

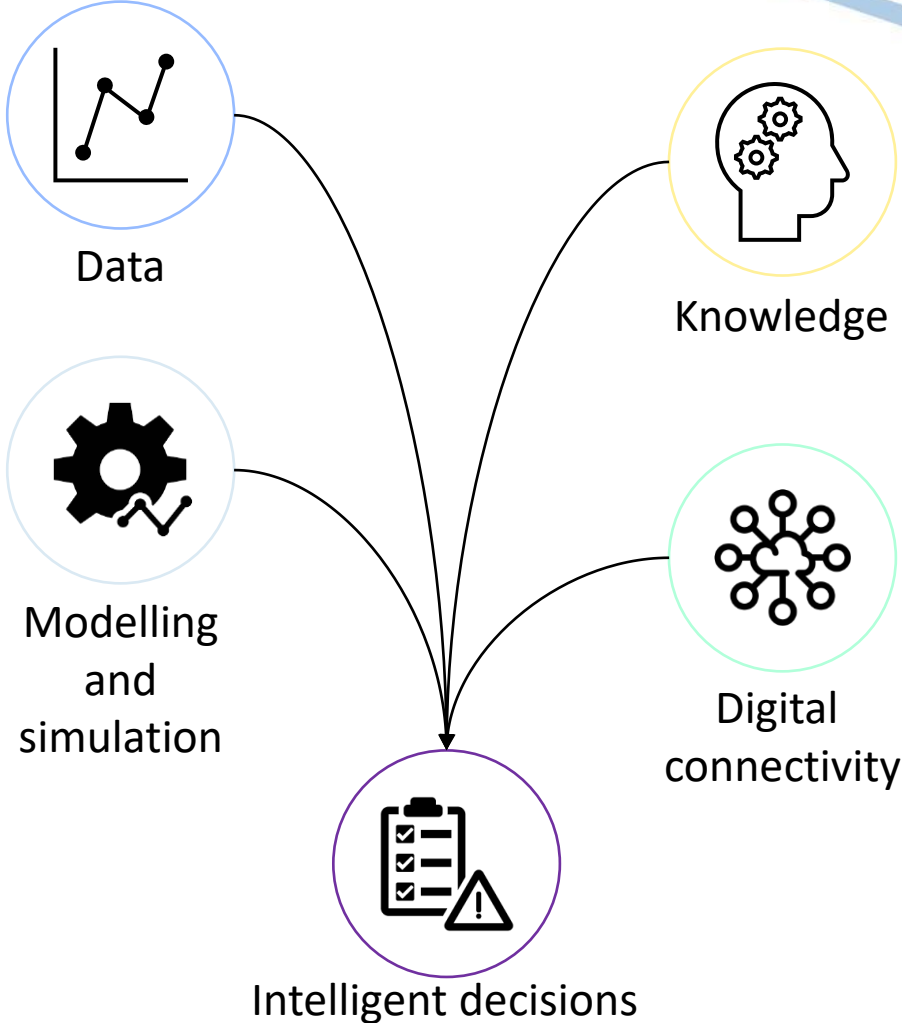
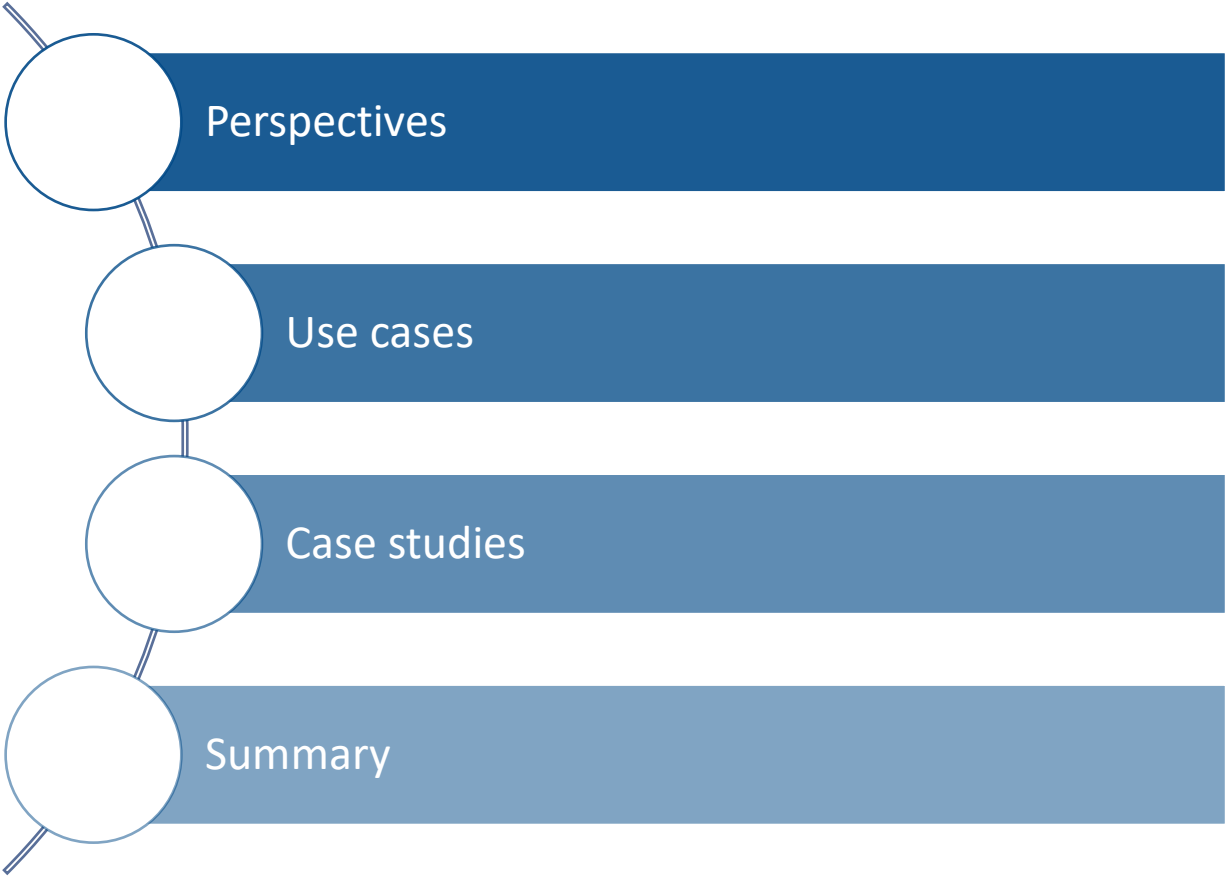
# Perspectives on Digital twins

Paul Gardner

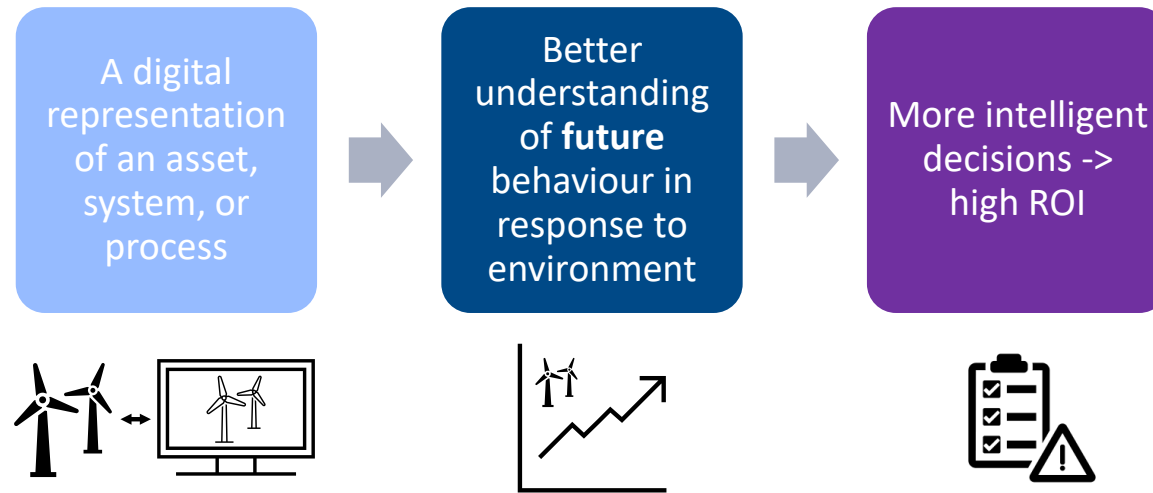
Digital Twins for Engineering Applications –  
The Emerging Science and Technology

