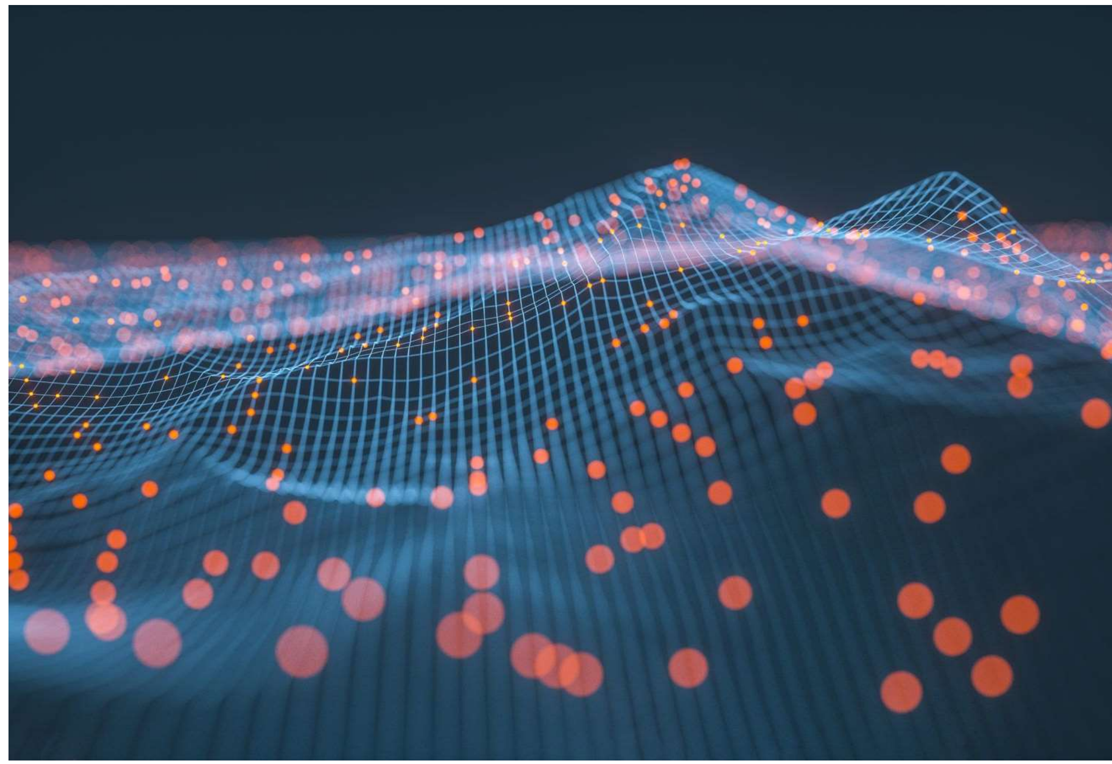
AI for Optimized SRF Performance of CEBAF Operations

Chris Tennant

for the Jefferson Laboratory Team

DOE PI AI/ML Exchange Meeting | December 5, 2023



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Outline

- **Jefferson Laboratory**
- **FOA LAB 20-2261: Year 3 Status**
  - ✓ *Cavity Instability Detection*
  - ✓ *C100 Fault Prediction*
  - ✓ *Field Emission Management*
- **Project Summary**
  - ✓ *Deliverables and Schedule*
  - ✓ *Budget*

"AI for Optimized SRF Performance of CEBAF Operations"

The project builds on a recent successful effort at Jefferson Lab to implement AI at CEBAF and seeks to extend the work for optimizing SRF operations. Specifically, the proposal presents a multi-faceted approach to:

A. develop tools to automate cavity instability detection
B. provide real-time fault prediction for C100 cavities
C. minimize radiation levels due to field emission in the linacs

Improving SRF performance in these ways would translate to increased beam availability and reliability of CEBAF, increased beam-on-target for nuclear physics users, and meet DOE's mission to maximize scientific output per operating dollar.

DEPARTMENT OF ENERGY
OFFICE OF SCIENCE

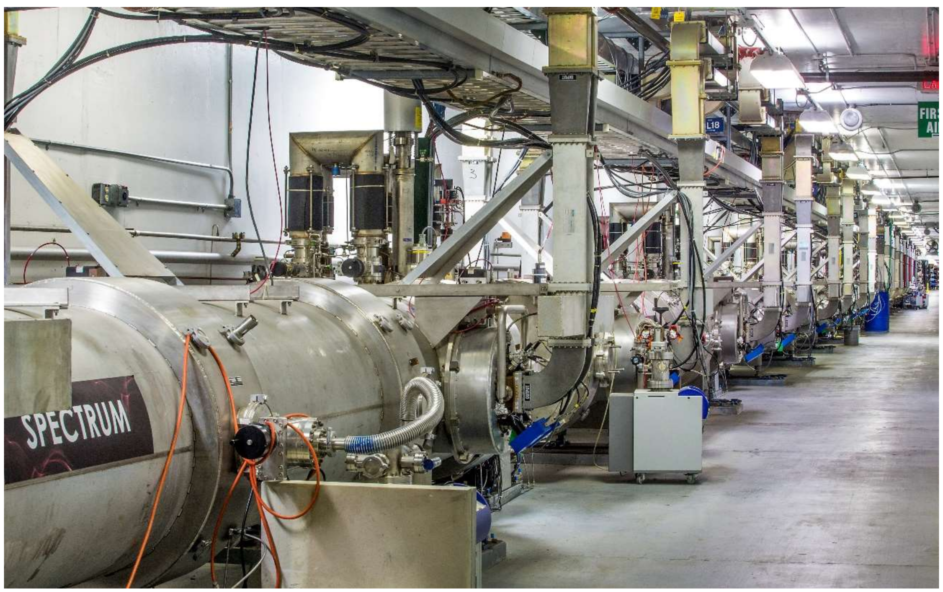
BASIC ENERGY SCIENCES
HIGH ENERGY PHYSICS
NUCLEAR PHYSICS

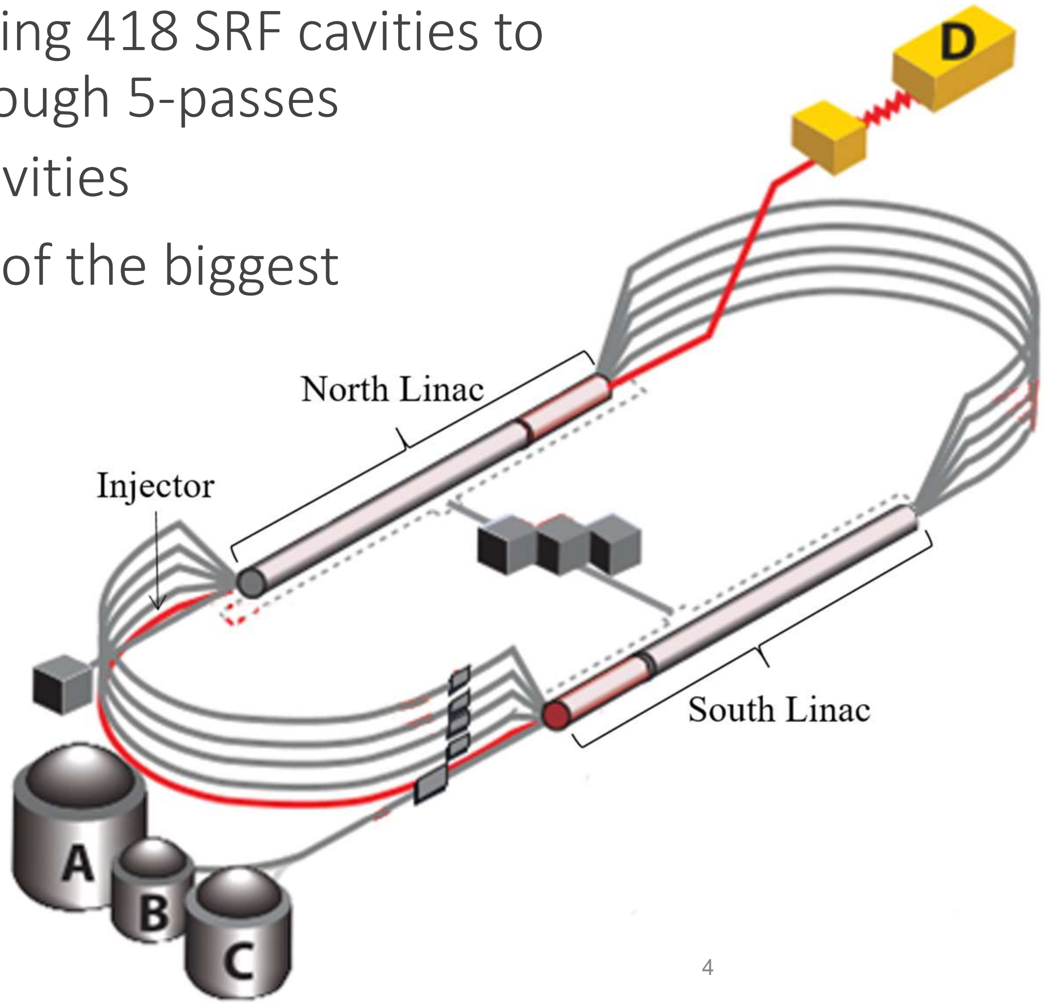
DATA, ARTIFICIAL INTELLIGENCE, AND MACHINE LEARNING AT DOE SCIENTIFIC USER FACILITIES

