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Residual Saturation During Multiphase Displacement in Heterogeneous Fractures with Novel Deep Learning Prediction

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Abstract

Multiphase flow through fractures is common in many fields, yet our understanding of the process remains limited. In general, this is because some factors which separate multiphase flow from single-phase flow (interfacial tension, wettability, residual saturation) are difficult to characterize and control in a laboratory setting, and are also challenging to implement in traditional numerical simulators. Here, we present a series of lattice Boltzmann simulations of CO_2 displacing brine in rough fractures with heterogeneous wettability. This extended abstract focuses on the application of this technique to predict irreducible brine saturation within the fractures. We show that this irreducible brine saturation may be greater than 25%, which could have significant impacts on production estimates from unconventional reservoirs and is typically not accounted for in reservoir simulators. However, performing these simulations at the field scale is not possible due to their computational expense. Therefore, we present a machine learning technique based on deep neural networks to predict the fluid distribution within these fractures at steady state trained upon on the lattice Boltzmann simulations. To our knowledge, this is the first example of machine learning being used to predict the distribution of fluid within a subsurface media. Here we show that a trained network is able to accurately predict the fluid residual saturation and distribution based solely on the dry fracture characteristics. This proves that machine learning holds promise for upscaling these simulations to a relevant scale for application to the oil and gas industry.

Introduction

Multiphase flow in fractures has implications to many fields including nuclear waste disposal, CO_2 sequestration, geothermal energy, and the oil and gas industry. During multiphase flow, factors that do not play a role in single-phase flow become important. These factors include the interfacial tension between fluids, the fluids viscosity ratio, and the wettability between the solid surfaces and each fluid. Compared to porous media, where the effect of wettability has been extensively researched, the influence of wettability during fracture flow is relatively unstudied. This is partly due to the difficulty in characterizing the wettability of natural rock cores and conducting experiments as well as the difficulty in including wettability into numerical simulations. Therefore, the importance, or lack thereof, of wettability during multiphase fracture flow remains uncertain.

Common practice in reservoir simulators is to assume that the relative permeability of fractures is equal to the saturation of the fracture and that there is no residual oil or irreducible water saturation. This is in contrast with well-known behavior in porous media and with experiments conducted within fractures (Diomampo, 2001). Production in unconventional reservoirs is characterized by an initial surge of water from the hydraulic fracturing process, followed by a sharp peak in oil production as the fractures are drained, and then a steady decline to the productivity of the rock matrix. The presence of residual oil and irreducible water saturation could have important implications for predicting this process and estimating production from these wells. While we know that wettability variation plays an important role in residual saturation and irreducible water saturation in porous media, its effect in fractures remains poorly understood. Due to the pore-scale processes which control these parameters and the difficulty in completing experimental measurements pore-scale simulations are a promising technique for exploring multiphase displacement in fractures.

The lattice Boltzmann method (LBM) is a particle-based simulation technique that allows for the approximation of the Navier-Stokes solution with multiple phases and the inclusion of wettability through an attractive or repulsive force near fracture surfaces in a straightforward way. These simulation techniques have been recently used to explore the effect of wettability in porous media (Zhao et al., 2018) as well as homogeneous wetting in fractures (Dou et al., 2013). The local nature of the LBM computation allows it to be highly parallelized, however the high resolution necessary to capture the wettability and aperture variation mean these experiments can only be conducted at small scale (few cm). Machine learning techniques hold the potential to greatly increase the computational efficiency of these simulations and upscale them to scales of interest to the oil and gas industry (Santos et al., 2020b). Here we present the results of recent LBM simulations of multiphase displacement in heterogeneous fractures with a focus on the effect of wettability as well as our efforts to conduct these simulations using machine learning.

