How can high-performance computing help design more efficient jet engines: physical insight and machine learning

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Background

- <u>Why do we need better jet engines?</u>

  - Today's engines a marvel of engineering – already vastly better than the first engines

    1) efficiency has gone from 20% (first jets) to 30% (B747) to >40% (A350)
    2) 30dB quieter than early engines (B707) – reduction of >80% of noise!
    3) 50% or more reduction in emissions (e.g. NOx)
    4) Much more reliable, can fly long distances with 2 engines, service intervals much longer, saving passengers money

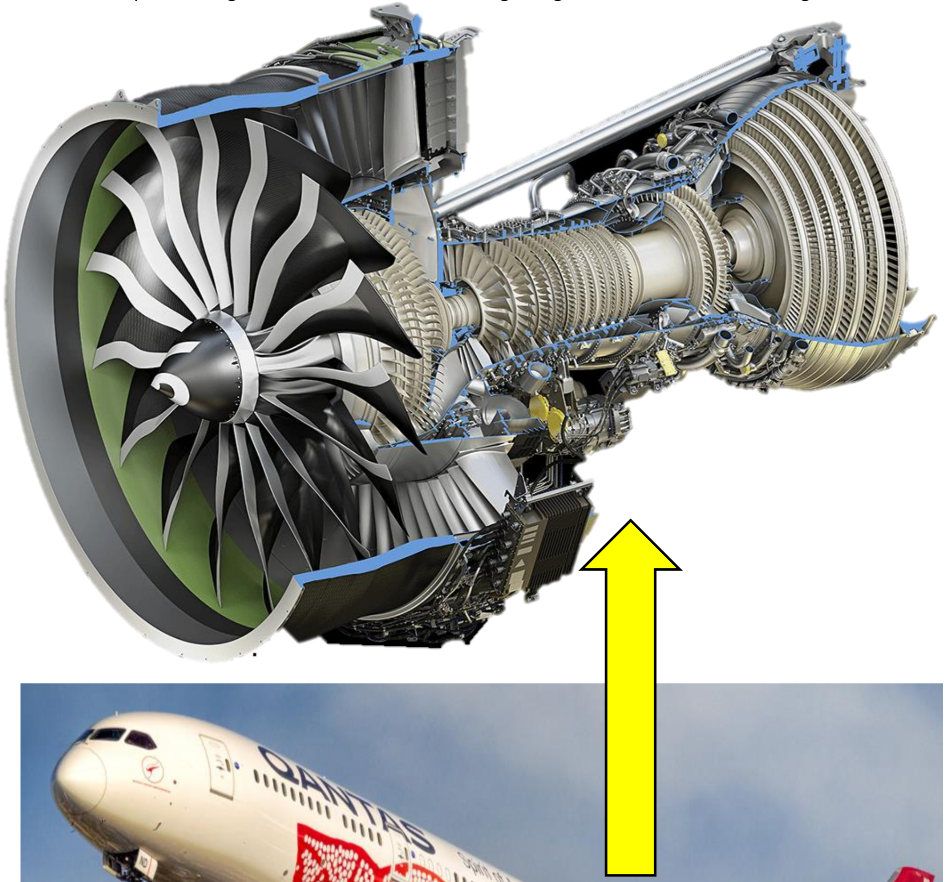
  - Aviation predicted to grow further
  - Need next-generation engines to do this sustainably
  - Commercial aviation burns around 350 billion liters fuel
  - For each % jet engines can be made more efficient:
    - reduce fuel cost by AUD billions/year (AUD60 million in AUS)
    - reduce CO_2 emissions by 1.5%

https://commons.wikimedia.org/w/index.php?curid=28787531

https://southpawcaptures.com/aviationblog/2018/10/16/vh-znd-qantas-787-9-yam-dreaming

Background

https://www.geaviation.com/commercial/engines/ge9x-commercial-aircraft-engine



- <u>How can HPC help?</u>

  - Today's engines really complex, with many parts

  - Takes long time (decade) to develop and billions of $

  - Building prototypes very expensive/time consuming

  - Difficult to measure airflow inside jet engine

    (very high temperatures, pressures, speeds)

Computational models could fast track designs, allowing designers to take 'virtual risks'

Computational Fluid Dynamics can tell engineers exactly what happens inside engine

https://southpawcaptures.com/aviationblog/2018/10/16/vh-znd-qantas-787-9-yam-dreaming

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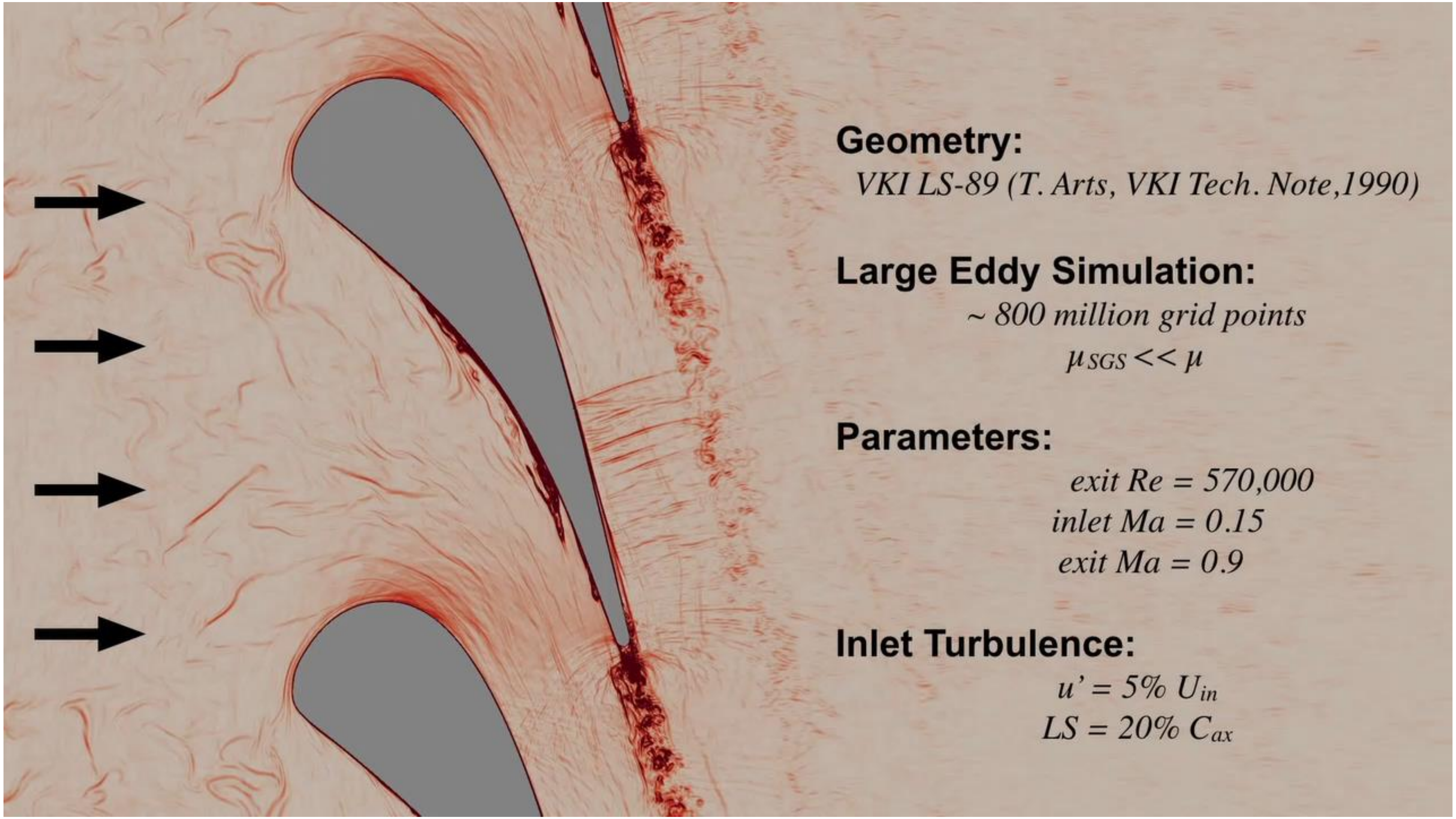
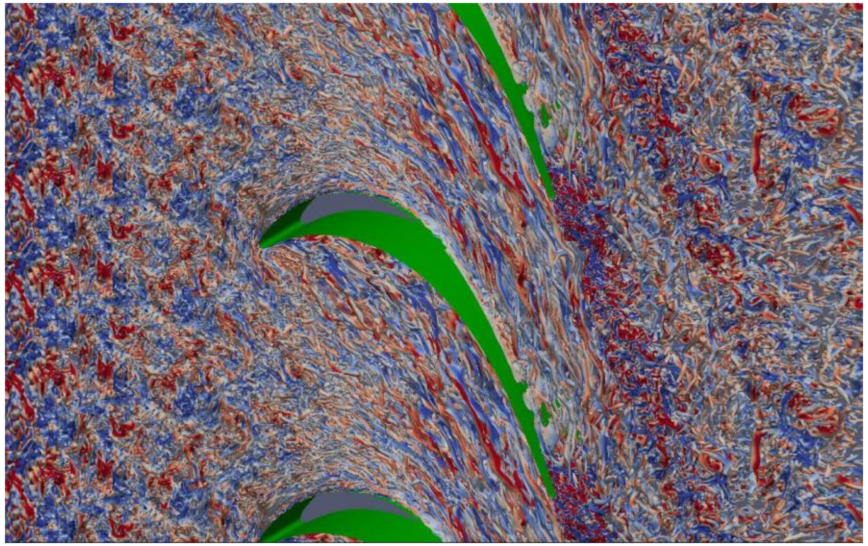
HPC – High-fidelity simulations HPT

