PETROPHYSICS, VOL. 56, NO. 2 (APRIL 2015); PAGE 147–157; 9 FIGURES

New Method to Estimate Porosity More Accurately from NMR Data with Short Relaxation Times[1]

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ABSTRACT

In conventional oilfield applications of low-field nuclear magnetic resonance (NMR), data acquisition and analysis are optimal for T_2 relaxation in the center of the spectrum, nominally between several milliseconds and several seconds. However, there are numerous applications where the measured magnetization data have short relaxation components, approaching or even below the time resolution of the downhole and/or laboratory measurement. Examples of these applications include heavy oil, organic–shale reservoirs and hydrocarbon and water in small pores. In these applications, the relaxation spectra of interest are typically a few milliseconds. Because the traditional algorithms used to analyze NMR data to estimate porosity and other petrophysical properties involving short relaxation times can be inaccurate, a new algorithm is proposed to improve the accuracy of these parameters. First, a T_2 distribution is estimated from the measured magnetization data using traditional inverse–Laplace–transform (ILT) methods. Second, a porosity sensitivity curve is computed for a given pulse sequence and a set of acquisition and inversion parameters. Third, a correction factor is derived from this sensitivity curve and applied seamlessly as part of the inversion so that the overall porosity sensitivity is more uniform at short relaxation times to obtain a modified T_2 distribution.

The efficacy of the algorithm is illustrated by Monte Carlo simulations and application on two field examples from unconventional shale reservoirs. Prediction of porosity from NMR measurements is particularly useful in unconventional reservoirs for two reasons. First, NMR measurements provide a direct estimate of effective porosity without requiring detailed knowledge of the complex mineralogy typical of shale formations. Second, the deficit between effective porosity predicted from NMR, and total porosity predicted from nuclear logs can be used to obtain accurate estimates of petrophysical quantities, such as, the kerogen content in shales and the hydrogen index in heavy-oil formations. The two field examples are from reservoirs in the Wolfberry trend in the southwestern United States. Application of the new algorithm to NMR data in the first field example results in an increase of up to 10% in porosity in zones with T_2 <10 msec. The porosity predictions from the new algorithm show improved correlation with core measurements. In the second field example, the deficit between total porosity and effective porosity predicted from NMR T_2 distributions using the new algorithm provides a more accurate estimate of the kerogen content.

INTRODUCTION

In oilfield applications of NMR to characterize petrophysical properties, low-field relaxation measurements may be dominated by short relaxation components, on the order of the time-resolution of downhole and/or laboratory tools. Typically, the tool resolution t_E varies from around 200 to 1,000 μsec, depending on the tool and whether the measurement is used in a laboratory or a field setting. Bulk relaxation of heavy oils often falls below 100 msec (see Fig. 3 in Cheng et al., 2009). Recent studies by Sondergeld et al. (2010) indicate that Barnett gas shales contain organic matter in the form of kerogen in various stages of maturation. Significant porosity is in small pores with kerogen-hosted sizes varying in diameter between 5 and 1,000 nm. This results in significant T_2 relaxation below 10 msec (see

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Fig. 3 in Sondergeld et al., 2010). Laboratory studies on Haynesville gas-shale cores also provide experimental evidence that fluid is restricted in nanopores, resulting in T_2 relaxations that are smaller than a few milliseconds (see Fig. 7 in Kaushik et al., 2011).

In oilfield applications, pulse sequences and data inversion are optimized for magnetization data that fall in the middle of the T_2 relaxation spectrum, between 50 and 500 msec. Traditionally, the sensitivity at shorter relaxation times was improved by acquiring NMR data in the enhanced precision mode (EPM). As described by McKeon et al. (1999) and Toumelin et al. (2011), this mode involves acquiring magnetization data at two or more different wait times. The data acquired with the short and long wait times are referred to as 'burst' and 'main', respectively. More recently, an improved precision of estimated porosity is obtained by acquiring data with an EPM-50 pulse sequence that involves increasing N_r, the number of repeats in the burst, thereby producing a higher signal-to-noise ratio (SNR) in the data (Hook et al., 2011).

The porosity sensitivity curve, shown in Fig. 1, is a plot of the estimated porosity obtained from applying a given pulse sequence and a set of acquisition and inversion parameters. It is a well-known technique to evaluate pulse sequences and study the effect of data acquisition and inversion on the estimated parameters. Ideally, for a perfect tool and inversion algorithm, the porosity sensitivity should be unity at all relaxation times, implying that the NMR tool sees and computes 100% of the porosity at all relaxation times.

As seen in Fig. 1, at short relaxation times (e.g., 200 to 1,000 μsec), porosity sensitivity is reduced due to finite echo spacing, which is typically on the order of 200 μsec. In this regime, the measured signal amplitude is small because the signal decayed significantly before the first data point was measured. At large relaxation times (e.g., >1 sec), porosity sensitivity is reduced due to incomplete polarization. At intermediate relaxation times, certain undulations in sensitivity are also observed; these undulations are a function of how the Laplace inversion handles the data and depends on the T_1/T_2 ratio, regularization, and SNR in the data.

