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Applying of an Adaptive Neuro Fuzzy Inference System for Prediction of Unsaturated Soil Hydraulic Conductivity

Mohamed A. Al-Sulaiman

Community College, Huraimla, Shaqra University, P.O. Box 300, Huraimla 11962, Saudi Arabia.

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The unsaturated hydraulic conductivity of soil (K_u) is one of the most principal parameters in the study of water movement in the soil. The field measurement methods of (K_u) are hard and expensive. So, indirect prediction of (K_u) has received considerable attention as published in the research papers to be an alternative approach. However, prediction models for soil hydraulic conductivity are now widely used informative tools for rapid and cost-effective assessment. Thus in this study, an attempt has been made to apply an adaptive neuro-fuzzy inference system (ANFIS) for predicting (K_u). The input variables were ECRatio (electric conductivity of water divided by electric conductivity of soil), SARRatio (sodium adsorption ratio of water divided by sodium adsorption ratio of soil), soil texture index (calculated from clay, sand and silt), suction rate, organic matter in the soil, initial soil moisture content and initial soil bulk density. The Gaussian membership function was the best for the input variables. The Hybrid learning was selected for predicting (K_u) with ANFIS. Three performance functions namely; root mean squared error (RMSE), mean error (ME) and coefficient of determination (R^2), were used to evaluate the predictive capability of the suggested (ANFIS). The obtained results for testing data (9 points) indicated that the R^2 values relating predicted versus measured estimates of (K_u) was 0.783, ME was found to be 0.118 cm/sec and RMSE was found to be 0.472 cm/sec. As a result, it appears that applying ANFIS suggests a new approach for determining (K_u) along with saving time and cost.

Key words: Soil and water samples; Adaptive Neuro-Fuzzy Inference System (ANFIS).

Knowing hydraulic properties of a soil is play an important role on solving many water management problems during applying soil water flow models (Torabi *et al.*, 2006). Soil hydraulic conductivity represents in two forms namely: saturated hydraulic conductivity and unsaturated hydraulic conductivity (Zhuang *et al.*, 2001). However, the most important soil hydraulic parameters is unsaturated hydraulic conductivity as it characterizes the ability of soil to conduct water when soil pore space is not fully filled with water (Guber, 2007). Additionally, quantifying unsaturated water flow into soil pores requires knowledge of soil hydraulic conductivity (Dane and Topp, 2002). So, equations were proposed to predict unsaturated soil hydraulic conductivity (Amer *et al.*, 2009; Amer *et al.*, 2014).

Direct measurement of soil hydraulic properties in the laboratory or in the field is time consuming and subject to large error (Jabro, 1992). In addition, such measurement of hydraulic conductivity of soil is difficult, tedious, relatively costly , labour intensive and time-consuming (Lakzian *et al.*, 2010; Emami *et al.*, 2012; Kalkhajeh *et al.*, 2012; Fereshte, 2014;Siltecho *et al.*, 2014). Thus, indirect methods using predictive approaches have been developed for estimation of hydraulic properties of soil from easily measurable soil properties (Schuh and Bauder, 1986;

* To whom all correspondence should be addressed.
E-mail: mohazizsu@yahoo.com

Vereecken *et al.*, 1990; Vereecken, 1995). Indirect estimations of the hydraulic conductivity function have gained considerable attention and efforts have been made by researchers to improve the estimates (Skaggs *et al.*, 2001).

A literature review shows that most studies in this line of research have used ANN (Tamari *et al.*, 1996; Ghanbarian-Alavijeh *et al.*, 2010, Moosavi and Sepaskhah, 2012; Nosrati *et al.*, 2012), multiple linear regression technique (Jabro, 1992) and support vector machine (SVM) and a nonlinear statistical regression approach (Elbisy,2015) for predicting the soil hydraulic conductivity.

For describing relationships between different combinations of inputs and outputs such as those that must be determined for accurately predicting soil hydraulic conductivity, ANN is currently the most widely used technique (Erzin *et al.*, 2009; Moosavi and Sepaskhah, 2012). Since Zadeh (1965) proposed the fuzzy logic approach to describe complicated systems, it has become popular and been successfully used to solve prediction purposes in various agricultural and engineering problems (Sarmadian and Mehrjardi, 2010). A recent literature review shows that the use of adaptive-network-based fuzzy inference system (ANFIS) (Jang, 1993; Ho *et al.*, 2011) for such purposes is relatively rare and applied in predicting soil properties in the conditions where there isn't enough information about how parameters relate to each other (El Awady *et al.*, 2002; Minasny *et al.*, 2004; Akbarzadeh *et al.*, 2009; Sezer *et al.*, 2009; Anari *et al.*, 2011; Yilmaz and Kaynar, 2011; Kalkhajeh *et al.*, 2012; Moosavi and Sepaskhah, 2012; Xue and Yang, 2013).

