

iMineralysis™ as a tool to optimize petrophysical multiminerall analysis: theoretical review

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In areas with mixed, complex, or simply uncommon lithologies, petrophysicists often use multiminerall analysis (Mayer and Sibbit, 1980; Mitchell and Nelson, 1988) to estimate volume fractions of individual fluid and mineral components of the rock. In this process, the log data is “inverted” at every depth to find the volumes of the constituents that form the rock.

A crucial assumption behind multiminerall analysis is that the response of any log selected for the analysis can be described as a linear combination of the individual log responses to each constituent weighted by the fraction of that constituent. Another important assumption is that the response of different logging tools when used to measure a “pure” constituent is also a known constant sometimes called an “end point”. This means, for instance, that the response of the density tool for pure quartz is always in the close vicinity of 2.65 g/cc. However, the response of other tools to other constituents may not always be known.

If the multiminerall analysis is performed understanding the assumptions of the process and correctly choosing the right constituents and their properties, the result is a very good approximation to the measured well logs with good estimates of the volume fractions of the different constituents. When the assumptions behind the method are violated, however, fractions estimated from the analysis may be incorrect and further analyses (such as rock physics modeling, for instance) may also yield erroneous results.

In this paper, we review the method of multiminerall analysis, its advantages and limitations, and propose solutions for some of these limitations that are implemented in the iMineralysis™ software. In particular, we discuss a solution to the problem of estimating the most appropriate “constant” that describes the response of a given logging tool to a particular constituent. We also explain ways to improve the multiminerall analysis by incorporating other types of data and information not commonly used in conventional petrophysical analyses.

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 weighted by its relative volume fraction.

Although the relation between log measurement, volume fractions and constituents' constants (tool responses for pure constituents) can be described in compact form by using indexes for the different variables, we will write out "long hand" an example of the equations that describe the relation between a typical carbonate system (limestone, dolomite, clay, gas and water) with a common suite of well logs (gamma ray, neutron, density, volumetric photoelectric factor U and conductivity Cx):

$$GR_{log} = V_{dol} GR_{dol} + V_{lim} GR_{lim} + V_{sh} GR_{cl} + V_{gas} GR_{gas} + V_{wat} GR_{wat}, \quad (1a)$$

$$NPHI_{log} = V_{dol} NPHI_{dol} + V_{lim} NPHI_{lim} + V_{sh} NPHI_{cl} + V_{gas} NPHI_{gas} + V_{wat} NPHI_{wat}, \quad (1b)$$

$$RHO_{log} = V_{dol} RHO_{dol} + V_{lim} RHO_{lim} + V_{sh} RHO_{cl} + V_{gas} RHO_{gas} + V_{wat} RHO_{wat}, \quad (1c)$$

$$U_{log} = V_{dol} U_{dol} + V_{lim} U_{lim} + V_{sh} U_{cl} + V_{gas} U_{gas} + V_{wat} U_{wat}, \quad (1d)$$

$$Cx_{log} = V_{dol} Cx_{dol} + V_{lim} Cx_{lim} + V_{sh} Cx_{cl} + V_{gas} Cx_{gas} + V_{wat} Cx_{wat}, \quad (1e)$$

where, for instance, V_{dol} is the volume fraction of dolomite, GR_{dol} is the GR response for dolomite (GR dolomite "constant"), and GR_{log} is the GR value measured by the logging tool at the well. The notation for other variables is analogous. In this example, we assume Archie's equation to estimate conductivity Cx from resistivity Rt: $Cx = 1/\sqrt{Rt}$. For simplicity, we will refer to the log value that corresponds to each pure constituent (either solid or fluid) as the "mineral constant" in the rest of the paper. Each of the linear equations shown above is called the "tool response" for that particular log. If the selected constituents describe all fluids and minerals present in the rock, they should also satisfy the following equation, also called the unity constraint:

$$1 = V_{dol} + V_{lim} + V_{cl} + V_{gas} + V_{wat}. \quad (1f)$$

If the mineral constants are known, the linear system of equations (1) can be solved for the volume fractions at each depth where log measurements are available.

