On Condition Monitoring of Wind Turbines without Speed Sensor

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ABSTRACT

We discuss implementation of wind turbine condition monitoring system (CMS) without speed sensor. The main method used is based on implementing Hilbert transform to extract the instantaneous frequency, where derivative of the analytic signal is done in the frequency domain. We analyze how to determine which vibration source, such as generator, gearbox high speed stage, or other turbine components should be used for speed extraction. The best choice of component is evaluated based on how good speed is estimated from various components in comparison to information from real speed sensor. Data from wind turbines collected over the years are used for statistical comparisons and selections of proper implementation. Information from estimated speed is then used along with an automatic diagnosis algorithm to detect different wind turbine faults.

1. INTRODUCTION

Condition monitoring of wind turbine requires monitoring magnitudes of certain frequencies or harmonics, also known as descriptors. These descriptors describe the state of a component and are trended for alarming purpose. Some of them require speed information of certain shafts to monitor, for example, unbalance in a generator and gear-related faults in a gearbox as described by Bartelmus and Zimroz, (2009) and Taylor (2000). This information is normally obtained from a speed sensor, where it measures how many rotations a shaft undergoes in a time period, such as revolutions per minute (rpm) or per second in unit Hertz (Hz).

In a wind turbine, the speed sensor is normally attached to the generator shaft. Shaft speeds and tooth mesh frequencies at various stages can be determined from the generator shaft speed using ratios of various shafts in the gearbox. A non-contacting eddy current displacement sensor is normally used for speed reference sensor. This type of sensor needs to be adjusted correctly to obtain correct speed measurement.

The generator shaft rotation often drifts over time, which could cause the initial speed sensor setting to be invalid. Incorrect speed sensor setting could cause speed reference measurement to be invalid, which results in unreliable speed-dependent descriptors. As a result, failure modes that require speed information for their detection may be missed. In reality, majority of failure modes detection require speed information, such as generator unbalance, misalignment, looseness, determination of inner or outer race bearing faults, and gear related faults.

Considering the criticality of speed information, it is imperative to correct a malfunction speed sensor. However, correcting a speed sensor can be costly, especially in offshore wind turbines. This is because a technician has to physically visit the turbine to do the correction. Huge saving in the cost of wind turbine CMS and operation can be achieved if the need of having a speed sensor can be eliminated.

Several works to mitigate the problem of invalid speed sensor reading have been presented (Coats, Sawalhi, & Randall, 2009), (Urbanek, Zimroz, Barszcz, & Antoni, 2012), (Zhao, Lin, Wang, Lei, & Cao, 2013), (Zimroz, Milioz, & Martin, 2010), (Zimroz, Urbanek, Barszcz, Bartelmus, Milioz, & Martin 2011), and (Skrimpas, Marhadi, Jensen, Sweeney, Mijatovic, & Holbøll 2015). They mostly involve detection of speed information from vibration; thus speed sensor is not required. In the work by Skrimpas, et al. (2015), speed information is estimated for wind turbine applications in case speed sensor becomes unavailable. In that paper, prior information from the sensor is required before it becomes unavailable for the algorithm to work.

Those works mainly focused on estimating the speed information itself rather than using it for faults detection. This paper focuses on using estimated speed in combination with an algorithm to automatically detect faults in wind turbines (automatic diagnosis). The speed is estimated using frequency demodulation of response vibration signals using Hilbert transformation as presented by Randall and Smith (2016 and 2018). Randall and Smith (2018) showed that it is the most accurate method to determine instantaneous speed of a shaft by frequency demodulation.

In estimating speed information, it is often required to know a frequency range where the actual speed information is present. Determining search frequency correctly will result in an accurate estimated speed. However, this requires a combination of expert knowledge, machine operating condition, and kinematical information of the machine. Current paper shows that the search range can be accurately defined based on operating condition and kinematic of the machine.

2. HILBERT TRANSFORM TO ESTIMATE SPEED

Randall and Smith (2018) showed that instantaneous phase and amplitude of a vibration signal can be determined by Hilbert transform techniques, which result in an analytic signal that corresponds to the real signal. This signal can be represented as:

$$x_a(t) = A(t)\exp\left(j\phi(t)\right) \tag{1}$$

where $\dot{\phi}(t) = \omega(t) = 2\pi f(t)$.

