Prognostic Health Monitoring for Wind Turbines

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Outline

- Background and motivation
- Prognostic health monitoring for wind turbines
- Online nonintrusive health monitoring for wind turbines: using current signals
- Theoretical foundation and challenges of current-based health monitoring: frequency and amplitude modulation by fault
- Signal conditioning: synchronous sampling
- Fault signature extraction: synchronous sampling-based frequency spectrum analysis
- Fault diagnosis: impulse detection and statistical analysis
- Experimental results for wind turbine blade, generator, bearing, and gearbox fault diagnosis using proposed technologies
- Benefits

Background and Motivation

- Wind turbines: situated on high towers, installed in remote areas, distributed over large geographic regions, subject to harsh environment and relatively high failure rates

Gear teeth: macropitting

DFIG: insulation failure

Blade damage: lighting strike

Main shaft bearing:
wear tracks on raceway

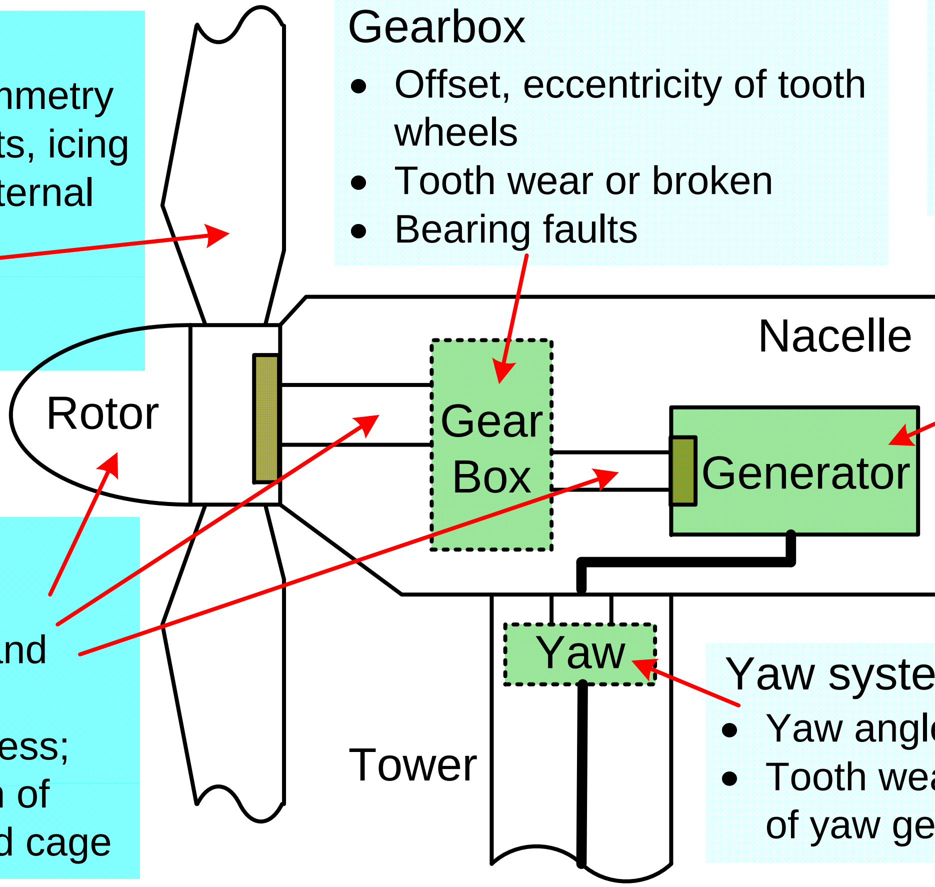
Blade: erosion on the leading edge

Major Failure Modes in Wind Turbines

Blades
- Imbalance, aerodynamic asymmetry
- Surface roughness and defects, icing
- Fatigue, cracks on surface, internal and impending cracks
- Delamination
- Pitch system failure

Gearbox
- Offset, eccentricity of tooth wheels
- Tooth wear or broken
- Bearing faults

Other Faults
- Sensor failure
- Control system failure
- Electric system failure



Generator
- Rotor imbalance
- Stator turn faults, overheating
- Bearing faults

Rotor and shaft
- Imbalance
- Fatigue, surface roughness, and impending cracks
- Bearings: generalized roughness; deformation, pitting, or broken of raceway, rolling elements, and cage

Yaw system
- Yaw angle offset
- Tooth wear or broken of yaw gear

➢ Our work has been focused on fault diagnosis and prognosis for bearings, blades, rotors/shafts, and generators of direct-drive wind turbines, gearboxes of indirect-drive wind turbines, and power electronic converters

W. Qiao and D. Lu, "A survey on wind turbine condition monitoring and fault diagnosis−Part I: Components and subsystems," *IEEE Trans. Industrial Electronics*, vol. 62, no. 10, pp. 6536-6545, Oct. 2015.

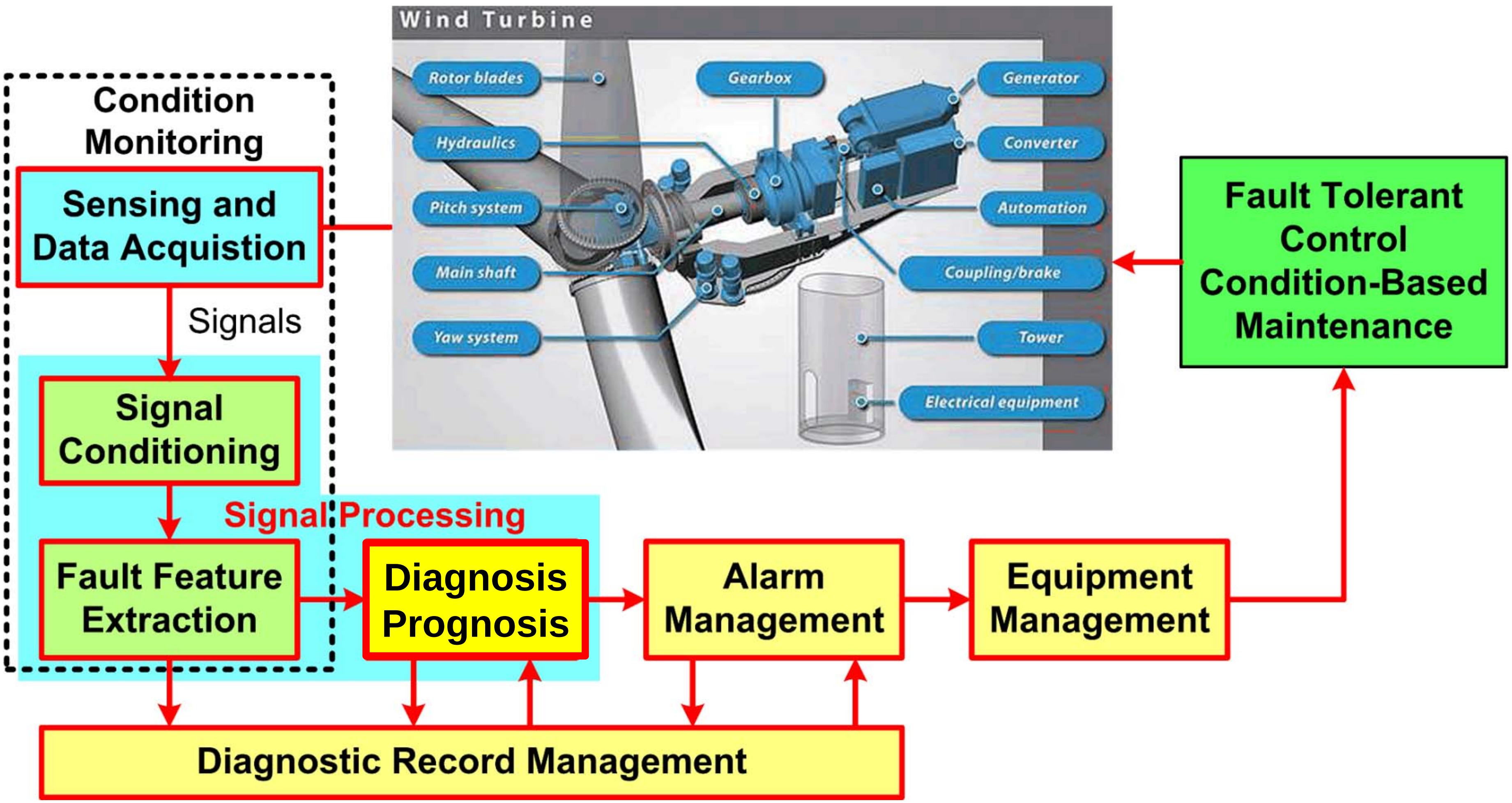
Background and Motivation (2)

- High O&M costs: 10-15% for onshore and 20-35% for offshore
- Online condition monitoring, diagnostics and prognostics
  - Improve wind turbine reliability, capacity factor and lifetime
  - Reduce wind turbine downtime and O&M costs
- Most existing technologies: require additional sensors and data acquisition devices to implement
  - Sensors are mounted on the surface or buried in the body of wind turbine components, difficult to access during wind turbine operation
  - The use of additional sensors and equipment increases the costs and hardware complexity of the wind turbine systems
  - Sensors and devices are inevitably subject to failure, causing additional problems with system reliability and additional O&M costs
- It is desired to develop nonintrusive, low-cost, reliable technologies to fully exploit the benefits of online condition monitoring, fault diagnosis and prognosis for wind turbines

W. Qiao and D. Lu, "A survey on wind turbine condition monitoring and fault diagnosis−Part II: Signals and signal processing methods," *IEEE Trans. Industrial Electronics*, vol. 62, no. 10, pp. 6546-6557, Oct. 2015.

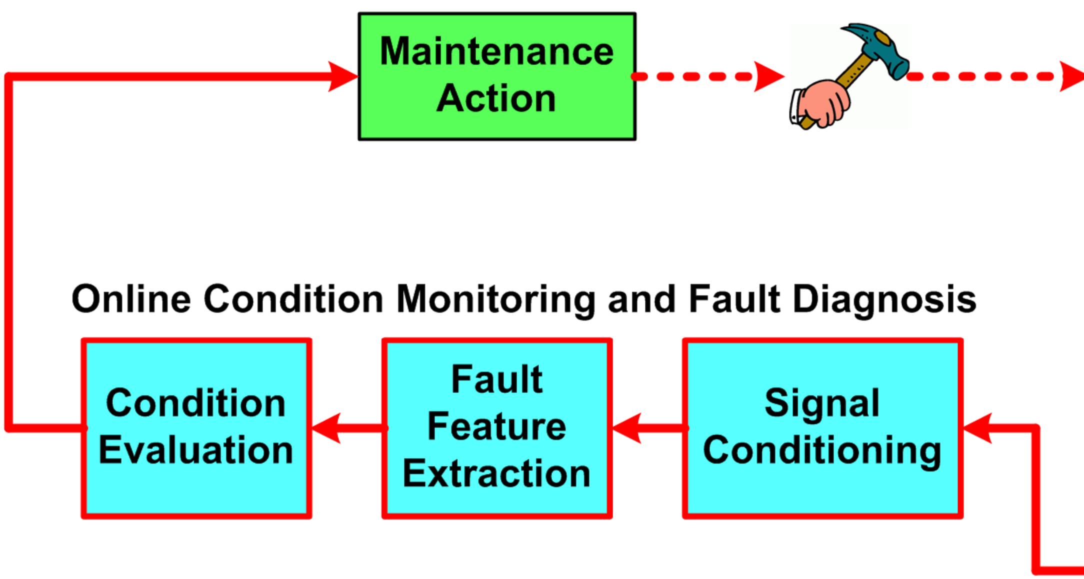
Prognostic Health Monitoring for Wind Turbines

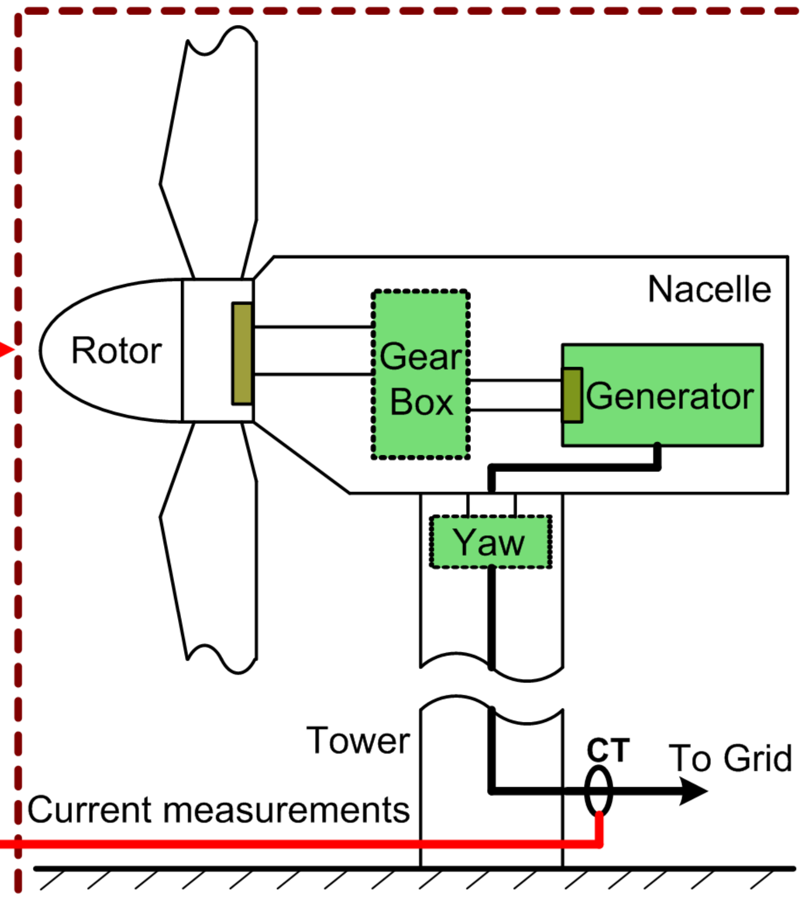
- Condition monitoring: a process of monitoring operating parameters of wind turbines
- Fault diagnostics: detect, locate and identify occurring faults and monitor the development of the faults from defects (incipient faults)
- Fault prognostics: predict the development of a defect into a failure and when the failure occurs



Online Nonintrusive Wind Turbine Fault Diagnosis

- Objective: develop online nonintrusive fault diagnosis technologies for wind turbines only using generator current measurements
  - Current signals are already used in wind turbine control systems; no additional sensors or data acquisition devices are required
  - Almost no additional cost
  - Current signals are reliable and easily accessible from the ground
  - Great potential to be adopted by wind industry





Theoretical Foundation: Frequency and Amplitude Modulation

- Wind turbine generator current signal: $C_s(t) = I_s(t)\cdot\sin\left[\int 2\pi\cdot f_1(t)\cdot dt\right]$
- A failure in wind turbine causes shaft torque vibration at a certain frequency f_{fault} (fault characteristic frequency), which can be detected by vibration sensors

$$T(t) = T_0(t) + A_v\cdot\cos\left[\int 2\pi\cdot f_{fault}(t)\cdot dt\right]$$

- The shaft torque vibration at the fault characteristic frequency will modulate frequency and amplitude of generator current signals: due to mechanical couplings between generator and failed wind turbine component(s) as well as eletromagnetic coupling between generator rotor and stator
- Current frequency modulation:

$$f_1(t) = f_{1,w}(t) + A_{1,v}(t)\cdot\sin\left[\int 2\pi\cdot f_{fault}(t)\cdot dt + \varphi_f(t)\right]$$

- Current amplitude modulation:

$$I_s(t) = I_{s,w}(t) + A_{s,v}(t)\cdot\sin\left[\int 2\pi\cdot f_{fault}(t)\cdot dt + \psi_f(t)\right]$$

