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Detection of Excessive Wind Turbine Tower Oscillations Fore-Aft and Sideways.

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Abstract— **Fatigue loads are important for the overall cost of energy from a wind turbine. Loading on the tower is one of the more important loads, as the tower is an expensive component. Consequently, it is important to detect tower loads, which are larger than necessary.**

This paper deals with both fore-aft and sideways tower oscillations. Methods for estimation of the amplitude and detection of the cause for vibrations are developed. Good results are demonstrated for real data from modern multi mega watt turbines. It is shown that large oscillations can be detected and that the method can discriminate between wind turbulence and unbalanced rotor.

I. Introduction

Excessive wind turbine tower oscillations are important to detect for many reasons:

- The tower fatigue increases.
- The tower cost is approximately 15% of total turbine cost [1].
- The oscillations will also effect other components e.g. blades.
- The oscillations can be a sign of failures.
- An early detection can be used for scheduled maintenance.

Large tower oscillations will normally occur either at the eigenfrequency or at the rotational frequency (1P) for modern large MW turbines. At the eigenfrequency the cause can be turbulence, perhaps in combination with the speed controller, or it can be waves for offshore turbines. At 1P the reason can be aerodynamic or mass imbalance. A pitch error on one blade or a blade being dirtier than the others can give aerodynamic imbalance. Mass imbalance can be due to different blade weight at installation or because one blade has cracks where moisture finds its way into the blade [2].

Detection and damping of tower oscillations has been given some attention in the patent literature. These patent are typically very general. Estimation of the tower oscillations "range" and using it for control is suggested in [3]. Both [4] and [5] suggests to use offline estimation of the tower frequency and then "use" it for control and avoid rotational speed at that frequency. At least the two last patents only mention the tower eigenfrequency and can then miss an oscillation at 1P. To the authors knowledge, modern wind turbines will monitor their tower vibrations, but it will only be based on simple methods e.g. range or standard deviation for a filtered acceleration signal focusing on the tower frequency. This acceleration indicator will not be used for control but when exceeding a threshold an error is issued and the turbine stops for a while. In the research literature there is many papers on the control of towers in normal operation [6], [7]. Detection of excessive tower oscillations is however not so well covered. The method mentioned above where the range or similar of 1P filtered acceleration signals are used with thresholds are also suggested in [2], [8]. Here, the thresholds are found from statistics from turbine with known tower behavior. The methods are demonstrated with simulation and on a small test turbine. Looking into the broader area of system identification of wind turbines more advanced methods as wavelet [9] and periodic subspace methods [10] are used but then the evaluation are typically only based on simulation.

The objective in this paper is: to develop a simple method for online detection of excessive tower vibrations that can be used on a standard modern turbine and to demonstrate the functionality on real data. Also, it must be capable of discriminating between at least the two causes 1) turbulence and/or wave and 2) imbalance. An indication of whether the imbalance is from aerodynamic or mass would of course be beneficial.

The paper proceeds with a section discussing the necessary physical background and modelling. Then, the estimation and detection methods are developed and discussed. These are demonstrated on real data from standard turbines and finally conclusions are given.

II. Turbine model

The aim is to keep the methods simple and therefore the models are also as simple as possible. Moreover, the modeling below is more to gain the conceptual understanding needed in the method developed in the next section than to build models for model based detection. Another reason to keep it simple is that the available experimental data is at one Hz sampling frequency so that only frequencies below half an Hz can be seen. Therefore, the focus is on the tower dynamics. The available data channels will also limit the type and complexity of useful models. The data channels for this investigation are quite standard: generator rpm, nacelle direction, pitch angle, power, power reference, rotor rpm, tower acceleration longitudinal and transverse, wind direction and wind speed. Notice that tower torsion and blade loads are not in the measurements.

Figure 1 illustrates the tower, nacelle and rotor and some of the turbine dynamics.

