



Estimation of equivalent non-uniform momentum source distribution for propeller modelling with Deep Learning model

Jaume Luis-Gómez, Alejandro González, Sergio Chiva, Raúl Martínez-Cuenca



6th FOAM@Iberia Meeting
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Grupo de Fluidos Multifásicos
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Universitat Jaume I

Outline

1. Motivation

2. State of the art: homogeneous momentum source

3. Methods: non-homogeneous momentum source

4. Results

5. Discussion

1. Motivation

Low computational cost simulations of rotating structures (propellers, wind turbines,...)

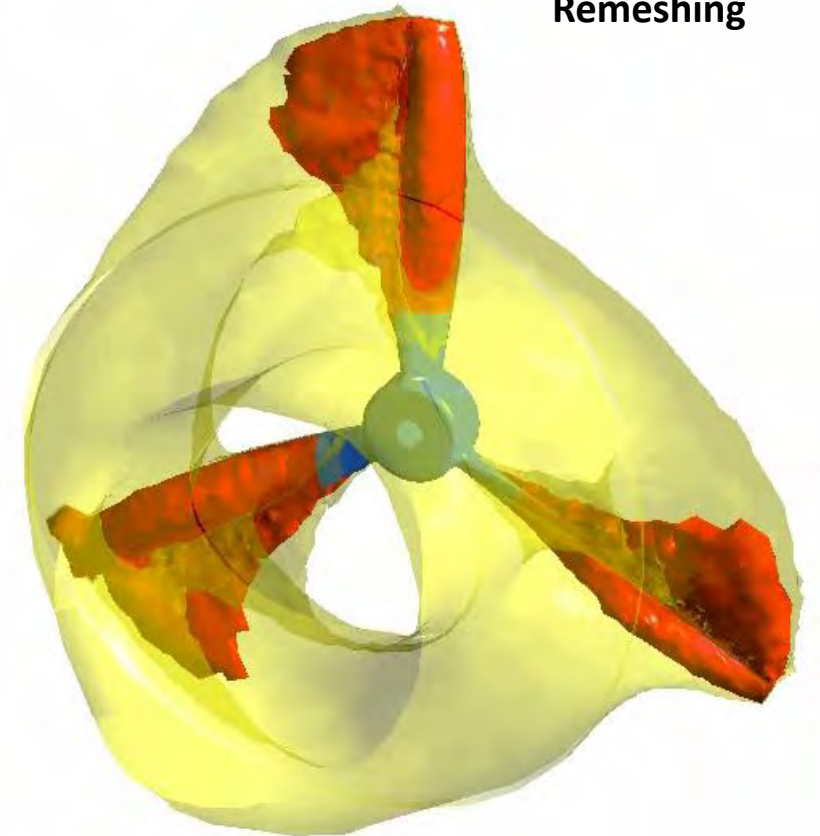


Focus on effects **far from the rotor**

Good enough **velocity field**

Good enough **turbulence field**

2 million cells
1 millisecond
Remeshing



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Low computational cost simulations of rotating structures (propellers, wind turbines,...)

