Machine-learning assisted cavity quench identification at the European XFEL.

LLRF Workshop 2022

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Brugg Windisch, 10.10.2022

Contribution ID 23

HELMHOLTZ RESEARCH FOR GRAND CHALLENGES

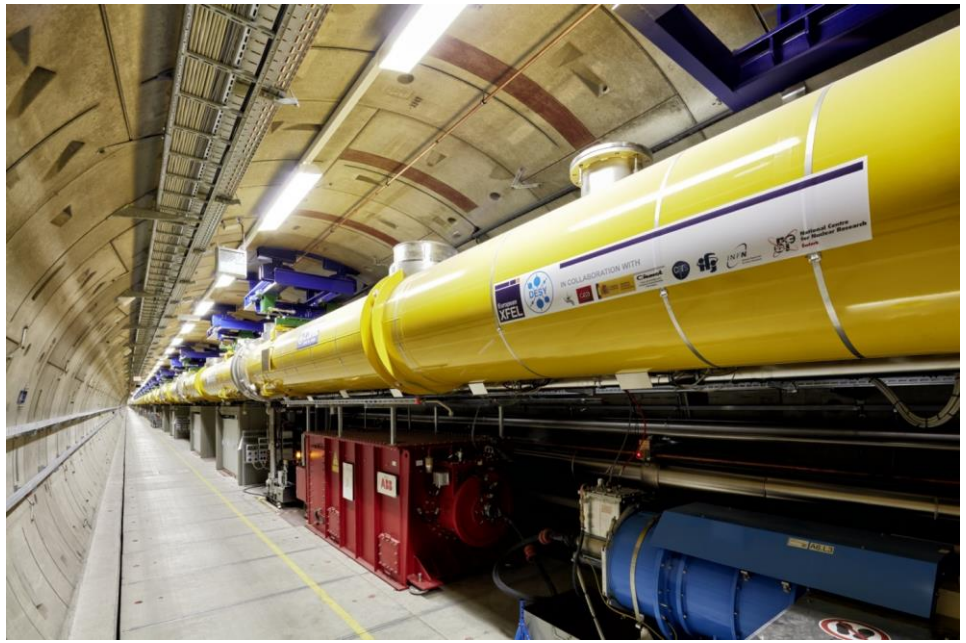
DESY.

MOTIVATION

Can we lower false positive rates of quench detection at European XFEL?

European XFEL

- 17.5 GeV pulsed electron FEL
- 800x 1.3 GHz SRF cavities
- In operation since 2017
- Hamburg Germany



MOTIVATION

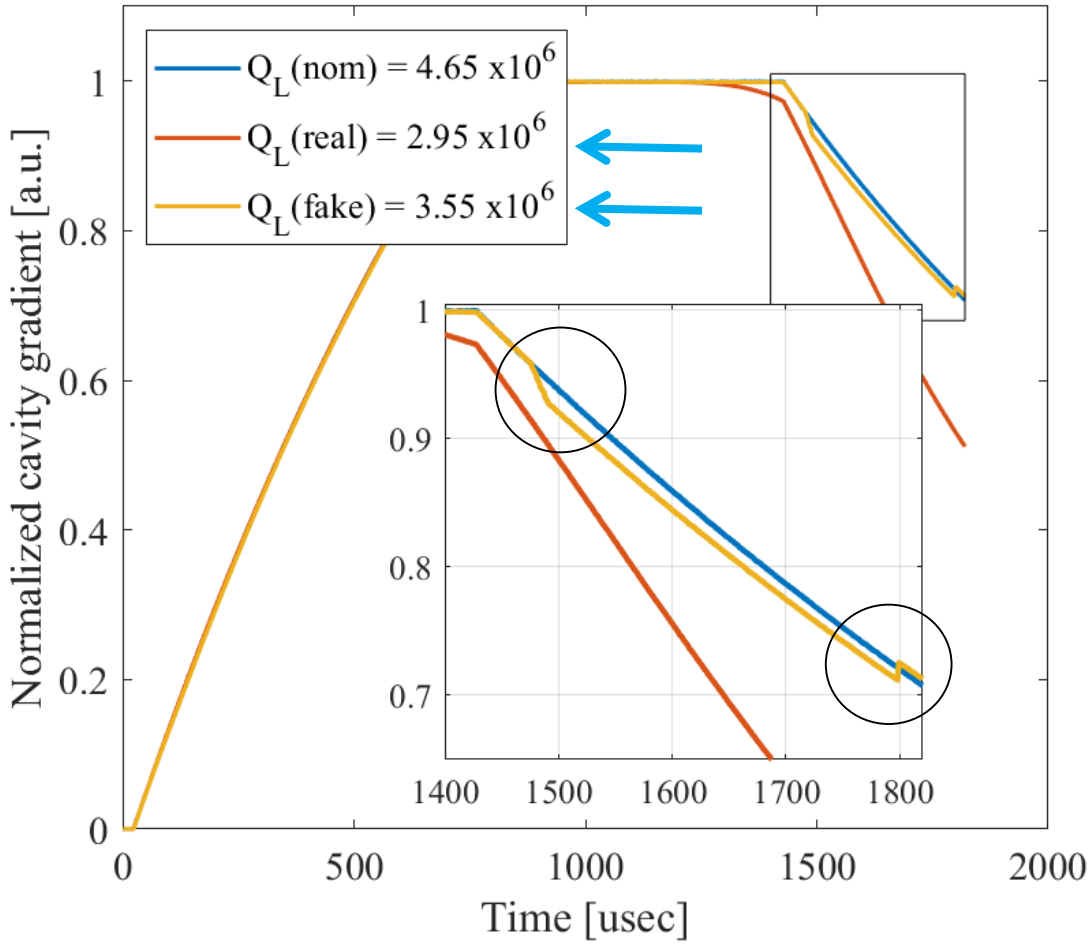
Can we lower false positive rates of quench detection at European XFEL?

