Fatigue stress estimation of offshore wind turbine using a Kalman filter in combination with accelerometers

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Abstract
An accurate stress or strain history at fatigue critical locations is often needed for a fatigue assessment. Unfortunately it is not feasible to install strain gauges as these fatigue hotspots. This contribution compares two techniques to obtain a reliable stress history at any location of the turbine structure, one is based on modal decomposition and expansion, the other is based on a Kalman filter. Both techniques will be validated and compared using data from an offshore wind turbine monitored by OWI-lab. The monitored turbine is instrumented with strain gauges at the interface between transition piece and tower and accelerometers at multiple levels. The installed strain gauges allow to validate the proposed techniques with respect to the reality.

1 Introduction

As wind farms are growing older, an accurate fatigue assessment of the turbines and their foundation becomes more valuable. A fatigue assessment is needed when deciding on a possible life time extension. Moreover, it can also be used to decide upon maintenance strategies and to improve the design of future turbines and their foundations.
Performing an accurate fatigue assessment of the support structure often requires measurements of the load history ([1],[2],[3],[4]). As some locations within the structure are more affected by loads, the fatigue induced by the load history at these hotspots is most valuable. Unfortunately, these hotspots are located below water level or subsoil. Therefore it is unfeasible or impossible to mount sensors at these critical locations. To resolve this limitation OWI-lab has worked on the concept of virtual sensing. Virtual sensing allows to estimate stresses at hotspots using measurements taken at more accessible locations within the structure such as on the tower structure. In particular accelerometers are favored as sensors, due to the ease of installation and their reliability on the long term. However, low frequency thrust loads cannot be captured using accelerometers. [5] introduced the idea to combine a thrust load estimation and accelerometers in order to estimate the full band stresses in the structure using a modal decomposition and expansion based virtual sensing technique. One of the drawbacks of this approach was the discontinuity in the frequency spectrum, since the signal was splitted in three frequency bands. A clear drop in accuracy around the frequency limits was observed.
An alternative course for tackling the problem of fatigue estimation on the basis of a limited number of vibration sensors has been taken by Papadimitriou et al. [6]. Such a course consists in fusing the available measurements with a Kalman filter for extrapolating the response at unmeasured locations. Within that context, a number of Kalman-type algorithms, able to operate on systems with unknown inputs, has been proposed and recently validated [7] under experimental conditions. Although such filters are subjected to

certain sensor requirements [8], their effectiveness on WT structures has been already demonstrated [9] on the basis of acceleration and inclination measurements. Alternatively, Naets et al. [10] proposed the use of dummy displacement measurements in order to stabilize the performance when only accelerations are available while in a recent contribution, Dertimanis et al. [11] extended the implementation to include the estimation of unknown system parameters.
This contribution will validate both approaches and compare the results.

2 Measurement Setup

The techniques proposed in this contribution will be validated using measurements taken at an offshore wind turbine located in the middle of the Belgian offshore wind farm Belwind, 46 km off the Belgian coast. This Vestas 3MW V90 turbine is installed on a monopile foundation and was instrumented with additional accelerometers and strain gauges. A total of eight accelerometers were installed at four different levels in the turbine tower (two per level) in order to capture vibrations in both X and Y direction. Additionally six strain gauges were installed on the lowest level, being the interface between tower and transition piece. An overview of the location of the sensors is given in Figure 1. The accelerations measured at all levels together with the thrust load will be used to predict the strains measured at the tower-TP interface and finally to predict the strains at hotspots located below the water level.

