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COMPARISON OF MULTIPLE LINEAR REGRESSION AND ADAPTIVE NEURO FUZZY INFERENCE SYSTEM FOR PREDICTING COHESION AND INTERNAL FRICTION ANGLE OF CULTIVATED SOILS

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ABSTRACT

Determination of cohesion (C) and internal friction angle (ϕ) of cultivated soils are crucial for the solution of several agricultural engineering problems such as modeling of draft of tillage implements. A laboratory or field test, which is usually performed for the determination of C and ϕ, is not easy to apply; however, it needs some arrangements and time. An alternative approach to such test is the prediction of C and ϕ, in terms of a number of affecting parameters. In this study, the ability of neuro-fuzzy systems is utilized for the prediction of C and ϕ. Test results on different types of soil texture are used to generate a database to train -adaptive neuro-fuzzy inference system (ANFIS), which is considered to predict the Cand ϕ. It is concluded that ANFIS structure is superior in the prediction of C and ϕ considering dry density, soil moisture content and soil texture index as inputs to the system compared with multiple linear regression model. The root mean square error was computed for each model to have an objective comparison.

INTRODUCTION

According to Gill and van den Berg (1968), soil strength is the ability or capacity of a particular soil in a particular condition to resist or endure an applied force. Many researchers have worked in this area investigating the characteristics of the shearing process. Johnson et al. (1987) evaluated methods and devices of shear measurements for agricultural soils. The most general envelope of shear strength was proposed by Coulomb as follows:

$$\tau_{max} = C + \sigma_n \tan\phi \quad (1)$$

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This envelope is referred to as the Mohr-Coulomb envelope. The researchers indicated that although the envelope cannot represent shear failure for all soil conditions, it is still valid enough to be a law. Mohr circles can be developed to determine cohesion (C) and internal friction angle (ϕ) graphically according to drawn stresses of σ_1, σ_2 and σ_3 which are obtained from practical tests. Based on this method, max τ (τ_{max}) can be obtained for a number of normal stresses, which are exerted to a defined soil sample. Having normal and maximum shear stresses (at failure point), Mohr circles are plotted as shown in Figure (1) where a common tangent to the circles can give C and ϕ.

Direct shear test could determine the cohesion and the angle of internal friction of soil (Perdok et al., 2002). The mechanical behavior of agricultural soils during laboratory shear loading is governed by many factors, namely, soil type and water content, organic matter, bulk density, shearing apparatus and shear rate.

The measurement of the cohesion and the angle of internal friction of cultivated soil are crucial for the solution of agricultural engineering problems such as modelling of draft requirements of tillage implements (Arvidsson and Keller, 2011), predicting the performance of a tractor in the field (Harrison and Cessford, 1969), furthermore, predicting soil cone index (Manuwa, 2007). However, a better understanding of soil mechanical properties is needed to assess soil compaction in the soil (Eko, 2001).

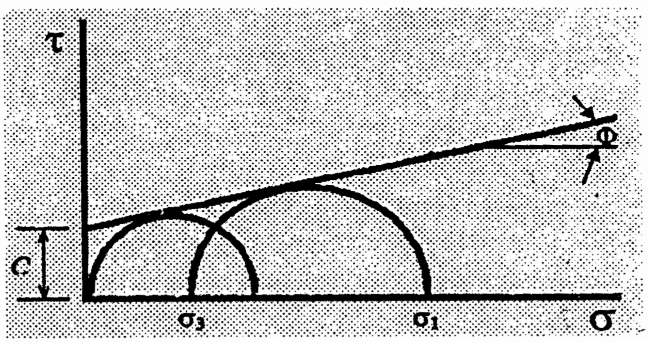

Figure (1). Schematic of Mohr- Coulomb's theory (Zadeh, 2006).

A laboratory or field test, as a direct measurement, which is usually performed for the determination of the cohesion and the angle of internal friction of soil, is not easy to apply; however, it is time-consuming and expensive (Zadeh and Asadi, 2012). An alternative approach to such test is the prediction of the cohesion and the angle of internal friction of soil, in terms of a number of affecting parameters. Accordingly, it has been attractive for practical agricultural engineers to discover indirect and accurate techniques to predict the value of the cohesion and the angle of internal friction of soil.

Soft computing techniques are widely applied to agricultural engineering problems. One of them is fuzzy logic which is particularly attractive due to its ability to solve problems in the absence of accurate mathematical models (Samhouri and Surgenor, 2005). It is a powerful concept for handling nonlinear, time varying, and adaptive systems. It permits the use of linguistic values of variables and imprecise relationships for modeling system behaviour (Hosseinzadeh et al., 2011). In fuzzy inference system, there are 5 steps such as fuzzy inputs, combination of inputs with AND (OR) method, implication, aggregation of all outputs and defuzzification (Tinkir, 2011).

Lately, fuzzy inference systems were employed as alternate statistical tool for developing of the predictive models to estimate the needed parameters and they have been successfully applied to solve different problems in agricultural engineering such as assessment of soil compaction due to traffic of agricultural implements on different soils (Elbanna et al., 2005), for prediction of soil penetration resistance based on soil physical properties (El Awady et al., 2002), for prediction of distribution uniformity coefficient of liquid pesticides (Al-Gaadi et al., 2011), for improvement efficiency of rice milling process (Aboukarima, 2003), for estimating of reference evapotranspiration (Hegazy et al., 2003), for determining of water infiltration (Aboukarima et al., 2007), for fruit production forecasting (Atsalakis and Atsalakis, 2009), for prediction of spray losses (Gil et al., 2008) and shear strength of reinforced concrete beams (Amani and Moeini, 2012).

Kayadelen et al. (2009) built an adaptive neuro fuzzy system (ANFIS) to predict ϕ. The inputs to the system were percentages of coarse and fine grained, bulk density and liquid limit. The results showed that the coefficient of determination (R^2) was 0.97 between measured and predicted ϕ.

Zadeh and Asadi (2012) employed a hybrid genetic fuzzy system to predict ϕ using some simply measurable characteristics of the soil. The inputs to the system were percentages of coarse and fine grained, bulk density and liquid limit. The results showed that R^2 was 0.989 between measured and predicted ϕ.

Besalatpour et al. (2012) used an ANFIS to predict soil shear strength. Particle size distribution (clay and fine sand), calcium carbonate equivalent, soil organic matter and normalized difference vegetation index were acted as inputs to ANFIS. The results showed that the correlation coefficient was 0.60 between measured and predicted data. Also, comparing to conventional regression model, ANFAS was more accurate.

The ultimate goal of this study was making a comparison between two models including: multiple linear regressions and adaptive neuro fuzzy inference system for predicting the cohesion and the angle of internal friction of soils. The data obtained from the actual experiments were used to test and train the two models.

