INTEGRATED CHARACTERIZATION OF HEAVY OIL RESERVOIR USING V_P/V_S RATIO AND NEURAL NETWORK ANALYSIS

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ABSTRACT

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The focus of this study is the southern portion of the Long Lake lease located approximately 40 km southeast of Fort McMurray, Alberta, Canada. The lease area is roughly 25,000 hectares and contains over 8 billion barrels of bitumen in place.

For heavy oil projects, the V_P/V_S ratio is a good lithology discriminator, and the objective of this paper is to predict a V_P/V_S ratio volume based on neural network analysis. Neural network estimation of reservoir properties has proven effective in significantly improving accuracy and vertical resolution in the interpretation of the reservoir. The strength of a neural network analysis is the ability to determine nonlinear relationships between logs and several seismic attributes.

The result is a new lithology calibrated attribute that, when co-rendered with edge detector attributes, can predict the presence of muddy intervals responsible for impacting the propagation of steam through the reservoir, thereby allowing us to more effectively describe enhanced oil recovery in the reservoir.

KEYWORDS: heavy oil, V_P/V_S, density, inversion, neural network.

INTRODUCTION

The oil sands reservoir related to the Long Lake South (LLS) Project is situated in the Athabasca oil sands that is the most areally extensive of the three main deposits (Peace River, Athabasca and Cold Lake Formation) of northern Alberta, Canada (Fig. 1).

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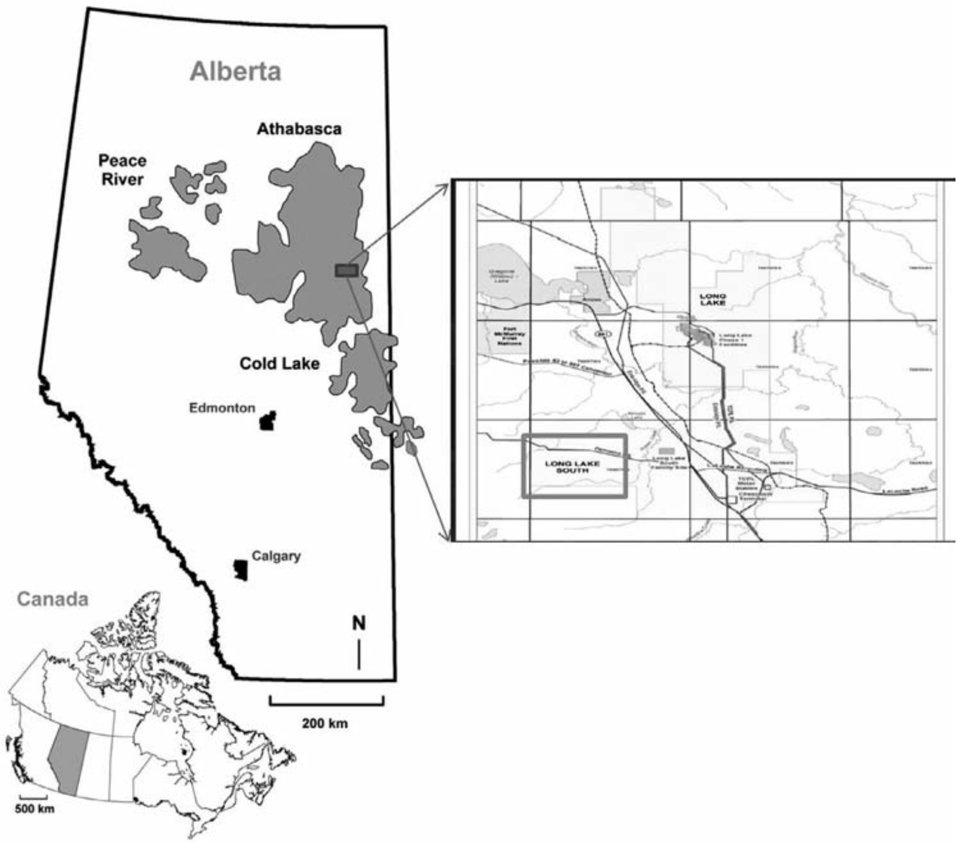

Fig. 1. Location of the three major oil sands deposits in Alberta (Athabasca, Cold Lake Formation, and Peace River), Canada (Crerar, 2007) and details about Long Lake South area.

This reservoir is contained within the McMurray Formation, which is the basal unit of the Lower Cretaceous Mannville Group. The McMurray Formation directly overlies the sub-Cretaceous unconformity, which is developed on Paleozoic carbonates of the Beaver Hill Lake Group, and overlain by the Wabiskaw, Clearwater and Grand Rapids Formations of the Mannville Group (Fig. 2).

The study area is located along the axis of the McMurray Valley system, which was localized by the dissolution of underlying Devonian evaporites, creating the preferred depositional fairway for the Lower Cretaceous McMurray sediments. The most significant bitumen reservoirs within the McMurray Formation are found within the multiple channels that represent lowstand system tracts, incised into the regional, prograding parasequence sets that represent highstand system tracts. During sea level rise, these incised channel systems were filled with a transgressive estuarine complex, consisting of sandy to muddy estuarine point bars. In the Long Lake area, the McMurray Formation is dominantly composed of these multiple, sand rich, fluvial and estuarine channels, which are incised into each other and stacked along a preferred path of deposition. This preferred path is aligned north-northwest to south-southeast in the Long Lake area (Dumitrescu et al., 2009).

