North Sea reservoir characterization using rock physics, seismic attributes, and neural networks; a case history

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Summary
A new method was developed to use core, well log, and post-stack seismic data to identify reservoir lithologies between wells. The method was based on a combination of rock physics modeling, seismic attribute generation and pattern recognition via neural network analysis. The result was a new lithologically calibrated attribute that showed the producing wells to be inside the indicated oil sand area and the non-producing wells to be outside this area.

Introduction
In many cases poststack seismic data is the only available source of information on interwell stratigraphy and lithology. In such a situation 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 lithologic knowledge from this 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 North Sea tertiary turbidite system. The seismic survey covering the area of interest was about 325 square km. There were 5 wells inside the survey area, two of which had encountered oil saturated pay sands. These wells had a full suite of high quality logs, and the two producing wells also had dipole shear wave data.

Reservoir Classification Using Borehole Data

Basic log analysis
Five wells were available for this study. Wells 2, 3, and 4 were non-producers in the Heimdal Formation or had no Heimdal sand present. Wells 5 and 6 had significant oil content in the Heimdal. These two wells also had measured dipole shear wave logs that were used to calibrate the Vs prediction in the other three wells. Other log curves available were gamma, neutron, density, sonic, ILD, caliper and in some wells, MSFL.

Total porosity (Phi), shale volume (Vshale), and water saturation (Sw) were computed first. The zones of interest were primarily sand-shale sequences between 2100 and 2300 meters. The shale volume was determined mainly from the gamma log, but in some cases we used gamma, neutron, and density logs. The total porosity was based mainly on the density log, which appeared to be of high quality throughout the entire zone of interest. In hydrocarbon-bearing intervals an average of neutron and density logs was used to find total porosity. Caliper logs showed good wellbore conditions in the zones of interest in all wells.

Core derived lithologic boundaries and well log derived volumetric curves were used to train a neural network to automatically identify five important lithologies from logs.

Shear wave velocity prediction
Two main methods of Vs prediction were tested in the non-hydrocarbon bearing wells. These methods are implemented within the PetroTools software package. The first was Greenberg-Castagna. In the producing wells this relation showed good agreement with the dipole shear log, except in the oil sands. This suggested that there might be a problem with mud invasion or wellbore washouts. But since the caliper log showed no indication of washout, the former was deemed more likely. The good agreement between Greenberg-Castagna and the dipole shear log in non-pay zones was considered to be at least partial confirmation of our Vshale and porosity values.

The second Vs prediction method was based on the Castagna “mudrock” equation calibrated to the two wells with known shear wave velocities. Only the water saturated portions of the wells were used to establish the calibration. The relationship derived was;

$$Vs = 0.73\ Vp - 767\ \text{(m/sec)}.$$

This simple relationship gave a slightly better correlation than Greenberg-Castagna so it was used to compute Vs in the water-saturated wells 2, 3, and 4.

Mud filtrate invasion correction
Deep and shallow resistivity logs indicated that water-based mud filtrate had invaded the near wellbore region in Well 5. Because density and sonic are both shallow investigation logs, we performed a calculation to obtain values that were more representative of the true reservoir. The resistivity from the MSFL curve (Rmsfl) showed that the near wellbore Sw was essentially 100%. It also indicated an apparent water resistivity (Rwa) that was very similar to that indicated by the deep induction log (Rt). This means that the reservoir brine and the mud filtrate have essentially the same salinity. Therefore to correct the sonic and density, we assumed that they responded to 100% Sw when logged and we performed a fluid substitution to the Sw indicated by the Rt log. This resulted in lower density and Vp in the pay zone than recorded by the logging tool. There was no shallow resistivity log available for Well 6 but comparisons of the dipole sonic to the predicted Vs from the modified mudrock equation suggested that this well also had significant mud filtrate invasion. Therefore, it was corrected for mud invasion in the same manner as Well 5.

