POLITÉCNICA

UNIVERSIDAD POLITÉCNICA DE MADRID

E.T.S. de Ingenieros Aeronáuticos

New avenues in computational fluid dynamics

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@FerrerCfd

Esteban Ferrer

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Ext. Collaborators: DA Kopriva (San Diego), C Hirsch (Numeca), Paniagua (Purdue), P García (Zaragoza) R Vinuesa (KTH), S Sherwin (IC), R Willden (Oxford), H Blackburn (Monash)

Industrial collaborators: Numeca-Cadence, Airbus, McLaren F1, Dassault Syst., Siemens-Gamesa…

Ferrer CFD

Students / Postdocs


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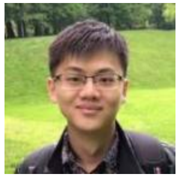
E Jané


G Ntoukas


O Marino


S Joshi,


J Kou


A Hurtado-Mendoza


W Laskowski


K Otmani


F Manrique de Lara


A Ballout


M de Frutos


S Colombo


D Huergo


A Portillo


J Manzanero


A Rueda


M Chavez


Y Wang


M Kompenhan


O Browne

Funding

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AGENCIA ESTATAL DE INVESTIGACIÓN

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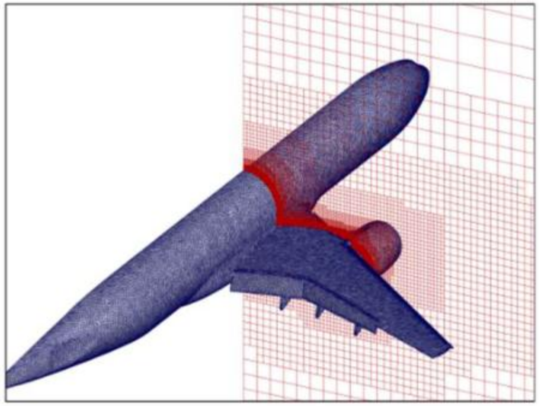
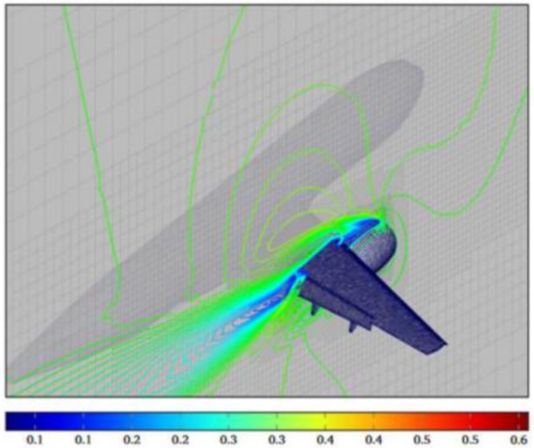
Collaborations with Industry

AIRBUS

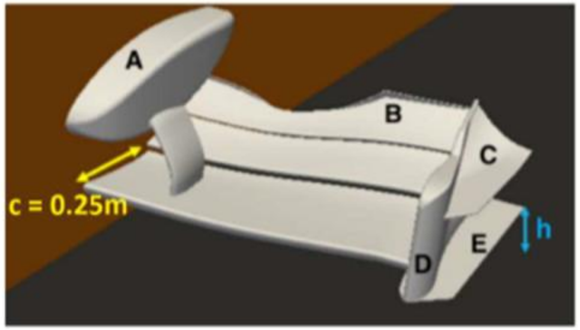
CRM Aircraft Mesh

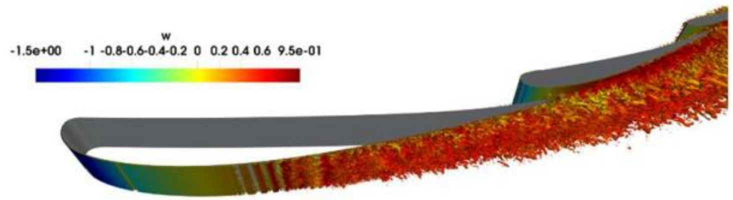


CRM, $\alpha = 8°$, VelocityMagnitude, Wall Model Deactivated

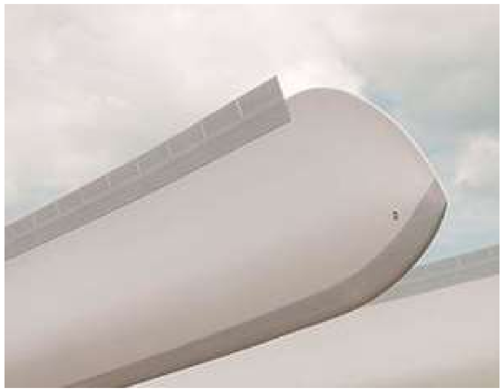


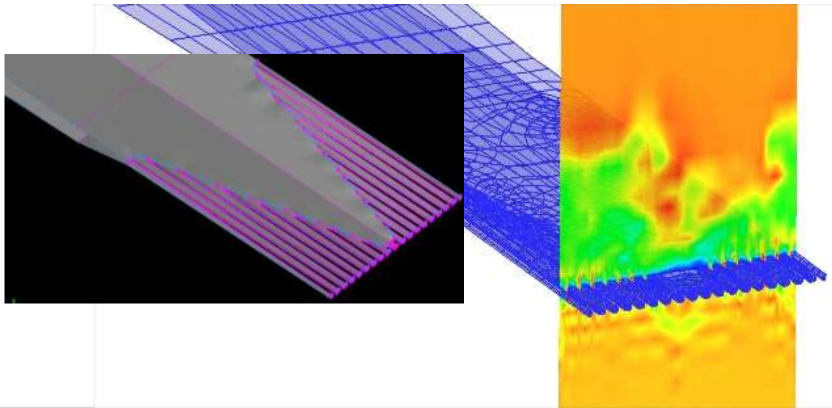
McLaren
FORMULA 1 TEAM



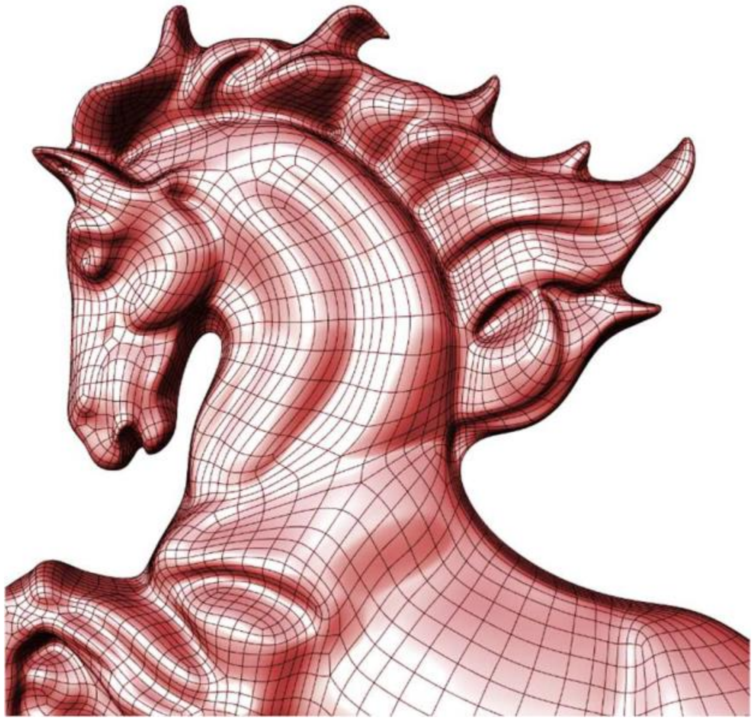


SIEMENS Gamesa
RENEWABLE ENERGY





Summary



1- Introduction to DG & Horses3d

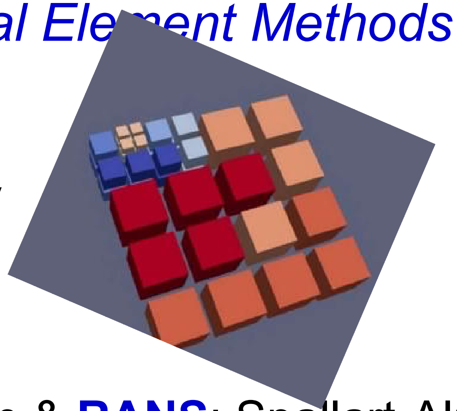
2- Multiphysics

→ 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

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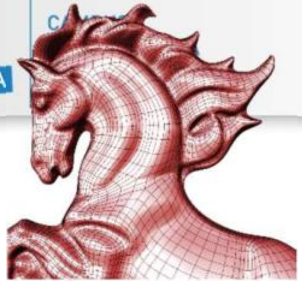
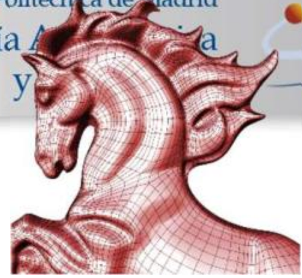
journal homepage: www.elsevier.com/locate/cpc

ELSEVIER

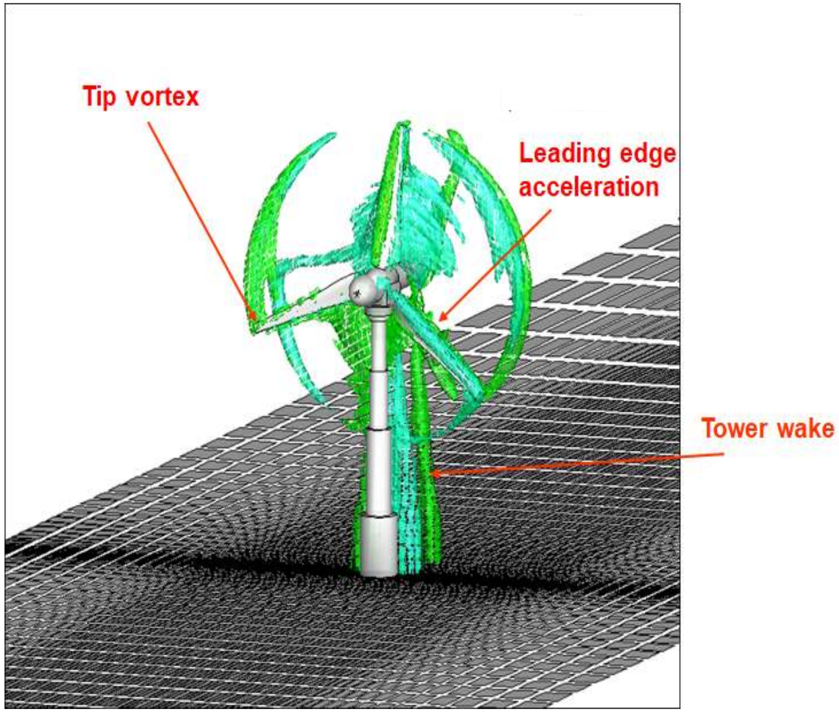
HORSES3D: A high-order discontinuous Galerkin solver for flow simulations and multi-physics applications ☆,☆☆

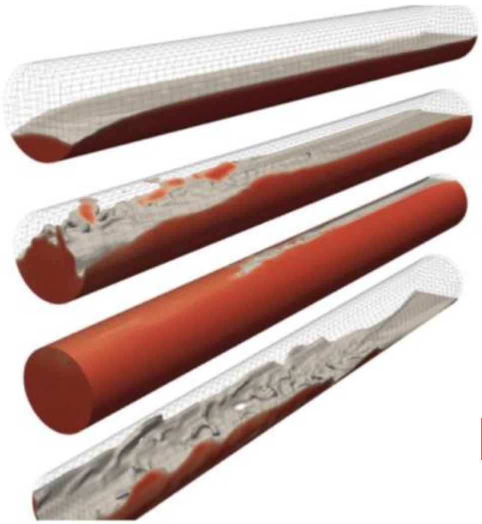
E. Ferrer [a,b], G. Rubio [a,b,*], G. Ntoukas [a], W. Laskowski [a], O.A. Mariño [a], S. Colombo [a], A. Mateo-Gabín [a], H. Marbona [a], F. Manrique de Lara [a], D. Huergo [a], J. Manzanero [e], A.M. Rueda-Ramírez [c], D.A. Kopriva [d], E. Valero [a,b]

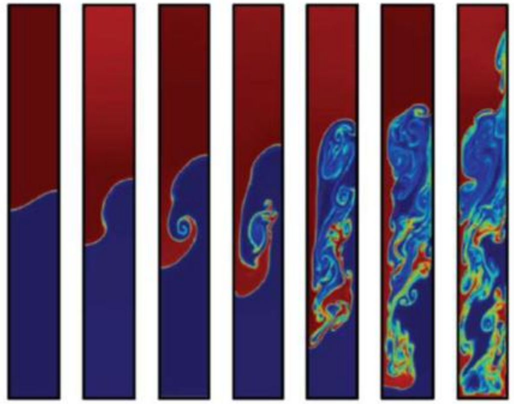



HORSES3D

http://github.com/loganoz/horses3d

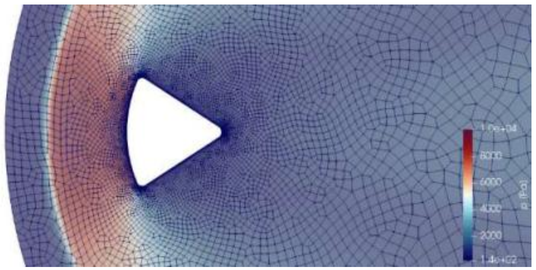


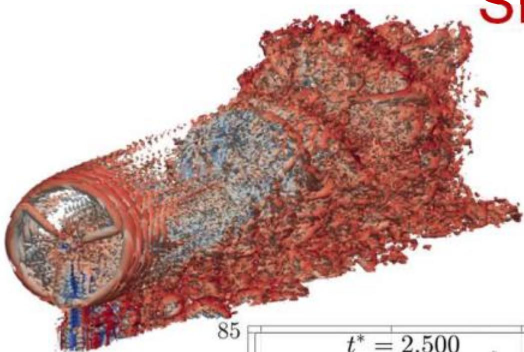


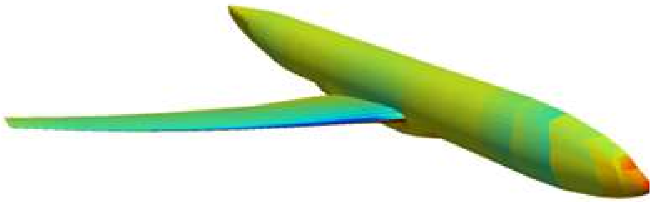


Multiphase

Shocks

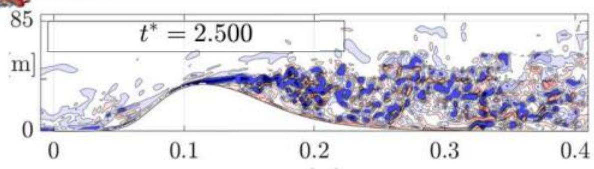


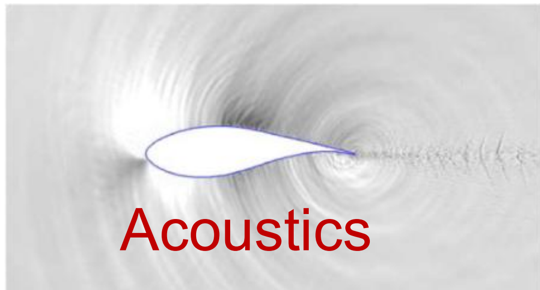




RANS

LES

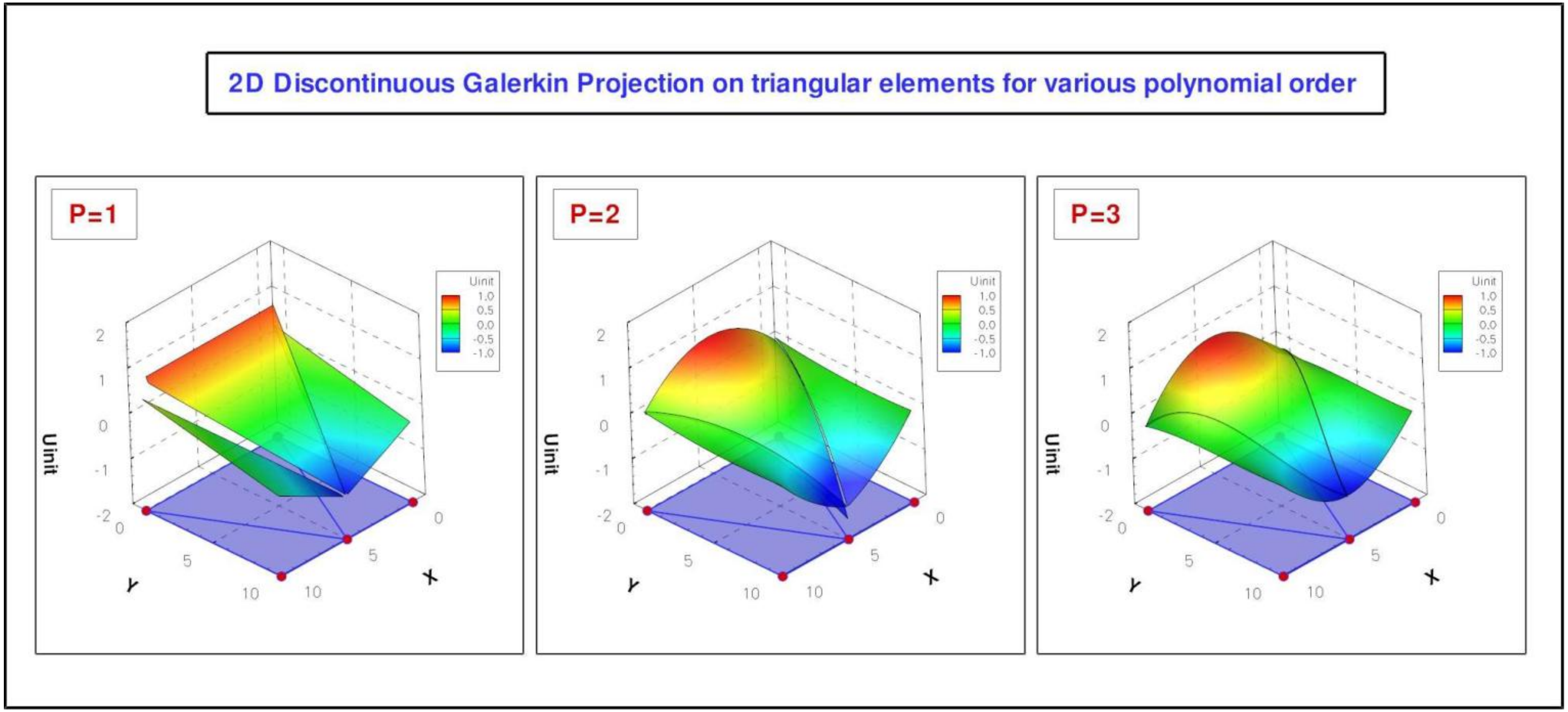




Acoustics

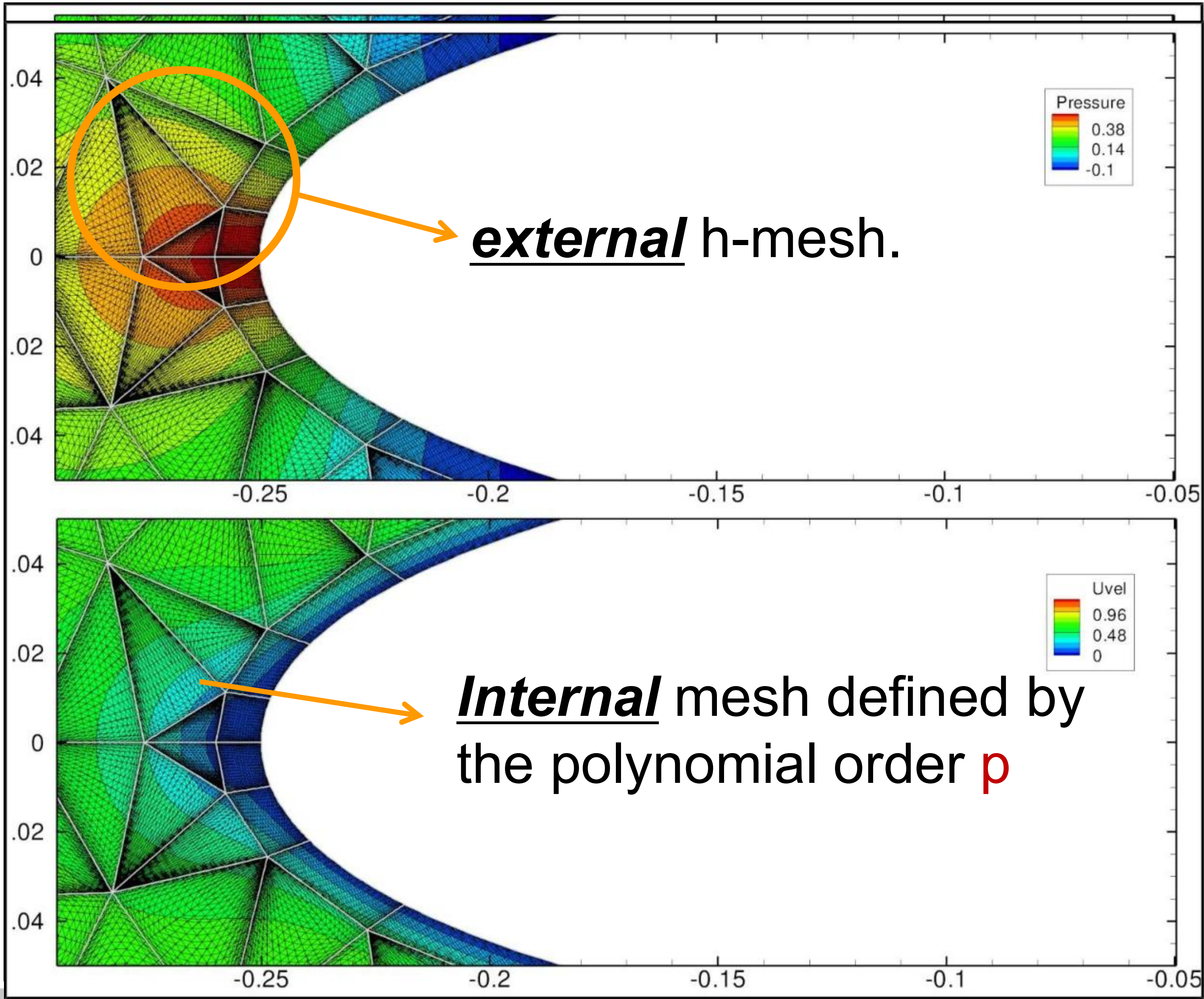
E Ferrer, G Rubio, G Ntoukas, W Laskowski, O Mariño, S Colombo, A. Mateo-Gabín, F Manrique de Lara, D Huergo, J Manzanero, AM Rueda-Ramírez, DA Kopriva, E Valero, "HORSES3D: a high order discontinuous Galerkin solver for flow simulations and multi-physic applications", *Computer Physics Communications*,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

High order methods

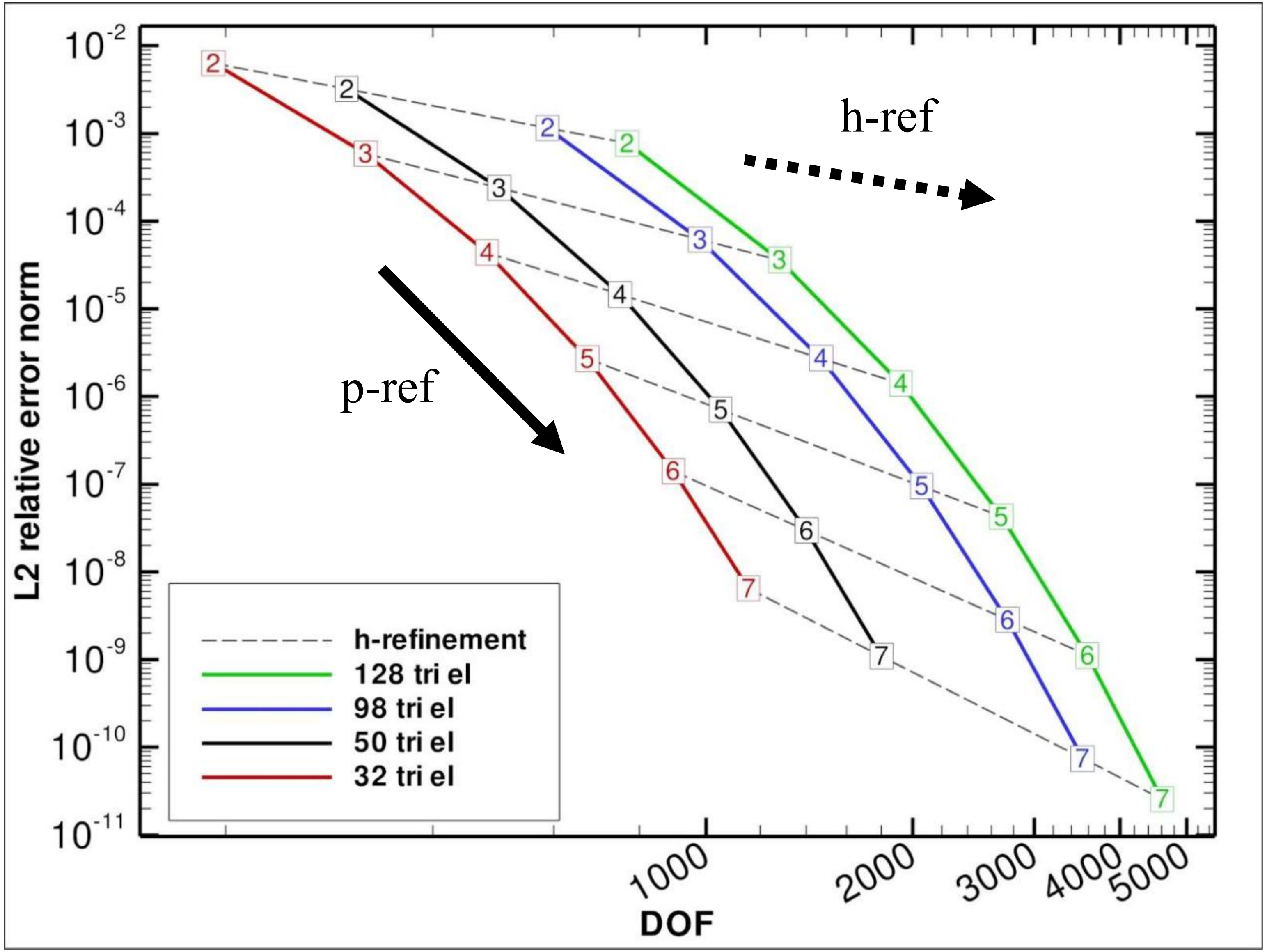


- **High order is generally defined for P ≥ 2**
- **High order allows *h/p* refinement**
  - ***h*-refinement offers constant decay of the error**
  - ***p*-refinement offers exponential decay of the error**

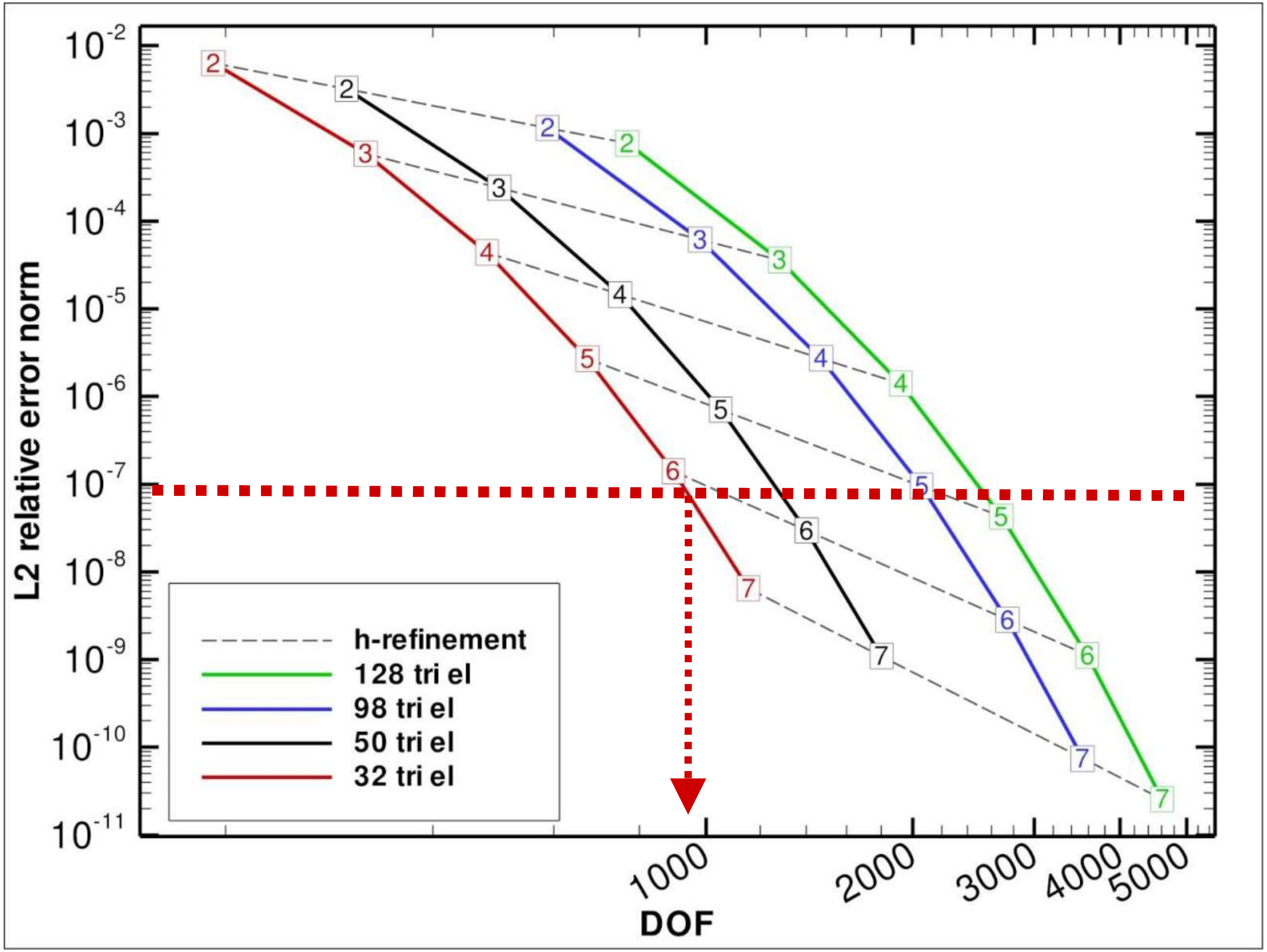
High order methods



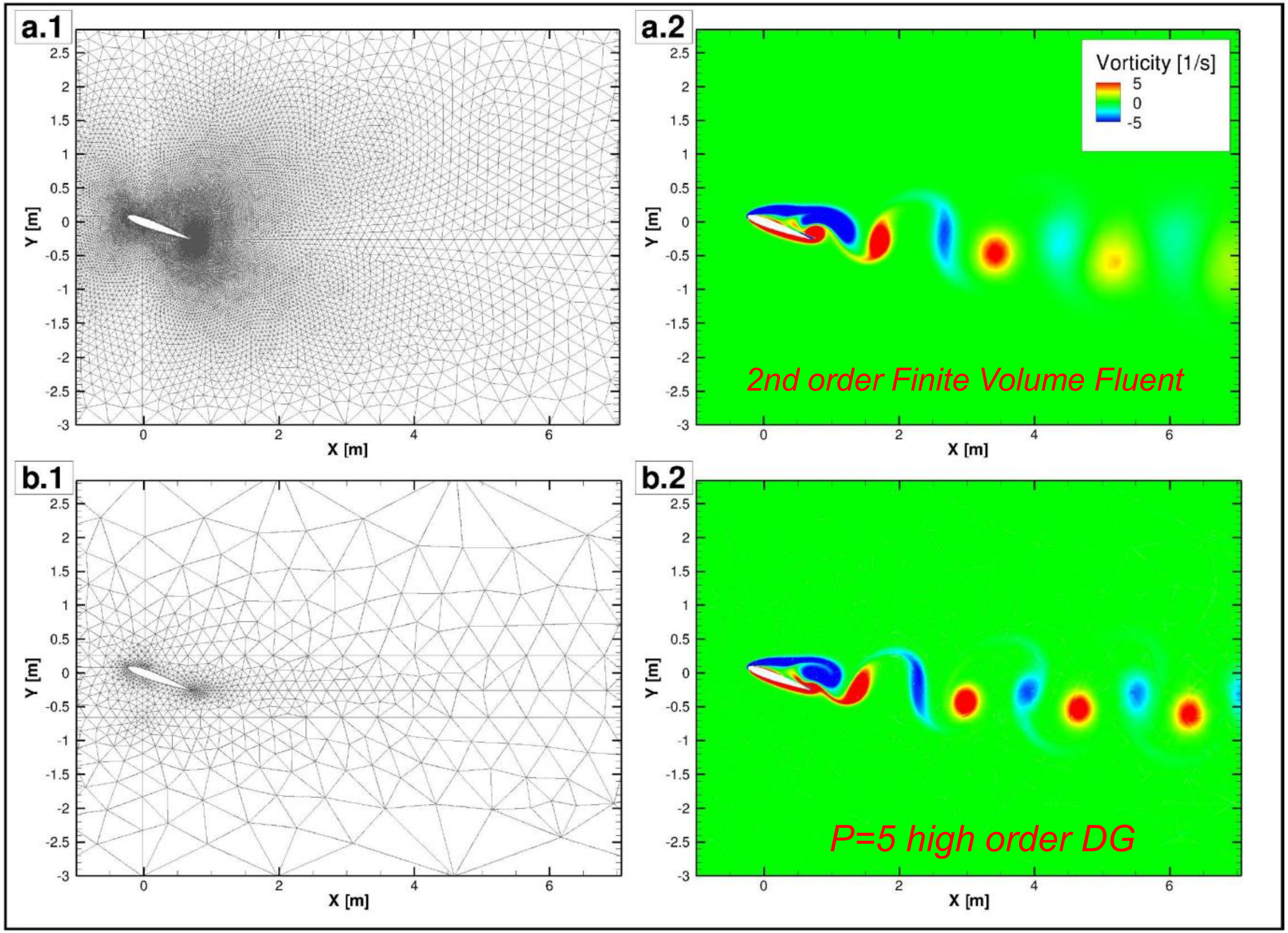
High order methods (Poisson eq.)



High order methods (Poisson eq.)



NACA0012 - Re=800 - Laminar flow

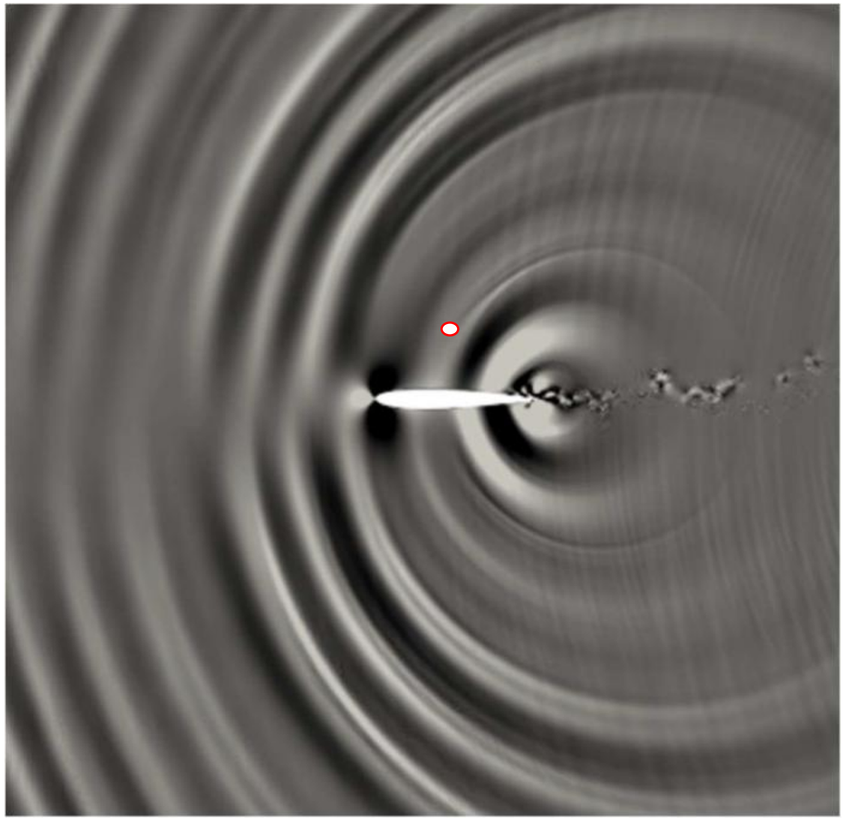


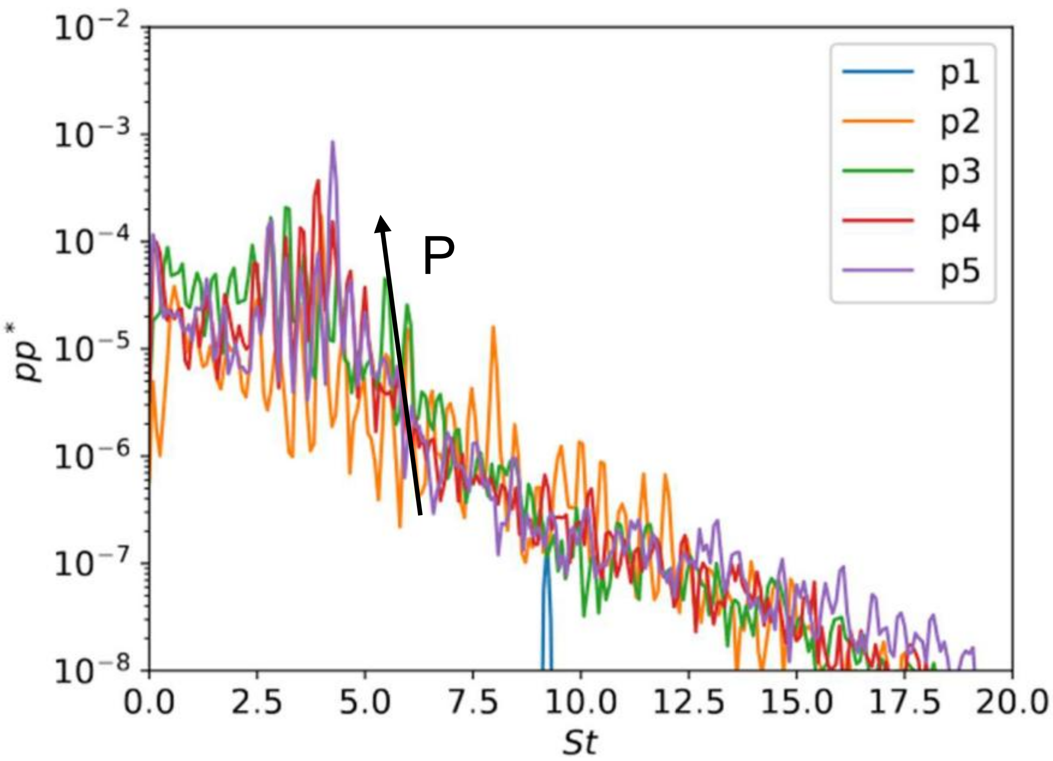
- **Ferrer, E**. A high Order Discontinuous Galerkin—Fourier Incompressible 3D Navier-Stokes Solver with Rotating Sliding Meshes for Simulating Cross-Flow Turbines. DPhil University of Oxford, 2012

Horses: accuracy

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

P ↑ : Error decreases **exponentially**

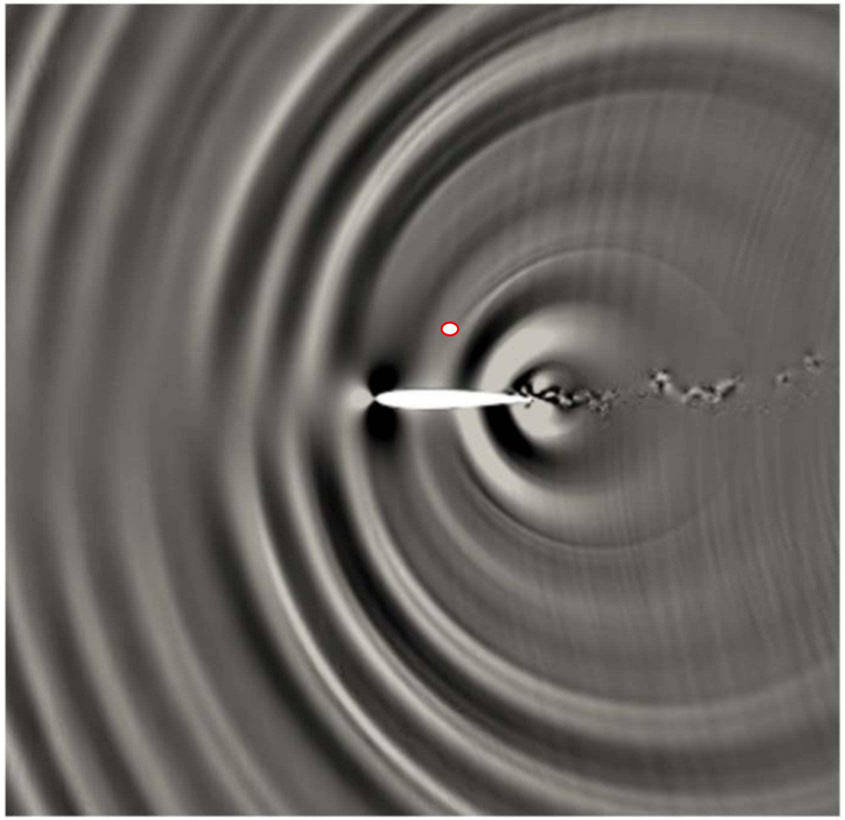


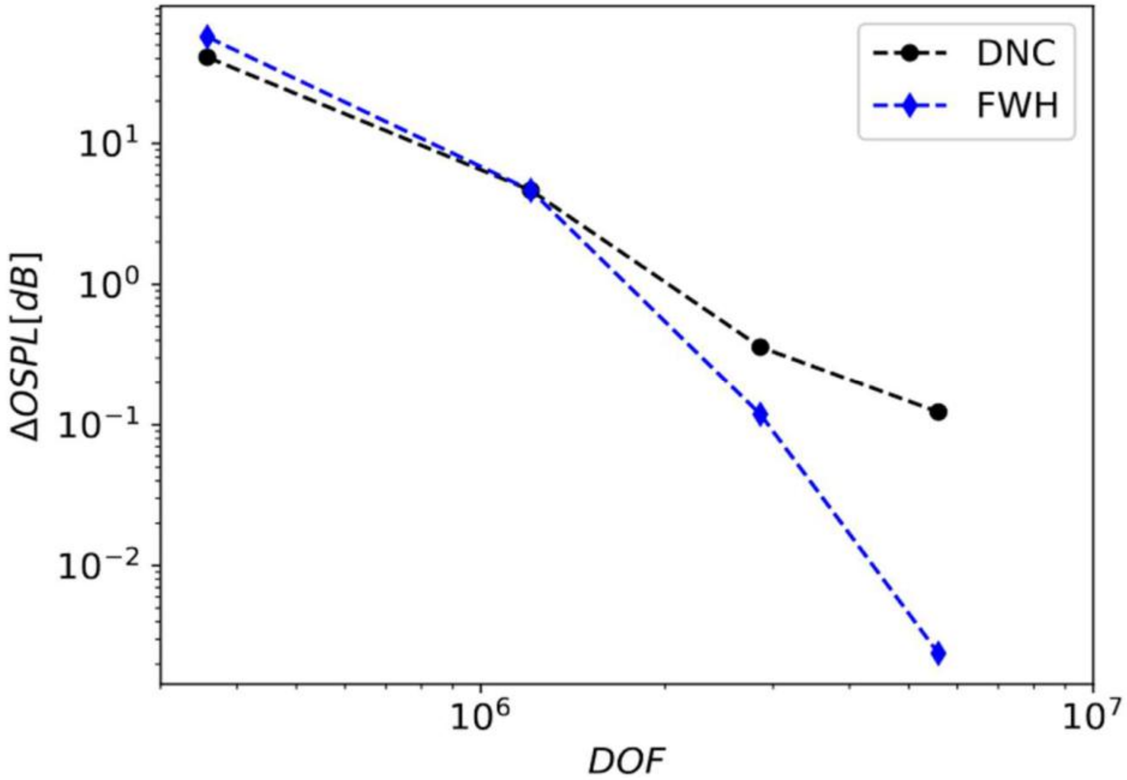


Horses: accuracy

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

P ↑ : Error decreases **exponentially**

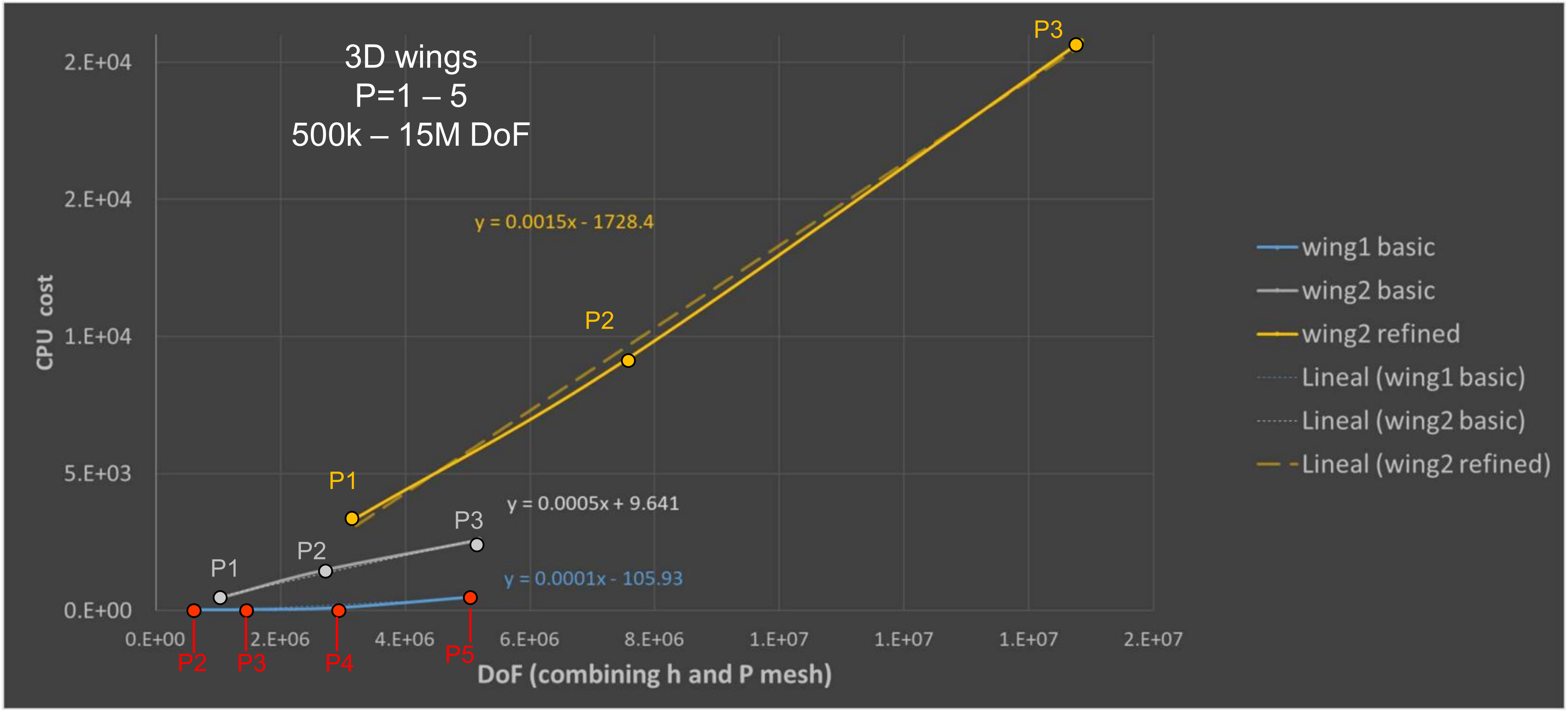




Horses: cost

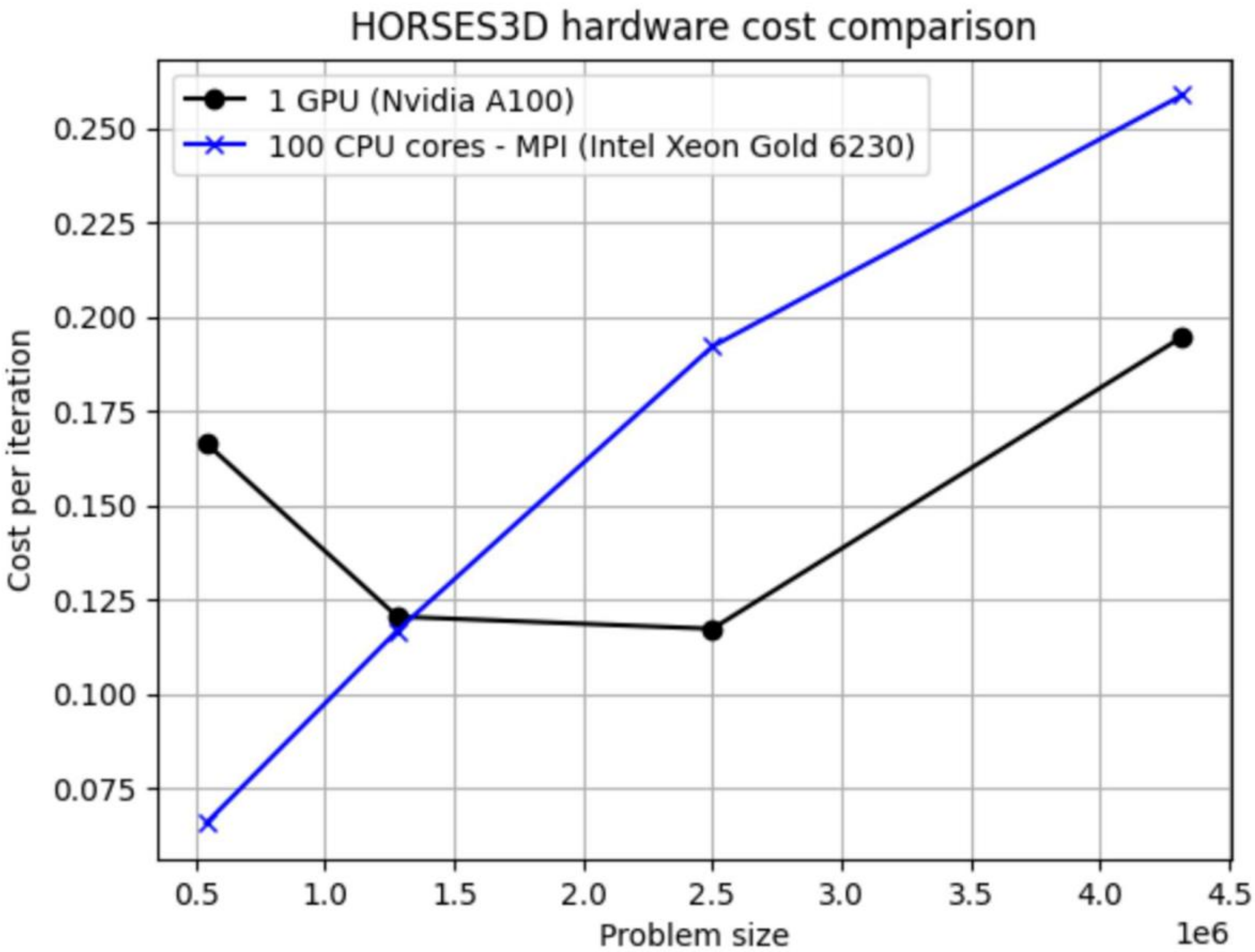
P ↑ : Error decreases **exponentially**

P ↑ : Cost increases **linearly**



Horses: cost → porting to GPUs (openACC on NVIDIA A100)

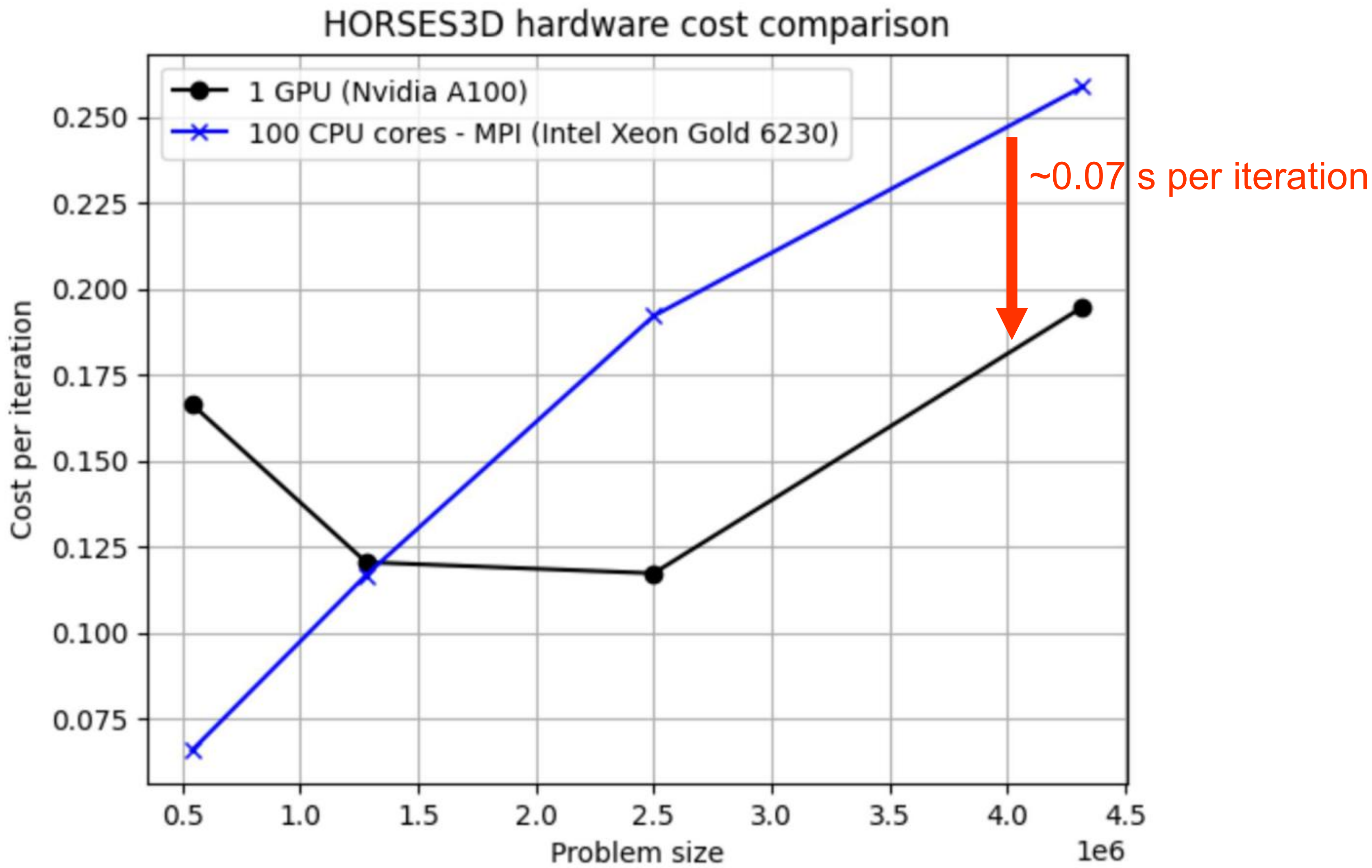
..underway..



