Machine learning based optimization of hard-/soft magnetic nanostructures

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Micro- and nanostructural design of magnetic materials is the most promising strategy for future high-performance but rare earth-lean permanent magnets. Exchange coupled composites follow this idea by combining materials with high magnetocrystalline anisotropy, i.e. hard magnetic materials, and others with high spontaneous magnetization, i.e. soft magnetic materials. If a cube-shaped model is divided into N uniformly sized smaller cubes, where each smaller cube is either magnetically soft or hard, there are 2^N possible configurations. To reduce the computational effort for finding the best hard/soft distribution, we propose to use a surrogate model for fast evaluation of the energy density product $BH_{\max}$ during optimization. A cube-shaped composite magnet with 120 µm edge length is divided into $8 \times 8 \times 8$ patches of either hard ($Nd_2Fe_{14}B$) or soft ($Fe_{65}Co_{35}$) magnetic material. Simulated demagnetization curves of 900 different distributions are used to train a convolutional neural network. Based on the best designs, the network is then used to propose new distributions with improved $BH_{\max}$. These designs are then validated by fast micromagnetic simulations. The training data are augmented with these newly obtained results and the weights of the network are re-trained in an active learning scheme. We test the performance of different optimization strategies to quickly find an optimal distribution for $BH_{\max}$ close to the theoretical maximum [1].

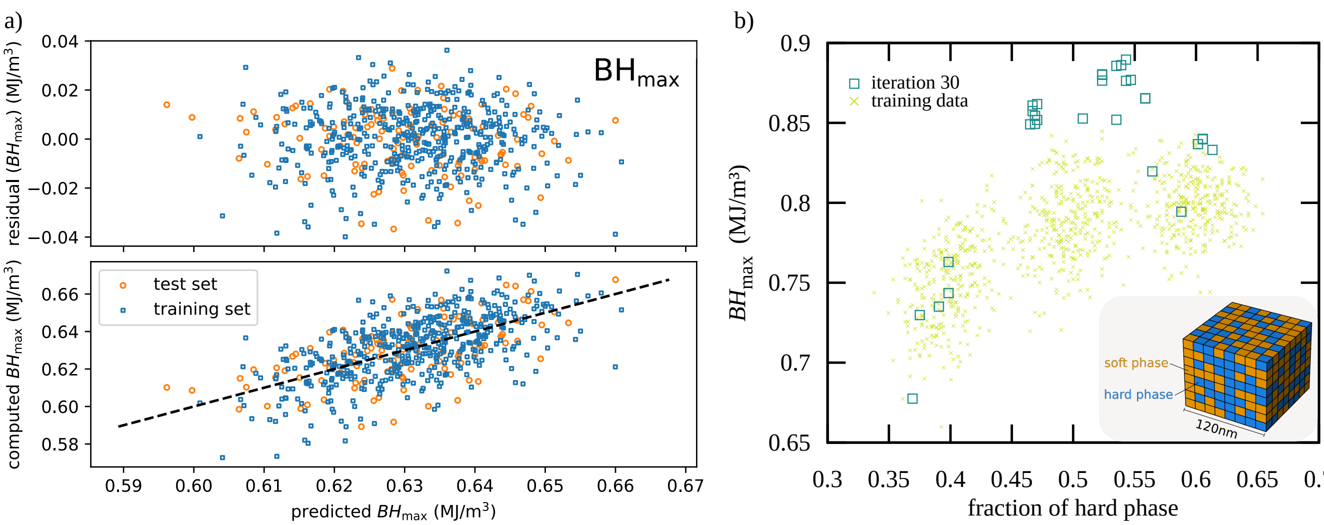

Figure 1: a) Residual and computed versus predicted values of the energy density product by the neural network. b) Energy density product of the initial training data (light green) and the validated designs after 30 optimization iterations.

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References

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