2024 Intelligent Maintenance Conference

Explainable Artificial Intelligence Guided Unsupervised Fault Diagnostics for High-Voltage Circuit Breakers

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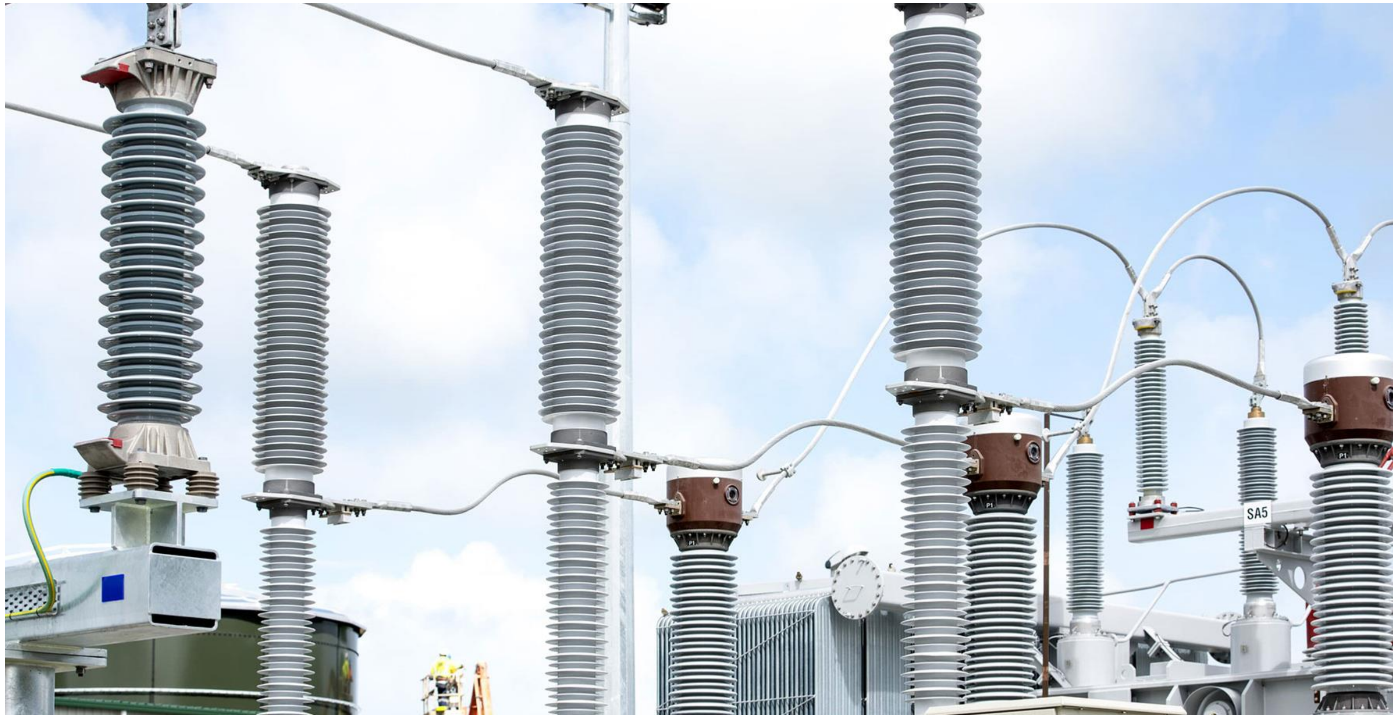
ETH zürich EPFL Hitachi Energy

Introduction

High voltage circuit breaker

Mechanical switching device capable of conducting and breaking electric current under:

- Normal electrical circuit operation
- Abnormal electrical circuit condition, such as a short circuit.



Maintenance for reliable operation

Introduction

High voltage circuit breaker maintenance

Time-based maintenance is performed in a predefined time-interval, having as risks:

- Unnecessary replacement of well-working components.
- Components might be planned to be replaced / repaired when it is too late.

Consequences

Cost increase and reliability issues.