Better perfomance than 100 CPU cores

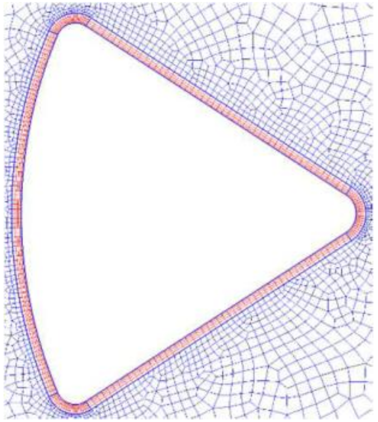
Horses: cost → porting to GPUs (openACC on NVIDIA A100)

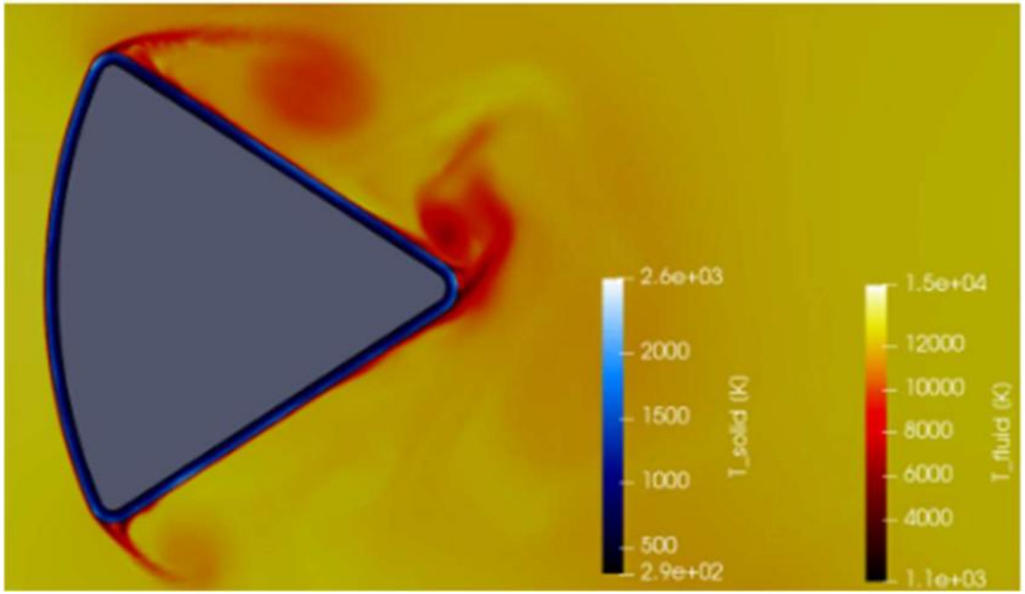
..underway..

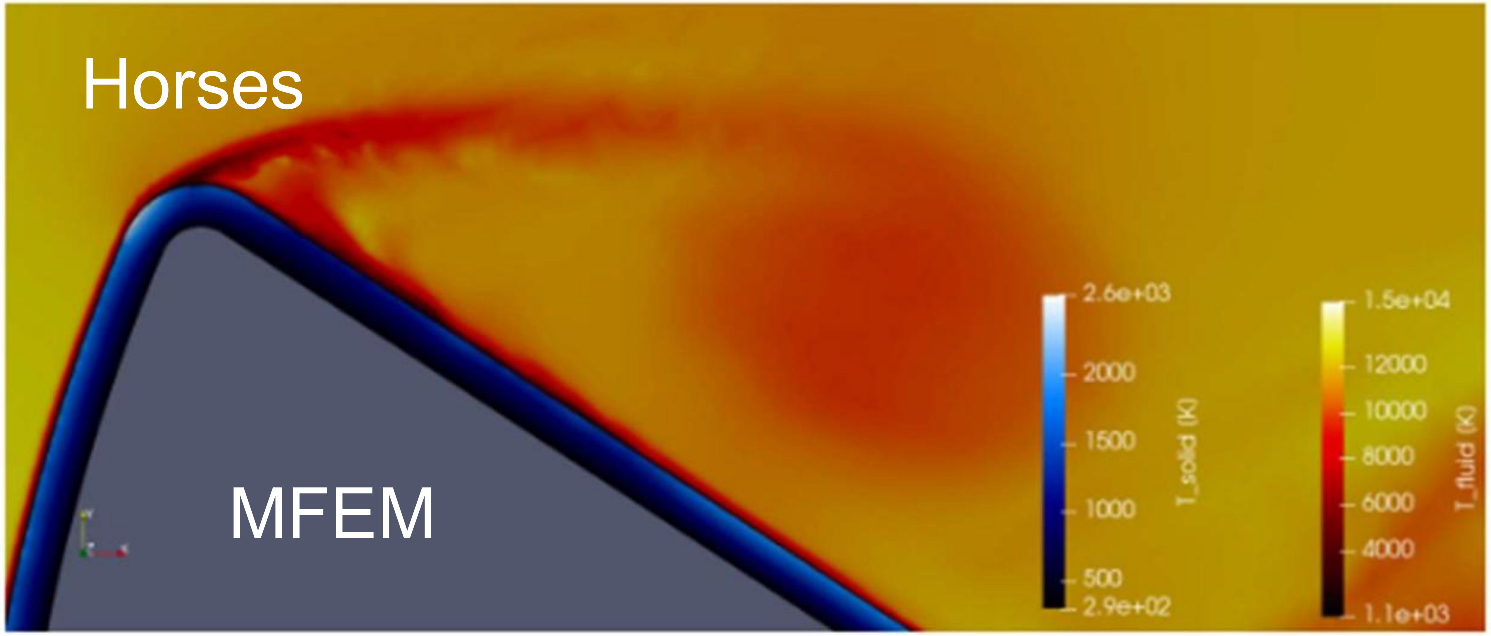


LES simulation → 1e8 time steps → 81 days faster than 100 CPUs

Horses & MFEM (*Python interface*): *example 1 - thermal coupling*







D Huergo (Master Thesis): "*High order methods for CFD simulation of a hypersonic flow on a reentry capsule*", ETSIAE-UPM, July 2022

Horses & MFEM (*Python interface*): *example 2 – incompressible solver*

$$\frac{\partial \boldsymbol{u}}{\partial t} = -\nabla \cdot (\boldsymbol{u}\boldsymbol{u}) - \frac{1}{\rho_0}\nabla p - \nabla \cdot (\nu \nabla \boldsymbol{u}) + \frac{\boldsymbol{f}_{\text{ext}}}{\rho_0}$$

$$\nabla \cdot \boldsymbol{u} = 0$$

$$\Downarrow$$

Step 1

$$\frac{\gamma_0 \boldsymbol{u}^* - \alpha_0 \boldsymbol{u}^n - \alpha_1 \boldsymbol{u}^{n-1}}{\Delta t} = -\beta_0 \boldsymbol{N}(\boldsymbol{u}^n) - \beta_1 \boldsymbol{N}(\boldsymbol{u}^{n-1}),$$

DG/FR-horses

Step 2

$$\nabla \cdot \left(\frac{1}{\rho_0} \nabla p^{n+1} \right) = -\frac{\gamma_0}{\Delta t} \nabla \cdot \boldsymbol{u}^*$$

DG/CG-MFEM

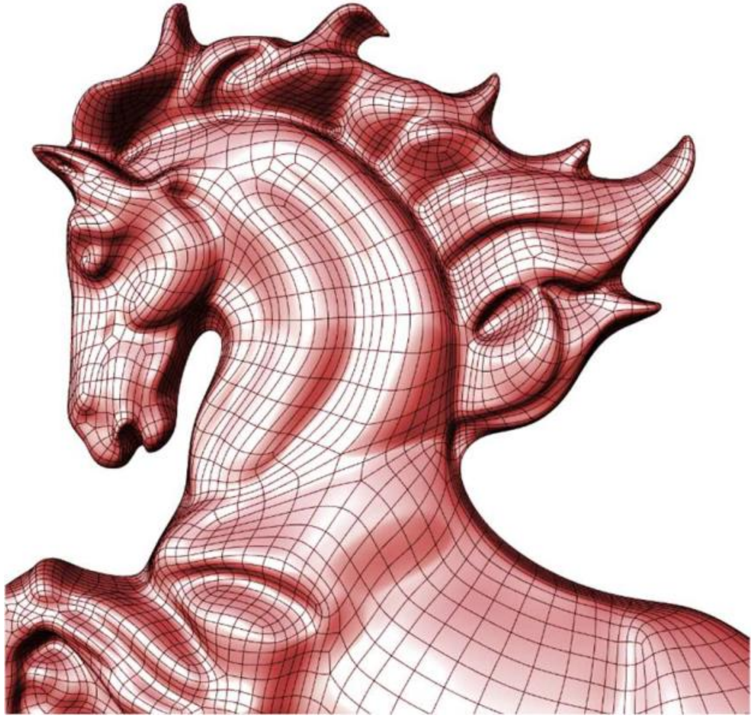
Step 3

$$-\nabla \cdot (\nu \nabla \boldsymbol{u}^{n+1}) + \frac{\gamma_0}{\Delta t} \boldsymbol{u}^{n+1} = \frac{\gamma_0}{\Delta t} \boldsymbol{u}^* - \frac{\nabla p^{n+1} + \boldsymbol{f}^n_{\text{ext}}}{\rho_0}$$

DG/CG-MFEM

A Hurtado-Mendoza (PhD): "*An Incompressible High-Order Solver with Thermal Coupling* ", ETSIAE-UPM & Numeca

Summary



1- Introduction to DG & Horses3d

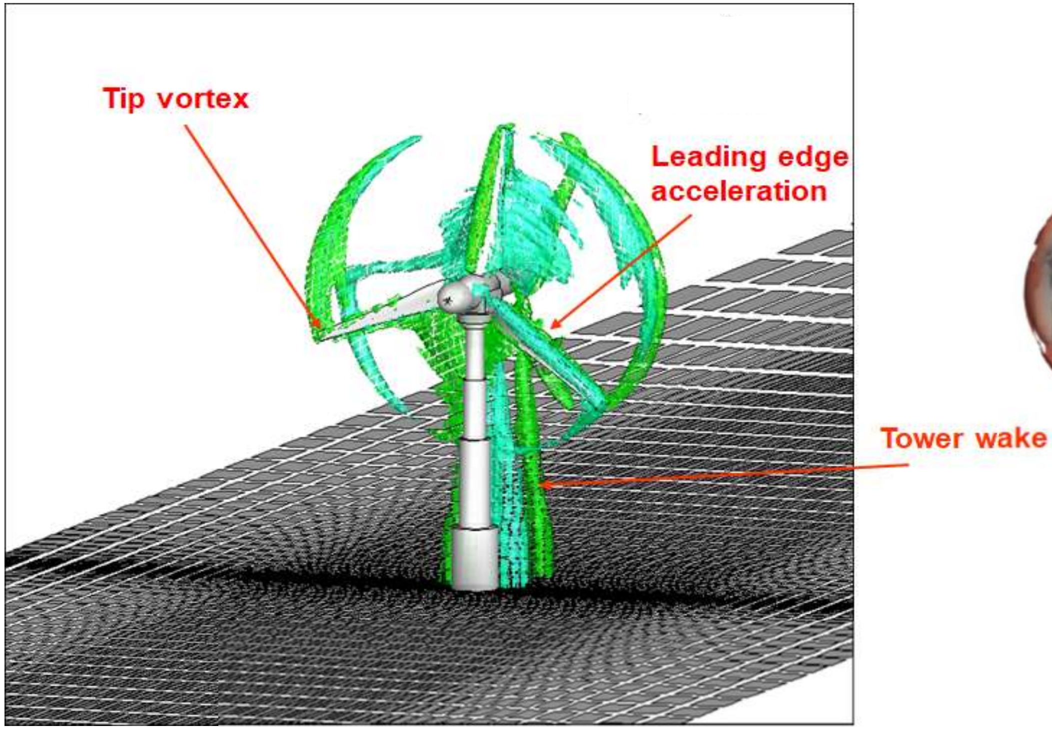
2- Multiphysics

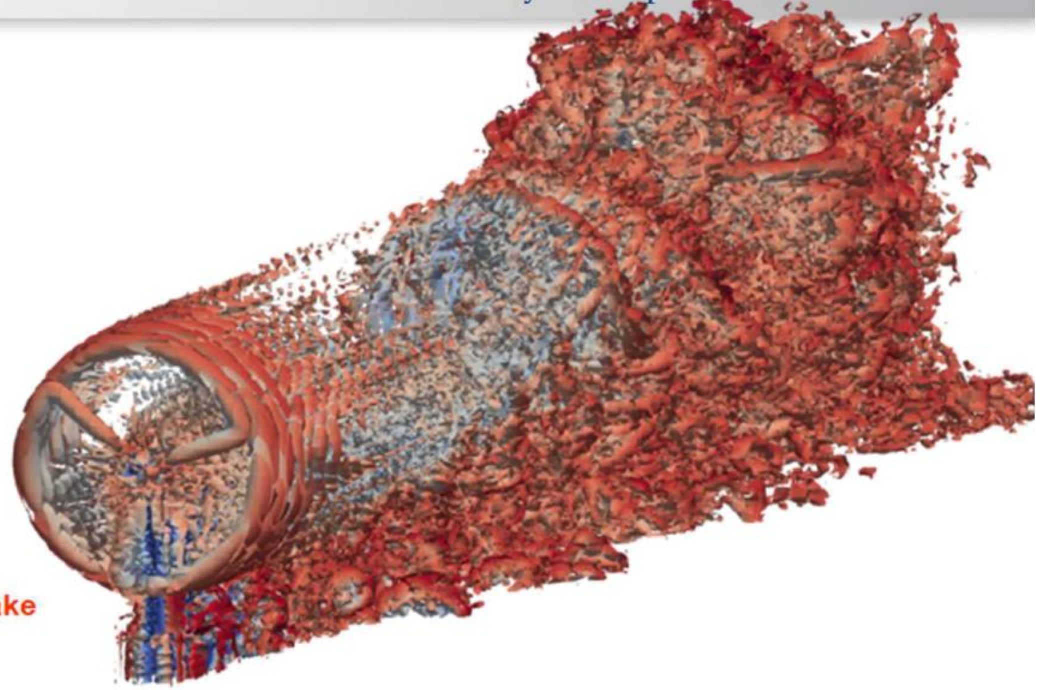
→ Wind turbines
→ Turbulence

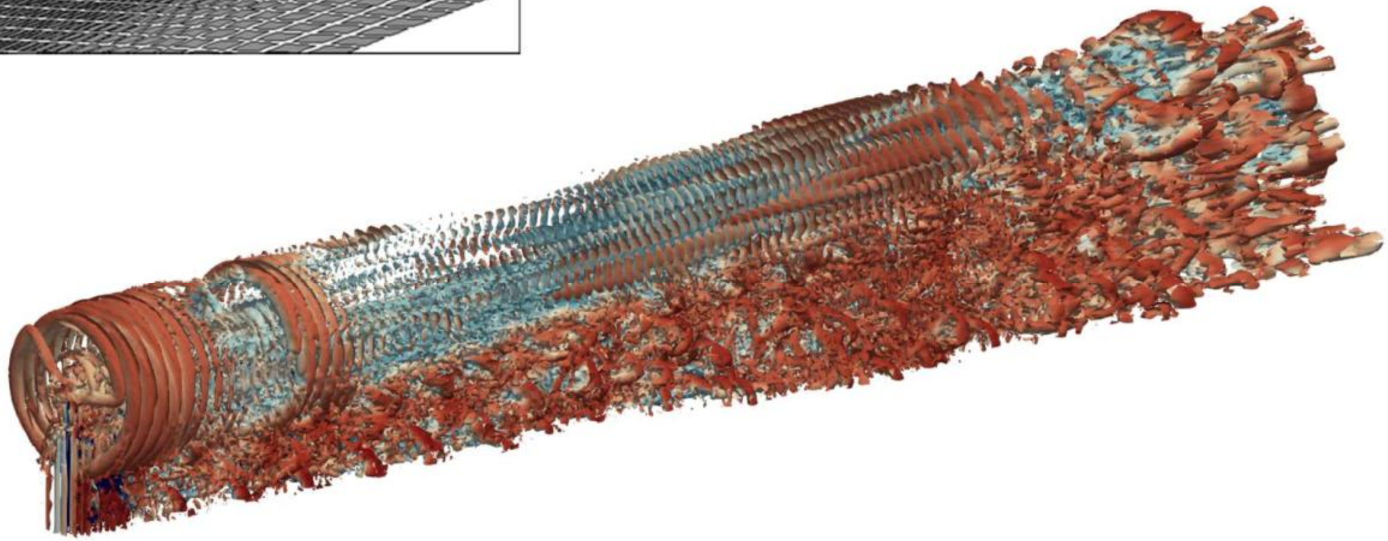
3. Machine Learning + CFD

→ Mesh adaption
→ NN acceleration
→ RL for automation

High order wind turbines

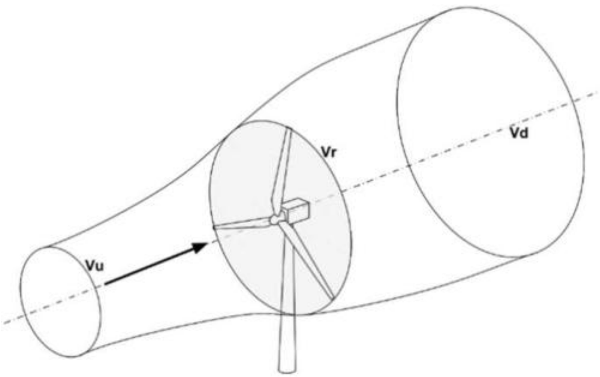






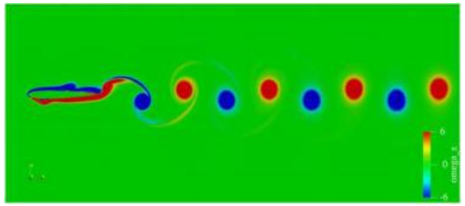
Require 2D aerodynamic data

Explicit 3D geometry

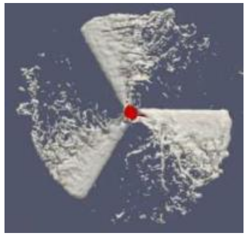


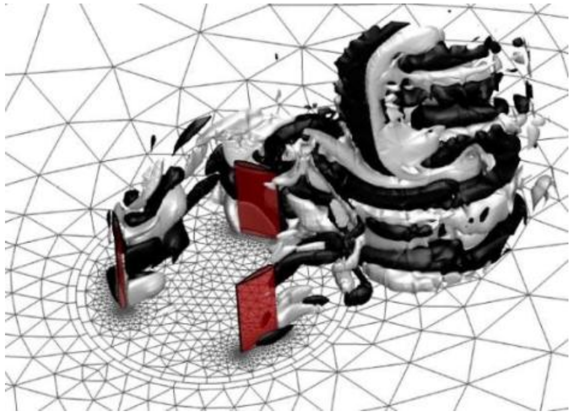
2-Actuator line

1-Actuator disc & BEM



3-Immersed boundaries



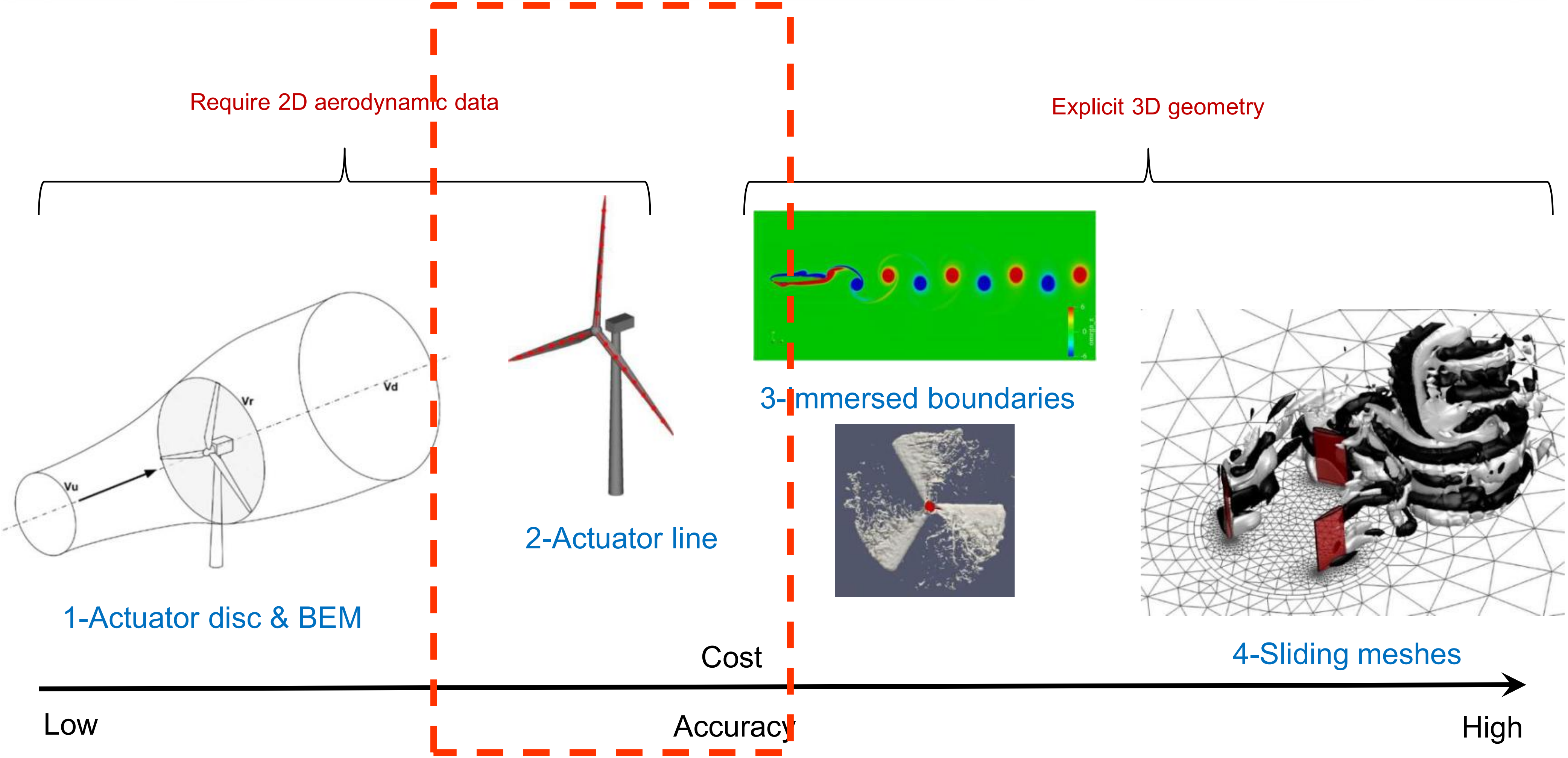


4-Sliding meshes

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



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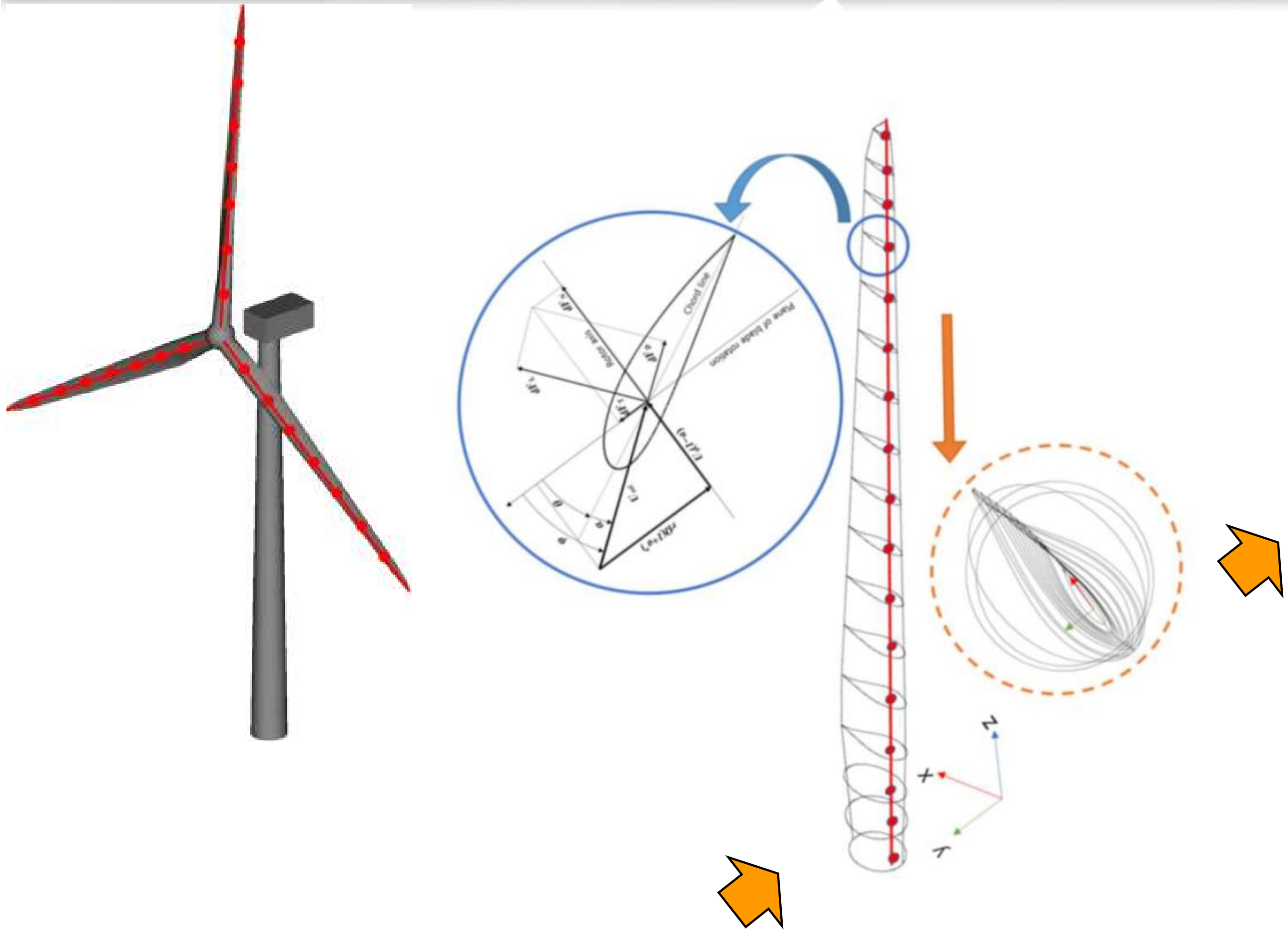
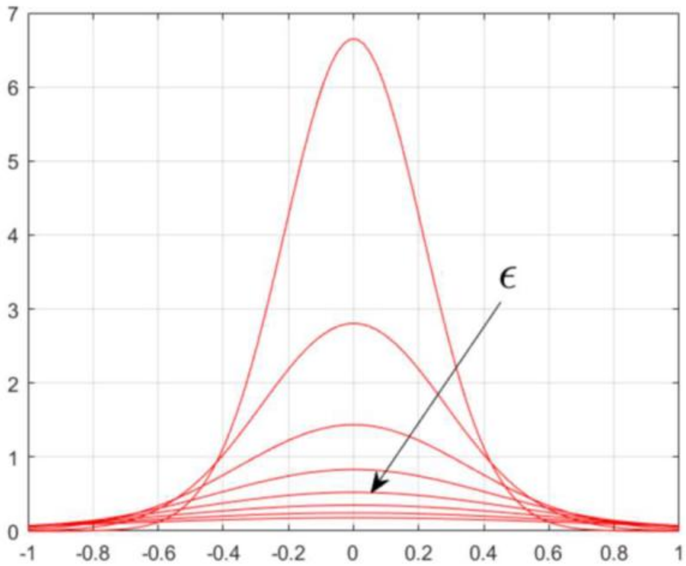
$$\frac{d\boldsymbol{Q}}{dt} = \mathcal{R}(\boldsymbol{Q}, \nabla \boldsymbol{Q}) + \mathcal{S}(\boldsymbol{Q})$$

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





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

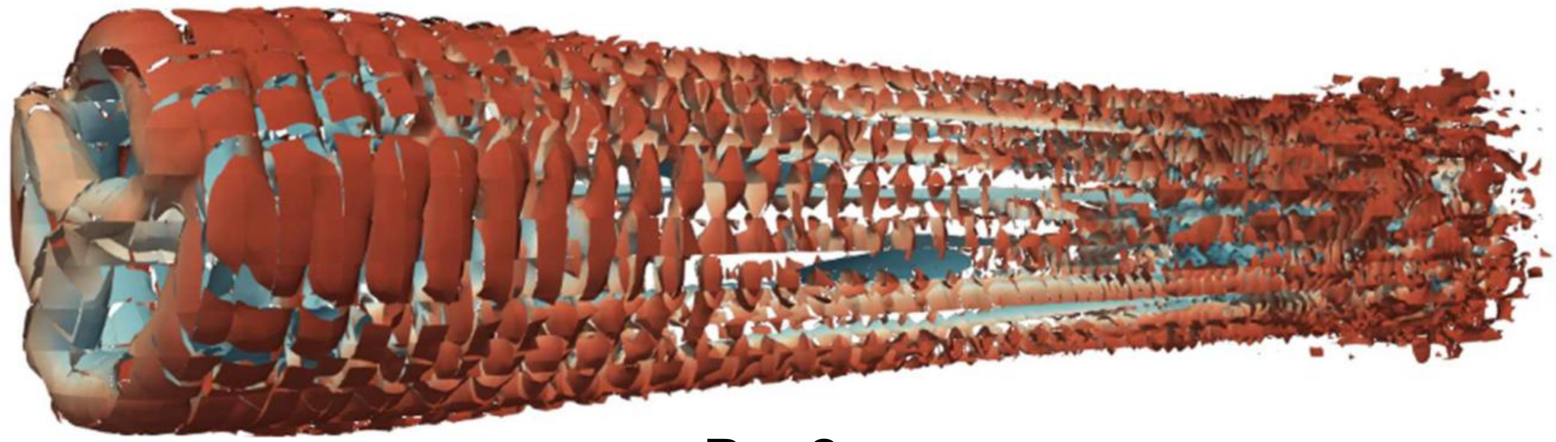
$$\epsilon_k = k \times \Delta_{grid} = k \times \frac{(\Delta_x \Delta_y \Delta_z)^{\frac{1}{3}}}{p+1}$$

Tabulated data

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

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



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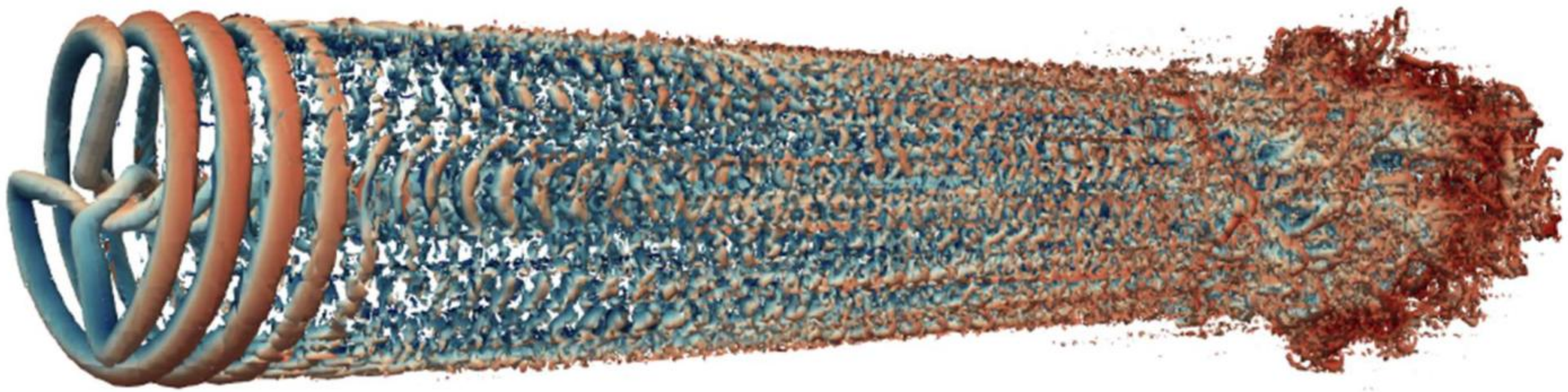
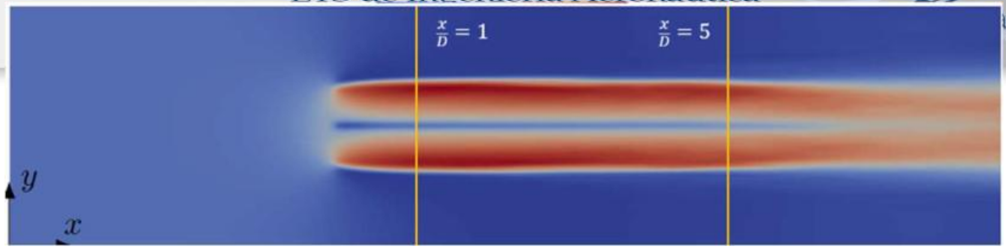
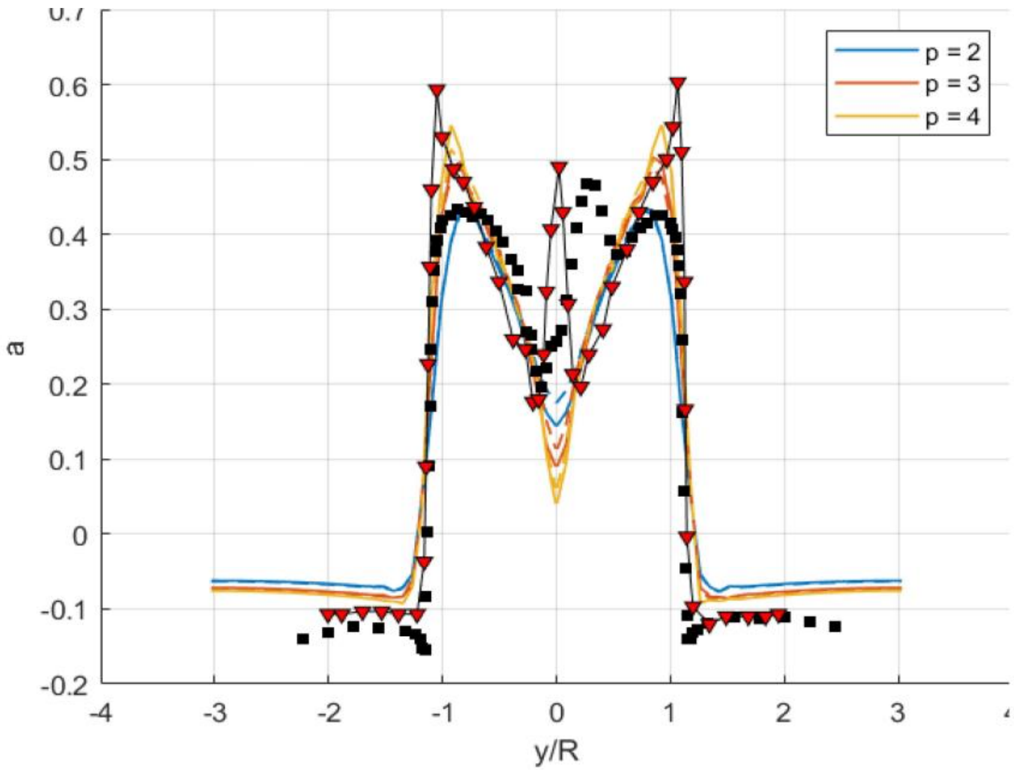


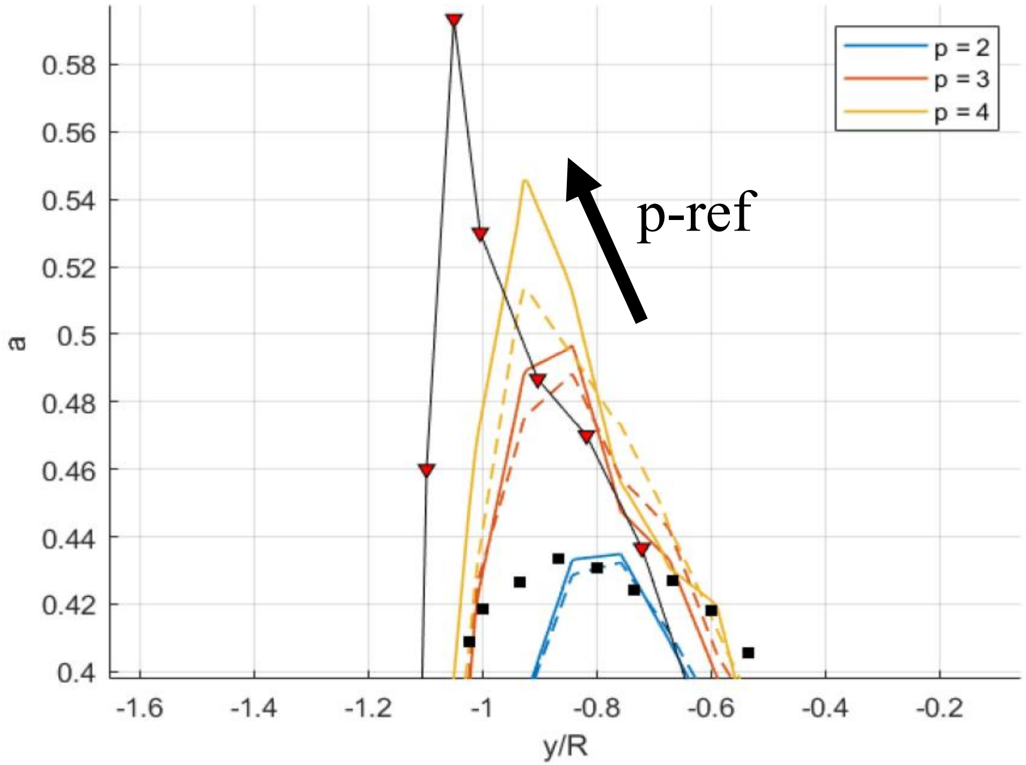
P = 5

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

Averaged velocity deficit





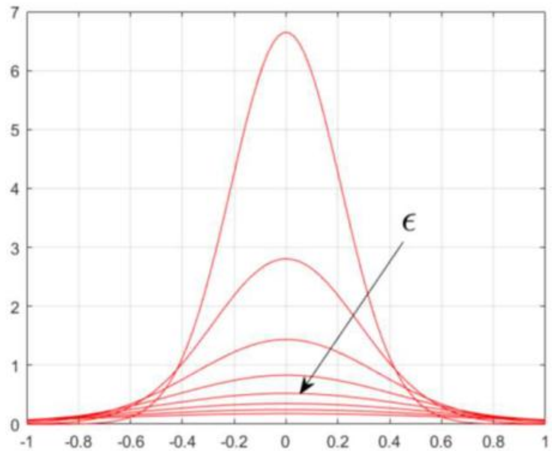


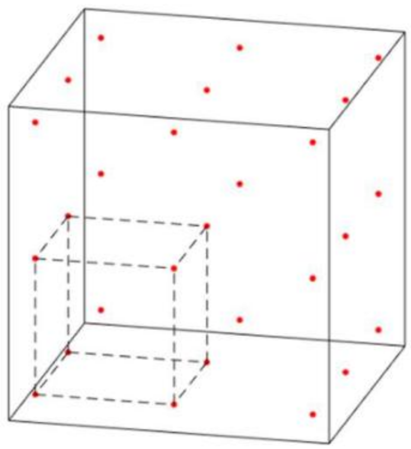
'■' Experimental

'-▽-' OpenFoam-Oxford Fine mesh → 190M elements

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

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





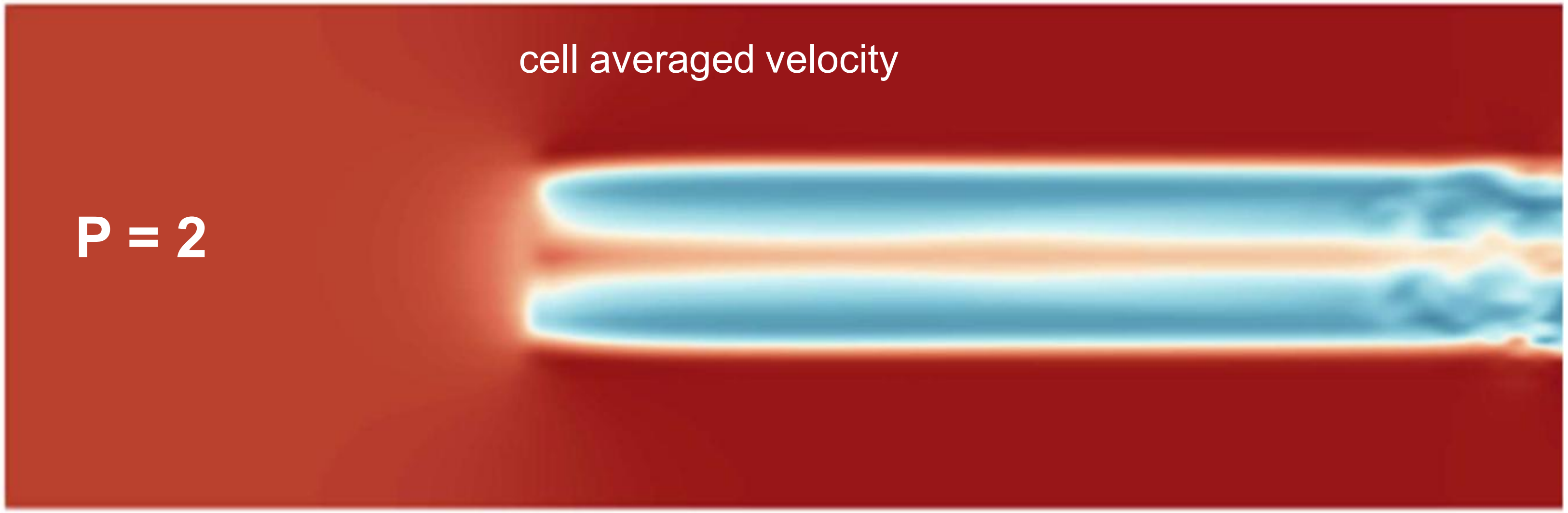
cell averaged velocity

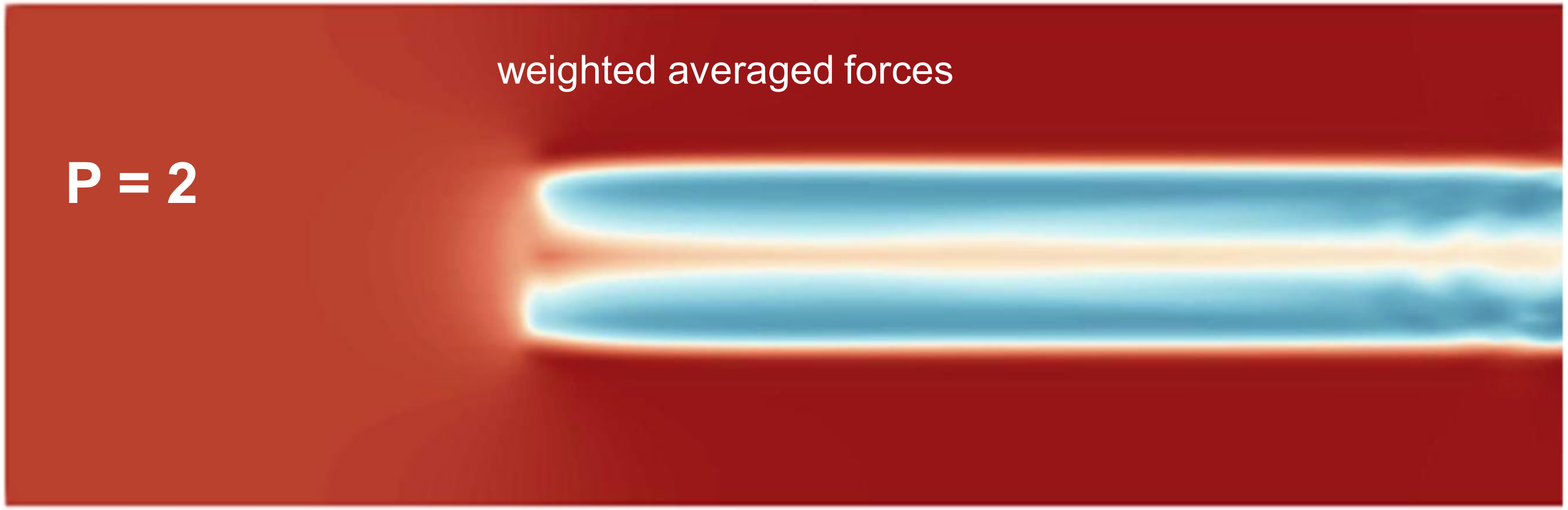
$$\overline{\mathbf{q_t}} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{q_t}_i$$

weighted averaged forces

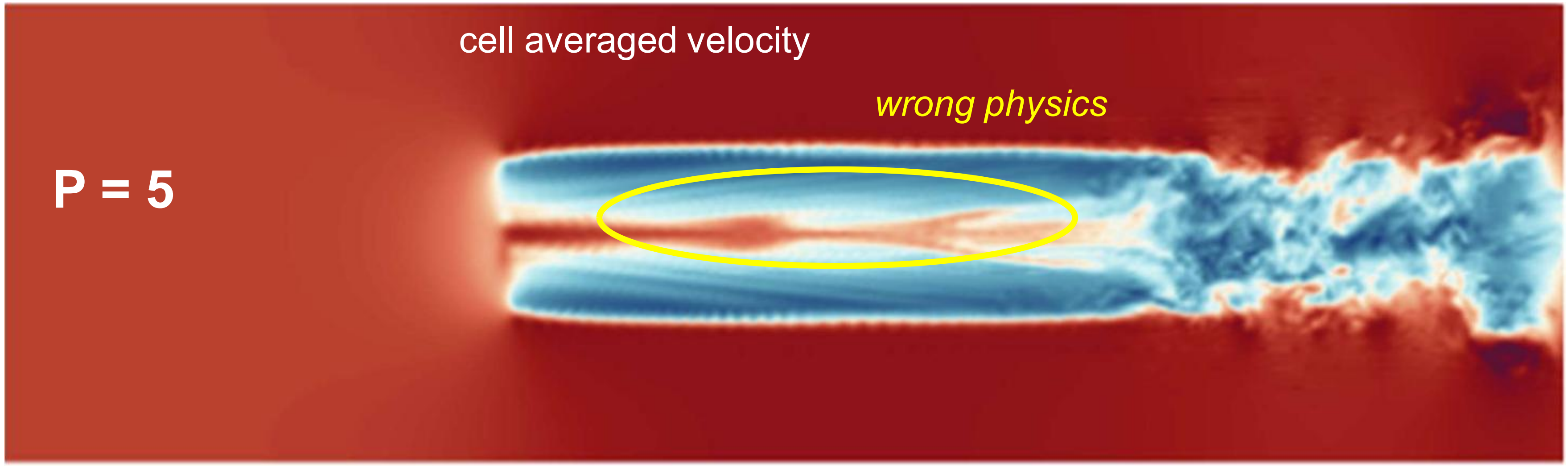
$$\overline{f}_j = \frac{\sum_{i=1}^{N} \eta_{ji}(d)\cdot f_i}{\sum_{j=1}^{N_a}\sum_{i=1}^{N} \eta_{ji}(d)}$$

