

Gas-bearing hydrothermal dolomite prediction using probabilistic neural networks in the Trenton-Black River Interval, NE Ohio

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Summary

Probabilistic neural networks (PNNs) are used in a NE Ohio gas field to validate and predict hydrocarbon accumulations, in the Trenton-Black River interval, associated with hydrothermal dolomite. The field is characterized by thin, below seismic resolution, stratigraphically variable hydrothermal dolomite. Pe curves are used to discriminate lithologies in carbonate environments. In productive wells, the Pe curve is characterized by minor perturbations and fluctuations that correspond to the thin dolomite sections. In dry, pervasively carbonate wells the Pe curve is relatively flat and constant. PNNs are used to convert the seismic data volume to a Pe curve volume. Pe curve perturbations, associated with thin dolomite intervals, are qualitatively detected using Pe curve amplitude envelope analysis in the new data volume.

Introduction

Artificial neural network applications were introduced to the geoscience community in the 1980's. Among other uses, artificial neural networks have the ability to recognize complex, non-linear relationships between seismic attributes and petrophysical data. These relationships are applied to seismic data to predict inter-well reservoir properties.

Historically, hydrocarbons found in intracontinental hydrothermal dolomites, or Mississippi Valley Type (MVT) deposits, have generated great interest. Unfortunately, many hydrothermal dolomite fields remain non-economic due to the use, and abuse, of different geological and geophysical methodologies (Keith and Wickstrom, 1990). Assuming all other aspects of the petroleum system are in place, hydrothermal dolomite production is a function of lithology; dolomite intervals are productive, limestone intervals are not.

PNNs are applied in a 10 BCFE hydrothermal dolomite field in Ashtabula County, NE Ohio. 6 successful wells have been drilled encountering thin, below seismic resolution, stratigraphically variable hydrothermal dolomite within the Trenton-Black River interval. Predicting inter-well dolomite intervals is difficult using other seismic methods.

PNNs combine high well log resolution with laterally continuous seismic data to convert the seismic data to a

relevant and interpretable petrophysical data volume (Ronen et al., 1994; Schultz et al., 1994a, b). Functional, predictable relationships between seismic attributes and available Pe curves are established and verified. In carbonate environments the Pe curve is used to discriminate lithology, which is important in hydrothermal dolomite fields.

Theory

Artificial neural networks adhere to the same basic principles as biological neural systems. Artificial neural networks and simplified biological neural systems are composed of multiple layers of interconnected nodes that process and relay information to each other.

The ability of artificial neural networks to detect and recognize data patterns and to exploit functional, complex non-linear relationships between multiple data inputs provides for a powerful exploration tool. Artificial neural networks are robust in noisy or missing data sections that solve ambiguities or differences between data inputs. Artificial neural network results are developed through repeated training. An input model may not be required to be successfully applied.

Since the 1980's many different artificial multi-layer feed-forward neural networks have been successfully applied to various geophysical problems. With good quality seismic and well log data the PNN is favored. The PNN does not depend on an input forward model and does not require knowledge of the seismic wavelet. It has less of a 'black box' approach associated with it and tends to be more stable than the traditional multi-layer feed forward neural network (Hampson et al., 2001).

PNNs establish relationships between seismic attributes and well logs over a specified time window. These relationships are related to the underlying rock properties and may be non-linear and difficult to discern. When found, and properly validated, seismic attributes may be converted to the desired petrophysical parameter, or well-log curve; unlike conventional seismic inversion techniques, artificial neural networks are not restricted to acoustic impedance analysis.

A PNN is a mathematical interpolation method implemented via a 3-layered feed forward neural network architecture. Training involves only one pass through each training node. The output target log values are assumed to

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be a linear combination of the log values available in the training data. The interpolation method emphasizes the importance of having multiple training scenarios, or a sufficient input log data distribution, in which data values may be interpolated and predicted.

Multiattributes, used as PNN inputs, may be geologically disconcerting; many attributes may be statistically significant but do not have theoretical explanations (Leiphart and Hart, 2001). Multi-attributes must be interpreted within a geologic framework, not a statistical one. Geologically plausible and physically realistic results are necessary to be confidently used for exploration and exploitation purposes.