Soft computing techniques such as adaptive neuro-fuzzy inference system (ANFIS) are new developed methods which probably can be used for prediction of soil properties (Minasny *et al.*, 2004; Azamathulla *et al.*, 2009). This study was, therefore, conducted to investigate the efficacy of ANFIS technique in developing prediction functions for estimating unsaturated soil hydraulic conductivity. However, ANFIS has shown potential in modeling nonlinear functions. It learns features of the data set and adjusts the system characteristics according to a given error criterion (Jang, 1993).

Adaptive neuro-fuzzy inference system architecture

Using a given input-output data set, ANFIS build a fuzzy inference system whose membership function parameters are adjusted through the learning process (Mohdeb and Mekideche, 2010). Figure (1) illustrates ANFIS architecture for Takagi-Sugeno type fuzzy inference system, where nodes of the identical layer have the same functions. In general, neuro-fuzzy system has input and output layers, and three hidden layers that represent membership functions and fuzzy rules. Each node in a layer receives input signals from a previous layer and transmits its output signals to nodes in the next layer (Mohdeb and Mekideche, 2010). In the adaptive network, the circle nodes describe fixed nodes and square nodes describe adaptive nodes.

Adaptive nodes have parameter sets while fixed nodes have none. The parameter sets are computing according to given training data and a learning procedure for complete a desired input-output data set (Mohdeb and Mekideche, 2010). 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 $f_1=a_1x_1+b_1x_2+q_1$……………………………………(1)

Rule 2: If x_1 is A_2 and x_2 is B_2, then $f_2=a_2x_1+b_2x_2+q_2$…………………………………..(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 (1) and consists of five layers (Jang, 1993).

In the first layer (fuzzy layer), x1 and x2 are the inputs of adaptive nodes Ai and Bi, respectively. Ai and Bi are the linguistic labels used in the fuzzy theory for describing the membership functions. 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.

$$O_{i,1} = \mu_{Ai}(x_1) \qquad i = 1, 2 \qquad ...(3)$$

or

$$O_{j,1} = \mu_{Bj}(x_2) \qquad i = 1, 2 \qquad ...(4)$$

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.

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, labeled Đ, is a stable node which multiplies incoming signals and sends the product out.

$$O_{2,i} = W_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2) \qquad i = 1,2 \quad ...(5)$$

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

$$O_{3,i} = \overline{W_i} = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \quad ...(6)$$

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: Where, 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.

$$O_{4,i} = \overline{W_i} f_i = \overline{W}(a_1 x_1 + b_1 x_2 + q_i) \qquad i = 1,2 \quad ...(7)$$

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

$$O_{5,i} = Y = \sum_{1}^{2} \overline{W_i} f_i = \frac{\sum_{1}^{2} \overline{W_i} f_i}{\sum_{1}^{2} \overline{W_i}} \quad ...(8)$$

MATERIALS AND METHODS

Soil and water samples characteristics and the select input variables

The experiments were conducted on soils located at different sites in Saudi Arabia during year of 2015. However, the experiments were conducted in the field. Three samples of the studied soil were taken by augur from the top 20 cm for soil moisture content and soil bulk density analysis. Other samples were taken for textural analysis, which showed that the samples could be classified as sand, sandy loam, loam and loamy sand. The initial soil water content (dry base) of the samples was measured by the help of electric oven for 24 h at 105°C. The characteristics of water used in filed experiments were measured in the laboratory using the standard methods.

To represent all soil components (sand, silt and clay) in one index, a soil texture index was determined (Oskoui and Harvey, 1992) to represent soil texture components as follows:

$$STI = \frac{\log\left(S_i^{CC_a}\right)}{100} \quad ...(9)$$

Where S_i and CC_a are % of silt and clay fractions in the soil, respectively. Meanwhile, the sand fraction is represented implicitly since the sum of sand, silt and clay fractions is always constant. Oskoui and Harvey (1992) showed that the STI reflects the effects of all three the soil fractions. The STI produces unique numbers for every combination of sand, silt and clay contents. Sodium adsorption ratio (SAR) is a measure of the sodicity of soil, as determined from analysis of water extracted from the soil. The formula for calculating sodium adsorption ratio for water and soil is as follows (Suarez et al., 2008):

$$SAR = \frac{Na^+}{\sqrt{\frac{1}{2}\left(Ca^{++} + Mg^{++}\right)}} \quad ...(10)$$

Where Na^+, Ca^{++}, and Mg^{++} represent concentrations expressed in milliequivalents per liter (meq/L).

