10MW Floating offshore wind turbine: Damage detection & damage magnitude estimation in the tower-base connection under varying operating conditions

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Analytics for Asset Integrity Management in Wind farms (AIMWind)

Adaptation and implementation of floating wind energy conversion technology for the Atlantic Region (ARCWIND)

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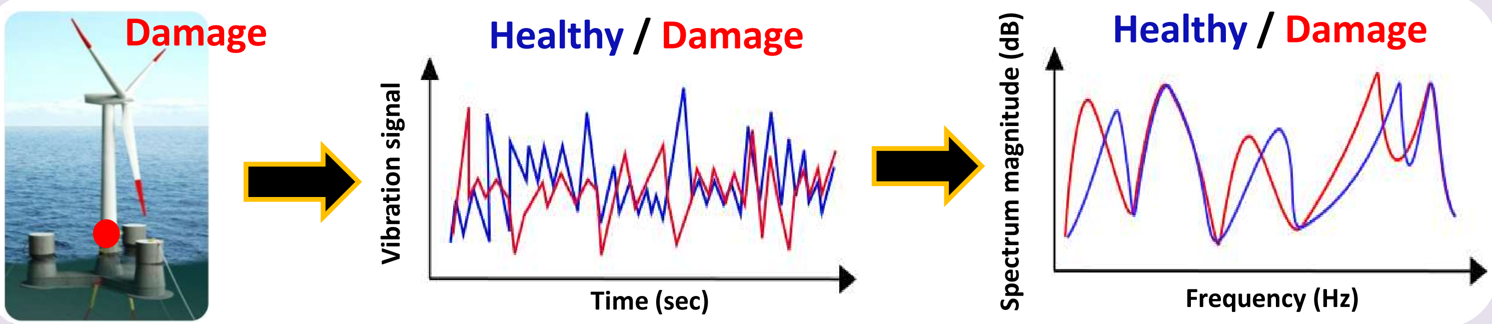
The problem and its importance

Damaged components (blades, nacelle, mooring system and **tower**) of Floating Offshore Wind Turbines (FOWTs) → disruption of the FOWTs operation, costly transfer on land for repair → Early damage diagnosis (detection, localization, magnitude estimation) being vital

Investigated in a limited degree and via vibration-based methods constant or varying operating conditions (OCs)

Fundamental principle of damage diagnosis methods based on vibration signals

Presence of a damage → **Changes in the FOWT's structural dynamics** → **Changes in the FOWT's vibration characteristics** → **Damage diagnosis**



Operating Conditions (OCs)

Varying OCs

↓

Partially or fully "masking" the effects of damages on the FOWT structural dynamics

↓

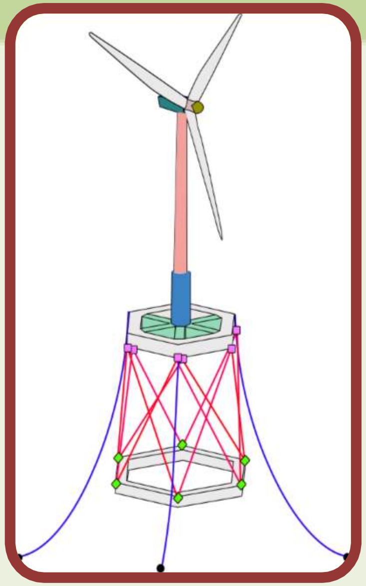
Highly challenging damage diagnosis

Simulated damages: stiffness reduction, **Damage detection:** Power Spectral Density, **Damage localization and damage quantification :** mode shapes from a finite element model (*Kim et al. 2019*)

Goal of the current study

Past work: Structural Health Monitoring (SHM) framework for detection and damage magnitude estimation in the tendons of a 10 MW FOWT with vibration signals from **one** measuring point (*Sakaris et al. 2021*)

Goal: **Extension** of the SHM framework to its **multivariate** form for detection and damage magnitude estimation in the critical connection area of the FOWT tower with the platform using vibration signals from **two** measuring points



