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Artificial Intelligence for prediction of porosity from Seismic Attributes: Case study in the Persian Gulf

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Abstract

Porosity is one of the key parameters associated with oil reservoirs. Determination of this petrophysical parameter is an essential step in reservoir characterization. Among different linear and nonlinear prediction tools such as multi-regression and polynomial curve fitting, artificial neural network has gained the attention of researchers over the past years. In the present study, two-dimensional (2D) seismic and well logs data of the Burgan oil field were used for prediction of the reservoir porosity. In this regard, broad-band acoustic impedance was first extracted from 2D seismic dataset, as the attribute most related to porosity. Next, other optimum seismic attributes were selected using stepwise regression and cross validation techniques. At the end, three types of neural network were used for inversion of seismic attributes and prediction of reservoir porosity. The results show that probabilistic neural network (PNN) is the best one for prediction of the reservoir porosity using seismic attributes.

Keywords: *Porosity, Seismic attributes, Well log data, Probabilistic neural network, Burgan reservoir.*

Introduction

The geophysical development of oil and gas fields relies on characterizing several petrophysical properties throughout the sedimentary interval containing the reservoirs [1]. Hence, laboratory measurements on core plugs, interpretation of geophysical well logs and inversion of seismic attributes provide valuable estimation about reservoir physical properties. Integration of these distinct methodologies is the best approach to determine uncertainties in the predictions, with direct implications on risk mitigation in drilling operations [2] .

Porosity is a key variable in characterizing a reservoir and in determining flow patterns in order to optimize the production of a field. Reliable prediction of porosity is also crucial for evaluating hydrocarbon accumulations in a basin-scale fluid-migration analysis and to map potential pressure seals in order to reduce drilling hazards. Several relationships have been offered which relate porosity to wireline readings, such as the sonic transit time and density logs. However, the conversion from density and transit time to equivalent porosity values is not simple. The common conversion formulae contain terms and factors that depend on the individual location and lithology, e.g. clay content, pore-fluid type, grain density and grain transit time for conversion from density and sonic logs, respectively, which in general are unknown and thus must be determined from rock sample analysis. Hence, porosity is generally measured in the laboratory on the cored rocks taken from the reservoir or can be determined by well-test data. However, the well testing and coring methods are very expensive and time-consuming [3]. Moreover, in a typical oil or gas field, almost all wells are logged using various tools to measure geophysical parameters such as porosity and density, while both well test and core data are available only for a few wells [4].

Recently, petroleum industry has witnessed significant advances in research of 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 properties such as lithology, rock type, porosity, water saturation, pore pressure, etc. Some research work has been carried out for prediction of reservoir properties from seismic attributes [5, 6, 7, 8 and 9]. Recently, prediction of porosity from seismic attributes has been done by performing statistical approach, neural networks, fuzzy logic and committee fuzzy inference system (CFIS) [5, 9]. In all of these works, only one type of neural network has been used for prediction and there is no specific comparison between the various types of neural networks to highlight their capabilities.

The main aim of this paper is to predict porosity using seismic attributes and three different types of neural networks. The Burgan reservoir in the south of Iran has been selected as a case study.

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2. Study area

The Burgan reservoir is characterized by severe heterogeneity due to a complex interplay of stratigraphic and diagenetic effects. This reservoir is located in one of the oil fields in the Bushehr province, Iran. The producing horizon in this field is the Albian and lower Cenomanian limestone and shale. Figure 1 shows the geographic position of this reservoir. This oil field contains different formations including Kazhdomi, Daryan, Gadvan, etc. The entire available well log data of this study was obtained from four wells located in the Burgan reservoir. UTM coordinates of these wells are given in Table 1.

Fig. 1. Geographical position of the Burgan reservoir.

Table 1. UTM coordinates of the three wells located in Burgan reservoir.

Well Name	X (UTM)	Y (UTM)
Noroz 11	342782.81	3260826.63
Noroz 16	343970.20	3261833.70
Abozar 2	358642.00	3238562.00

3. Materials and methodology

This study focuses on the application of artificial neural network techniques for prediction of Burgan reservoir porosity using seismic attributes. For the purpose of this study, 3 post stack 2D seismic time sections with good quality and available well log data of three wells were used (Figure 2). Density, porosity and sonic logs were available for the entire wells, but Check shot data was only available for one well. The 2D time section "5 SE-NW" showing general quality of seismic data across the Burgan reservoir is shown in Figure 3.

