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Using Adaptive Neuro Fuzzy Inference System (ANFIS) for Prediction of Soil Fertility for Wheat Cultivation

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ABSTRACT: In this study, an attempt has been made to Adaptive neuro fuzzy inference system (ANFIS) to predict soil fertility using soil phosphorus (P), copper (Cu), manganese (Mn), iron (Fe), zinc (Zn), organic matter (OC) and soil potassium (K) in Fars province, southwest Iran. The paper developed an ANFIS model using Sugeno method. Methodology consist of selection of dependent and independent soil parameter, fuzzification, fuzzy inference rule, membership function and defuzzification process. The results show that the model with error of 1.6543e0.5 and -1.5941e0.5 for train and checked respectively had most accuracy for prediction of fertility. So ANFIS is an efficient method to prediction of soil fertility.

Keywords: Soil fertility, Adaptive neuro fuzzy inference system and Sugeno method.

INTRODUCTION

Artificial neural networks (ANNs), fuzzy inference systems (FIS) and Adaptive neuro fuzzy inference system (ANFIS) have been much popularity as an alternate statistical tools in the modeling of various complex environmental problems (Yilmaz and Kaynar, 2011; Lohani and Krishan, 2015) . Many research try have been managed in relation to modeling various soil parameters through different artificial intelligence (Aqil *et al*, 2007), for estimation of soil erosion and nutrient concentrations in runoff (Kim and Gilley, 2008),for modeling of Pb(II) adsorption from aqueous solution (Yetilmezsoy and Demirel, 2008), for modeling soil cation exchange capacity (Tang *et al*, 2009), to determine of clay dispersibility (Zorluer *et al*, 2010), prediction of soil water retention and saturated hydraulic conductivity (Merdun *et al*, 2006), for estimating of groutability of granular soils (Tekin and Akbas, 2011), land suitability evaluation (Keshavarzi *et al*, 2011), prediction of swell potential of clayey soils (Yilmaz and Kaynar, 2011), comparison of multiple linear regressions and artificial intelligence-based modeling techniques for prediction the soil cation exchange capacity (Kianpoor Kalkhajeh *et al*., 2012) and prediction of soil fractions (Sand, Silt and Clay) in surface layer (Al-Hamed *et al*., 2014).

One of the method to prediction of soil fertility is Adaptive neuro fuzzy inference system (ANFIS) method. ANFIS have been successfully applied as control system in different area such as automatic control, data classification, decision system etc. ANFIS are associated with fuzzy rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers, and simply fuzzy systems (Kaur and Bharti, 2012).

An evaluation of Soil fertility was proposed using soil organic carbon, potassium, phosphorus and salinity factors by fuzzy logic (Salehi, *et al*., 2013). Neuro-Fuzzy Modeled was proposed for crop yield prediction and soil quality assessment by using fuzzy modeling (Stathakis *et al*., 2008; Salehi, *et al*., 2013). Fuzzy logic model can be used to combine soil and crop growth information for estimating optimum N rate (Tremblay, *et al*., 2009).

In the study area, agricultural produce is very important and consists of grain, fruit, and vegetables. The assessment of soil fertility for agricultural production in the study area is vital. So the main purpose of the study is the use of architecture of Adaptive neuro fuzzy inference system (ANFIS) for predictive soil fertility. The methodology employed in this study is summarized in Fig. 1.

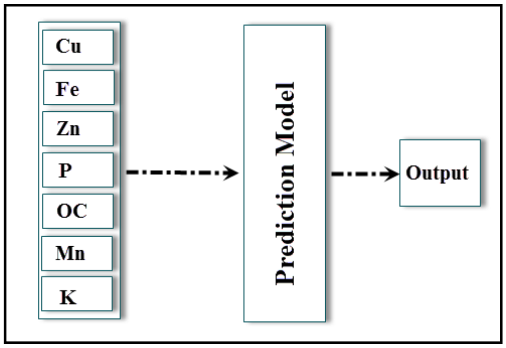


Fig. 1. Flowchart for the methodology used in this study to prediction of soil fertility using Fuzzy inference system (ANFIS).

