geoconvention
Calgary • Canada • May 11-13 2026

Efficient QC of Acoustic Logs through AI

David Gray
D'AVO Consulting

Summary

Like all data in the geophysicist's world, log data is subject to error and bias. We rely on logs to provide important information for tasks that we do like well ties, inversions, and reservoir property prediction. In my experience, the acoustic logs, sonic (mnemonic DT), shear sonic (DTS), and bulk density (RHOB) that we typically use for our work may not have gone through the same QC that key reservoir logs like porosity, Vshale, and saturation logs have received and therefore may have uncorrected errors. Often, geophysicists have a lot of wells to deal with in oilsands and shale plays. Using AI tools readily available to geophysicists with some appropriate predictors, a geophysicist can quickly QC and correct the acoustic logs ensuring that their work has the best possible logs.

This AI is done by using predictor logs that are commonly available and not typically as affected by borehole conditions as the acoustic logs, logs that tell us about borehole conditions, or logs that have already been QC'ed. Sometimes, if there are sufficient wells to be able to identify outliers, as will often be the case in shale and oilsands projects, work using these predictor logs will also lead to they themselves being edited if there are indications that they are in error. Typically, I will do the acoustic logs in the following order: 1. Vp, 2, Density, 3. Vs. Then, if I am QC'ing Density or Vs, if possible, I will use the logs that I've previously edited using this technique.

The result of this work is an estimate of the acoustic logs of interest which can be compared to the measured log. Then only well logs that show significant deviation from their prediction need to be edited. As is seen in the presentation, this method significantly reduces the number of logs that need to be QC'ed and confidence in the remaining logs and edited logs is verified. Serendipitously, in the example shown, this method also helped with the QC of the predictor logs because some were in error, but there were enough other wells with the same logs to be able to identify them. How this works is shown in the presentation.

Highlighting a small number of well logs that need further work significantly reduces the amount of additional work that needs to be done. Examples in my experience include reducing the number of logs requiring examination from ~600 to a dozen or two, a reduction in work required of 96-98%. Then log editing becomes the work of a day instead of a month. Modern AI software allows analyses of the type described here to be done in hours. Also, the AI analysis demonstrates the accuracy of the remaining well logs and informs and corroborates any log editing done. When the geophysicist is confident that all the other logs are sufficient for their geophysical purposes and can proceed to work with those logs instead of waiting for the other logs to be edited.

Workflow

If we can get a reasonable prediction of the acoustic logs, then those logs can be compared to the actual logs to determine what logs may require additional work, and more particularly, which logs do not require more work.

For many years acoustic logs have been predicted from other logs, e.g. Gardner's relationship (Gardner et al., 1974) and the 'Mudrock Line' (Castagna et al., 1985). Since this indicates that various acoustic logs can be predicted from other logs, then we propose that this can also be done using multi-attribute analysis on the local logs to generate a better prediction of the local acoustic logs.

Certain considerations need to be made when doing this. In particular, what logs are not as contaminated by borehole conditions as the acoustic logs that we are trying to predict and logs that tell us about those borehole conditions. Ideally, these will be logs that measure intrinsic properties of the rock. Logs less affected by borehole conditions that I have found useful are photo-electric factor (PEF), deep resistivity, gamma ray (GR), neutron porosity, and spontaneous potential (SP). Logs that inform about borehole conditions that I have found useful are caliper (CAL) and density correction. Logs that are already QC'ed are typically the logs calculated by the petrophysicist including porosity, saturation and Vshale, as well as logs that I have already QC'ed in earlier work.

Results

This workflow is demonstrated by comparing measured density logs to an AI prediction of the density log in an oilsands play. Figure 1 shows that the density logs in this play can be adequately predicted using just the Photoelectric (PEF) logs and the sonic logs. When a small number of logs can be used to make a good prediction that removes the risk of overprediction.

Figure 2 shows an example of the analysis done to examine the density logs in an oilsand play. Well 106 jumps out because of the terrible bias between the measured log (black) and AI predicted log (red). Quick examination of the predicted log shows that its values are significantly biased, coming in with average values of 2.5 g/cc, which is far too high for oilsands density. This leads us to examine the predictors which are shown in Figure 3. This quickly identifies the problem. The blue curve labeled PEF in the Figure has values between 900 and 2700 when it should be between 0 and 12. This suggests that this is an incorrectly labeled velocity log. We can now either find the correct PEF log for this well or drop this well from the analysis. We can now examine the other wells.

