Shale Gas reservoirs characterization using neural network

Sid-Ali Ouadfeul and Leila Aliouane

Algerian Petroleum Institute, IAP, Algeria
LABOPHYT, Faculté des Hydrocarbures et de la chimie, Université Mhamed Bougara de Boumerdès, Avenue de l'indépendance, Boumerdés, Algeria.
Souadfeul@ymail.com

Abstract. In this paper, a tentative of shale gas reservoirs characterization enhancement from well-logs data using neural netwok is established. The goal is to predict the Total Organic carbon (TOC) in boreholes where the TOC core rock or TOC well-log measurement does not exist. The Multilayer perceptron (MLP) neural network with three layers is established. The MLP input layer is constituted with five neurons corresponding to the Bulk density, Neutron porosity, sonic P wave slowness and photoelectric absorption coefficient. The hidden layer is forms with nine neurons and the output layer is formed with one neuron corresponding to the TOC log. Application to two boreholes located in Barnett shale formation where a well A is used as a pilot and a well B is used for propagation shows clearly the efficiency of the neural network method to improve the shale gas reservoirs characterization. The established formalism plays a high important role in the shale gas plays economy and long term gas energy production. **Keywords:** TOC, Prediction, Neural Network, MLP .

1 Introduction

The Total Organic Carbon prediction form seismic and well-logs data has becoming an important topic of research, Yeon et al (2009) have suggest an improvement of total organic carbon forecasting using neural networks discharge model.

Bhatt and Helle (1999) have used a neural network approach for porosity, permeability and TOC prediction form well-logs data using a neural network approach.

Ouadfeul and Aliouane (2014) have suggested the use of the Multilayer perceptron neural network model for the prediction of the TOC from well-logs data, the training algorithm is the Back Propagation. Obtained results clearly show the efficiency of the neural machine to predict the Total Organic Carbon , the suggested machine is able to replace the Schmoker's model in case of discontinuous measurement of the Bulk density log.

Here, we suggest the use of the Levenberg Marquardt training algorithm to predict the TOC form well-logs data using the Multilayer Perecptron (MLP) neural network machine. We start the paper by explaining the some geophysical definitions of the Total Organic Carbon and The Schmoker's method, after we explain the principle of the mulilayer Perceptron and the Levneberg Marquard Algorithm, we proposed neural machine is applied to well-logs data of a horizontal well drilled in the Barnett shale formation. We end the paper by results interpretation and a conclusion.

2 Total Organic Carbon

The Total Organic Carbon (TOC) is the amount of organic carbon in the source rock, there is no unit to quantify it. It is very important to have a high TOC (>5%) to talk about a good shale plays and sweet spots. Three methods are used for TOC measurement and estimation, the first is based on the direct measurement in the laboratory. The second one is based on the direct measurement using a well-logging tool. The last one is based on the empirical measurement, in this case two methods are used, the first one is the so-called the Passey's method and the second one is called the Schmoker's method.

2.1 Schmoker's method

Two widely used empirical approaches have been developed to quantitatively estimate TOC from log data. The first was developed in Devonian shales using bulk density logs (Schmoker, 1979 and 1980) and was later refined in Bakken shales (Schmoker and Hester, 1983). Based on the response of the bulk density measurement to low-density organic matter (~1.0 g/cm3), the Schmoker's method, as it is commonly called, computes TOC (Schmoker, 1980):

$$TOC = \frac{154.497}{\rho_b} - 57.261$$

where ρb is the bulk density in g/cm3 and TOC is reported in wt%. This equation assumes a constant mineral composition and porosity throughout the formation. Although the method was developed and refined based on specific environments, it is frequently used for TOC estimation in a wide variety of shale formations.

3 The Multilayer Perceptron

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate outputs. A MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable (Rosenblatt, 1961).

3.1 The Levenberg Marquardt Training Algorithm

Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as:

$$H = J * J^T$$

and the gradient can be computed as: $g = J^T$e

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$X_{k+1} = X_k - [J^T * J + \mu I]^{-1} * J^T e$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm.

4 Application to real data

4.1 Geological Setting

The Barnett Shale was deposited over present day North Central Texas during the late Mississipian Age in a time marine transgression caused by the closing of the lapetus Ocean Basin. By the end of the Pennsylvanian the Ouacita Thrust belt began encroaching into the present day North Texas area. The thrust belt owes its existence to the subduction of the South American plate under the North American plate The Ouachita Thrust's emergence created the foreland basin along the front of the thrust. Early studies of the basin attributed thermal maturation of the Barnett to burial history and the thermal regimes associated with depth of burial. Explorationists began to doubt this hypothesis as more data became available. Kent Bowker (2003) formerly of Mitchell Energy/Devon proposed a different model suggesting the maturation process was driven by displacement of hot fluids, from east to west, associated with the Ouachit Thrust. Figure 01 shows the stratigraphic column of Mississippian and the Pennesylvanian ages, our shale gas reservoir target is the lower Barnett, the top of the reservoir is located at 6650m (Givens and Zhao, 2014).

