Probing Pore Systems in Carbonates: Correlations to Petrophysical Properties

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ABSTRACT

The understanding of petrophysical and multiphase flow properties is essential for the assessment and exploitation of hydrocarbon reservoirs; these properties in turn are dependent on the geometric and connectivity properties of the pore space. The determination of the pore size distribution in carbonate rocks remains challenging; extreme variability in carbonate depositional environments and susceptibility to a range of post-depositional processes results in complex pore structures comprising length scales from sub-micron to several centimeters. In this paper we illustrate that combining experimental techniques including micro-computed tomography and scanning electron microscopy (SEM) allows one to probe the pore scale structure in carbonates across a continuous range over many decades of length scales (from 10 nm to cm scales). Image data at nanoscales can be incorporated into the prediction of petrophysical properties of 3D images. This is especially important in limestones. We describe the study of the internal structure of over 30 carbonate samples across this range of length scales. The samples include carbonates with different porosity classifications including end members ranging from depositional porosity, diagenetic porosity and fracture porosity and many hybrid samples with mixtures of pore types. Particular emphasis is placed on the quantification of the pore sizes, shapes and interconnectivities in three dimensions. Extreme variability in pore network structures is observed. The pore network statistics (e.g., coordination, aspect ratio, pore size) for the connected samples are often similar despite the clear visual difference in the network structures. This illustrates the danger of attempting to stochastically generate pore networks for different carbonate samples based on matching network statistics alone.

Petrophysical properties including resistivity, acoustic response and permeability are calculated on image data and where available, compared to experimental data. Comparisons between simulation and experimental data on the same core material are satisfactory. Flow properties of systems exhibiting significant microporosity require further development.

INTRODUCTION

Carbonate reservoirs contain more than 50% of the world's hydrocarbon reserves. In carbonate rocks, the processes of sedimentation and diagenesis produce a complex spatial distribution of pores and pore connectivity across several decades of length scales. Developing a reliable petrophysical interpretation for predicting the transport properties and producibility of carbonates remains difficult. Much of the poor reliability in estimating carbonate properties is due to the complex pore structure exhibited by carbonates. Unlike sandstones, many carbonate sediments have a multi-modal pore size distribution with organisms playing an important role in forming the reservoirs (Ramakrishnan et al., 2001; Cantrell and Hagerty, 1999; Clerke, 2007). Carbonate rocks are further complicated by significant diagenesis resulting from chemical dissolution, reprecipitation, dolomitization, fracturing, etc. For these reasons the pore structure is expected to be very heterogeneous and is known to exhibit pore sizes ranging from sub-micron to centimeters. This feature distinguishes the petrophysical properties and productivities of carbonate fields from other sedimentary rocks.

In previous work we have described the development of a capacity to characterize and predict petrophysical properties from experimental 3D microtomographic images of rock microstructures (Arns et al., 2005). Rock properties derived from fragments of a range of cores including homogeneous and reservoir sands have been compared with conventional laboratory measurements and shown to be in good agreement. In this paper thirty carbonate plugs are imaged and analysed over a range of length scales using high resolution X-ray microtomography (μ-CT) coupled with conventional thin section microscopy techniques. This allows a study of the range of pore structures in carbonates across many decades of length. The pore topology and geometry of samples are characterized and petrophysical properties derived from image
data are compared to experiment where available.

SAMPLES AND CHARACTERIZATION

Samples

Thirty samples are considered in this study. The samples are carbonates with different porosity classifications including end members ranging from depositional porosity, diagenetic porosity and fracture porosity and many hybrid samples with mixtures of pore types. Images of the samples are illustrated in Fig. 1-2. We loosely classify the samples into 4 groups: sucrosic dolomites (SD), fractured dolomites (F), moldic grainstones (MG) and other limestones (L); the latter group includes samples with a wide range of dominant pore types: interparticle, intraparticle, vuggy and microporous. A brief description of the samples along with the measured Mercury injection (MICP) porosity $\phi_{\text{micp}}$ for each is given in Table 1.

In all cases the sample size varies between 5-6 mm in diameter; samples of this size were cut using a diamond coring tool on plugs or sidewall cores.