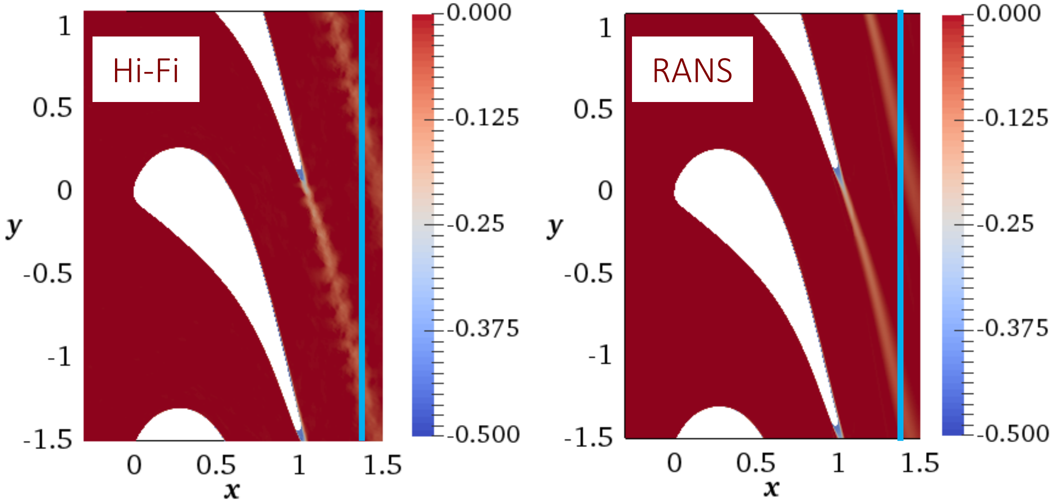


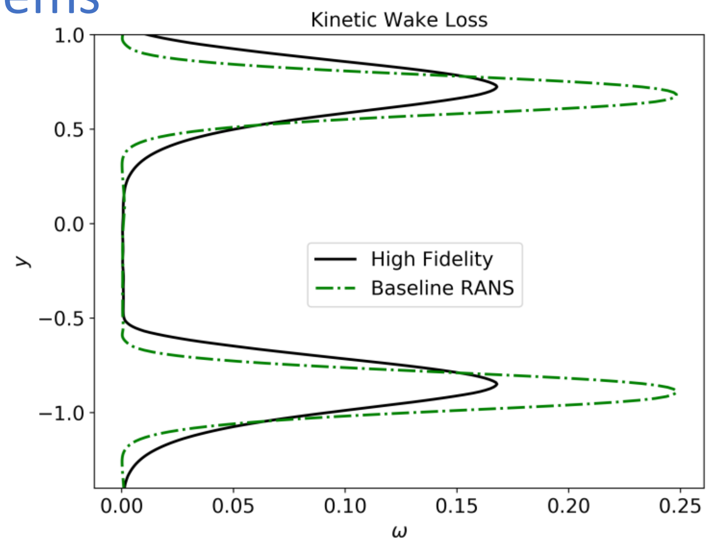
Background

- <u>HPC for detailed simulations</u>
  - Can run high-fidelity simulations that provide required accuracy
  - BUT: simulations very complex, with > 10^{16} degrees of freedom
  - Takes > 1000 years on notebook, can do in weeks on NCI



- <u>HPC's role in machine learning</u>
  - To avoid high simulation cost, industrial design uses modelling
  - Current models inaccurate for certain problems





limits impact CFD can have on technology development

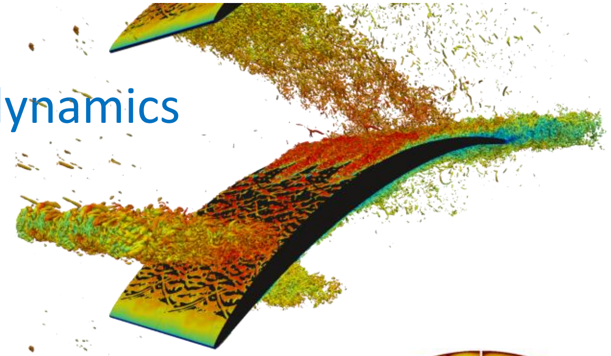
Use ML and Hi-Fi data to improve models

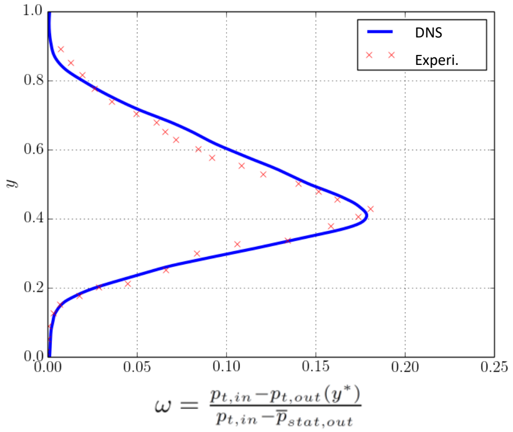
HPC for simulating what really happens

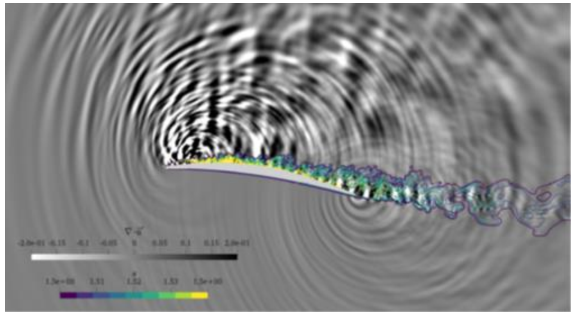
HPC - In house Simulation Code

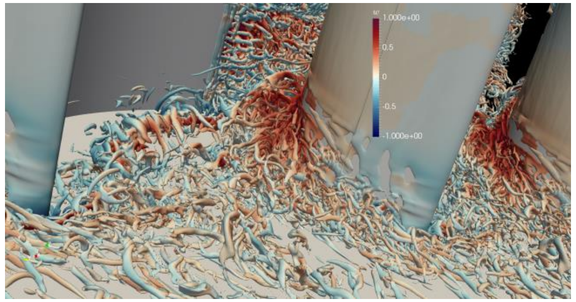
HiPSTAR: High-Performance Solver for Turbulence and Aeroacoustics Research

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



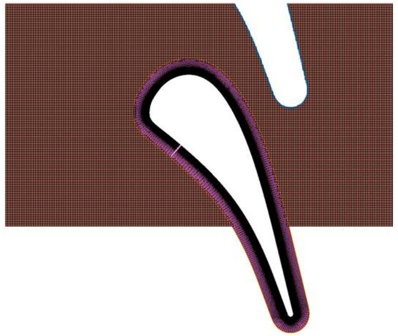


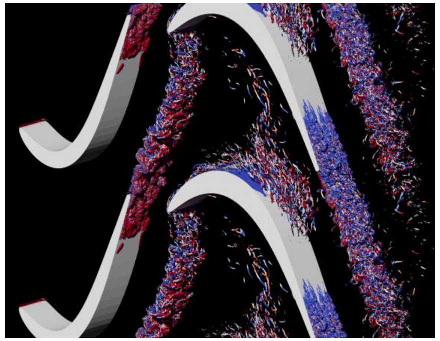


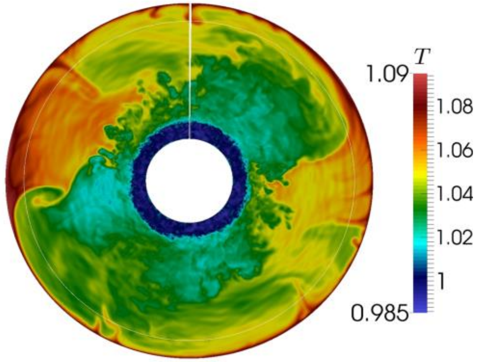


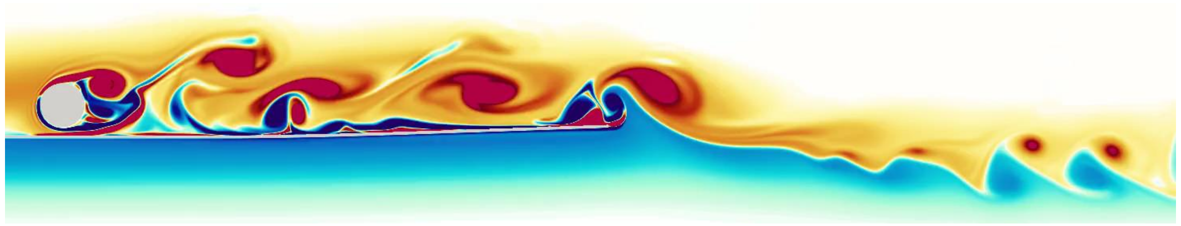
Flexible

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



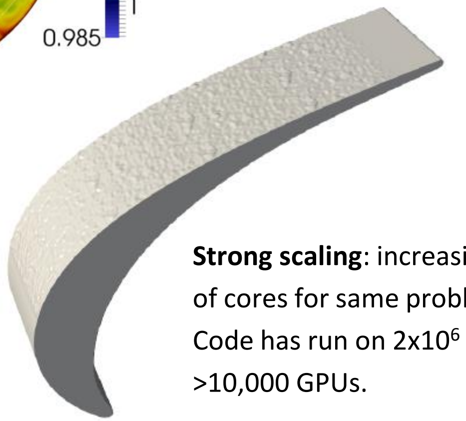




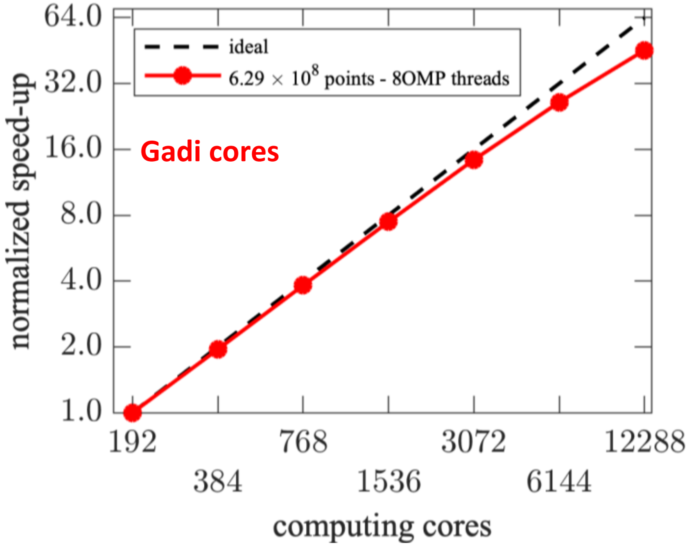


Fast

- Optimized for CPU and GPU



Strong scaling: increasing number of cores for same problem size. Code has run on 2x10^6 cores and >10,000 GPUs.