10 MW FOWT supported by the TELWIND platform

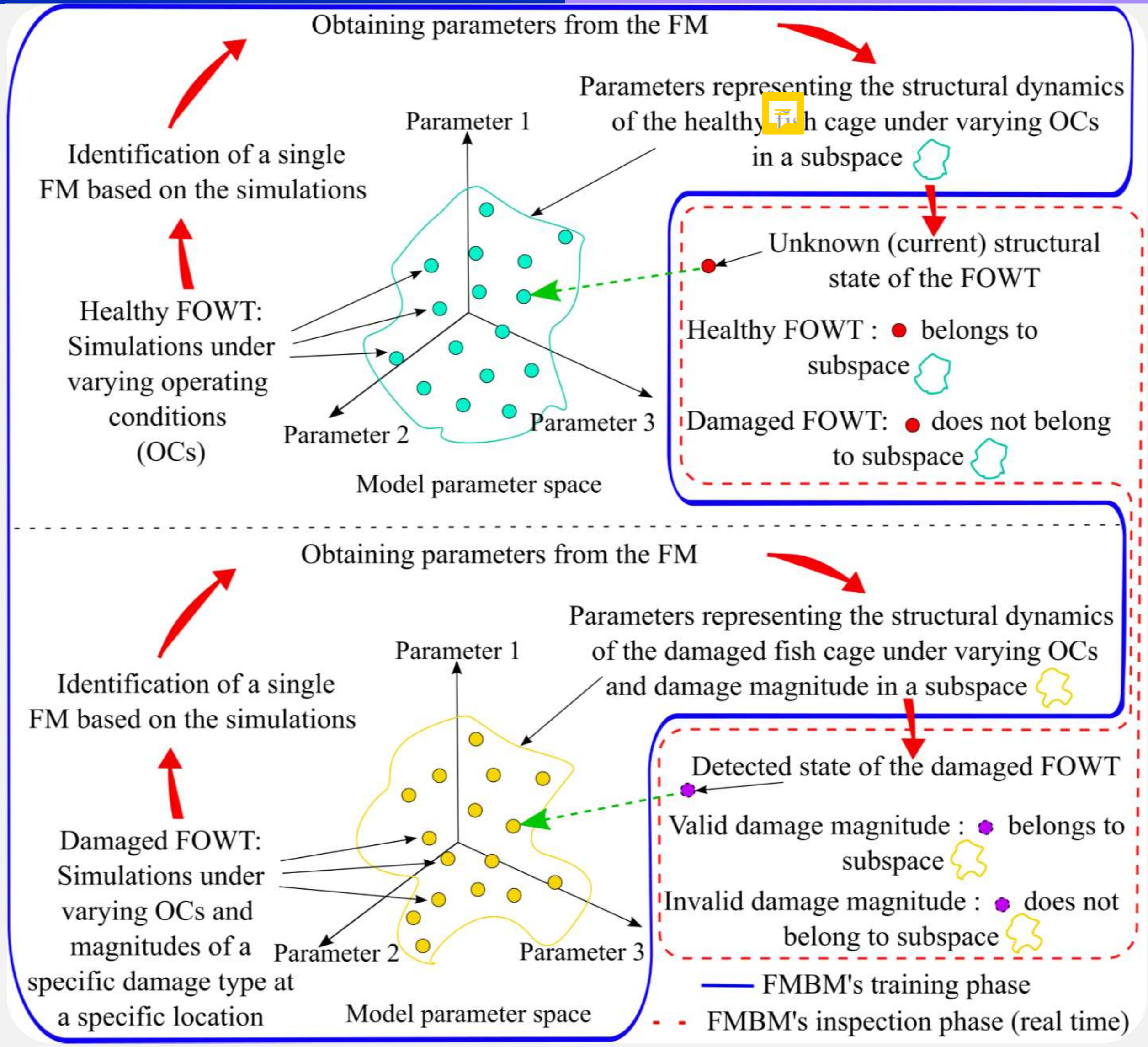
Varying operating conditions (OCs): wind speed and wave height

Employed statistical method for damage detection and damage magnitude estimation

- Functional Model Based Method (FMBM) equipped with two multivariate Functional Models (subspace selected via Genetic Algorithm, Particle Swarm Optimization, Bayesian Optimization)

Selection of the most sensitive to damage direction of measurement via three Power Spectral Density (PSD) based criteria

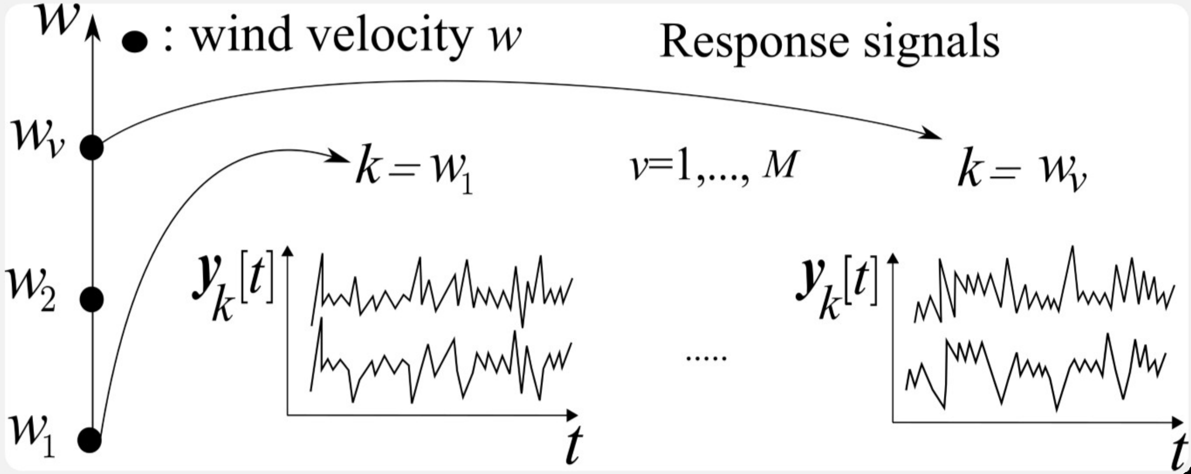
Concept of the FMBM



Functional Model Based Method (FMBM)

Baseline / Training phase

Healthy FOWT : response signals $\boldsymbol{y}_k[t]$ under a sample of wind velocity values $w_v \in w_1, w_2, \ldots, w_M$ $(k = w_v)$ covering range $[w_{min}, w_{max}]$



Data acquisition

Identification of a **Functionally Pooled - Vector AutoRegressive (FP-VAR)** (*Hios et al. 2014*) :

i) Model order na selection (Bayesian Information Criterion)

ii) Selection of the proper basis functions (optimization algorithm)

iii) Validation of the selected model (residual uncorrelatedness test)

The coefficients of projection $\boldsymbol{A}_{i,j}$ are estimated through Ordinary Least Squares

