UNIVERSIDAD POLITÉCNICA DE MADRID

E.T.S. de Ingenieros Aeronáuticos

POLITÉCNICA

New avenues in computational fluid dynamics

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Esteban Ferrer

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R Vinuesa (KTH), S Sherwin (IC), R Willden (Oxford), H Blackburn (Monash)

Industrial collaborators: Numeca-Cadence, Airbus, Dassault Syst., Siemens-Gamesa…

Funding

Comunidad de Madrid
Dirección General de Investigación e Innovación Tecnológica
CONSEJERÍA DE CIENCIA, NIVERSIDADES E INNOVACIÓN

Supported by the Government of the Community of Madrid and European Union's NextGeneration EU programme

Financiado por la Unión Europea NextGenerationEU
GOBIERNO DE ESPAÑA MINISTERIO DE UNIVERSIDADES

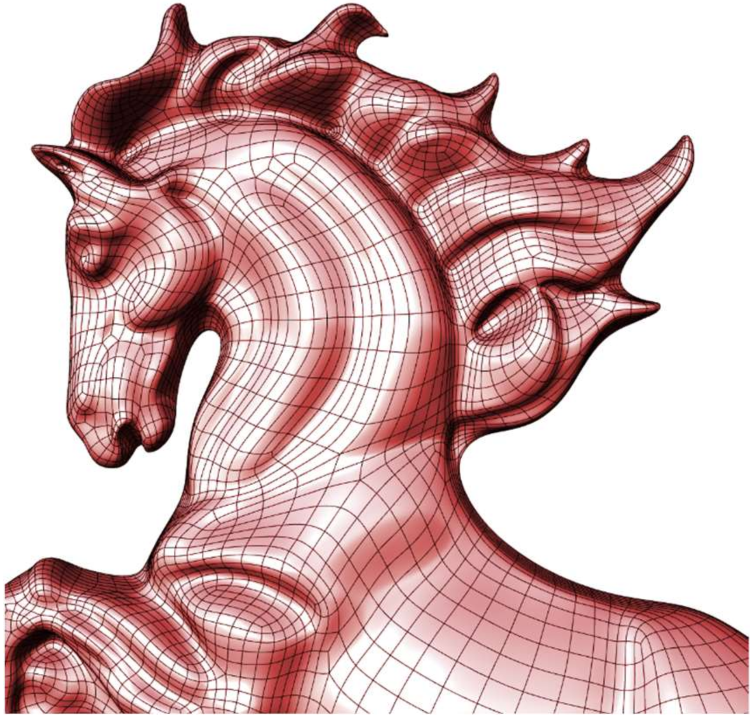
We thank the support of Agencia Estatal de Investigación for the grant "Europa Excelencia" for the project EUR2022-134041 funded by MCIN/AEI/10.13039/501100011033) y the European Union NextGenerationEU/PRTR

Funded by the European Union
European Research Council
Established by the European Commission

This research has been cofunded by the European Union (ERC, Off-coustics, project number 101086075). Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Council. Neither the European Union nor the granting authority can be held responsible for them

Summary

1- Introduction to DG & Horses3d



2- Multiphysics

→ Wind turbines
→ Turbulence

3. Machine Learning + CFD

→ Mesh adaption
→ NN acceleration
→ RL for automation

DGSEM: nodal Discontinuous Galerkin Spectral Element Methods

- **Compressible & Incompressible**
- **Entropy / Energy conserving schemes for stability**
- **Local p-adaption / h-adaption** (hanging nodes)
- **Explicit / implicit time stepping**
- **Turbulence models: LES**: SVV-Smag., Wale, Vreman & **RANS**: Spallart-Almaras
- **Multi-physics:** Multiphase, Immersed Boundaries, Shock etc..

HORSES3D https://github.com/loganoz/horses3d

Computer Physics Communications 287 (2023) 108700

Contents lists available at ScienceDirect

Computer Physics Communications

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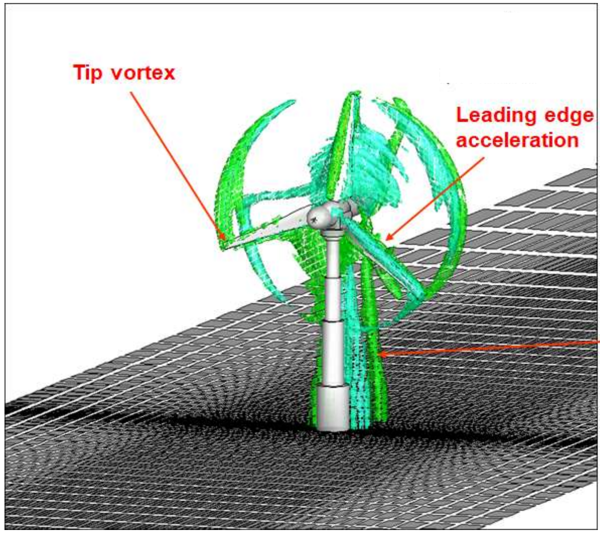
ELSEVIER

HORSES3D: A high-order discontinuous Galerkin solver for flow simulations and multi-physics applications ☆,☆☆

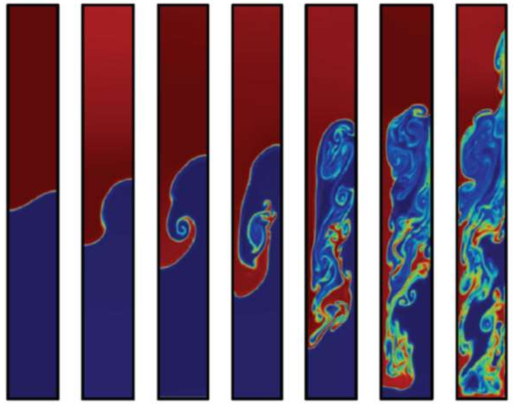
E. Ferrer [a,b], G. Rubio [a,b,*], G. Ntoukas [a], W. Laskowski [a], O.A. Mariño [a], S. Colombo [a], A. Mateo-Gabín [a], H. Marbona [a], F. Manrique de Lara [a], D. Huergo [a], J. Manzanero [e], A.M. Rueda-Ramírez [c], D.A. Kopriva [d], E. Valero [a,b]

HORSES3D

http://github.com/loganoz/horses3d

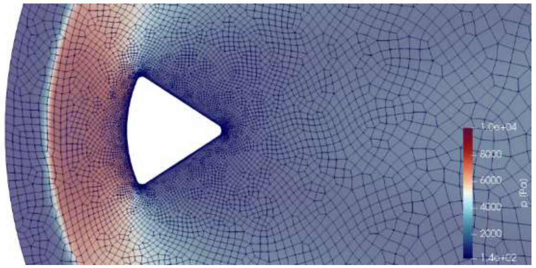


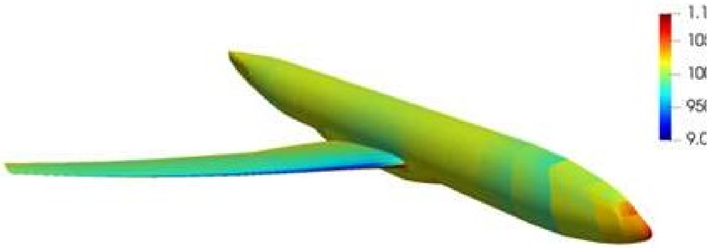
Mesh free



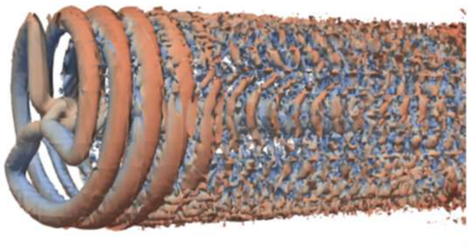
Multiphase

Shocks

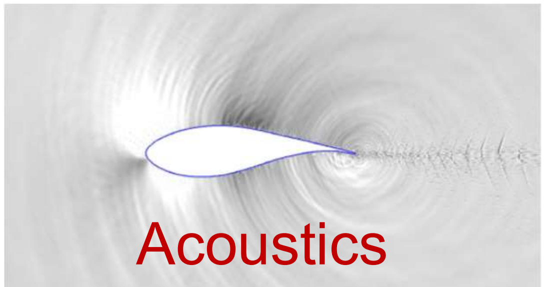




RANS



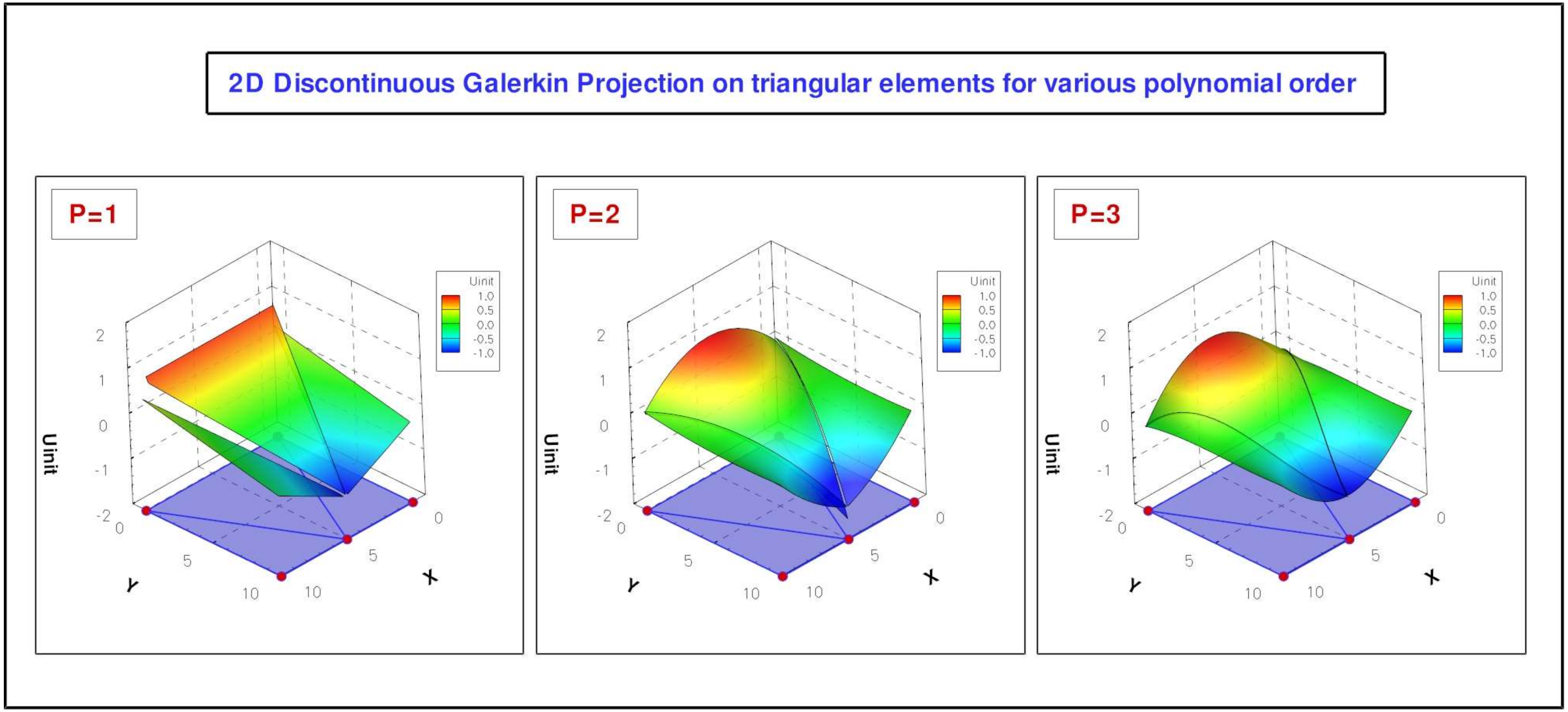
LES



Acoustics

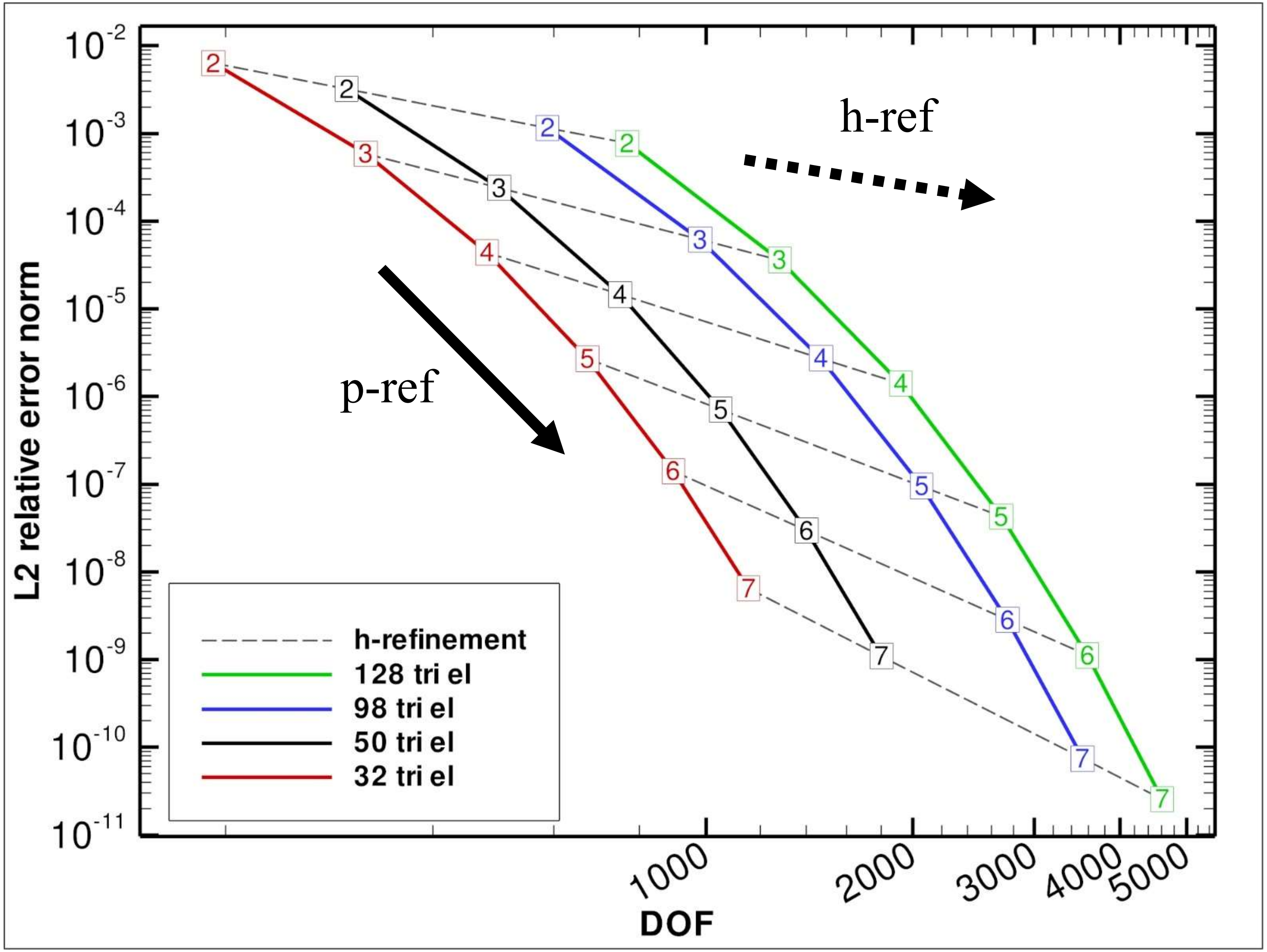
E Ferrer, G Rubio, G Ntoukas, W Laskowski, O Mariño, S Colombo, A. Mateo-Gabín, F Manrique de Lara, D Huergo, J Manzanero, AM Rueda-Ramírez, DA Kopriva, E Valero, "HORSES3D: a high order discontinuous Galerkin solver for flow simulations and multi-physic applications", *Computer Physics Communications*, Vol 287, 2023

High order methods

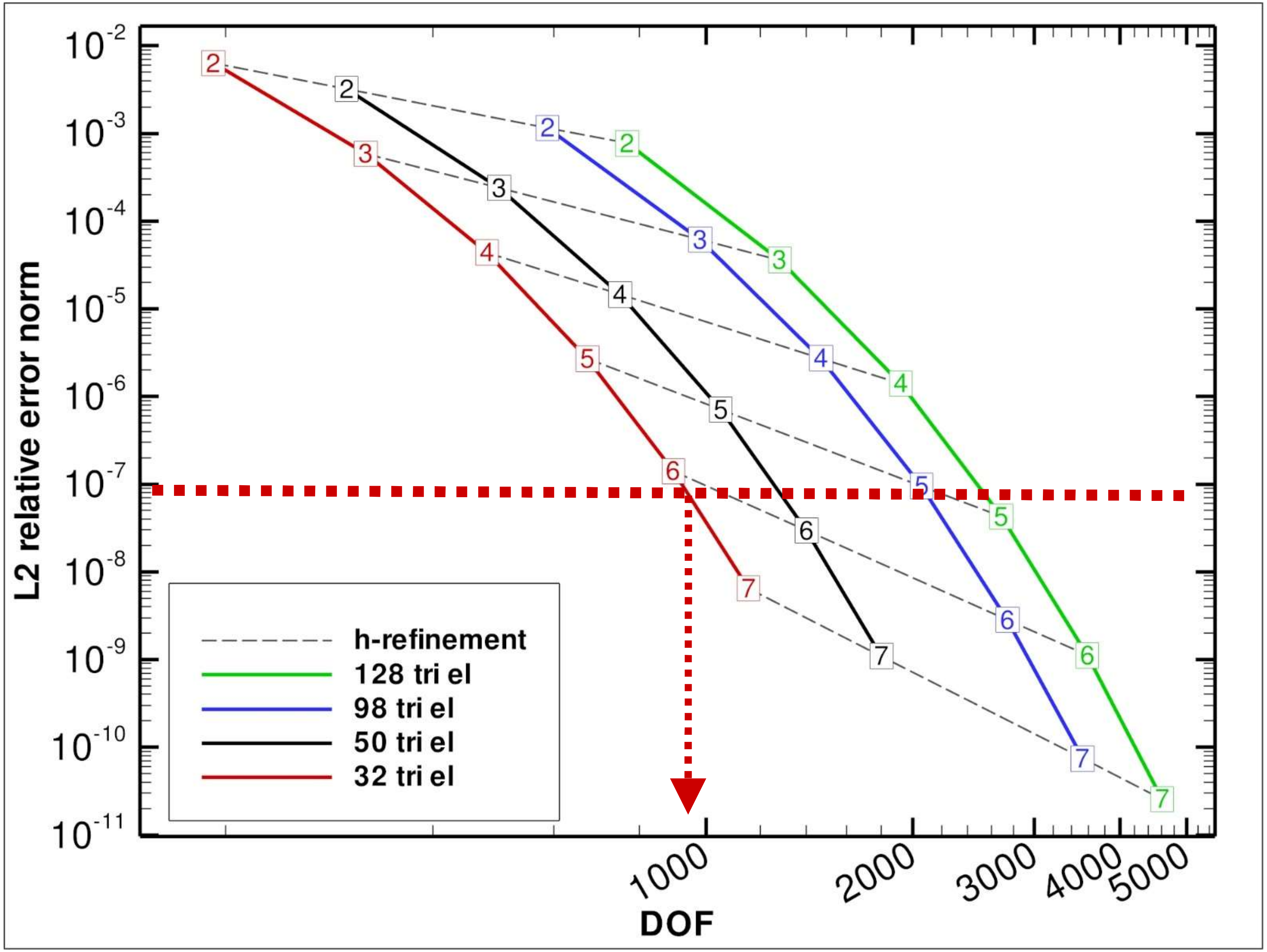


- **High order is generally defined for P ≥ 2**
- **High order allows *h/p* refinement**
  - ***h*-refinement offers constant decay of the error**
  - ***p*-refinement offers exponential decay of the error**

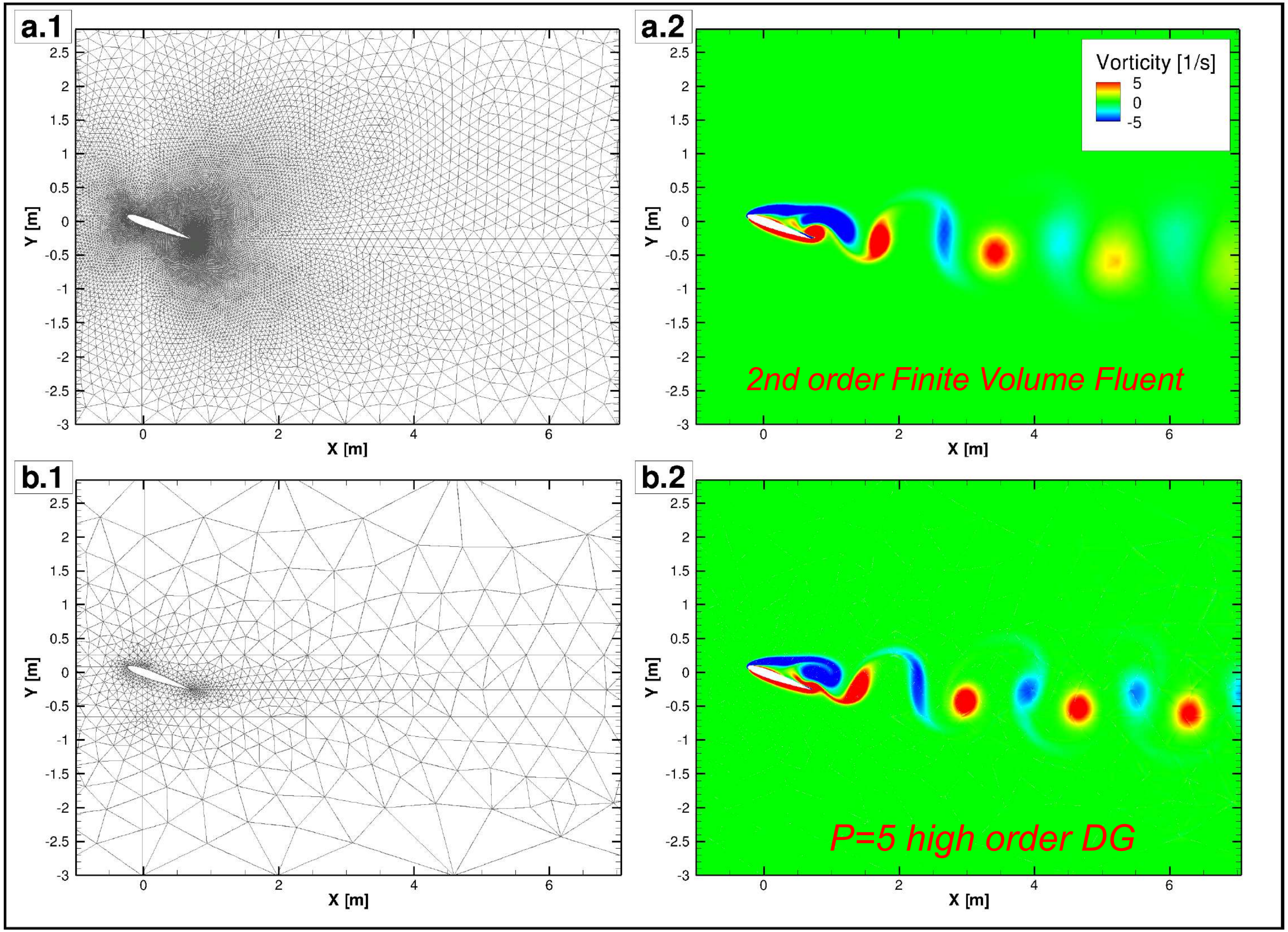
High order methods (Poisson eq.)



High order methods (Poisson eq.)



NACA0012 - Re=800 - Laminar flow

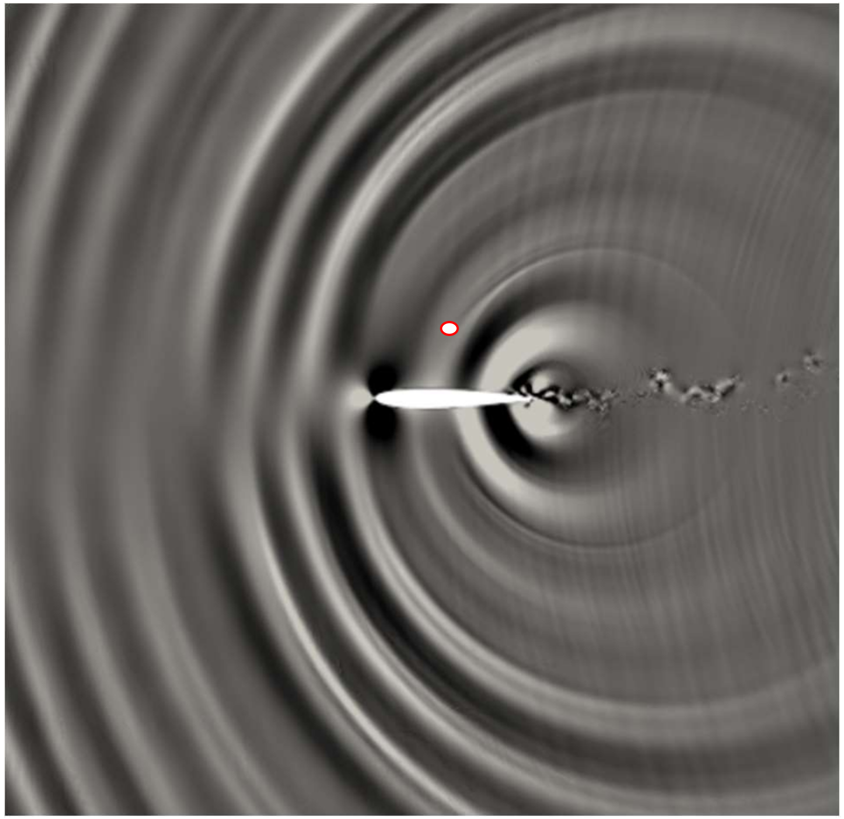


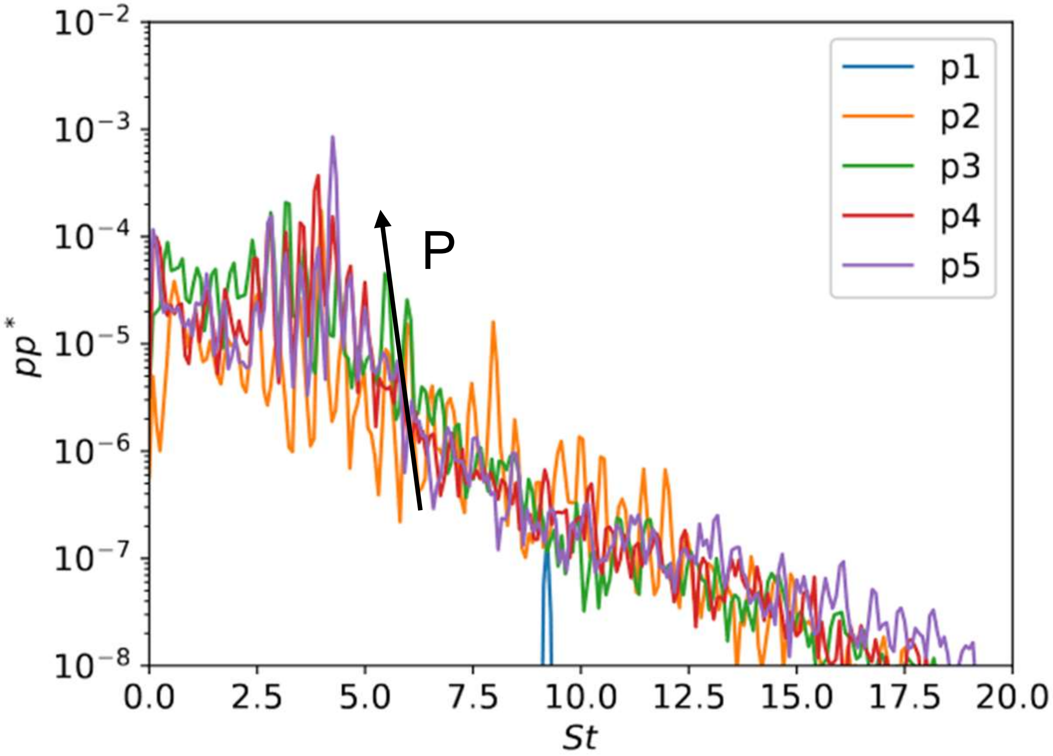
- **Ferrer, E**. A high Order Discontinuous Galerkin—Fourier Incompressible 3D Navier-Stokes Solver with Rotating Sliding Meshes for Simulating Cross-Flow Turbines. DPhil University of Oxford, 2012

Horses: accuracy

NACA0012 airfoil at Re = 105, M0 = 0.4 and AoA = 0◦

P ↑ : Error decreases **exponentially**





Horses: accuracy

NACA0012 airfoil at Re = 105, M0 = 0.4 and AoA = 0◦

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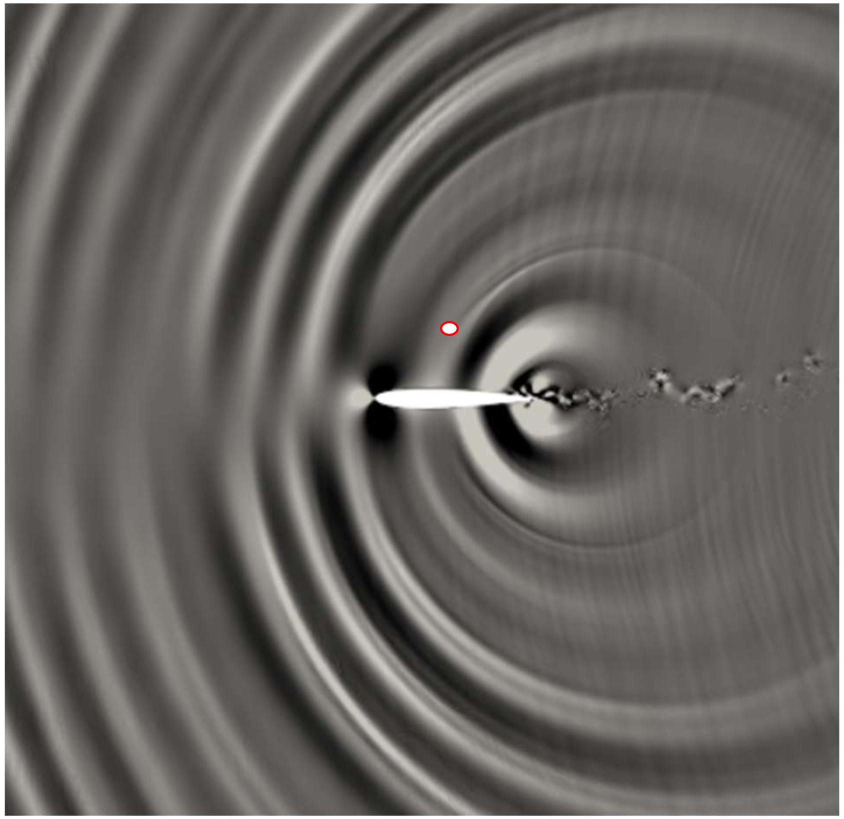
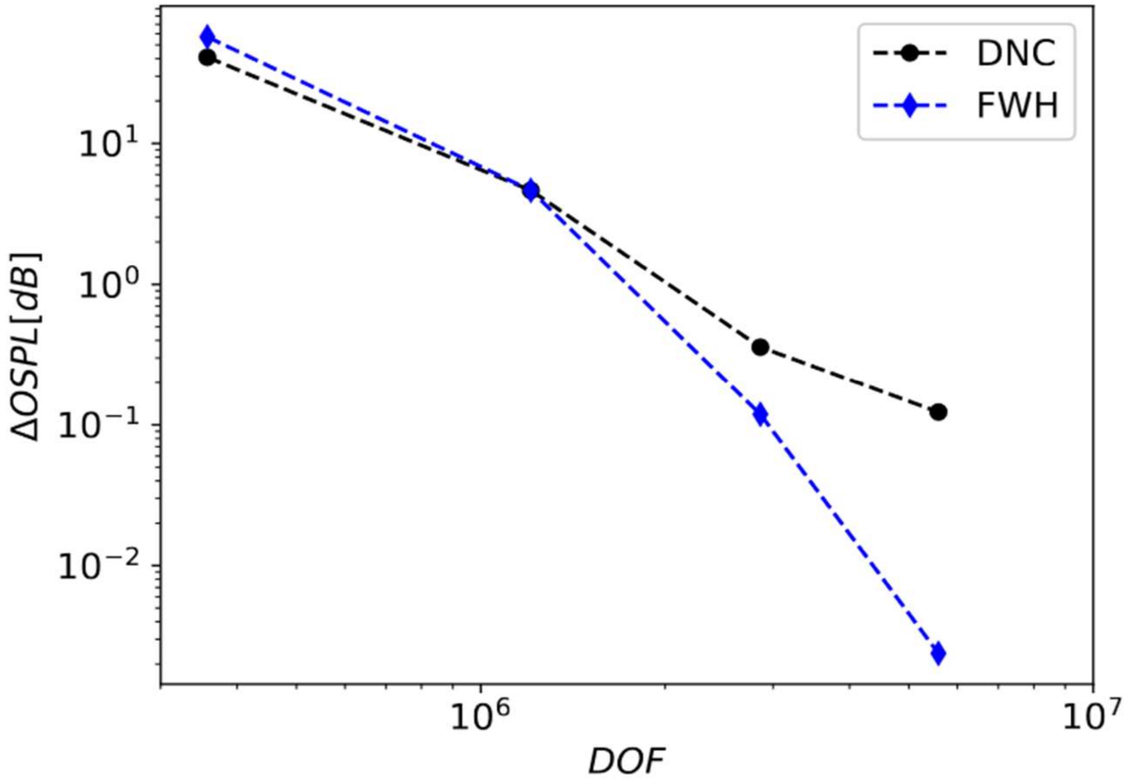
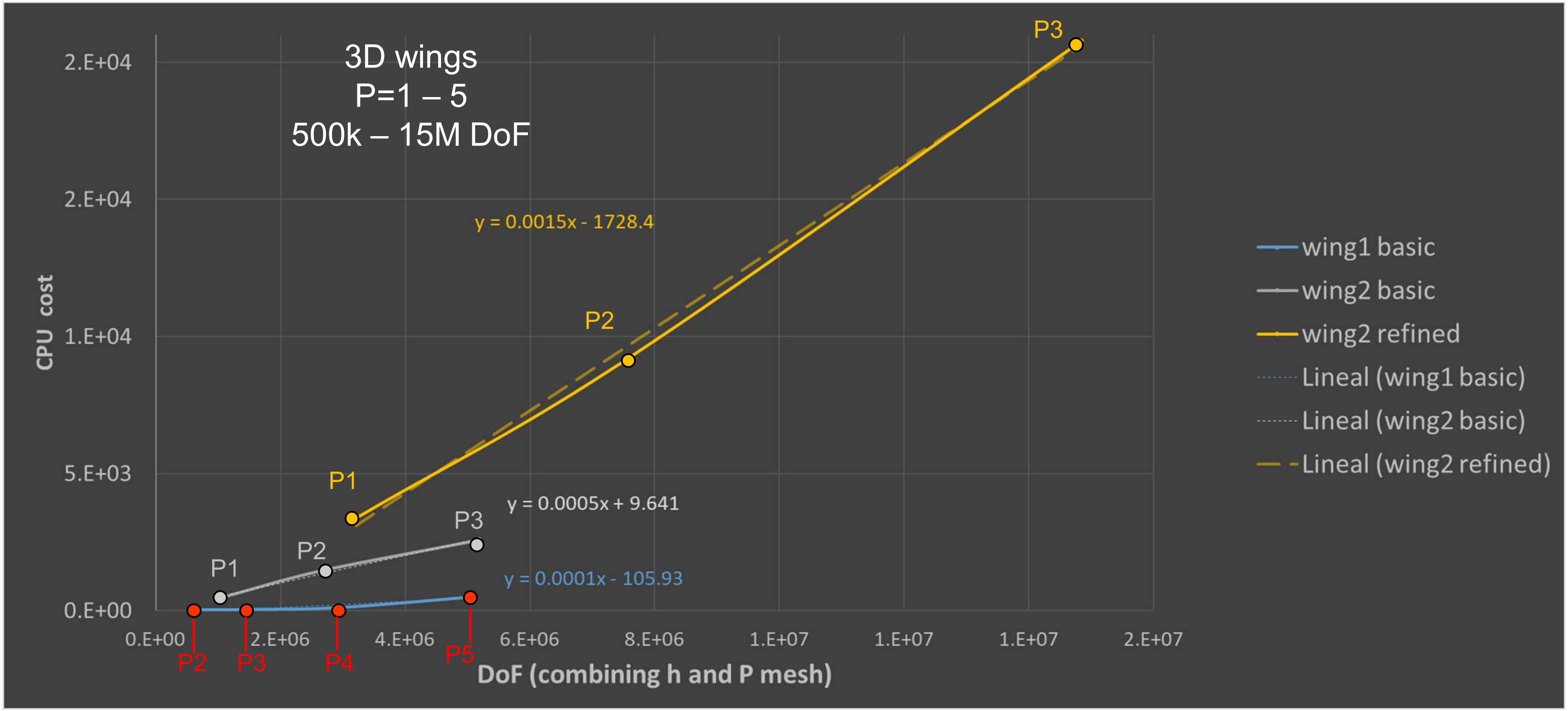




