Predicting oil sands viscosity from well logs, NMR logs, and calculated seismic properties

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Summary

Viscosity is the key parameter controlling heavy oil and oil sands production. While viscosity can be measured in the lab from well samples, it would be very useful to have a method to reliably estimate oil sands viscosity from well logs.

Donor Company has provided viscosity measurements from a major oil sands project, with multiple measurements per well.

Goal of this study: Develop a viscosity prediction model using standard well logs, and seismic properties calculated from logs. Such a prediction model can be used to estimate viscosity in any nearby well with a standard suite of logs.

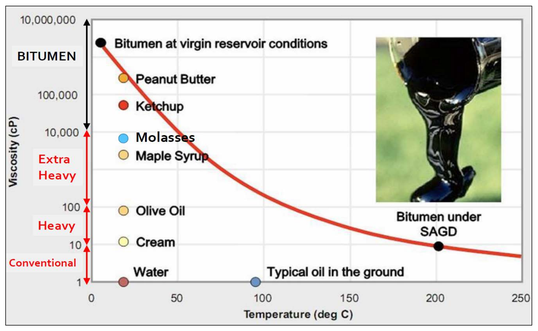

FIG. 1. Oil viscosities by grade category, compared to typical kitchen items. Viscosity has a logarithmic scale.

Project Data

Data from **40** wells with viscosity measurements at 3 depth samples per well were used. Viscosity values ranged from **10,000cP to 540,000 cP,** with a mean of **121,000cP** and standard deviation of **100,000cP.**

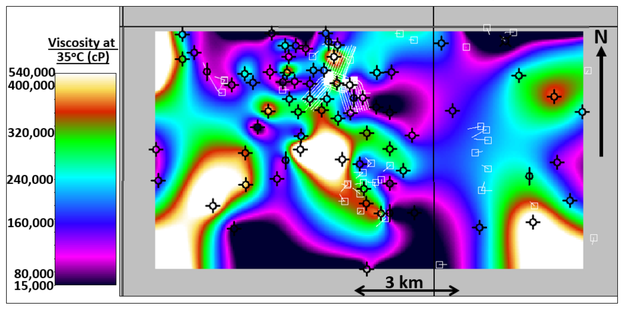

FIG. 2. Map of the ***base reservoir viscosity measurements.*** All of the data points (wells) are shown in black. Note significant lateral variations.

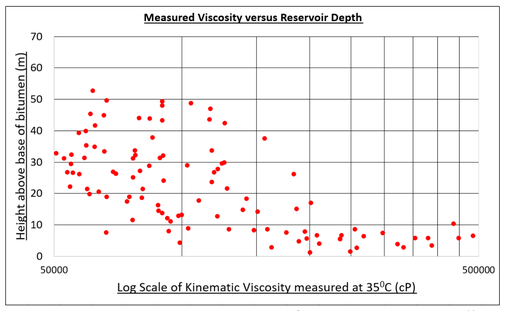

FIG. 3. Viscosity measurements from 40 project wells plotted against *height above base bitumen*.

Multi-Attribute Analysis

Suppose we are trying to predict viscosity using density (D), gamma ray (G), and resistivity (R), as shown in Figure 4. We can write the equation for linear prediction as:

$$V(z) = w_0 + w_1 D(z) + w_2 G(z) + w_3 R(z) \qquad (1)$$

where the *w* terms are the regression coefficients. This can be written in matrix form where each row represents a single depth sample:

$$\begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_N \end{bmatrix} = \begin{bmatrix} 1 & D_1 & G_1 & R_1 \\ 1 & D_2 & G_2 & R_2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & D_N & G_N & R_N \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ w_2 \\ w_3 \end{bmatrix} \qquad (2)$$

Or more compactly as: $\boldsymbol{V} = A\boldsymbol{W}$ (3)

The regression coefficients can be solved for using least-squares: $\boldsymbol{W} = [A^T A]^{-1} A^T \boldsymbol{V}$ (4)

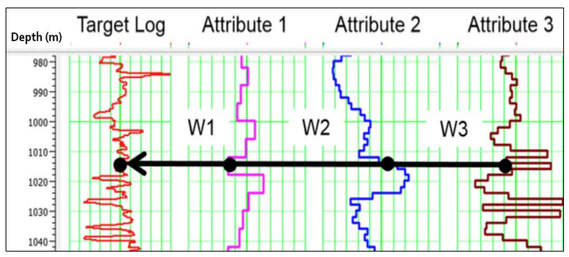

FIG. 4. The basic multi-attribute regression problem showing the target log and in this example, the 3 attributes to be used to predict the target.

