Dynamic Surrogate Modelling Enhanced by Artificial Intelligence and Machine Learning Techniques in Aerodynamics and Aeroacoustics

Public Workshop: Novel Tools for Novel Aircraft

Bristol, 06 February 2025

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(Roma Tre University)

eVTOL mUlti-fideliTy hybrid desIgn and Optimization for low Noise and high aerodynamic performance - Grant Agreement 101138209

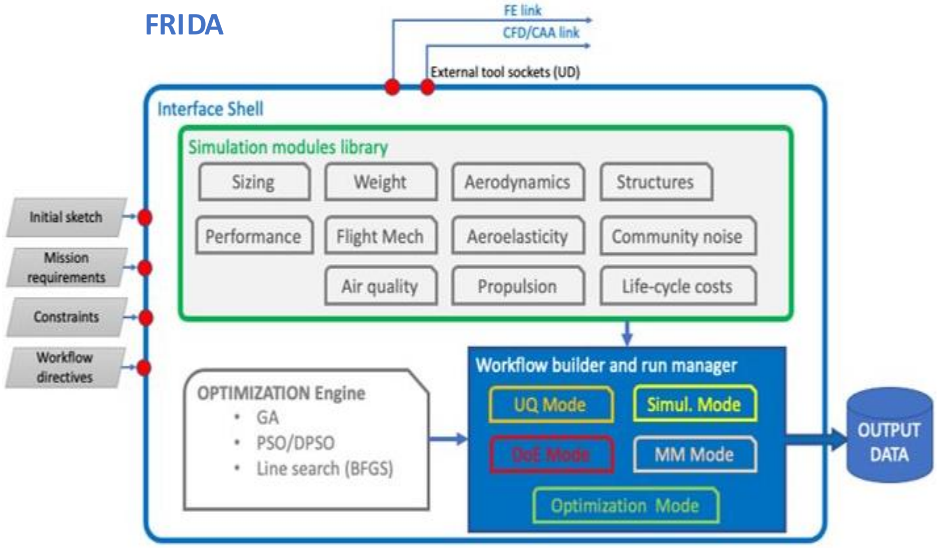
Context and motivations

WP2: Integration of design/optimization tools, experimental testing and flow/noise control

Objective:

include aerodynamics and aeroacoustics characterization of (installed) propellers in Multidisciplinary Conceptual Design Optimization (MCDO)

FRIDA



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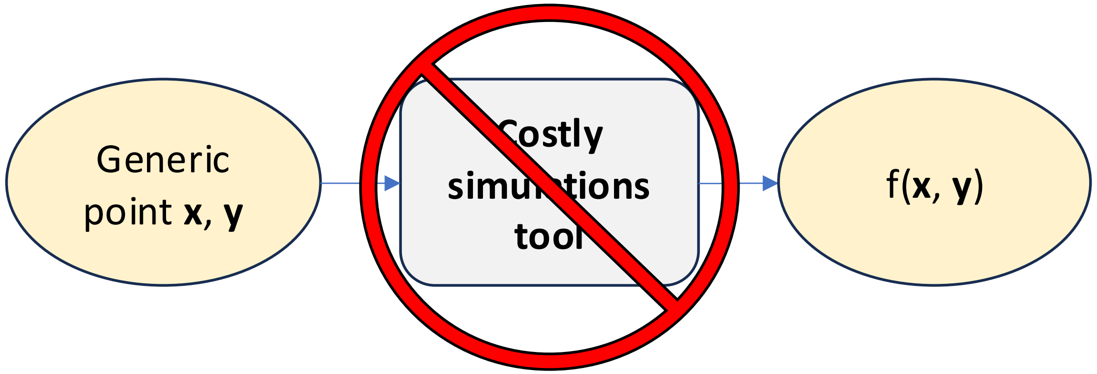
Influence of aeroacoustics on computing time	
~~*Semiempirical models*~~	~~50000 seconds~~
CAA	360000000 seconds
Surrogate Models	50400 seconds

Issues:

- ➢ Lack of experimental data and semi-empirical models available for disruptive layouts
- ➢ Simulations computationally expensive

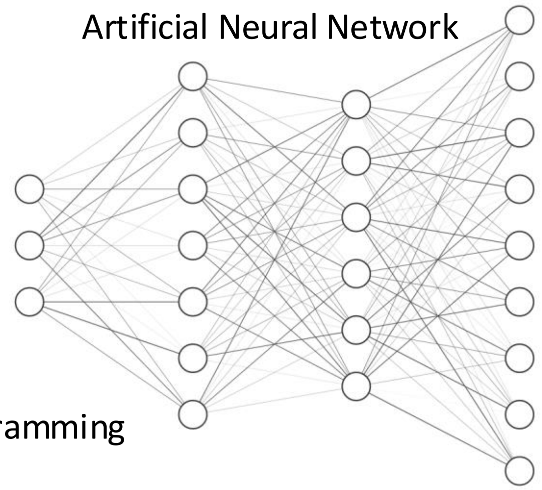


Context and motivations

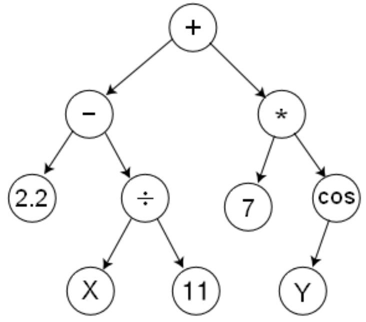
WP2: Integration of design/optimization tools, experimental testing and flow/noise control

Solution:

- Surrogate-Models (SM) as alternative solution to high-fidelity simulations can be used in MCDO frameworks
- Exploit AI and Machine Learning techniques to reduce computational time and improve SM reliability

