

2. An investigation of the Zephyros FOWT system based on in-situ and simulated data

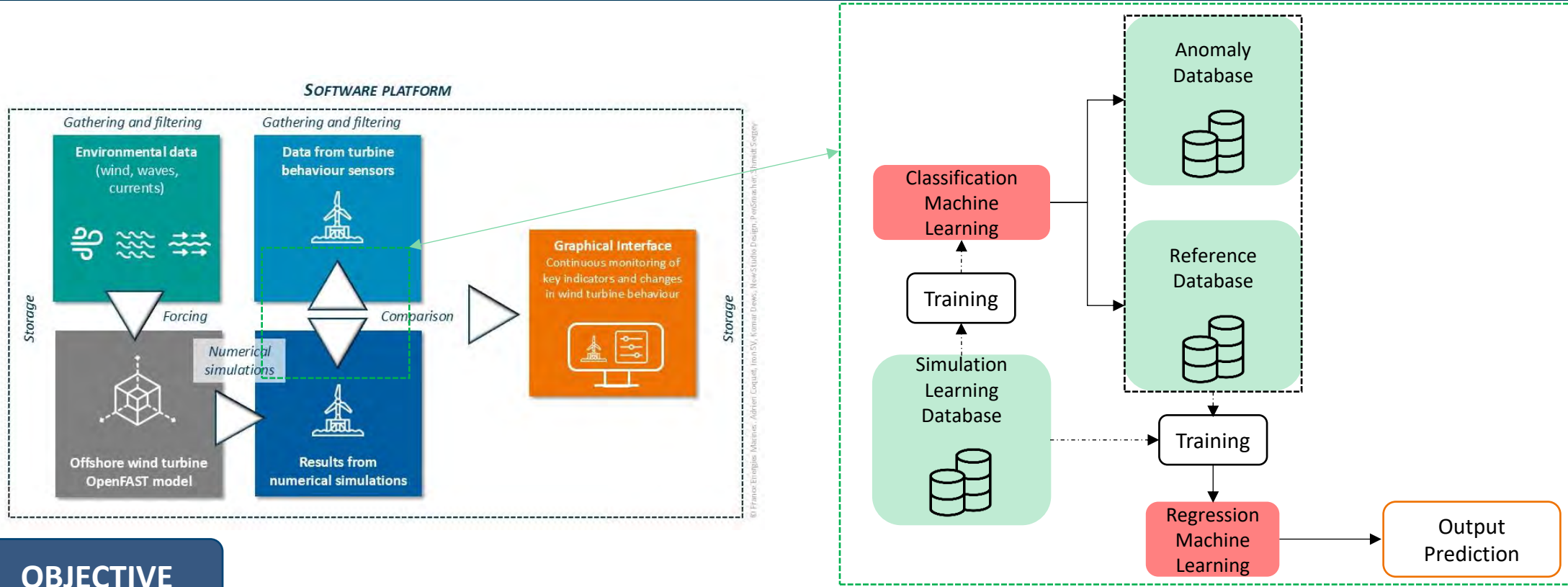
Part III – Machine learning approaches for floating offshore wind turbine



Adrien Hirvoas, FRANCE ENERGIES
MARINES



Machine learning – Objective



OBJECTIVE

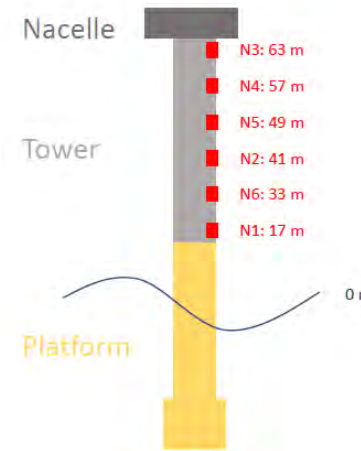
Use mathematical approaches to obtain information of the asset from in-situ and simulated data

“Prediction can be very difficult, especially about the future.”
(Niels Bohr, dans Teaching and Learning Elementary Social Studies, Arthur K. Ellis, 1970, p. 431.)