7<sup>th</sup> June 2023

# Introduction



# Why build a digital twin?



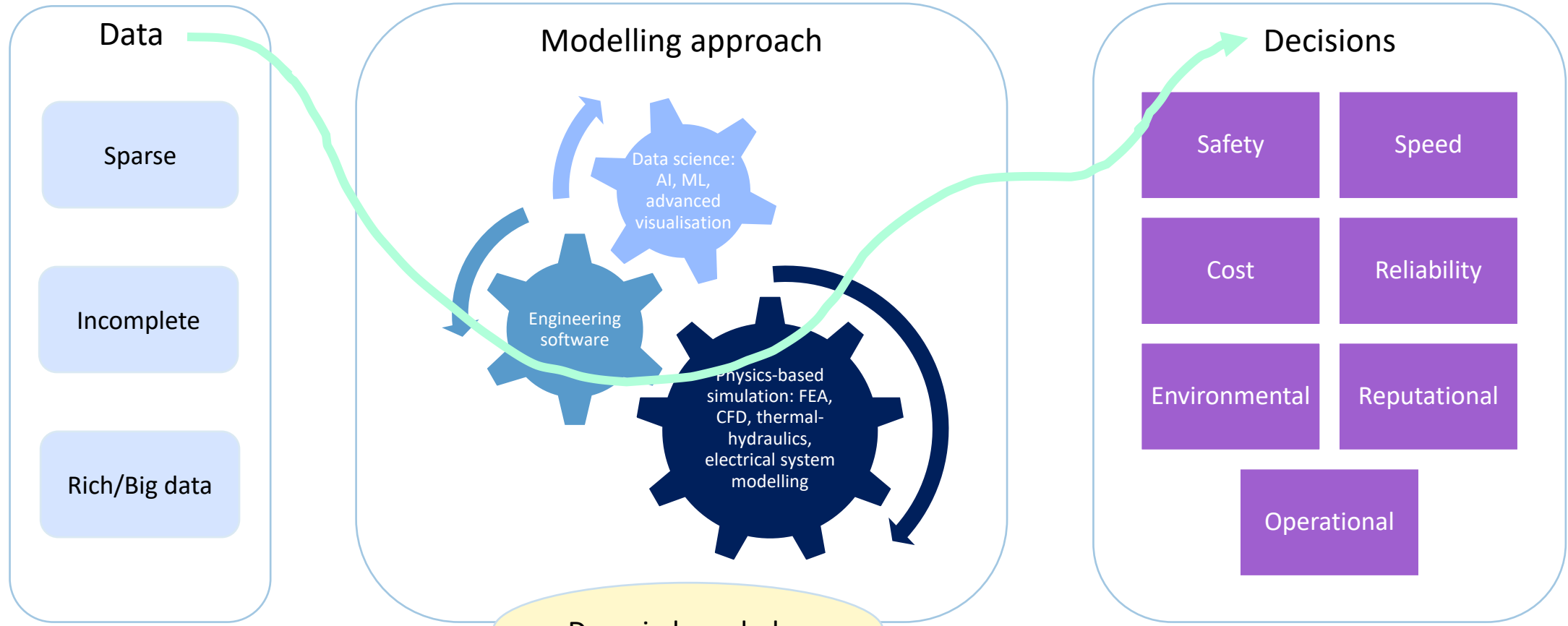
Key questions we often seek to answer:

- What is the current state of the asset, system, or process?
- How will it perform in the future?
- How will it perform under a range of hypothetical scenarios?
- What decisions can we take that will optimise future performance?

Understanding *why* helps scope the appropriate methodologies and model architecture to ensure a digital twin adds value

# Creating a line of sight

Capturing and documenting connections can become complex if you can't measure what you want directly...



Can we measure the critical output directly?

# Real time?

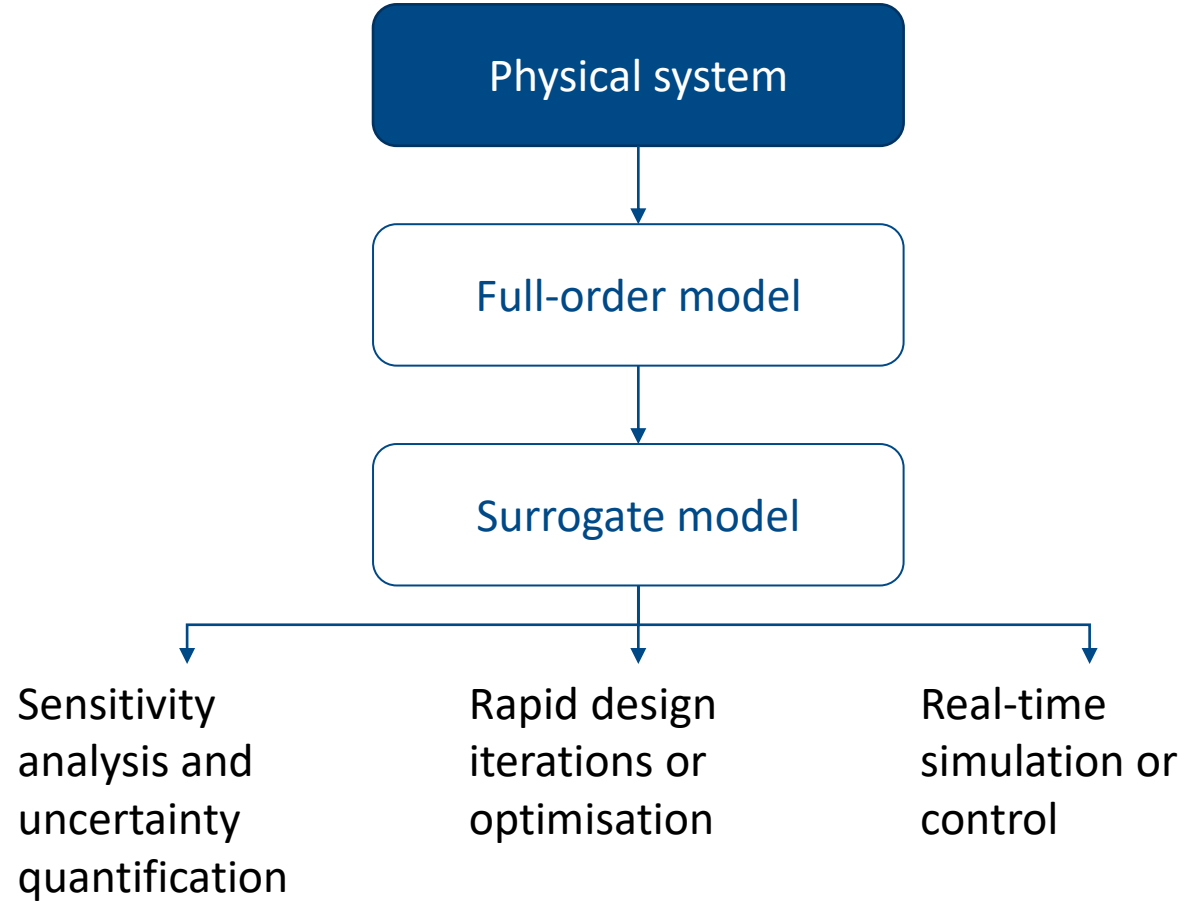
Predicting the future requires some notion of timescales.

Most classical engineering models (FEA, CFD etc.) are too slow and can restrict the utility of a digital twin.

Consider surrogate models:

- Physically-based reduced order models
- Machine learning approaches

Trade-off with impact on uncertainty?



