Delineating productive reservoir in the Canadian Oil Sands using neural networks approach

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Summary

The Long Lake Oil Sands Project, a joint venture between Nexen Inc. (Nexen) & Opti Canada Inc. (Opti), is located near Ft. McMurray in NE Alberta, Canada. The Long Lake Project aims to produce 70,000 bbls/d of raw bitumen via the Steam Assisted Gravity Drainage (SAGD) production technique from the McMurray Formation.

Density is a key physical property in differentiating between sand and shale within the oil sand bearing McMurray Formation of NE Alberta. Therefore, having a density volume available over a McMurray Formation oil sands project area is very useful for planning, well placement and evaluating production operations. Integrating 3-D seismic data with petrophysical measurements from wells using neural networks significantly improved the spatial description of density particularly in comparison with previous efforts to derive density directly from seismic data (Dumitrescu et al., 2003 and Gray et al., 2004).

About 38 wells with dipole sonic logs and five seismic volumes (attributes of the pre- and post-stack seismic data) were used to predict the density distribution within the McMurray Formation throughout the Long Lake 3-D.

A statistical approach, provided by the Hampson-Russell EMERGE software, including multi-attribute and probabilistic neural network (PNN) analysis was used to derive the relationship between attributes of the seismic data and density log data. The established relationship was used to estimate pseudo-density logs at each seismic trace on the 3-D. The estimated density volume shows good correlation with the density logs not only for the wells used on training the network but also for the rest of the wells.

Introduction

The Long Lake Project, covering approximately 70 square kilometers, has been independently estimated to contain over 2 billion barrels of bitumen in place. The Long Lake Project will use Steam Assisted Gravity Drainage (SAGD) technology to recover bitumen. First introduced in the 1970s, SAGD is a proven method of bitumen extraction that is applied to virtually all new commercial scale in situ oil sands developments. SAGD recovers bitumen through: drilling of horizontal well pairs, injecting steam into the upper well, steam rising through the oil sands and heating the bitumen, and, bitumen flowing with condensed steam (water) into the lower well, and then to the surface (Long Lake Project, 2004).

The reservoir at Long Lake contains bitumen-supported sands and shales within the Cretaceous McMurray Formation at a depth of 180-250m. The Lower McMurray consists of a fluvial low-stand systems tract of valleys incised into a paleo-karsted carbonate terrain. Braided channel sands were deposited in these valleys, with laterally discontinuous mudstones and “shale-plugs” occurring as overbank deposits and abandoned channel fills. The Upper McMurray is a transgressive system tract consisting of estuarine channel and point bar complexes in a shore-face environment (Hein et al., 2001).

Depending on their size and configuration, non-reservoir shale bodies can impede steam chamber growth and fluid drainage within a SAGD production process. Distinguishing between reservoir and non-reservoir using a conventional seismic interpretation approach has proved ambiguous. However, petrophysical analysis has determined that density is the key discriminator between sand and shale. Therefore deriving a density volume from seismic data is a useful and important objective.

The idea of using multiple seismic attributes to predict log properties was proposed by Schultz et al., (1994a) and Ronen et al., (1994). There are several case histories reported in literature for prediction of well-log properties using multi-linear regression and neural networks (Russell et al., 1997; Todorov et al., 1998; Hampson et al., 2001; Pramanik et al., 2004).

EMERGE integrates well log data and multiple seismic attributes to derive an estimate of density at each seismic trace. To achieve an optimal estimation of density, pre- and post-stack seismic attributes, such as P-wave and S-wave impedance reflectivities were used. P-wave and S-wave impedance are linked to the well log data via a physical model..

Method

For the Long Lake Project, 3-D seismic data and approximately 180 logged and cored wells are available. The 3-D seismic was acquired in 2002 and 2003 using the VectorSeis® digital multi-component recording system. Subsurface bins are 10m x 10m over a 42 square kilometer surface area. 38 wells with dipole sonic logs uniformly distributed over the 3-D have been used in the analysis (Figure 1).