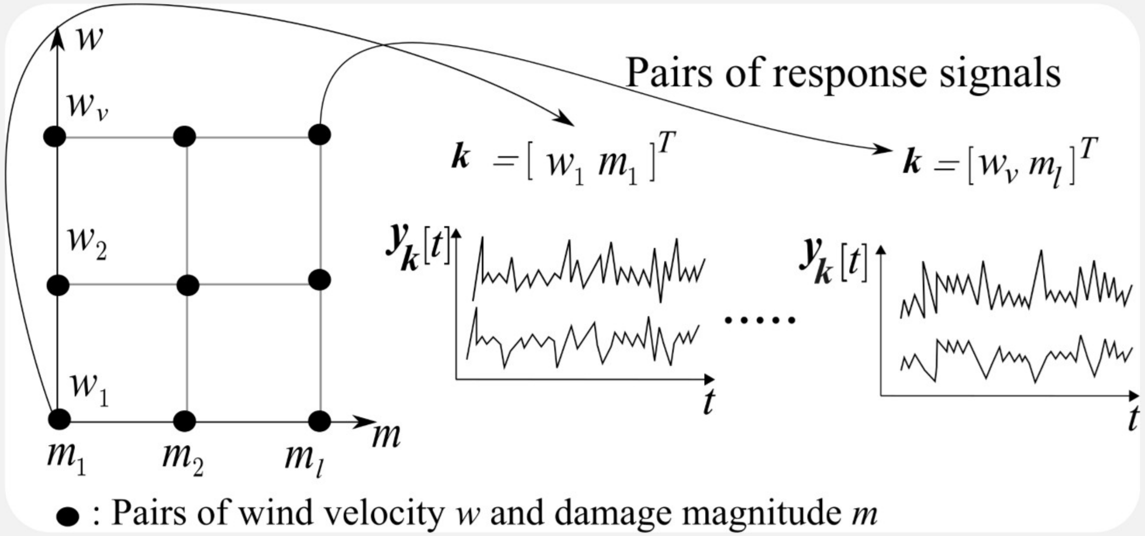
Modelling

Form of a **FP-VAR** model

$$\boldsymbol{y}_k[t] + \sum_{i=1}^{na} \boldsymbol{A}_i(k) \cdot \boldsymbol{y}_k[t-i] = \boldsymbol{e}_k[t]$$

- t : discret time, $t = 1, \ldots, N$
- $\boldsymbol{y}_k[t]$: response signals for k
- na : model order
- $\boldsymbol{e}_k[t]$: residual (error) signal for k with $\boldsymbol{e}_k[t] \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_{\boldsymbol{e}}(k))$
- $\boldsymbol{\Sigma}_{\boldsymbol{e}}(k)$: residual covariance
- $\boldsymbol{A}_i(k) = \sum_{j=1}^{p} \boldsymbol{A}_{i,j} \cdot G_j(k)$: model parameters
- $\boldsymbol{A}_{i,j}$: coefficients of projection
- $G_j(k)$: basis functions (orthogonal polynomials of one variable)

Damaged FOWT : response signals $\boldsymbol{y_k}[t]$, under a sample of wind velocities w and damage magnitudes m ($\boldsymbol{k} = [w_v \ \ m_l]^T$) covering ranges $[w_{min}, w_{max}]$, $[m_{min}, m_{max}]$



Data acquisition

Training phase

Identification of a **Vector Functionally Pooled - Vector AutoRegressive (VFP-VAR)** (*Dutta et al. 2020*) :

i) Model order na selection (Bayesian Information Criterion)

ii) Selection of the proper basis functions (optimization algorithm)

iii) Validation of the selected model (residual uncorrelatedness test)

The coefficients of projection $\boldsymbol{A}_{i,j}$ are estimated through Ordinary Least Squares

Modelling

Form of a **VFP-VAR** model

$$\boxed{\boldsymbol{y_k}[t] + \sum_{i=1}^{na} \boldsymbol{A}_i(\boldsymbol{k}) \cdot \boldsymbol{y_k}[t-i] = \boldsymbol{e_k}[t]}$$

- t : discret time, $t = 1, \dots, N$
- $\boldsymbol{y_k}[t]$: response signals for $\boldsymbol{k}$
- na : model order
- $\boldsymbol{e_k}[t]$: residual (error) signal for $\boldsymbol{k}$ with $\boldsymbol{e_k}[t] \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma_e}(\boldsymbol{k}))$
- $\boldsymbol{\Sigma_e}(\boldsymbol{k})$: residual covariance
- $\boldsymbol{A}_i(\boldsymbol{k}) = \sum_{j=1}^{p} \boldsymbol{A}_{i,j} \cdot G_j(\boldsymbol{k})$: model parameters
- $\boldsymbol{A}_{i,j}$: coefficients of projection
- $G_j(\boldsymbol{k})$: basis functions (orthogonal polynomials of two variables)

Damage detection and magnitude estimation methodology

Training phase

Coefficients of projection $\boldsymbol{A}_{i,j}$ of the FP-VAR model

Coefficients of projection $\boldsymbol{A}_{i,j}$ of the VFP-VAR model

Inspection phase

Current FOWT structural state

$k = w$ → Response signals $\boldsymbol{y}_u[t]$

Data acquisition

$$\boldsymbol{y}_u[t] + \sum_{i=1}^{na} \boldsymbol{A}_i(k) \cdot \boldsymbol{y}_u[t-i] = \boldsymbol{e}_u[t,k]$$

Modelling (FP-VAR model)

$$\hat{k} = \arg\min_k \det \frac{1}{N} \sum_{t=1}^{N} \boldsymbol{e}_u[t,k]\boldsymbol{e}_u^T[t,k]$$

Check of the uncorrelatedness (whiteness) of $\boldsymbol{e}_u\left[t,\hat{k}\right]$ though the Portmanteau test which detects changes in the autocorrelation matrix $\boldsymbol{R_e}[\tau]$ ($\tau = 1, \dots, h$ lag) of $\boldsymbol{e}_u\left[t,\hat{k}\right]$:

$Q \le \chi^2_{1-\alpha,n_y^2\cdot h}$ → $H_0: \boldsymbol{R_e}[\tau] = \boldsymbol{0}$ (White residual signals) → **Healthy structure**

