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Micromechanics-based surrogate models for the response of composites: a critical comparison between a classical mesoscale constitutive model, hyper-reduction and neural networks. (English) Zbl 07212908

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Summary: Although being a popular approach for the modeling of laminated composites, mesoscale constitutive models often struggle to represent material response for arbitrary load cases. A better alternative in terms of accuracy is to use the FE^2 technique to upscale microscopic material behavior without loss of generality, but the associated computational effort can be extreme. It is therefore interesting to explore alternative surrogate modeling strategies that maintain as much of the fidelity of FE^2 as possible while still being computationally efficient. In this work, three surrogate modeling approaches are compared in terms of accuracy, efficiency and calibration effort: the state-of-the-art mesoscopic plasticity model by

M. Vogler et al. ["Modeling the inelastic deformation and fracture of polymer composites – Part I: Plasticity model", Mech. Mater. 59, 50–64 (2013; doi:10.1016/j.mechmat.2012.12.002)], regularized feed-forward neural networks and hyper-reduced-order models obtained by combining the Proper Orthogonal Decomposition (POD) and Empirical Cubature Method (ECM) techniques. Training datasets are obtained from a Representative Volume Element (RVE) model of the composite microstructure with a number of randomly-distributed linear-elastic fibers surrounded by a matrix with pressure-dependent plasticity. The approaches are evaluated with a comprehensive set of numerical tests comprising pure stress cases and three different stress combinations relevant in the design of laminated composites. The models are assessed on their ability to accurately reproduce the training cases as well as on how well they are able to predict unseen stress combinations. Gains in execution time are compared by using the trained surrogates in the FE^2 model of an interlaminar shear test.

MSC:

74 Mechanics of deformable solids

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laminated composites; reduced-order modeling; hyper-reduction; artificial neural networks

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