International Journal of Physical Sciences Vol. 5 (1), pp. 047-056, January, 2010
Available online at http://www.academicjournals.org/IJPS
ISSN 1992 - 1950 © 2010 Academic Journals

Full Length Research Paper

Correlation between electrical resistivity and soil-water content based artificial intelligent techniques

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Accepted 19 November, 2009

By using an artificial intelligent approaches, the purpose of this study is to compare water content of soils obtained from electrical resistivity in order to better results from conventional techniques system. The input variables for this system are the electrical resistivity reading, the water content laboratory measurements. The output variable is water content of soils. In this study, 148 data sets are clustered into 120 training sets and 28 testing sets for constructing the fuzzy system and validating the ability of system prediction, respectively. Soil is a heterogeneous medium consisting of liquid, solid, and gaseous phases. The solid and liquid phases play an essential role in soil spontaneous electrical phenomena and in behavior of electrical fields, artificially created in soil. For our aim, study area is selected in Istanbul (Yesilkoy, Florya, Basinkoy) and Golcuk. In this area, the electrical resistivity is measured by VES (Vertical Electrical Sounding) in many points of these locations by field resistivity equipment. For geotechnical purposes, on the soil samples from borings, soil mechanics laboratory procedures was applied and it determined the soil water contents from these samples. Relationships between soil water content and electrical parameters were obtained by curvilinear models. The ranges of our samples are changed between 1 - 50 ohm.m (for resistivity) and 20 - 60 (%, for water content). For this range, it was found that classical regression relation between resistivity (R) and water content (W) of soils was $W = 49.21e^{-0.017R}$. An artificial intelligent system (artificial neural networks, Fuzzy logic applications, Mamdani and Sugeno approaches) based on some comparisons about correlation between electrical resistivity and soil-water content, for Istanbul and Golcuk Soils in Turkey was constructed for identifying water content with electrical resistivity of soils.

Key words: Soils, water content, electrical resistivity, artificial intelligent.

INTRODUCTION

Engineering properties of geomaterials are very important for civil engineers because almost everything they build - tunnels, bridges, dams and others – are in, on or with soils or rocks. For geotechnical engineers, the strength, the stress-deformation behavior and the fluid flow properties of earth materials are of primary concern and form the conventional framework of the geotechnical discipline (Mitchell, 2004).

Conventional techniques for the determination of these engineering properties can be generally divided into three categories – laboratory tests, in-situ tests and geophysical methods. Of these, geophysical methods have been least developed as regards to their suitability for specific quantification of soil properties (Liu, 2007).

Laboratory tests have the advantages of directly measuring the specified engineering properties under controlled boundary conditions and different environmenttal conditions. However, soil samples are usually disturbed during the drilling and sampling processes, which may make the measured engineering properties, deviate from their actual values (Liu, 2007).

Many kinds of electrical fields and potentials are often simultaneously observed in natural soil; thus, it is difficult to know what mechanism is responsible for their formation (Semenov, 1980). Electrical conductivity and resistivity of soils have been investigated in a large num-

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number of studies, which can be divided into three groups.

The first group includes laboratory studies of electrical conductivity and dielectric constant of different dispersed media (including soils) with electromagnetic waves (Jumikis, 1977; Palmer and Blanchar, 1980; Campbell, 1990). These studies help to develop relationship between electrical parameters. quantitative and qualitative compositions of electrolytic solutions (Chang et al., 1983). The relationships were enhanced by the studies of soil electrical parameters with constant electrical field (Rhoades et al., 1976). For some diluted soil solutions and groundwaters the methods are developed to calculate electrical conductivity from the solution compositions. Electrical conductivity of the extracted soil solutions have been studied vigorously (Cambell et al., 1948; Larsen and Widdowson, 1965; Rhoades et al., 1976; Rhoades et al., 1990). The second group of studies is devoted to laboratory measurements of surface electrical conductivity. The surface electrical conductivity is a major parameter describing structure of electrical double layer and its ion composition. There is only limited special research with experimental measurements of surface electrical conductivity in soils (Troizhky, 1979).The third group of studies includes measurements of electrical conductivity of soils, rocks, and sediments in situ with various geophysical methods (Pozdnyakova et al., 1996; Pozdnyakova, 1999).

In the literature the various models proposed to describe relationships between electrical parameters and soil water content, temperature, or salt content. Electrical conductivity and resistivity are usually measured as electrical parameters in laboratory and field conditions. Relationships between soil water content and electrical parameters were measured in field and laboratory conditions and mostly curvilinear models were obtained. Curvilinear relationships were also proposed between electrical resistivity and temperature (Raisov, 1973; Wells, 1978). But, Ananyan (1961) derived and experimentally proved exponential relationship between electrical resistivity, soil temperature, and water content based on a series of experiments.

The assessment of soil water content variations more and more leans on geophysical methods that are non invasive and that allow a high spatial sampling.

