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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. The present RF controls for the legacy cavities report at only 1 Hz, which is too slow to detect fast transient instabilities during these trip events. These challenges make the identification of an unstable cavity out of the hundreds installed at CEBAF a difficult and time-consuming task. To tackle these issues, a fast data acquisition system (DAQ) for the legacy SRF cavities has been developed, which records the sample at 5 kHz. An unsupervised learning framework has been developed to identify anomalous SRF cavity behavior. We will discuss the present status of the DAQ system and our framework, along with recent successes in detecting anomalous cavity behavior. Overall, our method offers a practical solution for identifying unstable SRF cavities, contributing to increased beam availability and machine reliability.

INTRODUCTION

CEBAF is a 5.5-pass, 12 GeV continuous wave (CW) electron accelerator [1]. CEBAF is comprised of two anti-parallel SRF linacs connected by two sets of recirculation arcs, enabling the acceleration of electron beams for delivery to up to four experimental halls (Figure 1).

Each linac is comprised of 200 SRF cavities, plus 18 cavities in the injector, which provide electron beam acceleration. During the operation of CEBAF, any one unstable SRF cavity can cause beam loss trips while the unstable cavities themselves do not necessarily trip off or present a fault.

The existing tools and diagnostics for identifying unstable SRF cavities at CEBAF are presently rather limited. Out of the 418 SRF cavities at CEBAF, 288 are of the original legacy CEBAF design which lacks the fast data acquisition capabilities of the newer cavities. The legacy cavity diagnostics are limited to what is presented to the EPICS [2] control system which is limited to a data rate of 1 Hz, which is not fast enough to capture transient instabilities. Also, simply the number of cavities in the machine makes the search for instabilities time consuming. Work described in [3] addresses fault classification for the newer SRF cavities at CEBAF. This work addresses identifying unstable cavities of the legacy design.

To address these problems, a new fast data acquisition (DAQ) system has been designed and is being installed on the legacy SRF cavities at CEBAF, along with an anomaly detection model based on Principal Component Analysis (PCA).

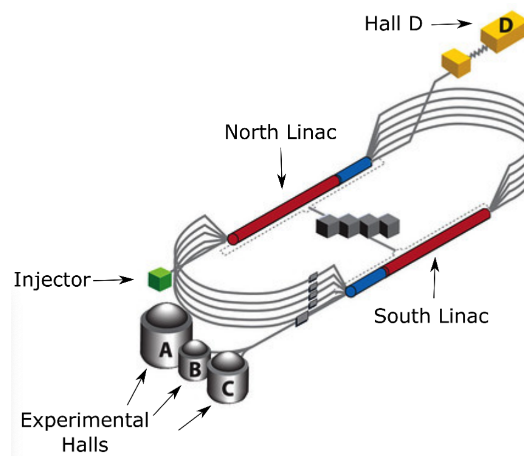

Figure 1: 12 GeV CEBAF overview. The legacy SRF cavities comprise most of the red regions of the linacs.

FAST DATA ACQUISITION SYSTEM

Each legacy SRF cavity has four analog outputs on its control module:

- GMES: Measured Gradient. Should mirror the GSET value in EPICS and should be stable to within 0.044 % during normal operations. Has DC and AC components.
- PMES: Measured Phase. This is the phase in the cavity measured against the absolute 70 MHz reference. This also should mirror PSET in EPICS and should be varying less than ±0.3°.
- GASK: Gradient Drive. The change in klystron incident power needed to maintain the GMES value within specifications. This signal will change in response to beam detuning or beam loading.

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- PASK: Phase drive. The change in klystron phase to the cavity needed to maintain the PMES value within specifications.

Each DAQ chassis has inputs for eight cavities, for a total of 32 channels. Each channel is saved into a dedicated 8k-sample fault buffer and records 1.6 seconds of samples (when the adjustable sample rate is set to 5 kHz). This fault buffer will fill up during either a software initiated fault or initiated by a loss of signal from the machine protection system. The buffer will "freeze" at the time of the fault signal being received.

Figure 2 shows an example of the DAQ fault buffer waveform data for a single cavity as it will be presented to the PCA model. Further details of the DAQ hardware are found in [4].

