XI International Conference on Computational Methods in Marine Engineering

Predicting airfoil pressure distributions using boundary graph neural networks

Sankalp Jena[1,*], Gabriel D. Weymouth[1], Artur K. Lidtke[2] and Andrea Coraddu [1]

[1] Delft University of Technology, The Netherlands
[2] Maritime Research Institute Netherlands, The Netherlands
[*] s.jena@tudelft.nl

ABSTRACT

Surrogate models are essential for fast and accurate surface pressure and friction predictions during design optimization of complex lifting surfaces, such as propellers operating near cavitation conditions. As an initial step toward this goal, this study focuses on predicting incompressible, sub-sonic, steady-state viscous pressure distributions over two-dimensional airfoils using a geometric deep-learning architecture based on graph neural networks (GNNs). GNNs offer a unique advantage in their ability to process non-parametric geometries, making them well-suited for analyzing shapes that are inherently challenging to parameterize.

We introduce Boundary Graph Neural Networks (B-GNNs) which operate *exclusively* on surface meshes and compare these to previous work on volumetric GNNs operating on volume meshes, analyzing their respective strengths and limitations in modeling fluid flows. We demonstrate the importance of all-to-all communication in GNNs to enforce the global incompressible flow constraint to ensure accurate pressure distribution predictions. We also explore the scaling of B-GNNs with nodes (N), showing that multi-level Boundary-Graph-U-Net (B-GUN) provides an efficient $\mathcal{O}(N)$ solution compared to single-level B-GNNs which require quadratic cost $\mathcal{O}(N^2)$ for all-to-all communication. For viscous flow prediction, we consider two approaches: using B-GUN directly and employing a preconditioning strategy combining potential flow solutions with single-level B-GNN. We investigate if a one-way message-passing scheme from leading to the trailing edge can still be effective when providing inviscid pressure distribution (e.g., XFOIL) as a feature. Furthermore, we investigate the generalization capabilities of the B-GNNs to out-of-distribution geometry and Reynolds number. As a benchmark, we compare the performance of B-GNNs with the previously published volumetric GUNet on the RANS database by Bonnet et al. (2022).

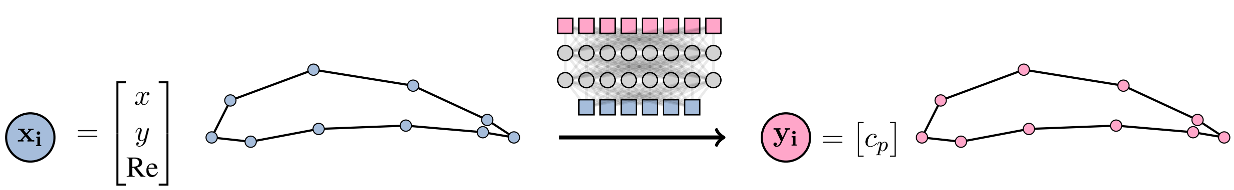

Figure 1: Boundary GNN framework used to learn the pressure distribution of an airfoil in steady viscous flow. i^{th} Node feature, $\mathbf{x_i}$, containing node coordinates (x, y) and Reynolds number (Re), is mapped to node prediction, $\mathbf{y_i}$, i.e. coefficient of pressure (c_p).

References

F. Bonnet, A. J. Mazari, P. Cinnella, and P. Gallinari. AirfRANS: High Fidelity Computational Fluid Dynamics Dataset for Approximating Reynolds-Averaged Navier-Stokes Solutions. In 36th Conference on Neural Information Processing Systems (NeurIPS 2022).