Framework for EUR correlation to Seismic Attributes in the Barnett Shale, TX

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Summary:

Neural Networks application can be useful in solving geophysical classification problems. Seismic attribute analysis is a great tool to enhance and isolate features related to seismic acquisition, processing and geology. Methods that recombine two or more primary attributes can be used to improve a complete and unique isolation of a target feature in the seismic data. Among other methods, Neural Networks are one of the most efficient to recombine multiple input attributes and achieve a high quality extraction of a target feature or rock property from seismic data. Moreover, attributes in peak production of wells can vary according to completion technologies, thickness of the perforation interval and time in which the well was drilled, so there must be some relation between the seismic attributes data and the data obtained of a certain suit of wells. The aim of this study is to propose a framework for using supervised Artificial Neural Networks (ANN) in order predict suitable production target zones in the Barnett Shale using Lamda-rho, Mu-Rho and AVAz attributes as input data.

Introduction:

The general objective of using seismic attributes is to isolate and map certain geology-related features in the seismic data. The quality of a seismic attribute can be quantified in terms of completeness and uniqueness of the geological target feature. Neural networks are commonly used to solve problems when the expression of the in the seismic data is highly variable, non-linear or weak and three or more attributes or attribute parameterizations are needed to adequately image the target. Moreover, the relationship between the attributes and geological target is complex, sometimes inconsistent and may involve non-linear features such as threshold values or altering sensitivity over the range, such is the case of appearance of gas in a reservoir.

In this study, well log data from vertical and horizontal wells on the Barnett shale (Figure 1), is going to be used to obtain Lambda-Rho, Mu-Rho and AVAz attributes volumes, which will be correlated with production data from each well in order to answer the following questions: Is there a relationship between production data and seismic attributes in the study area? Can that relationship be extrapolated in order to predict production for other suits of wells? Is that prediction consistent to the highly variable data?

Geological Setting:

The Barnett Shale extends over an area of 28,000mi^2 across the Fort Worth Basin and adjoining Bend Arch in north-central Texas (Figure 1). The gas-shale play covers roughly the eastern third of the entire geographic area of the Barnett (Reference). However, most Barnett production is restricted to the northern part of the basin, where the shale is relatively thick (Montgomery et. al, 2005).

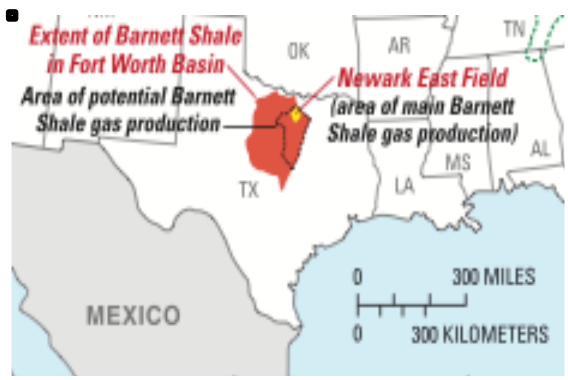

Figure 1. Location of the Missisipian Barnett Shale, Fort Worth Basin (Modified from Bruner and Smosna, 2011)

The core area (1,800mi^2) comprises the sweet spot of shale-gas production from three different zones close to the Texas/Oklahoma border. The non-core area (7,000mi^2) has been divided in two different zones, located south of the core area, based upon present level of development and assessed risk (Figure 2) (U.S. Geological Survey, 2004). The biggest risks involve estimating decline rate, thermal maturity, brittleness and an initial production rate.

Barnett Shale, Fort Worth Basin:

The Fort Worth Basin was formed during the late Paleozoic Ouachita Orogeny, generated by the convergence of Laurussia and Gondwana. It was part of the foreland basin situated on the southern leading edge of Laurussia.Today the basin is a shallow, asymmetric feature with a north-south structural axis that parallels the Ouachita Thrust front (Figure 2) (Bruner and Smosna, 2011). Paleographic reconstruction from several authors (e.g. Gutschick and Sandberg, 1983; Blakey 2005; and loucks and ruppel, 2007) suggests that the Fort Worth Basin was occupied by

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a narrow seaway, bordered by an island-arc chain to the east-southeast and the Eastern carbonate platform to the west. Therefore, Barnett deposition occurred during an early stage of foreland-basin development (Bruner and Smosna, 2011).

