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Gear-box fault detection using time-frequency based methods☆

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ABSTRACT

Gear-box fault monitoring and detection is important for optimization of power generation and availability of wind turbines. The current industrial approach is to use condition monitoring systems, which runs in parallel with the wind turbine control system, using expensive additional sensors. An alternative would be to use the existing measurements which are normally available for the wind turbine control system. The usage of these sensors instead would cut down the cost of the wind turbine by not using additional sensors. One of these available measurements is the generator speed, in which changes in the gear-box resonance frequency can be detected. Two different time–frequency based approaches are presented in this paper. One is a filter based approach and the other is based on a Karhunen–Loeve basis. Both of them detect the gear-box fault with an acceptable detection delay of maximum 100s, which is neglectable compared with the fault developing time.

1. Introduction

Wind turbines play a rapidly increasing role in the world's power grids. Consequently reliability of these turbines is of increasing importance both from a grid stability point-of-view and from a cost of energy (COE) perspective. Usages of modern fault detection, isolation and accommodation methods is one of the approaches which can be used to achieve this. One of the main objectives in wind turbine research and development is to lower COE of wind turbines. COE can basically be lowered by either increasing the energy production or lowering the costs of the installation and operation of the wind turbines. Better fault detection and accommodation can lower the maintenance costs as well as the down-time of turbines, thereby both lowering costs and increasing possible conversion of energy by increasing the reliability and availability of the wind turbines.

The predominant approach for fault detection and accommodation within the wind turbine industry is, at present, to use simple fault detection methods applied to the available control system sensor signals, like thresholds on measurements, and condition monitoring systems used on some of the expensive rotating parts like gear-boxes and bearings. These condition monitoring systems are using additional, often expensive measurements of accelerations, vibrations or sound. It is consequently an expensive add-on to the control system. More information on wind turbine condition monitoring can be found in Hameed, Ahn, and Cho (2010) and Yang, Tavner, Crabtree, and Wilkinson (2010). Reviews of wind turbine condition monitoring can be found in Amirat, Benbouzid, Al-Ahmar, Bensaker, and Turri (2009), Hameed, Hong, Cho, Ahn, and Song (2009) and Garcia Marquez, Tobias, Pinar Perez, and Papaelias (2012). It would clearly be beneficial if one could use the measurements available in the control system to detect changes in the condition of e.g. the gear-box in a wind turbine. To facilitate research for this problem a friction change in the drive train gear-box was included in the wind turbine fault detection, isolation and accommodation benchmark model proposed by the same authors in Odgaard, Stoustrup, and Kinnaert (2009). In the benchmark model the gear-box is modeled with a 3 state model and the fault is modeled by changing model parameters slightly and slowly to obtain a change both in the resonance frequency and the damping coefficient.

The wind turbine converts wind energy to electrical energy. The state-of-the-art wind turbine is an upwind three bladed turbine. Three blades are mounted on a rotor shaft and the wind forces are converted into torque on the rotor shaft by acting on the blades. This torque can be controlled by pitching the blades or by controlling the generator torque through a power converter. Between the rotor axis and the electrical generator, normally a gear-box is mounted, converting the low speed high torque rotor side of the gear-box to the high speed low torque generator side. For more details on turbines consult Bianchi, De Battista, and Mantz (2007) and Burton, Sharpe, Jenkins, and Bossanyi (2008). The generator speed measurement contains a frequency component due to the gear-box resonance frequency; this might be lowered with the usage of a drive train damper, which will

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move a part of this component to the generator torque control signal. More details regarding drive train dampers can be found in Licari, Ugalde-Loo, Ekanayake, and Jenkins (2012). Consequently, condition changes in the gear box can be detected by monitoring changes in frequency content of the generator speed measurement and/or the generator torque control signal. The challenges raised in the wind turbine benchmark, see Odgaard et al. (2009), are dealt with in a significant number of publications. Even though a gear-box fault is included in the benchmark model, the number of publications in which this fault is detected is limited. Some of the better contributions to the benchmark problem excluding the gear-box fault are evaluated in Odgaard, Stoustrup, and Kinnaert (2013).

In Odgaard and Stoustrup (2014a, 2014b), two different time–frequency based approaches were proposed for detection of faults in the gear-box included in the benchmark model. In this paper, we will show that the problem of detecting changes in the resonance frequency in the gear-box is a problem that can be appropriately handled by a time frequency based approach in which there is support in both time and frequencies. In this paper the two proposed approaches for time–frequency based fault detection are applied on the wind turbine gear-box problem, which is included in the previously mentioned benchmark model. A first approach could be to use a basis approximating the general trends of the original fault free frequency spectrum. The approximating basis is found by extracting a Karhunen–Loeve basis from a windowed Fast Fourier Transform (FFT) of fault free data, see Odgaard and Stoustrup (2014b). Details on the Karhunen–Loeve basis can be found in Wickerhauser (1994) and Mallat (1999). Examples of using Karhunen–Loeve basis for fault detection can be found in Odgaard, Stoustrup, Andersen, Wickerhauser, and Mikkelsen (2006) and Odgaard and Wickerhauser (2007). This approximating basis supports the general trends in the frequency spectrum. The gear-box fault can subsequently be detected by comparing relative energy content in the component supported by the approximating basis relatively to the entire energy content in the given window at which the FFT was performed. This approach has the advantage of detecting changes in the frequency spectrum, within a few samples, with the disadvantage of requiring quite a lot of computation to achieve this. The second approach detects changes in the frequency spectrum by using a filter based algorithm where decreases in the relative energy content at the gear-box resonance frequency would be detected, see Odgaard and Stoustrup (2014a). This energy content is compared with the total energy level in the signal investigated, which in this gear-box fault case is the generator speed sensor signal. The Energy content can be found by band-pass filtering the generator speed sensor signal using a band pass filter with center frequency at the gear-box resonance frequency. The energy for the original signal and the band-pass filtered one are computed in window length of the last N samples, to remove the dependency on fast changes in frequency content. A drawback of this approach is that it requires excitation of the original resonance frequency to detect changes in it. The approach requires a low level of computation, with the disadvantage of introducing a detection delay which is equal to the window length. As the fault is expected to be very slowly developing, both methods are acceptable, as the first method does not necessarily need to be computed for every sample, and for the second method the detection delay is not a problem. In Section 2 the wind turbine system is described. The proposed frequency based detection schemes are presented in Section 3, which is followed by simulations and evaluations of the two proposed schemes in Section 4. A conclusion is drawn in Section 5.