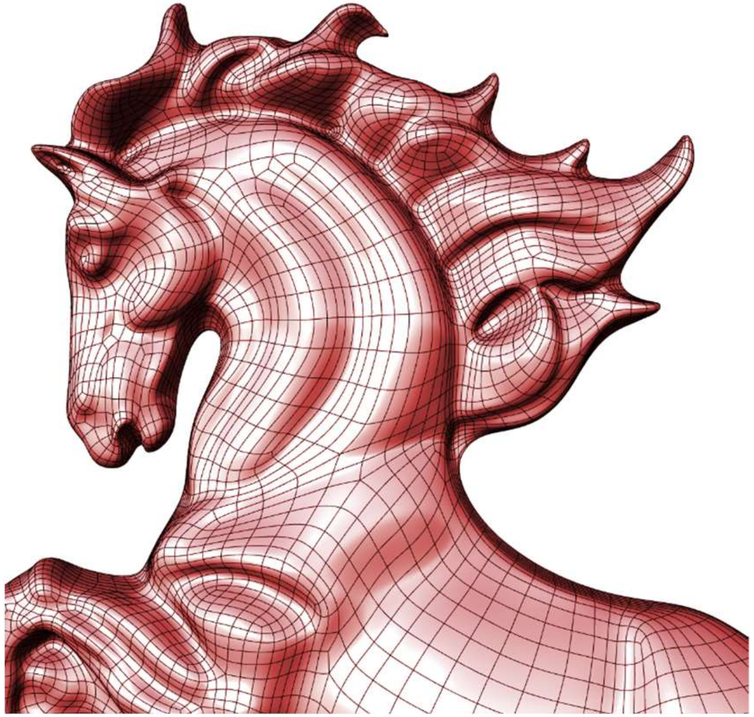
Horses: cost

P ↑ : Error decreases **exponentially**

P ↑ : Cost increases **linearly**



Summary



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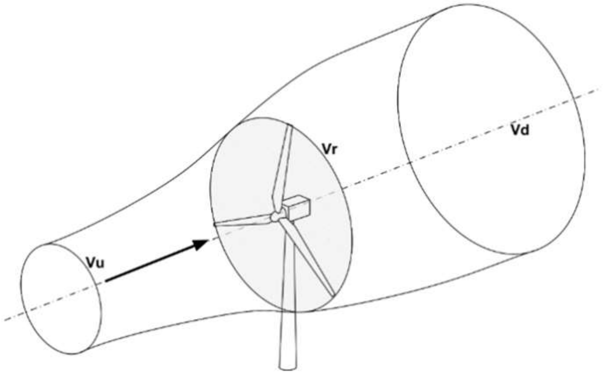
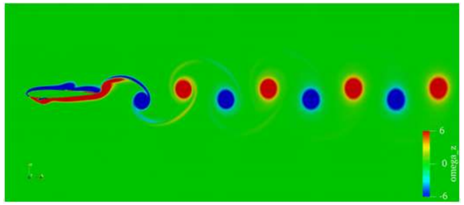
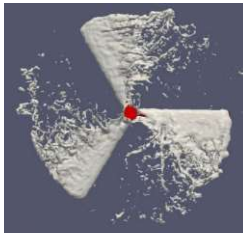
Require 2D aerodynamic data

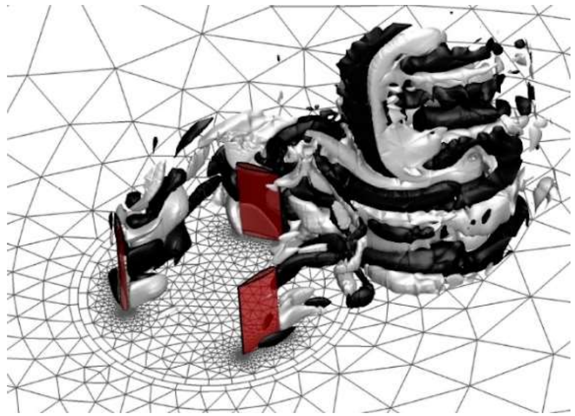
Explicit 3D geometry





3-Immersed boundaries





2-Actuator line

1-Actuator disc & BEM

Cost

4-Sliding meshes

Low

Accuracy

High

4- **E Ferrer** and RHJ Willden, A high order Discontinuous Galerkin - Fourier incompressible 3D Navier–Stokes solver with **rotating sliding meshes**, *Journal of Computational Physics*, 2012
4- **E Ferrer**, RHJ Willden, Blade–wake interactions in **cross-flow turbines**, *International Journal of Marine Energy,* 2015
3- J Kou, A Hurtado-de-Mendoza, S Joshi, S Le Clainche, **E Ferrer**, Eigensolution analysis of **immersed boundaries** for high-order schemes, *Journal of Computational Physics*, 2022
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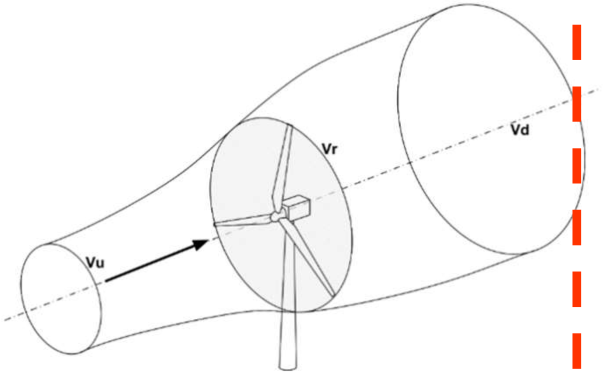
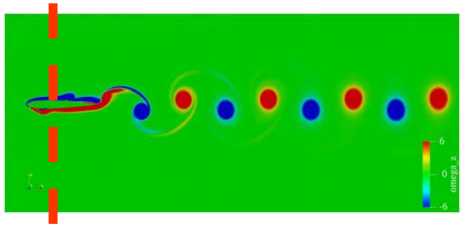
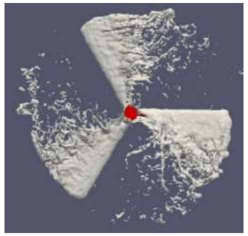
Require 2D aerodynamic data

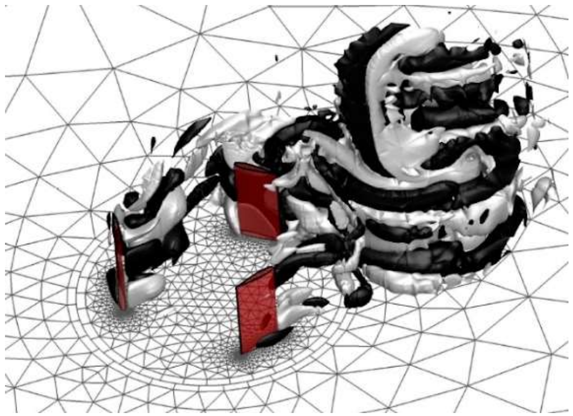
Explicit 3D geometry





3-Immersed boundaries





2-Actuator line

1-Actuator disc & BEM

4-Sliding meshes

Cost

Low — Accuracy — High

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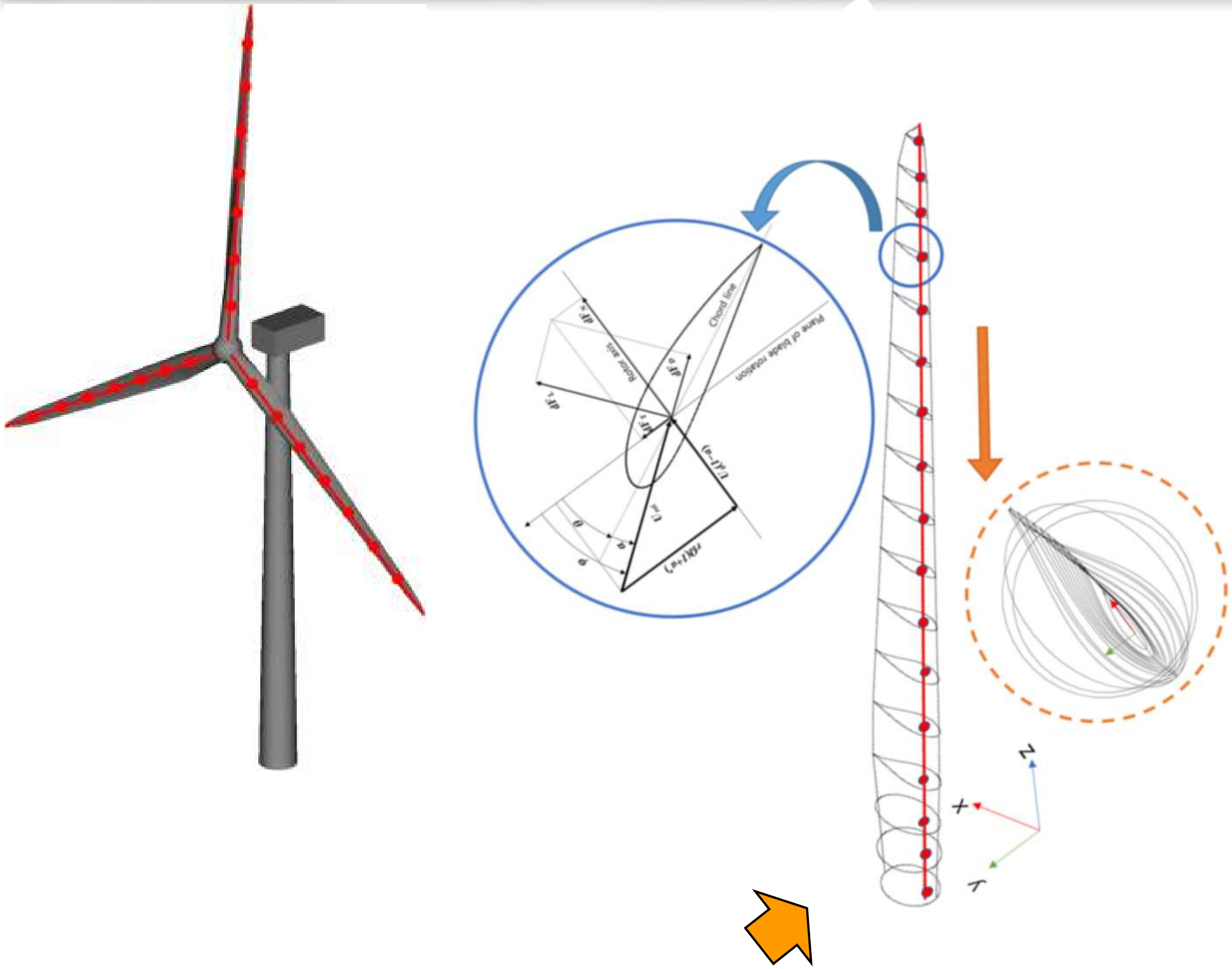
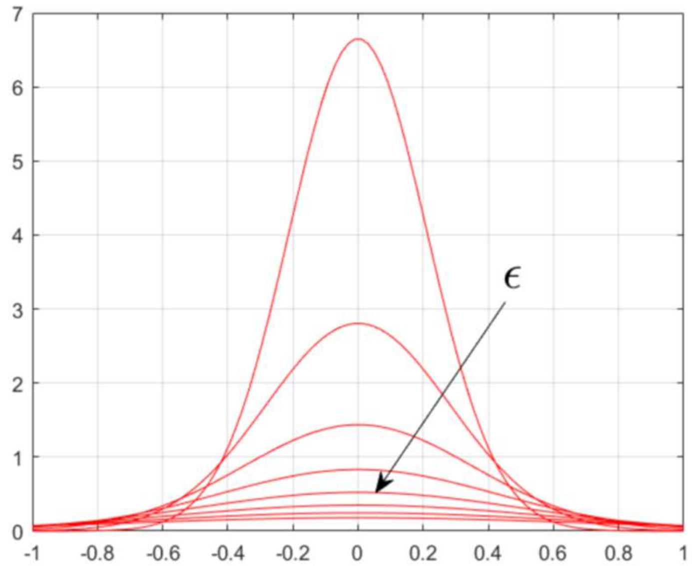
$$\frac{d\boldsymbol{Q}}{dt} = \mathcal{R}(\boldsymbol{Q}, \nabla \boldsymbol{Q}) + \mathcal{S}(\boldsymbol{Q})$$

$$\mathcal{S}(\boldsymbol{Q}) = \eta_\epsilon \mathbf{F}$$





Tabulated data

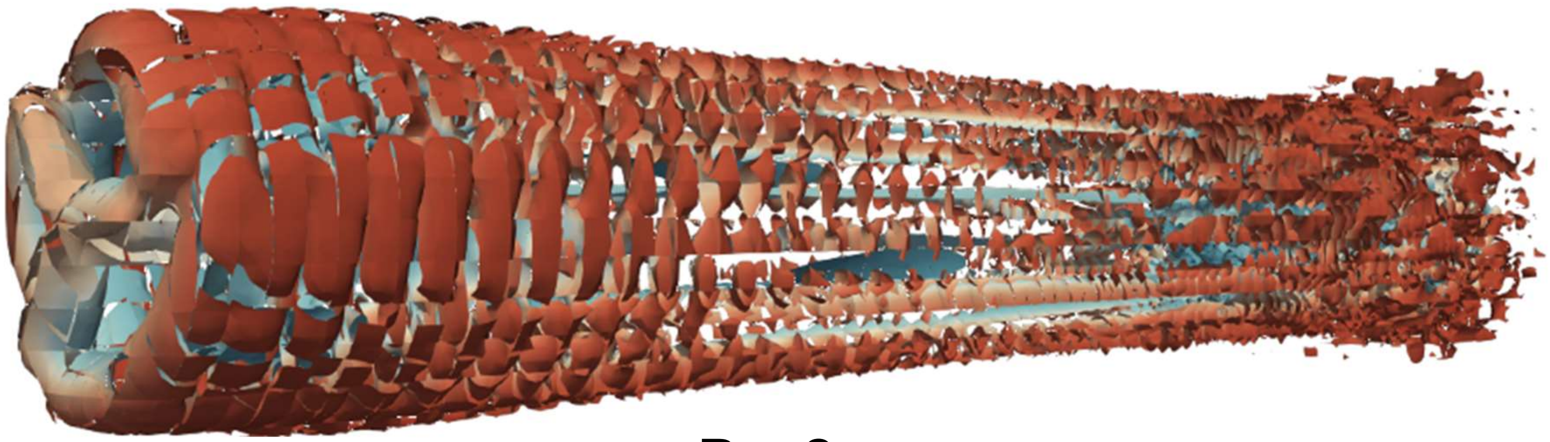
$$f_L = \frac{1}{2}\rho U_{rel}^2 S C_l, \qquad f_D = \frac{1}{2}\rho U_{rel}^2 S C_d,$$

$$\eta_\epsilon = \frac{1}{\epsilon^3 \pi^{\frac{3}{2}}} e^{-(\frac{d}{\epsilon})^2}$$

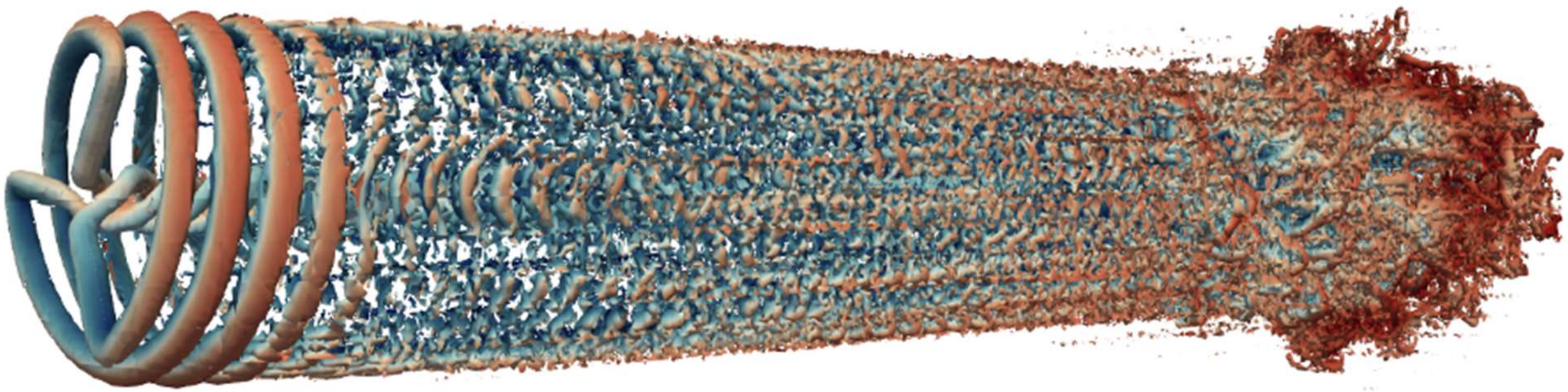
$$\epsilon_k = k \times \Delta_{grid} = k \times \frac{(\Delta_x \Delta_y \Delta_z)^{\frac{1}{3}}}{p+1}$$

OA Mariño, R Sanz, S Colombo, A Sivaramakrishnan, **E Ferrer**, "Modelling Wind Turbines through Actuator Lines in High-Order h/p Solvers“, *under review*

Improved solution using the same h-mesh



P = 2



P = 5

OA Mariño, R Sanz, S Colombo, A Sivaramakrishnan, **E Ferrer**, "Modelling Wind Turbines through Actuator Lines in High-Order h/p Solvers“, *under review*

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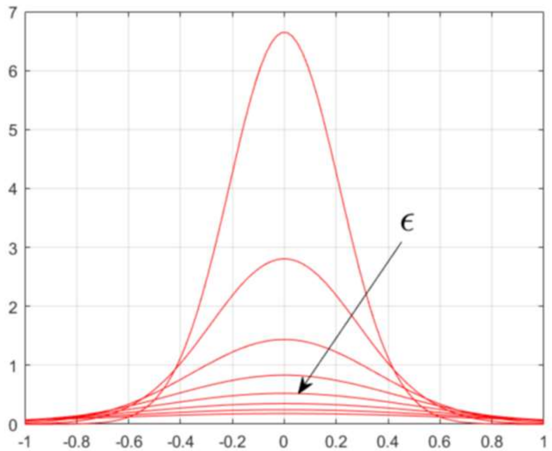
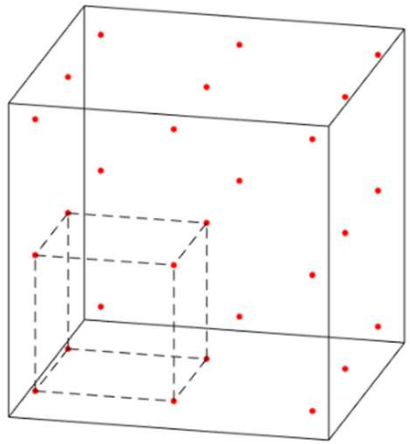




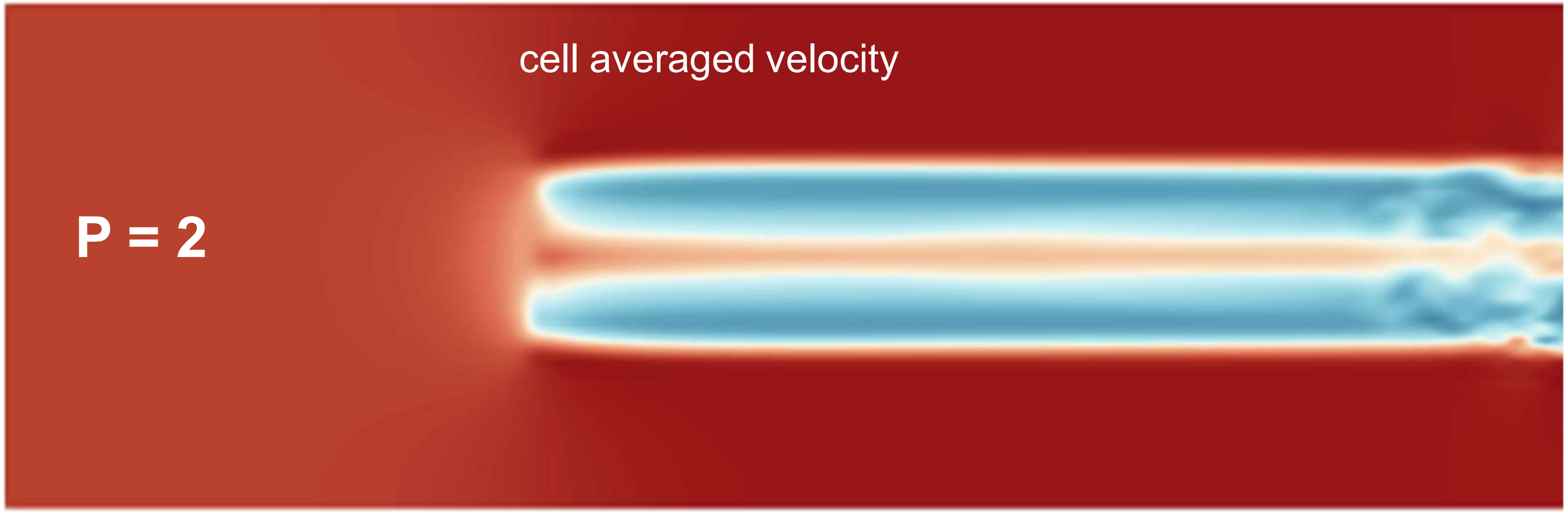
cell averaged velocity

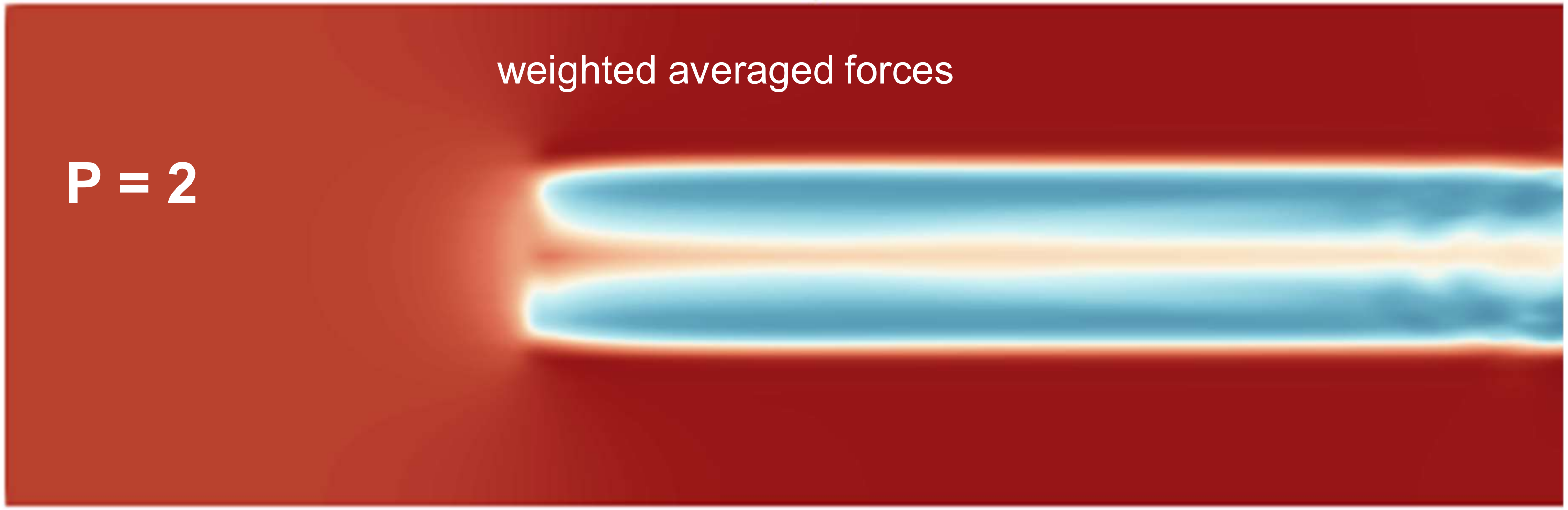
$$\overline{\mathbf{q_t}} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{q_t}_i$$

weighted averaged forces

$$\overline{f}_j = \frac{\sum_{i=1}^{N} \eta_{ji}(d) \cdot f_i}{\sum_{j=1}^{N_a}\sum_{i=1}^{N} \eta_{ji}(d)}$$

OA Mariño, R Sanz, S Colombo, A Sivaramakrishnan, **E Ferrer**, "Modelling Wind Turbines through Actuator Lines in High-Order h/p Solvers“, *under review*





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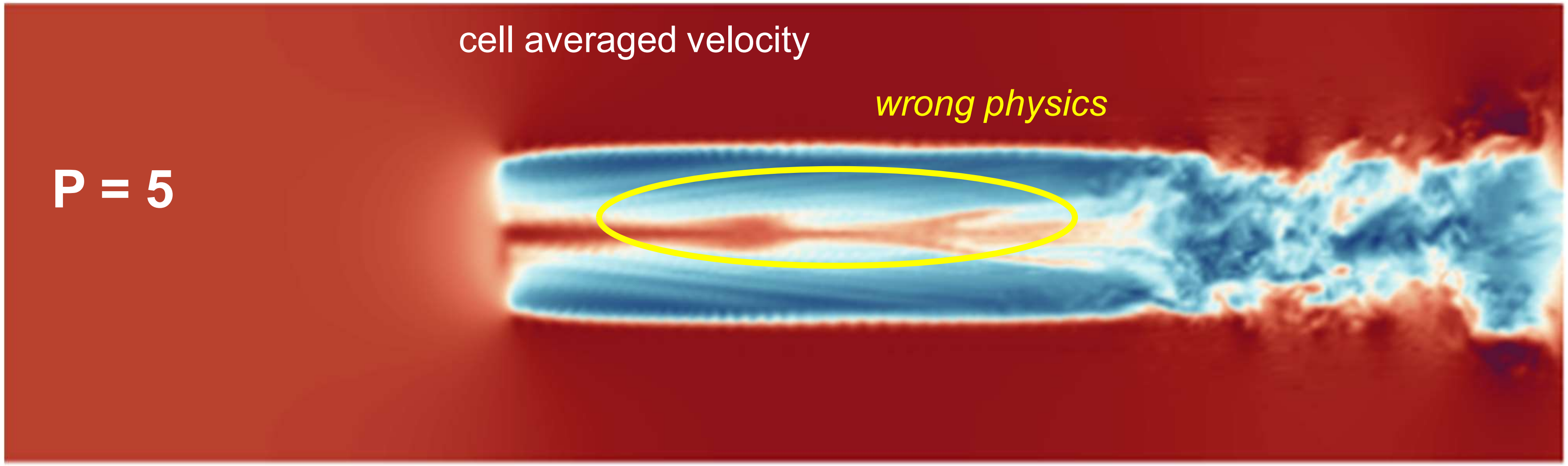

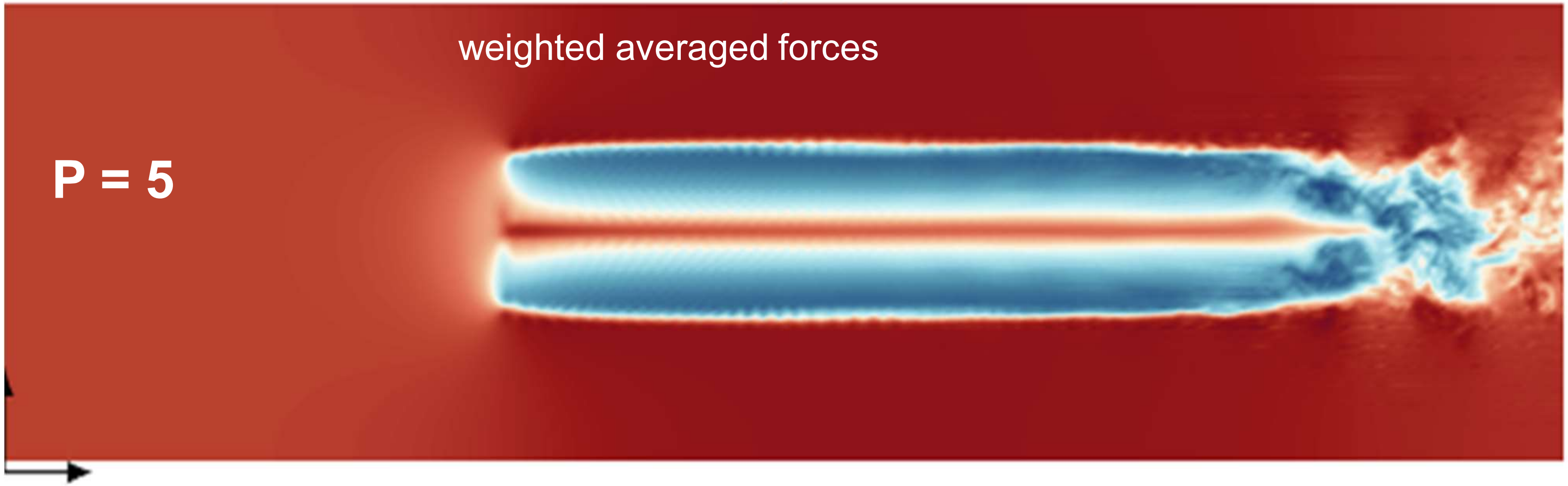

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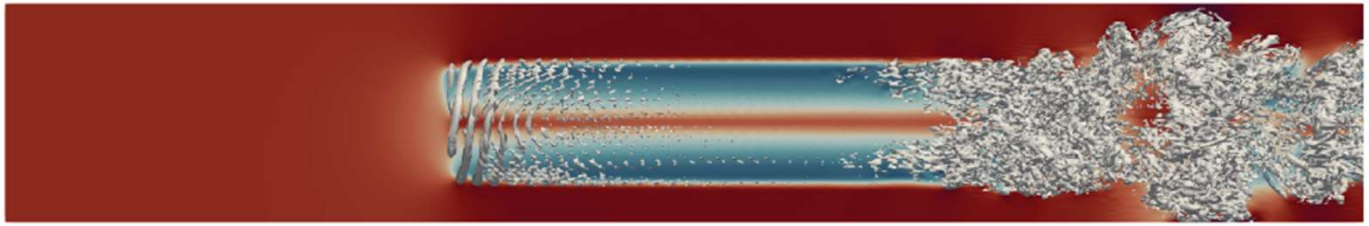
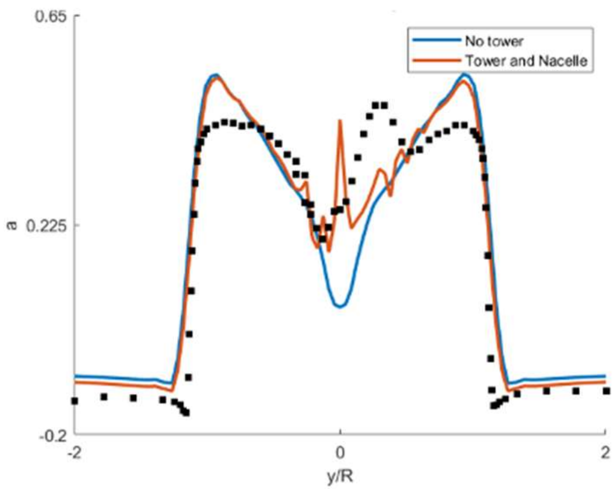
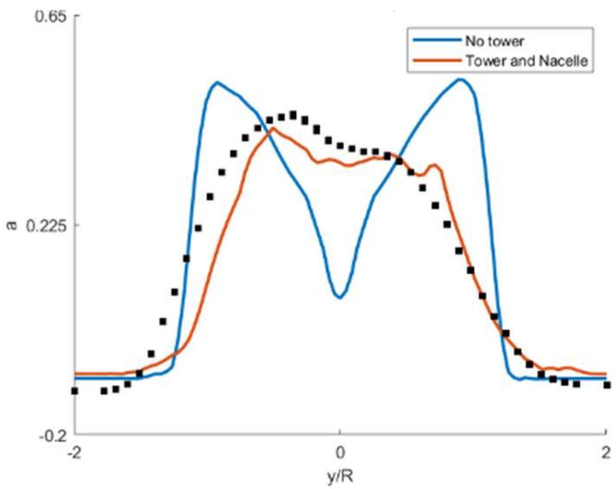


a) Actuator line without tower and nacelle.

