Applications of machine learning in diagnostics and prognostics of wind turbine generators

Alan Turnbull

Supervisors:

Dr. James Carroll (Strathclyde University)

Dr. Alasdair McDonald (Strathclyde University)

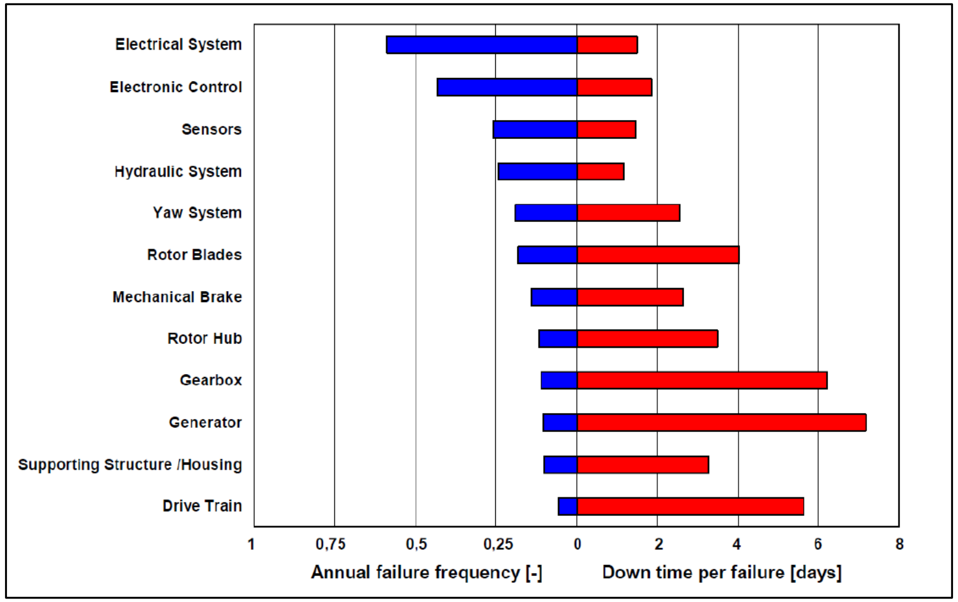
Contents

Motivation of research

- O&M can contribute significantly to overall LCOE
- Costs are expected to increase as wind farms are located further offshore
- Increasing reliability and optimising O&M becomes increasingly important
- As wind farms scale up the cost of specialist services will also increase

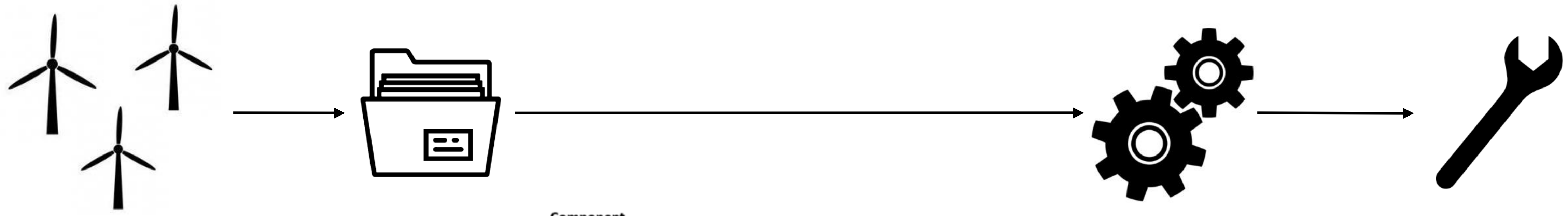
- Automation and big data analytics are key to driving down costs and addressing these issues

Why WT Generators?

