# Total Organic Carbon Prediction in Shale Gas Reservoirs using the Artificial intelligence with a comparative study between Fuzzy Logic and Neural Network

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## Abstract

**The main goal of this paper is to show the contribution of the artificial intelligence such as the Fuzzy logic and the Multilayer perceptron neural network with Levenberg Marquardt training algorithm in the prediction of the Total Organic Carbon from well-logs data. Our objective is to implant an intelligent system able to replace the Schmoker's model in case of lack of measurement of the Bulk density. Data of two horizontal wells drilled in the Barnett shale formation are used. The first one is used as a pilot well for the training while another well is used for generalization. Obtained results clearly show the power of the Multilayer perceptron than the Fuzzy Logic.**

## Introduction

Total Organic Carbon (TOC) prediction from well-logs data has becoming an important topic of research, Kumar and Sinha (2013) have suggested the prediction of the Total organic carbon for shale gas exploration using statistical clustering, multiple regression analysis, Ouadfeul and Aliouane (2014) haves shown the efficiency of the Multilayer Percptron neural network to predict the TOC in two horizontal wells drilled in the lower Barnett shale formation. Liu et al (2013) have used the support vector regression for quantifying the total organic carbon in shale Gas formations.

Two methods are mainly used in the estimation of the total organic carbon from well logs data, the first one is called the Passey's method or ΔLogR, for more details about this method we invite you to read the paper of Passey et al (1990), The second method is called the Schmoker's method, it requires a continuous measurement of the Bulk density (Schmoker, 1979, 1980; Ouadfeul and Aliouane, 2014). Here we compare between the fuzzy logic and the artificial neural network in the prediction of the total organic carbon in case of the lack of measurement of the Bulck density. Application to two horizontal wells drilled in the lower Barnett shale formation clearly shows the power of the Multilayer perceptron rather than the fuzzy logic in the prediction of the total organic carbon from well logs data

## 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; Schmoker, 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):

$$TOC = \frac{154.497}{\rho_b} - 57.261 \qquad (1)$$

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.

## The Fuzzy Logic

Fuzzy logic is an approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic on which the modern computer is based. The idea of fuzzy logic was first advanced by Dr. Lotfi Zadeh of the University of California at Berkeley in the 1960s. Dr. Zadeh was working on the problem of computer understanding of natural language. Natural language (like most other activities in life and indeed the universe) is not easily translated into the absolute terms of 0 and 1. Whether everything is ultimately describable in binary terms is a philosophical question worth pursuing, but in practice much data we might want to feed a computer is in some state in between and so, frequently, are the results of computing.

Fuzzy logic includes 0 and 1 as extreme cases of truth (or "the state of matters" or "fact") but also includes the various states of truth in between so that, for example, the result of a comparison between two things could be not "tall" or "short" but "0.38 of tallness."

Fuzzy logic seems closer to the way our brains work. We aggregate data and form a number of partial truths which we aggregate further into higher truths which in turn, when certain thresholds are exceeded, cause certain further results such as motor reaction. A similar kind of process is used in artificial computer neural network and expert systems. It may help to see fuzzy logic as the way reasoning really works and binary or Boolean logic is simply a special case of it (Passino and Yurkovich, 1998).

**The Multilayer Perceptron Neural Network**

A neural network is inspired from human biology; each neural network is composed of a set of neurons. Each neuron is connected with some neurons in the network. It receives a signal from other neurons and transforms to outside using a transfer function. The Multilayer Perceptron (MLP) is a feedforward artificial neural network. The MLP is composed of a set of layers; the first one is called the input layer, while the last one is called the output layer. The set of layers between these two layers are called hidden layers. It is shown that one hidden layer is enough for better approximations and the neural network will react better (Rosenblatt, 1961). The MLP uses the supervised learning mode were the couple input-desired output is known (Rosenblatt, 1961).
Many training algorithms have been suggested in the literature, the Back-propagation is one of the classical algorithms (Rosenblatt, 1961, Mohammadi and Rahmannejad, 2010). Traditional back propagation algorithms have some drawbacks such as getting stuck in local minimum and slow speed of convergence. The Leveneberg Marquardt training algorithm comes to resolve these ambiguities. In the next section, we will explain the principle of the Levenberg Marquardt training algorithm.

