Petrophysical rock classification in the Cotton Valley tight-gas sandstone reservoir with a clustering pore-system orthogonality matrix

Chicheng Xu1 and Carlos Torres-Verdín2

ABSTRACT

Petrophysical rock classification is an important component of the interpretation of core data and well logs acquired in complex reservoirs. Tight-gas sandstones exhibit large variability in all petrophysical properties due to complex pore topology resulting from diagenesis. Conventional methods that rely dominantly on hydraulic radius to classify and rank reservoir rocks are prone to rock misclassification at the low-porosity and low-permeability end of the spectrum. We introduce a bimodal Gaussian density function to quantify complex pore systems in terms of pore volume, major pore-throat radii, and pore-throat radius uniformity. We define petrophysical dissimilarity (referred to as orthogonality) between two different pore systems by invoking the classic “bundle of capillary tubes” model and subsequently classify rocks by clustering an orthogonality matrix constructed with all available mercury injection capillary pressure data. The new method combines several rock textural attributes including porosity, pore-throat radius, and tortuosity for ranking reservoir rock quality in terms of flow capacity. We verify the new rock classification method with field data acquired in the Cotton Valley tight-gas sandstone reservoir located in the East Texas basin. The field case shows that the new method consistently identifies and ranks rock classes in various petrophysical data domains, including porosity-permeability trends, pore-size distribution, mercury injection capillary pressure, and NMR transverse relaxation time ($T_2$) spectra. Relative permeability curves, which are difficult to measure in the laboratory for tight rocks, are quantified with Corey-Burdine’s model using the bimodal Gaussian pore-size distribution and are validated with core data.

INTRODUCTION

Petrophysical rock classification is one of the most important and fundamental steps in the interpretation of core data and well logs (Archie, 1950, 1952). Consistent rock classification among different physical measurements ensures an optimal selection of petrophysical parameters in various interpretation models (Xu, 2013). One classic example is Archie’s equation, which relates porosity, water saturation, and electrical resistivity. In Archie’s original equation, three free parameters, namely $a$, $m$, and $n$ need to be assigned values for a wide range of rocks. Using a set of fixed $a$, $m$, and $n$ values for all rock types leads to uncertainty in water saturation estimation, which may subsequently have a sizable impact on hydrocarbon reserves interpretation. Similar problems arise in permeability estimation with Timur-Tixier’s empirical model (Tixier, 1949; Timur, 1968) and saturation-height modeling (Xu and Torres-Verdín, 2012). Petrophysical rock classification provides an effective solution to mitigate this challenging problem by assigning a given set of petrophysical parameters to each rock class.

Archie (1950) defined petrophysical rock type based on the associated pore-size distribution, which acts as the hub linking the rock’s static and dynamic petrophysical properties (Figure 1). Numerous core-based rock classification methods have been advanced during the past decades, including Leverett’s reservoir quality index (RQI) (Leverett, 1941), Winland’s $R_{35}$ (Pittman, 1992), and the flow zone indicator (FZI) (Amaefule et al., 1993). However, these methods tend to use only one major pore system attribute — hydraulic radius — to classify rocks (Xu and Torres-Verdín, 2012). Even though such procedures have proven reliable and practical in many conventional reservoirs where one major petrophysical attribute satisfactorily describes the entire pore system, they become inadequate to quantify complex pore systems.
originating from diagenetic overprint, such as those of carbonate and tight-gas reservoirs (Lucia, 1995; Rushing et al., 2008). New methods for describing complex pore systems are needed for reliable petrophysical rock classification.

Mercury injection capillary pressure data (MICP) have been widely used in pore system characterization (Purcell, 1949; Peters, 2012). Several authors (Clerke, 2009; Gao et al., 2011) have documented work on using multiple Thomeer's (1960) hyperbolas to fit MICP to describe complex carbonate rock pore systems. This procedure implicitly invokes the derivative of Thomeer's hyperbolas (referred to as Thomeer's derivative) as the pore-size distribution function. Xu and Torres-Verdín (2013a) have introduced a bimodal Gaussian density function to characterize pore-size distributions in terms of incremental pore volume versus logarithmic pore-throat radius, which gives rise to six attributes of interpretable petrophysical meaning. An important remaining piece of work is to define the petrophysical dissimilarity (conceptualized as petrophysical orthogonality in this paper) between two pore systems based on all relevant attributes for a petrophysically consistent rock classification.

