Journal of Engineering Sciences and Information Technology
Volume (4), Issue (2): 30 June 2020
P: 90 - 109

AJSRP
ISSN: 2522-3321

مجلة العلوم الهندسية وتكنولوجيا المعلومات
المجلد (4)، العدد (2): 30 يونيو 2020م
ص: 90 - 109

Comparison of Artificial Neural Network and Regression Pedotransfer Function for prediction of soil cation exchange capacity at Iraq, Ray AL Jazeera, Mosul region

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Abstract: The study of soil characteristics such as the ability to exchange positive ions CEC (Cation Exchange Capacity) play a significant part in study of ecological researches, also it is important for decision concerning pollution prevention and crop management. CEC represent the quantity of negative charges in soil, since direct method for measuring CEC are cumbersome and time consuming Lead to the grow of indirect technique in guessing of soil CEC property. Pedotransfer function (PTFs) is effective in estimating this parameter of easy and more readily available soil properties, 80 soil sample were taken from diverse horizons of 20 soil profiles placed in the Aljazeera Region, Iraq.

The aim of this study was to compare Neural Network model (feed forward back propagation network) and Stepwise multiple linear regression to progress a Pedotransfer function for forecasting soil CEC of Mollisols and Inseptisols in Al Jazeera Irrigation Project using easily available features such as clay, sand and organic matter. The presentation of Neural Network model and Multiple regression was assessed using a validation data set. For appraise the models, Mean Square Error (MSE) and coefficient of determination R^2 were used. The MSE and R^2 resultant by ANN model for CEC were 2.2 and 0.96 individually while these result for Multiple Regression model were 3.74 and 0.88 individually. Result displayed 8% improvement in increasing R^2 and also improvement 41% for decreasing MSE for ANN model, this pointed that artificial neural network with three neurons in hidden layer had improved achievement in forecasting soil cation exchange capacity than multiple regression. So we can conclude that ANN model by use (MLP) multilayer perceptron for predicting CEC from measure available soil properties have more accuracy and effective compared with (MLR) multiple linear regression model.

Keywords: Neural Networks, CEC: Cation Exchange Capacity.

مقارنة بين نموذجي الشبكات العصبية والانحدار الخطي المتعدد في تخمين السعة التبادلية الكاتيونية للتربة باستخدام الدوال التحويلية في العراق في منطقة ري الجزيرة في مدينة الموصل

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الملخص: إن دراسة خواص التربة المختلفة مثل قابلية التربة على تبادل الايونات الموجبة والتي تدعى بالسعة التبادلية الكاتيونية للتربة Cation Exchange capacity والتي تلعب دورا هاما في دراسات التربة البيئية والإنتاجية والمشاريع الإروائية وكذلك في مجال منع تلوث التربة وإدارة المحاصيل الإنتاجية، وتمثل السعة التبادلية لكاتيونية مجموع الشحنات السالبة في التربة والتي تتجمع على سطوح دقائق التربة وكذلك فبي الفجوات الداخلية لبلورات المعادن الطينية وكذلك على سطوح المواد العضوية، ولما كانت الطرق المباشرة لتقديرها في التربة تعتبر مرهقة وتستغرق وقتا غير قليل هذا فضلا عن انها مكلفة لذا تم الاتجاه الى اتباع تقنيات غير مباشرة لتخمينها عن طريق استخدام التحويلية Pedotransfer Function (PTFs) والتي تستخدم لتخمين الصفات الصعبة القياس مثل الايصالية المائية للتربة وكذلك السعة التبادلية الكاتيونية اعتمادا على صفات التربة السهلة القياس .

تم الاعتماد على عينات التربة والتي بلغ عددها (80) عينة توزعت على (20) مقد تربة في منطقة مشروع ري الجزيرة، الموصل، العراق، وتم الاعتماد على الصفات التي تم تقديرها من قبل شركة دجلة والتي قامت بجميع الدراسات الميدانية للمشروع وكذلك التحاليل التي أجريت على تربة المشروع.

كان الهدف الأساسي من هذه الدراسة مقارنة نوعين من النماذج الرياضية باستخدام الدوال التحويلية وذلك لغرض تخمين السعة التبادلية الكاتيونية للتربة، الأول نموذج الشبكات العصبية الاصطناعية Artificial Neural Networks بأسلوب Feed forward back propagation والثاني الانحدار الخطي المتعدد المتدرج Stepwise multiple linear Regression لغرض تخمين السعة التبادلية الكاتيونية لتربة المشروع والمصنفة برتبة Mollisols, Inseptisolls بالاعتماد على صفات التربة سهلة القياس (الطين، الرمل، المادة العضوية) وتم استخدام بيانات مجموعة التحقق Validation dataset لغرض تقييم دقة النتائج المتحصل عليها لكل من النموذجين أعلاه ومن اجل تقييم النتائج تم استخدام معيارين الأول متوسط مربع الخطأ القياسي Mean square error (MSE) والثاني معامل التحديد Coefficients of Determination (R^2) حيث كانت قيم متوسط مربع الخطأ القياسي ومعامل التحديد الناتجة من تحليل الانحدار بمقدار (0.3.74 و0.88) على التوالي بينما كانت قيم متوسط مربع الخطأ و معامل التحديد في النتائج المتحصل عليها نتيجة استخدام الشبكات العصبية الاصطناعية بمقدار (2.2، 0.96) على التوالي أيضا وبذلك تظهر النتائج تحسنا في ارتفاع قيم معامل التحديد بمقدار 8% وكذلك تحسنا في انخفاض قيم متوسط مربع الخطأ القياسي بمقدار 41% في نموذج الشبكات العصبية عند استخدام (3) عصبونات في الطبقة المخفية hidden layer مقارنة باستخدام أسلوب الاندحار الخطي المتعدد.

الكلمات المفتاحية: الشبكات العصبية ، سعة تبادل الكاتيونات.

Introduction:

Evolution of simulation models in soil process has been growing quickly in current years. These models have been created to better understand the processes that occur in the soil and to serve as tools for assessing environmental and agricultural problems. Therefore, simulation models are now used to a high level in the field of research and management [1].

Capacity of exchangeable cation consider an essential soil characteristic required in soil databases [2]. And considered as one of the inputs into models of soil conservation [3]. CEC represent the sum of negative charge in soil that is used to connecting positively charged ions (cations). Which is necessary to plant nutrients such as K+, Ca+2, Mg+2 and NH4+ and destructive elements Na+, H+ and Al+3 cations. CEC is used as amount of fertility, nutrient holding size and the size to save ground water from ions pollution [4]. CEC reduces change in soil nutrients suitability as well as soil pH number changes.

