Clay characterization, the key for accurate petrophysical properties in shaly sands: Viking formation case.

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Summary

The interpretation of effective porosity (PHIE) in Petrophysics is the subtraction of Clay Bound Water (CBW) from total porosity (PHIT). Each type of clay has specific properties, among those the "Wet Clay Porosity (WCLP)," which indicates the volume of water-porosity contained by specific clay type. The vertical variation of clay typing and its fractions within the formation significantly impacts the CBW and as a result the PHIE calculation. The CBW is determined by summing all the clay mineral fractions present at each depth, weighted by their respective WCLP values. Characterizing the clay types and their respective fractions through log models is a critical step in the petrophysical evaluation of shaly-sands reservoirs, as it ensures precise determination of CBW that corresponds to the clay fraction.

Viking formation is a typical example of a shaly-sand formation, where identifying and quantifying the clay types and their fractions is essential for evaluation. X-ray diffraction (XRD) analysis reveals that the predominant clay types in the Viking formation are Illite, Smectite, and Kaolinite. Notably, the fraction of Smectite among the clay minerals can reach up to 30% in sandy intervals. Given that the typical WCLP for Smectite is about 40% of its volume fraction (Figure 1), this significantly impacts the PHIE calculation. Furthermore, the substantial presence of Smectite has implications for several petrophysical core measurements, such as permeability and water saturation (API, 1998). Therefore, relying on a mineral model with a single clay type may lead to inaccuracies in determining PHIE and subsequent calculations of petrophysical properties like permeability and water saturation (SW).

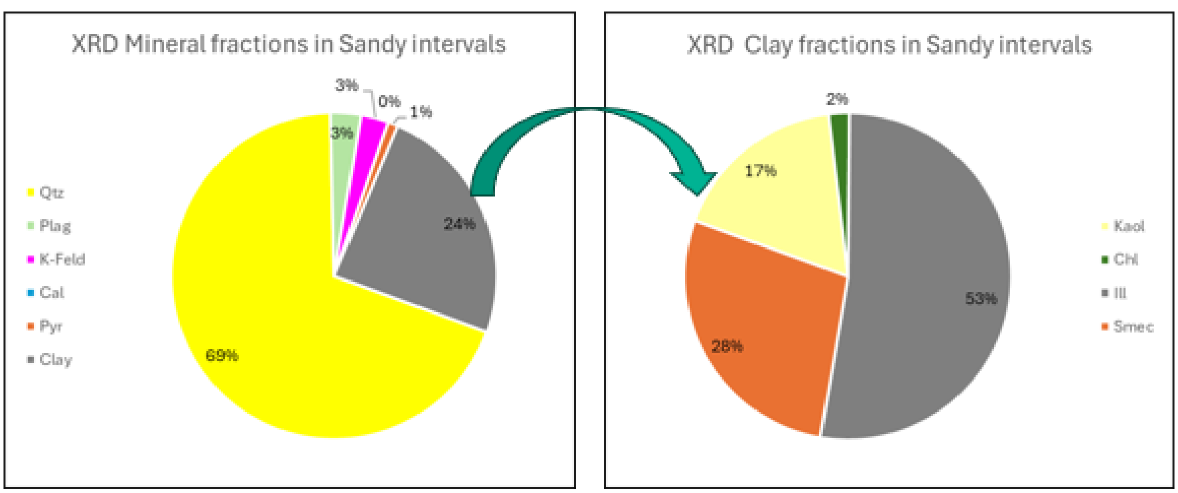

Figure 1 XRD analysis data samples in the sandy intervals (XRD weight clay fraction < 40 wt%). The pie charts show the Bulk and Clay fractions. The left pie chart shows the average of all mineral fractions including the sum of all clay minerals. The right pie chart shows the average of only clay mineral fractions.

This work presents an integrated Core-Log workflow, where the petrophysical log model primarily relies on Triple Combo logs but supported by other more specific logs, such as NMR and GR Spectral. We describe some of the nuances found with various core analysis data and how a proper integration of that data can be carried out into the petrophysical log model.

