Computational micromagnetics with physics-informed neural networks

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Physics-informed machine learning is a contemporary novel methodology for solving (partial) differential equations in (natural) sciences. A Physics-Informed Neural Network (PINN) can learn low-parametric solutions to a whole problem class in high dimensions in an unsupervised fashion, whereas traditional methods would not be able to interpolate the exponentially growing solution space. This talk covers the basics of PINNs and explains their advantages over current methods in micromagnetics. Specifically, we study the full static 3d micromagnetic equations via a PINN ansatz for the continuous magnetization configuration. Our model can learn to minimize the total Gibbs free energy for additional conditional model parameters such as the exchange length [1,2]. We also

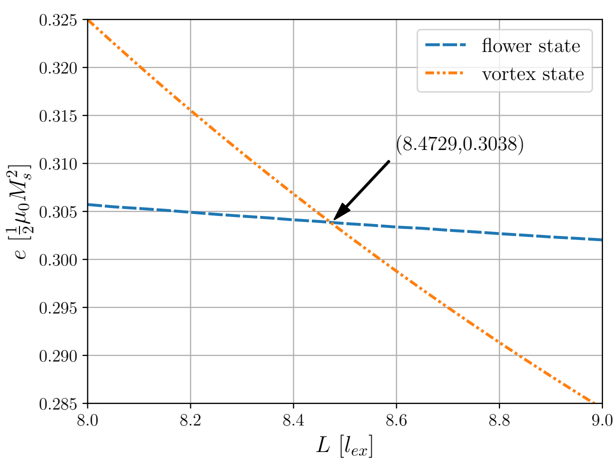

Figure 1: Energy crossing for the MAG Standard Problem #3. Each line is a single low-parametric neural network.

consider the important and computationally expensive stray field problem via PINNs, where we use a basically linear learning ansatz called extreme learning machines (ELM) [3] within a splitting method for the scalar potential. The stray field method is validated by numerical example comparisons from literature and we illustrate the full micromagnetic approach via the NIST standard problem #3, Fig. 1.

References

[1] S. Schaffer, T. Schrefl, N.J. Mauser, D. Suess, A. Kovacs, L. Breth, L. Exl, Physics-informed machine learning and stray field computation with application to micromagnetic energy minimization. (2023) arXiv preprint arxiv.org/abs/2301.13508.

[2] A. Kovacs, L. Exl, A. Kornell, J. Fischbacher, M. Hovorka, M. Gusenbauer, L. Breth, H. Oezelt, D. Praetorius, D. Suess, et al. Magnetostatics and micromagnetics with physics informed neural networks. Journal of Magnetism and Magnetic Materials, 548:168951, 2022.

[3] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew. Extreme learning machine: theory and applications. Neurocomputing, 70(1-3):489501, 2006.