Field Inversion and Machine Learning Approach for Improved Turbulent Predictions of Flows over Airfoils

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Motivation

- Feasibility of high-fidelity CFD for design process
  - *State-of-the-art practices in wind turbine design*
- Shortcomings of the current RANS based CFD
  - *Need for improvements in Turbulence and Transition models*

Field Inversion and Machine Learning Methodology

- Challenges with data-driven modeling
  - Data is not available in the form that is directly usable
  - High-fidelity CFD based data is also not coherent with RANS model quantities
- Physics-consistent and data-driven modeling technique
  - *Duraisamy et. al. (2015)*

Field Inversion and Machine Learning Methodology

- The transport equation of the SA model is

$$\frac{D\tilde{\nu}}{Dt} = P_{\tilde{\nu}} - D_{\tilde{\nu}} + \frac{1}{\sigma}\left[\nabla \cdot ((\nu + \tilde{\nu})\nabla\tilde{\nu}) + c_{b2}(\nabla\tilde{\nu})^2\right]$$

- A functional correction is introduced into the turbulence model through the field function β

$$\frac{D\tilde{\nu}}{Dt} = \boxed{\beta} P_{\tilde{\nu}} - D_{\tilde{\nu}} + \frac{1}{\sigma}\left[\nabla \cdot ((\nu + \tilde{\nu})\nabla\tilde{\nu}) + c_{b2}(\nabla\tilde{\nu})^2\right]$$

Field Inversion Process

An optimization problem is posed to identify the appropriate correction field for a particular flow scenario

$$\beta^* = \underset{\beta}{\text{argmin}} \left(\underbrace{J(\beta, d_{\text{true}})}_{\textit{Consistency with experiments}} + \lambda \underbrace{\|\beta - \beta_{\text{prior}}\|^2}_{\textit{Limiting large deviation}} \right)$$

Machine Learning Process

Appropriate small set of flow features (η) are identified and a functional ($\hat{\beta}(\eta)$) is modeled using the data obtained from the Field Inversion

$$\eta = \{P/D, |S|/|\Omega|, \delta, \chi\}$$

This correction is now embedded in the baseline turbulence model

$$\frac{D\tilde{\nu}}{Dt} = \hat{\beta} P_{\tilde{\nu}} - D_{\tilde{\nu}} + \frac{1}{\sigma}\left[\nabla \cdot ((\nu + \tilde{\nu})\nabla \tilde{\nu}) + c_{b2}(\nabla \tilde{\nu})^2\right]$$

ML Training with Ensemble Averages

$$\hat{\beta} = \sum_i w_i \hat{\beta}^{(i)}$$

- Generates simpler ML architectures, which are in some sense "generalizable"
- Avoids overfitting of the data
- Can be appropriately tuned to mimic the "memory effect"

Imposes additional requirements and/or additional computational overhead

S809 Airfoil - Experiments vs Baseline

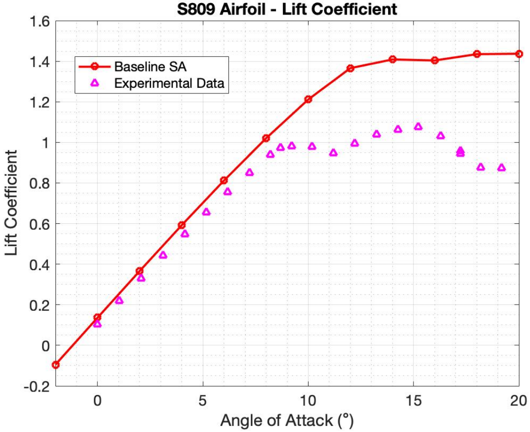
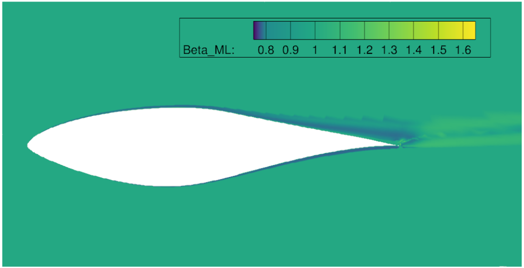
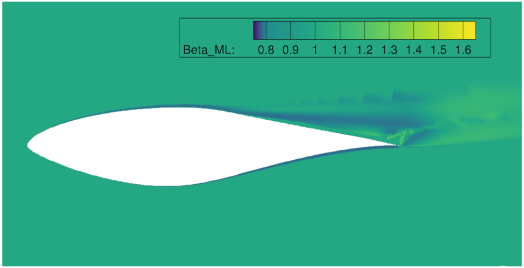


