

Time-frequency methods for signal analysis in wind turbines

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Abstract. Since wind turbines became one of the most often source of renewable energy, appropriate health and condition monitoring systems are required. Especially proper monitoring of offshore plants is very significant because the accessibility is difficult and inspections are very costly. In comparison with conventional rotating machine vibration monitoring, where steady conditions and stationary signal are usually assumed, the wind turbines are characterized by unsteady conditions due to variable rotational speed. Hence the vibration signal is non-stationary and interpretation of signal signatures may be more complex. The common approach to analyze such non-stationary signals is the use of a time-frequency method, usually Short-Time Fourier Transform, which is the most popular one due to its simplicity. Nevertheless, there are other methods which can give a different view at the analyzed data and provide new information. This article investigates the potential use of some other time-frequency methods, namely Wavelet Transform, Wigner-Ville distribution and Hilbert-Huang transform in wind plants monitoring systems and apply these methods to real measured data with additional simulated bearing fault signal. Finally, the mentioned methods are compared based on computational complexity, readability and interpretability. Though the last two criteria are very subjective, Short-Time Fourier Transform was finally chosen as the most effective method followed by Wavelet Transform.

1. Introduction

Renewable energy is currently very popular topic, especially in relation to the global fear of nuclear energy. It helps to bring new investments and money into this branch to make it maximally effective. Currently, many wind turbines are under construction and many were already built offshore or onshore. Since the investments at the beginning are not small as well as cost of maintenance, a great demand on turbine reliability and availability exists because it is the only way to make wind power more competitive [4].

The condition monitoring systems (CMS) provided by the commercial vendors are usually based on time-domain signal analysis and tracking and bearing vibration diagnostic methods. The time-domain features are simple to calculate and may indicate some faults, however, they cannot provide any information on which component the fault occurred. Moreover, these features are usually sensitive to load and speed. Therefore, the time-domain features are used as initial or additional fault indicators. Some of the more advanced system provides frequency-domain monitoring based on well known Fourier Transform. Nevertheless, due to the signal non-stationarity, the information may be



misleading and detection of fault occurrence is difficult. On the contrary, time-frequency representation (TFR) methods may enable tracking of signal components related to particular parts of the plant, thus significant information about time event caused by a defect can be provided for the HMS. The new trends in wind turbine condition monitoring are introduced in [1]. The most popular TFR is Short-Time Fourier Transform due to its simplicity and sufficient results. Nevertheless, the wavelet transform seems to be a proper alternative in CMS for specific fault detections [9],[10],[11]. The Wigner-Ville Distribution (WVD) was used in [12], but it is not common approach in wind turbine CMS as well as the Hilbert-Huang Transform (HHT).

Despite of the rich scientific literature, most of the sources apply the methods to fully simulated data with lack of relevant noise and other operating signal components [2] or the test is done with experimental test rig. It facilitates the demonstration of the pros and cons but without relation to reality. In this study, the mentioned methods are applied to real data measured in wind turbine. A reasonable fault signal was added to the real data to investigate the potential quality of fault detection of particular methods. Finally, the methods and theirs representations are compared from the viewpoint of computational complexity, readability, interpretability, resolution and the ability to detect the generated fault.

2. Wind Power Plants Vibration

Every rotating machine generates vibration, even in good condition. At least a rotating shaft generates a one-per-revolution frequency component caused by mass imbalance. It is demonstrated in Fig. 2, where the real signal (baseline) spectrum is shown. The vibration components are directly linked to periodic events in the machine operation, such as meshing gear teeth, irregularities on rolling elements in bearings, rotating electric fields and so on [3]. The specific frequencies give a direct indication of the source and enable its health evaluation. The most significant sources of vibration in wind power plant are rotor shaft, rolling elements bearings, gearbox, coupling and generator. Following figure shows the wind power plant schematic and sensor positions. The data used in this article were measured in main bearing by accelerometer (Sensor 08). Unfortunately, the details of measurement chain and data preprocessing were not provided.

