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PROPOSITION DE SUJET DE THESE

Intitulé : Data-driven modelling and model predictive control of turbulent flows

Référence : **Domaine-Département-Année de début-Numéro d'ordre**
(à rappeler dans toute correspondance)

Début de la thèse : octobre 2024	**Date limite de candidature :** juin 2024

Mots clés : data-driven identification, machine learning, feedback control

Profil et compétences recherchées :

Diplôme : Master2 ou diplôme d'ingénieur

Compétences recherchées : au moins dans un des domaines suivants :

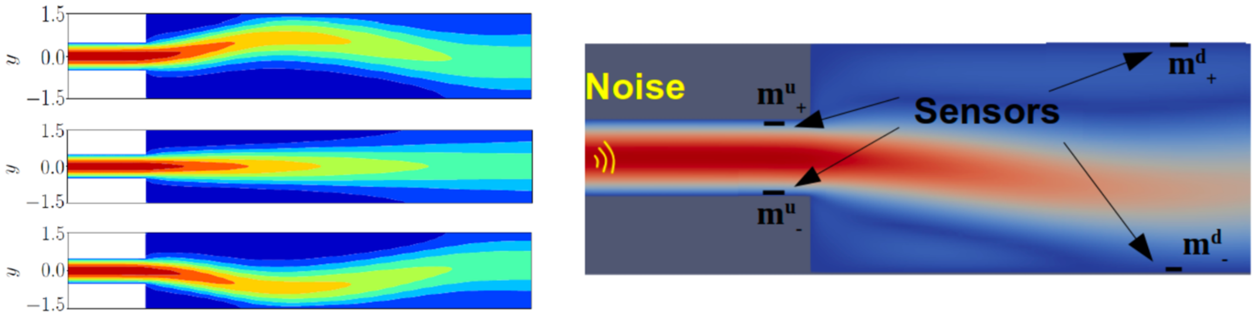
- Mécanique des fluides
- Mathématiques appliquées
- Sciences des données/Machine Learning
- Systèmes dynamiques

Présentation du projet doctoral, contexte et objectif

Flow control consists of introducing controlled disturbances to improve the operating performance of a dynamical system. In fluid mechanics, we can seek to improve aerodynamic performance (reduction of drag or instabilities, for example) while minimizing the energy consumed to introduce the control. For reasons of energy efficiency and robustness, we would like to develop closed-loop control strategies, i.e. taking into account the state of the system to determine at each time instant the optimal forcing to introduce. Historically, much work has been carried out using **model-based approaches**, developed from first-principles equations (Navier Stokes equations, for example) or simplified dynamical models based on different reduced basis (POD, DMD, stability modes, etc.). However, these models are known of being fragile in terms of parametric modeling, and are therefore often poorly suited to flow control applications. The aim of this thesis is to develop simplified dynamical models of separated flows using **data-driven modeling approaches**, and **to use these models to develop closed-loop control strategies**.

As linear control is a well-established control method, it may be interesting to model non-linear turbulent flows via linearized models. In this context, separated flows exhibiting bistability phenomena are of particular interest, due to their dynamical and modeling complexities. Indeed, bistable separation flows are characterized by two attracting equilibria and random switches from one to the other under the influence of finite-amplitude external perturbations. This type of behavior is found on multiple applications ranging from automotive (recirculation in the wake of a car [1]) to aerospace (vortex developing over a fighter aircraft/missile nose cone at high angle of attack [2]). In the automotive case, the asymmetric wake causes increased drag compared to a symmetric one, which penalizes fuel consumption. In the nose cone case, unsteady loads are detrimental to maneuverability and safety of the vehicle. Figure 1 shows the case of flow in a diffuser, which will be particularly used in this thesis to develop the methods.

For control purposes, the main challenge is to be able to predict the seemingly erratic behavior of bistable systems under the influence of external noise, i.e. random switches, using real-time data from sensors (see Fig. 1(b)). The aim of this thesis is therefore **to develop new tools and methodology for modelling and control of bistable flows from data, by coupling state-of-the-art machine learning techniques with dynamical system theory.**



(a) (b)

Figure 1: Diffuser flows with bistability. (a) Different types of flows in the diffuser. (b) Configuration with sensors to measure upstream disturbances and system state.

Several ideas will be investigated during this PhD. One option is to augment linear models based on the Koopman operator [5], by learning an ad hoc nonlinear term, which should activate slightly before bifurcation occurs [6,7]. As an illustration, Figure 2 shows that a single linearized model cannot describe the complete wake flow dynamics around a circular cylinder.

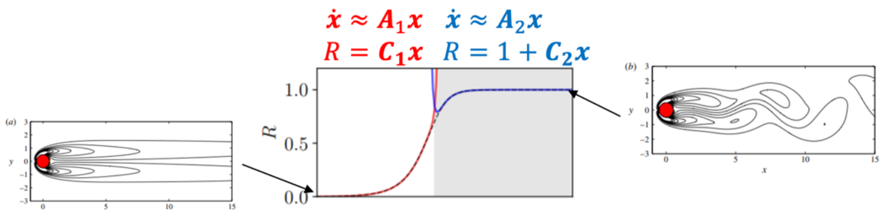


Figure 2: Koopman mode modelling for two invariant solutions. The case of the cylinder wake flow configuration [8].

Another option is to rely on echo state networks based on reservoir computing (see Figure 3). It has been shown that these networks may be used in chaotic systems to anticipate extreme events well beyond the characteristic predictability time [4]. This technique is therefore a good candidate for forecasting subcritical bifurcations in stochastically forced systems too. Finally, approaches blending modern nonlinear observer theory with machine learning will be investigated [9].

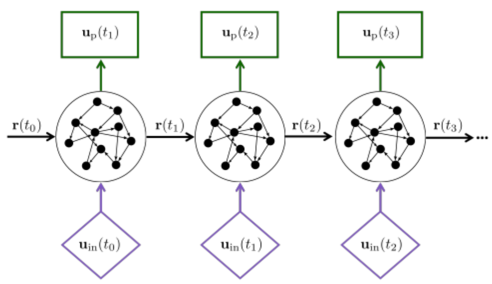


Figure 3: Nonlinear dynamical model using reservoir computing [2].

After the dynamics modelling phase, closed-loop control will be implemented using model predictive control [10]. This powerful framework takes full-advantage of the data by constantly re-tuning the control signal using receding-horizon optimization. It can also be made adaptive by constantly retuning the model on-the-fly using incoming data.

References

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Collaborations envisagées

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