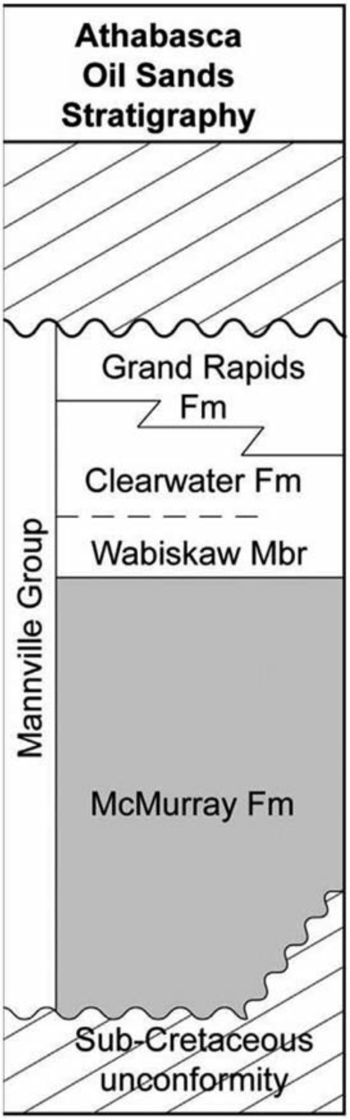

Fig. 2. Stratigraphy of the Athabasca Oil Sands deposit (modified from Hubbard et al., 1999).

A typical seismic line (IL-562) from the prestack time migrated volume, is presented in Fig. 3. The reservoir is between the McMurray and Devonian horizons. This high-quality seismic data reveals large-scale depositional elements such as sand-dominated point-bar deposits (#1) and mud-dominated abandoned channel fill deposits (#2).

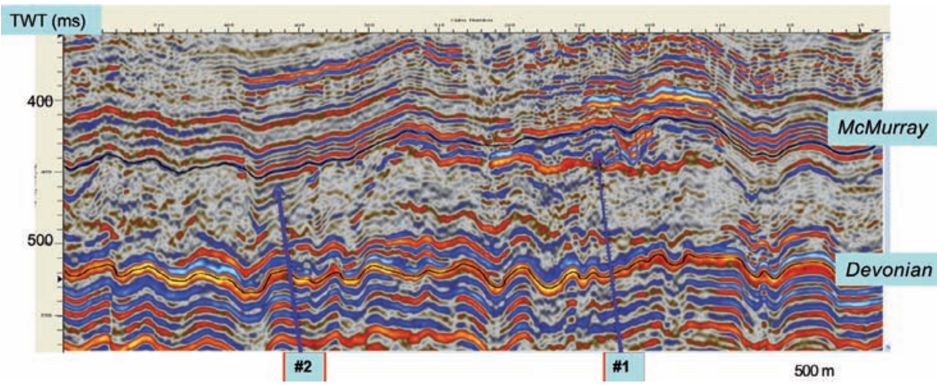

Fig. 3. IL-562 showing two features within the McMurray reservoir: sand-dominated point-bar deposit (#1) and mud-dominated abandoned channel fill deposit (#2).

These depositional elements can be visualized on horizon time slices cutting through edge-detector volume attributes such as semblance and volume curvature (most negative, most positive and dip curvature) calculated from the prestack time migrated volume. Fig. 4 is an example of a horizon time slice cutting through the semblance volume 10 ms below the McMurray Formation that shows a map view of features #1 and #2.

Depending on their size and configuration, non-reservoir shale bodies can impede steam chamber growth and fluid drainage within a steam assisted gravity drainage (SAGD) production process. Distinguishing between reservoir and non-reservoir using a conventional seismic data interpretation approach has proved ambiguous. However, petrophysical analysis has determined that V_P/V_S and density are key discriminators between sand and shale (Lines et al., 2005; Dumitrescu and Lines, 2008). Therefore deriving V_P/V_S and density volumes from seismic data is a useful and important objective.

It is well known and accepted by the industry that inversion is a necessary step in imaging and interpreting a reservoir, and there is a continuous struggle to improve the resolution of inverted volumes. Depending on the seismic data and the number of wells available, a V_P/V_S ratio volume can be obtained from:

(i) traveltime measurements on the vertical and radial components of multicomponent records (Lines et al., 2005), (ii) amplitude versus offset (AVO) analysis and prestack (simultaneous) inversion using only the PP component (Dumitrescu and Lines, 2006), or (iii) joint inversion of the PP and PS (registered in PP time) poststack seismic data (Dumitrescu and Lines, 2007).

For this project, the processing was designed to preserve prestack amplitudes and involved true amplitude recovery, noise attenuation, statics, and prestack time migration. These steps were followed by the creation of supergathers (5×5) with a bin size of 50 m × 50 m. Prestack (simultaneous) inversion was performed with the computed angle gathers. The output of this deterministic inversion consisted of volumes of P-impedance, S-impedance, V_P/V_S, and density. Neural networks analysis (NNA) was used for estimating a new seismic volume by integrating well information and several seismic volumes. The estimated V_P/V_S ratio volume was used successfully in mapping bitumen sands in heavy oil reservoirs.