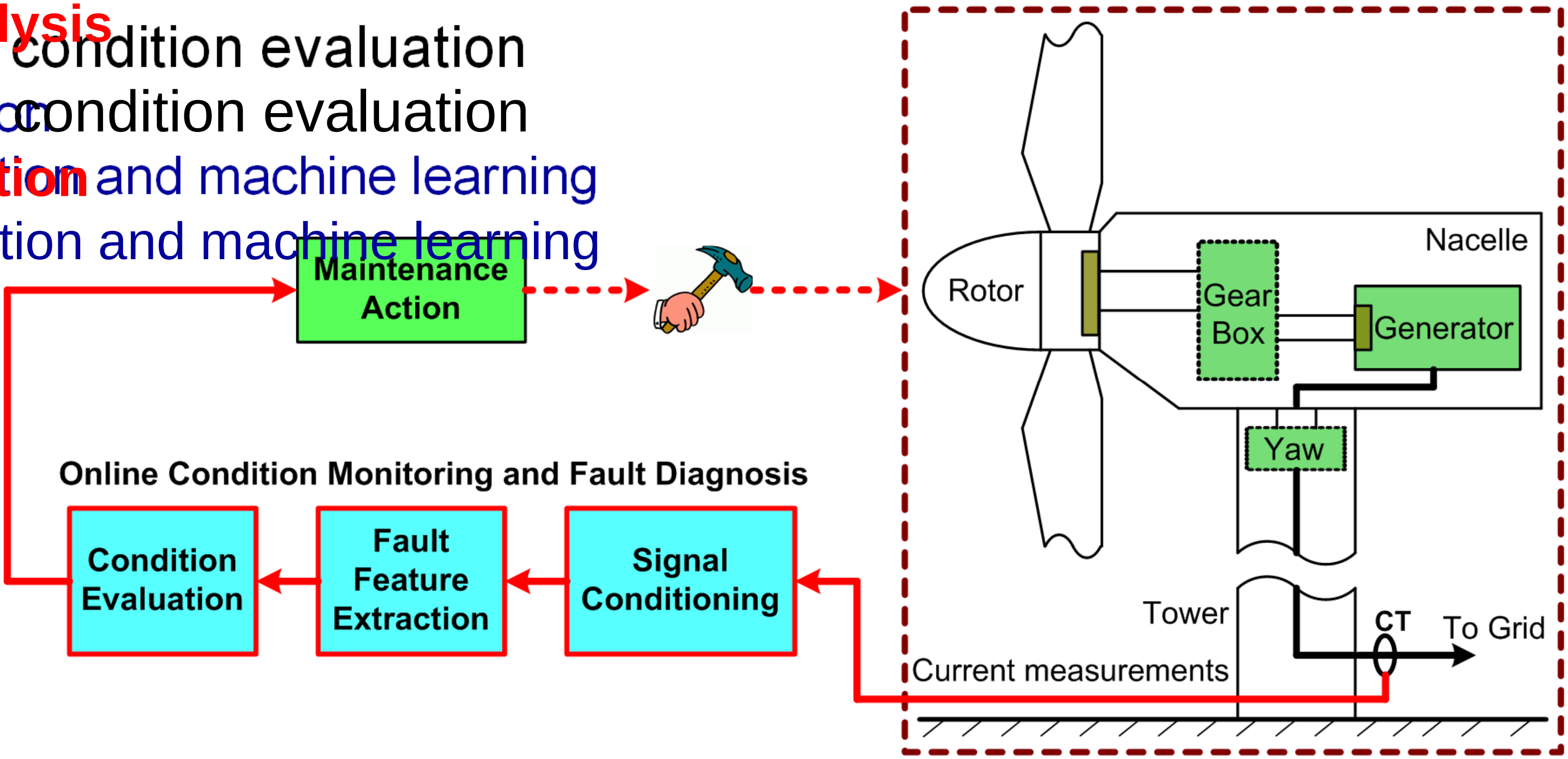
X. Gong and W. Qiao, "Bearing fault diagnosis for direct-drive wind turbines via current demodulated signals," *IEEE Trans. Industrial Electronics*, vol. 60, no. 8, pp. 3419-3428, Aug. 2013.

Challenges in Current-Based Fault Diagnosis

- A single fault characteristic frequency in vibration becomes multiple fault characteristic frequencies in current due to frequency and amplitude modulations
  - Excitations at fault characteristic frequencies in current could be masked by subbands of the dominant components that are irrelevant to fault in the frequency spectrum of current
  - Low signal-to-noise ratio (SNR): the total energy of excitations related to a fault will be dispersed into multiple fault characteristic frequencies
- Fault characteristic frequencies: nonstationary → challenging to extract fault features
  - Depending on shaft rotating frequency (i.e., 1P frequency)
  - Wind turbines: variable speed operation ➔ nonstationary fault characteristic frequencies ➔ cannot be effectively extracted by using standard spectrum analysis
- Fault diagnosis is expected to be automatic for online applications: need effective online fault detectors

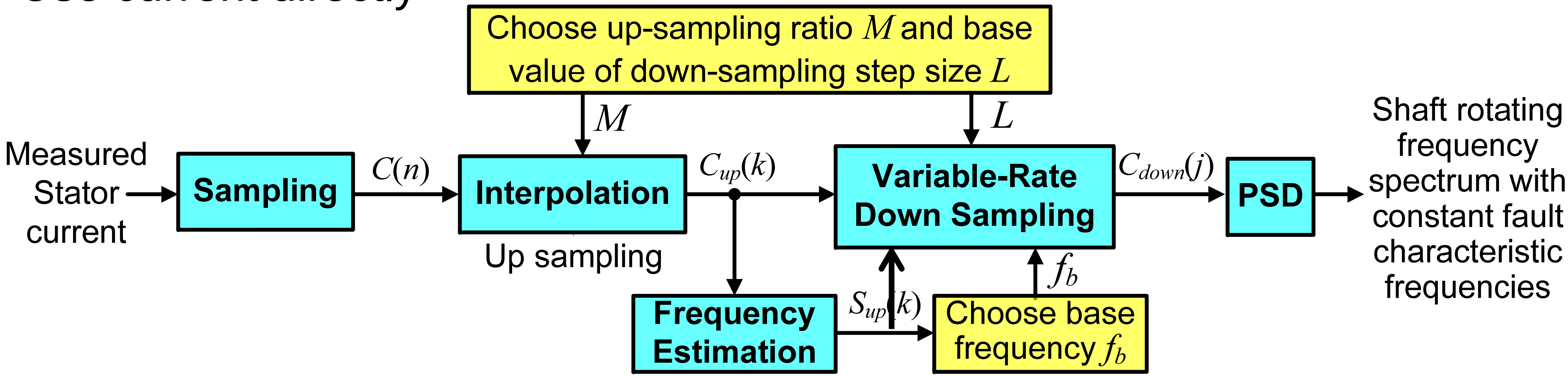
Accomplishments

- Signal conditioning: Improve SNR
  - Current frequency and amplitude demodulation: Demodulated signals explicitly contain fault characteristic frequency components
  - Adaptive synchronous sampling: Convert nonstationary fault features to stationary
  - **Adaptive synchronous sampling: Convert nonstationary fault features to stationary**
- Fault feature extraction from nonstationary signals
- Fault feature extraction from nonstationary signals
  - Frequency spectrum analysis
  - **Frequency spectrum analysis**
  - Time-frequency domain analysis: Wavelet filter, Hilbert-Huang transform
  - Time-frequency domain analysis: Wavelet filter, Hilbert-Huang transform
  - Statistical analysis
  - **Statistical analysis**
- Fault diagnosis: condition evaluation
- Fault diagnosis: condition evaluation
  - Impulse detection
  - **Impulse detection**
  - Pattern recognition and machine learning
  - Pattern recognition and machine learning
- Fault prognosis
- Fault prognosis

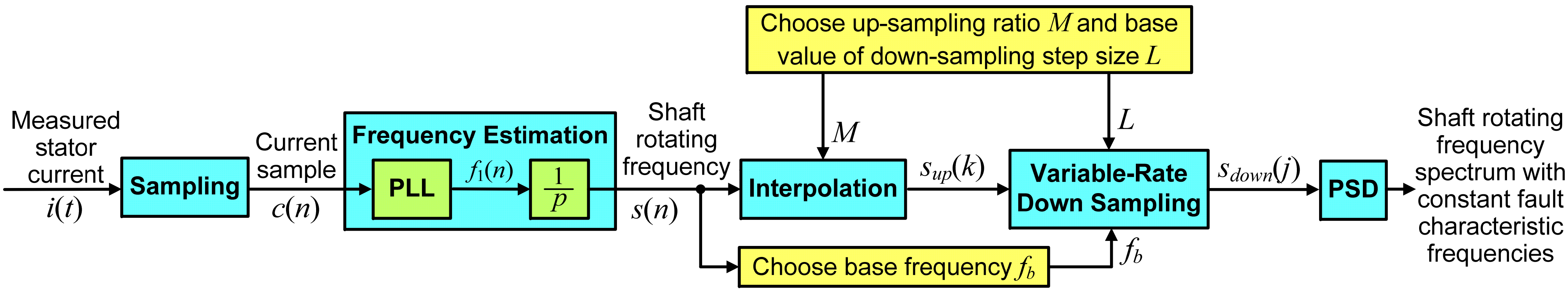


1P-Invariant PSD Method

- Use current directly

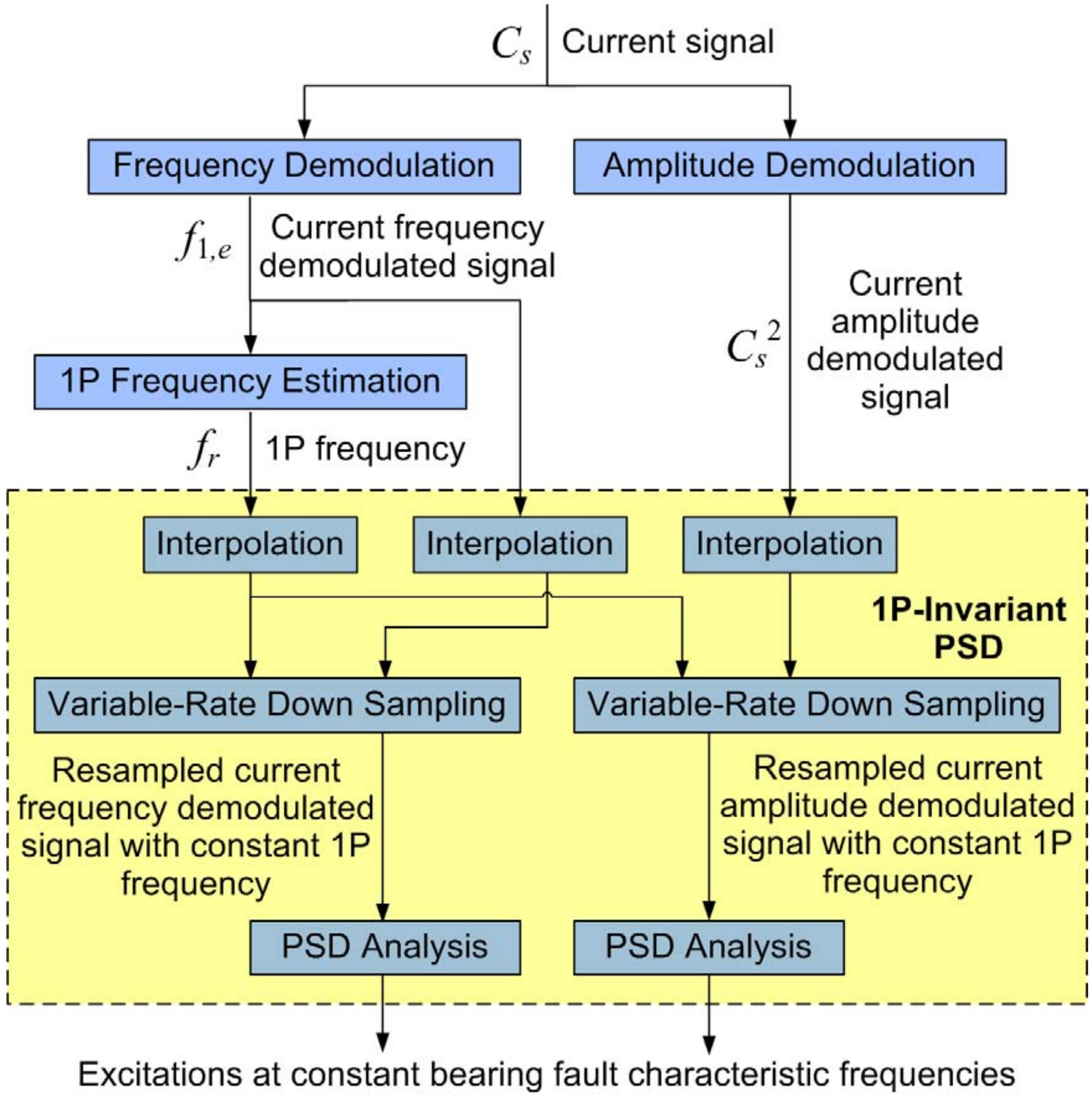


- Use estimated current frequency



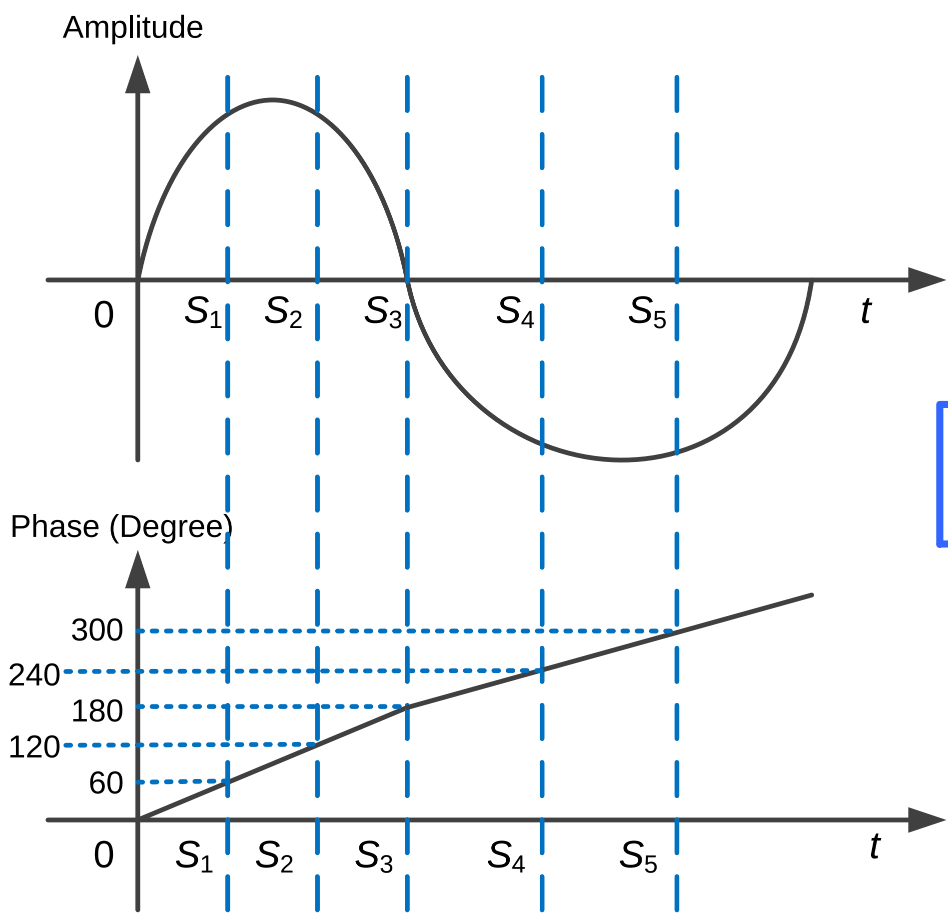
X. Gong and W. Qiao, "Imbalance fault detection of direct-drive wind turbines using generator current signals," *IEEE Transactions on Energy Conversion*, vol. 27, no. 2, pp. 468-476, June 2012.