- Software-based **quench detection is successful** at catching SRF cavity quenches **but** also **triggers for other faults**
- Can we make use of **machine learning** techniques to help identify **REAL** and "**FAKE**" quenches ?
- Make **use of data snapshots** generated at each trip

  ➡ build up on existing (unlabeled 😔) datasets

- Make use of well-known **cavity model** to compare measured probe and model prediction

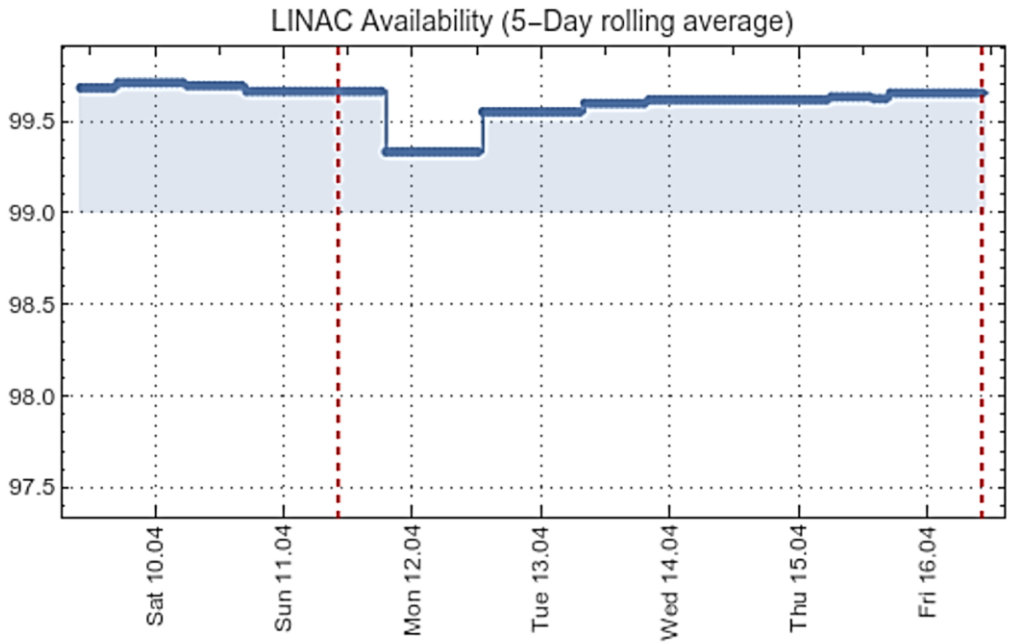
  ➡ no need for large training data sets 🤔



XTL report

Online trip root cause and uptime analysis

- Software tool developed over the last 2 years *
- Monitors 50+ **hardware** and **software** interlocks (i.e. QDS) available in control system
- Identifies **root cause** of trip
- Computes **down time**, available via web interface (update 1/hr)
- Updates **database** with down time root cause
- Generates **trip data snapshots** (20 seconds before and 5 seconds after trip)
- Trip data snapshots available for **postmortem analysis**



Clarify root cause and update DB

Stations	Type	Time	Duration	OnBeam	LinacDownTim…	RootCause
A12	Spare	Thu 15 Apr 2021 14:42:34	> 19.3 hours	Off	—	
A12	Service	Thu 15 Apr 2021 13:30:21	1.2 hours	Off	—	
A22	Trip	Thu 15 Apr 2021 13:28:19	44. seconds	On	44 seconds	UNKNOWN : FSM_VSUM_MISMATCH
A2	Trip	Sun 11 Apr 2021 18:34:20	23.8 minutes	On	23.8 minutes	LLRF : HARDWARE_FAULT
A2	Trip	Sat 10 Apr 2021 16:25:05	2.2 minutes	On	2.2 minutes	CRYO_VAC : UPSTREAM_P0_IGP
A17	Trip	Sat 10 Apr 2021 05:35:24	1.2 minutes	On	69 seconds	KLYSTRON : GUN_ARC

* work in collaboration with **Nick Walker**, DESY

1. Introduce a new metric

Residual and Generalized Likelihood Ratio

- Based on forward and probe RF waveforms, a **residual** is computed to track deviation of the cavity probe from expected behavior (based on standard cavity model)

