RÉPUBLIQUE FRANÇAISE
Liberté Égalité Fraternité

ONERA
THE FRENCH AEROSPACE LAB

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PROPOSITION DE STAGE EN COURS D'ETUDES

Référence : **DAAA-2025-23**
(à rappeler dans toute correspondance)

Lieu : Châtillon

Département/Dir./Serv. : DAAA / MSAE
PPRIME / DFTC

Tél. : 0146734629 ou 0146734625

Responsable(s) du stage : Christophe Blondeau, Pierre-Emmanuel Des Boscs,
Nassim Razaaly

Email. : christophe.blondeau@onera.fr
pierre_emmanuel.des_boscs@onera.fr
nassim.razaaly@ensma.fr

DESCRIPTION DU STAGE

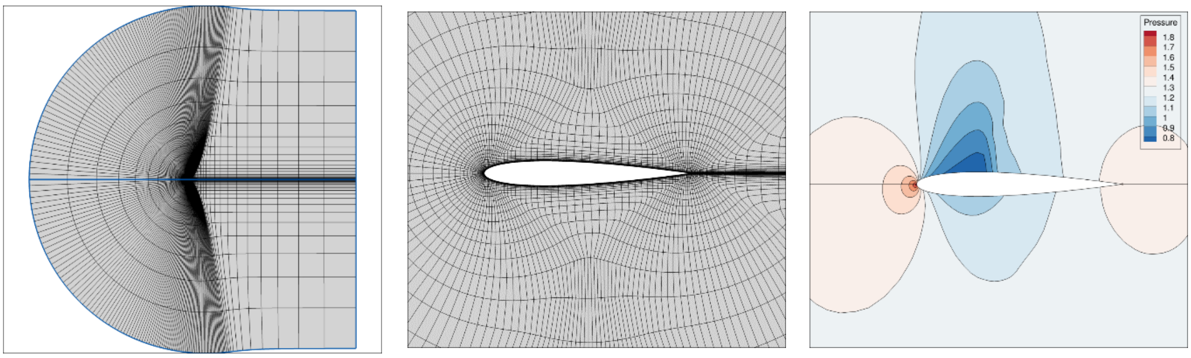
Thématique(s) : Optimisation multi-fidélité pour l'aérodynamique, l'aéroacoustique et l'aéroélasticité

Type de stage : ☐ Fin d'études bac+5 ☒ Master 2 ☐ Bac+2 à bac+4 ☐ Autres

Intitulé : Data-driven dimension reduction for aerodynamic shape optimization

This internship is a collaboration between Pprime Institute and ONERA, and as such, you will work in close collaboration with both institutions.

Subject : Aerodynamic shape optimization is a crucial step in aircraft design. By optimizing the shape of an aircraft, significant improvements in performance can be achieved, such as reducing fuel consumption or increasing flight range.
Mathematically, this optimization problem can be translated as a minimization problem. For example, find the set of shape parameters that minimizes a relevant cost function (*e.g.* the lift-to-drag ratio) for given flow conditions (Mach number, altitude, angle of attack, *etc.*). The cost function may exhibit local minima and is computationally costly to evaluate since a new flow has to be computed. Typically, tens to hundreds design variables are considered for a fine shape control.
On the one hand, modern computational fluid dynamics codes can readily compute gradients of the cost function with respect to the shape parameters, and classical gradient descent algorithms can be used to find a *local* minimum. These methods can cope with large numbers of design parameters. On the other hand, global optimizers often rely on so-called *surrogate* models that approximate the real cost function at any point and are computationally cheap to query. It is then much faster to use the surrogate model than the actual model for the optimization. However, these methods rely on an initial dataset from which the model must be learned. Unfortunately, these methods do not scale to large numbers of design parameters (above 20).
In this internship, we will to explore an alternative strategy and evaluate traditional deep neural network architectures (auto encoders, see *e.g.* [1, Chapter 14] or [2]) to learn a mapping between shape parameters and the flow state from which the cost function can be easily retrieved. Like the surrogate-based approach, the training phase will exploit a dataset consisting of transonic flow fields over a 2D airfoil together with integrated quantities (lift, drag, moment), but possibly also their gradients with respect to the shape parameters. This problem is challenging because this type of transonic flow is dominated by strong nonlinearities.



Aerodynamic grid for viscous flow computation past the NACA0012 airfoil and typical pressure field.

The work breakdown of the internship will be as follows. First, demonstrate the potential of a traditional autoencoder to discover a reduced latent space that captures the flow nonlinearities and also the parameter dependency.
Then, to assess whether the use of gradient information helps to reduce the amount of data needed by the neural network to learn a faithful representation of the flow state and the integrated quantities, including their derivatives with respect to the design variables.
Finally, compare the performance of this optimization strategy with other already existing surrogate-based and gradient-based methods [3].
The envisaged test case will consider the optimization of the drag coefficient of a NACA0012 symmetric airfoil in viscous transonic flow conditions. The student will make use of a deep learning environment such as PyTorch for the practical implementation.
By the end of the internship, you will have gained a hands-on experience in implementing recent neural network architectures and applied them to a realistic numerical optimization test case. You will also a have a deeper understanding of how to use these powerful mathematical tools to solve complex optimization problems.

References:

[1] I. Goodfellow, Y. Bengio, A Courville, Deep Learning, MIT Press, 2016 http://www.deeplearningbook.org.
[2] D. Kingma, M. Welling An Introduction to Variational Autoencoders, https://arxiv.org/abs/1906.02691
[3] J. Li, X. Du, J. Martins, Machine learning in aerodynamic shape optimization, Progress in Aerospace Sciences, **134**, 2022, https://doi.org/10.1016/j.paerosci.2022.100849 .

Est-il possible d'envisager un travail en binôme ? Non

Méthodes à mettre en œuvre :

☐ Recherche théorique ☐ Travail de synthèse

☒ Recherche appliquée ☒ Travail de documentation

☐ Recherche expérimentale ☒ Participation à une réalisation

Possibilité de prolongation en thèse : Oui

Durée du stage : Minimum : 5 months Maximum : 5 months

Période souhaitée : Spring 2025

PROFIL DU STAGIAIRE

Skills : mathematical optimization, machine learning, computational fluid dynamics. Python and Pytorch programming experience would be appreciated.	Ecoles ou établissements souhaités :