MULTISCALE PORE SYSTEM RECONSTRUCTION AND INTEGRATION

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ABSTRACT

Better understanding of single-/multi-phase flow through reservoir rocks largely relies on the characterisation of the pore system. For homogeneous rock materials, a complete description of the real pore structure can be obtained from the network extracted from a rock image at a single resolution. However, for complex rocks (e.g., carbonates, heterogeneous sandstones, deformed rocks etc.), a comprehensive description of the real pore structure may involve many decades of length-scales (e.g., from sub-micron to cm), which cannot be captured by a single-resolution image. Hence, the creation of a 3D multiple-scale model of a porous medium is an important step in quantitatively characterising such heterogeneous rocks and predicting their multi-phase flow properties using pore –scale network modelling.

In this paper, we describe a series of pore architecture models (PAMs) to reconstruct 3D reservoir rocks from 2D thin section images along with a set of pore analysis tools (PATs) to extract the corresponding pore network systems. Specifically, we created the multiple scale pore structure through "multiple scale reconstruction". We present a methodology to construct multi-scale (or combined) networks based on the statistical description of pore-networks of 3D rock images at multiple resolutions. Using such networks, two-phase network modeling results are presented for carbonate samples to illustrate the importance of topology in the hierarchical pore structure. We show examples where isolated large-scale pores (e.g. vugs) are connected by small-scale pores, thus determining the combined effective petrophysical properties (capillary pressure, absolute and relative permeability). Finally, we indicate how the stochastic network generation method can be used to combine information from multiple images at the same resolution but obtained at different locations.

Key words: Probability distribution, pore characterisation, heterogeneity, equivalent stochastic network, multi-scale network

INTRODUCTION

Quantitative characterisation of porous media at the pore scale is of fundamental importance in many scientific subjects. The pore structure of reservoir rocks is complex, but the geometry and topology of porous rocks must be known if we wish to predict *a priori* the physical rock properties. The pore geometry ultimately affects many

macroscopic phenomena associated with mechanical, acoustic and fluid flow responses. The understanding of fluid flow within the pore space of reservoir rocks has significantly increased in recent years, due to both improvements in extracting realistic pore networks from digital rocks and also in the pore level network modelling physics itself.

Although direct measurements of 3D microstructures are now available via x-ray computed microtomography (Dunsmoir *et al.*, 1991; Spanne *et al.*, 1994; Hazlett et al., 1998; Arns *et al*., 2001), it is often difficult and expensive to obtain reliable "images" of the 3D pore structure. When tomographic methods are applied in practice, there are a number of artefacts related to the approach. In particular, tomographic images require a trade-off between voxel size and physical sample size, and it is impossible to capture details while simultaneously placing them into a larger context, such as into submicron scale.

Recently, workers at the Australian National University (ANU) have made significant progress in generating micro-CT images of the 3D pore space of carbonate rocks (Arns *et al.*, 2005; Knackstedt *et al.*, 2007). These images show the larger pores and vugs in carbonates but they do not fully resolve all of the microporosity which is present in the carbonate samples. As alternatives to CT methods, several techniques have been proposed to statistically generate 3D pore structures from spatial information derived from readily-obtained 2D images (Joshi, 1974; Quiblier, 1984; Roberts, 1997; Hazlett, 1997; Yeong and Torquato, 1998; Manswart and Hilfer, 1998). In another approach, Bakke and Øren (1997) have developed a process-based reconstruction procedure, which directly models the particle sedimentation process. This paper follows the work of Wu *et al.* (2006), who described a stochastic reconstruction method that can in principle overcome some of the fundamental problems of the above described methods. The new method creates reconstructions of a (possibly) heterogeneous porous medium using Markov Chain Monte Carlo (MCMC) simulation. The models are referred to as "pore architecture models", or PAMs. This approach differs in one important aspect from earlier two-point (or multi-point) correlation methods (e.g. Okabe and Blunt, 2004 and 2007), in that it involves a multiple-voxel interaction scheme (a high-order neighborhood system) to preserve structural characteristics of the input data. Moreover, the PAMs approach is non-iterative, which allows much faster computations and therefore generation of significantly larger reconstructions. For more complicated rocks, such as carbonates, with distinctive macropore (pore size in 10s μm to mm) and micropore (pore size in sub-μm to μm) systems, our 3D Markov random field models can be used to reconstruct representative systems at each scale. For a carbonate sample, thin section images have been obtained under different microscope magnifications, allowing PAMs reconstructions from which we extract networks for the coarse and fine scales. A method is proposed to combine the reconstructions from the coarse and fine scales. We extract networks for the coarse, the fine and the combined scales and then we compare the predicted relative permeabilities at each scale.