3.1. Correlation of well logs to seismic data

As the first step of this study, seismic sections were interpreted and time horizons were picked based on the availability of one check shot in well A-2. Check shot was applied for initial time to depth conversion and then the first correlations of well logs to seismic data were carried out on wells N-11, N-16 and A-2 for extracting wavelet and making synthetic seismogram. After that, it was necessary to create synthetics and extract the wavelets iteratively for converting the well log data into time. At the end, suitable time-depth relationships were obtained. A well-to-seismic tie, at the well A-2, is shown in Figure 4, where the correlation between synthetic seismogram (blue) and composite trace (red) at vicinity of the well is 0.81.

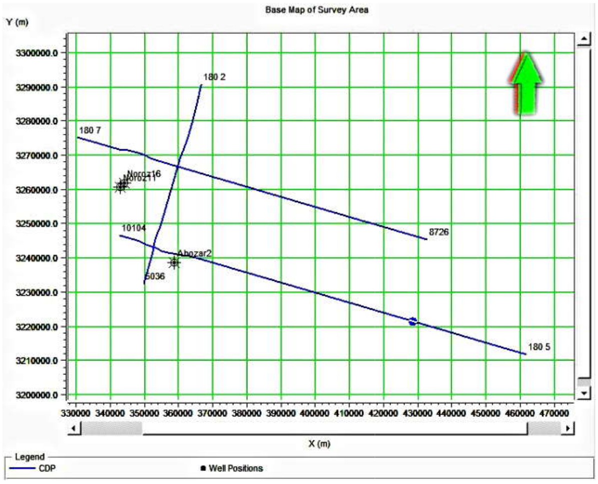

Fig. 2. A 2D Map showing the location of wells and 2D seismic sections across the Burgan reservoir.

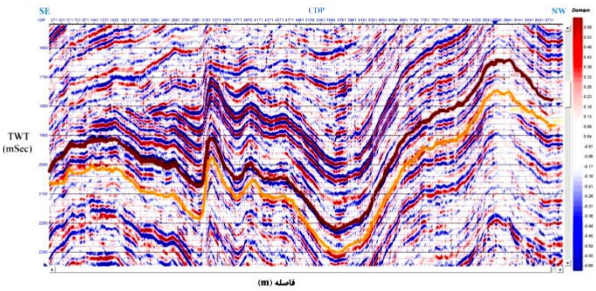

Fig. 3. 2D time section "5 SE-NW" showing the general quality of seismic data across the Burgan reservoir.

3.2. Selection of optimal seismic attributes

The reason for applying several statistical and intelligent approaches is to find linear or nonlinear relationships between two sets of input and output data. The relationship between input (seismic attributes) and output (porosity) data was investigated by stepwise-regression analysis and validation error was used a criterion to stop adding attributes to the input dataset [5]. The extracted attributes of this study are given in Table 2. According to Table 2, the first two attributes, acoustic impedance and average frequency, can be optimal inputs for prediction of porosity as the output in linearity and nonlinearity mode. Individual relationship between actual and predicted porosity of this study are shown in Figure 5.

