SOUND.AI

CALL 2 – 2023-24

APPLICATION FORM – v. 27/09/2023

PROJECT PROPOSAL

Title of the Doctoral Research Project:

Generalised AI-driven reduced-order model for model predictive control of complex flows

Thesis supervisor and supervisory team:

Main supervisor – Project Leader	
Surname	Sayadi
First name	Taraneh
Doctoral school of affiliation	SMAER
HDR	YES – SMAER
Research unit	Institut Jean-le-Rond d'Alembert - Pierre-Yves Lagrée FCIH - Suzie Protière
Professional address	4 Place Jussieu, 75005 Paris
Email	taraneh.sayadi@sorbonne-universite.fr
Phone	06 17 74 30 65
Doctoral students currently supervised by the thesis director	A. Quiros (2021) I. Zighed & M. Cayuela (2023)

Co-supervisor (if applicable)	
Surname	Thome
First name	Nicolas
Doctoral school of affiliation	EDITE
HDR	YES
Research unit	Prof -SU/ISIR- Name of the Unit director : Guillaume Morel Research team within the unit : MLIA Name of the team leader : P. Gallinari
Professional address	4 Place Jussieu, 75005 Paris
Email	nicolas.thome@isir.upmc.fr
Phone	01 44 27 87 80
Doctoral students currently supervised by the thesis director	Paul Couairon (2022)

Co-supervisor (if applicable)	
Surname	Sipp
First name	Denis
Doctoral school of affiliation	ED IPP
HDR	YES – Paris 6
Research unit	Director of Research - ONERA/DAAA - Head: MIALON BRUNO
Professional address	8 rue des Vertugadins 92190 MEUDON
Email	denis.sipp@onera.fr
Phone	01 46 23 51 55
Doctoral students currently supervised by the thesis director	LUCA SAVERIO 2023, MAXIME CASANOVA 2023, HUGO LEMARQUAND 2023, ARON CANNICI 2022, BARTOLOMEO FANIZZA 2021, KONSTANTINOS SARRAS 2021

Co-supervisor (if applicable)	
Surname	Leclercq
First name	Colin
Doctoral school of affiliation	ED IPP
HDR	NO
Research unit	ONERA DAAA - Laurent Jacquin MASH - Julien Dandois
Professional address	8 rue des Vertugadins, 92190 Meudon
Email	colin.leclercq@onera.fr
Phone	01 46 23 51 11
Doctoral students currently supervised by the thesis director	Mathieu Salmon (2021) Aron Cannici & Kevin Doria (2022)

Detailed Doctoral Research Project

Summary

High-fidelity simulations of unsteady and complex flows, while predictive, are very costly due to the multiple time and length scales involved in the computations. In multi-query applications, such as model predictive control, unsteady and high-fidelity simulations (full-order models) become quickly inapplicable due to this high cost of function evaluation. Reduced-order models (ROMs) can be used to represent approximate but cheap models of the full system, allowing for fast prototyping and multiple queries. However, to be applicable, they need to be robust and predictive. This requirement is not guaranteed, when applied to time-evolving (i.e. *dynamic*) data. In this context, data-driven models have proven to be unreliable in reconstructing the long-time behaviour of the analytical system, and lack robustness to changes in operating conditions or input parameters (i.e. generalisability). In this project we aim to address the lack of generalisability by relying on operator learning strategies and creating parametric mapping in the reduced space. Physical constraints will be added to the learning framework to reduce the amount of data required for training. Finally, by relying on physics-aware clustering techniques, the model will be locally adapted locally informed by the dynamics of the underlying system.

Title

Generalisable AI-driven reduced-order models for model predictive control of complex flows

Main supervisor

Dr. Taraneh Sayadi

Description of the project

Numerical simulations of multi-physics and multi-scale phenomena in fluid mechanics have made remarkable progress over the past decades. Complex physical processes can now be simulated with astonishing fidelity and accuracy. One of the products of such high-fidelity simulations is large data sets available for analysis and manipulation. Traditionally, such data has been used to create benchmarks and provide insight into existing structures/dynamics in the flow. However, recent advances in AI-driven techniques are enabling computational fluid dynamics (CFD) researchers to address existing bottlenecks in the simulation and modelling of complex fluid flows. In this project, we will consider the limitation of excessive dimensionality, which leads to significant cost and slow speed of high-fidelity simulations. In applications where quick access to an approximate but sufficiently accurate solution is required, or where many functional evaluations are needed (such as in control and optimisation studies), high-fidelity simulations are too slow or prohibitively expensive. This dilemma motivates the development and use of reduced-order or surrogate models in their place.