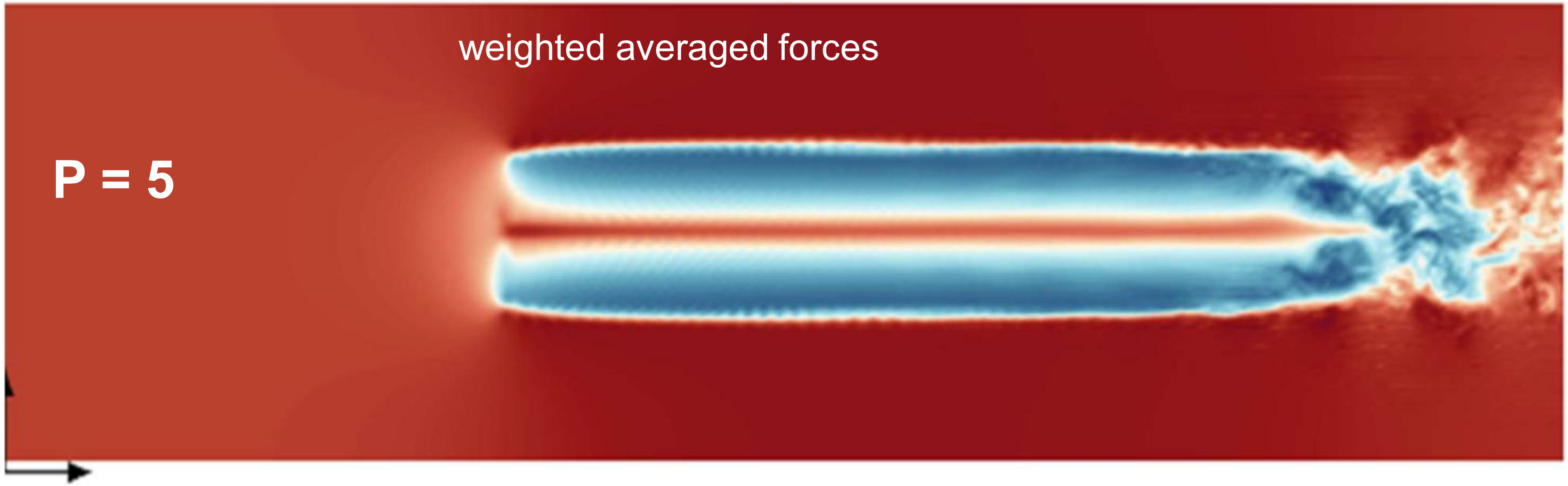
OA Mariño, R Sanz, S Colombo, A Sivaramakrishnan, **E Ferrer**, "Modelling Wind Turbines through Actuator Lines in High-Order h/p Solvers“, *under review*



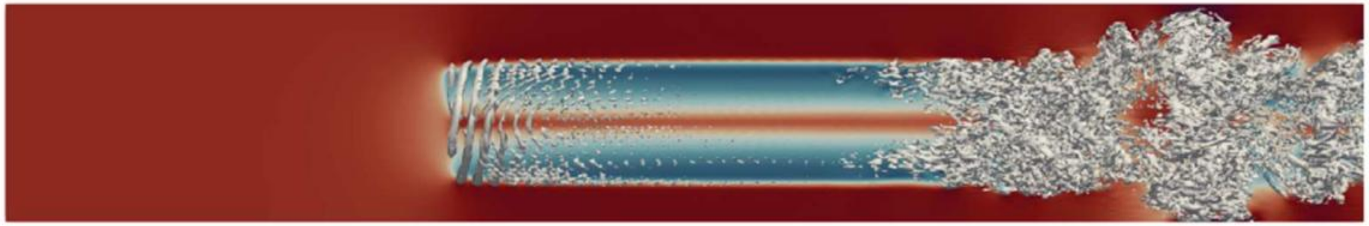


OA Mariño, R Sanz, S Colombo, A Sivaramakrishnan, **E Ferrer**, "Modelling Wind Turbines through Actuator Lines in High-Order h/p Solvers“, *under review*

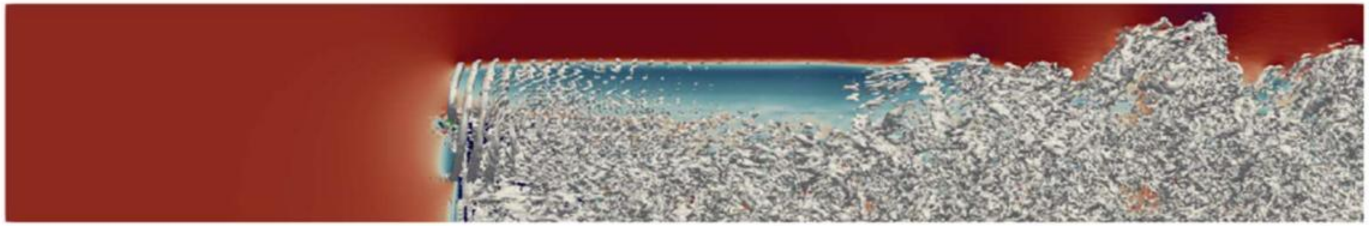




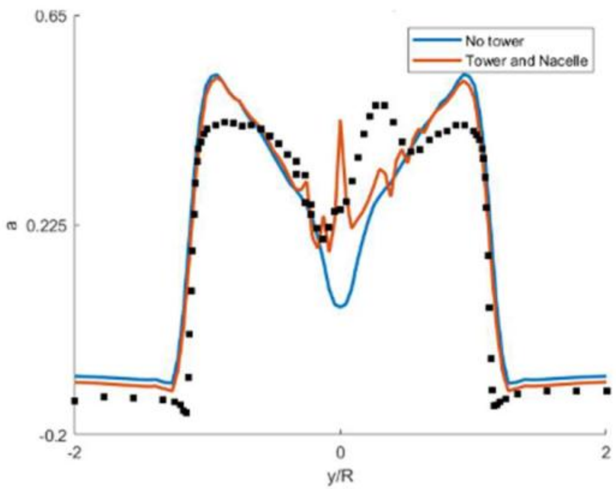
OA Mariño, R Sanz, S Colombo, A Sivaramakrishnan, **E Ferrer**, "Modelling Wind Turbines through Actuator Lines in High-Order h/p Solvers", *under review*

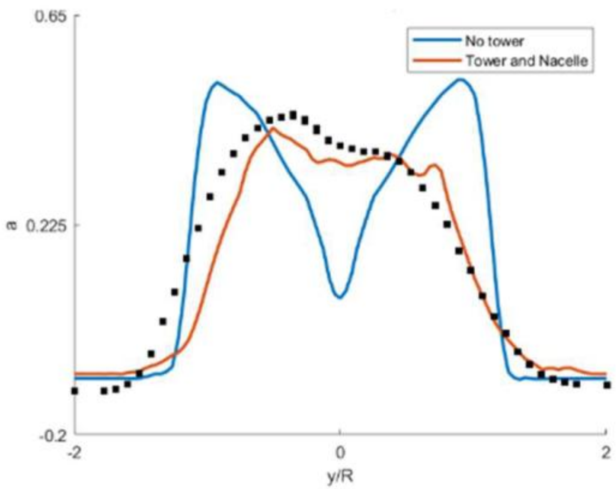


a) Actuator line without tower and nacelle.



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

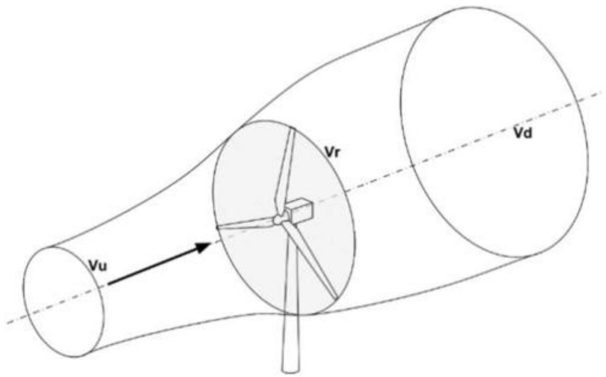


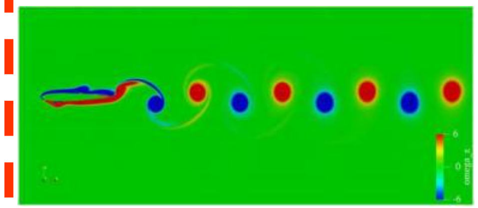


OA Mariño, R Sanz, S Colombo, A Sivaramakrishnan, **E Ferrer**, "Modelling Wind Turbines through Actuator Lines in High-Order h/p Solvers“, *under review*

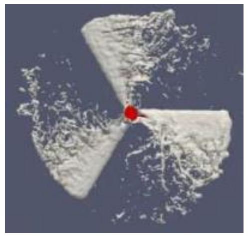
Require 2D aerodynamic data

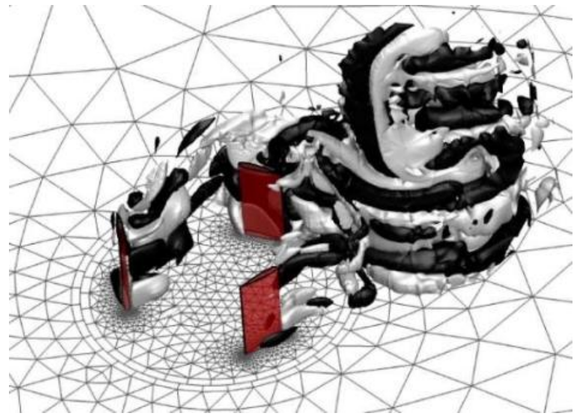
Explicit 3D geometry





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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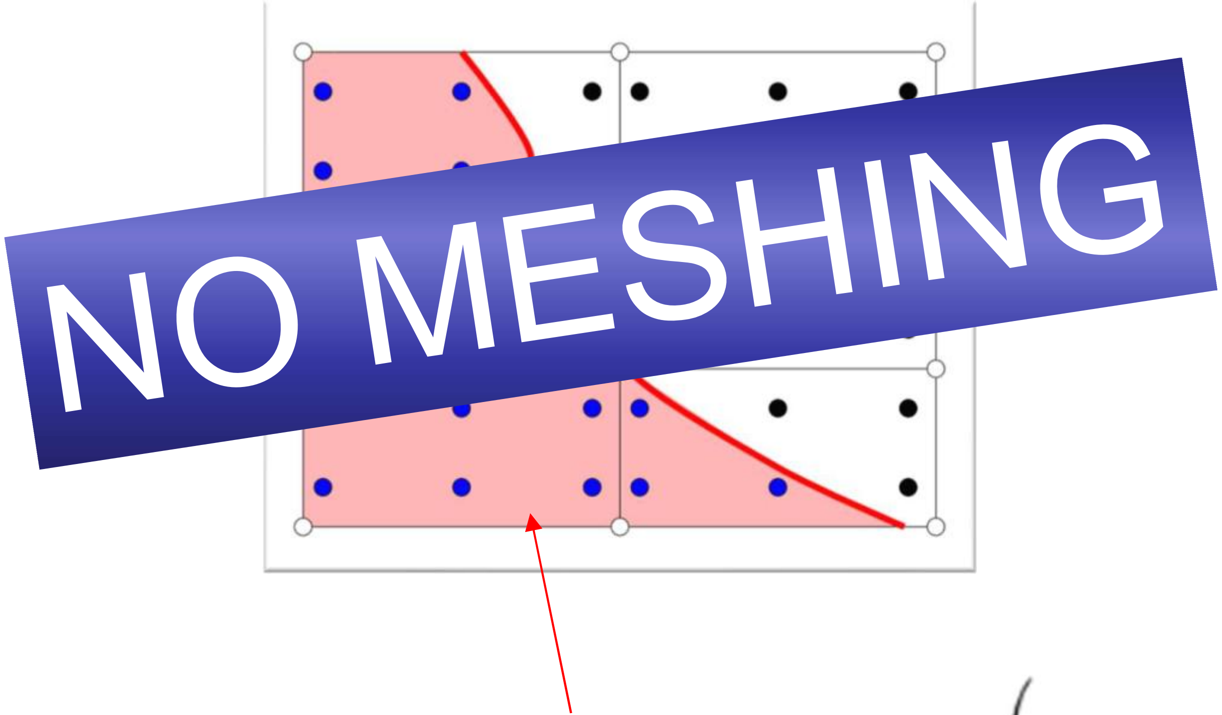
2 & 3- **E Ferrer**, S Colombo, O Marino, **"**Aeroacoustic predictions of wind turbines based on **actuator lines and immersed boundaries**", *Under review at Wind Energy*
1- **E Ferrer**, S Le Clainche, **Simple models for cross flow turbines**, *in Recent advances in CFD for Wind and Tidal Offshore Turbines*, 2019
1- **E Ferrer**, OMF Browne, E Valero, Sensitivity analysis to control the far–wake unsteadiness behind **turbines**, *Energies*, 2017

Immersed boundary method (penalty) → Mesh Free method

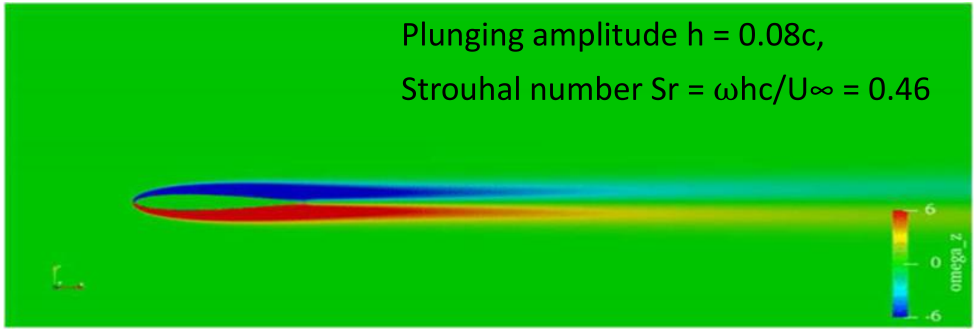
- Simple 'Cartesian' grids (with local P refinement)
- Complex geometries
- Moving geometries

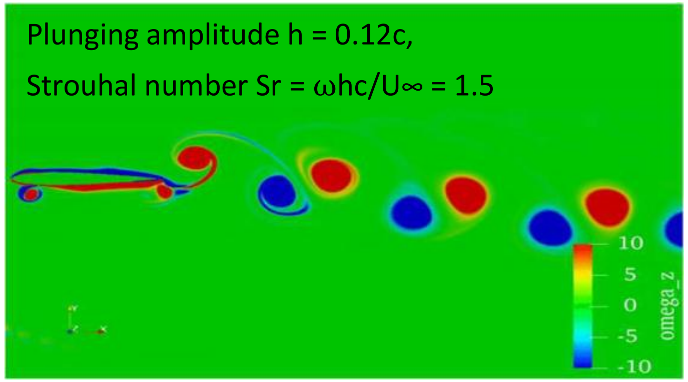


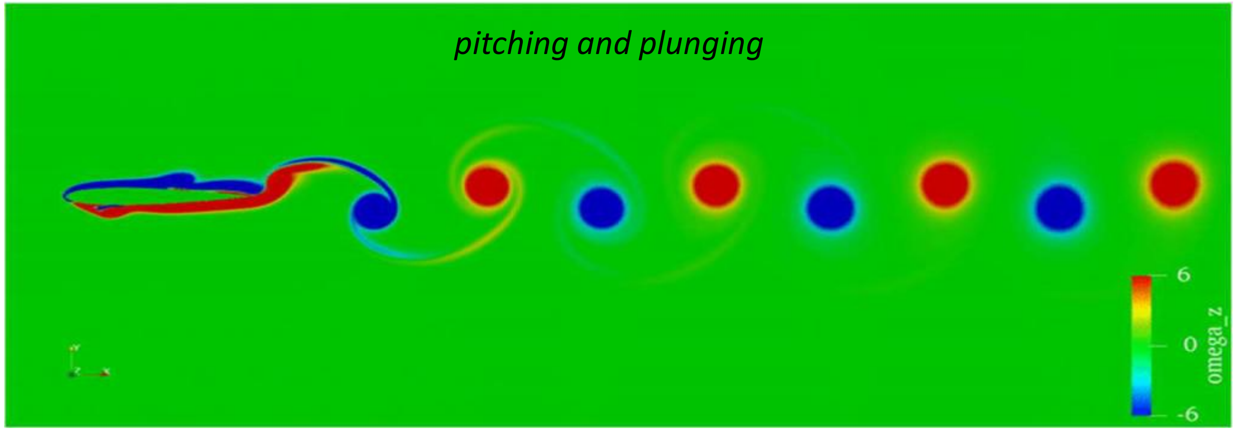
$$\frac{\partial \mathbf{U}}{\partial t} + \nabla \cdot \vec{\mathbf{F}}(\mathbf{U}) = \nabla \cdot \vec{\mathbf{G}}(\mathbf{U}, \nabla \mathbf{U}) + \boxed{\mathbf{S}(\mathbf{U}).}$$

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

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

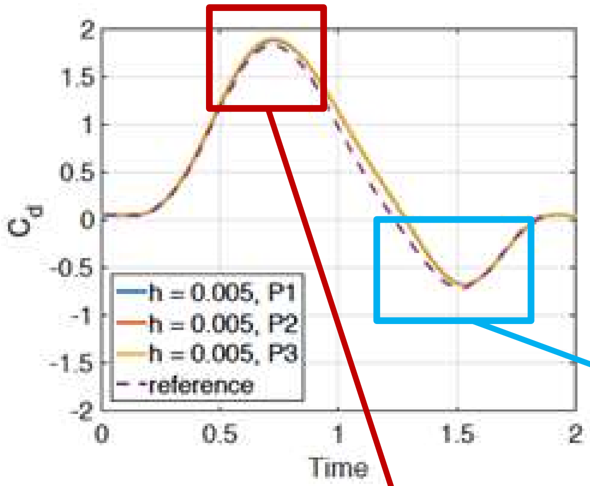


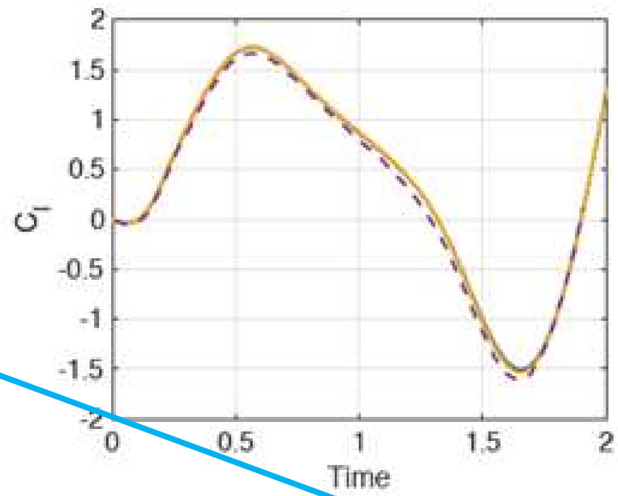


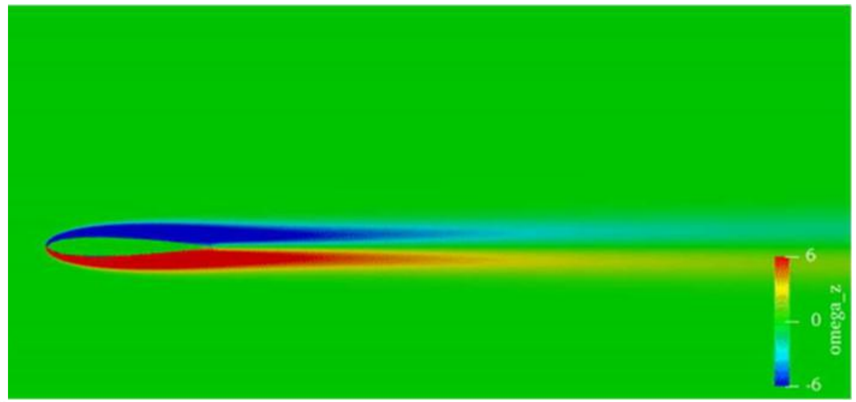


- J Kou, A Hurtado-de-Mendoza, S Joshi, S Le Clainche, **E Ferrer**, "Eigensolution analysis of immersed boundary method based on volume penalization: applications to high-order schemes", *Journal of Computational Physics,* Vol 449, 110817, 2022
- J Kou, S Joshi, A Hurtado-de-Mendoza, K Puri, C Hirsch, **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

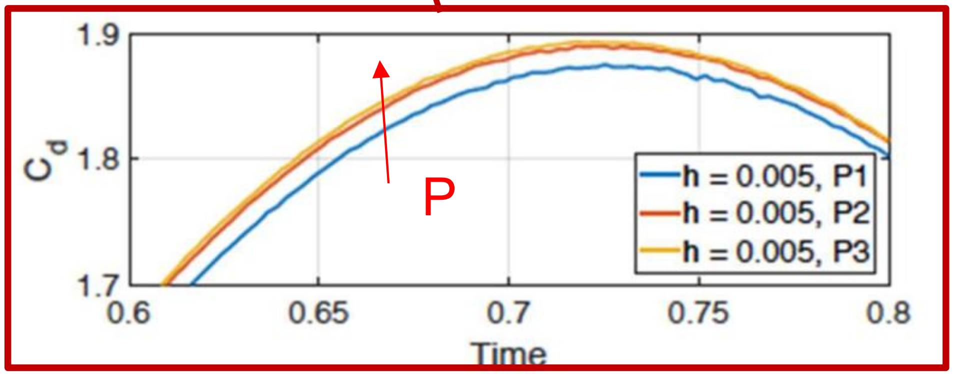
Moving NACA0012 at Reynolds number 1000, *pitching and plunging*:

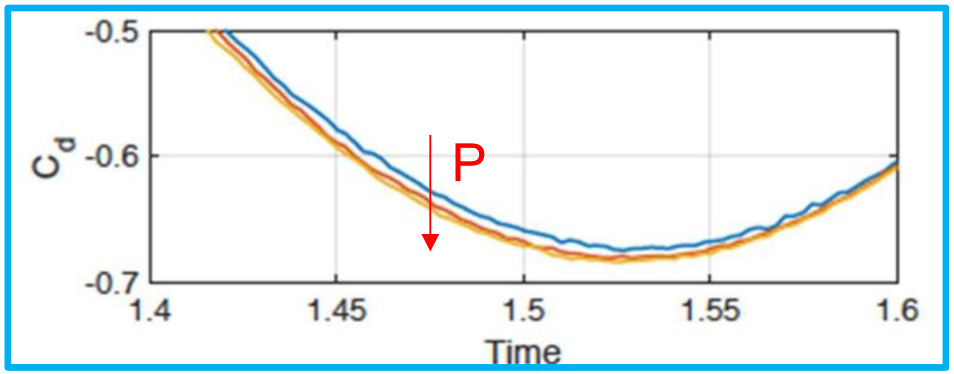






P-adaption increases accuracy





- 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
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- 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

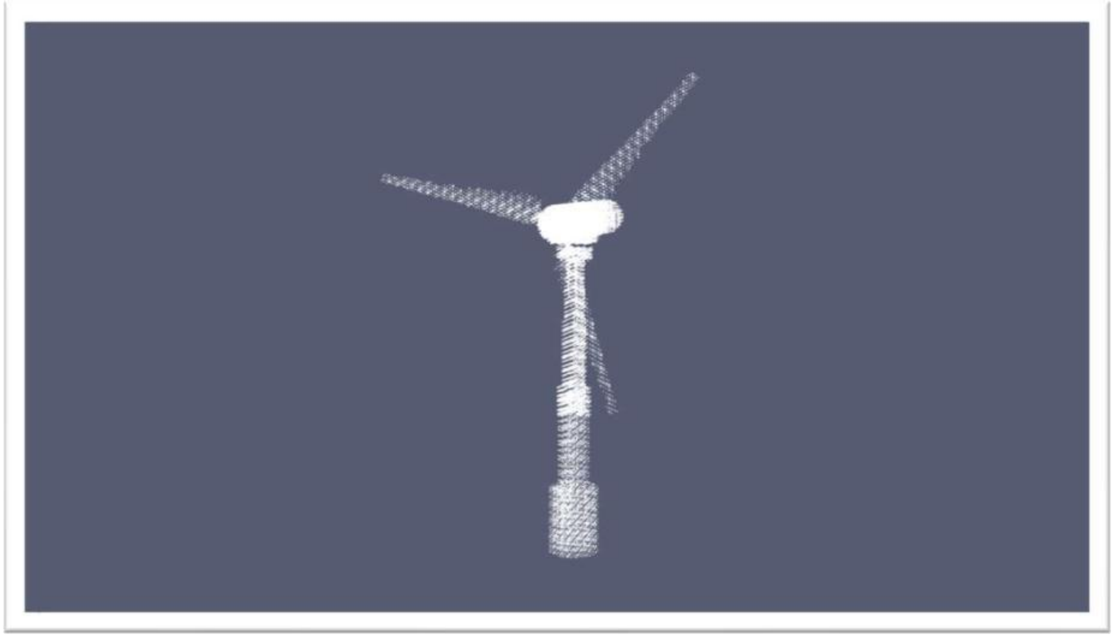
Immersed boundary method (penalty)

IB for rotating Wind turbine

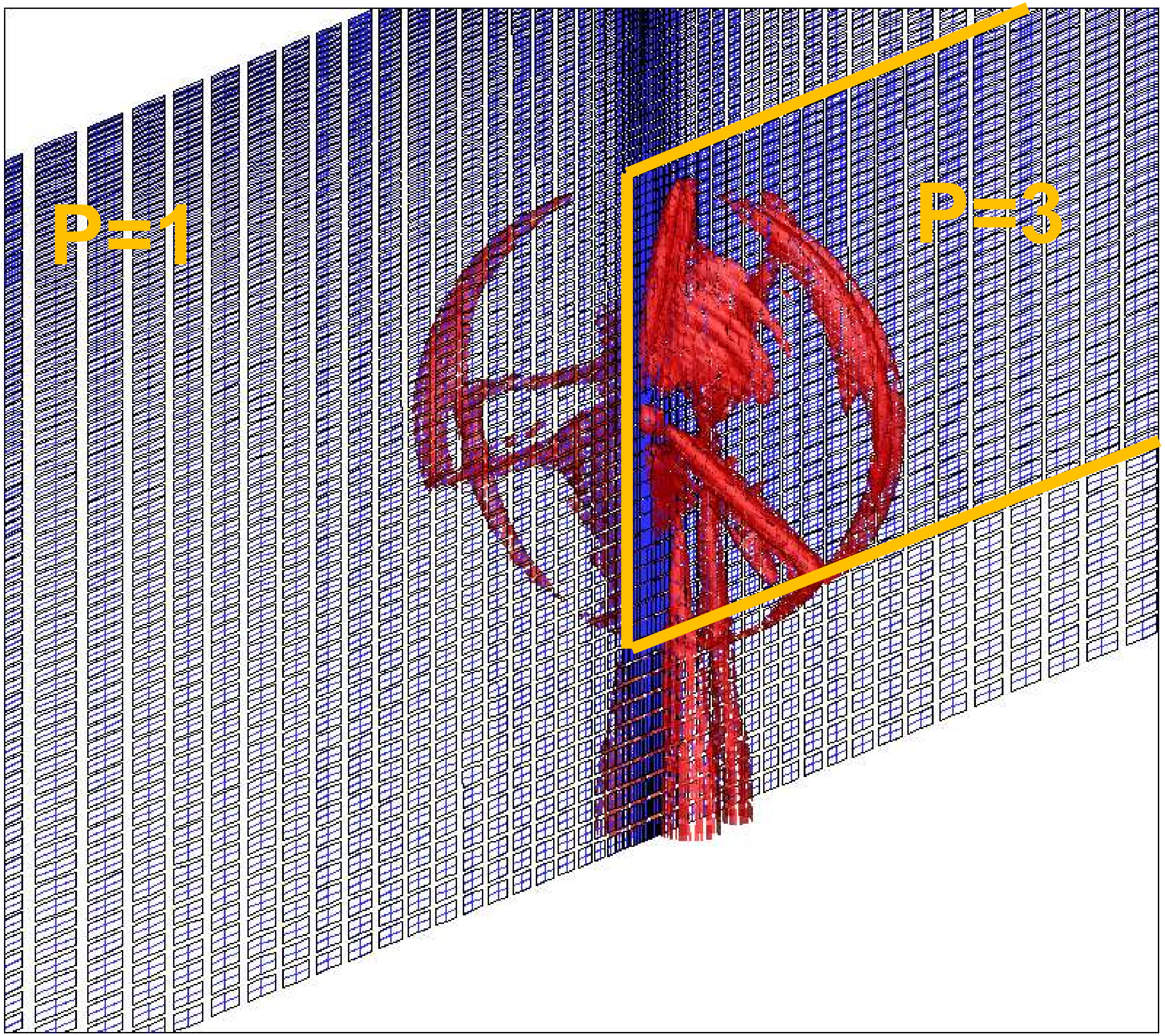
Only CAD '.stl' file
for the wind turbine

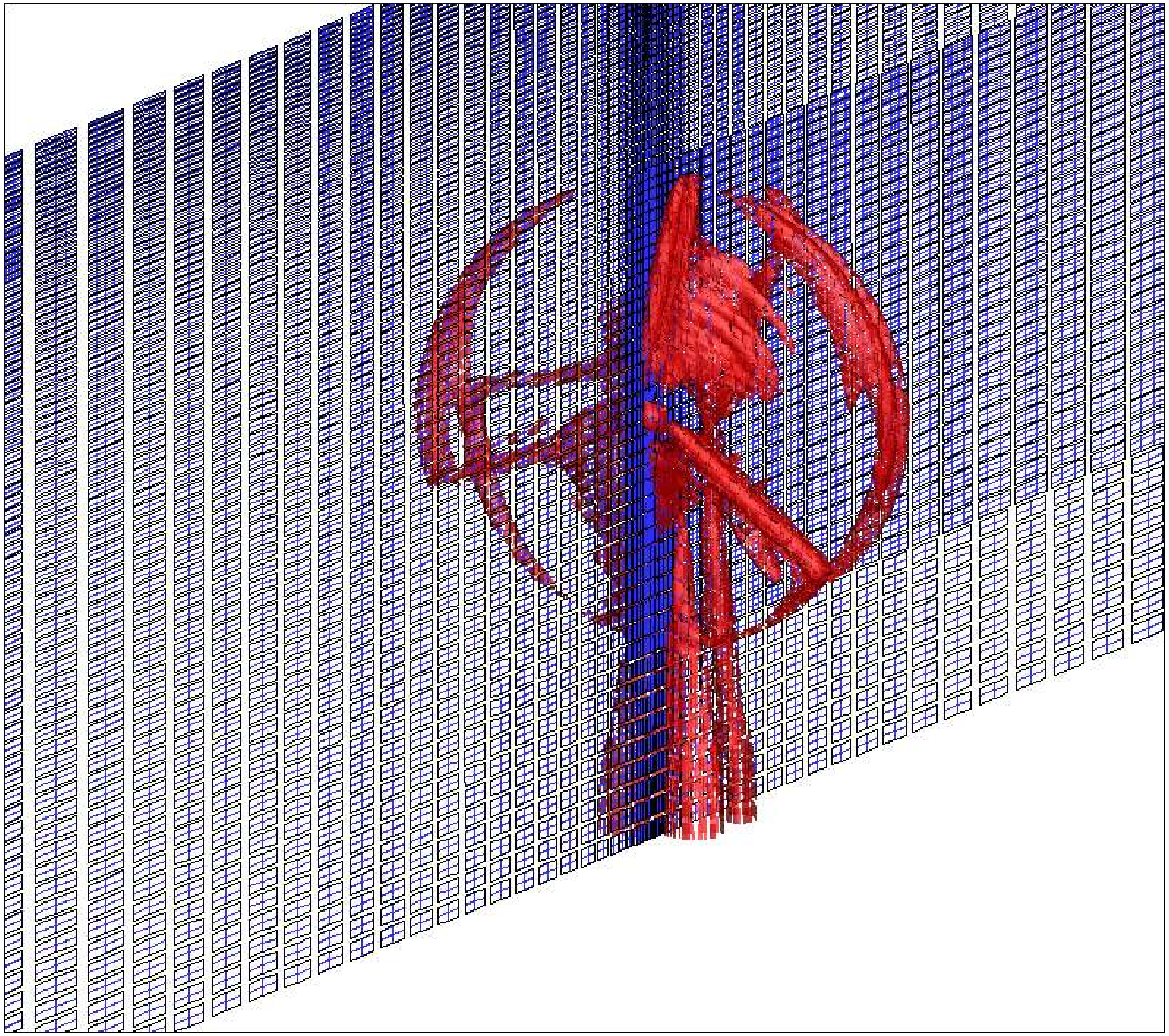
&

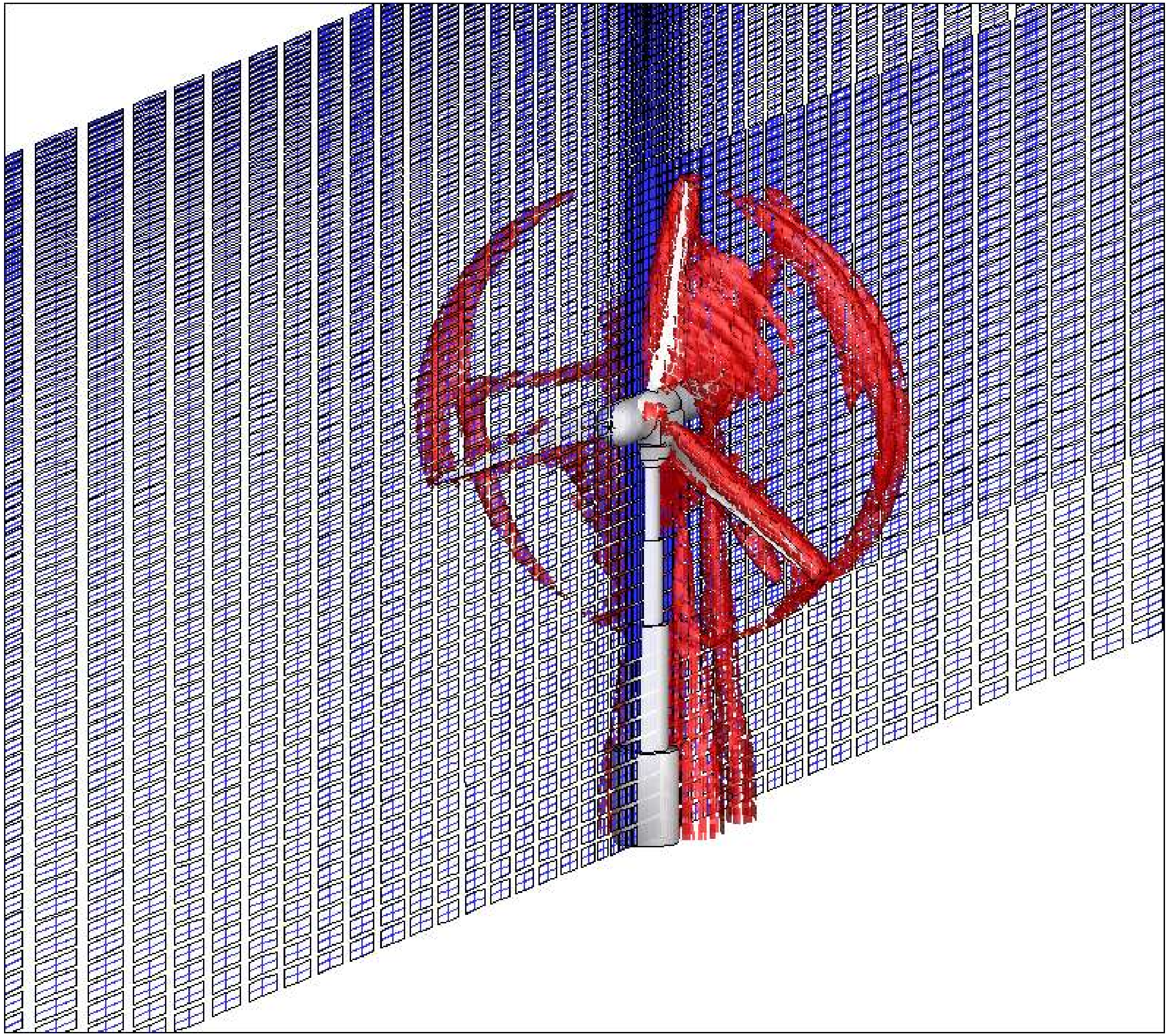
Simple Cartesian mesh

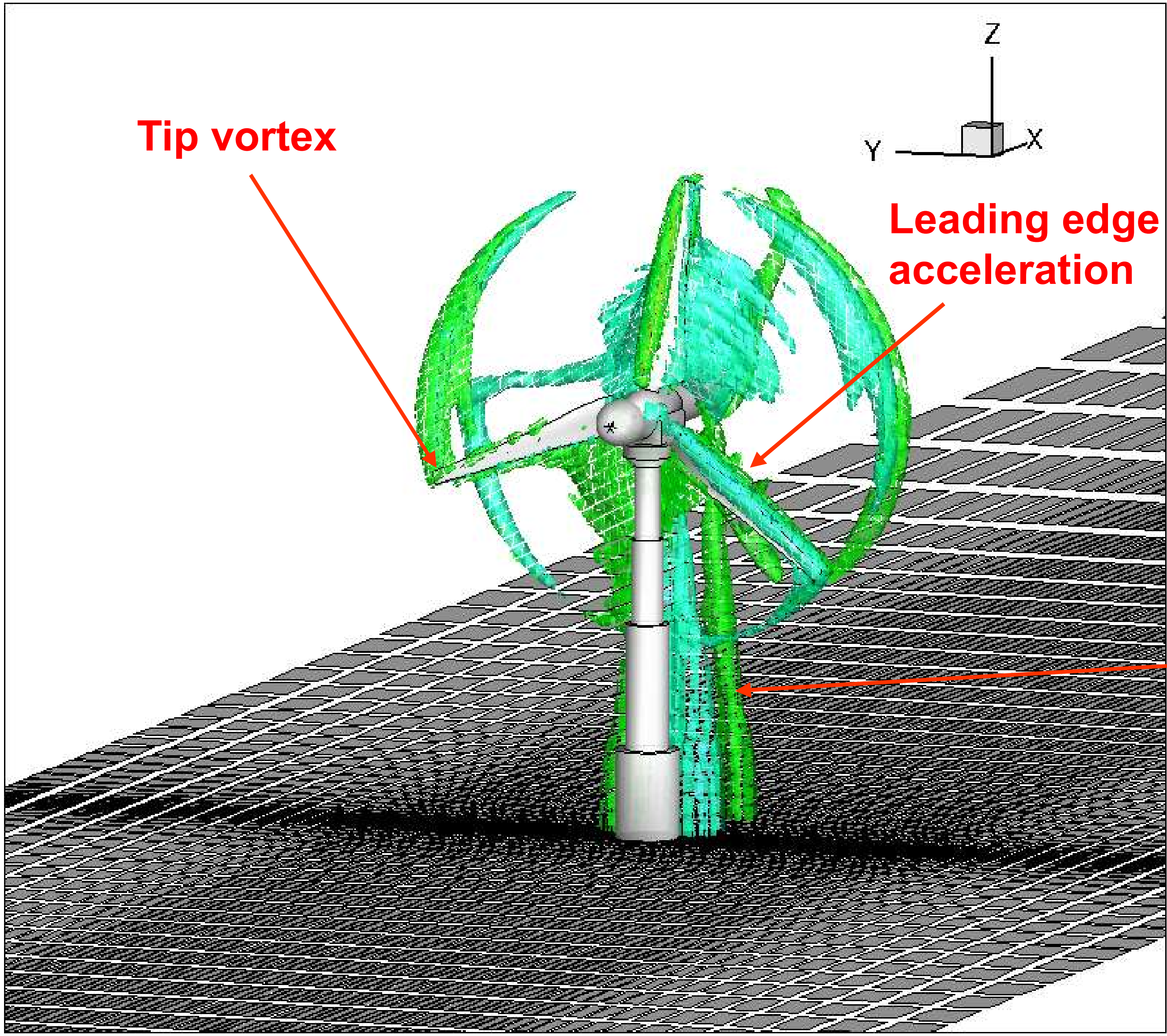


Penalty points for the wind turbine


P=1
P=3

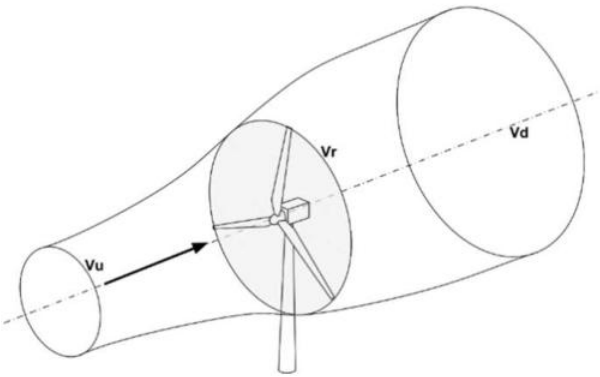


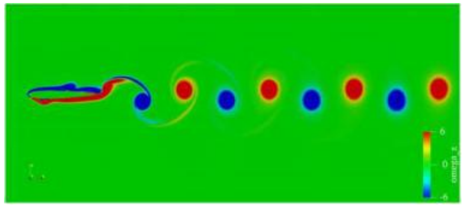



Tip vortex
Leading edge acceleration
Tower wake
Z
Y
X

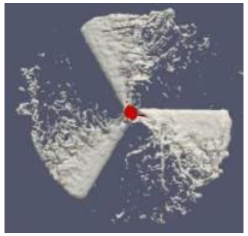
Require 2D aerodynamic data

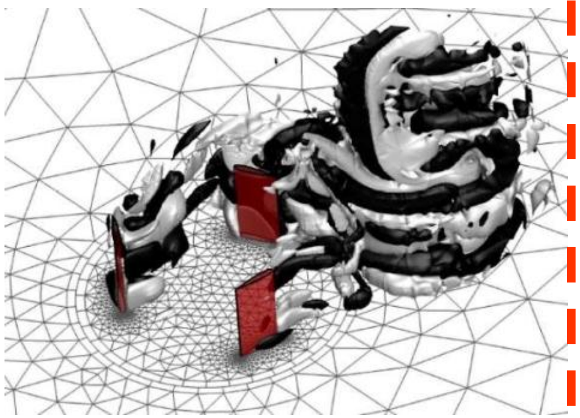
Explicit 3D geometry





3-Immersed boundaries





2-Actuator line

1-Actuator disc & BEM

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
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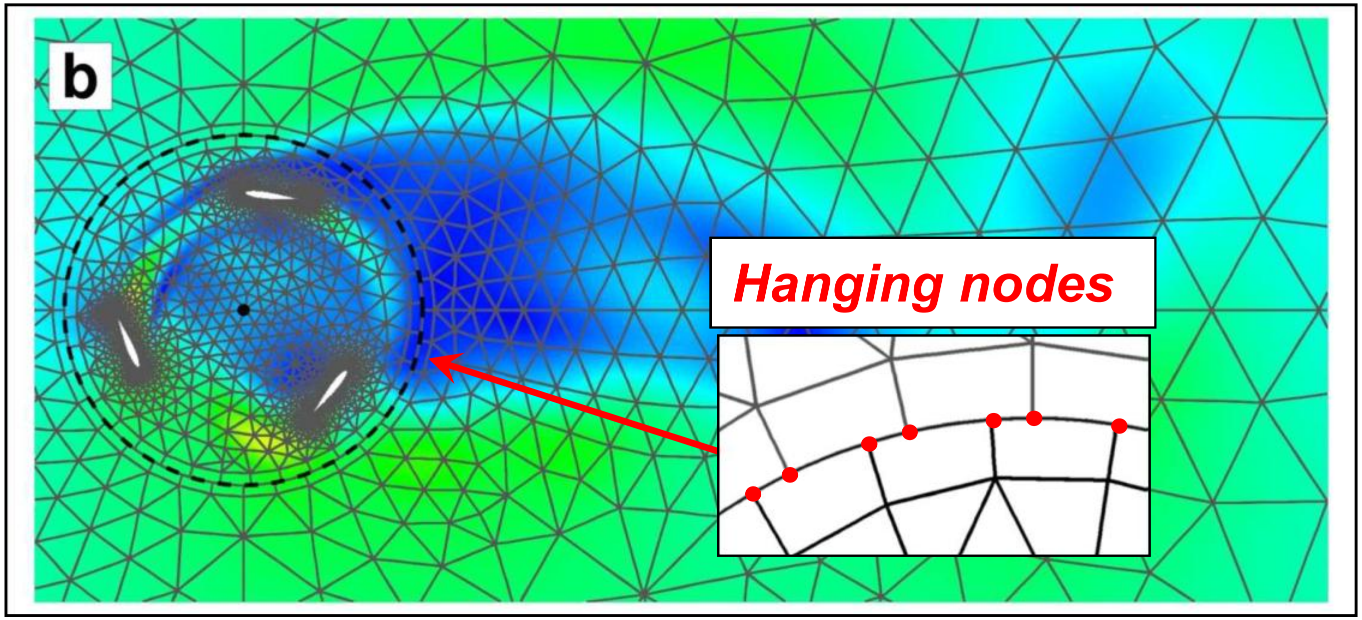
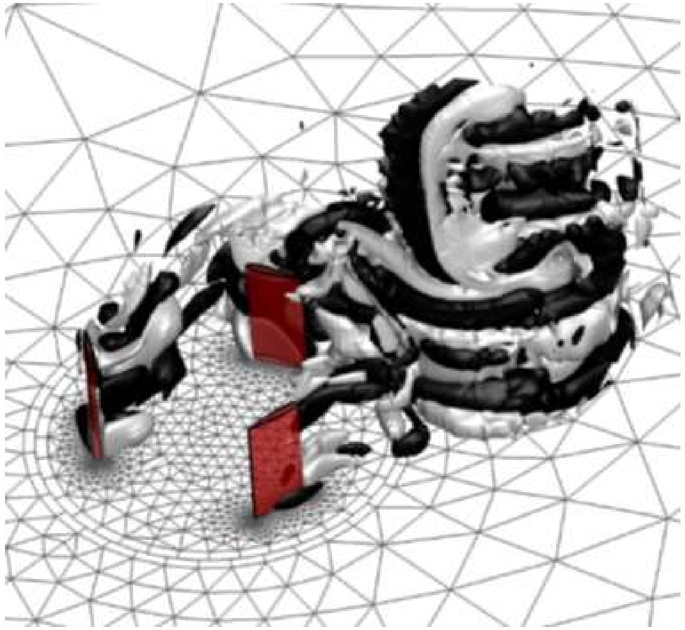
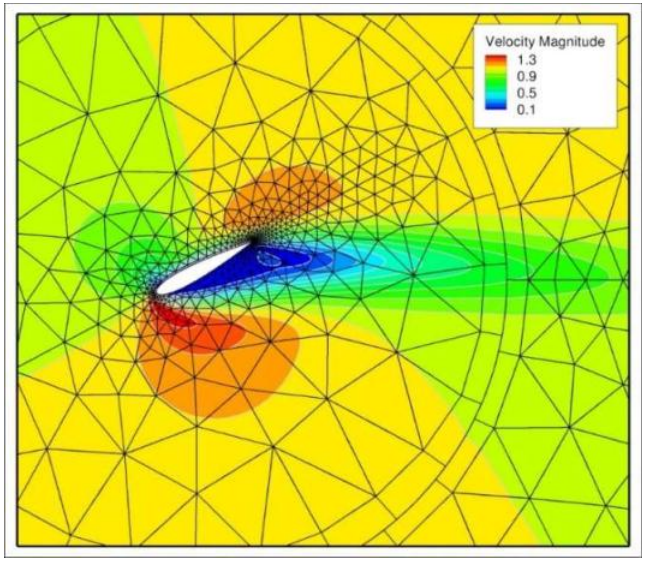
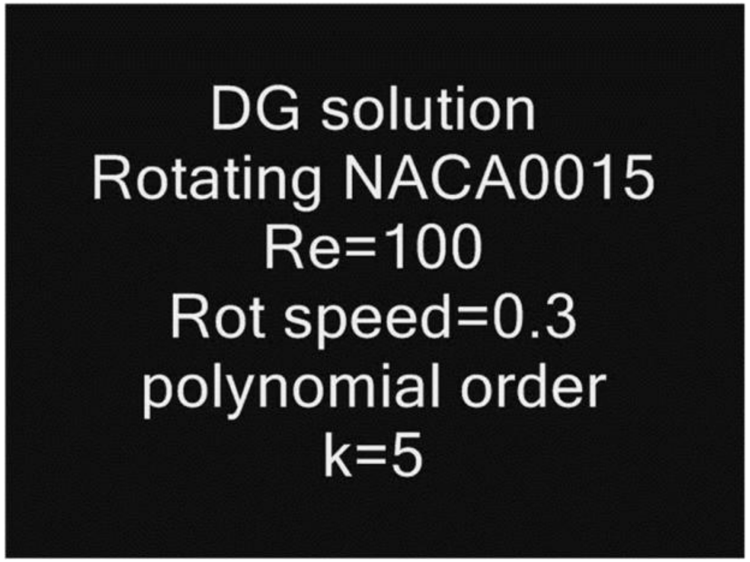
High order sliding meshes