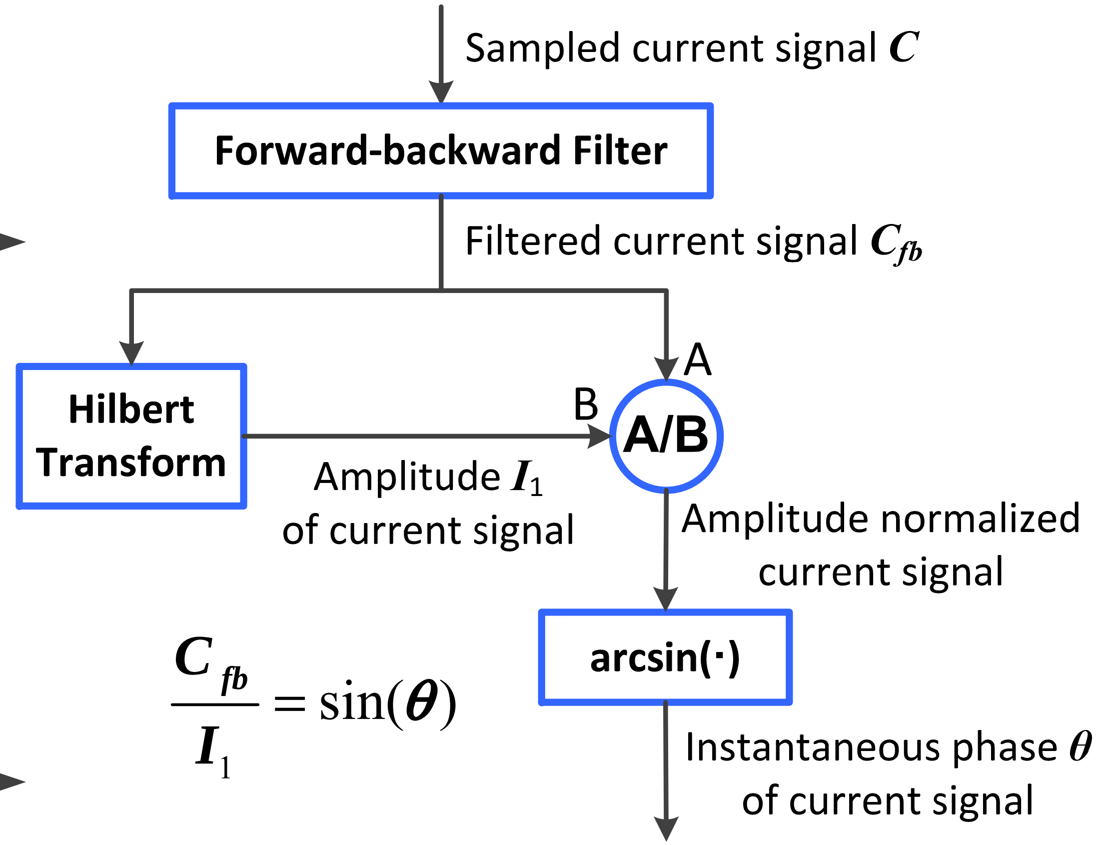
Current Demodulated Signals-Based 1P-Invariant PSD



X. Gong and W. Qiao, "Bearing fault diagnosis for direct-drive wind turbines via current demodulated signals," *IEEE Trans. Industrial Electronics*, vol. 60, no. 8, pp. 3419-3428, Aug. 2013.

Adaptive Synchronous Sampling

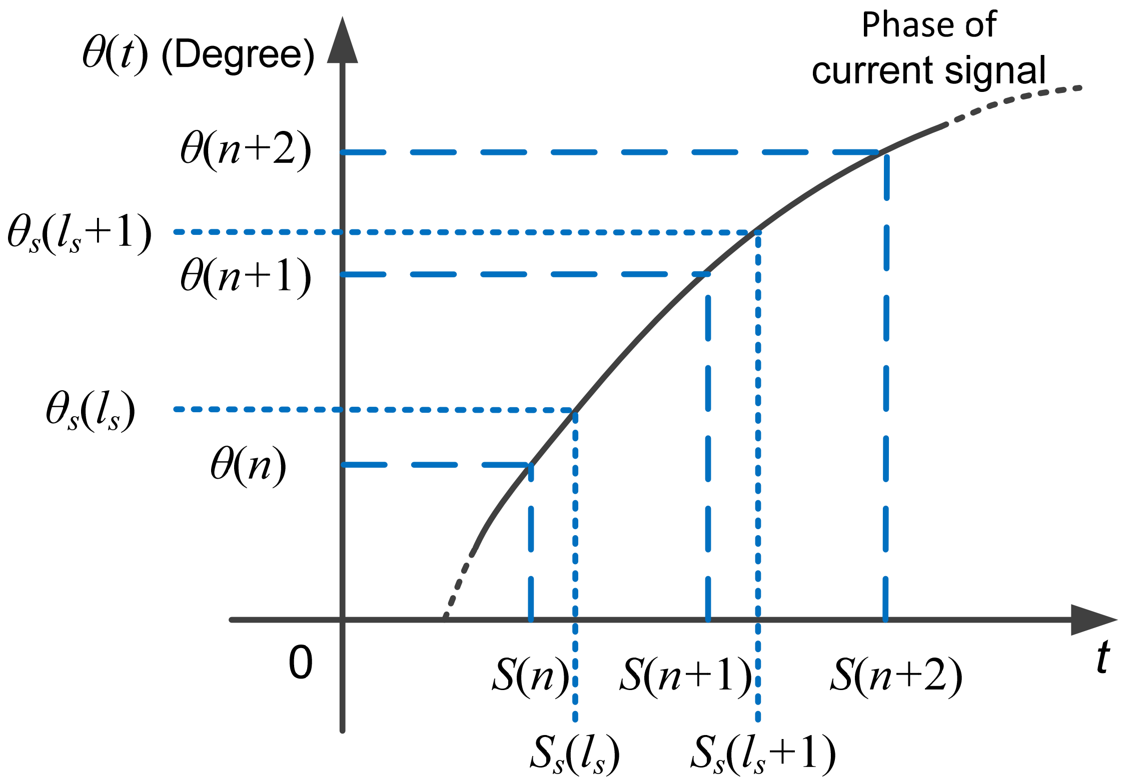


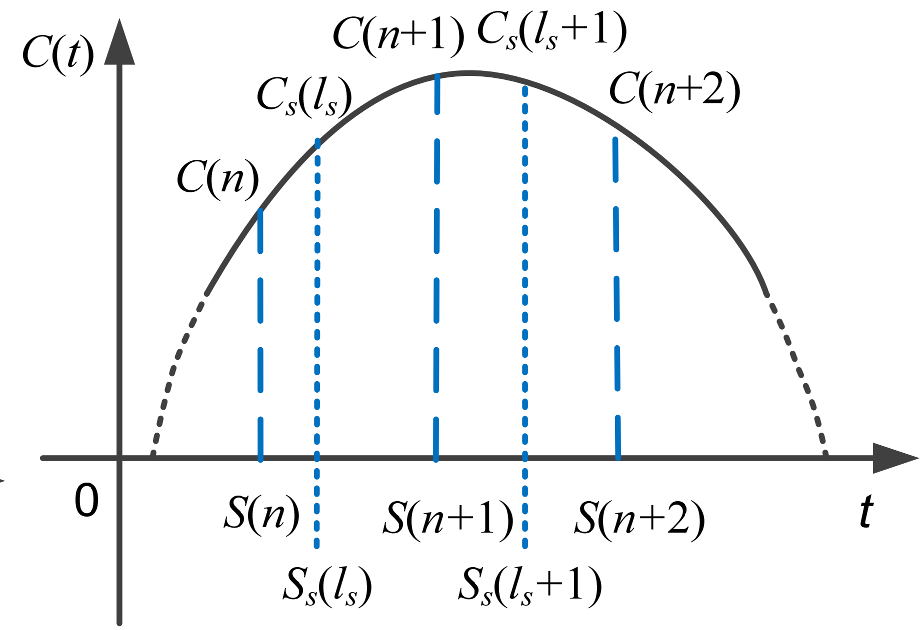


$$\frac{C_{fb}}{I_1} = \sin(\boldsymbol{\theta})$$

- Synchronously sampled nonstationary sinusoidal signal and its phase
- Nonstationary: amplitude, frequency, and/or phase of the signal are variable
- The phases, instead of the time intervals, of the time-domain sampling points are evenly distributed
- In each cycle of the synchronously sampled nonstationary sinusoidal signal, the number of the sampling points is a constant

Adaptive Synchronous Sampling (2)





Calculation of synchronous sampling times

Calculation of synchronous samples

$$S_s(l_s) = S(n) + \frac{S(n+1)-S(n)}{\theta(n+1)-\theta(n)} \cdot [\theta_s(l_s) - \theta(n)]$$

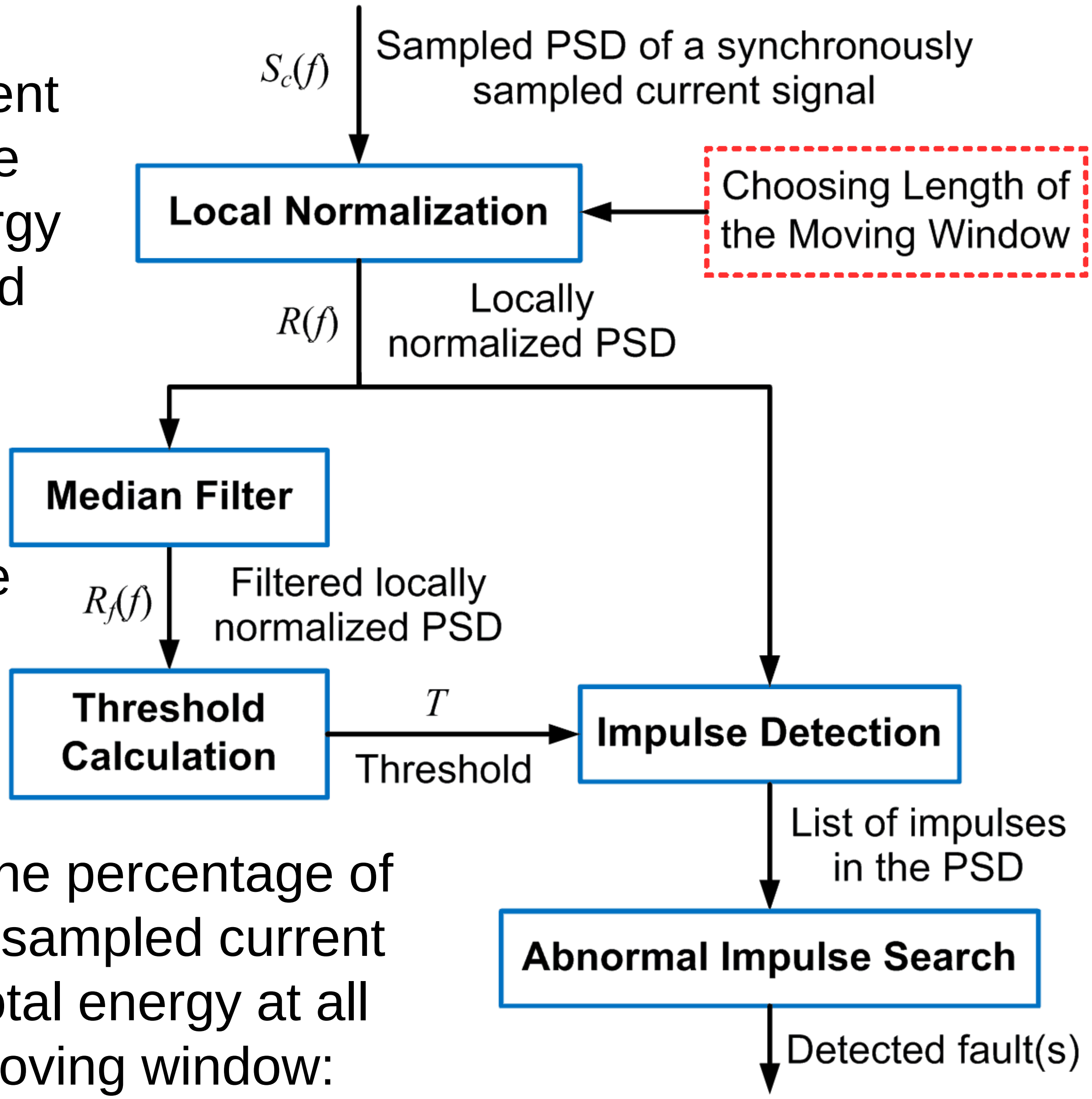
$$C_s(l_s) = C(n) + \frac{C(n+1)-C(n)}{S(n+1)-S(n)} \cdot [S_s(l_s) - S(n)]$$

X. Gong and W. Qiao, "Current-based mechanical fault detection for direct-drive wind turbine via synchronous sampling and impulse detection," *IEEE Trans. Industrial Electronics*, vol. 62, no. 3, pp. 1693-1720, Mar. 2015.

Fault Diagnosis: Impulse Detection

- $S_c(f)$: sampled PSD of an synchronously resampled current signal (f = 1, 2, 3, … F); F is the length of $S_c(f)$. Define the energy of the synchronously resampled current signal at frequency f:
  $P_x(f) = S_c(f)$

- A moving window of length $2W+1$ is applied to $S_c(f)$. Define the energy in the window:
  $P_W(f) = S_c(f-W)+S_c(f-W+1) +\ldots+S_c(f+W)$

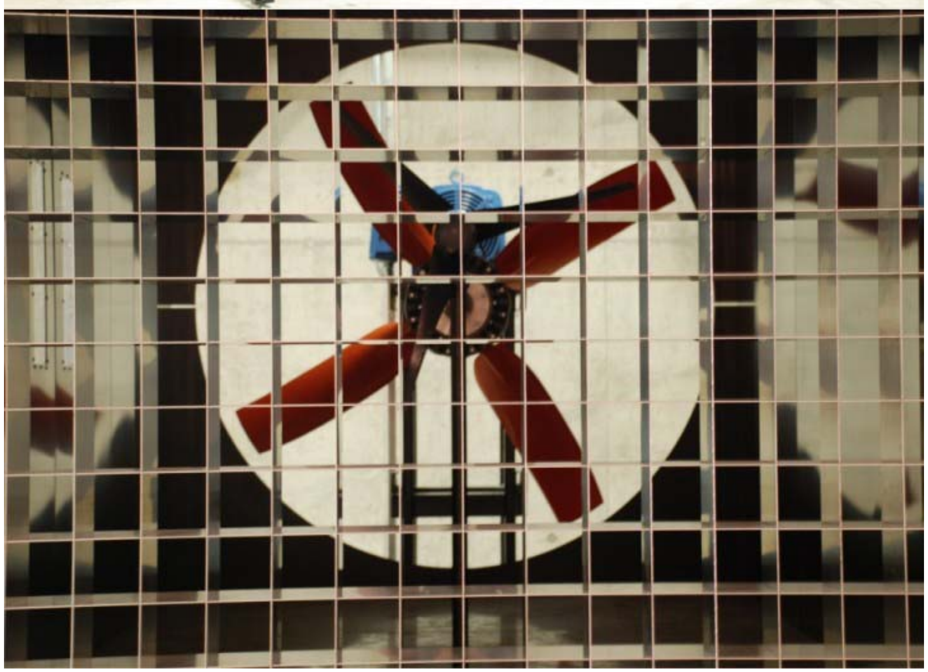


- The ratio $R(f)$ is defined to be the percentage of energy of the synchronously resampled current signal at f with respect to the total energy at all frequencies contained in the moving window:
  $R(f) = P_x(f) / P_W(f)$

