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A PINN based model for coupled hydro-poromechanics in reservoir simulations

C. Millevoi[1]*, N. Spiezia[2] and M. Ferronato[3]

[1] Dept. of Civil, Environmental and Architectural Engineering, Univ. of Padova, Italy, caterina.millevoi@phd.unipd.it

[2] M3E Srl, Padova, Italy, n.spiezia@m3eweb.it

[3] Dept. of Civil, Environmental and Architectural Engineering, Univ. of Padova, Italy, massimiliano.ferronato@unipd.it

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Physics-Informed Neural Networks (PINNs) are particular neural networks that in addition to data consider information from the physics by means of the governing equations of a phenomenon as well. PINNs reconcile data-driven machine learning models with traditional ones, by involving the residual of the governing PDEs as a constraint in the training. The NN ability to learn complex structures makes them particularly interesting for parameter estimation in large-scale problems. For this reason they have been selected for modeling the main coupled hydro-poromechanical processes of interest in reservoir simulations. Moreover, thanks to the machine learning nature of the method, the large amount of data coming from measuring instruments can be automatically incorporated in order to improve the prediction reliability and support in planning and decision-making processes.

A PINN-based approach is implemented for coupled hydro-poromechanics and investigated on classical benchmarks. An investigation of the influence of the hyper-parameter selection in PINN setup has been performed to identify the most appropriate and accurate architecture. The goal is to assess and validate the approach, thus laying the foundation of this method in coupled hydro-poromechanics. The PINN-based model developed in the present work is the starting point for future applications to challenging test cases typically encountered in reservoir modeling and real-world cases with data recorded by sensors.

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