The Nucleus **54**, No. 1 (2017) 10-15

www.thenucleuspak.org.pk

The Nucleus

ISSN 0029-5698 (Print)

ISSN 2306-6539 (Online)

Application of Multi-Layer Feed Forward Neural Network (MLFNN) for the Prediction of Porosity: A Case Study from Lower Indus Basin, Pakistan

M.F. Mahmood[1,2*] and Z. Ahmad[2]

[1]Bahria University, Islamabad, Pakistan

[2]Quaid-i-Azam University, Islamabad, Pakistan

fahad.mahmood@bui.edu.pk; fz97@hotmail.com

ARTICLE INFO

Article history :

Received : 14 December, 2016

Revised : 15 February, 2017

Accepted : 16 February, 2017

Keywords:

Porosity prediction,

Multilayered,

Feed forward,

Neural network

ABSTRACT

The geophysical formation evaluation plays a fundamental role in hydrocarbon exploration. Porosity is one of the main parameters that determine the amount of oil present in a rock formation. Accurate determination of porosity is a difficult problem due to failure in understanding of spatial porosity parameter distribution. Multi-layer feed forward neural network (MLFN) proved to be a powerful tool for mapping porosity across the whole field and proved to be a powerful tool for mapping complicated relationships in reservoir. In MLFN three layers are involved that is an input layer, an output layer and a variable number of hidden layers. Input for training eight external attributes are used which are P-impedance, S-impedance, density, fluid, lithology impedance, lamda-rho, mu-rho, and Vp/Vs. Five nodes are used in hidden layer and one output node for mapping total porosity of Badin gas field. In this study 3D cube of Badin field and 3 wells are used. The findings proved competence of multi-layer feed forward neural network in the porosity prediction process with an average error of 0.014 [v/v] and the correlation coefficient of 0.91 and helped in studying the lateral variations in the porosity along the reservoir. The A sands show same porosity values along both the well locations, while for B sand the porosity value decreases from Zaur-01 to Chakri-01 well while for C sand the porosity value increases from Zaur-01 to Chakri-01 well.

1. Introduction

Major activity in evaluating reservoir is examining the impact of reservoir heterogeneities on reservoir behavior. This heterogeneity in evaluating reservoir is referred to as non-linear and non-uniform spatial distribution of rock properties such as porosity. However it is difficult to predict porosity due to form and spatial distribution of heterogeneities. Understanding the form and spatial distribution of rock properties is fundamental to a successful characterization of reservoirs. In this prevalent situation, it is useful to construct a model that understands rock properties and has the capabilities to make a good prediction.

This is a typical problem that can be solved by multi-layer feed forward neural network. The Multi-Layer Feed Forward Neural Network (MLFN) is also known as the back propagation neural network (BPNN) or the "multi-layer perceptron" (MLP) [1]. It is a type of classical neural network. The advantage of multi-layer feed forward neural network is supervised learning, which means that it knows the desired output. Therefore it adjust the weight coefficients in such a way, that the calculated and desired outputs are as close as possible. In multi-layer feed forward neural network, there is an input layer, an output layer and a variable number of hidden layers. Each layer consists of neurons which are connected to other neurons for every previous and next layers set by weights. Between input and output layer, one or more hidden layers are possible. But commonly one hidden layer is used with number of nodes [2]. In hidden layer, large number of nodes tends to fit the training data reasonably well and could show good result. But care must be taken in this case because too many nodes can over fit the data and errors could be produced in prediction.

In the input layer, no computation is executed by neurons, because they are just the input layer nodes. The neurons in the output layers and hidden layers have biases and weights, which are connected to neurons in the preceding layer [3]. The weighted and biased input from each neuron in the previous layer is summed by each neuron and then filters the sum with a transmission function. Mathematically it can be written as in Eq. (1) :

$$\text{Neuron}'\text{s output } y = f\sum_{j=1}^{p} x_j w_j \qquad (1)$$

Where, w_j = synaptic connection weights, x_j = neuron input, f = activation function which defines the output in

[*] Corresponding author

terms of the input activity (e.g. amount of signals), p = number of neurons in the output layer, $x_j w_j$ summation is also called the Net Input.

