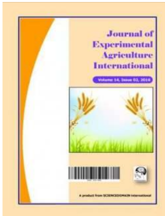

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Modelling of Sodium Adsorption Ratio of the Soil Using Adaptive Neuro Fuzzy Inference System

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Authors' contributions

This work was carried out in collaboration between all authors. Author AMA managed the laboratory experiments, performed both the statistical analysis and ANFIS analysis, managed the literature review and wrote the first draft of the manuscript. Author MSEM collected the required data, participated in data analysis, managed the literature review and wrote the first draft of the manuscript. Author AMG reviewed the data, participated in data analysis and in writing the first draft of the manuscript. Author AIE participated in the statistical analysis, managed the literature review and participated in writing the first draft of the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

Soil management for crop production is a major concern for sustainability agricultural. Sodium adsorption ratio (SAR) of the soil is needed to quantify the amount of amendments. The objective of this study was to evaluate the performance of Adaptive Neuro Fuzzy Inference System (ANFIS) for estimating the SAR of the soil. In this research, 153 observations of soil properties were

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collected from literature and actual laboratory analysis and SAR was calculated. Soil electrical conductivity (EC), soil pH, sand, silt and clay percentages were taken as inputs and the SAR in the soil was taken as output. Based on the membership functions, four ANFIS models were tested against the calculated sodium absorption ratio to assess the accuracy of each model. The tested membership functions were triangular-shaped membership function (trimf, ANFIS1), generalized bell-shaped membership function (gbellmf, ANFIS2), trapezoidal-shape membership function (trapmf, ANFIS3) and Gaussian curve membership function (gaussmf, ANFIS4). The results showed that ANFIS4 was the most accurate membership function where the training error was 0.10492. Meanwhile, the training error for ANFIS1, ANFIS2 and ANFIS3 were 0.1945, 0.22751 and 1.4297, respectively. The comparison between results of ANFIS and observed SAR using testing data set shows that the coefficient of determination was 0.9907. Results indicate that ANFIS modeling is a promising alternative to the traditional approach and it significantly decreases calculation time in determining SAR of the soil.

Keywords: Sodium adsorption ratio; ANFIS; soil.

1. INTRODUCTION

Soil management for crop production is a major concern for sustainability agricultural. Such management is necessary to estimate sodium absorption ratio (SAR) in the soil. The sodium absorption ratio of the soil is also considered as one of the important chemical characteristic of the soil [1] and it is a good means for practical management of a soil for quantifying the amount of amendments [2]. Most common method to evaluate the effects of sodium in a soil is by calculating SAR. To estimate soil SAR value, first a soil sample is saturated with distilled water to form a saturated soil paste, then, the excess water is extracted and analyzed is performed to determine the concentration of Na^+ (sodium), Ca^{++} (calcium) and Mg^{++} (magnesium) concentration in the soil sample, then SAR is calculated by using Eq. (1). A soil SAR value below 2 is most desirable, while SAR value above 13 is considered very high, and the soil is classified as sodic (Fig. 1). It is important to note, however, that sodium can potentially cause soil structure deterioration and water infiltration problems at SAR values as low as 5 to 6 [3]. The formula for calculating SAR [4]:

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

Where Na^+, Ca^{++} and Mg^{++} represent concentrations expressed in (meq L^{-1}).

As shown in equation 1, for determining SAR, samples of soil are taken to the soil lab and the tests related to the determination of Na^+, Ca^{++} and Mg^{++} are performed besides high costs which are required to be spent on laboratory materials, requires spending of time. Since laboratory procedures for estimating parameters for SAR calculation are required and this is cumbersome and time-consuming, it is essential to develop an indirect approach for prediction SAR from more readily available soil data.

