INTEGRATING NEURAL NETWORKS AND FUZZY LOGIC FOR IMPROVED RESERVOIR PROPERTY PREDICTION AND PROSPECT RANKING

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Summary

We use neural networks in conjunction with fuzzy logic to high-grade prospects containing hydrocarbon saturated reservoirs. We accomplish this by using fuzzy logic to formulate general rule of thumbs derived from rock physics data and interpreter's knowledge and experience. Integration of such linguistic rules with neural network ranking of most relevant attributes for prospect risking improves the process when compared against conventional "thresholding" methods. We show the benefits of combining neural network and fuzzy logic approaches where the strength of each method is combined. An example from onshore North America demonstrates the advantages of use of this technique.

Introduction

Neural networks (NN) have been used extensively used in different reservoir characterization problems, e.g. Nikravesh et al. (2002) and Aminzadeh and de Groot (2004). Fuzzy logic (FL), although not to the same extent as NN, has also been used in many reservoir property prediction problems. A brief review of such applications can be found at Nikravesh and Aminzadeh (2003), Sandham and Leggett (2003) and Aminzadeh and Wilkinson (2004). Integrating these two methods offers the possibility of making full use of their respective strengths. Aminzadeh and de Groot (2006) maintain NN and FL share the ability to improve prediction power in the face of uncertainty and when we have imprecise, and noisy data. They both have an advantage over conventional mathematical and statistical methods. The respective strengths and weaknesses of FL and NN can be summarized as follows:

Neural networks have many advantages, especially in dealing with uncertainty and non-linearity, fault tolerance and most importantly the ability to learn. However NN is not very effective in utilizing existing mathematical models or statistical information. It is also not very good for knowledge representation especially in connection with linguistic rules.

Fuzzy logic is an excellent tool for manipulating linguistic rules and representation of knowledge. It also performs well in handling uncertainty and real time operation. On the other hand the learning and optimization capability of FL is not very good.

Since neural network is fairly well established in the E&P community as a tool, we will not describe the method here. We will however give a brief overview of fuzzy logic. For more details of both NN and FL see Aminzadeh and de Groot (2006).

Fundamentals of Fuzzy Logic and potential applications in exploration

Much of the uncertainty in many situations is due to imprecision and subjectivity rather than an underlying randomness. Fuzzy logic is an appropriate tool to deal with uncertainty of this type, inherent in most physical or natural systems. The basic theory of fuzzy sets was first introduced by Zadeh (1965). It is a methodology aimed at obtaining rough solutions where the problem or rules are vague. In fuzzy logic, everything is a matter of degree. Since fuzziness and "gray area" is present in nearly everything we do, fuzzy logic with its "degree of membership" concepts allow proper treatment of "multi-valence". Unlike classical logic which is based on crisp sets whose members are either "True" or "False", fuzzy logic views problems as having a degree of "Truth."

To point out the fundamental differences between classical logic and fuzzy logic, we refer to Figure 1. A petro-physicist may consider sandstone with porosity of less than 3 as a low porosity one. An average porosity may be deemed to be those between 4 and 10 and those with porosity above 15 may be considered high porosity. Such classification with sharp boundaries, although mathematically

convenient, may not be practically sound and appropriate. In fuzzy logic a membership function is defined allowing belonging to more than one category (in this case low, average and high porosity) with different degrees of membership. For example in Figure 1 a porosity of 8 can be in a low porosity class with the membership of 20% and in average porosity class with that of 78% and the high porosity class with 2%.
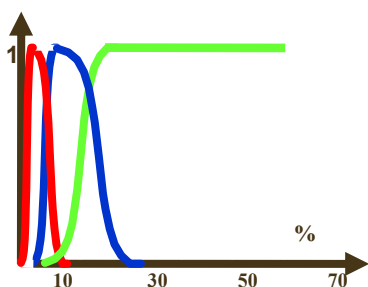

Figure 1- Representation of low porosity (red), average porosity (blue) and high porosity (green) through membership function.

