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Wind turbines structural identification framework for the representation of both short- and long-term variability

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Abstract

Wind energy has already proven to comprise a viable solution for green energy production and is expected to account for a significant portion of Europe's electricity in the near future. Despite the good level reached for the design stage of WTs, the management of these complex structures is still in its infancy, as evidenced by their relatively short nominal life-span, currently set at 20 years. Within such a context, methods and tools are required for guaranteeing the high performance and reliability of these systems, thereby maximizing the control of these assets and allowing owners to confidently explore look the future of these investments. In this work, a Structural Health Monitoring (SHM) framework is devised for addressing this need in both a short- and long-term scale by introducing diagnostics and metrics for condition assessment; prediction of deterioration and environmental effects influence (long-term); and detection of damage/extreme events (short-term). A Polynomial Chaos Expansion (PCE) tool is recombined with a time domain identification method, suited for the treatment of non-stationary systems, such as the operating WT system, in order to deliver this bi-component SHM framework able to provide information on the system in both the short- and long-term scale. The framework relies on the use of output only vibration response data, in the form of acceleration measurements, which is appropriately fused with temperature and wind load information that is routinely available via Supervisory Control and Data Acquisition (SCADA) systems.

1. Introduction

In recent years, Europe has been faced with the problem of continuous urbanization and excessive energy consumption, closing in on exhaustion of available energy resources. In view of this, the notions of sustainability and resilience have become paramount in resource management and policy-making. Within such a context, the European Union (EU) published the “Renewable Energy Road Map. Renewable energies in the 21st century: building a more sustainable future”, where a mandatory target of 20% for renewable energy's share in the EU by 2020 was established, with wind energy supplying 14% (Wilkes 2011). Based on the wind energy industry’s response, four years later the Energy Roadmap 2050 predicted that wind energy could supply between 31.6% and 48.7% of Europe's electricity (European Commission, 2011). Despite the level of refinement that has been reached in the past few years concerning the geometric, material and subassembly design of these systems, their life-cycle management is still at its infancy as evidenced via the short life-span of these components and the lack of efficient operation and maintenance (O&M) schemes.
Admittedly, the issue of devising appropriate O&M strategies for WT facilities is non-trivial, due to both the complexity of the WT system itself and the highly diverse operational loads it is exposed to (Abgayani, 2009). A WT is a highly complex system that comprises several components of structural and mechanical nature, which are exposed to intensive loading combinations, including wind gusts, turbulence, sea waves and severely corrosive environments. This diverse loading may give rise to unconventional problems, such as structural damage, collapse from turbine overspeed,

resonance, severe localized vibrations and so forth. As a result of the strenuous conditions they are subjected to, wind turbine components are designed to sustain a rather short life-span of 20 years. In fact, very few turbines have already reached their life expectancy, which further contributes to the lack of experience concerning the maintenance and optimal operation planning of these facilities. On the other hand, and in an effort to maximize the productivity of these units, WTs come with increased operational times. The conservative life-span has been adopted as a compromise which ensures the various components of the turbine work reliably for a joint benchmark amount of time. As far as major structural components are concerned however (blades, tower, foundation, substructure), it may prove beneficial to plan for a longer design life, whereas smaller (usually mechanical parts) can be intermittently refitted. From this point of view, efficient performance-based structural management can lead to improved designs for WT structures. Structural Health Monitoring (SHM) based solutions offer a tool towards this end.

Such tools build on the feedback gathered from appropriately placed sensor arrays able to provide a wide stream of information towards condition monitoring of WTs. Most installations already feature Supervisory Control And Data Acquisition (SCADA) systems, which typically provide data regarding the wind field, nacelle direction and power analytics at 10-minute averages (Tavner *et al.*, 2008). Although useful for monitoring possible faults primarily located in the nacelle and subassemblies, SCADA systems fail to provide comprehensive information on structural performance and may not be straightforwardly related to processes such as the onset of damage or fatigue accumulation. One step further, SHM systems have been recently proposed for improving safety and minimizing down time and maintenance costs (Abgayani, 2009), with a wider implementation for blade components. The thorough reviews provided by (Ciang *et al.*, 2008) and (Hameed *et al.*, 2009) discuss the criticality of benefiting from SHM methodologies for improving safety considerations, minimizing down time, lowering maintenance and logistic costs and providing reliable power generation. As correctly identified in (Yang & Sun, 2013), there is an urgent need for including feature extraction and damage detection algorithms in the computing cores of the SHM system to provide automated monitoring and diagnosis of the WT service condition. As further pointed out in the work of (Thöns 2012), appropriate use of monitoring data can support certification authorities in the development of a best practice methodology for modeling and assessing WTs.

