Wind turbine gearbox diagnostics using AI and condition monitoring data

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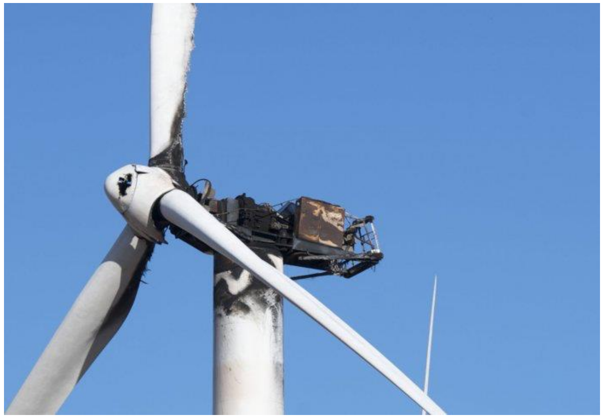
Wind Turbine Failures

Premature wind turbine failures lead to increased O&M costs.

"Wind turbines: the place where bearings go to die"
Prof Rob Dwyer-Joyce



Fire in the nacelle

Source: imperial.ac.uk

Tower failure

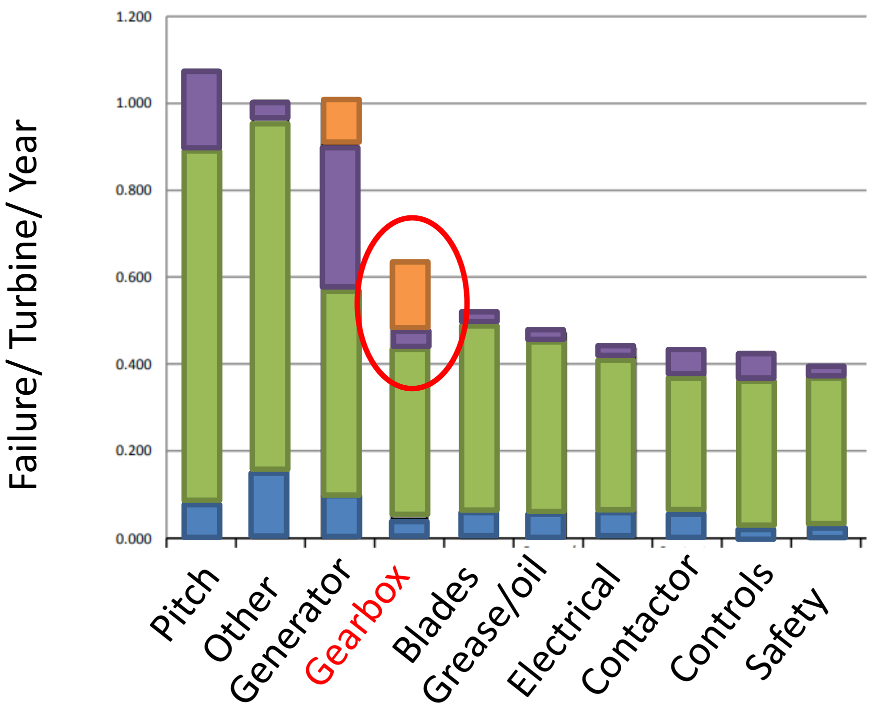
Source: windsorstar.com

Blade failure

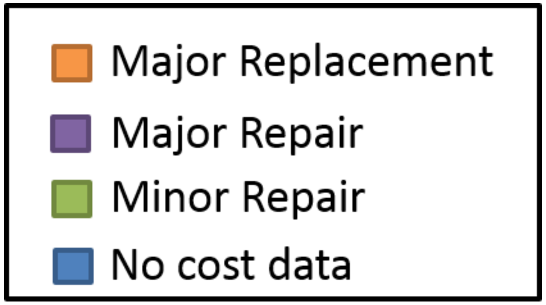
Source: enr.com

Failure Rates

- Gearbox downtime major drive for LCOE
- High material cost and repair time
- Gearbox and generator dominated by major replacements (>€10,000)