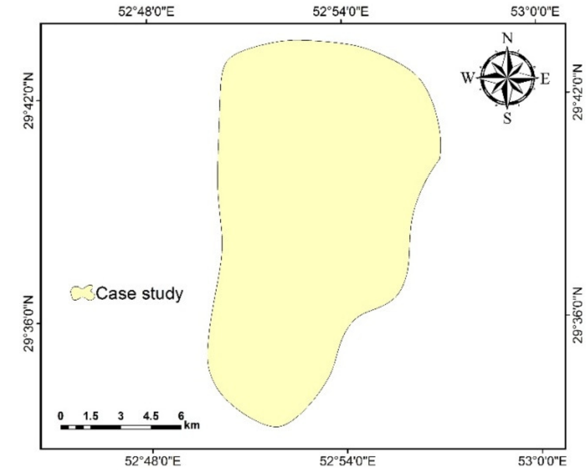


Fig. 2. Location of the study area.

MATERIAL AND METHODS

A. Case study

The study area was located in the Fars Province in the southwest of Iran, between latitudes 29° 33' 00" N-29° 43' 11" N and longitudes 52° 49' 12" E- 52° 57' 00"E with an area 161 km^2 (Fig. 2). The dataset was extracted from a land classification study done by the Fars Soil and Water Research Institute in the year 2012 (Table 1). Table 1 shows that there are a variety of the soil phosphorus (P), copper (Cu), manganese (Mn), iron (Fe), zinc (Zn), organic matter (OC) and soil potassium (K) in the study area.

The properties of data show in Table 1. Base on Table 1, the maximum and minimum value of P is 30 and 2 mg/kg, respectively. While the maximum and minimum value for K is 666 and 137 mk/kg, respectively. OC is between 0.18 to 1.75 %. The maximum value of Fe, Zn, Mn, Cu are 19, 4.7, 52.5 and 2.2 mg/kg, respectively. While the minimum value of Fe, Zn, Mn and Cu area 1, 0.1, 0.5 and 0.2 mg/kg, respectively.

Table 1: The statistic properties of the inputs for fertility.

Statistic parameter	P (mg/kg)	K (mg/kg)	Fe (mg/kg)	Zn (mg/kg)	Mn (mg/kg)	Cu (mg/kg)	OC (%)
maximum	30	666	19	4.7	52.5	2.2	1.75
minimum	2	137	1	0.1	0.5	0.2	0.18
average	14.03	312.48	4.62	0.69	14.51	0.99	1.02
STDEV	6.69	98.64	3.13	0.63	10.73	0.39	0.34

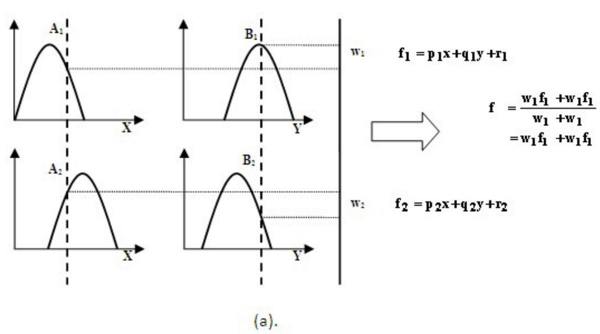
B. Method

Adaptive - Neuro Fuzzy Inference System (ANFIS). Adaptive Neuro-fuzzy Inference System (ANFIS), created by Prof. J.S. Roger Jang 1993, is based on the first-order Sugeno fuzzy model. The ANN paradigm used in a multiplayer feed-forward back-propagation network (Fig. 3).

To understand the working of ANFIS in simple meaning, the fuzzy inference system with two fuzzy IF THEN rules has been discussed here. For Sugeno fuzzy model, a typical rule set with two fuzzy. IF THEN rules can be expressed as ((Bisht and Jangid, 2011).)

Rule1 : IF x is A_1 and y is B_1 THEN $f_1 = p_1x+q_1y+r_1$ (1)

Rule2 : IF x is A_2 and y is B_2 THEN $f_2 = p_2x+q_2y+r_2$ (2)



(a).

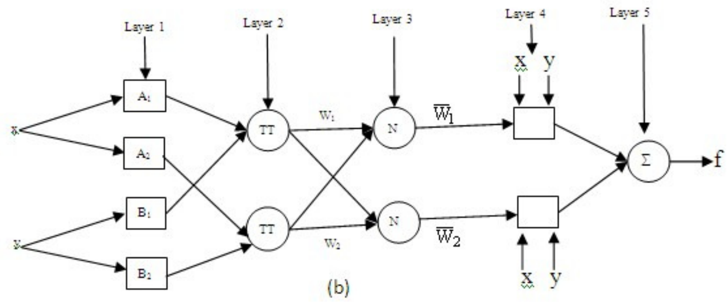


Fig. 3. (a). Fuzzy Reasoning. (b) Equivalent ANFIS (Bisht and Jangid, 2011).