Among the different methods, Direct Current (DC) electrical imaging is moving forward. DC Electrical resistivity shows indeed strong seasonal variations that principally depend on soil water content variations (Robain et al., 2003). Although there are many studies between electrical resistivity and water content of agricultural soils, on geotechnical or engineering soils there are little attentions (Asci et al., 2004a, b; Ozcep et al., 2005, Liu et al., 2006).

Background and objective of the this study intends reconstruction of correlation between electrical resistivity and soil-water content by using artificial neural network in this study, our analysis is conducted to set the relationships between soil electrical resistivity and water content.

ARTIFICIAL INTELLIGENT (AI) TECHNIQUES

Artificial neural networks (ANNs) are part of a much wider field called artificial intelligence, which can be defined as the study of mental facilities through the use of computational models (Charniak and McDermott, 1985). They are analogue computer systems, which are inspired by studies on human brain and known to be universal approximators. ANN is made up a large number of highly interconnected processing units (idealized neurons). Each processing unit receives input cells to which it is connected, computes an activation level and transmits it to other units.

They encompass computer algorithms that solve several types of problems. The problems include classifycation, parameter estimation, parameter prediction, pattern recognition, completion, association, filtering, and optimization (Brown and Poulton 1996). ANNs are composed of a large number of highly interconnected processing elements, or neurons, usually arranged in layers. These layers generally include an input layer, a number of hidden layers, and an output layer (Figure 1).

Signals that are generated from the input propagate through the network on a layer-by-layer basis in the forward direction. Neurons in hidden layers are used to find associations within the input data and extract patterns than can provide meaningful outputs (Saemi and Morteza, 2008). A neural network system uses the human-like technique of learning by example to resolve problems. Just as in biological systems, learning involves adjustments to the synaptic connections that exist between the neurons. The output of each neuron, responding to a particular combination of inputs, has an influence (or weight) on the overall output. Weighting is controlled by the level of activation of each neuron, and the strength of connection between individual neurons. Patterns of activation and interconnection are adjusted to achieve the desired output from the training data. Corrections are based on the difference between actual and desired output, which is computed for each training cycle. If average error is within a prescribed tolerance the training is stopped, the weights are locked in and the network is ready to use (Bishop, 1995; Javadi et al., 2005).

Fuzzy logic was first developed by Zadeh (1965) in 1960s for representing uncertain and imprecise information. It provides approximate but effective descriptions for highly complex or difficult to analyze mathematical systems. Fuzzy logic is considered to be appropriate to deal with the nature of uncertainty in system and human error, which are not included in current reliability theories. Unlike classical logic which is based on crisp sets of “true and false,” fuzzy logic views problems as a degree of “truth,” or “fuzzy sets of true and

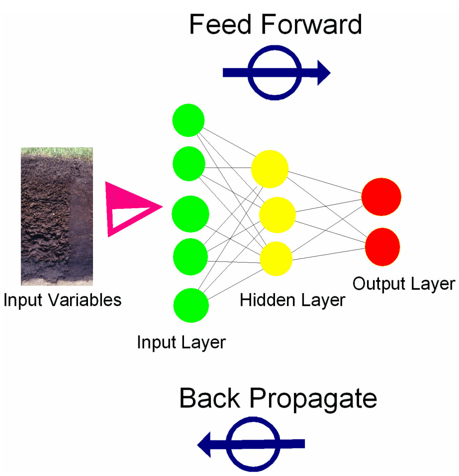

Figure 1. Neural network architecture.

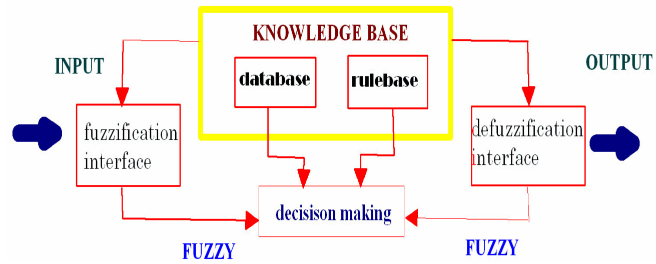

Figure 2. Fuzzy inference system.

false" (Nikravesh, 2004).

Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership.

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all of the pieces that are described in the following:

- Membership function (MF), is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1.The input space is sometimes referred to as the universe of discourse, a fancy name for a simple concept.
- If-then rules, if then rule statements are used to formulate the conditional statements that comprise fuzzy logic. A single fuzzy if-then rule assumes the form if x is A then y is B where A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively. The if-part of the rule "x is A" is called the antecedent or premise, while the then-part of the rule "y is B" is called the consequent or conclusion.
- Fuzzy logic operators, If there are multiple parts to the antecedent, apply fuzzy logic operators (AND, OR, and NOT) and resolve the antecedent to a single number between 0 and 1. This is the degree of support for the rule. Using AND, OR, and NOT functions, we can resolve any construction using fuzzy sets and the fuzzy logical operation.

A general Fuzzy Inference System (FIS) contains four major components: fuzzifier, fuzzy if-then rules base, inference engine, and defuzzifier. There are two types of fuzzy inference systems that can be implemented in the Fuzzy Logic Toolbox: Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined. Prototype publications for interested researchers to descriptions of these two types of fuzzy inference systems are (Mamdani and Assilian, 1975; Kaufmann and Gupta 1985; Jang and Sun 1997).