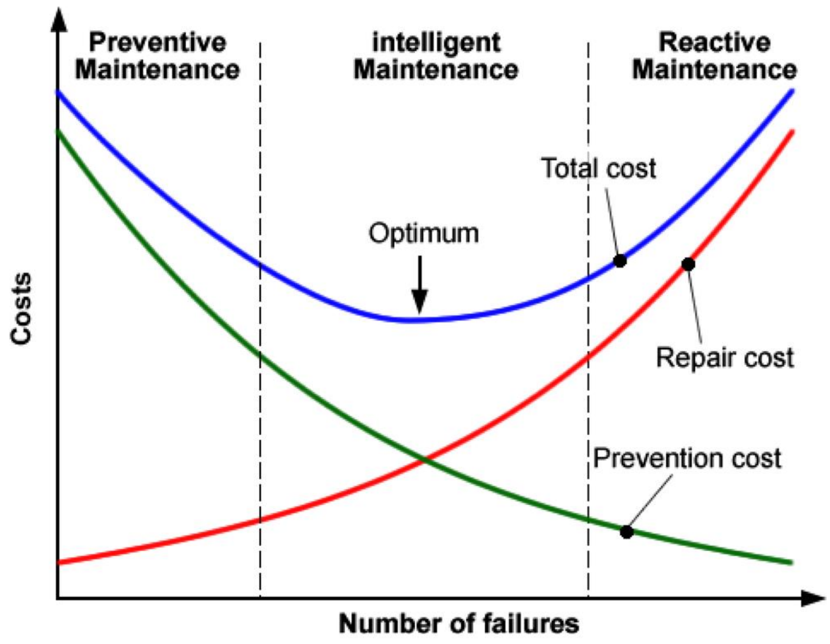
- ~350 offshore turbines
- 5 years
- Between 2 and 4 MW



Adapted from Carroll et al 2015.

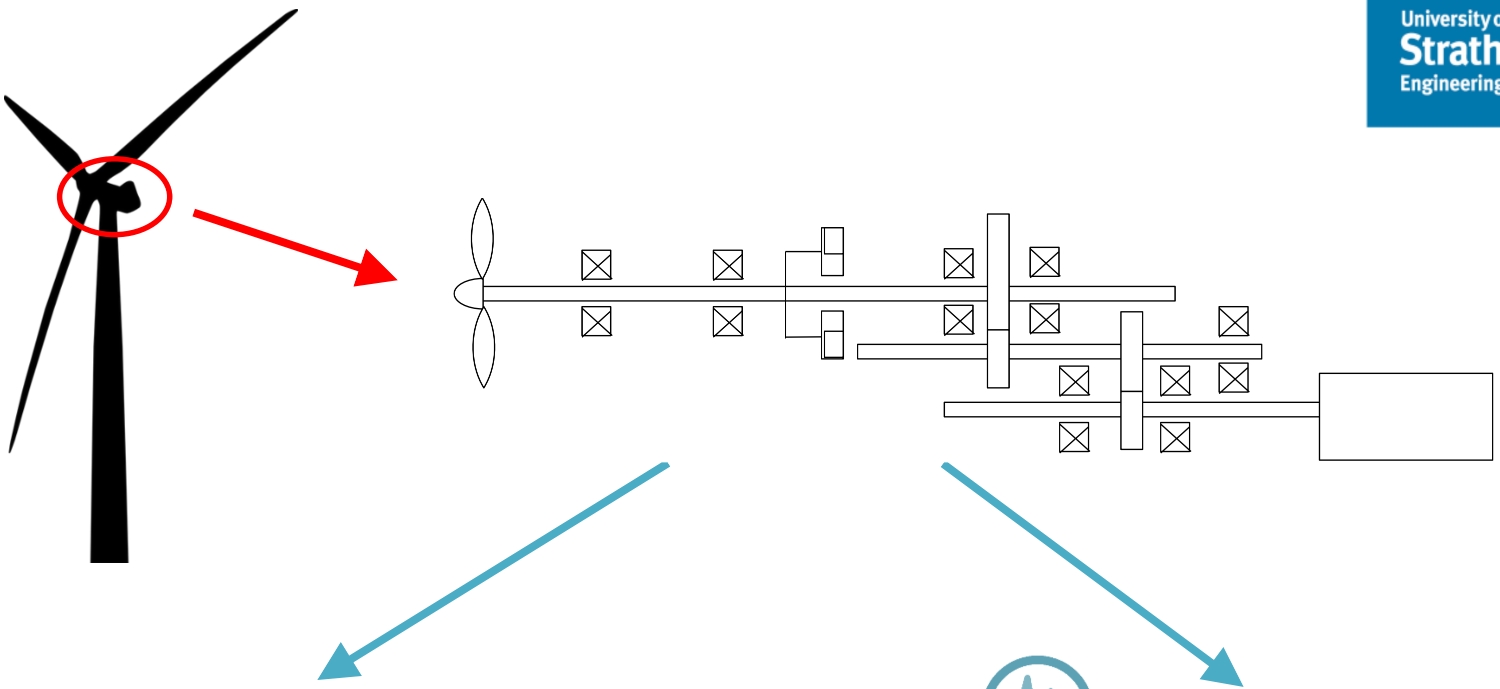
Failure rate Pareto chart for subassembly and cost category. Top 10 failure rates shown.

