Gaussian Process Models for Mitigation of Operational Variability in the Structural Health Monitoring of Wind Turbines

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Abstract

The analysis presented in this work relates to the quantification of the effect of a selected set of measured Environmental and Operational Parameters (EOPs) on the dynamic properties of low and high frequency vibration, in the context of a vibration monitoring campaign implemented on the blade of an operating wind turbine. To this end, a Gaussian Process (GP) time-series modelling approach is adopted, in which the coefficients of a time-series model are driven by a Gaussian Process Regression on the selected EOPs. The properties of the data acquisition system allow to evaluate low and high frequency dynamics, the former associated with the structural dynamics of the blade, and the latter with the wave transmission properties of the material, assessed with the help of an electro-mechanical actuator installed on the blade. In this form, a multi-temporal-scale approach is adopted here, where a GP Linear Parameter Varying Auto-Regressive model is selected to represent low frequency (structural) dynamics, while in parallel a GP Continuous Wavelet Transform model is used to represent high frequency dynamics (associated with wave transmission properties in the material). In both cases the blade is considered in its healthy state as well as in various operational regimes, including idle, and rotating at two different set points. As a result, it is demonstrated that GP time-series modelling succeeds in evaluating and isolating the influence of different EOPs in the features of the vibration response of the wind turbine blade, and at the same time, normalize their effects to enhance the detectability of damage.

Keywords: Environmental and operational variability, Structural Health Monitoring, non-stationary vibration, wind turbine, Gaussian process regression, time-series models.
1. Introduction

Recent advances on sensing, communications and computing technologies have facilitated the deployment of Structural Health Monitoring (SHM) systems on civil and mechanical structures and their sub-structural components. Such systems provide immense amounts of information in the form of vibration response (acceleration, strain), and operational or environmental variables (temperature, humidity, wind conditions, rotational speed, operational demands, and so on). In turn, this information allows engineers to supervise and monitor structural dynamics over extended periods of time, and to investigate the effects of environmental and operational variables onto structural behaviour. Such knowledge allows optimizing the operation and maintenance of structural assets, thereby contributing to the sustainable management of critical resources. However, in order to extract indicators of structural health in a robust and reliable manner, it is necessary to develop adequate processing methodologies capable of coping with the variable structural dynamics resulting from changing environmental and operational conditions.

Indeed, variable Environmental and Operational Parameters (EOPs) bear a significant influence on the characteristics of the vibration response of a structure [1, 2, 3, 4]. On the one hand, certain EOPs induce continuous changes on structural properties. For instance, structural stiffness depends on temperature, or even the gradients of temperature, in which a structure is exposed [2]. In turn, the effect of changing stiffness would manifest in a continuous trend on the natural frequencies extracted via vibration monitoring. On the other hand, discrete events introduce isolated shifts on structural properties or result in alteration of the operational regime of the structure. For instance, events relating to precipitation (draught / rain / hail / snow) introduce instantaneous modifications on the mass density or aerodynamic profile of structural components, which are in turn observed as instantaneous shifts on the power or frequency content of the vibration response. Similarly, actions induced via a control system will modify the operational regime of the structure.

These continuous and discrete EOP influences hinder the analysis of the dynamic response and damage detectability in long-term monitoring campaigns. This dependence of robust diagnostics of varying EOPs has been a matter of extensive research throughout in recent years within the SHM community [1, 2, 5, 6, 7], resulting in an abundance of methods, from which two fundamental classes of methodological approximations may be recognized.

The first methodological approximation is hinged solely on vibration data, and follows the traditional statistical pattern recognition paradigm established for SHM [1, 2, 8], namely: (i) estimate a number of characteristic quantities (features) out of vibration data –feature estimation--; (ii) select a feature subset from the original feature set to minimize the influence of variable EOPs and noise, and reduce data dimensionality –feature selection--; (iii) make an inference on the health of the structure based on the selected feature subset (damage diagnosis). In turn, damage diagnosis may involve either damage detection, damage localization, damage assessment, or a combination thereof. Estimated features comprise either estimates of physical quantities, where natural frequencies, mode shapes or spectra are most typically appraised [3, 9, 10], or abstract features, such as the coefficients of parametric models (AutoRegressive –AR– models for instance) [11, 12]. Subsequently, a relevant subset of features may be selected via projection methods, where linear or non-linear geometrical transforms are utilized to cast the original feature set into a subspace, where the influence of EOPs is presumably absent. Typical examples comprise Principal Component Analysis (PCA), Independent Component Analysis (ICA) and their extensions to non-linear feature sets [2, 5, 13, 14]. More recently, cointegration techniques have been utilized to remove trends on the feature set, by separating the original non-stationary
features into a finite set of stationary components [15, 16, 17, 18]. Given the obtained feature set, it is now possible to perform inferences on the health state of the structure with one of the vast number of methods available in statistics or pattern recognition, ranging from simple hypothesis tests or control charts, to support vector machines, Gaussian process classifiers, neural networks and so on.

The second methodological approximation utilizes both vibration data and EOP measurements to draw inference on the state of the structure. This group of methodologies is hinged on the fact that, as mentioned before, EOPs influence the dynamics of the structure, and as a remedy aim at capturing such influence on features extracted from the vibration response [6]. These methods operate in a manner that is similar to that of the vibration-only methods discussed before, namely: (i) feature estimation; (ii) feature normalization and selection; (iii) damage diagnosis. However, the main difference lies in the second step, where a feature normalization procedure is introduced. Feature normalization here refers to the process of directly capturing the influence of measurable EOPs on the estimated features by means of some sort of functional dependence model. Such a functional dependence model may be attained either via (deterministic) functional series expansions or regression models [1, 2, 3, 19, 20], or through stochastic methods such as Polynomial Chaos Expansions (PCE) [21, 22, 23], or Gaussian Process Regression (GPR) [6, 24]. Stochastic methods may be more powerful, since these are also suited to capture the uncertainty stemming from unobserved EOPs and noisy measurements. In addition, when discrete events may also influence the dynamics of the structure, then it is possible to build a “pool” of models as exemplified in [7, 25].

Certainly, “cause–effect” methods hold an advantage over traditional “effect-only” methods (cause: EOPs; effect: vibration response) when a sufficient set of EOPs are measurable, since these methods directly capture the variation on the vibration characteristics, instead of simply inferring those effects. However, the complexity of these methods largely increases, due to the necessity of building a functional dependence model on a potentially large quantity of variables included in the feature set. This problem further grows when multiple concurrent vibration measurements are present in long-term monitoring campaigns.

This work aims at streamlining the steps involving the “cause–effect” methodological approach and demonstrating its value on the analysis of a more realistic dataset, in consideration of the problem of large volumes of data coming from long-term monitoring sessions. To that end, the Gaussian Process (GP) time-series modeling approach postulated in [6] is adopted in this study. The GP time-series methodology is applied on monitoring data from a Vestas V27 wind turbine [26, 27]. The data contains multiple acceleration measurements obtained from a sensor network located throughout the low-pressure side of the blade, while environmental and operational data were concurrently obtained from the control system of the wind turbine and a weather mast located near the wind turbine. A damage (a trailing edge opening) was artificially introduced into the instrumented blade, and the amount of damage was gradually increased during the campaign. The in-operation monitoring data utilized in this study is endowed by certain features that render it an interesting subject of study. Firstly, the vibration data was measured at a high sampling rate (16 kHz) over five minute intervals. Secondly, an electro-mechanical actuator was fixed near the root of the blade, which introduced a periodic impact to the blade. In order to take full advantage of the characteristics of the data acquisition system, a multi-time-scale approach is adopted in this work, where the analysis is done separately for low- and high-frequency ranges of the measured signals. Low frequency range analysis aims at modelling the characteristics of the low-frequency structural dynamics of the blade in response to wind excitation, while high frequency range analysis aims at assessing the high-frequency wave transmission properties
of the blade material obtained in response to the actuator excitation. At the same time, the analysis encompasses both output-only and input-output frameworks: output-only in the context of low-frequency analysis, where the measured vibration corresponds to the response to unmeasurable wind excitation; input-output in the context of high-frequency analysis, where the vibration appears as a response of the actuator excitation.