By the help of the obtained water and soil salinities, the ECRatio (electric conductivity of water divided by l electric conductivity of soi) was determined to be the first input variable. Also, SARRatio (sodium adsorption ratio of water divided by sodium adsorption ratio of soil) was determined to be the second input variable. STI which calculated from clay, sand and silt was considered to be the third input variable. The rest input variables were suction rate (SR), organic matter in the soil (OM), initial soil moisture content (MC) and initial soil bulk density (BD). The combination during field experiments created 148 data points. Table (1) illustrates some of values of input variables and output variable.

Measurement of unsaturated soil hydraulic conductivity in the field

The unsaturated soil hydraulic conductivity (K_u) was measured in the field (Figure 2) using a mini disk infiltrometer (Decagon Devices

Inc.) with assistance of some calculations which are provided as excel worksheet soil (Decagon Devices Inc., 2012). The mini disk infiltrometer consists of two chambers (water reservoir and bubble chamber), which are connected via a Mariotte tube to provide a constant water pressure head of -0.5 to -7 cm (equivalent to -0.05 to -0.7 kPa).The bottom of the mini disk infiltrometer contains a porous sintered steel disk. The water filled tube is placed upon the soil surface (Figure 2) resulting in water infiltrating into the soil, with the volume of water and speed of infiltration depending on the sorptivity and hydraulic conductivity of the soil. A pressure head (suction rate) of -1 to -6 cm (equivalent to -0.1-0.6 kPa) was chosen in this study. All measurements within one sample test were taken on the same day. The mini disk infiltrometer measurements were taken three times for every soil sample. During the measurement, the volume of the water in the reservoir chamber was documented in regular intervals.

Calculating of unsaturated soil hydraulic conductivity (K_u)

The method proposed by Zhang (1997) is quite simple and works well for measurements of infiltration into dry soil from the recorded data by mini disk infiltrometer (Decagon Devices, 2012). The method requires measuring cumulative infiltration vs. time and fitting the results with the function:

$$I = C_1 t + C_2 \sqrt{t} \quad ...(11)$$

Where I is the cumulative infiltration (cm), t is the time (*sec*), and C_1 (cm/sec) and C_2 (cm/sec$^{-0.5}$) are parameters. C_1 is related to hydraulic conductivity and C_2 is related to soil sorptivity. The hydraulic conductivity (K) of the soil is then computed from

$$K = \frac{C_1}{A} \quad ...(12)$$

Where C_1 is the slope of the curve of the cumulative infiltration vs. the square root of time and (A) is a value relating the van Genuchten parameters for a given soil type to the suction rate and radius of the infiltrometer disk. (A) is computed from:

$$A = \frac{11.65\left(n^{0.1}-1\right)\exp\left[2.92(n-1.9)\alpha h_0\right]}{(\alpha r_0)^{0.91}} \qquad n \geq 1.9 \quad ...(13)$$

$$A = \frac{11.65\left(n^{0.1}-1\right)\exp\left[7.5(n-1.9)\alpha h_0\right]}{(\alpha r_0)^{0.91}} \qquad n < 1.9 \quad ...(14)$$

Where *n* and α are the van Genuchten parameters for the soil, r_0 is the disk radius and h_o is the suction at the disk surface.

Building of adaptive neuro-fuzzy inference system (ANFIS) for unsaturated soil hydraulic conductivity prediction

In the current study, ANFIS was used to model the relationship between inputs represented characteristics of irrigation water and soil and actual field measurements of unsaturated soil hydraulic conductivity under no changes of the soil conditions. The model was implemented using the fuzzy logic toolbox of MATLAB (2002), a Sugeno type of approach (Takagi and Sugeno, 1985). To construct ANFIS model, the obtained field data were divided into two different groups: training and testing. The training data matrix was composed of 139 data points. 9 data points, which are different from the training data, were used for the testing of the ANFIS model. There are no fixed rules for developing an ANFIS model (Yan *et al.*, 2010).

ANFIS model developed in this research has seven inputs (ECRatio, SARRatio, STI, SR, OM, MC,BD and an output (K_u) as depicted in Figure (3). The numerical ranges for each input were for ECRatio (0.05-3.35 dimensionless), for SARRatio (0.07-2.97 dimensionless), for MC (5.35-15.16%db), for BD (1.22-1.77 g/cm^3), for STI (0.02535-0.1535 dimensionless), for OM (0.97-3.73%) and for SR (-1: -6 cm). For the determination of the best fit in the fuzzy model, types of membership function for input are changed. The "gaussmf" membership functions were the best for each input.

A hybrid learning algorithm was employed to train the ANFIS model. In the ANFIS training process, each epoch is composed from a forward pass and a backward pass. In the forward pass, a training set of input patterns (an input vector) is presented to the ANFIS, neuron output is calculated on the layer-by-layer basis, and rule consequent parameters are identified. As soon as the rule consequent parameters are established, an actual network output vector, y_d, is computed and the error vector (e) is determine as ($e = y_d - y_n$) as y_n is actual output. This process finishes at desired epochs (Jang, 1993).