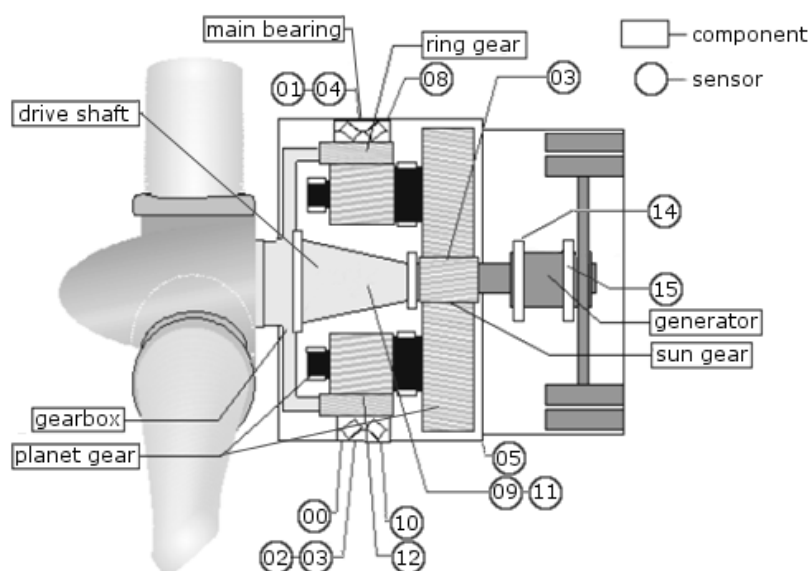


Figure 1: Wind power plant schematic and sensor positions.

2.1. Rotor vibration

Rotor shaft is the basic part of every rotating machine. The shaft is connected to all other parts and its vibrations are transmitted to them. The shaft imbalance component is always contained in the vibration signal because no shaft can be perfectly balanced. This imperfection is represented in spectrum by the peak in rotating speed frequency.

When two or more shafts are coupled together, a misalignment may occur. The dominant harmonics (order of rotating speed, X) are 1X for angular misalignment and 2X for axial misalignment. When misalignment becomes severe, it can generate high amplitude peaks at much higher harmonics.

Bent shaft generates high vibration and creates a lot of stress on other components. A permanent shafts bow produces similar response as a combination of unbalance and misalignment (especially angular one). Axial vibration measurement on one of the bearings usually reveals excited 1X when bow is near to the center of the shaft and 2X when bow is closer to coupling. The way to distinguish bent shaft from misalignment or unbalance is vibration phase measurement because the bent shaft is usually 180° out of phase in the axial direction.

Another common issue of a shaft are cracked shaft, eccentricity, looseness or rubbing.

2.2. Gearbox

Gearbox transmit power from one shaft to another, with change in speed and torque. Gearbox generates high vibration components even if not defect occurs. The vibration are caused by gear meshing when teeth meet together. Hence, the defect frequency is called gear mesh frequency (GMF). The spectrum can show the low harmonics as well as high harmonics. The reason is that the GMF is a product (multiplication) of the number of teeth and rotating speed. The common spectrum components are 1X and 2X of the speed, along with the GMF. Moreover, the GMF will have running speed sidebands relative to the shaft speed to which the gear is attached. These sidebands around GMF and its harmonics are quite common. Hence, the gearbox spectrum contains a range of frequencies due to different GMF and their harmonics. If the gearbox is in a good condition, all peaks have low amplitudes and no natural frequencies are excited.

Common defect of a gearbox are tooth wear and overload, gear eccentricity, backlash or misalignment, cracked or broken tooth or hunting tooth.

2.3. Bearings

A large bearing is used to support the rotor shaft and several smaller bearings support the generator shaft. Typical bearing defect frequencies are related to the bearing geometry and shaft speed and are associated with bearing component wear. The specific defect frequencies are related to cage, ball, outer and inner race wear and can be described by following equations.

$$\begin{aligned} \text{Fundamental Train Frequency (FTF)} &= \frac{f}{2} \left[1 - \frac{d}{D} \cos \phi \right], \\ \text{Ball Spin Frequency (BSF)} &= \frac{f d}{2D} \left[1 - \left(\frac{d}{D} \cos \phi \right)^2 \right], \\ \text{Ball Passing Frequency Outer Race (BPFO)} &= \frac{nf}{2} \left[1 - \frac{d}{D} \cos \phi \right], \\ \text{Ball Passing Frequency Inner Race (BPFI)} &= \frac{nf}{2} \left[1 + \frac{d}{D} \cos \phi \right], \end{aligned}$$

where D is the pitch diameter, d is the ball diameter, n is the number of rolling elements and ϕ is the contact angle.

Moreover, bearing defects generates an impulse which excites the natural frequencies of bearing components and the structure as a whole. Therefore a signal resulting from these impulses appears as periodic burst of high frequency energy at intervals determined by the particular bearing defect.

2.4. *Electric generator*

Electric motors and generators vibrations are generated by mechanical forces such a e.g. unbalance, mentioned above and electromagnetic forces. In wind power plants, there are usually installed permanent magnet synchronous generators. Typical generator defect cause peaks in spectrum in multiples of the line frequency, pole pass frequency, stator winding faults or air gap eccentricity.

2.5. *Blade passing frequency*

Any rotating machine with blades generates increased amplitudes in spectra at frequency that is number of blades times running speed. In case of three-blade power plant, higher amplitudes can be by three times running speed and multiples of this frequency.