Methods

Simulations of supercritical CO_2 (s-CO_2) displacing brine within rough fractures with heterogeneous wetting were conducted using the *Taxila* LBM simulator developed at Los Alamos National Lab (Porter et al., 2012). *Taxila* has been used to investigate the permeability of Berea sandstone and to simulate concurrent flow in parallel plate models (Coon et al., 2014). The simulator is highly parallelized and has been run on greater than 65,000 cores on the super computers at Oak Ridge National Lab (Coon et al., 2014). Synthetic fractures were generated using Synfrac (Ogilvie et al., 2006), a software for creating fractures based on natural analogs. Four fractures with increasing roughness were created and each of these fractures were varied in average aperture to create thin, regular, and wide apertures for a total of 12 unique fractures. Upon these fractures we simulated three different wettability distributions based on mineral content within natural shales along with a completely CO_2-wet and completely water-wet case. The wetting cases are denoted as A, B, and C with A being the least correlated field and C the most correlated. The entire model domain is 128 x 256 x 33 with a single planar fracture within it (Figure 1). The fracture is initialized with brine and s-CO_2 is injected along one side until steady state is reached.

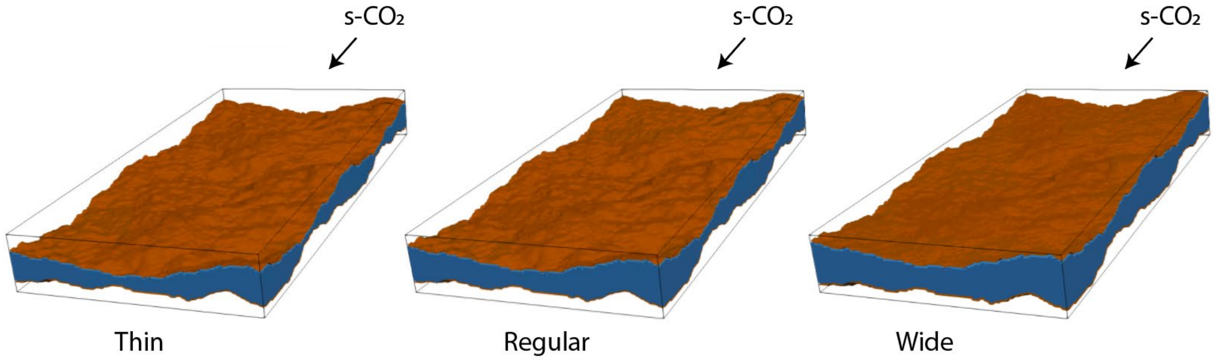

Figure 1: A brine (blue) filled fracture with fracture surface in orange. Supercritical CO_2 is injected upstream and brine and CO_2 exit the model downstream until a steady state is reached.

To create a predictive model that is able to learn from the LBM simulation outputs, we used a convolutional neural network (Santos et al., 2020a). This deep-learning model learns a functional mapping between the dry fracture properties and the residual saturation at steady-state (as shown in Figure 2). By using spatially-aware trainable kernels (that are constrained to honor the flow physics), the network extracts the main morphological features of the solid surfaces (roughness and wettability), that impact the amount and distribution of residual fluid after a CO_2 invasion.