MATERIALS AND METHODS

Soil samples sites and properties

Soil samples were taken with an auger from the surface to about 20 cm depth. The study was conducted during December 2011 in different cultivated sites, where soil samples from different sites at Al-Kharj, Al-Qassim, Wadi El-Dawaser, Hail, Aljouf, Tabuk and Riyadh regions in Saudi Arabia were collected. About 44 samples were prepared to find out soil particle size distribution. The fraction ranged from 3 to 21% for clay; from 63.36 to 88.9% for sand and from 7.2 to 20.1% for silt. Soil samples were prepared to determine the cohesion and the angle of internal friction of soil using direct shear box method. Levels of soil moisture content similar to the soil moisture content in the field were tested. A normal load is applied to the soil placed in the box through the top plate. The applied shear force and horizontal displacements were recorded for further analyses. The normal stresses used for shear testing were 0.5

kg/cm^2, 1.0 kg/cm^2, and 1.5 kg/cm^2. In order to obtain the shear strength characteristics of a soil (cohesion and internal friction angle), two tests on several identical samples under different normal loads were performed. By plotting the best linear fit through at three points (pairs of normal stress-peak shear stress), the Mohr-Coulomb failure envelope was obtained. From this failure envelope, C and ϕ were estimated. During the shear experiments, soil wet density of the soil was maintained in the range related to soil bulk density. The loading rate during shear tests was a constant rate of 0.12 mm/min. After carrying out shear box tests on a soil with different normal stresses, a graph of shear stress versus horizontal displacement was drawn as illustrated in Figure (2). After analyzing of shear stress versus horizontal displacement, another graph presents shear stress at failure against normal stress as shown in Figure (3) was drawn. From figure (3), it is usual to calculate the angle from the slope of the trend line, since tan ϕ = slope of trend line. When the trend line intersects with the vertical axis, this value of shear stress is called the cohesion C of the soil, measured in kg/cm^2.

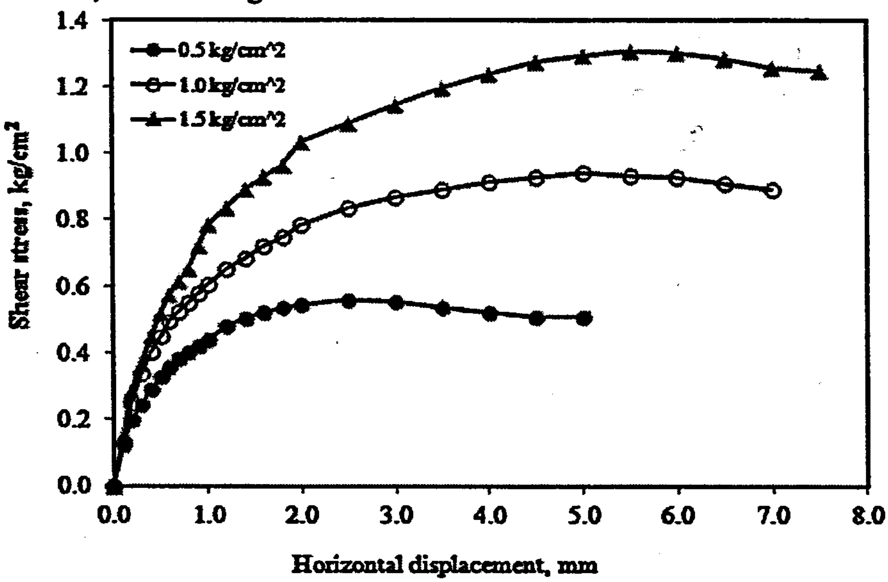

Figure (2). Shear stress versus horizontal displacement during direct shear box test under different normal stresses.

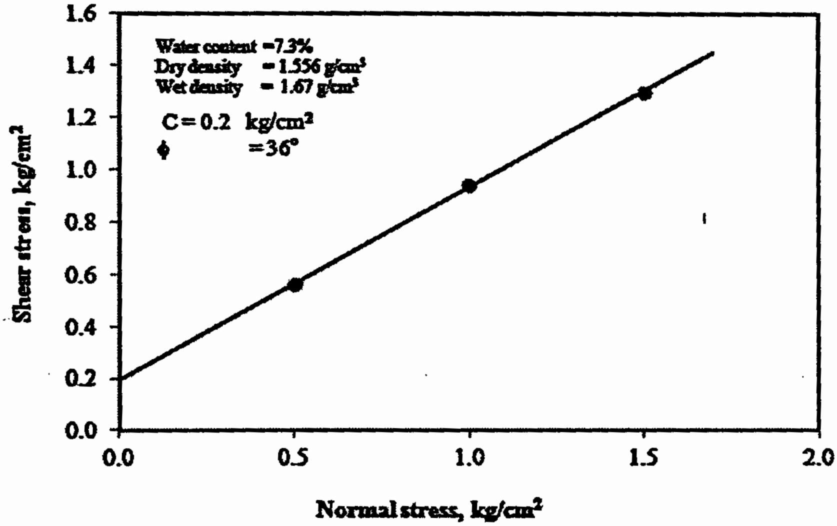

Figure (3). Shear stress at failure against normal stress during direct shear box test.

Representing soil texture

To combine all soil fractions, a soil texture index was developed similar to that developed by Oskoui and Harvey (1992). However, due to the sand content is a major component in the studied soils, followed by silt then clay, another formula, to calculate soil texture index (STI), was developed as follows:

$$STI = \frac{\log (Sa^{St} + CCa\ )}{100} \qquad (2)$$

Where Sa is the percentage of sand content in the soil, S_t and CC_a are the percentages of silt and clay contents in the soil. Oskoui and Harvey (1992) showed that the STI reflects the effects of all three soil fractions. The STI produces unique numbers for every combination of sand, silt and clay contents.

Multiple regression model

The general purpose of a multiple regression is to learn more about the relationship between several independent or predictor variables and a dependent variable. The general form of the regression equation is as follows:

$$Y = b_0 + b_1 X_1 + ... + b_3 X_3 + ... + b_n X_n \qquad .... (3)$$

Where Y is the dependent variable representing C or ϕ, b_0 is a constant, where the regression line intercepts the y-axis, $b_1 ... b_n$ are regression coefficients, representing the amount of changes of the dependent variable Y, when the corresponding independent changes one unit and $X_1 - X_n$ are independent variables referring to soil properties in this study.

Using Excel spreadsheet, multiple regression analysis was carried out to correlate the measured C and ϕ to three soil properties, namely, soil moisture content, dry density and texture index. A multiple regression model to predict C is given as:

$$C\,(kPa) = -64.109 + 0.0189MC + 39.988DD + 85.504STI \quad R^2 = 0.348 \quad ... (4)$$

A multiple regression model to predict ϕ is given as:

$$\phi\,(^\circ) = 11.061 - 0.430MC + 17.129DD + 9.329STI \qquad R^2 = 0.528 \quad ....(5)$$

Where MC is soil moisture content (% db), DD is soil dry density (g/cm^3) and STI (dimensionless) is soil texture index as calculated by Eq. (2).

Adaptive neuro fuzzy inference system (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is a fuzzy mapping algorithm that is based on Tagaki-Sugeno-Kang (TSK) fuzzy inference system (Jang et al., 1997). ANFIS is an integration of neural networks and fuzzy logic and have the potential to capture the benefits of both in a single framework (Kumar et al., 2012). ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN for automatic fuzzy if-then rule generation and parameter optimization (Kumar et al., 2012).

A conceptual ANFIS consists of five components: inputs and output database, a Fuzzy system generator, a Fuzzy Inference System (FIS), and an Adaptive Neural Network. The Sugeno- type Fuzzy Inference System, (Takagi and Sugeno, 1985) which is a combination of a FIS and an Adaptive Neural Network, was used in this study for C and ϕ modeling. The optimization method used is hybrid learning algorithms. For a first-order Sugeno model, a common rule set with two fuzzy if-then rules is as follows:

Rule 1: If x_1 is A_1 and x_2 is B_1, then $f_1=a_1x_1+b_1x_2+q_1$
Rule 2: If x_1 is A_2 and x_2 is B_2, then $f_2=a_2x_1+b_2x_2+q_2$
where, x_1 and x_2 are the crisp inputs to the node and A_1, B_1, A_2, B_2 are fuzzy sets, a_i, b_i and q_i (i = 1, 2) are the coefficients of the first-order polynomial linear functions. Structure of a two-input first-order Sugeno fuzzy model with two rules is shown in Figure (4) and consists of five layers (Jang, 1993). The five layers of ANFIS model are as follows:
Layer1: (Input nodes): Each node output in this layer is fuzzified by membership grade of a fuzzy set corresponding to each input.

$$O_{i,1} = \mu_{Ai}(x_1) \qquad i=1,2 \quad \text{.......} \quad (6)$$

$$O_{j,1} = \mu_{Bj}(x_2) \qquad j=1,2 \quad \text{.......} \quad (7)$$

Where, x_1 and x_2 are the inputs to node i (i = 1, 2 for x_1 and j = 1, 2 for x_2) and x_1 (or x_2) is the input to the i[th] node and A_i (or B_j) is a fuzzy label.