2.6. *Structural and other vibrations*

Besides kinematic frequencies of rotating parts, single components such as foundation, tower, rotor, blades or drive train can vibrate with their natural frequencies, The wind turbines are designed so that resonances are avoided.

3. **Time-Frequency domain analysis**

Time-Frequency domain methods are used to describe the distribution of amplitude (or energy) of signal in time and frequency domain simultaneously and allow to track changes of signal in time and frequency. The mentioned methods are described in more detail in [5],[6].

3.1. *Short Time Fourier Transform*

The fundamental method in time-frequency analysis is Short Time Fourier Transform (STFT) which naturally applies FT as it is shown in following equation

$$X(t, f) = \int_{-\infty}^{\infty} x(\tau) h(\tau - t) e^{-j2\pi f \tau} d\tau ,$$

where $h(t)$ is a window function with unit energy i.e.

$$\int_{-\infty}^{\infty} |h(t)|^2 dt = 1 ,$$

This window function allows to divide the non-stationary signal $x(t)$ into short parts which are assumed to be stationary. A long window leads to a representation coarsened in time but fine in the frequency domain and vice versa. The density of energy spectrogram is defined as

$$P_{SP}(t, f) = |X(t, f)|^2 = \left| \int_{-\infty}^{\infty} x(\tau) h(\tau - t) e^{-j2\pi f \tau} d\tau \right|^2$$

3.2. *Continuous Wavelet Transform*

Continuous Wavelet Transform (CWT) is another type of time-domain method defined as

$$CWT(a, b, \psi) = \int_{-\infty}^{\infty} x(\tau) \psi_{a,b}(\tau) d\tau$$

where ψ is mother wavelet and function $\psi_{a,b}$ denotes translation and scaling of mother wavelet

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right).$$

To obtain an admissible representation, $\psi(t)$ must have zero-mean i.e.

$$\int_{-\infty}^{\infty} \psi(t) dt = 0.$$

In comparison to STFT, which use complex exponentials as basis functions, wavelet transform basis is formed by orthonormal series generated by mother wavelet with use of scaling by a factor of a and translation by a factor of b . The change in scaling of wavelet function influences the time-frequency resolution because a window with variable length with only one wavelet is used. Hence, CWT enables to gather good frequency resolution for low frequencies at the expense of time accuracy. On the other hand, high frequencies can be analysed with fine time resolution at the expense of frequency one, which allows to reveal high-frequency time events. Therefore, CWT is so-called a multi-resolution technique.

In general, CWT is time-scale representation, since it displays the signal time-evolution at different scales. Nevertheless, there is a relation between scale and frequency. In case of Morlet wavelet used in this article, the scale-frequency relation is

$$f = \frac{f_0}{a}.$$

3.3. Wigner-Ville Distribution

Wigner-Ville Distribution (WVD) is an alternative method to STFT and CWT which decompose the signal into function basis. On the other hand, WVD is focused on decomposition of signal energy in the time-frequency domain.

By definition, it is a FT of central covariance function of a signal (instantaneous autocorrelation function)

$$WVD(t, f) = \int_{-\infty}^{\infty} x(t + \tau/2) x^*(t - \tau/2) e^{-j2\pi f \tau} d\tau,$$

where τ is the time lag and $*$ represents the complex conjugate of the signal x .

In comparison to STFT and CWT, the WVD does not require any window, which is the limitation for resolution in time and frequency described by uncertainty principle (*Heisenberg-Gabor limit*) as

$$\sigma_f \sigma_t \geq \frac{1}{2}.$$

In other words, when frequency resolution is increased, the time resolution is decreased and vice versa.

Nevertheless, the real signal is not infinite, therefore Pseudo Wigner-Ville Distribution (PWVD) was defined as

$$PWVD(t, f) = \int_{-\infty}^{\infty} p(\tau) x(t + \tau/2) x^*(t - \tau/2) e^{-j2\pi f \tau} d\tau,$$

where

$$p(\tau) = h^*(\tau/2) h(-\tau/2).$$

Inconvenience of WVD is its nonlinearity which is responsible for the introduction of interference terms. This property of WVD causes existence of fake signal component between two real ones. This side effect can be suppressed by modifying the WVD to so-called Smoothed-Pseudo Wigner-Ville Distribution (SPWVD) defined as

$$SPWVD(t, f) = \int_{-\infty}^{\infty} h(\tau) \int_{-\infty}^{\infty} g(\varepsilon - t) x(\varepsilon + \tau/2) x^*(\varepsilon - \tau/2) d\varepsilon e^{-j2\pi f\tau} d\tau.$$

However, interference term suppressing deteriorates time-frequency resolution. Although SPWVD provides better resolution than STFT and CWT, the computation is time-consuming especially for long signals.