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

P	probe
F	forward
B	beam
I	in-phase
Q	quadrature
$\omega_{1/2}$	half bandwidth

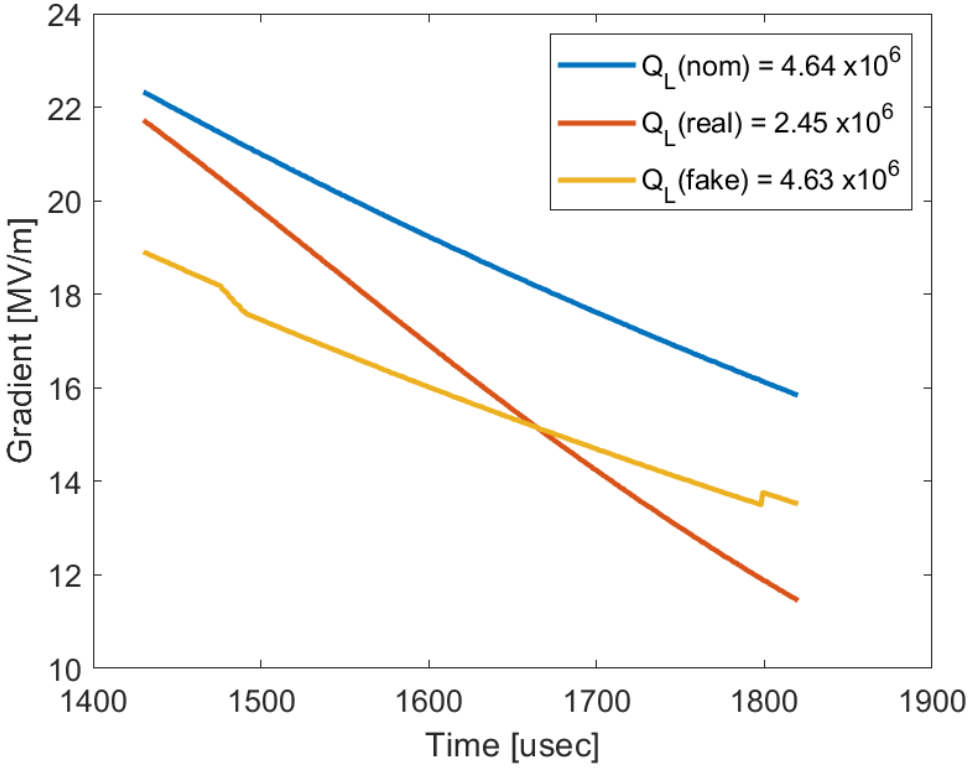
- A statistical evaluation of this residual, the **Generalized Likelihood Ratio (GLR)** is computed *
- The GLR quantifies if the residual indicates a fault
- The GLR is **robust against standard operation changes** (i.e. detuning)
- The GLR provides **very distinct signature for distinct trips**

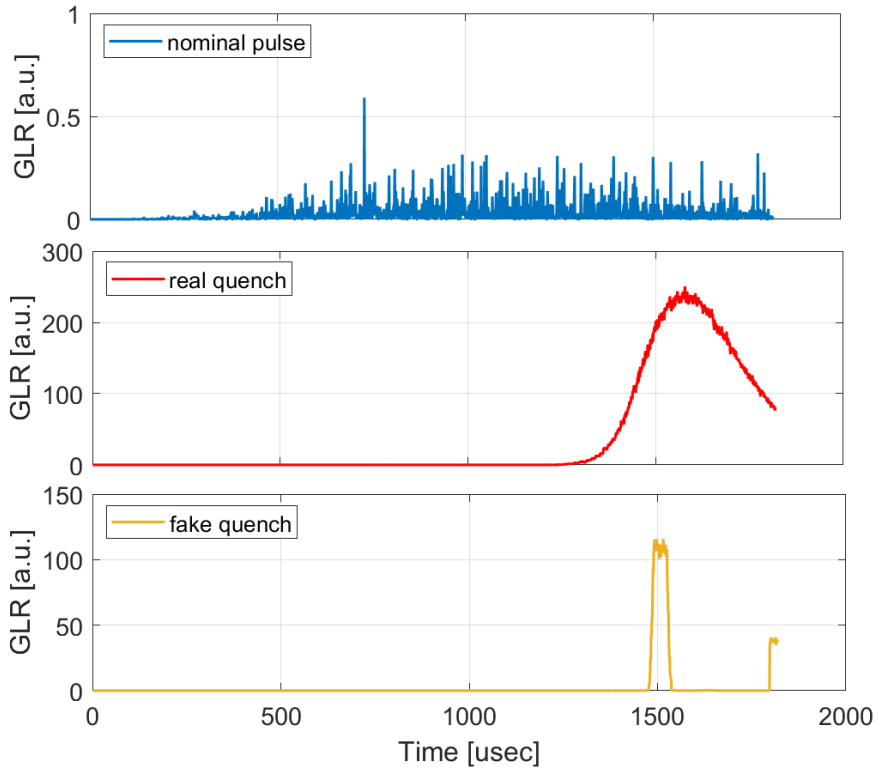
*** Reference**:
Anomaly Detection at the European XFEL using a Parity Space based Method A. Eichler *et al.* arXiv:2202.02051 [physics.acc-ph]

1. Introduce a new metric

Residual and Generalized Likelihood Ratio

- Quantifies **deviation of the cavity probe from model**
- Provides very **distinct signatures** for **different kinds of trips**

