APPLICATION OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR PREDICTION OF POROSITY FROM SEISMIC ATTRIBUTES; CASE STUDY, FAROUR.A OIL FIELD, PERSIAN GULF, IRAN

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ABSTRACT

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Reservoir characterization using seismic attributes has a great impact on quantitative and qualitative interpretation of subsurface property in petroleum industry. Among linear and nonlinear predicting tools like Multi-Regression, polynomial curve fitting and Neural Networks, methods based on Neuro-Fuzzy technique known as the Adaptive Neuro-Fuzzy Inference System (ANFIS) which is a hybrid intelligent system recently has attracted the attention of researchers in many academic, industrial, scientific and engineering areas. In this study, data set was 2D seismic and petrophysical well log data in the Farour.A oil field. First of all, by applying seismic inversion, broad band acoustic impedance as the most relevant seismic attribute to porosity was extracted from these data. Then, optimum numbers of relevant seismic attributes were selected by using stepwise regression and cross validation techniques. At the end, three types of neural network and ANFIS were applied for porosity prediction from seismic attributes. Results were shown that predicting porosity from seismic attributes by ANFIS was performed fast-converged and high accuracy against three types of neural networks.

KEY WORDS: porosity, seismic attributes, ANFIS, artificial neural networks.

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INTRODUCTION

The geophysical developments of oil and gas fields rely on characterizing several petrophysical properties throughout the sedimentary interval containing the reservoir (Archie, 1950). So, laboratory measurements on core plugs, interpretation of geophysical well logs and inversion of seismic attributes provide valuable estimates of physical property in reservoirs. Integration of these distinct methodologies is the best approach to determine uncertainties in the predictions, with direct implications on risk mitigation in drilling operation (Pennington, 2001).

Recently, the petroleum industry has witnessed significant advanced research of the intelligent system for prediction, classification, history matching and so forth between two sets of input and output data. Seismic data is a measurement of subsurface petrophysical properties such as lithology, rock type, porosity, water saturation, pore pressure, p-wave velocity and others. Several researches have been done for prediction of these properties from seismic attributes (Russell, 2004; Nikravesh, 2007; Ahmad, 2007; Solano, 2007; Kadkhodaie, 2009, etc.).

Porosity is one of the most important petrophysical properties for qualitative and quantitative interpretation and characterization of hydrocarbon reservoirs. Prediction of porosity from seismic attributes recently has been done by performing statistical approach, neural networks, fuzzy logic and committee fuzzy inference system (CFIS) (Russell, 2004; Kadkhodaie, 2009).

In this paper, porosity was predicted from seismic attributes by performing Adaptive Neuro-Fuzzy Inference System (ANFIS) as a hybrid intelligent system which combines the human-like reasoning style of the fuzzy system with learning structure of neural networks. Neuro-Fuzzy was proposed by Jang and is a system by means of if-then rules represented in a neural network structure. In this study its result was compared with three types of neural networks.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The fuzzy set theory was invented by Zadeh (1965). Each fuzzy set is represented by a membership function (MF). MFs are in several types such as Gaussian, triangular, trapezoidal, sigmoid, S-shape, Z-shape, Pi (Π)-shape, bell-shape, etc. FIS is a popular computing framework based on fuzzy set theory. Fuzzy if-then rules, fuzzy reasoning, and selection of if-then rules form the key component of it and can efficiently model human expertise in a specific application. There are several types of FIS, the most commonly used FISs are

Mamdani type and Sugeno type. The main important difference among FISs is the type of the output membership function.

Jang (1992, 1993) combined both fuzzy logic (FL) and neural network to produce a powerful processing tool named NFSs which has both NN and FL advantages and the most common one is ANFIS. It is a fuzzy Sugeno model put in the framework of adaptive system to facilitate learning and adaptation for a constant or linear output. One of the ANFIS advantages is using of a hybrid learning procedure for estimation of the premise and consequent parameters. ANFIS structure with two inputs and one output is shown in Fig. 1. For the first order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

Rule 1: if x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$,

Rule 2: if x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$,

Layer 1: every node i in this layer is an adaptive node with a node function, μ is a membership function and it is a function of premise parameters which control the shape of membership function:

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

or

$$O_{1,i} = \mu_{Bi-2}(y) \quad , \quad \text{for } i = 3,4. \tag{1}$$

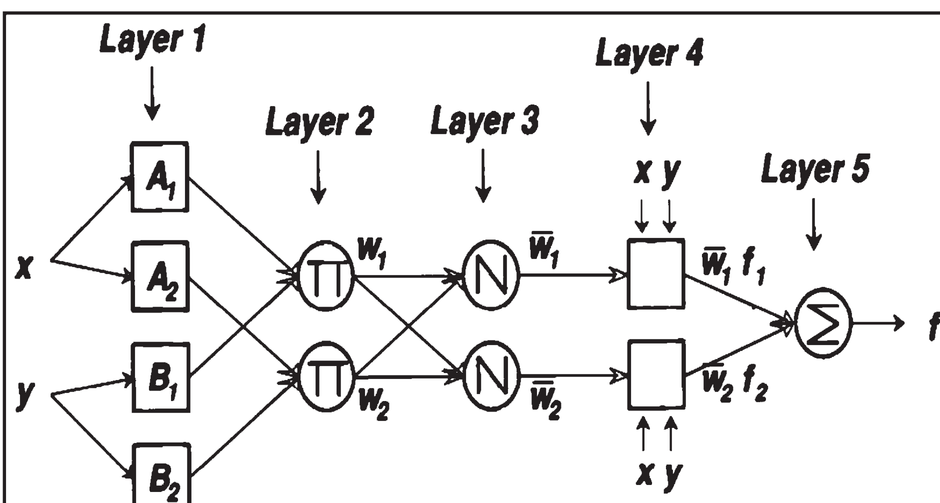

Fig. 1. ANFIS architecture for a two rules Sugeno type.

Layer 2: every node in this layer is a fixed node labeled Π, whose output is the product of all the incoming signals:

$$O_{2,I} = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \quad , \quad \text{for } i = 1,2. \tag{2}$$

Layer 3: every node in this layer is a fixed node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rule's firing strength:

$$O_{3,i} = \bar{w}_i = w_i/(w_1 + w_2) \quad , \quad i = 1,2. \tag{3}$$

Layer 4: every node i in this layer is an adaptive node function, $\{p_i, q_i, r_i\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters, in zero order Sugeno fuzzy model p_i and q_i are zero:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \ . \tag{4}$$

Layer 5: the single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals:

$$\text{overall output} = O_{5,i} = \sum_i \bar{w}_i f_i = \sum_i w_i f_i / \sum_i w_i \ . \tag{5}$$

APPLICATION TO THE FAROUR.A OIL FIELD

This study was focused on the application of the ANFIS method and comparison with ANNs on the Farour.A oil field (an Iranian offshore oil field in the Persian Gulf). 7*8 post stack 2D seismic time sections with good quality on the oil field and petrophysical data from three wells were available (Fig. 2). Dolomitic limestone Asmari reservoir was interested in this study. Density and porosity were available for all wells but in one of them, sonic log was missed and determined by statistical methods and Check shot data was only available for one well. 2D time section "5103 SE-NW" showing general quality of seismic data across the Farour.A oil field is shown in Fig. 3.

Correlation of well logs to seismic data

As the first step in this study, seismic sections were interpreted and time horizons were picked based on one available check shot in well FrB2. Check shot was applied for initial time to depth conversion. Then, first correlation of well log to seismic data for extracting wavelet and making synthetic seismogram was done on wells FrA1, FrA2 and FrB2. It is necessary to create synthetics and extract the wavelets repeatedly for the placement of the well log data in correct time. At the end, suitable time-depth relationships were obtained. A well to seismic tie, at well FrA1, is shown in Fig. 4, where the correlation between synthetic seismogram (blue) and composite trace (red) in the vicinity of the well is 0.68.

Selection of optimal seismic attributes

A reason for applying several statistical and intelligent approaches is finding linear and nonlinear relationship between two sets of input and output data and applying it on the relevant data set. Relationship between input (seismic attributes) and output (porosity log) data were investigated by stepwise-regression analysis with considering validation error as a criterion to stop adding attributes to the input data set (Russell, 2004). According to Table 1, the first two attributes, inverse of acoustic impedance and average frequency could be optimum inputs related to the logarithm of porosity as the output in linear and nonlinear mode. Individual relationship of seismic attributes and porosity that are considered in this process are shown in cross plots of Fig. 5.

