Wind & Marine Energy Systems CDT

University of Strathclyde Glasgow

Thermal modelling of wind turbine gearboxes for condition monitoring and fault detection

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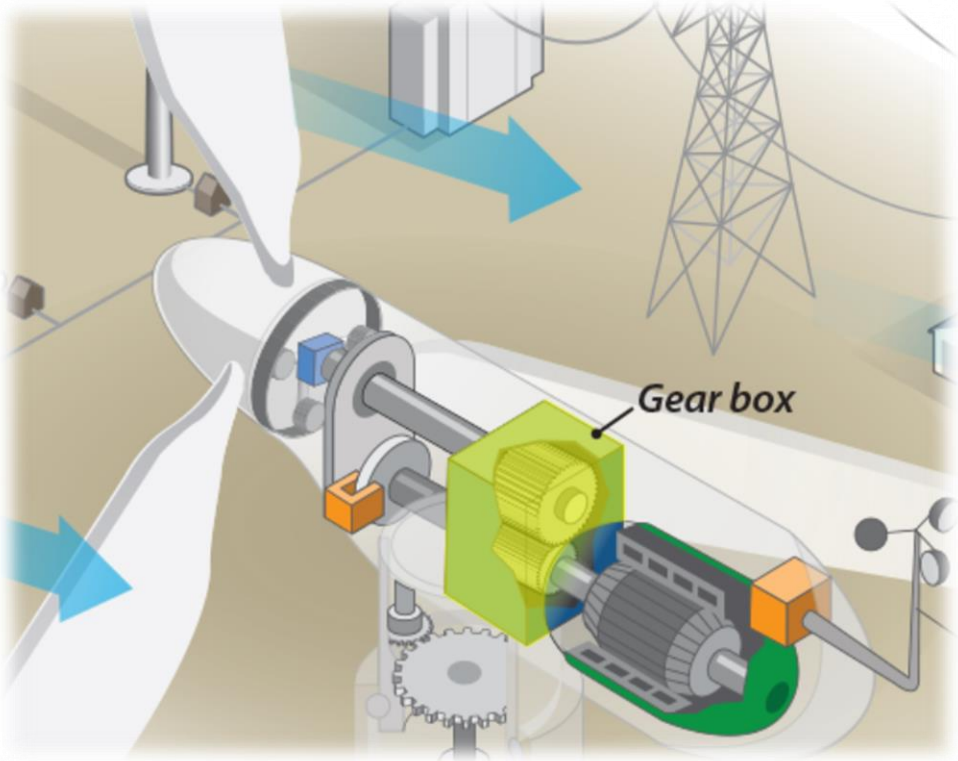
UKRI Engineering and Physical Sciences Research Council

Introduction

- Motivation
- Research overview
- Methodology
- Findings
- Summary
- Future work

Motivation

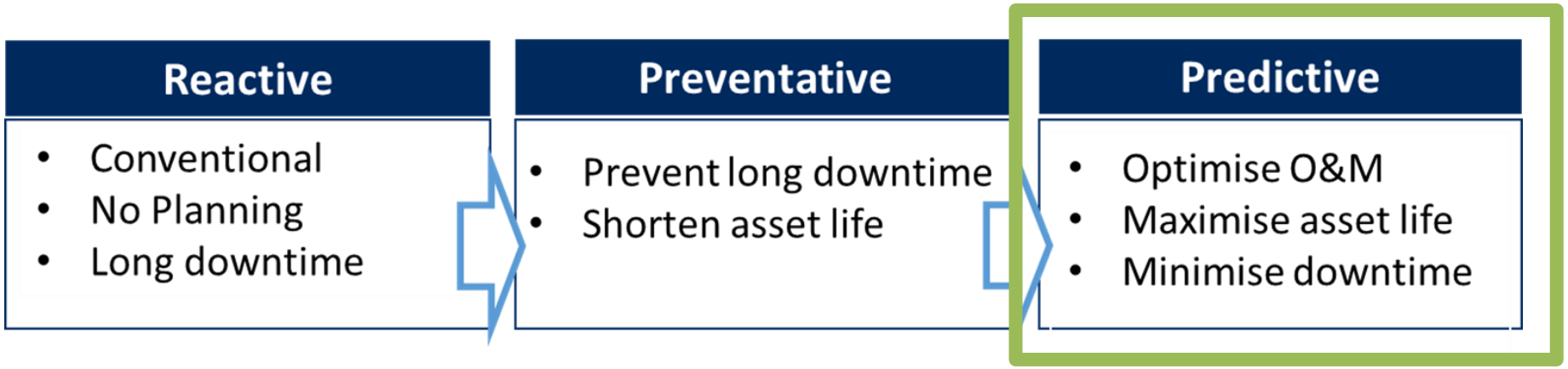
- Operation & Maintenance **20-30%** of Levelised Cost of Wind Energy [1]
- Gearbox responsible up to 1/3 lost availability [2]
- ~75% of wind turbines geared [3]