3.4. Hilbert-Huang Transform

Aforementioned methods use classic time-frequency analysis approach. It means that frequency determination is based on repetition of specific event with certain period. Thus, the event occurs in signal with certain frequency.

The approach in this section is based on knowledge of analytical signal (complex signal) which allows to define instantaneous phase and instantaneous frequency for each time sample of a signal.

The analytical signal is a complex signal

$$z(t) = x_r + jx_i = A(t)e^{j\varphi(t)},$$

where its real part is the real measured signal. The imaginary part x_i can be determined directly by Hilbert Transform (HT)

$$H[x(t)] = x_i = \frac{j}{\pi} P \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau = x(t) * \frac{1}{\pi t},$$

where P is Cauchy principal value. Parameters x_r and x_i form a complex conjugate pair.

The instantaneous amplitude and phase of analytical signal is then

$$A(t) = \sqrt{x_r^2 + x_i^2}; \quad \varphi(t) = \arctan \frac{x_i}{x_r}.$$

The instantaneous frequency is a derivation of instantaneous phase

$$\omega(t) = \frac{d\varphi}{dt} = \frac{x_i x_r - x_r x_i}{A^2}.$$

Unfortunately, the general signal is composed of many signal components, thus the theory mentioned above cannot be used directly. At first, the Empirical Modal Decomposition (EMD) must be carried out to decompose the signal to particular components. This algorithm is described in detail in [5].

EMD is an algorithm which is not covered by analytical definition [6] and is described by the following steps:

- I. Identification of all extrema of the signal $x(t)$
- II. Interpolation between minimal (maximal) ending up with some envelope $e_{min} (e_{max})$.
- III. Computation of the mean value:

$$m(t) = \frac{e_{min}(t) + e_{max}(t)}{2}$$

- IV. Extraction of the Intrinsic Mode Function (IMF) :

$$imf(t) = x(t) - m(t)$$

- V. Iteration on the residual $m(t)$.

This algorithm is repeated till $imf(t)$ is considered to be zero-mean or the stopping criteria is reached. Then, the set of IMFs is obtained and the instantaneous amplitude (IA) and frequency (IF) can be extracted with use of HT mentioned above. Finally, the time-frequency representation is obtained by displaying the evolution of IA and IF for each IMF.

4. Experimental Results

In this section, aforementioned methods and theirs representations are compared together. The data used for computation was measured by the accelerometer on the main bearing in a offshore wind

turbine during no-fault state, therefore it can be considered as baseline data. The defect signal is added to the data to simulate damaged bearing. Since the main bearing parameters are not available due to intellectual property policy of the wind turbine owner, the defect properties were proposed by estimation. It was suggested, that the bearing defect signal frequency BPFO is 6,3 Hz, which produces impulses with related period 0,16s. These impulses excite natural frequency of the bearing housing which was proposed to be 300 Hz. Then the bursts can be located in peak-free area in the time-frequency representation. The amplitude of the burst was chosen in respect to the amplitude of the baseline signal so that the defect signal does not exceed the baseline signal. Hence, the final fault signal does not contain any issue at first glance. The sampling frequency is 5kHz and the time length is 2s.