Else → $H_1: \boldsymbol{R_e}[\tau] \neq \boldsymbol{0}$ (Non-white residual signals) → **Damaged structure**

with $\chi^2_{1-\alpha,n_y^2\cdot h}$ the critical limit, α the risk level, n_y^2 the number of response signals

Damage detection

Detected damaged FOWT state $\boldsymbol{k} = [w\ m]$ → Response signals $\boldsymbol{y}_u[t]$

Data acquisition

$$\boldsymbol{y}_u[t] + \sum_{i=1}^{na} \boldsymbol{A}_i(\boldsymbol{k}) \cdot \boldsymbol{y}_u[t-i] = \boldsymbol{e}_u[t,\boldsymbol{k}]$$

Modelling (VFP-VAR model)

$$\widehat{\boldsymbol{k}} = \arg\min_{\boldsymbol{k}} \det \frac{1}{N} \sum_{t=1}^{N} \boldsymbol{e}_u[t,\boldsymbol{k}]\boldsymbol{e}_u^T[t,\boldsymbol{k}]$$

Check of the uncorrelatedness (whiteness) of $\boldsymbol{e}_u\left[t,\widehat{\boldsymbol{k}}\right]$ though the Portmanteau test which detects changes in the autocorrelation matrix $\boldsymbol{R_e}[\tau]$ ($\tau = 1, \dots, h$ lag) of $\boldsymbol{e}_u\left[t,\widehat{\boldsymbol{k}}\right]$:

$Q \le \chi^2_{1-\alpha,n_y^2\cdot h}$ → $H_0: \boldsymbol{R_e}[\tau] = \boldsymbol{0}$ (White residual signals) → **Valid $\widehat{\boldsymbol{k}}$**

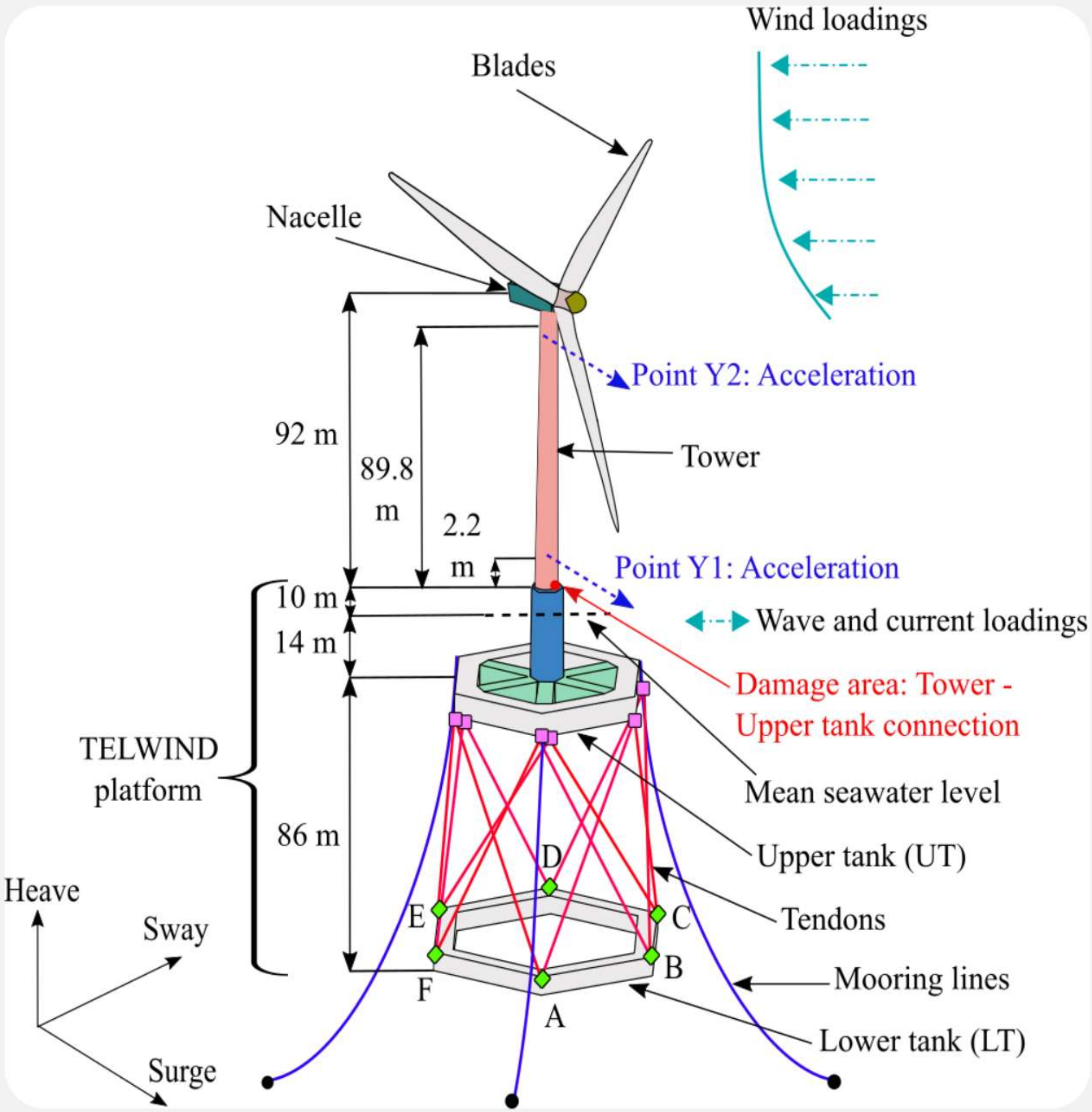
Else → $H_1: \boldsymbol{R_e}[\tau] \neq \boldsymbol{0}$ (Non-white residual signals) → **Invalid $\widehat{\boldsymbol{k}}$**