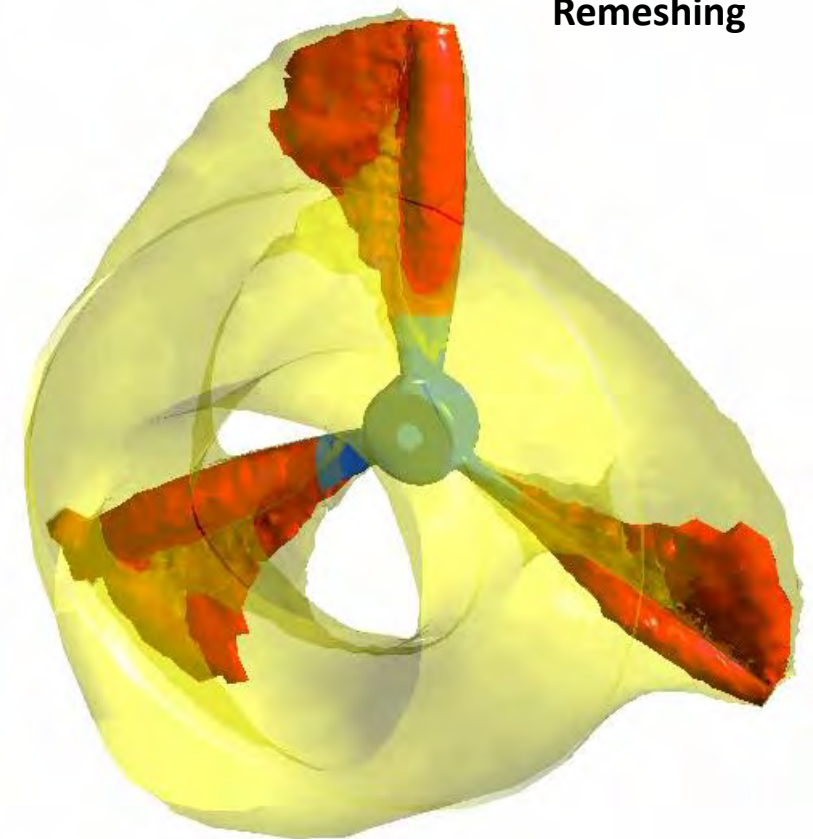


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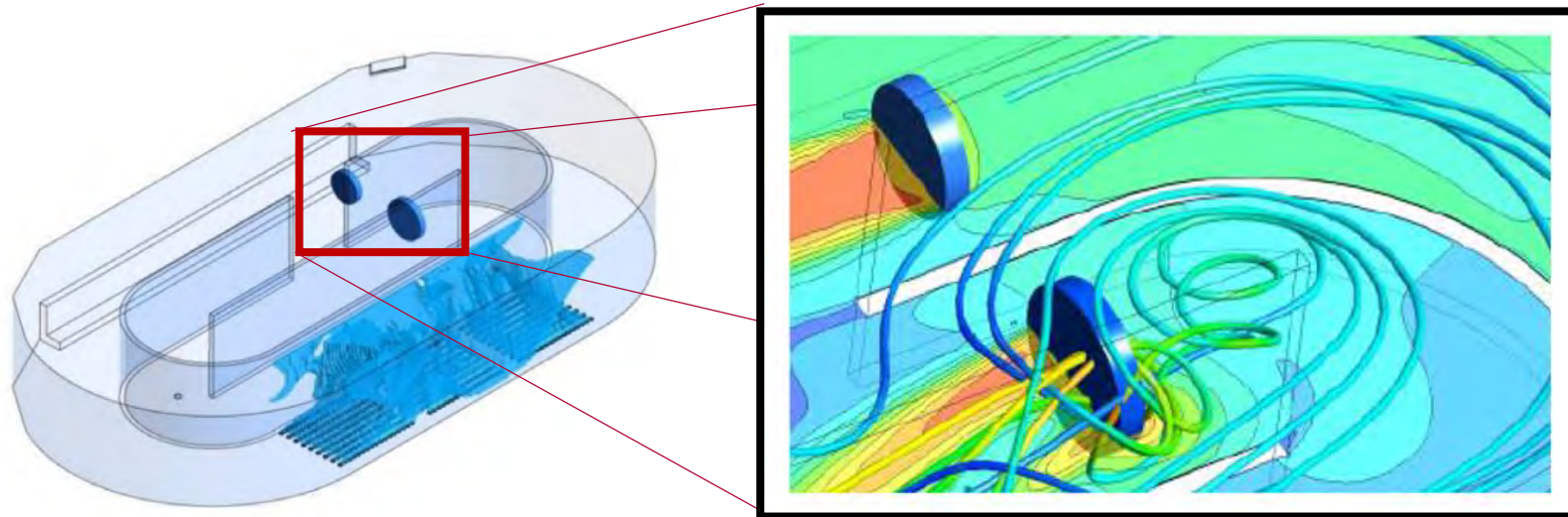
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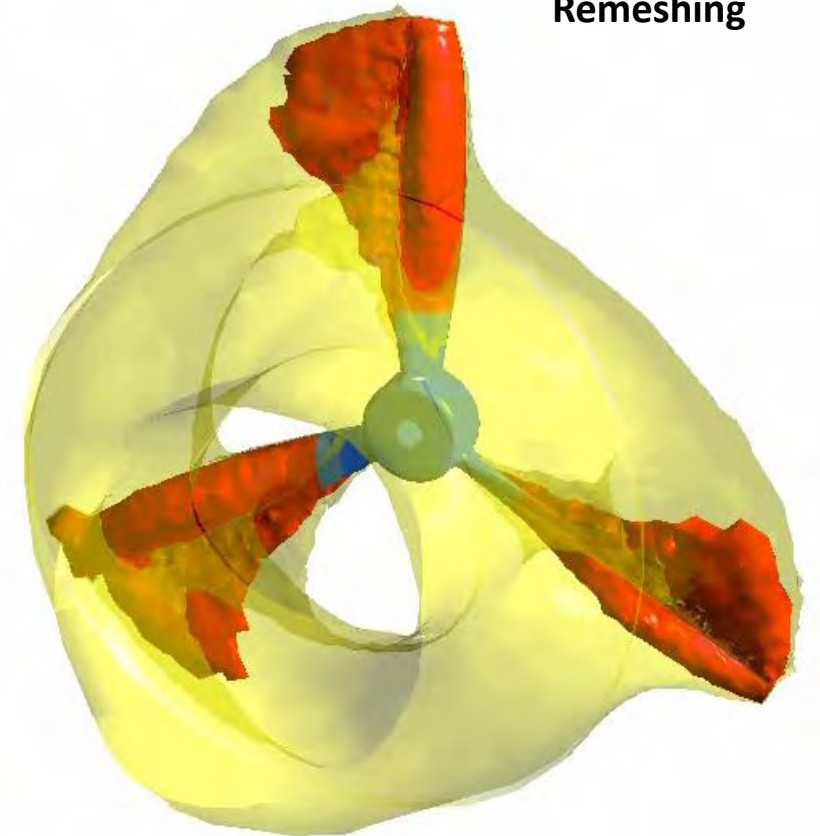
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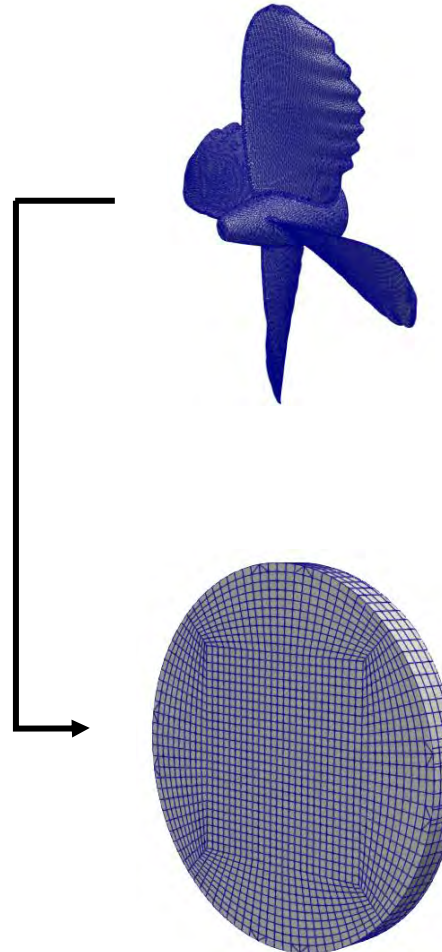
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1. Motivation

Low computational cost simulations of rotating structures (propellers, wind turbines,...)

- **Dynamic Meshing**
Complete blades' geometry
Rotation of the body: remeshing
- **Sliding Mesh**
Internal region rotates while external is fixed
Algorithm to couple both regions
- **Multiple Reference Frame**
Two regions, both stationary, one has non-inertial reference frame
Algorithm to couple regions
- **Momentum Source Term**
No explicit geometry
Same reference



Resolving interaction wall-fluid

Computational cost

Adding equivalent momentum source