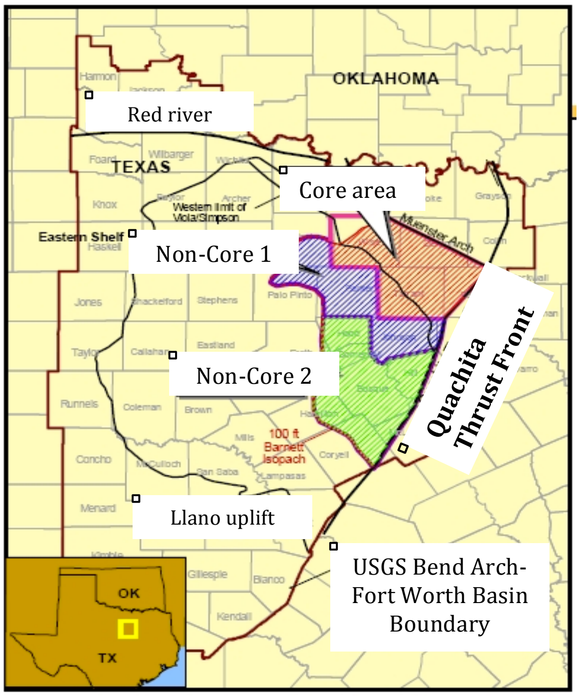

Figure 2. Core and Non-Core areas in the Barnett Shale, Fort Worth Basin (Advanced Resources Inc., 2005).

The Barnett Shale is mostly Mississippian in age and consists of dense, organic-rich, soft, thin-bedded, petroliferous, fossiliferous shale and hard, black, finely crystalline, petroliferous, fossiliferous limestone (Figure 3). In the northeastern portion of the basin, the Barnett is divided into informal upper and lower shale members by the presence of the intervening Forestburg Limestone Member (Bruner and Smosna, 2011). Where this unit is absent, the Barnett is treated as a single, undifferentiated formation.

The Viola Formation, consisting of micritic and dolomitic limestone, sandstone, anhydrite and halite, underlies the Barnett Shale in the northeastern part of the basin. Conformably overlying the Barnett is the Marble Falls Formation, which consists of two members, formed by: interbedded dark limestone and gray-black shale on the bottom and white to gray, crystalline limestone on the top (Figure 3).

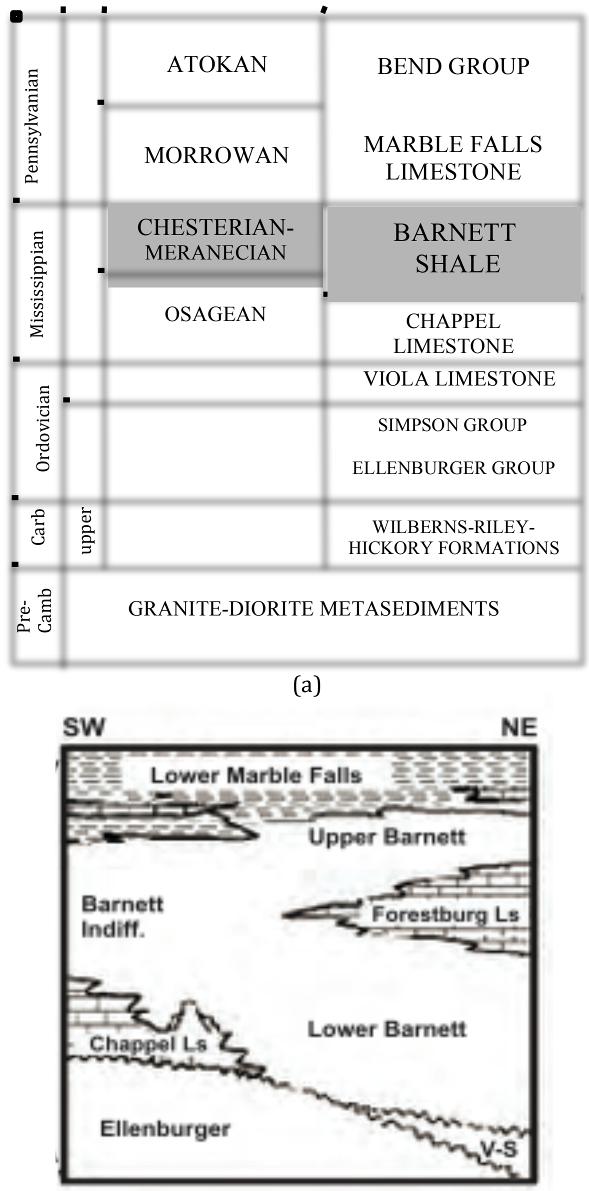

Figure 3. (a) Generalized stratigraphic column of the Fort Worth Basin, highlighting the Barnett Shale. (b) Expanded section of the Mississippian stratigraphy (Modified from Bruner and Smosna, 2011).