Tomographic Imaging

A high-resolution and large-field X-ray $\mu$CT facility has been used to analyse the 3D structure in the carbonate samples. The samples of 5-6 mm in diameter are imaged at resolutions from 2.5 microns to 3.3 microns per voxel. 2D slices through the 3D volumes are shown in Fig. 1-2. Images are composed of $2048^3$ voxels. Details of the equipment and experimental methodology used to image the microstructure of sedimentary rock have been given previously (Sakellarion et al., 2004; Arns et al., 2005).

Image Analysis, MICP and SEM

In this subsection we describe the image analysis, image quality control and calibration of images to other experi-
Table 1: Characteristics of the samples utilized in this study. $\phi_{exp}$ is the experimentally measured porosity, $\phi_{macro}$ the total resolved image porosity, $\phi_{image}$ the porosity measured below image resolution and $\phi_{tot}$ is the total image resolved porosity.

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<th>Description</th>
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<th>$\phi_{micro \ image}$ (%)</th>
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mental data. We consider the analysis undertaken for the four rock types individually.

Sucrosic Dolomites

The tomographic image consists of a cubic array of reconstructed linear x-ray attenuation coefficient values, each corresponding to a finite volume cube (voxel) of the sample. An immediate goal is to differentiate the attenuation map into distinct pore and grain phases for each of the samples imaged. Ideally one would wish to have a well separated multi-modal distribution giving unambiguous phase assignment of the pore and various mineral phase peaks. This is possible in the case of the sucrosic dolomites (Samples S1-S8 in Fig. 1). As MICP data for the eight SD samples (Fig. 3(a)) shows, the majority of pore throats are larger than 10 μm. The ideal phase assignment is therefore possible for these samples. The mineralogy is simple and the pore sizes are primarily larger than the image resolution. As an example Fig. 4(a) shows the attenuation histogram for sample S5. The resultant phase identification of the sample is trivial; this is the case for all eight SD samples.

A measure of the quality of the image based data is obtained by comparing the porosity measured on the image data to porosity measured via MICP. The agreement is good for all sucrosic dolomite samples (see Table 1). One can also directly compare the measurement of the pore throat size distribution from MICP experiments on the core material imaged via tomography to simulations of MICP undertaken directly on the images (Arns et al., 2005). Direct comparison of the numerically-based MICP simulation on a set of the sucrosic dolomite samples to experimental MICP data is given in Fig. 4(b) where close agreement can be seen.

Further quality control on the 3D micro-CT data is undertaken by registering (optimally aligning) higher-resolution optical or SEM data (Latham et al., 2008). A thin-section is extracted from the micro-CT sample and imaged with an optical or electron microscope. By aligning the high-resolution 2D thin-section images with the corresponding region of the 3D micro-CT image, one can directly gauge the quality of the micro-CT data. In Fig. 4(c-d) we show a comparison of a scanning electron microscope (SEM) image of a thin section of sample S5 with the registered slice through the tomogram. The images are essentially identical. The only differences noted are the absence of some small grains in the SEM; these are possibly removed during the thin section sample polishing. Registration of a thin section with a tomographic image also allows one to probe the mineralogy and obtain higher resolution information on the samples. All of the quality control measures allows one to conclude that the tomographic image of the sucrosic dolomite samples are a reliable representation of the 3D structure of the sample.

Figure 3: MICP data for three types of rock; Top, Sucrosic dolomites; Middle, limestones; and Lower, oomoldic rocks. In all three cases a thick dashed black line is shown which defines the image resolution. In the case of sucrosic dolomites most porosity is associated with throats greater than image resolution. This is not the case in the latter two cases.
Limestones

MICP data for the range of limestones is given in Fig. 3(b). In nearly all cases a significant fraction of the accessible porosity lies below the image resolution of the tomographic image. The presence of pores at scales below the image resolution leads to a broad spread in the low density signal in the tomogram making it difficult to unambiguously differentiate the pore from the solid mineral phase. To analyse these images we have undertaken a three phase identification process on the sample. This method, described in detail in (Sok et al., 2007) is summarized here.

Three phase segmentation:
The three phase separation process characterizes voxels in the sample as either resolvable pore phase, intermediate microporous phase or matrix phase. As an example, the intensity histograms for one microporous limestone sample is given in Fig. 5(a); a pore and solid peak are discernible; an extensive intermediate attenuation range which would be associated with the microporous phase is also noted.

