

DATA-DRIVEN PREDICTION OF AERODYNAMIC LOADS ON FLEXIBLE WINGS COMBINING NEURAL-NETWORKS AND LOW-DIMENSIONAL BALANCED PROJECTION

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ABSTRACT

The prediction of aerodynamic loads on flexible wings is a cornerstone of modern aero-elastic practice; yet conventional high-fidelity CFD solvers remain far too expensive for applications that require near-real-time results, such as rapid data-assimilation (des Bosc & Fabbiane, 2026) or rapid design-space exploration. This contribution introduces a purely data-driven surrogate that merges low-dimensional linear projection techniques with a compact neural-network, following an encoder-process-decoder workflow. The resulting surrogate model receives the displacement field \mathbf{x} at the wing surface as input and outputs the surface pressure field $p(\mathbf{x})$, thereby reproducing both local pressure distributions and integrated aerodynamic coefficients.

The diagram in Figure 1 shows the complete surrogate model pipeline. The displacement field on the surface of the wing \mathbf{x} is first encoded by the linear operator Ξ to produce the latent displacement vector ξ . Next, a neural network \tilde{N} processes ξ and outputs the predicted pressure latent vector $\tilde{\psi}$. Finally, the linear decoder Ψ maps $\tilde{\psi}$ back to the physical pressure field \tilde{p} . This compact flow chart highlights that, once the projection bases are built, only a small neural network is required for the mapping, dramatically reducing the dimensionality of the problem.

We explore two different data-driven methodologies to identify the projection basis for the displacement and pressure data (\mathbf{x}, p) onto the low-dimensional latent space (ξ, ψ) : the Proper Orthogonal Decomposition, POD (Loève, 1955), and the Balanced Proper Orthogonal Decomposition, BPOD (Willcox & Peraire, 2002). In the POD approach, the displacement and pressure snapshot matrices are processed independently. Each snapshot matrix is decomposed via singular-value decomposition (SVD), and the first ten left singular vectors are retained to form separate orthogonal bases, Ξ for displacement and Ψ for pressure. While this procedure yields energetically optimal bases for each field individually, it does not explicitly encode their aeroelastic coupling.

In contrast, BPOD constructs the reduced bases in a coupled manner. A joint SVD is applied to a cross-correlation matrix that links displacement and pressure snapshots, resulting in bi-orthogonal bases (Ξ, Ψ) . This formulation explicitly considers the mechanical work exchanged between aerodynamic forces and structural motion, as well as the intrinsic input-output relationship between displacement and pressure that characterizes aeroelastic systems.

For both linear projection approaches (POD and BPOD), a fully-connected neural network \tilde{N} is trained to map the displacement latent vector (ξ) onto the respective pressure one (ψ), therefore completing the identification of the surrogate model. A conventional approach based on stochastic gradient and the ADAM optimiser is employed to minimise the loss function

$$L(\theta) = \sum_i \|\psi^{(i)} - \tilde{N}(\xi^{(i)}; \theta)\|^2$$

with respect to the network parameters θ , where $(\psi^{(i)}, \xi^{(i)})$ are the reference data from the training set.

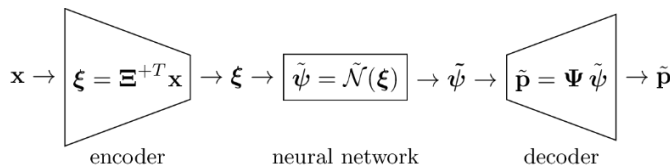


Figure 1

Encode-process-decode strategy employed, in the case of linear encoder and decoder.

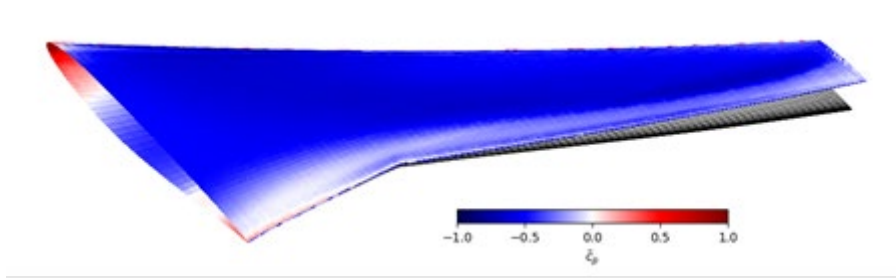


Figure 3

Pressure coefficient on the deformed aeroelastic shape at $AoA = 5^\circ$. The jig shape is also reported in black as a reference.

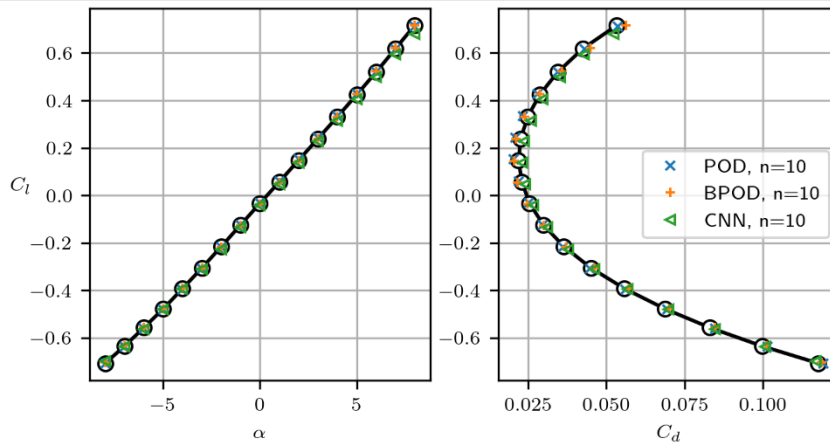


Figure 2

Lift coefficient as a function of angle of attack (left) and of the drag coefficient (right) for a static aeroelastic simulations. The black lines report the reference results from the full order simulations, while the symbols the one obtained by the reduced order surrogate models.

In order to validate and better illustrate the proposed surrogate methodology, a Design of Experiments (DoE) is generated starting on a simple structural configuration (Figure 2) aimed to transonic aeroelastic wind-tunnel testing (Fabbiane, Irisarri, Dillinger, & Lepage, 2022). Ten structural modal shapes (bending, torsion, higher-order flexure) are combined with angle-of-attack (AoA) rotations, generating 512 steady-Euler simulations at Mach 0.85. For each configuration the displacement vector \mathbf{x} and the pressure field p at the surface are stored, providing paired snapshots for basis construction and neural-network training (256 snapshots) and testing (256 snapshots). From this database, three different surrogate models are trained. The first two follow the methodology presented above, with the first using an encoder/decoder based on POD and the second on BPOD; the third – considered as a reference – employs instead a convolutional-neural-network (CNN) (Zahn, Weiner, & Breitsamter, 2024).

Figure 3 reports the comparison of the three surrogate models on coupled aeroelastic simulations against the full Euler fluid solver. All the three surrogate models are capable to provide the pressure load on the deforming structure in order to recover the correct deformed shapes and integrated aerodynamic forces. A more thorough analysis of the error introduced by the surrogate models highlights that the BPOD-based model outperforms the POD-based and CNN ones in predicting the aeroelastic deformation of the wing. This is possible thanks to the capability of the BPOD encoder/decoder of preserving the essential input-output coupling between the aerodynamic forces and the surface deformation. Moreover, the efficient encoder/decoder combined with a reduced latent space size allow for rapid predictions of the pressure field, making this architecture suitable for flight-control, preliminary design studies, or data-assimilation (des Bosc & Fabbiane, 2026).

References

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