Image Analysis and NMR modeling of Sedimentary Rocks

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Abstract

In this paper, the Nuclear Magnetic Resonance response of three sedimentary rocks (one sandstone and two carbonates) is modeled through random walk simulations. With this modeling, we aim to improve micro-porosity content and pore size estimation, by taking into account both surface relaxation and diffusive coupling. Experimental Magnetic Resonance data and microscopic image analysis are used to compare the results. We obtained a good match between simulated and experimental T_2 distribution curves. Geometrical parameters used as inputs in the model provide macro- and micro-porosity content as well as pore sizes.

Introduction

For the last twenty years Nuclear Magnetic Resonance (NMR) has been successfully used as a well-logging technology in the evaluation of hydrocarbon reservoirs. NMR is employed in estimating porosity, permeability and pore sizes. It can also provide information on fluid viscosity and water saturation (Dunn, 2002). NMR logging is today an important service and recent developments allow the measurement to be made while drilling, which results in data taken before significant wellbore invasion.

The NMR measurement is sensitive to ^{1}H present in the fluids saturating the rocks. The ^{1}H spins are excited by a radiofrequency (rf) pulse. Once the excitation is ceased, the spins will return to the equilibrium state, this process is known as relaxation and is described by the longitudinal and transversal relaxation times – T_1 and T_2, respectively.

Commonly, the Carr-Purcell-Meiboom-Gill (CPMG) pulse sequence is applied to measure T_2 for a given sample (Meiboom, 1958). The measured fluid relaxation rate can be defined as

$$\frac{1}{T_2} = \frac{1}{T_{2,bulk}} + \frac{1}{T_{2,s}}, \qquad \text{(Eq. 1)}$$

where $T_{2,bulk}$ and $T_{2,s}$ are, respectively, the bulk and surface contributions to the relaxation. For a given pore, the surface relaxation will depend on the pore space and on the surface relaxivity, ρ_2, according to

$$\frac{1}{T_{2,s}} = \rho_2 \frac{S}{V}, \qquad \text{(Eq. 2)}$$

where S/V is the surface to volume ratio. For fluids contained in restricted geometries (e.g., the pores of reservoir rocks) surface relaxation plays a dominant role and the measured T_2 distribution can provide valuable information about the pore space.

One could expect then that each pore would contribute independently to a final magnetization and the T_2 distribution curve would be directly related to pore sizes. However, experimental results show this is not true as T_2 distribution curves can be different than expected. This is as result of fluid molecules diffusing between micro and macro-pores (Ramakrishnan, 1999). Therefore, in order to estimate pore sizes from NMR responses, this phenomenon must be taken into consideration.

Microscopic pictures of thin sections can also be used to describe the size and shape of the pores and grains of sedimentary rocks. However, when dealing with carbonates, heterogeneity often plays an important role. Because thin sections capture only a small part of the rock, analysis based on a single thin section may not yield representative results. Nevertheless, thin section images provide useful qualitative information on the macro-porosity and the size and aspect ratio of the macro-pores.

Geometrical model

The Micro-Grain Consolidation (μ-GC) model (Zhang, 2011) is based on a three-dimensional packing of overlapping spheres which are, in turn, comprised of micro-spheres (Fig. 1). This allows us to represent mixed-porosity systems, such as rocks with bimodal pore size distributions.

The grains are arranged on a cubic lattice and by adjusting the radius of the macro and micro-spheres (i.e., the degree of overlap) one can control the macro- and micro-porosity of the system. The center to center distance can also be changed and is related to the over-all pore size. A scale factor controls the mismatch between the macro- and micro-grids.

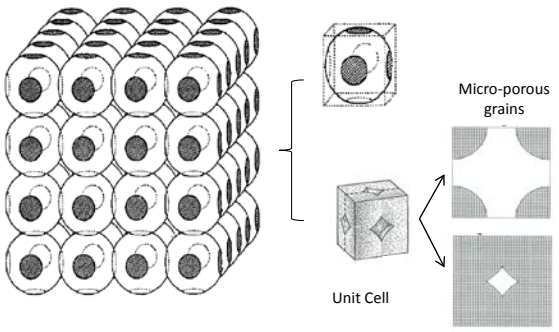

Figure 1. Micro-Grain Consolidation model. On the left, the three-dimensional packing of macro-spheres and, on the right, the unit cell and the micro-spheres contained within the macro-spheres.

Random walks

The model's NMR response can be simulated using random walks to represent diffusion together with relaxation at the pore-grain interface. The bulk fluid relaxation needs to be taken into account as well (for larger pores or vugs). But, as this relaxation mechanism is not dependent on time – only on the type of saturating fluid – it can be included at the final step.

