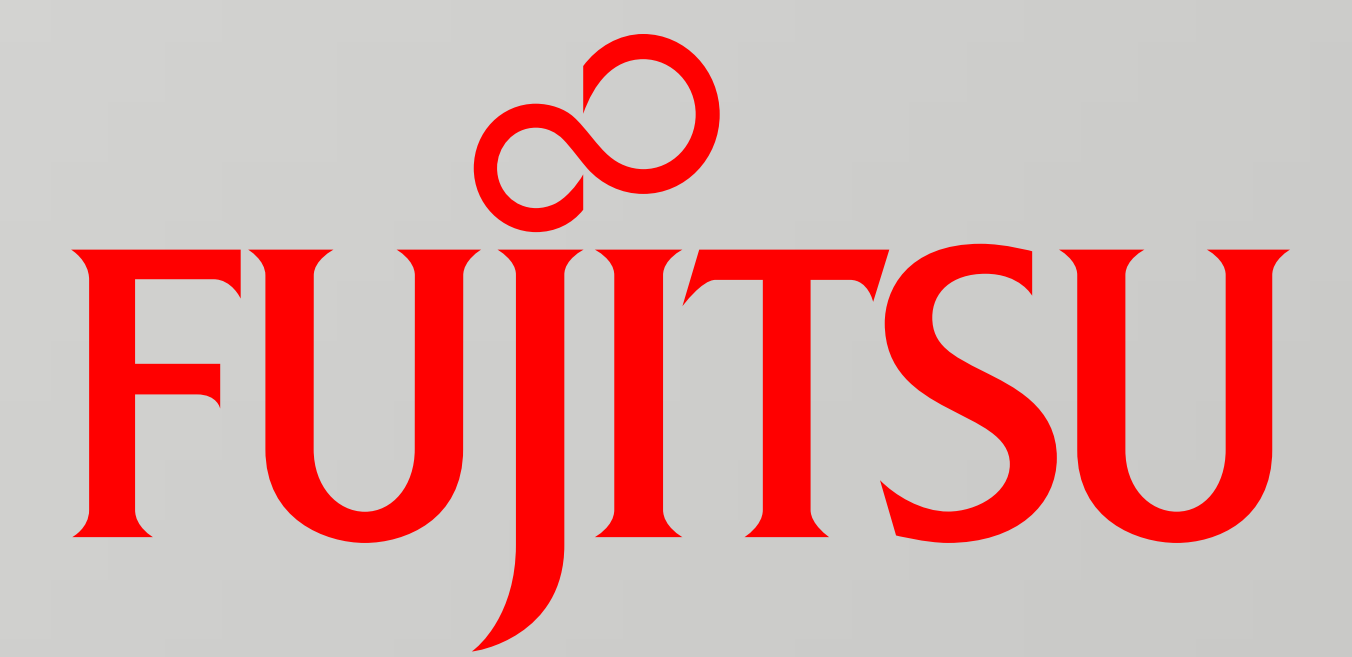


DeepSim-HiPAC: Deep Learning High Performance Approximate Calculation for Interactive Design and Prototyping

Ahmed Al-Jarro¹, Serban Georgescu¹, Yasumoto Tomita², and Kouta Nakashima²

¹Fujitsu Laboratories of Europe Ltd. (FLE), Hayes Park Central, Hayes End road, Hayes UB4 8FE, Greater London, UK

²Fujitsu Laboratories Ltd., 4-1-1 Kamikodanaka, Nakahara-ku, Kawasaki, Kanagawa 211-8588, Japan