DOE NATIONAL LABORATORY PROGRAM ANNOUNCEMENT NUMBER: LAB 20-2261

Continuous Electron Beam Accelerator Facility

- CEBAF is a CW recirculating linac utilizing 418 SRF cavities to accelerate electrons up to 12 GeV through 5-passes
- the heart of the machine is the SRF cavities
- RF related issues are consistently one of the biggest contributors to downtime



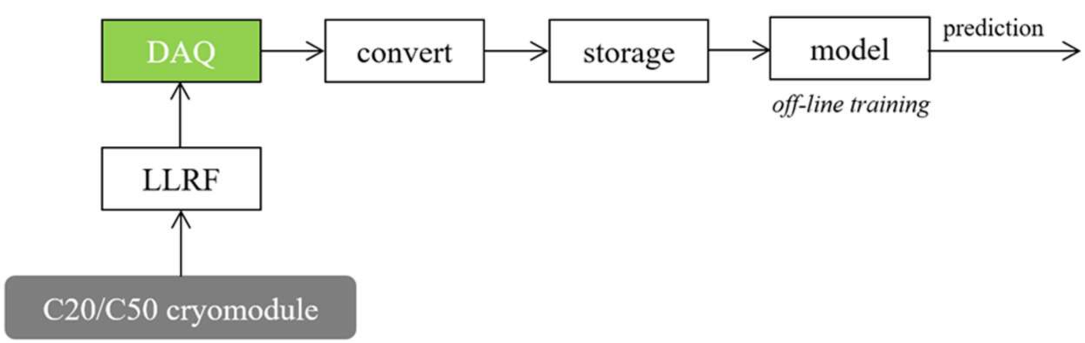


PROJECT A

PI: Dennis Turner
Graduate Student: Hal Ferguson (ODU)

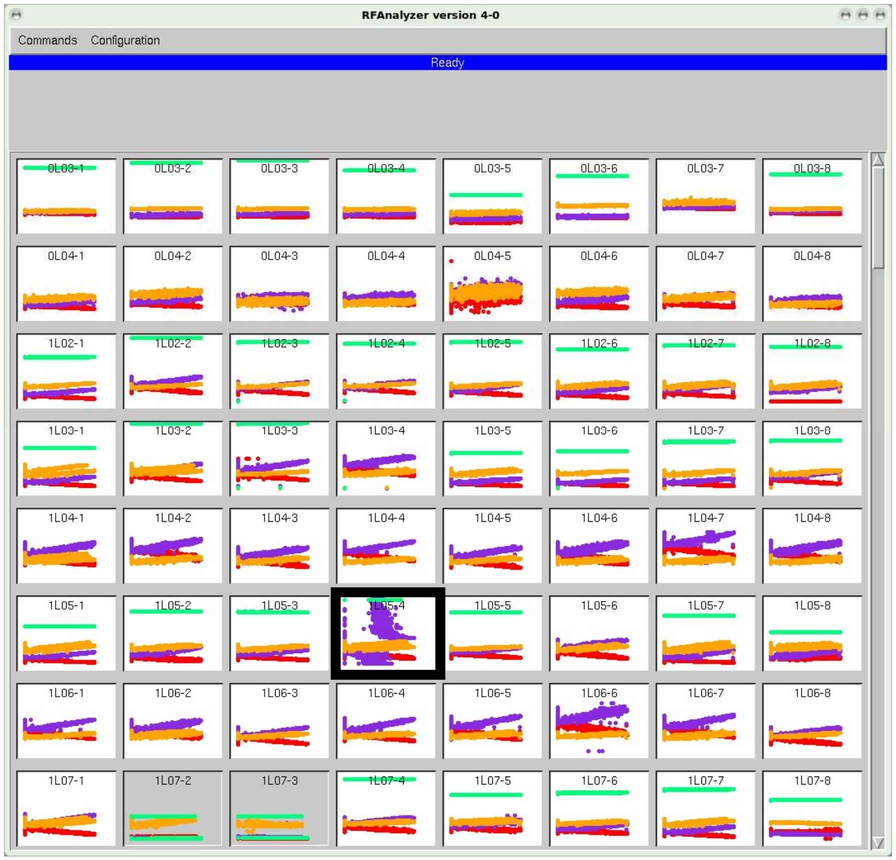
Project A: Cavity Instability Detection

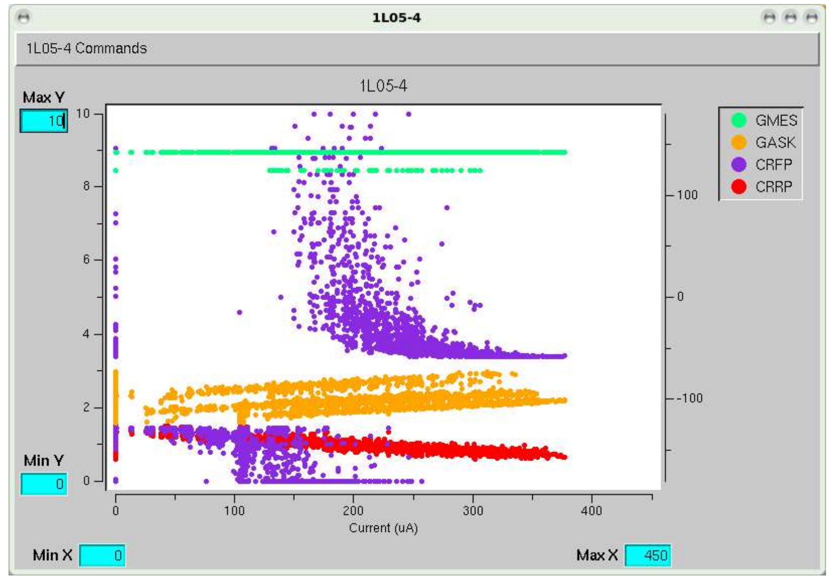
- **Goal:**
  automate the process of identifying unstable SRF cavities
- **Description:**
  SRF cavities can become unstable without presenting faults, identifying these unstable cavities with present diagnostics is difficult and time-consuming
- **Solution**:
  (1) develop and install a new fast DAQ system for the legacy SRF cavities
  (2) apply ML to identify unstable cavities



Cavity Instability Detection: Current Approach

RF Analyzer Tool





- note, this represents an obvious example
- not all instances are so easily detectable by an operator

