



# Enhancing Quench Detection in SRF Cavities at the European XFEL

## Machine Learning Approaches and Practical Challenges

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# The EuXFEL Overview

# The EuXFEL

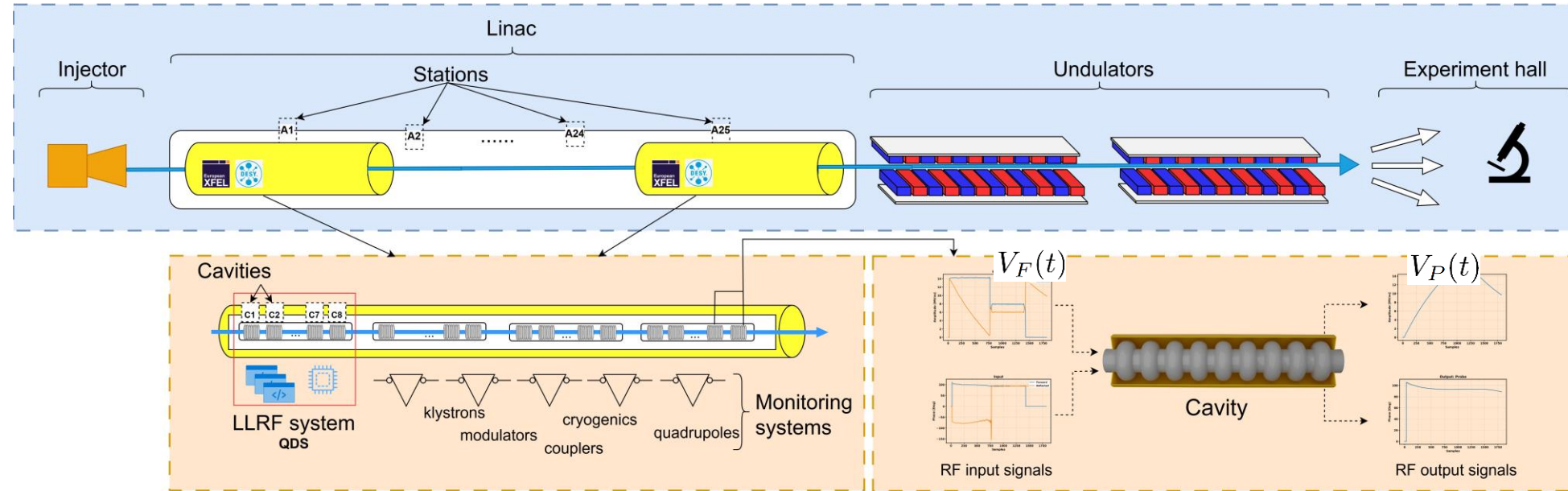
## In general



The course of the European XFEL

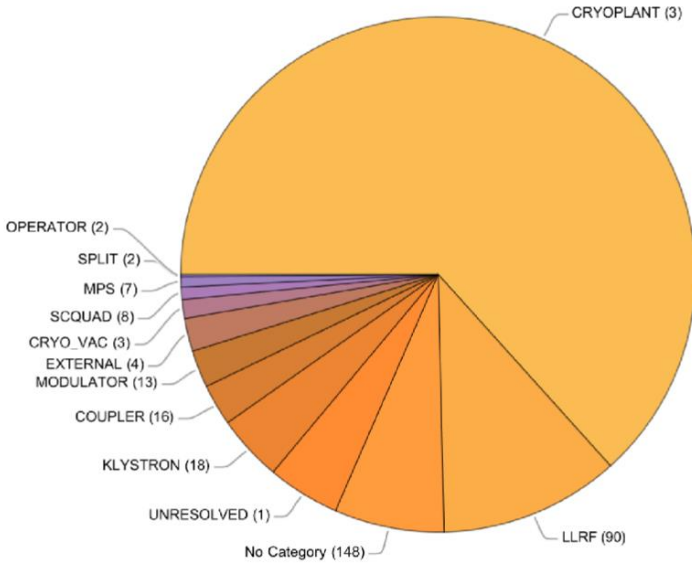
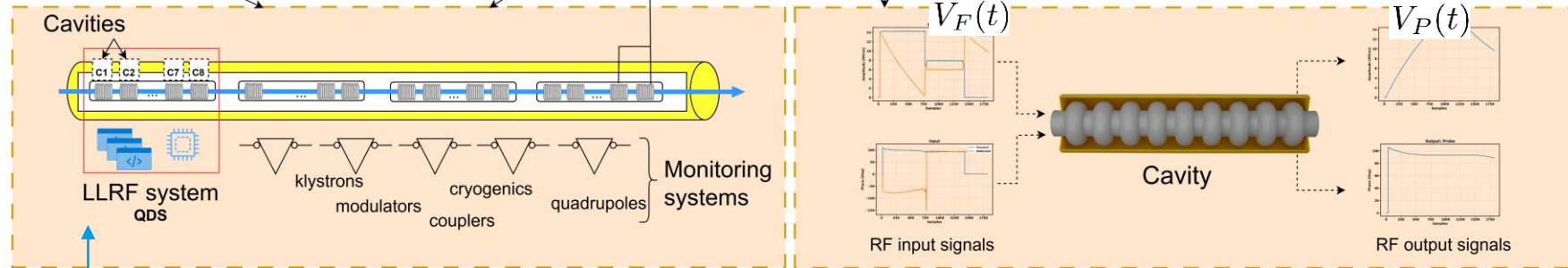
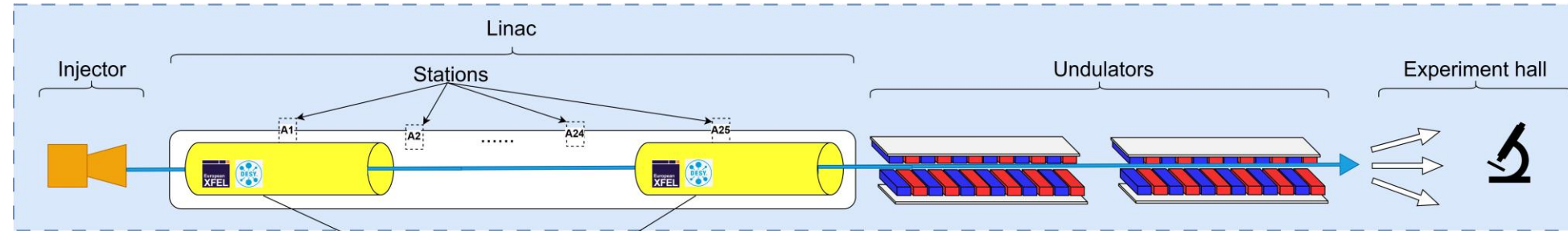
# The EuXFEL

## Linac and superconducting cavities



# The EuXFEL

## Linac and superconducting cavities



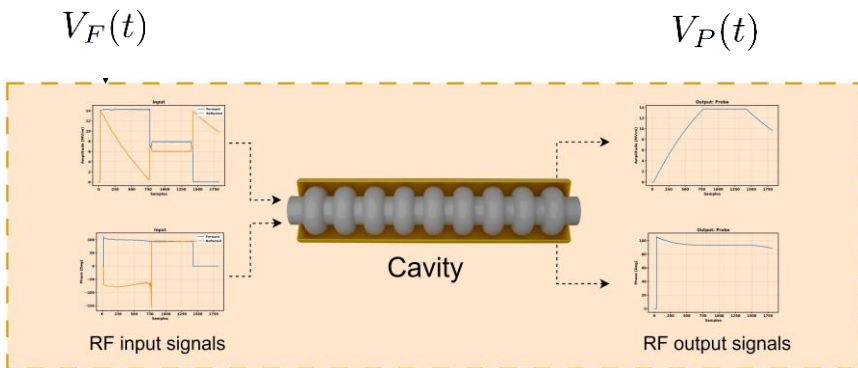
Distribution of event downtime (2023)