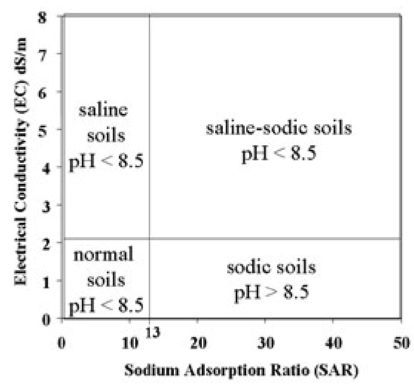

Fig. 1. Classes of salt-affected soils [3]

There is spatial variability of sodium adsorption ratio in areas within the same soil class [5]. Such variation of SAR in the soil is a function of physical and chemical parameters in the soil [6]. So, soil management requires simple but effective SAR estimation approaches, especially from measurable soil properties data. So, the researchers must adopt such approaches to enhance soil management process. The two common methodologies used to estimate SAR in the soil is regression [7-9] and artificial neural network [10] modeling techniques. Regression analysis is generally used to find the relevant coefficients in the model equations. Often, however, models developed for specific soil may not give adequate estimates for other soils. A more advanced approach to model sodium adsorption ratio in the soil is to make use of soft computing methods such as artificial neural network and fuzzy logic. However, fuzzy logic is particularly attractive due to its ability to solve problems in the absence of accurate mathematical models [11]. 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 behavior [12].

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 the field of soil sciences. One of such system is the adaptive neuro-fuzzy inference system (ANFIS) which has established itself as one of the most popular modeling techniques in the fields of control systems, expert systems and the modeling of complex systems and has frequently been used in the last decade due to its flexibility in modeling non-linear processes [13]. It can be used to capture complex and non-linear relationship between data [14].

In soil properties prediction field, Akbarzadeh et al. [15] developed indirect methods to estimate cation exchange capacity (CEC). These methods were multiple linear regression, Neuro-Fuzzy and feed-forward back-propagation network. The inputs were clay and organic carbon. Results showed that Neuro-Fuzzy was superior to artificial neural network and multiple linear regressions in predicting cation exchange capacity (CEC). Fuzzy logic could be used to evaluate soil compaction due to traffic of agricultural implements on different soils [16], also it could be used for prediction of soil penetration resistance based on soil physical properties [17]. Kayadelen et al. [18] used soft computing systems to predict soil internal friction angle. 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 soil internal friction angle. Furthermore, Aali, et al. [19] employed three methods namely artificial neural networks, multiple regression and ANFIS for estimation of saturation percentage of soils. Percent clay, silt, sand and organic carbon were used to develop the applied methods. ANFIS method was found to be superior over the other methods. Yilmaz and Kaynar [20] reported that the use of soft computing may provide new approaches and methodologies, and minimize the potential inconsistency of correlations during prediction of swell potential of clayey soils. They found that ANFIS had good ability to predict swell percent of soil. Besalatpour et al. [21] used ANFIS to build a prediction model for soil physico-mechanical properties management. Aboukarima [22] used ANFIS for predicting cohesion and internal friction angle of cultivated soils. Kianpoor et al. [23] used ANFIS to develop PTFs for predicting the cation exchange capacity of the soil. Five soil parameters including bulk density, $CaCO_3$, organic carbon, clay and silt were considered as input variables for proposed models. Besalatpour et al. [24] used 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. Elsewhere, ANFIS has been applied successfully and has provided high accuracy and reliability in predicting Atterberg Limits (liquid limit, plastic limit, and plasticity index) compared to artificial neural network model [25].

Basically, reclamation or improvement of sodic soils requires simple and effective estimation procedure, especially from measurable soil data to find SAR. Besides, monitoring SAR variability in soils is both time-consuming and expensive. Thus, presenting a method which uses easily obtained measurable soil data to estimate SAR indirectly is more optimal and economical. So, the aim of this research is to develop method to predict SAR in the soil using ANFIS based on measurable soil data. The required data were collected from literature and actual laboratory analysis.

2. MATERIALS AND METHODS

2.1 Data Collection and Laboratory Measurements

153 data points of measured of different soil properties were obtained from literature. These data included electric conductivity of soil (EC), soil pH, sand, silt, clay, Na^+, Ca^{++} and Mg^{++}. The SAR value was calculated to compile SAR database. The database covered wide range of soil EC, soil pH and soil texture. Actual laboratory measurements were performed for 9 soils which collected from different locations in Saudi Arabia and subjected to laboratory analysis to get soil EC, soil pH and components of sand, silt, clay, chemical analysis for Na^+, Ca^{++} and Mg^{++} to calculate.