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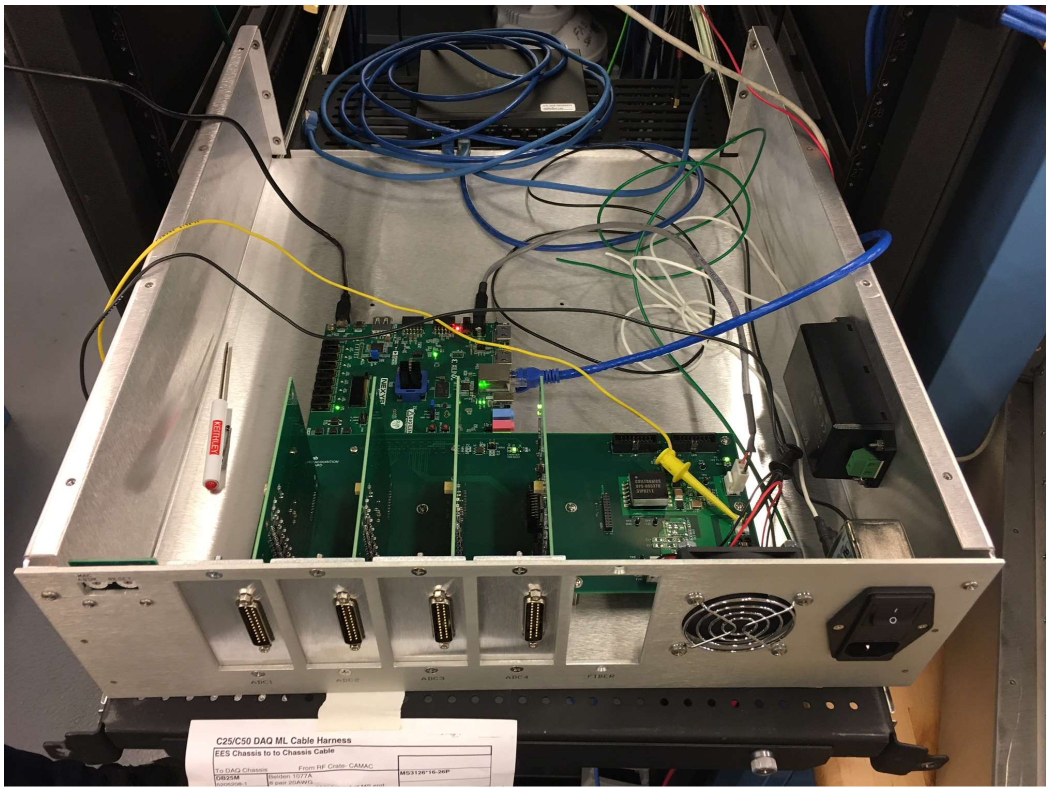
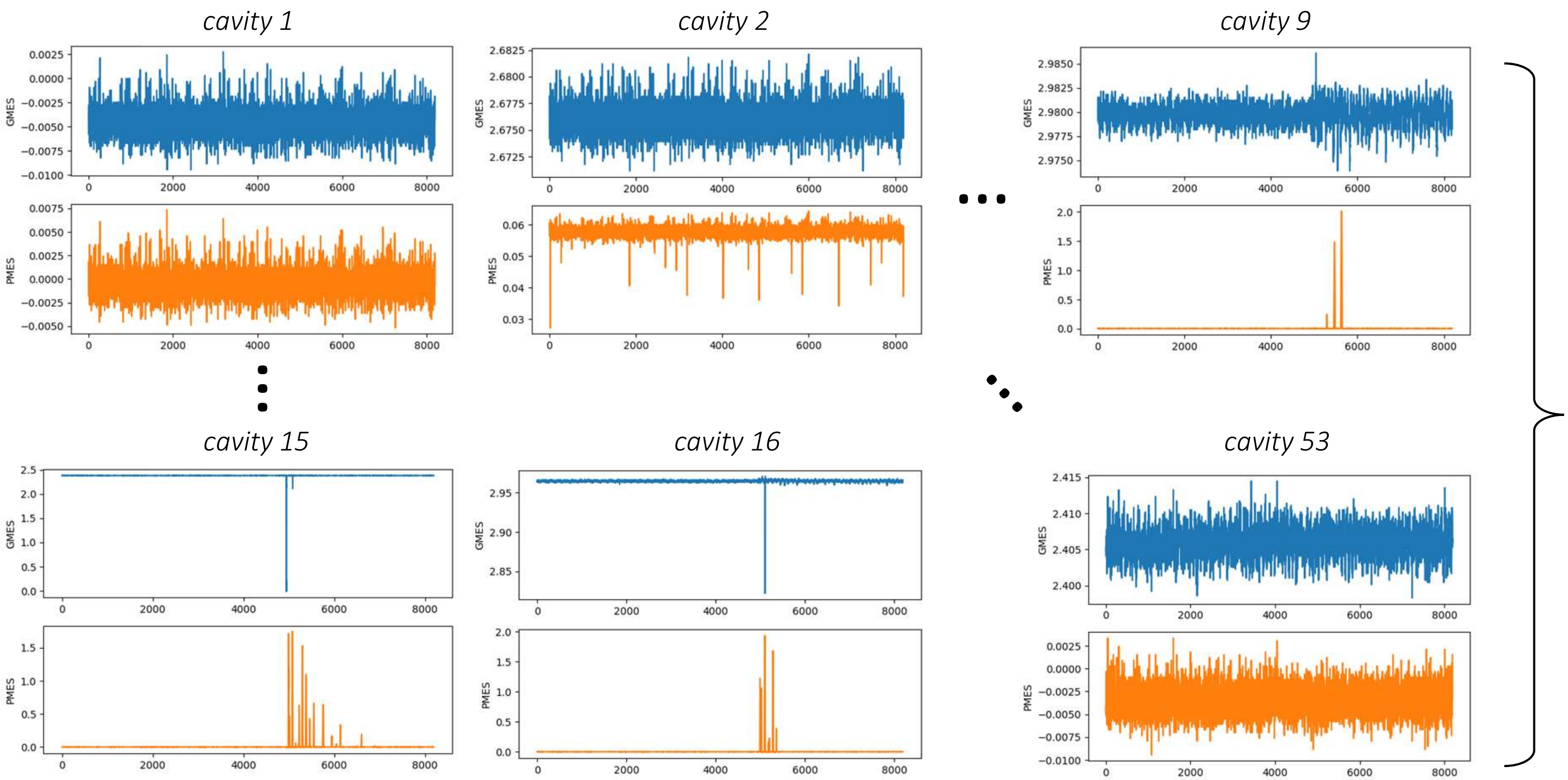
Cavity Instability Detection: Data Acquisition System (DAQ)

- 20 DAQs for NL (reduced scope due to rising costs)
- 17 are currently installed and collecting data



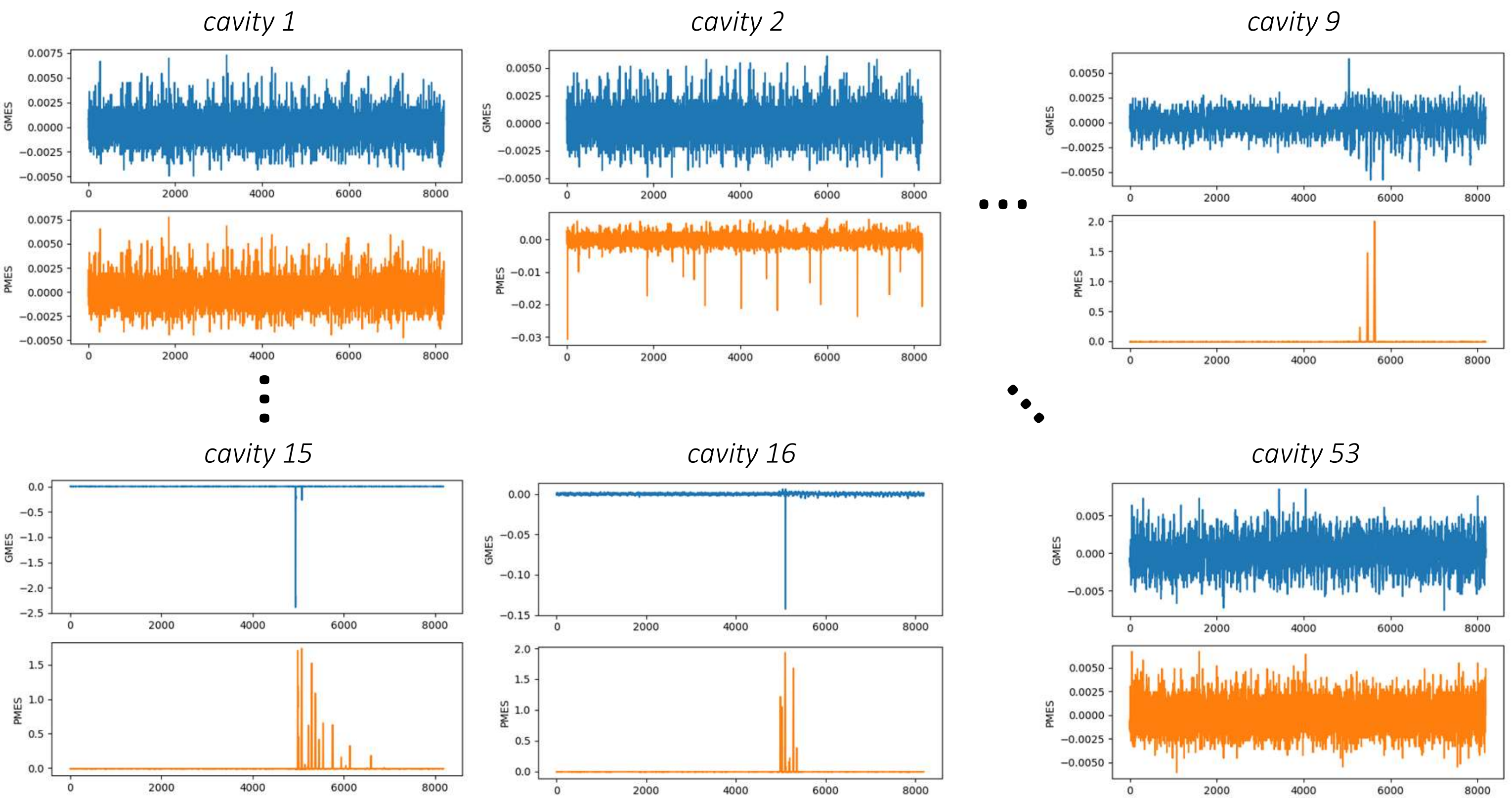
Filter and Collect Raw Signals from an Event