Anomaly Detection  
Quench Identification

# Anomaly Detection

# Anomaly Detection

## Model-based anomaly detection



Physical dynamics:

$$\begin{bmatrix} \dot{V}_{P,I}(t) \\ \dot{V}_{P,Q}(t) \end{bmatrix} = \begin{bmatrix} -\omega_{1/2} & -\Delta\omega(t) \\ \Delta\omega(t) & -\omega_{1/2} \end{bmatrix} \begin{bmatrix} V_{P,I}(t) \\ V_{P,Q}(t) \end{bmatrix} + 2\omega_{1/2} \begin{bmatrix} V_{F,I}(t) \\ V_{F,Q}(t) \end{bmatrix} - \omega_{1/2} \begin{bmatrix} V_{B,I}(t) \\ V_{B,Q}(t) \end{bmatrix}$$

$\omega_{1/2}$  : Half bandwidth  
 $\Delta\omega(t)$  : Detuning  
 $V_B$  : Beam field

Analytical redundancy:

$$r(t) = \frac{-\dot{V}_{P,I}(t) + \omega_{1/2} [-V_{P,I}(t) + 2V_{F,I}(t) - V_{B,I}(t)]}{V_{P,Q}(t)} - \frac{\dot{V}_{P,Q}(t) + \omega_{1/2} [V_{P,Q}(t) - 2V_{F,Q}(t) + V_{B,Q}(t)]}{V_{P,I}(t)}$$

GLR/Anomaly:

$$\text{GLR}(k) = \frac{K}{2} \left( \frac{1}{K} \sum_{i=k-K+1}^k r(i)^T \right) \sigma^{-1} \left( \frac{1}{K} \sum_{i=k-K+1}^k r(i) \right),$$

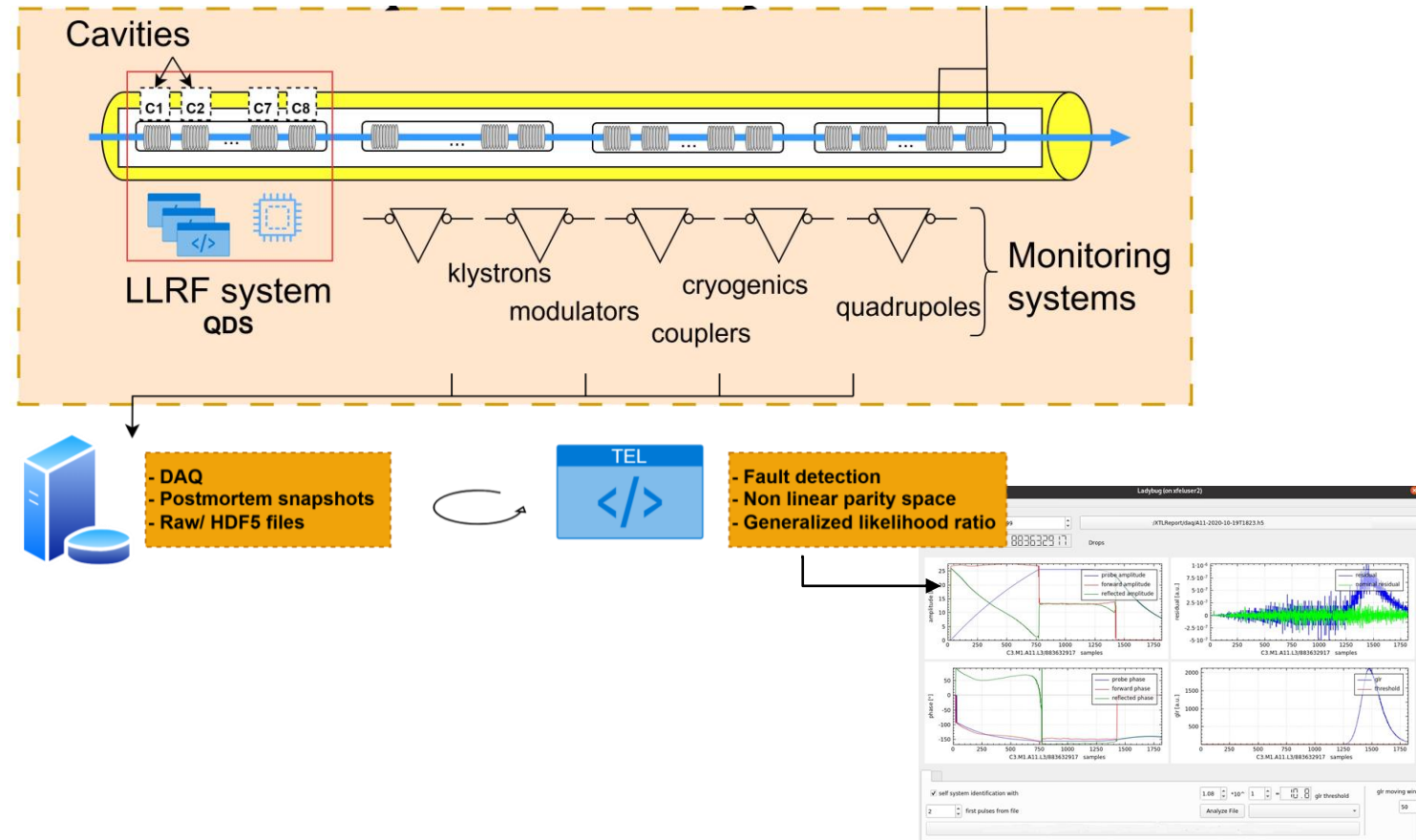
$K$  : Moving window  
 $\sigma$  : Variance  
 $T$  : Threshold

$$\text{Anomaly}_{\text{GLR}} = \begin{cases} 1, & \text{if } \exists k \text{ such that } \text{GLR}(k) > T, \\ 0, & \text{otherwise,} \end{cases}$$

# Anomaly Detection

## Deployment: Offline

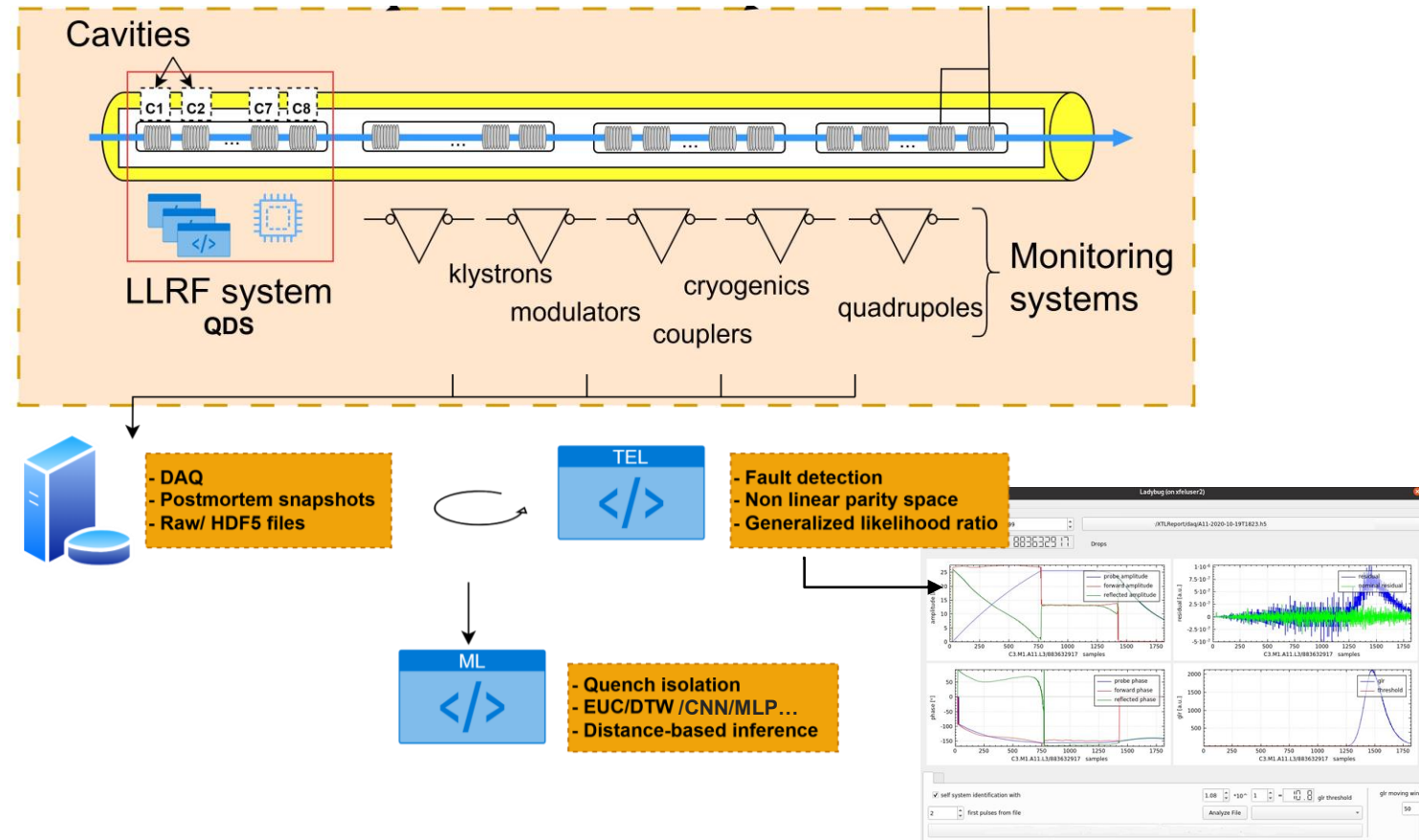
- 250 pulses (50 first nominal)
- RF signals sampled at 1 Mhz (1820 samples)
- Saved into hdf5 files, corresponding to station events
- Insights across different time scales