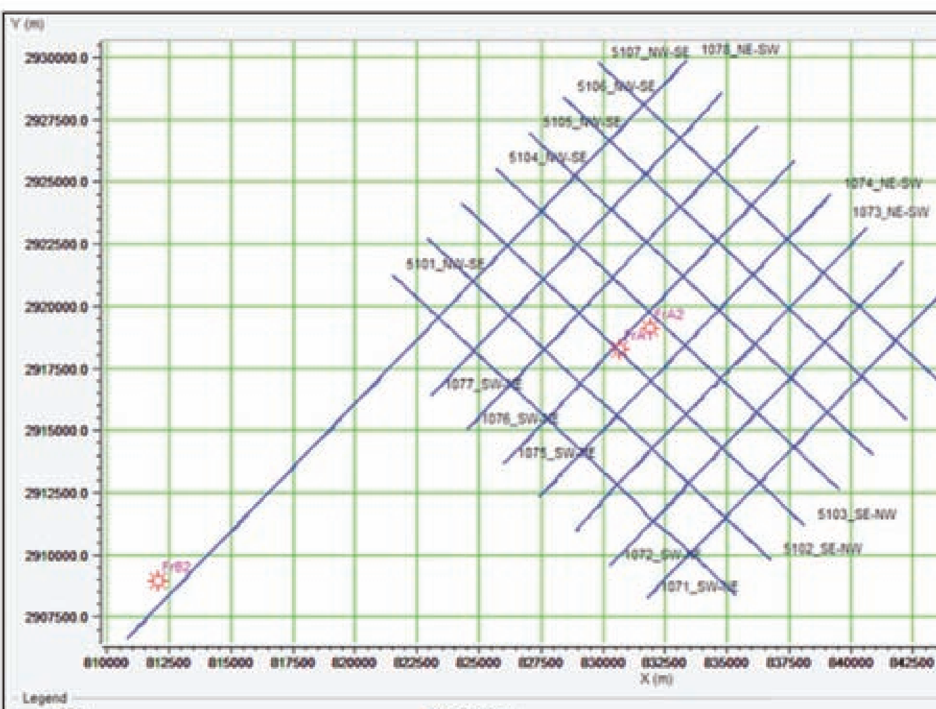

Fig. 2. Map showing location of wells and 2D seismic sections in The Farour.A offshore oil field.

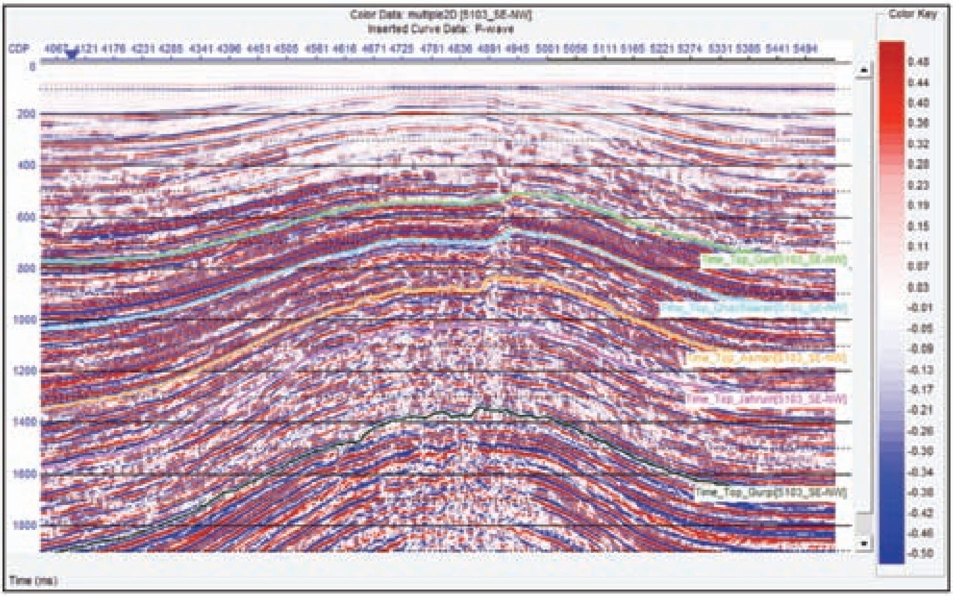

Fig. 3. 2D time section "5103 SE-NW" showing general quality of seismic data across the Farour.A oil field.

