geoconvention
Calgary • Canada • May 12-14 2025

Developing a regional Montney mineral model solution and applications for well placement optimization: A case study from NEBC

Author information – Claire Woods
Affiliation – PETRONAS Energy Canada Ltd.
Author information – Patricia Rodrigues
Affiliation – SeisPetro Geoconsulting, LLC

Theory / Method / Workflow

The mineral modelling work was undertaken in an effort to explain lower than expected production results in the Middle Montney. Core analysis and advanced petrophysical logs supported a negative correlation between increased calcite volume and lower EUR. Data coverage was limited to 20 control points across the study area, therefore a regional mineral model was proposed to characterize mineral variability away from core and advanced log control.

The area of interest includes 268 wells with modern logs Gamma Ray (GR), density (RHOB), neutron (NPHI), photoelectric factor (PEF), and resistivity (RT). Ten of those wells count with Electron Capture Spectroscopy (ECS) logs which were inverted for mineralogy and calibrated using XRD results from four wells.

Semi-automated log normalization and corrections
Before the multimineral analysis was performed, a semi-automated log normalization was done to remove non-geologic features due to different vintages, drilling environment, and different logging companies. Due to drilling with heavy muds, the photoelectric factor required significant corrections to be used in the analysis

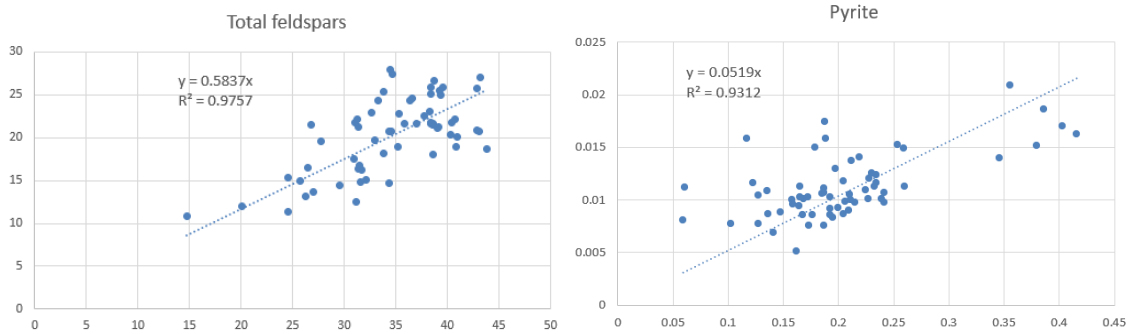
The complex mineralogy composition of the Montney formation, coupled with the limited number of logs in most wells, necessitates solving of mineral mixtures rather than individual minerals. Solving for mineral mixtures requires extensive refinement of mineral endpoints. To facilitate this process, the mineral model was developed utilizing an AI-enabled multimineral software tool that uses a genetic algorithm engineered to estimate minerology and fluid compositions in complex reservoirs (Michelena et.al. 2020).

Typical multimineral analysis requires the user to input the log properties (end-points) for each of the pure components of the rock. In complex reservoirs this task becomes difficult as there are many minerals present. In the area of the study, X-ray diffraction data (XRD) and total organic carbon analysis (TOC) of the Montney formation indicated the presence of at least twelve minerals

(quartz, K-feldspar, plagioclase, calcite, dolomite, siderite, apatite, pyrite, chlorite, Illite, kaolinite, and kerogen). Ten wells in the area had Electron Capture Spectroscopy (ECS) logs. These logs allow to solve for many rock component, but the application is limited due to the limited number of wells in the area with such data. However, these wells can provide consistent calibration points for the mineral model. These logs allow for a robust multimineral solution of a limited number of rock components.

The first step in the process was to analyze the XRD data and decide which rock components to solve for based on abundance and the objectives of the project. Based on observations the calcite volume seemed to be related to geomechanical behavior during the completion. Therefore, calcite needed to be solved explicitly in the mineral solution. Due to the high variability, quartz and dolomite are an important part of the solution, similarly with clays and kerogen. Completion operations also provided an indication that calcite may play an important role in the completion success, therefore the primary focus of the model was to predict the amount of calcite in the rock.