$$\frac{DU_i}{Dt} = -\frac{\partial p}{\partial X_i} + \frac{\partial}{\partial X_i} \left[(\mu + \mu_t) \left(\frac{\partial U_i}{\partial X_j} + \frac{\partial U_j}{\partial X_i} \right) \right] + M_i$$

Low accuracy

Equivalent momentum source term?

2. Methodology: momentum source approach

Mechanistic approaches:

- Mainly for axial component, based on **simplistic assumptions**
- **Lack of experimental information** for validation
- **Specifications available** (torque, rotational regime, thrust, etc.)

Machine learning based:

- **Three components** of momentum source
- Assumes **uniform momentum** source components
- Needs for **new specifications** of commercial rotors

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On the use of deep learning and computational fluid dynamics for the estimation of uniform momentum source components of propellers

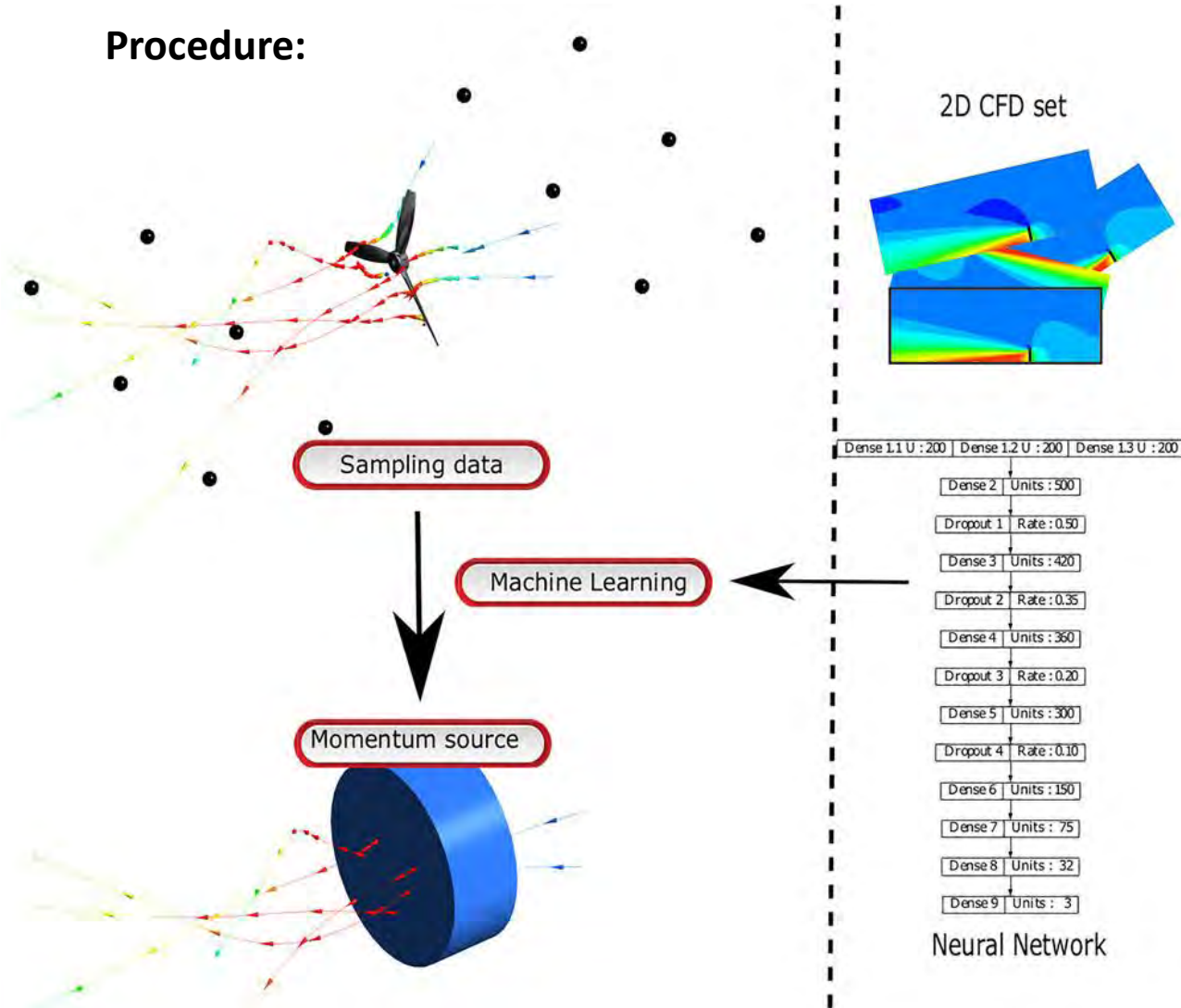
Raül Martínez-Cuenca ^{1,3} ✉ · Jaume Luis-Gómez ¹ · Sergio Iserte ² · Sergio Chiva ¹