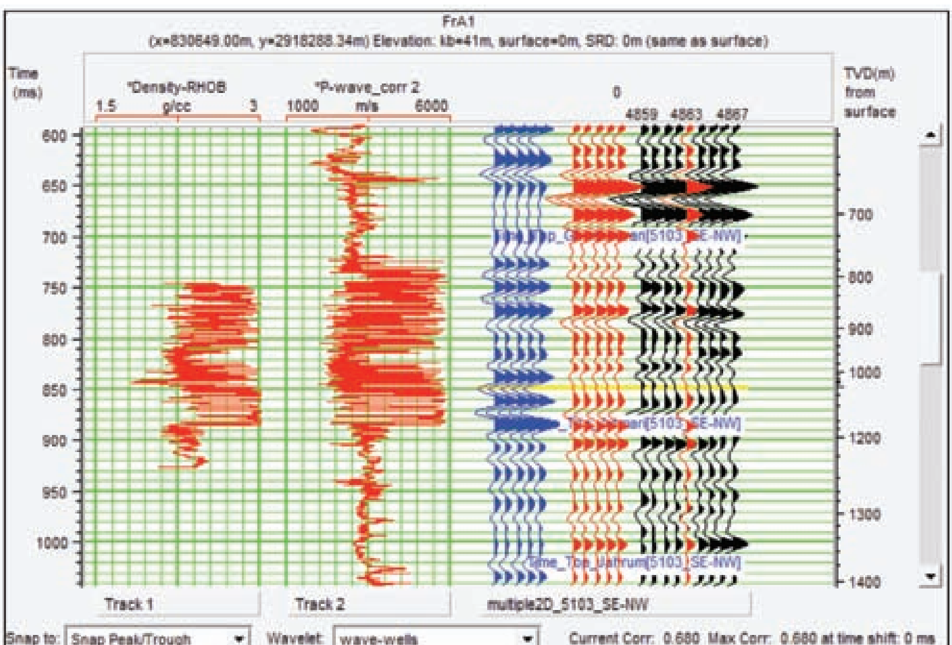

Fig. 4. A sample of well to seismic tie at well FrA1.

