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DATA-DRIVEN TURBULENCE MODELING FOR THE HIGH-LIFT TRANSPORT AIRCRAFT VIA ADDITIVE FINE-TUNING

Zhuo-Ran Liu
Stuttgart Center for Simulation Science
University of Stuttgart
70569, Stuttgart, Germany
zhuoran.liu@itlr.uni-stuttgart.de

Hao-Chen Wang
Stuttgart Center for Simulation Science
University of Stuttgart
70569, Stuttgart, Germany
haochen.wang@itlr.uni-stuttgart.de

Zhuo-Lin Zhao
Stuttgart Center for Simulation Science
University of Stuttgart
70569, Stuttgart, Germany
zhuolin.zhao@itlr.uni-stuttgart.de

Heng Xiao
Stuttgart Center for Simulation Science
University of Stuttgart
70569, Stuttgart, Germany
heng.xiao@simtech.uni-stuttgart.de

ABSTRACT

Turbulence modeling remains a major limitation for predicting complex aerodynamic flows, particularly those dominated by separation. In industrial simulations, Reynolds-averaged Navier–Stokes models are widely used but often lack accuracy when multiple flow mechanisms interact. This work presents a data-driven framework for constructing *specialist turbulence models* via additive fine-tuning. Starting from a *unified foundation model* trained on representative canonical flows, the approach adapts the model to target flow regimes through targeted fine-tuning on separation-dominated cases. The resulting model is applied to the NASA high-lift transport aircraft configuration, a challenging three-dimensional configuration with large-scale separation. The specialist model improves the prediction of separation, leading to more accurate drag, skin-friction, and pressure distributions compared to baseline models, while the lift prediction degrades due to unresolved three-dimensional effects. These results show that fine-tuning on canonical two-dimensional flows captures key separation physics but does not fully generalize to three-dimensional configurations. Extending fine-tuning to similar three-dimensional flows is expected to further improve predictive performance.

INTRODUCTION

Accurate prediction of turbulent flow around transport aircraft (Evans *et al.*, 2020) remains a central challenge in computational fluid dynamics. Such predictions are essential for aerodynamic design, performance assessment, and optimization in industrial settings. High-fidelity methods such as large eddy simulation and direct numerical simulation can resolve detailed flow physics, but their cost remains prohibitive for routine design, optimization, and uncertainty quantification (Slotnick *et al.*, 2014; Spalart, 2015; Xiao & Cinnella, 2019). As a result, industrial simulations continue to rely on Reynolds-averaged Navier–Stokes (RANS) models, even though their turbulence closures often lose accuracy in separated flows and other complex conditions.

A major difficulty is that realistic engineering flows rarely involve a single mechanism. Instead, attached boundary layers, separation, curvature effects, and secondary motions often coexist and interact. This has motivated increasing efforts to augment turbulence models using machine learning and, more ambitiously, to develop unified models capable of handling multiple flow mechanisms within a single framework. Data-driven approaches based on tensor basis neural networks (Ling *et al.*, 2016; Zhang *et al.*, 2022), symbolic regression (Weatheritt & Sandberg, 2016), and field inversion with machine learning (Parish & Duraisamy, 2016) have shown clear promise.

Recent attempts toward unified modeling have followed several directions. Multi-case symbolic training improves performance across wall-bounded flows, but its restrictive model forms and derivative-free optimization limit scalability when many objectives must be balanced (Fang *et al.*, 2023; Waschkowski *et al.*, 2022). Aggregation strategies combine multiple specialized models with local classifiers, but they require repeated evaluations and struggle when different mechanisms strongly interact within the same region (Cherroud *et al.*, 2025; Buchanan *et al.*, 2026). Generalized tunable closures, such as the generalized k–ω (GEKO) model, enhance flexibility but still rely on case-dependent manual tuning (Menter & Matyushenko, 2025). As emphasized by the NASA Langley workshop, a data-driven RANS model that is simultaneously predictive, generalizable, and robust remains an open challenge (Rumsey & Coleman, 2022).

Many industrial flows are dominated by one or two primary mechanisms. This motivates a practical strategy: start from a unified foundation model and adapt it to the target regime through fine-tuning. In this work, we follow this approach and construct a specialist turbulence model for separation-dominated flows via additive fine-tuning. The model is evaluated on the high-lift transport aircraft (NASA High-Lift Common Research Model), a challenging three-dimensional configuration with large-scale separation.

