In this talk, we present intrusive and nonintrusive data-driven approaches of reduced-order modeling for the dynamical prediction of fluid flows.

For the intrusive approach, Proper Orthogonal Decomposition based ROM (POD-ROM) is considered. First, we consider sparse regression methods issued from statistical learning to identify the linear unknowns of the ROM. A bootstrap method is then proposed to quantify in a probabilistic framework the uncertainties associated with the regression methods. Then, the POD-ROM is augmented with a nonlinear eddy viscosity model that provides an interpretable physics-based closed-form representation of the flow dynamics. Finally, the closure term parameters are estimated with a Dual Ensemble Kalman filter approach (Dual EnKF) which integrates the model outputs and measurements while taking into account the respective uncertainties.

For the nonintrusive approach, regression models based on Neural Networks (NN-ROM) are considered as an alternative to the POD-ROM. This method addresses the limitations of POD-ROM – the lack of an a priori guarantee of stability, and requirement of closure to account for the unresolved modes – at the cost of interpretability of the resulting surrogate model. The derived NN-ROM serves as a time-stepping method for the POD projection coefficients. A novel multistep, residual-based, parametrized neural network is then proposed. This framework is augmented with Data Assimilation (DA) to provide accurate long-term dynamical predictions.