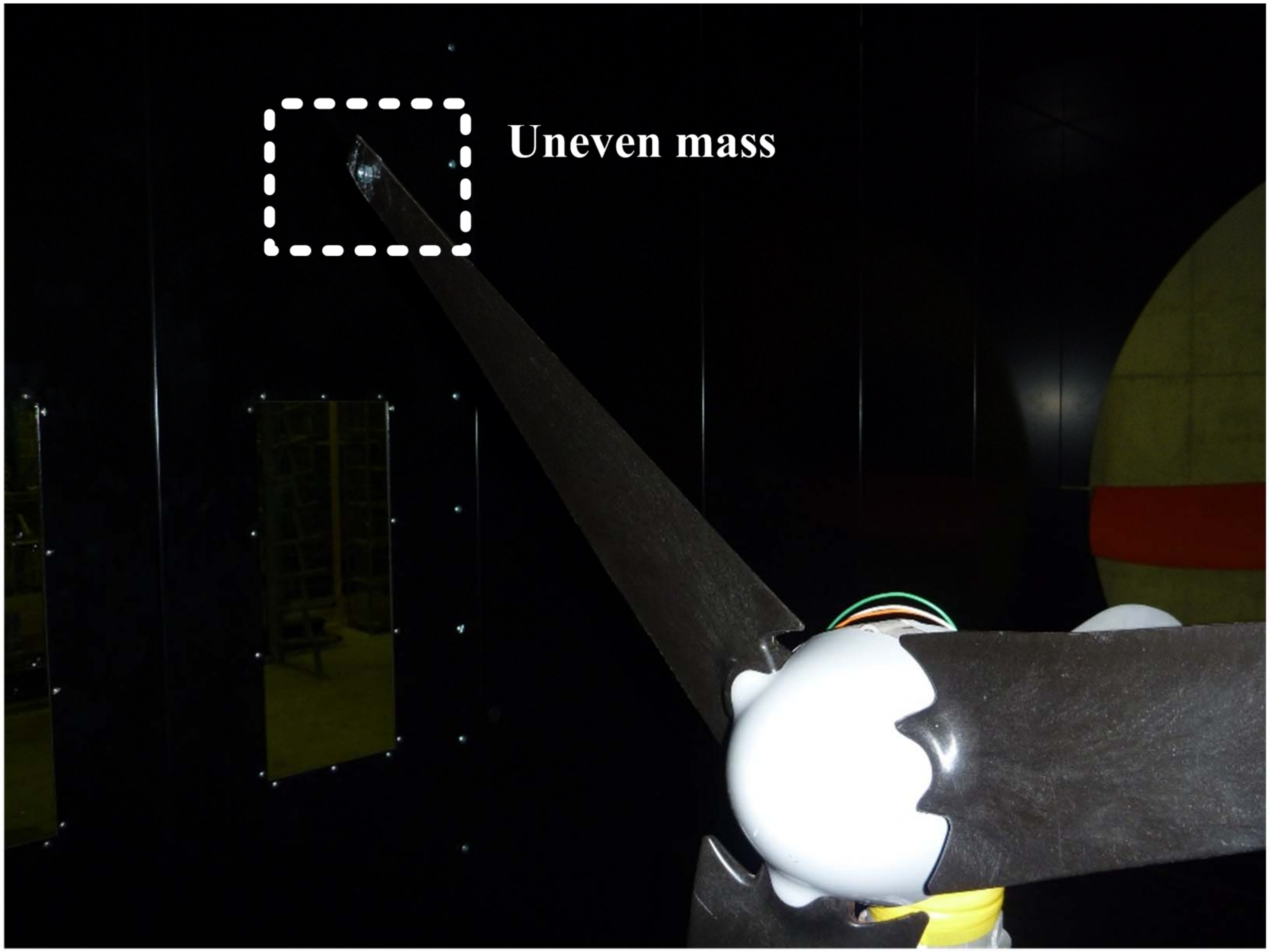
Fault Diagnosis: Impulse Detection (2)

- $R(f)$ represents the locally normalized PSD of the synchronously resampled current signal
- Automatically generate a threshold T from $R(f)$ for impulse detection
- Define $R_f(f)$ the result of $R(f)$ processed by a third-order median filter
  - $R_f(f) = \ Median[R(f-1), R(f), R(f+1)]$
- The threshold T is then set to be the maximum value of $R_f(f)$
  - $T = Maximum[R_f(f)]$
- Impulse: at a frequency where the PSD amplitude is larger than the threshold
- In the PSDs of the synchronously resampled current signal, the amplitudes of the impulses at the fault characteristic frequencies are the signatures for wind turbine fault diagnosis
- An alarm is generated if an impulse is detected at the characteristic frequencies of a fault

Testing Facilities and Equipment



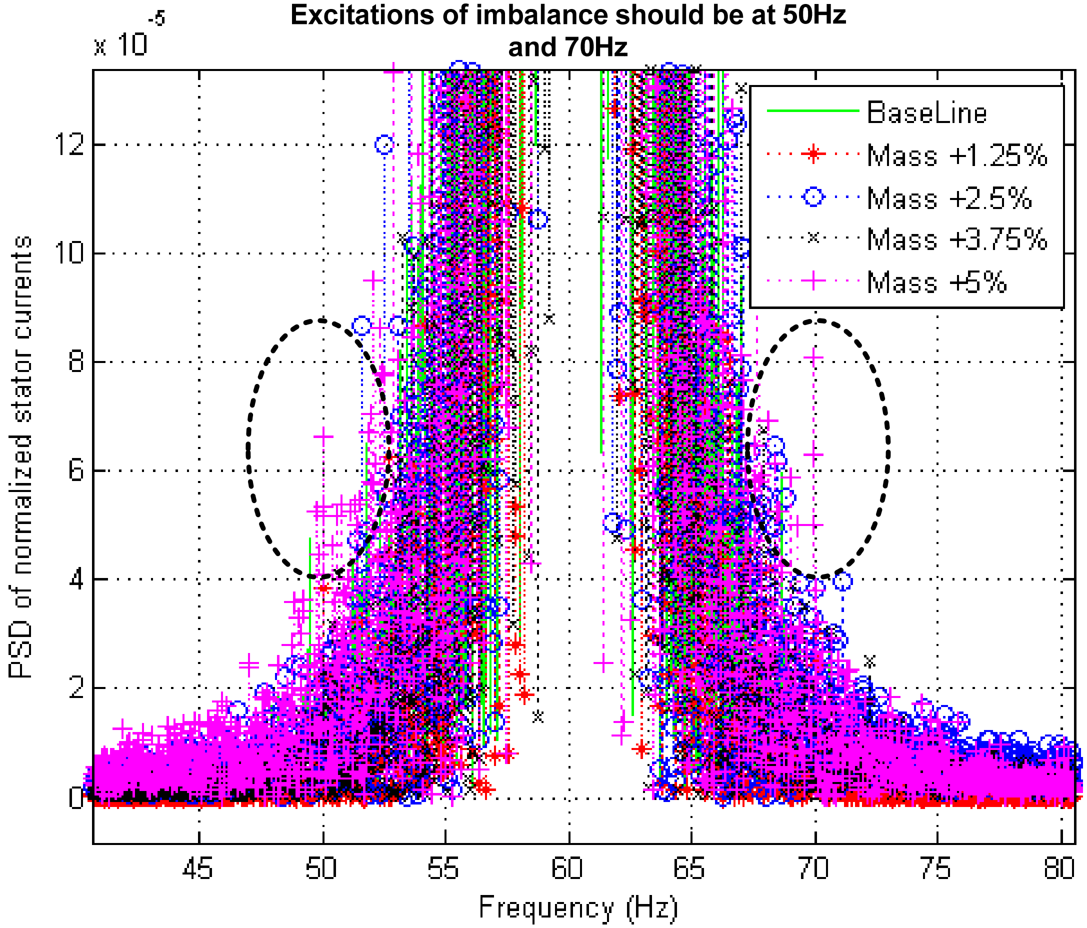
Blade Imbalance

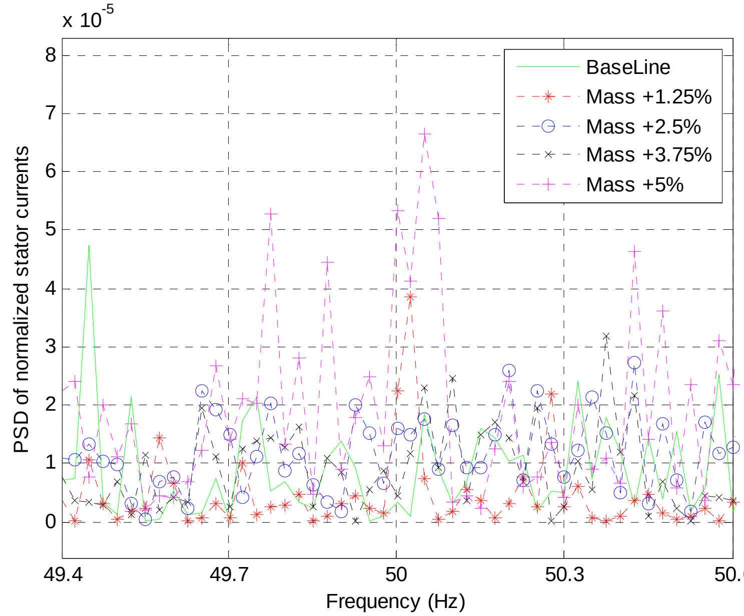


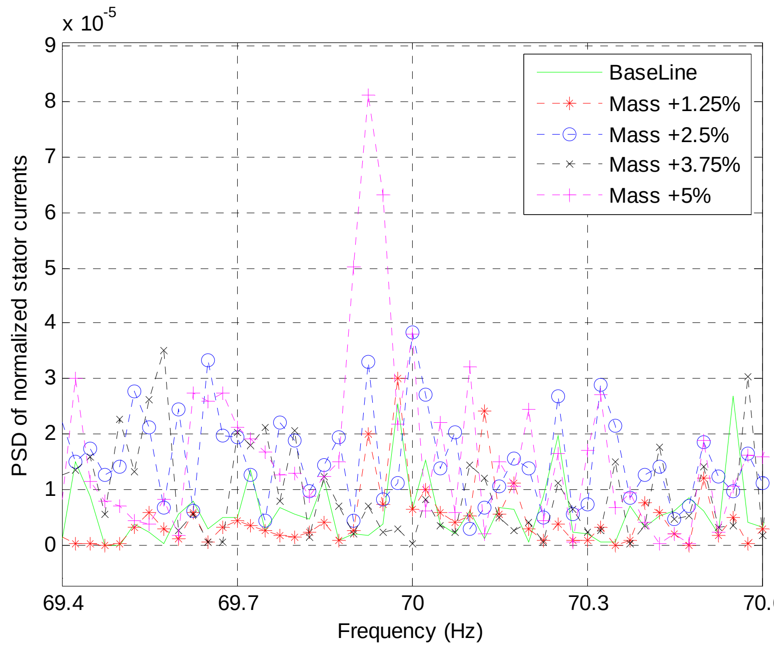
A Southwest Windpower Air Breeze wind turbine was used in the experiment

- Experiments were performed in four scenarios with the mass density of one blade increased by 1.25%, 2.5%, 3.75%, and 5%; while the mass densities of the other two blades are held constant

Blade Imbalance: Current

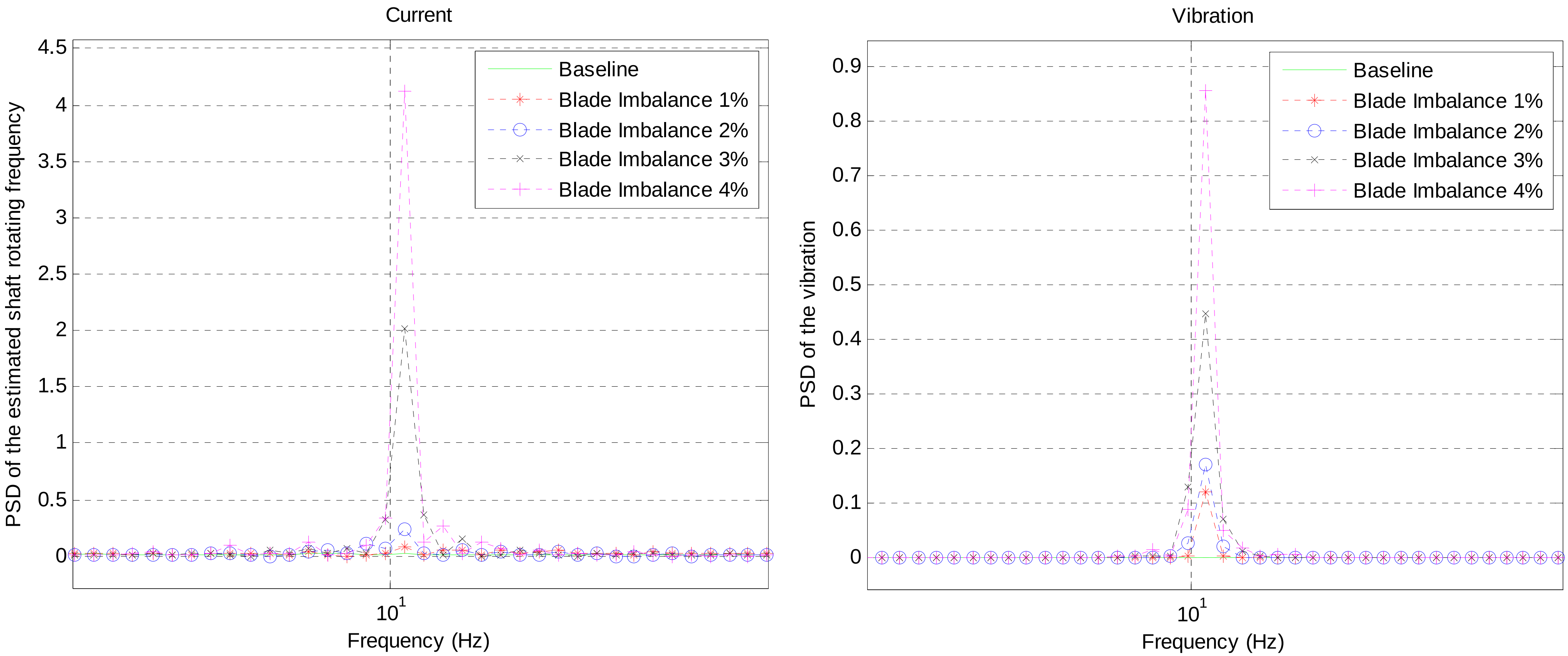






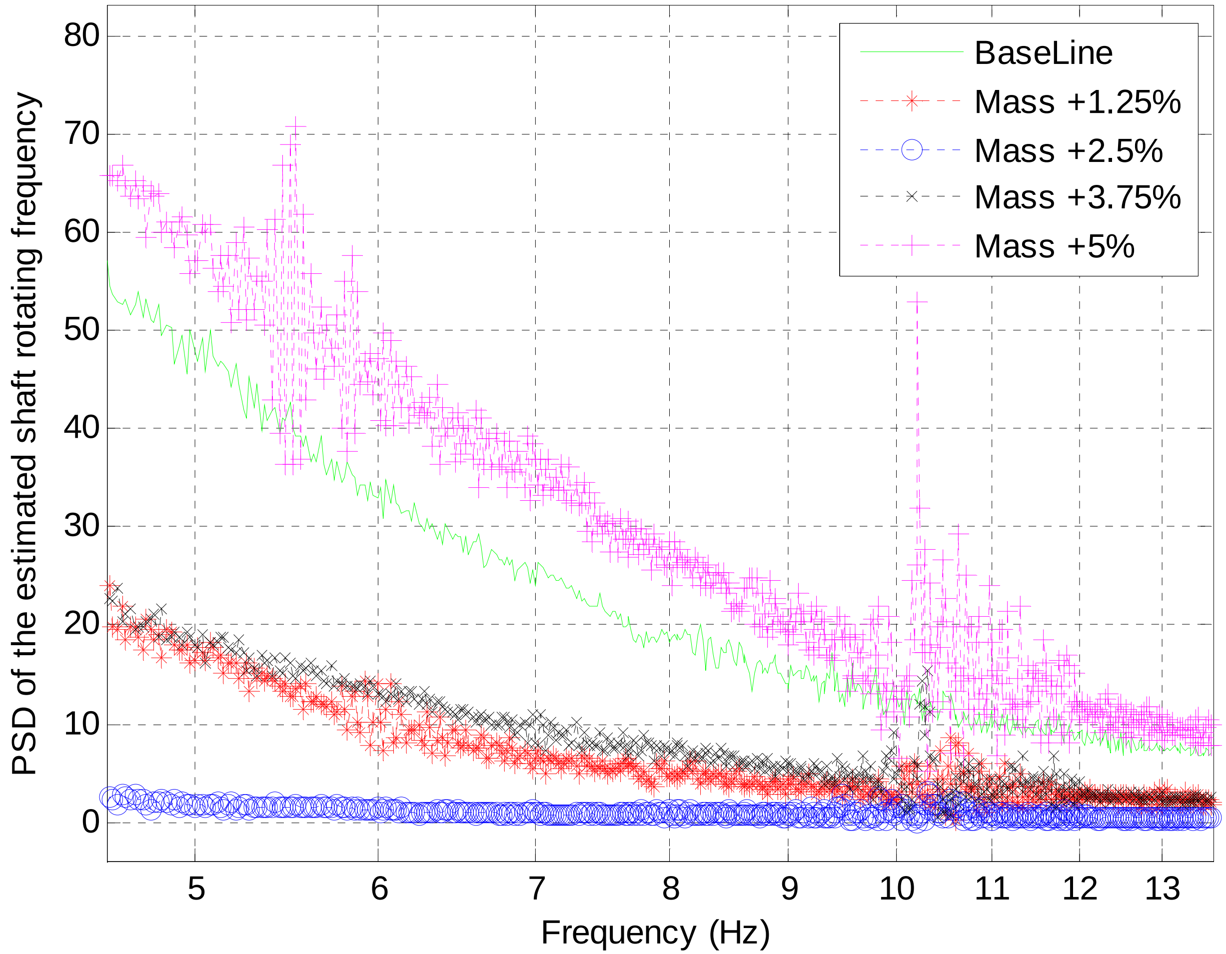
- 1P converts to 10 Hz, current to 60 Hz
- Excitations at 50 Hz and 70 Hz
- Excitations only appear in the worst case