Appropriate input seismic attributes are selected via forward step-wise regression. The attribute list is developed sequentially to save computation time. Kalkomey (1997) recognized that too many input seismic attributes yields spurious and noisy results. This is analogous to fitting higher order polynomials to a data set when, in fact, a lower order curve may have a better predictive potential (Hampson et al., 2001). The seismic attributes are cross-validated to avoid overtraining.

Crossvalidation systematically removes each well used in the training process from the training set. The multiattribute transform is recalculated with the well absent, or hidden, from the training process. The average predictive error of all the hidden wells is referred to as the validation error. The validation error is the error associated with applying the PNN to the entire seismic data volume.

Case Study: PNN Application

A PNN is used to find a relationship between seismic attributes and well log properties exclusive to hydrothermal dolomite. Seismic data attributes are constructed, correlated, and trained to recognize the Pe curve.

Given the lithologic dependence on production, the stacked seismic data is trained to recognize the Pe values at different wells. Productive zones characterized by intermediate Pe values are not pervasively or completely dolomitized. Pe values range between 3.5 and 4.5 barns/electron. Dolomitic zones cause small fluctuations, or perturbations of the Pe values. Tight regional limestone facies are characterized by slightly higher, relatively constant Pe values. Pe curve frequency variations exist between productive and non-productive lithologies.

Multiple seismic attributes are correlated and ranked, via stepwise regression, to available Pe curves for optimum correlation as outlined by Hampson et al. (2001). The optimum fit was obtained using a correlation window 7 samples, or 12 ms, large. Figure 1 shows the predictive

error's dependence on multiple seismic attributes. The bold line represents the attribute's predictive error when all wells are used in the PNN training process. The thin line represents the attribute's predictive error when target wells are systematically removed from the PNN training process; the PNN predictive capabilities decrease as the training input decreases.

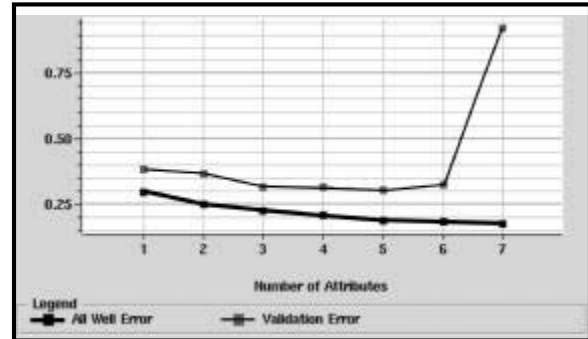


Figure 1: Predictive error's dependence on multiple seismic attributes. The error associated with using every seismic attribute is shown in bold. The cross-validation error, from selectively removing each well from the training process, is shown by a lighter curve. The vertical scale is the average error in barns/electron.

Additional seismic attributes are considered valuable as long as the validation error, the thin line in figure 1, is minimized. In this case, the optimum number of seismic attributes for PNN application is five. Additional attributes overtrain the data (Kalkomey, 1997). Each attribute is further evaluated for its significance within the established geologic framework (Leiphart and Hart, 2001). The seismic attributes used are:

1. 5-10-15-20 frequency filter
2. Integrated absolute amplitude. This is a running sum of the reflection strength minus a smoothed version of the reflection strength. The reflection strength is the absolute value of the complex trace magnitude. It is often used to determine lateral fluid, lithologic, and stratigraphic variations in reservoirs (Chen and Sidney, 1997).
3. Dominant frequency. To be useful, the dominant frequency attribute must be secondary to the propagating wavelet's frequency characteristics. The dominant frequency must reflect geologic frequency, which indicates the number of reflecting layers within a unit thickness of rock. Chen and Sidney (1997) advocate that a seismic wavelet's frequency bandwidth is spatially stable; a change in dominant frequency is mostly caused by local lithology and fluid variations. Lithologic fluctuations between dolomite and limestone are indicative of production.

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4. 45-50-55-60 frequency filter
5. 25-30-35-40 frequency filter
6. Instantaneous frequency
7. Cosine instantaneous phase

The data is trained over intervals inclusive to the Trenton-Black River. Wells included in the PNN training process and their respective training windows are shown in figure 2. Dolomitic wells are numbered.

