Predictive maintenance for fusion devices: an overview

infusion

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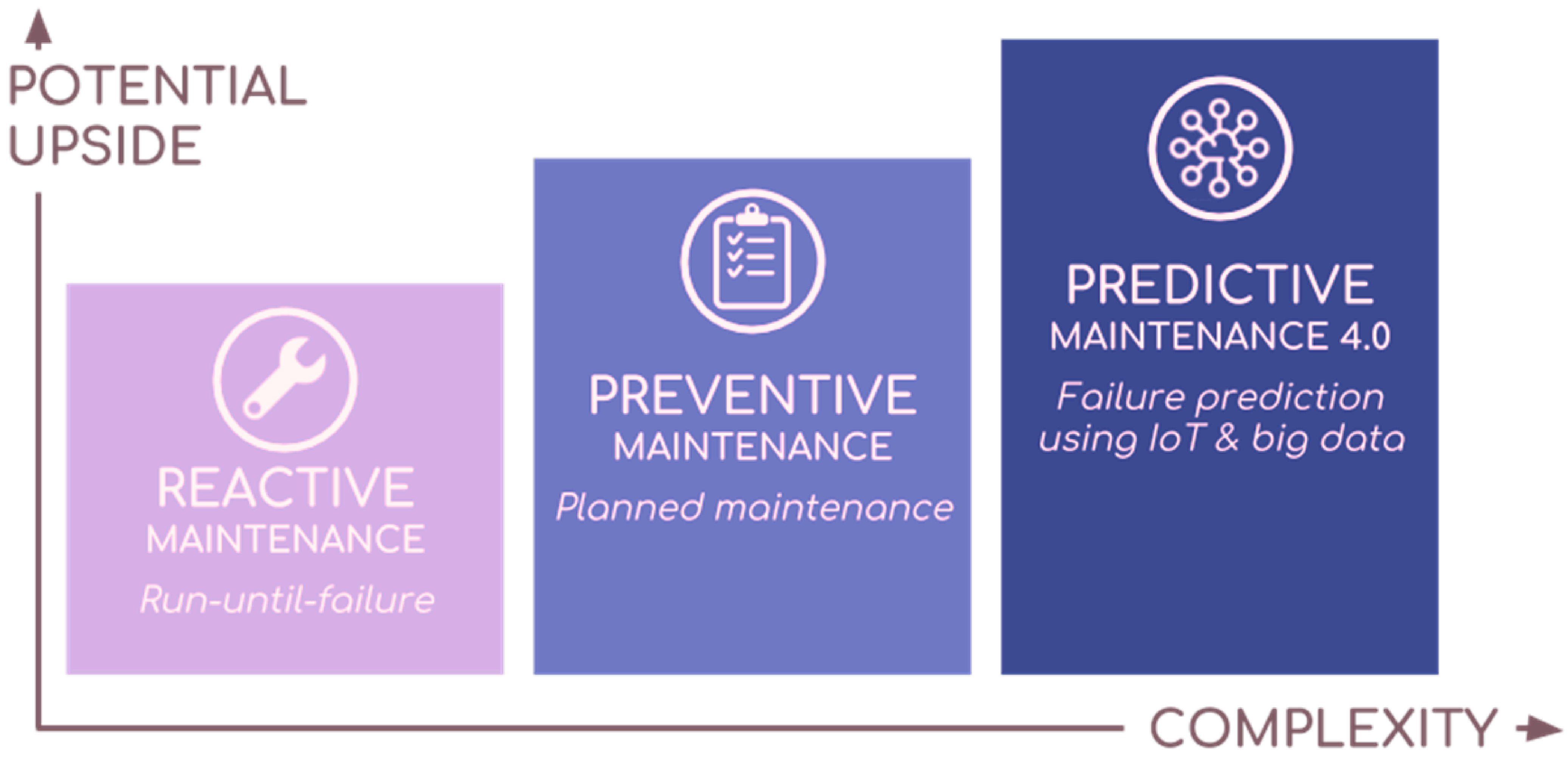
Outline

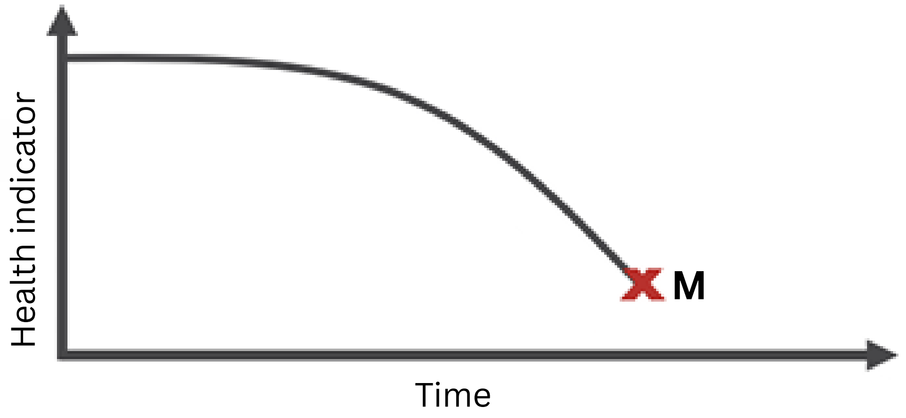
01

What is predictive maintenance?

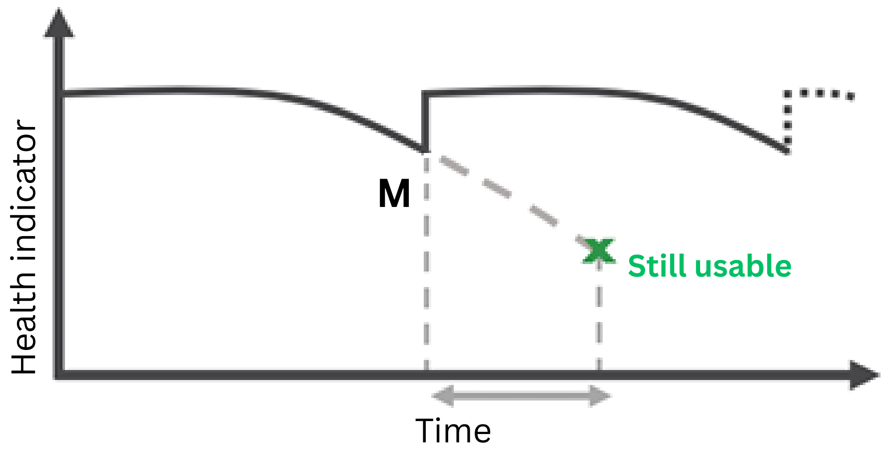
Maintenance strategies



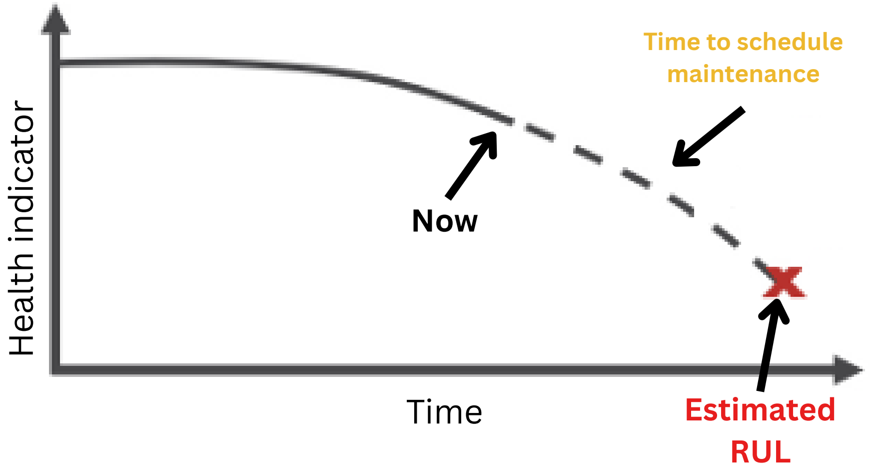
Reactive maintenance



Preventive maintenance



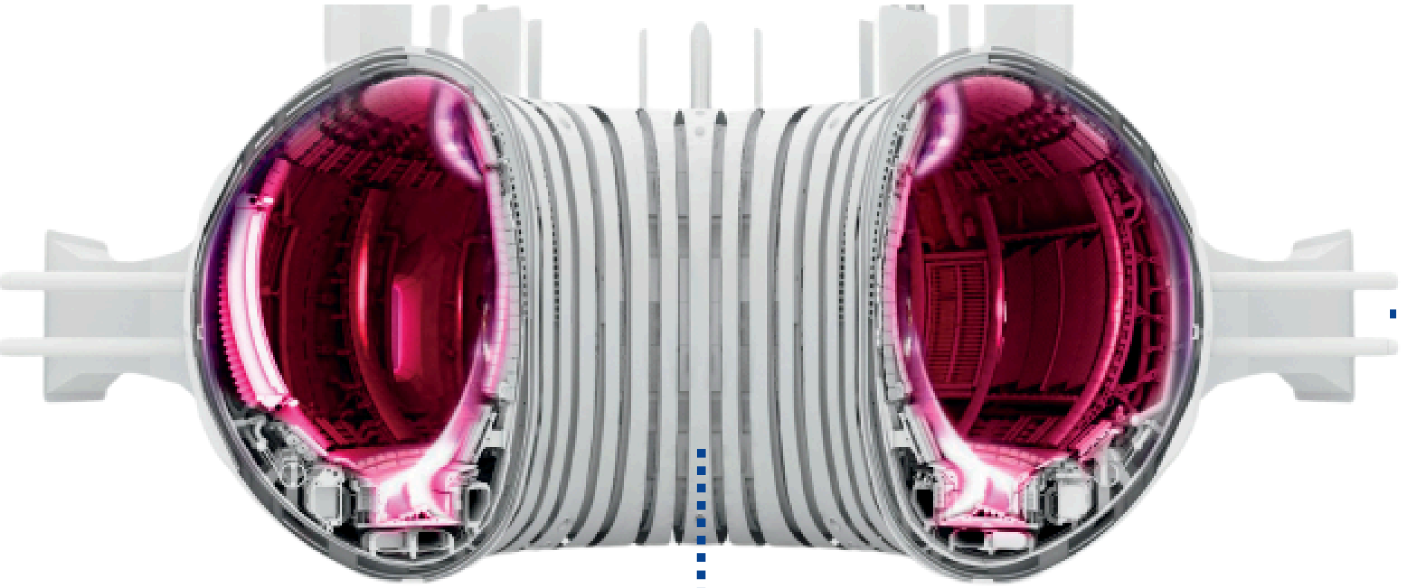
Predictive maintenance: remaining useful life (RUL)



02

Why predictive maintenance?

System availability



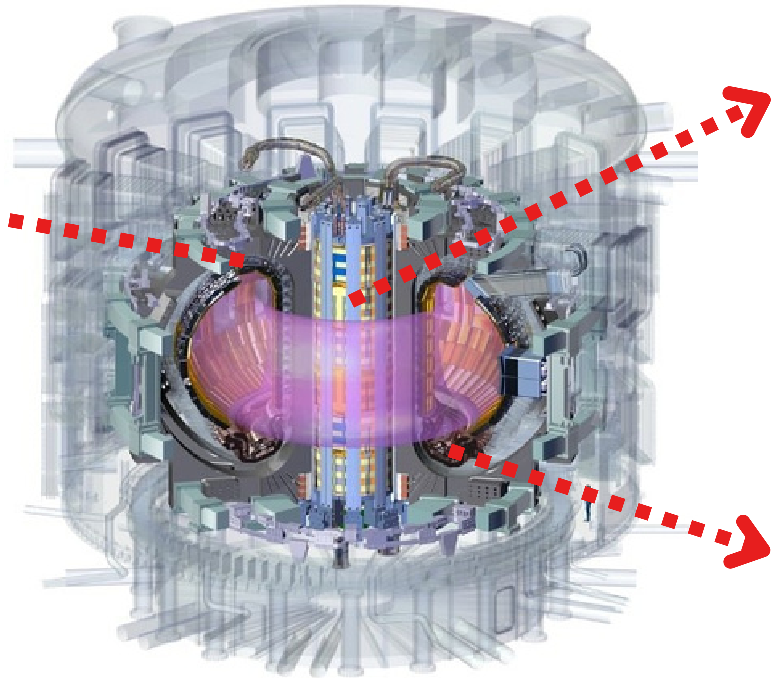
Efficient
Optimal operations

Safe
No catastrophic failures

Reliable
No downtime

To achieve the target of 50% plant availability, DEMO requires key subsystems to meet **exceptionally high individual availability** thresholds.