# Anomaly Detection

## Deployment: Offline

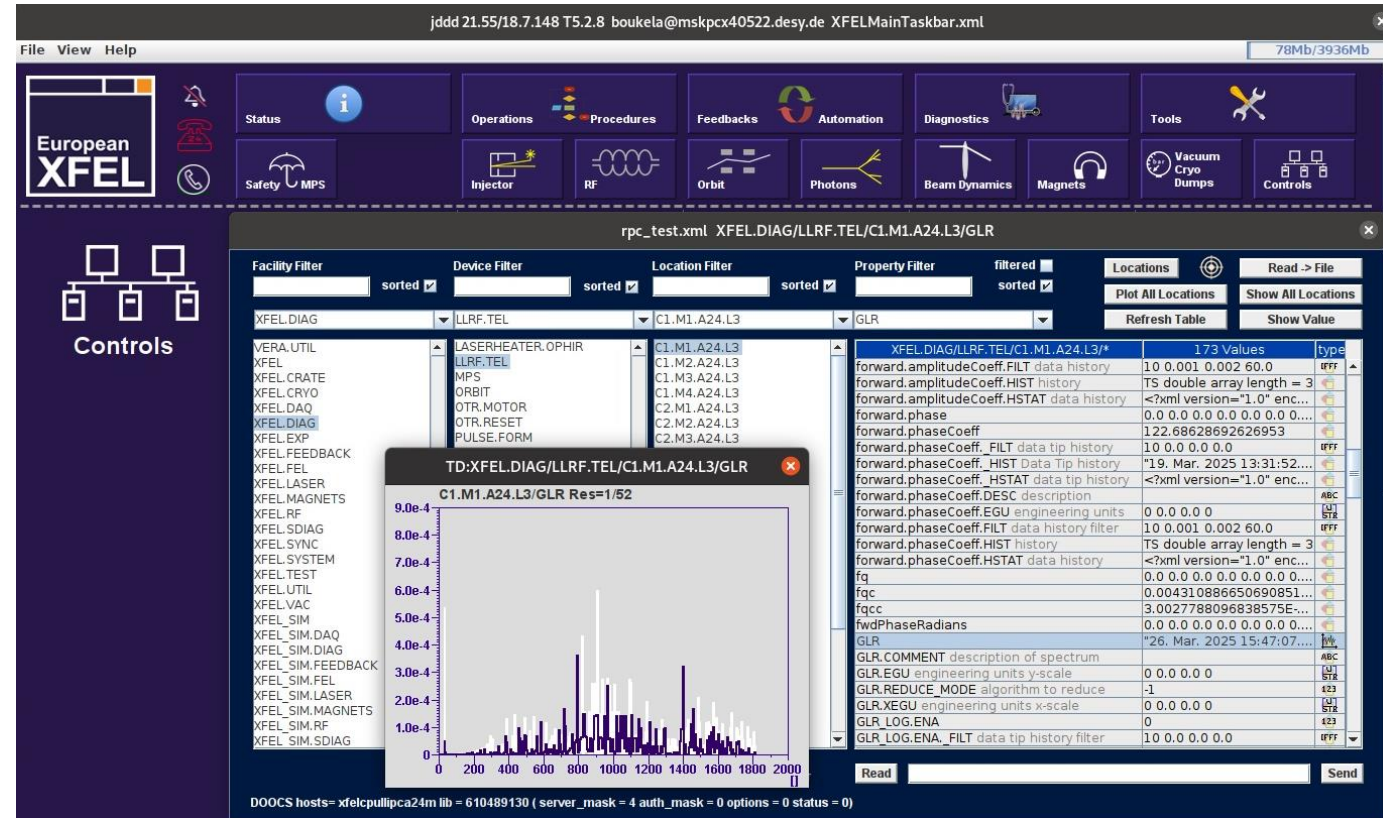
- 250 pulses (50 first nominal)
- RF signals sampled at 1 Mhz (1820 samples)
- Saved into hdf5 files, corresponding to station events
- Insights across different time scales
- Augmented with ML for anomaly identification



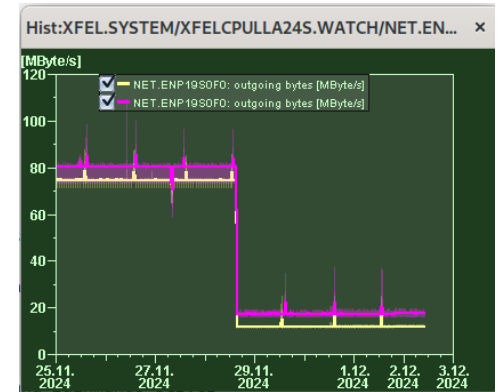
# Anomaly Detection

Deployment: Online | SW

- Two external CPUs are commissioned
- A24 as toy station
- Challenges:
  - Computing load on in-crate CPU
  - Bandwidth limitations, DAQ packet loss, had to shutdown some cavities
  - Getting the IQ components, data correction
  - Reliable beam information source (different station with a different timing)
  - Time-consuming go-to-production process



