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Frequency Based Fault Detection in Wind Turbines

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Abstract: In order to obtain lower cost of energy for wind turbines fault detection and accommodation is important. Expensive condition monitoring systems are often used to monitor the condition of rotating and vibrating system parts. One example is the gearbox in a wind turbine. This system is operated in parallel to the control system, using different computers and additional often expensive sensors. In this paper a simple filter based algorithm is proposed to detect changes in a resonance frequency in a system, exemplified with faults resulting in changes in the resonance frequency in the wind turbine gearbox. Only the generator speed measurement which is available in even simple wind turbine control systems is used as input. Consequently this proposed scheme does not need additional sensors and computers for monitoring the condition of the wind gearbox. The scheme is evaluated on a wide-spread wind turbine fault detection and fault tolerant control benchmark model, in which one of the included faults results in a change in the gear box resonance frequency. This evaluation shows the potential of the proposed scheme to monitor the condition of wind turbine gear boxes in the existing control system.

Keywords: Wind turbine, Fault Detection, Frequency Based Detection.

1. INTRODUCTION

One of the main objectives in wind turbine research and development is to lower cost of energy (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 turbine. Fault detection and accommodation is one of the areas to focus on to obtain this objective. Better fault detection and accommodation can lower the maintenance costs and as well the down-time of turbines, thereby both lowering costs and the increasing possible conversion of energy.

The predominant industrial approach for fault detection and accommodation is at present to use simple fault detection methods applied to the available control system sensor signals, like thresholds on measurements, and as well condition monitoring systems used on some of the expensive rotating parts like gearboxes and bearings. These condition monitoring systems are using additional often expensive, measurements of accelerations and vibrations or sound. More information on wind turbine condition monitoring can be found in Hameed et al. [2010] and Yang et al. [2010]. It is consequently an expensive add-on to the control system. Reviews of wind turbine condition monitoring can be found in Amirat et al. [2009], Hameed et al. [2009] and Garcia Marquez et al. [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 drive train in a wind turbine. To facilitative research in this problem a friction change in the drive train was included in the wind turbine fault detection, isolation and accommodation benchmark model proposed by the same authors in Odgaard et al. [2009], in which the parameters in the 3 state gearbox model change slightly both in frequency and 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 is 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. In between the rotor axis and the electrical generator, normally a gearbox is mounted, converting the low speed high torque rotor side with the high speed low torque generator side. For more details on turbines consult Bianchi et al. [2007] and Burton et al. [2008]. The generator speed measurement will contain a frequency component due to the gearbox resonance frequency; this might be lowered with the usage of a drive train damper, which will move a part of this component to the generator torque control signal. More on drive train dampers can be found in Licari et al. [2012]. It could consequently be relevant to detect condition changes in the gearbox by monitoring changes in frequency content of the generator speed measurement and/or the generator torque control signal. A number of published approaches have been applied to the previously mentioned benchmark model. Some of these contributions are evaluated in Odgaard et al. [2013]. Others of these contributions can be seen in Chen et al. [2011], Laouti et al. [2011], Ozdemir et al. [2011], Svard and Nyberg [2011], Zhang et al. [2011], Pisu and Ayalew [2011], Blesa et al. [2011], Dong and Verhaegen [2011], Kiasi et al. [2011], Simani et al. [2011a], Simani et al. [2011b] and Stoican et al. [2011]. To the knowledge of the authors none of these or other contributions to wind turbine fault detection and isolation have taken the approach of detecting frequency change in the generator speed sensor signal to detect condition changes in the gearbox, or did not have any success using other methods for detecting this.

Somehow this problem requires a time frequency based solution in which there is support in both time and frequencies. However, since the task is basically to detect changes in a frequency over time, a first approach would be to detect changes in the frequency spectrum by using a windowed FFT based algorithm where changes in the frequency spectrum would be detected.

