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Remaining useful life assessment of offshore wind turbines: Validation of virtual sensing on long term measurements

Alexandros N. ILIOPOULOS [1], Wout WEIJTJENS [2], Danny VAN HEMELRIJCK [1], Christof DEVRIENDT [2]

[1] Dpt Mechanics of Materials and Constructions, Vrije Universiteit Brussel (VUB), Pleinlaan, 2 Brussels 1050 Belgium, Alexandros.Iliopoulos@vub.ac.be

[2] Dpt Mechanical Engineering, Acoustics and Vibration Research Group, VUB, Pleinlaan, 2 Brussels 1050 Belgium

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Abstract

Fatigue life is often a design driver for the foundations of offshore wind turbines (OWTs). Moreover, conservatism in earlier designs might allow for future life time extension and re-use of existing foundations. Monitoring the consumption of fatigue life is thus an essential part in a full-scope structural health monitoring strategy for OWTs. To achieve this goal, the complete distribution of stresses along the structure with main emphasis at the fatigue hot-spots is to be known. However, for monopile OWTs most of the fatigue critical locations are located slightly above and below the soil level. Installing strain sensors at these hotspots is an expensive and challenging task, which is not always feasible. This motivates the virtual sensing approach. Virtual sensing allows to use the more reliable accelerometers and a few strain sensors installed at easily accessible locations of the tower to predict the strains and subsequently accurately assess the consumed fatigue.
Moreover, OWTs unlike other civil structures exhibit strong variations of their dynamics under different environmental and operating conditions (EOC). Low-frequent, near static contributions related to variations in the thrust loading of the turbine, e.g. due to gusts as well as the higher frequent dynamic contributions linked to additional sources of vibrations such as turbulence, rotor harmonics and wave loads are present. To accommodate for these different source the virtual sensing technique incorporates the optimal sensor and mode settings in different frequency bands and EOCs.
The concept of virtual sensing for response prediction on wind turbine has been extensively studied and validated over the past years. However, the method still needs to be verified on long term data over the wide variety of EOC (e.g. shut downs, cut-out, storms, high waves etc.). This contribution thus uses two weeks of data that cover a variety of operational conditions to validate virtual sensing under real life conditions.

1. INTRODUCTION

According to the latest report of the European wind energy association [1], monopile foundations hold the biggest share -approx. 80 %- of substructures for offshore wind turbines (OWTs). These foundation structures experience dynamic loads from the surrounding environment and their operation thus making fatigue life an important design consideration. The current practice for life time assessment during design is based on conservative design assumptions and simplifications. This conservatism though potentially leads to underestimation of the actual fatigue life.
On the contrary, a continuous monitoring system with the ability to assess the stress history and consequently the fatigue life consumption of individual turbines can support wind farm operation and maintenance (O&M) actions as well as end-of-life decisions. This system implies the installation of (strain) sensors for direct sensing at fatigue critical locations. However, there is a big limitation in the case

of monopile OWTs: the installation of such sensors at the fatigue hotspots which are mainly located beneath the water level (e.g. mudline) is practically unfeasible. This limitation establishes the need for implementation of virtual sensing techniques for fatigue assessment.

Two main approaches for virtual sensing exist. The state-space approach including robust observers [2, 3], Kalman filter based techniques [4–7], joint input-state filtering techniques [8–10] and the approach based on the concept of modal expansion [10–17]. A drawback of the state-space techniques is that they are potentially time consuming and computationally expensive due to the iterative algorithm.

In this paper a novel multi-band implementation of the well-known modal decomposition and expansion approach (MDE) for virtual sensing on OWTs is presented. In particular, the new scheme accounts for both quasi-static and dynamic loading using adaptive sensor/mode settings in different frequency bands and environmental and operating conditions (EOC). This contribution thus uses two weeks of data that cover a variety of EOC to validate virtual sensing under real life conditions including shut downs, cut-out, storms, high waves.

2. OFFSHORE MEASUREMENTS AND MDE THEORY FOR OWTS

2.1 Measurements

Acceleration measurements are taken at 3 levels using a total of 8 accelerometers. Six accelerometers (two per level) capture the vibrations in the X-Y direction and the two additional accelerometers at the highest level (tower top) are utilized to identify torsional vibrations in the tower. The locations are chosen based on the convenience of sensor mounting, such as the vicinity of platforms. Moreover two fiber Bragg grating (FBG) strain sensors at the middle of the tower and four FBG sensors at the Tower/Transition Piece interface have been installed. Acceleration and strain data of the upper levels are used in order to predict the strains at the lower levels at critical and inaccessible hotspot locations. Figure 1 gives an overview of the instrumented OWT at the Belwind farm as well as a schematic representation of the MDE concept for virtual sensing.