Individual availabilities



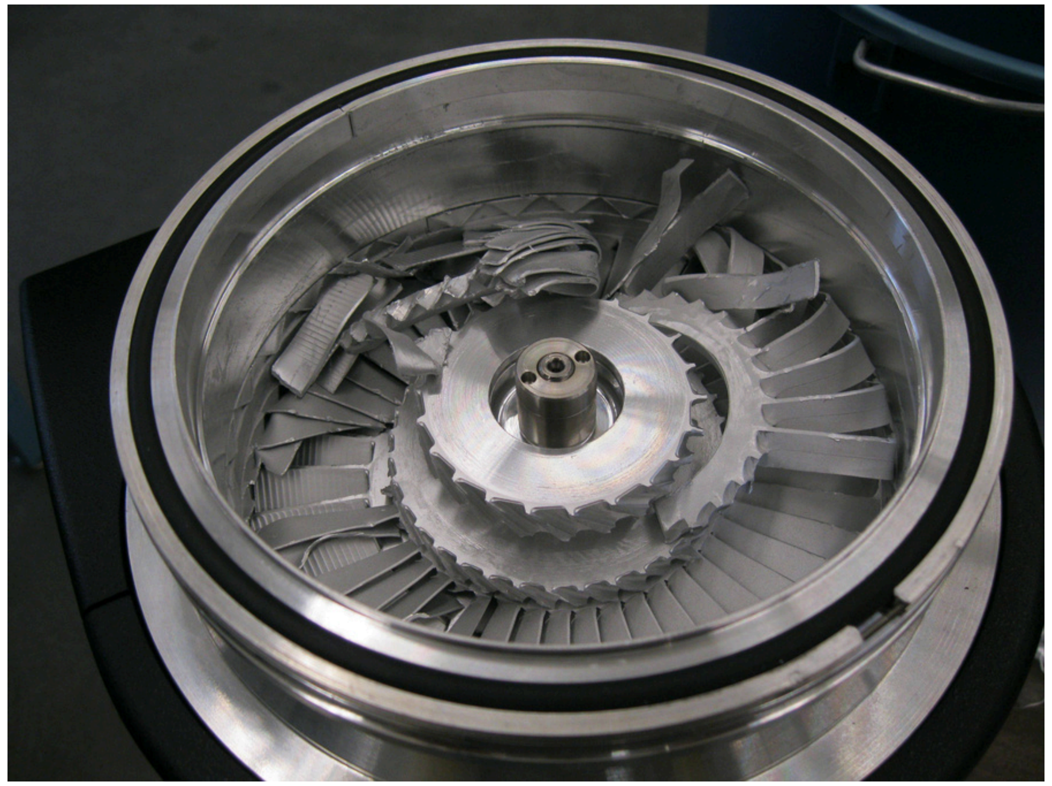
Heating and current drive
88.4%

Cryogenic system
97.8%

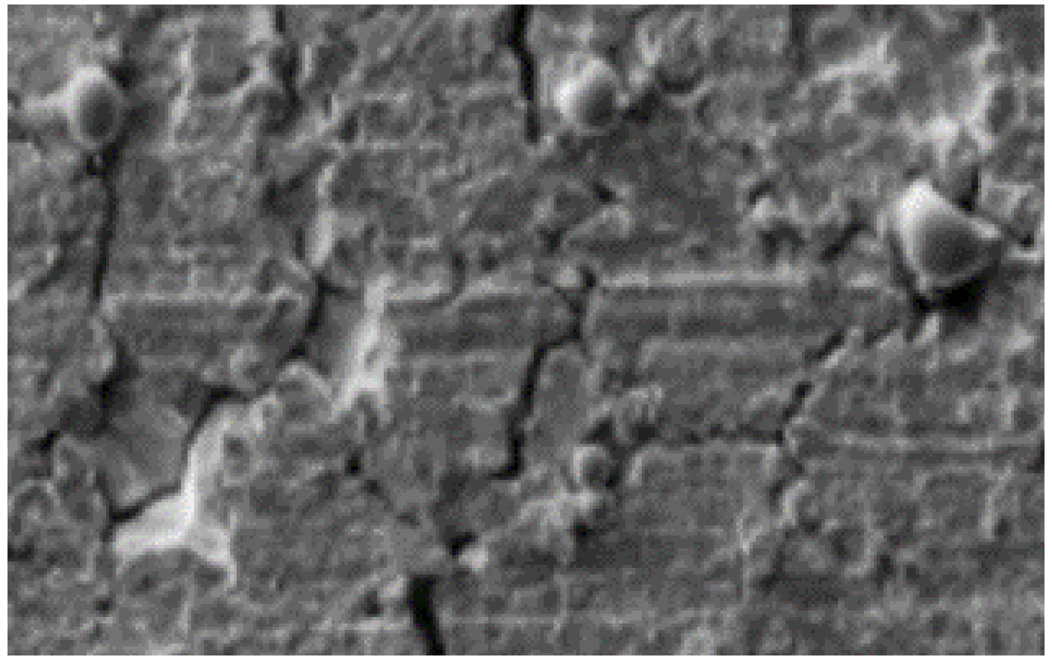
Divertor and first wall
87.1%

Use cases at *inf*usion

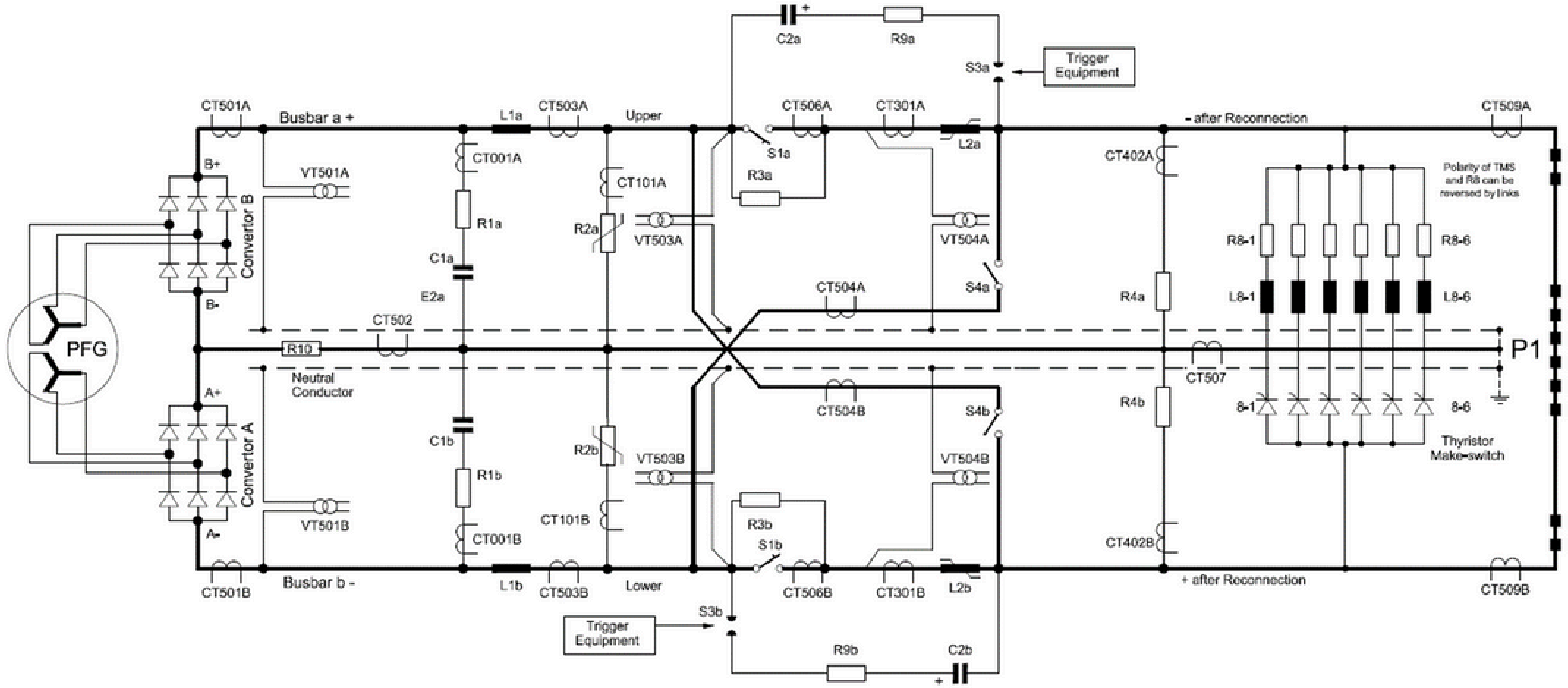
Turbomolecular pumps at JET

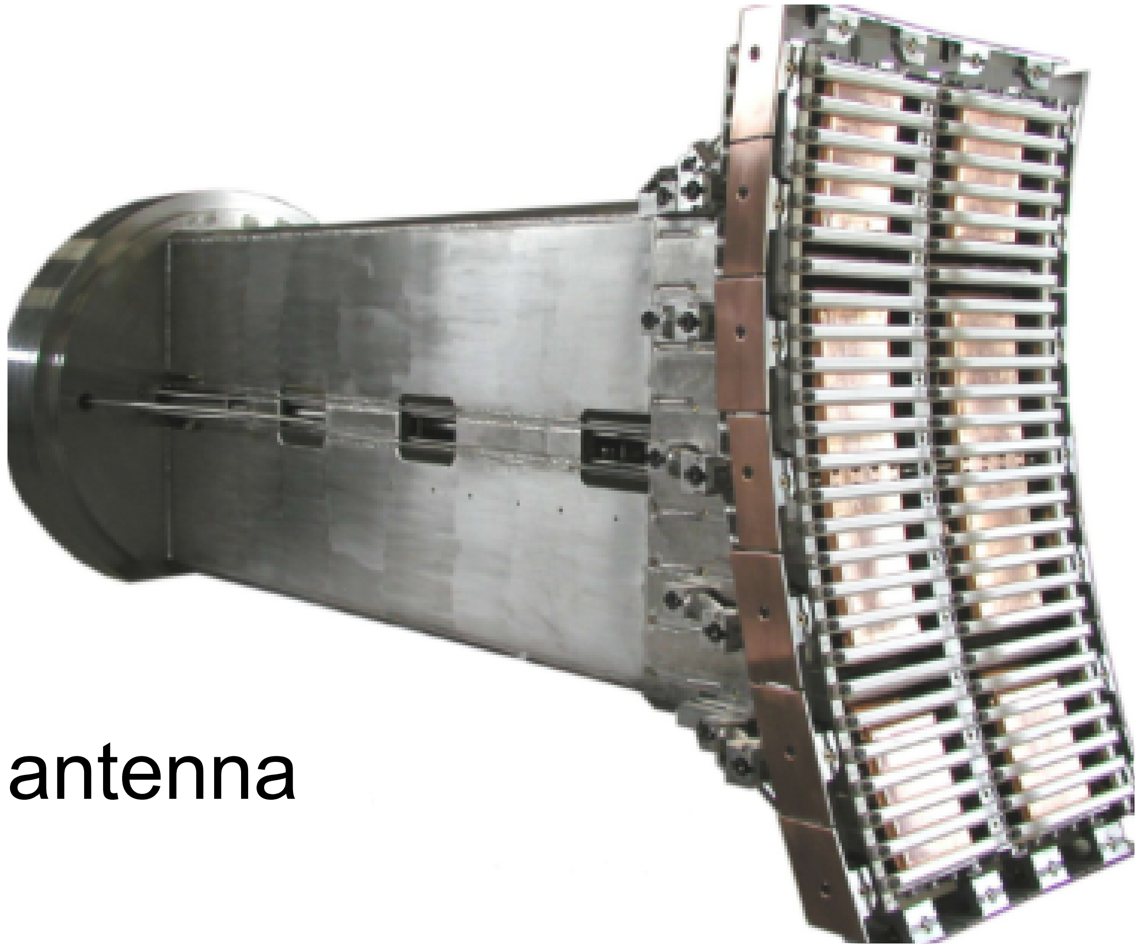


Material damage



Circuit breakers of the OH circuit at JET



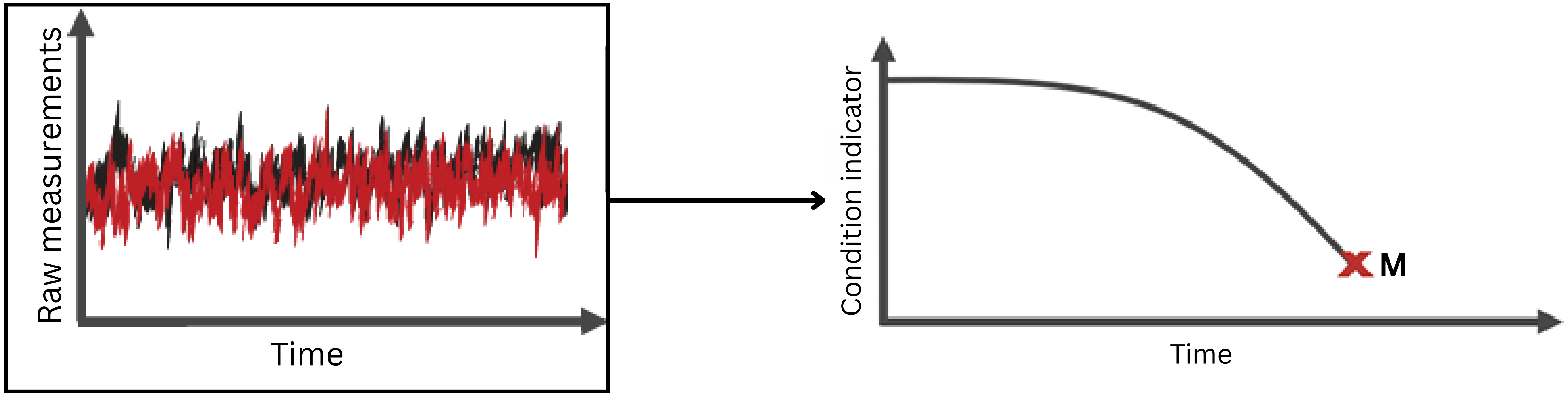


JET ICRH antenna

03

How?