METHODOLOGY

The proposed framework constructs a *specialist turbulence model* through additive fine-tuning of a *unified foundation model*, as illustrated in Fig. 1. It consists of three components: a flexible, frame-invariant model representation; construction of the unified foundation model from representative canonical flows using multi-objective ensemble learning; and application-specific adaptation via fine-tuning.

Flexible, frame-invariant model representation

We adopt a general eddy-viscosity framework based on the k–ω model, in which the Reynolds stress is expressed as

$$\boldsymbol{\tau} = 2k\boldsymbol{b} + \frac{2}{3}k\mathbf{I}, \tag{1}$$

where k is the turbulent kinetic energy and $\boldsymbol{b}$ is the normalized Reynolds stress anisotropy. The anisotropy $\boldsymbol{b}$ is modeled using the general eddy-viscosity model (Pope, 1975),

$$\boldsymbol{b} = \sum_{i=1}^{10} g^{(i)}(\theta_1, \ldots, \theta_5)\, \mathbf{T}^{(i)}, \tag{2}$$

with $\mathbf{T}^{(i)}$ tensor bases and θ_i scalar invariants of the mean velocity field, while the turbulence scales are governed by the k and ω transport equations (Wilcox, 1988),

$$\frac{\mathrm{D}k}{\mathrm{D}t} = P_k - \beta^* k\omega + \nabla \cdot [(\nu + \sigma^* \nu_t)\nabla k], \tag{3}$$

$$\frac{\mathrm{D}\omega}{\mathrm{D}t} = \alpha\, \frac{\omega}{k} P_k - \beta\, \omega^2 + \nabla \cdot [(\nu + \sigma \nu_t)\nabla \omega], \tag{4}$$

where P_k is the production term and ν_t is the eddy viscosity.

The constitutive relation coefficients $g^{(i)}$ and the transport equation coefficients (e.g., β) are jointly represented by a parallel tensor basis neural network. The network takes invariant features as input and separates dominant linear contributions from higher-order nonlinear corrections through parallel subnetworks, enabling independent regularization. In this work, only the first two tensor bases are retained, yielding a quadratic model. This coupled formulation ensures consistent learning of the full Reynolds stress.

Unified foundation model

The unified foundation model is constructed to capture multiple flow mechanisms within a single set of parameters (Liu *et al.*, 2025), as illustrated in Fig. 1A. The goal is to learn a model that remains robust and accurate across diverse flow regimes without requiring case-dependent tuning.

Training cases are selected based on the similarity of flow-feature distributions. Each flow is characterized by the distribution of local, frame-invariant features derived from the mean flow. Similarities between flows are computed in this feature space, and clustering is used to identify a compact set of representative cases. This selection ensures coverage of distinct flow mechanisms while avoiding redundant training data, enabling efficient learning from a limited number of canonical flows.

Model parameters are learned from sparse and indirect observations using a regularized ensemble Kalman method (Zhang *et al.*, 2020). The Reynolds stress predicted by the model is propagated through the RANS equations, and the resulting flow quantities are compared with available observations. This approach does not require adjoint or differentiable flow solvers, making it well suited for complex industrial CFD codes. A regularization term anchors the model to a baseline eddy-viscosity formulation, preventing unphysical deviations while allowing data-driven corrections.

To construct a unified model across multiple flows, training is formulated as a multi-objective optimization problem. Each flow and quantity of interest defines an objective, and their updates are combined to approximate a Pareto-optimal solution (Sener & Koltun, 2018). This ensures that improvements in one regime do not degrade performance in others. The resulting model achieves a balanced representation of multiple flow mechanisms within a single set of parameters, forming the unified foundation model used for subsequent fine-tuning.

Specialist model via additive fine-tuning

To improve accuracy for a target flow regime, we construct a *specialist model* by additive fine-tuning of the unified foundation model, as illustrated in Fig. 1B. Let the foundation model be defined by constitutive coefficients $\{g_{\mathrm{f}}^{(i)}\}$ and transport coefficient β_{f}. The specialist model introduces additive corrections,

$$g_{\mathrm{s}}^{(i)} = g_{\mathrm{f}}^{(i)} + \Delta g^{(i)}, \qquad \beta_{\mathrm{s}} = \beta_{\mathrm{f}} + \Delta\beta, \tag{5}$$

where $\Delta g^{(i)}$ and $\Delta\beta$ are predicted by a compact correction network.

