

A MULTI-FIDELITY NEURAL NETWORK FRAMEWORK FOR ENHANCING STRIP-THEORY AERODYNAMICS

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ABSTRACT

High-fidelity aerodynamic modeling remains one of the most significant computational bottlenecks in aircraft simulation and control, particularly when flexibility is taken into account, where real time solution of aeroelastic coupling is often desired. Even comparatively low-fidelity approaches, such as classical strip-theory, can become expensive when embedded inside flight-dynamics solvers, while still exhibiting noticeable deviations from experimental data. At the same time, a growing ecosystem of heterogeneous aerodynamic datasets is now available, ranging from wind-tunnel measurements to Computational Fluid Dynamics (CFD) and analytical models. This creates a fertile ground for physically consistent data-driven approaches, in which machine learning is used not as a black box, but as a consistent surrogate that respects the structure of the underlying physics. This work presents a scientific machine learning framework to enhance a strip-theory aerodynamic model for the TU-Flex wing (shown in Figure 1) by blending CFD, experimental, and analytical information into a unified neural-network-based surrogate.



Figure 1: TU-Flex's half-wing at the wind-tunnel facility.

The main objective of the proposed method is to produce a fast and accurate aerodynamic model that can replace the classical strip-theory model implemented in a particular simulation and control application. Beyond the immediate application to TU-Flex, the approach is intended as a test case for more complex extensions, including unsteady aerodynamics and flight-control simulations. A key aspect of the methodology is the deliberate exploitation of different data fidelities: CFD provides smooth, noise-free trends over a wide parameter space, while wind-tunnel measurements push the model to physical reality, and finally, strip-theory calculations provide a baseline physics-informed structure.

The learning framework consists of two coupled neural-network models. The first model is trained to represent aerodynamic loads, specifically lift and pitch moment, as functions of the relevant inputs. This model is first pre-trained exclusively on CFD data, allowing it to capture the general aerodynamic trends and smooth functional dependencies present in high-fidelity simulations. Transfer learning is then employed: selected layers of this network are frozen, and the model is subsequently fine-tuned using wind-tunnel data. In this way, the network inherits the broad physical trends from CFD while being corrected toward experimental reality where data are available. The architecture uses two hidden layers with 128 neurons each and hyperbolic tangent activation functions, optimized with the Adam algorithm over long training horizons to ensure convergence and stability.

The second neural-network model introduces an additional layer of physical consistency by operating in the space of structural modal coordinates. Instead of directly predicting aerodynamic forces, this model takes the modal deformation coordinates of the flexible structure as inputs and outputs generalized aerodynamic forces. These generalized forces are then projected back into physical lift and pitching-moment quantities, which are compared against the outputs of the first network. The loss function enforces agreement between the two representations, effectively tying the learned aerodynamics to the underlying structural dynamics. This coupling reflects the physics of aeroelastic systems, where aerodynamic loads act through structural modes rather than at isolated points, and it helps prevent the neural networks from learning nonphysical relationships.

The preliminary results shown in Figure 2 indicate that the proposed framework is able to reconstruct lift and pitch-moment coefficients with remarkable agreement to wind-tunnel measurements. When the generalized forces predicted by the second network are projected back into physical space, the resulting lift and moment curves closely match the experimental data across the tested conditions. In addition, the reconstructed spanwise distributions of lift and moment appear physically reasonable, although further validation against detailed measurements is still required. These results suggest that the combination of transfer learning, multi-fidelity data, and physics-aware loss functions can significantly improve the predictive capability of strip-theory-based aerodynamic models without sacrificing computational efficiency.

Future work will extend the present framework in several directions. CFD data incorporating structural flexibility will be included to enrich the training set and improve extrapolation to deformed configurations. The surrogate model will be replaced by the current aerodynamic model in the full TU-Flex simulation environment to assess computational speed-ups and accuracy in dynamic flight scenarios, including maneuvers and control inputs. Finally, the methodology will be generalized to unsteady aerodynamics, although data availability remains a major challenge. Overall, this work demonstrates a promising path toward fast, accurate, and physically consistent aerodynamic surrogate models for flexible aircraft.

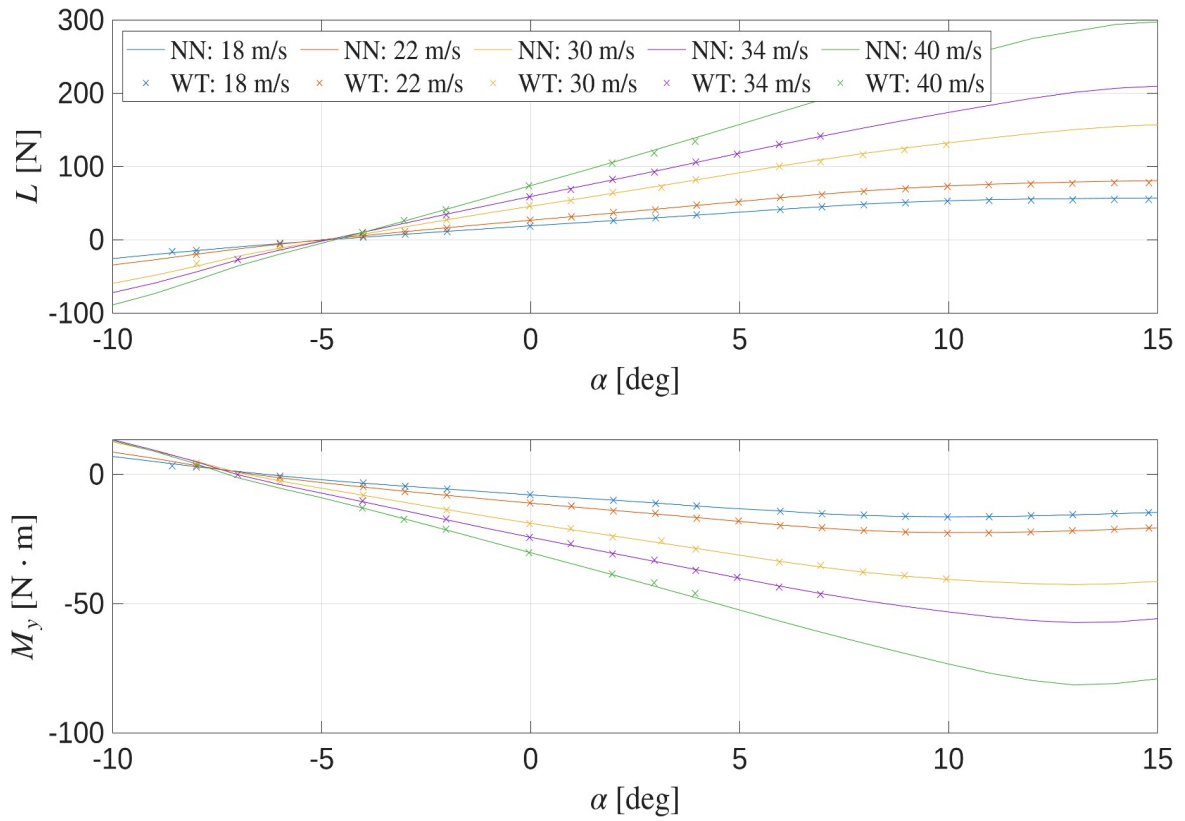


Figure 2: Lift and pitch moment coefficients predicted by the neural network (NN) compared against the wind-tunnel data (WT)