Table 1. Laboratory analysis and SAR calculation for 9 soils which collected from different locations in Saudi Arabia

Sample code	pH	EC ($dS\ m^{-1}$)	SAR	Sand %	Silt %	Clay %
S1	8.90	2.65	6.70	67	28	5
S2	9.10	10.8	8.20	80	13	7
S3	9.00	5.60	7.60	67	26	7
S4	8.80	5.67	6.10	85	2	13
S5	7.70	1.06	2.70	90	4	6
S6	7.75	1.80	2.00	90	7	3
S7	8.15	3.84	7.60	60	7	33
S8	9.00	2.81	4.30	95	4	1
S9	8.20	91.1	57.6	52	9	39

Table 2. Statistical description for the literature data of the soil SAR, soil EC, soil pH, sand, silt and clay

Statistical criteria	SAR	EC ($dS\ m^{-1}$)	pH	Sand (%)	Silt (%)	Clay (%)
Mean	17.3	9.04	7.98	56.2	26.8	17.0
Kurtosis	19.0	18.8	0.69	-1.27	-0.73	0.36
Skewness	4.04	3.90	0.28	-0.30	0.58	1.15
Minimum	0.18	0.34	6.50	1.00	0.67	0.47
Maximum	271	12.0	9.31	98.7	79.7	60.2
Standard deviation	38.37	16.4	0.49	31.2	20.8	15.6
Count	153	153	153	153	153	153

SAR using standard methods as shown in Table 1. Meanwhile, Table 2 shows statistical description for the whole data of the soil SAR, soil EC, soil pH, sand, silt and clay%.

2.2 Adaptive Neuro-fuzzy Inference System (ANFIS)

ANFIS is a method based on the input–output data of the system under consideration [26]. Success in obtaining a reliable and robust ANFIS network depends mainly on the choice of process variables involved as well as the available data set and the domain used for training purposes [27]. Basically, a fuzzy inference system is composed of five function blocks:

1. A rule base containing a number of fuzzy if-then rules.
2. A database which defines the membership functions of the fuzzy sets used in the fuzzy rules.
3. A decision-making unit which perform the inference operation on the rules.
4. A fuzzification inference which transforms the crisp inputs into degrees of match with linguistic values.
5. A defuzzification inference which transforms the fuzzy results of the inference into a crisp output.

For simplicity, a fuzzy inference system with two inputs x and y, and one output is assumed [28]. In this inference system the output of each rule is a linear combination of input variables added by a constant term. The final output is the weighted average of each rule's output. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if –then rules is defines 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 Fig. 2 and consists of five layers [27]. The five layers of ANFIS model are as follows:

Layer 1: (Input nodes): Each node output in this layer is fuzzified by membership grade of a fuzzy set corresponding to each input.

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

$$O_{j,1} = \mu_{Bj}(x_2) \quad j = 1,2 \tag{3}$$

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 ith 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 Π, is a stable node which multiplies incoming signals and sends the product out.

$$O_{2,i} = W_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2) \quad i = 1,2 \tag{4}$$

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

$$O_{3,i} = \overline{W_i} = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{5}$$

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

$$O_{4,i} = \overline{W_i} f_i = \overline{W}(a_1 x_1 + b_1 x_2 + q_i) \quad i = 1,2 \tag{6}$$

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

$$O_{5,i} = Y = \sum_1^2 \overline{W_i} f_i = \frac{\sum_1^2 \overline{W_i} f_i}{\sum_1^2 \overline{W_i}} \tag{7}$$

ANFIS requires a training data set of desired input/output pair (x_1, x_2…x_m ,*Y*) depicting the target system to be modeled. ANFIS adaptively maps the inputs (x_1, x_2…x_m) to the outputs (Y) through Membership Functions (MFs), the rule base and the related parameters emulating the given training data set.

2.3 Development of a Fuzzy System for Prediction of Soil SAR

Soil EC, soil pH, sand%, silt% and clay% were employed as input parameters to ANFIS. There are no fixed rules for developing an ANFIS model [29]. In this study, a three linguistic terms {L: low, M: Medium and H: High} were utilized. However, the only reason for having three linguistic terms for each input is to reduce the number of rules. Purpose of the training process in ANFIS model is to minimize the error between actual target and ANFIS output. In the performance phase, a new data set (test data) that is not present in the training set is introduced to the learned system for evaluation. If the test error is adequately small, it indicates that the system has a good generalized capability. The ANFIS model was implemented in Matlab software system [30].

