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Full Length Research Paper

Artificial neural network for soil cohesion and soil internal friction angle prediction from soil physical properties data

Saad Abdulrahman Al-Hamed[1], Mohamed Fouad Wahby[1*] and Abdulwahed Mohamed Aboukarima[2,3]

[1]Department of Agricultural Engineering, College of Food and Agriculture Sciences, King Saud University, P.O. Box 2460, Riyadh 11451, Saudi Arabia
[2]Agricultural Engineering Research Institute, Agricultural Research Center, Egypt
[3]Community College, Huraimla, Shaqra University, P.O. Box 300, Huraimla 11962, Saudi Arabia

*Corresponding author e-mail: wahby@ksu.edu.sa

ABSTRACT

An artificial neural network (ANN) model was employed to predict the soil cohesion and soil internal friction angle. The soil samples were collected from different cultivated sites in seven regions in Saudi Arabia. Direct shear box method was used to determine soil cohesion and soil internal friction angle. The input factors to ANN model were soil dry density, soil moisture content and soil texture index. The best 3-layer ANN model produced correlation coefficients of 0.9328 and 0.9485 between the observed and predicted soil cohesion and soil internal friction angle, respectively during training phase. Results of using testing data showed that the ANN model gave RMSE values of 4.826 kPa and 0.928 degree for soil cohesion and soil internal friction angle, respectively indicating that ANN-based model had good accuracy in predicting soil cohesion and soil internal friction angle.

Keywords: Artificial neural network, soil cohesion, soil internal friction angle, prediction

INTRODUCTION

Soil properties are a key factor in the functioning of soil (Khater et al, 2008). Soil mechanical properties are addressed by many items, among which the soil cohesion and adhesion are relevant for their major contributors to draft force of a tillage implement (Plasse et al, 1985). However, the amount of energy consumed during a tillage operation depends on three parameters including soil parameters, tool parameters and operating parameters (Zadeh, 2006).

Shear strength is the internal resistance of the soil to external forces that cause two adjacent areas of soil to move relative to each other. It is generally considered to be a function of cohesion between soil particles and inter-granular friction (Graf et al, 2009). The force acting on a failure surface in the soil body can be determined by Mohr-Coulomb equation as follows (Tong and Moayad, 2006).

$$\tau = C + \sigma_n \tan \phi \qquad (1)$$

where τ is the tangential stress, σ_n is the normal stress, C is the cohesion of soil, which is the resistance of soil particles to displacement due to intermolecular attraction and surface tension of the held water and it depends upon size of clayey particles, type of clay minerals, valence bond between particles, moisture content, and proportion of the clay (Jain et al 2010a), and ϕ is the internal frictional angle of soil, which depends upon soil dry density, soil particle size distribution, shape of particles, soil surface texture, and soil moisture content (Jain et al, 2010a).

The value of soil cohesion varies with soil moisture content, grain size of soil and its compaction (Abd El Maksoud, 2006). Lebert and Horn (1991) found that in homogeneous, non-structured soils, such as sands and silts with low clay content (15%, w/w), the shear parameters were mainly texture-dependent. Shainberg et al (1994) mentioned that the most commonly soil physical properties affected surface soil shear strength was particle size distribution. Sojka et al (2001) reported that soil strength depended on the interaction of soil moisture content and bulk density. Zhang et al (2001) measured the soil strength for the soils from sandy loam to clayey loam at soil surface at different bulk density and soil moisture content. The results indicated that significant effect of bulk density on soil strength. Bechmann et al (2006) showed that soil strength varied frequently due to changes in soil moisture conditions. Murthy (2008) reported that the values of soil cohesion and soil internal frication angle for any soil depend upon several factors such as textural properties, stress history of soil, initial state, and permeability characteristics of soil. Dadkhah et al (2010) reported that the soil friction angle and cohesion increase with increasing soil density. Mousavi et al (2011) found that as the soil grain size increases, the soil internal friction angle increases and its cohesion decreases.