In this paper an approach in which the energy content at the expected resonance frequency is found. This energy content is compared with the total energy level in the signal investigated, which in this gearbox fault case is the generator speed sensor signal. This can be found by band pass filtering the generator speed sensor signal with a band pass filter with center frequency at the gearbox resonance frequency. The energies 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 the approach is that it requires excitation of the original resonance frequency to detect changes in it.

In Sec. 2 the system and fault in question are described, which is the gearbox resonance frequency change in the FDI wind turbine bench mark model presented in Odgaard et al. [2009]. The proposed scheme is presented in Sec. 3, followed by simulations and evaluations of the proposed scheme in Sec. 4. The paper is finalized by a conclusion in Sec. 5.

2. SYSTEM DESCRIPTION

This paper considers a generic wind turbine of 4.8 MW described in Odgaard et al. [2009]. The benchmark model contains 9 different faults, of which the gearbox fault is one. This turbine is a variable speed three blade pitch controlled turbine, with a front horizontal axis rotor.

2.1 Wind Turbine Model

The used wind turbine model is from Odgaard et al. [2009], and is not described in details in this paper. The details can be found in the mentioned paper. An overview of the model can be seen in Fig. 1, 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, $\tau_{g,r}$ 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, Converter and Generator, and Controller. In addition the wind and sensors are modeled.

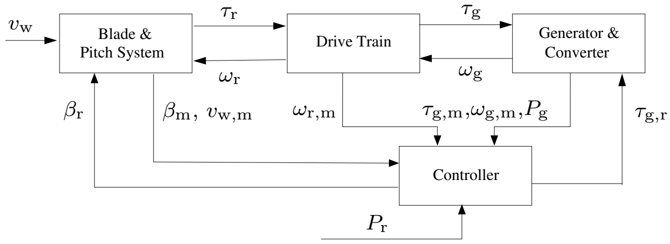

Fig. 1. This figure shows an overview of the benchmark model. It consists of four parts: Blade and Pitch Systems, Drive Train, Generator & Converter, and Controller. The variables in the figure are defined in text.

Each element of the model is shortly described in the following.

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

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.

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.

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.

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, electrical power. All the sensors are modeled as the measured variable added with random noise.

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 Region 2 & 3. In Region 2, the optimal rotor speed is obtained by using the converter torque as control 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 et al. [2006].

3. PROPOSED FREQUENCY DETECTION SCHEME

The considered problem of detecting changes in resonance frequency of a system, like the wind turbine gearbox, requires in principle a joint time frequency based method, which provides support both in time and frequency, see Mallat [1999], which covers a number of possible schemes from windowed FFT (Fast Fourier Transform) to Wavelet bases and other specific time frequency bases. This resonance frequency changing fault is illustrated in the frequency domain in Fig. 2, which shows an example of the resonance frequency decreasing in value.

In questions of finding a suited base for detecting certain phenomena in time, frequency or time/ frequency domains, it is important to find a base which supports the phenomenon which one wants to detect. In this case 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 such that short time variations in the operation is leveled out, while short enough to detect changes in frequency content of the measurements, like 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.

Instead an approach is proposed in which it is assumed that a certain energy level will be present 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 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. The energies, $E_{Hf}[n]$, for the energy in the band pass filtered signal, and $E[n]$ the energy in the normal signal, are computed as:

$$E_{Hf}[n] = \mathbf{y}_{Hf}[n] \cdot \mathbf{y}_{Hf}[n]^T, \tag{1}$$

$$E[n] = \mathbf{y}[n] \cdot \mathbf{y}[n]^T, \tag{2}$$

in which,

$$\mathbf{y}_{Hf}[n] = \left[y_{Hf}[n-(L-1)] \ \cdots \ y_{Hf}[n]\right], \tag{3}$$

$$\mathbf{y}[n] = \left[y[n-(L-1)] \ \cdots \ y[n]\right]. \tag{4}$$

Subsequently a ratio, $\gamma[n]$, between these two energies can be computed, which can be used to detect if the energy level at this frequency drops, which could indicate the frequency spectrum of the system changes.