Most of the other wells do not have significant differences between the measured density logs (black) and the AI predicted density logs. This indicates that we can have confidence that these logs have accurate measurements of density for 13 of the 17 wells, i.e. Well 101, 102, 104, 105, 107, 108, 110, 111, 112, 113, 115, 116, and 117. This immediately reduces our potential workload by 76%. We discuss the other wells below.

	Target	Final Attribute	Training Error	Validation Error
1	1 / (Density)	1 / (Photoelectric)	0.102984	0.103226
2	1 / (Density)	P-wave	0.079321	0.079482
3	1 / (Density)	Gamma Ray	0.078273	0.078500
4	1 / (Density)	1 / (Neutron Porosity)	0.077468	0.078411
5	1 / (Density)	Log(Resistivity Deep)	0.077003	0.077992
6	1 / (Density)	(Caliper)**2	0.076991	0.077918

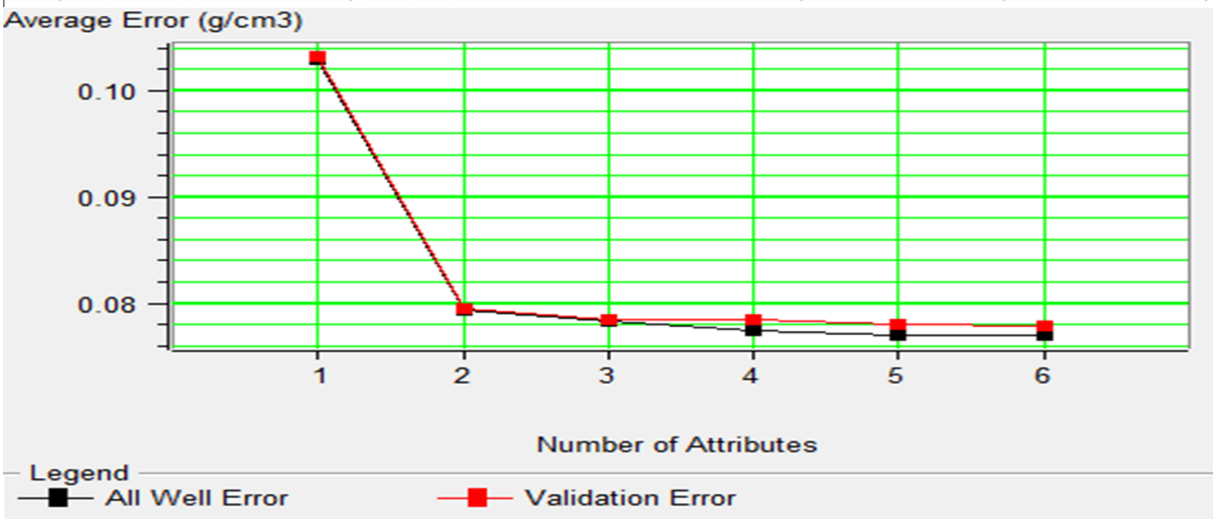


Figure 1: Error analysis to determine logs to use for the prediction of density. Both the All Well Error (black) and Validation Error plots (red) show that changes in bulk density can be predicted quite well using only the Photoelectric (PEF) log and the P-wave (Sonic or DT) log.

