

Generating near-optimal meshes using green AI

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Swansea University
Prifysgol Abertawe

Outline

- Motivation – The carbon footprint of HPC
- Our AI systems to predict mesh spacing using
 - Mesh sources
 - Background meshes
- Examples
- How green is the AI system?
- Concluding remarks

The carbon footprint of HPC

THE
MIT PRESS
READER

“The Cloud now has a greater carbon footprint than the airline industry. A single data centre can consume the same amount of energy as a small country. The Cloud is not the answer to our energy problems.”

HPC wire

“The Exascale era is here and power consumption for HPC is skyrocketing.”



“Carbon footprint, the (not so) hidden cost of HPC.”

ASIANSCIENTIST

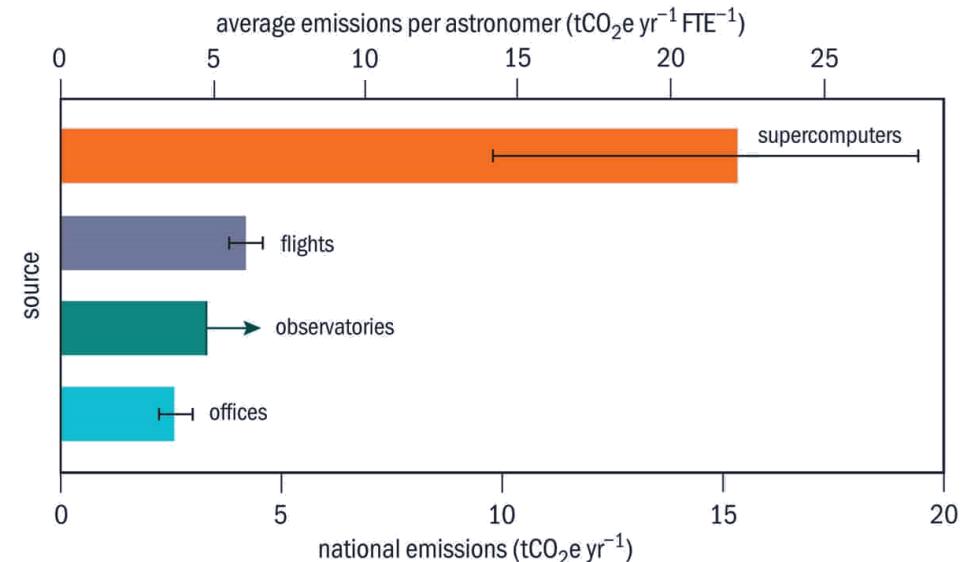
Powering the world's top 500 supercomputers pumps around 2M tCO₂/year

ICTFOOTPRINT EU

BMW Group moves HPC to Iceland to reduce CO₂ by 3.5K tCO₂/year

IOP Publishing

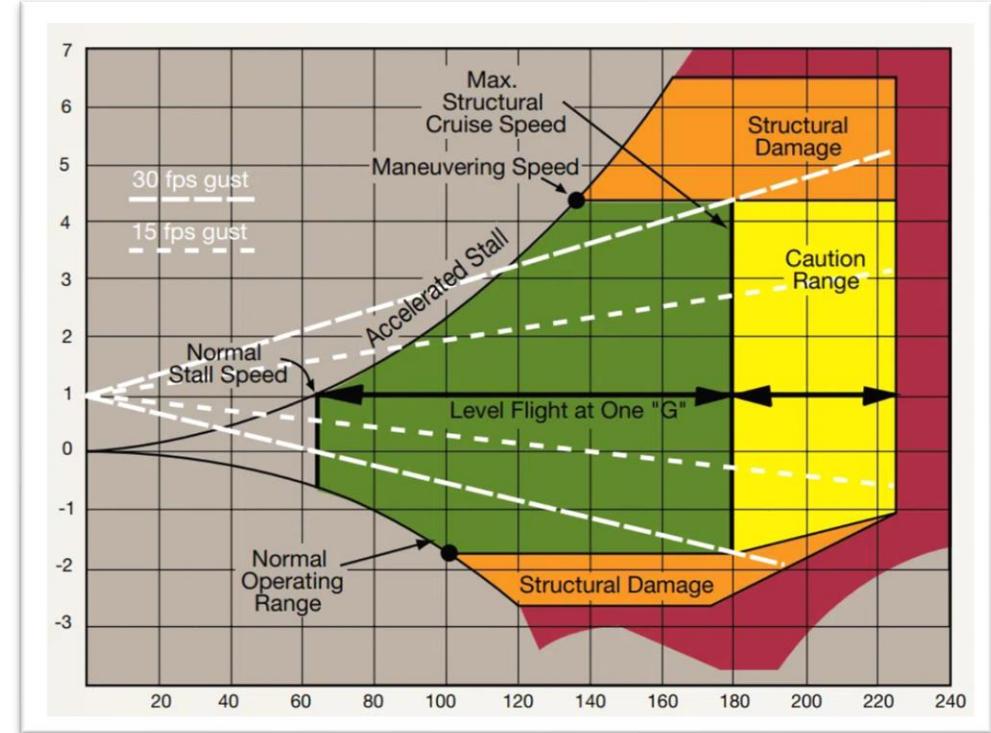
The huge carbon footprint of large-scale computing



The carbon footprint of HPC

CFD for the design of an aircraft

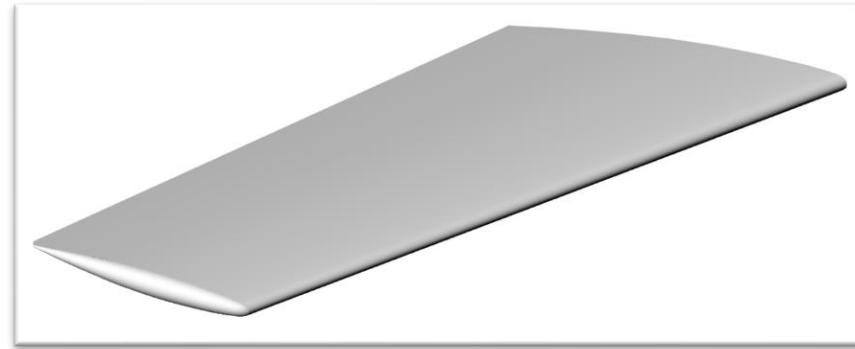
- At least 200 runs to cover the flight envelope
- Each run using ~100M elements (12h using 512 CPU processors)
- 1.7 T CO₂e to perform 200 runs
 - 15.5 MWh
 - 9,840 Km in a passenger car



- NASA estimates that, by 2030, simulations with ~20B elements will be commonplace
- 150 T CO₂e to perform 200 runs
 - 1,350 MWh
 - 858,000 Km in a passenger car (~20 times around the world!)

The carbon footprint of HPC

- From the point of view of simulation efficiency, each operating condition requires a different mesh



(a) $M_\infty = 0.41, \alpha = 8.90^\circ$ (b) $M_\infty = 0.79, \alpha = 5.39^\circ$ (c) $M_\infty = 0.80, \alpha = 8.19^\circ$