Which maintenance practice is the best?



"The economic benefit of onshore WT CM is clear in the majority of cases evaluated" D. McMillan et al 2008

Condition Monitoring Systems



Vibration data - *accelerometers*

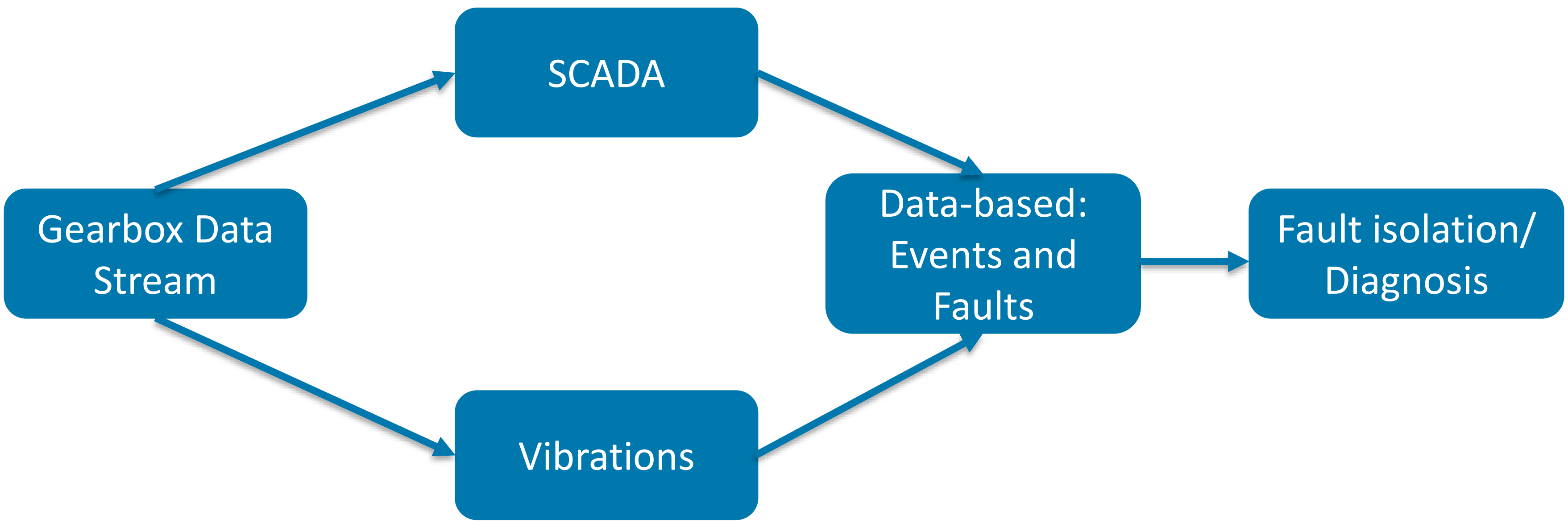
+ Well-known patterns for rotating parts
+ Easy diagnostics
- More costly

SCADA data

+ Flexible
+ Cheap
- Harder Gearbox Diagnostics

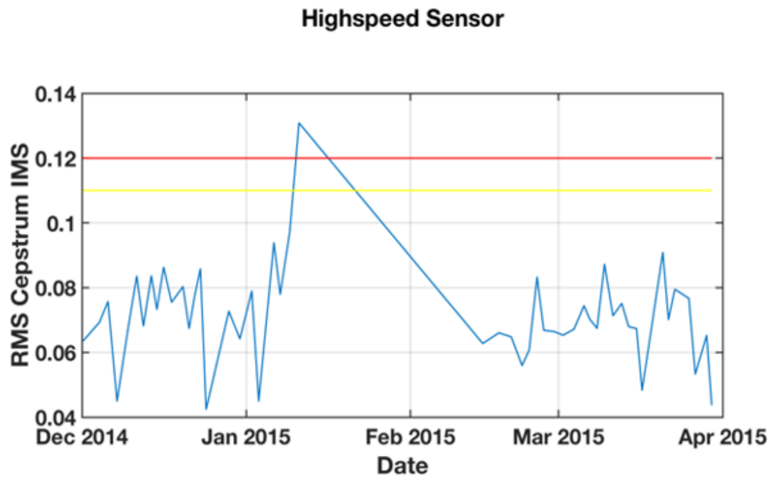
Research Question

How can incipient wind turbine gearbox component faults be predicted based on a combination of condition monitoring data and artificial intelligence before catastrophic failure occurs?



