Predicting heavy oil viscosity from well logs – testing the idea

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Summary

Viscosity is a critical parameter in selecting the best recovery method to exploit a heavy oil reservoir. While heavy oil viscosities can be measured in the lab from well samples, it would be very useful to have a method to reliably estimate heavy oil viscosity from well logs. In this study, data from thirteen wells were obtained from the Athabasca region of northern Alberta. Each well has laboratory oil viscosity measurements, as well as dipole sonic logs, and a full suite of the standard well log curves.

Multi-attribute analysis enables a target attribute to be predicted using other known attributes. In this study, the available well log curves were used to predict viscosity. Five wells were used to train the relation to blindly predict the viscosity of the remaining wells.

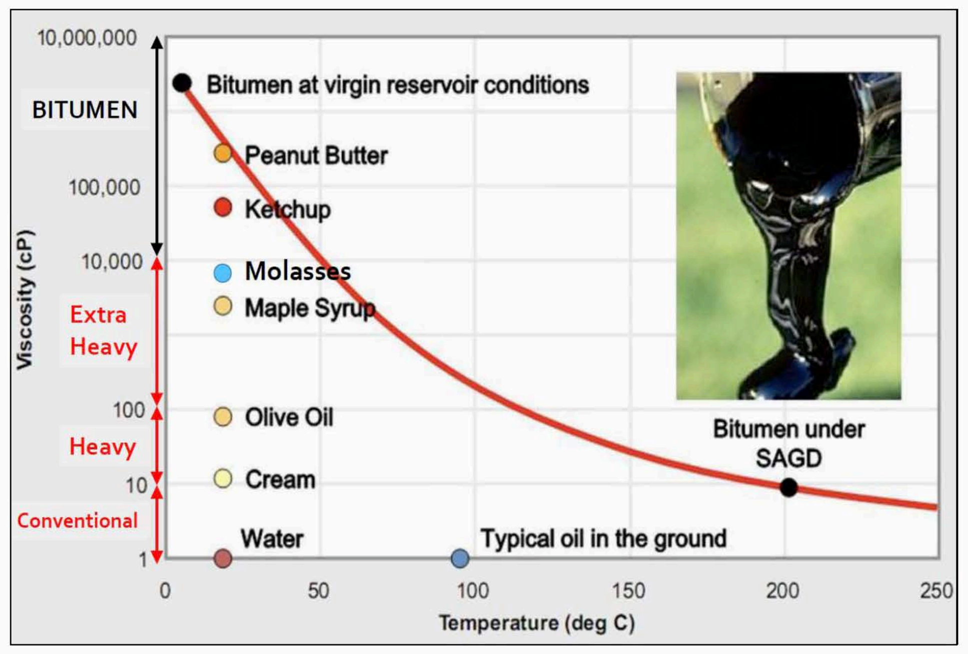


FIG. 1. Oil viscosities by grade category, compared to typical kitchen items. Viscosity has a logarithmic scale.

Goal of this study

Data from **13 wells** were obtained using AccuMap® from the Athabasca region of northern Alberta. Each well had laboratory oil viscosity measurements available, as well as dipole sonic logs, and a full suite of the standard well log curves. We wanted to address the following question:

Can multi-attribute analysis be used to train a relationship between viscosity and the well log data in only some of the wells, and then successfully predict the viscosity in the remaining wells?

Multi-Attribute Analysis

Suppose we are trying to predict *Vp* using three attributes: *A*, *B*, and *C*, as shown in Figure 2. We can write the equation for linear prediction as:

$$Vp(z) = w_0 + w_1 A(z) + w_2 B(z) + w_3 C(z) \qquad (1)$$

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

$$\begin{bmatrix} Vp_1 \\ Vp_2 \\ \vdots \\ Vp_N \end{bmatrix} = \begin{bmatrix} 1 & A_1 & B_1 & C_1 \\ 1 & A_2 & B_2 & C_2 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & A_N & B_N & C_N \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ w_2 \\ w_3 \end{bmatrix} \qquad (2)$$