ECRatio, SARRatio, STI, OM, MC and BD inputs were divided into two Gaussian memberships with two linguistic terms {Small (S), High (H)}. Meanwhile, SR input was divided into four Gaussian membership with four linguistic terms {Small (S), Medium (M), High (H) and very high (VH)}. The training error was 0.00259636 when the type of the membership function was "gaussmf" and output membership function was linear. The final membership functions of the model are shown in Fig. (4).

Specifications of the developed ANFIS are as follows

1. Number of nodes: 554
2. Number of linear parameters: 2048
3. Number of nonlinear parameters: 32
4. Total number of parameters: 2080
5. Number of training data pairs: 139
6. Number of fuzzy rules: 256

A plot of the estimated unsaturated soil hydraulic conductivity predicted by the ANFIS model

from training data versus actual unsaturated soil hydraulic conductivity (Figure 5) shows that the model captured the relationship between the input parameters and unsaturated soil hydraulic conductivity. The correlation R was 1. This value shows that ANFIS can predict the unsaturated soil hydraulic conductivity with a high accuracy. However, training data marked with (o) sign and the check data indicated with the plus sign (+) in the Figure (5).

Statistical performance evaluation criteria

The performance of the developed model is examined using some statistical measures that are well known in literature such as root mean square error (RMSE) and mean error (ME). However, ME has a unit and it is expressed as:

$$ME = \frac{\sum_{j=1}^{n}\left(Y_j - \hat{Y}\right)}{n} \quad ...(15)$$

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

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}\left(Y_j - \hat{Y}_j\right)^2}{n}} \quad ...(16)$$

RESULTS AND DISCUSSION

Descriptive statistics

Descriptive statistics of the used data are shown in Table (2). As indicated from this table, the initial soil moisture content values in the studied soil samples ranged between 5.35%db and 15.16%db with an average value of 10.4%db. It was also found that the OM in the studied soils is

Table 1. Some of values of input and variables output variable.

Input variables							Output variable
ECRatio	SARRatio	STI	SR	OM	MC	BD	Log K_U
(—)	(—)	(—)		%	%db	g/cm^3	cm/sec
1.11	0.72	0.07236	4	1.95	12.54	1.65	-3.11993
1.11	0.72	0.07236	5	1.95	13.67	1.55	-3.29847
0.90	0.51	0.07236	3	1.95	11.63	1.60	-3.04095
0.66	0.37	0.07236	1	1.95	14.50	1.56	-3.15499
0.66	0.37	0.07236	3	1.95	13.01	1.56	-3.20755
0.66	0.37	0.07236	6	1.95	12.00	1.55	-3.61421
0.47	0.45	0.07236	1	1.95	10.32	1.63	-2.74532
0.47	0.45	0.07236	2	1.95	10.05	1.58	-2.77886
0.47	0.45	0.07236	4	1.95	8.07	1.65	-3.0361
0.47	0.45	0.07236	5	1.95	13.04	1.52	-3.23777
0.87	0.61	0.07236	1	1.95	10.82	1.63	-2.63068
0.87	0.61	0.07236	2	1.95	8.73	1.49	-2.70512
0.87	0.61	0.07236	3	1.95	11.16	1.57	-3.0156
0.87	0.61	0.07236	5	1.95	10.81	1.59	-3.4234
0.87	0.61	0.07236	6	1.95	12.29	1.53	-4.52031

low, ranging from 0.97- 3.75%, with an average of 2.19%. Additionally, initial soil bulk density of the studied soils was in the range of 1.22-1.77g/cm^3 with an average value of 1.64 g/cm^3. The ECRatio (irrigation water salinity divided by soil salinity) was in the range of 0.051– 3.348 dimensionless with an average of 1.22 dimensionless. However the studied range of ECRatio could be allow to use different irrigation water salinity in different soil salinity to get wide range ECRatio. Moreover, SARRatio (sodium adsorption ratio of water divided by sodium adsorption ration of soil) was in the range of 0.075–2.97 dimensionless with an average of 1.4 dimensionless. However the studied range of SARRatio could be allow to use different irrigation water quality in different soil having different percentages of sodium concentration to get wide range of SARRatio. Additionally, STI (calculated from clay sand and silt) was in the range of 0.0254-0.1535 dimensionless with an average of 0.07dimensionless. However, STI allows different soils could be tested. Table (2) revealed that there was little variability in the sample distributions of the variables used in this study to develop unsaturated soil hydraulic conductivity prediction models, indicating that their values were all

Table 2. Summary statistics of soil properties, topographic and vegetation attributes used in developing the unsaturated soil hydraulic conductivity prediction models

