EngOpt2018 - 6th International Conference on Engineering Optimization
Instituto Superior Técnico, Lisbon Portugal • 17-19 September, 2018
Editors: H.C. Rodrigues, J. Herskovits, C.M. Mota Soares, et al.

Abstract ID 1015

TWO-SCALE TOPOLOGY OPTIMIZATION USING NEURAL NETWORK SURROGATE MODELS

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Keywords: structural mechanics,topology optimization,surrogate model,neural network

Abstract: Due to advances in manufacturing, particularly additive manufacturing, there is significant interest in the design and optimization of macro-scale structures that are realized via spatially-varying micro-scale lattices. Because the micro-scale feature size is 100x to 1000x smaller than the macro-scale dimensions, a fully resolved optimization of the spatially-varying micro-scale lattice is not feasible. Instead, a two scale off-line, on-line approach is proposed. The off-line step consists of highly resolved finite element simulations of lattices with known topology, this is achieved using adaptive mesh refinement to resolve the small features of the lattice. The results of these off-line simulations are used to construct a surrogate model of the elastic response of the lattice. The on-line step consists of a density-like topology optimization of the macro-scale structure, but with N decision variables per element. These N decision variables define the variation of the lattice. If the lattice of interest consists of rods, the decision variables are the radii of the rods. If the lattice of interest consists of spherical inclusions e.g. a foam-like material, the decision variables are the location and radii of the spherical inclusions. As another example, the decision variables can be the density and orientation of carbon fiber for a chopped fiber 3D printer. The surrogate model must accurately capture the effective stiffness of the lattice, including the most general forms of anisotropy. But it must also be efficient to evaluate. Radial basis function approximation is well suited for approximating surfaces and fields in higher dimensions. Radial basis function approximation can be of either interpolatory or regression form, and for this this particular application the regression form is more suitable because it provides smoother results with accurate derivatives which are essential for optimization. The regression form, also known as a least-square fit, is a special type of neural network called a radial basis function network. Results are presented for standard test problems such as cantilever beams, as well as for real-world problems such as optimization of civil and aerospace structures. We quantify the benefits of spatially varying versus uniform lattices, and anisotropic versus isotropic lattices.