Or more compactly as:

$$\boldsymbol{Vp} = \boldsymbol{MW} \qquad (3)$$

The regression coefficients can be solved for using least-squares:

$$\boldsymbol{W} = [M^T M]^{-1} M^T \boldsymbol{V_p} \qquad (4)$$

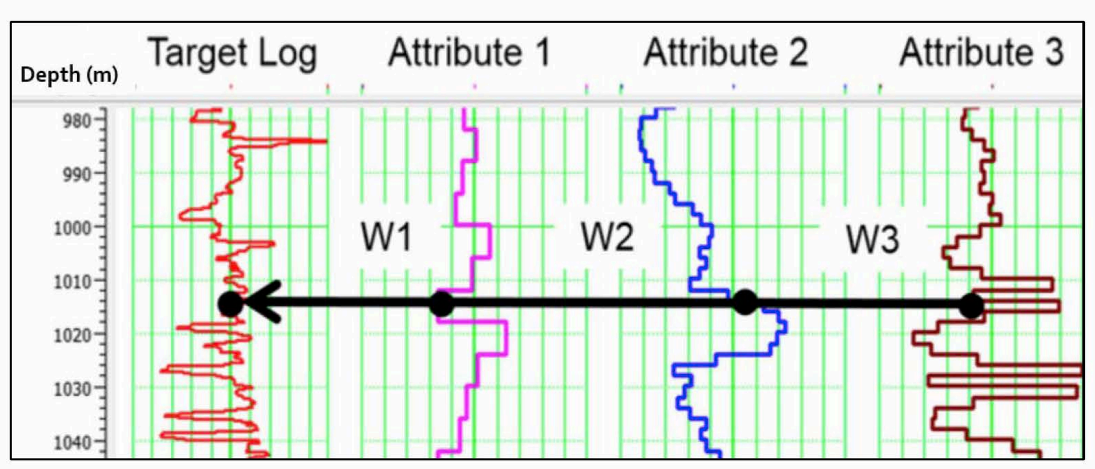


FIG. 2. The basic multi-attribute regression problem showing the target log and in this example, the 3 attributes to be used to predict the target.

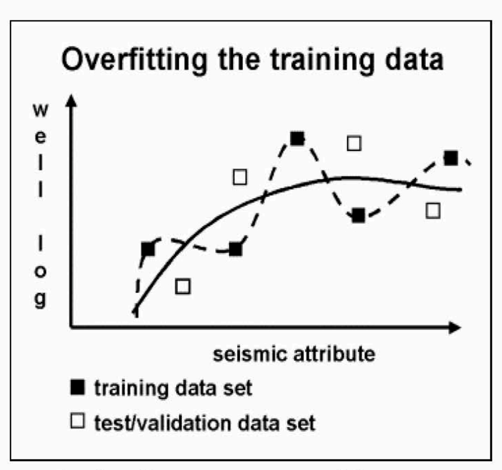


FIG. 3. Illustration of how data can be "over-trained."

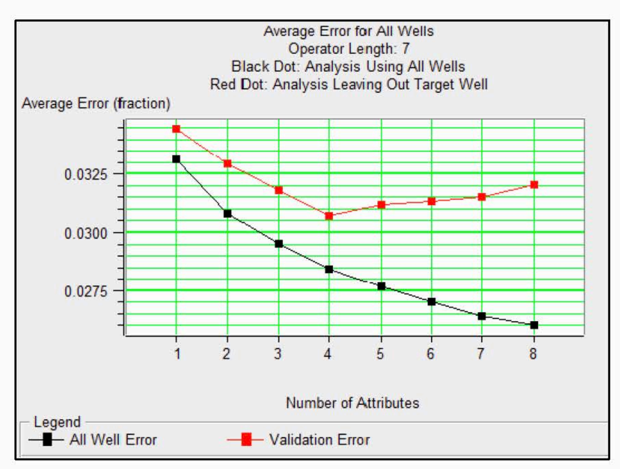


FIG. 4. Prediction error plot as a function of number of attributes used. All well error is in black and validation error is in red.

What are the best attributes to use? The attributes that minimize the ***prediction error*** between the true target log and the predicted log.

When do we stop adding attributes? Adding attributes is similar to fitting a curve through a set of points, using a polynomial of increasing order (Figure 3). Using too many attributes "over-fits" the data.

