Distribution Statistics and Modeling Porous Media for use in Multiphase Flow Simulations

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Abstract

Distribution Statistics and Modeling Porous Media for use in multiphase Flow Simulations. William B. Cribbs (College of the Sequoias, Community College, Visalia, California 93277) Liviu Tomutsa (DOE National Laboratory, Berkeley 94704).

A complete system for generating macroscopic properties of porous materials through computer modeling is presented. The particular focus is to make accurate models of sandstone by numerically modeling the sequence of main sandstone forming processes. Our depositional model includes sedimentation, compaction and diageneic processes. The input parameters for the model are extracted from the analysis of thin section radius distribution statistics. These statistics must also compensate for the fact that the 2D thin section distributions do not extrapolate directly to 3D volumetric distributions. Once an accurate volume of sandstone has been modeled, 3D image analysis can be used to extract the architecture of the pore network, its throats, and pore sizes geometry. The network descriptor is then fed into multiphase flow simulations producing transport properties which can be compared to available experimental data.

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Introduction

Why study porous rock? Well, gas prices are rising once again, as we well know, and they are most likely going to stay high. These prices are usually based on how many barrels of oil are produced from oil reservoirs. Therefore, getting the maximum oil from an oil reservoir is of major concern. This is why studying the porous rock that holds it is so important.

The oil industry then looks to scientists and engineers to help them make decisions on where to drill, how to drill, and at what rate they should pump the oil. Therefore, Geologists , Petroleum Geologists, and

Engineers research to get a handle on what is going on at different scales in the porous rock. Unfortunately, present techniques are both time consuming and uncertain, forcing big oil to make unwise, costly decisions. For example, in the case of reservoir coning, water will 'cone' up at a drill site, increasing water production, making it less productive and costing oil producers millions in water disposal costs.

The functions that govern field scale oil recovery relate directly to the physical characteristics of porous media. Once a sample has been imaged or modeled, these functions can be extracted by simulations of flow, leading to knowledge of correct pumping parameters.

Our group is working to better simulate this multiphase flow process (i.e. water, oil and gas) through various porous media. The pore networks of porous rock are constructed of pore bodies (the larger chambers), and pore throats (the passageways). By Using simulations of these pore networks on various porous rock structures one is able to

extract finite microscopic properties from them. These properties can then be upscaled to obtain macroscopic properties like engineering parameters relative to larger samples such

oil is recovered and at what rate' [8]. Relative permeability is defined as the fraction of the absolute permeability of the rock in the presence of another wetting fluid or phase.

by drainage, imbibition, and capillary pressure. These pore scale physics parameters can be used to model defining functions and maximize oil recovery.

in the lab using core plugs. This can last weeks and is very expensive if at all possible as core material is often not available. This is why we look to computer simulations as an

defining the porous rock at small scales (microns – cms). We are using advanced imaging techniques such as micro CT scanning, linear X-ray , and NMR imaging to obtain 2-D and

3DMA, developed by Brent Lindquist at SUNY and AnetSim by Tad Patzek at Berkeley[8].

scope. Because of its limited resolution (~5 microns a voxel), it can't always distinguish between smaller pore throats and the surrounding grain. This limitation keeps imaging

Berkeley Labs have adopted the approach of 'building' the rock from its grains in the computer by using a selection of grain sizes measured from the real rock in question.

Methods and materials

3D Stochastic modeling of Sandstone

Sandstone is the product of dynamic processes that affect its sedimentary basins. ‘schematically described, starts with erosion of quartz-bearing rocks, followed by sandgrain transport via air, water or ice, and, finally, deposition of grains in sedimentary basins’[1]. After deposition, the grains are subject to compaction as well as different diagenetic processes. To correctly model a 3D volume of sandstone, these processes must be applied to the model. Our algorithm, implemented by Kathy Hildenbrand and similar to that of S.Bakke and P. Oren (1997), includes compaction and diagenesis.

Sedimentation:

The Berkeley Labs implementation of these processes starts with the actual sand grain deposition. The algorithm implemented in MATLAB numerically models sandstone by using spherical (quartz-like) grains deposited in low-energy (local minimum of potential energy) environments. The grains are assumed to be spherical with varying radii. The grain sizes are then picked from a lognormal distribution curve. This distribution should correlate with the actual grain size distribution of the sandstone in question. It is important to note that obtaining data for this distribution through sifting a sample is time consuming, in addition, insufficient amounts of core plug material are usually not available. Instead, distributions can be quickly sampled using thin section (2-D) grain size distributions. Traditional analyses of pore geometry by image analysis of thin sections are normally based on Delesse’s principle, which states that 2-D observations are representative of the 3D sample. [9].

