

# AEROELASTIC DATA-ASSIMILATION OF WING TUNNEL EXPERIMENTS USING AERODYNAMIC REDUCED ORDER MODELS

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## ABSTRACT

In this study we present a data-assimilation technique for reconstructing the full displacement and pressure fields on a wing from partial experimental observations. We develop an iterative algorithm, analogous to the standard CFD-CSM workflow, that enables efficient aeroelastic data assimilation. To further accelerate the procedure, we incorporate a surrogate model described in (Fabbiane and des Bosc\*s 2026), leveraging its computational efficiency while maintaining sufficient accuracy.

In 2020 an experimental campaign was conducted at ONERA on a flexible composite wing (Fabbiane, et al. 2022) in transonic flow. The campaign produced rich experimental data, including Pressure Sensitive Paint (PSP) measurements, pointwise Model Deformation Measurements (MDM), and global aerodynamic coefficients. However, the data are incomplete: for practical reasons, PSP measurements are limited to the suction side, while MDM is available only on the pressure side. As a result, classical data-assimilation techniques are natural candidates to recover the full pressure and displacement fields on the wing surface. In the present work, we focus exclusively on steady-state configurations.

Given the incomplete pressure, displacement and aerodynamic scale data –  $\mathbf{m}_p$ ,  $\mathbf{m}_u$ ,  $\mathbf{m}_f$ , respectively – we aim to reconstruct the full pressure field  $p$  and displacements field  $\mathbf{u}$  over the wing surface  $\Omega_i$ . This is achieved by minimizing the following objective function:

$$J(p, \mathbf{u}) = \alpha_1 \|\mathcal{H}_p p - \mathbf{m}_p\|^2 + \alpha_2 \|\mathcal{H}_u \mathbf{u} - \mathbf{m}_u\|^2 + \alpha_3 \|\mathcal{H}_f p - \mathbf{m}_f\|^2,$$

such that the linear structural governing equation is respected

$$\mathcal{K}\mathbf{u} = \mathcal{P}p.$$

Here,  $\mathcal{H}_p$ ,  $\mathcal{H}_u$ , and  $\mathcal{H}_f$  are observation operators that map the pressure field to pressure evaluation at the pressure data location, the displacement field to displacement data location, and pressure field to integrated aerodynamics coefficients. The matrix  $\mathcal{K}$  denotes the structural stiffness matrix, while  $\mathcal{P}$  represents the operator performing the surface integration of the pressure loads  $\int_{\Omega_i} p \cdot \mathbf{n} \, dS$ . To ensure physically meaningful pressure fields, a penalization term must be added to incorporate prior knowledge of the pressure distribution. The resulting objective function to be minimized becomes

$$J_{total} = J(p, \mathbf{u}) + \beta \|p - p_{prior}\|_{H^1}^2.$$

For the wing considered here, solving this minimization problem is computationally inexpensive. The linear system arising from the Karush-Kuhn-Tucker (KKT) conditions is assembled and solved using LU factorization. When the same system must be solved repeatedly (e.g., for different experimental datasets or alternative pressure priors), and the LU decomposition can be reused; only the right-hand side needs to be rebuilt, reducing the total computation time. This makes the approach well suited for studies varying  $p_{prior}$  and/or the experimental data. Representative experimental results, comprising displacements and pressure distributions on the pressure side, are shown in Figure 1, together with the field reconstructions.

While the method recovers the wing displacement field with high accuracy, the quality of the pressure reconstruction is strongly dependent on the prior pressure distribution. To improve this prior, we introduce an iterative update (Figure 2) that closely follows the steps of aeroelastic flow-field computation. In this procedure, the structural data-assimilation step replaces the usual CSM solver. This approach is particularly attractive because it avoids the computation of a flow adjoint, which would

otherwise represent a major bottleneck for near-real-time data assimilation.

