Enhancing Quench Detection in SRF Cavities at the European XFEL

Machine Learning Approaches and Practical Challenges

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HELMHOLTZ RESEARCH FOR GRAND CHALLENGES

DESY.

Outline

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02 Anomaly Detection
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- Deployment: Offline | Online
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- NN-based

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The EuXFEL Overview

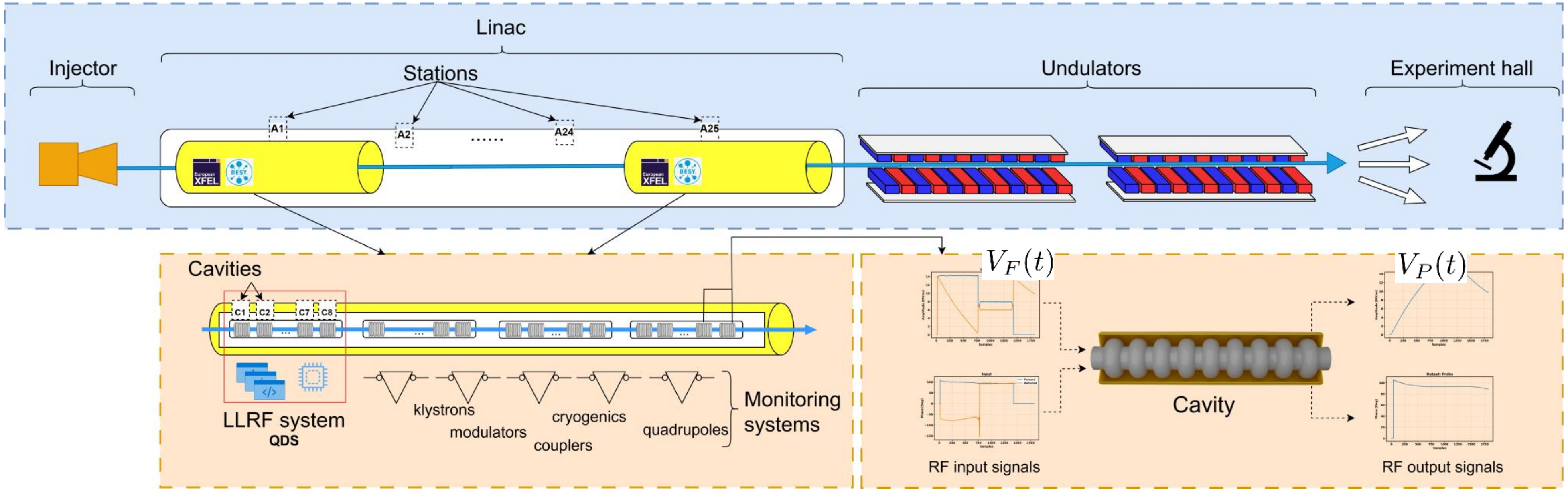
The EuXFEL

In general

The course of the European XFEL

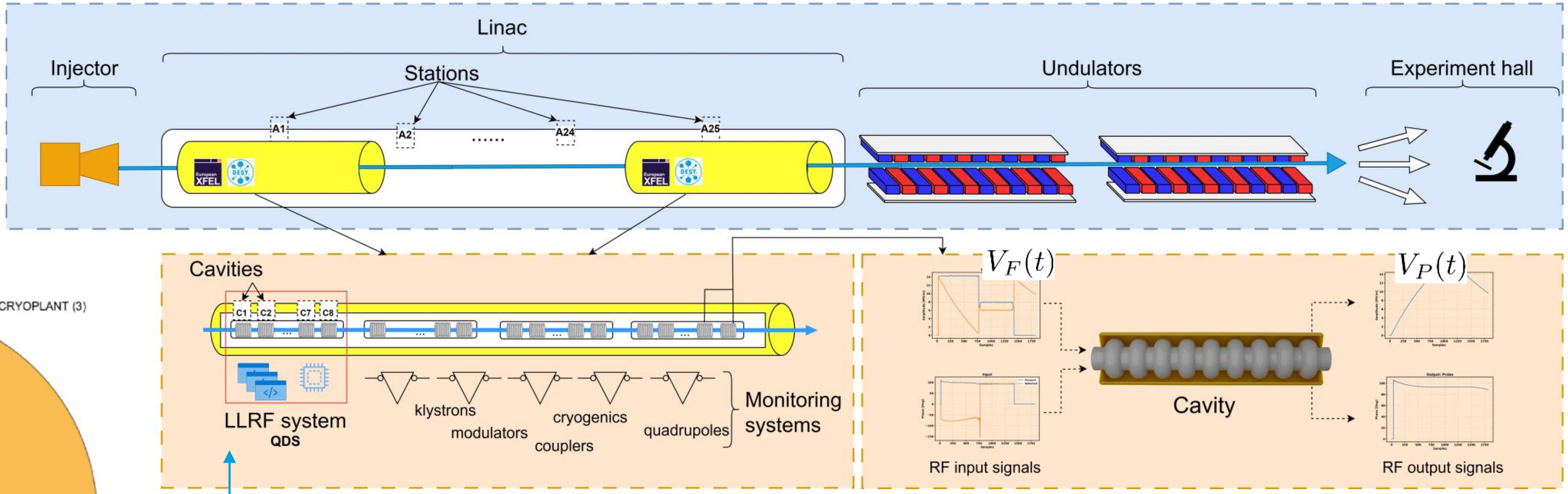
The EuXFEL

Linac and superconducting cavities



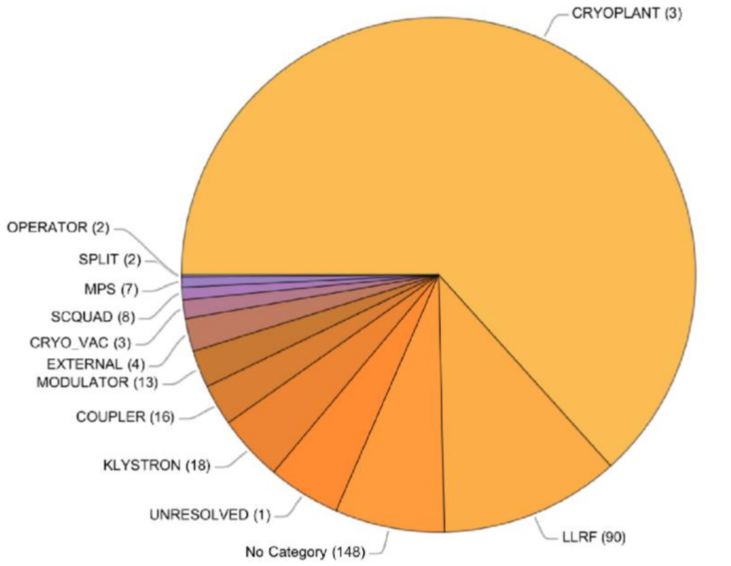
The EuXFEL

Linac and superconducting cavities



Anomaly Detection

Quench Identification



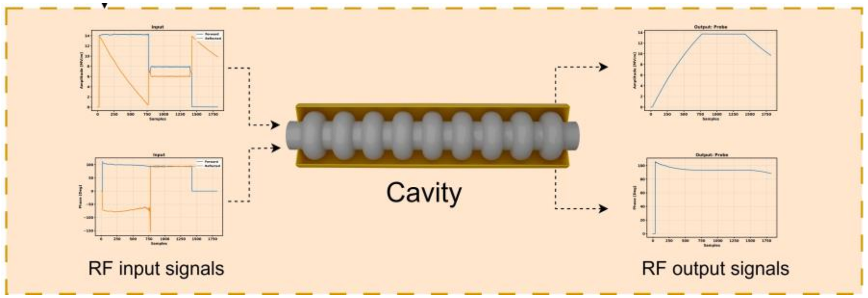
Distribution of event downtime (2023)