Current Pratice: Rule based monitoring

- Rule based condition monitoring sets thresholds on selected parameters
- Alarm when thresholds are exceeded
- Straightforward interpretation
- Cost-effective upscaling to a larger fleet using this method becomes a challenge because too much manual analysis is required for some failure modes.



Source: Own elaboration

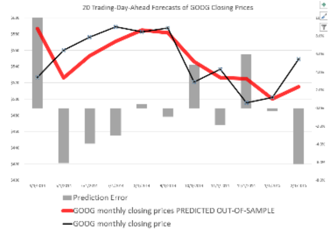
Buzzword alert: Machine Learning

Machine learning: *"Field of study that gives computers the ability to learn without being explicitly programmed." Arthur Samuels (1959)*
"…learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E." Tom Mitchell (1998)

Supervised Learning

- Classification
- Regression

Spam or not spam?

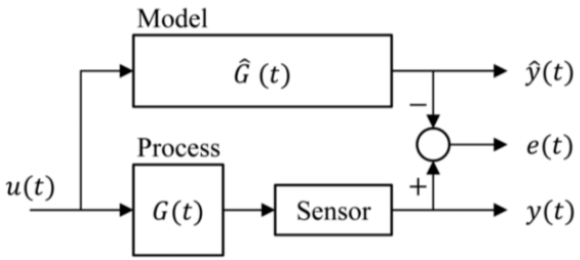


Stock price forecast

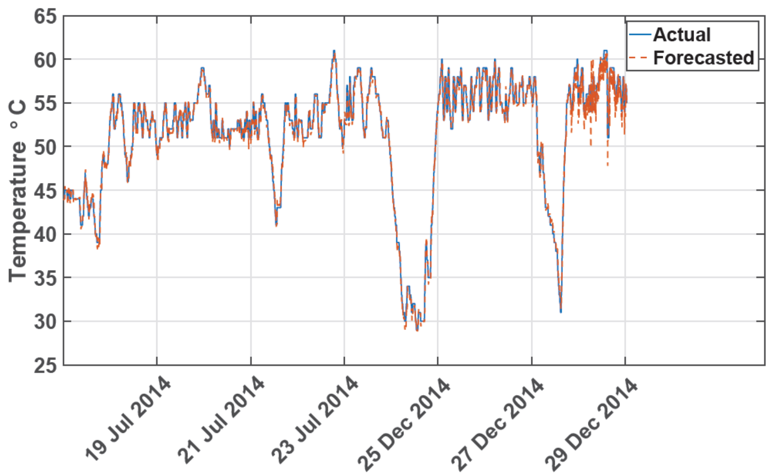
SCADA Anomaly Detection

Anomaly detection can be performed using normal behaviour modelling:

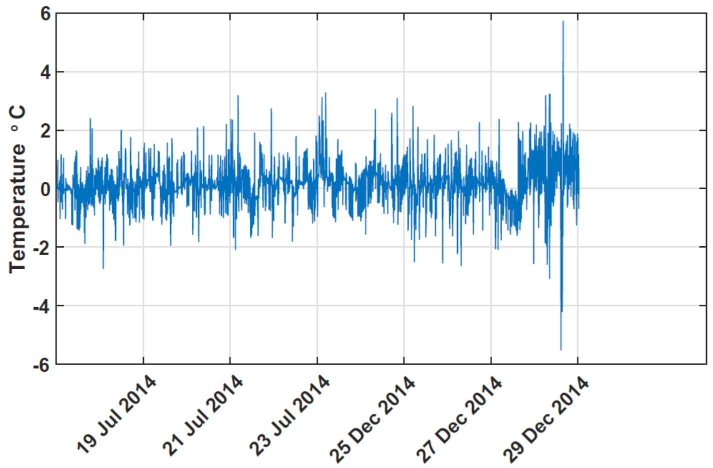
- The measured parameter is modelled empirically based on a training phase.
- The residual of measured minus modelled signal acts as a clear indicator of a possible fault.