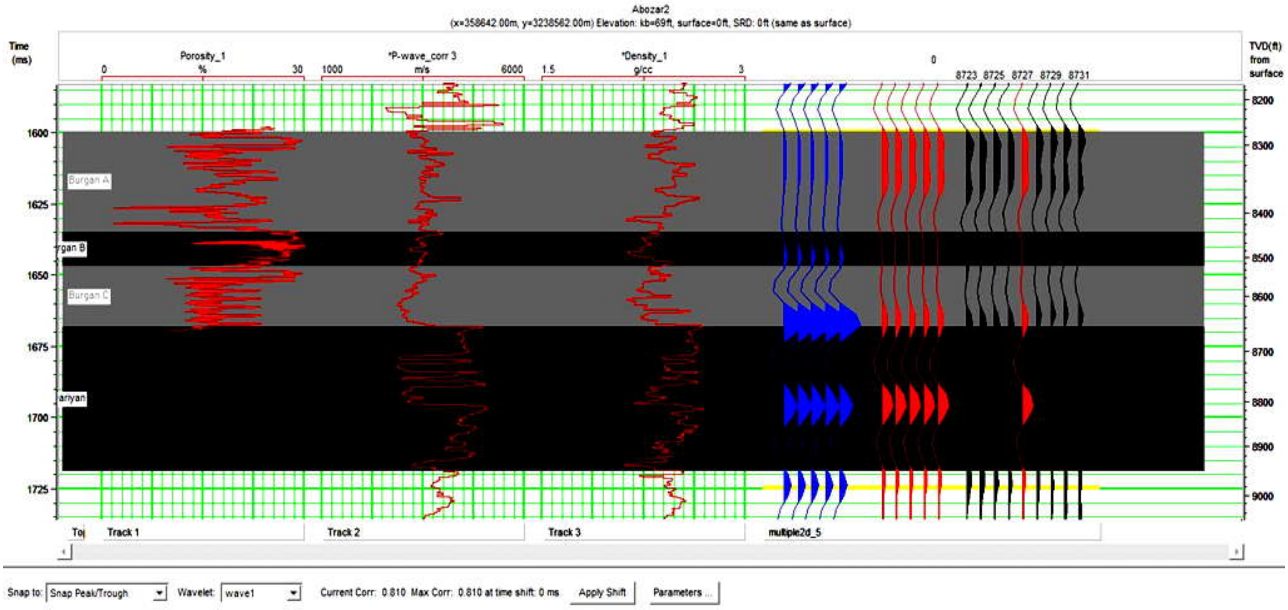

Fig. 4. A sample of well to seismic tie at well A-2.

Table 2. Multi-attributes extracted for predicting the porosity.

Number of attributes	Target	Final attribute	Training error	Validation error
1	Porosity	Acoustic Impedance	0.056038	0.065922
2	Porosity	Average Frequency	0.052839	0.063778
3	Porosity	Time	0.050521	0.064078

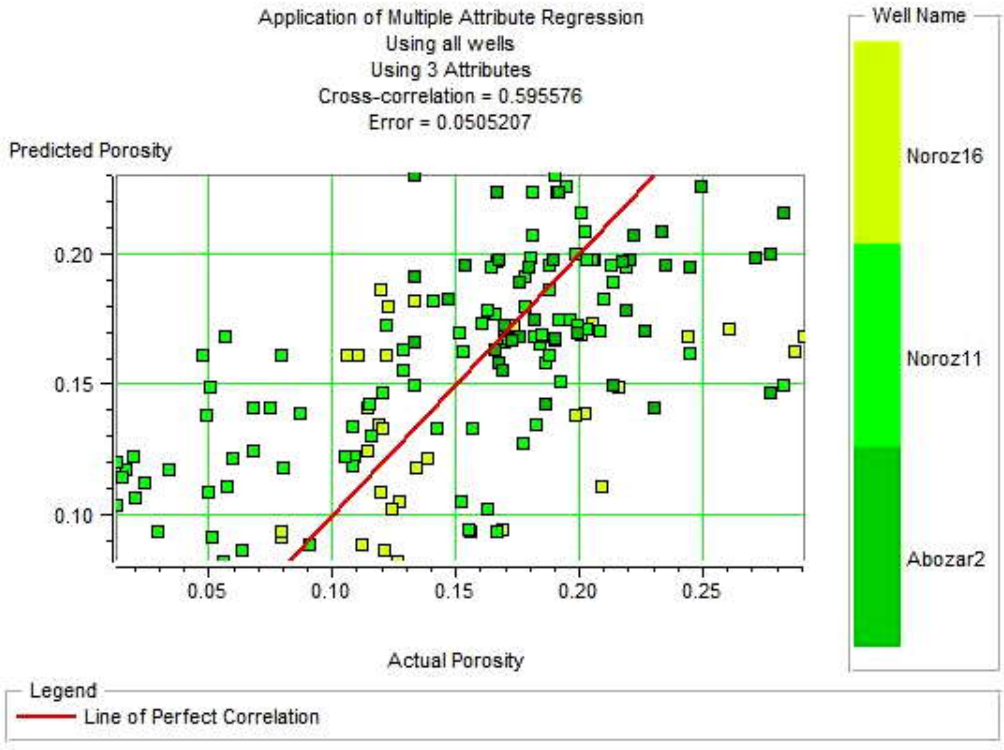

Fig. 5. A cross plot showing the relationships between actual and predicted porosity.