Content of Soil which defines interactive CEC values for the soils are organic matter and the amount of clay and silt quantity also contribute a few knives [5]. Soil CEC can be measured directly In laboratory procedure by using the ammonium acetate (NH4OAc) method through the replacement of sodium (Na +) ions with (NH4 +) ions but this method of measurement is difficult, time consuming and expensive especially in the Mollisols and Inseptisols of Iraq because these soils contain a large amounts of calcium carbonate * [6].

***Table (1) Series of Aljazeera region soil, Iraq, Mosul.**

Series	Text	order	suborder	Great groups
Mushairfa	*clay loam*	*mollisols*	*Xerolls*	*calcixerolls*
Al Azaym	*silty loam*	*mollisols*	*Xerolls*	*calcixerolls*
Debshia	*sandy loam*	*Inseptisol*	*Ochrepts*	*Xerochrpts*
Khan jadal	*silty clay loam*	*Inseptisol*	*Ochrepts*	*Xerochrpts*
Awainat	*sandy loam*	*Inseptisol*	*Ochrepts*	*Xerochrpts*
Rubia	*silty clay*	*Mollisol*	*Xerolls*	*Haplaxerolls*

So, it is essential to provide an alternative approach to predict CEC from more easily measurable and readily available soil properties.

Numerous tries have been made to guess difficult qualities of measurement in soil depending on the characteristics of ready and easy measurement in soil such as organic matter, clay content, bulk density, particle size distribution (sand, silt and clay content) and porosity, etc. using pedotransfer functions (PTFs) [7].

These functions are used to bridge the slit between the data accessible from soil and the properties that are most beneficial or essential for a specific model or for quality assessment. Several PTFs have been established to guess CEC from soil characteristics [2]; [8]. In such models CEC values are linear function of soil content of organic matter and clay [8]. The results indicate that more than 50% of the changes that occur in the CEC values can be attributed to the changes that occur in the soil content of clay and organic matter to most soils New Jersey [9]. As well as some soils Philippines [10]. A slight improvement was achieved when soil pH was added to the model for four Mexican soils [11]. It was found that the amount of fine clay in B horizons of soil, was more influential in the value of the soil exchange capacity than the soil content of the total clay [12]. There are two common methods used to construct authoritative functions PTFs here: multiple linear regression (MLR) method and Artificial Neural Network (ANN) [13]. Typically, we use linear regression analysis to look for related transactions in the equations form. However, models used for one region may not give appropriate guesses for different region [14].

Neural networks (ANN) are uses in modern approaches to modeling transformational functions PTFs [15]. Neural networks offer a different and radical approach for modeling soil behavior. ANN are superhuman brain sticks and consist of simple units called neurons, and have the potential to learn and generalize the empirical data if it is noisy and incomplete. In short, a neural network consists of an input, a hidden layer, an output layer and all containing “nodes”. The number of nodes in each of the input and output layers according to the different soil characteristics and is compatible with the number of input and output variables in the model [16]. One type of Neural network known as multilayer perceptron (MLP), which uses a back-propagation algorithm is usually used for generate transformative functions PTFs [17]; [18]. This network uses neurons whose output is biased to the weighted total of inputs. The main advantage of neural networks compared to other models use transformational functions is that It doesn't need an earlier concept of relationships between input and output data [15]. As a result of larger possibility, ANN models are superior in predicting as compared with MLR models [17].

Minancy [18], Evaluate the "cation exchange capacity" of soil in middle of Iran using soil content of clay and organic matter. They benefited from the application of Neural networks and five training models that were necessary in the Multiple regression for estimate the cation exchange capacity of soil. They showed that the use of transformational functions in neural network with eight hidden neurons was able of predicting CEC better than the transformational functions in multiple regression. They also found that the use of Neural Networks is improved the accuracy of the estimation of an origin to 25%. They have found that Neural networks models are more useful for capture of non-linear connection between variables. [19]. Confirmed that the technology of Neural Networks can be used successfully for the purpose of calibration of water infiltration equation in soil. They had also found that the Neural Networks model are able to perform very well if data availability is limited."In difference [20]. Confirmed however, there are differences between Neural Networks and regression models were not statistically important, Multiple regression forecast parametric and optimization for soil permeability better than ANN."Therefore, this study was conducted to compare between Neural Networks model and multiple linear regression model to estimate the capacity of exchangeable cation using some easily determinate soil properties in Aljazeera zone, Mosul city.

Materials and methods:

This academic study was carried out in Norther Aljazeera Irrigation project, Mosul city. Iraq, the land of the research is located between latitudes 36_o 33¯ and 36_o 53¯ N and between longitudes 42_o 0¯ and 42_o 25¯ E, which has the area about 750 km2 52% of Rubbia Region Area (1431km2). The average heights points of Rubbia Region district are 381 meters for the sea level, “the moisture and temperature regimes of region are Arid and thyme respectively based on soil taxonomy [21]. this region has soils in Inseptisol, Mollisols orders. Physical and chemical properties were determined for 80 soil samples taken from surface horizon of 20 profiles of soil in study area.

The soil characteristics measured for this study were soil particle size distribution, organic matter, and soil cation exchange capacity CEC.

"The subsequent investigative procedures were used to measure each of characteristic for this study (Om) was using Walkley-Black method [22]. Particle size spreading of soil using “pipette method [23]. The capacity of exchangeable cation in Cmol. Kg^{-1} soil using methods of ammonium acetate

(NH4OAc) (pH=8.2) [24]. and the assessment result were used as input variables of the model to forecast the cation exchange capacity of the soil. Two type analysis were used for estimation of soil Cation Exchange Capacity (CEC). Step_wise Multiple Linear Regression, SPSS package Ver: 25, and Artificial Neural Net Works (ANN), Mat lab package Ver: 19b

Multiple linear regression model:

The all-purpose aim of multiple linear regression is to acquire more about the association among autonomous variable and reliant on variable. Multiple linear regression (MLR) are the basic operation used in progress PTFs. The universal formula of regression equation is rendering to Equation 1:

$Y=b0+b1x1+b2x2+b3x3.........\ bnxn$ (1)

Where Y is the dependent variable which is equivalent to the cation exchange capacity value of the soil CEC, represent intercept point, b1.........bn represent regression coefficients and x1.... xn represent independent variables point to soil properties [13].

Artificial Neural Networks

Artificial neural network consists of several humble dispensation units called neurons are similar to the genetic neurons in the human brain. Neurons have similar properties in the ANN and are organized in assemblies named layers.

