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U-FNO - an enhanced Fourier neural operator-based deep-learning model for multiphase flow

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Numerical simulation of multiphase flow in porous media is essential for many geoscience applications. However, these numerical simulations are often very time-consuming and computationally intensive since they require fine spatial and temporal discretization to accurately capture the flow processes. Data-driven machine learning methods can provide faster alternatives to traditional simulators through the inference of neural network models trained with numerical simulation data mappings. Convolutional neural network (CNN)-based models have been successful in providing fast and accurate predictions for high-dimensional and complex multiphase flow problems. However, CNN-based models are often prone to overfitting, therefore requiring large numerical simulation data sets that can be unmanageable as the problem dimension grows. To resolve this problem, we present U-FNO, a novel neural network architecture for solving multiphase flow problems with superior speed, accuracy, and data efficiency.

U-FNO is designed based on the newly proposed Fourier neural operator (FNO) that learns an infinite-dimensional integral kernel in the Fourier space. The FNO has shown excellent performance on single-phase flow problems with great generalization ability and is significantly more data-efficient than CNN-based methods. We extend the FNO-based architecture to a CO2-water multiphase problem in the context of CO2 geological storage and propose the U-FNO architecture to enhance the prediction accuracy in multiphase flow systems. We apply the U-FNO architecture to predict dynamic pressure buildup and gas saturation in 2D-radial reservoirs with wide ranges of permeability and porosity heterogeneity, anisotropy, reservoir conditions, injection configurations, flow rates, and multiphase flow properties.

Through a systematic comparison among a state-of-the-art CNN benchmark and three types of FNO variations, we show that the U-FNO architecture has the advantages of both the traditional CNN and original FNO, providing significantly more accurate and efficient performance than previous architectures. Using the U-FNO architecture, the mean absolute error for gas saturation is reduced by 50% while the mean relative error for pressure buildup is reduced by 24% compared to the state-of-the-art CNN benchmark.

The U-FNO predicted gas saturation and pressure buildup is 6x10^4 times faster compared to traditional numerical simulators while maintaining similar accuracy, as long as the ranges for the test case input are within the training data range. The significant improvement in computational efficiency can support many engineering tasks that require repetitive forward numerical simulations. For example, the trained U-FNO model can serve as an alternative to full physics numerical simulators in probabilistic assessment, inversion, and site selection, tasks that were prohibitively expensive with desirable grid resolution using numerical simulation.

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References

Time Block Preference

Time Block A (09:00-12:00 CET)

Participation

Online

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