Stochastic simulation assessment of an automated vibration-based condition monitoring framework for wind turbine gearbox faults

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Abstract. Effectively monitoring the health of a wind turbine gearbox is a complex and often multidisciplinary endeavor. Recently, condition monitoring practices increasingly combine knowledge from fields like signal processing, machine learning, and mechanics. Such a diverse approach becomes necessary when dealing with the vast amount of data that is generated by the multitude of sensors that are typically placed on a wind turbine gearbox. Ideally, this approach needs to be automated and scalable as well, since it is unfeasible to perform all the necessary processing work manually in a continuous manner. This paper focuses on assessing the performance of such an automated processing framework for the case of gearbox fault detection using vibration measurements. A year of vibration measurements on a gearbox is simulated by stochastic variation of the operating conditions and the system behavior. A bearing fault is progressively introduced as to track the detection capabilities of the framework in such stochastic circumstances. The used signal model is based on previously obtained experience with experimental data sets originating from wind turbine gearboxes. The framework itself consists of multiple pre-processing steps where each step tries to deal with compensating for the external or unwanted influences such as speed variation or noise. Finally, multiple features are calculated on the pre-processed signals and trended as to see whether the processing scheme can provide any benefit compared to basic traditional statistical indicators. It is shown that the multi-step pre-processing approach is beneficial and robust for the advanced feature calculation and thus the early fault detection.

1. Introduction

Renewable energy is the world’s fastest-growing energy source and is projected to remain so for several years to come. Wind power in particular is growing at an average rate of 17% annually and is becoming increasingly popular all around the globe [1]. Predictions indicate there will be 800 GW of installed global wind power capacity by 2021 [2]. Given the increase in installed wind energy capacity, it becomes more and more essential to increase the reliability of wind turbine operation. Maintenance planning is an important aspect of upholding the continuity of wind energy production. Ideally, maintenance actions can be planned sufficiently on beforehand and preferably during a low wind and low electricity demand period. To attain such a maintenance scheme, it is imperative to be able to estimate the current condition of a wind turbine and to predict potential future failures.

The topic of condition monitoring has become a much discussed and investigated tool in the context of cost savings for wind turbines [2, 3]. Already more than a decade ago, the general...
consensus was that condition monitoring can lead to significant cost reductions for Operations & Maintenance (O&M) and electricity production. Thanks to continued research and further improvement in condition monitoring systems (CMS), the risks associated with investing in CMS have only decreased further. Therefore, a rapid rise in the amount of CMS installed in wind turbines can be observed over the past few years. One major issue that has come up due to this expansive condition monitoring strategy is the exponential growth of the quantity of measured data. Nowadays, it is almost standard to have multiple types of sensors installed in a wind turbine’s nacelle. All these sensors generate data that has to be processed and that ideally is put to good use. However, to truly take advantage of this vast quantity of available data, one needs to have access to an automated data processing framework. Manually processing and inspecting all that information is not feasible anymore and would require a whole team of experts.

In this paper such an automated processing framework for vibration measurements is proposed and assessed for its performance using stochastic simulations. The vibrations of a wind turbine gearbox contain a broad spectrum of mechanical signatures that can help in tracking the health of the system. The gearbox in the nacelle is on average a large contributor to downtime of a wind turbine. It contains gears and bearings which are one of the most sensitive components to failure. They require careful monitoring since they are prone to various premature failures. According to the statistics provided by the NREL gearbox reliability database, more than half (76%) of wind turbine gearbox failures are caused by bearings, with gear faults being the second major cause of failure (17.1%). Considering this information, it is desirable to have an effective condition monitoring program that is able to track the health of bearings and gears. However, the vibration signatures of these components are not always straightforward to track due to constant changes in the operating conditions of the system. Compensating for these varying operating conditions requires a analysis scheme that consists of multiple processing steps. The reason why this paper proposes the use of an extensive simulation scheme is to reduce the need for experimental data. Being able to optimize processing techniques for fault detection on a realistic simulation model allows for easier fine-tuning of methods and allows for a better performance afterwards on real data.