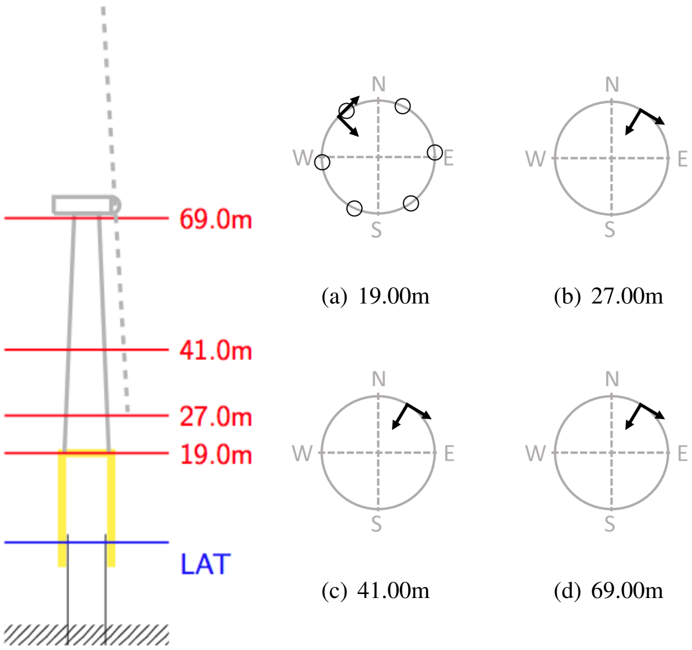


Figure 1: Locations of the additional sensors at of BBC01 wind turbine at the Belwind farm. The circles in (a) represent a strain gauge; the arrows in (a-d) represent an accelerometer.

In order to simplify the validation of both techniques presented in this paper, the thrust load signal used for this validation is obtained from the measured strain signal. To derive the thrust load signal from the strain measurements, the measured strains are transformed into a fore-aft and side-side bending moment. Additionally the low-frequent part (0 to 0.2 Hz) of the fore-aft bending moment is transformed into the acting thrust load using the distance between the location of the sensor and the hub. Ultimately the thrust load signal can be obtained using 1s SCADA data instead of strain measurements, as explained in [12].

3 Multi-band virtual sensing based on modal decomposition and expansion

The main goal of virtual sensing is to estimate the stresses at the fatigue-sensitive hotspots without the need of mounting sensors at these exact locations. This section will summarize the multi-band virtual sensing technique based on modal decomposition and expansion as explained in [5]. This technique combines measurements with a tuned finite element model (FEM) of the structure to predict stresses at any location of the structure. The FEM is created using pipe elements with the as design dimensions of the turbine. This FEM is tuned to match the modal properties obtained experimentally. More information about the finite element model and the tuning can be found in [5] and [13]. Figures 2 and 3 show the resulting structural and strain mode shapes respectively.

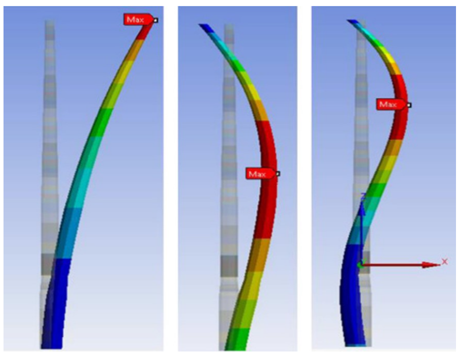


Figure 2: First three structural mode shapes of an offshore wind turbine. The first mode is captured best using the top accelerometer, while the second and third mode are captured better using the lower sensors.