The direct shear test is commonly used for measuring soil cohesion and soil friction angle of soils. Furthermore, a laboratory or field test, as a direct measurement of soil cohesion and soil friction angle is not easy to apply; however, it is time-consuming and expensive (Arvidsson and Keller, 2011; Zadeh and Asadi, 2012). Besides experimental determination of the soil cohesion and soil friction angle of soils is extensive, cumbersome and costly (Mousavi et al, 2011). An alternative approach to such test is the development empirical mathematical models for 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. This might be accomplished by some techniques such as experimental relations, statistical methods, etc. Recently, artificial neural networks (ANNs) have been used in soil science and agriculture. However, ANNs provide a method to characterize synthetic neurons to solve complex problems in the same manner as the human brain does (Ayoubi et al, 2011). A typical structure of ANNs consists of a number of processing elements, or nodes, that are usually arranged in layers: an input layer, an output layer and one or more hidden layers. The relative performance of ANNs over traditional statistical methods is reported in Zhang et al, (1998). One of the most important advantages of ANNs over statistical methods is that they require no assumptions about the form of a fitting function. Instead, the network is trained with experimental data to find the relationship; so they are becoming very popular estimating tools and are known to be efficient and less time consuming in modeling of complex systems compared to other mathematical models such as regression (Kalogirou, 2001; Pahlavan et al, 2012). An artificial neural network (ANN) model is usually employed when the relationship between the input and output is complicated or application of another available method takes a long computational time and effort (Noorzaei et al, 2005). Also, it employed when another available method gives less accuracy performance.

There are different potential applications of the ANN in soil applications such as predicting organic matter content in the soil (Ingleby and Crowe, 2001), soil erosion prediction (Licznar and Nearing, 2003), predicting the hydraulic conductivity of coarse grained soils (Akbulut, 2005), determination of volumetric soil moisture content (Chai et al, 2008) and modeling soil solution electrical conductivity (Davood et al, 2010).

Das et al (2008) made various attempts using neural network model to predict the residual friction angles based on clay fraction and Atterberg's limits. The ANN model with two inputs was the best model, based on statistical parameters, correlation coefficient and coefficient of efficiency, for training and testing data sets. Goktepe et al (2008) established correlation between index properties and shear strength parameters of normally consolidated clays by statistical and neural approaches. The results indicated that the ANN-based model is superior in determining the relationships between index properties and shear strength parameters. Jain et al (2010b) developed ANN models to predict cohesion and angle of internal friction of fine-grained high compressible soil. The ANN prediction models were developed from test results obtained by conducting series of unconsolidated undrained triaxial compression tests on soil samples. Dry densities, degree of saturations using different compaction energy, liquid limit, plasticity index and percentage of size of particles were acted as input parameters. The prediction was consistent with the observed data. Khanlari et al (2012) introduced artificial neural network models to predict friction angle and cohesion of soils. They used the percentages of passing the No. 200 (≠ 200), 40 (≠ 40) and 4 (≠ 4) sieves, plasticity index, and density as inputs factors. The results indicated that multilayer perceptron feed forward neural network model shows better performance rather than radial basis function neural network model. Rani et al (2013) made an attempt by the using of a multilayer perceptron network with feed forward back propagation to model soil cohesion and soil angle of internal friction in terms of fine fraction, liquid limit, plasticity index, maximum dry density and optimum moisture content by