Anomaly Detection

Anomaly Detection

Model-based anomaly detection

$V_F(t)$ $V_P(t)$



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:

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

GLR/Anomaly:

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

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

K : Moving window

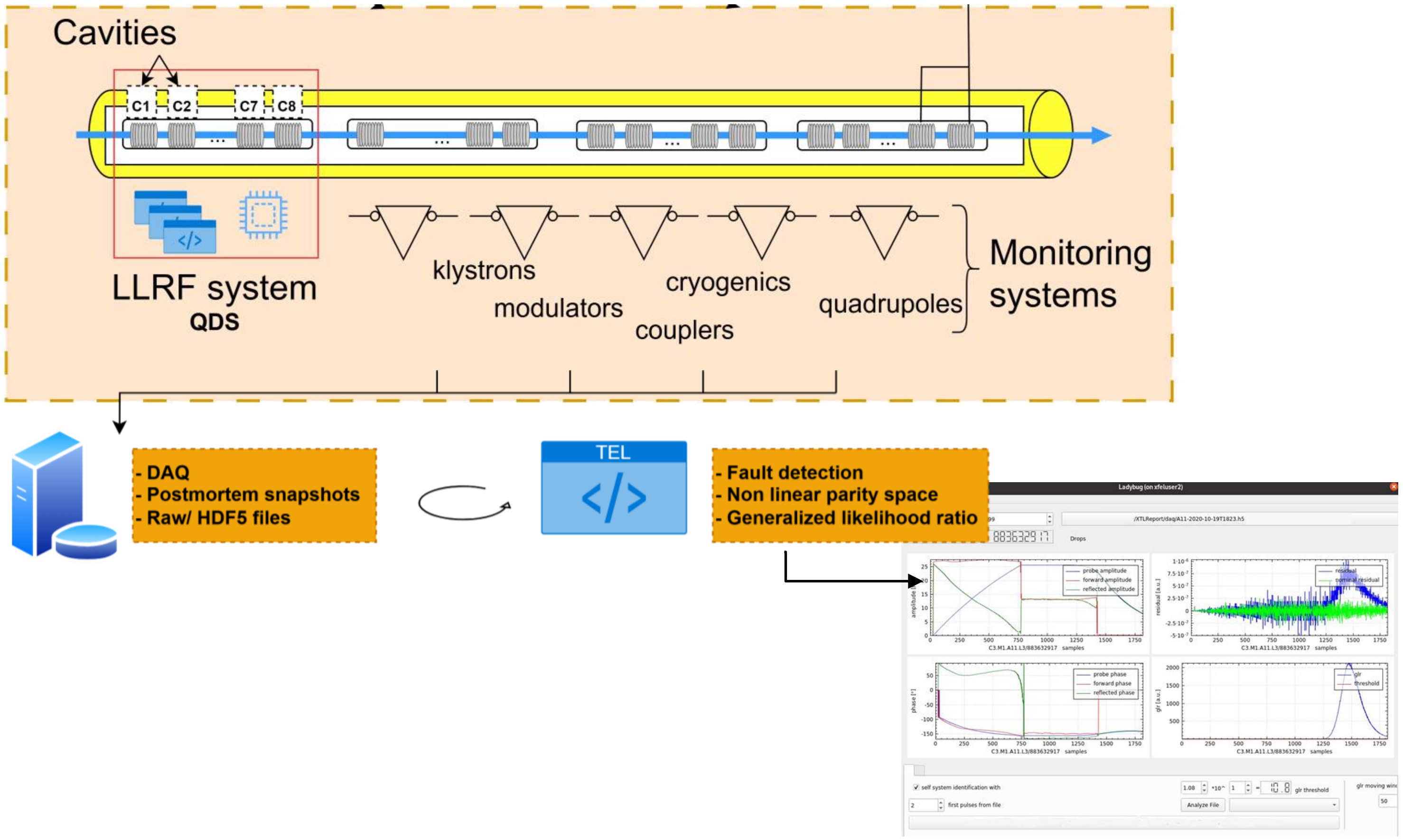
σ : Variance

T : Threshold

Anomaly Detection

Deployment: Offline

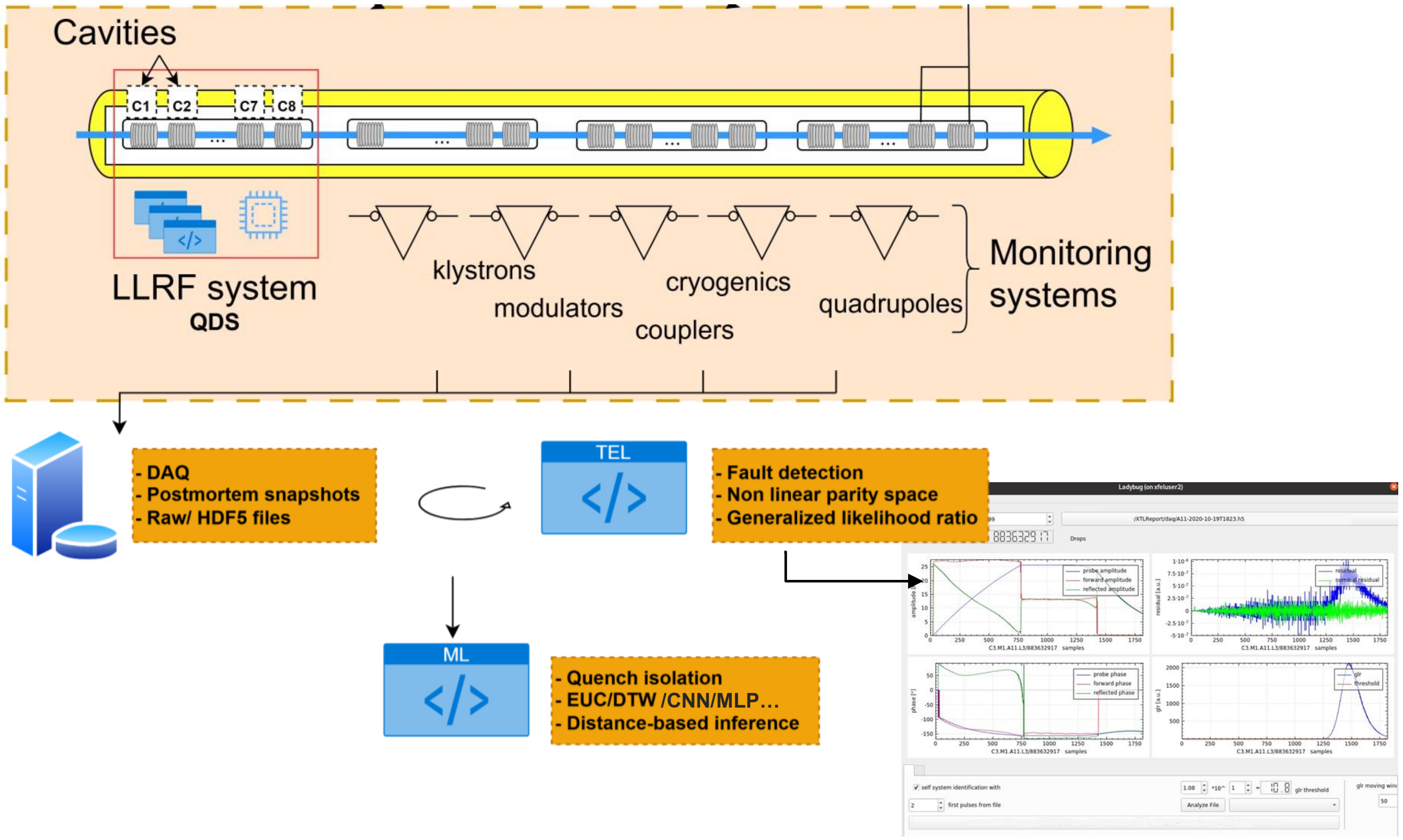
- 250 pulses (50 first nominal)
- RF signals sampled at 1 Mhz (1820 samples)
- Saved into hdf5 files, corresponding to station events
- Insights across different time scales