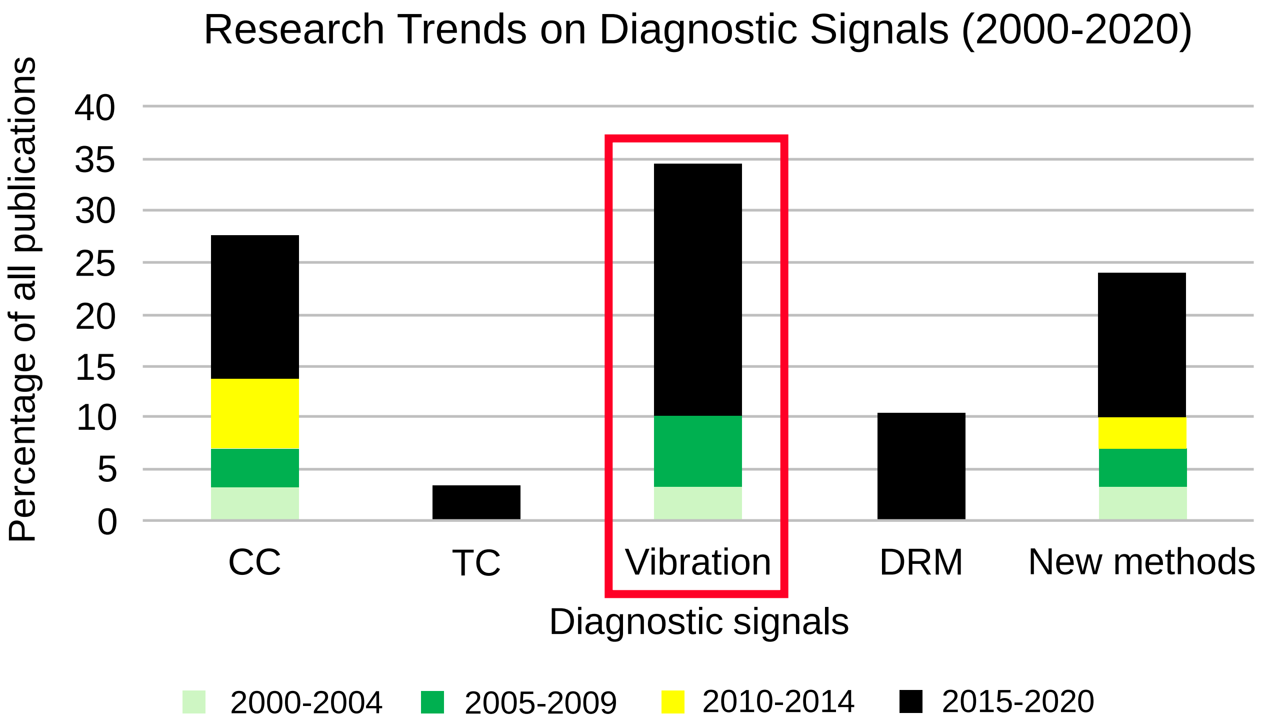
Condition-based maintenance: determined based on HVCB condition assessment, having as benefits:

- Increased availability, reliability and safety.
- Reduced cost by proactive and optimized maintenance.

Requirements

Reliable monitoring systems

Vibration monitoring



Razi-Kazemi et al. (2020)

