Uncertainty Quantification — overview

Numerical predictions that provide an explicit estimate of sensitivities and uncertainties naturally provide confidence and can be useful in generating insights and in stirring decision making. Thanks to a combination of algorithmic innovations, advances in computational resources and modern techniques to handle large datasets, the research community has proposed and exercised several strategies that are now being demonstrated in simplified industrial applications. However, realistic computational models pose a considerable challenge to rigorous analysis because of their inherent cost and complexity.

During the CTR Summer Program multiple projects revolved around the determination of sensitivities and uncertainties in complex fluid flow problems. Seven groups were involved in three main areas, roughly covering the study of sensitivity in high-fidelity flow simulations, the assessment of the effect of geometrical imperfections on flow evolution and the determination of the uncertainties induced by assumptions in physical models representing turbulence statistics.

Sayadi and coworkers focused on the analysis of an unsteady, reacting jet in crossflow to assess the sensitivity of integral measures of performance with respect to combustion and mixing characteristics. The group's work is based on the solution of the adjoint equations using a Lagrangian constrained optimization. Blonigan's group investigated the flow around a turbine blade and an axisymmetric body using Large Eddy Simulations and demonstrated the use of adjoint strategies to highlight the physical regions that are more susceptible to instabilities. Their approach extends previous efforts based on the Least Squares Shadowing strategy.

Two groups focused on the development of numerical techniques to study the effect of geometrical uncertainties on flow evolution. Nordstrom *et al.* investigated a novel computational strategy that maps the physical, uncertain domain into a nominal, simple counterpart. This transformation converts the original governing equations into a set of stochastic PDEs that can be solved efficiently. Ahlfeld and coworkers instead focused on a multi-fidelity strategy to represent the effect of geometrical variability on flow separation. The proposed method combines a small number of DNS analyses with a larger set of RANS computations to accurately represent the sensitivity of the flow characteristics.

The last set of projects in the UQ group targeted the assessment of the uncertainty induced by turbulence models on numerical predictions. Xiao *et al.* used machine learning techniques and DNS data combined with Reynolds stress eigenspace decomposition to infer optimal perturbations for second-order-type closures applied to square ducts. Thompson *et al.* focused on an approach to define and constrain the misalignment between Reynolds stress and mean velocity strain with application to a curved channel. Finally, Domino *et al.* explored the effect of subgrid stress anisotropy modeling on the Large Eddy Simulations of a turbulent channel flow. These approaches expand the idea of Reynolds stress eigenvalue perturbation introduced during the CTR Summer Program in 2014.

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