The method applied in this study makes use of variable step size random walks. Because we are dealing with a system with big discrepancies in pore sizes (micro- and macro-porosities), using a fixed step size algorithm would be prohibitively inefficient because the step size would have to small compared to size of the throats in the micro-pores. In our variable step size algorithm, the step size is defined as the radius R of the largest sphere that can be drawn around the walker without intersecting the pore wall. The walker goes to a random point in the surface of this sphere and the walker's clock advances by $R^2/(6D_0)$, where D_0 is the saturating fluid diffusion coefficient. Once more, the radius of the largest sphere is determined and the walker steps randomly. The procedure is repeated until the walker reaches a distance δR to the pore wall, where the algorithm will change into a fixed step size walk. Once inside this shell of width δR, the walker will have two possibilities: stepping until it passes out of the shell and then returns to the variable step algorithm, or stepping until it hits the pore wall (inside the macro- or micro-pore space). When the walker hits the wall it has a probability, γ $[0 < \gamma < 1]$, of dying (relaxing). γ is related to the surface relaxivity, ρ, and the diffusion coefficient, D_0, according to

$$\gamma = \frac{2\rho\varepsilon}{3D_0}, \qquad \text{Eq. 1}$$

where, ε is the step size when the walker is within the layer of width δR. The time at which the walker dies is recorded and another walker is released at a random location in the pore space.

Samples and NMR experiments

In this study, three sedimentary rock samples were evaluated: one sandstone (Red Massilon) and two carbonates (Indiana Limestone and Silurian Dolomite). The samples consisted of cylinders 1.5 inches long and 1.5 inches in diameter. At first, Helium gas porosity (ϕ) was measured for all samples. Prior to NMR measurements, samples were saturated with a 50,000 ppm KCl brine.

In a Maran Ultra by Oxford Instruments (UK), operating at a Larmor frequency of 2 MHz for ^{1}H, CPMG experiments were carried out with an echo spacing time of 400 µs and the acquisition of 32 scans. The resulting decay curves were processed with a Fast Laplace Inversion algorithm (Song, 2002) to produce the T_2 distribution curves.

Two-dimensional experiments were also performed for each sample. Such experiments consist of a set of Pulsed Field Gradient Stimulated Echo (PFG-STE) experiments (Tanner, 1970) followed by a CPMG measurement. This allows us to construct a two-dimensional plot correlating diffusion coefficient (D) and T_2. In these experiments the diffusion time was set to 40 ms and the gradient strength varied from 0 to 46 G/cm. The set of decay curves obtained for each sample was also processed using the Fast Laplace Inversion routine.

A recently developed application of D-T_2 plots in the study of reservoir rocks is the determination of the value of surface relaxivity ρ, using a Padé fitting approximation (Latour, 1993). The classical way of determining ρ_2 correlates the T_2 distribution curve and the mercury injection capillary pressure curve (Wong, 1999). This is a destructive method that can only be done in laboratory. By contrast, estimating the ρ_2 from D-T_2 measurements is non-destructive and employs data that can be acquired in down-hole measurementes. The ρ_2 values calculated for our samples are also presented in Table 1.

Table 1. Gas porosity, ϕ, and surface relaxivity, ρ_2, values for the studied samples.

Sample	ϕ (p.u.)	ρ_2 (µm/s)
Red Massillon	22.8	26
Indiana Limestone	15.1	8
Silurian Dolomite	18.3	7

Image Analysis

Thin section pictures were analyzed in an optical microscope and pictures of the most representative areas in the thin sections were taken. These pictures were evaluated according to the following procedure:

1) Point-count of visible macro-porosity (blue area);
2) Creation of binary image for selected pores and grains;
3) Measurement of grain and pore sizes and calculation of aspect ratios.

The gas porosity values were compared to the visual macro-porosity value from image analysis and an estimate on micro-porosity content was calculated. Grain and pore size and aspect ratio data were measured. In Figure 2, the microscopic picture and the grain and pore outlines are shown for the Silurian dolomite thin section.

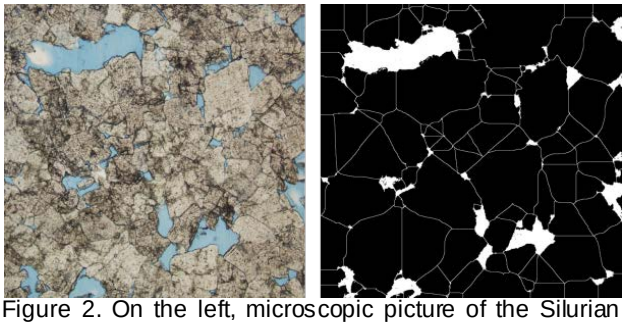

Figure 2. On the left, microscopic picture of the Silurian dolomite thin section. On the right, the grains (in black) and pores (in white) extracted from the binary image.

Simulations

In the numerical simulations several different geometrical inputs were tested. The gas porosity and surface relaxivity, ρ, values were kept fixed for each sample. The other geometrical parameters (micro and macro-porosity content, center to center distance and scale factor) were varied in an attempt to match the measured T_2 distributions.

The simulated magnetization decay was also processed with Fast Laplace Inversion algorithm (Song, 2002), and the T_2 distributions obtained were compared to the experimental ones (Figure 3).