Parameter	Descriptive statistics					
	Mean	Minimum	Maximum	Variance	Standard deviation	Skewness
ECRatio (-)	1.22	0.051	3.348	0.333723	0.577687	0.822749
SARRatio (-)	1.4	0.075	2.97	0.668552	0.81765	0.306609
STI (-)	0.07	0.0254	0.1535	0.000979	0.031294	0.514429
SR (-)	3.68	1	6	3.116463	1.765351	-0.10848
OM (%)	2.19	0.97	3.75	1.320498	1.149129	0.417279
MC (%,db)	10.4	5.35	15.16	8.666136	2.94383	-0.15317
BD (g/cm^3)	1.64	1.22	1.77	0.009861	0.099301	-1.6121

Table 3. Calculated coefficient correlations between used variables

Variable	ECRatio	SARRatio	STI	SR	OM	MC	BD
ECRatio	1						
SARRatio	0.588	1					
STI	-0.419	-0.725	1				
SR	0.001	-0.133	0.253	1			
OM	-0.421	-0.147	0.446	-0.056	1		
MC	-0.428	-0.462	0.675	0.013	0.802	1	
BD	0.248	0.596	-0.705	-0.244	0.069	-0.293	1
LogK_U	0.214	0.541	-0.541	-0.581	-0.103	-0.314	0.543

normally distributed. Additionally, Figure (6) shows the scatter plot matrices displaying interrelations between the input variables (i.e ECRatio, SARRatio, soil texture index, suction rate, organic matter in the soil, initial soil moisture content and initial soil bulk density) and unsaturated soil hydraulic conductivity (log K_u). This figure depicted the dependencies between the unsaturated soil hydraulic conductivity and input variables; however, the existing patterns and trends seem to be relatively complex and difficult. However, it seems that the input variables may directly or indirectly affect the unsaturated soil hydraulic conductivity and thus ANFIS or similar techniques might be useful to be used to derive the functions translating such data into predictions of unsaturated soil hydraulic conductivity.

Table (3) presents the calculated simple linear correlation coefficients (r) between unsaturated soil hydraulic conductivity (logK_U)

and input variables. It was found that there is a positive correlation between $\log K_U$ with ECRatio (r=0.214). Also, positive correlation between $\log K_U$ with SARRatio was observed (r=0.541) and positive correlation was observed between $\log K_U$ with BD (0.543). It is demonstrated that negative correlations were observed among $\log K_U$ with STI (r=-0.541), with SR (r=-0.581), with OM (r=-0.103) and with MC (r=-0.314).This indicates that increasing values of OM, MC and STI of soil will decrease unsaturated soil hydraulic conductivity.

Performance of ANFIS model for unsaturated soil hydraulic conductivity prediction

A plot of the predicted unsaturated soil hydraulic conductivity by the ANFIS model versus testing data (Figure 7) and Figure (8) shows the scatter plot and line of best fit. The two figures show that the model captured the relationship between the input parameters and unsaturated soil hydraulic conductivity. The coefficient of determination (R^2) was 0.7834. This value shows that ANFIS can estimate unsaturated soil hydraulic conductivity with a high accuracy. ME and RMSE values for the ANFIS model for testing data are 0.118 cm/sec 0.472 cm/sec, respectively. By browsing ME and RMSE values and additionally R^2 value, it is indicated that the ANFIS model is a useful tool for modeling unsaturated soil hydraulic conductivity. Figure (9) depicts the input–output surface yielded. Focusing on the three dimensional surface graphs of the two selected input and one output, it is possible to conclude that, there are nonlinear relationship among the parameters and unsaturated soil hydraulic conductivity.

a) The present research used the ANFIS and the training data collected through field experiments to construct the predicted model to estimate the unsaturated soil hydraulic conductivity. The predicted model was verified by comparing the

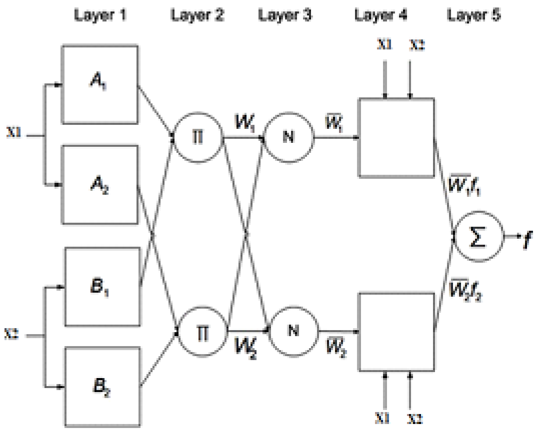

Fig. 1. ANFIS architecture

Fig. 2. Mini disk infiltrometer used in the field for measuring unsaturated hydraulic conductivity