The derivative of the instantaneous phase of an analytic signal can be represented as:

$$\omega(t) = \dot{\phi}(t) = Im\left[\frac{\dot{x}_a(t)}{x_a(t)}\right] \tag{2}$$

where $\dot{x}_a(t)$ is the derivative of $x_a(t)$. As explained by Randall and Smith (2016), the exact derivative can be obtained by multiplying the spectral values by $j\omega$ over the frequency ranges to be demodulated before performing inverse transform of the spectrum.

With Eq. 2, the instantaneous speed of a shaft can be determined from vibration signal at all times. However, the initial estimated speed needs to be smoothed out because the differentiation introduces noise in real vibration signal as described in (Randall and Smith, 2018). In the current paper, initial estimated speed is smoothed out using a FIR filter in the time domain as presented in (Randall and Smith, 2018).

A harmonic that is related to a shaft speed may not be the most dominant one. Demodulating a band around this particular harmonic must be free from any other components. Moreover, a shaft speed can have a big variation within a time interval. Thus it is important to ensure that all speed related harmonics, such as tooth mesh frequencies are proportionally considered according to kinematical data of the machine. This will ensure that a harmonic of interest can be initially estimated within a narrow search range without any other components.

The following is a procedure to determine an initial range of a harmonic or speed of interest:

1. Determine machine operating range where speed information is valid, e.g. between 15 and 30 Hz.
2. Generate the first power spectrum of vibration signal from which speed information is extracted.
3. Identify all possible peaks or harmonics in the spectrum.
4. Find a frequency factor (ω_e) within the speed operating range that maximizes the sum of harmonics that match machine's kinematical data, e.g. shaft speed family of harmonics and gear tooth mesh frequencies. The theory behind this is that summation of a speed related family harmonics will be maximized as opposed to summing them with random harmonics that may not have the correct speed relation.

Step 4 above can be expressed as an optimization problem:

$$\max_{\omega_e} f(\omega_e) = \textstyle\sum_i \omega_e i + \cdots + \sum_k \omega_e k \ , \tag{3}$$

where i to k represent speed related families of harmonics identified in the spectrum. Their information should be available in the machine's kinematical data.

Solving for ω_e in the above optimization problem is essentially a speed estimation procedure too. However it can be considered computationally more expensive if it is performed continuously as opposed to using Eq. (2). Moreover, it can only provide an estimated average speed in a period of the time waveform length; not at all times of the signal length. Thus the above procedure is only used in the beginning to determine initial guess range that is guaranteed free of other components, which is then demodulated to extract the actual speed information.

To take into account big speed variation, the vibration record is divided into overlapping segments. Solving Eq. (3) is only performed in the first segment of the record. Once ω_e is obtained, a band of ±1 Hz around ω_e is used as the demodulated range. Speed information in each segment is then determined using the aforementioned Hilbert transforms. This follows the method described by Randall and Smith (2016).

3. SPEED ESTIMATION IN WIND TURBINE MONITORING

In Bruel & Kjær Vibro wind turbine condition monitoring applications, time waveforms data are obtained approximately every two days. The time waveforms contain vibration signals from all components monitored. The length of each time waveform is 10.24 seconds with sampling rate of 25600 Hz. The types of wind turbines analysed in this study are those with gearbox configurations of one planetary and two helical stages (1P2H), two planetary one helical (2P1H), and three planetary and one helical stage (3P1H).

In a typical wind turbine monitoring, accelerometers are installed at various components of the turbine. There could be more than one sensor to monitor the same component. Designations of sensor locations in a wind turbine are the following: Generator Drive End (GnDe) and Non Drive End (GnNDe) Gearbox High Speed Stage Front (GbxHssFr) and Rear (GbxHssRr), Gearbox Intermediate Stage (GbxIss), Gearbox 1st Planetary Stage (Gbx1Ps), and Main Bearing (MnBrg). Speed information could be extracted from each vibration sensor. However, one sensor is enough to get the information. Thus it is necessary to find the best sensor from which to extract speed information from vibration signal.

To determine the best vibration sensor to extract speed information, equation (3) is solved for $\omega_e$for for the entire 10.24 seconds time waveform obtained from each channel available in a turbine. The result provides an average speed of interest in that period. In this study, speed of interest is the generator shaft speed. Speeds of other shafts in the turbine can then be calculated based on the kinematical data. The results, ω_e, is then compared with actual average speed obtained from a speed sensor. Sensor that gives the minimum error should be used.

In this study, the choice is also based on statistical analysis. Thousands of time waveforms from turbines of the same type under various operating conditions are analyzed. The results are summarized in Tables 1, 2, and 3 for turbines with gearbox configuration 1P2H, 2P1H, and 3P1H respectively. The number of time waveforms for each turbine type is 11951, 17392, and 9124, respectively.