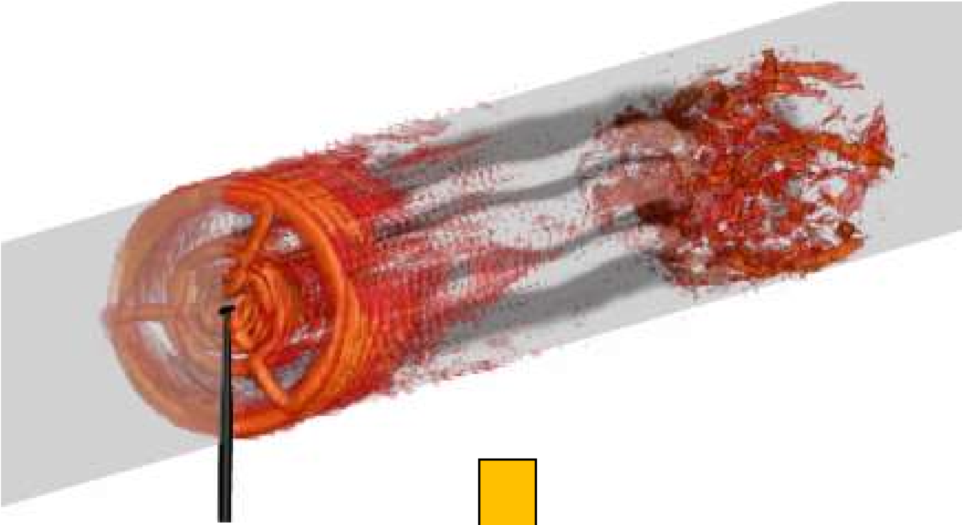
b) Actuator line with tower and nacelle, which are modeled using immersed boundaries.

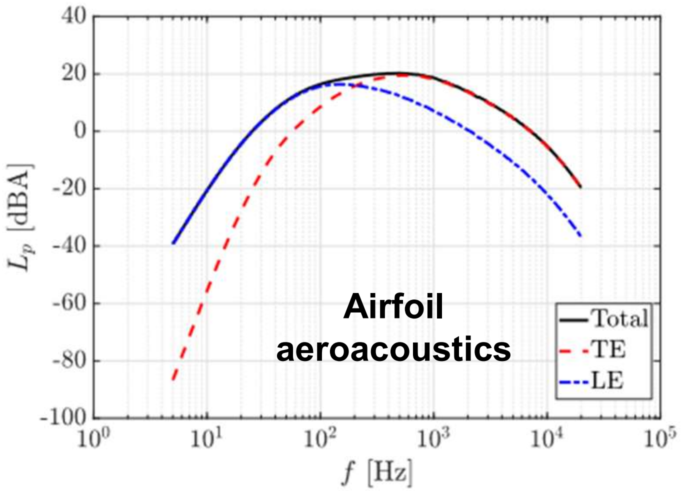


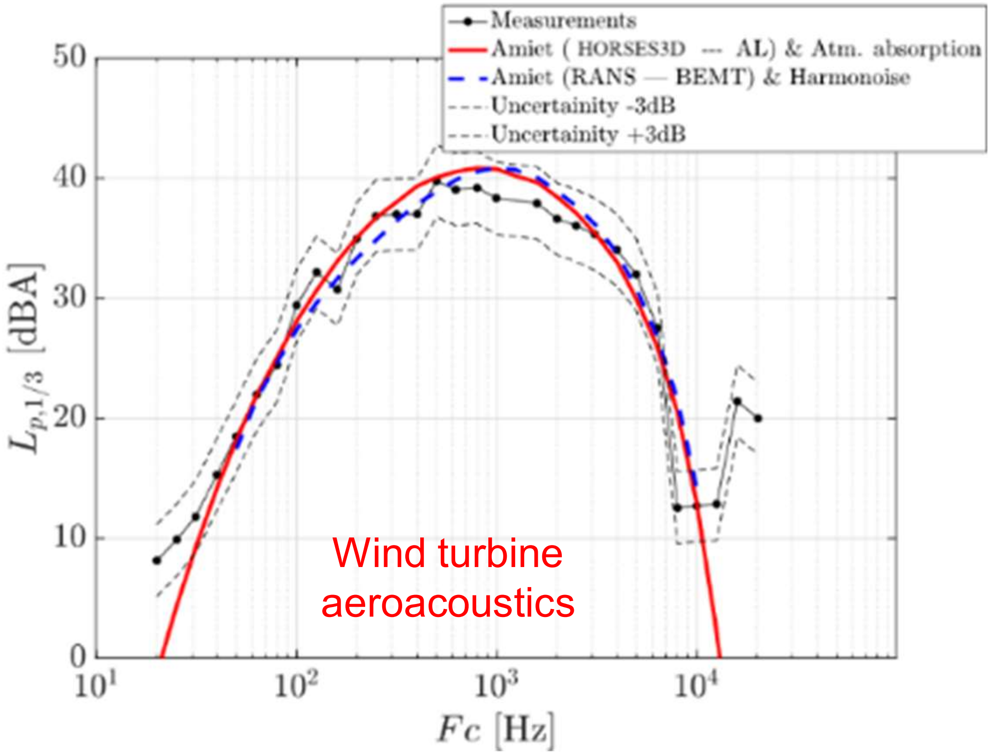


OA Mariño, R Sanz, S Colombo, A Sivaramakrishnan, **E Ferrer**, "Modelling Wind Turbines through Actuator Lines in High-Order h/p Solvers", *under review*

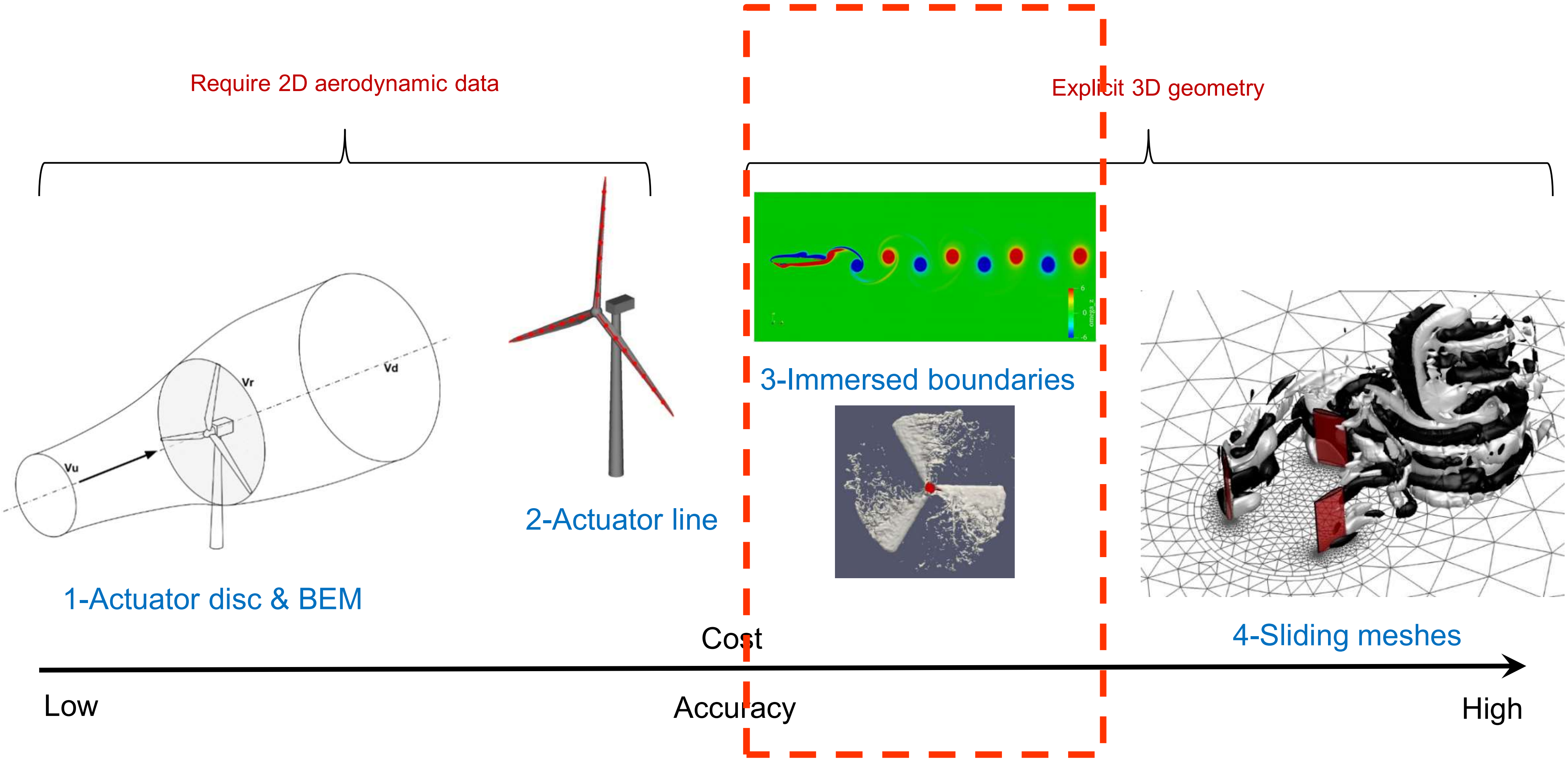
Computing acoustics with actuator lines + Amiet







L Botero-Bolívar, O A. Marino, C H. Venner, L D. de Santana, **E Ferrer**, Low-cost wind turbine aeroacoustic predictions using actuator lines, *Renewable Energy*, Vol 227, 2024,



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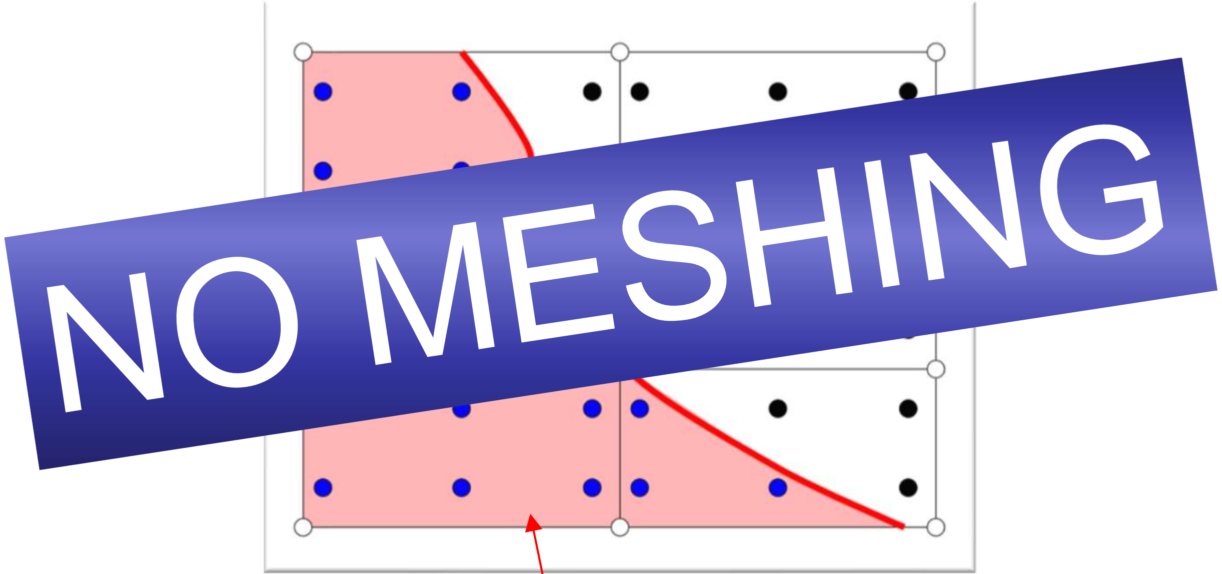
Immersed boundary method (penalty) → Mesh Free method

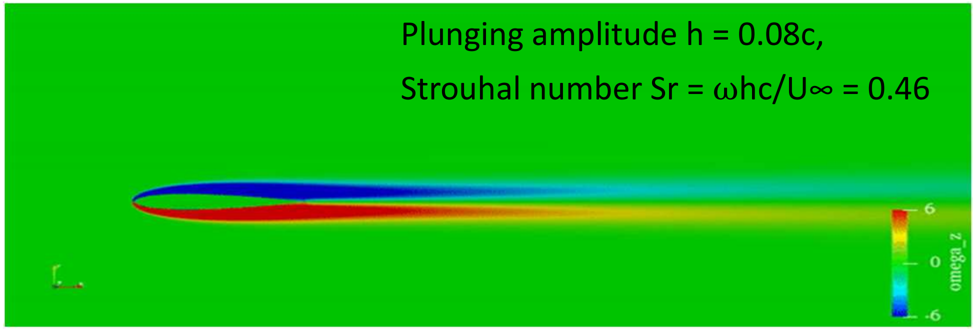
- Simple ‘Cartesian’ grids (with local P refinement)
- Complex geometries
- Moving geometries

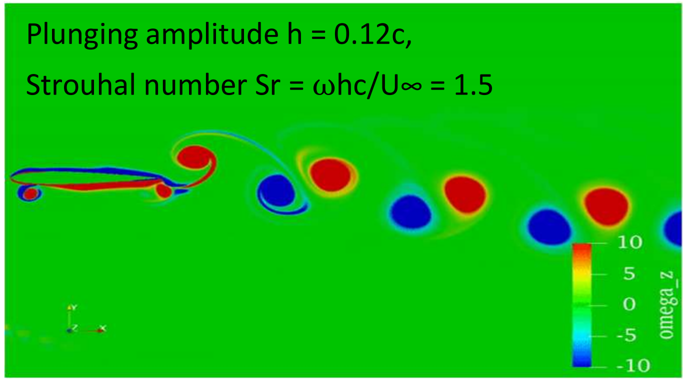


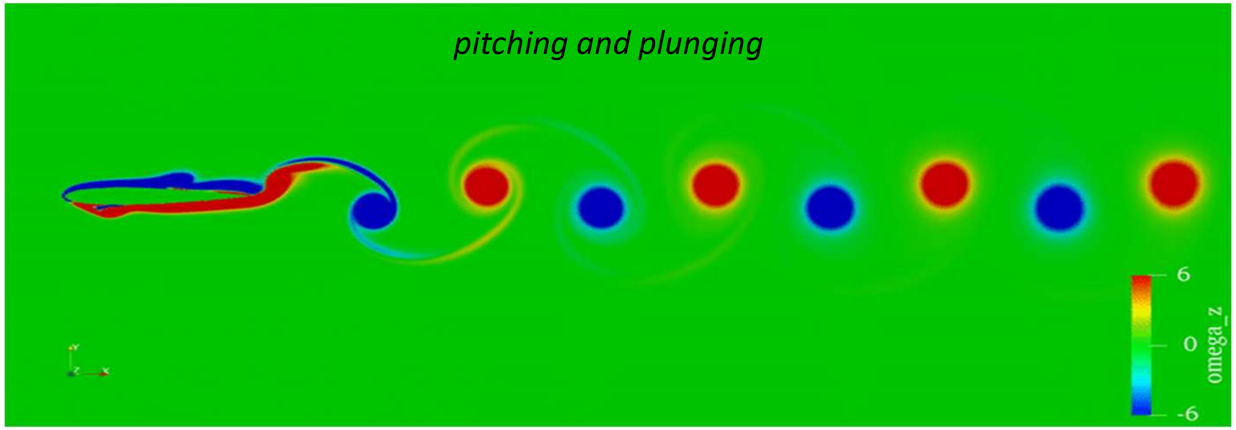
$$\frac{\partial \mathbf{U}}{\partial t} + \nabla \cdot \vec{\mathbf{F}}(\mathbf{U}) = \nabla \cdot \vec{\mathbf{G}}(\mathbf{U}, \nabla \mathbf{U}) + \boxed{\mathbf{S}(\mathbf{U})}.$$

$$\mathbf{S}(\mathbf{U}) = a \times \begin{pmatrix} 0 \\ \rho u_0 - \rho u \\ \rho v_0 - \rho v \\ \rho w_0 - \rho w \\ \frac{\varrho}{2}(u_0^2 + v_0^2 + w_0^2) - \frac{\varrho}{2}(u^2 + v^2 + w^2) \end{pmatrix}$$

Moving NACA0012 at Reynolds number 1000, *pitching and plunging*:

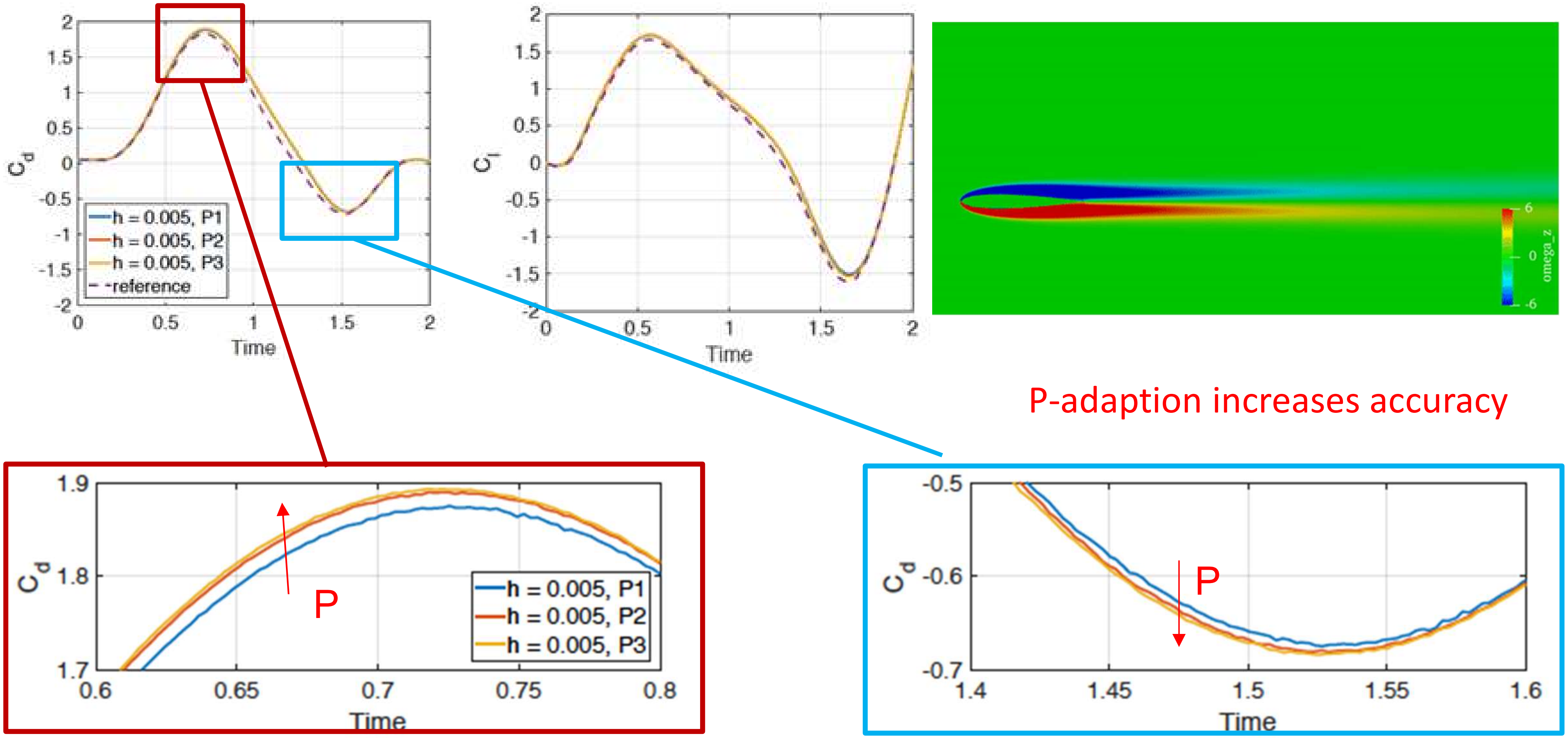






- J Kou, A Hurtado-de-Mendoza, S Joshi, S Le Clainche, **E Ferrer**, "Eigensolution analysis of immersed boundary method based on volume penalization: applications to high-order schemes", *Journal of Computational Physics,* Vol 449, 110817, 2022
- J Kou, S Joshi, A Hurtado-de-Mendoza, K Puri, C Hirsch, **E Ferrer**, "An Immersed boundary method for high–order flux reconstruction based on volume penalization", *Journal of Computational Physics,* Vol 448, 110721, 2022
- J Kou, VJ Llorente, E Valero, **E Ferrer**, "A Modified Equation Analysis for Immersed Boundary Methods based on Volume Penalization: Applications to Linear Advection-Diffusion and High-Order Discontinuous Galerkin Schemes" *Computers & Fluids*, Vol 257, 105869, 2023
- J Kou, **E Ferrer**, "A combined volume penalization / selective frequency damping for immersed boundary methods applied to high-order schemes" *Journal of Computational Physics*, Vol 472, 111678, 2023

Moving NACA0012 at Reynolds number 1000, *pitching and plunging*:



- J Kou, A Hurtado-de-Mendoza, S Joshi, S Le Clainche, **E Ferrer**, "Eigensolution analysis of immersed boundary method based on volume penalization: applications to high-order schemes", *Journal of Computational Physics,* Vol 449, 110817, 2022
- J Kou, S Joshi, A Hurtado-de-Mendoza, K Puri, C Hirsch, **E Ferrer**, "An Immersed boundary method for high–order flux reconstruction based on volume penalization", *Journal of Computational Physics,* Vol 448, 110721, 2022
- J Kou, VJ Llorente, E Valero, **E Ferrer**, "A Modified Equation Analysis for Immersed Boundary Methods based on Volume Penalization: Applications to Linear Advection-Diffusion and High-Order Discontinuous Galerkin Schemes" *Computers & Fluids*, Vol 257, 105869, 2023
- J Kou, **E Ferrer**, "A combined volume penalization / selective frequency damping for immersed boundary methods applied to high-order schemes" *Journal of Computational Physics*, Vol 472, 111678, 2023

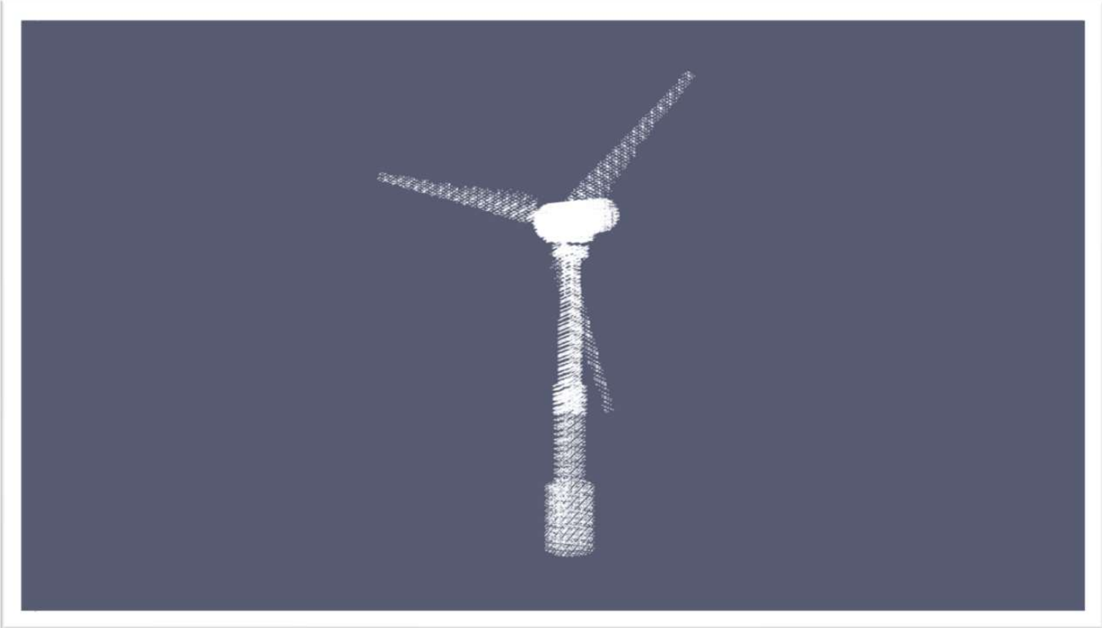
Immersed boundary method (penalty)

IB for rotating Wind turbine

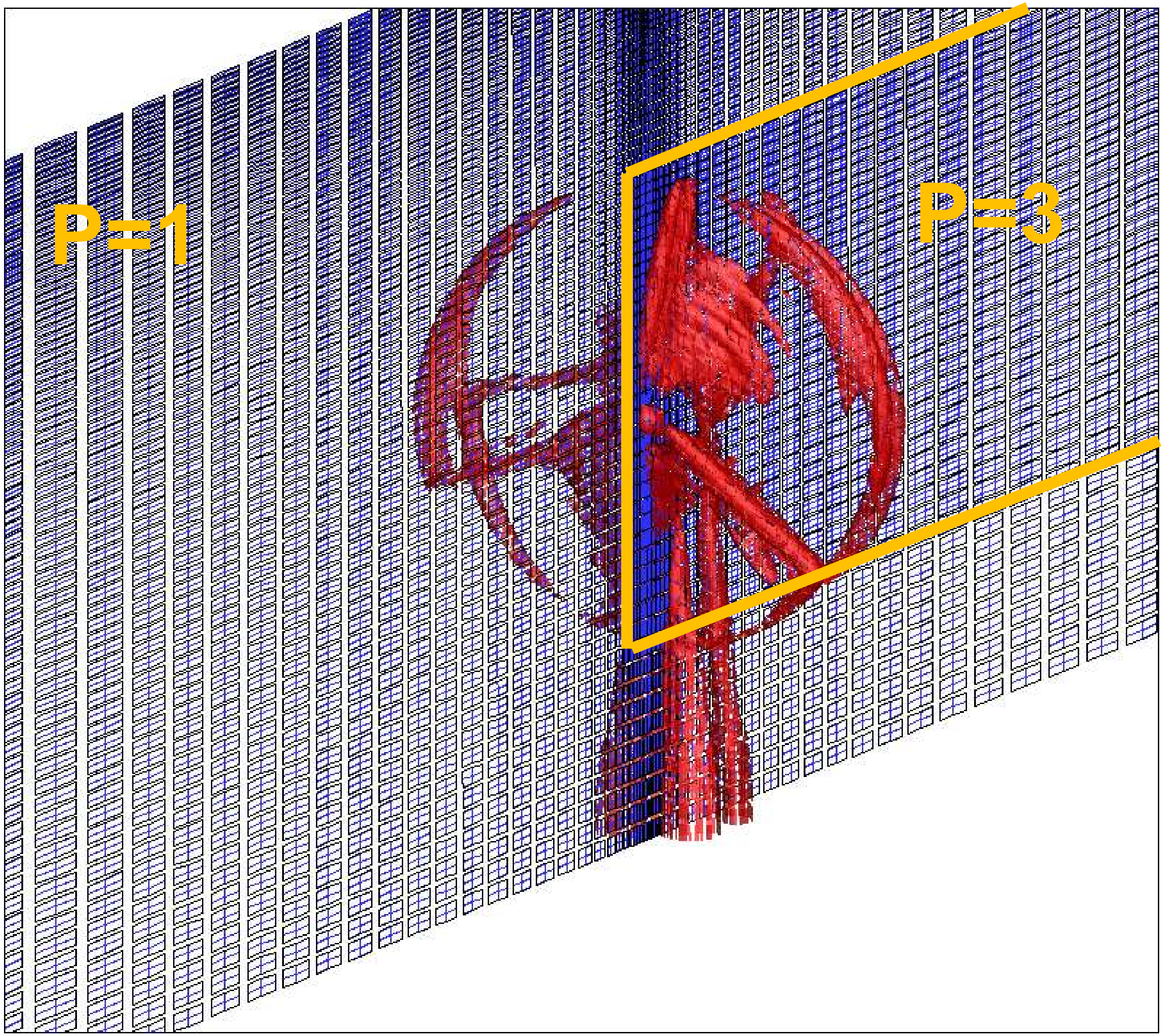
Only CAD '.stl' file
for the wind turbine