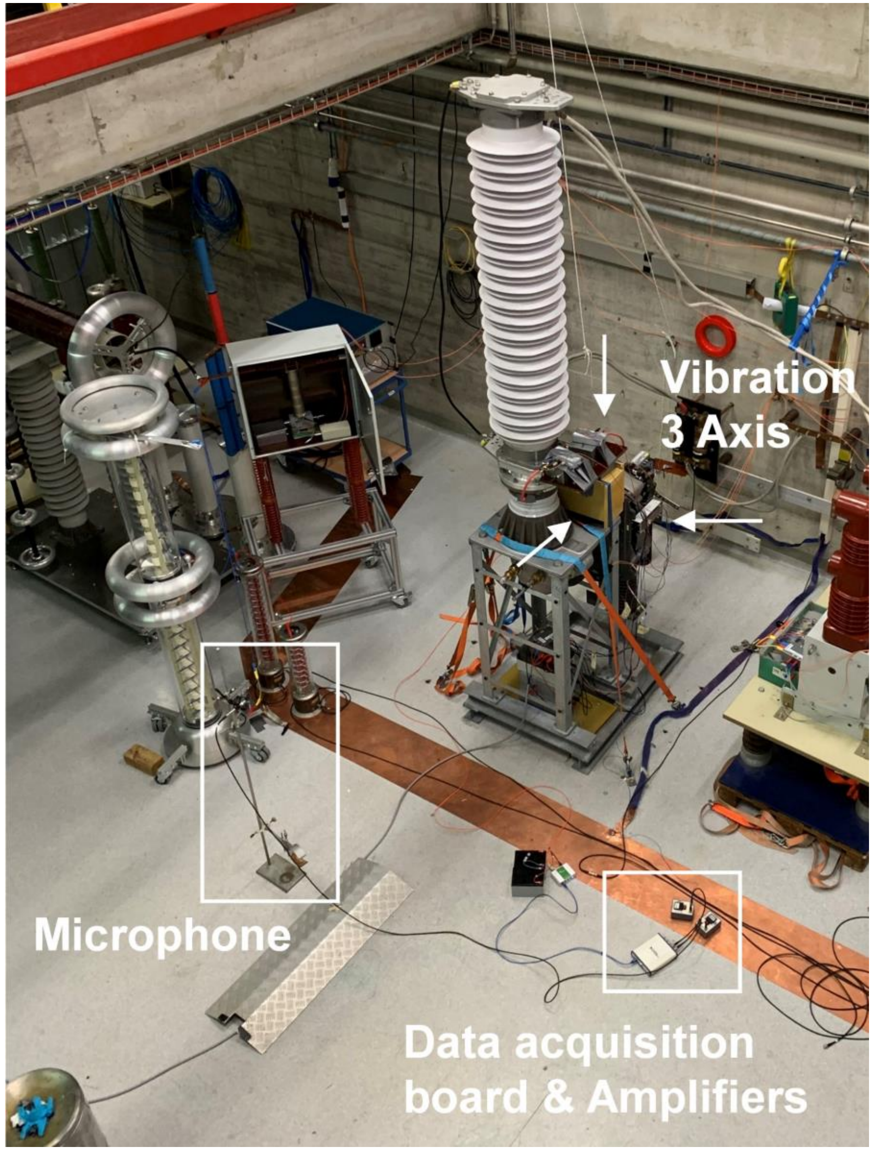
CC: Coil current
TC: Travel curve
DRM: Dynamic resistance measurement

- Vibration measurements cover all physical effects that contribute to the HVCB mechanical signal.
- Installation of such monitoring system is simple and not invasive.
- Challenges for vibration data analysis:
  - Short time duration (millisecond scale)
  - Wide frequency domain
  - Nonlinearity and non-stationarity

Yang et al. (2019)

Yang, Qiuyu, et al. "A new vibration analysis approach for detecting mechanical anomalies on power circuit breakers." IEEE Access 7 (2019): 14070-14080.
Razi-Kazemi, Ali Asghar, and Kaveh Niayesh. "Condition monitoring of high voltage circuit breakers: past to future." IEEE Transactions on Power Delivery 36.2 (2020): 740-750.

Experiments with seeded defects



Experimental setup:

- Live tank breaker with spring drive
- Mechanical operations (no current interruption)

Combinations of seeded defects:

- Spring charge (low, normal and high)
- Damper (normal and degraded)

