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Towards Efficient Heat Transfer Simulations: A Comparative Study of PINN vs. CFD

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Abstract

This work investigates the potential of Physics-Informed Neural Networks (PINNs) as an emerging tool for solving heat transfer problems, benchmarking their performance against traditional Computational Fluid Dynamics (CFD) methods. To configure the Neural Network (NN) models NVIDIA Modulus has been used.

As initial step, various PINN definition aspects have been examined: (i) the response of the model to various types of Boundary Conditions (BCs), (ii) the accuracy achieved through unsupervised learning compared to synthetic data-assisted learning, and (iii) the efficiency of parameterized cases. Heat conduction in a solid plate under various BCs, highlights the challenges posed by Neumann BCs (gradient-based), which lead to slower convergence, occasional instabilities, and loss in results accuracy. The same findings are demonstrated by a forced convection case in a microchannel, where the use of symmetry constraint, on one hand, speeds up training but, on the other hand, penalizes accuracy. These insights underscore the critical role of boundary condition handling in advancing PINN methodologies.

The subsequent analyses focus on a Conjugate Heat Transfer (CHT) simulation of a microchannel with water as the working fluid, in laminar conditions. Concerning the use of synthetic data to train the model, the microchannel case shows that an unsupervised approach can achieve comparable accuracy to supervised one, without significantly impacting the training time. However, specific measures are necessary, such as employing non-dimensional equations, had-hoc spatial weighting of various loss terms, and careful placement of sampling points.

Finally, the focus is switched to parametrized microchannel configurations. Here, PINNs showcase their unique strength: the ability to efficiently generalize across varying geometries. By parameterizing the channel's height and width over a continuous range, the results show that with training times comparable to a single-case model setup, multiple geometries can be investigated simultaneously, enabling cheap shape optimization potentials. Unlike traditional CFD, which requires separate simulations for each configuration, PINNs offer significant computational savings by consolidating multiple scenarios with a single training process into a one model.

In summary, while PINNs currently exhibit limitations in accuracy and robustness when applied to complex heat transfer scenarios, they demonstrate clear advantages for specific applications, particularly parameterized analyses. With further refinement, PINNs hold the potential to complement or even partially replace traditional CFD methods in selected contexts.

Keywords:

Physics-Informed Neural Networks (PINNs);

Computational Fluid Dynamics (CFD);

Heat Transfer;

Boundary Conditions (BCs);

Parameterized Cases;