Data Available:

Figure 4 shows a diagram of the study area over the Fort Worth Basin, the number of wells that are going to be used in this study and the seismic data available.

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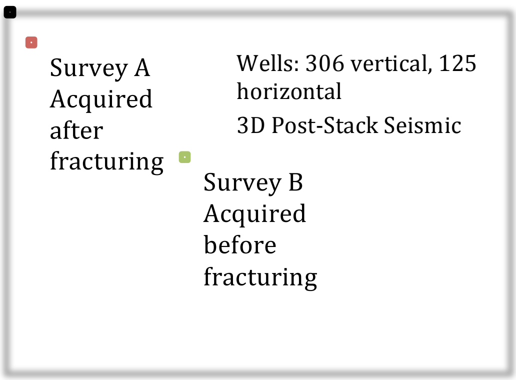


Figure 4. Diagram illustrating data availability

Theory and Method:

Artificial Neural Networks (ANN):

ANN have been inspired by what is known as the 'brain metaphor'. This means that these models try to copy the capabilities of the human brain into computer hardware or software. Neural network research started in the 1940s with McCulloch and Pitts (1943) description of the logical function of a biological neuron. The mathematical neuron proceeds in a similar but simpler way. The weighted sum of its inputs is fed to a nonlinear transfer function (i.e., the activation function) to rescale the sum (Figure 4).

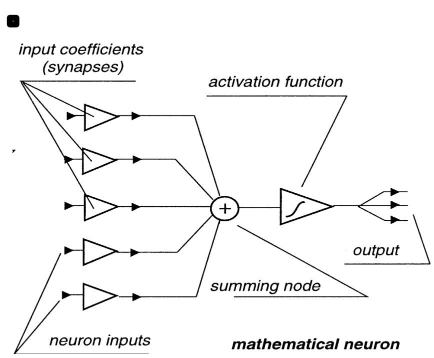


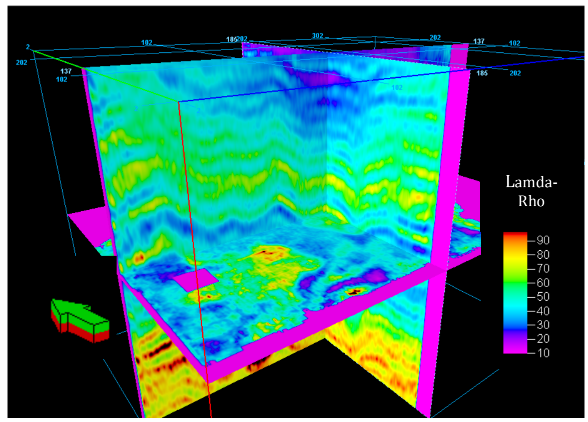
Figure 5. Mathematical Neuron (Modified from Bander Baan and Jutten, 2000).

Neural networks are increasingly popular in geophysics because they are universal approximators. These tools can approximate any continuous function with an arbitrary precision.

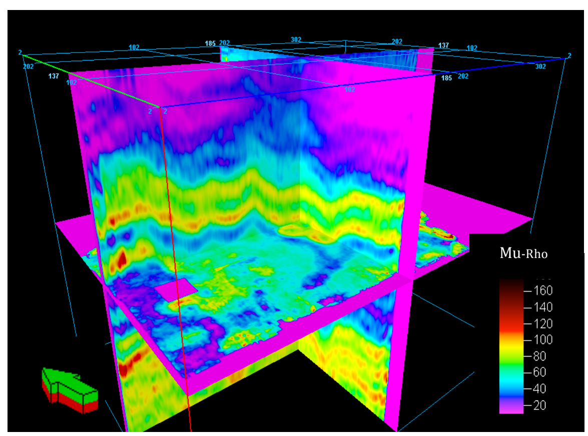
Workflow:

To accomplish the objectives of this study, the following framework is proposed:

1. Classify different production zones in order to be able to predict suitable future production targets.
2. Use attributes sensitive to lithology: Lambda-Rho (Figure 6), Mu-Rho (Figure 7) and AVAz to link the seismic data with the well log data.