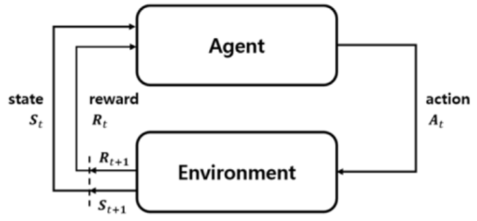


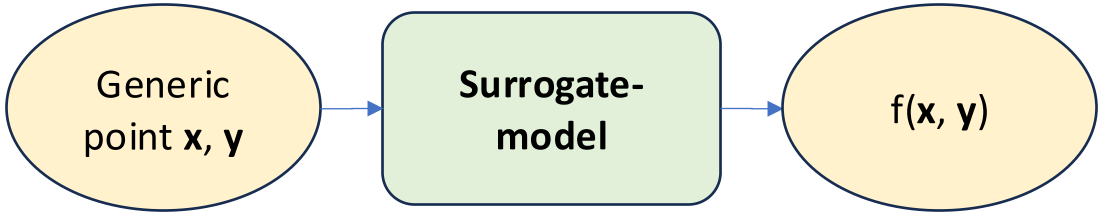
Genetic Programming



$$\left(2.2 - \left(\frac{X}{11}\right)\right) + \left(7 * \cos(Y)\right)$$

Reinforcement Learning





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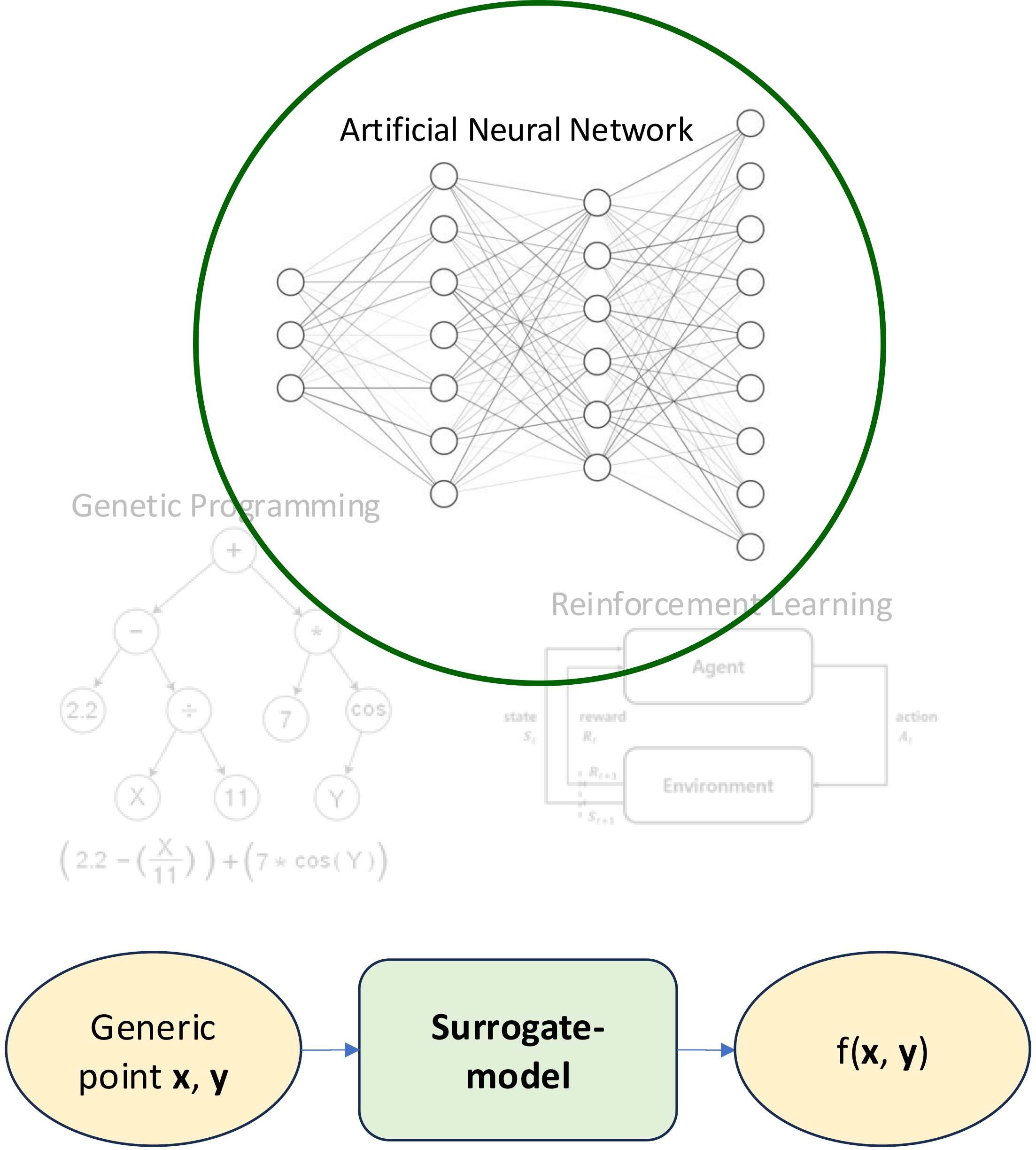
WP2: Integration of design/optimization tools, experimental testing and flow/noise control



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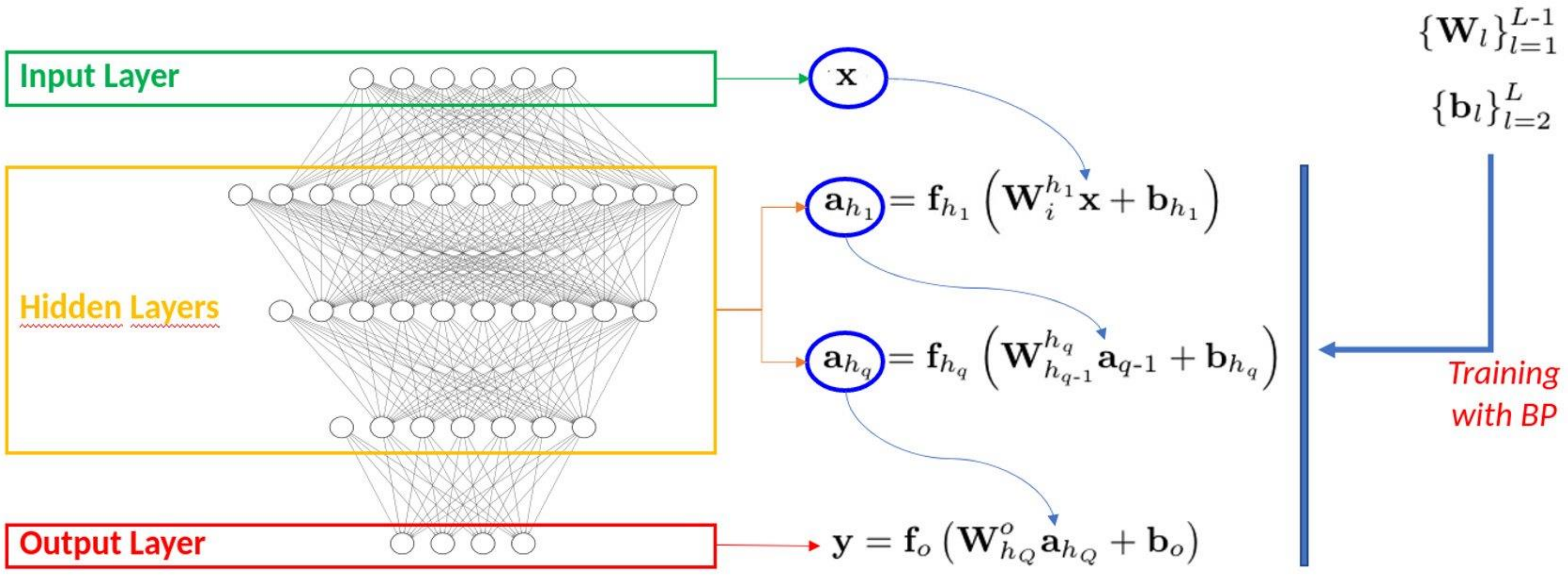
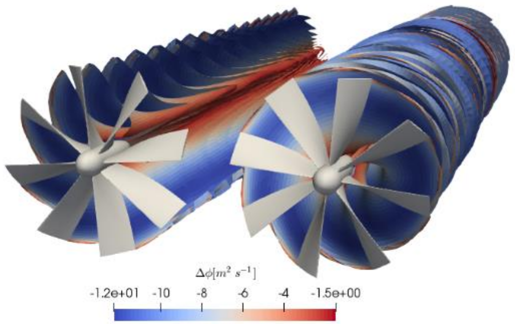
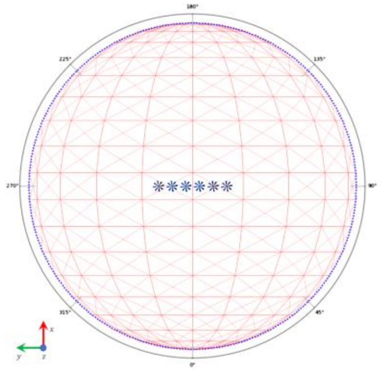
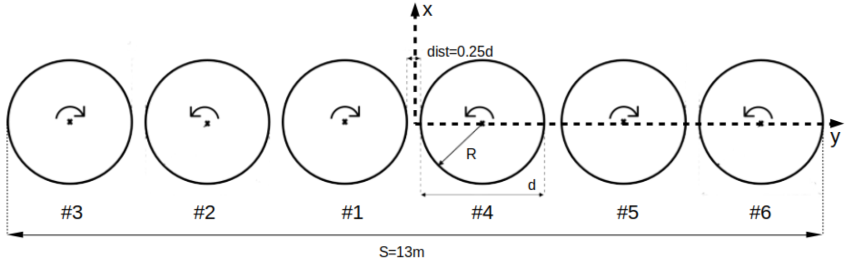
ANN overview