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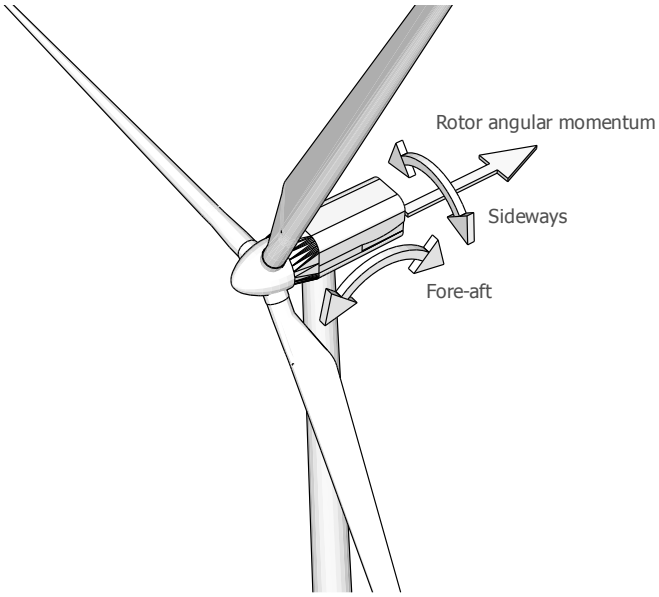

Fig. 1. Wind turbine tower, nacelle and rotor with indication of roll/transverse/side to side and pitch/longitudinal/fore aft dynamics.

The tower dynamics can be simplified as a large mass (nacelle) fixed on top of a mass less spring and a damper (tower) with the same characteristics in all directions. The spring also has torsional stiffness and damping. Fixed to the first mass is a rotating mass (rotor) with a large angular momentum.

If the mass on top of the tower is characterized by a pitch α, a roll β and a yaw γ where the pitch and the roll corresponds to the longitudinal and transverse movement respectively, then the simplified equations looks like:

$$I\ddot{\alpha} = -d\dot{\alpha} - k\alpha + hF_{as} + T_{auy} + T_{gy} \tag{1}$$

$$I\ddot{\beta} = -d\dot{\beta} - k\beta + T_g + T_{mu} \tag{2}$$

$$I_z\ddot{\gamma} = -d_z\dot{\gamma} - k_z\gamma + T_{auz} + T_{gz} \tag{3}$$

The right handed coordinate system used here is with x down wind, y to the side and z along the tower pointing upward. In (1) and (2) I, d, k are tower inertia, damping and stiffness for rotation around a horizontal axis on the ground. In (1) F_{as} is the aerodynamics symmetrical thrust i.e. the force that acts in the hub center and pointing down wind, T_{auy} is the torque component along the y axis from aerodynamics asymmetry and T_{gy} is the gyro reaction torque from the rotor also along the y axis. In (2) T_g is the generator torque and T_{mu} is the torque from a mass unbalance which would be along the x axis as the centrifugal force always is in the rotor plane pointing out from the hub center. In (3) T_{auz} is the torque component along the z axis from a aerodynamics asymmetry and T_{gz} is the gyro reaction torque. Notice that the aerodynamics asymmetry is assumed to give a force down wind, which however has its center displaced from the hub center.

The eigenfrequency and damping are:

$$\omega_n = \sqrt{\frac{k}{I}}\ ,\ \rho = \frac{d}{2\sqrt{kI}}. \tag{4}$$

The longitudinal and transverse eigenfrequency for MW turbines will be from 0.2 to 0.5 Hz. The damping for transverse movements is small as it is only due to materiel damping from steel, which is very low. In the longitudinal direction there is some significant additional damping from aerodynamics which enter via the thrust force F_{as} from the rotor.

The rotor and its coupling to the nacelle is assumed stiff. Then, the direction of the rotor angular momentum L_r follows the pitch, roll and yaw movements of the nacelle. The resulting torque necessary for this is given by:

$$T_r = \frac{dL_r}{dt}. \tag{5}$$

From (5) and figure 1, we see that pure roll with horizontal rotor axis, $\alpha = 0$, gives no change in L_r and hence no gyro effects. In contrast, yawing will require a torque along the y axis which then will give pitching movements. Consequently, yaw couples with pitch motion and visa verse but roll does not couple with the others. In practice, some coupling from the roll must be expected, as the rotor axis is not horizontal and the aerodynamic forces has transverse components under yaw. Still, the coupling between the yaw and the pitch is stronger than the coupling to the roll.