Where, *x* and *y* are the crisp inputs. Ai and Bi are the linguistic labels (low, medium, high, etc.) characterized by convenient membership functions and pi, qi and ri are the consequence parameters (i= 1 or 2). The corresponding equivalent ANFIS architecture can find in Fig. 3 (Bisht and Jangid, 2011).

RESULTS AND DISCUSSION

The Adaptive neuro fuzzy inference system (ANFIS) has made using Fuzzy Logic Toolbox graphical user interface (GUI) tools in MATLAB R2014a. Inputs data for soil fertility was soil phosphor (P), organic matter (OC), soil potassium (K), Cu, Fe, Mn and Zn.

The model of ANFIS for prediction of soil fertility using seven inputs (N, P, OC, Cu, Fe, Mn, Zn) show in Fig. 4. According to Figure 4 with seven inputs and using Sugeno model was predicted soil fertility.

Membership function are specified for seven inputs and one output soil parameter, all of them are presented as below. According to Fig. 5 MF is closer to 0 with decreasing importance of inputs (P, K, Cu, Fe, Mn, Zn, OC) for prediction soil fertility, while MF is closer to 1 with increasing importance of inputs for prediction of soil fertility. According to Figure 5, K value of 300 mg/kg was the best value for prediction of soil fertility that MF value was 1.

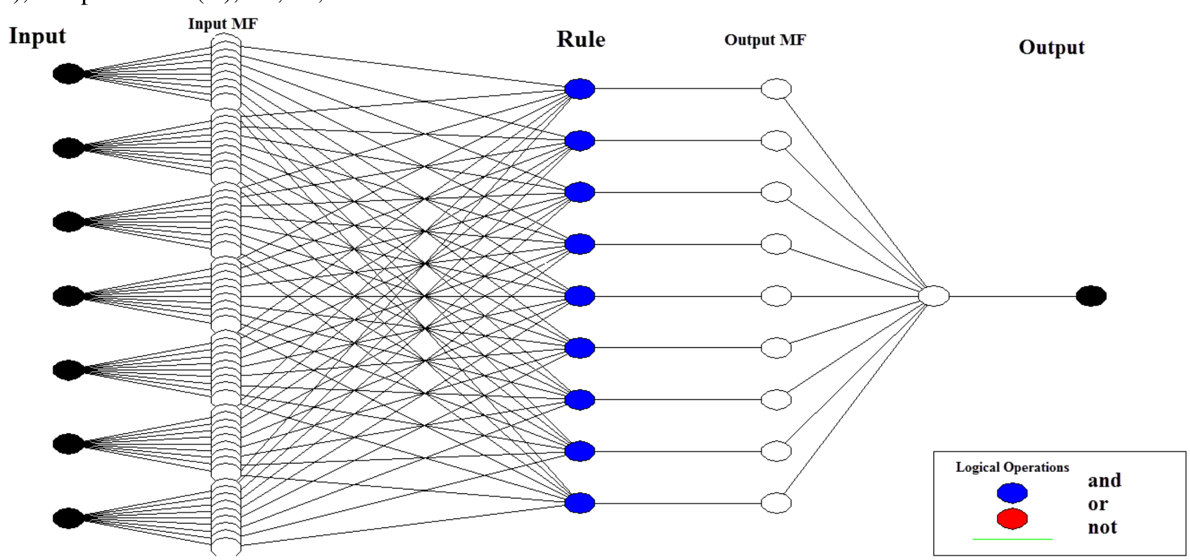
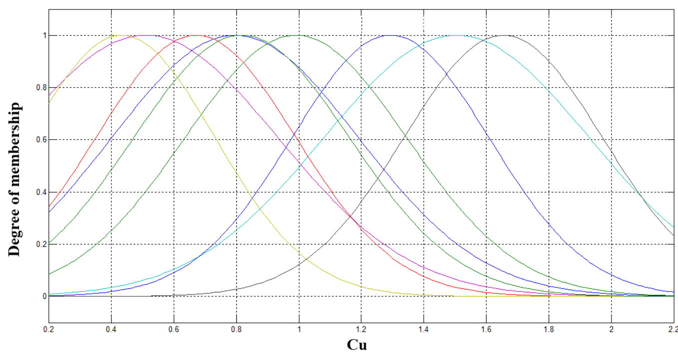
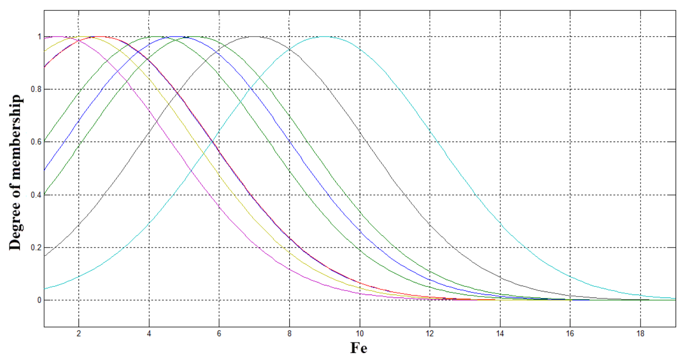