data from an event on
Feb. 1, 2023 03:36:14 AM

- filter collects data when a fault involves a BLM, ion chamber, or BLA trip but *not* a cavity trip
- 1 event = 20 cryomodules x 8 cavities/cryomodule x 2 signals/cavity = 320 signals (eventually)

Pre-Process and Extract Features



53 × 2n-features

$$\begin{bmatrix} f_{1,1} & \cdots & f_{1,2n} \\ \vdots & \ddots & \vdots \\ f_{53,1} & \cdots & f_{53,2n} \end{bmatrix}$$

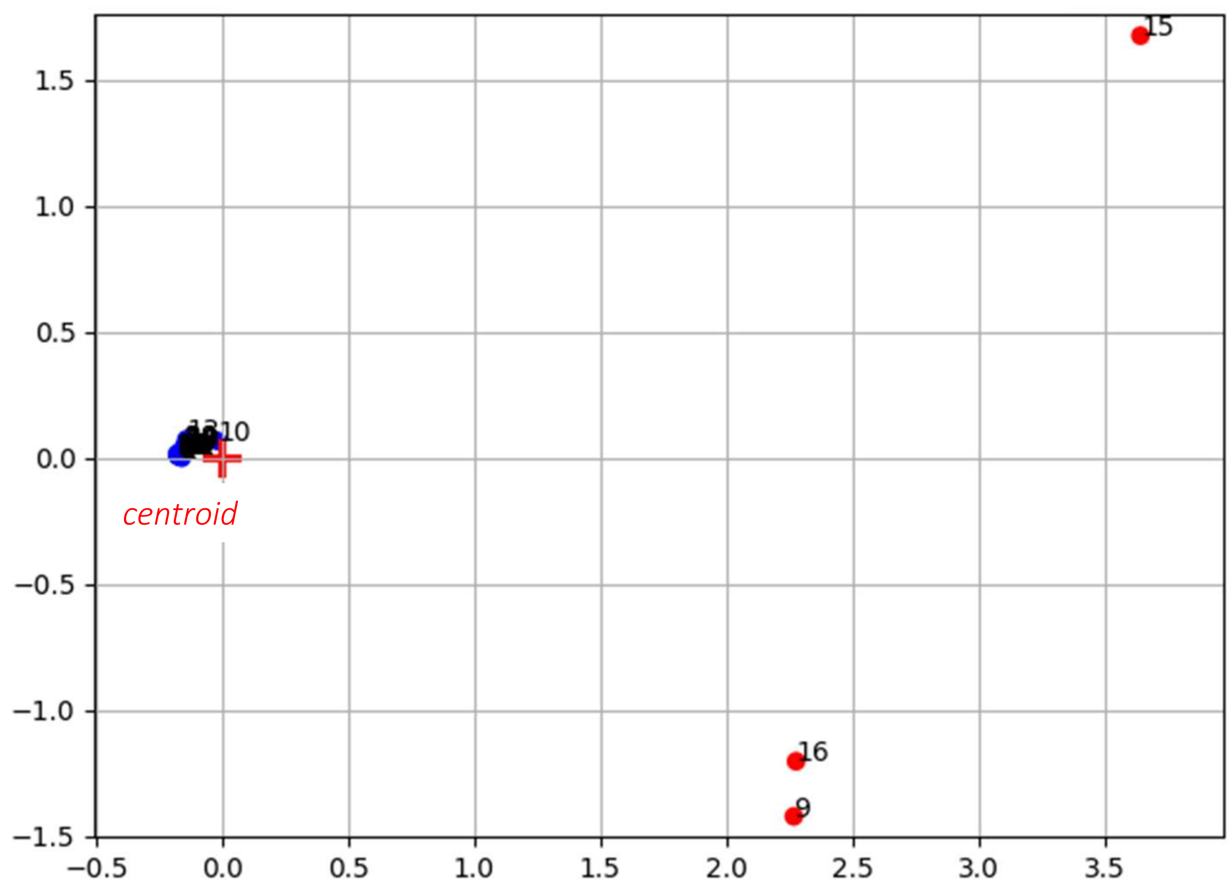
- standardize data
- extract *n*-features per signal using `tsfresh` and concatenate

Principal Component Analysis (PCA)

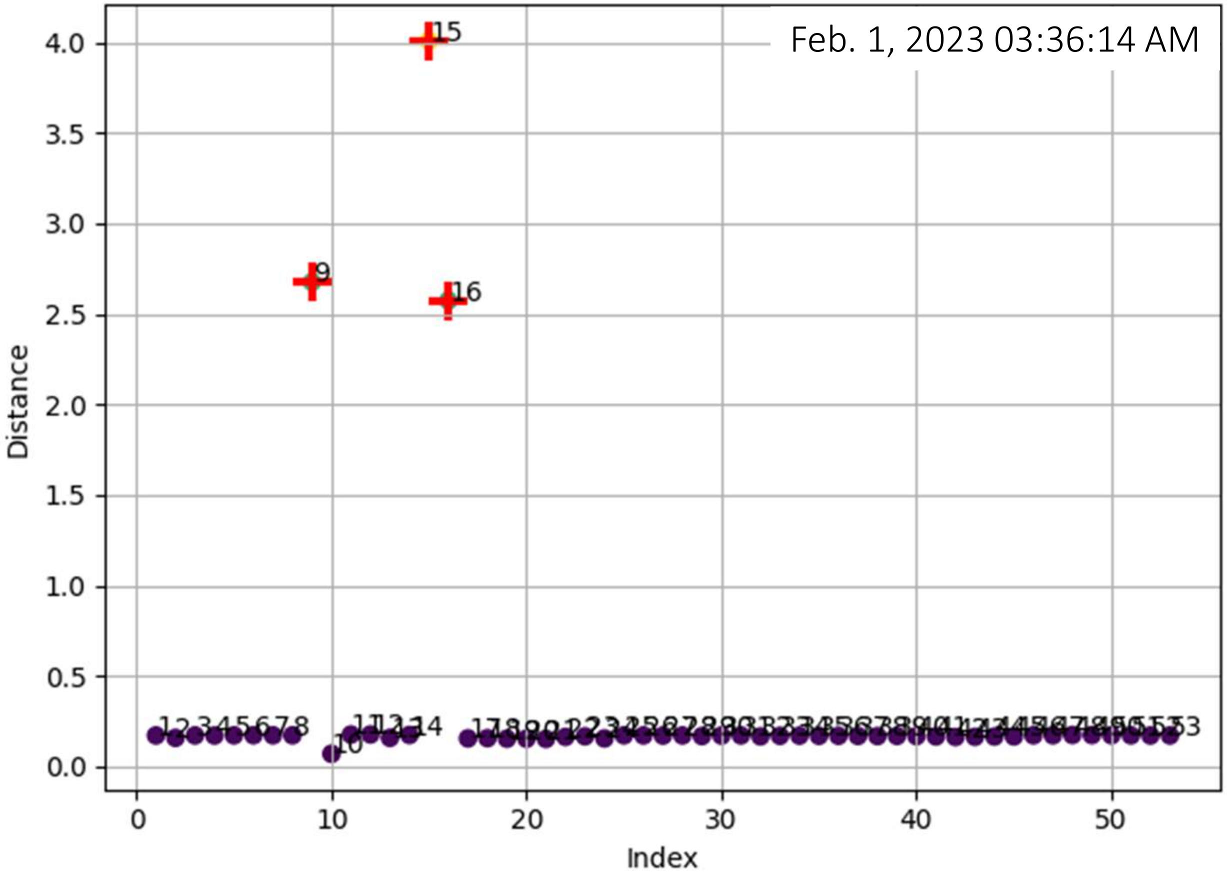
- use PCA to reduce dimensionality from $2n$ to 2 for visualization
- compute centroid of data points
- compute distance of every data point from centroid and plot