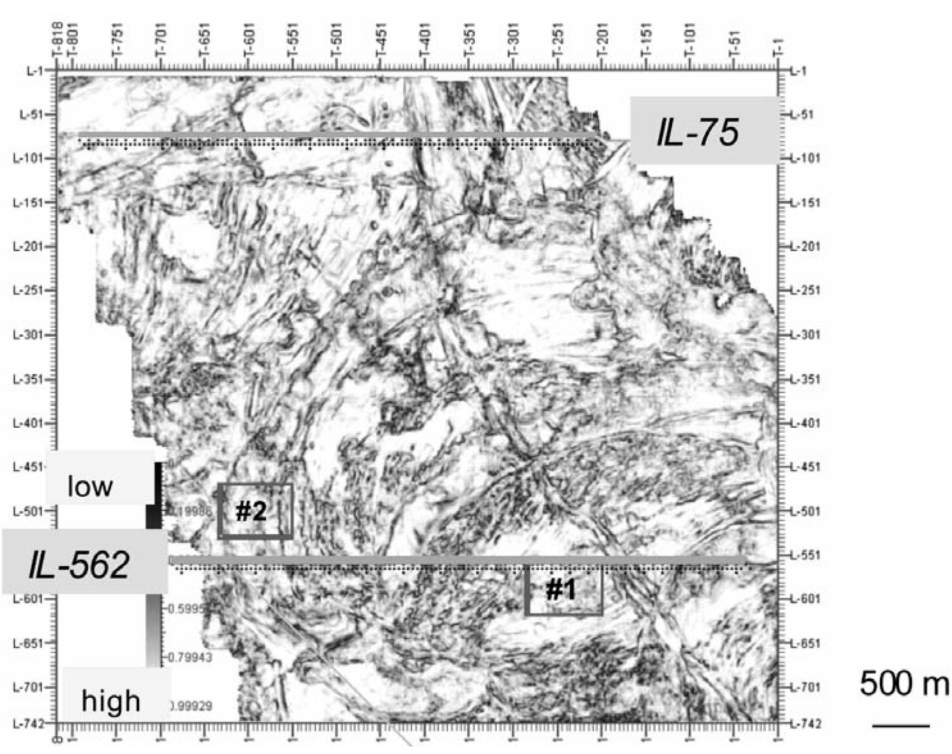

Fig. 4. Horizon time slice of the semblance at McMurray+10ms (showing features #1 and #2)

PETROPHYSICAL ANALYSIS

The LLS Project includes 3D seismic data and approximately 50 logged and cored wells over a 50 km² surface area. The 3D seismic data was acquired in 2005 using a Sercel digital multi-component recording system. Out of 42 wells with dipole sonic logs, only 31 were used in the NNA.

Petrophysical analysis was performed on all the wells in order to provide a trustworthy set of logs (Fig. 5) for inversions and neural networks analysis. The analysis included edits and corrections for poor-quality logs. Missing curves (e.g., shear sonic and density) were estimated using either the specific mud-rock line for the zone of interest or the multi-attribute analysis that allows us to estimate logs from existing logs (Hampson et al., 2001).

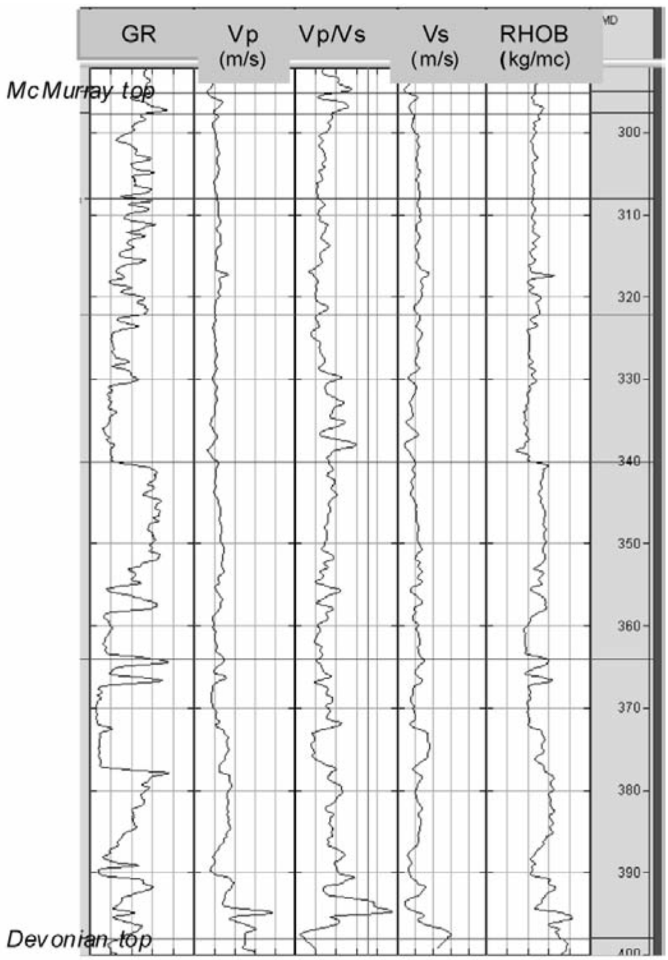

Fig. 5. Typical set of logs for a well in the project.

Crossplotting the well data can help identify the elastic properties of different lithologies and fluid fills. By using specific cut-offs, we separated gas sand, bitumen sand, and shale. This procedure answered two of the main questions: (1) what is the fluid content; and (2) what is the lithology variation? The crossplot in Fig. 6 shows density and V_P/V_S logs from wells in the study area. Four zones labeled gas sand, bitumen sand, water sand, and shale are defined based on the associated histograms. Gas sands have low density and the lowest V_P/V_S ratio, bitumen sands have low density and V_P/V_S values that vary with bitumen quality, and shales have high values for densities and V_P/V_S.

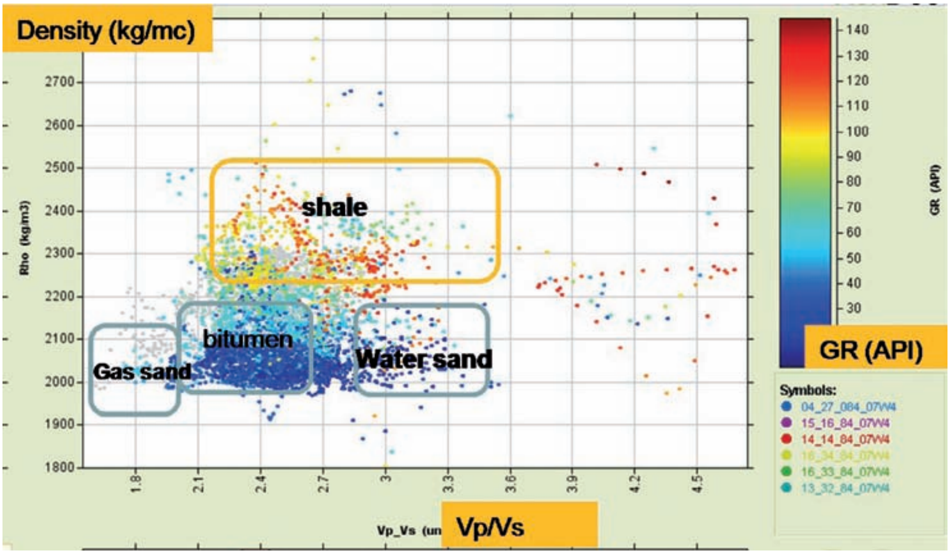

Fig. 6. Crossplot of density logs (vertical axis) and V_P/V_S (horizontal axis), colored by gamma ray (GR)