In this paper, we use bimodal Gaussian density functions to quantify complex pore systems in terms of pore volume, major pore-throat radii, and pore-throat radius uniformity. Six attributes for each density function are estimated and interpreted for petrophysical meaning and subsequently integrated to assess petrophysical orthogonality between two pore systems. We introduce a new petrophysical rock classification method by clustering an orthogonality matrix after fitting MICP data, which provides improved ranking of rock types as compared to existing rock classification methods and enforces petrophysical consistency among various static and dynamic petrophysical properties, including saturation-dependent capillary pressure and relative permeability. We apply the new method to field data acquired in the Cotton Valley tight-gas sandstone reservoir located in the East Texas basin.

Reservoir quality ranking in tight rocks: Leverett versus Winland's $R_{35}$ versus FZI

Existing core-based petrophysical rock classification methods tend to rely dominantly on hydraulic radius to rank reservoir rocks (Xu and Torres-Verdín, 2012). Among these methods, only Winland's $R_{35}$ is a direct derivative from MICP data. When MICP data are not available, all rock-classification methods adopt similar mathematical formulas to quantify reservoir quality in terms of porosity and permeability. Although such procedures are reliable and practical for conventional reservoirs where the same rock type exhibits narrow variability in porosity (Xu and Torres-Verdín, 2012), they can lead to misclassifications in cases of low-porosity and low-permeability rocks. Figure 2 shows three porosity-permeability trends (or rock types) identified by Leverett's, Winland's $R_{35}$, and FZI, respectively. They intersect at the point [10 p.u., 0.01 mD]; FZI exhibits the steepest trend, which tends to classify a rock of [2.5 p.u., 0.0002 mD] as belonging to the same group with a rock of [17 p.u., 0.5 mD]. However, these two rocks differ from each other significantly in terms of storage and flow capacity, whereby it is not petrophysically feasible to classify the two rocks into the same group. Geologically, it is very likely that these two rocks have undergone very different depositional and diageneric processes. Leverett and Winland's $R_{35}$ define flatter porosity-permeability trends compared to FZI, but still lack the ability to separate rocks with different storage capacity or effective pore volume.

It is therefore necessary to develop a new rock classification method that integrates pore volume, major pore-throat radii, and pore-throat radius uniformity to enforce petrophysical consistency among available static and dynamic properties, and which may provide a better link to diageneric facies in subsequent field studies. This requirement is particularly important for those rocks exhibiting significant pore-scale heterogeneity which leads to poor correlation between pore volume and pore-throat size distribution.
Pore-system Gaussian density function

Bimodal Gaussian density function

Pore-throat size is customarily described on a logarithmic scale due to its wide variability across several orders of magnitude (Basan et al., 1997). Therefore, all Gaussian density functions in this paper describe the distribution of pore-throat size on a logarithmic scale, i.e., log-normal distribution. A bimodal Gaussian density function is expressed as (Xu and Torres-Verdín, 2013a)

\[
p(\log R; w_1, \log \mu_1, \log \sigma_1; w_2, \log \mu_2, \log \sigma_2) = w_1 \frac{1}{\sqrt{2\pi} \log \sigma_1} e^{-\frac{(\log R - \log \mu_1)^2}{2(\log \sigma_1)^2}} + w_2 \frac{1}{\sqrt{2\pi} \log \sigma_2} e^{-\frac{(\log R - \log \mu_2)^2}{2(\log \sigma_2)^2}},
\]

where \( R \) is pore-throat radius in \( \mu m \), \( w_1 \) and \( w_2 \) are weighting coefficients for each Gaussian mode, \( \log \mu_1 \) and \( \log \mu_2 \) are the mean values of pore-throat radius on a logarithmic scale, and \( \log \sigma_1 \) and \( \log \sigma_2 \) are the corresponding standard deviations on a logarithmic scale. The petrophysical interpretation of these attributes is summarized as follows:

Pore volume: \( w_1 \) and \( w_2 \) are fractions of pore volume connected by large and small logarithmic pore-throat radius modes, respectively; \( w_1 \) correlates with residual nonwetting phase saturation during imbibition, whereas \( w_2 \) correlates with irreducible wetting-phase saturation during drainage.

Major pore: \( \log \mu_1 \) and \( \log \mu_2 \) are mean values of large and small logarithmic pore-throat radius modes, respectively; larger values indicate higher permeability and likely better pore connectivity.

