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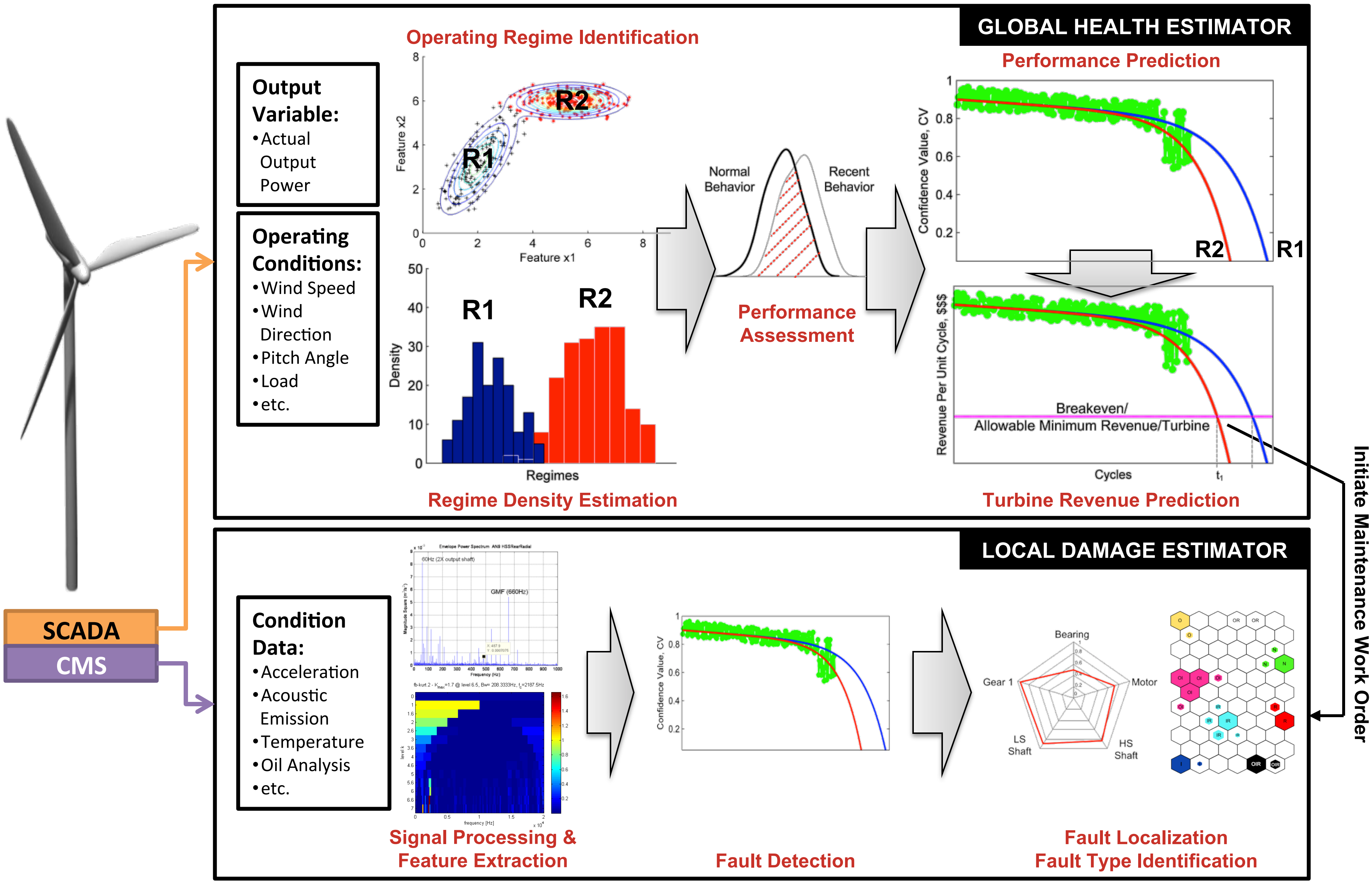
An Integrated Framework of Drivetrain Degradation Assessment and Fault Localization for Offshore Wind Turbines