## It won't be perfect

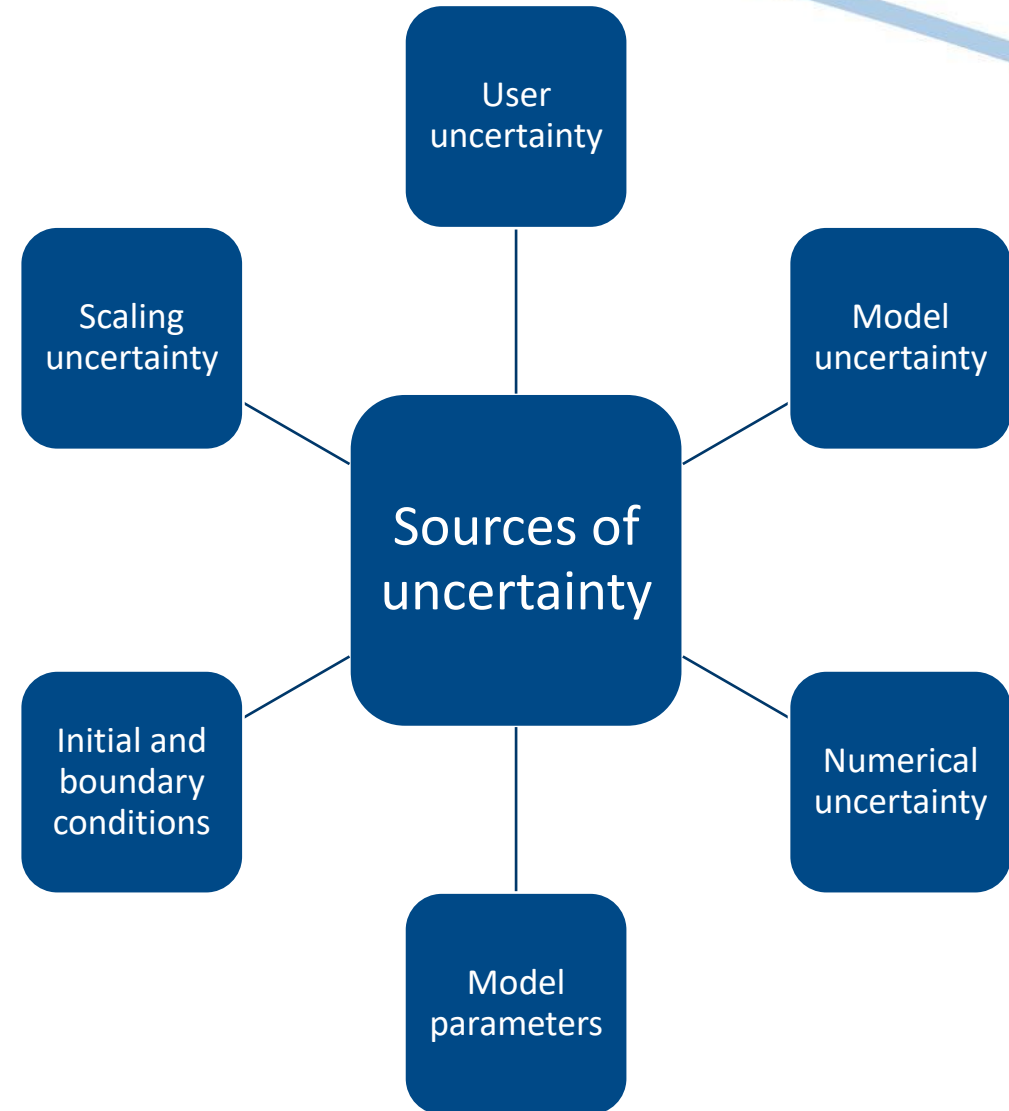
Comparing a digital twin's predictions to reality is essential to build confidence

Agreement unlikely to be exact due to uncertainty

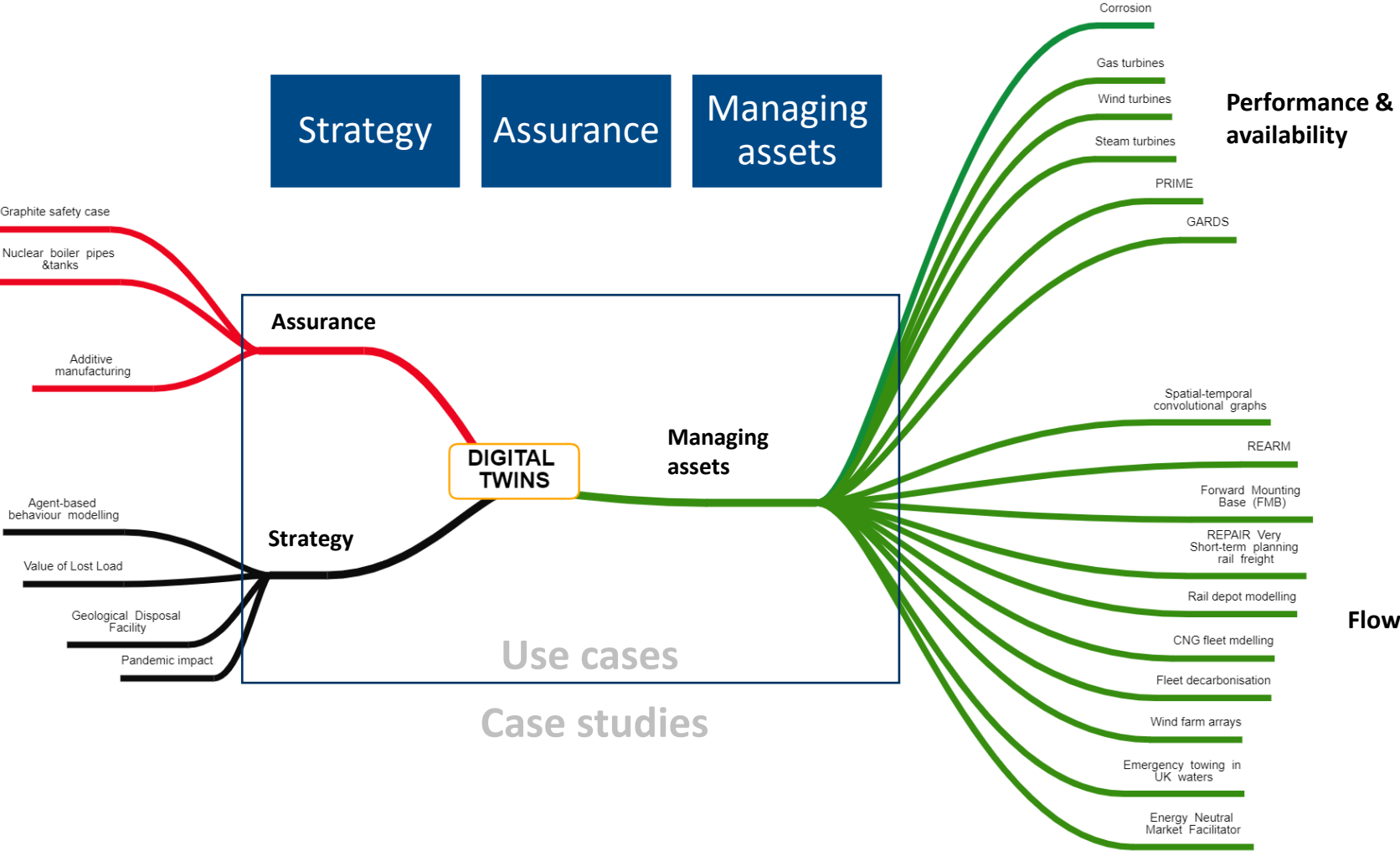
Effective validation and confidence building comes from defining:

- The behaviour range we expect to see?
- The range we'd be surprised to see?

An assessment of uncertainty is an essential part of building a digital twin



# Use cases and case studies



# Predictive maintenance for industrial gas turbines



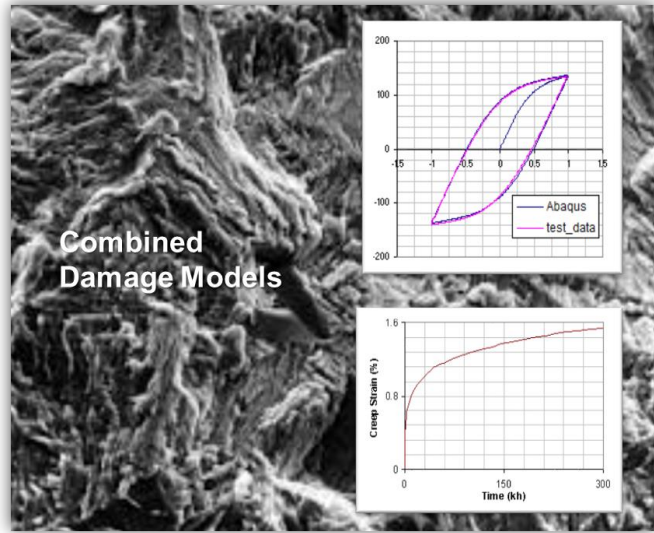
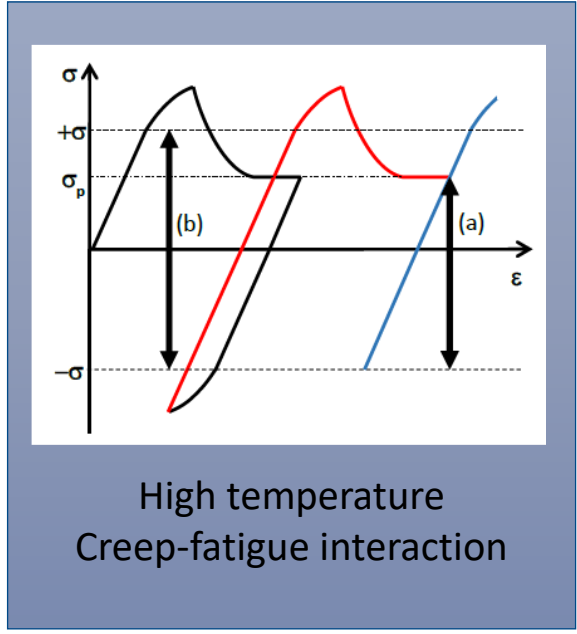
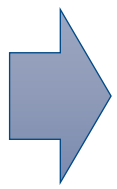