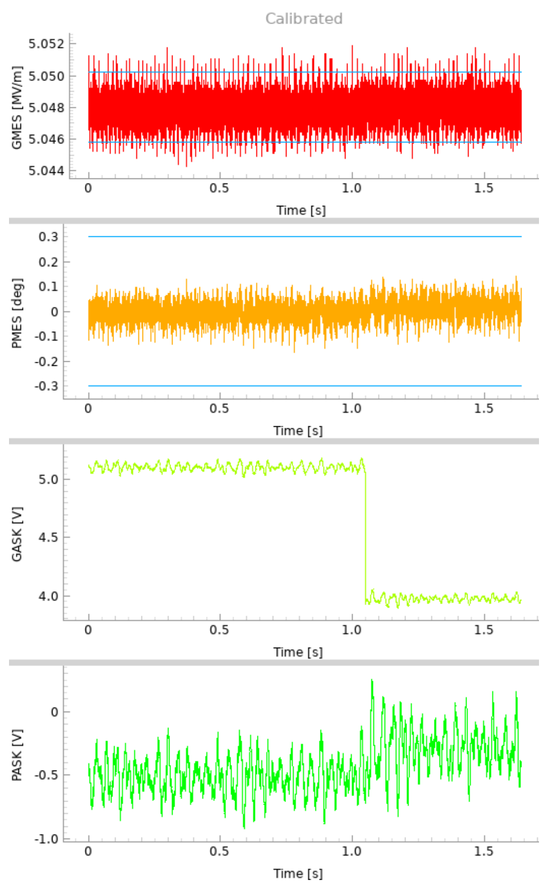

Figure 2: Fast DAQ waveform data.

There are presently DAQ chassis installed in all of the legacy zones in the North Linac. The original budget covered the cost of outfitting both linacs with the fast DAQ chassis, but the cost of components increased due to COVID-19 to the point that only one linac can be outfitted within the allocated budget.

DAQ DATA COLLECTION

For this project, we are only interested in waveform data that is associated with potential RF instability and not attributed to actual RF trips. Therefore, we collect waveform data upon trips that occur when the total linac beam current is greater than a configurable threshold (presently 10 μA), the trip is attributed to a beam loss monitor, ion chamber, or other device that indicates beam loss, and the trip is not associated with an actual RF trip (with an RF trip, the offending cavity is self-evident). We will refer to these data that contain potentially anomalous cavity waveforms as *filtered* data.

We also collect waveform data three times per day for one hour at two minute intervals at the end of each operational shift while beam current is above the aforementioned threshold, and no trips are occurring. These data represent a baseline for normal cavity operation. We will refer to these data as *normal* data.

As an aside, we also collect waveforms each time a cavity that is equipped with a DAQ chassis trips. These data are used for purposes outside this project.

ANOMALY DETECTION MODEL

An unsupervised approach was chosen for several reasons. First is that we are dealing with a completely new presentation of the SRF signals. There simply wasn't any pre-existing data with which to label for training a supervised model. Second, labeling itself is a time-consuming and laborious task. Lastly, the cavity operating conditions, and consequently the waveform data they produce, change over time as cavities are taken into or out of service, linac energy profiles change, and the like. As a result, we require a workflow that is robust against frequent changes in the presentation of normal data yet still able to identify deviations [5].

The model considers each cavity independently and a new model is trained each day. For each new model, the model analyzes the previous seven days of normal data and then looks for deviations in the present 24 hours. An overview of the data processing workflow is illustrated in Fig. 3 and described below.

Out of the four available signals for each cavity, we found that applying the model to only the GMES and PMES signals was sufficient.

The waveforms are first calibrated to engineering units, MV/m for GMES, degrees for PMES, and volts for GASK and PASK. The waveforms are then centralized by subtracting the mean so that purposeful changes to GMES or PMES are not identified as anomalous. The next step is to extract meaningful features from each of the waveforms. We use the Python library `tsfresh`, which is specifically designed to extract features from time-series data [6] [7]. Although `tsfresh` can compute hundreds of features per signal, we have found that the standard statistical features such as sum, median, mean, standard deviation, variance, RMS, maximum, absolute maximum, and minimum are sufficient.

Principal Component Analysis (PCA) is then applied to the previous seven days of normal and filtered data for each cavity. PCA is a dimensionality reduction technique that transforms a dataset into a set of orthogonal (uncorrelated) components, ordered by the amount of variance they capture