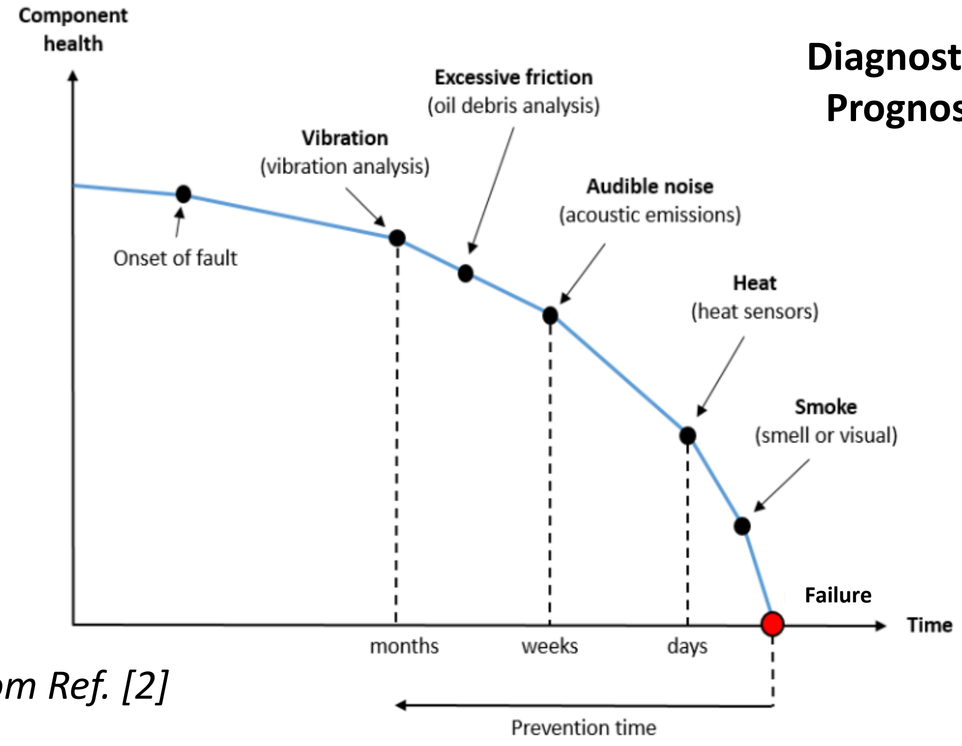


Ref. [1]

Wind farm condition monitoring



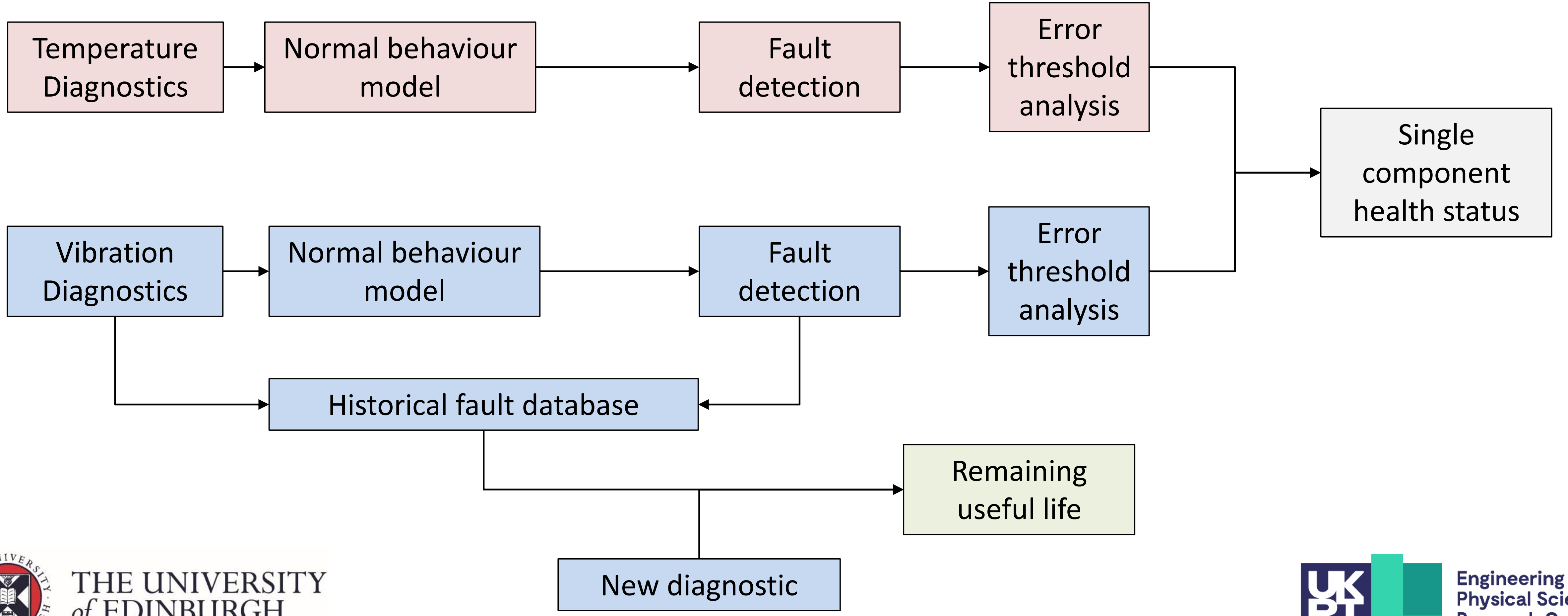
Wind Farm → **Operational Data** → **Diagnostics & Prognostics** → **Maintenance recommendation**



