SRF Cavity Instability Detection with Machine Learning at CEBAF*

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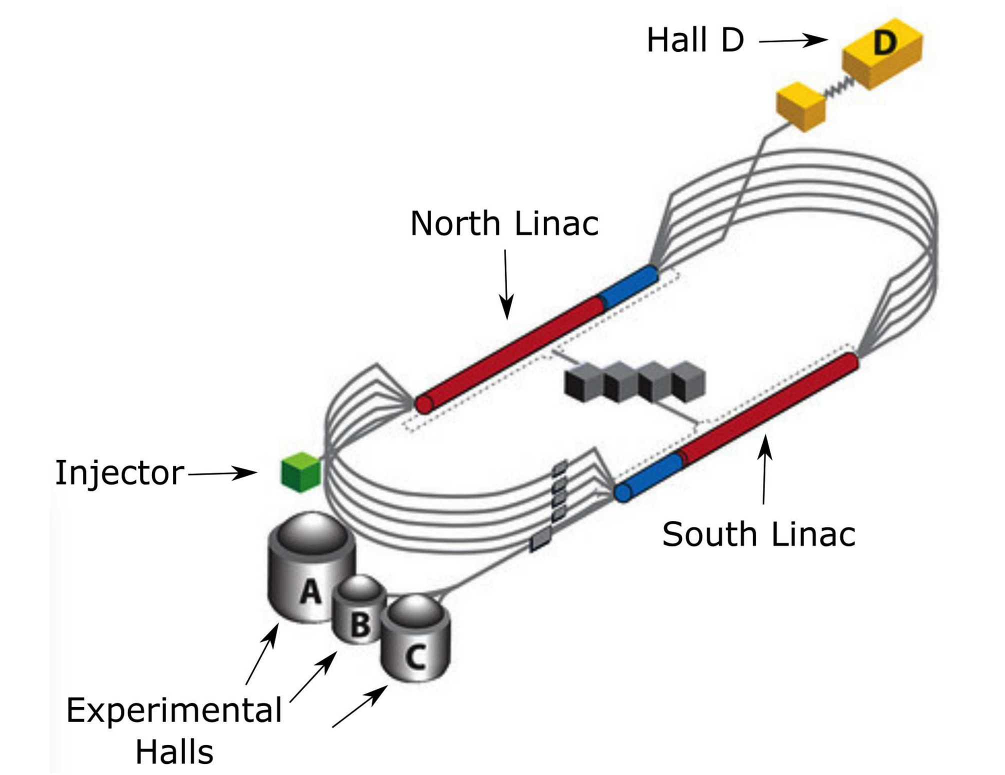
Abstract

During the operation of the Continuous Electron Beam Accelerator Facility (CEBAF), one or more unstable superconducting radio-frequency (SRF) cavities often cause beam loss trips while the unstable cavities themselves do not necessarily trip off or present a fault. Identifying an unstable cavity out of the hundreds of cavities installed at CEBAF is difficult and time-consuming. The present RF controls for the legacy cavities report at only 1 Hz, which is too slow to detect fast transient instabilities. A fast data acquisition system for the legacy SRF cavities is being developed which samples and reports at 5kHz to allow for detection of transients. An autoencoder based machine learning model is being developed to identify anomalous SRF cavity behavior. The model is presently being trained on the slow (1Hz) data that is currently available, and a separate model will be developed and trained using the fast (5kHz) DAQ data once it becomes available.