1. Identification of condition indicators



Signal-based condition indicators

Time-domain features
- Median
- Standard deviation
- Skewness

Frequency-domain features
- FFT
- Wavelet

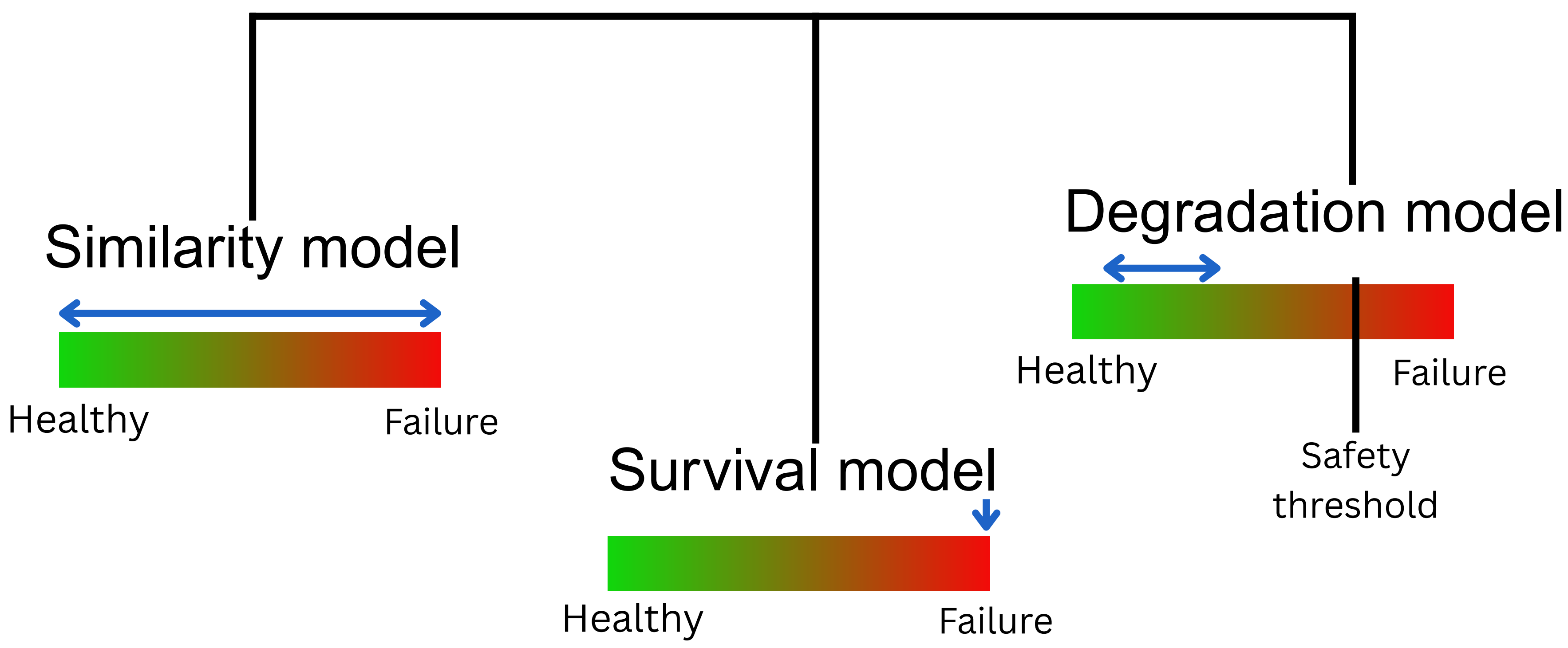
2. Choice of appropriate algorithm

Physics-based modeling **Data-driven modeling**

Physical model

- Kalman filter
- Physics-informed NN

RUL estimation models



First use case

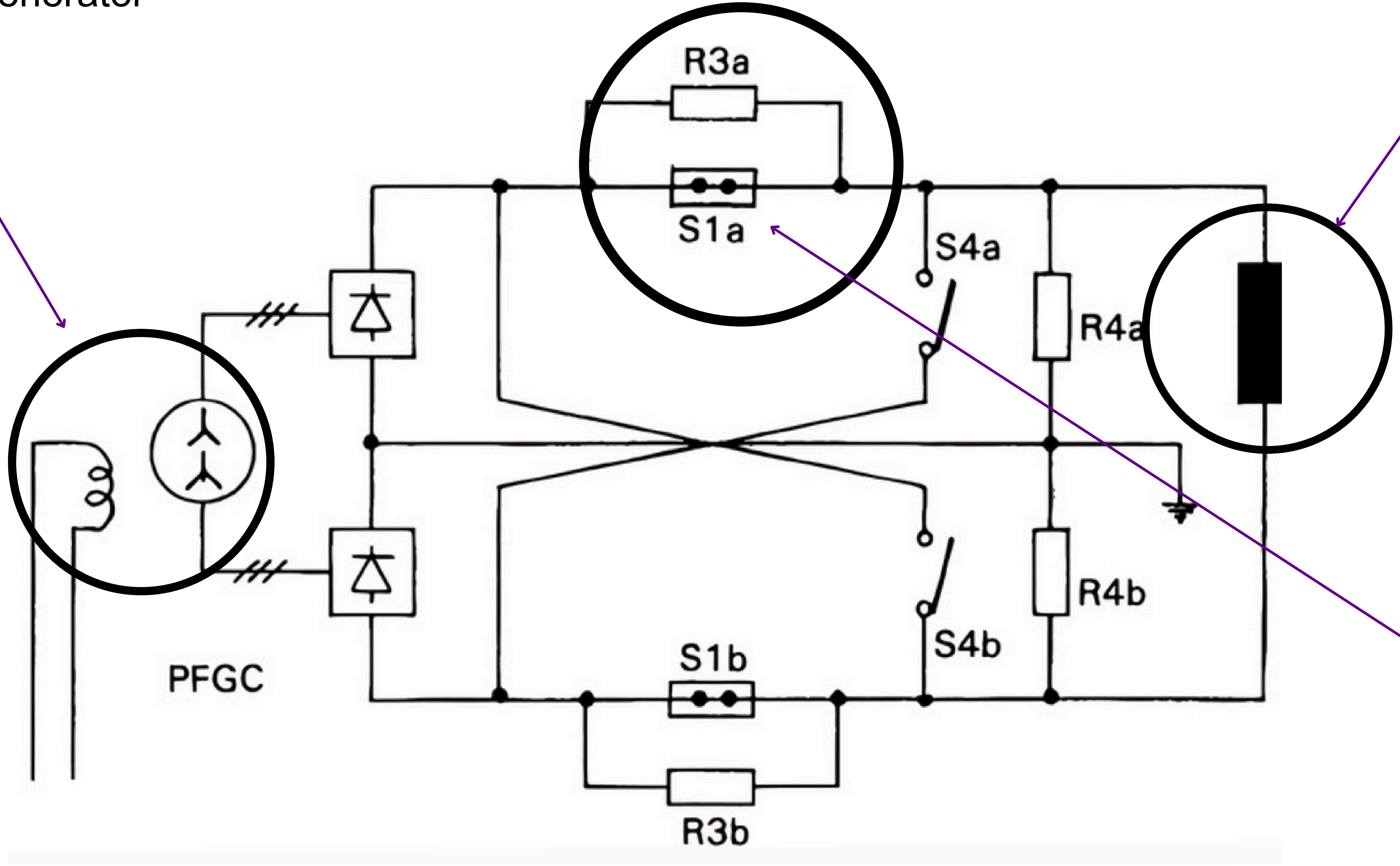
04
Condition monitoring of OH circuit breakers at JET

Caputo et al., 2025, Fus. Sci. Technol., submitted

JET OH circuit

Poloidal flywheel generator

Central solenoid



CCFE, UK

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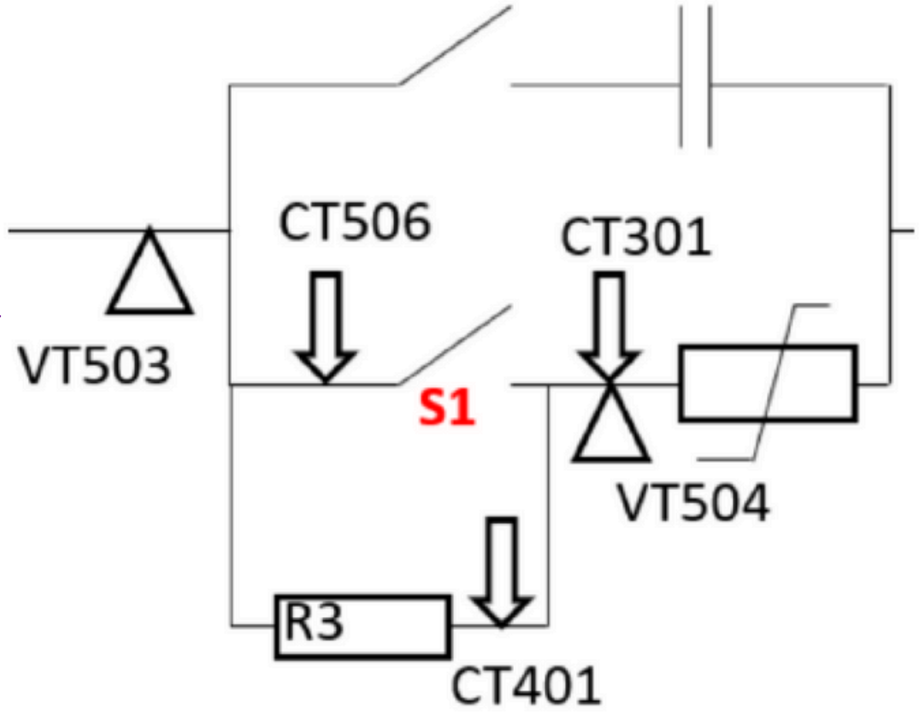
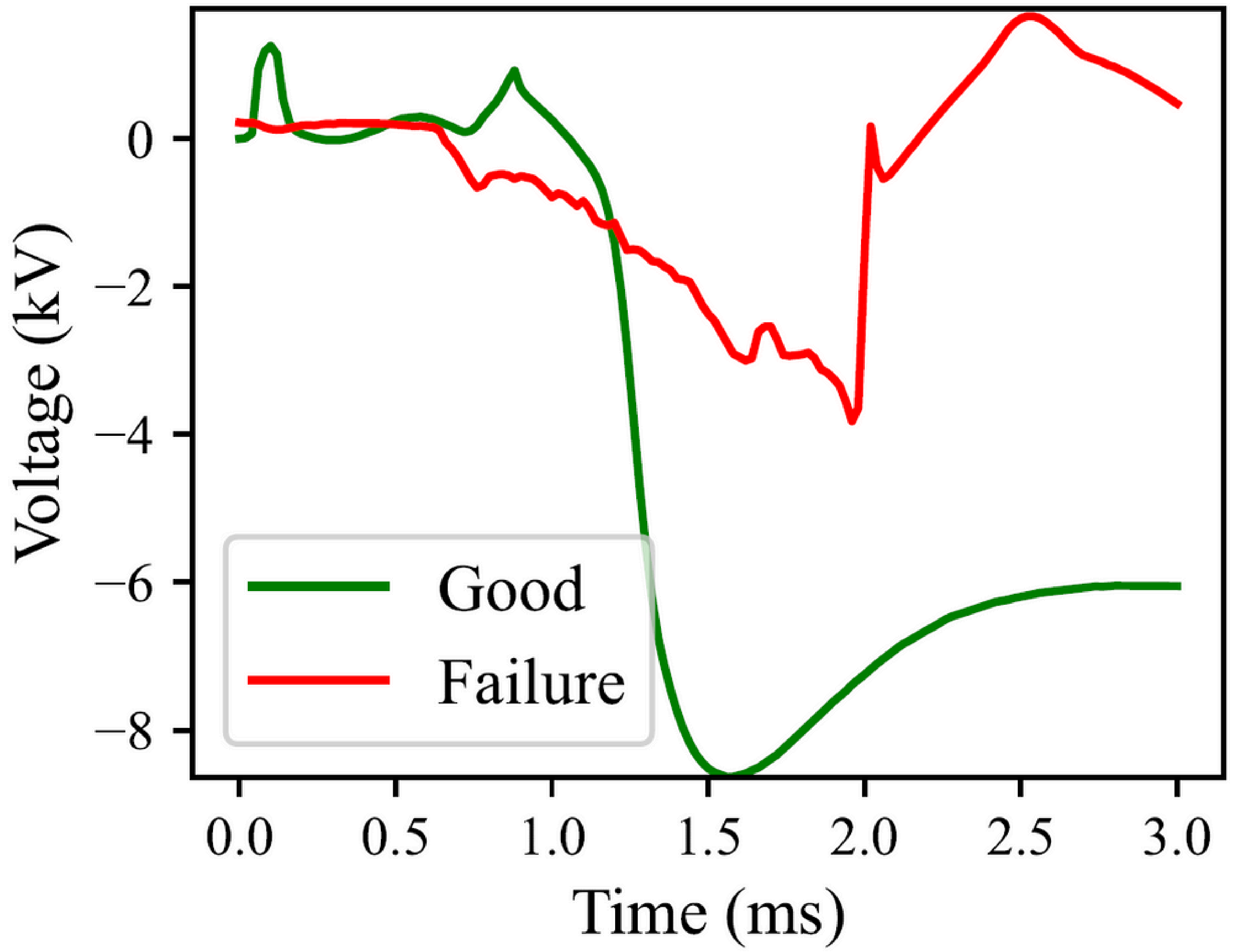
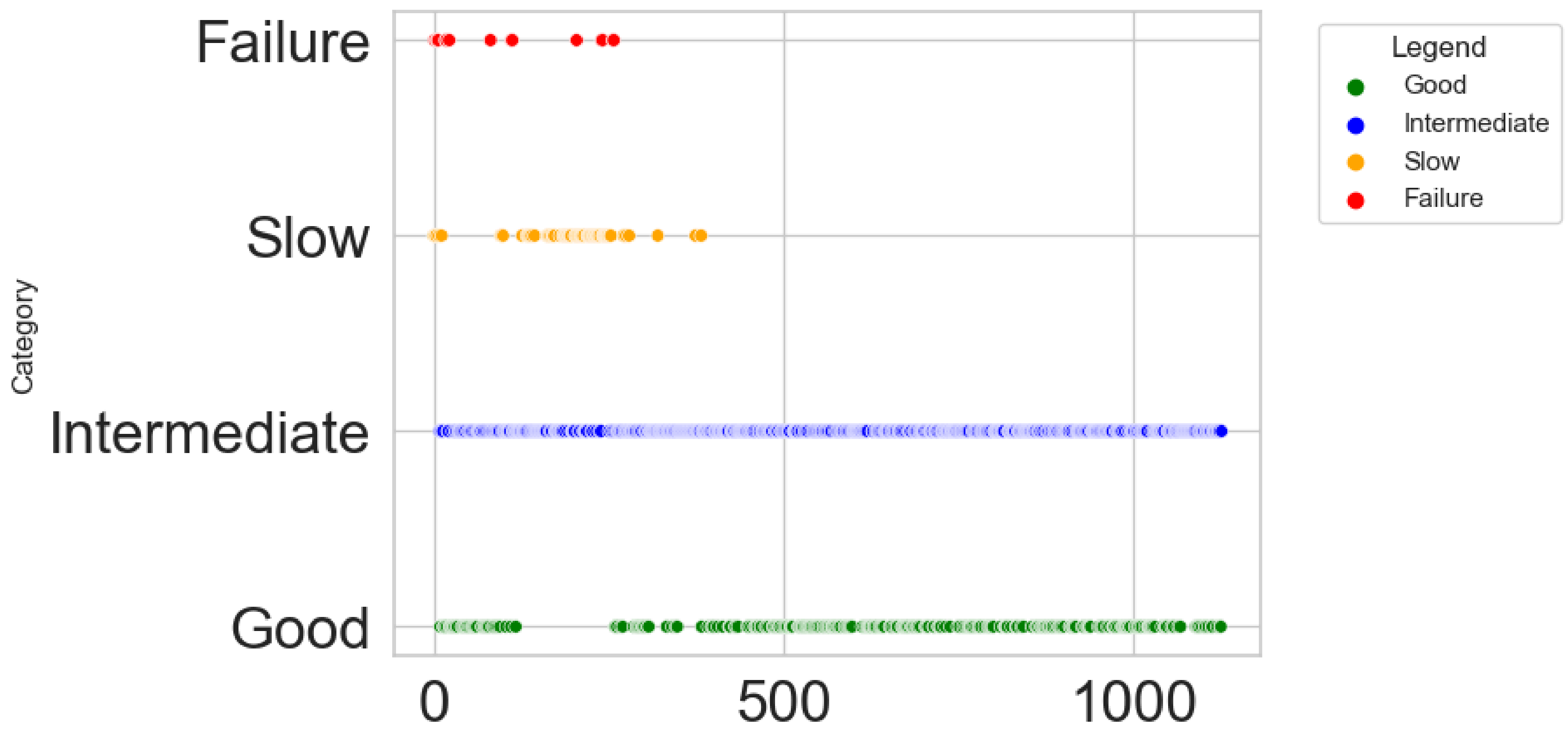
Circuit breaker



Failures and inefficient operations can cause long downtimes and high costs!

Voltage signal and expert classification



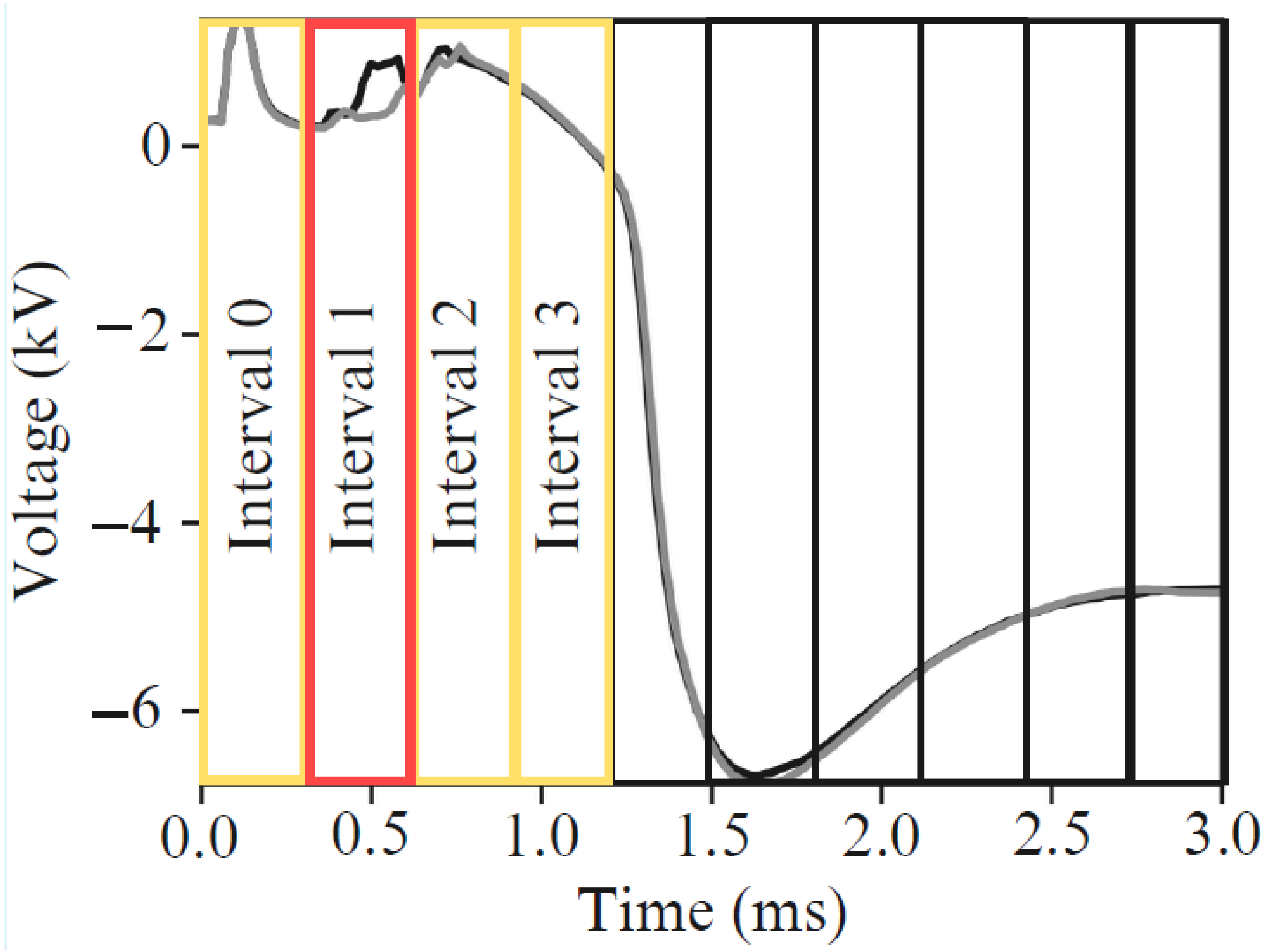


Challenges:

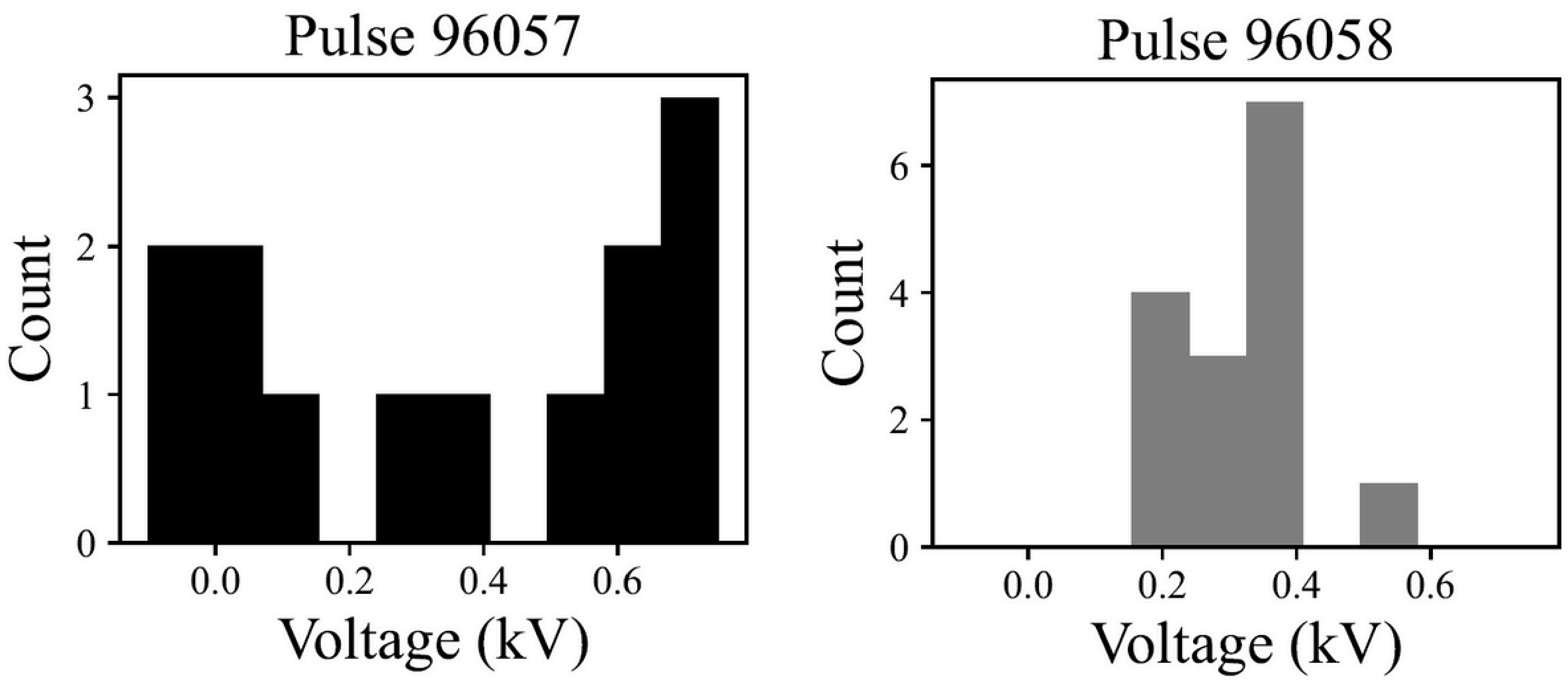
- Only electrical signal measurements are available
- Limited knowledge of the modes of failure
- Absence of a clear trend around failures

Feature extraction

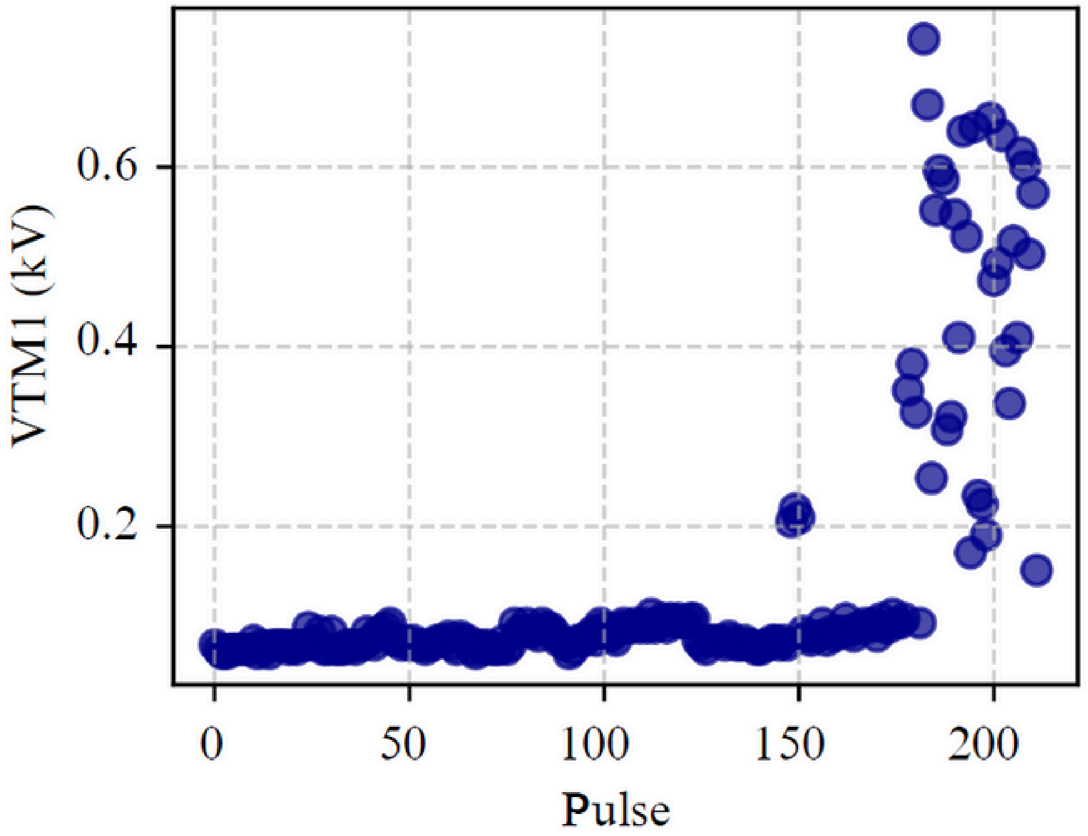
Step 1



Step 2



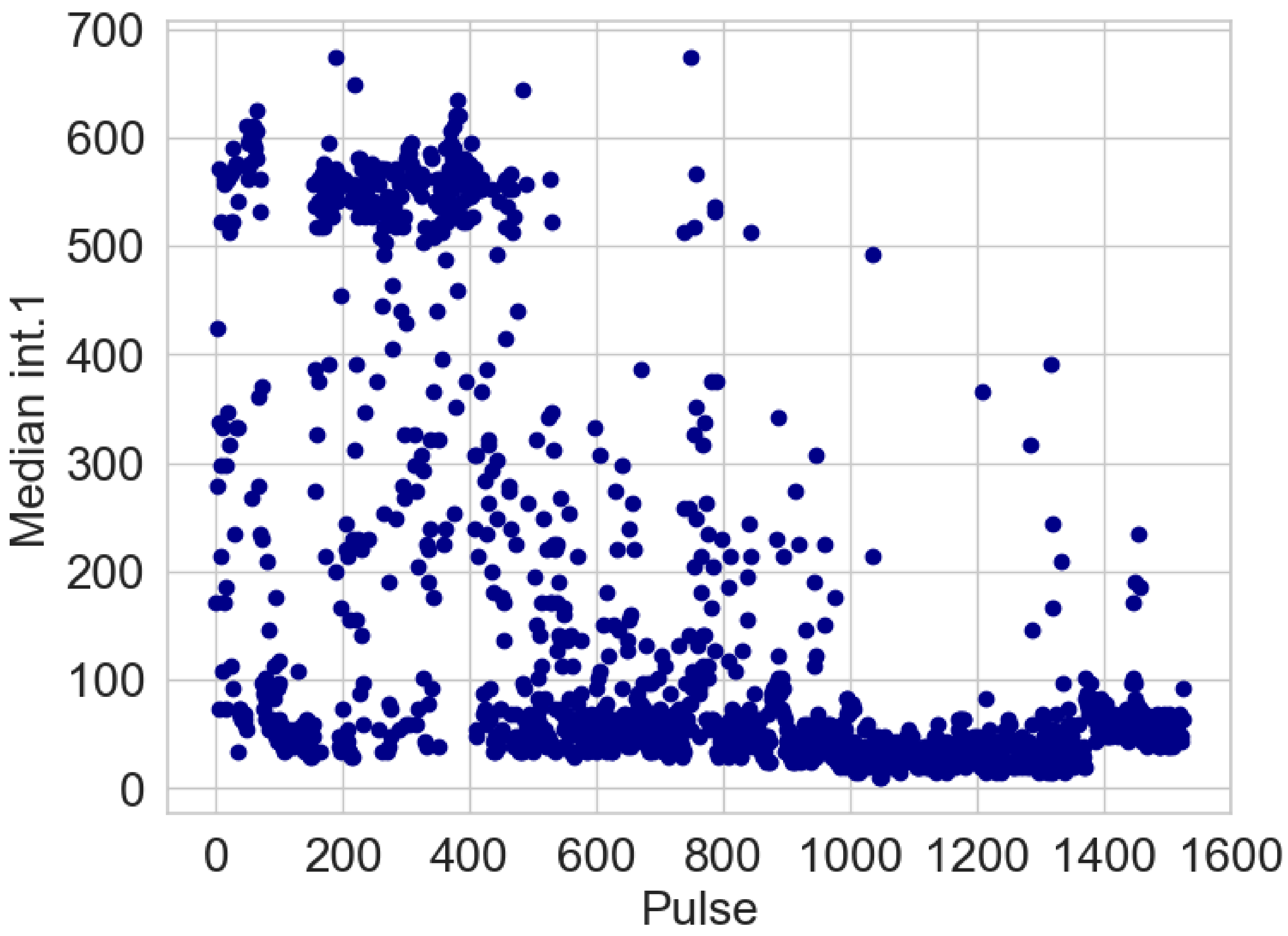
Step 3



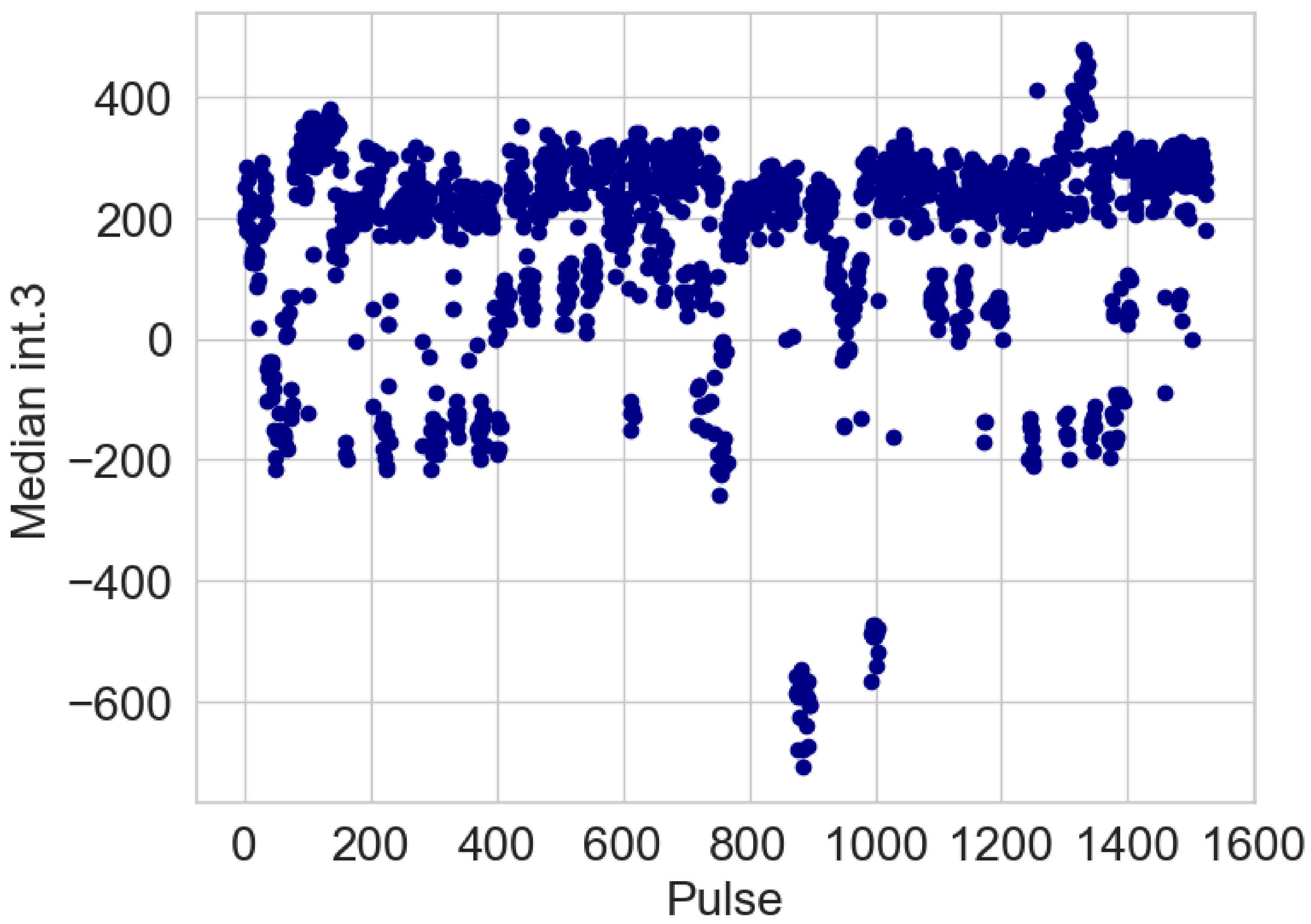
Median extracted from the first interval for each CB operation within a lifespan