(a)



(b)

Figure 6. (a) Lambda-Rho and (b) Mu-Rho volumes through the Barnett Shale (after Perez, 2012).

These attributes change due to porosity, depth of burial and other basin factors, because the impedance changes with such properties (Chopra and Marfurt, 2007), therefore, those parameters should be somehow associated with the EUR for a particular set of wells. Moreover, the mentioned attributes, as well as the well log production data are going to represent the input parameters for the Neural Network.

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3. Train the Neural Network using representative zones over the study area. The training method would consist in picking some spatial locations that are going to contain the extracted attributes and the expected production for that specific local point. In this sense, the ANN is trained to predict production from the seismic attributes in a way that is consistent with the examples it has been presented with.
4. Extract a seismic derived set of values at each seed location in order to predict production classes and derive a relationship between the attributes and the most likely EUR.
5. Apply the obtained relationship to a subset of wells that were not used in the creation of the transform in order to sustain the validity of this workflow.
6. Generate a production volume, which is going to determine the most likely EUR values at every grid node position beneath the seismic cube.

This workflow has been illustrated in Figure 7.

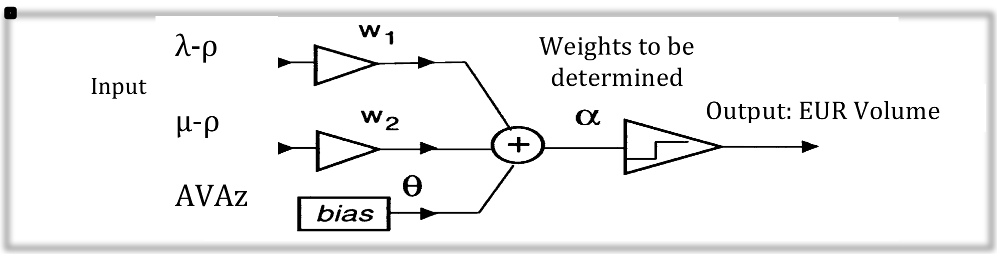

Figure 7. Proposed workflow to correlate EUR to seismic attributes on the Barnett Shale (modified from Bander Baan and Jutten, 2000)

Examples:

Verma et. al (2012) have attempted to perform regional distribution of frackability in the Barnett Shale through Gamma Ray volume prediction, using supervised neural network analysis (Verma et al., 2012). Using Gamma Ray logs, P-Impedance, S-Impedance, Spectral Components, Relative Impedance, Quadrature, Coherence and Sweetness 3D volumes as input parameters, Verma et al (2012) trained a supervised neural network and generated a Gamma-Ray volume. They concluded that, in the lower Barnett, high gamma ray values are possible zones of high TOC, while relatively low gamma zones are indicative of areas of high frackability. Moreover, the generated volume matches closely, not only with the gamma ray values from the wells that were used in the study, but with those that were not included in the neural network training process.

Perez (2012) has attempted to find EUR relative to the number of perforations that have been done in both, horizontals and vertical wells, as well as the length of those perforations in the upper and lower Barnett Shale.

Roy et. al (2012) did Principal Component Analysis (PCA) and Self-organizing Maps (SOM) on different horizontal wells and developed a clustering procedure which helps in predicting the most probable EUR for a well.

On the other hand, Thompson (2010) correlated EUR with most positive curvature in the Barnett Shale (Figure 8), and concluded that the larger EUR values are compartmentalized by the most positive curvature ridges.

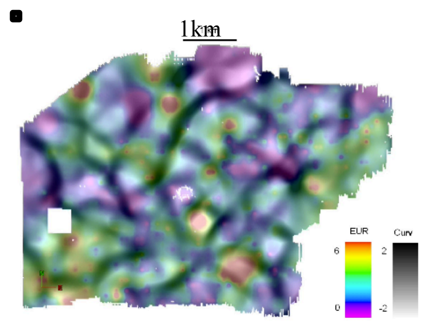

Figure 8. Relative EUR values, grided at 550ft by 550ft co-rendered with most positive curvature (Thompson, 2010).

Discussion and Expected Results.

Lambda-rho, mu-rho and AVAz attributes are related to lithology. These attributes tend to vary according to completion technologies, thickness of the perforation interval and time in which the well was drilled, so there must exist a non-linear relation between seismic attributes and EUR obtained of a certain suit of wells, and, moreover, that relation can be accurately assessed using supervised neural networks.

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EDITED REFERENCES

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