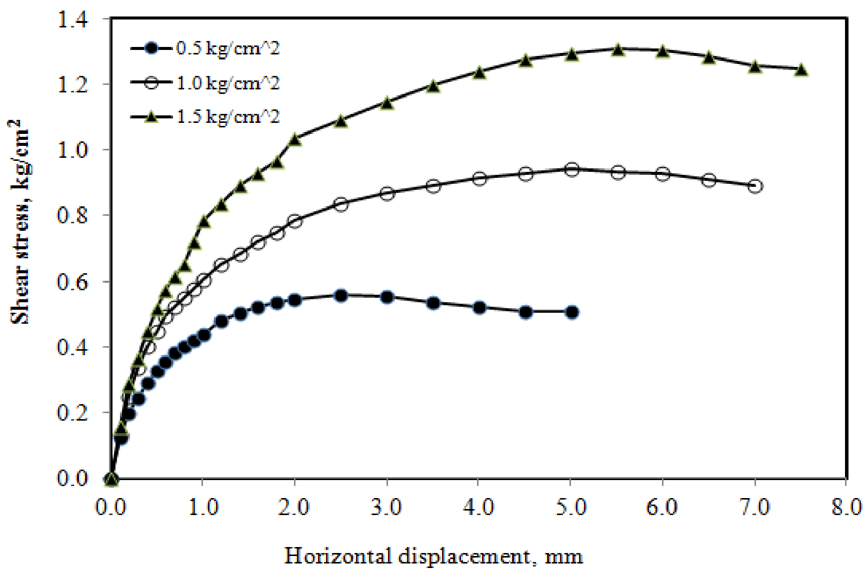

Figure 1. Shear stress versus horizontal displacement during direct shear box test under different normal stresses.

using ANN. The results indicated that predicted values of soil cohesion and soil angle of internal friction for training and testing process were close to observed values.

It is not always possible to conduct the tests on every new situation to get soil cohesion and soil internal friction angle. In order to cope with such problems, numerical solutions have been developed to estimate such parameters. With such arguments, there is need to find simple model to predict soil cohesion and soil internal friction angle in easy way. So, the objective of this study was to model the relationship between soil cohesion and soil internal friction angle and some soil variables such as soil texture index, soil dry density and soil moisture content. However, modeling soil mechanical properties is one of the most important tools in the assessment of tillage draft as well as energy requirements.

MATERIALS AND METHODS

Study sites

The study was conducted 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. Latitude, longitude and altitude of all the study sites were determined using a global positioning system (Garmin GPS 60) which is a satellite based positioning and navigation system that provides position with accuracy less than 15 meters. The latitude mean was ranged from 20.42 to 30.00 °N; the longitude mean was ranged from 36.62 to 47.65 °E and the altitude mean was ranged from 396.4 to 871.7 m.

Measuring soil properties

38 Soil samples were collected from surface to about 20 cm depth. Soil particle size distribution was determined. The clay fraction ranged from 3 to 21%; the sand fraction ranged from 63.36 to 88.9% and the silt fraction ranged from 7.2 to 20.1%. Direct shear box method was used in determining soil cohesion and soil internal friction angle. Levels of soil moisture content similar to the soil moisture content in the field were tested. During the shear experiments, soil wet density of the soil was maintained in the range related to soil bulk density. A soil sample is placed in a metal shear box and undergoes a horizontal force. The soil fails by shearing along a plane when the force is applied. The loading rate during shear tests was constant rate of 0.12 mm/min. 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. 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 1. After analyzing of shear stress versus horizontal displacement, another graph presents shear stress at failure against normal stress as shown in Figure 2 was drawn. From Figure 2, it is usual to