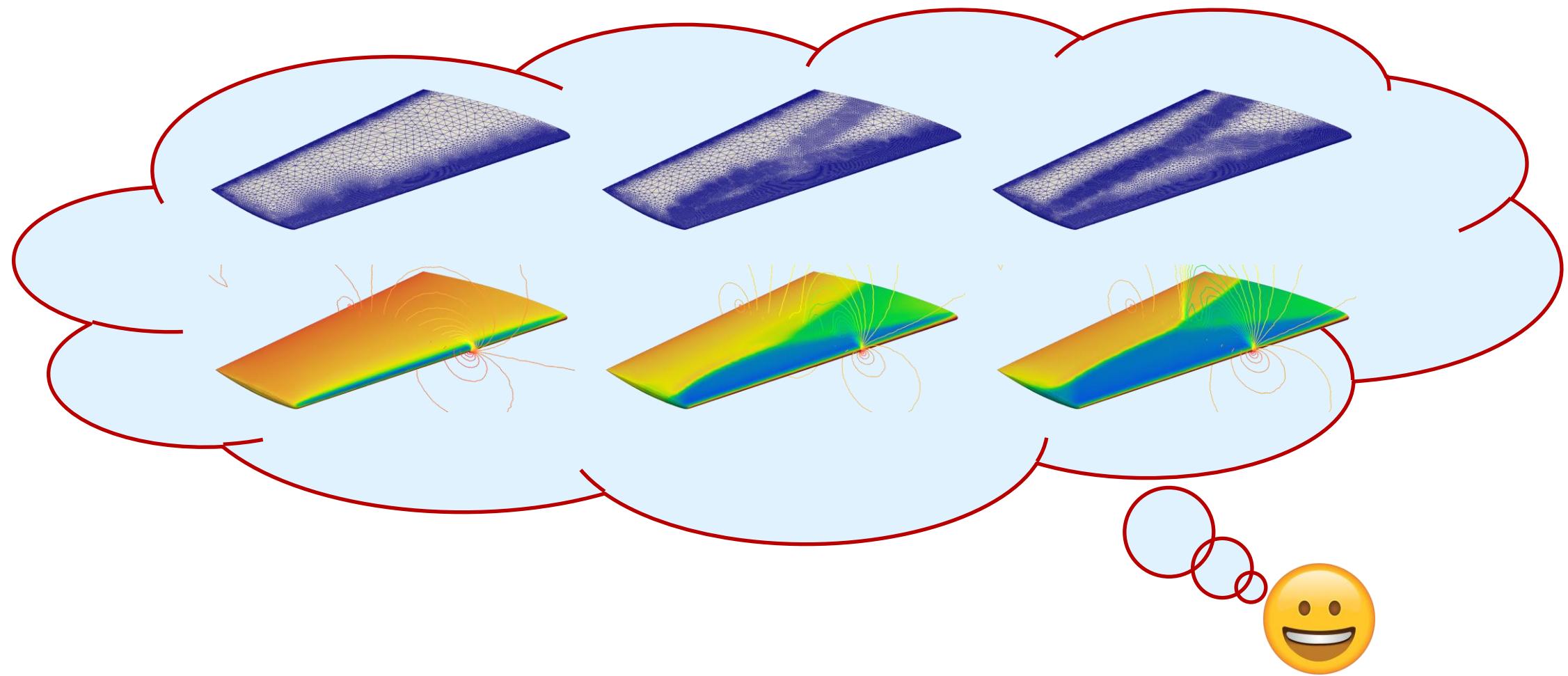
The carbon footprint of HPC

- From the point of view of **simulation efficiency**, each operating condition requires a different mesh

(a) $M_\infty = 0.41, \alpha = 8.90^\circ$

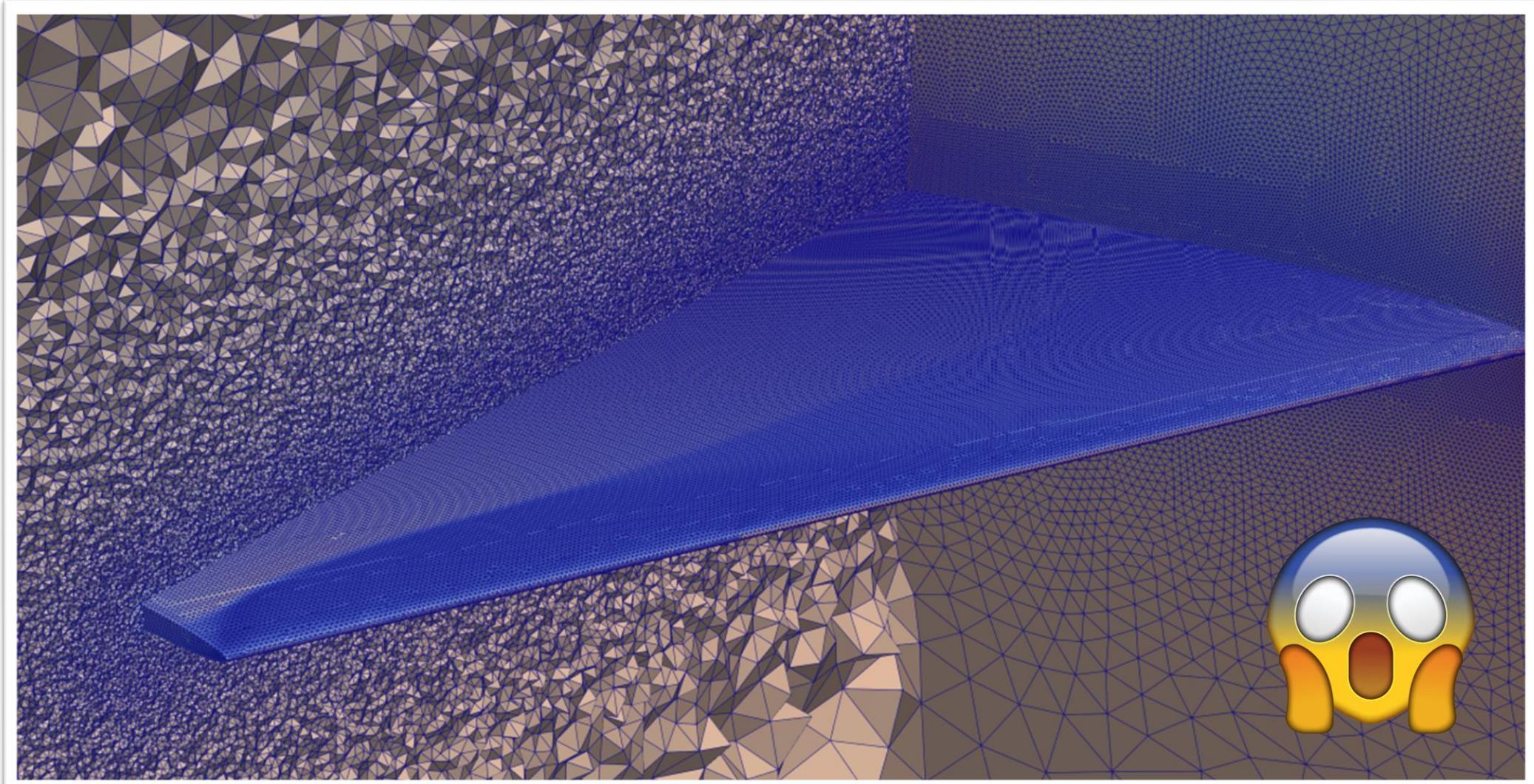
(b) $M_\infty = 0.79, \alpha = 5.39^\circ$

(c) $M_\infty = 0.80, \alpha = 8.19^\circ$



The carbon footprint of HPC

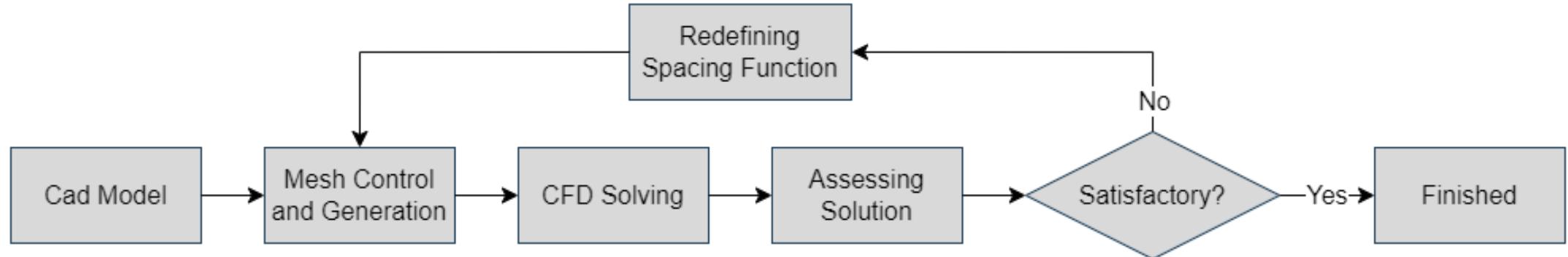
- But current industrial practice involves using over-refined meshes to avoid the requirements of **human expertise** and the **time-consuming** process of tailoring meshes



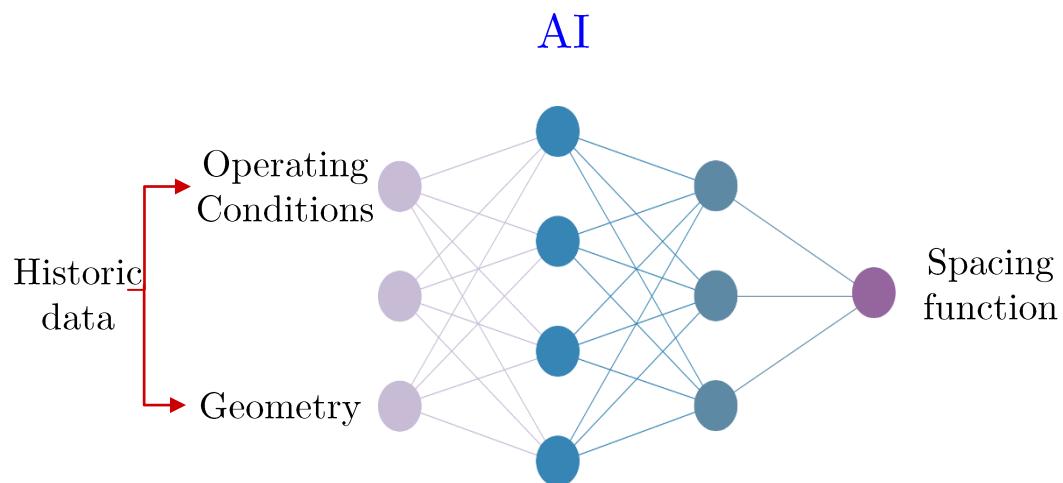
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AI system to predict mesh spacing