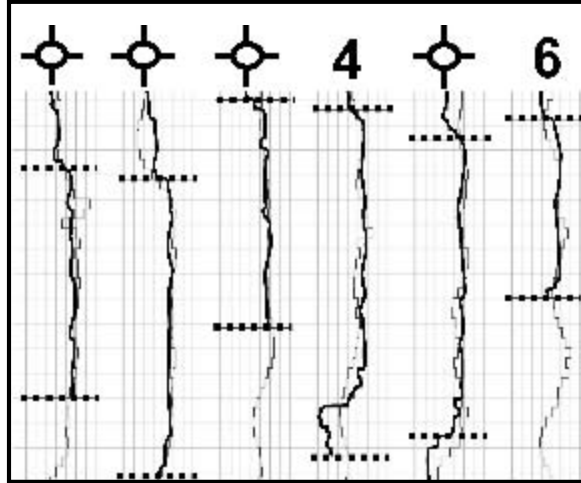


Figure 2: Pe curves, used to train and validate the PNN. Productive, or dolomite, wells are numbered. Solid bold lines indicate the predicted Pe curve when each well is systematically removed from the training process; lighter traces indicate the original Pe curves. The training window boundaries are indicated by the dashed horizontal lines. Pe curve scales range from 2.5 barns/electron, on the left, to 6 barns/electron on the right.

Quantitatively, the PNN does not sufficiently predict the original Pe values. The average error between the predicted and actual Pe values is 0.304 b/e; the correlation coefficient between the real and predicted Pe values is less impressive at 0.641.

Qualitatively, the PNN predicts the Pe curve frequency differences between limestone and interbedded dolomite facies. The non-productive limestone wells are all characterized by fairly flat Pe curves; the productive dolomite wells have more convoluted, or higher frequency, Pe values (figure 2).

The PNN is applied to the 3D seismic data volume yielding a 3D Pe curve volume. Sinuous dolomite related Pe curve characteristics are reflected in amplitude envelope attributes extracted from the 3D data volume. Figure 3 shows the Pe curve's maximum amplitude envelope over an analysis window that includes the entire Trenton-Black

River interval. Dolomite is characterized by generally high values of the maximum amplitude envelope. Within that trend, lower values indicate massive dolomite zones, while high values indicate thin interbedded dolomites.

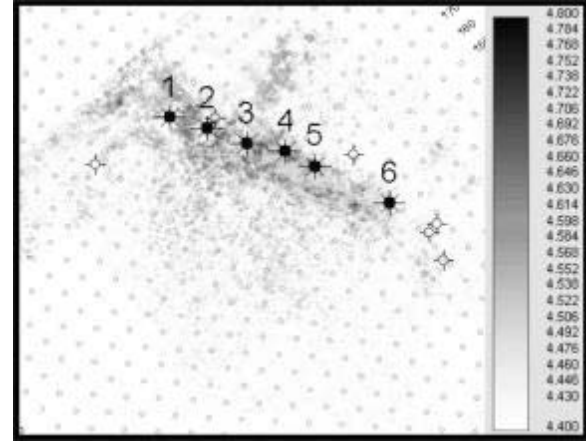


Figure 3: Maximum amplitude envelope of the Pe curve data volume. Analysis window includes the entire Trenton-Black River interval. Productive, gas-bearing, wells are numbered.

An anomalous trend exists to the south paralleling known production (figure 3). The southern trend is structurally similar as the known productive trend. Figure 4 shows a Trenton time-structure map. Dolomite wells occur along a synclinal sag en echelon to a basement related fault, which is a common characteristic of hydrothermal dolomite fields (Hurley and Budros, 1990). The SE sections of the two Pe curve maximum envelope anomalies are separated by a NW-SE trending structurally high ridge. The high maximum amplitude envelope anomalies merge towards the NW where the ridge diminishes.

