Reynolds Stress Anisotropy Tensor Predictions using Neural Networks

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Reynolds-Averaged Navier-Stokes (RANS) based turbulence modeling is the most widely-used approach for engineering interests due to its high cost-effectiveness. Even though, despite researchers' continued focus, the RANS approach still suffers from a universal and reliable closure model for the Reynolds stress anisotropy tensor. In recent years, advances in computing power have opened up a new way to tackle this problem with the aid of machine learning techniques.

The objective of the present paper is to fully predict the Reynolds stress anisotropy tensor for both interpolation and extrapolation scenarios using neural networks.

Several case studies are performed upon two types of neural network architectures: the Multi-Layer Perceptron (MLP) and the Tensor Basis Neural Network (TBNN)[1]. Representative physical parameters characterizing the properties of turbulent flows are carefully identified and pre-processed. Different input feature combinations are fed into the MLP to acquire a complete grasp of the role of each parameter. A deeper theoretical insight is taken into the TBNN in order to clarify some remaining ambiguities in the literature, concerning the application of Pope's general effective-viscosity hypothesis[2]. The predictive capacity and the robustness of these two types of neural networks are compared. Excellent interpolation and extrapolation predictive capability of the Reynolds stress anisotropy tensor is achieved upon our testing flow configuration. The results of an extrapolation test compared with the DNS data[3] for channel flow at $\mathrm{Re}_\tau = 10,000$ are shown in Fig. 1 for illustration. A promising future could be expected by integrating these neural networks into an in-house CFD code.

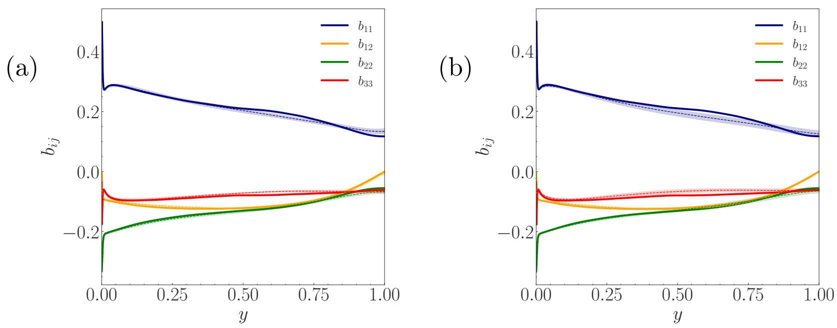

Figure 1: Averaged predicted Reynolds stress anisotropy tensor b_{ij} in function of wall distance y given by (a) an MLP and (b) an augmented TBNN. DNS data are shown in dotted lines.

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[1]Ling et al., *J. Fluid Mech.* **807**, 155-166 (2016).
[2]Pope, *J. Fluid Mech.* **72**, 331-340 (1975).
[3]Hoyas et al., *Phys. Rev. Fluids* **7**, 014602 (2022).