Abstract

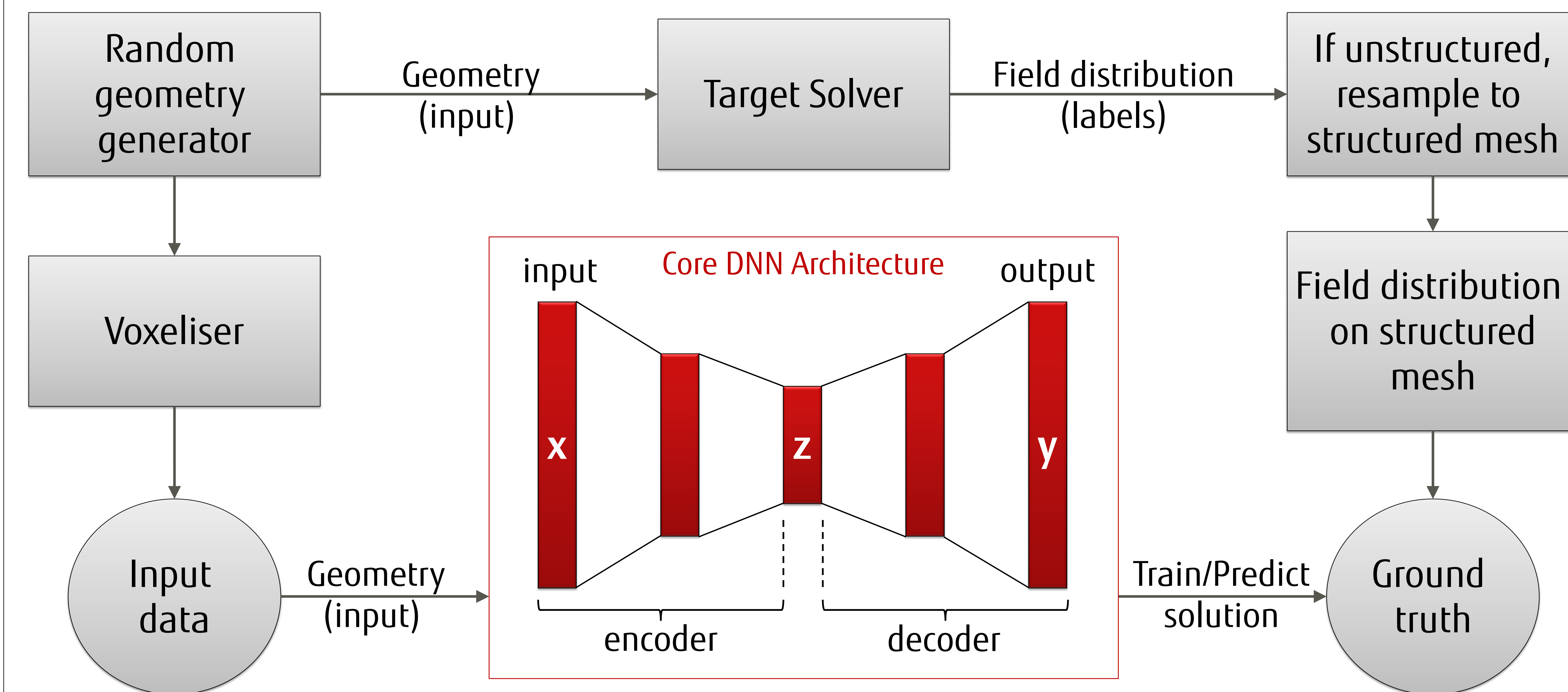
We present a data-driven technique that can learn from physical-based simulations for the instant prediction of field distribution for 3D objects. Such techniques are extremely useful when considering computer aided engineering (CAE), where computationally expensive simulations are often required [1]. Here, we propose a deep learning framework that can predict the principal field distribution given a 3D object. We show that our convolutional neural network engine, DeepSim-HiPAC, can estimate steady state field distribution several orders of magnitude faster, up to 250000X, than the native calculations and at a cost of low error rate.

Methodology

DeepSim-HiPAC: High Performance Approximate Calculation Engine

- In this work, we demonstrate the effectiveness of our technique to aid the prediction of field distribution for two distinctive applications: i) micro-magnetics design in computational electromagnetics (CEM) and ii) interactive cooling systems design in computational fluid dynamics (CFD).
- We use an auto-encoder inspired neural network [2] and a structured end-to-end mapping between the input (x) and output (y) that are of the same size.