Source: Tautz et al 2016



Gearbox oil temperature



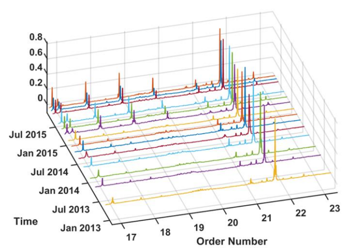
Model Error

Source: Own elaboration

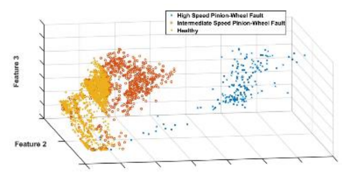
Machine learning vibration monitoring

Vibration Data Collection → **Signal Processing** → **Feature Extraction** → **Pattern Recognition Model** → **Fault Isolation/ Diagnosis**

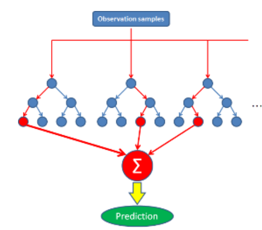
Accelerometers, Encoders



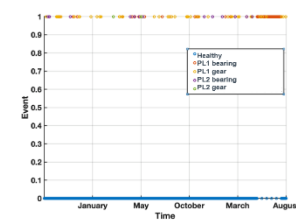
FFT, Cepstrum, Envelope, etc



Narrowband Health Condition Indicators



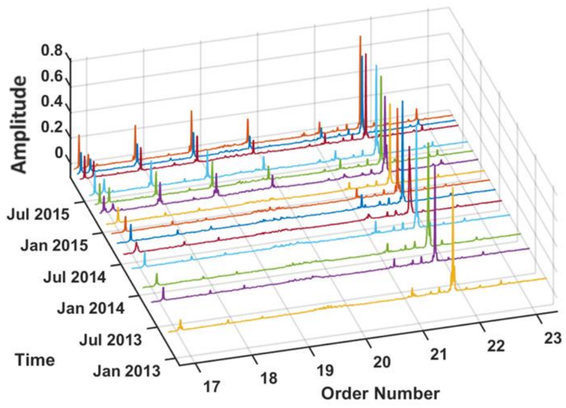
Random forests, neural networks etc



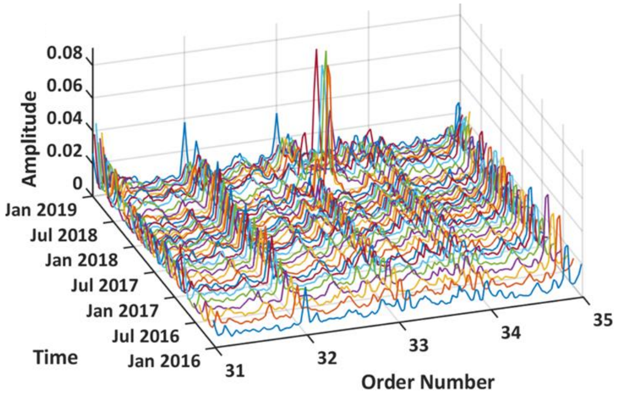
Event: Faulty bearing!

Fault signatures

- Fault patterns can appear in the spectrum of an incipient failure **before it becomes catastrophic**.
- Each gearbox component failure mode has a **unique signature** (more clear in the frequency domain).