Pore-throat radius uniformity: \( \log \sigma_1 \) and \( \log \sigma_2 \) are standard deviations of large and small logarithmic pore-throat radius modes, which describe the uniformity of “capillary tube sizes” (Childs and Collis-George, 1950); a larger value of standard deviation of pore-throat radius indicates lower sorting of tube sizes, hence higher tortuosity of the pore network.

Xu and Torres-Verdín (2013a) have introduced differentiation and inversion methods to derive bimodal Gaussian density functions from MICP data. The inversion method is preferred because it generates stable and smooth pore-size distribution functions. Figure 3 shows the workflow of the inversion method and Figure 4 illustrates results obtained when applying the inversion method to an example of MICP data from the Cotton Valley tight-gas field.

Permeability calculation with a “bundle-of-capillary-tubes” model

For a “bundle-of-capillary-tubes” model that exhibits a pore-size distribution function \( f \), absolute permeability can be calculated as (Peters, 2012)

\[
k = \frac{\phi}{32\sqrt{\tau}} \left[ \int_{0}^{\infty} f(\delta) \delta^4 d\delta \right] = \frac{\phi}{32\sqrt{\tau}} (\bar{R})^2,
\]

where \( \phi \) is porosity, \( \bar{R} \) is mean pore-throat radius, and \( \tau \) is tortuosity of the capillary tubes which is inversely proportional to the uniformity of capillary-tube sizes (Al-Tarawneh et al., 2009; Hirasaki, 2009). Equation 2 implies the following petrophysical interpretations:

Figure 3. Workflow used to derive a bimodal Gaussian density function by iteratively matching MICP data with an inverse approach (Xu and Torres-Verdín, 2013a).

Figure 4. Example of derivation of a bimodal Gaussian pore-size distribution from MICP using the inversion method. The left panel compares the modeled MICP with the lab-measured MICP, whereas the right panel shows the inverted bimodal Gaussian density function.
1) Permeability is linearly proportional to porosity (pore volume) given the same major pore-throat radius and pore-throat radius uniformity; 
2) Permeability is linearly proportional to the square of mean pore-throat radius given the same pore volume and pore-throat radius uniformity; 
3) Permeability is inversely proportional to the square root of tortuosity (pore-size uniformity) given the same pore volume and major pore-throat radius.

Figure 5 further describes reservoir-quality differences between rocks of different pore volume, major pore-throat radius, and pore-throat radius uniformity. For rocks with the same pore-throat size distribution but significantly different pore volume, capillary pressure curves \( P_c \) versus \( S_w \) alone cannot differentiate their reservoir quality. However, when capillary pressure is plotted against mercury-invaded pore volume, they can be easily differentiated (Figure 5c). This exercise indicates that pore volume is very important when classifying rocks based on MICP data.

**Pore-system orthogonality**

To synthesize the interpretations indicated by equation 2 for quantifying petrophysical dissimilarity between two pore systems, we implement a logarithmic transformation on both sides of equation 2 to obtain

\[
\log k = \log \phi + \log \bar{R}^2 + \log \frac{1}{\sqrt{\tau}} - 1.51, 
\]

where \( k \) is permeability, \( \phi \) is porosity, \( \bar{R} \) is mean pore-throat radius, and \( \tau \) is tortuosity. Three components, namely \( \log \phi, \log \bar{R}^2, \) and \( \log \frac{1}{\sqrt{\tau}} \), fully characterize the pore system in the data space of \( \log k \). In analogy with analytical geometry, we define petrophysical orthogonality as the \( L_1 \) norm between two rock samples of properties: \((\phi_1, \bar{R}_1, \tau_1)\) and \((\phi_2, \bar{R}_2, \tau_2)\). After substituting tortuosity \( \tau \) with the pore-size uniformity parameter, the formula is expressed as

\[
\text{ORT}_{1,2} = \left[ \log \frac{\phi_1}{\phi_2} \right] + \left[ \log \left( \frac{1}{\sqrt{\sigma_1}} \right) - \log \left( \frac{1}{\sqrt{\sigma_2}} \right) \right] 
+ \left[ \log \left( \frac{\bar{R}_1}{\bar{R}_2} \right) \right] 
= \log \left( \frac{\phi_1}{\phi_2} \right) + 2 \log \left( \frac{\bar{R}_1}{\bar{R}_2} \right) 
- 0.5 \log \left( \frac{\sigma_1}{\sigma_2} \right). 
\]

where \( \text{ORT}_{1,2} \) stands for orthogonality between two single-mode Gaussian pore-size distributions. A positive value indicates better reservoir quality, whereas a negative value indicates poorer reservoir quality. Under this definition, orthogonality has the following properties:

1) the orthogonality between two identical pore systems (if they do exist) is zero;
2) \( \text{ORT}_{1,3} = \text{ORT}_{1,2} + \text{ORT}_{2,3} \).