As it is well-known, acoustic impedance is a product of sonic velocity and bulk density. Because the acoustic impedance was selected as a suitable seismic attribute for prediction of porosity, a broad band acoustic impedance model for the entire oil field was extracted via seismic inversion integrating high frequency of seismic data and low frequency of well logs data. The average frequency is a signature of the events and the effects on the abnormal attenuation due to the presence of the hydrocarbons [10].

3.3. Artificial Neural Network

The goal of Artificial Neural Network (ANN) research is to develop a mathematical model of biological events in order to imitate the capability of biological neural structures with the purpose of designing an intelligent information processing system. The first mathematical model was introduced by Warren McCulloch and Walter Pitts [11]. An adaptive Neural Network is a network structure consisting of a number of nodes connected through directional links; all or part of the nodes are adaptive which means the outputs of these nodes depend on modifiable parameters belonging to these nodes.

3.3.1 Multi-layer Feed Forward Neural Network (MLFN)

Multilayer feed forward network, or MLFN, is the classic neural network and referred to as multi-layer perceptron (MLP). Supervised learning using the perceptron model was first presented by Rosenblatt, [12]. It has the capability of solving nonlinear problems but its disadvantage is that the final answer is dependent on the initial guess of the weights. Figure 6 shows a structure of a multi-layer perceptron with M inputs and K perceptron.

The first layer in the MLP is referred to as the input layer, the second layer as the hidden layer, and, the third layer as the output layer. Between input and output layers, one or more hidden layer is possible but it is common to use one layer with optimal number of nodes. Any function with a finite collection of points and any function that is continuous and bounded can be solved with 3 layers. The 3 layer model can handle many functions that do not have these criteria [13]. The input to the MLFN is a vector of M attributes, value $x^T_j = [x_{1j}, x_{2j}, ..., x_{Mj}]$, where $j=1, \dots, N$, is the number of seismic samples. The output of the weighting and summation in first layer can be written as:

$$y^{(1)}_{kj} = \sum_{i=0}^{M} w^{(1)}_{ki} x_{ij} = W^{(1)T} x_j, k = 1,2,...,K, \quad (1)$$

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

$$y^{(2)}_{j} = \sum_{k=0}^{k} w^{(2)}_{ki} z^{(1)}_{kj} = w^{(2)T}_{j} z^{(1)}_{j}, j = 1,2,...,N, \quad (2)$$

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

$$f(x) = \text{logist}(x) = \frac{1}{1+\exp(-x)}, \quad (3)$$

The final output for MLFN with two layer perceptron which is shown in Figure 6 can be written as:

$$z^{(2)}_{j} = f^{(2)}(w^{(2)T} f^{(1)}(w^{(1)T} x_j)). \quad (4)$$

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

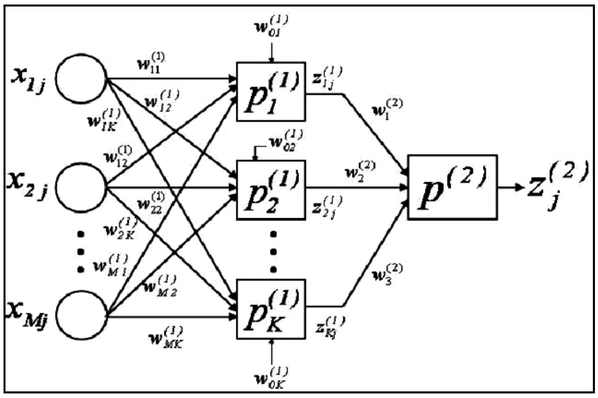

Fig. 6. A multi-layer perceptron with M inputs, K perceptrons, and a single output.