Anomaly Detection

Deployment: Offline

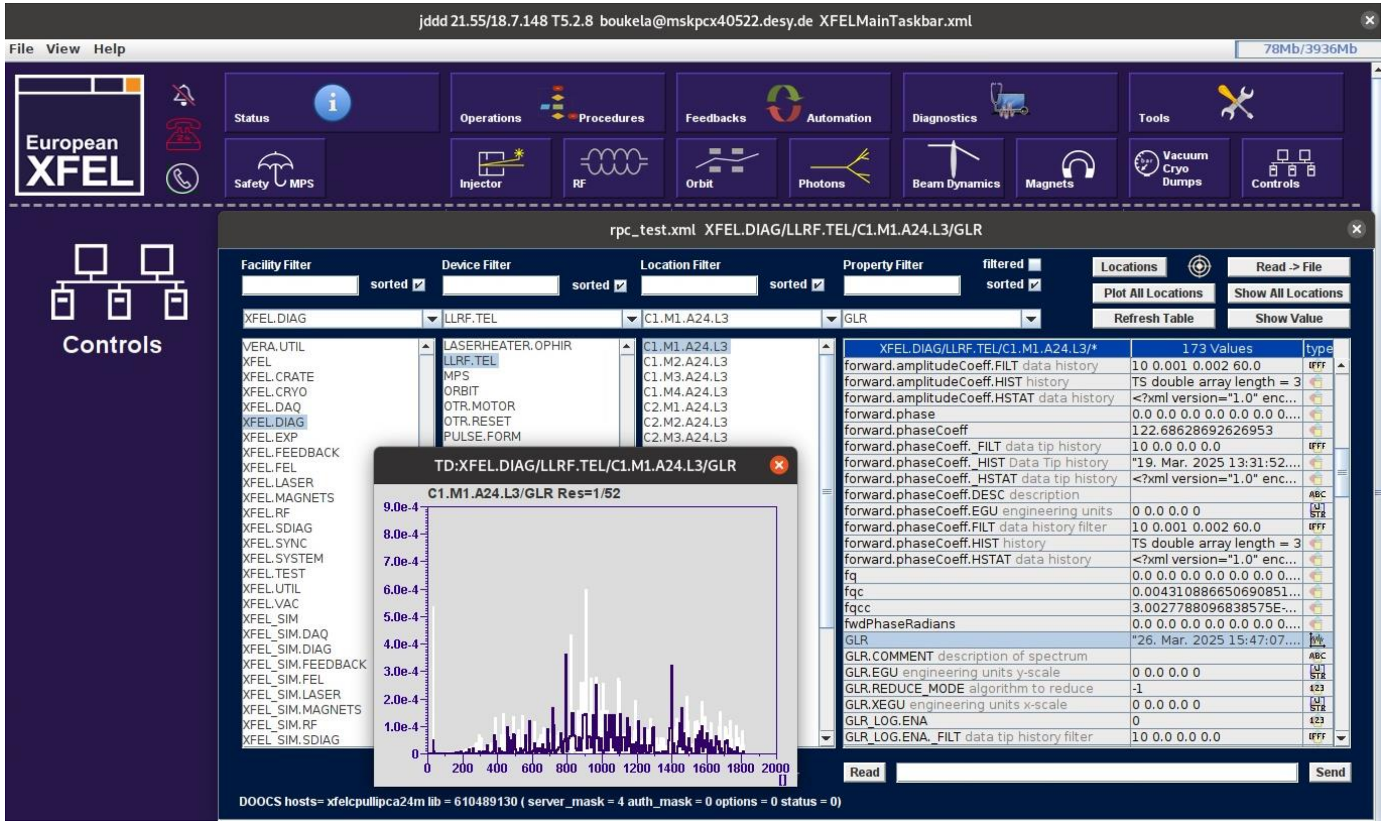
- 250 pulses (50 first nominal)
- RF signals sampled at 1 Mhz (1820 samples)
- Saved into hdf5 files, corresponding to station events
- Insights across different time scales
- Augmented with ML for anomaly identification