ANN: Aeroacoustics of DEP

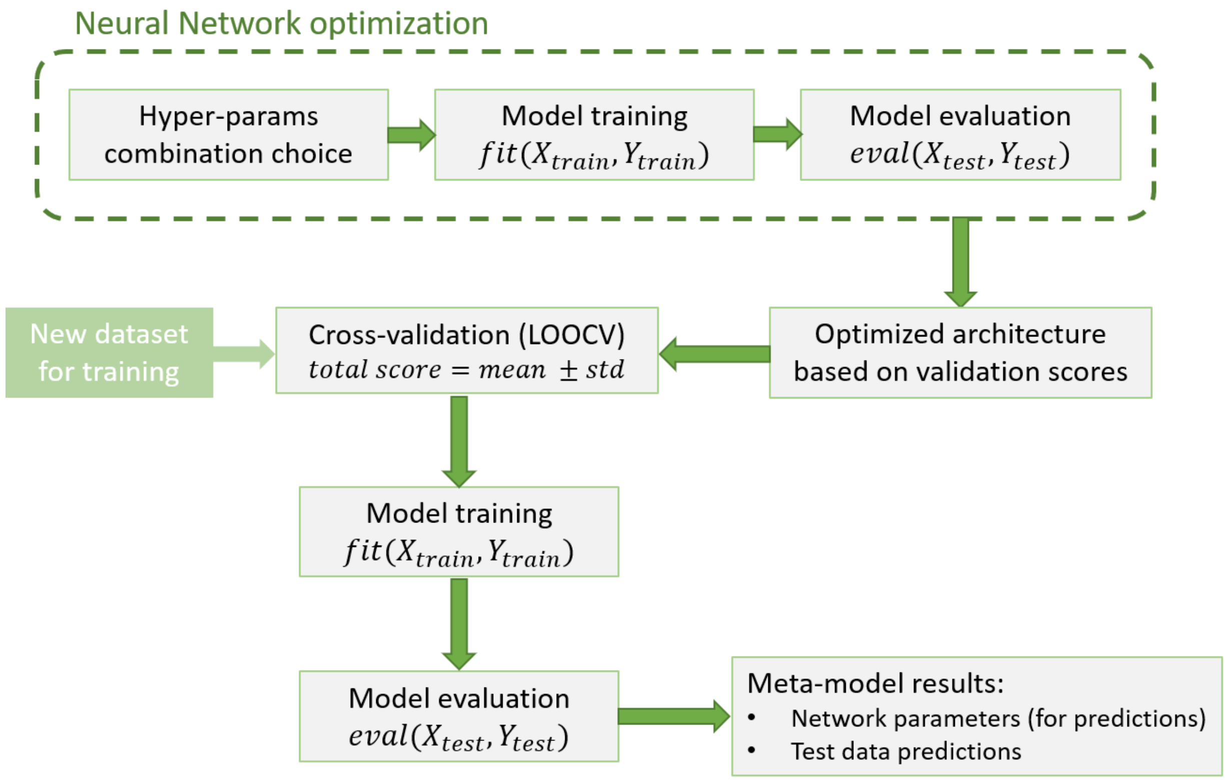






Design variables

Variable	Lower Bound	Upper Bound
No. of blades, n_b	6, evenly spaced	10, evenly spaced
Chord, c	0.324 m	0.396 m
Angular velocity, ω	2000 rpm	2250 rpm



Keras TensorFlow python

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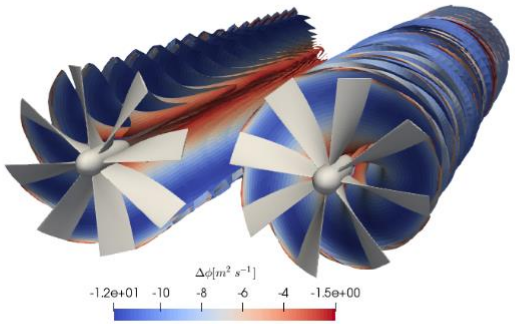
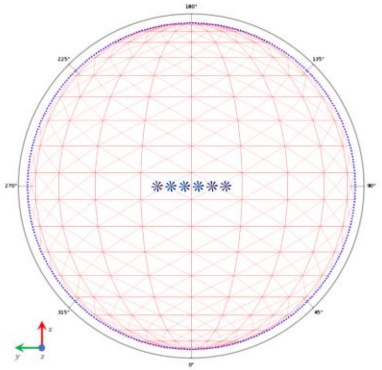
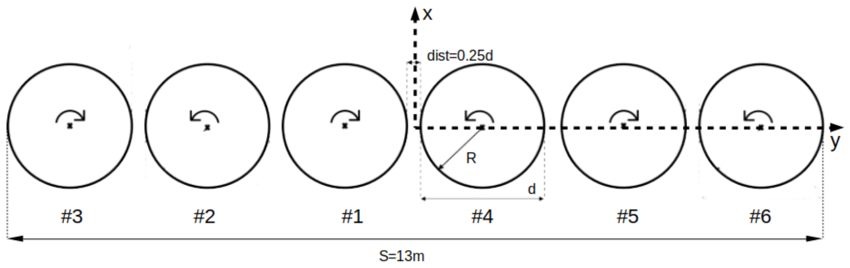
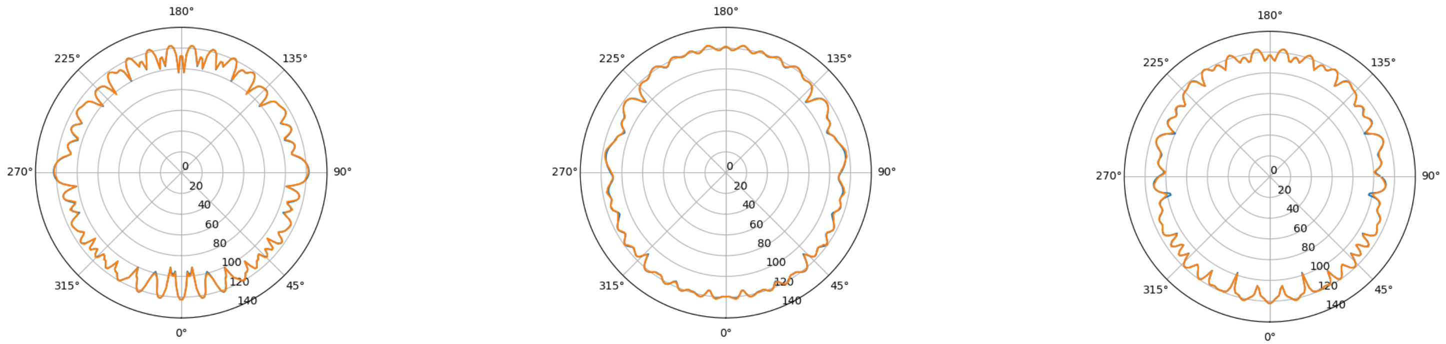


