

Field-Inversion-Guided Gene Expression Programming for RANS

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ABSTRACT

Reynolds-averaged Navier–Stokes (RANS) equations offer an attractive balance between accuracy and computational cost for high-Reynolds-number turbulent flows, but the predictive capability of standard closures is often limited by separation and transition in the flow field. Recent data-driven methods can improve RANS predictions by introducing model corrections inferred from reference data [1]. Two promising approaches are field inversion and machine learning (FIML) and gene expression programming (GEP).

In FIML [2], an optimization problem is solved to identify a correction field that minimizes the mismatch between RANS results and reference high-fidelity data. The correction is then generalized via regression, which can be challenging when the relationship between local flow features and the correction is not well captured by a function of the selected features. A key advantage of FIML is that inversion and regression are decoupled: the inversion is not limited by assumptions on the regression function. By contrast, GEP [3] assumes the existence of a functional relationship between selected flow features and the correction, and uses a genetic algorithm to build an explicit analytical expression from elemental building blocks. This yields interpretable formulas but restricts the correction to a limited function space, potentially reducing generality compared with field inversion.

In this work, we combine the strengths of both methods—FIML’s generality and GEP’s ability to deliver analytical corrections—across a set of classical aerospace test cases. We first apply GEP and assess the resulting error reduction against experimental data. When improvements are limited, we perform field inversion on the same case to obtain a less constrained correction and quantify the achievable performance gain. The field-inversion results then guide refinement of the GEP model, for example by increasing functional complexity or targeting a different term in the turbulence model.

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