Figure 5. Comparison of (a) pore size distribution, (b) MICP \( P_c - S_w \) plot, and (c) MICP \( P_c \) versus mercury-invaded pore volume plot for two rock types of different pore volume (upper panel), pore-throat radius (center panel), and pore-throat radius uniformity (lower panel).

Figure 6. Orthogonality between two rocks with different bimodal Gaussian pore-size distribution functions. ORT_1: orthogonality between the large pore-throat size modes; ORT_2: orthogonality between the small pore-throat size modes.
Rocks commonly exhibit bimodal Gaussian pore-size distributions in reservoirs with significant diagenesis, such as carbonates and tight-gas sandstones. Therefore, the definition of orthogonality needs to be extended to a bimodal case. A simple way to achieve this is to define orthogonality between large and small pore-size modes separately (Figure 6). Orthogonality between large pore-size modes differentiates permeability or flow capacity while orthogonality between small pore-size modes differentiates nonmovable wetting phase saturation. Pore-system orthogonality provides a metric for quantifying the petrophysical dissimilarity between two rocks, thereby becoming an important attribute for classifying petrophysical rock types.

Field case: Cotton Valley tight-gas sandstone, East Texas Basin

The Cotton Valley formation is a tight-gas play located in Northeast Texas and Northwest Louisiana. Upper Jurassic/Lower Cretaceous Cotton Valley tight-gas sandstones have significantly contributed to U.S. gas production during the past decades. The formation is spatially heterogeneous due to complex depositional controls and diagenetic overprints (Liu et al., 2011), consisting mainly of tightly cemented, very fine- to fine-grained sandstone interbedded with mudstone, siltstone, and carbonate (Spain et al., 2011). Depositional facies are interpreted as stacked shoreface/barrier bar deposits, tidal channel, tidal delta, and inner shelf and back-barrier deposits (Wescott, 1983; Spain et al., 2011). The reservoir has an average porosity lower than 10% and permeability in the microdarcy range.

To enable high-resolution reservoir description, comprehensive core samples and associated laboratory measurements were acquired from a key study well — TW George 8H (Liu et al., 2011; Spain et al., 2011). Routine core porosity and permeability measurements were performed on more than 200 core plugs. In addition, high-pressure MICP (0–60,000 psi) and NMR measurements were conducted on thirty preserved core plugs covering a range of depositional facies from a continuous full-diameter whole core.

Core data show large variability in all petrophysical properties, which renders petrophysical modeling and rock classification very difficult. In our study, we first model pore-size distributions with bimodal Gaussian density functions for all core-measured MICP curves and then assess petrophysical orthogonality between each core sample pair. A new petrophysical rock classification method is proposed to classify these complex tight-gas sandstones by clustering the orthogonality matrices to simplify reservoir description. Rock classification results are then used to rank other petrophysical properties, including porosity-permeability trends, pore-size distribution, MICP, and core NMR T2 spectra.

Pore-size distribution modeling

We apply the inversion method to estimate bimodal Gaussian pore-size distributions from 30 MICP curves. Histograms of the six Gaussian attributes (Figure 7) indicate that rocks exhibit extreme variability in all petrophysical properties. We observe that the standard
deviation of the logarithmic large pore-throat radius mode is much smaller than that of the small pore-throat radius mode, thereby suggesting that most rocks in this study have a narrowly distributed dominant pore-throat size.

**Rock classification by clustering orthogonality matrices**

After fitting all MICP curves, we assess the petrophysical orthogonality between each core sample pair using equation 4 for large and small pore-size modes, which are summarized in the form of 30 × 30 matrices, as shown in Figure 8. Diagonal elements of orthogonality matrices are all zero. Red and blue colors identify large petrophysical orthogonality in positive and negative domains, respectively. For example, samples 17–19 exhibit the lowest reservoir quality, whereby a blue color belt is observed in the map (highlighted in the red dashed boxes). The matrix ranks all core samples in terms of reservoir quality and hence becomes suitable for petrophysical rock classification. We apply a dissimilarity matrix clustering technique (Hahsler and Hornik, 2011) to the orthogonality matrices and classify the 30 core samples into five rock types, denoted as A, B1, B2, C, and D with descending reservoir quality.

