A Comparative Study on Damage Detection in the Delta Mooring System of Spar Floating Offshore Wind Turbines

Christos S. Sakaris, Rune Schlanbusch

Smart Instrumentation and Industrial Testing research group, Norwegian Research Centre - NORCE , 4879 Grimstad, Norway

Anja Schnepf, Muk Chen Ong

Department of Mechanical and Structural Engineering and Materials Science, University of Stavanger

ACD 2022 IFAC

Analytics for Asset Integrity Management in Wind farms (AIMWind)

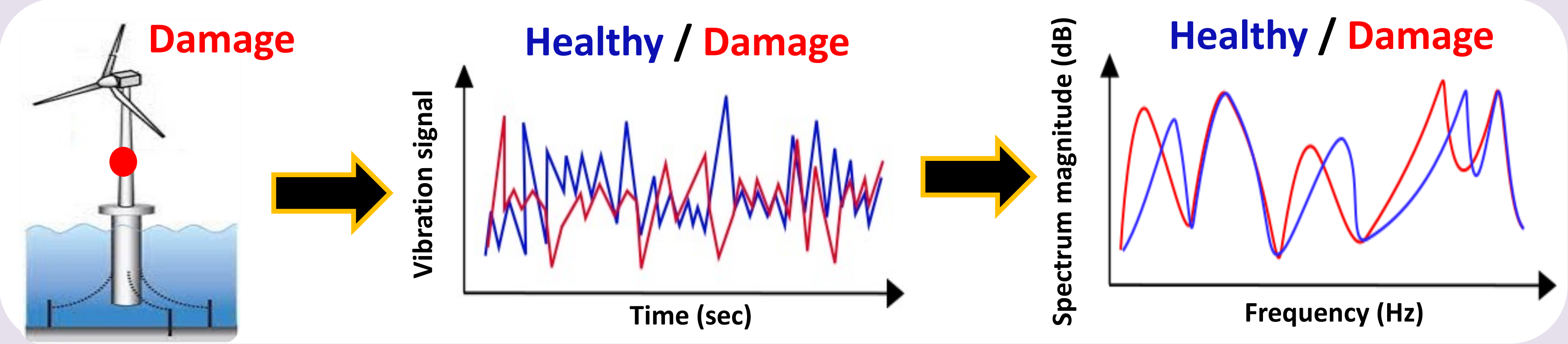
AIMWind

Importance of Damage Detection

Damage in the mooring lines’ → increase of tension → loss of stability, high maintenance cost → Floating Offshore Wind Turbine (FOWT) collapse and endangerment of human safety → Early damage detection being important

Fundamental principle of damage detection methods based on vibration signals

Presence of damage → Change in the structural dynamics → Change in the vibration response signals → Damage detection



Environmental Conditions (ECs)

Varying ECs

↓

Partially or fully “masking” the effects of damages on the structural dynamics

↓

Highly challenging damage detection

Vibration-based damage diagnosis in the mooring lines of FOWTs under constant and varying ECs

Characteristics of the methods used for damage diagnosis in the mooring lines of FOWTs

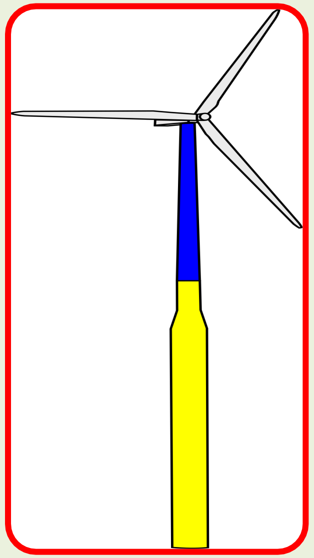
- **Data based models** (developed with acquired signals from the structure)
  - Neural Networks (*Dehkharghani et al. 2021, Gorostidi et al. 2022*)
  - Power Spectral Density (*Jamalkia et al. 2016, Liu et al. 2021*)
- **Explicit modelling methods** (models fully describing the effects of varying ECs on the structural dynamics)
- **Requirement of a large number of data records under different ECs in the baseline (training) phase** (*Gorostidi et al. 2022*)
- **Treatment of damage detection as a classification problem** (an unknown state classified as a healthy or a damage state)

