Reduced order methods meet machine learning for accelerating computational fluid dynamics: focus on turbulent parametric flows

Gianluigi Rozza[1]

Computational Fluid Dynamics (CFD) is a cornerstone for the analysis of complex flow phenomena.

However, the computational cost of high-fidelity simulations often restricts their use in many-query scenarios such as design optimization, uncertainty quantification, and parametric analysis.

Reduced Order Models (ROMs) alleviate this limitation by constructing low- dimensional surrogates that retain the dominant flow dynamics at a significantly reduced computational cost [1]. This work presents a set of complementary data-driven strategies that combine reduced-order modeling and scientific machine learning to improve the accuracy, robustness, and generalization capabilities of ROMs for CFD applications.

A first contribution focuses on non-intrusive ROMs and introduces a space- dependent aggregation framework in which multiple surrogate models—obtained from different combinations of dimensionality reduction techniques, regression methods, or turbulence models—are locally combined through spatially varying convex weights learned from data. This approach enhances predictive accuracy in challenging benchmark problems, including transonic airfoil flows [2].

A second contribution addresses intrusive ROMs through parametric closure modeling, where a deep operator network is trained to learn reduced correction operators that compensate for unresolved dynamics, enabling reliable generalization across the parameter space [3]. Finally, a hybrid reduced-order modeling framework is developed for high- Reynolds-number fluid–structure interaction problems in an Arbitrary Lagrangian–Eulerian setting. The approach combines POD–Galerkin projection for the fluid equations with machine-learning- based models for the turbulent eddy viscosity and reduced interpolation techniques for mesh motion, enabling accurate and efficient simulation of flow- induced vibration phenomena [4].

Overall, the proposed methodologies advance hybrid reduced-order modeling by unifying surrogate aggregation, operator learning, and data-driven turbulence closure within a flexible and scalable framework, providing fast and reliable CFD predictions for complex, turbulent, and parameter-dependent systems.

References:

[1] Ivagnes, A., Khamlich, M., Siena, P., Rozza, G. Reduced Order Modeling in Computational Fluid Dynamics: An Overview of Methods and Applications. In International Conference on Emerging Technologies in Computational Science for Industry, Sustainability and Innovation (pp. 1-20). Cham: Springer Nature Switzerland. (2023, May).

[2] Ivagnes, A., Tonicello, N., Cinnella, P., Rozza, G. Enhancing non-intrusive reduced-order models with space-dependent aggregation methods. Acta Mechanica, 1-30. (2024).

[3] Ivagnes, A., Stabile, G., Rozza, G. Data-driven Closure Strategies for Parametrized Reduced Order Models

[1]SISSA
grozza@sissa.it

via Deep Operator Networks. arXiv preprint arXiv:2505.17305. (2025).

[4] Ngan, V. N., Stabile, G., Mola, A., Rozza, G. A hybrid reduced-order model for segregated fluid-structure interaction solvers in an ALE approach at high Reynolds number. Computers & Mathematics with Applications, 180, 299-321. (2025).