Based on all turbines analysed, it is best to use Generator Non Drive End (GnNDe) sensor. The reason is because across different turbine platforms, it gives minimum median value. Moreover, generator non drive end usually only contains harmonics of the generator shaft. Thus vicinity of the first harmonic of the running speed is usually free from other components. This provides a cleaner speed estimation result using Hilbert transform techniques.

Table 1. Error statistical analysis for 1P2H turbines in Hertz

	Median	Q3	Q1	Mean Error
GnDe	0.062	0.183	0.03	6.87
GnNDe	0.059	0.160	0.03	0.48
GbxHssRr	4.98	6.30	0.04	6.47
GbxHssFr	5.15	6.26	0.06	6.66
GbxIss	0.140	5.80	0.04	4.97
Gbx1Ps	0.109	5.31	0.03	5.10
MnBrgFr	1.84	10.8	0.05	6.32
MnBrgRr	0.988	10.1	0.05	6.11

Table 2. Error statistical analysis for 2P1H turbines in Hertz

	Median	Q3	Q1	Mean Error
GnDe	0.123	6.30	0.03	5.82
GnNDe	0.142	6.98	0.03	5.89
GbxHssRr	0.280	4.53	0.04	5.78
GbxHssFr	4.16	15.0	0.06	8.29
GbxIss	0.657	4.89	0.04	6.88
Gbx2Ps	0.209	4.36	0.04	3.47
Gbx1Ps	3.95	4.71	0.07	4.72
GbxRotBrg	4.60	30	0.616	10.8
MnBrg	4.24	9.72	0.185	8.14

Table 3. Error statistical analysis for 3P1H turbines in Hertz

	Median	Q3	Q1	Mean Error
GnDe	0.038	0.082	0.017	0.752
GnNDe	0.035	0.068	0.017	0.734
GbxHssRr	2.473	2.819	2.265	2.502
GbxHssFr	2.497	2.825	2.340	2.974
GbxIssFr	2.492	2.826	2.324	2.919
GbxIssRr	2.492	2.800	2.337	2.709
Gbx1Ps2	3.014	20.66	2.431	9.898
Gbx1Ps1	2.645	3.196	2.411	4.612
MnBrg	2.524	2.927	2.308	3.018
GbxRotBrg	21.17	24.89	19.81	20.04

4. FAULT DETECTION USING SPEED ESTIMATION AND AUTOMATIC DIAGNOSIS

The estimated speed is converted in terms of rotation angle to perform order analysis, i.e. angular resampling vibration signals, and to track the orders of interest. This is done by integrating the estimated instantaneous speed over time to get the cumulative rotations as a function of time.

An automatic diagnosis algorithm is used to detect faults. This algorithm is based on automatic identification of peaks in an order spectrum; generated based on speed information. Automatic diagnosis requires that kinematical data of a turbine, such as shaft speed ratio at various stages of a gearbox, gear number of teeth, and bearing fault frequencies/orders, are known beforehand. With this information, peaks related to various failure modes can be identified accurately in an order spectrum. The method will determine if peaks are present at known orders, e.g. 1st, 2nd, 3rd order running speed, and sidebands around gear or tooth mesh frequencies/orders. The determination takes into account resolution or the number of order bins in an order spectrum. The finer the resolution of the spectrum, the better it is in differentiating various faults. Maximum resolution used in this work is in the order 10^{-2}.

Identification of peaks is prioritized according to the failure modes to be identified, e.g. unbalance, rotating looseness, or bearing faults. For example, on detecting bearing faults, running speed harmonics of the shaft are excluded before identification of peaks related to the bearing fault harmonics, such as inner race (BPFI) and outer race and ball pass (BPFO). The automatic diagnosis algorithm produces a descriptor that describes a particular failure mode. The descriptor is a square sum or Euclidian norm of the identified peaks related to a particular failure mode. This descriptor is then trended over time.

A failure mode is detected if a descriptor that describes the fault crosses an alert level. This alert level is determined statistically based on the same descriptor across many turbines over various conditions. The criterion is 5th percentile of the descriptor value among population considered. A danger or breakdown level is also defined based on the maximum value of the descriptors across the same population considered. Details of this automatic diagnosis algorithm can be seen in the work of Saputra and Marhadi (2019 and 2020).