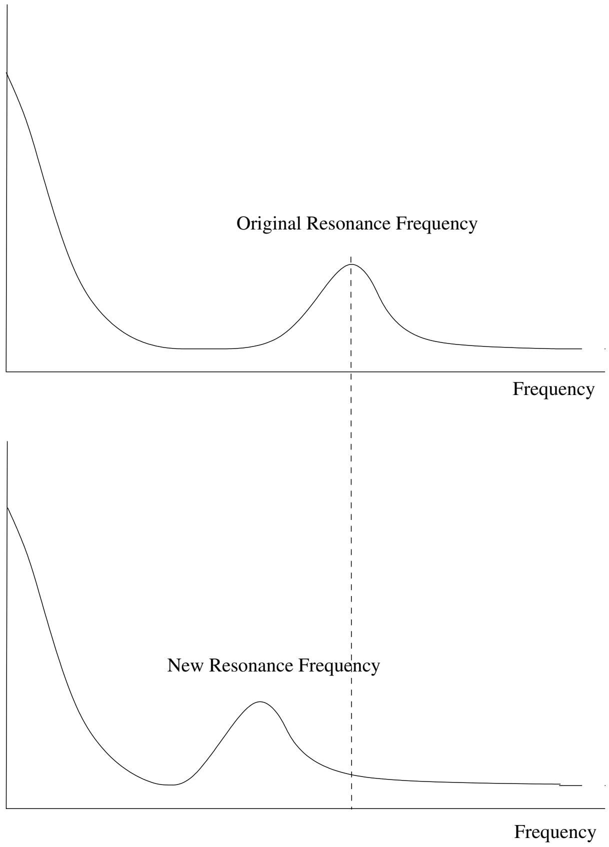

Fig. 2. Illustration of a changed resonance frequency plotted in the frequency domain.

$$\gamma[n] = \frac{E_{Hf}[n]}{E[n]}. \tag{5}$$

This ratio $\gamma[n]$ would subsequently be compared with a threshold κ.

In cases where the resonance frequency is depending on operational conditions, the center frequency of the H_f filter can depend on this, and a number of filters might have to be computed in advance.

3.1 Specific Design

In this considered case the sample frequency is at 100 Hz. In the specific application 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. 3. 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 (6).

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

$H_f[z]$ was designed using the Matlab function *butter*, which designs Butterwoth filters. A filter of order 3 with a center frequency at 4.47 Hz was designed. The amplitude

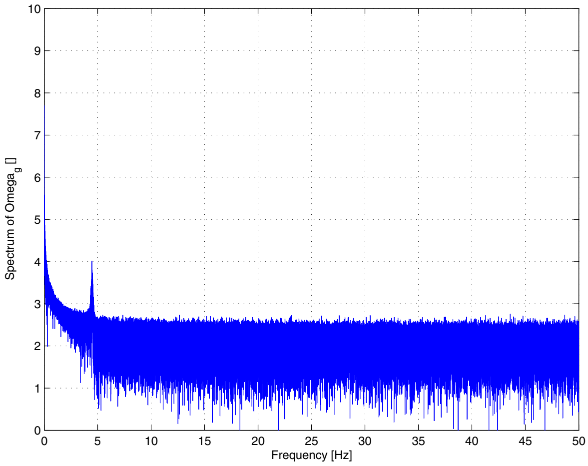

Fig. 3. Frequency spectrum of the ω_g. The main energy content is located below 0.5 Hz and notice the gearbox resonance frequency at 4.47Hz

of this filter can be seen in Fig. 4. The filter itself can be seen in (7), where it is defined in the Z-domain.