To generate fuzzy IF-THEN rules, the first order Takagi-Sugeno system was employed with five inputs. The hybrid learning algorithm is employed to determine the parameters of Sugeno-type fuzzy inference systems. For all membership functions tested, the number of epochs were not altered and fixed to 5 epochs and the corresponding training error was obtained. The training error is the difference between the training data output value, and the output of the fuzzy inference system corresponding to the same training data input value. The number of nodes was 524, number of linear parameters was 1458, number of nonlinear parameters was 45, the total number of parameters was 1503 in the models and number of fuzzy rules was 243. The performances for 4 ANFIS models are obtained.

Different membership functions were tested. They included triangular-shaped membership function (trimf, ANFIS1), generalized bell-shaped membership function (gbellmf, ANFIS2), trapezoidal-shape membership function (trapmf, ANFIS3) and Gaussian curve membership function membership function (gaussmf, ANFIS4). The results showed that ANFIS4 was the most accurate membership function where the training error was 0.10492. Meanwhile, the training error for ANFIS1, ANFIS2 and ANFIS3 were 0.1945, 0.22751 and 1.4297, respectively. The Gaussian curve membership function membership plots after training ANFIS model are presented in Figs. 3 through 7, respectively for EC, pH, sand, silt and clay.

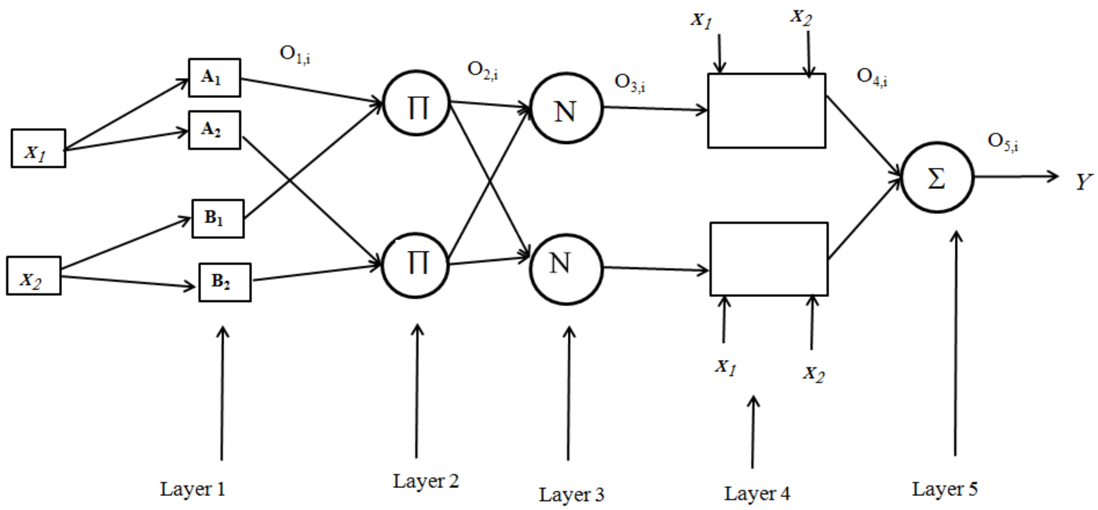

Fig. 2. A typical ANFIS architecture [27]