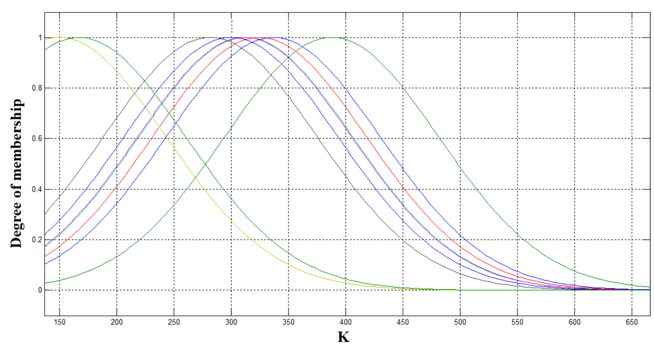
Fig. 4. Developed Fuzzy Inference System.

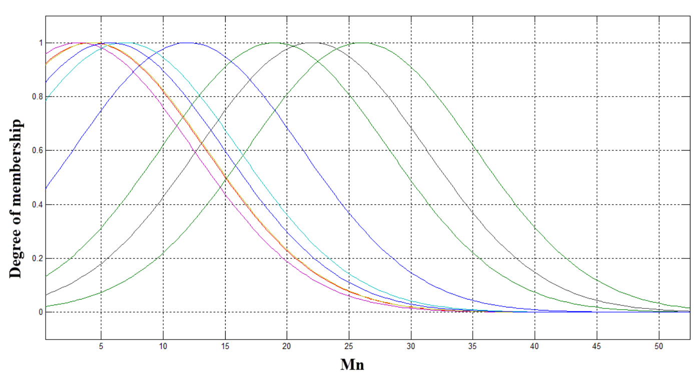
The value of lower and higher than the 300 mg/kg were received MF lower than 1. Also According to Figure 5, OC value of about 1 % was the best value for prediction of soil fertility that MF value was 1. The value of lower and higher than the 1 % were received MF lower than 1. Finally was determined that P value of about 14 mg/kg was the best value for prediction of soil fertility that MF value was 1. The value of lower and higher than the about 14 mg/kg were received MF lower than 1. Zn value of about 0.5 mg/kg was the best value for prediction of soil fertility that MF value was 1. The value of lower and higher than the about 0.5 mg/kg were received MF lower than 1. Mn value of about 25 mg/kg was the best value for prediction of soil fertility that MF value was 1.

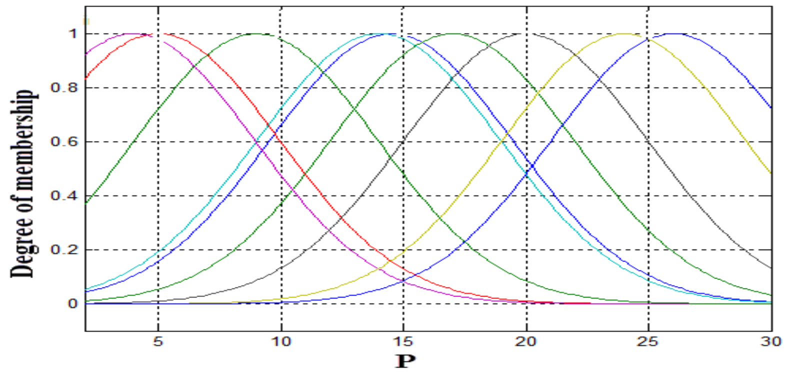
The value of lower and higher than the about 25 mg/kg were received MF lower than 1. Fe value of about 9 mg/kg was the best value for prediction of soil fertility that MF value was 1. The value of lower and higher than the about 9 mg/kg were received MF lower than 1. Cu value of about 1 mg/kg was the best value for prediction of soil fertility that MF value was 1. The value of lower and higher than the about 1 mg/kg were received MF lower than 1.