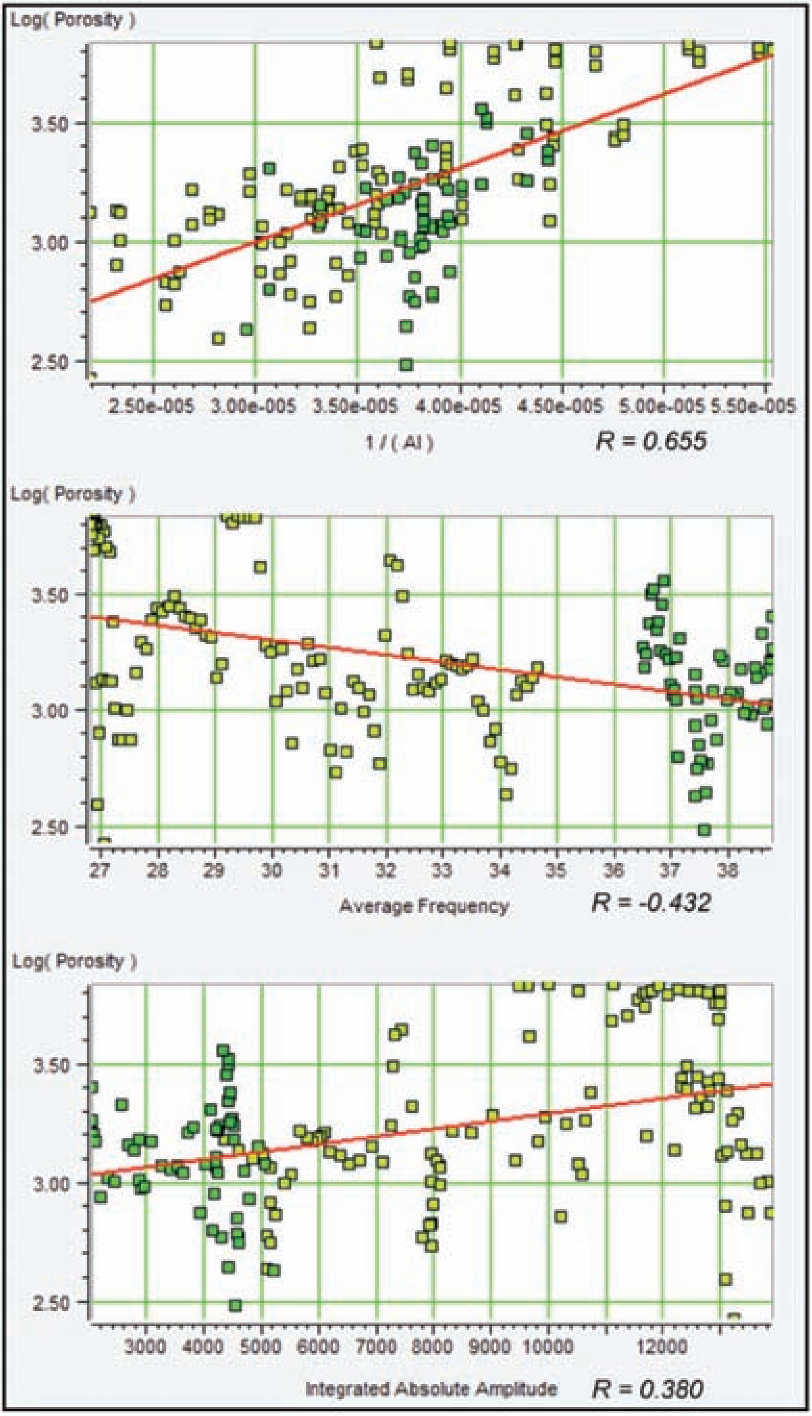

Fig. 5. Cross plots showing relationships between seismic attributes and logarithm of porosity.

Table 1. Multi-attribute list for predicting porosity.

Number of attributes	Target	Final attribute	Training error	Validation error
1	Log(Porosity)	1/(Acoustic Impedance)	6.517	8.153
2	Log(Porosity)	Average Frequency	5.554	7.056
3	Log(Porosity)	Integrated Absolute Amplitude	5.292	38.402

Acoustic impedance is a product of sonic velocity and bulk density. Accordingly, porosity is an inverse function of it. A broad band acoustic impedance model on the oil field was extracted by seismic inversion, which integrates high frequency of seismic data and missed low frequency of seismic data by well log data.

Average frequency is a signature of the events and effects of the abnormal attenuation due to the presence of the hydrocarbons (Taner, 1994).

Artificial Neural Networks (ANNs)

The goal of ANN researches is developing the mathematical model of the biological events in order to imitate the capability of the biological neural structures in purpose of designing an intelligent information processing system. The first mathematical model was introduced by Warren McCulloch and Walter Pitts (McCulloch, 1943). An adaptive NN is a network structure consisting of a number of nodes connected through directional links, all or part of the nodes is adaptive, which means the output of these nodes depends on modifiable parameters belonging to these nods.

Table 2. Results of different ANNs methods for prediction of porosity.

Method	RMSE	Correlation Coefficient
RBFN	7.28	0.60
MLFN	6.53	0.68
PNN	6.11	0.74

Multi-layer Feed Forward Neural Network (MLFN)

Multi-layer feed forward neural network, or MLFN, is the classic neural network and referred to as the multi-layer perceptron (MLP). Supervised learning using the perceptron model was first presented by Rosenblatt (1958). It has the capability of solving nonlinear problems but its disadvantage is the final answer which is dependent on the initial guess of the weights. Fig. 6 shows a structure of a multi-layer perceptron with M inputs and K perceptrons. In the MLP, the first layer is referred to the input layer, the second layer is referred to the hidden layer and the third layer is referred to the output layer. Between input and output layers, one or more hidden layers are possible, but it is common to use one layer with optimum numbers of nodes. Any function with a finite collection of points and any function that is continuous and bounded can be solved with three layers. The three layers model can handle many functions that do not have these criteria (Masters, 1993). The input to the MLFN is a vector of M attributes $x_j^T = [x_{1j}, x_{2j}, \ldots, x_{Mj}]$, where j = 1, ..., N, is the number of seismic samples. The output of the weighting and summation in the first layer can be written as:

$$y_{kj}^{(1)} = \sum_{i=0}^{M} w_{ki}^{(1)} x_{ij} = W^{(1)T} x_j \quad , \quad k = 1,2,\ldots,K. \tag{6}$$

