Seismic reservoir characterization of a U.S. Midcontinent fluvial system using rock physics, poststack seismic attributes, and neural networks

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In a U.S. Midcontinent gas field, a channel feature contained shale and reservoir sands ranging in porosity from 6% to 20%. Well logs, core data, and 3D seismic data were combined in a reservoir characterization study to map the lithology and variability of porosity within the target sand. The project was conducted in two phases—a qualitative, uncalibrated seismic attribute study and a detailed well-log-calibrated reservoir characterization.

In the first phase, multiple seismic attributes were computed and a statistical tool was used to combine them to illuminate variations in lithology and porosity. These rapidly computed “hybrid” attributes can reveal important structural and stratigraphic features.

In the second phase, well log and core data were used to calibrate the velocity-porosity relationship. This model was subsequently used to perturb the porosity of the reservoir sands using representative wells. The resulting “pseudo wells” were used as input into a 1D ray-tracing synthetic seismic program. Prestack and poststack seismic attributes were computed. The well logs were used to classify the geologic column into carbonate, shale, and four different sand porosity classes. A neural network was then trained to relate these classes to the modeled seismic attributes. Once trained, this neural network was used to classify the entire 3D seismic volume. This classification provided a more reliable indication of higher quality reservoir zones than available from the uncalibrated seismic attributes.

The geologic setting of the study area includes Mississippian St. Louis and St. Genevieve carbonates and overlying Mississippian Chester clastics deposited in a broad, flat shelf environment north of the deep Anadarko Basin. The Chester sands targeted by this study were deposited in a narrow channel cut through the St. Genevieve carbonates and into the underlying St. Louis limestone. At the end of Meramacian deposition (St. Genevieve), sea level dropped, exposing the broad carbonate platform. A major fluvial system and its tributaries flowed across this surface, cutting a shallow valley several miles wide. Upon further sea level drop, the river channel incised itself into the St. Genevieve, cutting a wide canyon (750-1000 ft) to depth of 200 ft for many tens of miles. Some of the lowest sands in the channel may be remnant deposits of this fluvial system, but most sand and shale filling the incision are Chester-age estuarine sediments deposited during multiple transgressive events. Finally, the whole system was buried by the marine Notch shale during maximum flooding.

Data and attribute generation. The 3D seismic survey in the area of interest covers about 25 square miles. The survey was of good quality with a broad-frequency bandwidth and a central frequency of about 50 Hz. Figure 1 shows the input data set flattened on the top of the reservoir. Seismic attributes computed on the 3D volume over the target reservoir included envelope, first derivative of envelope, second derivative of envelope, instantaneous phase, instantaneous frequency, relative acoustic impedance, lithologic indicator, similarity, and thin-bed indicator.

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Figure 2 shows the relative acoustic impedance attribute 20 ms below the top of the reservoir. Figure 3 shows the similarity attribute, which highlights lateral variation in seismic character. All attributes were combined in a statistical classification system known as Kohonen Self-Organizing Maps (SOMs). Our implementation of SOM is a volume-based multivariate, multidomain clustering system that identifies regions of common characteristics based on attribute properties. In the classified SOM image in Figure 4, the incised channel and other features are clearly visible.

The next step involved incorporation of calibration information obtained from the borehole. Fortunately, a comprehensive suite of log curves, excluding shear-wave data, was available for each well in Figure 1.

A core analysis report for about 100 ft of the reservoir interval from one well 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 lithologies and the range of porosity to be modeled.

To model the offset-dependent seismic reflectivity, a shear-wave velocity ($V_S$) 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, predicted $V_S$ was compared to measured $V_S$ in a nearby well. The Krief method was selected because it provided a slightly better agreement to measured $V_S$ from the dipole sonic log than the others (Figure 5).

To create pseudowells in which porosity of the reservoir interval is perturbed from its actual value, a relationship must be found that relates $V_P$, $V_S$, and density to porosity. One relationship that worked quite well for modeling the reservoir sand intervals is Nur’s (1991) critical porosity model. Average fluid properties for the porosity models and $V_S$ predictions were computed using a homogenous mixing algorithm (Reuss average) in which the fluid phases were brine and gas. Properties of the brine and gas at reservoir conditions were computed using the Batzle-Wang (1992) relations.

Modeling and synthetics. After analysis of well logs, six lithology classes were defined: shale, carbonate and sands with 5%, 10%, 15%, and 20% porosity. Gas saturation for each modeled case was the original in-situ saturation. A wavelet extracted from the data was used to generate synthetic seismograms.

Offset and stacked synthetics were generated using 16 offsets ranging from 0 to 7040 ft, a range representative of the seismic data. Ray tracing was performed over the depth interval 6750-7200 ft. Figure 8 is a representative display of the stacked synthetics and modeled wells.

From the synthetic seismograms at each well, a suite of 11 poststack and 2 prestack attributes, computed from the synthetics, was examined to determine those with the highest sensitivity to the rock physics modeling. These seven computed attributes can be computed on single traces, so they do not include any geometric attributes. These attributes are envelope, first derivative of envelope, second derivative of envelope, instantaneous phase, instantaneous frequency, thin-bed indicator, and relative acoustic impedance.

A number of approaches combine well-log-derived information and seismic attributes to predict rock properties. The
The technique we use is based on a proprietary artificial neural network and is an adaptation of the Rummelhart method that employs the delta rule with back-propagation of errors. Neural networks are basically adaptive, multichannel, nonlinear Wiener filters. They are multichannel, because we can use any number of attributes as input for classification of a number of classes. They are nonlinear because the relationship between input and output may not be described by a simple linear expression. Their most impressive characteristic is that they are adaptive, so they learn from data. In conventional Wiener predictive filtering, the process determines the predictive portion of the data from the past and predicts the future. In the adaptive process, operators are updated as the prediction proceeds to minimize prediction errors. The correction is in the direction of steepest descent of the error function. This method is adopted to the optimization of the artificial neural network (ANN) weights and biases. In our implementation, the neural network contains an input layer of nodes, an output layer, and one "hidden" layer in between.