$$H_f[z] = \frac{\mathbf{B}_2 \cdot \mathbf{Z}_6}{\mathbf{A}_2 \cdot \mathbf{Z}_6} \tag{7}$$

in which the parameter vectors are defined as

$$\mathbf{B}_2 = \begin{bmatrix} 3.86 \cdot 10^{-9} \\ 0 \\ -11.59 \cdot 10^{-9} \\ 0 \\ 11.59 \cdot 10^{-9} \\ 0 \\ 3.86 \cdot 10^{-9} \end{bmatrix}^T \tag{8}$$

$$\mathbf{A}_2 = \begin{bmatrix} 1 \\ -5.7574 \\ 14.0466 \\ -18.5644 \\ 14.0172 \\ -5.7343 \\ 0.9937 \end{bmatrix}^T \tag{9}$$

$$\mathbf{Z}_6 = \begin{bmatrix} 1 \\ z^{-1} \\ z^{-2} \\ z^{-3} \\ z^{-4} \\ z^{-5} \\ z^{-6} \end{bmatrix}. \tag{10}$$

The window length L and the threshold value κ is found based on trial and error on the benchmark model. These parameters are found in Section 4 in which the proposed scheme is simulated and evaluated.

4. SIMULATION AND EVALUATION OF THE PROPOSED SCHEME

A part of this design is based on trial and error on the benchmark model, meaning that certain parameters are found based on simulations with the model. The first parameter to find 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, but on the other hand the detection delay is proportional to L. Experiments on the benchmark model has shown that a value of L equal to $10 \cdot 10^4$ is a good trade-off. It corresponds to a detection delay of 100 s, which seems as a long delay, but one should have in mind that changes in the gearbox resonance frequency are occurring slowly, so this delay is acceptable.

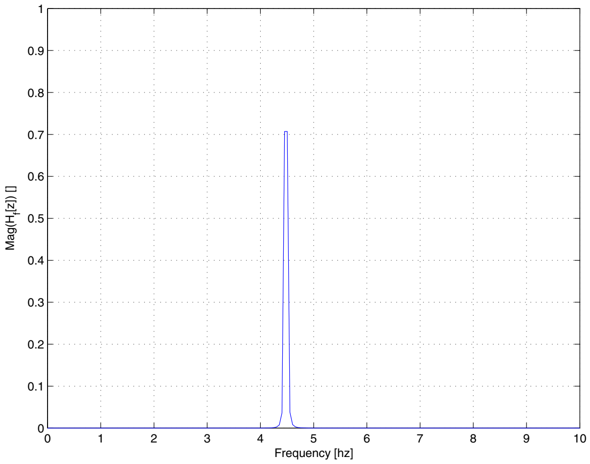

Fig. 4. The amplitude of the $H_f[z]$ plotted as a function of frequencies.

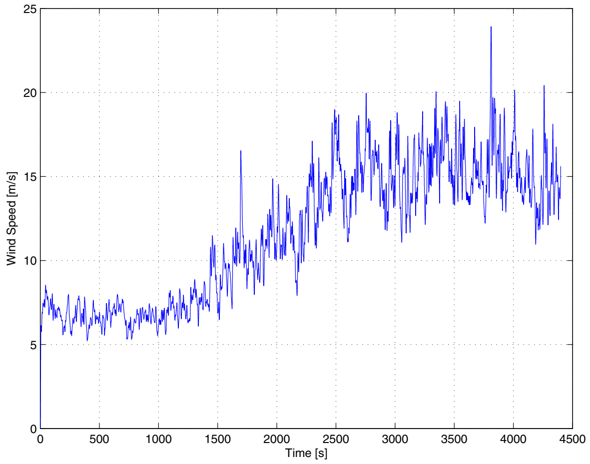

Fig. 5. Plot of wind speed sequence used in the benchmark model.

It is also noticed that the resonance frequency in which changes should be detected is required to be excited in order for the scheme to work. In this application this means that the wind turbine is required to operate in full power mode. A plot of the wind speed sequence used in the benchmark model can be seen in Fig. 5. Fault 9 which changes the gearbox resonance frequency occurs from 4000 s to 4200 s.