From this the following types of oscillation can be identified:

- On the tower eigen frequency
  - Longitudinal tower pitching coupled with smaller transverse roll component due to turbulence, blade pitching and waves.
  - Generator torque variation and transverse waves can increase the transverse component.
- On the 1P frequency
  - Yawing coupled with longitudinal tower pitching due to aerodynamic asymmetry.
  - Transverse rolling oscillation with minor longitudinal components due to mass imbalance.

III. Estimation and detection methods

A brief discussion of possible approaches is presented before a method is developed. For the estimation of the size of the oscillation, the following main methods can be identified: Standard deviation of band filtered accelerations, FFT based methods, System identification (SI) based methods and Kalman filter (KF) based methods.

In particular, the FFT approach, but also the first approach, will have to be performed on batches of say 600 1 sec. samples. This is considered a disadvantage. SI methods can be used on-line for adaptive estimation. This makes it possible to follow changing 1P frequency and to detect sudden large oscillations fast. The KF based approach can also be included in the class of SI methods. Here SI methods points to simpler black box type models while KF methods

means more tailored models with many inputs and outputs [11]. Also, for the detection part there is a choice between simple threshold methods and more advanced methods based on statistical test theory. As already stated the idea here is to develop as simple methods as possible. To this end the SI black box methods are developed next.

A. Parameter estimation in transfer function models

Following [12] the general transfer function model can be formulated as

$$\begin{aligned} A(q)y(t) &= \frac{B(q)}{F(q)}u(t) + \frac{C(q)}{D(q)}e(t) \ , \\ e(t) &\in \mathrm{NID}(0, \sigma^2), \end{aligned} \tag{6}$$

where $A(q)$ to $F(q)$ are shift operator polynomials of orders n_a to n_f, $y(t)$ is the output, $u(t)$ the input and $e(t)$ is white noise. The simplest and most numerical robust models are so called ARX models with $F(q) = C(q) = D(q) = 1$. These ARX models will be used initially and it will be tested if extensions to more flexible models give worth-while improvements.

To model the tower eigenfrequency oscillations a second order model is necessary. For turbines without structural problems the eigenfrequency will be constant or might change change slowly e.g. because of varying water level offshore. To model oscillations at 1P, one possibility is to use the rotor azimuth ϕ for a harmonic input function by defining two auxiliary inputs as follows:

$$\begin{aligned} u_1(t) &= \omega_r^2 sin(\phi(t)) \ , \\ u_2(t) &= \omega_r^2 cos(\phi(t)), \end{aligned} \tag{7}$$

where the term ω_r^2 account for the centrifugal force dependence. The simplest ARX version of this would then be with $n_a = 2$ and only two parameters in $B(q)$ as follows:

$$\begin{aligned} &(1+a_1 q^{-1} + a_2 q^{-2})y(t) \\ &\quad = b_1 u_1(t) + b_2 u_2(t) + e(t). \end{aligned} \tag{8}$$

Notice that the amplitude and phase of the harmonic are fixed for given parameters at $\sqrt{b_1^2 + b_2^2}$ and $\arctan(\frac{b_1}{b_2})$ respectively.

Another possibility is simply to use a second order model for a narrow band process representing the possible mass or aerodynamic asymmetry. This would give more flexibility as the amplitude and phase then will have a variation that increases with bandwidth. The total model including both eigenfrequency dynamics and 1P input would then be of 4th order. The simple ARX version is then with $n_a = 4$ and no input so it will be a AR(4) model which is short for Auto Regressive with no eXogenous input and of forth order. The estimation can be made adaptive to follow changes in rotor speed.

For a AR(n_a) model structure, the recursive adaptive estimation based on the "forgetting factor" [12] method is given by:

$$\begin{aligned} \epsilon(t) &= y(t) - \hat{y}(t) \ , \\ \hat{y}(t) &= \phi^{\mathrm{T}}(t)\hat{\theta}(t) \ , \\ \phi^{\mathrm{T}}(t) &= \big(y(t-1) \ \ldots \ y(t-n_a)\big) \end{aligned} \tag{9a}$$

$$\varepsilon(t) = \begin{cases} -\varepsilon_m(t) & , \epsilon(t) < -\varepsilon_m(t) \\ \epsilon(t) & , |\epsilon(t)| < \varepsilon_m(t) \\ \varepsilon_m(t) & , \epsilon(t) > \varepsilon_m(t) \end{cases} \ , \tag{9b}$$