Blade Imbalance: Estimated Shaft Speed (2)



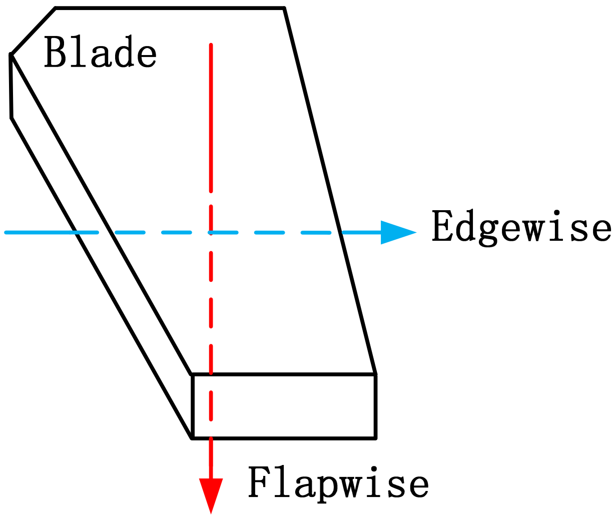
- The variable 1P frequency is converted to a constant value of 10 Hz
- Health case: no excitation observed at 1P in the PSD curve
- Blade imbalance cases: magnitude of 1P excitation increases with the increase of degree of imbalance

Blade Imbalance: Standard PSD

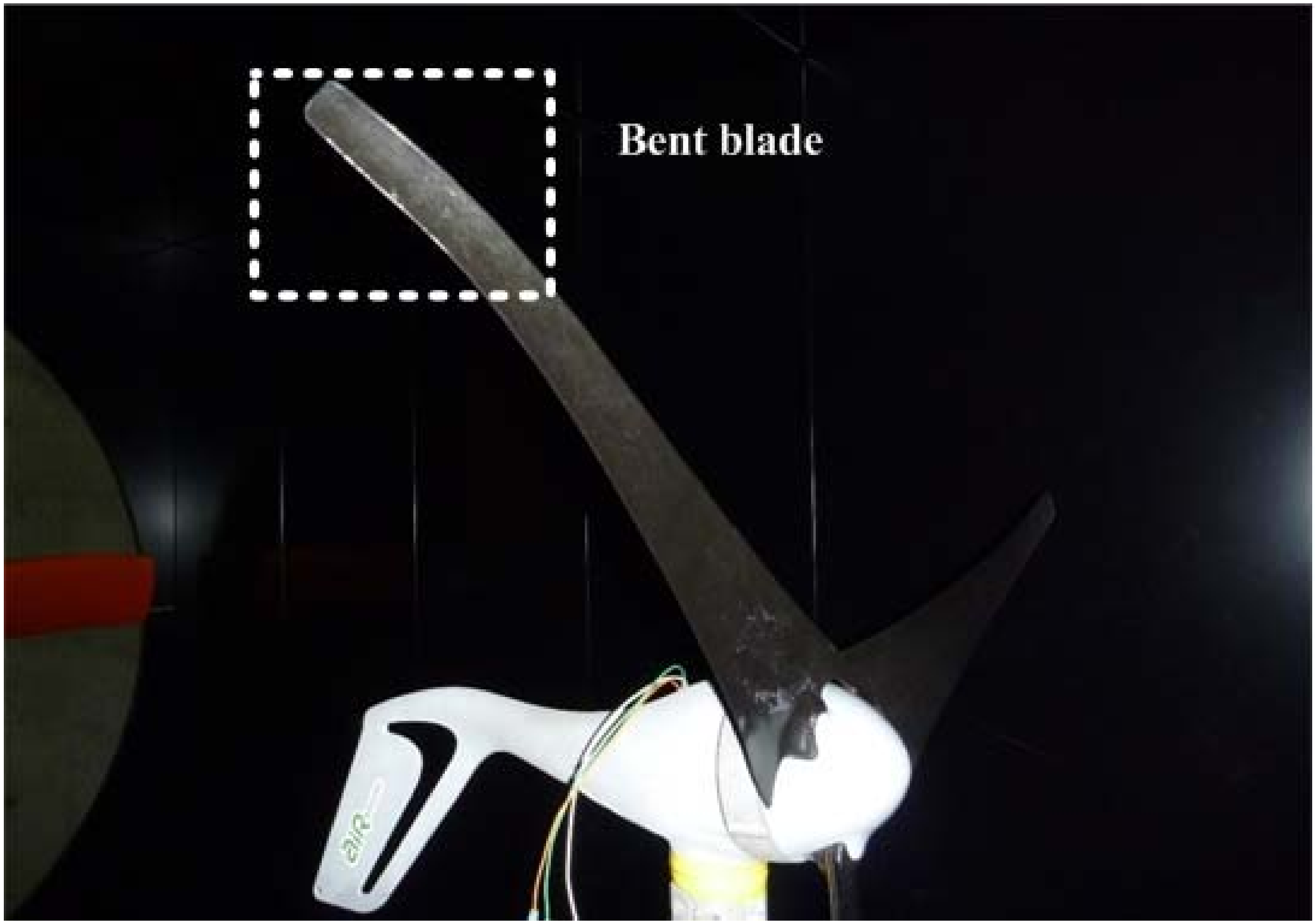


- ➢ Excitation at 1P frequency in the range of 6-13 Hz
- ➢ It is difficult to quantify and evaluate the fault
- ➢ It is difficult to identify fault signatures from the interferences near 1P frequency

Bent Blade

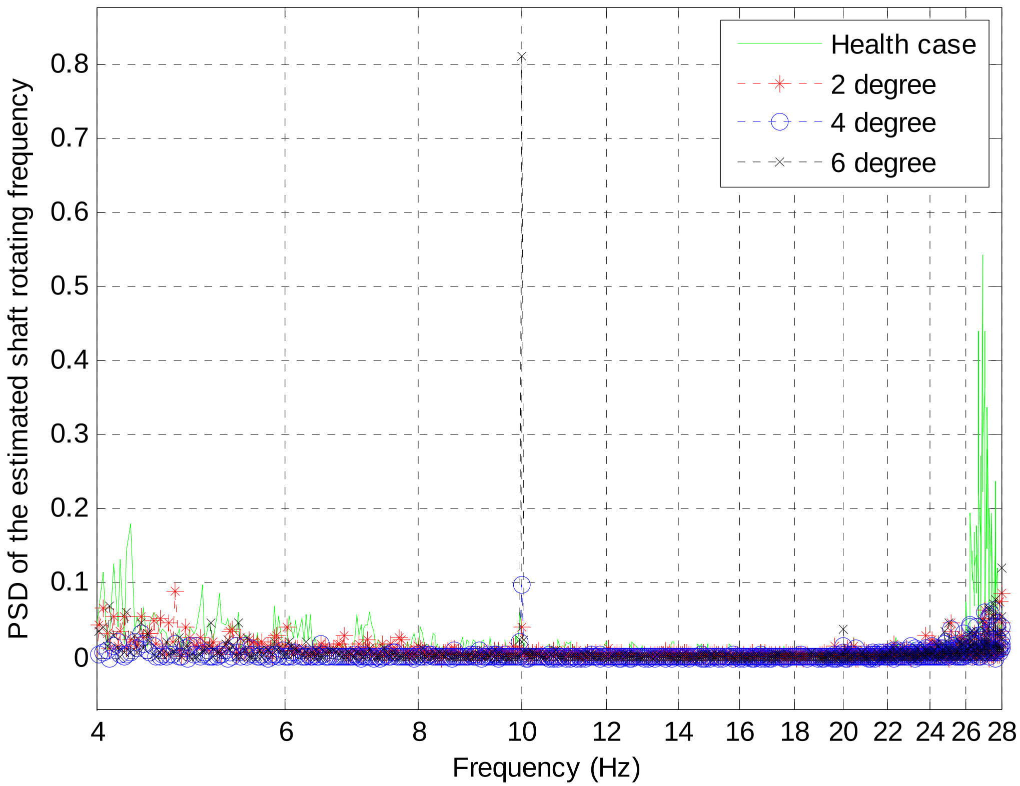


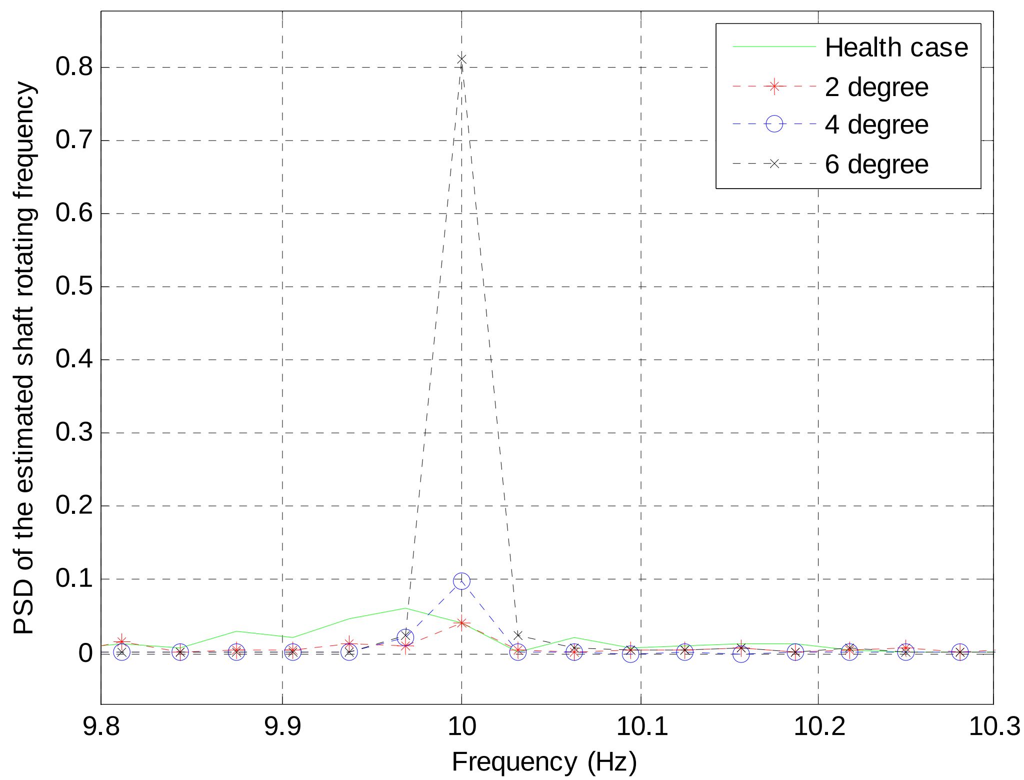
Flapwise and edgewise deformation (bend) of a wind turbine blade



- One blade was bended while the other two blades were unchanged before experiment

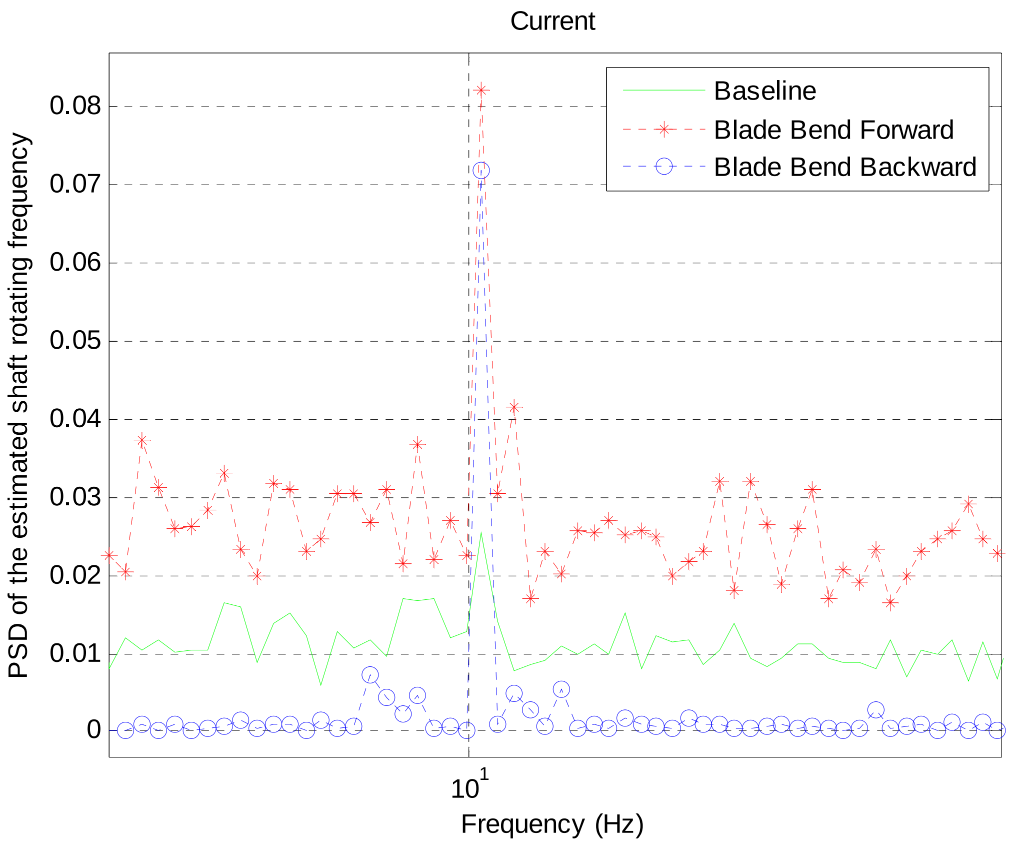
Edgewise Bent Blade

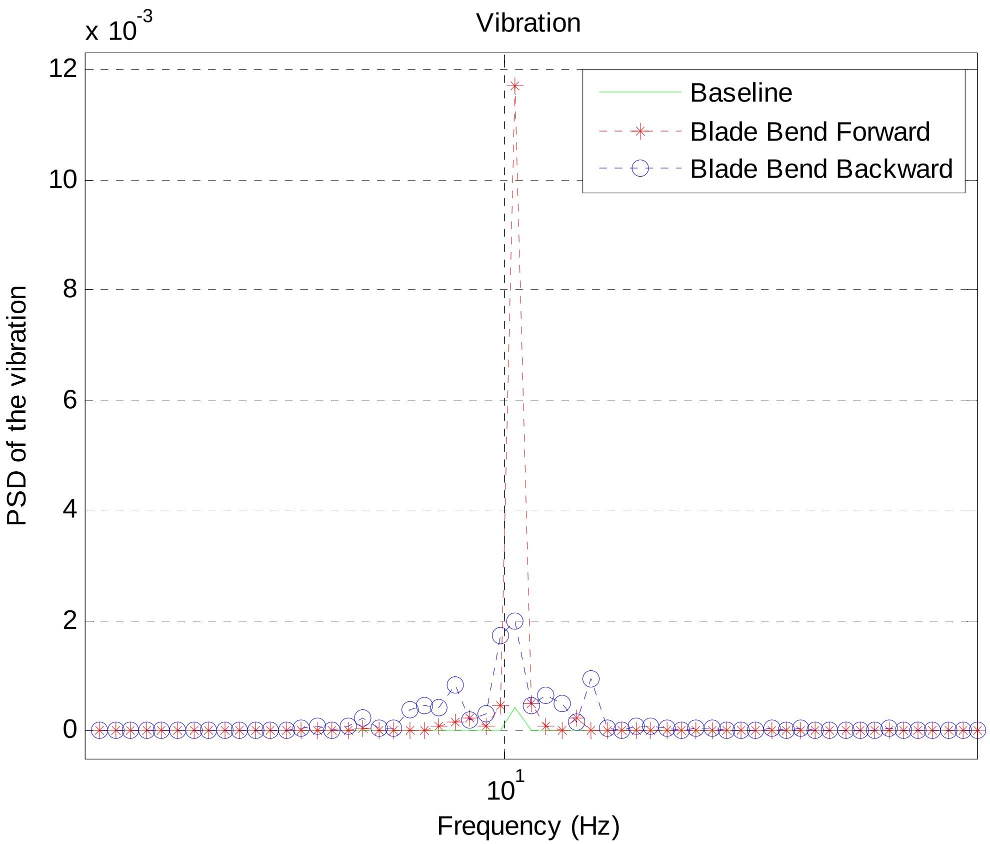




- The variable 1P frequency is converted to a constant value of 10 Hz
- Health case: no excitation observed at 1P in the stator current PSD
- Bent blade case: significant excitation observed at 1P in the stator current PSD

