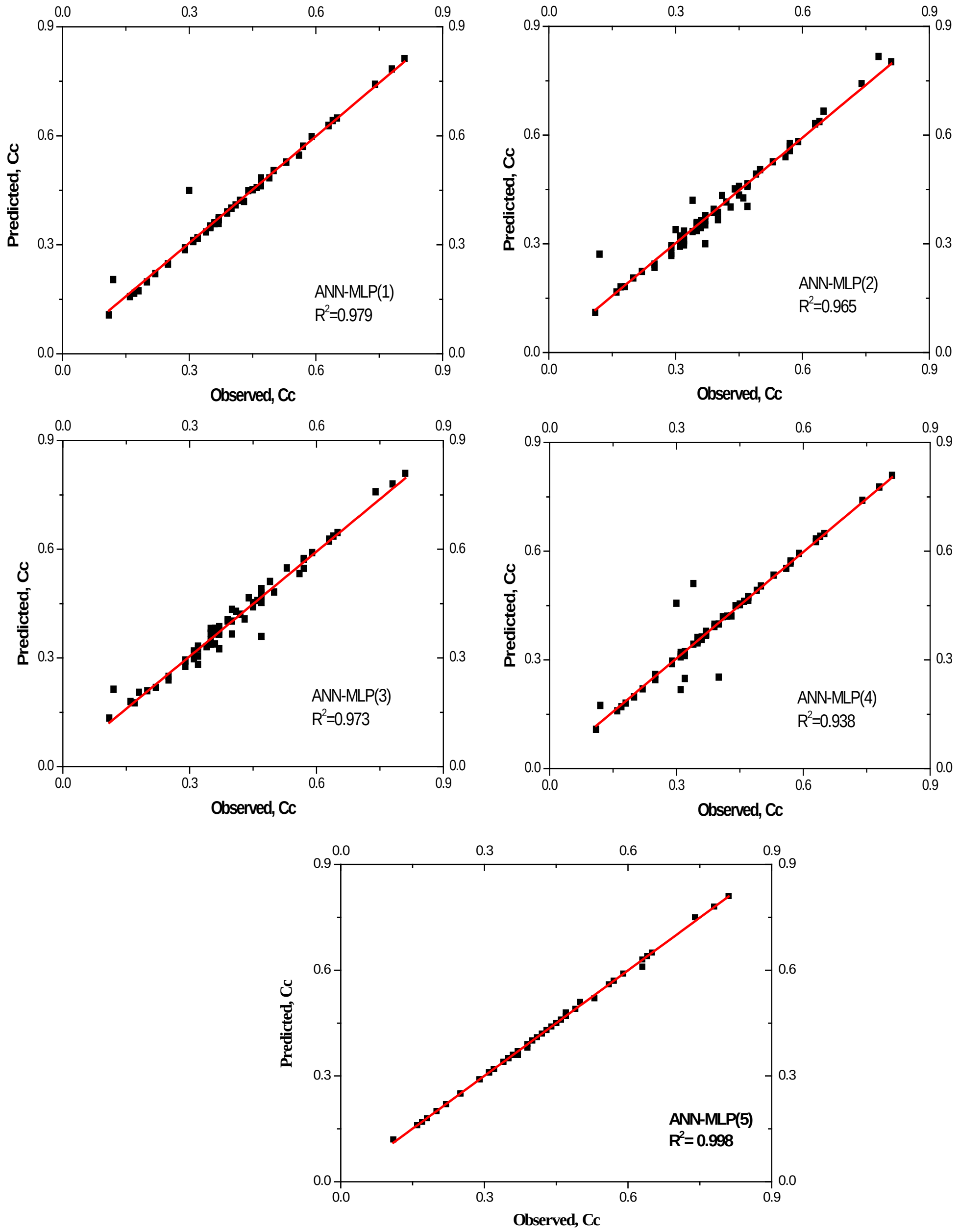


Figure 8: Relations between the observed and predicted values of C_c for ANN-MLP models.