The phase assignment is performed in two stages. The small peak at lower attenuations is associated with the pore phase. The peak at highest attenuation corresponds to the solid matrix phase. For the first stage we choose four attenuation coefficient thresholds, $T_1$ to $T_4$, and a gradient threshold $G$. $T_1$ is the absolute upper bound of the pore phase, $T_4$ is the absolute lower bound of the solid phase. Attenuations between $T_2$ and $T_3$ are labelled as the intermediate phase under the restriction that the local intensity gradient is below some cutoff $G$. We do this to make sure that the voxels which are on the interface between pore and solid phases (which potentially have values between $T_2$ and $T_3$, but a high gradient) are not assigned to the intermediate phase but are recognized as interface voxels. The remaining voxels are for now labelled as unknown. In the second stage we then assign these unknown voxels. We use the voxels that are already assigned as seed regions for our converging active contour algorithm (Sheppard et al., 2004).

The intensity distributions of the resulting phase assignments after segmentation is indicated in Fig. 5(b) with the dashed lines. A solid (matrix) phase, pore and intermediate phase is identified. The total resolvable porosity from the image $\phi_{image}^{macro}$ is defined. Values for the limestone samples imaged are given in Table 1. We note that in most cases the directly resolvable porosity is significantly less than the experimentally measured porosity; $\phi_{image}^{macro} < \phi_{exp}$.

Microporous assignment of intermediate phase porosity:
Voxels of the intermediate phase are assigned a microporosity value by analysing the individual voxel intensities. Voxels that have a value that is within one stan-
Figure 5: (a) Intensity histogram for Sample L2 with thresholds T1-T4, seed regions for the three phase segmentation, shown. (b) shows the resultant histogram leading to the three phase partitioning. The vertical dotted lines bound the region defined as the microporous phase. (c) shows a small inset of the original image (left); the central figure shows the partitioning into grain (white), pore (black) and intermediate (grey) phases. (middle). The right hand figure shows the grey-level encoded microporosity embedded in the intermediate phase regions.

The standard deviation of the mean attenuation of the pore or solid phase (Fig. 5(b)) are assigned 100% and 0% porosity respectively. Voxel in the range between these two automatic thresholds are assigned a microporosity value \( \phi_{\text{micro},n} \) based on an assumption of linear scaling of attenuation. This allows one to estimate the total porosity of the image.

\[
\phi^\text{tot}_{\text{image}} = \phi^\text{macro}_{\text{image}} + \frac{\sum_{n=0}^{N_i} \phi_{\text{micro},n}}{N_i},
\]

(1)

where \( N_i \) the number of voxels in the intermediate phase. The phase volumes associated with the three phases and the porosity associated with the resolved \( \phi^\text{macro}_{\text{image}} \) and microporosity \( \phi^\text{micro}_{\text{image}} \) phases are given in Table 1. \( \phi^\text{total}_{\text{image}} \) for most samples matches or is slightly less than that measured on the same sample via MICP (compare \( \phi^\text{image} \) and \( \phi^\text{exp} \) in Table 1).

Direct comparison of the numerically-based MICP simulation on the limestone samples generally leads to a good match to experimental MICP data up to the resolution of the tomo gram (see (Sok et al., 2007)). However, as noted in Fig. 3(b), much of the accessible porosity lies below the image resolution. Clearly there is a need to probe the structure of these samples at finer resolutions. This is achieved by undertaking complimentary SEM studies on the same core material.

An SEM of a thin section from a grainstone (L12) is shown in Fig. 6(a). The registered slice within the tomo gram is given in Fig. 6(b). The images match well, but it is clear from both the tomogram and the SEM that structure exists at length scales below image resolution. Electron microscopy enables one to probe regions of the thin section at higher resolutions; from microns down to nanometres. In Fig. 6(c-d) we show images of small subsets of the full sample imaged at 110 nm resolution. The presence of grains and pores at submicron scales are clear.