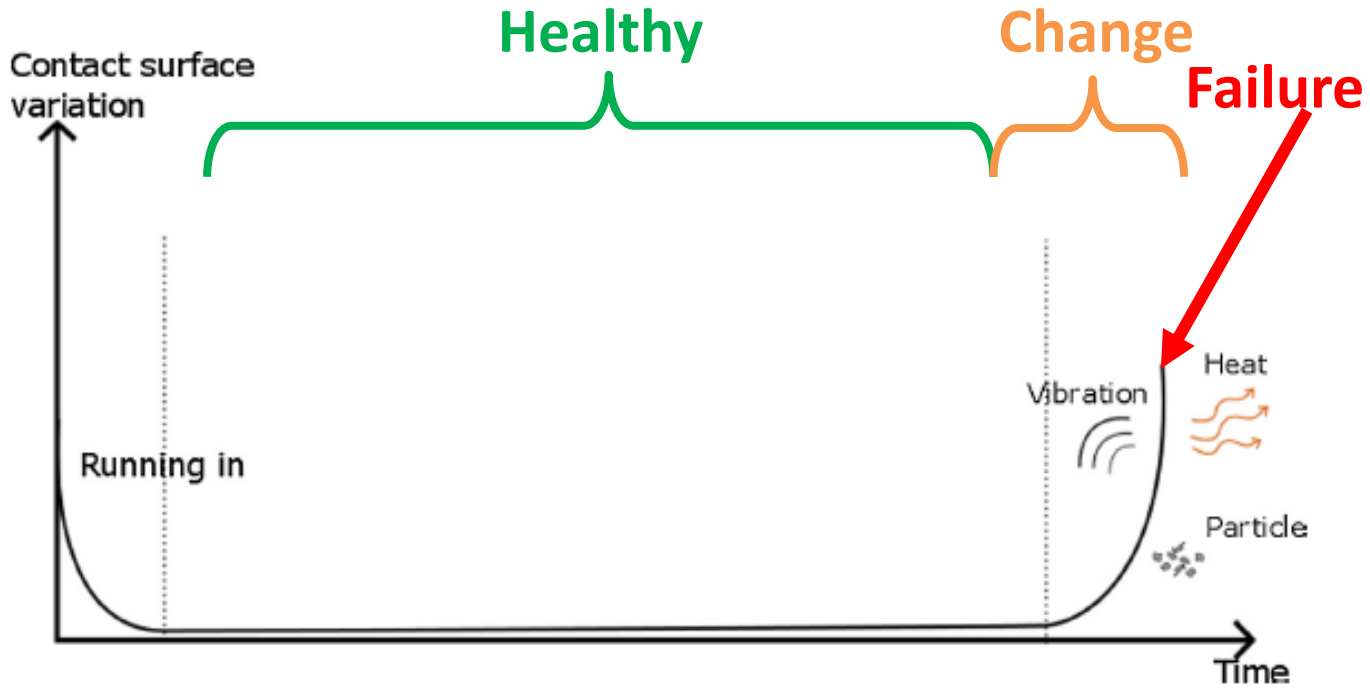
[1] M. I. Blanco, "The economics of wind energy," *Renew. Sustain. Energy Rev.*, vol. 13, pp. 1372–1382, 2009.
[2] Y. Feng, et al., "Monitoring wind turbine gearboxes," *Wind Energy*, vol. 16, no. 5, pp. 728–740, Jul. 2013.
[3] V. L. Jantara and M. Papaelias, "Wind turbine gearboxes: Failures, surface treatments and condition monitoring," in *Non-Destructive Testing and Condition Monitoring Techniques for Renewable Energy Industrial Assets*, 2020

Motivation

- Potential cost reduction by optimising maintenance strategy
- Condition monitoring
  - Current research data driven
  - Relies on historical data