Because the linear system (1) needs to be determined or overdetermined, the number of volume fractions that can be estimated at each depth is limited by the number of well logs available. The more logs we have, the more minerals we can solve for. In the example described by the system of equations (1) (5 measurements from different logs plus the unity constraint), we can solve for the 5 volume fractions of different minerals we are interested in. Since we have 6 equations and five unknowns, we could still attempt to estimate one more mineral fraction if we suspect that the system has other lithologies and if we assume that mineral constants are perfectly known. If the system is overdetermined, we can solve it by using least squares and include other constraints that relate to the error in individual log measurements.

A typical workflow to estimate volume fractions in a selected depth interval along a well is:

1. Select 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 from the interval of interest.
2. Use tabulated values (from the literature or software vendor) or previous knowledge from the area to fix the mineral constants.
3. Solve the linear system of equations (1) for volume fractions (one depth a time).
4. Calculate modeled logs for the interval of interest using volume fractions estimated in 3.
5. Visually examine fit between real and modeled logs.
6. Manually adjust mineral constants related to logs where largest mismatches are observed.
7. Repeat steps from 3 to 6 until the fit is “acceptable” and the volumes fractions are “reasonable”.

LIMITATIONS OF CONVENTIONAL MULTIMINERAL ANALYSIS

The main assumptions of multimineral analysis (linearity of responses and known mineral constants) are also the main limitations of the method.

The first limitation refers to the linearity of the well log response with respect to the volume fractions. If the response of a particular log cannot be approximated by a linear equation, log measurements should be “converted” first, if possible, into another log that shows the assumed linear behavior before performing any analysis. In some cases, these transformations can be simple, like in the case of the photoelectric factor (PE) which should be converted into volumetric photoelectric factor (U) by doing a simple transformation that uses the density log. In the case of the resistivity log, it can be easily transformed into pseudo-conductivity by assuming Archie’s equation with $m=n$ and $a=1$, but with the intrinsic limitations of this equation. For the sonic log, however, the linear approximation that relates measurements, fractions

and mineral constants is not always valid; this approximation is Wyllie’s time average equation which may be valid only for certain rocks (Mavko, et al., 1998). If sonic logs are used in multiminerall analysis, we have to make sure that Wyllie’s approximation is valid for the type of rocks considered and if not, less weight should be given to the sonic data during the analysis.

In rocks made of a large number of minerals, it is very tempting to use as many logs as possible to solve for the largest number of minerals we can. This approach, however, may lead to major errors if all logs cannot be expressed as a linear combination of mineral constants and volume fractions. If several logs measure related properties, the system may also become degenerate or ill-conditioned.

The second important limitation of multiminerall analysis refers to the assumption that the mineral constants are well known. The log response to some pure minerals (or fluids) is well known and indeed can be found in numerous tables in the literature and in the manuals of software vendors. Problems arise, however, when different tables report different values or when the range of variability of one particular mineral constant is so large that, in practice, this mineral constant becomes another unknown in the analysis. An example of this problem for clay minerals is shown in Table 1 for illite and kaolinite. Three different sources in the literature report, for instance, four different values for the density of illite. Which is the correct value? All? None? Are these values valid in our area of interest? Additionally, we may face situations where more than one type of clay is present or we don’t know what type of clay is present in the reservoir.

	Source	GR (API)	RHO (g/cc)	NPHI (v/v)	U (B/CC)	DT (us/f)
Illite	Lesas Software	275	2.52	0.3	8.73	50
	Mavko et al.	na	na	na	na	70
	Hearts et al. (page 362)	68	2.78	0.16	na	na
	Hearts et al. (page 193)	na	2.76	na	8.37	na
	Schon	250-300	na	na	na	na
	Wang et al.	na	2.71	na	na	51
Kaolinite	Lesas Software	105	2.41	0.37	4.44	100
	Mavko et al.	na	1.58	na	na	211
	Hearts et al. (page 362)	6	2.62	0.45	na	212
	Hearts et al. (page 193)	na	2.64	na	3.92	na
	Schon	80-130	na	na	na	na
	Wang et al.	na	2.44	na	na	54.5

Table 1. Mineral constants (“tool responses”) suggested in the literature and petrophysical software for illite and kaolinite. Not all values are available (“na”) in all sources. Notice how different sources may report different values for the same mineral and the same tool.

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, and therefore, porosity.

In other cases, even if we know the mineral constants that describe all the constituents of the rock, the number of different well logs available may not be sufficient to solve for all their volume fractions. In this case, an experienced petrophysicist will introduce “pseudo-minerals” by mixing some of the original minerals to reduce the number of unknowns. However, the uncertainty in the constants of these new “pseudo-minerals” can also be large.