DeepSim-HiPAC: High Performance Approximate Calculation



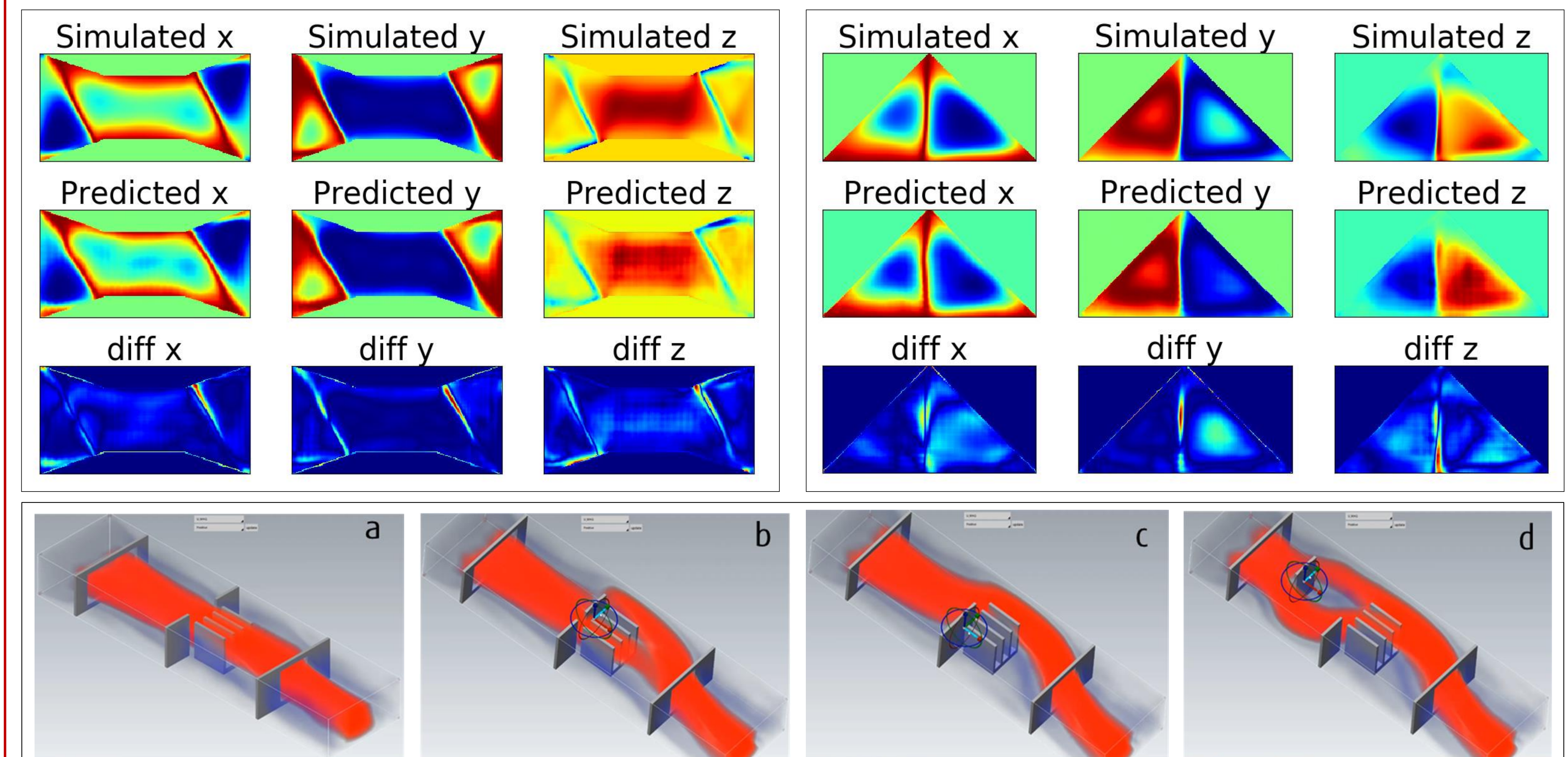
- We obtain our training dataset by feeding arbitrarily shaped 3D geometries into solvers widely used in micro-magnetics and CFD that solve the Landau-Lifshitz-Gilbert and Navier-Stokes equations, respectively.

Conclusion

We demonstrate our technique suitable for providing immediate response for real-time and interactive design iterations at the initial stage where extremely high fidelity results is not mandatory; enabling exceptionally rapid predictions for dynamic design and prototyping. As showcased therein, the attraction of this technique is its applicability to learn wide range of tasks benefiting many fields in engineering design and prototyping problems with extremely fast response. Our initial speedup performances for DeepSim-HiPAC are recorded up to 250000 times faster than those directly calculated by the native (target) solver and at a low error rate.

Use Cases & Performance Results

- We demonstrate and evaluate our DeepSim-HiPAC engine for two different use cases that are of distinctive physical behaviour: i) micro-magnetics computations and ii) air flow around electronic components.
- In i), we consider the same conditions as those used in the evaluation of the so-called standard problem 4, SP4, [3] whereby a 3D sample with the material parameters of permalloy is prepared in an equilibrium S-state. This is obtained after applying and slowly reducing a saturating field along the [1,1,1] direction to zero. Then the time evolution of the system under the influence of an external field is computed until steady state.
- In ii) we consider similar conditions to those found in a server cooling scenario, whereby air enters the domain from an inlet positioned at the left, passes between (and/or around) the fins of a heatsink and leaves the domain through a smaller outlet that is located on the right as shown in the 1x4 panel below.
- In both cases, i) and ii), we aim to learn the steady-state status of the 3D fields distribution.
- In the 3x3 panels, we illustrate the quality of prediction for a cross-sectional plane, located at the middle of the z-axis, of an extruded 3D bow-shaped and triangular geometries for the conditions set in case i).
- The top and bottom panels show the ground truth simulations (S) and those predicted (P) by DeepSim-HiPAC. The bottom panels show the absolute difference between the two sets of results across the principal field values, i.e. $\text{diff}_i(x, y, z) = |P - S|$, where $\max(\text{diff}) \approx 0.0338$.
- In the 1x4 panel, we illustrate the agility of DeepSim-HiPAC when applying it for the interactive design of a cooling system as per the conditions set in case ii). Here, we interactively adjust the position of the components within the domain as desired, where the 3D flow prediction is updated instantly and on demand (a $\rightarrow$ b $\rightarrow$ c $\rightarrow$ d).



References: [1] X. Guo, W. Li, and F. Iorio, "Convolutional Neural Networks for Steady Flow Approximation," in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 481–490, ACM, 2016. [2] J. Schmidhuber. 2015. Deep Learning in Neural Networks: An Overview. Neural Networks 61, 85–117. Published online 2014; based on TR arXiv:1404.7828, 2015. [3] Micromagnetic Modeling Activity Group - μ Mag, National Institute of Standards and Technology, Gaithersburg, MD (2008), <http://www.ctcms.nist.gov/rdm/mumag.org.html>.