WENYU ZHAO
DR. DAVID SIEGEL
PROF. JAY LEE
LIYING SU

UNIVERSITY OF CINCINNATI

CENTER FOR INTELLIGENT MAINTENANCE SYSTEMS

IMS Smart Wind Turbine PHM Framework



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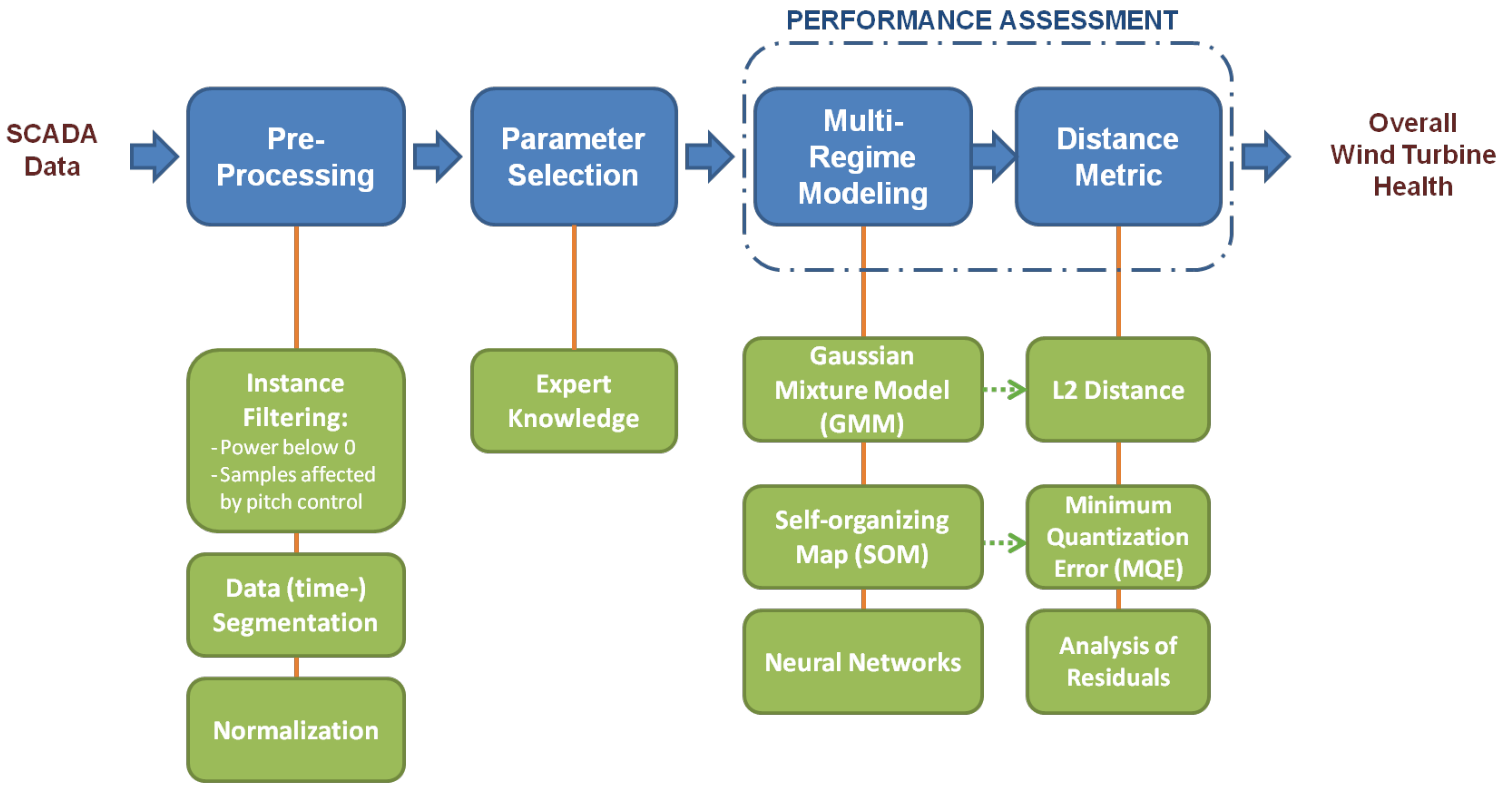
Global Health Estimator (GHE)

» It is based on the power generation performance of a wind turbine.

» Multi-regime modeling techniques are investigated to accommodate the wind turbine's dynamic operating conditions.[1]

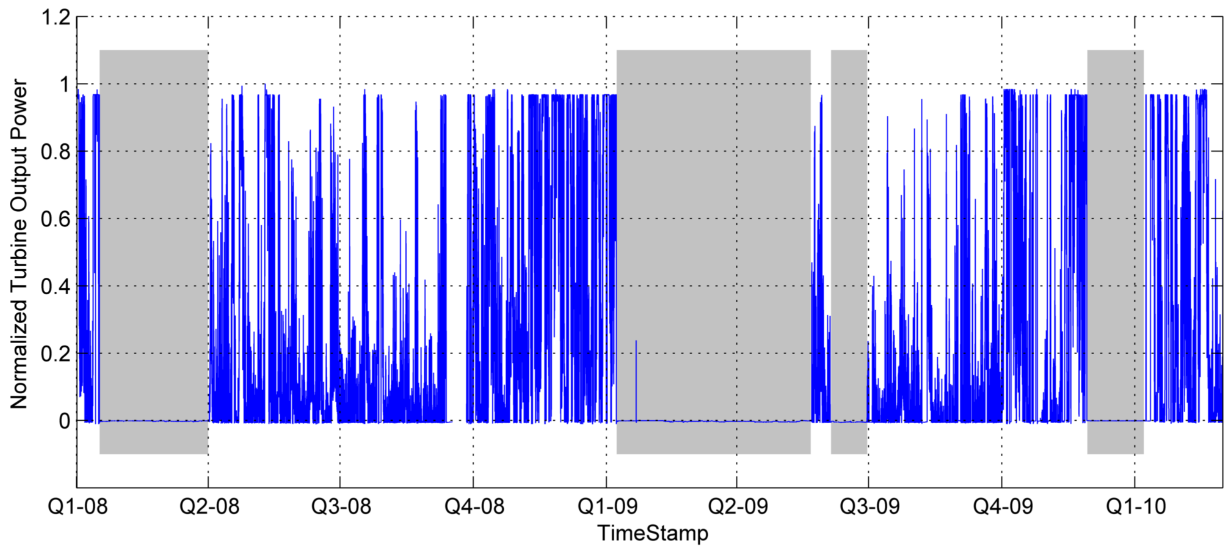


[1]Lapira E, Brisset D, Davari H, Siegel D and Lee J (2012) *Wind turbine performance assessment using multi-regime modeling approach*. International Journal of Renewable Energy. 45: 86-95

GHE – Power Performance Assessment

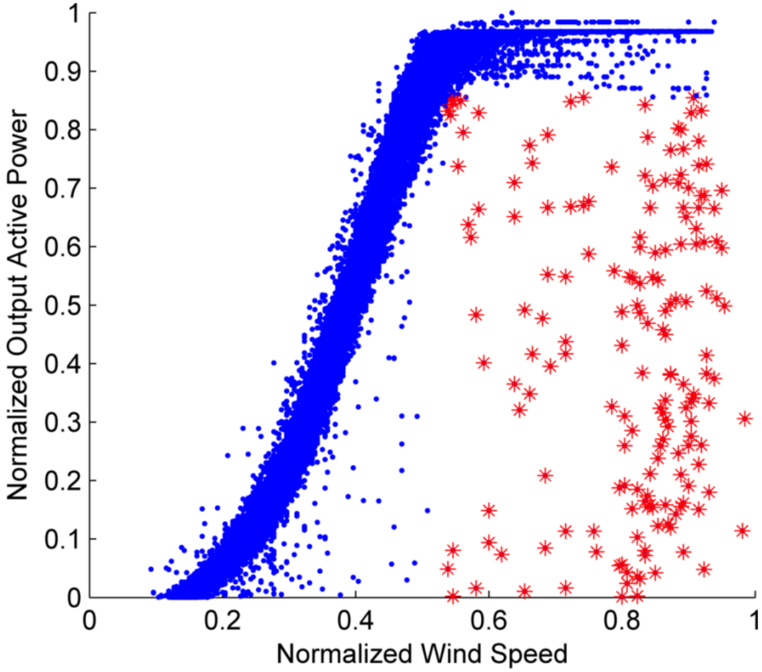
- Data was sampled every 10 minutes from a large scale, on-shore wind turbine. The collected data spanned approximately 26 months from January 1, 2008 to March 2, 2010. Within the duration of the data collection, there are four downtime events (gray-shaded regions).

