Accelerated thermomechanical modeling of additive manufacturing using laser-based powder bed fusion

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Abstract

Additive manufacturing opens the possibility to create optimal tools and devices in industrial manufacturing. A key aspect is that there are very few or no geometric restrictions. Particularly, the 3D printing of metals allows one to make complex, durable, custom parts. [1]

We look at the numerical modeling of 3D printing of metals in a laser-based powder bed fusion (L-PBF) printer. We take a process industry viewpoint, using the theory of axially moving materials [2]. This change of perspective, along with aggressive simplification, allows us to see fundamental features of the process itself we would otherwise miss, were we to model the printing of some specific object in detail. Particularly, with axially moving materials, we can easily look at what happens around the melt pool as the focus spot of the laser moves over the powder bed.

The simulation is based on a 2D thermomechanical continuum model, which extends the earlier 1D model reported in [3]. The model is solved numerically with the finite element method (FEM), using the FEniCS framework [4]. Each instance of the simulation requires some computing time on a conventional CPU-based multicore workstation, with MPI parallelization.

To interpolate in the solution space more quickly, we aim to accelerate repeated simulations with slightly different initial conditions or parameter values with the help of artificial intelligence (AI) techniques, namely neural networks. Particularly, deep neural networks [5] have become popular in AI during the last decade as hardware has become more powerful.

In an engineering sciences context, deep neural networks can be used for dimension reduction, producing a reduced model that runs much faster, while retaining most of the fidelity of the original. A particularly promising class of deep neural networks for this application are continuous latent space models, such as variational autoencoders (VAE) [6].

References

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