Motivation



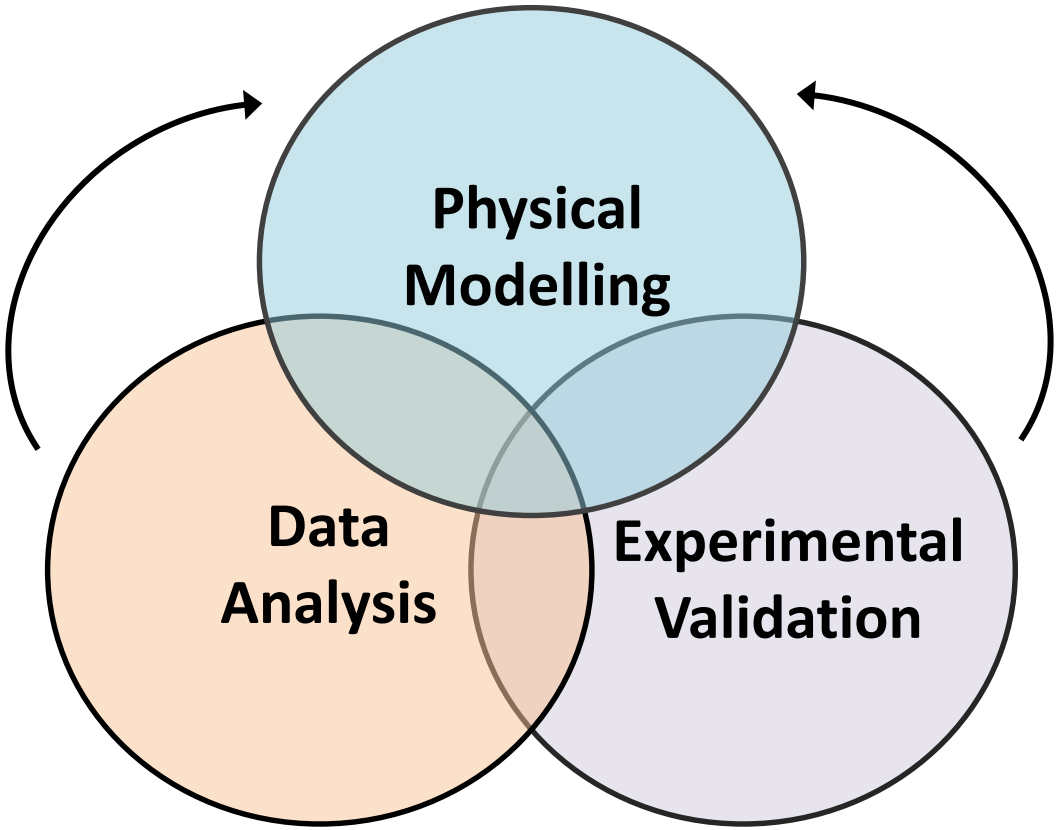
Physical understanding to model condition

- Understand “Healthy” gearbox
- Does behaviour change with fault?
- How do we see this change?

Figure adapted from:
T. Touret, C. Changenet, F. Ville, M. Lalmi, and S. Becquerelle, “On the use of temperature for online condition monitoring of geared systems – A review,” *Mech. Syst. Signal Process.*, vol. 101, no. Supplement C, pp. 197–210, Feb. 2018.

Research Overview

To what extent can temperature be used to detect and/or locate faults?