Fault 9 which changes the gearbox resonance frequency occurs from 4000 s. The computed value of $\gamma[n]$ is plotted, see Fig. 6 for the time interval from 3500 s to 4400 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.

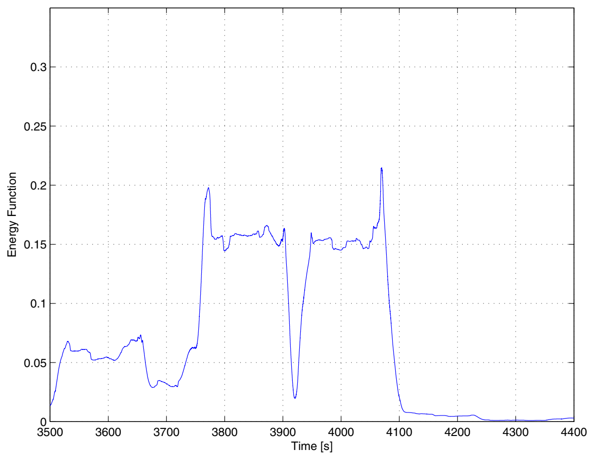

Fig. 6. A zoom on $\gamma[n]$ for the time interval 3500s to 4400s.

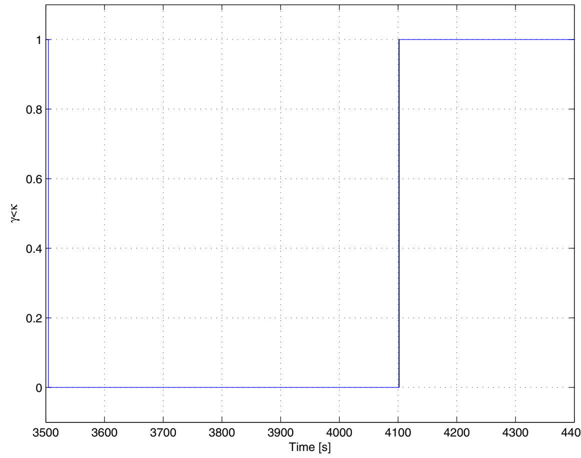

Fig. 7. A zoom on the detection based on $\gamma[n] < \kappa$ for the time interval 3500s to 4400s.

From Fig. 6 it can be seen that $\gamma[n]$ clearly drops when the gearbox resonance frequency changes at 4000s with a delay on approximately 100s. 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. The detection can be seen in Fig. 7 for the time interval 3500s-4400s.

These results obtained by applying the proposed scheme for frequency change detection to data from the mentioned wind turbine benchmark model, see Odgaard et al. [2009], show a potential for using this scheme to detect changes for specific dominating frequencies 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 a fault.

4.1 Further Work

It would be relevant to test the proposed scheme for a more detailed model of the wind turbine gearbox and fault, which is operated in a realistic wind turbine simulation. Examples on such model and simulations can be found in Nejad et al. [2012] and Nejad and Moan [2012].

It would also be relevant to perform this scheme on multiple sensors and actuator signals, e.g. it is relevant to include the generator torque reference in the drive train resonance frequency case considered in this work, since this would during partial load suppress variations in the generator speed, and thereby dampen the gearbox forces.

5. CONCLUSION

In wind turbines changes, in the condition of a gearbox are most often monitored with a condition monitoring system, which is a system running in parallel with the control system, and typically also using additional often expensive sensor signals. In this paper an approach which can be applied to measurements already available in the control system is proposed. A band-pass filter based approach is proposed to detect changes in different frequencies describing a given system. It is applied to the generator speed measurement. The proposed scheme is designed for and simulated on a well-known benchmark model of wind turbine FDI and FTC. These simulations shows a potential for this proposed scheme for detecting changes in resonance frequencies, and thereby using such a scheme in the existing control system instead of an expensive additional condition monitoring system.

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