For the proposed solutions to be readily implementable into practice, a significant hurdle has to be overcome relating to the inherently stochastic nature of the WT systems. Stochasticity emanates from the uncertainty associated with a number of factors, such as limited or incomplete sensory information, lack of a detailed structural model, incomplete understanding of the loading conditions, intricate site-specific conditions including soil characteristics at the given location, varying environmental conditions and several more. In this work a SHM framework is devised, with respect to both a short- and long-term scale, by introducing diagnostics and metrics for condition assessment accounting for the influence of environmental effects (long-term), and allowing for detection of damage/extreme events (short-term). A Polynomial Chaos Expansion (PCE) tool is combined with a time domain identification method, suited for the treatment of non-stationary systems, such as the operating WT system, in order to deliver this bi-component SHM framework able to provide information on the system in both the short- and long-term scale. The framework relies on the use of output only vibration response data, in the form of acceleration measurements, able to account for the lack of precise input (loading) information. The latter is appropriately fused with temperature and wind load information that is routinely available via SCADA systems. The performance of the proposed framework is validated on the successful tracking of the performance of an actual WT tower located in Lübbenau Germany. The suggested condition assessment framework can be almost straightforwardly extended to fatigue assessment, especially when combined with strain information, a problem of paramount importance for WT structures.

2. Monitoring Framework

The goal of the work presented herein lies in the accurate modeling of WT structural dynamics based on ambient vibration response measurements as well as measurements of the operating conditions in the form of temperature and wind load information. The work is organized across two main scales, as aforementioned, namely the short- and long-term scale. In the short-term scale, which pertains to high sampling rates and units in the range of fractions of a second, the driving forces are of aerodynamic, gravitational and inertial nature (Hameed *et al.*, 2009; Hau, 2013). In the long-term scale, which pertains to a wider range from minutes to hours to days, the driving elements consist in the wind-flow profile (gust, turbulence), temperature, wave loading (for off-shore) amongst other factors.

2.1 Short-term Monitoring Framework

The short-term framework requires the modeling of the WT vibrating system in real-time. The system response refers to two separate conditions, namely the parked and operational WT. When the WT is parked, the tower and foundation are excited by ambient wind loads. In regular operation, the dynamics of the WT becomes non-stationary due to the rotation of the rotor, which induces a *"periodic variability"*. This may be attributed to:

i. The increase in wind speed with height causes a spatially non-uniform over the rotor-swept area wind flow, which is translated into cyclic load changes on the rotating rotor.
ii. The inertial forces due to the dead weight of the rotor blades also cause periodic loading conditions.

This periodic variability, pertains to components of the WT system itself and therefore evolves in a so-called short-term scale. In appropriately simulating this short-term variability, Time-varying AutoRegressive Moving Average (TARMA) models constitute a suitable tool for tracking the time evolution of the dynamics using a compact parametric formulation. More specifically, a TARMA model of order AR/MA order equal to n is given by the following equation:

$$y[t]+a_1[t]y[t-1]+\ldots+a_n[t]y[t-n]=e[t]+c_1[t]\mathrm{e}[t-1]+\ldots+c_n[t]e[t-n], \qquad e[t]\sim \mathrm{NID}(0,\sigma_e^2[t]) \quad (1)$$

where t designates discrete time (with $t=1,2,\ldots,N$, the observed nonstationary signal, $e[t]$ the residual sequence, that is the unmodeled part of the signal, which is assumed to be normally identically distributed with zero mean and time-varying variance $\sigma_e^2[t]$, and $a_i[t]$, $c_i[t]$ the time-varying AR and MA parameters, respectively.

