A hybrid physics-enhanced turbulent model for high-fidelity flow predictions

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Abstract. This study introduces a novel turbulence modeling approach that combines physical principles with data-driven techniques to enhance the accuracy of Reynolds-Averaged Navier-Stokes (RANS) simulations for high-Reynolds-number flows. The proposed framework employs a hybrid neural network architecture, consisting of a fully connected network and a tensor-based network, to estimate the eddy viscosity coefficient and higher-order turbulence relationships. By integrating pressure and turbulent kinetic energy gradients as additional inputs, the model captures more complex physical phenomena, such as non-equilibrium effects and pressure-driven turbulence. Validation tests were performed on a two-dimensional NACA0012 hydrofoil and a three-dimensional SUBOFF hull model. The results show that the enhanced model provides more accurate predictions of flow fields and pressure distributions compared to standard RANS models, particularly in regions like the hydrofoil's leading edge and the bow and stern of the SUBOFF model. The modified model achieves significant reductions in prediction errors, demonstrating its potential for high-fidelity simulations of complex fluid dynamics. This work advances the development of intelligent, physics-informed models for both two-dimensional and three-dimensional flow applications.