2. System description

The purpose of a wind turbine is to convert wind energy into electrical energy. Modern state-of-the-art industrial wind turbines are typically of the multi-megawatt size. They are variable speed upwind three bladed turbines. Three pitchable blades are mounted on a rotor shaft. The blades are used to convert wind energy to mechanical energy by lift forces acting on the blade, which in turn exert a torque on the rotor shaft. Most turbine uses a gear-box to connect the low speed rotor shaft with the generator in the wind turbine, which operates with a higher rotational speed than the rotor. The generator in turn is connected to the power grid through a power converter. The power converter enables variable speed operation of the wind turbine as the generator is not directly connected to the power grid. It does as well provides controllability of the generator torque. Some industrial turbines are made without a gear-box; however, such turbines are not considered in this work. The gear-box balances the torques from rotor and generator sides, where the generator side is well controlled, as the generator is torque controlled by the wind turbine power converter, which connects the generator to the grid, enabling variable speed operation. The rotor torque is driven by the wind, and only partly controlled by pitch actions of the blades and indirectly by the rotor speed. This potential torque imbalance will over time lead to wear and tear and fatigue damage of the gear-box. The wind turbine controller could in principle suppress some of these resonances of the gear-box, such that some of the changes cannot be detected. In practice the relevant gear-box resonance frequencies are located in a frequency region above the controller bandwidth.

3. Proposed detection scheme

The considered problem of detecting changes in resonance frequency of a system, like the wind turbine gear-box, can be appropriately addressed by applying a joint time frequency based method, which provides support both in time and frequency, see Mallat (1999). A number of possible schemes from windowed FFT to Wavelet bases and other specific time frequency bases can be considered. The situation with the resonance frequency changing fault is illustrated in the frequency domain in Fig. 1, which provides an example of a decreasing resonance frequency. In order to determine a basis suitable for detecting certain phenomena in time, frequency or time/ frequency domains, it is important to find a base that supports the phenomenon which one wants to detect. Here the problem is to detect a changing resonance frequency. It would be relevant to consider a windowed FFT or cosine base, which basically shows the frequency domain for given time intervals/ windows. The window length should be selected wide enough to ensure that short time variations in the operation are leveled out, while short enough to detect changes in frequency content of the measurements, e.g., arising from changes in different resonance frequencies. The frequency responses obtained by the windowed FFT algorithm would subsequently be compared to determine if the response is as expected. The problem with such a scheme is that it is relatively computationally demanding, and consequently problematic to use in the existing control system. A fix to this problem could be to avoid computing a FFT for each sample, which enables distributions of the FFT computation over a number of sample periods. In this paper the detection problem is dealt with by using two different approaches. These two approaches are:

- a Karhunen–Loeve base approach, which is presented in Section 3.1. This approach checks if the frequency spectrum of the gear-box changes. This scheme is computationally demanding. However, the computations can be distributed over a number of samples, as the detection scheme can be operated with a lower sample frequency than the normal wind turbine controller, due to the slow development of the considered faults in the gear-box; and
- a filter based approach, which uses the identified resonance to detect if the energy content in the frequency range in which the resonance decreases. This approach is presented in Section 3.2.

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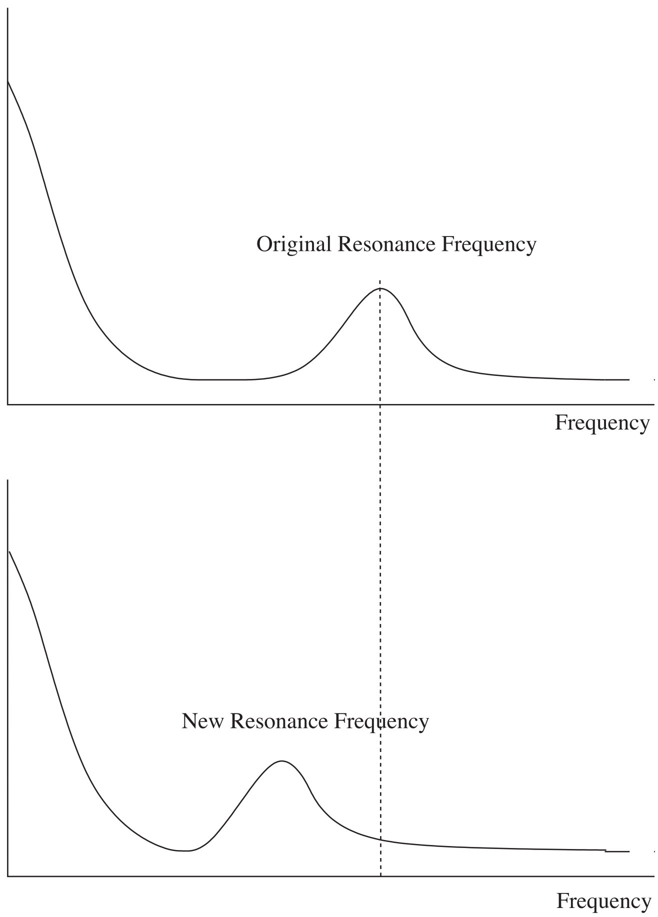

Fig. 1. Illustration of a changed resonance frequency plotted in the frequency domain.