- The data consists of:
  - Temperature (gearbox oil, gearbox bearing, gen slip ring, etc.)
  - Environmental Conditions (wind speed, wind direction, ambient temp, etc.)
  - Production (active power, reactive power, etc.)



Data Pre-processing

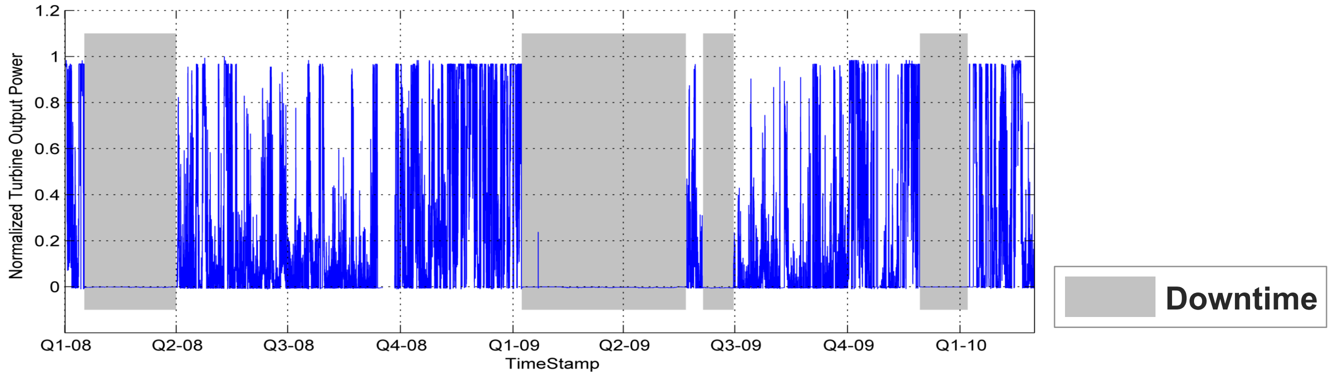
» Instance Filtering
- Data instances were removed when active power is below 0 W
- Sample points (blue dots), when the wind turbine's pitch control mechanism is engaged, are removed (red asterisks).



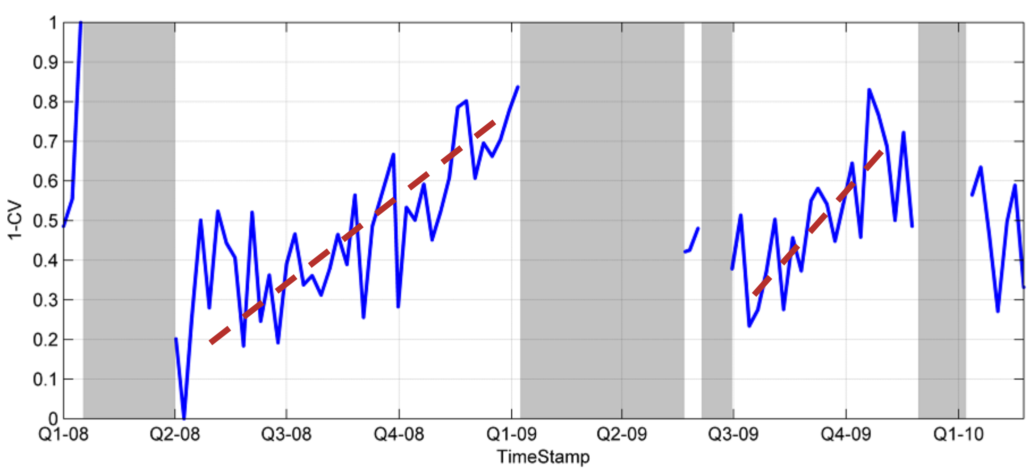
» Data Segmentation
- Test data was divided into week long intervals.

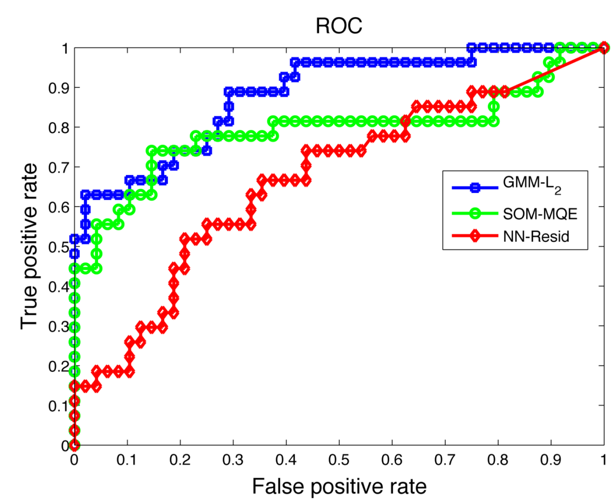
Result: Performance Degradation Assessment

» GMM, SOM and Neural Networks are applied separately.