In the case of Smoothness Priors models, stochastic difference equations of the following form govern each of the AR and MA parameters (Spiridonakos *et al.*, 2010):

$$(1-B)^{\kappa} a_i[t]=w_{a_i}[t], \qquad w_{a_i}[t]\sim \mathrm{NID}(0,\sigma_{w_a}^2[t]) \quad (2)$$

$$(1-B)^{\kappa} c_i[t]=w_{c_i}[t], \qquad w_{c_i}[t]\sim \mathrm{NID}(0,\sigma_{w_c}^2[t]) \quad (3)$$

where B is the backshift operator ($B^{\kappa}x[t]=x[t-\kappa]$), κ designates the difference equation order, and $w_i[t]$ zero-mean, uncorrelated, mutually uncorrelated and also uncrosscorrelated with $e[t]$, Gaussian sequences with time-dependent variance.
The smoothness of evolution of the AR/MA parameters is controlled by the order of the difference equation constraints κ, and the variance $\sigma^2_{w_i}[t]$ – where a small variance indicates smooth evolution of the corresponding time-varying parameter and vice-versa.
In order to illustrate the model parameter estimation through a simple example, consider the TAR(n) case and a second order $(\kappa=2)$ stochastic smoothness constraint:

$$(1-B)^2 a_i[t]=w_{a_i}[t]\Rightarrow a_i[t]=2\cdot a_i[t-1]-a_i[t-2]+w_{a_i}[t] \qquad (i=1,\ldots,n) \tag{4}$$

The constraints corresponding to all AR parameters may be written as:

$$\begin{bmatrix} a_1[t] \\ \vdots \\ a_n[t] \\ a_1[t-1] \\ \vdots \\ a_n[t-1] \end{bmatrix} = \begin{bmatrix} 2 & \ldots & 0 & -1 & \ldots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \ldots & 2 & 0 & \ldots & -1 \\ 1 & \ldots & 0 & 0 & \ldots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \ldots & 1 & 0 & \ldots & 0 \end{bmatrix} \cdot \begin{bmatrix} a_1[t-1] \\ \vdots \\ a_n[t-1] \\ a_1[t-2] \\ \vdots \\ a_n[t-2] \end{bmatrix} + \begin{bmatrix} 1 & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & 1 \\ 0 & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & 0 \end{bmatrix} \cdot \begin{bmatrix} w_{a_1}[t] \\ \vdots \\ w_{a_n}[t] \end{bmatrix} \tag{5}$$

In a similar manner, it may be shown that the general (κ-th order) smoothness constraint of Eqs. (2) and (3) may be expressed as:

$$\mathbf{z}[t]=\mathbf{F}\cdot\mathbf{z}[t-1]+\mathbf{G}\cdot\mathbf{w}[t] \tag{6}$$

with:

$$\mathbf{z}[t]\triangleq\left[a_1[t]\ldots a_n[t]\vdots\ldots\vdots a_1[t-\kappa+1]\ldots a_n[t-\kappa+1]\right]^T_{\kappa\cdot n\times 1} \tag{7}$$

$$\mathbf{w}[t]\triangleq\left[\ w_{a_1}[t]\, w_{a_2}[t]\ldots w_{a_n}[t]\right]^T_{n\times 1} \tag{8}$$

and $\mathbf{F},\mathbf{G}$ matrices of the following forms (depending upon the value of κ):

