

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

THPOPA26

LINAC 2022, Oral poster

Branlard, Julien (DESY)  
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HELMHOLTZ RESEARCH FOR  
GRAND CHALLENGES



# MOTIVATION

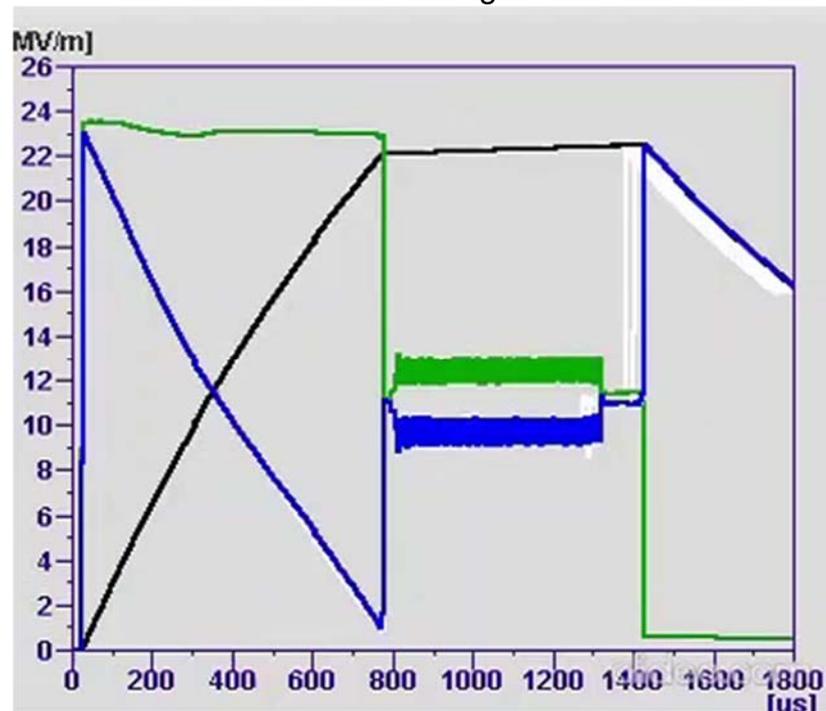
Can we lower false positive rates of quench detection at European XFEL?

