MACHINE LEARNING ASSISTED CAVITY QUENCH IDENTIFICATION AT THE EUROPEAN XFEL.

THOPOPA26

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, tripping the accelerating station when failures other than quenches occur. Using the post-mortem data snapshots generated for every trip, an additional signal (referred to as residual) 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", two 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 distributed to 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.

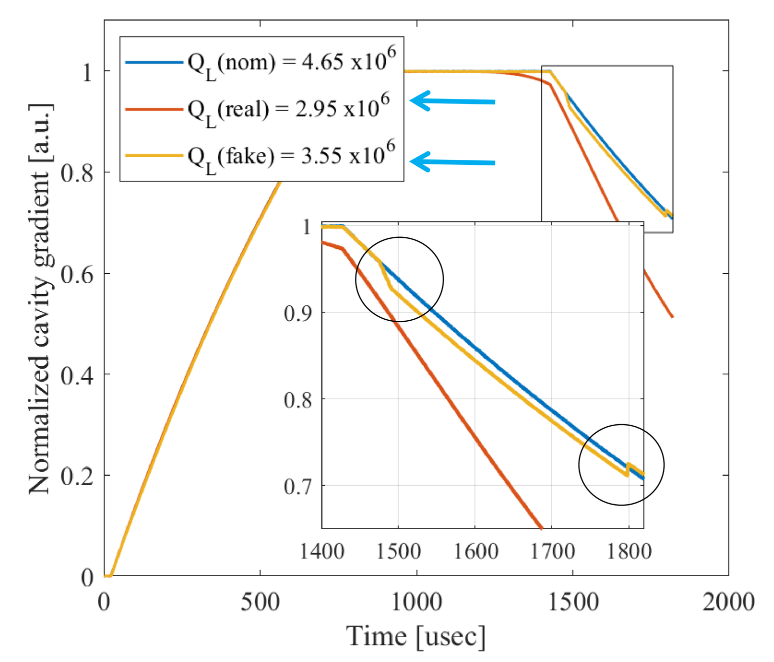
Motivation

The XFEL relies since beginning of operation (2017) 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 **loaded quality factor Q_L** during decay (from probe signal)
- If $Q_L < Q_L$(mean) – threshold → QUENCH
- Reaction : the **RF** for this station **is stopped**

"Real" and "Fake" quenches

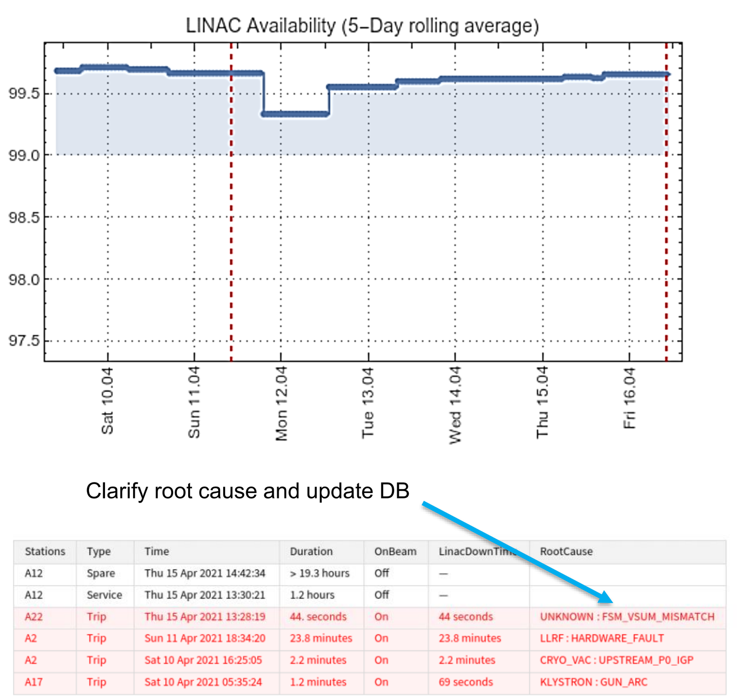
Both real and fake quenches tripped the QDS