Next, the grains are dropped from random (x,y) positions. The model then incorporates a circular search space in which it will decide if the grain is to drop onto another grain already in place or settle in its current (x,y,z) coordinate. When a set number of grains have been deposited we see a characteristic "mound", figure 1.

Compaction(λ):

Compaction results in bulk volume reduction as well as a decrease in porosity. The compaction is usually a result of stress normal to the XY plane. Athy has, indeed, found that the variation of clay porosity(ϕ) with depth(x) can be represented by [2]:

$$\phi = \phi_o e^{-ax}$$

To physically approximate this compaction our model incorporates a linear compaction on the Z axis:

$$Z = Z_o(1-\lambda)$$

Z being the array of new Z-coordinates , Zo the old ones, and λ a compaction factor ranging between 0 and 1. Thus, every grain center is shifted downward an amount proportional to its original height. Also, note that because of the dense packing of the sediment, grains are not likely to rearrange themselves, and translation of the X and Y arrays are not considered in compaction.

Diagenesis(κ):

Diagenetic processes are necessary to mimic the cementing overgrowth found in many sandstones. Figure 2 shows an example of this overgrowth in Foolite sandstone. Quartz cementation overgrowth can be simulated by increasing uniformly the radii of each grain used in the model by a constant factor(κ), further reducing porosity. However,

quartz cementation overgrowth is the only Diagenetic process modeled by this transformation of the grain structure. Note that there are also many other diageneic processes not modeled by this simulation. In the future these processes should be studied and incorporated into the sedimentation model code.

Generating the volume

After the sediment is prepared, it is then volumetrically gridded. This process includes taking slices through the mound of spheres and stacking them until a 3D grid is produced as shown in Figure 3. Thus, the boundary typically ranging from an array of (80x80x80) to (300x300x300) is cut from the inside of the mound. These arrays are now characteristic of an image produced with X-ray diffraction or NMR imaging technologies with increased resolution and can be immediately used in pore network simulations.

Flow simulations through porous media

Once a core sample has been imaged or modeled it can be used in simulations. Of primary interest to us is the pore network and network connective descriptions. This analysis can then be used by Berkeley's AnetSim to find capillary pressure, relative permeability, porosity, and other fluid transport information. To obtain the pore network and its parameters from image arrays, we used publicly available code, 3DMA[4]. Brandon Peden, a Summer Researcher at LBNL has been visualizing 3DMA's program output, achieving some degree of success extracting relevant pore networks.

However, for 3DMA to use raw gray scale images we must first segment them into grain space and pore space. Using NoeSys Transform we were able to pick stable thresholds to segment the data. Figure 4 shows the 3D composite raw image and its

binarized 2D thin section image. The binarized data was then analyzed by medial axis algorithms in 3DMA. Figure 5 shows the output of 3DMA's medial axis calculations.

HCP

Lastly, in order to get a better handle on 3DMA's algorithmic efficiency, we decided that some elementary sandstone models would be appropriate. A model constructed of (hexagonally close packed) spheres (HCP) gives a basic 'honey comb' media axis and flow path structure. Successfully building the HCP structure in MATLAB was a product of first placing the correct (x,y) centers of each sphere correctly in the Z plane. Next, translating to the next plane and increasing the z coordinate by the calculated amount, see schematic 6c. The rhombohedral structure of the HCP is commonly studied in chemistry as well as material science.

This structure helped us determine what 3DMA was doing to the medial axis and if the program was calculating it correctly. Figure 6b shows this structure along with its complementary ANetSim output, which seems to give nice, physically resembling relative permeability and capillary pressure curves.

Results

Grain size distributions and the Sedimentation Model

To interface this model with the real world, correct grain size distributions must be chosen for our depositional model. As I have touched on earlier, for most commonly found reservoir sandstone a lognormal distribution of grain sizes have been observed[3].

Most size distributions are measured from thin slices of the real rock in question. Taking the distribution from 2D thin sections, however, does not numerically correlate directly to volumetric radius distributions. Commonly, the slice grain size radius will be less than or equal to that of the volumetric radius. Thus, different sandstone and sediments require entirely different input distributions which must be extrapolated and approximated from the distributions obtained from real rock thin sections.