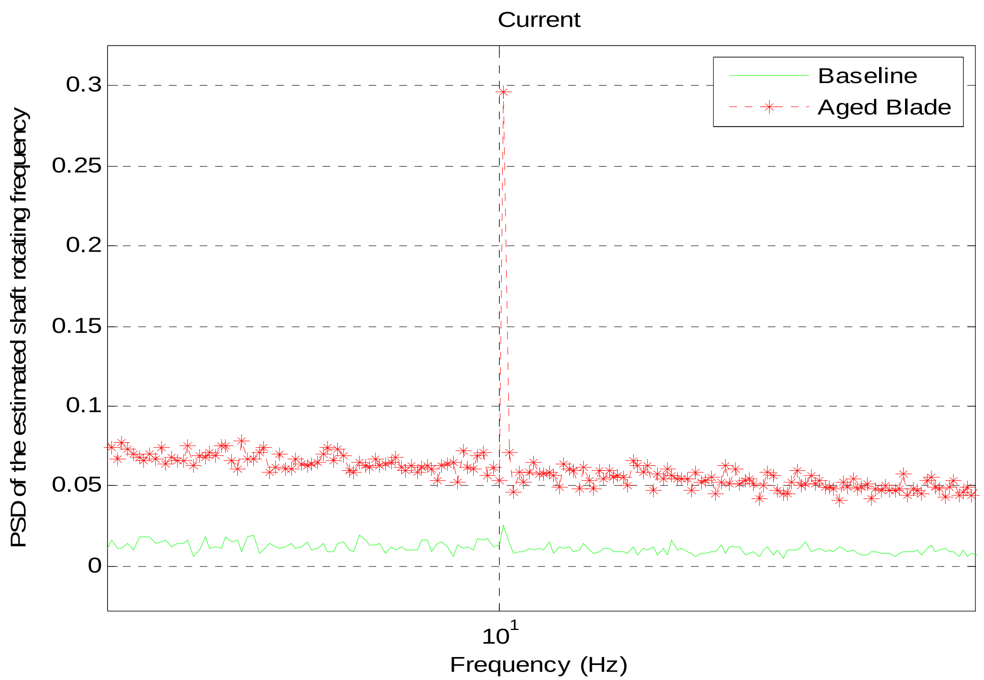
Flapwise Bent Blade

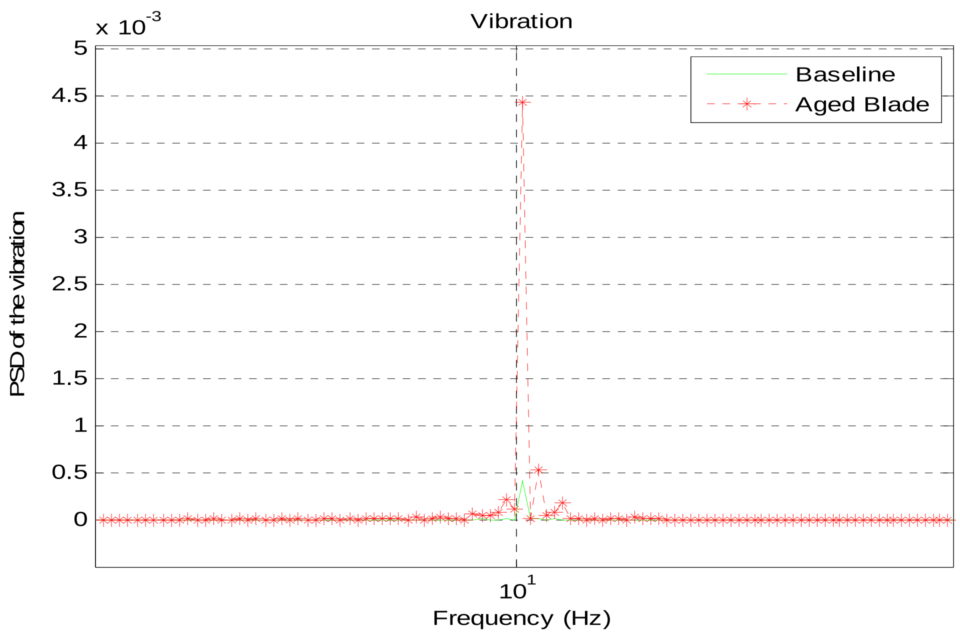




- The variable 1P frequency is converted to a constant value of 10 Hz
- Health case: no excitation observed at 1P in the stator current PSD
- Bent blade case: significant excitation observed at 1P in the 1P-invariant PSD

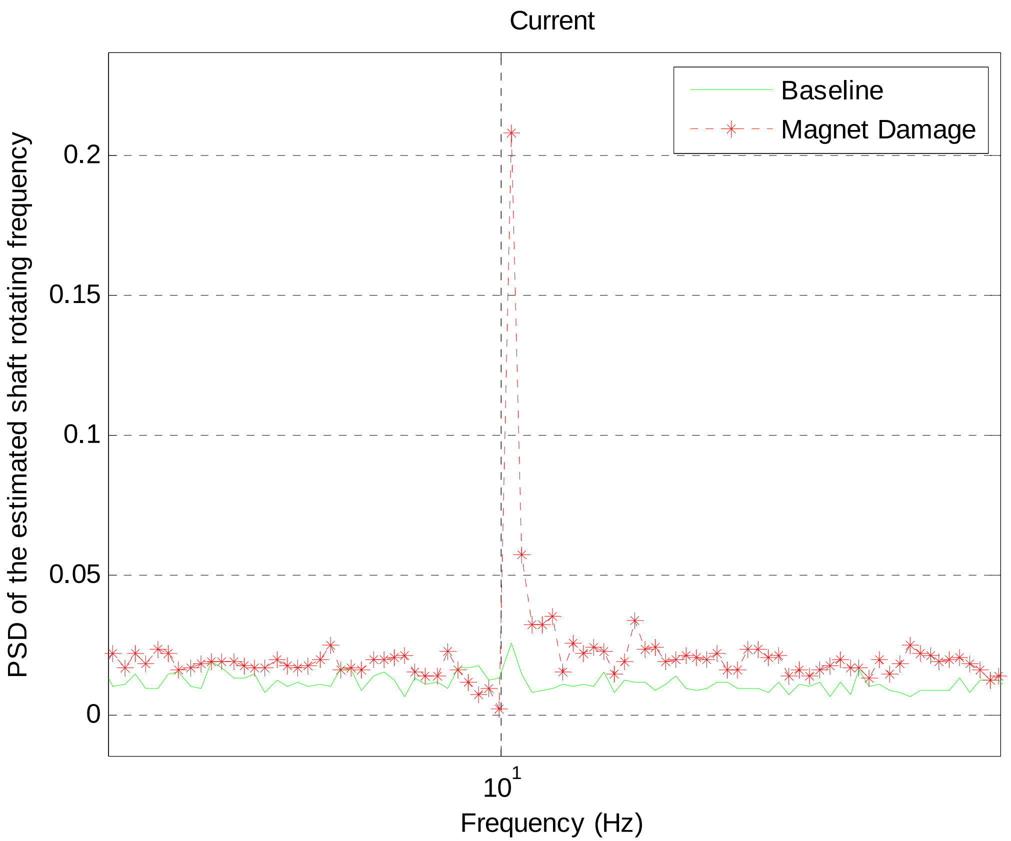
Aged Blade

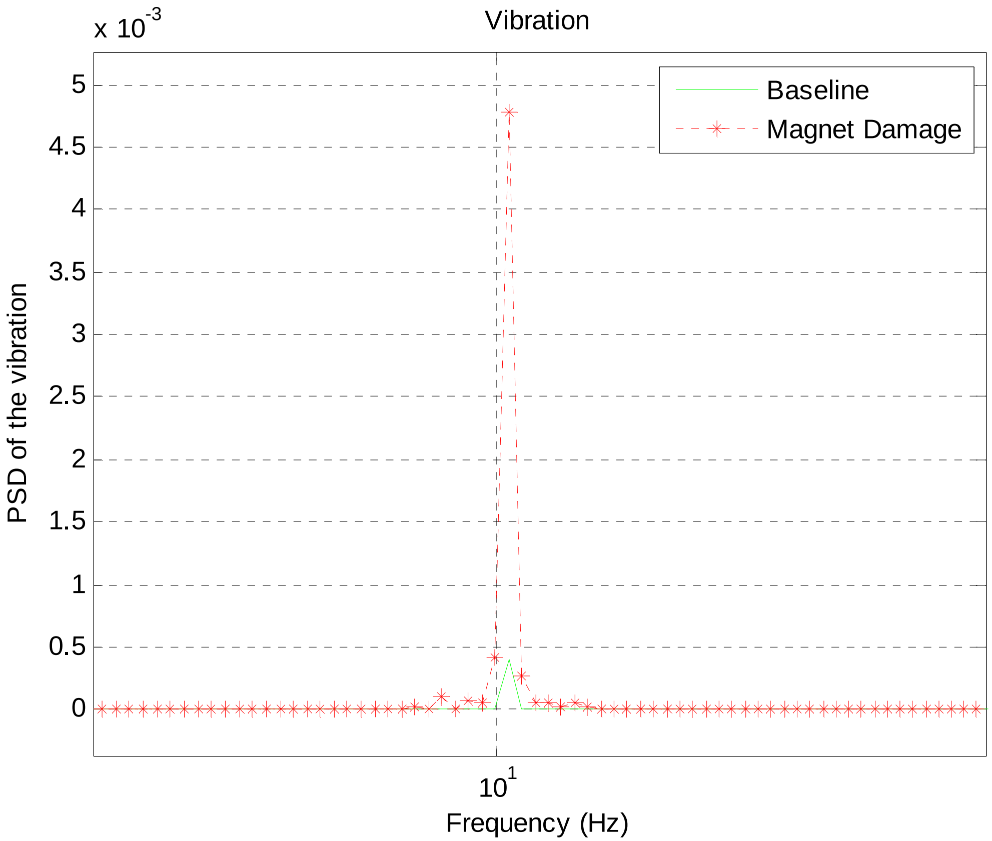

Current
PSD of the estimated shaft rotating frequency
0.3
0.25
0.2
0.15
0.1
0.05
0
Baseline
Aged Blade
10^1
Frequency (Hz)


Vibration
x 10^{-3}
PSD of the vibration
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Baseline
Aged Blade
10^1
Frequency (Hz)


New Blade
Aged Blade

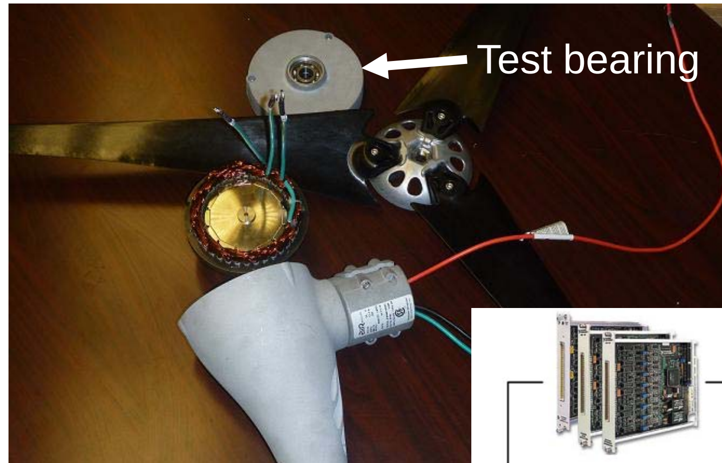
Magnetic Damage

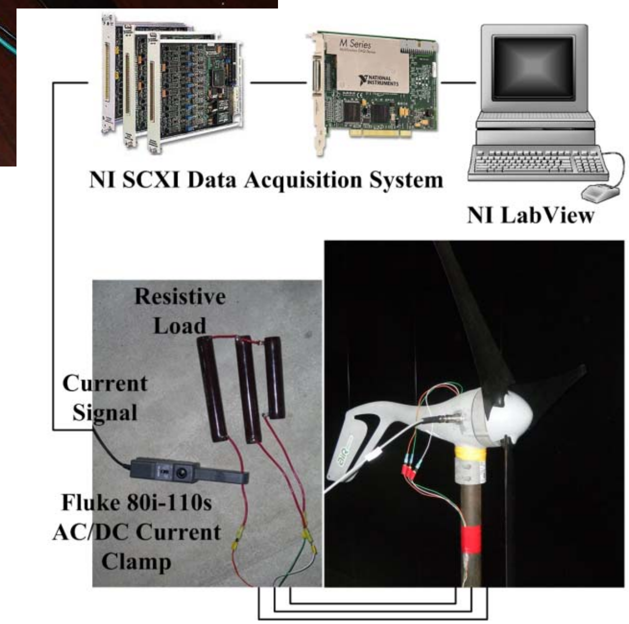




- The variable 1P frequency is converted to a constant value of 10 Hz
- Health case: no excitation observed at 1P in the stator current PSD
- Blade defect cases: significant excitation observed at 1P in 1P-invariant PSD

Bearing Fault Diagnosis: Test Setup

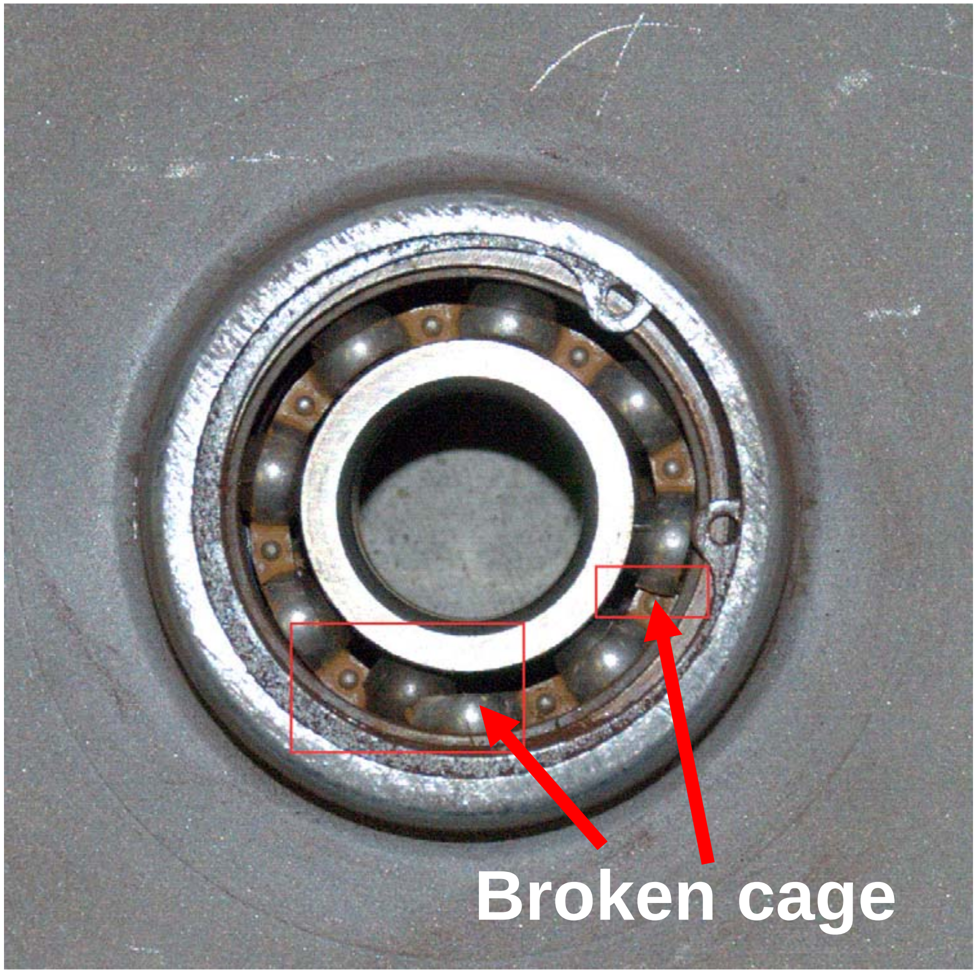




(1) A Southwest Windpower Air Breeze wind turbine was used in the experiment
(2) The testing bearing is located between the rotors of the turbine and the generator
(3) The bearing was pretreated by removing the lubricant to accelerate the failure process
(4) The wind turbine had been operated at variable speed condition (500-700 rpm) in the wind tunnel for 25 hours