Decreased sensitivity at short and long relaxation times, poor SNR in the field data, as well as nonlinear aspects of the inversion pose challenges in estimation of parameters from the measured data. The objective of this paper is to describe a method to more accurately estimate parameters, such as, porosity, logarithmic-mean T_2 and bound fluid volume, from measured data at short relaxation times. For a set of acquisition and inversion parameters, our aim is to characterize the sensitivity curve for the parameter and use the curve to modify the sensitivity such that the resulting parameter is more accurate over the range of the T_2 relaxation domain.

This paper is organized as follows. We propose a method for improved porosity estimation in the next section. Simulations discussed in the following section compare the performance of the newly proposed method with the traditional inverse–Laplace–transform (ILT)–based algorithm. We show that the new method enhances the accuracy while marginally decreasing the precision of the estimated porosity. In general, we find that the new algorithm offers enough improvement in porosity to offset the decrease in precision. When this method is coupled with the EPM-50 pulse sequence proposed by Hook et al. (2011), the estimated porosity has enhanced accuracy as well as precision. In the last section, we describe application of this method to field data. We use case studies to demonstrate how the improved accuracy and precision of the estimated porosity provides a better estimate of the kerogen content of the formation.

PROPOSED METHOD

The porosity sensitivity curve is a plot of the estimated porosity obtained from applying a given pulse sequence to the NMR tool, and using a set of acquisition and inversion parameters on the received signal, obtained as follows. For each location of the Dirac-delta function in the T_2 domain, the magnetization data with 100% porosity are simulated with white Gaussian noise with zero-mean and standard deviation σ. The SNR for the 'main' part of the dataset is $1/\sigma$. The simulated and noisy NMR data are then analyzed by an algorithm, such as ILT to estimate the T_2 distribution $\phi(T_2)$ (Bachman et al., 2007). The ILT method involves minimizing a cost function Q with respect to a non-negative T_2 distribution f,

$$Q = \|G - Lf\|^2 + \alpha \, \|f\|^2, \tag{1}$$

where G is a vector representing the measured EPM data, L is the matrix relating the T_2 distribution to the NMR measurement, and f is the discretized vectorized version of the underlying 'binned porosity' $\phi(T_2)$, referring to the estimated T_2 distribution for a specified relaxation time T_2. The first term in the cost function is the least-squares error between the data and the fit. The second term is referred to as the regularization and incorporates smoothness in the expected relaxation amplitudes. The parameter α denotes the compromise between the fit to the data and an a priori expectation of the distribution. In Eq. 1, α is the weight given to the regularization and can be chosen by a number of different methods (Galatsanos and Katsaggelos, 1992). The total NMR porosity is the sum of the porosity over all

T_2 bins. Thus, the relative error (or bias) in porosity at a particular relaxation time T_2 is

$$B(T_2) = \langle \phi(T_2) \rangle - 1, \quad (2)$$

where the average $\langle\ .\ \rangle$ is computed over many different realizations of noise. For a set of acquisition and inversion parameters, the bias B is computed as the location of the Dirac-delta function systematically scans the T_2 spectrum and is therefore a function of T_2.This bias can be used to compute a correction factor as follows.

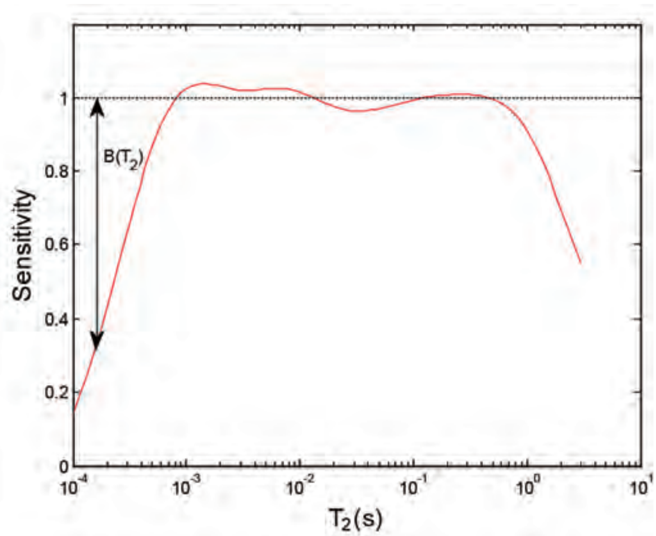

Fig. 1—Porosity sensitivity curve obtained on data simulated with echo spacing of 200 µsec. The 'main' data have 1,000 echoes and a wait time of 10 sec and has a SNR of 5. The 'burst' data have 50 repetitions, 30 echoes, and a wait time of 20 msec. They are analyzed with the ILT with α = 10. The T_2 bins used in the data analysis are logarithmically spaced between $T_{2,min}$ = 300 µsec and $T_{2,max}$ = 3 sec.