Confidence intervals for **valid** $\widehat{\boldsymbol{k}}$

$$\left[\hat{w} \pm t_{1-\frac{\alpha}{2},N-1} \cdot \hat{\sigma}_w\right], \left[\hat{m} \pm t_{1-\frac{\alpha}{2},N-1} \cdot \hat{\sigma}_m\right]$$

$\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{k}}$: Cramer-Rao lower bound

Damage magnitude estimation



Simulated FOWT supported by TELWIND floater

(ARCWIND project)

The Structure and Damage

- Tower of a FOWT based on the TELWIND floater (Esteyco)
- Single damage (buckling at bottom of the tower): Stiffness reduction (%)
- Measurements: Acceleration at bottom (Y1) & top of tower (Y2)

Simulation details

- Varying operating conditions: wave height and wind velocity
- Sampling frequency : fs = 10 Hz
- Operational bandwidth : [0 – 5] Hz
- Signal length : N = 20 000 samples
- Number of simulations: 40 (healthy state under various wind velocities (WVs))

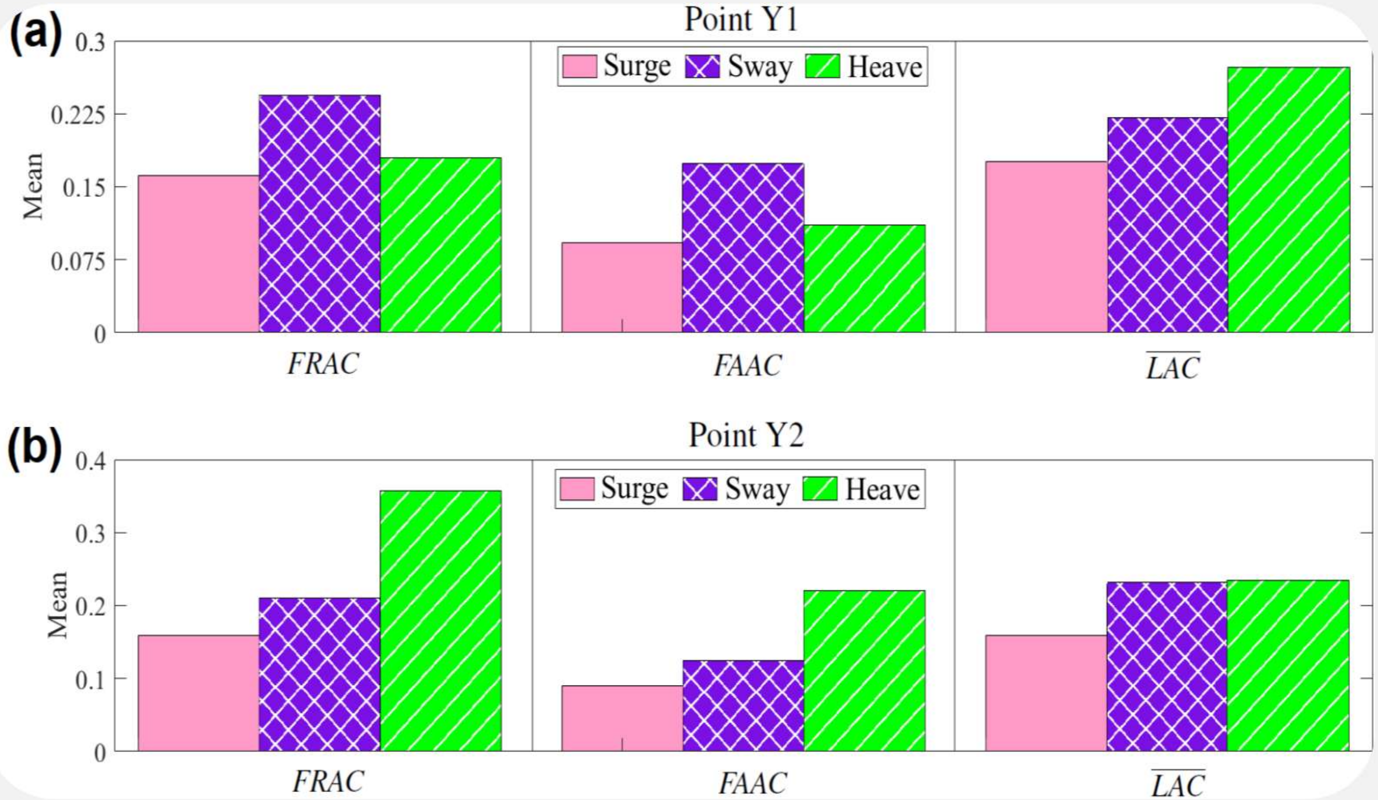
  228 : (various damage states under various wind velocities)

Selection of the most dominant motion

Selection of the most dominant motion based on its sensitivity to damage *(Zang et al. 2001)*:

- Frequency Response Assurance Criterion (FRAC)
- Frequency Amplitude Assurance Criterion (FAAC)
- Average Local Amplitude Criterion ($\overline{LAC}$)

The most sensitive motion leads to criteria values maximally deviating from unity!



