Delft University of Technology
German Aerospace Center (DLR)

Project: Domain Decomposition-based Physics-Informed Neural Networks for Compressible Flows around Airfoils

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Project Description

The simulation of compressible flows using Computational Fluid Dynamics (CFD) plays a crucial role in aerodynamics, enabling precise predictions of density, pressure, and temperature variations in high-speed flows around aircraft and spacecraft. Traditional CFD techniques, such as the finite volume method [1], solve the governing partial differential equations (PDEs) of compressible flows by discretizing them on a computational mesh. The PDEs of compressible flow are particularly challenging to solve due to the presence of discontinuous solutions, such as shock waves, which are a common phenomenon in compressible aerodynamics; see Figure 1.

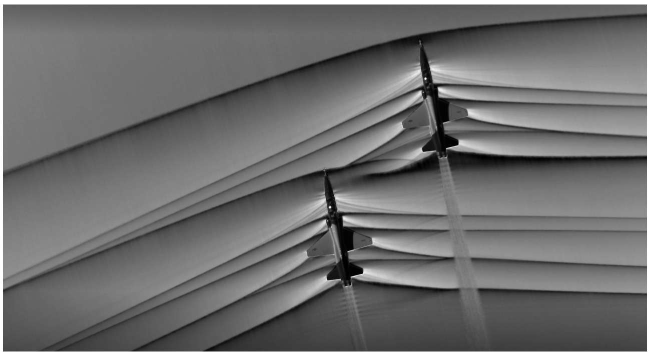

Figure 1: Schlieren image of shock waves around supersonic aircraft. Image credit: NASA Photo

Recently, physics-informed neural networks (PINNs) have emerged as an alternative approach for solving problems involving partial differential equations [7]; the approach dates back to the 1990s [2, 4]. A PINN uses a neural network as a global ansatz function for the approximation of a PDE solution. The PINN is trained by incorporating the PDE directly into a loss function used for optimizing the trainable parameters of the neural network. Compared to classical numerical methods, PINNs are better applicable to inverse problems and can solve parametric forward problems; see, e.g., Figure 2. They can offer significant computational speed-ups in parametric scenarios, particularly in multi-query contexts [8].

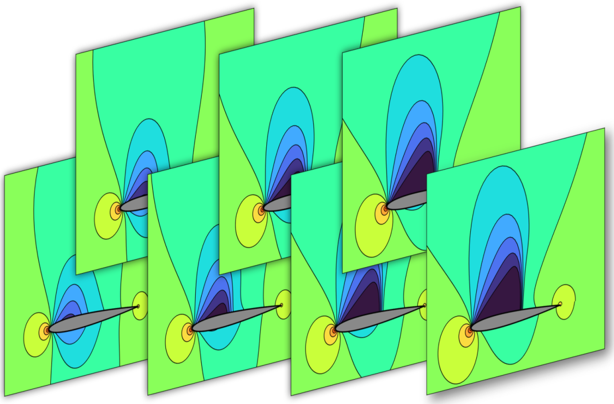

Figure 2: A single parametric PINN model can predict multiple solutions at once as shown here for the pressure field around an airfoil at different angles of attack.

Vanilla PINNs are computationally less efficient than classical solvers [5] and typically struggle with multi-scale problems [6], which is particularly problematic for compressible flows in aerodynamics that require large domains and exhibit strong nonlinearities near deflecting objects and shocks. To address these challenges, domain decomposition approaches such as finite basis PINNs (FBPINNs) [3, 6] have been proposed. Neural networks suffer from spectral bias—the tendency to learn low-frequency components more easily than high-frequency ones—making it difficult to capture sharp gradients and discontinuities. By partitioning the domain and using separate networks in each subdomain, domain decomposition reduces the frequency range each network must learn. While it does not fully eliminate spectral bias, it significantly alleviates it and can substantially improve computational efficiency and solution accuracy [3].

The goal of this project is to apply domain decomposition approaches to solve a compressible flow around an airfoil with a PINN model and to explore the potential for acceleration and possible improvements in accuracy.

Tasks

- Familiarize yourself with relevant methods and software:
  - PINNs for compressible flows [8]
  - Domain decomposition approaches using FBPINNs [3, 6]

  Develop a novel PINN-based solver that combines the acceleration potential of domain decomposition with the ability to handle complex geometries (e.g., airfoils) in high-speed aerodynamics:
  - for forward problems,
  - for problems with parametric boundary conditions,
  - and for problems with parametric geometries.

  Validate the model and benchmark its performance against classical numerical methods (e.g., finite volume solvers) and standard PINNs (without domain decomposition). Assess whether your model can outperform existing approaches and mitigate spectral bias.

Contact

Are you interested or do you have any questions? Send an email to Alexander Heinlein (a.heinlein@tudelft.nl) and/or Simon Wassing (simon.wassing@dlr.de).

References

[1] J. Blazek. *Computational fluid dynamics: Principles and applications*. Butterworth-Heinemann an imprint of Elsevier, Amsterdam and Boston and Heidelberg, third edition edition, 2015. ISBN 9780080999951.

[2] M. W. M. G. Dissanayake and N. Phan-Thien. Neural-network-based approximations for solving partial differential equations. *Communications in Numerical Methods in Engineering*, 10(3):195–201, 1994.

[3] V. Dolean, A. Heinlein, S. Mishra, and B. Moseley. Multilevel domain decomposition-based architectures for physics-informed neural networks. *Computer Methods in Applied Mechanics and Engineering*, 429:117116, 2024.

[4] I. Lagaris, A. Likas, and D. Fotiadis. Artificial neural networks for solving ordinary and partial differential equations. *IEEE Transactions on Neural Networks*, 9(5):987–1000, Sept. 1998. Conference Name: IEEE Transactions on Neural Networks.

[5] N. McGreivy and A. Hakim. Weak baselines and reporting biases lead to overoptimism in machine learning for fluid-related partial differential equations. *Nature Machine Intelligence*, 6(10):1256–1269, 2024.

[6] B. Moseley, A. Markham, and T. Nissen-Meyer. Finite basis physics-informed neural networks (fbpinns): a scalable domain decomposition approach for solving differential equations. *Advances in Computational Mathematics*, 49(4), 2023.

[7] M. Raissi, P. Perdikaris, and G. E. Karniadakis. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378:686–707, 2019.

[8] S. Wassing, S. Langer, and P. Bekemeyer. Physics-informed neural networks for transonic flows around an airfoil. 2024.