Inversion-based method for estimating total organic carbon and porosity and for diagnosing mineral constituents from multiple well logs in shale-gas formations

Zoya Heidari¹ and Carlos Torres-Verdín²

Abstract

Reliable estimates of petrophysical and compositional properties of organic shale are critical for detecting perforation zones or candidates for hydro-fracturing jobs. Current methods for in situ formation evaluation of organic shale largely rely on qualitative responses and empirical formulas. Even core measurements can be inconsistent and inaccurate when evaluating clay minerals and other grain constituents.

We implement a recently introduced inversion-based method for organic-shale evaluation from conventional well logs. The objective is to estimate total porosity, total organic carbon (TOC), and volumetric/weight concentrations of mineral/fluid constituents. After detecting bed boundaries, the first step of the method is to perform separate inversion of individual well logs to estimate bed physical properties such as density, neutron migration length, electrical conductivity, photoelectric factor (PEF), and thorium, uranium, and potassium volumetric/weight concentrations. Next, a multilayer petrophysical model specific to organic shale is constructed with an initial guess obtained from conventional well-log interpretation or X-ray diffraction data; bed physical properties are calculated with the initial layer-by-layer values. Final estimates of organic shale petrophysical and compositional properties are obtained by progressively minimizing the difference between calculated and measured bed properties. A unique advantage of this method is the correction of shoulder-bed effects on well logs, which are prevalent in shale-gas plays. Another advantage is the explicit calculation of accurate well-log responses for specific petrophysical, mineral, fluid, and kerogen properties based on chemical formulas and volumetric concentrations of minerals/kerogen and fluid constituents.

Examples are described of the successful application of the new organic-shale evaluation method in the Haynesville shale-gas formation. This formation includes complex solid compositions and thin beds where rapid depth variations of mineral/fluid constituents are commonplace. Comparison of estimates for total porosity, total water saturation, and TOC obtained with (a) commercial software for multiminerale analysis, (b) our organic-shale evaluation method, and (c) core/X-ray diffraction measurements indicates a significant improvement in estimates of total porosity and water saturation yielded by our interpretation method. The estimated TOC is also in agreement with core laboratory measurements.

Introduction

Evaluation of shale properties such as total organic carbon (TOC), total porosity, gas-filled porosity, fluid saturation, and grain composition remains a technical challenge to the hydrocarbon industry. Conventional well-log interpretation methods are not reliable for these unconventional reservoirs; no general guidelines exist for the petrophysical evaluation of organic-shale formations (source-rock formations).

Accurate mineralogy evaluation together with geologic knowledge can improve the evaluation of in situ mechanical properties and, consequently, aid in determining perforation intervals in hydrocarbon-bearing shale. Improving estimates of volumetric concentrations of mineral constituents also improves the estimation of porosity, TOC, and water saturation. Furthermore, reliable mineralogy assessment improves evaluation of mechanical properties when combined with compressional-, shear-, and Stoneley-wave velocity logs. Several methods have been developed to estimate or measure volumetric/weight concentrations of mineral constituents, including commercial multiminerale linear solvers, neutron-capture spectroscopy, spectral gamma-ray (GR), X-ray diffraction (XRD), and core measurements

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of elemental chemistry of the solids such as Fourier transform infrared transmission (FTIR) spectroscopy and X-ray fluorescence (XRF). Even though some of these methods are reliable in conventional reservoirs, they are not in the presence of thin beds and complex mineral compositions. Among such methods, core measurements are regarded as the most reliable estimates of mineral concentrations, even though XRD and FTIR spectroscopy measurements can be inconsistent and inaccurate when evaluating clay minerals and, sometimes, grain constituents (Sondergeld et al., 2010).

