Mitteilung

Fachgruppe: Turbulenz und Transition

Experiences and Lessons Learned using the FI/ML Approach for Data-driven Turbulence Modeling

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Introduction:

Reynolds-averaged Navier-Stokes (RANS) turbulence models, due to their robustness and relatively low computational cost, are extensively used in aeronautical applications. Nevertheless, they show limited accuracy in complex flow conditions, such as separated flows, highly curved surfaces, and shock–boundary layer interactions. To enhance RANS predictions in such scenarios, a promising approach known as Field Inversion and Machine Learning (FI/ML) has been developed [1], which leverages data-driven techniques and machine-learning algorithms. RANS models enhanced with FI/ML have shown promising results when evaluated under flow conditions consistent with the training data, but their performance has been more limited in scenarios outside the training regime. This highlights the challenge of generalization, which has motivated the development of advanced training strategies [2], alternative machine-learning algorithms [3], conditional field-inversion techniques [4], and sensor-based modular modeling approaches [5].

Numerical methodology:

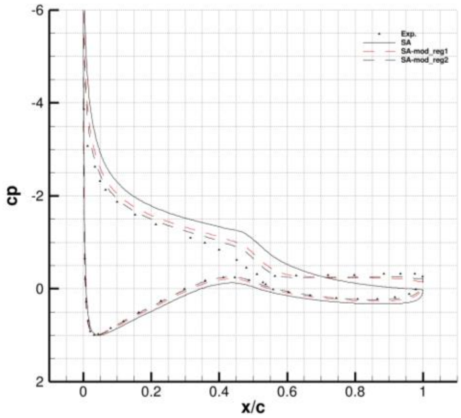
A data-driven FI approach infers a spatially-varying correction term β from experimental or high-fidelity numerical data, designed to reduce model form errors in RANS. The corresponding correction for the negative Spalart–Allmaras (SA-neg) turbulence model is presented in the equation below:

$$\frac{D\tilde{\nu}}{Dt} = \boldsymbol{\beta} P(\mathrm{U}, \tilde{\nu}) - D(\mathrm{U}, \tilde{\nu}) + \mathrm{T}(\mathrm{U}, \tilde{\nu})$$

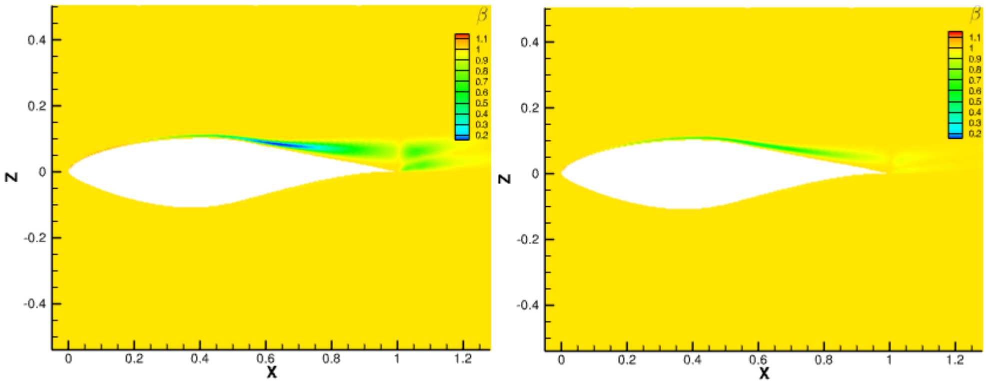
Here, β denotes the correction field, $\tilde{\nu}$ the SA-neg variable, P the production term, D the destruction term and T the diffusion term. Each β field obtained via FI reflects the specific local and global characteristics of a given flow case, and machine-learning models aim to generalize the mapping between angle of attack, Mach number, Reynolds number, local features (η), and β. However, the FI process does not yield a unique correction field — multiple β fields can reproduce the same observational data equally well, reflecting the **multi-solution nature** of the inversion problem, which poses a significant challenge to the generalization capacity of ML-based approaches.

Results:

It is well documented in the literature that the SA-neg model tends to overpredict the eddy viscosity under adverse pressure gradient (APG) conditions. Therefore, in the modified SA-neg model, the correction field β is applied in a way that suppresses turbulence production under these conditions. To illustrate this, FI was performed on S809 airfoil at 12.2 ° under different magnitude of regularization settings (reg1, reg2). The regularization penalizes large modifications and prevents unphysical adjustment. As shown in the figure 1, the resulting correction fields β demonstrate the multi-solution nature of the inversion problem. Despite yielding similarly accurate pressure-coefficient predictions compared to the reference data, these solutions were obtained from different β distributions. The correction introduced through FI enables the reproduction of the pressure plateau in the rear region of airfoil in agreement with the experimental data, which is not captured in the baseline solution.



a) Pressure coefficient distribution



b) β field distributions with reg1 und reg2 parameter

Figure 1: Results on the S809 airfoil with various regularization parameter

Conclusion and Outlook:

The FI/ML approach was applied to case with APG. Under these conditions, the correction field β can capture the characteristic pressure plateau that arises due to boundary layer separation. Moreover, it becomes evident that different flow conditions yield different β fields, highlighting the multi-solution nature of the β fields. This issue has been widely studied in the literature, as it poses challenges for the generalization capacity of FI/ML-based models. Future work aims to address this problem by investigating the influence of selected flow features and the flow regime on the correction behavior.

References:

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