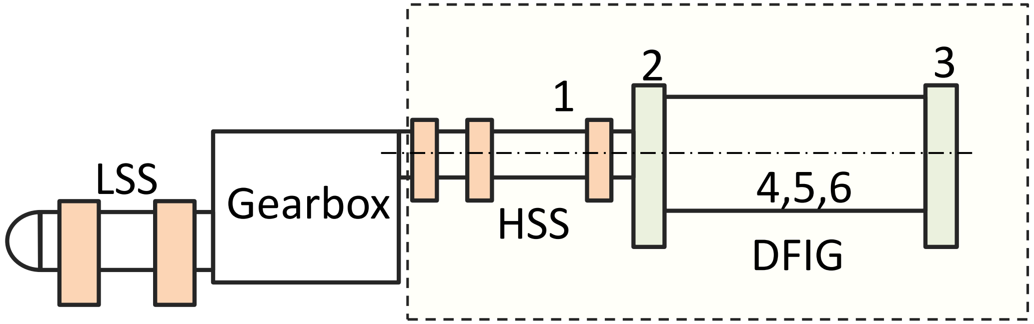
Adapted from Ref. [2]

PhD Overview -

Machine learning for fault diagnosis & prognosis



PhD Overview - Fault diagnostics



Anomaly detection (assembly level) → Specific fault classification (component level)

Accuracy of prediction will depend on:
- Capabilities of diagnostic indicator
- Models inputs/predictors and training data available
- How well previous examples of faults/failures are classified and labelled

Vibration   Temperature

Bearings:
1. HSS
2. Gen DE
3. Gen NDE

Other mechanical:

4. Rotor imbalance
5. Gen misalignment

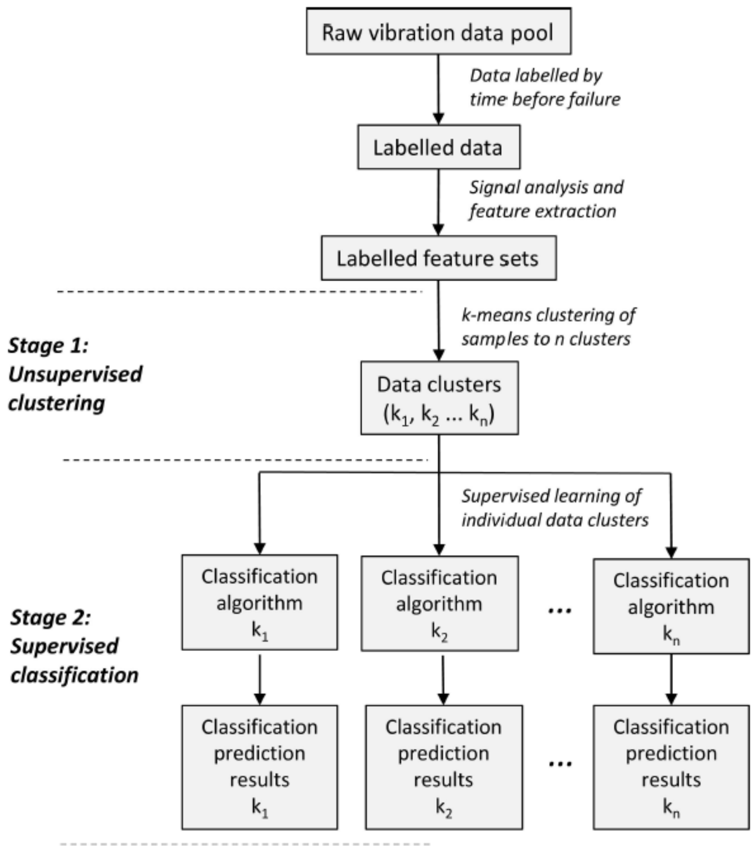
Electrical:

6. Gen windings

Gen DE bearing – RUL prediction

Methodology:

1. Determine diagnostics for possible generator bearing faults
2. Create database of failure examples
3. Analyse how diagnostics change leading up to failure
    - How different is fault progression between failures?
    - Can we identify ‘end-of-life’ indicators?
4. Feature engineering – what features influence baseline diagnostic level?
5. Label and group failure data
6. Train, validate and classification model
7. Use on new data to identify fault and RUL



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Data pool in numbers

7 wind farms

15 wind turbines

306 vibration samples (per sensor)

~ **10**s sample time with ~**25**kHz sample rate

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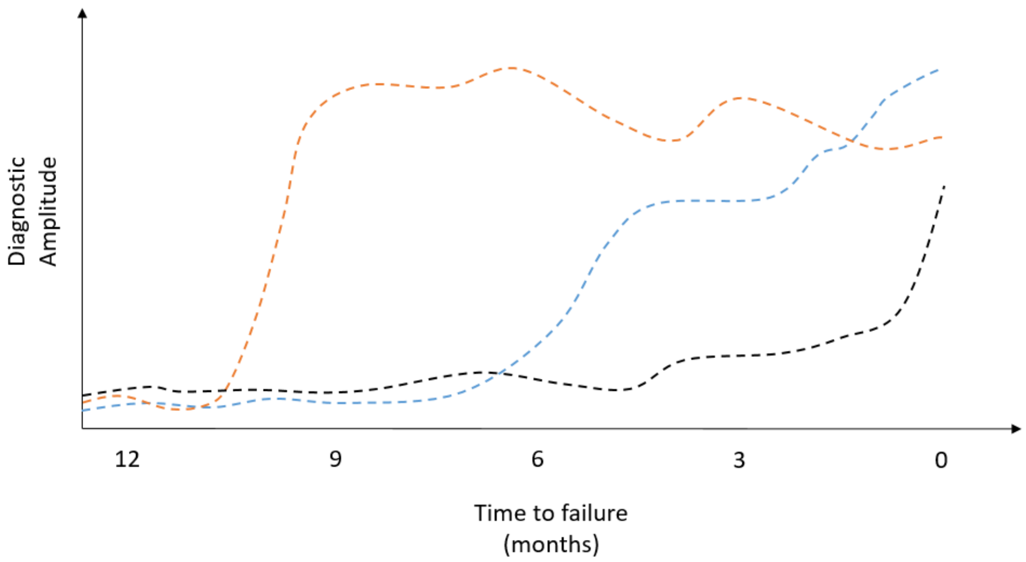