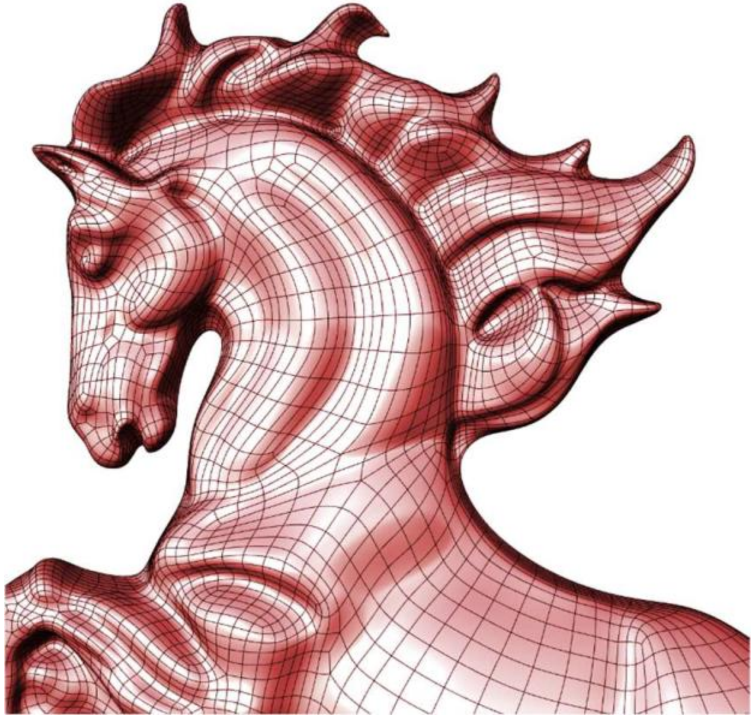






- E Ferrer and RHJ Willden, "A high order DG- Fourier incompressible 3D Navier-Stokes solver with rotating sliding meshes", *JCP*, 231, 2012

Summary



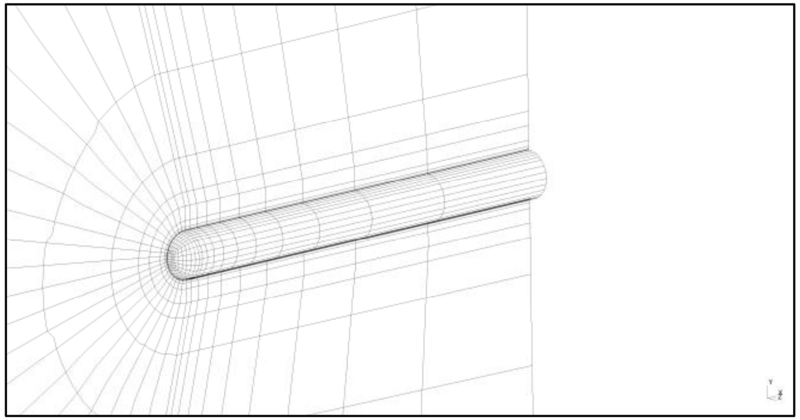
1- Introduction to DG & Horses3d

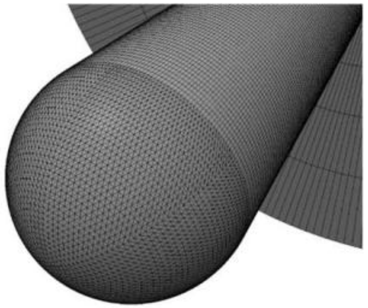
2- Multiphysics
→ Wind turbines
→ Turbulence

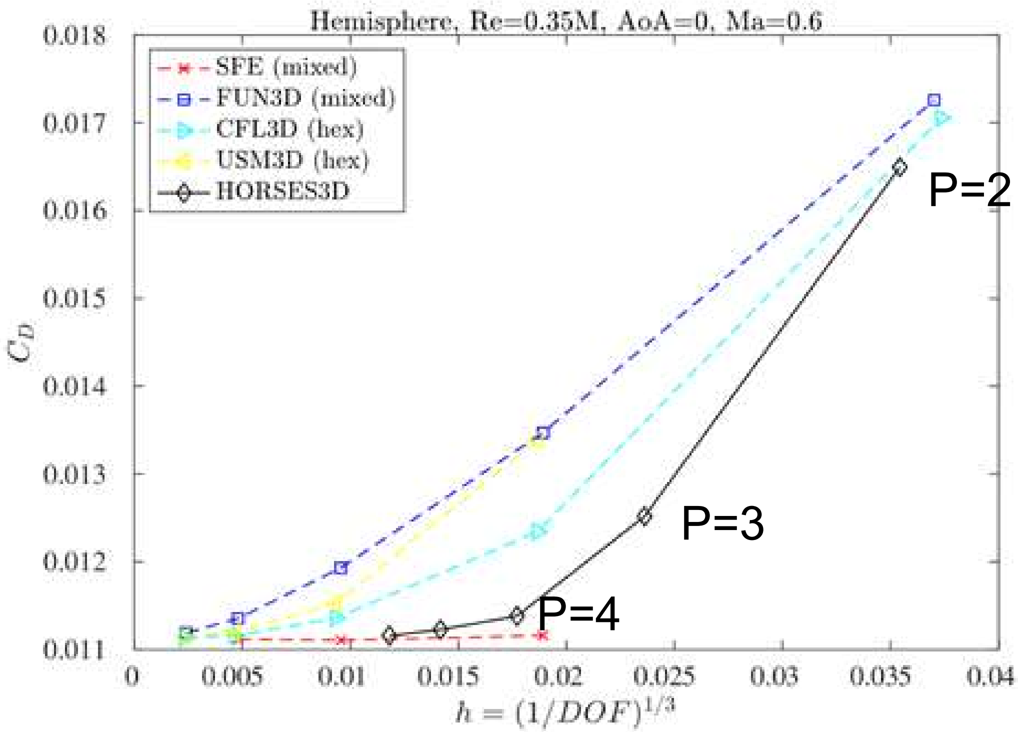
3. Machine Learning + CFD
→ Mesh adaption
→ NN acceleration
→ RL for automation

High order RANS (SAneg)

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

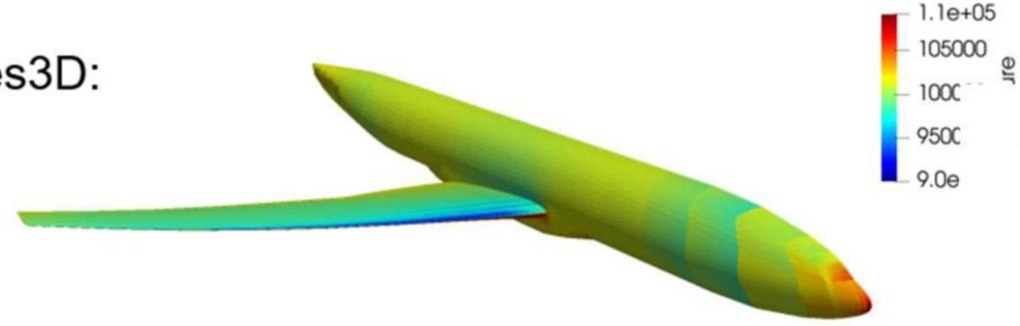




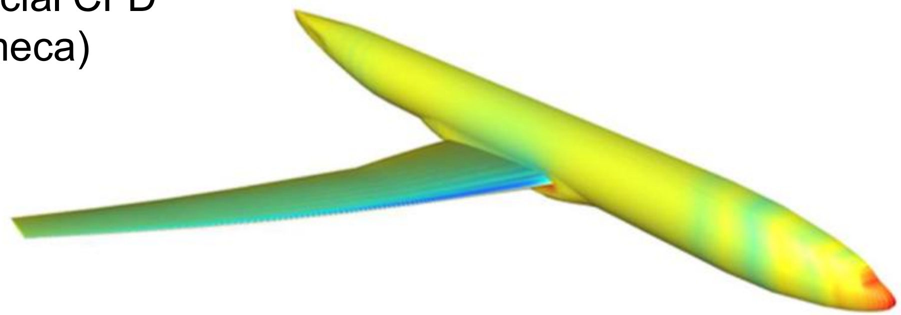


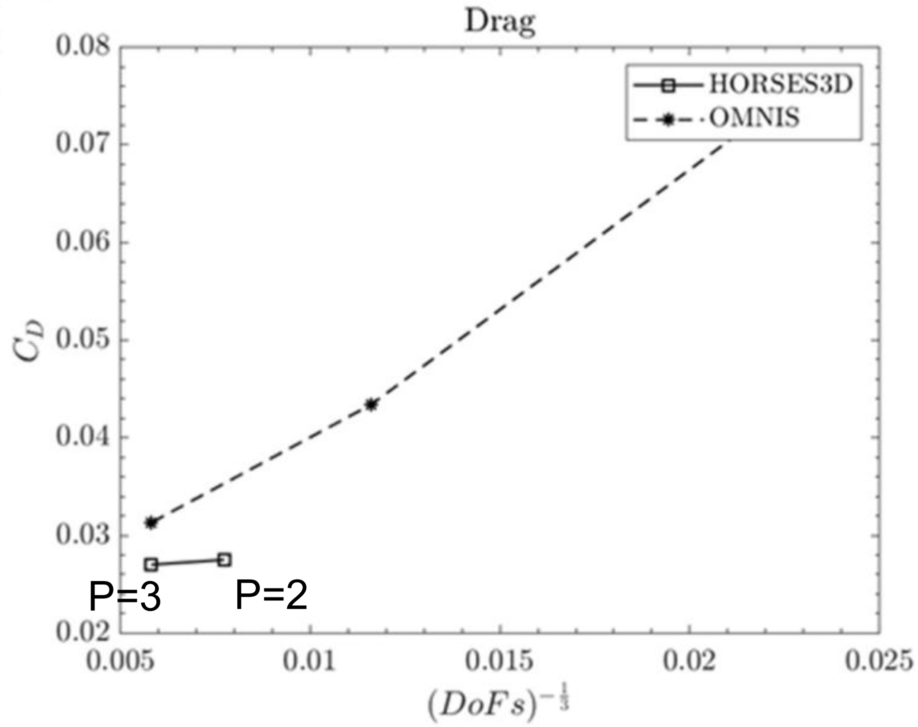
High order RANS (SAneg)

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

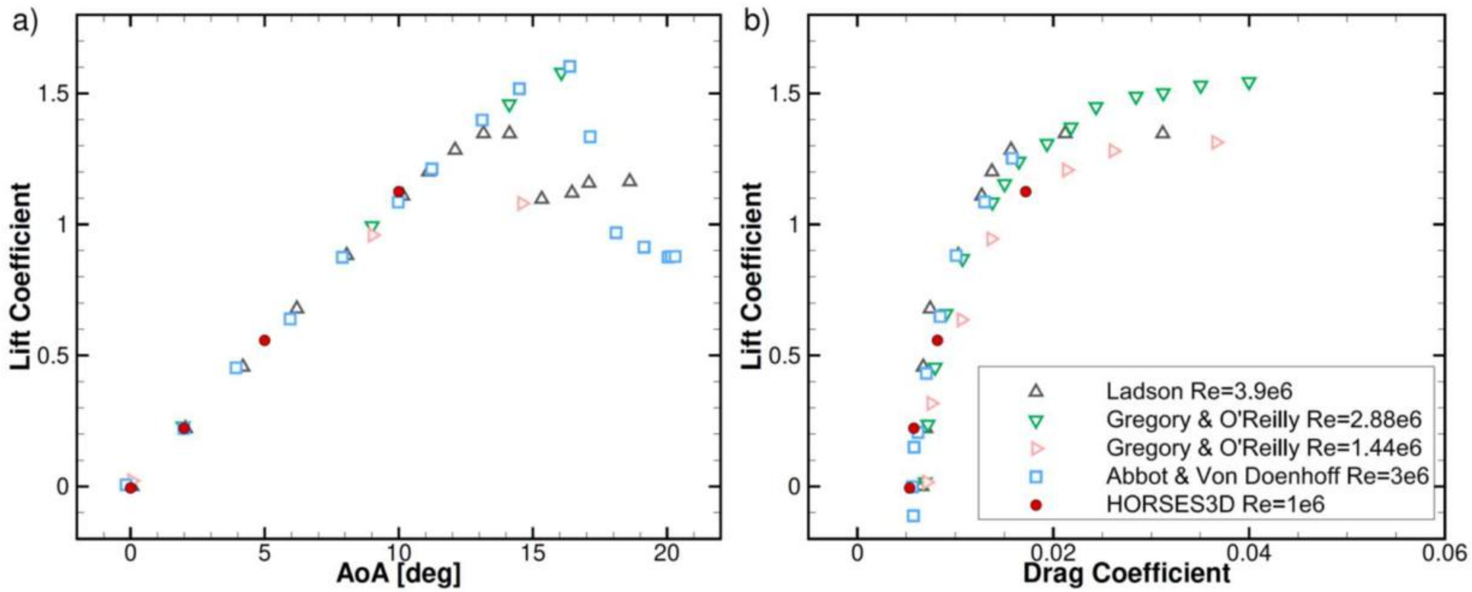
Re=1.000.000
AoA = 0 deg

Re=1.000.000
AoA = 5 deg

contrours of velocity: [0.85; 1.2]

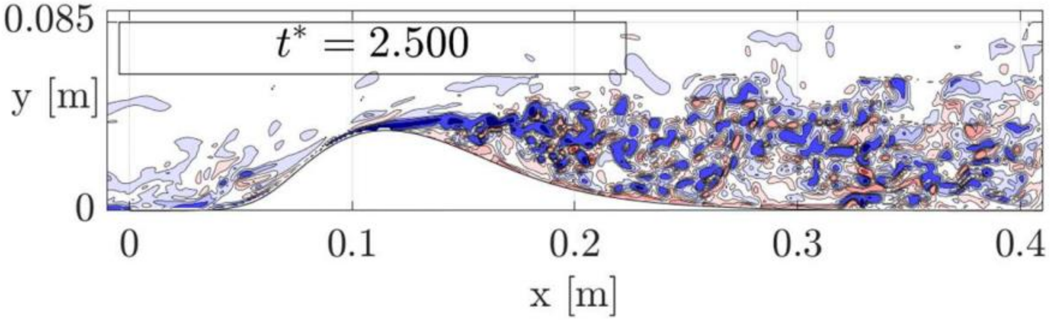
Re=1.000.000
AoA = 10 deg

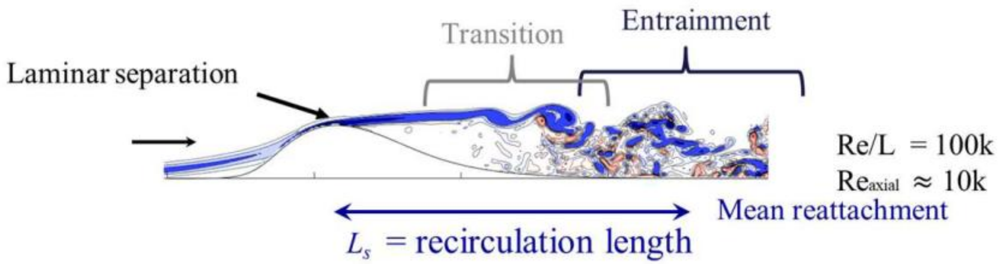
NACA0012 at various AoAs



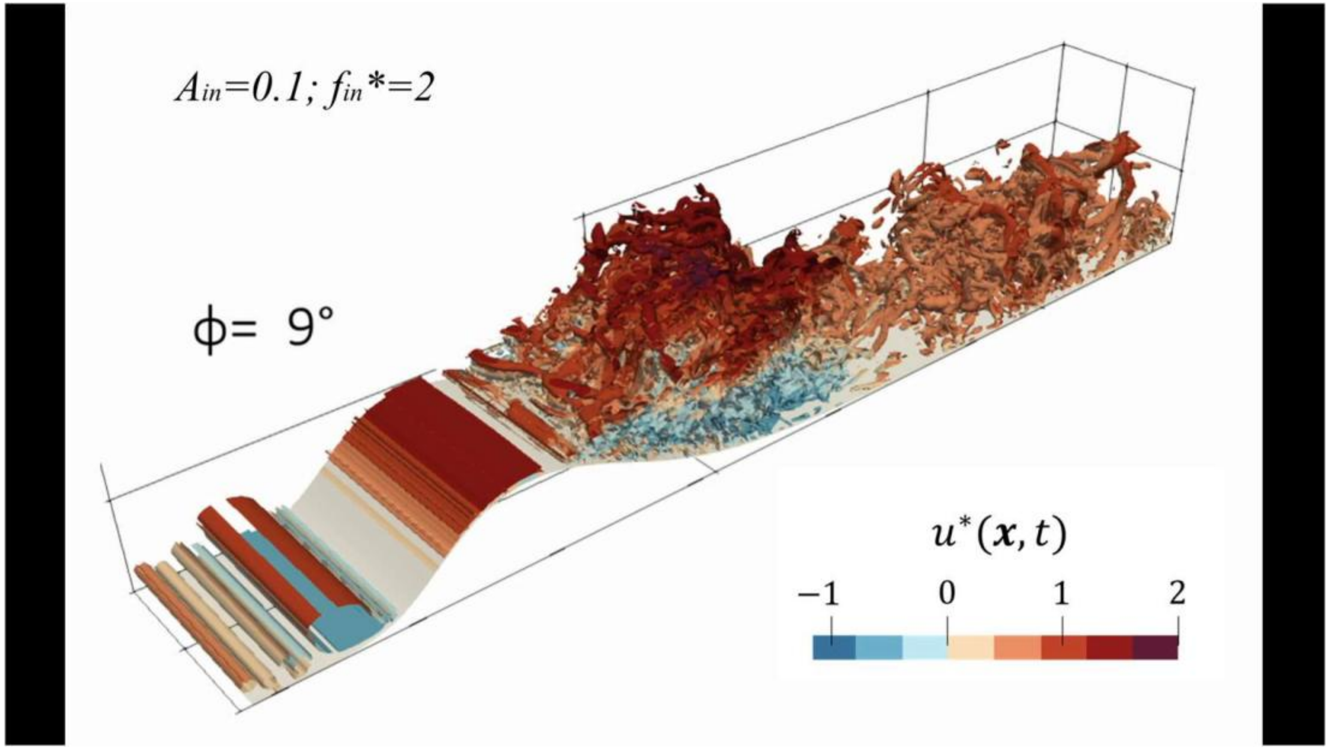
HORSES3D: Compressible DGSEM – energy-stable - SBP-SAT & Roe fluxes & BR1

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*





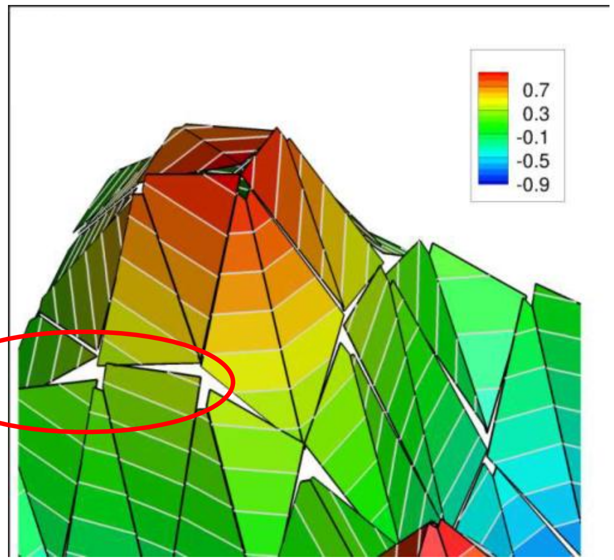
Implicit LES



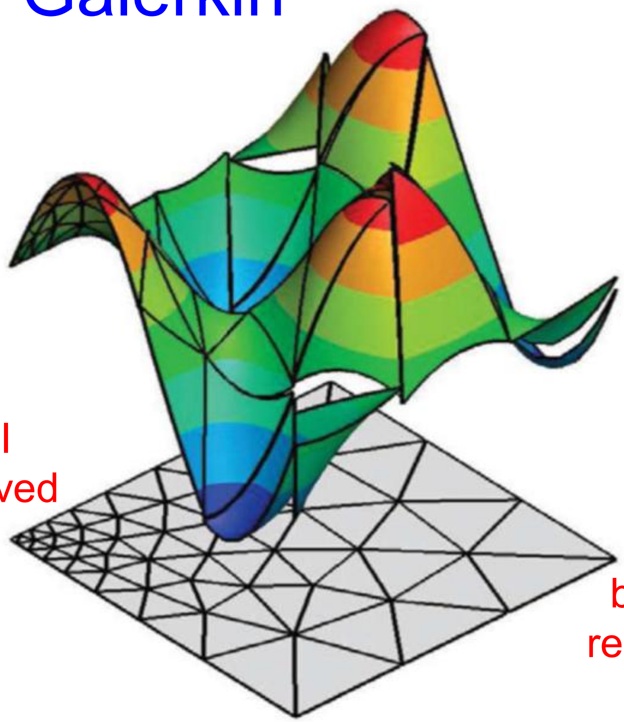
H Marbona, D Rodríguez, A Martínez-Cava, E Valero, *Physical Review Fluids,* 2024

New turbulent models for discontinuous Galerkin

Discontinuous solutions



well resolved



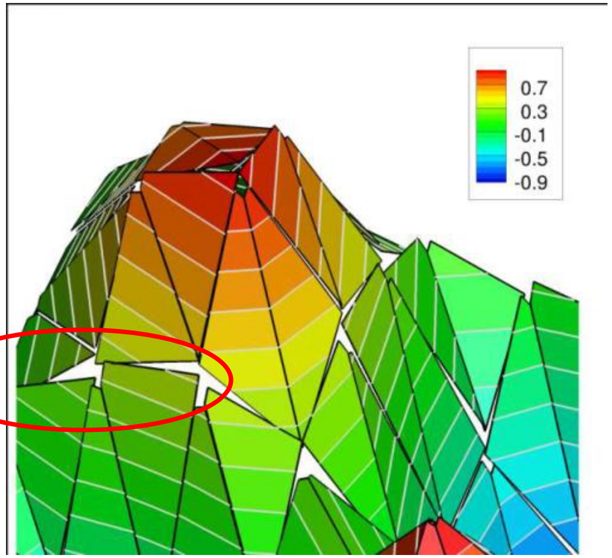
badly resolved

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

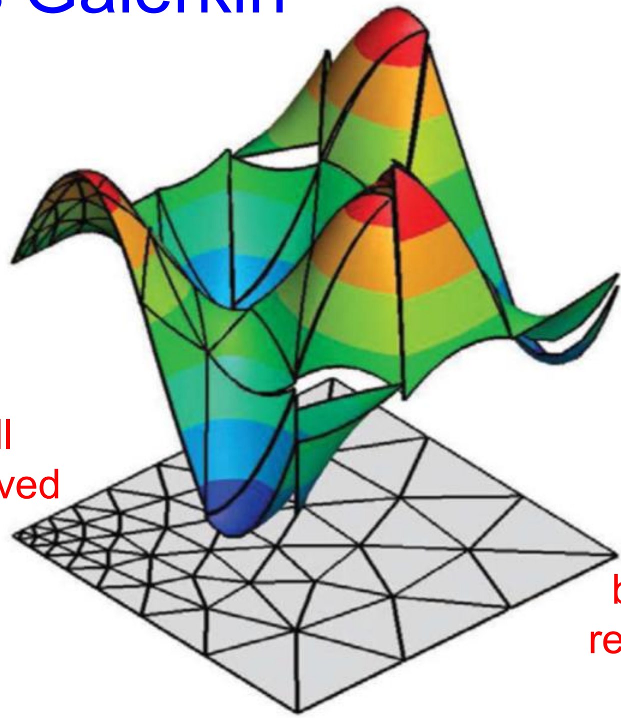
E Ferrer, "An interior penalty stabilised incompressible DG–Fourier solver for implicit Large Eddy Simulations", *Journal of Computational Physics,* Vol 348, 2017

New turbulent models for discontinuous Galerkin

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

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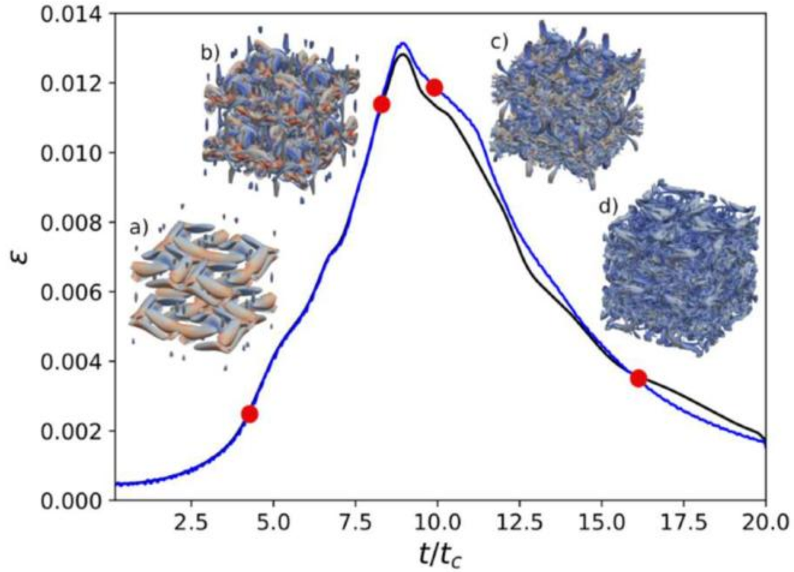
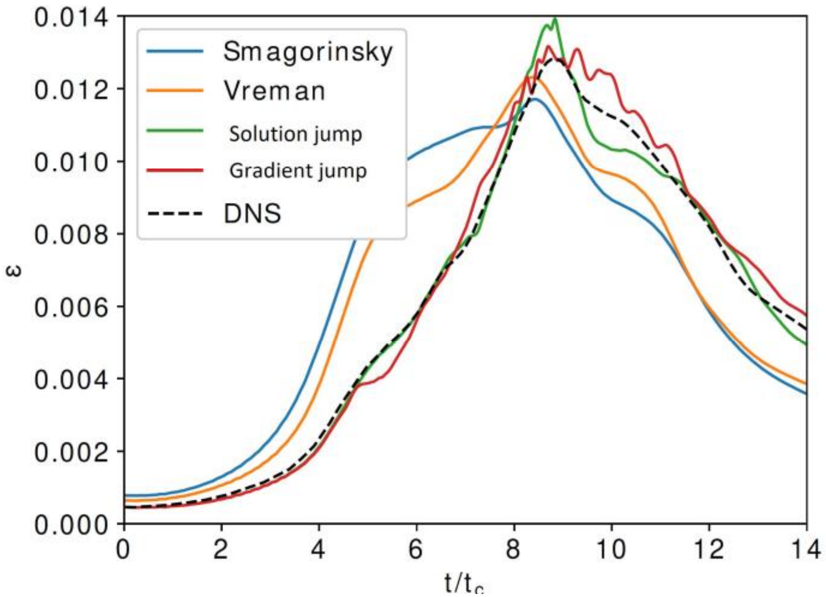
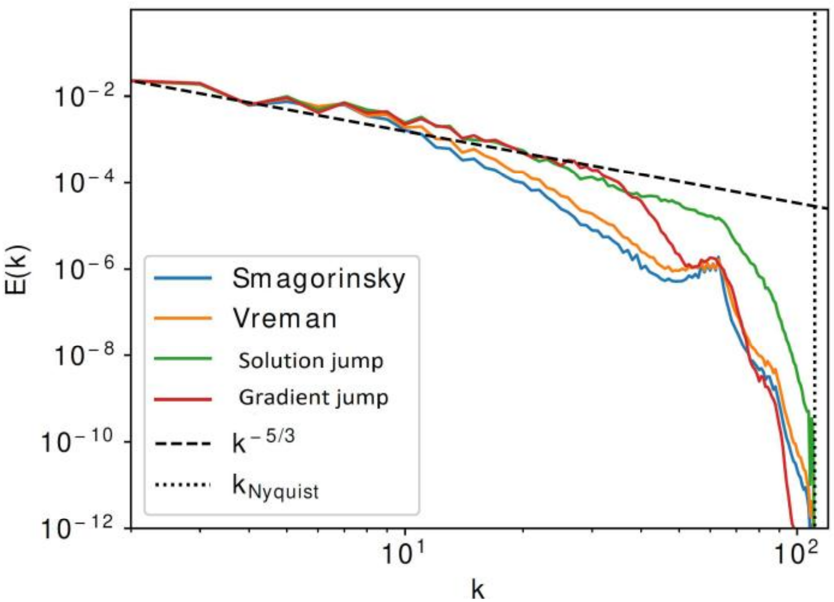
New turbulent models for discontinuous Galerkin



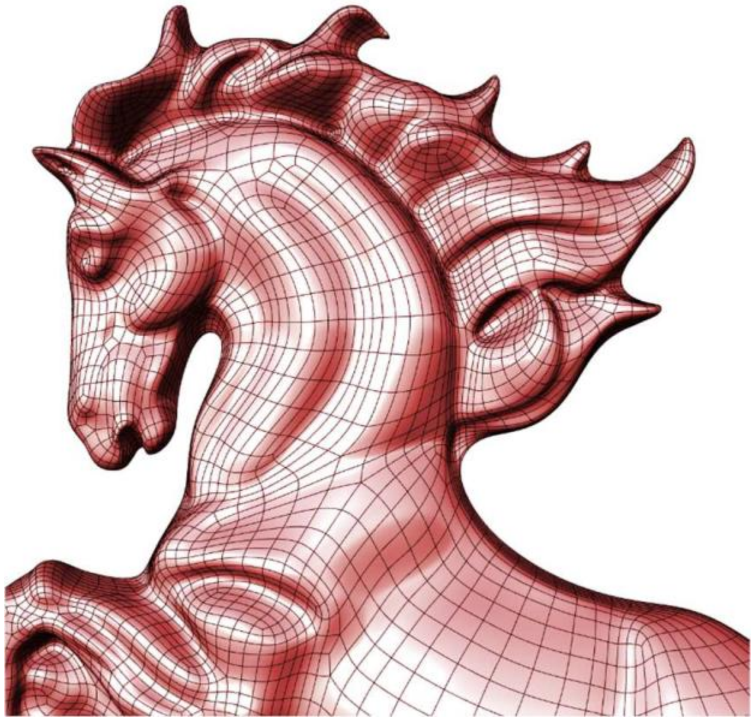
Taylor Green Vortex
Re=1600





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

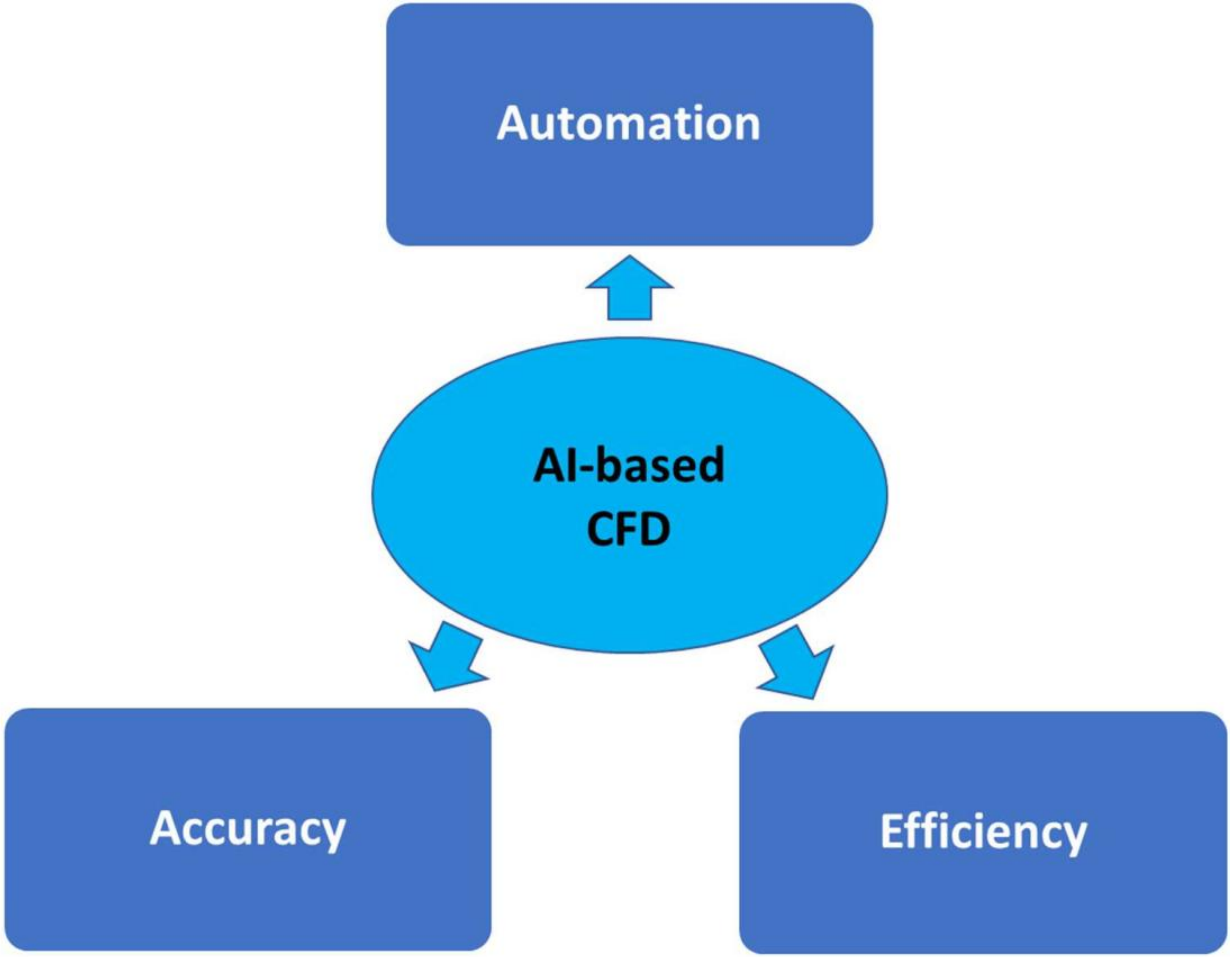
2- Multiphysics

→ Wind turbines
→ Turbulence

3. Machine Learning + CFD

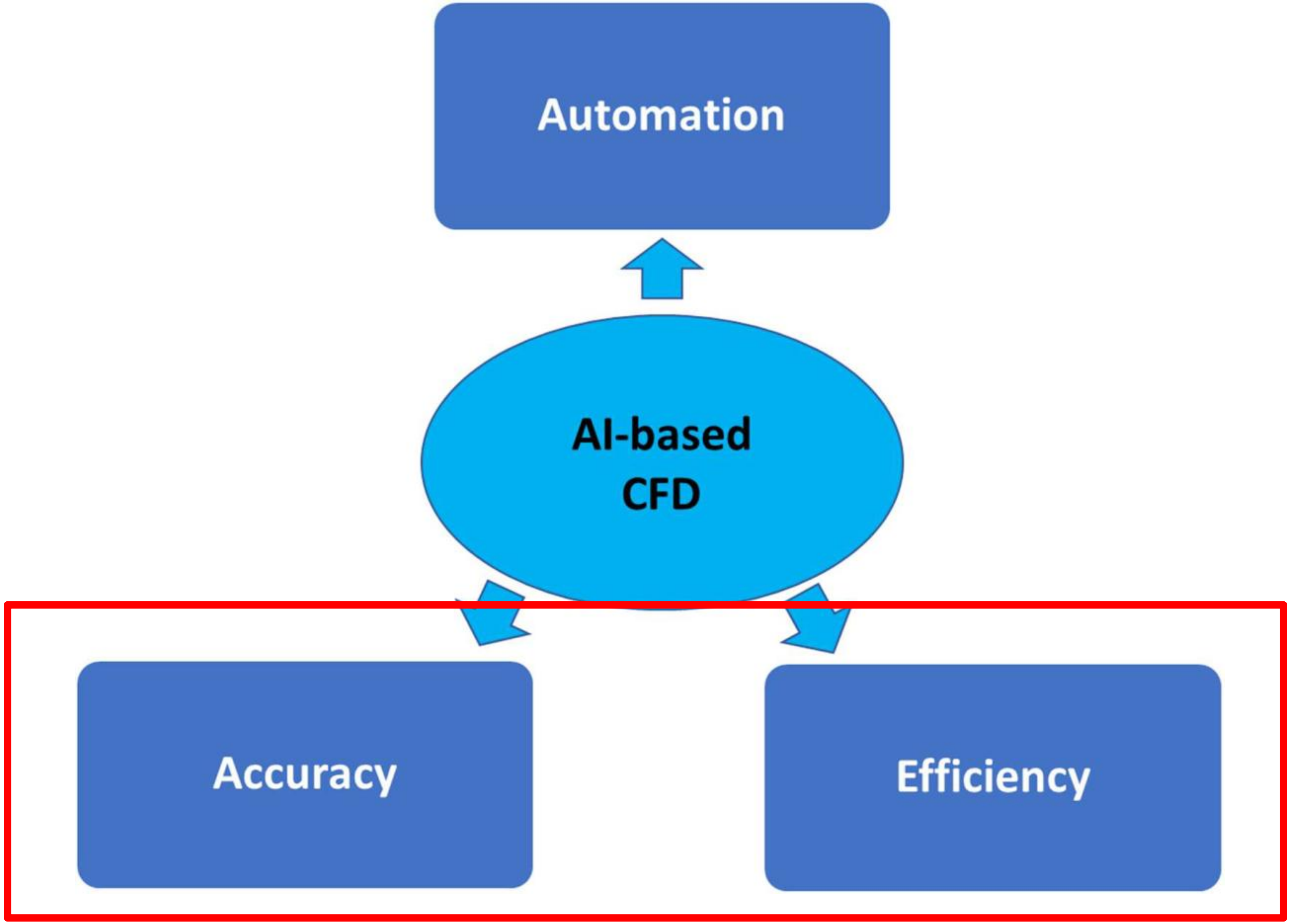
→ Mesh adaption
→ NN acceleration
→ RL for automation

Towards AI-based Computational Fluid Dynamics



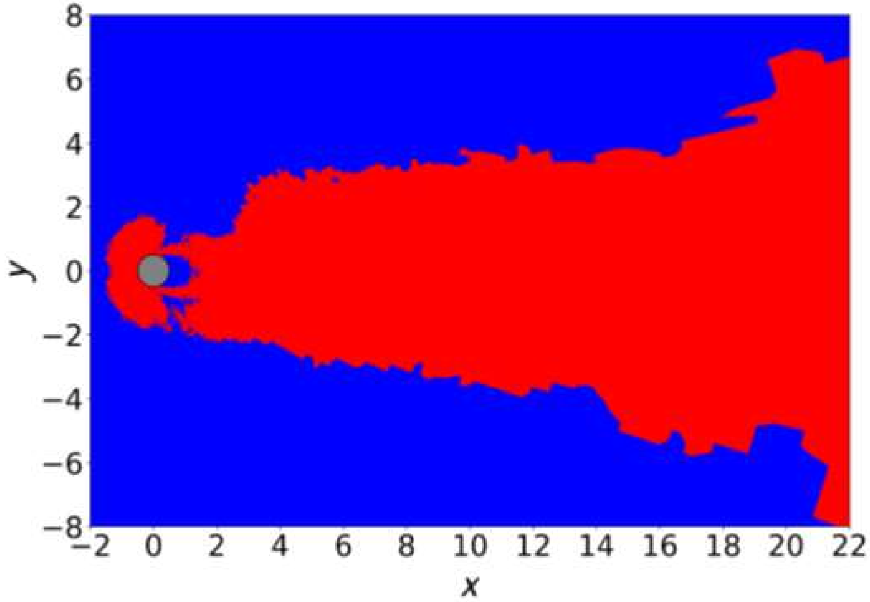
S Le Clainche, **E Ferrer**, S Gibson, E Cross, A Parente, R Vinuesa, "Improving aircraft performance using machine learning: a review", *Aerospace Science and Technology,* Vol 138, 108354, 2023

Towards AI-based Computational Fluid Dynamics

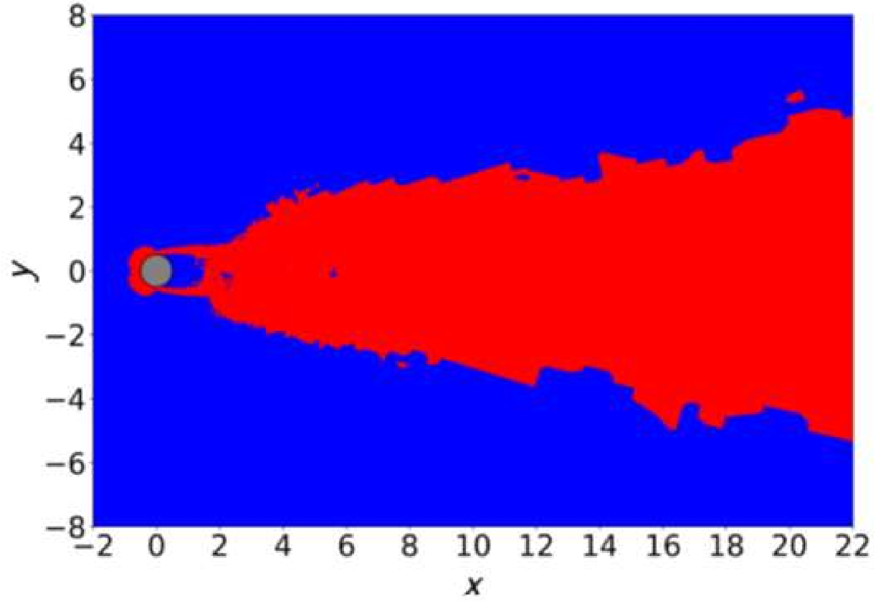


Machine Learning to detect flow regions

F=1.25

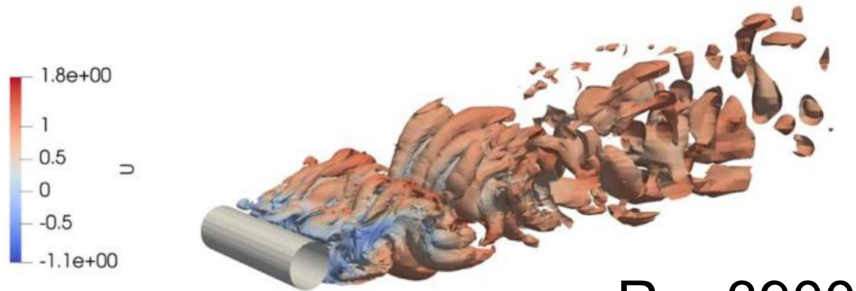


F=1.5



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", *Vol 35, 027112, 2023*
-K Tlales, KE Otmani, G Ntoukas, G Rubio, **E Ferrer**, "Machine learning mesh-adaptation for laminar and turbulent flows: applications to high order discontinuous Galerkin solvers", Engineering with Computers, 2024

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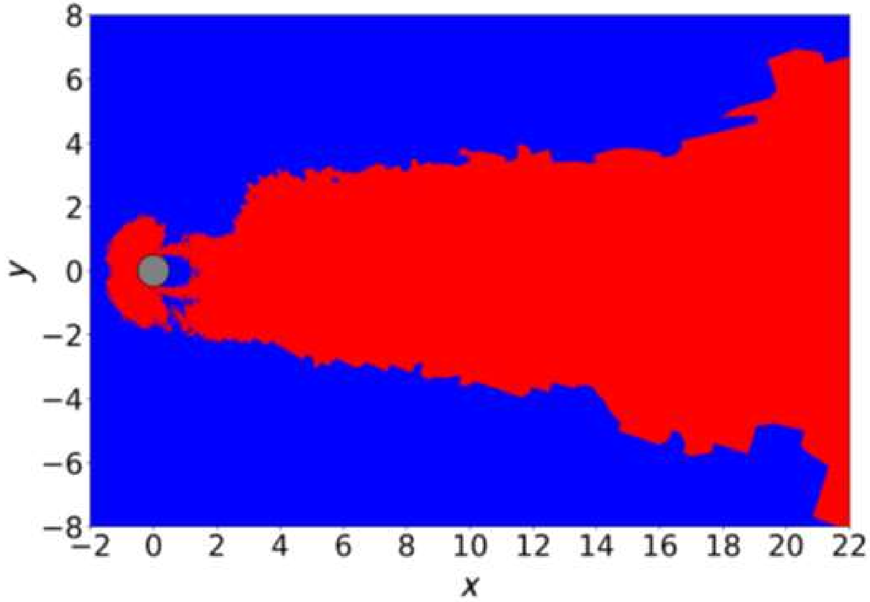
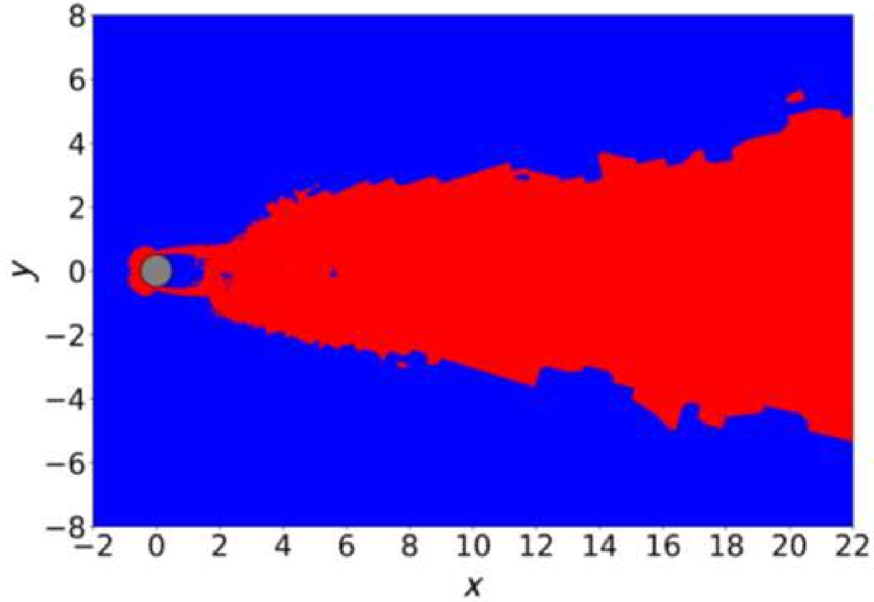