Reduced-order models (ROMs) are an alternative to expensive high-fidelity simulations, i.e. full-order models (FOMs). ROMs are approximate but cheap models of the full system, allowing fast prototyping. However, to be applicable, ROMs, which are typically derived using non-intrusive data-driven techniques, must be predictive. This requirement is not guaranteed when applied to time-evolving (i.e. *dynamic*) data. In this context, data-driven ROMs have been shown to be unreliable in reconstructing the long-term behaviour of the analytical system and lack robustness to changes in operating conditions or input parameters (i.e. generalisability. In other words, they lead to unreliable predictions when used in extrapolation mode, which is often the case in unsteady problems. To make matters worse, building ROMs requires a large amount of data, which makes them not directly applicable to the problems of interest to this project where limited data are available.

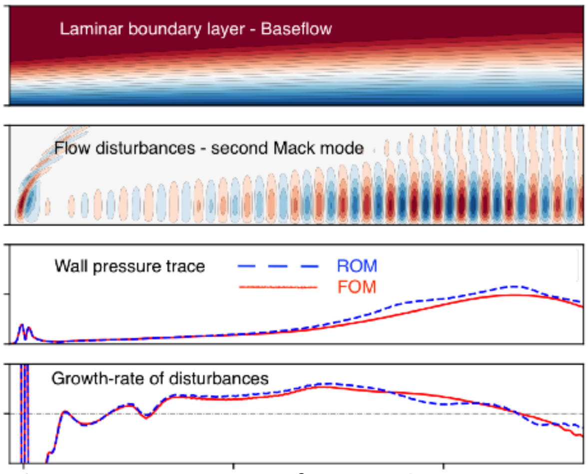

Fig. 1: Comparison of FOM & ROM in a canonical laminar boundary layer [2].

Relying on "adaptive" data-driven strategies (active learning) [1,2], we have successfully combined techniques from nonlinear model reduction, network clustering and manifold embedding to extract efficiently and adaptively a data-driven ROM. This model has already been benchmarked in simulations of high speed flows, where the physicochemical properties of the flow are successfully evaluated using the ROM, while the flow properties are evaluated using the high fidelity solver. The ability of the model to adapt to new states as they dynamically appear in the flow shows great promise in the ability of this approach to ensure predictability. **Fig. 1** shows that, following this approach, a model trained on a steady state solution to the problem is able to quickly adapt to an unsteady environment where perturbations are introduced into the flow.

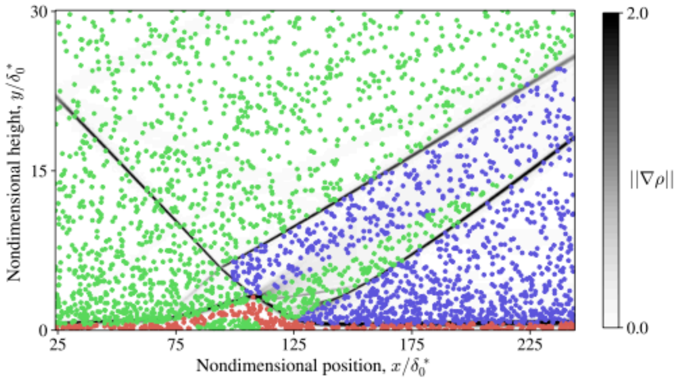

Fig. 2: Identifying different regions of the flow using physics-informed clustering techniques. Each cluster is identified by a different colour.

However, as mentioned above, the current approach is only applied to model the physicochemical states inside the flow. With this project, we aim to extend this modelling strategy to the entire flow field by the following steps:

1. Improve the efficiency of the reduced-order model by performing physics-informed clustering [3] of the spatial domain to obtain low-order approximations of the flow state in a number of dynamically distinct subdomains. An example of this clustering is shown in **Fig. 2** for a case of a chock boundary layer interaction. The clustering techniques separates the regions of high and low temperatures in the flow (three different colours of clusters), where different dynamics might arise. Therefore the first stage of the

modelling would be to extract a separate model for each cluster. An approximation of the flow in the full domain can then be handled by a domain decomposition technique to fit the ensemble of local representations [4]. Decomposing the domain based on the dynamical features of the flow allows local adaptation of the model.

2. On each cluster, a data-driven non-linear reduction strategy (based on an auto-encoder architecture) is used to construct the latent space. The model is then advanced in time on this lower dimension. At this stage, the most appropriate network structure needs to be chosen at this stage to achieve the best reduction.
3. The latent space will then be incrementally updated using our active learning strategy [1] until no extrapolation is detected.

