Physics-Informed Neural Networks for Heterogeneous Poroelastic Media

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1. INTRODUCTION & OBJECTIVE

Subsurface systems are inherently complex and involve an intricate coupling between several physical processes. Computational modeling of coupled subsurface phenomena is often essential because direct measurements and experiments are either infeasible or expensive. A virtual testing ground is provided through computational modeling to analyze operational behavior, enabling informed engineering decision-making. Several prevailing subsurface computational modeling frameworks are broadly categorized as either physics-based models or data-driven models. In physics-based models, the various physical processes in the subsurface are represented mathematically through coupled partial differential equations (PDEs). These PDEs must be solved numerically through appropriate numerical techniques such as the finite element method (FEM). However, generating meshes that conform with subsurface features such as natural fracture networks, faults, and stratified crusts is computationally intensive. The pre-processing step of mesh generation often acts as a bottleneck and significantly increases the turn- around time of computational analysis.

By contrast, data-driven models aim to leverage data-centric artificial neural networks (ANN) to predict subsurface behavior. However, the accuracy of these ANN models is contingent upon the volume and caliber of the accessible training data. Unfortunately, subsurface systems are characterized by sparse data availability due to economic constraints. As such, the effectiveness of purely data-driven models is reduced for such systems. Physics-Informed Neural Networks (PINNs), a recently invented hybrid approach, combines physics-based and data-driven modeling (Raissi et al. 2019) approaches. On the one hand, these methods are not mesh-based thereby eliminating the need for generating conforming meshes. On the other hand, these methods obtain the solution of desired field quantities by minimizing a loss-functional constructed through fundamental physical laws thereby eliminating the need for large training datasets.

The main objective of our study is to develop a PINNs framework to model poroelasticity in heterogeneous materials. Although PINNs have been applied to model poroelasticity earlier (Amini et al. 2023, Haghighat et al. 2023), these studies are limited to homogeneous materials where the governing equations describing solid deformation and fluid flow are only loosely coupled. In this work, we propose a modified PINNs framework that successfully addresses both the above limitations.

2. RESULTS & HIGHLIGHTS OF IMPOINTANT POINTS

We demonstrate that for successfully modeling the governing poroelasticity equations in heterogeneous media, the underlying neural network architecture must be modified appropriately. The following modifications are prescribed. Firstly, a composite neural network is used such that for constructing an approximation for each output field variable (displacement and pressure), a distinct neural network is used. The neural networks use the same activation functions but are trained separately for all other parameters. Secondly, we handle the challenges of heterogeneous material interfaces by seamlessly integrating the neural network into the Interface-PINNs (I-PINNs) framework, by using different activation functions across any material interface so that discontinuities in solution fields and their gradients are accurately captured (Sarma et al. 2023a,b). Furthermore, we assess a single neural network architecture, comparing it against our composite neural network. The performance of this modified PINNs architecture is compared with conventional PINNs through several benchmark examples. It is observed that the proposed method is better suited for heterogeneous poroelasticity problems compared to conventional PINNs in terms of both accuracy and cost.

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