Using artificial intelligence to Prediction of permeability and rock type derived from fuzzy c -means clustering in uncored well in one of the Iran gas field.

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Abstract
Permeability, rock type and core facies are the most important parameters of the reservoirs and accurate reservoir simulation and management requires a quantitative model of the spatial distribution of reservoir properties. Geological and petrophysical survey has an important role in producing of really three-dimensional models of the reservoir. determination of permeability, and rock type are the challenge for reservoir scientist in uncored well.Rock type represent the certain facies with a defined range of porosity and permeability and play an important role in recognition of flow units and reservoir modeling.In this study Rock types were defined utilizing fuzzy c-means clustering from porosity and permeability of well cores.So that each obtained cluster was assigend to a special rock type. . It has been attempted in this study that Rock types and permeability are predicted indirect from electrical logs by using artificial intelligence like Backpropagation Neural Network(BPNN) and Fuzzy logic method.The section of Fuzzy logic in Geolog software is used in estimate Rock types and permeability from petrophysical logs. The results reveal a good match between the core data analyses and the intelligent technique determination of permeability and rock types.

Keywords: *Artificial intelligence; Rock type; Fuzzy logic; BPNN; Fuzzy c-means clustering; Permeability;*

1.Introduction
In this paper, we highlight role of Soft Computing techniques for intelligent reservoir characterization,. Reservoir characterization plays a crucial role in modern reservoir management.The reservoir characteristics include pore and distribution and depositional environment.This paper suggests intelligent technique using fuzzy logic and Neural network to determine permeability and rock type in well where core data are not available, from wire-line logs data in one gas field of iran . The basic theory of fuzzy sets was first introduced by Zadeh (1965). 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 false". Despite the meaning of the word "fuzzy", fuzzy set theory is not one that permits vagueness. It is a methodology that was developed to obtain an approximate solution where the problems are subject to vague description. In addition, it can help engineers and researchers to tackle uncertainty, and to handle imprecise information in a complex situation. During the past several years, the successful application of fuzzy logic for solving complex problems subject to uncertainty has greatly increased and today fuzzy logic plays an important role in various engineering disciplines. In recent years, fuzzy logic, and intelligent solution, has been applied extensively in many reservoir characterization studies. For example in Bois (1984), Baygun et

al.(1985), Baygun et al.(1985), Nordlund (1996), Cuddy (1997), Fang and Chen (1997) , Huang et al.(1999), Nikravesh and Aminzadeh (2000), Huang *et al* 2001, Saggaf and Nebrija 2003, the authors applied fuzzy logic and neural networks to solve number of reservoir characterization problems in several fields.

2.Method used

2.1.Fuzzy c-means Clustering

Cluster analysis encompasses a number of different classification algorithms that can be used to organize observed data into meaningful structures. Fuzzy clustering partitions a data set into fuzzy clusters such that each data point can belong to multiple clusters. Fuzzy c-means (FCM) is a well-known fuzzy clustering technique that generalizes the classical (hard) c-means algorithm and can be used where it is unclear how many clusters there should be for a given set of data. FCM is based on minimization of the
following objective function (Ozer 2005):

$$j_m = \sum_{i=1}^{n} \sum_{j=1}^{c} \mu^{c}{}_{ij} \parallel x_i - c_j \parallel^2 \tag{1}$$

$1 \le m < \infty$

where n is the number of objects to be clustered, c is the number of clusters, uij is the degree of membership of object i in cluster j, xi is a vector of h characteristics for object i, vj is a vector of the cluster means of the h characteristics for cluster $j$and c is the weighting exponent varying in the range [1,∞]. Equation (1) represents the sum of squared errors and is a goal function that the FCM algorithm tries to minimize.

2.2.BPNN(Back-propagation neural network)

ANN is a new tool for solving complex problems in petroleum industry. A back propagation artificial neural network (BP-ANN) is a supervised training technique that sends the input values forward through the network then computes the difference between calculated output and corresponding desired output from the training dataset. The error is then propagated backward through the net, and the weights are adjusted during a number of iterations. The training stops when the calculated output values best approximate the desired values (Bhatt and Helle, 2002).