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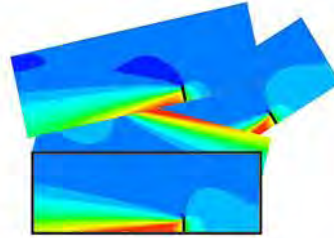


2. Methodology: momentum source approach

Procedure:



2D CFD set



← 500 CFD simulations with

$$\vec{M} = M_z \vec{u}_z + M_r \vec{u}_r + M_\theta \vec{u}_\theta$$

Dense 1.1 U : 200 | Dense 1.2 U : 200 | Dense 1.3 U : 200

Dense 2 | Units : 500

Dropout 1 | Rate : 0.50

Dense 3 | Units : 420

Dropout 2 | Rate : 0.35

Dense 4 | Units : 360

Dropout 3 | Rate : 0.20

Dense 5 | Units : 300

Dropout 4 | Rate : 0.10

Dense 6 | Units : 150

Dense 7 | Units : 75

Dense 8 | Units : 32

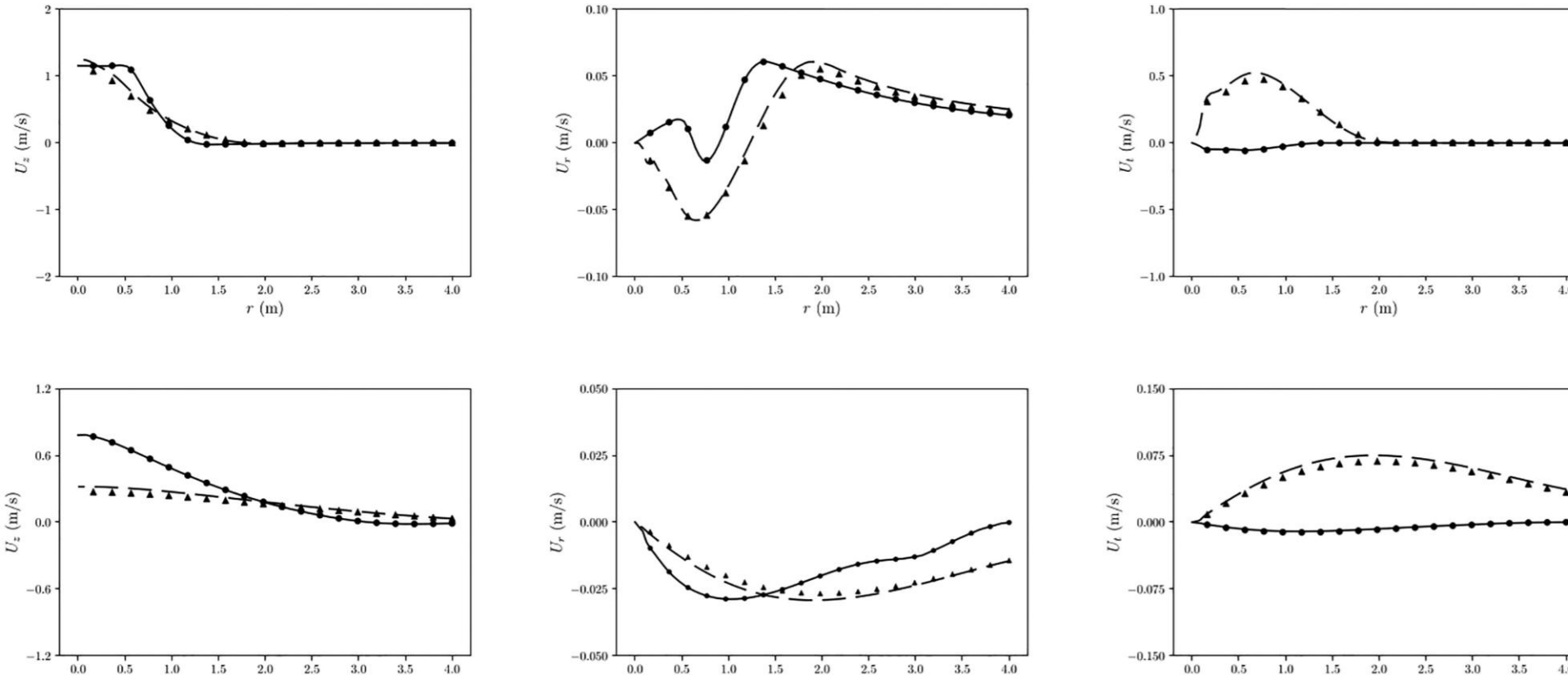
Dense 9 | Units : 3

Neural Network



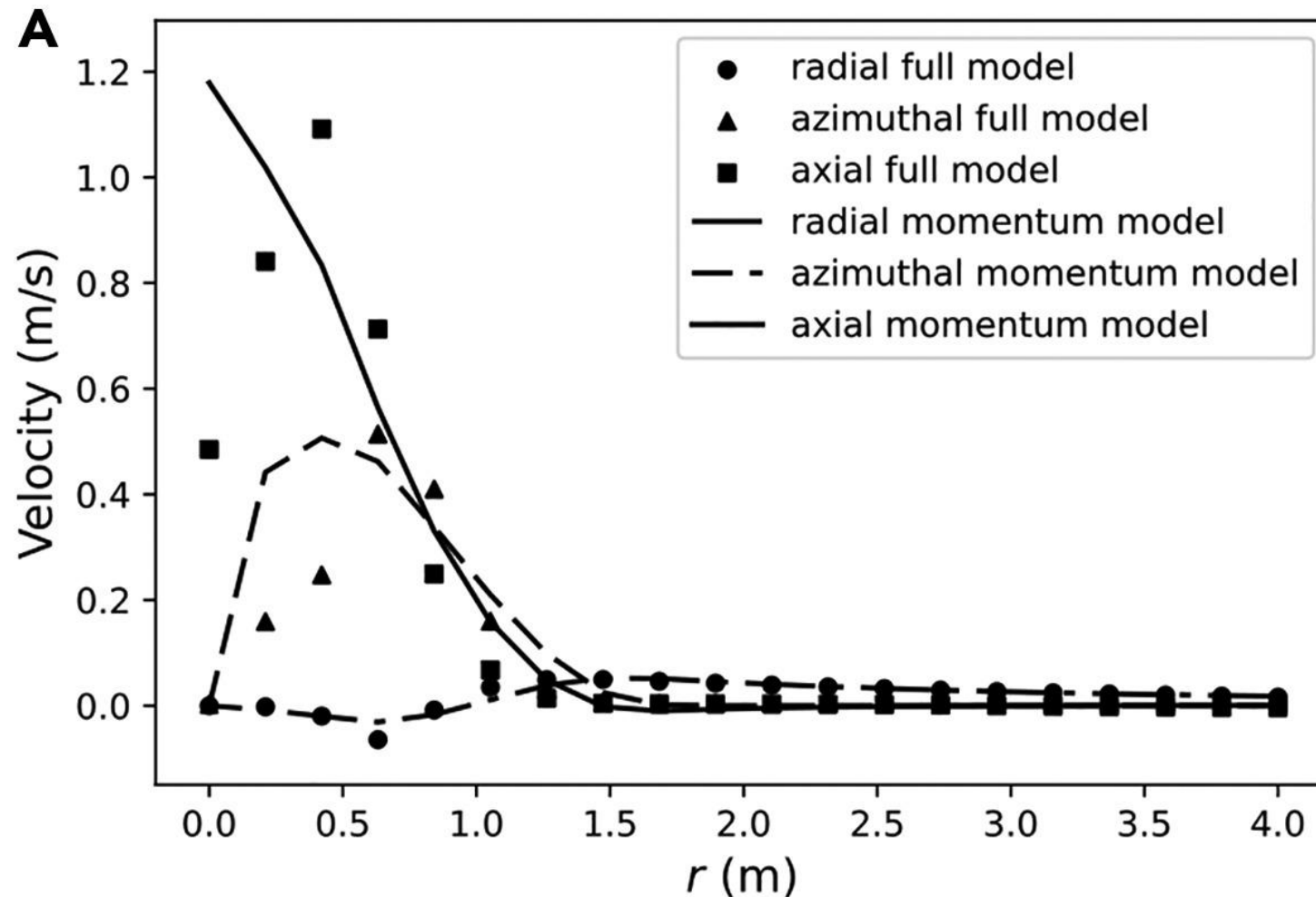
2. Methodology: momentum source approach

Results: simulations with homogeneous momentum source components



2. Methodology: momentum source approach

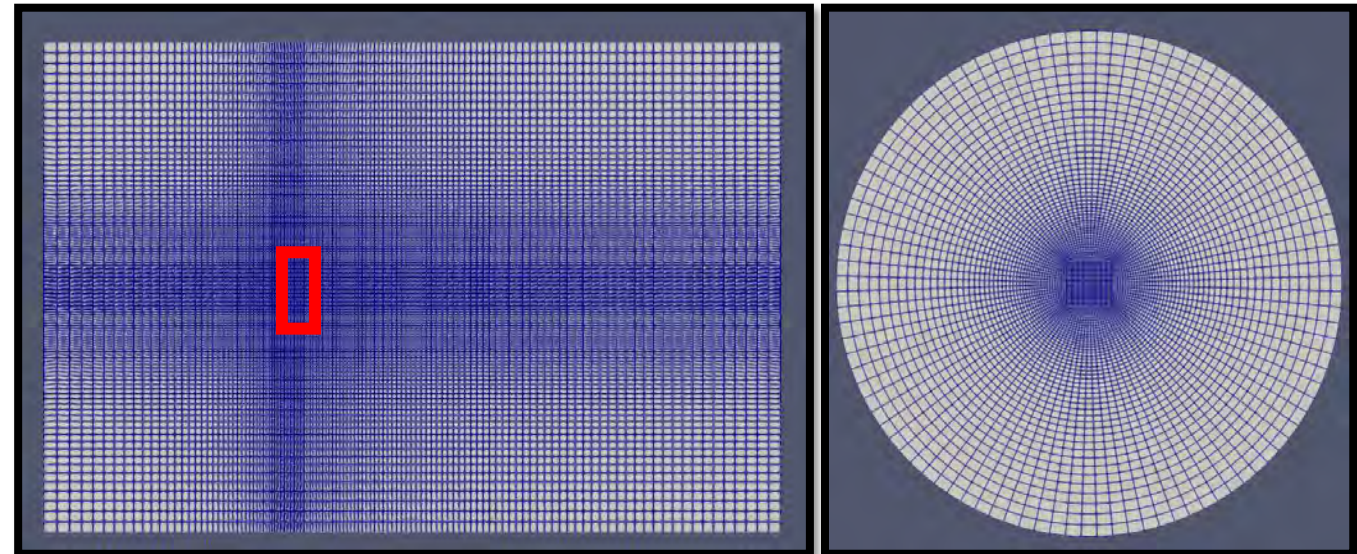
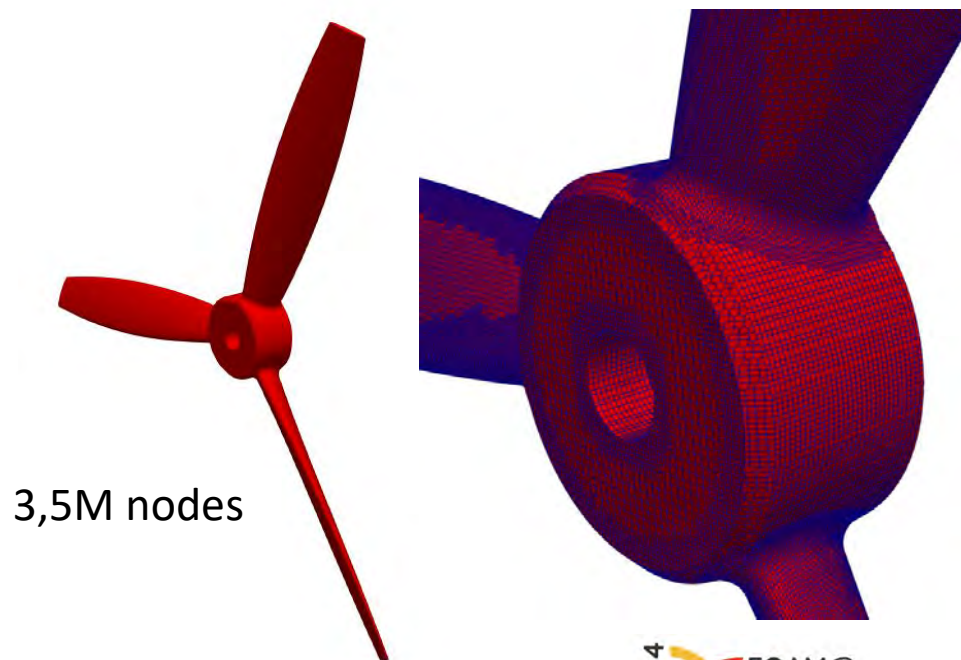
Results: inference for a real propeller



