Cost-effective vibration based detection of wind turbine blade icing from sensors mounted on the tower

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Abstract

Ice throw from the blades of operational wind turbines is a safety concern when wind turbines are installed in a densely built environment. While several commercial solutions exist to detect icing or prevent ice build up altogether, there is still a desire for a more effective low-cost solution. In this contribution a previously instrumented onshore wind turbine is used to proof the concept of a novel ice detection strategy. In this new approach an accelerometer in the tower is used to infer the presence of icing on the rotor. Two approaches are investigated one based on natural frequencies extracted from operational modal analysis and the second based on Gaussian Process time series models.

1 Introduction

The build-up of icing on the rotor blades of wind turbines is a well known and thoroughly investigated topic in the field of wind energy. In cold climates with long periods of icing, the build up of ice introduces additional loads and reduced production output. To mediate these issues, often anti-icing solutions are applied to remove the icing from the blade, e.g. through blade heating. Yet, for areas with occasional or moderate icing such systems might not be cost-effective as production losses due to icing are marginal [1]. However, in densely built areas with occasional icing, the risk of ice throw from a rotating wind turbine still raises concern for the operators. Previous studies revealed that the ice thrown from a wind turbine can travel distances exceeding 100 m and weigh well above 1 kg [2], potentially harming property or causing injury. As a safety measure to avoid ice throw, an operational wind turbine should be shut down when icing is likely. This does imply a direct loss of production during the period of standstill. It is therefore essential to use an ice detection technique that is as accurate as possible, avoiding unnecessary standstill.

Over the years, industry has developed several methods to detect the presence of ice on wind turbine blades. A critical review of existing ice detection and anti-icing solutions is given in [3] and an overview of technology currently available in industry, including an estimate of number of systems deployed, is given in [4]. In general, the different techniques to detect ice can be divided in two families. One family of techniques assesses the meteorological conditions on or near the site and infers the likelihood of ice formation on the blades from those readings. Common examples are the measurements of the humidity and air temperature or the difference between the wind speeds measured by a heated and
an unheated anemometers. Other sensors in this family directly detect ice on the sensor and infer the presence of ice on the blades. A second family aims to detect the ice build up directly on the blade itself. One strategy in that family is to continuously monitor the resonance frequencies or vibrations of the blades. The basic concept is that the added mass of icing on the wind turbine blades will decrease the natural frequencies of the rotor blades [5, 6]. Techniques presented in [7] for mass detection, quantification and localization were also suggested to detect icing on the blades. However, as the natural frequencies of the blades will differ due to variations in the state of the machine a data normalization step is typically required using Environmental and Operational Parameters (EOP).

There is a general consensus within industry that the direct measurement of ice build up on the blades is the most accurate solution. However, the previous techniques require that sensors are installed on the blades and both power and data is transferred between the blade and the non-rotating parts. Typically implying the use of slip-rings or wireless data transfer solutions. In addition the installation in the blades poses a risk towards lightning strikes. While all these risks can be mitigated, the total cost of these systems is higher than the solutions mounted on the nacelle or tower. Therefore, at sites with low risk of icing often the cheaper environmental based solutions is chosen.

The aim of this project is to investigate the feasibility of a direct ice measurement from measurements on the tower of an operational wind turbine rather than in the blades. Thus reducing the hardware and installation cost. This concept is motivated from earlier results in [8] and [9]. These results revealed that the natural frequencies of the rotor modes are perceivable from accelerometers installed on the substructure, i.e. the tower. These observations hold for both standstill (parked) and rotating (operating) conditions of the turbine. As such, part of the dynamics observed from the tower are related to the rotor dynamics and could potentially be used to detect icing.

2 Measurement setup

The considered structure is a 2 MW wind turbine located in Flanders, Belgium. It was instrumented with a bi-axial ICP accelerometer, strain gauges and temperature sensors in late 2016. The main focus of the project was to record the loads of the turbine. As such the sensors were installed close to the bottom of the wind turbine, Fig. 1. The monitoring system logs independently at 100 Hz and the recorded data is transmitted through an network connection available in the wind turbine. The system has been in continuous operation and is currently still measuring the loads and accelerations. The recorded accelerations are transformed into the frame of reference of the nacelle (Fore-Aft and Sideways) using the yaw angle recorded in the turbine SCADA.