Problems with the aforementioned methods

- **Not clear handling of the different ECs in the baseline phase** (*Liu et al. 2021*)
- **The examination of only damage cases in the inspection (real time) phase** (*Dehkharghani et al. 2021, Liu et al. 2021*)

Goal of the current study

Damage detection in the Delta Mooring System of a Spar Floating Offshore Wind Turbine (FOWT) under varying wind speed and wave height



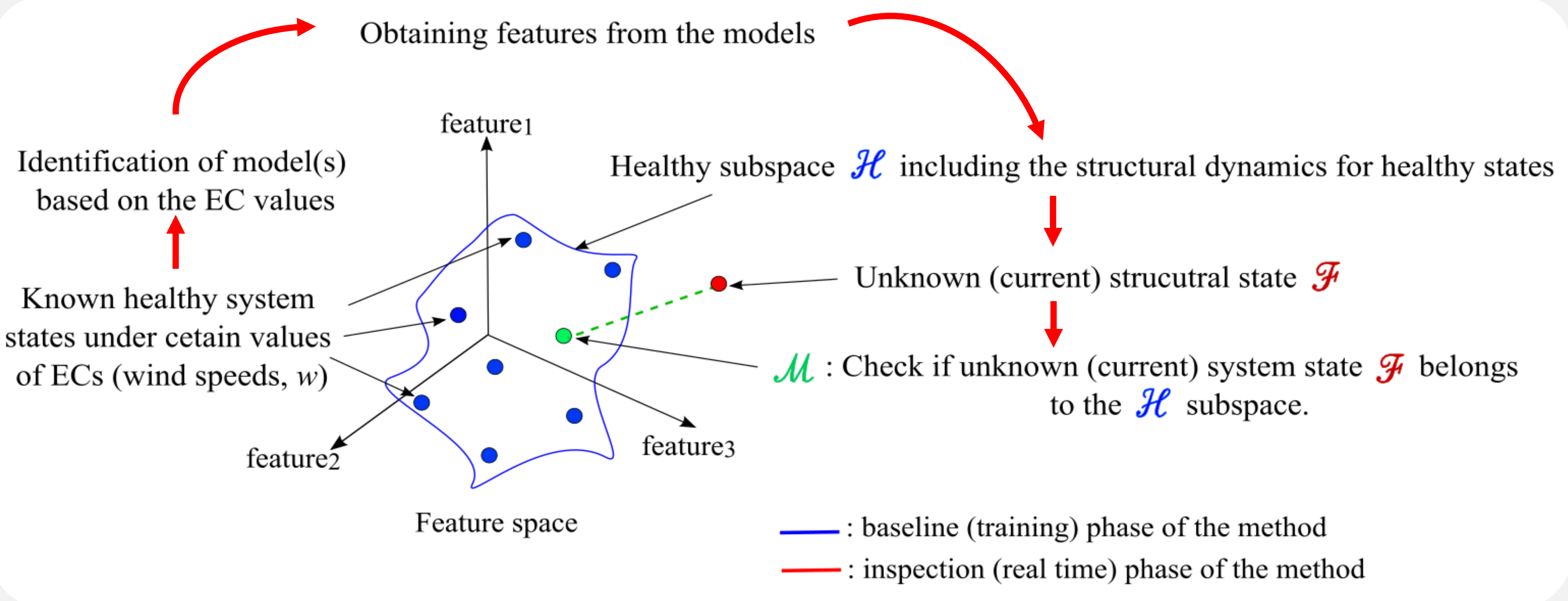
Spar FOWT

The examined part of the mooring line is chain

Employed statistical methods for damage detection

- Multiple Model – Power Spectral Density (MM-PSD) method equipped with multiple Power Spectral Density (PSD) models
- Multiple Model – AutoRegressive (MM-AR) method equipped with multiple AutoRegressive (AR) models
- Functional Model Based Method (FMBM) equipped with a single Functional Model (FM)

Concept of the MM-PSD method (equipped with multiple PSDs), the MM-AR method (equipped with multiple AR models) and the FMBM (equipped with a single FM)



Varying ECs: Wind speed (WS, symbolized by w) and wave height (WH) . **Only WS considered as the main ECs by the methods**.