If a speed sensor is available, order spectrums used in automatic diagnosis is generated based on information from the speed sensor. In this study, faults detected by automatic diagnosis based on estimated speed are compared with the results from the one based on real speed information. The main interest is to check whether descriptors generated with estimated speed information can detect faults around the same time as descriptors generated with real speed information. It is also to check if the descriptor produced by automatic diagnosis using estimated speed information is about the same magnitude as the one using real speed information.

4.1. Third Stage Rotating Looseness Fault

To detect rotating looseness, the Euclidean norm of running speed harmonics of the shaft of interest was monitored as an automatic diagnosis descriptor. Figure 1 displays the trend of the descriptor for a 1P2H turbine having a rotating looseness problem due to the presence of a bearing fault. Both descriptors that are generated using estimated and real speed information are shown.

The figure shows that both descriptors generated using estimated and real speed information follow the same trend. Both of them detect looseness around the same time in early January 2018. This is despite the fact that trend of descriptor generated with estimated speed is consistently lower than the one generated with real speed before the fault occurrence. Both of them also react at the same time and about the same magnitude as the fault got worse and crossed the danger level or breakdown threshold.

After the trend crossed danger level, the turbine went into repaired. Unfortunately speed sensor in the turbine experienced problems after repair, and it could not provide necessary information. Thus descriptor based on real speed could not be generated after the repair. However, descriptor based on estimated speed continued to be produced and confirmed that a repair was performed. The descriptor went from above 12 m/s^2 to almost zero.

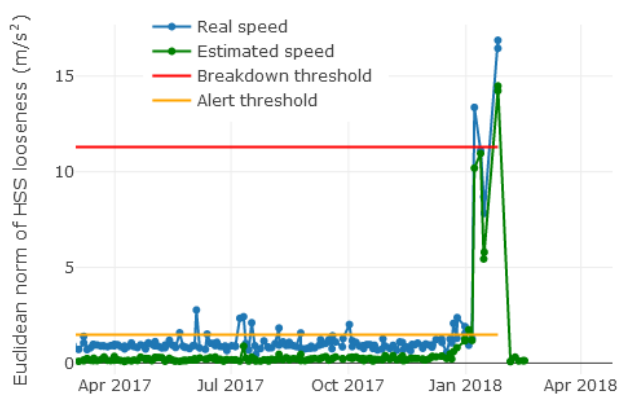

Figure 1. Rotating Looseness Fault descriptor trend.

4.2. Generator Unbalance

To detect unbalance, the first running speed harmonic of generator shaft was trended as an automatic diagnosis descriptor. Figure 2 displays the trend of the descriptor from a 2P1H turbine having generator unbalance problem in early April of 2020. It can be seen from the graph that trends of both descriptors based on estimated and real speed increase rapidly on the 1st of April, 2020.

Descriptors generated by both estimated and real speed information follow each other very closely in this example. They detect the fault at the same time, and both indicate unacceptable condition as they crossed breakdown threshold. After crossing breakdown threshold, the speed sensor was malfunction, thus descriptor based on real speed information could not be generated. However, using estimated speed, it can be seen that the trend returns to an acceptable level after the turbine was repaired.

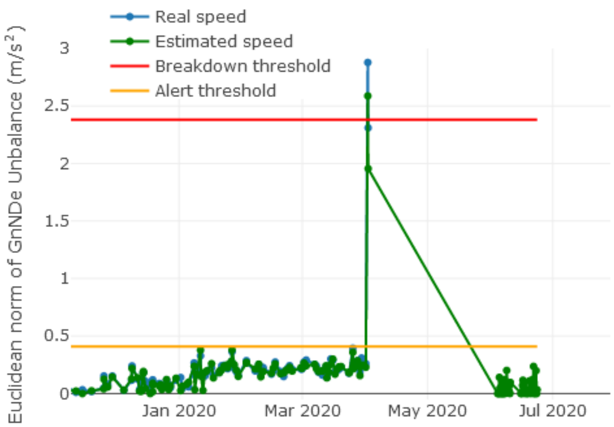

Figure 2. Generator Unbalance Fault descriptor trend.

4.3. Pinion Fault on Gearbox 2nd Stage

A 1P2H turbine type had a broken tooth on the 2nd stage pinion. This fault had been detected as early as beginning of August 2015 using Automatic Diagnosis descriptor as shown in figure 3. The descriptor is based on Euclidian norm of sidebands around the 2nd stage tooth mesh frequencies spaced at the running speed of the shaft where the pinion was attached. Descriptors based on both real and estimated speed information are shown in the figure.