In parallel to the measurements, a simplified structural model of the turbine tower was built assuming a clamped connection. From this model the expected frequencies and mode shapes were calculated, as shown in Fig. 1.(b). According to these results the first order mode is expected at 0.375 Hz and the second tower mode is expected at 1.85 Hz. As the model does not include the rotor geometry, the expected rotor modes are unknown.
Figure 1. The accelerometers were installed at 18.5 m above the ground level. This is relatively low on the turbine as the contributions (quantified by the mode shapes) of the first and second order mode are relatively small.

3 Blade icing detection via observed tower structural dynamics

During the winter of 2016-2017 several icing events were recorded by the (indirect) ice detection system on the wind turbine and as a consequence operation was stopped. In Fig. 2 the spectrum of the accelerations (fore-aft) direction is plotted during such an icing event in January and during a day in July when no icing was present. Both spectra show the contribution of several modes, including the first order mode at 0.34 Hz. However, several modes around 2 Hz have a lower frequency during the winter measurements.

Figure 2. Power spectral density recorded using the accelerometer on the tower during stand-still for (orange) a day in summer (blue) during an icing alarm of the turbine. The vertical dashed lines are identified structural modes using the methodology presented in Section 3.2.1

There is thus a clear indication that the winter conditions have modified the dynamics of the tower. While icing is not confirmed from an secondary measurement, eye-witness reports confirm the presence of ice in that period. Moreover, the change in dynamics matches with what is expected during icing. The added mass of the icing would decrease the frequencies of the rotor modes [8, 10]. Contrarily, the tower modes would be less affected by any icing on the blades as the mass of icing is small compared to the total mass of the Rotor-Nacelle-Assembly (RNA) [10]. In Fig. 2 two modes did not shift in
frequency, those at 0.345 Hz and 1.8 Hz, coincidentally the two modes closest to the model predictions for the tower modes, according to Fig. 1. While unconfirmed, it is highly likely occurred during the January measurement.

Given the aforementioned observations there is sufficient motivation to further investigate the feasibility of an icing detection system using tower accelerations. In a collaboration between the Vrije Universiteit Brussel and ETH Zürich, two different approaches were investigated. The shared element behind both approaches is the compensation for variable EOP on characteristic quantities extracted from the raw vibration response of the wind turbine by means of *Gaussian Process Regression* (GPR). Indeed, GPR is a powerful tool in Structural Health Monitoring applications, since it considers the uncertainty in the characteristic quantities originating from both measurable and unmeasurable EOPs, as demonstrated previously in [11, 12].

In the first one of the approaches, a GPR model is built from measurable EOPs to characteristic quantities extracted by *Operational Modal Analysis* (OMA). In the second one, a hierarchical GP Vector Auto-Regressive (GP-V AR) modeling approach is adopted, in which the VAR model is used to represent the vibration response in the tower, while a GPR is utilized to represent the variation on the parameters of the VAR model as a function of measurable EOP. In both cases, the considered EOPs correspond to variables measured by the *Supervisory Control and Data Acquisition* (SCADA) system of the wind turbine and the temperature sensors on the tower.

In the next sections we describe the proposed framework in further detail as well as its application for detection of icing in the wind turbine. In Section 3.1 the GPR framework is introduced, while in Sections 3.2.1 and 3.2.2 respectively are discussed the OMA and GP-V AR model based methods to derive characteristic quantities from the vibration response measured in the tower.

### 3.1 Gaussian Process Regression of Characteristic Quantities

#### 3.1.1 Definition

At each period of analysis, a (vector) vibration response of the structure $\mathbf{y}[t] \in \mathbb{R}^n$, $t = 1, \ldots, T$, with a corresponding vector of EOPs $\mathbf{\xi} \in \mathbb{R}^m$ are collected from the structure. Subsequently, a set of characteristic quantities $\mathbf{\theta}_j$, $j = 1, \ldots, d$, is extracted from the vibration response. A *Gaussian Process Regression* (GPR) model is built to capture the stochastic functional relationship from the EOP vector $\mathbf{\xi}$ to the characteristic quantity vector $\mathbf{\theta}_j$. In the GPR model, the $j$th characteristic quantity $\theta_j$ is represented through the following stochastic functional series expansion [13, p. 8]:

$$
\theta_j = \mathbf{f}^T(\mathbf{\xi}) \mathbf{w}_j + u_j, \quad u_j \sim \mathcal{N}(u_j|0, \sigma^2_{u_j}) \tag{1a}
$$