Consider a measured magnetization decay, analyzed using the same acquisition and inversion parameters employed to derive the porosity sensitivity curve. By equating the expected error to the previously computed bias, we can get a more accurate estimate of the binned porosity at any relaxation time T_2,

$$\phi_c(T_2) = C_f(T_2)\phi(T_2), \quad (3)$$

where the correction factor

$$C_f(T_2) = \frac{1}{1+B(T_2)}. \quad (4)$$

The role of the correction factor in Eq. 4 is to increase the binned porosity where it tends to be underestimated, and to reduce the porosity where it is overestimated. This results in a more uniform sensitivity and accurate estimate of the binned and total porosity over the range of the T_2 spectrum.

An alternate expression for the correction factor can be obtained by taking into account the SNR of the T_2 distribution at a given T_2,

$$C_f(T_2) = \frac{1}{1+B(T_2)\frac{R(T_2)}{\beta\langle R(T_2)\rangle + R(T_2)}}\ \text{, where } R(T_2) = \frac{\phi(T_2)}{\sigma_{\phi(T_2)}}. \quad (5)$$

Here $R(T_2)$ corresponds to the SNR of the T_2 distribution for a given T_2 and β is a scalar whose magnitude is typically on the order of unity and average $\langle\ .\ \rangle$ is computed over T_2. The parameter $\sigma_{\phi(T2)}$ refers to the uncertainty in each bin of the T_2 distribution (Prange et al., 2009). Thus, the resultant porosity obtained from the traditional algorithm and proposed algorithm is,

$$\phi = \textstyle\sum_{T_2}\phi(T_2) \text{ and } \phi_C = \sum_{T_2}\phi_C(T_2) \quad (6)$$

Some features of the proposed correction factor $C_f(T_2)$ in Eq. 5 are:

1. The factor $\frac{R(T_2)}{\beta\langle R(T_2)\rangle + R(T_2)}$ tends to serve as a regularization parameter and takes values between 0 and 1. When $R(T_2)$ is small compared to the average, this factor is close to 0. When $R(T_2)$ is larger than the average, this term is close to 1.
2. Although this correction factor can be applied throughout the T_2 spectrum, the objective in this manuscript is to apply it to fast relaxing data. Therefore, the correction factor is only applied at relaxation times between the echo spacing and a few milliseconds. For relaxations larger than a few milliseconds, the correction factor is unity.
3. Relaxation times smaller than the echo spacing of the tool are within the null space of the forward mapping of the tool. They are invisible to current generation downhole NMR tools.
4. The correction factor depends on the T_2 distribution. The magnitude of the T_2 distribution as well as the uncertainty in each bin dictates the exact shape of the correction factor.
5. In real-time downhole applications, the sensitivity curve must be computed relatively quickly at each depth level. When it is computed using the method described earlier in this section, it involves several nonlinear and time-consuming inversions of the forward mapping that relate the parameter space of T_2 distribution to the measured data. We found that the linear-least-squares estimate of the forward mapping to be both an accurate and fast proxy to Monte Carlo simulations. In the absence of computation on uncertainty estimates in the T_2 bins, assuming the uncertainty to be the same in all the T_2

bins provides reasonable estimates.

As the correction factor is larger than unity at short relaxation times, the error bar in the resulting overall porosity is larger than that obtained with the traditional ILT method. A central question is: Does the proposed algorithm offer sufficient improvement in porosity accuracy to offset the increase in the error-bar? We attempt to answer this question by means of simulations in the next section and show that the proposed method performs reasonably well and provides sufficient improvement in accuracy to offset the decrease in precision.

The use of the correction factor proposed in Eq. 5 is illustrated in Fig. 2. Figure 2a shows a T_2 distribution from which magnetization data are simulated in the EPM mode. The true porosity of the T_2 distribution is 11 p.u. and the simulated main and burst data with additive noise with SNR = 5 are shown in Fig. 2b. The results of the analysis on a dataset using an ILT with standard inversion parameters and α = 10 are shown in Fig. 2c. The results of the new algorithm with the same inversion parameters are also shown. It is seen that components corresponding to short relaxation times are enhanced to a small degree while the T_2 distribution at intermediate relaxation times have undergone almost negligible change. The estimated porosities from the two methods are displayed in Fig. 2d.

Let the normalized root-mean-square error (NRMSE) of the porosity be defined as,

$$NRMSE = 100\,\frac{\sqrt{(\phi-\phi_{True})^2}}{\phi_{True}}. \qquad (7)$$

One hundred different noise realizations of the data were obtained from the T_2 distribution in Fig. 2a and analyzed using the ILT and the proposed method. The mean and estimated standard deviation of the ILT-derived porosity was 10.01 ± 0.7 p.u., resulting in a NRMSE of 10.4%. The mean and estimated standard deviation of the derived porosity from the proposed method was 10.9 ± 0.8 p.u., resulting in a lower NRMSE of 7.6%.

SIMULATION

In this section, we demonstrate the performance of the algorithm on simulated data in the presence and absence of short relaxation components. We also show results on data at different SNRs and discuss the effect of acquisition parameters.