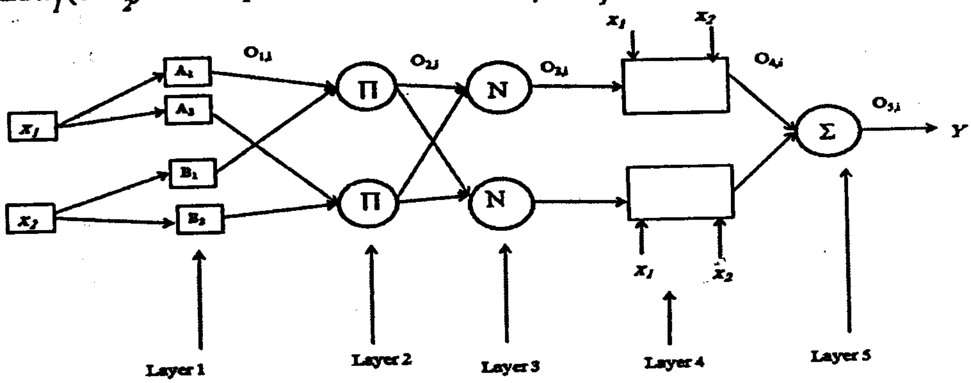

Figure (4). ANFIS architecture.

Layer 2: (Rule nodes): Each node output in this layer represents the firing strength of a rule, which performs fuzzy, AND operation. Each node in this layer, labelled Π, is a stable node which multiplies incoming signals and sends the product out.

$$O_{2,i} = W_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2) \qquad i=1,2 \quad \text{.......} \quad (8)$$

Layer 3: (Average nodes): In this layer, the nodes calculate the ratio of the i[th] rules firing strength to the sum of all rules firing strengths

$$O_{3,i} = \overline{W}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \qquad \text{(9)}$$

Layer 4: (Consequent nodes): In this layer, the contribution of i[th] rules towards the total output or the model output and/or the function calculated as follows:

$$O_{4,i} = \overline{W}_i f_i = \overline{W}\left(a_1 x_1 + b_1 x_2 + q_i\right) \qquad i = 1,2 \qquad \text{(10)}$$

Where $\overline{W}_i$ is the output of layer 3 and a_i, b_i, q_i are the coefficients of linear combination in Sugeno inference system. These parameters of this layer are referred to as consequent parameters.

Layer 5: (Output nodes): The node output in this layer is the overall output of the system, which is the summation of all coming signals

$$O_{5,i} = Y = \sum_1^2 \overline{W}_i f_i = \frac{\sum_1^2 \overline{W}_i f_i}{\sum_1^2 \overline{W}_i} \qquad \text{(11)}$$

ANFIS requires a training data set of desired input/output pair $(x_1, x_2 \ldots x_m, Y)$ depicting the target system to be modeled. ANFIS adaptively maps the inputs $(x_1, x_2 \ldots x_m)$ to the outputs (Y) through Membership Functions (MFs), the rule base and the related parameters emulating the given training data set. It starts with initial MFs, in terms of type and number, and the rule base that can be designed intuitively. ANFIS applies a hybrid learning method for updating the FIS parameters. It utilizes the gradient descent approach to fine-tune the premise parameters that define MFs. It applies the least-squares method to identify the consequent parameters that define the coefficients of each output equation in the Sugeno-type fuzzy rule base. In this study, the training process continues till the desired number of training steps (epochs) is achieved. Detailed information of ANFIS can be found in Jang (1993).

ANFIS Model development

There are no fixed rules for developing an ANFIS model (Yan et al., 2010). In current study, the soil moisture content (MC), soil dry density (DD) and soil texture index (STI) were used as inputs and C and ϕ were used as outputs.

The data in ANFIS are usually divided into two sets: training set and testing set. The training data are used for the training of ANFIS, while the testing data are used to evaluate the model performance. In this study, C and ϕ data (total of 44 observations) were divided into two data sets. The first data set containing 37 patterns of the records was used as the training data; the second data set containing 7 patterns of the records was applied as the testing data.

ANFIS models developed in this study using MATLAB toolbox (MATLAB 7.11) has three inputs (MC-DD-STI) and an output C in the first model and ϕ in the second model. Different MFs available in MATLAB toolbox and numbers were tested (data not included) and 4 "trimf" (triangle) MFs were elected for each input due to their small training error compared with other MFs. The numerical range were used for MC (1.3-15.1% db), for DD (1.2-1.85 g/cm^3), for STI (0.1411-0.3656).

In the training of the models a "hybrid learning algorithm" was used and the number of epochs was chosen as 100. The number of the MFs is 4 for each input with four linguistic terms {low, medium, high, very high} and the total rules were 64 ($4 \times 4 \times 4$). The number of nodes was 158, of linear parameters was 256, and of nonlinear parameters was 36. The total number of parameters was 292 in the models. The error of the model was 0.00001250 for C and the type of the membership function was "trimf", output membership function is linear. For ϕ ANFIS model, the error was 0.00001238. The membership function, ANFIS architecture, and the error changing during training process of the model are shown in Figures (5), (6) and (7), respectively for C. Meanwhile, the membership function, ANFIS architecture, and the error changing during training process of ϕ ANFIS model are shown in Figures (8), (9) and (10), respectively.