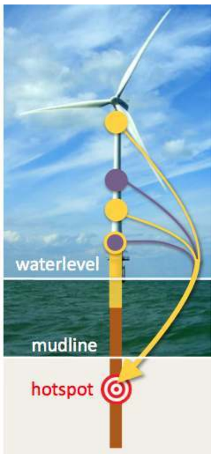


Figure 1 : Instrumentation of the monopile OWT at the Belwind farm. In yellow are the installed accelerometers and in purple the attached strain gauges. The upper levels of acceleration and strain are used in order to predict the strains at the lower levels.

2.2 Dynamic strain prediction

The theoretical background of the MDE approach for response prediction has been extensively presented in previous works of the author [11, 14, 15, 18]. For brevity, this section will focus only on the strain prediction.

The dynamic strains are predicted with the following principle: Firstly, a double integration in the Laplace domain of the estimated modal coordinates from the acceleration measurements is performed resulting in $\frac{1}{s^2}$ operation. Then a transformation in the time domain is done using the inverse Laplace operator $\mathscr{L}^{-1}\{\bullet\}$. Finally a multiplication with the corresponding numerically obtained strain mode shape component is performed. The aforementioned dynamic strain prediction based on acceleration measurements is shown in Equation (1) .

$$\varepsilon_{\mathbf{p}}(t) = \Phi_{\varepsilon p}\mathscr{L}^{-1}\left\{\frac{1}{s^2}\mathscr{L}\{\mathbf{q}(t)\}\right\} \tag{1}$$

where $\Phi_{\varepsilon p}$ are strain mode shapes of the considered modes at the DOFs which correspond to the virtual sensor locations p, $\mathbf{q}(t)$ are the modal coordinates that quantify the participation of each mode and $\mathscr{L}\{\bullet\}$ is the Laplace transformation.

2.3 Quasi-static strain prediction

As seen in Equation (1) , a double integration of accelerations takes place for the prediction of strains. This inevitable operation implies a high risk of blowing up the low frequent noise of the measured accelerations resulting in large errors in the near-static components of the predicted strains.
Moreover, near the static region of frequencies (very low frequencies situated well below the first eigenfrequency and below the site-specific wave peak frequency), the static deflection shape of the turbine is not accurately described by the lowest structural mode and therefore different strain components should be considered (see Figure 2). In order to obtain the numerical strain components due to static load a static analysis is performed with the aid of the tuned FEM. This analysis considers a representative load at the tower top derived from measured bending moments. Equation (2) is used for the prediction of the quasi-static strains:

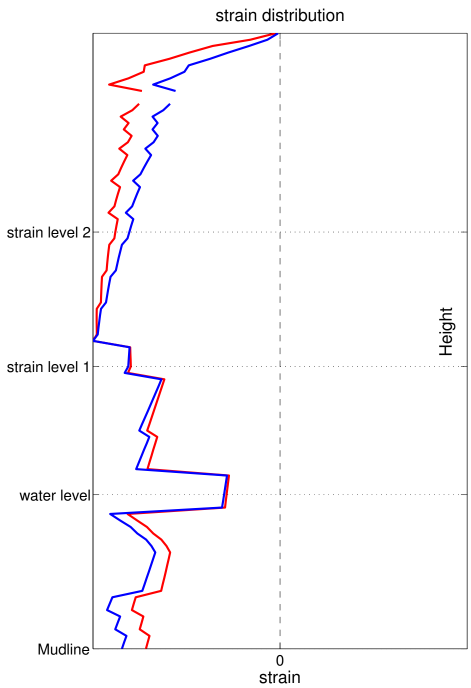


Figure 2 : Static strain distribution (red) and 1^{st} FA/SS strain mode shape (blue) from mudline to tower top level

$$\varepsilon_{\mathbf{p}}^{\mathbf{QS}}(t) = \phi_{\varepsilon\mathbf{p}}^{\mathbf{QS}} q^{QS}(t) = \frac{\phi_{\varepsilon\mathbf{p}}^{\mathbf{QS}}}{\phi_{\varepsilon m}^{QS}} \varepsilon_m(t) \tag{2}$$