$$\varepsilon_m(t) = \gamma\hat{\sigma}(t-1) \tag{9c}$$

$$\hat{\sigma}^2(t) = \lambda\hat{\sigma}^2(t-1) + (1-\lambda)\varepsilon(t)^2 \tag{9d}$$

$$\begin{aligned} P(t) = \frac{1}{\lambda}\Bigg(&P(t-1) - \\ &\frac{P(t-1)\phi(t)\phi^{\mathrm{T}}(t)P(t-1)}{\lambda + \phi^{\mathrm{T}}(t)P(t-1)\phi(t)}\Bigg) \end{aligned} \tag{9e}$$

$$\hat{\theta}(t) = \hat{\theta}(t-1) + P(t)\phi(t)\varepsilon(t-1) \tag{9f}$$

The above procedure (9) is standard except for (9b)–(9d) which is needed in case of outliers, where γ is then typical chosen in the range 1.5–3. The same procedure is applied for ARX models with one or more input signals by extending the ϕ vector in (9a). The advantage with this procedure for ARX models is that it is always stable except when the input is not sufficiently exciting which is not a problem with the AR model as there is no input. Adaptive estimation procedures for model structures with $C(q), D(q), F(q)$ polynomials different from 1 also exists but they will have stability issues to deal with.

B. Detection methods

In the development of detection methods the focus will be on the AR(4) model as this turned out to be the most successful for the real data. One method is developed for both longitudinal and transverse oscillations. The AR(4) model will give at most two peaks in the spectrum. It seems reasonable to base the detection on the heights and frequency for these peaks. There will always be exactly four poles often in two complex conjugated pairs. One measure would be the damping and frequency of these poles. Of cause lower damping at a particular frequency means higher spectral peak but the same damping on different frequencies gives different peak heights. Also, poles and then damping and frequencies cannot be found analytically but require numerical iterative methods.

An alternative analytical solution that directly gives the frequencies and peak heights is hence presented. The spectrum of the AR(4) process

$$\begin{aligned} y(t) &= G(q)e(t) = \frac{1}{A(q)}e(t) \ , \\ A(q) &= \sum_{j=0}^{4} a_j q^{-j} \ , \ a_0 = 1 \end{aligned} \tag{10}$$

is given by

$$\begin{aligned} \Phi_y(\omega) &= G(e^{i\omega})G(e^{i\omega})\Phi_e(\omega) \\ &= G(e^{i\omega})G(e^{i\omega})\frac{1}{2\pi}\sigma^2 \\ &= \frac{1}{A(e^{i\omega})A(e^{-i\omega})}\frac{1}{2\pi}\sigma^2, \end{aligned} \tag{11}$$

where $i = \sqrt{-1}$.

Clearly the maximum of $\Phi_y(\omega)$ can be found from the minimum of $X(\omega)$

$$\begin{aligned} X(\omega) &= A(e^{i\omega})A(e^{-i\omega}) \\ &= \sum_{j=0}^{4} a_j e^{ji\omega} \sum_{k=0}^{4} a_k e^{-ki\omega} \\ &= \sum_{j=0}^{4} g_j \cos(j\omega) \\ &= \sum_{j=0}^{4} h_j \cos(\omega)^j, \end{aligned} \tag{12}$$

where the coefficients g_j and h_j are functions of a_j.

To find the minimum of $X(\omega)$ the first derivative must be zero and the second must be positive.

$$\begin{aligned} \frac{dX(\omega)}{d\omega} &= \\ &- \sin(\omega) \sum_{j=1}^{4} h_j j \cos(\omega)^{j-1} \end{aligned} \tag{13}$$

$$\begin{aligned} \frac{d^2X(\omega)}{\omega^2} &= \\ &- \cos(\omega) \sum_{j=1}^{4} h_j j \cos(\omega)^{j-1} \\ &+ \sin^2(\omega) \sum_{j=2}^{4} h_j j(j-1) \cos(\omega)^{j-2} \end{aligned} \tag{14}$$

The crucial point is now that the first derivative in (13) includes a third order polynomial in $\cos(\omega)$ which mean that there is an analytical solution. However, the explicit formulas to go from the estimated parameters a_j to g_j, h_j, Φ_y and the first and second derivatives of X is to too long to state here. For the same reason they are derived using Maple.