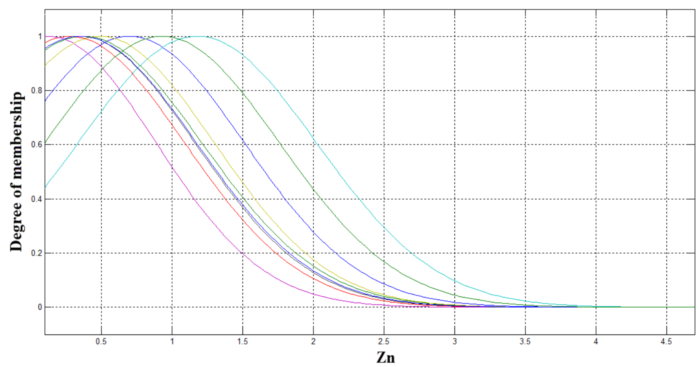


Fig. 5. Membership function for input and output parameters.

Rules were created with the Adaptive neuro fuzzy inference system (ANFIS). The rules was determined using Matlab software automatically. The ANFIS model according train data (soil fertility) and considering the lowest error define rules. Total number of rules are 9 that show in the following.

1. If (in1 is in1cluster1) and (in2 is in2cluster1) and (in3 is in3cluster1) and (in4 is in4cluster1) and (in5 is in5cluster1) and (in6 is in6cluster1) and (in7 is in7cluster1) then (out1 is out1cluster1) (1)
2. If (in1 is in1cluster2) and (in2 is in2cluster2) and (in3 is in3cluster2) and (in4 is in4cluster2) and (in5 is in5cluster2) and (in6 is in6cluster2) and (in7 is in7cluster2) then (out1 is out1cluster2) (1)
3. If (in1 is in1cluster3) and (in2 is in2cluster3) and (in3 is in3cluster3) and (in4 is in4cluster3) and (in5 is in5cluster3) and (in6 is in6cluster3) and (in7 is in7cluster3) then (out1 is out1cluster3) (1)
4. If (in1 is in1cluster4) and (in2 is in2cluster4) and (in3 is in3cluster4) and (in4 is in4cluster4) and (in5 is in5cluster4) and (in6 is in6cluster4) and (in7 is in7cluster4) then (out1 is out1cluster4) (1)
5. If (in1 is in1cluster5) and (in2 is in2cluster5) and (in3 is in3cluster5) and (in4 is in4cluster5) and (in5 is in5cluster5) and (in6 is in6cluster5) and (in7 is in7cluster5) then (out1 is out1cluster5) (1)
6. If (in1 is in1cluster6) and (in2 is in2cluster6) and (in3 is in3cluster6) and (in4 is in4cluster6) and (in5 is in5cluster6) and (in6 is in6cluster6) and (in7 is in7cluster6) then (out1 is out1cluster6) (1)
7. If (in1 is in1cluster7) and (in2 is in2cluster7) and (in3 is in3cluster7) and (in4 is in4cluster7) and (in5 is in5cluster7) and (in6 is in6cluster7) and (in7 is in7cluster7) then (out1 is out1cluster7) (1)
8. If (in1 is in1cluster8) and (in2 is in2cluster8) and (in3 is in3cluster8) and (in4 is in4cluster8) and (in5 is in5cluster8) and (in6 is in6cluster8) and (in7 is in7cluster8) then (out1 is out1cluster8) (1)
9. If (in1 is in1cluster9) and (in2 is in2cluster9) and (in3 is in3cluster9) and (in4 is in4cluster9) and (in5 is in5cluster9) and (in6 is in6cluster9) and (in7 is in7cluster9) then (out1 is out1cluster9) (1)

The Rule Viewer allows to understand the entire ANFIS process at once and shows how the shape of certain membership functions influences the overall result. In this sense, Rule Viewer presents a sort of micro view of the fuzzy inference system as shown in Figure 6. The Figure 6 show that inputs data (. Input 1, input 2, input 3, input 4, input 5, input 6 and input 7 were Zn, P, OC, Mn, K, Fe and Cu respectively) and corresponding values of an average of the range of output (soil fertility) are also equal 0.5.