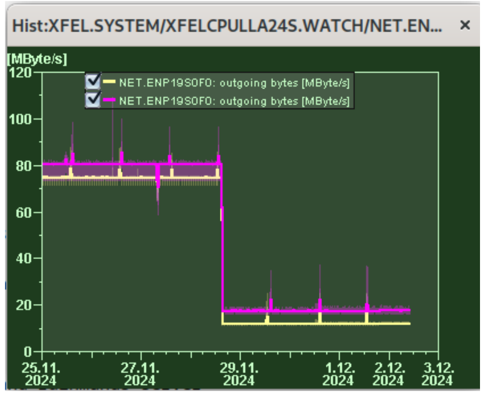
Anomaly Detection

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

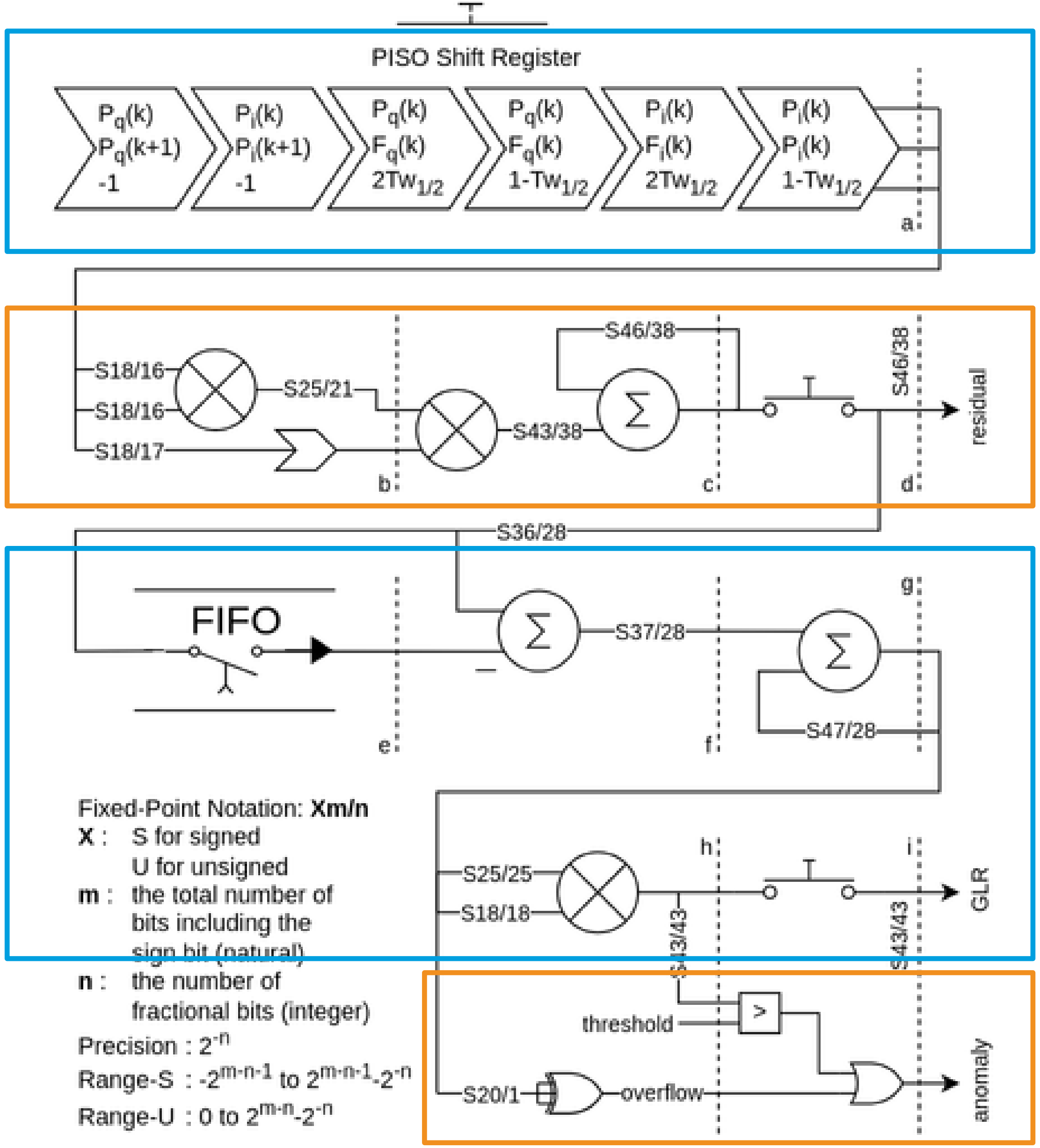


Courtesy: Nadeem Shehzad

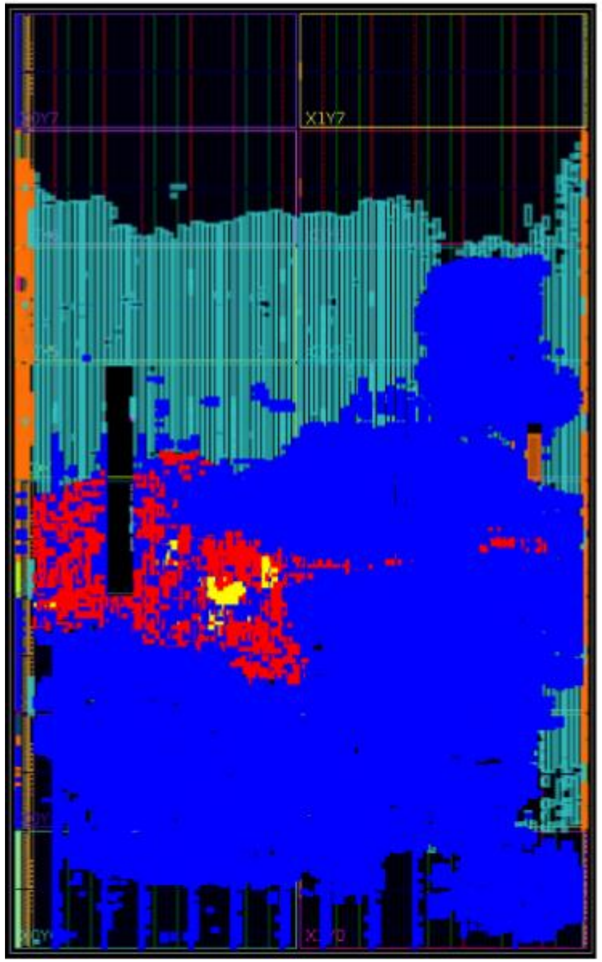
Anomaly Detection

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



Courtesy: Burak Dursun



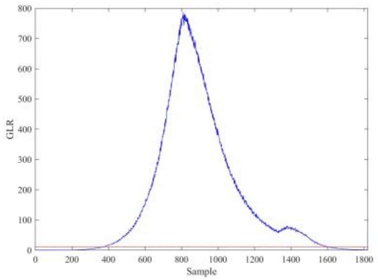
FPGA implementation layout (yellow: single cavity anomaly detection, red: anomaly detection for 15 cavities, blue: LLRF controller for 32 cavities)