HPC – High-fidelity simulations

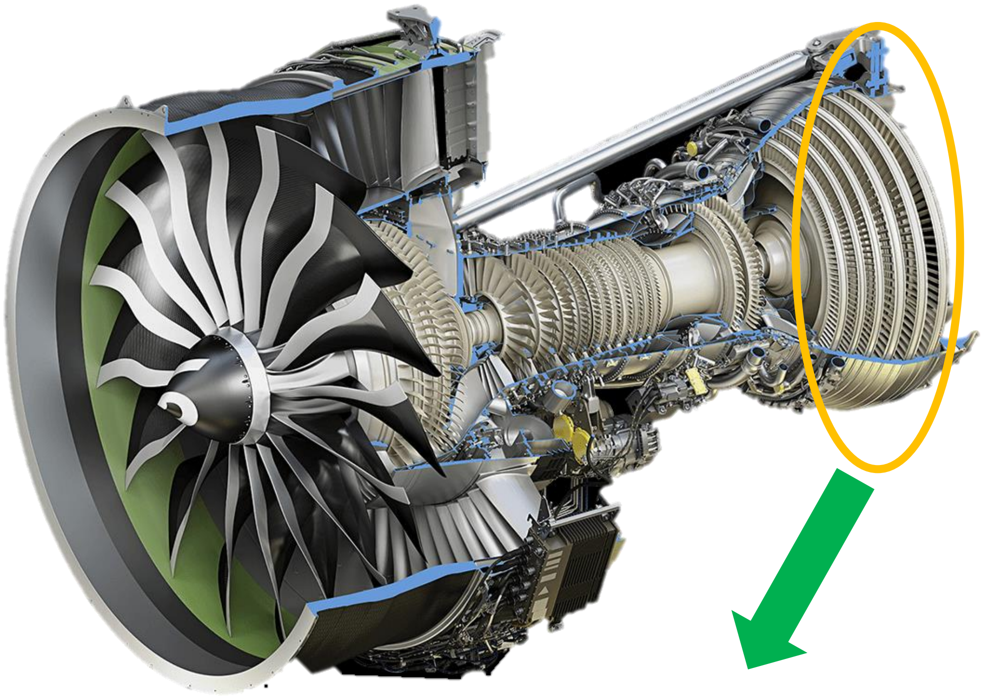
Low-pressure turbine

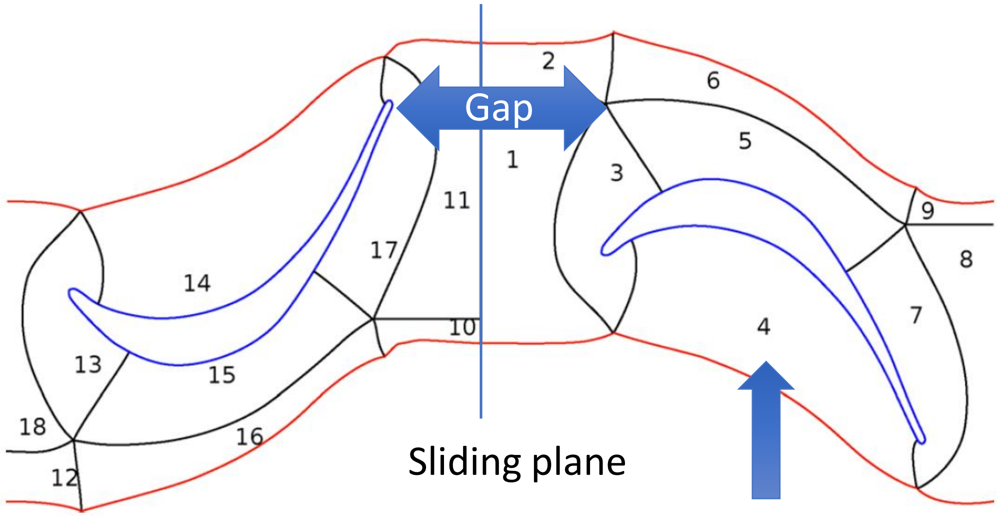
Optimal spacing between turbine blades (for minimal loss)?

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≈100,000, Ma ≈0.6
- f_{red} ≈0.7
- Gap sizes: 21.5% (SG) and 43% (LG) rotor chord
- Simulations with O(10^{14}) DOF
  (grid independence was found)

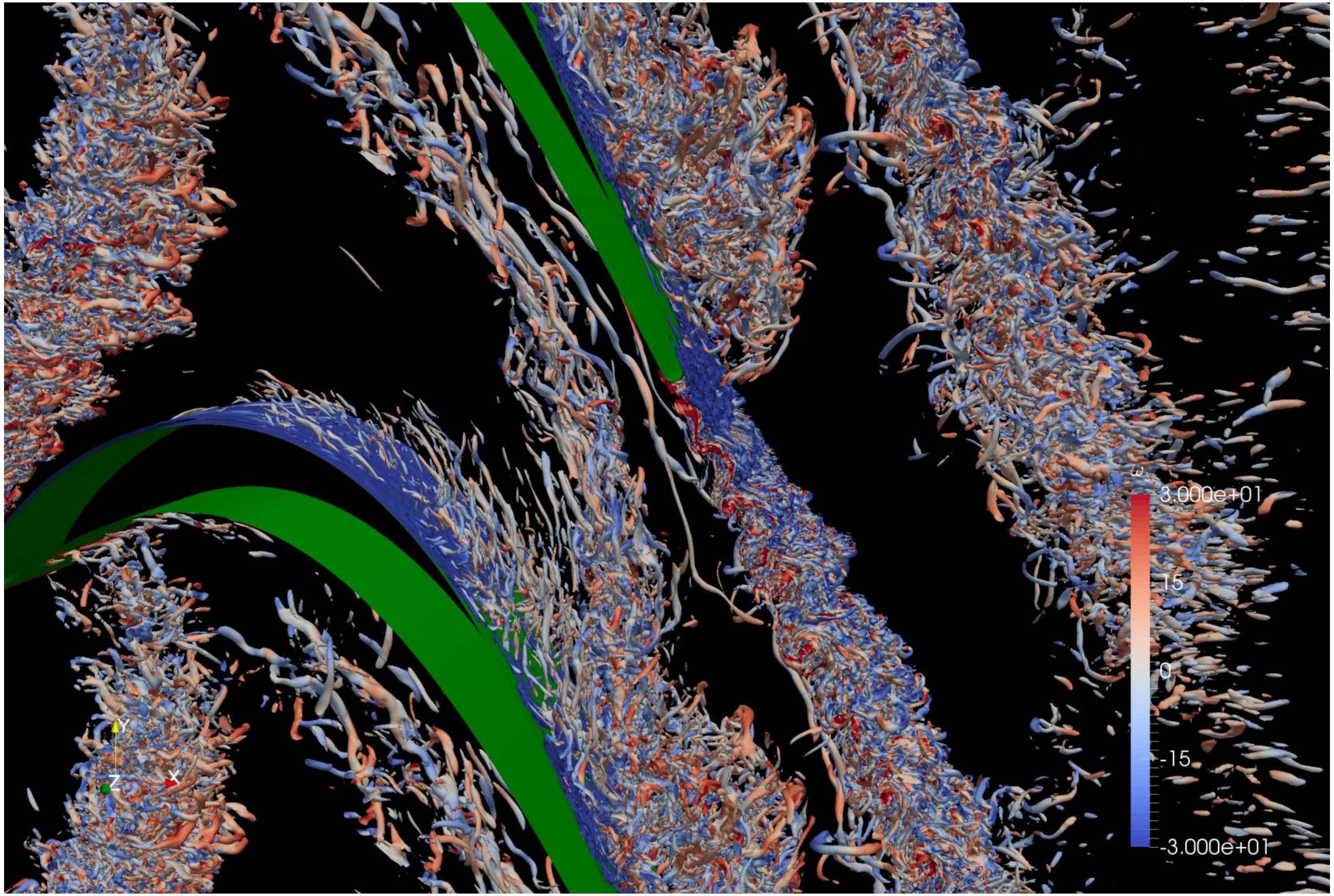




HPC – High-fidelity simulations LPT

Instantaneous structures (λ_{ci}=10, coloured by spanwise vorticity)

SG



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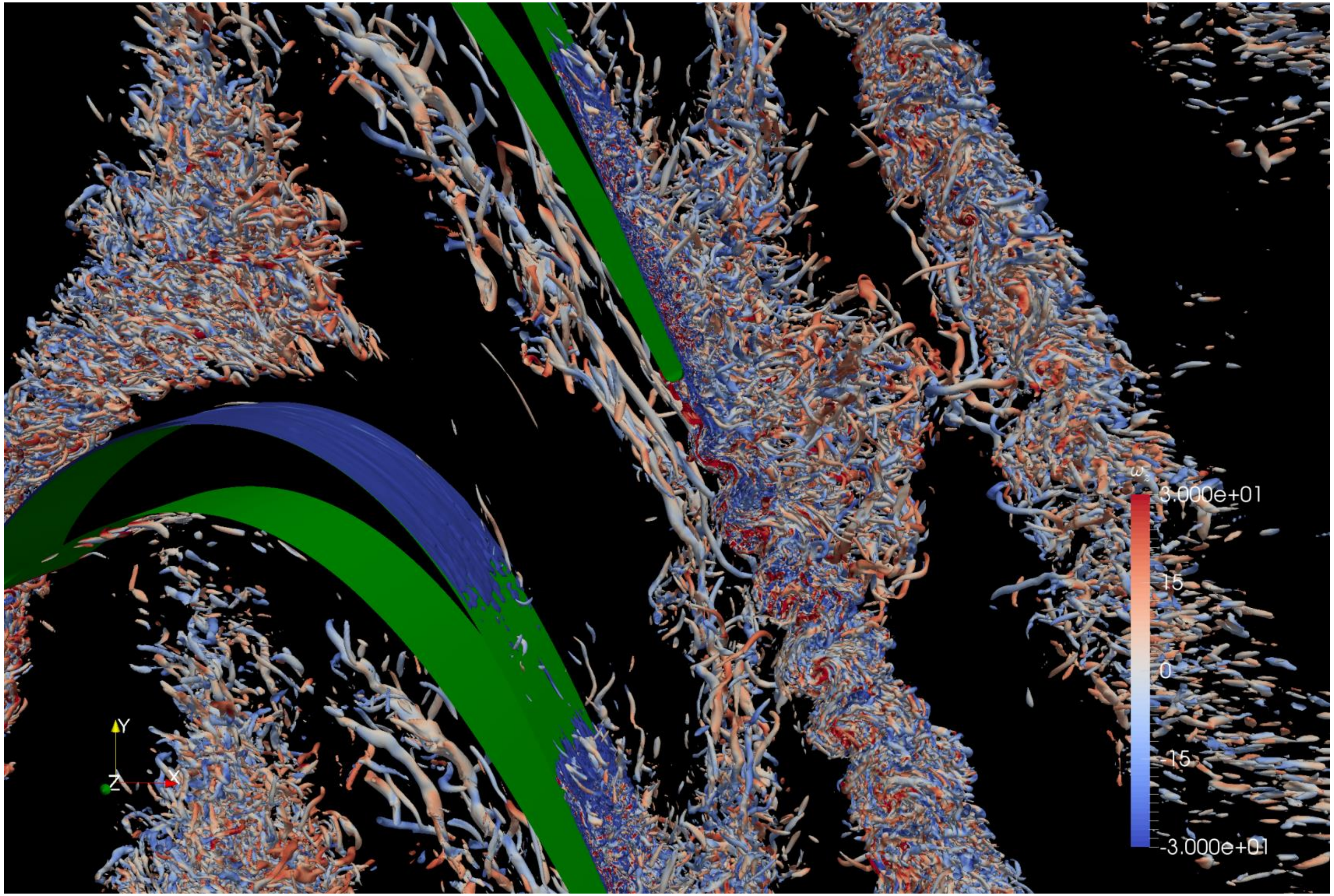