The Surface Viewer is use for presenting the mapping from seven inputs (Zn, P, OC, Mn, K, Fe and Cu) to one output that for soil fertility show in Figure 7.

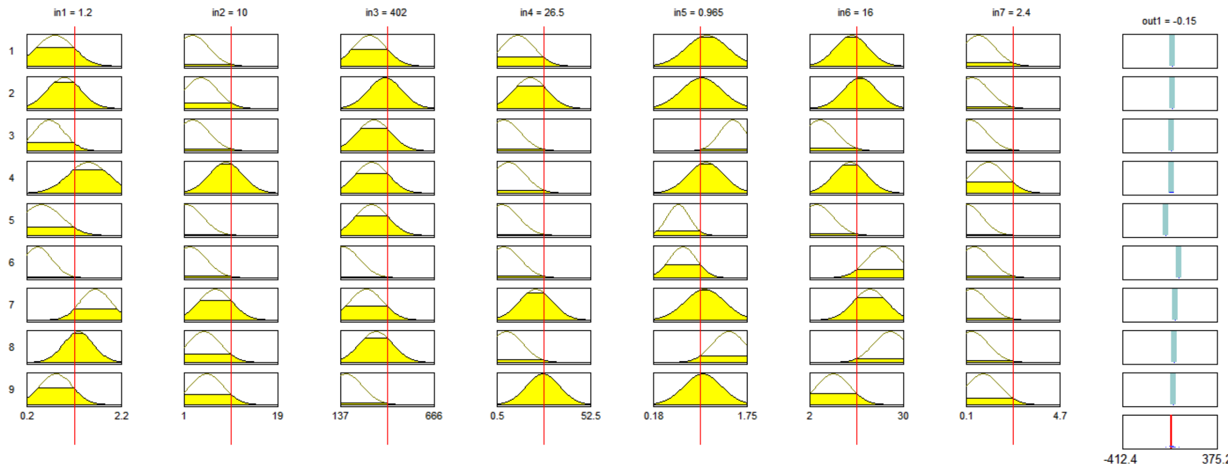


Fig. 6. Rule Viewer for FIS in Fuzzy Logic Toolbox.