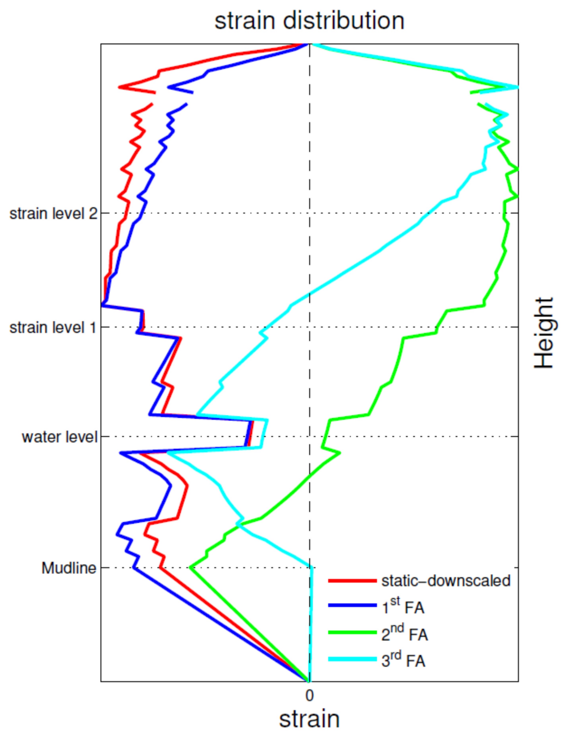


Figure 3: The static strain mode shape together with the strain mode shapes of the first three modes.

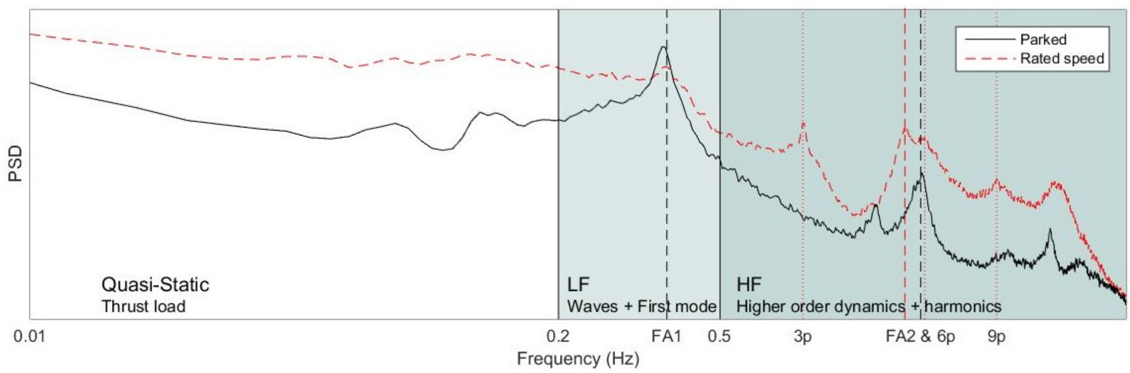


Figure 4: Frequency spectrum of the different loads acting on an offshore wind turbine in parked conditions and at rated rotor speed. The quasi-static load is dominated by the thrust load induced by variations in wind. Dynamic variations are induced by waves, structural dynamics and rotor harmonics.

The stresses observed at any location in the structure are induced by a variety of loads, each acting in a different frequency range. This can be seen in Figure 4. Since the structure responds differently to quasi-static loads then to dynamic loads, the resulting stresses are obtained differently.
The quasi-static thrust load (0 to 0,2 Hz), as induced by the variations in wind, is combined with the static strain mode shape obtained from the tuned FEM (Figure 3), to predict the quasi-static strains.
The dynamic part of the prediction is based on the modal decomposition and expansion technique. Each deflection of the structure is considered a combination of deflection caused by the excitation of different modes. Based on the acceleration measurements and the acceleration mode shapes a modal decomposition is performed. This is visualized by Figure 5. The resulting "acceleration" modal coordinates are then double integrated to obtain displacement modal coordinates. Multiplication of the displacement modal coordinates with the corresponding strain mode shapes from the tuned FEM (Figure 3) results in the dynamic strain prediction.
For this contribution, the dynamic frequency band was divided into the low frequency band (0,2 to 0,5 Hz) dominated by waves and first mode and the high frequency band (above 0,5 Hz) dominated by higher order dynamics and rotor harmonics. The difference in calculation between both bands is the number of considered modes. Since the low frequency band is dominated by the first mode, only one mode is considered. For the high frequency band, also the second and third mode are considered.
As both quasi-static loads and dynamic, both low and high frequency, loads are acting simultaneously, all predictions are superposed.