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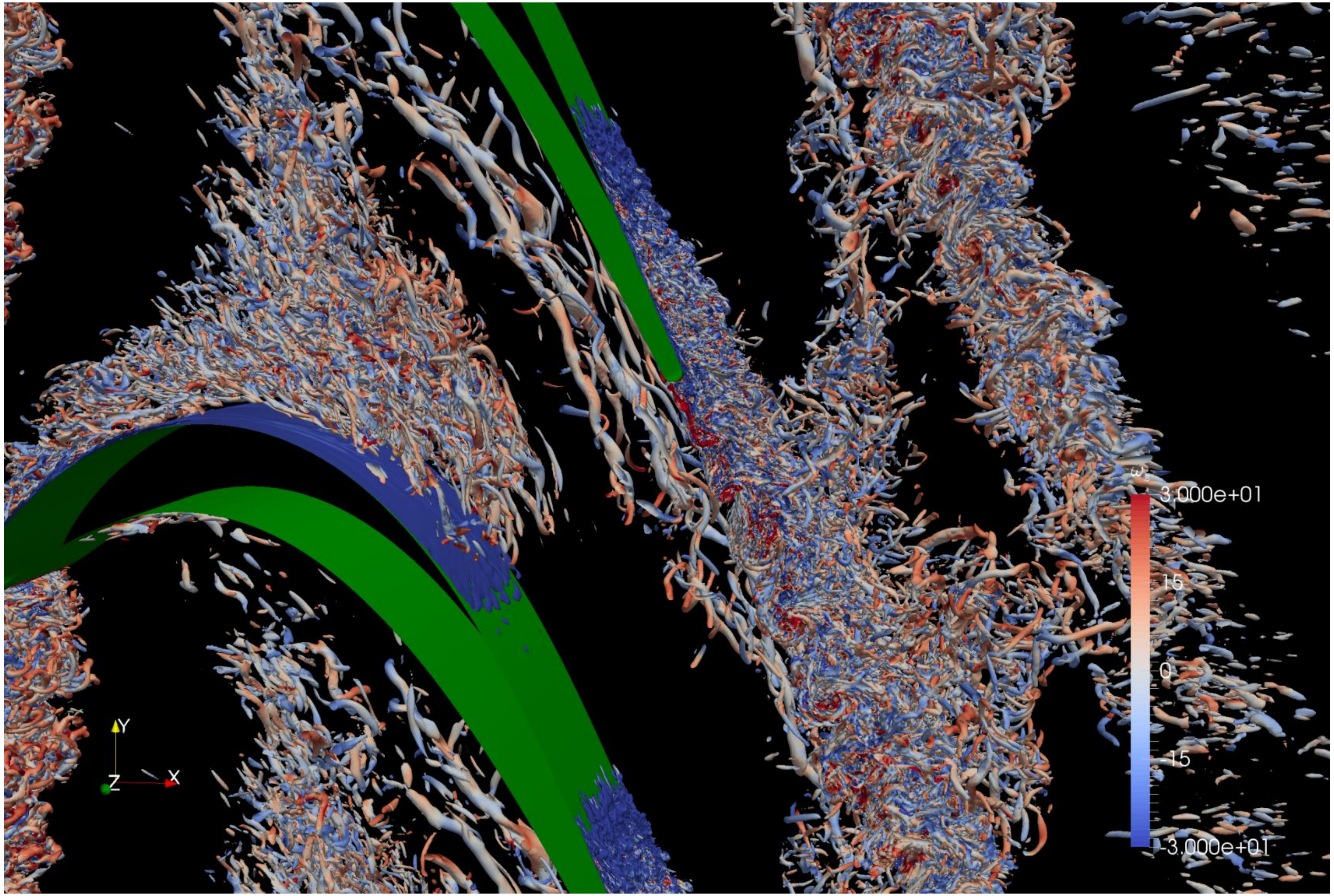

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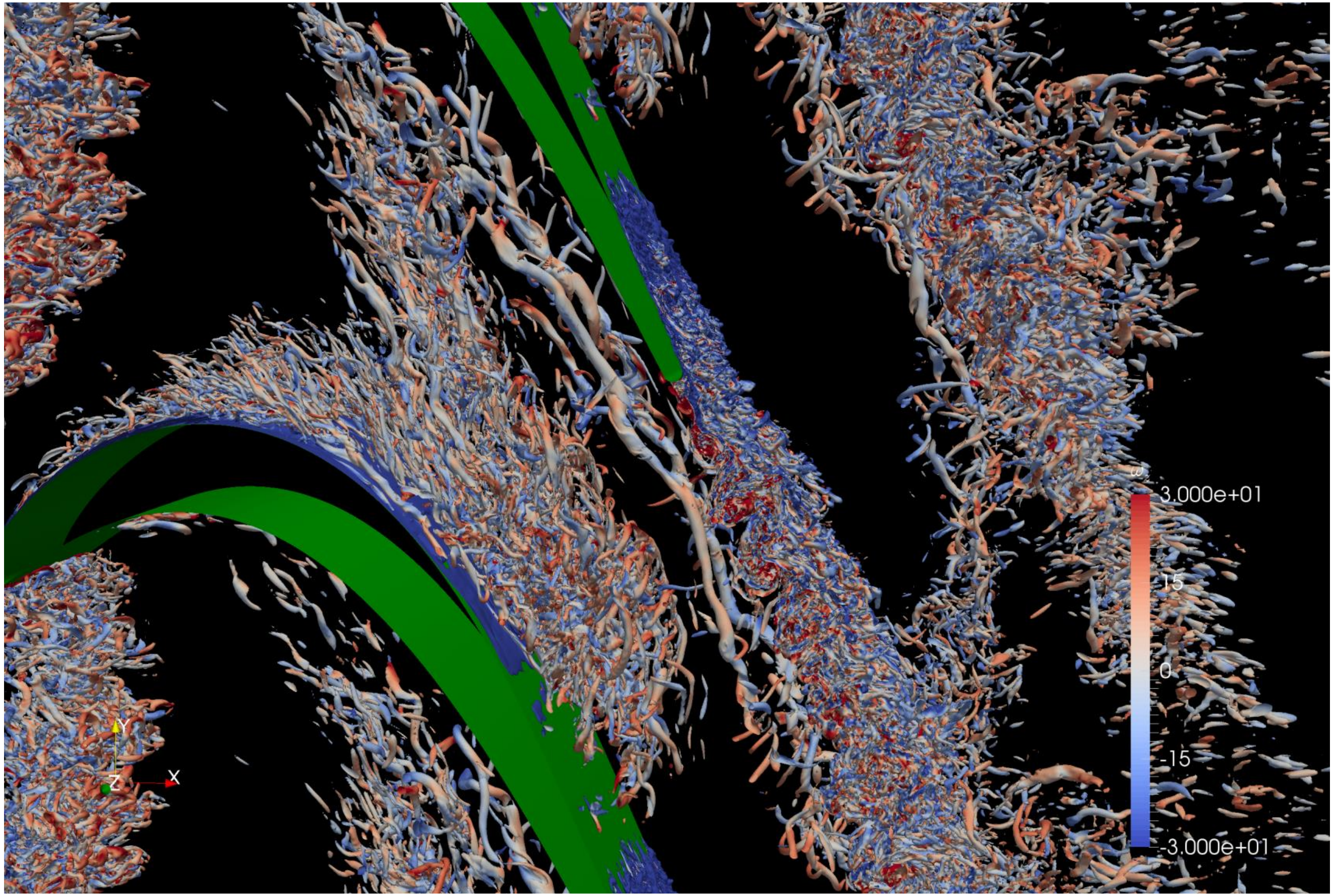

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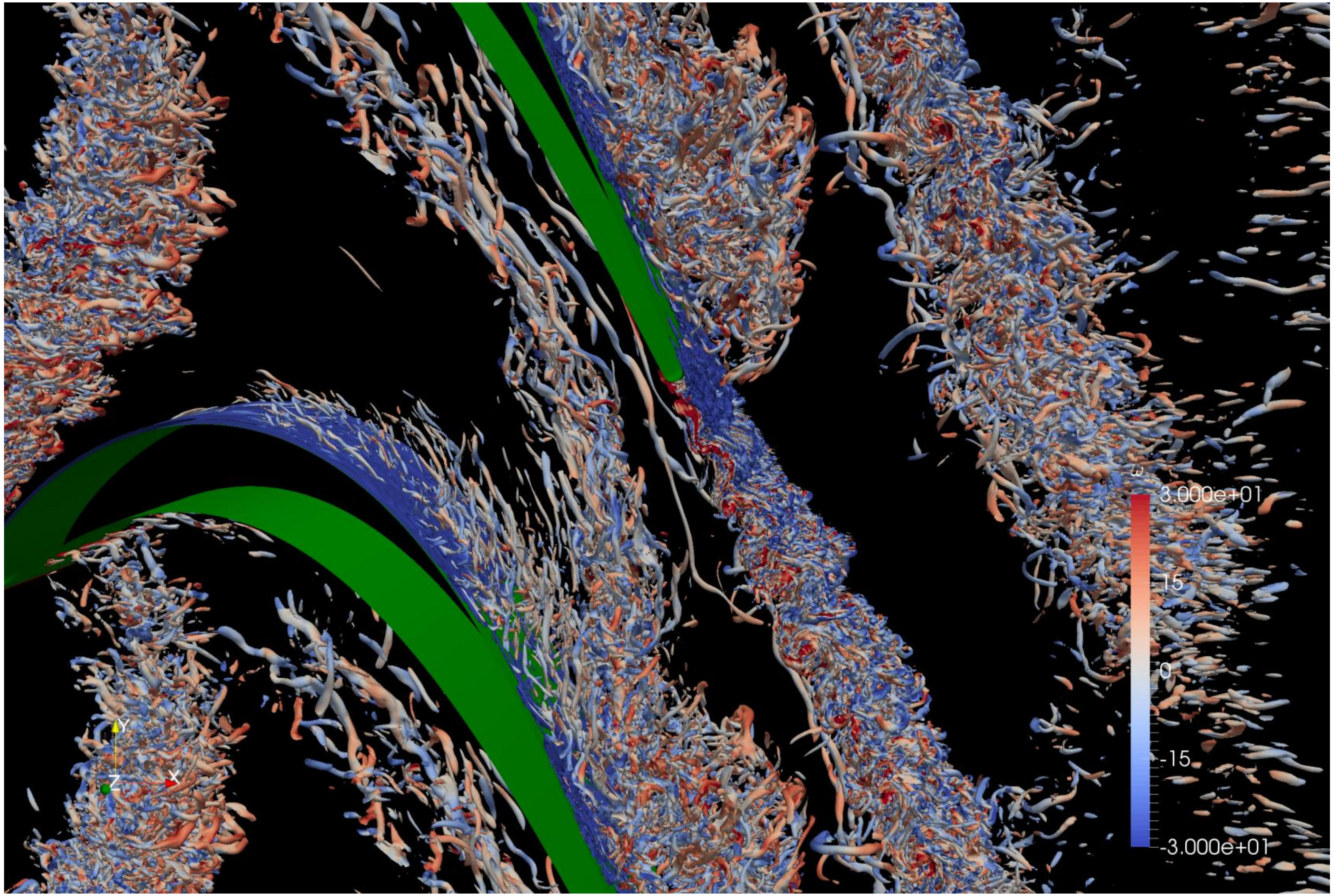

