Delineating Reservoir Sands Using PP and PS Seismic Data
Bruce Mattocks, Bob Montgomery, John Gibson, Steve Roche, Veritas DGC; M.B. Holland, Output Exploration LLC.

Summary
Thin reservoir sands less than 40m thickness at an approximate depth of 2800m were successfully delineated using both P-wave (PP) and converted-wave (PS) shear data. Reflectivity associated with the reservoir sands is more clearly seen on the PS data than on the PP data. 58 wells with SP logs were used to train a neural network using both PP and PS data as input. Including the PS data was required to successfully predict the distribution of the reservoir sands. One well has been drilled on these results, with two others planned in early 2006. Training the neural network to predict the reservoir sands using P-wave data (migrated data and AVO attribute volumes) could not accurately delineate the reservoir sands without the PS data.

Introduction
Using multicomponent seismic data allows the interpretation of both PP and PS data volumes, providing a complementary image of the subsurface reflectivity. By using both wave modes, more complete knowledge of the subsurface bulk rock properties can be obtained, thus reducing economic risk in exploration and development.

Multicomponent Data Acquisition
The Harvest 3C3D survey was acquired onshore USA in December 2004. Survey area was approximately 70km$^2$ (see Figure 1). Acquisition parameters are listed in Figure 1. Source was dynamite and the multicomponent recording utilized a single 3C digital Micro-Electro-Mechanical Systems (MEMS) sensor per receiver station. Active recording spread was 2160 3C stations (6480 channels recorded per shot). 2880 source points were acquired over a 7 day period. Data quality is excellent.

Multicomponent Data Processing
Processing of the PP data included controlled amplitude and phase surface-consistent processes, followed by prestack time migration. Since the data were recorded using 3C sensors, polarization filtering was used to attenuate surface wave energy based on the elliptical particle motion associated with Rayleigh wave propagation. Although the surface wave noise was not severe, removing groundroll improved the prestack S/N ratio, particularly for velocity estimation and PP AVO analysis.

AVO analysis of the prestack PP data produced standard intercept and gradient volumes along with normal incidence reflectivity, P-wave reflectivity, S-wave reflectivity and fluid factor volumes for interpretation. It was assumed that PP AVO would be the primary interpretation method for delineating the reservoir sands in the project area.

Interpretation
Acquiring the data using multicomponent sensors allowed for the development of a converted shear-wave (PS) image. Understanding the anisotropic coordinate system was essential for PS data processing. After sensor correction to true vertical using recorded gravity values, an azimuthal rotation analysis determined the “fast” shear wave polarization direction to be approximately N50°E. This direction is consistent with the regional horizontal stress field in the Harvest 3C3D survey area. After rotation to “fast” PS1 and “slow” PS2 orientations, the PS data were processed through ACP surface-consistent statics, velocity analysis and gamma estimation, followed by CCP binning, velocity estimation, stack and PS migration.

The PP PSTM volume, AVO attributes and the two PS datasets (“fast” PS1 and “slow” PS2 orientations) were used for interpretation. A first step in interpretation was to integrate the
available well control with the PP data. Figure 2 shows an arbitrary line through the survey with borehole SP curves superimposed on the migrated seismic image. The geologic setting is a clastic sand and shale deltaic sequence (“A” and “B” sands in Figure 2), underlain by a limestone erosional surface (“C”). The “A” sand is regionally consistent and wet. The “B” sand is the economic target with sand thickness ranging from 0m to 40m at an approximate depth of 2800m. Reservoir sand porosity averages 15%. The SP curve is a good lithologic indicator for this sand-shale system.