Methodology

The integrated core-log workflow for petrophysical analysis described in this work includes measurements from standard triple combo logs, nuclear magnetic resonance (NMR), X-ray diffraction (XRD), and routine petrophysical core analysis (RCAL).

The first step in developing the mineralogical model is to analyze the predominant minerals identified through the XRD analysis and to determine the potential relationships or ratios between the fractions of the minerals. These ratios are essential for formulating the equations needed to integrate with other logs, providing the necessary inputs to solve the volumetric model using a simultaneous equation solver tool, commercially known as Quanti.Elan or Mineral Solver.

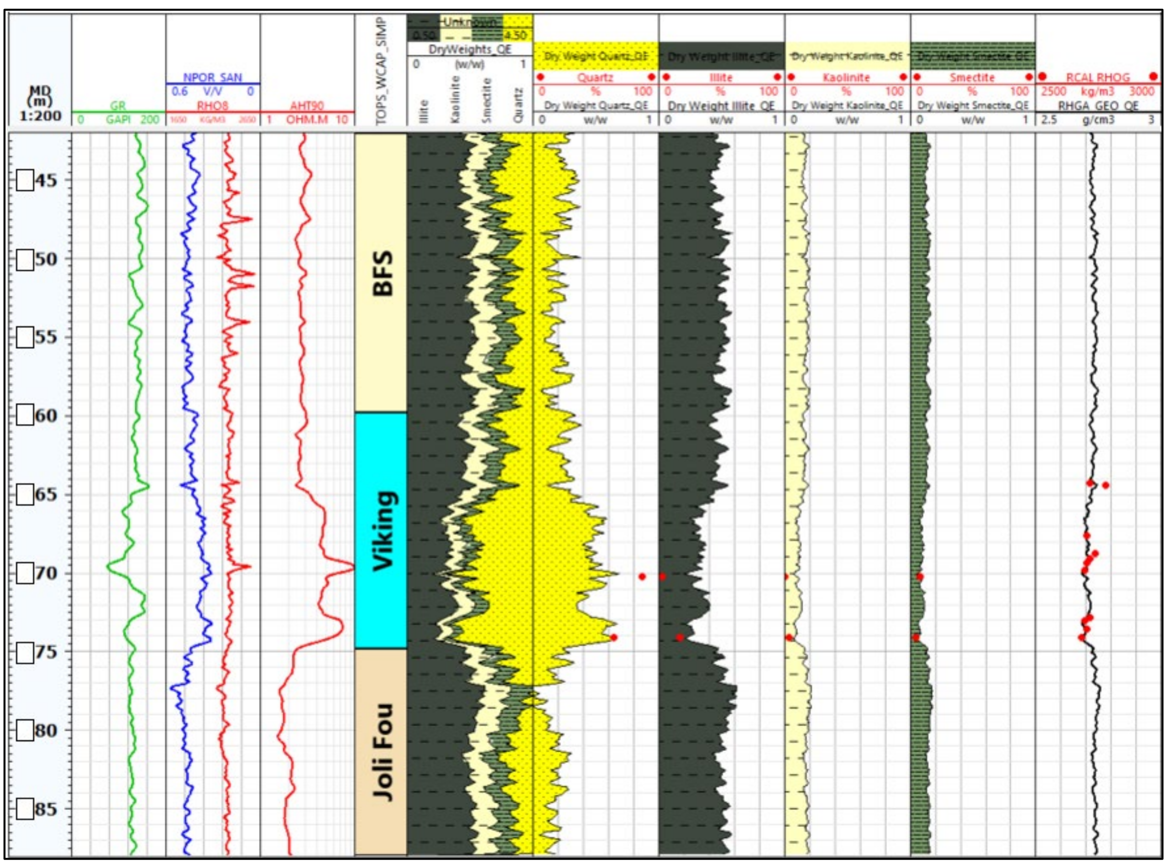

Figure 2 The comparison plot illustrates a strong correlation between the dry weight fractions of minerals derived from the log model and those measured by X-ray diffraction (XRD), represented by the red dots. The minerals displayed include quartz, illite, kaolinite, and smectite. The final track on the left side compares the grain density calculated from the mineral log model (black curve) with the core grain density obtained from routine core analysis (RCAL) after correcting for the presence of organic materials.