Gear fault progressively before failure

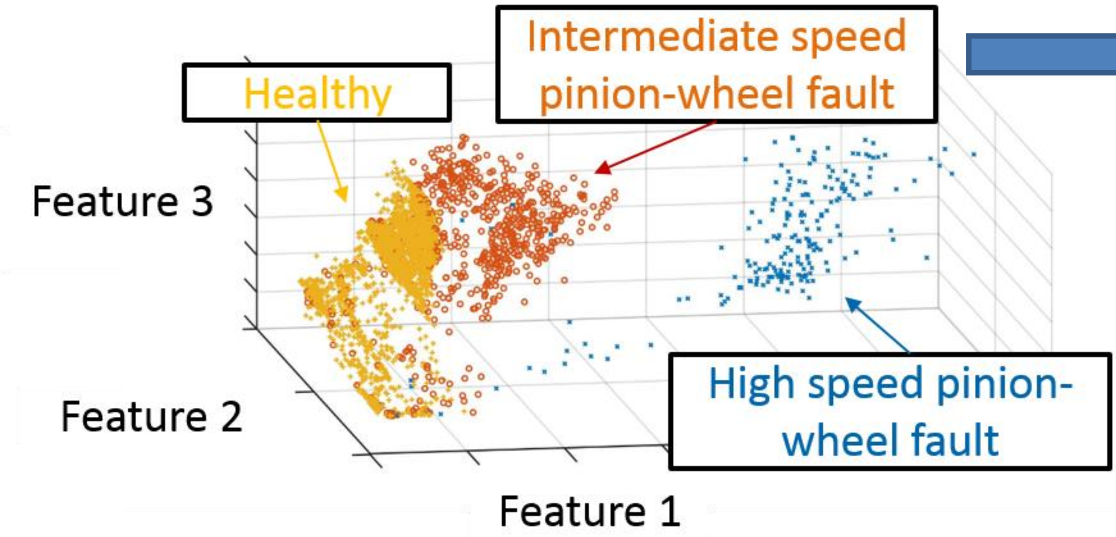


Bearing fault progressively before failure

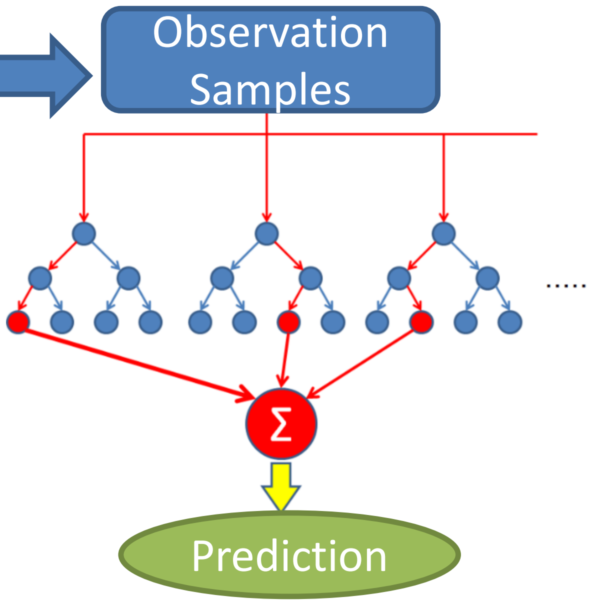
Source: Own elaboration

Feature Separation

- **Domain knowledge**: different failures at different gearbox stages and components correspond to different fault frequencies in the spectrum
- **Fault indicators:** Statistical features can be calculated at narrow-bands of fault frequencies
- **Pattern recognition inputs:** features can be used as inputs in machine learning models