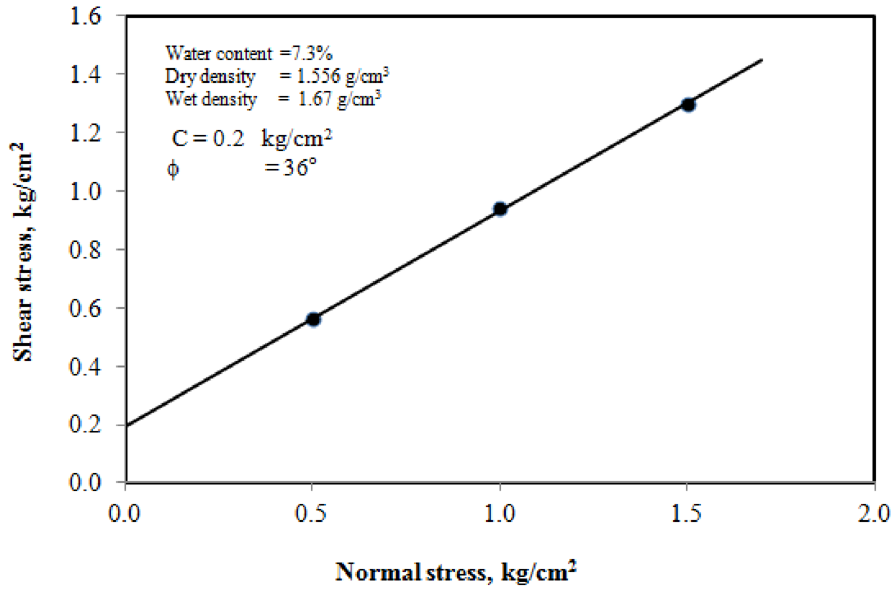

Figure 2. Shear stress at faliur against normal stress during direct shear box test.

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 of the soil (C) in kg/cm^2.

To combine all soil fractions, a soil texture index was developed similar to one appeared in Oskoui and Harvey (1992), but due to the sand content is the major component in the studied soils, followed by silt then clay so, another formual to calculate soil texture index (STI) will be developed as follows:

$$STI = \frac{log\,(Sa^{Si} + CCa\ )}{100} \quad \text{..........................} \qquad (2)$$

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

Artificial neural network architecture

ANN is one of the computing methods. It uses simple processing elements named neuron. ANNs discovers the inherent relationship between parameters through learning process and creates a mapping between input space (input layer) and target space (output layer) (Chayjan et al, 2007). The multilayer perceptron network and radial basis function networks are the most commonly used feed forward ANNs. A multilayer perceptron network consists of one input layer, one or more hidden layers and one output layer (Hassan-Beygi et al, 2007).

The network architecture used in this research consists of three layers of neurons connected by weights. The weights connecting input neuron i to hidden neuron j are denoted by w^h_{ji}, while the weights connecting hidden neuron j to output neuron are denoted by w^o_j. The input of each neuron is the weighted sum of the network inputs, and the output of the neuron is a sigmoid function value based on its inputs. More specially, for the jth hidden neuron (Zhang et al, 2005).

$$\begin{cases} net^h_j = \sum_{i=1}^{n} w^h_{ji} x_{t-1} + b_j \quad , \\ y_j = f\left(net^h_j\right) \end{cases} \quad \text{..................................} \qquad (3)$$

While for the output neuron

$$\begin{cases} net^o = \sum_{j=1}^{m} w^o_j y_j + c \quad , \\ \tilde{x}_t = f\left(net^o\right) \end{cases} \quad \text{..................................} \qquad (4)$$