» Sample results (GMM-L_2) and benchmarking:

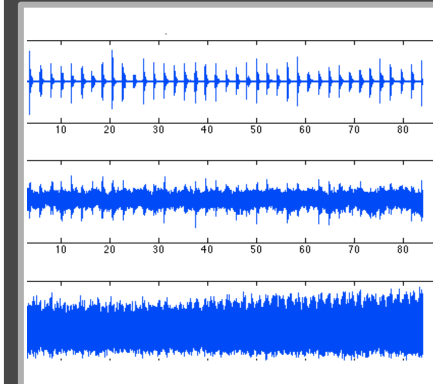




Local Damage Estimator (LDE)

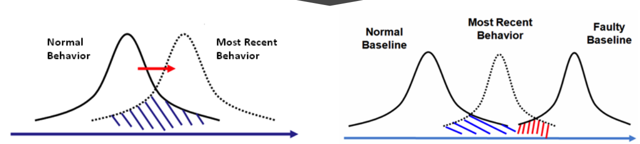
DRIVETRAIN COMPONENTS

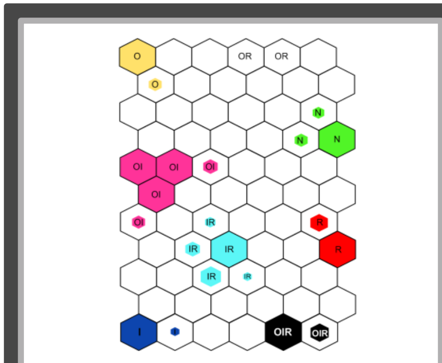
FILTERING & SIGNAL PROCESSING



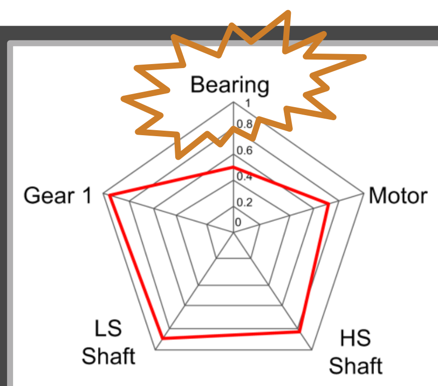
FEATURE SELECTION TOOLBOX

COMPONENT	FAULT TYPE	ANALYSIS
GEARBOX	• Bearing Faults • Gear Abrasion • Gear Eccentricity • Axle Misalignment • …	• ANN, BPNN • STFT / FFT / Envelope • Fuzzy Logic + PMP • Wavelet Analysis • …
GENERATOR	• Stator Faults • Rotor Misalignment • Bearing Faults • Shorted Winding Coil • Short Circuit • …	• Time Domain Analysis • Wavelet + FFT • Radial Basis NN • Time Series Tech. • …
ROTOR	• Rotor Unbalance • Bearing Faults • Mass Imbalance • Aerodynamic Asymmetries • Surface Roughness • …	• Time Domain Analysis • Fuzzy Logic • Spectral Analysis • Order Analysis • …
ELECTRONICS	• Overload • Thermo-mechanical Fatigue • …	

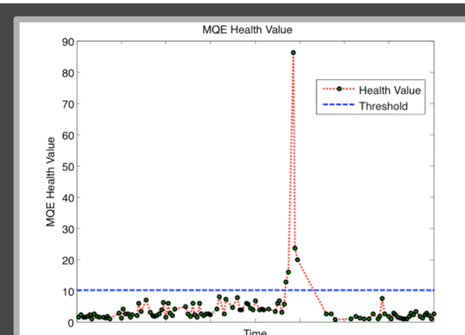




FAULT DIAGNOSIS



FAULT LOCALIZATION

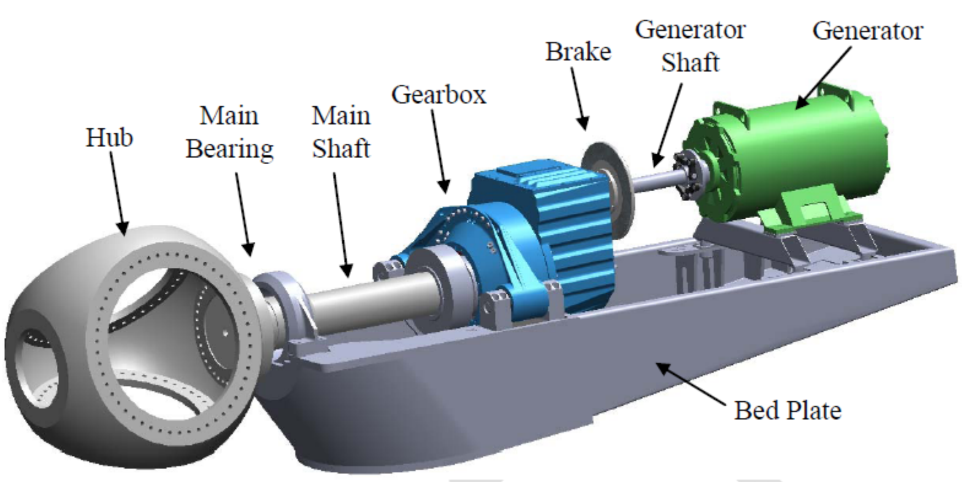


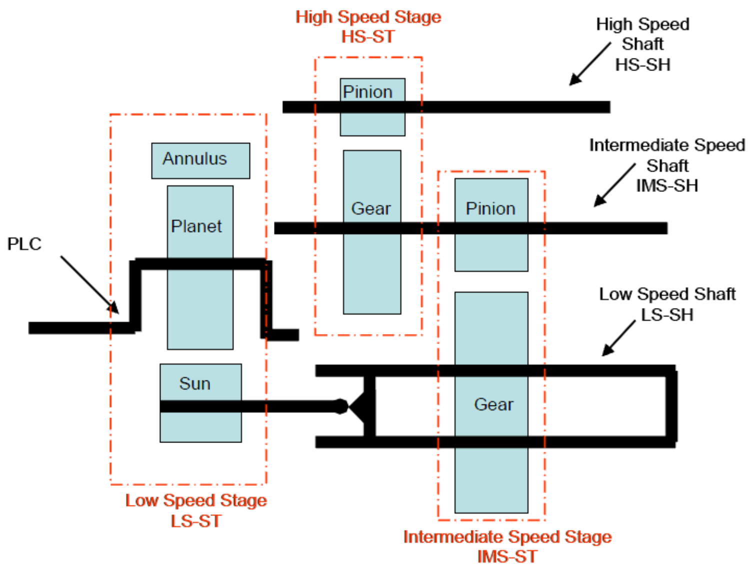
DEGRADATION ASSESSMENT

LDE: Drive Train Fault Diagnosis

» The National Renewable Energy Laboratory (NREL) sponsored a gearbox reliability collaborative (GRC) condition monitoring study for benchmarking various methods and algorithms with invited universities and industry participants.