This work is organized as follows. Section 2 provides a brief description of the vibration data and the monitoring campaign. Section 3 provides the rationale behind the methodology and briefly summarizes its details. Section 4 provides details on the analysis of low-frequency vibration components, while Section 5 provides a similar analysis on high-frequency vibration components. Section 6 provides a brief evaluation on damage detection based on the proposed methodology. Finally, Section 7 provides a discussion on the obtained results, while Section 8 summarizes the main conclusions of the study.

2. Brief description of the monitoring campaign and vibration data

The study is based on the experimental data obtained from a monitoring campaign performed on a 225 kW Vestas V27 wind turbine installed near the town of Roskilde, Denmark. Full details on the monitoring campaign can be found in [26, 27], and only a brief description is provided for completeness. The Vestas V27 wind turbine is a three-bladed pitch regulated horizontal axis wind turbine, with 27 m rotor diameter and nominal power 225 kW. One of the blades of the wind turbine was instrumented with 11 monoaxial accelerometers and an electro-mechanical actuator. An additional DC accelerometer was mounted in the spinner to derive the blade azimuth and rotational speed. The accelerometers and the actuator were connected to the data acquisition system installed in the spinner, which wirelessly transmitted the data to a computer located inside the tower. The sensor and actuator network installed in the blade is depicted in Figure 1.

Simultaneously with the vibration data, meteorological data were collected from a weather mast located a few hundred meters away from the wind turbine. The weather data includes temperature, wind speed, direction and turbulence intensity at different altitudes, atmospheric pressure and precipitations, which are sampled every 1 min. Likewise, power production data, yaw angle and pitch angle were also available from the wind turbine control system.

The monitoring campaign lasted 104 days, from November 2014 to March 2015. During the campaign, the wind turbine was driven in regular mode (i.e. governed by its own control system), though, when in damaged states, the wind turbine was manually set to the idle mode at nights and during weekends. An artificial damage, implemented via a trailing edge opening of the instrumented blade, was introduced and gradually extended during the campaign; in total, the blade experienced five health states: undamaged, 15, 30, and 45 cm trailing edge openings, and repaired state.
The data acquisition system was programmed to record the blade vibration response in 5 min intervals, including a single actuator-induced excitation, with a sampling frequency of 16 384 Hz. In total, a set of about 25 000 excitation/response 5 min. data sets were recorded, covering representative range of weather conditions typical for a Danish winter.

3. Methodological approach

3.1. Rationale and overview of the methodology

Figure 2(a) illustrates a typical vibration response signal of the blade and its spectrogram. The spectrogram is calculated via the MATLAB command `spectrogram`, using a Gaussian window of 16 384 samples, with an overlap of 16 256 samples, and aperture parameter 32. In the resulting spectrogram is observed that most of the spectral content of the signal is concentrated in the low frequency range (under 1 kHz), except when the blade is excited by the actuator (about 10 s), where the spectral content of the blade response covers almost all the range of frequencies. This transient event lasts about 200 ms. Figure 2(b) provides a detailed view of the transient period after the actuator excitation, where it is evident that the impulse excites most of the frequency range, particularly from 1 to 5 kHz. Nonetheless, the influence in the low frequency range is almost negligible, particularly under 100 Hz.

Accordingly, the methodological approach considered in this work consists in separating the original signal into two spectral regions: a low frequency range from zero to 64 Hz, aiming to
capture the structural dynamics characteristics in the response; and a high frequency range, from 128 Hz and above, aiming at capturing the characteristics of the transient induced by the actuator impulse. These frequency ranges are selected due to the following criteria: (i) structural dynamics of similar blades are characterized by modes lying within the 40 Hz interval; (ii) following from Fig. 2(b), actuator dynamics are evident only from about 100 Hz and above. Subsequently, two independent Gaussian Process (GP) time-series models [6] are utilized to capture the variations in the vibration characteristics in both low and high frequency ranges. The GP time-series models are driven by the respective wind speed, turbulence intensity and ambient temperature measured at the analysis interval. In addition, operational regime indicators are manually calculated on the basis of the average rotation speed of the wind turbine, thus assigning the wind turbine into one of three operational regimes, namely idle, operating at 34 rpm and operating at 43 rpm. The methodological approach is depicted in Fig. 3.

![Diagram of the monitoring and damage detection methodology](image)

Figure 3: Flow chart describing the adopted multi-scale monitoring and damage detection methodology.

The approach presented here considers three different time-scales associated with the dynamics of the blade, namely: high-frequency dynamic vibration characteristics associated to the dynamics excited by the actuator, structural dynamics features observed in the blade vibration in response to natural excitation, and long-term variations in the blade dynamics occurring as a result of varying EOPs.

Since the characteristics of the blade vibration response are differentiated in the high and low frequency ranges, two different time-series modeling methods are ought to be implemented. Low frequency vibration response is non-stationary and highly dependent on the rotor azimuth, then a Linear Parameter Varying Vector AR (LPV-VAR) modeling approach is used, as already demonstrated in [11, 28]. On the other hand, the dynamics of the high frequency components of the vibration are non-stationary and transient in nature. Therefore, the Morlet Continuous Wavelet Transform (Morlet CWT) is used to capture the characteristics of such transient phenomenon [29].
Both modeling approaches lead to a set of matrix features characterized by high redundancy, which would lead to a poor representation if directly cast into a GP time-series model. Therefore, dimensionality reduction is attempted via a Principal Component Analysis (PCA)-based technique.

Subsequently, the PCA-reduced dynamic features from both low and high frequency ranges are represented individually as the response of Gaussian Process Regression (GPR) with inputs including the average wind speed, turbulence intensity and ambient temperature, plus the estimated operational regime indicator. These variables are selected, since these are readily available from most wind turbine SCADA systems. In addition, wind speed and turbulence dictate the aeroelastic damping of the blade, while temperature and RPM modify the stiffness of the blade. Other variables, like pitch angle or precipitation are not included in the analysis to preserve the model compactness. The influence of each one of these EOPs is evaluated by means of a sensitivity analysis performed on the basis of the Bayes factor of the GP time-series models obtained with the full set of variables and the same model built with a subset of EOPs.

Each one of the previously enumerated components of the methodological approach is described in further detail next.

3.2. Linear Parameter Varying Vector AR models

The low frequency vibration components are hereby represented by means of LPV-V AR models, which use the instantaneous rotor azimuth as scheduling variable. A brief overview of the LPV-V AR modelling approach is described next. Further details may be found in [28]. A recent overview on the topic of identification of LPV models is available in [30].