Further focusing to pixel sizes of 50 nm allows one to visualize the sorting of the calcite crystals (Fig. 7(a-b)). The microporous matrix consists primarily of 1-3 micron calcite crystals that are randomly packed to yield a well connected network of micropores. SEM studies on a number of other limestone samples has confirmed the presence of microporosity in grains, matrix and cement phases (Cantrell and Hagner, 1999) at the submicron to micron length scales. The grain sizes within the microporous phases can be measured via image analysis methods on the thin section image. In Fig. 7(c) we show the grain size distribution measured on an extensive set of thin sections from 7 limestone samples from different formations. In all systems the resultant grain size data is similar (primarily 1-3 microns). The consistent grain sizes observed across the range of samples strengthens the argument that complex limestone pore systems are combinations of a small number of modes of pore systems (Clerke, 2007).

Moldic Samples

The oomoldic samples exhibit large amounts of visible macroporosity (Fig. 1). On comparison of \( \phi^\text{image} \) and \( \phi^\text{exp} \) in Table 1 for the seven samples we observe that five samples O1-O3 and O6-O7 exhibit minimal microporosity, while samples O4 and O5 exhibit approximately 8 - 10 p.u. of microporosity. In contrast, (recall Fig. 3) the MICP data for the moldic grainstones shows that only one sample exhibits large intrusion diameters while four samples exhibit porosity only accessible via throat diameters in the submicron range. The pore systems in moldic grainstones, where the original intergranular porosity has
Figure 6: (a) shows a thin section through an end piece of the core imaged in 3D (1.4 microns per pixel) and (b) shows the registered slice from the 3D tomogram (2.8 microns per pixel). The two black boxes in (a) define regions where higher resolution images shown (c) and (d) are taken. (c) and (d) show submicron resolution information from the thin section (110 nm per pixel); the grains exhibit a small extent of microporosity.

Figure 7: (a-b) Two higher resolution images (Mag=1000x, pixel size = 50 nm) of the microporous regions of the L2 sample. The microporous matrix consists primarily of 1-3 micron calcite crystals. (Bottom) Grain sizes measured from thin section images of seven limestone samples.

been filled by microporous calcite cements and the original ooid grains dissolved are influenced heavily by the connectivity and pore size of the neighboring molds; this impacts on the range of petrophysical and multiphase flow properties. The connectivity of the pore space cannot be resolved directly from 2D images and can only be measured from full 3D spatial information. This will be illustrated in the following section.

The quality of the images is illustrated by comparing
2D SEM image to a slice within the 3D tomographic image; an example is given in Fig. 8(a-b). The image match is good. It is noted that a matrix phase visualized within several of the molds in the tomographic image data are no longer present in the registered SEM image; this phase may be friable and may have been removed in the preparation of the thin section. SEM imaging of the moldic sample at higher resolutions allows one to probe the pore size and structure of the microporous calcite cementing phase between the molds. An example of this is shown in Fig. 8(c). Information about the effective pore size between molds can be quantified and this information built into predictions of the petrophysical properties on the 3D images.

**PORE STRUCTURE and NETWORKS**

Network simulations are increasingly used to estimate the properties of multiphase flows in porous materials (Blunt et al., 2002). The guiding idea is that, in the context of capillary dominated flow, the pore space can be naturally discretised into subvolumes separated at the locally narrowest constrictions. The subvolumes and the constrictions can then be identified with the nodes (pore bodies) and links (pore throats) of a network. The advancement of the fluid-fluid interface through a link or node in the network is governed by the relationship between the capillary pressure, the material wettability and the local channel cross-section geometry. Network representations provide valuable new data to quantify the topological properties of the pore space. In this section we describe the generation of pore-throat networks of the carbonate samples and highlight the range of pore network structures that are observed across the different rock types.

**Sucrosic Dolomites**

Pore networks are generated for all sucrosic samples. 2D snapshots of the pore partitioning of samples S5 and S8 along with a 3D representation of a small subset of the 3D images are shown in Fig. 9. Pore network files contain up to 400,000 individual elements. Plots of the distributions of a range of connectivity and geometric parameters can be generated; in Fig. 10 we give examples for Sample S8. Statistical parameters for the pore networks are summarized in Table 2. Seven samples exhibit 100% pore connectivity. We note a weak correlation in the mean coordination number <Z> with decreasing porosity for all samples, although within samples from the same reservoir, a stronger correlation was noted. A significant variation in <Z>_avg is noted across the samples; larger values of this measure are often associated with the presence of a smaller fraction of large and well connected pores. Networks with these character-

![Figure 8](image_url)
istics may have distinct flow properties. Pore to throat aspect ratio and other statistics of the pore network (e.g., pore shape, throat shape; data not shown) exhibit little dependence on the porosity of the samples.