3.3.2. Radial Basis Function Network (RBFN)

The radial basis function network, or RBFN, was originally developed as a method for performing exact interpolation of a set of data points in multi-dimensional space [14]. It was derived using regularization theory and Gaussian basis functions and firstly applied by Ronen et al. [15]. It is a feed-forward network where the Gaussian bell curve is the basic function.

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

$$t(s_i) = \sum_{j=1}^{N} w_j \varphi\left(\left|s_i - s_j\right|\right) = \sum_{j=1}^{N} w_j \varphi_{ij}, i = 1,2,...,N, \quad (5)$$

Where, the function $\varphi\left(\left|s_i - s_j\right|\right)$ is a set on N radial basis functions that depends on the attribute distance. A radial basis function is a function the response of which decreases monotonically with distance away from a central point [16]. It has been found that the most efficient function is the Gaussian basis function. So, (5) can be written as:

$$t(s_i)=\sum_{j=1}^{N} w_j \varphi_{ij}=\sum_{j=1}^{N} w_j \exp\left[-\frac{|s_i-s_j|^2}{\sigma^2}\right], i=1,2,...,N, \quad (6)$$

Where w_j , $j= 1, \ldots , N$, are the desired weights.
Equation (6) in matrix form can be written as:

$$t=\O w, \quad (7)$$

The solution of (7) is given by:

$$w=\left[\O+\lambda I\right]^{-1} t, \quad (8)$$

Where, λ is the prewhitening factor and I is the identity matrix. Once the weights have been computed then they can be applied to application dataset by:

$$y(x_k)=\sum_{j=1}^{N} w_j \exp\left[\frac{|x_k-s_j|^2}{\sigma^2}\right]. \quad (9)$$

The key parameter in the RBFN method is the sigma (σ) value. Unfortunately, no efficient method of optimizing σ as a function of each attribute has been obtained for the RBFN method [5]. Therefore, the parabolic search method [17] was used to find the optimum value for σ. For the present study, the RBFN for prediction of porosity by pre-weightening 10 was performed and the optimum σ=0.444 calculated by the parabolic search method.

3.3.3. Probabilistic Neural Network (PNN)

The probabilistic neural network is a neural network implementation of the Parzen window, and was initially proposed by Specht [18]. The PNN can be used as a tool for predicting the continuous or discrete data and for mapping input data to their outputs It is a fast and efficient method. For a vector of x_i as the input to the PNN, the output $O_N(x_i)$ is calculated as the linear combination of n data points in training dataset by the following equation:

$$O_N(x_i)=\frac{\sum_{i=1}^{n} O_{Ni}\exp(-D(x,Px_i))}{\sum_{i=1}^{n}\exp(-D(x,x_i))}, \quad (10)$$

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

$$D(x,x_i)=\sum_{j=1}^{k}\left(\frac{x_j-x_{ij}}{\rho_j}\right)^2. \quad (11)$$

Where k is the number of input data, and ρj 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 ρj is obtained when the validation error is minimum, in which a sample of training was left out and then predicted from the other samples. Next, the mean square error was computed by repeating this procedure for all the training samples and by averaging the errors, the validation error could be obtained [5].

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

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

4. Discussion

The results of this study are shown in Table 3 and Figure 7. As seen, PNN is the best method among the selected ANNs because it can provide the maximum correlation of determination and the least root mean square error (RMSE) in the test dataset. Better prediction of porosity using seismic attributes via PNN approves the results obtained by Kadkhodaie-Ilkhchi et al. [9] but rejects the results of Russell [5]. The predicted porosity for the Bourgan reservoir in the vicinity of 2 wells on 2D seismic section “5 SE-NW” by different ANNs is shown in Figure 7.

Table 3. Results of different artificial neural network methods used for prediction of porosity.

Method	RMSE	Correlation Coefficient
RBFN	0.071	0.444
MLFN	0.063	0.554
PNN	0.058	0.609

5. Conclusion

In this research work, attempts have been carried out to utilize seismic attributes for the prediction of hydrocarbon reservoir porosity. The results obtained have shown that Acoustic Impedance, Average Frequency and Time are the most relevant attributes to be used for prediction of porosity (Table 2).

Later, three different types of neural networks (radial basic function network, multi-layer feed forward neural network and probabilistic neural network) were used for inversion and subsequent prediction of porosity.