METHOD - NEURAL NETWORK ANALYSIS

Neural network analysis (NNA) acts as a pattern-recognition tool, similar to the human brain. We used a supervised neural network technique to quantitatively predict reservoir properties (such as V_P/V_S and density) away from the wells. This technique tie well properties to seismic attributes derived from inversions. Some of the inversion attributes (P-impedance (Z_P), S-impedance (Z_S), and V_P/V_S) used in the NNA are results from prestack inversion. Prestack inversion is a relative impedance inversion that uses a low-frequency model build from interpolating well log data. Prestack inversion uses the fact that the basic variables Z_P, Z_S, and density are coupled by two relationships which should hold for the background "wet" trend. Fig. 7 presents two crossplots in logarithmic domain between: (1) P-impedance and S-impedance, and (2) P-impedance and density. These regional rock property trends were derived from log data within the Wabiskaw to Devonian interval. Impedances are important in inversion because they bridge the gap between petrophysical variation and seismic amplitudes.

The NNA was performed on wells and several seismic attributes that can be classified as: (i) instantaneous attributes, derived from a combination of the input seismic trace and the Hilbert transform of the trace (i.e., trace envelope, instantaneous phase and instantaneous frequency), (ii) recursive attributes, derived by applying a recursive operator along a seismic trace (i.e., the integrated and differentiated seismic trace), (iii) bandpass attributes of the seismic trace, (iv) AVO attributes derived from prestack seismic data (i.e., P and S-wave reflectivity and fluid factor) (v) attributes derived from prestack inversion (i.e., P and S-impedance and V_P/V_S) and from previous NNA (density) (Herrera et al., 2006).

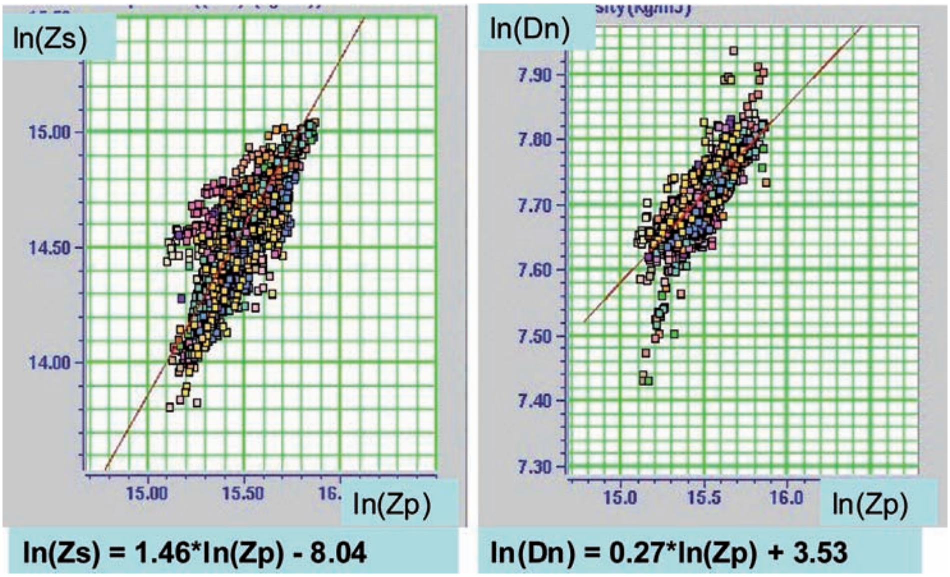

Fig. 7. Crossplots of (left) $\ln(Z_S)$ versus $\ln(Z_P)$ and (right) $\ln(Dn)$ versus $\ln(Z_P)$ using data from the Wabiskaw to Devonian interval measured in 20 wells.

Neural networks analysis consists of four steps:

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

Neural networks can be classified (i) by the type of problem that can be solved, i.e., classification or prediction, and (ii) by the type of training used, i.e., supervised or unsupervised. In our approach we used a supervised prediction type that has the advantage that the output can be interpreted based on the training values. In terms of implementations, there are several different types of neural network: (i) a multilayer feedforward neural network (MLFN), (ii) a probabilistic neural network (PNN), and (iii) a radial basis function (RBF). In our approach we selected the PNN that uses Gaussian weighting functions which fit seismic attributes to training samples by a generalized nonlinear regression approach. The key parameter in the PNN method is the sigma factor that controls the width of each Gaussian function and is allowed to vary for each input attribute (Hampson et al., 2001).

Using the ranking process available within the software and after checking the errors, we selected the attributes for training the networks. The neural networks were used in an effort to account for non-linear relationships between properties taken from the real wells and the attributes extracted from the seismic at those locations, after first testing the linear multi-attribute method alone. The final product is a property cube which can be used in a reservoir simulation model.

NEURAL NETWORK ANALYSIS RESULTS

With respect to the Long Lake project, neural network analysis was used to predict V_P/V_S and density in an attempt to get a better definition of bitumen sand and to better differentiate between sands and shale in the McMurray Formation. Fig. 8 shows a comparison between a V_P/V_S volume from deterministic inversion and one from a neural network analysis. V_P/V_S results are comparable with the deterministic data, but NNA results are less noisy and calibrate better with logs. Later we will try to integrate this lithology indicator attribute with the edge detector attributes in order to ease the interpretation.