Anomaly Detection

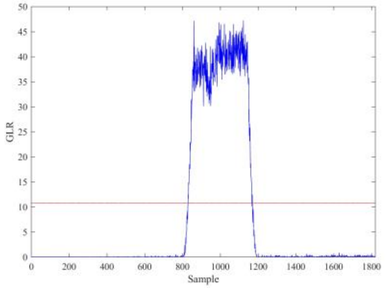
Data labeling

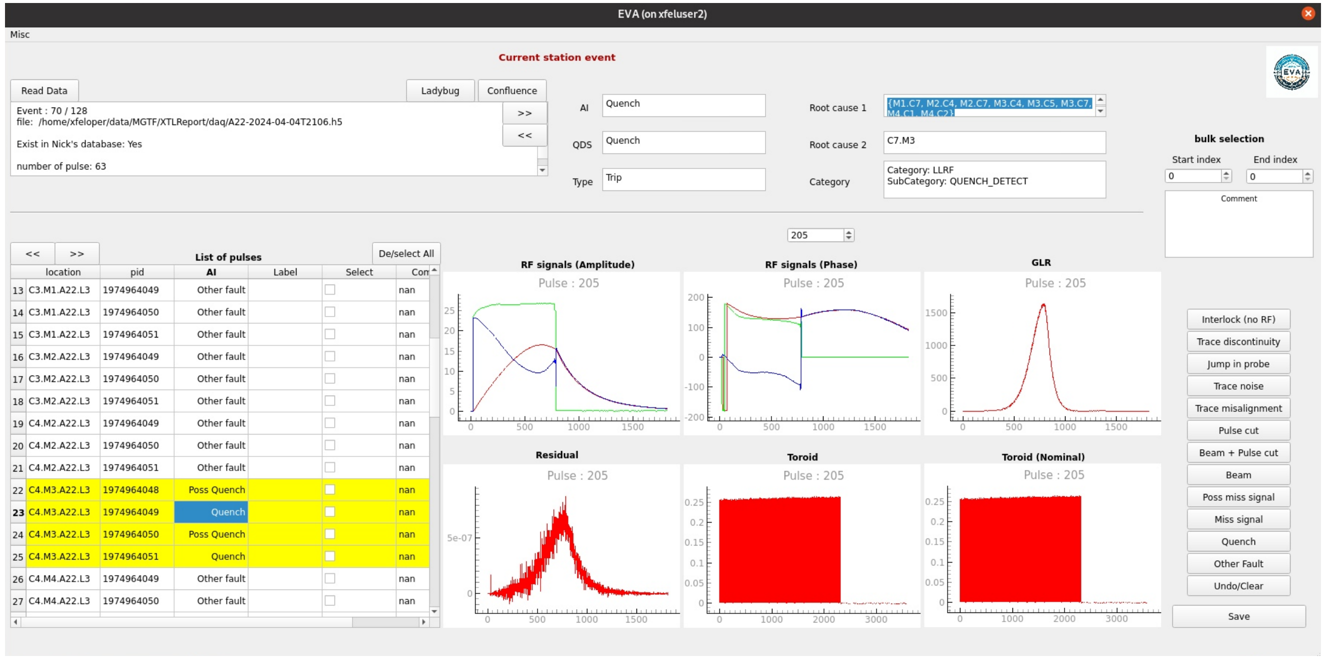
- Goal: streamline the process for the LLRF experts
- Faults distinguishable with the RF waveforms and GLR, helps with labeling
- Only anomalous pulses are retained for labeling
- QDS and AI findings are displayed
- Quenches (as identification enabled) are highlighted
- Toroid data plotted to help with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

GLR Anomaly 1



GLR Anomaly 2



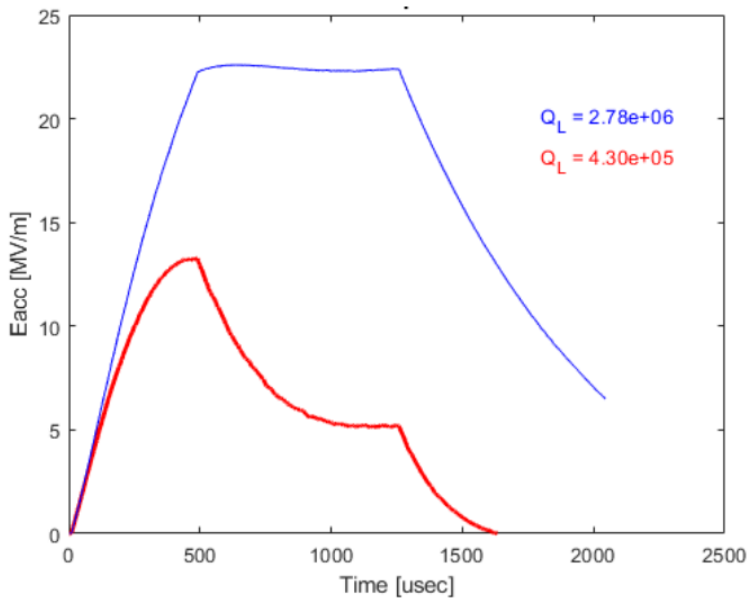


ML for Quench Detection

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



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

Loaded

External

Unloaded

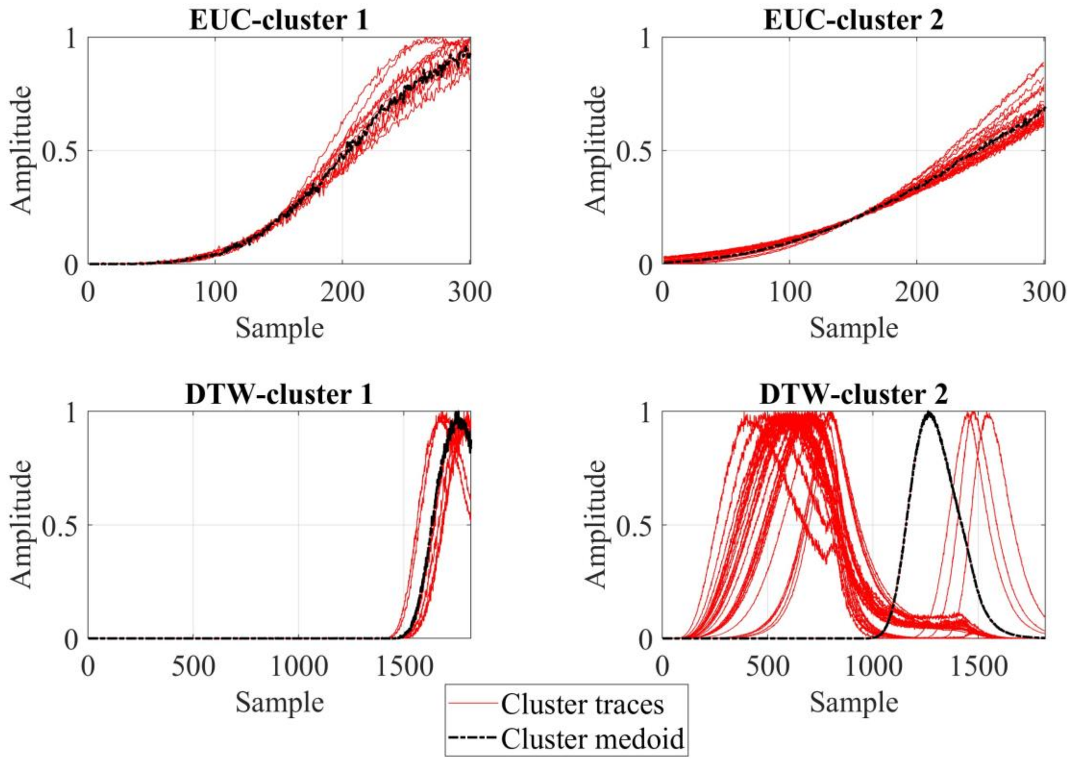
$$Q_0 \gg Q_{ext} \rightarrow Q_L \approx Q_{ext}$$