Fuzzy inference system (FIS) is a rule based on system consisting of three conceptual components. These are: (1) a rule-base, containing fuzzy if-then rules, (2) a database, defining the membership functions (MF) and (3) an inference system, combining the fuzzy rules and produces the system results (Takagi and Sugeno 1985). There are two types of widely used fuzzy inference systems, Takagi- Sugeno FIS and Mamdani FIS (Jang et al. 1997).

Adaptive neuro-fuzzy inference system (ANFIS) applies the hybrid–learning algorithm, consists of the combination of the ''gradient descent'' and ''least squares'' methods (Figure 2). The gradient descent method is used to assign the nonlinear input parameters and the least-squares method is employed to identify the linear output parameters (Firat and Gungor, 2009). The detailed algorithm and mathematical background of these algorithms can be found in Jang et al. (1997) and Nayak et al. (2004).

For simplicity, we assume the fuzzy inference system under consideration has two inputs, x and y, and one output, z. For a first-order Sugeno fuzzy model (Takagi and Sugeno, 1985), a typical rule set with two fuzzy if–then rules can be expressed as

Rule 1: If x is A1 and y is B1 then $z1 = p1 * x + q1 * y + r1$
Rule 2: If x is A2 and y is B2 then $z2 = p2 * x + q2 * y + r2$

where pi, qi and ri (i = 1 or 2) are linear parameters in the then-part (consequent part) of the first-order Sugeno fuzzy model. The architecture of ANFIS consists of five layers (Figure 3), and a brief introduction of the model is as follows (Chang and Chang, 2006).

To construct the adaptive system, five layers are used as shown in Figure 1. Each layer involves several nodes described by a node function. The circles in the network represent nodes that possess no variable parameters, while the squares represent nodes that possess adaptive parameters to be determined by the network during training. The node function in each layer is described below (Chang and Chang, 2006).

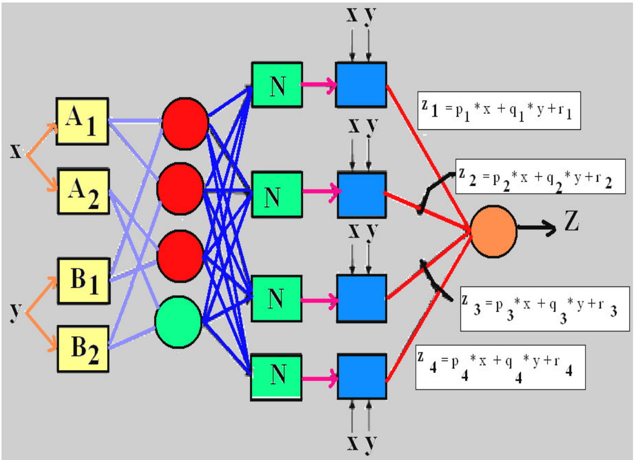

Figure 3. ANFIS architecture for two-input Sugeno fuzzy model with four rules (Redrawn from Chang and Chang, 2006).

Layer 1: input nodes. Each node of this layer generates membership grades to which they belong to each of the appropriate fuzzy sets using membership functions.

$$O_{1,i} = \mu_{Ai}(x) \qquad \text{for } i = 1, 2$$

$$O_{1,i} = \mu_{Bi-1}(y) \qquad \text{for } i = 3, 4$$

Where x, y are the crisp inputs to node i, and Ai, Bi (small, large, etc.) are the linguistic labels characterized by appropriate membership functions μAi; μ Bi, respectively.

Due to smoothness and concise notation, the Gaussian and bell-shaped membership functions are increasingly popular for specifying fuzzy sets. The bellshaped membership functions have one more parameter than the Gaussian membership functions, so a nonfuzzy set can be approached when the free parameter is tuned.

Layer 2: rule nodes. In the second layer, the AND operator is applied to obtain one output that represents the result of the antecedent for that rule, i.e., firing strength. Firing strength means the degrees to which the antecedent part of a fuzzy rule is satisfied and it shapes the output function for the rule. Hence the outputs O2,k of this layer are the products of the corresponding degrees from Layer 1.

$$O_{2,k} = wk = \mu_{Ai}(x) \times \mu_{Bj}(y) \quad k = 1, \ldots, 4;$$

$$i = 1, 2; \; j = 1, 2$$

Layer 3: average nodes. In the third layer, the main objective is to calculate the ratio of each ith rule's firing strength to the sum of all rules_ firing strength. Consequently, wi (avr.) is taken as the normalized firing strength.

$$O_{3,i} = w_{i(avr.)} = wi / (\textstyle\sum_{k=1}^{4} wk) \qquad i = 1, \ldots, 4$$

Layer 4: consequent nodes. The node function of the fourth layer computes the contribution of each ith rule's toward the total output and the function defined as

$$O_{4,i} = wi(avr.)\, f_i = w_{i(avr.)}\,(p_i x + q_i y + r_i) \qquad i = 1, \ldots, 4$$

Where $w_{i(avr.)}$ is the ith node's output from the previous layer. As for {pi,qi, ri}, they are the coefficients of this linear combination and are also the parameter set in the consequent part of the Sugeno fuzzy model.