Outgoing traffic rises from 20 MB/s to 80 MB/s when anomaly detection is active

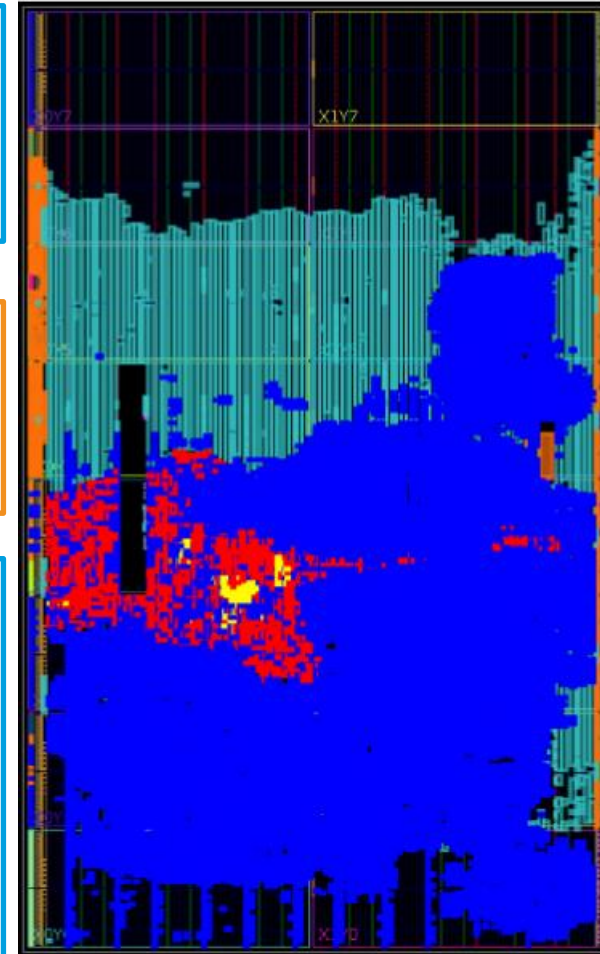
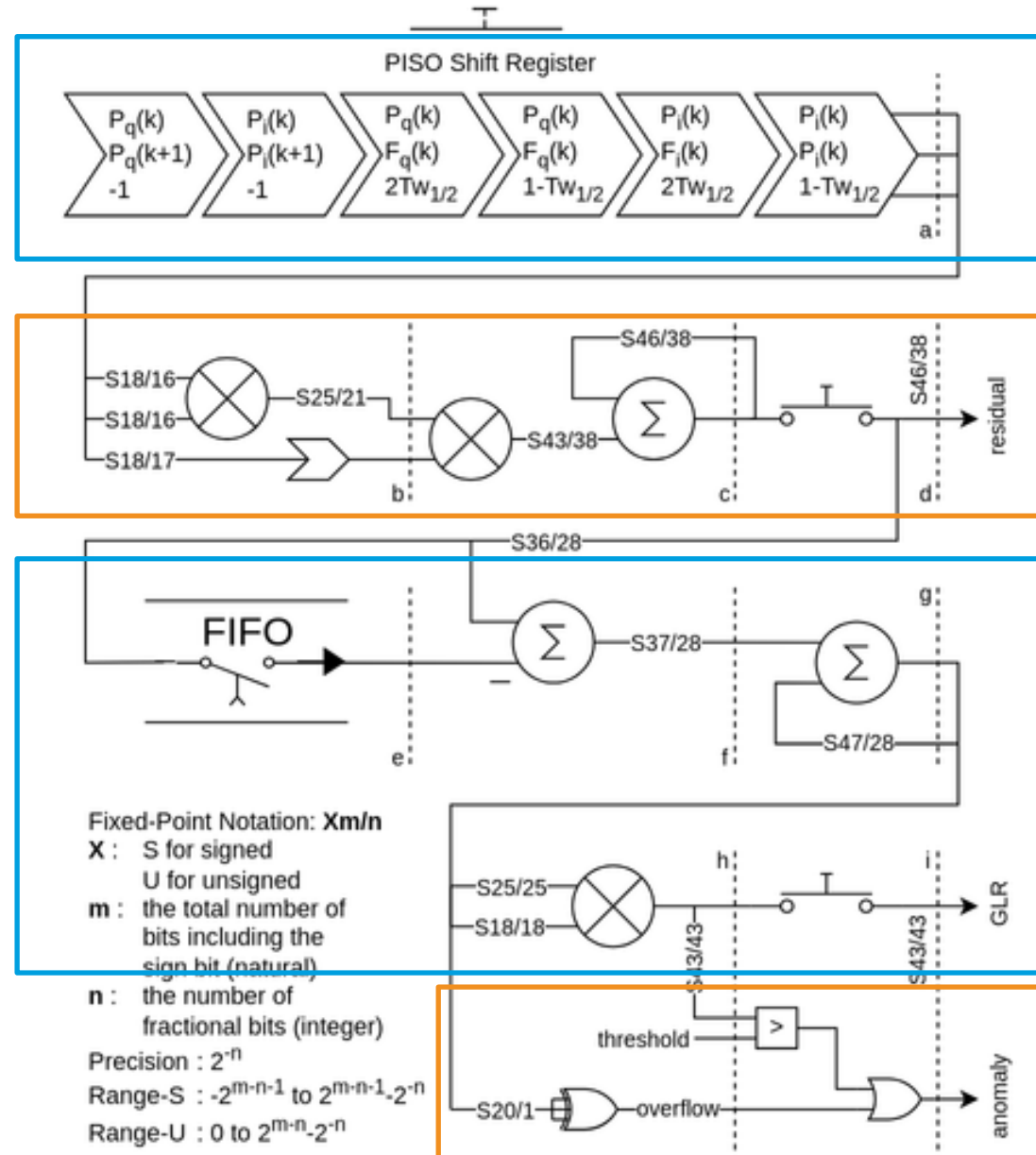


Courtesy: Nadeem Shehzad

# Anomaly Detection

## Deployment: Online | FW

- Implemented on tck7
- Application clock: 81.25 MHz
- Throughput: 1/7 clock cycles
- Latency: 9 clock cycles for residual, 12 clock cycles for GLR, ~50us for K=450
- Challenges :
  - Sufficient performance and throughput while minimalizing resources.
  - Co-simulation against software implementation using anomaly data that is captured from the machine



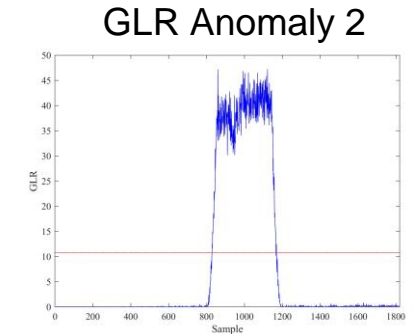
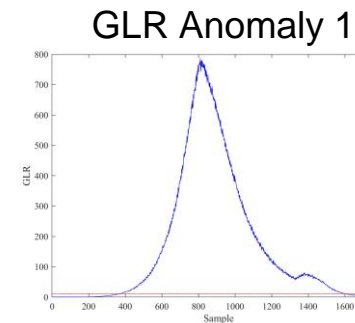
FPGA implementation layout (yellow: single cavity anomaly detection, red: anomaly detection for 15 cavities, blue: LLRF controller for 32 cavities)

Courtesy: Burak Dursun

# Anomaly Detection

## Data labeling

- Goal: streamline the process for the LLRF experts
- Faults distinguishable with the RF waveforms and GLR, helps with labeling
- Only anomalous pulses are retained for labeling
- QDS and AI findings are displayed
- Quenches (as identification enabled) are highlighted
- Toroid data plotted to help with the beam case
- New anomaly types are added



EVA (on xfeluser2)

Misc

Current station event

Read Data Ladybug Confluence

Event : 70 / 128  
File : /home/xfeloper/data/MGT/XTLReport/dag/A22-2024-04-04T2106.h5  
Exist in Nick's database: Yes  
number of pulse: 63

AI: Quench  
QDS: Quench  
Type: Tip

Root cause 1: [M1.C7, M2.C4, M2.C7, M3.C4, M3.C5, M3.C7]  
Root cause 2: C7.M3  
Category: LLRF  
SubCategory: QUENCH\_DETECT

bulk selection  
Start index: 0  
End index: 0  
Comment:

location	pid	AI	Label	Select	Con
13 C3.M1.A22.L3	1974964049	Other fault		<input type="checkbox"/>	nan
14 C3.M1.A22.L3	1974964050	Other fault		<input type="checkbox"/>	nan
15 C3.M1.A22.L3	1974964051	Other fault		<input type="checkbox"/>	nan
16 C3.M2.A22.L3	1974964049	Other fault		<input type="checkbox"/>	nan
17 C3.M2.A22.L3	1974964050	Other fault		<input type="checkbox"/>	nan
18 C3.M2.A22.L3	1974964051	Other fault		<input type="checkbox"/>	nan
19 C4.M2.A22.L3	1974964049	Other fault		<input type="checkbox"/>	nan
20 C4.M2.A22.L3	1974964050	Other fault		<input type="checkbox"/>	nan
21 C4.M2.A22.L3	1974964051	Other fault		<input type="checkbox"/>	nan
22 C4.M3.A22.L3	1974964048	Poss Quench		<input type="checkbox"/>	nan
23 C4.M3.A22.L3	1974964049	Quench		<input checked="" type="checkbox"/>	nan
24 C4.M3.A22.L3	1974964050	Poss Quench		<input type="checkbox"/>	nan
25 C4.M3.A22.L3	1974964051	Quench		<input type="checkbox"/>	nan
26 C4.M4.A22.L3	1974964049	Other fault		<input type="checkbox"/>	nan
27 C4.M4.A22.L3	1974964050	Other fault		<input type="checkbox"/>	nan