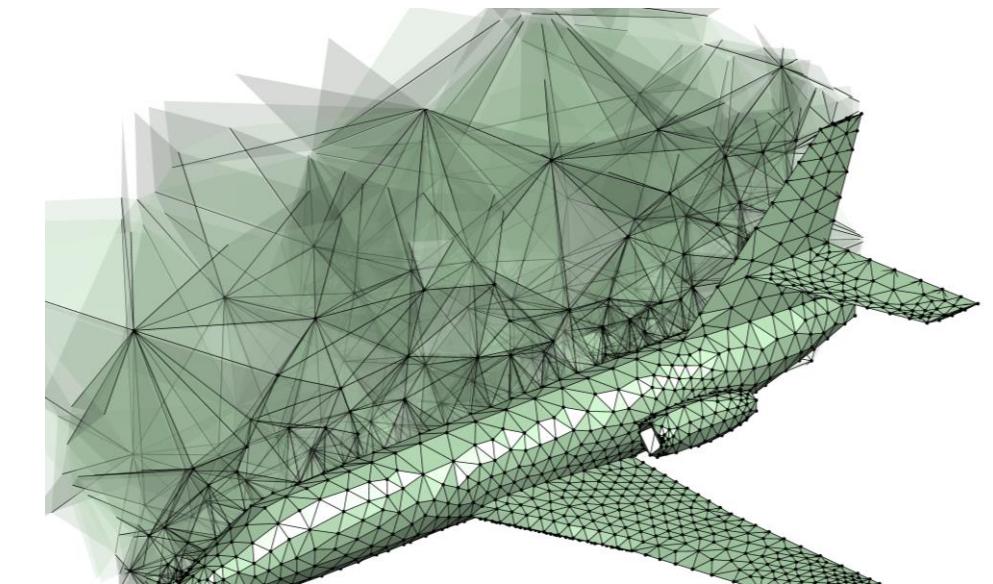
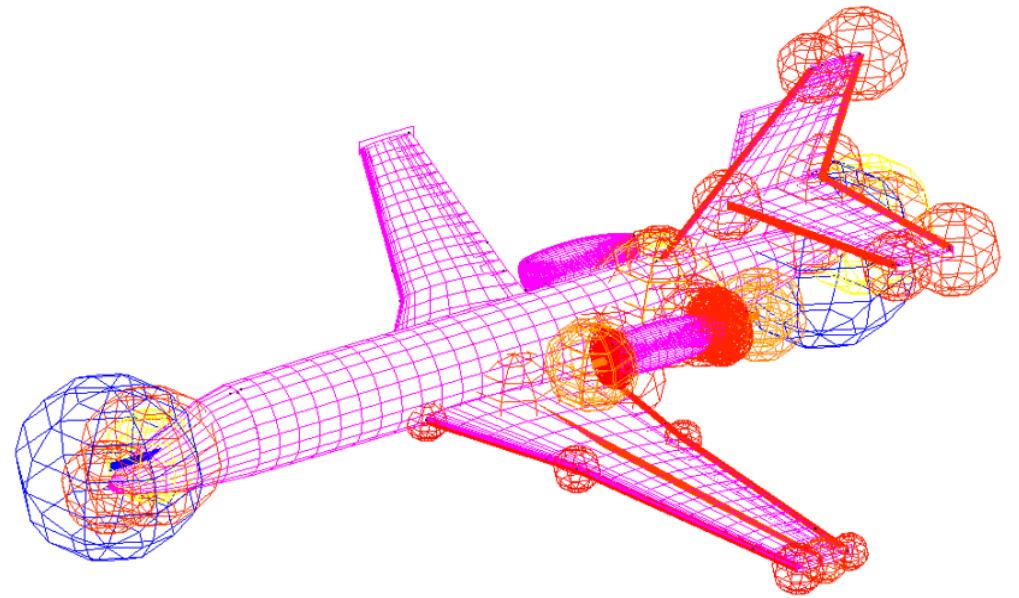


- Develop an AI capable of **speeding up and automating** the mesh generation process
- Accelerate **mesh independent solution** and speeding up the design process
- Preserving and utilising **previous learnt knowledge**



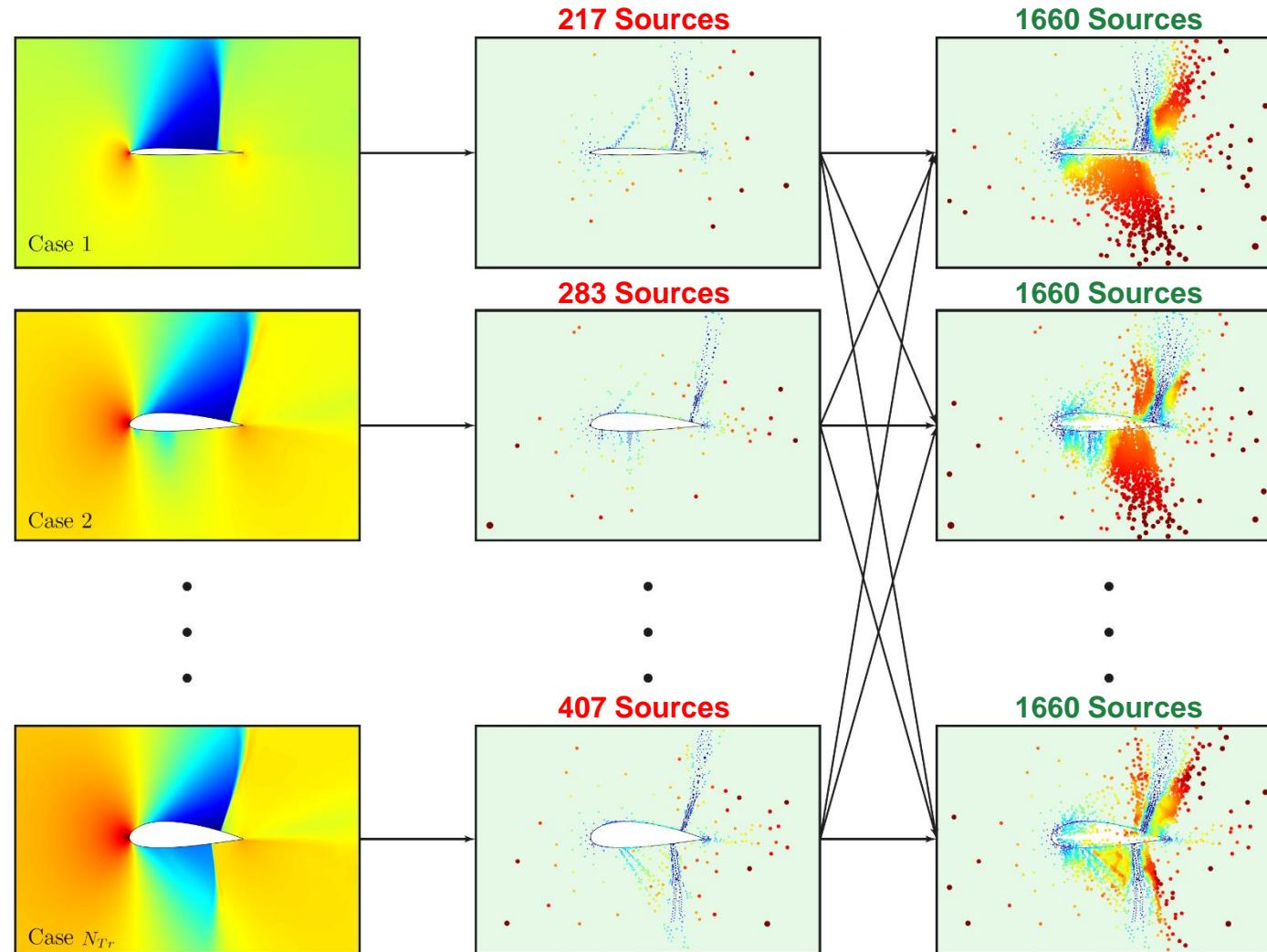
AI system to predict mesh spacing

- How is a **spacing function** usually defined?
- **Mesh sources** (point, lines, planes, etc)
 - A point source is defined by a **position**, a desired **spacing** and a **radius** of influence
 - The spacing at any point is calculated as the minimum spacing defined by all the sources
- **Background mesh**
 - A (discrete) **nodal spacing** function is given
 - The spacing at any point is interpolated from the nodal spacing function in the (coarse) background mesh