DATA – SERCEL SA

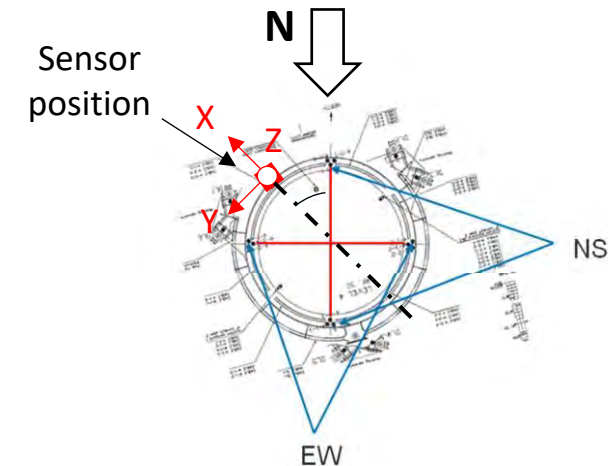
6x NEURON system nodes on the tower [6]

- Tri-axis high perfs **accelerometers**
- Suitable for large size structure
- IP65, 100m Subsea, and ATEX Z1 housing
- Interoperability with external sensors



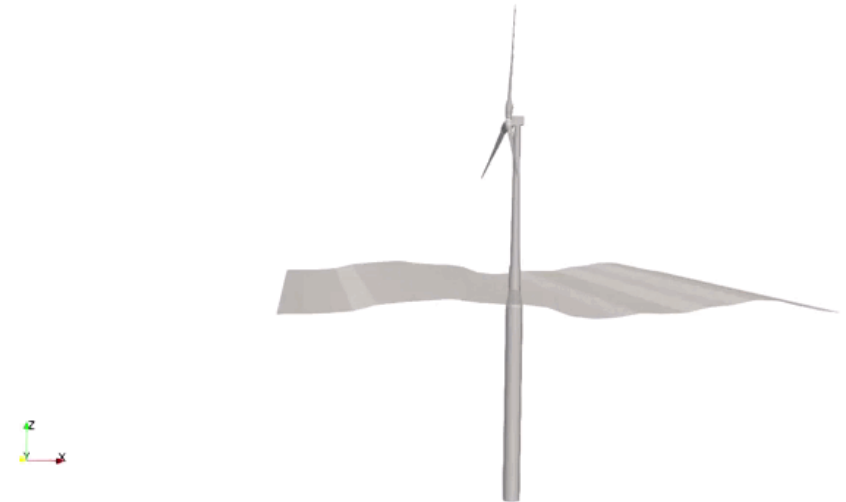
DATA – Metocean weather

- **Wind:** speed and direction – ARPEGE Europe (Météo France)
- **Wave:** period, significant height, and direction – MFWAM (SHOM)
- **Current:** speed and direction [Not yet considered]



Numerical model

- **Software:** OpenFAST v3.5.0
- **Hydrodynamic:**
 - Radiation-Diffraction model
 - Linear hydrostatic stiffness
 - Additional quadratic and linear damping
- **Analysis:** Time Domain
- **Mooring:** Catenary chain represented by Lumped-Mass Mooring Dynamics



Classification

▪ Anomaly detection

- Identification of **non-operating** period based on S-MORPHO accelerations
- A neural network based on **autoencoder** model
- An autoencoder is **trained** to copy its **input** to its **output**
- Applied to **detect** anomalies by reconstructing normal operational **patterns**
- Use deep learning for detection engineering **without** access to **SCADA** data

Hirvoas, A., Aguilera, C., Perrault, D., Desbordes, D., and Ribault, R. Comparative anomaly detection for floating offshore wind turbines using in-situ data, *soon published*

Regression

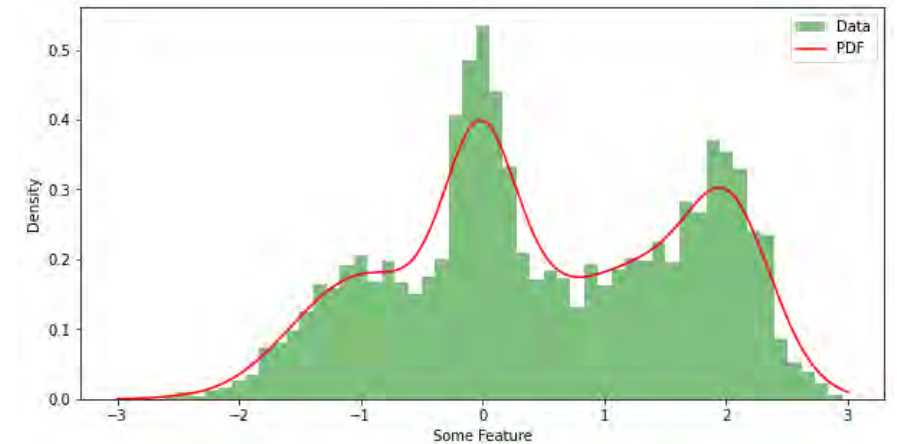
▪ Continuous monitoring

- **Replacement** of the numerical **model**
- **Supervised** learning technique that trains a model to follow the observations. Regressors also called **surrogates**.
- **Synthetic** data used for training
- **Multidimensional** regression
- Propagation of **uncertainties**