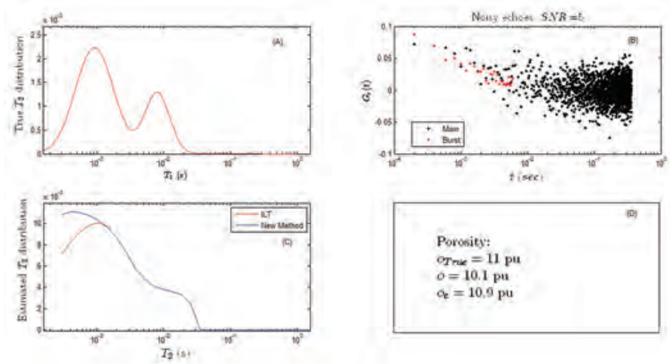

Fig. 2—(a) T_2 distribution from which data are simulated in the EPM mode with SNR = 5. (b) Simulated data have an echo spacing of 200 msec, a main Carr-Purcell-Meiboom-Gill sequence (black dots) with 1,800 echoes and a wait time of 2.4 sec, and a burst (red dots) with 10 repetitions, 30 echoes, and a wait time of 20 msec. (c) Estimated T_2 distribution from the ILT and new method, obtained with α = 10 assuming 30 bins for the T_2 distribution logarithmically spaced between $T_{2,min}$ = 300 μsec and $T_{2,max}$ = 3 sec.

Analysis of Data with Short and Intermediate Relaxation Times

Data are simulated from the five T_2 distributions shown in Fig. 3. For simplicity, all distributions have a total porosity of 20 p.u. The EPM pulse sequence is used with 1,800 and 30 echoes in the main and burst, respectively. The wait times are 2.4 sec and 20 msec, respectively. There are 10 repeats in the burst. The SNR of the ‘main’ in these datasets is 5, representing challenging NMR conditions in the field data.

These data are analyzed using the ILT and the newly proposed method. Default inversion parameters are used for inversion with the ILT with 30 bins in the T_2 domain, $T_{2,min}$ = 0.3 msec, $T_{2,max}$ = 3 sec and an automated regularization parameter (Butler et al., 1981; Galatsanos and Katsaggelos, 1992). In the new algorithm, the parameter $\sigma_{\phi(T_2)}$ in Eq. 5 was considered to be the same in all T_2 bins. Data from 100 different datasets obtained with different realizations of noise from each of the five models are analyzed to estimate the mean accuracy and precision in porosity. These parameters for the five models when analyzed with ILT (red) and proposed method (blue) are shown in Fig. 3b. The x-axis is akin to inaccuracy and the y-axis represents imprecision in porosity. For example, for Model No. 5 (M5), the inaccuracy in porosity using the ILT method is 10%. The imprecision in porosity is 6%.

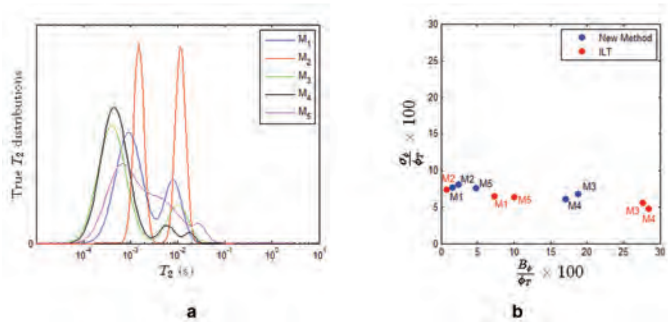

Fig. 3—(a) Five T_2 distributions with 20 p.u. porosity from which data are simulated in EPM mode with SNR = 5. (b) 100 datasets obtained with different noise realizations from each of the five models in (a) are analyzed with ILT and new algorithm. The relative error (inaccuracy) and uncertainty (imprecision) in porosity are shown. An ideal estimator yielding infinitely accurate and precise porosity would be at the origin of this plot.

Comparing the performances of the ILT and the new algorithm, we make two observations. First, the proposed algorithm decreases the inaccuracy in porosity. For example, for Model No. 5, the inaccuracy in porosity decreases from 10 to 5%. Second, the proposed algorithm increases the imprecision in porosity. For Model No. 5, the imprecision increases from 6 to 7%. Because the improvement in accuracy sufficiently offsets the decrease in precision, we conclude that the algorithm is performing reasonably well.

Increasing the Number of Repeats in the Burst Improves Precision

The EPM-50 sequence proposed by Hook et al. (2011) suggests increasing the number of repeats in the burst, N_r, from the default value of 10 to 50. A larger number of repeats leads to increased SNR in the burst. The porosity sensitivity curves in Fig. 4a show that increasing N_r results in an increase in accuracy and a decrease in the error bar at short relaxation times. This is also demonstrated in our simulations. Data are simulated from the five T_2 distributions shown in Fig. 3a with the same acquisition parameters as before, but with 50 repeats in the burst. They are analyzed using the ILT and the new algorithm.

The relative average inaccuracy and imprecision obtained from analysis of 100 datasets obtained with different noise realizations from each model are shown in Fig. 4b. It is seen that the new algorithm increases the accuracy while also marginally decreasing the precision in porosity. The increase in accuracy is much larger than the decrease in precision. Fig. 3b is obtained on data with 10 repeats in the burst while Fig. 4b is obtained on data with 50 repeats in the burst. Comparing Figs. 3b and 4b, it is seen that increasing N_r significantly improves the precision (reduce uncertainty) of estimated porosity for both the ILT and new algorithm. It also has a modest improvement on the accuracy. Thus, the EPM-50 sequence significantly increases the porosity precision while use of the method proposed in this manuscript helps improve the accuracy. Combining the new algorithm with data obtained from EPM-50 pulse sequence can help improve both the accuracy and precision of porosity estimates.