In the following sections, we use the rock types to rank different petrophysical data, including porosity-permeability trends, pore-size distribution, MICP, and core NMR T2 spectra. Relative permeability curves are described for each reservoir facies using Corey-Burdine’s model and based on the associated bimodal Gaussian pore-size distribution.

**Ranking porosity-permeability**

We use the classification results obtained from clustering orthogonality matrices to color-code the porosity-permeability crossplot (Figure 9). Distinct porosity-permeability trends emerge for all rock types. Table 1 summarizes the statistics of porosity and permeability. For comparison, Figure 10 shows the same porosity-permeability crossplot ranked with rock types classified from MICP-derived Winland’s R35. Two rock samples of extremely low porosity (highlighted with a dashed red circle) are classified as the rock type of the best reservoir quality (rock type A). In fact, the two samples exhibit a very small pore volume but very large pore-throat size, which may deserve the inclusion of a new rock type in detailed reservoir analysis. Another hypothesis is that these two core samples might be fractured, whereby their permeability values are not representative of in situ conditions. No matter what the actual rock conditions are, the new pore-system orthogonality ranking criteria segregated these two samples because of the weight assigned to pore volume (highlighted with a dashed pink circle in Figure 9). In our study, to keep the number of rock types manageable, we still classify them as rock type B2 based on overall reservoir quality instead of only invoking hydraulic radius in the classification.

**Table 1. Statistical distributions of porosity, permeability, and NMR T2LM for each rock type classified from MICP data.**

<table>
<thead>
<tr>
<th>Rock Type</th>
<th>Porosity (p.u.)</th>
<th>Permeability (10^-3 mD)</th>
<th>T2LM (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>7.1 ± 1.3</td>
<td>70 ± 48</td>
<td>29.5 ± 26.6</td>
</tr>
<tr>
<td>B1</td>
<td>6.5 ± 2.6</td>
<td>9.0 ± 4.0</td>
<td>7.16 ± 2.65</td>
</tr>
<tr>
<td>B2</td>
<td>5.3 ± 2.7</td>
<td>6.0 ± 2.0</td>
<td>5.0 ± 1.54</td>
</tr>
<tr>
<td>C</td>
<td>5.2 ± 1.4</td>
<td>0.76 ± 0.03</td>
<td>1.9 ± 0.7</td>
</tr>
<tr>
<td>D</td>
<td>2.6 ± 1.0</td>
<td>0.0025 ± 0.001</td>
<td>0.93 ± 0.29</td>
</tr>
</tbody>
</table>

**Figure 9.** Porosity-permeability crossplot ranked with rock types detected and classified from the clustering orthogonality matrices.

**Figure 10.** Porosity-permeability crossplot ranked with rock types classified from MICP-derived Winland’s R35. The two points highlighted within the red dash circle are classified as the best rock type despite their extreme low porosity. In reality, these two core samples might be fractured and their measured permeability may not be representative. The latter hypothesis has more evidence support in Figures 11 and 12.
The industry standard, high-pressure (0–60,000 psia) MICP was used to assess pore-throat size and total pore volume of core plugs. We used classification results to color-code MICP data and the associated pore-size distribution (in terms of incremental pore volume versus logarithmic pore-throat size). Figure 11 shows the ranked MICP data in the form of $P_c$ versus $S_w$, where MICP curves of rock type B1 and rock type B2 intermix with each other. However, when MICP data are plotted in the form of $P_c$ versus invaded pore volume (Figure 12), MICP curves of rock type B1 and rock type B2 separate well. Figure 13 shows MICP-derived pore-size distributions ranked with rock types classified from clustering orthogonality matrices. Rock types A, B1, and B2 all exhibit a major pore-size distribution and a tail of small pore-size distribution; rock type C mostly exhibits a balanced pore-volume fraction between the large and small pore-size mode; rock type D has a unimodal behavior in pore-size distribution.