MM-PSD (*Kaliorakis et al. 2020*) and MM – AR method (*Vamvoudakis et al. 2018, Aravanis et al. 2019*)

Form of an AutoRegressive (AR) model

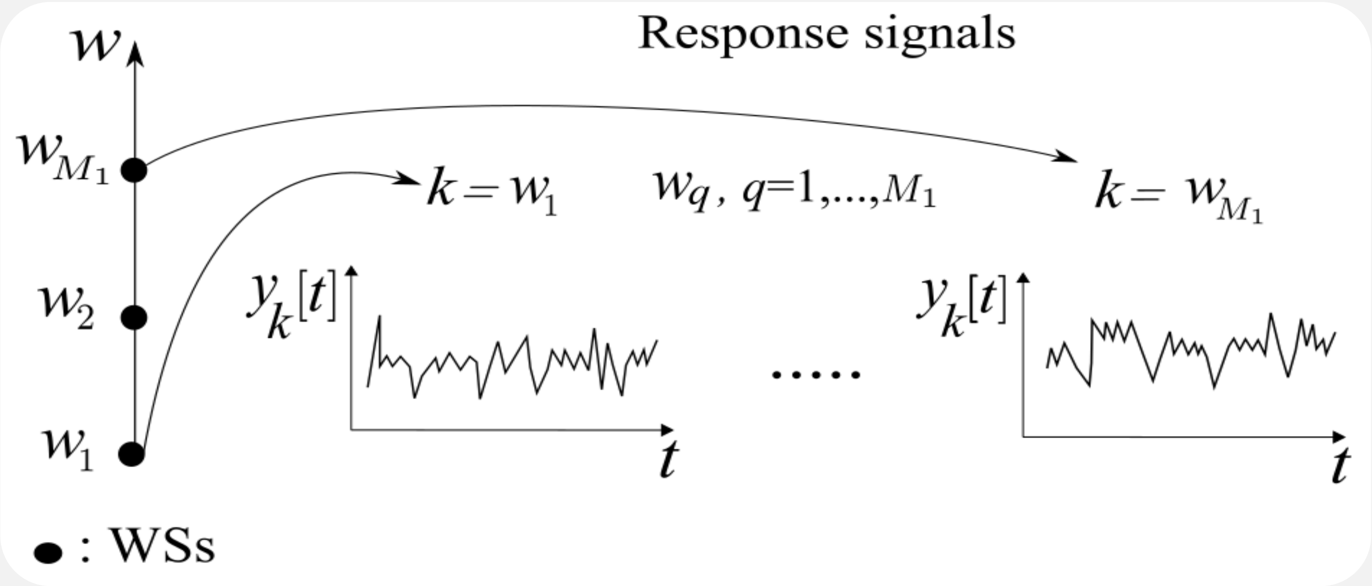
$$\boxed{y[t] + \sum_{i=1}^{na} \alpha_i \cdot y[t-i] = e[t]}$$

- t : discreet time
- $e[t]$: residual signal
- $y[t]$: response signal
- na : AR order
- α_i : AR parameters

Only wind speed (WS, symbolized by w) is considered as the main varying EC by the methods.

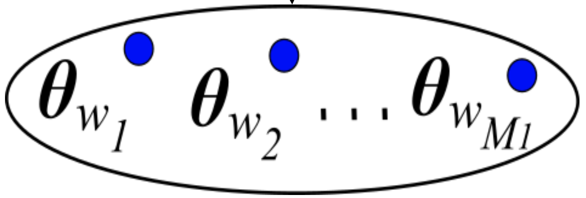
Baseline / Training phase

Healthy state: response signal $y_k[t]$ under each WS value $k = w_q,\ q = 1, \dots, M_1$



Data acquisition

Identification of a model per w_q value & extraction of feature vector $\boldsymbol{\theta}_k$



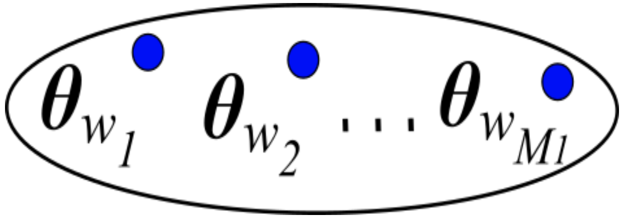
Modelling

MM-AR: AR parameters as features

MM-PSD: PSD magnitudes as features

Baseline / Training phase

Identification of a model per w_q value & extraction of feature vector $\boldsymbol{\theta}_k$



