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Transfer learning enhanced physics informed neural network for phase-field modeling of fracture

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In this work, we present a new physics informed neural network (PINN) algorithm for solving brittle fracture problems. While most of the PINN algorithms available in the literature minimize the residual of the governing partial differential equation, the proposed approach takes a different path by minimizing the variational energy of the system. Additionally, we modify the neural network output such that the boundary conditions associated with the problem are exactly satisfied. Compared to conventional residual based PINN, the proposed approach has two major advantages. First, the imposition of boundary conditions is relatively simpler and more robust.

Second, the order of derivatives present in the functional form of the variational energy is of lower order than in the residual form used in conventional PINN and hence, training the network is faster. To compute the total variational energy of the system, an efficient scheme that takes as input a geometry described by spline based CAD model and employs Gauss quadrature rules for numerical integration has been proposed. Moreover, we note that for obtaining the crack path, the proposed PINN has to be trained at each load/displacement step, which can potentially make the algorithm computationally inefficient. To address this issue, we propose to use the concept 'transfer learning' wherein, instead of re-training the complete network, we only re-train the network partially while keeping the weights and the biases corresponding to the other portions fixed. With this setup, the computational efficiency of the proposed approach is significantly enhanced. The proposed approach is used to solve four fracture mechanics problems. For all the examples, results obtained using the proposed approach match closely with the results available in the literature. For the first two examples, we compare the results obtained using the proposed approach with the conventional residual based neural network results. For both the problems, the proposed approach is found to yield better accuracy compared to conventional residual based PINN algorithms.