# Predictive maintenance for industrial gas turbines



# Predictive maintenance for industrial gas turbines

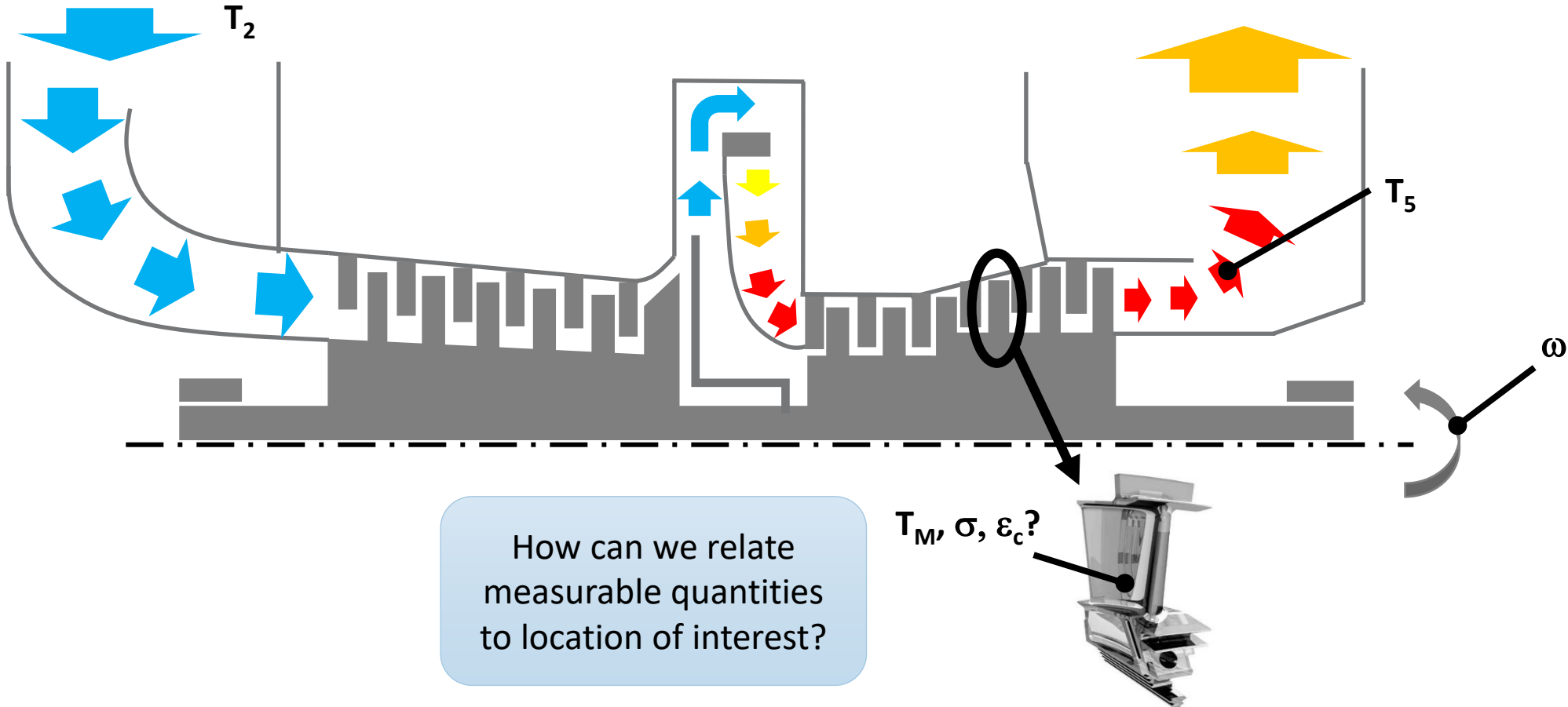
Understand how a single crystal blade degrades to provide a rigorous foundation to optimising the intervention strategy



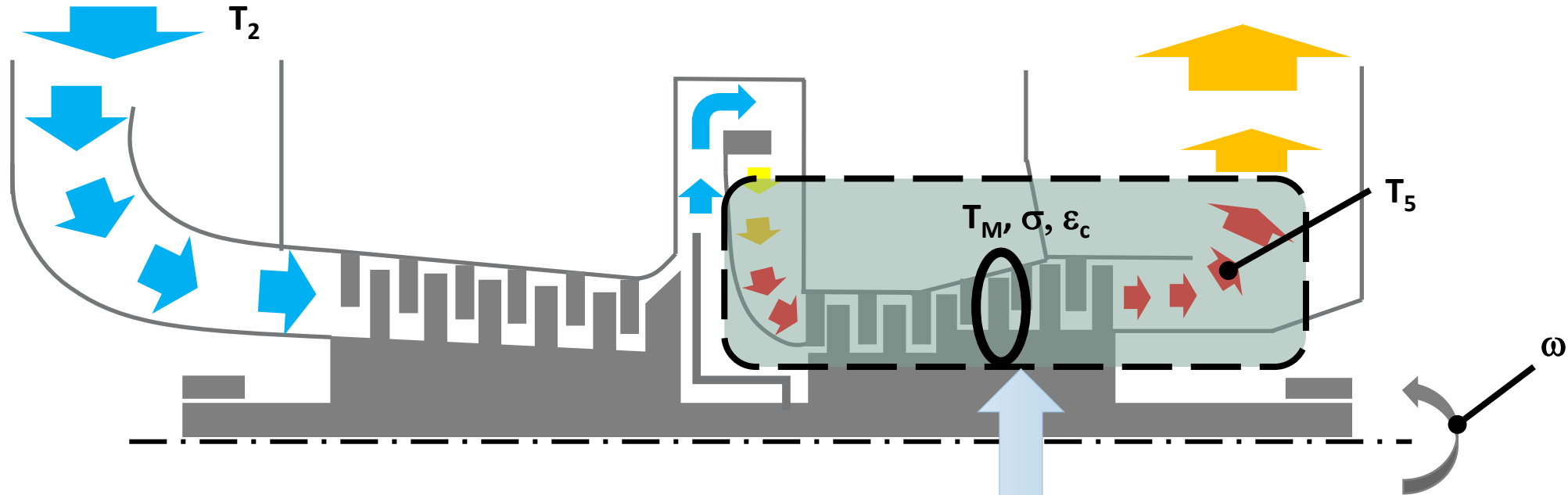
Validate against test specimens

An upward-pointing arrow connects this text box to the SEM image and graphs above.