During fine-tuning, the foundation model parameters remain fixed, and only the correction terms are optimized using a regularized ensemble Kalman update with separation-dominated training cases. This formulation enables targeted adaptation to the flow regime of interest while preserving the multi-mechanism capability of the foundation model. The correction network is kept compact to limit overfitting and ensure that modifications remain localized. As a result, the specialist model inherits the generalizability of the unified foundation model while introducing focused improvements for separation-dominated flows.

RESULTS

The proposed framework is evaluated on a high-lift transport aircraft, the high-lift common research model (CRM-HL), a challenging three-dimensional flow in which large-scale separation is the dominant mechanism, accompanied by strong adverse pressure gradients and three-dimensional effects. The case corresponds to a low-speed configuration at Mach $= 0.2$ and Re $= 5.49 \times 10^6$, providing a stringent test for turbulence models.

The specialist model is obtained by fine-tuning a unified foundation model trained on representative canonical flows. The foundation model is constructed using nine training cases selected from a library spanning separated, secondary, and free-shear regimes based on flow-feature similarity. It is then adapted using two separation-dominated cases (flows over bump and curved step), while the CRM-HL case is excluded from training.

The specialist model improves the prediction of separation, leading to more accurate skin friction, pressure distributions, and drag predictions. At low angle of attack before

Angle of attack	7.05°		21.47°	
	C_D	C_L	C_D	C_L
Ground truth	0.16	1.80	0.39	2.39
Baseline k–ω model	0.21	1.77	0.73	2.20
Specialist model	**0.20**	**1.81**	**0.50**	1.95

Table 1: Drag and lift coefficients (C_D, C_L) for the high-lift common research model predicted by the specialist model, compared with the ground truth and the baseline k–ω model at low and high angles of attack.

stall (7.05°), the baseline k–ω model already provides reasonable predictions, and the specialist model maintains comparable accuracy. At high angle of attack after stall (21.47°), however, the baseline model significantly overpredicts separation, resulting in excessive drag, whereas the specialist model corrects this behavior and substantially improves the drag prediction (Table 1). Consistent improvements in separation patterns and near-wall shear are observed in the skin friction distribution (Fig. 3) and pressure coefficients (Fig. 4). These improvements are most pronounced near the wing root, moderate at mid-span, and negligible toward the tip, reflecting the increasing influence of three-dimensional flow effects, particularly spanwise flow. The lift prediction, however, degrades at high angle of attack, indicating that the model does not fully capture the underlying three-dimensional flow structures. While fine-tuning on two-dimensional separated flows improves key separation physics, it remains insufficient to represent complex three-dimensional effects. Further improvement requires fine-tuning on similar three-dimensional flows to better capture the relevant flow mechanisms of the CRM-HL configuration.

Overall, additive fine-tuning enables effective adaptation of a multi-mechanism turbulence model to separation-dominated flows. The results demonstrate clear improvements in separation-related quantities, while highlighting the need for three-dimensional training data to achieve fully consistent aerodynamic predictions.

CONCLUSION

This work demonstrates that additive fine-tuning enables the construction of specialist turbulence models for separation-dominated flows. Starting from a unified foundation model trained on representative canonical flows, the specialist model improves separation prediction, leading to more accurate skin friction, pressure, and drag predictions for a high-lift transport aircraft. Fine-tuning on two-dimensional separated flows captures key separation physics but remains insufficient to represent three-dimensional effects, as reflected by degraded lift prediction. Further improvement requires incorporating similar three-dimensional flows during fine-tuning. Overall, combining a unified foundation model with targeted fine-tuning provides a practical pathway toward improved turbulence modeling for complex aerodynamic applications.