This paper illustrates the performance of conventional statistical feature tracking and more advanced feature tracking using the preprocessing approach proposed in [4] in combination with other filtering techniques for bearing fault detection in wind turbine gearboxes. The multi-step procedure proposed in [5] makes use of a combination of techniques such as angular resampling, automated cepstral editing, filtering based on kurtosis, and enveloping of the vibration signal. Recent developments in cyclostationary analysis [6, 7] of vibration signals, such as the cyclic spectral coherence, show promising results and thus are investigated further in this paper to examine whether they provide a valuable addition to the processing scheme.

2. Methodology

2.1. Signal model

A year of single-channel accelerometer vibration measurements is simulated using the following signal model:

\[ x(t) = d(t) + q(t) + n(t) + b(t) \]  \hspace{1cm} (1)

with \( x(t), d(t), q(t), n(t) \) and \( b(t) \) being respectively the resulting vibration signal, the deterministic harmonic components, the random contributions of gears, the noise, and the bearing fault signal. This type of additive signal model leads to realistic vibration signals based on the expertise gained analyzing experimental gearbox vibration data sets in the past, e.g. the NREL wind turbine gearbox condition monitoring round robin study [5, 8].

The deterministic components represent the shaft and gear vibrations which typically show up as discrete peaks in the frequency spectrum. They are simulated using following signal model:
\[ d(t) = \sum_{n=1}^{N} (A(t)\sin(2\pi f(t)t)) \ast h_d(t) \]  

(2)

where \( N \) is the number of harmonics, \( A(t) \) is the time-dependent amplitude, \( f(t) \) is the time-dependent frequency, \( h_d(t) \) is the system impulse response to encompass the transmission path of excitation to accelerometer, and \( t \) is simply the time vector.

The random contributions of gears \( q(t) \) are modeled as the product of Gaussian noise modulated by the fundamental frequency of that gear, which is speed-dependent. The convolution of the gear signal components with the transmission path response is done in the frequency domain by using the transfer function for a standard Single-Degree of Freedom (SDOF) system:

\[ H(s) = K \frac{s}{(s - p_1)(s - \bar{p}_1)} \]  

(3)

with \( s = j\omega \) the complex frequency, \( K \) the transfer gain, \( p_1 \) the first pole, and \( \bar{p}_1 \) its conjugate pole. Afterward, \( d(t) \) and \( q(t) \) are obtained by transforming the result back to the time domain using the inverse Fourier transform. The SDOF transfer function can be adapted for Multiple Degree of Freedom systems too, but this is not elaborated here. The noise \( n(t) \) is sampled using a normal Gaussian distribution.

The bearing signal is simulated as a train of Dirac impulses \( \delta_{T_i}(t) \) convoluted with an exponentially decaying sine whose frequency corresponds to the bearing’s resonance frequency \( f_n \):

\[ b(t) = (e^{-t/\tau}\cos(2\pi f_n t)) \ast \delta_{T_i}(t) \]  

(4)

with \( \tau \) being the exponential time constant. The fundamental period of the Dirac impulses can correspond to a typical Ball Pass Frequency of the Outer ring (BPFO) or Inner ring (BPFI). This impulse train can be amplitude modulated as well, depending on the type of fault one wishes to simulate. Also the jitter on the period of the Dirac impulses varies randomly as defined in [9]:

\[ \Delta T_i = T_{i+1} - T_i \]  

(5)

2.2. Stochastic simulation

A year of daily vibration measurements is simulated by generating multiple one minute-long measurements for every day of continuous vibration data with fluctuating speed.

Introducing random perturbations of the amplitudes of the individual components and speed variation enables the simulation to test the sensitivities of the different techniques and features to different scenarios. As such the gains for the resonances of the random contributions of the gears are normally distributed as can be seen in Fig. 1a. The jitter or slip on the fundamental fault period of the bearing signal and the damping of the bearing resonance frequency are as well normally distributed, as shown in Fig. 1b. The normal distribution is used since its properties are well-known and because there are a lot of unknown effects that can influence parameters like e.g. jitter. The central limit theorem establishes that when independent random variables are added, their sum tends toward a normal distribution.