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

Data

Well #	UWID	Producing Formation	Total TVD (meters)	Bottom-hole Temperature (deg C)	Absolute Viscosity at 20ºC (cP)	API Gravity at 15ºC (ºAPI)
01	102/01-09-087-23W4	Wabiskaw	346.00	14.00	6685.20	12.35
02	102/10-29-086-23W4	McMurray	328.90	23.00	15831.08	11.08
03	100/10-29-086-23W4	McMurray	330.50	20.00	17431.14	10.99
04	100/15-29-086-23W4	McMurray	330.30	19.00	18374.29	10.67
05	102/07-32-086-23W4	McMurray	328.40	25.00	11128.87	11.00
06	100/02-32-086-23W4	McMurray	327.90	21.50	14289.35	10.70
07	102-14-29-086-23W4	McMurray	330.30	25.00	15084.85	10.89
08	103-14-29-086-23W4	McMurray	329.20	20.00	14360.26	11.06
09	100-11-20-086-23W4	McMurray	328.00	33.00	11551.59	11.05
10	100-03-32-086-23W4	McMurray	328.30	22.00	12771.49	11.32
11	103-03-32-086-23W4	McMurray	327.80	28.00	14530.67	11.28
12	102-02-32-086-23W4	McMurray	328.10	30.00	13290.69	11.61
13	100-12-32-078-24W4	Wabiskaw	480.30	34.00	67332.10	9.23

Table 1. Summary of the 13 project wells. The bottom-hole temperature values are from the LAS files, and the rest of the information is from AccuMap®

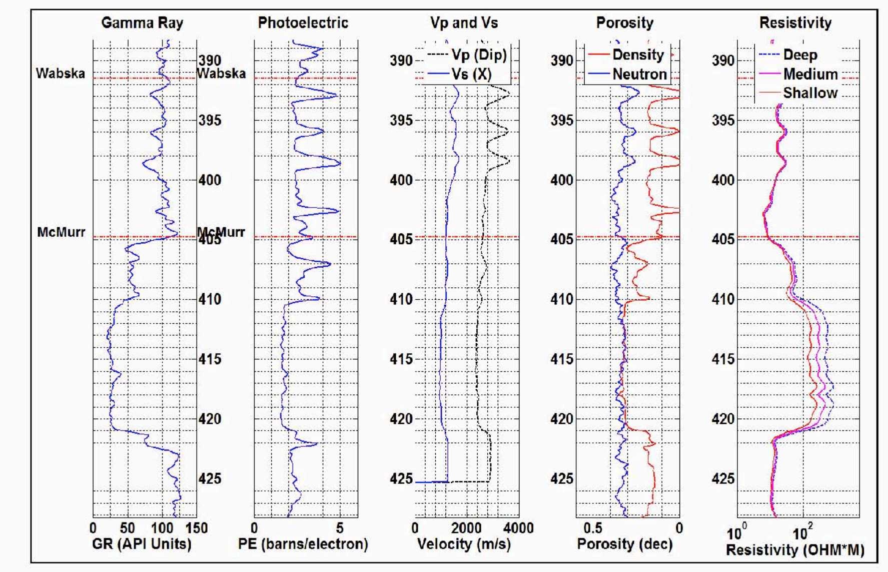
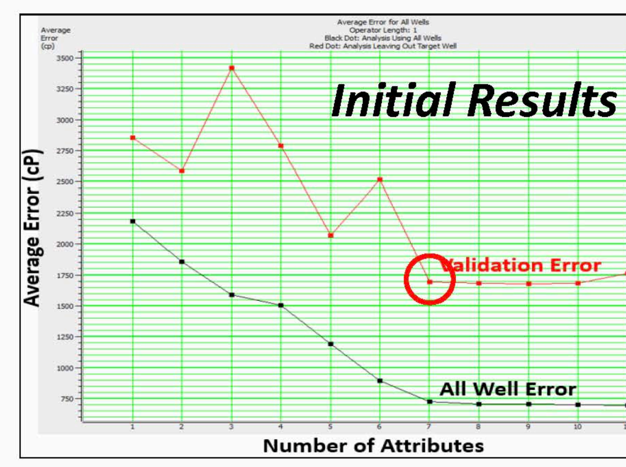


FIG. 5. Type-well of the study area (Well #2).

Viscosity Prediction Results

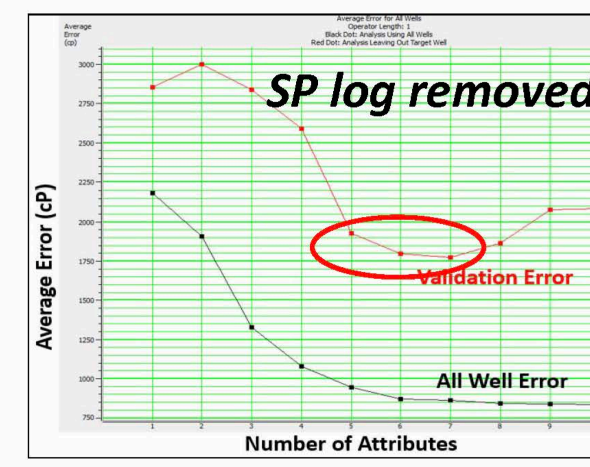
Wells 1 to 5 were used to train the relationship, the training results are shown in Figure 6 and Figure 7.