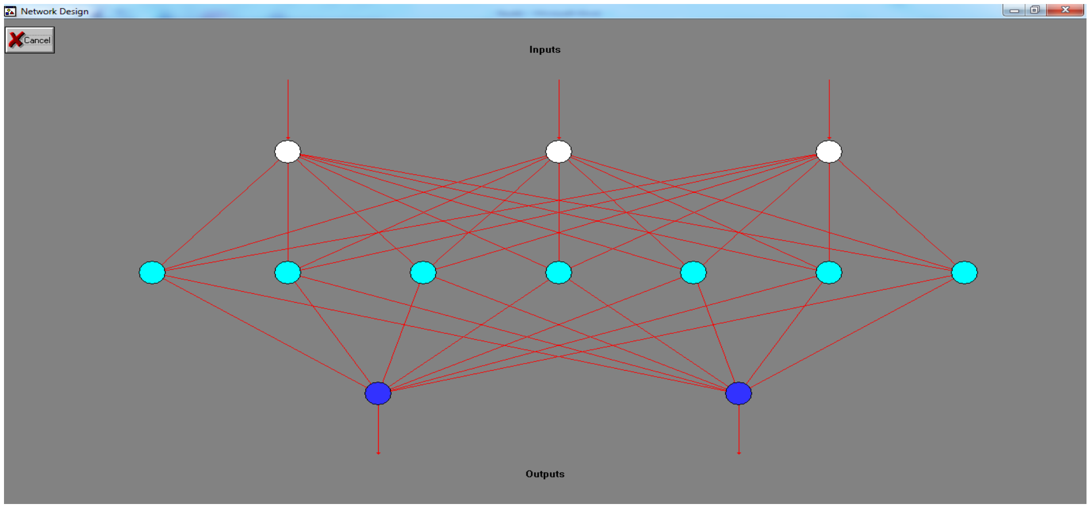

Figure 3. The developed 3-7-2 ANN model for predicting soil cohesion and soil internal friction angle.

Where b_j and c are thresholds (bias), this network has n neurons in the input layer and m neurons in the hidden layer, f is typically taken to be a sigmoidal function, such as the logistic function

$$f(x) = \frac{1}{1+e^{-x}} \qquad (5)$$

The inputs to this network are soil dry density (ρ), soil moisture content (θ), soil texture index (STI), the output has two $\tilde{x}_t$ that are soil cohesion and soil internal friction angle. Given a finite number of pattern pairs consisting of an input pattern X_t and a target output pattern x_t, this network is trained by supervised learning. Generally, the backpropagation algorithm, which is the most popular learning algorithm, is adopted to perform steepest descent on the total mean squared error (MSE):

$$MSE = \frac{1}{2}\sum_{t=1}^{N}(\tilde{x}_t - x_t)^2 \qquad (6)$$

Where N is the total number of pattern pairs.

Building of artificial neural network model

The data of inputs and outputs were 38 rows. 33 of these data were used to build the artificial neural network model and the rest was used to test the model. In order to build ANN model, commercial Neural Network software of QNET 2000 for WINDOWS (Vesta Services, 2000) was used. The ANN used in this study was a standard back-propagation neural network with three layers: an input layer, a hidden layer and an output layer. Before training, a certain pre-processing steps on the network inputs and targets to make more efficient neural network training was performed. The range of input and targets values was from 0.15 to 0.85, i.e., normalizing the inputs and target values using the following formula:

$$T = \frac{(V - V_{\min})}{(V_{\max} - V_{\min})} \times (0.85 - 0.15) + 0.15 \qquad (7)$$

Where V is the original values of input and output parameters, T is the normalized value; V_{max} and V_{min} are the maximum and minimum values of the input and the output parameters, respectively.

The randomized data were used in training. Three various layers ANN structures were investigated, including different number of neurons in the hidden layer, different values of the learning coefficient, different values of the momentum, and different transfer functions. Training a given neural network was achieved. Its performance was evaluated using correlation coefficient. The best ANN structure and optimum values of network parameters were obtained on the basis of the lowest error on training data by trial and error. Preliminary trails indicated that one hidden layer network performed better results than other hidden layers ANN to learn and predict the correlation between input and output parameters. To determine the optimal number of neurons in hidden layer, training was used for 3-n1-2 architectures. The number of neurons in the hidden layer (n1) was studied from 1–25. Results show that among the various structures, the best training performance to predict soil cohesion and soil internal friction angle belonged to the 3-7-2 structure. Figure 3 illustrates the developed ANN model for predicting soil cohesion and soil internal friction angle. The training parameters were 0.058718 for training error, 0.15 for learning rate, 0.8 for momentum and 200000 for iterations. Table 1 illustrates network statistics after training phase.

Table 1. Network statistics from Qnet software of training data of 3-7-2 ANN model.

Criteria	Output nodes	
	Soil internal friction angle (°)	Soil cohesion (kPa)
Standard deviation	1.351	5.969
Bias	0.0308	-0.414
Maximum error	3.98	13.56
Correlation coefficient (dimensionless)	0.9485	0.9328

Table 2. Pearson's correlation coefficients between soil cohesion (C) and soil internal friction angle (ϕ) as the dependent variables and soil dry density (ρ), soil moisture content (θ) and soil texture index (STI) as independent variables.