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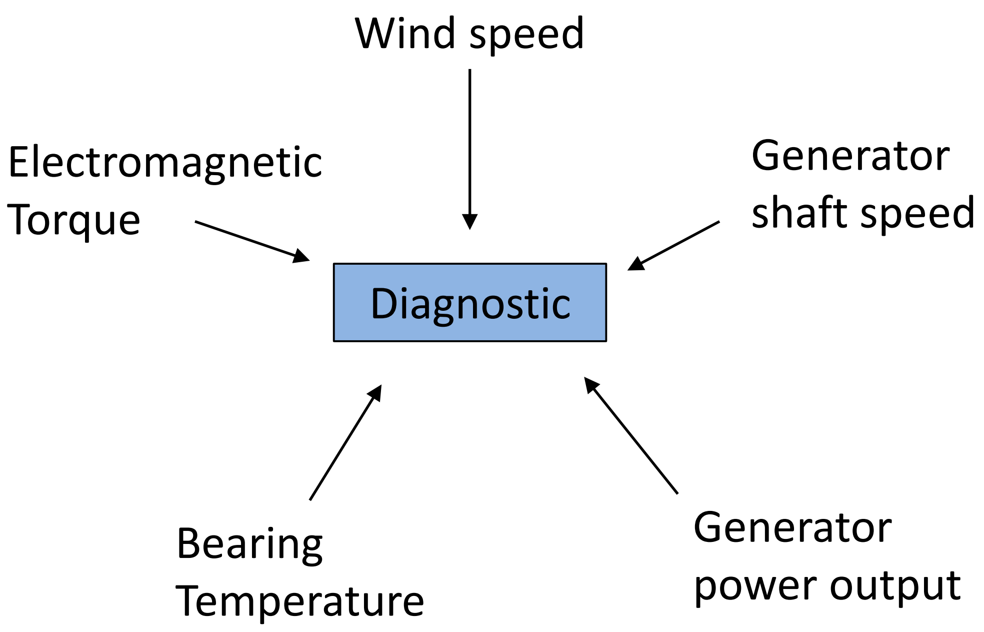

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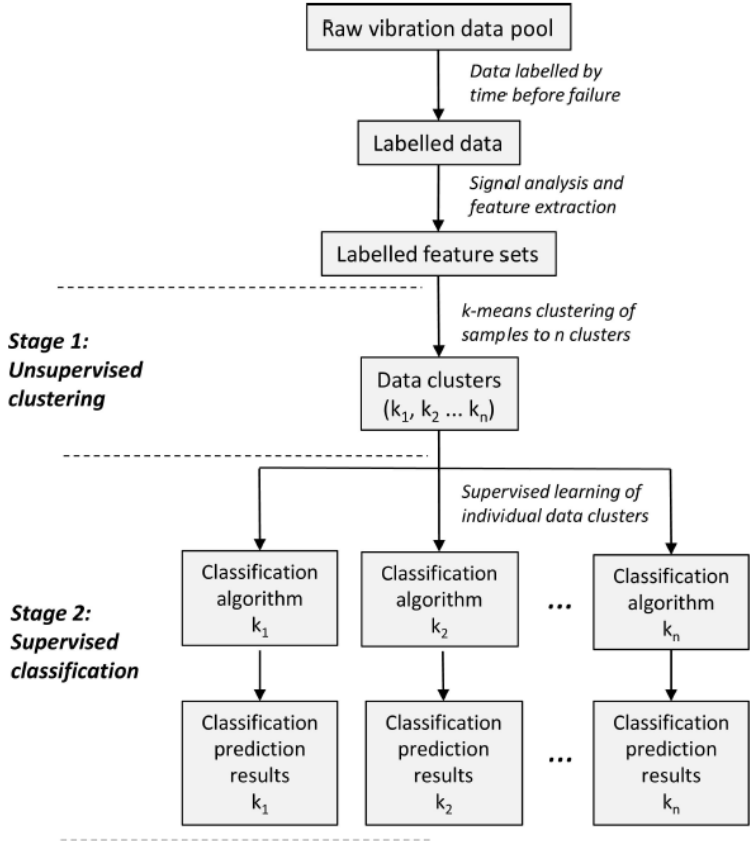