**Definition.** An LPV-V AR model of a multivariate non-stationary signal \( y[t] \in \mathbb{R}^n \), with \( t \in \mathbb{Z} \) designating the normalized discrete time, is defined as follows [28]:

\[
y[t] = -\sum_{i=1}^{n_a} A_i(q) \cdot y[t-i] + w[t] = \Theta \cdot \phi[t, q] + w[t] \quad w[t] \sim \text{NID}(0, \Sigma_w) \quad \text{(1)}
\]

where \( A_i(q), i = 1, \ldots, n_a \) denotes the parameter matrices of the LPV-V AR model of order \( n_a \), \( q \equiv q[t] \) is a scheduling variable which non-linearly influences the response of the system, \( w[t] \in \mathbb{R}^n \) is a zero mean Normally and Identically Distributed (NID) innovations process with covariance matrix \( \Sigma_w \in \mathbb{R}^{n \times n} \), \( \Theta \in \mathbb{R}^{n \times d} \), \( d = n \cdot n_a \cdot p_a \), is the coefficient matrix, and \( \phi[t, q] \in \mathbb{R}^d \) is the regression matrix, both defined as:

\[
\Theta = \begin{bmatrix}
A_{1,1} & \cdots & A_{1,p_a} & \cdots & A_{n_a,1} & \cdots & A_{n_a,p_a}
\end{bmatrix} \quad \text{(2a)}
\]

\[
\phi[t, q] = \begin{bmatrix}
y[t - 1] \\
y[t - 2] \\
\vdots \\
y[t - n_a]
\end{bmatrix} \otimes \begin{bmatrix}
f_1(q) \\
f_2(q) \\
\vdots \\
f_{p_a}(q)
\end{bmatrix} \quad \text{(2b)}
\]

where the symbol \( \otimes \) indicates the Kronecker product.

In the construction of the regression form of the LPV-V AR model, the parameter matrices of the LPV-V AR model are expanded as \( A_i(q) = \sum_{j=1}^{p_a} A_{i,j} \cdot f_j(q) \), based on the functional expansion basis \( f_j(q) \in \mathbb{R}, j = 1, \ldots, p_a \), while the matrices \( A_{i,j} \in \mathbb{R}^{n \times n} \) represent the expansion coefficient of the decomposition.
Identification and model structure selection. Given a single sample signal $y(t), t = 1, \ldots, N$, with a corresponding scheduling variable $q(t)$, the identification of an LPV-V AR model consists on determining the coefficient matrix $\Theta$, the innovations covariance matrix $\Sigma_w$, and the model and basis orders $n_a$ and $p_a$, respectively, as well as determining the functional expansion basis $f_j(q), j = 1, \ldots, p_a$. The parameter estimation follows from the maximum likelihood method as thoroughly explained in [28]. On the other hand, the selection of the model structure, consisting on the model order $n_a$, the basis expansion dimensionality $p_a$, and the functional expansion basis $f_j(q), j = 1, \ldots, p_a$, can be achieved by alternative criteria aiming at penalizing model complexity. These include either the Bayesian Information Criterion (BIC) and the cross-validation error (or empirical risk). An important detail here relates to the fact that a single model structure is necessary to accommodate a large number of different dynamics so that comparison and regression are facilitated in the upcoming stages. In this sense, a single model structure may be selected on the basis of the complete set or a subset of signals available during a training period, and subsequently assume that the structure of the dynamics (or system’s memory) remains approximately the same. Further details can be found in [6, 28, 31].

3.3. The Morlet Continuous Wavelet Transform

The high-pass filtered and segmented acceleration signals are represented via the complex Morlet Continuous Wavelet Transform (CWT), which is ideal for capturing the characteristics of the transient wave induced by the actuator. In the CWT, a (continuous-time) signal $y(t) \in \mathbb{R}$ is represented by means of convolutions with shifted and scaled versions of a base signal, referred to as the mother wavelet, as shown in the following equation [29, p. 103]:

$$ Y(u, s) = \langle y(t), \psi_{a,s}(t) \rangle = \int_{-\infty}^{\infty} y(t) \frac{1}{\sqrt{s}} \psi^*(\frac{t-u}{s}) \, dt \quad \psi_{a,s}(t) \equiv \frac{1}{\sqrt{s}} \psi^*(\frac{t-u}{s}) $$ (3)

where $\psi_{a,s}(t) \in \mathbb{C}$ represents the wavelet function shifted $a$ time units and scaled by the factor $s$, while the symbol $*$ stands for the complex conjugate. In the present case, the complex Morlet wavelet function is appraised [29, p. 111]. Although this selection follows heuristic criteria, optimal selection of the mother wavelet can be achieved with the methods discussed in [32]. The application of the CWT defined in Eq. (3) involves the transformation of the integrals into sums, while the time and scale quantities are sampled on a grid of values of interest. In this sense, a discrete scalogram matrix may be obtained on the signals from sensors $i = 1, \ldots, N_s$, as follows:

$$ \Theta = \begin{bmatrix} \Theta_1 & \Theta_2 & \cdots & \Theta_{N_s} \end{bmatrix} $$

$$ \Theta_l = \begin{bmatrix} [Y(l\Delta_i, m\Delta_s)]_l^2 \end{bmatrix}_{l=1}^{L \times M} \quad l = 1, 2, \ldots, L, \quad m = 1, 2, \ldots, M $$

where $Y(l\Delta_i, m\Delta_s)$ is the CWT computed at sensor $i$ on trial $k$, while $|\cdot|$ stands for the complex magnitude, $\Delta_i$ and $\Delta_s$ denote the time and scale sampling steps, and $L, M$ denote the respective number of time and scale units.

3.4. PCA for dimensionality reduction on matrix data

The ultimate objective of the methodology is to obtain a stochastic representation from input variables to vibration features, presently accomplished via the coefficient matrices of LPV-V AR models on low-frequency components, or CWT scalograms on high-frequency components. Nonetheless, these feature sets are highly correlated, while direct regression of these coefficients
would lead to very complex representations prone to numerical instabilities. To tackle these limitations, Principal Component Analysis (PCA) is implemented to obtain an alternative orthogonal representation of the highly correlated feature matrices obtained from both LPV-V AR modeling and the Morlet CWT. To this end, the feature matrices corresponding to the kth vibration response dataset $\Theta_k \in \mathbb{R}^{n_t \times m_o}$ is transformed into a vector $\tilde{\Theta}_k = \text{vec}(\Theta_k) \in \mathbb{R}^{d_o}$, where $d_o = n_t \cdot m_o$ is the dimension of the original feature vector, $n_t$ and $m_o$ are the number of rows and columns of the feature matrices, and where the operator $\text{vec}()$ represents the vectorization function, which stacks the columns of the matrix in the argument into a single vector. Subsequently, PCA is carried out as fully described in [33]. As a result, the vector of reduced principal components $\alpha_k$ is obtained from the original feature vector $\tilde{\Theta}_k$, through the projection:

$$\alpha_k = \tilde{U}^T \cdot \tilde{\Theta}_k$$

where $\tilde{U} \in \mathbb{R}^{d_o \times d_i}$ is the trimmed principal vector matrix with $d_i << d_o$, and composed by the principal vectors $u_i$ with corresponding largest principal values $\lambda_i$.

### 3.5. Gaussian Process time-series models

A GP time-series model of the time-series $y[t]$ is defined through the equation set [6]:

$$y[t] = \phi^T[t] \cdot \alpha + w[t], \quad w[t] \sim \text{NID}(0, \Sigma_u) \quad (6a)$$

$$\alpha = \alpha_{\ast}(\xi) + u, \quad u \sim \text{N}(0, \Sigma_u) \quad (6b)$$

where $\phi[t]$ is a regressor at time $t$, $\alpha$ is the feature (coefficient) vector, which is itself represented as a Gaussian Process Regression (GPR) based on the vector of input variables $\xi \in \mathbb{R}^L$. Additionally, $w[t]$ is a zero mean NID process with covariance matrix $\Sigma_u$, while $u$ is a multivariate zero-mean normally distributed process with covariance matrix $\Sigma_u$. Both random processes satisfy $\mathbb{E}[w[t], u] = 0$ for any value of $t$. The noise process $w[t]$ represents noise in the measurement of the time-series mostly attributed to ambient noise. On the other hand, $u$ represents the component of the feature vector $\alpha$ that cannot be explained by the input variables $\xi$, which appear as a result of unaccounted sources of uncertainty—v.g.r., unmeasured inputs— and estimation error.

