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Forward and Inverse Modeling of Nonisothermal Multiphase Poromechanics using Physics-informed Neural Networks (PINNs)

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Solving the inverse problem (identifying the parameters of PDEs) typically poses exceptional challenges due to the nonlinear nature of the governing equations, their strong coupling, and the extremely high dimensionality of the problem. Classical data assimilation and optimization techniques treat forward solvers as black-box estimators and therefore typically require an unfeasible number of forward simulations during the optimization. Physics-informed neural networks (PINNs), developed to extend the inherent capabilities of artificial neural networks to incorporate PDE constraints (Raissi et al., JCP 2019), offer the potential of a unified forward and inverse solver, and thus a framework to inherently combine measured data and model predictions. Here, we develop such a framework for forward and inverse modeling of thermo-hydro-mechanical (THM) problems using PINNs.

While PINNs have received exponentially increasing attention in recent years since their advent in 2019, their application to forward and inverse modeling of multiphysics problems remains challenging. In our experience this is because, when the physical processes are strongly coupled, network training is fragile and slow. In our recent works (Haghighat et al., CMAME 2021, Amini et al., JEM 2022), we proposed a sequential training strategy for the forward solution of HM and THM processes in porous media. Here, we build on these previous studies to develop a strategy for the solution of the inverse problem. To this end, we propose a revised nondimensionalization of the THM formulation that is more suitable for inverse problems. We validate the algorithm on benchmark porous media problems, including Terzaghi's consolidation problem, Barry-Mercer's injection-production problem, and consolidation under non-isothermal partially-saturated conditions. Although we use synthetic data to validate our algorithm, we restrict the total number of sensors to a very small number. Our results show the applicability of the PINN approach for inverse modeling of THM processes, thus paving the way for the application of PINNs to inverse modeling of complex nonlinear multiphysics problems.

Participation

In-Person

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