3.1. Karhunen–Loeve basis based detection scheme

The Karhunen–Loeve basis provides basis vectors ordered with respect to their approximating capacity of a given data set. The basis vectors are generated and sorted in such a way that the first basis vector supports the largest fraction of the energy in the data set. This means the remaining basis vectors support the differences from each sequence in the data set, see Wickerhauser (1994). Consequently, this basis can be used to compare the general trends in different data sequences. In this approach the trends in the frequency domain are approximated, and consequently an FFT algorithm is applied to the data set before the Karhunen–Loeve basis is computed. This Karhunen–Loeve basis can be used to detect changes in the general trends in the frequency domain.

Define a matrix $\mathbf{X}$ of u column vectors in $\mathcal{R}^m$, where $u >= m$. The Karhunen–Loeve basis minimizes the average linear approximation error of the column vectors in $\mathbf{X}$. In this scheme $\mathbf{X}$ is constructed by vectors, x_i, with the absolute values of the FFT of the data vectors of length m. The low frequency part of the FFT is not of interest since it contains dynamics from the rotation of the wind turbine and other resonances like the tower. The high frequency part is not of interest, since it does not contain the relevant resonances. Only a part of the frequency range in the FFT is included in the x_i vector. The frequency range used is bounded by the lower frequency denoted as f_l and the upper frequency denoted as f_u. f_l should be selected above the controller bandwidth, to remove resonance frequencies in the wind turbine which depend on the rotational speed of the wind turbine. f_h should be selected as twice the value of the highest relevant gear-box resonance frequency, as considering the Nyquist frequency.

A given vector x_i can be found from the measured data vector, y_i as follows.

- compute the FFT of y_i, $y_{\text{fft},i}(f) = \text{fft}(y_i)$;
- set x_i as $x_i = [y_{\text{fft},i}(f_l) \ \cdots \ y_{\text{fft},i}(f_u)]^T$.

The Karhunen–Loeve basis $\mathcal{K}$ is defined as

$$\mathcal{K} = \{v_1, \ \ldots, v_m\}, \tag{1}$$

which is an orthonormal basis of eigenvectors of $\mathbf{XX}^T$, ordered in such a way that v_n is associated with the eigenvalue λ_n, and $\lambda_i \geq \lambda_j$ for $i \leq j$. This means that a basis of the l most approximating basis vectors, $\mathbf{K}_\text{L}$ can be defined as

$$\mathbf{K}_\text{L} = \{v_m, v_{m-1}, \ldots, v_{m-l+1}\}. \tag{2}$$

Now the approximating Karhunen–Loeve basis is found. The coefficients, κ_i, for these basis vectors can be found for a given data vector y_i.

- Compute the FFT of y_i, $y_{\text{fft},i}(f) = \text{fft}(y_i)$.
- Set x_i as $x_i = [y_{\text{fft},i}(f_l) \ \cdots \ y_{\text{fft},i}(f_u)]^T$.
- Compute κ_i as $\kappa_i = x_i^T \cdot \mathbf{K}_\text{L}$.

The approximation of x_i, denoted as $\bar{x}_i$ is subsequently computed as

$$\bar{x}_i = \mathbf{K}_L \cdot \kappa_i^T. \tag{3}$$

The last part of this detection scheme is to compute the ratio, $\gamma[n]$, which is defined as the ratio between the energy supported by the $\mathbf{K}_L$ basis and the energy in the original signal

$$\gamma[n] = \frac{\bar{x}_i^T \cdot \bar{x}_i}{y_{\text{fft},i}^T \cdot y_{\text{fft},i}}. \tag{4}$$

$\gamma[n]$ is computed for each sample n. This ratio will decrease if the relative energy content in the approximated frequencies, at which it is expected that the gear-box will have an energy content, are decreasing due to a changed dynamic behavior of the drive train. Gear-box faults can be detected by comparing $\gamma[n]$ with a threshold $\kappa[n]$. $\kappa[n]$ can be determined either using different methods for threshold selection, e.g. Stoustrup, Niemann, and la Cour-Harbo (2003) or by using the experimental data, such that false positive detections due to measurement noise are avoided. The proposed scheme given as an algorithm in pseudo-code is provided as:

Procedure KARHUNEN LOEVE BASED DETECTIONy_i
    Compute $y_{\text{fft},i}(f) = \text{fft}(y_i)$
    $x_i = [y_{\text{fft},i}(f_l) \ \cdots \ y_{\text{fft},i}(f_u)]^T$
    Compute $\kappa_i = x_i^T \cdot \mathbf{K}_\text{L}$
    Compute $\bar{x}_i = \mathbf{K}_L \cdot \kappa_i^T$
    Compute $\gamma[n] = \frac{\bar{x}_i^T \cdot \bar{x}_i}{y_{\text{fft},i}^T \cdot y_{\text{fft},i}}$
    if $\gamma[n] > \kappa[n]$ **then**
        gear-box fault detected
    end if
end procedure

This proposed scheme is somewhat computationally demanding since a FFT is required to be computed for each sample of data with the window length, L, where L should be so large that a reasonable frequency resolution in the interval between f_l and f_u is present.

3.2. Frequency based detection scheme

This approach uses time frequency based analysis to design a filter based approach which detects changes in the resonance frequency. It is assumed that a certain energy level will be presented at a given frequency, e.g. due to resonance frequency, f. Define the signal on which the frequency detection should be applied, $y[n]$.

The first step is to extract the energy in the signal at and around the requested frequency, by a band pass filter, $H_f[z]$. This filter is subsequently applied to the signal $y[n]$ to obtain $y_{Hf}[n]$.