The validation of the mineral log model is demonstrated by the good match between the dry weight fraction derived from the model and the XRD mineral data, as well as the consistency between the grain density estimated from the mineral log model and the core grain density. This confirms the model’s accurate representation of the mineral fractions (Figure 2).

Having the NMR log is crucial for validating the PHIT and the CBW estimated from the mineral log model. However, NMR data are not used as inputs in the mineral solver tool, as they fall outside the standard log set and are only available in a limited number of wells. The strong correlation between PHIT and CBW from the mineral log model, and the NMR log outputs, core porosity demonstrates the robustness of the log model (Figure 3).

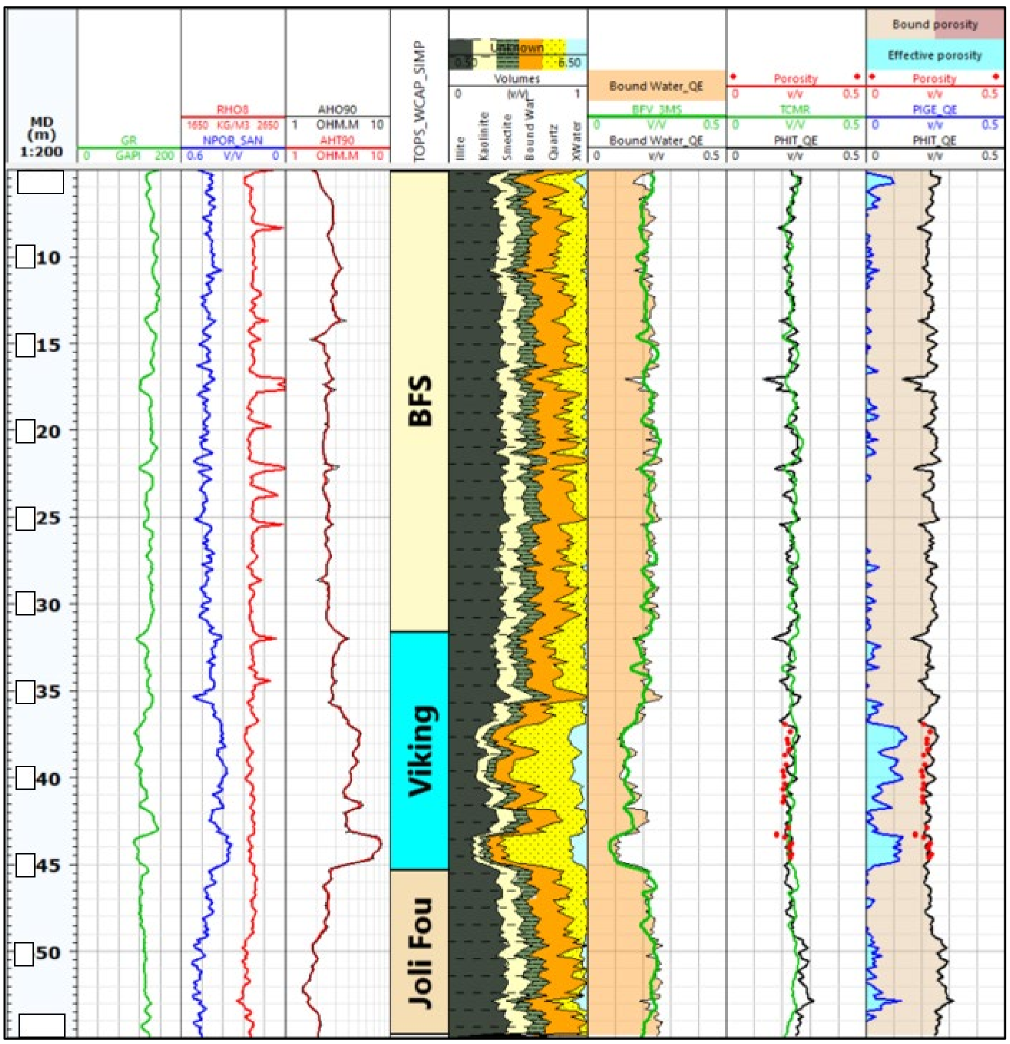

Figure 3 The comparison plot shows a good match between the log model outputs and NMR outputs. The Bound Water QE log (black curve with orange shading) shows an excellent correlation with the BFV_3MS (green curve). Both curves refer to Clay Bound Water (CBW). Likewise, a good correlation is observed between the total porosity from the log model (PHIT_QE – black curve), total porosity from the NMR log (TCMR – green curve), and core porosity from the routine core analysis (RCAL). The good correlation between the outputs indicates the fair representation of the log model in terms of mineralogy and porosities, total and effective.

The next step is to compute SW and absolute permeability. Given the significant impact of extra conductivity in the system due to the important clay fraction, it is essential to select a resistivity-based water saturation (SW) equation that incorporates clay properties, such as overall volume (Vcl), intrinsic porosity (CBW), and resistivity (Rcl), to account for its effects. Various SW equations that include the clay/shale term have been reviewed, including Juhasz, Dual Water, Simandoux, and the Indonesia method (Figure 4). Most of the parameters and logs required as input for these equations are obtained from laboratory analyses, such as the formation water resistivity (Rw), but