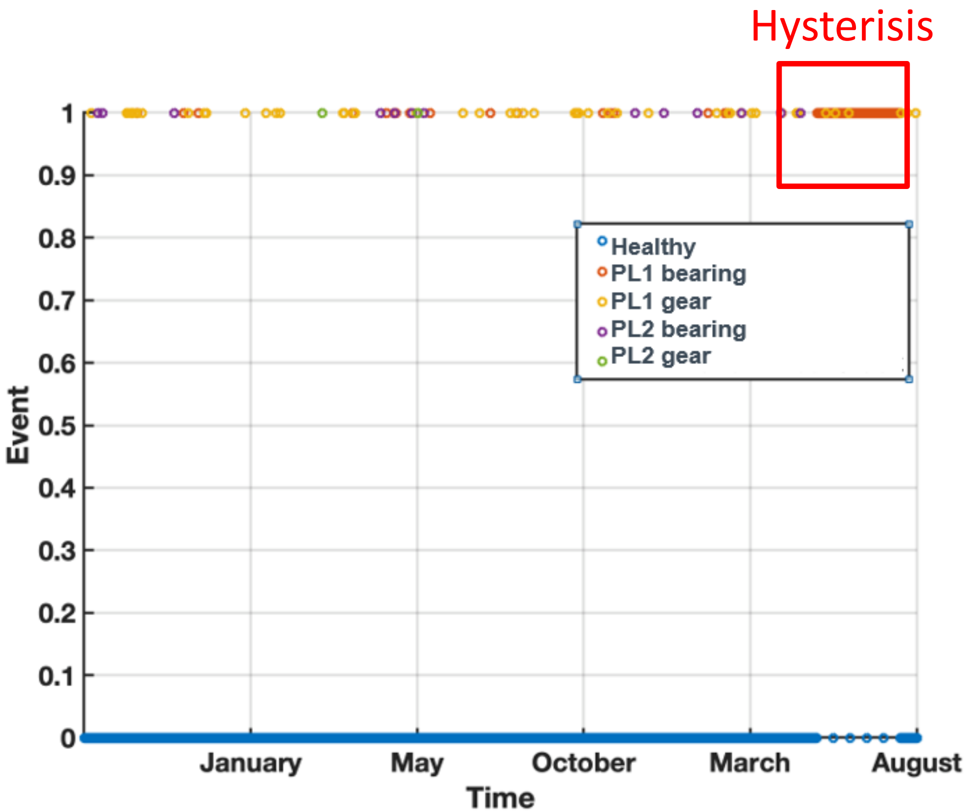
Source: Own elaboration

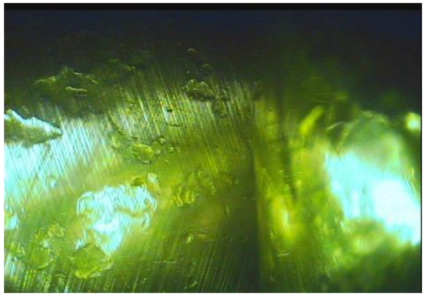


Source: hatenablog.com

Fault Isolation and Diagnosis

Pattern Recognition Model Output → Fault Location → Failure Mode





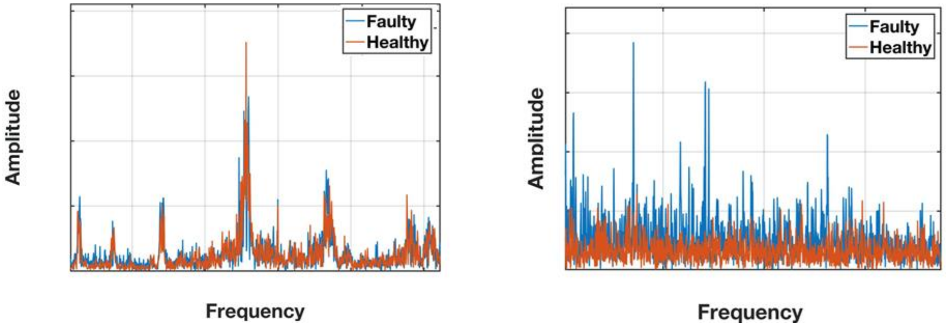
For example:

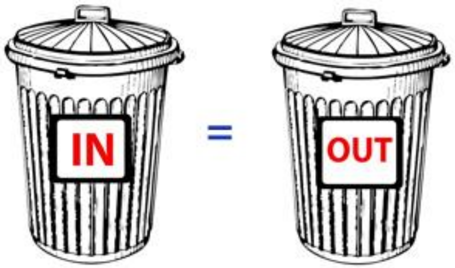
1. *Fault on the Planet Bearing of the 1st planetary stage.*
2. *Failure mode is inner race spall.*

Source: Own elaboration

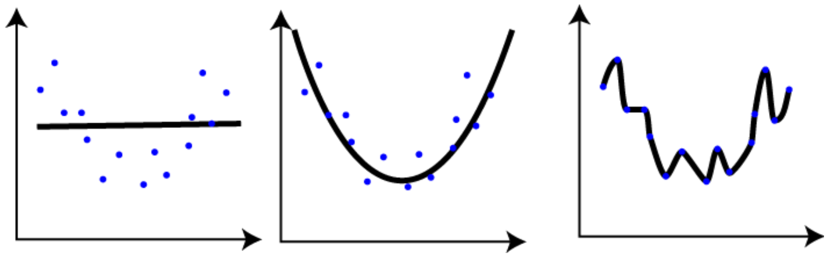
Best Practices

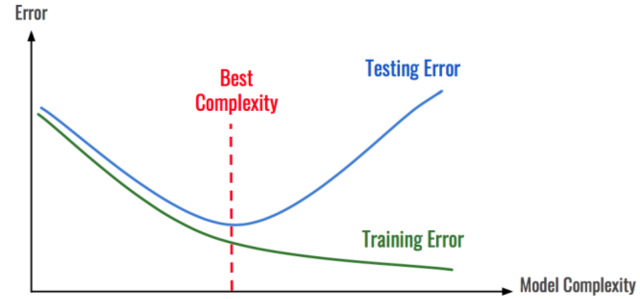
1. Signal processing to reveal fault patterns