The next step is to compute the energy in the signals for a given window length, L. $E_{Hf}[n]$ denoting the energy in the band pass filtered signal, and $E[n]$ the energy in the normal signal, are computed as:

$$E_{Hf}[n] = \mathbf{y}_{Hf}[n] \cdot \mathbf{y}_{Hf}[n]^T, \tag{5}$$

$$E[n] = \mathbf{y}[n] \cdot \mathbf{y}[n]^T, \tag{6}$$

in which,

$$\mathbf{y}_{Hf}[n] = [y_{Hf}[n-(L-1)] \ \cdots \ y_{Hf}[n]], \tag{7}$$

$$\mathbf{y}[n] = [y[n-(L-1)] \ \cdots \ y[n]]. \tag{8}$$

Subsequently a ratio between these two energies, defined as $\gamma[n]$, can be computed, which can be used to detect if the energy level at the resonance frequency drops. This could indicate that the frequency spectrum of the system has changed.

$$\gamma[n] = \frac{E_{Hf}[n]}{E[n]}. \tag{9}$$

This ratio $\gamma[n]$ would subsequently be compared with a threshold $\kappa[n]$. Again as in the Karhunnen–Loeve based scheme $\kappa[n]$ can be determined either using different methods for threshold selection or by using the experimental data, such that false positive detections due to measurement noise are avoided. In cases where the resonance frequency depends on operational conditions, the center frequency of the H_f filter should as well depend on this, and a number of filters might have to be computed in advance. The proposed scheme given as an algorithm in pseudo-code is provided as:

Procedure FILTER BASED DETECTIONy_i
  Compute $\mathbf{y}[n] = [y[n-(L-1)] \ \cdots \ y[n]]$
  Compute $\mathbf{y}_{Hf}[n] = [y_{Hf}[n-(L-1)] \ \cdots \ y_{Hf}[n]]$
  Compute $E[n] = \mathbf{y}[n] \cdot \mathbf{y}[n]^T$
  Compute $E_{Hf}[n] = \mathbf{y}_{Hf}[n] \cdot \mathbf{y}_{Hf}[n]^T$
  Compute $\gamma[n] \frac{E_{Hf}[n]}{E[n]}$
  if $\gamma[n] > \kappa[n]$ **then**
    gear-box fault detected
  end if
end procedure

4. Simulation and evaluation of the proposed s cheme

The two proposed schemes are evaluated in this section with respect to their potential of detecting the gear-box fault, evaluated on a well known wind turbine fault detection benchmark model. Computational requirements are not evaluated as these requirements depend on the actual industrial hardware and software platforms.

4.1. Wind turbine model

The used wind turbine model is from Odgaard et al. (2009), and is not described in details in this paper. An overview of the model can be seen in Fig. 2, in which v_w denotes the wind speed, τ_r denotes the rotor torque, ω_r denotes the rotor speed, τ_g denotes the generator torque, ω_g denotes the generator speed, β_r denotes the pitch angle control reference, β_m denotes the measured pitch angles, $\tau_{w,m}$ denotes the estimated rotor torque, $\omega_{r,m}$ denotes the measured rotor speed, $\tau_{g,m}$ denotes the measured generator torque, $\omega_{g,m}$ denotes the measured generator speed, P_g denotes the measured generated electrical power, $v_{w,m}$ is the measured wind speed, $\tau_{g,r}$ denotes the generator torque reference, and P_r denotes the power reference. The figure shows the relation between the different model parts, those are described below. They are: Blade and Pitch System, Drive Train,

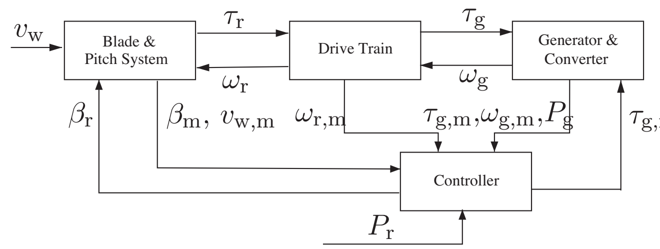

Fig. 2. An overview of the benchmark model. It consists of four parts: Blade and Pitch Systems, Drive Train, Generator and Converter, and Controller. The variables in the figure are defined in text.

Converter and Generator, and Controller. In addition the wind and sensors are modeled. Each element of the model is shortly described in the following.

4.1.1. Wind model

The wind speed is given by a wind model including mean wind trends, turbulence, wind shear and tower shadow.

4.1.2. Pitch and Blade model

Aerodynamics and pitch actuators are modeled in the Blade and Pitch System model, the pitch actuator is modeled as a second order transfer function with constraints. The aerodynamics are modeled by a static mapping from the pitch angle, rotor and wind speeds to the torque acting on the wind turbine rotor.

4.1.3. Drive Train model

The Drive Train, which is used to increase the speed from rotor to generator, is modeled with a flexible two-mass system. The drive train model includes the inertia of the rotor (which includes blades and the main shaft) and generator.

4.1.4. Converter model

The Converter which controls the generator torque is modeled by a first order system with constraints. This model covers both the electrical behavior of the generator and converter.

4.1.5. Sensor models

This model is not shown on the figure, since models of each sensor in the figure are included in the relevant part models. The model contains a number of sensors, generator and rotor speed, pitch angles, wind speed, converter torque, and electrical power. All the sensors are modeled as the measured variable added with random noise.

4.1.6. Controller

The wind turbine operates in principle in 4 regions: Region 1 in which wind speeds are too low for the wind turbine to operate, Region 2 in which the turbine operates up to a nominal wind speed (partial load), Region 3 between nominal and rated wind speed, where the nominal power can be produced, Region 4 above rated wind speed, where the wind turbine is closed down in order to limit extreme and fatigue loads on the wind turbine. The controller is active in Regions 2 and 3. In Region 2, the optimal rotor speed is obtained by using the converter torque as a signal. In Region 3 the rotor speed is kept at a given reference value by pitching the blades, (the converter keeps the power at the reference taking care of fast variations in the speed). In this paper only the second region control is considered. The basic controller in the different regions is described in Johnson, Pao, Balas, and Fingersh (2006).