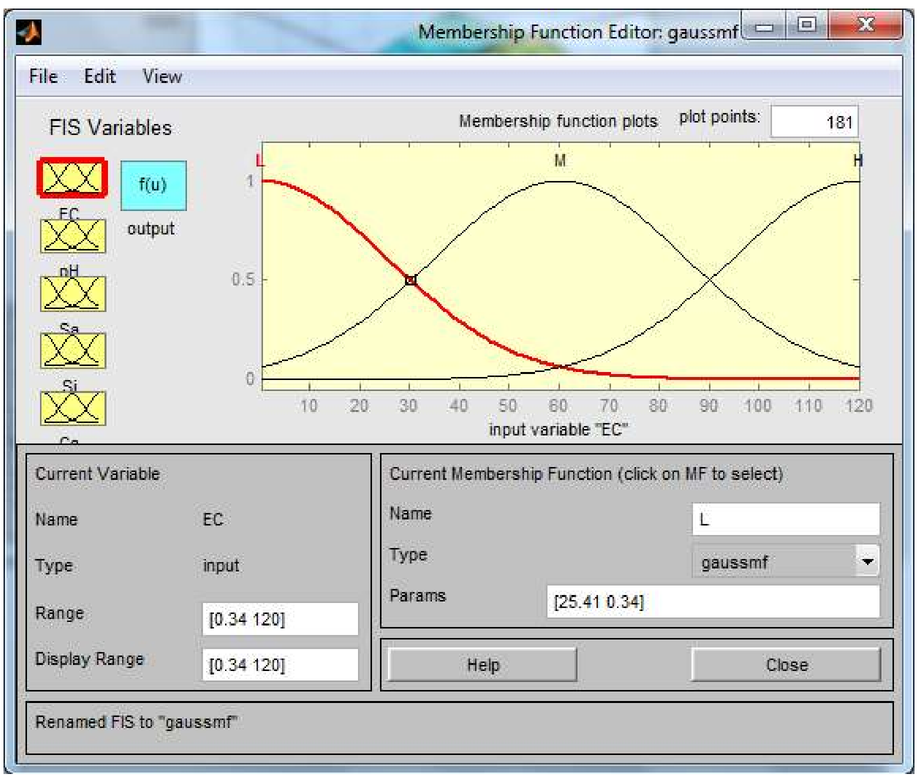

Fig. 3. The Gaussian curve membership function membership plot after training ANFIS for input EC

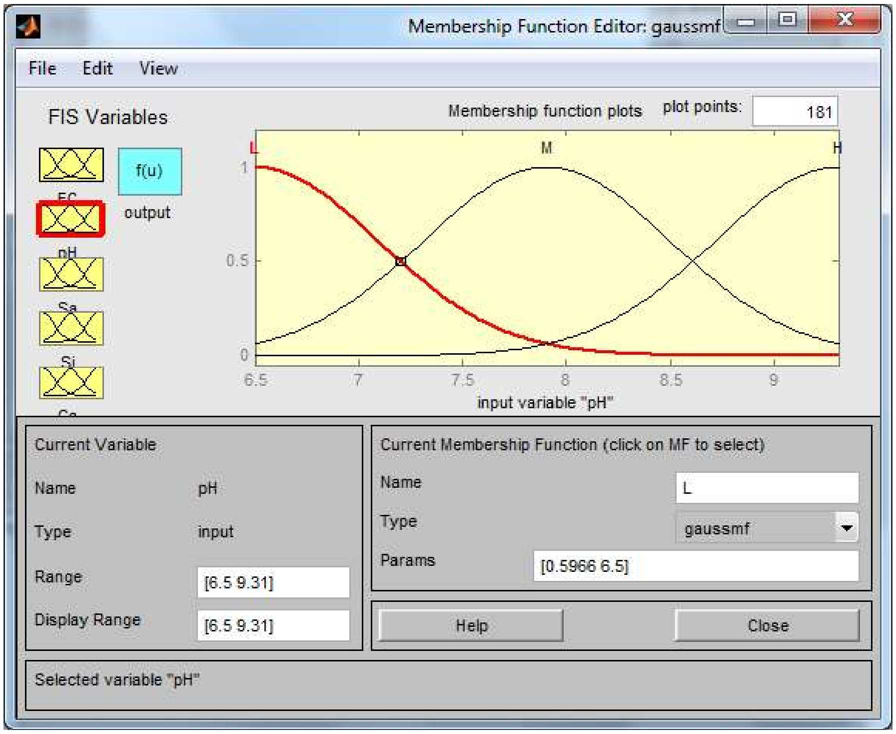

Fig. 4. The Gaussian curve membership function membership plot after training ANFIS for input pH

