Phase-field fracture model solved by a mixed formulation for physics-informed neural networks

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This study investigates employing physics-informed neural networks (PINNs) to solve the phase-field method's coupled partial differential equations (PDEs) in fracture. The phase field damage model shows the great capability to address different fracture phenomena, such as crack nucleation, propagation, and branching through finding the solutions to the displacement and damage field PDEs.

By incorporating physical constraints, including physical laws, and initial and/or boundary conditions into the network's loss function, the neural network is able to obtain the solution to a boundary value problem, see [1]. The earlier works have shown the capability of deep learning tools to predict the crack path in quasi-brittle materials, see [2, 3].

In this work, the standard PINNs approach is extended to the mixed PINN formulation, see [4], to address fracture by solving phase-field fracture PDEs. We explore different neural network architectures and training procedures (coupled or sequential) and examine the impact of various material parameters.

The results demonstrate the superior performance of the mixed PINNs formulation in obtaining a unique solution to the problem with respect to other PINNs methodologies. The latter is shown through different numerical examples in 1-D and 2-D setups for different multi-physical problems, thermo-elasticity, and phase-field fracture. The obtained results from the network are later compared to the results of the finite element method that is utilized to solve the identical boundary value problem. Finally, the computational cost and ideas for generalizing the network's predictions for different boundary value problems are discussed.

References

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