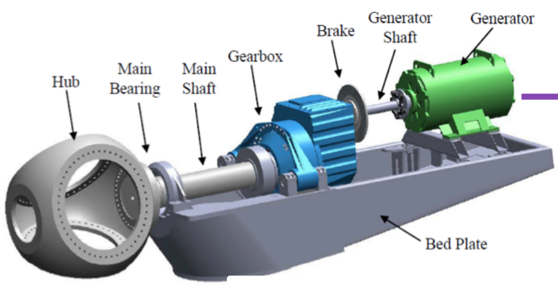
» The Center for Intelligent Maintenance Systems leveraged their previous experience in rotating machinery and has further advanced their algorithm tool set for wind turbines and other large scale drive trains.





Gearbox Reliability Collaborative Condition Monitoring Round Robin Document, National Renewable Energy Laboratory, 2011.

Feature Extraction Toolbox for Wind Turbine Drive Trains

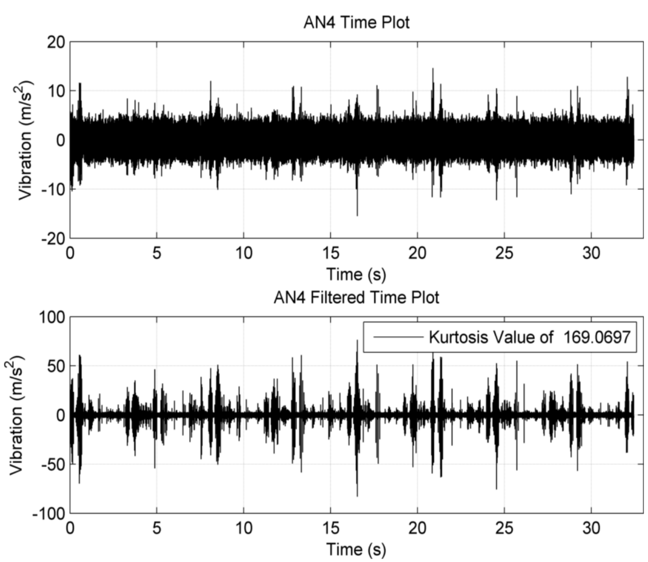


a) Available signals
b) Operating environment
c) System configuration

Select the right tool for the given component and application

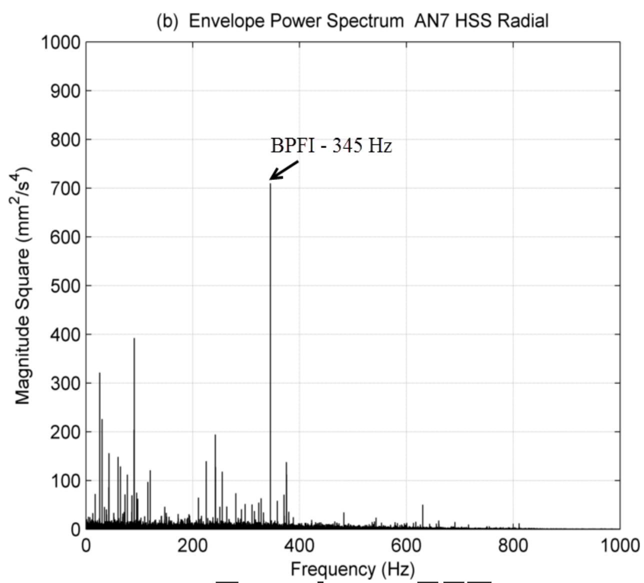
Knowing which tool to use is key

Planetary Gearbox Health



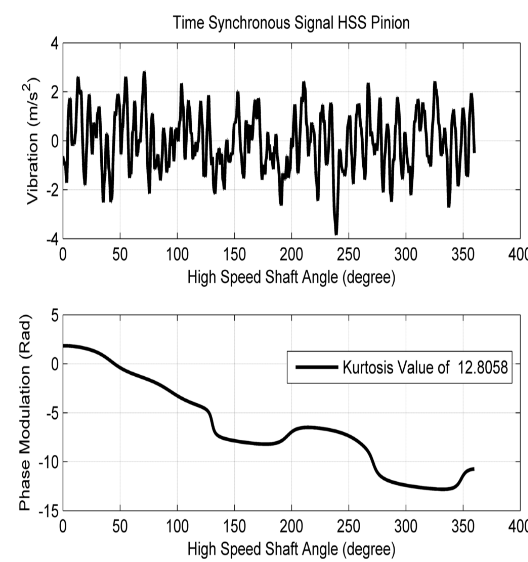
Spectral Kurtosis Filtering

Bearing Health



Envelope FFT

Gear Tooth Health



TSA Narrowband Methods

Summary of Results – NREL Study

LEGEND: **L**-Low Confidence, **M**-Medium Confidence, **H**-High Confidence, **NA**-Not Applicable