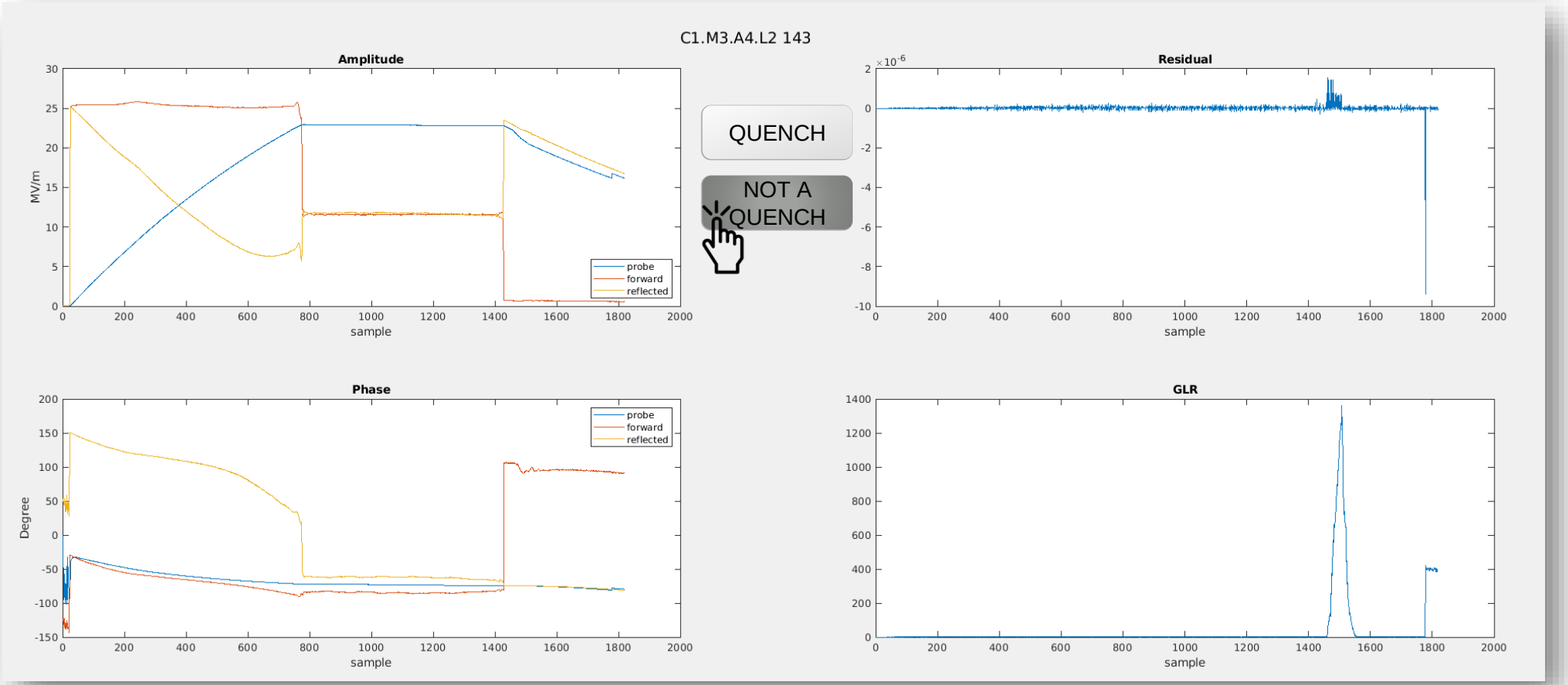




2. Training phase

Training set manually labeled “QUENCH” or “NOT QUENCH”

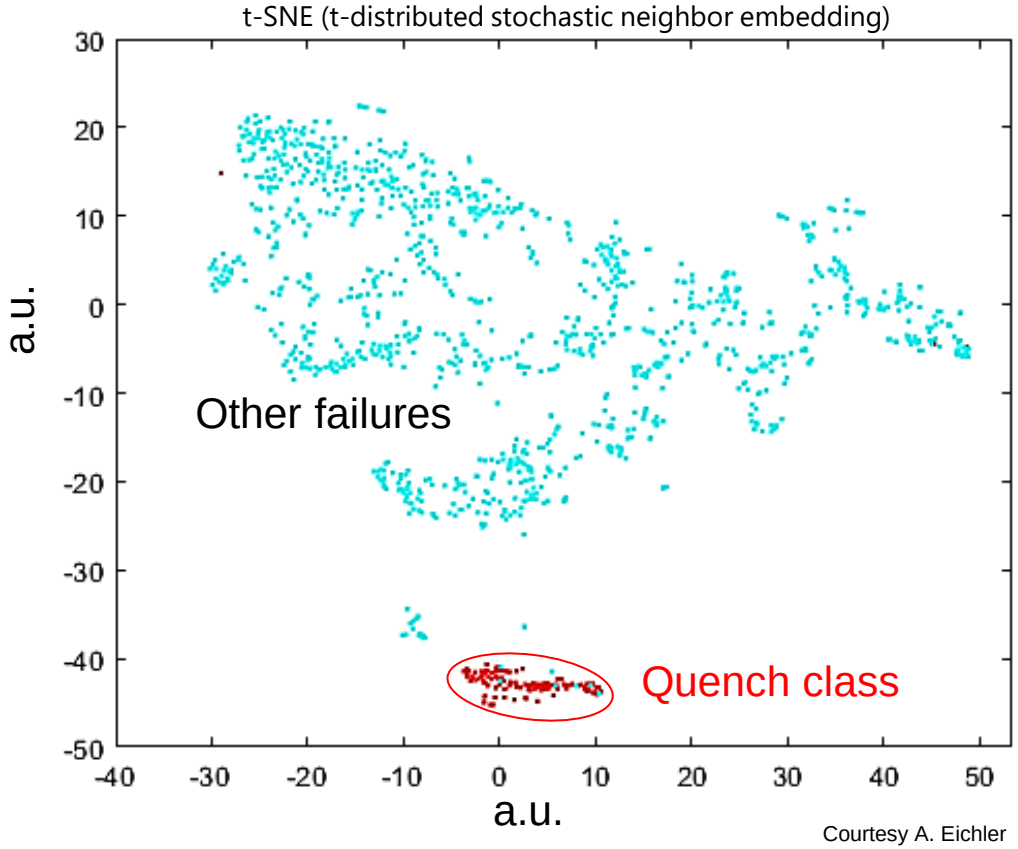
- **Training set** of 453 trips reviewed by expert
- Tagged as “**real**” or “**false**” quench