The overlapping class boundaries is more evident in many rock physics cross plots, making fuzzy logic an ideal tool for representing such classes. In Figure 2 we have superimposed likely membership functions for different types of rocks with respect to their P-Wave and S-Wave Impedance ($\underline{Z^p}$ and $\underline{Z^s}$) values. These triangular membership functions are defined such that they have their maximum (1) at the center of the respective region, going to 0 as we reach the edge of the region. With more information on the distribution, population and density of the regions for different rock types more relevant membership functions could be defined. Now, based on the value of $\underline{(Z^p, Z^s)}$ for a given data point, we can assign membership grades to different rock types depending on their degree of belonging to them.

Consider the following example. For a normalized value of (5.0, 2.75), we can have immature sand, mature sand or conglomerates. We can assign membership grades that are inversely proportional to the distance to the centers of different classes, with zero membership when appropriate. We can also calculate membership grades of the separate

projections of a point to the Z^p and Z^s axes. We can then multiply the resulting membership grades and normalize them. For example sample point (5, 2.75) would approximately have membership grades of (0.0, 0.5, 0.2, 0.0, 0.1, 0.2, 0.0) with respect to Z^p and (0.0, 0.2, 0.0, 0.0., 0.25, 0.35, 0.2) with respect to Z^s. Note that classes are ordered according to their color codes (C, Y, G, B, R, O, P) and the numbers are derived from the intersection of horizontal and vertical black lines with membership function after normalization to have membership functions add up to 1. From combining Z^p and Z^s membership values we obtain an overall membership value of (0.0, 0.5, 0.0, 0.0., 0.13, 0.37, 0.0).
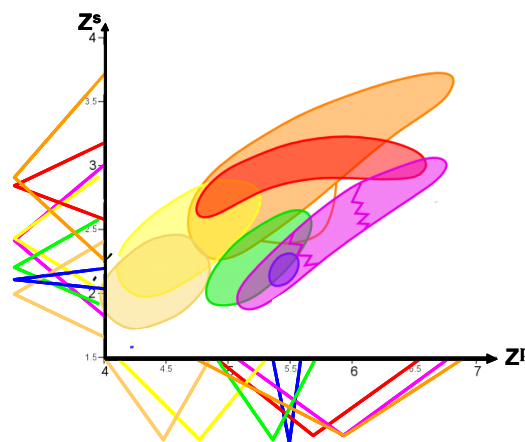

Figure 2- Membership grade functions for different types of rocks with respect to their Z^p & Z^s values (from Aminzadeh and de Groot, 2006).

Description of neuro-fuzzy approach for predicting hydrocarbon probability

Hydrocarbon probability prediction technique based on meta-attribute concept of Aminzadeh et al. (2005) is suitable for reconnaissance type work as a basis for more detailed model-based work. Briefly, the method is based on using different attributes that are known to be reasonably good HC indicators. Among them are pre-stack information (e.g. near, mid, far stack) data volumes, absorption, and other frequency information (such as lower parts of the frequency spectrum, indicating areas with high frequency loss) and possibly velocity information. Combining all this

information through a neural network and providing some training to the NN with representative data points from existing wells and interpreter's insight helps highlight areas with higher hydrocarbon probability. The neural network will identify attributes most discriminating. Figure 3 shows the procedure schematically.
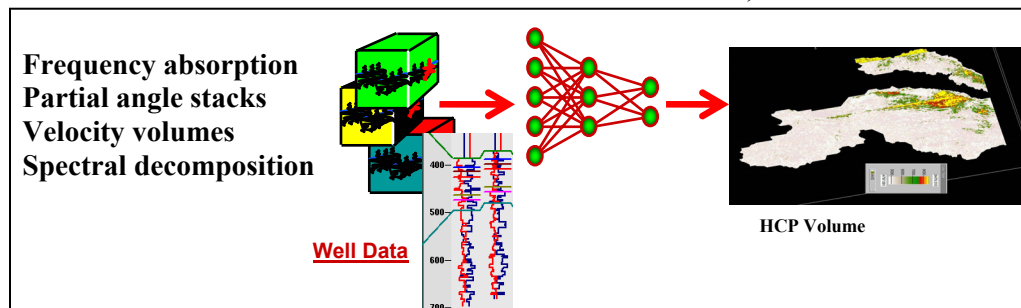

**Frequency absorption
Partial angle stacks
Velocity volumes
Spectral decomposition**

Well Data

HCP Volume

Figure 3, Creation of HCP and identification attributes.