$$
\mathbb{E}\{u_j \cdot u_j^T\} = \sigma^2_{u_j} \cdot \delta[j - j'] \tag{1b}
$$

where $\mathbf{w}_j = [w_{1,j} \ w_{2,j} \ \cdots \ w_{p,j}]^T$, is the coefficient vector of the $p$-order functional series expansion, $\mathbf{f}(\mathbf{\xi}) = [f_1(\mathbf{\xi}) \ f_2(\mathbf{\xi}) \ \cdots \ f_p(\mathbf{\xi})]^T$ is the functional representation basis vector, composed by each one of the multivariate basis functions $f_j(\mathbf{\xi}) : \mathbb{R}^m \mapsto \mathbb{R}$. In addition, $u_j$ is a zero mean white Gaussian innovations with variance $\sigma^2_{u_j}$, while the notation $\mathcal{N}(\mathbf{x}\mid \mathbf{\tilde{x}}, \mathbf{\Sigma})$ stands for a (multivariate) normal density on the random variable (vector) $\mathbf{x}$ with mean $\mathbf{\tilde{x}}$ and variance (covariance matrix) $\mathbf{\Sigma}$. Eqn. (1b) indicates that
the innovations from different characteristic quantities are assumed uncorrelated, which is considered to keep the model simple. Such an assumption can be simply fulfilled in practice by the application of decorrelation techniques such as Principal Component Analysis (PCA) on the characteristic quantity vector.

3.1.2 Bayesian interpretation of the GPR

In a Bayesian framework, the GPR model can be associated with a posterior density of the coefficient vector \( \mathbf{w}_j \), \( j = 1, \ldots, d \), given the training data set consisting of inputs \( \Xi = [\xi_1 \ \xi_2 \ \cdots \ \xi_N] \), and outputs \( \mathbf{\theta}_j = [\theta_{j,1} \ \theta_{j,2} \ \cdots \ \theta_{j,N}]^T \), as:

\[
p(\mathbf{w}_j | \Xi, \mathbf{\theta}_j) = \frac{p(\mathbf{\theta}_j | \Xi, \mathbf{w}_j) \cdot p(\mathbf{w}_j)}{p(\mathbf{\theta}_j | \Xi)} = \mathcal{N}(\mathbf{w}_j | \mathbf{\hat{w}}_j, \mathbf{A}^{-1}) \quad (2)
\]

where the mean and precision matrix of the multivariate normal density are:

\[
\mathbf{\hat{w}}_j = \sigma_{u_j}^{-2} \cdot \mathbf{A}^{-1} \cdot \mathbf{F} \cdot \mathbf{\theta}_j \\
\mathbf{A} = \sigma_{u_j}^{-2} \cdot \mathbf{F}^T \mathbf{F} + \Sigma_w^{-1}
\]

and where \( \mathbf{F} = [f(\xi_1) \ f(\xi_2) \ \cdots \ f(\xi_N)] \) is a matrix with the functional representation basis vectors evaluated on the training input EOPs. Moreover, the likelihood, prior and marginal (likelihood) densities, \( p(\mathbf{\theta}_j | \Xi, \mathbf{w}_j) \), \( p(\mathbf{w}_j) \), \( p(\mathbf{\theta}_j | \Xi) \) respectively, appearing in Eq. (2) are defined as follows [13, pp.8-9]:

\[
p(\mathbf{\theta}_j | \Xi, \mathbf{w}_j) = \mathcal{N}(\mathbf{\theta}_j | \mathbf{F}^T \mathbf{w}_j, \sigma_{u_j}^2 \mathbf{I}_N) \\
p(\mathbf{w}_j) = \mathcal{N}(\mathbf{w}_j | \mathbf{0}_{p \times 1}, \Sigma_w) \\
p(\mathbf{\theta}_j | \Xi) = \mathcal{N}(\mathbf{\theta}_j | \mathbf{0}_{N \times 1}, \mathbf{K(\Xi, \Xi)} + \sigma_{u_j}^2 \mathbf{I}_p)
\]

where \( \mathbf{K(\Xi, \Xi)} := \mathbf{F}^T \Sigma_w \mathbf{F} \) indicates the covariance matrix function associated with the Gaussian process. Each one of the entries of the covariance matrix function are characterized by terms of the form \( k(\xi_a, \xi_b) = f^T(\xi_a) \Sigma_w f(\xi_b) \), where the function \( k(\cdot, \cdot) \) is referred to as the kernel function associated with the Gaussian process.