2. Training phase

Training set manually labeled “QUENCH” or “NOT QUENCH”

- **Training set** of 453 trips reviewed by expert
- Tagged as “**real**” or “**false**” quench
- **Unsupervised** classification based on **k-means** to define quench classes
- Class **threshold** defined using the quenched and non-quenched trips of training data set
- Evaluation of new trip = **compute the distance to the class centre point**
- If | GLR – GLR_quench_class | < threshold → QUENCH



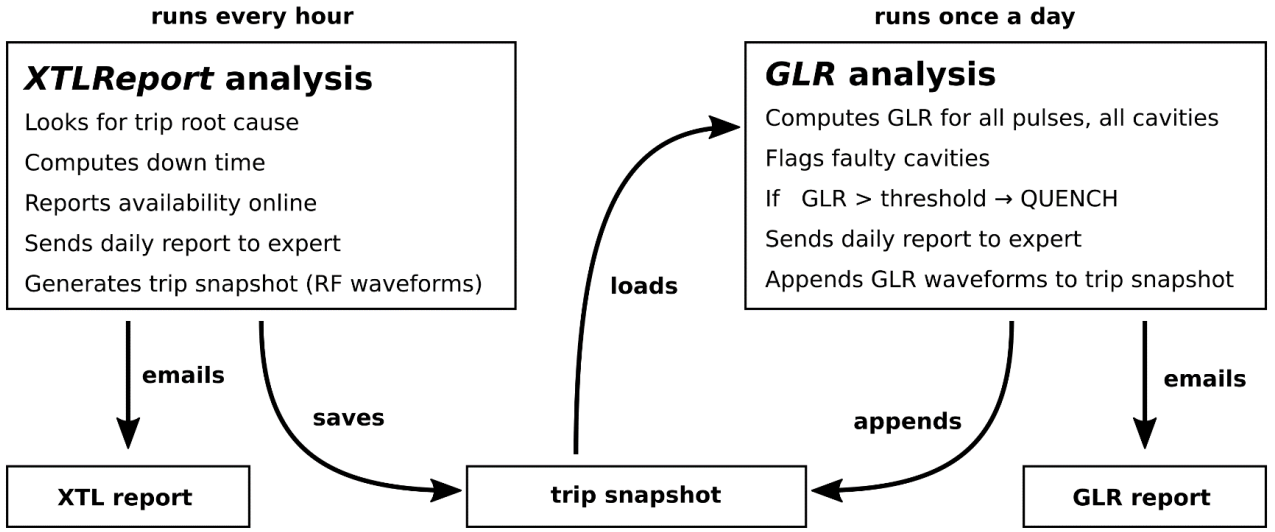
Courtesy A. Eichler

Reference:
Probabilistic Model-Based Anomaly Detection for the European X-Ray Free Electron Laser, A. Nawaz PhD Thesis, 2021

3. Run the GLR analysis

on all new trip data snapshots

- **GLR analysis as a cron job***
  - runs **once a day**
  - loads any **trip snapshot**
  - computes **residual and GLR**
  - labels trip as **quench** or **not quench**
  - **appends** new plots to snapshot dataset
  - **sends** outcome to experts



*** Reference**

The Trip Event Logger for Online Fault Diagnosis at the European XFEL, J. Timm *et al.* IPAC'21