3. Methods: non-homogeneous momentum source

CFD simulation: *Sliding mesh VS nonm-homogeneous momentum source*

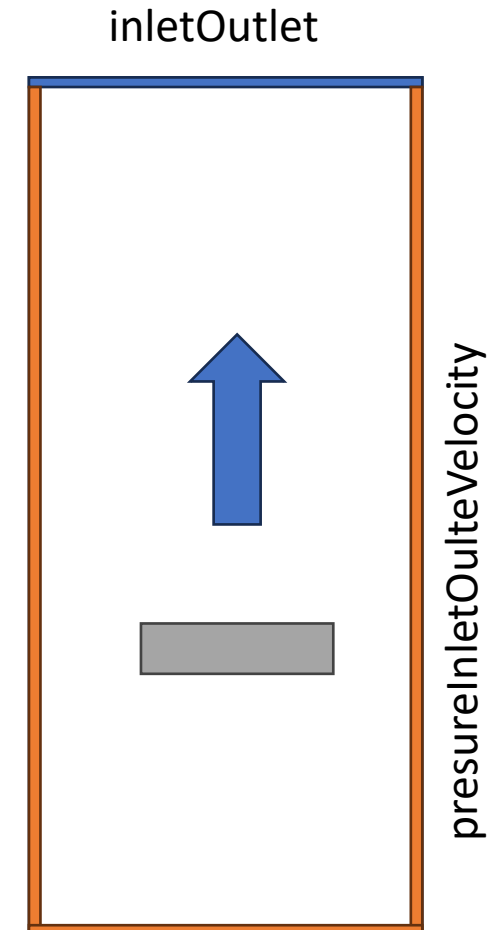
- Openfoam mesher (SnappyHexMex)
- pimpleFoam (35 seconds, time step $2 \cdot 10^{-5}s$)
- SST turbulence model



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CFD simulation: *Sliding mesh VS nonm-homogeneous momentum source*

- Openfoam mesher (SnappyHexMex)
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- SST turbulence model
- Boundary conditions
- Velocity fields initialized at 0,1 m/s axial speed



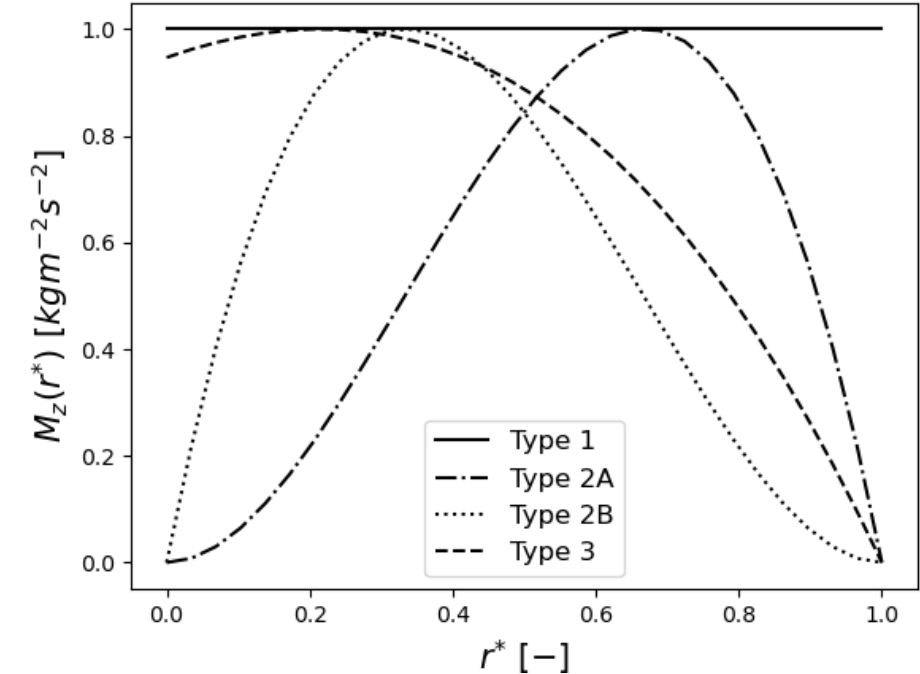
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- SST turbulence model
- Boundary conditions
- Velocity fields initialized at 0,1 m/s axial speed
- Non-homogeneous axial component,
rest of components homogeneous

$$M_z \left(\frac{r}{R} \right) = S_z K(a_1, a_2, a_3, b_1, b_2) \underbrace{\left[a_1 + a_2 \left(a_3 + \frac{r}{R} \right)^2 \right]}_{\text{Parabolic}} \cdot \underbrace{\left(b_1 + b_2 \frac{r}{R} \right)}_{\text{Asymmetry}}$$

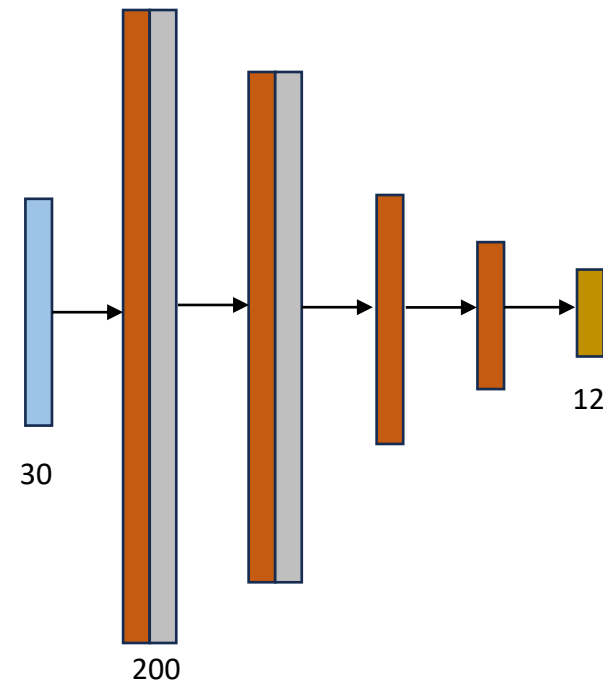
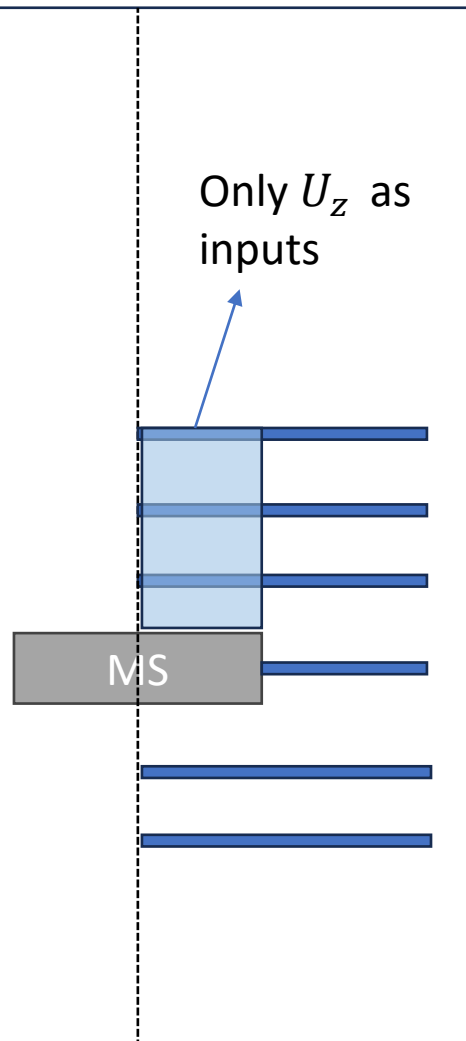
Modulus
Normalization
Asymmetry