The LPV-V AR models and Morlet CWT can be shown to correspond to specific forms of Eq. (6a), while the topic of concern in the following part of the work is on how to construct the GPR representing the coefficient vector $\alpha$.

To this end, consider the GPR of the feature vector $\alpha \in \mathbb{R}^M$ defined as follows:

$$\alpha = \alpha_{\ast}(\xi) + u := W^T \cdot f(\xi) + u, \quad u \sim \mathcal{N}(0, \Sigma_u) \quad (7)$$

where $\xi \in \mathbb{R}^L$ is the vector of input variables, $f(\xi) : \mathbb{R}^L \to \mathbb{R}^M$ is a multivariate functional representation basis, and $W \in \mathbb{R}^{L \times M}$ is the GPR coefficient matrix. Given a sample of input variables $X = [\xi_1, \xi_2, \cdots, \xi_{N_{rec}}]$ and respective feature vectors $A = [\alpha_1, \alpha_2, \cdots, \alpha_{N_{rec}}]$, the ordinary least squares estimates of the GPR coefficient matrix and the innovations covariance matrix are obtained as follows:

$$\hat{W} = (F(X) \cdot F^T(X))^{-1} \cdot F(X) \cdot A^T \quad (8a)$$

$$\hat{\Sigma}_u = \frac{1}{N_{rec}}(A - \hat{W}^T \cdot F(X)) \cdot (A - \hat{W}^T \cdot F(X))^T \quad (8b)$$
where \( \mathbf{F}(\mathbf{X}) = [f(\xi_1) \ f(\xi_2) \ \cdots \ f(\xi_{N_{\text{rec}}})] \). The multivariate functional representation basis may be constructed on Kronecker products of the individual input variables, as follows:

\[
\mathbf{f}(\xi) = \bigotimes_{i=1}^{l} \mathbf{f}_i(\xi_i) = \mathbf{f}_1(\xi_1) \otimes \mathbf{f}_2(\xi_2) \otimes \cdots \otimes \mathbf{f}_l(\xi_l)
\]

where \( \mathbf{f}_i(\cdot) \in \mathbb{R}^{L_i} \) indicates the vector with the \( L_i \) functional basis on the input variable \( \xi_i \), where \( L = \prod_{i=1}^{l} L_i \) is the dimensionality of the multivariate functional representation basis.

The critical step in the calculation of the GPR coefficient matrix relates to the calculation of the inverse of the matrix \( \mathbf{F}(\mathbf{X}) \cdot \mathbf{F}^T(\mathbf{X}) \), which relates to the well-posedness of the matrix \( \mathbf{F}(\mathbf{X}) \). In general, the matrix \( \mathbf{F}(\mathbf{X}) \) is well-posed if the number of unknowns (size of the coefficient matrix \( \mathbf{W} \)) is lower than the data size (\( N_{\text{rec}} \)). However, as the model dimensionality increases, \( \mathbf{F}(\mathbf{X}) \) may become numerically inaccurate. For this reason, a good practice consists on monitoring the condition number of \( \mathbf{F}(\mathbf{X}) \), to ensure that the matrix inversion operation is numerically accurate.

**Computational complexity.** The computational complexity of the methodology can be separated into that attributed to the training process and that attributed to the evaluation of the obtained model, for instance to provide estimates of the feature vector given a current value of the input variables. On training, the main computational cost derives from the feature calculation, which involves the calculation of the LPV-V AR model coefficients or CWT scalograms in the total set of training records. Hence, the computational cost is dictated by the number of training records and the dimension of the original features. Once a GPR model is available, calculation of the feature vector estimate involves two matrix-by-vector multiplications, the first to obtain the estimates of PCA coefficients given input variables, as in Eq. (7), and the second to project the PCA coefficients into the space of original features, as in Eq. (5). Therefore, the computational complexity is determined by the size of the reduced feature set, the size of the original feature set, and the order of the GPR basis.

### 3.6. Sensitivity analysis

A sensitivity analysis may be carried out to determine the influence of each one of the input variables in the GPR. Hereby, three different types of models are considered: (i) a model considering the whole set of input variables represented by the likelihood \( \mathcal{L}(\mathbf{\alpha} | \mathbf{\xi}) \); (ii) a model considering a single input variable \( \xi_i \), represented by the likelihood \( \mathcal{L}(\mathbf{\alpha} | \mathbf{\xi}_i) \); (iii) a model considering all but the single input variable \( \xi_i \), represented by the likelihood \( \mathcal{L}(\mathbf{\alpha} | \tilde{\mathbf{\xi}}) \). Then, a sensitivity analysis is performed in terms of the following log-Bayes factors:

\[
S(\mathbf{\alpha} | \tilde{\mathbf{\xi}}) = \ln \mathcal{L}(\mathbf{\alpha} | \tilde{\mathbf{\xi}}) - \ln \mathcal{L}(\mathbf{\alpha} | \mathbf{\xi}) \quad (10a)
\]

\[
S(\mathbf{\alpha} | \mathbf{\xi}_i) = \ln \mathcal{L}(\mathbf{\alpha} | \mathbf{\xi}_i) - \ln \mathcal{L}(\mathbf{\alpha} | \mathbf{\xi}) \quad (10b)
\]

where the inclusive sensitivity \( S(\mathbf{\alpha} | \tilde{\mathbf{\xi}}) \) represents the change in the likelihood of the GPR model including only the input variable \( \xi_i \) compared to the model including all the input variables \( \mathbf{\xi} \), while the exclusive sensitivity \( S(\mathbf{\alpha} | \mathbf{\xi}_i) \) represents the change in the likelihood of the GPR model including all the input variables but \( \xi_i \) compared to the model including all the input variables. In this context, \( \tilde{\mathbf{\xi}} \) denotes the set of input variables excluding \( \xi_i \). Following from Eq. (7), the log-likelihood functions in Eq. (10) are of the form:

\[
\ln \mathcal{L}(\mathbf{\alpha} | \mathbf{\xi}) = -\frac{N_{\text{rec}}}{2} \ln \sigma_u^2 - \sum_{k=1}^{N_{\text{rec}}} \frac{(\alpha_{jk} - \mathbf{w}_j^T : \mathbf{f}(\xi))^2}{2\sigma_u^2 t^2_{u,ji}} \quad (11)
\]
where $\mathbf{\alpha}_{j} = [\alpha_{j,1} \quad \alpha_{j,2} \quad \cdots \quad \alpha_{j,N_{\text{rec}}}]^{T}$ is a vector with the set of feature variables $\alpha_{j}$ available for evaluation.

4. Low-frequency analysis

4.1. Pre-processing

As explained in the previous section, the selected frequency range for this study includes frequencies from 0 to 64 Hz. Therefore, pre-processing of the raw acceleration signals consists of low-pass filtering and down-sampling to the analysis sampling frequency $f_{s} = 128$ Hz. A window-based Finite Impulse Response (FIR) filter design (achieved through the MATLAB command `fir1`) is considered for the low-pass filter, with a cut frequency $f_{c} = f_{s}/2$ and 800 th-order. Subsequently, the signal is mean centered.