Modelling

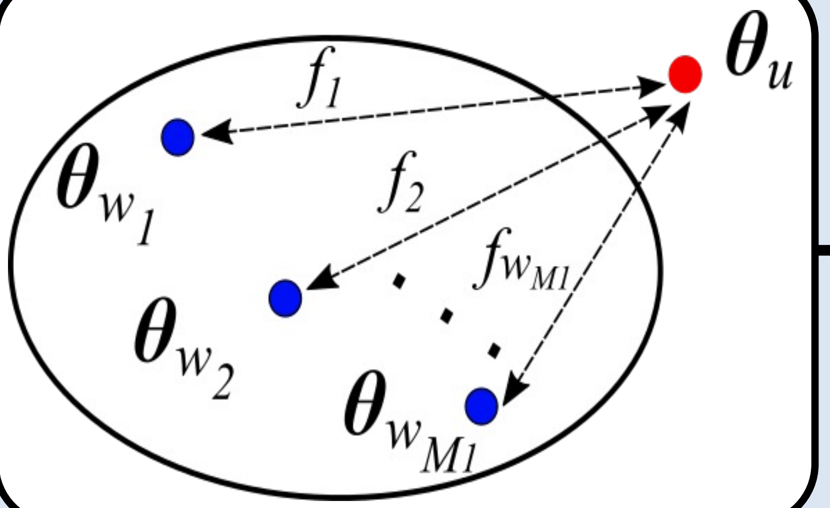
Inspection phase: Damage detection

Response signal $y_u[t]$ from an unknown structural state u

Data acquisition

Identification of a model and extraction of feature vector $\boldsymbol{\theta}_u$

Modelling



Calculation of Euclidean or Mahalanobis distance $f_k, \; k = w_q, \; q = 1, \ldots, M_1$

If $\mathrm{Q} = \min_k f_k \leq l_{lim}$ ➡ **Healthy structure**

Otherwise ➡ **Damaged structure**

Damage detection

(l_{lim} : threshold defined in baseline phase)

FMBM (*Aravanis et al. 2019, Sakaris et al. 2021*)

Baseline phase: Identification of a FM which is a Functional Pooled - AR (FP-AR) model

Form of FP-AR model

- $k = w, \; w$: wind speed (WS) (only WS considered as varying EC / wave height not considered due to its dependance to WS)
- A single FP-AR model is able to describe the structural dynamics under varying WS of any potential value $k = w$

$$y_k[t] + \sum_{i=1}^{na} \alpha_i(k) \cdot y_k[t-i] = e_k[t] \qquad \text{with } \; e_k[t] \sim \text{iid}\, \mathcal{N}\left(0, \sigma_e^2(k)\right) \; \text{and} \; k \in R$$

- $a_i(k) = \sum_{j=1}^{p} a_{i,j} \cdot G_j(k)$ (the model's AR parameters $a_i(k)$ are expressed as functions of the varying WS $k = w$)
- t : discreet time ($t = 1, \ldots, N$)
- na : AR order
- $y_k[t]$: response signal
- $e_k[t]$: residual signal
- $\sigma_e^2(k)$: residual variance
- $G_j(k)$: basis functions (polynomials of one variable)
- $\boldsymbol{\theta}$: vector containing the AR coefficients of projection $a_{i,j}$

Healthy structure → Response signals $y_k[t]$ under a sample of WSs $k = w_q,\ q = 1, \dots, M_1$ → FP-AR model identification

Data acquisition

The FP-AR model identification includes (*Sakaris et al. 2016*)

- i) model order na determination (Bayesian Information Criterion)
- ii) Selection of the proper basis functions (Genetic Algorithm)
- iii) validation of the selected model (residual whiteness test)

The AR coefficients of projection $a_{i,j}$ are estimated through Weighted Least Squares

Modelling

Inspection phase: Damage detection

Current (unknown) structural state → Response signal $y_u[t]$ & measured wind speed $k = w$