3. Methods: non-homogeneous momentum source

Neural network 1: classify constant/parabolic

$$M_z \left(\frac{r}{R} \right) = S_z K(a_1, a_2, a_3, b_1, b_2) \left[a_1 + a_2 \left(a_3 + \frac{r}{R} \right)^2 \right] \cdot \left(b_1 + b_2 \frac{r}{R} \right)$$



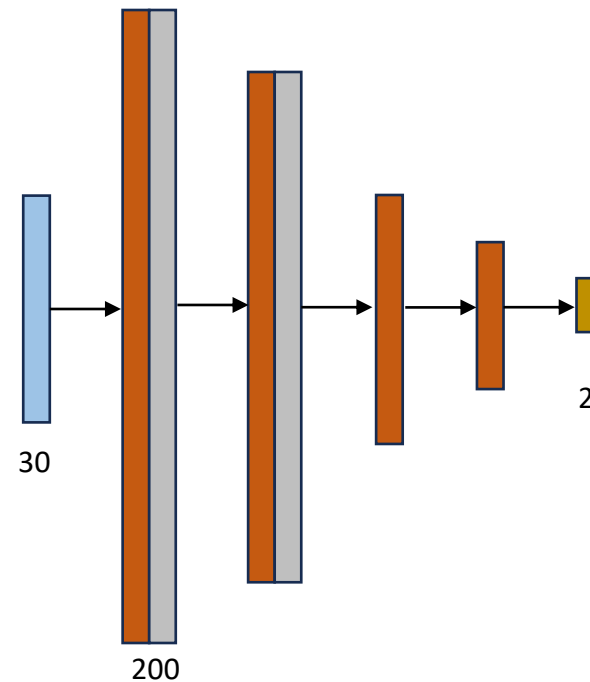
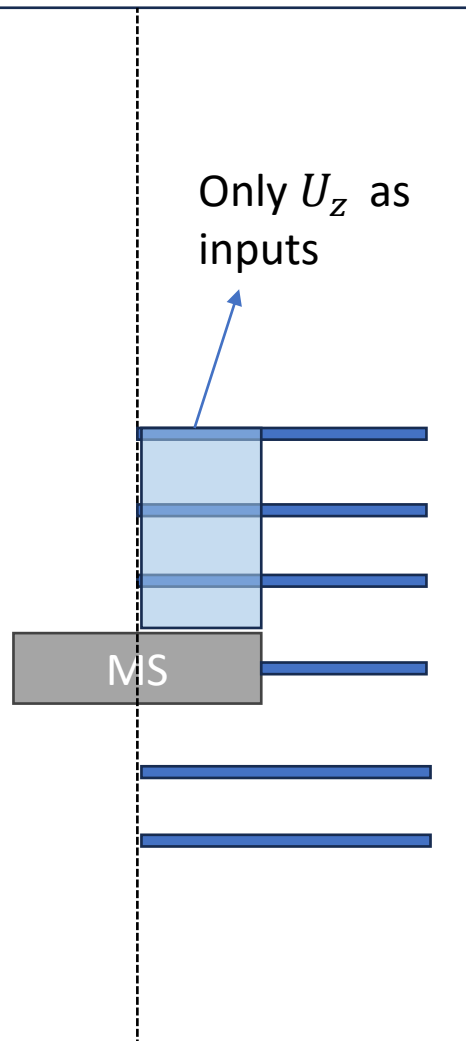
-  Velocity profile inputs
-  Fully connected layer
-  Dropout layer
-  Classification layer for radial distribution coefficients





Hyperbolic tangent used as activation function for every layer except last one (sigmoid)

3. Methods: non-homogeneous momentum source

Neural network 2: inference of assymetry (only if parabolic)

$$M_z \left(\frac{r}{R} \right) = S_z K(a_1, a_2, a_3, b_1, b_2) \left[a_1 + a_2 \left(a_3 + \frac{r}{R} \right)^2 \right] \cdot \left(b_1 + b_2 \frac{r}{R} \right)$$



-  Velocity profile inputs
-  Fully connected layer
-  Dropout layer
-  B1 and B2 values

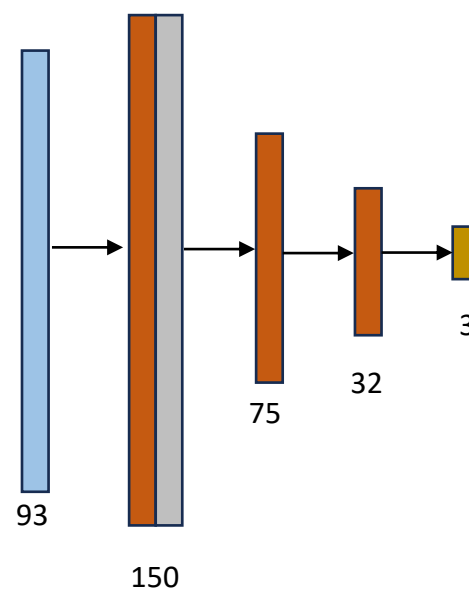
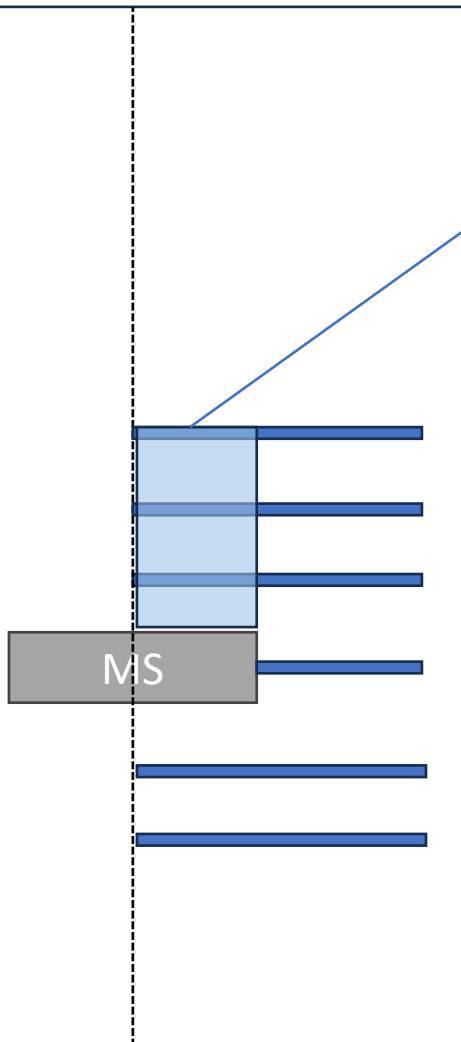
Exponential Linear Unit (ELU) used as activation function with alpha parameter = 0,3

3. Methods: non-homogeneous momentum source

Neural network 3: momentum source components

$$M_z \left(\frac{r}{R} \right) = S_z K(a_1, a_2, a_3, b_1, b_2) \left[a_1 + a_2 \left(a_3 + \frac{r}{R} \right)^2 \right] \cdot \left(b_1 + b_2 \frac{r}{R} \right) \text{ and } M_r, M_\theta$$