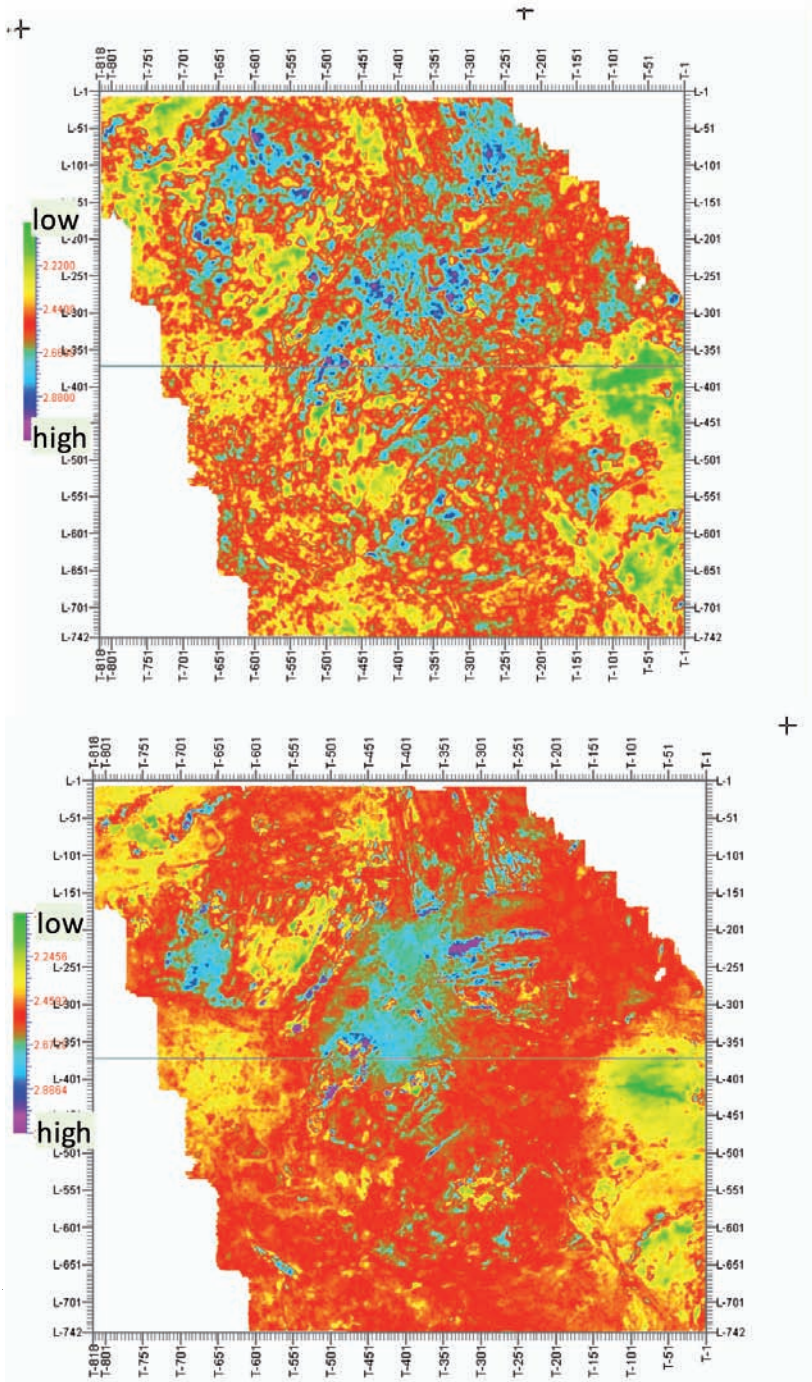

Fig. 8. Horizon slice at McMurray + 7ms on V_P/V_S volume obtained from (top) prestack inversion and from (bottom) neural network analysis.

The logs used for petrophysical analysis were used in the prestack inversion and in the neural networks analysis. Only well ties with good correlations were used in the analysis. As a result, 31 out of 42 wells were used. For each well, the data used in the training procedure were the V_P/V_S curve, along with eight extracted and correlated seismic attributes at each well: the PSTM stack, P-wave reflectivity (R_P), S-wave reflectivity (R_S), fluid factor (FF), P-impedance (Z_P), S-impedance (Z_S), V_P/V_S and density from NNA (Dn_NNA). An example of training data for well 16-34 is presented in Fig. 9. For each of the reflectivity traces, we used not only the trace itself but also transforms of this trace, such as instantaneous phase, instantaneous frequency, etc.

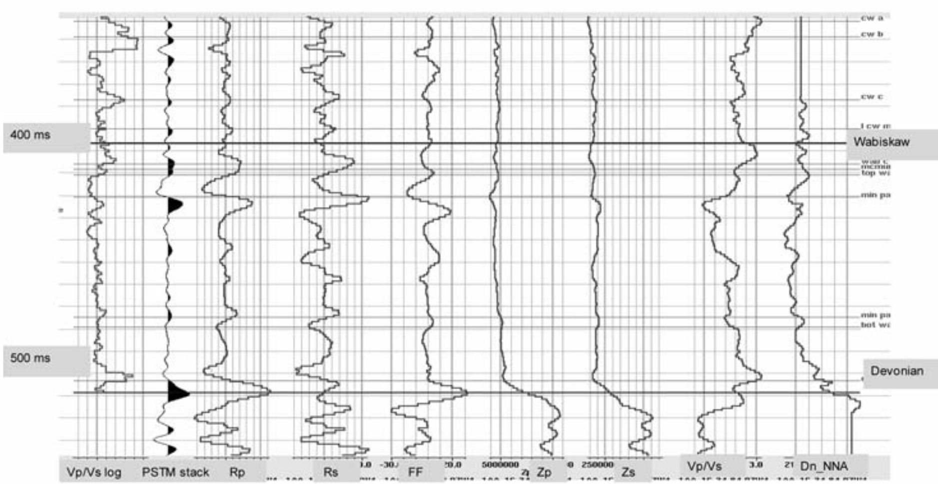

Fig. 9. An example (at well 16-34) of the V_P/V_S log and the seismic attributes used in the training procedure. The first track from the left is the V_P/V_S log, the second is the PSTM stack, the third is R_P, the fourth is R_S, the fifth is FF, the sixth is Z_P, the seventh is Z_S, the eighth is V_P/V_S, and the ninth is Dn_NNA.