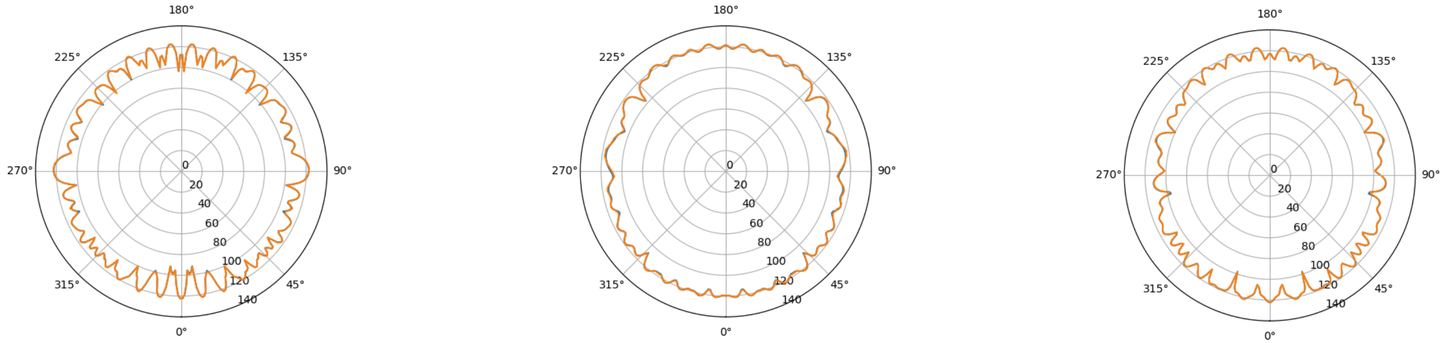




ANN: Fully-Connected Feed-Forward OPT. method: Bayesian



ANN: Fully-Connected Feed-Forward OPT. method: Random-Search



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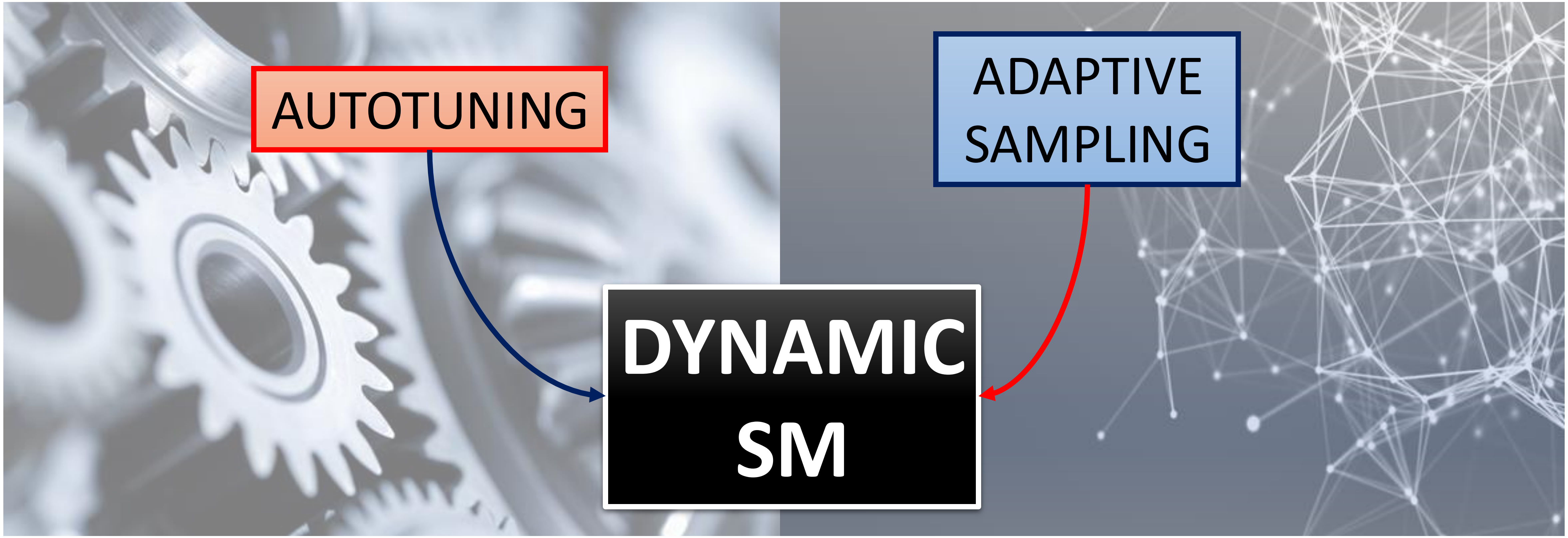
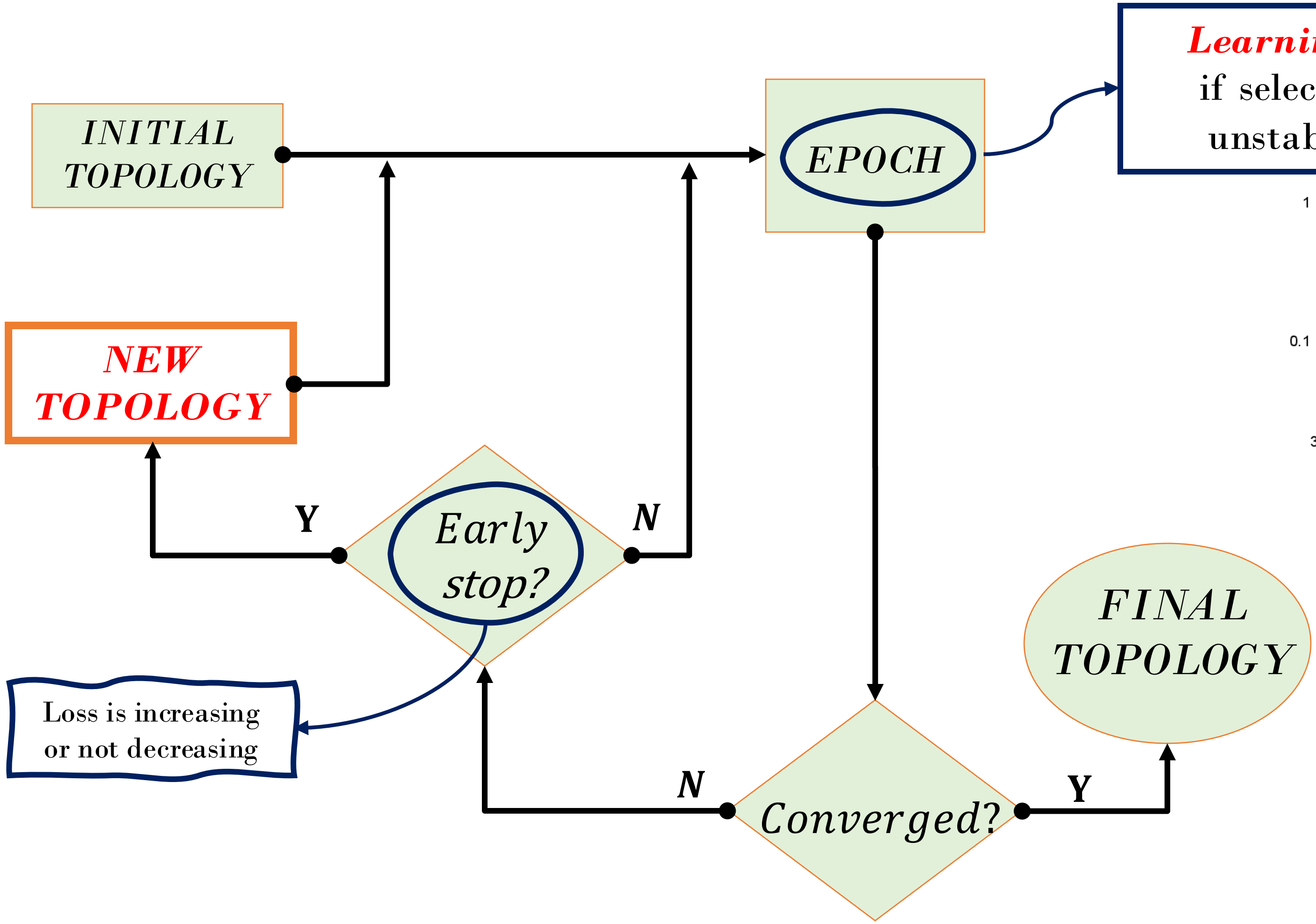
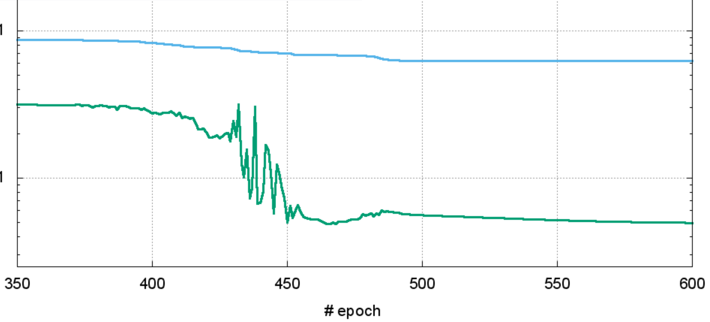
Poggi, C., Rossetti, M., Serafini, J., Bernardini, G., Gennaretti, M., Iemma, U., Neural network meta-modelling for an efficient prediction of propeller array acoustic signature, *Aerospace Science and Technology*, 2022.