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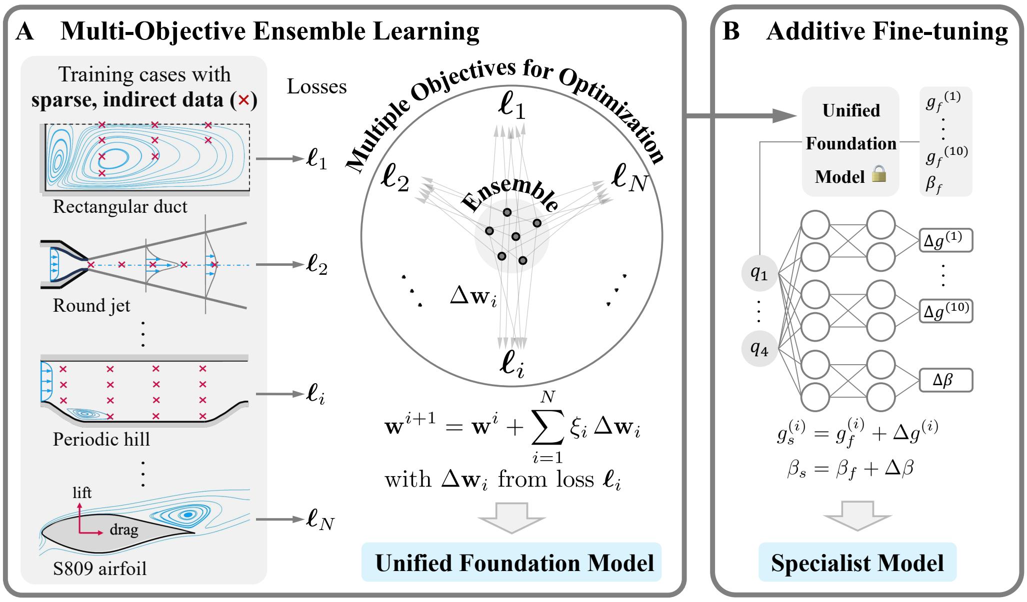


Figure 1: Overview of the proposed methodology for constructing a specialist turbulence model. Firstly, a unified foundation model is learned from representative flows using a frame-invariant model representation, distribution-based training case selection, and multi-objective ensemble learning from sparse, indirect observations. Then, the foundation model is adapted to a target flow regime through additive fine-tuning, where compact correction modules introduce targeted modifications to the model coefficients while preserving the foundation model behavior.