Limestone Samples

A slice through a limestone sample and the pores which macroscopically connect is shown in Fig. 11. Only a subset of the resolvable pores are connected at the image resolution. Nine of the thirteen samples exhibit pore networks which are macroscopically connected. Examples of pore nets for a set of these samples is given in Fig. 12. Clearly the extreme variability in depositional environments and the range of post-depositional processes possible in carbonates leads to a wide variety of pore network structures.

Pore network statistics for the nine connected samples are summarized in Table 3. The contribution of the connected porosity to \(\phi_{\text{image}}\) is given and generally of the order of 60–80%—two poorly connected samples are noted. The percentage of the total porosity resolved is smaller; e.g., for L4 the percentage of total porosity in the connected macroporous network is 37%. These results are consistent with the MICP data for the cores; much of the porosity in reservoir limestone cores remains disconnected at image resolution.

The pore network statistics (e.g., coordination, aspect ratio, pore size) for the connected samples are often similar despite the clear visual difference in the network structures; the sample in Fig. 12(b) which has significant proportions of primary porosity has almost identical pore network coordination, pore size and aspect ratio to the sample in Fig. 12(c). Despite these similarities in network parameters one would not assume that the petrophysical and multiphase flow properties would coincide. This illustrates the danger of attempting to stochastically generate pore networks for different carbonate samples based on matching network statistics alone.

The variability in the pore structure in the limestone cores inevitably leads to a question of the representivity of the sample data—is the sample volume sufficiently large to obtain useful petrophysical properties? To measure the correlation length scale we calculated the autocorrelation of the intensity. The values of the function range from 1 at distance zero and decreases with increasing distance. At large length scales the function goes to zero. The correlation length \(\zeta\) was defined (arbitrarily) as the length scale where the autocorrelation goes below 0.05. Length scales measured on this basis are given in Table 3; values less than 1 mm are observed. This indicates that one may obtain useful predictions on the scale of the images, but measurement of the correlation functions on larger samples should also be undertaken to confirm this.

Figure 9: (a) Pore labelling of a slice of Sample S5 and (b) a small subset of the 3D network. (c) and (d) show slice and subset of network for Sample S8. In (d) some pores are isolated from the connected cluster at image resolution.
Table 2: Details of the network structure for the sucrosic samples (S1-S8 in Fig. 1). %Conn gives the percentage of the pore space which macroscopically connect through the sample. $Z_m$ gives the number-based mean coordination number, $Z_{vol}$ the pore volume weighted mean coordination number. $r_p$ and $r_t$ are respectively the volume weighted mean pore and throat radii. The mean $<\frac{R_t}{R_p}>$ and volume weighted $<\frac{R_t}{R_p}>_{vol}$ pore to throat aspect ratios are also given.

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<td>19.7</td>
<td>3.5</td>
<td>5.8</td>
</tr>
<tr>
<td>S6</td>
<td>100</td>
<td>4.1</td>
<td>7.8</td>
<td>66</td>
<td>11.4</td>
<td>2.7</td>
<td>4.1</td>
</tr>
<tr>
<td>S7</td>
<td>100</td>
<td>3.8</td>
<td>7.3</td>
<td>62</td>
<td>11.0</td>
<td>2.6</td>
<td>4.4</td>
</tr>
<tr>
<td>S8</td>
<td>88</td>
<td>4.4</td>
<td>7.4</td>
<td>45</td>
<td>9.3</td>
<td>2.6</td>
<td>3.6</td>
</tr>
</tbody>
</table>

Table 3: Details of the network structure for limestone samples which exhibit connected porosity at the tomographic image resolution. Labels are as defined in Table 2.

