Wind turbine gearbox planet bearing failure prediction using vibration data

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Motivation

- Wind turbines are machines that operate under harsh conditions and therefore component failures happen before the end of the expected life of the turbine.
- Catastrophic failures increase O&M costs and consequently the LCOE.
- Predictive maintenance is applied in wind turbine industry so that O&M actions are optimised accordingly.

Figure: Wind Turbine on fire.[1]

[1] Source

Average Repair Time and Costs in Offshore Wind

Average repair times and costs for major replacements are given per failure category [2].

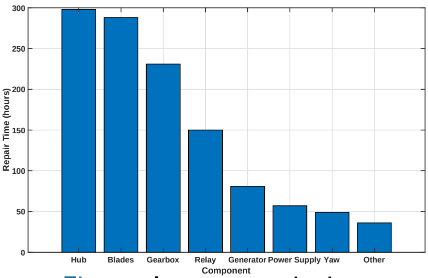

Figure: Average repair time.

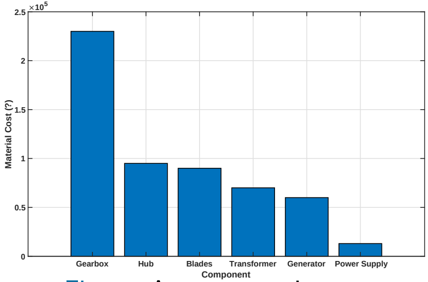

Figure: Average repair cost.

- The top three average repair times occur in the hub, blades and gearbox.
- The gearbox has the highest average cost per failure.
- From the CM perspective, a wind turbine gearbox consists of three major components: **bearings**, gears and lubricant.

Paper Objective

Create an automated failure prediction framework for wind turbine gearbox bearing faults. This framework is based on two stages:

Vibration Analysis and Feature Extraction

Find trends at varying times prior to component failure.

Extract features based on those trends.

Classification

Use features as inputs to a pattern recognition model.

Learn the behaviour characteristics of the trends for prognosis of degradation and failure prediction.

Bearing Vibration Theory

- Bearing faults introduce a shock that excites high frequency resonances.
- Bearing signatures:
  - masked by other components in the gearbox.
  - stochastic.
- Planetary stage hard to diagnose.
- Ball passing frequency (repetition frequency) depends on:
  - speed (f).
  - dimensions.

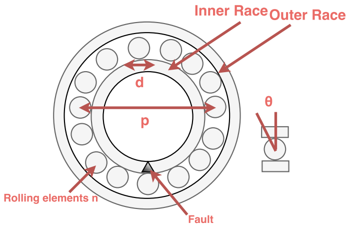

Figure: Bearing with an inner race fault and its significant dimensions.

$$\mathrm{BPFI} = f\frac{n}{2}\left(1 + \frac{d}{p}\cos(\theta)\right)$$

Vibration Signal Pre-processing

- Deterministics (gear) and random (bearing) components need to be separated. This can be done using an adaptive filter.
- Envelope analysis -often used in bearing diagnostics- demodulates the signal in a high frequency band.
- In order to choose the right band, spectral kurtosis indicates how kurtosis is distributed in the frequency domain and shows the impulsiveness of the signal. Thus it can be used as a filter [3].

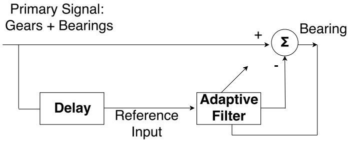

Figure: Adaptive filter.

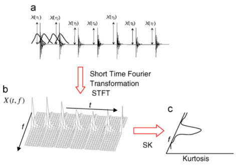

Figure: Spectral Kurtosis [3].

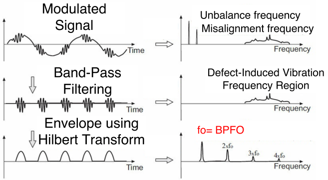

Figure: Envelope Analysis.

Classification: k Nearest Neighbours

kNN

- kNN classifier classifies unlabelled observations by assigning them to the class of the most similar labelled examples [1].
- Non parametric and instance based.
- k tuning using cross validation.
- Features used as input in a bearing fault case could be energy around ball passing frequency and its harmonics.