Assessment of TOC in organic-shale formations is another salient technical challenge. Uranium concentration can usually be invoked for the estimation of TOC in marine source rocks (typically type II kerogen). However, there is not always a robust statistical correlation between uranium concentration, natural GR response, and TOC in, for instance, the case of lacustrine source rocks (e.g., type I kerogen, Green River oil shale, and Rundle shale; Passey et al., 2010). Passey et al. (1990) introduced and later revised (Passey et al., 2010) the \( \Delta \log R \) technique to estimate TOC, which has become popular among shale-gas petrophysicists; the \( \Delta \log R \) technique is, however, an empirical procedure which was not developed from “rock physics” principles.

Evaluating total porosity and fluid saturations requires accurate density estimates of pure minerals and their volumetric concentrations, as well as a reliable fluid saturation model. Uncertainty remains, however, in the density estimation for kerogen and clay minerals. Most of the available saturation models also depend on electrical resistivity logs, which are themselves affected by pyrite and by the conductive highly mature kerogen often present in hydrocarbon-bearing organic shale. Fundamental research is still needed to advance reliable porosity-saturation-resistivity models for shale-gas formations.

In addition to complications in estimating TOC, gas-filled porosity, and volumetric concentrations of mineral/fluid constituents in shale-gas formations, significant vertical heterogeneity and prevalent thin beds make well-log interpretation significantly more challenging than in conventional plays. Some publications describe algorithms and techniques for optimized well-log interpretation in organic-shale formations (Quirein et al., 2010, 2012). However, none of the conventional depth-by-depth well-log interpretation methods addresses the problem of shoulder-bed effects due to interbedding in shale-gas formations. Shoulder-bed effects are not only observed in well logs such as neutron-capture spectroscopy but can also bias conventional interpretation methods when implemented directly on well logs.

Recent publications have introduced new methods to reduce shoulder-bed effects to improve the petrophysical evaluation of thinly bedded siliciclastic formations from conventional well logs (Sanchez-Ramirez et al., 2009), and to improve the lithology evaluation in thinly bedded, invaded carbonates, and siliciclastic formations (Heidari et al., 2012). In this paper, we adapt Heidari et al.’s (2012) procedure to reduce shoulder-bed effects in the evaluation of mineral/fluid compositions of organic-shale formations. The adaptation of Heidari et al.’s (2012) method includes a new automatic nonlinear joint inversion algorithm to estimate volumetric/weight concentrations of mineral, fluid, and kerogen from well logs in the presence of complex matrix composition in organic-shale formations.

The following sections briefly describe the adapted nonlinear inversion method for combined interpretation of multiple well logs. We also document two examples of application: one challenging synthetic organic-shale formation constructed to replicate an actual field case, and one example of field data acquired in the Haynesville shale-gas formation.

Method

Heidari et al. (2012) introduce an inversion-based interpretation method referred to as “fast nonlinear joint inversion of bed physical properties” to estimate volumetric concentrations of mineral constituents, porosity, and fluid saturations from multiple conventional well logs in thinly bedded, shaly sand, and carbonate formations. This method performs optimally in reservoirs where mud-filtrate invasion is negligible or can be assumed piston-like. In the case of organic-shale formations, we assume that mud-filtrate invasion effects on well logs are negligible. Following this assumption, fast nonlinear joint inversion of bed properties becomes an effective method for petrophysical and compositional evaluation of organic-shale formations with complex lithology and thin beds. In the present paper, we modify the fast nonlinear joint inversion of bed physical properties for organic-shale formations by invoking a petrophysical model for organic shale to accurately correlate volumetric/weight concentrations of mineral/fluid constituents with physical properties measured by well logs. The following sections describe the assumed petrophysical model for organic shale and briefly explain the adapted inversion technique.

Assumed model for organic shale

Several recent publications assume a petrophysical model for organic shale which includes organic matter, nonorganic minerals (e.g., clay minerals and nonclay minerals), and total pore space (LeCompte et al., 2009; Ambrose et al., 2010; Passey et al., 2010; Quirein et al., 2010). The total pore space consists of bound water saturation, free water saturation, hydrocarbon saturation (e.g., sorbed gas and free gas saturation), and isolated pore volume. More recently, Alfred and Vernik (2012) have introduced a new petrophysical model for organic shales, which invokes two independent pore systems: organic porosity and inorganic porosity.