	ϕ	C	STI	θ	ρ
ρ					1
θ				1	-0.168
STI			1	0.152	-0.185
C		1	0.222	-0.109	0.477
ϕ	1	0.508	0.053	-0.338	0.669

Table 3. Error criteria during testing process of 3-7-2 ANN model.

Variables	R^2 (dimensionless)	MAE	RMSE
Soil cohesion (kPa)	0.9311	3.613	4.826
Soil internal friction angle (°)	0.9813	0.725	0.928

Criteria of evaluation

The performance of the developed model in this study has been assessed using various standard statistical performance evaluation criteria. The statistical measures considered have been three criteria. The first criterion is correlation coefficient. The second one is mean absolute error (MAE). The third criterion is root mean square error (RMSE). The MAE and RMSE are calculated according to the following equations:

$$MAE = \frac{1}{N_a}\sum_{i=1}^{N_a}\left|Y_a - Y_p\right| \qquad (8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N_a}(Y_a - Y_p)^2}{N_a}} \qquad (9)$$

Where Y_a and Y_p are the observed and predicted data, respectively and N_a is the number of data points.

RESULTS

A correlation matrix was formed to explore the power of the linear relationships between the variables included in this study. For that purpose, the correlation matrix was produced by using excel spreadsheet under data analysis tools to the training data set in an attempt to define the degrees of linear relationships between all variables. In correlation analysis, Pearson's correlation coefficients between soil cohesion (C) and soil internal friction angle (ϕ) being the dependent variables, and the other selected soil's properties, being independent variables, have been investigated. Pearson's correlation coefficients (r values) are given in Table 2.

The prediction performance of the ANN model was tested using a data of 13 % cases, which were not used in the initial training of the ANN model. The ANN model predicted soil cohesion with a RMSE of 4.826 kPa, a MAE of 3.613 kPa and a coefficient of determination of 0.9311 as depicted in Table 3. The ANN model predicted soil internal friction angle with a RMSE of 0.928 degree, a MAE of 0.725 degree and a coefficient of determination of 0.9813 as depicted in Table 3.

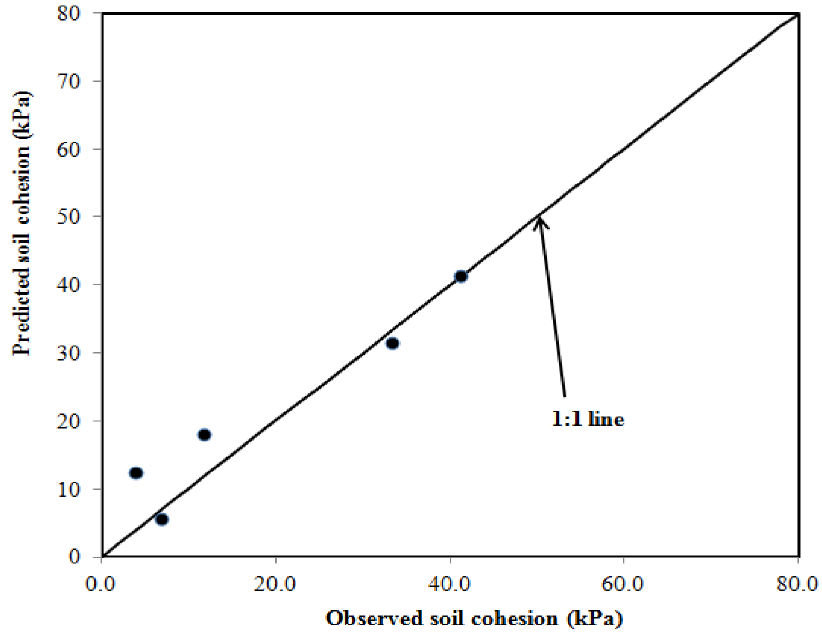

Figure 4. Relationship between the observed and the predicted values during testing phase using of 3-7-2 ANN model for soil cohesion.