With respect to reinforcement learning techniques, the present approach has the advantage of incorporating models obtained by physical governing equations and should therefore be more accurate and robust to extrapolation. This feature allows the overall algorithm to be faster in finding the descent path to the control objective. Several parameters are available to tune the accuracy of the models: number of subdomains, size of the adaptive reduced basis in each subdomain, number of points used in the reduction technique to force the residuals of the Navier-Stokes equations to be zero, correction or closure term that can in principle be added to match past and current observations in the case where the reduced order model captures only part of the frequency content of the model.

Finally, considering that the model may only be an approximation of the true dynamics, transfer learning techniques [5,6] will be investigated to fine-tune the reduced-order model to actual high-fidelity measurements.

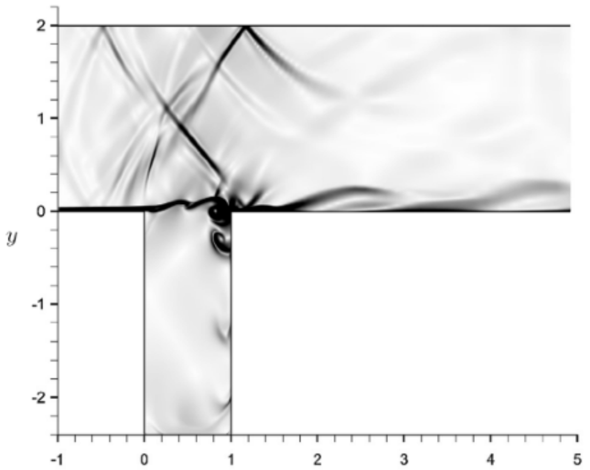

Fig. 3: Pseudo-Schlieren of subsonic cavity flow (2D URANS) [7].

We will apply the methodology to cases of increasing complexity:

1. Stabilisation of 2D incompressible open-cavity flow at Re=7500 with a model consisting of 2D incompressible Navier-Stokes equations.
2. Stabilisation of a subsonic open-cavity flow with data obtained from a 2.5D LES simulation and model obtained by projection of a 2D URANS model (see **Fig. 3**).

PROPOSED INDUSTRIAL AND/OR INTERNATIONAL SECONDMENTS

Onera is the National Research Institute for aerospace in France. Onera contributes in aerospace techniques through its fundamental research which complements that carried out in university laboratories, through its applied research supporting long and medium term projects, and by direct assistance to industry. Onera has set up four major scientific branches: Fluid mechanics and Energetics, Physics, Materials and Structures, Information

Technology and Systems. Onera is involved in nearly all scientific disciplines needed to drive progress in aerospace. Also, many Onera scientists participate to training activities in universities or engineering schools.
ONERA DAAA hosts around 60 PhD students for 200 Researchers and is affiliated to Institut Polytechnique de Paris.
The PhD student will have access to the High-Performance Computer of ONERA and to in-house developed CFD codes to simulate aerodynamic configurations of interest.
The PhD student will share its time between ONERA (50%) and Sorbonne Université (50%). Sorbonne Université will be in charge of the reduced order modelling strategy while ONERA will set-up the numerical simulation / aerodynamic configuration to be controlled.

REFERENCES

[1] C. Scherding (2023). Predictive Modeling of Hypersonic Flows in Chemical Nonequilibrium: Physics-based and data-driven approaches. *PhD dissertation (Sorbonne University)*.
[2] C. Scherding, G. Rigas, D. Sipp, P.J. Schmid, & T. Sayadi (2023). Data-driven framework for input/output lookup tables reduction -- with application to hypersonic flows in chemical non-equilibrium. *Phys. Rev. Fluids*.
[3] Costanzo, S. (2022). Numerical methods for control and optimisation of fluid flows (Doctoral dissertation, Sorbonne Université).
[4] Riffaud, S., Bergmann, M., Farhat, C., Grimberg, S., & Iollo, A. (2021). The DGDD method for reduced-order modeling of conservation laws. Journal of Computational Physics, 437, 110336.
[5] Z. Wang *et al.* (2023). A general deep transfer learning framework for predicting the flow field of airfoils with small data, Computers & Fluids, 251.
[6] K. D. Humbird, J. L. Peterson, B. K. Spears and R. G. McClarren (2020). Transfer Learning to Model Inertial Confinement Fusion Experiments, *IEEE Transactions on Plasma Science*, 48 (1): 61-70.
[7] C. Mettot (2013). Stabilité linéaire, sensibilité et contrôle passif d'écoulements turbulents par différences finies. Mécanique des fluides [physics.class-ph]. Ecole Polytechnique X.