Previous approaches to direct density extraction using AVO and inversion (e.g. Gidlow et al., 1992, Roberts, 2000, Gray, 2003) have been marginally successful due to the fact that density cannot be distinguished as a separate attribute from pre-stack seismic data with less than 30 degrees offset angle. The procedure presented in this paper differs by first using AVO-derived P-wave and S-wave reflectivity as external attribute volumes for multi-attribute and PNN techniques available in EMERGE. In addition, three other seismic volumes have been used as input for the PNN analysis: the migrated stack, P-wave impedance and S-wave impedance. The neural network was used in an effort to account for non-linear relationships between logs and seismic after first testing the linear multi-attribute method alone.

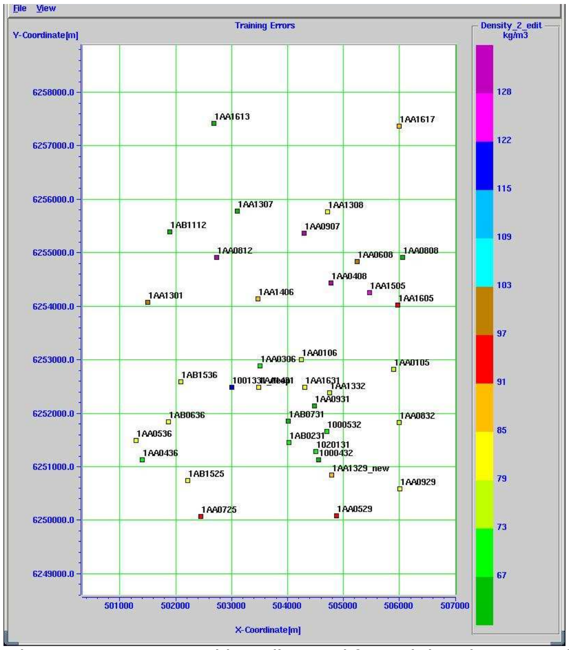

Figure 1: Basemap with wells used for training the network

PNN analysis, has four steps: 1. perform a multi-attribute step-wise linear regression and its validation, 2. train neural networks to establish the nonlinear relationships between seismic attributes and reservoir properties at well locations, 3. apply trained neural networks to the 3-D seismic data volume, 4. validate results on wells withheld from training.

The multi-attribute step-wise linear regression analysis was performed for 38 wells using five input volumes (seismic impedances and reflectivities) and a seven-point operator. Using the ranking process in EMERGE and after checking the errors, the attributes selected for training the network were the following: P-impedance, average frequency, quadrature trace and P-wave impedance reflectivity. The same attributes were used in PNN analysis.

Results

The data used for estimating the density volume are density logs, attributes of pre- and post-stack seismic data, as well as inversions. These attributes have been ranked on their ability to predict the density logs. The highest ranking attributes are then fed into a neural network to generate estimates of the density throughout the 3-D volume. Thus density is predicted at actual well locations and between existing well control.

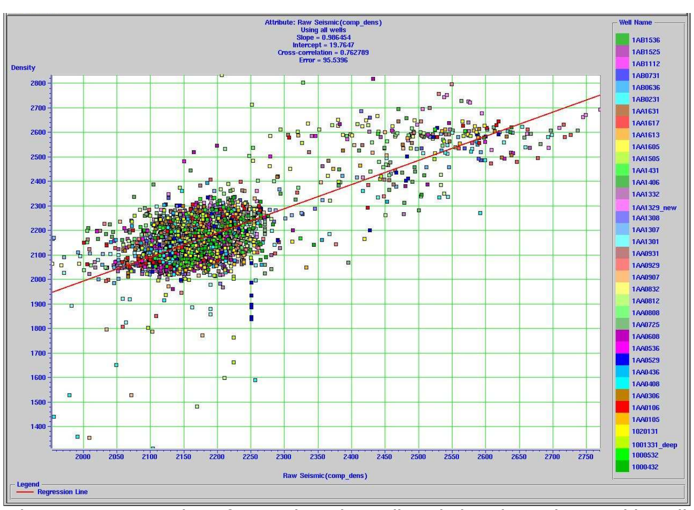

Figure 2: Cross-plot of actual and predicted density using multi-attribute analysis. Data points from the analysis zone of all 38 wells. The cross-plot shows a clear tendency to predict density values characteristic of sand and shale (2050 – 2250 kg/mc).