Regime transitions

Shows regular clusters

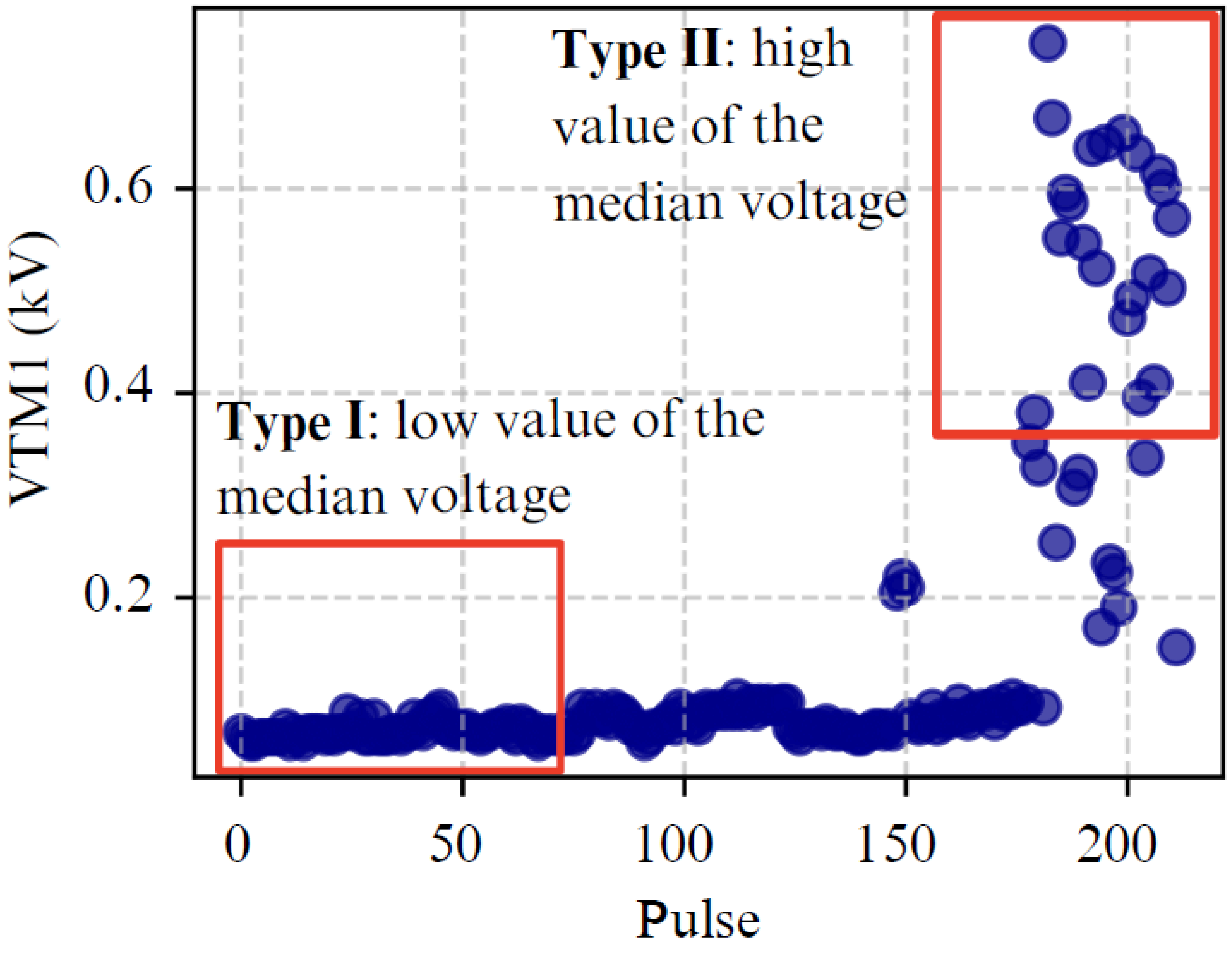


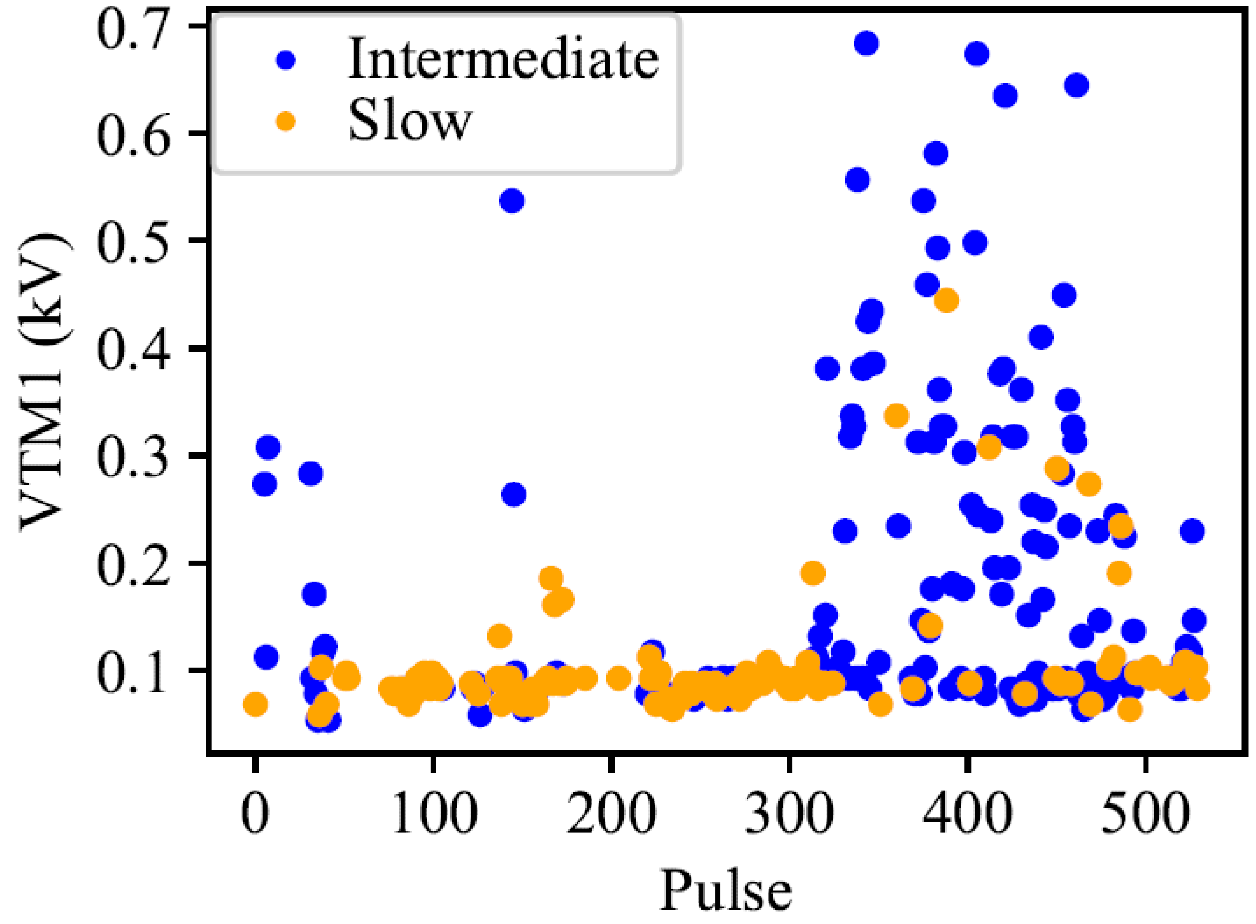
No regular clusters

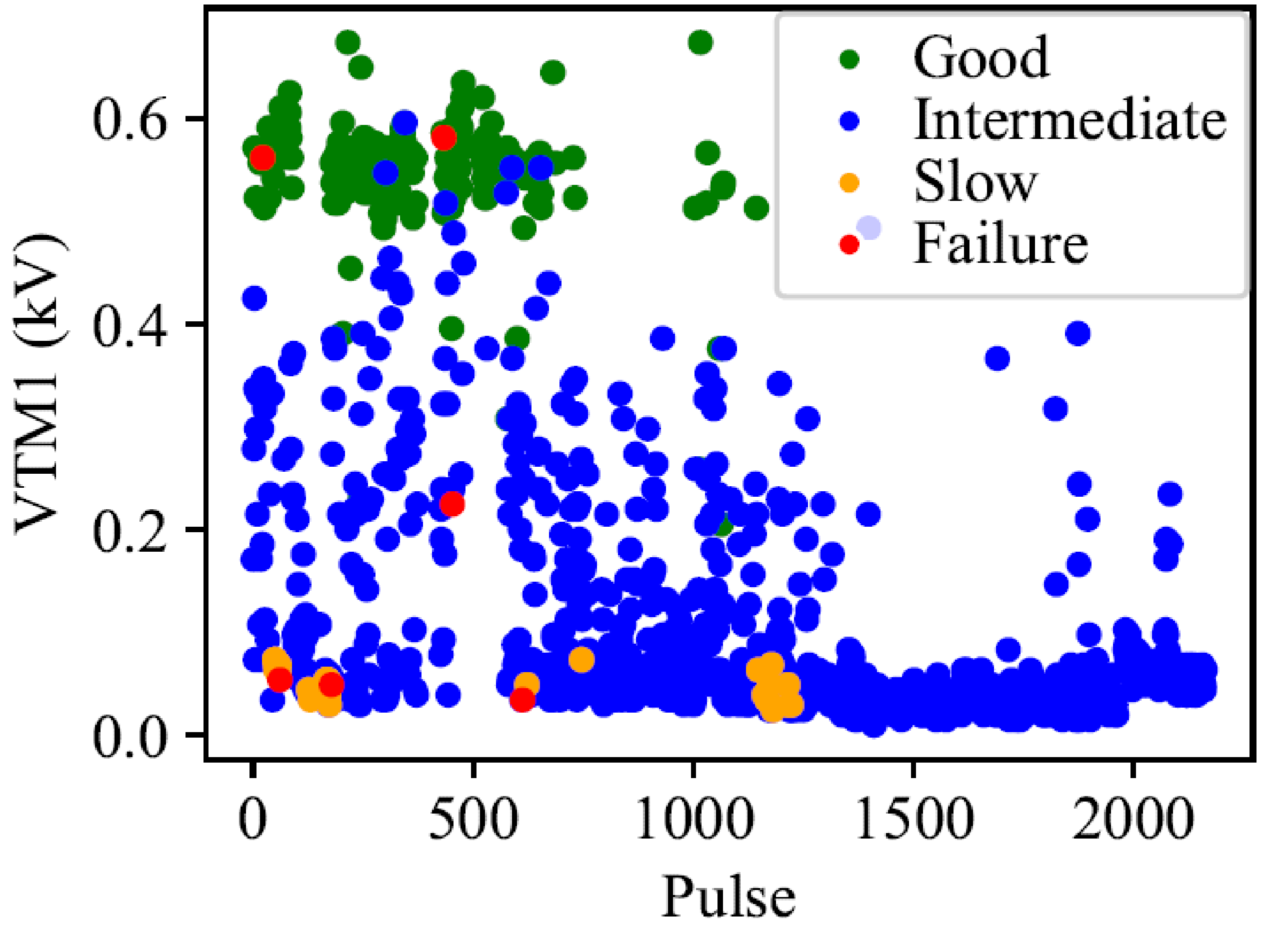


- Median from the 1st interval suggests different behaviour along the lifespan of many CBs
- Changing behaviour for 11 out of 17 CBs

Regime types vs. expert labels

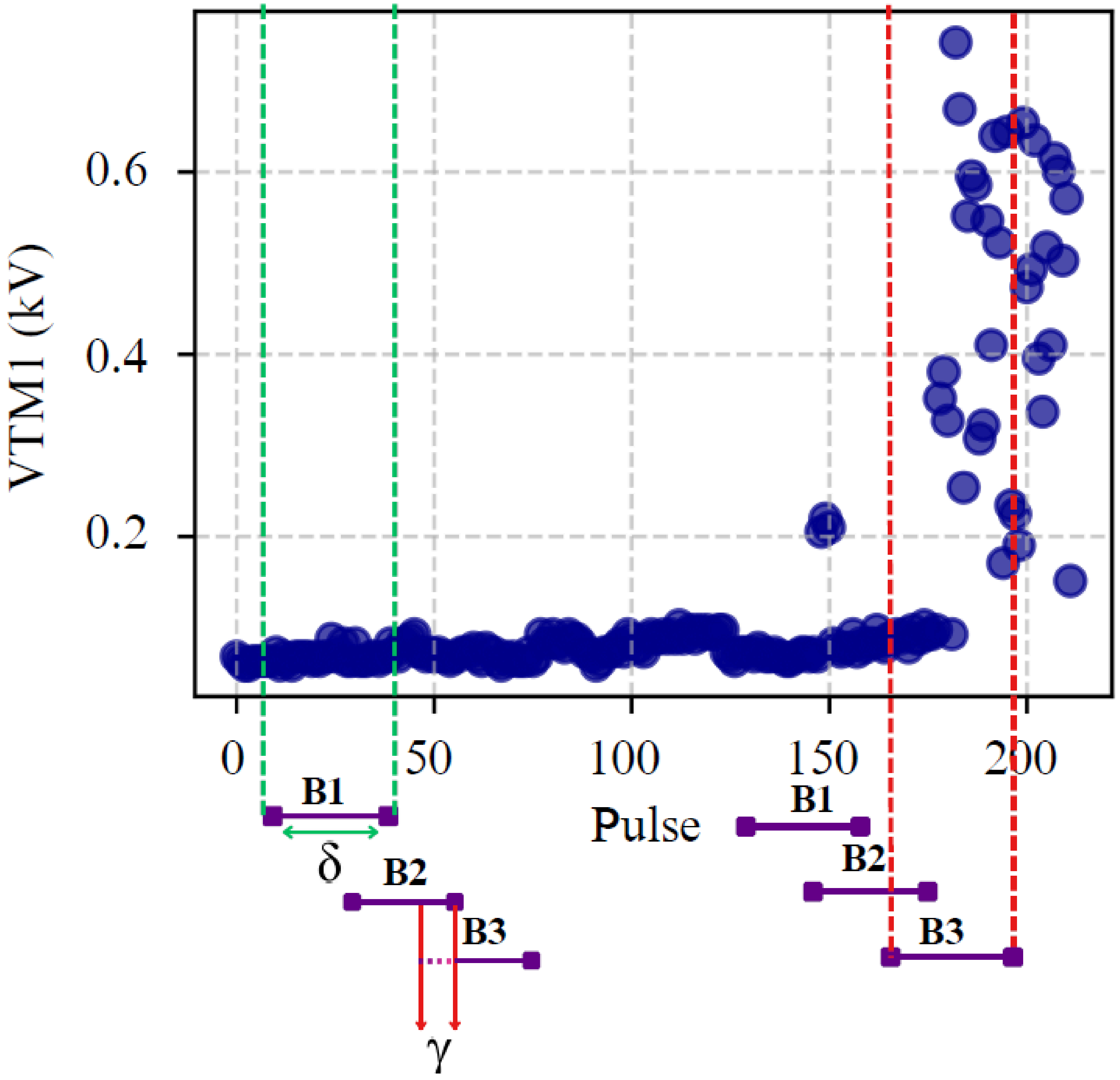






Median from the 1st window suggests a changing working regime linked with a change in performance of the CB

Change point detection algorithm



Procedure

- Percentage of below/above threshold
- Comparison of B1 with B2 and B3
- Repeat for each batch

