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Automated wind turbine gearbox bearing diagnosis algorithm based on vibration data analysis and signal pre-whitening

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Abstract

In this paper an automated wind turbine gearbox bearing diagnosis algorithm is presented. The algorithm is based on most recent research results for separating discrete (gear) from random (bearing) frequency components using Cepstral Editing Procedure (CEP) based signal Pre-Whitening (PW). The proposed automated procedure builds up on the semi-automated procedure described by Sawalhi et al. in 2007. The procedure is updated with regards to the most recent achievements made concerning signal separation and extended with a frequency content identifier and rule based diagnosis to fully automate the diagnosis process. Furthermore, this paper gives a selection of important statements made in literature throughout the last decade to summarize the algorithms used and focus on the most important issues. Each of the involved processing steps is discussed with respect to its effectiveness based on real data.

The proposed procedure is applied to wind turbine data coming from seventeen wind turbines of the 2 MW class, for which vibration data are available containing both healthy and damaged states. Three application examples are given, where the automated procedure successfully diagnosed High Speed Shaft (HSS) bearing damages in the data sets.

Nomenclature

<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
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<tbody>
<tr>
<td>AIC</td>
<td>Akaike entropy based information criterion</td>
</tr>
<tr>
<td>ANC</td>
<td>Adaptive noise cancellation</td>
</tr>
<tr>
<td>AR</td>
<td>Autoregressive</td>
</tr>
<tr>
<td>BPFI</td>
<td>Ball pass frequency inner race</td>
</tr>
<tr>
<td>BPFO</td>
<td>Ball pass frequency outer race</td>
</tr>
<tr>
<td>BSF</td>
<td>Ball spin frequency</td>
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<tr>
<td>CEP</td>
<td>Cepstral editing procedure</td>
</tr>
<tr>
<td>DRS</td>
<td>Discrete/random separation</td>
</tr>
<tr>
<td>FCI</td>
<td>Frequency content identifier</td>
</tr>
<tr>
<td>FL</td>
<td>Fuzzy logic</td>
</tr>
<tr>
<td>FFT</td>
<td>Fast Fourier transformation</td>
</tr>
<tr>
<td>FTF</td>
<td>Fundamental train frequency</td>
</tr>
<tr>
<td>FRF</td>
<td>Frequency response function</td>
</tr>
<tr>
<td>HSS</td>
<td>High speed shaft</td>
</tr>
<tr>
<td>IMS</td>
<td>Intermediate speed shaft</td>
</tr>
<tr>
<td>LP</td>
<td>Linear prediction</td>
</tr>
<tr>
<td>MED</td>
<td>Minimum entropy deconvolution</td>
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<tr>
<td>MF</td>
<td>Membership function</td>
</tr>
<tr>
<td>OT</td>
<td>Order tracking</td>
</tr>
<tr>
<td>PSD</td>
<td>Power spectral density</td>
</tr>
<tr>
<td>PW</td>
<td>Pre-whitening</td>
</tr>
<tr>
<td>RMS</td>
<td>Root mean squared</td>
</tr>
<tr>
<td>RPM</td>
<td>Revolutions per minute</td>
</tr>
</tbody>
</table>
1 Introduction

Wind turbine condition monitoring is of increasing importance as the wind turbines are built more and more in remote locations. A special challenge is the placement of wind turbines at sea (offshore). Here the energy yield is usually much higher than on land (onshore), but special (expensive) logistics is required for construction, service & maintenance and decommissioning. Although the higher energy yield is desirable, the cost of energy is still very high in comparison to onshore turbines. From a society perspective a sharp drop in cost of energy must be achieved in the coming years. Next to the usually high construction costs of wind power plants offshore, unexpected downtime due to component failure bears large potential for cost reduction, if faults can be foreseen.

Difficulties with effective monitoring of wind turbines arise from the number installed units, which is increasing rapidly. A 2 GW conventional power station may consist of four 500 MW units, which can be monitored constantly in a cost effective manner [1], but several hundred 3 MW offshore wind turbines would be required to achieve this installed capacity, each in need of monitoring. Hence, a high degree of automation is required to reduce monitoring costs.

Due to their crucial role the components main bearing, gearbox and generator are usually monitored via vibration measurements at offshore turbines. Vibration analysis is by far the most prevalent method for machine condition monitoring [2]. However, other information sources can be considered such as Supervisory Control And Data Acquisition (SCADA) data, e.g. temperatures, currents, voltages, power output, etc. in case no vibration measurements are available or to enhance diagnostics [3]. In general, operators should consider all information at hand in order to schedule their service & maintenance and achieve their cost reduction targets. In this research the focus lies on automated wind turbine gearbox bearing diagnosis based on vibration data analysis using signal Pre-Whitening (PW).

A large part of condition monitoring consists of separating the mixed signals at each measurement point into components coming from individual sources [2]. Here the task is to separate the deterministic (e.g. originating from gears) from the random and cyclostationary (e.g. originating from rolling element bearings) components in the signal. Signal PW is a comparably new method and can be used for this separation.


In the same year Sawalhi et al. [5] studied the enhancement of fault detection and diagnosis in rolling element bearings using Minimum Entropy Deconvolution (MED) combined with Spectral Kurtosis (SK). This corresponds to step III and IV of the semi-automated procedure. The results show that using the MED technique dramatically sharpens the pulses originating from the impacts of the balls with the spall and increases the kurtosis value to a level that reflects the severity of the fault [5]. In this work a good match between the fault size and the Spectral Kurtosis (SK) value was found, when MED is applied to enhance the signals impulsiveness. The effect of MED as pre-process is further studied and a significant increase in diagnostic information found by Barszcz and Sawalhi [6] in 2012. These findings are further discussed in this research for the case of wind turbine gearbox bearings.

Using the same three test cases as described by Sawalhi and Randall [4], the proposed semi-automated method is summarized and further developed in 2011 by Randall and Antoni [7] who presented a tutorial for rolling element bearing diagnostics. In this tutorial different processing techniques for discrete and random separation are summarized (corresponding to step II of the semi-automated procedure), which are: Linear Prediction (LP), Adaptive Noise Cancellation (ANC), Self Adaptive Noise Cancellation (SANC), Discrete/Random Separation (DRS) and Time Synchronous Averaging (TSA).

In the LP approach an autoregressive linear model built with past values is used to model the current value. Such a model can only represent the deterministic part of the signal. The random part is given by the residual. However, the model order (number of previous values considered) is generally unknown, which requires some search for an optimum order.
The ANC algorithm requires a simultaneously measured coherent signal from a different location, for adjustment of the adaptive filter. Such synchronous data recordings are not always available for operators. In this case the SANC algorithm can be used, in which a delay of the input signal is taken for adoption of the adaptive filters. Antoni and Randall [8] show however, that the same effect could be achieved, but much more efficiently using DRS.

