PROPOSITION DE SUJET DE THESE

Intitulé : State estimation and modeling of compressible flows through data assimilation and machine learning

Référence : MFE-DAAA-2021-14
(à rappeler dans toute correspondance)

Début de la thèse : Octobre 2021  Date limite de candidature : Juin 2021

Mots clés : Assimilation de données, machine learning, compresseur axial


Présentation du projet doctoral, contexte et objectif

Achieving accurate estimation of instantaneous flow state remains an open challenge that is relevant for both fundamental and industrial applications, such as, for example, the design of closed-loop control strategies to prevent the occurrence of the surge phenomenon in axial compressors. In order to reach this objective, data assimilation techniques are more and more considered, as they permit to combine computational fluid mechanics (CFD) predictions with experimental fluid mechanics (EFD), i.e. measurements that may be local in space and time, to provide a complete and accurate description of flows of interest.

Among these data assimilation methodologies, the Kalman filter and its ensemble variants appear as appropriate candidates for accurate state estimation of complex flows [1-4]. The sequential character of the Kalman filter approach, i.e. its ability to update flow predictions as new observations are available in time, makes the latter suitable for real-time applications and facilitates its application to highly turbulent/chaotic flows. While demonstrations of the capabilities of such techniques for the estimation of incompressible flows have been provided [1,3-4], their application to unsteady compressible flows and around complex 3D geometries that are representative of aeronautical applications is still to be accomplished, as embryonic developments for simplified cases are currently under investigation [5]. Among others, a remaining issue is to ensure that the Kalman filter-correction is compatible with the conservation principles of compressible flows and to avoid the generation of spurious waves during the data assimilation procedure. Thus, one of the main objectives of this PhD project is to provide advancement in the field of data assimilation for compressible flows, aiming complex settings. In addition to fully address the previously mentioned difficulty, the project aims to provide advancement for two essential open challenges, which are described in the following.

Illustration of the tip leakage flow around an isolated non-rotating blade, from [10].
The first aspect deals with the computational resources required by the data assimilation method. The main drawback for the straightforward application of Kalman filter techniques for complex 3D application is the computational cost required, in particular when deployed in conjunction with high-fidelity CFD solvers. As a stochastic data assimilation approach, the Kalman filter requires the propagation of statistics associated to the uncertainties in the flow prediction. Even with the most elaborate ensemble-based approaches (EnKF), the computational cost of the data assimilation procedure to evaluate the flow statistics is equivalent to O(10)-O(100) CFD simulations. A recent proposal relying on multi-fidelity/multi-grid techniques [5] will be considered and extended to alleviate this computational burden.

Another promising path consists in exploring the numerous possibilities in combining data assimilation with machine learning techniques. Machine learning, including deep learning approaches which have been made popular by the computer vision community, are increasingly considered in fluid mechanics applications as they allow revisiting various modeling issues, in particular for turbulence/subgrid-scale modelling. Thus, a second main objective of this PhD project is to investigate the use of machine learning in conjunction with data assimilation. Two strategies are envisioned. The first one will be dedicated to the application of machine learning to identify and model various parameters/quantities in the data assimilation procedure which are generally unknown while always required in practice [6]. A second path of innovation will aim for combining data assimilation and machine learning to infer model corrections in order to compensate for discretization and/or turbulent modeling errors, in the case of coarse grid/low-fidelity simulations [7]. More generally, the developed methodologies could help identifying models, in particular subgrid-scale models, from limited and possibly noisy data, in contrast with current data-driven modeling approaches which may require fully resolved flow fields [8,9].

In summary, the two main objectives of this PhD project, whose respective weights could be adapted to the applicant’s interests, consist in (i) the application of sequential data assimilation techniques to the estimation of complex compressible flows (ii) while investigating the coupling of data assimilation tools with machine learning approaches, in particular to design efficient data-driven modeling methodologies relying on limited data. The applicant will benefit from the framework provided by two internal research projects at ONERA, which are respectively dedicated to data assimilation and machine learning. The applicant will have initial access to academic CFD codes. This will provide an optimal interface to obtain methodological developments. These findings will be then integrated in high-performance computing (HPC) ONERA codes for three-dimensional, complex applications. In particular, the capabilities of the developed data assimilation and machine learning tools will be finally demonstrated for flow configurations which are relevant for turbomachinery applications, such as the subsonic/transonic flows around isolated non-rotating [10]/rotating blades for which experimental and/or numerical data are available.

[7] Brajard, Carrassi, Bocquet and Bertino, Combining data assimilation and machine learning to infer unresolved scale parametrization, arXiv, 2020
[8] Xie, Li, Ma and Wang, Modeling subgrid-scale force and divergence of heat flux of compressible isotropic turbulence by artificial neural network, Phys. Rev. Fluids, 2019
[10] Deveaux, Fournis, Brion, Marty and Dazin, Experimental analysis and modeling of the losses in the tip leakage flow of an isolated, non-rotating blade setup, Exp. Fluids, 2020
Collaborations envisagées

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