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PREDICTING THE THREE-DIMENSIONAL BLUFF BODY WAKE FLOWS USING PINN

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ABSTRACT

Accurate prediction of complex separated flows around bluff bodies remains a central challenge in fluid dynamics, particularly when data are sparse and high-fidelity simulations are computationally expensive. This work investigates the use of Physics-Informed Neural Networks (PINNs) for reconstructing three-dimensional mean flow fields in such environments, using the airwake of a simplified frigate ship as a representative test case.

The proposed framework integrates sparse observational or simulation data with the governing Reynolds-Averaged Navier–Stokes (RANS) equations within a unified learning process. A systematic training strategy is employed, including controlled data sparsity, optimization of loss-term weighting, and residual-based adaptive sampling to improve accuracy in regions of strong gradients. The model is trained on a limited set of flow conditions and evaluated on unseen configurations.

Results demonstrate that the PINN accurately reconstructs key flow features—including separation, recirculation, and asymmetric wake structures—even when trained on highly limited data. Compared to a purely data-driven neural network baseline, the physics-informed approach consistently improves generalization and spatial coherence, particularly in regions dominated by shear layers and wake interactions.

Although demonstrated on a ship airwake, the findings extend to a broad class of bluff body flows encountered in engineering applications such as buildings, ground vehicles, and aerospace structures. The results highlight the potential of physics-informed learning as a data-efficient surrogate modelling approach for complex flows, enabling faster parametric studies and improved predictive capability in scenarios where measurements or simulations are limited.