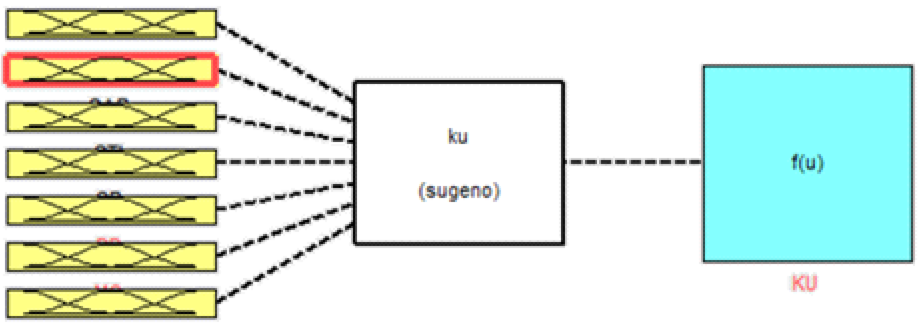

Fig. 3. ANFIS model with seven inputs and one output

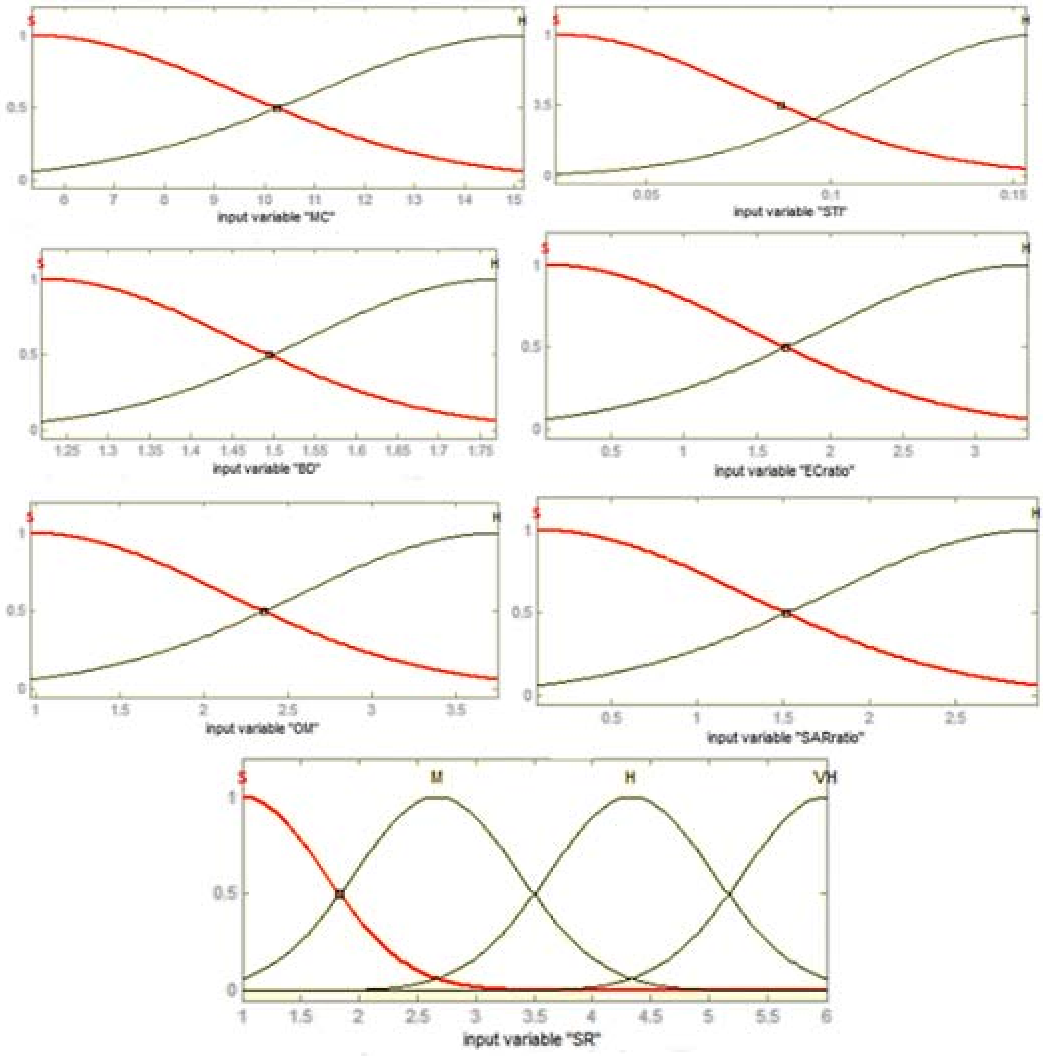

Fig. 4. Final Gaussian membership functions for seven input derived by training process