# Predictive maintenance for industrial gas turbines



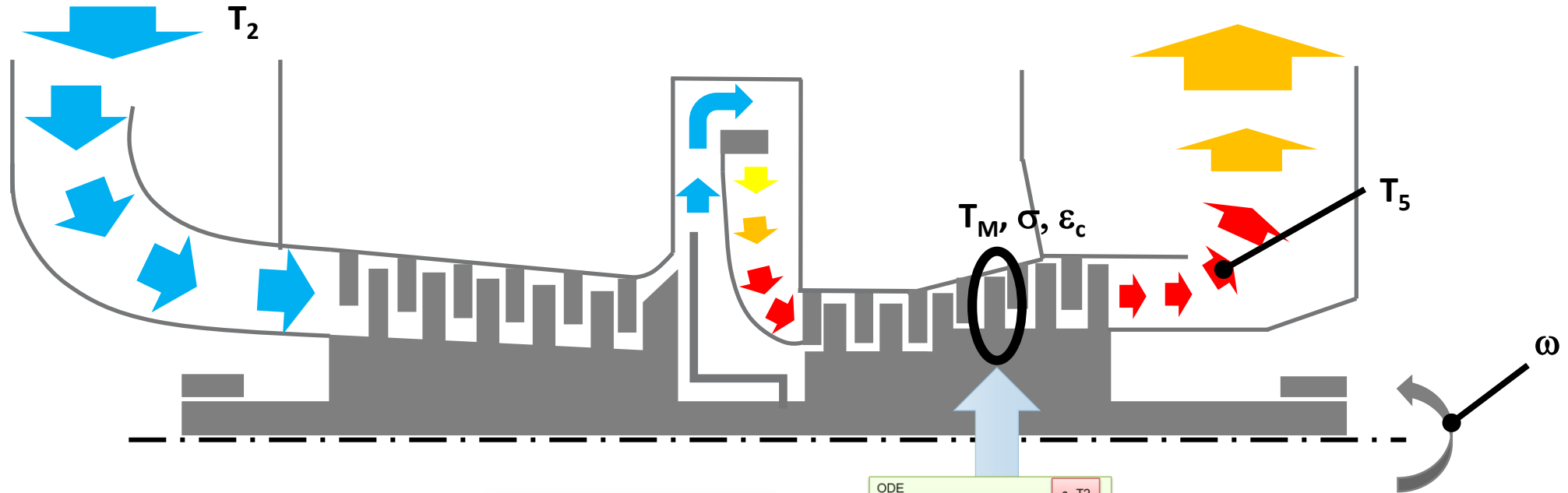
# Predictive maintenance for industrial gas turbines



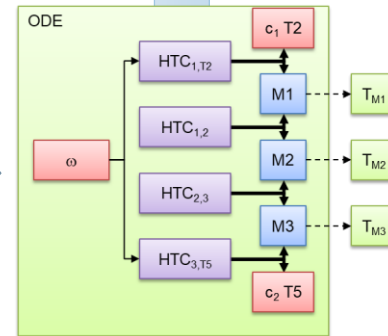
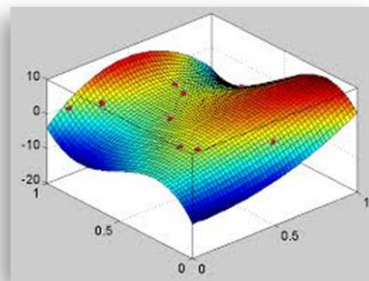
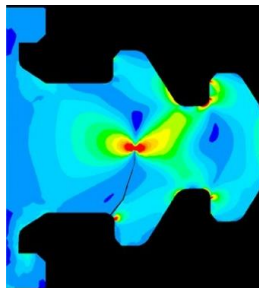
Validated against a fully-instrumented unit

Detailed CFD and FE analysis to understand behaviour of hot gas path

# Predictive maintenance for industrial gas turbines

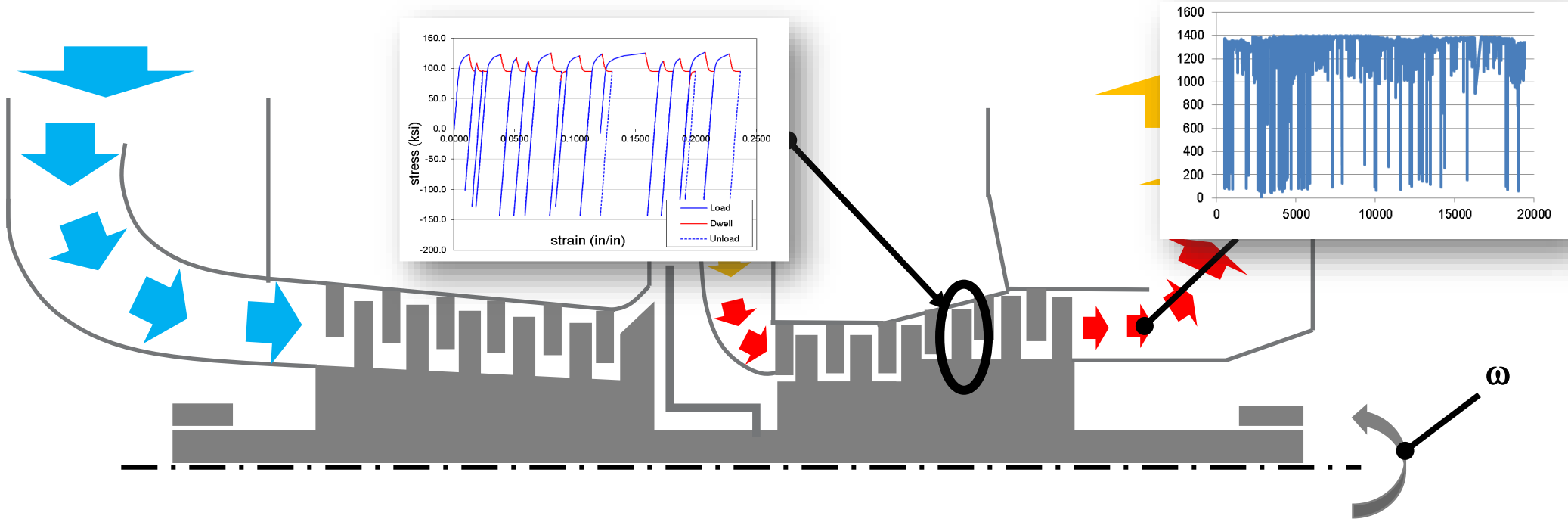


Expensive, time consuming and inflexible

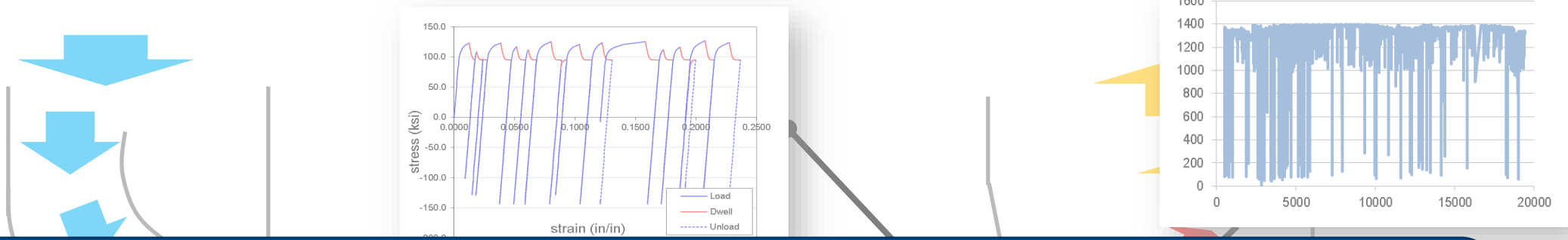


- Sufficiently accurate
- Adaptable and fast to solve
- Risk managed through probabilistic analysis