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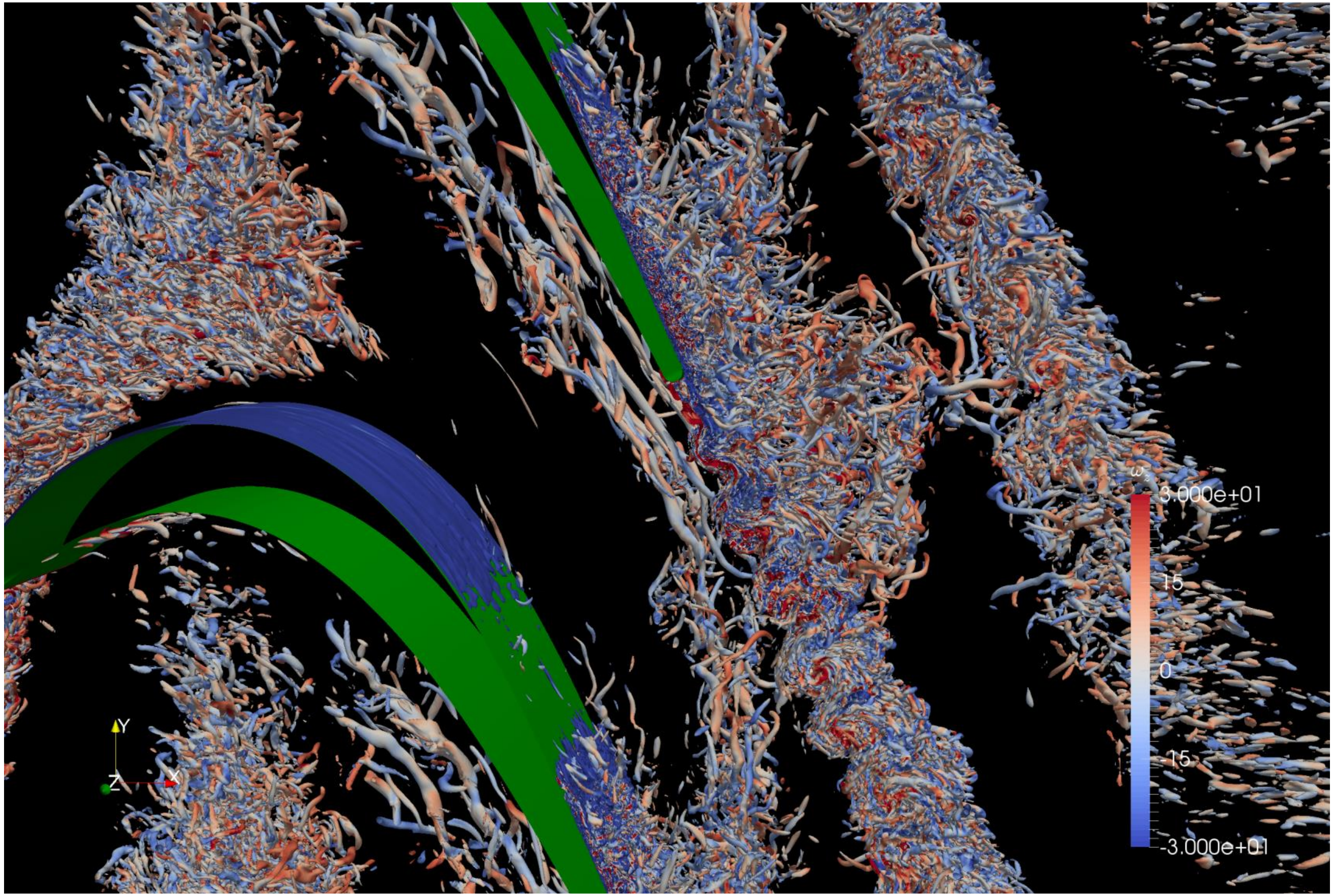

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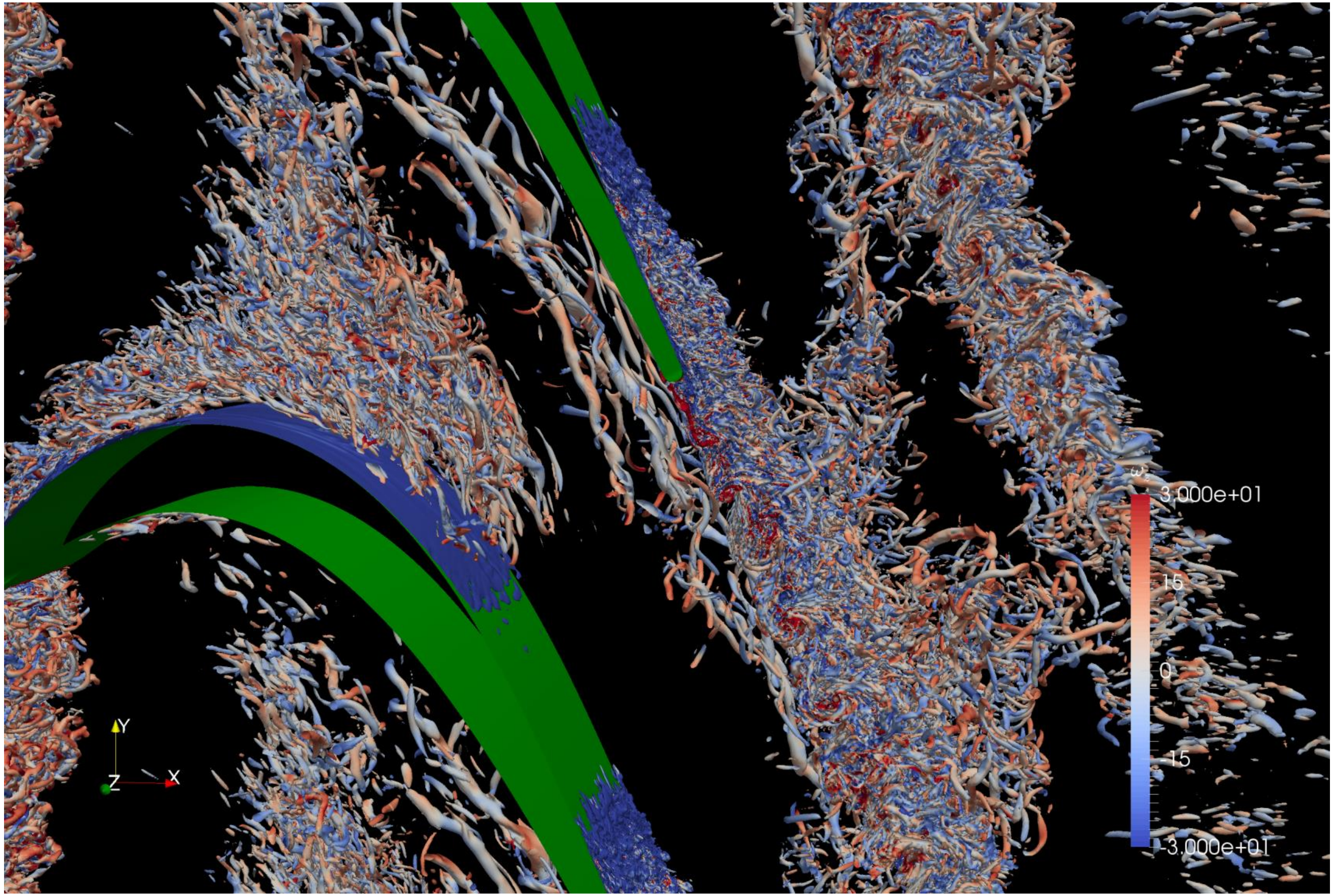