Figure: Comparison of the baseline SA model with experiments

Field Inversion Results (AoA $= 10^\circ, 14^\circ$)





Improvements in Lift Coefficient

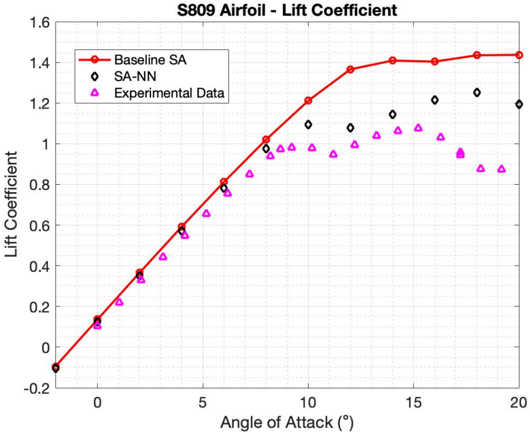


Figure: Improvements in Lift coefficient

Drag Polar Predictions

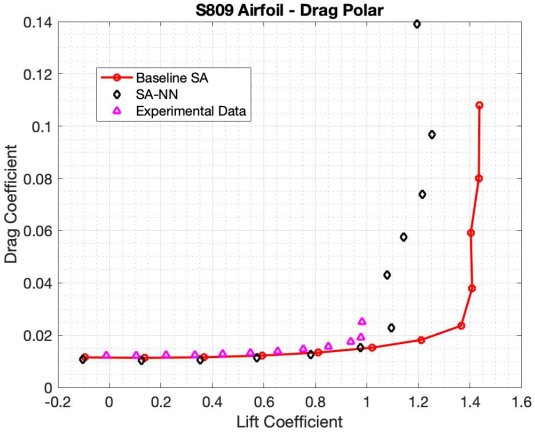


Figure: Improvements in Drag polar

Validation Case: NACA0012 Airfoil - Lift Predictions

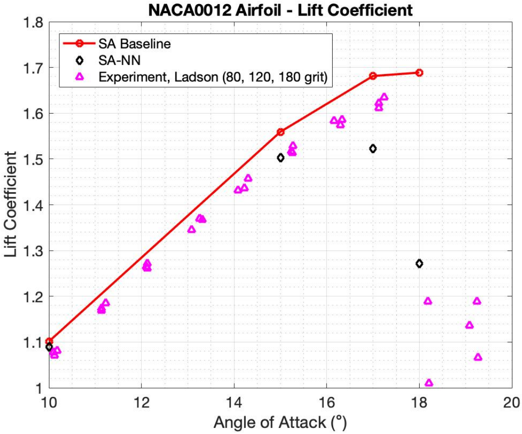


Figure: Improvements in Lift Coefficient

Validation Case: NACA0012 Airfoil - Drag Predictions

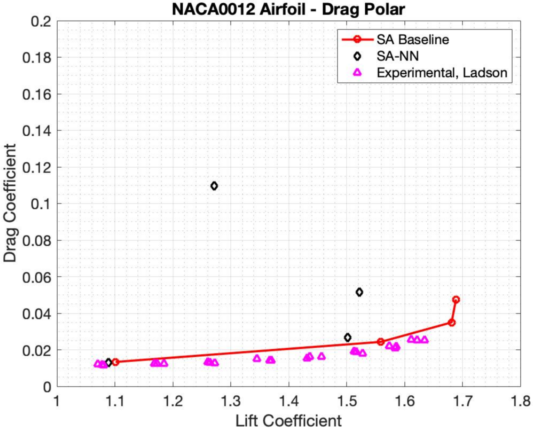
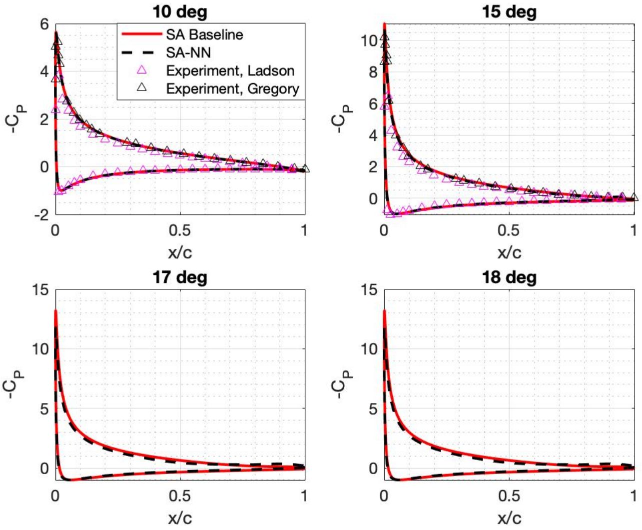
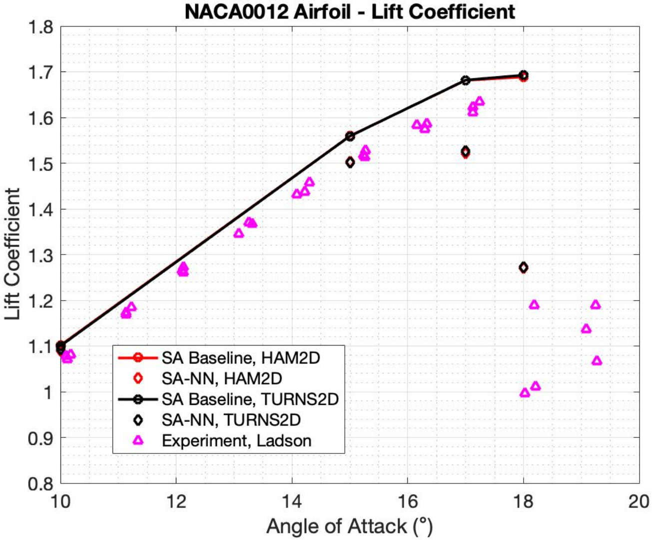


Figure: Drag coefficient predictions

Validation Case: NACA0012 Airfoil - Surface Pressure



Portability of the Model



Validation Case: ZPG Flat Plate

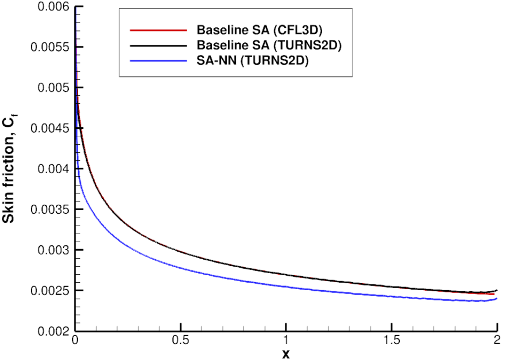


Figure: Skin Friction Coefficient Prediction

Validation Case: ZPG Flat Plate

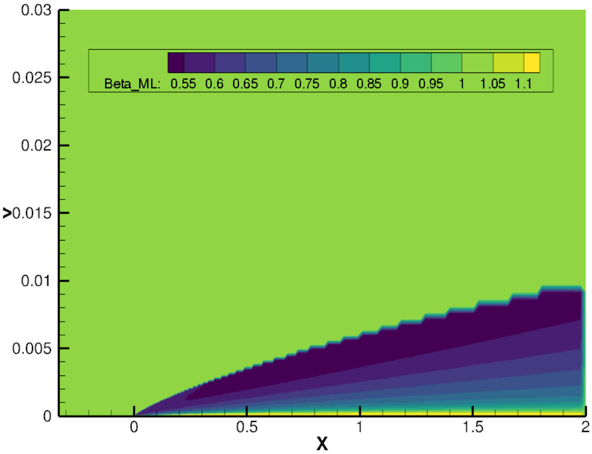


Figure: Correction field for the ZPG Flat Plate Case

Validation Case: ZPG Flat Plate

Ideally, the correction term should vanish or is negligible ($\beta \equiv 1$) for this case

Given that a sudden velocity jump occurs at the leading edge, is the theoretical self similarity valid near the leading edge?

Also any poor choice of the input features can falsely correlate to the correction term

Summary

A paradigm to achieve memory effect in FIML methodology is proposed, and tested on flows over S809 airfoil

The trained correction model is tested for portability and solver independence

The modifications resulted in improved predictions of airfoil flow physics and stall scenario

Key Takeaways

While FIML improves the predictions in flow scenarios similar to the trained cases, the generalizability of such correction is questionable

Human intervention is absolutely necessary and must come in the form of the expertise in feature selection, identifying appropriate "representative" flow cases for training, imposing rigid constraints, etc.

There is always a possibility of overfitting with ML, and can be mitigated using extremely simple architectures and robust training methodologies

Thank you!