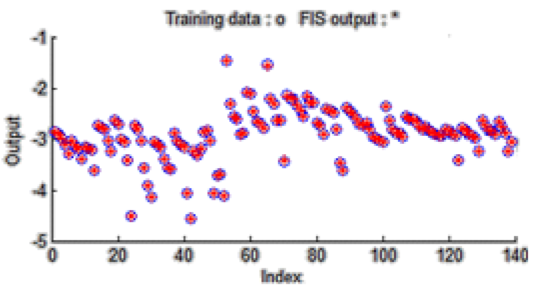

Fig. 5. Pattern of variation of measured and predicted unsaturated soil hydraulic conductivity for the training set

predicted values with the checking data. Based on our research, the following conclusions are drawn:

b) The model constructed using the ANFIS (Sugeno method) can effectively predict unsaturated soil hydraulic conductivity by using seven parameters (ECRatio, SARRatio, soil texture index, suction rate, organic matter in the soil, initial soil moisture content and initial soil bulk density).

c) The mean absolute error value equal to 0.472 cm/sec suggests that the model is properly trained and appropriate inputs are used for modeling.

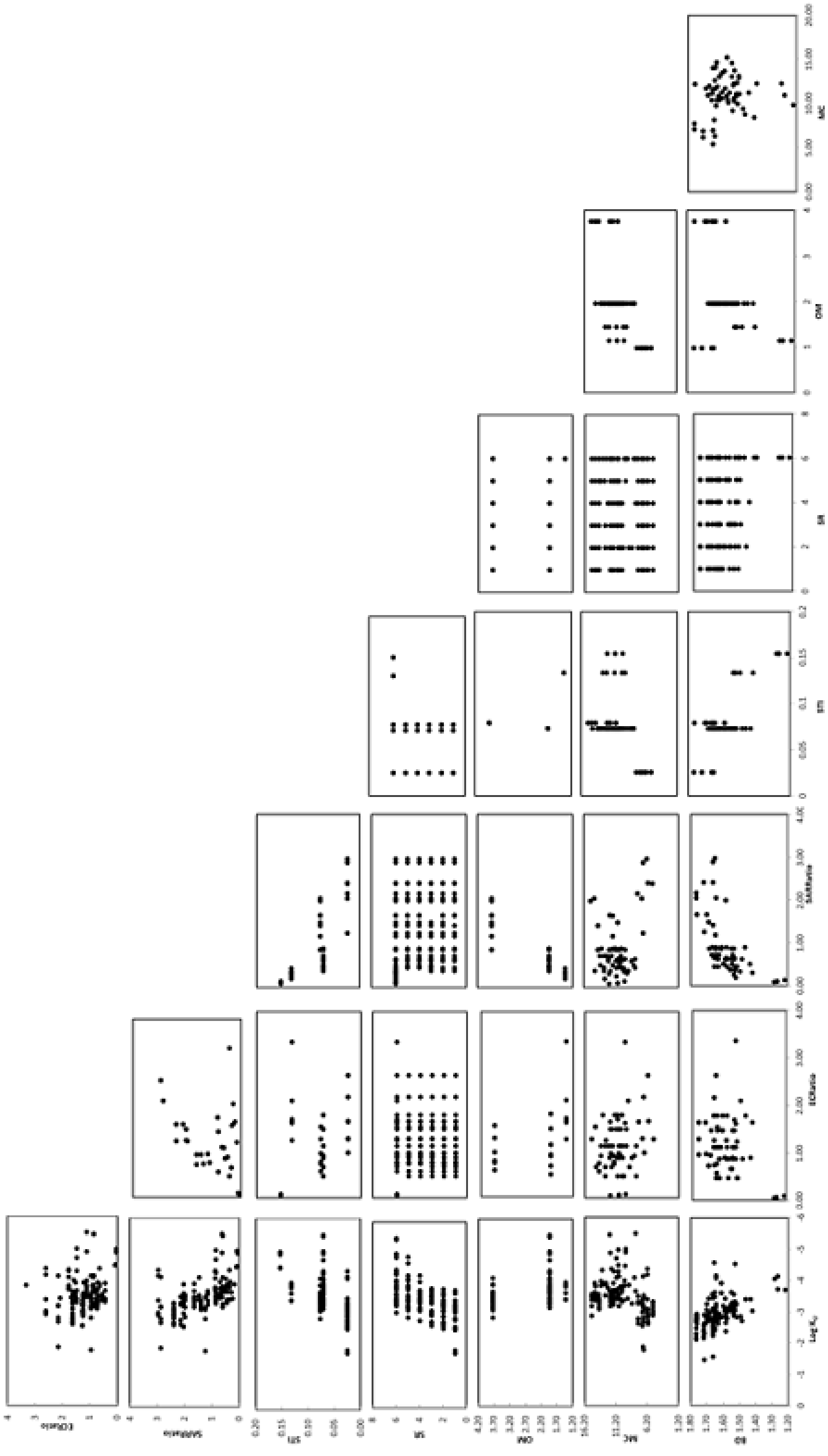

Fig. 6. Scatter plot matrices displaying the relationships between the analyzed variables EC ratio (water electric conductivity divided by soil electric conductivity), SAR ratio (sodium adsorption ratio of water divided by sodium adsorption ration of soil), soil texture index (calculated from clay sand and silt), suction rate, organic matter in the soil, initial soil moisture content and initial soil bulk density and unsaturated soil hydraulic conductivity (log K_u).