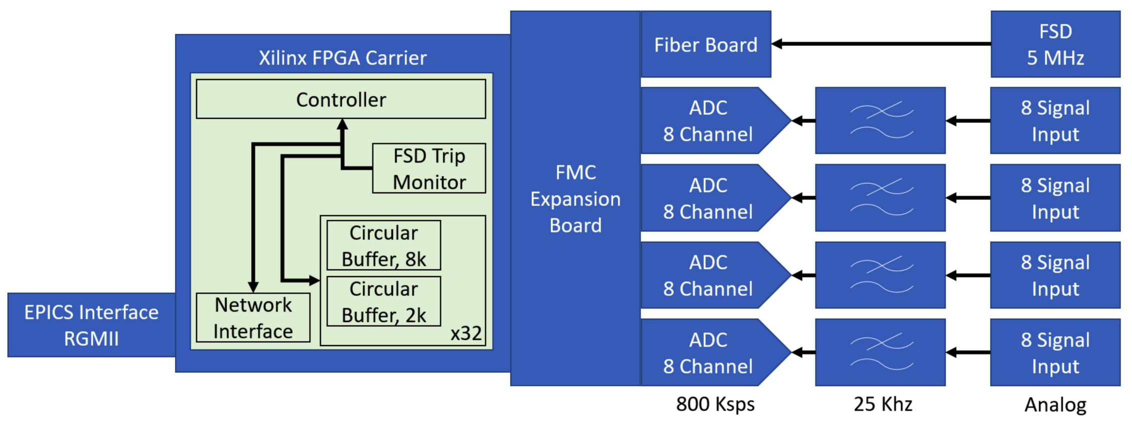
CEBAF Overview



CEBAF Overview

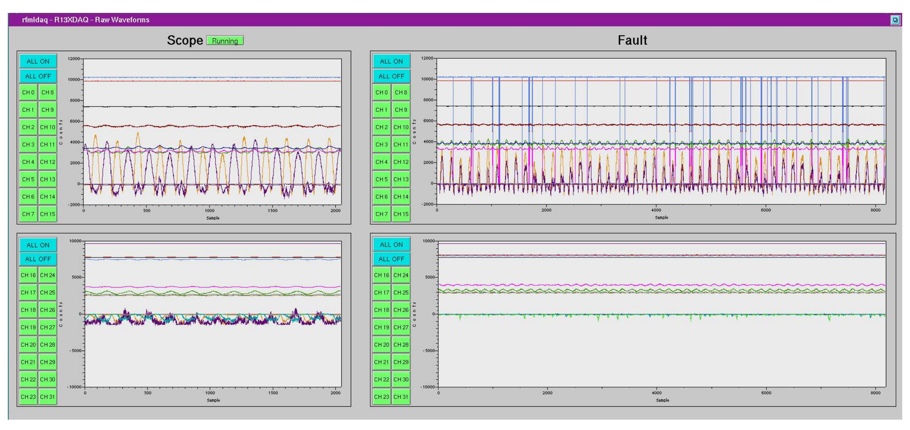
- 5.5-pass, 12GeV continuous wave electron accelerator.
- Beam is accelerated two anti-parallel SRF linacs connected by two sets of recirculation arcs.
- Beam is then extracted to up to four experimental halls.
- There are 418 SRF cavities in CEBAF, 306 of which are of the legacy style which do not presently have data acquisition fast enough to detect transient instabilities.
- A new fast data acquisition (DAQ) system has been designed and is being installed on the legacy SRF cavities at CEBAF.
- An autoencoder based machine learning anomaly detection model is being developed to identify cavity instabilities from the Fast DAQ data along with archived EPICS data recorded by the MYA archiver.