4.1.7. Wind scenario

A plot of the wind speed sequence used in the benchmark model can be seen in Fig. 3. Fault 9 from the used benchmark model which changes the gear-box resonance frequency occurs from 4000 s to

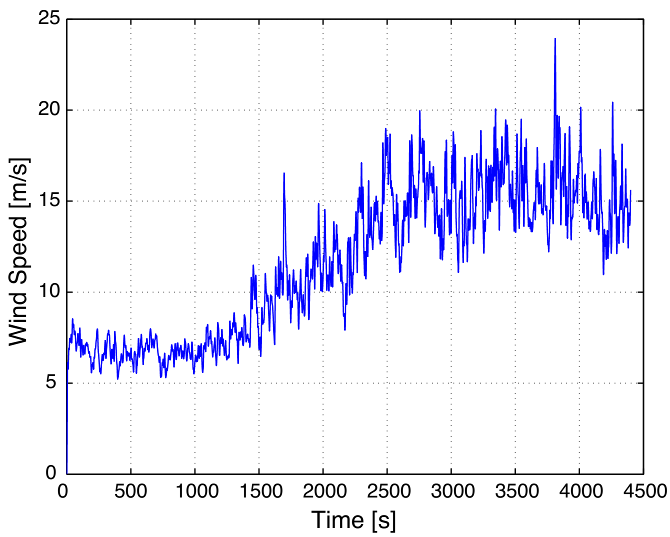

Fig. 3. Plot of wind speed sequence used in the benchmark model.

4200 s. During this fault the wind turbine is only operating in full power mode, which can be used for these initial tests, as it means the generator speed will be relatively constant. The purpose of this evaluation is to see if the proposed scheme can detect the gear-box fault included in this benchmark model. It is less important to evaluate robustness towards model uncertainties as the purpose of the scheme is to detect that the resonance has changed from its known starting point. However, robustness toward operational-depending changes are tested using the specific wind scenario. The two methods are tested and evaluated in the order they are presented.

4.2. Simulation and evaluation of the Karhunen–Loeve based scheme

The Karhunen–Loeve basis is computed based on data from the benchmark model without gear-box fault present. The proposed detection scheme presented in Section 3, includes a number of parameters which can be adjusted in the tuning process. The window length used in the FFT computation is set to 2000. The frequency range for which the Karhunen–Loeve basis is given by $f_l = 2$ Hz and $f_u = 6$ Hz, and since the sample frequency is 100 Hz, the frequency resolution in the $\mathbf{K}_L$ basis is equal to $\frac{100\,\text{Hz}}{2000} = 0.05$.

The five most approximating basis vectors, $\{v_{m-4}, \ldots, v_m\}$, can be seen in Fig. 4. The coefficients in these vectors, $\{\kappa_{m-4}, \ldots, \kappa_m\}$ are shown in Fig. 5. This shows that the best potential for detection is obtained by using the fourth most approximating basis vector, i.e. $l = 3$. This also means that $\gamma[n]$ is computed based on $\kappa_{m-3}[n]$ only. Fault 9 which changes the gear-box resonance frequency occurs from 4000 s. The computed value of $\gamma[n]$ is plotted, see Fig. 6 for the time interval from 3400 s to 4300 s, in order to ensure that the wind turbine is operating in the full power mode, and that the fault is present in a part of the interval. It is assumed that the wind turbine operates in full power mode for this initial design evaluation. From Fig. 6 it can be seen that $\gamma[n]$ clearly drops when the gear-box resonance frequency changes at 4000 s with a delay on approximately 10 s. Based on Fig. 6 the value of σ can be found. It seems that $\sigma = 0.25$ provides the best tradeoff between detection delay and avoidance of false positive detections, by trial and error experiments on these data. The detection can be seen in Fig. 7 for the time interval 3400–4300 s. It can be seen from the test that the proposed scheme has a clear detection of the gear-box fault. The Detection is a bit slow but quite robust to different operational conditions, in terms of avoiding potential false positive detections, since $\gamma[n]$ has a clear distinctive reaction during the fault. These initial tests clearly shows a potential of detecting gear-box faults using existing rotational speed measurements using the Karhunen–Loeve based scheme, and thereby a possible cost reduction by monitoring the gear-box condition from the control system without additional sensors.

4.3. Frequency based scheme

4.3.1. Specific design

In this considered case the sample frequency is at 100 Hz. It is necessary to filter out the low frequency content in the signal $y[n]$ before the proposed scheme is applied to $y[n]$, since the main energy content is located in the frequency range below 0.5 Hz, see Fig. 8. Consequently, a low pass filter with a cut-off frequency at 0.5 Hz is applied to $y[n]$. The output of this filter is subtracted from $y[n]$, and the difference is used for the computation of $E[n]$. The used low-pass filter, $L[z]$, can be seen in (10).

$$L[z] = \frac{1.935 + 5.806z^{-1} + 5.806z^{-2} + 1.935z^{-3}}{1.0000 - 2.9497z^{-1} + 2.9007z^{-2} - 0.9510z^{-3}} \cdot 10^{-6}. \quad (10)$$

$H_f[z]$ was designed using the Matlab function *butter*, which designs Butterworth filters. A filter of order 3 with a center frequency at 4.47 Hz was computed. The amplitude of this filter can be seen in Fig. 9. The filter itself can be seen in (11), where it is defined in the Z-domain.

$$H_f[z] = \frac{\mathbf{B}_2 \cdot \mathbf{Z}_6}{\mathbf{A}_2 \cdot \mathbf{Z}_6} \quad (11)$$

in which the parameter vectors are defined as

$$\mathbf{B}_2 = [3.86 \;\; 0 \;\; -11.59 \;\; 0 \;\; 11.59 \;\; 0 \;\; 3.86] \cdot 10^{-9} \quad (12)$$

$$\mathbf{A}_2 = [1 \;\; -5.7574 \;\; 14.0466 \;\; -18.5644 \;\; 14.0172 \;\; -5.7343 \;\; 0.9937] \quad (13)$$

$$\mathbf{Z}_6 = [1 \;\; z^{-1} \;\; z^{-2} \;\; z^{-3} \;\; z^{-4} \;\; z^{-5} \;\; z^{-6}]^T. \quad (14)$$

A part of this design is based on trial and error on the benchmark model, meaning that certain parameters are found based on simulations using the benchmark model. The first parameter is the window length L. If the value of L is too low the scheme will react too much on various disturbances, which means that it is preferable to use a high value for L, consequently the detection delay is proportional to L, therefore it is important to select a good tradeoff between detection correctness and detection delay. Experiments on the benchmark model have shown that a value of L equal to 10^5 is a good trade-off. It corresponds to a detection delay of 100 s, with none false positive detections. The detection delay seems a long delay, but one should have in mind that changes in the gear-box resonance frequency are occurring slowly, developing over months, so this delay is acceptable.