Data acquisition

$$y_u[t] + \sum_{i=1}^{na} \alpha_i(k) \cdot y_u[t-i] = e_u[t,k]$$

→ Residual signal $e_u[t,k]$

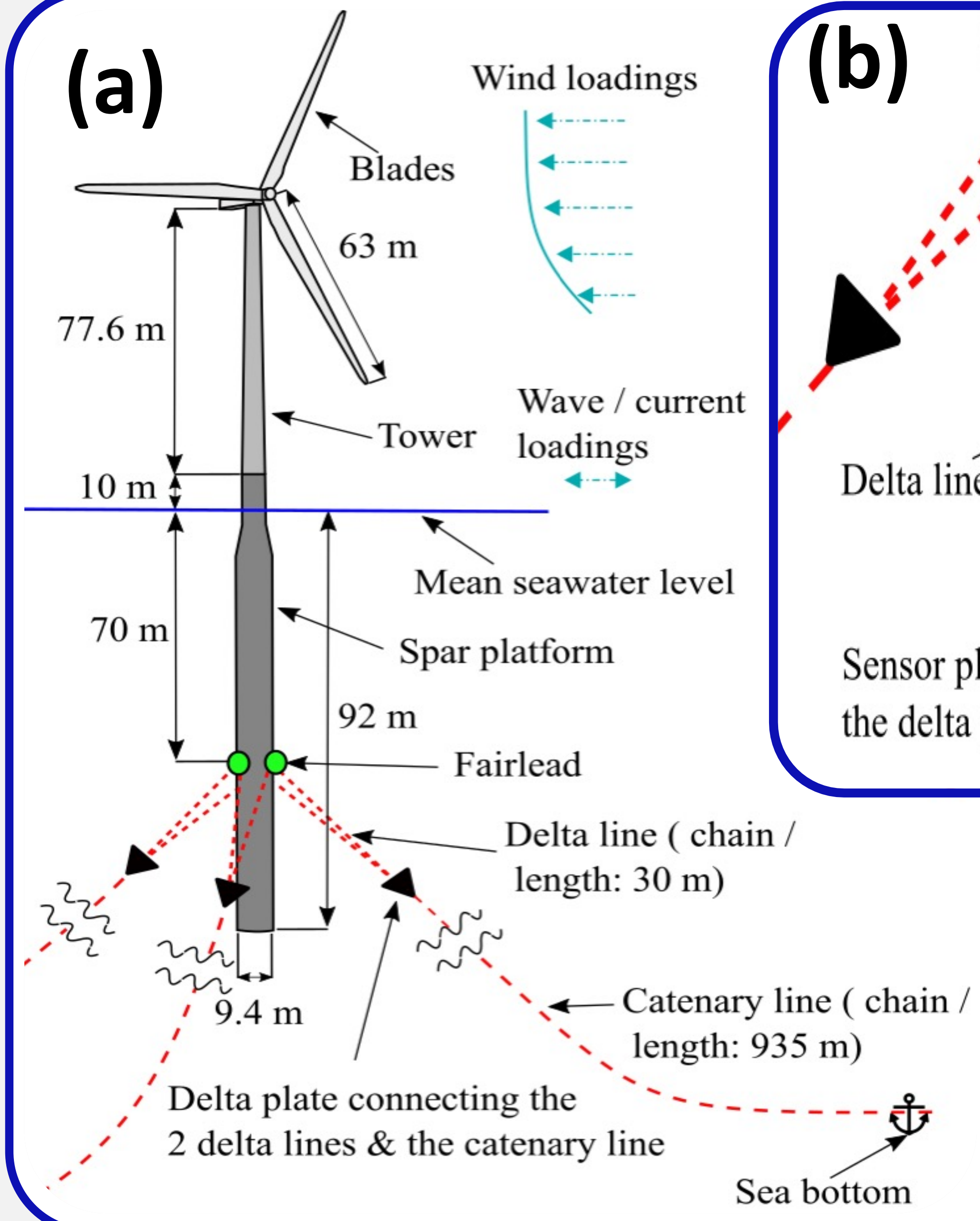
Modelling

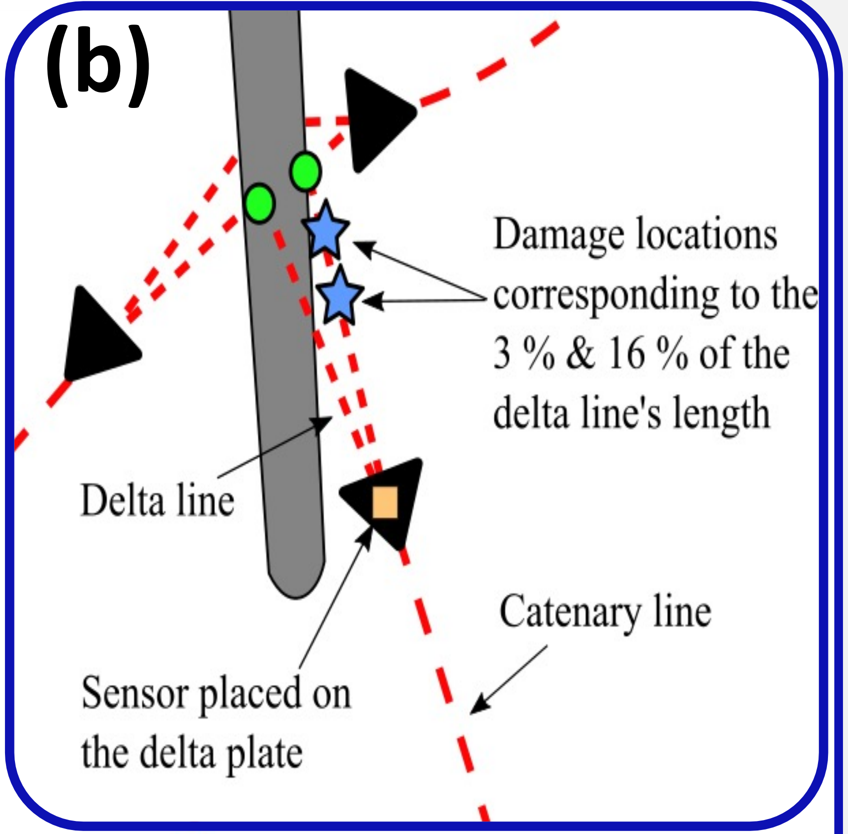
Damage detection → Check of the uncorrelatedness (whiteness) of $e_u[t,k]$ though a statistical hypothesis test which detects changes in the partial autocorrelation function $\pi_e[\tau]$ ($\tau = 1, \dots, h$ lag) of $e_u[t,k]$ (*Pena et al. 2006*) .

$-Z_{1-\alpha} \leq \mathrm{D} \leq Z_{1-\alpha}$ → $H_o\!: \pi_e[\tau] = 0$ (White residual signal) → **Healthy structure**