For samples showing a too high ρ_2, such as the Red Massilon, finding the optimal parameters for the simulation is very difficult. In this cases, small changes in pore size leads to significant changes in the T_2 distribution. This explains why the overlap between the experimental and simulated curve for the Red Massilon is not as good as the others. In general, carbonates have much lower values of ρ and the algorithm is able to model these rocks with a very good match, as can be seen for the Indiana limestone and Silurian dolomite samples.

In Table 2, the parameters used in the simulation are compared to the pore diameters measured from thin section images. Although there are big discrepancies in the average macro-pore sizes, when we look at histograms for the macro-pore sizes from image analysis (Figure 4) we see that there are macro-pores as big as 300 μm in the Silurian Dolomite, 160 μm for the Red Massilon and 200 μm for the Indiana Limestone, which corresponds much better with the simulation inputs.

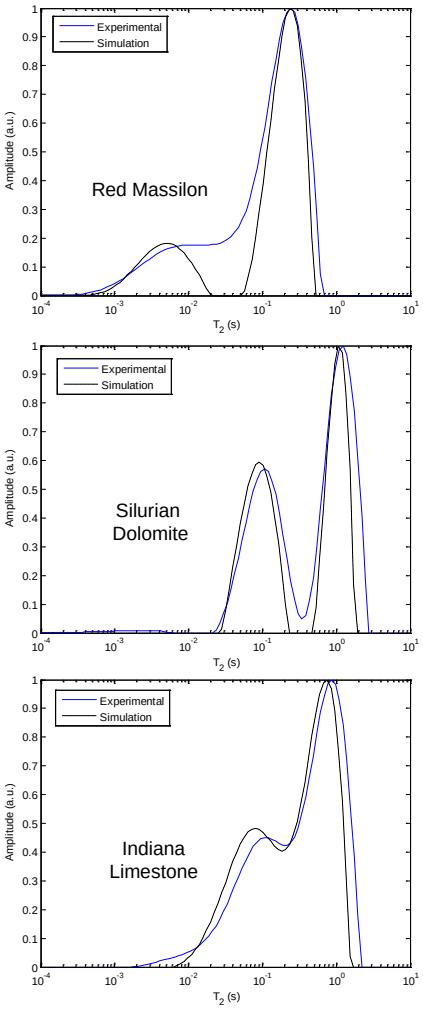

Figure 3. Experimental (blue line) and simulated (black dashed line) T_2 distributions for the studied samples.

Table 2. Macro-porosity content and average macro-pore diameter determined by image analysis. The values that gave the best match for the T_2 distribution curve for each sample are shown.

Sample	Macro-porosity (p.u.)		Average macro-pores diameter (μm)	
	Image Analysis	Simulation	Image Analysis	Simulation
Red Massilon	15.7	12.6	35.2	200
Silurian	8	8.1	28	300
Indiana	3.4	7.8	11.6	200

It is important to notice that with the modeling, it is possible to capture the macro and micro-porosity content taking into account the diffusive coupling. Better resolution images, such as confocal microscopic images, would help corroborate the amount of micro-porosity estimated by the NMR modeling.

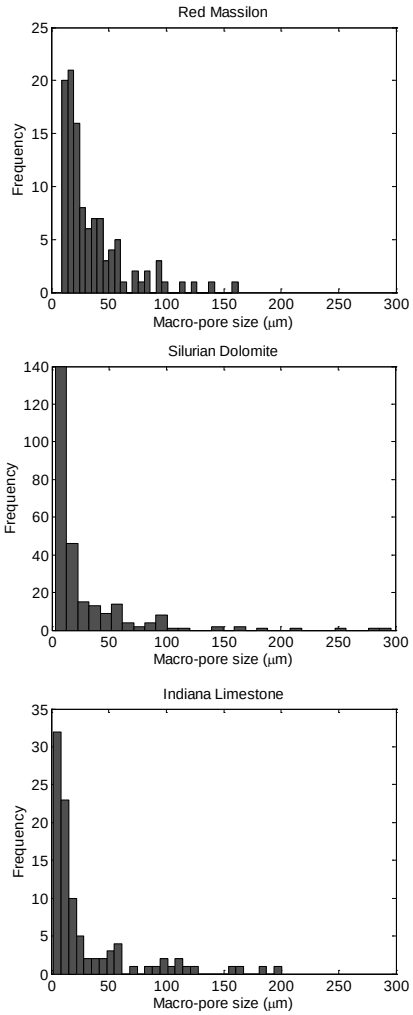

Figure 4. Histograms for macro-pore sizes for Red Massilon, Silurian Dolomite and Indiana Limestone from image analysis. Although they show average macro-pore size between 10 and 30 μm, they also show macro-pores as big as 300 μm.

Conclusions

With the μ-GC model and random walk simulations it is possible to model the NMR response of sedimentary rocks with good agreement. As the process takes into account diffusive coupling, the model gives a better estimative of macro- and micro-porosity content for the porous media. Moreover, the numerical simulations provide an estimate of the average pore-sizes for the rocks based on the geometrical model.

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