<table>
<thead>
<tr>
<th>Sample</th>
<th>%Conn</th>
<th>$&lt; Z &gt;$</th>
<th>$&lt; Z &gt;_{vol}$</th>
<th>$r_p$</th>
<th>$r_t$</th>
<th>$&lt; \frac{R_t}{R_p}&gt;$</th>
<th>$&lt; \frac{R_t}{R_p}&gt;_{vol}$</th>
<th>$\zeta$ (μm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L4</td>
<td>73</td>
<td>4.0</td>
<td>10.3</td>
<td>79.2</td>
<td>15.1</td>
<td>3.0</td>
<td>6.8</td>
<td>474</td>
</tr>
<tr>
<td>L5</td>
<td>43</td>
<td>3.6</td>
<td>10.9</td>
<td>57.8</td>
<td>11.8</td>
<td>2.6</td>
<td>5.7</td>
<td>543</td>
</tr>
<tr>
<td>L7</td>
<td>66</td>
<td>3.6</td>
<td>7.5</td>
<td>64.8</td>
<td>13.2</td>
<td>2.9</td>
<td>4.2</td>
<td>851</td>
</tr>
<tr>
<td>L8</td>
<td>81</td>
<td>3.8</td>
<td>7.6</td>
<td>53.9</td>
<td>11.5</td>
<td>2.9</td>
<td>3.9</td>
<td>340</td>
</tr>
<tr>
<td>L9</td>
<td>70</td>
<td>3.3</td>
<td>6.3</td>
<td>48.2</td>
<td>11.0</td>
<td>2.7</td>
<td>3.4</td>
<td>200</td>
</tr>
<tr>
<td>L10</td>
<td>32</td>
<td>0.5</td>
<td>2.4</td>
<td>28.9</td>
<td>8.2</td>
<td>2.3</td>
<td>2.8</td>
<td>211</td>
</tr>
<tr>
<td>L11</td>
<td>76</td>
<td>4.1</td>
<td>16.1</td>
<td>98.2</td>
<td>14.3</td>
<td>3.1</td>
<td>7.9</td>
<td>301</td>
</tr>
<tr>
<td>L12</td>
<td>92</td>
<td>3.6</td>
<td>8.2</td>
<td>73.5</td>
<td>16.4</td>
<td>2.6</td>
<td>3.6</td>
<td>425</td>
</tr>
<tr>
<td>L13</td>
<td>88</td>
<td>4.2</td>
<td>7.4</td>
<td>37.5</td>
<td>7.9</td>
<td>2.8</td>
<td>3.8</td>
<td>297</td>
</tr>
</tbody>
</table>

Table 4: Details of the network structure for 3 moldic samples which exhibit connected porosity at the tomographic image resolution. Data for the fractured sample is also given. Labels are as defined in Table 2.

<table>
<thead>
<tr>
<th>Sample</th>
<th>%Conn</th>
<th>$&lt; Z &gt;$</th>
<th>$&lt; Z &gt;_{vol}$</th>
<th>$r_p$</th>
<th>$r_t$</th>
<th>$&lt; \frac{R_t}{R_p}&gt;$</th>
<th>$&lt; \frac{R_t}{R_p}&gt;_{vol}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>O1</td>
<td>17</td>
<td>3.3</td>
<td>7.6</td>
<td>124</td>
<td>14.5</td>
<td>3.0</td>
<td>7.8</td>
</tr>
<tr>
<td>O6</td>
<td>90</td>
<td>4.4</td>
<td>19.7</td>
<td>280</td>
<td>34</td>
<td>2.6</td>
<td>19.1</td>
</tr>
<tr>
<td>O7</td>
<td>74</td>
<td>4.7</td>
<td>8.7</td>
<td>54</td>
<td>13.3</td>
<td>2.9</td>
<td>4.7</td>
</tr>
<tr>
<td>F1</td>
<td>90</td>
<td>...</td>
<td>5.5</td>
<td>17.4</td>
<td>5.6</td>
<td>1.7</td>
<td>1.8</td>
</tr>
<tr>
<td>F2</td>
<td>85</td>
<td>4.5</td>
<td>5.7</td>
<td>16.5</td>
<td>5.4</td>
<td>1.8</td>
<td>1.8</td>
</tr>
</tbody>
</table>

10
Moldic Samples

Three of the seven moldic samples exhibit connected porosity at the resolution of the images. Network statistics for the three samples are summarized in Table 4. Sample O6 exhibits a significant fraction of connected porosity; the resultant network is well connected at all scales and an image of the network is given in Fig. 13(a). The network is made up of large pores decorated with regions of tight pores. As the moldic pores are connected at the resolution of the tomogram the aspect ratios of the network are large; $< \frac{R_c}{R_e} >_\text{vol}$ is twice as large as that measured on any other sample.