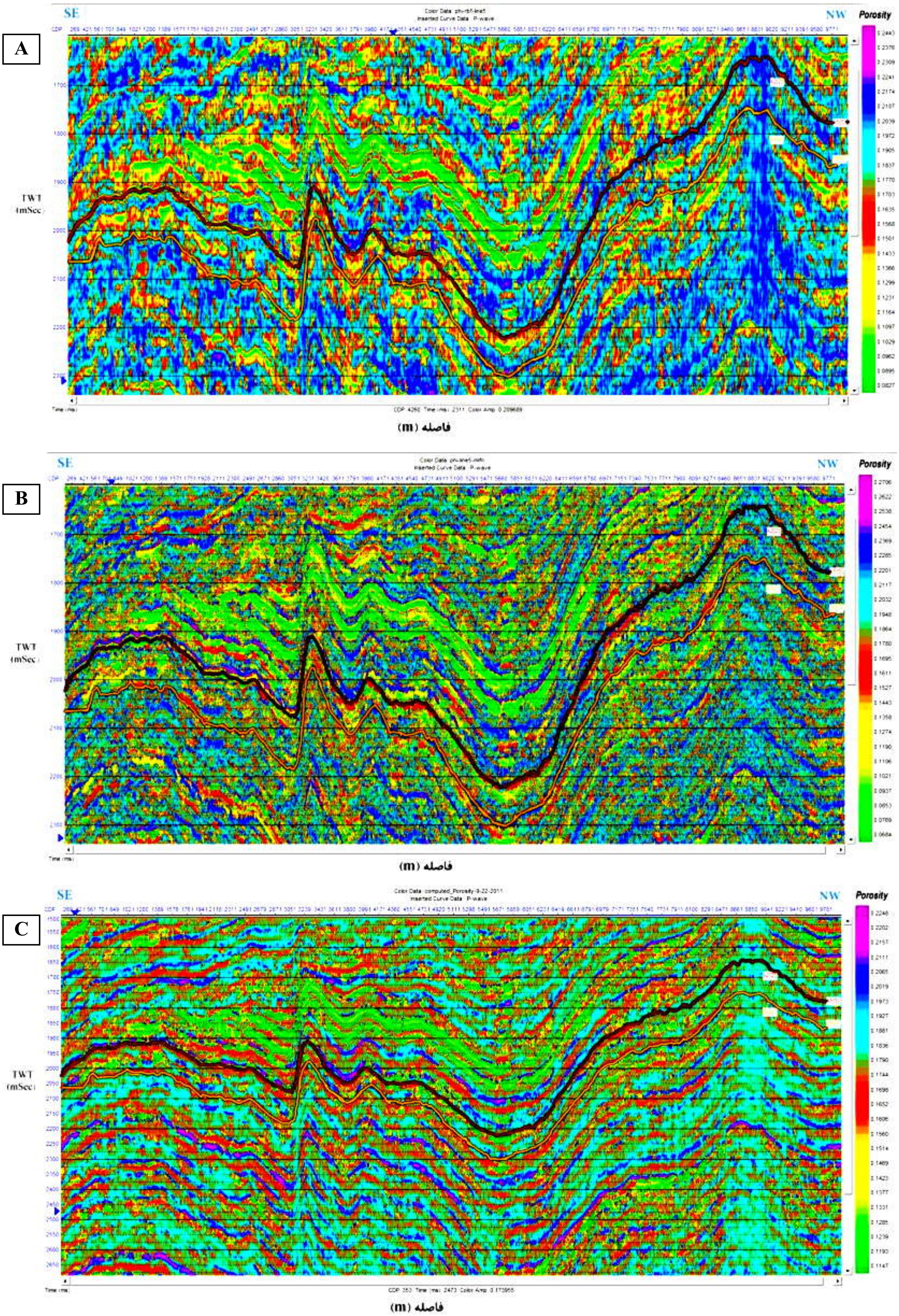

Fig. 7. Predicted porosity for the Bourgan reservoir across the Nowrooz oil field: (A) RBFN, (B) MLFN, (C) PNN.

