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Petrophysical multimineral analysis using genetic optimization to solve complex mineral composition in unconventional reservoirs

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Summary

Petrophysical modeling in unconventional reservoirs requires tools that take into account their complex mineral composition and lack of log information necessary to resolve this complexity in detail. We pose the estimation of properties of mineral constituents of the rock as a stochastic nonlinear optimization problem where a genetic algorithm (a type of algorithm in the artificial intelligence spectrum) replaces the time-consuming, manual trial-and-error process of adjusting properties and fitting the input logs in conventional multimineral analysis. The method requires interpretative inputs based on prior knowledge and experience, but such inputs are provided in the form of ranges instead of single property values, facilitating the work of the analyst. By testing adaptively thousands of solutions and considerably reducing the time needed to fit the input logs with a consistent set of properties, it becomes then possible to test other scenarios of input data and constituents, quantify the uncertainty and non-uniqueness of individual parameters, and shed light upon higher-level petrophysical questions such as spatial variations in kerogen maturity, water resistivity, or clay composition. We illustrate the use of the methodology to estimate fractions of constituents for the mineralogically complex Bakken Formation and to estimate variations of thermal maturity with depth in the Marcellus, shale gas Formation.

Introduction

Unconventional reservoirs can vary significantly in their mineral composition. Even though the term "shale" is often used as a synonym of unconventional reservoirs, these mudrocks are a complex mixture of different types of clay, quartz, and carbonates. Organic matter in the form of kerogen is also present. Identifying the proportion of the different constituents of the mixture determines the estimated volumes of hydrocarbon (porosity, Sw), the deliverability of the host rock (permeability), and its geomechanical response to hydraulic fracture stimulation.

Petrophysical multimineral analysis (Mayer and Sibbit, 1980; Mitchell and Nelson, 1988) is a tool that can help relate the complexity of the rock composition to the well log measurements by assuming the log response is a linearized combination of individual constituents of known properties or "end-points". For simplicity, in this abstract we will refer to the properties of the constituents as "mineral constants" which also includes fluid properties. Even though the assumption of linearity of the log response is usually valid, the assumption of known properties is typically the exception rather than the norm in unconventional reservoirs due to the complexity of the rock mixtures, inconsistencies in tabulated properties of the same mineral, uncertain kerogen properties, and scarce or unreliable measurements of water salinity. Often, due to the limited number of logs available, the petrophysicist is forced to create artificial, composite minerals (i.e., "matrix") whose effective properties are unknown. When both the fractions of constituents and their properties are unknown, the multimineral analysis becomes an underdetermined nonlinear problem which is currently solved manually by trial-and-error.

We pose the problem of estimation of both fractions of minerals and their properties as a stochastic nonlinear optimization that is solved in two steps with the help of a genetic algorithm (a family of algorithms in the artificial intelligence toolkit). In the first step, we generate multiple trial models for expected ranges of variability of mineral constants. Then, we solve the linear equations that correspond to each model, keep the model that yields the smallest misfit with the input data, modify the other solutions adaptively by using genetic rules and imposing additional constraints, and repeat the process until an acceptable solution is found.

After revisiting the basic concepts and assumptions behind multimineral analysis, we explore its limitations and introduce our approach based on stochastic nonlinear optimization. Finally, we discuss the application of the algorithm to the estimation of fractions of constituents in the mineralogically complex Bakken Formation and the estimation of variations of thermal maturity with depth in the Marcellus shale gas.

Multimineral analysis: what is it?

Multimineral analysis is a method to estimate mineral and fluid volume fractions present in the reservoir from well log measurements. The log response at every depth is assumed to be a linear combination of the individual responses of the different logging tools to each constituent (mineral constants) weighted by its relative volume fraction (Mayer and Sibbit, 1980; Mitchell and Nelson, 1988). The theoretical log response for each depth can be expressed as

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$$d = \boldsymbol{C} f, \qquad (1)$$

where d the vector of log measurements, $\boldsymbol{C}$ is the matrix of mineral constants, and f is a vector of unknown volume fractions of constituents. When solving the system of equations (1), we also require the fractions to be positive and to add up to 1 (unity constraint). Each of the linear equations in expression (1) is called the "tool response" for a particular log. If the constituents are known, the system of equations (1) can be solved for the volume fractions at each depth where log measurements are available.

The adequacy of multimineral analysis to address a particular mineral estimation problem depends on whether the following assumptions are satisfied:

- Constituents are known.
- Mineral constants are known.
- Log response and mineral constants are linearly related.

