Data-Driven Turbulence Modeling with Physics-Driven Corrections

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Typical Reynolds-averaged Navier-Stokes (RANS) turbulence models are known to be unreliable in predicting complex flow, including separated and compressible flow. Data-driven RANS modeling with neural networks has gained attention for improving turbulence models for such complex flow[1,2]. Nonetheless, early data-driven models could not yield acceptable universality[3], presumably due to deficiency in satisfying constraints well-known in conventional turbulence modeling[4]. The current study incorporates major constraints in the field inversion and machine learning (FIML) framework. Note that early FIML versions[5,6] rely on a flow feature which depends on the Reynolds number, one of so-called hard fallacies in the modeling guideline[7]. Therefore, the current study explores various flow features to comply with well-established constraints.

Figure 1 illustrates a neural network model whose inputs are judiciously determined from well-designed turbulence model corrections, including compressibility and rotation corrections[8,9]. Physics-driven corrections that satisfy recommended criteria for turbulence modeling are employed to identify appropriate input features for machine learning. The current neural network model is trained with compressible separated flow across the Mach number. As Fig. 1 shows, supersonic separated flow includes rapid expansion at the separation and recompression around the rear stagnation point in the supersonic base flow. The current study demonstrates that physics-driven corrections as input features that satisfies turbulence modeling constraints eventually help to enhance the performance of the machine-learning model. Enhanced performance of the trained turbulence model is attributed to the proper adjustment of compressible separated flow. Detailed input features and the mechanism for model improvement will be discussed in the presentation.

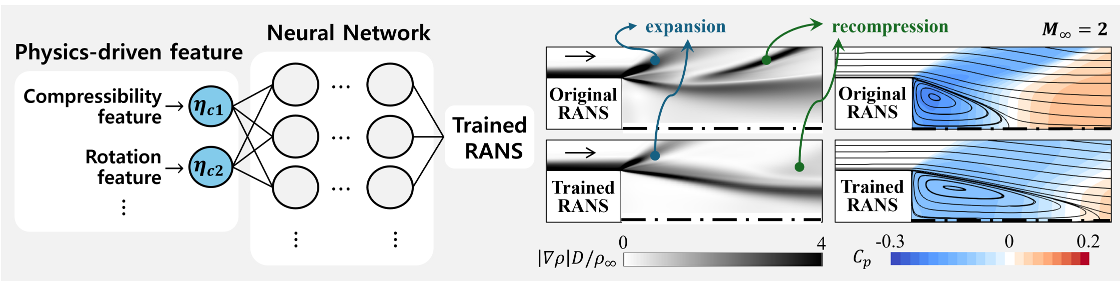

Figure 1: Overview of data-driven turbulence modeling with physics-driven corrections

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