Even though the rest of the minerals won't be solved for explicitly, they must be included within other minerals (as mineral mixes), because the logs are affected by its presence and therefore need to be accounted for. In order to do this, XRD analysis was explored and relation between minerals corroborated to create mineral mixes. In figure 1a) we show the relation between quartz and total feldspars for one calibration well. In figure 1(b), the relation between clays and pyrite is shown.



(a) (b)

Figure 1

Similarly, many combinations of minerals were explored and together with modeling observations the final rock components solved for were: QFMs (quartz, felsdspars, and mica), dolomite (which is mixed with other heavy components like siderite), clays and others (Illite, kaolinite, and pyrite), calcite, and kerogen. Reducing the problem to five rock components and two fluids (seven components in total). However, the number of logs available is five plus the unity equation we get six equations, therefore we require an additional restriction or log to be able to solve the problem. The preliminary work done in the area using a deterministic approach to predict porosity and kerogen showed a very good correlation with core data, so after several tests we decided to incorporate the porosity from deterministic methods to add an equation to the solution.

The second step is to decide if/how to split the Montney formation. Based on the iMineralysis optimization results, the Montney formation was split in three subintervals for modeling purposes (Upper, middle and lower Montney).

The third step is to find adequate end-points for the new rock components. As explained above, since we are mixing some of the minerals, the default properties reported in the software are not adequate. iMineralysis® allows to set limits to the rock component properties to be used by the genetic algorithm as it searches for a solution. The software intelligently tests hundreds of combinations of endpoints within the specified user defined ranges. Petrophysical and regional knowledge were essential to define these ranges. This application of AI and petrophysical expertise significantly decreased the time required to complete the study compared to a classical mineral modeling approach. Figure 3 shows the comparison of the mineral models from ECS vs multimineral analysis.

The fourth step was to determine a water saturation model for the area that statistically matched the water saturation measurements from core. For this area we used a modified Archie's model with m and n equal to 1.8 and salinity of 140 Kppm. We used a fixed temperature gradient model with depth to calculate water resistivity (Rw) from salinity.

The fifth and final step was to generate uncertainty maps and curves were generated, taking into account various factors such as proximity to well logs, proximity to calibration wells, degree of log normalization, and the inherent non-uniqueness of the multimineral model. The maps were constructed to evaluate the reliability of the mapped data across the area. The curves were created to flag areas of high, medium, and low confidence to complement the asset team workflow.

1) Proximity to calibration wells: distance to wells with core and/or ECS logs.
2) Level of log normalization: percent normalization of all logs with respect to the original log data. A global indicator was estimated using the average for all logs.
3) Inherent non-uniqueness of the multimineral model: end-points are calculated using five different seeds for the genetic algorithm and average and standard deviation of the realizations is estimated for each mineral output.

Results, Observations, Conclusions

The mineral model results are now standard in the geologist tool kit for landing zone selection. Landing zones are selected on the basis in part on their mineral composition, well results have improved with targeted zone selection and geosteering to remain in zone. Full integration of the data is still ongoing and results to date show correlation between mineral composition and EUR.

Results show 3 primary and 2 secondary targets within the area which correlate to low calcite and high QFM volumes.

Novel/Additive Information

The use of this AI-enabled multimineral tool facilitated the quick calibration of a model that was applied to hundreds of wells within the region. Calibration was achieved using results from Elemental Capture Spectroscopy (ECS) logs and core data in ten wells, blind tested on five wells and applied to 268 wells in the area.

Acknowledgements

References

Reinaldo J. Michelena; Kevin S. Godbey; Michael J. Uland; Patricia E. Rodrigues. Petrophysical multimineral analysis using genetic optimization to solve complex mineral composition in unconventional reservoirs. SEG International Exposition and Annual Meeting, Virtual, October 2020. SEG-2020-3425780