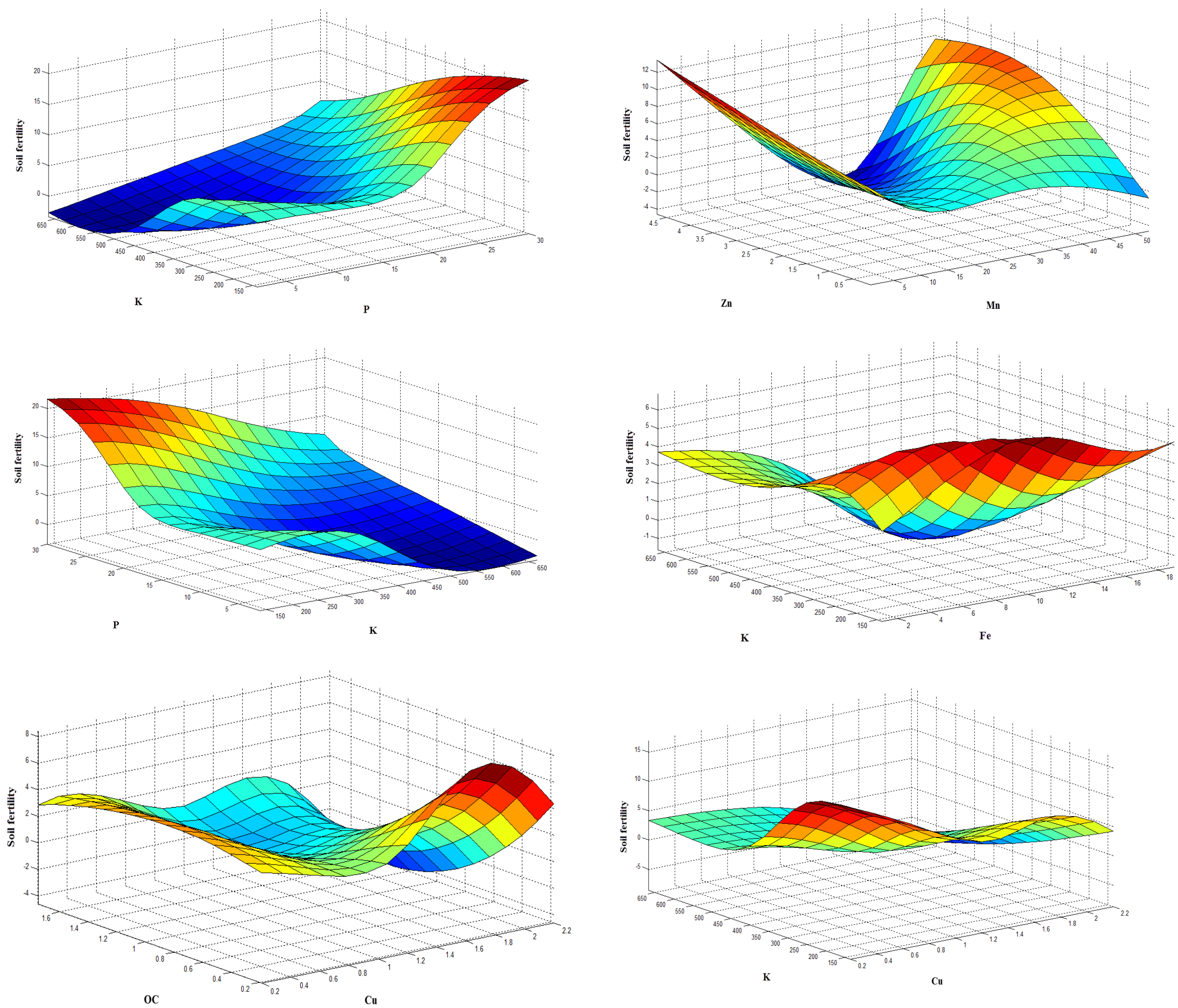
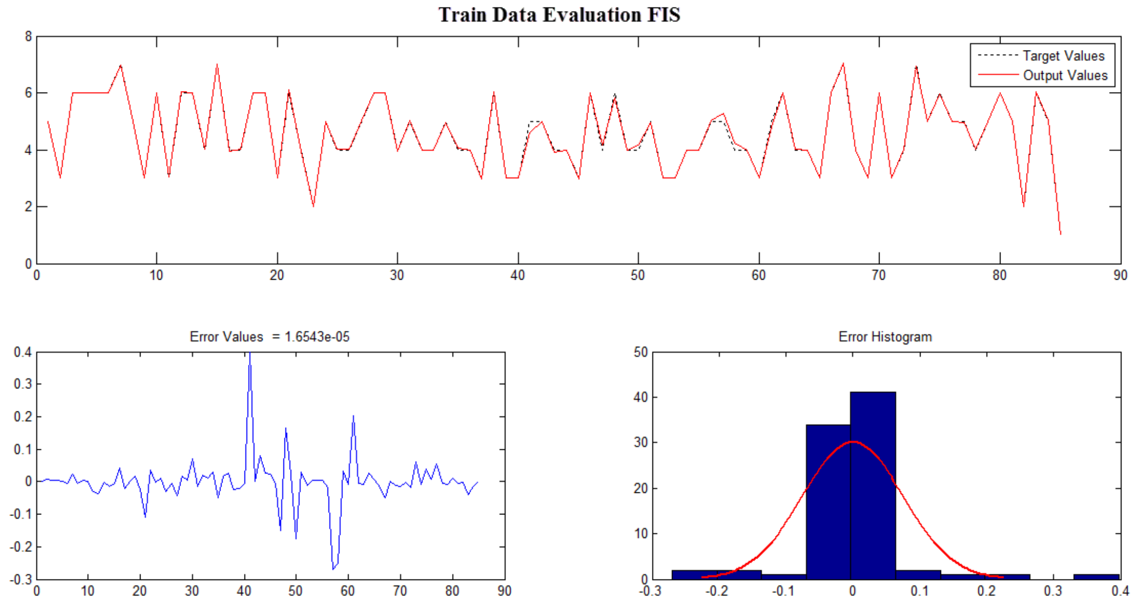
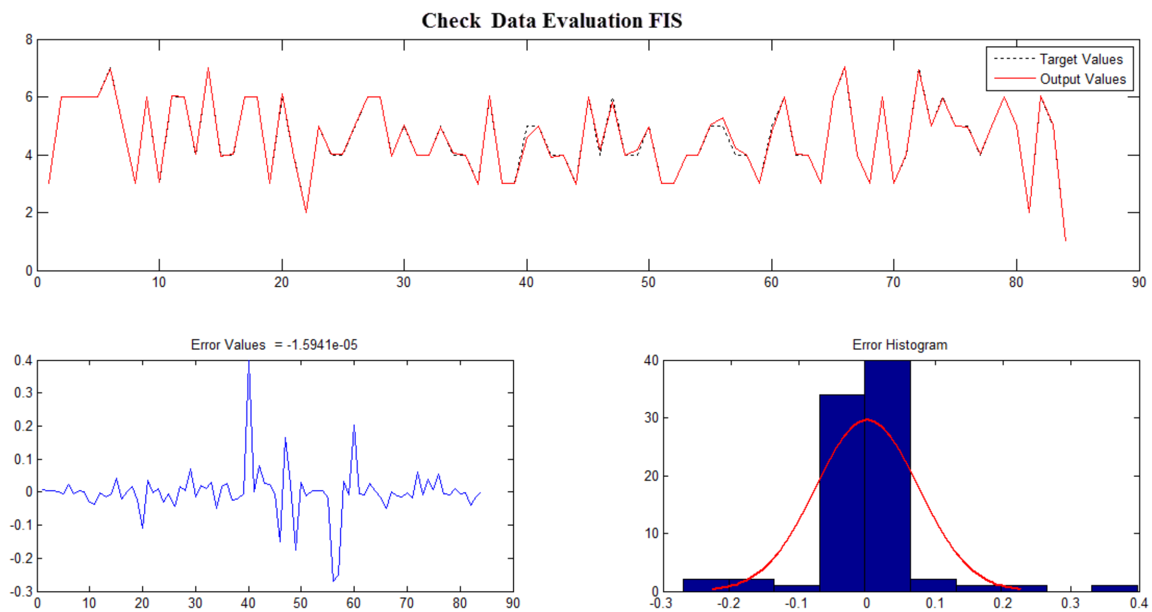