Dridi, N., Drumetz, L., Hirvoas, A., and Ribault, R. Estimation de l'incertitude pour les réseaux de neurones: application pour la prédiction de mouvement d'éolienne en mer., 2023, *29^{ème} Colloque sur le traitement du signal et des images*

Definition of anomaly

- An **observation** that can be considered significantly **outside** what is « normal »
- Requires some idea what constitutes « **normal** »
- **Statistically**: given input data X , an anomaly is a sample with a specific value for its pdf, $p(X)$
- Calculating p is also very much non-trivial



Idea

- **Supervised** classification: used labeled anomalies from the numerical models to train machine learning algorithms for their identification.
- **Unsupervised** classification: automatically detect patterns in normal data.



Based on in-situ data

Working Principle of Autoencoders

▪ Definition

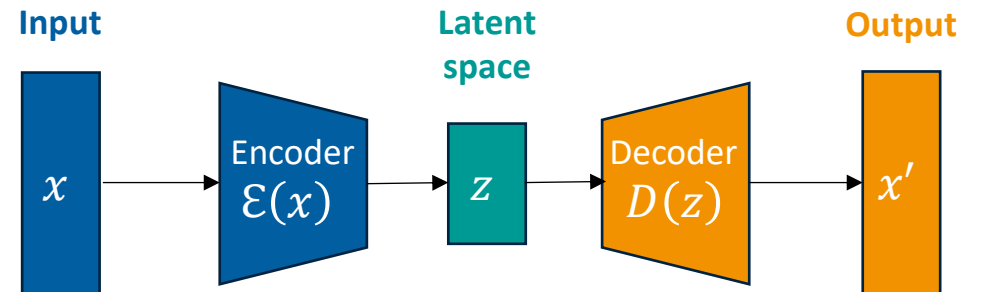
Let X be a random variable with values in \mathbb{R}^n . An artificial neural network **autoencoder** models a function \mathcal{H} such that:

$$\|\mathcal{H}(x) - x\| \leq \epsilon$$

The autoencoder decomposes into two parts:

- An **encoder**, i.e., a function $\mathcal{E} : \mathbb{R}^d \rightarrow \mathbb{R}^n$
- A **decoder**, i.e., a function $D : \mathbb{R}^n \rightarrow \mathbb{R}^d$

With $\mathcal{H} = D \circ \mathcal{E}$ with the objective to determine \mathcal{E} and D such that $D \circ \mathcal{E} \simeq Id$