RF signals (Amplitude) Pulse : 205  
RF signals (Phase) Pulse : 205  
GLR Pulse : 205  
Residual Pulse : 205  
Toroid Pulse : 205  
Toroid (Nominal) Pulse : 205

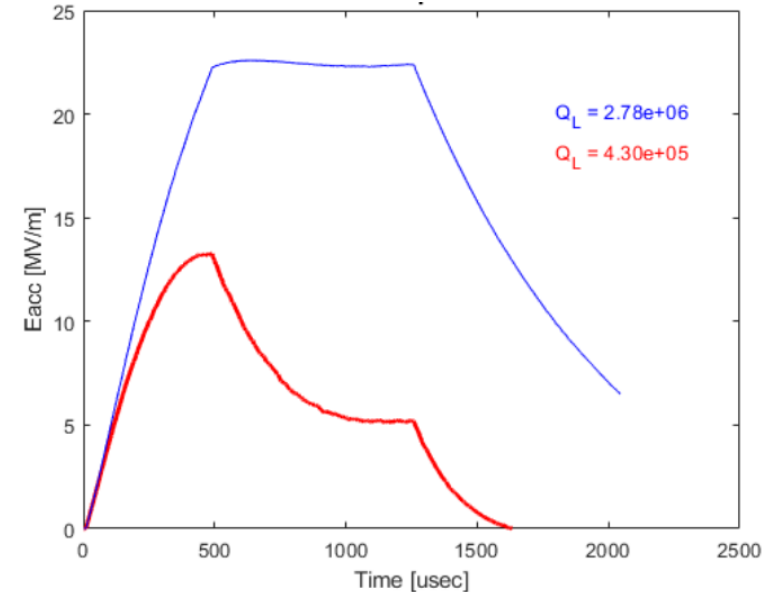
Interlock (no RF)  
Trace discontinuity  
Jump in probe  
Trace noise  
Trace misalignment  
Pulse cut  
Beam + Pulse cut  
Beam  
Poss miss signal  
Miss signal  
Quench  
Other Fault  
Undo/Clear  
Save

# ML for Quench Detection

# ML for Quench Detection

## Current solution

- The SRFCs are characterized by their quality factor (QL), which is an indicator of the field coupling and power dissipation
- Currently, the quenches are detected with the QDS by monitoring and setting a threshold on the QL
- QL is computed for every pulse and compared to a running average from the previous 100 pulses
- The QDS is however not robust enough
- A new ML-powered approach is developed



$$\text{Loaded } Q_L = \frac{1}{\frac{1}{Q_{ext}} + \frac{1}{Q_0}} \text{ Unloaded}$$

External

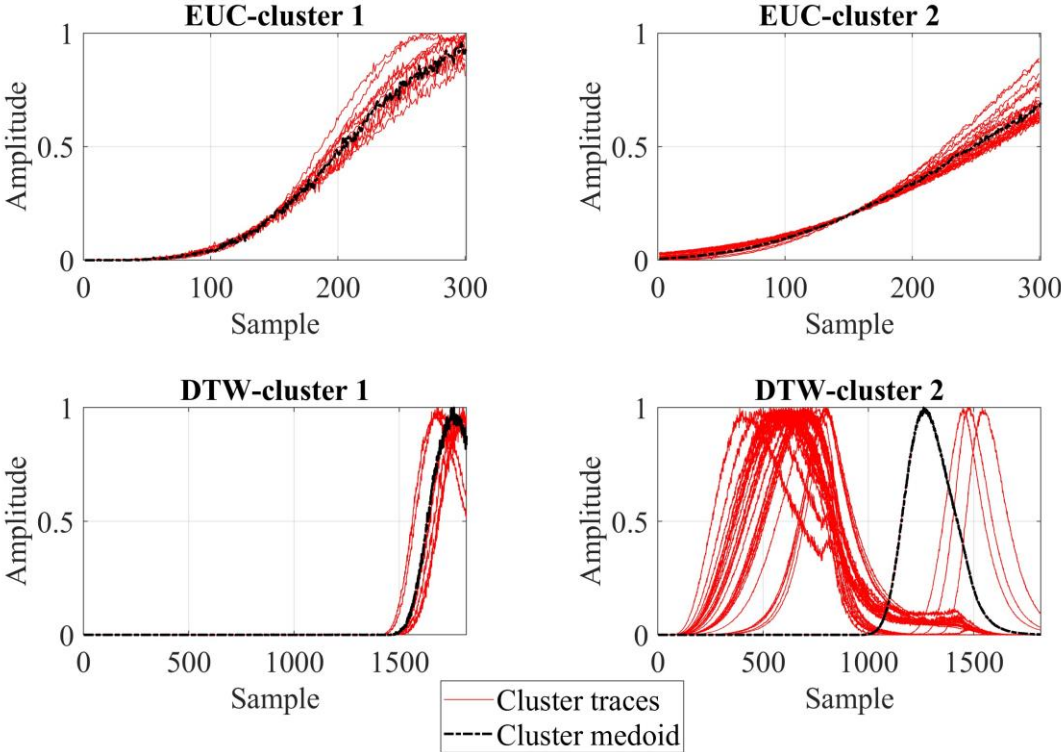
$$Q_0 \gg Q_{ext} \rightarrow Q_L \approx Q_{ext}$$

# ML for Quench Detection

## Clustering –based

K-medoids with two similarity measures

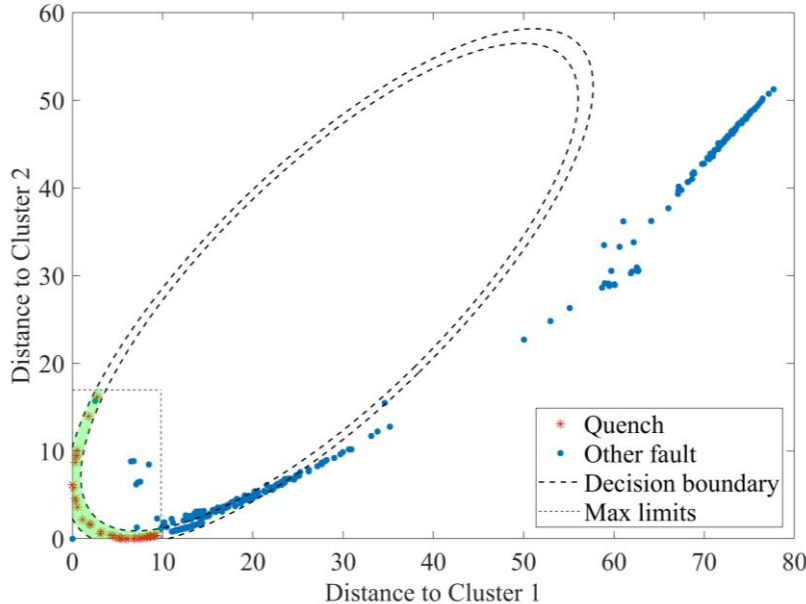
$$\text{DTW}(x_1, x_2) = \arg \min_{i,j} \sum \text{dist}(x_1^i, x_2^j) \quad \text{EUC}(x_1, x_2) = \sqrt{\sum_{i=1}^n (x_1^i - x_2^i)^2}$$



# ML for Quench Detection

## Clustering –based

- Inference in distance space
- Fitting different based on the similarity measure
- Thresholds & decision boundaries
- EUC



$$\mathcal{Q}_{EUC} = \{q \mid q \in \mathbb{R}^d, \\ \text{EUC}(q, m_j) < \max(\text{EUC}(x_i, m_j)) + \epsilon, \\ (r^i)^2 < \mathcal{H}_{EUC}(\text{EUC}(q, m_1), \text{EUC}(q, m_2)) < (r^o)^2 \\ \forall x_i \in X, \forall m_j \in M\},$$