In DRS the efficient Fast Fourier Transformation (FFT) is used. The transfer function between the primary signal and its delayed version (representing only the deterministic part) is calculated in the same way as the H1 Frequency Response Function (FRF) [9]. This has a value near one at discrete frequencies and near zero at other frequencies [9]. This property is used to filter the signal by fast convolution in the frequency domain. However, it does give a notch filter of fixed width that can have detrimental effects at high and low frequencies [9]. At low frequencies (low harmonics of the bearing frequencies if they exist), the bearing harmonics may still be within the bandwidth of the comb filter and they may be treated as discrete frequencies [9]. At high frequencies, some random modulation of the discrete frequency components may be left in the form of a narrow-band noise and not completely removed [9].

In TSA specific discrete frequency components can be removed by averaging together a series of signal segments each corresponding to one period of a synchronising signal [7]. The drawback is that it requires separate operation for every different harmonic in the signal including a separate resampling in each case so as to give a specified integer number of samples per period [7].

Further research was carried out by Sawalhi and Randall with regards to the separation of the discrete and random components (corresponding to step II of the semi-automated procedure). In 2011 a method based on cepstrum editing is proposed by Sawalhi and Randall [10] to remove selected components from a time signal. The cepstrum collects uniformly spaced harmonics and sideband families such as arise from gear mesh harmonics and modulations of these by the gear rotational speeds [10]. For removal of undesired components, the real cepstrum is computed, selected components (quefrencies) are set to zero and the result inverse transformed back to the initial time domain.

Also in 2011 this procedure was given the name Cepstral Editing Procedure (CEP) by Randall and Sawalhi [9]. Further application examples are given and a performance comparison to the traditionally used TSA and DRS method is made. It is pointed out that this method has a number of advantages compared with alternative methods. Unlike TSA and DRS, it can remove sidebands as well as harmonics and also narrow-band noise peaks rather than just discrete frequency harmonics [9].

Sawalhi and Randall [11] presented an even more drastic editing in the cepstrum, by setting all components to zero except that at zero quefrency.

In 2012 Niaoqing et al. [12] tested the method using test rig data and inner ring faults with different fault sizes. They used a Stochastic Resonance Model (SRM) to enhance the Envelope spectrum. The method proved to be robust and suitable for the application with more vibration interference. However, the stochastic resonance method requires tuning of the system parameters, which can be difficult in practical applications, involving a large number of units to be monitored. In this work, also the SK value as fault size indicator (first used by Dyer and Stewart [13]) was examined. Results show that the SK after signal processing, contains some fluctuations, but in general is sensible to the fault size. The findings confirm the findings from Sawalhi et al. [5], who conclude that the SK value can be used as fault size indicator after impulsiveness enhancement. In the case of Sawalhi et al. this was achieved by MED in contrast to the SRM algorithm used by Niaoqing et al. [12].

The main original contribution of this paper lies in the further evaluation of signal PW using the CEP in combination with the SK value as a fault size indicator for wind turbine gearbox bearings. Furthermore an automated method for bearing diagnosis is presented using the achievements made by Sawalhi and Randall, as well as own research results. In this respect the semi-automated method as proposed by Sawalhi and Randall is updated with regards to the most recent developments and further developed with regards to automated envelope spectra diagnosis as it is required for wind turbine gearbox bearing diagnosis.

For this purpose data from seventeen operating wind turbines are available, both in fault free states as well as in states where the fault signatures indicate bearing damage. Using these data the effectiveness of the automated procedure is shown. Additionally the use of the SK value as fault size indicator is discussed using the available data and faults.

In this paper many statements are collected from related papers in this research area in order to summarize the most important conclusions and findings necessary for the understanding of the automated procedure. These statements are consistently cited, allowing finding more information about the specific topics of interest in the original source.
In section 2 of this paper, the available data sets are introduced. In section 3 the automated procedure for
bearing fault diagnosis is described in detail with a focus on the individual processing steps involved.
Furthermore the efficiency and the effect the involved pre-processes are evaluated. Three application examples
are given in section 4. Results and Discussion are made in section 5 and necessary future research discussed in
section 6. Finally conclusions are drawn in section 7.

2 Data Set Descriptions

The data sets available come from seventeen Wind Turbine Generators (WTGs) of the 2 MW class, where
vibration measurements are recorded cyclically every second week. The gearbox is equipped with three
accelerometers (type: Gram&Juhl GJ1200M8), with one sensor placed at the planetary stage, one in the Inter
Mediate Shaft (IMS) region and one in the High Speed Shaft (HSS) region (see Figure 1).

The cyclic measurements available for research are sampled with the settings as summarized in Table 1.

<table>
<thead>
<tr>
<th>Name</th>
<th>Sampling freq.</th>
<th>Sample lengths</th>
<th>Number of samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>2.59 kHz</td>
<td>12.51 s</td>
<td>32000</td>
</tr>
<tr>
<td>#2</td>
<td>15.36 kHz</td>
<td>4.17 s</td>
<td>64100</td>
</tr>
<tr>
<td>#3</td>
<td>41.67 kHz</td>
<td>1.54s</td>
<td>64100</td>
</tr>
</tbody>
</table>

Around 32 measurements per turbine, sensor and sampling frequency are available from the past 1.5 years of
operation. Thus in total around 1632 recordings are available. The recording system is set up to only record,
when the turbine is operating under full load to allow comparison of measurements at different times (causing
the slight differences in number of measurements available for each turbine).

![Wind turbine schematic](image1)

Due to their longer recording times of measurement #1 and #2, these time series are given by the system as
tracked time series. By tracking, speed variations are encountered by resampling the signal synchronous to the
speed of the shaft. Here these data are resampled to the nominal speed. For #3 resampling is not necessary as the
recording length is short.

3 Automated procedure for bearing fault detection

The semi-automated procedure presented by Sawalhi and Randall [4] in 2007 consists of a five step strategy
to arrive at the envelope spectrum to be interpreted for fault signatures. Due to recent advances made by the
different researchers, this procedure requires an update with regards to the algorithms used and the signal
processing steps involved.