Having derived detailed information from 3D rock images/models, pore networks can be extracted, which are much more realistic than the idealised networks of simplified regular pores and throats. However, tomographic images require a trade-off between voxel size

and sample size, thus it is impossible to capture the details of tight and heterogeneous rocks such as carbonate materials for large core samples (at least representative volume, e.g. several millimetre in diameter) at the submicron scale. As a direct consequence, the utilization of commonly used network extractions is primarily limited by the size of 3D images. However current imaging technology and computer processing capacity are unable to acquire a 3D rock image of several millimetres in diameter at submicron scale (e.g. the number of voxels > 3^{32}). In fact, large rock samples are necessary for many rocks such as carbonates that commonly have multiple scales of porosity. Therefore, it is necessary to introduce a method to generate a pore network of arbitrarily large size but representing the pore structure and pore interconnection (i.e. equivalent network), based on the statistical information rather than superimposing the rock images themselves. Idowu and Blunt (2008) present a method to generate stochastic networks with given input pore and throat size distribution and connectivity in aim of overcoming the constraints of the network generation direct from rock images. But it is still computationally expensive and fixed in dimensions, which is impractical to scale up to core scale and beyond.

Our multiscale pore network construction technique is based on our recent work on this topic (Jiang *et al.,* 2011). There are three major steps involved in the stochastic network generation: (1) stochastically assigning and randomly allocating nodes in a virtual volume controlled by certain distributions such as the node size, shape factor and node volumes etc., (2) creating appropriate bonds according to certain probability distributions, and (3) connecting all nodes and bonds by the connectivity function and the conditional probability distribution. We validate the methodology by comparing the extracted original and the generated stochastic networks on both structural and petrophysical properties using several real rock samples. The reconstructed stochastic networks with corresponding original networks reproduce both the structural features and petrophysical properties compared with the original rock samples. Furthermore, we introduce a more advanced algorithm to generate an integrated multi-scale network of two or more pore networks at different pore scales, using our stochastic network generating method. Later in this paper, we apply this method to the integration of multiscale pore structure in carbonate rocks. This provides insight into the role of rock macro- and microstructure in determining multiphase flow in heterogeneous materials such as carbonates.

3D PORE RECONSTRUCTION AT MULTIPLE SCALES

The PAM reconstruction procedure has proven to be relatively straightforward for reservoir sandstones which have a single pore system (Wu *et al.*, 2006). However, some serious challenges arise when we consider more difficult rocks, such as carbonates. The main difficulty arises from the fact that the pore system in these rocks has ***multi-scale*** features, e.g. macropores and micropores coexist, and therefore thin section images at different scales have to be considered in their reconstruction. In capillary dominated fluid flow calculations, both pore systems may play an important role in multi-phase flow depending on the topology of how these systems are joined together. We explain the method of integration from different scales below.

The micropores can be observed in fine-scale (submicron) images, while coarse resolution images have to be used to visualise the macropores and fractures in a relatively large frame. Because of computer memory limitations, we can only deal with a small volume for a 3D image (perhaps to ~500^3 voxels). If the model has macropores, then in a high resolution reconstruction, there would be only a few scattered large pores which would dominate the model. For example in Figure 1, the reconstructed cube is 300^3 in volume of voxels and the resolution is 1 voxel = 0.14 microns. If we have macropores, at say 28 microns in diameter, located within the cube, a single pore will take up about 214^3 voxels - 70 % of the volume of the cube. In addition, the transition probabilities, derived from the training image, would not properly represent the micropores because the variations occur at scales that are larger than our template. To overcome this problem, we here show an approach in which we sub-sample a small part of the training image at high resolution, focusing on the smaller pores, i.e. the high resolution training image does not contain any complete large (macro pores), and we reconstruct a separate model that gives a good representation of the micropore system. After separate scale reconstructions, we integrate them together as a single nested pore systems image with two scales , as explained below.