2.3. FUZZY LOGIC

In recent years, it has been shown that uncertainty may be due to fuzziness rather than chance. Fuzzy logic isconsidered to be appropriate to deal with the nature of uncertainty in system and human error, which are notincluded in current reliability theories. The basic theory of fuzzy sets was first introduced by Zadeh (1965). 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 false" [6]. Despite the meaning of the word "fuzzy", fuzzy set theory is not one thatpermits vagueness. It is a methodology that was developed to obtain an approximate solution where the problemsare subject to vague description. In addition, it can help engineers and researchers to tackle uncertainty, and to handle imprecise information in a complex situation. During the past several years, the successful application of fuzzy logic for solving

complex problems subject to uncertainty has greatly increased and today fuzzy logic playsan important role in various engineering disciplines. In recent years, considerable attention has been devoted to theuse of hybrid neural network-fuzzy logic approaches as an alternative for pattern recognition, clustering, andstatistical and mathematical modeling. It has been shown that neural network models can be use to construct11nternal models that capture the presence of fuzzy rules. However, determination of the input structure and number
of membership functions for the inputs has been one of the most important issues of fuzzy modeling.Fuzzy logic provides a completely new way of modeling complex and ill-defined systems. The major concept offuzzy logic is the use of a linguistic variable, that is a variable whose values are words or sentences in a natural orsynthetic language. This also leads to the use of fuzzy if-then rules, in which the antecedent and consequents arepropositions containing linguistic variables.

3.Rock type classification

The methodology is described as below:

First, input porosity and permeability data was passed from the following function of Matlab,[*center,U, obj f cn*] = fcm *(data, cluster n)*

where *data* (input matrix of porosity and permeability), *cluster n* (number of cluster to be derived) and *fcm* (Matlab's fuzzy c-means clustering algorithm) are input arguments of the function. The output arguments are *center* (matrix of final cluster centres), *U* (membership function matrix) and *obj fcn* (values of the objective function during iterations). By specifying arbitrary values for *cluster n*, clusters were derived for the reservoir studied. Then each cluster was deemed as a unique rock type of the reservoir.in figure2 crossplot of ten rock type that detemined by permeability and porosity are shown. Statistic data of ten rock type are shown in table1.

4.Prediction rock type by fuzzy logic

In this section, rock types were estimated from well log data using fuzzy logic. For this purpose, the distribution of well log data for the identified
rock types was first investigated. According to figure1 which shows an example of the distribution of RHOB log values for the one rock types derived in previous stage, the data sets have been fitted by a Gaussian function(figure3). The normal distribution of data by a Gaussian function is as below:

$$P(x, \sigma, c) = \frac{e^{-(x-c)^2 \;/\; \sigma^2}}{\sigma\sqrt{2\pi}} \qquad (2)$$

where *f (x,σ, c)* is the probability function that an observation x is measured in the data set by amean *c* and standard deviation *σ*. This curve was used to estimate relative probability or 'fuzzy possibility' that a data value belongs to each rock type. The methodology described here is similar to Cuddy's approach (1998) for lithofacies estimation using fuzzy mathematics. Each log data value may belong to any FCM clustering derived rock type to a degree that can be calculated from a Gaussian membership function using equation (2). Each rock type has its own mean and standard deviation, namely, for *n* number of rock types; there are *n* pairs of *c* and *σ* rock type. For example, the fuzzy possibility that a RHOB log data belongs to rock type 1 is obtained by substituting *c* rock type 1 and *σ* rock type 1 in equation (2):

$$P(RHOB) = \frac{\exp^{-(RHOB - c_{rt1})^2 / \sigma_{rt1}{}^2}}{\sigma_{rt1}\sqrt{2\pi}} \tag{3}$$