## European XFEL

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



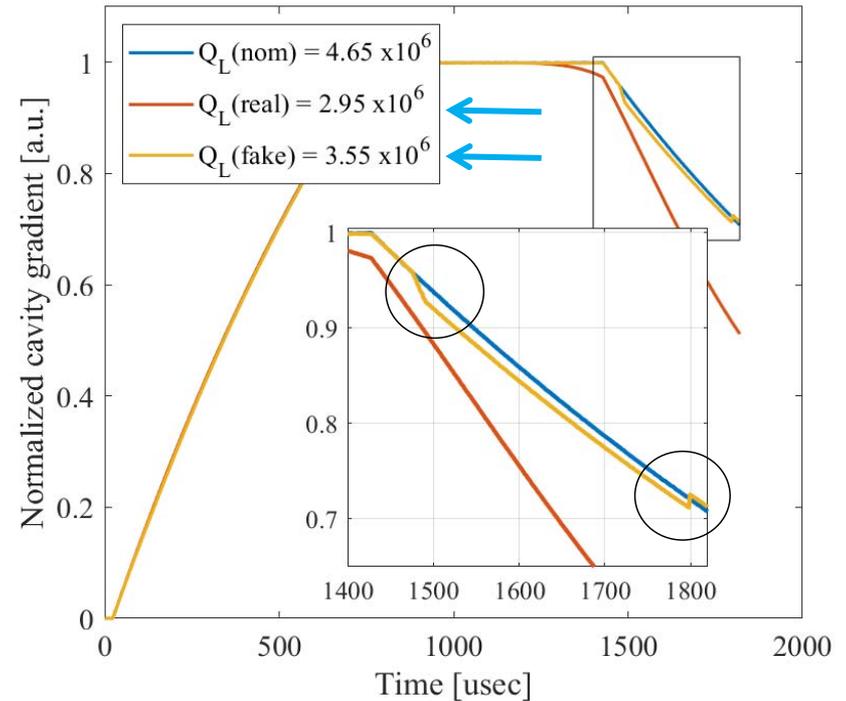
Data from August 2022



# MOTIVATION

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

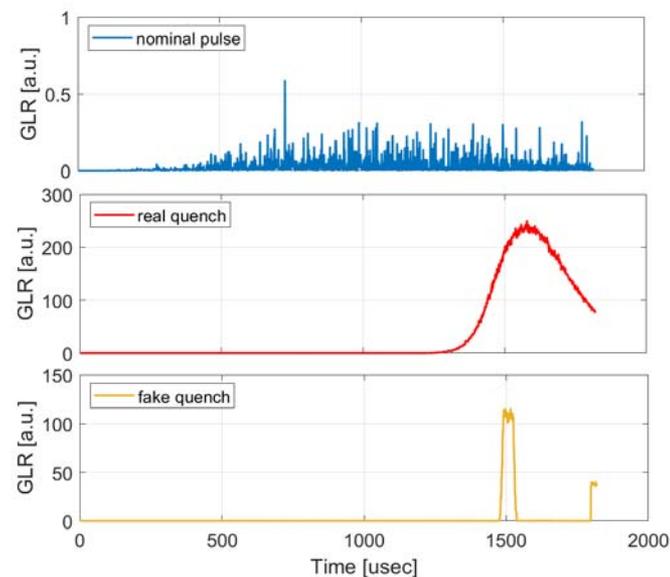
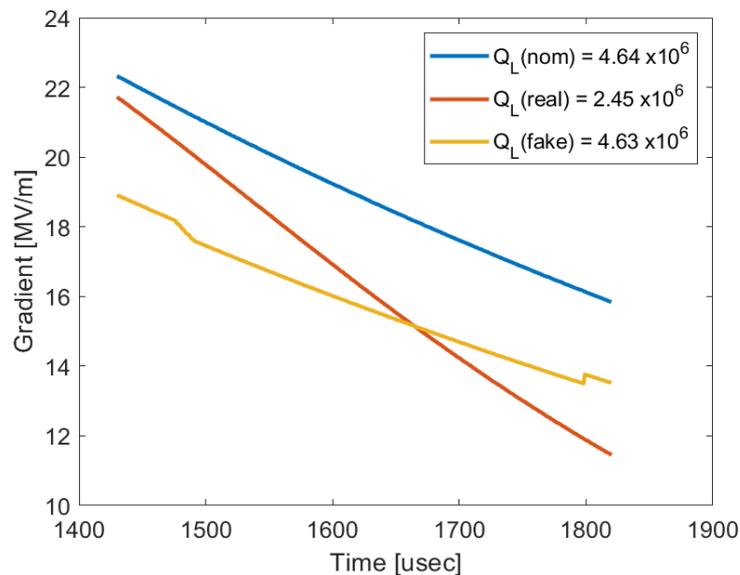
- Software-based **quench detection is successful** at catching SRF cavity quenches **but** also **triggers for other faults**
- Can we make use of **machine learning** techniques to help identify **REAL** and **“FAKE”** quenches ?
- Make **use of data snapshots** generated at each trip
  - ➔ build up on existing datasets
- Make use of well-known **cavity model** to compare measured probe and model prediction
  - ➔ no need for large training data sets



# 1. Introduce a new metric

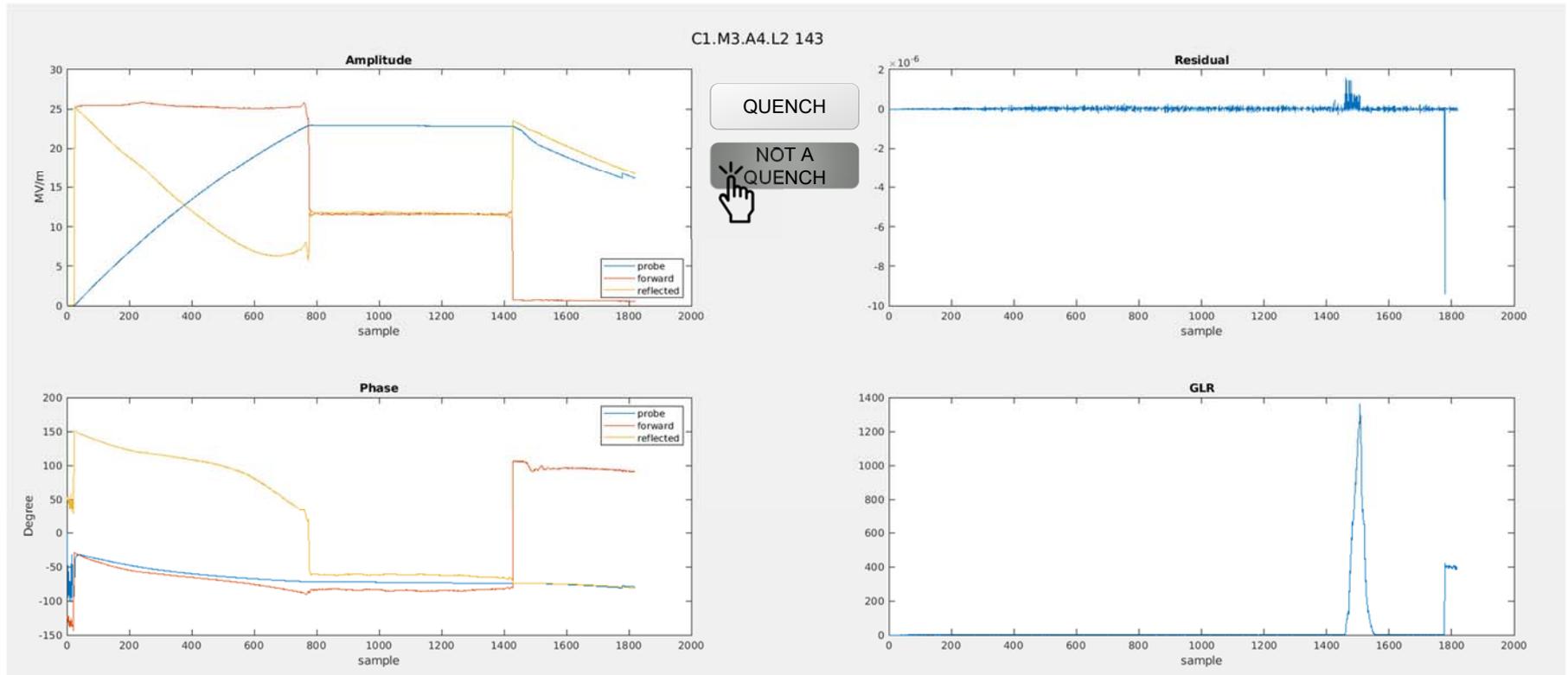
## Residual and Generalized Likelihood Ratio