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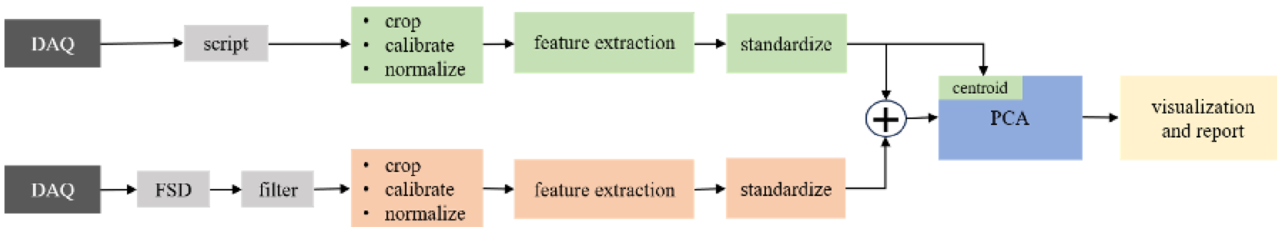

Figure 3: Data processing workflow for normal data (top) and filtered data (bottom).

from the original data [8]. We use the two largest computed principal components to simplify the data into a format that is easily visualized in two dimensions. We then compute the centroid of the normal data in the reduced two-dimensional plane.

As new data arrives in the present 24 hour period, the same feature extraction and PCA analysis are applied to the new data. The PCA distance from the previously computed centroid is then computed. The cavities can then be sorted by the PCA distance and displayed to the operators and technicians in the smartRAT GUI [4]. Each day, a list of the cavities with the 25 largest PCA distances is automatically compiled and emailed to RF subject matter experts for further evaluation.

RESULTS

Figure 4 show the PCA plot of a single cavity over a seven day period. The fact that the normal data (blue markers) and filtered data (red markers) are all clustered around the centroid (black cross) indicates that the cavity did not exhibit anomalous behavior during that seven day period.

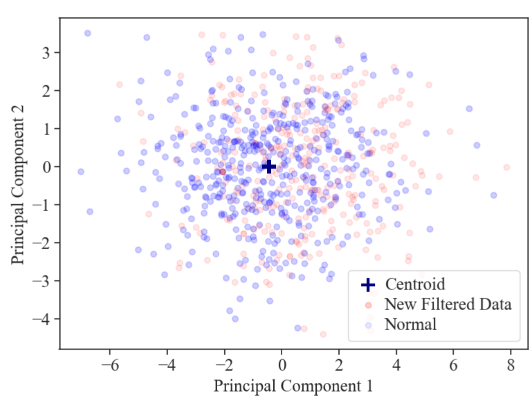

Figure 4: PCA plot for a single cavity without anomalous behavior.

Figure 5 is an example of a PCA plot for a cavity that exhibited anomalous behavior over the seven day period. Note the outlier point (red marker, bottom right) that lies far outside the cluster around the centroid.

Figure 6 shows the waveforms of the outlier instance, clearly showing gradient and phase instability around the time of the beam trip.

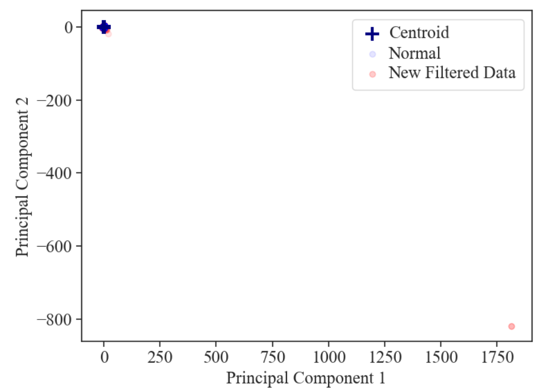

Figure 5: PCA plot for a cavity with anomalous behavior.

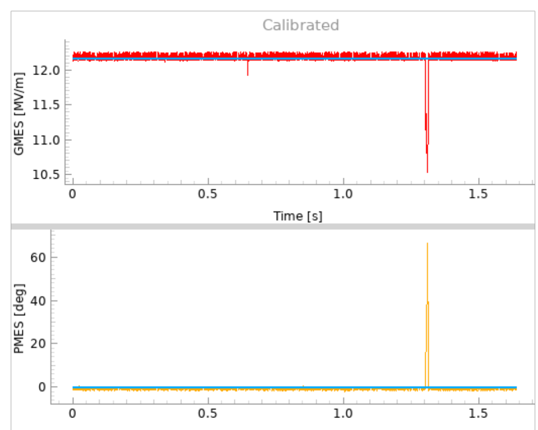

Figure 6: Waveform plots for a cavity with anomalous behavior.

CONCLUSION

We have described an unsupervised learning approach for detecting anomalous SRF cavity behavior at CEBAF. Future work includes outfitting the remainder of the legacy SRF cavities at CEBAF with the new DAQ chassis, and improving the existing user interface and reporting tools. Additional tools are being developed to correlate beam energy excursions detected on beam position monitor waveforms to SRF cavity instability [9].

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