As mentioned before, the first step in NNA is to perform a multi-attribute step-wise linear regression and its validation. The analysis indicated that the optimum number of attributes to use was nine, and the attributes, ranked on their ability to predict the V_P/V_S logs, were:

- V_P/V_S ratio,
- integrated fluid factor trace,
- integrated S-wave reflectivity trace,

- PSTM stack,
- density from neural networks analysis,
- apparent polarity of the fluid factor,
- amplitude weighted frequency of the PSTM stack,
- filter 5/10 - 15/20 of the S-wave reflectivity,
- quadrature trace of the P-wave reflectivity.

The correlation coefficient between the actual and the predicted result was 0.73 and the prediction error was 0.22. The validation was computed by leaving out one well at a time and then predicting values for that well using the other wells in the training and the defined linear relationship.

The next step was to train the neural networks (using the PNN algorithm) and to establish the nonlinear relationships between seismic attributes and reservoir properties at well locations. A comparison between real V_P/V_S and predicted V_P/V_S logs is presented in Fig. 10.

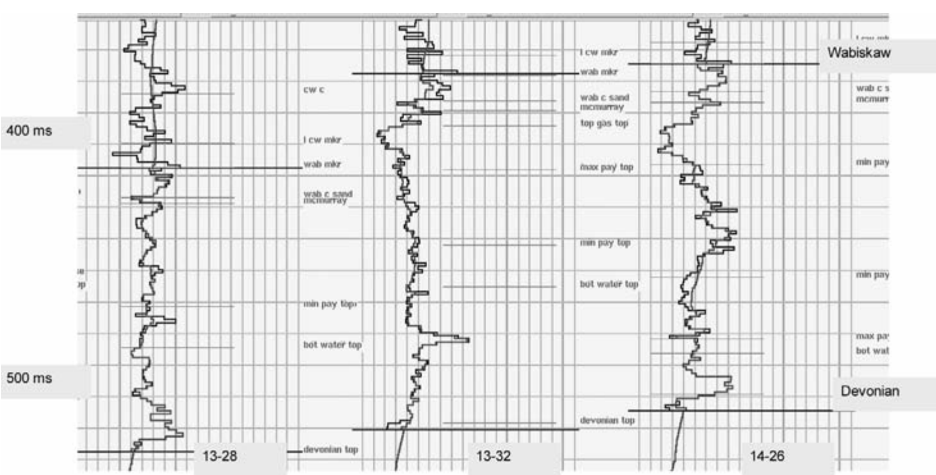

Fig. 10. Application of the PNN comparing predicted V_P/V_S logs (in red) and real V_P/V_S logs for some of the wells used in the training.

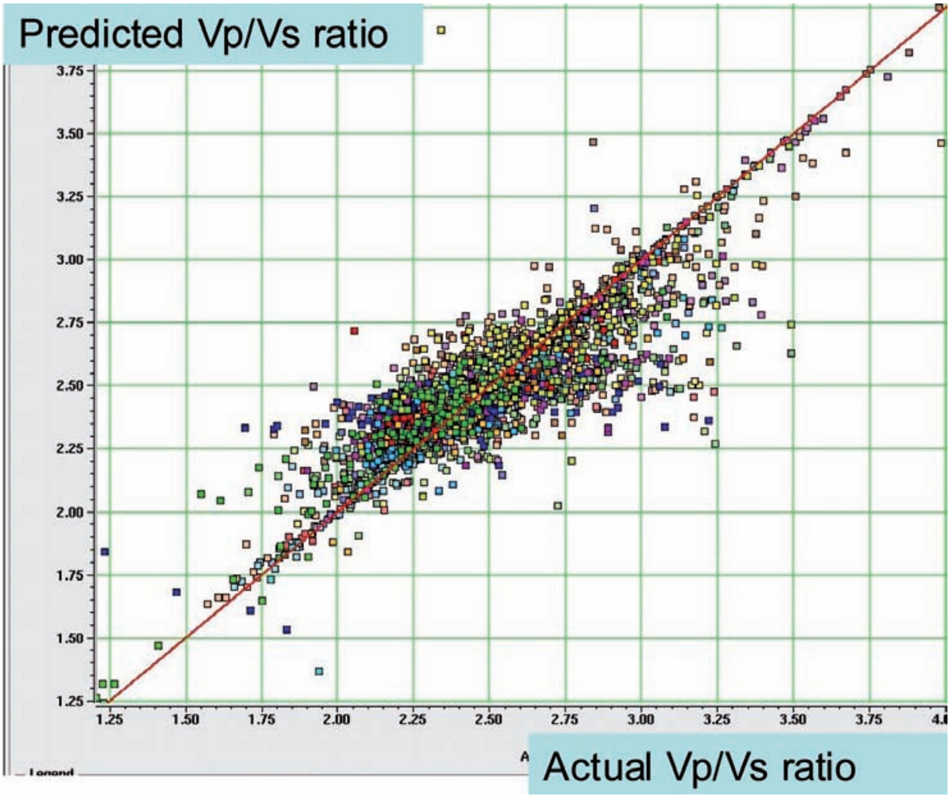

Fig. 11. Crossplot of the V_P/V_S predicted by the neural networks analysis versus the actual V_P/V_S. Data points are from the analysis zone of all 32 wells.