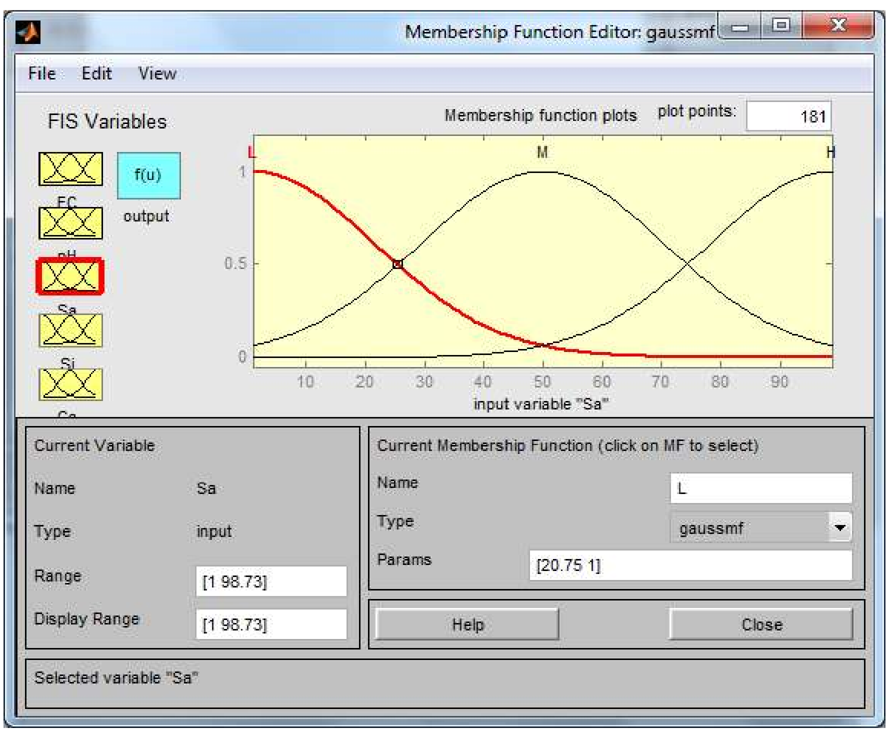

Fig. 5. The Gaussian curve membership function membership plot after training ANFIS for input Sand

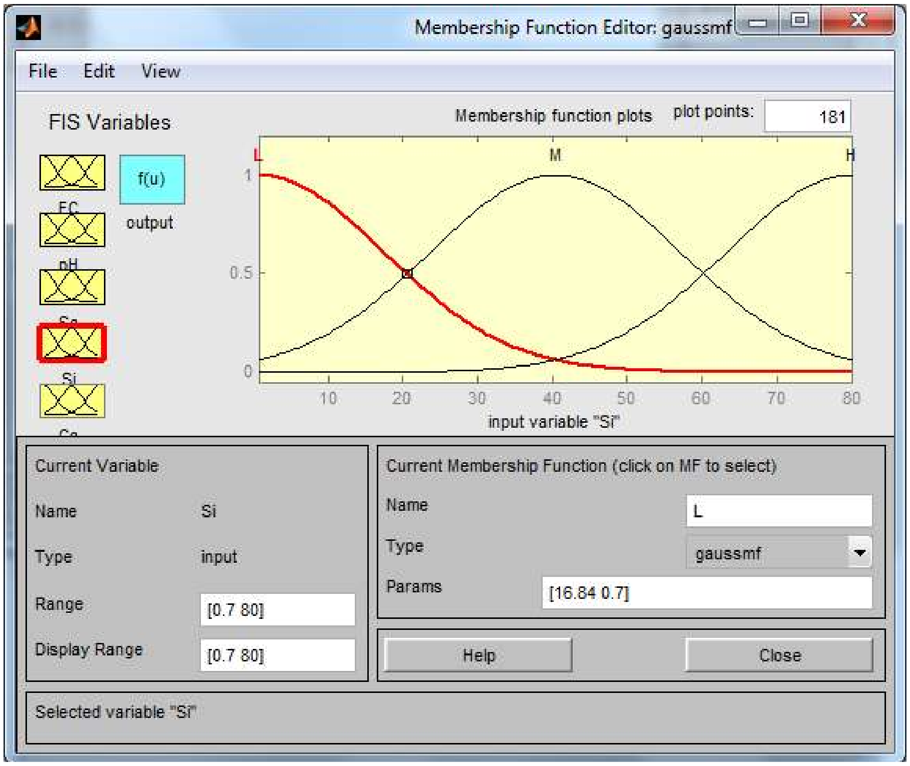

Fig. 6. The Gaussian curve membership function membership plot after training ANFIS for input Silt