Figure 1 describes the petrophysical model assumed in this paper to conduct inverse/forward numerical
Joint inversion of multiple well logs to assess shale petrophysical and compositional properties

The main reasons for the choice of fast nonlinear joint inversion of bed physical properties are (a) algorithmic efficiency in the presence of thin beds, (b) negligible mud-filtrate invasion in organic shale, (c) reliable quantification of nonlinear effects of mineral and fluid constituents on conventional well logs, and (d) fast bed-by-bed joint inversion of bed physical properties.

The adapted organic-shale interpretation method begins with preanalysis of well logs such as density, neutron porosity, electrical resistivity, photoelectric factor (PEF), natural GR, and spectral GR logs. Preanalysis includes data quality control, depth shifting, and the assessment of formation mineral/fluid types and properties. Bed boundary locations are subsequently detected based on any desired combination of well logs or image logs. In this paper, bed boundary locations are chosen based on inflection points of density, PEF, or image logs. The next step is separate inversion of well logs, which yields bed and array-induction apparent resistivity logs. The next are chosen based on inflection points of density, PEF, or image logs. In this paper, bed boundary locations are subsequently de-

Joint inversion of multiple well logs to assess shale petrophysical and compositional properties

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Finally, we implement a nonlinear joint inversion algorithm on the previously estimated bed physical properties to estimate volumetric concentrations of solid and fluid constituents. This is accomplished with the minimization of the layer-by-layer quadratic cost function given by

\[
C(\mathbf{x}) = \| \mathbf{W}_d \cdot [\mathbf{p}(\mathbf{x}) - \mathbf{p}_m]\|_2^2 + \alpha^2 \| \mathbf{x} \|_2^2,
\]

subject to

\[
0 \leq x_i \leq 1,
\]

and

\[
\sum_{i=1}^{n_b} C_i + C_k + \phi_i = 1.
\]

where \( \mathbf{W}_d \) is a data-weighting matrix, \( \mathbf{p}(\mathbf{x}) \) is the vector of physical properties in each bed (e.g., density, PEF, Ur, Th, and K concentrations, neutron migration length, and deep electrical conductivity), \( \mathbf{p}_m \) is the vector of model physical properties estimated from separate inversion of well logs in each bed, \( \alpha \) is a regularization (stabilization) parameter, \( n_b \) is the predefined number of clay and nonclay mineral constituents, \( C_i \) is volumetric concentration of the assumed clay and nonclay mineral constituents, \( C_k \) is volumetric concentration of kerogen, \( \phi_i \) is total porosity, and \( \mathbf{x} \) is the vector of unknown formation properties, given by

\[
\mathbf{x} = [C_1, C_2, \ldots, C_{n_b}, C_k, \phi_1, S_w]^T,
\]

where \( S_w \) is total water saturation and the superscript \( T \) designates transpose. The vector of numerically simulated layer-by-layer physical properties is given by

\[
\mathbf{p} = [L_{ni}, \rho_b, \text{PEF}, \sigma, \text{Ur, Th, K}]^T.
\]

where \( L_{ni} \) is neutron migration length, \( \rho_b \) is bulk density, and \( \sigma \) identifies the apparent deep electrical conductivity logs.

We control the importance of each well log/physical property included in the inversion using the data-weighting matrix in equation 1, given by

\[
\mathbf{W}_d = \begin{bmatrix}
W_{d,1} & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & W_{d,n_b}
\end{bmatrix},
\]

where \( n_b \) is the number of available well logs and \( W_i \) is written as

\[
W_i = \frac{1}{P_{ni}}.
\]

The quadratic cost function defined in equation 1 is minimized with the Levenberg-Marquardt method (Marquardt, 1963), which requires assessment of the Jacobian matrix (partial derivatives of the entries of vector \( \mathbf{p} \) with respect to entries of vector \( \mathbf{x} \)) at each

![Figure 1. Petrophysical model for organic shale assumed in the forward/inverse numerical simulations described in this paper.](image)
linear iteration. We calculate the Jacobian matrix numerically (finite differences) using linear correlations between physical and petrophysical properties of the formation (e.g., density) and Schlumberger’s SNUPAR commercial software (McKeon and Scott, 1989) to estimate neutron migration length and PEF. The stabilization parameter in equation 1, \( \alpha \), guarantees a smooth convergence of the nonlinear minimization and is automatically selected via Hansen’s (1994) L-curve method.