# Predictive maintenance for industrial gas turbines



# Predictive maintenance for industrial gas turbines



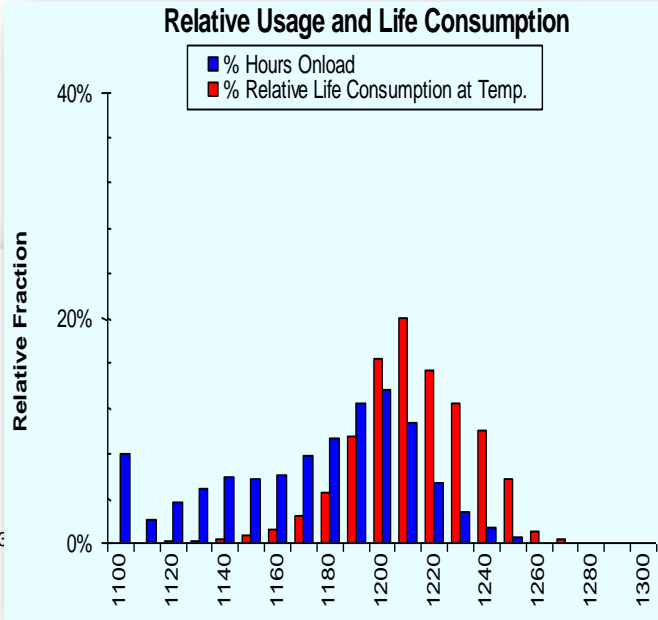
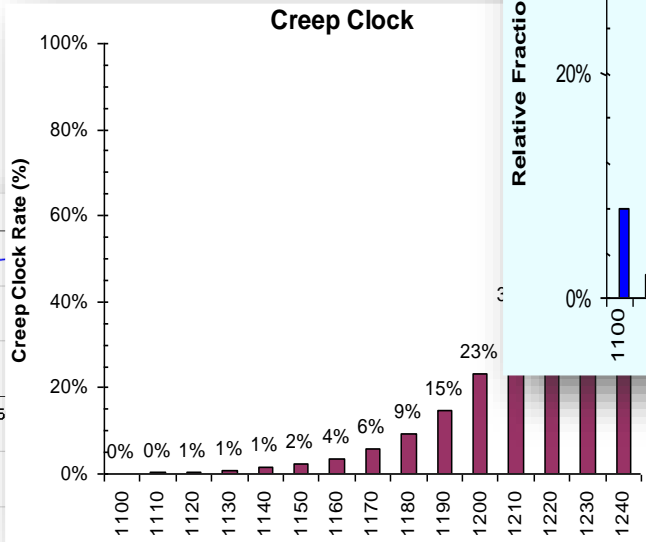
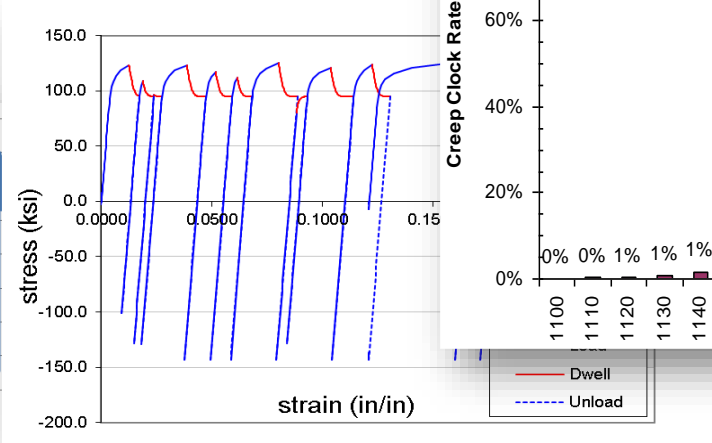
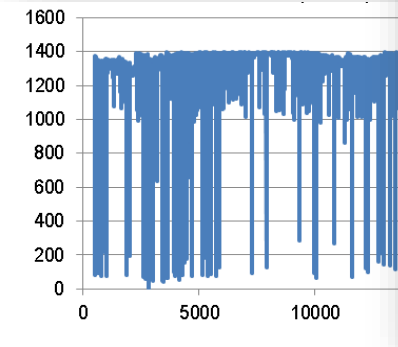
**We can now quickly and reliably determine unit-specific blade damage from engine monitoring data**



# Predictive maintenance for industrial gas turbines

...calculate remaining life

For each engine...





# Predictive maintenance for industrial gas turbines

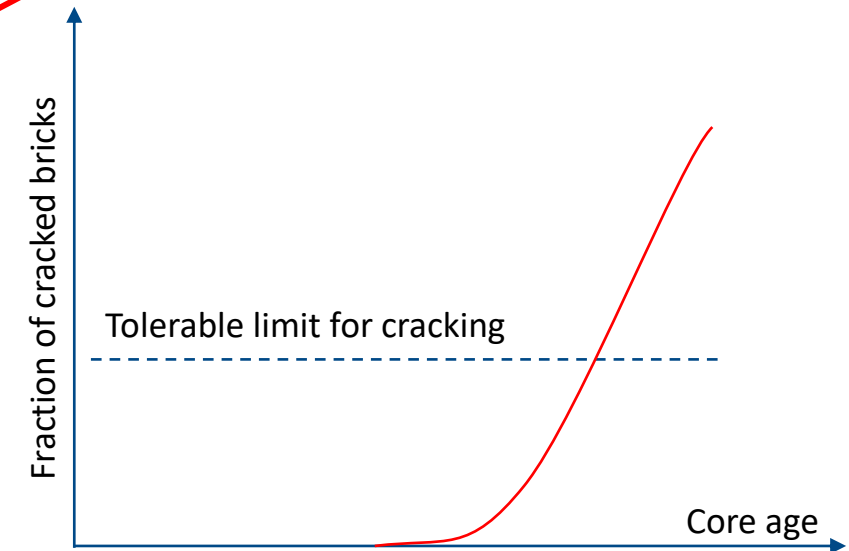
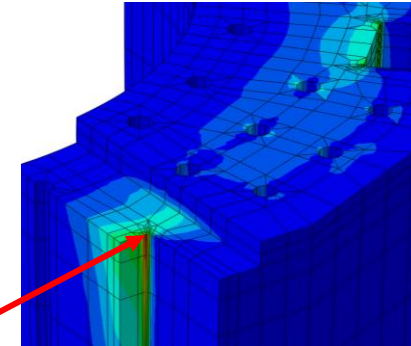
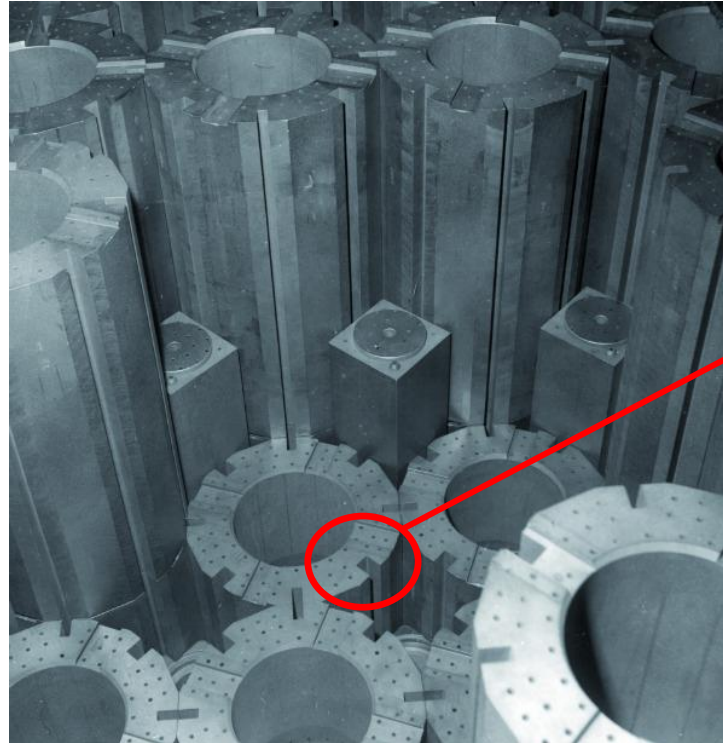