The following update is proposed to fully automate diagnosis:

1. Order tracking – Remove speed fluctuations (optional)
2. Pre-Whitening (PW) based on CEP - Signal decomposition
3. Minimum Entropy Deconvolution (MED) – Remove smearing effect of the signal transfer path (optional)
4. Spectral Kurtosis (SK) – Determine optimum band for filtering and demodulation (optional)
5. Envelope analysis – Determine fault characteristic frequencies
6. Frequency content identification – Identify frequency components and modulations

3.1 Order Tracking

Order Tracking (OT) means resampling the time series according to the angular position of the shaft. It is useful for variable speed machines in order to remove the rotational speed related frequency fluctuations. For OT generally a tacho signal or a once per revolution trigger is required that indicates the shafts angular position. In case no tacho signal is available Bonnardot and Randall [14] found it to be possible to extract the instantaneous speed information by phase demodulation of a number of gear mesh frequencies.

When applying digital or analog OT, frequency components which are independent of the shaft speed such as natural frequencies will shift and consequently their amplitude in the spectra will decrease.

For the automated bearing diagnosis algorithm OT is recommended, but not necessarily mandatory, if the speed variations are limited and the CEP is used [9].

3.2 Pre-whitening

Decomposition of vibration signals into deterministic and nondeterministic parts is recommended for machinery diagnostics as it can be used for the separation of signals emitted from different machinery elements [15]. One of the major sources of masking the relatively weak bearing signals is discrete frequency “noise” from gears, since such signals are usually quite strong, even in the absence of gear faults [7]. Even in machines other than gearboxes, there will usually be strong discrete frequency components that may contaminate frequency bands where the bearing signal is otherwise dominant [7]. It is usually advantageous therefore to remove such frequency noise before proceeding with bearing diagnostic analysis [7].

The fundamental idea of separation is based on the assumption that gear related vibrations are phase locked to the rotational speed, i.e. after order tracking they will appear as discrete frequencies in the spectrum. However, bearings virtually always have some slip for the following reason: the load angle \( \phi \) from the radial plane varies with the position of each rolling element in the bearing as the ratio of local radial to axial load changes, and thus each rolling element has a different effective rolling diameter and is trying to roll at a different speed [2]. The cage ensures that the mean speed of all rolling elements is the same, by causing some random slip [2]. This slip is typically of the order of 1-2\%, both as deviation from the calculated value and as a random variation around the mean frequency [2]. The slip, while small, does give a fundamental change in character of the signal, and is the reason why envelope analysis extracts diagnostic information not available from frequency analysis of the raw signal [2].

The separation method here is signal PW for the reasons given in the introduction.

Basic element of the signal PW procedure is the real cepstrum. The cepstrum has a number of versions and definitions, but all can be interpreted as a “spectrum of a log spectrum” [9]. The complex cepstrum reads:

\[
\mathcal{C}(\tau) = \Im^{-1}\log(\Im[x(t)])
\]

\( \mathcal{C}(\tau) \) is the complex cepstrum; \( \Im^{-1} \) is the inverse Fourier transform; \( \Im \) is the Fourier transform; \( x(t) \) is the time signal.

In order to arrive at the real cepstrum, only the real part of the complex cepstrum in considered. Information about the history of the cepstrum is summarized by Oppenheim and Schafer [16]. Additional general information in the context of vibration analysis is given by Randall and Hee [17] and in the context of cepstrum editing by Randall and Sawalhi [9].

The procedure to achieve signal PW is depicted in Figure 2. In order to proceed from the real cepstrum to the edited cepstrum, all quefrencies are set to zero, apart from the first, which is determining the mean value of the log spectrum and thus giving appropriate scaling of the resulting signals [9].

After editing, the edited log amplitude spectrum is exponentiated and recombined with the original phase spectrum to form the complex log spectrum [9]. When processing the signals with Matlab® the required polar to cartesian coordinate transformation can be done with the pol2cart function using the phase and the exponentiated edited log amplitude spectrum as input. The output can be interpreted as the real and imaginary part of the complex spectrum.
Since the procedure is based on the efficient Fast Fourier Transformation (FFT), the whole editing procedure is very fast to calculate and can be fully automated without the need of parameter optimization. The real cepstrum before editing of #3, measurement 29 at WTG 02 is shown in Figure 3.

![Figure 2: PW based on CEP schematic](image)

The HSS mesh frequency as well as the HSS speed can be clearly identified, together with other deterministic components of unknown source. The effect of PW on the corresponding time series as well as the Root Mean Squared (RMS) spectrum is illustrated in Figure 4.

![Figure 1: Real cepstrum before editing (#3, HSS, meas. 31, WTG 02)](image)
Prior PW, the raw time series (a) was contaminated with deterministic components causing cyclical fluctuations. The PW procedure removed the dominance of these components and reduced them to the noise level (b). The RMS spectrum before PW contained dominating frequency components and frequency bands containing more energy (c). After PW the RMS spectrum has the same level for all frequencies (d).

### 3.3 Minimum Entropy Deconvolution

The Minimum Entropy Deconvolution (MED) method is designed to reduce the spread of impulse response functions, to obtain signals closer to the original impulses that gave rise to them [7]. It was first proposed by Wiggins [18] to sharpen the reflections from different subterranean layers in seismic analysis [7]. The basic idea is to find an inverse filter that counteracts the effect of the transmission path, by assuming that the original excitation was impulsive, and thus having high kurtosis [7].

\[
K \text{ is the Kurtosis; } \sigma \text{ is the standard deviation; } N \text{ is the number of data points; } \bar{Y} \text{ is the mean.}
\]

The name MED derives from the fact that increasing entropy corresponds to increasing disorder, whereas impulsive signals are very structured, requiring all significant frequency components to have zero phase simultaneously at the time of each impulse [7]. Thus, minimizing the entropy maximizes the structure of the signal, and this corresponds to maximizing the kurtosis of the inverse filter output (corresponding to the original input to the system) [7]. The method might just as well be called maximum kurtosis deconvolution because the criterion used to optimize the coefficients of the inverse filter is maximization of the kurtosis (impulsiveness) of the inverse filter output [7]. The MED method was applied to bearing diagnostics by Sawalhi, Randall and H. Endo [5].

Using the MED method, the kurtosis can be increased, if impulses are present. Note that in case the discrete frequencies are not removed prior the MED, they will also be amplified.

The Matlab® code used for performing the MED was developed by G.McDonald [19] based on the algorithm proposed by Wiggins [18].

A critical choice using MED is the filter size. If the filter size is chosen too large, start-up and ending transients may occur, dominating the minimization method and leading to a loss of diagnostic information. The effect of the filter size on the time series is illustrated in Figure 5, for a time series with start-up and ending transients for large filter size (a) and medium filter size (b). For a low filter size (c) reasonable impulse amplification is achieved without transients. (d) shows the Time Series (TS) after PW without MED.