Dynamic Surrogate Modelling (DSM)



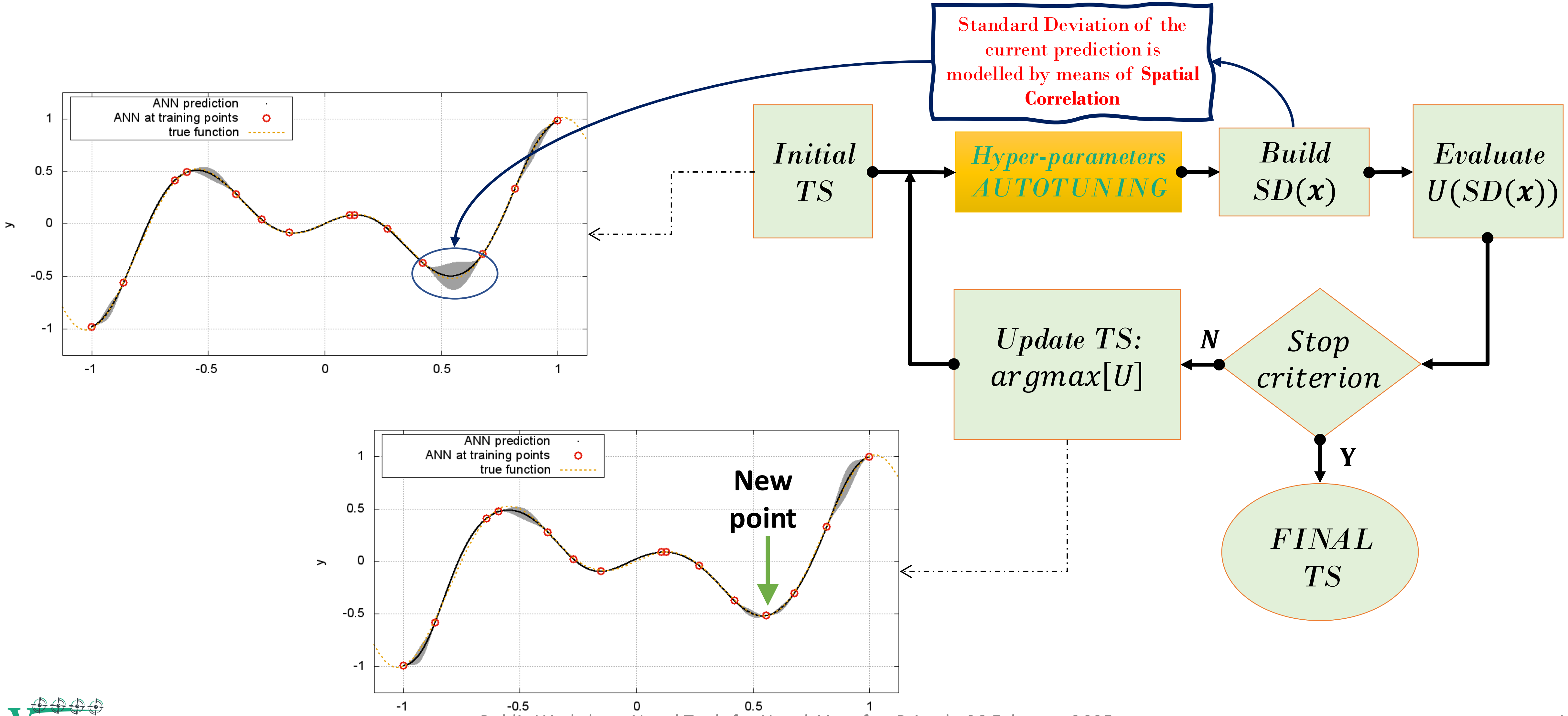
Dynamic Artificial Neural Network: autotuning





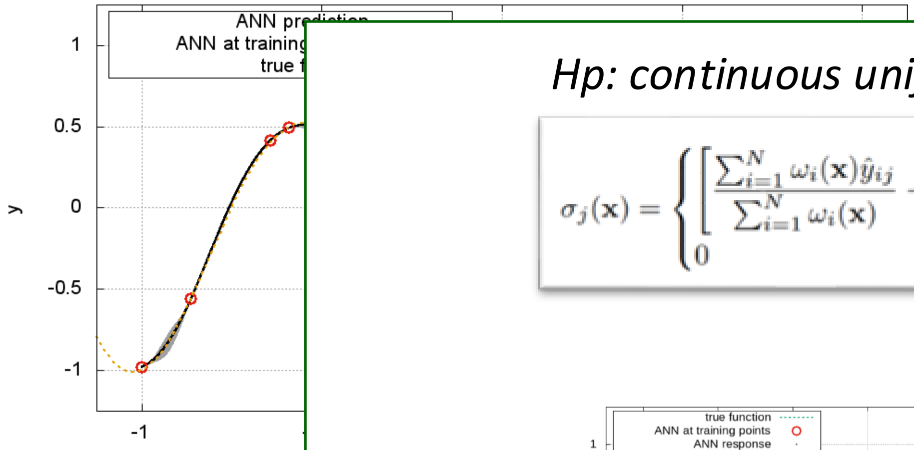
Class	Parameter	Description
Training	B	Batch size
	$\mathbf{W}_0$	Weights initial values
	$\mathbf{b}_0$	Biases initial values
	T	Number of training epochs
	η	Learning rate
Architectural	Q	Number of hidden layers
	N_{h_q}	Neurons per hidden layer
	$\mathbf{f}$	Activations

Dynamic Artificial Neural Network: adaptive sampling



Dynamic Artificial Neural Network: adaptive sampling

Standard Deviation of the current prediction is modelled by means of **Spatial Correlation**

