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AN ITERATIVE FRAMEWORK FOR MACHINE-LEARNING BASED TURBULENCE MODELING

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Abstract. Machine learning (ML) offers the potential to be an efficient tool for dealing with complex, high-dimensional input-output relations [1] and can shed light on the closure problem of the Reynolds-averaged Navier-Stokes (RANS) equations. Recent studies have proved the feasibility of the integration between turbulence models and machine learning algorithms [2, 3] utilizing data obtained from high-fidelity Direct Numerical Simulation (DNS). In the present study, a framework of machine-learning based turbulence modeling is developed to close the Reynolds stress term in the RANS equations. The framework, which adopts an artificial neural network as the ML engine, can learn from high-fidelity simulations and give a converged RANS result. The framework leverages traditional turbulence transport equations as scalar transport equations based on the frozen DNS velocity field for the preparation of training data, so that empirical estimations of the local turbulence behavior can be incorporated into the system. It also maintains the consistency of the input data used in the training stage and the CFD solver when the initial field is given the same as DNS mean velocity. Therefore, a built-in reproducibility of training cases could be achieved by the framework.

In this study, the ML model is trained with data from DNS of incompressible turbulent channel flow at Reynolds numbers, Re_τ, ranging from 180 to 1020, and the model is then applied to RANS simulation of channel flows within and beyond the training Reynolds numbers. The evolutions of the residuals of velocity and eddy viscosity show that the simulation is well converged (as shown in Figure 1). Figure 2 shows that the developed ML model can give an accurate mean velocity profile and a better prediction of the high-order statistics than the traditional k-ω SST model. For the case at a Reynolds number beyond the training range ($Re_\tau = 2000$), the ML model can also give an accurate prediction of mean velocity and velocity gradient, showing a favorable extrapolation capability of the framework.

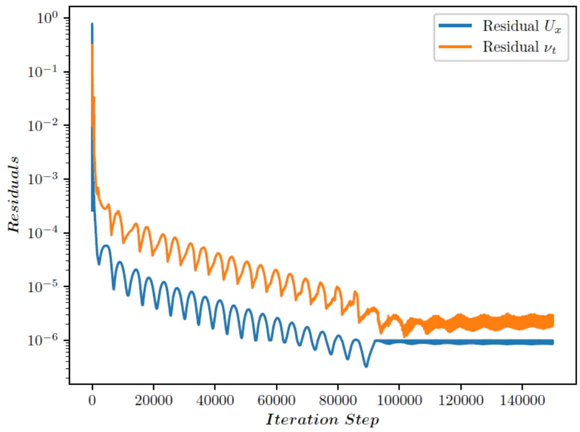

Figure 1: Evolution of residuals of a RANS simulation of a channel flow at Reynolds number, $Re_\tau = 180$, with the current ML based turbulence model

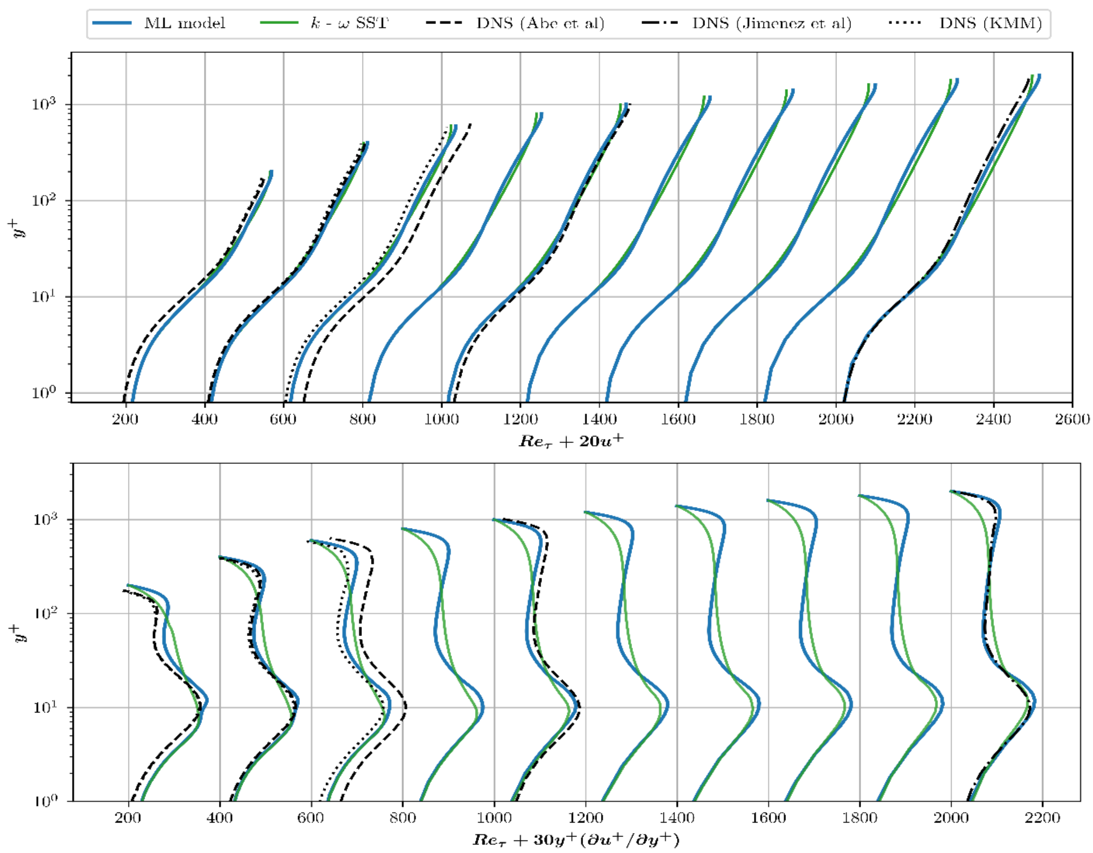

Figure 2: Comparison of ML model with the original k-ω SST model for turbulent channel flow at different Reynolds numbers. The profiles of mean velocity and mean velocity gradient are shown in the upper and lower figures, respectively.

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