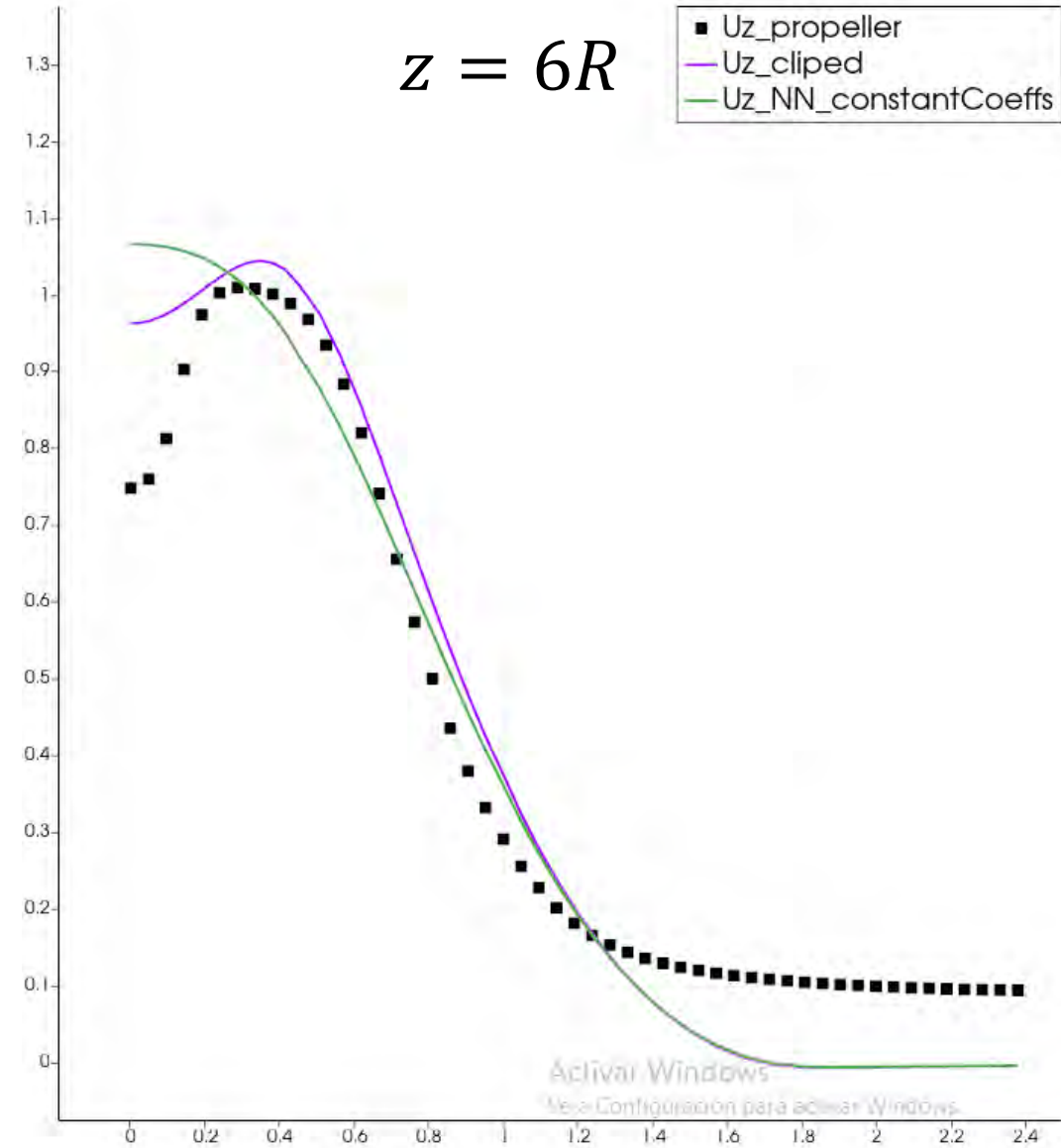
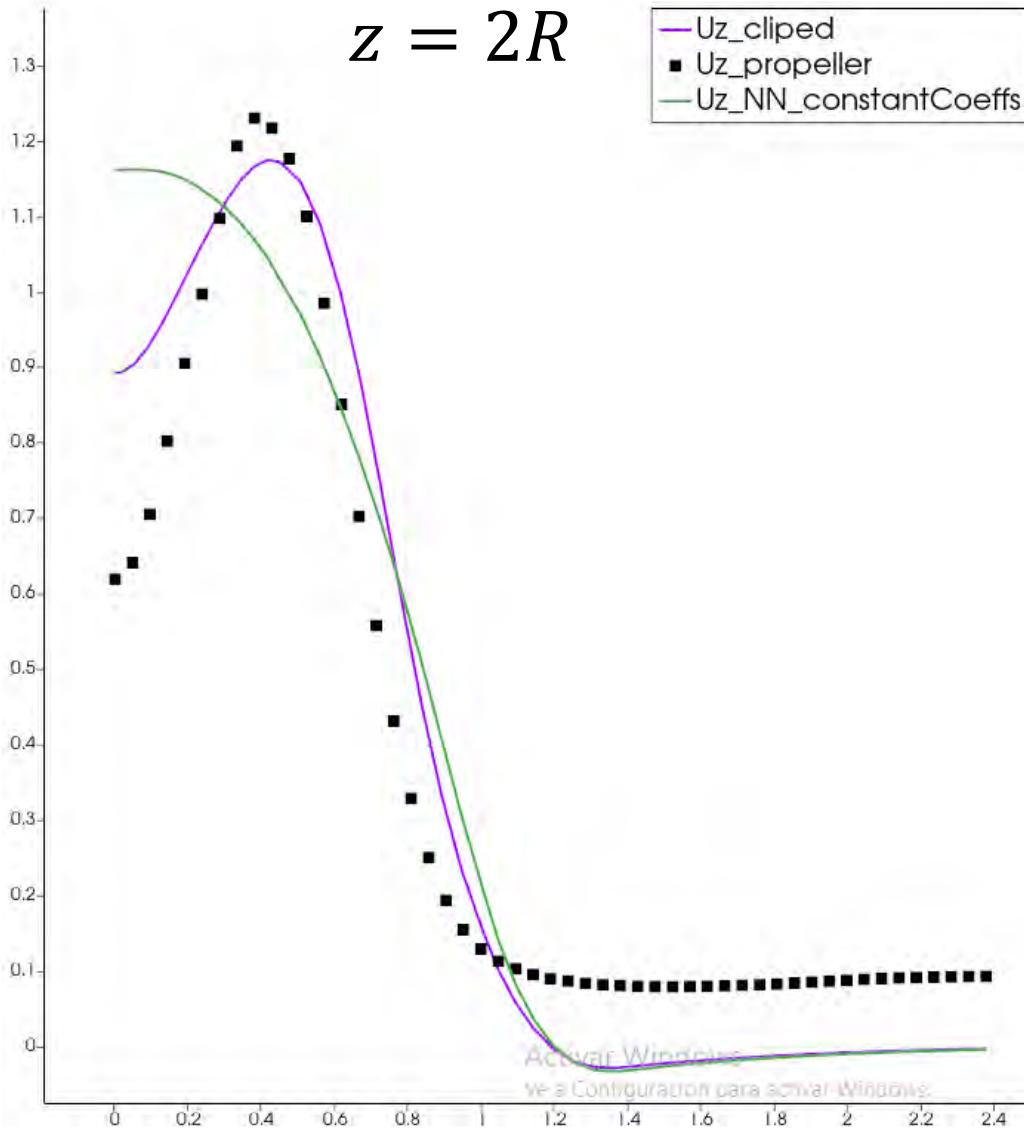
All velocity components (90 points) + maximum value of U_z at each row