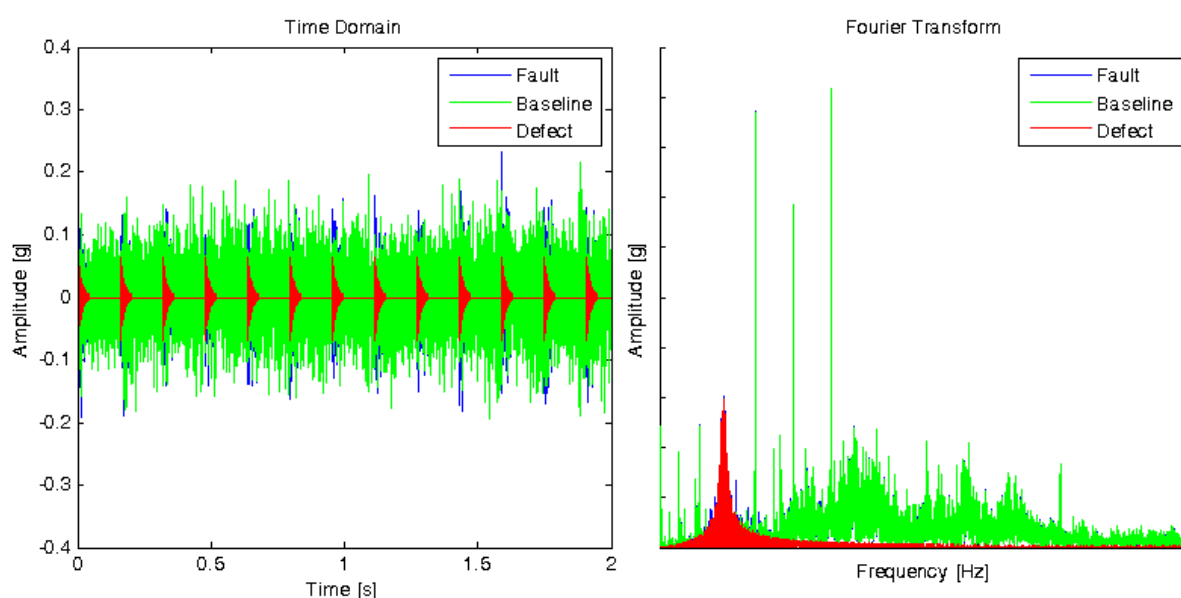


Figure 2: Time Domain and Fourier Transform Representation.

In the figure above, it is shown the signals in time domain. The fault signal (blue) represents the addition of baseline and defect signals. In the FT representation, an extra peak is apparent in the spectrum but it can be confused with regular signal component. Moreover, there is no time information about events.

Following figures show the time-frequency representation of baseline and fault signal acquired with use of aforementioned methods. Setting of particular methods was

- STFT - Hanning window of 512 samples with 99% overlap.
- CWT - Morlet Wavelet with central frequency $f_0 = 2Hz$.
- WVD, PWVD, SPWVD - Number of frequency bins is 5000.
- HHT

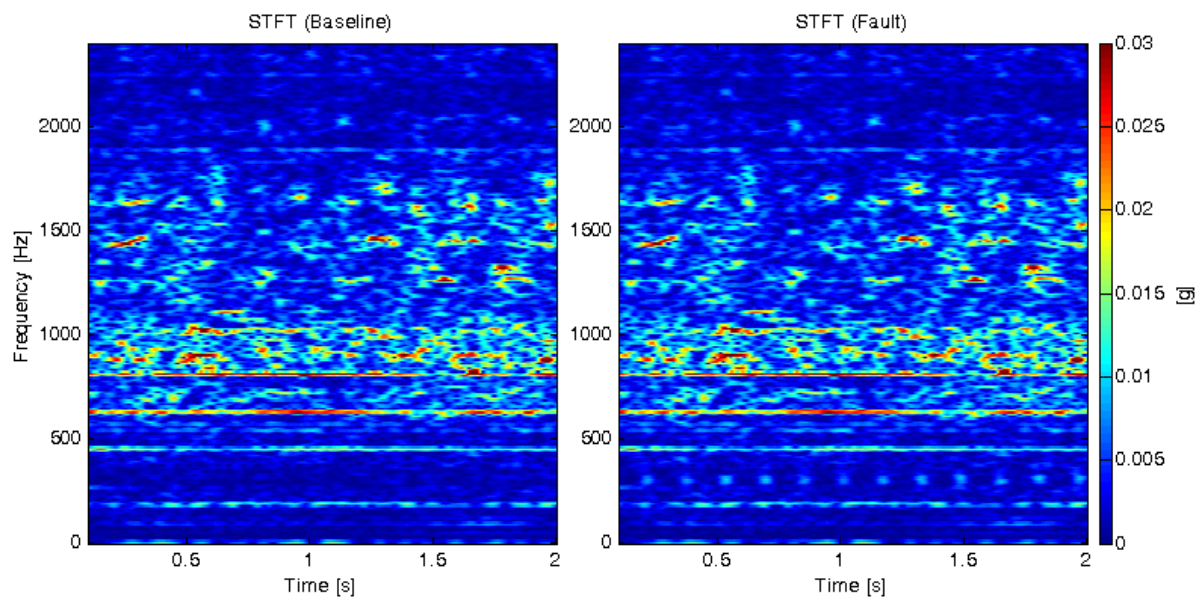


Figure 3: Short Time Fourier Transform of Baseline and Fault signal.

