Nonlinear two-scale beam simulations accelerated by thermodynamics-informed neural networks

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Abstract

Beam-based architected materials can be subjected to large strains in a range of applications such as shock absorption or soft robotics. Finding efficient and accurate models for these materials at finite strains is a challenging task as their microstructures consist of many individual slender beam members that exhibit nonlinear effects due to their geometry (large rotations) and behavior (e.g., hyperelastic materials). Classical 1D models ignore nonlinearities due to hyperelastic constitutive laws and full 3D finite element analysis comes at a prohibitive computational cost. Therefore, there is a need for an efficient modeling approach capable of accurately capturing the physics of these large, complex systems. Following a formal asymptotic dimension reduction approach, we decompose the problem into an efficient macroscale simulation of the beam's centerline and a finite elasticity problem on the cross-section (microscale) at each point along the beam. From the solution on the microscale, an effective energy is passed to the macroscale simulation, where it serves as the material model. However, this two-scale approach comes at a high computational cost. To leverage the efficiency of the macroscale beam simulation, we therefore introduce a Sobolev-trained thermodynamics-informed neural network, which serves as a surrogate model for the costly microscale simulations. We compare three different neural network architectures, viz. two well-established Multi-Layer Perceptron based approaches as well as a recently proposed Kolmogorov-Arnold (KAN) network, and we evaluate their suitability. The models are trained on varying cross-sectional geometries, all of varying sizes and degrees of hollowness. Based on its smooth and accurate prediction of the energy landscape, which allows for automatic differentiation, the KAN model was chosen as the surrogate material model, whose effectiveness we demonstrate in a suite of examples, ranging from cantilever beams to 3D beam networks.

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