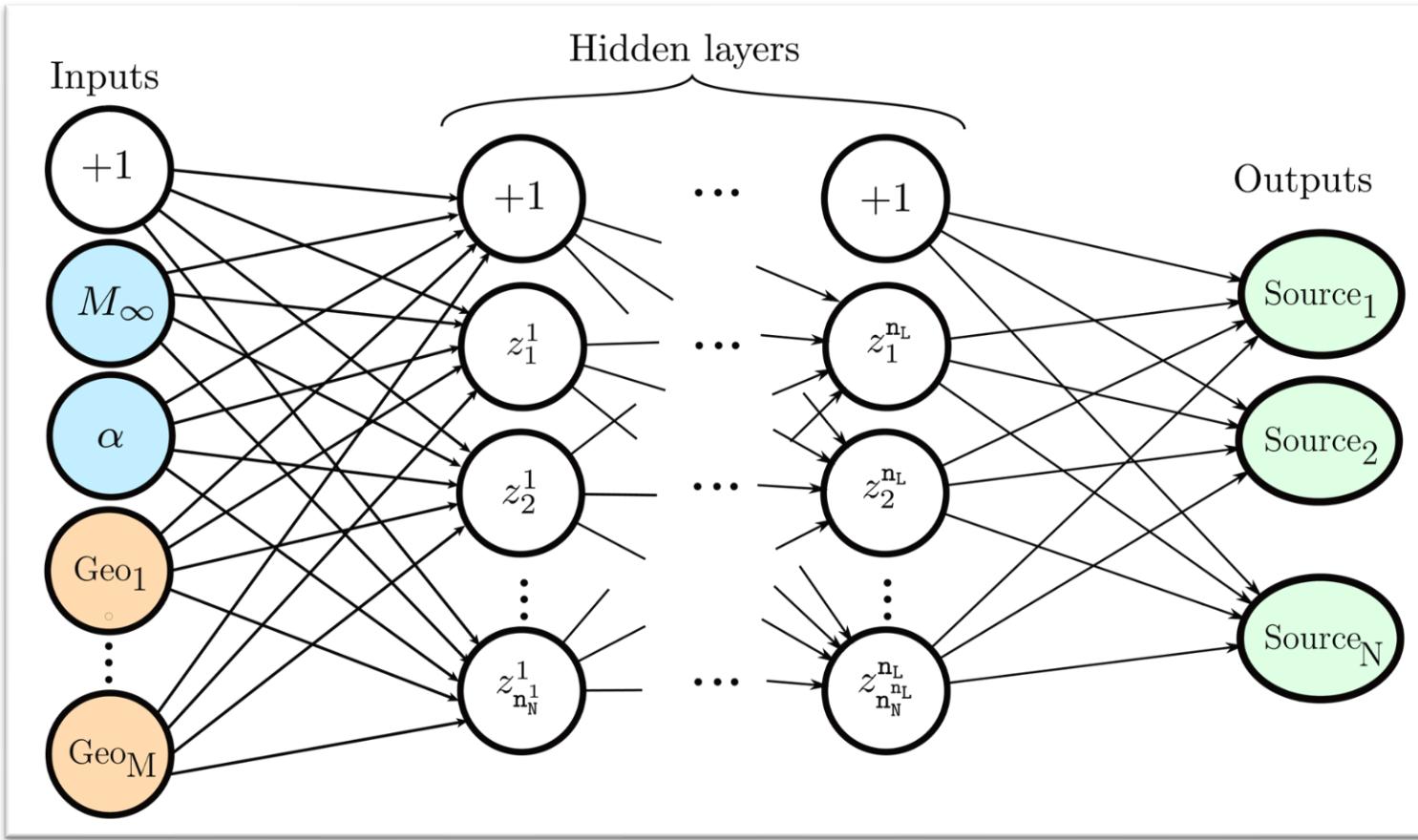
AI system to predict mesh spacing (using sources)

- Step 1 – Generate **point sources** from a given solution
- Step 2 – Generate **global sources** from sets of local sources



AI system to predict mesh spacing (using sources)

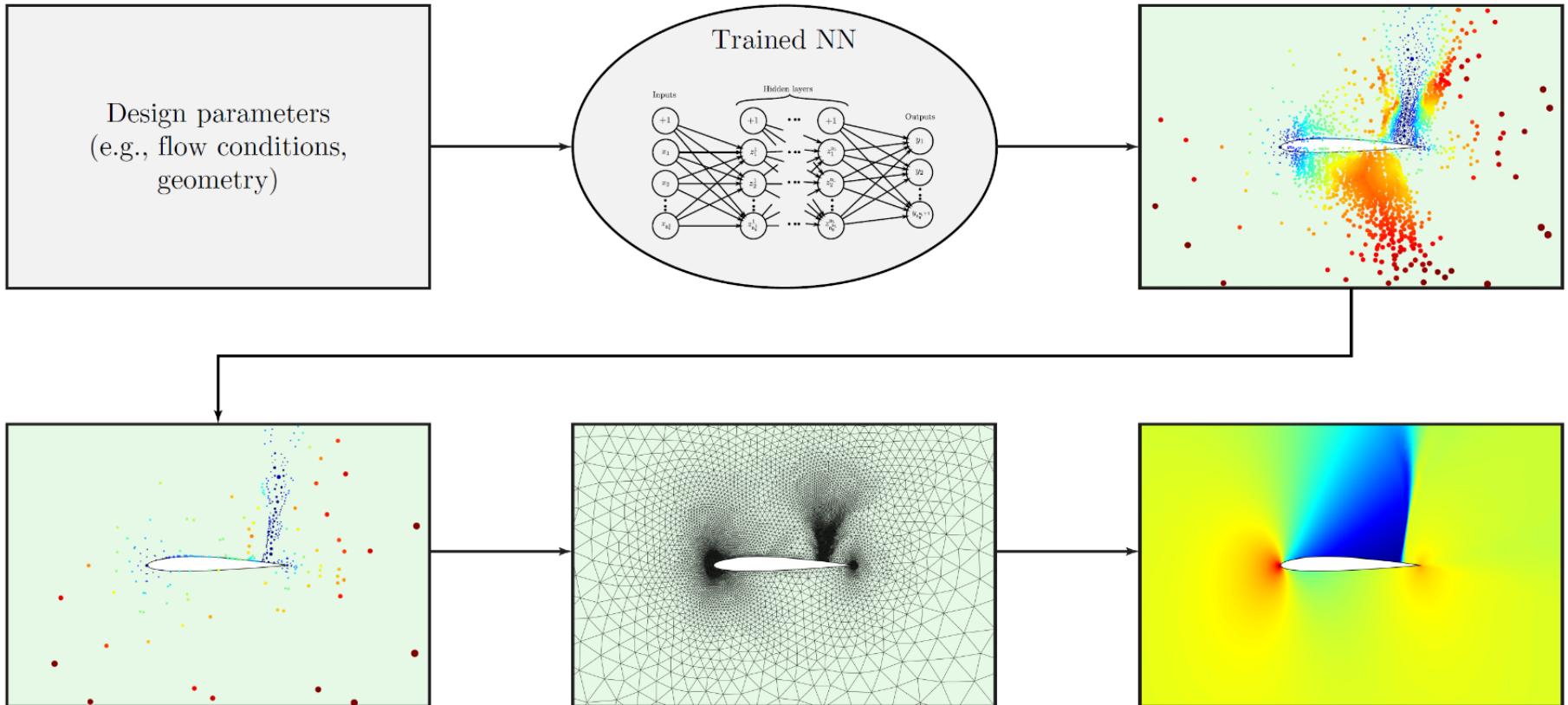
- Neural network architecture



- Each output involves a **position** (3 coordinates), a **spacing** and a **radius** of influence.

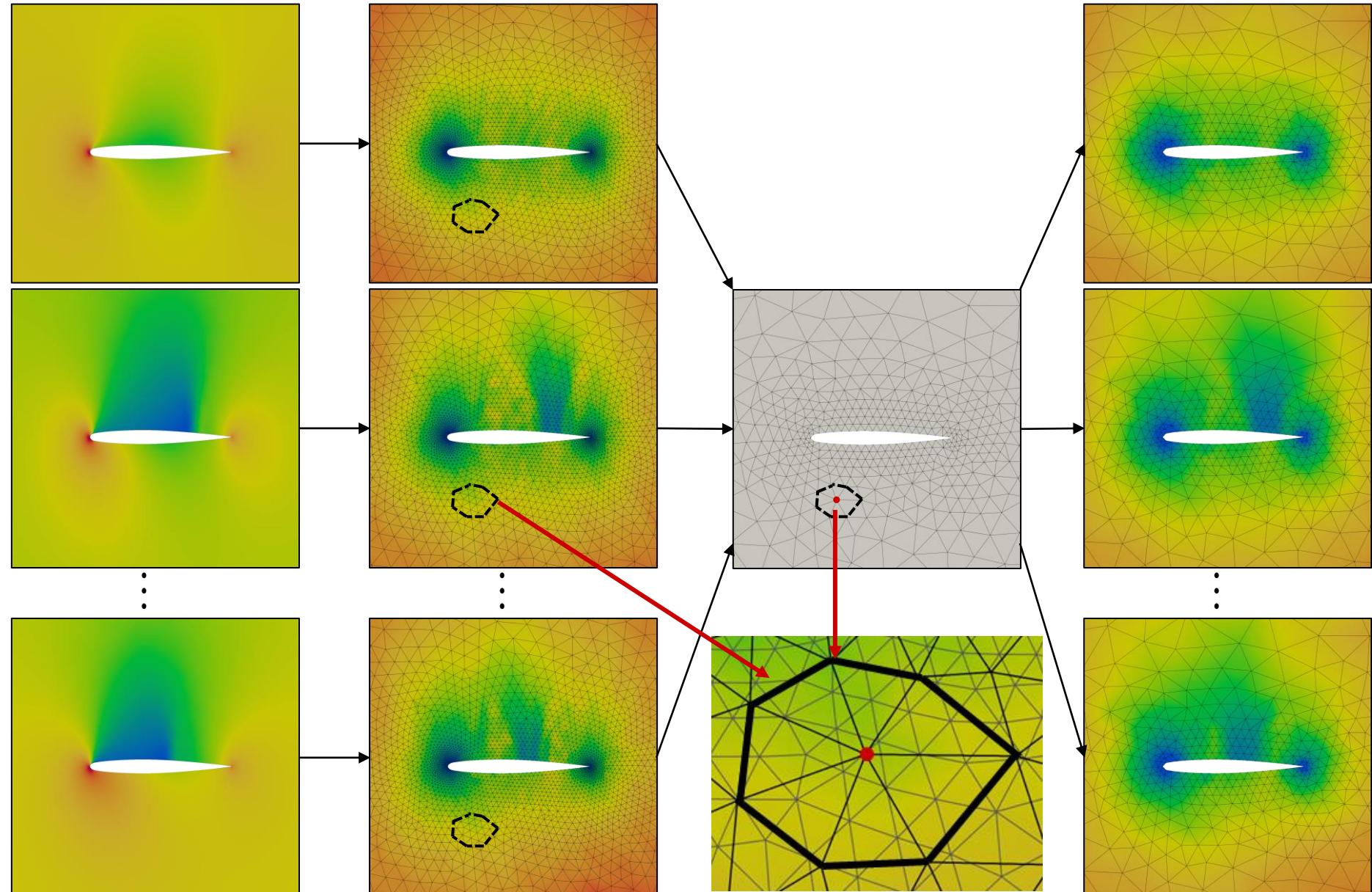
AI system to predict mesh spacing (using sources)