The ratio of the fuzzy possibility for each rock type with the fuzzy possibility of the mean or most likely observation is obtained by de-normalizing equation (3). The fuzzy possibility for mean of RHOB in rock type 1 is obtained by substituting
RHOB by *c*rock type 1 in equation (3):

$$P(RHOB) = \frac{\exp^{-(c_{rt1} - c_{rt1})^2 / \sigma_{rt1}{}^2}}{\sigma_{rt1}\sqrt{2\pi}} = \frac{1}{(\sigma_{rt1})\sqrt{2\pi}} \tag{4}$$

The relative fuzzy possibility R(RHOBIrock type1) of a RHOB porosity RHOB belonging to rock type 1 compared to the fuzzy possibility of measuring the mean value *c*rock type 1 is equation (3) divided by equation (4):

$$R(RHOB_{rt1}) = e^{-(RHOB - C_{rt1})^2 / 2\sigma_{rt1}{}^2} \tag{5}$$

Each value derived from equation (5) is now indicated to possible rock types. To compare the relative fuzzy possibilities of this equation between rock types, equation (5) is multiplied by a coefficient named relative occurrence of each rock type
i√n the reservoir interval. For rock type 1, it is noted as

$$F(RHOB_{rt1}) = \sqrt{n_{rt1}}\, e^{-(RHOB - C_{rt1})^2 / 2\sigma_{rt1}{}^2} \tag{6}$$

The obtained fuzzy possibility from equation (6) is based on RHOB log data only. This process should be repeated for other logs such as sonic (DT), neutron (NPHI), . . . at
this point. This will give F(DTrock type1), F(NPHIrock type1), . . . for rock type 1. These fuzzy possibilities are combined harmonically to give a final fuzzy possibility:

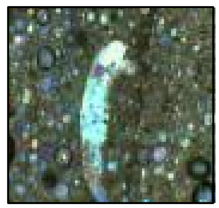
$$\frac{1}{C_{rt1}} = \frac{1}{F(RHOB_{rt1})} + \frac{1}{F(DT_{rt1})} + \ldots. \tag{7}$$

This process is repeated for other rock types and all derived fuzzy possibilities are combined harmonically. Then, the rock type with the highest combined fuzzy possibility is taken as the most possible rock type at that point. A comparison between FCM clustering derived and fuzzy predicted rock types versus depth for the test well that was not used to model construction is shown in figure 4. The fuzzy Possibilities in fuzzy logic are combined harmonically, whereas, statistical methods such as Bayes theorem, combine probabilities geometrically. When comparing rock types that are equally likely, with similar probabilities, the harmonic combination emphasizes any indicator which suggests the lithology selection is unlikely. Secondly, fuzzy logic weights the possibilities by the square root of the proportion in the calibrating data set, whereas Bayes uses the direct proportion (Cuddy 1998).in the next section permeability estimated by neural network and fuzzy logic figure 5 show comparison beetwen core permeability and fuzzy predicted permeability and crossplot of this comparison.

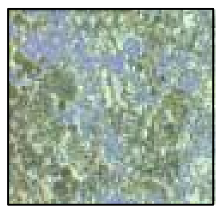
Table1:Rock types(1-10) derived by the FCM clustering method in this rock type porosity and permeability are important and show production potential and (xpl,×23.6) ,

Rock type1(cluster1)		
	k(md)	(%) φ
Min	0.01	0.1
Max	1.41	3.89
Mean	0.10	1.30
St.Dev	0.21	0.97

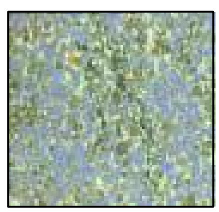
Rock type2(cluster2)		
	k(md)	(%)φ
Min	0.07	4.85
Max	2.43	10.64
Mean	0.54	6.89
St.Dev	0.72	1.62



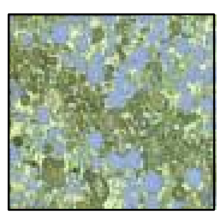
Rock type3(cluster3)		
	k(md)	(%)φ
Min	3.93	17.81
Max	10.27	21.64
Mean	6.90	19.73
St.Dev	1.71	1.28