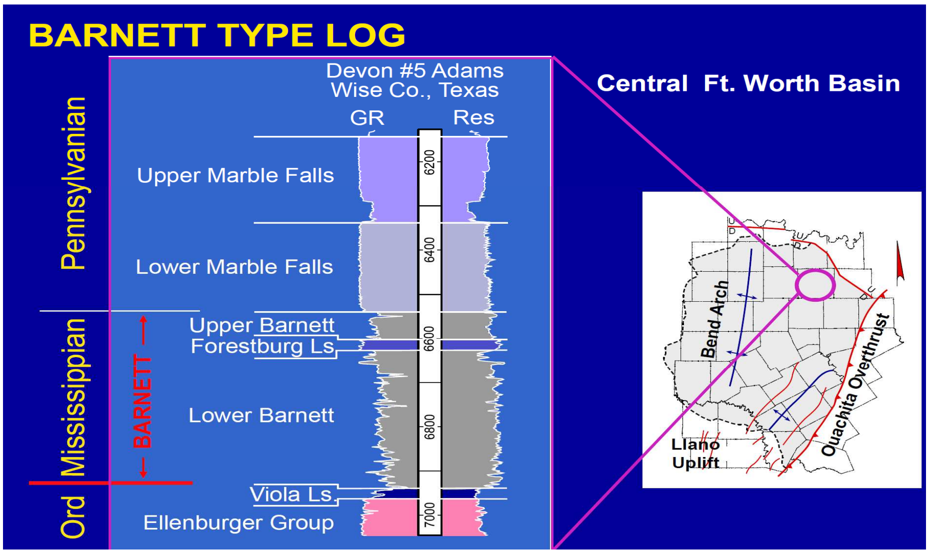

Fig. 1. Stratigraphic column of the Mississippian

4.2 Data Processing

Data of two horizontal wells drilled in the Lower Barnett are used, the first first well W01 is used for the training, and however the data of the second well W02 are used for the propagation. Figure 02 shows the recorded well-logs data of W01, the first track is the depth, the second track presents the Bulck density log, the third is the neutron porosity, the fourth and the fifth shows the Primary and the Shear wave Slowness, the last is the calculated TOC using the Schmoker's model.

In this cas we suppose that we have not the Bulk density measurement and we use the four first logs as an input and the calculated TOC as an output to train a multilayer perceptron neural network using Levenberg Marquardt training algorithm.

After training the weights of connections between neurons are calculated.

To check the efficiency of the neural network machine the data of the second horizontal well are propagated trough the neural machine using the weights of connections calculated previously. Figure 03 shows the measured well-logs data for the second well, data that are propagated through the neural machine have the same kind of those used as an input. Figure 04 shows the predicted total organic carbon compared with the estimated TOC using the Schmoker's model.

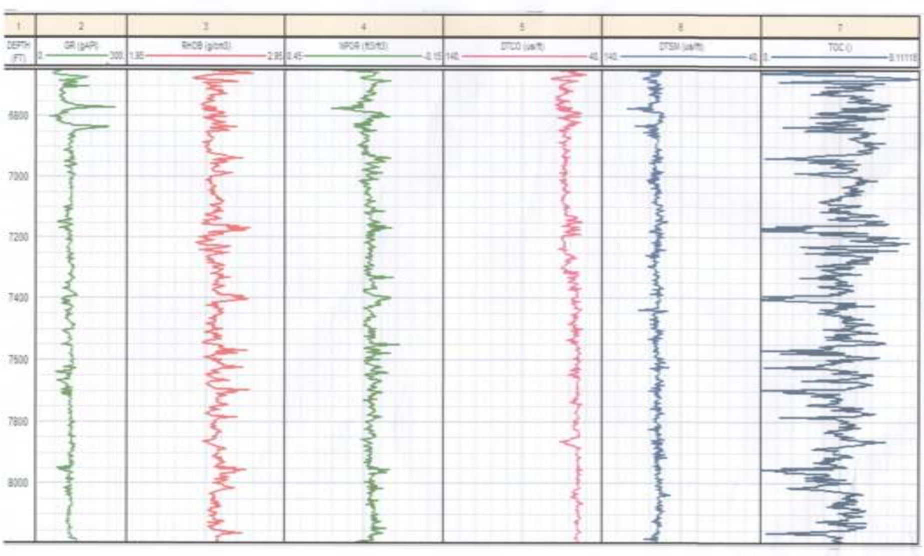

Fig. 2. Well logs data recorded in a horizontal well drilled in the Lower Barnett used as a pilot

