Modeling Turbulence and Transition Using Data-Driven Approaches group: overview

Turbulence modeling and its applications are foundational activities of the Center for Turbulence Research. The name is now preceded by the term "data-driven," which refers to progress compelled by data rather than by only physical insight and intuition. This might give the impression that data-driven turbulence modeling has recently emerged as a new branch within the realm of fluids, although the exploitation of data to enhance our physical understanding and modeling capabilities has been at the core of turbulence research from its early years. This is especially true since the advent of numerical simulations in the 1980s and 1990s. Even the experiments in transitional pipes by Osborne Reynolds in the 1880s could be regarded as "data-driven." Nonetheless, it is undeniable that current advances in machine learning and data science have incited new efforts to complement the existing turbulence modeling approaches in the fluids community. Moreover, technological considerations call for the exploration of machine learning venues to avoid paradigm lock in the field. The stakes are high—for example, the impact of turbulence models enabling the reduction of transportation drag by 5% is estimated to be equivalent to that of doubling the U.S. wind energy production.

During the 2022 CTR Summer Program, five projects dedicated to turbulence modeling for engineering applications have contributed to the development of new, groundbreaking ideas in the field. The focus of the group revolves around the common theme of data-driven modeling, and 11 scientists from 8 institutions worked for a month at Stanford University. The participants, supported by eight hosts, tackled problems of fundamental and technological significance, ranging from novel large-eddy simulation (LES) modeling strategies for complex flows to high-speed laminar-to-turbulent transition and computationally efficient methods for operator recovery.

The activities during the Summer Program include a subset of projects on novel approaches for LES. Ling *et al.* developed a unified subgrid-scale (SGS) and wall model for LES by devising the flow as a collection of building blocks. The model, referred to as BFM, computes an eddy viscosity via artificial neural networks (ANNs) that accounts for zero-pressure-gradient wall-bounded turbulence, adverse pressure-gradient effects, separation and laminar flow. The ANNs were trained to guarantee consistency with the numerical discretization and are applicable to complex geometries. The authors showed that BFM outperforms traditional SGS/wall models in the NASA Common Research Model High-Lift, becoming the first demonstration of a successful ANN-based LES model in a realistic aircraft configuration. Hansen *et al.* used proper orthogonal decomposition (POD) to augment the law of the wall in the traditional equilibrium wall model. The first POD mode extracted from a canonical turbulent channel flow was included as an additional term in the equilibrium wall model with a constant determined through a second matching location. They showed that the augmented model provides improved predictions in turbulent channel flows under non-equilibrium conditions such as strong mean unsteadiness and adverse pressure-gradient effects. The authors also hypothesized that further data-driven corrections from modal analysis might further improve the predictions in a wide variety of flows. The third wall model application is offered by Zhou *et al.*, who developed a model using multi-agent reinforcement learning (RL) that captures pressure-gradient effects. In the RL approach, agents distributed along the wall learn

how to predict the wall stress guided by a judiciously chosen reward. The model was trained in a periodic hill at low Reynolds number and successfully deployed over periodic hills at higher Reynolds numbers. An important outcome of the work is that imposing the wall shear stress through an eddy-viscosity is superior to the traditional wall shear stress boundary condition in terms of predicting the mean flow in the separated region.

The second group of applications includes modeling of high-speed laminar-to-turbulent transition and efficient operator recovery. Marxen *et al.* studied perturbation amplification in a Mach-4.8 flat-plate boundary layer with two-dimensional discrete roughness. High-fidelity simulation data was collected to train a neural network capable of predicting the effect of roughness on disturbance amplification. In addition, further physical insight into the mechanism for perturbation growth was gained using an autoencoder. The latter showed that disturbance frequency and roughness location can be combined into a single parameter. Bryngelson *et al.* presented a computationally efficient methodology to accurately reconstruct eddy-diffusivity operators using only a few simulations. The method utilizes peeling and sparse factorization to reduce the number of simulations required to recover key physical features of the operator. The approach was leveraged to reconstruct the RANS eddy-viscosity tensor in a turbulent channel flow and was shown to be 100 times more economical than recovering the operator by perturbing degrees of freedom individually.

Finally, I thank all of the participants in the Modeling Turbulence and Transition Using Data-Driven Approaches group for many intellectually stimulating discussions and ideas that helped in opening new venues to advance the field. A general consensus from our discussions is that truly revolutionary improvements in turbulence modeling will encompass advancements in multiple fronts: physics, numerics, grid generation, wall/SGS modeling and so on. There is obviously also a data science component to the problem, such as the need for efficient and reliable machine learning techniques and efficient data analysis tools. Much progress has been made, as shown by the results discussed above, although machine learning is still far from being a panacea to solve long-standing problems in turbulence modeling. As in the times of Osborne Reynolds, physical understanding remains the cornerstone of turbulence modeling. Machine learning offers a set of powerful tools to accelerate progress as long as we recognize that problems are not solved by tools but by the people using the tools.

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