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PROPOSITION DE SUJET DE THESE

Intitulé : Coupling data-assimilation and machine learning to improve RANS simulations of aeronautical flows

Référence : **MFE-DAAA-2024-03**
(à rappeler dans toute correspondance)

Début de la thèse : Octobre 2024	**Date limite de candidature :** 30/6/2024

Mots clés

data assimilation, machine learning, RANS, turbulence, aerodynamics

Profil et compétences recherchées

école d'ingénieurs et/ou master en aérodynamique / mathématique appliquée

Présentation du projet doctoral, contexte et objectif

In the aerospace industry, due to its cheap computational cost, Reynolds-Averaged Navier-Stokes (RANS) simulations continue to be an irreplaceable tool in the design, analysis, and optimization of high-Reynolds-number turbulent flows. In this approach, only the mean flow is considered and a mathematical model is required to capture the effect of turbulence via the unknow Reynolds stresses. The essence of RANS modeling is based on expressing these unknown terms as a function of known mean quantities. One of the most widespread assumptions in RANS modeling is based on the Boussinesq hypothesis, which assumes a linear relationship between the turbulent Reynolds stresses and the mean-velocity gradient tensor; the proportionality constant being the turbulence-eddy viscosity. Classical eddy-viscosity models the turbulent eddy viscosity by solving one or two partial differential equations (PDE) that describe the transport of turbulent quantities (such as the modified viscosity, the turbulence kinetic energy, its specific rate of dissipation, the turbulent dissipation, etc). More complex models such as the explicit algebraic Reynolds stress model (EARSM) [Wallin & Johansson 2000 J. Fluid Mech.], or the differential Reynolds stress model (DRSM) [Cécora, Radespiel, Eisfeld & Probst 2015 AIAA J.] solve an equation for each one of the 6 Reynolds stress components, and a seventh transport equation for the length-scale-determining variable. Despite the huge improvement in the physics description of the latter method, this type of model lacks robustness and a perfect RANS model is still missing, especially when dealing with flows with large separations, high streamline curvature, strong pressure gradients, etc.

With the undeniable success of machine learning (ML) and artificial intelligence (AI) in numerous fields, from image and speech recognition, up to self-driven cars and medical diagnosis, CFD aerodynamic calculations are also beginning to benefit from this technology [Duraisamy 2021 Phys. Rev. Fluids]. It is therefore natural to use this technique to improve the deficiencies of RANS turbulence models. Well-disseminated approaches consist of fixing existing models, such as the Spalart-Allmaras (SA) model, by training an AI algorithm on a selected dataset and extrapolating to other cases, that are not included in the training set. Parish and Duraisamy (2016, J. Comp. Phys.) and Singh et al. (2017, AIAA J.) proposed to correct the source terms in turbulence transport equations using data assimilation and machine learning. On the other hand, Ling et al. (2016, J. Fluid Mech.), Wang et al. (2017, Phys. Rev. Fluids) and Wu et al. (2018, Phys. Rev. Fluids) proposed to directly predict the Reynolds stresses, or their discrepancies compared to the truth. Volpiani et al. (2021, Phys. Rev. Fluids) opted to introduce a correction to the Boussinesq-hypothesis by adding a forcing term in the momentum equations. They employed variational data assimilation to infer the vectorial source correction from high-fidelity numerical data and machine learning to reconstruct this quantity from the local mean-flow features. More recently, the same group from ONERA used machine learning techniques to infer a turbulent-eddy-viscosity correction for the SA model and successfully improved RANS results of flows over bi-dimensional bumps (Volpiani, Bernardini & Franceschini 2022 Int. J. Heat Fluid Flow).

So far, the majority of studies that proposed to augment RANS models though AI or ML have treated in the most part academic flow configurations at low Reynolds and Mach numbers. The goal of this PhD program is to apply recent developed and new ML methodologies to treat more complex industrial cases such as transonic profiles and 3D wings at high Reynolds number. To deal with such realistic scenarios, we propose to correct RANS models using solely experimental data and then generalize the correction term using ML. Different FIML methodologies will be tested (classic and direct approaches). Providing augmented turbulence models for the aeronautical industry, with the ability to cover the physical modelling of separated and complex flow configurations with the correct degree of confidence and reliability, would improve aircraft performance and lower design uncertainties throughout the whole flight envelope. To summarize, the goal of this PhD project consists of correcting RANS models based on machine learning and show its potential for the aeronautical industry.

To strengthen the international collaboration on data-driven topics the PhD project is organized as a co-funded PhD project with the DLR, i.e. a close cooperation and exchange between two PhDs is planned. The PhD projects are also co-supervised at ONERA and DLR and mutual visits and research stays of the PhD candidates are expected.

Collaborations envisagées

Laboratoire d'accueil à l'ONERA

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