This is in contrast to the findings of Barszcz and Sawalhi [6] who found very large filters (filter size > 2000) to perform better in case of their surveyed wind turbine gearbox bearing inner ring damage.
Their finding is based on the kurtosis values achieved, apparently using a TS where MED does not lead to start-up and end transients. For blind analysis the filter size used should give reasonable results for all TS processed.
Figure 6 shows the effect of the filter size for a time series without transients. It is seen that choosing a filter size of six already gives a reasonable impulse amplification and increase in kurtosis, which is why this filter size is used throughout the research as a stable compromise.

Figure 7 illustrates the kurtosis as a function of the filter size for the TS with and without transients.

The kurtosis for the TS without transients occurring converges with increasing filter size, whereas the kurtosis values with transients stepwise increases. The transients are believed to be caused by the first and the last value in the time series. In case of their occurrence, these values may be modified or deleted to avoid the transients and obtain proper results. However, further root cause investigation is required, which is outside the scope of this paper.

For the proposed automated procedure, applying MED is not necessarily required, since after successful PW the impulsiveness of the TS is already enhanced, building a good basis for a consecutive envelope analysis. Figure 8 shows the effect of MED of the PW signal in the time domain.

In the raw time series (a) the individual impulses are visible, but they are embedded in the cyclic variations of the deterministic components. Signal PW removes the deterministic components, but leaves a high noise level embedding the impulses (b). Applying MED enhances the impulses and gives the clearest signal (c). The kurtosis increased from 4.5 after PW to 8.0 after PW & MED. After introduction of the envelope spectrum the influence of MED in the frequency domain will be discussed.

3.4 Spectral Kurtosis

Spectral kurtosis (SK) provides a means of determining which frequency bands contain a signal of maximum impulsivity [7]. The definition is given by equation 3.

\[
SK = \frac{\langle H^4(t,f) \rangle}{\langle H^2(t,f) \rangle^2} - 2
\]  

(3)

SK is the spectral kurtosis, \( H(t, f) \) is the Amplitude envelope function.

Figure 6: The time series a) no processing, b) PW, c) PW & MED (#3, HSS, meas. 31, WTG 02)
It was first used in the 1980s for detecting impulsive events in sonar signals [20]. It was based on the Short Time Fourier Transform (STFT) and gave a measure of the impulsiveness of a signal as a function of frequency [7]. The spectral kurtosis extends the concept of the kurtosis, which is a global value, to that of a function of frequency that indicates how the impulsiveness of a signal, if any, is distributed in the frequency domain [7]. The principle is analogous in all respects to the Power Spectral Density (PSD) which decomposes the power of a signal vs frequency, except that fourth-order statistics are used instead of second order [7]. This makes the spectral kurtosis a powerful tool for detecting the presence of transients in a signal, even when they are buried in strong additive noise, by indicating in which frequency bands these take place [7]. However, the optimal window length used for the STFT is generally unknown. To obtain a maximum value of kurtosis, the window must be shorter than the spacing between the pulses but longer than the individual pulses [2]. The center frequency and bandwidth (window length and center) is thus varied continuously from low to high values, while recording the SK of each window and thus arriving at a full kurtogram, which can be used to identify the optimum filter settings (center frequency and bandwidth). This procedure is used for bearing diagnosis by Antoni and Randall [21].

The signal is filtered according to the optimum filter settings determined, arriving at a signal that has maximum kurtosis for envelope analysis.

However, computation of the kurtogram for all possible combinations of center frequencies and bandwidths is obviously costly and not convenient for practical purposes [7]. Therefore the fast kurtogram was proposed by Antoni [22] in 2007. A ,,1/3-binary tree“ was used, where each halved-band is further split into three other bands, thus producing a frequency resolution in the sequence 1/2 , 1/3, 1/4, 1/6, 1/8, 1/12,…,2^{-k-1} with corresponding “scale levels“ k=0, 1, 1.6, 2, 2.6,… to compute the SK in this bands.

With this limited amount of combinations the computational time could be drastically decreased, but virtually the same result can be achieved than with using the full kurtogram. The fast kurtogram algorithm for detection of transient faults proposed by Antoni [22], was made available for public in terms of a Matlab® function [23], which is used here.

Figure 9 shows the kurtogram for the example wind turbine and time series after PW and PW & MED.

Figure 7: Kurtogram based on 4th order statistics a) raw time series, b) PW, c) PW & MED (#3, HSS, meas. 31, WTG 02)

The maximum SK is achieved at different frequency bands, depending on the processing involved. The kurtogram for the raw time series (a) has its maximum at k = 2.6, corresponding to a center frequency of 12.1 kHz and a bandwidth of 3.7 kHz. After PW (b) maximum SK is in the band with a center frequency of 17.6 kHz and a band width of 6.9 kHz (k=1.6). After PW & MED (c), maximum kurtosis is in the full frequency band.
Sawalhi and Randall [11] conclude in their research, based on a fault in a planetary bearing at a helicopter gearbox, that even without filtration in the optimum frequency band, complete whitening of the spectrum means that faults have a good chance of manifesting themselves in an envelope analysis covering the full frequency range, because the most impulsive bands will tend to dominate peaks in the time signal. It is further concluded, that if desired, spectral kurtosis can in any case be applied after cepstral PW, to give an optimal result. In general, a shift of the maximum kurtosis to a lower scale level (broader band) is desirable, as this allows a broader frequency spectrum to be analyzed in the envelope spectrum. A small bandwidth can cause problems in spectra interpretation as the higher harmonics may not be visible, due to the limited maximum frequency.

3.5 Envelope Analysis

Envelope analysis has become one of the prominent vibration signal processing techniques for detection and diagnosis of rolling element bearing incipient failure [24].

The envelope can be calculated by performing a Hilbert transform of the squared signal. The signal is band pass filtered according to the band width and center frequency identified through the SK and the kurtogram beforehand. The envelope is then further transformed via a FFT to the frequency domain to arrive at the squared envelope spectrum, which can be used to identify the damage frequencies. Next, the effect of the different pre-processing algorithms (PW, MED and SK) on the squared envelope spectrum is discussed.

3.5.1 The effect of PW

The focus lies on the improvement of the envelope spectra when the time series is pre-whitened. A comparison is made between the raw TS, the PW TS and the LP residual.