F=1.5



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", *Vol 35, 027112, 2023*
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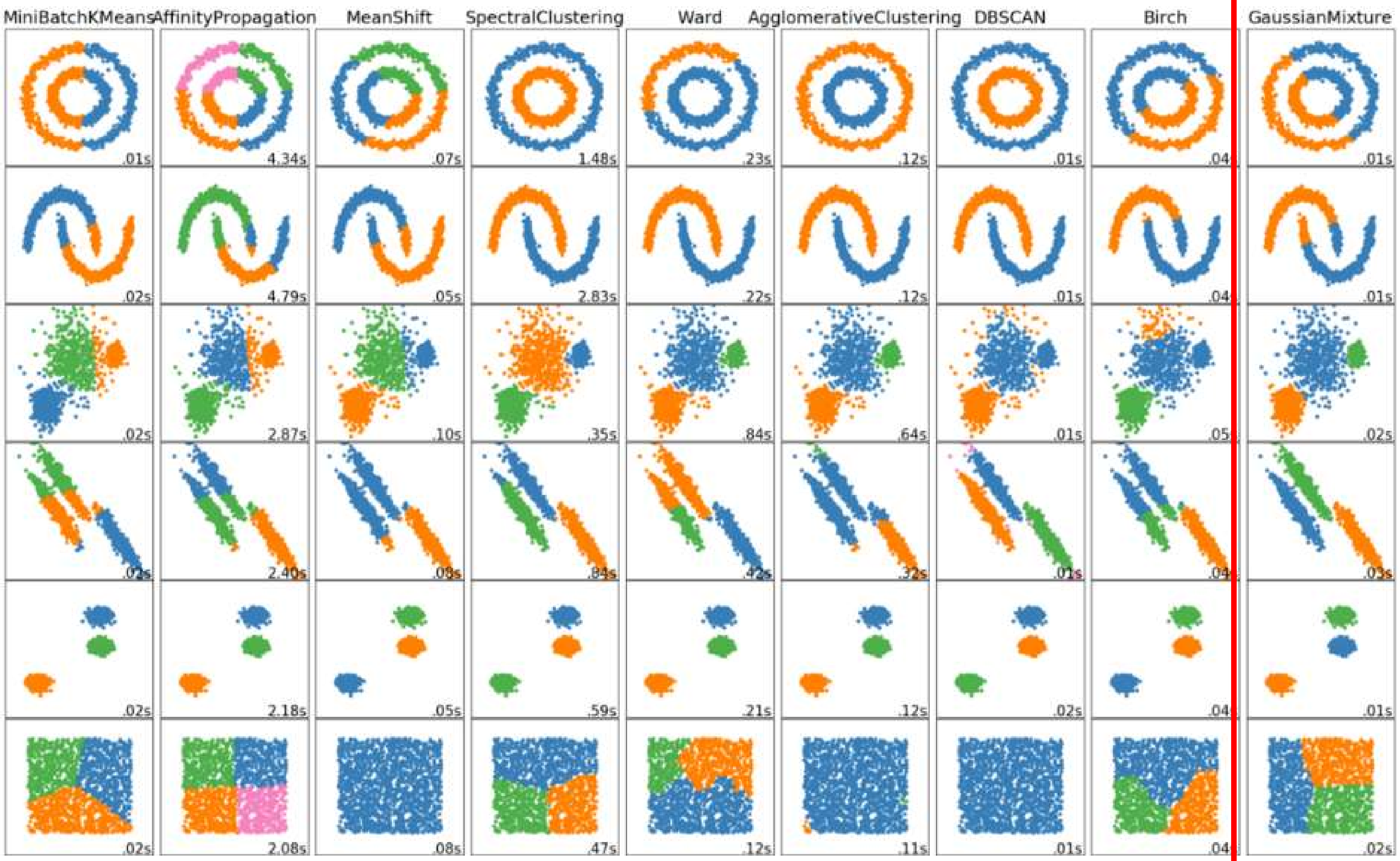
Machine Learning to detect flow regions

Clustering (classify data): Gaussian mixture model



Machine Learning to detect flow regions

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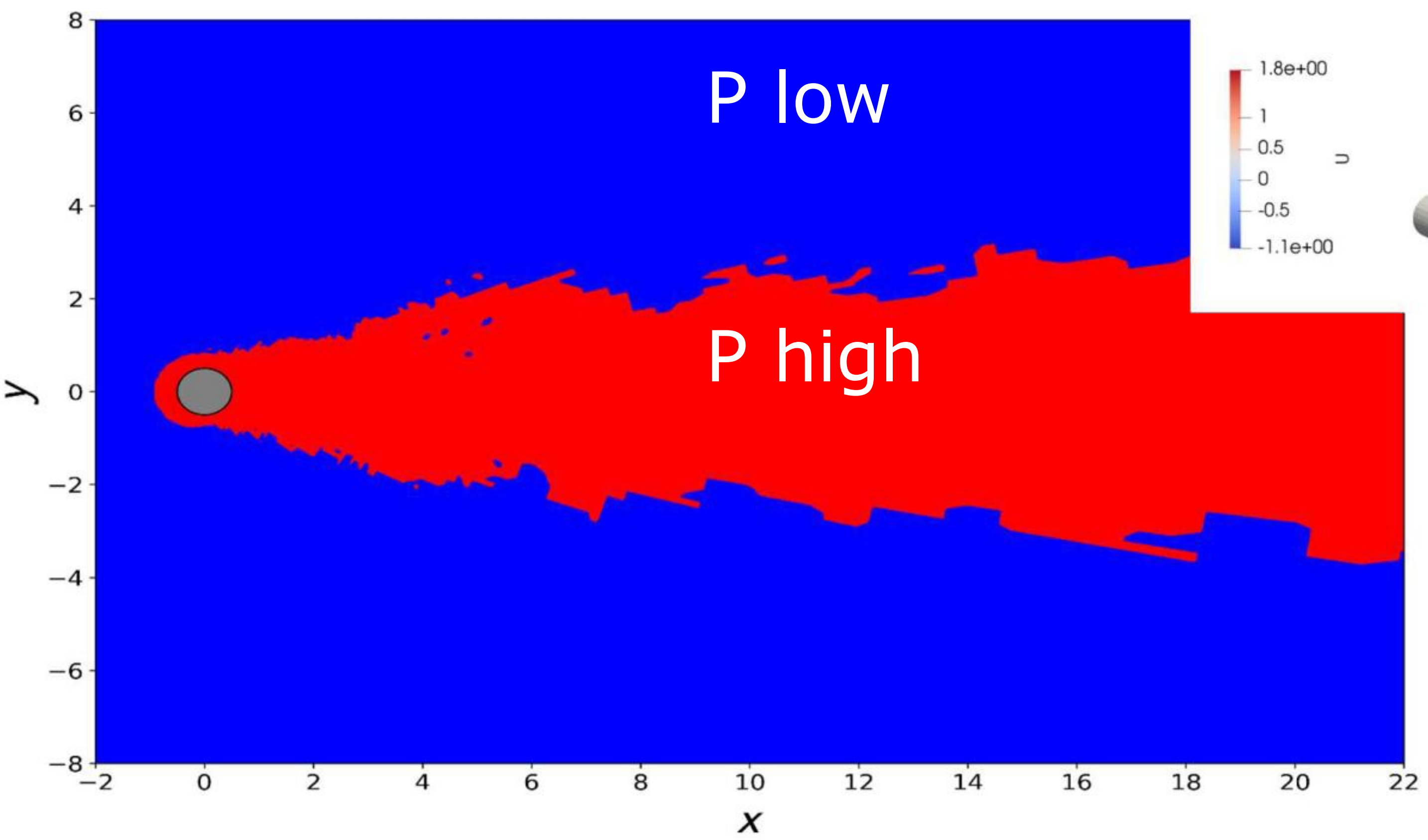
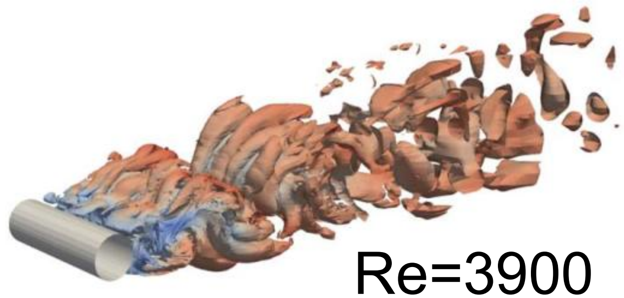




Re=3900

Automate the detection
(no thresholds)

Use a robust feature space
for a variety of Re

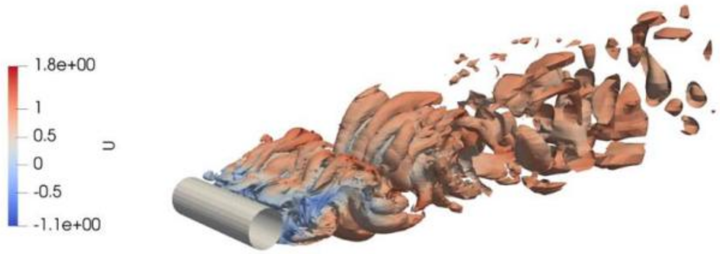
Invariants of strain and rotational rate tensors

-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 mesh-adaptation for laminar and turbulent flows: applications to high order discontinuous Galerkin solvers", Engineering with Computers, 2024

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", *Vol 35, 027112, 2023*
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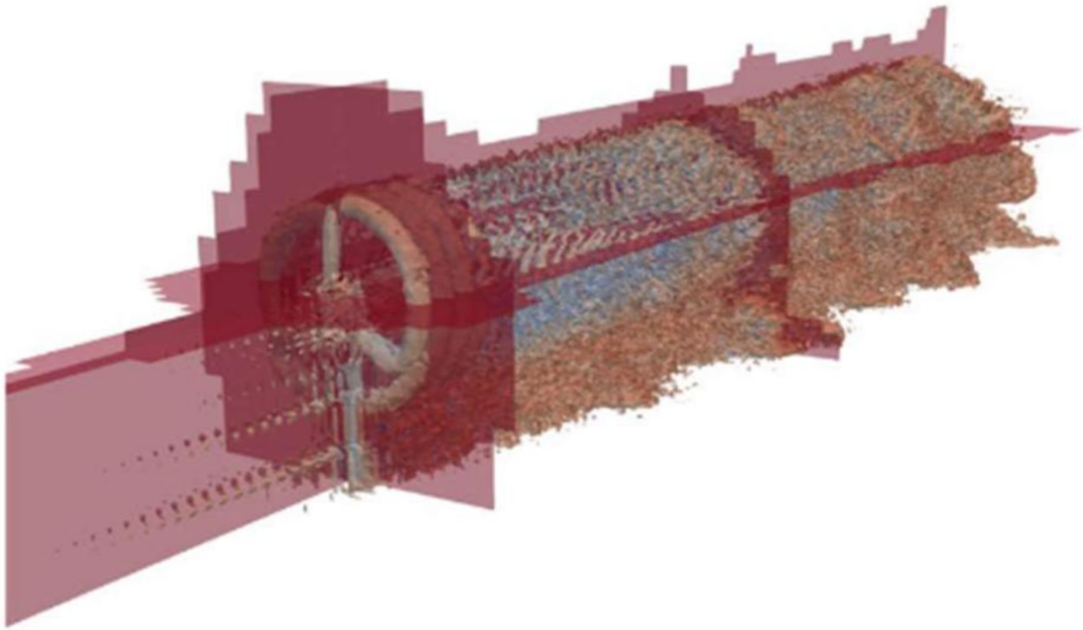
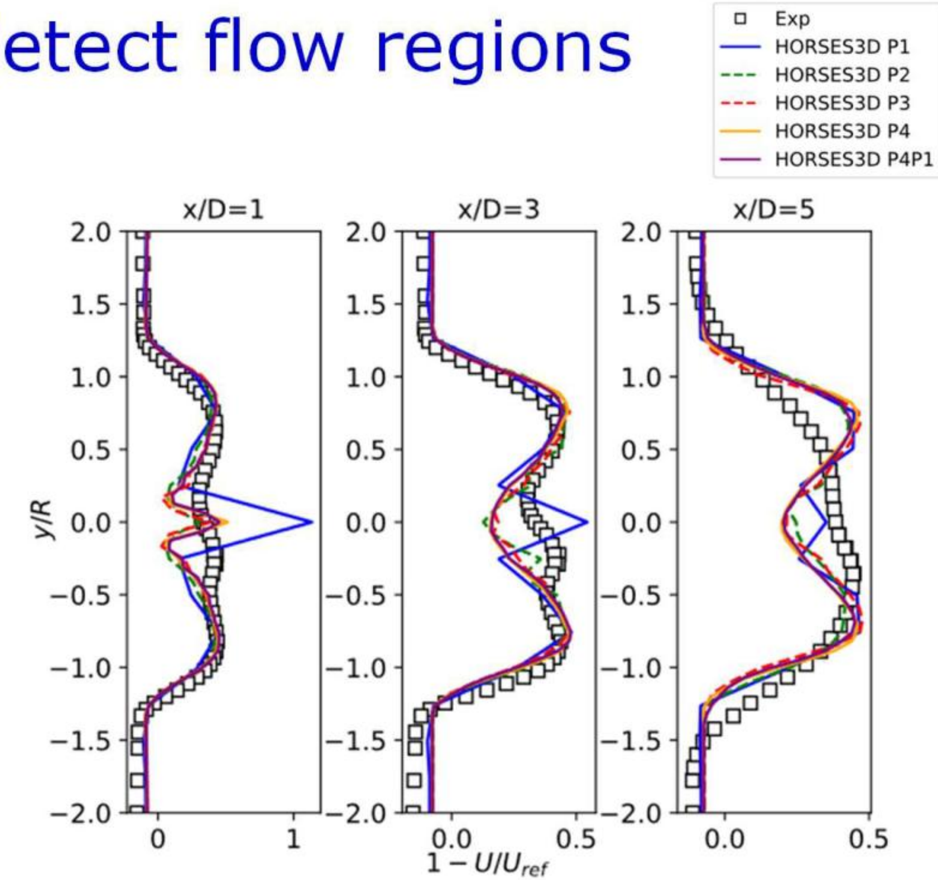
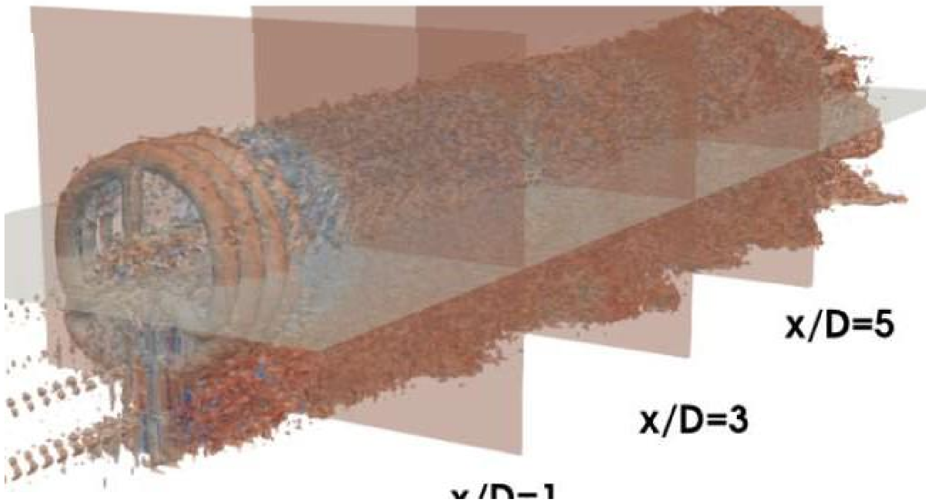
Machine Learning to detect flow regions

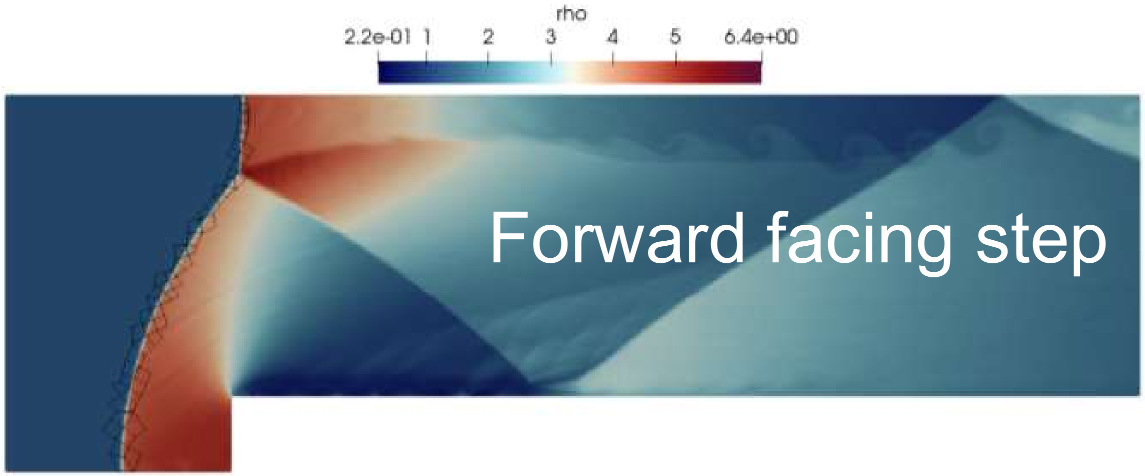


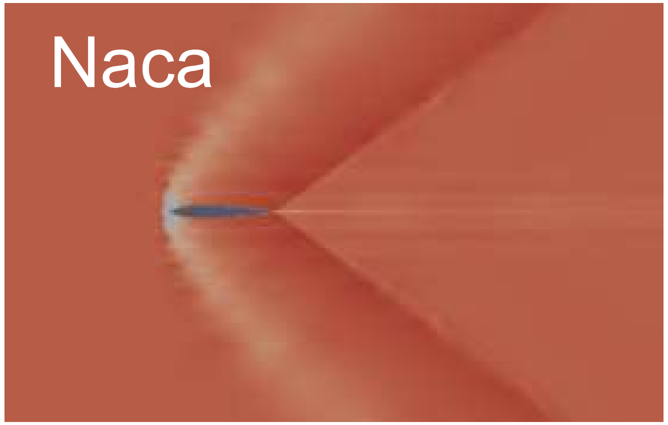


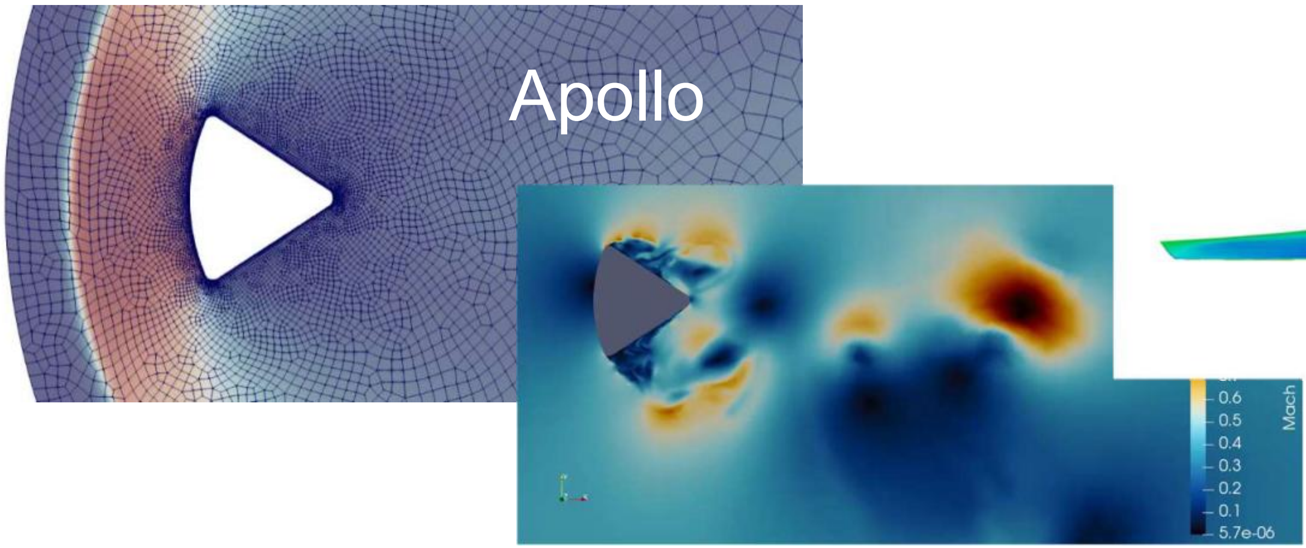


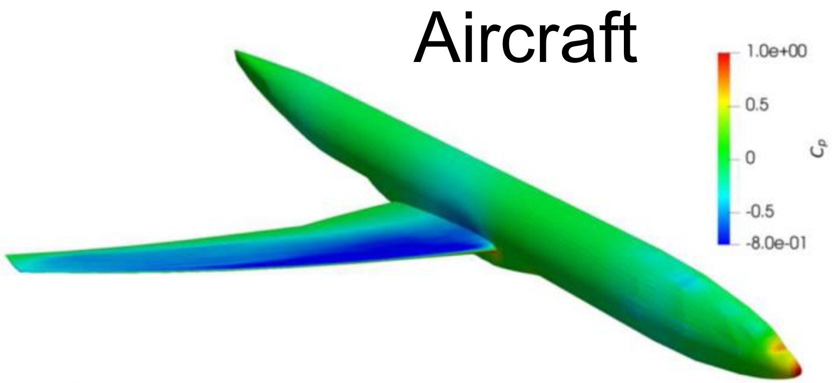
	DoFs	reduction of DoFs	reduction of comp. time
Uniform P1	0.59M	93.6%	92.7%
Uniform P2	1.99M	78.2%	86.5%
Uniform P3	4.72M	48.7%	54.1%
Uniform P4	9.22M	-	-
Cluster-Adapt P4-P1	3.58M	61%	43%

Supersonic & Shock capturing







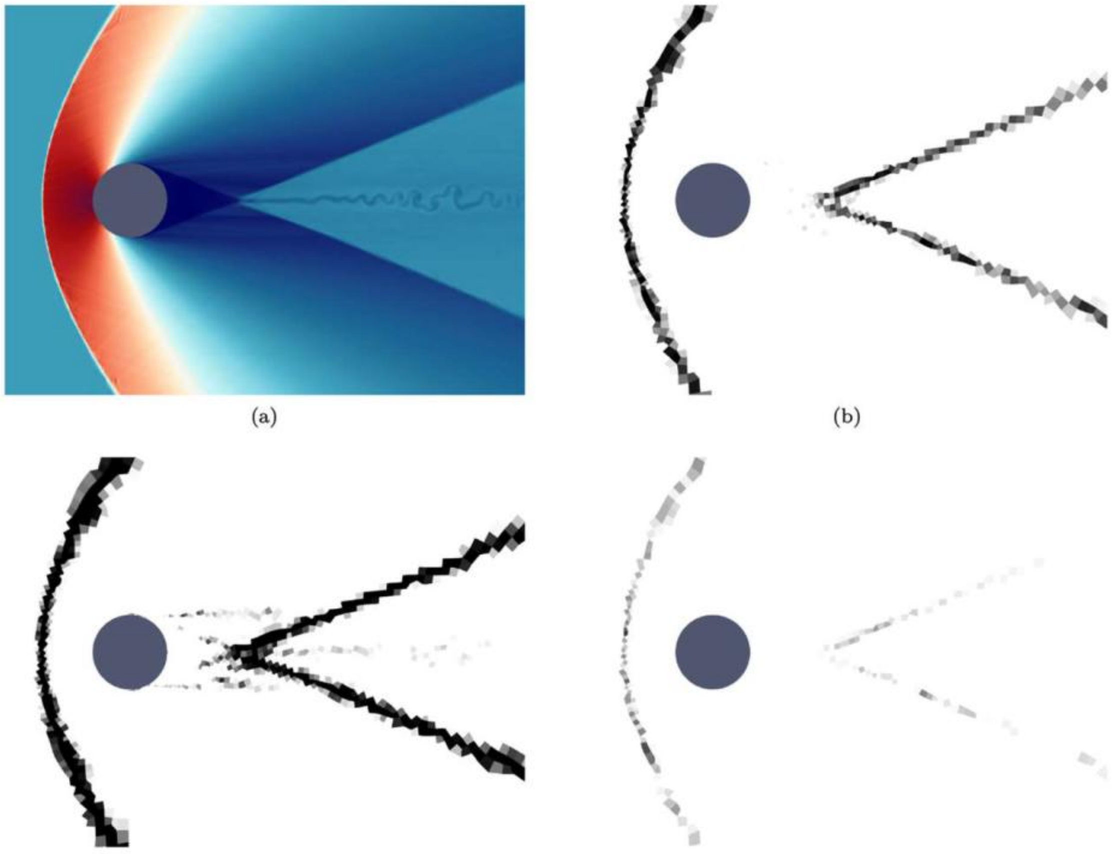


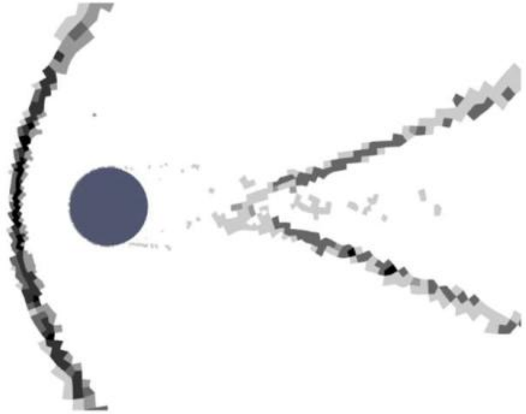
-E Ferrer, G Rubio, G Ntoukas, W Laskowski, O Mariño, S Colombo, A. Mateo-Gabín, H Narbona, F Manrique de Lara, D Huergo, J Manzanero, AM Rueda-Ramírez, DA Kopriva, E Valero, "HORSES3D: a high order discontinuous Galerkin solver for flow simulations and multi-physic applications", *Computer Physics Communications*,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

What about shocks?

Classic feature based sensors (fine tunned)

GMM
(no tunning)



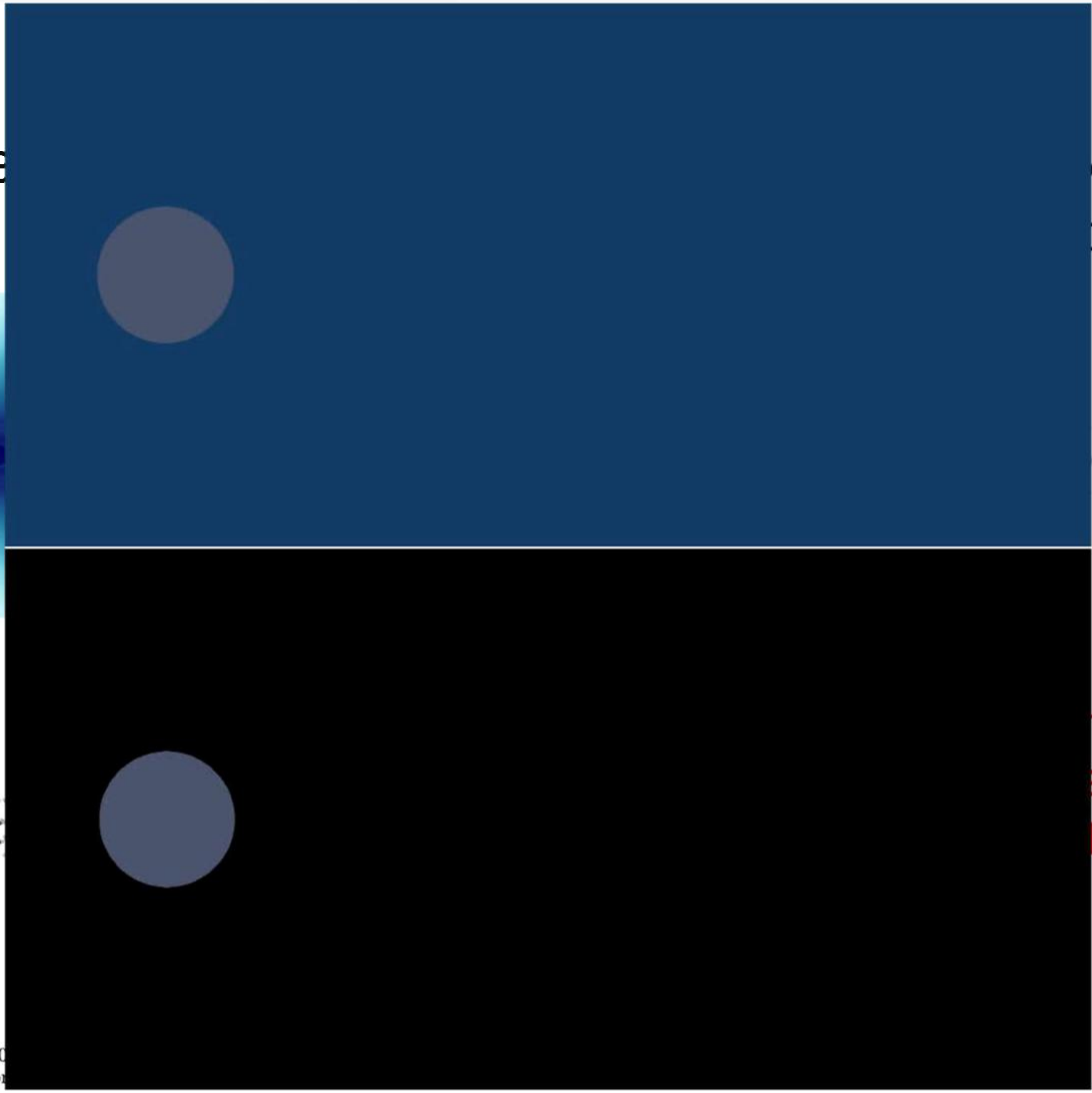


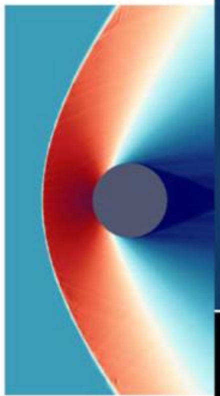
Similar result to state of the art without tunning!

FIG. 10. Viscous case after 300,000 iterations with the modal sensor of section IV A, using pp. a) density field, b) sensor with $s_0 = -2.5$ and $\Delta s = 1$. Sensor applied to the last iteration with $s_0 = -3.5$, $\Delta s = 1$ (c), and with $s_0 = -1.5$, $\Delta s = 1$ (d).

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

Classic fe ... MM
... tunning)





...milar result to
...ate of the art
...thout tunning!

FIG. 10. Viscous case after 30 ...
$s_0 = -2.5$ and $\Delta s = 1$. Senso...

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

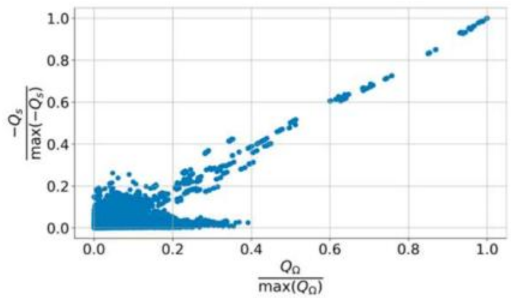
RESEARCH ARTICLE | FEBRUARY 08 2023

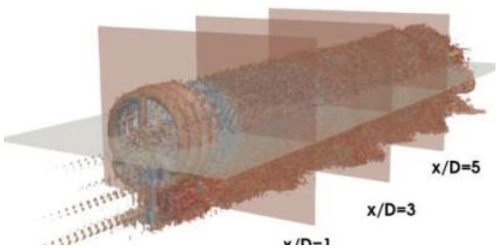
Toward a robust detection of viscous and turbulent flow regions using unsupervised machine learning

Kheir-Eddine Otmani ; Gerasimos Ntoukas ; Oscar A. Mariño ; Esteban Ferrer

Check for updates

Physics of Fluids 35, 027112 (2023)
https://doi.org/10.1063/5.0138626





Engineering with Computers
https://doi.org/10.1007/s00366-024-01950-y

ORIGINAL ARTICLE

Check for updates

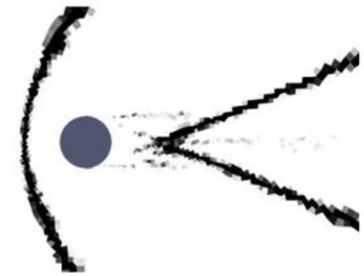
Machine learning mesh-adaptation for laminar and turbulent flows: applications to high-order discontinuous Galerkin solvers

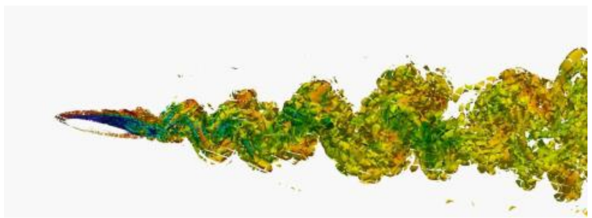
Kenza Tlales[1] · Kheir-Eddine Otmani[1] · Gerasimos Ntoukas[1] · Gonzalo Rubio[1,2] · Esteban Ferrer[1,2]

An unsupervised machine-learning-based shock sensor for high-order supersonic flow solvers

Andrés Mateo-Gabín,[1, a)] Kenza Tlales,[1] Eusebio Valero,[1, 2] Esteban Ferrer,[1, 2] and Gonzalo Rubio[1, 2]
[1)] *ETSIAE-UPM-School of Aeronautics, Universidad Politécnica de Madrid, Madrid-Spain*
[2)] *Center for Computational Simulation, Universidad Politécnica de Madrid, Madrid-Spain*

(Dated: 10 October 2023)



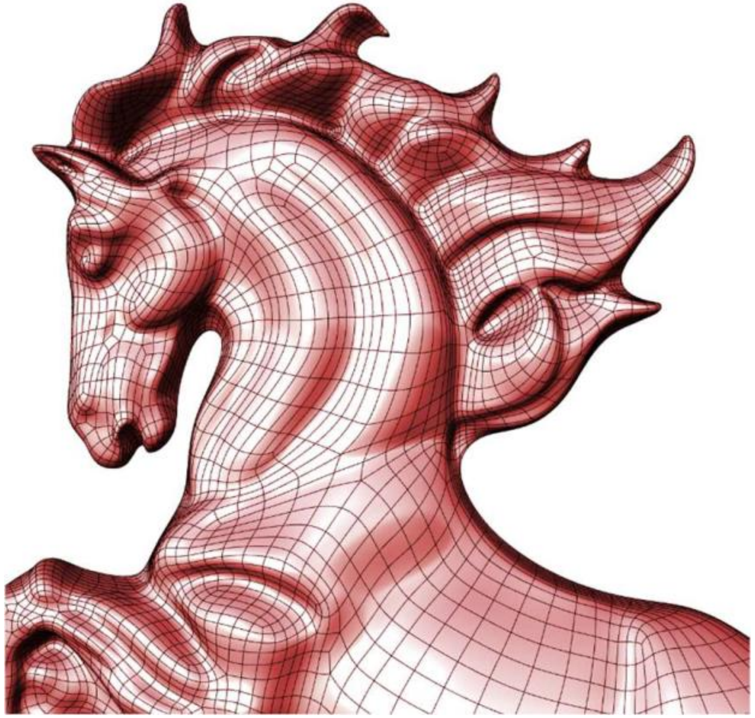


Accelerating high order discontinuous Galerkin solvers through a clustering-based viscous/turbulent-inviscid domain decomposition

Kheir-Eddine Otmani*[1], Andrés Mateo-Gabín[1], Gonzalo Rubio[1,2], and Esteban Ferrer[1,2]

[1]ETSIAE-UPM-School of Aeronautics, Universidad Politécnica de Madrid, Plaza Cardenal Cisneros 3, E-28040 Madrid, Spain
[2]Center for Computational Simulation, Universidad Politécnica de Madrid, Campus de Montegancedo, Boadilla del Monte, 28660 Madrid, Spain

Summary



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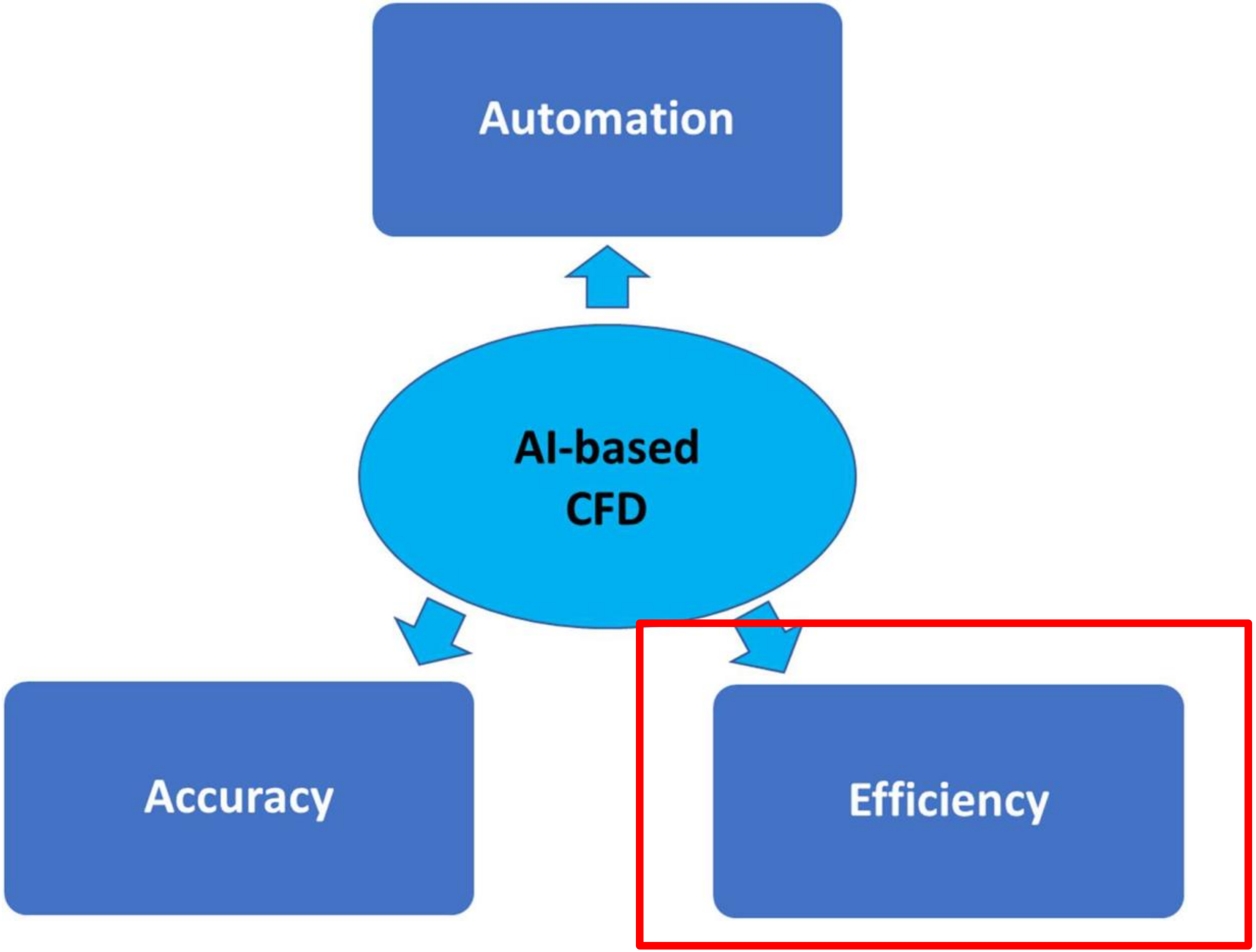
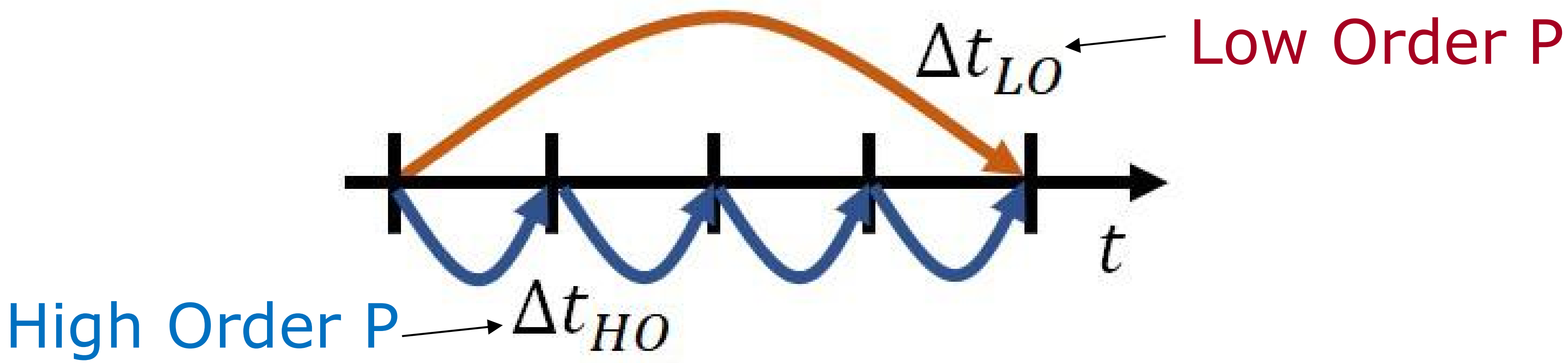
Towards AI-based Computational Fluid Dynamics

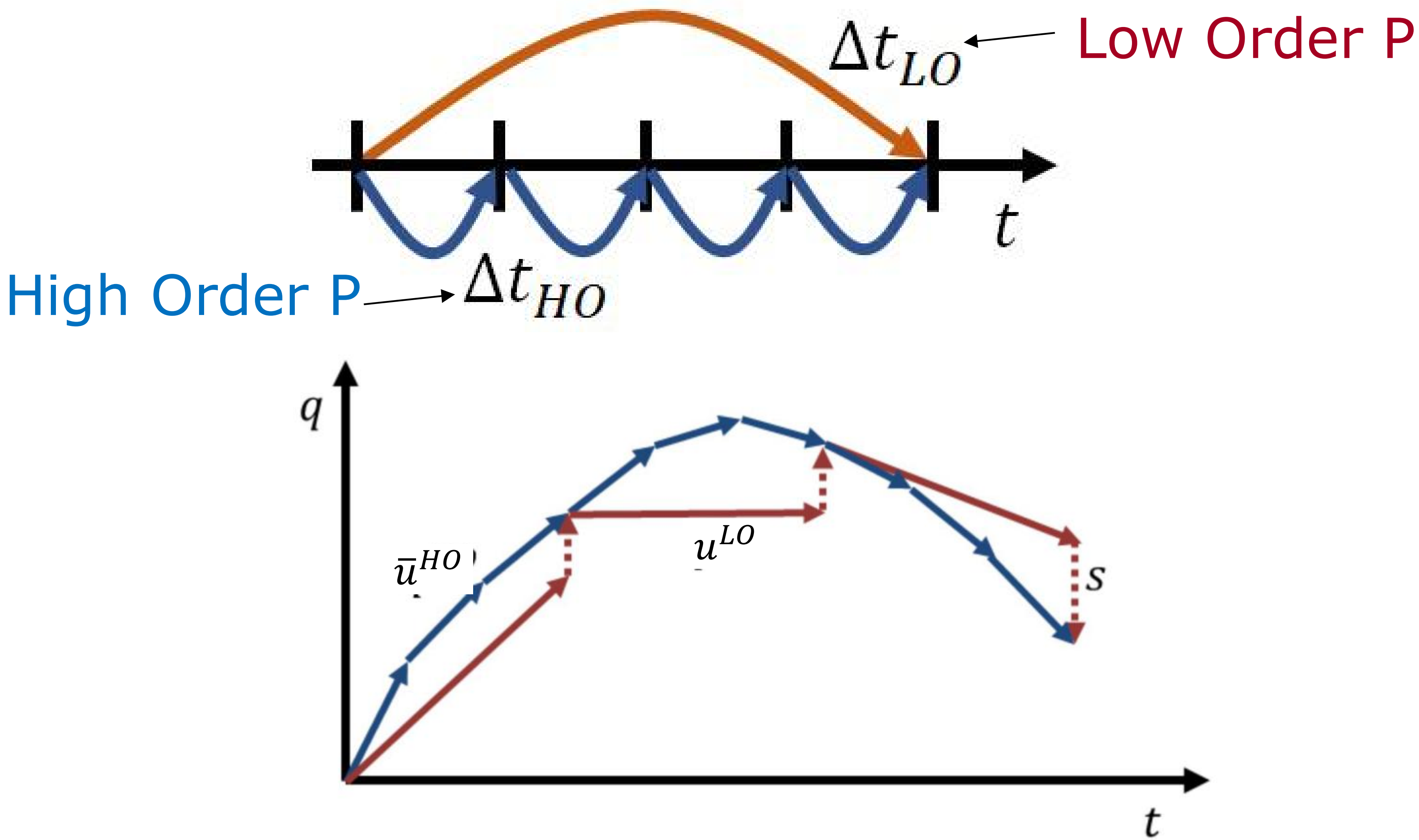


Machine Learning to accelerate CFD



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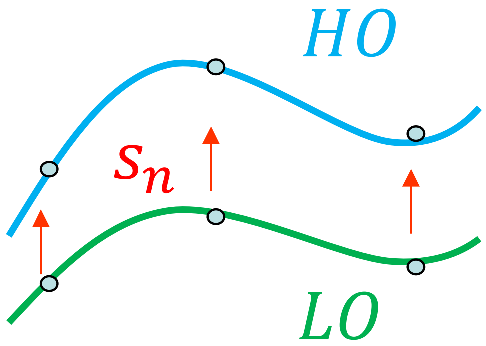

LO-NN corrected:

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

-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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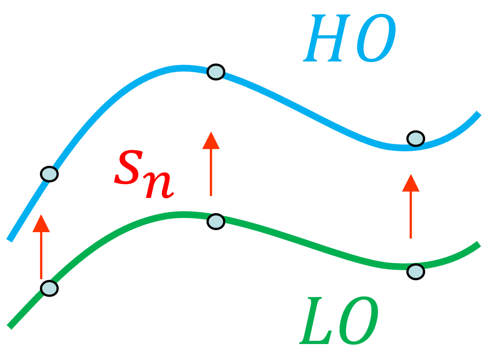
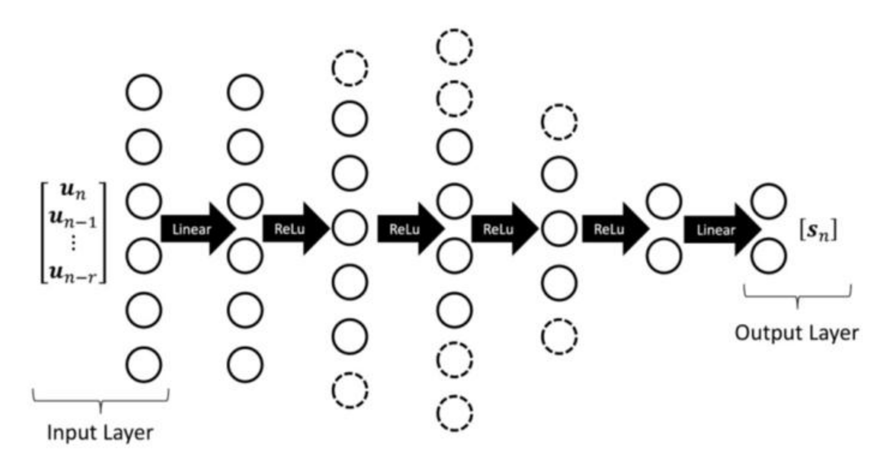


LO-NN corrected:

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

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

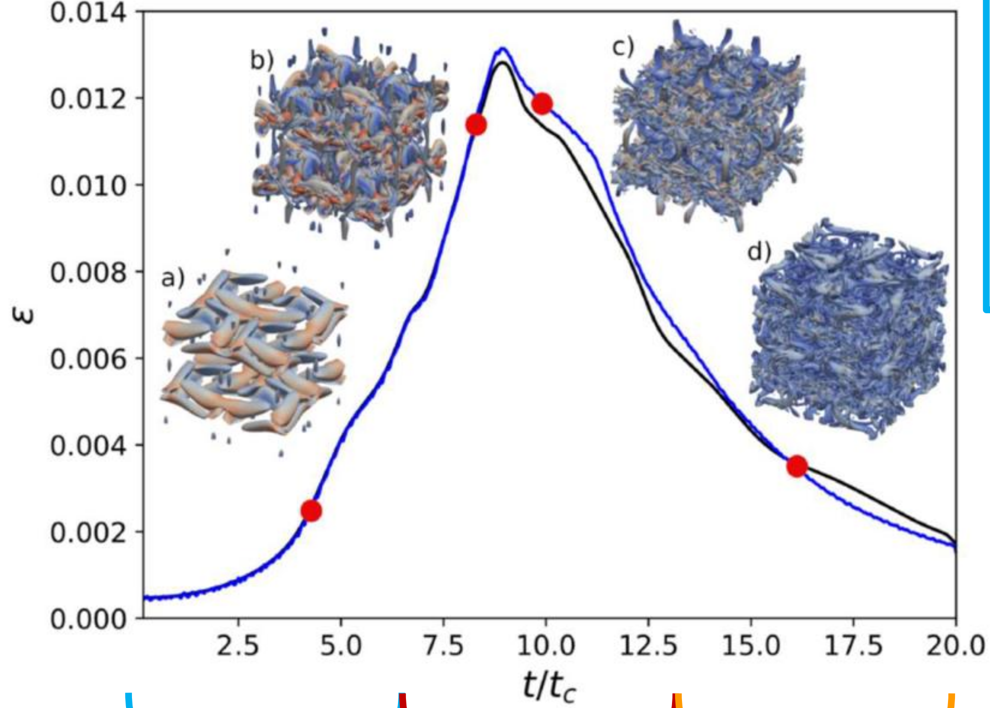
Trained to give HO solution



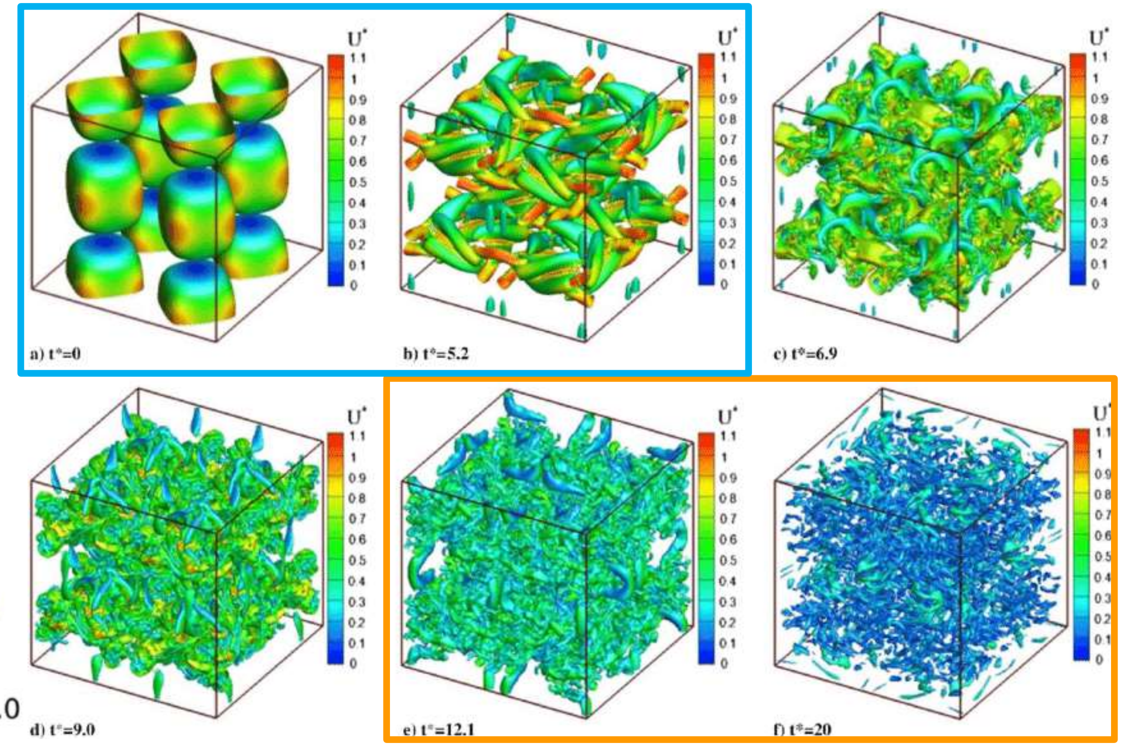
Machine Learning to accelerate CFD

3D Navier-Stokes - LES

Taylor-Green – Reynolds 1600



laminar
transitional
turbulent



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Machine Learning to accelerate CFD