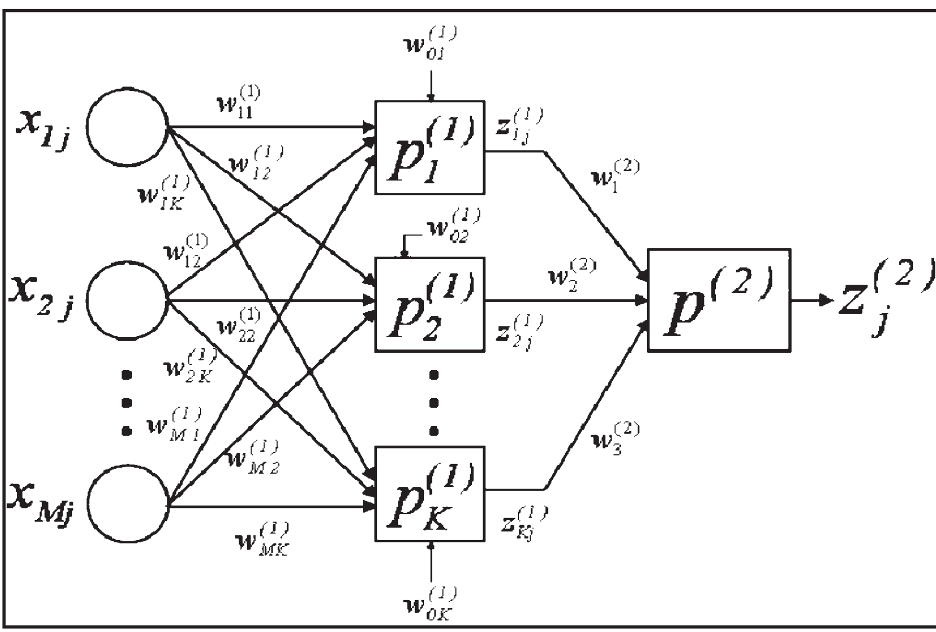

Fig. 6. A multi-layer perceptron with M inputs, K perceptrons, and a single output.

The input to the single perceptron in layer 3 can be written as:

$$y_j^{(2)} = \sum_{k=0}^{k} w_{ki}^{(2)} z_{kj}^{(1)} = w_j^{(2)T} z_j^{(1)} \quad , \quad j = 1,2,\ldots,N. \tag{7}$$

where $z_{kj}^{(1)}$ is a nonlinear function that imposes to the output of layer 1, one of the most commonly used in MLFN is the logistic function (3) in which the output is constrained between -1 and $+1$.

$$f(x) = \text{logist}(x) = 1/[1 + \exp(-x)] \ . \tag{8}$$

Final output for MLFN with two layer perceptron which is shown in Fig. 6 can be written as:

$$y_j^{(2)} = f^{(2)}[w^{(2)T} f^{(1)}(w^{(1)T} x_j)] \ . \tag{9}$$

Weights of the network are computed via error back propagation algorithm in which errors are back propagated through the network and used to improve the fitness between the actual output and the training value.

Radial Basis Function Neural Network (RBFN)

The radial basis function neural network, or RBFN, was originally developed as a method for performing exact interpolation of a set of data points in multi-dimensional space (Powell, 1987). It was derived from using regularization theory and Gaussian basis function, and it is a feed-forward network where the Gaussian bell curve is the basis function, and it was applied by Ronen (1994) for the first time.

Consider t_i values as the training samples and s_i values as the attributes vector, in general form the problem can be formulated as:

$$t(s_i) = \sum_{j=1}^{N} w_j \varphi |s_i - s_j| = \sum_{j=1}^{N} w_j \varphi_{ij} \quad , \quad i = 1,2,\ldots,N. \tag{10}$$

where the function $\varphi |s_i - s_j|$ is a set on N radial basis function depends on the attribute distance. A radial basis function is a function which its response decreases monotonically with distance away from a central point (Orr, 1996). It has been found that the most efficient function is the Gaussian basis function. So, (5) can be written as:

$$t(s_i) = \sum_{j=1}^{N} w_j\varphi_{ij} = \sum_{j=1}^{N} w_j \exp[-|s_i - s_j|^2/\sigma^2] \quad , \quad i = 1,2,\ldots,N. \tag{11}$$

where w_j, j = 1,...,N, are the desired weights. Eq. (6) in matrix form can be written as:

$$t = \text{Ø}w \quad , \tag{12}$$

Solution of (7) is given by:

$$w = [\text{Ø} + \lambda I]^{-1}t \quad , \tag{13}$$

where, λ is the pre-whitening factor and I is the identity matrix. Once the weights have been computed then they can be applied to application data set by:

$$y(x_k) = \sum_{j=1}^{N} w_j \exp[-|x_k - s_j|^2/\sigma^2] \quad , \tag{14}$$

The key parameter in the RBFN method is the sigma (σ) value. No efficient method for optimizing of σ as a function of each attribute has been obtained for the RBFN method (Russell, 2004) so parabolic search method (Press, 1992) was used to find the optimum value of σ. The RBFN for prediction of porosity by pre-whitening 10 was performed and optimum value of σ = 0.668 was calculated by parabolic search method.