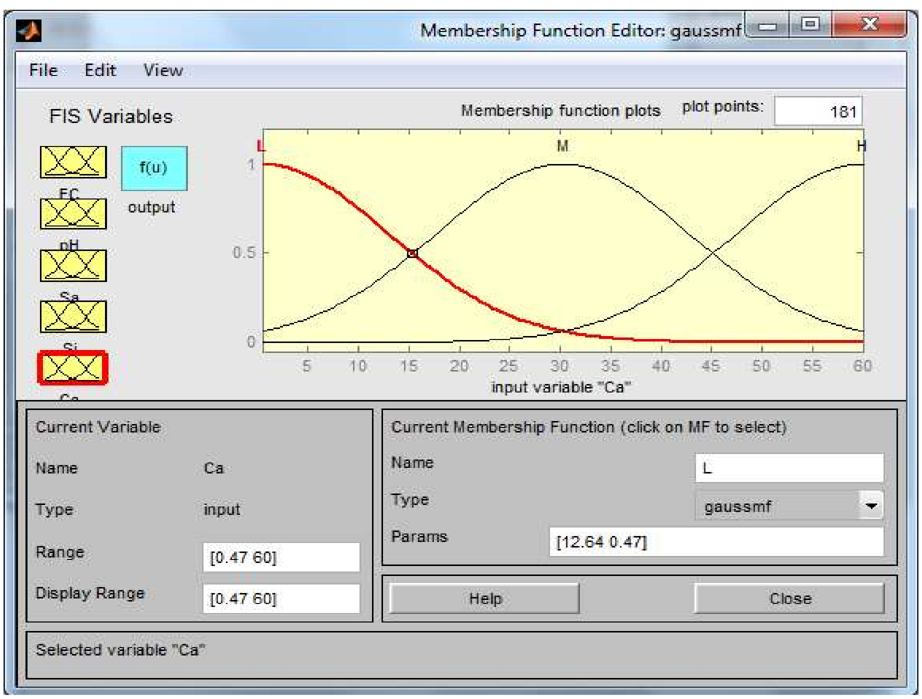

Fig. 7. The Gaussian curve membership function membership plot after training ANFIS for input clay

3. RESULTS AND DISCUSSION

In the present study, easily measurable soil properties parameters were used in the prediction of soil SAR using ANFIS model. However, ANFIS model with four membership functions i.e. triangular-shaped membership function (trimf, ANFIS1), generalized bell-shaped membership function (gbellmf, ANFIS2), trapezoidal-shape membership function (trapmf, ANFIS3) and Gaussian curve membership function membership function (gaussmf, ANFIS4) was trained for iterations of 5. Based on the training error, one model was selected, which was ANFIS model with Gaussian curve membership function membership function (ANFIS4). Plot of training error vs. number of epochs for training data in ANFIS4 is shown in (Fig. 8). Online distribution of predicted and actual SAR in training stage is depicted in (Fig. 9) where ○ symbol indicates actual output and * symbol represents ANFIS data.

The qualitative assessment of the selected model is made by a new data set (test data) that is not present in the training set (9 points) as shown in Table 1. The observed and predicted value using ANFIS4 model is shown in Fig. 10. It is observed from the Fig. 10, that there is a close agreement between the predicted and observed soil SAR, and overall shape of the plot of predicted SAR is similar to that of the observed SAR. Therefore, qualitative performance during training has been found satisfactory. The relationship between observed and predicted SAR using data other than training data and termed as testing data (9 points) as shown in Table 1 is shown in Fig. 11. It is clear that coefficient of determination (R^2) between observed and predicted SAR is 0.9907 as shown in Fig. 11. ANFIS model is powerful tools for building complex nonlinear relationships between inputs and outputs by learning from a data set. The findings of this research could be applied in practice for the indirect monitoring of sodium adsorption ratio.