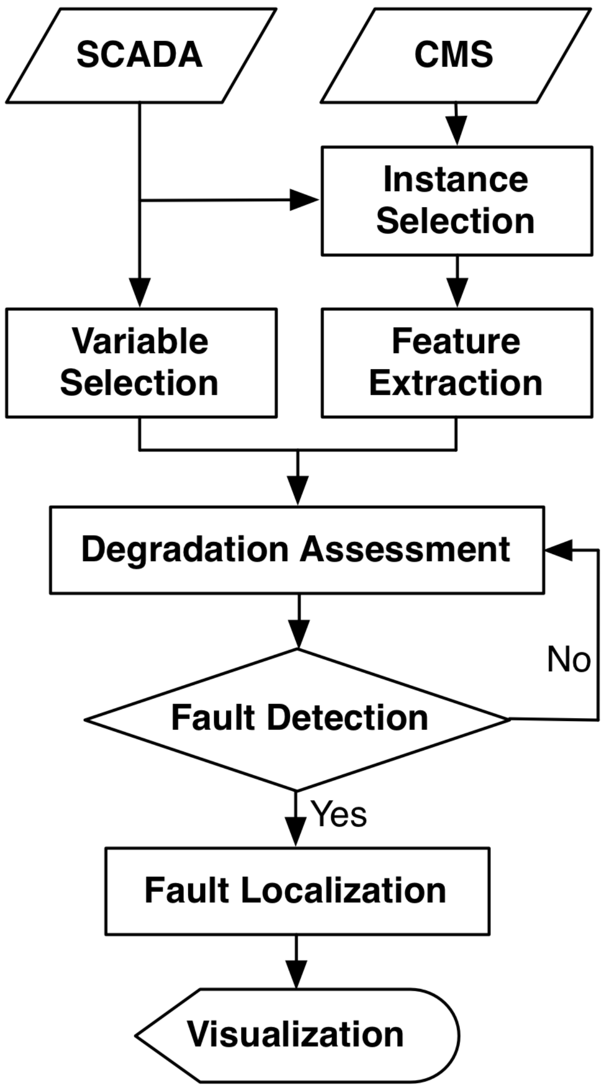
Tools / Failed Components	Frequency Domain	Cepstrum	Spectral Kurtosis	Bearing Envelope Analysis	TSA – Residual Signal	TSA – Amplitude / Phase Modulation
HSS Pinion	**H**	**H**	NA	NA	L	**H**
HSS Gear	L	L	NA	NA	L	M
ISS Pinion	M	M	NA	NA	L	L
ISS Gear	L	M	NA	NA	L	L
Ring Gear	NA	NA	**H - stage**	NA	L	**H**
Sun Pinion	NA	NA	**H - stage**	NA	M	L
ISS Upwind Bearing	NA	NA	NA	**H**	NA	NA
ISS Downwind Bearings	NA	NA	NA	**H**	NA	NA
HSS Downwind Bearings	NA	NA	NA	**H**	NA	NA
Planet Carrier Upwind Bearing	NA	NA	NA	M	NA	NA

»A toolbox approach is beneficial considering that the algorithms are tuned to different failure modes

»The results show that the algorithm suite can diagnose most of the gear wheel and bearing defects[1].

[1]Siegel D, Zhao W, Lapira E, AbuAli M and Lee J. *A Comparative Study on Vibration – Based Condition Monitoring Algorithms for Wind Turbine Drive Trains*. Wind Energy Journal (Special Issue)

An Integrated Approach for Drivetrain Monitoring



- » SCADA and CMS systems are intended for different purposes.
- » However they both have variables that can be used to assess drivetrain condition.
- » Literature has shown SCADA can be used for fault detection.
- » GL Renewables Certification has recently recommended integrating SCADA into CMS data analysis (AWEA 2013).

Instance Selection

- » Common practice is to sample CMS instances (snapshots) at a constant rate.
- » SCADA variables are used to determine turbine operation when CMS data is collected.
- » If the turbine had been stopped, CMS data is discarded.
  - When maximum rotor speed is zero;
  - When maximum generator speed is zero.

SCADA Variable Selection

- There are two ways of selecting SCADA variables:
  - Variable and feature selection through machine learning algorithms.
  - Heuristic method to select measurements related with drivetrain condition:
    - Key component temperature
      - Rotor
      - Gearbox
      - Generator
    - Oil temperature
    - System alarms

CMS Data Feature Extraction

» Time Domain Features:

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} {X_i}^2}{N}}$$

$$Kurtosis = \frac{\sum_{i=1}^{N}(X_i - \bar{X})^4}{N} \Bigg/ \left[\frac{\sum_{i=1}^{N}(X_i - \bar{X})^2}{N}\right]^2$$

$$Crest\ Factor = max(|X_i|)/RMS$$

» RMS represents the energy in vibration signal.

» Kurtosis indicates peakedness, or impulsiveness of the signal.

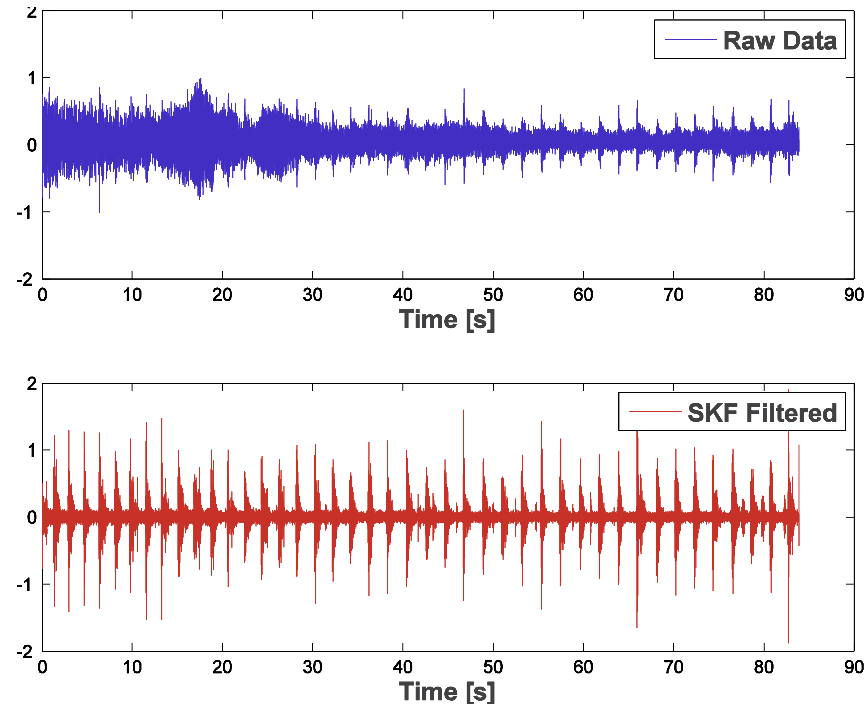
» Crest factor can detect high-amplitude impacts in the signal.