$$53 \times 2n\text{-features} \xrightarrow{\textbf{PCA}} 53 \times 2 \rightarrow$$

$$\begin{bmatrix} f_{1,1} & \cdots & f_{1,2n} \\ \vdots & \ddots & \vdots \\ f_{53,1} & \cdots & f_{53,2n} \end{bmatrix} \quad \begin{bmatrix} PCA_{1,1} & PCA_{1,2} \\ \vdots & \vdots \\ PCA_{53,1} & PCA_{53,2} \end{bmatrix}$$



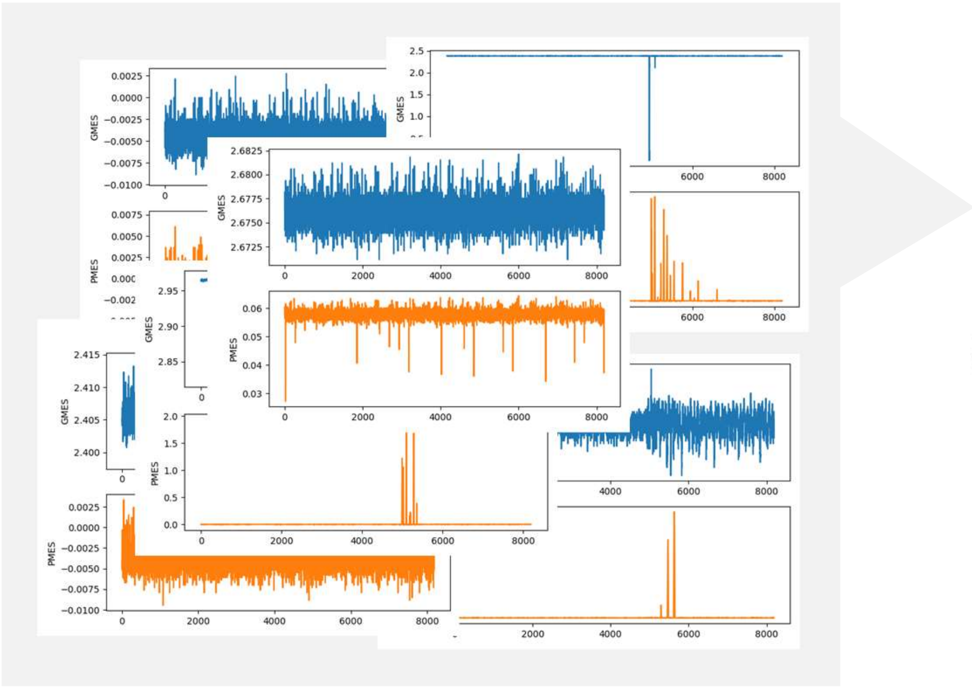
Distance from Centroid

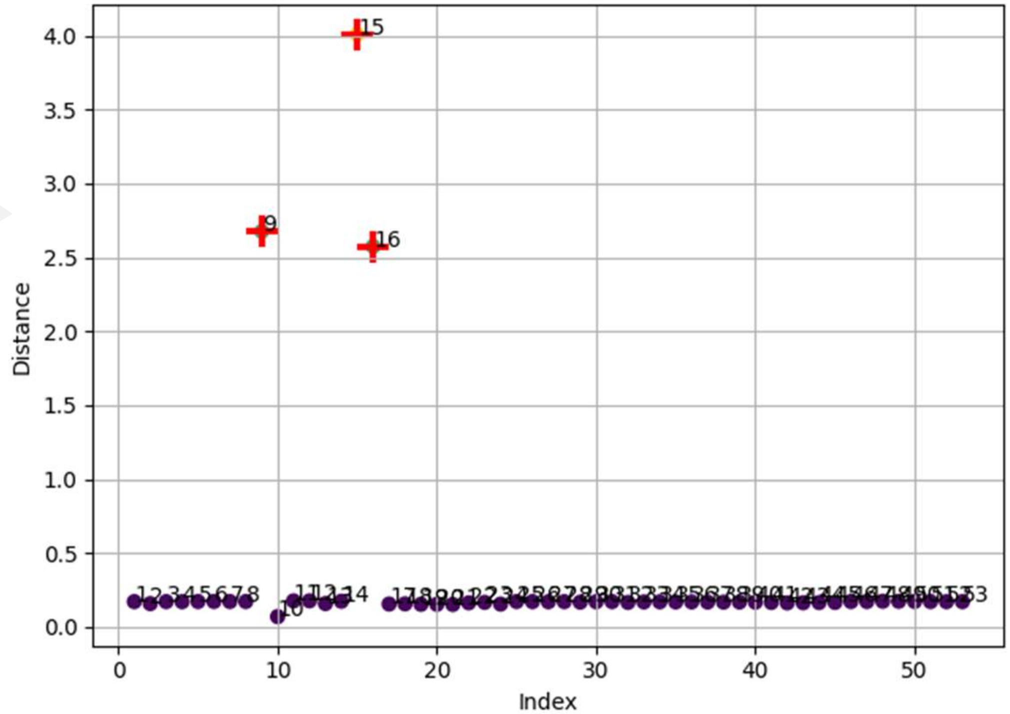


• anomalous cavities are easily identified as outliers

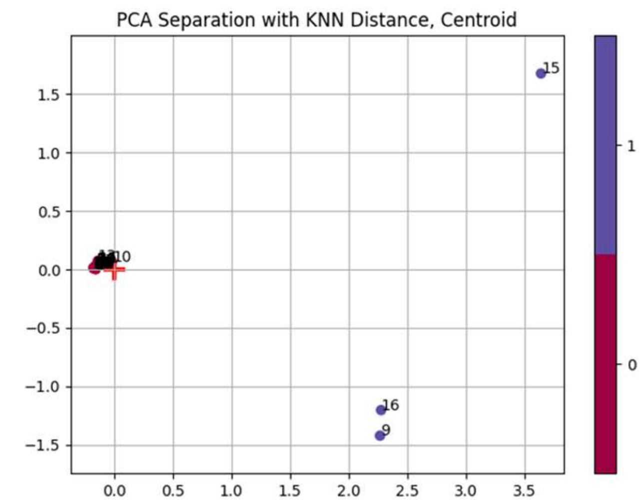
Final Workflow

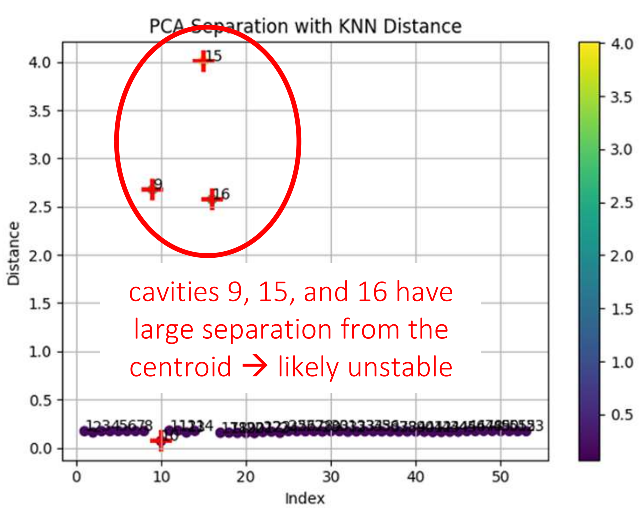
1 event = 160 cavities × 2 signals/cavity × 8,192 points/signal