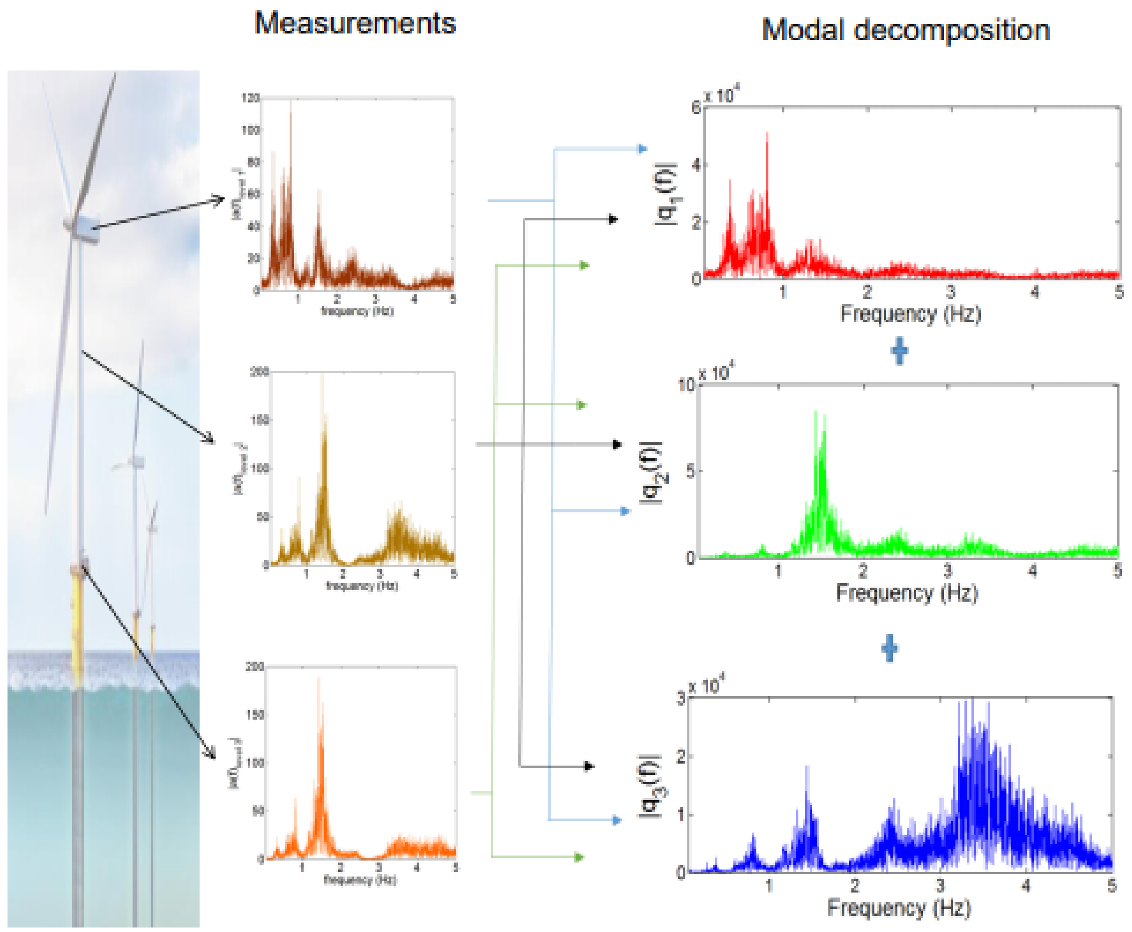


Figure 5: "Acceleration" modal coordinates are obtained based on accelerations measured at various locations in the tower and known acceleration mode shapes.