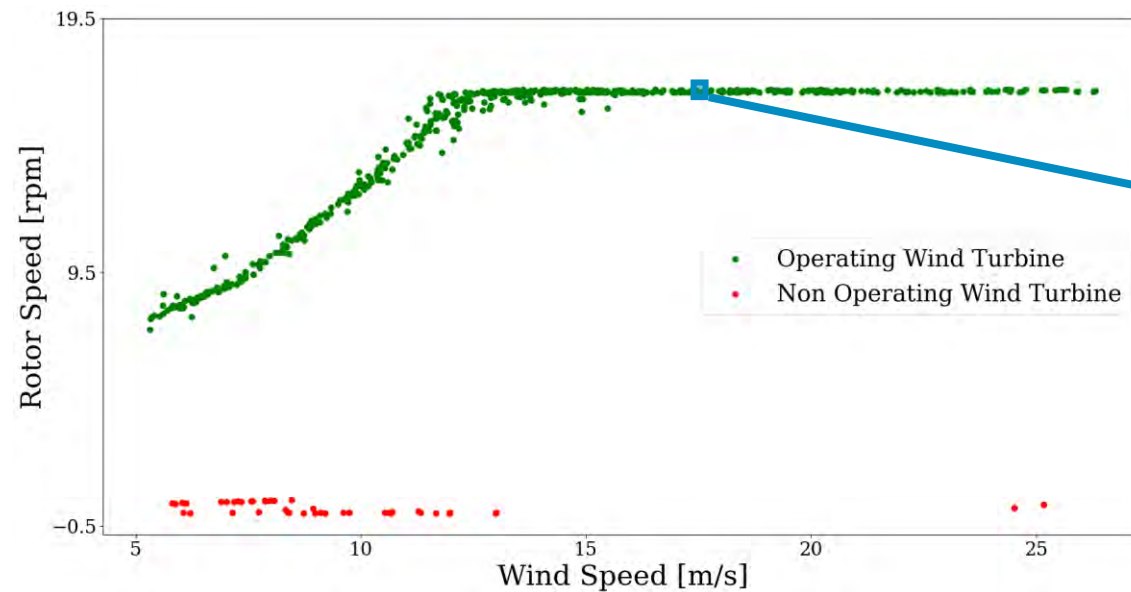
Objective

- **Detect anomalies by reconstructing normal operational patterns**

Based on in-situ data

Identification of operating/non-operating period

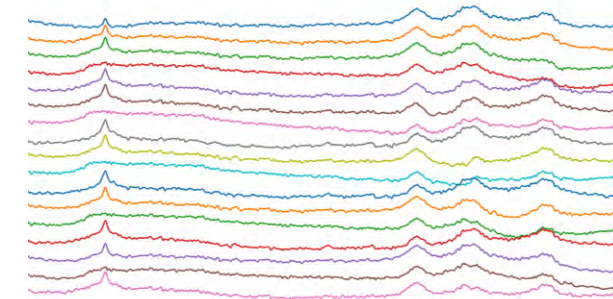
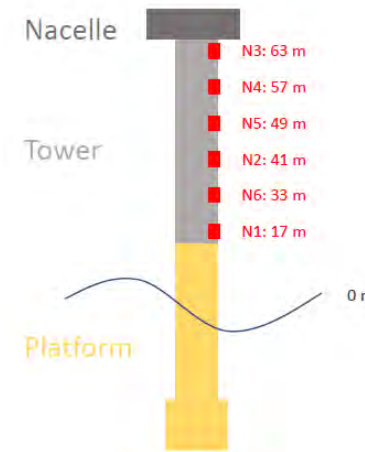
- 1-month of limited **SCADA**
- From 01/12/2022 to 31/12/2022
- Available **variables**: wind speed [m/s], yaw angle [°], rotor speed [rpm]



Input for autoencoder

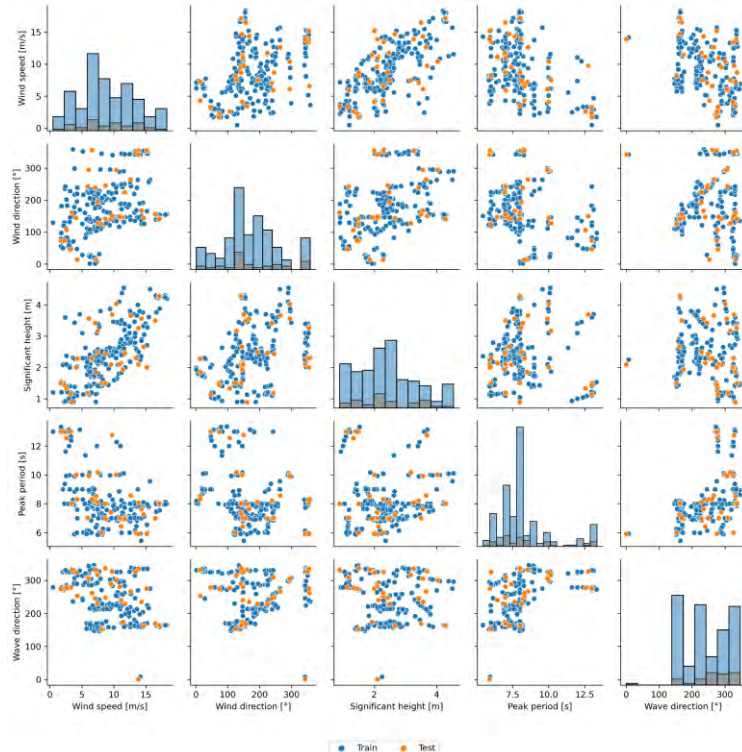
18 **accelerations** for each identified period