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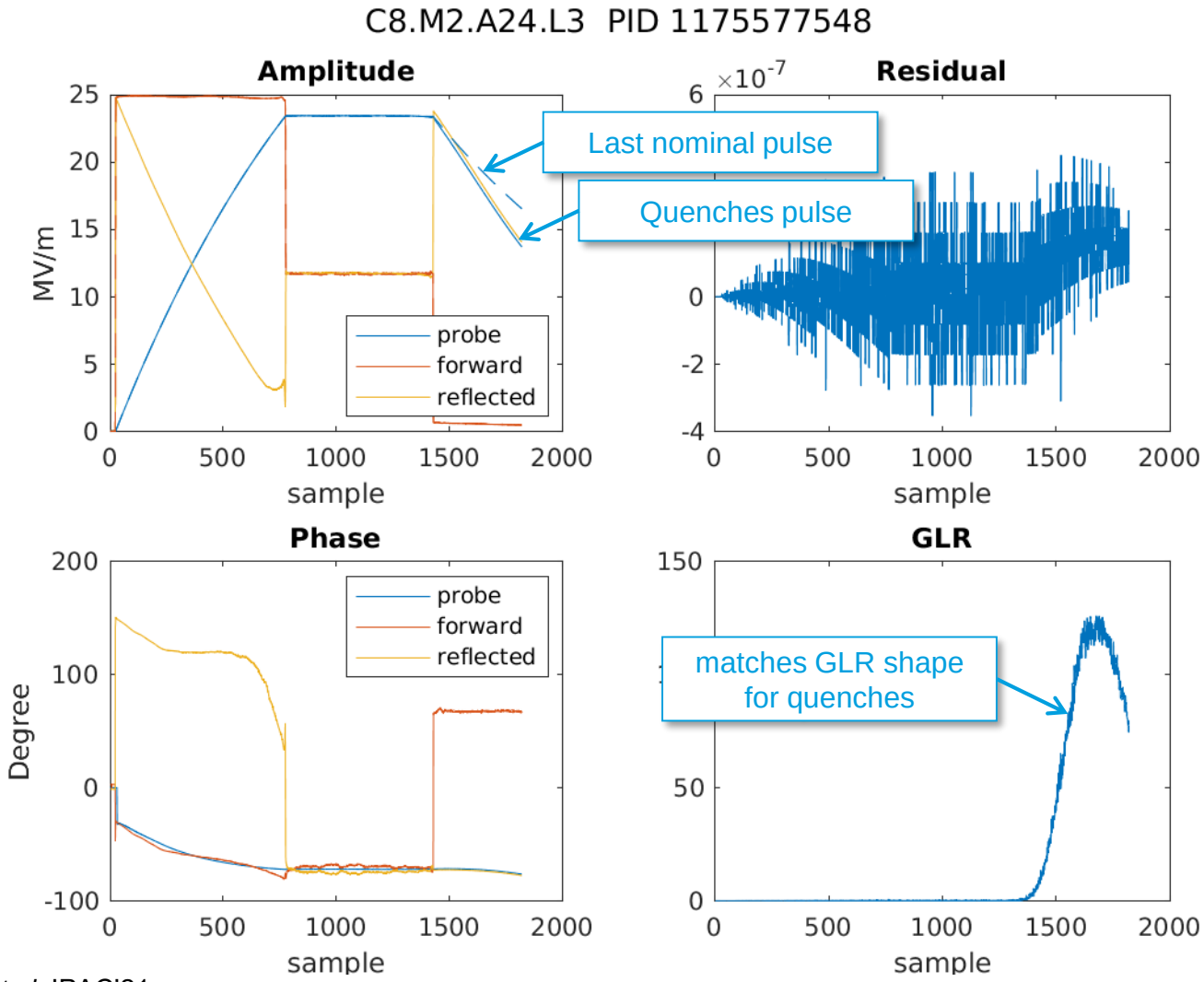
➡ REAL QUENCH



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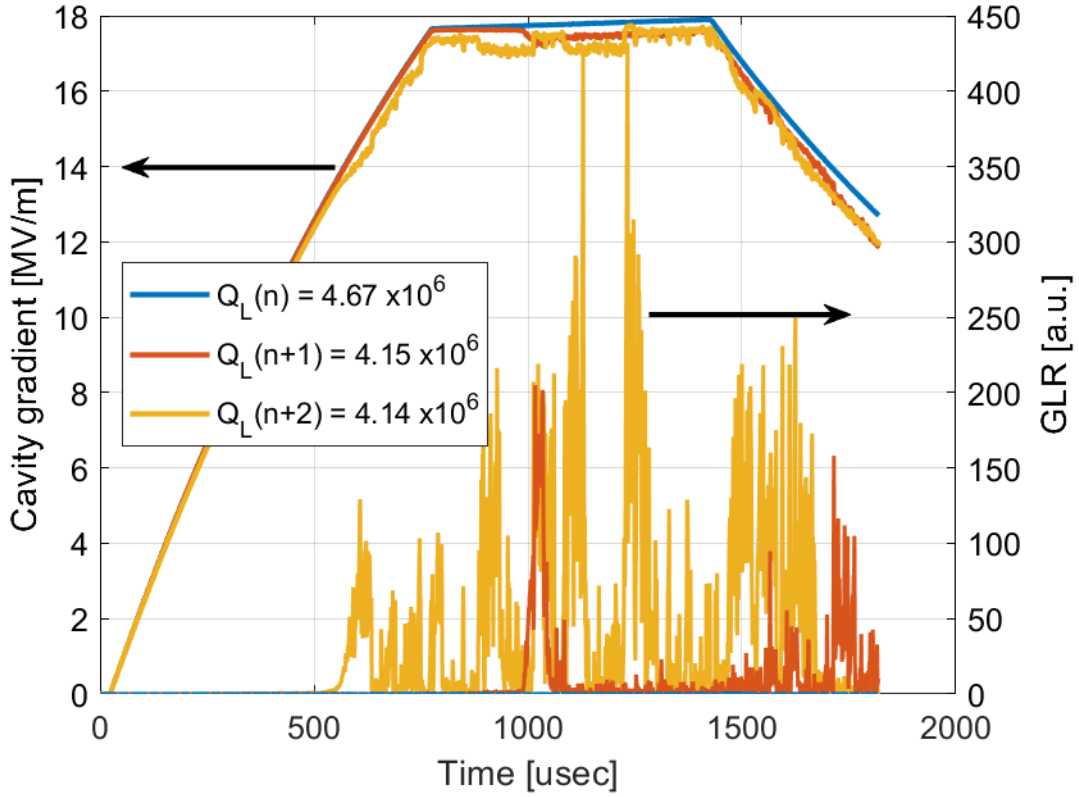
Results