where $\phi_{\varepsilon\mathbf{p}}^{\mathbf{QS}}$ is the quasi-static strain distribution at the DOFs which correspond to the virtual sensor locations p and $\phi_{\varepsilon m}^{QS}$ is the quasi-static strain mode shape component at the measured DOF and $\varepsilon_m(t)$ is the actual measured strain for each time instance t. Figure 2, motivates the use of the static strain modeshapes to predict low-frequent strain contributions in Equation (2) instead of using the strain mode shape components of the 1st FA/SS mode $\phi_{\varepsilon\bullet}^{FA1/SS1}$.

$$\frac{\phi_{\varepsilon p}^{QS}}{\phi_{\varepsilon m}^{QS}} \neq \frac{\phi_{\varepsilon p}^{FA1/SS1}}{\phi_{\varepsilon m}^{FA1/SS1}} \tag{3}$$

2.4 Multi-band MDE for OWTs

In order to predict the entire strain time history, the two distinctive strain contributions namely quasi-static and dynamic contributions are superimposed. The quasi-static contributions can mainly be attributed to gust induced low-frequent variations in the thrust loading or current loading whereas the dynamic contributions are linked to wave loads and turbines dynamics and modal behavior.
Accelerometers on their own cannot capture the very low frequency band below 0.2 Hz due to limitations related to measurement noise. It should be highlighted that this lower frequency bound can be pushed further down by using accelerometers with better noise properties. ICP accelerometers in general have good noise properties but they always have a lower frequency bound inhibiting their use for these quasi-static strains. MEMS accelerometers allow measurements down to 0 Hz, but in general have poorer noise properties. To tackle these restrictions thus the necessary information at the very low-frequent band up to 0.2 Hz is obtained using the measured strains and the static strain components according to Equation (2) .
The dynamic frequency band of interest ranging from 0.2 Hz up to 2 Hz is subdivided in two parts. The first part captures the lower frequency turbine dynamics including the first structural mode (0.2 Hz up to 0.5 Hz) and the second part (0.5 Hz up to 2 Hz) captures all the remaining dynamics and modal behavior of the structure. By doing so, an optimal configuration can be selected for each dynamic sub-band. E.g. at lower frequencies the motion is dominated solely by the first tower mode, with lower level sensors barely measuring above the noise floor . To avoid that this noise is used for strain prediction, the lower frequency band only considers the top sensor and the first order mode. However, for higher modes the top sensor is less sensitive and an optimal solution might imply not to use the top sensor, as such a band-by-band optimal setting is achieved. This band-by-band setting can also be interpreted as a crude form of weighing the frequency spectrum in different bands. The aforementioned process summarized in Equation (4) is hereafter called multi band virtual sensing. Figure 3 gives an overview of the multi-band virtual sensing scheme.

$$\varepsilon_{\mathbf{p}}(t) = \varepsilon_{\mathbf{p}}^{\mathbf{QS}}(t) + \varepsilon_{\mathbf{p}}^{\mathbf{D}}(t) = \varepsilon_{\mathbf{p}}^{\mathbf{QS}}(t) + \left(\varepsilon_{\mathbf{p}}^{\mathbf{LF}}(t) + \varepsilon_{\mathbf{p}}^{\mathbf{HF}}(t)\right) \tag{4}$$

where $\varepsilon_{\mathbf{p}}^{\mathbf{D}}(t) = \varepsilon_{\mathbf{p}}^{\mathbf{LF}}(t) + \varepsilon_{\mathbf{p}}^{\mathbf{HF}}(t)$ is the dual band dynamic response at the virtual sensor locations p calculated from the superposition of the corresponding low-frequent dynamic strain contribution $\varepsilon_{\mathbf{p}}^{\mathbf{LF}}(t)$ and the higher-frequent dynamic strain contribution $\varepsilon_{\mathbf{p}}^{\mathbf{HF}}(t)$.