Table 1. Synthetic case: Summary of assumed Archie’s parameters and fluid and formation properties.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
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<tr>
<td>Winsauer factor in Archie’s equation, ( a )</td>
<td>1.00</td>
<td>—</td>
</tr>
<tr>
<td>Archie’s porosity exponent, ( m )</td>
<td>2.00</td>
<td>—</td>
</tr>
<tr>
<td>Archie’s saturation exponent, ( n )</td>
<td>2.00</td>
<td>—</td>
</tr>
<tr>
<td>Connate-water salt concentration</td>
<td>200 kppm NaCl</td>
<td></td>
</tr>
<tr>
<td>Bound-water salt concentration</td>
<td>200 kppm NaCl</td>
<td></td>
</tr>
<tr>
<td>In situ water density</td>
<td>1.00 g/cm(^3)</td>
<td></td>
</tr>
<tr>
<td>In situ gas density</td>
<td>0.19 g/cm(^3)</td>
<td></td>
</tr>
<tr>
<td>Formation temperature</td>
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<td></td>
</tr>
<tr>
<td>Wellbore radius</td>
<td>10.16 cm</td>
<td></td>
</tr>
</tbody>
</table>

In organic-shale formations, the number of unknown shale petrophysical properties and volumetric/weight concentrations of rock/fluid constituents is usually greater than the number of available well logs, which gives rise to nonuniqueness of results. The choice of initial guess for the joint inversion becomes important to mitigate nonuniqueness. Additionally, a realistic initial guess expedites the convergence rate and, consequently, reduces CPU time. We recommend three choices for initial guess: (1) an initial guess based on XRD/core data, (2) an initial guess based on point-by-point nonlinear joint inversion (Heidari et al., 2012), and (3) an initial guess based on conventional petrophysical interpretation and linear multiminerals solvers. For the synthetic case, however, a parsimonious (constant) initial guess is chosen to test the robustness of the method.

**Synthetic case**

We construct the synthetic case based on specific petrophysical properties of a Haynesville shale-gas field example. The objective is to investigate the efficiency of our estimation method in the presence of shoulder-bed effects, complex lithology, and kerogen. It consists of a combination of layers from 1 to 10 ft thickness. Assumed mineral constituents and fluids include quartz, calcite, pyrite, illite, chlorite, plagioclase, kerogen,
water, and gas. Well logs input to the inversion are array-induction apparent resistivity, neutron porosity, density, PEF, and spectral GR (Th, Ur, and K logs). Table 1 summarizes the assumed formation properties for this synthetic case.

Figure 2 compares numerically simulated well logs, separate inversion results for each log, and actual bed physical properties assumed in the multilayer synthetic case. Although shoulder-bed effects are significant in thin beds, the relative difference between model and estimated bed physical properties is lower than 1%. There is a significant difference, however, between estimated and measured center-bed values of neutron migration length. Next, we use the estimated bed properties as inputs to the joint inversion algorithm to estimate static petrophysical properties and volumetric concentrations of mineral constituents and kerogen.

Figure 3 compares initial guess, estimated values, and actual total porosity, total water saturation, and volumetric concentrations of mineral constituents and kerogen. Error (uncertainty) bars for estimated properties in each layer were calculated by adding 5% zero-mean Gaussian random perturbations to all the well logs input to the inversion. Results indicate that the uncertainty of inversion products due to noisy data increases with decreasing layer thickness.