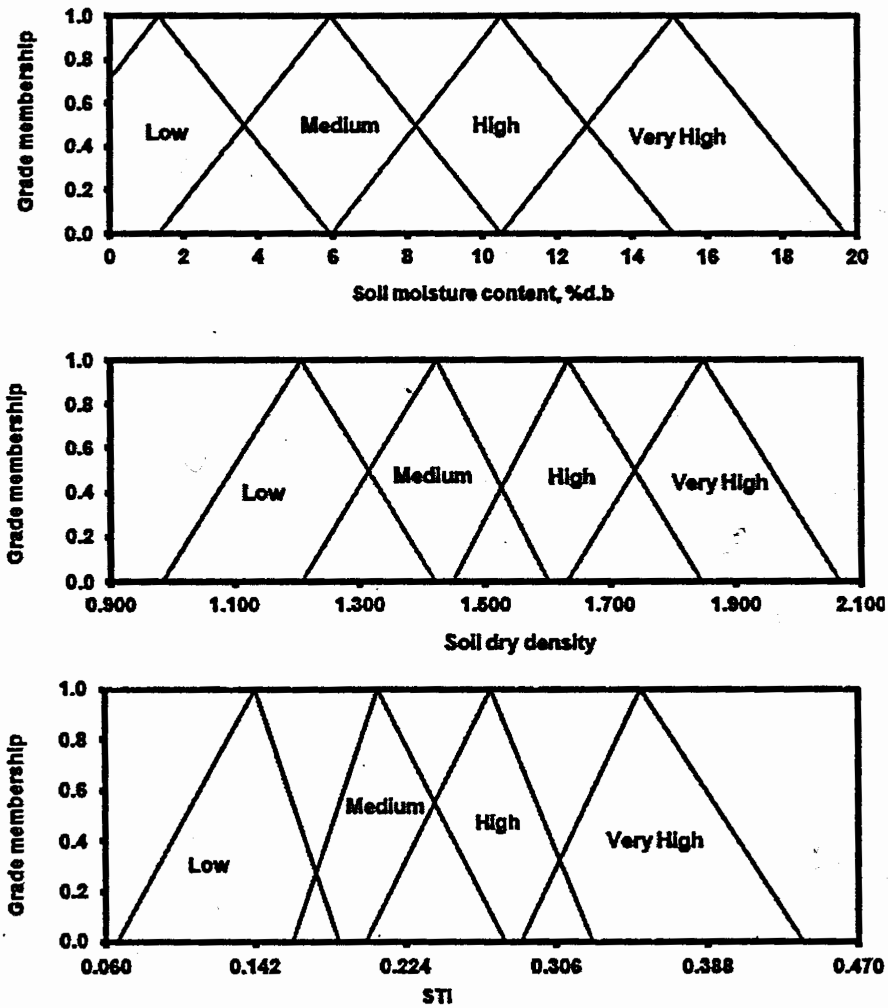

Figure (5). Membership function for input variables for soil cohesion ANFIS model.

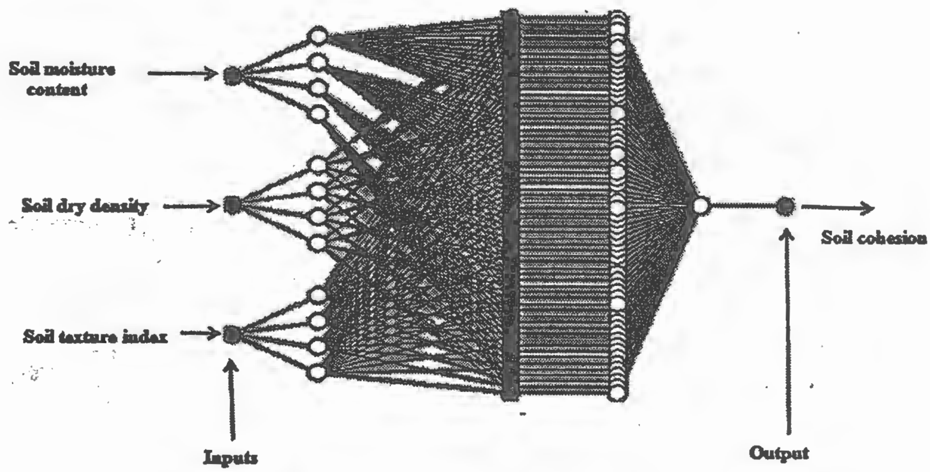

Figure (6). Architecture of the ANFIS model developed for prediction of soil cohesion.

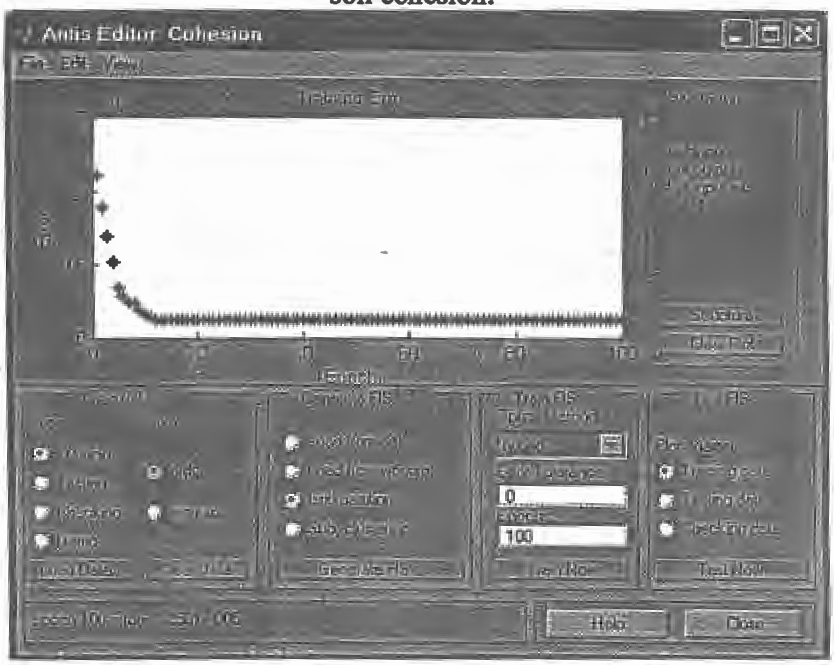

Figure (7). Error changing during training process of the ANFIS soil cohesion model.

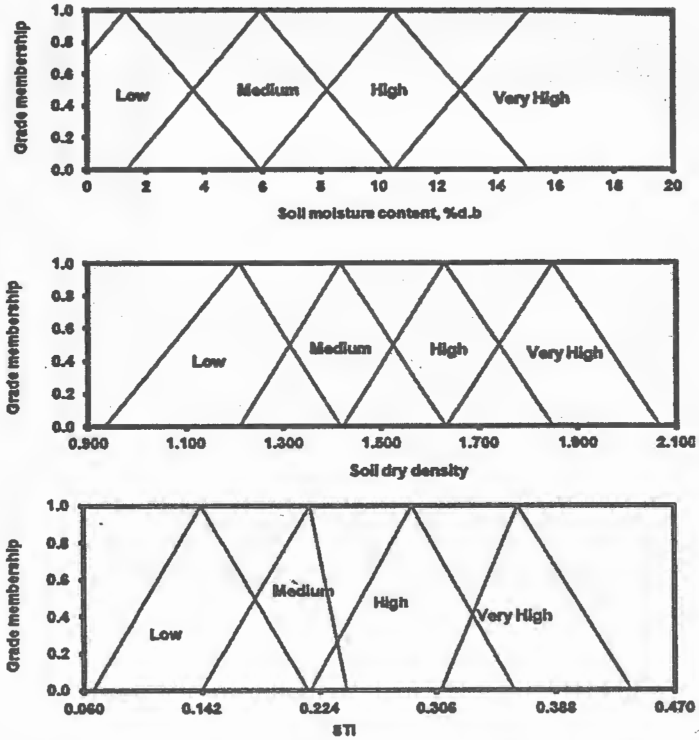

Figure (8). Membership function for input variables for soil internal friction angle ANFIS model.

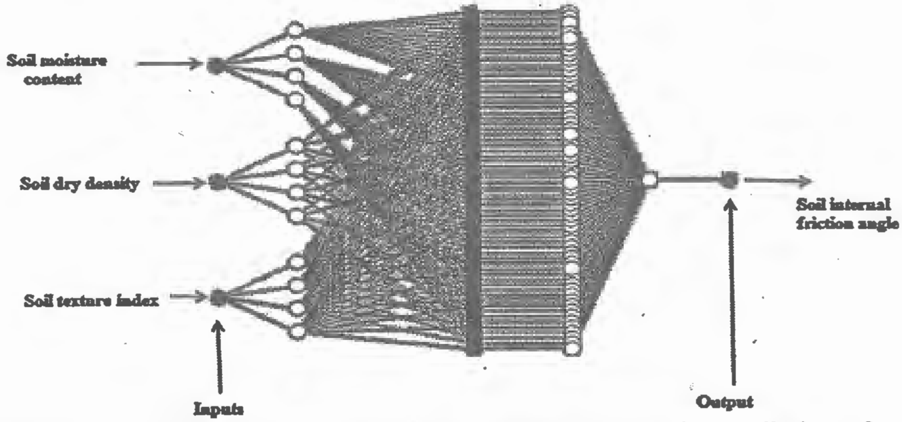

Figure (9). Architecture of the ANFIS model developed for prediction of soil internal friction angle.