Probabilistic Neural Network (PNN)

The probabilistic neural network is a neural network implementation of the Parzen window, and was initially proposed by Specht (1990). The PNN is such a fast and efficient method that can be used as a tool for predicting continuous or discrete data and for mapping input data to their outputs. A vector of x_i as the input to the PNN, the output $O_N(x_i)$ is calculated with a linear combination of n data points in training data set by the following equation:

$$O_N(x_i) = \{\sum_{i=1}^{n} O_{Ni} \exp[-D(x,Px_i)]\}/\{\sum_{i-1}^{n} \exp[-D(x,x_i)]\} \quad , \tag{15}$$

where $D(x,x_i)$ is the distance between the input point x and each of the training points, and it is calculated as follows:

$$D(x,x_i) = \sum_{j=1}^{k} [(x_j - x_{ij})/\rho_j]^2 \quad , \tag{16}$$

where k is the number of input data and ρ_j is the distance scale factor for each of the input attributes and the only parameter of the PNN which needs to be optimized. In comparison with the other types of neural network, such as MLFN that requires many parameters to be optimized, PNN is simple, fast and efficient. The optimal value of ρ_j is obtained when the validation error is minimum, in which a training sample was left out and then predicted from the other samples, after that the mean square error was computed, by repeating this procedure for all the training samples and averaging the errors, the validation error would be obtained (Russel, 2004).

For optimizing distance scale factor ρ_j, its range was taken between 0.10 and 3.00. The numbers of ρ_j value to try was set to 25. The optimized values of ρ_j for porosity prediction were obtained as follows:

Inverse of Inversion result: 0.124; average frequency: 0.258; Global ρ_j: 0.342.

Design of ANFIS

For the prediction of porosity at interested zone, ANFIS with linear and constant Sugeno models with 4 and 9 rules and different membership functions were constructed. Training of the network was done by using the hybrid learning algorithm and optimal irritation selected based on validation error. The learning algorithms of ANFIS consist of the following two parts: (a) the learning of the premise parameters by back-propagation and (b) the learning of the consequence parameters by least-squares estimation (Jang, 1993). At the end, these networks were trained with all input data set and their results for the test data set are shown in Table 3.

RESULTS AND DISCUSSION

Results of this study are shown in Tables 2 and 3 and Fig. 7. Between ANNs, PNN has had the best correlation and less error in the test data set and between ANFIS investigations, zero order Sugeno type with four rules and Pi (Π)-shape membership function was the best one, comparison of the ANNs and ANFIS showed ANFIS has had a better result than ANNs. Better prediction of porosity from seismic attributes by PNN between ANNs approved Kadkhodaie (2009) result and reject Russell (2004) result which considers RBFN as the best one, and ANFIS like CFIS (Kadkhodaie, 2009) was the best against ANNs. Predicted porosity for Asmari formation near two wells on 2D seismic section "5103 SE-NW" by ANNs and ANFIS is shown in Fig. 7.

Table 3. Results of ANFIS with different architecture for prediction of porosity.

ANFIS Architecture			RMSE	Correlation Coefficient
Sugeno type	Membership Function	Number of Rules		
Zero Order	Gaussian	4	5.975	0.750
Zero Order	Gaussian Combination	4	5.965	0.751
Zero Order	Pi (Π)-shape	4	5.683	0.765
Zero Order	Generalized bell-shaped	4	5.961	0.751
Zero Order	Gaussian	9	10.065	0.426
Zero Order	Gaussian Combination	9	755722.702	-0.156
Zero Order	Pi (Π)-shape	9	946971.858	-0.046
Zero Order	Generalized bell-shaped	9	15.698	0.359
First Order	Gaussian	4	6.170	0.742
First Order	Gaussian Combination	4	6.274	0.735
First Order	Pi (Π)-shape	4	6.515	0.707
First Order	Generalized bell-shaped	4	6.354	0.721
First Order	Gaussian	9	167.500	0.522
First Order	Gaussian Combination	9	896522877.852	0.486
First Order	Pi (Π)-shape	9	293484.311	0.123
First Order	Generalized bell-shaped	9	1747.265	0.500