**Levenberg-Marquardt training Algorithm**

The Levenberg Marquardt (LM) training algorithm is an approximation of Newton's method for artificial neural network. The LM technique is known to be the best algorithm for optimization problems applied to artificial neural network.
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:

$$H = J * J^T \quad (2)$$

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:

$$X_{k+1} = X_k - [J^T * J + \mu I]^{-1} * J^T e \quad (3)$$

In practice this algorithm, in particular in the case of neural networks, can converge with much fewer iterations. But each iteration requires more calculations, in particular for the inversion of the matrix, and therefore its use is limited to cases where the number of parameters to optimize is not very high. Indeed the number of operations required for a matrix inversion is proportional to, as the size of the matrix, and also by the size of the vector. For more details about the Levenebrg Marquardt training algorithm we invite you to read the paper of Hagan and Menhaj (1994).

**Application to Barnett Shale**

**-Geological Context**

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. 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).

**-Data Processing**

To check the efficiency of the fuzzy logic to predict the Total Organic Carbon (TOC) from well-logs data in case of lack of measurement of the Bulk density, a fuzzy machine is trained in a supervised mode using the following well-logs data as an input: (1) natural gamma ray, (2) the neutron porosity, (3) slowness of the P wave, (4) slowness of the shear wave. The output is the calculated total organic carbon using the Schomker's model. Figure 02 shows these logs versus the depth.
After the training of the fuzzy logic system, data of another horizontal well drilled near the first well are propagated through the fuzzy machine and a curve of the TOC is predicted. Figures 03 shows the raw well-logs data of this well and figure 04 shows the predicted TOC using Fuzzy logic compared with the calculated TOC using the Schmoker's model.

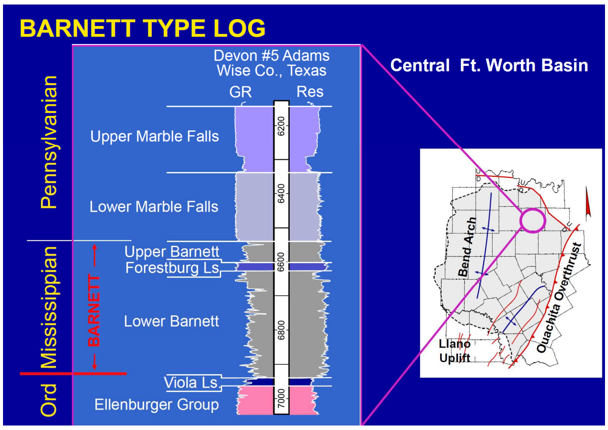


Figure 01: Stratigraphic column of Mississippian and the Pennesylvanian ages (Browning and Martin, 1980)

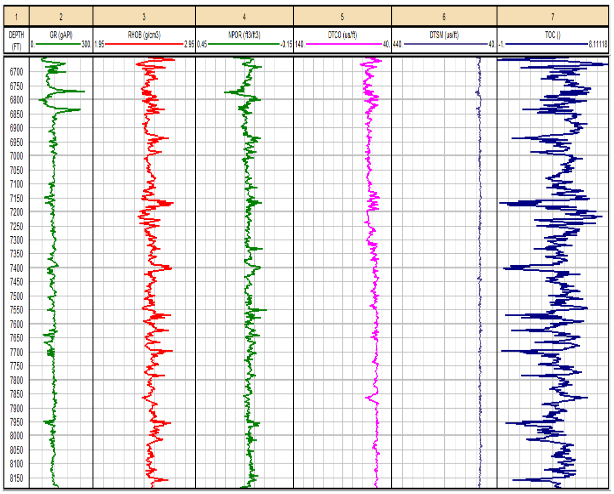

Figure 02: Well-logs data of the well01: (01 depth, (02) natural gamma ray, (3) bulk density, (03) neutron porosity, (04) slowness of the P wave, (05) slowness of the S wave, (06) calculated TOC using the Schmoker's model.