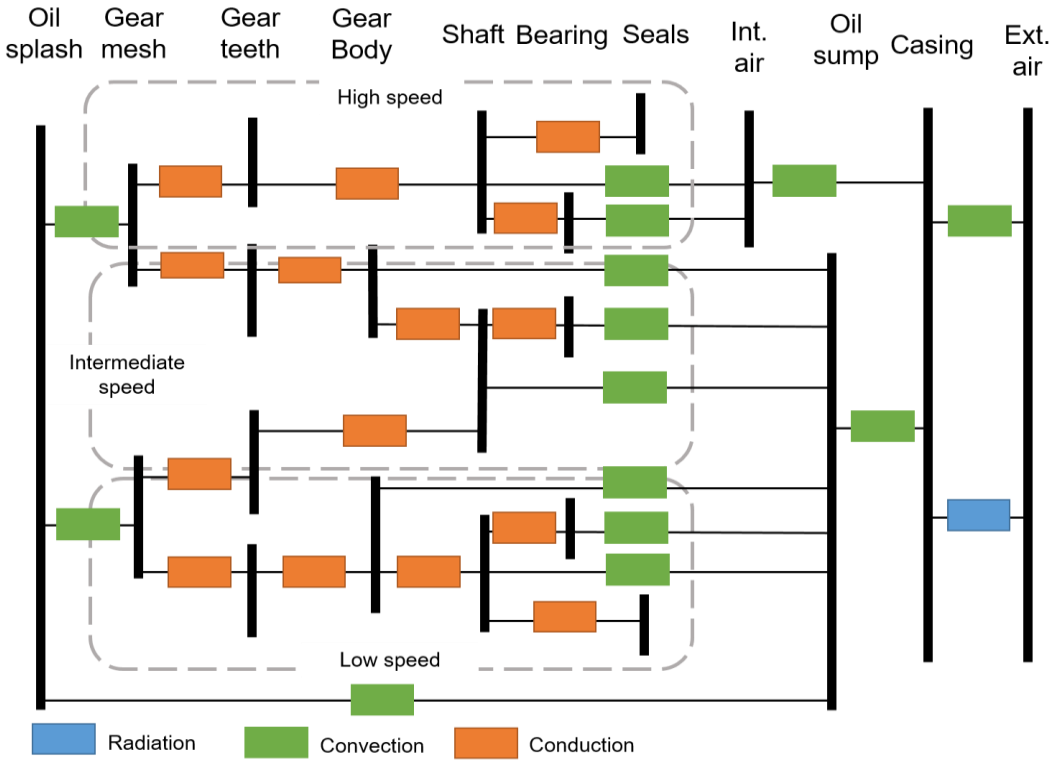


Physical Modelling

- Tribology
  - Calculate gearbox losses
  - Based on geometry, torque, rotational speed, lubrication
- Thermal network model

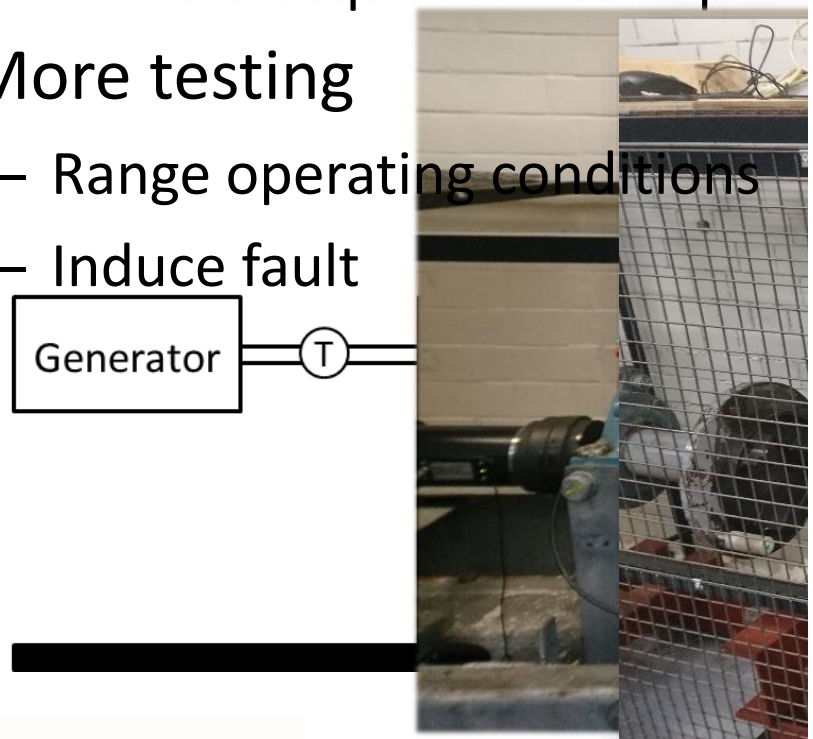