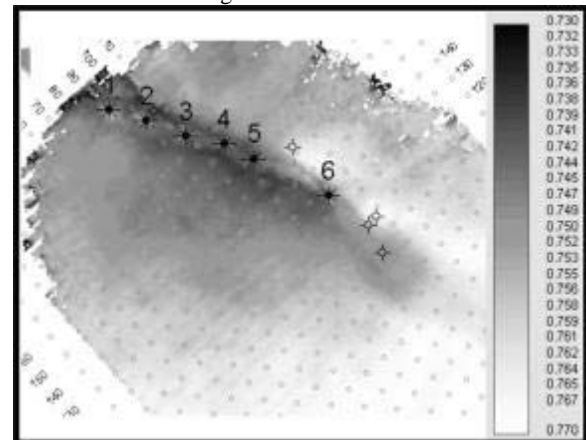


Figure 4: Trenton two-way traveltime structure. Known production occurs along an en echelon synclinal sag.

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Wells 1 and 2 do not have large Pe curve maximum envelope values associated with them. Unlike other wells that produce from thin dolomite sections, well #2 is pervasively dolomitic throughout much of the Trenton-Black River interval. Thick dolomite sections are characterized by relatively constant low Pe values rather than highly oscillatory values associated with thinly bedded dolomite zones.

Well #1's abnormal response is related to seismic data issues. Two surveys were previously processed into one. The second survey encompasses the NW portion of figure 3. The two data volumes are effectively separated by a NE-SW trending line between wells 1 and 2 (figure 3). The PNN is trained using the SE data set. Seismic attributes used in PNN training cannot be compared across different seismic data vintages.

Conclusions

PNNs trained to recognize Pe values provide an excellent method of dolomite/limestone discrimination. Dolomite trends are characterized by high Pe curve amplitude envelopes whereas limestones are not. Dolomite reservoirs are either thinly bedded and/or pervasive throughout the Trenton-Black River interval. Pe curve perturbations, associated with thin dolomite intervals, are qualitatively detected using Pe curve amplitude envelope analysis. More pervasive and prolific dolomite intervals existing along the same trend have relatively low Pe curve amplitudes.

References

- Boadu, F.K., 1997. Rock properties and seismic attenuation: neural network analysis: Pure and Applied Geophysics, **149**, 507-524.
- Chen, Q., and Sidney, S., 1997. Seismic attribute technology for reservoir forecasting and monitoring: The Leading Edge, **5**, 445-456.
- Hampson, D., Schuelke, J., and Quirein, 2001. Use of multi-attribute transforms to predict log properties from seismic data: Geophysics, **66**, 220-236.
- Hurley, N.F., and Budros, R., 1990. Albion – Scipio and Stoney Point Fields – USA, Michigan Basin. . In E.A. Beaumont, and N.H. Foster, eds., *Stratigraphic Traps – Atlas of Oil and Gas Fields*. AAPG Treatise of Petroleum Geology, 1-37.
- Kalkomey, C.T., 1997. Potential risks when using seismic attributes as predictors of reservoir properties: The Leading Edge, **10**, 11-15.
- Keith, B.D., and Wickstrom, L.H., 1990. Lima-Indiana Trend – USA Cincinnati and Findlay Arches, Ohio and Indiana. In E.A. Beaumont, and N.H. Foster, eds., *Stratigraphic Traps – Atlas of Oil and Gas Fields*. AAPG Treatise of Petroleum Geology, 347-367.
- Leiphart, D.J., and Hart, B.S., 2001. Case History: Comparison of linear regression and a probabilistic

neural network to predict porosity from 3-D seismic attributes in Lower Brushy Canyon channelled sandstones, southeast New Mexico: Geophysics, **66**, 1349-1358.

- Ronen, S., Schultz, P.S., Hattori, M., and Corbett, C., 1994. Seismic guided estimation of log properties, part 2: Using artificial neural networks for nonlinear attribute calculation: The Leading Edge, **13**, 674-678.
- Schultz, P.S., Ronen, S., Hattori, M., and Corbett, C., 1994. Seismic guided estimation of log properties, part 1: A data-driven interpretation methodology: The Leading Edge, **13**, 305-310.
- Schultz, P.S., Ronen, S., Hattori, M., Mantran, P., and Corbett, C., 1994. Seismic guided estimation of log properties, part 3: A controlled study: The Leading Edge, **13**, 770-776.

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