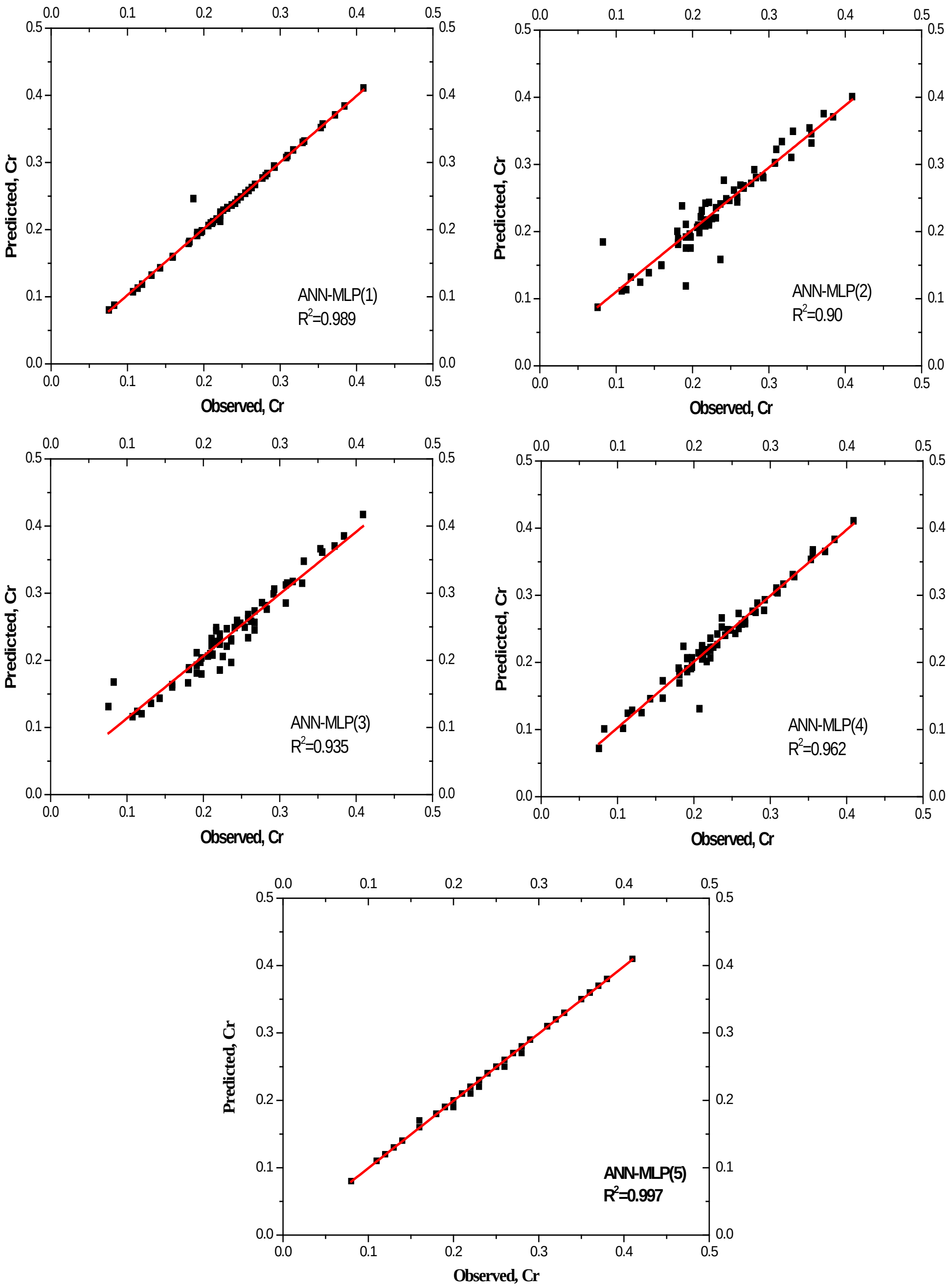


Figure 9: Relations between the observed and predicted values of C_r for ANN-MLP models.

6. Conclusions

Database consisting of 102 data sets containing consolidation and physical properties test results has obtained during the last years from different areas of Ramadi city which used to perform a statistical study to determine adequate correlations for predicting compression index and compression ratio.

A simple, multiple linear regression, and ANN-MLP analysis were adopted and a parametric study was carried out in order to obtain the most suitable and practically applicable relationships.

The main conclusions of the present study are as follow:

- The evaluation of the database indicates that the compression index for Ramadi cohesive soil is intermediate.
- Compression index and compression ratio values using independent variables such as $W_n\%^*$, $LL\%$, $PL\%$, PI, G_s, e_o, γ_d, Pc. The best result was found in the initial void ratio by simple linear regression models.
- The best values of compression index and compression ratio of Ramadi cohesive soil can be obtained when more than one index property are used in the regression analysis.

- Five new equations involving multiple soil parameters have been proposed in this paper which have high coefficients of determination (R^2) for each of the compression index and compression ratio.
- The ANN-MLP model make a high performance than multiple regression for predicting C_c and C_r and model accuracy between 0.81 to 16 percent. This will provide a good method for minimizing the potential inconsistency of correlations.
- Suggest field case studies to check the validity of the proposed empirical equations.

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تطوير نماذج من الشبكة العصبية الاصطناعية والانحدار الخطي المتعدد للتنبؤ بدليل ونسبة الانضغاطية للترب الانضغاطية في مدينة الرمادي

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الخلاصة

الشبكة العصبية الاصطناعية (ANN) تقنية جديدة استخدمت لتطوير نماذج تنبؤ للحصول على المتغيرات المطلوبة في مجال الهندسة الجيوتقنية لكي يتم استخدامها للمقارنة مع نتائج الفحوصات المختبرية والحقلية وهذا يساعد على توفير الوقت والجهد وتخفيض الكلفة. تقنيات الحوسبة المرنة استخدمت كاداة احصائية بديلة لتحليل وتقييم بيانات الفحوصات المختبرية من 102 فحص انضمام اجري على انواع من الترب الغير مشوشة. معادلات الانحدار طورت لتخمين دليل ونسبة الانضغاطية من البيانات المبوبة. نموذج المستقبلات المتعدد الطبقات(MPL) هو نموذج عصبي استخدم لحساب دليل ونسبة الانضغاطية للترب وتم مقارنته مع نتائج النموذج الاحصائي للانحدار الخطي المتعدد MLR. اظهرت النتائج ان MLP ذات اداء اعلى في التنبؤ مقارنتا مع MLR بالنسبة لدليل ونسبة الانضغاطية للترب وبدقة تتراوح بين (0.81 -16) % وهذا سوف يوفر وسيلة جيدة لتقليل التعارض في الموثوقية الكامنة في العلاقات الاحصائية .