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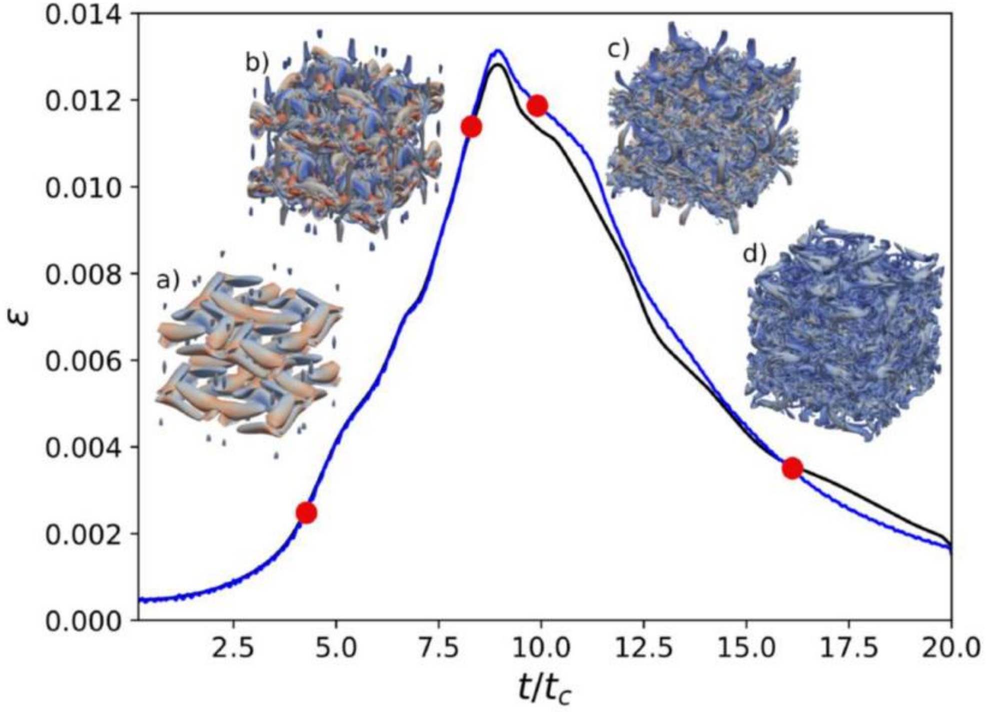
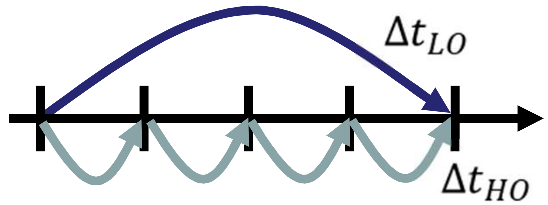




$$P8 \rightarrow P3$$

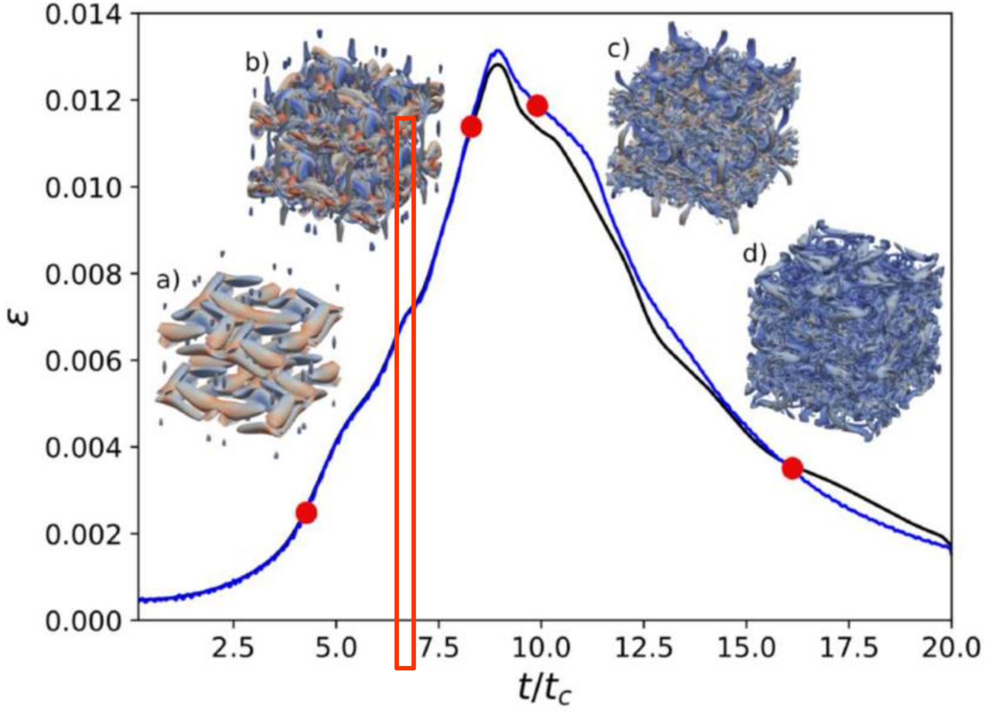
$$\Delta t_{LO}/\Delta t_{\mathrm{HO}} = 3$$

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

Taylor-Green – Reynolds 1600



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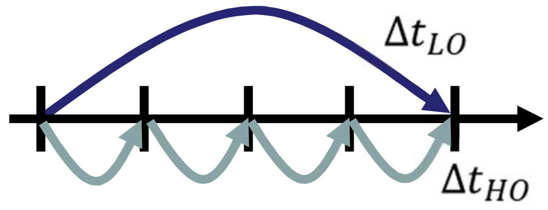

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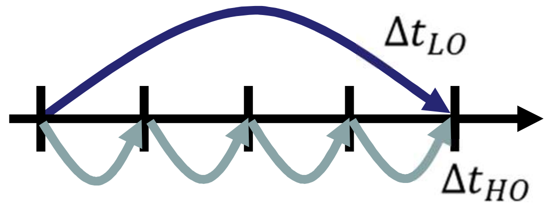
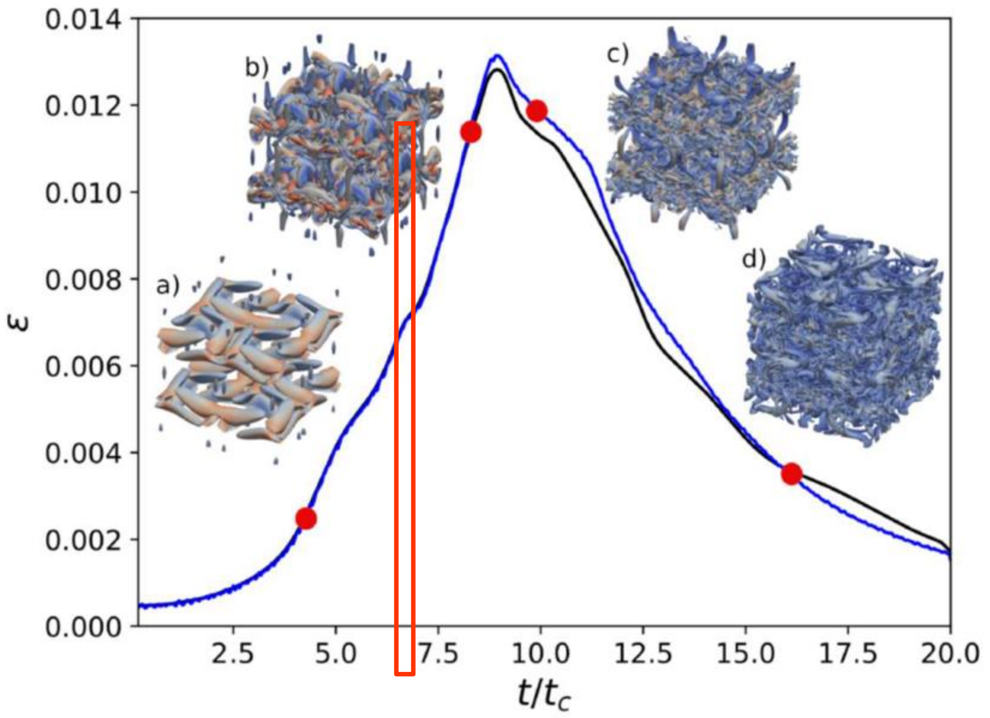
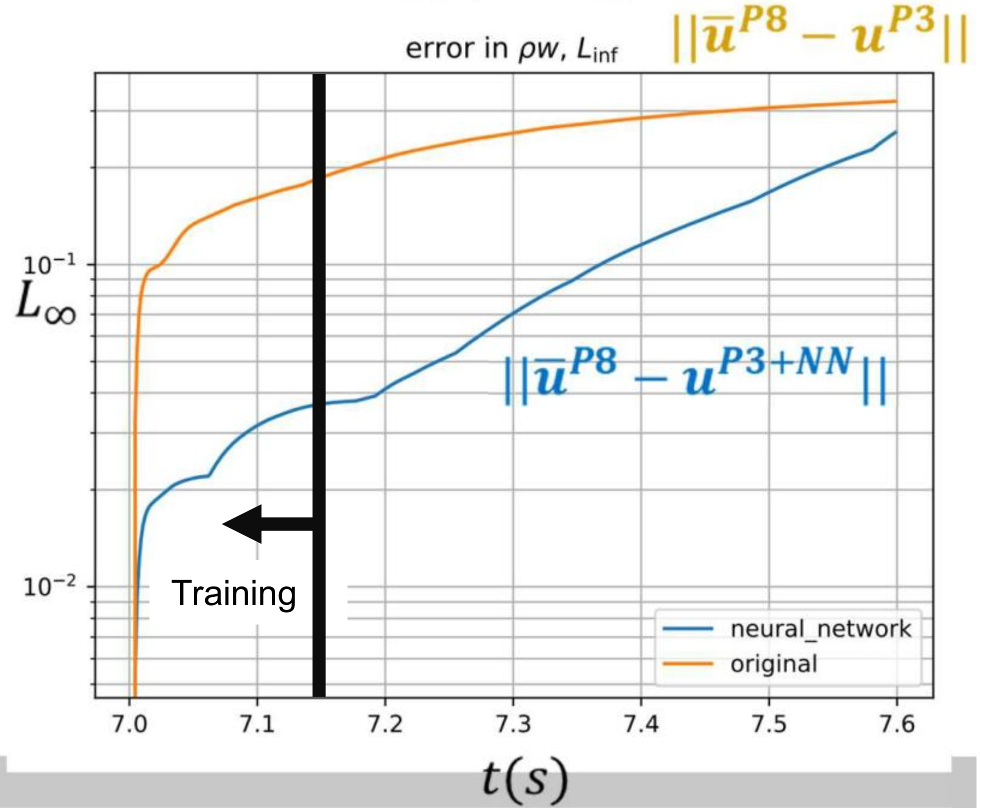




$P8 \rightarrow P3$

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

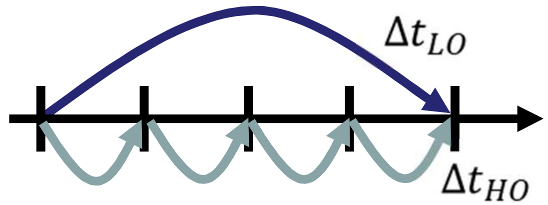


12 times faster

Machine Learning to accelerate CFD

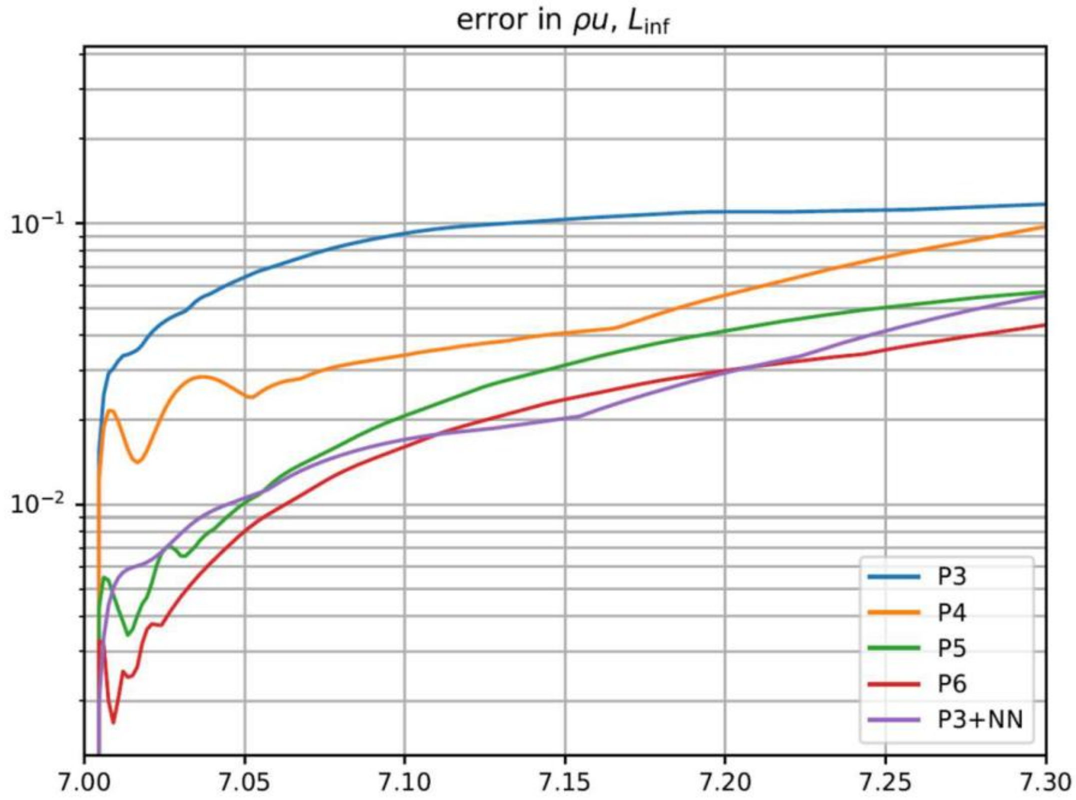
3D Navier-Stokes - LES

Taylor-Green – Reynolds 1600



$$P8 \rightarrow P3$$

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



What is the real accuracy?

Probably P=6

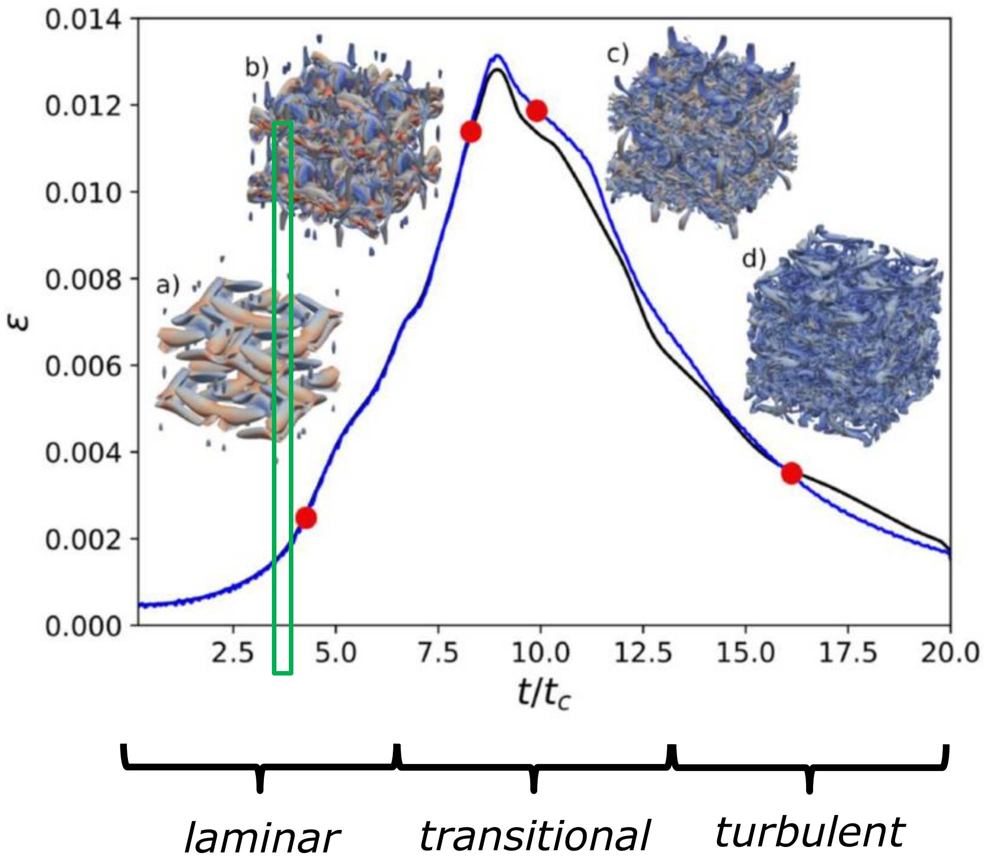
P3+NN is 4-5 times faster
(compared to P6)

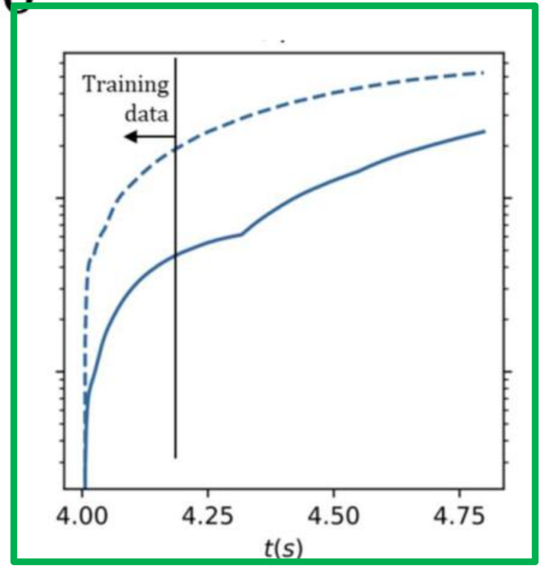
F Manrique de Lara, **E Ferrer,** "Accelerating High Order DG Solvers using Neural Networks: 3D Compressible Navier-Stokes Equations", *Journal of Computational Physics,* Vol 489, 112253, 2023

Machine Learning to accelerate CFD

3D Navier-Stokes - LES

Taylor-Green – Reynolds 1600

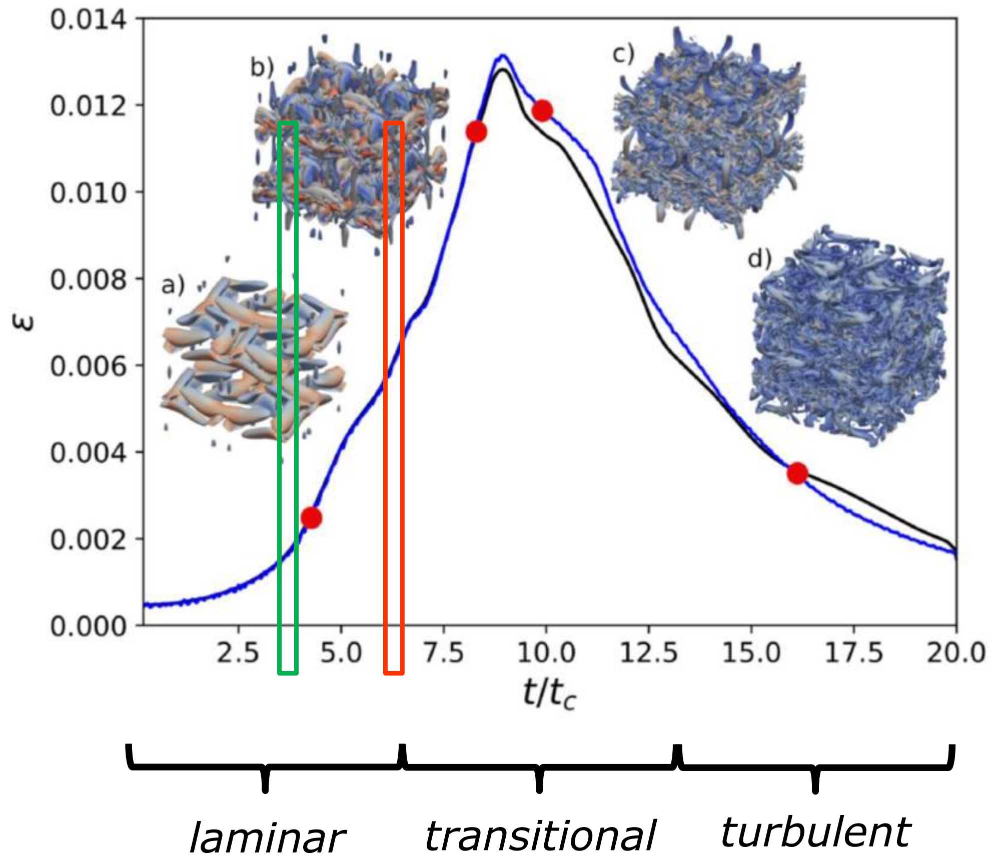


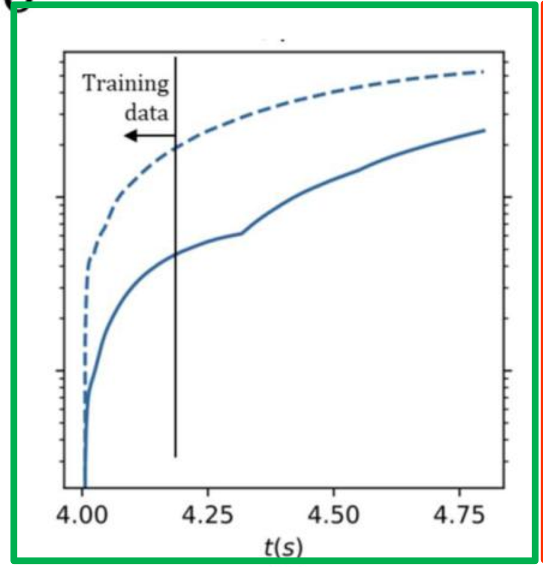


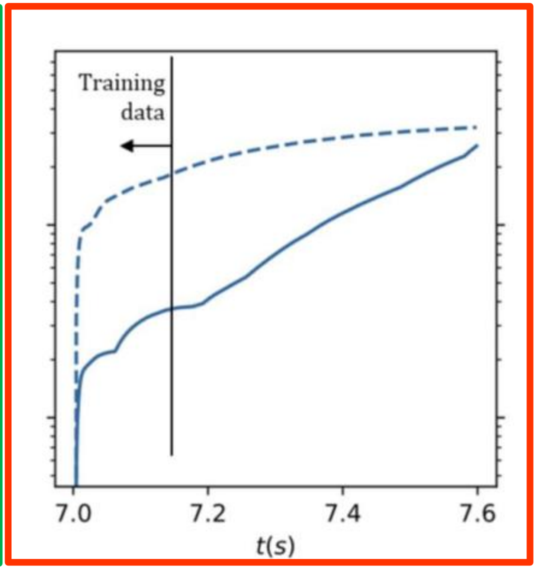
Machine Learning to accelerate CFD

3D Navier-Stokes - LES

Taylor-Green – Reynolds 1600







Machine Learning to accelerate CFD

3D Navier-Stokes - LES

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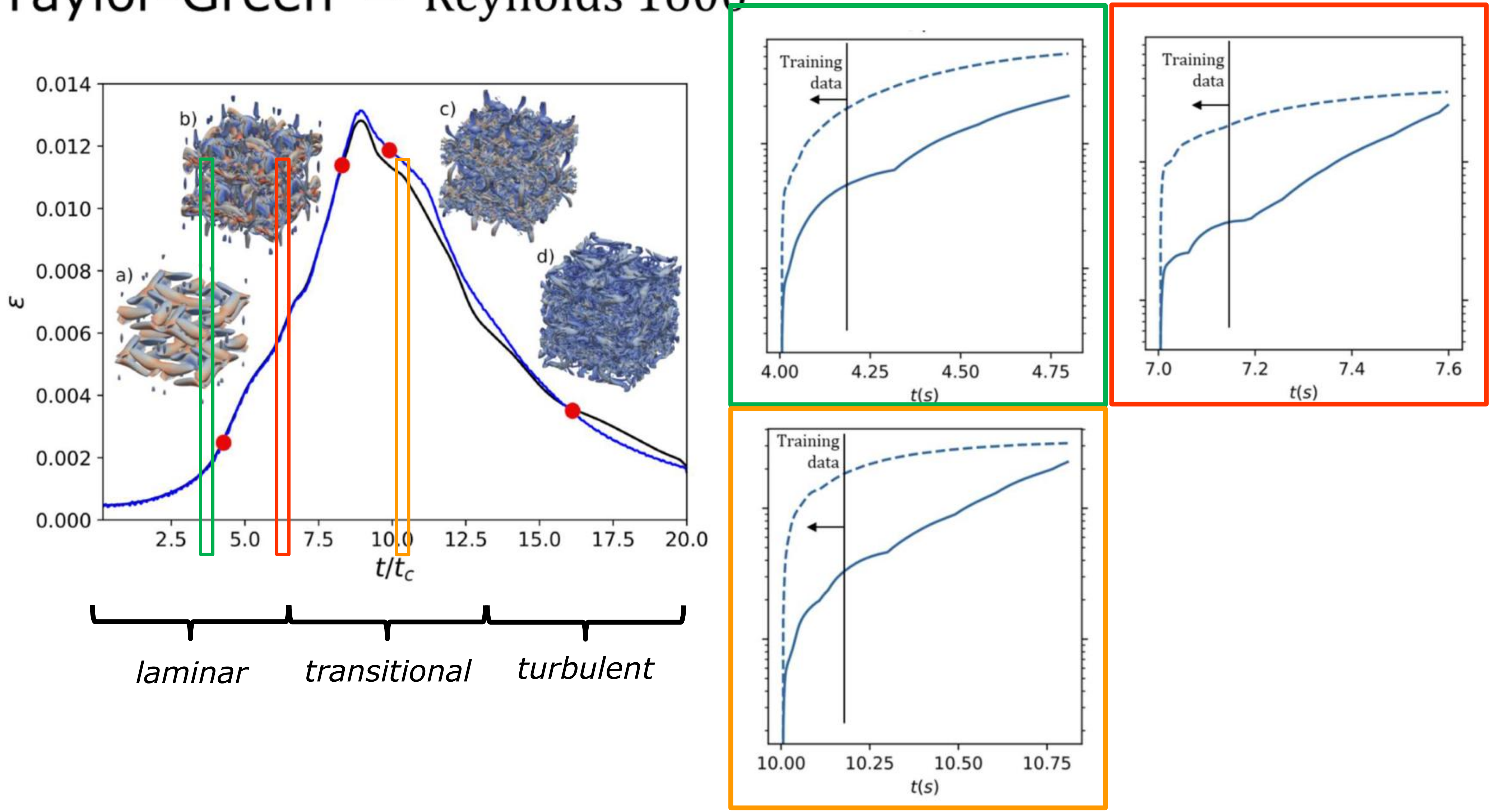

Machine Learning to accelerate CFD

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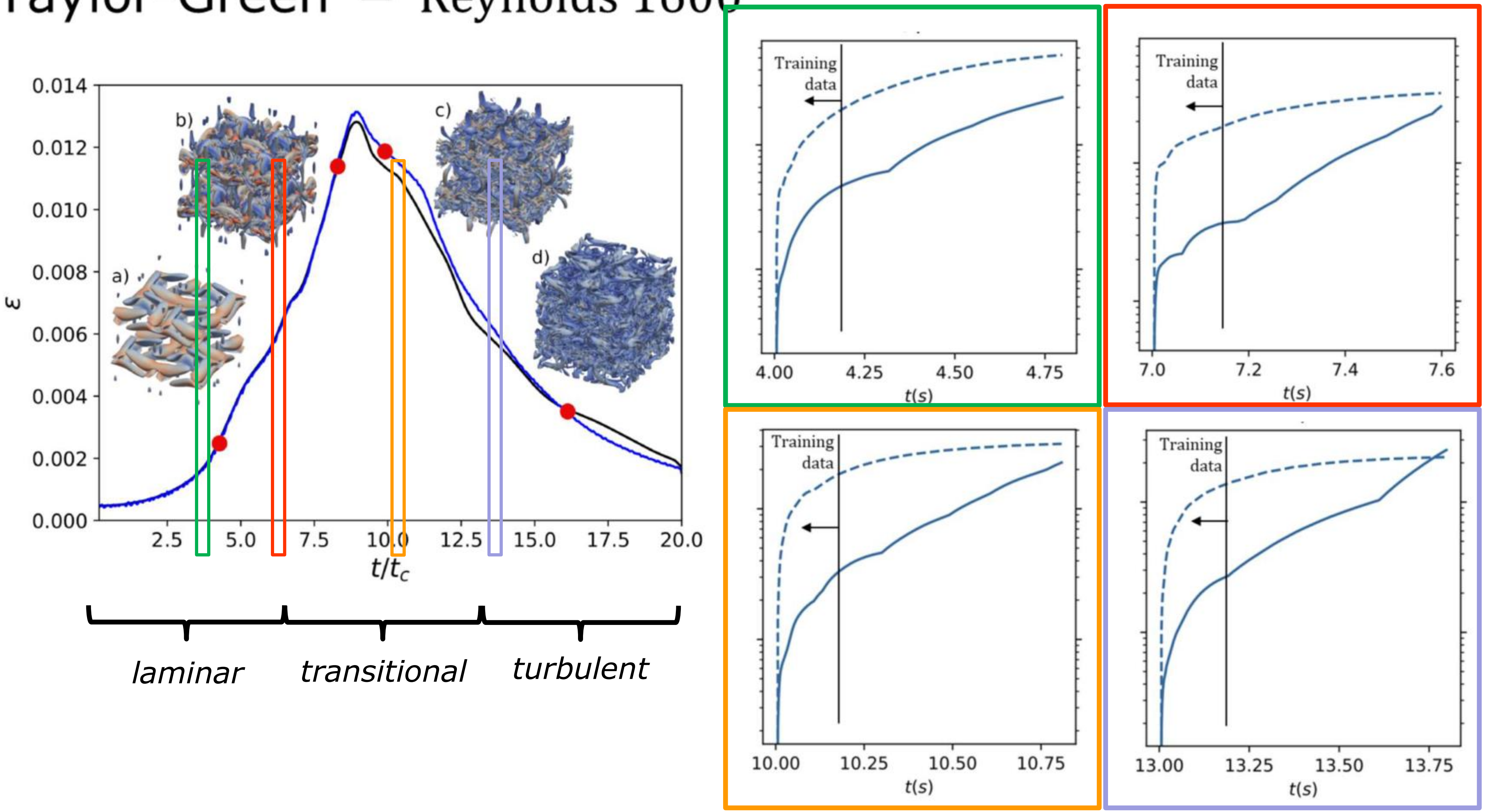
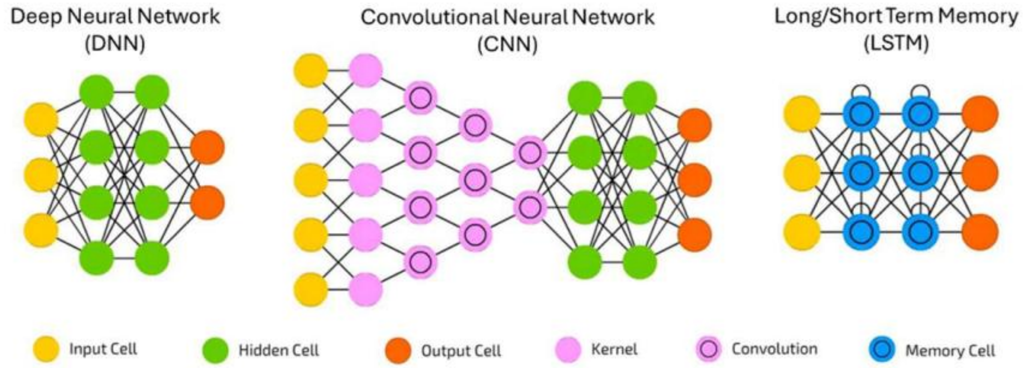
Taylor-Green – Reynolds 1600

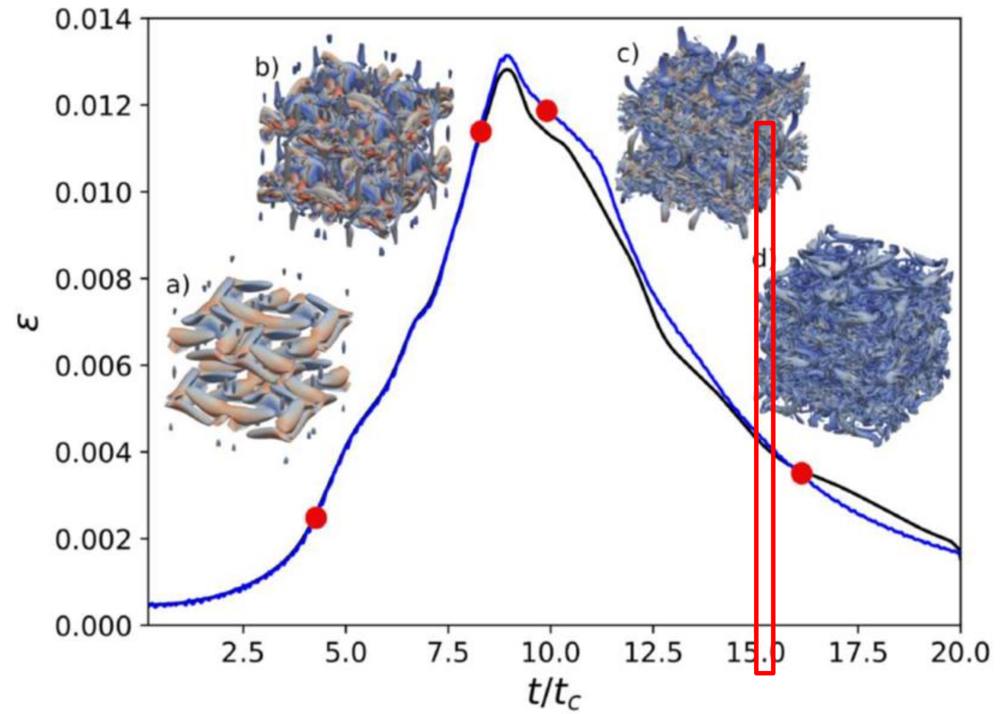


Machine Learning to accelerate CFD

3D Navier-Stokes - LES

Taylor-Green – Reynolds 1600





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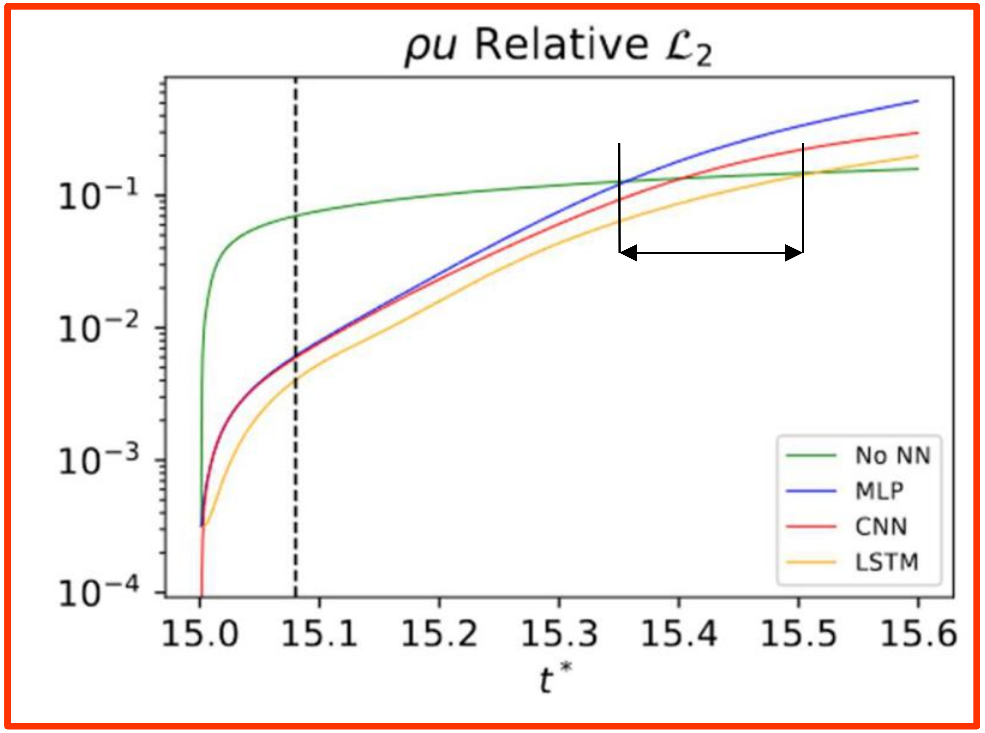
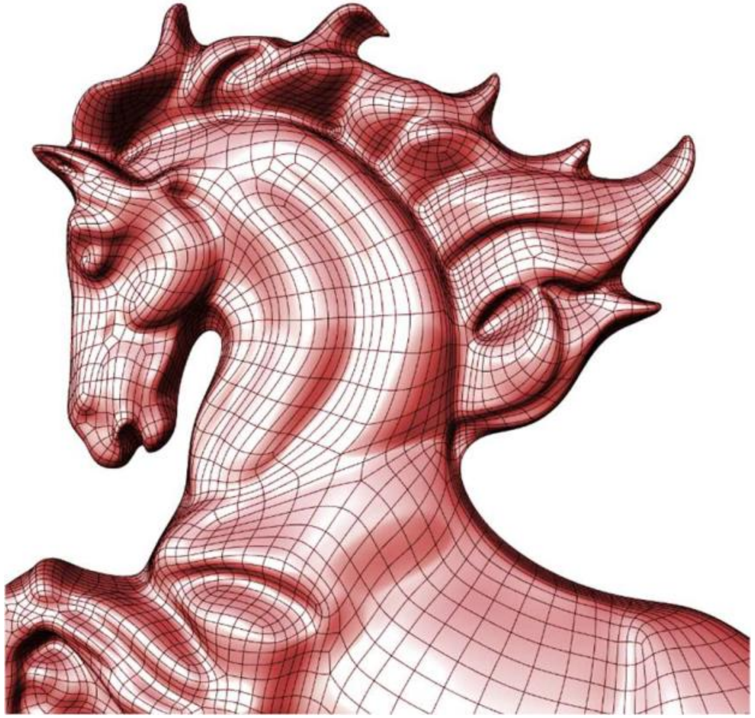


O Marino, A Juanicotena, J Errasti, D Mayoral, F Manrique de Lara, R Vinuesa, **E Ferrer**, Accelerating High Order DG Solvers using Neural Networks: ***A Comparison of Neural Network architectures*** to accelerate the Taylor Green vortex problema, *Under Review*

Summary

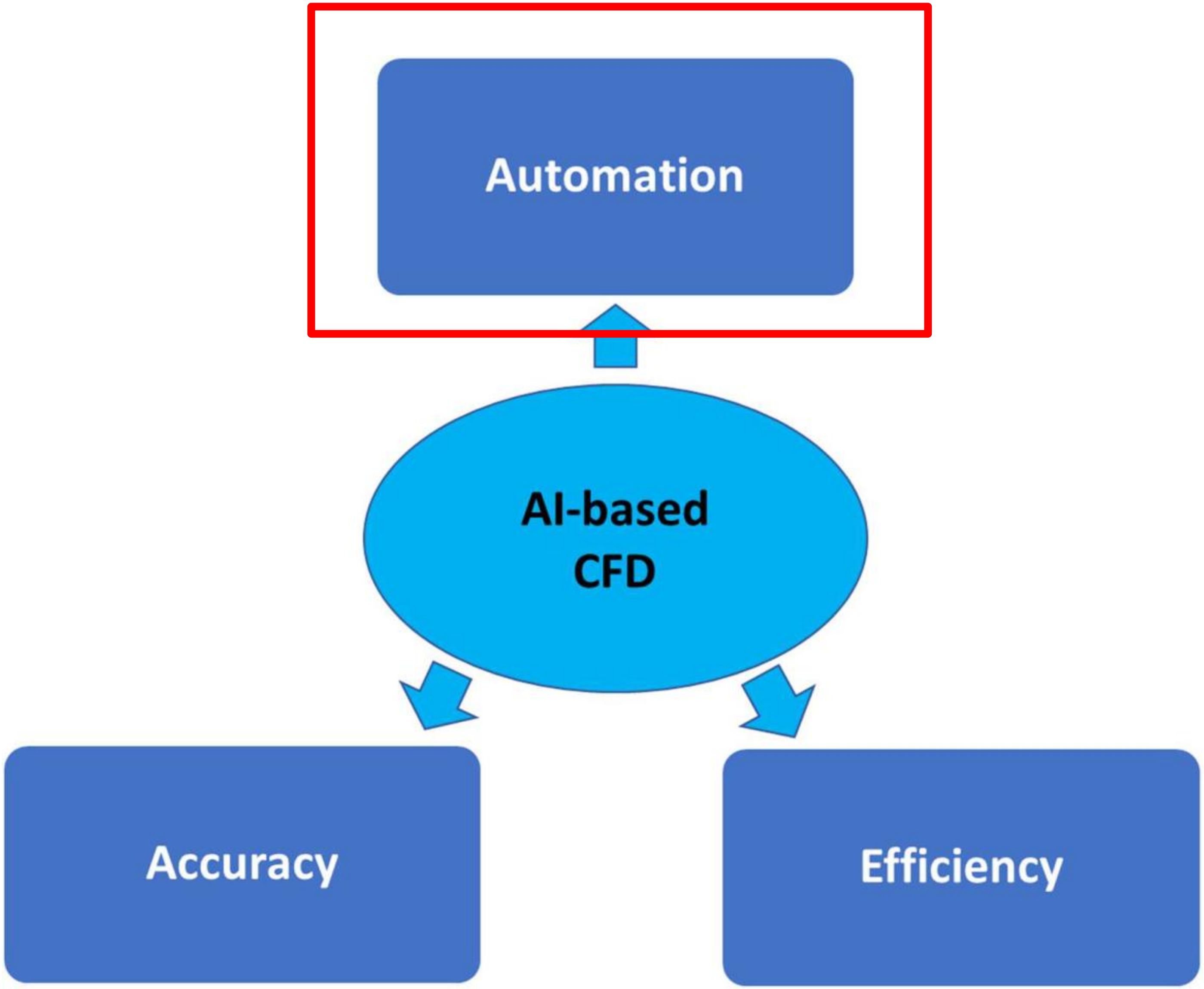


1- Introduction to DG & Horses3d

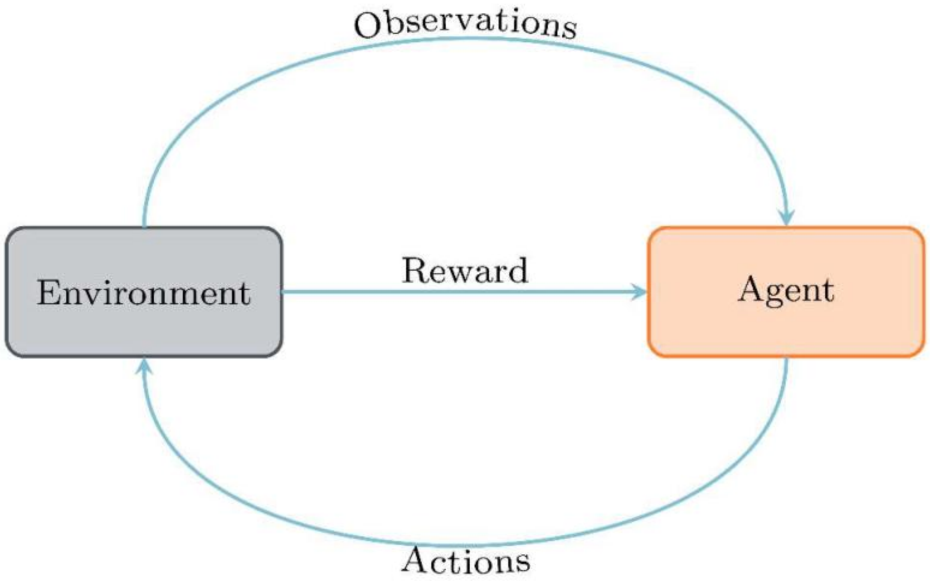
2- Multiphysics
→ Wind turbines
→ Turbulence

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

Towards AI-based Computational Fluid Dynamics

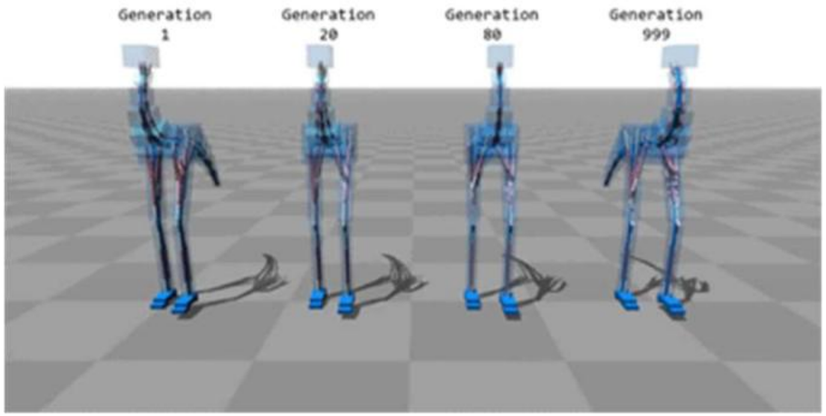


Machine Learning and Reinforcement Learning

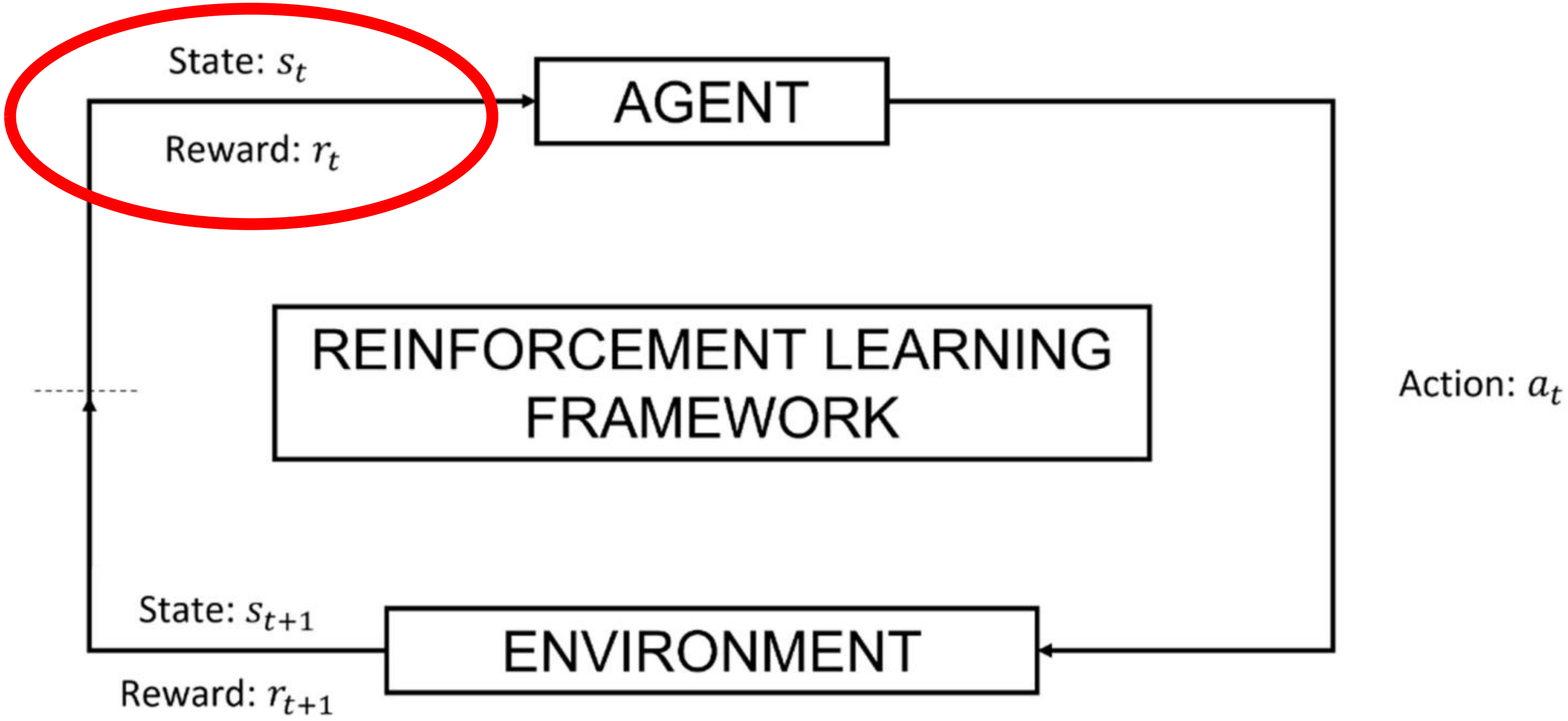


Go game

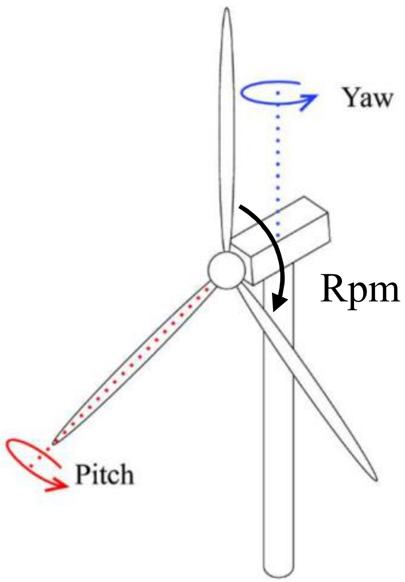
Chess game



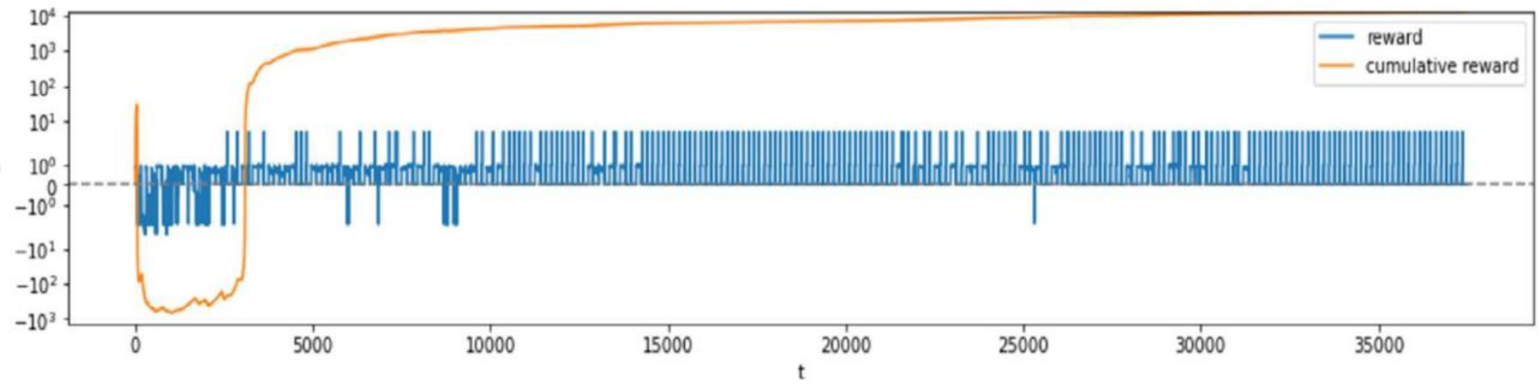
Defining the state, actions and rewards are the key aspects of RL