To accurately map the inputs to the output, the weights and biases are constantly updated by the network, which connect each of the neurons until some performance condition is achieved. This procedure is known as training. In description, the weights are best when the prediction error is lessened, that is when the predicted value for each training point is as close as conceivable to the actual value. This is a non-linear optimization problem with many local minima. MLFN uses an amalgamation of simulated annealing and conjugate-gradient analysis to find the global minimum. Each of the total iterations consists of a pass of the conjugate gradient analysis, accompanied by an attempt at simulated annealing to search for a better starting point [4].

For the reservoir characterization to measure the reservoir properties like porosity number of techniques are available like discriminant analysis, Kohonen network etc. While discriminant analysis is a well-established statistical classification method and in Kohonen network unsupervised training is involved and the output is not known. Therefore to acquire a stable state number of iterations are involved in this network. Prediction of porosity using MLFN is a relatively new concept. The MLFN approach, while subject to a degree of trial and error as regards the selection of the optimum configuration of middle nodes, is shown to be capable of excellent performance. Therefore MLFN is preferred more for porosity prediction as compared to other available techniques.

2. Database

Three wells named Zaur-01, Zaur-03 and Chakri-01 from Badin gas field Pakistan were used to provide log data. The log data consisted of bulk density (DEN), compensated neutron porosity (CNL), acoustic (AC) and deep induction resistivity (ILD). The DEN, ILD and AC respond to the characteristics of rock directly adjacent to the borehole. A combination of these logs provides more accurate estimation of porosity. These geophysical logs are also known as porosity logs.

The data from Zaur-01 and Zaur-03 wells are used for training purposes. The logs of these wells are up-scaled to seismic resolution of 4 milliseconds and converted to time domain. For Zaur-01 well the well window from 1412 to 1536 milliseconds, and for Zaur-03 well, the well window from 1368 to 1480 milliseconds was used for training purposes. The Chakri-01 well is left out as blind test well for the validation of network.

3. Methodology

Input for training eight external attributes are used which are P-impedance, S-impedance, density, fluid, lithology impedance, lamda-rho, mu-rho, and Vp/Vs [5], which are derived using pre-stack seismic inversion. Five nodes are used in hidden layer and one output node for mapping total porosity [9]. The parameters used for neural networks are:

- The network is in mapping mode
- The network is not cascaded
- Number of iterations = 5
- Number of nodes in hidden layer = 5
- Number of conjugate – gradient iterations = 5

Using the above mentioned parameters, the results of the training process is shown in Fig. 1. The training process shows that MLFN is able to predict the porosity efficiently with an average error of 0.014 [v/v] and the correlation coefficient of 0.91 is achieved as shown in Fig. 2a. The training process proves the competence of multi-layer feed forward neural network in the prediction process [6]. However, using the blind well test step, the performance of this network is validated. The porosity log data of well Chakri-01is used to test the constructed network further. The actual log and the modeled log for training and validation data sets with correlation coefficient and average error is shown in Fig. 2b.

The validation step show the correlation coefficient of 0.86 is achieved with the validation error of predicted porosity at blind well is 0.02 [v/v]. These results proved that MLFN has done a tremendous job of porosity prediction. It should be noted that this well is 15 km away from the training area; therefore this method can be used to predict the porosity along the whole field for reservoir interval [7].

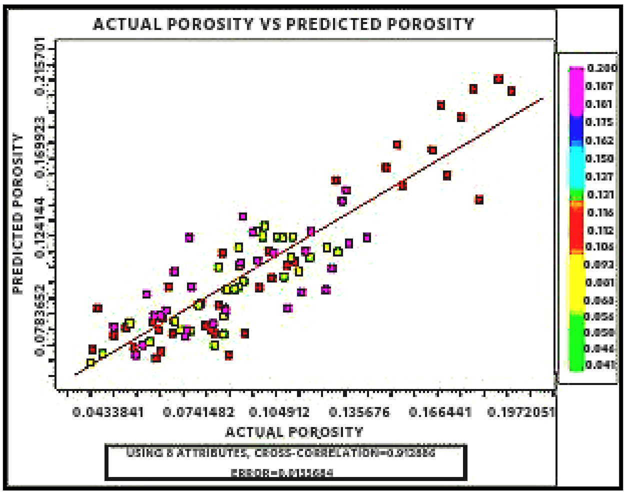

Fig. 1: Results of training of MLFN using eight attributes, using two wells. The well data is up scaled to seismic resolution