Spectral representation

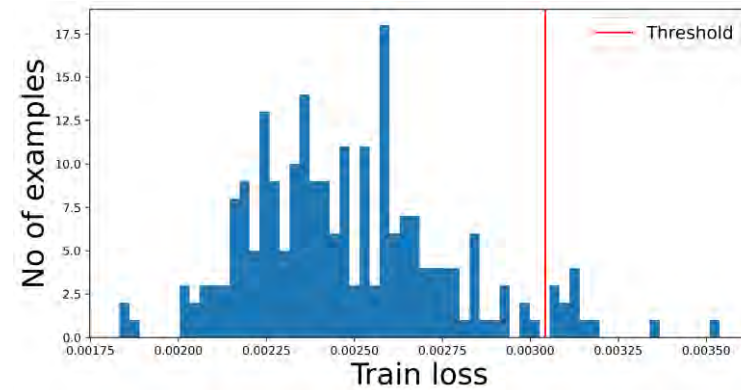


Auto-encoder train on identified operating accelerations

- Stratified train/test selection based on the associated weather input space
- Train set: 225 / Test set: 32



Threshold based on reconstruction error on operating accelerations



$$Recall = \frac{\#TruePostives}{\#TruePostives + \#FalseNegatives}$$

	Kurtosis procedure		Convolutional ANN	
	Operating	Not-Operating	Operating	Not-Operating
Recall	0.939	0.750	0.970	0.917

CONCLUSION

- Identification of non-operating period based on accelerations
- Auto-selection of the threshold based on statistics

Machine learning – Continuous monitoring

Based on synthetic data

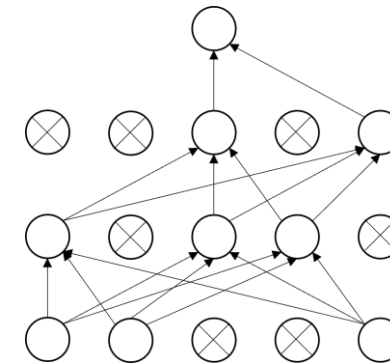
Regression problem

We are aiming at obtaining a (mathematical)

Deep Learning architecture

- Feed-forward neural network (FFN)
- Transpose 2D convolutional neural network (T-2D CNN)
- Dropout

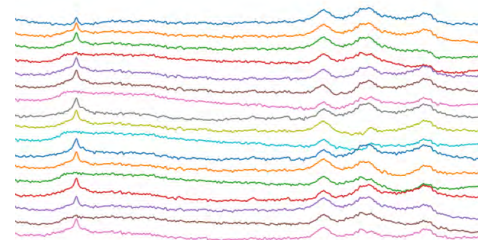
In our case



$$y = g(x, \theta) + \epsilon$$

- $g(x)$ is a probabilistic model that outputs a set of inputs x , the output is given in terms of a probability distribution
- The error term represents measurement uncertainty in y
- Model training amount error ϵ

