PROPOSITION DE SUJET DE THESE

Intitulé : Data assimilation and machine learning for the prediction of three-dimensional mean flows past wings

Référence : **MFE-DAAA-2026-08**
(à rappeler dans toute correspondance)

Début de la thèse : Automne 2026	Date limite de candidature : 30/06/2025

Mots clés

Data assimilation, machine learning, computational fluid dynamics, turbulence modeling, flow reconstruction

Profil et compétences recherchées

Master 2/diplôme d'ingénieur en mécaniques des fluides et/ou mathématiques appliquées. Expérience en simulation numérique pour la mécanique des fluides souhaitée.

Présentation du projet doctoral, contexte et objectif

Turbulence modeling is an essential tool to make affordable the numerical prediction of flows at high Reynolds number past airfoils as encountered in aerodynamics applications. Among various turbulence modeling strategies, the most appropriate and most commonly used one for industrial applications remains the Reynolds-Averaged Navier-Stokes (RANS) approach, where all the unsteady content of the flow is modeled and one only solves for the time-averaged mean flow. While RANS-based simulations may provide accurate results for attached flows encountered for instance in cruise conditions of an aircraft, some physical phenomena such as flow separation, stall or corner flows, among others, are well known to be challenging to capture by RANS (as illustrated through Figure 1) and limit the use of these models in design stages at the border of the flight envelope.

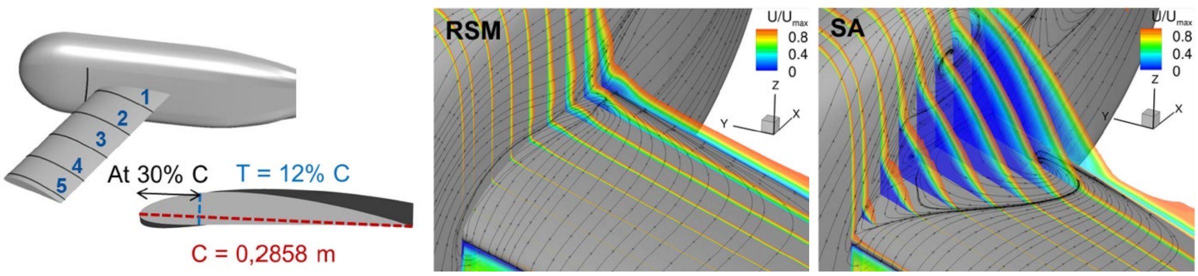

Figure 1: left sub-figure: PANDA wing and NACA412 profile; middle sub-figure: numerical prediction of the flow in the PANDA configuration with a high-fidelity turbulence model; right sub-figure: numerical prediction obtained with a lower-fidelity turbulence model, which significantly overpredicts the corner separation [1].

As such, and aside from traditional modeling efforts, there has been a growing interest in recent years in leveraging data-driven techniques to quantify errors in RANS simulations and learn corrective terms to improve their fidelity [2]. Among the various data-driven approaches that have been proposed to improve RANS modeling, we will here consider the so-called Field-Inversion Machine-Learning (FIML) framework [3], which corresponds to a two-step procedure:

- The first step, Field-Inversion, consists in, based on available data, inferring samples of the corrective term in the RANS equations (e.g. contribution to the divergence of the Reynolds-stress tensor) that we want to learn. This step, which may also be referred to as a data assimilation procedure, also provides full flow descriptions from the considered data (e.g. limited number of wall-pressure measurements from wind-tunnel experiments). As such, this field-inversion/data-assimilation step is already of great interest for experimentalists and flow reconstruction purposes in order to build detailed reference databases to be exploited by other researchers and industry partners.
- The second step, Machine-Learning, amounts to relying on machine-learning techniques to infer actual models to be implemented in CFD codes from the samples of the corrective term that have been obtained in the previous step. The so-obtained data-driven RANS model may then be applied to other flow

configurations than the ones for which data are available. From an experimental point view, this may allow us to generate reliable full flow predictions for some values of the physical parameters (Reynolds number, Mach number, angle of attack, etc.) that have not been investigated in an experimental campaign.