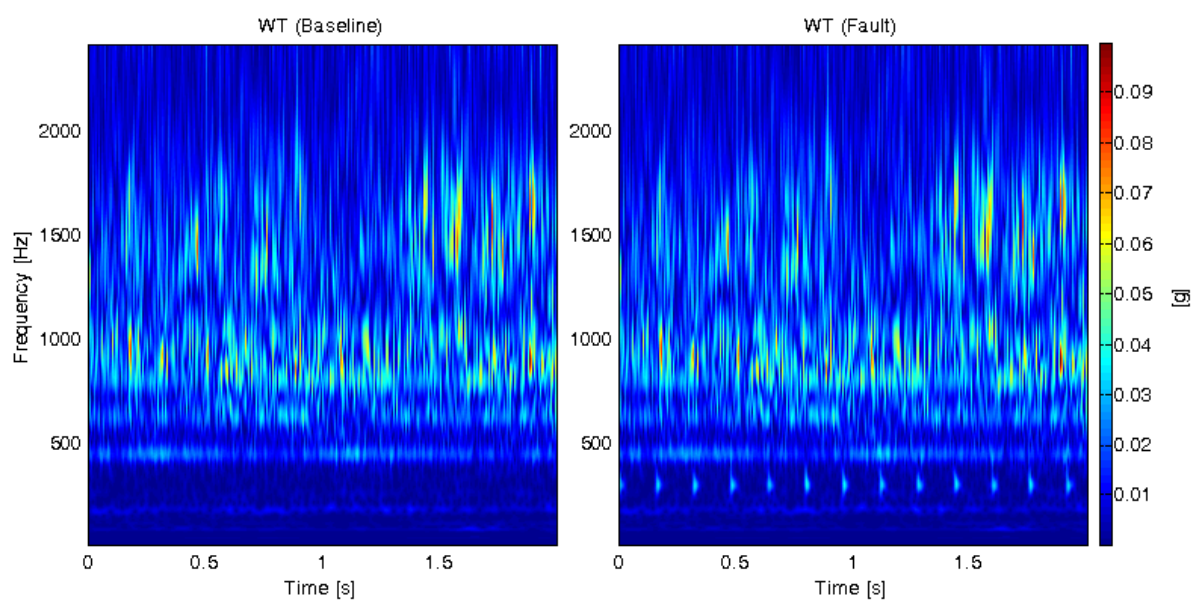


Figure 4: Wavelet Transform of Baseline and Fault signal.

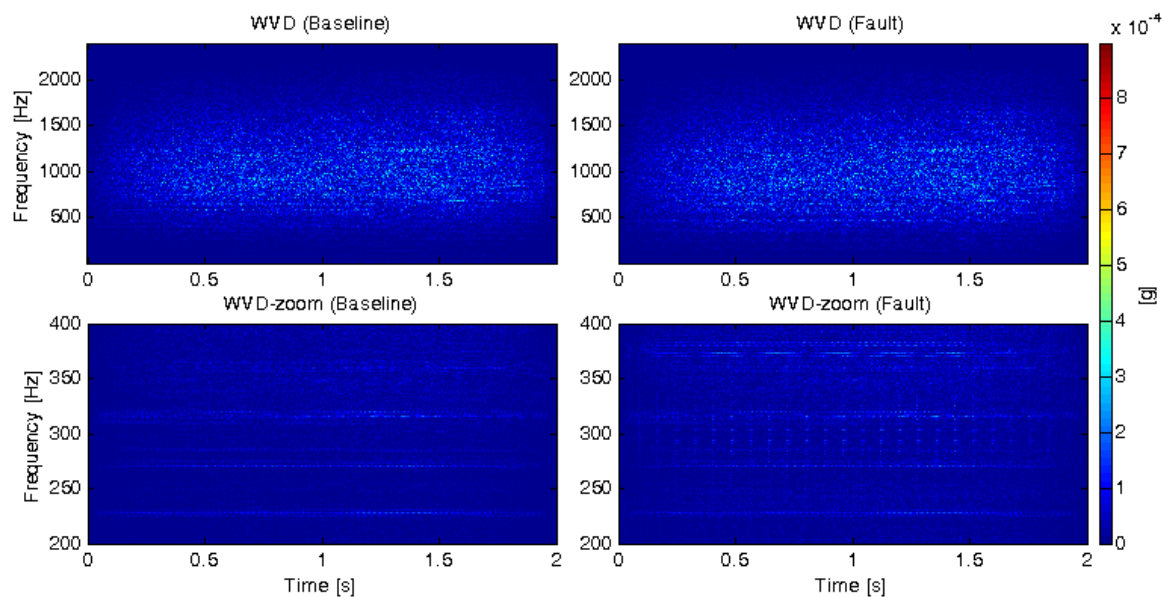


Figure 5: Wigner-Ville Distribution of Baseline and Fault signal.

