

## PROPOSITION DE SUJET DE THESE

**Intitulé : Aeroelastic Reduced-Order-Model for Real-Time Data Assimilation.**

Référence : **MFE-DAAA-2024-028**  
(à rappeler dans toute correspondance)

**Début de la thèse :** Octobre 2024

**Date limite de candidature :** 30/6/2024

### Mots clés

Aeroelasticity, Dimension Reduction, Machine learning, Time-series predictions, Data assimilation.

### Profil et compétences recherchées

Applied Mathematics, Fluid Mechanics, Python, Fortran

### Présentation du projet doctoral, contexte et objectif

In modern aircraft design, the key goal is to cut down on fuel usage. This is done by making the aircraft lighter, using lightweight structure, and extending its wingspan. These changes result in more flexible structures and increased aeroelastic interactions. At ONERA, various experiments investigating different aeroelastic interactions are being carried out. These experiments yield massive amounts of data, which are then post-processed and compared with simulations in a second phase, often months if not years after the experiments took place. Therefore, on-the-fly hybridization of experimental data with simulation data could have significant impact on the way experiments are designed, carried on, and post-processed.

The aim of the PhD project is to design a method that can infer with real-time capabilities the whole aeroelastic state (flow and structure variables), given experimental data such as wing displacements, or flow velocity measurements. The targeted database has been already gathered, and aims at better understanding aeroelastic coupling in various flows conditions, in regimes where aeroelastic instabilities are present. To reach the real-time inference, one should necessarily rely on Reduced-Order Models (ROM), tailored for fluid-structure interaction problems and built using simulation data. This data will be generated using an inhouse code. Once these inexpensive models are built, one will use classical data assimilation techniques, such as Kalman filters, to obtain flow and structural state estimations. The developed methodology will help experimentalists monitoring the experiment, or provide first-hand state estimation.

The construction of ROM can reproduce the structure of the aeroelastic solver. There exist two types of solvers for unsteady aeroelastic flows: the monolithic one, for which all equations are solved together, and the partitioned one, for which the equations are iteratively solved [1]. Industrial codes more often rely on partitioned approaches, as they are easier to implement since different solvers can be employed separately. Monolithic approaches are in general more stable but require all of the physics to be implemented within the same code. It is therefore interesting to develop ROMs that are following both strategies, monolithic and partitioned, in order to stick to the way they were produced, and investigate if, for instance, it also affects the ROM stability.

Among many ways to build ROMs, a conventional approach involves reducing the model's dimensionality by projecting the flow state and equations onto a smaller basis of carefully selected modes, through a Galerkin approach. The modes are typically obtained from a linear transformation of snapshot simulation data that captures the most significant flow features. This procedure is called proper orthogonal decomposition (POD) [1, 2]. The selection of modes forms a Reduced Order Basis (ROB). For problems that are linear or quadratic (i.e. incompressible flows, with no deformations), the projection on the ROB is rather trivial. However, for aeroelastic flows in ALE formulations, the equations are not even polynomial with respect to the variables, and a hyper-reduction method can be exploited in order to bypass the strong non-linearity of the physical problem [3].

This reduction results in a significantly lower-dimensional model, typically around 10 dimensions, enabling real-time predictions. However, this linear dimension reduction approach encounters limitations when dealing with advection-dominated systems, and requires an excessive number of modes (>100) to achieve accurate

system representation. In such cases, the original goal of dimension reduction is compromised. If one retains only a reasonable number of modes (~10), some of the system's dynamics are lost, potentially leading to a degradation in the reduced model's accuracy. To mitigate this problem several approaches can be employed, and we aim at testing two among many.

In the first approach, a correction to the Galerkin projection or *closure* term must be identified to incorporate some of the omitted dynamics. Lately, neural networks have gained popularity for learning this closure term, and a recent concept, Neural Ordinary Differential Equations [4] seems very promising to learn this closure term. Yet, these learned closure models were performed on simpler cases, where only the fluid is modeled. It is then necessary to build architectures adapted to the aeroelastic framework, and tailored for both monolithic and partitioned approach.

A second approach, developed for instance in [3], is to use a more suitable but also more involved projection: the least square Petrov-Galerkin projection. Although it is numerically more intensive than the Galerkin projection, it often has better stability properties and increased accuracy. It can be combined as in [3] with a several local ROB, from which the most suitable basis is picked on-the-fly during the reduced model evaluation.

Finally, a successful implementation and comparison of both methods enables a streamlined data assimilation process, where an estimation of flow state variables can be deduced from experimental observations. Bayesian data-assimilation techniques, such as Kalman filters [5] or particle filters are of particular interest. These methods would allow for an estimation of the state variables given experimental observations as well as they do enable a quantification of the uncertainty on the reconstructed state, by considering the uncertainties on the experimental observations and on the reduced-order model.

### References

- [1] Nonino *et al.* (2021) A monolithic and a partitioned, reduced basis method for fluid–structure interaction problems, *Fluids*
- [2] Weiss (2019) A tutorial on the proper orthogonal decomposition, AIAA Aviation Forum.
- [3] Grimberg *et al.* (2020) Mesh sampling and weighting for the hyperreduction of nonlinear Petrov-Galerkin reduced-order models with local reduced-order bases, *Int. J. Numer. Methods. Eng.*
- [4] Menier *et al.* (2023) CD-ROM : Complementary Deep – Reduced Order Model, *Comput Methods Appl Mech Eng.*
- [5] Roger R. Labbe Jr (2020), *Kalman and Bayesian Filters in Python.*

### Collaborations envisagées

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