Fluid substitution
Biot-Gassmann's relations were used to create additional "pseudo-wells" in which the oil saturation was removed from the actual oil sands and oil was added to one of the wells where the Heimdal was water saturated. The following properties of the solid and fluid components were used in the fluid substitution. The fluid moduli and density varied with pressure and temperature as described by Batzle and Wang:

Solid	*Moduli and Density*
Quartz	K=36.6 Gpa, u=45 Gpa, rho=2.65 g/cm3
Shale	K=20.8 Gpa, u=6.9 Gpa, rho=2.58 g/cm3

Fluid	*Description*
Oil	32 API, GOR = 65 L/L
Brine	60,000 PPM NaCl (~0.05 Ohm-m @ 80C)

Training of neural network with well log data
The purpose of this step was to:

- Define lithology classes to be identified at the wells and ultimately across the 3-D volume.
- Build a classification scheme using neural network training to predict the lithology classes.

Lithology classes were defined as sedimentary units with distinguishable characteristics such as clay content, bedding configuration (massive or interbedded), grain size, cementation, and rock mineral properties. Also pore fluids of the specific identified reservoir units were included in the classifications. These parameters were obtained from the 75 meters of classified core from well 5. The following reservoir classifications were used:

1. Pure shale; 2. Silty shale; 3. Interbedded sandstone-shale; 4. Massive wet sand; 5. Unconsolidated wet sand; 6. Planar laminated oil sand; 7. Unconsolidated oil sand; 8.Undefined.

In addition to the lithologic column output, multiple well log curves were provided as inputs. These curves were density, total porosity, Vp, Vs, clay volume, and water saturation.

The neural network used this information and developed weights and scalars by iterative correction to minimize the discrepancies between the predicted lithology results and the actual classes. The training was done on a limited range of depths encompassing the reservoir interval. We selected an interval from 2100m to 2300m for the reservoir classification. An example of this classification for Well 5 is shown in Figure 1. Once the training operations were completed and validated, the neural network weightings and scalars were applied to the processed logs to obtain a reservoir classification at each well. Where core data was available in Well 5 the match between actual and predicted lithology was 92%.

Reservoir Classification Using Seismic Data

Synthetic seismic generation
To tie the well log-derived attributes and the seismic-derived attributes, synthetic seismograms were generated and used to train the seismic properties to predict the lithology classes.

The following tasks were performed:

1) Wavelets were extracted at each well location based on a 9X9 grid of seismic traces around the well.
2) Logs input to the synthetic seismogram program were Vp, Vs, and density, after correction for mud filtrate invasion. The predicted classification curves at each well were also input for later conversion to seismic travel time.
3) Synthetic seismograms were calculated based upon the extracted wavelet and wireline logs. The synthetics were calculated by building a synthetic offset model of 10 offsets spanning a range of 0-5000m. The offsets then had normal moveout applied and were summed to generate a stacked synthetic trace.
4) The reservoir classification curves were then resampled to time using the synthetic seismogram - derived time-depth curve.

At this point the calculated synthetic seismograms and time-converted lithology classes were available for attribute generation and neural network training.

Generation of seismic attributes
We define all seismic-derived parameters as seismic attributes. They can be velocity, amplitude or rate of change of any of these with respect to time or space. Furthermore, we are able to classify these attributes based upon their computational characteristics, e.g., some of the attributes that are computed from the complex trace such as envelope, frequency and phase, etc., correspond to various measurements of the propagating wavefield. For these attributes we adopt the term 'Physical Attributes'. Other attributes are computed from the reflection configuration and continuity properties of the sub-surface and we group these together as 'Geometric Attributes'.

The principle objective of computing seismic attributes is to provide accurate and detailed information to the interpreter on structural, stratigraphic and lithological parameters of the seismic prospect (Taner et al.).

For this project we calculated a suite of attributes on the synthetic seismograms and selected those that were physically meaningful and which produced the most effective training set for predicting the lithology classes away from the boreholes. The same attributes were generated for the 3-D seismic data volume and used to estimate the lithology classes. We calculated 16 different attributes and employed these in the neural network-testing phase.