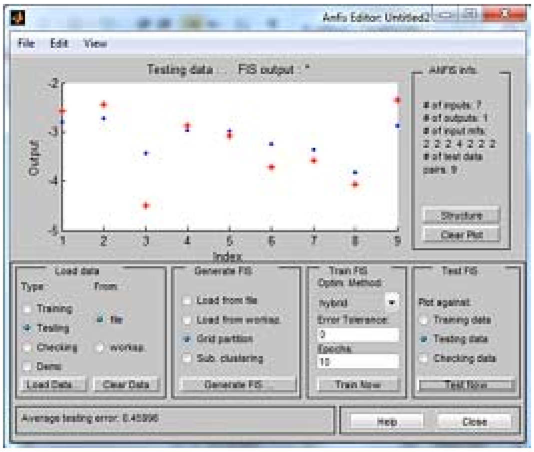

Fig. 7. Testing data and FIS output

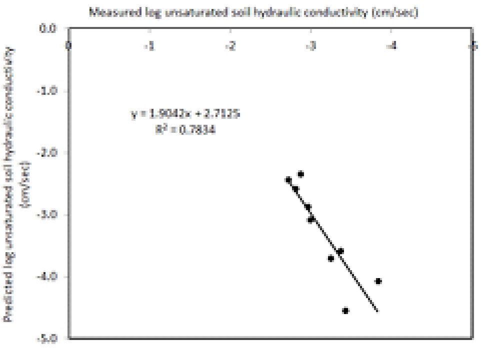

Fig. 8. Scatter plot and line of best fit

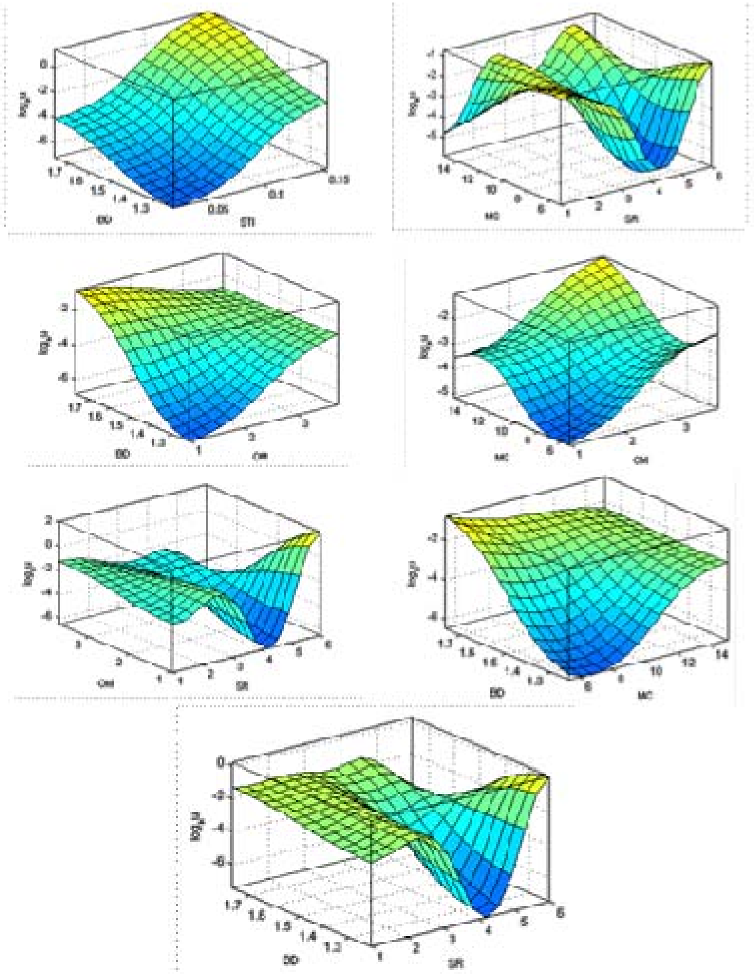

Fig. 9. Diagram of relationship between different input variable and output (log K_U)

d) The ANFIS could account for approximately 78.3% of variation in the test data set. In conclusion, the obtained results demonstrate that the ANFIS presented in this study can be used as a tool to predict unsaturated soil hydraulic conductivity.

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