ANN has several interesting characteristics. It learns properly if its input contains proper discriminators. It cannot converge if input data contain characteristics not related to the items to be classified. This is generally the most difficult set of parameters to define. The second characteristic is that ANN can only recognize classes for which it has been trained. Any item belonging to a class beyond the training set will not be recognized. The act or process of training is developing weights and biases that will produce minimum errors in identifying the data set used in training. The method we use is back-propagation of the error function. The method involves computation of steepest-descent direction of the error function for each weight and bias. Then, for each input, the difference between the actual out-

Figure 5. To model the offset-dependent seismic reflectivity, a shear-wave velocity ($V_s$) 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. Average fluid properties for these models were computed using a homogenous mixing algorithm (Reuss average) where the fluid phases were brine and gas. To evaluate the relative success of each method, the predicted $V_s$ is compared to the measured $V_s$ in a nearby well. The Krief method of $V_s$ prediction was selected because it provided a slightly better agreement to the measured $V_s$ from the dipole sonic log. The figure shows predicted and measured $V_s$ curves, B2 well. $V_s$ rock = dipole sonic log; $V_s$ CP = $V_s$ computed from critical porosity model where $V_s$ GC = $V_s$ is computed from Greenberg-Castagna model; $V_s$ Krief = $V_s$ computed from Krief model.

Figure 6. The velocity-porosity models were refined by comparing the model predictions to data from well 1. In the critical porosity model, the default value of $\phi_c$ is 37% but the real value can range from 28% to 46% depending on rock type. By comparing well log data to the predictions, critical porosity can be optimized. In this case a $\phi_c$ of 32% gave the best agreement between computed and measured velocity. Plots of predicted $P$-wave velocity ($V_p$rock, CP) and sonic log-derived $P$-wave velocity ($V_p$rock) versus porosity. Porosity greater than 5% occurs mostly in the sands. In the velocity/porosity crossplot, red Xs represent $V_p$ values from the well between 6800 and 7200 ft. Blue squares are computed $V_p$ values.
put and the desired output is computed. This is the error, which is distributed as in adaptive filtering along the network starting from the output layer back toward the input layer according to the error gradient at each node. The method will adjust each weight by a small amount with each training data set. The rms velocity and absolute error are monitored during the iteration. Once the amount of error is reduced to a satisfactory level, the ANN is deemed trained.

In most instances, known data are kept out of the training data set and used to verify the training. The iterative training process was performed until the neural network developed a set of weights and scalars that minimized discrepancies between predicted results and the actual classes at the training wells. At that point, the network was considered to have achieved acceptable convergence and to be well trained.

The classification for lithology and porosity produced extremely encouraging results. The neural network was trained on two calibration wells, each modeled for porosity variation in the sand. Figure 9, an example of the results of the training on well 1, shows four pairs of lithology columns. In each pair, the column on the right shows the well-log-derived lithology classes (with porosity replacement zone indicated by red vertical bar). The column on the left shows ANN-predicted lithology classes. For each case, the calibrated neural network was able to locate the sand and predict its porosity. The success rate for predicting the correct porosity class in the sands was greater than 80% for the calibration wells.

Interwell classification. The trained neural network developed from the calibration wells was then applied to the real seismic data. Separate lithology and porosity classifications were performed on a sample-by-sample basis on attributes computed from the entire 3D seismic volume using the
derived neural weights and scalars. Figure 10 is a flattened
time slice through the volume classified for lithology and porosity. Colors indicate lithology and four different sand porosity classes as shown at the bottom of Figure 11.

We have compared the lithology from the calibrated seis-
mic attribute-based reservoir characterization to the well-log
data in six wells. Figure 11 shows a cross section of the lithol-
ogy volume through well 1. The gamma-ray and SP-log
curves are superimposed over the lithology classes between points A and A’”. There is good agreement between the log-indi-
cated sand section and the sand classification computed from the trained neural network and applied to the 3D seismic-attribute volume.

However, due to stratigraphic variations within the chan-
el, the neural net classification does not always properly
determine all reservoir variations within the analysis win-
dow. It is limited to characterizing only those wells that fit

within the range of reservoir variations of the selected wells. Classifications of other combinations of wells in the study showed that different weights and scalars for the same set of attributes are necessary to produce similar agreement between observed and predicted sand sections. The final training network was chosen to identify the characteristics of the wells with the most similar reservoir stratigraphy.

Since the project was completed, we have learned that some sands in some withheld wells in the channel are wet, not gas-filled as we had originally believed. Future work in this area should include more wet sand classification in addition to the gas-filled, multiple porosity classes, to sample more of the reservoir complexity.

Warning! A common assumption is that higher-porosity sands cause higher reflection amplitudes. However, our cal-
librated classification shows that this is not true in some areas of our data set. Figure 12 shows that some high-porosity zones are in regions that have lower amplitude (black circle), and others correspond to high amplitude areas.

Conclusions. Seismic attributes were computed on a 3D seismic volume over a sand-filled channel in the United States Midcontinent. These attributes were classified using both supervised and unsupervised methods. The unsuper-
vized classifications were helpful in defining the extent and shape of the reservoir sands. A trained artificial neural net-
work using poststack seismic attributes was able to classify the seismic data volume for lithology, porosity, and thick-
ness in the targeted sands with an acceptable degree of con-
fidence.


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