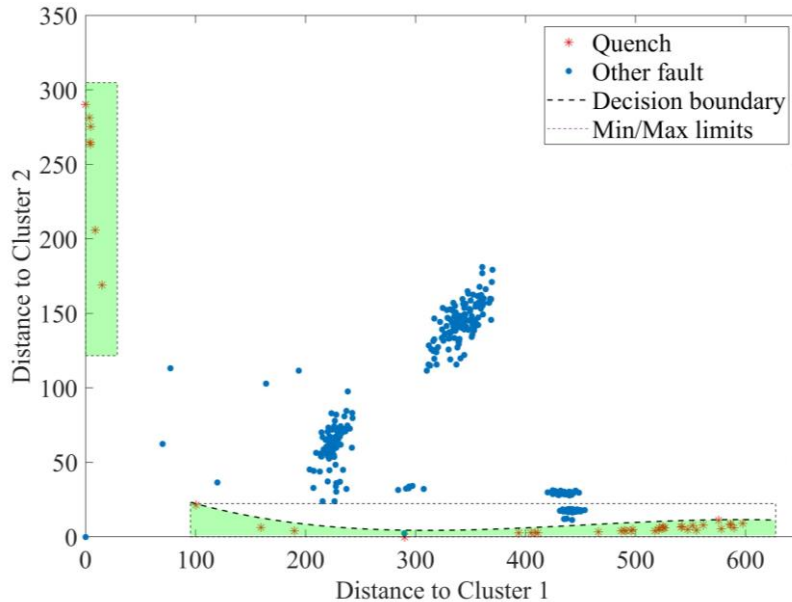
$$\text{Inference}_{EUC}(g) = \begin{cases} \text{Quench}, & \text{if } g \in \mathcal{Q}_{EUC} \\ \text{Other fault}, & \text{otherwise.} \end{cases}$$

$$\mathcal{H}_{EUC}(s_1, s_2) = \frac{\left( (s_1 - s_1^0) \cos(\phi) - (s_2 - s_2^0) \sin(\phi) \right)^2}{a^2} + \\ \frac{\left( (s_1 - s_1^0) \sin(\phi) + (s_2 - s_2^0) \cos(\phi) \right)^2}{b^2} = r^2.$$

# Quench detection

## ML-based quench identification

- Inference in distance space
- Fitting different based on the similarity measure
- Thresholds & decision boundaries
- DTW



$$\mathcal{H}_{DTW}(s_1) = as_1^3 + bs_1^2 + cs_1 + f$$

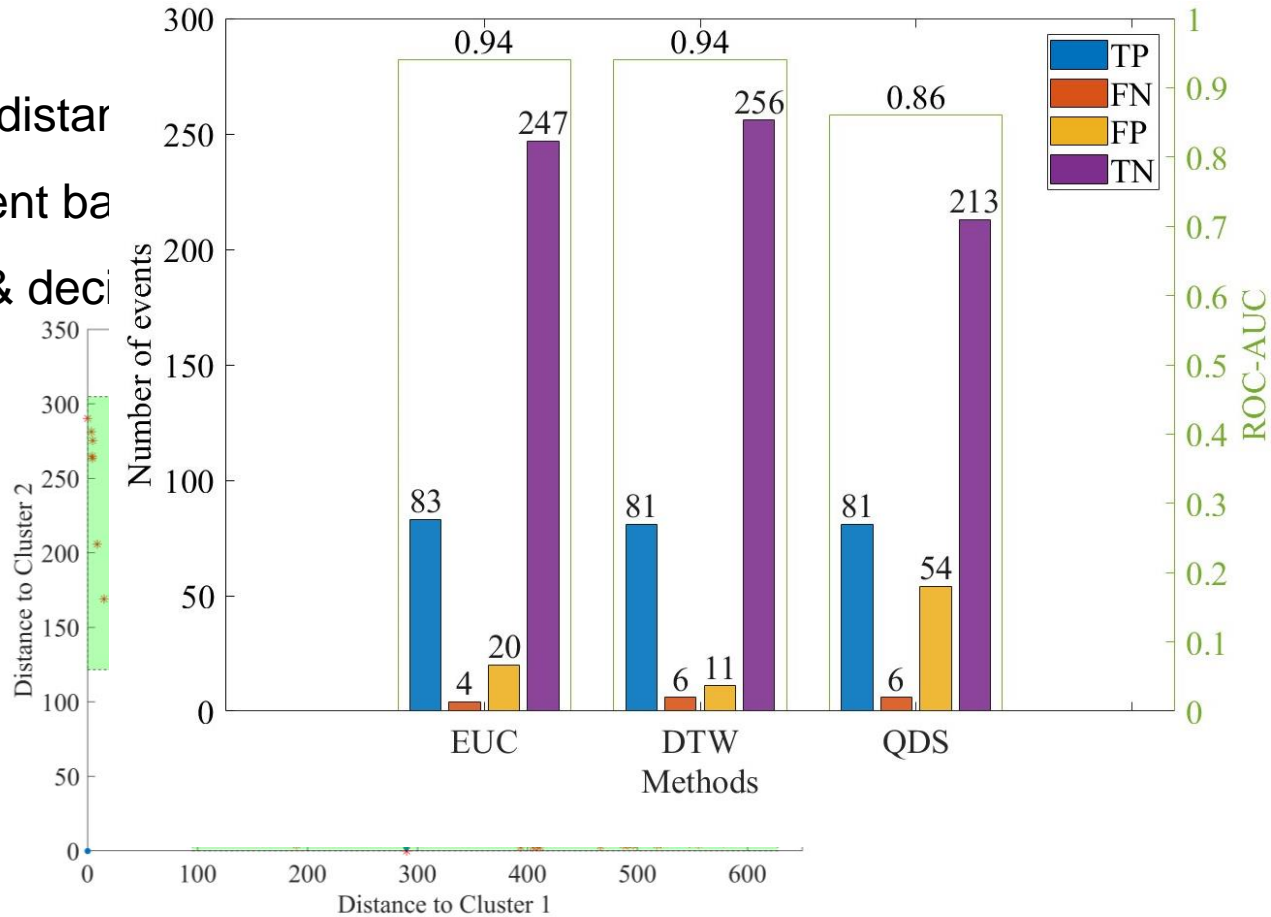
$$\mathcal{Q}_{DTW} = \{q \mid q \in \mathbb{R}^d, \\ DTW(q, m_j) < \max(DTW(x_i, m_j)) + \epsilon, \\ DTW(q, m_j) > \min(DTW(x_i, m_j)) - \epsilon, \\ DTW(q, m_2) < \mathcal{H}_{DTW}(DTW(q, m_1)), \\ \forall x_i \in X, \forall m_j \in M\},$$

$$\text{Inference}_{DTW}(g) = \begin{cases} \text{Quench}, & \text{if } g \in \mathcal{Q}_{DTW} \\ \text{Other fault}, & \text{otherwise.} \end{cases}$$

# Quench detection

## ML-based quench identification

- Inference in distar
- Fitting different ba
- Thresholds & deci
- DTW



$\{$   
 $< \max(\text{DTW}(x_i, m_j)) + \epsilon,$   
 $> \min(\text{DTW}(x_i, m_j)) - \epsilon,$   
 $< \mathcal{H}_{DTW}(\text{DTW}(q, m_1)),$   
 $i \in M\},$