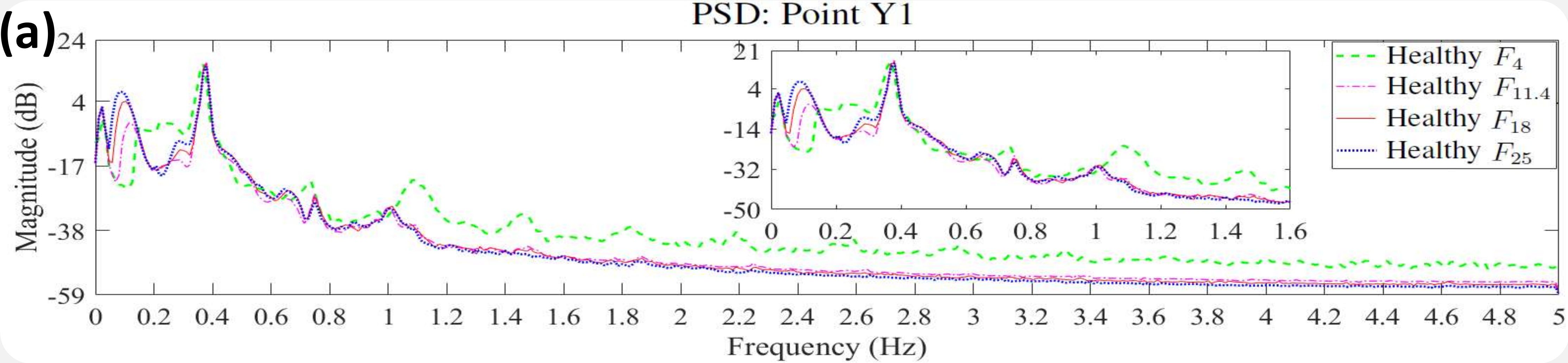
160 healthy-damaged combinations

- 4 simulations from the healthy FOWT, one per wind speed [4, 11.4, 18, 25] m/s
- 40 simulations from the damaged FOWT, one per combination between the damage magnitudes [10, 20, 30, 40, . . . , 100] % stiffness reduction and the wind speeds [4, 11.4, 18, 25] m/s

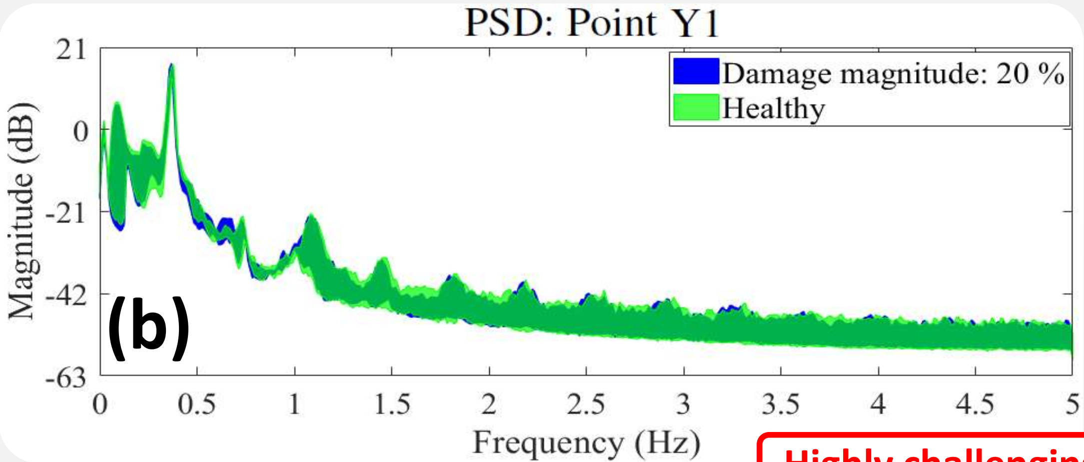
Selected motion: Surge

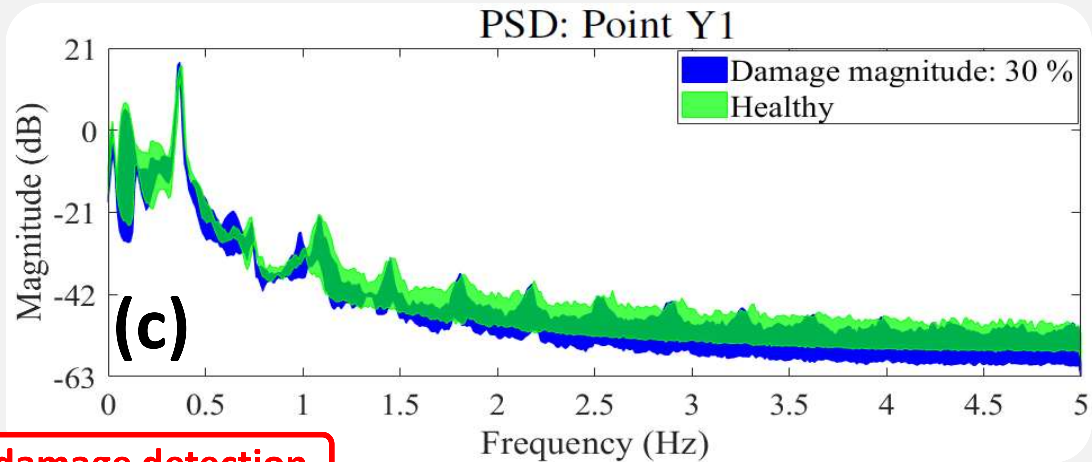
Effects of four different wind speeds on the healthy FOWT's dynamics though a comparison of Power Spectral Densities (PSDs)

(a)



Comparison of the PSDs for the healthy FOWT and FOWT with damage of magnitudes 20%, 30 and under the four wind speeds