For the load bin limits, simple uniformly spaced limits are chosen, however, in reality the power bin limits are usually based on the wind distribution during a full year. Figure 2a displays the signal-to-noise ratio (SNR) evolution (in dB) of the bearing fault based on the cumulative Weibull distribution. The Weibull distribution is one of the most widely used lifetime distributions in reliability engineering. Even though the choice of the exact evolution is arbitrary, the shape corresponds to a typical degradation trend of a bearing fault. This CDF can be used to compare the trending of the developed features.
The fluctuating speed profiles that are used as inputs for the generation of the frequency varying harmonics and bearing signal, are generated by a random walk constrained between a minimum and maximum speed. In order to ensure mechanical continuity, there is an additional constraint by defining a maximum possible speed change (in $Hz/s$) and by taking into account weighted previously generated speeds. This ensures that the generated speed profiles are smooth and realistic as can be seen in the spectrogram of a simulated signal in Fig. 2b.

Finally, the individual components are also amplitude modulated based on the generated rotation speed profile. Since higher vibration levels are typically associated with higher rotation speeds and higher power outputs of a wind turbine, it is only logical to ensure that this modulation is proportional to the instantaneous speed. Therefore, a modulation profile $A_m(t)$ is calculated based on the speed profile of the high-speed shaft $f_{HSS}(t)$ but the actual amplitude modulation is distributed normally around the directly calculated value.

$$A_m(t) \propto f_{HSS}(t)$$

Making the vibration amplitude dependent on the instantaneous speed allows for binning of the generated vibration signals based on their overall speed and RMS levels. This practice of...
Figure 3: Quasi-uniform distributions for the load bins and rotation speeds for the simulated year of data.

Figure 4: Overview of the proposed framework.

2.3. Processing techniques
The automated processing scheme used on the generated data consists of a combination of techniques, as described in [4, 5, 10]. The methods are briefly summarized here and an overview of the proposed framework is shown in Fig.4.

2.3.1. Speed estimation
Speed variation of the rotor of a wind turbine and connected shafts and gears is inherent to the operating conditions of a wind turbine. This requires an effective method to compensate for the speed fluctuations. In order to effectuate this, one can install angle encoders or tachometers on one of the shafts to measure the shaft speed directly. However, this is costly, since you need measurement equipment which requires installation and time. The instantaneous angular speed (IAS) of the relevant shaft is estimated directly from the vibration signal in this paper. Since the speed of a typical high-speed shaft in a wind turbine gearbox varies anywhere between 0 and 30 Hz, it is difficult to use phase demodulation methods for every generated signal. This is because these techniques typically assume some knowledge about the minimum and maximum speed in the vibration signal as to define a proper band-pass filter around a speed-related harmonic. In practice, a speed value is often available through SCADA data, but this is usually an average value for the whole vibration signal. Therefore, a method based on the
The harmonic structure present in the spectrogram is employed for the IAS estimation in this paper, namely the multi-order probabilistic approach (MOPA) [10, 11]. This method uses the available kinematic information about the system and does not require to associate one harmonic with the correct order. Knowledge of the gear ratios is sufficient to extract an accurate estimation of the IAS from the vibration signal.

The general idea behind MOPA is based on regarding the instantaneous spectrum (which can be obtained through a short time Fourier transform) of the vibration signal as a probability density function (pdf) of the IAS. If the spectrum has a high amplitude at frequency $f$, there is a high probability that the shaft frequency is equal to $f/H_i$ with $H_i$ being the excitation order or for the cases described below the gear ratios. It is important to define a range for the IAS in which the user expects the IAS to reside. To improve the IAS estimation and utilize more of the information potential of the spectrum, one has to include more than just one pdf based on one gear ratio or meshing order. Afterward these different pdfs can be combined together in one pdf by multiplication. By assuming that the actual mechanical speed is continuous and limited in its acceleration, one can smooth the extracted most likely speed profile from the pdfs. This speed can then be converted to an approximation of the instantaneous phase. Using the phase, the signal can be resampled to the angular domain with an equal angular spacing for the signal samples. Spectral smearing of shaft-related peaks is greatly reduced afterward, making the interpretation easier. The interested reader is referred to [10, 11] for more details about the MOPA method.