Fast Data Acquisition



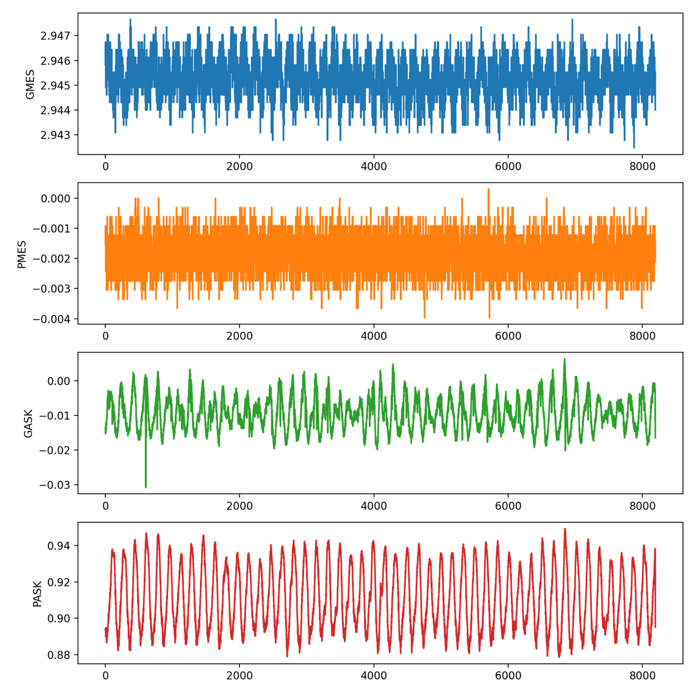
- Each chassis has inputs for 8 cavities, 4 channels per cavity (Measured gradient, measured phase, gradient drive, phase drive).
- High frequency noise filtered by analog circuitry before ADC.
- Each ADC is an 8 channel ADC sampling at 800 ksps (100 ksps per channel).
- 2K Scope Buffer for real time analysis of control signals.
- 8K Fault Buffer captures data leading up to a fault (1.6 seconds at 5kHz).

Fast DAQ Waveform Data



- Left: 2K Scope Buffer
- Right: 8K Fault Buffer
- 32 channels, 8 cavities, 4 channels per cavity

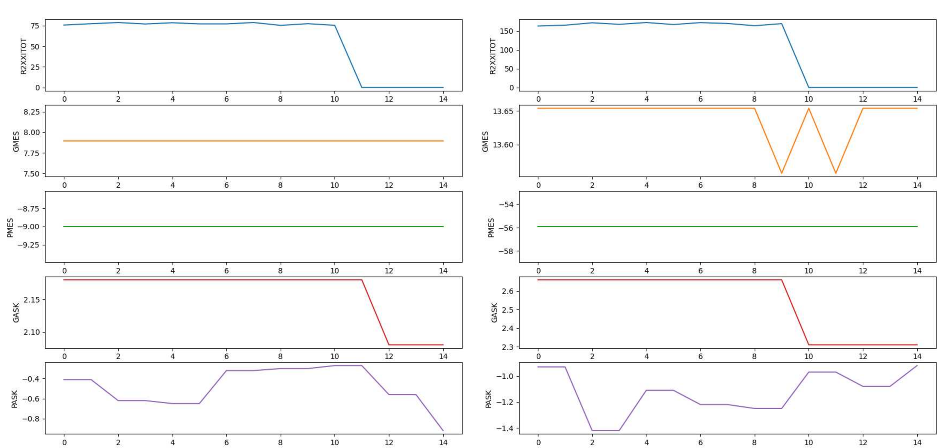
Fault Buffer Data for One Cavity



Status of DAQ Chassis Production

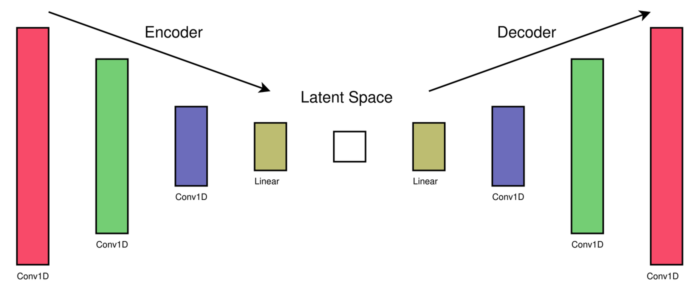
- Presently one prototype DAQ chassis is installed in one zone of the North Linac for testing.
- The prototype works well; data has already been collected from it.
- Supply chain problems related to COVID-19 delayed production of the remaining chassis.
- Costs increased due to COVID-19 as well. Now only one linac can be outfitted with the new DAQ chassis given the allocated budget.
- Components are presently being procured and assembly has begun for the remaining chassis, which will all be installed in the North Linac.