Test Bearing

(a)



(b)

The bearing before and after experiment: (a) the healthy bearing before the experiment; (b) the bearing with broken cage after the experiment

Bearing Broken Cage Detection

- **Bearing cage breaks: theoretical characteristic frequencies**
  - **Theoretical characteristic frequencies in shaft rotating speed**

$$f_c^{\Omega} = k\frac{f_r}{2}\left(1 - \frac{D_b \cos\theta}{D_p}\right)$$

  - **Theoretical characteristic frequencies in stator current**

$$f_c^{I} = f_1 \pm k\frac{f_r}{2}\left(1 - \frac{D_b \cos\theta}{D_p}\right)$$

f_c: characteristic frequencies of cage break fault in stator currents

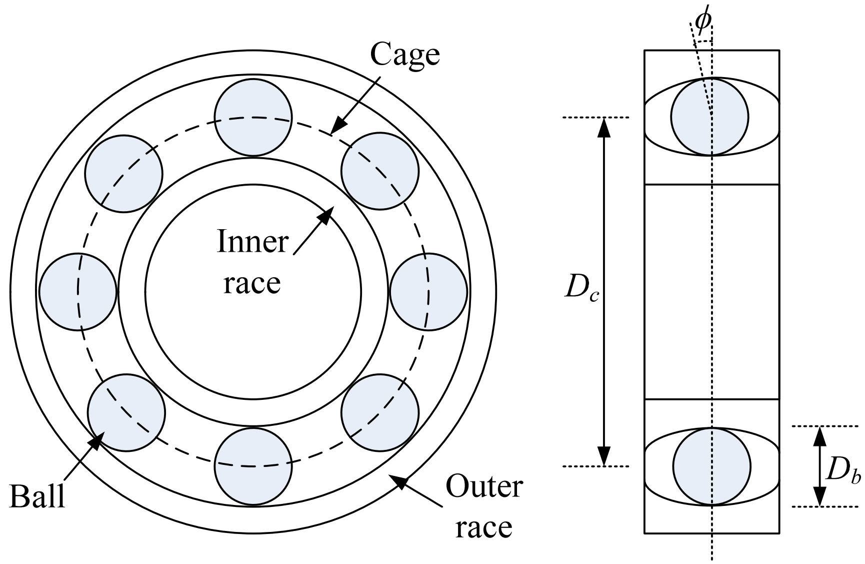
f_1: fundamental frequency of stator currents

f_r: shaft rotating frequency

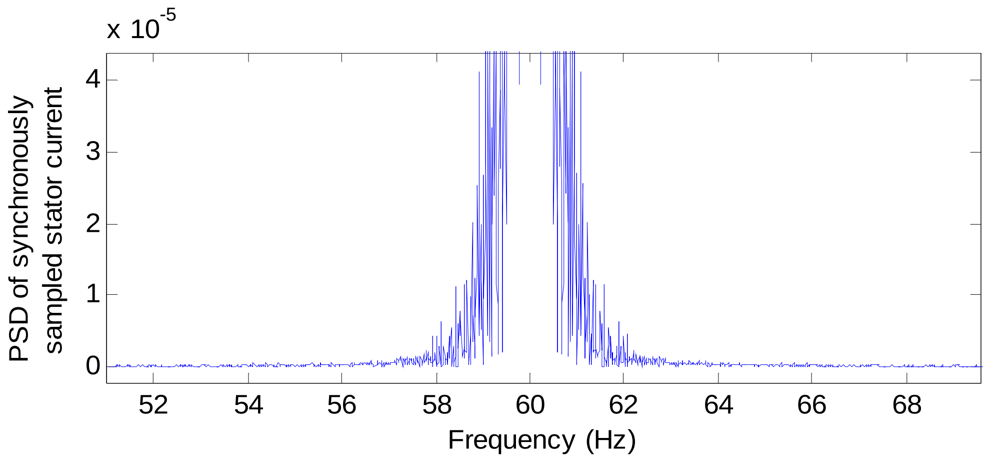
D_b: ball diameter

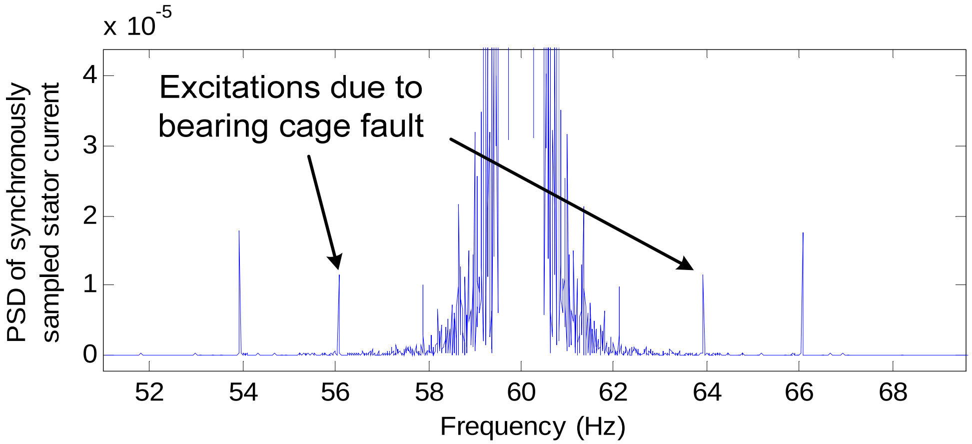
D_p: pitch diameter

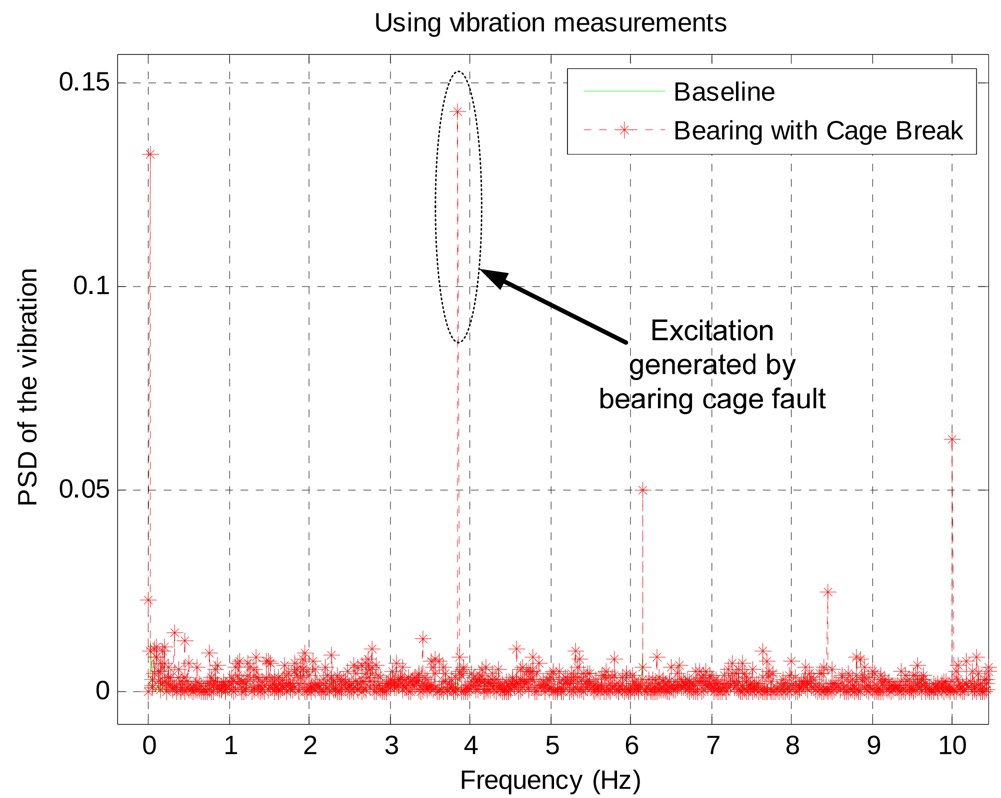
θ : contact angle



Results: Current and Vibration Signals

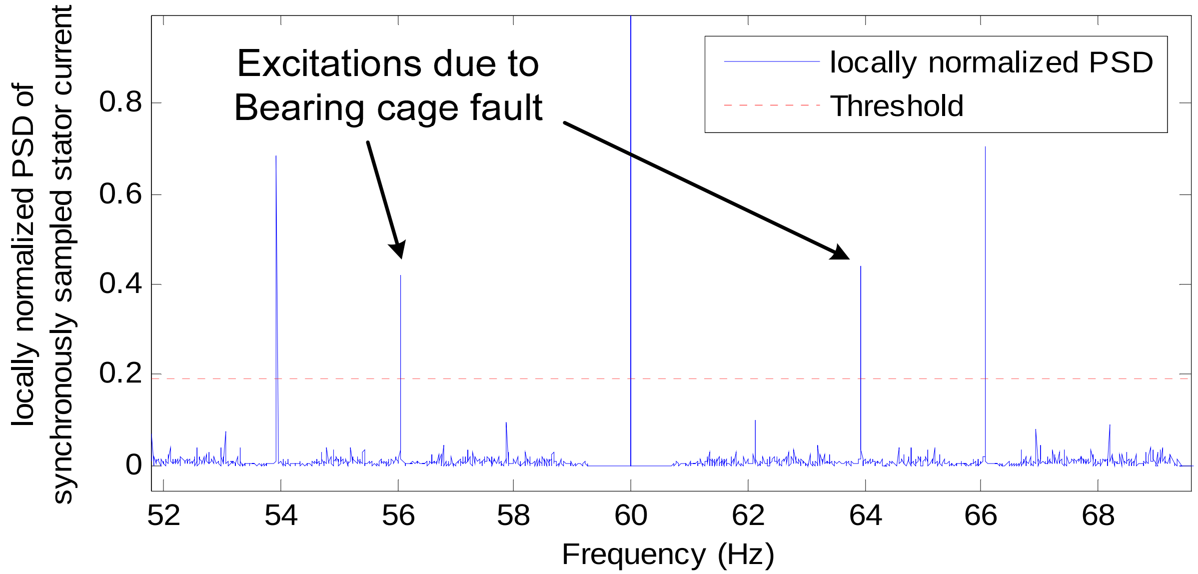




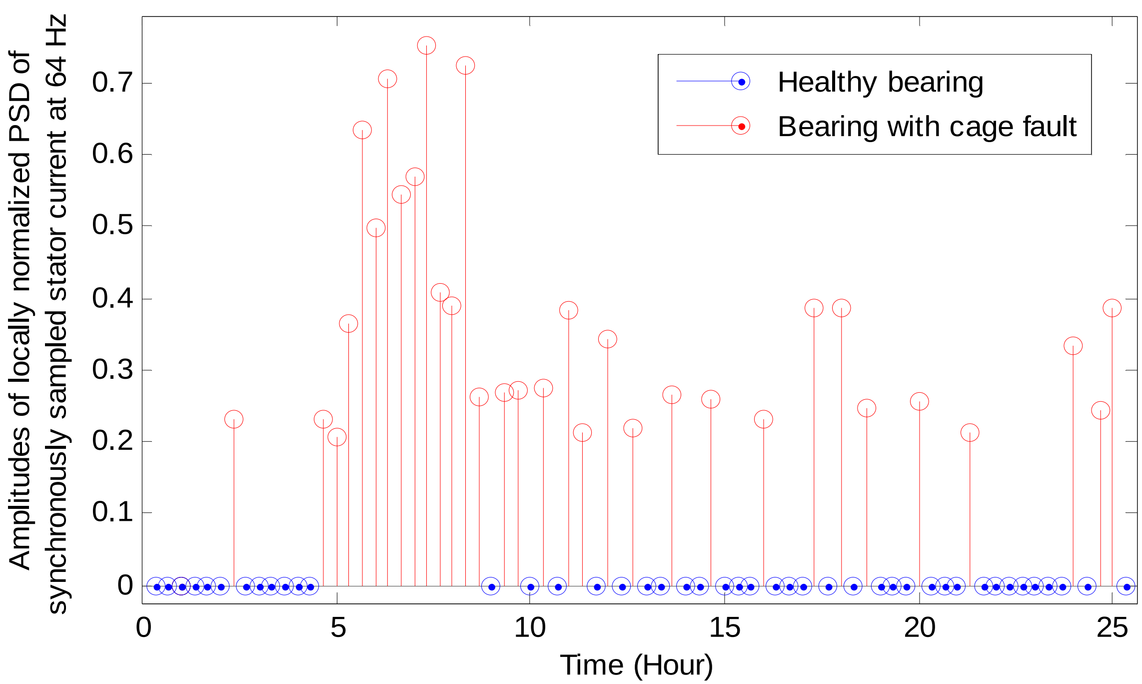


- Theoretical fault characteristic frequency in vibration measurement: 4 Hz
- Theoretical fault characteristic frequencies in current measurement: $60 \pm 4n$ Hz ($n = 1, 2, \cdots$)

Fault Diagnosis: Impulse Detection

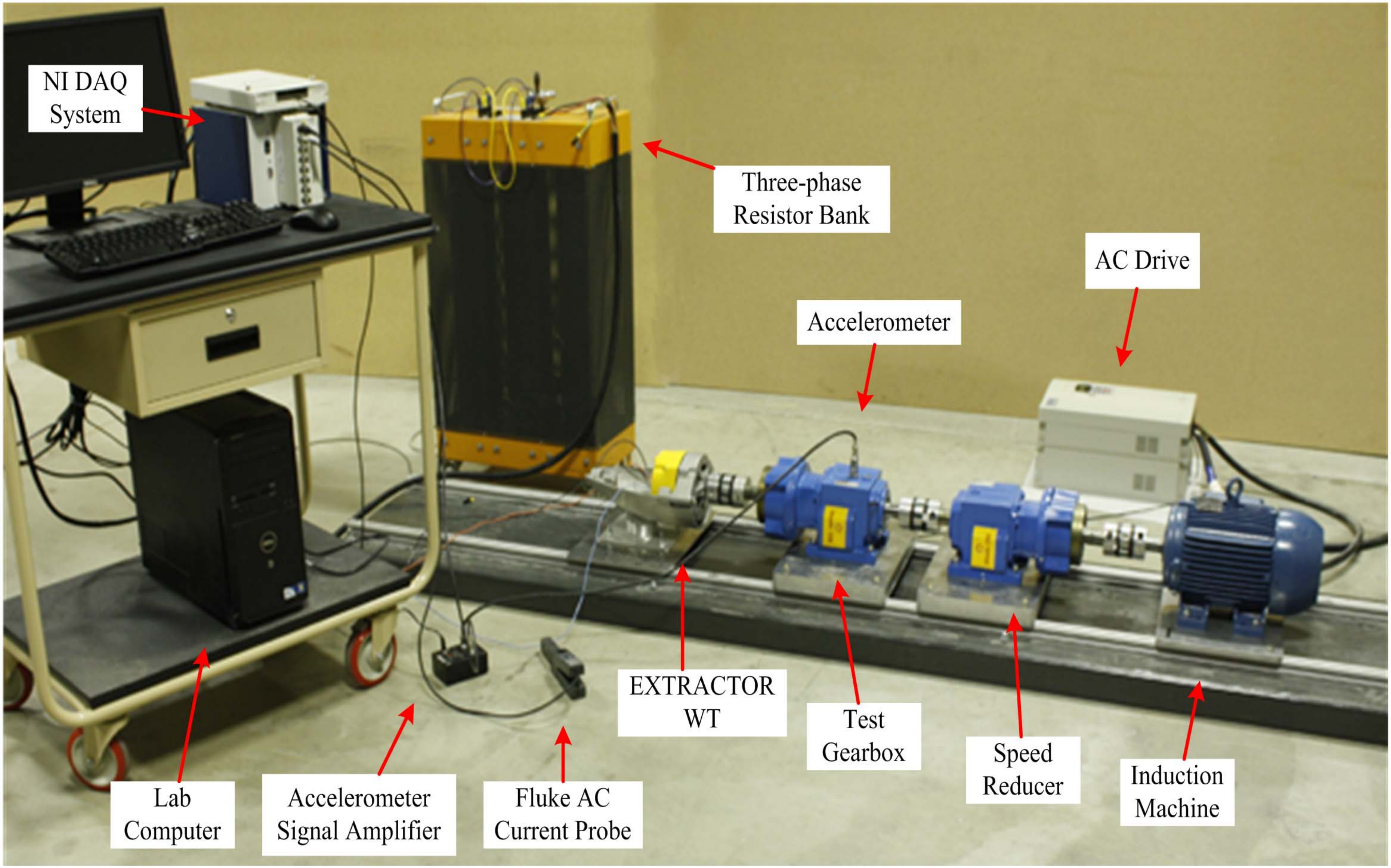


The impulse detection was applied to extract the excitations in the PSD of the synchronously resampled current signal for bearing cage fault diagnosis