Heat loss (W) $\longrightarrow Q_{a-b} = \dfrac{(T_a - T_b)}{R_{a-b}}$ $\longleftarrow$ Temperature (K)

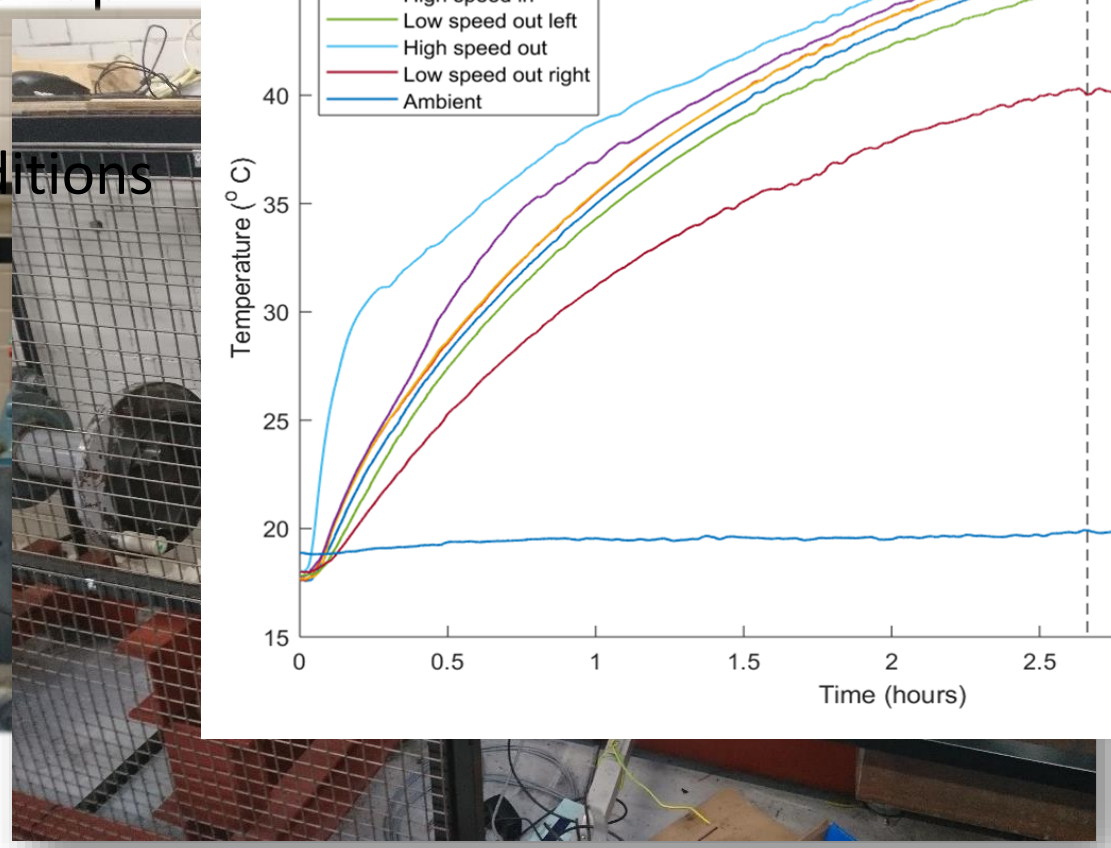
$\longleftarrow$ Thermal resistance (K W^{-1})