2.3.2. Deterministic component removal

The next processing step entails the reduction of the deterministic content present in the vibration signal. Since a bearing signal is considered stochastic due to the random jitter on its fundamental fault period, it is unaffected by such a reduction. The method used for this purpose is the automated cepstrum editing procedure [4]. The vibration signal is transformed to the cepstral domain by taking the forward Fourier transform of the signal, then taking the logarithm of the absolute value, and finally inverse Fourier transforming it. In the cepstrum the harmonics of a shaft or gear are grouped in so-called rahmonics (cepstral terminology is similar to its spectral counterparts, apart from the switching of the first three letters). These rahmonics are then liftered out using a comb lifter that is automatically defined using a peak detection algorithm. Transforming the liftered cepstrum back to the time domain results in a vibration signal that consists mainly out of stochastic content. For more info about the cepstrum editing procedure, the reader is referred to [4].

2.3.3. Filtering

The final signal-altering processing step in the original procedure is band-pass filtering based on kurtosis values or spectral coherence values of different frequency bands. The kurtogram [12] is used for finding the maximum kurtosis frequency band. Often the signal of interest, i.e. the bearing fault signature, is amplified by a resonance of the bearing or its housing. Therefore, using a band-pass filter around this resonance frequency band amplifies the fault signature and reduces unwanted noise and/or other content. Kurtosis is utilized since it is a measure for the impulsiveness of a signal, and fault impacts are generally expected to be impulsive. Recently, the development of a fast algorithm for the calculation of the cyclic spectral correlation and coherence has opened up the way for finding the optimal filter band based on the coherence values in the generated 2D map. The cyclic spectral coherence is defined as:

$$\gamma(\alpha, f) = \frac{S_{xx}(\alpha, f)}{\sqrt{S_{xx}(0, f)S_{xx}(0, f - \alpha)}}$$
with $S_{xx}(\alpha, f)$ being the cyclic spectral correlation at cyclic frequency $\alpha$ and $f$ the carrier frequency. Finding the carrier frequency band that exhibits the strongest modulation at a certain cyclic frequency can now be extracted by looking at the adjacent cyclic frequency bins corresponding to the fault frequency.

### 2.4. Feature calculation
To detect potential changes in the gearbox vibration behavior, a number of features are defined on the preprocessed signals. A combination of statistical and spectral features are calculated for each generated signal.

#### 2.4.1. Statistical features
There are a lot of possible statistical features that can serve as condition indicators for the gearbox [13]. In this paper the investigated fault is a localized bearing fault on the outer race, thus mainly the short impacts are expected to influence the statistical trending of the signal. A set of features that can detect this deviation from Gaussian behavior are employed for the trending visualization. In total four features are examined:

- RMS: This gives an indication of the overall energy level present, $x_{RMS} = \sqrt{\frac{1}{N} \sum_{n} x[n]^2}$.

- Crest factor: Max peak value over RMS, $CF = \frac{|x_{\text{peak}}|}{x_{RMS}}$.

- Kurtosis: A measure for the dispersion of the signal’s distribution, $\kappa = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^4 - 3$.

- Moors kurtosis: An alternative implementation of kurtosis based on quantiles [14], $\kappa_{\text{Moors}} = \frac{(E_7 - E_5) + (E_3 - E_1)}{E_6 - E_2}$.

#### 2.5. Spectral features
Analyzing the spectral content of the signal can allow for more accurate detection of potential faults. Usually, the fault frequencies are known a-priori enabling a more specific search for level increases at that frequency. For gear faults, the autopower spectrum is typically examined for increases in the energy level of the fundamental gear frequencies or in the number of sidebands around the meshing frequencies. However, since the investigated fault in this work is a bearing fault, the squared envelope spectrum is employed since it is less sensitive to the random slippage of the bearing which causes pseudo-cyclostationary behavior of the fault signature [6]. A spectral feature is calculated by exploiting the max amplitudes or energy present in a very small frequency band around the theoretical fault frequency in the normalized envelope spectrum. These amplitudes are then tracked in time to see if they increase corresponding to a fault emerging.

### 3. Results & Discussion
Statistical and envelope spectrum features are calculated on every generated signal after speed estimation and angular resampling. In order to compare some of the differences between the various processed signals and to keep the amount of figures limited, only the key figures to illustrate the main findings are presented.

