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Seismic reservoir characterization of a mid-continent fluvial system using rock physics, poststack seismic attributes and neural networks; a case history

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Summary

In a mid-continent gas field, reservoir sands range in thickness from 5ft to 80ft and in porosity from about 6% to 20%. Well logs, core data and 3D seismic data were combined in a reservoir characterization study with the objective of mapping the variability of porosity within the target sands to identify zones of greater sand thickness. The project was conducted in two phases, a feasibility study and a reservoir characterization study using the full 3D seismic volume. The resulting classified volume accurately predicted the lithology distribution, porosity variability and sand thickness.

Introduction

In many cases poststack seismic data are the only available source of information on inter-well stratigraphy and lithology, but the amount of information that can be extracted on reservoir properties such as porosity or hydrocarbon content is usually quite limited. This project had core, well log, and fully processed 3-D poststack seismic data available. To extract the most knowledge about rock and fluid properties from these data, a method was developed that combined rock physics, seismic modeling, neural networks and seismic attributes in a unique way.

The geologic setting for this study was a mid-continent fluvial system. The seismic survey covering the area of interest was about 20 square km. Log curves from 6 wells which had encountered gas saturated pay sands were used.

Objective of Feasibility Study

The goal of the feasibility study was to determine the sensitivity of seismic attributes to changes in rock porosity. This involved 1) the production of "pseudo" well logs by adjusting compressional (Vp) and shear wave (Vs) velocities and density values as predicted from changes in porosity, 2) generating synthetic seismograms and 3) studying the sensitivity of seismic attributes to the modeled lithological changes. The result of the feasibility study was a validation of the proposed reservoir characterization technique for this specific reservoir.

Input Data Set

Well Logs

A reasonably comprehensive suite of log curves, excluding shear wave data, was available for each of the six wells shown in Figure 1.0. A dipole shear wave velocity log from a well adjacent to the study area was used to calibrate the Vs prediction.

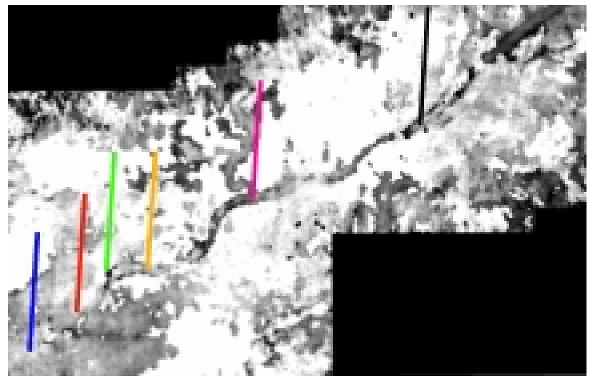

Figure 1. Hybrid depositional indicator attribute detailing well locations.

A core analysis report for about 100ft of the reservoir interval from one of the wells was also used. The porosity estimate from the density log, and the volume of clay predicted from SP and Gamma Ray logs showed good agreement with values from the core data. Similar log analyses were performed for the other wells and used to determine the ranges of thickness and porosity to be modeled.

Seismic Data

A 3D survey of good quality with a broad frequency bandwidth and a central frequency of about 50Hz covers the field. A wavelet extracted from the data was used to generate the synthetic seismograms..

Petrophysics

Shear Wave Velocity Estimation

In order to model the offset-dependent seismic reflectivity, a shear wave velocity (Vs) curve for each well is required. When this information is not available, it can be estimated from other log curves in a number of ways. To evaluate the relative success of each method, the predicted Vs was compared to the measured Vs in a nearby well. The Krief method of Vs prediction was selected because it is generally well suited to consolidated formations and is less affected by very low porosity than most other methods.

Property Changes with Porosity

The velocity-porosity models were refined by closely matching the model predictions to the data from one of the wells. In a Critical Porosity model, the only adjustable parameter is the value of critical porosity itself. The published value is 37%. For this study, it was determined that the real value ranged from about 28% to 46% depending on the rock type. Another variable that can be changed, depending on which well is used, is the average mineralogy of the pay zone. By comparing the well log data to the predictions, the parameters used in the modeling can be optimized. In this case, a critical porosity = 32%, average quartz = 88%, average clay = 7%, and average calcite = 5% were used. Plots of the predicted velocity, density, and Poisson's ratio versus porosity are shown in Figure 2.

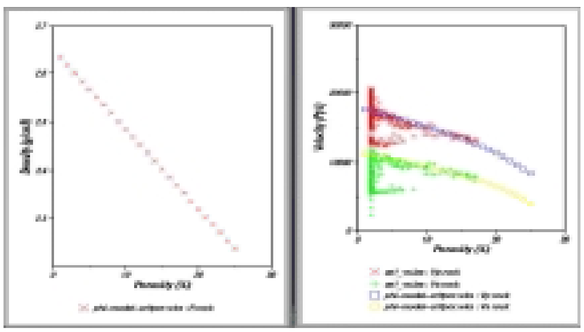

Figure 2. Cross plots of predicted density (L) and velocity (R) versus porosity

In the velocity/porosity crossplot of Figure 2, the red points represent Vp values from one of the project wells between 6800ft and 7200ft, the green points are estimated Vs values as described above and the blue and yellow points represent predicted Vp and Vs respectively used in the modeling. Variations of the data points from the predicted curve are due to the changes in water saturation and clay content over the depth range plotted. The figure on the right confirmed the selection of the Critical Porosity model and helped to choose the appropriate value of 28% for PhiC.