- Step 3 –
Use the trained
NN to **predict**
the sources
characteristics
- Step 4 –
Reduce the
global set of
sources



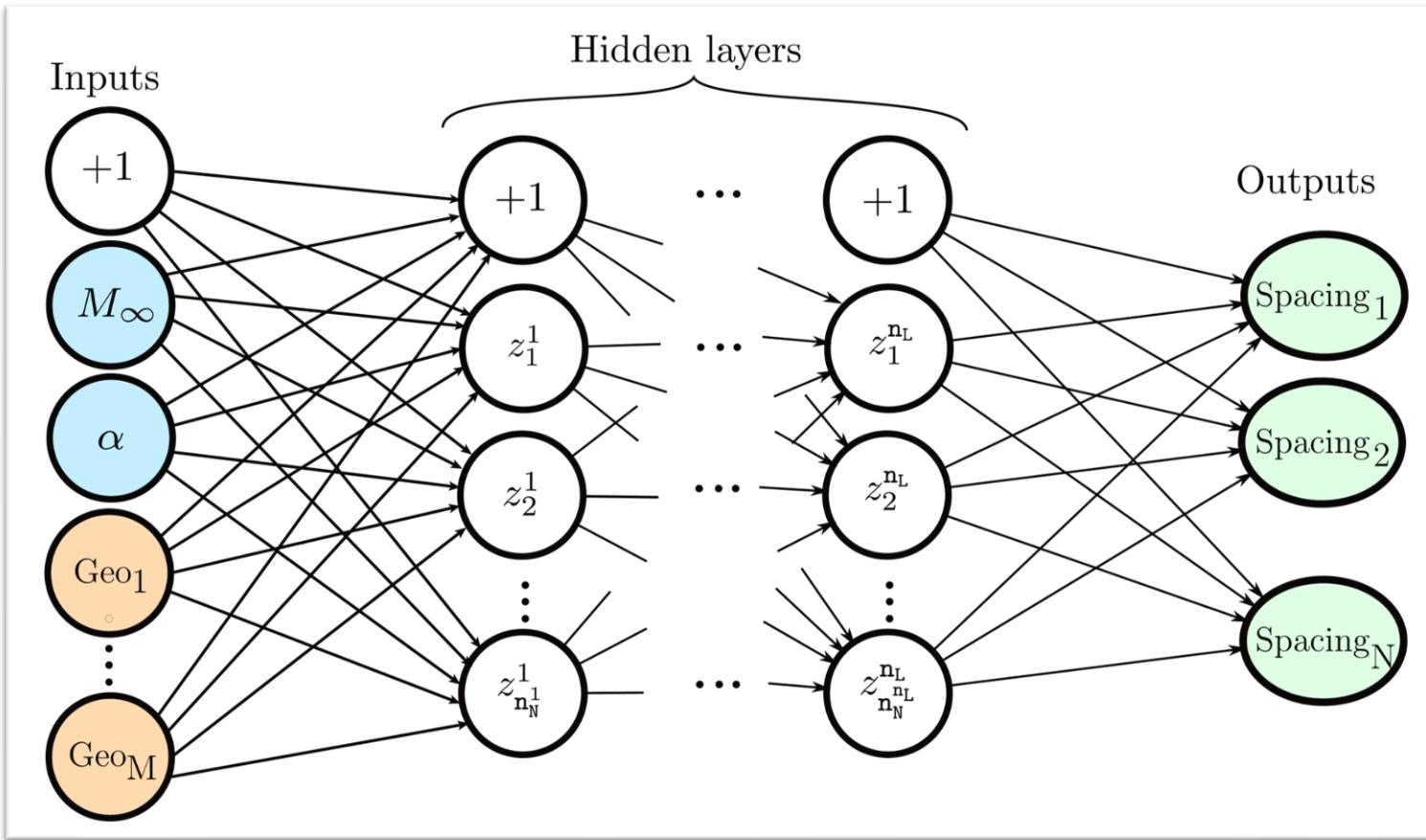
AI system to predict mesh spacing (using a background mesh)

- Generate a **spacing function** from a given solution
- Interpolate the spacing onto a background mesh
- Take a conservative approach to interpolation



AI system to predict mesh spacing (using a background mesh)

- Neural network architecture



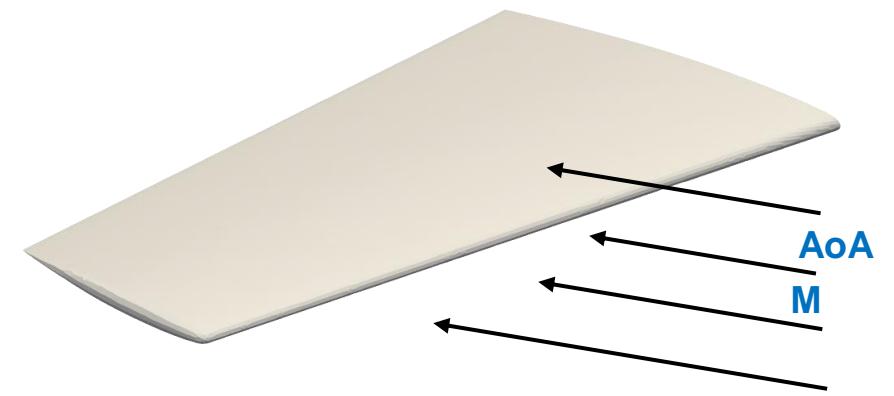
- Each output involves a spacing
- It requires **mesh morphing** for variable geometric configurations

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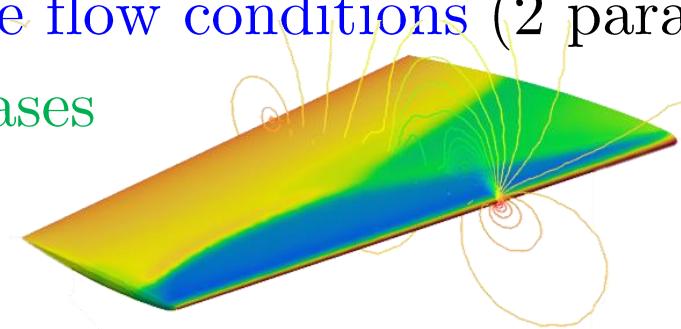
Examples

- ONERA M6 wing – Variable flow conditions
 - Mach [0.3, 0.9]
 - Angle of Attack [0, 12]
- Solution from an inviscid compressible flow solver
- 10, 20, 40, 80, 120, 160 training cases, with 100 test cases
- Hyperparameters are tuned
 - Number of hidden layers – 1, 2,...,6
 - Neurons per layer – 25, 50, 75, ..., 200, 225, 250
- Using sources
 - 19,345 global point sources
- Using background mesh
 - 14,179 nodes