Consolidated post-mortem quench classification

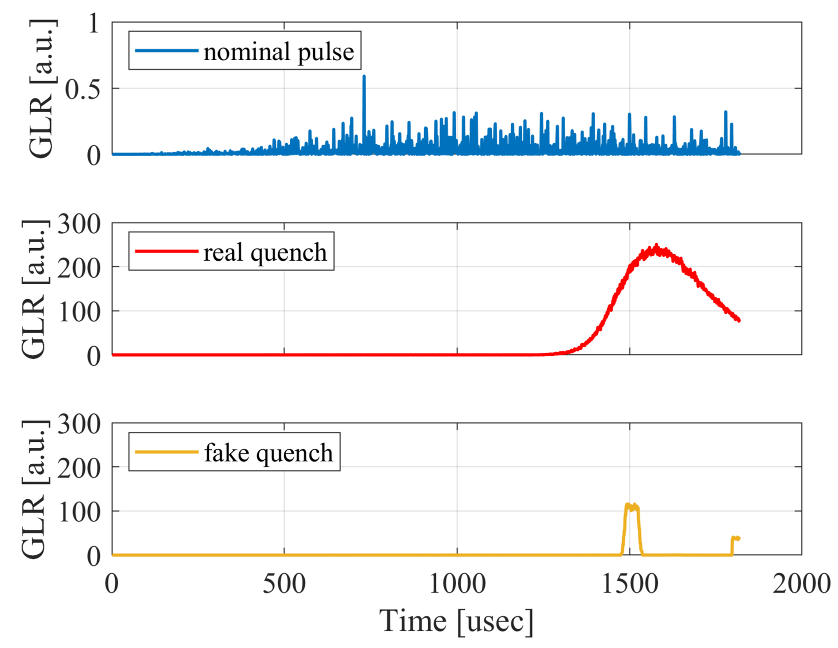
1. XTLReport

- 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**



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 (model)
- 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**



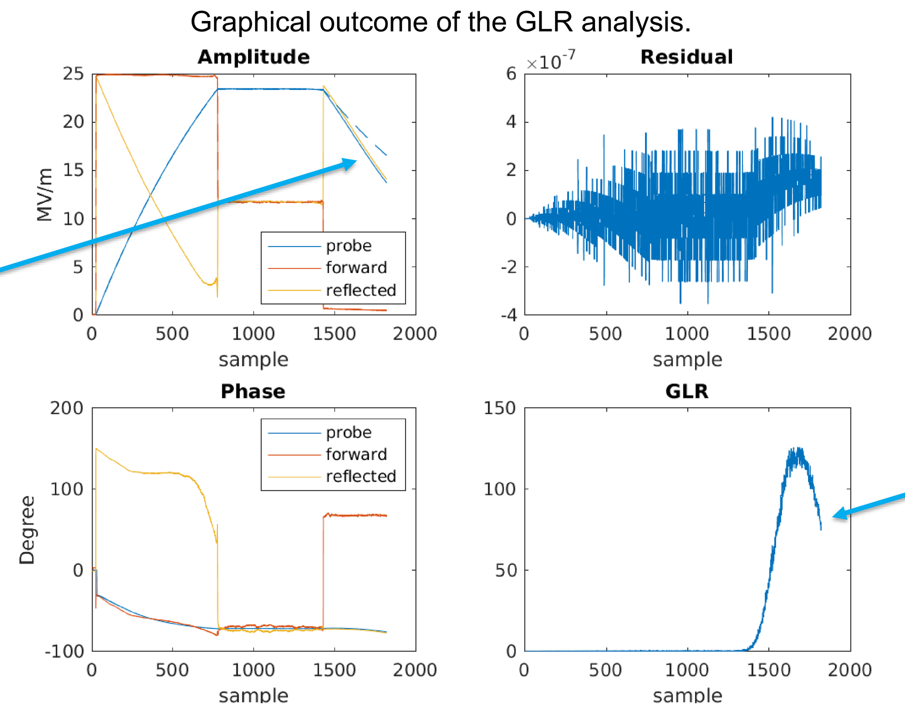
The Generalized Likelihood Ratio (GLR) proved to be a useful metric to categorize trips. The shape and magnitude of the GLRs differs greatly between trips

Residual

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

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

Graphical outcome of the GLR analysis.

