Combining high-fidelity CFD and Machine-Learning to better predict flow in jet engines

Professor Richard Sandberg
richard.sandberg@unimelb.edu.au
• Why improve flow prediction in jet engines?
  - Better predictions → better engines
  - In 2018, Australia consumed 9.4 billion liters aviation fuel
  - Passenger numbers forecast to continue growing
  - For each % jet engines can be made more efficient:
    • reduce fuel cost by AUD60 million/year
    • reduce CO2 emissions by 1.5%

• What does computing have to do with it?
  - Correlation-based approaches unable to further improve efficiency
  - Experiments/testing expensive

Computational Fluid Dynamics (CFD) predictions essential for design of modern gas turbines
• So why HPC?
  - Can run high-fidelity simulations that provide required accuracy
  - BUT: high cost to resolve all features of turbulent flow can have $>10^{16}$ degrees of freedom

• And why Machine-Learning?
  - Industrial design uses modelling
  - Current models inaccurate for certain problems

Use ML and Hi-Fi data to improve models

limits impact CFD can have on technology development
**HiPSTAR: High-Performance Solver for Turbulence and Aeroacoustics Research**

**Thoroughly validated** e.g. wake loss low-pressure turbine →

**Flexible**
- Internal/External Aerodynamics
- Full 3D geometries
- Sliding/Overset mesh
- Buoyancy effects
- Immersed boundary

**Fast**
- Optimized for CPU and GPU

**Weak scaling:** increasing GPU count with constant grid points on each GPU. The largest job in each case has around 51 billion grid points.
Low-pressure turbine

Optimal spacing between turbine blades (for minimal loss)?

Large gap: longer, heavier machine  
Small gap: shorter, lighter machine

Study of realistic turbine stage, varying axial gap size  
(Pichler et al., GT2017-63407, JoT 2017)

- Modern LPT sections (aviation)
- $Re \approx 100,000$, $Ma \approx 0.6$
- $f_{red} \approx 0.7$
- Gap sizes: 21.5% (SG) and 43% (LG) rotor chord
- Simulations with $O(10^{14})$ DOF  
  (grid independence was found)
Instantaneous structures ($\lambda_{ci}=10$, coloured by spanwise vorticity)
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Production of turbulence kinetic energy (TKE)

Significantly higher TKE production in SG case
- assuming backscatter negligible, TKE eventually dissipated
- increased loss in SG case due to wake distortion
- increased loss in SG case seen in passage

Conclusion: halving axial gap increases kinetic loss by 0.25%
High-pressure turbine

- HPTs operate at Temperatures above melting point of metal → require cooling

- To understand cooling requirements need to accurately predict heat transfer

- Heat transfer affected by complex flow features (shocks, inlet turb, ...)

INCITE 2015: High-Fidelity Simulations of Gas Turbine Stages with GPU Acceleration
INCITE 2016: GPU accelerated LES of high-pressure turbine stator-rotor at engine conditions
1. Large-scale Incoming structures
2. Interaction with leading edge
3. Stretched under pressure gradient
4. Shocks on suction side
5. Laminar–turbulent transition
6. Acoustic waves
7. Vortex shedding
8. Highly disturbed pressure-side boundary layer
HPC – High-fidelity simulations
Parametric study of realistic turbine vane, varying inflow conditions
(Pichler et al., GT2017-63079, Zhao & Sandberg, JFM 2020)

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Machine Learning
What goes wrong in current turbulence modelling?

Linear coupling between turbulent (Reynolds) stress and strain

Linear Reynolds stress models do not capture anisotropy of turbulent flows
- Reynolds stress prevalent in all areas of turbulence models

How can we improve Reynolds stress model?

Extend the linear model to include higher order gradients

\[ \overline{u_i u_j} - \frac{2}{3} k \delta_{ij} = -2 \nu S_{ij} + 2k \sum_{k=1}^{10} \zeta_k(I_1, I_2, I_3, I_4, I_5) T_{ij}^k \]

Scalar that linearly relates deviatoric stress to strain rate

With high-fidelity data try to find \( \zeta_k \) as functions of independent variables \( I_k \)

Unknown coefficients, functions of independent variables

**Basis functions**
(Pope, 1975)

Independent tensor variables
How can we find $\zeta_k$ that give us best model?
- Want $\zeta_k$ symbolically $\rightarrow$ interpretable, plug and play
- Evolve suitable functions for $\zeta_k$
- Evolutionary concepts borrowed from biology
  - survival of the fittest
  - incremental improvements via genetic operations (cloning, mutation, crossover)

How do we evolve symbolic expressions that are syntactically correct?
- Gene Expression Programming (GEP) transforms symbols to equations:

**Expression tree**

**Chromosome** - list of symbols (exists in code)

**Predictive model** (valid expression - can be nonlinear)
Schematic of evolutionary algorithm:

1. Initialize random population
2. Evaluate fitness of models
3. Natural selection
4. Update population to next generation
5. Apply genetic modifications (mutations, transpositions, combinations)

- Set of predictive models (population) is developed over multiple generations to fit the available training data
- The fittest model of the last generation is the training outcome
- Can do that with tensors and vectors as well (Weatheritt & Sandberg, JCP 2016)
Cost functions:

- Definition of **cost functions** are critical to the quality of trained models
- **Frozen**: $a$-priori cost function based on given data (commonly used)
- **In-the-Loop**: novel approach with $a$-posteriori cost function - running external software

**Example**: anisotropy tensor training for wake mixing models

**Frozen**: deviation between stresses from GEP model and Hi-Fi data

\[
J_{\text{fro}} = \frac{1}{N} \sum_{n=1}^{N} \sum_{i,j} \frac{|a_{ij}^{\text{HiFi}} - a_{ij}^{\text{GEP}}|}{|a_{ij}^{\text{HiFi}}|}
\]

**In-the-Loop**: wake profile predictions from industrial CFD solvers

\[
\Delta x = \frac{1}{L_y} \int_{0}^{L_y} \left( \frac{\omega_{\text{HiFi}}(y) - \omega_{\text{TRANS}}(y)}{\max_y(\omega_{\text{HiFi}})} \right)^2 dy
\]

\[
J_{\text{CFD}} = \Delta x_1 + \Delta x_2
\]

\[
\omega(y) = \frac{p^i - p(y)}{p^i - p^0}
\]
**Benefits of In-the-Loop training:**

- **Flexible**: cost function can be any (important) feature/parameter
- **Robust**: does not require a full set of Hi-Fi data for training
- **Ready-to-apply**: models can be directly plugged into industrial software with no extra validation
Model trained on HPT data at Re=570,000

New model trained on one data set performs well on all test cases, at different flow conditions and for different geometries.

Tested on:

- HPT at Re=1,100,000
- LPT at Re=60,000
- LPT at Re=100,000

Error reduced by factor > 5
Machine-learning framework applied to heat flux modelling

New models tested on 9 other cases with different slot geometries and blowing ratios - 2 examples:

GEP model:
\[ \alpha_{t}^{mod,1} = \{6.806 I_2 - 109.407 J_1 + 2.0 J_2 + 2.368\} \nu_t \]

EDM:
\[ \overline{u' T'} = -\alpha_t \frac{\partial \overline{T}}{\partial x_i} \]

TE slot heat flux models
(Sandberg et al., JoT 2018)
Ultimate Goal

1) Physical insight
2) Machine-learn models

Use HPC to perform Hi-Fi simulations

More accurate design calculations

Simplify
Thank you for your attention

Questions?

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