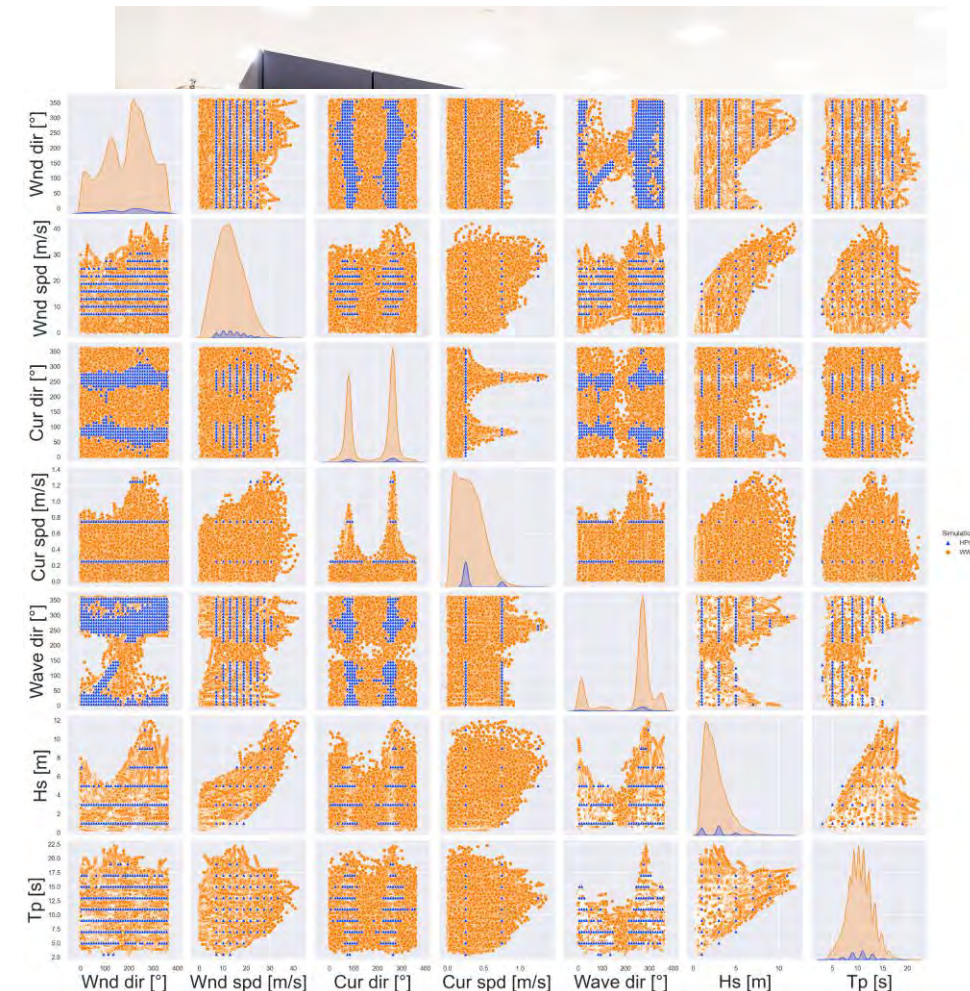
18 synthetic accelerations



dir [°]
[m/s]
dir [°]
m]