We then select center-bed values of each log as input to the joint inversion algorithm instead of results obtained from the separate inversion of well logs. The difference between center-bed well-log values and actual bed properties is significant for neutron porosity and electrical resistivity, where lower vertical resolution gives rise to severe shoulder-bed effects. Figure 4 compares actual volumetric concentrations of minerals, fluids, and kerogen and their estimated values obtained when choosing center-bed well-log values as inputs to the joint inversion. Neglecting shoulder-bed effects causes significant relative errors in estimates of volumetric concentrations of mineral constituents and kerogen (i.e., more than 20% relative error in estimates of kerogen compared to core measurements) across beds thinner than 3 ft.

Field example: Haynesville shale-gas formation

The field example considers a well located in the Haynesville shale-gas formation. It is selected to examine the accuracy and reliability of the introduced interpretation method for evaluation of organic-shale formations. The late-Jurassic Haynesville formation is

Figure 3. Synthetic case: Comparison of model (actual) values (black solid line), initial guess (green dashed line), and final estimates (red dashed-dotted line) of volumetric concentrations of mineral constituents, total porosity, volumetric concentration of kerogen, and total water saturation along with corresponding uncertainty bars (calculated with 5% zero-mean Gaussian random perturbations on the original synthetic well logs, including array-induction apparent resistivity, density, neutron porosity, spectral GR, and PEF). Panels from left to right show total porosity, volumetric concentrations of quartz, calcite, kerogen, plagioclase, pyrite, illite, chlorite, and total water saturation.
located in east Texas and northwestern Louisiana. It was deposited in a restricted intrashelf basin on the evolving Gulf Coast passive margin (Quirein et al., 2010; Spain et al., 2010). Mature TOC is between 2% and 5%, while clay content is usually lower than 50% (Quirein et al., 2010). Completion planning is critical in the Haynesville formation due to significant variations in mineral and petrophysical properties. Erroneous decisions about completion intervals can turn a potentially productive well into a poorly completed one (LeCompte et al., 2009).

For organic shale evaluation in this example, we use neutron porosity, density, array-induction resistivity, and PEF logs as inputs to the estimation methods. Figure 5 shows the well logs available in the selected depth interval, where the top zone is an organic-shale formation and the bottom zone is a carbonate formation. The focus of the study is on the top zone; however, we also apply the introduced method to the bottom zone to verify its accuracy and reliability.

The choice of initial guess is important in complex formations such as organic shale due to the pervasive nonuniqueness of inversion results in the presence of a large number of mineral constituents. In this field example, we choose an initial guess based on XRD data. In zones where XRD data are not available, the initial guess can be selected from results obtained with commercial/linear multiminer solvers.

Based on XRD reports and laboratory measurements, we assume that the Haynesville shale consists of nonclay minerals such as quartz, calcite, plagioclase, pyrite, and negligible amounts of dolomite, clay minerals such as illite and chlorite, and type II kerogen. XRD analysis indicates presence of some minerals with less than 2% average weight concentration. We eliminate those minerals in the estimation or lump them together with similar minerals to decrease nonuniqueness of inversion results.

Another way to reduce nonuniqueness of inversion results is to impose constraints on them. We investigate XRD data to explore possible statistical correlations among volumetric/weight concentrations of minerals. Figure 6a and 6b shows linear relationships between weight concentrations of quartz and plagioclase, and weight concentrations of illite and chlorite, respectively. We enforce these linear relationships as constraints in the joint inversion to reduce nonuniqueness and increase accuracy of results.

Figure 4. Synthetic case: Comparison of model (actual) values (black solid line), initial guess (green dashed line), and final estimates (red dash-dotted line) of volumetric concentrations of mineral constituents, total porosity, volumetric concentration of kerogen, and total water saturation. Separate inversion of well logs does not correct shoulder-bed effects. Bed properties are selected from center-bed values. Panels from left to right show total porosity, volumetric concentrations of quartz, calcite, kerogen, plagioclase, pyrite, illite, chlorite, and total water saturation.
Different rock types exhibit specific sets of formation properties, and consequently, specific sets of petrophysical properties, TOC, and mineral concentrations. Thus, rock classification is desirable in the compositional and petrophysical interpretation of organic shale. We classify rock types based on the estimated weight concentration of calcite, weight concentration of quartz, natural GR response, and porosity. Calcite and quartz are chosen because they are the most dominant minerals in the formation. Estimates of the required parameters in rock classification can be obtained from either (a) XRD/core measurements or (b) values estimated with joint inversion. We choose the second approach for the field example because XRD data are not continuous and are not available at all desired depths.