The LP (AutoRegressive (AR)) model used here for comparison takes the form

\[
\hat{x}(n) = \sum_{k=1}^{p} a(k)x(k - n)
\]  

(3) [2]

\(\hat{x}(n)\) is the predicted current value, \(p\) is the number of previous values (model order), \(a(k)\) is the weighting coefficient and \(x(k - n)\) is the previous value.

The weighting coefficients are obtained using the Yule-Walker equations model and Akaike’s entropy-based Information Criterion (AIC) [25] to estimate the model order \(p\).

Although the model order can be estimated using AIC it must be determined for each time series individually as the rotational speed can vary slightly, influencing the discrete frequency components and hence requires different model parameters. The model order can be quite high for time series with a high sampling frequency. The AIC lead to an optimum model order of 598 for the example TS used. Here PW gives some advantage as no parameter must be optimized, making PW a computationally very efficient method.

Figure 10 emphasizes that the PW procedure gives virtually the same result as LP (b and c for all WTGs are very similar). The fundamental IMS frequency (6.4 Hz), the IMS meshing frequency (115.1 Hz), the HSS meshing frequency (550 Hz) component as well as the modulations of the meshing frequency have been successfully removed by both methods at all WTGs (b,c), leaving the bearing damage frequency (297 Hz), its harmonics and shaft speed modulations (±24.8 Hz) together with the fundamental shaft speed (24.8 Hz). The PW based on CEP thus gives good results in a very efficient manner.

Without separation, the envelope spectra can be dominated by the deterministic frequencies (compare WTG 04 (a) and WTG 10 (a)), making it impossible to diagnose the bearing defect reliably.

3.5.2 The effect of MED

It was already shown that the MED method can increase the kurtosis value in the time domain and enhance the impulsiveness of the signal. In this section it will now be investigated, whether or not this gives an advantage in respect of fault visibility in the envelope spectra using the available data sets. The fault visibility is increased, when typical fault patterns (e.g. damage frequencies) are enhanced, allowing a certain diagnosis. Figure 11 shows the squared envelope spectra of the TS with PW and PW & MED. The strongest improvement archived is at WTG 04. Here the shaft speed modulations around the damage frequency (297 Hz ± 24.8Hz) are stronger pronounced with MED. The same is true for WTG 02. At the other turbines the improvement is marginal as (a) and (b) are very similar. However, the amplitudes of PW & MED are higher, which becomes evident by the lower noise level.

It can be concluded, that MED can improve the results and is thus recommended, but diagnosis should also be possible without MED.
3.5.3 The effect of band pass filtering using SK

The time series of the four example WTGs of Figure 10 and Figure 11, have the highest SK value in the full band after applying MED. Hence SK filtering does not give any improvement. Figure 12 compares the envelope spectra with and without optimal band pass filtering prior MED, but after PW.

Both spectra clearly show the present inner race damage signature, which consists of the Ball Pass Frequency Inner race (BPFI) (297 Hz) and present modulations at the shaft speed (24.8 Hz). Differences exist in the amplitudes and the higher modulation of the shaft speeds around the second harmonic of the BPFI. The results appear to be slightly better with band pass filtering. The conclusion drawn by Sawalhi and Randall [11] can thus be confirmed with the data at hand at least prior MED.

The SK algorithm is fast to compute, (the kurtogram shown in Figure 9 was calculated in 0.5s using a regular 2.6 GHz processor). It is therefore recommended to apply optimal band filtering based on the SK, bearing in mind that in most cases, no improvement to the envelope spectra is made. However, a few cases existed in the data, where the maximum SK was not in full band. In these cases, it is expected that SK filtering improves the envelope spectrum in a fault situation.
3.6 Frequency content identification

For bearing diagnosis, the bearing damage frequencies as well as the individual shaft speeds are required. This information is usually available, either through theoretical calculations based on the geometry and design or in terms of damage frequencies coming from the bearing manufacturer (potentially originating from experimental studies). For further analysis it is assumed that these frequencies are available. In case those frequencies are not at hand, estimation methods can be applied.

Figure 11: The effect of MED; a) PW without MED, b) PW & MED (#3, HSS, meas. 31, WTG 01, 02, 04, 10)
As pointed out by Randall and Antoni [7], the deviations from the theoretical values of the damage frequencies may be in the range of 1-2%. Any algorithms developed must therefore be capable of dealing with variations of this order, without affecting the diagnosis.

The Frequency Content Identifier (FCI) developed here deals with this by applying a tolerance band around the known damage frequency with a variation tolerance of 2%. Next to the pure damage frequencies, the presence of modulation sidebands is of interest, too. The developed concepts of damage and modulation frequency identification are visualized in Figure 13.

Before applying the FCI the envelope spectrum must first be checked for present peaks.

A data point is a local peak if (a) it is large and locally a maximum value within a window; the value need not necessarily be large nor a global maximum; and (b) it is isolated i.e. not too many points in the window have similar values [26].

Using this definition two types of peak detectors are set up, which are visualized in Figure 14. Both detectors consist of a moving window shifting along the whole envelope spectrum.
Differences exist in which of the values within the window is checked for being a peak. In the window centered method two conditions are checked, before the value is assigned a peak:

- Is the centered value larger than the maximum value in the window excluding itself?
- Is the centered value larger than the mean plus x times the standard deviation of the values in the window excluding itself?

In the window max method only one condition is checked, before the value is assigned a peak:

- Is the maximum value in the window larger than the mean plus x times the standard deviation of the values in the window excluding the maximum value?

The properties of these two peak detectors are quite different. While the window centered method cannot detect multiple values per peak, the window max detector has this property. In both methods the window is moving value by value. Dependent on which property appears to be more suitable either of the methods can be applied. For peak detection in the envelope spectrum the window max method is more suitable, since the peaks in the envelope spectrum can be spread over more than one spectral line, and the spectral components can be close to each other.

Since the peaks used for analysis should be clearly distinct, a tough bound with \( x = 6 \) (multiplier of the standard deviation) is chosen for peak definition here. In order to avoid false diagnosis, the detected peaks should be of reasonable magnitude. If it is assumed that the random noise in the envelope spectrum is normal distributed, it can be an option to mark detected peaks as true peaks only if they are larger than five times the standard deviation of the envelope values. This gives a high likelihood that the detected components are significant and thus carry some information. This filter is applied after peak detection here. Figure 15 illustrates a zoom of the squared envelope spectrum and the detected peaks using this setting.

In the following the true value of the envelope spectrum is only kept where a peak is detected and set to zero otherwise (see Figure 16).
The remaining envelope spectrum can now be analyzed for different frequency contents. For bearing diagnosis, the frequency contents given in Table 2 and Table 3 are checked for.