The number of volume fractions that can be estimated at each depth is limited by the number of well logs available. Usually, only the "most important" minerals are modeled to be able to achieve a "unique" solution. The more logs we have, the more minerals we can solve for. A common workflow to estimate volume fractions at a selected depth interval along a well is shown in Figure 1. The process starts by selecting the minerals and fluids to solve for. Minerals can be selected from core data analyses, previous petrophysical analyses or any form of prior knowledge or experience in the interval of interest. Then, use tabulated values (i.e., Hearts et al., 2000; Schon, 2004; Mavko et al., 2009) or previous knowledge from the area to generate the matrix of mineral constants $\boldsymbol{C}$ and solve the system of equations (1) for volume fractions (one depth a time). Once the system of equations is solved for all the depths of interest, calculate modeled logs. The fit between modeled and measured logs is performed visually in the computer screen and, if needed, the petrophysicist manually adjusts the mineral constants related to logs where the largest mismatches are observed. All steps above are repeated in a trial-and-error fashion until the fit is "acceptable" and the volumes fractions are "reasonable".

Limitations of multimineral analysis

The limitations of the method arise when the main assumptions are not satisfied. The limitations that our proposed method will address are the following:

1. Unknown mineral constants: Often, the log response to some pure constituents is well known and indeed can be found in tables in the literature and software manuals. Problems arise, however, when different tables report different values or when the range of variability of a mineral constant (in clays, for instance) is so large that, in practice, the constant becomes another unknown in the analysis, making equation (1) nonlinear due to the coupling between fractions and mineral constants.

In addition to the constants related to the solid portion of the rock, fluid constants (like water resistivity) obtained from specific laboratory analyses may not always be available or may vary across the field. Errors in fluid constants may result in important variations in volumes of water and hydrocarbons.

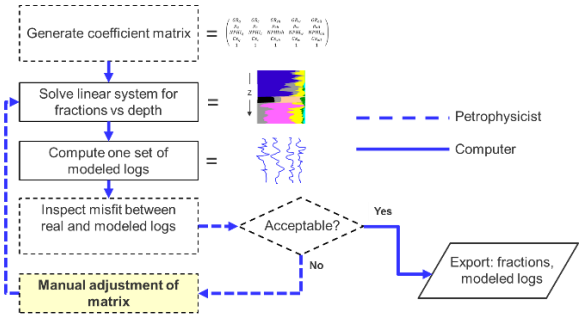

Figure 1. Conventional multimineral analysis to estimate fractions of constituents. The matrix of mineral constants is adjusted manually by trial-and-error until an acceptable match is obtained.

2. More unknown minerals than logs available: In some unconventional reservoirs, even if we know the constants of all minerals in the rock, the number of available well logs may not be sufficient to solve for all of them. In this case, an experienced petrophysicist will introduce "pseudo-minerals" (that may be called "matrix" or "shale" or named after a dominant mineral) by mixing some of the actual original minerals to reduce the number of unknowns. However, the uncertainty in the constants of these new "pseudo-minerals" can also be large.

3. Manual solution of a complex undetermined problem: Since all constants and volumes are related through the system of equations (1), changes in one constant will likely affect the volume fractions of all constituents and therefore, we may also need to adjust the constants we thought we knew well. The coupling of all variables makes this trial-and-error process (Figure 1) time consuming, tedious, and extremely dependent on the experience of the petrophysicist. Besides, there is a limit on the number of combinations that even an experienced petrophysicist can test to solve the (nonlinear) system of equations (1) by trial-and-error.

Nonlinear multimineral analysis using genetic optimization

As explained before, when mineral constants are also unknown, the system of equations (1) becomes not only

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nonlinear but also undetermined. For a given set of log measurements, the less we know about the constants, the more underdetermined and nonlinear equation (1) becomes.

Besides using as much information as we can about the constants of constituents, underdetermination in equation (1) is addressed by analyzing more depths simultaneously and assuming that the constants do not change within the interval of interest. As long as the system of equations at each depth is overdetermined in the volume fractions, each additional depth we consider will add more equations than unknowns to the overall problem. Adding more depths will transform the system of equations (1) into an overdetermined one.