Sample O7 has an intermediate percentage of the porosity connected at the tomogram resolution. The original 2D slice and the same slice showing only the connected pores is given in Fig. 13(b-c); the connectivity of different pores in the 2D slice would be difficult to discern based on the 2D information alone. Tomographic imaging allows one to directly identify pores which connect and therefore will dominate the flow properties of the rock. The volume weighted coordination number $\langle Z \rangle_\text{vol}$ in Table 4 is significantly smaller than the value for sample O6. This indicates a poorer connectivity between the large molds at image resolution. The result on the network is observed by comparing Fig. 13(a) and Fig. 13(d). The resultant network shows little connectivity between the large molds; highly tortuous pore pathways are therefore evident in the resultant network. Sample O2 has a small fraction of the moldic pores which connect at the image resolution (3 microns). The connected pores within the tomogram slice shown in Fig. 1 are shown in Fig. 13(e).

Fractured Samples

The pore network of one of the fractured samples is shown in Fig. 14. The network statistics are given in Table 4. The fractured sample exhibits regions of planar networks with a reasonably tight distribution of coordination number (4, 5, and 6 connected pores). Highly connected pores are noted at fracture plane junctions. The fracture networks also exhibit a very low pore to throat aspect ratios (factor two times smaller than any other network); this is expected given the network structure is dominated by roughness of the fracture surfaces.

PETROPHYSICAL PROPERTIES

In this section we highlight some results that have come from petrophysical analysis of the image data including comparisons to experiment (where available).
Figure 14: Inset of a pore network of the fractured sample.

Resistivity

The resistivity calculations are based on a solution of the Laplace equation with charge conservation boundary conditions (Arns et al., 2001). For the formation factor calculation we consider an idealized case assigning zero conductivity to the solid phase and $\sigma_{macro} = 1$ for the resolved (macroporosity). Voxels in the microporous phase are assigned the conductivity of the microporous phase via Archie’s law; $\sigma_{micro} = (\phi_{micro})^m$, where $m = 2$ (Sok et al., 2007). Simulations are undertaken on grids up to 1800$^3$.

Data for sucrosic dolomites is compared to experiment in Fig. 15. The increase in $m$ with decreasing porosity is observed in both experiment and simulation. In Fig. 15(b) the $m$ vs $\phi$ correlation for the limestones is shown. Little to no correlation is observed. The value of the cementation exponent in vuggy limestones has been related (Lucia, 1983) to the amount of connected macroporosity in limestones; the presence or absence of touching vugs (see Fig. 7 of (Lucia, 1983)). We show in Fig. 15(c) that the general trend observed by (Lucia, 1983) is observed in many of the limestone samples considered here. The correlation of $m$ to the connectivity of the macroporosity is superior to the $m : \phi$ correlation.

Permeability

The permeability calculation is based on the lattice-Boltzmann method (LB) (Arns et al., 2004). The resultant permeability can be viewed as a dry single phase permeability at ambient pressure. In Fig. 16 we show the comparison of the permeability of two sets of sucrosic dolomites to experimental data (Ehrenberg et al., 2007) from the two fields. The overall poro-perm trends are consistent. Given the importance of microporosity to the flow properties of the limestone and moldic samples one would wish to study the flow properties of the core material in-
incorporating both the resolvable porosity and the micro-
porosity. While this is easily handled in the case of re-
sistivity, it is not simple in the case of permeability; this
is being currently undertaken on the samples and results
will be reported later.

**Acoustic Properties**

We use a finite-element method (FEM) to estimate the
elastic properties of the model system. The digital image
is assumed to have periodic boundary conditions. The
FEM solver is based on previous work (Arns et al., 2002;
Bohn and Garboczi, 2003). Simulations are undertaken
on grids up to 1200³.