ML for Quench Detection

Clustering –based

K-medoids with two similarity measures

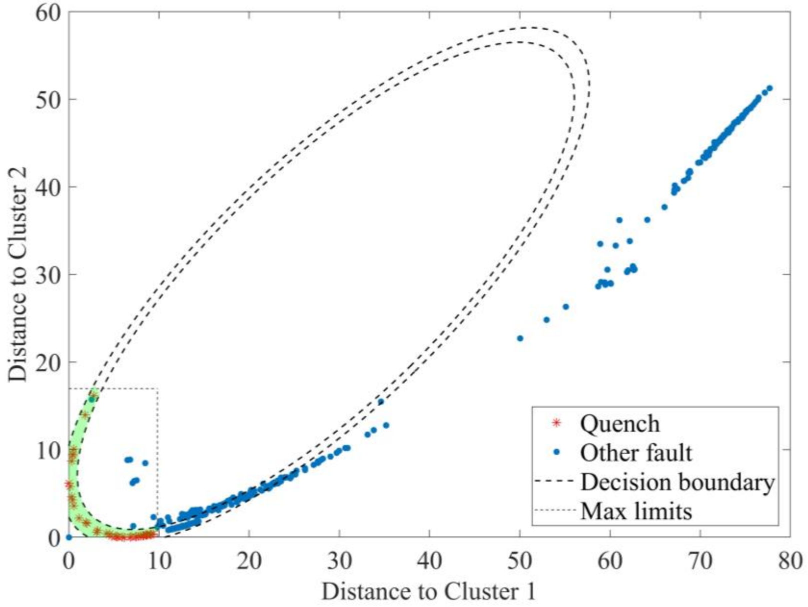
$$\mathrm{DTW}(x_1, x_2) = \arg\min_{i,j} \sum \mathrm{dist}(x_1^i, x_2^j) \qquad \mathrm{EUC}(x_1, x_2) = \sqrt{\sum_{i=1}^{n} (x_1^i - x_2^i)^2}$$



ML for Quench Detection

Clustering –based

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



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

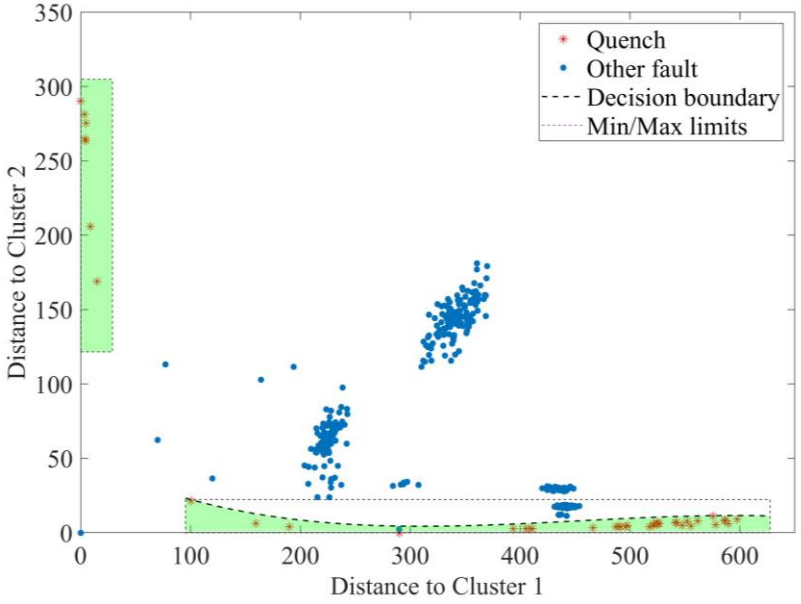
$$\mathrm{Inference}_{EUC}(g) = \begin{cases} \text{Quench}, & \text{if } g \in \mathcal{Q}_{EUC} \\ \text{Other fault}, & \text{otherwise.} \end{cases}$$

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

Quench detection

ML-based quench identification

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



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

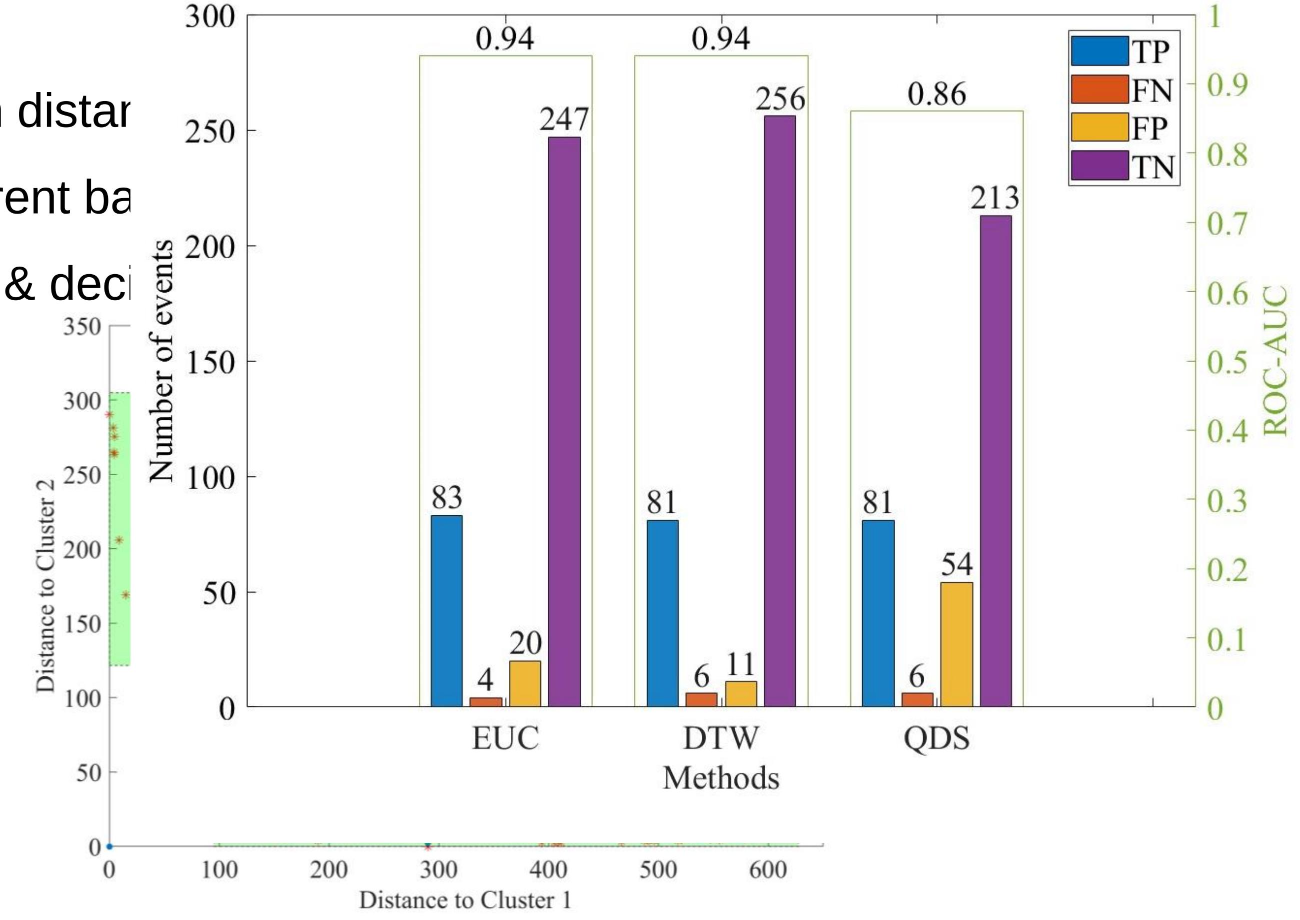
$$\begin{aligned} \mathcal{Q}_{DTW} = \{q \,|\, q \in \mathbb{R}^d,\ & \\ & \mathrm{DTW}(q, m_j) < \max(\mathrm{DTW}(x_i, m_j)) + \epsilon, \\ & \mathrm{DTW}(q, m_j) > \min(\mathrm{DTW}(x_i, m_j)) - \epsilon, \\ & \mathrm{DTW}(q, m_2) < \mathcal{H}_{DTW}(\mathrm{DTW}(q, m_1)), \\ & \forall x_i \in X,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