Figure 2 illustrates the exploration problem in delineating the reservoir “B” sands using PP data. Both the “A” sand and underlying “C” limestone are easily tied to the seismic data based on reflectivity. These two horizons form the basis for time-depth conversion. The “B” marker is difficult to pick as a consistent waveform on the PP data. Therefore the “B” sand was extrapolated from well control (greater than 70 wells) and projected into the seismic volume using the time-depth relationships from the “A” and “C” horizons. Where the “B” sand has non-zero thickness, two horizon lines delineate the top and base of sand (Figure 2). Interpretation of the PP migrated stack and associated PP AVO volumes failed to reliably predict the presence of the “B” sand marker. However the “fast” PS1 volume does show reflectivity associated with the “B” sand marker. PS data along the same arbitrary profile as in Figure 2 is shown in Figure 3. Figure 4 shows two maps with the arbitrary profile indicated. The lower right map is from well control while the upper left map is a simple amplitude extraction from the PS1 volume along the “B” sand horizon. There is good spatial correlation, leading to the observation that the PS reflectivity provides greater sensitivity to the reservoir “B” sands.

We do not have dipole log support in the survey area, although plans include acquiring dipole logs in future wells to aid in the interpretation. Our working hypothesis is that the presence of sand is more directly related to changes in rigidity than to changes in compressibility, thus the PS reflectivity is the more direct sand indicator.

**Lithology Estimation using Neural Network**

Using 58 wells, we trained a neural network to accept PP reflectivity, PP AVO volumes, and PS1 and PS2 reflectivities as seismic input for predicting SP curves as a measure of lithology (sands and shales). Figure 5 shows the results with nine wells along the arbitrary traverse. Both the “A” and “B” sands are accurately estimated, particularly the updip limit of the “B” sands pinchout between wells #1 and #2. Of the top ten seismic attributes, six are derived from the converted-wave data.

The client on this project, who wishes to remain anonymous, notes that the “B” sand thickness is predicted to within 5m for 65 out of 72 wells. A subsequent well drilled after this analysis found 18m of “B” sand while the neural net prediction was 16m.

We repeated the experiment, training the neural network using only PP data as input (stack and AVO attribute volumes). These results (Figure 6) do not accurately delineate the “B” sands. The updip limit is not properly determined. Well #7 has “B” sand present but was not predicted using the PP data alone.

**Conclusions**

Delineating the “B” sand reservoir can be successfully done by integrating well control with both PP and PS data. Using a neural network algorithm trained to predict lithology using SP curves, the converted-wave data was required for a successful prediction of the SP curves. Subsequent drilling has confirmed this workflow for predicting the reservoir “B” sand using PP and PS data.
Acknowledgements
The authors thank our anonymous client for permission to show this work and Veritas DGC for supporting these efforts to demonstrate the economic value of using multicomponent data for oil & gas exploration and development.
### Data Acquisition Grid and Parameters

#### Recording
- MEMS 3C Digital Sensor
- 18 lines by 120 stations
- 2160 stations (6480 channels)
- 2 msec sample

#### Receiver
- 67m (220') receiver interval
- 402m (1320') line spacing
- 2890 total receiver stations

#### Source
- Dynamite (5.5lbs @ 24m depth)
- 67m (220') source interval
- 402m (1320') line interval
- 2880 total source points

Data were recorded using digital MEMS sensors and occupied an approximate 70km² area.

---

Figure 1. Data acquisition grid and parameters for the Harvest 3C3D survey. Data were recorded using digital MEMS sensors and occupied an approximate 70km² area.

---

Figure 2. Arbitrary line through the P-wave 3D migrated volume. Well logs shown are spontaneous potential (SP). The “A” marker is a regional sandstone and the “C” marker is an underlying limestone horizon. The target “B” sand thickness is represented by the diverging horizons.

---

Figure 3. Same arbitrary line as Figure 2 through the “fast” PS1 migrated data volume. Reflectivity associated with the target “B” sand is readily apparent.
Figure 4. Thickness of target “B” sand from well control (lower right) compared to an amplitude extraction map from the PS1 data volume along the “B” sand horizon. Arbitrary line location is annotated. “B” sand thickness ranges from 0m to 40m at a depth of 2800m.

Figure 5. Results using a neural network algorithm to predict SP (lithology) using both PP and PS data as input. The PS data provided six of the top ten seismic attributes used in the prediction. The regional (wet) “A” sand and target “B” sand are very well imaged. White and blue colors represent sand, red indicates shale.

Figure 6. Results using a neural network algorithm to predict SP (lithology) using the PP data only as input. The PP data failed to correctly predict the target “B” sand, especially the updip limit of the field (left).