Laboratory NMR experiments were performed on the same 30 core samples (100% water saturated) using a MARAN Ultra Magnetic Resonance Core Analyzer (operating frequency ~2 MHz) with multiple interecho spacing of 300, 600, and 1200 μs. Transverse relaxation time ($T_2$) distributions were obtained by inverting multiexponential echo data with 51 preset decay times evenly spaced logarithmically between 0.1 and 10,000 ms (Liu et al., 2011). Because diffusion effects on proton relaxation are negligible in water-filled rocks, relaxation times are mainly determined by pore-body size (Winkler et al., 2006). With the assumption that pore-body size is well correlated with pore-throat size, it is possible to derive synthetic capillary pressure curves from NMR $T_2$ spectra (Altunbay et al., 2001). Therefore, rock types derived from MICP data should also rank NMR $T_2$ spectra consistently. Figure 14 shows the core NMR $T_2$ spectra grouped by rock types and Figure 15 shows the crossplot of permeability and logarithmic mean of $T_2$ ($T_2LM$) color coded by rock type. Generally, the $T_2$ peak locations shift to left side (lower relaxation times) as rock type number increases (and overall reservoir quality decreases). Table 1 summarizes the statistics of NMR $T_2LM$ for each rock type. The relatively large standard deviations observed in $T_2LM$ for each rock type indicates that the correlation between pore-body size and pore-throat size may not be as high as initially assumed.

Laboratory measurements of relative permeability measurements can take a significant amount of time when performed on tight-gas sandstone samples. Therefore, it would be useful to model relative permeability
curves from MICP data (Byrnes, 2008; Cluff and Byrnes, 2010). Liu et al. (2012) use rock types to guide the prediction of dynamic flow behavior in the Cotton Valley formation. Here, we derive primary drainage relative permeability curves from the bimodal Gaussian pore-size distribution using Corey-Burdine’s model (Burdine, 1953; Huang et al., 1997). Critical water saturation ($S_{w \text{crit}}$) is calculated from its correlation with parameter $w_2$, whereas the end point of gas relative permeability is predicted by its correlation with parameter $\mu_1$. The end point of water relative permeability is set to 1.0 while residual gas saturation ($S_{gr}$) is set to 0 in a primary drainage process. Table 2 lists the gas relative permeability properties of each rock type.

Burdine’s wetting phase relative permeability is given by

$$k_{rw} = (S_w)^2 \frac{\int_0^{S_w} \frac{1}{(P_c)^2} dS_w}{\int_0^1 \frac{1}{(P_c)^2} dS_w} = (S_w)^2 \frac{\int_0^{S_w} R^2 dS_w}{\int_0^1 R^2 dS_w},$$

(6)

and nonwetting phase relative permeability by

$$k_{rnw} = (1 - S_w)^2 \frac{\int_0^{1 - S_w} \frac{1}{(P_c)^2} dS_w}{\int_0^1 \frac{1}{(P_c)^2} dS_w} = (1 - S_w)^2 \frac{\int_0^{1 - S_w} R^2 dS_w}{\int_0^1 R^2 dS_w},$$

(7)

where $P_c$ is capillary pressure and $R$ is the corresponding pore-throat radius; $S_w$ is normalized water saturation, defined as

Table 2. Gas relative permeability properties for each rock type in a primary drainage process.

<table>
<thead>
<tr>
<th>Rock type</th>
<th>Average $S_{w \text{crit}}$</th>
<th>Average $K_{r0}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.38</td>
<td>0.78</td>
</tr>
<tr>
<td>B1</td>
<td>0.50</td>
<td>0.62</td>
</tr>
<tr>
<td>B2</td>
<td>0.43</td>
<td>0.51</td>
</tr>
<tr>
<td>C</td>
<td>0.71</td>
<td>0.42</td>
</tr>
</tbody>
</table>

Figure 14. Core-measured NMR T2 spectra grouped by rock type: (a) rock type A, (b) rock type B1, (c) rock type B2, (d) rock type C, and (e) rock type D.

Figure 15. Crossplot of permeability and T2LM, color coded by rock type.

Figure 16. Primary drainage relative permeability curves ($S_{gr} = 0$) modeled with Burdine’s equations for each rock type. The colored points identify the core-measured relative permeability for each rock type.
Based on MICP-derived bimodal Gaussian pore-size distribution, primary drainage relative permeability curves for each rock type are calculated with Corey-Burdine’s equations (Figure 16). The modeled primary drainage relative permeability curves qualitatively agree well with core data and show consistency with the data presented in Byrnes’ (2008) work.