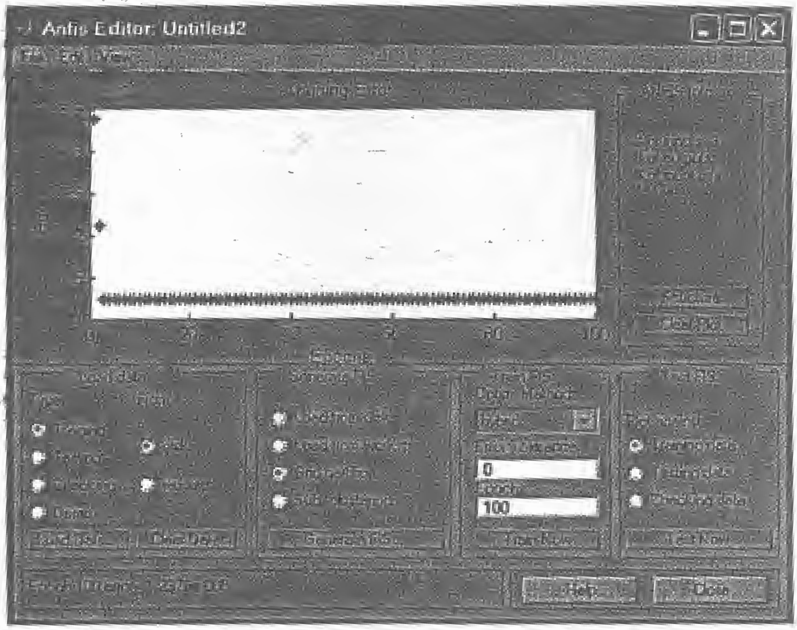

Figure (10). Error changing during training process of the ANFIS soil internal friction angle model.

Models verification

The performance of the models is examined using some main statistical measures that are well known in literature such as root mean square error (RMSE), mean absolute deviation (MAD) (Bisht et al., 2011). However, mean absolute deviation is used for measuring of mean absolute deviation of the measured values from the predicted values. It has a unit. It is expressed as,

$$MAD = \frac{\sum_{j=1}^{n} \left| Y_j - \hat{Y}_j \right|}{n} \quad \text{...} (12)$$

Where, Y and $\hat{Y}$ are the measured and predicted values respectively and n is the number of observations. RMSE yields the residual error in terms of the mean square error expressed as,

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n} \left(Y_j - \hat{Y}_j \right)^2}{n}} \quad \text{...} (13)$$

RESULTS AND DISCUSSION

This study presents the application of two methods; simple-multiple regression analysis and ANFIS for the prediction of C and ϕ of cultivated soils as related to three soil properties. Inputs and measured and predicted outputs using ANFIS and MLR models of some training and testing data sets are presented in Table (1). It is clear that C and ϕ are related to soil moisture content, dry density and texture index.

Online distribution of measured and predicted C and ϕ for the training set is shown in Figure (11) and Figure (12), respectively. In both figures, the circles symbol indicates measured output and asterisks symbol represents predicted data. As seen in the figures, the ANFIS successfully learned the relationship between the input and output data.

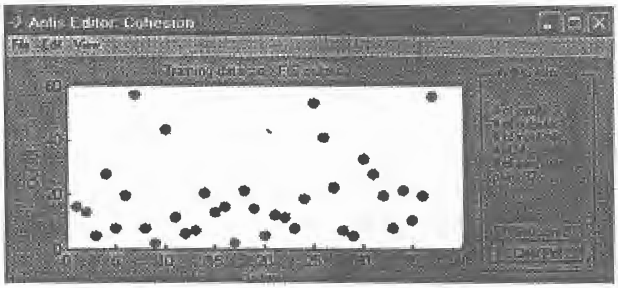

Figure (11). Online distribution of predicted and measured soil cohesion in training stage (o indicates measured output and * represents predicted data).

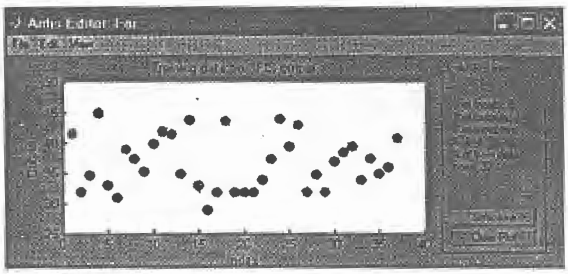

Figure (12). Online distribution of predicted and measured soil internal friction angle in training stage (o indicates measured output and * represents predicted data).

Table (1). Inputs and measured and predicted outputs using ANFIS and MLR models of some training and testing data sets.

Inputs			Outputs						Data set
			Measured		ANFIS		MLR		
MC,	DD	STI	C	ϕ	C	ϕ	C	ϕ	
%db	g/cm^3	----	kPa	Degree	kPa	Degree	kPa	Degree	
2.75	1.59	0.28304	15.70	41.50	15.70	41.50	23.57	39.69	Training
10.65	1.80	0.17222	5.89	41.50	5.89	41.50	22.80	38.92	Training
3.20	1.50	0.18817	7.85	37.50	7.85	37.50	12.02	37.13	Training
8.85	1.80	0.19670	18.64	44.00	18.70	44.00	24.86	39.92	Training
9.67	1.57	0.28389	53.96	39.40	54.00	39.40	23.13	36.44	Training
4.10	1.67	0.31925	41.20	43.00	41.20	43.00	30.05	40.88	Training
9.82	1.33	0.25868	22.56	32.00	22.60	32.00	11.38	32.03	Training
5.30	1.50	0.31342	6.87	35.00	6.87	35.00	22.77	37.40	Training
7.50	1.37	0.29904	4.91	32.00	4.92	32.00	16.27	34.04	Training
10.60	1.54	0.32125	33.35	37.00	33.30	37.00	25.02	35.83	Training
5.36	1.85	0.14111	27.47	38.50	27.50	38.50	22.04	41.76	Training
7.08	1.77	0.32231	19.62	39.40	19.80	39.40	34.52	41.41	Training
8.87	1.33	0.29730	7.85	34.00	7.85	34.00	14.66	32.80	Training
3.00	1.80	0.17222	21.58	37.40	21.60	37.40	22.65	42.21	Training
5.63	1.57	0.18402	10.79	35.00	10.80	35.00	14.59	37.28	Training
7.30	1.56	0.23899	19.62	36.00	19.80	36.00	18.69	36.80	Training
9.92	1.57	0.36560	55.92	40.80	55.60	40.80	30.28	37.17	Training
8.00	1.56	0.31533	21.58	39.60	23.60	41.50	25.39	37.28	Testing
5.77	1.70	0.14029	23.54	42.00	14.00	43.90	16.05	39.04	Testing
11.20	1.44	0.17920	3.92	34.00	16.00	32.10	9.01	32.58	Testing
10.65	1.50	0.17222	4.91	34.70	3.05	34.30	10.80	33.78	Testing
3.20	1.80	0.18817	44.15	40.00	31.40	37.90	24.02	42.27	Testing
7.50	1.58	0.29577	73.58	43.00	49.30	40.20	24.50	37.66	Testing
5.62	1.88	0.14029	24.53	41.00	28.30	37.40	22.97	42.07	Testing

The surface plots of ANFIS models are shown in Figures (13) and (14) for C and ϕ, respectively. The two figures present the relationship between input variables and their contribution to the output variable. They provide a visual impression of the possible combinations of the two input variables and the output in a three-dimensional view. They are fast and visual method of showing C and ϕ to the agricultural engineers.