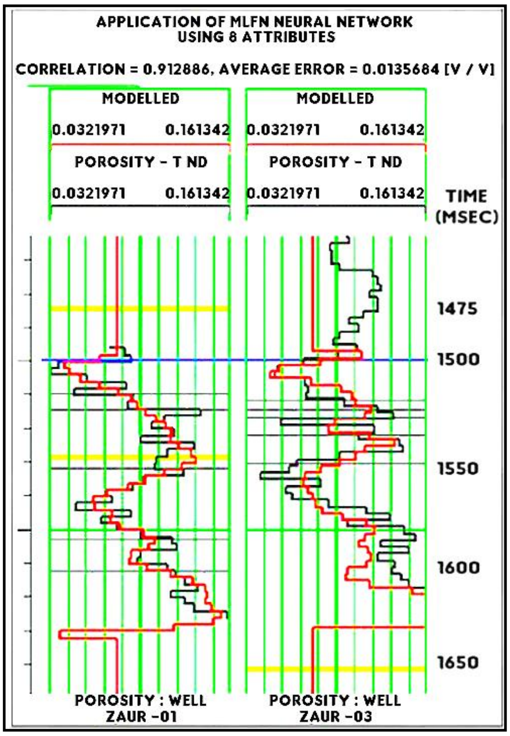

Fig. 2a: The training data of the MLFN using eight designated attributes

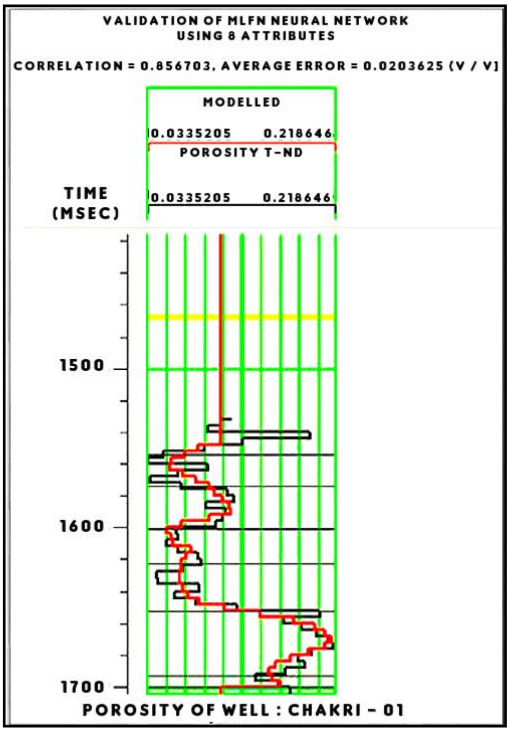

Fig. 2b: Validation of blind well of the MLFN using eight designated attributes

The same methodology is applied to predict the porosity variations along Inlines and crosslines of 3D cube of Badin area.

4. Results

The training and validation of multilayer feed forward neural network produce very good results. For training of data Zaur-01 and Zaur-02 wells are used while for validation purpose Chakri-01 well is used. After validation of data, MLFN is applied to inlines and crosslines of 3D cube for predicting lateral variations in porosity. The predicted porosity profiles along inlines, inserted with porosity logs at well locations for Zaur-01 and Chakri-01 wells, are shown in Fig. 3 and Fig. 4. It can be observed from figures that along the inline of Zaur-01 well, for training Zaur-01 well the well based porosity match with adjacent predicted porosity traces. At Chakri-01 well the porosity log at blind well is nearly identical with the adjacent porosity traces along the seismic profile. It proves that neural network in predicting the porosity is better than any other methods [8]. In this the lateral variations in the porosity are observable along the reservoir interval [10]. According to the results, A sands have same porosity values along both the well locations, while for B sand the porosity value decreases from Zaur-01 to Chakri-01 well, while for C sand the porosity value increases from Zaur-01 to Chakri-01 well.

After the validation step is completed, the volume of porosity cube is computed. The total porosity maps averaged for the reservoir sands are shown in Figs. 5, 6 and Fig. 7. For A sand the high porosity of > 8% is concentrated at the centre of survey while low porosity of < 8% is concentrated at the edges of survey. While for B sands, the high porosity of > 8% is located mostly along central south. While in case of C sands, the high porosity > 8% is concentrated mostly along north eastern side. These results can be associated with log interpretation results, as Chakri-01 well shows some oil potential in C sands, which can be associated with higher porosity on these maps.