All well-log interpretation techniques, including the method described above, require a rock-physics model for correlating rock electrical resistivity to petrophysical properties such as porosity and water saturation. The reliability of conventional resistivity-porosity-saturation models in organic-rich source rocks is questionable, which makes the accuracy of interpretation results highly dependent on model calibration against core data. Despite all these uncertainties, the application of Archie’s or dual-water equations is still a common practice in the industry. We implemented the dual-water model in this paper and calibrated its parameters (Winsauer’s factor $a$, porosity exponent $m$, and saturation exponent $n$) using core measurements. Additionally, we assumed that salt concentrations of bound water and connate water were equal, which rendered the dual-water model equal to Archie’s model. Salt concentration of connate-water was assumed equal to 200 kppm of sodium chlorite equivalent based on available water samples.

To classify rock types based on inversion results, we first assume one rock type in the formation, estimate petrophysical properties, TOC, and volumetric/weight concentrations of mineral constituents via joint inversion, and perform rock typing based on those concentrations. After classifying rock types, we repeat the analysis with updated model properties for the identified rock types and improve shale petrophysical evaluation. In turn, updated results for petrophysical and compositional evaluation can later improve rock classification. Figure 7a shows a crossplot of final estimates for weight concentrations of quartz and calcite and the two classified rock types. The color bar identifies natural GR magnitude, which can be roughly correlated with the amount of clay-minerals/kerogen in some cases. The crossplots in Figure 7 show two main rock types in this formation: carbonate-rich lithofacies (i.e., rock type A) and silica-rich lithofacies (i.e., rock type B). In rock type B, weight concentration of calcite increases with a decrease in weight concentration of quartz. Natural GR magnitude and clay concentration also decrease in rock type B. Figure 7b describes the variation of porosity in addition to weight concentrations of calcite and quartz for the two rock types. Total porosity is lower in rock type B than in rock type A. Figure 8 shows the location of the two rock types. Based on rock classification, different Archie’s
parameters are assigned to rock types A and B in the estimation of properties via joint inversion.

Table 2 summarizes the assumed Archie’s parameters and matrix, fluid, and formation properties in the field example. The well was drilled with water-base mud (WBM), but we neglect the effect of mud-filtrate invasion on well logs.

Figure 8 compares the final estimates of total porosity, total water saturation, TOC, and weight concentrations of mineral constituents against estimates obtained with commercial software for multimineral analysis, XRD data, and core measurements. There is a good agreement between estimates of total porosity and total water saturation obtained with the two methods and core measurements. However, commercial software yields relative errors higher than 80% and 50% in the assessment of total porosity and total water saturation compared to core measurements, respectively. Estimates of weight concentrations of mineral constituents are also in agreement with XRD data, while commercial software overestimates weight concentration of quartz and underestimates weight concentration of calcite. Estimates of TOC obtained with joint nonlinear inversion and commercial software are in agreement with laboratory measurements. In this example, we assumed a typical chemical formula for type II kerogen in the petrophysical rock model invoked by the inversion. Estimates of volumetric/weight concentration of kerogen, and consequently, TOC, could be readily improved by adopting a more accurate chemical formula for kerogen.

Comparison of results obtained with different methods for the field example confirms the accuracy and reliability of the nonlinear inversion methods introduced in this paper for petrophysical and compositional evaluation of organic shale.