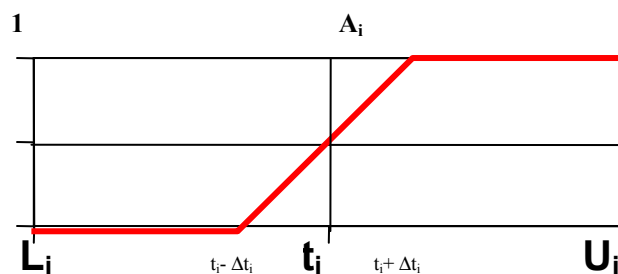*Figure 4, Hydrocarbon probability, A_i based on attribute i.*

This method has been applied in many cases including Aminzadeh et al (2005). Such method can be enhanced by introducing aspects of fuzzy logic concept. The method takes selected attributes from the above mentioned procedure that are considered to be key HC indicators. From the well data and interpreter's experience a set of "fuzzy" rules are defined that provides a subjective rule for the ranges of different attributes below which the probability of having hydrocarbon is very low (zero) and above a level where the probability is very high (1).

Typically, a smooth (e.g. linearly varying) function is defined. Figure 4 shows an example of such function. Note that in the simple case of $\Delta t_i = 0$, a non-fuzzy or hard threshold determines having probability 0 or 1 of HC if the ith attribute is less than or greater than the threshold value.

Also, it is noted that if an attribute does not have perfect correlation with good or bad reservoir in the extreme high and low ranges, the value of the probability can be adjusted to be other than 1 and 0. Defining similar function for all the chosen attributes, we then use the following equation to calculate the final HC probability values.

$$\text{HC Probabilty} = \left(f_1(A_1) f_2(A_2)...f_N(A_N) \right)^{1/N}$$
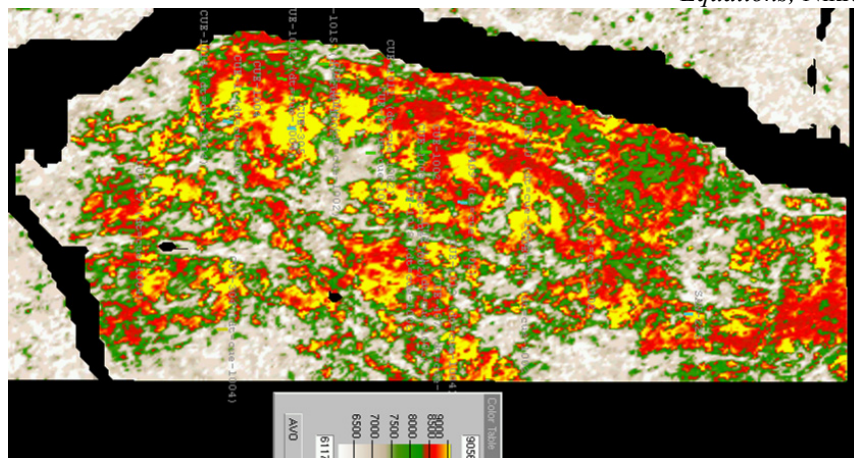
.

Figure 5 shows an example of use of this approach in a North American field. The attribute most effective in discrimination in this case was DimAndGrad that combines the low amplitude with large AVO gradient

After obtaining fuzzy logic based output, one can go back to the meta-attribute approach making new picks and retraining the neural network. Several iterations using both neural networks and fuzzy logic approaches could thus be performed until satisfactory results are obtained.

Conclusions

Neural network in conjunction with fuzzy logic helps in high-grading prospects containing hydrocarbon-saturated reservoirs. General rule of thumbs derived from rock physics data and interpreter's knowledge and experience can be best formulated through use of fuzzy logic. Combination of such rules in conjunction with neural networks ranking of most relevant attributes for prospect risking improves the process when compared against conventional thresholding

methods. We demonstrated the benefits of combining neural network and fuzzy logic approaches where the strength of each method is combined.

Figure 5 an example of HCP with fuzzy rules.

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