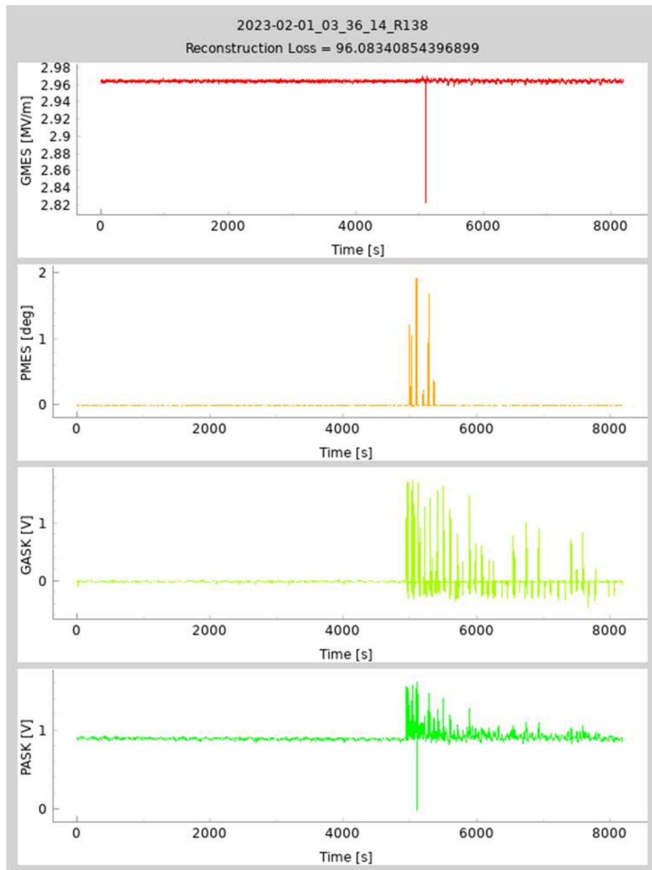




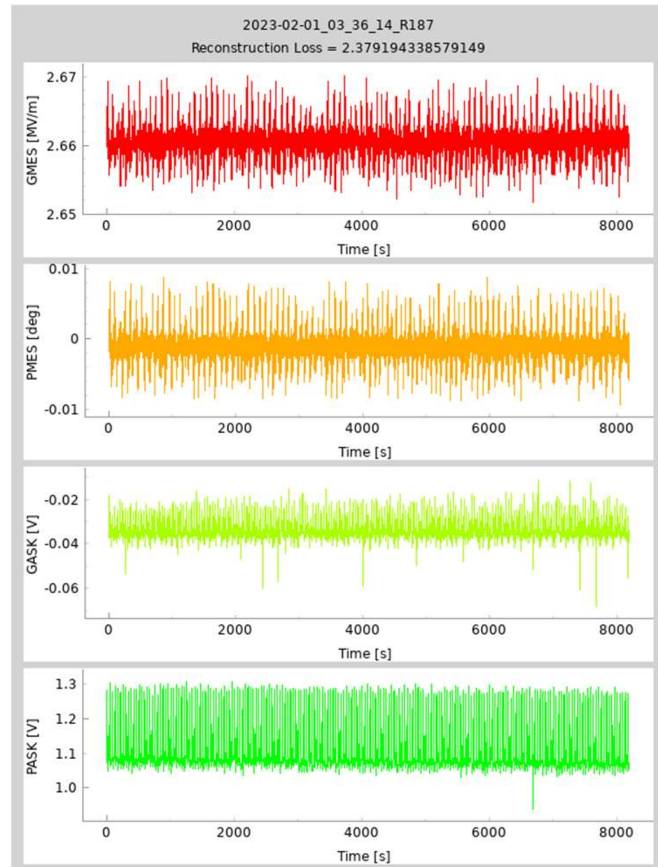
Cavity Instability Detection: Connecting PCA with Data







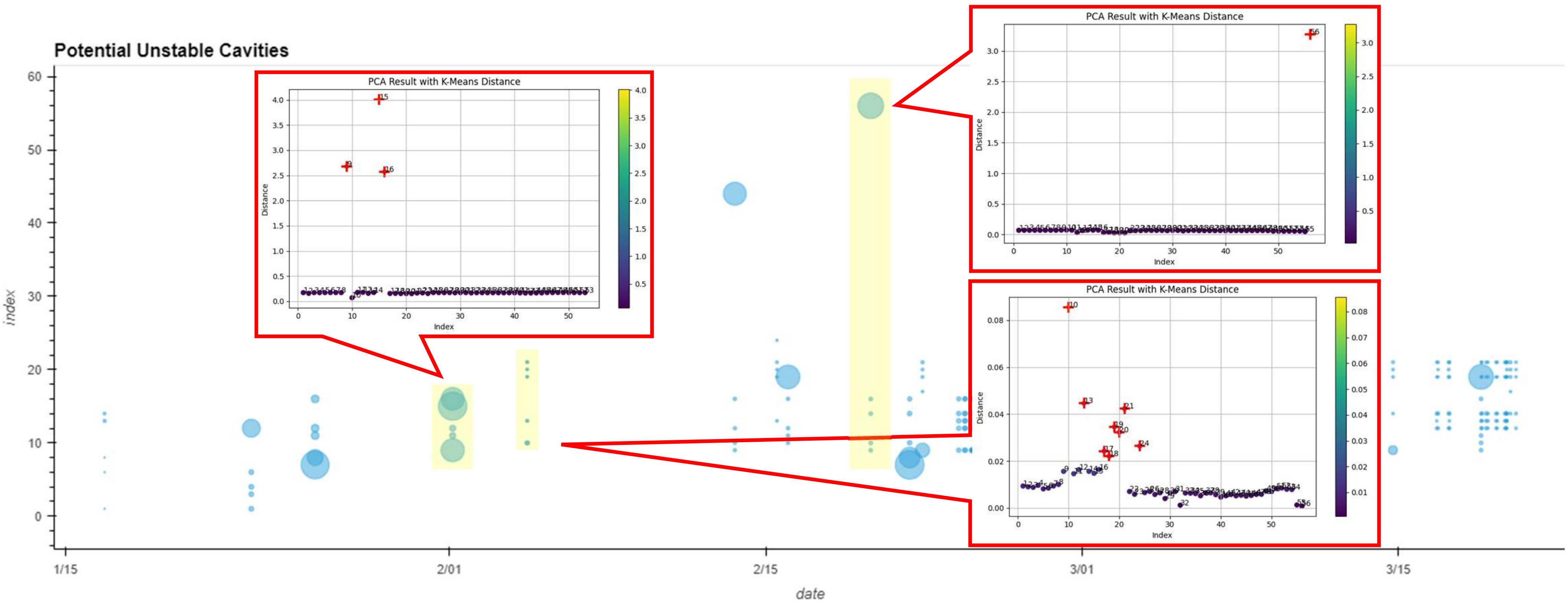
cavity index 15, unstable



cavity index 22, stable

Timeline View: Multiple Events

- plot the top 5 distances as a function of time from 61 events in early 2023
  - ✓ y-axis is cavity index
- marker size is proportional to distance from centroid
  - ✓ the bigger the marker, the more anomalous the cavity behavior



Cavity Instability Detection: Current Status

- feature engineering for better performance
  - ✓ need to re-engineer features to more closely match what labelers are looking for

