Take-home Exercise

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1 Motivation

The paper, "Prediction of porous media fluid flow using physics informed neural networks," was published by the Journal of Petroleum Science and Engineering, which has a citescore of 6.8 and the highest percentile of 98%. I chose this article because it implemented the machine learning technique I was working on for my dissertation: Physics Informed Neural Networks (PINN).

2 Problem description

The authors of the paper, implements a physics informed neural network (PINN) technique that incorporates information from the fluid flow physics as well as observed data to model the Buckley-Leverett problem. The classical problem of drainage of gas into a water-filled porous medium was used to validate their implementation.

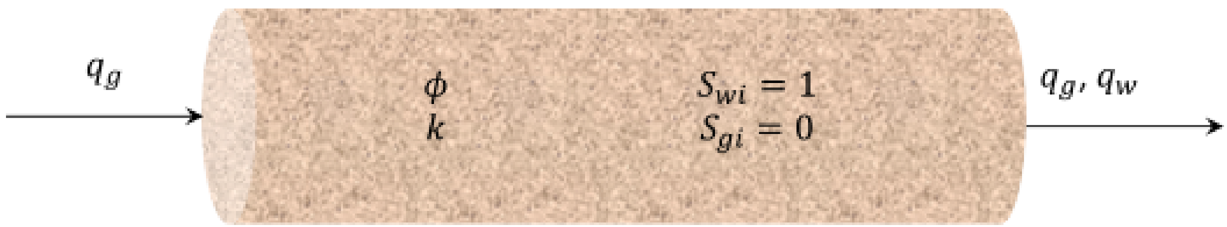


Figure 1: Schematic showing a drainage process set up.

3 Data processing pipeline

In this case, they think of a core flooding experiment where the profile saturations are measured using X-ray tomography. The experiments provide slice-averaged saturation values at various positions along the core's length. To simulate this, they provide 11 saturation profiles to the network, each consisting of 100 points. These 11 saturation profiles are taken from the analytical profiles generated to compare the neural network's output with and are shown in Figure 2

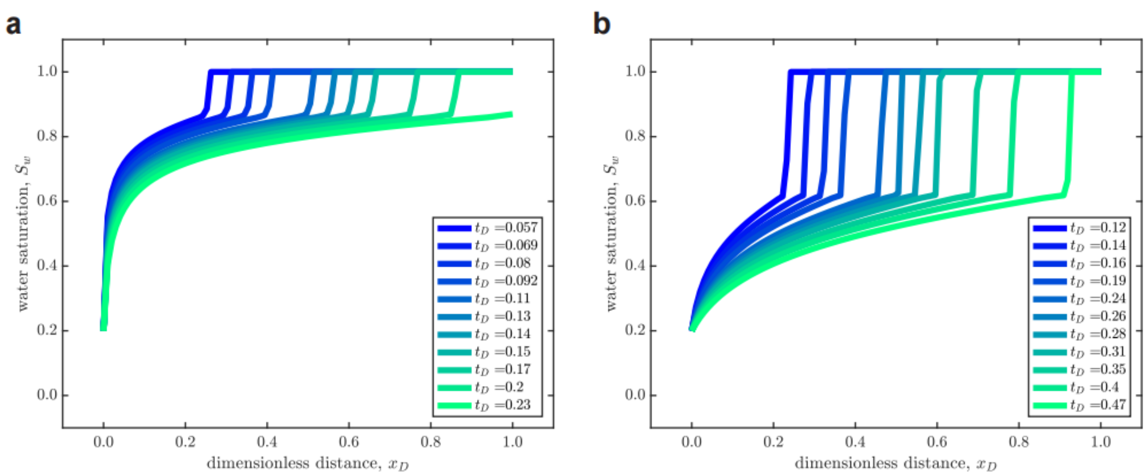


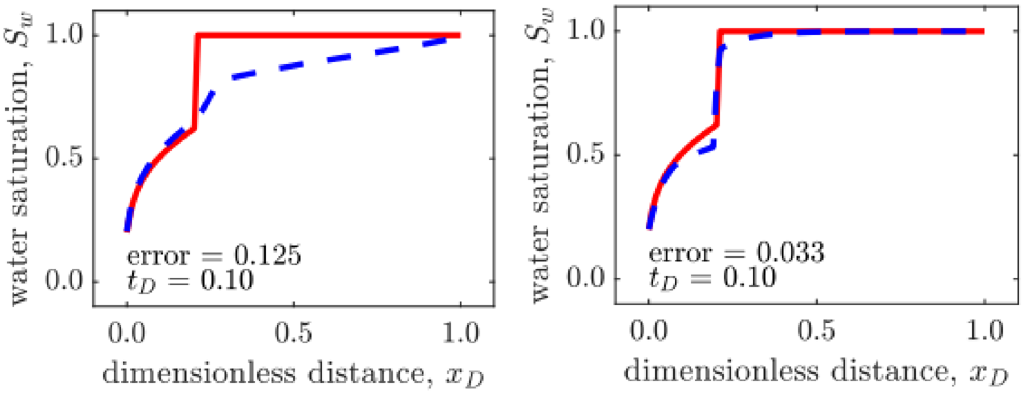
Figure 2: Spatial water saturation profiles at different time-steps that are used as observed data for (a) small mobility ratio scenarios and (b) large mobility ratio scenarios.

4 Results

They investigated the performance of the PINN with the availability of observed data, the trainability of the multiphase flow parameters, and the addition of a diffusive term. In the absence of observed data that informs the PINN solutions, the predictions were suboptimal even though they predicted physically acceptable values (between 0 and 1). When the PINN was anchored to observed data, its performance was enhanced, but the solution remained largely inaccurate. Adding a diffusive term to the hyperbolic PDE improved the solutions marginally. However, the most significant improvement in the predicted saturation profiles was observed when the multiphase parameters were allowed to be trained.

5 Contributions

Several cases are tested that signify the importance of the coupling between observed data and physics-informed neural networks for different parameter space. Their results indicate that PINNs are capable of capturing the overall trend of the solution even without observed data but the resolution and accuracy of the solution are improved tremendously with observed data.



(a) without observed data (b) with observed data

Figure 3: Comparison between PINNs (dashed blue) results and analytical solutions (solid red).