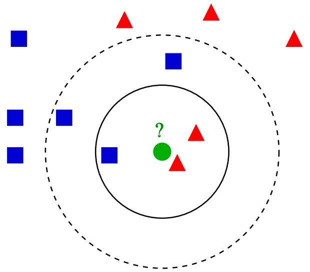

Figure: Example of kNN classification.

Wind Turbine Considered in This Study

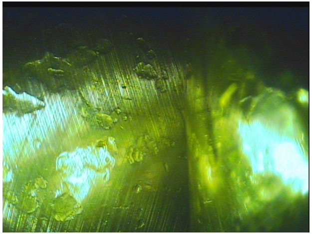

Figure: Faulty bearing.

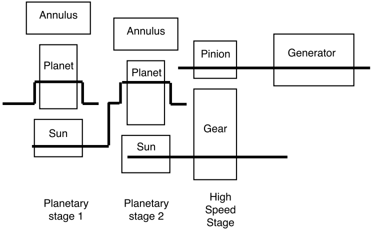

Figure: Gearbox internal structure.

- Wind turbine rated between 2.5-3.5MW.
- Double planetary stage gearbox, commonly found offshore.
- Inner race spalling.
- 95 samples collected at various times prior to failure (2.5 years to 1 week before).
- Acceleration data collected on a sampling rate between 20-30kHz for 10-15s. [2]

[2] Ranges are given for confidentiality reasons

Raw Vibration Data Analysis Results

RMS of the data as a function of load at different times before the component failure.

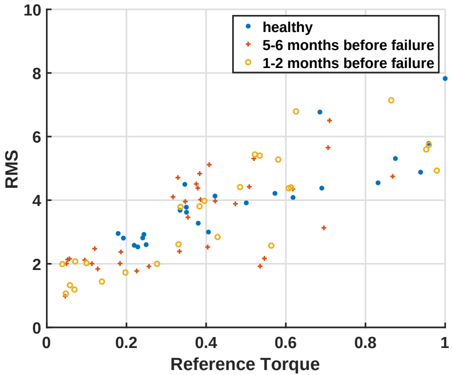

Figure: RMS of raw vibration signals.

Signal Processed Vibration Data Analysis Results

Envelope spectra of vibration signal for similar loading conditions. Only 3s of each signal are used and where they are assumed to be stationary.

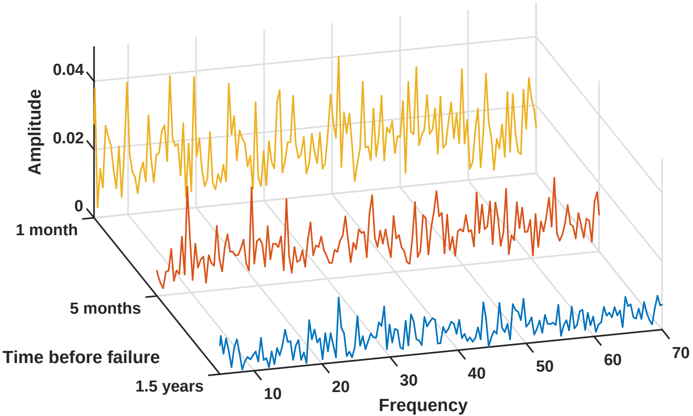

Figure: Envelope Spectra (based on spectral kurtosis) at different times prior to failure.

Classification Results

Predicted Class

Actual Class		1-2 months	5-6 months	healthy
	1-2 months	**75%**	18%	7%
	5-6 months	21%	**69%**	9%
	healthy	6%	12%	**79%**

Table: 3 Class Classification Results

Predicted Class

Actual Class		5-6 months	healthy
	5-6 months	**89%**	11%
	healthy	17%	**83%**

Table: 2 Class Classification Results

- Classes are assigned based on the acquisition time of the signal with respect to failure.
- 5-fold cross validation used

Conclusion and Future Work

Conclusion

Low speed stage bearing faults may not be diagnosed through raw vibration data.

Signal processing can help enhance the bearing fault impulses.

Given sufficient samples, features can be extracted from vibration data and given as inputs to machine learning classification models.

Classification models are able to classify signals based on their health state, useful for diagnosis and prognosis.

Conclusion and Future Work

Future work

Other types of classification methods, e.g. neural networks could increase accuracy.

Order tracking techniques can improve the filter and the overall accuracy results.

More historic data samples will train more robust models.

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