$$\begin{aligned}
&\kappa=1: && \mathbf{F}\triangleq\mathbf{I}_n, && \mathbf{G}\triangleq\mathbf{I}_n \\
&\kappa=2: && \mathbf{F}\triangleq\begin{bmatrix} 2\cdot\mathbf{I}_n & -\mathbf{I}_n \\ \mathbf{I}_n & \mathbf{0}_n \end{bmatrix}, && \mathbf{G}\triangleq\begin{bmatrix} \mathbf{I}_n \\ \mathbf{0}_n \end{bmatrix} \\
&\kappa=3: && \mathbf{F}\triangleq\begin{bmatrix} 3\cdot\mathbf{I}_n & -3\cdot\mathbf{I}_n & \mathbf{I}_n \\ \mathbf{I}_n & \mathbf{0}_n & \mathbf{0}_n \\ \mathbf{0}_n & \mathbf{I}_n & \mathbf{0}_n \end{bmatrix}, && \mathbf{G}\triangleq\begin{bmatrix} \mathbf{I}_n \\ \mathbf{0}_n \\ \mathbf{0}_n \end{bmatrix}
\end{aligned} \tag{9}$$

and so on,

where $\mathbf{I}_n$ and $\mathbf{0}_n$ designate the $n\times n$ dimensional identity and zero matrices, respectively. As indicated by the above expressions, $\mathbf{z}[t]$ forms a state vector, whereas $\mathbf{w}[t]$ consists of the residuals entering in each constraint expression. The TAR(n) representation may then be expressed as:

$$x[t]=\mathbf{h}[t]^T\cdot\mathbf{z}[t]+e[t] \tag{10}$$

with:

$$\mathbf{h}[t]=\left[-x[t-1]\ldots-x[t-n]\,\vdots\,0\ldots0\;\right]^T_{\kappa\cdot n\times 1} \tag{11}$$

Thus, the SP-TAR(n) model may be completely expressed in state space form [Eqs. (6) and (10)], and its estimation may be achieved via the Kalman Filter (KF) approach for given κ order and residual variance ratio $\nu=\sigma_w^2[\mathrm{t}]/\sigma_e^2[\mathrm{t}]$ which is considered to be constant for all time instants t [for more details see (Spiridonakos *et al.*, 2010, Kitagawa & Gersch, 1996)]. However, the full SP-TARMA case leads to a nonlinear state estimation problem due to the unknown residual sequence of $e[t]$ in $\mathbf{h}[t]$. For this reason, the Extended Least Squares (ELS) algorithm is presently employed for the recursive estimation of the state vector $\mathbf{z}[t]$ (Spiridonakos *et al.* 2010).

The model inferred through this process will be referred to as "short-term" in the sense that it may represent the WT dynamics for a given set of observed conditions. The ability to predict the response of the system through such a parametric, and therefore low-cost, simulation model lays the ground for the subsequent derivation of metrics for detecting abnormalities/damage.

2.2 Long-term Monitoring Framework

The long-term monitoring framework aims at the accurate description of the dynamic properties of the structure for a range of acting, operational and environmental conditions. In this case, we refer to a variability that is different from the short-term one treated in Section 2.1. This "long-term" variability pertains to the loading and environmental conditions which are continually changing within the range of hours, or even minutes:

i. Non-periodic, stochastic loads caused by wind gusts and turbulence (within the order of minutes)
ii. Changes in the input wind flow profile (within the order of minutes).
iii. Environmental conditions variation (temperature, humidity, solar radiation, wave loading and others; within the order of hours).

For modeling the evolution of the system as a function of changing conditions, the following process is followed herein, as introduced in previous works of the authoring team (Spiridonakos & Chatzi, 2014a; 2014b) Features extracted from the estimated nonstationary SP-TARMA representation, defined in Section 2.1, are projected onto the stochastic spaces of the recorded operational and environmental conditions of the WT. In this way, a statistical model may be built, incorporating the effects of environmental and operational conditions and alleviating the danger of misinterpreting these as damage. A PCE method, coupled with the SP-TARMA model, enables the transition from short (structure on its own) to long (structure in interaction with its environment) delivering performance indicators that ensure enforcement of this scheme in a uniform and repeatable, i.e., standardized manner. In analogy to the widely employed neural networks approach, the formulation of performance indicators (indices) essentially requires a training period after which these are able to predict performance within regular operation and compare it to the actually measured one. Deviations of these indices from normal bounds, indicate irregularity in the operation of the WT and serve as a warning/alarm. This "long-term" stochastic framework provides a means of quantifying the uncertainty pertaining to the evolution of the dynamic behavior of a WT during its complete operational spectrum.