Neurons in one layer are linked to those in the adjacent layers but not to those in the similar layer, and represent the forte of communication between neurons in a layer with that in the adjacent layer of what is known as contact strength (Weight). The Neural Networks contain three layers. the input layer, hidden layer and the output layer.

In a Network called feed forward, activation is only in the frontward path from the input to the output layer [13]. On the other hand, in a repeated network there is an extra weight used to feed the pervious stimulation back on the network, the building of feed forward ANN is revealed in Fig1. This ANN is a general neural network which identified as the back-propagation process presented by [25]. This ANN had many inputs and one output parameter. Moreover, important step in development of the Neural Networks model and in the weight matrix training. The weight is initially randomly formed in appropriate ranges, and weights are then updated when progressing in the training mechanism [18].

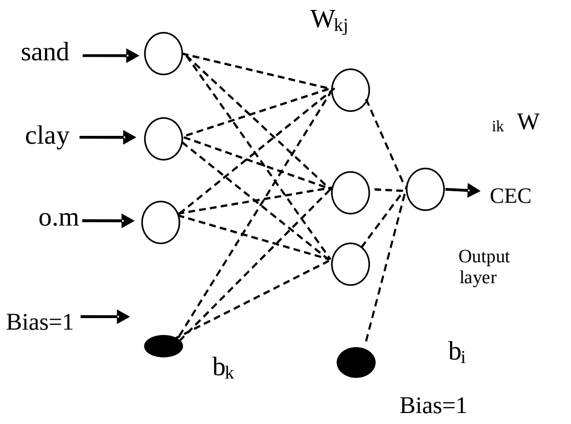

Figure (1) Structure of Feedforward ANN

Performance evaluation criteria:

Two different types of performance evaluation criteria were used to control the predictive correctness of the developed model, these are Mean square error (MSE) and the coefficient of determination (R^2). The two performance evaluation criteria used in the current study can be calculated according to the following equations 2 and 3 [26].

$$R^2 = 1 - \sum_{i=1}^{n} \frac{(Yi - \hat{Y}i)}{(Yi - \bar{Y}i)^2} \quad (2)$$

$$MSE = 1/n \sum_{i=1}^{n} (Yi - \bar{Y}i)^2, \quad (3)$$

Where n represent number of data, Yi represent the measured value of each variable $\hat{Y}$i represent the estimate value of each variable and $\bar{Y}$ is the average of estimate value of each variable.

Result and Discussion:

Table (2) gives descriptive statistics for soil physical properties used to devise of Transforming functions using step-wise multiple linear regression (MLR) and artificial neural Network (ANN) for estimation of CEC of the soil. As seen from this table (2) CEC of studies soil sample varied between 4.0 and 43.73 meq.100gm-1 soil with a medium value of 26.28 meq.100gm^{-1}, soil organic matter is low fluctuating from 0.035 % - 2.3%, with mean of 0.827%, the report of general Diggla company Indicate that the soil of Aljazeera project has high fertility for the crop production. The restricted amount of organic matter present in soil can be lost rapidly during the cultivation of soil for the purpose of crop production. Alternatively, clay with an average of 37.18% (8.8 – 59.2) % among the distribution of soil particle-size had larger amount than the sand%. Table (3) offerings the calculated correlation coefficients among input variables and soil cation exchange capacity. we found that there is appositive and highly important correlation between CEC and content of soil from clay, the detected correlation between CEC and clay 0.91** was larger than CEC and OM (0.456*). It is pointed that most of negative charges in the studied soil were known as eternal charge. The correlation among CEC and sand content was found negative and significant (-0.661**). This show that the present of high amount of sand in soil will decrease CEC. Commonly, the result gotten for the correlation between CEC and soil physical proportion so we can conclude that the soil CEC is chiefly resolute by the quantity of clay and organic matter. "In order to contribute to these properties in the production of negative charge and the phenomenon of ion exchange that is referred to in previous studies [27]. In order to develop the model of the manufacturing function PTFs the proposed models we used to guess the exchange capacity in soil. Data is divided into three set 60% for training or calibration and 25% for validation the remaining data 15% were used for purpose of testing the accurate and efficient of the model guessing.

Multiple linear regression (MLR):

Establishment of PTFs using MLR model for forecasting soil CEC in irrigation project in Al-Jazeera area, Mosul was complete by using of SPPS 18 program. In the regression analysis, the data to be analyzed must be retrieved so as to have Normal distribution property. There for the normality of the data were assessed by the "Kolmogorov – Simonov method". By use this method it was found that Sand, Clay and OM conform to the normal distribution. Equation of linear regression for training data set was devised through multiple regression, backward method. In this technique all data has been entered as input data and therefore the less important influential were excluded in the backward method, one MLR models was derivative among cation exchange capacity and soil physical characteristics (Table 4). We have found that the derived equation through multiple regression model between CEC and input variable were moderate strong statistically, "we have also found that the increase of the number of inputs parameter in model will reduced the precision and efficiency of the estimation of soil cation exchange capacity [15];[30]. Therefore, the top regression equation was devised for training data as employed in the following equation Eq 4.

$$CEC_{predict} = 5.295 + 0.571 * Clay - 0.084 * Sand + 2.034 * OM \; ...... (4)$$

"After calculating the regression equation and for evaluating the precision of multiple regression model the result of this model equated with real data. Coefficient of determination (R^2) was calculated between the real and predicted values to assess the efficiency of completion of the model [28]. Table 5 show the values of R^2 and MSE for validation data set, the R^2 and MSE value have been obtained 0.88 and 3.74, respectively However the results were agreed those reported by [13]. The results indicate high correlation coefficient (r=0.78) for the prediction of soil CEC by means of multiple regression. [13].