Here we illustrate the use of the PAM approach to reconstruct multi-scale pore systems based on different-scale training images. In this work, we use two 2D thin section images for each sample at two respective resolutions differing by a factor of 4 (e.g. . 1.34 μm and 0.33 μm These two-scale images are used as inputs for the reconstruction of 3D carbonate macro- and micro-pore structures, respectively, as shown in Figure 1.

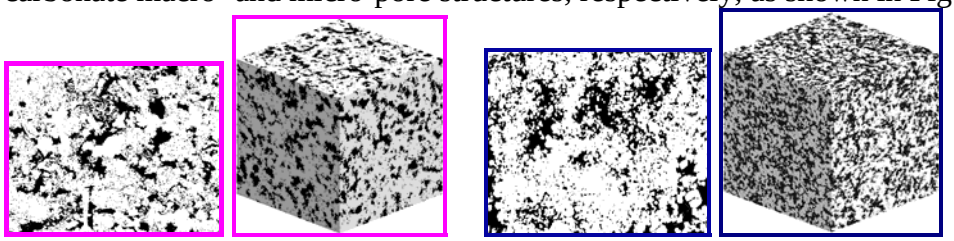


Figure 1. Carbonate SEM images and reconstructions: (a) Coarse resolution image of 1.34 μm /pixel; (b) coarse-scale reconstruction with volume of 300^3 voxels; (c) fine resolution image 0.33 μm /pixel; (d) fine-scale reconstruction with volume of 300^3 voxels.

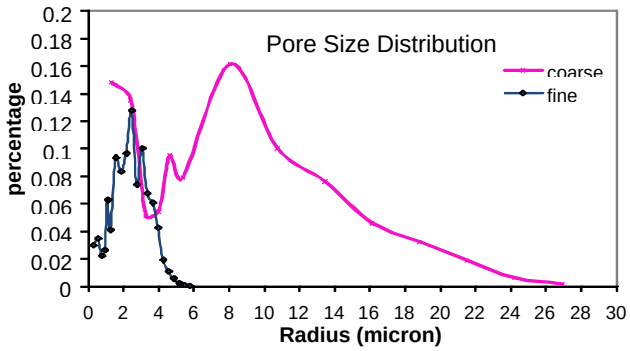


Figure 2. Pore size (equivalent sphere radius) distributions in the reconstructed carbonate from Fig 1

The resulting pore-size distributions (Figure 2) clearly show the effects associated with image resolution. The higher-resolution models (sub-micron scale PAM) indicate an average pore-size diameter of approximately 2 μm. In contrast, the coarse-resolution models (micron scale PAM) show a much larger mode for the pore size of about 10 μm. Using a single resolution image, it is not possible to reproduce all scales simultaneously in the reconstruction because of the huge demand of computer ram as we discussed before. However, it may be possible (see below) to combine the different-scale models to derive a better understanding of the composite material.

MULTI-SCALE PORE SYSTEM INTEGRATION

From a 3D image of a rock at a certain scale, we are able to quantify and characterise the pore space in terms of distributions of properties of the extracted pore network. Furthermore, we can also generate equivalent stochastic networks of arbitrary size based on these statistics. The details of this stochastic network method can be found in Jiang et al. (2011). What we have found is that for homogeneous porous materials, a 3D rock image at a proper resolution is sufficient to characterise the pore structure, in that we can make accurate prediction on the flow properties (Jiang *et al.*, 2010). As noted above, this is not possible for carbonate rocks with multi-scale levels of heterogeneity.

With two or more images acquired at different resolutions for a sample, we may take two different approaches to construct a digital rock model. One direct method is to refine the 3D image to the equivalent resolution of the finer scale and then superimpose these two structures with the same volume into a single model (as carried out in Jiang et al., 2011). The key problem with this image voxel based method is that it will result in a very large model, making it too difficult even for modern computer systems to handle. In this study, we developed a more efficient method by integrating pore networks, one for each 3D model at each scale into a single nested multiscale network as discussed in the following sections.