Modeling and Synthetics

Modeled porosities ranged from 5% to 25% in increments of 5% and modeled thicknesses ranged from 20ft to 100ft in increments of 20ft. This generated a 5 by 5 matrix representative of sand conditions in the area. The upper sand in the cored portion of one of the wells was the starting point for the model. The reference well encountered 30ft of sand, with the top 10ft being tight and the remainder having gas saturation of about 80%.

Offset and stacked synthetics were generated using 16 offsets ranging from 0 to 7040ft; a range representative of the seismic data. Ray tracing was performed over the interval from 6750 to 7200ft. A representative display of these synthetics is depicted in Figure 3.

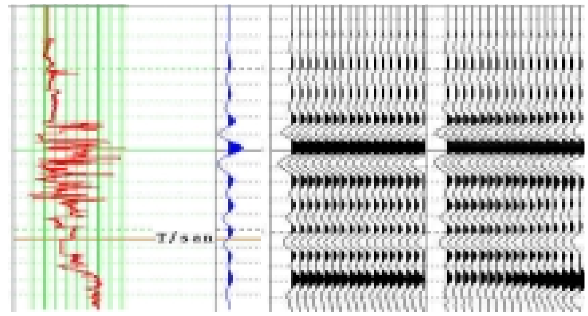

Figure 3. Stack (L) and gather synthetic (R) for 60ft sand at 15% porosity.

Attributes

A suite of 11 poststack and 2 prestack attributes were computed from the synthetics and these attributes were rigorously examined to determine those with the highest degree of sensitivity to the rock physics modeling. The list of computed attributes is shown in Table 1 below.

Input
Envelope
First Derivative of Envelope
Second Derivative of Envelope
Instantaneous Phase
Instantaneous Frequency
Thin Bed Indicator
Acceleration of Phase
Dominant Frequency
Bandwidth
Instantaneous Q
Relative Acoustic Impedance
Gradient
Gradient*Intercept

Table 1. Computed attributes

Relating Seismic Attributes to Rock and Fluid Properties

There are a number of approaches that combine well log-derived information and seismic attributes for the purpose of predicting rock properties. The technique used for this study is a proprietary artificial neural network, and is an adaptation of the Rummelhart method that employs the delta rule with back-propagation of errors.

Based on analysis, six lithology classes were modeled: shale, carbonate and sands with 5%, 10%, 15% and 20% porosity. The subset of attributes that were the most diagnostically sensitive to the rock physics modeling was quantitatively determined in order to train the artificial neural network to predict the lithology and porosity classes at each well. The attributes listed in Table 2 were selected for the training.

Envelope
First Derivative of Envelope
Second Derivative of Envelope
Instantaneous Phase
Instantaneous Frequency
Thin Bed Indicator
Relative Acoustic Impedance

Table 2. Diagnostic attributes

The iterative training process was performed until the neural network developed a set of weights and scalars that minimized the discrepancies between the predicted results and the actual classes. At that point, the network was considered to have achieved an acceptable level of convergence and to be well trained.

The initial classification for lithology and porosity produced extremely encouraging results and a second classification was generated for thickness. In this case, the modeling was limited to four classes: shale, carbonate, thin sands (ca. 25ft.) and thick sands (ca. 65ft.)

Inter-well Classification

Separate lithology/porosity and thickness classifications were performed on a sample-by-sample basis on attributes computed from the entire 3-D seismic volume using the derived neural weights and scalars as described above. A flattened time-slice through the volume classified for porosity-thickness is shown in Figure 4.

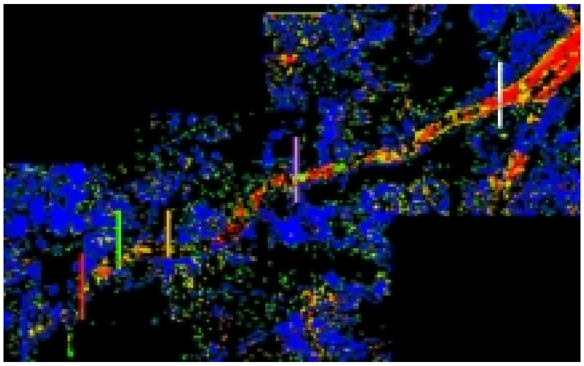

Figure 4. Flattened time-slice through volume classified for porosity-thickness (phi-h).

Conclusions

An artificial neural network trained only by ***poststack*** seismic attributes was able to classify a seismic data volume for lithology, porosity and thickness within the targeted sands with an acceptable degree of confidence.

Recommendations for Future Work

Reservoir classification using logs, seismic attributes and neural networks is a powerful technique. However, significant improvements can be made with additional work in the following areas:

Incorporation of additional classes of attributes, e.g. energy absorption, acoustic and elastic impedance, AVO; re-examination of log analyses using available core data (porosity, permeability, capillary pressure, resistivity, etc.); exploration of different well log classification methods, e.g., reservoir quality index.

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