Call for 2025 Doctoral Projects SCAI

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Title: *AI-aided ROM for nonlinear control of open flow aerodynamics*

Objectives: This thesis aims to apply and extend existing ML techniques to build robust and generalisable reduced-order models for nonlinear control of open-flow aerodynamics. Physically informed deep autoencoders will be used to discover surrogate models that capture the autonomous dynamics of the original system, and real-time nonlinear control will be attempted using only the reduced model learned from the unforced dynamics. Uncertainty measures will be added to the model to achieve robustness. As a test case, we choose an open cavity flow because of its ubiquity in aeronautical applications.

Description: In aeronautics, suppressing flow instabilities is a significant challenge with industrial potential, including drag reduction and noise minimisation. For instance, open-cavity flows are subject to an aeroacoustic feedback mechanism leading to spontaneous oscillations, which may induce high dynamic loads, potentially causing structural fatigue failure. Solving or mitigating this issue appears crucial. Standard feedback control requires a linear time-invariant model, which is why linear strategies remain common due to their simplicity and robustness[1,2]. However, strongly nonlinear systems, as open cavity flows in typical operational conditions, present challenges that linear techniques still struggle to address. More sophisticated nonlinear control strategies formally exist, but for high-dimensional dynamical systems, the dimensionality of the governing equations, i.e. Navier-Stokes equations, becomes a bottleneck, and solving nonlinear Model Predictive Control (MPC) problems in an online fashion becomes intractable; low-dimensional approximations of these equations are, therefore, desired.

State of art: Machine learning (ML) algorithms based on the Spectral Submanifold (SSM) theory have recently emerged as powerful fully data-driven, yet physically interpretable, model reduction tools, identifying the slow manifold over which the nonlinear dynamic evolves together with the corresponding reduced coordinates[3]. Specifically, SSM reduction produces a parsimonious low-dimensional surrogate model of the original system that obeys a precise mathematically well-founded structure; internal resonance identification also allows the recasting of these models as normal form equations, useful to study bifurcations of both natural and forced dynamics[4]. Furthermore, the reduced model learnt by observing the system's spontaneous dynamics alone has been shown, for a wide class of problems, to generalise well to make predictions on the system's response to an external forcing, hence offering an ideal platform for nonlinear control.

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1 **C. Leclercq**, F. Demourant, C. Poussot-Vassal & **D. Sipp** 2020 *Linear iterative method for closed-loop control of quasiperiodic flows* J. Fluid Mech

2 **D. Sipp**, O. Marquet, P. Meliga & A. Barbagallo 2010 *Dynamics and Control of Global Instabilities in Open-Flows: A Linearized Approach* App. Mech. Review

3 M. Cenedese, J. Axås, B. Bäuerlein, K. Avila & G. Haller 2022 *Data-driven modeling and prediction of non-linearizable dynamics via spectral submanifolds* Nat.Comm.

4 **A. Bongarzone** 2023 *Self-sustained dynamics and forced resonant oscillations in flows: cross-junction jets and sloshing liquids* PhD Thesis, EPFL

Despite promising results in engineering fields such as fluid-structure interactions[5], ML-based reductions have rarely been applied to control as a common application. In the application of interest to this work in particular, this application is made even more challenging because the inherent mathematical properties of the governing equations, such as non-normality, hinder the predictive power of most data-driven reduced models. In addition, to achieve robustness, uncertainties[6] in the predictions need to be assessed. Adding uncertainty measures to ML-based models is an ongoing area of research, which will be explored in this thesis. The originality of this thesis lies in its interdisciplinarity, with AI-driven approaches, applied mathematics, nonlinear control and fluid mechanics, which makes this topic fit well within the general scope of the SCAI project.

