Thesis subject 2021

Laboratory : Institut Jean Le Rond d’Alembert, Equipes FCIH et MPIA (dans le cadre de l’axe transverse Interactions Fluide-Structure)

University: Sorbonne Université, CNRS, UMR 7190

Title of the thesis: Fluid-Structure Interactions and Data-Assimilation using Hybrid Deep Neural Networks

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This subject can be published on the doctoral school’s web site: yes

Thesis’s summary (abstract):

Fluid-structure interactions (FSI) may exhibit complex wake-flow dynamics and instabilities such as vortex-induced vibrations, galloping or nonlinear flutter of elastically mounted rigid bodies. In addition, the understanding of the underlying physical mechanisms may require a large number of evaluations of the high-fidelity flow solver (e.g the Navier-stokes equations) in order to perform parametric investigations, uncertainty quantification and data-assimilations studies of the FSI system. In order to reduce the corresponding computational burden, reduced order model (ROM) can be used to extract the main features of the FSI dynamics. This doctoral project intends to combine state-of-the-art deep learning techniques with projection-based ROM in order to alleviate the well-known lack of robustness of conventional reduced order model for the long-term prediction of bluff body wake-flows. The second part of this research will be devoted to the development of deep learning-based data-assimilation schemes for parameter identification of fluid-structure interactions problems.
1. Problem Statement

Fluid-structure interactions (FSI) of fluid–rigid body interactions may exhibit complex wake-flow dynamics such as vortex-induced vibrations and nonlinear flutter. The time-domain response of the coupled system must be carefully estimated in order to given reliable estimations of reduced frequency, damping factor and the critical instability boundary. Such issue can be efficiently addressed by using high-fidelity CFD solvers based on the solution of the Navier-Stokes equations formulated using an Arbitrary Lagrangian Eulerian (ALE) framework (Figure 1).

![Figure 1 Example of vortex-shedding due to the aeroelastic flutter of a 3DOF elastically mounted typical bridge section (results are obtained using the ALE Navier-Stokes solver CAEL [2,4])]()

Although efficient moving grid-based implicit techniques are employed to speed up the computation of the solution in time-domain, high fidelity approaches still require a large amount of computational resources due to the long transient required for the prediction of the limit-cycle oscillations of the coupled fluid-structure system. Moreover, the numerical burden increases considerably when the stability of the FSI system must be assessed using parametric study or bifurcation diagrams, based on a large number of aeromechanical parameters. Similar bottleneck arises for solving inverse problem in FSI, such as identifying the aeromechanical parameters and initial conditions responsible for a particular mechanism of fluid-structure interactions.

2. State of the art

Reduced Order Models (ROM) are developed since many years in order to preserve the accuracy and predictive capability of the original Full Order Model (FOM) but at much lower computational costs [1]. To this end, the ROM is derived as a low-dimensional data-driven representation for modeling the FOM dynamical systems. Parametrized ROM methodologies can be used to construct surrogate models for uncertainty quantification and data assimilation [2]. Many approaches may be considered to reduce the dimensionality of the full order model, like for instance, the projection onto a small set of optimal basis functions using proper orthogonal decomposition (POD). Therefore, FSI-based ROM have been actively developed over the last decade, mostly using intrusive approaches which require to modify the FOM in order to build the FSI-ROM.
Unfortunately, dealing with highly nonlinear dynamical problems may dramatically reduce the efficiency of the ROM due to increase in the number of operations involved in the evaluation of the nonlinear terms. Hyper-reduction techniques can then be employed to efficiently approximate nonlinear terms [3]. Recently, this approach has been implemented within an ALE-based POD approach for the prediction of LCO of an elastically mounted cylinder freely vibrating in heave motion [4]. Although this work has demonstrated the ability to predict the temporal evolution of the aerodynamic coefficients, further improvements are needed in order to better model the non-linear dynamics of the FSI-FOM. More generally, the present main issues in developing reliable ROM are accuracy preservation, long-term stability and their ability to address parametric investigations [5].

3. Methodology and work plan

Due to major advances in computer sciences, scientific machine learning techniques have gained a growing interest in the field of computational fluid mechanics [6]. In particular, some studies based on the use on deep neural networks have shown interesting results for the reduction of large-scale dynamical systems involving regression steps based of time series of unsteady flows [7]. Recently, dense and recurrent deep learning ROM have successfully recovered the dynamics of FSI systems [8,9].

The purpose to this PhD thesis is to overcome the lack of accuracy and parametric robustness of POD-ROM for unsteady compressible flows by using deep learning techniques in the projection step. More precisely, hybrid neural network will be investigated by combining the POD for the extraction of the main dynamic flow features with deep learning (DL) techniques for the learning of the time-dependent coefficients of the POD subspace. An interesting feature of the developed data-driven deep neural networks is that they will be trained using the same data used in the ROM projection step while keeping the non-intrusiveness properties of the FOM. The scope of this Doctoral project is twofold:

- The main objective of the first part is to derive a non-intrusive hybrid DL-POD method specially designed to deal with dynamic meshes and ALE formulation. First, both convolutional and recurrent neural networks will be considered to improve the long-term predictive capabilities of current state-of-the art conventional POD-ROM based on hyper-reduction techniques. Various highly nonlinear wake region past bluff bodies will be considered to assess the performance of the hybrid POD-deep learning ROM. In particular, tuning optimization of the network hyperparameters will be thoroughly investigated. In a second step, a proper mathematical framework will be derived to apply the hybrid deep neural networks to ALE-based POD for FSI. To this end, it will be necessary to learn separately the non-linear spatial features of the FOM by projection on a fixed mesh and the ALE displacements due to the moving computational domain. Applications of these data-driven DL methods will be devoted to the prediction of vortex induced oscillations, galloping, and fluttering of elastically mounted solid bodies.

- The second objective of this work is to employ the previously developed hybrid DL ROM in the context of data assimilation for fluid-structure interactions. More precisely, we intend to couple the DL-POD algorithm with ensemble smoother approaches for parameter estimations. Such DL-based surrogate models could help to reduce the computational time due to repetitive evaluation of the high-dimensional FOM. Finally, the potential ability of using deep learning techniques for maintaining the accuracy of ensemble smoother DA schemes in the presence of non-Gaussian distributions of input parameters, quantities of interest and measurement errors, will be investigated.
References