After this second step, the correlation coefficient increased to 0.87 and the error dropped to 0.15. A crossplot of the predicted V_P/V_S and the actual V_P/V_S for all the wells in the study area is presented in Fig. 11.

The last step was to apply the trained PNN to the whole 3D seismic volume. Fig. 12 shows the estimated V_P/V_S results on inline 75 located in the north part of the 3D area and wells no more than 50 m offline. The V_P/V_S volume was estimated within a target interval extending from 5 ms above the McMurray Formation to 5 ms below the Devonian. (All the data outside the calculation interval are extrapolated end points values.)

The predicted V_P/V_S volume obtained from the NNA analysis provides meaningful and reliable information about the McMurray Formation reservoir. Density is also an excellent discriminator between gas sand, bitumen sand, and shale. Fig. 13 shows the estimated V_P/V_S and density on a horizon time slice at McMurray Formation+7ms.

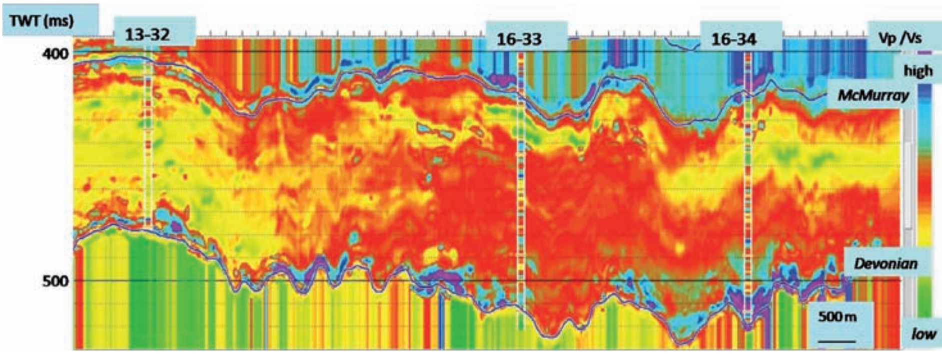

Fig. 12. V_P/V_S results at IL-75 with inserted V_P/V_S logs. All the wells shown tie this line within a 50 m projection distance.

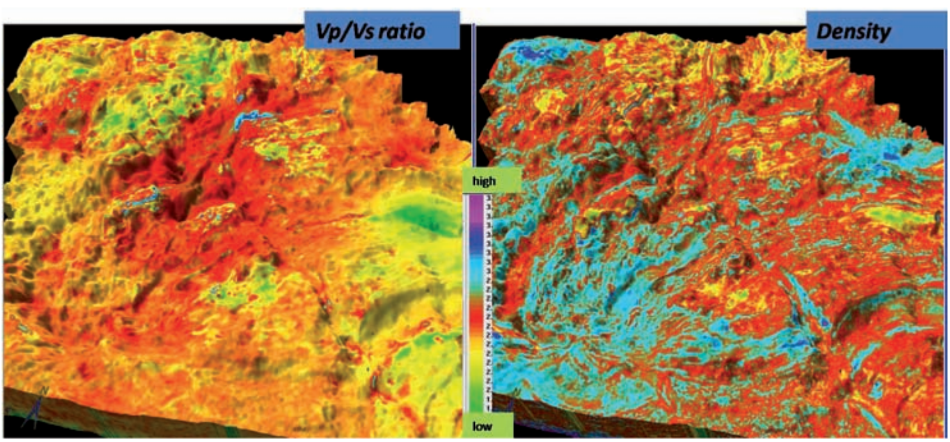

Fig. 13. Horizon time slice at McMurray+7ms from V_P/V_S (left) and from the density volume (right) obtained from neural networks analysis.

INTEGRATION OF NEURAL NETWORK ATTRIBUTES WITH OTHER SEISMIC ATTRIBUTES

By integrating all available attributes we characterized and mapped reservoir heterogeneities impacting SAGD operations, i.e. the extent of bitumen sand, gas saturated, and shale zones. Two ways of doing this are presented here: (i) crossplotting the rock physics volumes (Fig. 14) and (ii) co-rendering V_P/V_S with semblance (Fig. 15). Fig. 14 shows the spatial distribution of the