Table (2) Descriptive statistic of the data sets for all, training, testing and validation ((MLR and ANN)

ALL data							Training data					
Variable	Units	Min	Max	Mean	S. D		Variable	Units	Min	Max	Mean	S. D
SAND	%	1.00	85.00	19.96	20.21		SAND	%	1.00	85.00	20.16	21.91
CLAY	%	8.80	59.2	37.18	13.28		CLAY	%	8.80	59.21	36.14	13.7
OM	%	0.035	2.30	0.827	0.522		OM	%	0.035	2.3	0.835	0.567
CEC	Meg.100gm^{-1}	4.00	43.73	26.28	9.529		CEC	Meg.100gm^{-1}	4.00	43.73	25.93	9.75
Testing data							*Validation data*					
Variable	Units	Min	Max	Mean	S. D		*Variable*	*Units*	*Min*	Max	Mean	S. D
SAND	%	2.0	54.00	14.52	16.26		*SAND*	*%*	*5.0*	*72*	21.65	18.35
CLAY	%	17.6	56.16	33.21	10.21		CLAY	%	17.00	56.8	42.02	13.48
OM	%	0.035	1.9	0.784	0.63		OM	%	0.1	1.4	0.836	0.328
CEC	Meg.100gm^{-1}	13.8	38.7	24.18	5.77		CEC	Meg.100gm^{-1}	7.0	40.69	28.38	10.74

OM: organic matter, CEC: cation exchange capacity

Table (3) Calculated Correlation coefficient between used variables

Variable	Sand	Clay	Om	CEC
SAND%	1			
CLAY%	-0.596**	1		
OM%	-0.709	0.304	1	
CEC Meg.100gm^{-1}	--0.601**	0.91**	0.456*	1

Table (4) Coefficient of variable used in MLR model to develop PTFs for estimating TFs for estimating CEC.

In dependent variable	Coefficient	Std. error	t-value	sig.	Beta
constant	5.295	2.39	2.215	0.032	
Sand	-0.084	0.03	-2.80	0.008	-0.19
Clay	0.571	0.048	11.85	0.0001	0.802
Om	2.034	0.945	2.153	0.037	0.118

** Correlation is significant at the 0.01 level

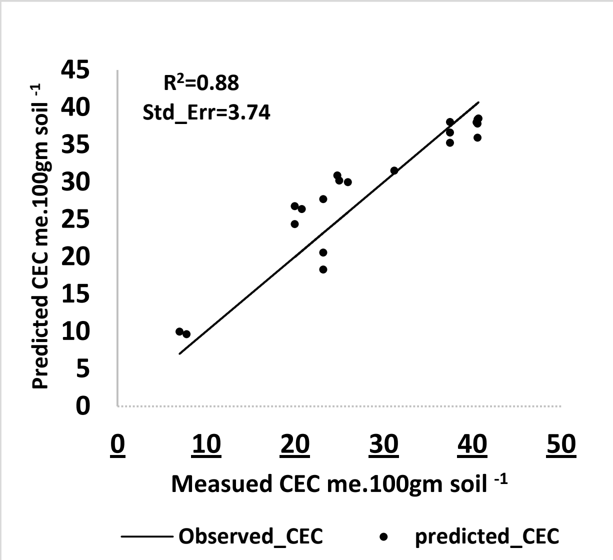

Figure (2) The scatter plot of measured versus predicted CEC using MLR model with validation dataset

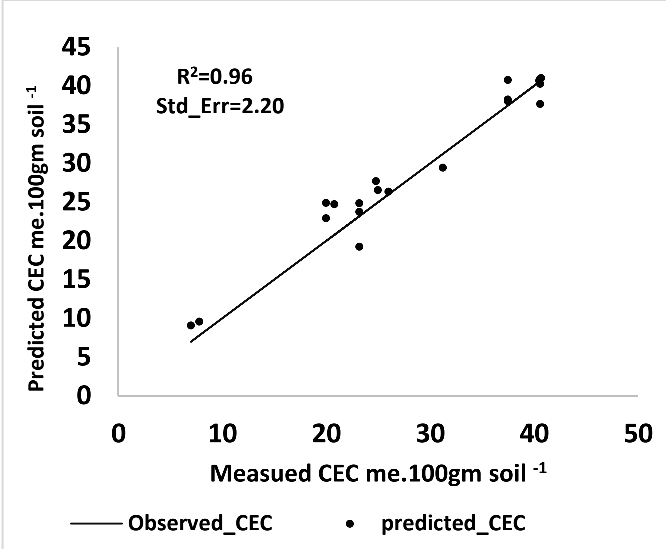

Figure (3) The scatter pot of measured versus predicted CEC using ANN model with validation dataset

The scatter plot of the measured against predicted CEC value obtained from MLR model for the Validation dataset is shown in Fig 2. The result show almost good agreement between predicted **and measure CEC value, where it is noted that the predicted CEC value are more dispersed around values of observed soil CEC. The Coefficient of determination (R^2) equal to 0.88 and MSE equal to 3.74 table 5.**

Table (5) Performance indices (R^2 and MSE) for different models

Model	Archittecture	Thresbold	Training		Validation	
			R^2	MSE	R^2	MSE
MLR	--------	Only Purelin	0.868	3.93	0.88	3.74
MLP	3-3-1	Tansig-Purelin	0.91	2.95	0.96	2.20

Artificial neural network (ANN):

In this study predicting soil properties by ANN model. We have not resorted to increasing the number of inputs in building artificial neural network because according to finding of increasing of number of input variables introduced in the model will reduce the efficiency and precision of the prediction [29, 30]. As we find by testing the equation when constructing a model for predicting difficult soil characteristics based on easy-to-measure properties, if only one type of input data has a low correlation coefficient with output characteristics, the model precision will mechanically be lessening. However, the input data in this model consist of the sand%, clay% and organic matter. A three-layered feed-forward ANN construction with one input layer, one hidden layer and one output layer as shown in

Fig. 1 were instructed for estimate CEC by ANN models in Aljazeera project. The performance of ANN model **is** determined based also on (R^2, MSE) values criteria of validation data set as shown in table 5. The input layer consists of three neurons but the output layer contains only one neuron. The hidden layer also consists of three neurons, the transference function of hidden layer construct of tan sigmoid function but the output layer construct of linear function this structure of ANN model offered the top results.

As shown in table 5, the value of R^2 and MSE among ANN outputs and the measure data (R^2= 0.96,

MSE= 2.2) had higher accuracy than MLR ones (R^2 =0.88, MSE=3.74) for validation data set respectively.

Amini [30]. reported that the PTFs obtained by Neural Networks was higher effective compared with Multiple regression for estimate the capacity of exchangeable cation". Minasny [31]. Notice that when the number of input parameters is more than three, ANNs usually achieve better compared with regression procedure, especially when doubts in the superiority of the data were small". Also, several researchers have stated that the (ANN) model with one hidden layer is proficient of resembling any restricted non-liners function with very high precision, [32, 33]. The plot between observed versus predicted CEC using Neural Network (MLP) model are indicated in Figure 3. The result shows perfect agreement between predicted **and measure CEC value, where it is noted that the predicted CEC value are almost identical to the values of observed soil CEC. The Coefficient of determination (R^2) equal 0.96 and MSE equal 2.2 table 5.**

Conclusion:

In this study we compare between multiple linear Regression (MLR) and Neural Network multi-layer perceptron (MLP) to find transformational function (PTFs) for estimating soil capacity of exchangeable cation by using presented soil proportion.