PCE concerns the expansion of a random output variable on polynomial chaos basis functions which are orthonormal to the probability space of the system's random inputs. More specifically, let us consider a system $\mathcal{S}$ which has M random input parameters represented by independent random variables $\{\Xi_1,\ldots,\Xi_M\}$, e.g. temperatures or wind velocities, measured at different locations of the structure, gathered in a random vector Ξ of prescribed joint Probability Density Function (PDF) $p_{\Xi}(\xi)$ (Blatman & Sudret, 2010). The system output, e.g. the variance of the SP-TARMA model residuals, denoted by $Y=\mathcal{S}(\Xi)$ will also be random. Provided that Y has finite variance, it can be expressed as follows:

$$Y=\mathcal{S}(\Xi)=\sum_{\boldsymbol{d}\in\mathbb{N}^M}\theta_d\varphi_d(\Xi) \tag{12}$$

where θ_d are unknown deterministic coefficients of projection, $\boldsymbol{d}$ is the vector of multi-indices of the multivariate polynomial basis, and $\varphi_d(\Xi)$ are the PC functions orthonormal to $p_{\Xi}(\xi)$. These basis functions $\varphi_d(\Xi)$ may be constructed through tensor products of the corresponding univariate functions.

Each probability density function may be associated with a well-known family of orthogonal polynomials (Table 1). A list of the most common probability density functions along with the corresponding orthogonal polynomials and the relations for their construction may be found in (Xiu & Karniadakis, 2002).

PDF	Support	Polynomials
Normal (Gaussian)	(-∞, ∞)	Hermite
Gamma	[0, ∞)	Laguerre
Beta	[0,1]	Jacobi
Uniform	[-1, 1]	Legendre

Table 1. Types of Wiener-Askey polynomial chaos and their underlying random variables.

For purposes of practicality the basis functions series must be truncated to a finite number of terms, with the usual approach being the selection of the multivariate polynomial basis with total maximum degree $\left|\boldsymbol{d}_j\right|=\sum_{m=1}^{M}d_{j,m}\leq P$ for every j. In this case the dimensionality of the functional subspace is equal to:

$$p=\frac{(M+P)!}{M!P!} \tag{13}$$

where M is the number of random variables and P the maximum basis degree.

Therefore, when truncating the infinite series of expansion of Eq. (12) to the first p terms, the resulting PCE model is fully parametrized in terms of a finite number of deterministic coefficients of projection θ_d. Parameter vector θ_d may be estimated by solving Eq. (12) in a least squares sense. Toward this end, the data of the output variables and the PDFs of the input variables have to be employed. The PDFs of the input variables may be obtained by fitting known statistical distributions to the observed input variables values.

Considering for example a structural system subjected to ambient excitation which is susceptible to changes of the environmental conditions, a given output variable, such the estimates of its first natural frequency, could be expanded on a PC basis constructed to be orthogonal to the experimentally estimated PDF of temperature data. In this way, an indication is obtained on the sensitivity of the natural frequencies of the structure to the manner in which stochasticity related to environmental conditions propagates through the structural system.

3. Application, WT facility in Lübbenau, Germany

The SHM framework introduced in the previous sections is presently applied on the case study of a real WT under operation. The WT under study is one of the eight V90 2MW Vestas generators of a wind farm in Lübbenau in northern Germany owned by Repower Deutschland GmbH. The vibration response of the WT were measured by triaxial accelerometers (STM LIS344ALH MEMS sensors) at five distinct locations of the WT tower (Fig. 1). A 10-minute-long dataset was recorded every half hour for 29 days (from 18/18/2013 till 15/1/2014), resulting in 1392 datasets. The signals recorded at 200 Hz were lowpass filtered and downsampled to 12.5 Hz (cutoff frequency at 5 Hz).