A typical signal after pre-processing, and its corresponding spectrogram and Welch-based PSD are shown in Figure 4. The spectrogram is computed via the MATLAB command `spectrogram` based on a Gaussian window of 1024 samples, with an overlap of 1023 samples, and aperture parameter 16. The PSD estimate is computed with the Welch method, based on a 1024-sample hamming spectral window with 512 sample overlap.

Three important features on the obtained down-sampled signal may be remarked. First, no effects from the actuator excitation –occurring at about 10 s– are visible, either in the time-domain signal or in the spectrogram. Second, the signal appears to be mostly dominated by the rotor frequency of 34 rpm (0.565 Hz). Third, the spectrogram demonstrates that some of the resonance frequencies of the signal appear to be modulated, with modulating period equal to the period of the rotor. These features coincide with the characteristics of the vibration response of an operating wind turbine tower reported in [34].

4.2. Identification of the low frequency vibration component via LPV-VAR models

A high-resolution representation of the low-frequency vibration response measured on the three sensors in the spar of the blade is obtained with the Linear Parameter Varying Vector AR (LPV-VAR) models explained in Sec. 3.2, where the instantaneous rotor azimuth acts as the scheduling variable. The instantaneous rotor azimuth is estimated by calculating the phase angle of the Hilbert transform of the respective DC accelerometer signal. After following the recommendations for model structure selection provided in [6, 28], an LPV-VAR model with $n_{a} = 14$ and $p_{a} = 5$ is achieved.

4.3. Analysis of low-frequency identification results

LPV-VAR models with $n_{a} = 14$ and $p_{a} = 5$ are estimated for each one of the vibration response datasets obtained on the healthy state of the wind turbine blade. This amounts for a total of 3065 LPV-VAR models corresponding to the same quantity of vibration response datasets, from which 235 correspond to the idling wind turbine, 1 529 to the wind turbine operating at 32 rpm, and 1 301 to the wind turbine operating at 43 rpm. Subsequently, a reduced dimensionality representation is sought by means of PCA based on the entire set of LPV-VAR model parameter vectors, as explained in Sec. 3.4. In the present case, a set of 45 principal components out of 630 components is selected, which represent 95% of the complete dataset variance. Further analysis of the obtained LPV-VAR model coefficients and the captured long-term dynamics is presented in the sequel.
4.3.1. Distribution of LPV-VAR parameter estimates

The estimated values of the LPV-VAR model innovations variance associated with the signal measured in sensor 7 are displayed in Fig. 5. The innovations variance estimates are plotted against time, temperature, wind speed and turbulence intensity. In addition, each individual value is associated with a specific color according to the operational state of the wind turbine (idle, 32 rpm, and 43 rpm). In the time plot (Fig. 5(a)), it is evident that the innovations variance is time-dependent, while presents regime changes at different operational states. More specifically, when the wind turbine is idling, the innovations variance tends to be at the lowest values, and then tends to increase according to the rotor speed. This tendency is also evident in the wind speed plot (Fig. 5(c)), where low wind speeds are associated with low innovations variance, while high wind speeds lead to higher innovations variance values. This is an expected result, since the innovations variance is directly associated with the vibration power, which should be higher with higher excitation (in the form of wind speed). Weaker functional relations can be observed in the temperature and the turbulence intensity. Moreover, it is very clear that each operational regime of the wind turbine may be related to specific clusters on the innovations variance values. Similar behaviour is observed in the remaining LPV-VAR model parameters as well as in the respective PCA coefficients.

4.3.2. Gaussian Process Regression of the LPV-VAR model coefficients

A GPR model is constructed with the aim of capturing the relation from a selected set of input (operational) variables to the coefficients of the LPV-VAR model, as seen in Fig. 5. For this purpose, the temperature, wind speed and turbulence intensity are selected as input variables in the vector $\xi$, while the LPV-VAR model PCA coefficients are defined as output variables, in
the variable $\alpha$, as in Eq. (7). The selection of the model structure of the GPR model follows similar guidelines as those discussed for the construction of LPV-V AR models previously described. Ideally, a single structure should be sought per PCA coefficient, on the cost of added modelling complexity. Otherwise, the approach appraised here consists on selecting a model that fits best the components containing most of the data variability. In accordance, by simple observation of the first PCA coefficients of the LPV-V AR model at each operational regime suggests that the functional relation on each input variable is linear or quadratic at most. Moreover, theoretical and experimental analysis indicates that temperature within a relatively small range such as that appraised in the monitoring session has an effect on the material stiffness that can be accurately approximated as linear [35]. Similarly, it has been shown that the wind speed introduces an aeroelastic damping component in the dynamics of a blade which is quadratic on the instantaneous wind speed component [36, Ch. 8]. Accordingly, it is assumed that the influence of the temperature is linear ($L_1 = 2$), while the influence of the wind speed and turbulence intensity assumed to be quadratic ($L_2 = L_3 = 3$). For each one of the input variables, a Hermite orthogonal polynomial basis is appraised.

### 4.3.3. Sensitivity analysis

A sensitivity analysis is carried out to determine the influence of each one of the input variables in the PCA-transformed LPV-VAR model parameters. The results obtained on each one of the PCA coefficients with the wind turbine operating at 43 rpm are displayed in Fig. 6. Fig. 6(a) displays the obtained exclusive sensitivities per PCA coefficient, where it may be seen that removing the wind speed has a larger negative impact on the model performance, whereas removing temperature or turbulence intensity has a lesser impact on the model. On the other hand, the inclusive sensitivities shown in Fig. 6(b) confirm that the wind speed and, in a lesser extent,
the turbulence intensity drive most of the variability in the PCA coefficients. On the other hand, it is observed that the temperature has a notable influence in some of the PCA coefficients, while the effect in others is negligible.

A summarized sensitivity analysis of the PCA coefficients of the LPV-V AR model parameters of the wind turbine at different operational regimes is presented in Fig. 7. Figures 7(a)–(c) show the exclusive sensitivities of the idle wind turbine, and the wind turbine operating at 34 and 43 rpm, respectively. Likewise, Figures 7(d)–(f) display the corresponding inclusive sensitivities. The results indicate that when the wind turbine is idling (Figs. 7(a),(d)), the change in the sensitivities is low, which implies that the effect of environmental variables is reduced. Interestingly, the temperature appears to have most of the influence on the dynamics of the idling wind turbine. Otherwise, with the wind turbine operating either at 34 or 43 rpm, the wind speed and, subsequently, the turbulence intensity are main drivers of the dynamics. On the other hand, the temperature has a lower influence in the dynamics. However, this result may be due to the limited span of variation on the temperature, due to the relatively short analysis period (1 month on the health condition).

![Figure 6: Individual sensitivities of the LPV-V AR model PCA coefficients $\alpha_{j}$, $j = 1, \ldots, N_{pc}$ on the temperature, wind speed and turbulence intensity with the wind turbine operating at 43 rpm. (a) Exclusive sensitivity – effect of removing an input variable. (b) Inclusive sensitivity – effect of employing only a single input variable.](image)

4.3.4. Model based analysis of the low frequency response dynamics

The obtained LPV-VAR models of the wind turbine low frequency vibration response may be used to analyse the dynamic features of the wind turbine. The LPV-VAR model-based time-dependent (“frozen”) Power Spectral Density (PSD) [31] of the wind turbine low frequency vibration measured in sensor 10 (S10) is calculated as a function of the instantaneous rotor azimuth over a single revolution, and is displayed in Fig. 8. The surfaces demonstrate the non-stationary behaviour of the wind turbine vibration response as well as a clear dependency on the rotor azimuth. The first two blade “frozen” modes, located about 2.5 Hz and 6.2 Hz remain relatively stable on frequency value, although the instantaneous vibration power has significant changes as the blades change position. Otherwise, higher frequency modes exhibit larger changes in frequency and power over a single revolution of the rotor.