**Table 1: Wanted frequency contents**

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Harmonic</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPM</td>
<td>0, 1, 2, 3, 4 (*)</td>
</tr>
<tr>
<td>BPFI</td>
<td>0, 1, 2, 3, 4 (*)</td>
</tr>
<tr>
<td>BPFO</td>
<td>0, 1, 2, 3, 4 (*)</td>
</tr>
<tr>
<td>FTF</td>
<td>0, 1, 2, 3, 4 (*)</td>
</tr>
<tr>
<td>BSF</td>
<td>0, 1, 2, 3, 4 (*)</td>
</tr>
</tbody>
</table>

(*): 0: fundamental frequency; 1: first harmonic; 2: second harmonic etc.

**Table 2: Wanted modulation contents**

<table>
<thead>
<tr>
<th>Modulation frequency</th>
<th>RPM</th>
<th>BPFI</th>
<th>BPFO</th>
<th>FTF</th>
<th>BSF</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPM</td>
<td>-</td>
<td>0, 1*</td>
<td>0, 1*</td>
<td>0, 1*</td>
<td>0, 1*</td>
</tr>
<tr>
<td>BPFI</td>
<td>0, 1*</td>
<td>-</td>
<td>0, 1*</td>
<td>0, 1*</td>
<td>0, 1*</td>
</tr>
<tr>
<td>BPFO</td>
<td>0, 1*</td>
<td>0, 1*</td>
<td>-</td>
<td>0, 1*</td>
<td>0, 1*</td>
</tr>
<tr>
<td>FTF</td>
<td>0, 1*</td>
<td>0, 1*</td>
<td>0, 1*</td>
<td>-</td>
<td>0, 1*</td>
</tr>
<tr>
<td>BSF</td>
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<td>0, 1*</td>
<td>0, 1*</td>
<td>0, 1*</td>
<td>-</td>
</tr>
</tbody>
</table>

In these tables RPM is the shaft speed; BPFI is the ball pass frequency inner race; BPFO is the ball pass frequency outer race; FTF is the fundamental train frequency and BSF is the ball spin frequency.

The result of the FCI for each component is stored in a matrix (see Table 4). If the frequency content is present (Pres.) the matrix entry will contain a one or zero otherwise. This matrix can afterwards be used to set up rules for automatic diagnosis. Note that the frequency contents labeled Mod_ are identified using the modulation frequency identifier and the other frequency contents are identified using the damage frequency identifier (compare Figure 13).

**Table 3: Content matrix**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>RPM h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>2</td>
<td>RPM h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>3</td>
<td>RPM h2</td>
<td>0/1*</td>
</tr>
<tr>
<td>4</td>
<td>RPM h3</td>
<td>0/1*</td>
</tr>
<tr>
<td>5</td>
<td>RPM h4</td>
<td>0/1*</td>
</tr>
<tr>
<td>6</td>
<td>BPFI h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>7</td>
<td>BPFI h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>8</td>
<td>BPFI h2</td>
<td>0/1*</td>
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<tr>
<td>9</td>
<td>BPFI h3</td>
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<td>10</td>
<td>BPFI h4</td>
<td>0/1*</td>
</tr>
<tr>
<td>11</td>
<td>BPFO h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>12</td>
<td>BPFO h1</td>
<td>0/1*</td>
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<tr>
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<td>0/1*</td>
</tr>
<tr>
<td>14</td>
<td>BPFO h3</td>
<td>0/1*</td>
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<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>23</td>
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<td>24</td>
<td>BSF h3</td>
<td>0/1*</td>
</tr>
<tr>
<td>25</td>
<td>BSF h4</td>
<td>0/1*</td>
</tr>
<tr>
<td>26</td>
<td>Mod RPM h0 BPFI h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>27</td>
<td>Mod RPM h0 BPFI h1</td>
<td>0/1*</td>
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<tr>
<td>28</td>
<td>Mod RPM h0 BPFO h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>29</td>
<td>Mod RPM h0 BPFO h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>30</td>
<td>Mod RPM h0 FTF h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>31</td>
<td>Mod RPM h0 FTF h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>32</td>
<td>Mod RPM h0 BSF h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>33</td>
<td>Mod RPM h0 BSF h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>34</td>
<td>Mod BPFI h0 RPM h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>35</td>
<td>Mod BPFI h0 RPM h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>36</td>
<td>Mod BPFI h0 BPFO h0</td>
<td>0/1*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>45</td>
<td>Mod BPFO h0 BPFI h0</td>
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</tr>
<tr>
<td>46</td>
<td>Mod BPFO h0 FTF h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>47</td>
<td>Mod BPFO h0 FTF h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>48</td>
<td>Mod BPFO h0 BSF h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>49</td>
<td>Mod BPFO h0 BSF h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>50</td>
<td>Mod FTF h0 RPM h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>51</td>
<td>Mod FTF h0 RPM h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>52</td>
<td>Mod FTF h0 BPFI h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>53</td>
<td>Mod FTF h0 BPFI h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>54</td>
<td>Mod FTF h0 BPFO h0</td>
<td>0/1*</td>
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<tr>
<td>55</td>
<td>Mod FTF h0 BPFO h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>56</td>
<td>Mod FTF h0 BSF h0</td>
<td>0/1*</td>
</tr>
<tr>
<td>57</td>
<td>Mod FTF h0 BSF h1</td>
<td>0/1*</td>
</tr>
<tr>
<td>58</td>
<td>Mod BSF h0 RPM h0</td>
<td>0/1*</td>
</tr>
</tbody>
</table>
This setup allows for future addition of further contents in envelope spectra that may be checked for. This could be for instance higher harmonics of interest. In this case the content matrix can be extended.

For the application example used here the frequency content around the BPFI frequency together with the tolerance limits is shown in Figure 17. In line with Figure 17, the entries: BPFI_h0 and Mod_RPM_h0_BPFI_h0 will contain a “1”, since the fundamental BPFI frequency as well as shaft speed modulations around this frequency are present.

3.7 Diagnosis

The FCI outputs the content matrix containing the indicators of whether a particular frequency or frequency pattern (modulation) is present in the envelope spectrum.