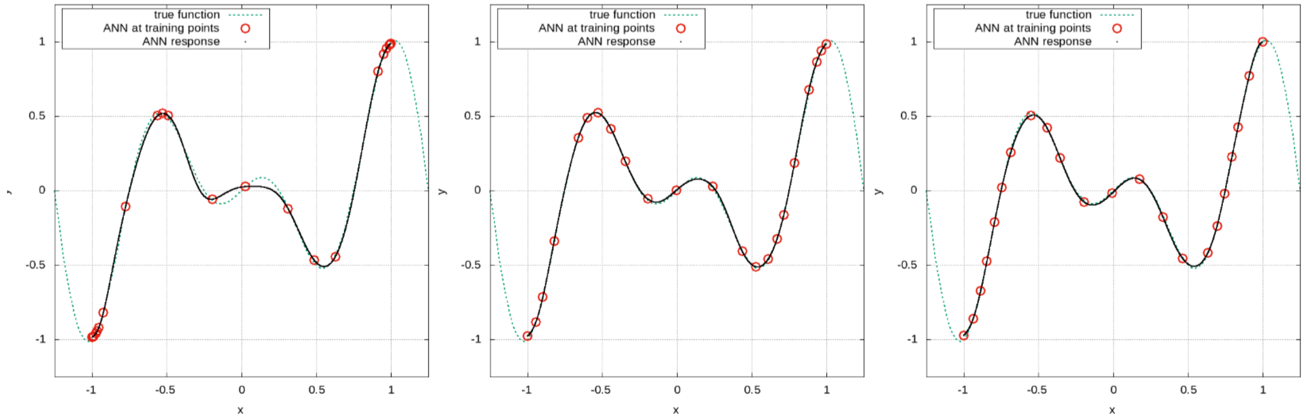


Hp: continuous uniform distribution

$$\sigma_j(\mathbf{x}) = \begin{cases} \left[\dfrac{\sum_{i=1}^{N} \omega_i(\mathbf{x}) \hat{y}_{ij}}{\sum_{i=1}^{N} \omega_i(\mathbf{x})} - g_j(\mathbf{x}) \right]^2 & \text{if} \quad \Delta_i(\mathbf{x}) \neq 0 \quad \forall i \\ 0 & \text{if} \quad \exists i | \Delta_i(\mathbf{x}) = 0 \end{cases}$$

$$\Delta = d(\mathbf{x}, \mathbf{x}_i)$$

$$\omega_i(\mathbf{x}) = \Delta_i^{-\alpha}$$



(a) $\alpha = 0.3$ (b) $\alpha = 1.5$ (c) $\alpha = 20$

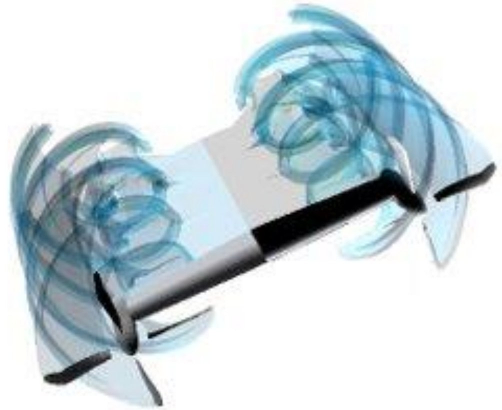
Evaluate $U(SD(\boldsymbol{x}))$

Numerical tools for the aerodynamics and the aeroacoustics of propeller

Aerodynamic solver: Unsteady potential solver based on Boundary Integral Equation Method

Main features:

- 3D – potential incompressible flows
- Free wake formulation
- Multi-bodies aerodynamic interference effects captured
- Vortex interaction captured



Acoustic solver: Radiated noise evaluated through Farassat 1A Boundary Integral formulation for the solution of the Ffwocs Williams and Hawkings equation

Thickness noise – Loading noise – Quadrupole noise neglected (no transonic/supersonic range)

Widely validated with experimental data for isolated and installed multi-body configurations

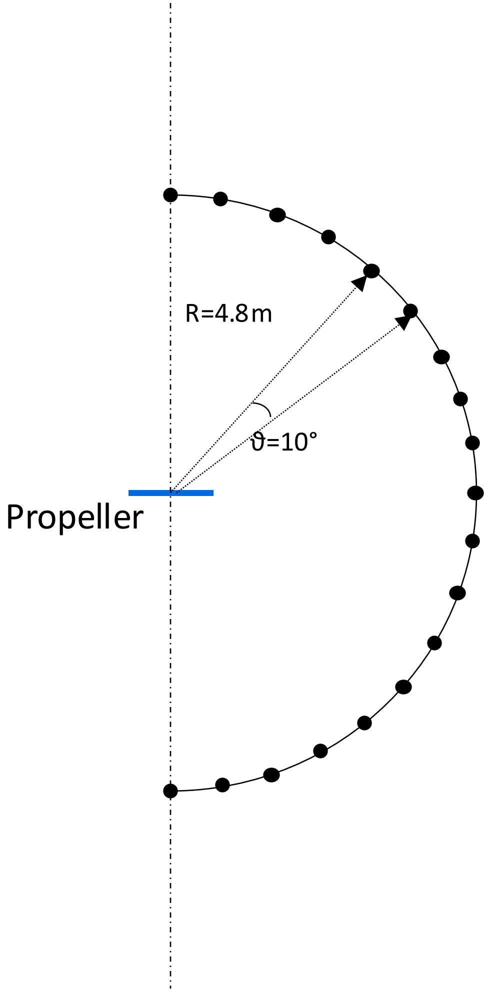
Case study: isolated 4B aft propeller (10% model scale)

Variable ranges:

Angular velocity [RPM]	Vertical velocity [m/s]
5000 - 9000	0 - 8

Output:

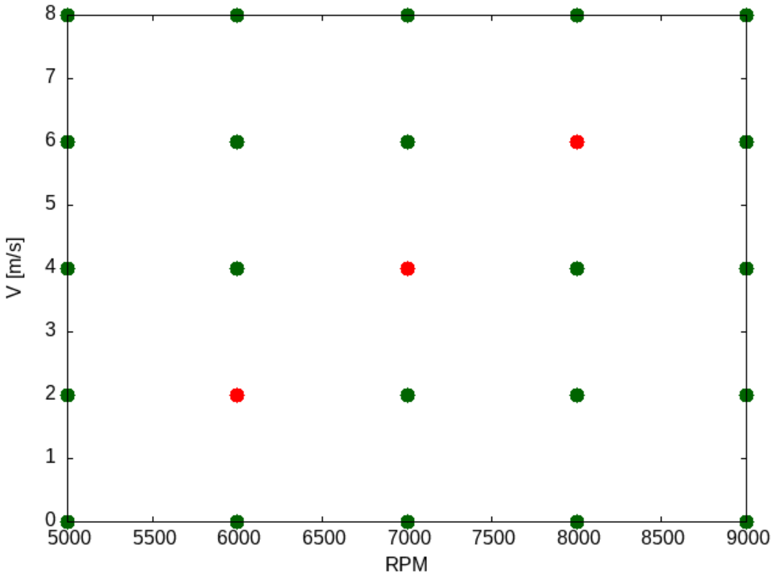
- **Thrust**
- **Torque**
- **OASPL**



Simulation details:

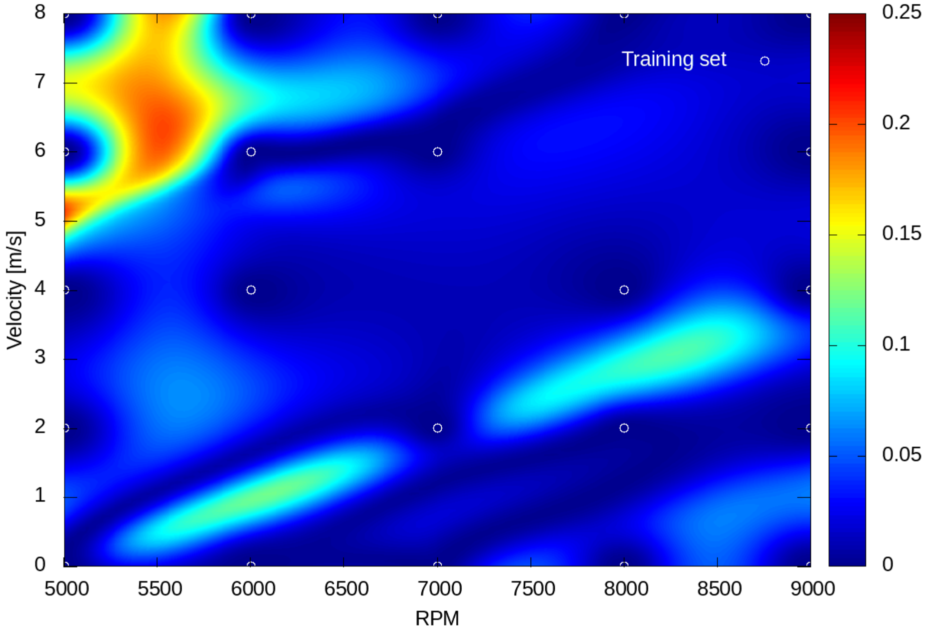
- Mesh: 50 (span) x 50 (chord)
- Wake: 7 spirals
- Time resolution: 1 timestep/deg
- # Revs: 13
- # BPF: 45