3.1.3 Model selection and adjustment of hyperparameters

Identification of the GPR model is based upon the maximization of the marginal likelihood \( p(\mathbf{\theta}_j | \Xi) \), defined in Eq. (4c). To this end, models with different complexities are compared, and subsequently, the one providing the maximum marginal likelihood is selected. Practical computation is typically based on the logarithm of the marginal likelihood, or log-marginal, which takes the form [13, p. 9]:

\[
\ln p(\mathbf{\theta}_j | \Xi) = -\frac{1}{2} \mathbf{\theta}_j^T \cdot (\mathbf{K(\Xi, \Xi)} + \sigma_{u_j}^2 \mathbf{I}_p)^{-1} \mathbf{\theta}_j - \frac{1}{2} \det(\mathbf{K(\Xi, \Xi)}) + \sigma_{u_j}^2 \mathbf{I}_p | - \frac{N}{2} \ln 2\pi \quad (5)
\]

The marginal likelihood is a comprehensive model assessment tool, which as evident in Eq. (5), is composed by a first term penalizing the representation error in the training set, and a second term which disfavors model complexity. In addition, the marginal likelihood can be used to adjust the hyperparameters of the GPR model, noted by \( \mathcal{P} \) and constituted by the innovations variance \( \sigma_{u_j}^2 \), the coefficient vector covariance matrix \( \Sigma_w \), and any other adjustment parameters, as those that could be associated with the
functional representation basis. In that case, the marginal likelihood is noted instead as $L(\mathcal{P}|\theta_j, \Xi) \equiv p(\theta_j|\Xi, \mathcal{P})$, where in this time the hyperparameters are shown explicitly as part of the function.

3.1.4 Prediction based on the GPR model

Once a GPR model is available, a model-based prediction of the response $\theta_j^*$ to a new input EOP vector $\hat{\xi}^*$ may be calculated. In that case, the predictive density $p(\theta_j^*|\hat{\xi}^*, \Xi, \theta_j)$ determines the probability of the output characteristic quantity $\theta_j^*$ conditioned on the new input EOP vector, and the training input/output data. The predictive density is defined as [13, p. 11]:

$$p(\theta_j^*|\hat{\xi}^*, \Xi, \theta_j) = \int p(\theta_j^*|\hat{\xi}^*, w_j) \cdot p(w_j|\Xi, \theta_j) \, dw_j = \mathcal{N}(\hat{\theta}_j^*, \alpha_j^2) \quad (6)$$

where the mean and variance of this normal predictive distribution are defined as:

$$\hat{\theta}_j^* = \alpha_j^T \cdot k(\Xi, \hat{\xi}^*) \quad (7a)$$

$$\alpha_j = (\sigma^2_{\theta} \cdot j_p + K(\Xi, \Xi))^{-1} \cdot \theta_j \quad (7b)$$

$$\sigma_{\theta,j}^2 = k(\xi^*, \xi^*) - k^T(\Xi, \xi^*) (\sigma^2_{\theta} \cdot j_p + K(\Xi, \Xi))^{-1} k(\Xi, \xi^*) \quad (7c)$$

while $k(\Xi, \xi^*) := F^T \Sigma_w f(\xi^*)$ stands for the covariance function between the training input data $\Xi$ and the new input vector $\xi^*$, and $k(\xi^*, \xi^*) := F^T(\xi^*) \Sigma_w f(\xi^*)$ is the variance function of the new input EOP vector.

Note that the mean of the predictive density is hinged on a functional expansion based on the parameter vector $\alpha_j$ and the kernel function evaluated between all the training inputs and the new input. In this sense, the GPR is generally performed in terms of the kernel function $k(\cdot, \cdot)$ instead of the functional expansion basis $f(\cdot)$. This procedure is known as the kernel trick. Further details on the definition and selection of kernel functions are provided in [13, Ch. 4].