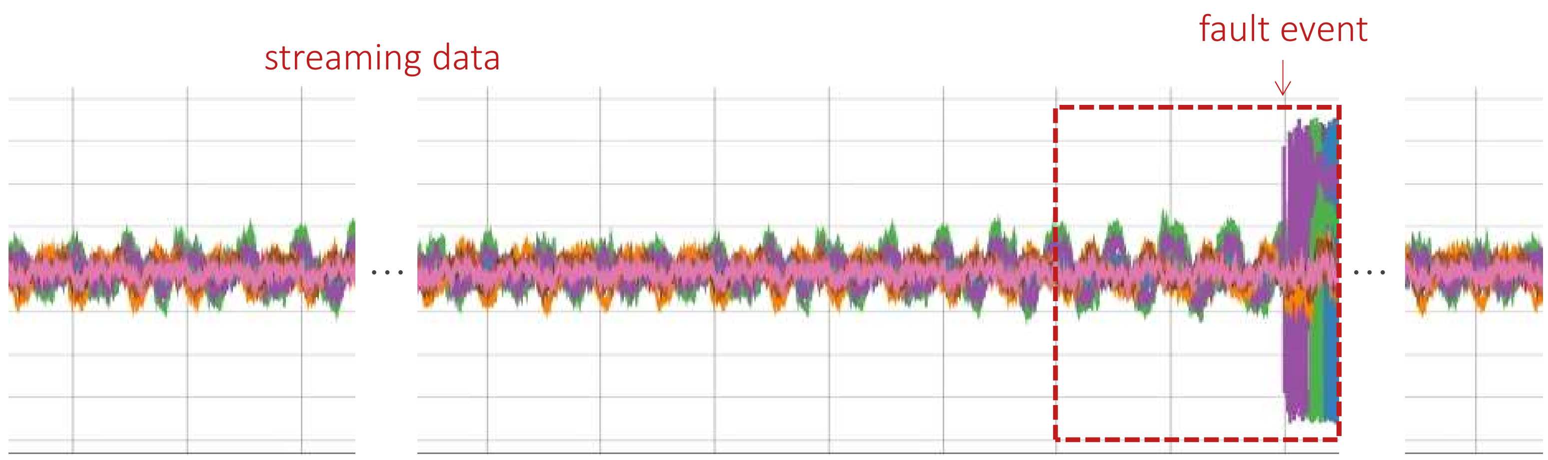
- continue to collect and label data for a benchmark test
- software is currently available in the control room

PROJECT B

PI: Chris Tennant
Graduate Student: Md. Monibor Rahman (ODU)

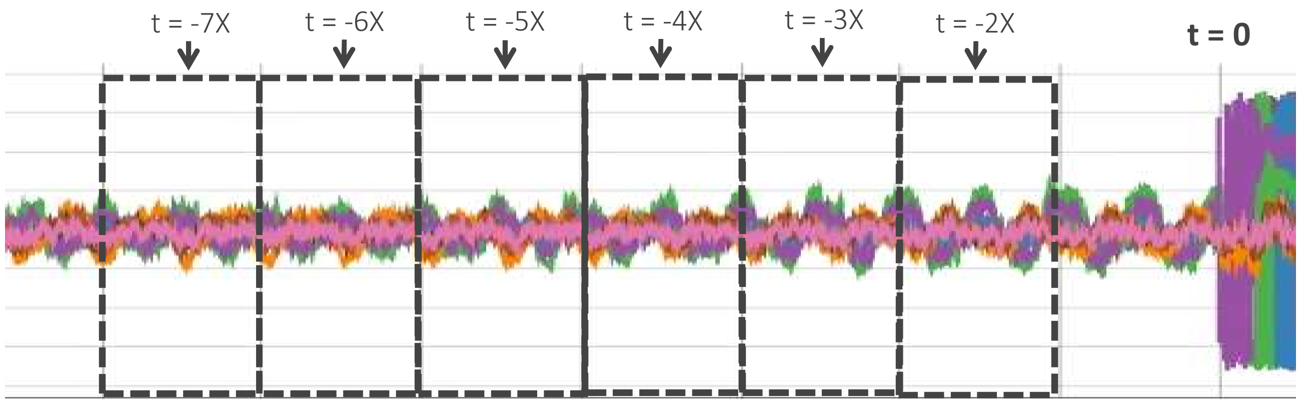
Project B: C100 Fault Prediction

- **Goal:**
  Proactively *predict* if a C100 cavity fault will occur
- **Description:**
  Previous work used ML models analyze data *after* a fault has occurred. Investigate the use of machine learning to predict if a fault will occur.



Binary Classifier: Scope of the Problem

- while the problem definition can be simply stated, it is deceptively complex
  - ✓tune for slow faults or fast faults or both?
  - ✓how to set duration of the time window?
  - ✓what should the confidence threshold be set to (default = 0.5)?
  - ✓how many consecutive windows to make prediction?
  - ✓for the choice of those parameters, is the predictive power sufficient?



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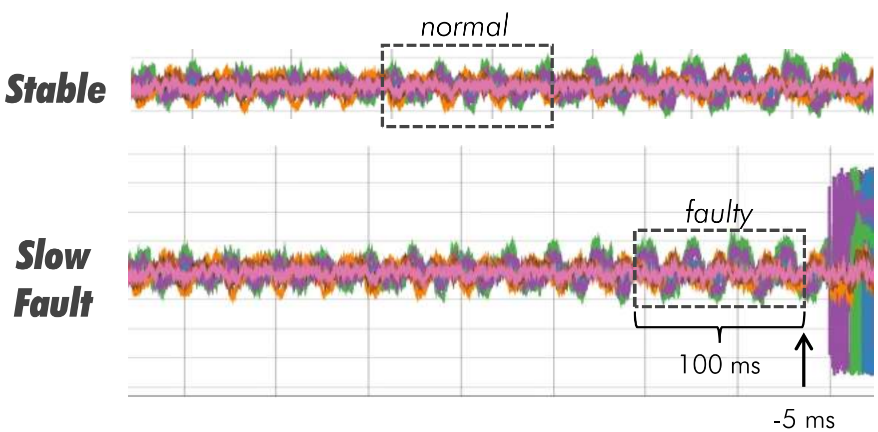
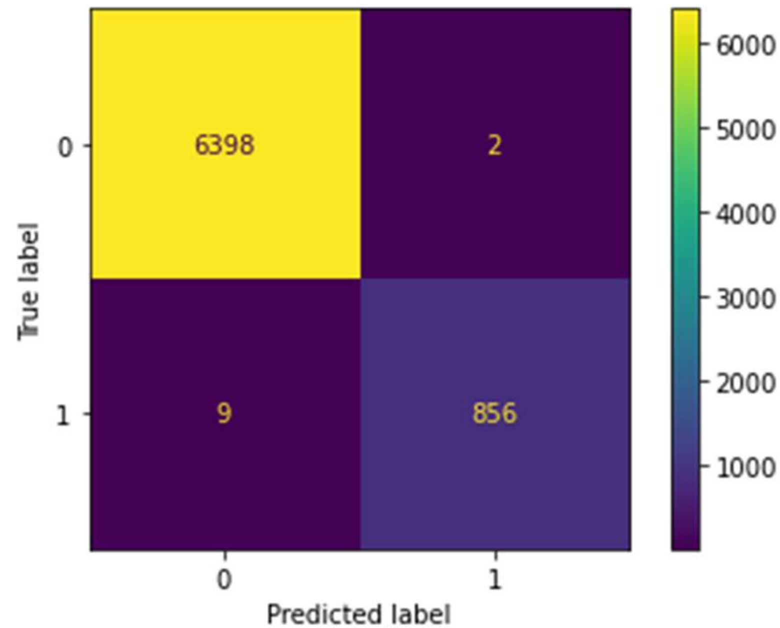
Zone Level Binary Classifier: Window-wise Performance

- a single model for all 6 zones/cryomodules did not meet performance specifications → *requires training a unique model for each zone*
- train a model to distinguish between windows of stable and impending *slow* fault data
- window-wise results for cryomodule R1N