This network was consisted of one hidden layer with a sigmoid activation function and a linear activation function in output layer and levenberg-Marquardt training algorithm used due to efficiency and simplicity for estimation the soil cation exchange capacity by mean of PTFs, the input data were consisted of the percentage of Clay, Sand and Organic matter for CEC forecasting. The arithmetical estimation performance of used model is obtained in form of Determination Coefficient (R^2) and Mean Square Error (MSE). The result show as we found that ANN model by use (MLP) multilayer perceptron for predicting CEC from easily measure available soil properties have more accuracy and effective compared with (MLR) multiple linear regression model, for training dataset and Validation data set .table(5). since soil CEC is not a site specific parameter; this method could also be used in other parts of the world.

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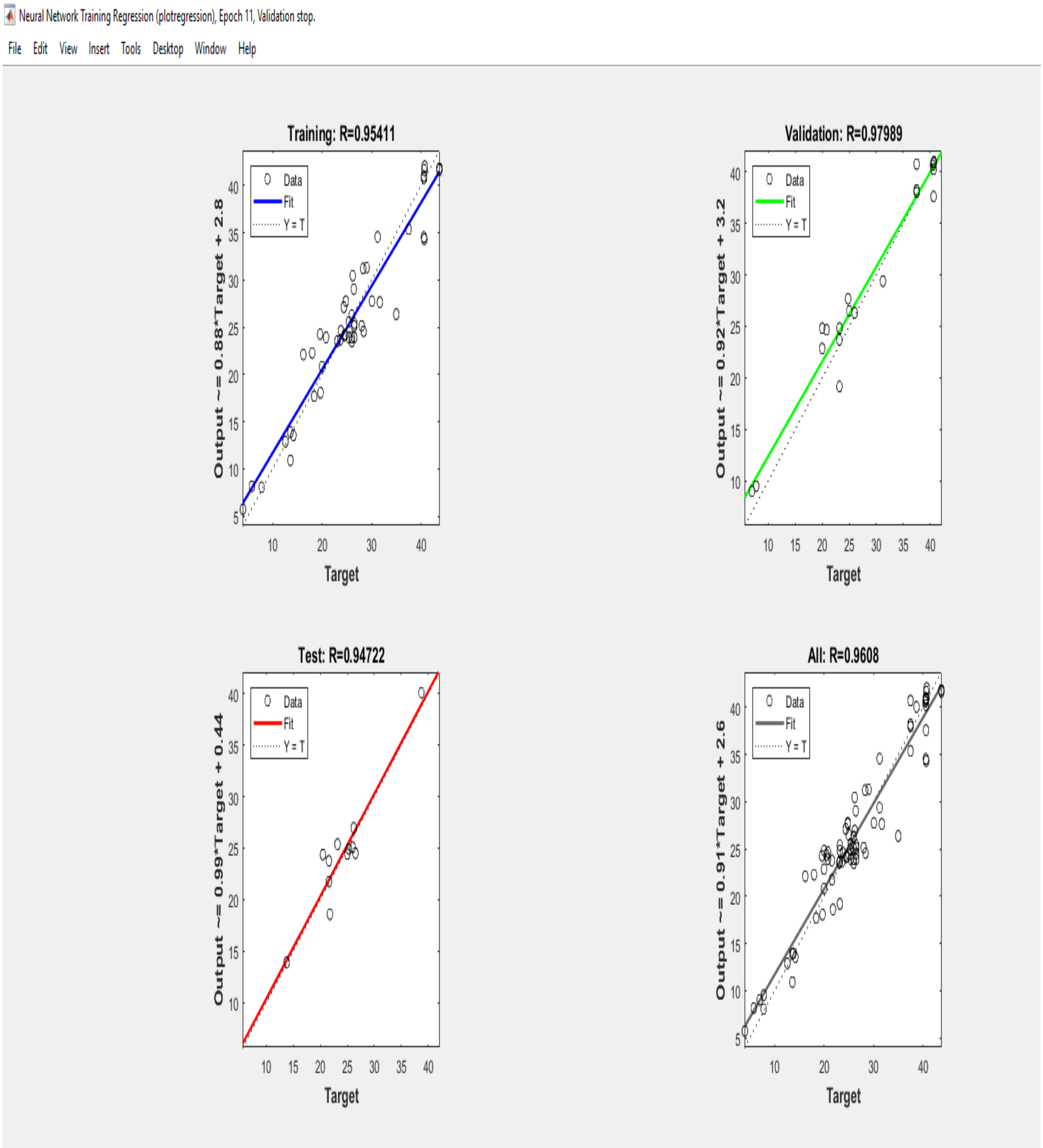
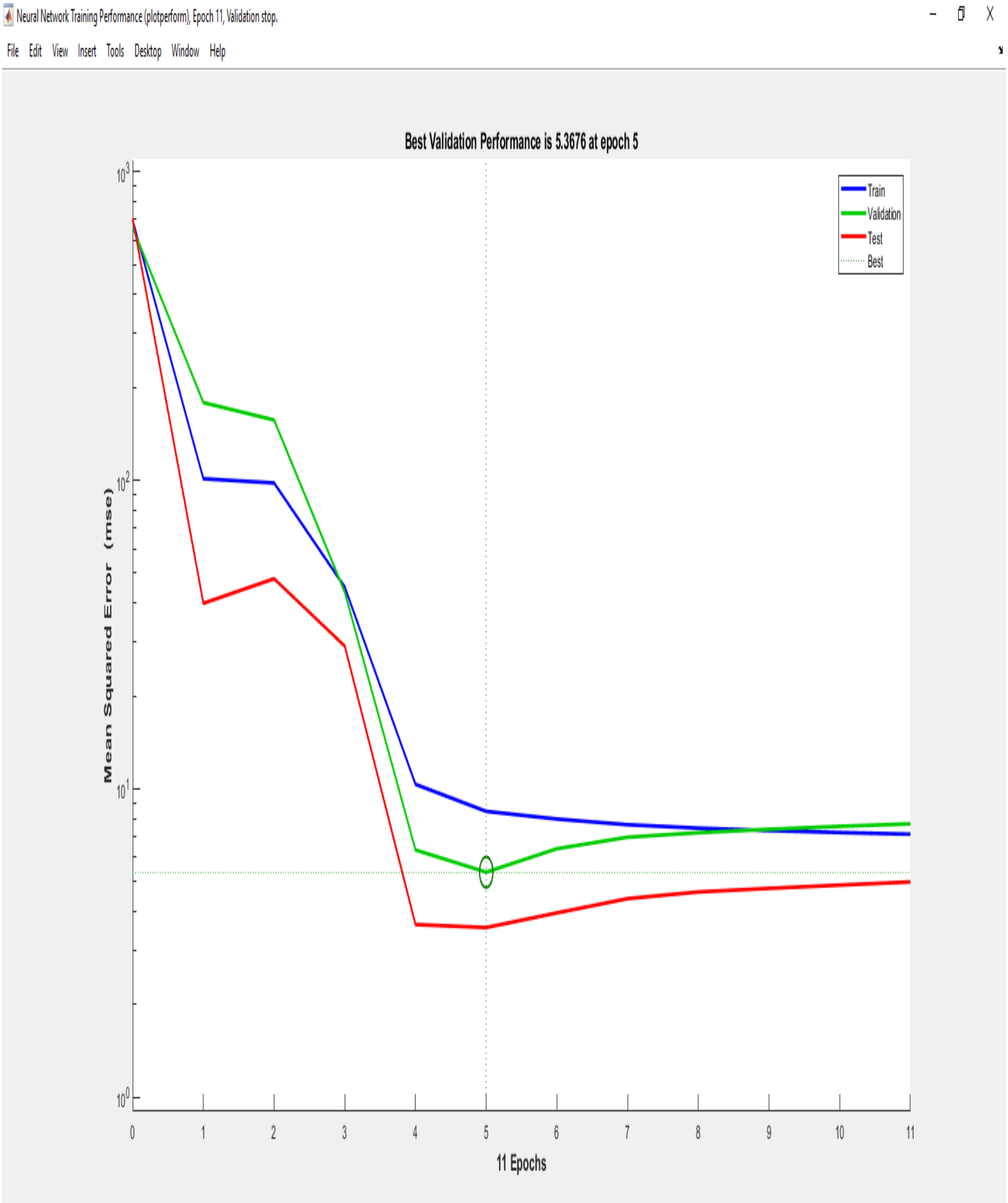
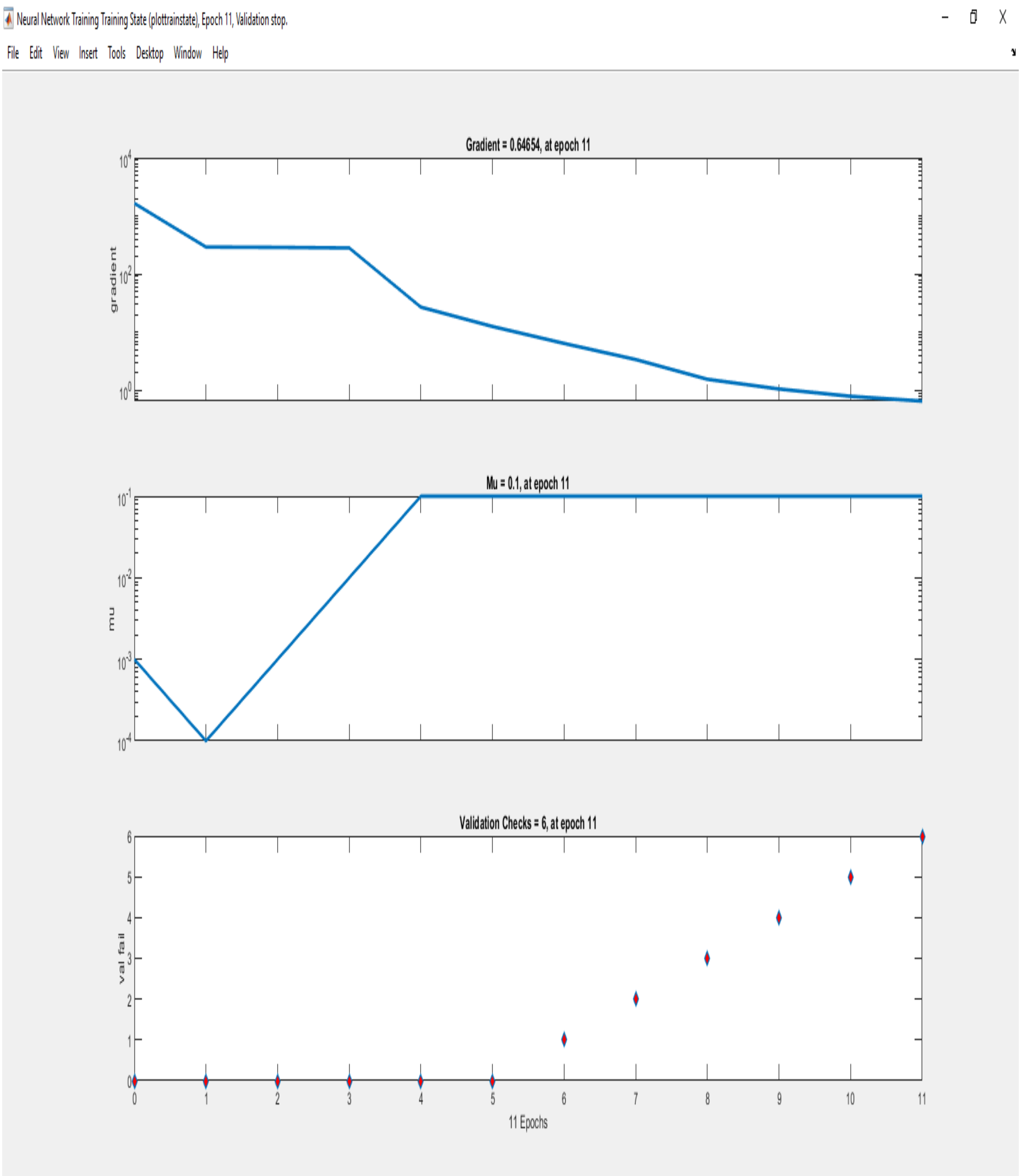
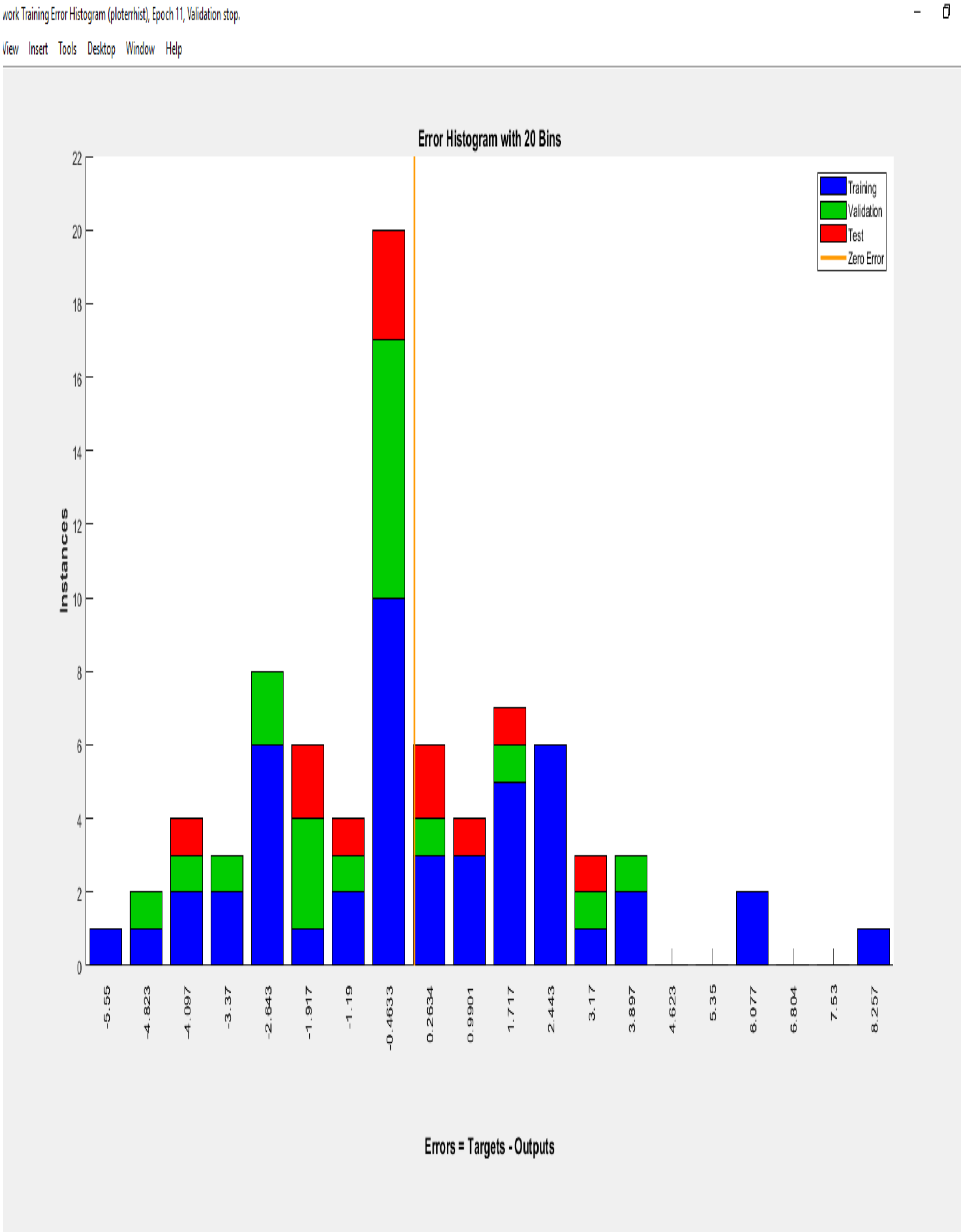
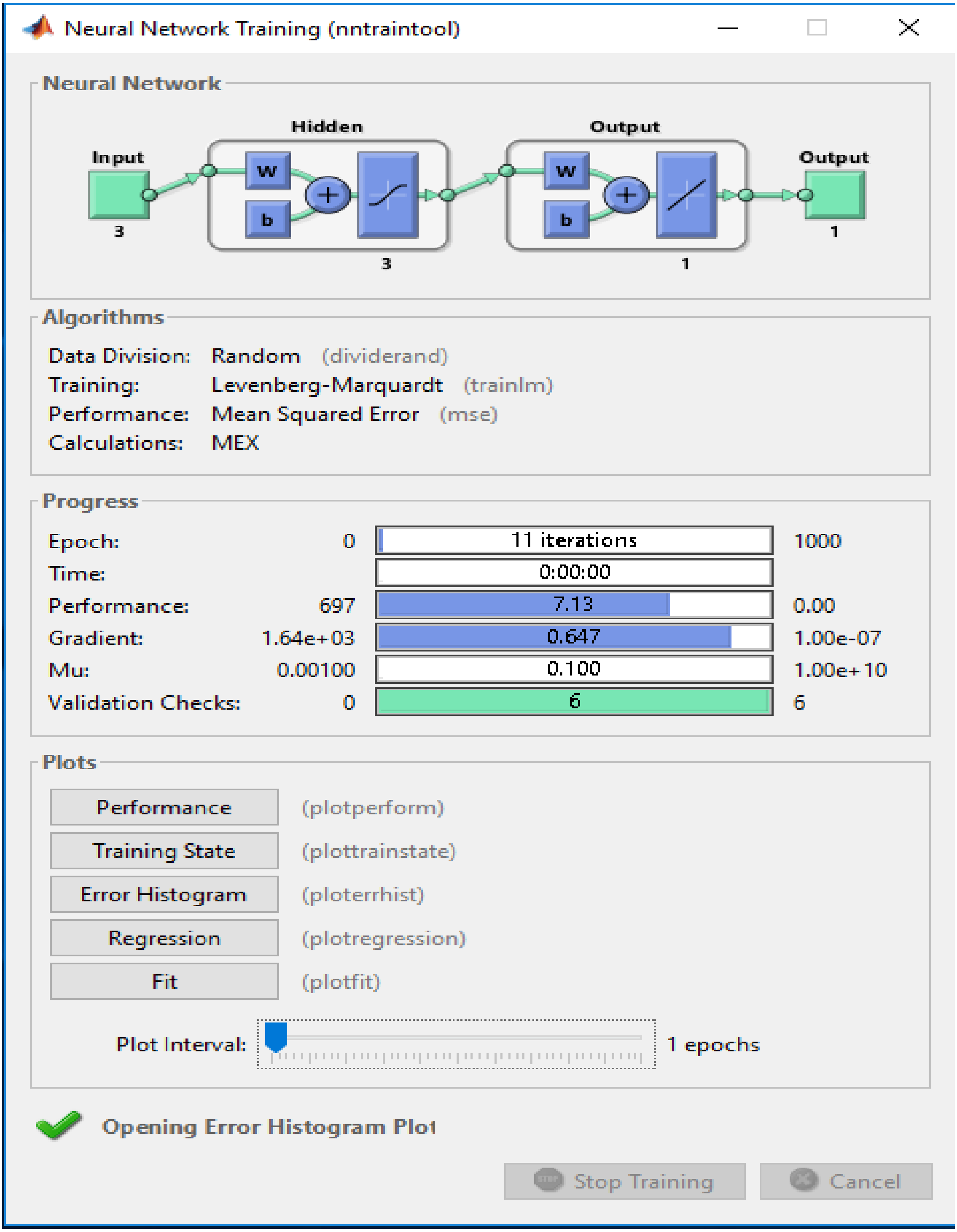