3.1.5 Decision based on the GPR model

The predictive density may be used to determine if a newly obtained characteristic quantity $\theta_j^*$ complies with a GPR model built for the structure on its healthy or nominal state $\mathcal{M}_o$ with input EOP $\hat{\xi}^*$. Following with the Bayesian formulation, this decision is hinged on the following posterior probability ratio:

$$B(\mathcal{M}_d, \mathcal{M}_o) = \frac{p(\mathcal{M}_d|\theta_j^*, \xi^*)}{p(\mathcal{M}_o|\theta_j^*, \xi^*)} = \frac{1}{p(\mathcal{M}_o|\theta_j^*, \xi^*)} - 1 \quad (8)$$

where $p(\mathcal{M}_o|\theta_j^*, \xi^*)$ denotes the posterior probability of the nominal state of the structure represented by the model $\mathcal{M}_o$ given data $\theta_j^*$ and $\xi^*$, while $p(\mathcal{M}_d|\theta_j^*, \xi^*) = 1 - p(\mathcal{M}_o|\theta_j^*, \xi^*)$ represents the same posterior density, this time on a model of the structure on the non-healthy state. Here, non-healthy represents any other state of the structure rather than healthy. Thus, one can state that only two states exist, so that $p(\mathcal{M}_o|\theta_j^*, \xi^*) + p(\mathcal{M}_d|\theta_j^*, \xi^*) = 1$.

Then, according to the Bayes theorem, the posterior probability of the structural state can be calculated as follows:

$$p(\mathcal{M}_o|\theta_j^*, \xi^*) = \frac{p(\theta_j^*|\xi^*, \mathcal{M}_o) \cdot p(\mathcal{M}_o)}{p(\theta_j^*|\xi^*)} = \frac{p(\theta_j^*|\xi^*, \Xi, \theta_j) \cdot p(\mathcal{M}_o)}{p(\theta_j^*|\xi^*)} \quad (9)$$
where presently the model \( \mathcal{M}_o \) stands for the GPR model constructed on the input/output training data \( \Xi \) and \( \theta_j \). In addition, \( p(\cdot | \mathcal{M}_o) \) designates the prior probability of the model of the nominal/healthy state, which represents the degree of belief that the structure is in its nominal state. Finally, \( p(\theta_j^* | \xi^*) \) denotes the marginal density of the characteristic quantity given the measured input EOPs regardless of the model, which in the present case can be evaluated via Eq. (4c).

After replacing the posterior model probability in Eq. (9) in the Bayes factor defined by Eq. (8) and after some algebraic manipulations, then, the decision can be performed as follows [14]:

\[
\frac{p(\theta_j^* | \xi^*)}{p(\theta_j^* | \xi^*, \Xi, \theta_j)} \leq 2 p(\mathcal{M}_o) \quad \text{The structure is in its nominal state (10)}
\]

Otherwise \( \text{The structure is out of its nominal state} \)

where, as observed, the prior probability \( p(\mathcal{M}_o) \) enters in the decision making process as a threshold that biases the decision towards a certain structural state.

### 3.2 Characteristic quantities for icing detection

#### 3.2.1 Characterization by means of operational modal analysis

A first of two approaches uses an automated version of the Least Squares Complex Frequency (LSCF) estimator adapted for operational modal analysis [15]. The algorithm defines a frequency-domain common denominator model for the output crosspower spectrum \( S_{yy}[\omega] \in \mathbb{C}^{n \times n} \) of the observed accelerations \( y[t] ; \), calculated using the correlogram approach.

\[
S_{yy}[\omega] = \frac{\sum_{i=0}^{n_n} N_i f_i(\omega)}{\sum_{i=1}^{n_d} d_i f_i(\omega)} \quad (11)
\]

in which \( N_i \in \mathbb{C}^{n \times n} \) and \( d_i \in \mathbb{C} \) represent the \( i \)-th order numerator and denominator model coefficients. The frequency basis \( f_i(\omega) \) is chosen for a discrete time model \( f_i(\omega) = e^{-j\omega T_s \cdot i} \).

The model coefficients are determined with a least squares cost function for increasing model orders \( n_n \) and \( n_d \) with \( d_{n_d} \) constrained to 1. For each model, the poles \( \lambda_{n_d,m}, m = 1, \ldots, n_d \), i.e. the roots of \( \sum_{i=1}^{n_d} d_i f_i(\omega) \), are determined.