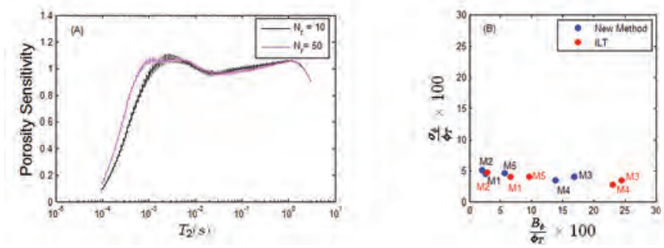

Fig. 4—(a) The sensitivity curve for 10 and 50 repetitions of the burst shows that increased repetitions in the burst enhances the SNR of the measured burst and therefore enhances the porosity accuracy and precision. (b) Data from T_2 distributions in Fig. 3a with 50 repeats in the burst are analyzed with the ILT and the new algorithm. The new algorithm is seen to improve the accuracy. Comparing this to Fig. 3b, it is also observed that increasing the number of repeats in the burst significantly increases the precision in porosity.

Analysis of Data with High SNR

The simulation results described in the above subsection hold for high-quality laboratory data as well. The EPM data simulated from the five T_2 distributions in Fig. 3a with SNR = 50 were analyzed with the ILT and the proposed algorithm and the results are shown in Fig. 5. It is observed that similar to analysis of lower SNR data, using the proposed algorithm improves the accuracy of the estimated porosity for high SNR data as well.

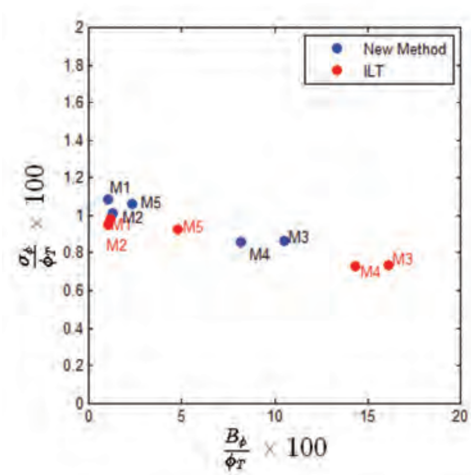

Fig. 5—Analysis of simulated data with high SNR. Data are simulated from each of the five models in Fig. 3a. The SNR of the data is 50. They were analyzed with the ILT and the new algorithm. The new algorithm is observed to increase the accuracy in porosity while marginally decreasing the precision.

Analysis of Data with No Short and Intermediate Relaxation Times

Consider the five T_2 distributions, each with porosity of 20 p.u. shown in Fig. 6a. These distributions have significantly larger relaxation times than the distributions in Fig. 3a. We expect the new method to marginally change the estimated porosity. To test this hypothesis, EPM data are simulated from these models with SNR = 5.

The simulated data are analyzed using ILT and the new algorithm. Default analysis parameters are used with automated regularization. The mean relative error and uncertainty obtained from analysis of 100 different datasets simulated from each of the five models is summarized in Fig. 6b. As expected, it is seen that both methods are comparable for most models and there is no significant statistical difference between the two analysis methods. The only exception is Model B (Fig. 6b), which is provided as a reference and has significant short relaxation times. Thus, for this model, the new algorithm provides a more accurate and less precise estimate of porosity. Thus, the benefit of this algorithm is restricted to T_2 distributions that have significantly short relaxation times.

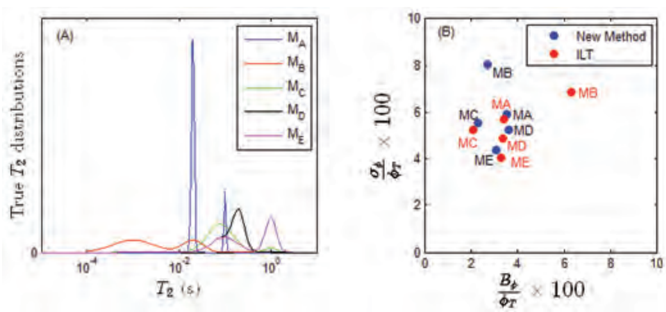

Fig. 6—Analysis of data with little or no short relaxation times. (a) Five T_2 distributions from which data are simulated in the EPM mode with SNR = 5. (b) The inaccuracy and imprecision obtained from analysis of 100 different datasets from each model are shown. It is seen that the new algorithm does not appreciably modify the accuracy or precision of estimated porosity.

Application to Field Data

The new algorithm was applied to two field datasets.

Case Study I: Kerogen Volume in the Permian Basin. This is an example from a well in the Permian basin, West Texas, drilled through Sprayberry and Wolfcamp formations. The section presented here represents organic-rich shale with some zones containing high fractions of carbonate minerals.