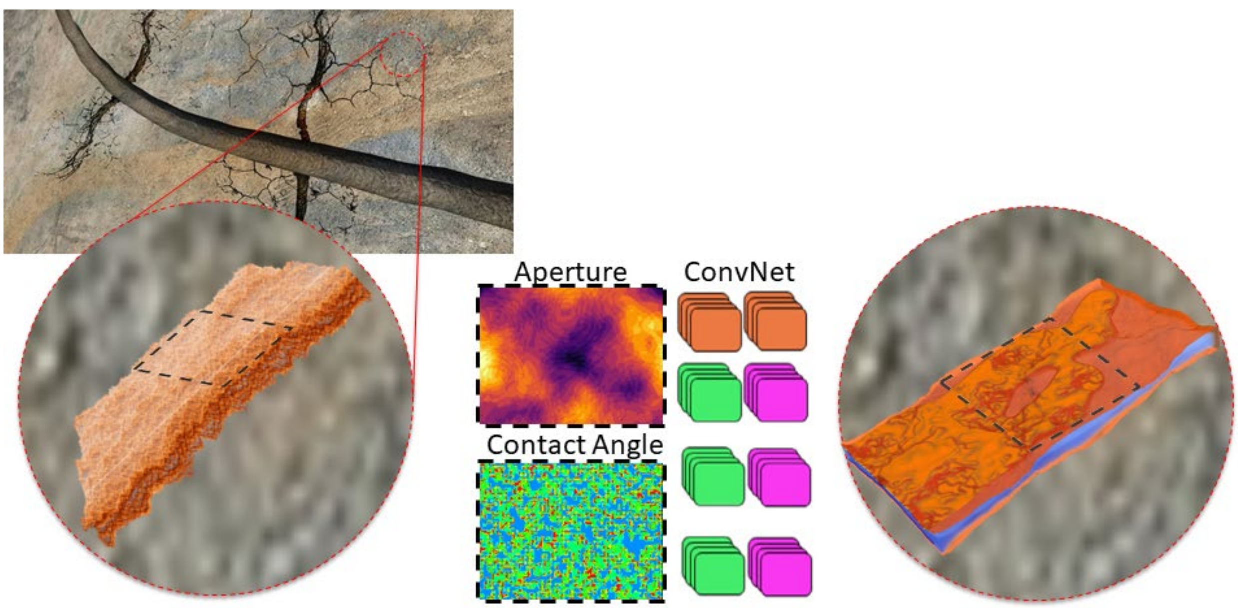

Figure 2: Machine learning workflow. Our fracture within the larger fracture network of a hydraulically fractured well [left, modified from (Parshall, 2017)]. The neural network receives the aperture field and wettability map as inputs (middle) and it outputs the residual water saturation at steady-state (right).

Results

The s-CO_2 enters the fracture from the top and proceeds to displace brine within the fracture until a steady state saturation of s-CO_2 is reached. We define the steady state point when the change in saturation is less than 0.5% of the saturation at the current timestep:

$$\frac{Sat_{CO2}^{t} - Sat_{CO2}^{t-1}}{Sat_{CO2}^{t}} < 0.005, \tag{1}$$

where Sat_{CO2}^{t} is the saturation of CO_2 at timestep t. The time that each simulation takes to reach steady state is a function of the aperture width and the wetting condition applied to the fracture walls (Figure 2). The CO_2-wet fractures reach steady state the first and leave no irreducible water saturation. As heterogeneous wetting distributions are incorporated, the time until steady state is increased and the CO_2 saturation is decreased (an increase in irreducible water saturation). In general, wetting distribution C that has the most correlated heterogeneous wetting has the lowest CO_2 saturation and longest time to steady state of the wetting distributions. The water-wet fracture exhibits the least CO_2 saturation and the longest time until steady state.

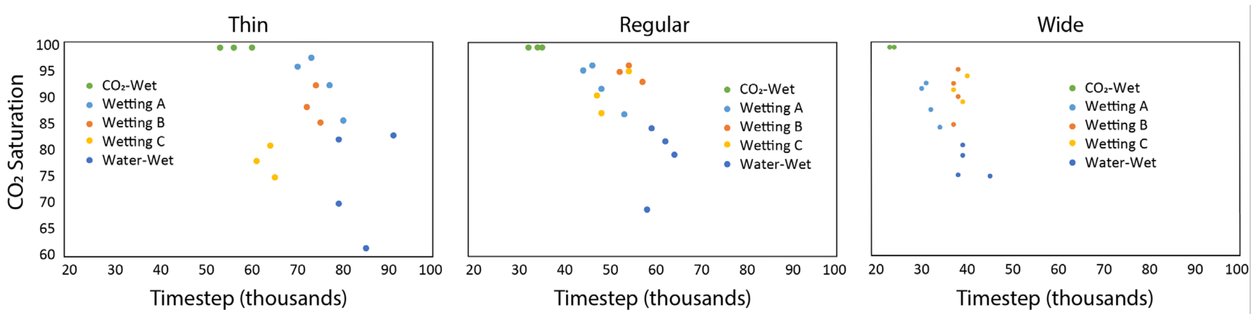

Figure 3. Steady state CO_2 saturation and time till steady state are plotted for each wetting distribution in the thin, regular, and wide fractures.

