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Hybrid machine learning reduced order models for efficient forecasting and data generation in fluid dynamics databases.

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Abstract

Fluid dynamics are involved in most natural and anthropogenic processes, from blood irrigation in the human body to large-scale flows in urban environments [1]. Understanding the behavior of fluids in motion has been a primary interest for researchers in both industry and academia due to its crucial role in human life and potential technological applications. Numerical methods are widely used to accurately recreate and analyze the behavior of flows, but they tend to be computationally expensive in terms of both memory footprint and computation time. For practical applications, several simulations must be performed at different flow conditions to gain a broader understanding of the phenomenon, further increasing the computational cost.

Reduced order models (ROMs) obtained through modal decomposition are a data-driven alternative to overcome the limitations of numerical methods applied in fluid dynamics due to their capability of accurately representing high-dimensional systems in a simplified form, extracting the main patterns of a flow [2]. In this context, Singular Value Decomposition, Dynamic Mode Decomposition and its variants are modal decomposition methods that have demonstrated their robustness for the analysis of fluid mechanics problems, successfully extracting the underlying physics of the problem under study [3][4]. On the other hand, machine learning algorithms can learn from initial sets of information, identifying patterns, generalizing them, and providing accurate predictions for new, never-seen input data [5].

By combining modal decomposition methods with machine learning, high-fidelity hybrid physics-based ROMs can be obtained for analyzing and predicting complex flow dynamics. Using this approach, we have defined a new multi-parametric tool capable of predicting the behavior of fluid dynamics problems over time and generating data for unseen flow conditions starting from reduced databases. More specifically, the tool provides high-resolution solutions from low-resolution data and predict new flow conditions for specific variables and flow states. The proposed methodology has been validated on a dataset describing the 2D flow around square cylinder section under forty different conditions, defined in terms of Reynolds number (Re) and angle of attack (AoA).

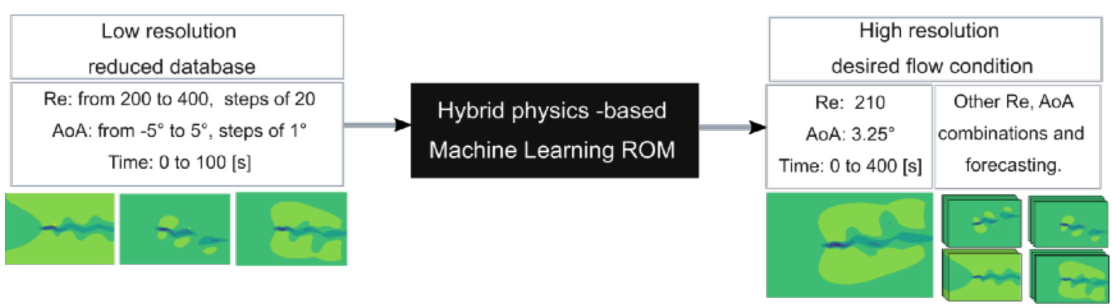

Figure 1. Scheme of the proposed hybrid ML physics-based ROM methodology.

Keywords: Machine Learning, ROMs, physics-based, modal decomposition

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