The PNN analysis based on multi-attribute analysis with four attributes shows high cross-correlation (0.78) between actual and predicted density for the 38 wells in the study area. After applying the neural network to the 3-D volume, the predicted density values at each well location have been compared with the density logs (Figure 3). It is clear that the predicted density volume obtained from PNN analysis provides meaningful information about the McMurray reservoir.

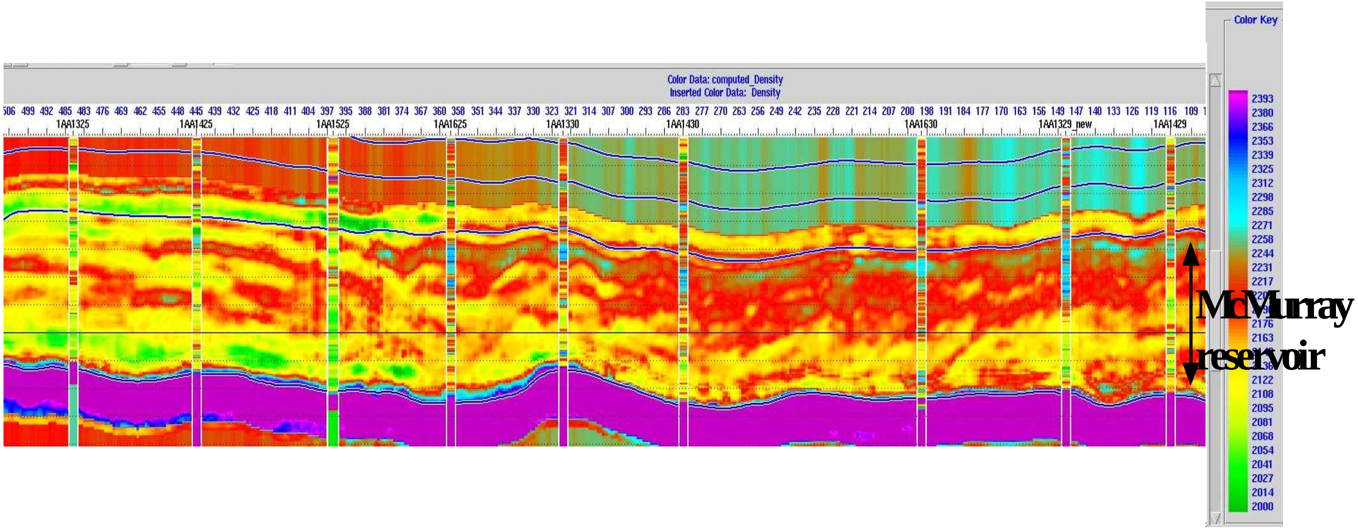

Figure 3: Density results at one line from the 3-D. Inserted in color are the density logs. Only the second density log from the right has been used for training. All the others tie this line within a 50 m projection distance.

Conclusions

The derived density results show strong correlation with the density logs, both at training well locations and for the rest of the wells suggesting that density can be accurately estimated from neural network analysis in the McMurray reservoir interval over the Long Lake Project area.

In this area, our analysis has shown that neural networks provide a better image of subsurface density distribution than multi-attribute analysis alone because the networks' architecture can better capture the nonlinear relationship between seismic attributes and density log and gives priority to well information. In this way, it can offer significant improvement in the accuracy of the computed density volume in comparison with current methods of direct extraction of density from PP and/or PS AVO.

Utilizing the density volume computed with neural network analysis will minimize uncertainty in bitumen sand and shale identification thereby contributing to optimal horizontal well placement. This will in turn have the ultimate effect of increased production and economic efficiency.

Acknowledgement

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