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



## 2. Training set on QUENCH – NOT QUENCH

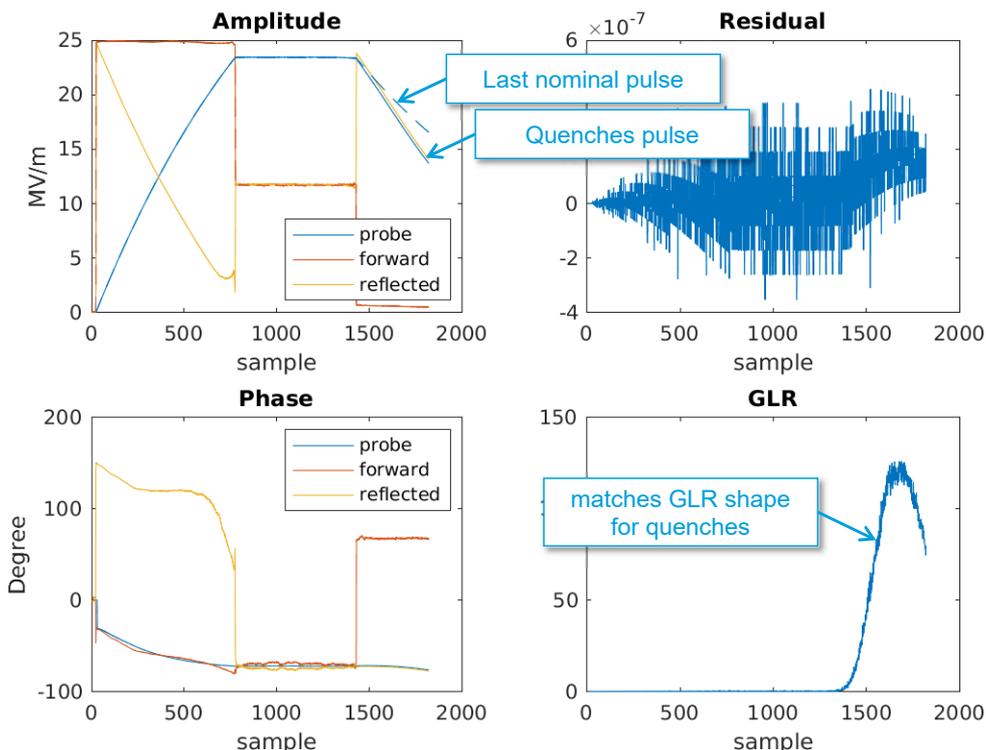
453 trips reviewed by RF expert



# 3. Run the GLR analysis on all new trip data snapshot

Daily cron job since September 2021

C8.M2.A24.L3 PID 1175577548



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

# See you at poster THPOPA26

## Contact

**DESY.** Deutsches  
Elektronen-Synchrotron

www.desy.de

Julien Branlard  
MSK, DESY

[julien.branlard@desy.de](mailto:julien.branlard@desy.de)