Else → $H_1\!: \pi_e[\tau] \neq 0$ (Non-white residual signal) → **Damaged structure**

with $-Z_{1-\alpha}, Z_{1-\alpha}$ the critical limits and α the risk level





OC3-HywindSpar FOWT – Delta line

The Structure and Damage

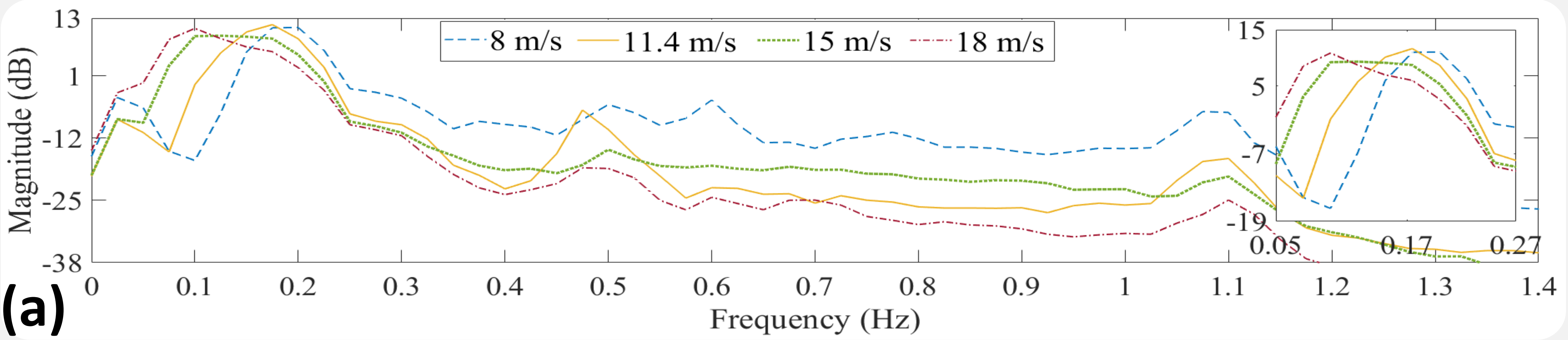
- Delta line (chain) of FOWT's mooring line
- Single damage: Stiffness reduction (%) at of a specific magnitude and at a specific location (2 magnitudes & 2 locations)
- Measurements: heave acceleration ( )