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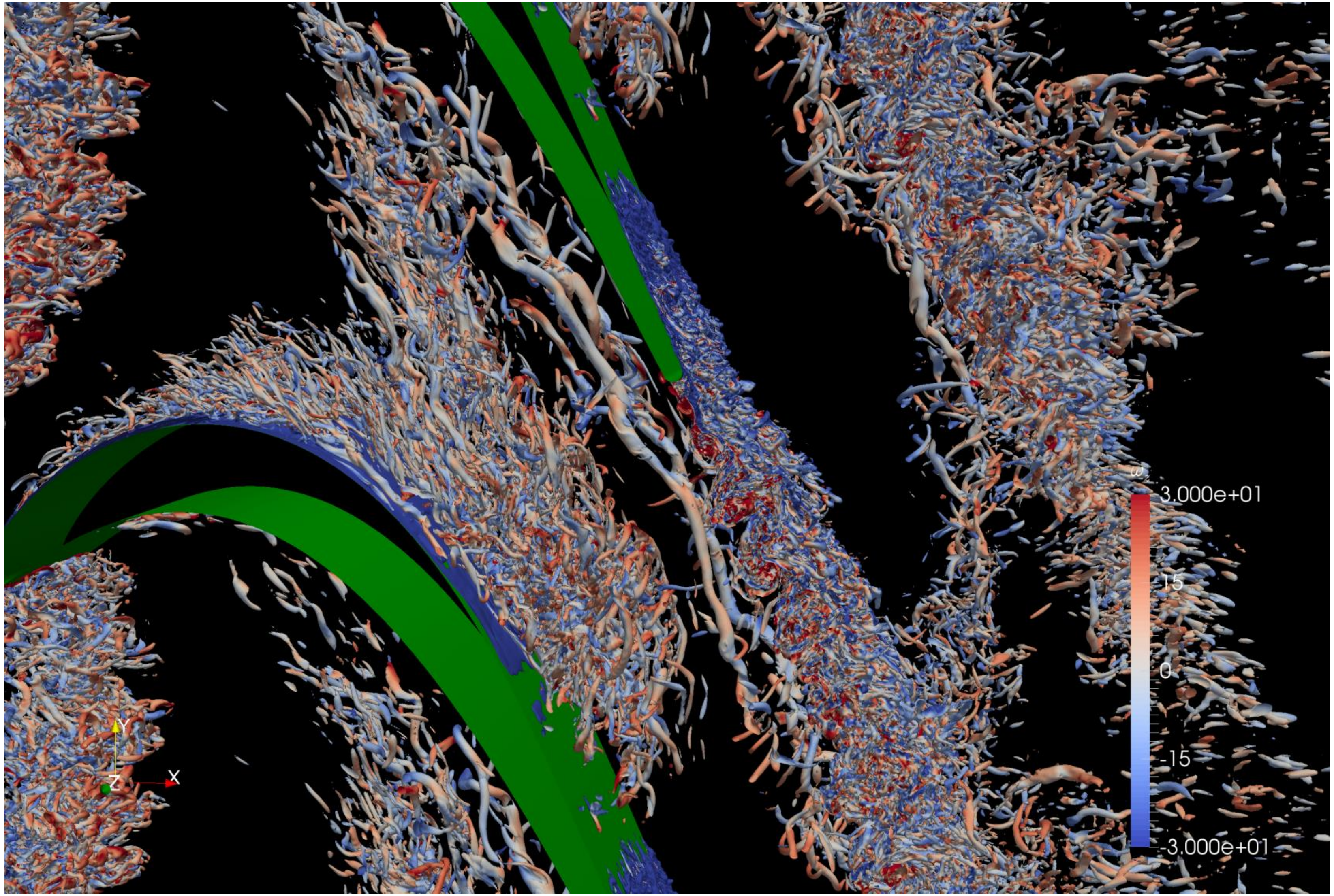
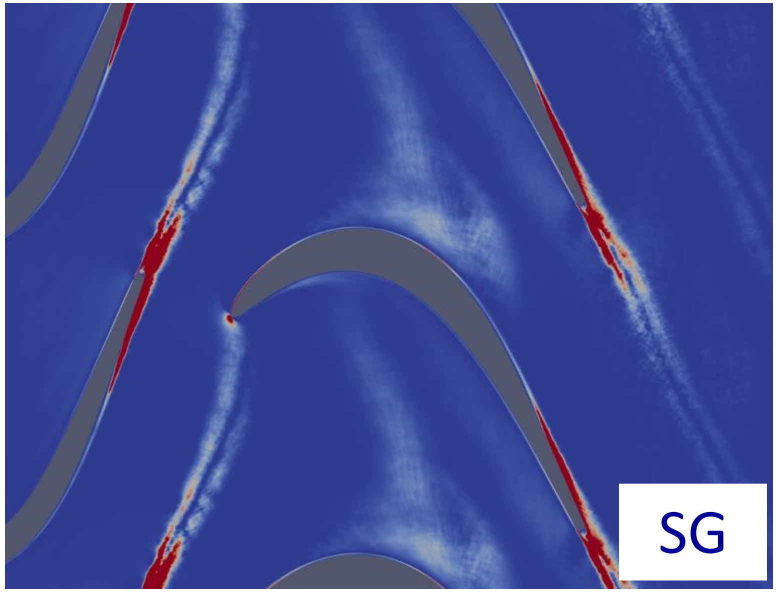
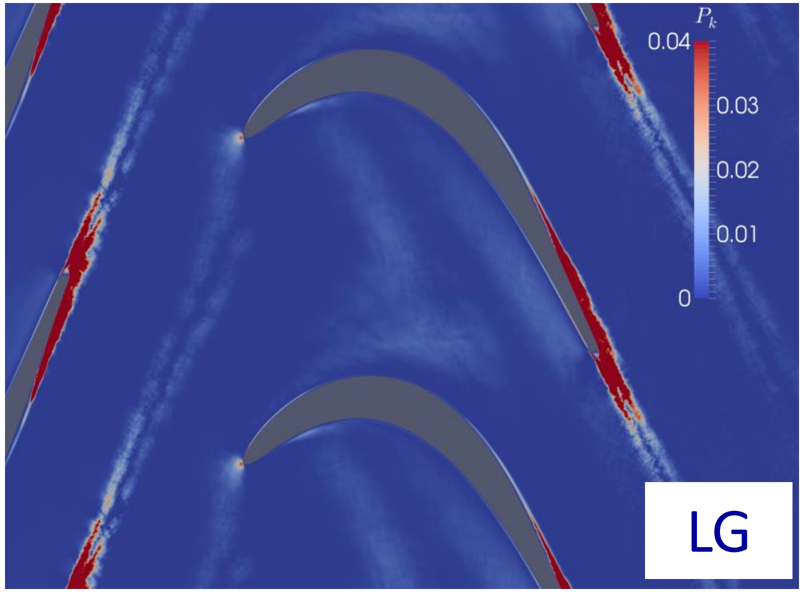
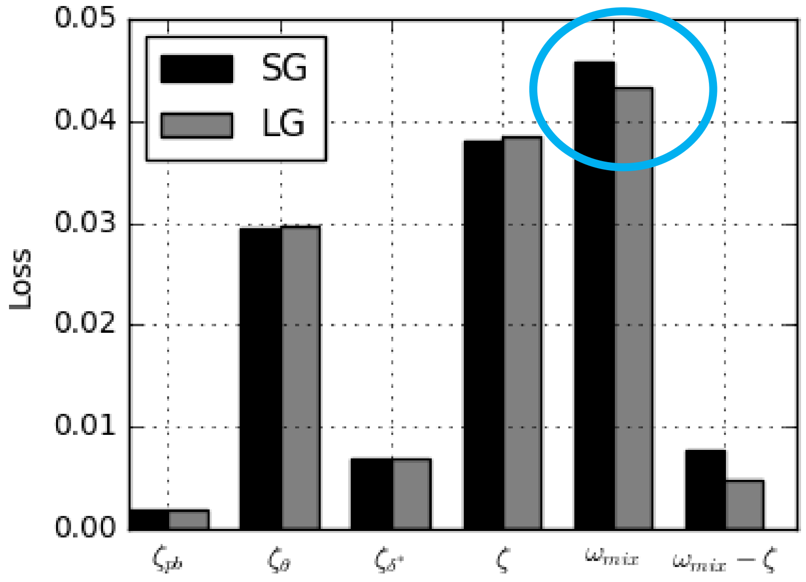


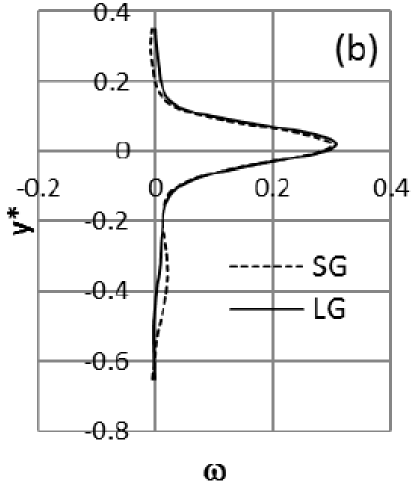
HPC – High-fidelity simulations LPT

Production of turbulence kinetic energy (TKE)









Significantly higher TKE production in SG case
→ TKE eventually dissipated, leads to entropy generation (loss)
→ 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%

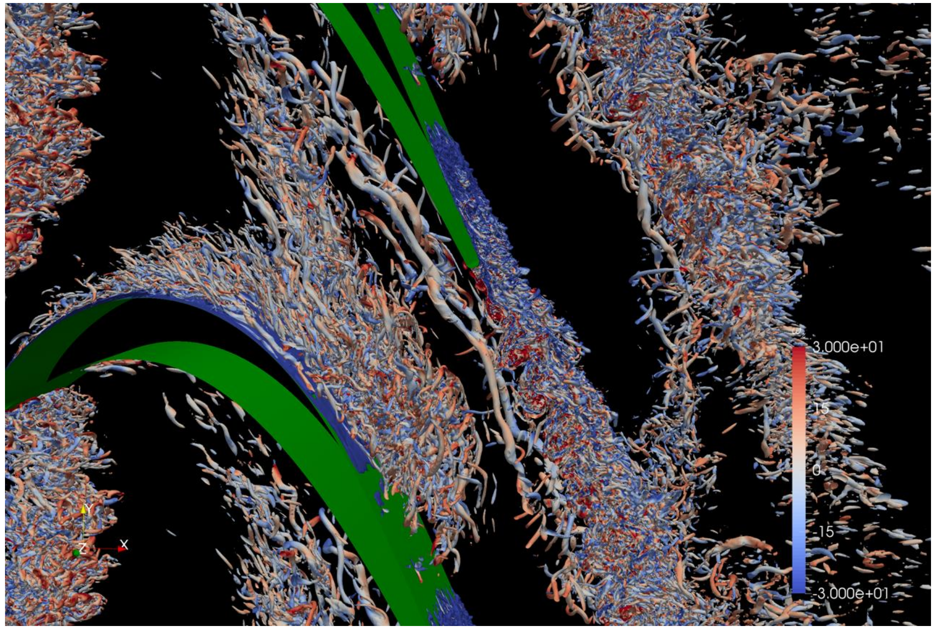
Machine Learning

What does turbulence modelling look like?

High cost of simulations due to need to resolve all turbulence scales

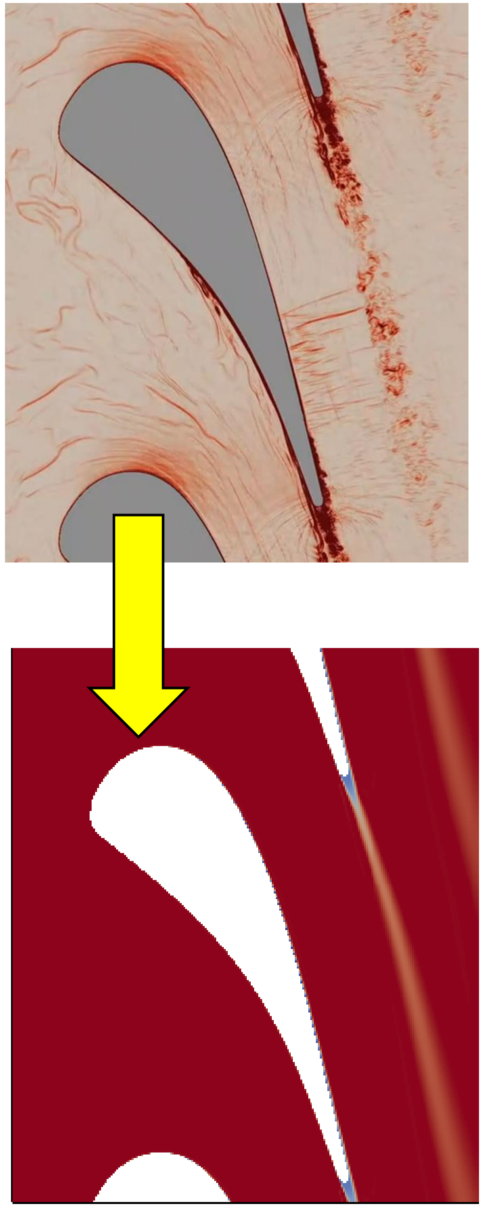
Solution: do not resolve all the turbulent scales, but model their effect on the mean flow

Need model that represents ALL scales of turbulence



Turbulence essentially provides extra dissipation of energy
→ model analogously to molecular diffusion

$$\overline{u_i u_j} - \frac{2}{3} k \delta_{ij} = -2\nu_t S_{ij}$$



What goes wrong in current turbulence modelling?