Discussions

This paper documents the application of a newly developed, inversion-based interpretation method to estimate petrophysical and compositional properties of shale-gas formations from multiple well logs. Inputs to the interpretation method are conventional well logs, such as density, neutron porosity, electrical resistivity, natural GR, spectral GR, and PEF. The method remains stable in the absence of any of these logs. However, nonuniqueness of results increases with a decrease in the number of input logs and an increase in the number of unknown formation properties. In such cases, an accurate initial guess and the enforcement of model or data constraints can improve the reliability and accuracy of results. Including additional well logs such as borehole acoustic and neutron capture spectroscopy to the inversion can decrease the uncertainty of results.

Even though, in most of the test examples, the method introduced was reliable and accurate to evaluate shale properties, presence of layers thinner than 0.914 m (3 ft) and more than 5% Gaussian random noise in well logs affected the estimates of total porosity and water saturation by more than 30% and the estimates of weight concentration of kerogen by more than 10%. We found that separate inversion of well logs can be used to diagnose dubious quality data. Well-log inversion is also helpful in detecting depth shifts in well logs. Inaccuracies in bed-boundary locations, as well as depth shifts in well logs can significantly affect inversion results (Heidari and Torres-Verdin, 2012). Furthermore, the effect of bed-boundary location on inversion results becomes significant in the presence of thin beds.

One of the advantages of the new method for petrophysical evaluation of organic shale is its efficiency and reliability in the presence of thin beds. Inversion results in beds thinner than two times the depth sampling interval of well-logging tools, however, may not be reliable. Whenever petrophysical and compositional properties of organic-shale formations change below twice the depth sampling interval of routine logging tools, the analysis will inevitably face averaging of shale properties at that scale.
Finally, we invoked dual-water and Archie’s resistivity-porosity-saturation models to correlate rock electrical resistivity with petrophysical properties. In principle, these models should not be adequate for the quantification of organic-rich source rocks without calibration of model parameters. Even though the interpretation method introduced in this paper is not dependent on calibration against core data for assessment of porosity and water saturation, it still requires calibration of the assumed resistivity-porosity-saturation model (i.e., Archie’s and dual-water models in this paper) against core porosity and saturation measurements for reliable assessment of water saturation.

Figure 7. Field example: Rock classification based on (a) estimated weight concentrations of quartz and calcite, and (b) estimated total porosity and weight concentrations of quartz and calcite for the depth interval X258.3-X301.0 m. The color bar describes GR magnitude. Two major rock types, designated as A and B, are identified in this formation.

Figure 8. Field example: Comparison of results for total porosity (seventh left-hand panel), total water saturation (eighth left-hand panel), TOC (ninth left-hand panel), weight concentrations of mineral constituents from XRD data (tenth left-hand panel), weight concentrations of mineral constituents estimated with the nonlinear joint inversion method introduced in this paper (eleventh left-hand panel), and weight concentrations of mineral constituents calculated with commercial software (twelfth left-hand panel). Panels from left to right show depth, natural GR, caliper, and density correction, array-induction apparent resistivity, neutron porosity and density, spectral GR, and PEF logs. The right-hand panel describes the two rock types inferred in this formation.
Table 2. Field example: Summary of assumed Archie’s parameters and matrix, fluid, and formation properties.

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<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Units</th>
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<tr>
<td>Winsauer factor in Archie’s equation $a$</td>
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<td>Archie’s porosity exponent $m$ for Rock Type A</td>
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<td>Archie’s porosity exponent $m$ for Rock Type B</td>
<td>2.00</td>
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<tr>
<td>Archie’s saturation exponent $n$</td>
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<td>—</td>
</tr>
<tr>
<td>Connate-water salt concentration</td>
<td>200 ppm NaCl</td>
<td></td>
</tr>
<tr>
<td>Bound-water salt concentration</td>
<td>200 ppm NaCl</td>
<td></td>
</tr>
<tr>
<td>In situ water density</td>
<td>1.00 g/cm³</td>
<td></td>
</tr>
<tr>
<td>In situ gas density</td>
<td>0.19 g/cm³</td>
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<tr>
<td>In situ kerogen density</td>
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<td>Formation temperature</td>
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<td>Wellbore radius</td>
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</table>