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

Quench detection

ML-based quench identification

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



$< \max(\mathrm{DTW}(x_i, m_j)) + \epsilon,$

$> \min(\mathrm{DTW}(x_i, m_j)) - \epsilon,$

$< \mathcal{H}_{DTW}(\mathrm{DTW}(q, m_1)),$

$_j \in M\},$

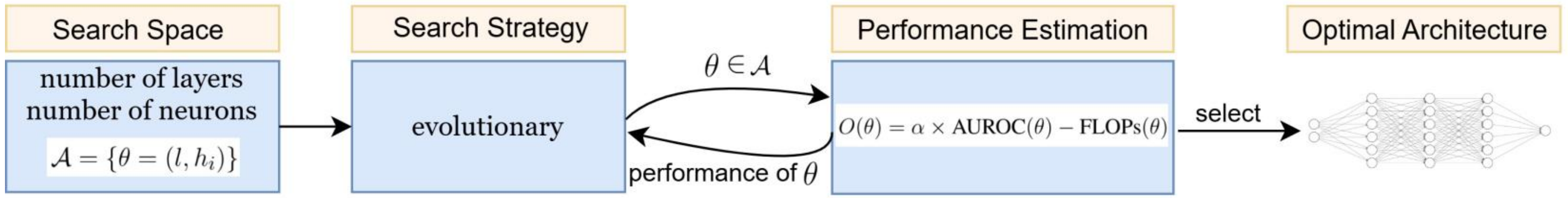
$$\begin{cases} \text{Quench}, & \text{if } g \in \mathcal{Q}_{DTW} \\ \text{Other fault}, & \text{otherwise.} \end{cases}$$

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

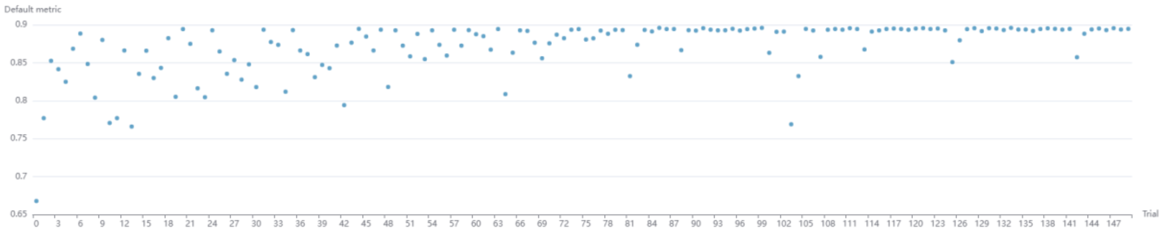
ML for Quench Detection

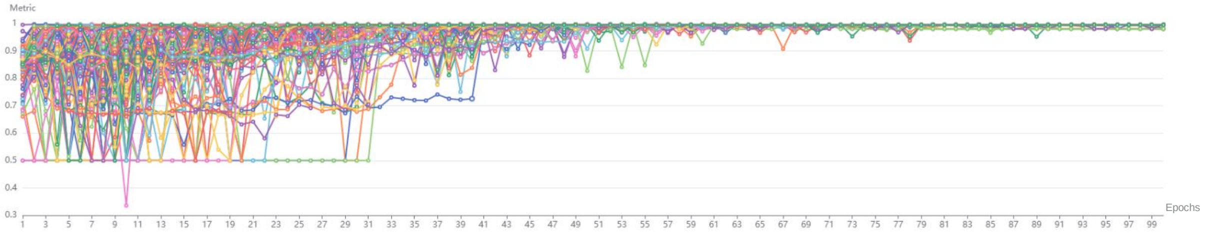
NAS for lightweight models

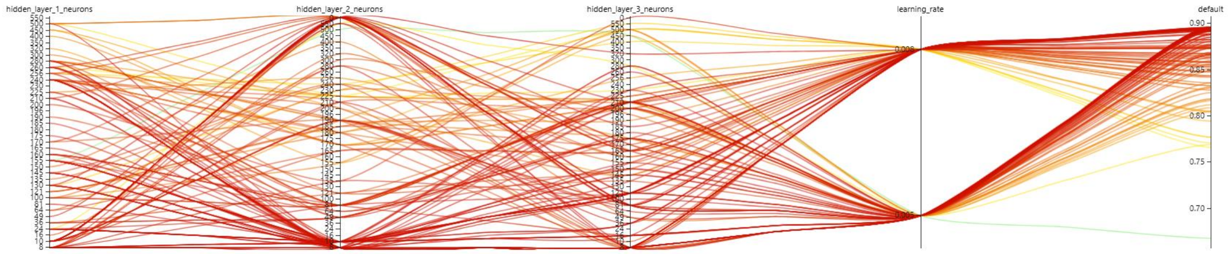
- Multi-objective hardware-agnostic optimization

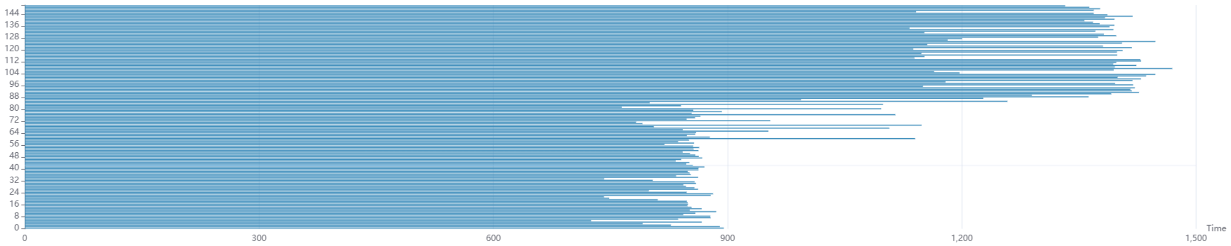


Model	TPR	FPR	AUROC	FLOPs / Size
NAS-MLP$_{\text{EUC}}$	0.9861	0.0049	0.9950	11367/10847
MAN-MLP$_{\text{EUC}}$	0.9861	0.0055	0.9903	38305/37537
NAS-MLP$_{\text{DTW}}$	0.9583	0.0259	0.9662	241/193
MAN-MLP$_{\text{DTW}}$	0.9583	0.0257	0.9663	551/471