Neural Network Training Regression (plotregression), Epoch 11, Validation stop.
File Edit View Insert Tools Desktop Window Help
Training: R=0.95411
Output ~= 0.88*Target + 2.8
Data
Fit
Y = T
Target
Validation: R=0.97989
Output ~= 0.92*Target + 3.2
Data
Fit
Y = T
Target
Test: R=0.94722
Output ~= 0.99*Target + 0.44
Data
Fit
Y = T
Target
All: R=0.9608
Output ~= 0.91*Target + 2.6
Data
Fit
Y = T
Target


Neural Network Training Performance (plotperform), Epoch 11, Validation stop.
File Edit View Insert Tools Desktop Window Help
Best Validation Performance is 5.3676 at epoch 5
Train
Validation
Test
Best
Mean Squared Error (mse)
11 Epochs



Neural Network Training Training State (plottrainstate), Epoch 11, Validation stop.
File Edit View Insert Tools Desktop Window Help
Gradient = 0.64654, at epoch 11
gradient
Mu = 0.1, at epoch 11
mu
Validation Checks = 6, at epoch 11
val fail
11 Epochs


work Training Error Histogram (ploterrhist), Epoch 11, Validation stop.
View Insert Tools Desktop Window Help
Error Histogram with 20 Bins
Training
Validation
Test
Zero Error
Instances
0
2
4
6
8
10
12
14
16
18
20
22
-5.55
-4.823
-4.097
-3.37
-2.643
-1.917
-1.19
-0.4633
0.2634
0.9901
1.717
2.443
3.17
3.897
4.623
5.35
6.077
6.804
7.53
8.257
Errors = Targets - Outputs


Neural Network Training (nntraintool)
Neural Network
Hidden
Output
Input
Output
W
b
3
3
1
1
Algorithms
Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MEX
Progress
Epoch: 0 11 iterations 1000
Time: 0:00:00
Performance: 697 7.13 0.00
Gradient: 1.64e+03 0.647 1.00e-07
Mu: 0.00100 0.100 1.00e+10
Validation Checks: 0 6 6
Plots
Performance (plotperform)
Training State (plottrainstate)
Error Histogram (ploterrhist)
Regression (plotregression)
Fit (plotfit)
Plot Interval: 1 epochs
Opening Error Histogram Plot
Stop Training
Cancel

Regression

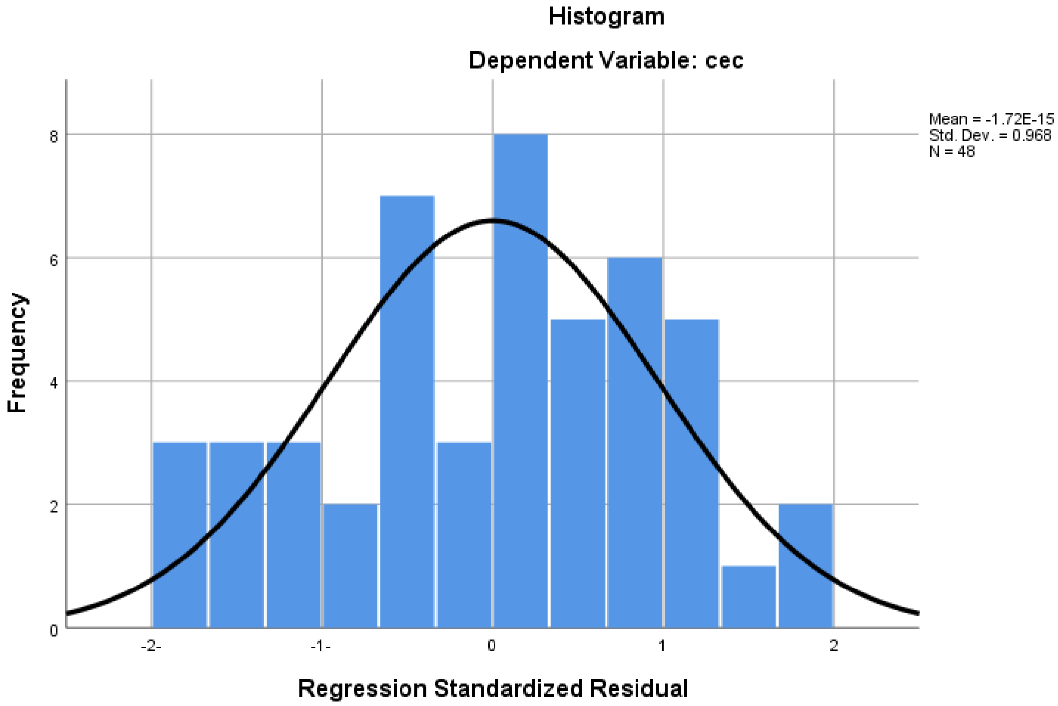
Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	om, sand, clay[b]	.	Enter
a. Dependent Variable: cec			
b. All requested variables entered.			

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.931[a]	.868	.859	3.740	1.944
a. Predictors: (Constant), om, sand, clay					
b. Dependent Variable: cec					

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3876.494	3	1292.165	96.066	.000[b]
	Residual	591.835	44	13.451		
	Total	4468.329	47			
a. Dependent Variable: cec						
b. Predictors: (Constant), om, sand, clay						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.295	2.390		2.215	.032
	clay	.571	.048	.802	11.854	.000
	sand	-.084-	.030	-.190-	-2.803-	.008
	om	2.034	.945	.318	2.153	.037
a. Dependent Variable: cec						

Charts



Correlations

Correlations					
		clay	sand	om	cec
clay	Pearson Correlation	1	-.596-**	.304	.910**
	N	48	48	48	48
sand	Pearson Correlation	-.596-**	1	-.709-**	-.601-**
	N	48	48	48	48
om	Pearson Correlation	0.304	-.709-**	1	.456
	N	48	48	48	48
cec	Pearson Correlation	.910**	-.601-**	.456	1
	N	48	48	48	48
**. Correlation is significant at the 0.01 level (2-tailed).					