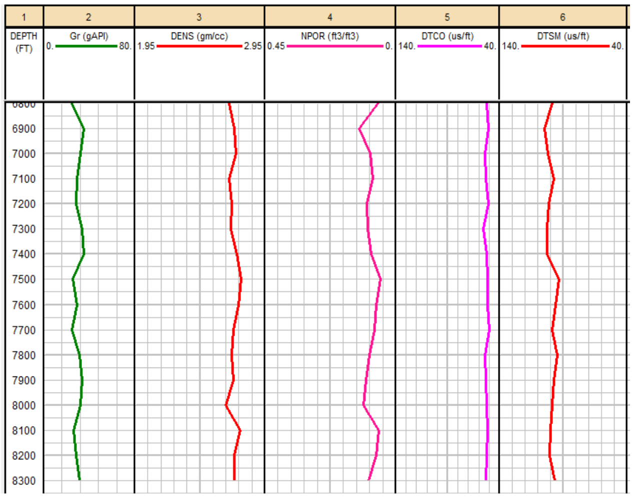


Figure 03: Well-logs data of the well02: (01 depth, (02) natural gamma ray, (3) bulk density, (03) neutron porosity, (04) slowness of the P wave, (05) slowness of the S wave.

## Results Interpretation and Conclusions

Comparison between the predicted TOC using the Fyzzy Logic and the calculated TOC using the Schmoker's model (see figure 04) clearly shows the disability of the Fuzzy system to predict the TOC. To compare between neural network and fuzzy logic we have presented in figure 05 the predicted TOC for the same horizontal well using the multilayer perceptron (MLP) with Levenberg Marquardt training algorithm. Comparison between figures 04 and 05 clearly shows the power of the multilayer perceptron with Levenebrg Marquardt training algorithm compared to the Fuzzy logic system to predict the total organic carbon in case of lack measurement of the bulk density. By consequence we suggest the use of the artificial neural network in the prediction of the TOC in shale gas reservoirs rather than the Fuzzy logic. Predicted Total organic carbon can be used for sweet spots discrimination, Kerogen volume estimation and basin modeling.

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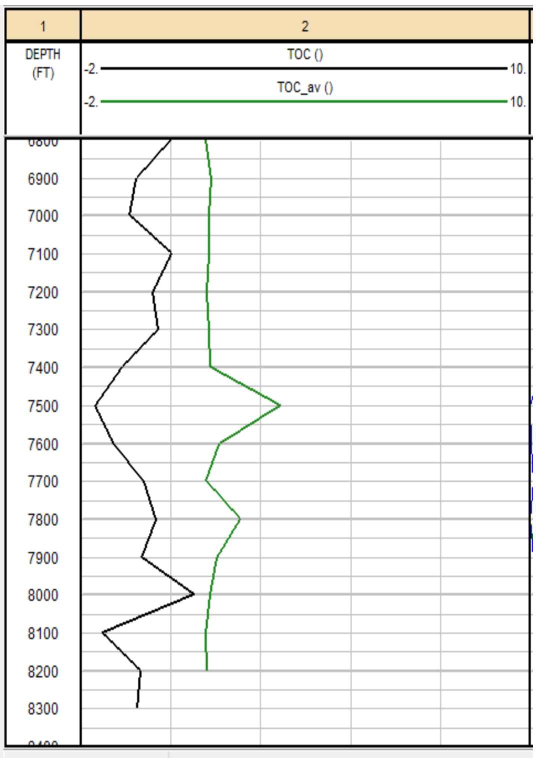


Figure 04: Calculated TOC using Schmoker's model (Black color) compared with the predicted TOC using the Fuzzy logic (Green color).

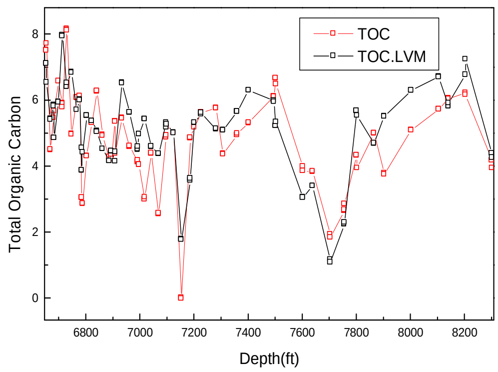


Figure 05: Calculated TOC using Schmoker's model (TOC) compared with the predicted TOC using the MLP with Levenberg Marquardt training algorithm (TOC.LVM).