Layer 5: output nodes. The single node computes the overall output by summing all the incoming signals. Accordingly, the defuzzification process transforms each rule's fuzzy results into a crisp output in this layer.

$$O_{5,1} = \textstyle\sum_{i=1}^{4} w_i f_i = \sum_{i=1}^{4} w_i f_i / \sum_{i=1}^{4} w_i$$

This network is trained based on supervised learning. So our goal is to train adaptive networks to be able to approximate unknown functions given by training data and then find the precise value of the above parameters.

STUDY AREAS

Study area is located in Istanbul (Yesilkoy, Florya, Basinkoy) and Golcuk areas). Location map of study areas are given in Figure 4. In our study area located in Istanbul (Yesilkoy, Florya, Basinkoy) and in Golcuk, it measured the electrical resistivity by VES (Vertical Electrical Sounding) in many points. On the other hand, on the soil samples from borings, soil mechanics laboratory procedures were applied and it determined the soil water contents from these samples. Investigation depth for soil mechanics procedures and geoelectrical measurements is up to 15 m. The ranges of our samples are changed between 1 - 50 ohm.m (for resistivity) and 20 - 60 (%, for water content).

DATA COLLECTING AND MEASUREMENTS

In geotechnical engineering, water content determination is a routine laboratory test to determine the amount of water present in a quantity of soil in terms of its dry mass (Bowles, 1992). As a definition,

$$W = MW / MS \times 100\ (\%)$$

Where MW is the mass of water present in soil mass (g) and Ms is the mass of soil solids (g). In the other hand, electrical resistivity of any material is defined as the electrical resistance of a cylinder with a cross section of unit area and with unit length. In most earth materials, porosity and chemical content of water filling the pore spaces are more important in governing resistivity than is the conductivity of mineral grains of which the material itself is composed (Dobrin and Savit, 1988).

Electrical resistivity is measured by VES (Vertical Electrical Sounding) in 210 points of this location by resistivity equipment in a microzonation project (Bayat, 2000) for Istanbul city. For geotech-

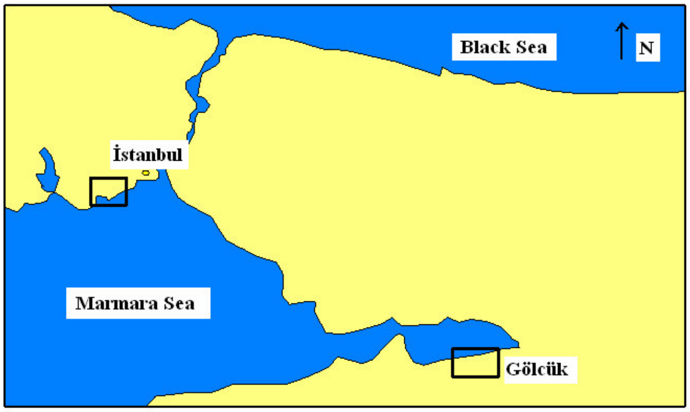

Figure 4. Location map of study areas.

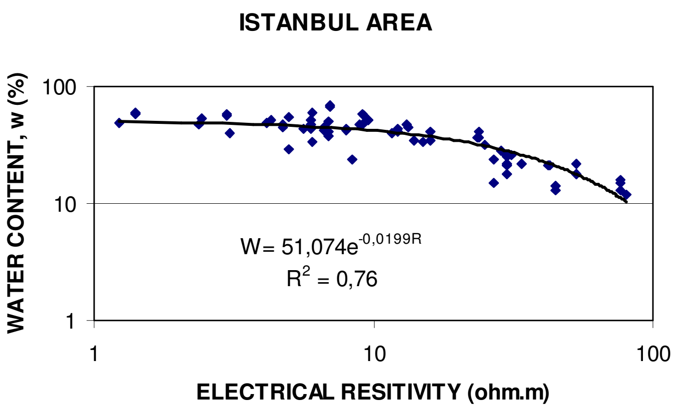

Figure 5. Relationships between soil electrical resistivity and water content for Istanbul Area, Turkey (Ozcep et al, 2009).

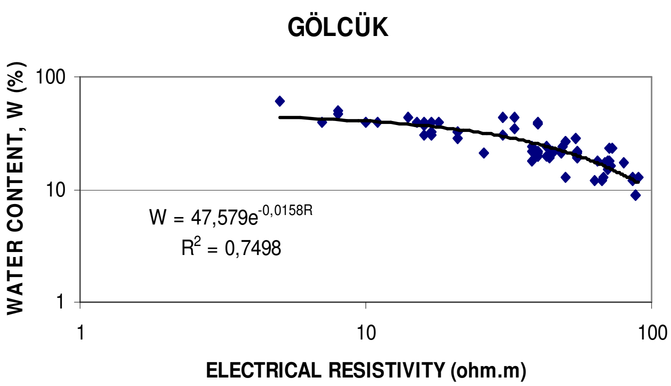

Figure 6. Relationships between soil electrical resistivity and water content for Golcuk area, Turkey (Ozcep et al, 2009).

nical purposes, boring was carried out in this region and it was applied soil mechanics laboratory procedures on the soil samples from borings, and is determined the soil water contents from these samples. Soil samples are selected from only sandy soils. In Figure 5, 6 and 7, the obtained relations are given (Ozcep et al., 2009).