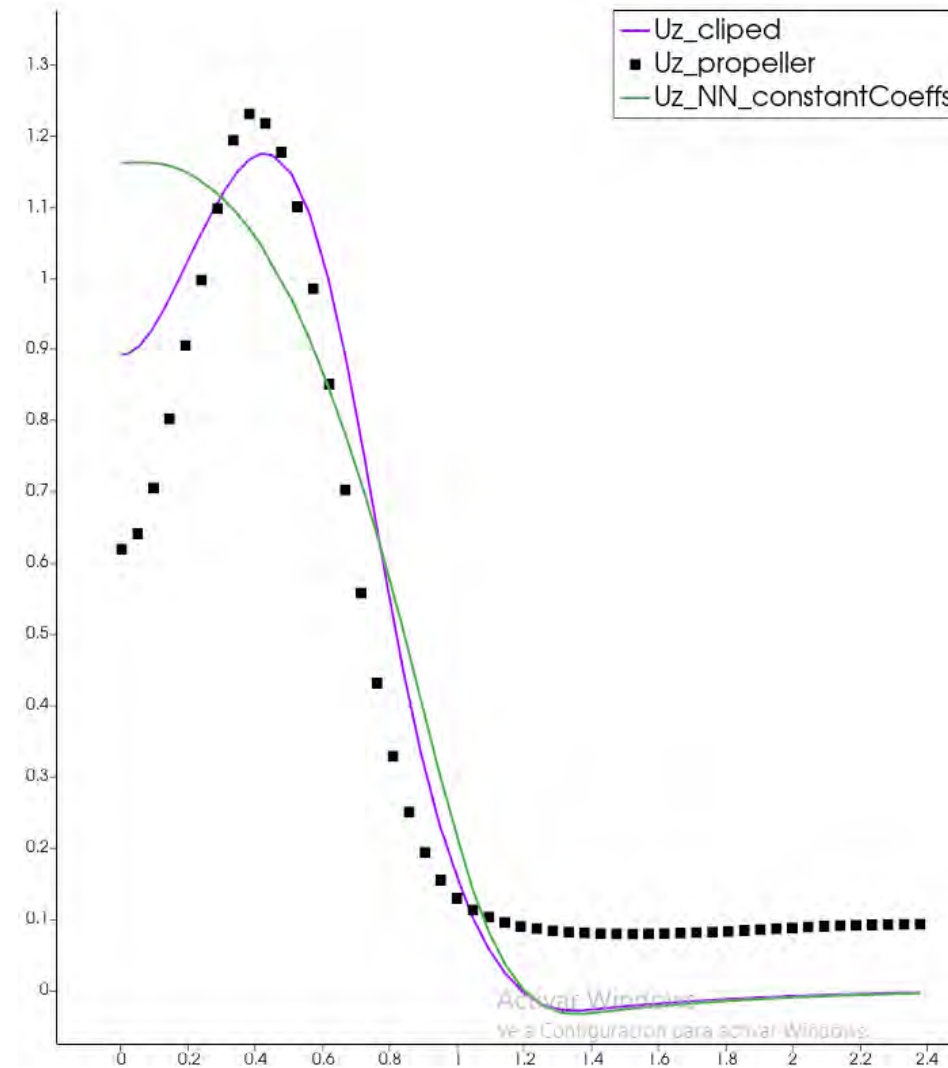
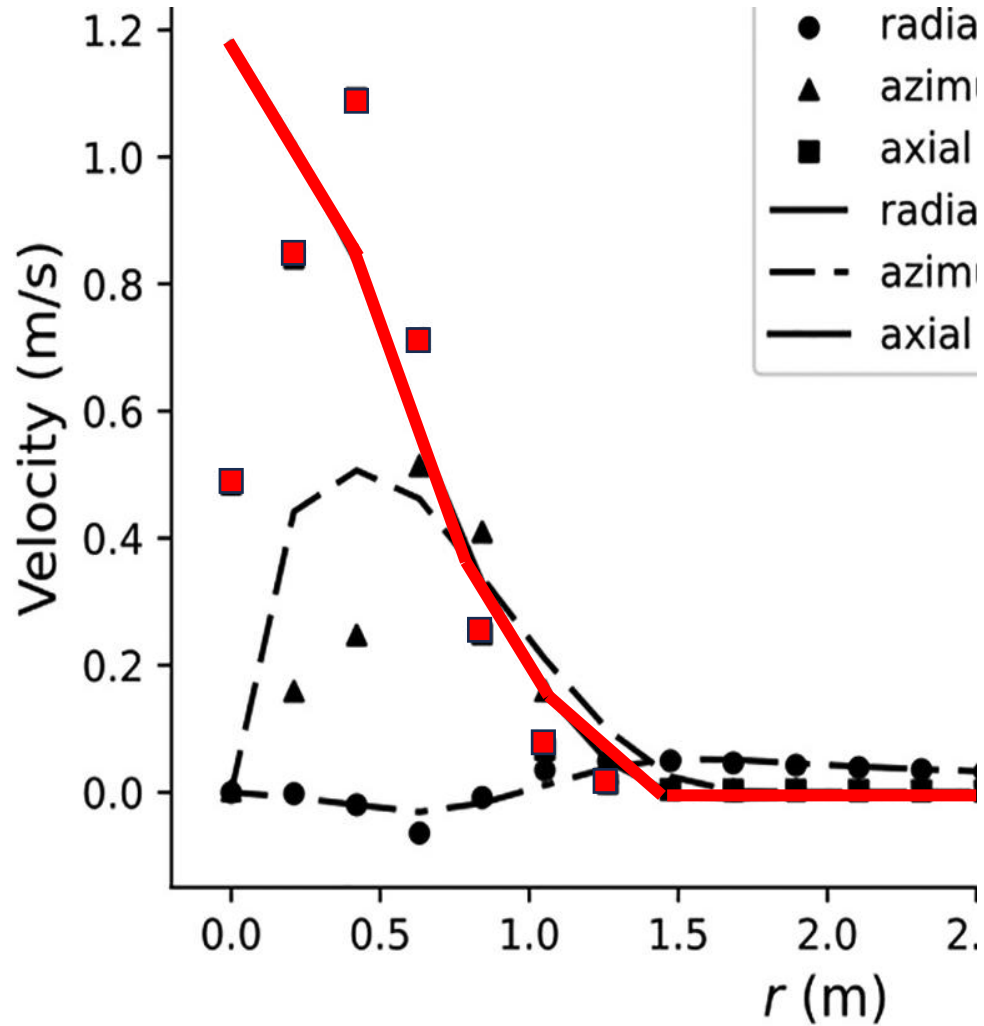
- Velocity profile inputs
- Fully connected layer
- Dropout layer
- Momentum term values

Exponential Linear Unit (ELU)
alpha parameter = 0,3

4. Results



4. Results



5. Discussion

Conclusions

- Improved performance with just axial non-homogeneous component
- Reduction of a factor 6 in number of nodes
- Steady state

Future work

- Extend the non-homogeneity to all the components
- Work with simpler representations (Hermite, Zernike, etc)
- Transient effects



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