1st Low spring charge, normal damper

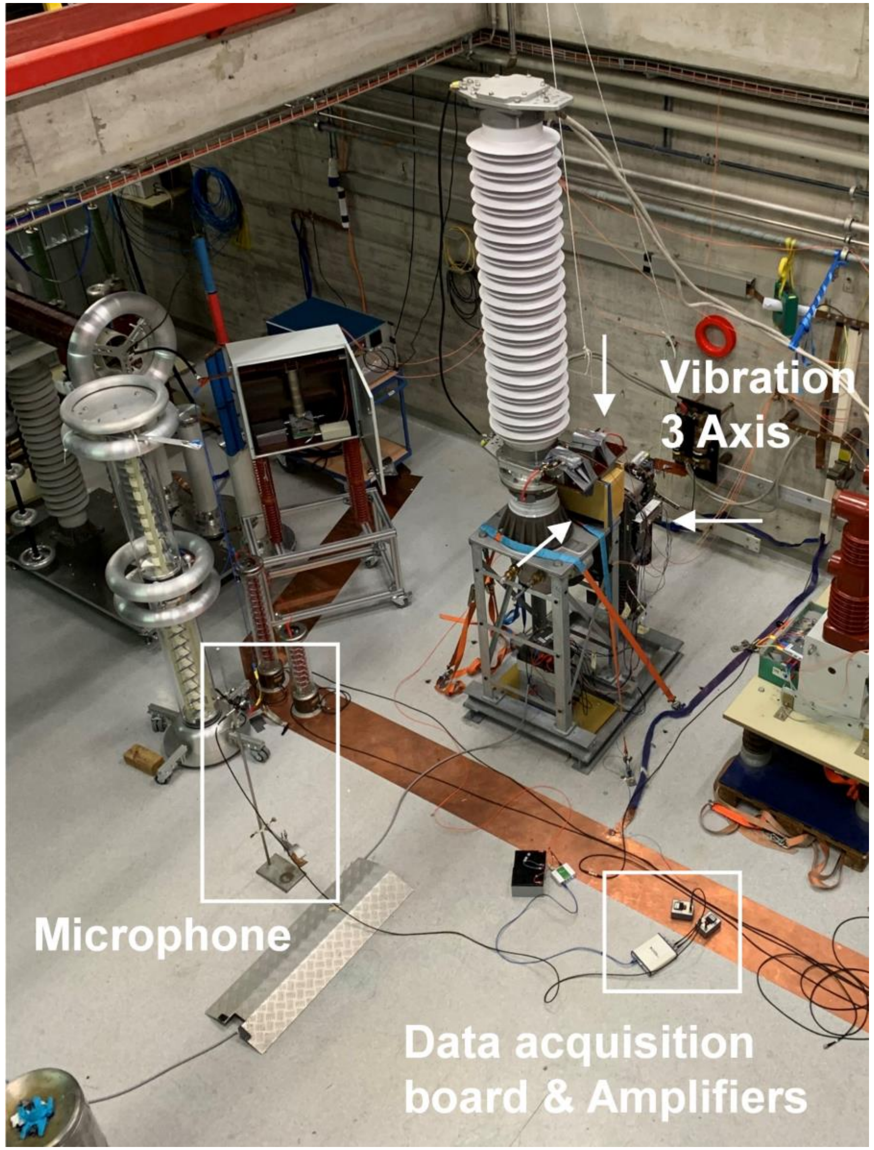
2nd High spring charge, normal damper

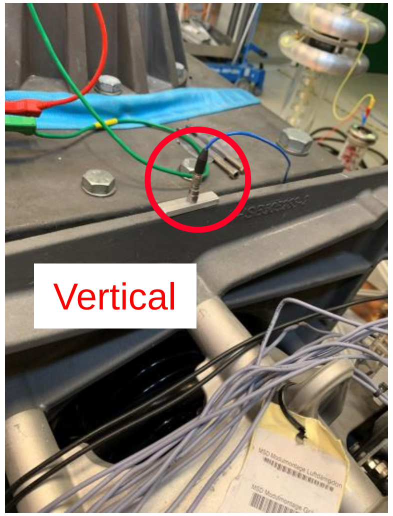
3rd Low spring charge, degraded damper

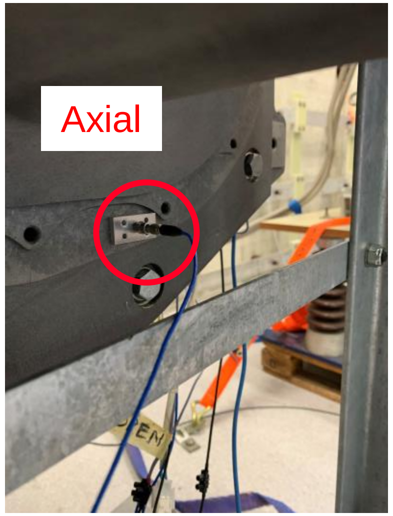
4th Normal spring charge, degraded damper