It should also be noted that for the detection scheme to work the wind turbine should be excited with frequencies at the expected resonance frequency. In Fig. 10 the computed value of $\gamma[n]$ is plotted for the time interval from 3500 s to 4400 s. This interval is selected in order to ensure that the wind turbine is operating in the full power mode, and that the fault is present in a part of the interval. From Fig. 10 it can be seen that $\gamma[n]$ clearly drops when the gear-box resonance frequency changes at 4000 s with a delay of approximately 100 s. Based on the same test sequence the value of κ can be found. It seems that $\kappa = 1.8 \cdot 10^{-2}$ provides the best tradeoff between detection delay and avoidance of false positive detections, a slightly higher value would have resulted in a false positive detection at 3900 s. The detection can be seen in Fig. 11 for the time interval 3500–4400 s. This result obtained by applying the proposed scheme for frequency change detection on data from the mentioned wind turbine benchmark model, see Odgaard et al. (2009), shows a potential for using this scheme to detect changes for specific dominating frequencies

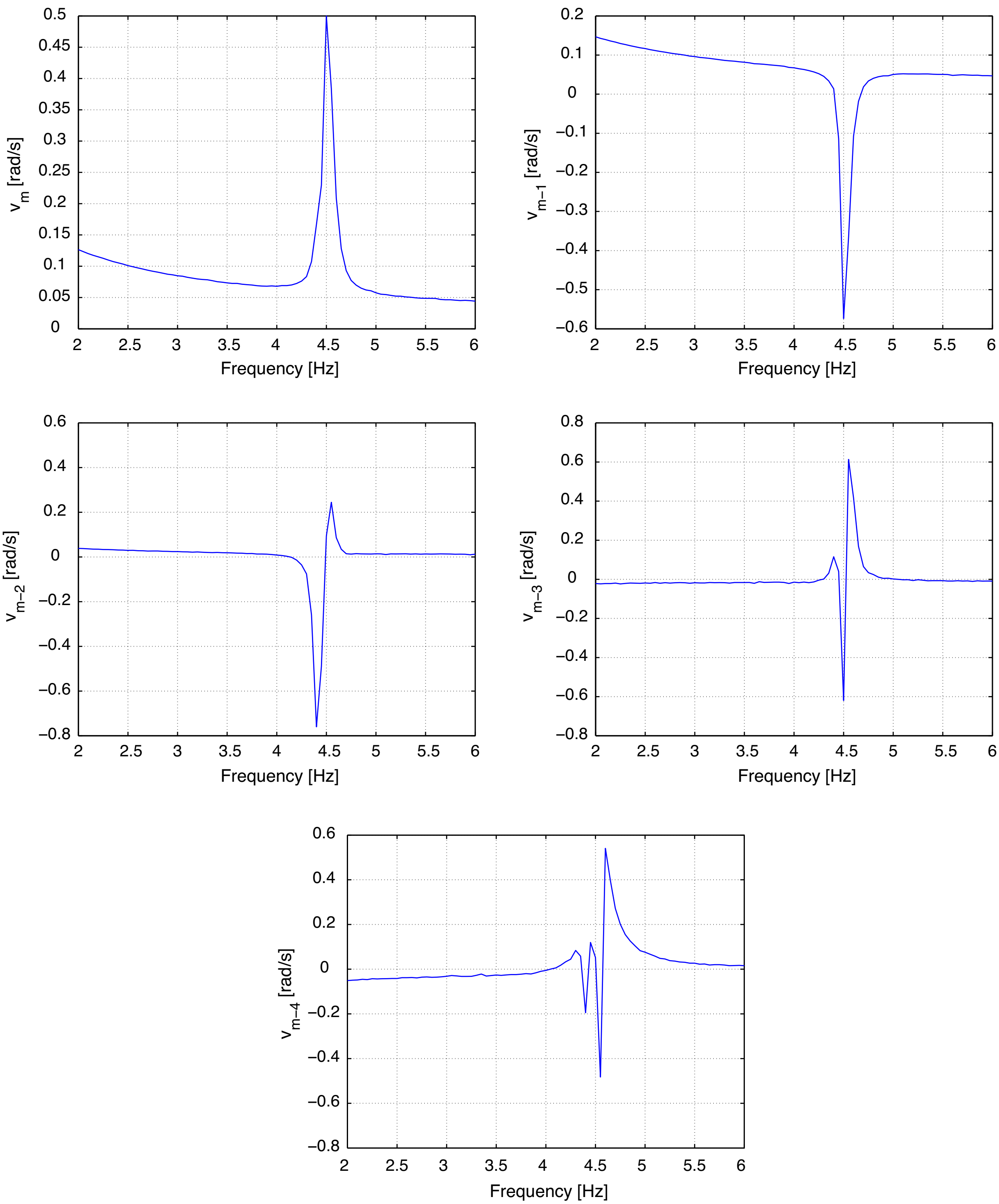

Fig. 4. Plot of the five most approximating Karhunen–Loeve basis vectors, $v_{m-4} - v_m$.

which can be seen in different measurements from a system. In the specific case it detects that the resonance frequency changes from its normal value due to the simulated fault.

