Abstract : Reynolds-averaged Navier-Stokes (RANS) models are commonly used in industrial applications due to their efficiency in simulating complex fluid flows, offering a practical balance between accuracy and computational cost. However, RANS models have inherent limitations that can affect their accuracy, particularly in cases involving separated or highly complex flows. One significant issue is the discrepancy in Reynolds stresses compared to high-fidelity data obtained from Direct Numerical Simulation (DNS) or experimental measurements. These disparities can lead to inaccuracies in flow characteristic predictions, underscoring the need for improved modeling approaches to enhance the reliability of RANS results.

In this work, we propose two innovative approaches aimed at addressing these discrepancies while retaining the computational efficiency of the Menter Shear Stress Transport (SST) model. The first approach involves an explicit algebraic model paired with a neural network (specifically a multilayer perceptron, or MLP) to correct the turbulent characteristic time within the RANS model. The second approach targets the Boussinesq approximation itself, using either an MLP or a Generative Adversarial Network (GAN) to directly correct this approximation based on data-driven insights.

Further, to ensure physically consistent predictions, we integrate realizability constraints within both models by introducing penalization terms. Realizability conditions are essential for turbulence models, as they ensure that the predicted stress tensors align with fundamental physical principles, such as the positivity of turbulent kinetic energy. Incorporating these constraints enhances model stability and reliability during both the training and application phases.

The proposed Reynolds stress model, augmented with characteristic time correction (via the MLP) and Boussinesq approximation correction (via MLP or GAN), demonstrates strong predictive performance in both in-sample and out-of-sample flow configurations. Tested across various flow scenarios, the model accurately captures key turbulent flow characteristics while maintaining physically realistic predictions. These findings indicate that our approaches enhance the adaptability and reliability of RANS models, enabling more accurate simulations of complex, industrially relevant flow conditions without the high computational costs associated with DNS.

Keywords : Numerical modeling, High-performance computing, Machine learning