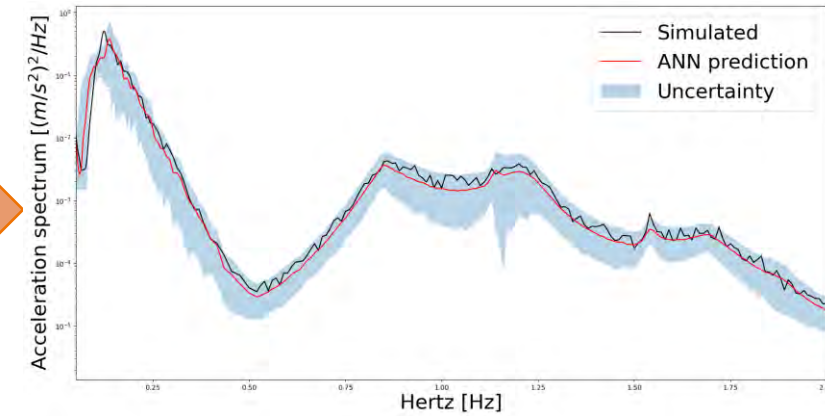
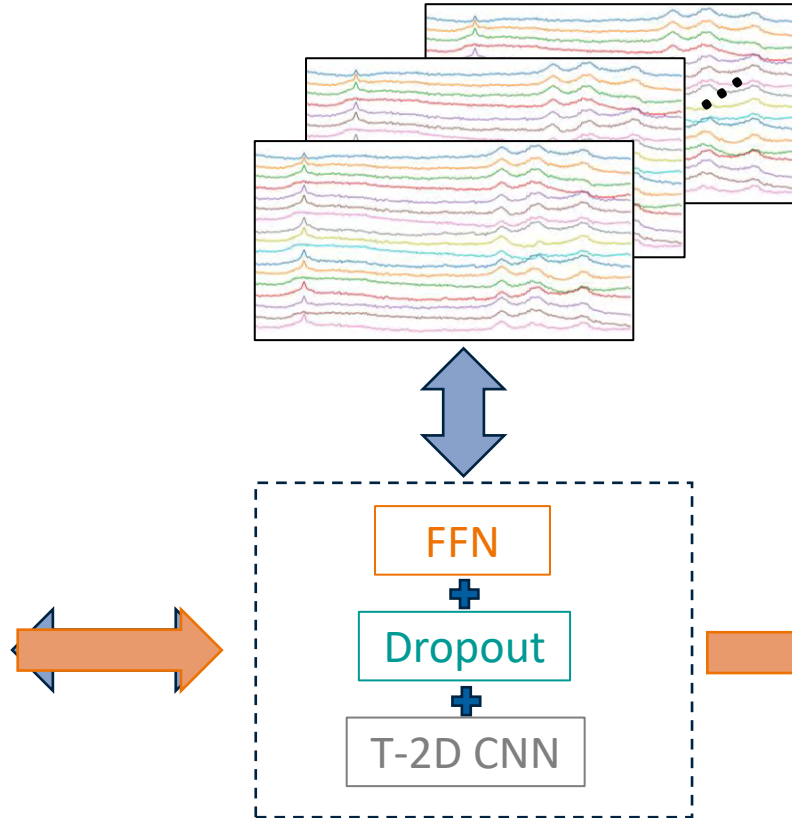
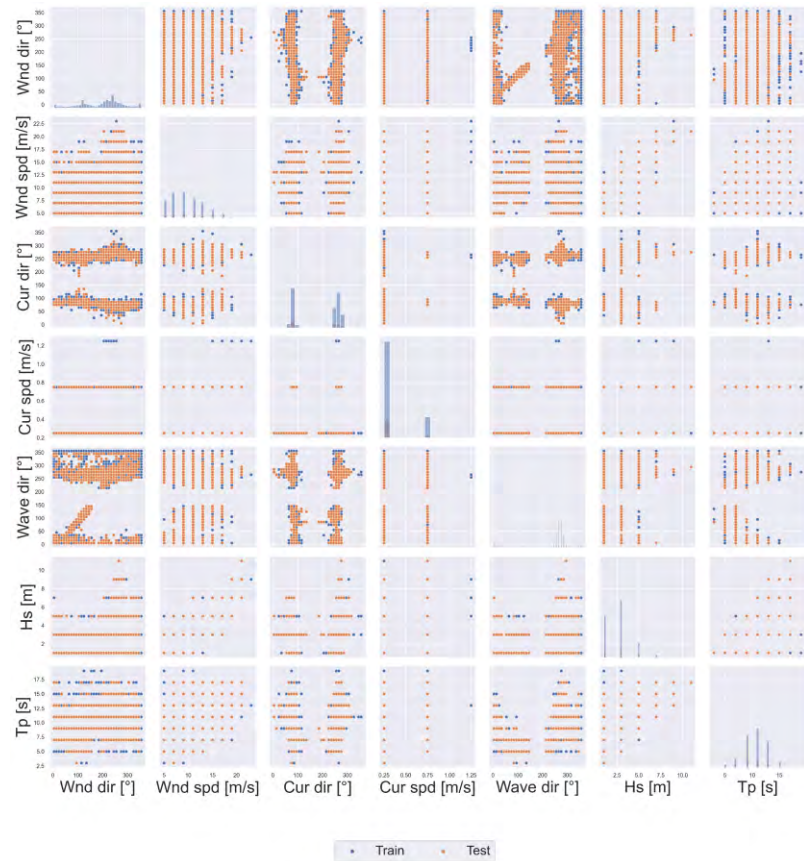
High-performance computing

- **CPU partition** – 1528 scalar computer nodes with:
 - 2 Intel Cascade Lake 6248 processors (20 cores at 2.5 GHz), namely 40 cores per node
 - 192 GB of memory per node
- **Weather** for HPC numerical simulations
 - Weather data from WW3 global run for the period 2006 – 2019
 - 7 variables of interest:
 - Wind direction (Wnd dir [°])
 - Wind speed (Wnd spd [m/s])
 - Current direction (Cur dir [°])
 - Current speed (Cur Spd [m/s])
 - Wave direction (Wave dir [°])
 - Significant height (Hs [m])
 - Peak period (Tp [s])
 - Reduction of the weather prediction space
- **Numerical modelling**
 - Turbulent full-wind field generated thanks to TurbSim with NTM Class-A
 - Uni-directional wave generated based on a JONSWAP spectrum
 - 10,000 parallel simulations – total simulations: 36817



Machine learning – Continuous monitoring

2 Test phase



- When applied to floating offshore wind turbines, deep learning methods:
 - Can be easily **implemented**
 - Can find **patterns** within data
 - Are fast to evaluate: ideal for **real-time** applications
 - Depend on the **data** availability (mitigate by the use of synthetic data from numerical **model**)
- Future work
 - To employ in-situ data from **other sensors**
 - To investigate more **complex architectures**
 - To consider **other** anomaly detection **applications**