Figure 5a shows the RMS trend of raw data without any preprocessing as to illustrate the differences in RMS levels based on the load bins. For the other figures the features are normalized between 0 and 1 to simplify the potential thresholding. Figure 5b & 5c show the difference in feature evolution that can be obtained by doing filtering. The former figure shows the result after high-pass filtering with a cut-off frequency at 1 kHz and the latter figure after a low-pass filter using the same cut-off. Since the bearing resonance is located in a high-frequency band, only noise is obtained for the latter figure as expected.
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(a) RMS values of the raw, non-preprocessed data.
(b) Moors kurtosis after high-pass filter.
(c) Moors kurtosis after low-pass filter.

Figure 5: Statistical feature trends.

(a) Envelope feature on raw, non-preprocessed data.
(b) Envelope feature and RMS trend on data after CEP.
(c) Envelope feature and kurtosis trend on data after CEP.

Figure 6: Comparison of envelope feature and statistical feature trends.

Figure 6a displays the normalized envelope feature on the raw data without any preprocessing. Clearly, the feature is unable to track any increase indicating a fault because it is totally skewed by the presence of all the non-fault related signal content. This erroneous feature trending is due to the lack of deterministic component removal. Without it, discrete frequencies show up in the tracking band used for the calculation of the feature, which is a typical occurrence in experimental data. Therefore, the use of the cepstrum editing procedure (CEP) is very helpful in removing this negative influence. The result of the CEP processed data is shown in Fig. 6b. The trends shown is after doing a moving average with a window size of one week for all measured load bins. Thanks to the CEP method, the envelope feature is not anymore dominated by the discrete content, but clearly evidences the rise of a fault over time. Additionally, it manages to detect the fault much earlier than simple statistical measures. For comparison, the RMS in Fig. 6b and the kurtosis in Fig. 6c is displayed. Setting an arbitrary threshold at 0.3 allows comparing the SNR detection levels. It can be seen that the RMS is significantly slower (around +3 dB) than the envelope feature (-12 dB) in detecting the fault. The kurtosis, which is better suited at detecting impulsive behavior, is an improvement compared to the RMS but still falls short (-4 dB) compared to the envelope feature. This indicates that detailed tracking of individual fault frequencies using multiple preprocessing steps does provide an added benefit in detecting potential faults compared to simple statistical measures.

In order to analyze the performance of the filtering pre-processing step for the envelope feature, the filter band determination and influence on the feature is compared. Figure 7 shows the pass-band cut-off frequencies as determined by the cyclic spectral coherence maps for the case without (left) and with (right) cepstral editing of the signal. Ideally, the pass-band should be around 1.8 kHz since the simulation used this value for the bearing’s resonance. Again the CEP method seems to improve the convergence and stability of the pass-band towards this frequency zone compared to the situation without. This indicates that also the search for the
optimal demodulation band is influenced by the deterministic content and can thus be improved by removing it.

Finally, the actual difference in the envelope feature trends for the case with and without band-pass filtering after CEP is compared in Fig. 8. In this case, only a small improvement is made by the additional band-pass filter (~3 dB difference) but experience in experimental cases learns that this difference can sometimes be substantially greater. Nevertheless, the main takeaway is that decreasing the residual noise by finding an optimal demodulation band after CEP is also a recommended practice when looking for bearing faults.

4. Conclusion

In this paper the advantages of using a multi-step processing approach using current state-of-the-art techniques are highlighted using simulated vibration data. A simulation model is proposed based on the standard mechanical responses measured by accelerometers. The simulated signal of interest is a bearing fault that progressively develops. This fault signal and its evolution is used to compare the different processing steps and the performance of different features. A year of vibration data is simulated by stochastically varying the input parameters of the different signal parts. The results show that trying to remove as much non-fault related signal content as possible by different processing techniques can lead to significant improvements in the SNR detection threshold.
While the used signal model tries to capture the main influences experienced in experimental vibration measurements, it is not complete and can be extended in future work. In reality, there might be random impulses or impulsive noise from external factors, which would skew statistical features such as the kurtosis. The harmonic pattern used for the speed estimation might also become less dominant for different operating regimes making the speed harder to track. The actual fault might not exhibit impulsive behavior which negatively influences techniques such as the kurtogram. The energy level of the fault also depends on the operating conditions. As such it might be influenced by varying temperature, oil film thickness, load and speed. The model can also be generalized for other bearing fault types and gear faults. All these factors are potential improvements for the model that can spark development of new techniques to address these challenging influences.

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