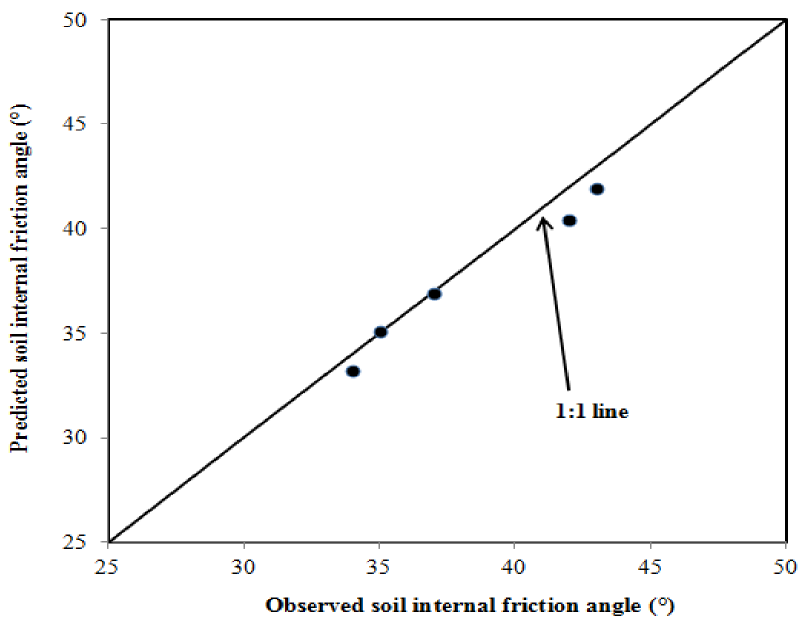

Figure 5. Relationship between the observed and the predicted values during testing phase using of 3-7-2 ANN model for soil internal friction angle.

Figure 4 shows the relationship between the observed and the predicted values of soil cohesion during testing phase using 3-7-2 ANN model for the soil cohesion. The figure clearly shows that the points are uniformly scattered around the 1:1 line. Figure 5 shows the relationships and coefficients of determination between the observed and the predicted soil internal friction angle values during testing phase using 3-7-2 ANN model for the soil internal friction angle. The figure clearly shows that the points are uniformly scattered around the 1:1 line.

Qnet2000 neural network software was also used to explore the magnitude of the impact of each individual variable in the network outcome. The results of