Pore Network Extraction from each individual scale 3D rock image

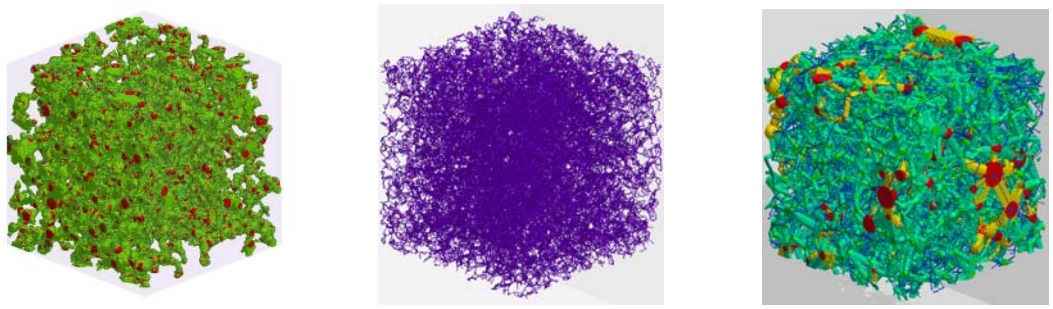
Using the reconstructed 3D structure of Figure 1, we extract separate pore networks Figures 3(a) and 3(b) at different scales. The statistical features of these pore systems were then fully analysed. In multiscale pore system network integration, we propose (1) to use a set of statistical parameters (Jiang *et al.*, 2011) to characterise the pore geometry and topology in terms of probability distributions, correlation functions and connectivity functions, and (2) to reconstruct a representative pore network integrating the original different networks that are extracted from different scale rock images. The generated network combines various pore systems in a virtual manner and is of arbitrarily large size. It consists of all pore networks determined by the corresponding individual images and interconnected by the comprehensive topology among different scale networks. To characterise the pore geometry and topology, we must examine the resulting integrated networks in some detail. In fact, we find that for most typical rocks the pore shape factor is normally distributed while the pore inscribed radius (diameter) is log-normally distributed. In addition to this, the pore connectivity is considered to be more accurate and reliable by using the connectivity function (Eq 1). The connectivity of the pore space

plays an important role in rock flow properties (Vogel and Roth, 2001; Jiang et al., 2010). The local connectivity is given by the node coordination number NC, which is defined as the number of bonds connected to a given node. Nevertheless, the NC distribution and its statistical properties (i.e. mean and standard deviation) do not provide sufficient global topological information about the pore structure. Vogel and Roth (2001) introduced the connectivity function, which is defined as the specific Euler number calculated for the reduced pore space of pore size (radius) equal to or larger than a given value. This quantity provides information of pore connectivity both within and between different classes of pores. By removing levels of the smaller sized pores step by step, the connectivity gradually decreases (and the specific Euler number increases), until a globally unconnected state is reached (and the specific Euler number is positive). It has be shown that the connectivity function for a network is simply computed as

$$\chi_V(r) = \frac{N_N(r) - N_B(r)}{V}, \quad (1)$$

where $N_N(r)$ is the number of nodes and $N_B(r)$ the number of bonds with radii larger than or equal to r (Vogel and Roth, 2001), where each bond for $N_B(r)$ is only used to connect nodes that are counted for $N_N(r)$.

Imaging technology cannot obtain both very high resolution and large volume images. Practically it is much easy to obtain high resolution images for a very small rock sample. Thus, we are able to generate an integrated stochastic network if the combined information can be correctly obtained based on several original pore networks extracted from corresponding rock images at different pore levels. Based on these parameterised descriptors, the generation of the multi-scale network (see Fig. 3c) will be explained below.



(a) (b) (c)

Figure 3 Independent Multi-scale network, (a) coarse pore networks extracted from Figure 1b; (b) fine scale network extracted from Figure 1d and (c) a zoomed sub integrated network combining with (a) and (b).

Multi-scale Network Generation

A multi-scale network is defined as the network of nodes and bonds integrating various scales of pore system information. In the following, we only consider the generation of a two-scale network from a coarse image (coarse network) and a fine image (fine network),

and this methodology can easily be extended to more than two level multi-scale networks. This work consists of two steps:
(1) Generate the representative stochastic network of the coarse network and fine network;
(2) Integrate with nodes and bonds from combined information.