Spectral Kurtosis Filtering (SKF)

- SKF optimizes setup of band-pass filter for denoising.
- It calculates kurtosis of the short-time Fourier transform of signal, and uses a significance level to determine how to amplify the impulsive frequency content:

$$SK_X(f) = \frac{\langle H^4(t,f)\rangle}{\langle H^2(t,f)\rangle^2} - 2$$

$$S_\alpha = u_{1-\alpha}\frac{2}{\sqrt{K}}$$



Example of SKF result

Envelope Analysis

» Damage in bearings usually result in amplitude modulation in vibration signal, where high-frequency resonance is modulated by low-frequency fault frequencies.

» A band-pass filter is first applied around the excited resonance frequency.

» Hilbert Transform is used to compute principal value *y(t)* and analytical signal *z(t)*:

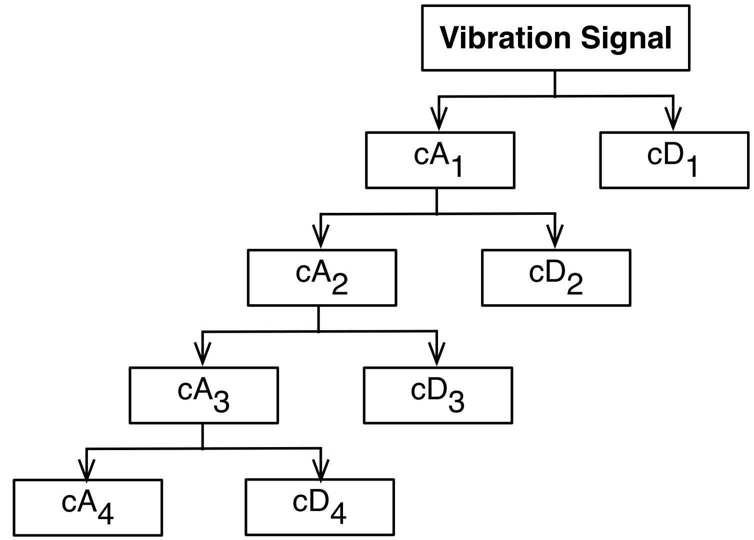
$$y(t) = \frac{1}{\pi} PV \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \qquad z(t) = x(t) + iy(t)$$

» The envelope is the absolute value of *z(t)*.

» Bearing fault frequencies can be extracted from the envelope signal.

Wavelet Energy Analysis

- Wavelet decomposition decomposes signal into detail (high frequency) and approximation (low frequency).
- It further decomposes the approximation.
- Energy at each node is computed.
- Energy feature is computed as percentage of energy at each node over total energy.



$$Energy\ A_4 = \sum_{i=1}^{N} {w_{a4i}}^2$$

$$\frac{100 \times \sum w_{a4}^2}{\sum w_{d1}^2 + \sum w_{d2}^2 + \sum w_{d3}^2 + \sum w_{d4}^2 + \sum w_{a4}^2}$$

Overall Degradation Assessment

» Self-organizing Maps (SOM) is selected to cope with the varying operating regimes of wind turbine.

» Euclidean distance between feature vector x_i and a weight vector w_j is compute, to find the best matching unit w_c for the feature vector:

$$\|x_i - w_c\| = \min_i \{\|x_i - w_j\|\}$$

» During training, a SOM model is generated from data of healthy condition.

» During testing, a minimum quantization error (MQE) is computed as a distance measure that indicates degradation:

$$MQE = \|x - w_{BMU}\|$$

Fault Detection and Localization

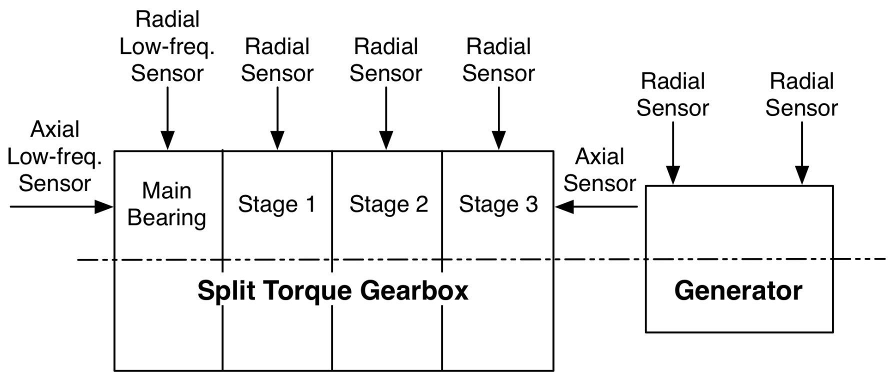
» Fault is detected when the MQE value exceeds a threshold.

» The threshold is generated through estimating the probability density function of MQE by Monte Carlo based method with a desired Probability of False Alarm (PFA), which can be at a user/operator' preference.

» Fault localization is determined by calculating contribution of features related with each component made to the overall MQE.

$$MQE = \sqrt{e_1^2 + e_2^2 + \cdots + e_k^2} \qquad Contribution = \frac{\sum e_i^2}{MQE^2}$$

Case Study – 3MW Offshore Turbine



Stage	Gear	No. Of Tooth	Rotation Direction
1^{st}	Sun	66	CW
	Planet (8)	37	CW
	Ring	142	CCW
2^{nd}	Sun	30	CCW
	Planet (4)	62	CCW
	Ring	154	CW
3^{rd}	Input	116	CCW
	Pinion	26	CW

» CMS Configuration:
- 8 accelerometers;
- Sampling rate: 6250Hz;
- Sampling duration: 85 seconds;
- Snapshot frequency: 1 day.

» SCADA Configuration:
- Over 100 variables;
- Sampling rate: every 10 minutes.

» Data duration:
- 15 months.

SCADA Variable Pre-processing

» Drastic outliers exist in SCADA variables.

» A filtering algorithm is applied to reject outliers, using Grubbs' test.

- H_0: There is no outlier in a distribution;
- H_1: There is at least one outlier in the distribution.

$$G = |\bar{X} - X_i|/\sigma \qquad Z = \frac{N-1}{\sqrt{N}}\sqrt{\frac{t^2}{N-2+t^2}}$$

- ***G*** is the Grubbs' test statistics, and ***Z*** is a critical value based on sample size ***N*** and t-distribution critical value ***t***.