# Predicting brick cracking in advanced-gas cooled reactors



# Advanced-Gas Cooled Reactors

Scenario



# Advanced-Gas Cooled Reactors

## Challenges

## Solutions

Potential failure point cannot be monitored directly

DT's modelling and data chain predicts failure point

Limited measurements

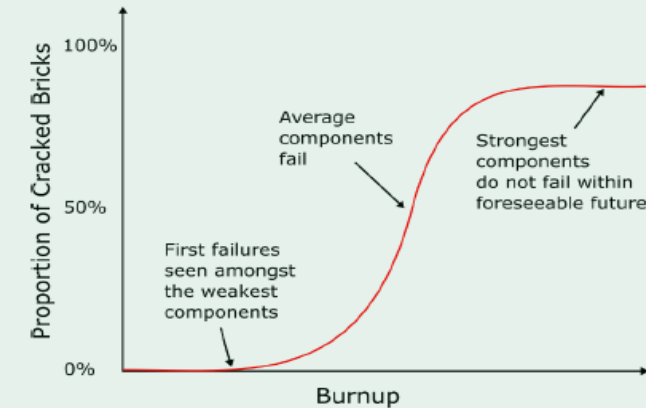
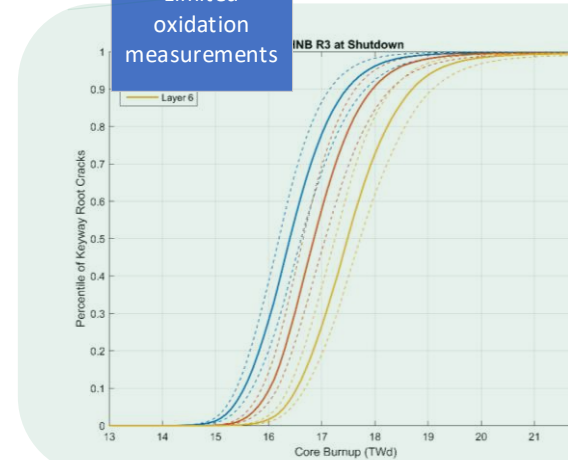
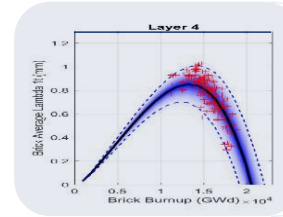
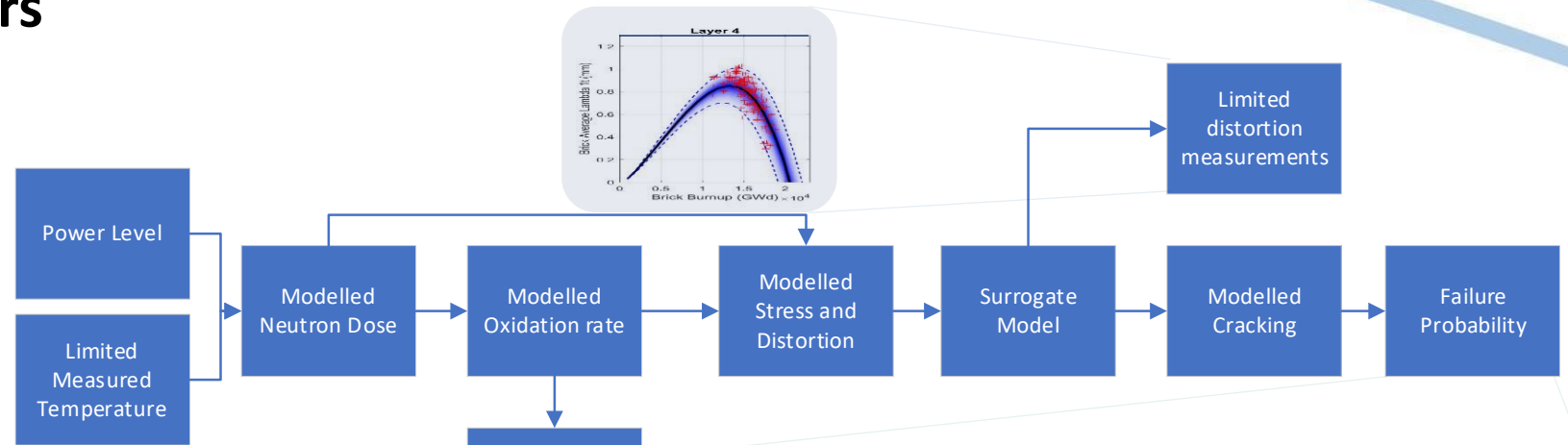
Aggregation of additional data sources into DT

Inherent uncertainty

Model incorporated and quantified uncertainty

Expensive-to-run physical models

DT uses efficient surrogate models

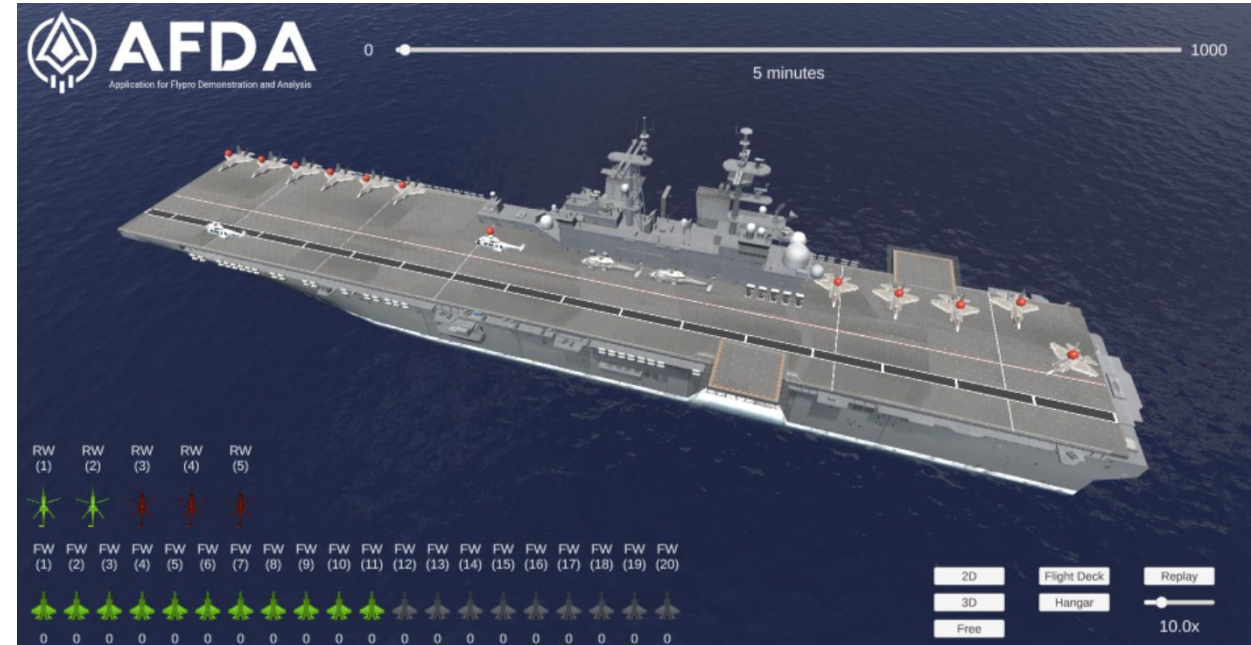


- Probabilistic forecasts suggest period between detectable cracking and safety limit
- Approach successful and extended generation significantly – many times ROI

## Understanding flight operations on an aircraft carrier



# A simulation and agent-based approach



# Predicting future condition of an electrical power network



# 'LV Predict': predicting future condition of an electrical power network

*How can we predict the condition of underground Low Voltage (LV) cables?*



Asset integrity

Innovative data sources

Data science

Visualisation

...that will enable...

## Benefits

Improved understanding of LV cable degradation

Provide insight to maintenance planning

Understand how Net-Zero will influence network condition

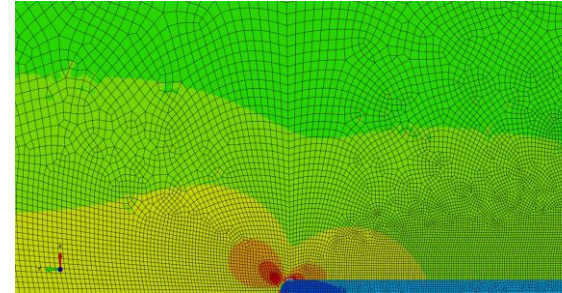


# 'LV Predict': predicting future condition of an electrical power network

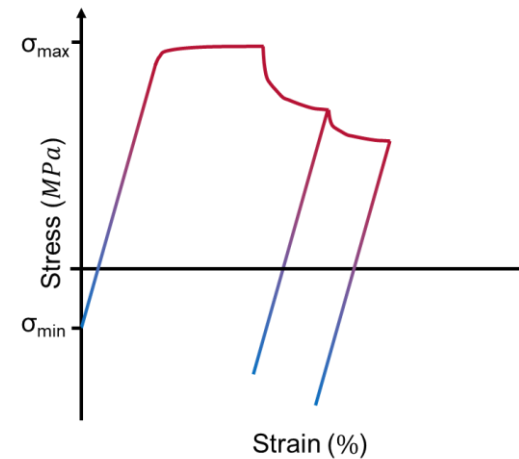
*How can we predict the condition of underground Low Voltage (LV) cables?*