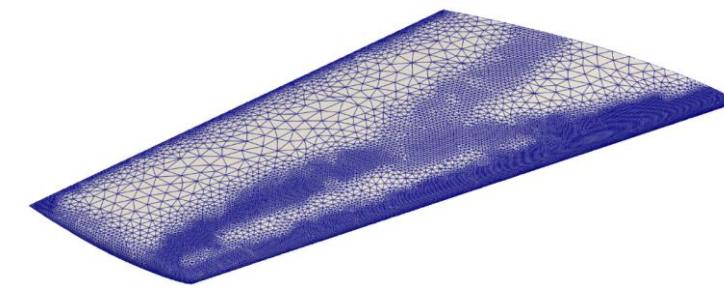


Examples

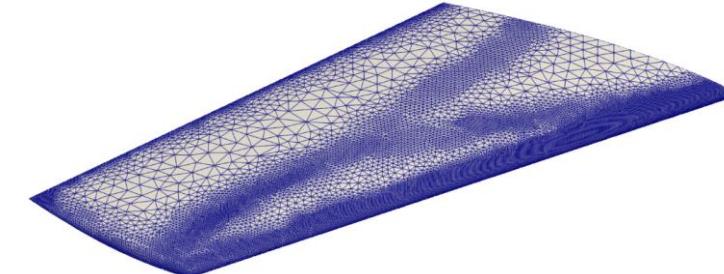
- ONERA M6 wing – Variable flow conditions (2 parameters) – 160 training cases
- Prediction for **unseen test cases**
 - $M=0.79$, $AoA=5.39^\circ$



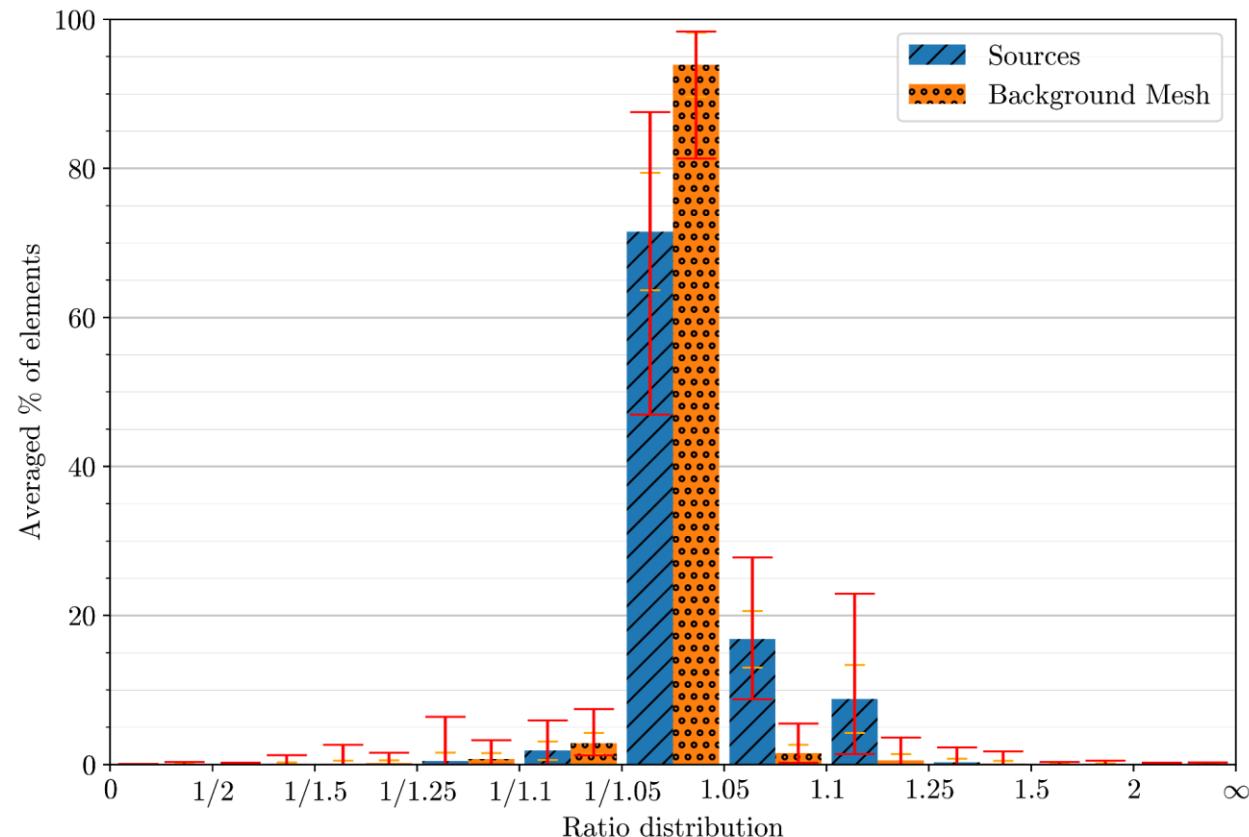
Target



ML
Prediction

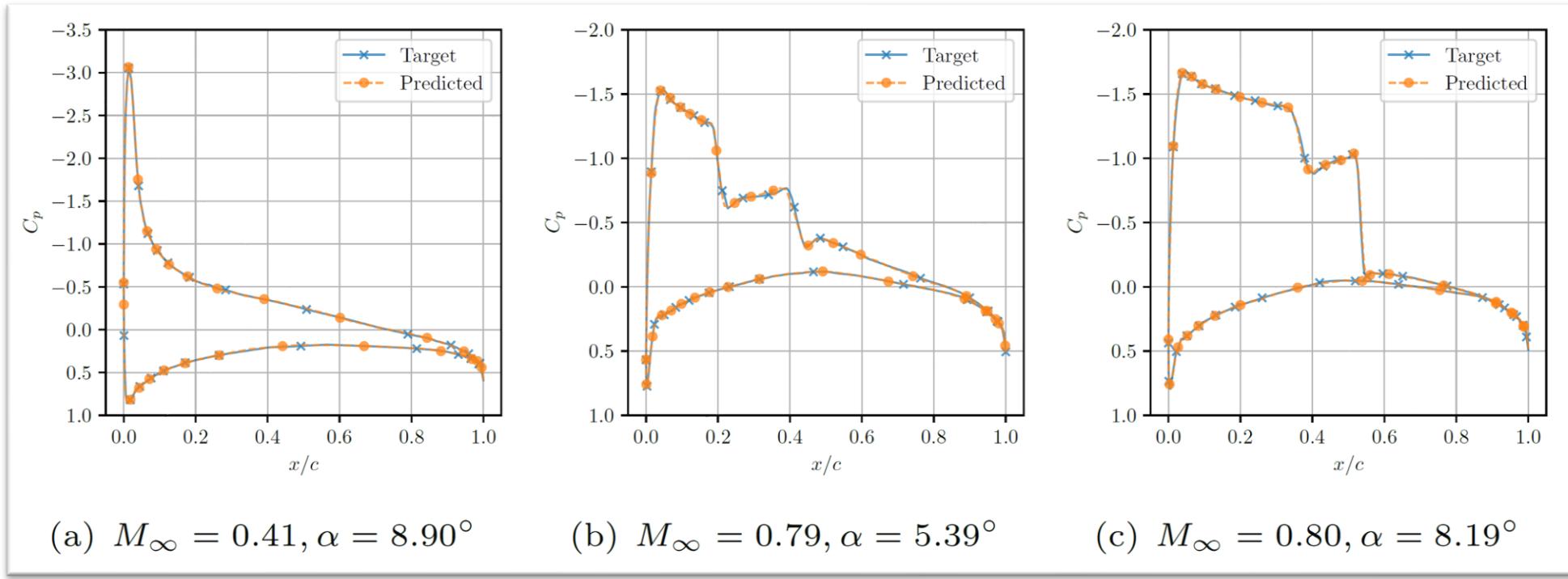


- Using sources, the spacing at **72% of the points** are predicted within 5% of the target
- Using a background mesh, the spacing at **94% of the points** are predicted within 5% of the target



Examples

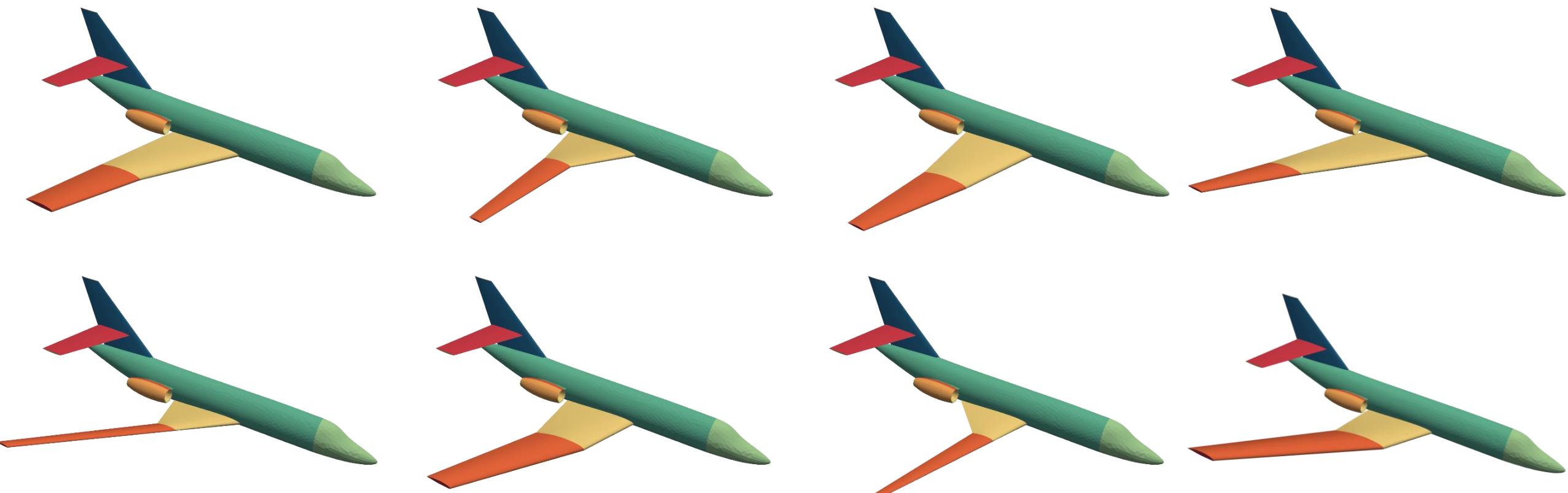
- ONERA M6 wing – Variable flow conditions (2 parameters) – 160 training cases
- Suitability of predicted meshes to perform simulations