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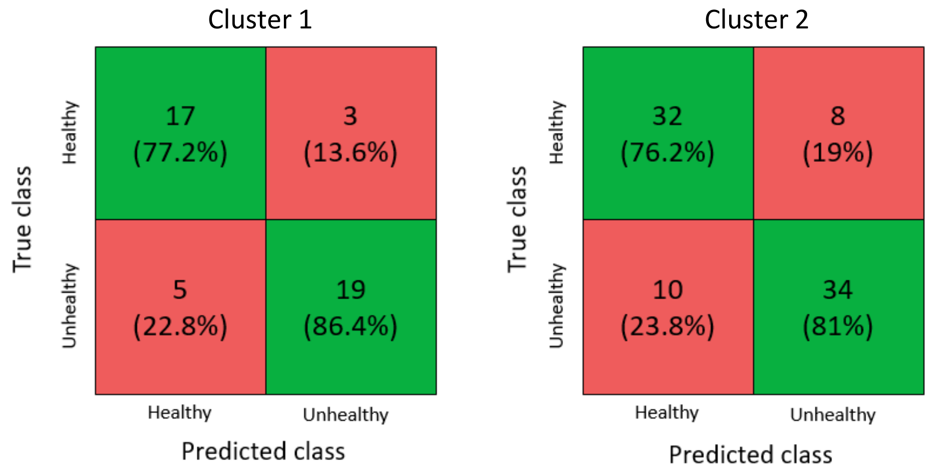
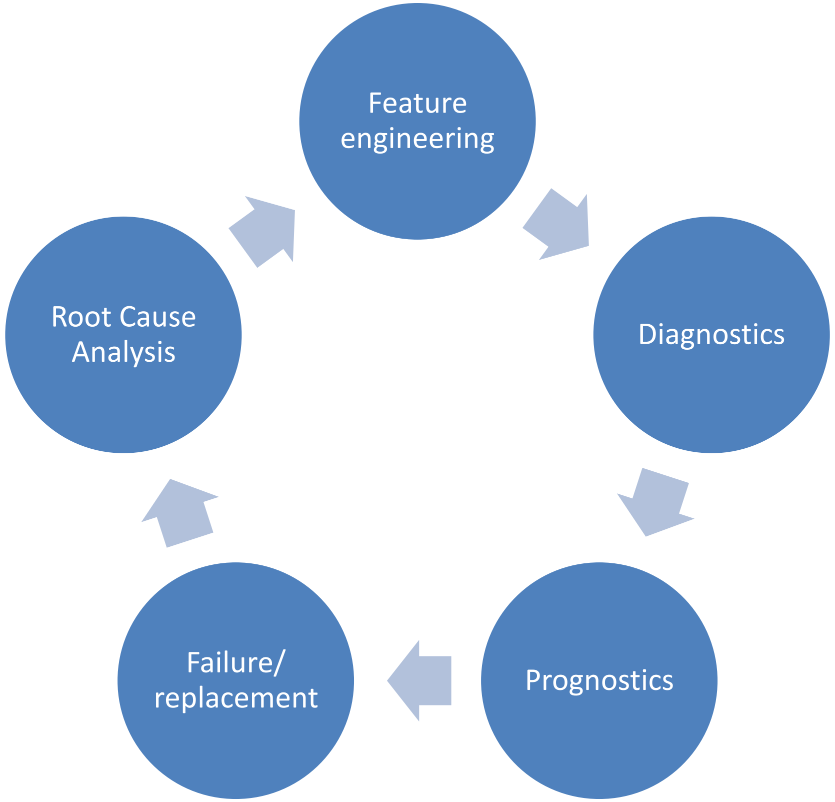
Results

- **Diagnostics:** Correctly diagnosis of bearing fault with up to ~98% accuracy
- **Prognostics:** Correctly predicting failure within 1-2 months with up to ~86 % accuracy



Conclusions

- Machine learning can assist engineers in many aspects of condition monitoring including automated anomaly detection and fault classification
- Specialist engineering knowledge is fundamental to unlock this potential by understanding underlying component kinematics and fault diagnostics for feature engineering
- Improvements in prognostics requires more examples of components that have been run to failure to be made available, or more information about fault progression at the time of replacement – data that is lacking in academic research



Thank you for the attention, any questions?

References

[1] P. Tchakoua, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. A. Tameghe, and G. Ekemb, "Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges," *Energies*, vol. 7, no. 4, pp. 2595–2630, 2014.

[2] B. Hahn, M. Durstewitz, and K. Rohrig, "Reliability of wind turbines - experiences of 15 years with 1,500 wts," *Wind Energy*, pp. 329–+, 2007.

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