Conclusions

We successfully tested a new method for petrophysical evaluation of organic shale based on nonlinear joint inversion of multiple conventional well logs. The method estimates total porosity, volumetric/weight concentration of kerogen, and volumetric/weight concentrations of mineral/fluid constituents. It was tested on examples of synthetic measurements as well as with field data acquired in the Haynesville shale-gas formation. Accurate petrophysical and compositional evaluation makes rock classification possible in organic shale. We observed an improvement of more than 50% in estimates of total porosity and water saturation obtained with nonlinear joint inversion of well logs compared to results obtained with commercial software for multimineral analysis. The estimated porosity, water saturation, and TOC were also in agreement with laboratory measurements in field examples.

Most available commercial software for multimineral analysis requires either XRD/core data for calibration in the evaluation of lithology, or empirical relationships for assessment of TOC. The interpretation method introduced in this paper does not require empirical relationships to estimate volumetric/weight concentration of kerogen or arbitrary calibration factors. Only reliable chemical formulas for kerogen and mineral constituents are necessary to secure reliable results. Another advantage of the new organic-shale evaluation method over conventional well-log interpretation methods (e.g., commercial/linear multimineral software) or measurement techniques (e.g., neutron-capture spectroscopy) is that it implicitly reduces shoulder-bed effects on well logs in the presence of thin beds, which is a significant concern in the petrophysical evaluation of organic shale. The interpretation method introduced in this paper evaluates properties across depth intervals where well logs are available with minor preprocessing and/or calibration efforts. This feature becomes important in cases where XRD measurements and/or core data are sparse or not available.

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List of symbols

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\begin{align*}
\alpha & = \text{Winsauer factor in Archie’s equation} \\
C_i & = \text{Volumetric concentration of clay/nonclay minerals} \\
C_k & = \text{Volumetric concentration of kerogen} \\
C_X & = \text{Cost function} \\
L_m & = \text{Neutron migration length (cm)} \\
m & = \text{Archie’s porosity exponent} \\
n & = \text{Archie’s saturation exponent} \\
n_c & = \text{Number of mineral constituents} \\
n_l & = \text{Number of well logs} \\
p & = \text{Vector of simulated layer-by-layer properties} \\
p_m & = \text{Vector of model layer-by-layer properties} \\
S_w & = \text{Total water saturation} \\
U & = \text{Volumetric photoelectric cross section} \\
W_\text{ch} & = \text{Weight concentration of chlorite} \\
W_\text{ill} & = \text{Weight concentration of illite} \\
W_\text{plag} & = \text{Weight concentration of plagioclase} \\
W_\text{qtz} & = \text{Weight concentration of quartz} \\
W_d & = \text{Data weighting matrix} \\
\alpha & = \text{Regularization parameter} \\
\phi_t & = \text{Total porosity} \\
\rho_b & = \text{Bulk density (g/cm}^3\text{)} \\
\sigma & = \text{Electrical conductivity (S/m)}
\end{align*}
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LIST OF ACRONYMS

\[
\begin{align*}
\text{AT} & = \text{Array-induction two-foot resistivity} \\
\text{AIT®} & = \text{Array-induction tool} \\
\text{CPU} & = \text{Computer processing unit} \\
\text{DCAL} & = \text{Differential caliper (in)} \\
\text{FTIR} & = \text{Fourier transform infrared transmission} \\
\text{GR} & = \text{Gamma-ray (API)}
\end{align*}
\]
HDRB = Difference between bulk density and apparent density from back scatter non-sensor inversion (g/cm³)

K = Potassium (%)
kppm = Kilo parts per million

LS = Water-filled apparent limestone units

PEF = Photo electric factor (b/e)

SNUPAR = Schlumberger nuclear parameter code

T = Transpose of a matrix

Th = Thorium (ppm)

TOC = Total organic carbon (weight fraction)

Ur = Uranium (ppm)

WBM = Water-base mud

XRD = X-ray diffraction

XRF = X-ray fluorescence

References