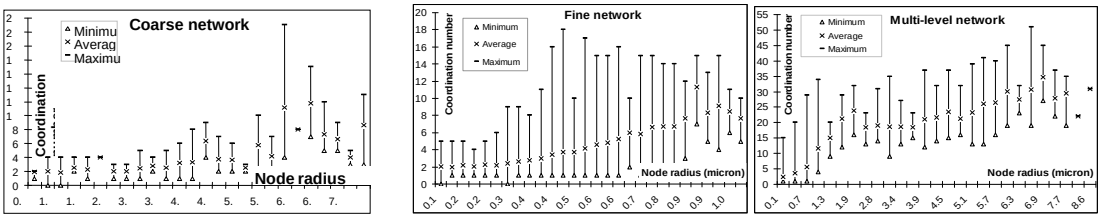
The first step is implemented using our stochastic network method, but the nested volume must be taken into account. A nested volume is a virtual 3D domain within which all node centres are going to be allocated. Using the image space of the original coarse image as the nested volume may lead to a huge number of nodes and bonds from the fine network, which may go beyond the capacity of computer processing and storage. In a relatively smaller representative volume, the problem can be avoided.

With the equivalent coarse network within a proper nested volume, we then assign a certain number of nodes and bonds in the nested volume based on the specific node number by Eq (1) for the fine network. Here, an important issue is how to effectively allocate node centres without overlapping each other. After that, we focus on the assignment of bonds in the nested volume. The radius, shape factor, length and volume of a bond can be easily determined by the corresponding distributions or correlations extracted from the fine network. But the difficulty falls on how to connect nodes with bonds: the nodes can come from the coarse network (coarse nodes) or the fine network (fine nodes), and the fine bonds can be used to link any kind of two nodes. Thus, we need a combined connectivity function (1) to guide the connecting by fine bonds (see fig.5). From Fig. 3a, we notice that a lot of large pores at coarse pore-scale are not connected at the coarse scale, but they could be connected by the bonds at the fine scale. It is reasonable if we assume that the connectivity function under the two pore-level have the minimum value obtained from the coarse connectivity function. Doing so makes it more likely to connect coarse nodes to fine nodes by the fine bonds.

Validation

Using our approach, an algorithm was developed to generate a network composed of different scale networks. In doing this, we carried out a series of numerical experiments to determine which scale is appropriate for a given rock sample 3D image. As an application of the multi-scale network method, we investigate the pore structure and connectivity of complex rocks such as carbonate. Some preliminary results are given which illustrate the importance of integrating the pore structure at various scales in determining rock petrophysical properties. Using the PAM method, we can acquire several 3D images at different pore levels from micron to sub-micron resolution as illustrated in the last section. In Table 1, such a fine scale image is shown from a sub-domain of volume ~5.93×10^{-5} mm^3 with voxel size of 0.16 and 0.33 μm, while the coarse image is shown from a region of volume ~1.88×10^{-2} mm^3 at resolution of 1.33 and 1.66 μm. Before integration, we carry out a series of statistical analyses for all network elements on both coarse and fine networks extracted from the carbonate rock. In Figure 4, the range of coordination number against node radius from coarse, fine network and

integrated network are presented. The porosity measured from the coarse image is 20.14% which is well below its bulk porosity because all pores smaller than 1.33μm in diameter cannot be identified in the coarse image (i.e. they are regarded as being part of the solid matrix). Separately, for each image in Table 1 an original pore network can be extracted and its structure can then be characterised in terms of either distributions or parameters. These analyses for all network connectivities, i.e. specific Euler Number for both coarse, fine network and integrated network are presented in Figures 5.