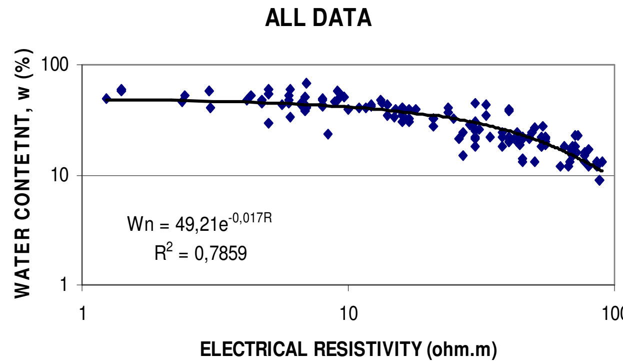

Figure 7. Relationships between soil electrical resistivity and water content for all data (Ozcep et al, 2009).

WATER CONTENT ESTIMATION BY USING ARTIFICIAL INTELLIGENT

Artificial neural networks applications

ANN (i,j, k) architecture that indicates i,j and k respectively input, hidden and output are formed in this study. ANN models was formed by taking i and k values as 1 and j value as 3, 5 and 10. Analysis of 148 data couple with a input vector (ROA) and output vector (Wn) was carried out. To apply the models, all data was normalized between 0.1 and 0.9 in the flowing relation:

$$X_i = 0,8 \,.\, (X_i - X_{MIN}) / (X_{MAX} - X_{MIN}) + 0,1 \qquad (1)$$

Where, Xi normalized values, X_{MAx} and X_{MIN} maximum and minimum measurement values.

By the normalization process, data can be dimensionless. Data are divided in to two categories as training and testing data. Training set includes 120 values, and other 28 testing data were used in the performance evaluation. Performance values obtained by ANN models were given in Table 1.

In this study, neuron number of hidden layer after several tests are determined 5 from performance evaluation of test set (as shown in Table 1). ANN (1 5 1) model that has maximum performance was shown in Figure 8.

Fuzzy logic applications

Mamdani method application and results

It was formed 5 different sub-sets. In the formation of sub-set, triangle membership function was used. These sub-sets are defined as very lower, (VL), lower (L), middle (M), high (H) and very high (VH). Figure 9 shows the membership functions of sub-sets of ROA input. In Figure 10, the membership functions of sub-sets of Wn output were shown.

In this study, the rules were defined between ROA and Wn by using sub-sets. For example ''If ROA is VL, then Wn is VH''. Fuzzy logic rules to estimate water content was given in Table 2. 120 data set was used in Mamdani-Fuzzy logic modelling. This formed model was tested by 28 data set that used in testing of artificial neural networks. In evaluation of performance of test group, MAEP and R^2 values are calculated respectively 19.99 and 0.8268.

Sugeno method application and results

In this approach, calculations based on mathematical relations each

Table 1. Performance Evaluation of Test Data of ANN models

Model	MAEP (Mean absolute error percent)	MSE (Mean square error)	R^2
ANN (1 3 1)	17.66	30.50*	0.8754
ANN (1 5 1)	17.76	33.62	0.8844*
ANN (1 10 1)	16.53*	34.97	0.8723

Note: best results signed as '*'

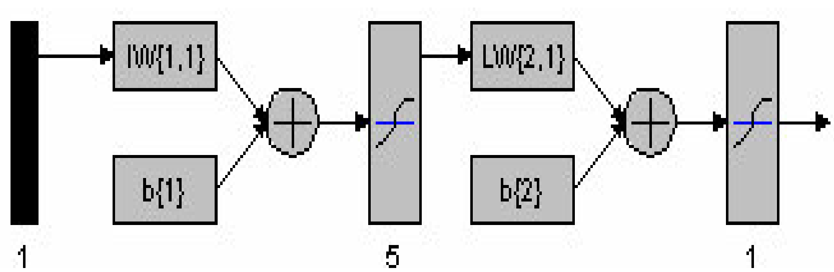

Figure 8. Achitecture of ANN (1 5 1) Model.