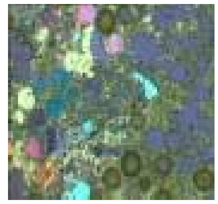
Rock type4(cluster4)		
	k(md)	(%)φ
Min	0.346	23.94
Max	3.18	31.09
Mean	1.21	25.93
St.Dev	0.86	1.69



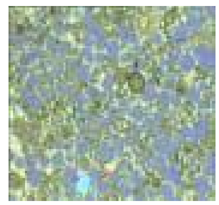
Rock type5(cluster5)		
	k(md)	(%)φ
Min	4.20	22.11
Max	9.17	26.99
Mean	6.81	23.86
St.Dev	1.61	1.33



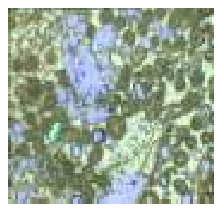
Rock type6(cluster6)		
	k(md)	(%)φ
Min	0.25	18.44
Max	3.71	2.66
Mean	1.494	21.66
St.Dev	0.96	1.402



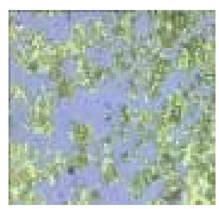
Rock type7(cluster7)		
	k(md)	(%)φ
Min	11.739	19.43
Max	16.22	22.02
Mean	14.21	21.05
St.Dev	2.27	1.41



Rock type8(cluster8)		
	k(md)	(%)φ
Min	9.61	13.79
Max	9.61	13.79
Mean	9.61	13.79
St.Dev		



Rock type9(cluster9)		
	k(md)	(%)φ
Min	20.01	22.16
Max	25.51	24.65
Mean	23.81	23.28
St.Dev	2.60	1.11



Rock type10(cluster10)		
	k(md)	(%)φ
Min	0.19٠	12.41
Max	4.85	15.36
Mean	1.41	14.15
St.Dev	2.28	1.24

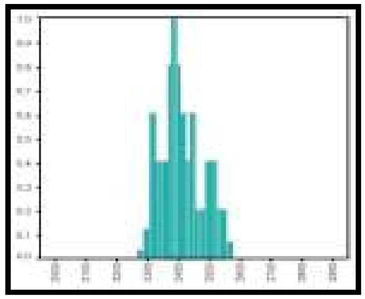


Figure1:distribution of RHOB log of one rock type derived by fcm by Gaussian function