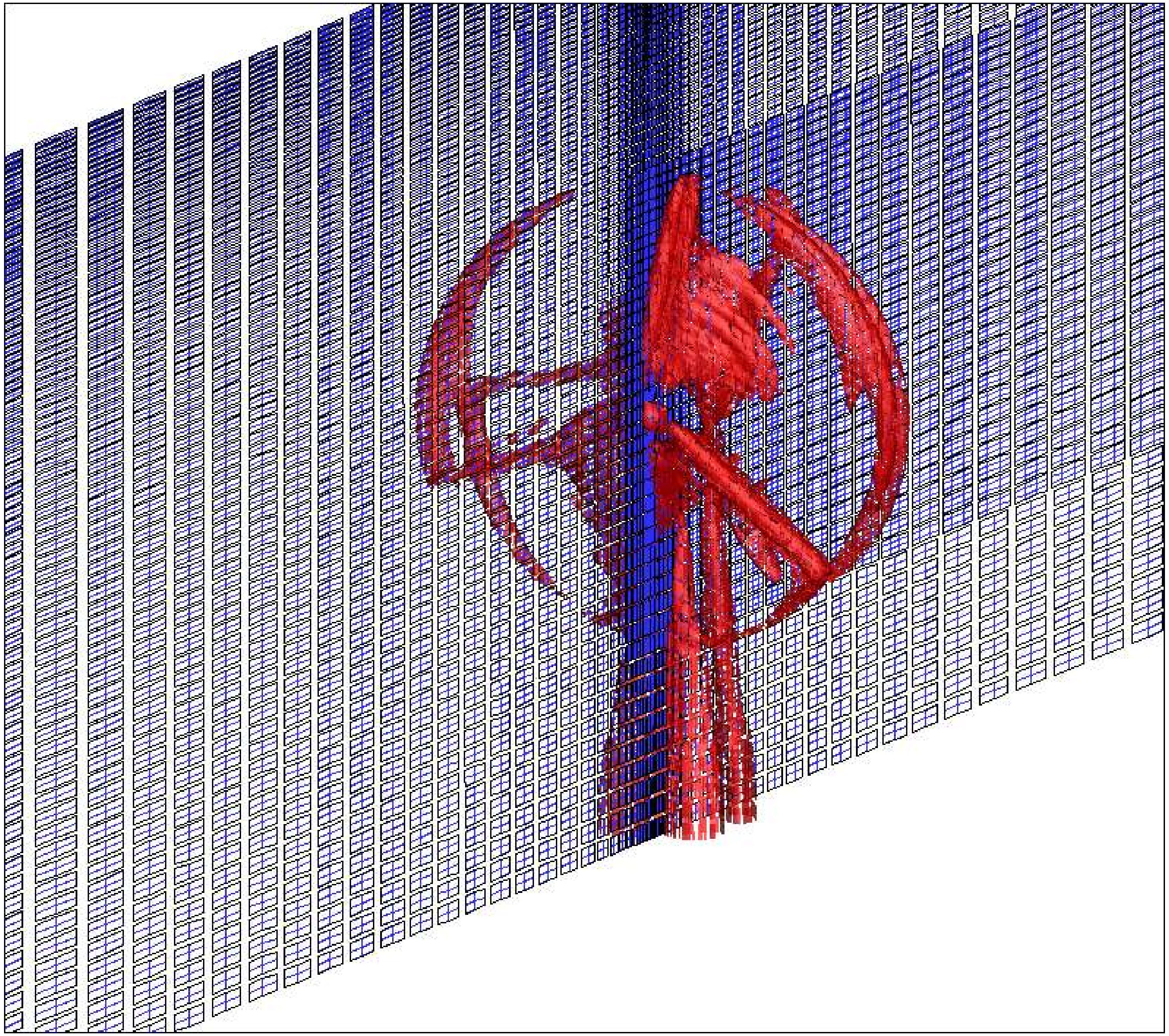
&

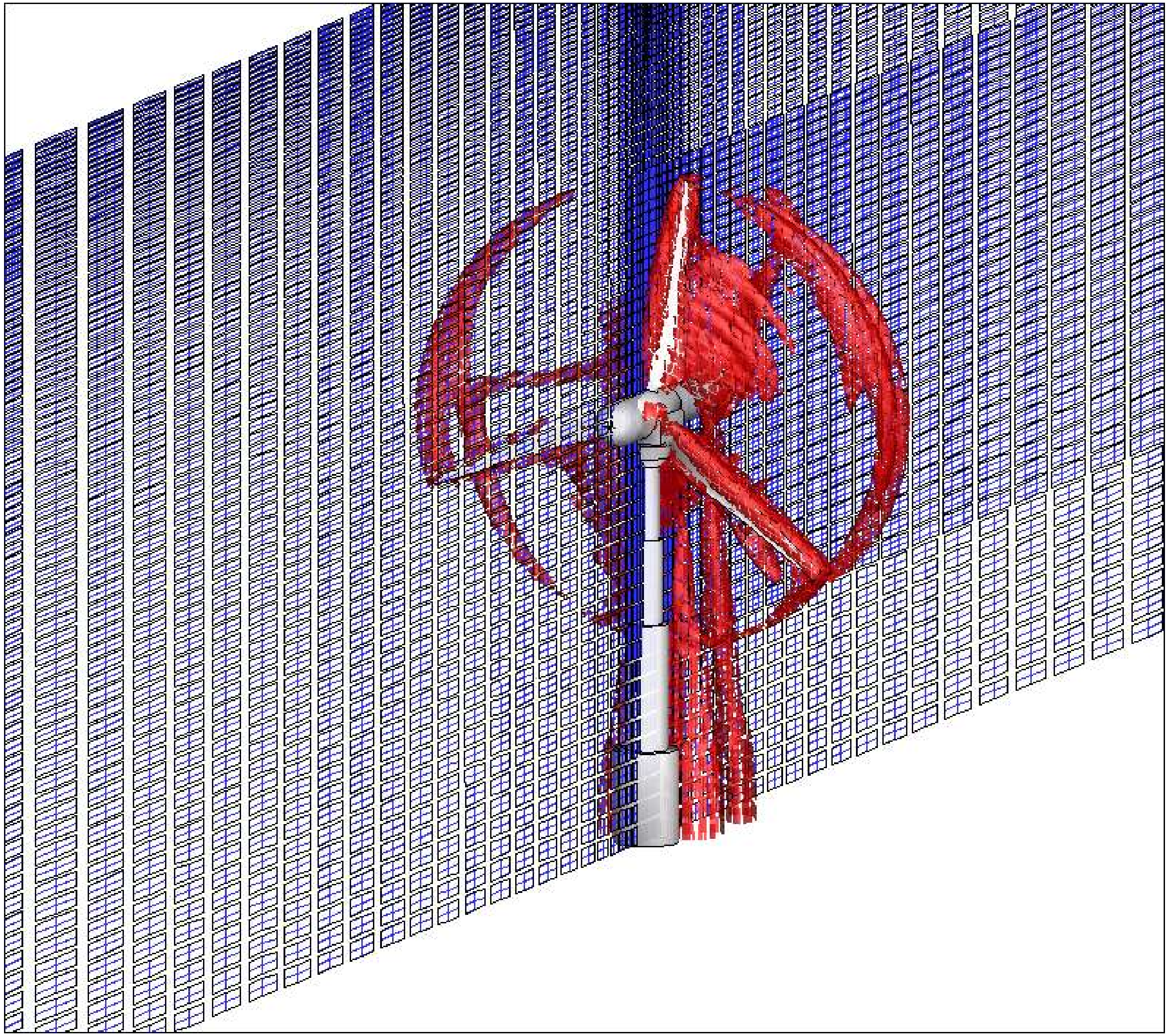
Simple Cartesian mesh

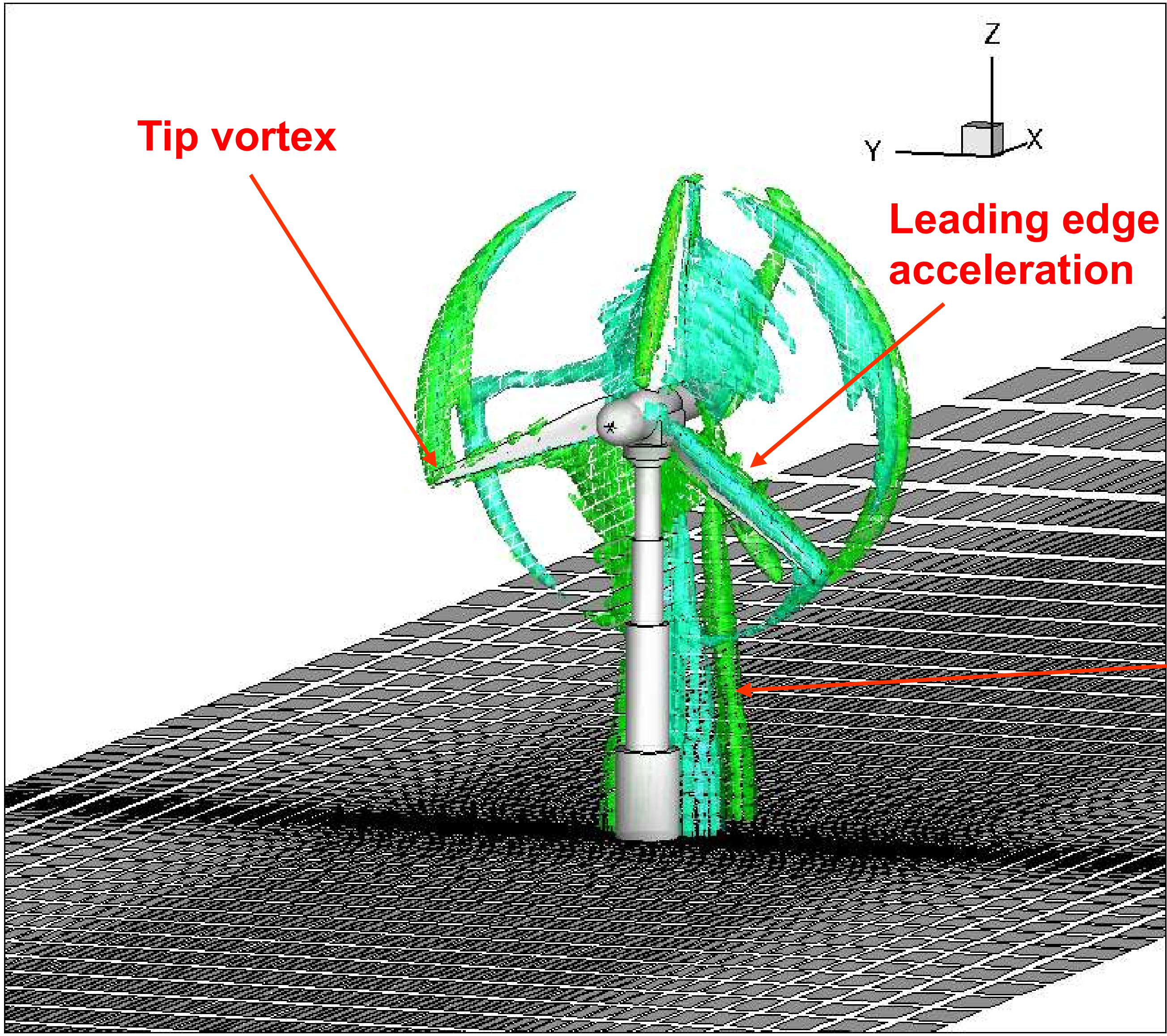


Penalty points for the wind turbine


P=1
P=3

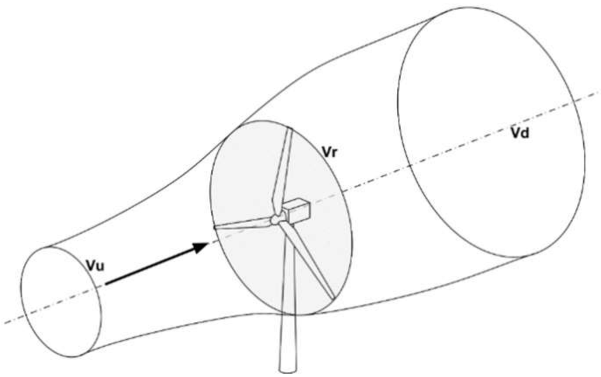





Tip vortex
Leading edge
acceleration
Tower wake
Z
Y
X

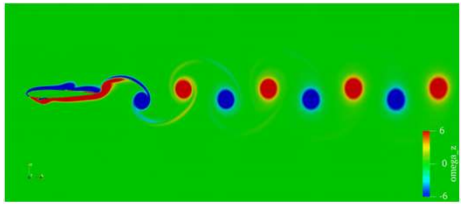
Require 2D aerodynamic data

Explicit 3D geometry

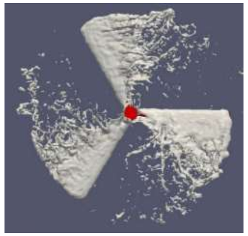


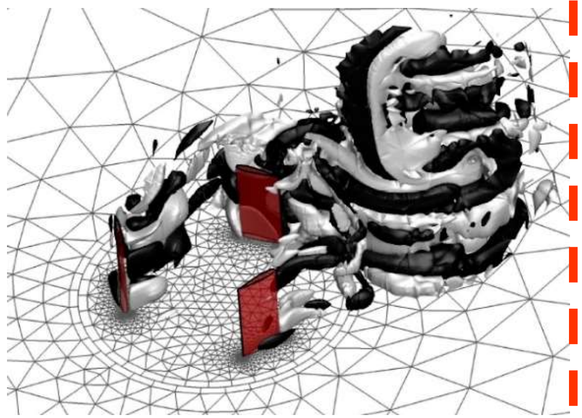
1-Actuator disc & BEM

2-Actuator line



3-Immersed boundaries





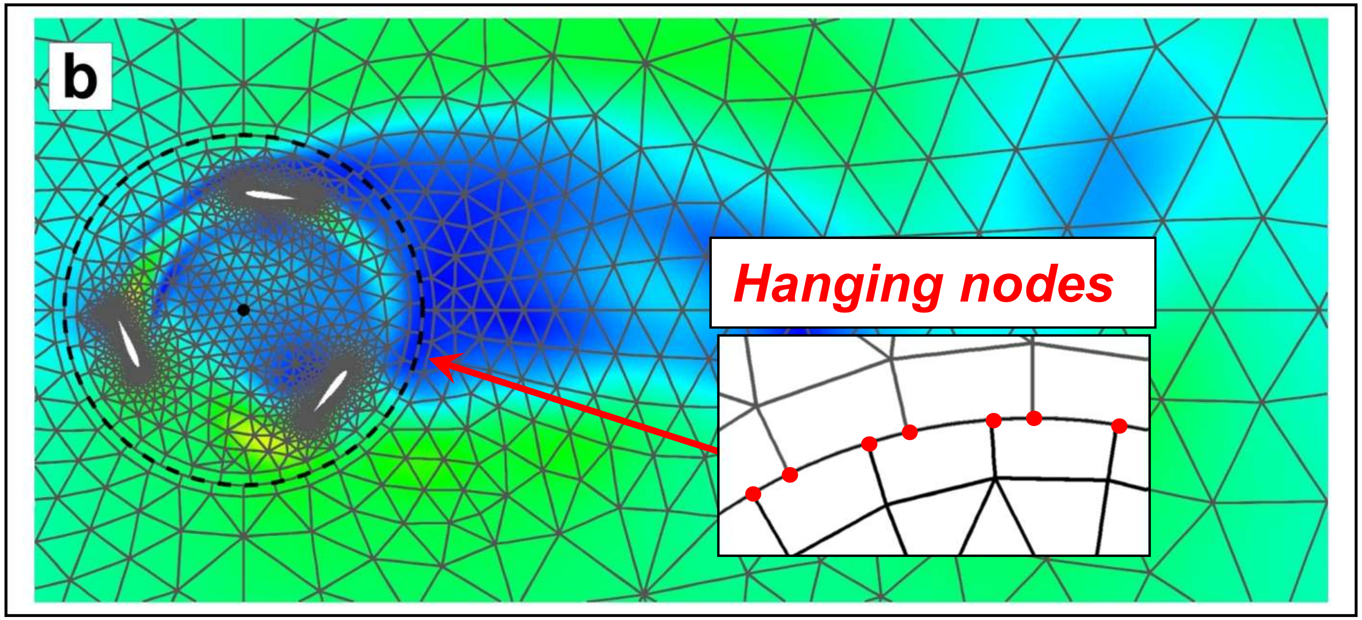
4-Sliding meshes

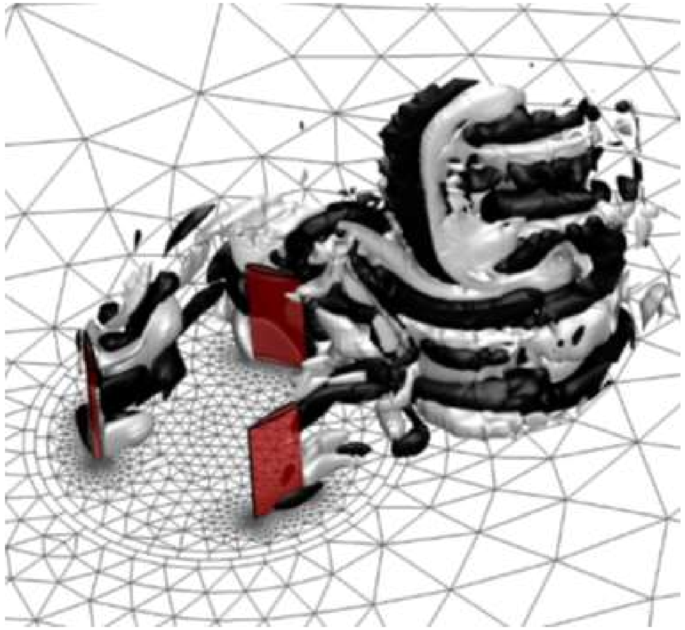
Cost

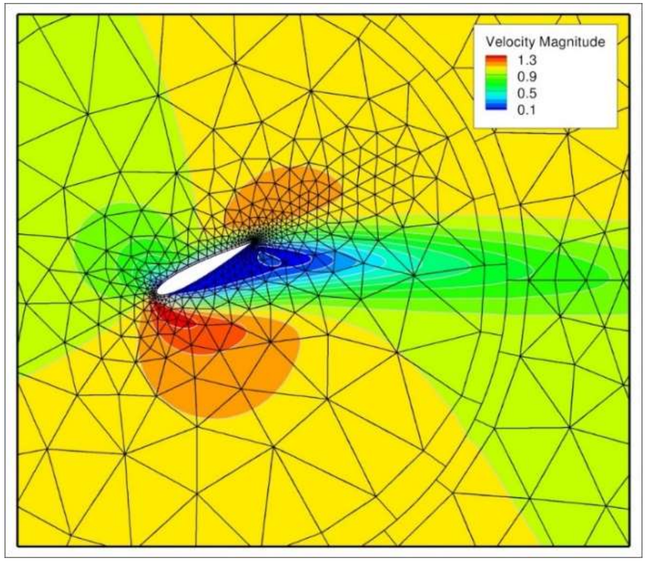
Low — Accuracy — High

4- **E Ferrer** and RHJ Willden, A high order Discontinuous Galerkin - Fourier incompressible 3D Navier–Stokes solver with **rotating sliding meshes**, *Journal of Computational Physics*, 2012
4- **E Ferrer**, RHJ Willden, Blade–wake interactions in **cross-flow turbines**, *International Journal of Marine Energy*, 2015
3- J Kou, A Hurtado-de-Mendoza, S Joshi, S Le Clainche, **E Ferrer**, Eigensolution analysis of **immersed boundaries** for high-order schemes, *Journal of Computational Physics*, 2022
3- J Kou, S Joshi, A Hurtado-de-Mendoza, K Puri, C Hirsch, **E Ferrer**, An **Immersed boundary** method for high–order flux reconstruction, *Journal of Computational Physics*, 2022
2 & 3- **E Ferrer**, S Colombo, O Marino, "Aeroacoustic predictions of wind turbines based on **actuator lines and immersed boundaries**", *Under review at Wind Energy*
1- **E Ferrer**, S Le Clainche, **Simple models for cross flow turbines**, *in Recent advances in CFD for Wind and Tidal Offshore Turbines*, 2019
1- **E Ferrer**, OMF Browne, E Valero, Sensitivity analysis to control the far–wake unsteadiness behind **turbines**, *Energies*, 2017

High order sliding meshes







DG solution
Rotating NACA0015
Re=100
Rot speed=0.3
polynomial order
k=5

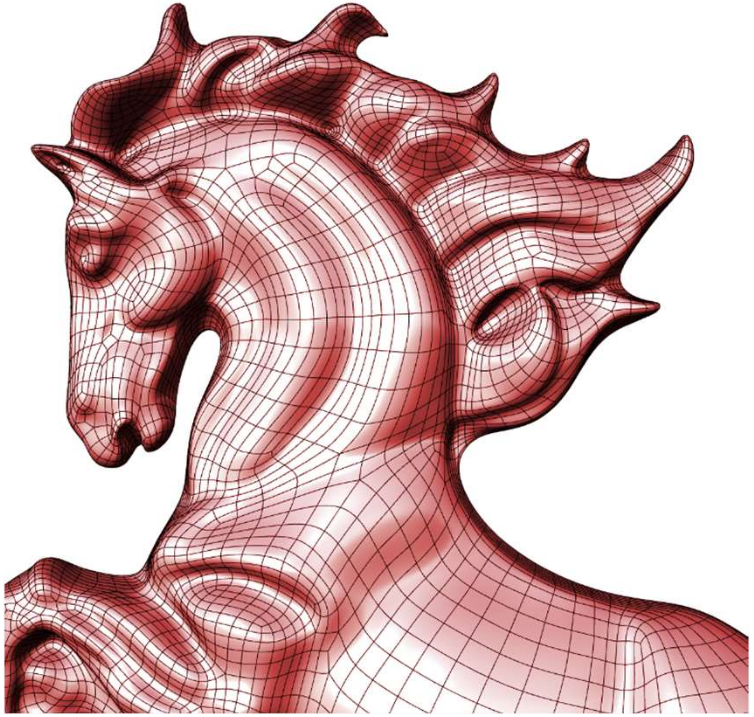
- E Ferrer and RHJ Willden, "A high order DG- Fourier incompressible 3D Navier-Stokes solver with rotating sliding meshes", *JCP*, 231, 2012

Summary

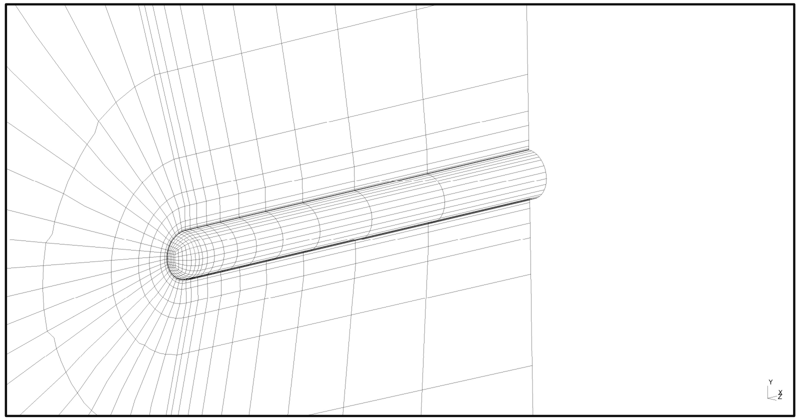
1- Introduction to DG & Horses3d

2- Multiphysics
→ Wind turbines
→ Turbulence

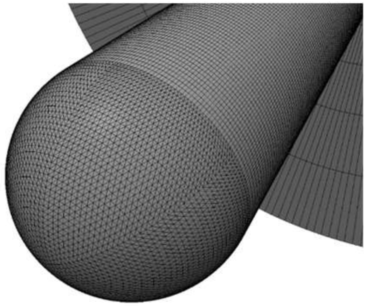
3. Machine Learning + CFD
→ Mesh adaption
→ NN acceleration
→ RL for automation

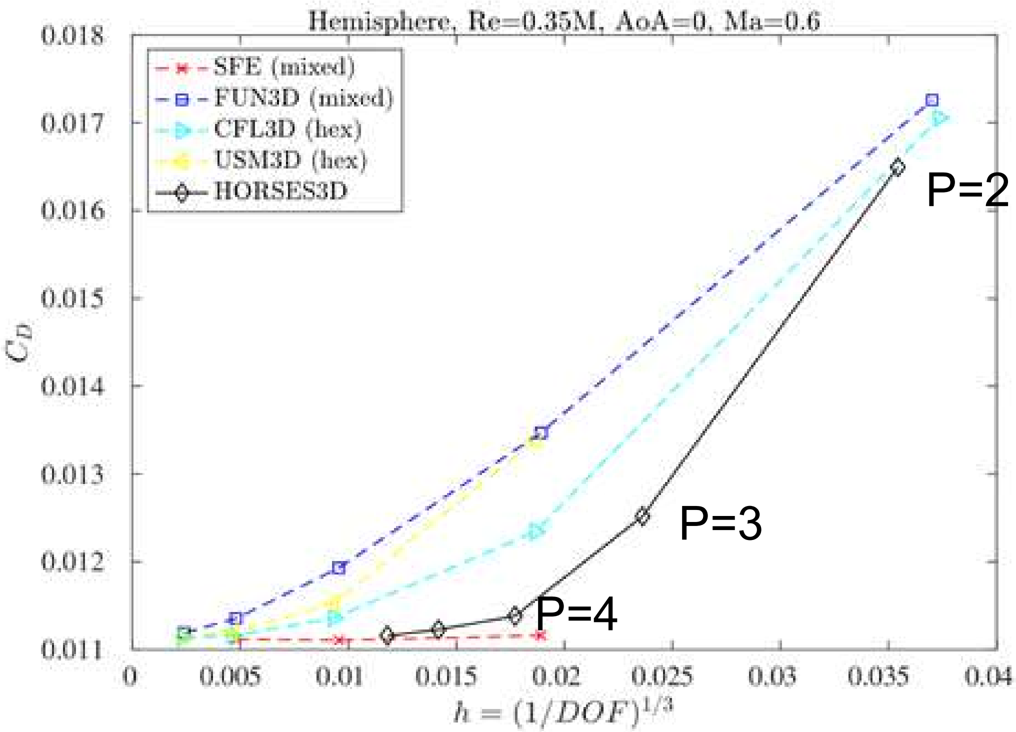


High order RANS (SAneg)



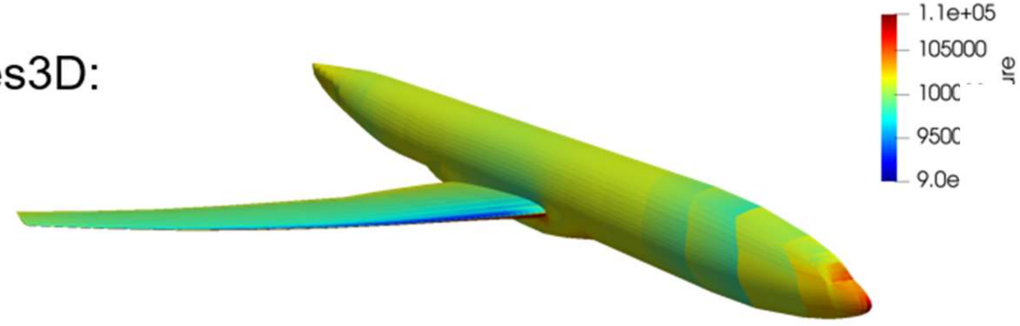
NASA workshop
https://turbmodels.larc.nasa.gov/hc3dnumerics_val.html



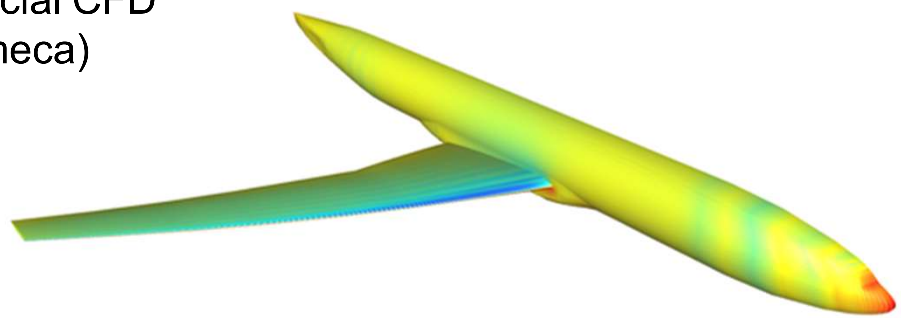


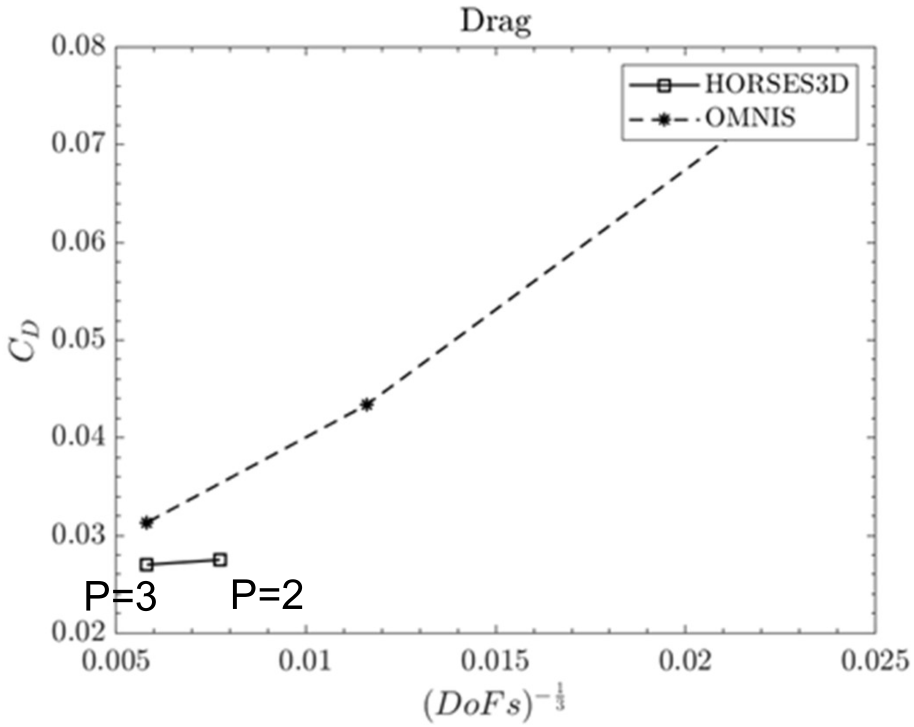
High order RANS (SAneg)

Horses3D:



Commercial CFD (Numeca)





CRM Family Of Models
From Left to Right: High-Speed CRM, High-Lift CRM, CRM with NLF wing and Icing Research Tunnel CRM.

Implicit LES

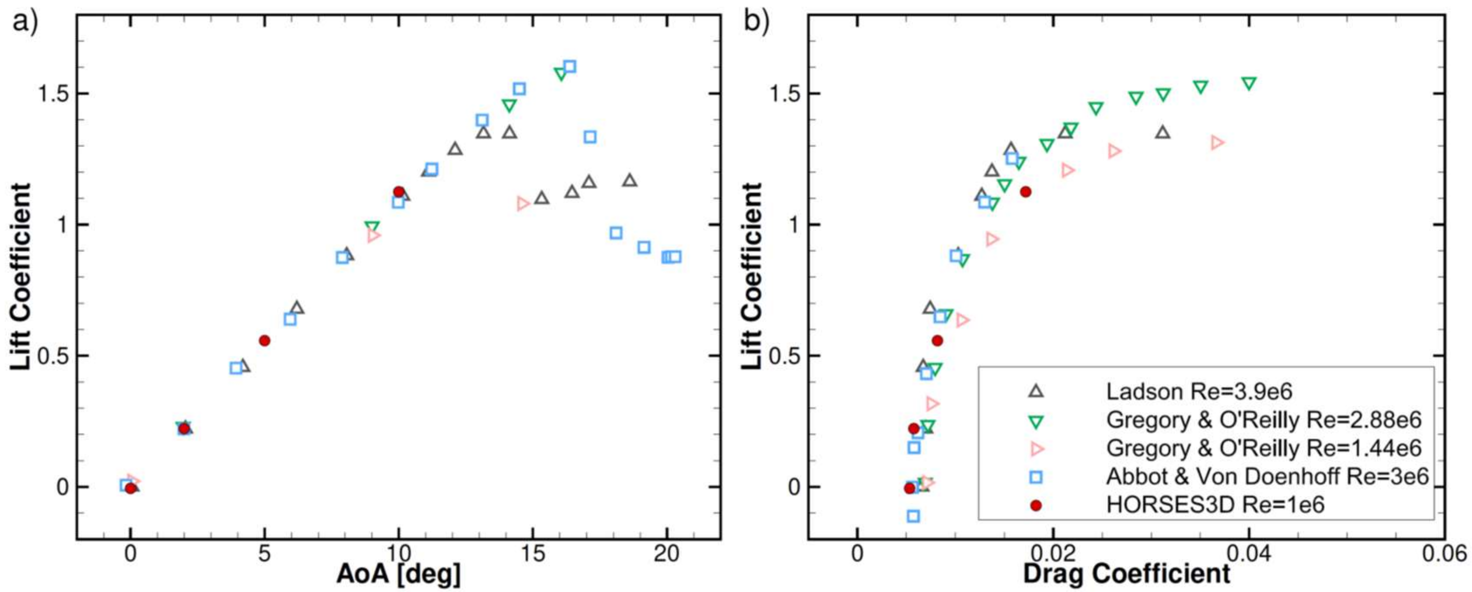
Re=1.000.000
AoA = 0 deg

Re=1.000.000
AoA = 5 deg

contrours of velocity: [0.85; 1.2]

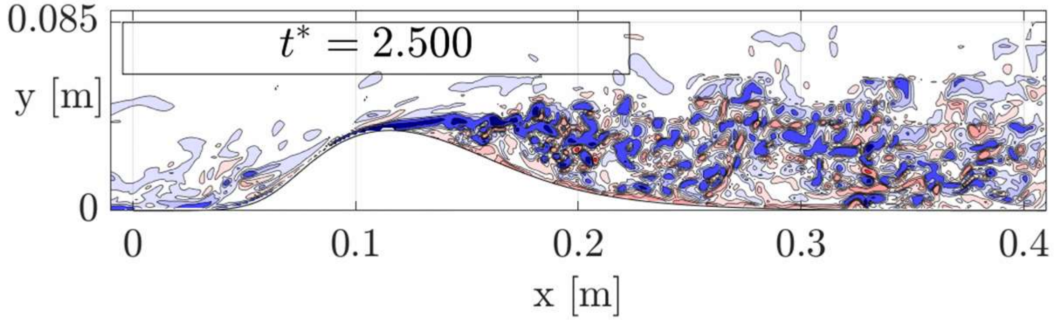
NACA0012 at various AoAs

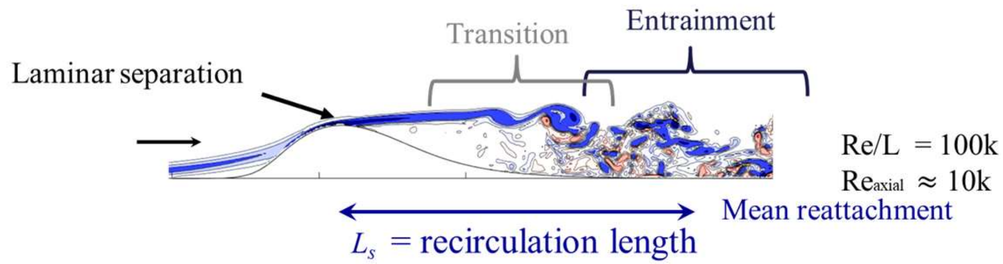
Re=1.000.000
AoA = 10 deg



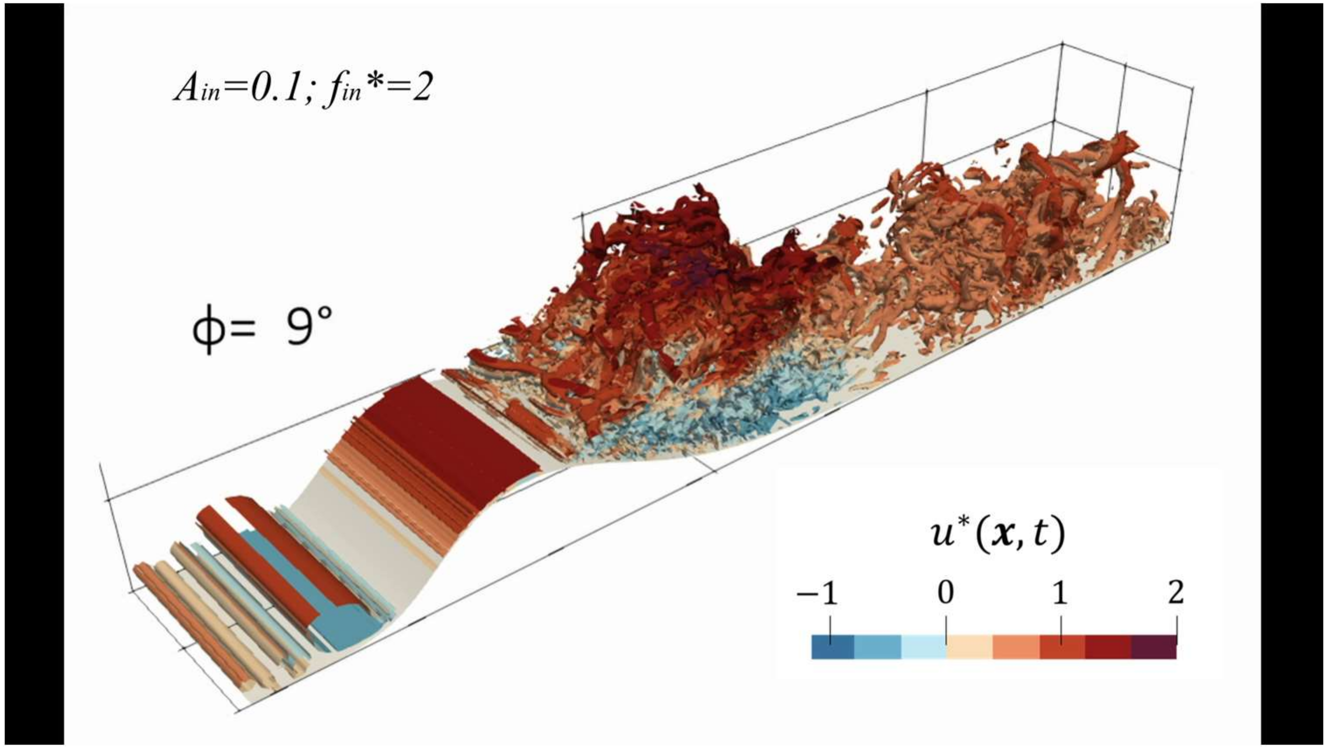
HORSES3D: Compressible DGSEM – energy-stable - SBP-SAT & Roe fluxes & BR1

