MIT

Numerical Solutions for Partial Differential Equations

Machine Learning Building-Block Models for Computational Fluid Dynamics

Adrian Lozano-Duran (MIT)

Abstract:

One of the primary factors hindering the adoption of transformative low-emissions aircraft designs is the time-consuming (taking years) and costly (costing billions of dollars) experimental campaigns required during the design cycle. Computational fluid dynamics (CFD) might accelerate the process and alleviate the cost. However, current turbulence models do not meet the stringent accuracy requirements demanded by the industry. Here, we have devised a new closure model for CFD to bridge the gap between our current predictive capabilities and those required by the aerospace industry. This model, referred to as the building-block-flow model, conceives the flow as a collection of simple units that contain the essential flow physics necessary to predict complex flows. The approach is implemented using two artificial neural networks: a classifier that identifies the contribution of each building block in the flow, and a predictor that estimates the effect of missing scales through a combination of the building-block units. The training data are directly obtained from CFD with exact modeling for mean quantities to ensure consistency with the numerical discretization. The model's output is accompanied by confidence in the prediction, which is used for uncertainty quantification. The model is validated in realistic aircraft configurations.

§1 Introduction

- Aircraft certification requires rigorous numerical simulation with minimal error tolerance
- Simulation of aerodynamics requires fluid dynamics, different flow physics
- Single model for all flow physics, captures complex geometries

§2 Equations

- Conservation of mass
- Conservation of momentum
- Boundary limits at surface edge

§3 Assumptions

- Learn flow physics from a collection of small cases, thus
  'There are a collection of essential physics flows that can be combined to model flows at larger scales'
- Flows at scale of flight simulation is a combination of essential flows at smaller scales

§4 Model Architecture (NNs) (Wall Model)

- Predictor: force at location given flow class
  Each flow has a predictive model (hence building block)
- Classifier: essential physical flow

§5 Data

- Numerical solutions to training data can help label data and ensure consistency across data used in ML vs Numerical methods

§6 Validation

- Well understood physical models at small scales can be used as validation cases for ML models

§7 Conclusions

- Ensemble of classifier and predictor is quite interesting
- "Information Theory can describe the amount of information inputs contain about the output. No information about the output can be predicted without it being in the input data.