In unconventional reservoirs the kerogen content of the rock is a critical parameter providing an understanding of the hydrocarbon resource. The total kerogen content across the completion zone may have a bearing upon the well production behavior. Hence the availability of this parameter in a timely manner is important. Several log-based methods are used in the industry to estimate kerogen. Since it has a lower density (1.1 to 1.4 g/cm^3) as compared with other common sedimentary rock lithology, its presence in a sedimentary rock reduces its bulk density. The Schmoker method (Schmoker and Hester, 1983) relies mainly on this density contrast of the kerogen to the matrix to estimate kerogen volume, and requires local calibration. This method is the accepted standard used for the evaluation of this organic rich shale.

Alternately, kerogen can also be estimated using the porosity-deficit method as follows. The density porosity is modified to incorporate lithology effects (provided by elemental capture spectroscopy measurements). Together, with NMR porosity, MRP, this provides an evaluation of kerogen volume (Gonzalez et al., 2013),

$$Vker = \left(\frac{RHOG-RHOB}{RHOG-RHOK} - MRP\right) * \frac{RHOG-RHOF}{RHOG-RHOK}. \quad (8)$$

Here, RHOG is matrix density, RHOB is bulk density, RHOF is fluid density, and RHOK is density of kerogen. Comparison of the kerogen estimated from both methods is shown in the last track of Fig. 7. Both methods have their own challenges and the accuracy of the estimated kerogen volume depends on many factors. The Schmoker method requires local calibration of the empirical parameters, which are often unknown. The NMR deficit method assumes that the NMR porosity accounts for all nonkerogen fast relaxing fluid components. In general, we observe a reasonable and reassuring agreement between the estimated kerogen from two independent methods.

Case Study II: Estimation of Kerogen Volume Fraction in an Organic-Shale Reservoir. The new algorithm was also applied to log data collected in an unconventional organic-shale reservoir in West Texas (Fig. 8). The presence of nanopore systems (Loucks et al., 2012) in this type of reservoir typically shows very short relaxation times, on the order of few milliseconds. Quantification of TOC is critical to the evaluation of organic shales because it can be related to the reservoir quality of gas shales because the producible pore fluids are contained within the organic matter (Ambrose et al., 2010).

Over the depth interval shown in Fig. 8, the new algorithm shows an increased NMR porosity of up to 1 p.u. in the second track from the right (MRP_DIFF_FARE). In the last track, the TOC content measured in the lab on sidewall cores is displayed. The weight scales have been adjusted using a commonly used factor of 1.2 to relate the kerogen mass to carbon mass (Tissot and Welte, 1978). The match between core and estimated kerogen volume is generally quite good. A third independent TOC measurement from a new spectroscopy tool that measures carbon (Radtke et al., 2012) also shows a good agreement with the estimated kerogen volume.

In our case study, the agreement between core data and this TOC method can be evaluated by computing the average absolute deviation (AAD). Figure 9 shows a crossplot comparing core TOC to NMR log-derived TOC with a computed ADD on the order of 25%.