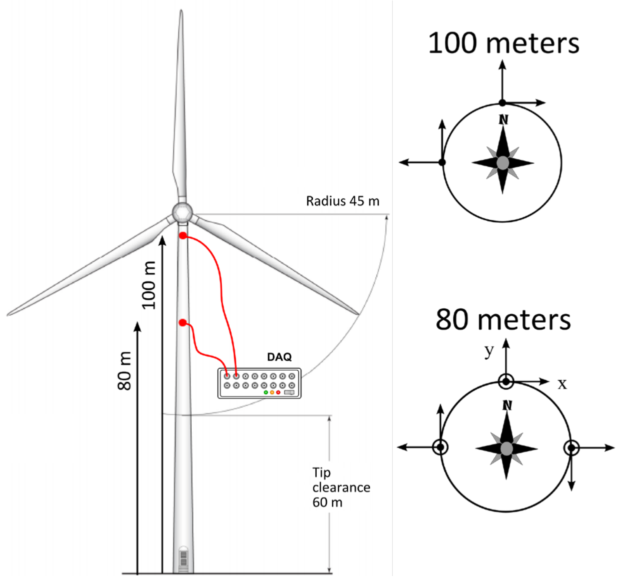
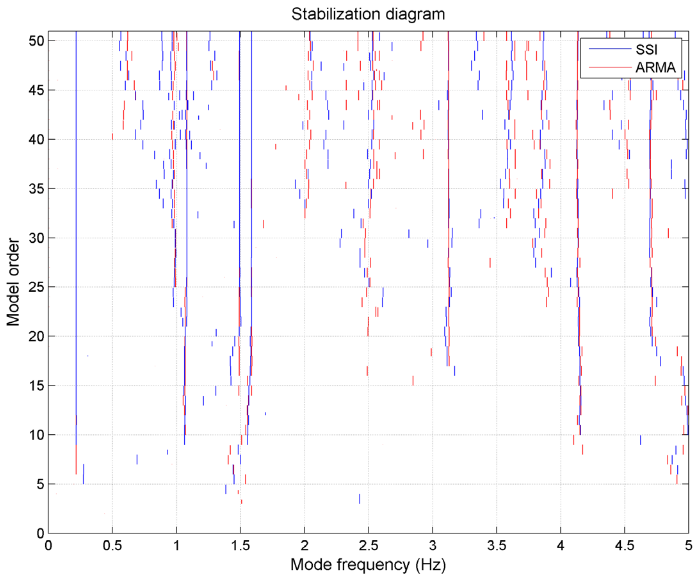


Figure 1: Schematic diagram of the experimental setup.

A dataset corresponding to the parked WT is initially used for extracting its modal properties for the purposes of comparison. Toward this end, the y-axis response measured at 80 m height (North sensor location; Fig. 1) and stationary ARMA method based on prediction error method are utilized (the results of a stochastic subspace identification method based on the canonical variate algorithm are also shown for comparison). The resulting stabilization diagram for model orders between 2 and 50 is shown in Fig. 2. The final AR/MA orders are selected equal to 32 and the estimated natural frequencies and damping ratios based on ARMA model are also summarized in this figure (only the natural frequencies with damping ratio less than 5% are presented).
In contrast to the stationary dynamics of the parked WT the dynamics of the operating WT are susceptible to change within some minutes as clearly shown by the spectrogram of the signal recorder at 8:30 am, 26/012/2013 in Fig. 3 (Short Time Fourier Transform; Hamming data window; NFFT = 512; overlap 98%). Furthermore, it may be clearly observed that some additional frequencies are introduced in the spectrogram due to the rotation of the WT. On the same figure, the evolution of the estimated natural frequencies based on SP-TARMA(32,32) with smoothness

constraints ordrer κ equal to 1 and variance ratio $\nu = 0.01$ are shown by blue solid lines while in dashed gray lines the corresponding estimates of an conventional ARMA(32,32) model are also shown. The latter are of course incapable of tracking any variability and they normally return averages of the nonstationaty natural frequencies, in contrast to the nonstationary SP-TARMA model which tracks with good accuracy the evolution of the dynamics when compared to the spectrogram shown in the background.