Training of neural network with seismic attributes

Seismic attributes generated from the synthetic seismograms were associated with the time domain lithology columns at each well using a neural network tool. This process is illustrated in Figure 2.

The neural network used the time domain lithology classes and seismic attribute information and developed weights and scalars by iterative correction to minimize the discrepancies between the predicted results and the actual classes. This process was iterated until an acceptable convergence was achieved. At that point the network was considered to be trained. It was then used to classify the remainder of the dataset. Had the classification not been satisfactory, a new set of input attributes would have been selected and the process repeated. (McCormak et al.)

Once acceptable results were attained the neural weights and scalars were passed to a classification module that applied the training to the attribute data. In our case study, numerous combinations of attributes were attempted and ultimately five attributes were chosen that gave acceptable results.

Estimation of lithology classes away from boreholes

Lithology classification was performed on a sample-by-sample basis on the attributes computed from the entire 3-D seismic volume using the neural weights and scalars derived from an analysis of a sub-set of the initial suite of attributes derived from the synthetics.

The resulting lithology attribute volume for the study area was imported into a commercially available volume visualization software package. The resulting images of the reservoir were flattened on a time horizon that corresponded to the midpoint of the pay sand near the two producing wells. Figure 3 shows a time slice through this flattened horizon

Conclusions

- Using a neural network trained to core data gives lithology from logs with about 90% accuracy;
- Using a neural network trained to log lithology in the time domain gives lithology from synthetic seismic with reasonable accuracy at the well locations;
- Applying the synthetic-derived neural network weights to attributes computed from real seismic shows the producing wells 5 and 6 to be inside the indicated oil sand area and the non producing wells to be outside this area.

Recommendations for future work

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

- Reprocess prestack data for improved surface-consistency, amplitude and phase preservation and wavelet unitization.
- Improve quality of match between synthetic seismograms and seismic data through the use of prestack time migration and use of intercept stack volume.
- Incorporate additional classes of attributes, e.g. energy absorption, acoustic and elastic impedance, AVO.
- Re-examine log analyses using available core data (porosity, permeability, capillary pressure, resistivity, etc.)
- Explore different well log classification methods, e.g. reservoir quality index.

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Reservoir characterization using rock physics, seismic attributes, and neural networks

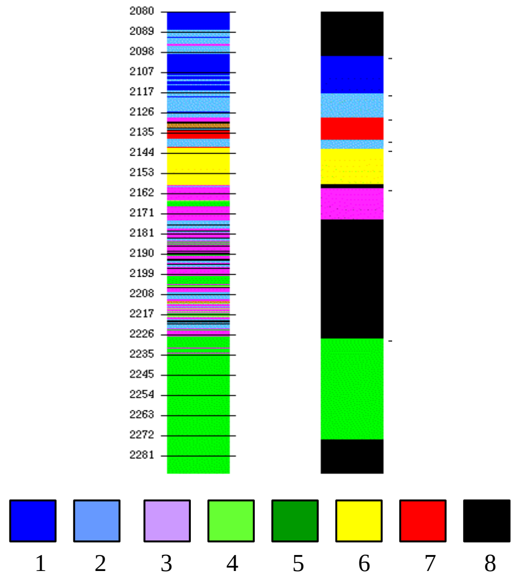

Figure 1: Lithology determined from log curves in Well 5 using a neural network trained to core lithologies. 1, Pure shale; 2, silty shale; 3, interbedded sandstone-shale; 4, massive wet sand; 5, unconsolidated wet sand; 6, planer laminated oil sand; 7, unconsolidated oil sand; 8, undefined.

