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Physics-informed Neural Networks to Simulate Subsurface Fluid Flow in Fractured Media

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Reliable reservoir characterization of the strata, fractures, and hydraulic properties is needed to determine the energy storage capacity of geothermal systems. We apply the state-of-the-art Physics-Informed Neural Networks (PINN) to model subsurface flow in a geothermal reservoir. A PINN can incorporate any physical laws that can be described by partial differential equations. We obtain a ground truth dataset by running a virtual pumping-well test in the numerical code "Code_Bright". This model consists of a low-permeability rock matrix, intersected by high-permeability fractures. We approximate the reservoir permeability $k(\mathbf{x})$ with an Artificial Neural Network (ANN) denoted by $\hat{k}(\mathbf{x})$. Secondly, we model the fluid pressure evolution with the PINN $\hat{p}(\mathbf{x}, t)$ by informing it about the experimental well-testing data. Since observation wells are sparse in space (only the injection well in our case), we feed $\hat{k}(\mathbf{x})$ into a hydraulic mass balance equation. The residual of this equation enforces the loss function of $\hat{p}(\mathbf{x}, t)$ for random collocation points inside the domain. Our results indicate that the ANN is able to approximate $k(\mathbf{x})$ even for a high permeability contrast. In addition, the successful interpolation of $p(\mathbf{x}, t)$ proves the PINN is a promising method for matching field data with physical laws. In contrast to numerical models PINNs shift the computational efforts toward the training, while reducing the resources needed for the forward evaluation. Nevertheless, training a 3D reservoir model can hardly be achieved on an ordinary workstation since the training data may include several millions of entries. In addition, computational costs increase due to the inclusion of multiphysics processes in the PINN. We plan to prepare the PINN model for training using parallelized GPUs to significantly increase the training speed of the ANNs.