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Neural networks with embedded physics-based material models to accelerate multiscale finite element simulations

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In concurrent multiscale analysis (FE^2), a microscopic model is linked to each integration point of the macroscale, allowing the explicit modeling of the material microstructure. Despite its appeal, the computational bottleneck created by nesting finite element models results in prohibitive computational costs for most practical applications. In this scenario, machine learning offers an opportunity to improve the computational efficiency of FE^2. One way to tackle it is to replace the solution of the microscopic boundary value problem with an inexpensive surrogate model.

Popular choices for surrogate constitutive modeling include Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNNs). While these methods yield significant acceleration, several challenges remain unaddressed. A notorious drawback of ANNs is their limited ability to extrapolate well outside their training range, which is particularly disadvantageous when path-dependent behavior is present. Although RNNs can account for that to some extent given a large enough dataset [1], they are still severely limited by the curse of dimensionality associated with sampling arbitrarily long strain paths. A more recent and promising alternative has been gaining traction: reintroducing physical knowledge to the surrogate model.

In the present work, this is done by employing the same material models used in the micromodel as activation functions within the network. The ANN consists of one or more feed-forward layers encoding the local strain concentration distribution, a layer with several concatenated fictitious material points and a feed-forward neural network decoder homogenizing the resulting local stresses. Since every material point has its own internal variables evolving in time, path-dependency is captured naturally. To illustrate the capabilities of the proposed approach, a set of challenging scenarios for data-driven models is considered and its performance is compared to the one of a RNN. A striking outcome of the physics-infused network is the ability to predict unloading/reloading behavior without seeing it during training.

REFERENCES

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