#	Natural freq. (Hz)	Damping ratio (%)
1	0.2170	0.2716
2	1.0817	1.4520
3	1.4927	0.6207
4	1.5864	0.3858
5	2.0033	3.3644
6	2.5115	3.7262
7	3.1251	0.6683
8	3.6084	0.9387
9	3.8287	2.4248
10	4.1340	1.3802
11	4.7153	1.0199

Figure 2: Dynamics of the parked WT. Stabilization plot for the stationary ARMA and SSI methods (model orders from2 to 50) and the estimated natural frequencies and damping ratios based on an ARMA(32,32) model.

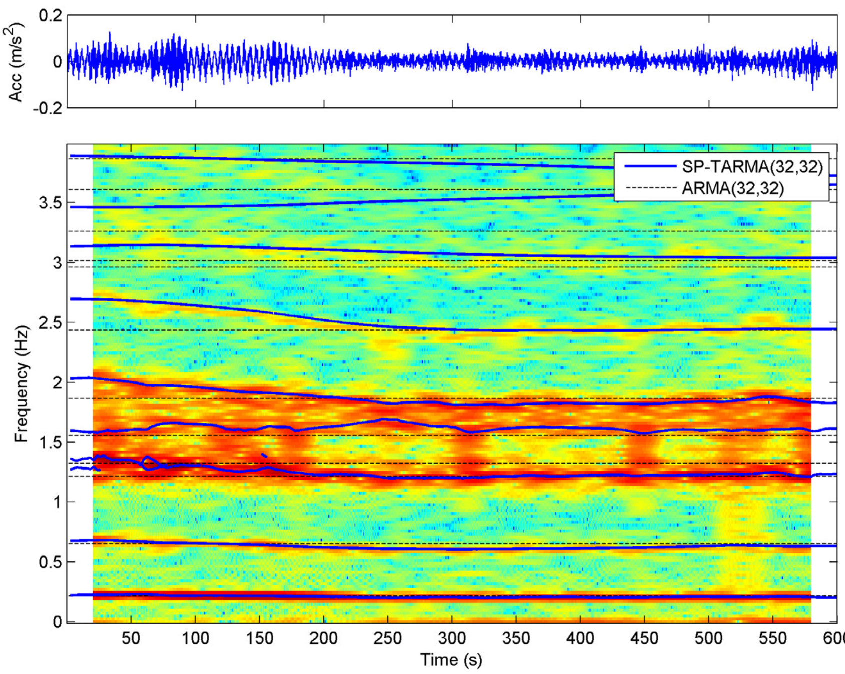


Figure 3: Dynamics of the WT under normal operation. Stationary ARMA(32,32) natural frequency

estimates are compared with those of the nonstationary SP-TARMA(32,32) model (spectrogram in the background).

For the long-term monitoring the SCADA data are also employed. The list of available operational and environmental parameters are listed in Fig. 5, with those selected for the subsequent analysis shown in bold and also plotted (these values correspond to the 1392 datasets of the vibration response measurements). These variables are available in 10-minute averages format and for this reason the output was also selected to be the standard deviation (std) of the SP-TARMA(32,32) residuals for the 10 minute intrevals, that is the mean value of the nonstationary residuals std. The input variables were transformed in uniform variables and thus the Legendre polynomials are used for the PCE while the maximum polynomial order was selected equal to seven (R^2 criterion is used for this selection; Blatman & Sudret 2010). The residuals std for each dataset and the corresponding PCE model estimates are shown in Fig. 5. It is noted that the total number of datasets is divided into a 1000-long estimation set and a 392-long validation set. The PCE errors are also shown in the lower part of Fig. 5 along with the corresponding 95% confidence intervals calculated for the fitted Gaussian distribution of the estimation set errors. Evidently, a statistical hypothesis testing could be adopted in this case for damage detection, offering an automated SHM tool which would necessite little or no user inference after the initial model training period.