The used automated version of LSCF was introduced in [8] to continuously monitor the resonance frequencies of offshore wind turbines. In brief, the automation uses a clustering algorithm to reduce the classic stabilization diagram, to several clusters \( \lambda_c \) of \( n_c \) observations of the same pole, based on a threshold distance between clusters, over the different model orders. For each cluster, the mean values of the resonance frequencies are calculated. The final output of the OMA algorithm is thus a set of resonance frequencies for each time interval.

To optimize the performance towards ice detection only the \( n_f \) modes sensitive to icing should be retained for monitoring in \( f \in \mathbb{R}^{n_f} \). In particular tower modes which are insensitive to icing, will not contribute to the detection of icing and should not be considered. A final assumption is that the accretion of ice would induce a linear change in all frequencies associated with the rotor.

\[
f = \tilde{f} - \theta \Delta f \quad (12)
\]
in which $\bar{f}$ is the mean value of the monitored frequencies in absence of icing and $\Delta f$ is the sensitivity of the individual frequencies to an unknown amount of icing, both are obtained by training the model using both periods with and without confirmed icing. As such $\theta$ becomes a metric proportional to the amount of ice, and could in theory be used to quantify the amount of ice. Successive estimations of $\theta$ are combined in $\theta = [\theta_1 \, \theta_2 \, \cdots \, \theta_N]^T$ and used for decision support as proposed in Section 3.1.

3.2.2 Characterization by means of GP Vector AutoRegressive models

A Gaussian Process (GP) time-series model of the response vector is defined through the equation set [11]:

$$y[t] = \phi^T[t] \cdot \theta + \varepsilon[t], \quad \varepsilon[t] \sim \text{NID}(0_{n \times 1}, \Sigma_\varepsilon)$$

(13a)

$$\theta = f^T(\xi)W + u, \quad u \sim \mathcal{N}(u(0_{d \times 1}, \Sigma_\theta))$$

(13b)

where $\phi[t] \in \mathbb{R}^{d \times n}$ is the regression matrix, $\theta \in \mathbb{R}^d$ is a random parameter vector, and $\varepsilon[t] \in \mathbb{R}^n$ is a vector Normally and Identically Distributed (NID) innovations, with zero mean and covariance matrix $\Sigma_\varepsilon$. In the present case, the characteristic quantity corresponds to the random parameter vector, which is a Gaussian process determined by the coefficient matrix $W = [w_1 \, w_2 \, \cdots \, w_d], W \in \mathbb{R}^{p \times d}$, the GP functional basis $g(\xi) \in \mathbb{R}^p$, and the parameter covariance matrix $\Sigma_\theta$.

The specific type of GP time-series model is determined by the structure of the regression matrix. In the present context, the selected time-series model corresponds to a Vector AutoRegressive (VAR) model, defined as follows [11]:

$$y[t] = \sum_{i=1}^{n_a} A_i \cdot y[t-i] + \varepsilon[t], \quad \varepsilon[t] \sim \text{NID}(0_{n \times 1}, \Sigma_\varepsilon)$$

(14)

where $A_i \in \mathbb{R}^{n \times n}$ is the $i$-th AR parameter matrix and $n_a$ is the autoregressive order. Eq. (14) may be cast into the following equivalent regression form [11]:

$$y[t] = \phi^T[t] \cdot \theta + \varepsilon[t], \quad \phi[t] = I_n \otimes z[t], \quad \theta = \text{vec}(A)$$

(15)

where $A = [A_1 \, A_2 \, \cdots \, A_{n_a}], A \in \mathbb{R}^{n \times n_a \times n}$ is the coefficient matrix of the VAR model, $z[t] = [y^T[t-1] \, y^T[t-2] \, \cdots \, y^T[t-n_a]]^T$, $z[t] \in \mathbb{R}^{n 

4 Preliminary results

4.1 Results from OMA characterization

The LSCF-OMA method is performed on the fore-aft vibration signal from the wind turbine tower during periods of standstill. Figure 3.(a) shows the stabilization chart, a typical outcome to OMA, and the found resonance frequencies through clustering.

In Figure 3.(b) exemplary results obtained on a longer tracking period of the modes around 2 Hz with the wind turbine on standstill are shown. The variation of the natural frequencies is reduced, indicating a limited relation to the environmental conditions.
However, there is a noticeable reduction in the observed frequencies for the initial analysis period, coinciding with instances from January 2017 which are likely linked to icing events. Based on these results, the second (FA2), fifth (FA5) and 6th mode (FA6) are withheld to detect the presence of icing. The tracked frequencies are combined in the monitoring parameter $f = [f_{FA2}, f_{FA5}, f_{FA6}]^T$. The tracked values are plotted as histograms in Figure 4. For each time stamp the characteristic quantity $\theta$ is calculated using Equation (12) and the estimated sensitivities $\Delta f$, i.e. the shift in frequency for the first day of confirmed icing.