(a) (b) (c)

Fig. 4. The coordination number/connectivity of the multi-level network: (a) the range of connection against node radius from the coarse network, (b) the range of connection against node radius from the fine network, (c) the range of connection against node radius from the multi-level network

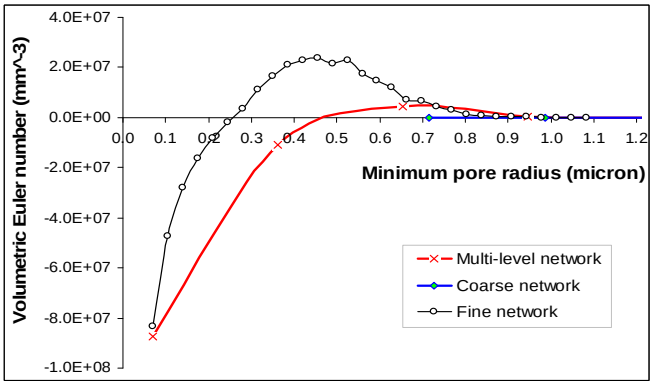
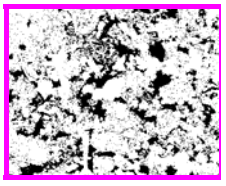
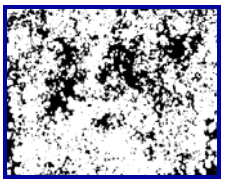
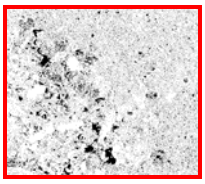
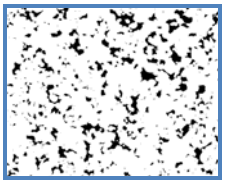
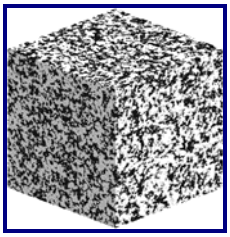
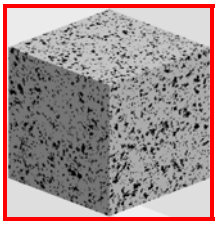
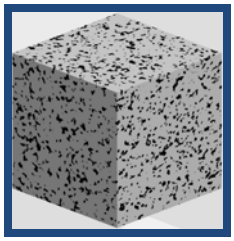
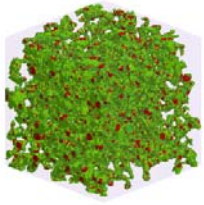
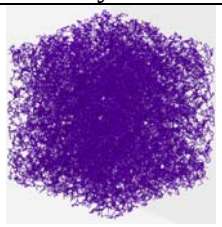
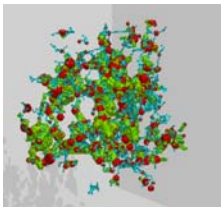
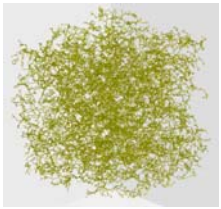
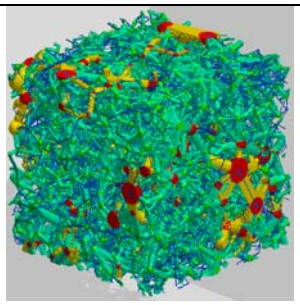
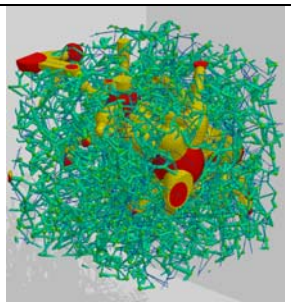


Fig. 5 Three connectivity functions for coarse, fine and multi-level networks

Among all GT properties, the connectivity of the multi-level network changes most significantly, compared with the original coarse and fine networks. Figures 4 and 5 show the range of connection and the connectivity functions vs. node radius. This indicates the high importance of generating accurate multi-level networks in the simulation of single/multi-phase fluid flow. Using pore level network models, the absolute permeabilities, relative permeabilities and capillary pressure curves can be calculated based on these integrated networks.

Table 1: Two Carbonate samples with fine and coarse scale images, and their properties.