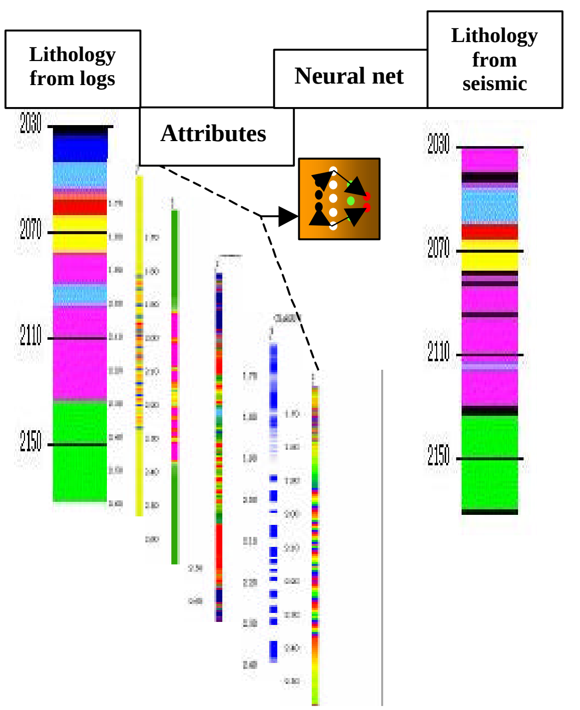

Figure 2: Lithology column in time domain is extracted from seismic attributes at the Well 5 location using a neural network trained on the log lithologies.

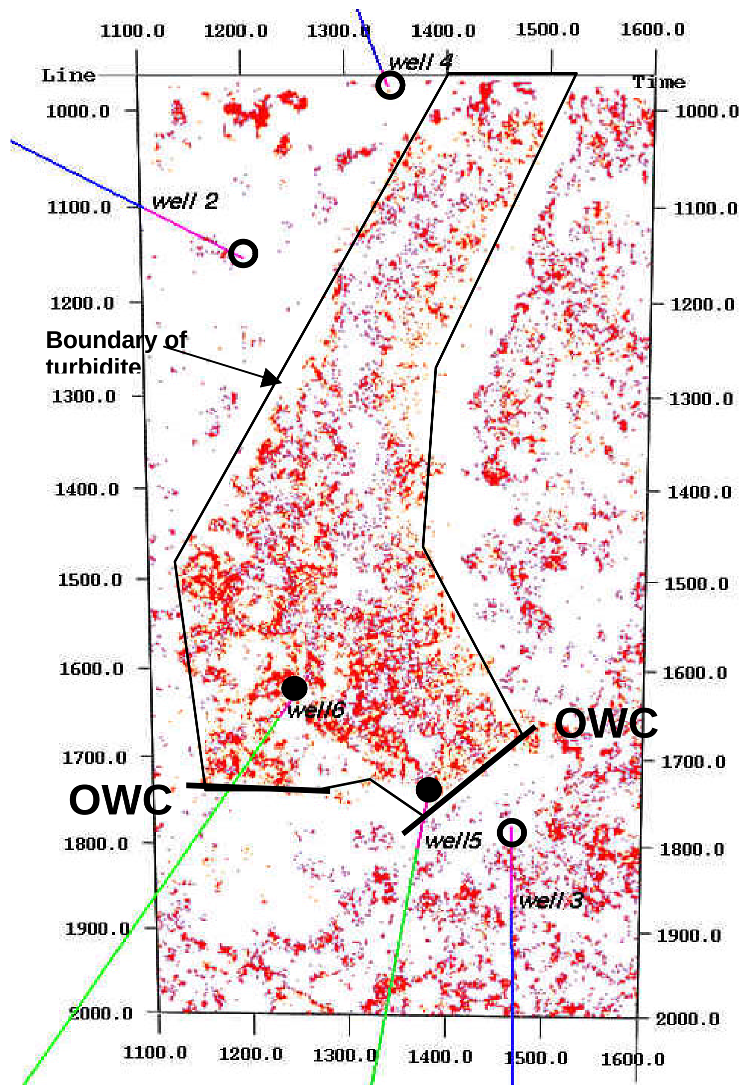

Figure 3: Time slice of flattened horizon showing lithology attribute. Here the two oil sand lithologies were grouped together (red) and all of the non-reservoir quality lithologies were combined (white).