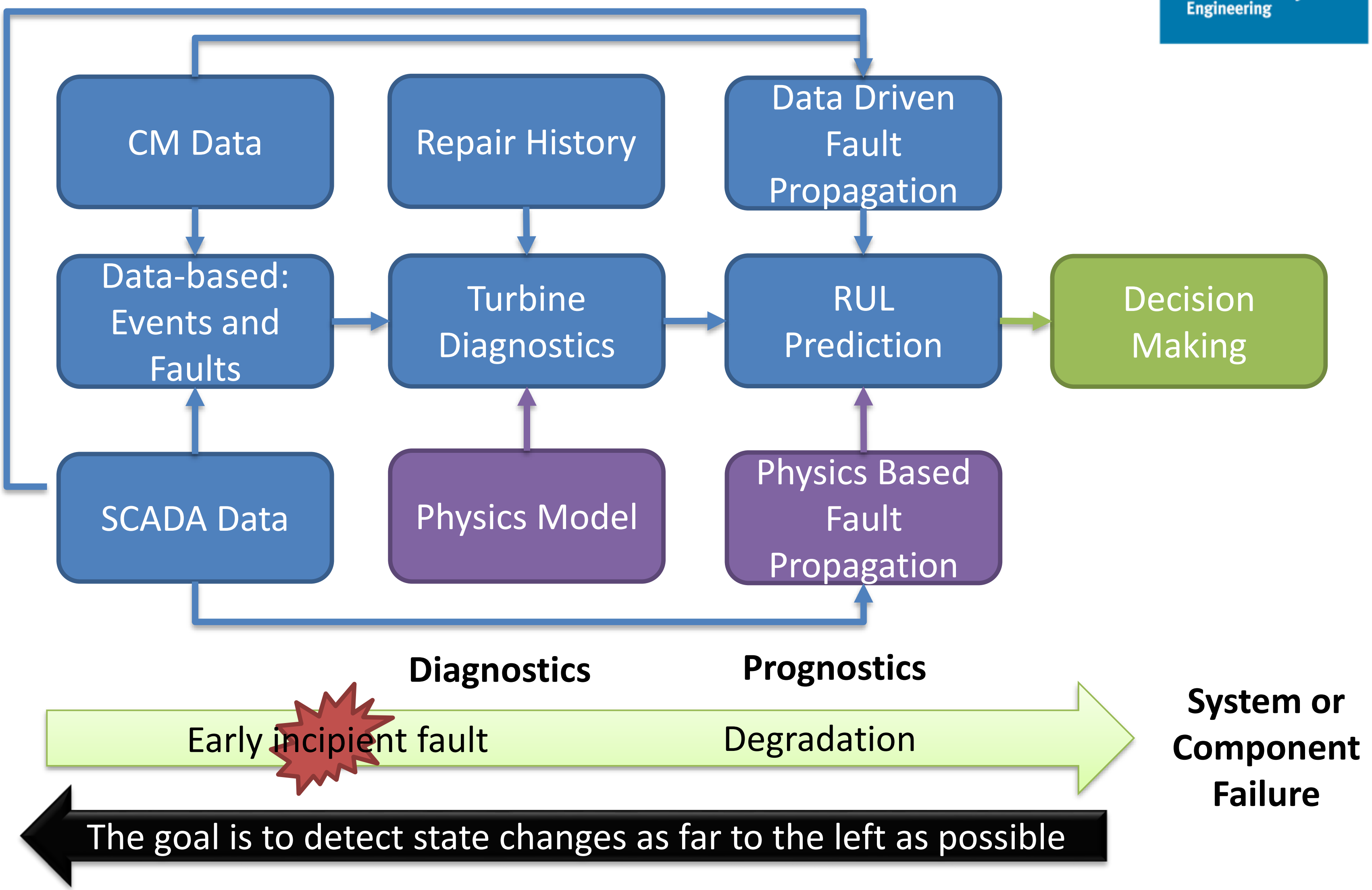


2. Best fit and generalization





The big picture



Conclusions

- AI can be used in CM to improve maintenance decisions and avoid manual interpretation of a large amount of wind turbine CM data.
- Sufficient number of training data and failure examples should be used to create pattern recognition models.
- Signal processing is important to reveal fault signatures.
- Domain knowledge helps, use it!

Source: powerengineeringint.com

Thank you for your attention!

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