primarily from volumetric analyses conducted with a mineral solver tool, which provides porosities, clay volume, and clay porosity (CBW). The clay resistivity (Rcl) is estimated using a crossplot of Vcl and Rt. An exception is Archie's textural parameters, for which no electrical properties analysis is available. As a result, there is an inherent uncertainty in the tortuosity factor, as well as in the cementation and saturation exponents. To address this uncertainty, a "Two Extremes Sw" approach is utilized to establish a range for SW, adjusting textural parameters, as necessary. One extreme represents the minimum SW expected, which is the irreducible water saturation (SWI), derived from the CBW and PHIT. This SWI, obtained from logs, is validated against SWI from capillary pressure curves, which indicate values of approximately 49%. The other extreme, representing the maximum SW expected, is defined as SW = 1.

	Rt	Rw	PHI Tot	PHI Ef	Vcl	PHI Clay	Rcl	a	m	n
Dual Water	×	×	×		×	×	×	×	×	×
Juhasz	×	×	×		×	×	×		×	×
Simandoux	×	×		×	×		×	×	×	×
Indonesia	×	×		×	×		×	×	×	×
	☑	☑	☑	☑	☑	☑	☑	?	?	?

Figure 4 shows a summary table of the SW methods evaluated. An "x" indicates the inputs required for the SW computation. The boxes marked with a check signify that these inputs are reliable and have been obtained from the log model, external logs, or data sources. The red question marks indicate that these input parameters are unknown.

Among the evaluated methods, the Dual Water (DW) equation provides the most comprehensive results based on the aforementioned approach. In this case, the DW model effectively accounts for the extra conductivity introduced by the abundant clay fractions. In contrast, other SW methods tend to yield either overly pessimistic or excessively optimistic values that do not align with historical fluid production data from wells (Figure 5). Coates (1973) expanded upon Timur's permeability equation using the Dual Water model, which stipulates that permeability decreases to zero as SWI increases and fills the entire pore space. With confidence in the computed SWI, the absolute log permeability is determined using this methodology.

