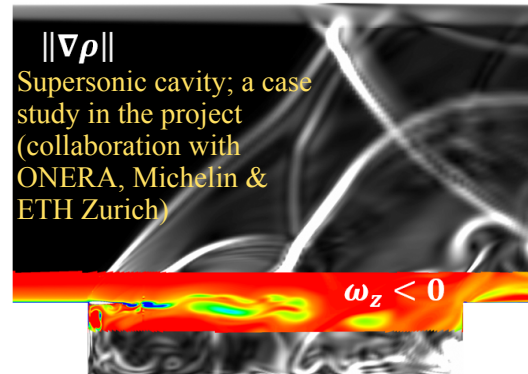


Data-driven model reduction for robust design and optimisation of complex engineering applications (French-Swiss ANR project: DINAMIC)

Type of offer :
Stage (Internship)

Location :
Mathematical & Numerical Modelling Laboratory (M2N)
Applied Mathematics & Statistics Department (EPN6)
Conservatoire Nationale Arts et Métiers (le CNAM)
2 rue Conté
75003, Paris Cedex 03



Context :

Data-driven (ML-based and nonintrusive) models have been shown to be unreliable in reconstructing the long-term behaviour of the engineering systems and lack robustness to changes in operating conditions or input parameters. However, their data-driven and non-intrusive nature makes them very attractive for such applications, especially when model inference is also required and is a priori unknown. While the use of ML to identify the reduced dimension has been investigated in recent years, in this project we address the lack of generalisability by relying on operator learning strategies and creating a parametric mapping in the reduced space. In the operator learning framework [1, 2], in contrast to conventional neural networks that aim to learn the map between finite-dimensional vector spaces, the learning problem is formalised as a mapping of function spaces, which is particularly generalisable and suitable for systems governed by partial differential equations. Preliminary results [3] show their ability to construct predictive and parametrised surrogates of the underlying physical system and also the possibility of their application in an inverse problem for calibration purposes, which is of great importance in engineering applications. In this project we will specifically rely on Fourier Neural Operators (FNOs) [4]. The advantage of FNOs in this respect is that physical laws can be easily integrated into the learning process as well [3], leading to a physics-aware but still data-driven model. Adding model-based knowledge to this learning framework has been shown to make these operators easily generalisable to different parametric and geometric conditions, which would be of interest to this project as the model will be used to analyse a wide range of parameters (due to the control objective). There have been studies in the past that have attempted to produce such mappings from data such as SINDy [5]. However, the approach proposed by DINAMIC learns the mapping without making any assumptions about the feature space, allowing for the most general description of the model.

Scientific partners of DINAMIC: ETH Zurich, ONERA, Michelin and CNAM.

Moreover this project also funds a PhD position in the same topic, starting October 2025.

Profile :

The candidate should pursue a MSc degree or equivalent (engineering diploma) in mechanics or applied mathematics, with experience in scientific computing.

Skills :

Programming experience and expertise in data-driven techniques will be considered very positively.

Duration and start date :

The stage position is offered for the duration of 5 months, from March 1st, 2025 to July 31, 2025.

Required documents :

The applicant should include a CV, and a motivation letter.

Contacts :

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References :

- [1] N. Kovatchki et al., Neural operator: Learning maps between function spaces with applications to PDEs, *J Machine Learning Research*, 24 (2023), pp. 1–97.
- [2] L. Lu, P. Jin, and G. Pang et al, Learning nonlinear operators via deepnet based on the universal approximation theorem of operators, *Nat Mach Intell*, 3 (2021), p. 218–229.
- [3] Z. Li *et al*, Physics-informed neural operator for learning partial differential equations, arXiv:2111.03794, (2023).
- [4] Z. Li *et al*, Fourier neural operator for parametric partial differential equations, arXiv:2010.08895, (2021).
- [5] S. Brunton, J.L. Proctor, and J.N. Kutz, Discovering governing equations from data by sparse identification of nonlinear dynamical systems, *Proceed. National Academy Science*, 113 (2016), pp. 3932–3937.