![Envelope spectrum](image)

**Figure 14:** Envelope spectrum after peak filtering and the tolerance limits (#3, HSS, meas. 29, WTG 02)

Based on this matrix rules can be set up which allow the expert to implement his knowledge in fault diagnosis. Rules based on common knowledge about typical bearing damages are for instance:

- **When** BPFI frequency present & shaft speed modulations around BPFI present then Inner race damage
- **When** FTF frequency present then Rolling element damage
- **When** BPFO frequency present then Outer race damage
- **When** BPFO frequency present & shaft speed modulations around BPFO present then Outer race damage + unbalance or misalignment

Instead of formulating rules in a classical way, Fuzzy Logic (FL) is applied, since FL rules can be expressed in a very compact manner. Note that the advantages of fuzzification are not used here. Each line in the content matrix has its own input variable to the FL system. Because the content matrix does only contain two values - either “0” (frequency content not present) or “1” (frequency content present) - the shape of the Membership Function (MF) does not influence the result. The applicable MF has always full membership, due to the functions being centered around 0 and 1. The output is the diagnosis based on the rule evaluation. The initialized MFs are visualized in Figure 18 and Figure 19.
4. Application examples

From the seventeen wind turbines in the power plant, six have inner race damage at the high speed shaft bearing. Unfortunately this bearing cannot be inspected by endoscopic methods due its closed design. Hence tracking of the fault size was not possible. However, after bearing replacement factory investigations confirmed straight axial cracks.

In this section three application examples for the automated fault detection algorithm are given, using the proposed procedure.

4.1 Example 1

The available discontinuous measurements are evaluated for faults after PW & MED and SK processing. The envelope spectra after filtering are analyzed via the FCI and the rules specified. Figure 21 shows a waterfall plot of the envelope spectra together with the spectral kurtosis values of the full frequency band of the most recent ten measurements.
Rising amplitudes in the envelope spectra are visible. This corresponds nicely with the increase in SK of the full frequency band. Since March 2012 a rise in SK value can be observed. Although it is not proven here, the findings of Sawalhi et al. [5], Niaoqing et al. [12] and Sawalhi and Randall [27] make it very likely that the increase in SK can be linked to the crack growths at the inner ring.

Note that here the SK of the full band is plotted, instead of the SK of the band with maximum impulsiveness. This choice was made to avoid fluctuations in the SK trend, simply due to shifts in the frequency band with maximum SK. In this sense the same reference band is used.

Moreover it was realized that the MED algorithm makes the SK values in a healthy state more fluctuating. Hence the SK trend in Figure 21 is based on SK values prior application of MED. It is visible that the SK trend corresponds with the envelope spectra. Repair took place in November 2012.

Figure 22 illustrates the SK trend after applying MED as a comparison. This figure presents a novelty as for the first time the SK evolution is shown over time covering both, the long healthy and the damaged period.
The fluctuations in the healthy state are characterized by a large variation. Once the crack develops, the SK values stabilize and indicate a trend, most likely linked to the crack size. Beyond 2012-08-19 the SK values decrease. A similar behavior was observed by Sawalhi and Randall [28]. They suspected the decrease to be due to the fact that the entry and exit edges of the spall would tend to wear [2]. The actual fault here aids this presumption, as the characteristic fault frequency amplitude decreases in the later time series, but rich sideband modulations occur.

Differences in the SK trend with and without MED exist in the healthy period as well as in the overall amplitude level. The fluctuating pattern of the SK trend prior fault development makes the SK trend after MED a more difficult parameter to monitor, which is why the SK trend without MED is preferred.

A further difference can be observed at 2011-12-06, where the SK trend without MED shows a noticeable increase, whereas it is not as obvious in the SK trend after MED. The increase at 2011-12-06 has its reason, as in this period the envelope spectra gives indication of fault (see Figure 23), which disappear again after 2012-01-03. This phenomenon is potentially caused by flattening of the developing crack due to overrollment and a continuous crack growth beyond 2012-03-17.

Figure 18: Envelope spectra and spectral kurtosis (WTG 02)

Figure 24 shows the envelope spectrum for the most recent measurement together with the most important frequency contents.
The BPFI₀ is around 297.8 Hz, f₀ around 24.8 Hz and BPFO₀ 221.6 Hz. After FCI, the following entries in Table 4 contain a “1” for frequency content being present.

- RPMₜ₀ (fₜ₀)
- RPMₜ₁ (f₁)
- BPFIₜ₀ (BPFI₀)
- BPFIₜ₁ (BPFI₁)
- BPFIₜ₂
- BPFIₜ₃
- BPFIₜ₄
- BPFOₜ₀
- BPFOₜ₁
- BPFOₜ₂
- BPFOₜ₃
- BPFOₜ₄
- FTFₜ₄
- BSFₜ₂
- Mod_RPMₜ₀_BPFIₜ₀
- Mod_RPMₜ₀_BPFIₜ₁
- Mod_BPFOₜ₀_BPFIₜ₁
- Mod_BPFOₜ₀_BPFIₜ₂
- Mod_BPFOₜ₀_BPFIₜ₃
- Mod_BPFOₜ₀_BPFIₜ₄

The following four rules were established based on common faults pattern of different failures:

a) If BPFOₜ₀ & BPFOₜ₁ & Mod_RPMₜ₀_BPFOₜ₀ & Mod_RPMₜ₀_BPFOₜ₁ then outer race signature + unbalance or misalignment
b) If BPFOₜ₀ & BPFOₜ₁ & BPFOₜ₂ then outer race signature + unbalance or misalignment
c) If BPFIₜ₀ & BPFIₜ₁ & BPFIₜ₂ & Mod_RPMₜ₀_BPFIₜ₀ then inner race signature
d) If FTFₜ₀ & FTFₜ₁ & FTFₜ₂ & then rolling element signature

Next to the speed and BPFI components also BPFO and BSF components have been detected. The BPFO is around 216 Hz and thus close to BPFIₜ₀ – RPMₜ₂ (219 Hz). BPFOₜ₂ (649 Hz) is close to BPFIₜ₁ + RPMₜ₂ (653 Hz). A similar explanation can be found for the BPFOₜ₃, the BPFOₜ₄ and the BSF component.

In classical logic, this fact would give problems in diagnosis, since there is the risk of collision with rule b). However, with FL each rule can be assigned a weight. Although in this example the outer race signature rule would not have fired, it proved useful assigning simple rules (based on simple patterns) a lower weight to avoid misdiagnosis. In such cases the rule with the higher weight would fire.

Applying the rules, rule c) fired indicating an inner race fault at the HSS bearing.
4.2 Example 2

The automated analysis highlighted five more turbines with inner race signature and inner race damage. Figure 25 shows a waterfall plot of the envelope spectra together with the SK trend of the most recent ten measurements of WTG 05.