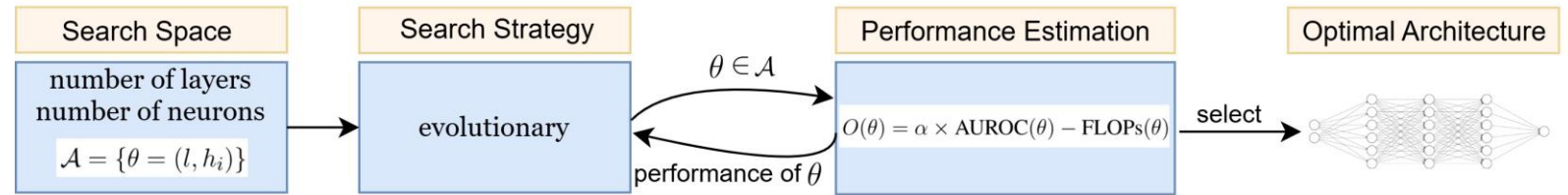
Quench, if  $g \in \mathcal{Q}_{DTW}$   
 Other fault, otherwise.

$$\mathcal{H}_{DTW}(s_1) = as_1^3 + bs_1^2 + cs_1 + f$$

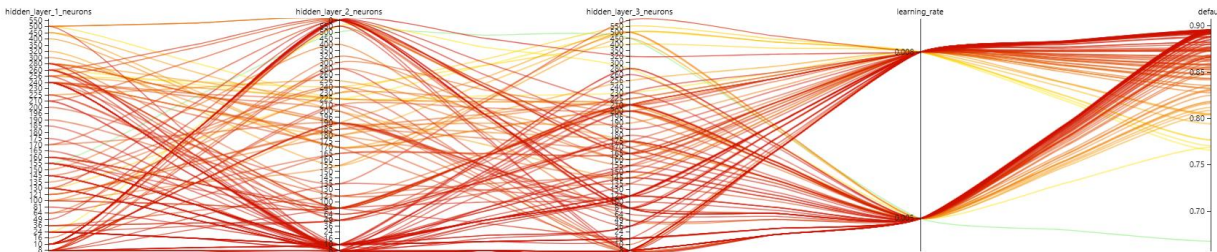
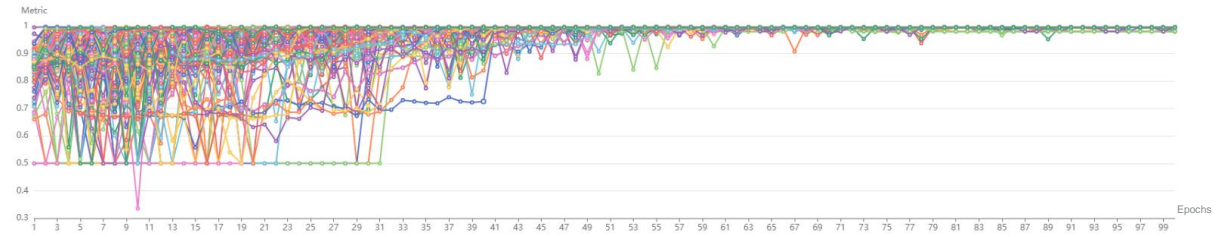
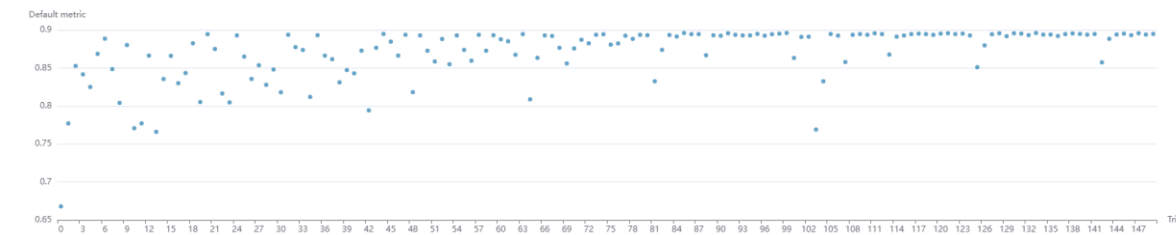
# ML for Quench Detection

## NAS for lightweight models

- Multi-objective hardware-agnostic optimization



Model	TPR	FPR	AUROC	FLOPs / Size
NAS-MLP <sub>EUC</sub>	0.9861	0.0049	0.9950	11367/10847
MAN-MLP <sub>EUC</sub>	0.9861	0.0055	0.9903	38305/37537
NAS-MLP <sub>DTW</sub>	0.9583	0.0259	0.9662	241/193
MAN-MLP <sub>DTW</sub>	0.9583	0.0257	0.9663	551/471

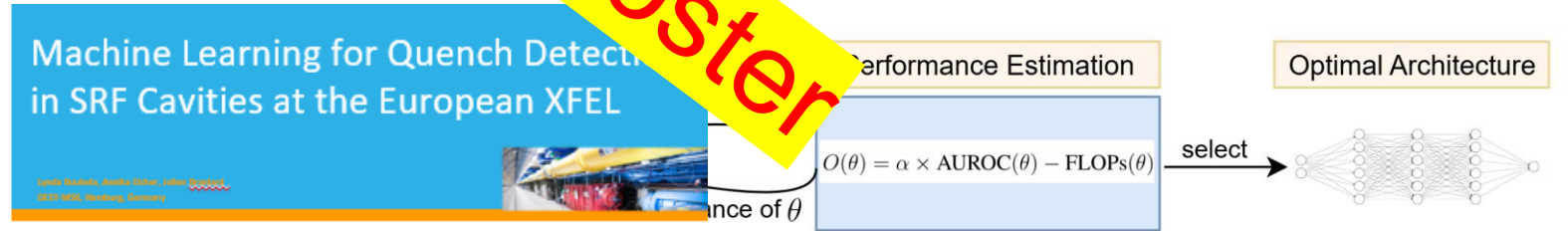


# ML for Quench Detection

## NAS for lightweight models

- Multi-objective hardware-agnostic optimization

Poster



**Machine Learning for Quench Detection in SRF Cavities at the European XFEL**

Lynda Boukela, Malapa Malapa, 2025, 2025-04-08, 2025-04-11, CERN

**1. Study**

Identifying quenching events within an accelerator superconducting cavity structure, which can cause significant loss of superconductivity, is a significant challenge. When operated for high-current applications, these cavities are often subjected to high electric and magnetic fields, which can lead to the formation of localized hotspots through the bulk material. This paper presents the physical model and the machine learning approach to detect quenching events in SRF cavities. The proposed model is based on the physical model of the cavity and the machine learning approach to detect quenching events in SRF cavities. The proposed model is based on the physical model of the cavity and the machine learning approach to detect quenching events in SRF cavities.

**2. Context**

- Accelerator cavities are vital for accelerating the ultra-relativistic particles in accelerators such as synchrotrons.
- SRF is the largest particle accelerator for high-energy physics.
- SRF cavities are used to accelerate particles to high energies up to 10 GeV and provide high-current beams for various applications.
- Various anomalies occur due to the internal functioning of the cavities, which are often unexplained.
- Quenching is a loss of an SRF's superconductivity and thus an operational interruption of a cavity's performance. It can be detected by changes in the magnetic signals and noise in the beam's position.
- Quench detection is of increasing importance as well as the availability of the facility's lightweight and well-performing models are required given the real-time constraints.

**3. Quench detection system**

- The SRF cavities are divided into three parts: the input, the middle, and the output.
- Currently, the cavities are monitored by the SRF monitoring and control system (SRF-MCS).
- The SRF-MCS is a complex system that monitors the cavities and provides real-time data for the SRF-MCS.
- The SRF-MCS is a complex system that monitors the cavities and provides real-time data for the SRF-MCS.
- The SRF-MCS is a complex system that monitors the cavities and provides real-time data for the SRF-MCS.

**4. Anomaly detection**

The SRF-MCS is a complex system that monitors the cavities and provides real-time data for the SRF-MCS. The SRF-MCS is a complex system that monitors the cavities and provides real-time data for the SRF-MCS. The SRF-MCS is a complex system that monitors the cavities and provides real-time data for the SRF-MCS.

**5. ML for quench identification**

- Deep learning.
- A machine learning model of the cavities' behavior is trained on the SRF-MCS data.
- The machine learning model is used to detect the data, with a number of layers, a number of nodes, and a number of nodes.
- The machine learning model is used to detect the data, with a number of layers, a number of nodes, and a number of nodes.