E Ferrer, J Manzanero, AM Rueda-Ramirez, G Rubio, E Valero, "Implicit large eddy simulations for NACA0012 airfoils using compressible and incompressible DG solvers", *Spectral and High Order Methods for Partial Differential Equations ICOSAHOM 2018, Lecture Notes in Computational Science and Engineering, Springe*





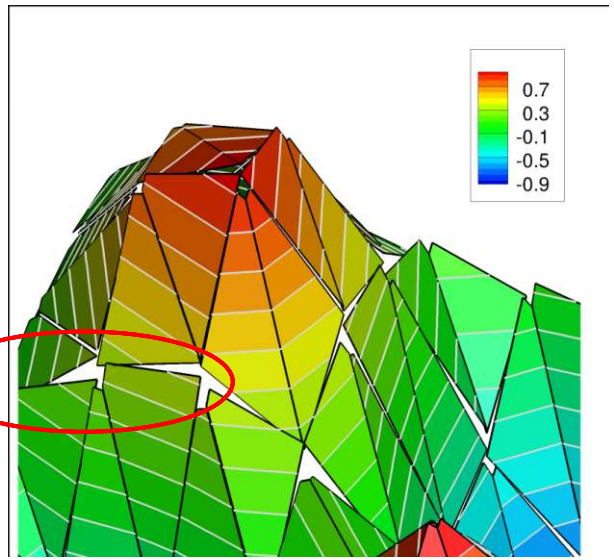
Implicit LES



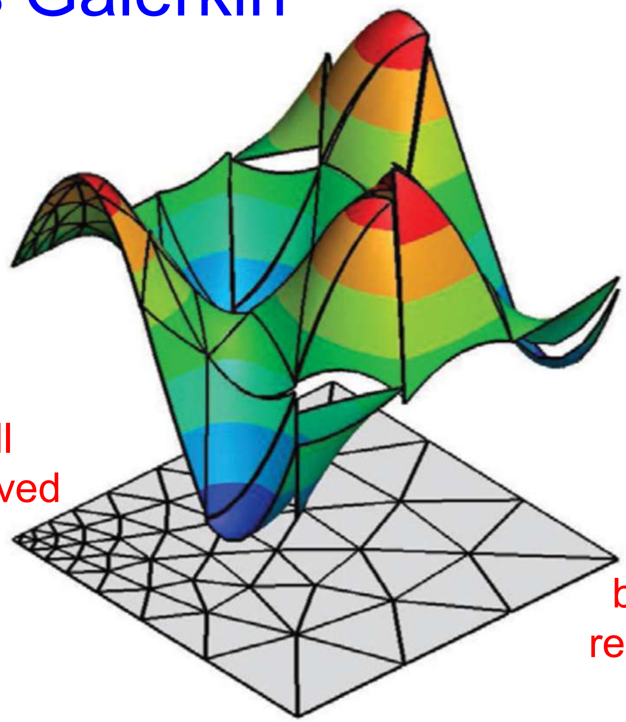
H Marbona, D Rodríguez, A Martínez-Cava, E Valero, *Physical Review Fluids,* 2024

New turbulent models for discontinuous Galerkin

Discontinuous solutions



well resolved



badly resolved

Viscosity proportional to jumps (associated to under-resolution)

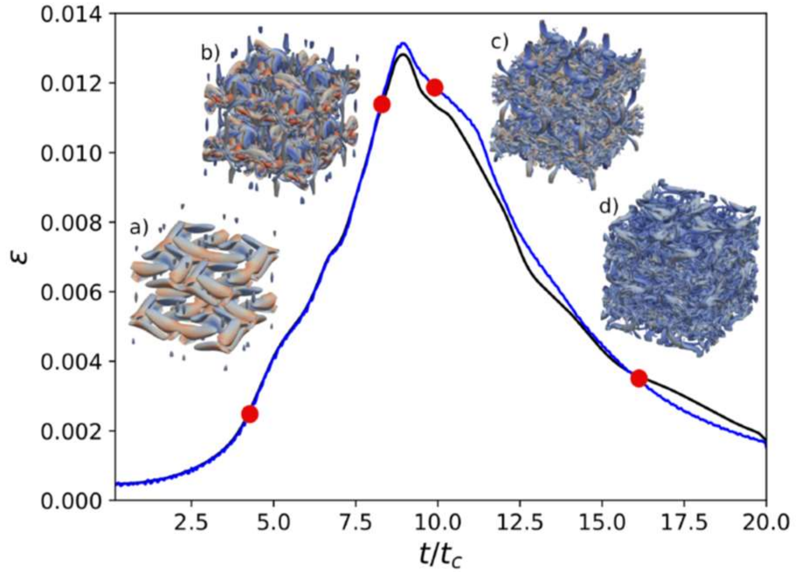
Solution: $\frac{\tau_s}{Re}\int_{\partial\Omega_n} [\![\tilde{\mathbf{q}}]\!]\phi_i.$ — Ferrer 2017

Gradients: $-\frac{\tau_g h^2}{Re}\int_{\partial\Omega_n} [\![\nabla\tilde{\mathbf{q}}]\!]\nabla\phi_i\cdot\mathbf{n}$ — Burman et al 2010, Moura et al 2022

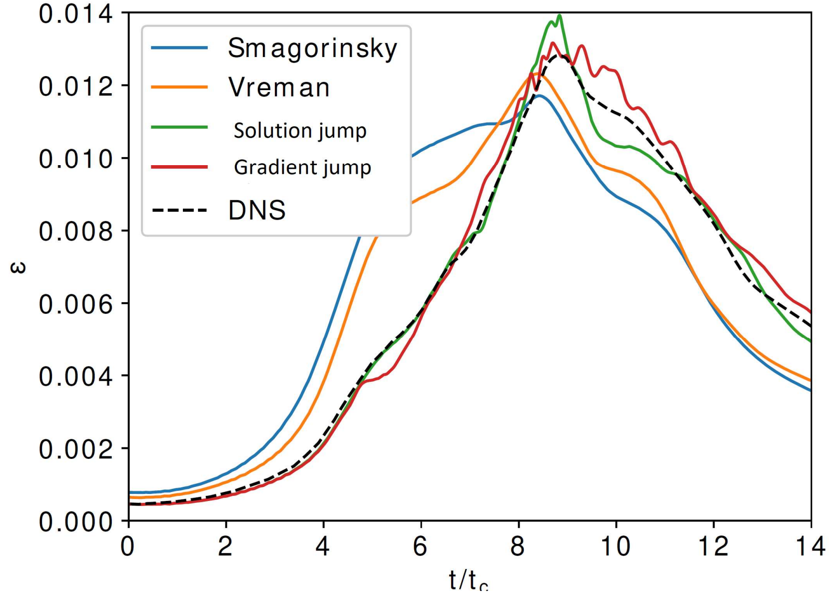
J Kou, OA Marino, **E Ferrer**, "Jump penalty stabilisation techniques for under-resolved turbulence in DG schemes" *Journal of Computational Physics*, Vol 491, 112399, 2023

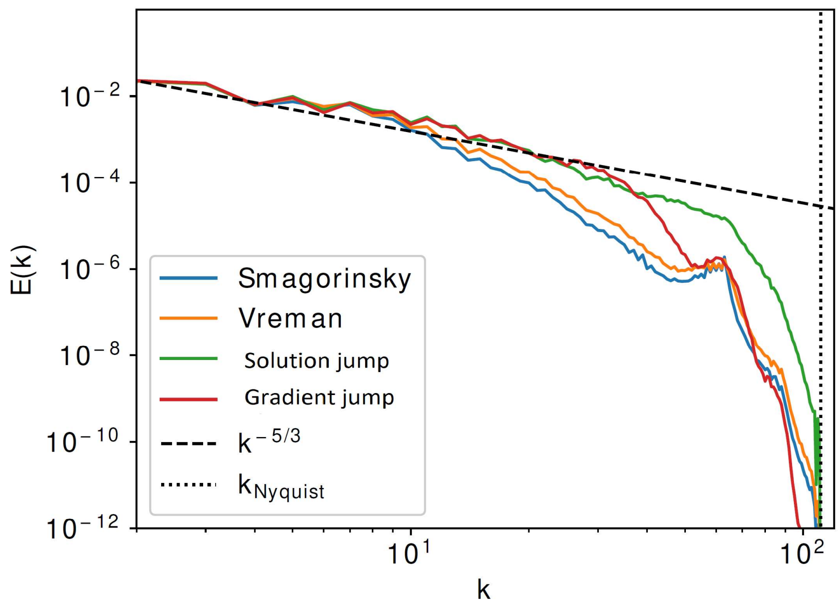
E Ferrer, "An interior penalty stabilised incompressible DG–Fourier solver for implicit Large Eddy Simulations", *Journal of Computational Physics,* Vol 348, 2017

New turbulent models for discontinuous Galerkin



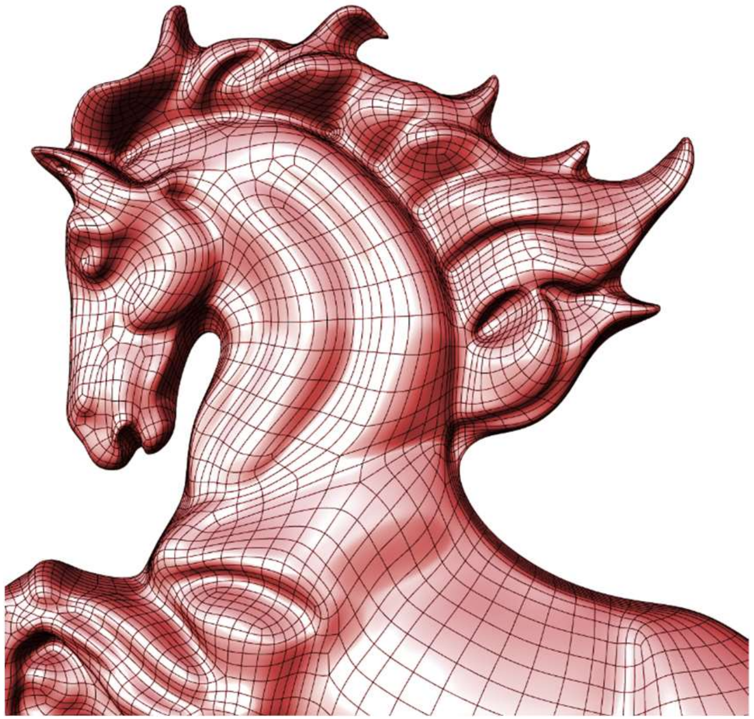
Taylor Green Vortex
Re=1600





J Kou, OA Marino, **E Ferrer**, "Jump penalty stabilisation techniques for under-resolved turbulence in DG schemes" Journal of Computational Physics, Vol 491, 112399, 2023

Summary



1- Introduction to DG & Horses3d

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→ Wind turbines
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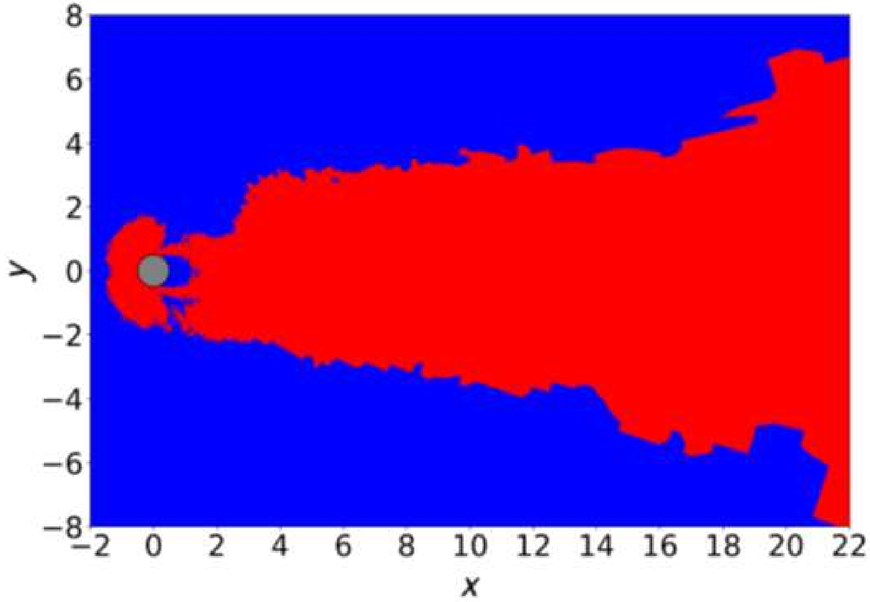
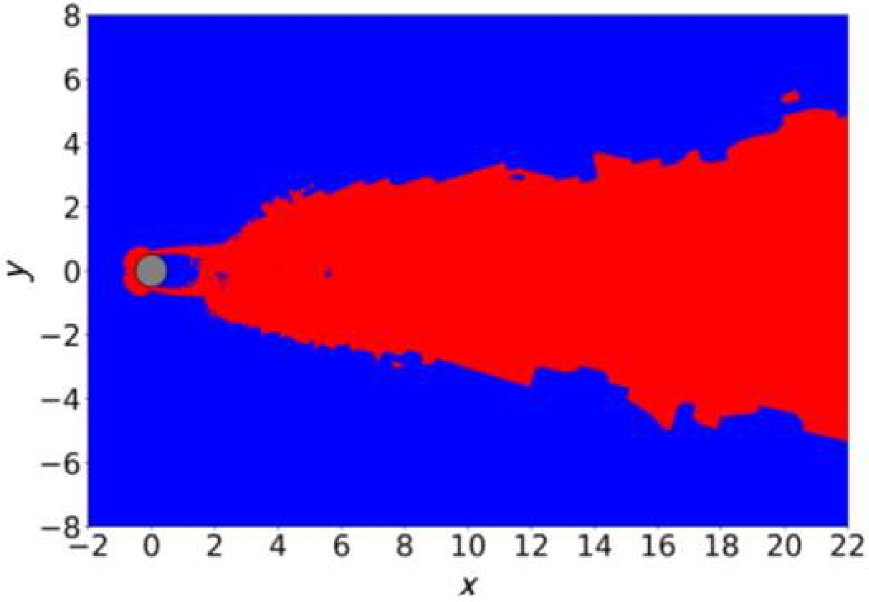
Machine Learning to detect flow regions

F=1.25

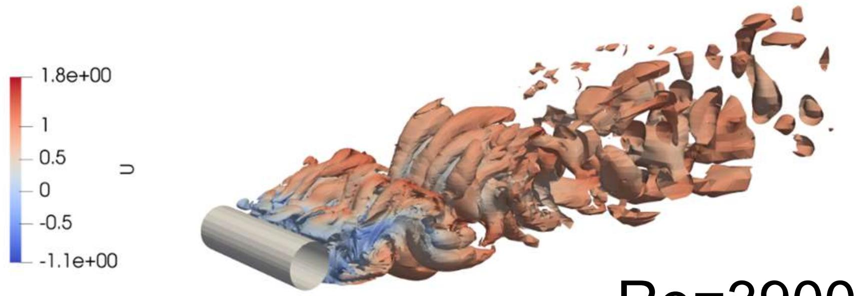


F=1.5



Feature based sensors
Eddy viscosity sensor

$$F_{\mu_t} = \frac{\mu + \mu_t}{\mu}$$



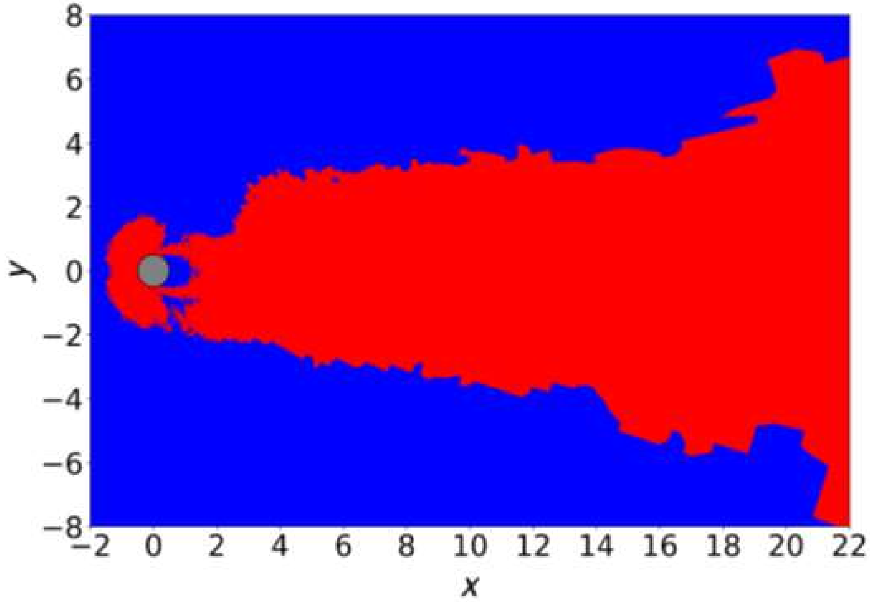
Re=3900

-KE Otmani, G Ntoukas, **E Ferrer**, "Towards a robust detection of flow regions using unsupervised machine learning", *Physics of Fluids*, *35, 027112, 2023*
-K Tlales, KE Otmani, G Ntoukas, G Rubio, **E Ferrer**, "Machine learning adaptation for laminar and turbulent flows: applications to high order discontinuous Galerkin solvers“ *Under review*

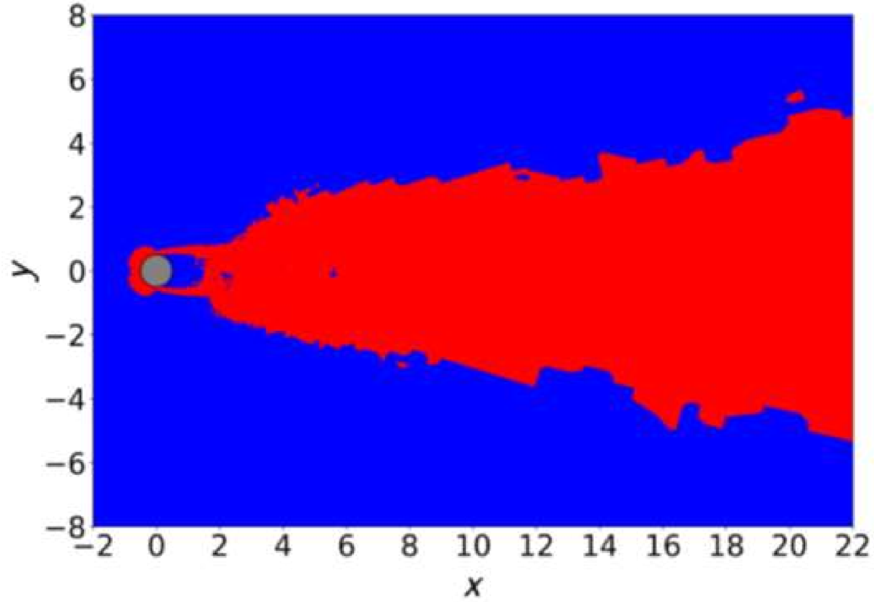
Machine Learning to detect flow regions

Re=3900

F=1.25



F=1.5



Feature based sensors
Eddy viscosity sensor

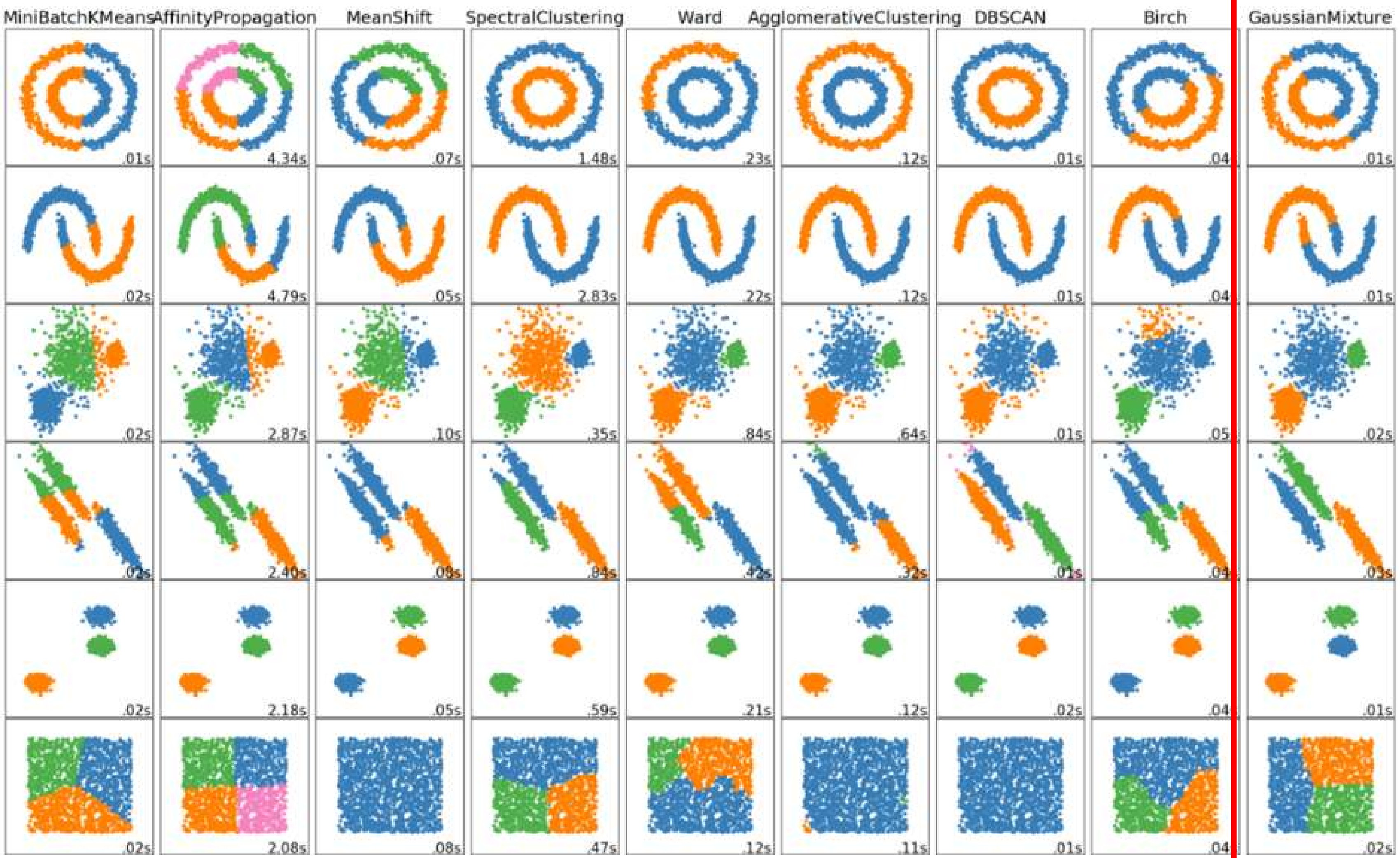
$$F_{\mu_t} = \frac{\mu + \mu_t}{\mu}$$

- **Very sensitive to threshold**
- **Cannot detect mixed regions (e.g. laminar-turbulent)**

-KE Otmani, G Ntoukas, **E Ferrer**, "Towards a robust detection of flow regions using unsupervised machine learning", *Physics of Fluids*, *35, 027112, 2023*
-K Tlales, KE Otmani, G Ntoukas, G Rubio, **E Ferrer**, "Machine learning adaptation for laminar and turbulent flows: applications to high order discontinuous Galerkin solvers" *Under review*

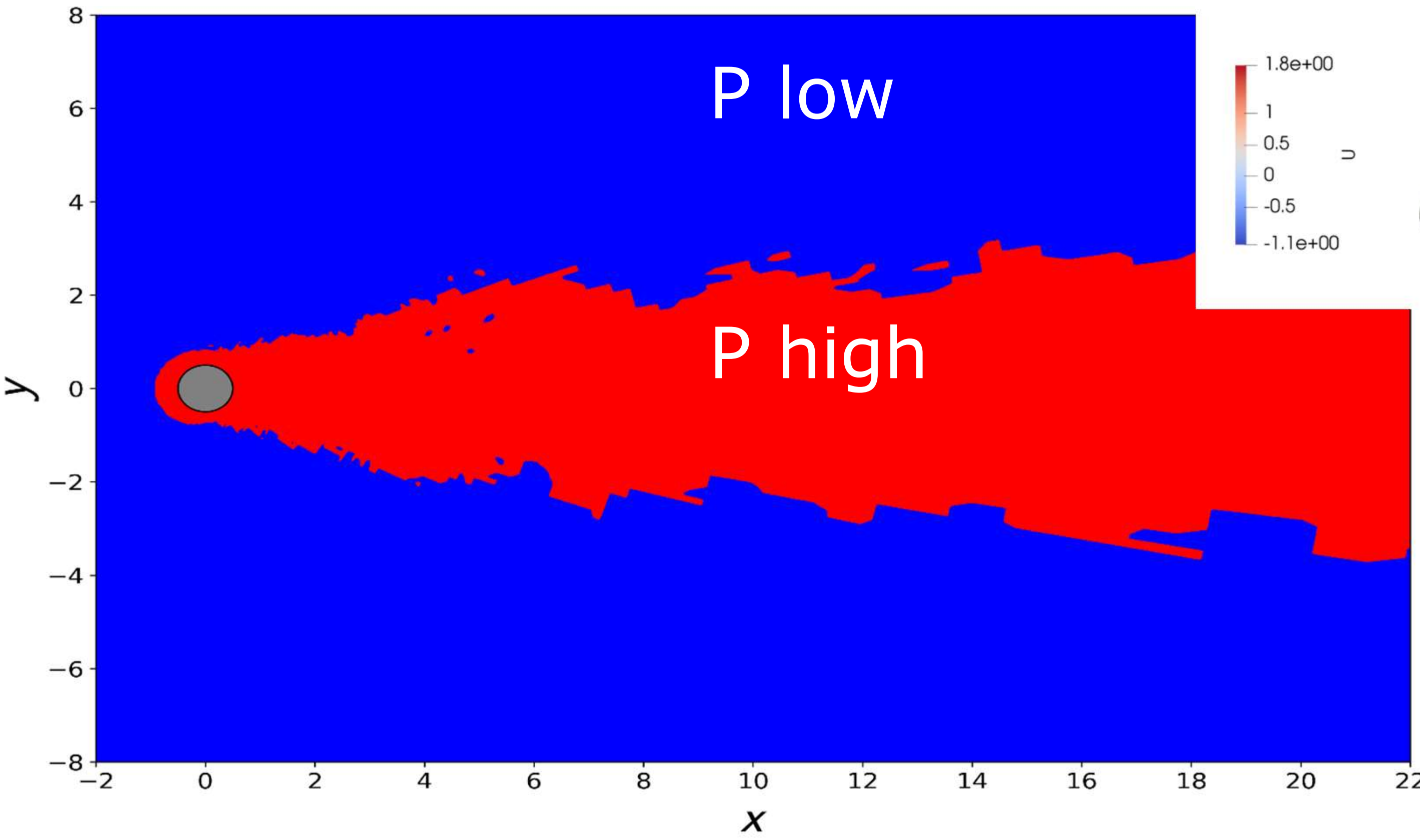
Machine Learning to detect flow regions

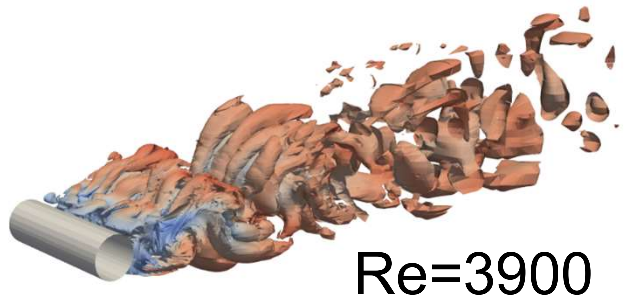
Clustering (classify data): Gaussian mixture model



Machine Learning to detect flow regions

Clustering (classify data): Gaussian mixture model





Re=3900

Automate the detection (no thresholds)

Use a robust feature space for a variety of Re

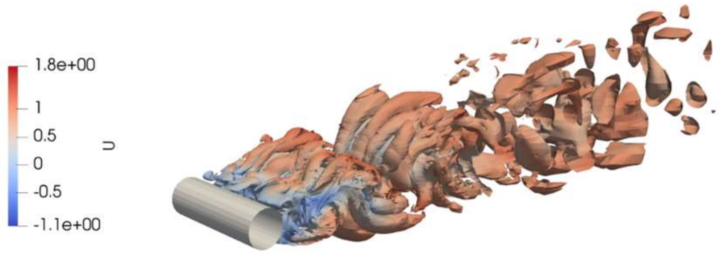
Invariants of strain and rotational rate tensors

-KE Otmani, G Ntoukas, **E Ferrer**, "Towards a robust detection of flow regions using unsupervised machine learning", *Vol 35, 027112, 2023*
-K Tlales, KE Otmani, G Ntoukas, G Rubio, **E Ferrer**, "Machine learning adaptation for laminar and turbulent flows: applications to high order discontinuous Galerkin solvers“ *Under review*

Machine Learning to detect flow regions

Clustering: Gaussian mixture model

	St	C_d	L_r	$L_z \backslash D$
Uniform P3	0.202	0.7844	1.36	π
Uniform P4	0.203	0.9513	1.64	π
Cluster-Adapt P4-P2	0.204	0.9506	1.63	π
Parnadeau et al.[40]	0.208	-	1.56	π
Snyder and Degrez [45]	0.207	1.09	1.30	π
Kravchenko and Moin[46]	0.210	1.04	1.35	π
Breuer [47]	-	1.07	1.20	π
Franke and Frank [48]	0.209	0.98	1.64	π
(DNS) Ma et al. [41]	0.219	1.59	-	π
Ouvrard et al. [49]	0.223	0.94	1.56	π