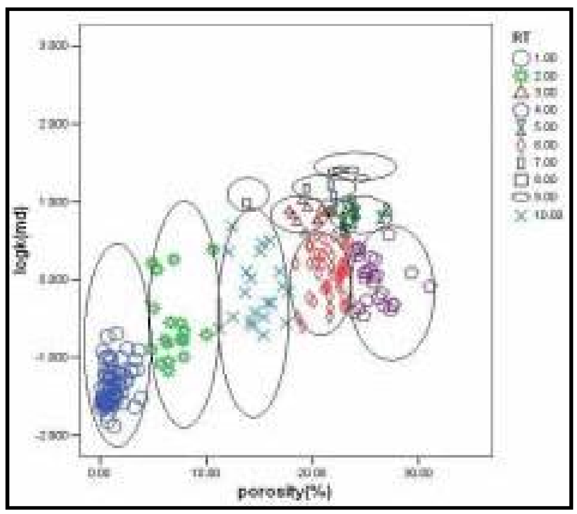


Figure2:ten rock type derived from porosity and permeability by fcm method

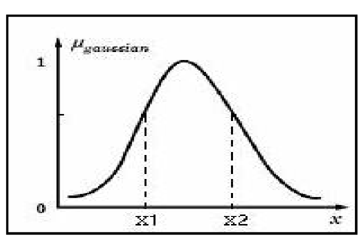


Figure3:Gaussian membership

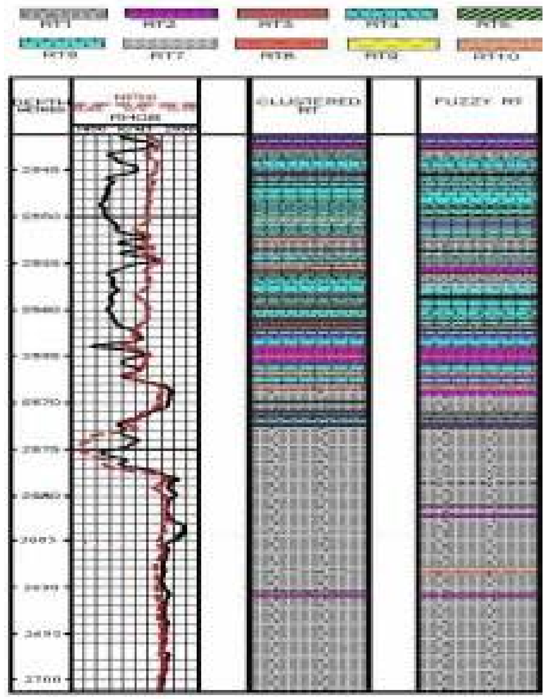


Figure4:Acomparison between clustering derived and fuzzy predicted rock types versus depth

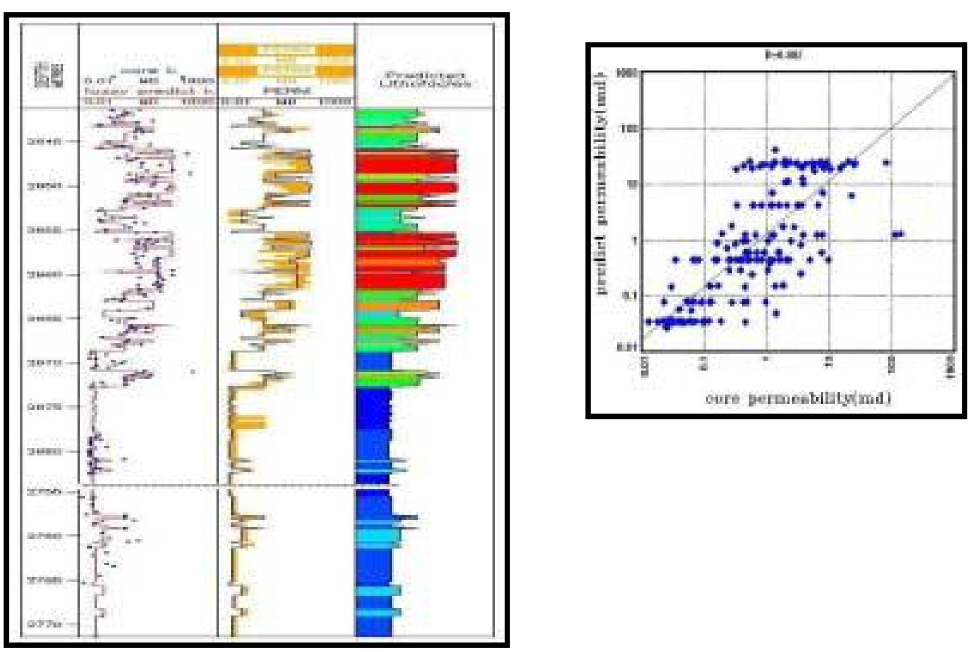


Figure5:A comparison beetwen core permeability and fuzzy predicted permeability and crossplot of this comparison

5.Conclusions

Intelligent systems including fuzzy logic and BPNN have been successful to predict for rock type and permeability in gas field in iran. Fuzzy c- means clustering is good technique to rock type definitation. Fuzzy logic based on the fuzzy possibility concept is efficient tool to prediction rock type derived by fcm clustering.

A comparison between measured and predicted permeability and rock type versus depth are good agreement for the two intelligent techniques.

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