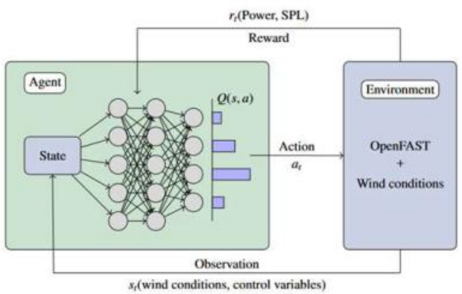


Deep reinforcement learning for wind turbine control



Training with simple winds



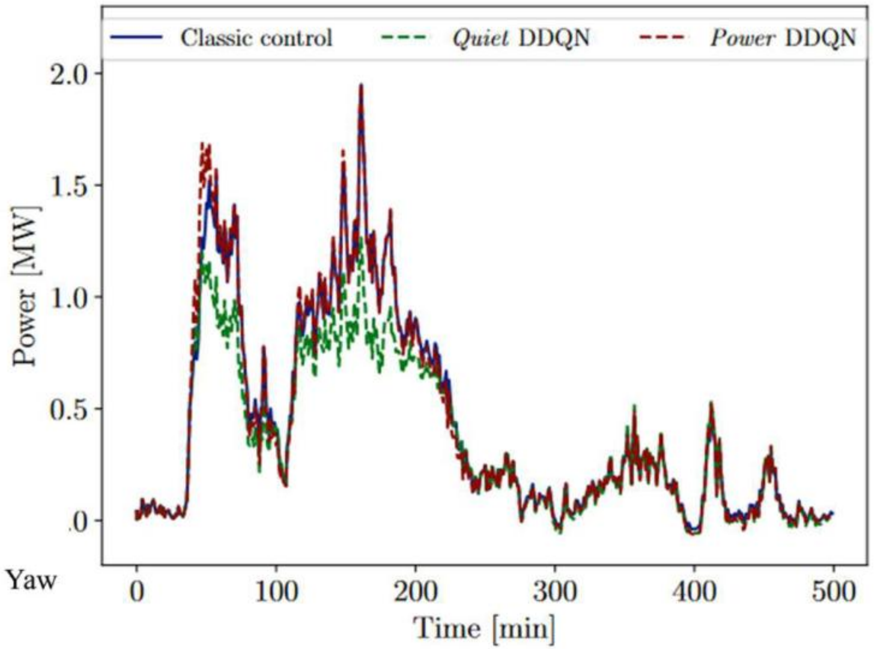


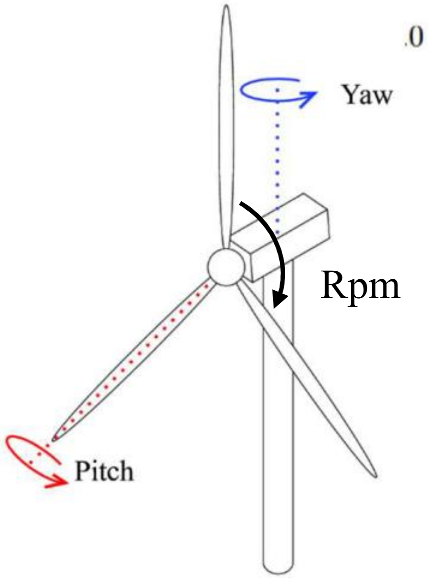
Validation with turbulent real winds

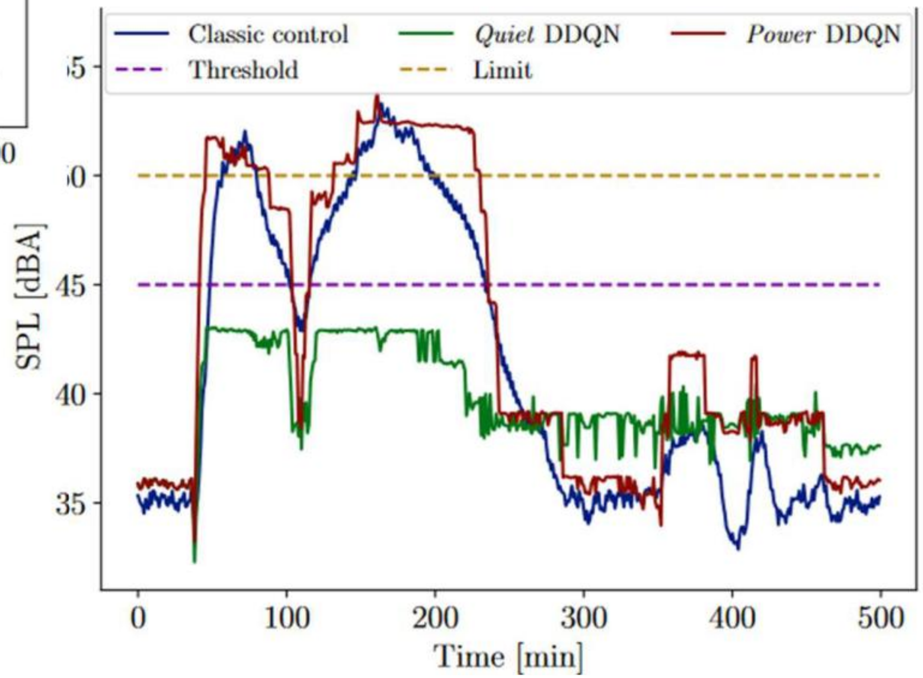
Metric	DDQN1	VI	PID	Uncontrolled
Control Capacity Factor (%)	91.31	87.50	57.60	12.77
Capacity Factor (%)	20.95	20.50	12.49	1.59
Yearly Production (MWh)	4162.95	4073.45	2481.97	316.12

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

Deep reinforcement learning for wind turbine control
Adding Noise Constraints



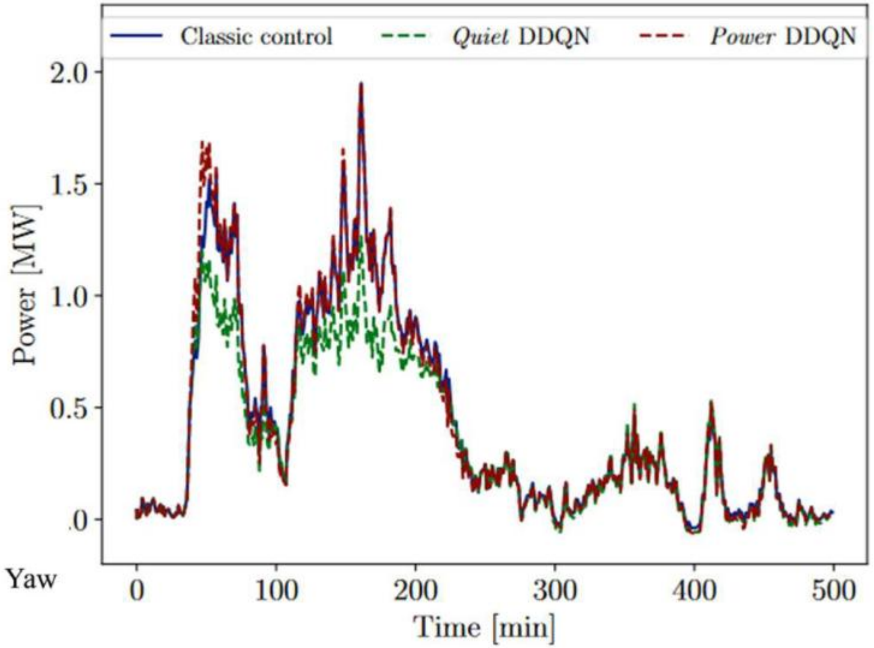


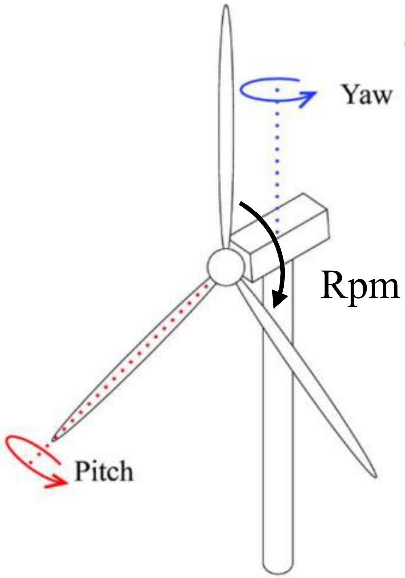


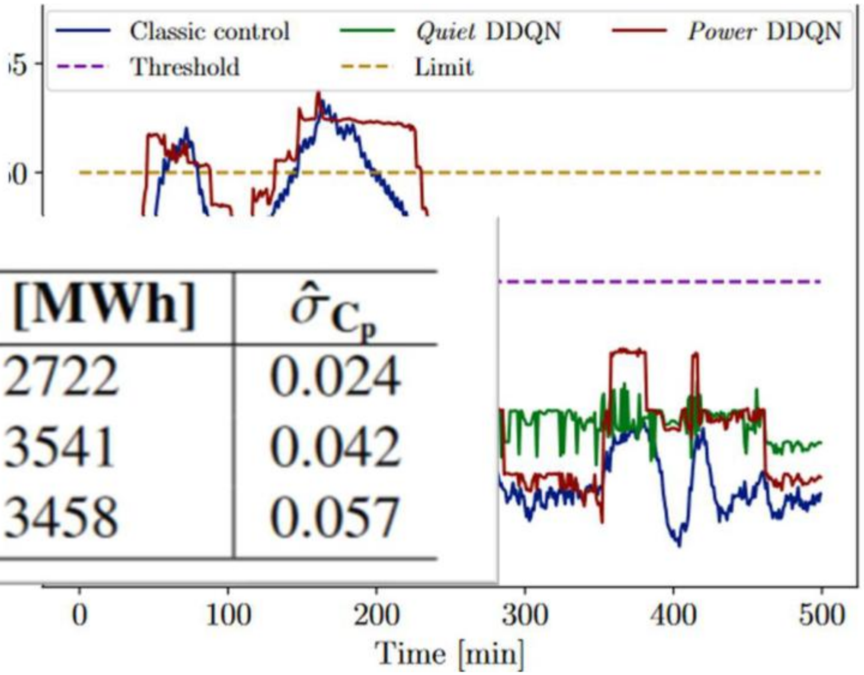
M de Frutos, O Mariño, D Huergo, **E Ferrer**, "Reinforcement Learning for Multi-Objective Optimization: Enhancing Wind Turbine Energy Generation while Mitigating Noise Emissions", under review

Deep reinforcement learning for wind turbine control

Adding Noise constraint



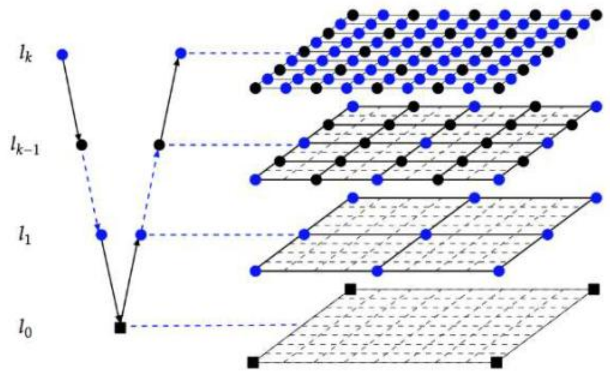




Controller	E_w [MWh]	$\hat{\sigma}_{C_p}$
Quiet DDQN	2722	0.024
Power DDQN	3541	0.042
Classic Controller	3458	0.057

M de Frutos, O Mariño, D Huergo, **E Ferrer**, "Reinforcement Learning for Multi-Objective Optimization: Enhancing Wind Turbine Energy Generation while Mitigating Noise Emissions“, under review

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

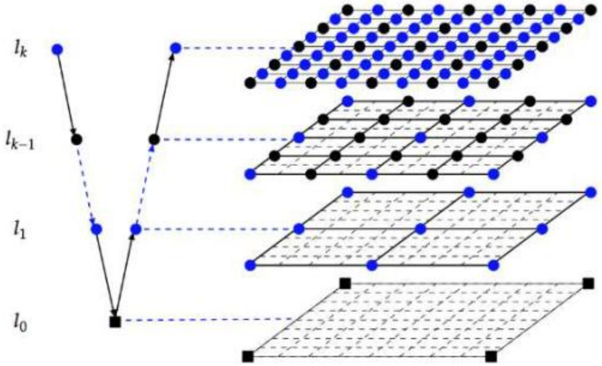
$$u_t + a u_x - \nu u_{xx} = S$$

Optimal parameters in p-multigrid multigrid?

- Sweeps
- Relaxation between levels

D Huergo, M de Frutos, E Jané, G Rubio, **E Ferrer**, "Reinforcement learning for anisotropic p-adaptation and error estimation in high-order solvers“, *under review*

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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	P5			IC: Sine7				471				U	U	U
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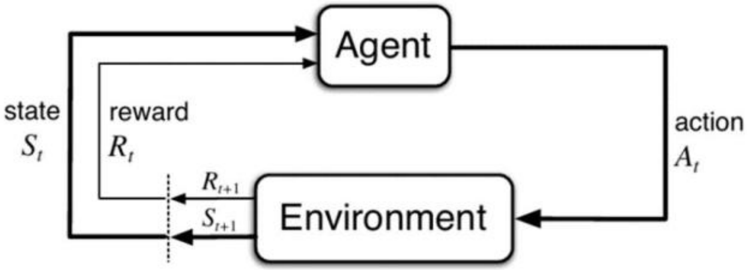
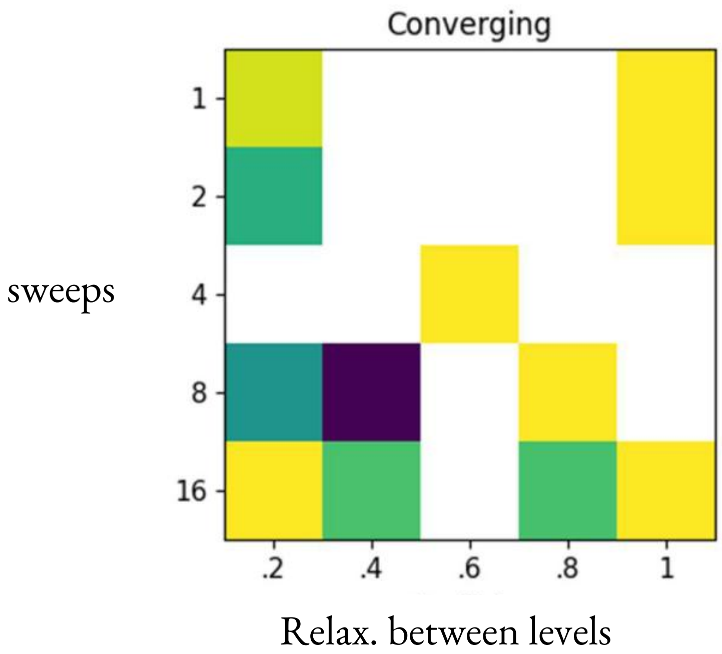
	P7			IC: Sine7				1207				1205	U	U
				IC: sine				1207				1205	U	U
				IC: exp				1207				1205	U	U
	P9			IC: Sine7				2466				U	U	U
				IC: sine				2466				U	U	U
				IC: exp				2466				U	U	U
	P3		R10	IC: Sine7	229	146	144	142	140	138	136	1188	U	U

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

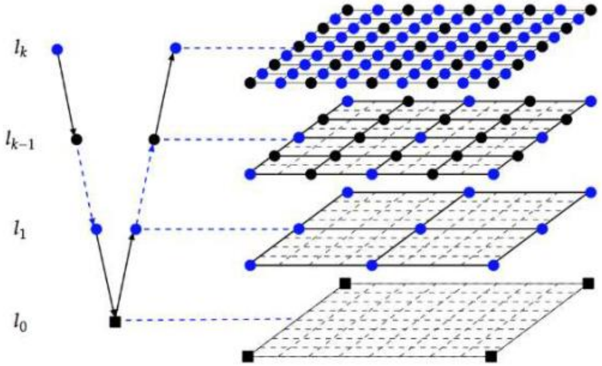
Reward: f(Relative drop in residual, time taken)





Yellow → action taken
Blue do not take it

Reinforcement learning for p-multigrid



p-multigrid

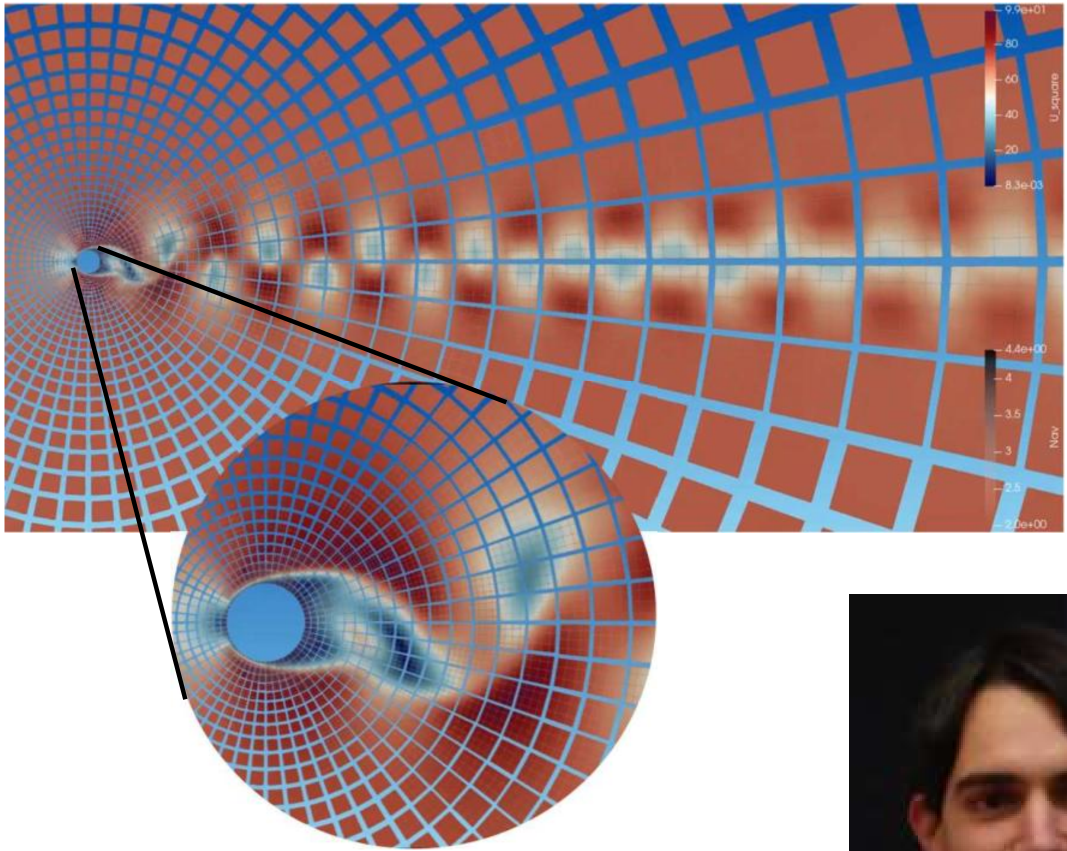
				Cases	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Advection-diffusion	P3	L0	R0	IC: Sine7		135	126	121	121	123	124	1186	U	U
				IC: sine				121				1186	U	U
				IC: exp				121				1186	U	U
	P5			IC: Sine7				471				U	U	U
				IC: sine				471				U	U	U
				IC: exp				471				U	U	U
	P7			IC: Sine7				1207				1205	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

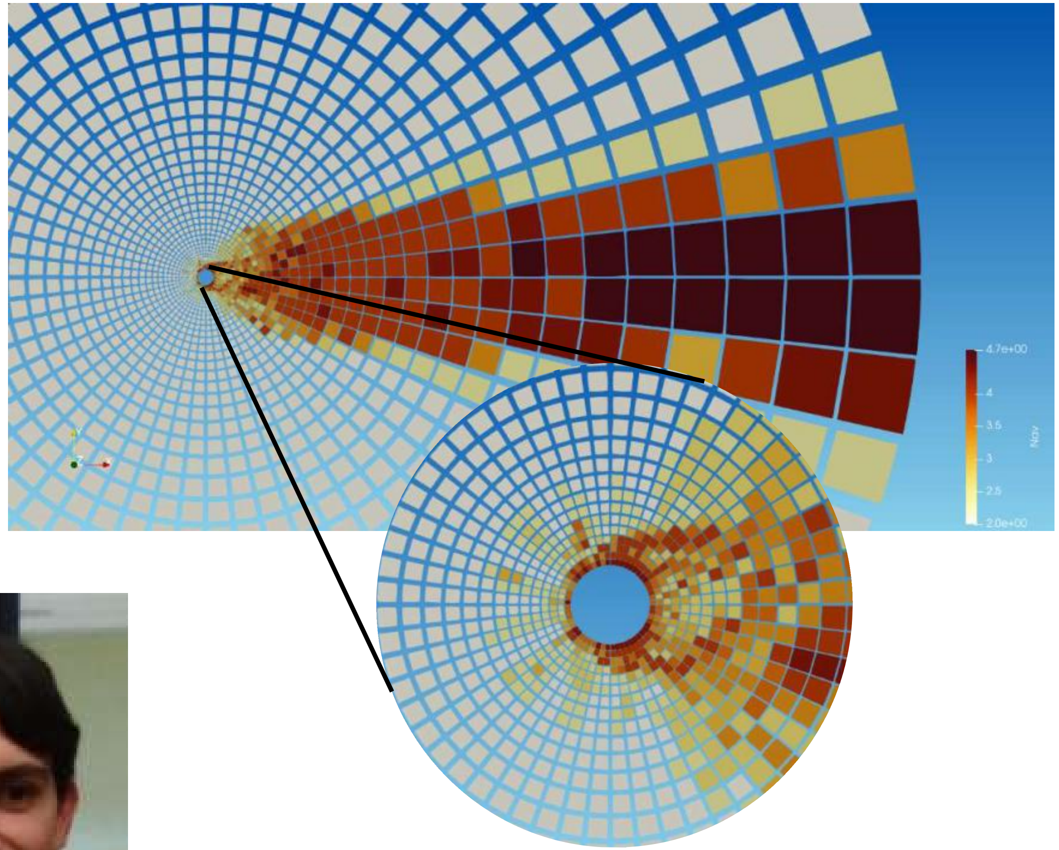
$$u_t + a u_x - \nu u_{xx} = S$$

"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

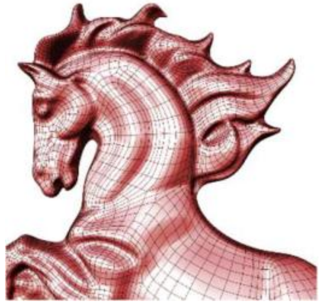
Reinforcement learning for p-adaptation

Cylinder $\boldsymbol{Re = 200}$



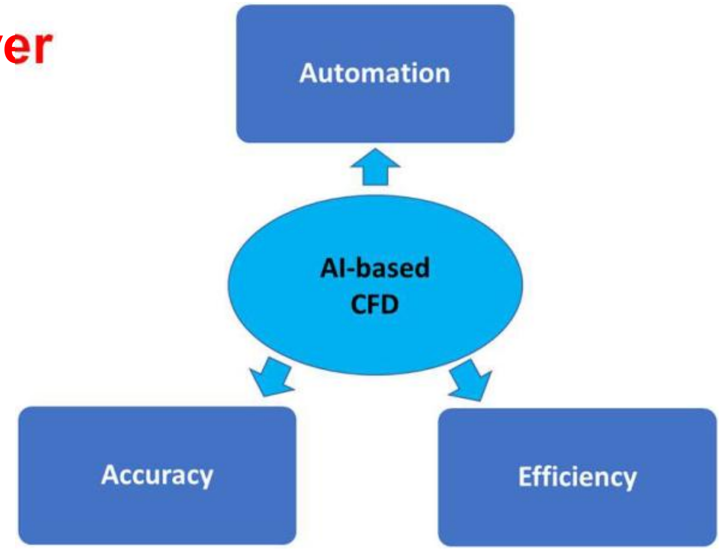


Conclusions



- **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**



Doc & PostDoc availables in the group

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

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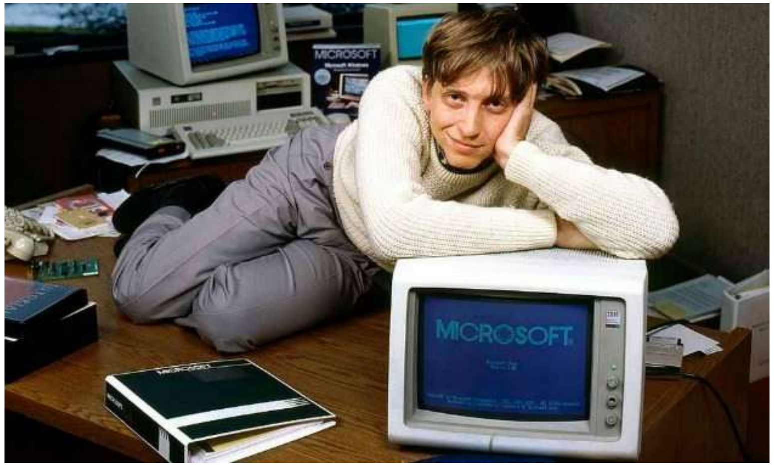
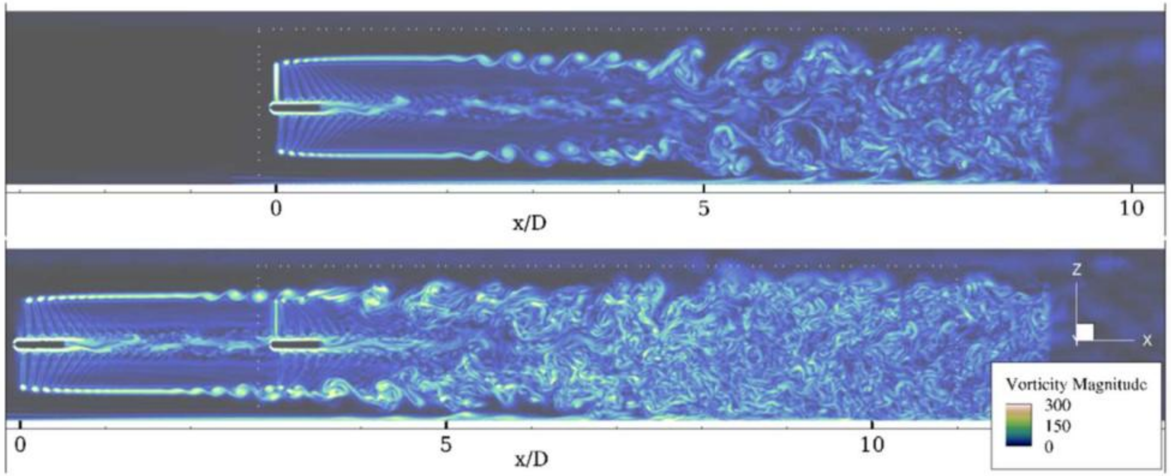
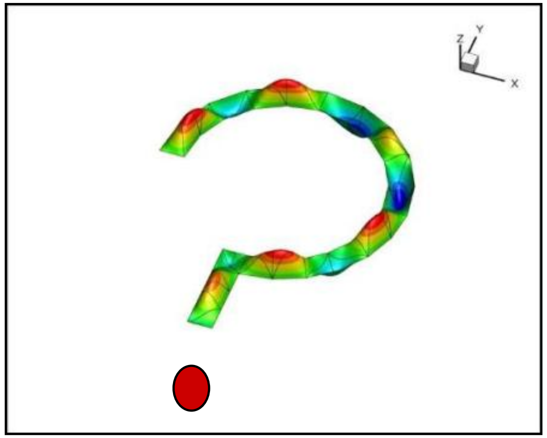




If you like computers (like B. Gates), fluids, wind turbines, etc.

Thank you very much



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Reinforcement Learning for Anisotropic p-Adaptation and Error Estimation in High-order Solvers

David Huergo Perea

UPM Collaborators:

M. de Frutos, E. Jané, O. Mariño, G. Rubio, E. Ferrer

Funding

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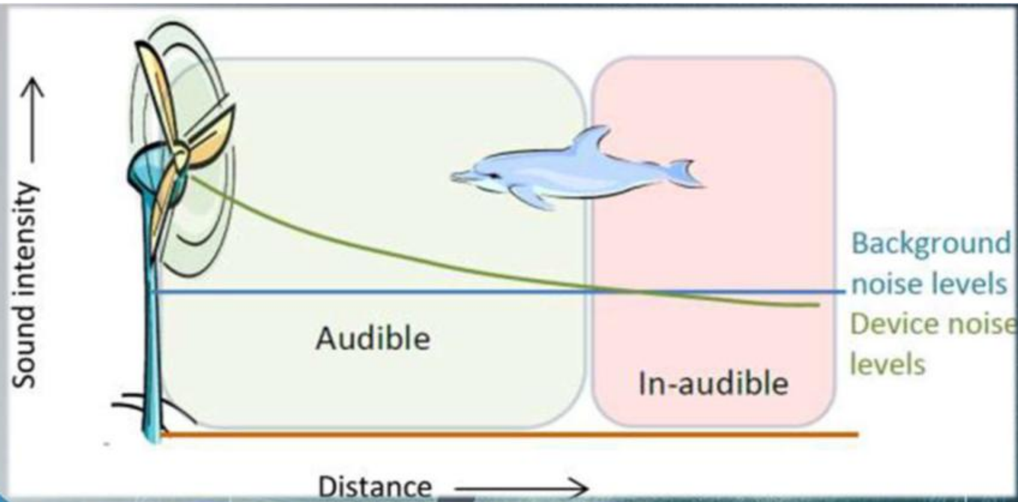
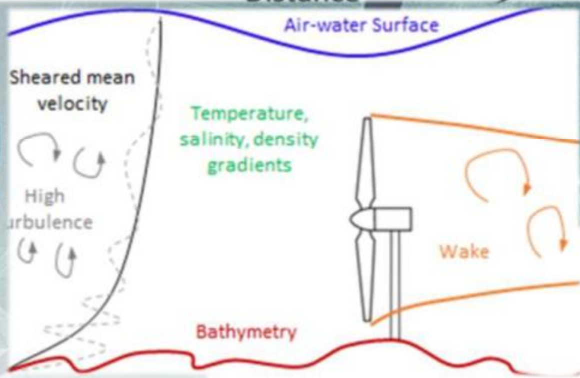
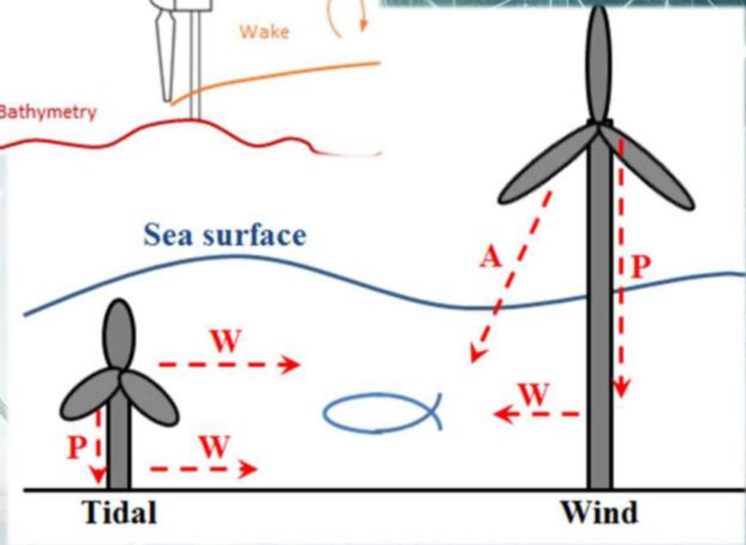




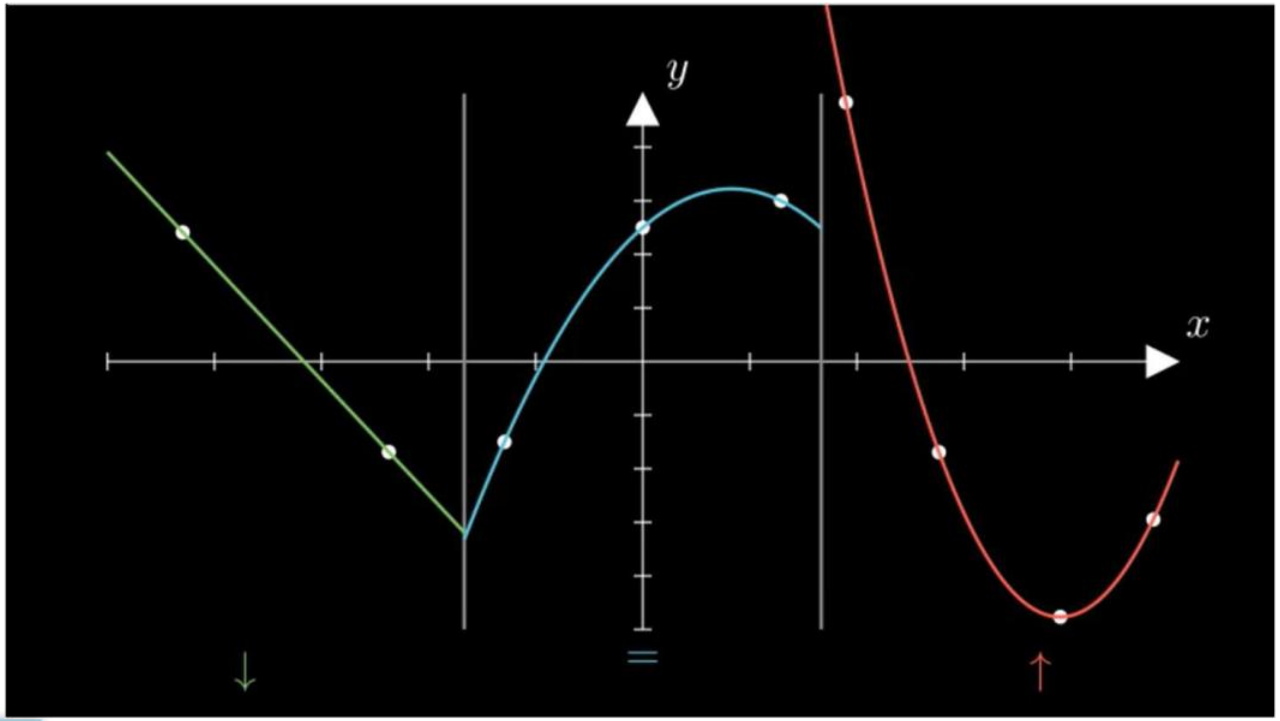


Contents

p-Adaptation in DGSEM solvers

1.1. p-Adaptation for DGSEM

Discontinuous Galerkin Spectral Element Method



- The solution is approximated in each element using **Lagrange polynomials** based on **Legendre-Gauss nodes**.
- p-Adaptation allows to select the **optimal polynomial in each element** of the mesh to obtain **accurate solutions** with a **reduced computational cost**.
- Manual p-adaptation requires to know beforehand the behaviour of the solution.

1.2. p-Adaptation with Truncation Error

DGSEM simulation

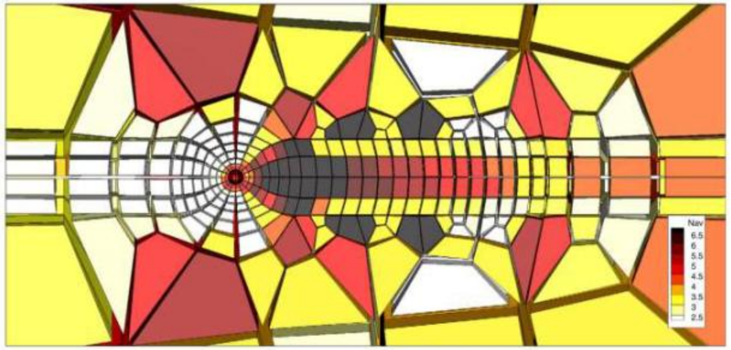
Example of a p-adapted mesh, based on the **Truncation Error**, for the flow around a sphere at Reynolds 200.

The contours indicate the average polynomial order (Nav=(N1 +N2 +N3)/3). [1, 2]

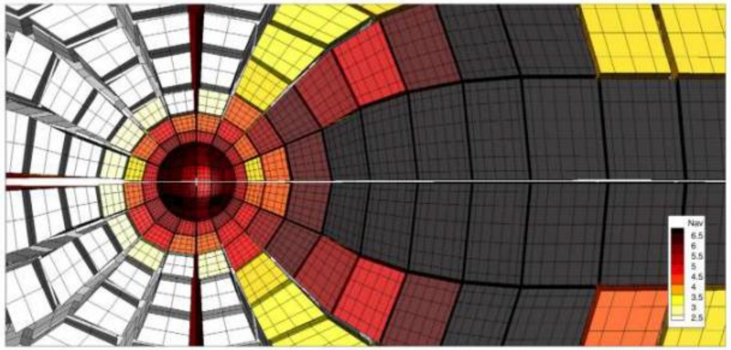
Simulated using HORSES3D

https://github.com/loganoz/horses3d

[3] E. Ferrer, G. Rubio, W. Laskowski, O.A. Mariño, S. Colombo, A. Mateo-Gabín, H. Marbona, F. Manrique de Lara, D. Huergo, J. Manzanero, A.M. Rueda-Ramírez, D.A. Kopriva and E. Valero, HORSES3D: A high-order discontinuous Galerkin solver for flow simulations and multi-physics applications, Computer Physics Communications 287 (2023): 108700.



(a) Average polynomial order (N_{av}).

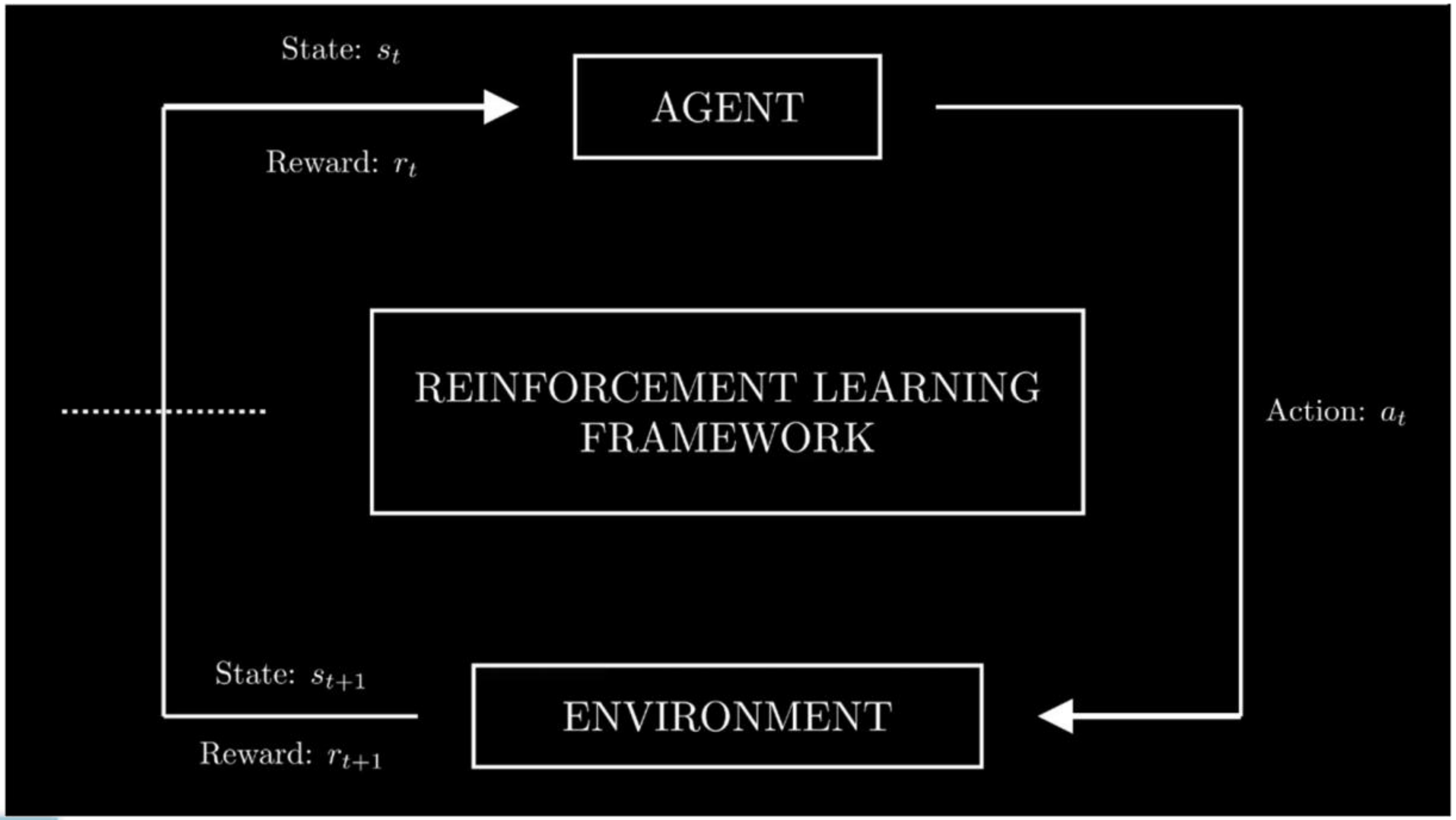


[1] A. M. Rueda-Ramírez, J. Manzanero, E. Ferrer, G. Rubio, E. Valero, A p-multigrid strategy with anisotropic p-adaptation based on truncation errors for high-order discontinuous Galerkin methods, Journal of Computational Physics 378 (2019).

[2] A. M. Rueda-Ramirez, G. Ntoukas, G. Rubio, E. Valero, E. Ferrer, Truncation Error-Based Anisotropic p-Adaptation for Unsteady Flows for High-Order Discontinuous Galerkin Methods, International Journal of Computational Fluid Dynamics, 37(6), 430–450 (2024).

Reinforcement Learning for p-adaptation

2.1. The RL framework

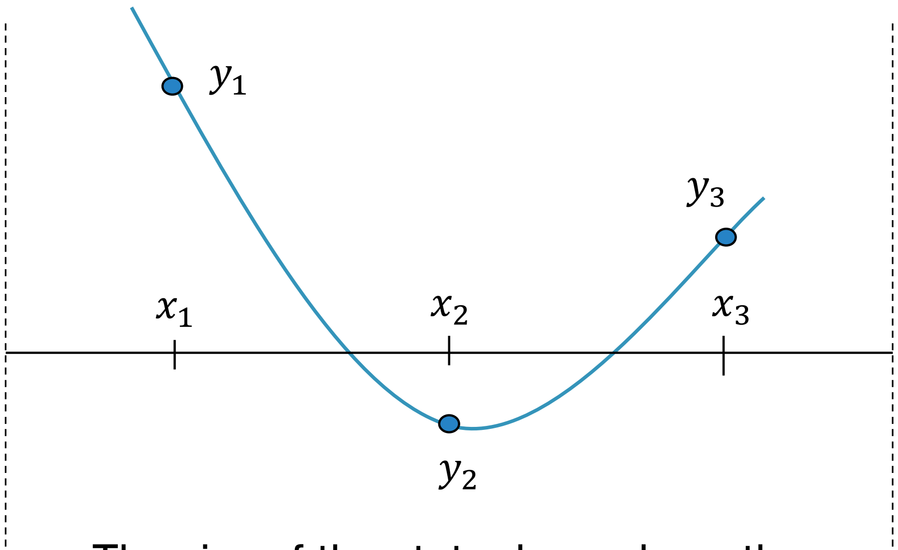


- **Agent**: Decides the action.
- **Environment**: Current problem (our DGSEM solver).
- **Action**: Increment or decrement the polynomial order p.
- **State**: To be defined.
- **Reward**: To be defined.

2.2. State and Reward

State

$$s = [y_1, y_2, \dots, y_n]$$



The size of the state depends on the polynomial order.

Reward

Two main objectives:

- **Minimum polynomial order**: Computational cost is reduced.
- **High accuracy**: High order required if strong gradients are present.

$$reward = \left(\frac{p_{max}}{p}\right)^{\alpha} e^{-\frac{rmse^2}{2\sigma^2}}$$

- $rmse$: Between the solution and the analytical function in 14 points.
- σ $= 0.05$: Standard deviation.
- p_{max} $= 6$: Maximum order allowed.
- α $= 0.9$: Control parameter.