In summary, some constants may require adjustments that are usually performed in a trial-and-error fashion during the multiminer analysis. The petrophysicist has to make sure that the values used are “reasonable” because they represent the mineralogy of the formation and yield the “expected” volumetric solution for the area. Experience of the petrophysicist and prior knowledge of the area are crucial in this process.

Since all constants and volumes are related through a system of equations similar to (1), changes in one constant will likely affect the volume fractions of all minerals and therefore, we may also need to adjust the constants we thought we knew well. The coupling of all variables makes the trial-and-error process 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 a system of equations like (1) by trial-and-error, which becomes nonlinear if the mineral constants are also unknown.

In the following section, we describe how iMineralysis™ addresses the problem of unknown mineral constants and helps the petrophysicist to obtain faster, accurate, and consistent solutions when performing multiminer analysis.

AUTOMATIC ESTIMATION OF MINERAL CONSTANTS: THE ESSENCE OF IMINERALYSIS™

As explained before, multiminer analysis requires the solution of a system of equations similar to (1) for each depth. For the particular example of system (1), we have to solve an overdetermined system of 6

equations and 5 unknown volume fractions. In the extreme case where no mineral constants are known, we would have to solve for an additional 25 unknowns; this is obviously not possible if we use log measurements from just a single depth. Besides being highly underdetermined, the system of equations (1) with volume fractions and mineral constants as unknowns is also significantly nonlinear because the unknowns multiply each other.

Underdetermination is addressed by adding depths into the solution of the problem and assuming that the mineral constants do not change within the interval of interest. As long as the system of equations at each depth is overdetermined in volume fractions, each additional depth will add more equations than unknowns. In our example of equation (1) and assuming that we want to estimate all 25 mineral constants, we would need to use at least 25 depths to have a system of nonlinear equations with the same number of equations as unknowns. Adding more depths will transform the system of equations into an overdetermined one, but due to the nonlinearity of the problem, this still but may not be enough to estimate a unique solution that also makes physical sense. In some problems, we may need to be less ambitious in the number of mineral constants we want to estimate and focus only on those with the largest uncertainties.

To address the nonlinear aspect of the problem due to the multiplicative nature of the unknowns, we separate the selection of mineral constants from estimation of volume fractions, using a genetic algorithm (GA) (Goldberg, 1989) to generate sets of candidate values for the constants and least squares to estimate volume fractions for each candidate at each depth. Candidates are rated by several measures (how well the logs calculated from their estimated volume fractions match the measured logs, along with other constraints), and the GA iteratively optimizes candidates over a number of generations by propagating good mineral constant values from one generation to the next.

There is no limit on the number or nature of constraints that can be used to rate candidate values. These constraints do not need to be linear since they are applied within the GA iteration but outside the linear solver. Examples of these constraints are:

- Volumetric: all volume fractions are positive; fluid fractions cannot add up to more than certain values based on experience and their sum, porosity, cannot be greater than a predetermined maximum value that varies from one area to another; expected volume fractions in some intervals must be less than a predetermined value.

- Porosity: calculated porosities should be similar to ones observed in cores or porosity curves from NMR. NMR porosity logs can be also used as an independent curve to increase our ability to estimate more minerals.
- Mud log: volume fractions should be similar to the ones observed in lower resolution descriptions of mud logs.

Our implementation of multiminer analysis in iMineralysis™ also considers other factors in the solution of the linear system of equations that are not described in this paper for the sake of simplicity. Prior references in multiminer analysis (Mayer and Sibbit, 1980; Mitchell and Nelson, 1988) describe these additional factors in detail.

SUMMARY

iMineralysis™ is a nonlinear optimization method that can help the petrophysicist to solve the problem of estimating volume fractions when some mineral constants are unknown in areas of complex lithologies. iMineralysis™' use of GA for optimization automates both the time-consuming, manual trial-and-error process of estimating mineral constants and the application of constraints which cannot be included in a linear model such as (1). This frees the petrophysicist to explore at a higher level, for example by considering different logs or components or even the spatial variations in important parameters such as water resistivity, kerogen maturity, and clay composition. Even though the method is largely automatic, it still requires interpretative inputs based on experience and prior knowledge to be able to solve the problem successfully.

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