Asset integrity



Cyclic stress-strain curve



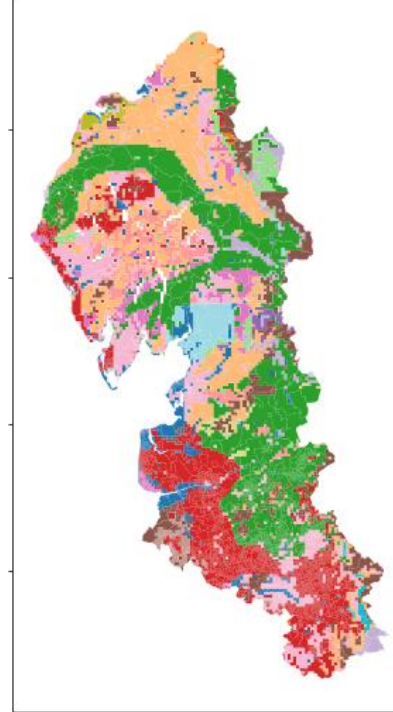
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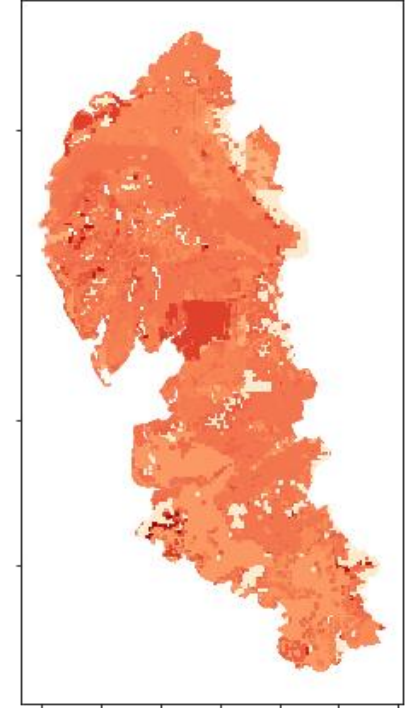


Innovative data sources

The different soil types in the Electricity North West region



The most likely thermal conductivity of soil in the Electricity North West region (W/mK)

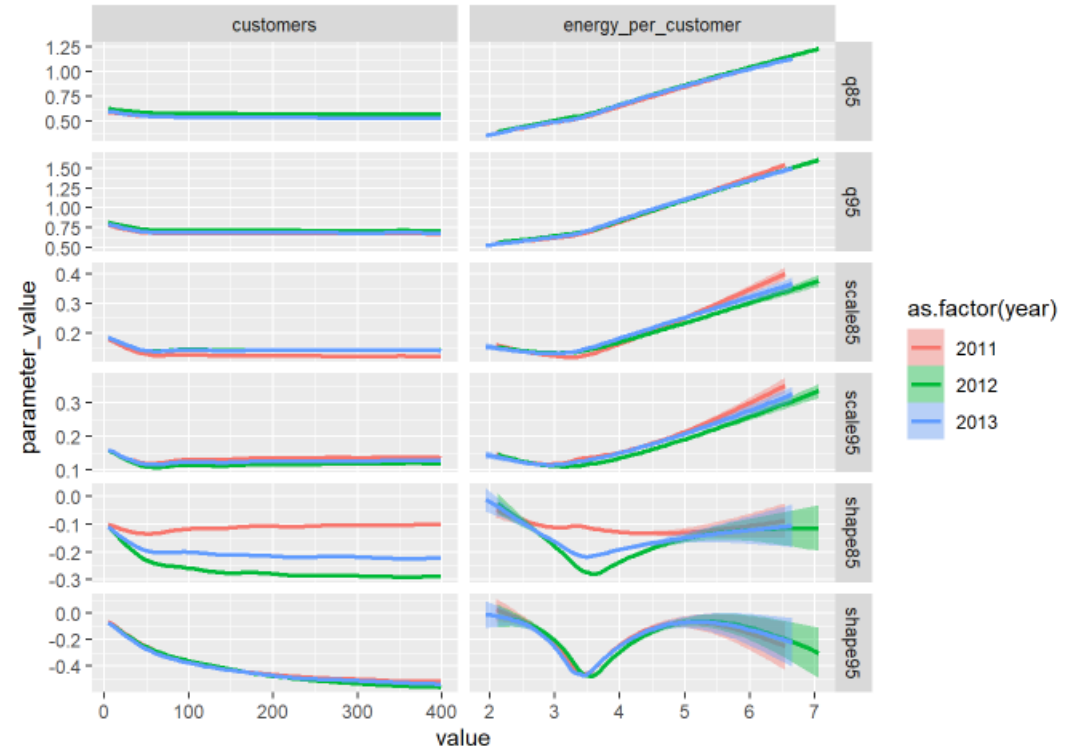


# 'LV Predict': predicting future condition of an electrical power network

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Data science



# 'LV Predict': predicting future condition of an electrical power network

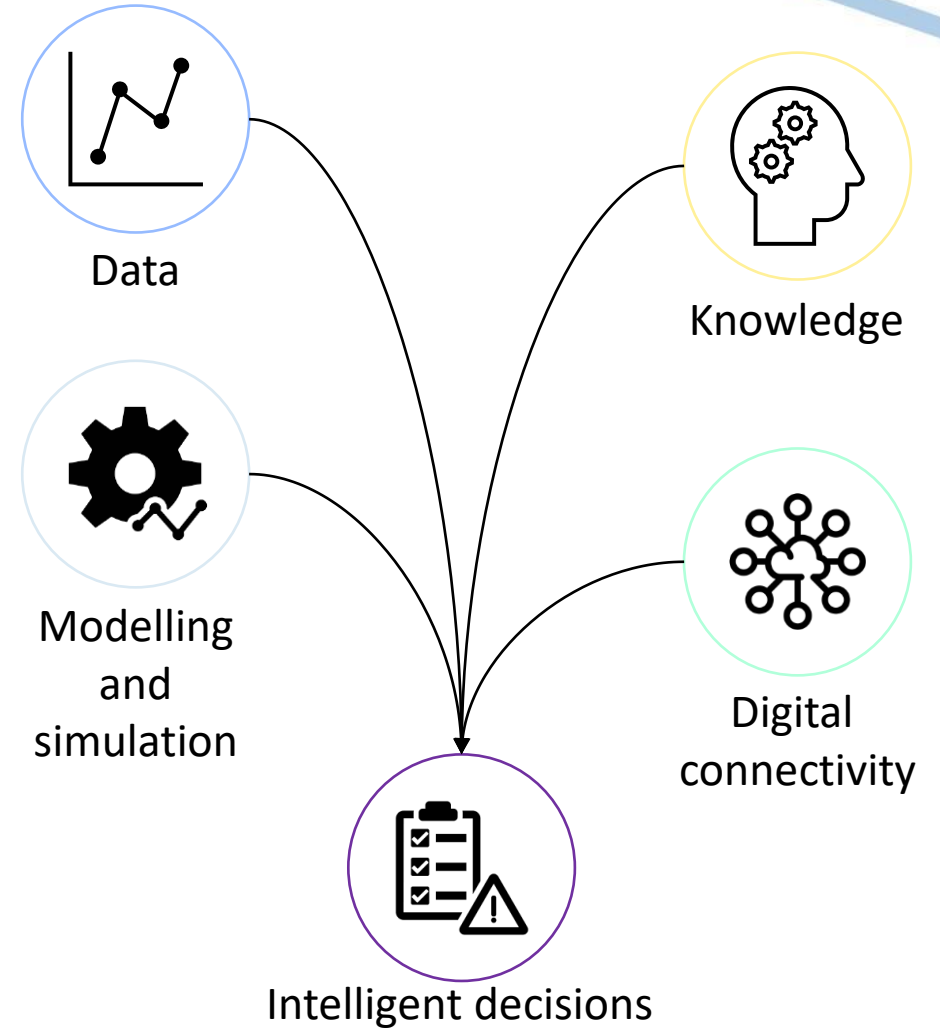
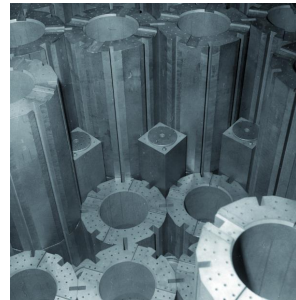
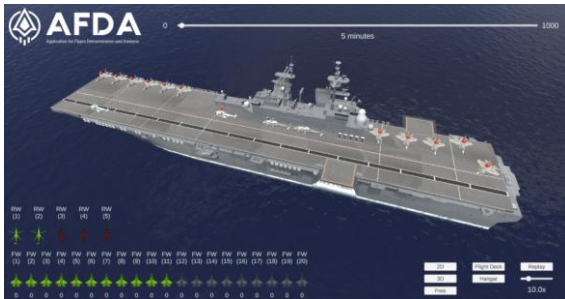
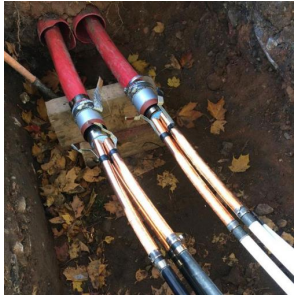
*How can we predict  
the condition of  
underground Low  
Voltage (LV) cables?*



Visualisation

<https://lv-predict.fnc.digital/>

# Summary



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