Simulation details

- Varying environmental conditions: wave height and wind speed
- Sampling frequency : fs = 10 Hz
- Operational bandwidth : [0 – 1.4] Hz
- Signal length : N = 20000 samples
- Number of simulations: 14 (healthy state under various wind speeds)

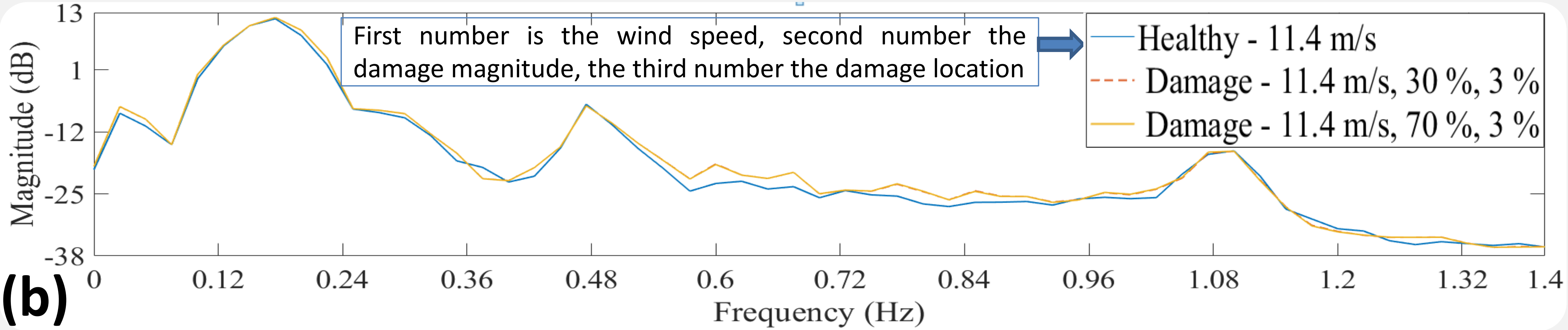
  : 9 (various damage states under various wind speeds)

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



(a)

Comparison of the effects of damages of different magnitude at same location and the effects of the healthy state (PSDs)



(b)

Results / Baseline phase

- M=7 simulations from the healthy state, one per wind speed 8, 10.3, 11.4, 13.8, 15, 17.3, 18 m/s (one acceleration signal per simul.)
- Signal length per simulation.: N=20000 samples

PSD identification (used in the MM-PSD method)

- Estimated models : 7 Welch-based PSDs, one PSD per wind speed
- Frequency range: [1 – 1.4] Hz
- Frequency resolution: 0.025 Hz
- Dimension of feature (PSD magnitude) vector : $[57 \times 1] \rightarrow [50 \times 1]$

AR identification (used in the MM-AR method)

- Estimated models : 7 AR(260) models, one AR model per wind speed
- Dimension of feature (AR parameter) vector : $[260 \times 1] \rightarrow [255 \times 1]$

FP-AR identification (used in the FMBM)

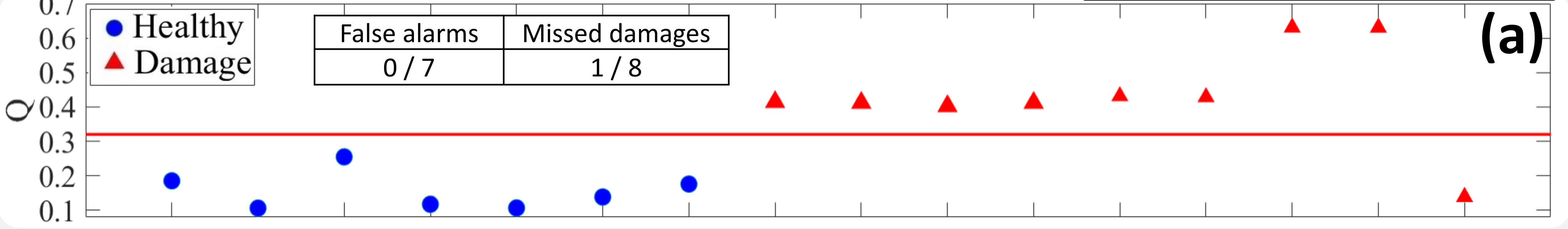
- Estimated models : 1 FP-AR(140) model
- Selected basis functions: 6 Shifted Legendre polynomials of variable