4 Kalman Filter

The starting point for implementing a Kalman filter towards state estimation on WTs, is the continuous-time linear system of dynamic equations of motion, which is transformed to a discrete-time modally reduced state-space system. Such an approach is widely reported in the literature and herein it is only briefly elaborated since the entire formulation and notation is adopted from [14]. In this sense, the system and measurement equations may be written as

$$\boldsymbol{\zeta}_{k+1} = \mathbf{A}\zeta_k + \mathbf{B}\mathbf{p}_k + \mathbf{w}_k \tag{1}$$

$$\mathbf{y}_k = \mathbf{G}\zeta_k + \mathbf{J}\mathbf{p}_k + \mathbf{v}_k \tag{2}$$

where $\boldsymbol{\zeta}_k \in \mathbb{R}^{n_\mathrm{s}}$ is the state vector containing modal displacements and velocities, $\mathbf{y}_k \in \mathbb{R}^{n_\mathrm{y}}$ is the output vector, $\mathbf{p}_k \in \mathbb{R}^{n_\mathrm{p}}$ is the input force vector and $\mathbf{w}_k \in \mathbb{R}^{n_\mathrm{s}}$ along with $\mathbf{v}_k \in \mathbb{R}^{n_\mathrm{p}}$ are zero-mean white processes, with covariance matrices $\mathbf{Q} \in \mathbb{R}^{n_\mathrm{s} \times n_\mathrm{s}}$ and $\mathbf{R} \in \mathbb{R}^{n_\mathrm{y} \times n_\mathrm{y}}$, representing the system and measurement noise, respectively. Finally, $\mathbf{A} \in \mathbb{R}^{n_\mathrm{s} \times n_\mathrm{s}}$ and $\mathbf{B} \in \mathbb{R}^{n_\mathrm{s} \times n_\mathrm{p}}$ are the system matrices while $\mathbf{G} \in \mathbb{R}^{n_\mathrm{y} \times n_\mathrm{s}}$ and $\mathbf{J} \in \mathbb{R}^{n_\mathrm{y} \times n_\mathrm{p}}$ are the output and feedthrough matrices. These matrices are based on a modal model, composed of the first six, three fore-aft and three side-to-side, vibration modes. These modes are obtained from a simple Finite Element (FE) model which is tuned in order to be in accordance with the identified modal properties, i.e. frequencies, damping ratios and mode shapes.

In the absence of information with respect to the driving forces, the state of the system may be augmented with the input vector, so that $\boldsymbol{\zeta}_k^a = \mathrm{vec}([\boldsymbol{\zeta}_k \;\; \mathbf{p}_k]) \in \mathbb{R}^{n_\mathrm{s}+n_\mathrm{p}}$, in order to form the so-called augmented state-space model

$$\boldsymbol{\zeta}_{k+1}^a = \mathbf{A}^a \boldsymbol{\zeta}_k^a + \mathbf{w}_k^a \tag{3}$$

$$\mathbf{y}_k = \mathbf{G}^a \boldsymbol{\zeta}_k^a + \mathbf{v}_k \tag{4}$$

where superscript^a designates the augmented quantities. By doing so, the evolution of input is dictated by the augmented system matrix $\mathbf{A}^a \in \mathbb{R}^{(n_\mathrm{s}+n_\mathrm{p}) \times (n_\mathrm{s}+n_\mathrm{p})}$, whereby it is postulated that the input can be captured by a random-walk process.

$$\mathbf{p}_{k+1} = \mathbf{p}_k + \boldsymbol{\eta}_k \tag{5}$$

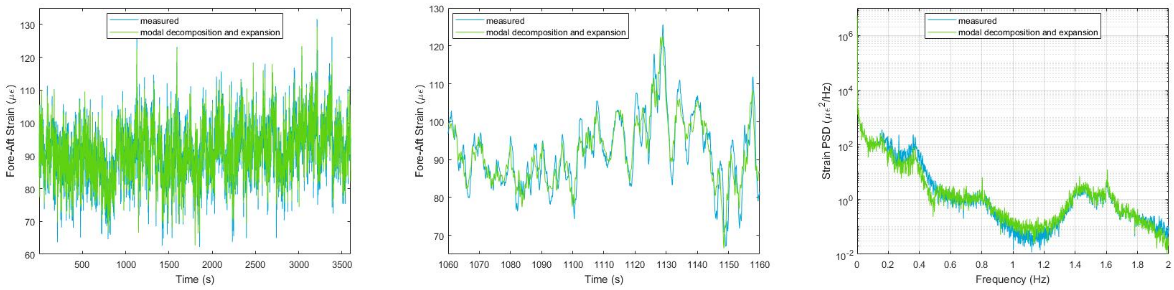
with $\boldsymbol{\eta}_k$ being a zero-mean white Gaussian process with covariance matrix $\mathbf{S} \in \mathbb{R}^{n_\mathrm{p} \times n_\mathrm{p}}$. Within this context, both input and state may be estimated recursively through the standard Kalman filter operating on the augmented state-space model.