Results: OASPL - static SM

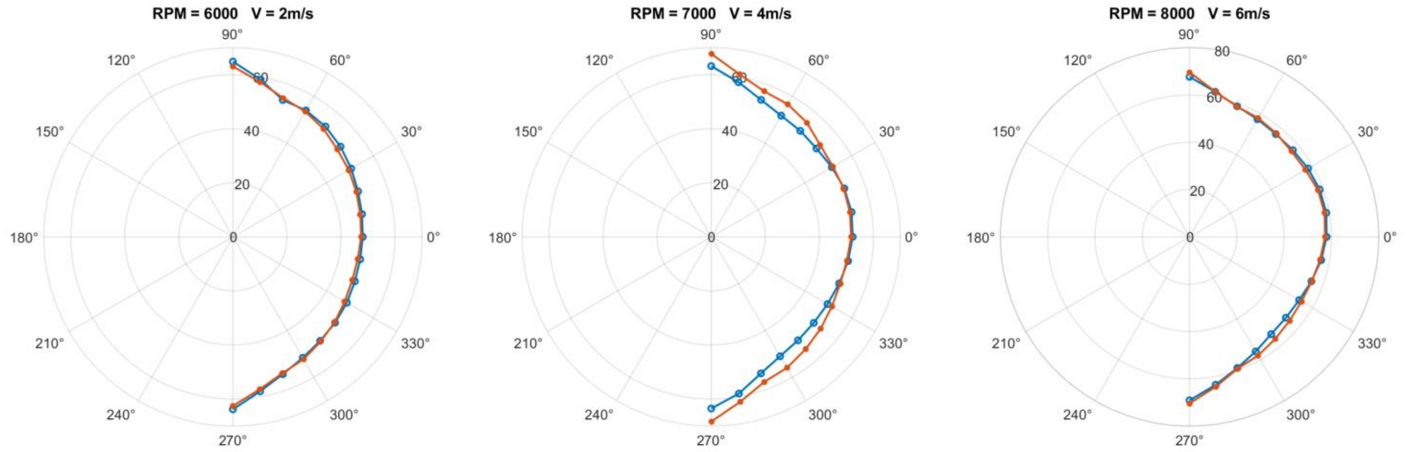


- Training Set (22 points)
- Validation Set (3 points)