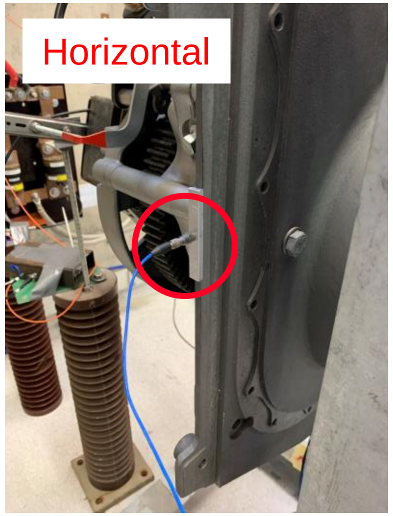
5th Normal spring charge, normal damper

Experiments with seeded defects









Monitoring sensors

- Accelerometer PCB 352A60 (installed horizontally)
- Accelerometer PCB M352C18 (installed vertically)
- Accelerometer PCB 353B14 (installed axially to the drive)
- Microphone 378B02

Challenges

No labels in substation

Once fault is detected, we do not know what fault it is

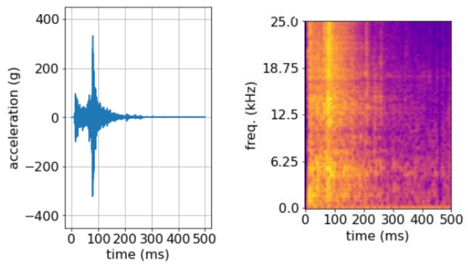
Supervised learning is popular in literature (laboratory) but not suitable in reality

Can we identify/cluster faulty samples without labels?

Proposed Framework

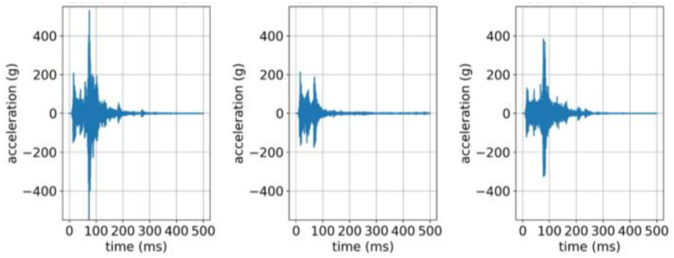
Condition Monitoring Data

Vibration and microphone signals, features extraction - spectrograms (4 sensors)



Fault Detection
Convolutional autoencoders (CAE)

Model learns “what is healthy” and outputs: Healthy or Faulty



Fault Segmentation
K-means clustering

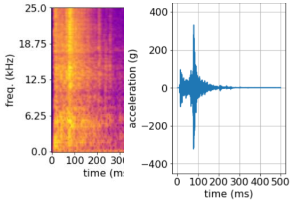
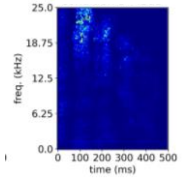
Segment the faults into different types, without any knowledge which cluster corresponds to which fault type

Fault Diagnostics
Explainable Artificial Intelligence (XAI)

Identify fault types (spring fault, damper fault, …)

Fault Diagnostics using XAI (Integrated Gradients)

- Why is this <u>sample</u> classified as this <u>label</u>? Because of the <u>attribution maps</u>