Highly challenging damage detection

Results / Training phase

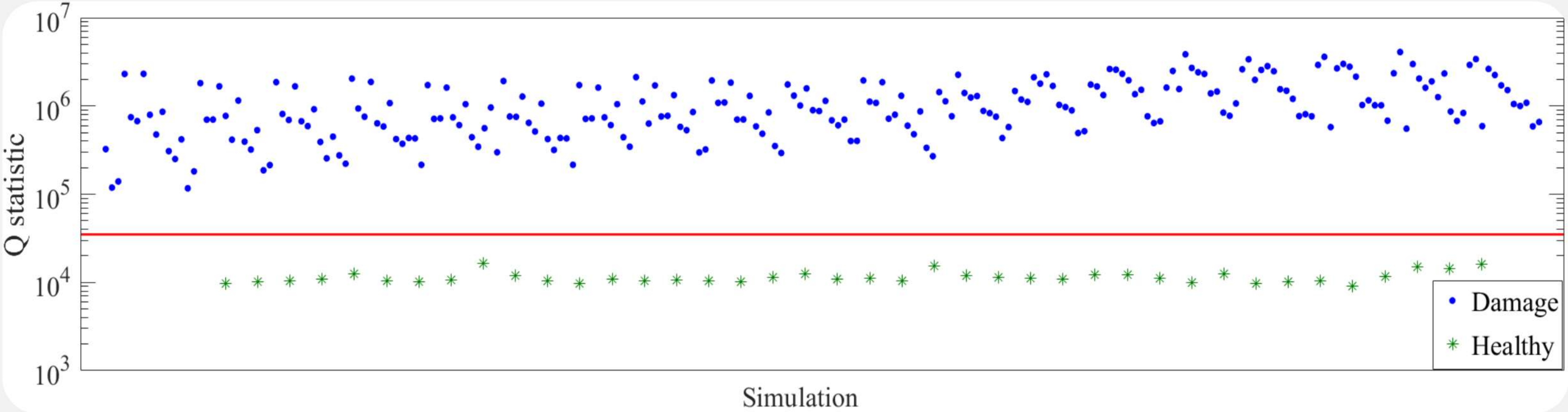
- M= 4 simulations from the healthy FOWT, one per wind speed [4, 11.4, 18, 25] m/s (*FP-VAR model identification*)
- M= 40 simulations from the damaged FOWT, one per combination between the damage magnitudes [10, 20, 30, 40, . . . , 100] % stiffness reduction and the wind speeds [4, 11.4, 18, 25] m/s (*VFP-VAR model identification / Three optimization algorithms: Bayesian optimization (BO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA)*)

FOWT structural state	Optimization algorithm	Identified model	No. of simulations	BIC
Healthy	-	VAR(170)	1	-20.42
Healthy	Genetic Algorithm (GA)	FP-VAR(170)$_3$	4	-79.42
Damaged	Genetic Algorithm (GA)	VFP-VAR(170)$_{15}$	40	-810.68
Damaged	Particle Swarm Optimization (PSO)	VFP-VAR(170)$_{19}$	40	-810.34
Damaged	Bayesian Optimization (BO)	VFP-VAR(170)$_{16}$	40	-810.24