4.4. Summary

Both proposed methods detect the gear-box fault provided in the used wind turbine benchmark model. The Karhunen–Loeve based method detects the fault faster with a delay at 10 s, but also requires more computations as an FFT is computed for each sample. The filter based approach has a detection delay at 100 s, which corresponds to the memory block length used. As the gear-box fault is slowly developing both methods are applicable, since neither the detection delay or the high computational burden is a real problem. The high computational burden can be dealt with by distributing the computation over a number of samples, which will result in extra delay on the detection of the fault. The detection delay will be increased by the number of extra sample which is used to compute the detections. In the perspective that the gear-box fault is evolving over months, these delays are relatively short and are consequently of no concern.

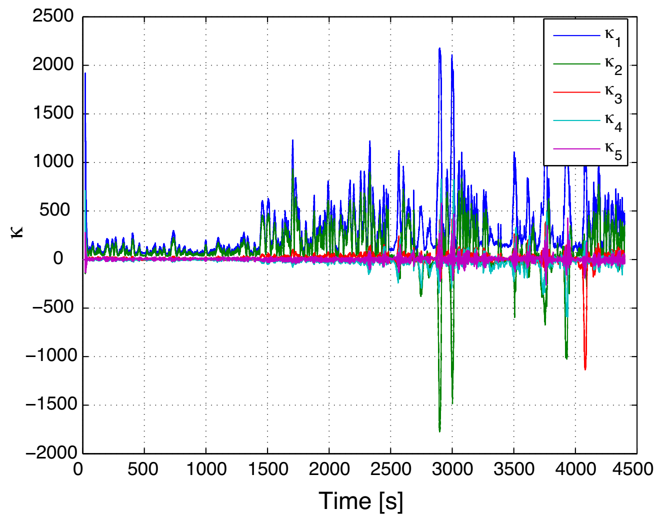

Fig. 5. $\{\kappa_{m-4}, \ldots, \kappa_m\}$ the coefficients in the five most approximating basis vectors.

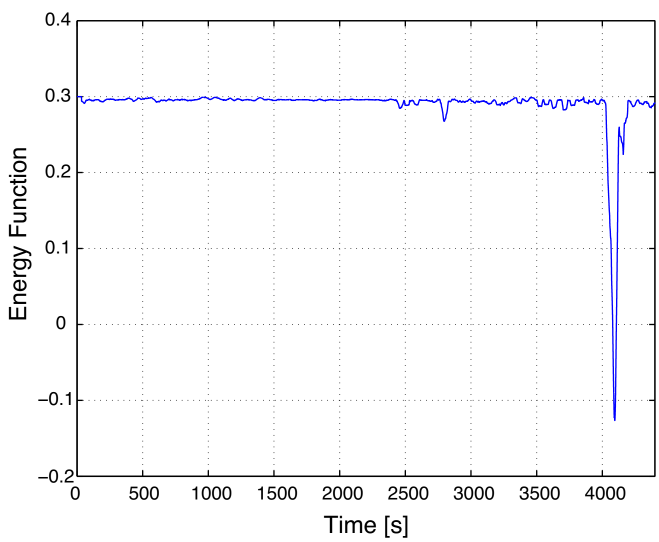

Fig. 6. A zoom on $\gamma[n]$ for the time interval 3400–4300 s.

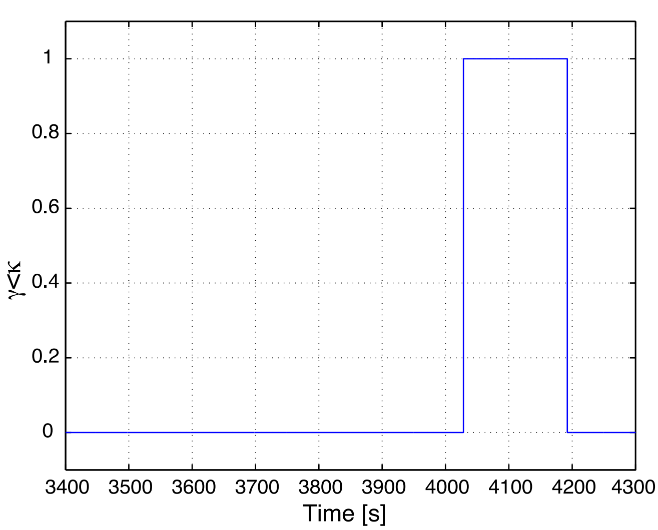

Fig. 7. A zoom on the detection based on $\gamma[n] < \sigma$ for the time interval 3400–4300 s. Notice that a value of 1 is corresponding to a detected fault.

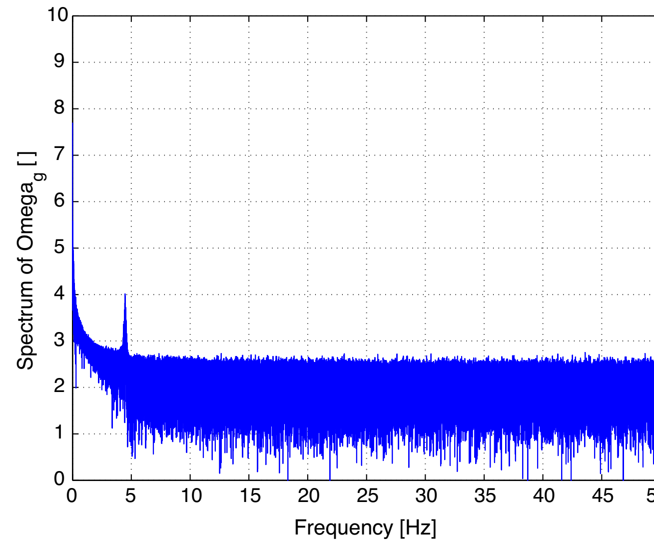

Fig. 8. Frequency spectrum of the ω_g. The main energy content is located below 0.5 Hz and notice the gear-box resonance frequency at 4.47 Hz.