Linear coupling between turbulent (Reynolds) stress and strain

$$\overline{u_i u_j} - \frac{2}{3}k\delta_{ij} = -2\nu_t S_{ij}$$

Scalar that linearly relates deviatoric stress to strain rate

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

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

With **high-fidelity data** try to **find** ζ_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 ζ_k that give us best model?

- Want ζ_k symbolically → interpretable, plug and play
- Evolve suitable functions for ζ_k
- Evolutionary concepts borrowed from biology
  - survival of the fittest
  - incremental improvements via genetic operations (cloning, mutation, crossover)

Evolutionary Algorithm

How do we evolve symbolic expressions that are syntactically correct?

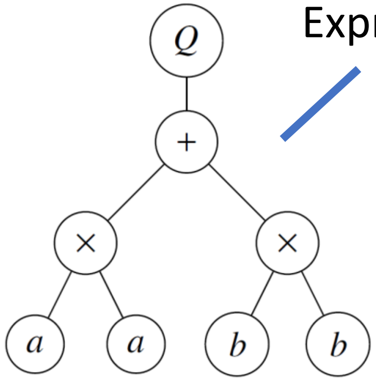
- Gene Expression Programming (GEP) transforms symbols to equations:

Head – function set | Tail – terminal set

0	1	2	3	4	5	6	7	8	9	10	11	12
Q	$+$	$\times$	$\times$	a	a	b	b	a	a	b	c	1

Chromosome - list of symbols (exists in code)

→



Expression tree

→

$$\sqrt{a^2 + b^2}$$

Predictive model (valid expression - can be nonlinear)

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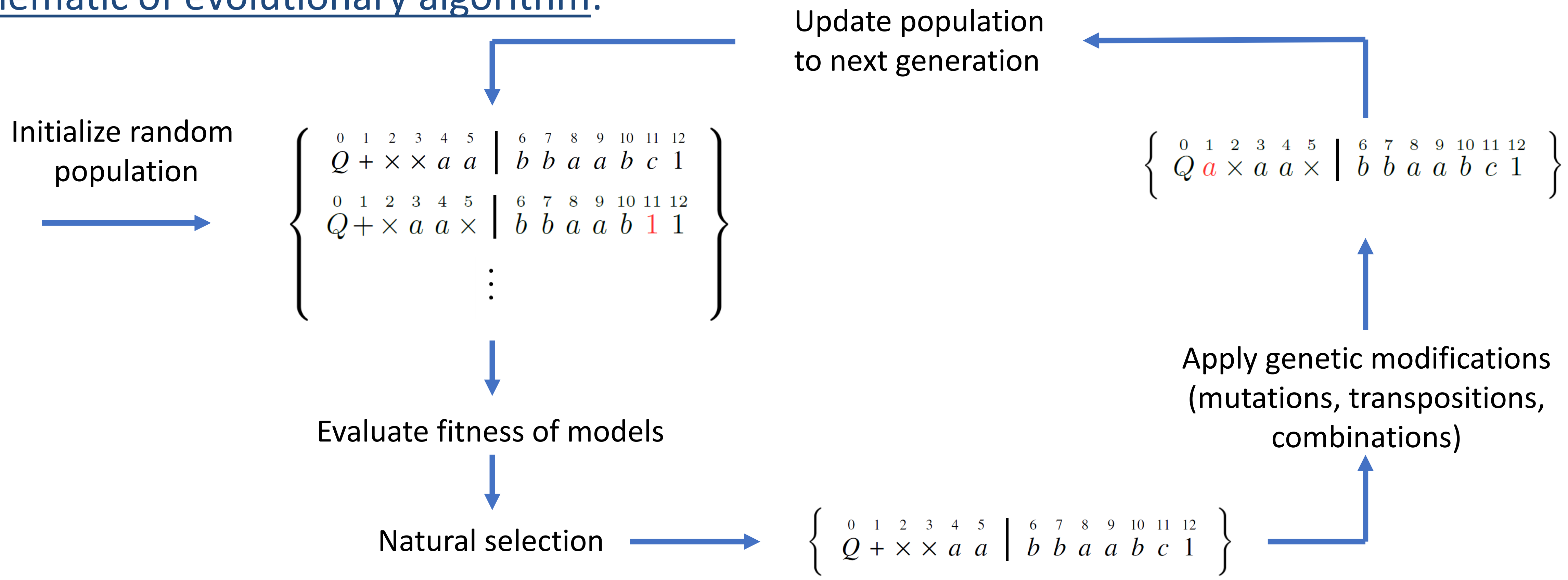
Machine-Learning (GEP)

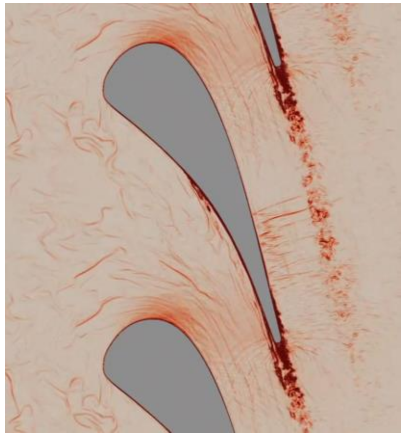
Schematic of evolutionary algorithm:



- 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)

Machine-Learning (GEP)

Model trained on HPT data at Re=570,000



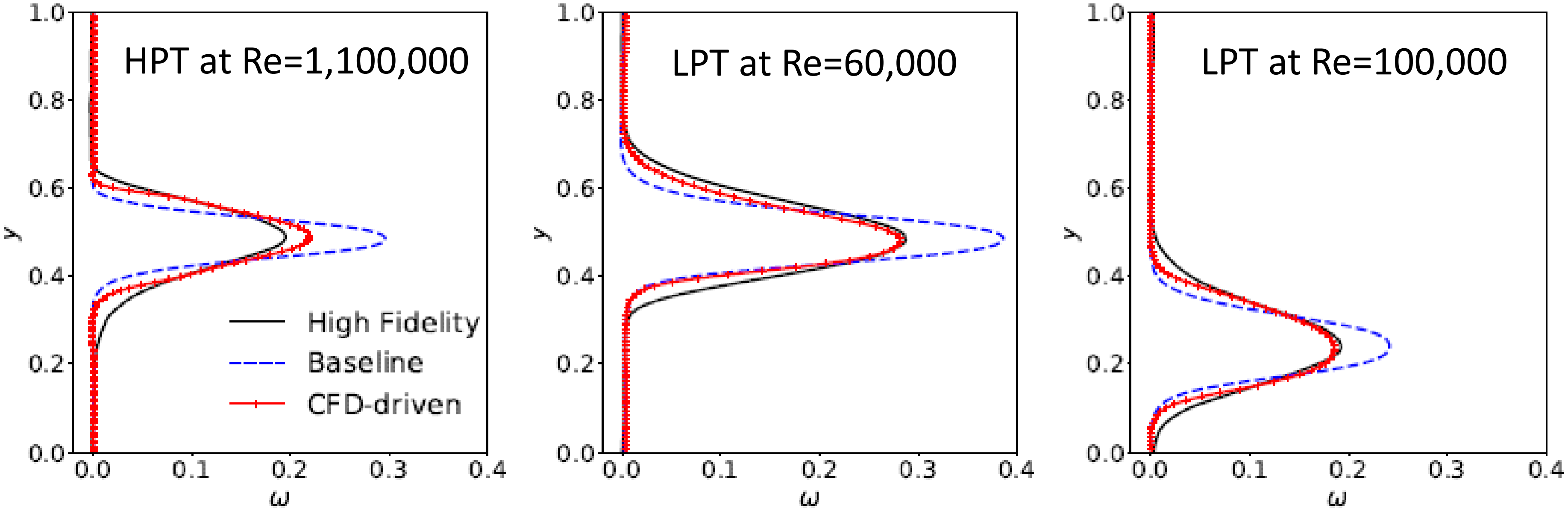
$$\overline{u_i u_j} - \frac{2}{3}k\delta_{ij} = -2\nu_t S_{ij}$$

Standard linear model (baseline)

$$+2k\left[\left(-3.57 + I_1\right)T_{ij}^1 + 4.0T_{ij}^2 + \left(-0.11 + 0.09 I_1 I_2 + I_1 I_2^2\right)T_{ij}^3\right]$$

Machine-learnt model extension

Tested on:

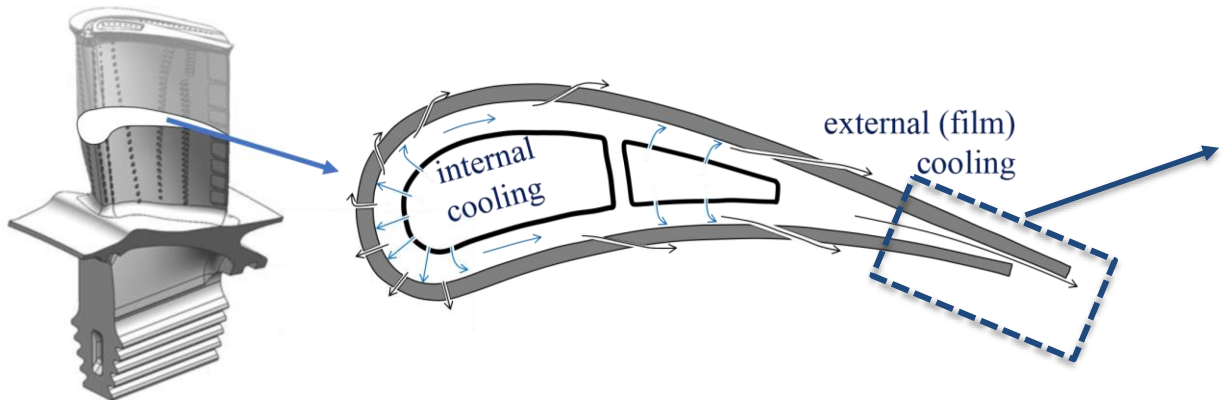


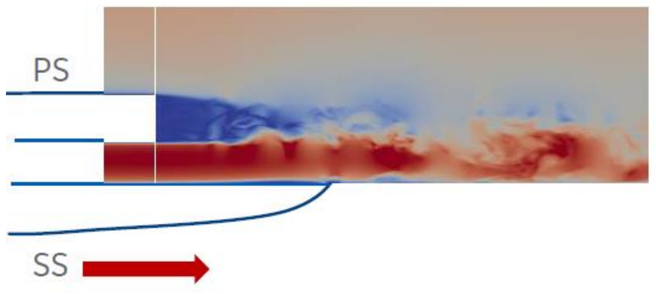
Error reduced by factor > 5

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

Machine-Learning (GEP)

