IntelliQuench – Real Time detection of magnet quenches in superconducting accelerator magnets.

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New perspective 2020 - Fermilab
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Outline

I. Overview of magnet quenches
II. Deep neural network for anomaly detection
III. Results
IV. Summary & Outlook
Magnet quenches

- Superconducting accelerator magnets must operate at very low temperatures to maintain superconductivity (no resistance).

- Due to several reasons (mechanical imperfections, conductor motion, ...), a specific spot in the magnet heats up.

- This causes the magnet to become resistive, and with huge amount of current pumping through, it can be catastrophic.
In **2008**, magnet quench occurred in **100 magnets at the LHC at CERN**, leading to a loss of approximately **six tonnes** of liquid helium.

The escaping vapour expanded with **explosive force**, damaging a total of 53 superconducting magnets (each costs **several millions dollar**.)
Acoustic sensors

• We placed 5 acoustic sensors around the magnet to detect abnormal sound signatures.
Acoustic sensors

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Signals’ statistical features

- From the main signals, we calculate two features, **standard deviation** and **mean of the amplitude**.

- These features are calculated using a **rolling window**.

![Diagram showing signal with a rolling window, window size: 20ms, step size: 100μs, time label associated with the window.](image-url)
Deep Neural Networks

- Each **input** multiplied by a **weight**.
- **Weighted values** are summed, **Bias** is added.
- Non-linear **activation function** is applied
- Trained by varying the **parameters** to minimize a **loss function** (quantifies how many mistakes the network makes)
Deep Neural Network Auto-encoder

Root mean square error (RMS)

\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y^{(i)} - \hat{y}^{(i)})^2} \]

Large error? Anomaly
Reconstruction loss visualization

![Graph showing reconstruction loss over time with an anomaly point and quench time highlighted.](image-url)

- **Anomaly point**
- **0 is quench time**

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Results

Every trigger time of each ramp (Log threshold 3.3)

- Reached previous max current
- Training started

Ramp number vs. Time (s)
Zoomed in -25s near the quench

Every trigger time of each ramp (Log threshold 3.3)

- Reached previous max current
- Training started

Ramp number vs. Time (s)
Results – summary

14 Quenches

- Trigger on TRIP: 1/1
  - Not triggered at all: 1/14
  - Trigger points within 25s: 12/14
  - Trigger points entirely outside 25s: 1/14
  - Trigger points entirely inside 25s: 11/14
  - Trigger points before -25s as well: 1/14
  - Only at quench time: 1/14
  - Seconds before the quench: 10/14
Magnet quenches are expensive.

We are using Deep Neural Network to detect anomaly sound signals, which hopefully enable us trigger before the quench happens.

We’ve achieved some promising results and will be moving on to verification step on unseen data.

Eventually, we want to have a real-time system deployed on FPGAs to process streaming acoustic data.
Back-ups
Dynamic learning

• To adapt to increasing higher level of noise as we get to higher current, we also implement a dynamic learning algorithm.

For each 10-second section

Base model

Preprocessing

Training model

Evaluation of error.

> 3.3 log loss median of previous distribution? trigger!
Reconstruction loss visualization

Anomaly point

0 is quench time

$\log_{10}(\text{loss})$
Problems with static learning

You generally see very clean signal when doing static learning (just learn on the first few seconds)

However, the loss scale is different in each ramp and it’s hard to set a consistent threshold.
Dynamic threshold

Training started

Reached previous quench’s max current