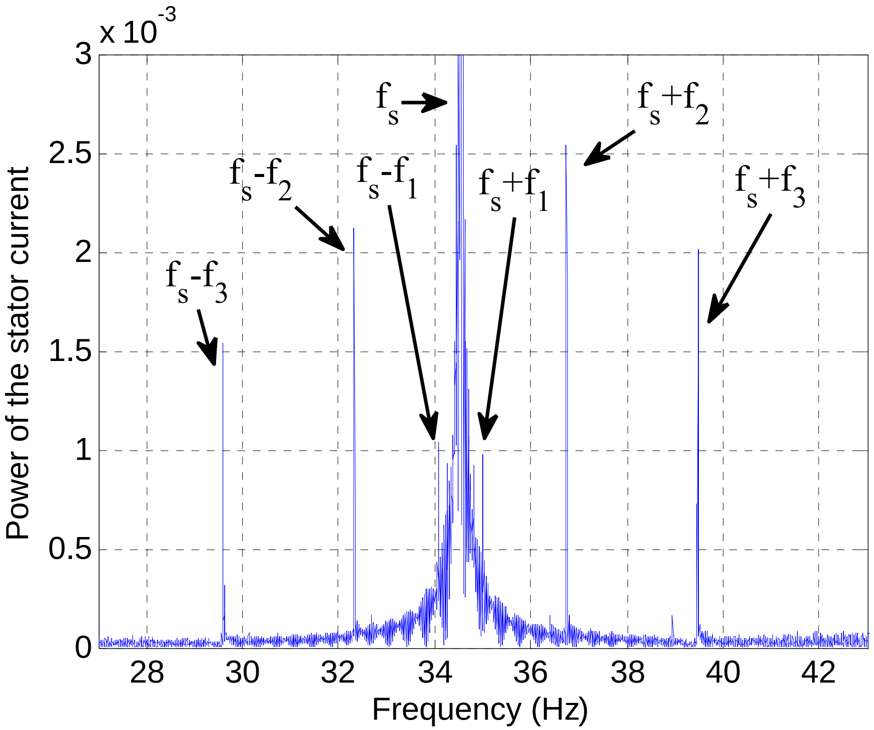


Impulses of the PSDs of the synchronously resampled stator current records at a bearing cage fault characteristic frequency of 64 Hz during the 25-hour experiment

Gearbox: Testing Facilities and Equipment



Fault Diagnosis: Statistical Analysis



Frequency spectrum of the baseline stator current signal

- Statistical analysis on stator current signatures
- For the six sidebands around the fundamental or a harmonic, the magnitude of each sideband, M_i $(i = 1 \cdots 6)$, is first normalized. Then the mean value of each sideband pair $f_s \pm f_i$ is calculated for both the healthy case and tooth break case:

$$M_{f_s \pm f_i}' = \frac{M_{f_s \pm f_i}}{\sum M_{f_s \pm f_i} / 6}$$

- Sum of normalized power of each pair

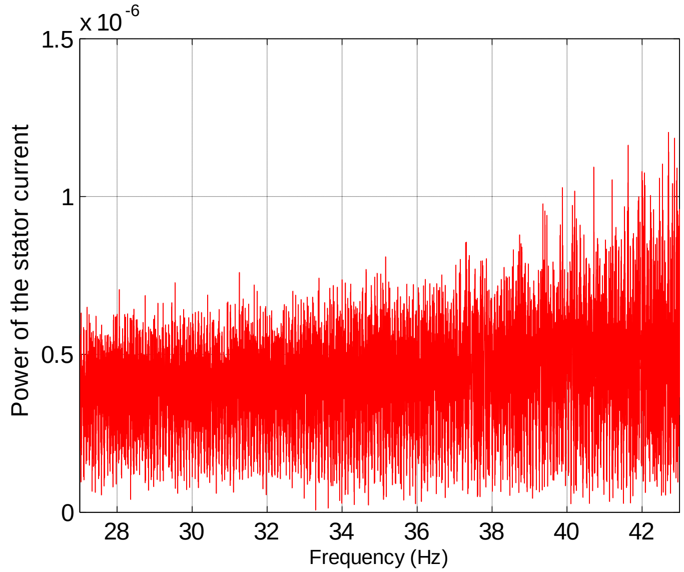
$$M = \frac{1}{2}(M'_{fs-fi} + M'_{fs+fi})$$

- Normalized power difference (NPD)

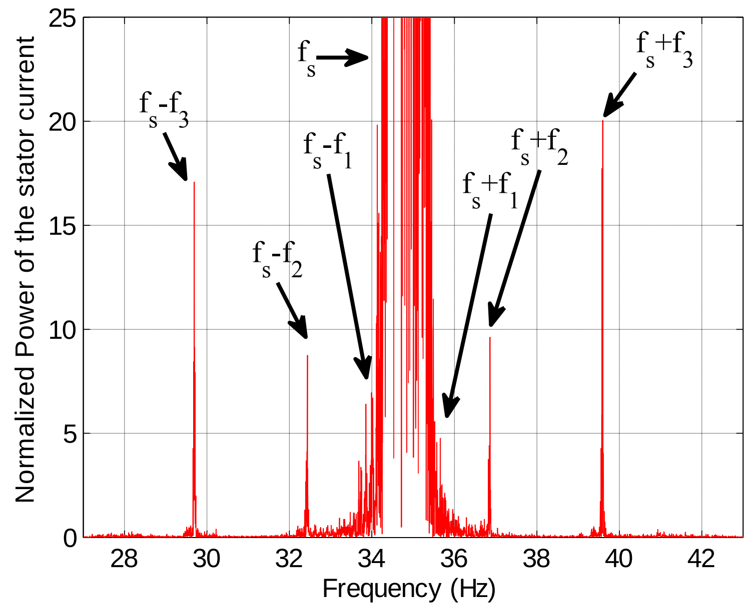
$$NPD_j = M_{fault} - M_{health}$$

Experimental Results: Gear Tooth break

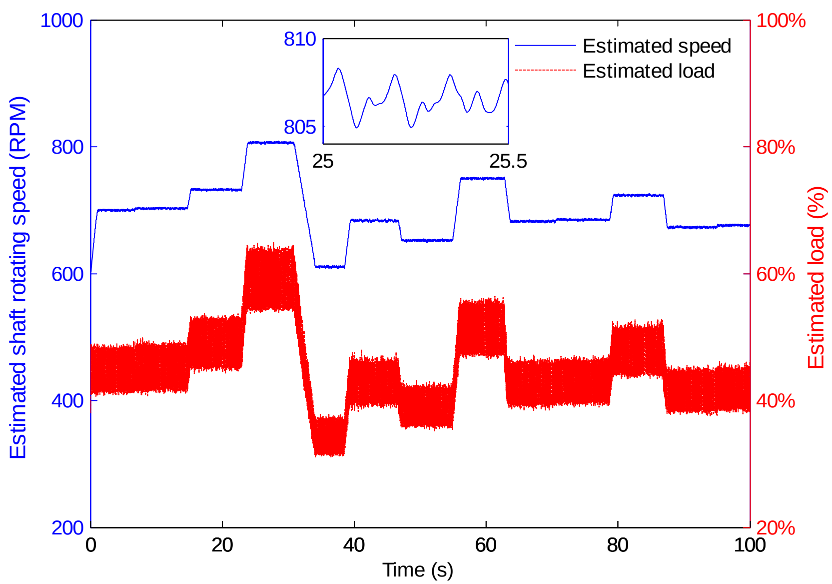
Test gear pretreated by removing one tooth



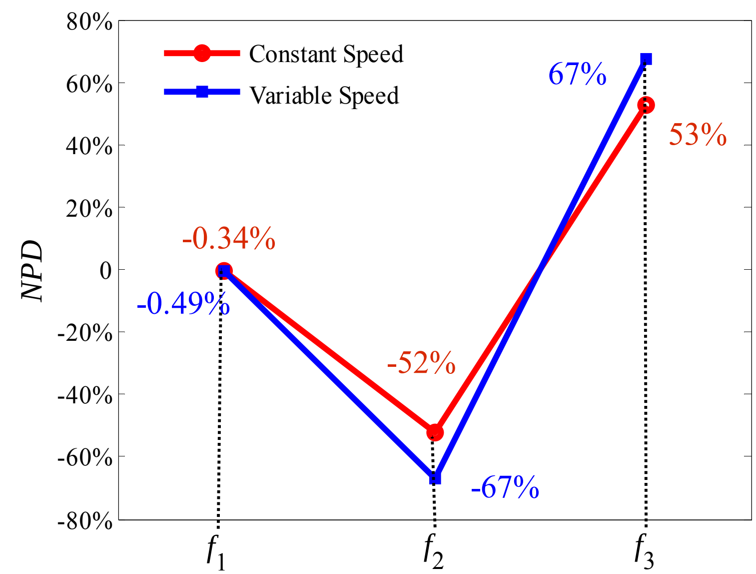
Frequency spectrum: classical FFT



1P-invarianet frequency spectrum



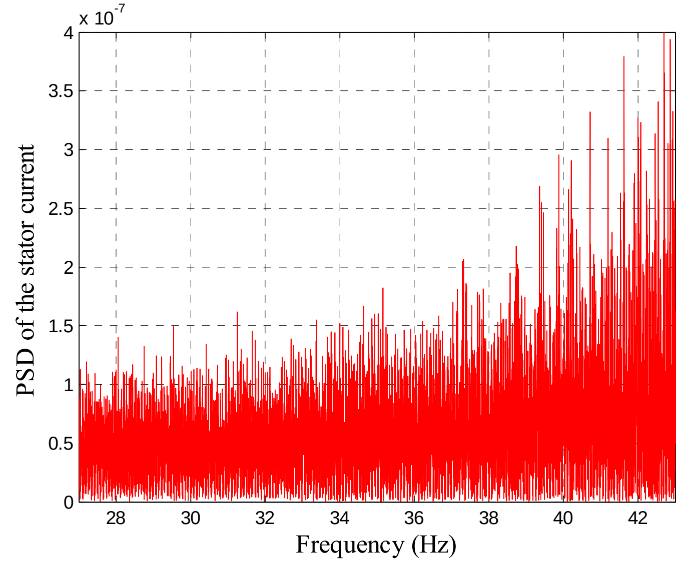
Estimated shaft rotating speed and load



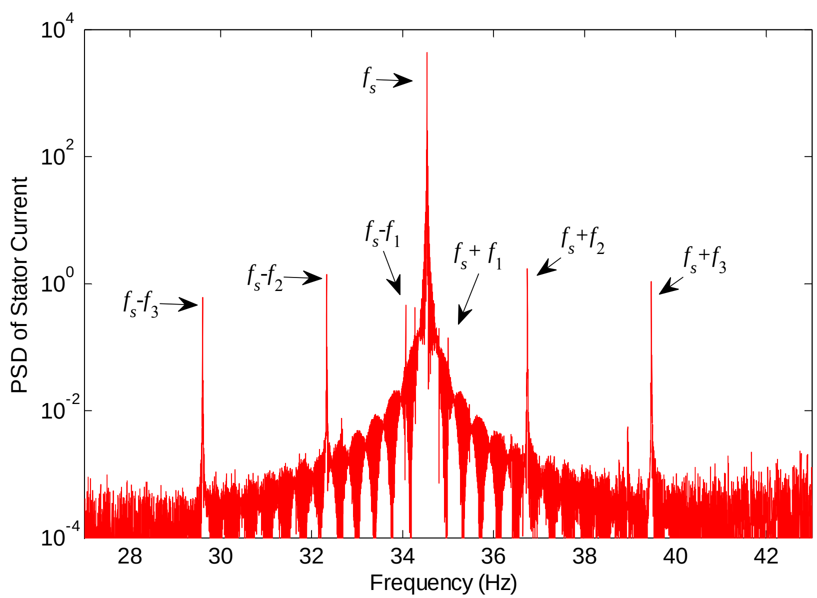
Normalized power difference (NPD) between healthy and faulty cases

Experimental Results: Gear Crack

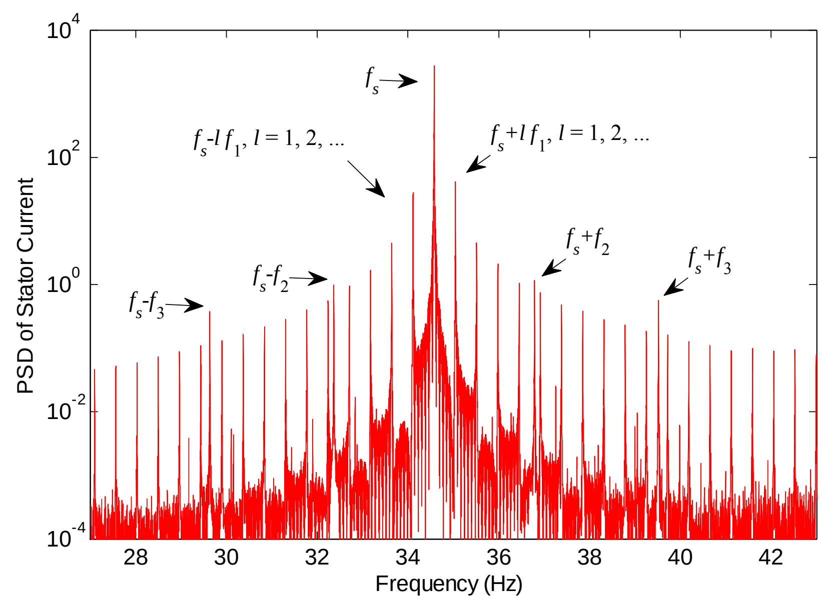
Test gear with a crack



Current frequency spectrum obtained from the classic FFT



1P-invariant current PSD spectrum for healthy gearbox



1P-invariant current PSD spectrum for faulted gearbox

Benefits

- Proposed methods are nonintrusive: only using generator current measurements, which are already being used in wind turbine control and protection systems
- Proposed methods can be easily integrated into existing wind turbine condition monitoring, control and protection systems
- Condition monitoring and fault diagnosis can be implemented remotely from the wind turbines being monitored
- Proposed methods provide an alternative to sensor-based condition monitoring and fault diagnosis : reduce cost, size and hardware complexity
- Proposed methods can be combined with sensor-based methods
  When there are problems with sensors, the proposed methods will ensure proper CM for the wind turbine: improve mechanical robustness and reliability
- Proposed methods offer an effective means to achieve condition-based smart maintenance for wind turbines

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Thank you!