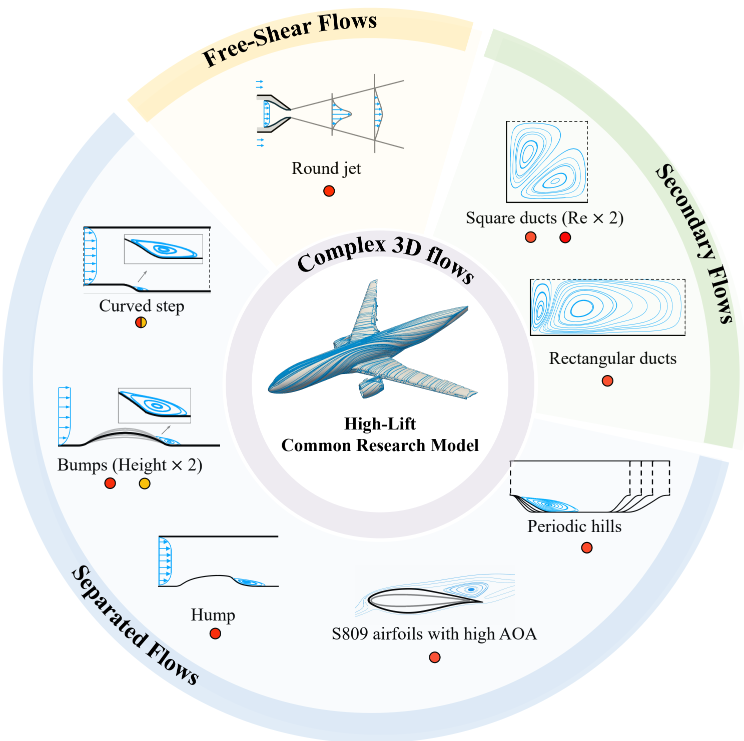
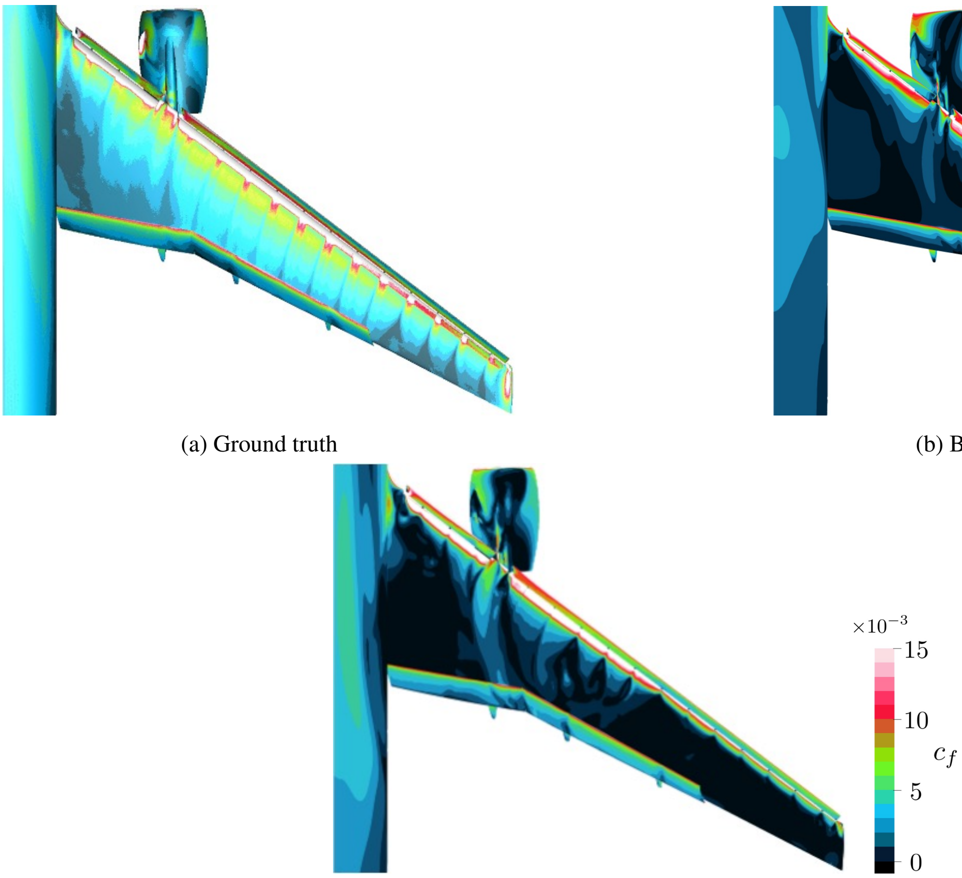


Figure 2: Overview of unified training, fine-tuning, and evaluation cases. The library spans multiple flow mechanisms, including free-shear, secondary, and separated flows. Red markers denote representative cases selected for training the unified foundation model based on flow-feature similarity, while yellow markers indicate separation-dominated cases used for fine-tuning the specialist model, namely the curved step and bump flows. The central configuration represents the target complex flow, the high-lift transport aircraft (NASA High-Lift Common Research Model).