Experimental Validation

- Test rig set up - 11kW
  - Data acquisition set-up
- More testing
  - Range operating conditions
  - Induce fault

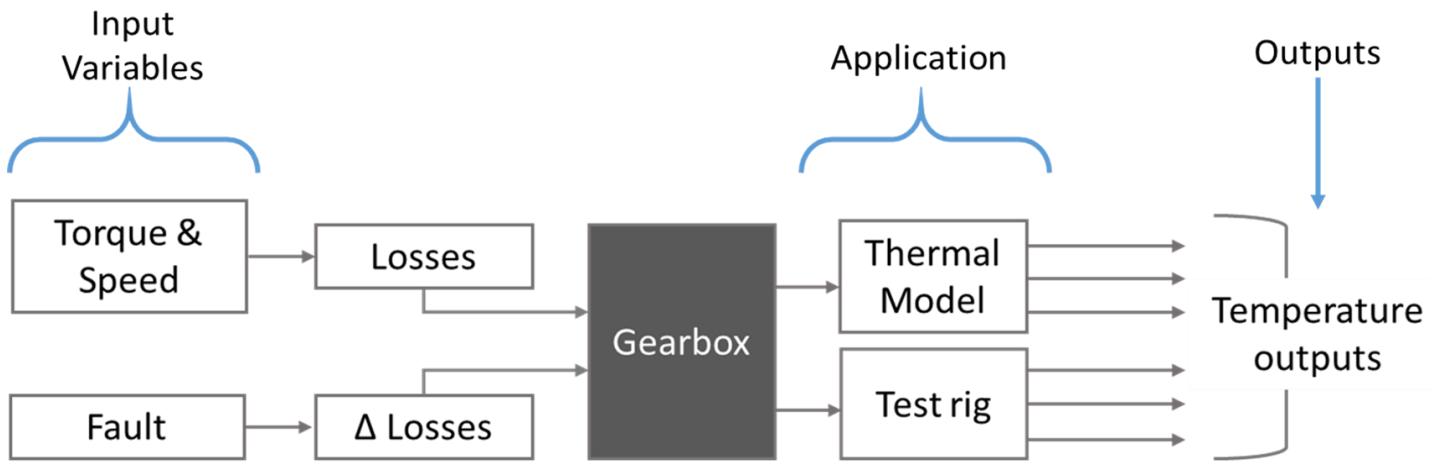




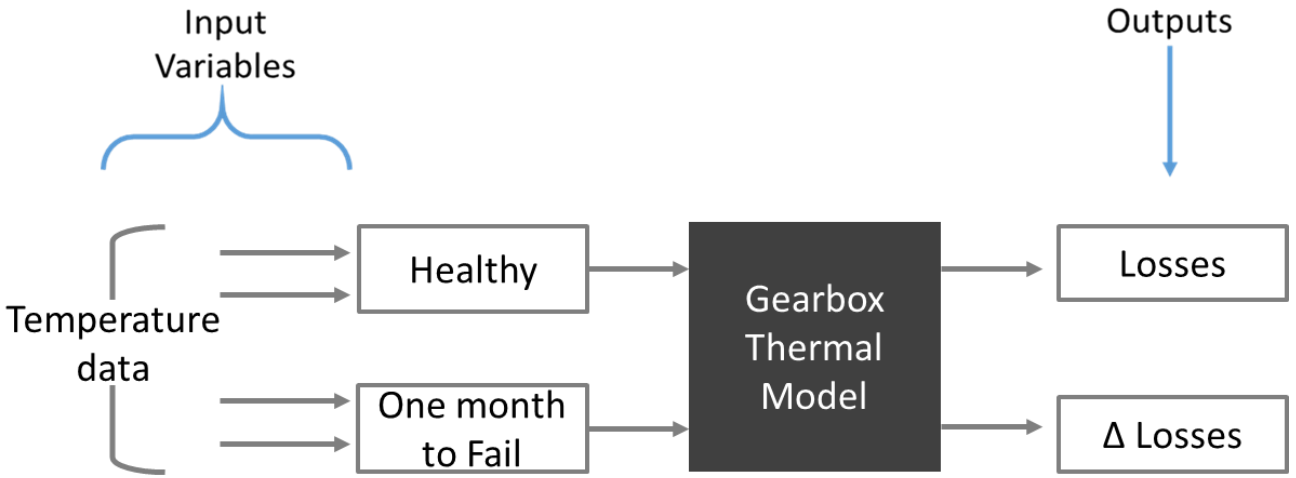
Methodology