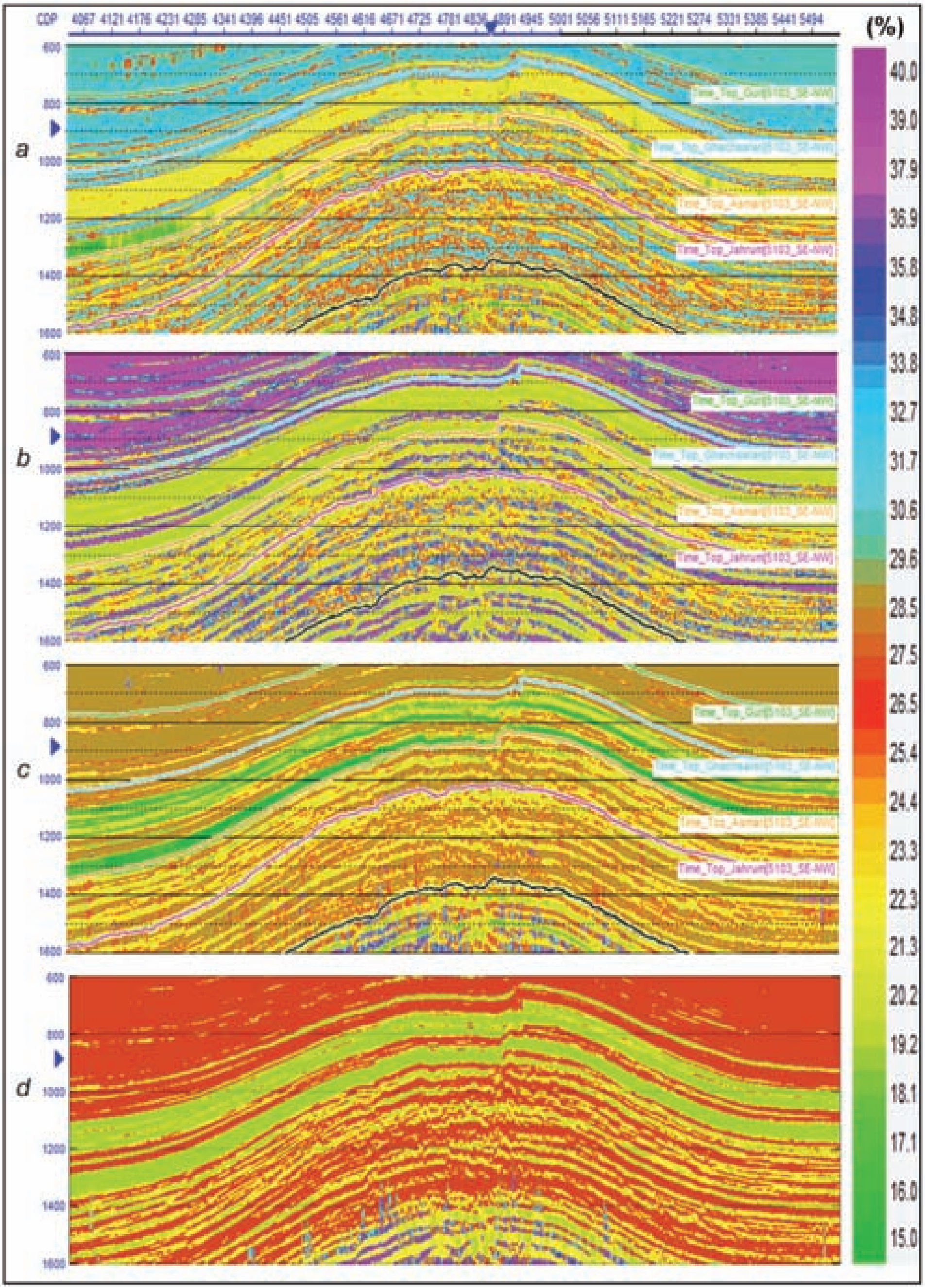

Fig. 7. Predicted porosity for Asmari reservoir across the Farour.A oil field by using RBFN(a), MLFN(b), PNN(c), ANFIS(d).

CONCLUSION AND FUTURE WORK

ANFIS was used for formulating porosity from seismic attributes. Based on this research ANFIS was more accurate, reliable and fast for prediction of porosity from seismic attributes against ANNs. It can decrease cost and exploration risk by an accurate prediction in hydrocarbon exploration programs. As future work, it is better to perform ANNs, ANFIS and CFIS on more oil fields and adjust parameters that influence them.

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