A Data-Driven Turbulence Modelling Framework based on Machine Learning for Industrial Aero-Engine Design

George Klavaris
Ansys UK LTD.
Horsham,
West Sussex,
United Kingdom

Andreas Gantner
Ansys Germany GmbH.
Staudenfeldweg 20,
83624 Otterfing,
Germany

Tobias Danninger
Ansys Germany GmbH.
Staudenfeldweg 20,
83624 Otterfing,
Germany

Wolfgang Bower
Ansys Germany GmbH.
Staudenfeldweg 20,
83624 Otterfing,
Germany

Abstract

As the aerospace industry advances toward developing more efficient and sustainable aero-engine technologies, accurate and computationally efficient turbulence modelling becomes increasingly critical to achieving future performance and environmental targets.

This study presents an advanced workflow developed in Ansys Fluent, integrating field inversion, adjoint optimization, and machine learning (ML) to enhance Reynolds Averaged Navier-Stokes (RANS) turbulence models. The approach aims to bridge the fidelity gap between RANS and Scale-Resolved Simulations (SRS), enabling data-driven turbulence modelling tailored to industrial applications.

The methodology employs the generalized k-omega (GEKO) turbulence model, utilizing adjoint-based sensitivity analysis to optimize model parameters. High-fidelity SRS data is employed as a reference to calibrate RANS predictions. Using field inversion, optimal parameter distributions are identified and subsequently leveraged to train neural networks, enabling generalization across diverse flow conditions and ensuring robust model performance in practical design scenarios.

This workflow is demonstrated on a representative aerodynamic application involving a Low Reynolds Number Outlet Guide Vane (LRNOGV) cascade. The study is conducted under the Horizon Europe-funded Sci-Fi Turbo project, which aims to advance scale-resolving simulation technologies for turbomachinery innovations in alignment with EU sustainability objectives. Results demonstrate that the adjoint-ML-augmented GEKO model significantly improves accuracy, especially in predicting critical flow features such as wake loss distribution. The approach also reduces predictive uncertainties and enhances agreement with experimental and SRS data, offering a scalable framework for robust multi-fidelity optimization applicable to industrial design cycles.

Keywords: *Turbulence Modelling, Machine Learning, Neural Networks, Aero-engine design*