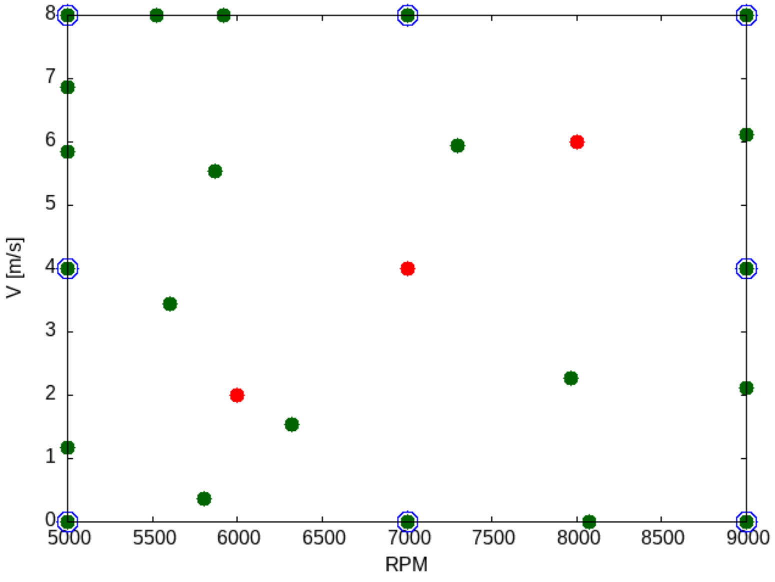
Global uncertainty



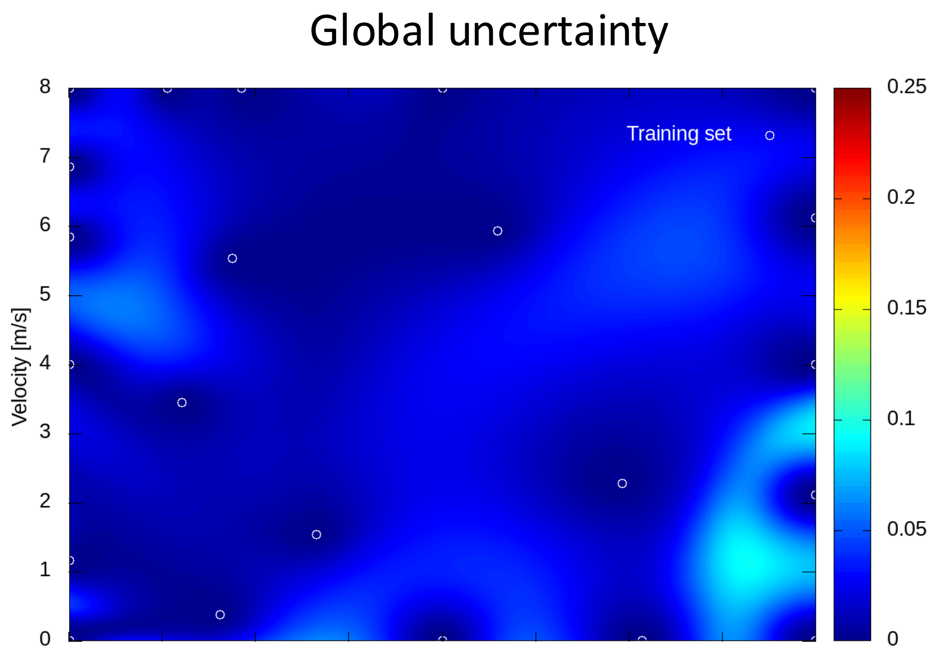
Validation set: ANN prediction

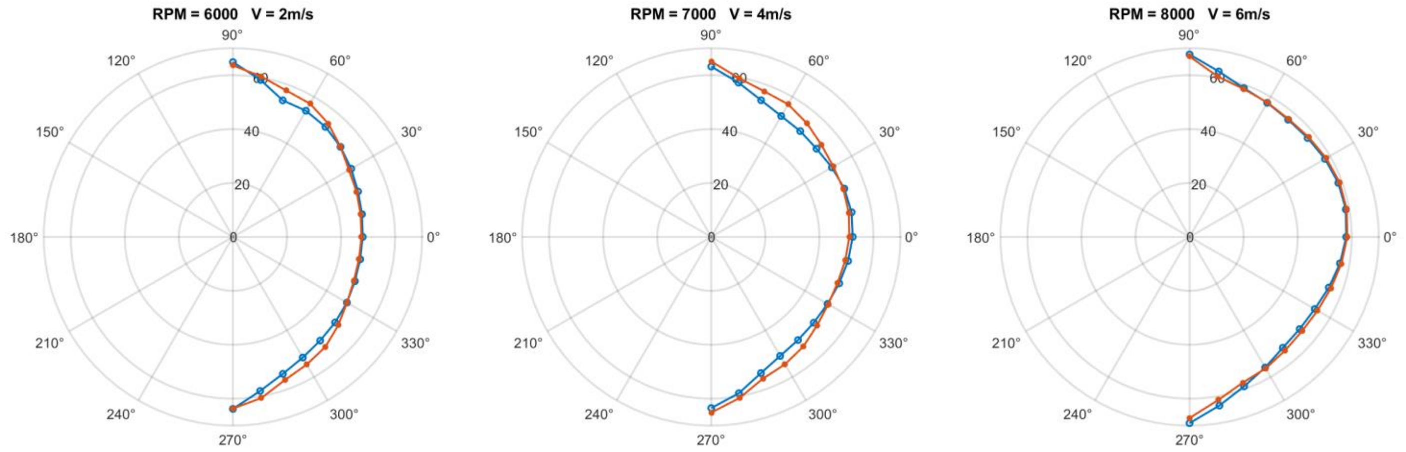


Results: OASPL - dynamic SM

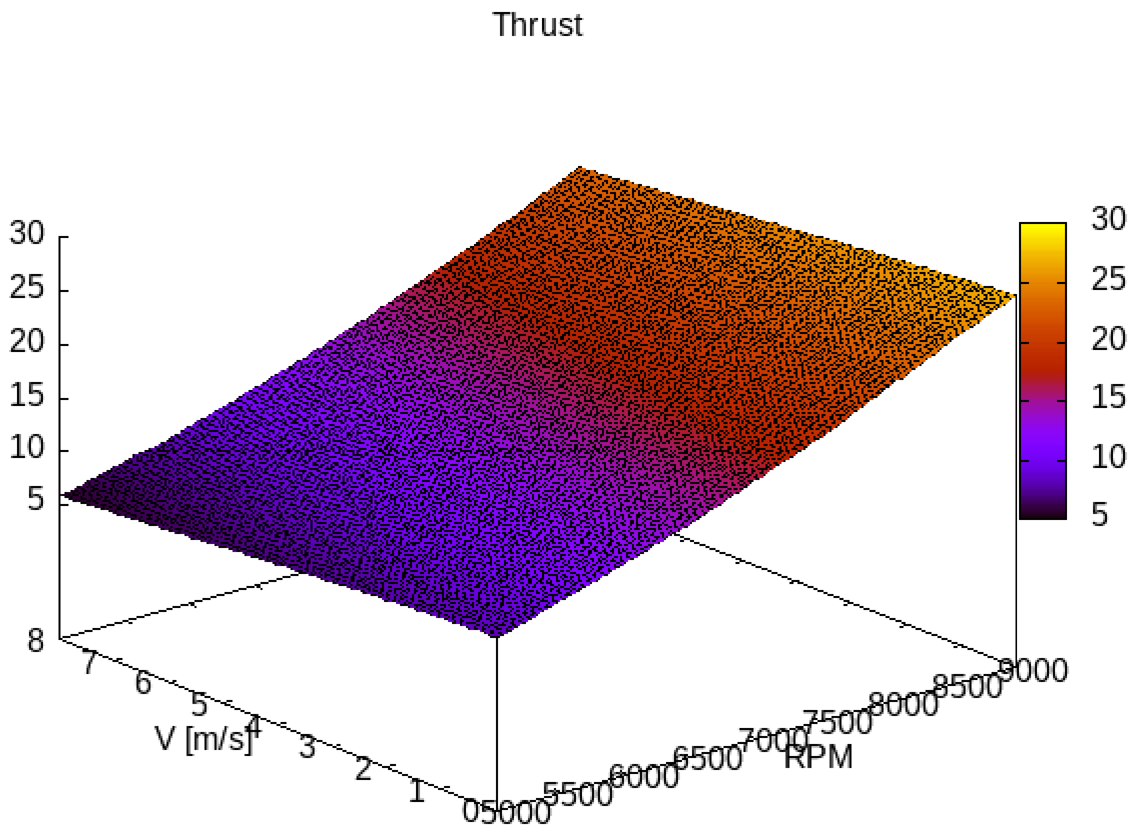


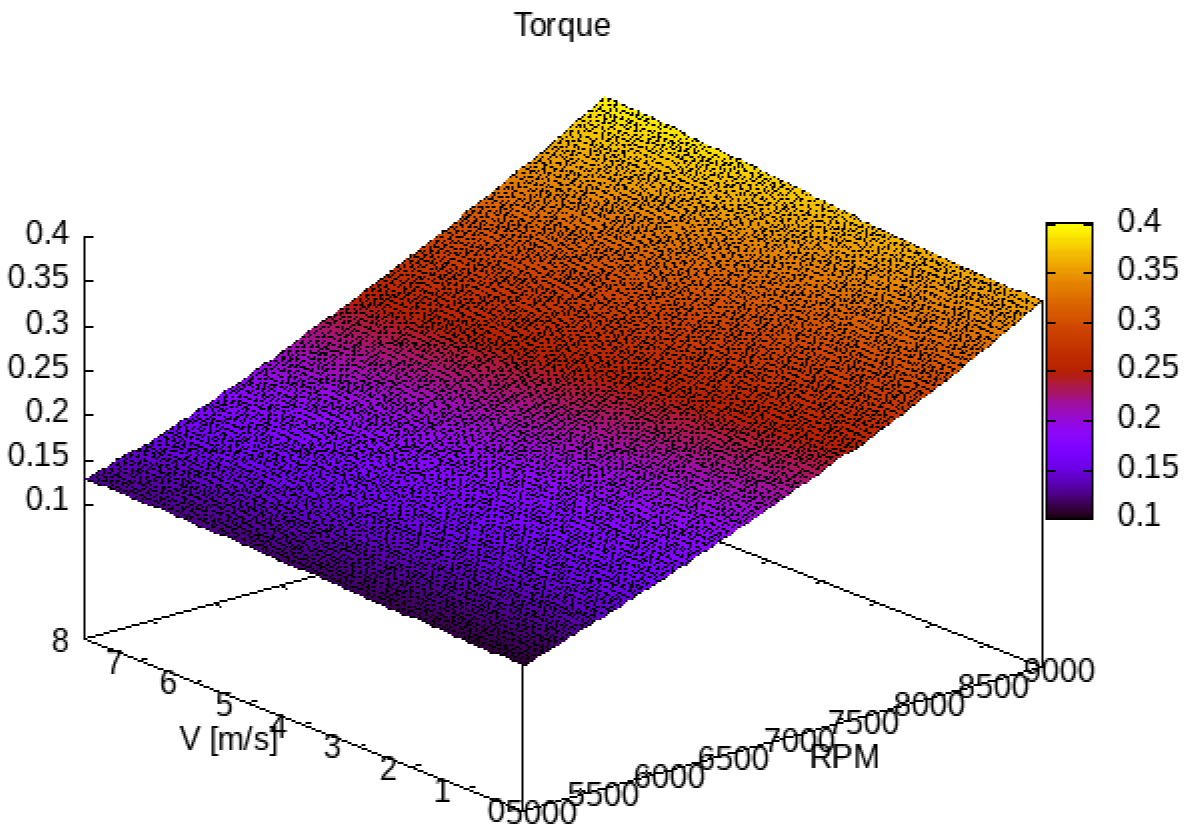
- Initial Training Set (8 points)
- Validation Set (3 points)
- Final Training Set (22 points)





Results: Thrust and Torque





Global validation loss: 0.5%

Remarks

- Preliminary tests confirm that Dynamic ANN is a promising tool for developing reliable Surrogate Models for the aerodynamics/aeroacoustics of propellers in the MCDO framework.

- Adaptive sampling leads to a significant reduction in the SM uncertainty when compared to the static (fixed budget) approach.

Next steps:

- A dynamic validation set build strategy is required to avoid overlaps with training points during the adaptive sampling.
- Develop SMs to be used in the optimization tasks (blade geometry and trajectory) of configs. B2 and B3.