5. Discussion

The multilayer feed forward neural network is applied to 3D seismic data of Badin area for the prediction of porosity. Zaur-1 and Zaur-3 wells are used to train the data, which is cross-validated using the Chakri-1 well as blind well. The correlation of 86% is achieved after validation and applied to the whole 3D cube for prediction of porosity. The final analysis showed that B-sands on the south eastern side of study area proved to be good quality porous sands. Therefore this side is productive and having more hydrocarbon saturation. A sand does not show any significant presence of good quality sands while C sands show good porosity values near Chakri-01 well. All of these results are consistent with well data. Multilayer feed forward neural network has successfully predicted the porosity values at inter-well region by completely honoring the well data. Therefore,

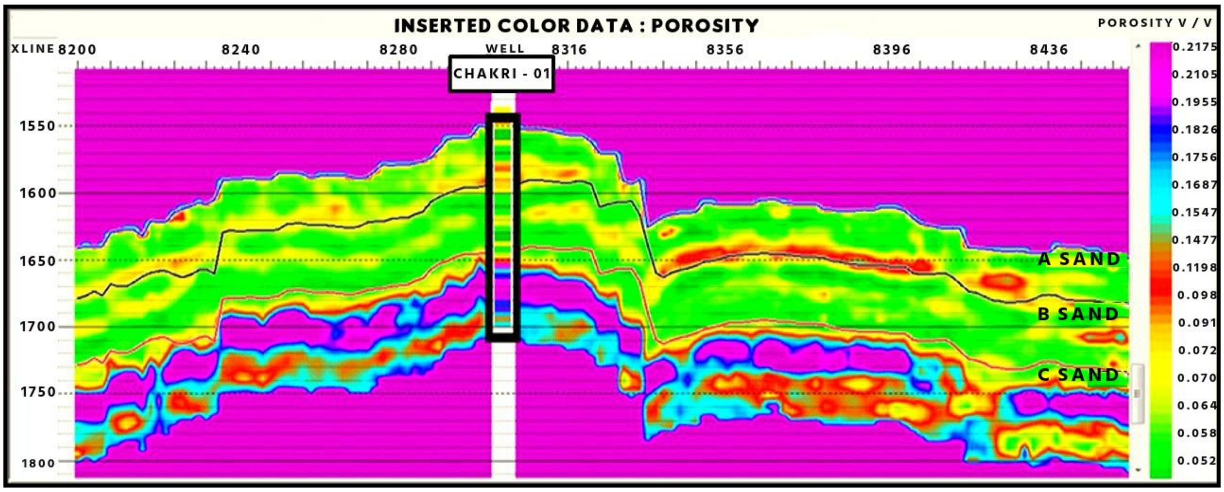

Fig. 3: Display of predicted porosity using neural network along inline, inserted with porosity log for Chakri – 01 well. The inserted log is colored and upscaled to seismic resolution

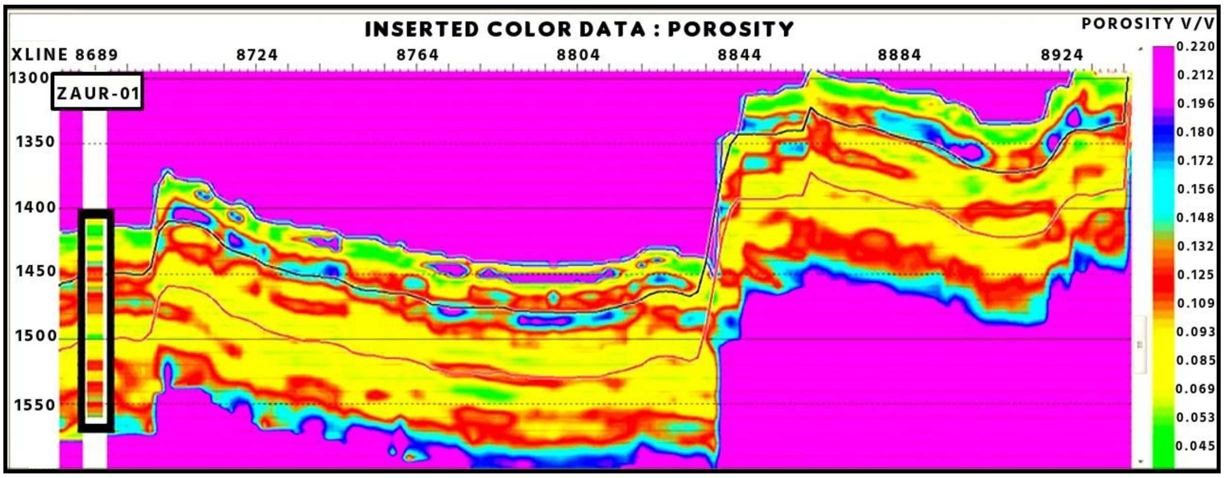

Fig. 4: Display of predicted porosity using neural network along inline, inserted with porosity log for Zaur – 01 well. The inserted log is colored and upscaled to seismic resolution