The above peak heights and frequencies are used in the detection procedure below where normal peak height can be based on statistics from turbines with known normal operation. Finding the right thresholds for the peaks is not part of this investigation.

- A peak height is to too high:
  - If it is at the tower frequency, signal high tower oscillations due to something else than asymmetry.
  - If it is at the 1P frequency, signal high tower oscillations due to asymmetry.
    - If the peak height for transverse oscillations are high enough compared to longitudinal oscillations, signal mass unbalance.
    - Signal aerodynamic unbalance otherwise.

At least approximate uncertainties on the frequency and peak height can be developed. The covariance on the parameter estimate for a_j can be approximated by

$$\mathrm{Cov}(\hat{\theta}(t)) = P(t)\hat{\sigma}^2(t) = \Sigma. \tag{15}$$

From this follows

$$z = \Sigma^{-\frac{1}{2}}(\hat{\theta} - \theta_0) \Rightarrow z^{\mathrm{T}} z \in \chi^2(4)\ , \tag{16}$$

$$\Sigma^{-\frac{1}{2}} = E\Lambda^{-\frac{1}{2}}, \tag{17}$$

where E is the eigenvector matrix for Σ and Λ is the diagonal matrix holding the eigen values. Then, the $1-\alpha$ "confidence points" for $\hat{\theta}$ are given by

$$\theta = \hat{\theta} \pm \Sigma^{\frac{1}{2}} e_1 \sqrt{\chi^2(4)_{1-\alpha}}, \tag{18}$$

where e_1 is any vector of length 1. If the four basis vectors are chosen this gives points corresponding to the columns of $\Sigma^{\frac{1}{2}}$ i.e. the scaled eigen vectors of Σ. An approximate confidence interval for the frequency and peak height can then be found by using minimum and maximum for the results based on $\hat{\theta}$ and the eight "confidence points". Alternatively, a Monte Carlo like procedure using a number of random points can be used.

IV. Demonstration on real data

The available data consist of the channels listed in section II. There are 20379 1 Hz samples equal to 5 hours and 20 min. Considering that the interesting frequencies are from 1/4 to 1/3 Hz, the ideal sampling frequency would be higher than the 1 Hz available. The data is from modern multi-MW turbines placed in a farm.

To demonstrate that the method is useful, a number of turbines has been analysed using FFT with the Welch [13, sec. 10.1] method where all data are included. Among these, one with small transverse tower oscillation and one with large transverse oscillations are chosen. The FFT-Welch estimated spectra are shown in figures 2 and 3.

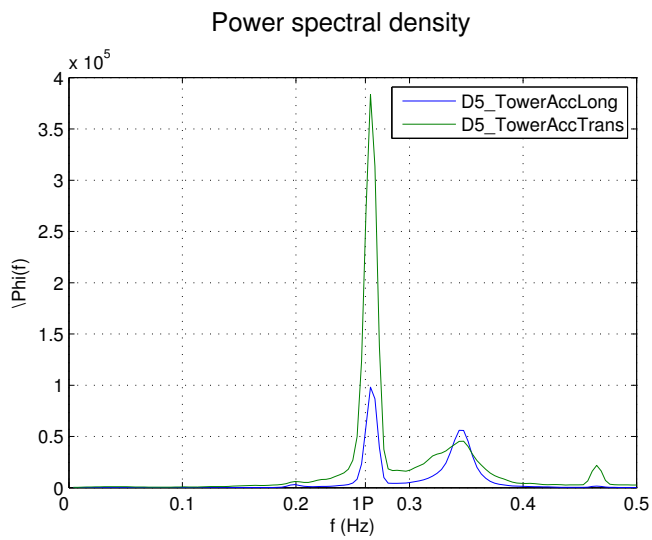

Fig. 2. Power spectrum for longitudinal and transverse tower oscillations estimated by the Welch method for a turbine with transverse oscillations. 1P on the x-axis marks the average 1P frekvency.