2.3. Training

Drawbacks

Expensive training when coupled with a CFD solver

Reward function based on **analytical solution**

Solution

Training based on **polynomial functions** in a single element

Advantages

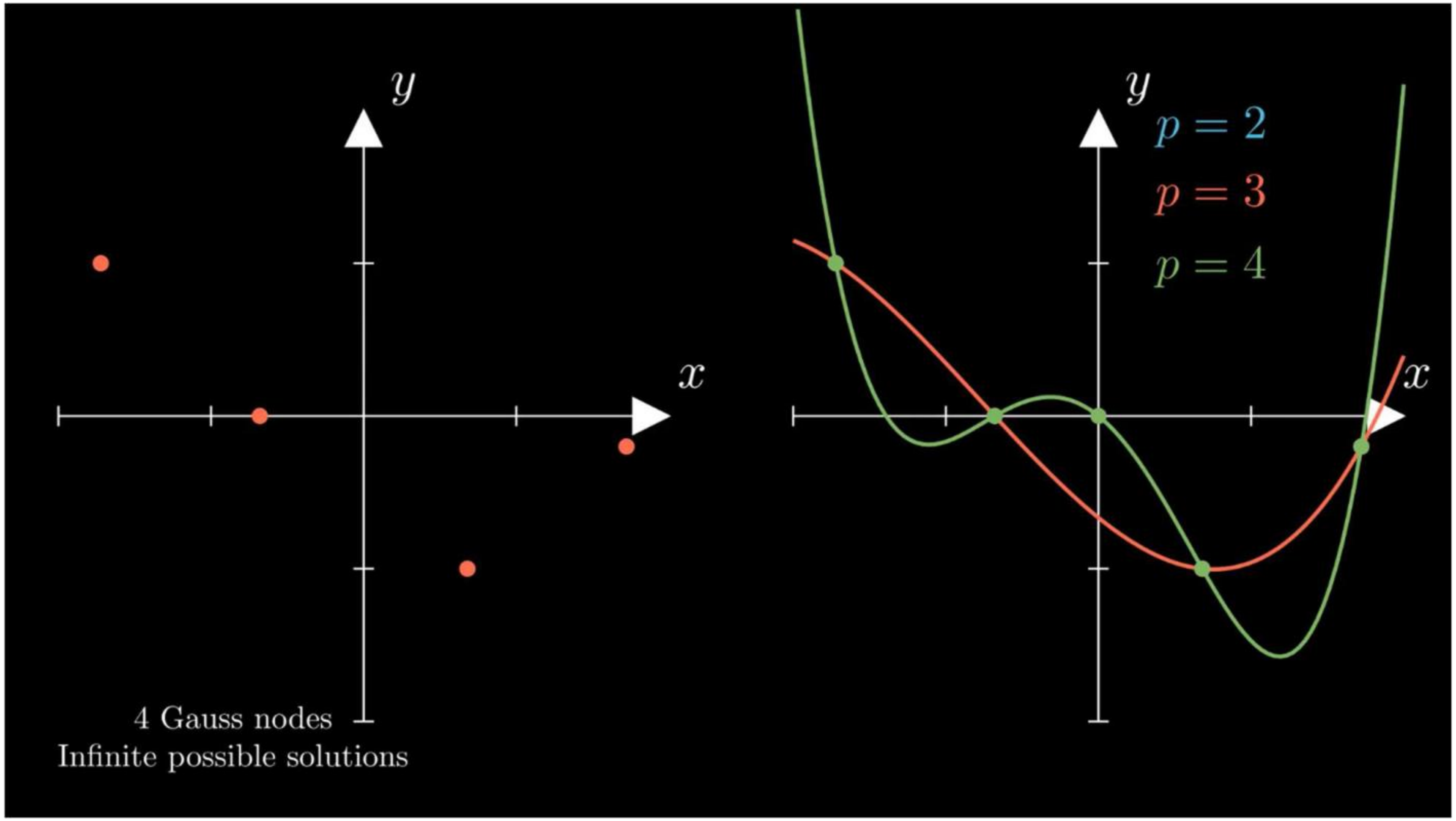
CFD not required during the training

Analytical solution known during the training

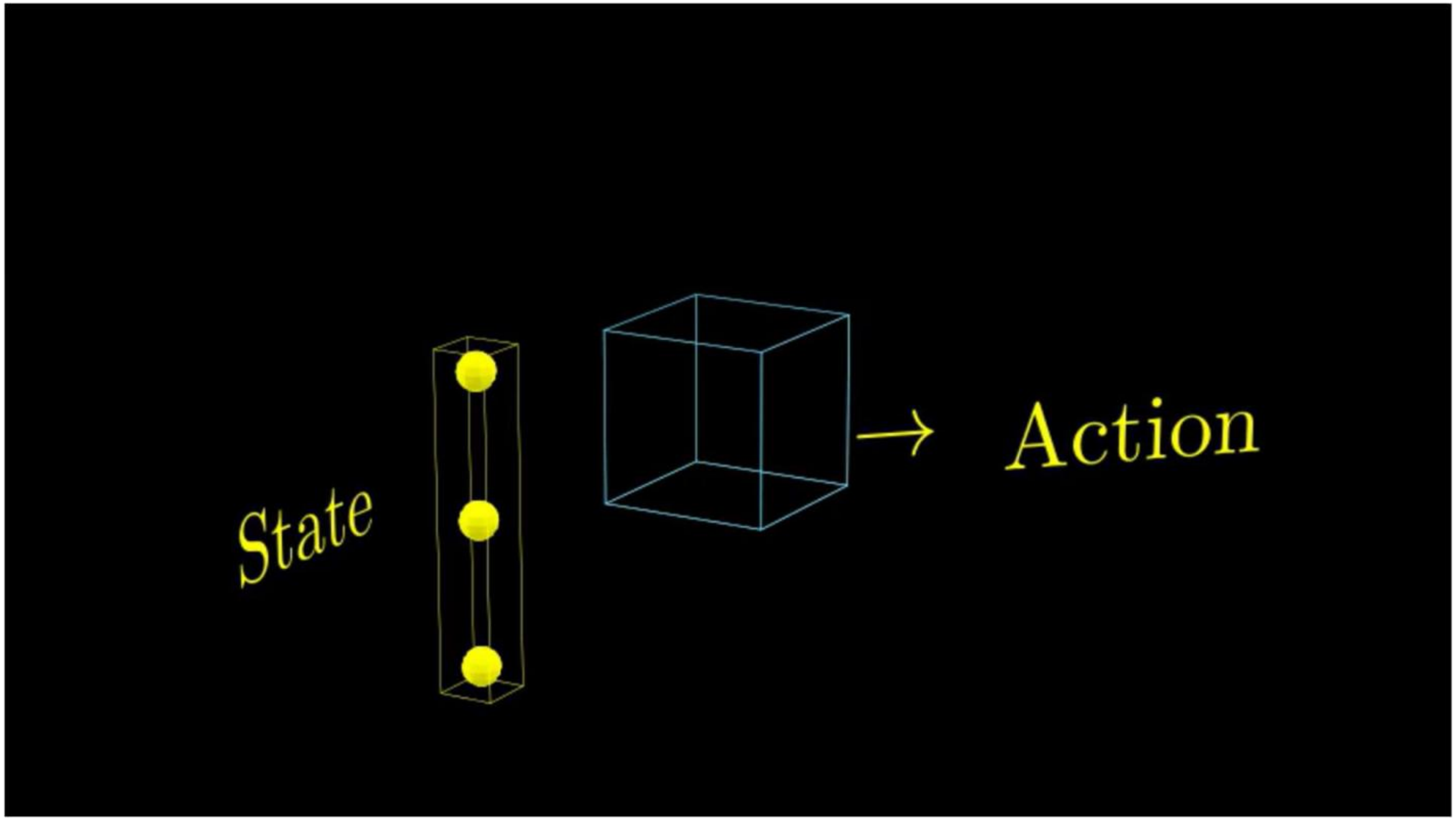
The resulting agent:

- Has to be **trained only once**.
- **Can be potentially applied to any PDE** solved with a DGSEM solver.
- **Can be used in an arbitrary mesh**: the agent chooses the optimum polynomial order individually for each element.

2.3. Training



2.4. Extrapolation for 3D cases



2.5. Error Estimation

Bellman Optimality Equation

$$\boxed{V^*(s)} = \max_a \sum_{s',r} \boxed{p(s',r \mid s,a)}[\boxed{r} + \boxed{\gamma}\boxed{V^*(s')}]$$

- **V-values**
- **Reward**
- **Discount factor**
- **Probability transition function**

$$\widehat{rmse} = \sqrt{-2\sigma^2 \log\left(\frac{V^*(s) - \bar{r} - \gamma\overline{r'}}{\gamma^2 V_{\max,p}}\right)}$$

The error estimation:

- Provides the **spatial error that the RL agent believes to be real** inside each element.
- **Is learned during the training** and can be applied without additional knowledge of the problem to be solved.
- **Is more accurate if coupled with p-adaptation.**

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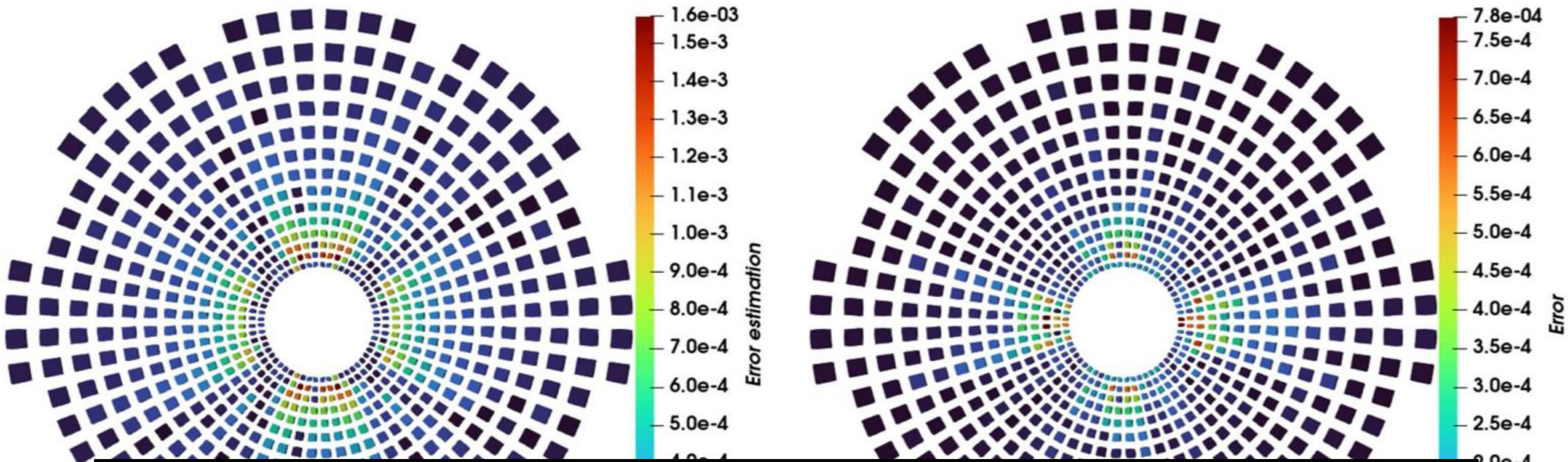
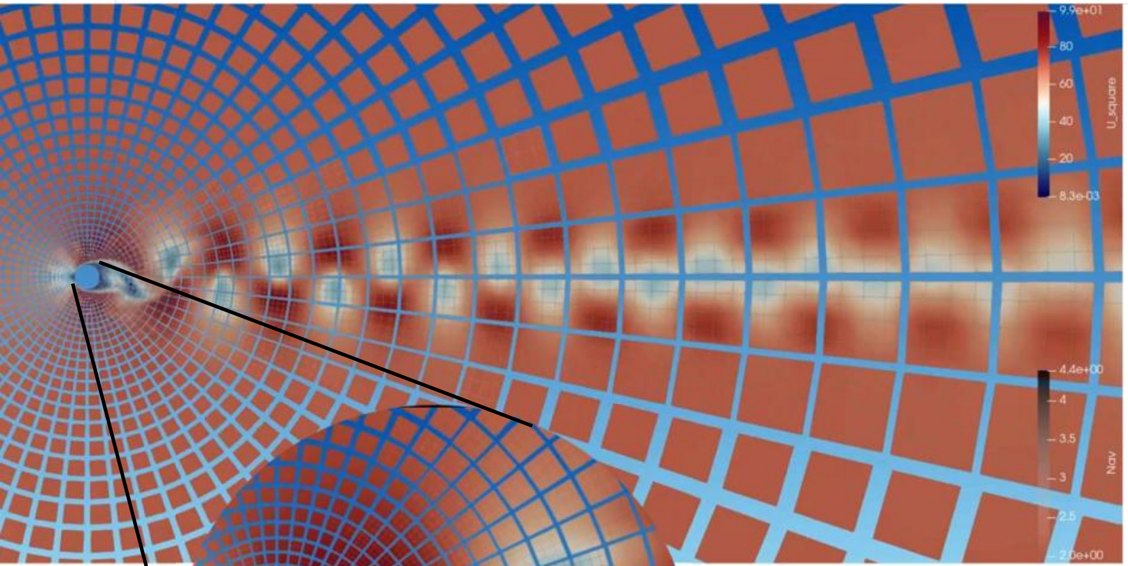
Results

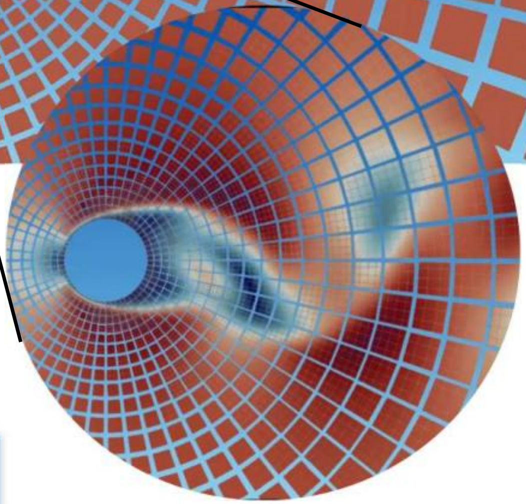
3.1. Euler Flow around a cylinder

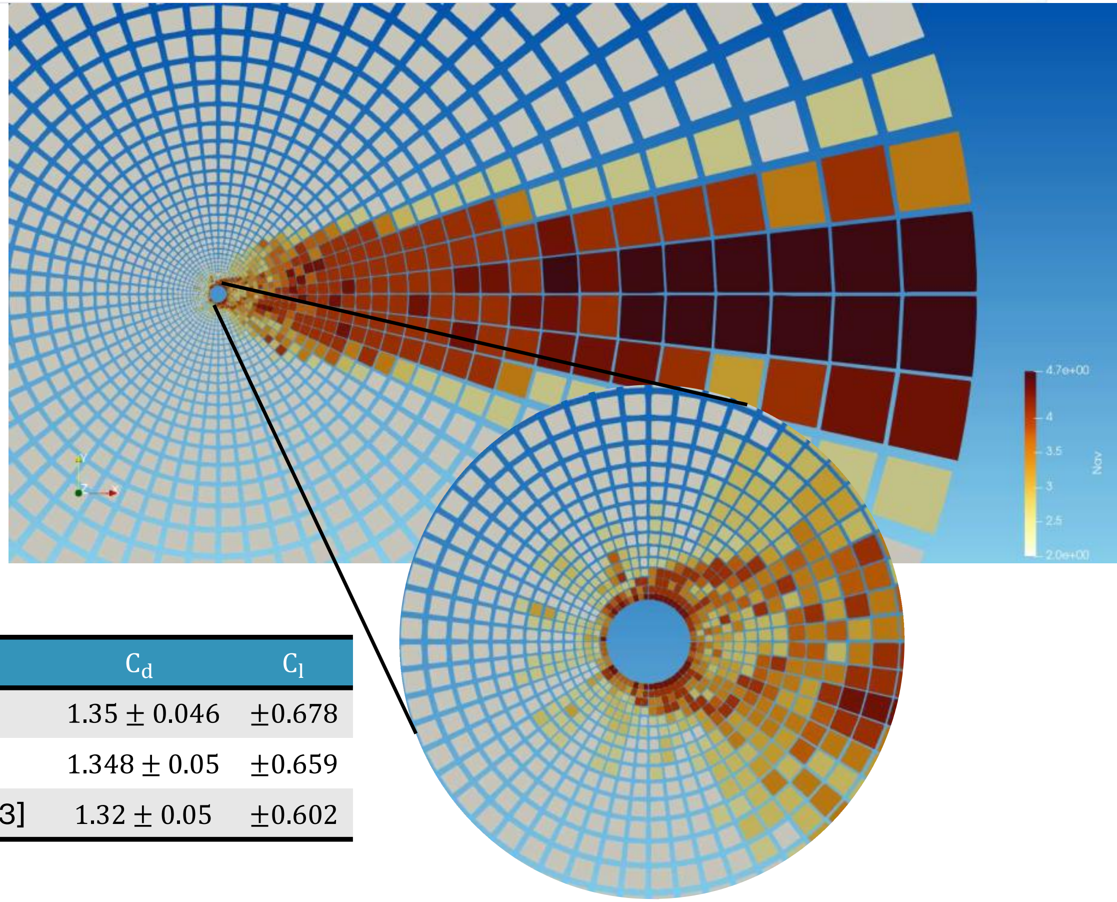


Polynomial order	DOFs	Computational cost (s)	Real Error	Error Estimation
$p = 2$	58968	252	$8.1 \cdot 10^{-3}$	$2.1 \cdot 10^{-3}$
$p = 3$	139776	431	$6.7 \cdot 10^{-4}$	$2.8 \cdot 10^{-4}$
$p = 4$	273000	737	$6.5 \cdot 10^{-5}$	$3.0 \cdot 10^{-5}$
$p = 5$	471744	1181	0.0 (reference)	0.0 (reference)
$\mathbf{p - adapted}$	**27708**	**197**	$\mathbf{7.8 \cdot 10^{-4}}$	$\mathbf{1.6 \cdot 10^{-3}}$

3.2. Cylinder $Re = 200$



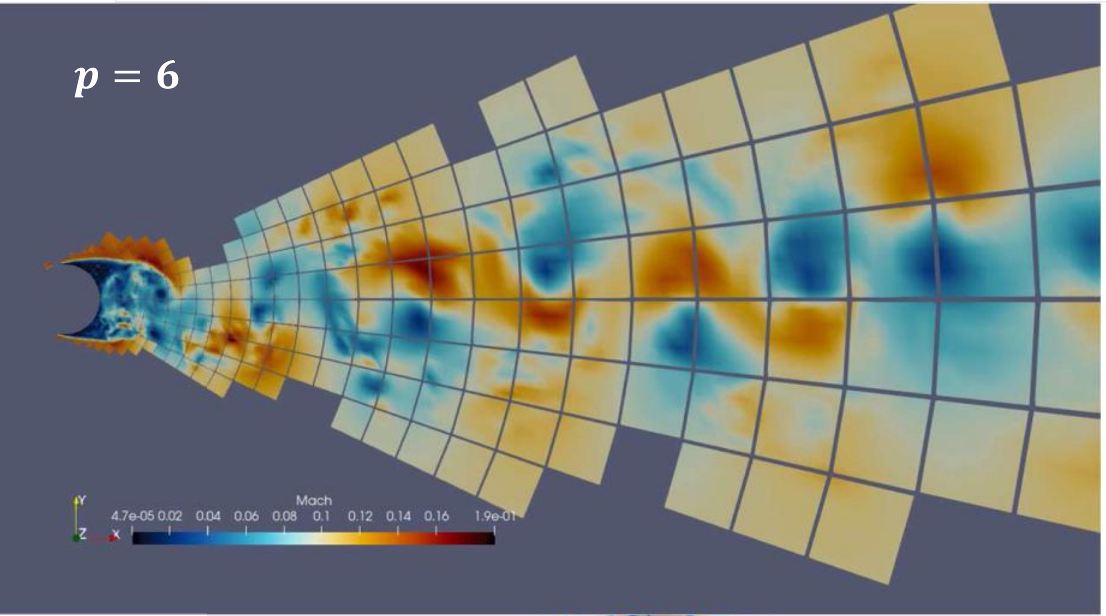


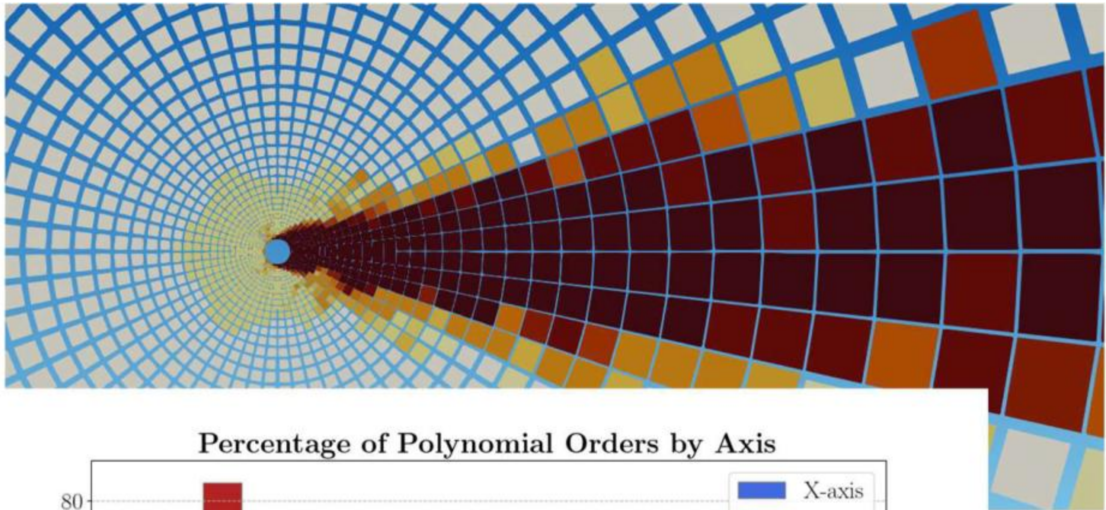


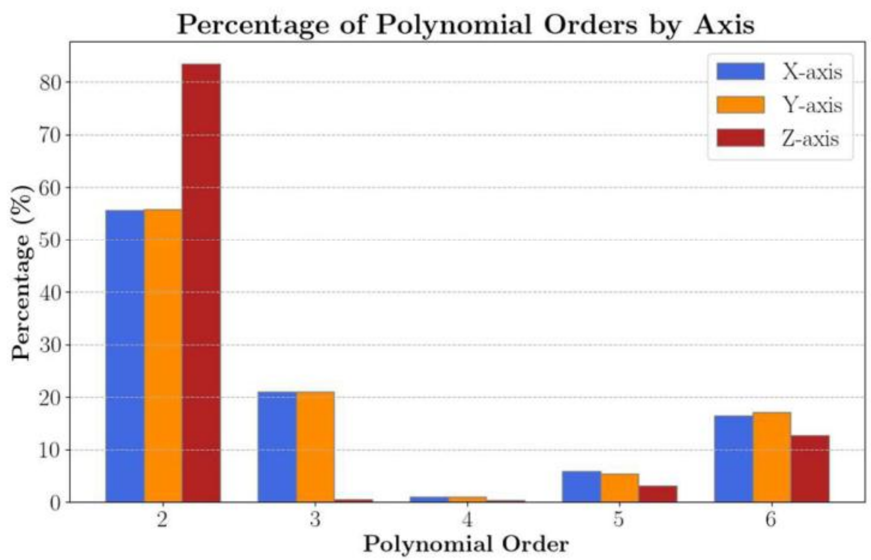
Author	C_d	C_l
RL p-Adaptation (ours)	1.35 ± 0.046	± 0.678
Ding et al. (2007) [3]	1.348 ± 0.05	± 0.659
Harichandan et al. (2012) [3]	1.32 ± 0.05	± 0.602

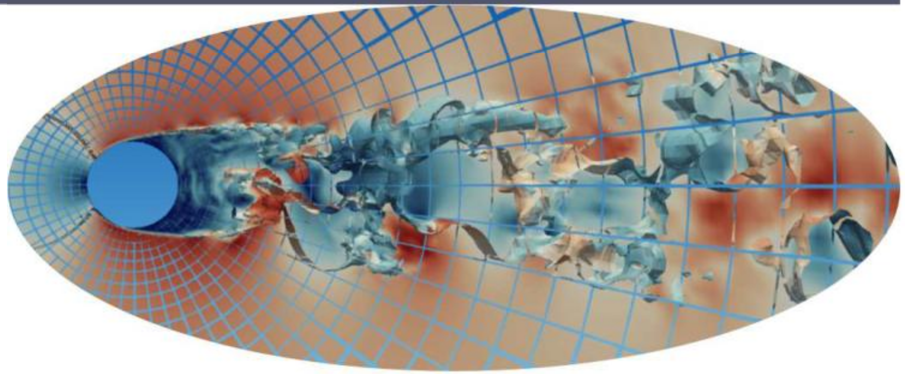
[3] AB Harichandan and A Roy. Numerical investigation of flow past single and tandem cylindrical bodies in the vicinity of a plane wall. Journal of Fluids and Structures, 33:19–43, 2012.

3.3. Cylinder $Re = 3900$

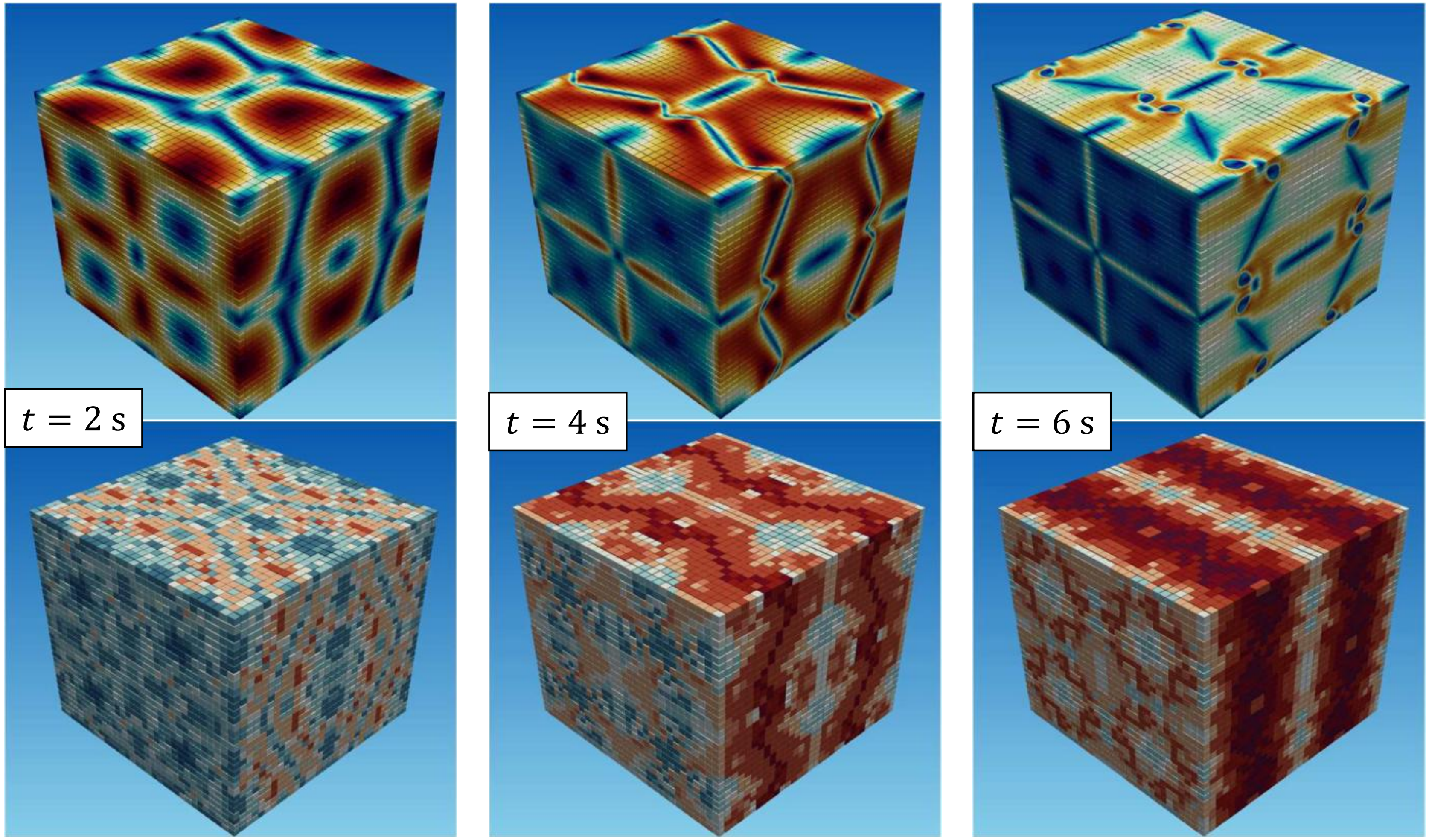








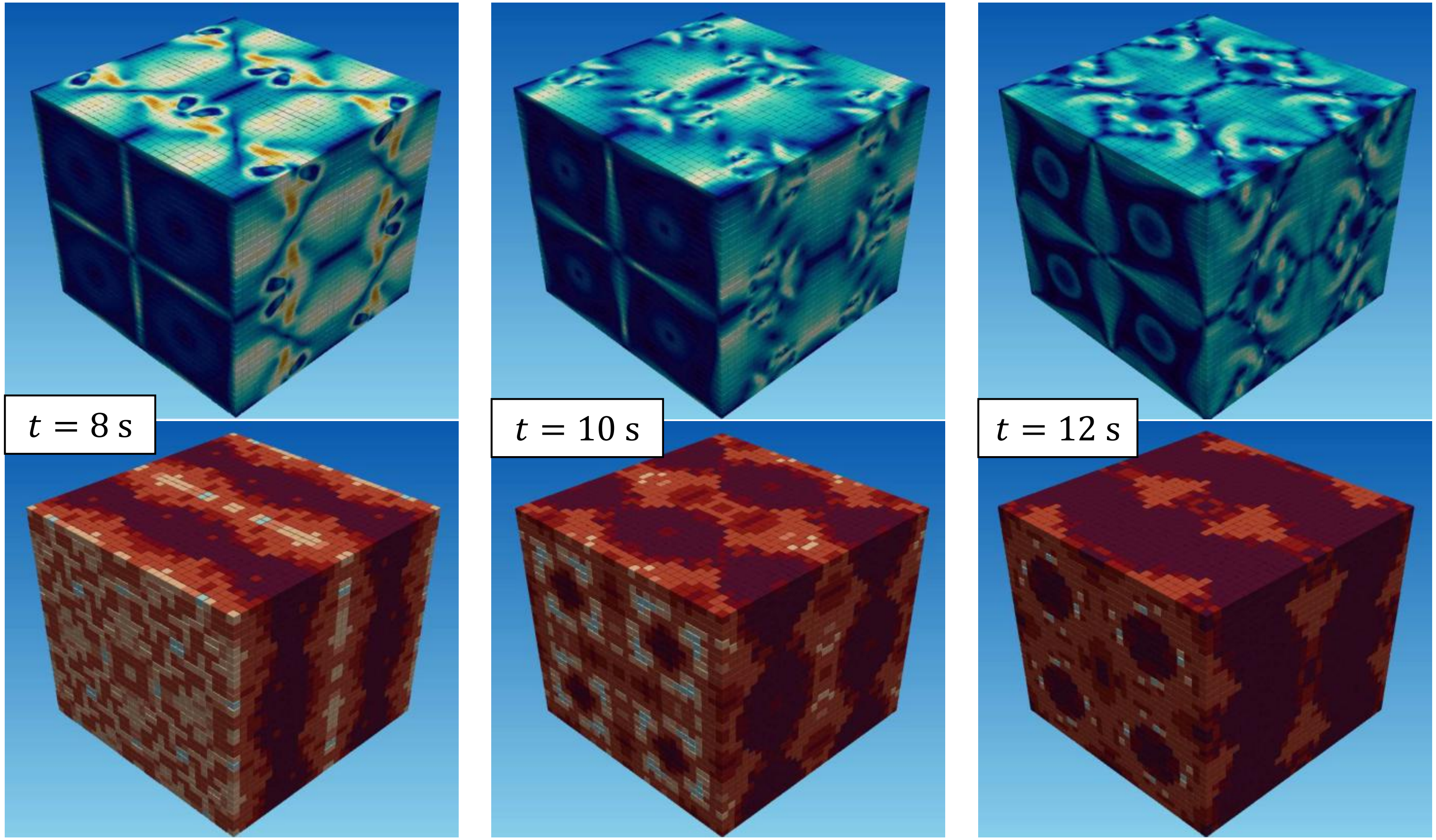
3.4. Taylor Green Vortex



Velocity magnitude

p_{av}

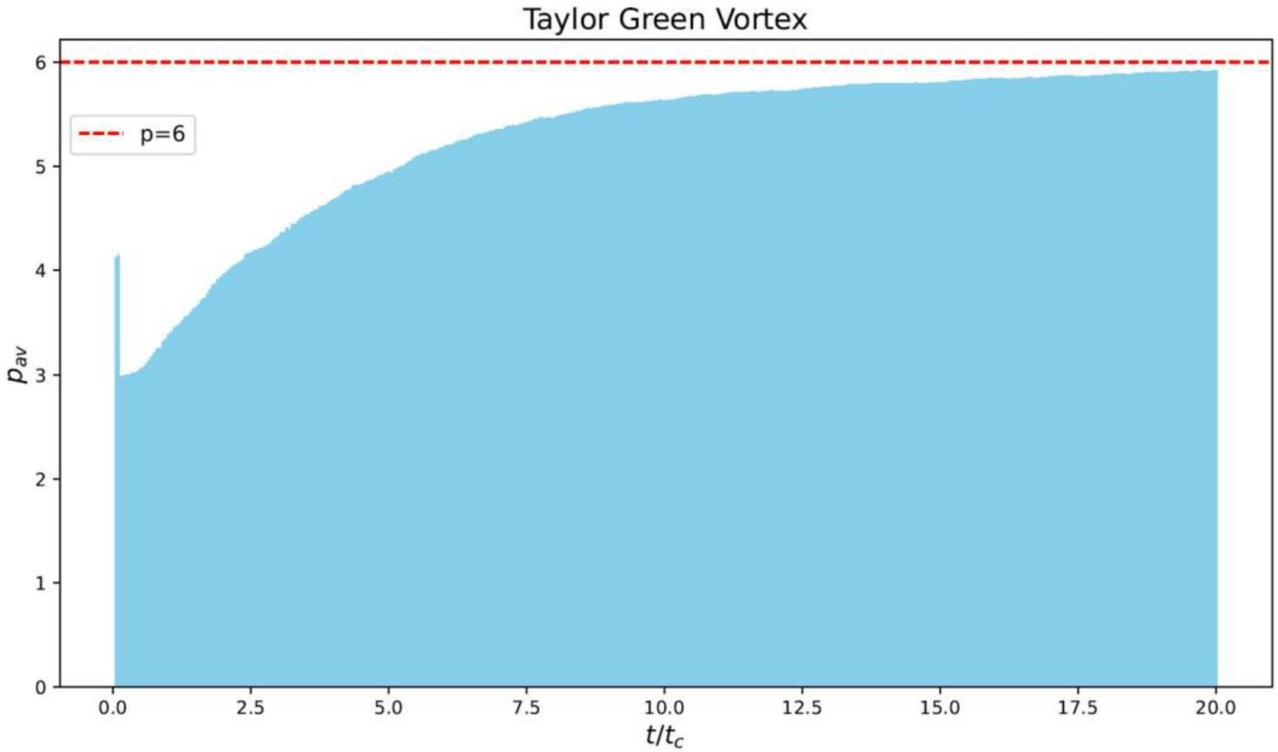
3.4. Taylor Green Vortex

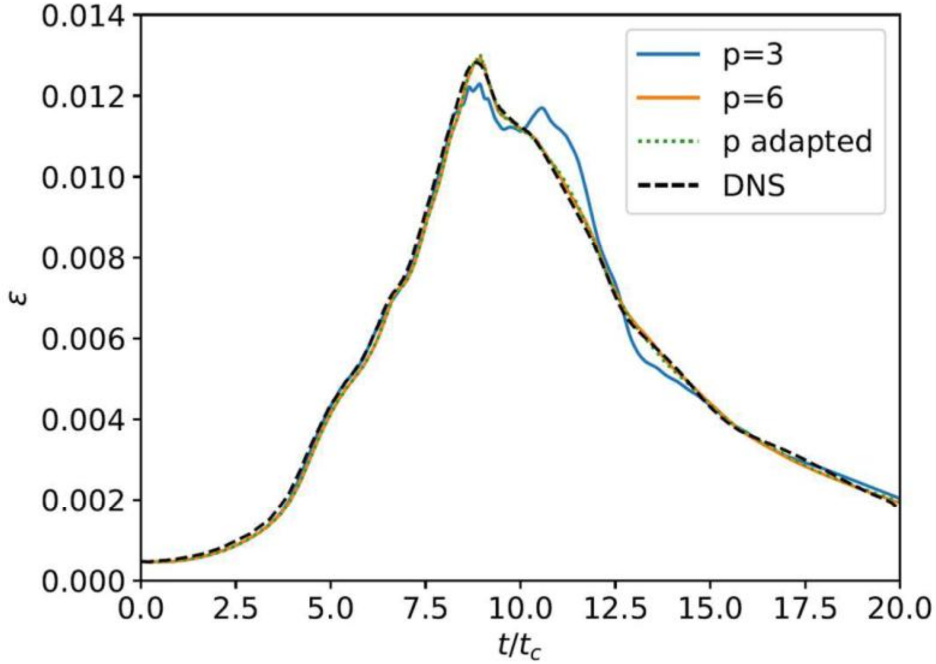


Velocity magnitude

p_{av}

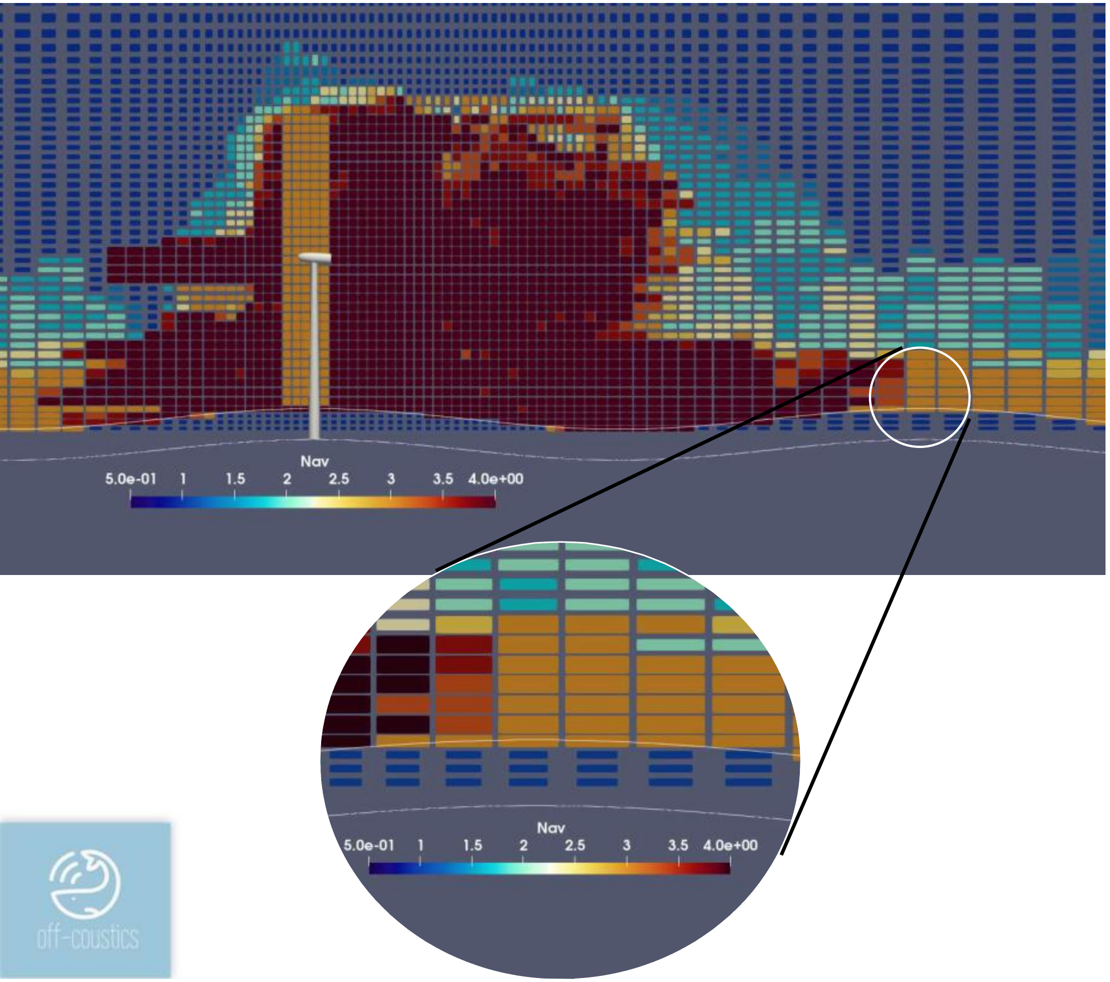
3.4. Taylor Green Vortex

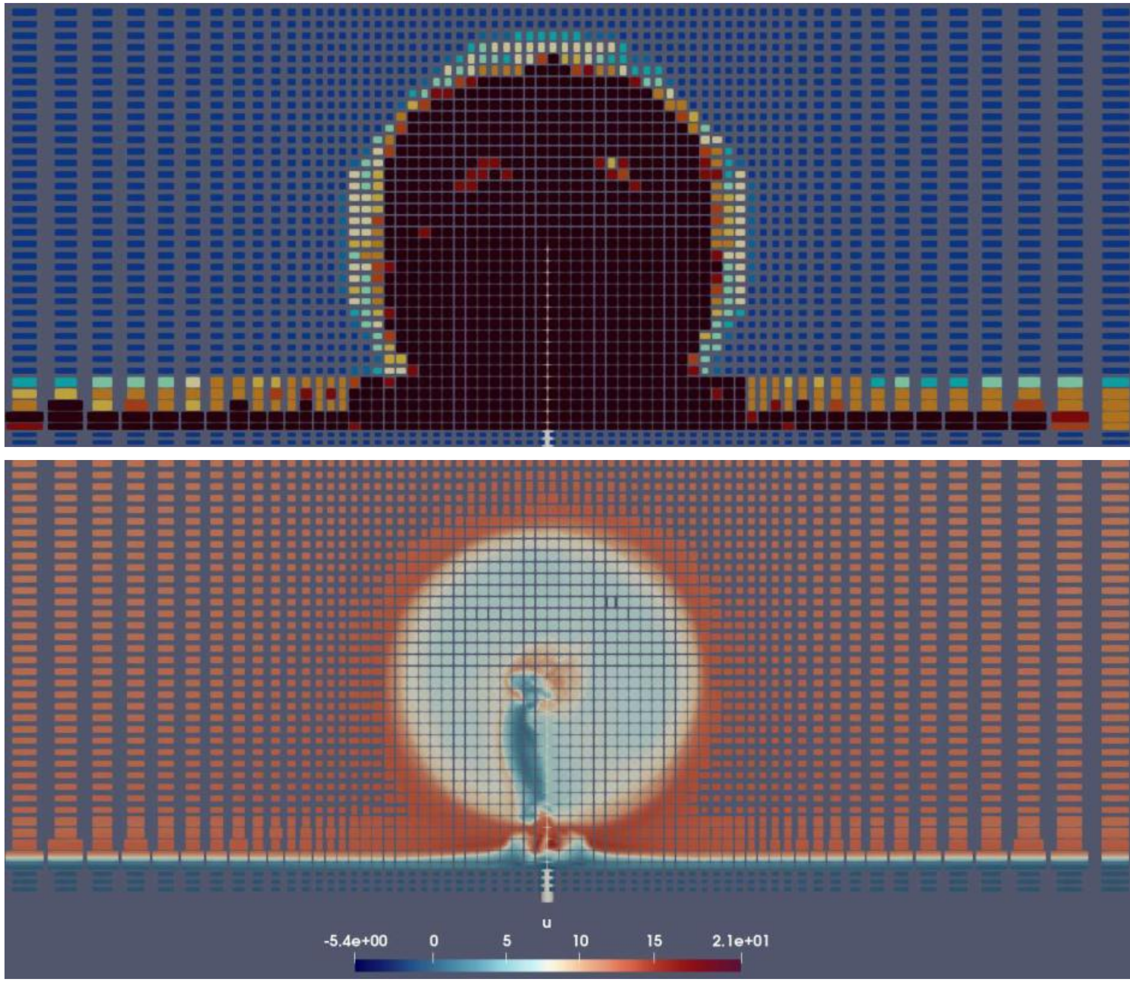




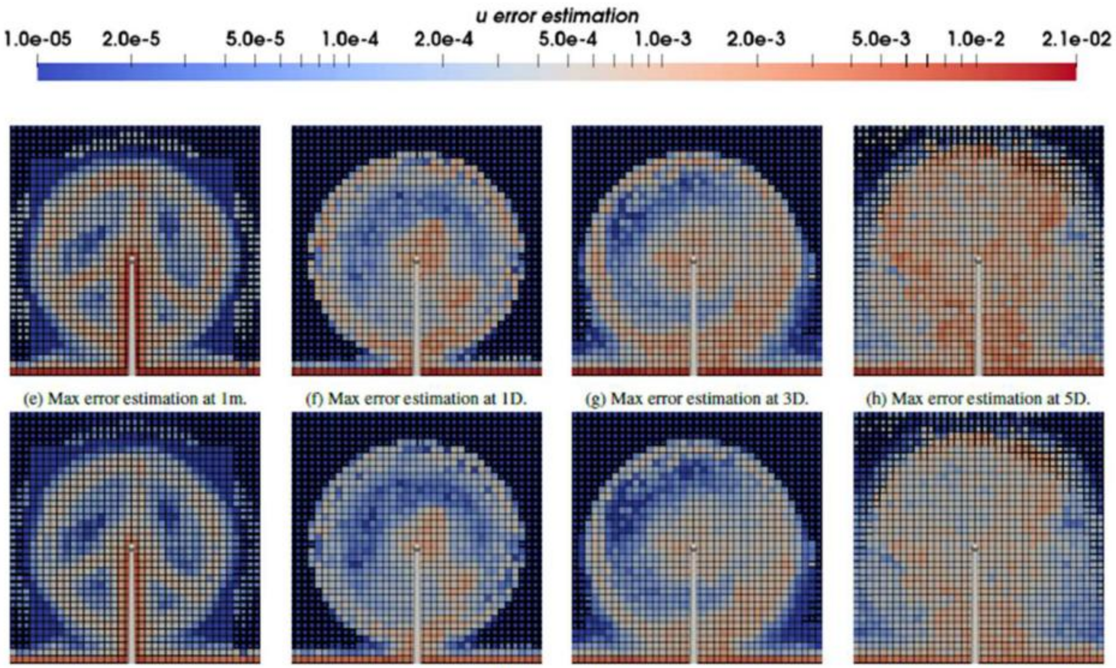
	$p = 6$	$p_{adapted}$
Computational cost (h)	102	41

3.5. Offshore Wind Turbine DTU 10MW



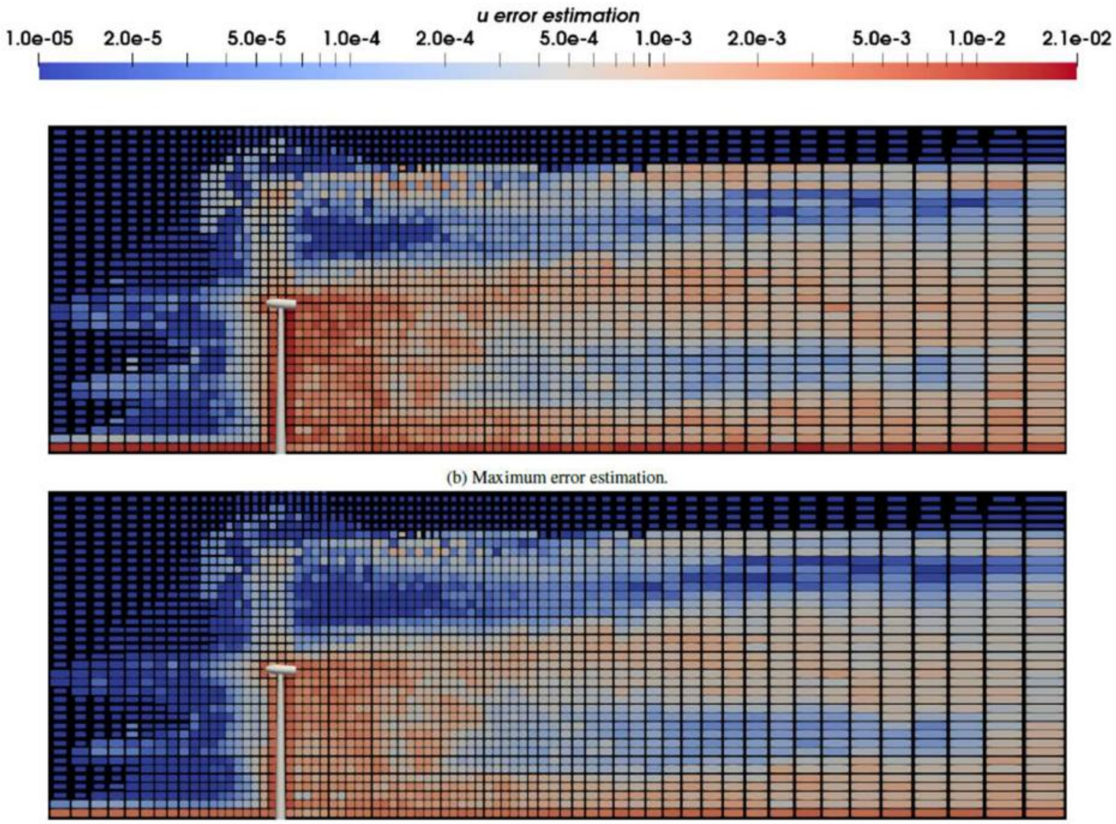


3.5. Offshore Wind Turbine DTU 10MW



(e) Max error estimation at 1m. (f) Max error estimation at 1D. (g) Max error estimation at 3D. (h) Max error estimation at 5D.

(i) Avg error estimation at 1m. (j) Avg error estimation at 1D. (k) Avg error estimation at 3D. (l) Avg error estimation at 5D.



(b) Maximum error estimation.

(c) Average error estimation.

The error is higher:

- Near the **Actuator Line**.
- On the **no-slip wall boundary condition**.
- Inside the **Immersed Boundaries (tower and nacelle)**.
- Inside the **wake.**

Ongoing Work

4. Ongoing work

- RL p-adaptation for moving **Immersed Boundaries**.
- RL p-adaptation for **acoustics**.
- **Comparison** with different state-of-the-art p-adaptation algorithms.
- Dynamic **load balancing** to improve MPI parallelization for evolving meshes.

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Full Length Article

A reinforcement learning strategy for p-adaptation in high order solvers

David Huergo [a], Gonzalo Rubio [a b], Esteban Ferrer [a b]

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Reinforcement learning for anisotropic p-adaptation and error estimation in high-order solvers

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Conclusions

5. Conclusions

- RL for **p-adaptation** leads to a general approach to **improve the accuracy** and **reduce the computational time** of CFD simulations.

- The proposed methodology can be potentially applied for **any PDE and computational mesh**.

- The RL agent **has to be trained only once for 1D** cases, but provides an **accurate adaptation in 3D turbulent simulations**.

- The proposed methodology provides a cheap **estimation of the spatial error in each element** of the computational mesh.

Reinforcement Learning can be applied to **minimize manual intervention**, to **improve the accuracy** of numerical simulations and to **speed-up** a CFD code.

Thank you!

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