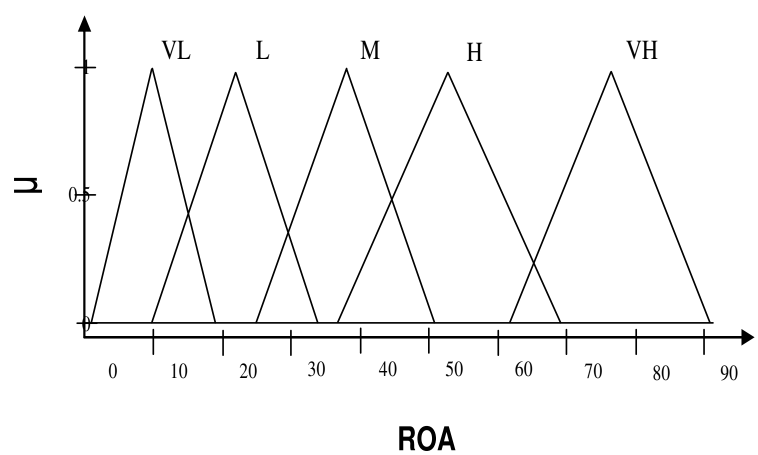

Figure 9. The membership functions of sub-sets of ROA input.

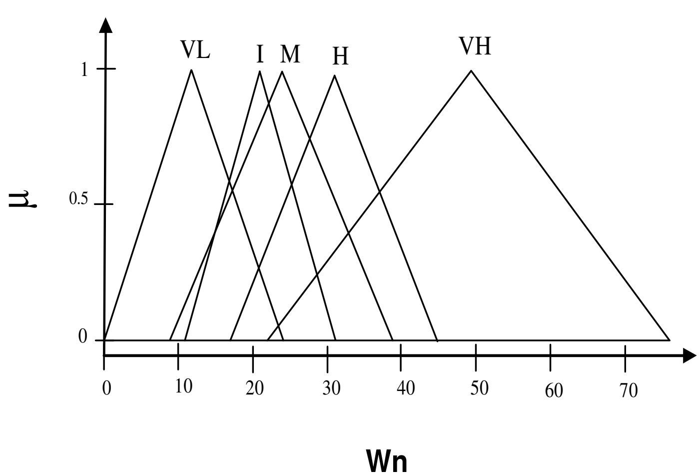

Figure 10. The membership functions of sub-sets of Wn output

Table 2. Fuzzy logic (Mamdani) rules that shows relation between water content (Wn) ile electrical resistivity ROA

If (ROA = VL), then (Wn = VH)
If (ROA = L), then (Wn = H)
If (ROA = M), then (Wn = M)
If (ROA = H), then (Wn = L)
If (ROA = VH), then (Wn = VL)

Table 3. Fuzzy logic (Sugeno) rules that indicates relation between water content and ROA.

If (ROA = VL), Then (Wn = -1,0882(ROA) +54,652)
If (ROA = L), Then (Wn = -0.6672(ROA) + 47,761)
If (ROA = M), Then (Wn = -0,2849(ROA) + 35,122)
If (ROA = H), Then (Wn = -0,3128(ROA) + 36,426)
If (ROA = VH), Then (Wn = -0,2132(ROA) + 31,028)

sub-set. In this study, 5 sub-sets was formed by considering data distribution, and curve equation for each sub-set was obtained. Distribution of these sub-sets was shown in Figure 11a to e.

Apart from Mamdani approach, sub-set of Sugeno method was formed by using linear relation between input-out. Rule definitions' of these sub-sets was shown in Table 3. Membership function of sub-set for input and variations of membership grade was given in Figure 12.

With the training of 120 input-output, data set was used in Sugeno-Fuzzy logic modelling. In evaluation of performance of test group, MAEP and R^2 values are calculated respectively 17.63 and 0.8025.

Sugeno-Fuzzy logic approach gives more effective results than Mamdani-Fuzzy logic approach. Moreover, by using Sugeno-Fuzzy logic approach, formation of fuzzy logic model is very easy than Mamdani-Fuzzy method.

Regression method estimations

In this study, to compare regression techniques and artificial intelligent techniques and to determine advantages and disadvantages, a regression model was formed. For 120 data set, an exponential regression model was formed and empiric relation was determined (Figure 7). In evaluation of performance of estimations, MAEP and R^2 values are calculated respectively 20.85 and 0.8454.

Comparison of models

In this study, regression coefficient and Mean Error Squares (MES) was used for performance evaluation. These methods didn't give any information about errors distribution. For this reason, MAEP (Mean Absolute Error Percent) was used to evaluate performance efficiently. Performance evaluations of formed models were given in Table 4.

Among the models, method that gives the best results is ANN (1 5 1) as shown in Table 4 and in Figure 13.

RESULTS AND DISCUSSION

This paper presents a comparative study on the water content estimations of soils from electrical resistivity by using several AI approaches.

The electrical properties of soils are the parameters of natural and artificially created electrical fields in soils and influenced by distribution of mobile electrical charges, mostly water content, in soils.

Based on the laboratory and in geoelectrical data, by choosing the appropriate relationship, development of a relation that provides an estimation of soil water content from electrical resistivity data of soils have been accomplished for study areas. Applications of the electrical measurements for studying soil water content provides useful tool for geotechnical engineering. For this range, it found the relation between resistivity and water content of soils as $W = 51,764e^{-0,0188R}$. In the estimated volumetric water contents, determination coefficient (R^2) fall approximately 78 %.