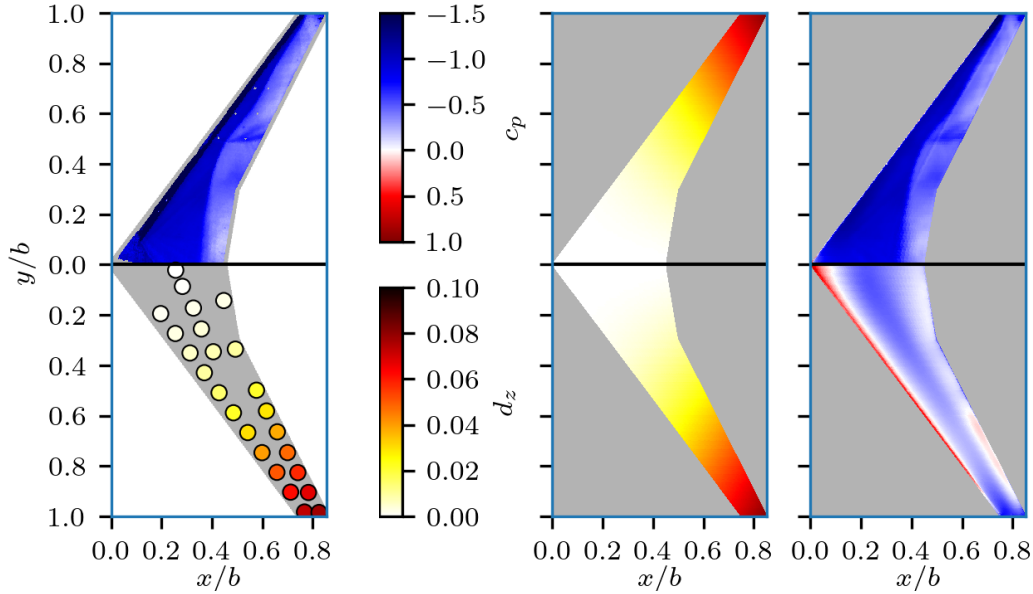


Figure 1(left) Experimental measurement of (top) pressure coefficient via PSP on the suction side, and (bottom) displacements obtained via MDM on the pressure side. Displacement and pressure coefficient distributions reconstructed by data assimilation in middle and right panels, respectively.

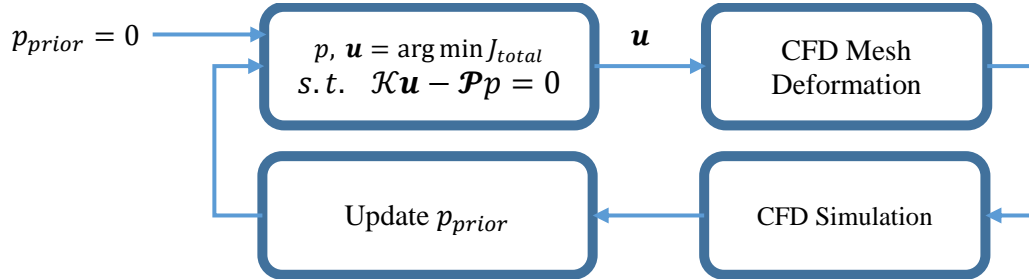


Figure 2: Workflow of the aeroelastic data-assimilation

The remaining computational bottlenecks are the CFD mesh deformation and the CFD simulation itself. The surrogate model described in (Fabbiane and des Boscqs 2026) can replace both steps. It was built from snapshots of an inviscid transonic flow, gathered in a computationally intensive offline phase. Based on projections in a very small latent space, the reduced order model allows for efficient queries during the online data assimilation phase.

By combining an inexpensive structural solver with a fast flow reduced-order model and by avoiding costly flow adjoint computations, the proposed method offers a practical and rapid solution for aeroelastic data assimilation. It can be readily integrated into routine aeroelastic analysis, design optimization workflows, and the rapid interpretation of experimental data.

## References

- Fabbiane, N., F.X. Irisarri, J. Dillinger, and A. Lepage. 2022. “Aeroelastic-tailoring of a wind-tunnel model for passive alleviation of static and dynamic loads.” *CEAS Aeronautical Journal* 13: 967–977.
- Fabbiane, Nicolò, and Pierre-Emmanuel des Boscqs. 2026. “Data-driven Prediction of Aerodynamic Loads on Flexible Wings combining Neural-Networks and Low-Dimensional Balanced Projection.” In *International Forum on Aeroelasticity and Structural Dynamics*. Goettingen, Germany.