Figure 20: Envelope spectra and spectral kurtosis (WTG 05)

At this turbine a very clear trend in SK is visible since January 2012, with the recent measurements slightly fluctuating. The envelope spectra follow this trend, with rising amplitudes and more harmonics showing up. Repair took place in November 2012. Plotting the SK trend after MED gives the results presented in Figure 26. Also for this turbine the SK has a high variance in the healthy period. A trend first establishes at 2011-03-18, which is two month later than with the SK values without MED. Hence, for the data sets available, it appears preferable using the SK values without MED for trending. However, this is in contrast to the findings of Sawalhi et al. [5] in which a case is shown where SK trending was not possible without MED.

Figure 27 shows the most recent envelope spectrum, the detected peaks and the filtered spectrum passed to the FCI.

Figure 21: Spectral kurtosis trend after MED (WTG 05)
The identified frequency contents by the FCI are:

- RPM\_h0 (f_0)
- RPM\_h1 (f_1)
- RPM\_h3 (f_3)
- BPFI\_h0 (BPFI_0)
- BPFI\_h1 (BPFI_1)
- BPFI\_h2 (BPFI_2)
- BPFI\_h3
- BPFI\_h4
- BPF0\_h3
- BSF\_h2
- Mod\_RPM\_h0\_BPFI\_h1
- Mod\_RPM\_h0\_BPFI\_h1
- Mod\_BPFO\_h0\_BPFI\_h2
- Mod\_BPFO\_h0\_BPFI\_h2

The present frequency contents evaluated via the rules implemented highlight the inner race signature and the potential damage fully automatized, together with the correct diagnosis.
4.3 Example 3

Another turbine with detected inner race damage is WTG 04. Again the most recent ten envelope spectra and the spectral kurtosis trend is illustrated in Figure 28 and the SK trend with MED in Figure 29.

![Envelope spectra: WTG 04](image)

**Figure 23:** Envelope spectra and spectral kurtosis (WTG 04)

At this turbine many measurements in a healthy state exist, as the crack develops comparably late. However, the SK sharply increases 2012-06-29 again well in line with the envelope spectra amplitude rise. Bearing replacement took place in October 2012.

![Spectral kurtosis trend (full freq. band)](image)

**Figure 24:** Spectral kurtosis trend after MED (WTG 04)

Also the SK after applying MED shows the steep rise. However, the healthy state is also for this turbine characterized by a larger variance. Because of this a trend is reliably detectable first at 2012-07-27, in contrast to trend establishment in the SK values without MED, where the trend can be identified two weeks earlier.
Figure 30 visualizes the most recent envelope spectrum and the detected beaks together with the envelope spectrum passed to the FCI and important frequency components.

Figure 25: Envelope spectrum and detected peaks (top); envelope spectrum after peak filtering (#3, HSS, meas. 31, WTG 04)

The detected frequency content is:

- $\text{RPM}_h0$ ($f_0$)
- $\text{RPM}_h1$ ($f_1$)
- $\text{RPM}_h2$
- $\text{BPFI}_h0$ ($\text{BPFI}_0$)
- $\text{BPFI}_h1$ ($\text{BPFI}_1$)
- $\text{BPFI}_h2$ ($\text{BPFI}_2$)
- $\text{BPFI}_h3$
- $\text{BPFI}_h4$
- $\text{BPFO}_h0$
- $\text{BPFO}_h2$
- $\text{BPFO}_h3$
- $\text{BPFO}_h4$
- $\text{BSF}_h2$
- $\text{Mod}_\text{RPM}_h0\text{BPFI}_h0$
- $\text{Mod}_\text{RPM}_h0\text{BPFI}_h1$
- $\text{Mod}_\text{BPFO}_h0\text{BPFI}_h0$
- $\text{Mod}_\text{BPFO}_h0\text{BPFI}_h1$

Based on the frequency content present, an inner race signature was automatically detected, which is the correct diagnosis for the pattern existing.

5. Results and discussion

The given examples emphasize the successful application of the proposed procedure to real measured data and fault diagnosis.

Moreover research showed the benefits of using the CEP based signal PW for signal separation into deterministic and non-deterministic components. The performance of PW is close to the LP residual, but without the need of parameter optimization, which makes it an efficient method and very fast to compute.

Using MED as a further pre-process step prior envelope calculation proved useful to emphasizing present fault pattern both in the time and frequency domain. Attention must be paid to the choice of filter order. It was found that a too high filter order can lead to start-up and end transients in the time series preventing successful diagnosis. For practical applications, it is thus recommended using a rather low filter order, accepting that the impulse amplification may be less effective than with a higher filter order, but avoiding the risk of transients.

Furthermore the effect of the spectral kurtosis based optimal filter band selection was studied. Results show that in many cases the combination of PW & MED lead to the situation that band pass filtering gives no improvement. However, in some cases a frequency band can be found that gives higher spectral kurtosis values and accordingly a clearer fault pattern in the envelope spectrum. By applying the fast kurtogram (proposed by...
Antoni [22]) the search for an optimal frequency band is fast to compute and should thus supplement the automated procedure.

Finally the effect of MED on the SK values trend (used as a fault size indicator) was under research. A higher variance of the SK values was observed for bearings in a healthy state when MED is used prior SK value calculation. This variance lead in some cases to a later establishment of observable trends, but both methods (with and without MED) show trends in the fault state, potentially linked to the crack size. The SK without MED appears to be superior to use, because of the more direct link between present patterns in the envelope spectra and high SK values as well as lower variance in the values.

6. Future research

Identifying HSS bearing faults in wind turbine gearboxes is a comparably simple task, because of the high rotational speed. Future research will focus on the efficiency of the proposed method to automatically detect and diagnose faults in the IMS and the planetary stage of wind turbine gearboxes. At least for the IMS stage (rotating with approx. 350 rpm) it is expected that the proposed procedure will give good results. However, the available data sets did not contain any bearing damages of the IMS or the planetary stage. Hence the efficiency for intermediate and low speed bearings must still be evaluated and is left for future research.

7. Conclusions

The proposed procedure proved capable of automatically process and analyse vibration time series for bearing defect frequencies in the envelope spectra. The diagnosis is based on rules which are set up using common knowledge about typical bearing fault signatures. The rules are implemented using fuzzy logic, building the basis for flexible and reliable fault diagnosis.

The proposed technique is an extension of the semi-automated procedure for bearing diagnosis (originally proposed by Sawalhi and Randall [4]) with regards to the application of a frequency content identification and rule based diagnosis. Moreover state of the art pre-processing techniques, namely CEP based signal PW and MED have been successfully applied and their effectiveness shown. In comparison to LP models for separating random from discrete components, CEP based signal PW proved to be an efficient and fast to compute method for separation.

8. References

I. References