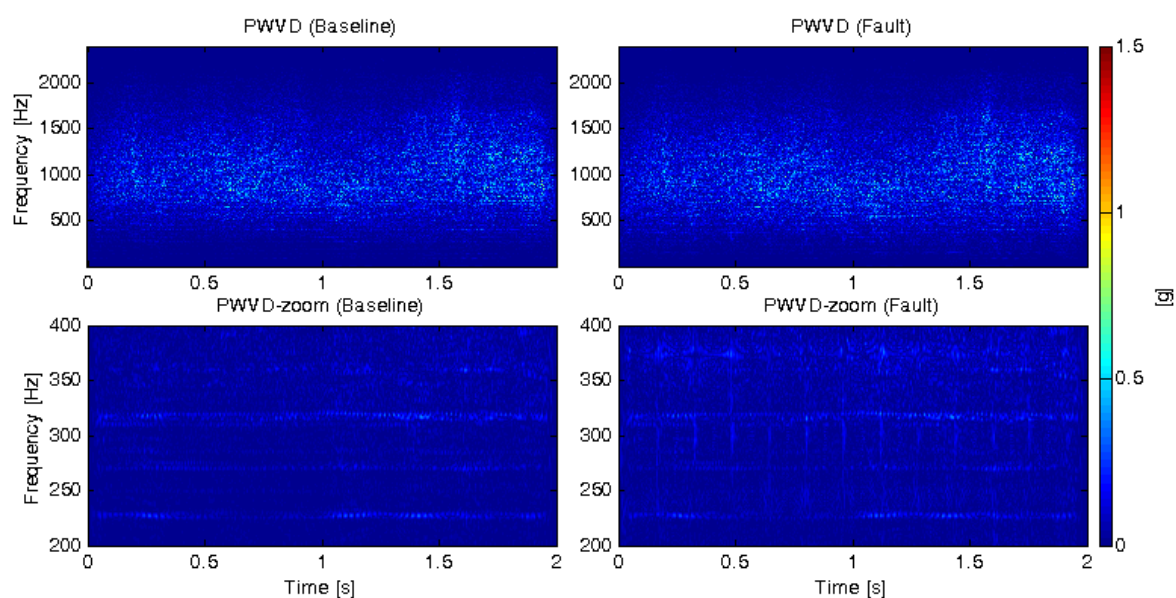


Figure 6: Pseudo Wigner-Ville Distribution of Baseline and Fault signal.

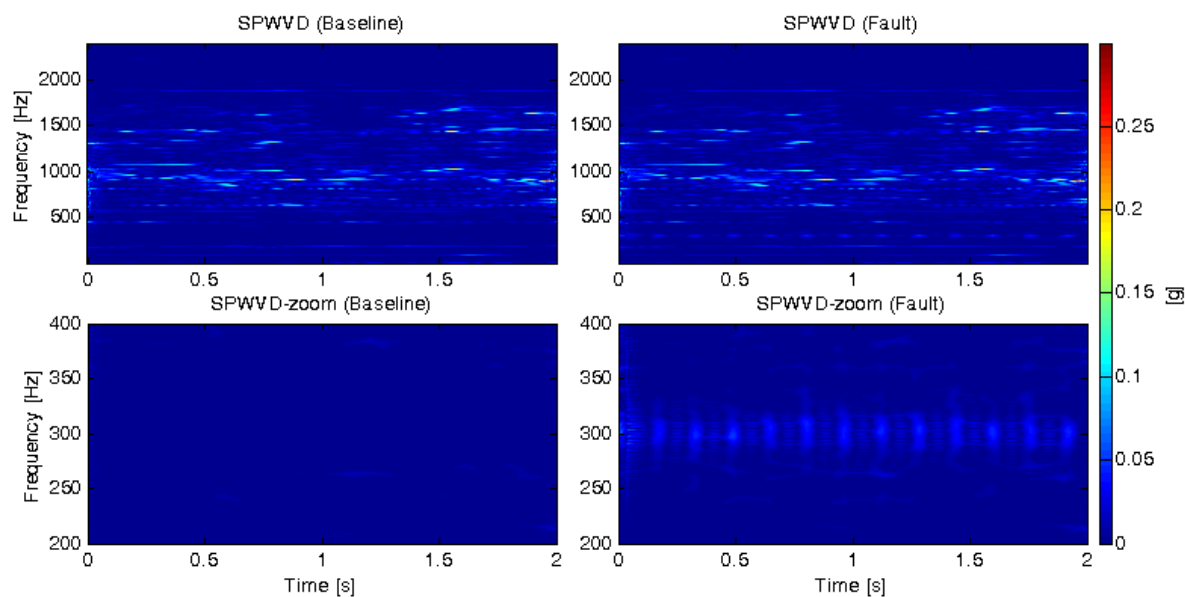


Figure 7: Smoothed Pseudo Wigner-Ville Distribution of Baseline and Fault signal.