Long-term tendencies of the dynamic characteristics of the low-frequency wind turbine vibration may be analysed with the help of the GPR of the (PCA-transformed) LPV-VAR model parameters built in Sec. 4.3.2. The quantities of interest in the present analysis are the mean natural frequencies and damping ratios, which are extracted from the best LTI approximation of
the LPV-V AR model parameter and results in a conventional VAR model built only with the constant parameter matrices $A_i$ of the LPV-V AR model. Thus, the procedure to obtain the best-LTI approximation of the modal quantities from the GPR of the (PCA-transformed) LPV-V AR model parameters is as follows:

1. Select a range of values of each one of the input variables $\xi$.
2. Compute the GPR prediction of the PCA-transformed LPV-V AR model parameters for the selected range of input variables as

$$\hat{\alpha}(\xi) = \hat{W}^T \cdot \hat{f}(\xi)$$

3. Project the predicted PCA coefficients $\hat{\alpha}(\xi)$ back into the space of LPV-V AR model parameters as follows:

$$\hat{\vartheta}(\xi) = U \cdot \hat{\alpha}(\xi)$$

4. Reconstruct the parameter matrices $\hat{A}_{i,j}(\xi)$, $i = 1, \cdots, n_u$, $j = 1, \cdots, p_u$ of the LPV-V AR model by arranging the entries of the predicted parameter vectors $\hat{\vartheta}(\xi)$.

5. Compute best LTI approximation of the natural frequencies and damping ratios as the roots of the polynomial matrix

$$A(z, \xi) = I + \sum_{i=1}^{n_u} \hat{A}_{i,j}(\xi) \cdot z^{-i}$$
Three scenarios are considered with the wind turbine operating at 43 rpm: (i) changing temperature in the range from 2 to 8 Celsius; (ii) changing wind speed in the range from 5 to 15 m/s; (iii) changing turbulence intensity in the range from 5 to 50%. At each scenario, the remaining variables are set as the median value obtained at the respective operational state. The natural frequencies and damping ratios as a function of temperature, wind speed and turbulence intensity resulting from the previously described analysis are displayed in Fig. 9. Note that only the modes with damping under 20% are displayed. Analysis of the results found at each scenario are provided next:

*Changing temperature.* The results shown in Fig. 9(a) demonstrate that there is a slight decrease of the natural frequency as the temperature rises. The reduction is more evident at higher order modes. Additionally, the damping ratio of the first three modes tends to increase with increasing temperatures.

*Changing wind speed.* In the present case, the results displayed in Fig. 9(b), show a mixed tendency in the natural frequency and damping ratio values. In the first two modes, there is an increment of the natural frequency and a reduction of the damping ratio. Contrariwise, the
second pair of modes have larger reduction on the natural frequency, while the damping seems to peak at about 8 to 12 m/s.

Changing turbulence intensity. The behavior observed in the turbulence intensity, as observed in Fig. 9(c), appears to reflect the main features of the changes observed with changing wind speed. In this case, the damping ratios of the second pair of modes also seem to peak at about 30 to 40% of turbulence intensity.

5. High-frequency analysis

5.1. Pre-processing

In contrast to the low-frequency analysis, high-frequency analysis is focused on the frequency range from 128 to 8 192 Hz (Nyquist frequency of the original signal), and aims at capturing the transmission properties of the travelling wave induced by the electro-mechanical actuator installed on the blade. For this purpose, the original signal is high-pass filtered and then, the segment of 80 ms after the actuator hit is selected for further analysis. A window-based FIR high-pass filter design (computed with the MATLAB command `fir1`) with cut frequency of 128 Hz and order 800 is considered for the high-pass filter. The analyzed segment is extracted by detecting the beginning of the peak in the actuator control signal. After this processing, a signal of 1310 samples is obtained. As in the previously presented low-frequency analysis, sensors 7, 10 and 13 are selected for further analysis. In the left column of Fig. 10 are shown...
typical acceleration responses in the three considered sensors after the previously described pre-processing.

5.2. Representation via Continuous Wavelet Transform

Typical high resolution scalograms of the acceleration response of the wind turbine blade, evaluated at 1024 scales on the range 1 to 80, computed for the three considered sensors are shown in the right column of Fig. 10. The scalograms evidence two types of behavior in the transient wave induced by the actuator hit, consisting of mid and high-frequency components. As expected, components on the lower end of the frequency range vanish fast along the blade, whereas higher frequency components tend to travel a longer distance on the blade. Therefore, with the aim of assessing the characteristics of traveling waves along the whole extent of the blade, the analysis should be centered on the range of scales from 4 to 23 and the time interval from 0 to 50 ms after the actuator hit. Thus, for the upcoming analysis the CWT of all the acceleration responses in the healthy state of the structure in sensors 7, 10 and 13 are computed on 80 scale values in the range 4 to 23.

![Figure 10: Typical accelerations measured in sensors 7, 10 and 13 after high-pass filtering and segmentation (left column top to bottom) and the corresponding surfaces of the Morlet CWT scalogram (right column).](image-url)
5.3. Analysis of high-frequency identification results

5.3.1. Analysis of sub-band energy and wave arrival times

Sub-band energy may be defined as the average energy measured in a sub-band (range of scales) in the scalogram, according to the integral on the scale domain:

\[
\tilde{E}_{s_1,s_2}(u) = \frac{1}{s_2 - s_1} \int_{s_1}^{s_2} |Y(u,s)|^2 \, ds,
\]

where \( s_1 \) and \( s_2 \) denote the upper and lower limits of the sub-band of interest. In the practical implementation, the sub-band energy is computed from a discrete domain CWT, and consequently, the integral is replaced by a weighed sum. In agreement with the analysis carried out in the previous section, three frequency sub-components were identified centered at scales 7, 10 and 15. Sub-band energies are calculated for each one of these sub-components on the sub-bands defined in Tab. 1. The average sub-band energy time-series obtained at each sub-component, for the three different operational conditions, i.e. idle, and rotating at 34 and 43 rpm, and at each one of the sensors considered in the analysis are shown in Fig. 11.

<table>
<thead>
<tr>
<th>Sub-component</th>
<th>Lower limit ( s_1 )</th>
<th>Center</th>
<th>Higher limit ( s_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5 (3280 Hz)</td>
<td>7 (2340 Hz)</td>
<td>8 (2048 Hz)</td>
</tr>
<tr>
<td>2</td>
<td>8 (2048 Hz)</td>
<td>10 (1638 Hz)</td>
<td>12 (1365 Hz)</td>
</tr>
<tr>
<td>3</td>
<td>13 (1260 Hz)</td>
<td>15 (1092 Hz)</td>
<td>17 (964 Hz)</td>
</tr>
</tbody>
</table>

Table 1: Definition of the sub-bands associated with each one of the frequency sub-components identified in the high-frequency acceleration response components.

The resulting sub-band energy time-series observed in Fig. 11 demonstrate a clear dependency of the arrival time of the frequency sub-components on the operational condition of the wind turbine. Indeed, the induced wave seems to travel slower through the blade when the wind turbine is idling, while it accelerates as the rotor speed increases. This effect may be explained by the stiffening of the blade due to its rotation. In turn, a stiffer blade facilitates the transmission of the induced wave. The average wave peak arrival times summarized in Tab. 2 indicate similar outcomes, where it is clear that the higher frequency (lower scale) components travel faster through the blade in contrast to lower frequency (higher scale) components.