$M_\infty = 0.41, \alpha = 8.90^\circ$		$M_\infty = 0.79, \alpha = 5.39^\circ$		$M_\infty = 0.80, \alpha = 8.19^\circ$		
Target	Prediction	Target	Prediction	Target	Prediction	
C_L	0.605	0.603	0.469	0.468	0.722	0.723
C_D	0.0342	0.0340	0.0289	0.0287	0.0828	0.0828

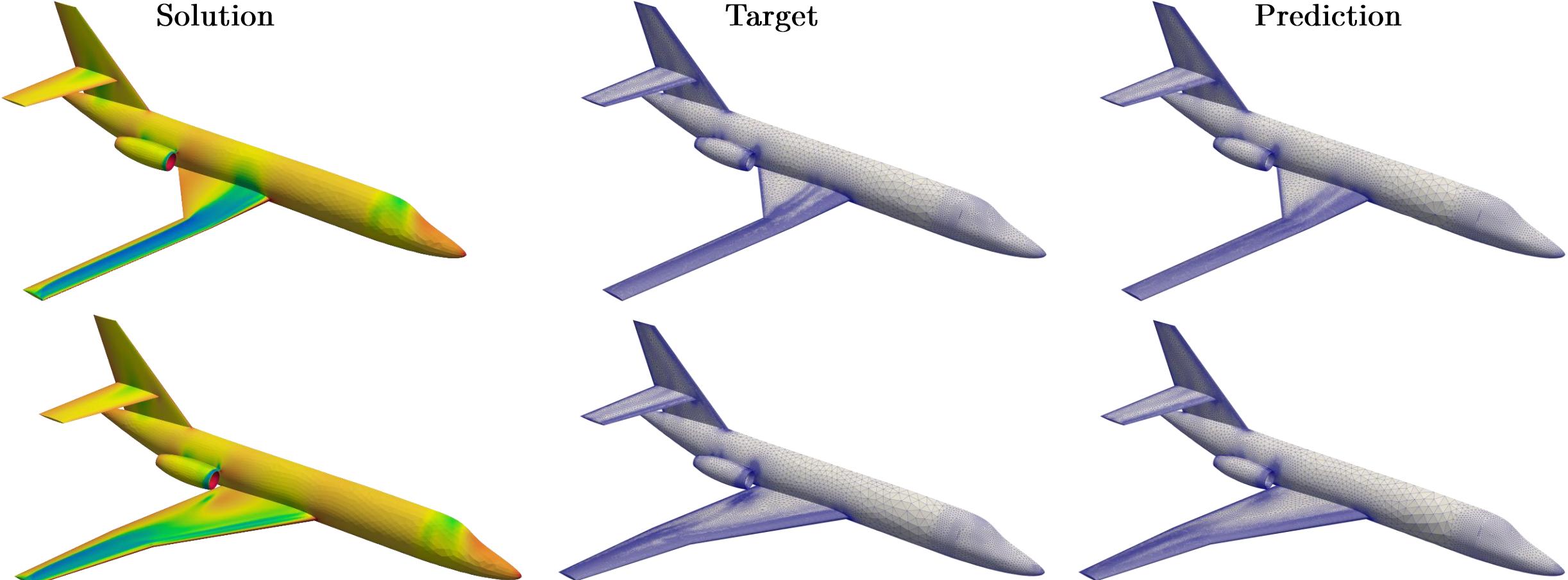
Examples

- Full aircraft – Variable geometry (11 parameters)
 - Spacing prediction using a background mesh
 - Flow conditions – $M=0.8$, $AoA=2^\circ$



Examples

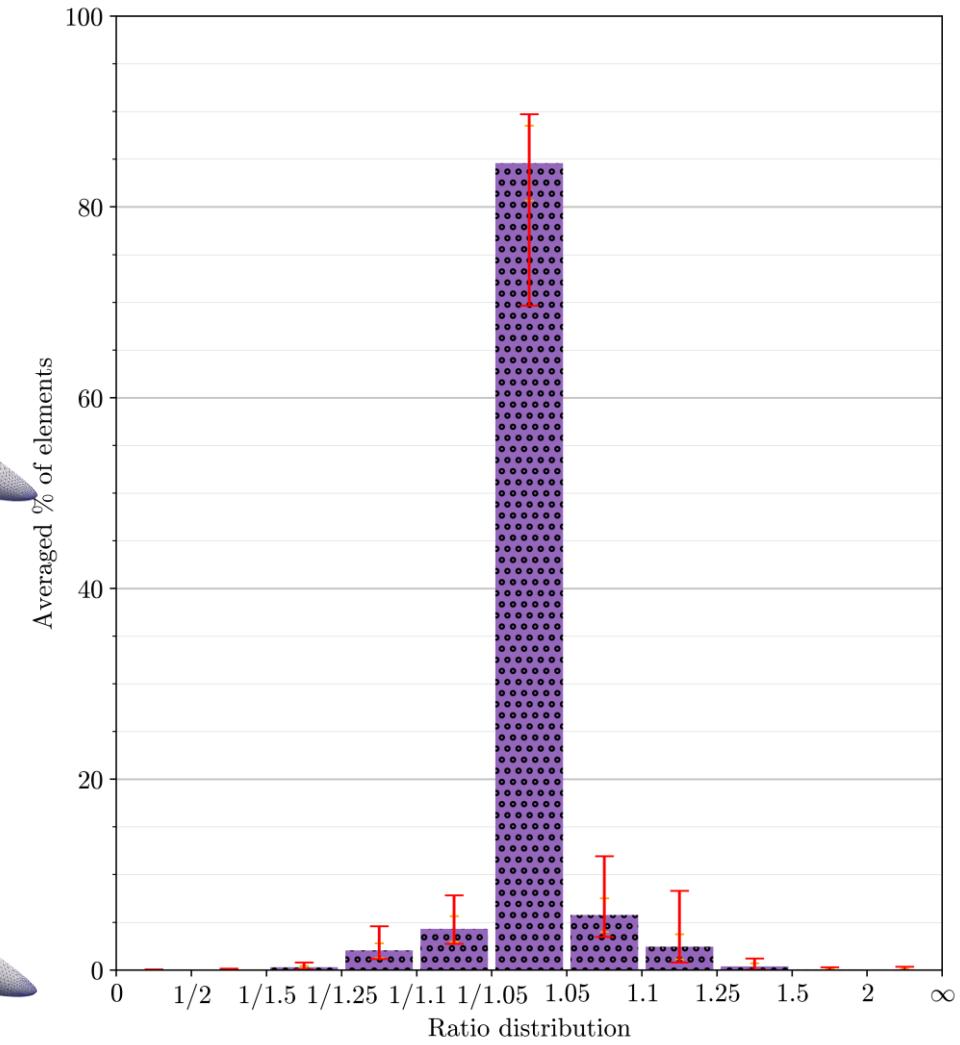
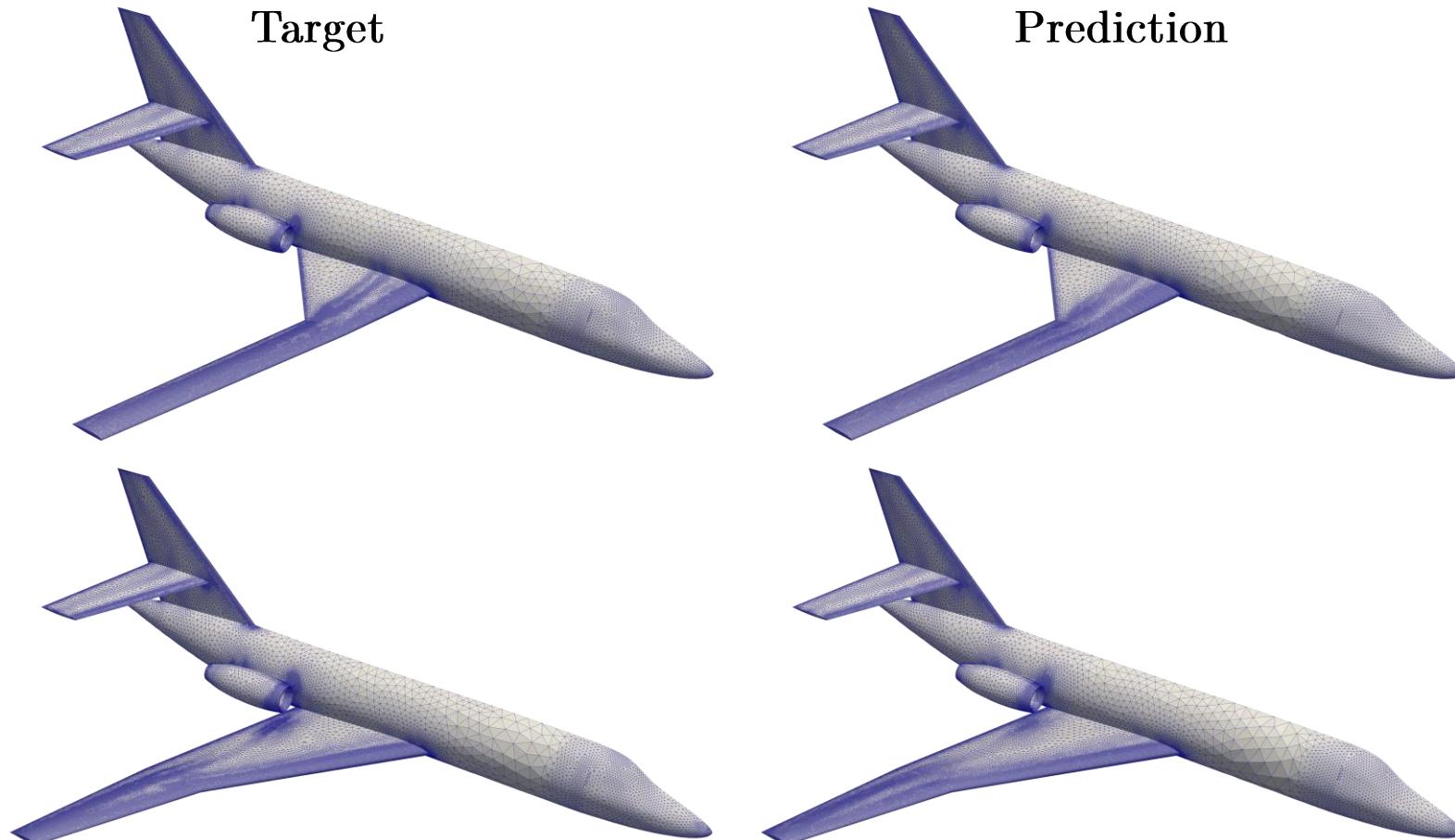
- Full aircraft – Variable geometry (11 parameters) – 160 training cases
 - Spacing prediction using a background mesh
 - Flow conditions – $M=0.8$, $AoA=2^\circ$