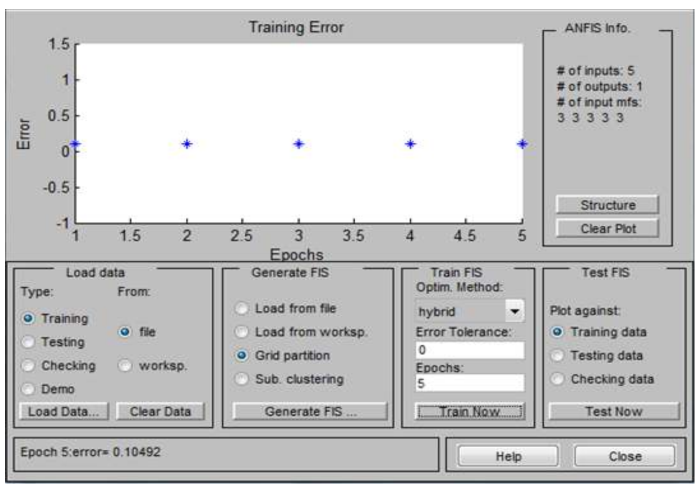

Fig. 8. Plot of training error vs. number of epochs for training data in ANFIS4

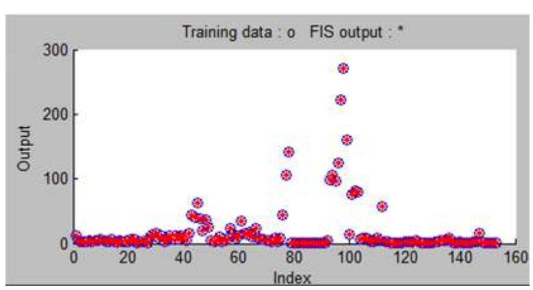

Fig. 9. Online distribution of predicted and actual SAR in training stage is depicted in where ○ symbol indicates actual output and * symbol represents ANFIS data

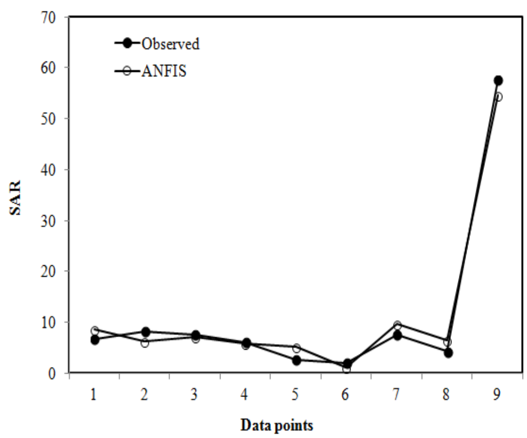

Fig. 10. The observed SAR and predicted SAR using ANFIS4

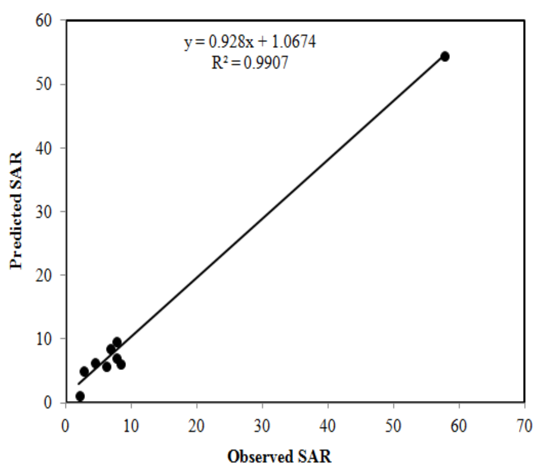

Fig. 11. The relationship between observed and predicted SAR using data other than training data

4. CONCLUSION

In this study, five soil properties including sand, silt and clay percentages, soil electrical conductivity and soil pH are combined together through an ANFIS model to generate a new tool that can be used as a prediction tool for soil sodium adsorption ratio instead of laboratory analysis. The comparison between results of ANFIS and observed SAR using testing data set shows that the coefficient of determination was 0.9907. Results indicate that ANFIS modeling is a promising alternative to the traditional approach and it significantly decreases calculation time in determining soil SAR.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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