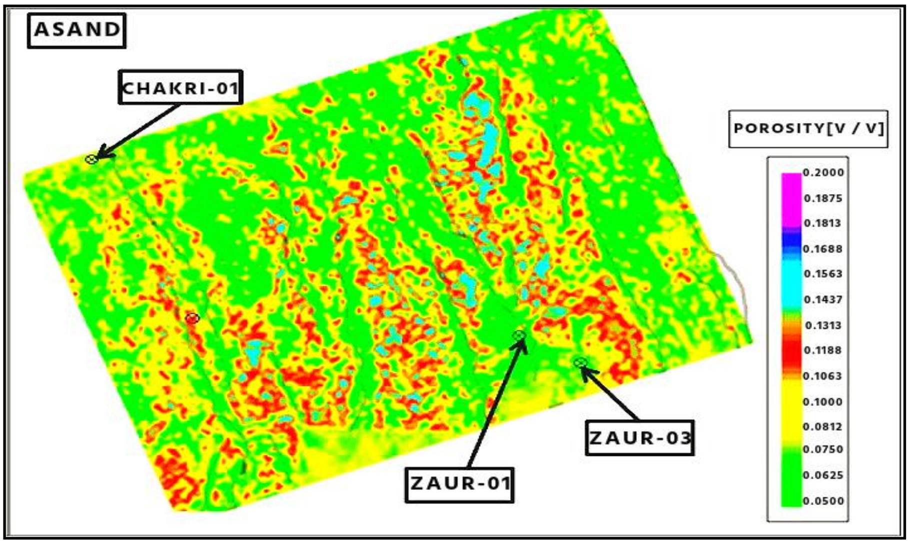

Fig. 5: Average porosity map for A sands

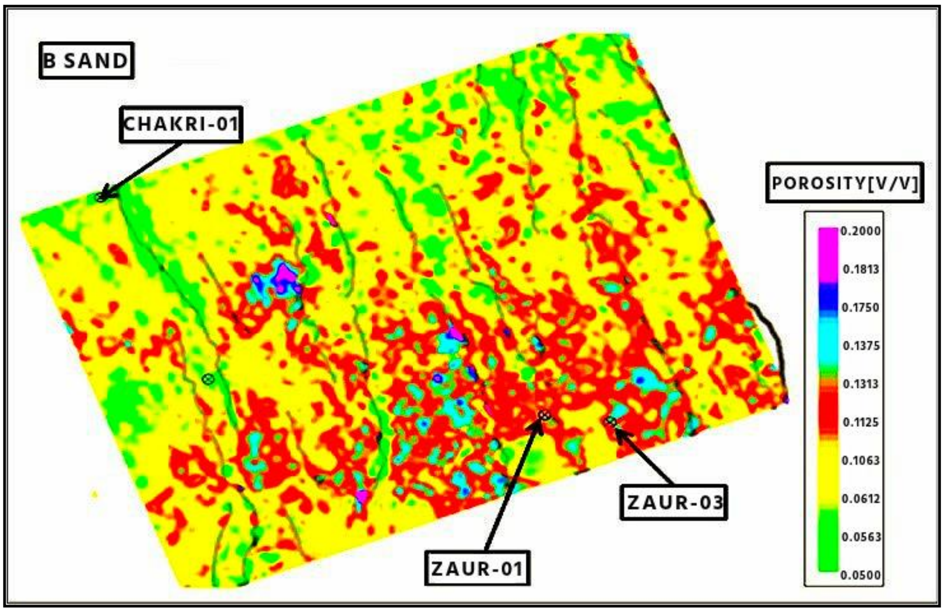

Fig. 6: Average porosity map for B sands

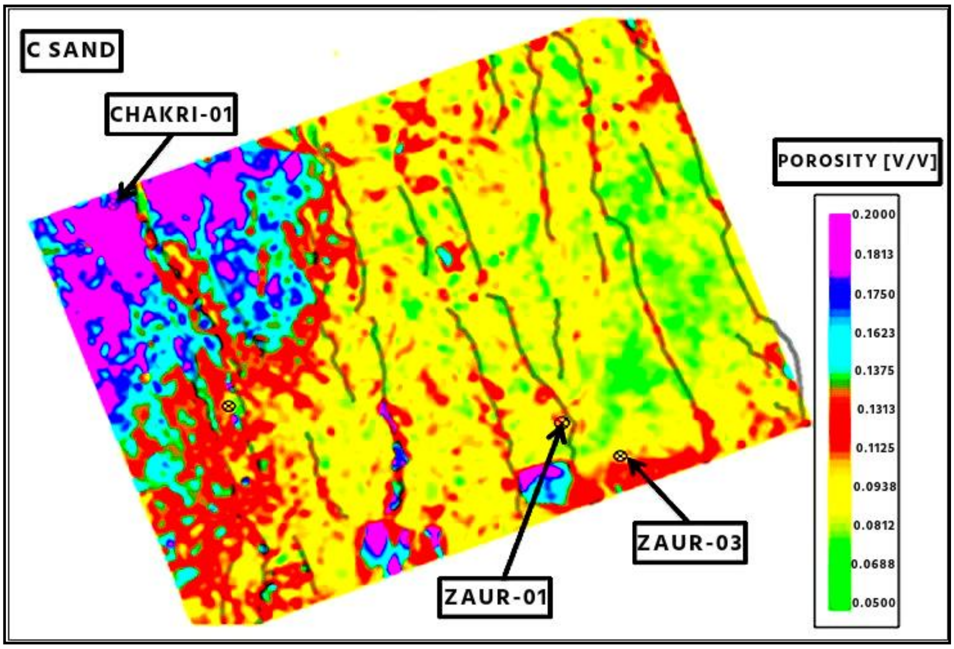

Fig. 7: Average porosity map for C sands

for the prediction of porosities multilayer feed forward neural network is preferred method rather than using conventional analysis.

6. Conclusions

The prediction of seismic porosity from seismic data helps in improving the reservoir characterization by the estimation of rock property away from well control. The improved image of reservoir by porosity prediction using multi-layer feed forward neural network help eventually to more advantageous placement of future production wells.

References

[1] B. Goodway, T. Chen and J. Downtown, "Improved AVO fluid detection and lithology discrimination using Lame petrophysical parameters; lambda rho, mu rho and lambda/mu fluid stack, from P and S inversions", Society of Exploration Geophysics Expanded Abstracts, 16, pp.183-186, 1997.

[2] D.P. Hampson, J.S. Schuelke and J.A. Quirein, "Use of multi-attribute transforms to predict log properties from seismic data", Geophysics, vol. 66, no. 1, pp. 220-236, 2001.