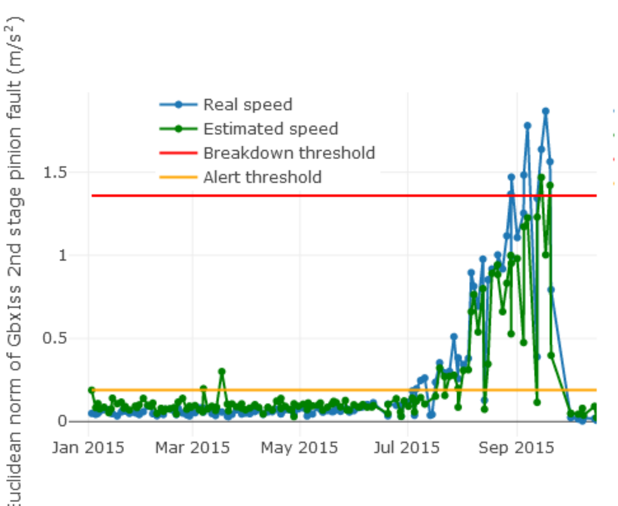

Figure 3. Second Stage Pinion Fault descriptor trend.

Again in this example, both descriptors based on real and estimated speed follow the trend very closely. Both detect the fault around the same time, and show trend returns to an acceptable level after repair. As the fault got worse, magnitudes of the descriptor based on estimated speed tend to be lower than the ones based on real speed. This is also observed in the previous two examples.

As estimated speed information is used for angular resampling, the order spectrum based on this resampled time waveform is not very precise. In other words, some peaks may move a few order bins to different positions from their correct locations. For example, the peak of first order harmonic is supposed to be at bin 1.00 for an order spectrum with resolution 0.01. With estimated speed, the peak could be at bin 1.01. As a consequence, automatic diagnosis algorithm may not see a peak at bin 1.00 or detect a lower magnitude at this location. This could result in incorrect faults identification as shown in the next example.

4.4. Wheel Fault on Gearbox 3rd Stage

A 2P1H turbine type operated with a wheel fault on the 3rd stage gearbox for an extended period of time as shown in figure 4. The descriptor is based on Euclidian norm of sidebands around the 3rd stage tooth mesh frequencies spaced at the running speed of the shaft where the wheel was attached. The problem had been identified since the beginning of 2015 and known by the turbine operator. However as the figure shows, only descriptor based on real speed information increases over time. The one based on estimated speed is consistently lower than the one based on real speed.

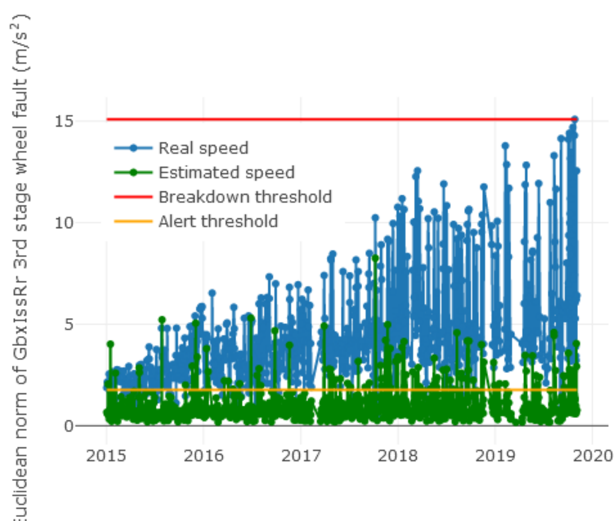

Figure 4. Third Stage Wheel Fault descriptor trend.

On the other hand using estimated speed information, automatic diagnosis identified bearing inner race problem at the shaft where 3rd stage wheel was attached as shown in figure 5. Similar to wheel fault, the inner race fault descriptor is based on Euclidian norm of sidebands around bearing inner race defect orders. As shown in the figure, the magnitude of this descriptor is approximately as high as the wheel fault descriptor using real speed information. In contrast, actual inner race fault based on real speed information had been low until early 2020. This example shows misidentification of fault when estimated speed information is used along with automatic diagnosis algorithm.