Limitations
Attention should be paid to the limitations of the classic bundle of capillary tubes often used to describe pore networks. In this model, capillary tubes do not communicate with each other, whereby it cannot effectively describe pore connectivity in terms of coordination number. However, the model is still effective to identify the major pore throat radius and the pore volumes accessible to the nonwetting phase at a given value of capillary pressure. The model remains useful when quantifying permeability from MICP data. Comisky et al. (2007) compare 13 models commonly used to derive absolute permeability from capillary pressure curves of tight-gas sandstones and conclude that Purcell’s (1949) model ranks highly in the comparison. Advanced pore-network models should be applied when more detailed data are available, such as 3D pore-scale images.

Conclusions
Conventional rock classification methods dominantly emphasize hydraulic radius and tend to neglect the impact of effective pore volume and pore-throat radius uniformity on overall petrophysical quality. Consequently, they are prone to misclassifications in tight-gas sandstones that exhibit poor correlation between hydraulic radius and other pore-system attributes. We introduce a bimodal Gaussian density function to describe complex pore systems analytically in terms of pore volume, major pore-throat radii, and pore-throat size uniformity. A new concept, referred to as pore-system orthogonality, is introduced to quantify petrophysical dissimilarity between two pore systems, which takes into account several relevant pore-system attributes, including porosity and pore-throat size distribution. Rock classification via clustering orthogonality matrices enables consistent reservoir quality ranking in various petrophysical data domains, including porosity-permeability trends, pore-size distribution, MICP, and core NMR $T_2$ spectra. The analytical bimodal Gaussian pore-size distribution model also lends itself to the prediction of saturation-dependent, primary drainage relative permeability with Corey-Burdine’s model. A test of the new method on thirty core samples of Cotton Valley tight-gas sandstones, East Texas, verified its advantage over conventional rock classification methods.

Acknowledgments
We would like to thank BP America North America Gas unit for providing the field data used in this study. A note of special gratitude goes to David Spain, Shujie Liu, Chris Morton, and German Merletti for their thought-provoking discussion on tight-gas sand reservoir characterization. The work reported in this paper was funded by The University of Texas at Austin’s Research Consortium on Formation Evaluation, jointly sponsored by Afren, Anadarko, Apache, Aramco, Baker-Hughes, BG, BHP Billiton, BP, Chevron, China Oilfield Services, Ltd., ConocoPhillips, ENI, ExxonMobil, Halliburton, Hess, Maersk, Marathon Oil Corporation, Mexican Institute for Petroleum, Nexen, ONGC, OXY, Petrobras, PTTEP, Repsol, RWE, Schlumberger, Shell, Statoil, Total, Weatherford, Wintershall, and Woodside.

Figure 17. Proposed workflow for integrating the rock classification method advanced in this paper for reservoir description. The procedures highlighted in green have been implemented in this paper. Yellow and pink frames require additional research efforts.
Petroleum Limited. We are indebted to Yonghe Sun and several anonymous reviewers for their constructive technical and editorial comments that improved the first version of the manuscript.

**Nomenclature**

- \( \alpha \) = Archie’s tortuosity factor, \([\]\]
- \( k \) = Absolute permeability, \([\mu D]\]
- \( k_{rg} \) = Gas relative permeability, \([\text{frac}]\]
- \( k_{rw} \) = Water relative permeability, \([\text{frac}]\]
- \( m \) = Archie’s porosity exponent, \([\]\]
- \( n \) = Archie’s saturation exponent, \([\]\]
- \( \text{ORT} \) = Orthogonality
- \( p \) = Density function of logarithmic pore-throat size
- \( P_c \) = Capillary pressure, \([\text{psi}]\]
- \( R \) = Pore-throat radius, \([\mu m]\]
- \( S_{gr} \) = Residual gas saturation, \([\text{frac}]\]
- \( S_w \) = Water saturation or wetting-phase saturation, \([\text{frac}]\]
- \( S'_{w} \) = Normalized water saturation, \([\text{frac}]\]
- \( S'_w \) = Critical water saturation, \([\text{frac}]\]
- \( S_{wirr} \) = Irreducible water saturation, \([\text{frac}]\]
- \( T_g \) = NMR transverse relaxation time, \([\text{ms}]\]
- \( \text{T2LM} \) = Logarithmic mean value of NMR transverse relaxation time, \([\text{ms}]\]
- \( w_1 \) = Fraction of pore volume connected by large pore-throat size, \([\text{frac}]\]
- \( w_2 \) = Fraction of pore volume connected by small pore-throat size, \([\text{frac}]\]
- \( \log \mu_1 \) = Mean value of the large pore-throat size Gaussian mode, \([\mu m]\]
- \( \log \mu_2 \) = Mean value of the small pore-throat size Gaussian mode, \([\mu m]\]
- \( \log \sigma_1 \) = Standard deviation of the large pore-throat size Gaussian mode, \([\mu m]\]
- \( \log \sigma_2 \) = Standard deviation of the small pore-throat size Gaussian mode, \([\mu m]\]
- \( \phi_i \) = Total porosity, \([\mu u]\]
- \( \tau \) = Pore network tortuosity, \([\]\]