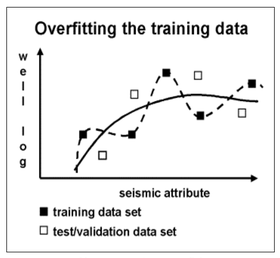

FIG. 5. Illustration of how data can be "over-trained."

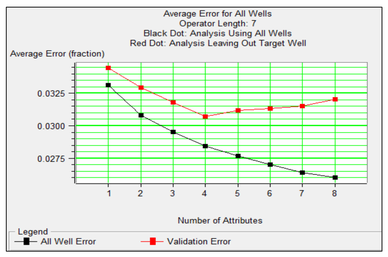

FIG. 6. Prediction error plot as a function of number of attributes. All well error is **black** and validation error is **red.**

Best attributes to use? The ones that minimize the ***prediction error*** between the target log and the predicted log.

When do we stop adding attributes? Using too many attributes "over-fits" the data, as shown in Figure 5.

Cross Validation: *Leave out a test well*, and solve the regression coefficients using only the remaining wells to *blindly predict* the target attribute in the test well. Repeat for each well, and compute average validation error. Figure 6 shows an example validation error plot, where using 4 attributes gives the best result.

Updated Viscosity Prediction Model

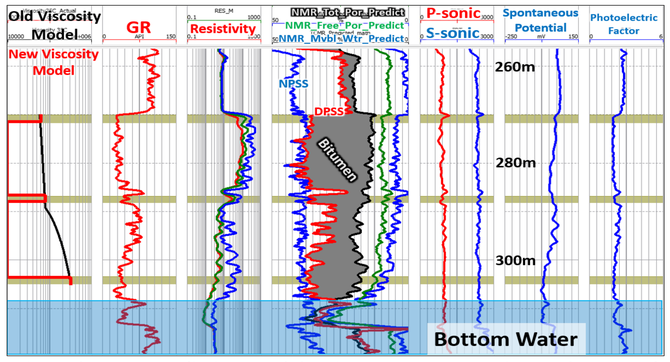

FIG. 7. The new prediction model trains over a 1-meter interval centered around the true sample depths (left track in red). The old model used an interpolated target viscosity log (black), which has greater uncertainty. The dark gray area is the separation between the NMR Total Porosity and Density Porosity logs, which occurs because NMR cannot detect bitumen.

Top viscosity predictors from well logs and NMR logs:

	Target (cP)	Attribute (normalized)	Units	Validation Error (cP)
1	Viscosity	1 / (Medium Resistivity)	1 / [ohmm]	84,200
2	Viscosity	ln |Gamma Ray|	ln |API|	77,300
3	Viscosity	1 / (SP)	1 / [mV]	74,800
4	Viscosity	(NMR Total – NMR Free)^2	[decimal]^2	71,600
5	Viscosity	(NMR Total Porosity)^2	[decimal]^2	71,200
6	Viscosity	1 / (S-wave sonic)	1 / [µs/m]	69,500

Table 1. Top prediction attributes with their validation errors. Each row in the list corresponds to a particular multi-attribute transform *and includes all the attributes above it.*

Top predictors from calculated seismic properties:

	Target (cP)	Attribute (normalized)	Units	Validation Error (cP)
1	Viscosity	1 / (P-wave sonic)	1 / [µs/m]	95,700
2	Viscosity	1 / (P-Impedance)	[m/s * g/cc]$^{-1}$	93,600

Table 2. Top predictors from calculated seismic properties.

Note: *None of the viscosity wells have NMR data. The NMR logs were predicted in all 40 viscosity wells using 25 nearby NMR wells to train the relationship. Resistivity, P-wave sonic, and Gamma Ray were the top NMR predicting attributes.*

Viscosity Prediction Results

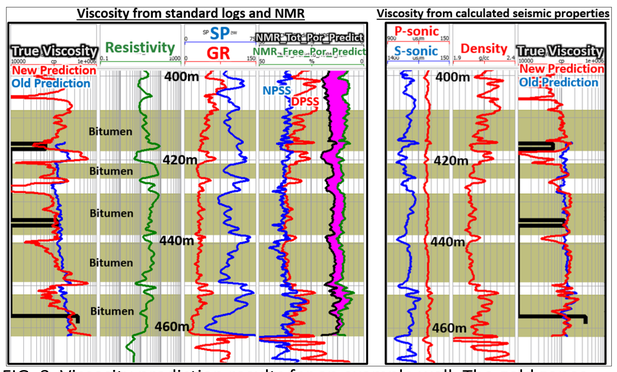

FIG. 8. Viscosity prediction results for an example well. The gold zones are the bitumen intervals. The new model (from logs) **predicts two viscosity gradients from 440m to 460m**, while matching the true values