To address the nonlinear aspect of the problem due to the multiplicative nature of the unknowns, we separate the estimation of constants from the estimation of volume fractions using a genetic algorithm (GA) (Goldberg, 1989). The GA generates sets of candidate values for the constants; then, we use least squares to estimate volume fractions for each candidate at every depth. Candidates are rated by several measures (i.e., how well the logs calculated from their estimated volume fractions match the measured logs), and the GA iteratively optimizes candidates over several generations (or iterations) by propagating good mineral constant values from one generation to the next.

Figure 2 shows the workflow for our proposed nonlinear multimineral analysis. Unlike the process outlined in Figure 1, in this case, the process starts by defining ranges of variability and initial values of the constants for a given depth range and generating N random matrices $\boldsymbol{C}$ (equation 1). Then, we solve N systems of linear equations, compute the corresponding modeled logs, and calculate the misfits between measured and models logs. The solution with the smallest misfit is kept from one iteration to the next (ensuring improvement in the iterative process) and the other matrices are adjusted adaptively by the generic algorithm to generate a new set of trial models. The process is repeated M times (for a total for $N \times M$ tested models) until no changes are observed for "several" iterations. There is no guarantee, however, that this solution represents a global minimum for the optimization problem. If readjustment of the input ranges is needed, the process is repeated. Many models can be tested in a short amount of time. If $N = M = 1$, the process is reduced to conventional multimineral analysis since no automatic optimization is performed. Due to the severe non-uniqueness of the solutions, careful review by the petrophysicist and calibration with independent information are both crucial to make sure these solutions make sense.

Any constraint we add in the form of additional equations or limits in the range of variability of the constants will contribute to finding a more robust solution. Examples of these constraints are theoretical effective media bounds of elastic moduli from rock physics, volumetric limits for constituents, limits on porosity, and low-resolution trends from mud logs or x-ray diffraction (XRD) lab data.

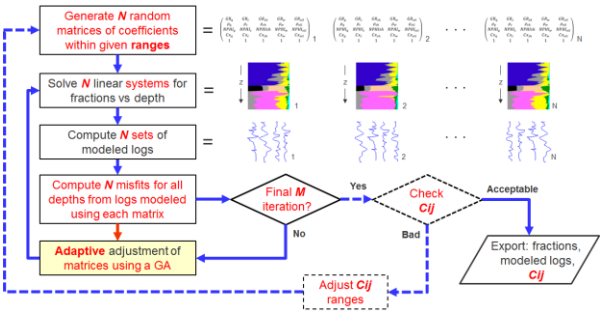

Figure 2. Nonlinear multimineral analysis to estimate fractions and mineral constants. Different matrices of constants are adjusted automatically until an acceptable match is obtained.

Applications to unconventional reservoirs

Estimation of lithology mixtures in the Bakken Formation. The output of the nonlinear multimineral analysis consists of two parts: volume fractions and updated mineral constants. As explained above, if the constituents exceed the number of available logs, the constituents must be grouped but then, the properties of the mixtures that result are uncertain. For instance, in the Bakken Formation in the Williston Basin (North Dakota), XRD data show a complex mineralogy that consists of dolomite, calcite, "quartz" (which is typically a mixture of pure quartz, K-feldspar, and albite), seven types of clay (predominantly illite) grouped under a category called "shale", pyrite, and kerogen. The result of the multimineral analysis in this mixed mineralogy scenario is shown in Figure 3. In this case, the input logs consisted of conductivity, gamma ray, neutron-porosity, density, and volumetric photoelectric factor U. Three different models (1, 2, and 3) of five constituents each were used to describe the interval of interest. Another rock category called "matrix" (a mixture of dolomite and quartz) was defined in the Upper Bakken Shale interval (model 2) to be able to solve for kerogen using the same five logs. Since pyrite is not explicitly modeled, the optimization will adjust for that and other rocks may end up "heavier" than they actually are after the optimization.

The initial matrix (created by the petrophysicist) and the final matrix (estimated by the method) for model 2 in the Upper Bakken Shale, are shown in Figure 4. The properties of the mixed minerals ("quartz" and "shale") are initially uncertain but the optimization yields reasonable values that produce a good match between measured and modeled logs (Figure 3). Depending on the range of variability allowed for each constant, some of them don't change during the optimization while others may depart considerably from

their initial guesses. More variability is allowed for the more uncertain mineral constants.