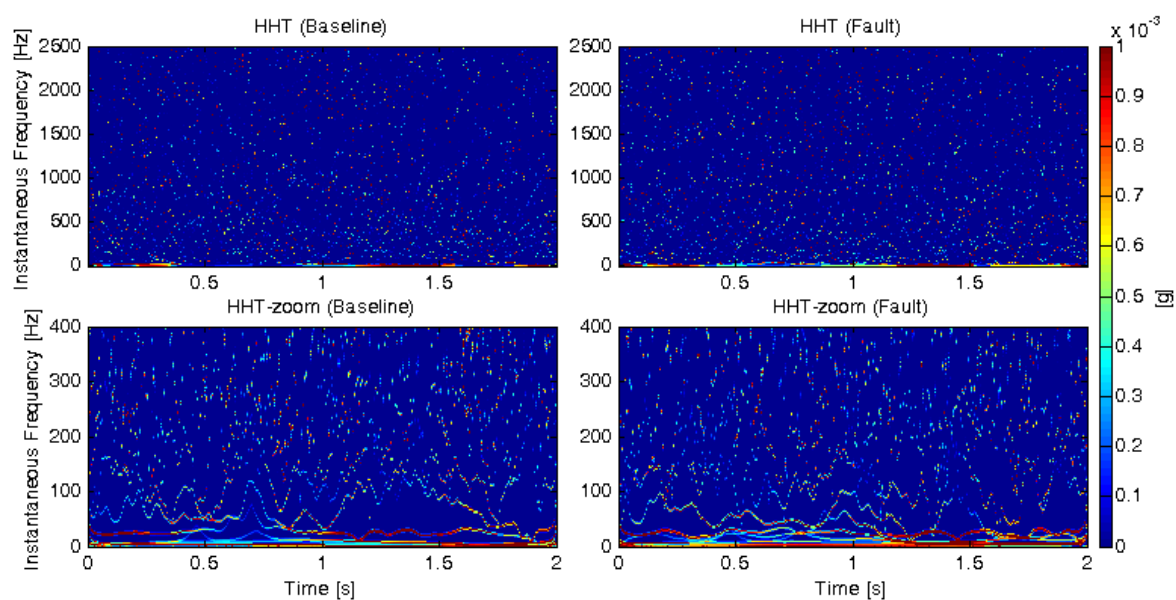


Figure 8: Hilbert-Huang Transform of Baseline and Fault signal.

4.1. Computational Complexity

The mentioned methods were programed in Matlab and were run offline in the same PC with configuration CPU Intel Core i5/2,7GHz and 8 GB RAM. The computational complexity results are reported in the following table.

Method	Time [s]
Short Time Fourier Transform	0,05
Continuous Wavelet Transform	3,2
Wigner-Ville Distribution	13,3
Pseudo Wigner-Ville Distribution	16,4
Smoothed Pseudo Wigner-Ville Distribution	440,0
Hilbert-Huang Transform	2,8

Table 1: Computational Complexity

It is obvious, that only STFT can be used in real-time systems, in practice.

4.2. Representation readability and interpretability

Figures 2-7 display the time-frequency representations for baseline and fault signals. It is apparent, that there are strong differences among particular representations in readability and interpretability of the results.

All of the methods except HHT revealed some disturbances in the frequency around 300 Hz, which was set in simulated defect signal as bearing natural frequency. The STFT and WT representations show the defect the most clearly followed by SPWVD. However, the SPWVD representation is affected by the cross-terms effect. The WVD and PWVD also display the defect, but the readability is very low and it can be easily confused with noise. Moreover, the presence of cross-terms is obvious.

The resolution of STFT and CWT is significantly lower compared to WVD, PWVD and HHT which confirms mentioned Heisenberg-Gabor uncertainty principle.

5. Conclusion

This article has dealt with time-frequency methods and their potential usage in analysis of wind turbine data to detect faults. The Short Time Fourier Transform, the Continuous Wavelet Transform, the Wigner-Ville Transform and Hilbert-Huang Transform have been applied to real data. The data was measured in main bearing in offshore wind power plant and a simulated bearing defect signal was added to it.

It has been shown, that all methods except Hilbert-Huang transform were able to reveal the defect, however with various resolution, readability and of the resultant representation, which is tricky to compare. Further, the computational complexity of the methods were also compared. The final results are summarized in the following table.

Method	Readability	Resolution	Computational Cost	Defect Revealed
STFT	Excellent	Good	Excellent	Yes
CWT	Excellent	Good	Good	Yes
WVD	Bad	Excellent	Bad	Yes
PWVD	Bad	Excellent	Bad	Yes
SPWVD	Good	Good	Very Bad	Yes
HHT	Good	Excellent	Good	No

Table 2: Time-frequency method comparison results.

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