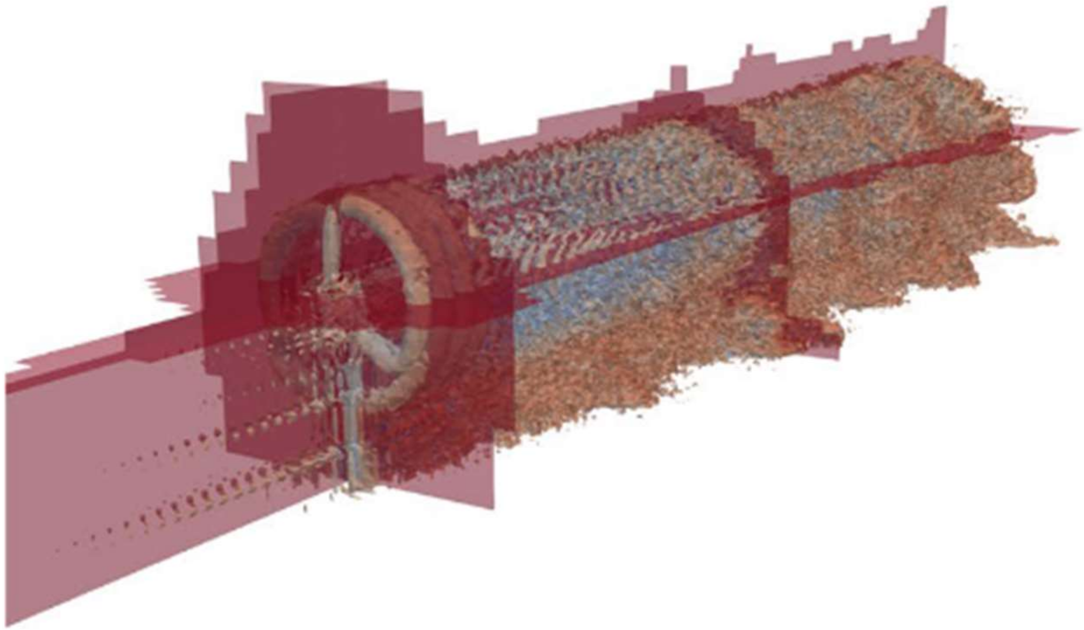


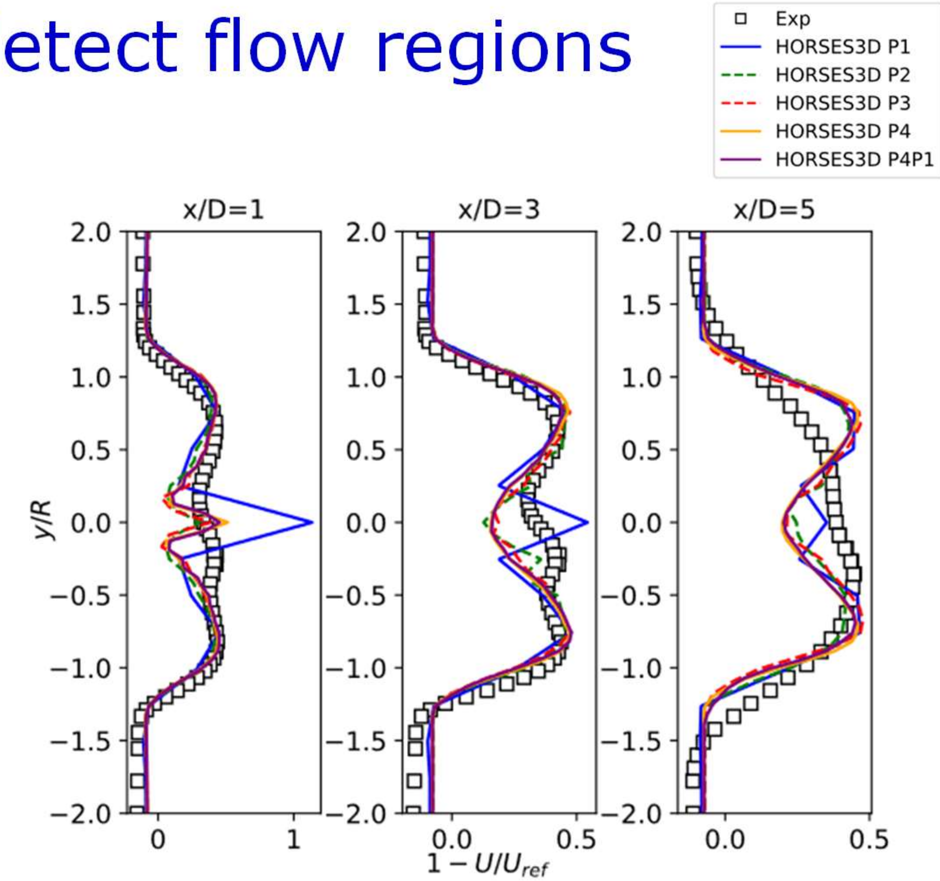
Re=3900

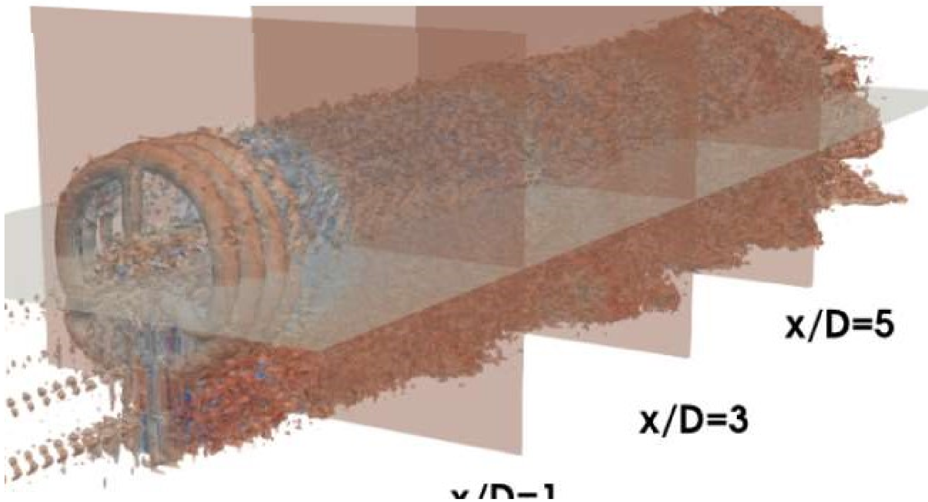
	DoFs	reduction of DoFs	reduction of comp. time
Cluster-Adapt P4-P2	1.55M	41%	33%

-KE Otmani, G Ntoukas, **E Ferrer**, "Towards a robust detection of flow regions using unsupervised machine learning", *Physics of Fluids*, *35, 027112, 2023*
-K Tlales, KE Otmani, G Ntoukas, G Rubio, **E Ferrer**, "Machine learning adaptation for laminar and turbulent flows: applications to high order discontinuous Galerkin solvers“ *Under review*

Machine Learning to detect flow regions

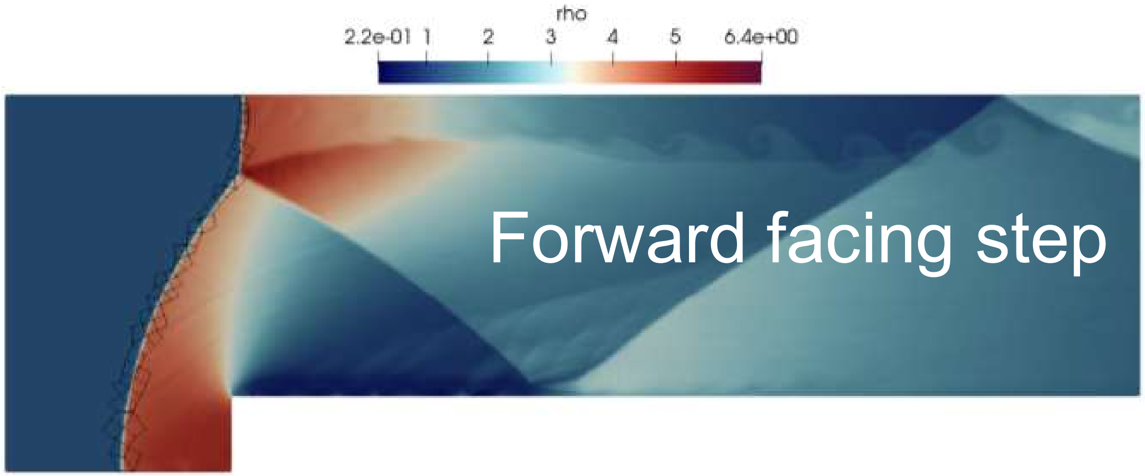


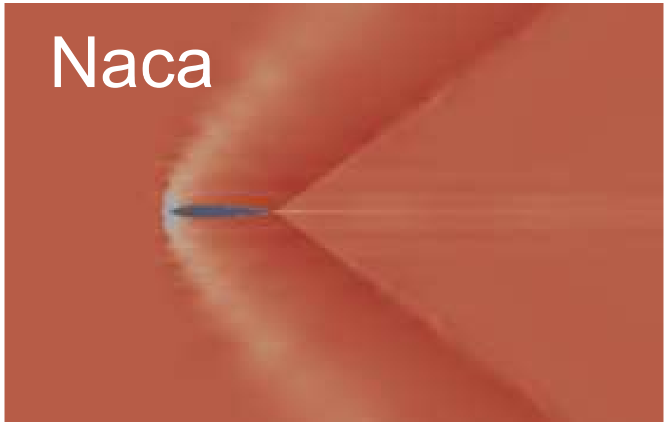


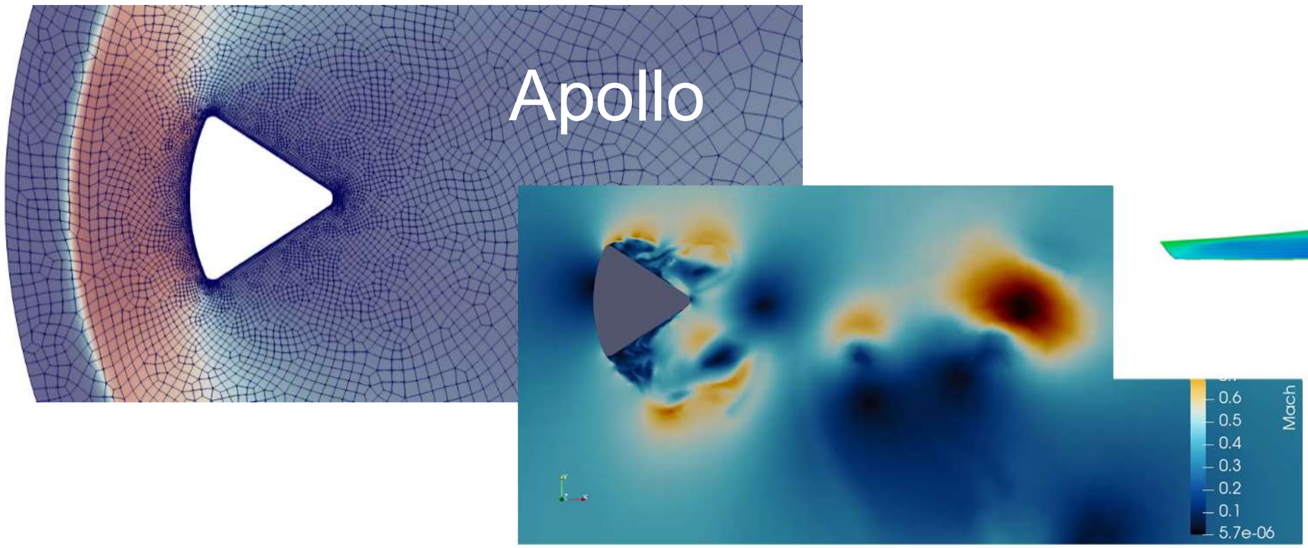


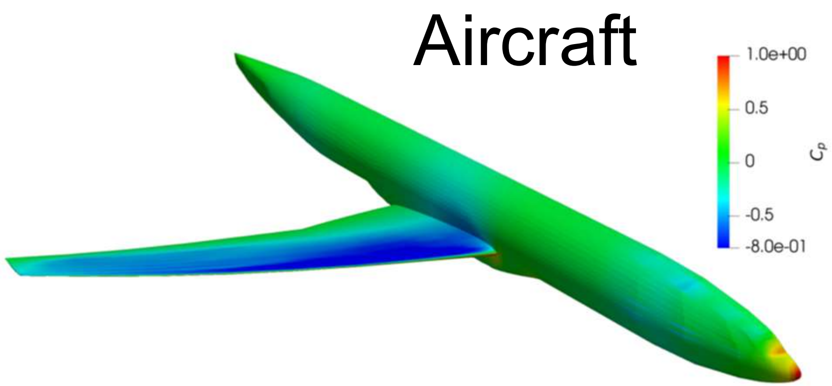
	DoFs	reduction of DoFs	reduction of comp. time
Uniform P1	0.59M	93.6%	92.7%
Uniform P2	1.99M	78.2%	86.5%
Uniform P3	4.72M	48.7%	54.1%
Uniform P4	9.22M	-	-
Cluster-Adapt P4-P1	3.58M	61%	43%

Supersonic & Shock capturing









-E Ferrer, G Rubio, G Ntoukas, W Laskowski, O Mariño, S Colombo, A. Mateo-Gabín, H Narbona, F Manrique de Lara, D Huergo, J Manzanero, AM Rueda-Ramírez, DA Kopriva, E Valero, "HORSES3D: a high order discontinuous Galerkin solver for flow simulations and multi-physic applications", *Computer Physics Communications*, Vol 287, 2023
-A Mateo-Gabín, J Manzanero, E Valero, An entropy stable spectral vanishing viscosity for discontinuous Galerkin schemes: Application to shock capturing and LES models, *Journal of Computational Physics*, Vol 471,2022

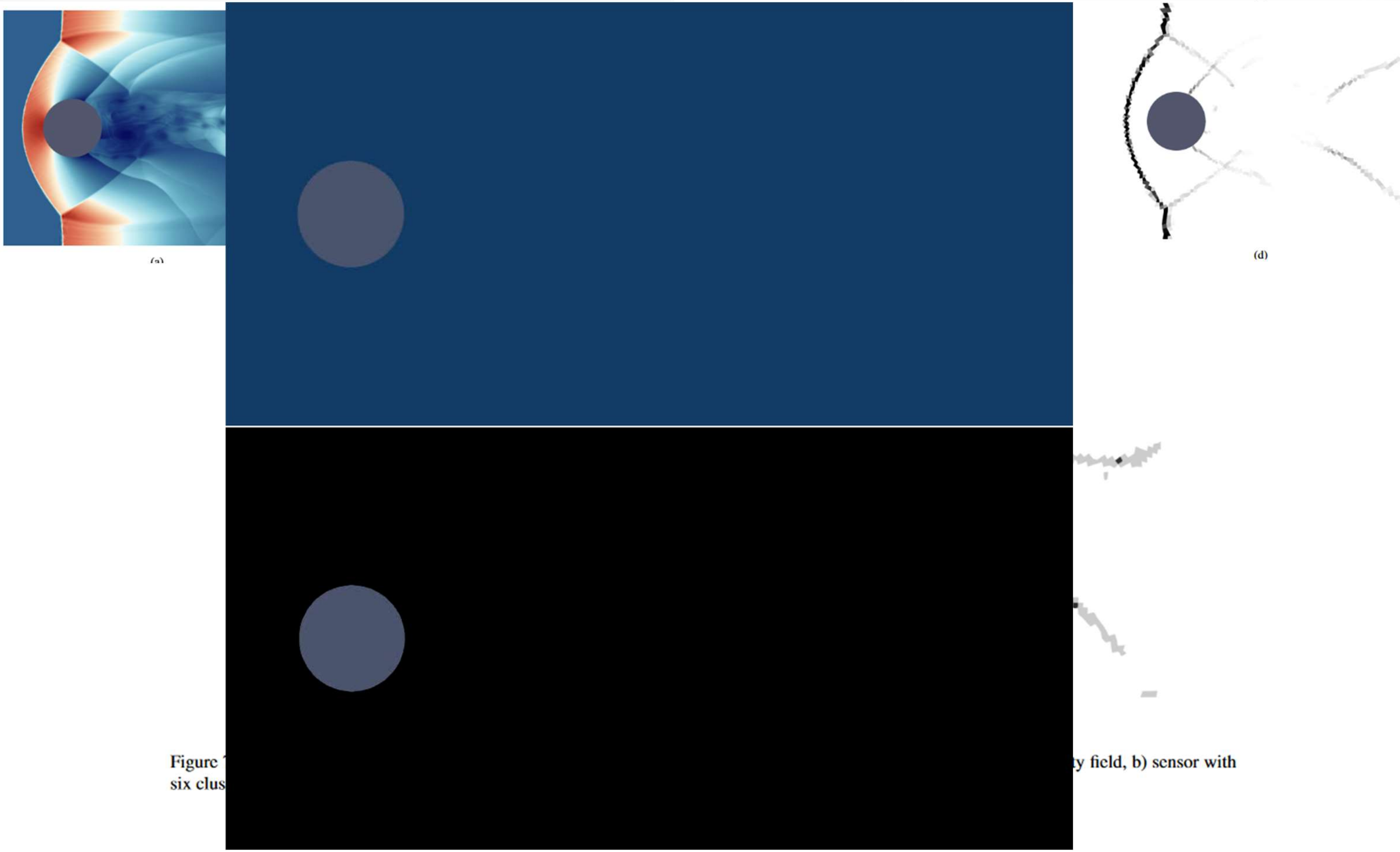


Figure … ty field, b) sensor with
six clus…

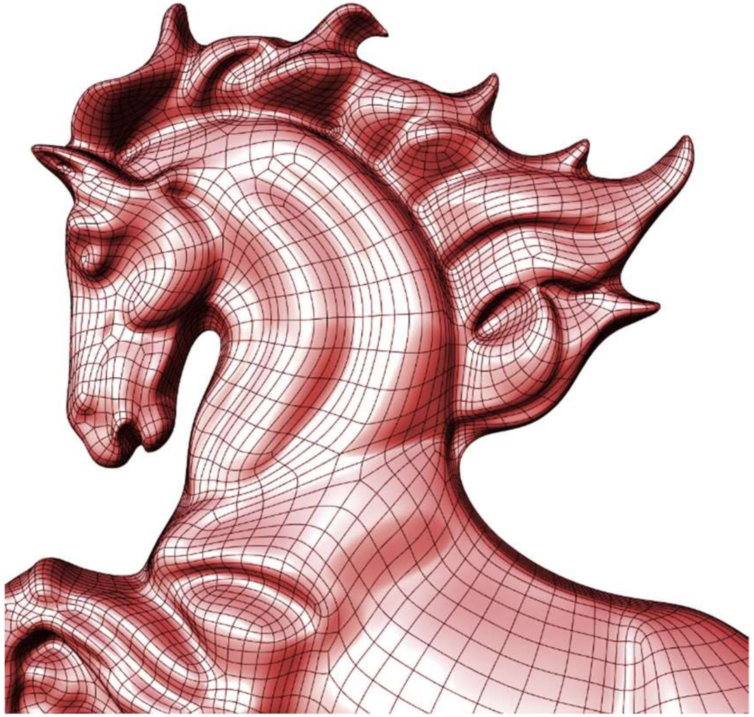
A Mateo-Gabín, K Tlales, E Valero, **E Ferrer**, G Rubio, "Unsupervised machine learning shock capturing for High-Order CFD solvers“, *under review*

Summary

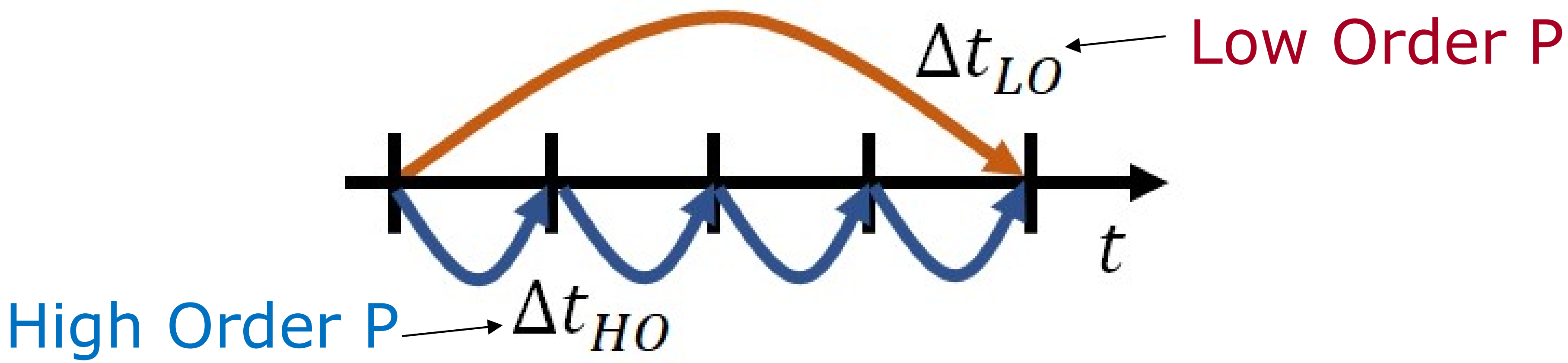
1- Introduction to DG & Horses3d

2- Multiphysics
→ Wind turbines
→ Turbulence

3. Machine Learning + CFD
→ Mesh adaption
→ NN acceleration
→ RL for automation

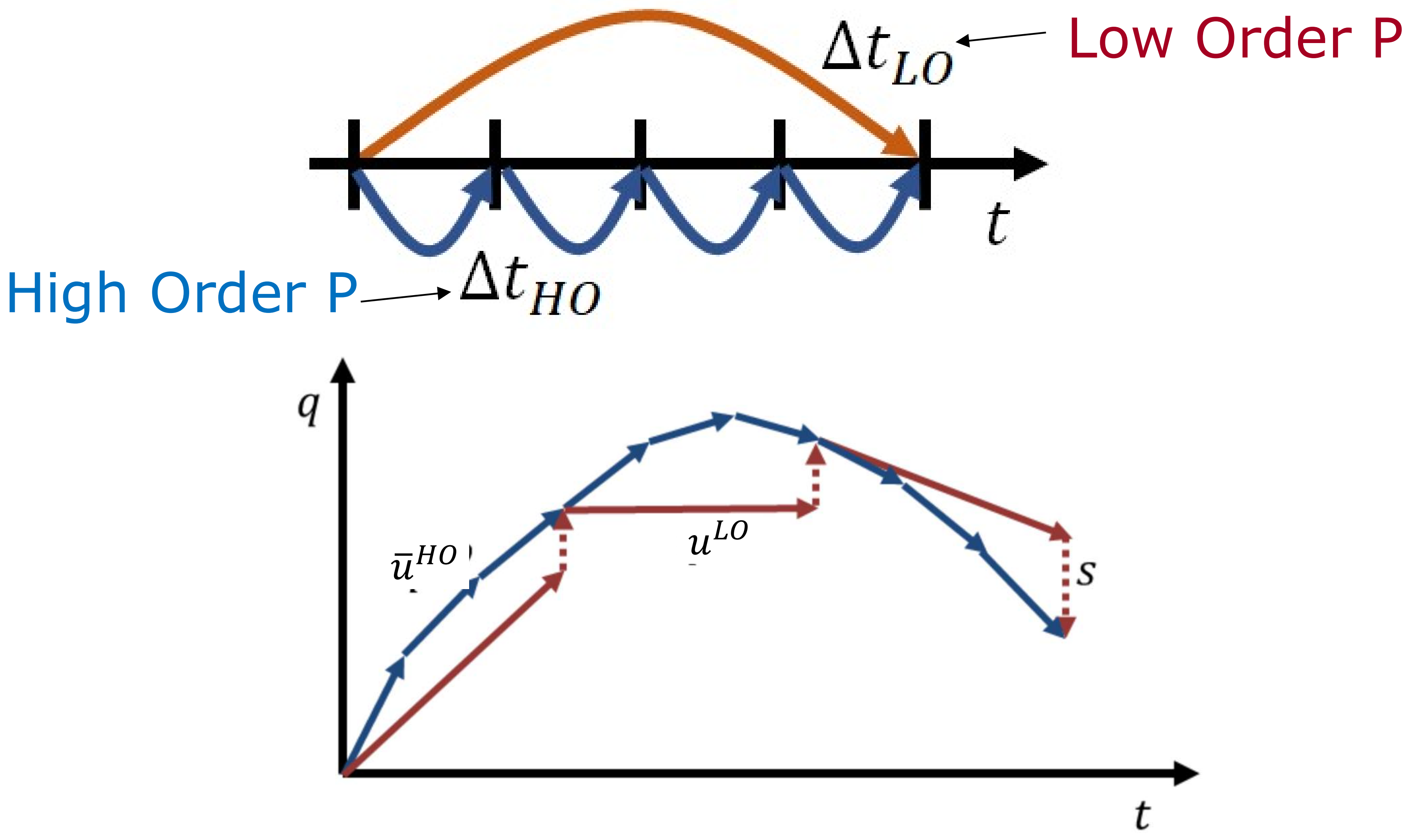


Machine Learning to accelerate CFD



-Manrique de Lara F**, Ferrer E,** Accelerating High Order Discontinuous Galerkin solvers using neural networks: 1D Burgers, Vol 235, *Computers & Fluids, 2022*
-Manrique de Lara F, **Ferrer E**. Accelerating high order discontinuous Galerkin solvers using neural networks: 3D Navier-Stokes equations. *Accepted JCP*

Machine Learning to accelerate CFD



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Machine Learning to accelerate CFD

LO evolution:

$$u_{n+1}^{LO} = u_n^{LO} + \Delta t_n q^{LO}(u_n^{LO}; t_n)$$

Filtered HO:

$$\bar{u}_{n+1}^{HO} = \bar{u}_n^{HO} + \Delta t_n \bar{q}^{HO}(u_n^{HO}; t_n)$$

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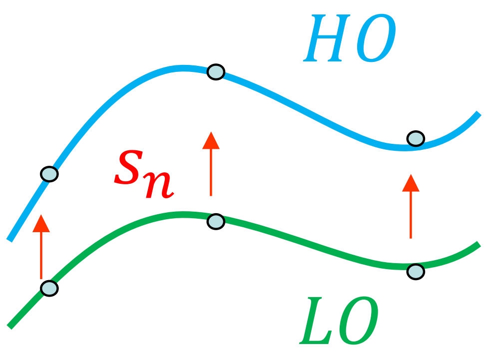

LO-NN corrected:

$$u_{n+1}^{NN} = u_n^{NN} + \Delta t_n [q^{LO}(u_n^{NN}; t_n) + s_n]$$

-Manrique de Lara F, **Ferrer E,** Accelerating High Order Discontinuous Galerkin solvers using neural networks: 1D Burgers, Vol 235, *Computers & Fluids, 2022*
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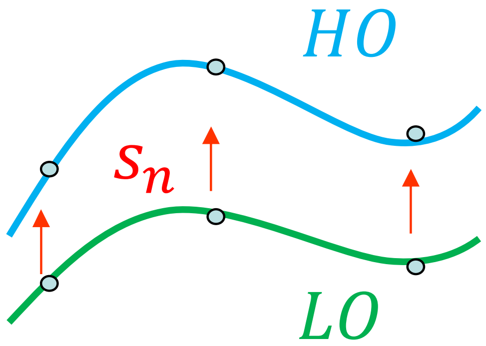
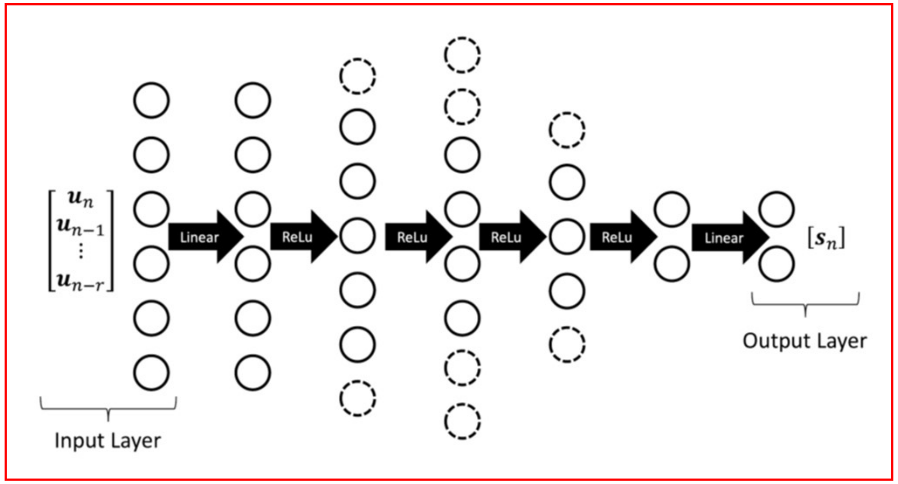


LO-NN corrected:

$$u_{n+1}^{NN} = u_n^{NN} + \Delta t_n [q^{LO}(u_n^{NN}; t_n) + s_n]$$

$$s_n = f(u_n^{NN}, u_{n-1}^{NN}, u_{n-r}^{NN}, \bar{u}^{HO})$$

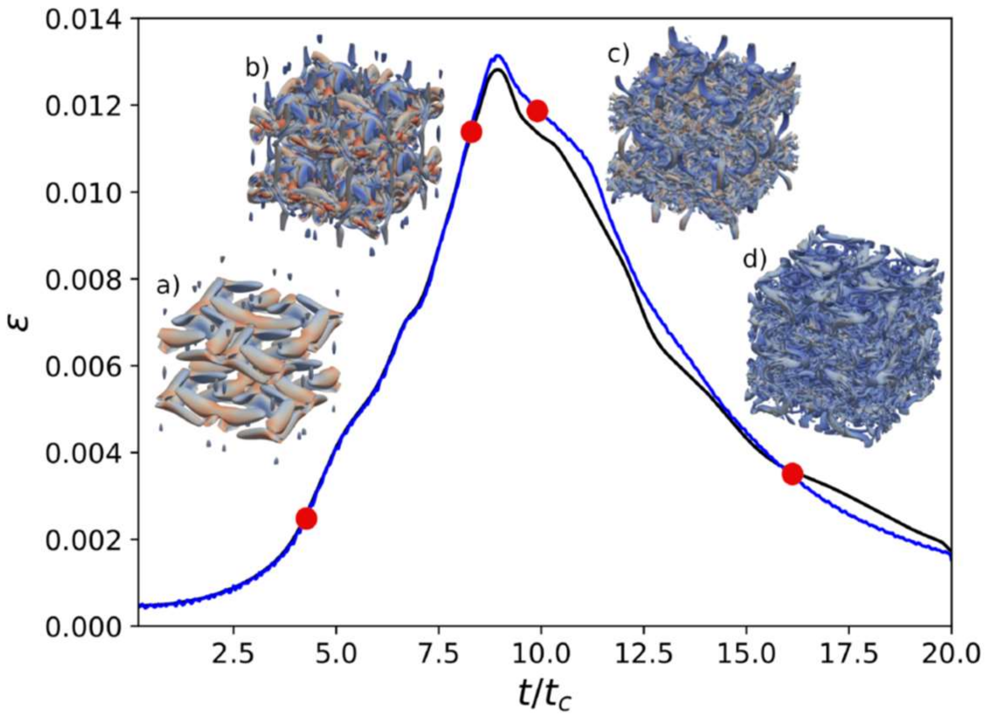
Trained to give HO solution



Machine Learning to accelerate CFD

3D Navier-Stokes - LES

Taylor-Green – Reynolds 1600



F Manrique de Lara, **E Ferrer,** "Accelerating High Order DG Solvers using Neural Networks: 3D Compressible Navier-Stokes Equations", *Journal of Computational Physics,* Vol 489, 112253, 2023

Machine Learning to accelerate CFD

3D Navier-Stokes - LES

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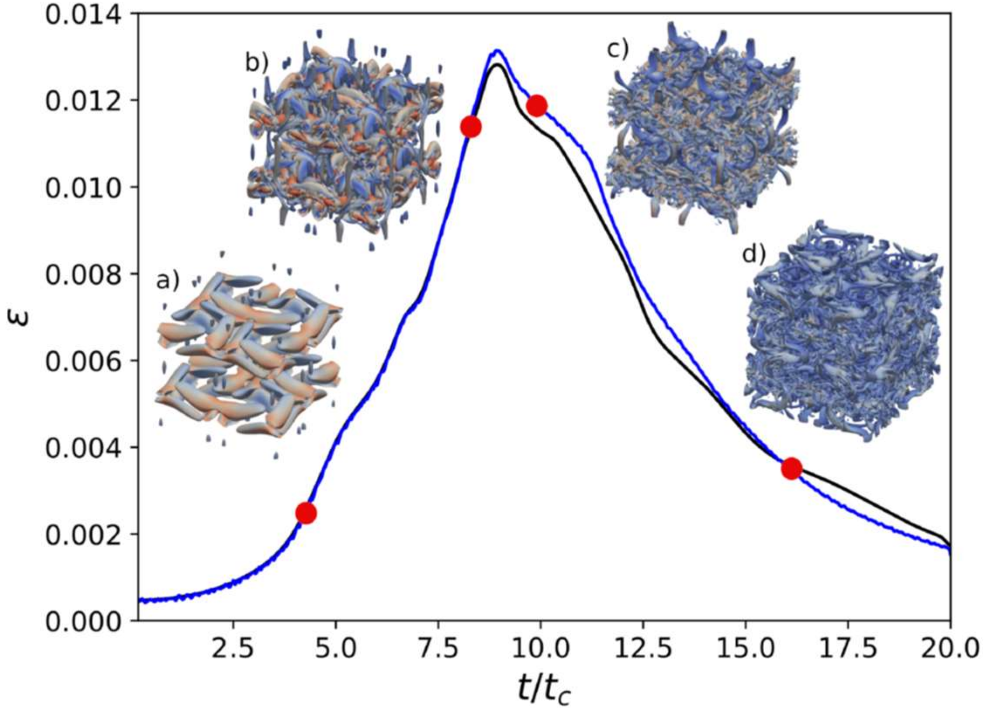

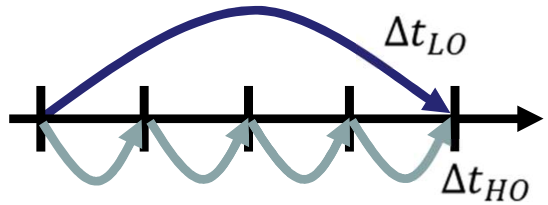

$P8 \rightarrow P3$

$\Delta t_{LO}/\Delta t_{HO} = 3$

F Manrique de Lara, **E Ferrer,** "Accelerating High Order DG Solvers using Neural Networks: 3D Compressible Navier-Stokes Equations", *Journal of Computational Physics,* Vol 489, 112253, 2023