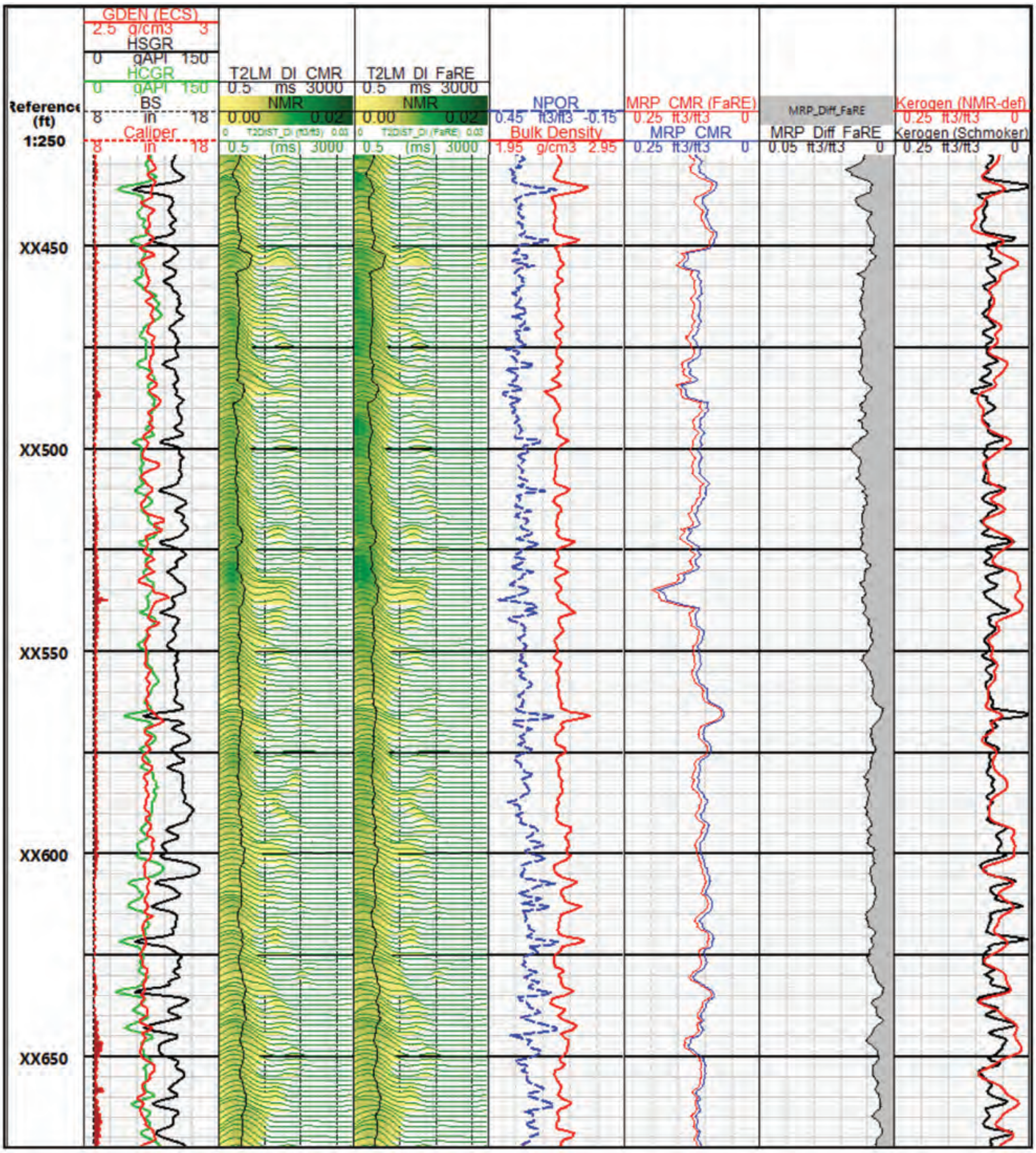

Fig. 7—Case Study I. Track 1 is the gamma ray and caliper. Tracks 2 and 3 from the left are the T_2 distributions of the traditional and the proposed NMR algorithms respectively. Track 4 shows the neutron and bulk density porosity. Track 5 shows the NMR porosity from the traditional (red) and proposed (blue) algorithms. The difference between the two is shown Track 6. Track 7 shows the kerogen estimated from the Schmoker (black) and the NMR deficit (red) methods.