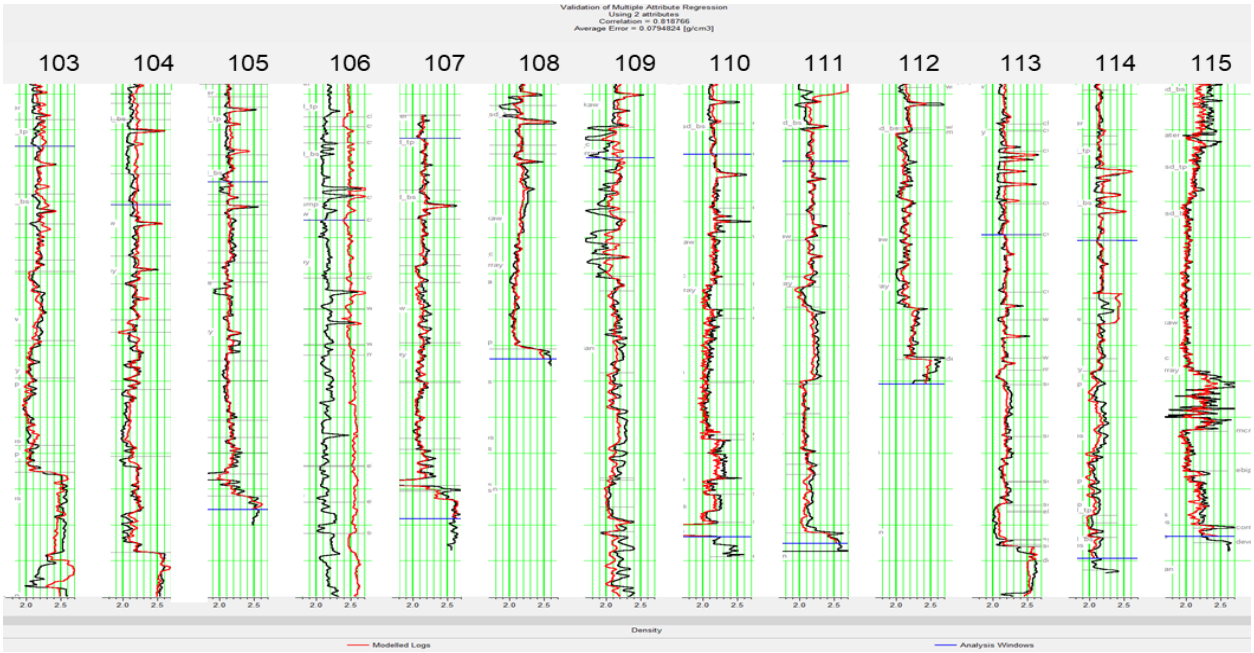


Figure 2: Measured and predicted density well logs for labelled wells. Measured density is in black and predicted logs are in red.

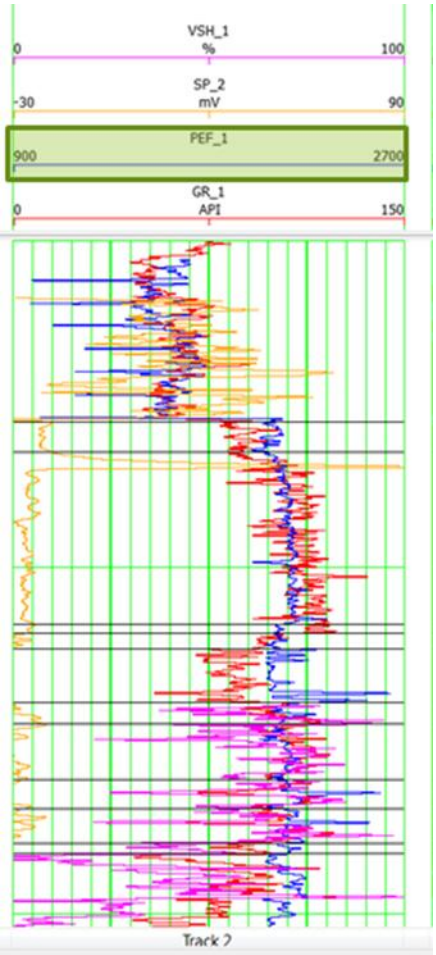


Figure 3: Well log panel from Well 106. The blue curve is the PEF log.

Well 103 has significant differences between the measured and predicted density logs at the bottom of the curve, but these are below the zone of interest and so can be ignored.

Well 108 has significant differences near the top of the curve, but once again these are out of the zone of interest and so can be ignored.

Well 109 does not have as good a match as the other wells, although the predicted density does seem to be trying to follow the trend of the measured density. This is a well that might benefit from editing.

Well 114 clearly has errors in the middle of its density logs. This well will clearly benefit from editing. Another benefit is that by comparing the measured density to the actual density we can determine exactly what part of the log needs to be edited and the AI prediction provides reasonable values to use in that edit.

Now that we have identified which of the well logs need edits in the zone of interest, our potential workload is reduced by 88% from 17 to 2 well logs.

Figure 4 shows a method used to quickly identify wells that require editing. The red dots and line show the average difference between the measured density logs and the AI predictions of those logs.