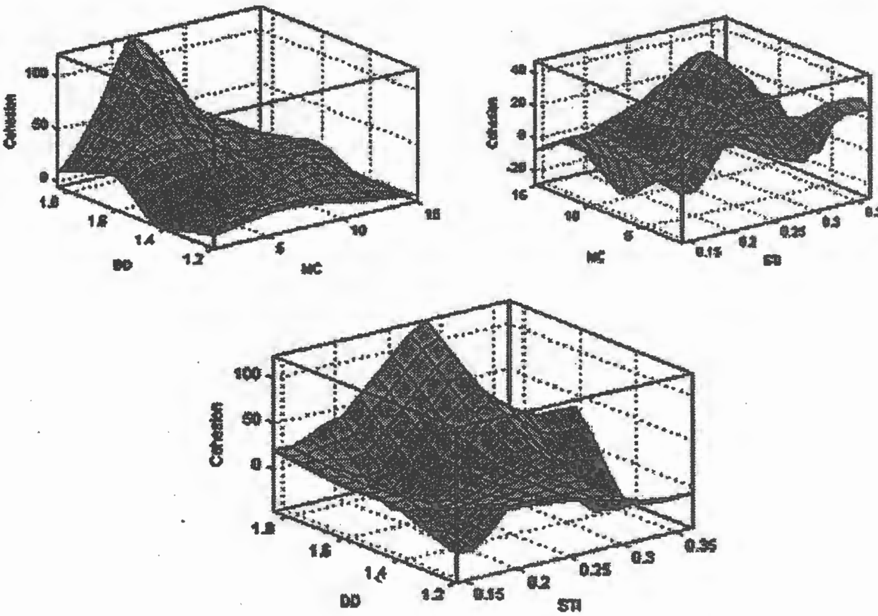

Figure (13). The surface plots of soil cohesion ANFIS model.

ANFIS prediction indicated that there exist acceptable correlation between soil properties and both C and ϕ in training and testing stages as shown in Figure (15) and Figure (16), respectively. Besides, ANFIS showed a higher performance than traditional MLR models for predicting C and ϕ in training and testing stages. ANFIS prediction indicated strong correlation (R^2= 1) between studied soil properties and C in training stage, meanwhile in testing stage, R^2 = 0.8467. Additionally, ANFIS prediction indicated strong correlation (R^2= 0.9999) between studied soil properties and ϕ in training stage, meanwhile in testing stage, R^2 = 0.7097.

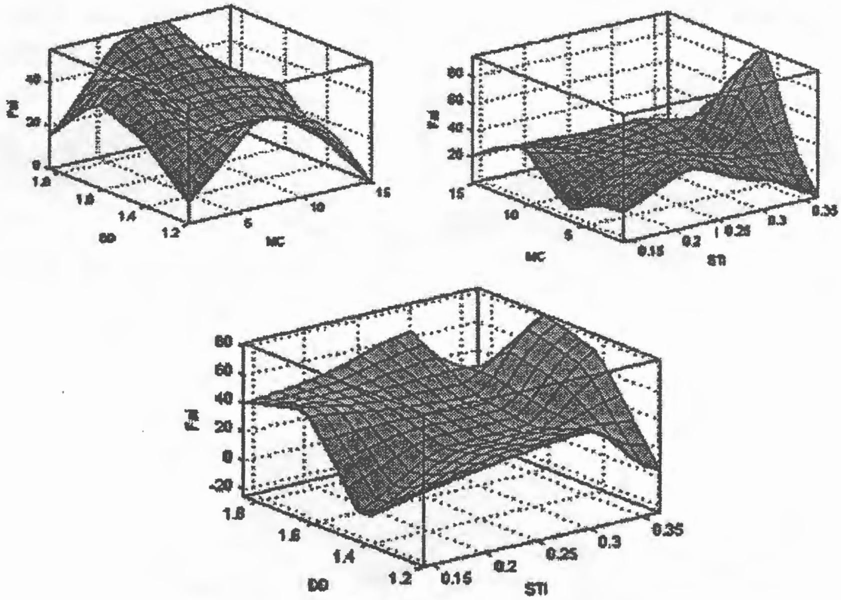

Figure (14). The surface plots of soil internal friction angle ANFIS model.

It has been shown that the correlation equations (Eqs. 4 and 5) obtained by regression analyses are found to be nearly reliable in practical situations for C and ϕ. From regression curves between measured C and predicted C via MLR model for training data and testing data (Figure 15), it can be observed that data are not well fitted because a low degree of coefficient of determination (R^2), 0.3476 for training and as 0.5114 for testing data, is obtained. Also, from regression curves between measured ϕ and predicted ϕ via MLR model for training data and testing data (Figure 16), it can be observed that data are not well fitted because a low degree of coefficient of determination (R^2), 0.5276 for training and as 0.5709 for testing data, is obtained. Root mean square error and mean absolute deviation for training and testing data sets in the prediction of soil cohesion and soil internal friction angle using ANFIS and MLR models are given in Table (2).

When using ANFIS in predicting C, the RMSE values for training and testing data are found to be 0.083 kPa and 12.0142 kPa, respectively as illustrated in Table (2). Meanwhile, when using MLR in predicting C, the RMSE for training and testing data are found to be 11.854 kPa and

20.517 kPa, respectively (Table 2). The MAD values for training and testing data are found to be 0.044 kPa and 9.470 kPa, respectively (Table 2), when using ANFIS in predicting C. Meanwhile, when using MLR in predicting C, the MAD values for training and testing data are found to be 8.880 kPa and 13.289 kPa, respectively (Table 2).

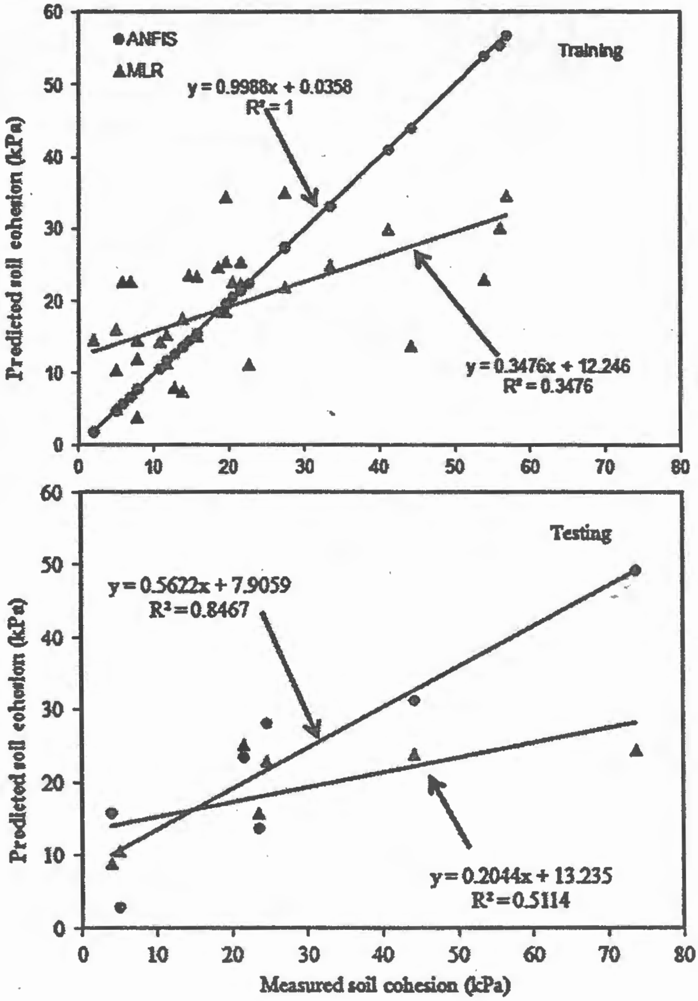

Figure (15). Correlation of predicted and measured data of soil cohesion during training and testing stages.