	Case 1		Case 2	
Resolution	Coarse scale 1.33µm/pixel	Fine scale 0.33µm/pixel	Coarse scale 1.66µm/pixel	Fine scale 0.16µm/pixel
2D Training image				
3D reconstruction image				
Dimensions (voxels^3)	200×200×200 Porosity 0.20	300×300×300 Porosity 0.26	200×200×200 Porosity 0.13	300×300×300 Porosity0.20
extracted network				
Perm (mD)	16.09 mD	3.45 mD	0.37 mD	0.02 mD
Integrated sub network nodes in red bonds in green				
Integrated Perm Lab Perm	Perm = 109 mD, Porosity 0.32 Perm = 103 mD		Perm = 1.5 mD, Porosity 0.22 Perm = 1.9 mD	

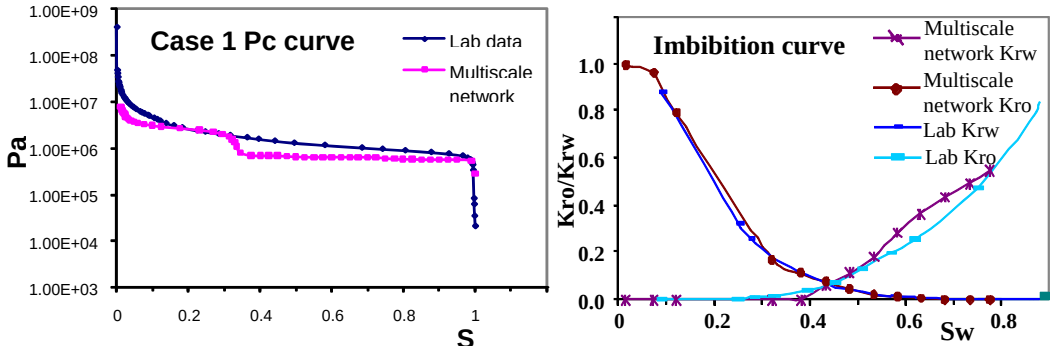
RESULTS

Using two carbonate examples, we illustrate our approach to integrating micron scale and submicron scale pore systems based on separate 2D SEM images at various resolutions. The results are summarised in Table 1 where the two cases shown are good examples of how our integration method can effectively tackle the heterogeneity of reservoir rocks; Case 1 is a higher permeability rock and Case 2 is a lower permeability carbonate.

In addition, the two phase flow properties are calculated using pore network modelling and compared with core laboratory measurements, which are presented in Figure 6.

In Table 1, we note that the predicted permeability is increased significantly from the stochastic coarse network to the integrated network, which reveal an inherent relationship between large nodes and small bonds. And also the imbibition curve and Pc curves give us some insight on the understanding of macroscopic phenomena when multi-scale network is taken into account.

In Figure 6a, the threshold capillary pressure from network prediction matched lab data quite well, considering the relative small network volume, which is only 0.02 mm^3. It is also interesting to note that there is a jump at Sw=0.3, which indicates the connection from macro- to micro-pore systems. Furthermore, the imbibition relative permeability curves in Figure 6b show good agreement between the multiscale network predictions and the laboratory data. Therefore, with the statistical information based on the original networks extracted from 3D rock images, we validate the consistency of our method by comparing the morphological/topological features and macroscopic properties such as absolute/relative permeability. These results provide insight into the role of rock microstructure in determining recovery and production characteristics.



(a) (b)

Figure 6: Comparison lab measurements with simulated mercury injection curve (a) and imbibition prediction curve (b) for case 1.

CONCLUSIONS

In summary, we have described a series of procedures from multiscale pore system reconstruction to multiscale pore network integration. This approach is relatively easier than using pore architecture models (PAMs) to directly reconstruct 3D reservoir rocks from 2D thin section images along with a set of pore analysis tools (PATs) to extract pore network systems. Specifically, we created the multiple scale pore structure through a process we refer to as “multiple scale reconstruction”. This methodology to construct multi-scale (or combined) networks is based on the statistical description of pore-networks of 3D rock images at multiple resolutions. The multi-scale network flow model has been tested by comparing results from it with lab two-phase flow data. From the

multi image and pore structure analysis, it has been concluded that the topology or pore connectivity plays a major role in the hierarchical pore structure. This is illustrated in these carbonate examples where isolated large-scale pores (e.g. vugs) are connected by small-scale pores, thus determining the combined effective petrophysical properties (capillary pressure, absolute and relative permeability). Finally, it should be noted that the stochastic network generation method can be used to combine information from multiple images at the same resolution but obtained at different locations.

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