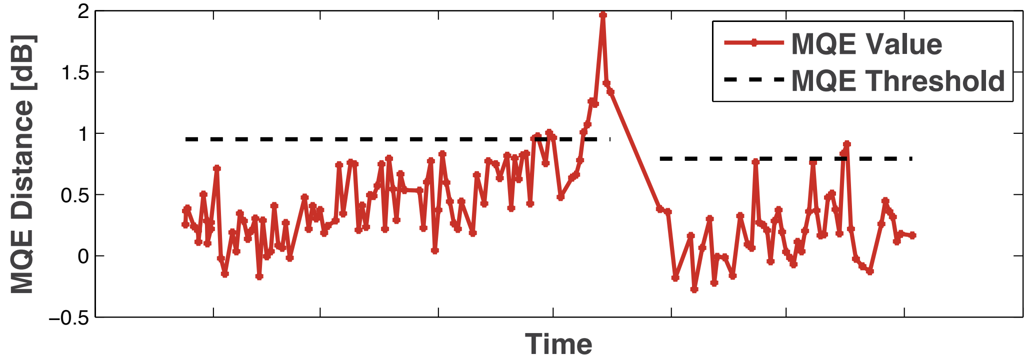
- If ***G>Z***, Xi is determined to be an outlier.

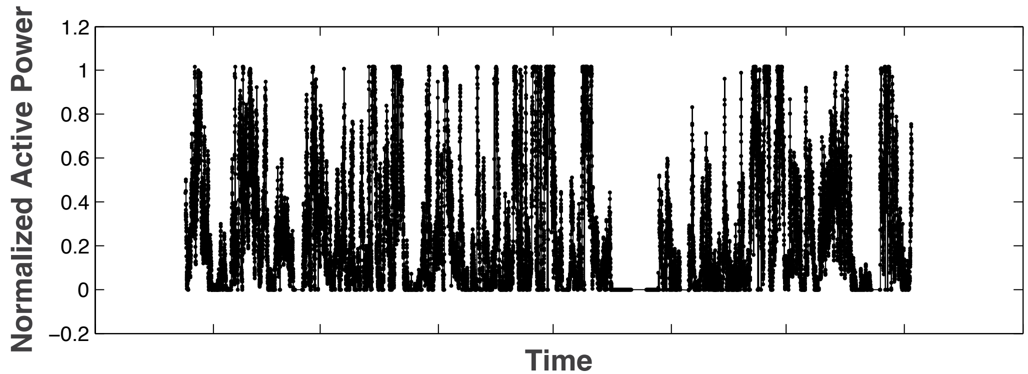
Selected Features

» SCADA Variables:
- Rotor bearing temperature (avg.);
- Gearbox stage 1 temperature (avg.);
- Gearbox stage 2 temperature (avg.);
- Gearbox stage 3 temperature (avg.).

» CMS Features:
- Time domain: RMS, kurtosis, crest factor;
- SKF features: RMS, peak-to-peak, kurtosis;
- Envelope features: RMS of envelope, RMS of band-pass filtered data, peak value of envelope spectrum in low frequency range, frequency index of the peak, crest factor of envelope spectrum;
- Wavelet features: four energy bands for four levels of detail signal, one energy band for level 4 approximation signal.

Degradation Assessment Result

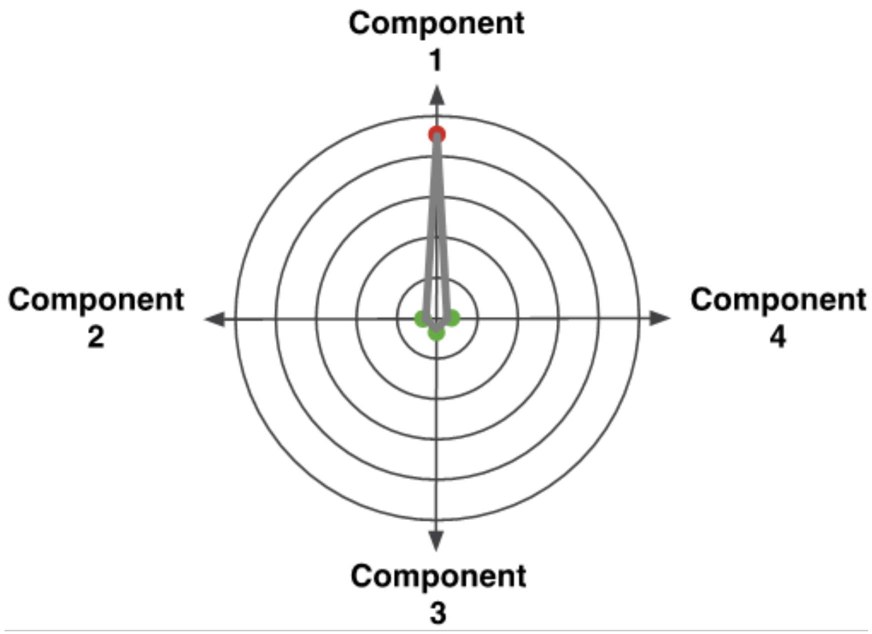




» MQE is tested to fit a Rayleigh distribution, and it exceeds the computed threshold five (5) days before turbine is shutdown for maintenance.

» Threshold is recalculated after maintenance based on new training data.

Fault Localization



- A radar chart is used to visualize the contribution of each component.
- The farther the point is from the center, the higher the contribution is.

Conclusion and Future Work

» Conclusion

- An integrated methodology of degradation assessment and fault localization for wind turbine drivetrain components is presented.
- The approach is validated with a planetary gearbox drivetrain of an offshore wind turbine.

» Future Work

- To apply and benchmark other multimodal methods, such as Gaussian Mixture Model (GMM).
- To apply more advanced feature extraction method with addition of tachometer signal, which provides rotation speed, and information about bearing specifications.
- To apply the approach on more turbines for validation and algorithm tuning.

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Thank you.