Examples of Archived EPICS Data



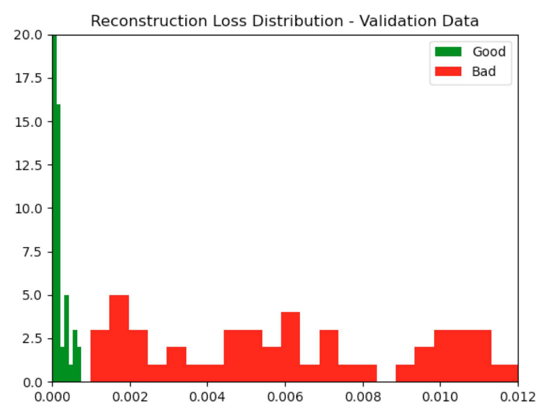
- Data includes 10s before trip, 5s after.
- Top trace is total linac current, note drop to zero at $t = 10$s indicating a trip.
- Left: Example of stable cavity
- Right: Example of unstable cavity. Measured gradient unstable around the time of the trip, hence it's more likely to have caused the trip.

Autoencoder Model



- An autoencoder model was chosen because most of the data will likely be of stable cavities; unstable cavities are expected to be fewer and farther between.
- The problem is one of anomaly detection rather than classification.
- Implemented in Python and PyTorch.
- Developed and trained using archived EPICS data.
- A similar model will be developed and trained using the new Fast DAQ data once it becomes available.

Initial Autoencoder Results

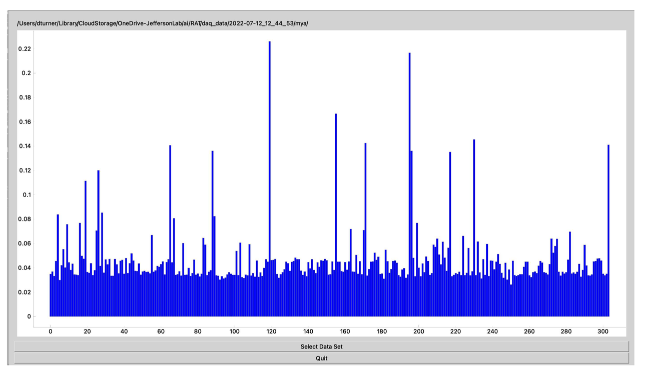


- Above plot shows reconstruction losses for cavity data sets labeled "good" (i.e. "stable") and cavity data sets labeled "bad" (i.e. "unstable").
- Using 0.001 as the threshold between "good" and "bad", we get an accuracy of ~ 0.99 (7 out of 1036 samples falsely identified as "bad"). Development continues.
- A similar model will be developed and trained using the Fast DAQ data once it is available.

Data Collection Daemon

- Selectively (to conserve disk space) harvests DAQ data for inference by the autoencoder model.
- When the daemon detects a fast shutdown trip, it determines which machine protection device(s) initiated the trip to decide the nature of the trip.
- If the nature of the trip indicates that the trip was possibly caused by an unstable SRF cavity which did not itself present a fault, the DAQ Fault Buffer data, along with a timestamp for retrieval from the archiver, are stored on disk for inference by the autoecoder.

Operator Interface



- Provides an interface to the autoencoder model to operators and technicians.
- Displays a histogram of reconstruction loss for each cavity for one trip event.
- Reconstruction loss is interpreted as the likelihood of a cavity having caused a beam loss trip due to instability.
- Allows operators and technicians to quickly identify cavities that the autoencoder predicts are unstable and causing beam loss trips.

Conclusion

The initial results of the autoencoder model with the archived EPICS data look promising. Data labeling, model development, and model training will continue, along with model development for the Fast DAQ data and software tool development. Procurement, assembly, and installation of the Fast DAQ hardware is underway.

References

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