As already mentioned, the simple AR(4) accelerations signal model (10) eventually turn out to be the best model as its prediction performance was only improved slightly by other more complicated model structures (6). Moreover, it has the advantage of being a simple and robust parameter estimation procedure (9). This conclusion is the result of

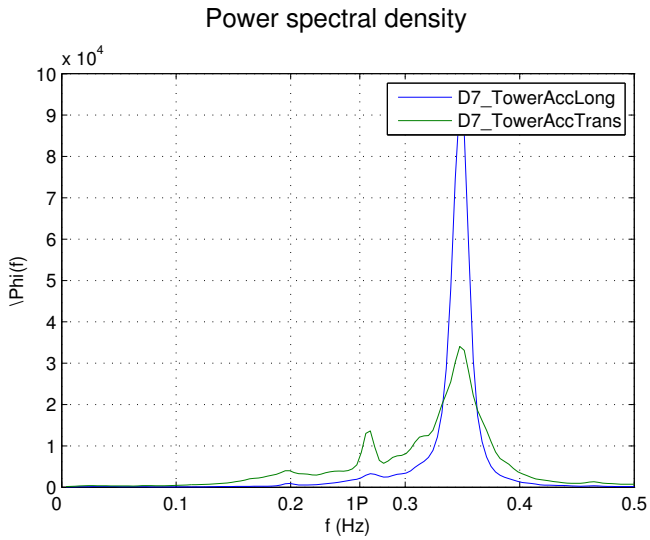

Fig. 3. Power spectrum similar to figure 2 but for a turbine with only small transverse oscillations.

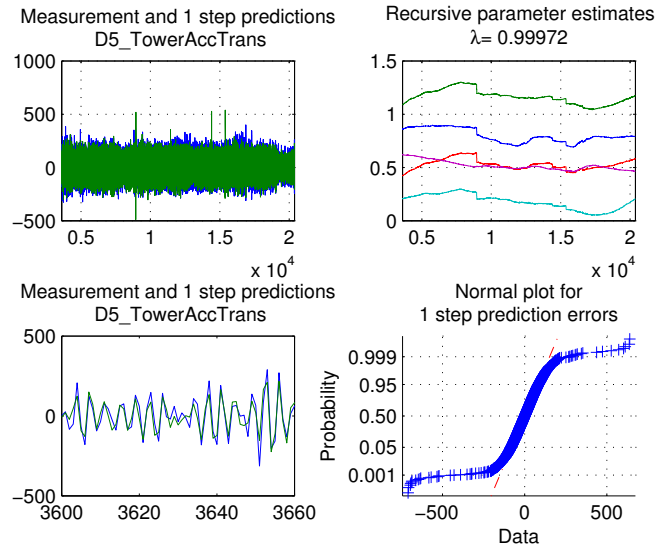

Fig. 4. Illustration of the adaptive parameter estimation. Se text for details. Except for the lower right subplot the x axis is time.

offline cross validation i.e. estimating parameters on an estimation data set and evaluating the prediction performance on another validation data set. This was done for a number of potentially promising models including AR, ARX with different versions of azimuth harmonic input, generator torque as input to transverse direction, full flexible PEM models (6) with all polynomial A, B, C, D, F in play.

When investigating the model including the harmonic azimuth in the input, it was observed that the amplitude of 1P oscillations seems to vary with time. Also, the azimuth was not in the measurements but had to be calculated as the integral of the rotor speed, which then will results in a drifting error. To account for both of these effects a recursive adaptive estimation was tested but still without success.

Consequently, the AR(4) model parameters obtained from adaptive estimation then was used in the above procedure to obtain corresponding peak frequencies and heights. The results are shown in figures 4, 5 and 6.

Figure 4 illustrate the adaptive estimation. The upper left corner subplot shows the measurements and 1 step prediction errors and the subplot below is a zoom covering 60 sec. so it is possible to see the signals and that the prediction follows the measurement. The lower right subplot is a "normal plot" of the 1 step prediction errors. For a normal distribution it would follow the straight red line. Clearly there are many extreme outliers which also spoils the estimation completely if the robustification (9b) is not used. The parameter estimates, including $\hat{\sigma}/100$, is shown in the top right subplot. Here γ in (9b) is 2.