Daily GLR analysis since September 2021

- Analysis run as **cron job**, daily
- Period Sept. 22nd 2021 to June 8th 2022
- **195 days of nominal RF operation** (removing machine shutdown, startup or software development days)
- **124 trips snapshots** were recorded



Example of a **fake quench** correctly discarded by the GLR analysis

Results

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Algorithm accuracy

$$a = \frac{TP + TN}{TP + TN + FP + FN}$$

TP : true positive (accurately detected a quench)
TN : true negative (accurately recognized a trip was not a quench)
FP : false positive (a "fake" quench)
FN : false negative (algorithm failed to identify a real quench)

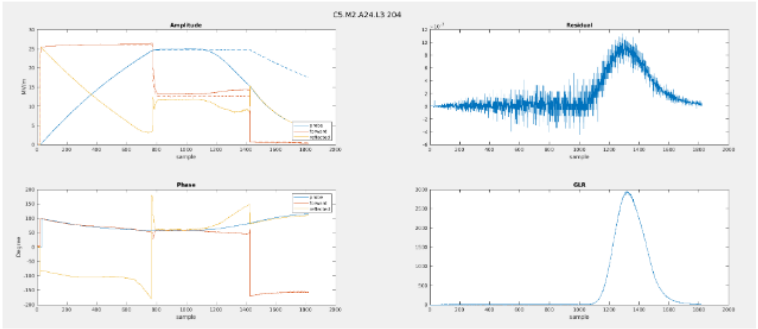
	TP	TN	FP	FN	a
QDS	55	56	10	3	~90%
GLR	55	65	1	3	~97%

improved accuracy

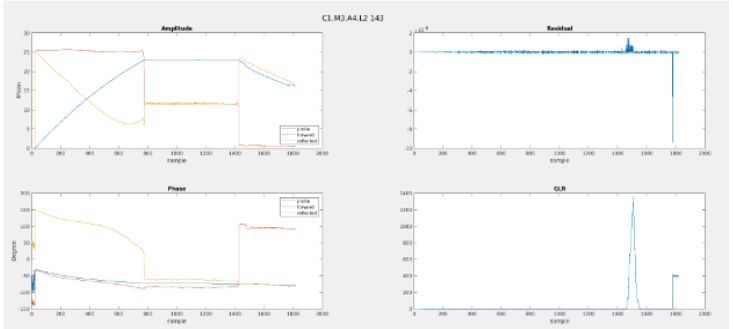
Why use machine learning ?

Not just quench detection but anomaly categorization

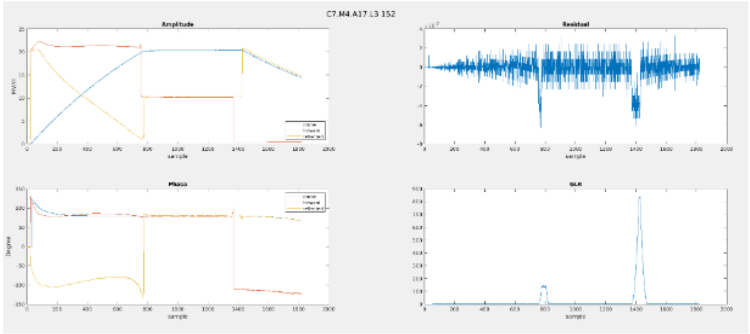
(0) classic quench



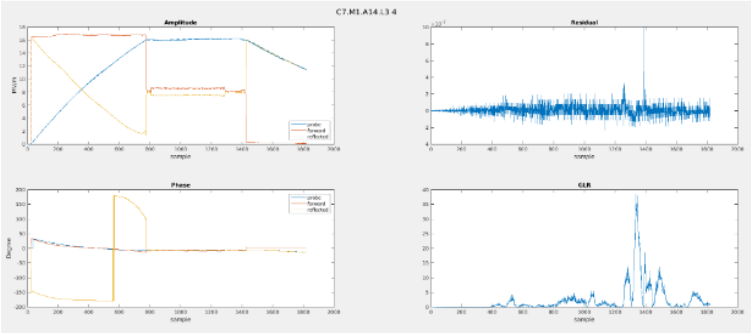
(1) timing jump (during decay)



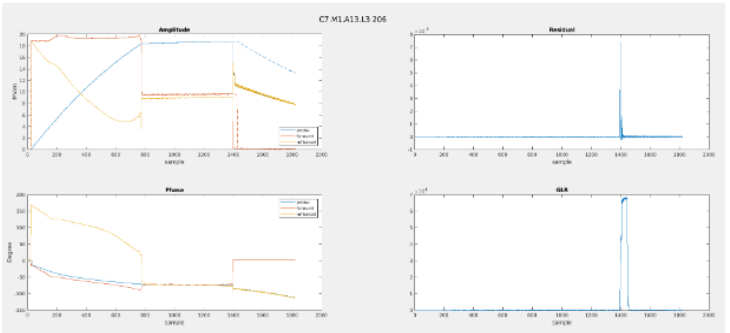
(2) probe / forward / reflected misalignement