Table (2). Comparison of error indicators for ANFIS versus MLR models during training and testing data sets in the prediction of soil cohesion and soil internal friction angle.

	Soil cohesion (kPa)				Soil internal friction angle (degree)			
	ANFIS	MLR	ANFIS	MLR	ANFIS	MLR	ANFIS	MLR
	Training		Testing		Training		Testing	
RMSE	0.083	11.854	12.014	20.517	0.040	2.968	2.274	2.721
MAD	0.044	8.880	9.470	13.289	0.011	2.499	2.086	2.328

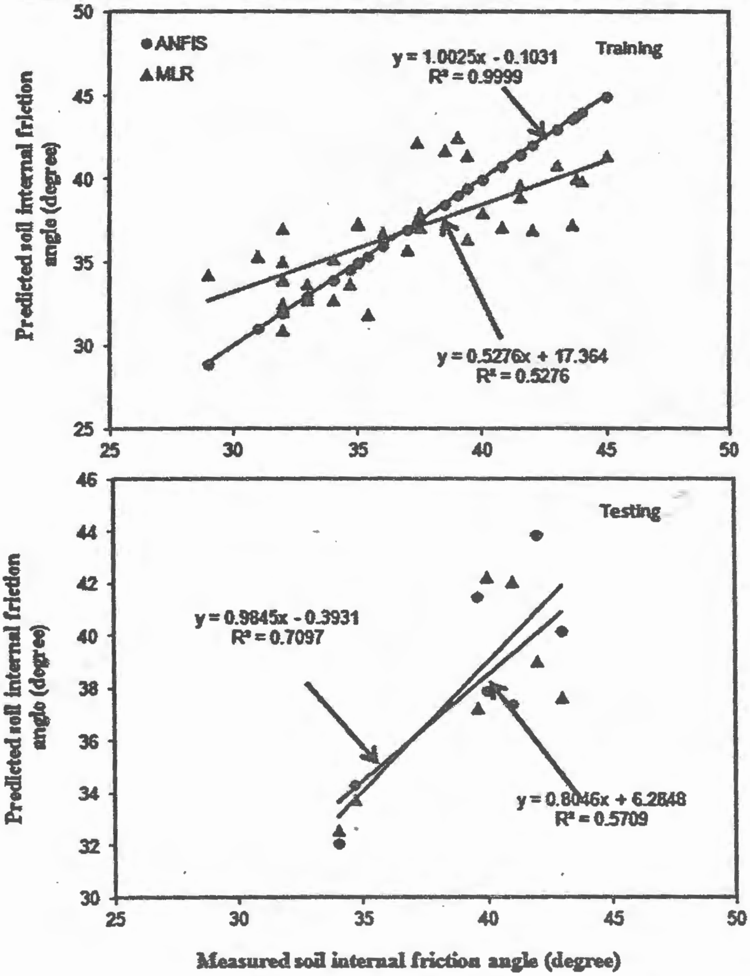

Figure (16). Correlation of predicted and measured data of soil internal friction angle during training and testing stages.

RMSE values for training and testing data are found to be 0.04 degree 2.274 degree, respectively (Table2), when using ANFIS in predicting ϕ. Meanwhile, when using MLR in predicting ϕ, the RMSE values for training and testing data are found to be 2.968 degree and 2.721 degree, respectively (Table 2). The MAD values for training and testing data are found to be 0.011 degree and 2.086 degree, respectively (Table 2), when using ANFIS in predicting ϕ. Meanwhile, when using MLR in predicting ϕ, the MAD values for training and testing data are found to be 2.499 degree and 2.328 degree, respectively as illustrated in Table (2).

A graphical depiction of the 64 rules generated to map the input data (antecedent) with the output (consequent) for the soil cohesion in the ANFIS is shown in Figure (17). This figure shows that each rule is represented by an individual row, while variables are represented by individual columns. The first three columns depict the membership functions for the three input variables (MC, DD and STI), referenced by the antecedent or the "if-part" of each rule. The fourth column, however, which consists of 64 plots, shows the membership functions used by the consequent or the "then-part" of each rule. The vertical lines in the first three columns indicate the current data inputs for MC (soil moisture content), DD (soil dry density) and STI (soil texture index) to be 8.2 % db, 1.52 g/cm^3 and 0.253, respectively. The bottom plot in the right column represents the aggregate of each consequent. Whereas, the defuzzified output value is represented by a thick line passing through the aggregate fuzzy set. For system inputs of MC of 8.2, DD of 1.52 and STI of 0.253, the defuzzified output (soil cohesion) is shown to be 24.8 kPa (Figure 17). Meanwhile, for system inputs of MC of 8.2, DD of 1.52 and STI of 0.253, the defuzzified output (soil internal friction angle) is shown to be 33.4 degree (Figure 18).