Top predictors:

1. S-wave velocity
2. 1 / (Spontaneous potential)
3. 1 / (Gamma Ray)
4. 1 / (Shallow Resistivity)
5. Sqrt(Deep Resistivity)
6. Sqrt(Medium Resistivity)
7. 1 / (Neutron Porosity)

FIG. 6. Prediction error plot and top attributes using ALL logs.



Top predictors:

1. S-wave velocity
2. Deep Resistivity
3. Medium Resistivity
4. 1 / (Shallow Resistivity)
5. 1 / (Neutron Porosity)
6. 1 / (Photoelectric factor)
7. 1 / (Density Porosity)

FIG. 7. Prediction error plot and top attributes with SP log REMOVED.

Equation 5: Viscosity prediction equation (trained using wells 1 to 5)

$$\eta = 2331.90 + 8751259.00(\boldsymbol{Svelocity}) + 49.33(\boldsymbol{ResDeep}) - 72.02(\boldsymbol{ResMedium}) + 566728.13\left(\frac{1}{\boldsymbol{ResShallow}}\right) - 2788.40\left(\frac{1}{\boldsymbol{NPHI}}\right) + 16271.04\left(\frac{1}{\boldsymbol{PEF}}\right)$$

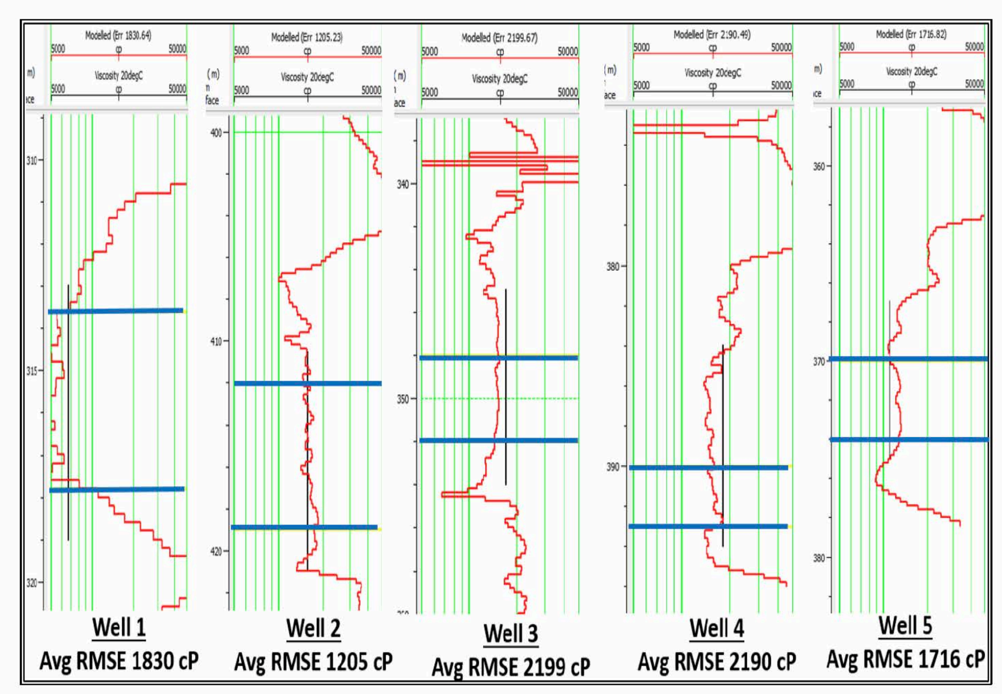


FIG. 8. Cross-validation results for the 5 training wells. The **black lines** are the measured viscosities and the **red curves** are the predicted viscosities. The blue lines outline the training intervals.