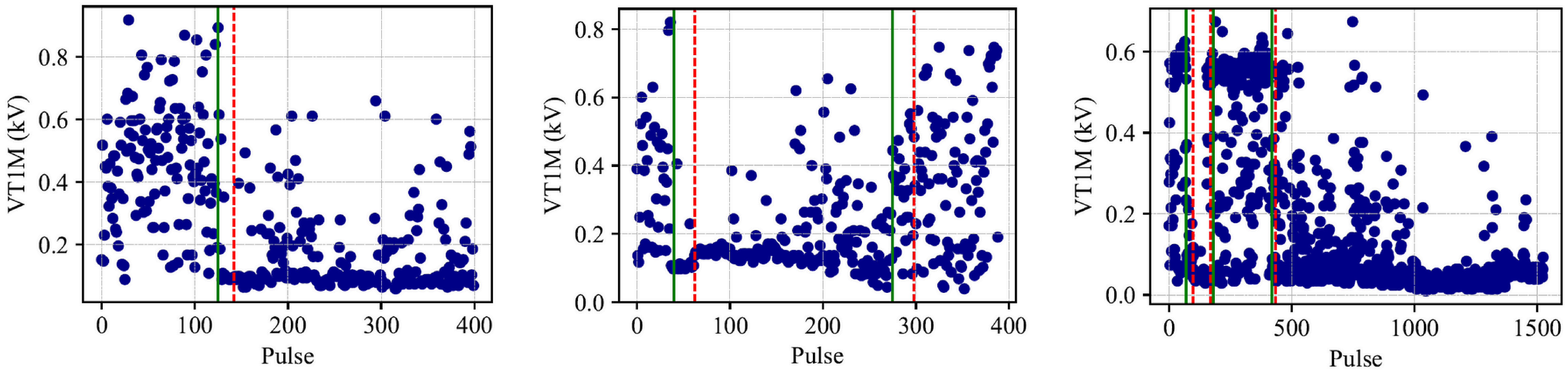
Parameters

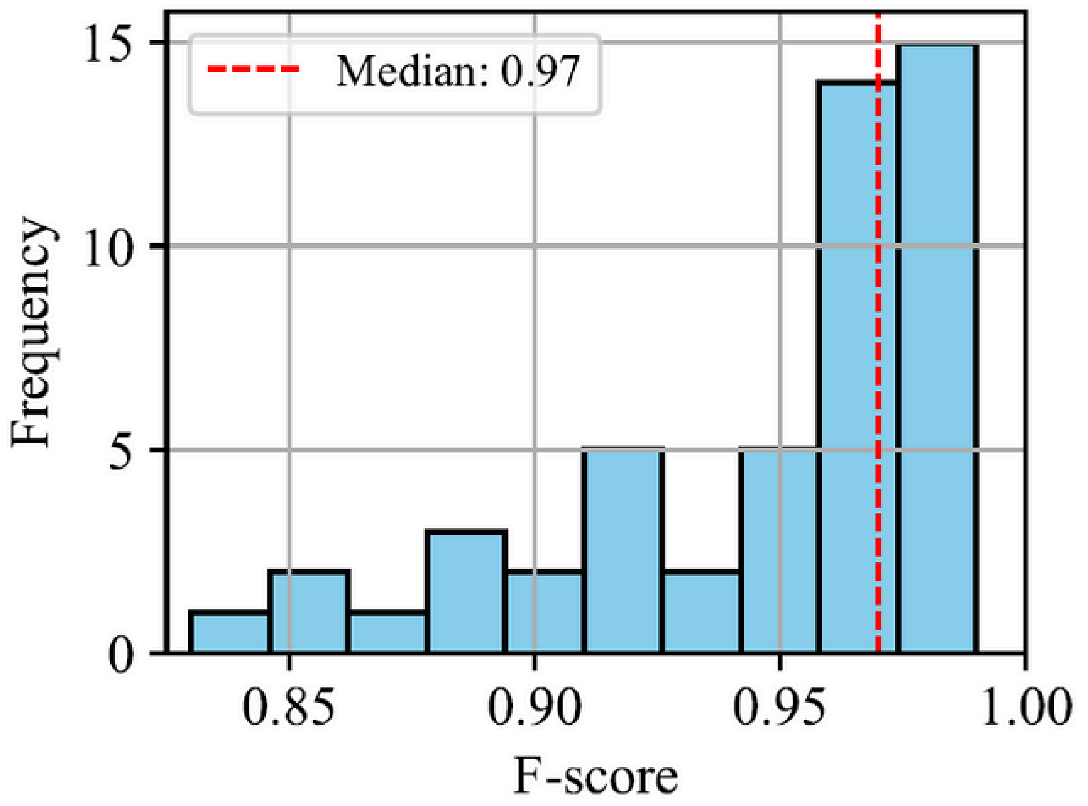
- δ_t Batch length
- ω Overlap
- θ Deviation parameter
- τ Tolerance

Challenges

- The algorithm has to work nearly real-time
- The changing regimes can be either sudden or gradual
- Concept drift

Training, evaluation, generalization





- **Robustness** assessed by repeating the training with different training set
- **Generalization** assessed by re-training the algorithm after each tested lifespan
- **Optimal parameters** found using Bayesian optimization (about 1 min)

Second use case

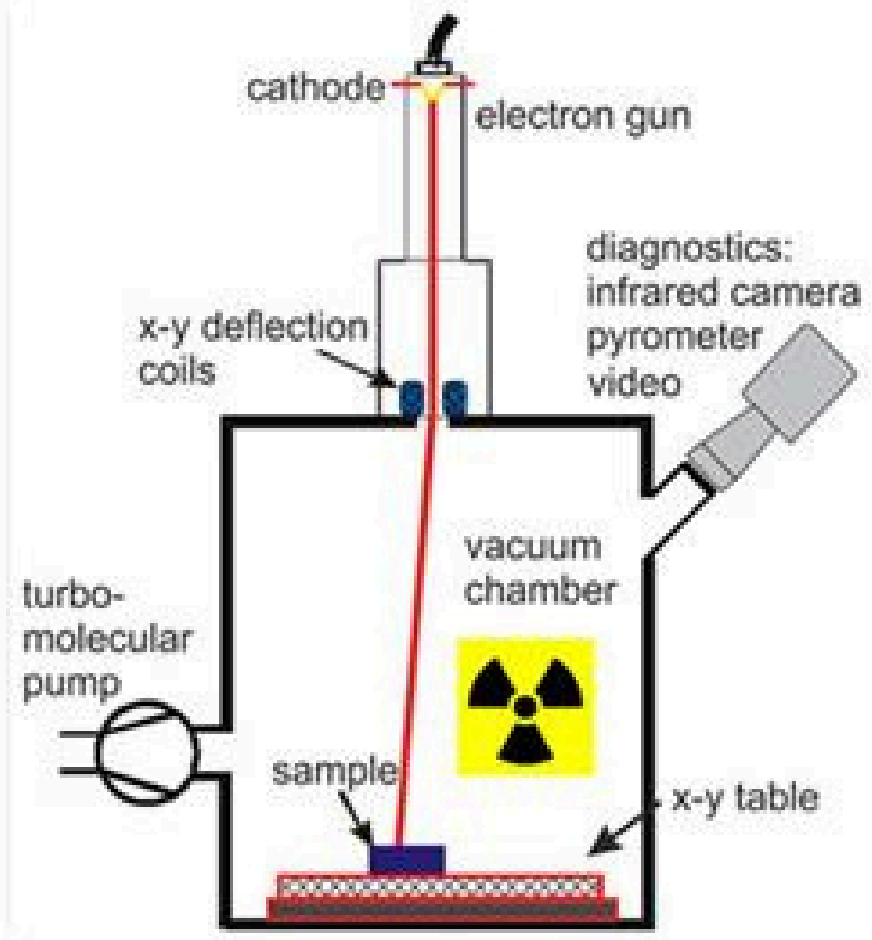
05

RUL estimation for plasma-facing components using a similarity-based approach

Caputo et al., 2025, in preparation

Experimental campaign at electron beam facilities

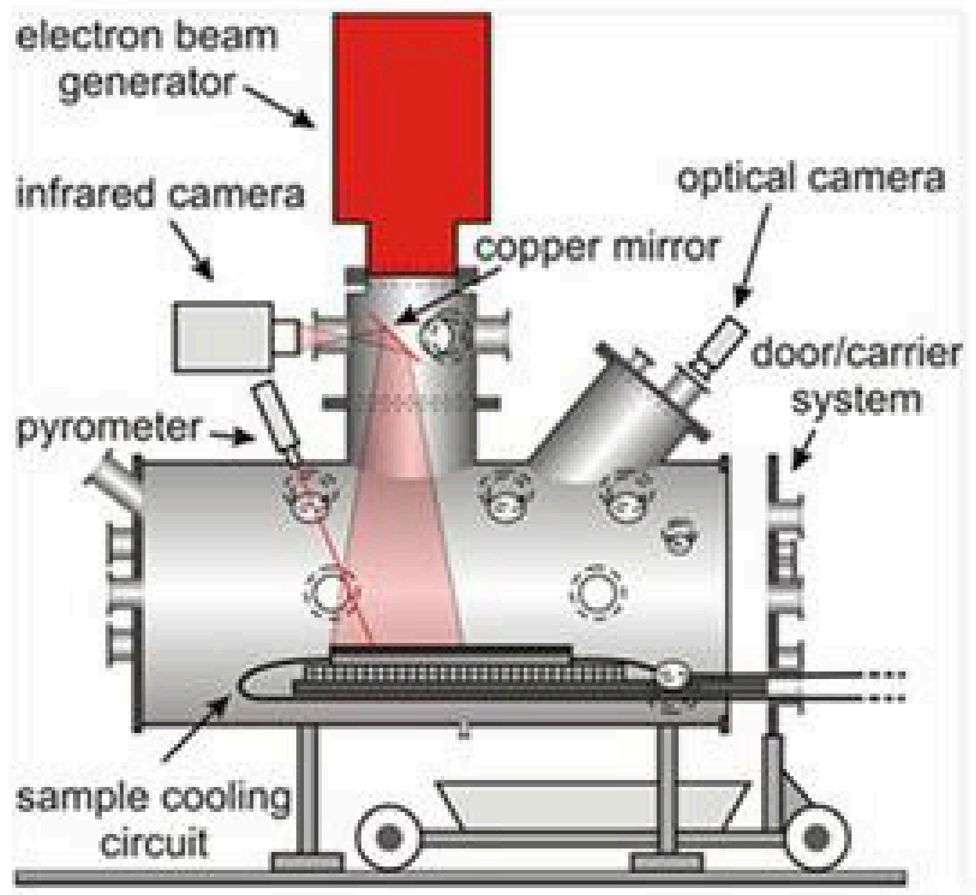
Electron beam facility JUDITH 1



- max. power 60 kW
- acceleration voltage < 150 kV
- EB diameter ~1 mm FWHM
- loaded area 10 x 10 cm^2

Allows activated materials

Electron beam facility JUDITH 2



- max. power 200 kW
- acceleration voltage 30 – 60 kV
- EB diameter ≤ 5 mm FWHM
- loaded area 40 x 40 cm^2

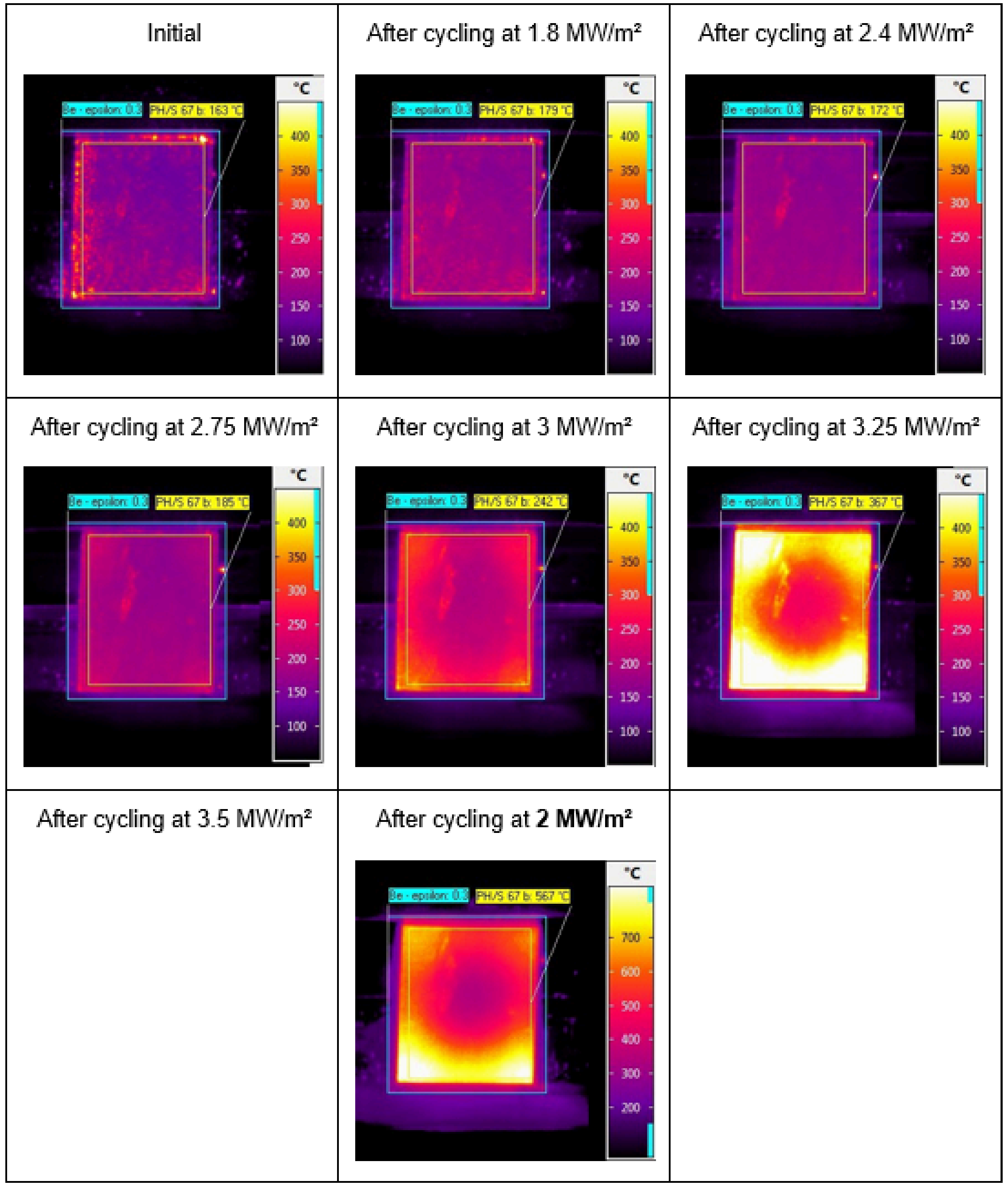
Customization of
electron beam path

FZ-Jülich, Germany

JÜLICH Forschungszentrum

Hirai et al., 2005, Mater. Trans. 46(3), 412–424

Experiments and dataset



Tile exposed to electron beam at increasing power load until failure

Tile considered failed if surface temperature > 750 ^{o}C

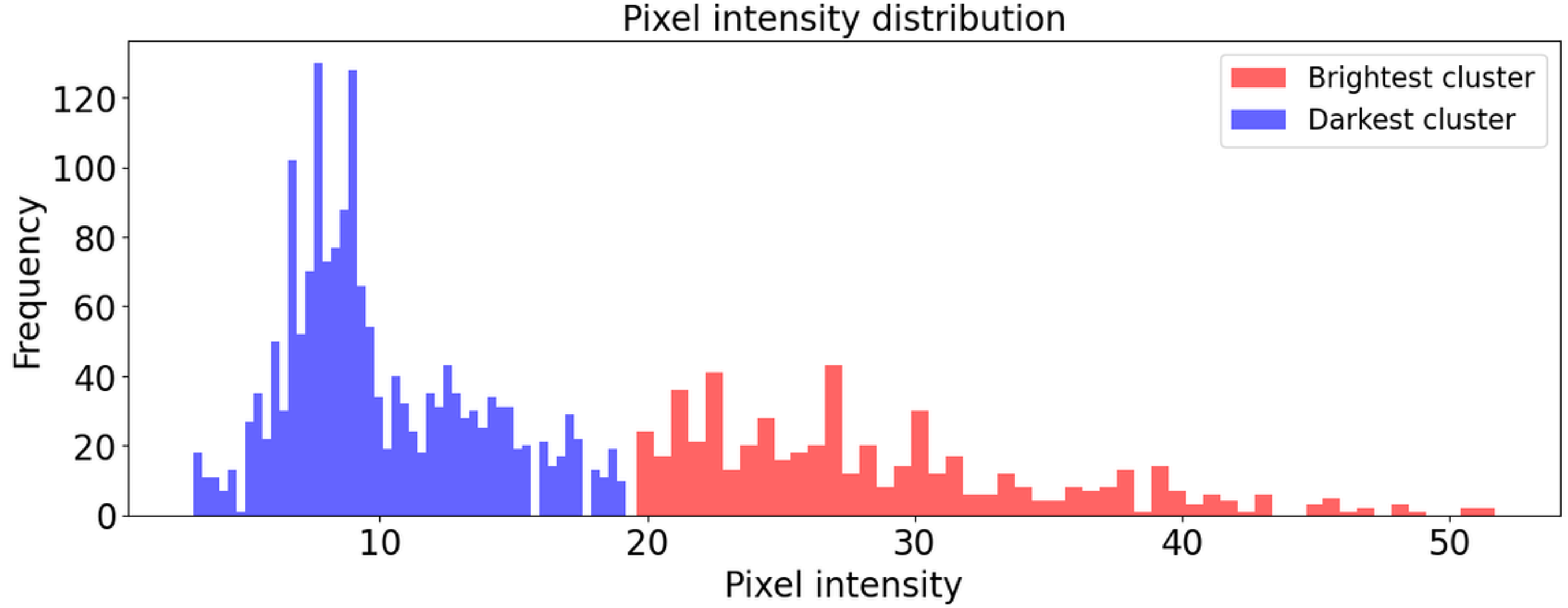
Infrared images of 10 tiles for each cycle