- Spacing at 83% of the points are predicted within 5% of the target

Examples

- Full aircraft – Variable geometry (11 parameters) – 160 training cases
 - Spacing prediction using a background mesh
 - Flow conditions – $M=0.8$, $AoA=2^\circ$



- Spacing at 83% of the points are predicted within 5% of the target

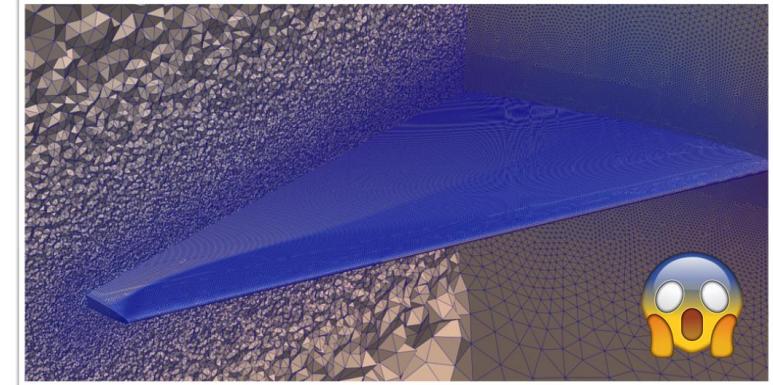
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How green is the AI system?

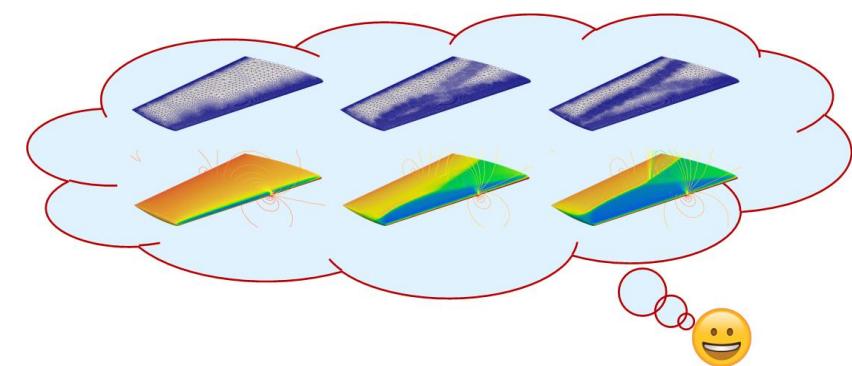
- Carbon footprint for the parametric study using a **fixed mesh**

Task	Wall clock (H)	Carbon (Kg CO ₂ e)	Energy (MWh)
Mesh generation	1.0	3.61×10^{-3}	5.89×10^{-5}
CFD solution	3,432.10	527.17	2.28
Total	3,433.0	527.17	2.28



- Carbon footprint for the parametric study using **AI predicted meshes**

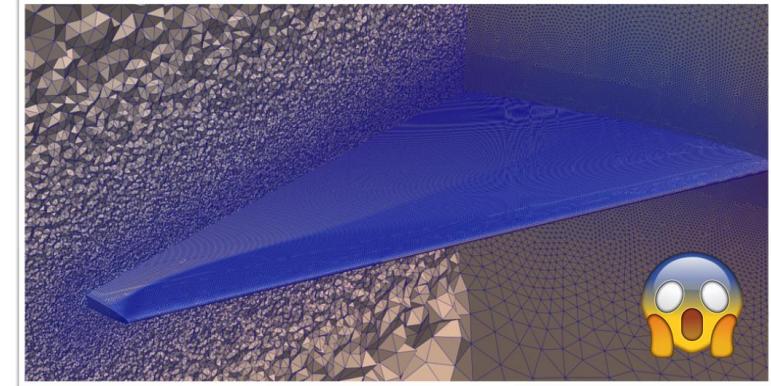
Task	Wall clock (H)	Carbon (Kg CO ₂ e)	Energy (MWh)
Mesh generation	23.8	0.32	1.40×10^{-3}
CFD solution	143.0	12.36	5.35×10^{-2}
Total	166.8	12.68	0.055



How green is the AI system?

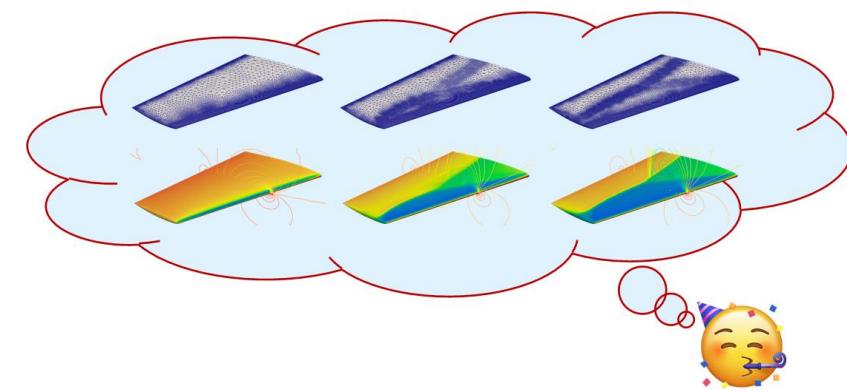
- Carbon footprint for the parametric study using a **fixed mesh**

Task	Wall clock (H)	Carbon (Kg CO ₂ e)	Energy (MWh)
Mesh generation	1.0	3.61×10^{-3}	5.89×10^{-5}
CFD solution	3,432.10	527.17	2.28
Total	3,433.0	527.17	2.28



- Carbon footprint for the parametric study using **AI predicted meshes**

Task	Wall clock (H)	Carbon (Kg CO ₂ e)	Energy (MWh)
NN tuning and training	156.6	2.13	9.22×10^{-3}
Mesh generation	23.8	0.32	1.40×10^{-3}
CFD solution	143.0	12.36	5.35×10^{-2}
Total	323.4	14.81	0.064



TOTAL carbon footprint is more than 35 times lower

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Concluding remarks

- A green AI system to predict near-optimal mesh spacing for new simulations
 - Operating conditions
 - Geometric variations
- Prediction of mesh spacing within 5% of target for 83% of points for geometric variations involving 11 parameters and using 160 training cases in 3D
- Meshes proved to be suitable to perform simulations of unseen cases
- Current work focuses on
 - Turbulent compressible viscous flows and CAD integration
 - Predicting mesh anisotropy
 - Automatic selection of a background mesh or combine sources and a background mesh