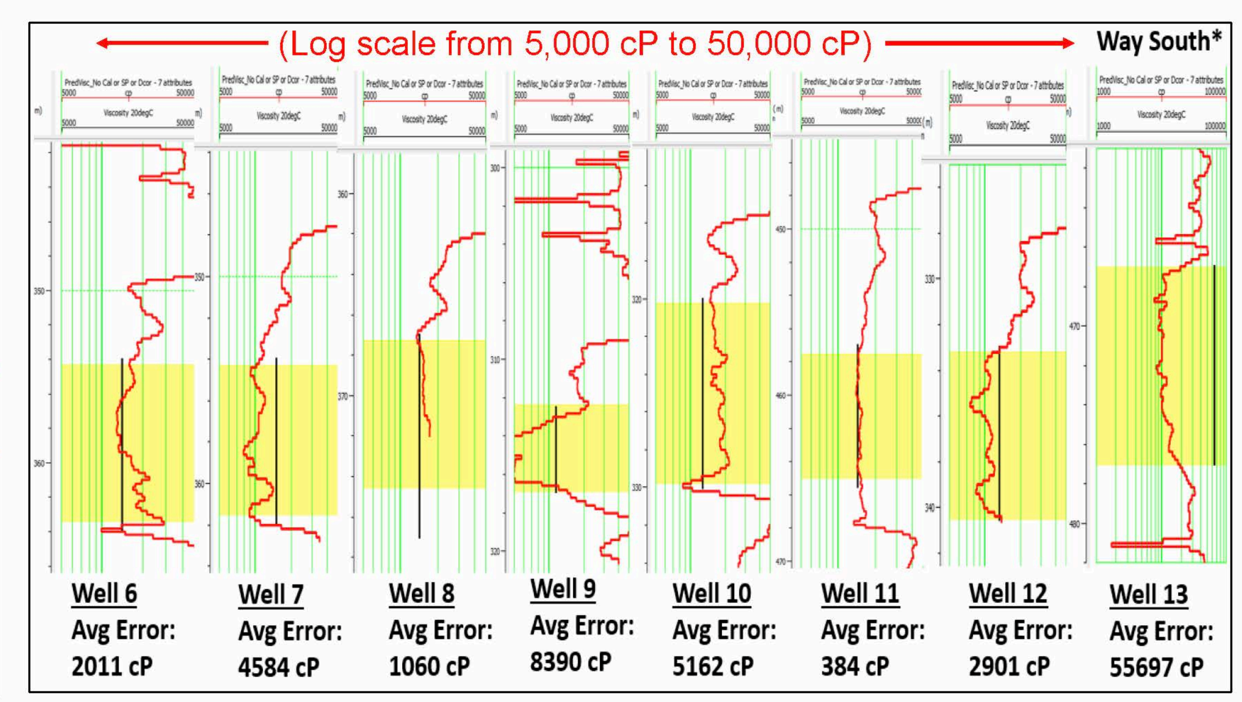


FIG. 9. Blind viscosity prediction results of the remaining wells using Equation 5. The **black lines** are the measured viscosities and the **red curves** are the predicted viscosities. The yellow areas highlight the reservoir intervals.

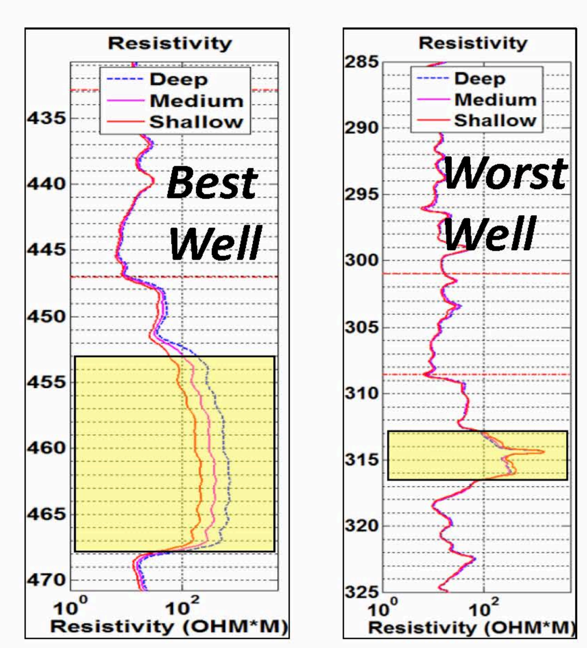


FIG. 10. Resistivity logs from the best predictor well (left – Well 11) and the worst predictor well (right – Well 9)

Conclusions

- Viscosity was predicted within 25% error in 4 out of the 7 blind test wells
- The **shear sonic log** was found to be the most important viscosity predictor
- Observations suggest that the prediction is most successful when there is *separation between the resistivity curves.*

Future Work

- **Nexen – CNOOC** has provided a large viscosity dataset for their Long Lake and Kinosis oil sands projects.
- Goal is to define an **empirical relationship** to predict a wide range of viscosities using only standard well log curves.
- My oral presentation (Friday Dec 4th) focuses on this.