In Figure 5 the final resulting control chart, using the framework presented in Section 3.1 and considering wind speed and air temperature is shown. A minor modification is made as the plot also takes into account the sign of each instance of $\theta$, by multiplying the control metric with the sign of $\theta$. Assuming icing by default introduces a decrease in frequency, results with an increase in frequency can be excluded. The results in Figure 5 show that for the instrumented machine only icing was detected in January 2017. With the heaviest icing happening early in the month. Surprisingly several time instances in summer also triggered an alarm. However, by considering the sign of $\theta$ they were not flagged as icing. In fact they represent days during which the resonance frequencies were significantly higher than expected. What is the cause of these observations is unclear at this moment.
4.2 Results from GP-VAR model-based characterization

For the presently discussed method, a GP-VAR model is constructed from the vibration signals of the tower measured in the $x$–$y$ plane (not adjusted to the reference frame of the nacelle) during periods of standstill. The EOP variables considered to construct the GPR are the wind speed and the wind direction. Model structure selection follows the guidelines discussed in [11]. Principal Component Regression (PCR) is appraised to decorrelate the parameters of the GP-VAR model, as also discussed in [11].

The GP-VAR model-based likelihoods of the healthy structural state versus wind speed, wind direction and time, are shown Fig. 6. Red dots indicate the instances which most likely correspond to periods of icing. The plots displaying the likelihood versus wind speed and direction evidence that the distribution on normal and icing conditions are different. Also, it can be observed that the most persistent outliers in the winter season correspond to periods of time with a high probability of icing. Nonetheless, in warmer months there are also several outliers which cannot be properly explained, as it is in the case of the method based on natural frequencies.

4.3 Discussion

The results obtained with both methods demonstrate the potential for detecting ice accretion in the blades of a wind turbine from “cheap” measurements in the tower. Nonetheless,
the current set-up is too limited to make any definitive conclusions on the actual reliability or sensitivity of both strategies, as no independent (reliable) measurement of the actual icing is conducted. A more elaborate set-up is desired to fully assess the reliability of the method, preferably at a site where icing occurs more regularly.

Both strategies identified several periods in which the dynamics differed from those used in training, evidenced by the presence of persistent outliers. On both approaches, the most likely icing occurred during the beginning of the campaign. In the OMA-based approach, the use of resonance frequencies yields a large number of alarms, often associated with a single frequency deviating from its expected value. The additional constraint introduced by Eq. (12) helps to reduce the number of false positives and allows to distinguish the direction of the change on the resonance frequency, and thus to recognize the presence of icing. Nonetheless, the OMA-based approach is limited in the sense that the OMA method should be able to recognize the three modes so that a decision can be achieved. Otherwise, the distance metric can not be calculated.

On the other hand, the GP-VAR model based method has further advantages. Firstly, the method is based on direct vibration measurements, while adjustment for changing wind speed and direction is intrinsically made through the GPR. In addition, the method avoids the cumbersome process of extracting and cleaning-up natural frequency estimates. Hence, decision is always possible, as long as there are measurements available. Moreover, the VAR model is a more comprehensive representation of the dynamics of the wind turbine vibration, in contrast to a representation solely based on natural frequencies. Thus, decision is potentially more reliable.

The next challenge is to extend the current approach to rotating conditions, where the dynamics become more complex. In particular, an important increment of damping is expected due to aeroelastic interactions. In addition, the rotor modes observed from the tower reference frame become dependent of the rotational speed and are visible as the so-called whirling modes. The GPR scheme of Section 3.1 should be able to compensate these variations, although uncertainty is expected to increase.

5 Conclusion

The current contribution showed the concept of detecting ice on wind turbine rotor blades using the accelerations measured on the tower structure. This sensor-setup promises a potential cost reduction over sensors in the blades. A first proof of concept during parked conditions reveals that this approach is sufficiently sensitive to pick up the changed dynamics, likely caused by icing on the rotor blades. Future work will focus on further tuning this method to become reliable and accurate and extend the method towards rotating conditions.

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