The relationship model developed in this study provides a very useful tool to relate the water content of a soil i.e. its fluid behavior. The model can only be used for soil - water mixtures carefully.

As Robain et al (2003) and Ozcep et al (2005) point out; soil solid components are generally electrical insulators, the conduction of electrical current only lies on phenomenon occurring in water. Volume conduction controlled by the electrolyte concentration in water and the geometrical characteristics of macro voids network. For the water contained in macro voids the pre-eminent phenomenon seems to be volume conduction while for the water contained in micro voids, it seems to be surface conduction.

Some comparisons on correlation between electrical resistivity and soil-water content were carried out by using artificial intelligent techniques. A new approach on soil-water content estimations was obtained. Artificial intelligent techniques are more effective and reliable than classical regression technique. In this study, the specific artificial neural networks, fuzzy sets (Mamdani and Sugeno) of input variables were established.

This paper deals with the problem of estimation of the water content of soils. The objectives and the conclusions of the paper are:

- The prediction accuracy of AI system was fairly good (predictive ability and for the coefficient of correlation) based on the results of the testing performance, and the calculated coefficient of correlation of training and testing.
- The compared results by classical (regression) analysis, artificial neural networks and fuzzy estimates show that the conventional regression method can easily estimate a value of water content from electrical resistivity, but it is weak in the evaluation of performance of estimations.
- The foregoing discussions clearly indicate that the ANN model performs better than the and Fuzzy and Regression models in predicting water content of soils.

Regression coefficient (R^2), mean error squares (MES),

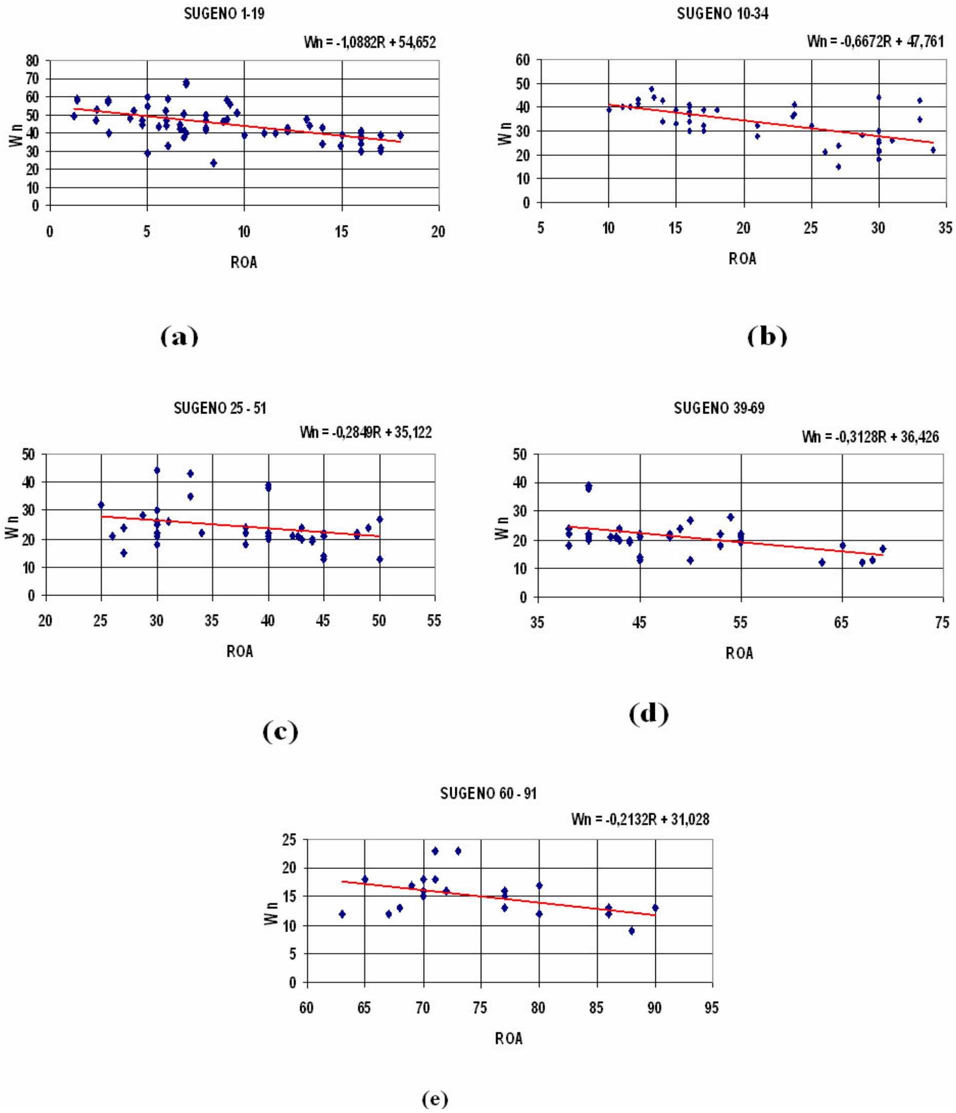

Figure 11. Formation of sub-set according to the ROA variations.