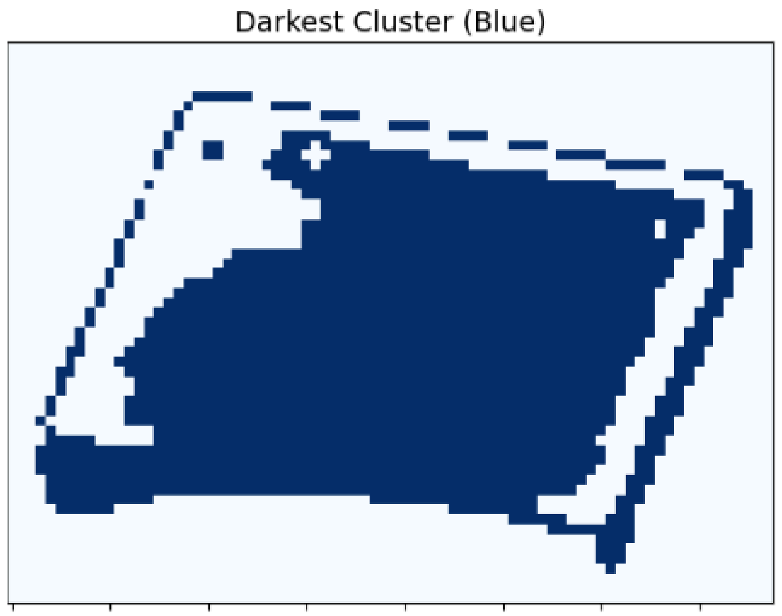
Metadata

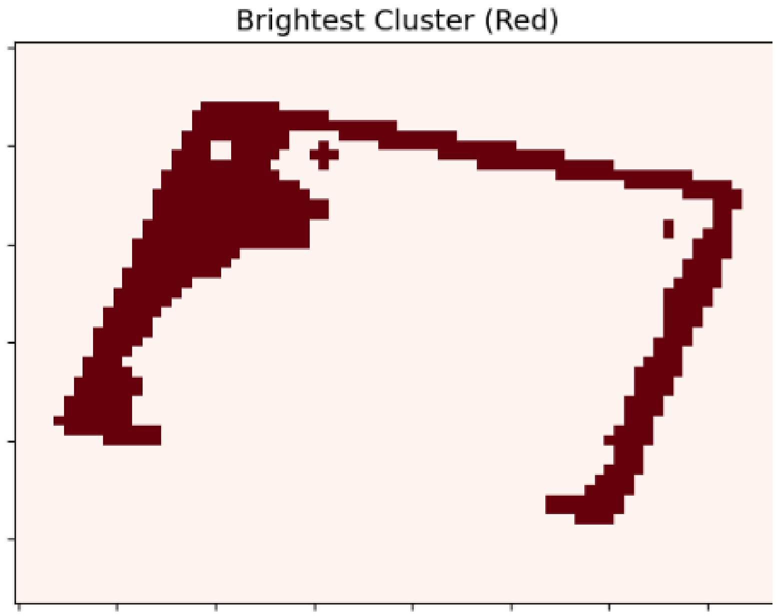
- Cycle number, beam power...
- Qualitative annotations

Local emissivity and regions of interests

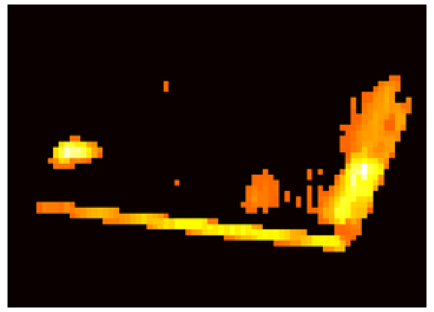
Segmentation using k-means algorithm



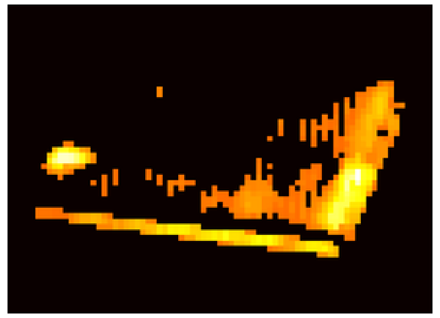




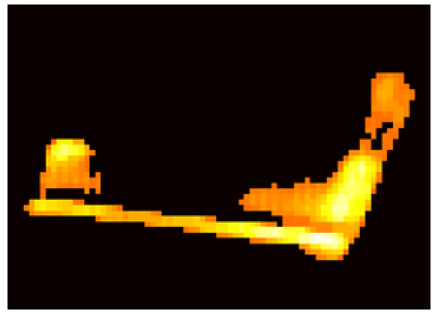
Evolution of centroid distance over the lifespan



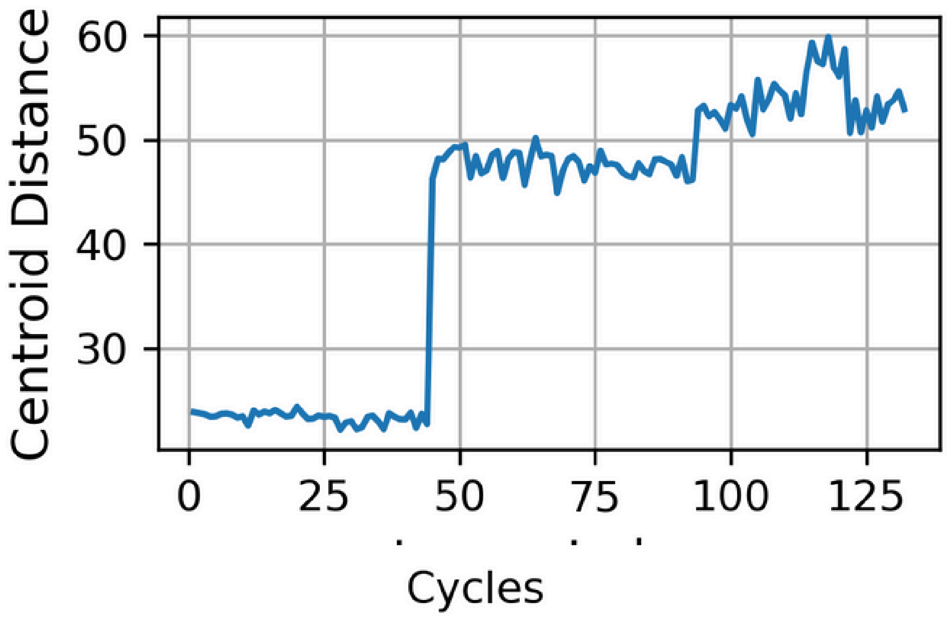
Cycle nr.60



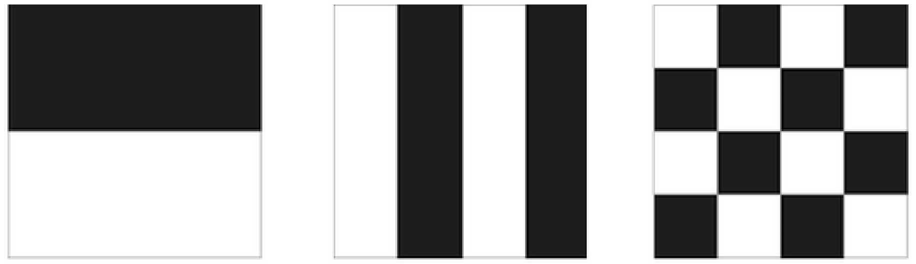
Cycle nr.100



Cycle nr.120



Extraction of texture features



Why?

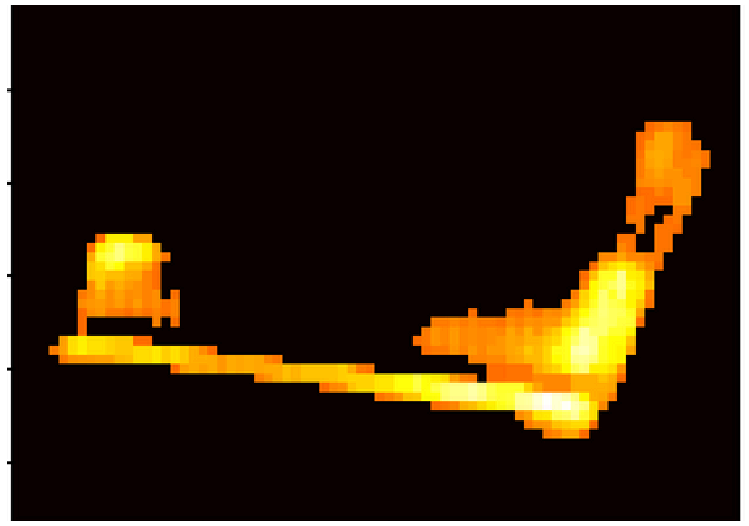
- Anomalous correlation between pixels can be an indication of damage
- Robust to changes in absolute brightness
- Translation-invariant

Gray Level Co-occurrence Matrix (GLCM)

- Counts how often gray-level pairs occur at a fixed distance/angle.
- Extracted metrics: Contrast, Energy, Homogeneity, Correlation.

Local Binary Patterns (LBP)

- Compares each pixel to neighbors.
- Encodes as binary number
- Captures local micro-textures (edges, corners, flat regions).



Fast Fourier Transform (FFT)

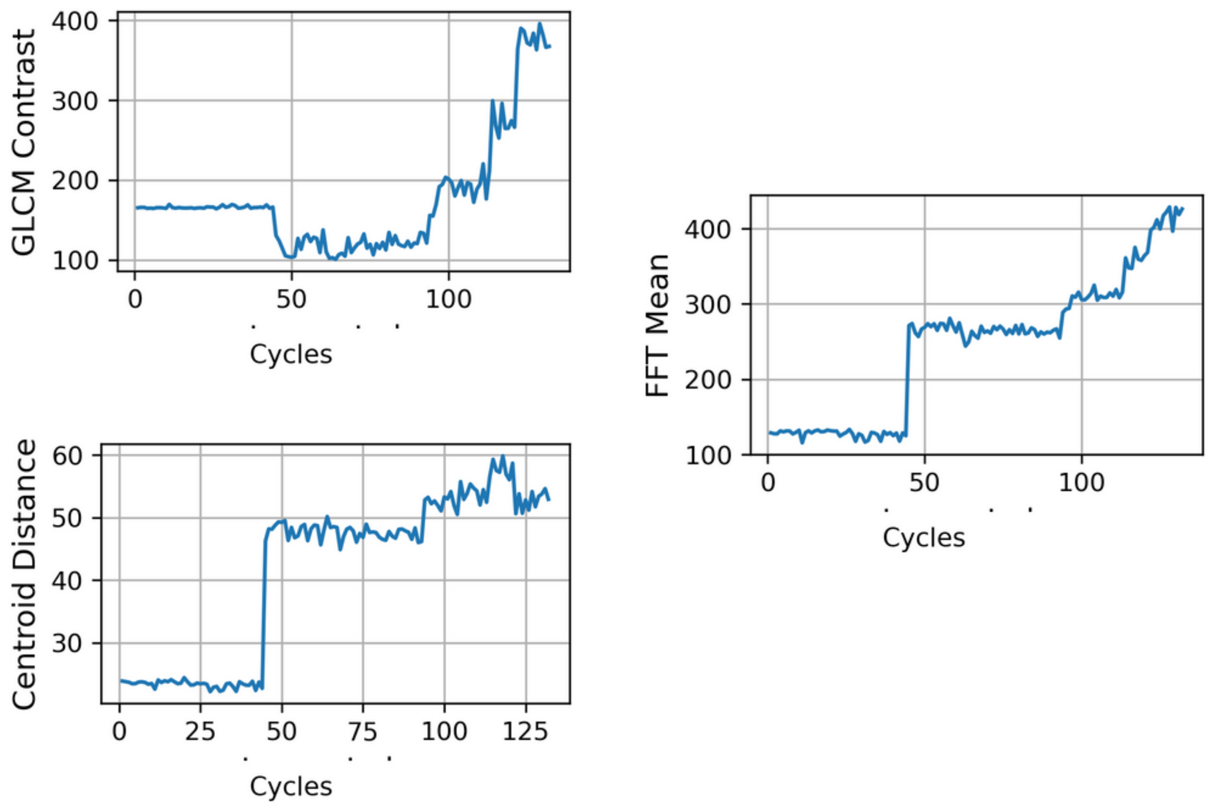
- From spatial → frequency domain.

Wavelet Transform

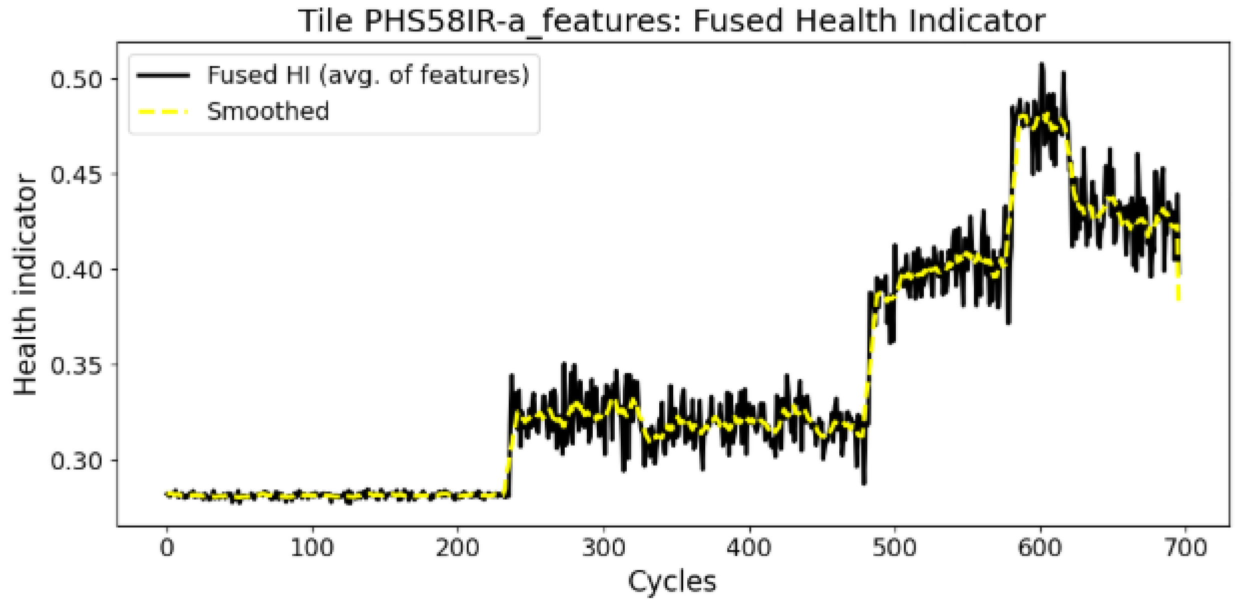
- Multi-resolution decomposition (LL, LH, HL, HH bands).