Fig. 7. Surface view of Sugeno type ANFIS.

Finally in order to determination of accuracy modelling of fertility using ANFIS model were train and checked the output of modelling by ANFIS model and target value. The results show that the model with error of 1.6543e0.5 and -1.5941e0.5 for train and checked respectively had most accuracy for prediction of fertility (Fig.8).



(a)



(b)

Fig. 8. Accuracy of check and train data for prediction of fertility (a): train, (b): checked.

Using ANFIS for prediction of soil parameters that their measurement is requires a lot of time and money is very good. In the method, the input and output data category multiple classes that for each class obtains only one law. In fact in areas where there is not enough information or extraction of rules is hard, use ANFIS. The several research used ANFIS for prediction of soil parameters. Such as Kianpoor Kalkhajeh and *et al* (2012) used ANFIS for prediction of saturated hydraulic conductivity (Ks).

The results show that the ANFIS yields had better MSE and R2 for estimating Ks. So using ANFIS is better than the other method such as fuzzy and ANN for prediction of soil parameters.

CONCLUSION

In paper, an attempt is made to prediction of soil fertility in Fars province, Iran based on ANFIS. To make the model data driven, experimental data is used. The model is developed using MATLAB. The paper developed a fuzzy logic model using Sugeno fuzzy inference system. In the model for prediction of soil fertility used to predict soil fertility using Zn, P, OC, Mn, K, Fe and Cu as inputs data. The rules were determined using ANFIS model in Matlab software automatically. The ANFIS model according train data (soil fertility) and considering the lowest error define rules. Also the results show that the model with error of 1.6543e0.5 and -1.5941e0.5 for train and checked respectively had most accuracy for prediction of fertility. So using Gaussian membership function if ANFIS model can prediction soil fertility. The advantage of this model than the other models is definition membership function according train data (soil fertility) automatically. In fact definition membership function using ANFIS model and due to the reduction expert opinion causes that the error probability to be zero.

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