We used 60% of our simulation results to train the network, and we withheld the rest for testing the model's capacity of abstracting the multiphase phenomena complexities. Our neural network model is trained to satisfy the following equation:

$$S = A * R_x = A * \int \big(f(A) + g(\theta)\big),$$

where S represents a two dimensional saturation distribution after flooding (right side of figure 2), A is the original fracture aperture and Rx is the aperture reduction matrix (which is constrained from 0 to 1 by a sigmoid function). Rx represents the amount the fracture aperture is reduced due to the residual saturation of brine. For example, at a particular point in the fracture the aperture may be ten voxels wide, but due to brine films on the top and bottom of the fracture walls the s-CO_2 may only occupy eight voxels. In this case S is equal to eight and Rx is two. The Rx matrix is developed by two independent neural networks, the first one (f) is a function of the original aperture and the second one (g) of the wettability distribution. Intuitively, one captures the viscous displacement effects while the other one focuses on the impact of the capillary forces. They work together to minimize the square difference of the predicted aperture vs the output of the LBM simulations. The results are presented in Figure 4. It is worth noting that the simulation of each fracture took approximately 1 hour on 3,600 cores while the prediction of the network took less than a second in a regular desktop.

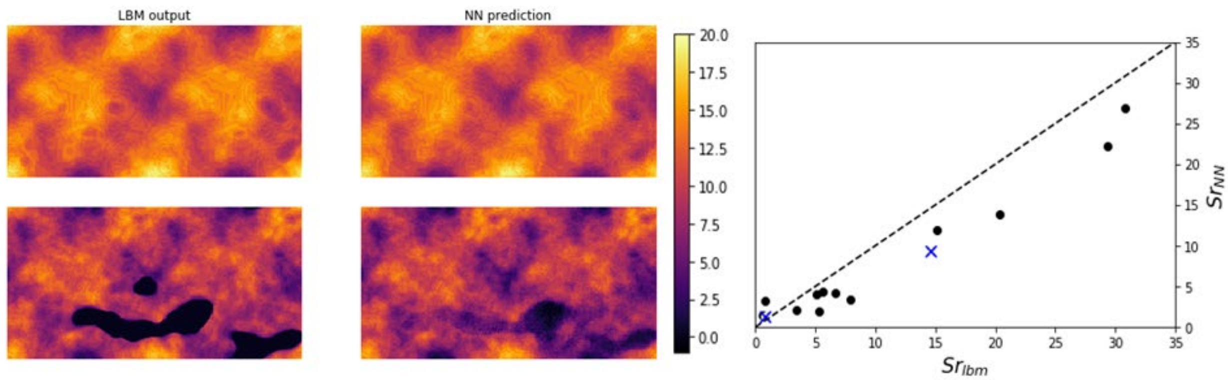

Figure 4: Results of the neural network models. The left panel shows two comparisons between the output of our trained model and the LBM simulations, it can be seen that the model captures the main features of the fluid trapping. The right panel shows the residual saturation comparison between the model and LBM of our test set. The two blue crosses are the examples shown to the left.

Conclusions

We show that heterogeneous wettability distribution affects the steady state residual saturation during multiphase displacement in fractured systems. This implies that pore-scale forces that are often ignored in reservoir simulators, such as wettability, may have important effects on relative permeability and estimated ultimate recovery from unconventional reservoirs. Due to the computationally expensive nature of our simulations we attempt to achieve higher efficiencies using a machine learning algorithm. By treating our aperture and saturation as two-dimensional fields we are able to rapidly predict an "aperture reduction matrix" which is representative of the residual brine saturation within the fracture. This algorithm is able to capture both residual saturation due to viscous forces as well as the effect of wettability. Future work will expand on this effort by incorporating pore-scale experiments for validation and upscaling with physics constrained machine learning.

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