Label	Sample	Attribution Maps
Camera		
Fireboat		
School bus		
Fault Cluster1 …		

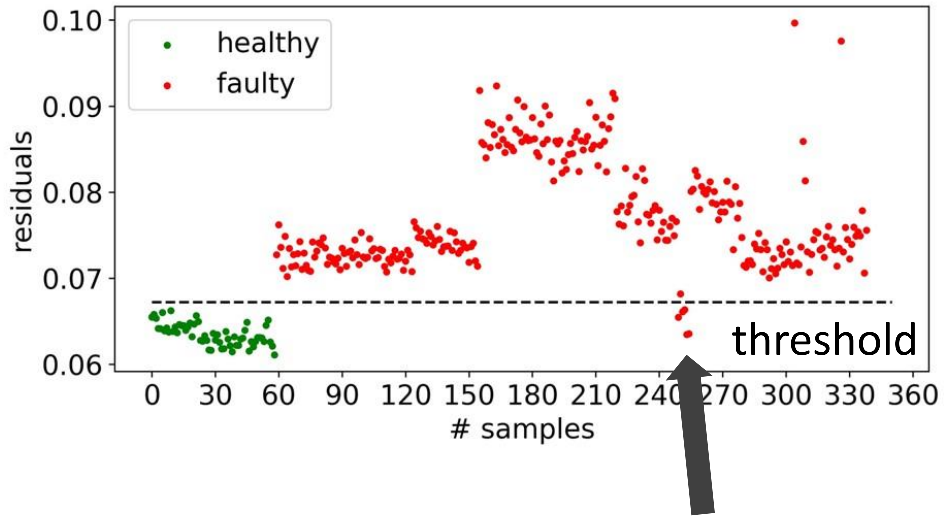
Physics explanation

Sundararajan, Mukund, Ankur Taly, and Qiqi Yan. "Axiomatic attribution for deep networks." *International conference on machine learning*. PMLR, 2017.

Results

Fault detection using CAE

- Model learns "what is healthy" and reconstructs the signals
  - When faulty data is given, model failed to reconstructs the signals
  - Spectrogram from different sensors used as "channels"
- Residuals: difference between input and reconstructed signals



Faulty samples, but model says they are healthy
False negative rate: 1.79%

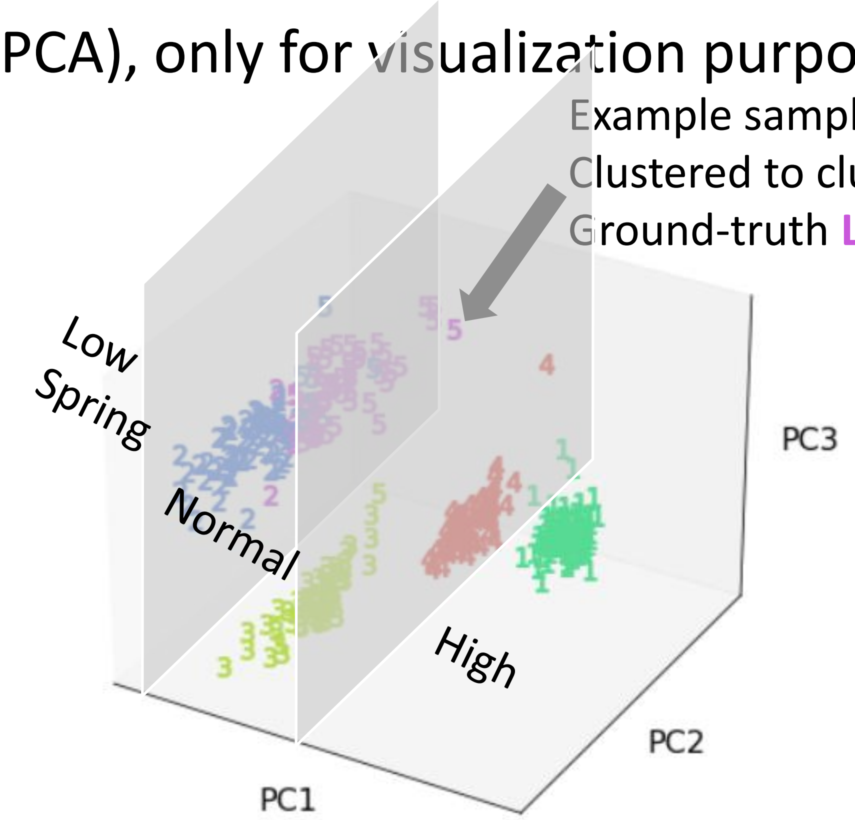
Fault segmentation using K-means clustering

- Samples are grouped into five different clusters
  - Principal component analysis (PCA), only for visualization purpose

Number: clustering results
Color: ground-truth (unknown in reality)

: normal spring normal damper
: normal spring degraded damper
: high spring normal damper
: low spring normal damper
: low spring degraded damper

Example sample:
Clustered to cluster #5,
Ground-truth **Low spring degraded damper**