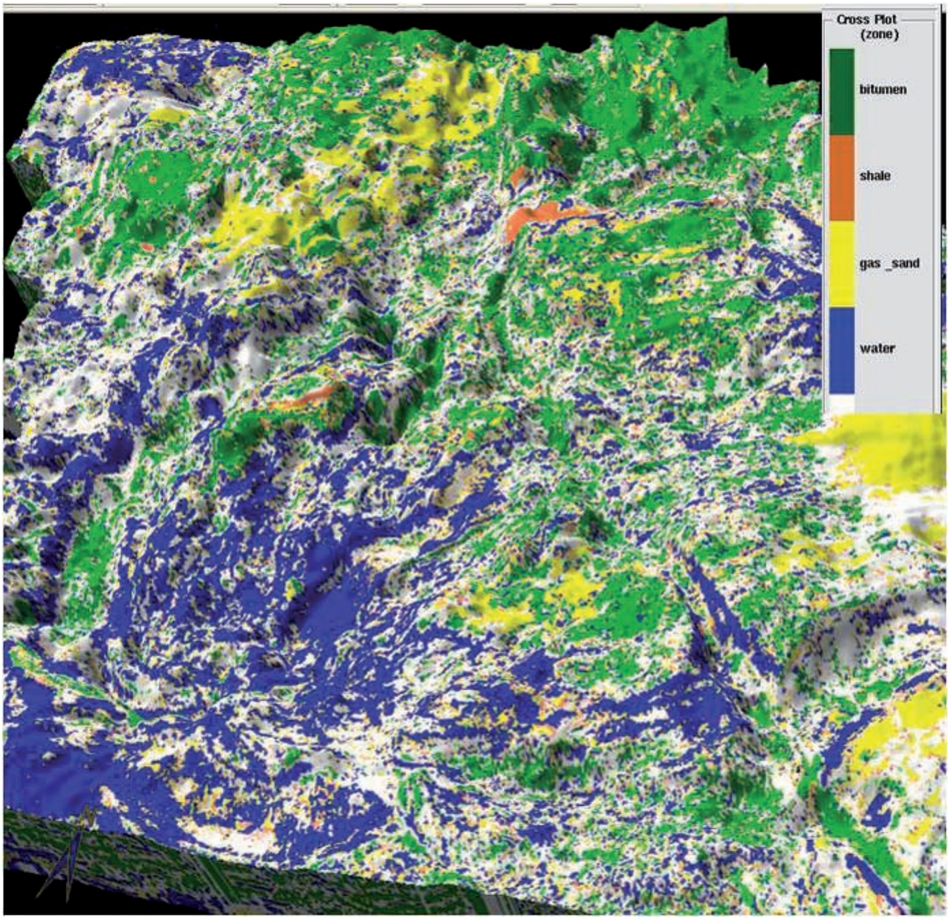

Fig. 14. Horizon slice at McMurray + 10 ms showing the distribution of gas sand (yellow), bitumen sand (green), and shale (brown) resulting from crossplotting density versus V_P/V_S.

three zones created in the crossplot given in Fig. 6. Fig. 15 shows a horizon slice at 10 ms below the McMurray Formation from the V_P/V_S volume co-rendered with semblance. By displaying these two attributes in this manner, we combined edge information with the variation of a physical property (the V_P/V_S ratio).

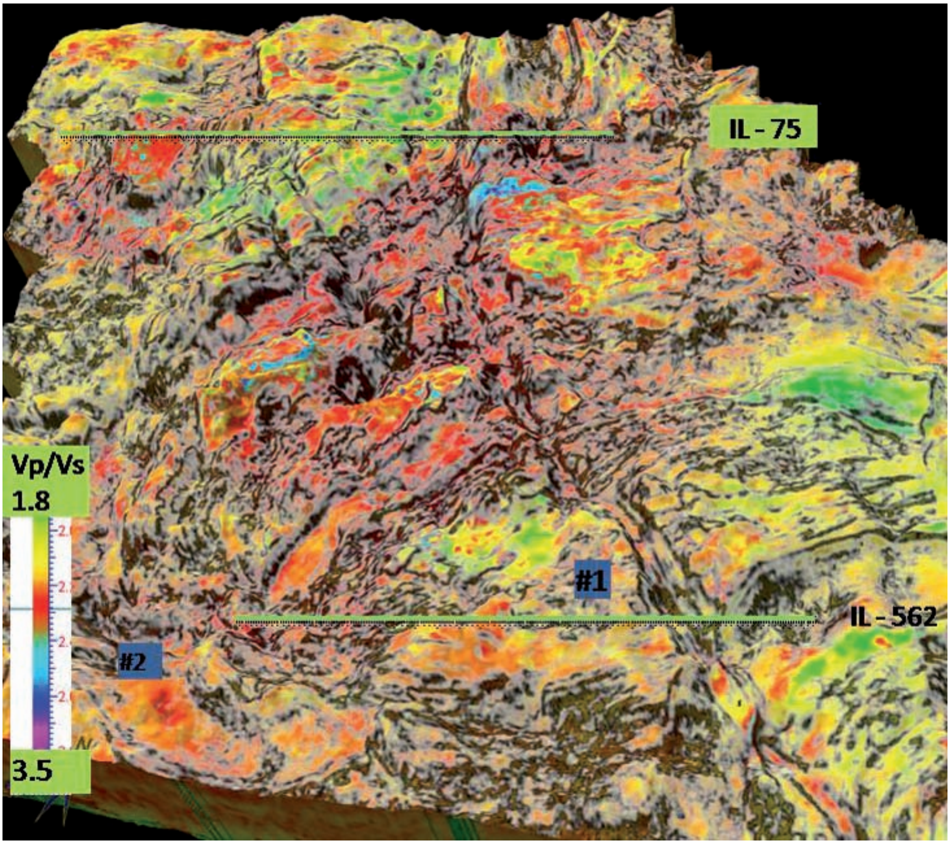

Fig. 15. Horizon slice at McMurray + 10 ms showing V_P/V_S results from neural networks analysis co-rendered with semblance.

CONCLUSIONS

The combination of rock physics, AVO analysis, prestack inversion, and neural network analysis can provide properties such as V_P/V_S and density that are useful for reservoir simulation.

We have presented a case study for improving the resolution of a V_P/V_S volume (obtained from deterministic inversion) by using neural networks analysis. The first step in the NNA was multi-attribute regression that provided the optimum number and ordering of attributes. The next step was to use a probabilistic neural network to increase the resolution of the predicted V_P/V_S logs. The attributes that were used were standard seismic attributes as well as attributes from AVO analysis and prestack inversion. The derived neural networks results showed a strong correlation with target logs, both at training well locations and other wells, suggesting that rock properties can be accurately estimated with neural networks analysis when deterministic inversion results are used as external attributes in training the networks.

The results of this analysis correlated well with recent drilling, making neural networks analysis part of the workflow for future projects. Utilizing the V_P/V_S volume computed with neural networks analysis minimizes the uncertainty in gas sand, bitumen sand, and shale identification, thereby contributing to optimal horizontal well placement. This outcome has the ultimate effect of increased production and economic efficiency.

Finally, the integration of edge attributes with rock physics attributes creates a realistic geological model that can be used for oil sands development purposes.

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