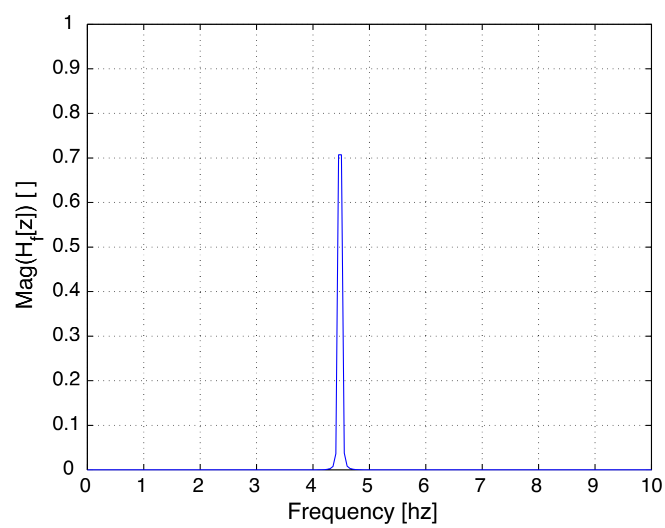

Fig. 9. The amplitude of the $H_f[z]$ plotted as a function of frequencies.

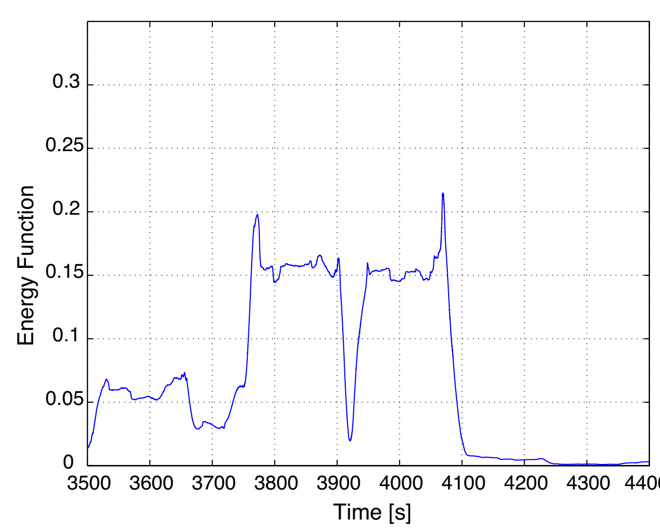

Fig. 10. A zoom on $\gamma[n]$ for the time interval 3500–4400 s.

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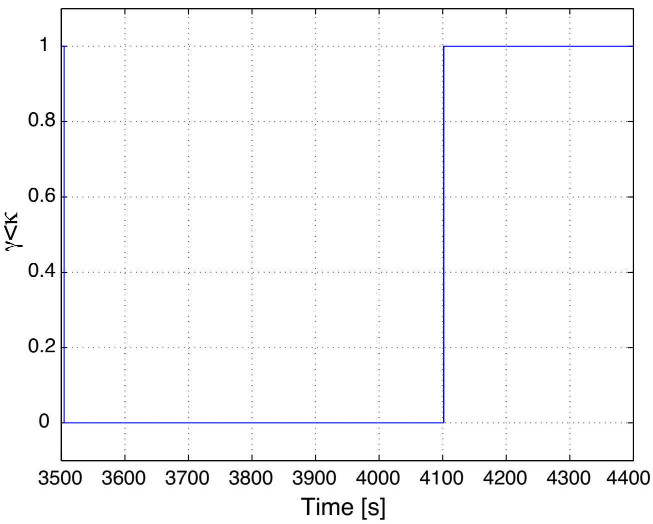

Fig. 11. A zoom on the detection signal based on $\gamma[n] < \kappa$ for the time interval 3500–4400 s.

4.5. Further work

It would be relevant to test the proposed scheme for a more detailed model of the wind turbine gear-box and fault, which is operated in a realistic wind turbine simulation. Examples on such model and simulations can be found in Nejad, Xing, and Moan (2012) and Nejad and Moan (2012), and an a test of an simple detection scheme has been applied to such a model in Nejad, Odgaard, Gao, and Moan (2014) and Odgaard and Nejad (2014).

The proposed schemes could be modified to incorporate multiple sensors and actuator signals, e.g. it could be relevant to include the generator torque reference in the drive train resonance frequency case considered in this work, since this would suppress variations in the generator speed during partial load, and thereby dampen the gear-box forces.

It would as well be relevant to test and analyze the robustness of the proposed schemes with respect to changes in operational conditions like changes in wind speed, which results in variable rotor speed, which in turn changes some of the other resonance frequencies in the wind turbine. This might influence the gear-box resonance frequencies. Another aspect is to use other methods for detection of the change gear-box resonances. Some potential methods could be to use recursive identification of Auto-regressive models, see Ljung (1999), oscillation based estimation methods like seen in Landau, Alma, and Airimitoaie (2011). Again another approach could be to use optimal frequency shaping to detect the changes see Tibaldi and Zattoni (1996). It could as well be relevant to use an internal model and observer based approach to detect the resonance changes, see for example Odgaard and Mataji (2008).

5. Conclusion

In wind turbines, changes in the condition of a gear-box are most often monitored with a condition monitoring system, which is a system running in parallel to the control system, and typically also using additional often expensive sensors. In this paper two different time–frequency based approaches for detection of this fault are presented and evaluated. Both approaches can be applied to measurements already available in the control system. Both methods are applied to the generator speed measurement. The first approach is based on a Karhunen–Loeve basis of the frequency spectrum, this scheme has a detection delay at 10s, this method is computationally intensive but of little significance to detection of this fault. The second approach is a filter based approach which detects the fault with a detection delay at 100 s. Neither the computational requirements nor the detection delay are actual problems as this fault is very slowly developing and, therefore, these issues can be dealt with in the implementation. The proposed schemes are tested on a well established wind turbine Fault Detection and Isolation (FDI) and Fault Tolerant Control (FTC) Benchmark Model. These tests show potentials of the proposed schemes for detecting gear-box faults. This enables the possibility of using generator and rotor speed measurements for gear-box fault detection in wind turbines, and thereby reducing costs by removing the need for expensive auxiliary condition monitoring systems.

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