<table>
<thead>
<tr>
<th>Sub-component</th>
<th>Operational cond.</th>
<th>Peak arrival time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>34 rpm</td>
<td>Sensor 7</td>
</tr>
<tr>
<td>1</td>
<td>Idle</td>
<td>6.41</td>
</tr>
<tr>
<td></td>
<td>43 rpm</td>
<td>6.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.86</td>
</tr>
<tr>
<td>2</td>
<td>Idle</td>
<td>8.73</td>
</tr>
<tr>
<td></td>
<td>34 rpm</td>
<td>8.54</td>
</tr>
<tr>
<td></td>
<td>43 rpm</td>
<td>8.24</td>
</tr>
<tr>
<td>3</td>
<td>Idle</td>
<td>7.45</td>
</tr>
<tr>
<td></td>
<td>34 rpm</td>
<td>7.20</td>
</tr>
<tr>
<td></td>
<td>43 rpm</td>
<td>6.90</td>
</tr>
</tbody>
</table>

Table 2: Average wave peak arrival time at each sensor for each frequency sub-component separated per operational condition.
5.3.2. Principal Component Analysis of the CWT scalograms

A more thorough analysis of the wave transmission properties of the blade is carried out by means of Principal Component Analysis (PCA) of the scalograms derived from the Morlet CWT evaluated on the healthy vibration records. The procedure to compute the principal components on a scalogram follows the approach described in Sec. 3.4 with the guidelines described in [33]. Following this procedure a relatively small number of principal vectors is achieved, in this case corresponding to 158 of 3,065 total components, which accurately represent up to 95% of the variance contained in the scalograms. Fig. 12 shows the estimated sample mean scalograms $E_{i,0}$ and the first four principal surfaces $\Phi_{i,j}$ (principal vectors transformed back into matrices). The principal surfaces display the main types of variations around the sample average scalogram. For instance, the principal surfaces observed in the second row of Fig. 12 demonstrate variations in the overall shape of the main transient wave components, while those observed in the third row would be mostly linked to variations in the initial segment of the main transient wave. On the other hand, the components observed in the principal surfaces of the fourth row may be associated to a secondary wave appearing after the main transient, possibly originating from reflections throughout the surface of the blade.
Figure 12: Sample average scalograms and principal vectors obtained from PCA in the whole set of vibration responses of the healthy wind turbine blade. Top row: sample average scalograms at sensors 7 to 13. Second to fifth row: first four principal vectors transformed back into matrices at each one of the sensors.

5.3.3. GPR of the PCA-CWT coefficients and sensitivity analysis

A GPR model is constructed with the aim of capturing the stochastic relation from selected variables, including the ambient temperature, wind speed, turbulence intensity and rotor azimuth, to the PCA projection coefficients extracted from the CWT scalograms. To this end, a multivariate functional basis is built for the temperature, wind speed, turbulence intensity and the instantaneous rotor azimuth, using first order (constant and linear) basis for the first three variables, and a Fourier basis for the rotor azimuth (including the constant component and the first two pairs of sines/cosines). The GPR model definition and construction are the same as described in Sec. 4.3.

A sensitivity analysis on each one of the input variables is performed based on the obtained
GPR model of the PCA coefficients. As in Sec. 4.3.3, inclusive and exclusive sensitivities are computed for each one of the input variables. The obtained results are shown in Fig. 13. In the present case, the influence of the rotor azimuth on the response features is prominent particularly with the wind turbine in-operation. This is evidenced by the exclusive sensitivities in Fig. 13(b)-(c) showing that the GPR is impaired when the rotor azimuth is removed, while in Fig. 13(e)-(f) it is evident that the GPR preserves most of its predictive ability when only the rotor azimuth is considered. Temperature, wind speed and turbulence follow in the ranking, when the wind turbine is in-operation. Otherwise, when the wind turbine is idling, the relative change in the exclusive sensitivity is low (see Fig. 13(a)), while the inclusive sensitivities also show a low change on the GPR predictive ability (see Fig. 13(d)). The combination of these results indicate that adding or removing variables does not have a significant effect in the GPR when the wind turbine is idling. Nonetheless, it should be expected that the temperature have an important effect in the transmission properties of the material of the blade, however, it might be that the limited temperature range and reduced number of instances conceal this effect. Similar observations may be asserted on the wind speed and turbulence.

Figure 13: Aggregated sensitivities of the CWT scalogram PCA coefficients $\alpha$ on the temperature, wind speed, turbulence intensity and rotor azimuth at different operational regimes. (a) Effect of removing an input variable – idle wind turbine. (b) Effect of removing an input variable – wind turbine @ 32 rpm. (c) Effect of removing an input variable – wind turbine @ 43 rpm. (d) Effect of using only a single input variable – idle wind turbine. (e) Effect of using only a single input variable – wind turbine @ 32 rpm. (f) Effect of using only a single input variable – wind turbine @ 43 rpm.

5.3.4. Analysis of the high frequency vibration response features under changing environment

Given the derived GPR model for the PCA coefficients of the CWT scalograms, it is possible to analyze how the scalograms change under variation of each environmental or operational variable. The procedure to reconstruct a scalogram from the GPR is very similar to that made for
the LPV-V AR model coefficients and explained in Section 4.3.4.

Two scenarios are considered with the wind turbine operating at 34 and 43 rpm: (i) changing temperature in the range from 2 to 8 Celsius; (ii) changing rotor azimuth on a complete revolution ($-\pi$ to $\pi$ rad). At each scenario, the remaining variables are set as the median value obtained at the respective operational state. To provide a more compact visualization, the results are presented in terms of the sub-band energy on sub-band 3 (see Tab. 1). The obtained results are presented in Figs. 14 and 15. An analysis of the results obtained from each scenario is provided next:

**Changing temperature.** The effect of changing temperature on the characteristics of the sub-band energy is very subtle, although some differences are visible. Firstly, a small difference on the arrival times can be found. Secondly, the power of some of the reverberations (reflections of the first wave) seems to diminish as the temperature increases. These changes are more or less consistent within the three considered sensors.

**Changing rotor azimuth.** As mentioned before, the rotor azimuth is the main driver of the variations on the characteristics of the vibration response. This fact is clear when observing the sub-band energy as a function of the rotor azimuth. More precisely, the main effect is on the variation of the wave arrival time, with a minimum when the blade is at position 0, and maximum when the blade is located at 180 degrees. In addition, the energy of the reverberations seems to be modulated by the rotor azimuth. For some angles, the reverberations are very powerful, while for other are almost vanished. These changes may be explained by the changing distribution of local stresses of the blade as it rotates. This in turn modifies the local stiffness at different regions of the blade.

6. **A brief assessment on damage detectability**

Once a model for the dependency of low or high-frequency features is obtained, it is possible to perform damage detection based on the differences observed between the model predictions and the actual vibration features captured from the in-operation structure. Although a complete assessment on damage detection goes beyond the scope and reasonable length of this paper, a brief examination of the damage detectability achieved by both GPR models on low and high frequency ranges is presented next.

6.1. **Damage detection based on the features of low frequency vibration response**

The obtained GPR model of the PCA-transformed LPV-V AR model coefficients is used as a baseline model for the healthy state of the blade. A simple damage detection procedure consists on determining if the parameters of the LPV-V AR model of a newly obtained signal correspond to the baseline model. To that end, the Mahalanobis distance measure is considered:

$$d_m^2(\alpha^*) = (\alpha^* - \hat{W}^T \cdot f(\xi^*))^T \cdot \hat{\Sigma}_u^{-1} \cdot (\alpha^* - \hat{W}^T \cdot f(\xi^*))$$  
(13)

given a test signal $Y^*$, with corresponding LPV-V AR model coefficient vector $\theta^* = \text{vec}(\Theta^*)$ and a vector of input variables $\xi^*$.