[3] D.H. Han, A. Nur and D. Morgan, “Effect of porosity and clay content on wave velocity in sandstones”, Geophysics, vol. 51, pp. 2093-2107, 1986.

[4] R.B. Latimer, R. Davison and P. van Riel, “An interpreter's guide to understanding and working with seismic-derived acoustic impedance data”, The Leading Edge, vol. 19, no.3, pp. 242-256, 2000.

[5] M.D. McCormack, “Neural computing in geophysics”, The Leading Edge, vol. 10, pp. 11-15, 1991.

[6] T. Masters, “Practical Neural Network Recipes in C++”, Academic Press, London. p.. 493, 1993.0

[7] B.H. Russell, “The application of multivariate statistics and neural networks to the prediction of reservoir parameters using seismic attributes”, Ph.D. Dissertation. University of Calgary, Alberta, 2004.

[8] R.K. Shrestha, “Reservoir characterization of high impedance sands in the Ada field, North Louisiana, USA. Society of Exploration Geophysicists Spring Symposium Technical Program vol. 11, pp. 5-16, 2008

[9] T. Todorov, R. Steward, D.P. Hampson and B.H. Russell, “Well Log Prediction Using Attributes from 3C-3D Seismic Data”, Expanded Abstracts, vol. 8, pp. 1574-1576, 1998.

[10] M.D. Zoback, “Reservoir geomechanics”, University Press, Cambridge, p. 449, 2007.