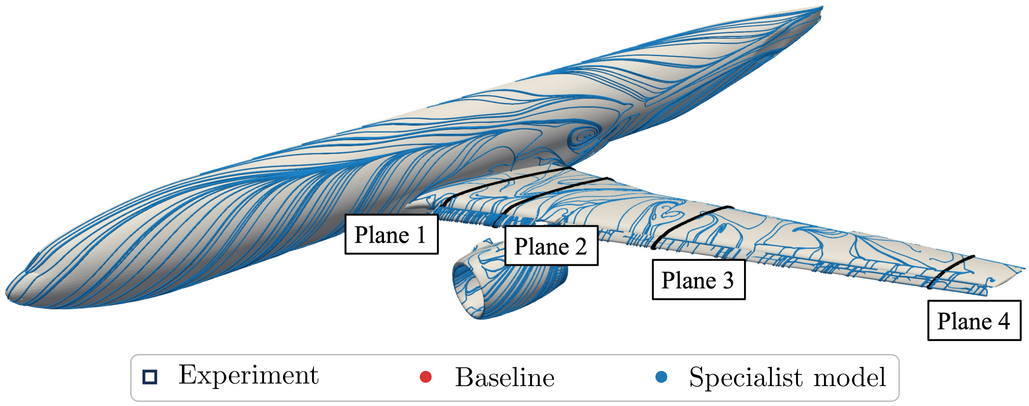


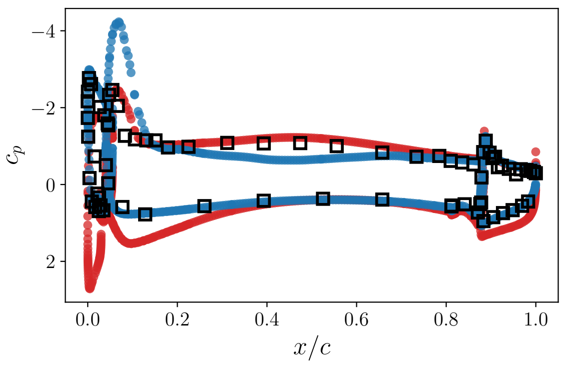
(a) Ground truth

(b) Baseline k–ω model

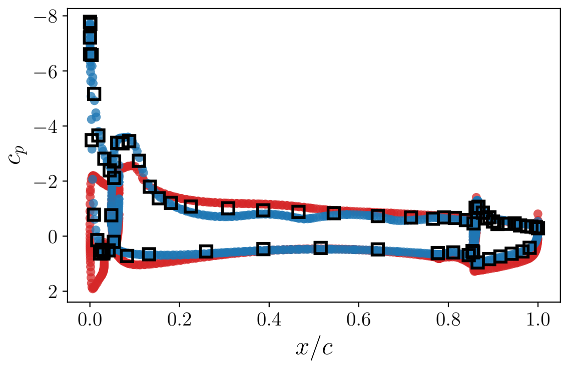
(c) Specialist model

Figure 3: Comparison of surface skin frictions on the high-lift transport aircraft at AOA $= 21.47°$. The baseline k–ω model overpredicts the extent of separated regions, while the specialist model provides improved prediction of separation patterns and near-wall shear, yielding closer agreement with the ground truth (Goc *et al.*, 2024).

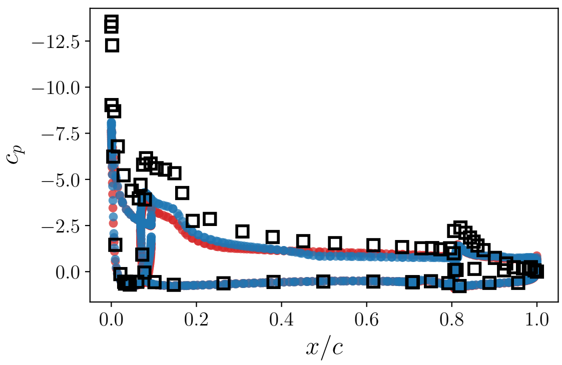




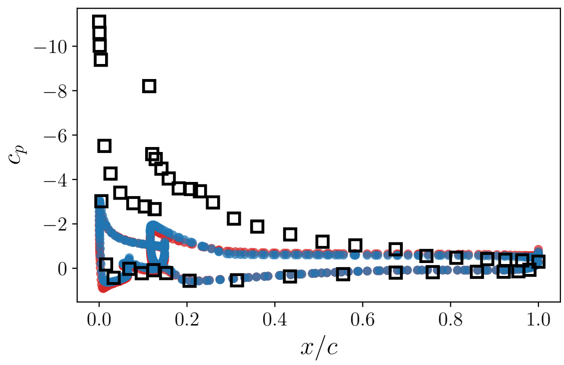
(a) Pressure coefficient at Plane 1



(b) Pressure coefficient at Plane 2



(c) Pressure coefficient at Plane 3



(d) Pressure coefficient at Plane 4

Figure 4: Surface streamlines and pressure-coefficient distributions on the high-lift transport aircraft at AOA = 21.47°. Pressure coefficients are shown at four spanwise sections from root to tip (Planes 1–4). The specialist model improves pressure predictions near the wing root (Planes 1 and 2), shows slight improvement at mid-span (Plane 3), and yields similar results to the baseline at the outer span (Plane 4). These trends reflect improved modeling of separation-dominated regions, while limitations remain in capturing fully three-dimensional flow behavior toward the wing tip.