Inspection phase

- 7 simulations from the healthy state, one per wind speed 10, 11.7, 12, 14.8, 16, 17.3, 18 m/s
- 8 simulations from damage state (magnitudes: 30 & 70 % stiffness reduction, locations: 3 & 16 % of the delta line's length)

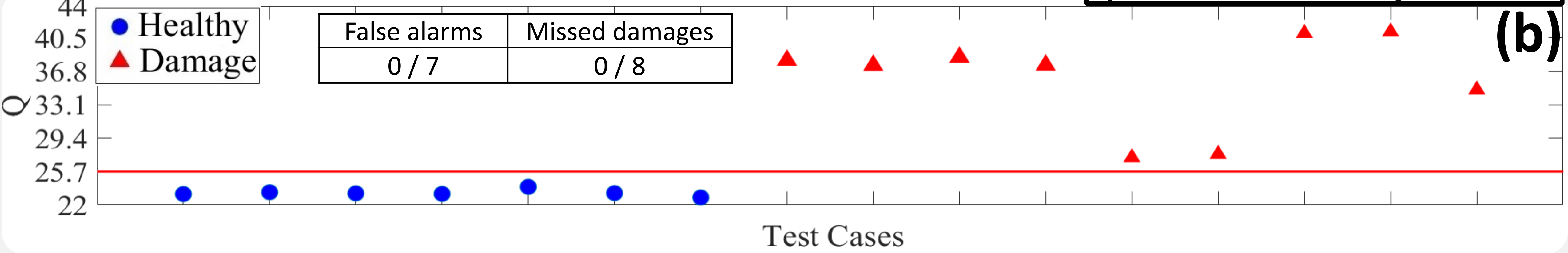
Damage detection based on the MM-PSD method

Q above the limit → damaged structure



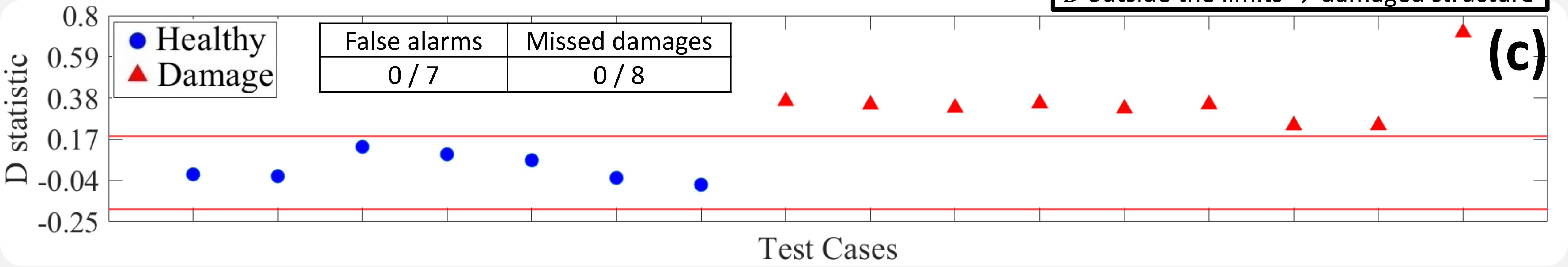
Damage detection based on the MM-AR method

Q above the limit → damaged structure



Damage detection based on the FMBM

D outside the limits → damaged structure



Conclusions

- **Mooring line damages having small effects on the structural dynamics and thus making damage detection very difficult**
- **More precise description of a spar FOWT dynamics though the parametric models AR and FM**
- **Successful damage detection in the mooring system of a spar FOWT through the statistical methods MM-AR and FMBM**

Acknowledgement: Funded by the Research Council of Norway through the projects i) Analytics for asset Integrity Management of Windfarms (AIMWind), grant no. 312486 ii) Design Optimisation of Power Cable, Shared Electrical Line and Mooring configurations for Floating Offshore Wind Turbines, grant no. 320902.