The peak frequencies and heights for the turbine with transverse oscillations are shown in figure 5. Notice that only peaks are shown so "holes" in the curves means the peak disappear i.e. the damping gets to too high. For this turbine there are clearly two peaks for longitudinal oscillations, one at the 1P frequency shown with the violet curve and one at the tower frequency, the tower frequency peak around 2.210^4 is higher than the 1P peak. The transverse part shows a clear peak at 1P which is around 110^5 which is much higher than the tower frequency peak when it is present, and it is at least five times higher than the longitudinal peaks. Specific thresholds are not found here. According to the detection procedure it can at least be suggested that this turbine suffers from a transverse tower oscillation due to mass imbalance.

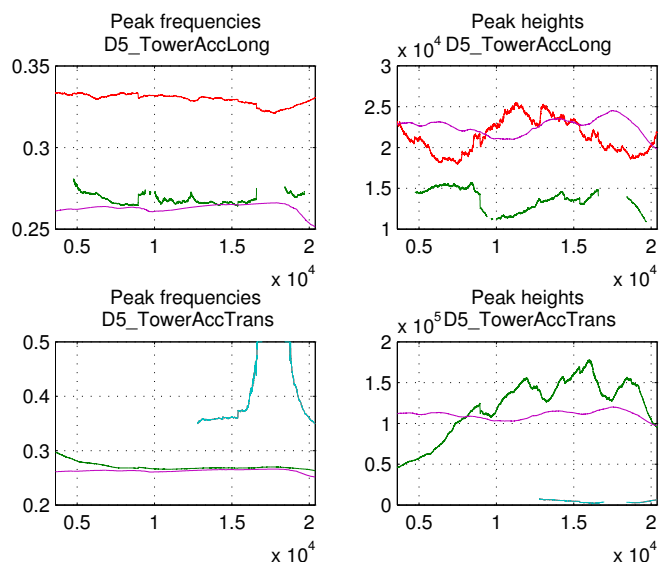

Fig. 5. Spectral frequencies and peaks for a turbine with transverse oscillations. The violet curve in the frequency plot is the LP filtered 1P frequency. The violet curve in the peak plot is a scaled version of the squared LP filtered wind speed. The x axis is time. See text for more details.

For the turbine in figure 6 there are only 1P peaks sometimes for the transverse oscillations and in this case the peak is small and also small compared to the tower frequency peak, which means that no mass or aerodynamic imbalance

is present. The longitudinal tower frequency peaks are up to 110^5 which might be high.

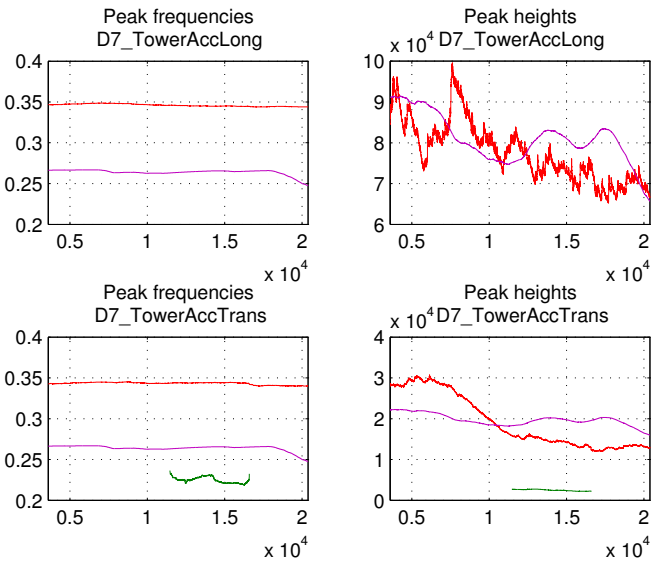

Fig. 6. Spectral frequencies and peaks for a turbine with small transverse oscillations. See 5 more details.

V. Conclusion

Estimation and detection methods for excessive tower oscillations in modern multi-MW turbines are developed in this paper. The aim is to obtain a simple solution, which can be demonstrated to be useful on real standard turbine data. Several different approaches has been considered. The resulting method developed only uses tower longitudinal and transverse accelerations sampled with 1 Hz. An analytical solution to finding the spectral peak frequencies and heights for a AR(4) process is develop. The parameters for this AR(4) process is obtained from an adaptive robust estimation. The advantage with this method is that everything is analytical i.e. no, potentially newer ending, numerical search is necessary. The method is shown to be useful on real data. Finally, a method to calculate the uncertainty for estimated peak frequencies and heights are also given.

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