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Image-based physics-constraint workflow for multi-phase flow simulation in heterogeneous media

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The prediction of multi-phase flow in heterogeneous porous media traditionally relies on physics-based numerical simulation with high computational costs. Due to the intrinsic heterogeneity of porous media and the non-linearity of the governing partial differential equations (PDEs), high fidelity simulation models can lead to solving expensive large-scale system of equations, which can be unmanageable given the computational infrastructure at one's disposal. Therefore, developing techniques to honor the trade-offs between efficiency and accuracy has always attracted attention from researchers. Apart from traditional numerical techniques, deep learning has come into sight in recent years and there have been a lot of studies on the ability of neural networks in solving nonlinear differential equations and model reductions. Moreover, compared to traditional fully connected neural networks, image-based neural networks such as convolutional neural networks (CNN) usually have sparser connectivity, which benefits training efficiency, especially under circumstances with high dimensional data. This sheds lights on the possibility of maintaining fidelity in fluid dynamics with lower computational costs. The objective of this work is to investigate efficient image-based deep learning techniques for approximating the dynamics of multi-phase flow.

By breaking down the coupled governing nonlinear PDEs into pressure and saturation equations, we describe a hybrid workflow in predicting the evolution of pressure and saturation as multi-phase fluids flow in heterogeneous porous media. As opposed to an expensive implicit pressure solver, we construct image-based neural networks to capture spatial and temporal patterns. The surrogate model takes inputs including images of permeability field, production information, and the initial fluid status, and predicts pressure fields at different time steps. Physics-constraint is introduced as loss penalty to impose the match of network output with inherent physics in fluid dynamics. The predicted pressure fields are further fed into an efficient explicit numerical solver for saturation calculation. As a result, the workflow brings decent accuracy but reduces the associated computational cost. The performance and effectiveness of the aforementioned workflow will be discussed by numerical examples. Our experiments show that, by training image-based networks with physics-based loss functions, the evolution of fluid dynamics can be predicted accurately and with certain temporal stability maintained. The results also suggest that the proposed hybrid deep learning numerical workflow is capable of providing accurate approximation for solutions in nonlinear multi-phase flow problems with considerable efficiency.

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References

Time Block Preference

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

Participation

In person

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