Neural Surrogate Modeling for Fluid Flows

Development and Analysis Based on the Universal Physics Transformer

Graduate

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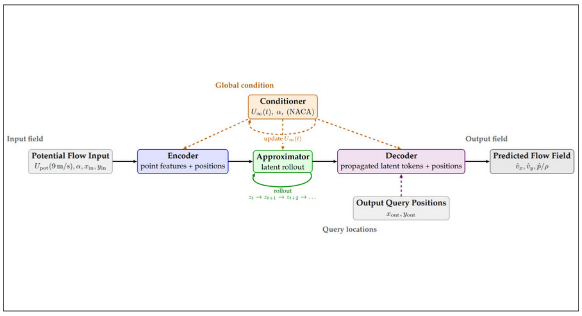
Introduction: Numerical simulation of fluid flows using computational fluid dynamics (CFD) is a key tool in aerodynamics. However, high-resolution CFD simulations involve significant computational costs, which limits their use in extensive parameter studies, optimization procedures, and real-time applications. Neural surrogate models offer the potential to significantly accelerate such simulations by learning the underlying physical relationships.
Neural operators have shown promising results for various physical simulation tasks. However, their application to aerodynamic flow fields on unstructured grids and transient flow phenomena remains challenging. The recently introduced Universal Physics Transformer (UPT) has also been studied only to a limited extent in this context. In this work, we therefore investigate UPT for predicting flow fields around two-dimensional NACA 4-digit profiles in steady-state and transient regimes, using the established MeshGraphNet (MGN) as reference model.

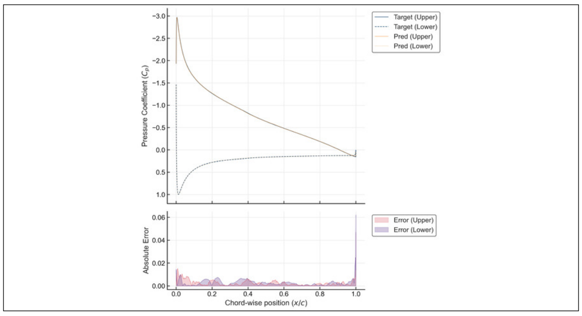
Approach / Technology: A complete pipeline for automated data generation using OpenFOAM is developed, producing flow field datasets for approximately 475 different NACA airfoil geometries over a range of angles of attack and freestream velocities. A computationally efficient potential flow solver provides the 9 m/s flow field used as model input. For steady-state simulations, CFD-computed target fields cover 10 to 100 m/s in 10 m/s increments. For transient simulations, the initial 9 m/s flow field is followed by an inflow ramp with an acceleration of 10 m/s per 0.1 s, reaching 100 m/s. Therefore, after training, no CFD software is required during inference.
Based on these datasets, different preprocessing, conditioning, and training strategies are investigated. For steady-state simulations, freestream-based feature transformation, geometric information through the Signed Distance Function (SDF), and global conditioning using the NACA parameters significantly improve prediction accuracy. In contrast, additional physical constraints, such as lift and divergence losses, provide only limited improvement. Compared with MGN, UPT achieves higher overall prediction accuracy while requiring less memory and shorter training and inference times.
For transient simulations, a progressive rollout training strategy combining a gradually increasing prediction horizon with targeted noise injection and time-dependent error weighting substantially improves long-term stability and reduces error accumulation compared with conventional next-timestep training.

Conclusion: Overall, the results show that UPT is a powerful approach for data-driven approximation of flow simulations. In particular, integrating prior physical and geometric information proves decisive for high prediction quality. While generalization to unknown profile geometries is very successful, previously unobserved angles of attack remain a significant challenge.The trained models are integrated into the prototype application FoilFlow, developed to demonstrate practical deployment of neural CFD surrogate models. FoilFlow enables interactive, near real-time flow field prediction and fundamental aerodynamic analysis of airfoils, highlighting the potential of data-driven CFD surrogates for engineering and optimization.

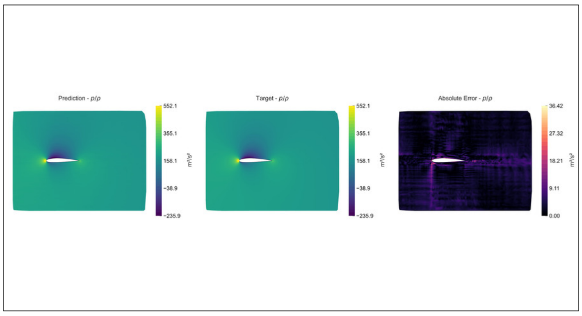
UPT architecture and setup, from potential-flow input and conditioning to the predicted flow field.
Own presentment



Target and predicted pressure coefficient (Cp) on the NACA 2412 boundary in steady state, showing very high accuracy.
Own presentment



Transient NACA 2412 flow field after 30 steps (40 m/s), showing the predicted kinematic pressure field.
Own presentment



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