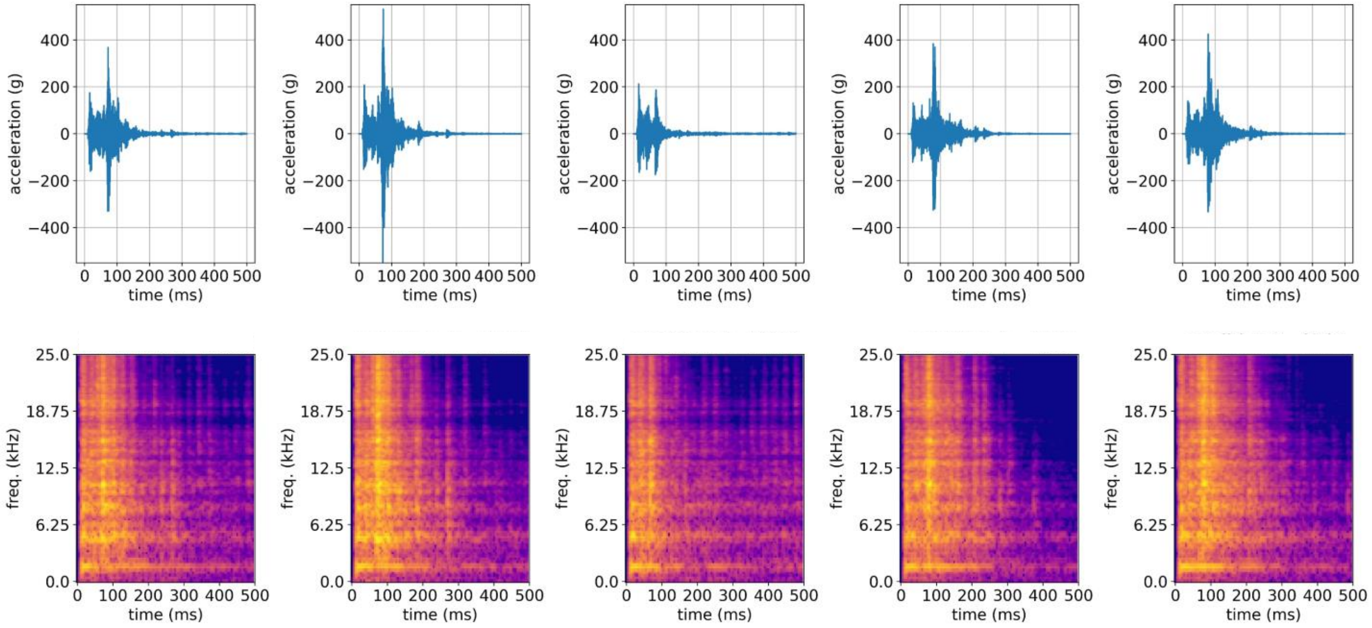
Spring condition has more impact than damper condition

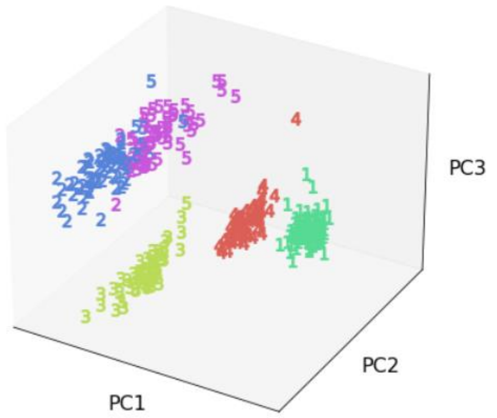
Fault Diagnostics using XAI

	Cluster #4	Cluster #3	Cluster #1	Cluster #2	Cluster #5
	nSnD	nSdD	hSnD	lSnD	lSdD

Vibration signals

Spectrogram





nS: normal spring tension
nD: normal damper viscosity
lS: low spring tension
dD: degraded damper viscosity
hS: high spring tension

Low spring cases:
no attributions in low frequency part

Conclusions and Outlooks

- Unsupervised fault detection and segmentation framework proposed and evaluated on a high-voltage circuit breaker dataset
- Assist domain experts with fault diagnostics, identifying potential fault types by XAI

- Future directions
  - Minimize number of sensor needed (Physics-informed)
  - Distinguishing between different severities of the same fault type
  - Transferability to different CBs (rating, operating mechanism…)

Questions

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