Physical Modelling

Experimental

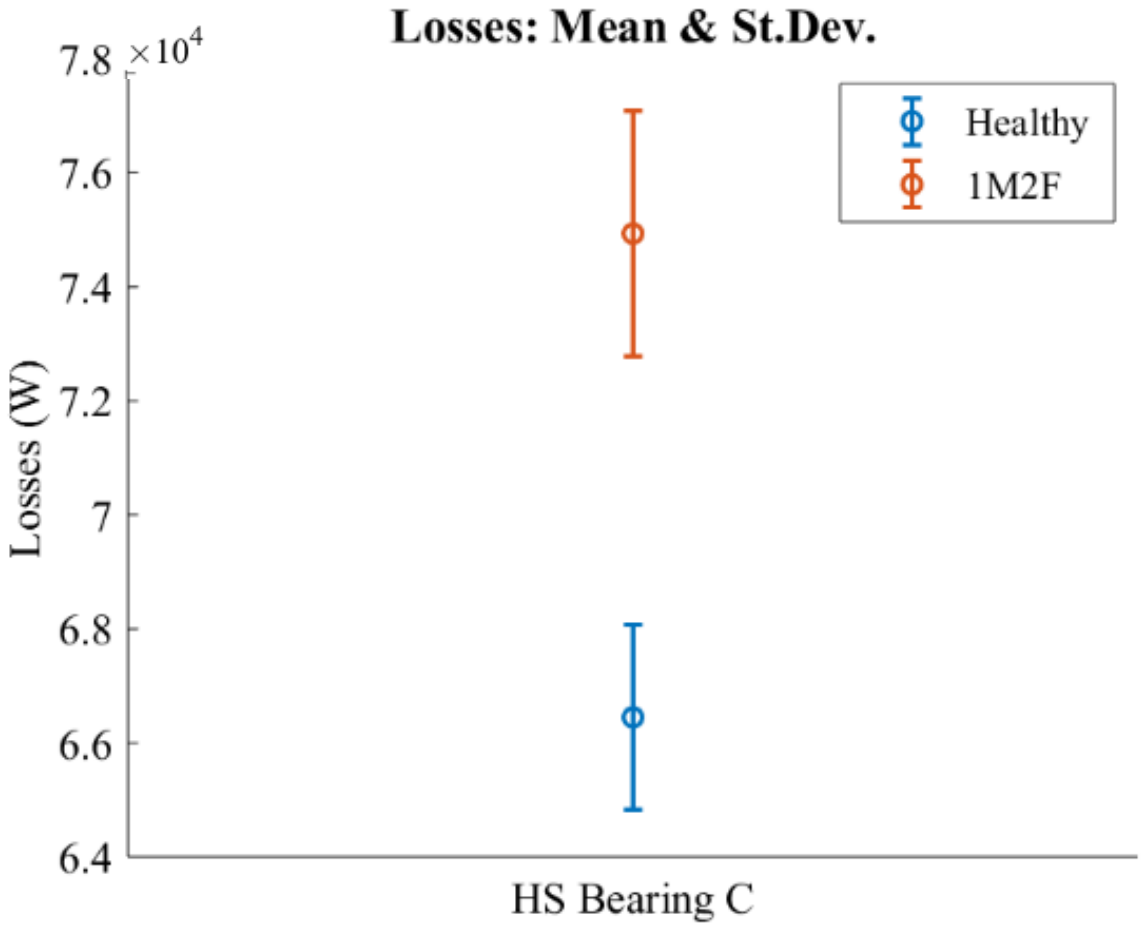


Data Analysis



Data Analysis

- Using operati
  - Inverted the
  - “healthy” ar

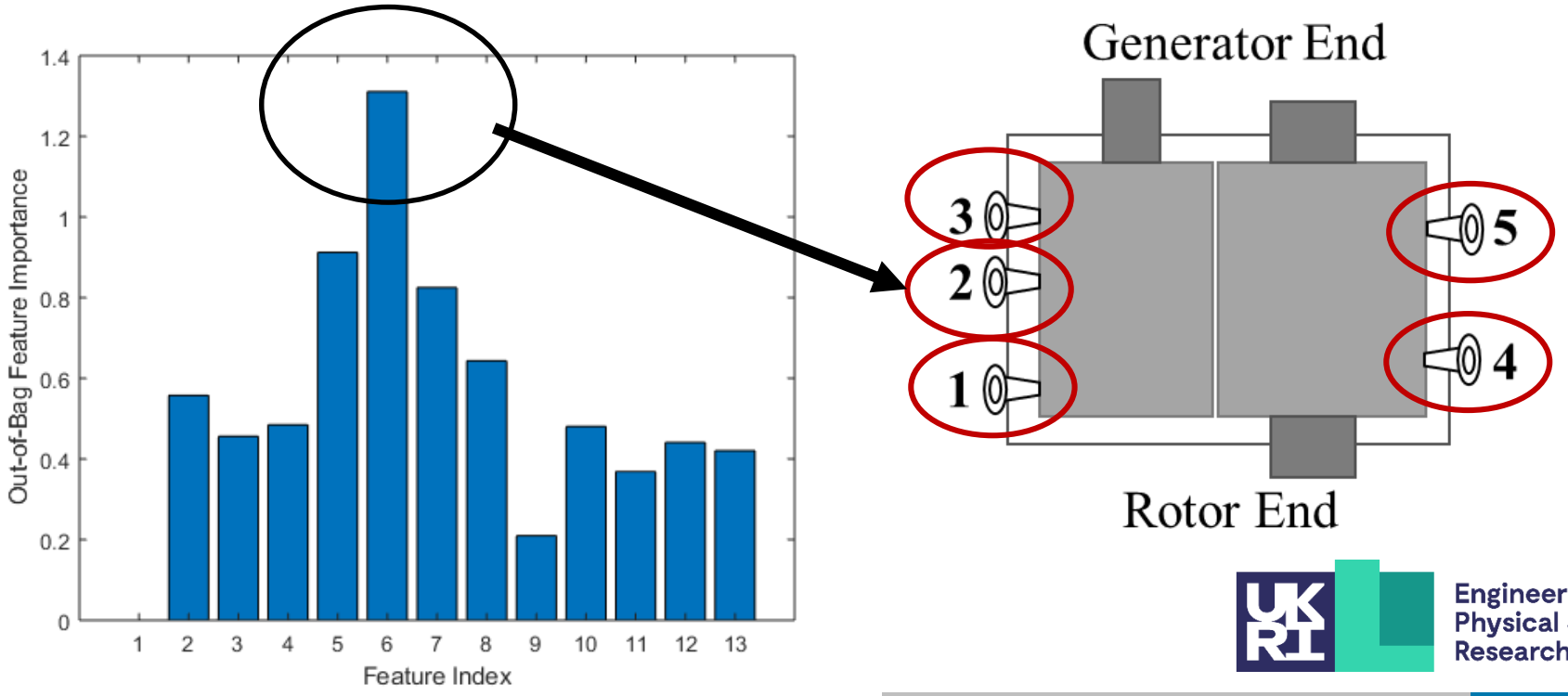


$T_b)$ ← Temperature (K)