Machine Learning to accelerate CFD

3D Navier-Stokes - LES

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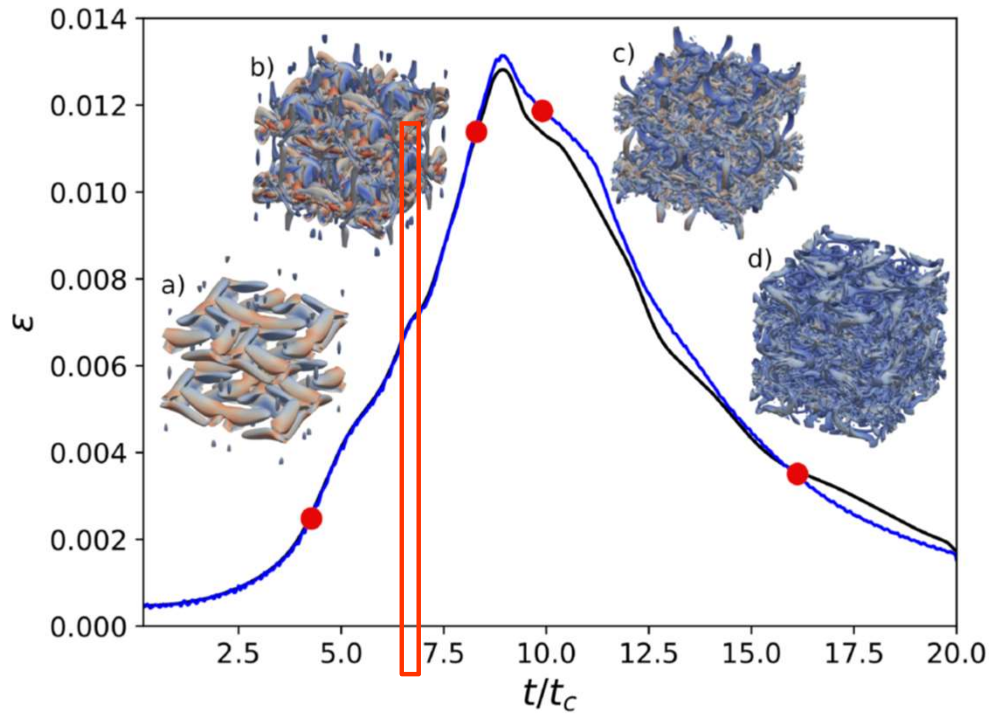
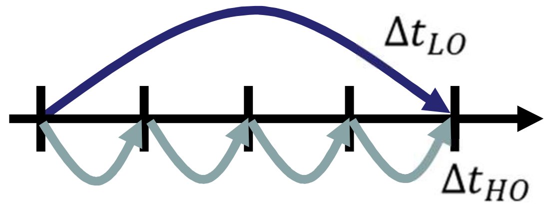


training



$$P8 \rightarrow P3$$

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Machine Learning to accelerate CFD

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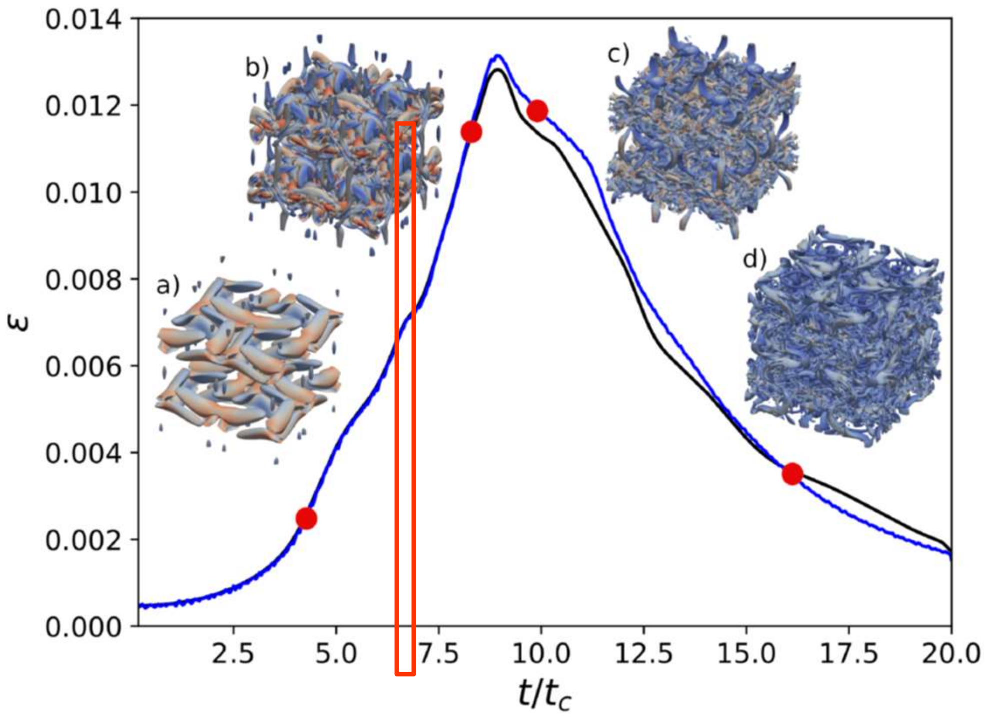

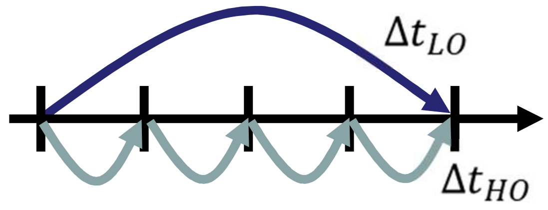

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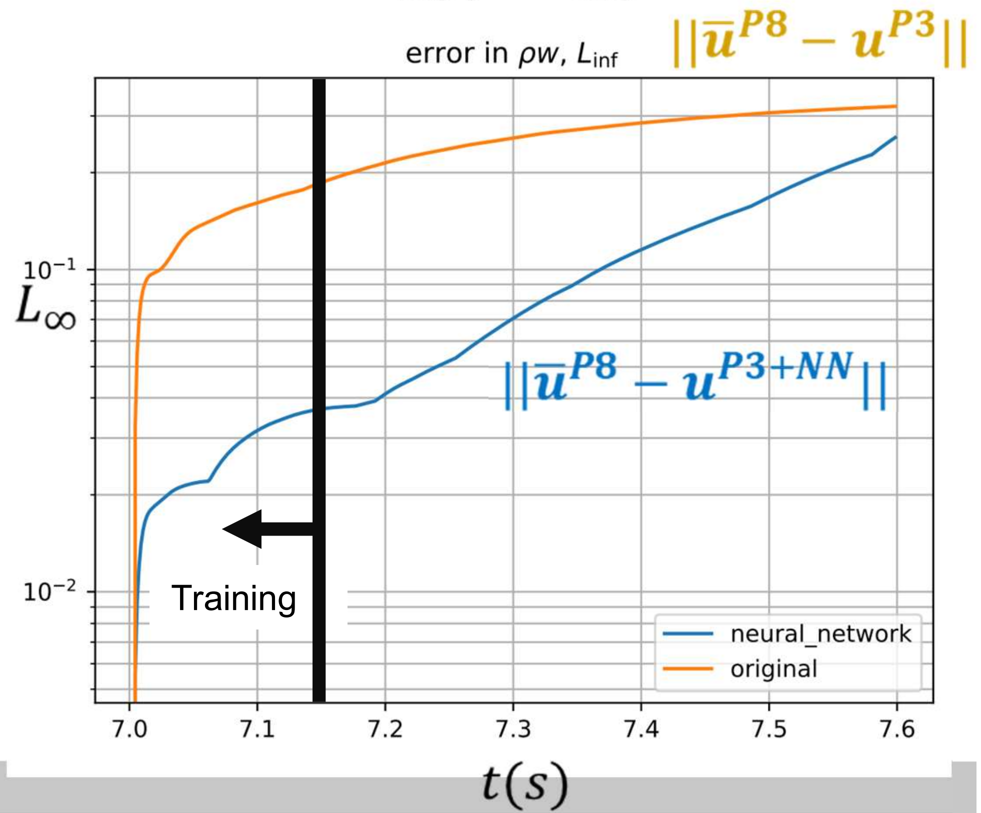
$$\Delta t_{LO}/\Delta t_{HO} = 3$$

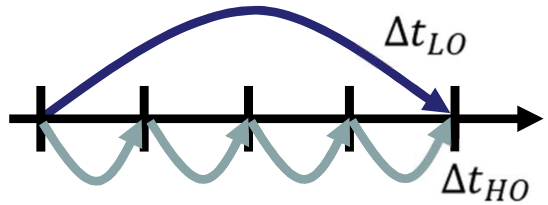


12 times faster

Machine Learning to accelerate CFD

3D Navier-Stokes - LES

Taylor-Green – Reynolds 1600



$$P8 \rightarrow P3$$

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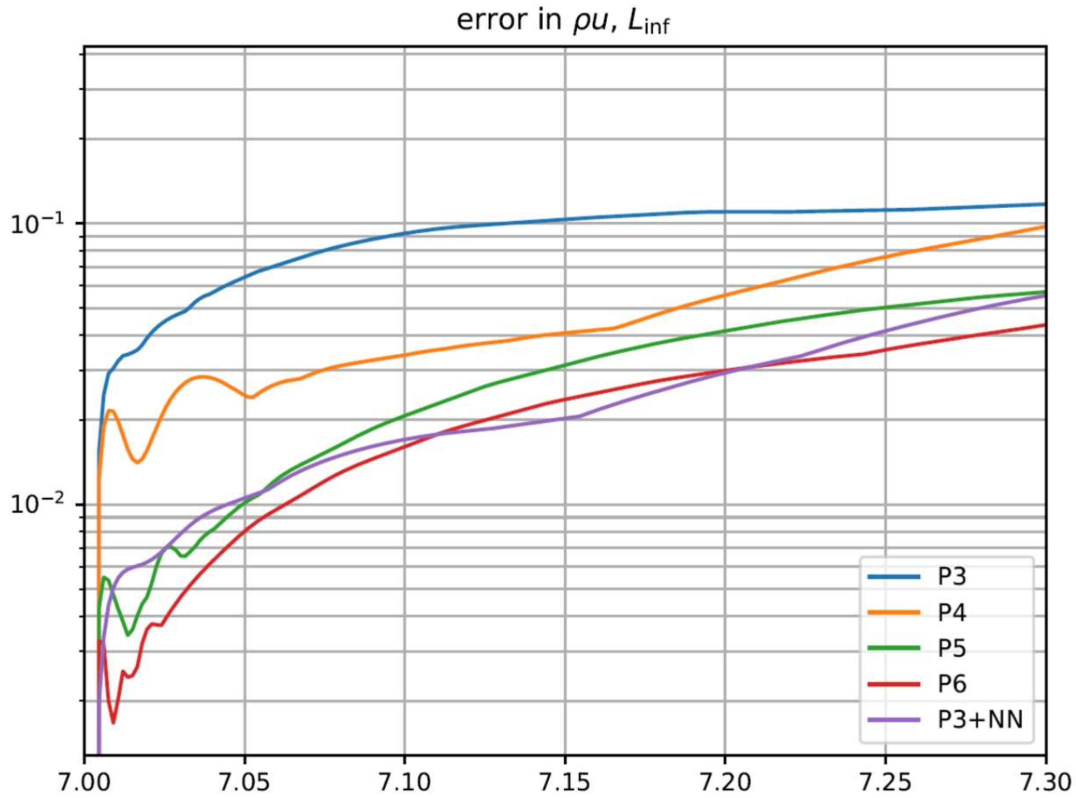

What is the real accuracy?

Probably P=6

P3+NN is 4-5 times faster
(compared to P6)

F Manrique de Lara, **E Ferrer,** "Accelerating High Order DG Solvers using Neural Networks: 3D Compressible Navier-Stokes Equations", *Journal of Computational Physics,* Vol 489, 112253, 2023

Machine Learning to accelerate CFD

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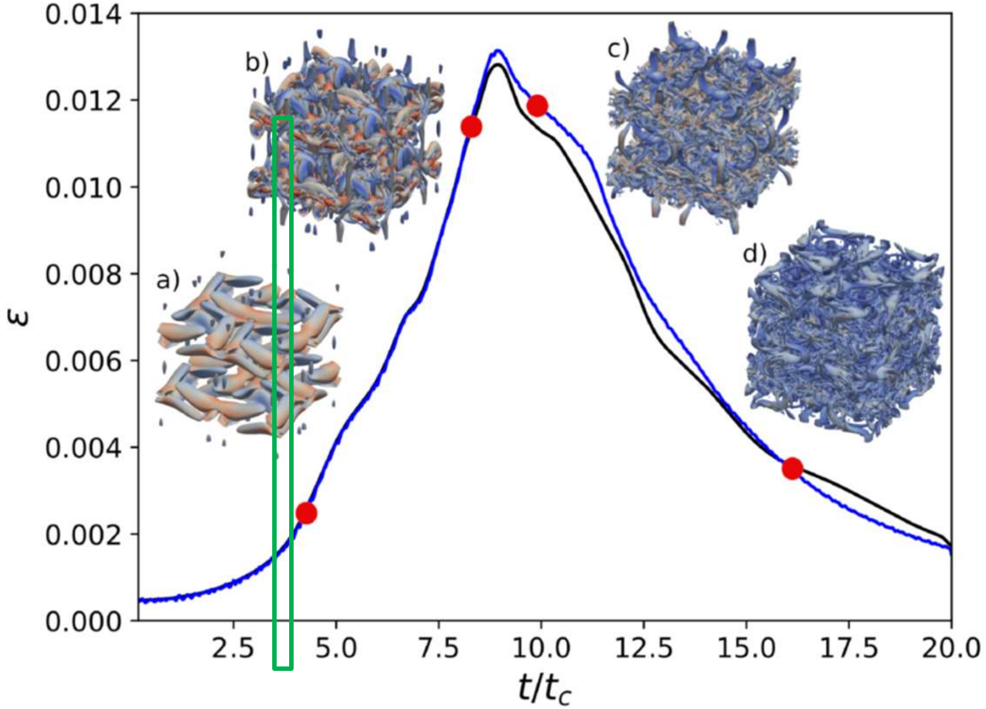
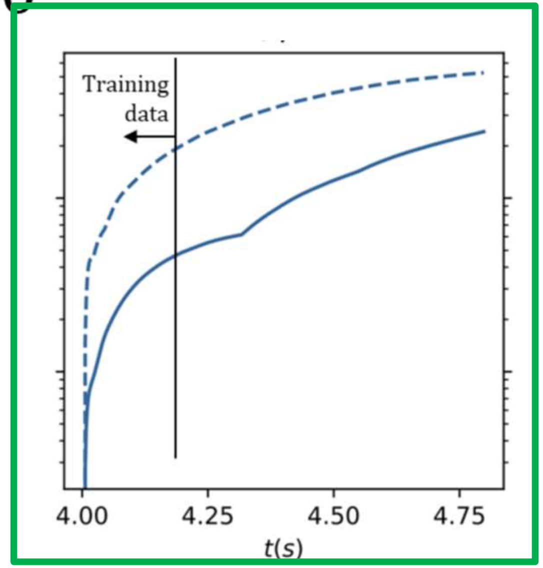
Taylor-Green – Reynolds 1600



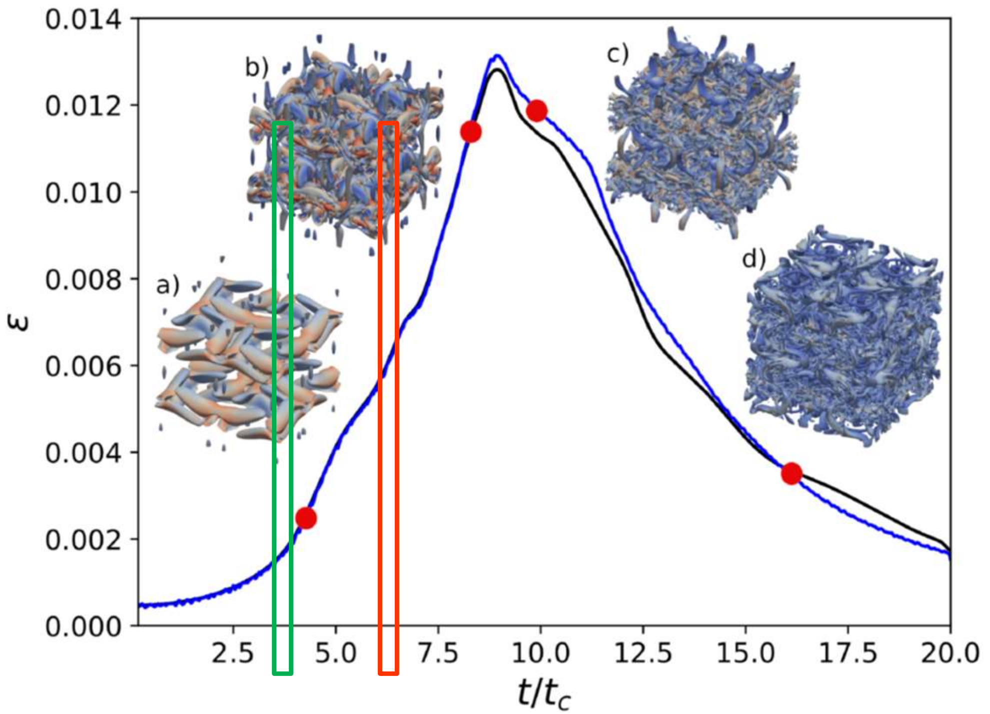


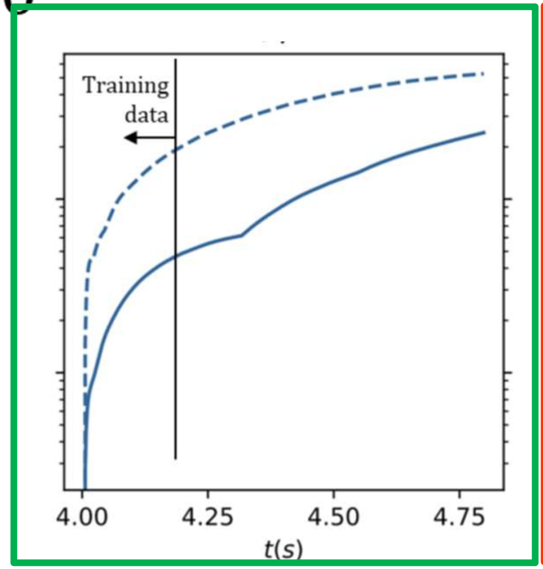
training

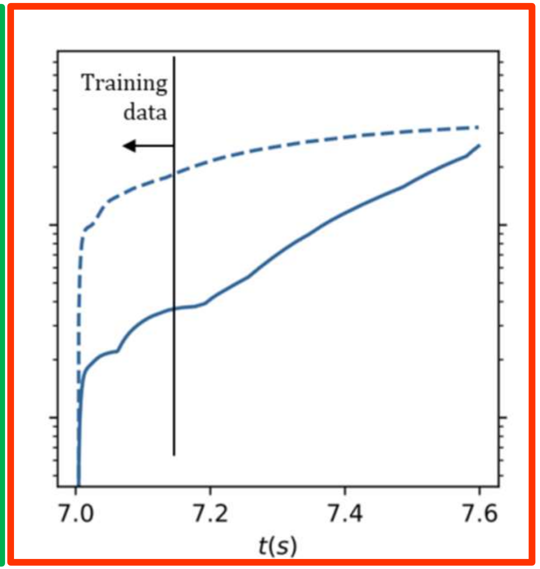
Machine Learning to accelerate CFD

3D Navier-Stokes - LES

Taylor-Green – Reynolds 1600







training

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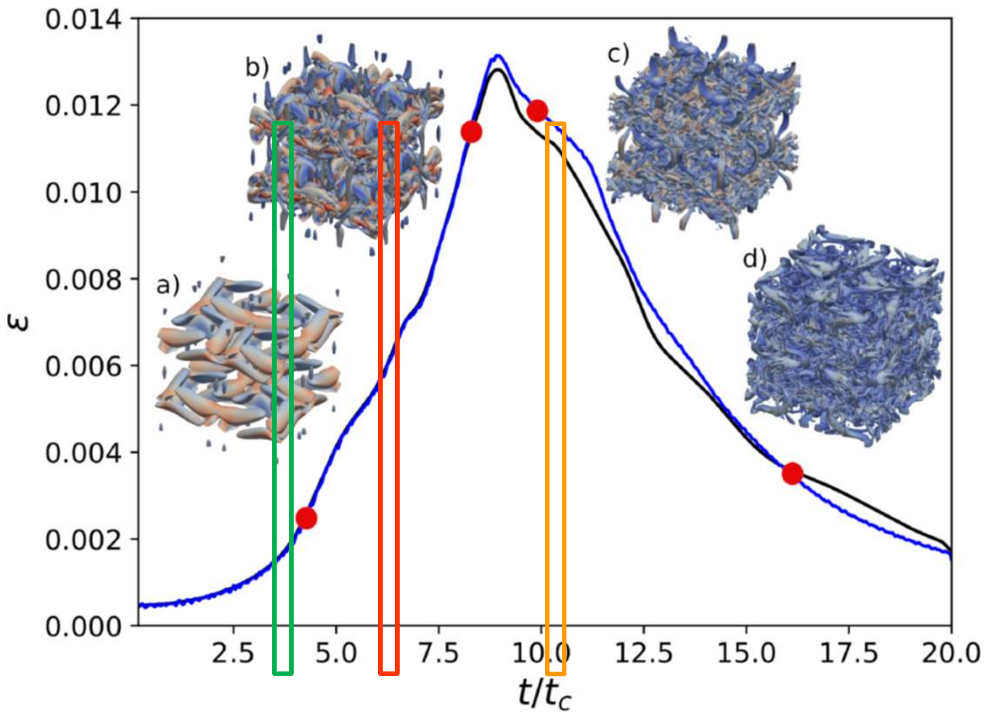

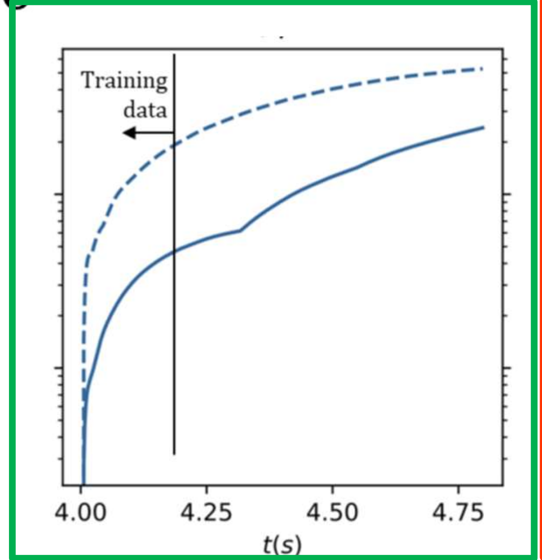

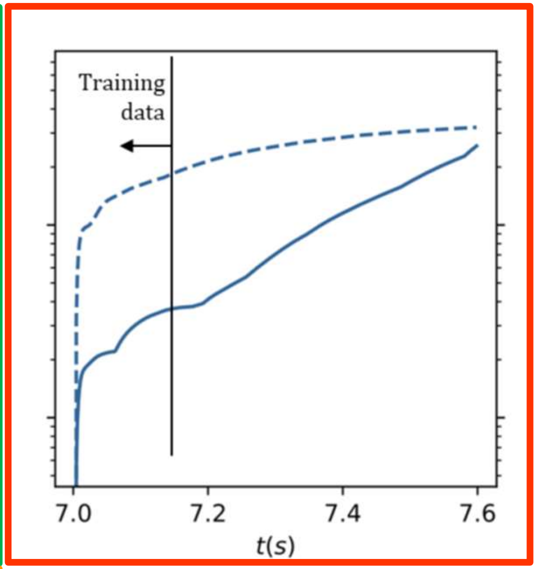

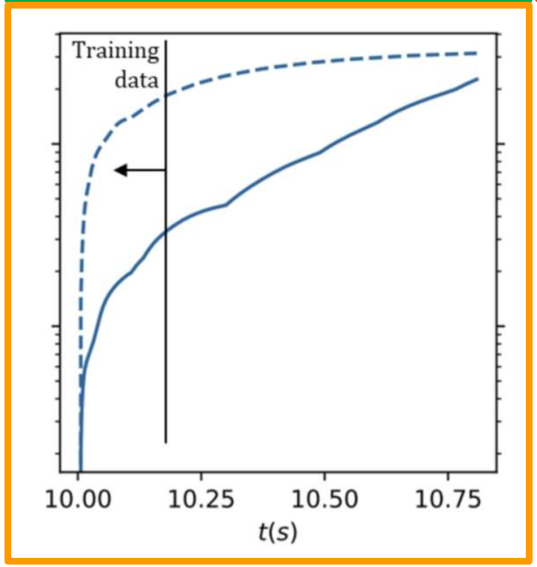

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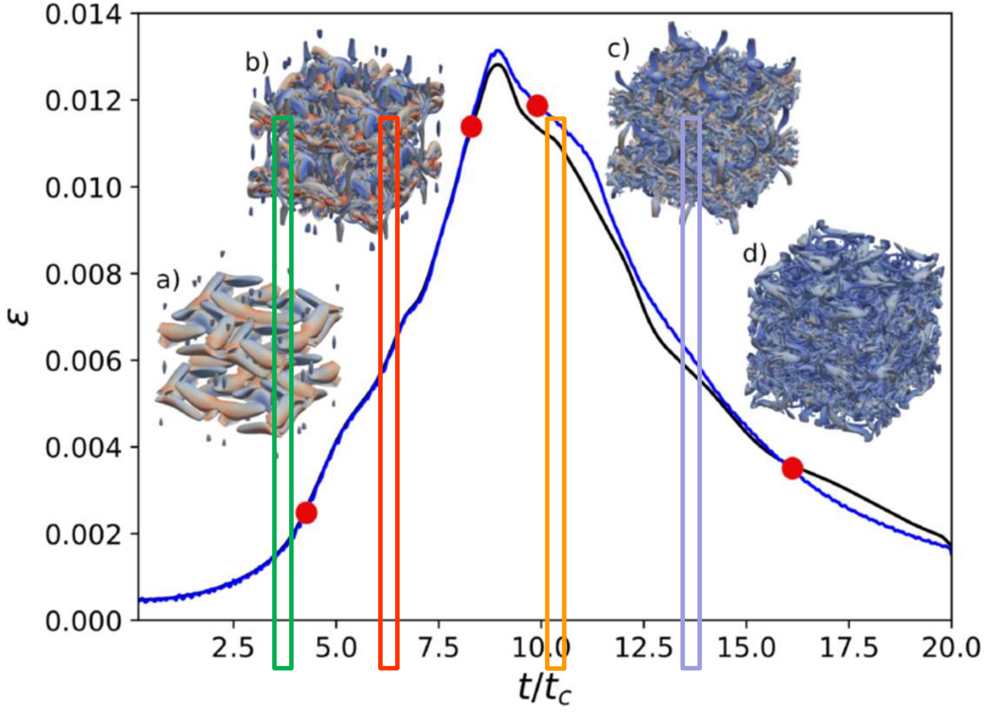

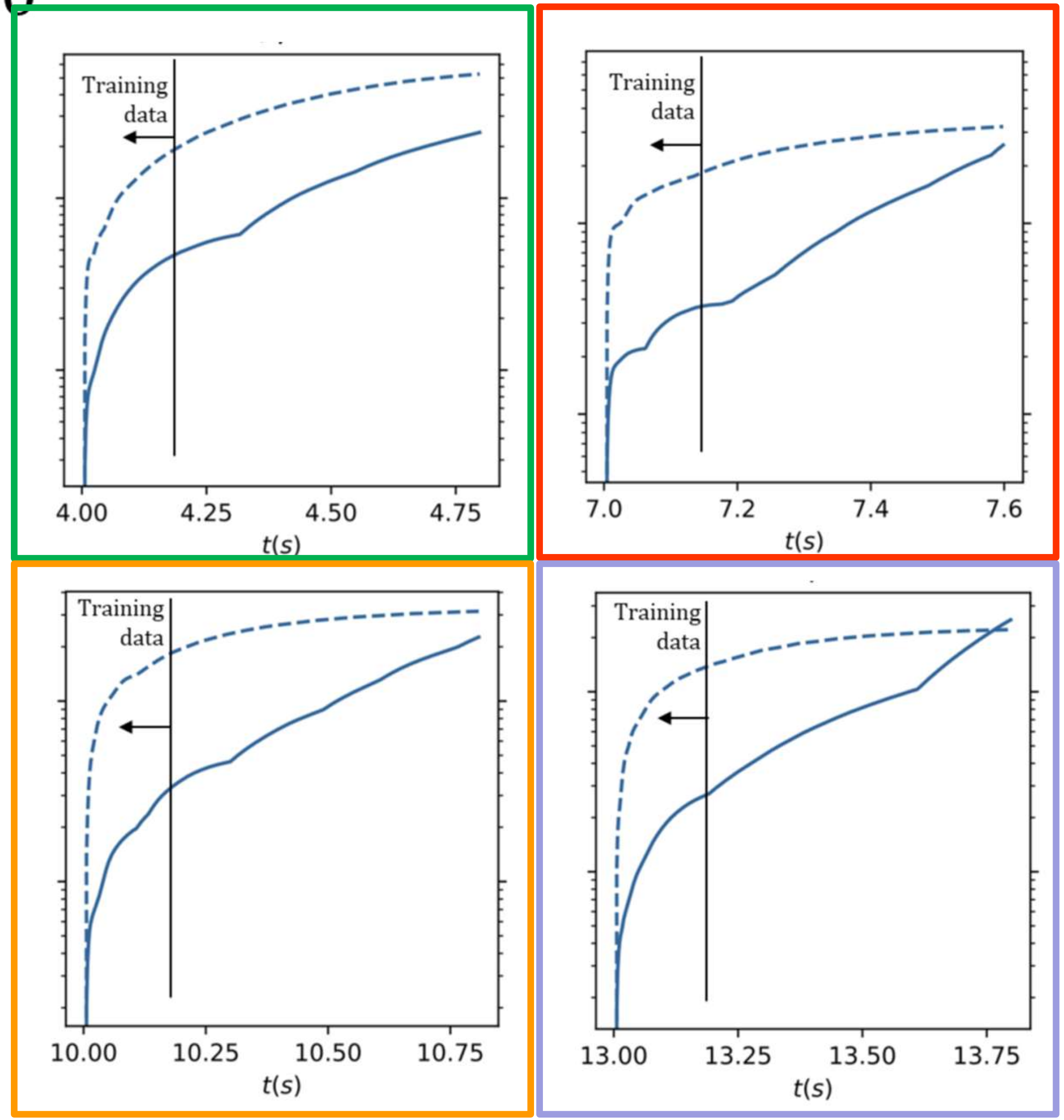

training

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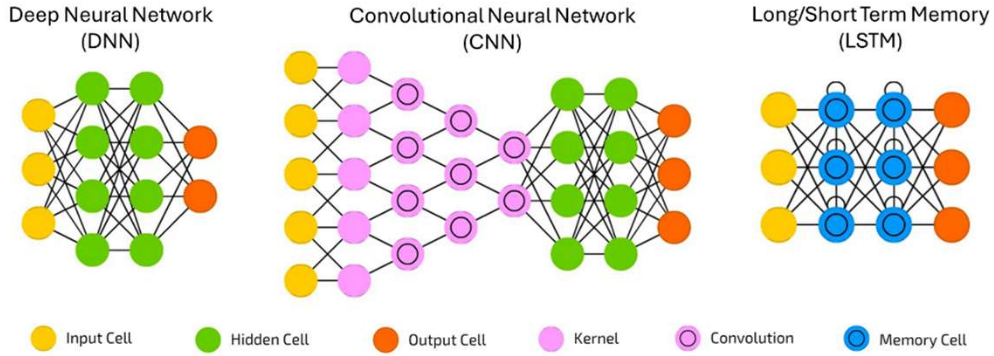