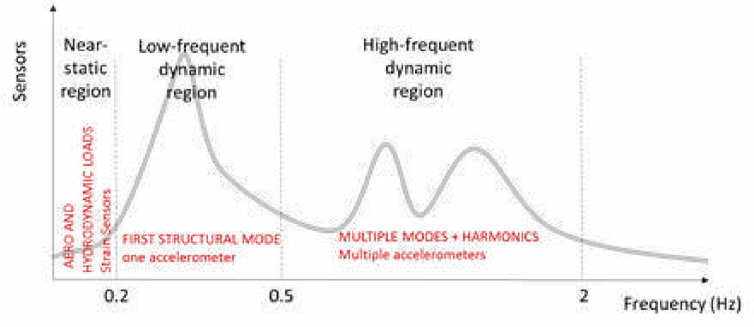


Figure 3 : Multi-band virtual sensing scheme

3. RESULTS AND DISCUSSION

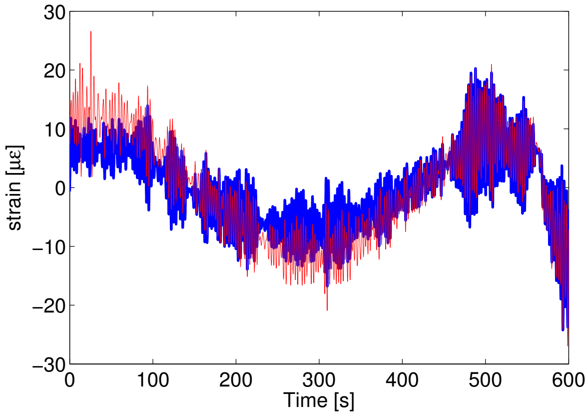
A major difference between OWTs and other civil structures is the strong variation of its dynamics under different EOC. To accommodate for them, the datasets are divided into different operating cases as suggested in [19]. For each operating case, the optimal sensor and mode settings are chosen in order to generate the optimal virtual strains during system changes. A simple reasoning is explained hereafter; e.g. during parked conditions the first mode is the most important component in the tower and vibrations whereas during rotating conditions more modes are active and a different optimal configuration is found.

Except the normal operating conditions, the OWTs is often subjected to short term sudden events. One of these events is a so-called rotor stop-start event. The rotor stop-start occurs automatically when the wind speed is larger than the so-called cut-out wind speed. When the wind speed is again below this cut-out speed, the turbine starts up again. A stop-start cycle thus implies a near immediate drop of the thrust load and a fast build-up of the thrust loading afterwards. This cycle can potentially heavily influence the fatigue life of the OWTs and therefore should be captured well during its lifetime.

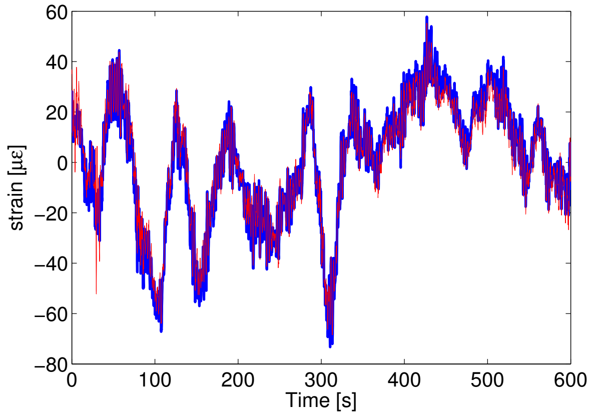
To demonstrate the techniques performance under different EOC, the responses for a subset of normal operating conditions covering idling, run-up and fully rotating cases as well as during an extreme event are presented in Figure 4.

A very good agreement both in terms of amplitude and in terms of temporal evolution is achieved for all the examined cases but during idling. The lowest correlation exhibited in the idling case is attributed to a mismatch between the signals at the very low frequencies as the low strain levels during idling are more prone to measurement/estimation errors.

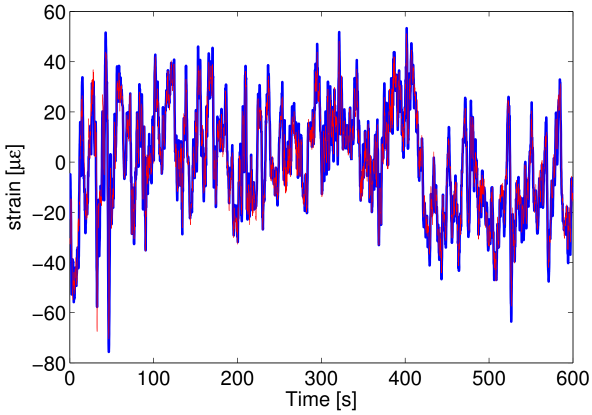
Finally the virtual sensing technique is validated for the case of strong wave activity during a summer storm. Waves induce significant fatigue loading and therefore the strain responses due to waves should be continuously monitored during its entire life. A time domain and frequency domain overview of the prediction quality during a strong wave activity is given in Figure 5. As observed, the peaks attributed to very low frequent wave activity are well captured by the technique.