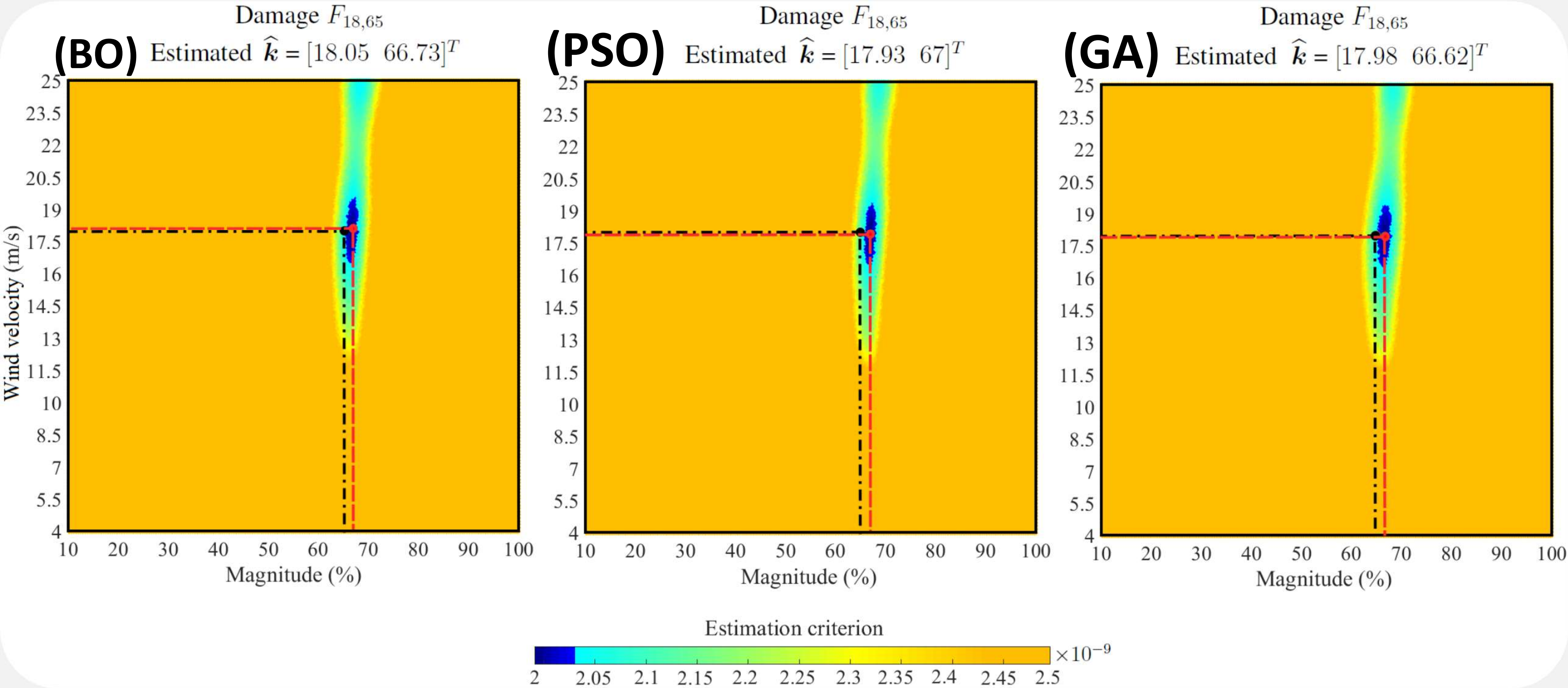
Inspection phase

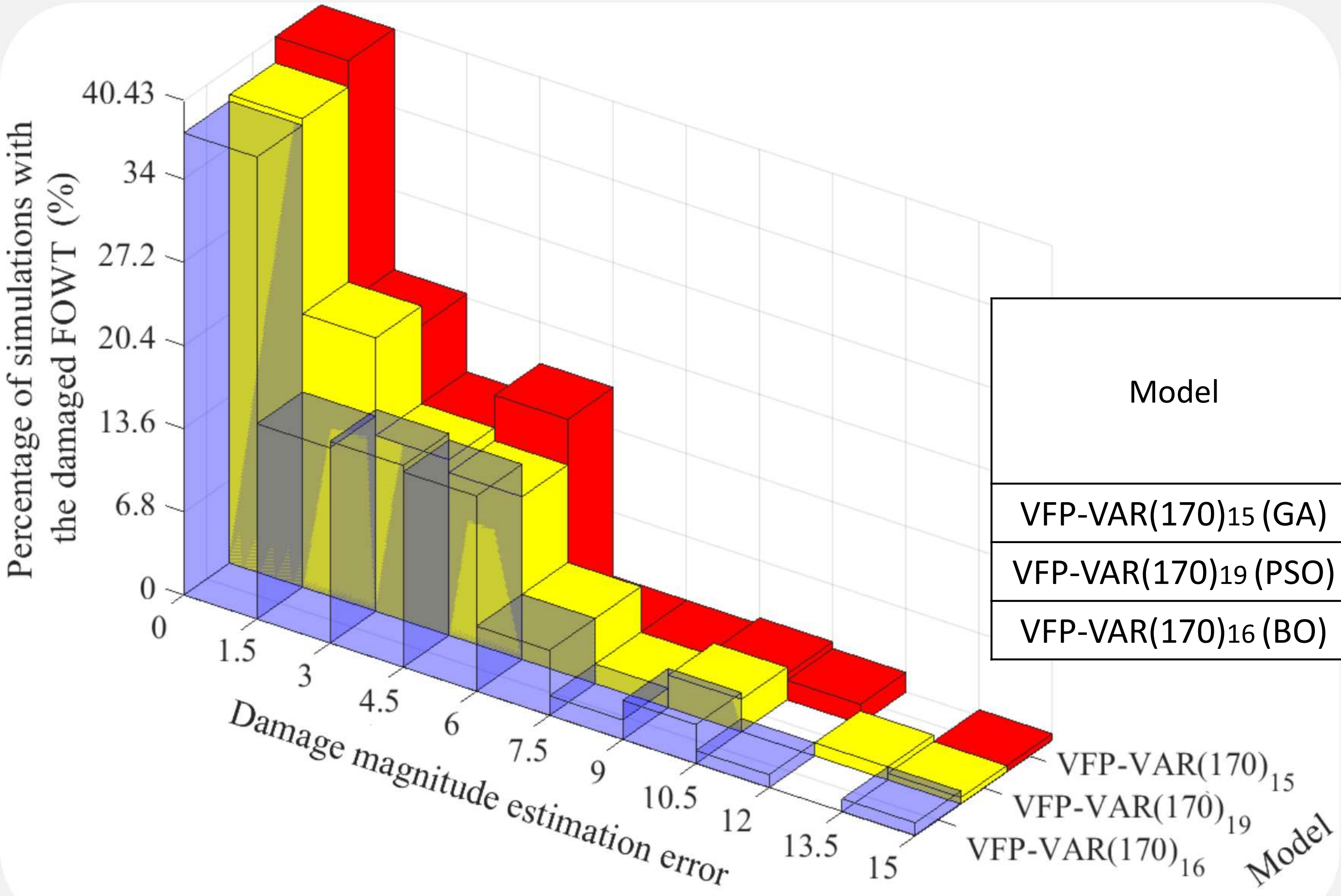
- 36 simulations from the healthy FOWT, nine per wind velocity [10, 11.7, 12, 14.8, 16, 17.3, 18] m/s
- 188 simulations from the damage FOWT (damage magnitudes: [10, 15, 20, 25, 30, . . . , 95, 100] % stiffness reduction, wind velocities: [4, 11.4, 18, 25] m/s)

Damage detection



Damage magnitude estimation of damage magnitude and wind speed





Model	Mean estimation error - Wind velocity	Mean estimation error – Damage magnitude
VFP-VAR(170)15 (GA)	0.17	3.28
VFP-VAR(170)19 (PSO)	0.08	2.93
VFP-VAR(170)16 (BO)	0.07	2.79

Concluding remarks

- **Three formulated PSD-based criteria for the selection of the measurement direction being the most sensitive (dominant) to damages**
- **Damage magnitudes smaller than 30% of stiffness reduction to the tower base → very similar effects to the dynamics as the varying OCs to the healthy FOWT → challenging damage detection**
- **Achievement of 100% correct detection of the FOWT health state in all considered simulations with the healthy and damaged FOWT through the multivariate version of the FMBM**
- **Remarkably low (∼ 3%) mean damage magnitude estimation error from the damaged FOWT, with all actual damage magnitudes being within or very close to the constructed confidence intervals**
- **Performance of the FMBM in damage magnitude estimation almost unaffected by the optimization algorithms (BO, PSO, GA) used for the selection of the functional models' basis functions**

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