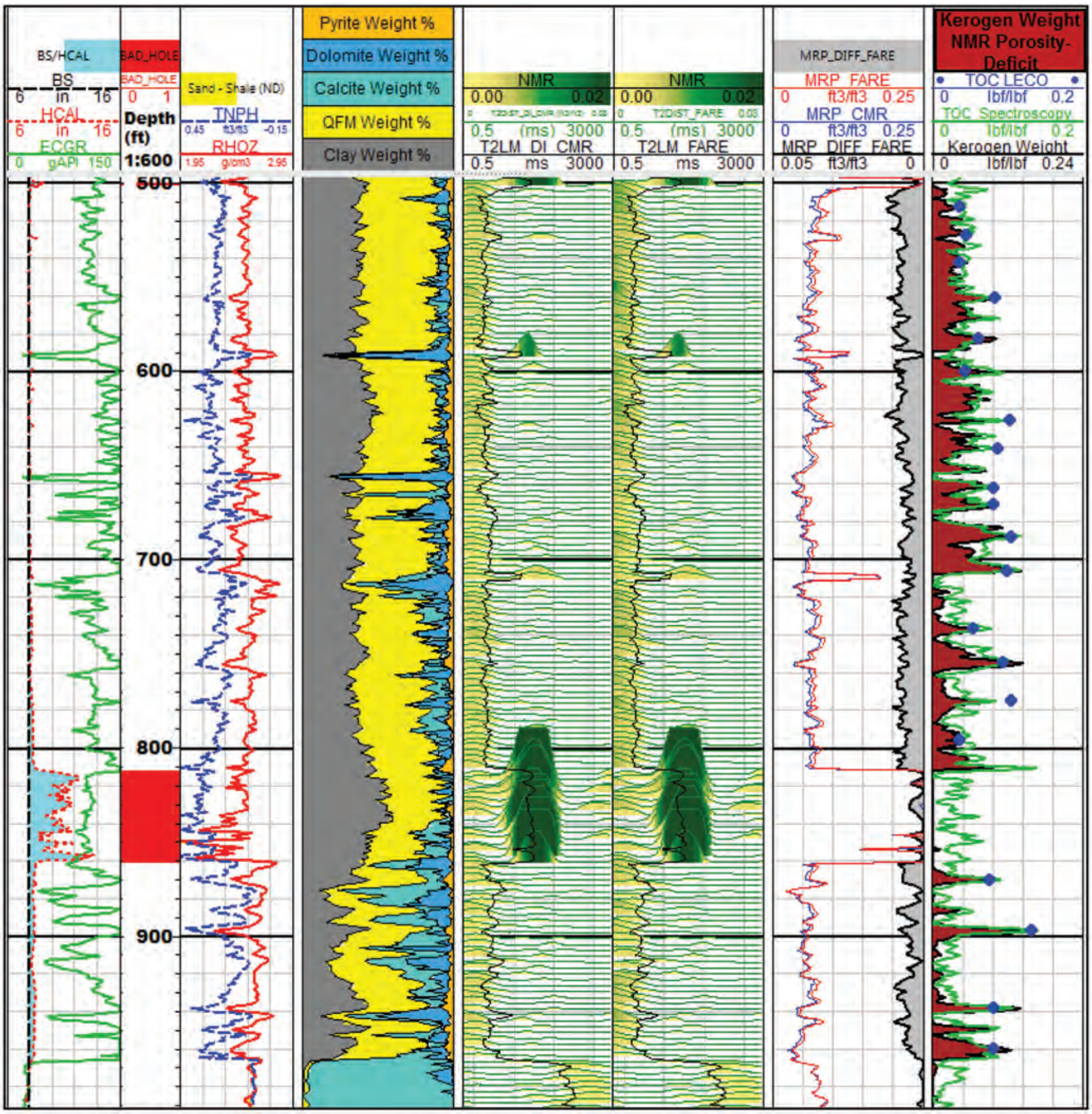

Fig. 8—Case Study II: The first three tracks from the left are gamma ray and neutron density followed by a mineral solver solution. Tracks 4 and 5 are the T_2 distributions of the traditional and the proposed NMR algorithms respectively. The large relaxation times between 810 and 850 ft correspond to a washout. The porosities from the traditional and proposed algorithm are displayed in Track 6. The difference in porosity between the two algorithms is labelled MRP_DIFF_FARE. Track 7 shows the kerogen estimated from the NMR deficit method as well as TOC from estimated from spectroscopy core TOC.

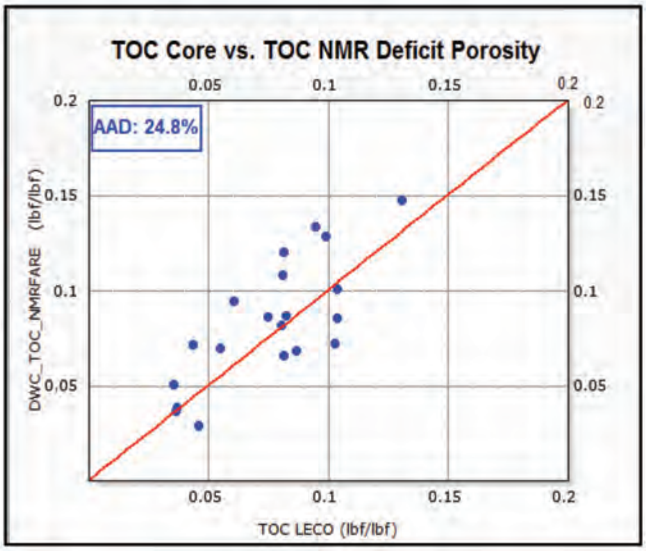

Fig. 9—There is a strong correlation between log-derived TOC (using the NMR deficit method with the proposed algorithm used to calculate NMR porosity) and core TOC (LECO) in the horizontal axis. Average absolute deviation (AAD) is also displayed.

SUMMARY

T_2 relaxation in unconventional resources such as oil shales, gas shales, shale oil, heavy oils, and tight sandstones can be on the order of the echo spacing of the downhole measurement. In these cases, we demonstrate that the traditional ILT-based algorithm used to analyze NMR data may underestimate the total porosity.

We propose a new algorithm to improve the accuracy of NMR porosity. The new algorithm uses a correction factor derived from the porosity sensitivity curve to estimate a more accurate T_2 distribution at short relaxation times. The T_2 distribution at relaxation times greater than a few milliseconds is unaffected. The algorithm was benchmarked on simulated data. When the data have short relaxation times, the proposed algorithm increases the accuracy and decreases the precision in estimated porosity. However, the increase in accuracy seems to be sufficiently significant to offset the decrease in precision. When the data do not have short relaxation times, the algorithm does not appreciably change the estimated T_2 distribution.

The proposed algorithm is illustrated by application to two field examples from unconventional shale reservoirs in the southwestern United States. Application of the new algorithm to NMR data in the first field example results in an increase of up to 10% in porosity in zones with T_2 <10 msec. The porosity predictions from the new algorithm show improved correlation with the core measurements. In the second field example, the deficit between total porosity and effective porosity predicted from NMR T_2 distributions using the new algorithm provides a more accurate estimate of the kerogen content. It was found to be consistent and in reasonable agreement with the Schmoker method of estimating kerogen.

The proposed algorithm complements the EPM-50 sequence proposed to increase sensitivity at short relaxation times (Hook et al., 2011). Our simulations show that the EPM-50 sequence increases the porosity precision while use of method proposed in this manuscript helps improve the accuracy.

NOMENCLATURE

T_1 = longitudinal relaxation time (sec)
T_2 = transverse relaxation time (sec)
f = T_2 distribution
α = regularization parameter
$B(T_2)$ = the relative error in porosity at relaxation time T_2
$\phi(T_2)$ = binned porosity at relaxation time T_2
$\phi_c(T_2)$ = corrected porosity at relaxation time T_2
$C_f(T_2)$ = correction factor at relaxation time T_2
$\sigma_{\phi(T_2)}$ = uncertainty in the porosity at relaxation time T_2

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