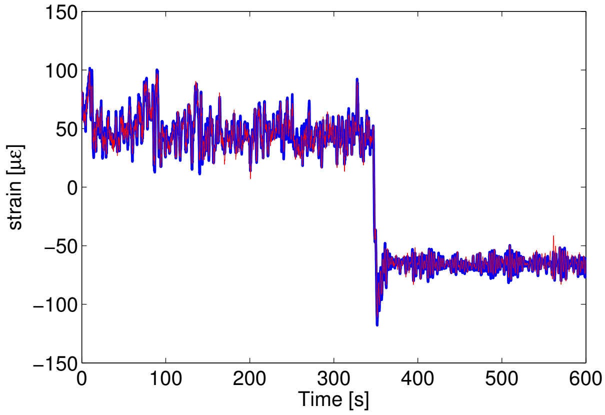
(a) Idling



(b) Run-up

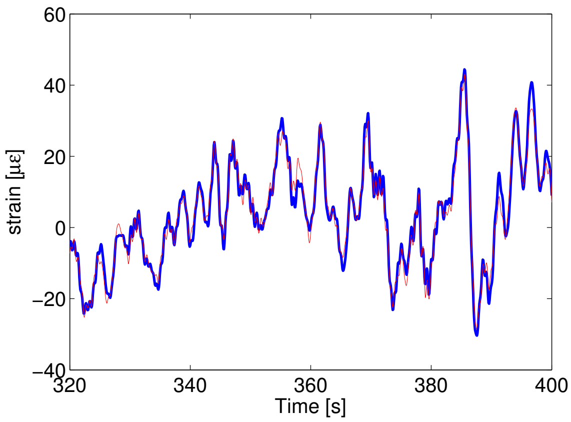


(c) Fully-rotating at rated speed

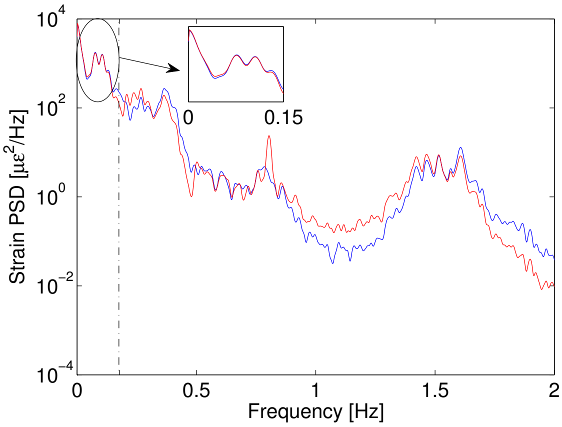


(d) Rotor stop-start event

Figure 4 : (a-c) Normal operating conditions, (d) rotor stop-start extreme event. Ten minute strain time histories;In blue are the measured strain responses and in red are the predicted strains with the proposed multi-band virtual sensing scheme



(a)



(b)

Figure 5 : Strain response on a wavy day. (a) Time domain response. In blue are the measured strain responses and in red are the predicted strains with the proposed multi-band virtual sensing scheme, (b)Power spectral density (PSD) of the measured (blue) and predicted (red) signals.

4. CONCLUSIONS

This paper introduced a novel technique for estimation of strain responses and subsequently accurate fatigue assessment of monopile OWTs. The approach is based on a multi band virtual sensing approach, which provides reliable and accurate predictions in time and frequency domain both in terms of amplitude and in terms of temporal evolution. The proposed methodology is validated for different conditions of the OWT including normal operating conditions (idling case, run-up and fully operating case), short term extreme event (rotor stop-start cycle) as well as strong wave activity during a summer storm. All the conditions are well captured and as such it is highlighted that this new structural health monitoring approach has the ability to interrogate an entire structure and accurately assess fatigue life consumption and remaining useful life at the true fatigue hot spots.

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