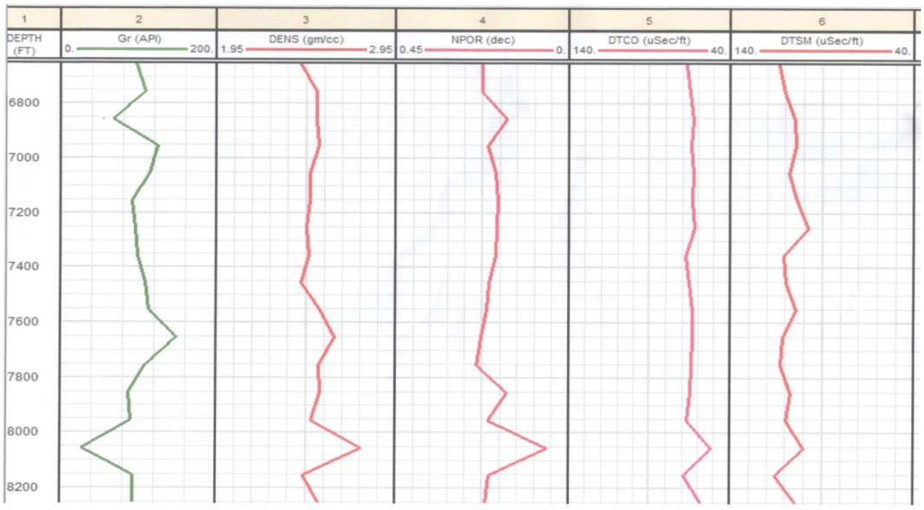

Fig. 3. Well logs data recorded in a horizontal well used for the data propagation

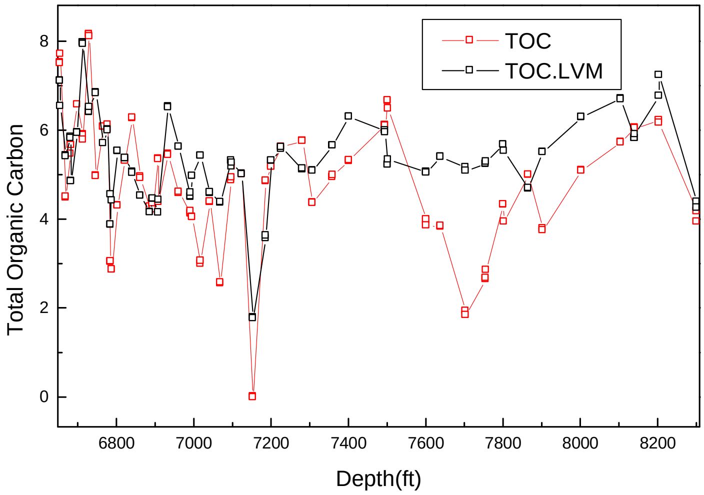

Fig. 4. Calculated TOC using Schmoker's model compared with the predicted TOC using the MLP with Levenberg Marquardt training algorithm.

5 Results interpretation and Conclusions

Figure 04 shows a comparison between the predicted total organic carbon using Levenberg Marquardt training algorithm and the total organic carbon using the Schmoker's model. It is clear that the proposed Multilayer Perceptron neural network machine is able to predict with a good precision the Total Organic Carbon in the second horizontal well without measurement of the Bulk density. The proposed neural network machine can be greatly used to replace the Schmoker's model and to provide a value of the Total organic carbon in case of discontinuous measurement of the Bulk density.

6 References

1. Bhatt, P., Helle, Hans B.: Porosity, permeability and TOC prediction from well logs a neural network approach, EAGE Helsinki June 7-11, Expanded abstract (1999).
2. Givens, N., Zhao, H.: The Barnett Shale: Not so Simple after all, Republic Energy (2014).
3. Rosenblatt, F.: Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms. Spartan Books, Washington DC (1961).
4. Ouadfeul, S., Aliouane, L., Shale Gas Reservoirs Characterization Using Neural Network, EGU General Assembly, held 27 April - 2 May, 2014 in Vienna, Austria, id.17019 (2014).

5. Schmoker, J.: Determination of Organic Content of Appalachian Devonian Shales from Formation-Density Logs, American Association of Petroleum Geologists Bulletin, 63, 1504-1537 (1979).
6. Schmoker, J.: Organic Content of Devonian Shale in Western Appalachian Basin: American Association of Petroleum Geologists Bulletin, 64, 2156-2165 (1980).
7. Schmoker, J., and Hester, T.: Organic Carbon in Bakken Formation, United States Portion of Williston Basin: American Association of Petroleum Geologists Bulletin, 67, p. 2165-2174 (1983).
8. Yeon, IS, Jun, KW, Lee HJ.: The improvement of total organic carbon forecasting using neural networks discharge model. Environ Technol. Jan; 30(1):45-51. doi: 10.1080/09593330802468780 (2009).