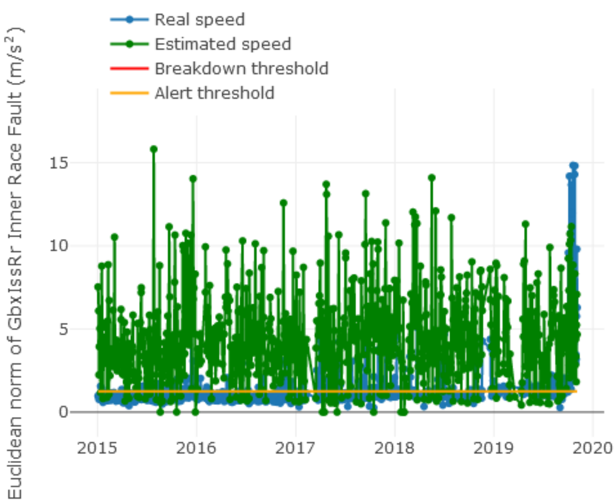

Figure 5. Inner Race Fault descriptor trend

Misidentification in this example is because peaks in the order spectrum are not at the correct order locations when estimated speed information is used. Meanwhile, automatic diagnosis algorithm labels those peaks according to various specific fault orders. Thus sidebands around 3rd stage gear mesh could be mistakenly labeled as sidebands around bearing inner race harmonics, and identified as related to bearing inner race problem and not gear fault. For human eyes, the order spectrums based on estimated and real speed information are quite similar as shown in figures 6 and 7 for the case of wheel fault on 3rd stage gearbox. A trained diagnostic engineer is more likely to identify the fault correctly even when the order spectrum is based on estimated speed. Thus there is still work to be done to perform automatic diagnosis with order spectrums based on estimated speed information.

5. CONCLUSION

Along with automatic diagnosis algorithm, estimated speed information can be used to compute descriptors for detecting failure modes in wind turbines with varying gearbox configurations, namely 1P2H, 2P1H, and 3P1H. The resulting descriptors can also detect faults at the same time as the ones using real speed information. This gives the possibility of condition monitoring of wind turbines without speed sensor and automatic monitoring, which could significantly reduce the overall cost of wind turbine condition monitoring. However, there is still work to be done because automatic diagnosis can misidentify fault due to imprecise order spectrum based on estimated speed information.

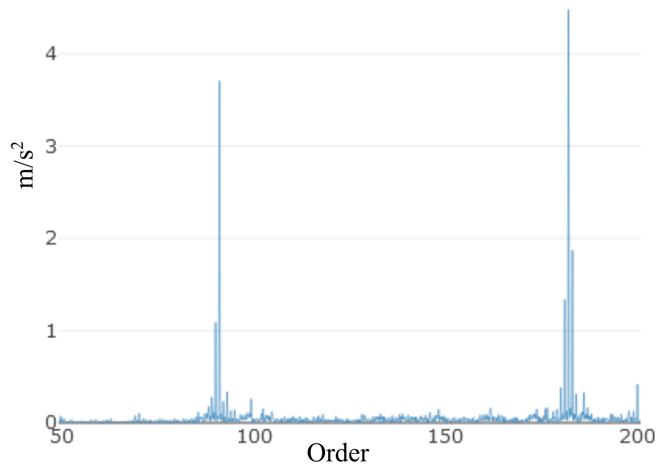

Figure 6. Order spectrum based on real speed information showing two tooth mesh orders with sidebands

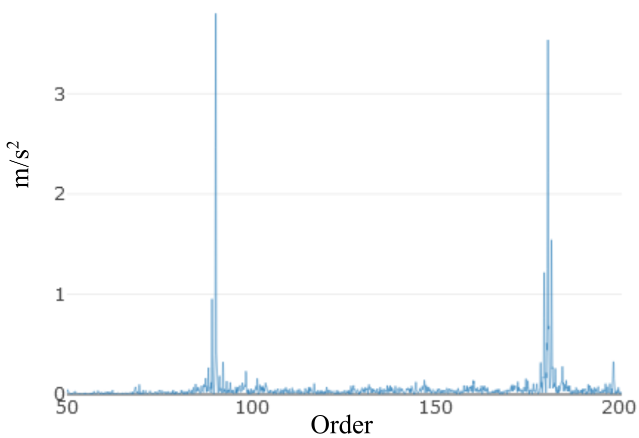

Figure 7. Order spectrum based on estimated speed information showing two tooth mesh orders with sidebands

There are several factors that need to be considered when applying wind turbine monitoring without speed sensor: availability of kinematical data, selection of vibration source for speed information extraction, and selection of frequency or harmonic to be demodulated. Without correct kinematical information, speeds at different shafts of the turbine cannot be determined correctly. Selection of the vibration source will also determine whether the band around the selected frequency to be demodulated is free from other components or not, which subsequently determine the correctness of the estimated speed.

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BIOGRAPHIES

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