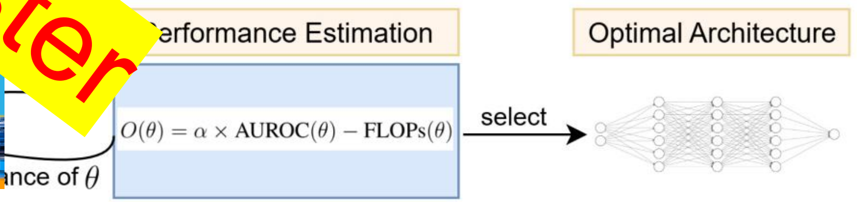


ML for Quench Detection

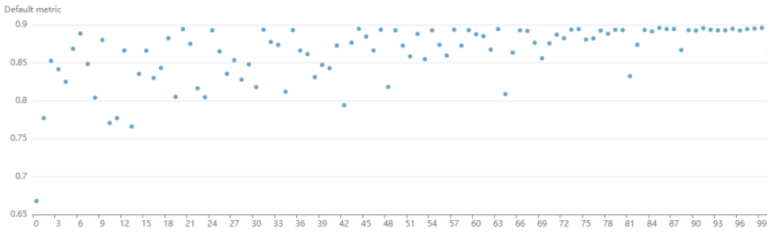
NAS for lightweight models

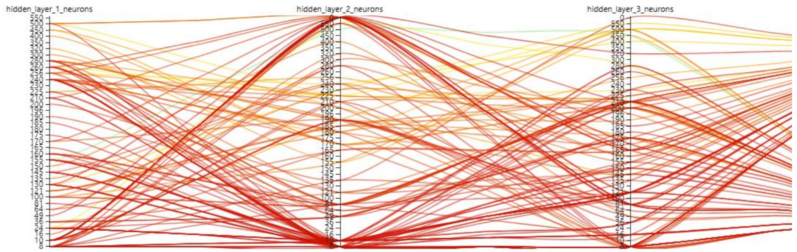
- Multi-objective hardware-agnostic optimization

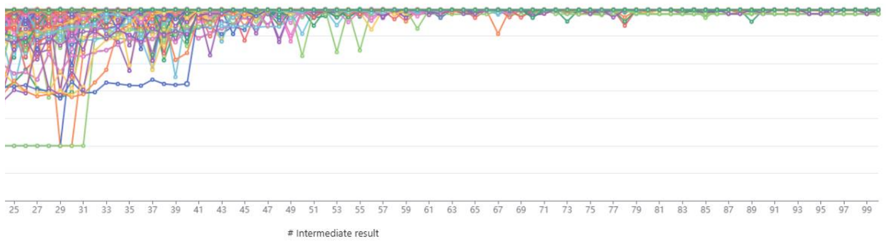
Poster

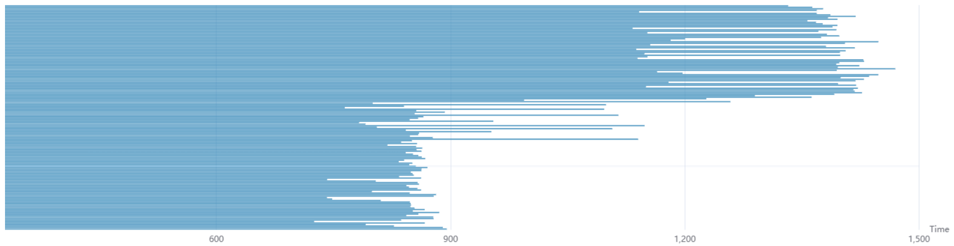


Mo	FLOPs / Size
NAS-M	11367/10847
MAN-M	38305/37537
NAS-M	241/193
MAN-M	551/471



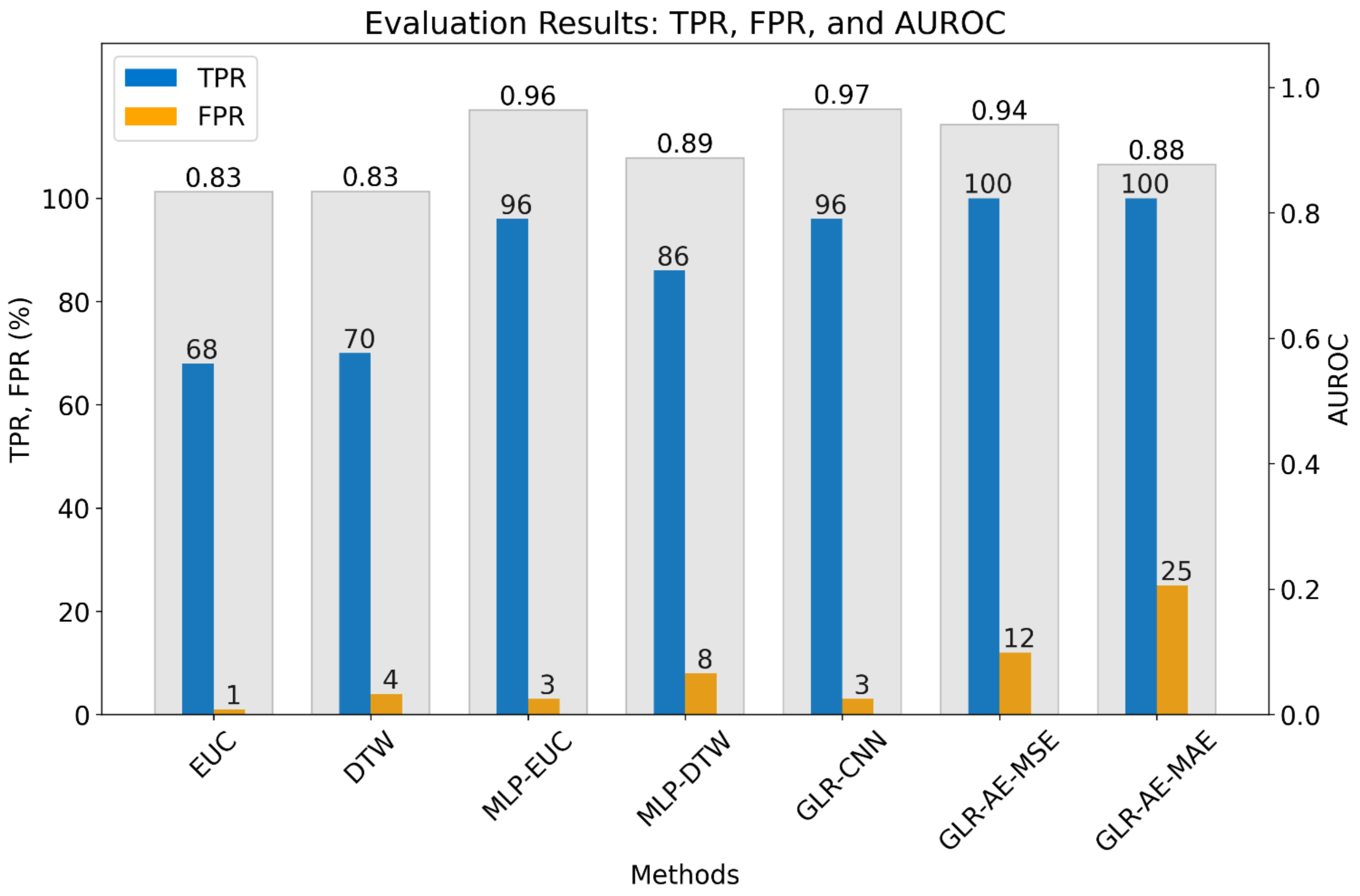






ML for Quench Detection

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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