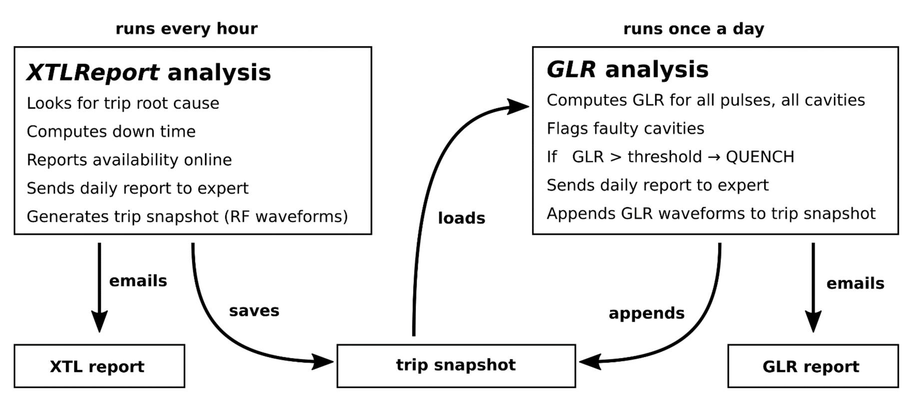


Last nominal pulse (dashed) and next quenched pulse (solid)

GLR shape and amplitude match those of a quench

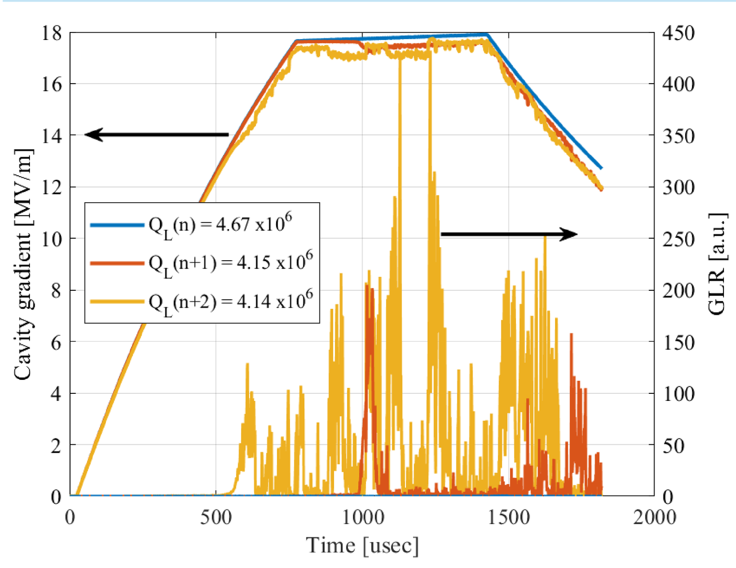
3. GLR quench evaluation as cron job

- **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 5e5 threshold)
- Post-mortem GLR analysis correctly labelled this trip as **faulty**, but **discarded it as a quench**

Statistics

	TP	*TN*	*FP*	*FN*	*a*
QDS	55	56	10	3	**89.5%**
GLR	55	65	1	3	**96.8%**

- Accuracy

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

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

- 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.

Summary and future work

An overview of an approach relying on machine-learning methods to categorize trips as quench or not-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 quite expensive in terms of FPGA resources. Both options are currently under evaluation. Another future work consists of looking into adapting the GLR algorithm for normal conducting cavities (such as the RF gun). The GLR approach could then help categorize different gun trips.

* julien.branlard@desy.de

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