+49 (0)40 8998 1599

## MACHINE LEARNING ASSISTED CAVITY QUENCH IDENTIFICATION AT THE EUROPEAN XFEL.

THPOPA26



J. Branlard\*, A. Eichler, J. Timm, N. Walker DESY, Hamburg, Germany

### Abstract

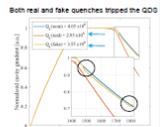
A server-based quench detection system is used since the beginning of operation at the European XFEL (2017) to stop driving superconducting cavities if they experience a quench. While this approach effectively detects quenches, it also generates false positives, stopping the accelerating cavities when failures other than quenches occur. Using the post-mortem data snapshots generated for every trip, an additional signal (referred to as residuals) is systematically computed based on the standard cavity model. Following an initial training on a subset of such residuals previously tagged as "quench" / "non-quench", the independent machine learning engines analyse routinely the trip snapshots and their residuals to identify if a trip was indeed triggered by a quench or has another root cause. The outcome of the analysis is automatically appended to the data snapshots and approved by a team of experts. This constitutes a fully deployed example of machine-learning-assisted failure classification to identify quenches, supporting experts in their daily routine of monitoring and documenting the accelerator uptime and availability.

### Motivation

The XFEL relies since beginning of operation (OOI) on a quench detection server (QDS) to stop the RF when a quench occurs

- The QDS has very seldom false negatives (i.e. detects quenches when they happen)
- BUT other faults can trigger the QDS (i.e. false positives)
- The QDS computes based quality factor  $Q_L$  during decay (from probe signal)
- If  $Q_L < Q_L(\text{mean}) - \text{threshold} = \text{QUENCH}$  the reaction: the RF for this station is stopped

### "Real" and "Fake" quenches



### Consolidated post-mortem quench classification

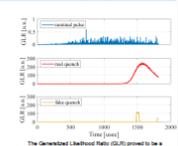
#### 1. XTLReport

- Software tool developed over the last 2 years
- Monitors IO+ hardware and software interlocks (i.e. QDS) available in control system identifies root cause of trip
- Computes down time, available via web interface (update: 1min)
- 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



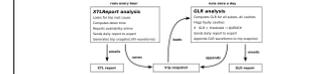
#### 2. Computation of Residual and Generalized Likelihood Ratio (GLR)

- Residual computation makes use of well-known cavity model
- Based on forward and probe RF waveforms, a residual is computed to track deviation of the cavity probe from expected behavior (mode)
- A Generalized Likelihood Ratio (GLR) is computed to quantify 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



#### 3. GLR quench evaluation as oron job

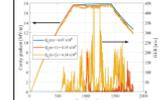
- Training set of 453 trips reviewed by expert
- Tagged as "real" or "false" quench
- Unsupervised classification based on k-means square to define quench classes
- Class threshold defined using the quenched and non-quenched trips of training data set
- Evaluation of new trip - compute the distance to the class centre point.
- If GLR > threshold -> QUENCH



### Results

Example: quench correctly identified as "fake" by GLR

- 3 consecutive pulses shown (1 nominal and 2 "fake" quenches pulses)
- Corresponding  $Q_L$  values and GLR shown
- QDS triggered (change in  $Q_L$  above SET threshold)
- Post-mortem GLR analysis correctly labelled this trip as faulty, but discarded it as a quench



#### Statistics

QDS	TP	FP	FN	TPR	FPR	MRP
QDS	25	25	10	3	88.2%	

Accuracy:  $\frac{TP + TN}{TP + FP + FN + TN} = 74\%$

Legend: TP: True positive (i.e. the algorithm accurately identified a quench), FP: True negative (the algorithm accurately recognized that a trip was not a quench), FN: False positive (i.e. a "fake" quench), TN: True negative (the algorithm failed to identify a real quench)

### Summary and future work

An overview of an approach relying on machine-learning methods to categorize trips as quench or non-quench recently implemented at the European XFEL was presented. This approach relies on existing trip snapshots to compute additional metrics (referred to as residuals) to evaluate if the quench is real. The next step consists of running this analysis on live data (as opposed to post-mortem). There are 2 options: a software- and a firmware-based approach. Running the analysis is computationally expensive so that the software approach cannot be implemented on the front-end CPUs. A solution would be to use external CPUs sharing a direct PCIe bus connection to the front-end CPU. The firmware solution is attractive because it doesn't require additional hardware, but might be subtle expensive in terms of FPGA resources. Both options are currently under evaluation. Another future work consists of looking into adding the GLR algorithm for normal conducting cavities (such as the RF gun). The GLR approach could then help categorize different gun trips.