Comparison of the acoustic properties for three of the
sucrosic samples (S1-S3) to experiments (Bächle et al.,
2004) performed on plugs of the same material are shown
in Fig. 17(a); the match to the velocity-porosity trend is
satisfactory. Experimental work on a set of oomoldic
rocks (Bächle et al., 2007) has observed that a large scatter
exists in the P-wave velocity-porosity relationship. A
difference of well over 1000 m/s difference is observed
for the same moldic pore type system. Of the six samples
considered in this study, three were slow and three were
significantly stiffer. Simulation of the elastic properties
of the six samples and the comparison to experiment are
shown in Fig. 17(b); results from simulation for the three
slower samples follow the experimental trend for sam-
ps from the same field. The simulation results for the
three faster samples are distinctly different from the first
three, but the velocity increases observed experimentally
are not as dramatically different for the simulation data.
The differences will be associated with the frame modu-
lus of the rock as well as the connectivity of the over-
all frame material. This can be probed by combining
micro-CT analysis with higher resolution SEM (recall
permeability is strongly correlated to pore connectivity. Connectivity is difficult to infer from classical techniques (e.g., 2D petrography) but can be directly enumerated via 3D imaging and analysis. In Fig. 18 we show the pore size distribution for all resolved pores on the moldic sample O1 (see Fig. 13(e)). On the same plot we illustrate the pore size distribution of the connected pores; pores connected via a cutoff throat size of 3 microns or more. We observe that the largest pores in the pore size distribution do not form part of the macroscopically connected cluster at this cutoff throat size, but pores of varying sizes do contribute to the connected porosity. Information on pore size distribution of the connected porosity at different cutoff length scales will improve NMR: permeability correlations for the range of carbonate pore types.

Figure 17: Elastic properties of (a) sucrosic dolomites and (b) moldic grainstones.

Simulations of the acoustic response of the fractured samples lead to a number of observations; firstly we observe that the elastic stiffness tensor exhibits anisotropy (orthorhombic symmetry). On comparison of the calculated stiffness to current theoretical predictions based on the commonly used Differential Effective Medium (DEM) theory for oblate pores, we find that the conventional predictions significantly overestimate the stiffness of fractured samples.

DISCUSSION

In this paper we have illustrated the potential to directly enumerate the connectivity, pore structure and geometry of a range of complex carbonate core material in 3D. This advance, coupled with the ability to simulate resistivity, permeability, acoustic and NMR response (see Arns et al., this proceedings) enables one to directly test a range of cross property correlations. An important example is the testing of how well NMR response can be linked to permeability estimations for different rock types. Samples with similar mineralogy, porosity and surface-to-volume will generally give a similar NMR response, but

Figure 18: Black) Size distribution of all pores in Sample O1 and (red) size distribution of the connected pores based on a 3 micron cutoff throat size.

A clear challenge posed by the results shown in this paper is the need to integrate information from the microporous phase (the submicron scales) into the computational analysis of petrophysical properties in 3D at the plug scale. This has been done for the resistivity and acoustic modeling by incorporating tested empirical or theoretical (e.g., effective medium modeling) properties. Information on pore connectivity, geometry and shape are required for better analysis of the flow, NMR response and multiphase flow properties in the microporous phases. This will require further effort.

One further challenge is to undertake more extensive testing of the simulated data to conventional laboratory core measurements on the same core material. This will lead to improvements in the digital core methods and would lead to a more systematic study of the assumptions, interpretations and analysis methods commonly applied within industry. Ultimately it should lead to better correlations between petrophysical properties and logging measurements.
CONCLUSIONS

• Combining micro-CT data with complimentary microscopy data allows one to explore and quantify the structure of carbonate core material from the nanometer to millimeter scales. Image data at nanoscales can be incorporated into the prediction of petrophysical properties of 3D images. This is especially important in limestones (see e.g., Fig. 6 and Fig. 8).

• The extreme variability in depositional environments and the range of post-depositional processes possible in carbonates leads to a wide variety of pore network structures. The pore network statistics (e.g., coordination, aspect ratio, pore size) for the connected samples are often similar despite the clear visual difference in the network structures. This illustrates the danger of attempting to stochastically generate pore networks for different carbonate samples based on matching network statistics alone.

• Comparisons between simulation and experiment data on the same core material for resistivity, acoustic and flow properties are satisfactory. Flow properties of systems exhibiting significant microporosity require further development.

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REFERENCES CITED


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