As stated in Section 2, the measured response quantities of the considered WT comprise accelerations at four different elevations with a sampling rate of 20Hz, as well as the thrust force with a sampling rate of 1Hz. Due to this difference in the sampling rates, the above-described filter is employed in a multi-rate fashion which is materialized with the use of time-varying measurement noise. Considering that the lack of measurements is equivalent to optimal filtering with large measurement errors [15] and hence zero gain, the measurement noise corresponding to the thrust is set to an arbitrarily large value when thrust measurements are not available and it is reset to the tuned value as soon as thrust is measured again.

The estimation is subsequently performed assuming that the dynamics of the turbine are driven by the thrust force, applied on the tower top, and an equivalent wave force exerted at the hydrodynamic center. In contrast with the modal decomposition and expansion technique, the estimation using the Kalman filter does not assume any explicit distinction between quasi-static, low frequency and high frequency regimes. Instead, the quasi-static part of the response is captured by the thrust force, sampled at a rate of 1Hz, and the higher frequency dynamics are dictated by the acceleration measurements.

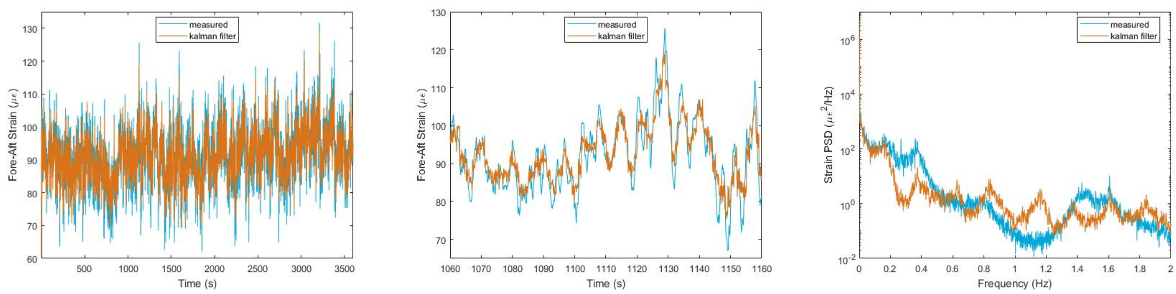
5 Results

Both proposed techniques are applied on the same case study, as presented in Section 2. Figure 6 shows the measured and predicted strain signal for the technique based on modal decomposition and expansion for one hour of measurements. Figure 7 does the same for the technique based on the kalman filter.
In general, the predicted signals by both techniques match the measurements good in time domain. This is also represented by a fairly low value of mean absolute error between measurement and prediction of 2,73$\mu\epsilon$ and 2,89$\mu\epsilon$ for the technique based on modal decomposition and expansion and the one based on the kalman filter respectively.
In the frequency domain both techniques can estimate quasi-static strain signals up to 0,2 Hz almost perfectly, while for higher frequencies the differences are clearly higher. In case of the modal decomposition and expansion technique, the signals seem to match pretty well, although the first mode is slightly underestimated.
Moreover, a drop can be observed around 0,2 Hz and more clearly around 0,5 Hz. These frequencies coincide with the limits at which the signal is divided to determine the different contributions to the resulting strain signal (quasi-static, low frequent and high frequent). This means the accuracy of the predicted signal reduces at the chosen limits in frequency for the different frequency bands. At those frequencies not only one of the possible loads dominates the response but an interaction between multiple loads results in the actual response. However, the prediction only captures one load, the one presumingly dominating the response.