	Variables
1	**Wind direction [deg]**
2	Min wind speed [m/s]
3	**Average wind speed [m/s]**
4	Max wind speed [m/s]
5	Min power [kW]
6	**Average power [kW]**
7	Max power [kW]
8	Nacelle direction [deg]
9	Nacelle temperature [°C]
10	**Ambient temperature [°C]**

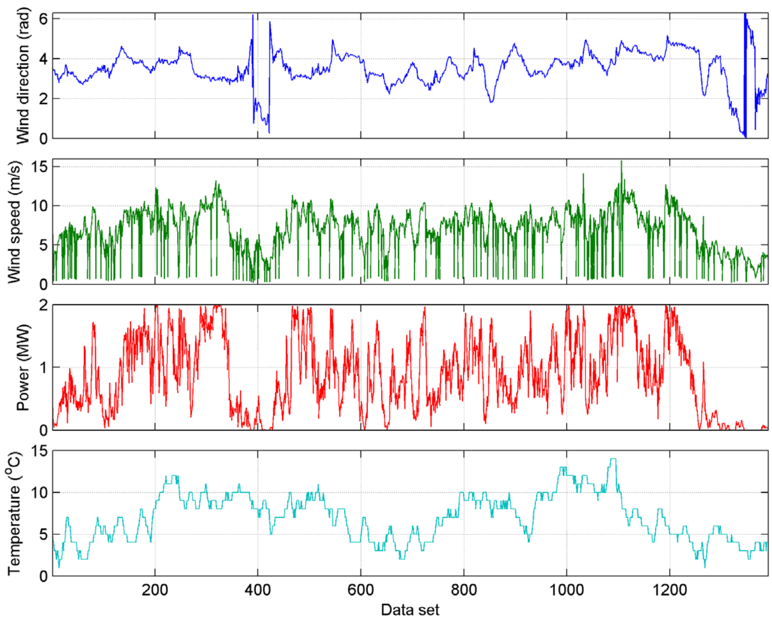


Figure 4: Long-term monitoring. List of available operational and environmental conditions through the SCADA system and the plot of the four selected input variables versus time (1392 values corresponding to the recorded vibration response datasets).

Since no damages were observed during the almost one month measurement campaign described above, a monitoring of the WT for a longer period of time, which will allow the assessment of the method and its capabilities for damage detection, is already planned. Moreover, SCADA data measured at higher sampling frequencies could allow the better statistical characterization of the PCE input variables potentially leading to improved performance of the method.

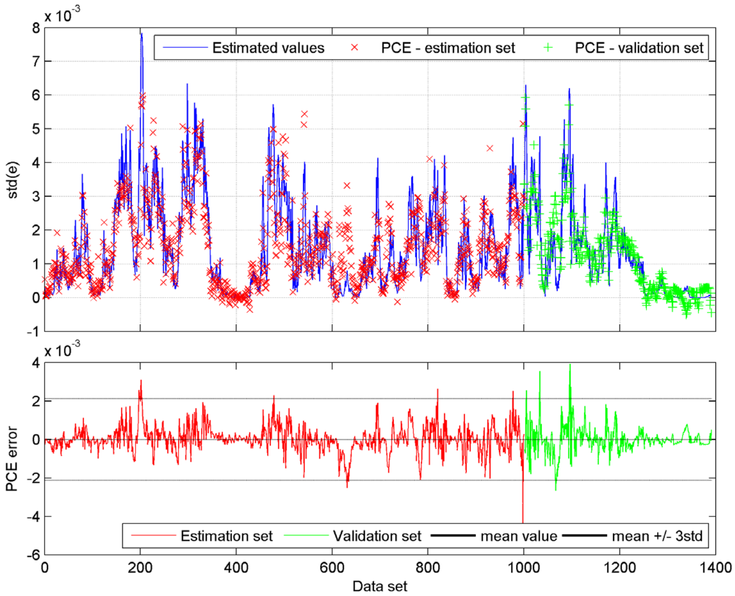


Figure 5: Long-term monitoring. SP-TARMA(32,32) model residual std as obtained from the modelling of each vibration response dataset along with the PCE model expansion values. The PCE errors along with 95% confidence intervals (calculated from the estimation set) are also shown in the bottom.

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