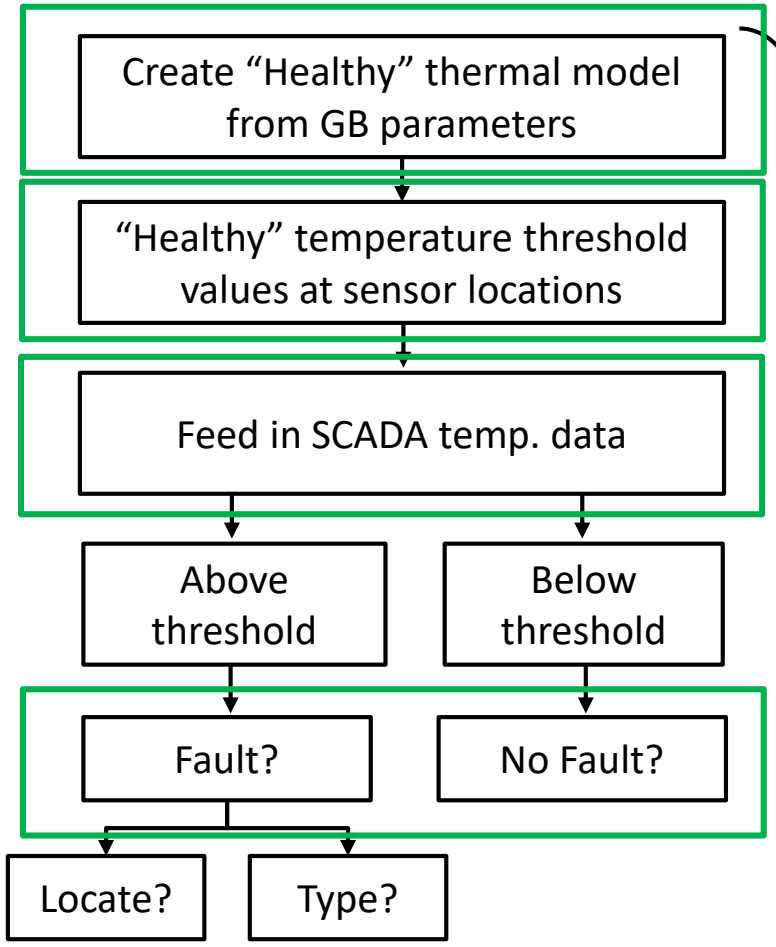
b ← Thermal resistance (K W^{-1})

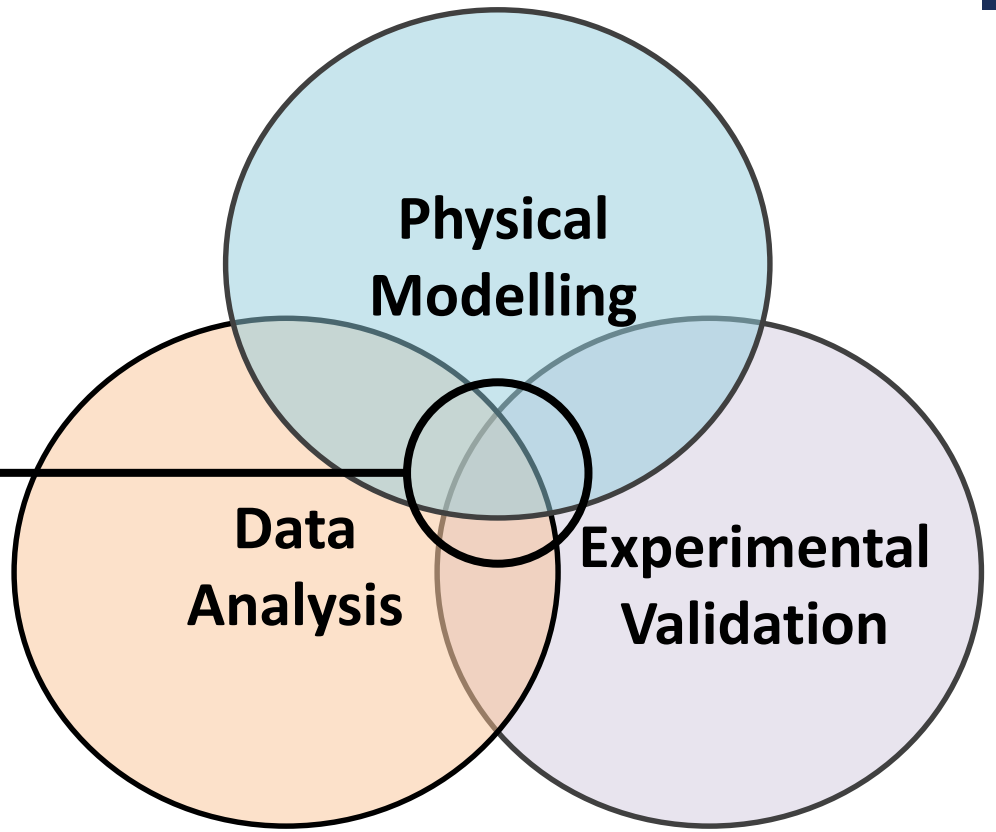
Data Analysis

- Machine learning
  - Permutation Feature Importance
  - Quantify effect each variable has on classification result



End Goal


Create “Healthy” thermal model from GB parameters
“Healthy” temperature threshold values at sensor locations
Feed in SCADA temp. data
Above threshold
Below threshold
Fault?
No Fault?
Locate?
Type?


Physical Modelling
Data Analysis
Experimental Validation

Future Work

- Generalise to different configurations
- Quantify uncertainty
- Applications
  - Combine with Machine Learning/AI techniques
  - Potential to apply to other components - generator

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Thank you for the attention, any questions?

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