Three different scenarios corresponding to increasing modeling complexities are examined:

- **Case 1**: no separation of operational states and feature normalization is considered in the model construction (as in conventional damage detection methods);
Case 2: operational states are separated but no feature normalization is performed in the model construction;

Case 3: operational states are separated and GPR feature normalization is performed.

For all three cases the coefficient vectors for all records in the healthy and damaged states of the blade are computed, with the respective Mahalanobis distances defined in Eq. (13) subsequently computed. The results are displayed in Fig. 16. Starting by Case 1, it is clear that with no consideration of operational variability, the Mahalanobis distance shows noticeable variations while still in the healthy state. These variations obscure the changes observed when the wind turbine enters the damaged states. As more conditions are introduced into the representation of the healthy state (cases 2 and 3) it is clear that the variations of the Mahalanobis distance in the healthy state of the structure get significantly reduced. In this way, it is possible to observe a very subtle change in the Mahalanobis distance on the damaged states of the blade while in-operation.

6.2. Damage detection based on high frequency vibration response

CWT scalograms are calculated on the high frequency vibration responses of the wind turbine, this time including the three damage levels. The distribution of the first four PCA coefficients of the CWT scalograms are displayed in Fig. 17. It can be observed that the coefficients
$\alpha_1$ and $\alpha_2$ are distributed over a circular manifold, while coefficients $\alpha_3$ and $\alpha_4$ appear to follow a Gaussian distribution. Although a small shift is noticeable in the distribution of the PCA coefficients of the vibration response under damage, the difference is not quite clear. Therefore, the added non-linearity and overlapping of the considered features would lead to poor results on damage detection. A totally different perspective is obtained in Fig. 18, where the first two PCA coefficients, $\alpha_1$ and $\alpha_2$ are plotted as a function of the rotor azimuth. In this case, it is evident that there is a difference on the distribution of the PCA coefficients, but it is concealed within the rotor azimuth. These findings demonstrate the uttermost importance of considering operational variables in damage detection.

Following up on the previous result, the GPR model constructed for the PCA coefficients of the CWT scalograms of the vibration response on the healthy state of the blade is used as a baseline model for comparison with the vibration responses on the three damage states of the blade. As in low-frequency analysis, the Mahalanobis distance based on the GPR predictions defined in Eq. (13) is used as damage statistic. The obtained results shown in Fig. 19 demonstrate the difference on the Mahalanobis distance on the healthy and damaged states of the blade. Moreover, larger differences are evident when the wind turbine is idling (confirming the findings of low-frequency analysis), while changes are also evident (in lower magnitude) when the wind turbine is in-operation.
Figure 16: Mahalanobis distance of the LPV-VAR model parameter estimates for all the vibration response records in the healthy and damaged states of the wind turbine, for: (a) Case 1; (b) Case 2; (c) Case 3. Each color distinguishes an operational state. Different shades of gray in the background indicate the periods corresponding to each structural state of the blade.

7. Discussion of the results

7.1. Low frequency analysis:

(i) Low frequency vibration response on wind turbine blades is highly non-stationary. Through this study it is confirmed that the rotor azimuth is the principal driver for the dynamics in short term, while the wind speed is for extended analysis intervals.

(ii) The operational regime also plays an influential role in the dynamic features of the vibration.

(iii) Other variables, like turbulence intensity and temperature have a minor, but still visible, influence on the dynamics. Nonetheless, the case of temperature may have been underestimated in this study since the actual range of temperatures was rather limited. Further studies should focus on this issue.
Damage has a reduced effect on the low-frequency vibration characteristics of the in-operation wind turbine. However, damage seems to be detectable at least while the wind turbine is idling.

7.2. On high frequency analysis:

(i) As in the case of low frequency, high frequency vibration response on wind turbine blades is also highly non-stationary. Based on this study it may be confirmed that the instantaneous rotor azimuth clearly determines the characteristics of the transient wave moving through the blade, while other environmental variables have a lesser effect on the dynamics.

(ii) Also, as in the previous case the operational regime determines the characteristics of the induced wave.

(iii) As previously mentioned, the influence of temperature may have been underestimated since the actual range of temperatures observed during the study was rather limited. Further studies shall focus on this issue.

(iv) The influence of damage in the high frequency dynamics of the blade vibration response is observable in all the operating regimes.

7.3. Overall outcomes of the study:

(i) Low and high frequency characterizations are recommendable to study the dynamic behavior of wind turbines. In the case of damage detection, high frequency analysis has the potential to yield enhanced damage detection results. On the other hand, low frequency analysis facilitates the analysis of structural dynamics and fatigue loads.
Figure 18: Distribution of the first two PCA coefficients of the CWT scalograms as a function of the rotor azimuth for all the vibration response records on healthy and damaged states, with the wind turbine operating at 34 and 43 rpm.

(ii) The consideration of environmental and operational variables is essential to the analysis of the dynamic response of wind turbines. Here, wind speed, turbulence intensity and temperature are found to be the most influential variables, but over longer periods of analysis, other variables may also emerge. This calls for further studies and analysis methods which may deal with continuous variables (e.g., temperature) and discrete events (e.g., operational regimes, precipitation).

(iii) The damage type considered in the study was visible on both the dynamic characteristic of high and low frequency ranges, although in high frequency, damage is visible at any operating regime, while in the low frequency range this is only evident when the wind turbine is idling.

(iv) The GPR time-series model based dynamic characterization procedure proposed in this work reveals salient potential in analyzing the complex non-stationary dynamic characteristics of in-operation wind turbines. Nonetheless, further work should be devoted on finding a more parsimonious initial time-series characterization (particularly in the case of the CWT scalograms) to improve the computational efficiency on further steps of the dynamic characterization procedure.

8. Concluding remarks

This work has been devoted to the analysis of the in-operation vibration response of a wind turbine equipped with a sensor network and an excitation source in the form of an impulse introduced by an electro-mechanical actuator every five minutes. The analysed data comes from a
monitoring campaign extending on a total period of three months, over which the wind turbine moves through different operating regimes, and significant variation of environmental conditions (wind and temperature). In addition, damage, in the form of an artificially introduced crack in the trailing edge of the blade, was gradually extended over the second month of the monitoring campaign.

The analysis has been separated into low and high frequency ranges. Analysis of low frequency vibration response aimed at characterizing the blade structural dynamics, whose main source of excitation is the wind, while remains unaffected by the artificial impulse excitation. Linear Parameter Varying Vector AutoRegressive (LPV-VAR) models are selected to represent the vibration response on five minute intervals, characterized by time-periodic dynamics modulated by the instantaneous rotor azimuth.
On the other hand, analysis of high frequency vibration response aims mainly at characterizing the transmission properties of the material of the blade excited by the impulse excitation. The Continuous Wavelet Transform (CWT) spectrograms are used to represent the high frequency vibration response over the period of 50 ms after the actuator excitation, covering most of the extent of the transient introduced by the artificial excitation source.

The main contributions of this work may be summarized in the following items:

- Provides guidelines and exemplifies the application of “cause–effect” methodologies on actual long-term monitoring data, considering the complexities of such data, which include the influence of both discrete events and continuous variables on the dynamic characteristics of the structure, and different temporal scales characterizing the vibration response (low and high frequency);
- Provides a comparison of the damage detection potential of traditional vibration-only methods against the appraised “cause–effect” approach;
- Provides a direct comparison of the damage detection potential obtained by evaluating changes in structural dynamics (low-frequency), against those offered by wave transmission properties through the material (high-frequency) in wind turbine blades.

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References