Similarity-based RUL estimation

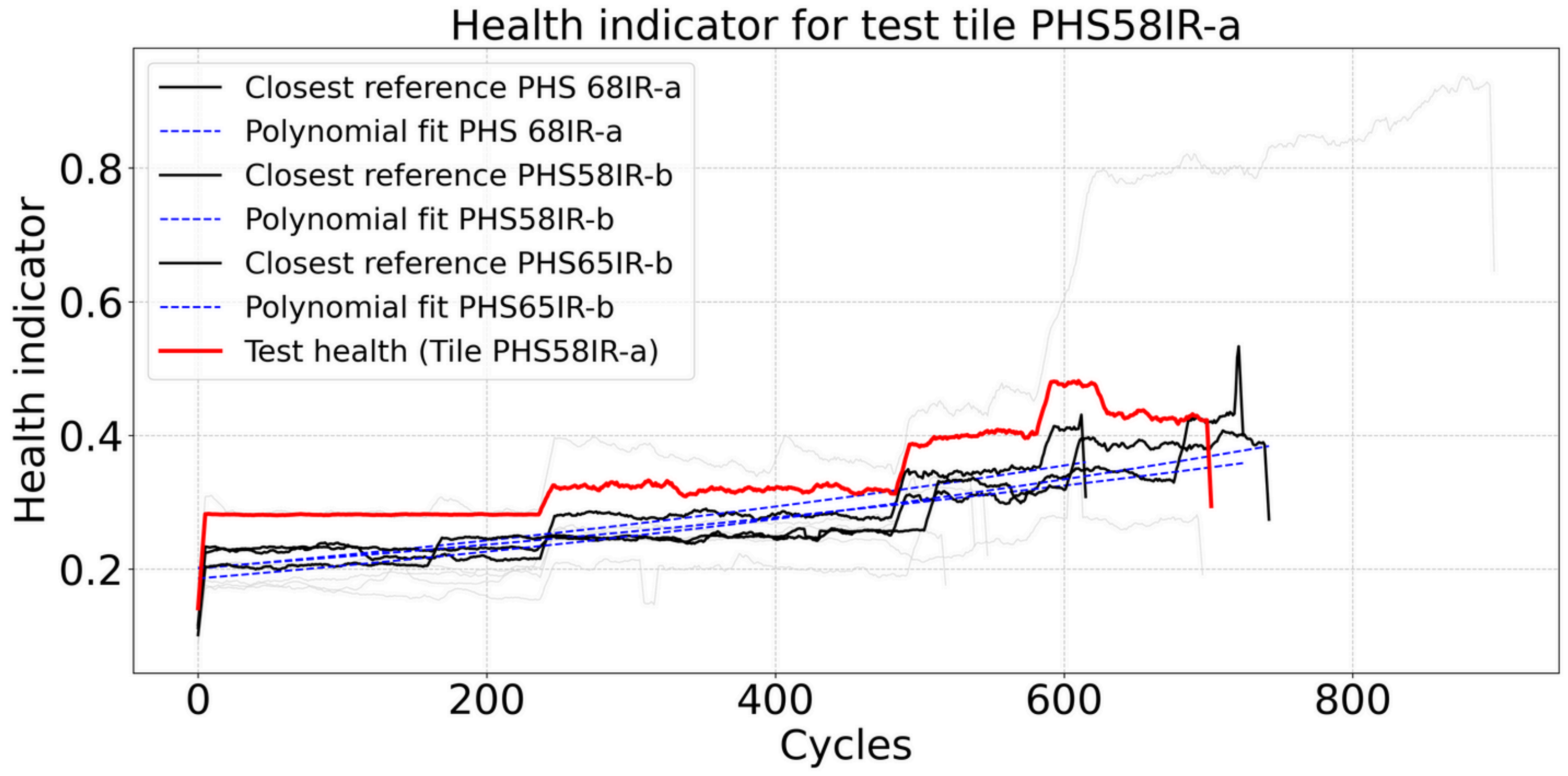
Feature fusion



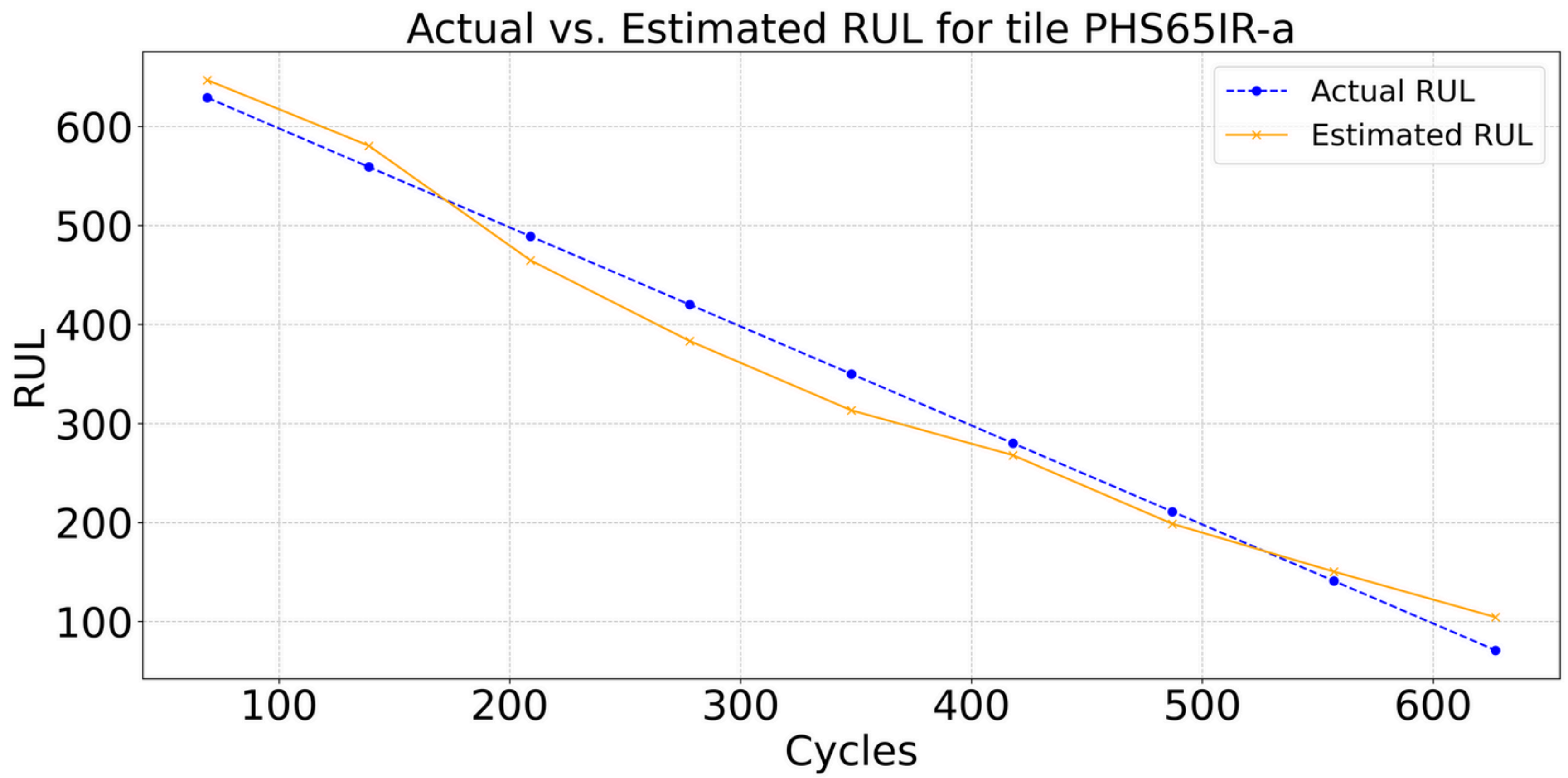
Health indicator

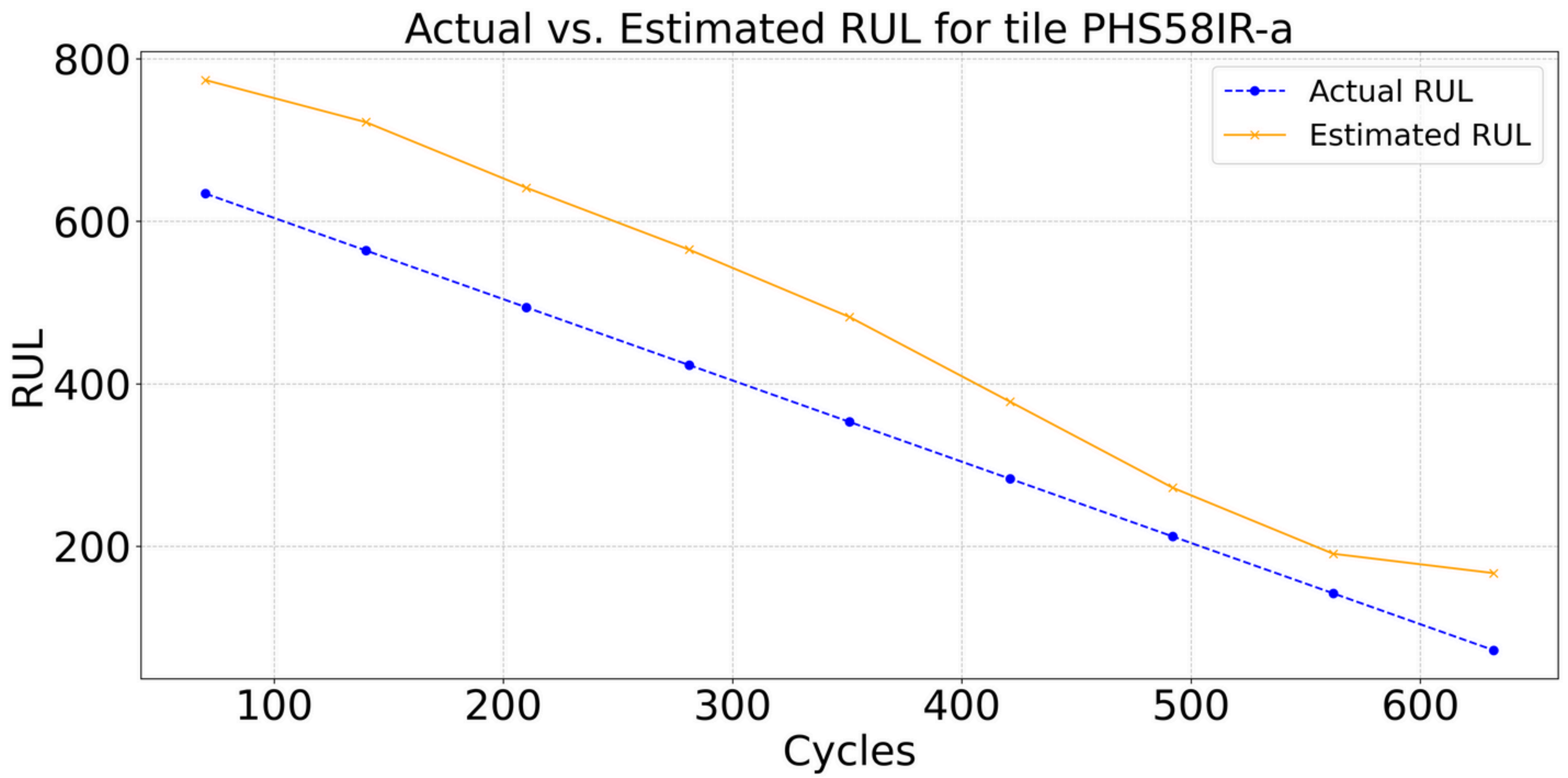


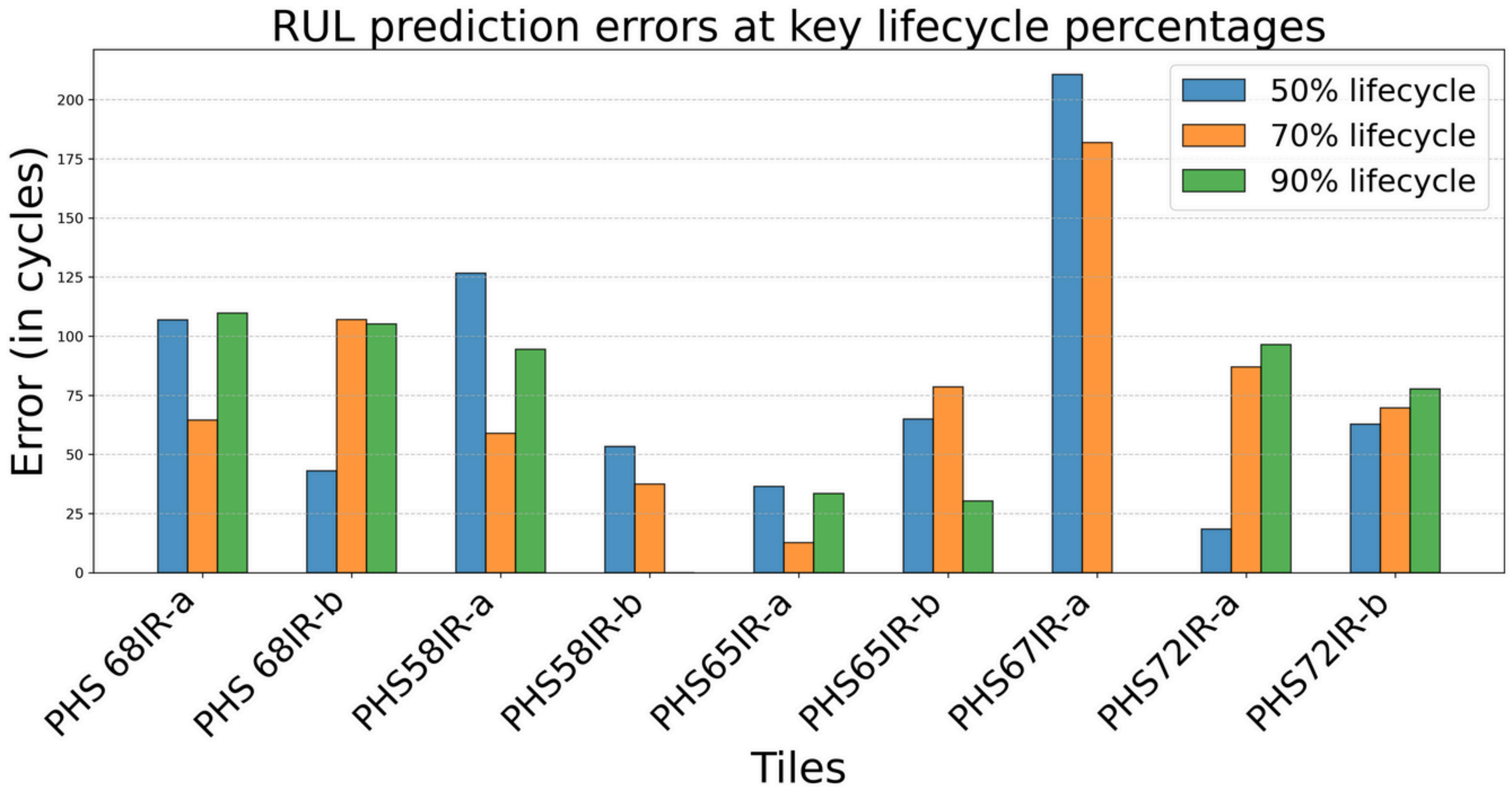
Predicted RUL = average RUL for 3 closest trajectories



RUL evaluation







Conclusion

Predictive maintenance is essential to ensure availability, safety, and cost-efficiency in fusion power plants.

Multiple critical use cases demonstrate feasibility

Key challenges:

- Limited sensors/diagnostics
- Limited or absent historical data for critical components
- Near ‘real-time’ requirements