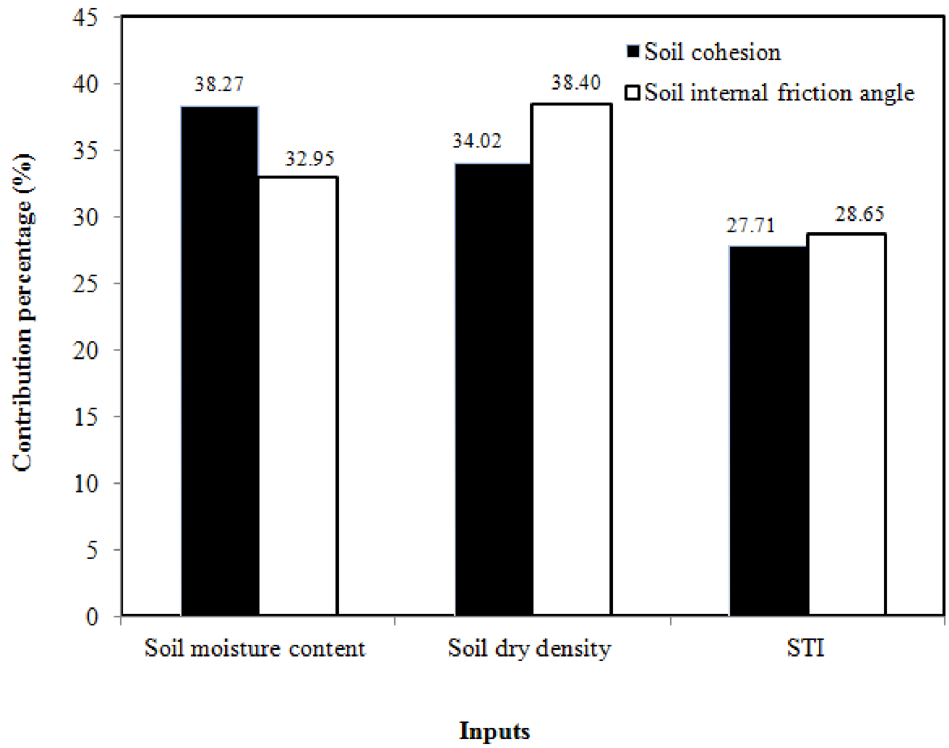

Figure 6. The contribution percentage of the three input variables to the outputs.

contribution analysis can judge what parameters are the most significant (have the high contribution values) in comparison with other inputs. In this work, the relative influence of each of the input variables upon predicted soil cohesion and soil internal friction angle was presented as a percentage contribution of each variable to the network predictions. The contribution percentage of the three input variables to the outputs was illustrated in Figure 6.

DISSCUSSION

According to correlation analysis (Table 2), soil dry density has influences on soil cohesion and soil internal friction angle with positive r-values of 0.477 and 0.669 for C and ϕ, respectively. This finding was agreed with Abd El Maksoud (2006). However, soil moisture content has negative effect on soil cohesion and soil internal friction angle with negative r-values of -0.109 and -0.338 for C and ϕ, respectively. Again this result is agreed with the findings of Abd El Maksoud (2006). Soil texture index has low effect on soil cohesion and soil internal friction angle with positive r-values of 0.222 and 0.053 for C and ϕ, respectively

As indicated by the values of RMSE and MAE, it was concluded that the developed ANN model could be used for prediction of soil cohesion and soil internal friction angle. However, the potential benefit of estimating soil cohesion and soil internal friction angle from soil physical properties is that the measurements of soil physical properties can be achieved using simple instrumentations in laboratory or in the field. The results reported in this work are valid only over the range investigated.

As it can be seen in Figure 6 the highest contribution value (38.27%) belonged to soil moisture content which showed the highest impact of this input between three evaluated factors on soil cohesion. The result was agreement with the findings of Bechmann et al (2006) who indicated that soil strength varied frequently due to changes in soil moisture conditions. Besides, the highest contribution value (38.40%) belonged to soil dry density which showed the highest impact of this input between three evaluated factors on soil internal friction angle as illustrated in Figure 6. The result was agreement with Zhang et al (2001) research results which indicated that soil strength for the soils from sandy loam to clayey loam at soil surface was significant affected by soil density.

CONCLUSION

This study evaluated the ability of an artificial neural network (ANN) model to predict and model the relationship between the soil dry density, soil moisture content and soil texture index and its corresponding the soil cohesion and soil internal friction angle. Three factors were selected as the most important factors which can affect (or have effect on) soil cohesion and soil internal friction angle. The main conclusions are as follows:

(1) The ANN model with 3-7-2 structure was recognized as the best model for predicting the soil cohesion and soil internal friction angle. The validity of developed model was confirmed due to the high value of the coefficient of determination (R^2 = 0.9311) and the low values of mean absolute error (MAE = 3.613 kPa) and the root mean square error (RMSE = 4.826 kPa) for soil cohesion. Meanwhile, these values for soil internal friction angle were R^2 = 0.9813, MAE = 0.725 degree and RMSE = 0.928 degree.

(2) The contribution analysis of input parameters on outputs revealed that soil moisture content has the higher contribution on soil cohesion in comparison with soil dry density and soil texture index. Again, contribution analysis of input parameters on outputs revealed that soil dry density has the higher contribution on soil internal friction angle in comparison with soil moisture content and soil texture index .From the results of this study, it is concluded that the ANNs are useful tools to predict the soil cohesion and soil internal friction angle with respect to the soil physical properties factors which impact on soil strength parameters.

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