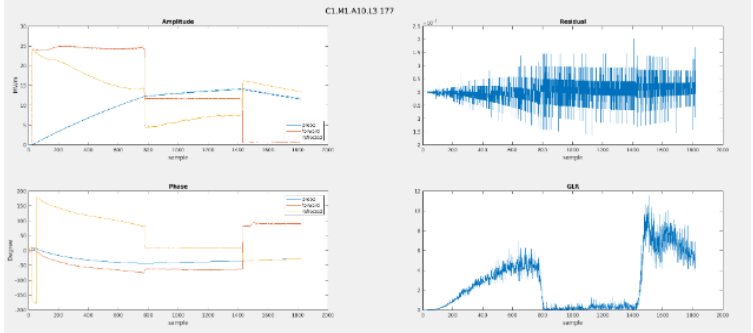
(3) broken hardware (down converter failure)



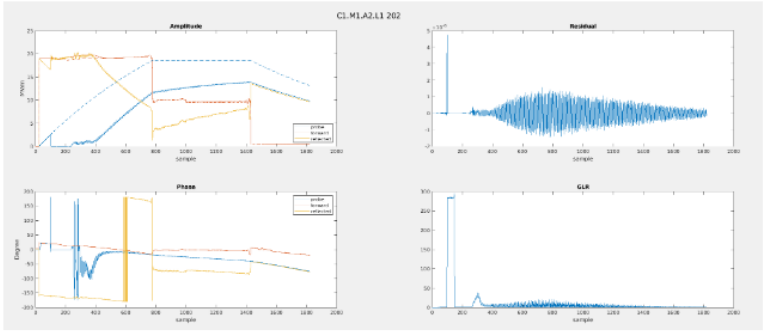
(4) pulse cut



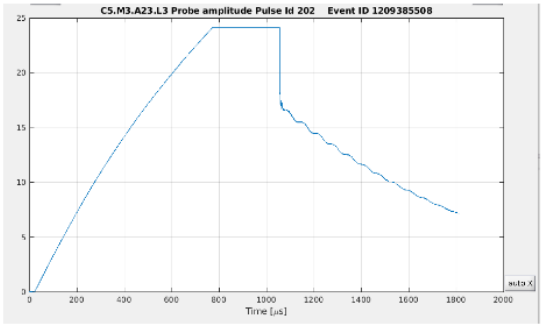
(5) calibration issue

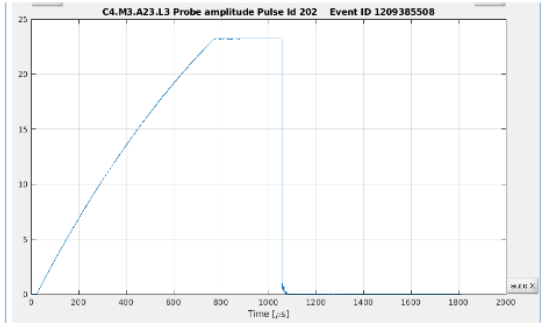


(6) still unlabeled (not understood)



(7) plasma discharge





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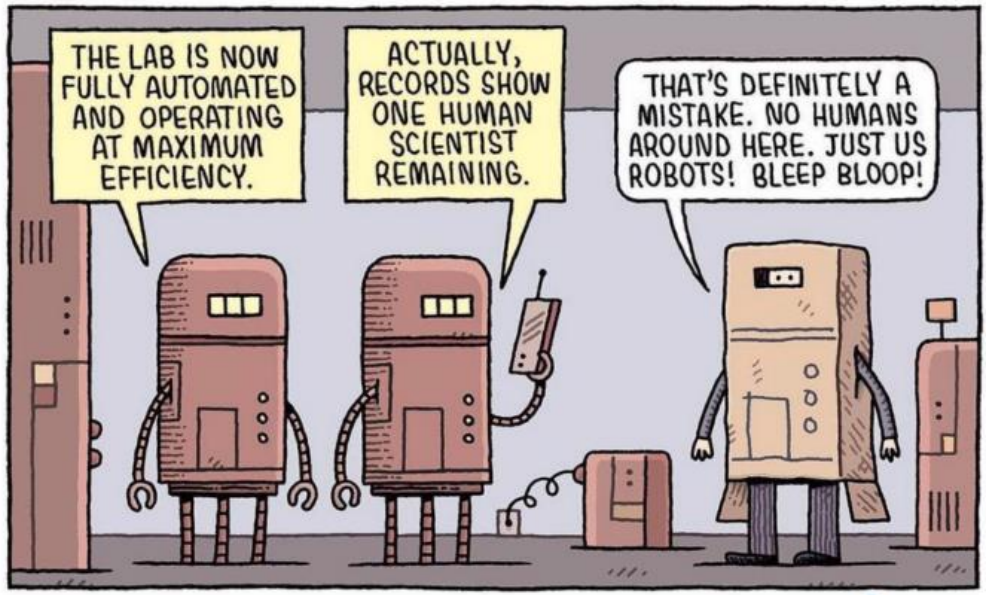
Summary and Outlook

- Using machine learning for trip classification was **already implemented** in other labs (JLab)
  - the approach chosen here **relies on the cavity model** rather than pure data driven (black box)
  - i.e. make use of what we already know about the cavity system → smaller training data sets

- Positive first outcome
  - **speeds up expert routine trip evaluation**

- Next steps
  - proceed with **further GLR signatures**
  - extend analysis to **NRF** (gun)
  - implement analysis on **live data** → catch all pulses
    - firmware / software implementation ? (pros and cons)



Thank you

All my colleagues, in particular: Annika Eichler, Nick Walker, Jan Timm

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