Auto-weighting multitask inverse problems for reactive flows at the pore-scale with evolving fluid-solid interface and related uncertainty quantification

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Résumé

Pore-scale modelling of reactive flows in porous media is intrinsically related to X-ray microtomography experiments. Advances in this imaging technique coupled with efficient numerical simulation offer a valuable opportunity to investigate dynamical processes and study their impact on the macro-scale properties such as the upscaled porosity and permeability. This is of great importance in risk management from the perspective of CO2 storage in natural underground reservoirs. Ensuring the reliability of pore-scale modelling and simulation is, therefore, crucial and it requires embedding uncertainty quantification concerns. Uncertainties arise from the microtomography imaging process itself where artefacts, noise and unresolved morphological features are intrinsic limitations inducing important deviations in the estimation of petrophysical properties (1). In addition, proper assessment of the kinetic parameters in dissolution processes also raises challenges. Mineral reactivities are critical parameters to account though they commonly suffer from discrepancies of several orders of magnitude (2). Therefore, we aim to quantify both morphological uncertainties due to unresolved features in X-ray microtomography and kinetic parameter uncertainties for reactive processes in porous media.

In this presentation, we focus on a multitask inverse problem for reactive flows at the pore scale through a data assimilation approach that incorporates uncertainty quantification by means of a Bayesian Physics-Informed Neural Network (BPINN). This novel approach combines dynamical imaging data and physics-based regularization induced by the PDE model of calcite dissolution. This PDE model is a two-scale porosity formulation, similar to the benchmark introduced in (3).

We build the present technique upon the efficient data-assimilation framework developed in (4), which robustly addresses multi-objective and multiscale Bayesian inverse problems including latent field reconstruction. The strategy relies on an adaptive and automatic weighting of the target distribution parameters and objectives. It benefits from enhanced convergence and stability compared to conventional formulations and reduces sampling bias by avoiding manual tuning of critical weighting parameters (5). The adjusted weights bring information on the task uncertainties, improve the reliability of the noise-related and model adequacy estimates and ensure unbiased uncertainty quantification.

*Intervenant

Finally, we present posterior distributions on the chemical inverse parameters in addition to local morphological uncertainties on the micro-porosity field for pore-scale imaging on calcite dissolution.

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