While previous studies have demonstrated the potentialities of the FIML framework in enhancing the quality of RANS-based predictions, in particular at ONERA [4,5], the vast majority of them considered two-dimensional and rather simplistic flow configurations. In this context, the main objective of the present PhD project is the development of data-driven strategies to improve the RANS-based estimation of three-dimensional flows around wing configurations that are representative of industrial applications.

To achieve this goal, the PhD project will in particular involve the implementation and use of field-inversion/data-assimilation techniques in conjunction with state-of-the-art Computational Fluid Dynamics (CFD) solvers developed at ONERA, which will allow us to perform flow reconstruction and the inference of corrective terms from limited data for complex flow configurations. Several methodologies (adjoint-based, ensemble-based, …) [6] will be compared to identify a good compromise between efficiency, computational cost and ease of deployment in the present context of ambitious configurations. Similarly, appropriate machine-learning techniques that may handle scarce data and may be transferable to complex CFD codes will be designed.

From a modeling point of view, it will be of interest to consider more advanced turbulence models as basis for the FIML procedure compared to the ones used in previous works that were dedicated to two-dimensional flow configurations. In particular, quadratic extensions to the Spalart-Allmaras model [7,1] will be considered to better handle secondary flows, which are specific to three-dimensional configurations. The considered test cases will correspond to three-dimensional configurations such as the ONERA M6 wing and the so-called PANDA configuration (see Figure 1), for which both experimental and reference numerical data from a scale-resolving simulation will be available.

In summary, the present PhD project will pioneer the development of data-driven approaches to enhance the numerical prediction of complex, three-dimensional separated turbulent flows through RANS modeling. This work will be of interest both from a modeling point of view and for experimentalists who are interested in performing flow reconstruction from sparse wind-tunnel data.

[1] L. L. Prudenzano, F. Gand, S. Deck. *Critical Assessment of Quadratic Closures for Prediction of Corner Flow Separation*. AIAA Journal 63, 1819-1834, 2025

[2] K. Duraisamy, G. Iaccarino, H. Xiao. *Turbulence Modeling in the Age of Data*. Annual Review of Fluid Mechanics 51, 357-377, 2019

[3] E. J. Parish, K. Duraisamy. *A paradigm for data-driven predictive modeling using field inversion and machine learning*. Journal of Computational Physics 305, 758-774, 2016

[4] P. S. Volpiani, M. Meyer, L. Franceschini, J. Dandois, F. Renac, E. Martin, O. Marquet, D. Sipp. *Machine learning-augmented turbulence modeling for RANS simulations of massively separated flows*. Physical Review Fluids 6, 064607, 2021

[5] B. Fanizza, P. S. Volpiani, F. Renac, E. Martin, D. Sipp. *Adjoint-based optimization for non-linear inverse problems with high-order discretization of the compressible RANS equations*. Applied Mathematical Modelling 142, 115984, 2025

[6] V. Mons, J.-C Chassaing, T. Gomez, P. Sagaut. *Reconstruction of unsteady viscous flows using data assimilation schemes*. Journal of Computational Physics 316, 255-280, 2016

[7] P. R. Spalart. *Strategies for turbulence modelling and simulations*. International of Heat and Fluid Flow 21, 252-263, 2000

Collaborations envisagées

Laboratoire d'accueil à l'ONERA

Département : Aérodynamique, Aéroélasticité, Acoustique

Lieu (centre ONERA) : Meudon

Contact : Vincent Mons, Pedro Volpiani, Fabien Gand

Tél. : 0146235066 Email : vincent.mons@onera.fr, pedro.stefanin_volpiani@onera.fr, fabien.gand@onera.fr

Directeur de thèse

Nom : Taraneh Sayadi

Laboratoire : CNAM/M2N

Tél. :

Email : taraneh.sayadi@lecnam.net

Pour plus d'informations : https://www.onera.fr/rejoindre-onera/la-formation-par-la-recherche