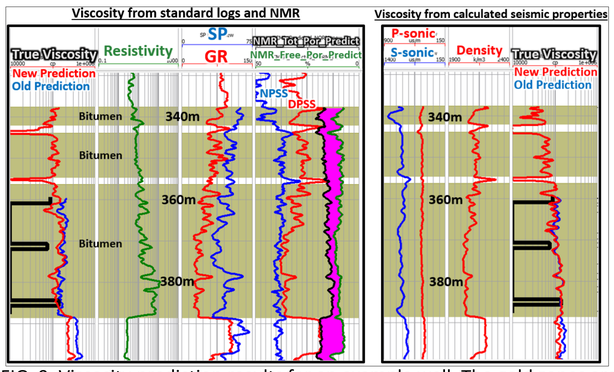

FIG. 9. Viscosity prediction results for an example well. The gold zones are the bitumen intervals. Both predictions (from logs and seismic properties) show a **smooth trend of decreasing viscosity** to the top of the reservoir.

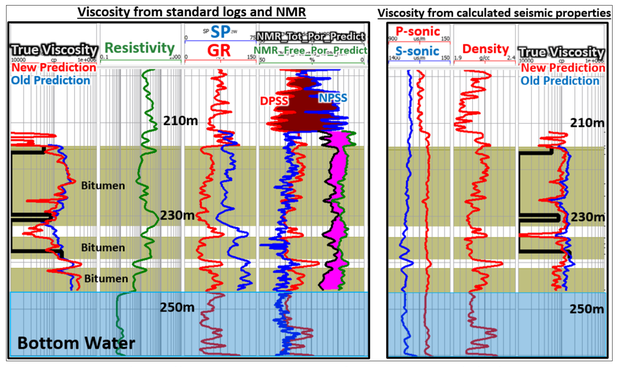

FIG. 10. Example well. **Two viscosity gradients** are modeled throughout the bitumen. Gas cap is influencing prediction at the top.

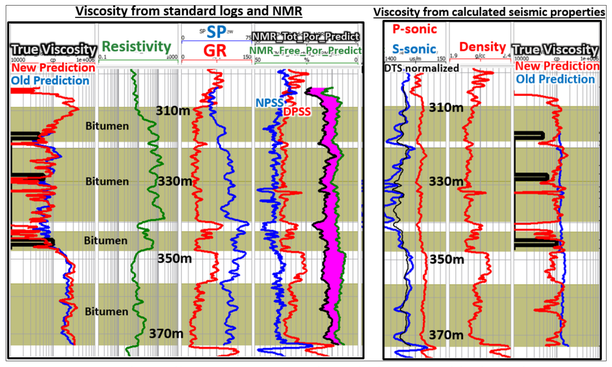

FIG. 11. Example well. Variations predicted above and below the viscosity measurements. **Slow shear sonic from 330m to 350m** causes problems with the predictions (from logs – left track).

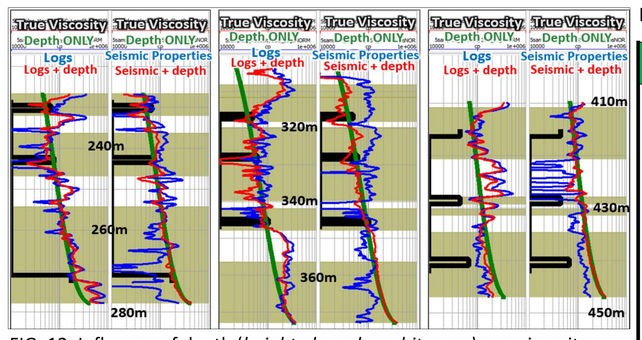

FIG. 12. Influence of depth (*height above base bitumen)* as a viscosity predictor for three example wells (see depth correlation in Figure 3).

Conclusions

- Standard logs (+ NMR) successfully predicted viscosity with an average error of 70,000 cP (0.70 of 1 standard dev.), and detected variations between control points.
- Calculated seismic properties (from logs) predicted viscosity with an average error of 94,000cP (0.94 of 1 standard dev.), but detected less variations.
- Including depth improves the prediction in most cases, but will always overestimate viscosity if the base reservoir has a low viscosity (shown on the right side of Figure 12).

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