6. Future Work

For the future work, Artificial Neural Network Fuzzy Inference System (ANFIS) will be used for formulating porosity via seismic attributes. Based on the research conducted by Kadkhodaie-Ilkhchi et al, [9]. ANFIS is a very accurate, reliable and fast method for the prediction of porosity when seismic attributes are taken into account. This method can significantly decrease the associated cost and exploration risk of reservoir exploration, management and production by providing more accurate predictions. As a future work, it is recommended that the performance of ANNs should be compared with that of an ANFIS and a Committee Fuzzy Inference System (CFIZ) to provide a better insight into the capabilities of each network.

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References

[1] Archie, G.E. 1950, Introduction to petrophysics of reservoir rocks, Bulletin of the American Association of Petroleum Geologists, v. 34, p. 943–961.
[2] Pennington WD. 2001, Reservoir geophysics, Geophysics, v. 66, p. 25–30.
[3] Bhatt, A. & Helle, H. B. (2002), Committee neural networks for porosity and permeability prediction from well logs, Geophysical Prospecting, v. 50, p. 645–660.
[4] Tiab, D. & Donaldson, E.C. 2004, Petrophysics - Theory and Practice of Measuring Reservoir Rock and Fluid Transport Properties (2nd Edition), Elsevier.
[5] Russell, B.H. 2004, The application of multivariate statistics and neural networks to the prediction of reservoir parameters using seismic attributes: Ph.D. Dissertation, University of Calgary, Alberta, 392 pp.
[6] Nikravesh, M. 2007, IRESC: Reservoir characterization. IFSA 2007 World Congress, JUN 18-21, 2007 Cancun, MEXICO, Theoretical Advances and Applications of Fuzzy Logic and Soft Computing, Book Series: ADVANCES IN SOFT COMPUTING, Volume: 42, p.404-414.
[7] Ahmad, N., Spadini, G., Palekar, A. & Subhani, M.A., 2007, Porosity Prediction using 3D Seismic Inversion Kadanwari Gas Field, Pakistan: Pakistan Journal of Hydrocarbon Research, v.17, p.95-102.
[8] Solano, P. 2007, Modified approach to predict pore pressure using the D exponent method: An example from the Carbonera formation, Colombia, CT&F - Ciencia, Tecnologíay Futuro - v.3 (3), p. 103–111.
[9] Kadkhodaie-Ilkhchi A., Rezaee, M.R., Bonab, H.R., Chehrazi, A. 2009, Petrophysical data prediction from seismic attributes using committee fuzzy inference system, Computers & Geosciences, v. 35, p. 2314–2330.
[10] Taner, M.T., Schuelke, J., The S., O'Doherty, R. & Baysal, E. 1994, Attributes revisited. SEG (Society of Exploration Geophysicists) Expanded Abstracts, 13, p. 1104–1107.
[11] McCulloch, W.S. & Pitts, W. 1943, A logical calculus of the ideas imminent in nervous activity. Bulletin of Mathematical Biophysics, v. 5, p. 115–133.
[12] Rosenblatt, M. 1958, The perceptron: A probabilistic model for information storage and organization in the brain: Psychological Review, v. 65, p. 386–408.
[13] Masters T. 1993, Practical Neural Network Recipes in C++, Academic Press, SanDiego, CA.
[14] Powell, M.J.D. 1987, Radial basis functions for multivariable interpolation: a review. In J.C. Mason and M.G. Cox (Eds.), Algorithms for Approximation, Oxford, Clarendon, p. 143–167.
[15] Ronen, S., Schultz, P.S., Hattori, M., & Corbett, C. 1994, Seismic-guided estimation of log properties, Part 1, 2, and 3: The Leading Edge, v. 13, p. 305-310, p. 674-678, and p. 770-776.
[16] Orr, M. J. 1996, Introduction to Radial basis function neural networks: Research Report for the Institute of Adaptive and Neural Computation, Division of Informatics University of Edinburgh.
[17] Press, William H.; Teukolsky, Saul A.; Vetterling, William T.; Flannery, Brian P. 1992, Numerical recipes in FORTRAN. The art of scientific computing, 2nd ed., Cambridge: University Press.
[18] Specht, D.F. 1990, Probabilistic neural networks: Neural Networks, v.3(1), p.109–118.