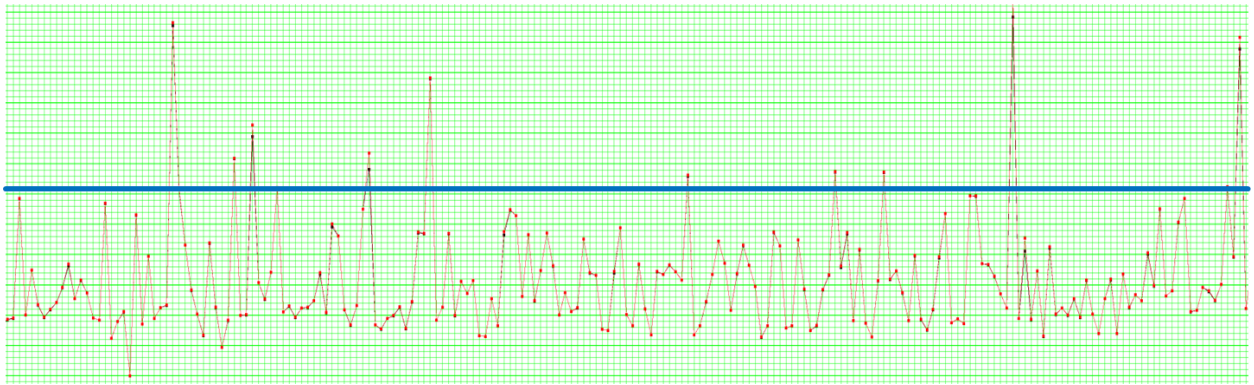


Figure 4: Plot of average difference between measured and predicted density logs for all wells in the project. Wells with differences above the blue line are edited and others are not.

The blue line in Figure 4 is what we use to quickly identify wells for which we want to edit the density logs. Any wells with values above the blue line are examined for editing using plots like Figure 2 and the other wells are considered adequate as they are. The height of the blue line should be determined by examining the differences between measured and predicted density logs from wells that are close to the line. In this case, 12 of the 196 density logs are highlighted for further examination. Therefore, using this method has shown that 184 wells are good enough to work with further and only 12 or 6% of the wells require further work. If it is decided to edit any of the 12 logs, then start with the logs from the wells with either the highest or lowest average differences in Figure 4 and examine and edit these wells in order of the size of these differences. Alternatively, the 12 wells identified in Figure 4 can be eliminated from further analysis if possible or if time is short.

Conclusions

A method for quickly identifying well logs that required further examination and editing has is demonstrated. The method uses AI to predict the log of interest and that log is compared to the log that is measured in situ. Large differences between the measured and predicted log indicate that that measured well log should be examined in further detail. Small differences indicate that the measure log is reasonably accurate. In the example shown, density logs were predicted using only PEF and sonic logs, which is a good result since it is unlikely that the predicted density logs are overpredicted from only two predictors. In this example, the number of density logs requiring examination is reduced from the 196 total wells with density logs down to 12, a 94% reduction in work. If examining and editing these logs took a day, then doing the same for all the wells would take three weeks. This is a significant savings in time for perhaps investing a day to do a similar analysis.

Novel/Additive Information

Quick QC and assessment of acoustic logs using AI generating greater confidence in the geophysicist in their workflows.

References

Castagna, J.P., Batzle, M.L. and Eastwood, R.L., 1985, Relationships between compressional-wave and shear-wave velocities in clastic silicate rocks, Geophysics, 50, pp. 571-581. https://doi.org/10.1190/1.1441933

Gardner, G. H. F., Gardner, L. W. and Gregory, A. R., 1974, Formation velocity and density - The diagnostic basics for stratigraphic traps: Geophysics, 39, no. 06, 770-780. http://library.seg.org/doi/abs/10.1190/1.1440465

Gray, D., 2023, Using Machine Learning to Simplify our Interactions with Other Disciplines, *CSEG Luncheon Talk Abstract, February 14, 2023*. https://cseg.ca/wp-content/uploads/Abstract-and-Bio_David-Gray-Technical-Luncheon-02142022.pdf

Hampson, D., Todorovic, T., and Russell, B., 2000, Using multi-attribute transforms to predict log properties from seismic data, Exploration Geophysics, Volume 31, Issue 3, Jun 2000, p. 481 – 487, https://doi.org/10.1071/EG00481