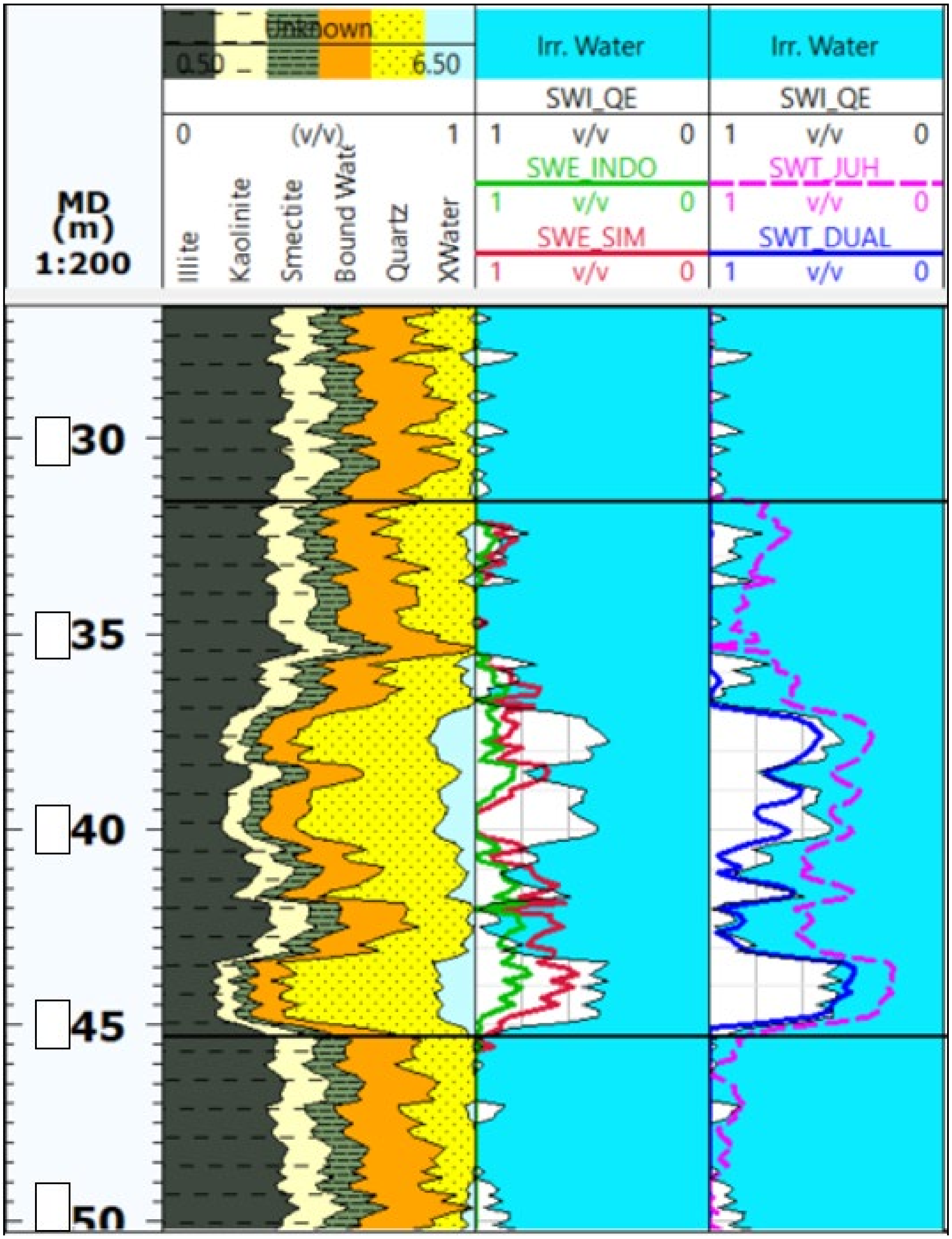

Figure 5 illustrates a comparison of the evaluated SW methods. It is observed that the SWE methods, such as Simandoux (SWE_SIM - red curve) and Indonesian (SWE_INDO - green curve), yield more pessimistic results. Additionally, in front of the shaly intervals (x40-x43), these methods do not compensate well for the SW. The Juhasz method (SWT_JUH - pink dashed curve) produces lower SW values than SWI, which is not feasible. In contrast, the Dual Water method (SWT_DUAL - blue curve) appears to effectively compensate for the excess clay conductivity.

Conclusions

This work details the workflow, the applied methodologies and presents concrete examples that illustrate the effectiveness of this quantitative approach. The remarkable good match obtained between the mineral log model, NMR porosities, XRD and Routine Core Analysis data confirms the robustness of the methodology.

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