**6. NAS for lightweight models**

The machine learning model is used to detect the data, with a number of layers, a number of nodes, and a number of nodes. The machine learning model is used to detect the data, with a number of layers, a number of nodes, and a number of nodes.

**7. Streamlining the data labeling process**

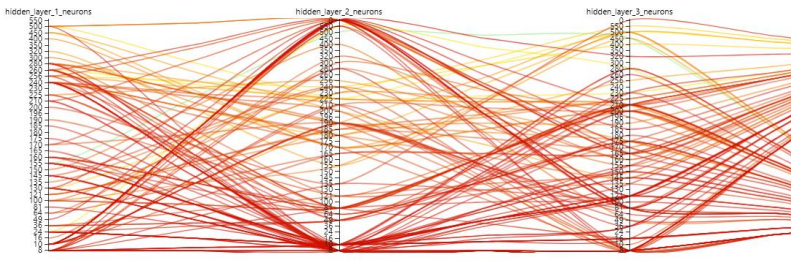
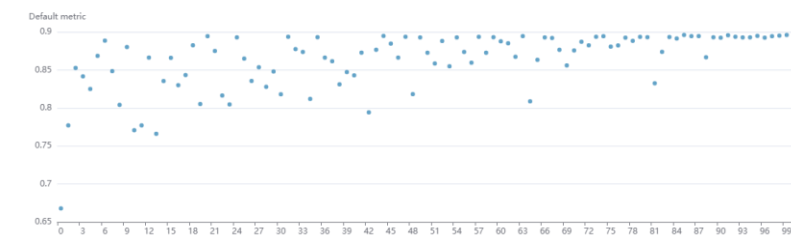
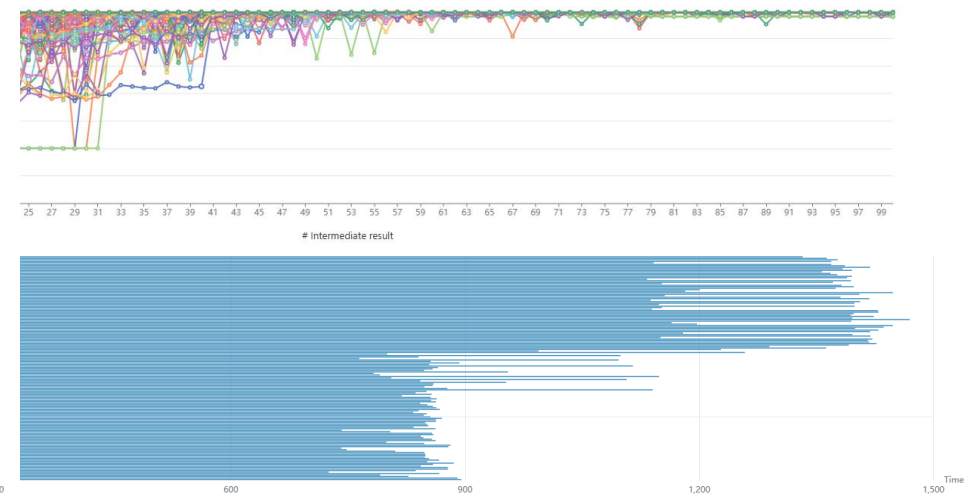
The machine learning model is used to detect the data, with a number of layers, a number of nodes, and a number of nodes. The machine learning model is used to detect the data, with a number of layers, a number of nodes, and a number of nodes.

**References**

Boukela, Lynda, Malapa, Malapa, & C. "A Two-Stage Machine Learning-Based Approach for Quench Identification at the European XFEL." In 2025 IEEE International Symposium on Applied Artificial Intelligence (IASI), 2025.

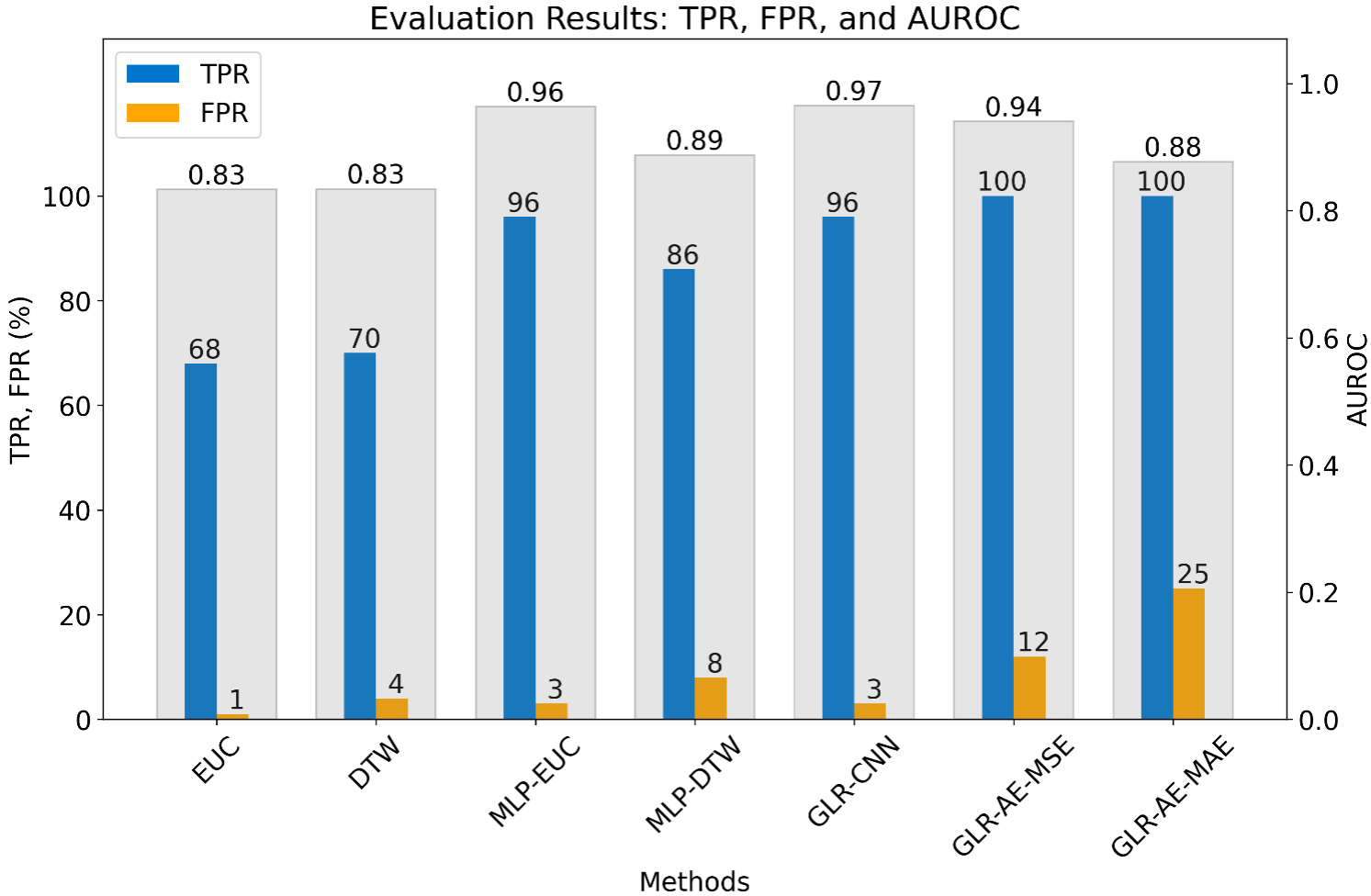
DESY, HELMHOLTZ AI, ARTIFICIAL INTELLIGENCE COORDINATION UNIT, EUROPEAN XFEL

FLOPs / Size
11367/10847
38305/37537
241/193
551/471



# ML for Quench Detection

NN - based



# Summary

# Summary

## And outlook

- Expensive into-production deployment process
- Promissig results
- Laborious data labeling process, but can be further streamlined
- More anomalies to detect

# Thank you

## Contact

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