Work program: The main idea of the thesis is that the original data-based SSM algorithm can be interpreted as a special autoencoder, where the encoder is linear and the decoder is polynomial. **T1**. The first task is therefore to recast the SSM framework into an ML-based architecture. The resulting autoencoder will be trained using data from numerical experiments on a two-dimensional cavity flow. The identified (data-based) sub-manifolds will be evaluated using the centre-manifold theory, which is a model-based approach to identify the sub-manifolds. **T2**. The resulting reduced model will then be used to implement a non-linear control strategy and attempt to suppress the flow instabilities. **T3**. After exploring the range of applicability of the initial setup, we will gradually relax the specific form of the autoencoder by replacing the encoder and decoder with more general functional relations, e.g. deep NNs (see Figure 1a), making the description of the sub-manifolds more generic. Finally, uncertainty measures are added to the prediction of the model. This will allow us to design an effective controller capable of completely suppressing the flow unsteadiness (see Figure 1b) in the nonlinear regime.

Role of each supervisor: I. Mortazavi (CNAM) and N. Thome (Sorbonne) will be co-directors; their knowledge and experience with data-driven frameworks for mechanical engineering and machine learning will be essential in guiding the candidate through this thesis. A. Bongarzone and D. Sipp (ONERA) will be co-supervisors for this thesis, combining their expertise in normal form equations and control, respectively.

Candidate's profile: Engineering degree and/or Research Master in Fluid Mechanics/ Computer Science/Applied Maths. A good level of Python is required. Basic knowledge of CFD and ML-NN is highly appreciated.

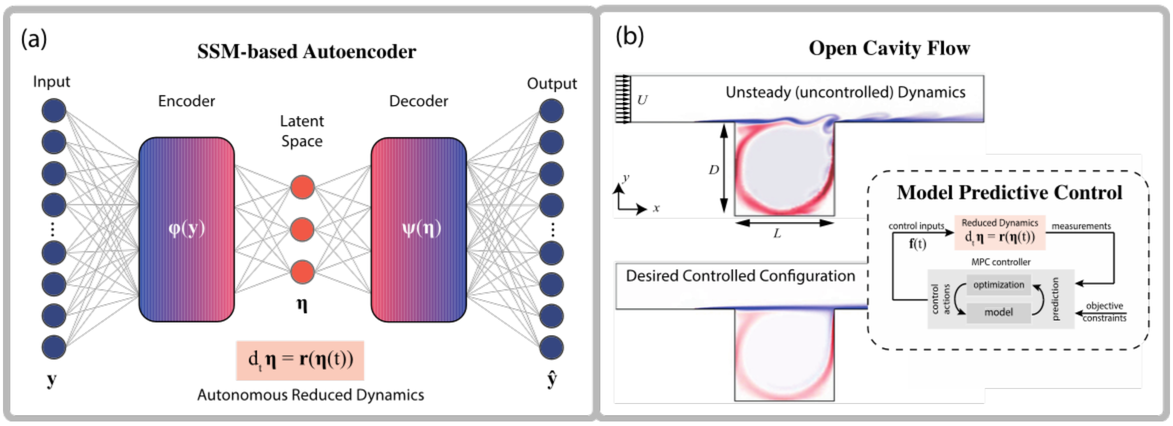

Figure 1: (a) Sketch of the SSM-based autoencoder. (b) Numerical snapshot [2] of the unsteady uncontrolled dynamics in a 2D open cavity flow (top) and the desired controlled configuration (bottom). Inset: nonlinear closed-loop control using the reduced-order model.

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[5] *A.Tiba, T. Dairay, F. De Vuyst, **I. Mortazavi,** J. Berro Ramirez (2024) Non-intrusive reduced order models for partitioned fluid–structure interactions, J Fluids and Structures, 128, pp. 104156.*

[6] *C. Corbiere, M. Lafon, **N. Thome**, M. Cord, P. Pérez, 2021, Beyond first-order uncertainty estimation with evidential models for open-world recognition. In ICML 2021 Workshop on Uncertainty and Robustness in Deep Learning.*