A triple-scale discrete-continuum coupling method for path-dependent porous media enhanced by recurrent and recursive deep learning

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Abstract:

Many geological materials, such as shale, mudstone, carbonate rocks, limestone and rock salt are porous media in which pores of different scales may co-exist in the host matrix. When fractures initiate and propagate, the void created by the crack propagation may induce significant increase the magnitude of the permeability tensor and rotate the principal direction. At the meso-scale level, the pore-fluid inside the cracks and the pores of host matrix may interact and exchange mass, but the difference in hydraulic properties of these pores often means that a single homogenized effective permeability tensor field is insufficient to characterize the evolving hydraulic properties of these materials at smaller time scale. Furthermore, the complexity of the hydro-mechanical coupling process and the induced mechanical and hydraulic anisotropy originated from the micro-fracture and plasticity at grain scale also makes it difficult to propose separated macroscopic constitutive laws for multiphysical simulations. This article presents a data-driven technique designed to capture the multiscale hydro-mechanical coupling effect of porous media with pores of various different sizes. At each scale, data-driven models generated from supervised machine learning are hybridized with classical constitutive laws in a directed graph that represents the numerical models. By fusing experimental data with sub-scale simulations, an offline homogenization procedure is used to replace the upscaling procedure to generate cohesive laws for localized physical discontinuities at both grain and specimen scales. Through a proper homogenization procedure that preserves spatial length scales, the proposed method enables field-scale simulations to gather insights from meso-scale and grain-scale micro-structural attributes. This method is proven to be much more computational efficient than the classical DEM-FEM or FEM^2 approach while at the same time more robust and flexible than the classical surrogate modeling approach. Due to the usage of bridging-scale technique, the proposed model may provide multiple opportunities to incorporates different types of simulations and experimental data across different length scales for machine learning. Numerical issues will also be discussed.