Machine-learning framework applied to heat flux modelling

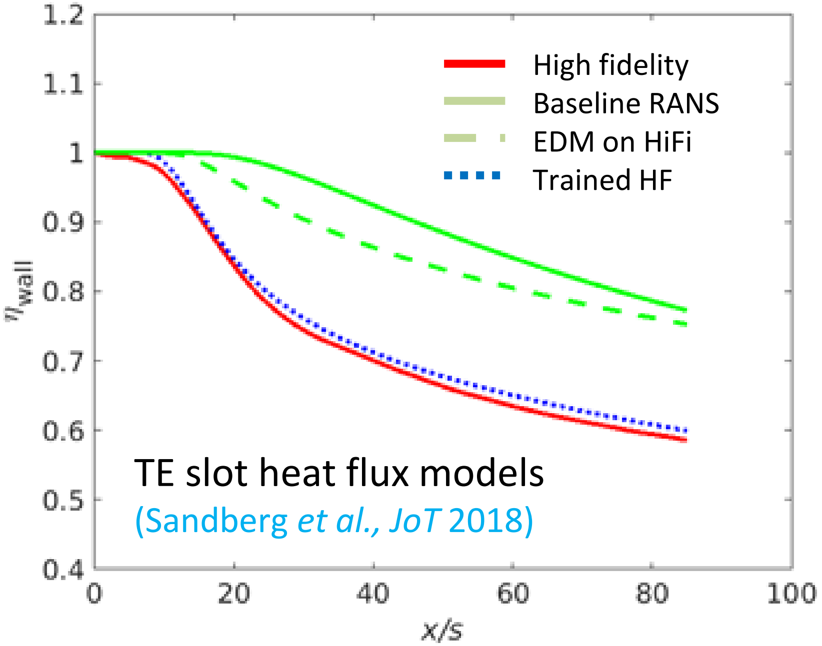




$$\overline{u_i'T'} = -\alpha_t \frac{\partial \overline{T}}{\partial x_i}$$

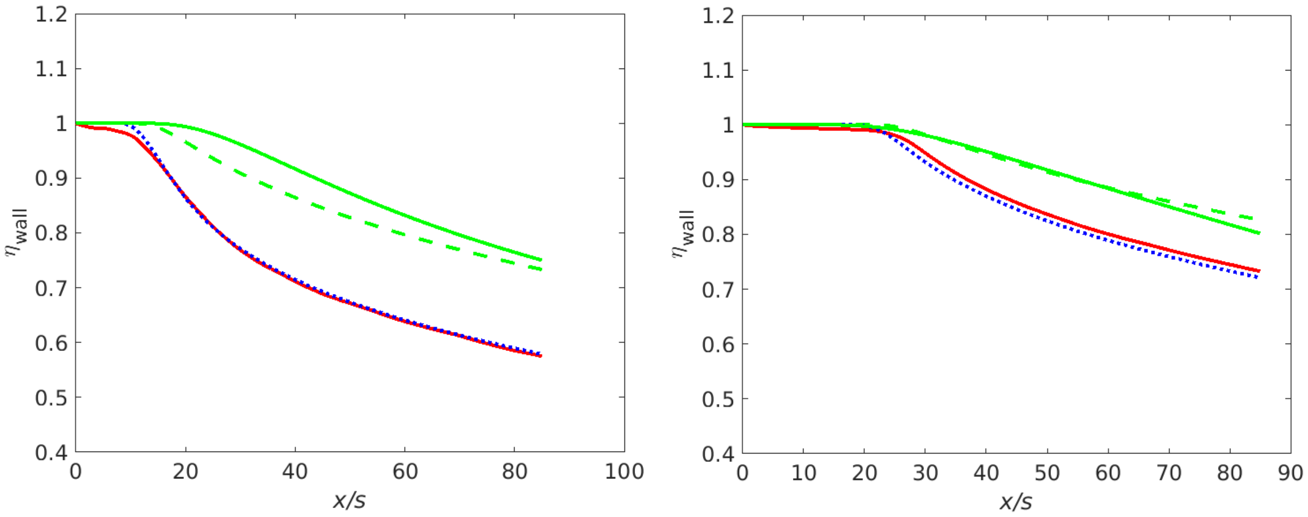
EDM: $\alpha_t = \frac{\nu_t}{Pr_t}$

GEP model: $\alpha_t^{mod,1} = \{6.806 I_2 - 109.407 J_1 + 2.0 J_2 + 2.368\}\, \nu_t$



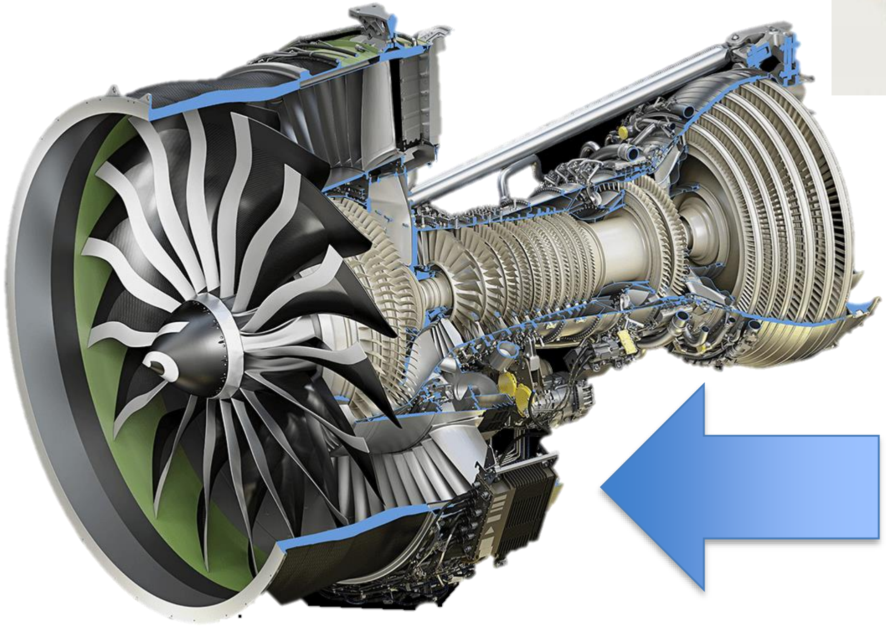
TE slot heat flux models
(Sandberg *et al.*, *JoT* 2018)

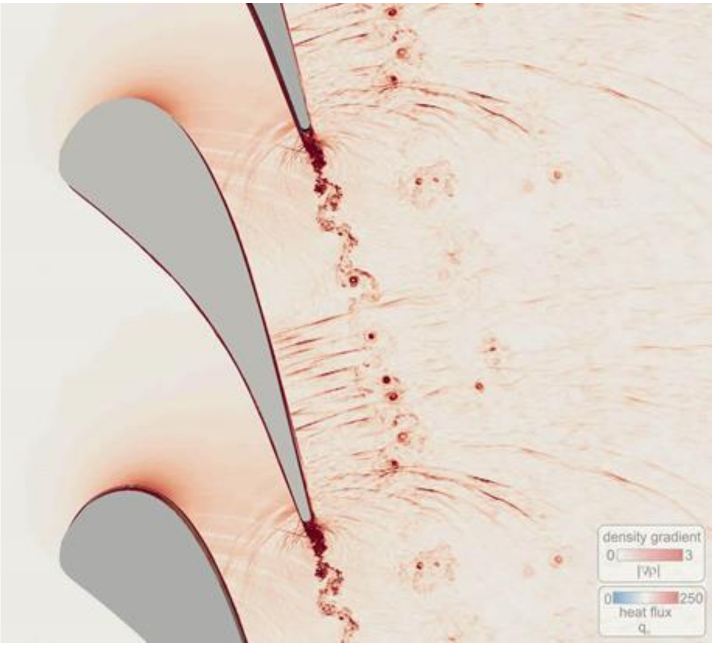
New models tested on 9 other cases with different slot geometries and blowing ratios - 2 examples:

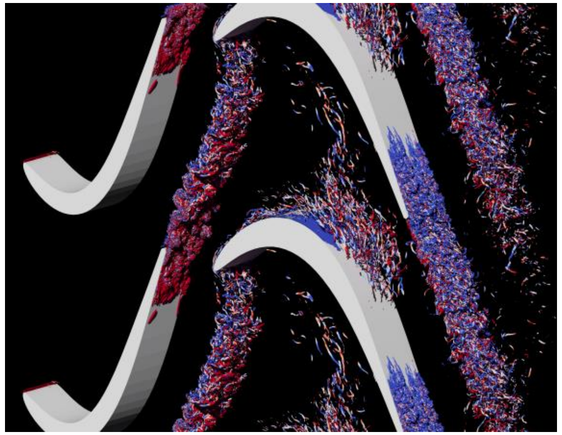


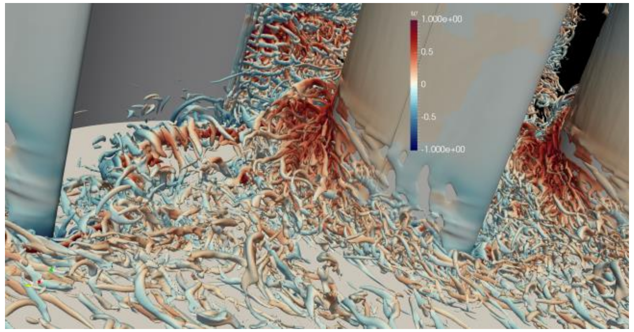
Ultimate Goal

Simplify









Use HPC to perform Hi-Fi simulations

More accurate design calculations

2) Machine-learn models

1) Physical insight

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Thank you for your attention

Questions?

Acknowledgements: Dr J Weatheritt, Dr R Pichler, Dr Y Zhao, Dr A Haghiri, Dr C Lav, F Waschkowski

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