Figure 7 shows a histogram of a grain size distribution typical of our depositional model. The distribution is modeled by interpolating between a bounded random number and cumulative probabilistic curve. See CDF figures, figure 8. The lognormal probability distribution function used:

$$p(x) = \frac{1}{b^2\sqrt{2p}\,x} e^{-\frac{(\ln(x)-a)^2}{2b}}$$

The integral of this function, or cumulative distribution represents the real rock volumetric grain size distributions with input parameters of logarithmic mean and variance: α and β respectively. There is no size limitations for the grain size distribution, and rocks ranging from siltstones to conglomerates may be modeled.[1]

Input parameters must then build the correct model. Table 1 shows the input parameter data for the depositional model code and its resultant logarithmic mean and variance from thin section analysis. Also, figure 9 shows the model input and the thin section output composite grain size histograms. Note that the tails of the 3D distribution curves are not exhibited in the 2D distribution. The thin sections seem to only give clues about the mean and not the extent to which the tail fans out.

Investigating further, we found that these generated models contained a lognormal distribution only up to a maximum grain size. Thus, the normalized curve for the input distribution is cut before it reaches its full distribution as shown in Figure 10.

Discussion and Conclusion

As one can see the data gained from thin section analysis dose not extrapolate directly to the 3D grain space model. In fact, the structure of such materials can be described only in statistical terms. [2] However, there is some possible correlation between the statistics obtained from the numerical deposition of lognormal distribution and the thin section distributions. Increasing the input variance showed a decreasing volumetric mean but an increasing mean of the output distribution as well. This may also be a product of the maximum grain size. Plotting the variance vs. the ratio of 2D to 3D radial means, an almost linear relationship is achieved. However, when changing the compaction factor for the same input distribution the same linearity was not reproduced See figure 11. It is possible to conclude from this that for a particular compaction factors an numerical interpolation to the 3D distributions from the 2D distribution is possible. This linear trend is only applicable to these particular samples of maximum grain size distribution. So, at this point in time however, it can only make for approximate bounded data. Thus, for industry a more beneficial correlative technique would be a construction of a complete catalogue of tables and different curves.

This catalogue should contain the 4 dimensions of α,β,λ,and κ standing for lognormal mean and variance of both the 2D and 3D slices , the compaction factor and the Diagenetic growth constant, respectively. Maximum grain size should also be explored

since it might lead to clues in correct distribution of the larger grain sizes. In time we hope to gather all the needed data for a complete catalogue making this modeling process applicable to many different sandstone distributions. Thus far only preliminary catalogues of distribution curves were processed from the depositional model, using compaction factors ranging from 0 to twenty percent.

This process starts the first iteration of interfacing depositional modeling to real porous media. In the future, different distributions such as bimodal and binomial distributions should be modeled. Once all this information is catalogued correctly, samples can then be run though the simulation processes and matched with physical mercury injection data. The turn around time for building an accurate volume of oil bearing rock then will be very quick and cost effective.

When the correct parameters have been set, the image analysis then becomes important. 3DMA, although having problems with parts of the code particularly in the clean up of the media axis, yields fairly accurate base media axis interpretations. Our group hopes to further streamline this code. To accomplish this improvements should be made specifically to the memory routines. We have already made some progress here, specifically with modifications to files: \statistics\mamod.c and ..masets.c. However, it may be more preferable to write new code that incorporates 3DMA's algorithms. This way the programmer will be more familiar with the algorithms and routines. This is recommended because it increases the ability to modify the code and to increase the medial axis clean up routines accuracy and stability.

Conclusions / Recommendations

Simulating the processes of forming sandstone leads to cost-effective, and rapid methods for obtaining 3-D pore scale models. From which critical reservoir pumping parameters can be obtained through image analysis and numerical simulation on verified simulations like ANetSim. This can be accomplished with the continued study of grain size distributions and physical simulation parameters. An imaging system consisting of a microscope and a sander for use in thick section extraction is also recommended. This may lead to enough information on the maximum of the curve and the variance of the distribution.

In the future, when enough generated data is accumulated, it is expected that we will have a fully automatic process to exact porous media properties based on grain size analysis. This would be of great interest and benefit to oil companies and consumers alike.

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