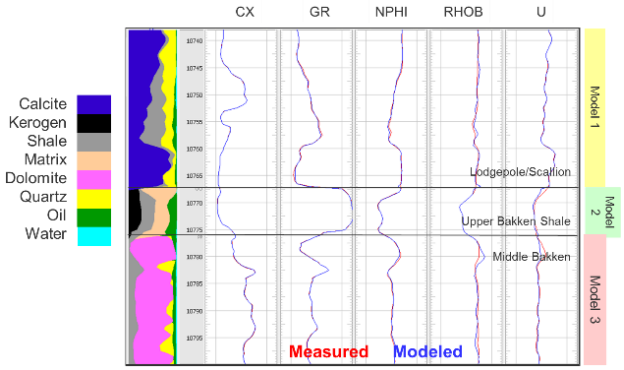

Figure 3. Result of multimineral analysis in the Bakken Formation. The good agreement between measured (red) and modeled (blue) logs indicates that the estimated fractions and mineral constants are plausible.

Initial matrix (model 2)

	Kerogen	Shale	Matrix	Oil	Water
CX	0	0.03	0	0	11.0
GR	700	150	15	0	0
NPHI	0.35	0.2	-0.02	0.95	0.90
RHOB	1.5	2.75	2.70	0.90	1.10
U	0.90	10	11	0.07	0.10

Final matrix (model 2)

	Kerogen	Shale	Matrix	Oil	Water
CX	0	0.05	0	0	10.7
GR	889	246	29	0	0
NPHI	0.27	0.22	-0.03	0.92	0.87
RHOB	1.64	3.45	2.79	0.98	0.97
U	1.20	11.8	12.1	0.02	0.27

Figure 4. Matrices of mineral constants before and after the optimization. Cells in red indicate constants whose values have changed more than 50% from the initial value.

Determination of kerogen maturity variability in the Marcellus Formation. When nonlinear multimineral analysis is performed in different wells within the same interval of interest, we can also analyze the spatial variability in the mineral constants of the resultant matrix related to measurements (e.g. kerogen density) that may not be available across the whole area of interest. Figure 5 shows an example of this application in the Marcellus Formation in the Northern Pennsylvania region. In this case, we performed nonlinear multimineral analysis in seven wells that penetrated the Lower Marcellus at measured depths that range from 350 m to 1800 m. Same mineral constants were used to initiate the optimizations in individual wells. The modeled kerogen density from the final matrix of optimized coefficients for each well was compared to measurements of thermal maturity Ro from vitrinite reflectance available at the same wells. As Figure 5 (left) shows, thermal maturity increases with depth. The kerogen density estimated with our method, as expected, also increases with depth (not shown) and exhibits a high correlation with the measured thermal maturity, as shown in Figure 5 (right). This result indicates that modeled kerogen density can be used to estimate variations in thermal maturity with depth from log data using wells where this measurement is not available.

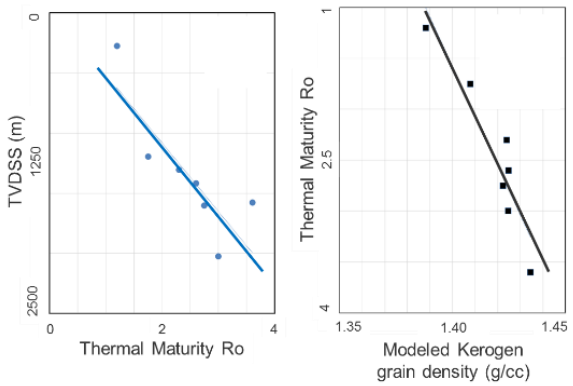

Figure 5. Thermal maturity from vitrinite reflectance Ro for the Marcellus Formation. Left: Variation of Ro vs depth. Right: Correlation of modeled kerogen density vs Ro.

Conclusions

We introduced a fundamental modification to the conventional petrophysical multimineral analysis that allows to expedite the estimation of mineral constants (for solids and fluids) in areas where such constants are uncertain, a common problem in unconventional reservoirs.

Even if only one coefficient is unknown, the conventional linear multimineral analysis becomes nonlinear and this nonlinearity is addressed by using a genetic algorithm. The process automates the time-consuming, manual, trial-and-error process of estimating constants and generates a multimineral solution that predicts the input logs and estimates the fractions of fluids and minerals present in the rock.

The automated, fast nature of the proposed method allows the petrophysicist to explore different assumptions and estimate spatial variations in important parameters such as kerogen maturity, water resistivity, and/or clay composition. As with any other petrophysical analysis tool, the judgment of the petrophysicist and calibration with independent data are still fundamental to ensure the solutions are adequate for the problem we are solving.

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