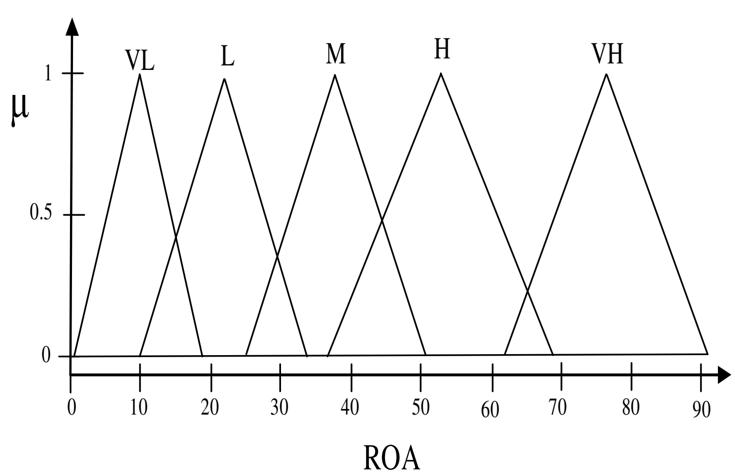

Figure 12. Membership functions of sub-set for input and variations of membership grade.

Table 4. Performance evaluations and comparisons of formed models.

	ANN (1 5 1)	MAMDANI	SUGENO	REGRESION
MAEP	17,76	19,99	17,63*	20,85
MES	33,62	43,12	32,59*	50,39
R^2	0,8844*	0,8268	0.8825	0,7859

Note: Best results was indicated the sign '*'.

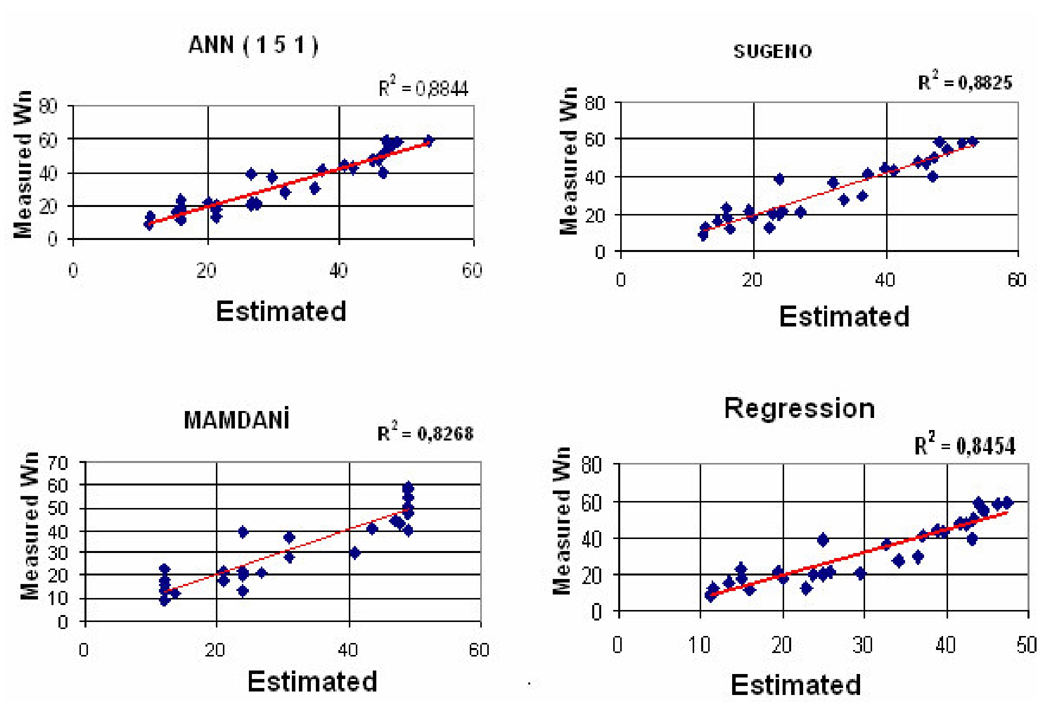

Figure 13. Comparasions between estimated and measured water content .

mean absolute error percent (MAEP) values are ranged respectively 0.8844, 33.62 and 17.76 for the ANN (1 5 1) model, 0.8268, 43.12 and 19.99 for the Mamdani model, 0.8825, 32.59 and 17.63 for the Sugeno model and 0.8485, 50.39 and 20.85 for the Regression model.

Fuzzy or other AI systems, system to estimate water content can improve with more data. Moreover, in the future, several possible applications are:

- To study the effects of load effect on soil hydraulic conductivity and strength.
- To study the electromagnetic properties of soils in context of the water content
- To study the effect of temperature on soil water content and resistivity

This study has shown that the obtained model has the capability of investigating the effects of water content on soil resistivity. More work needs to be done by measuring the electrical properties of other type of soils (for example clay and silts) at different locations so that how the water content changes the soil resistivity wil be known.

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