Deep Neural Networks for Data-Driven Turbulence Models

Andrea Beck, University of Stuttgart

Machine learning (ML) methods and in particular deep learning via artificial neural networks have generated significant enthusiasm in the last years. This interest reaches beyond the ML community itself into other fields of science and engineering. Since these methods can provide approximations to general, non-linear functions by learning from data without a-priori assumptions, they are particularly attractive for the generation of subspace models for multi scale problems. In the area of computational fluid dynamics, research into how ML methods can enhance current capabilities is an active topic of investigation. Deep learning methods have been shown to provide accurate shock-capturing sensors, improve RANS turbulence models and provide approximate deconvolutions of a coarse-scale flow fields.

In this presentation, we present a novel data-based approach to turbulence modelling for Large Eddy Simulation by deep learning via artificial neural networks. We first discuss and define the exact closure terms including the discretization operators and generate training data from direct numerical simulations of decaying homogeneous isotropic turbulence. We then present the design and training of artificial neural networks based on local convolution filters to predict the underlying unknown non-linear mapping from the coarse grid quantities to the closure terms without a priori assumptions.

All investigated networks are able to generalize from the data and learn approximations with a cross correlation of up to 47% and even 73% for the inner elements, leading to the conclusion that the current training success is merely data-bound and not method-bound. We further show that selecting both the coarse grid primitive variables as well as the coarse grid LES operator as input features significantly improves training results. Finally, we show how to construct a stable and accurate LES model from the learned closure terms. Therefore, we translate the model predictions into a data-adaptive, pointwise eddy viscosity closure and show that the resulting LES scheme performs well compared to current state of the art approaches. While we use a high order Discontinuous Galerkin framework as an LES baseline scheme, the methods and modeling ideas presented here are independent of the discretization scheme. In addition, our approach can also take advantage of existing DNS results and incorporate data from external sources to further improve training.