(a) Time series of 1 hour (b) Zoom of 100 s (c) Frequency spectrum

Figure 6: Multi-band virtual sensing based on modal decomposition and expansion validated for a period of 1 hour. The blue line represents the actual measured signal and the green line the predicted signal. A mean absolute error between measured and predicted signal (of one hour) of 2,73$\mu\epsilon$ is found for the technique based on modal decomposition and expansion.



(a) Time series of 1 hour (b) Zoom of 100 s (c) Frequency spectrum

Figure 7: Multi-band virtual sensing based on a Kalman filter validated for a period of 1 hour. The blue line represents the actual measured signal and the red line the predicted signal. A mean absolute error between measured and predicted signal (of one hour) of 2,89$\mu\epsilon$ is found for the technique based on the kalman filter.

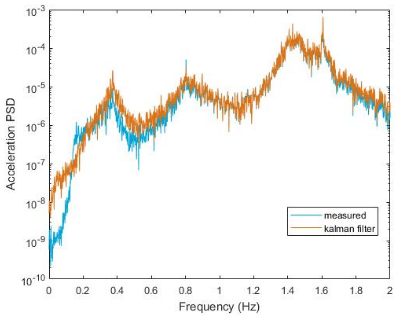


Figure 8: Frequency spectrum of the predicted and measured accelerations at the level of 19.0m using the Kalman filter.

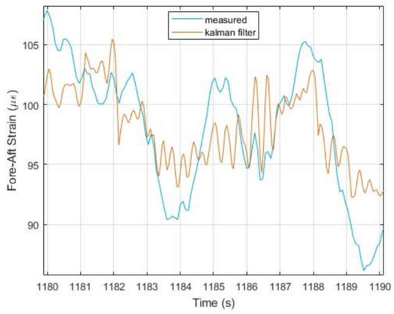


Figure 9: A drop in predicted strain is observed around 1182 s due to the discontinuous updating of the thrust force signal.

As seen in Figure 7, the measurement setup based on the Kalman filter provides sufficiently good response estimation, which additionally does not suffer from instability issues, as is usually the case in acceleration-only setups [10]. However, in terms of the frequency domain of the strain signal the match is not as good as for the results obtained using modal decomposition and expansion.
It should be underlined that despite the straight-forward way of fusing different types of measurements, tuning of the covariance matrices is always the key feature in obtaining an optimal estimation using Kalman-type filters. This is herein achieved by firstly adjusting the system and measurement covariances, so that the predicted accelerations show good agreement with the measured ones. This is highlighted in Figure 8, through the frequency domain representation of the two signals, which are well matching. Finally, once the two covariance matrices are adjusted, the input process is tuned using the L-curve.
Although the frequency spectrum of measured and predicted acceleration signal is well matching (Figure 8), this didn't result in a similar match between both strain signals. The predicted strain signal by the Kalman filter is based on acceleration measurements at the lower three levels. The top level acceleration signal is dominated by the first mode and therefore out of phase to the other acceleration signals. Such an effect is heuristically seen to work at the expense of the stress estimates and as as result the top acceleration was not used in the filter.
Another possible explanation for the mismatch in frequency domain is the lower measurement frequency of the thrust signal. This causes the prediction to be updated at some intermediate timestamps and results in big jumps in the predicted signal, as shown in Figure 9.

6 Conclusions

This contribution compared two possible techniques to reconstruct a strain history at fatigue critical locations of monopile foundations of offshore wind turbines. Both techniques combine measured accelerations and a measured thrust load signal. The first technique is based on modal decomposition and expansion, the second is based on a Kalman filter. For both techniques a good match is obtained in time domain. However in frequency domain, the technique based on modal decomposition and expansion showed better results than the Kalman filter.

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