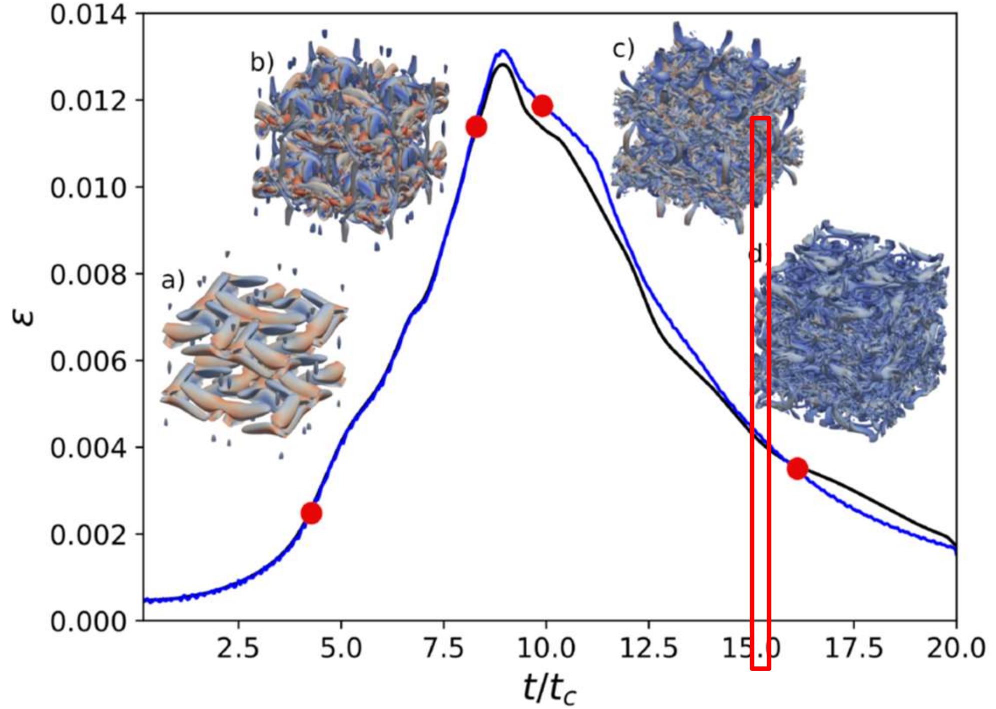

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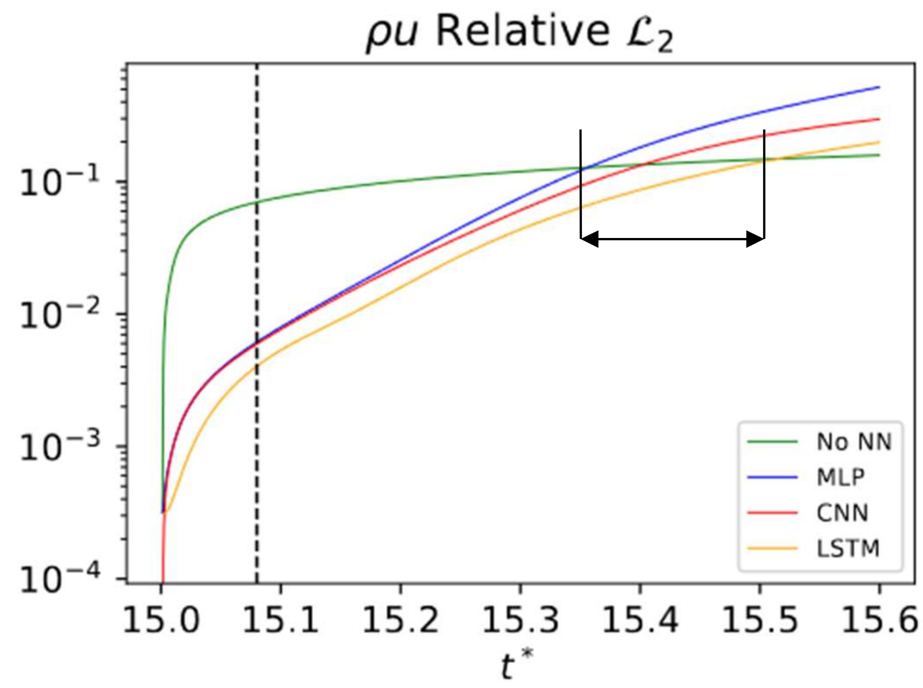
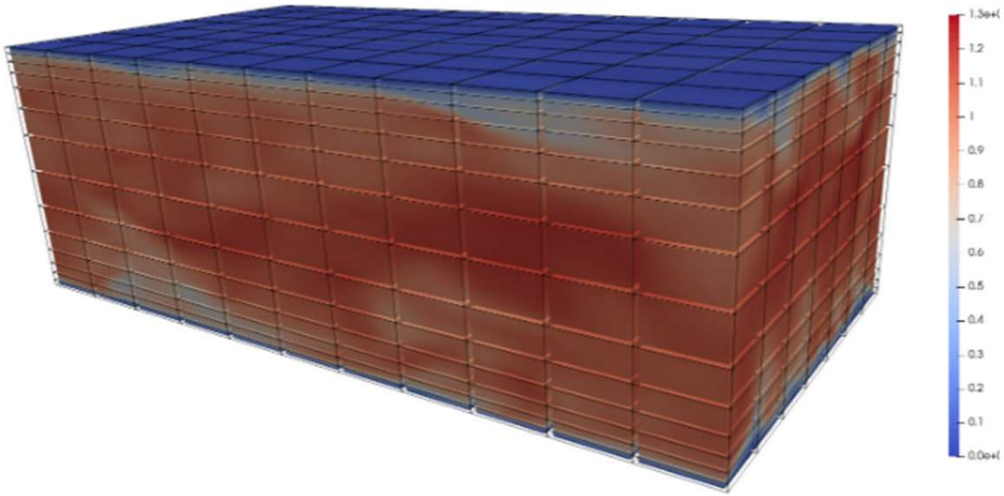
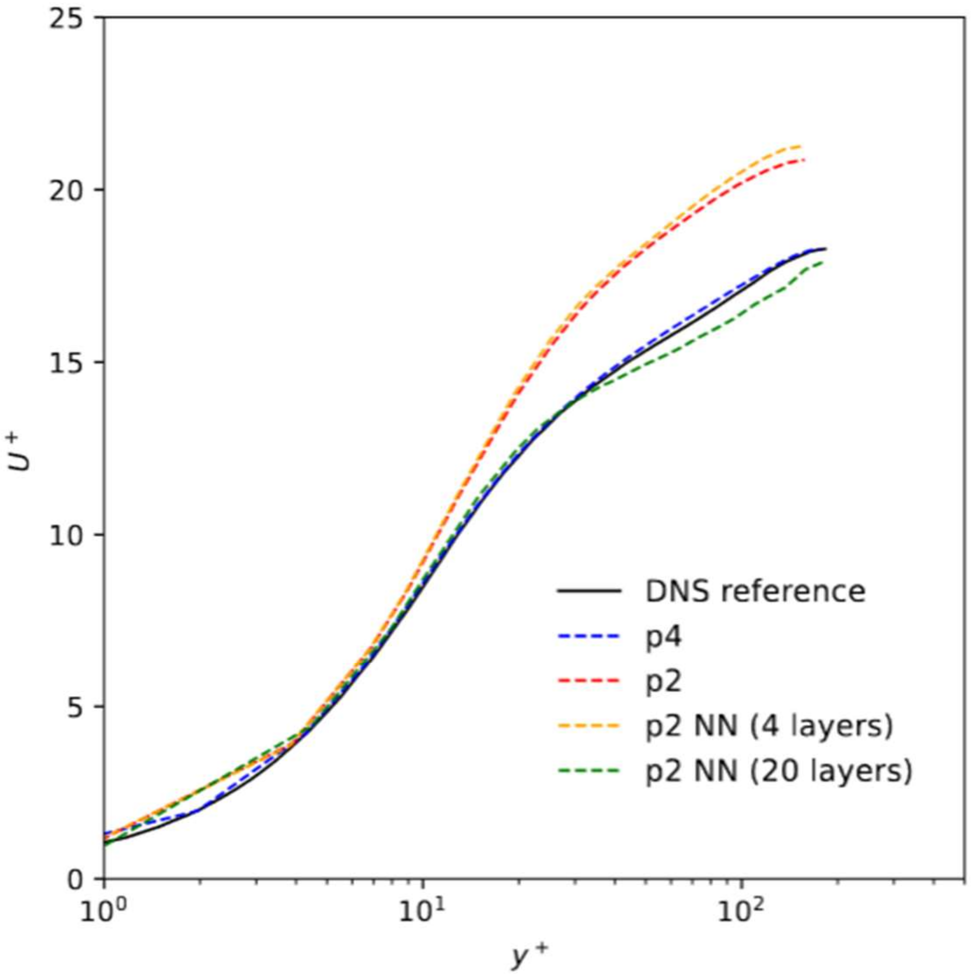


O Marino, A Juanicotena, J Errasti, D Mayoral, F Manrique de Lara, R Vinuesa, **E Ferrer**, Accelerating High Order DG Solvers using Neural Networks: **A Comparison of Neural Network architectures** to accelerate the Taylor Green vortex problema, *Under Review*

Machine Learning to accelerate CFD: *Wall bounded flows*



$Re_\tau = 182$



OA. Marino, D Mayoral, A Juanicotena, F Manrique de Lara, **E Ferrer**, "Accelerating high order discontinuous Galerkin solvers using neural networks: Wall bounded flows", *J. Phys.: Conf. Ser.* 5th Madrid Turbulence Workshop Madrid, Spain, Vol 2753 012023, 2024

Summary

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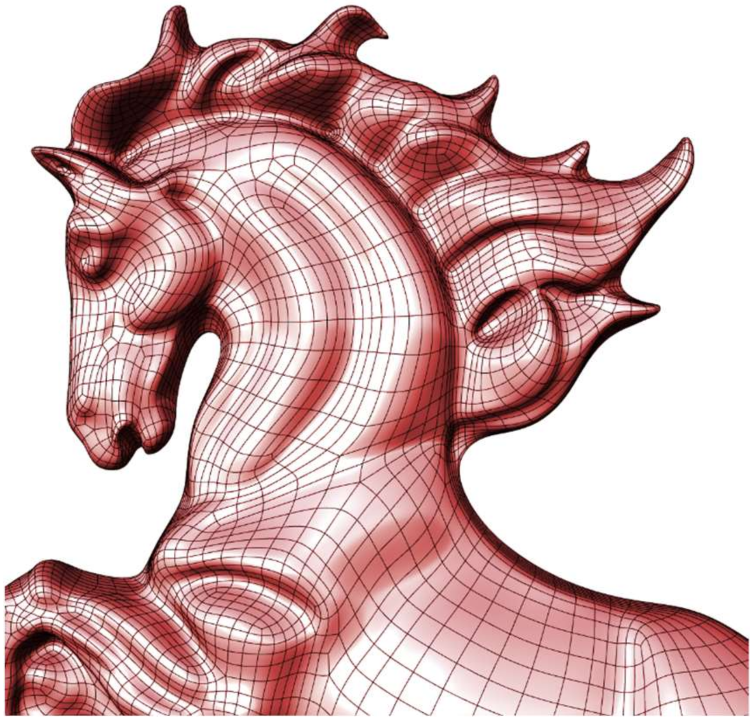
2- Multiphysics

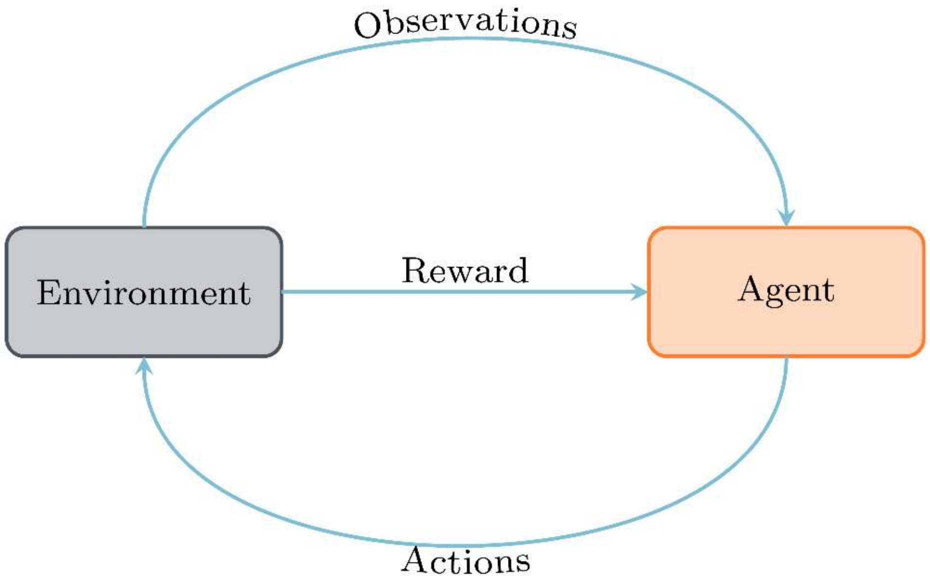
→ Wind turbines
→ Turbulence

3. Machine Learning + CFD

→ Mesh adaption
→ NN acceleration
→ RL for automation

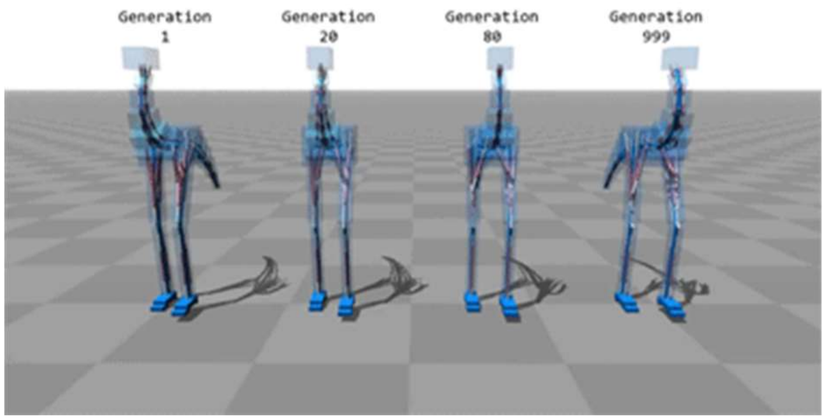


Machine Learning and Reinforcement Learning

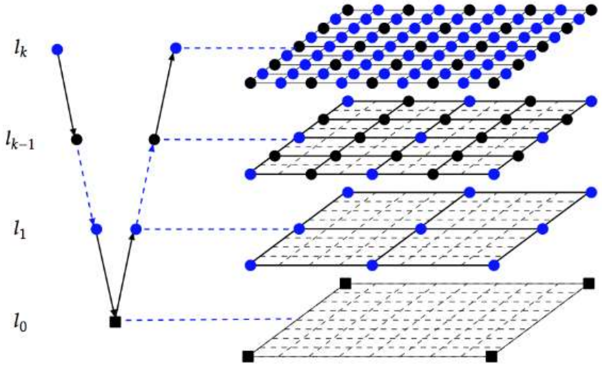


Go game

Chess game



Reinforcement learning for p-multigrid



p-multigrid

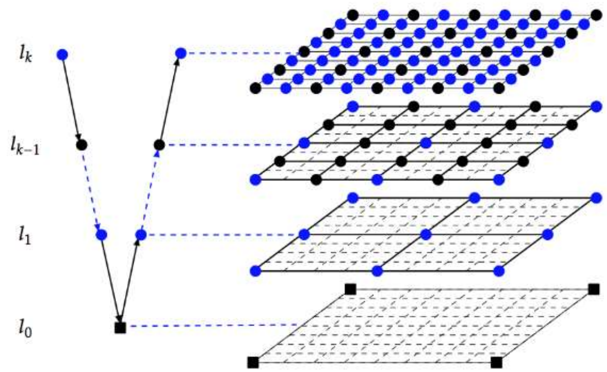
					0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
		Cases												
Advection-diffusion	P3	L0	R0	IC: Sine7		135	126	121	121	123	124	1186	U	U
				IC: sine				121				1186	U	U
				IC: exp				121				1186	U	U
	P5			IC: Sine7				471				U	U	U
				IC: sine				471				U	U	U
				IC: exp				471				U	U	U
	P7			IC: Sine7				1207				1205	U	U
				IC: sine				1207				1205	U	U
				IC: exp				1207				1205	U	U
	P9			IC: Sine7				2466				U	U	U
				IC: sine				2466				U	U	U
				IC: exp				2466				U	U	U
	P3		R10	IC: Sine7	229	146	144	142	140	138	136	1188	U	U

$$u_t + a u_x - \nu u_{xx} = S$$

Optimal parameters in p-multigrid multigrid?

- Sweeps
- Relaxation between levels

Reinforcement learning for p-multigrid



p-multigrid

Cases					0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
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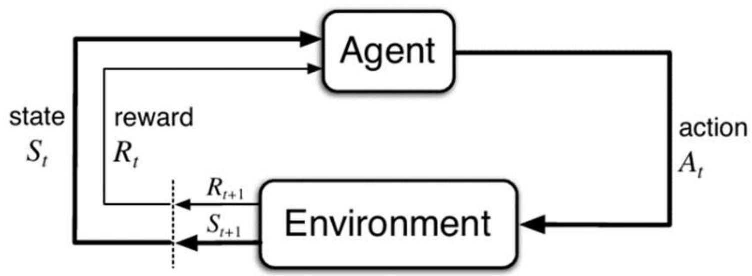
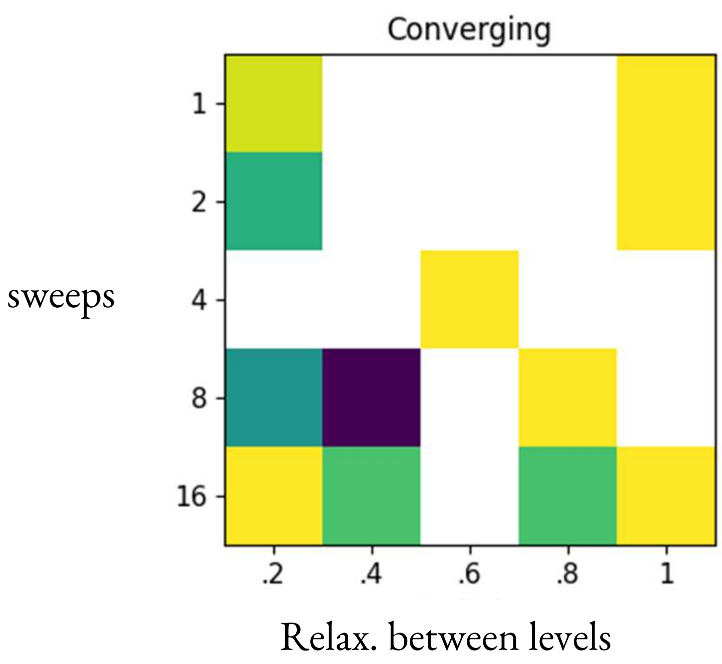
				IC: sine				121				1186	U	U
				IC: exp				121				1186	U	U
	P5			IC: Sine7				471				U	U	U
				IC: sine				471				U	U	U
				IC: exp				471				U	U	U
	P7			IC: Sine7				1207				1205	U	U
				IC: sine				1207				1205	U	U
				IC: exp				1207				1205	U	U
	P9			IC: Sine7				2466				U	U	U
				IC: sine				2466				U	U	U
				IC: exp				2466				U	U	U
	P3		R10	IC: Sine7	229	146	144	142	140	138	136	1188	U	U

$$u_t + a u_x - \nu u_{xx} = S$$

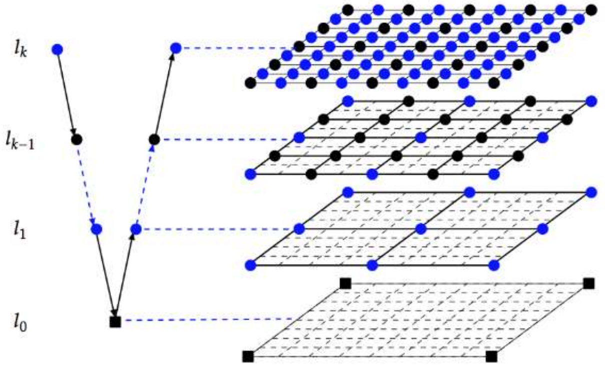
Reward: f(Relative drop in residual, time taken)





Yellow → action taken
Blue do not take it

Reinforcement learning for p-multigrid



p-multigrid

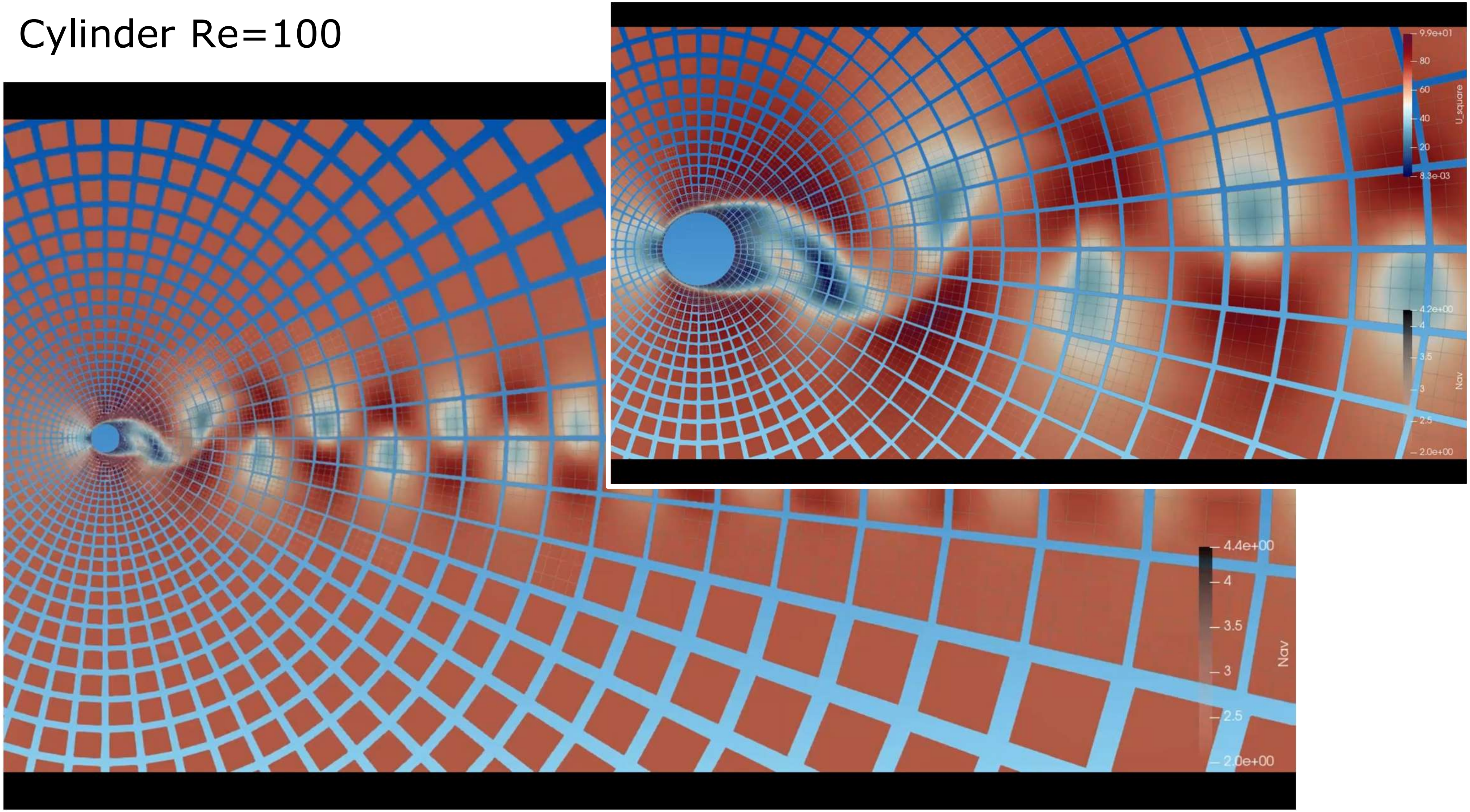
Cases					0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Advection-diffusion	P3	L0	R0	IC: Sine7		135	126	121	121	123	124	1186	U	U
				IC: sine				121				1186	U	U
				IC: exp				121				1186	U	U
	P5			IC: Sine7				471				U	U	U
				IC: sine				471				U	U	U
				IC: exp				471				U	U	U
	P7			IC: Sine7				1207				1205	U	U
				IC: sine				1207				1205	U	U
				IC: exp				1207				1205	U	U
	P9			IC: Sine7				2466				U	U	U
				IC: sine				2466				U	U	U
				IC: exp				2466				U	U	U
	P3		R10	IC: Sine7	229	146	144	142	140	138	136	1188	U	U

$$u_t + a u_x - \nu u_{xx} = S$$

"Arbitrary"		MC		PPO		
runtime	**iter**	**runtime**	**iter**	**runtime**	**iter**	**res**
AD - Order 2						
a= 1., v = 0.01						
69.7168839	197	49.38292694	197	31.02763486	626	9.67E-09
a= 0.5., v = 0.01						
80.01094651	207	51.54315066	207	31.81400156	651	8.33E-09
a= 0.5., v = 0.5						
808.6031666	2178	480.8234568	2178	33.21327591	652	9.31E-09
a= 0.4, v = 0.6						
634.2691302	3166	582.4802358	3166	31.52360582	654	9.29E-09
a= 0.2, v = 0.8						
1476.47674	8063	1278.344407	7163	31.47797155	648	9.98E-09

Reinforcement learning for p-adaptation

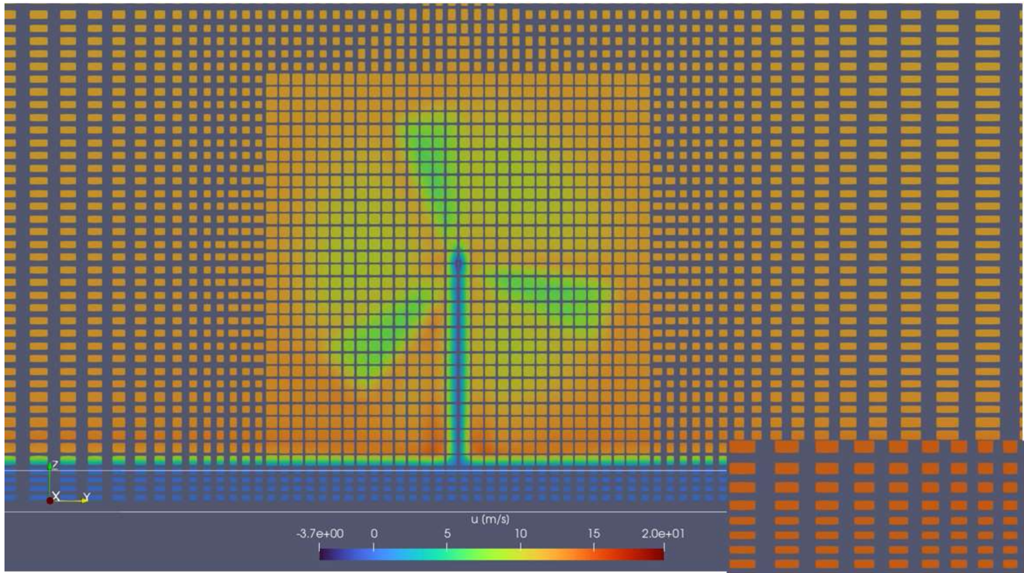
Cylinder Re=100

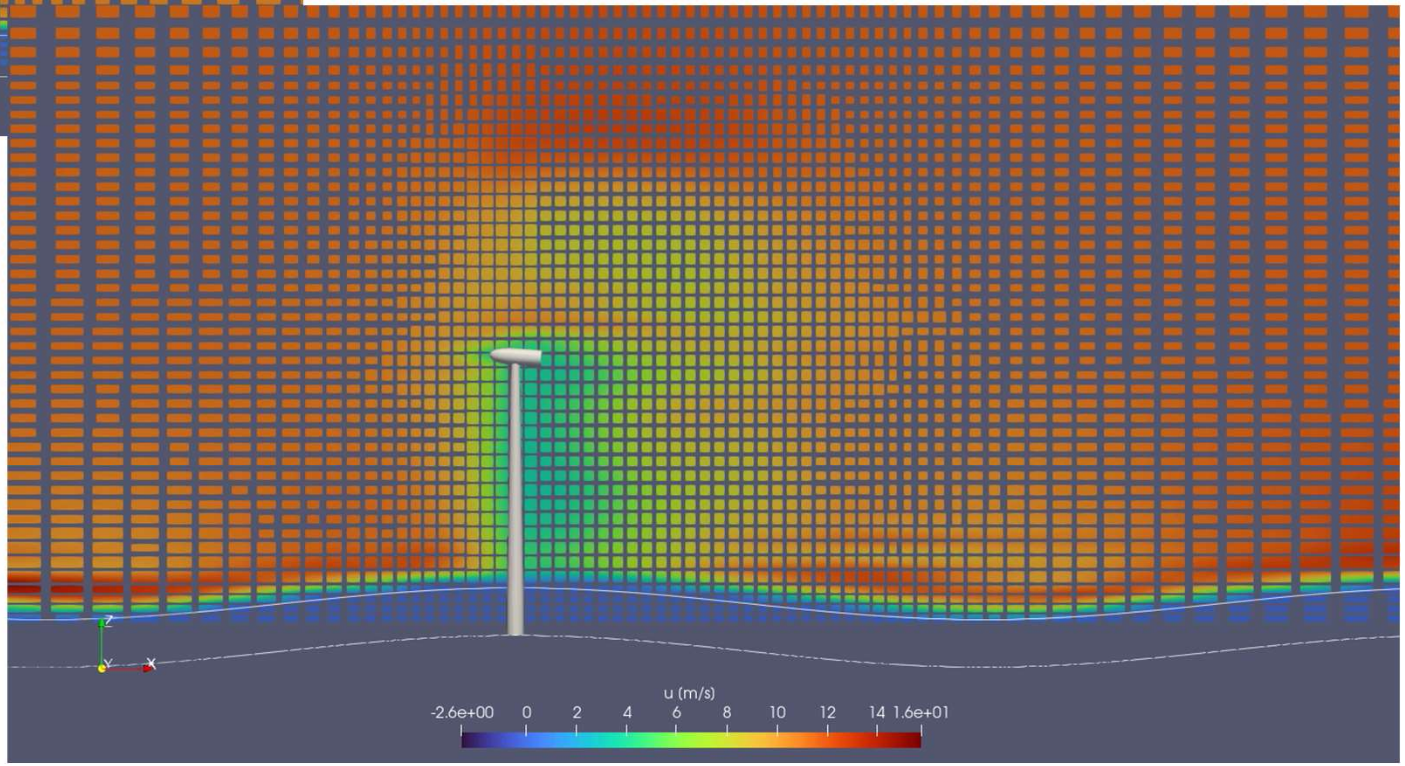


D Huergo, G Rubio, **E Ferrer**, "A reinforcement learning strategy for p-adaptation in high order solvers", *Results in Engineering,* Vol 21, 101693, 2024

Reinforcement learning for p-adaptation

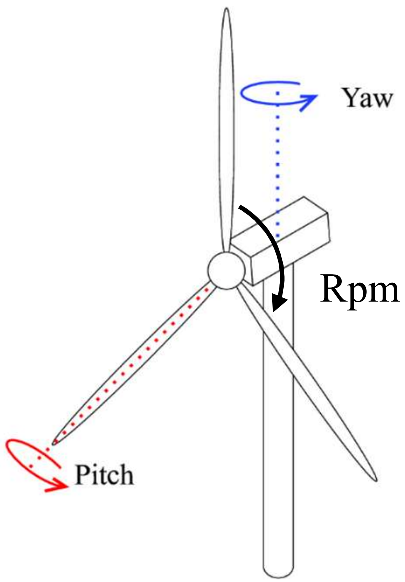
DTU 10MW offshore wind turbine



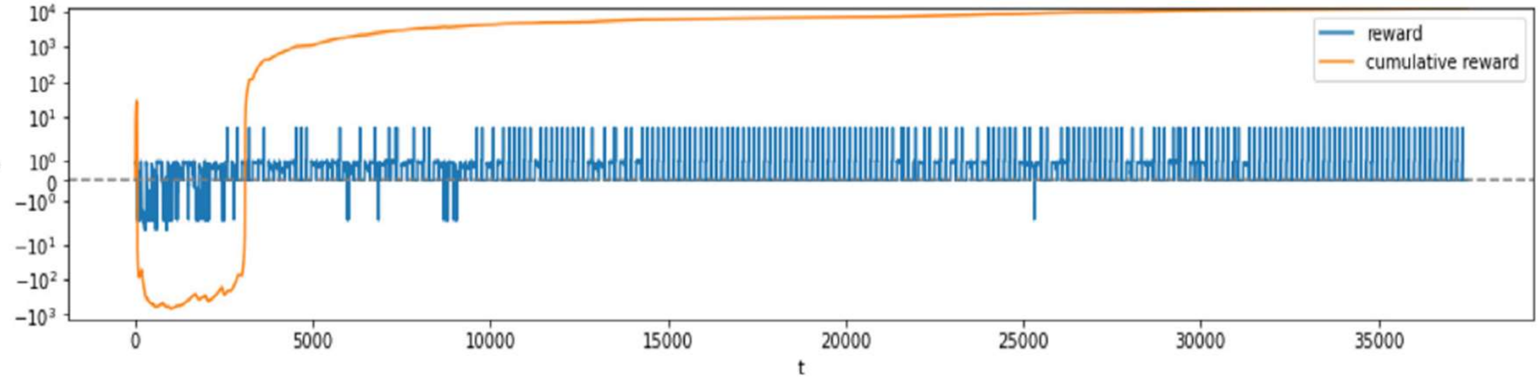


D Huergo, E Jane, G Rubio, **E Ferrer**, “Reinforcement learning for high order h/p solvers", *in preparation*

Reinforcement learning for wind turbine control



Training with simple winds

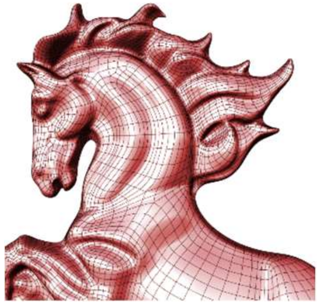


Validation with turbulent real winds

Metric	DDQN1	PID	Uncontrolled
Control Capacity Factor (%)	91.31	57.60	12.77
Capacity Factor (%)	20.95	12.49	1.59
Yearly Production (MWh)	4162.95	2481.97	316.12

D Soler, O Marino, D Huergo, M de Frutos, **E Ferrer**, "Reinforcement learning to maximise wind turbine energy generation", *Expert Systems with Applications,* Vol 249, Part A, 123502, 2024

Conclusions



- **High order DG methods fairly well developed**
  - **Incompressible flows & Compressible flows**
- **Multiphysics:**
  - **Wind turbines with various methods**
  - **Turbulence** (iLES & explicit LES)
  - **Aero-acoustics**
  - **Supersonic & Shocks**
- **AI-based Solver**

Thank you very much

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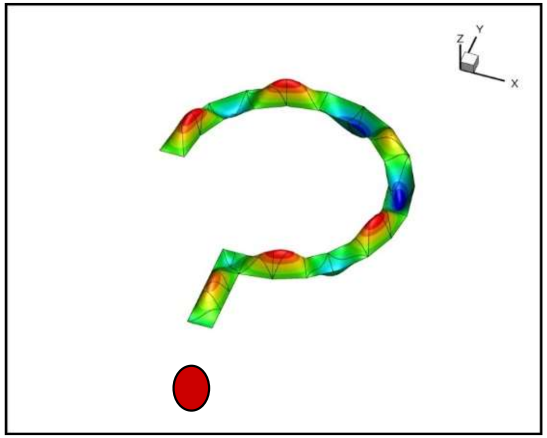

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http://sites.google.com/site/eferrerdg/publications

Funding

Comunidad de Madrid

Dirección General de Investigación e Innovación Tecnológica
CONSEJERÍA DE CIENCIA, UNIVERSIDADES E INNOVACIÓN

Supported by the Government of the Community of Madrid and European Union's NextGeneration EU programme

Financiado por la Unión Europea NextGenerationEU

GOBIERNO DE ESPAÑA | MINISTERIO DE UNIVERSIDADES

We thank the support of Agencia Estatal de Investigación for the grant "Europa Excelencia" for the project EUR2022-134041 funded by MCIN/AEI/10.13039/501100011033) y the European Union NextGenerationEU/PRTR

Funded by the European Union

European Research Council
Established by the European Commission

This research has been cofunded by the European Union (ERC, Off-coustics, project number 101086075). Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Council. Neither the European Union nor the granting authority can be held responsible for them