**Acronyms**

- FZI = Flow zone indicator
- MICP = Mercury injection capillary pressure
- NMR = Nuclear magnetic resonance
- RQI = Reservoir quality index
- RT = Rock type

**References**


Cluff, R. M., and A. P. Byrnes, 2010, Relative permeability in tight gas sandstone reservoirs — The “permeability jail” model: 51st Annual Logging Symposium, SPWLA, LLLL.


Liu, S., D. R. Spain, C. Devier, D. Buller, and E. Murphy, 2011, Integrated petrophysical study in North American Cotton Valley tight gas sand: Cotton Valley formation, East Texas: 52nd Annual Logging Symposium, SPWLA, D.


Spain, D. R., S. Liu, and C. Devier, 2011, Petrophysical rock typing in tight gas sands: Beyond porosity and saturation — An example from the Cotton Valley formation, East Texas: Middle East Unconventional Gas Conference and Exhibition, SPE, 142808.


Winkler, M., J. J. Freeman, E. Quint, and M. Caputi, 2006, Evaluating tight gas reservoirs with NMR — The perception, the reality and how to make it work: 47th Annual Logging Symposium, SPWLA, BB.

Xu, C., 2013, Reservoir description with well-log-based and core-calibrated petrophysical rock classification: Ph.D. dissertation, University of Texas at Austin.


Xu, C., and C. Torres-Verdín, 2013b, Multi-scale orthogonal rock class decomposition: Top-down reservoir characterization integrating logs and core in tight-gas sands: 54th Annual Logging Symposium, SPWLA, FF.

Carlos Torres-Verdin received a Ph.D. (1991) in engineering geoscience from the University of California at Berkeley. During 1991–1997, he held the position of research scientist with Schlumberger-Doll Research. From 1997–1999, he was a reservoir specialist and technology champion with YPF (Buenos Aires, Argentina). Since 1999, he has been affiliated with the Department of Petroleum and Geosystems Engineering at the University of Texas at Austin, where he is currently full professor, holds the Zarrow Centennial Professorship in petroleum engineering, and conducts research on borehole geophysics, formation evaluation, well logging, and integrated reservoir characterization. He is the founder and director of the Research Consortium on Formation Evaluation at the University of Texas at Austin, which is currently sponsored by 32 companies. He has published more than 115 refereed journal papers and 130 conference papers, has served as guest editor for Radio Science, as associate editor for the Journal of Electromagnetic Waves and Applications, SPE Journal, and Petrophysics (SPWLA) and is currently associate editor for Geophysics and editorial board member of The Leading Edge (SEG). He is recipient of the 2006 Distinguished Technical Achievement Award from SPWLA, the 2008 Formation Evaluation Award from SPE, the 2003, 2004, 2006, and 2007 Best Paper Awards in Petrophysics by SPWLA, and the 2006 Best Presentation Award and the 2007 Best Poster Award by SPWLA.

Chicheng Xu received his Ph.D. degree in Petroleum Engineering at The University of Texas at Austin in 2013. He received his B.S. in Physics from the University of Science and Technology of China in 2002 and his MPhil in Physics from the Chinese University of Hong Kong in 2004. Before joining the Formation Evaluation Research Consortium group in the Department of Petroleum and Geosystems Engineering at the University of Texas at Austin, he worked at Schlumberger Beijing Geoscience Center as software engineer from 2004 to 2009. He is now a petrophysicist in BP America. He had more than 10 technical papers published in conferences and journals.