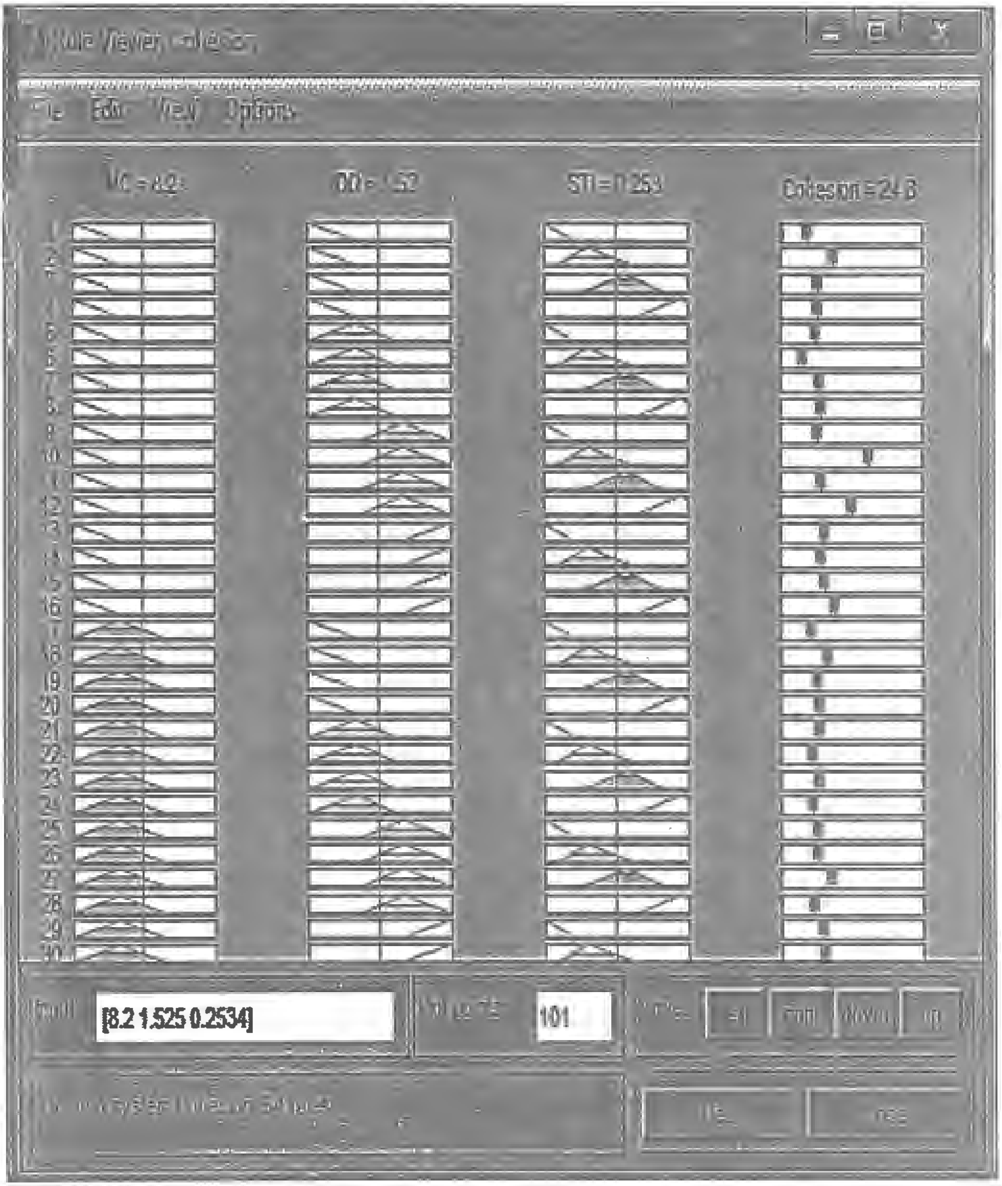

Figure (17). Graphical representation of the rules for soil cohesion model.

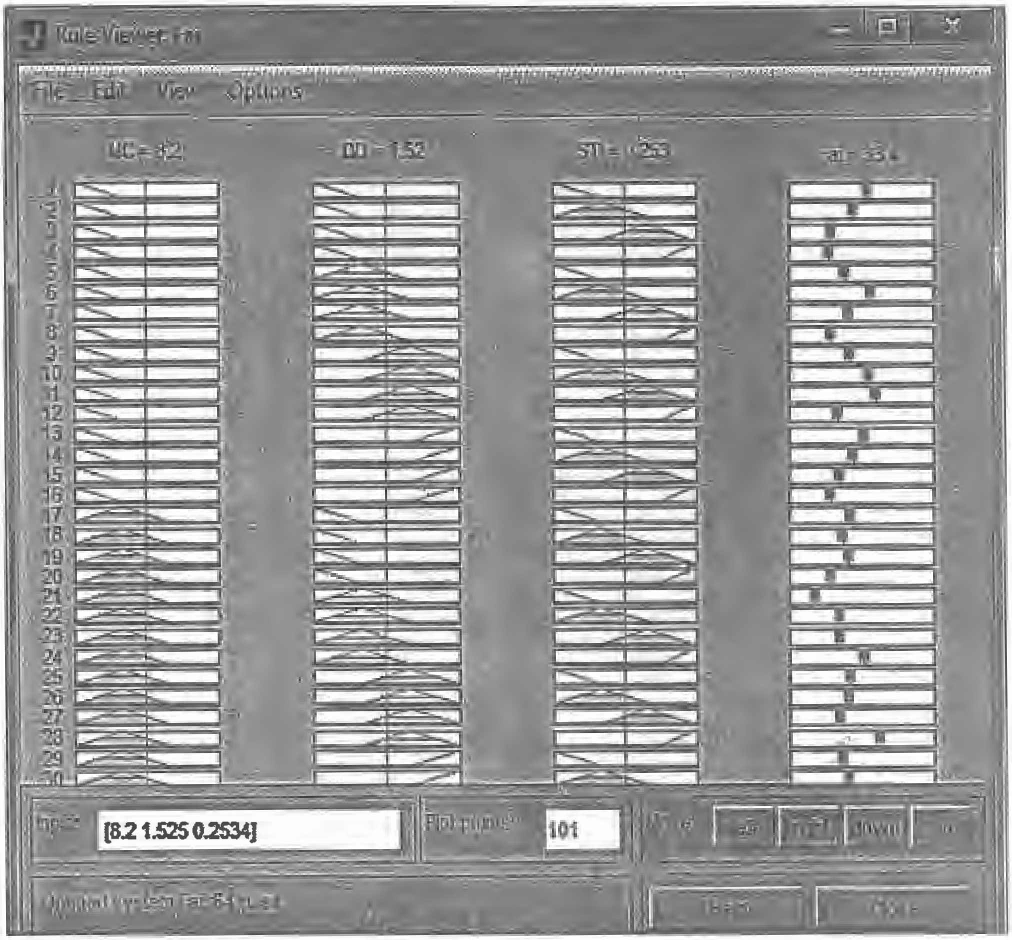

Figure (18). Graphical representation of the rules for soil internal friction angle model.

CONCLUSION

An adaptive neuro-fuzzy system (ANFIS) and multiple linear regression (MLR) were applied to predict soil cohesion (C) and soil internal friction angle (ϕ) of cultivated soils. The basic soil properties parameters were used as inputs to the ANFIS and MLR to predict C and ϕ. The following conclusions can be drawn from this study:

1. The ANFIS model could predict C for training data with RMSE of 0.083 kPa when a triangle membership function is applied, while MLR model could predict C for training data with RMSE of 11.854 kPa .
2. The ANFIS model could predict ϕ for training data with RMSE of 0.04 degree when a triangle membership function is applied, while MLR model could predict ϕ for training data set with RMSE of 2.968 degree.
3. The developed ANFIS model can be effectively used to predict C and ϕ within the ranges of variables studied comparing with MLR model.

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الملخص العربي

مقارنة الإرتداد الخطي المتعدد ومنظومة استنتاج عصبية مشوشة مكيفة للتنبؤ بتماسك وزاوية الإحتكاك الداخلي للترب الزراعية

د./ عبد الواحد محمد أبو كريمة*

يعتبر تقدير كلاً من تماسك التربة وزاوية الإحتكاك الداخلي لها من الأمور الهامة لإيجاد حلول عديدة لمشاكل تطبيقات الهندسة الزراعية مثل نمذجة قوى الشد لمعدات الحراثة. في المقابل نجد أن القياسات الحقلية أو المعملية تنفذ عادة لإيجاد مثل تلك الخاصيتان. وهذه القياسات الحقلية أو المعملية تحتاج لترتيبات خاصة ووقت. لذا لابد من البحث عن طرق بديلة لتقدير مثل تلك الخاصيتان مثل تقديرهما بالتنبؤ بدلالة بعض المتغيرات التي تؤثر فيهما. لذا هدف هذا البحث إلى التعرف على مقدرة منظومة استنتاج عصبية مشوشة مكيفة للتنبؤ بتماسك وزاوية الإحتكاك الداخلي للترب الزراعية. استخدمت نتائج تجارب معملية فعلية على أنواع تربة مختلفة لإيجاد قاعدة بيانات مكونة من مدخلات ومخرجات لتطوير مثل تلك المنظومة. من النتائج وجد أن هذه المنظومة قادرة على التنبؤ بتلك الخاصيتان من المحتوى الرطوبي للتربة والكثافة الجافة للتربة ومن دليل قوام التربة. وبالمقارنة مع الإرتداد الخطي المتعدد، وجد أن تلك المنظومة أفضل بكثير من نموذجي الإرتداد الخطي المتعدد للتنبؤ بتماسك وزاوية الإحتكاك الداخلي للترب الزراعية من خلال قيم معامل التحديد R^2 والذي قيمته كانت ١ عند استخدام منظومة استنتاج عصبية مشوشة مكيفة لتطوير نموذج للتنبؤ بتماسك التربة، بينما عند استخدام نموذج الإرتداد الخطي المتعدد لتطوير نموذج للتنبؤ بتماسك التربة كانت قيمة R^2 هي 0.3476.

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