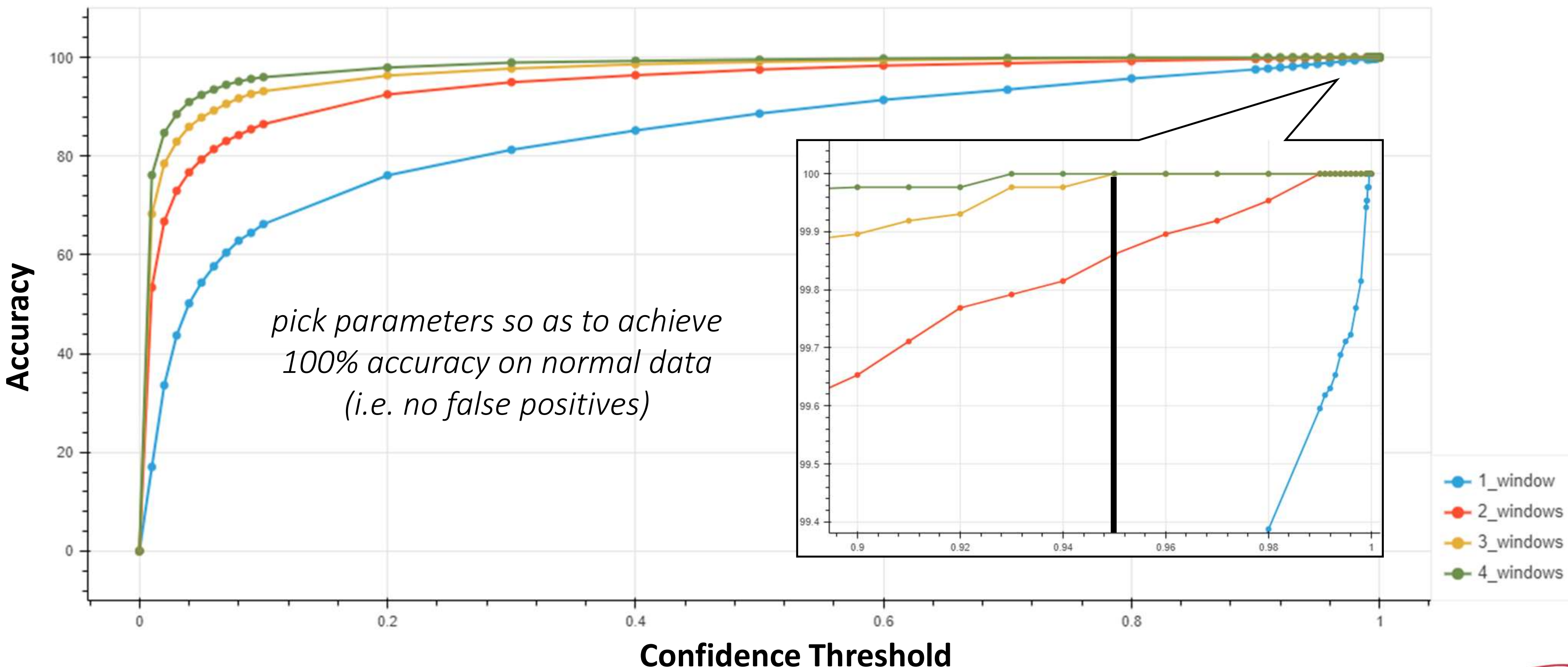




fault accuracy = 98.95 %
normal accuracy = 99.96%

Zone Level Binary Classifier: Optimization

- model uses Monte-Carlo Drop-Out (MCDO) to provide estimates of confidence
- need to jointly optimize (1) confidence threshold and (2) number of consecutive windows required to make a prediction *on normal data*



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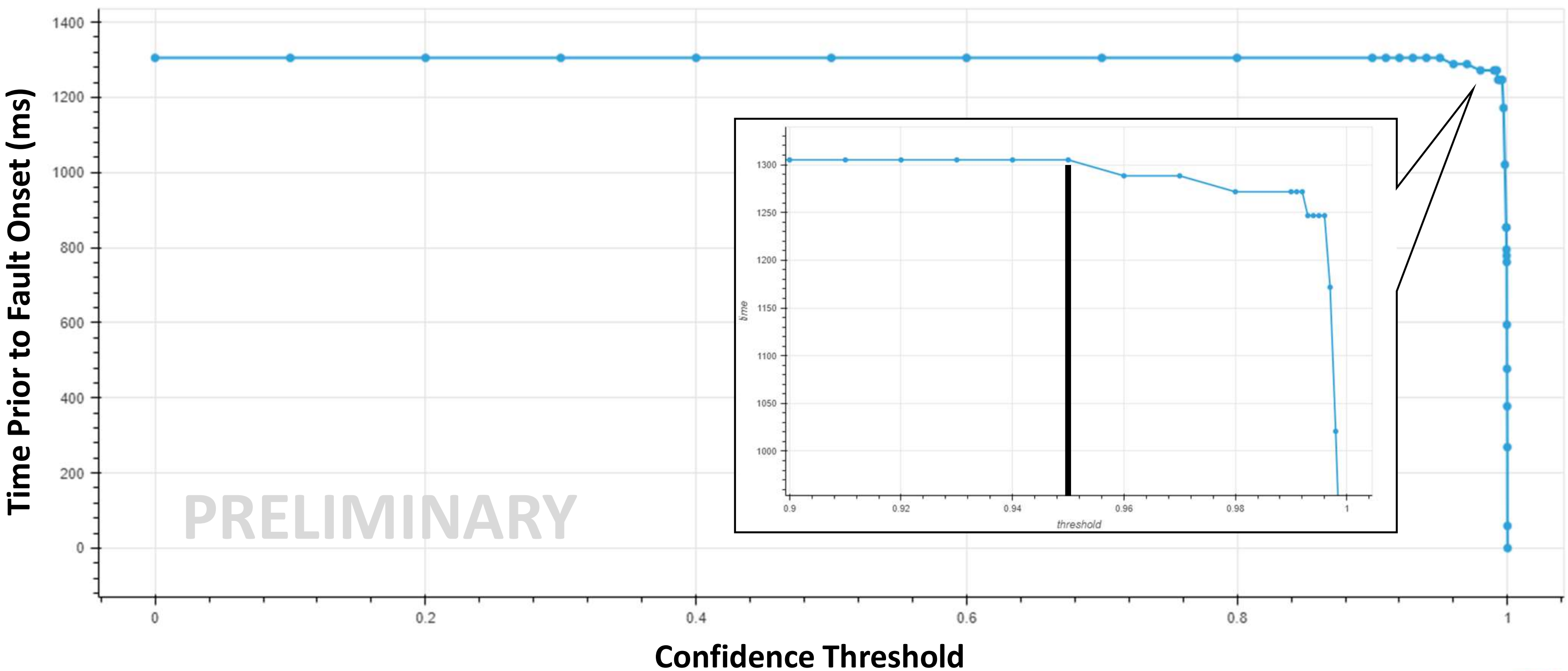
Zone Level Binary Classifier: Predictive Power

- once the confidence threshold and number of consecutive windows parameters are optimized, need to evaluate predictive power of the model *on faulty data*



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Zone Level Binary Classifier: Demo

- results for R1N on a large data set of normal data collected from March 3-6, 2023
  - ✓ confidence threshold is set to 0.95
  - ✓ number of consecutive windows to make a fault prediction is set to 3
- because normal data collection is not synchronized across cavities, need to run model on each cavity separately

	Cavity 1	Cavity 2	Cavity 3	Cavity 4	Cavity 5	Cavity 6	Cavity 7	Cavity 8
# of Examples	8652	8569	8027	8393	8637	8661	8508	8245
Normal	8652	8569	8027	8392	8637	8661	8508	8245
Faulty	0	0	0	1	0	0	0	0
Accuracy	100	100	100	99.9881	100	100	100	100

PROJECT C

PI: Adam Carpenter and Riad Suleiman
Postdoc: Steven Goldenberg
Graduate Student: Kawser Ahammed (ODU)

Project C: Field Emission Management

- **Goal**:

  maintain low levels of field emitted (FE) radiation without invasive interruptions to physics

- **Description:**

  use ML to model radiation levels and allow for off-line optimization of gradient distribution, identify cavities where FE onsets have changed

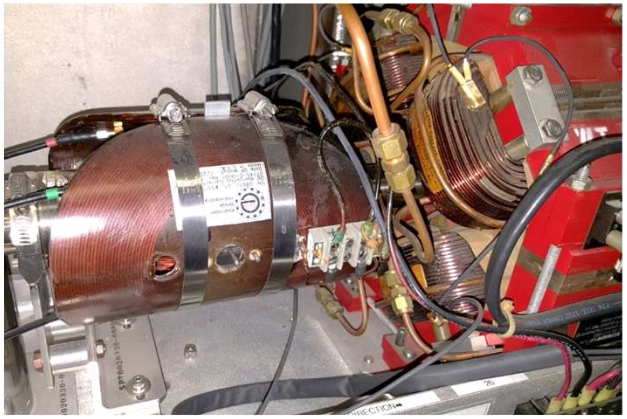
- **Solution:**

  optimize surrogate model to minimize radiation via gradient reduction

radiation area

damaged beamline valve

damaged magnet and cables

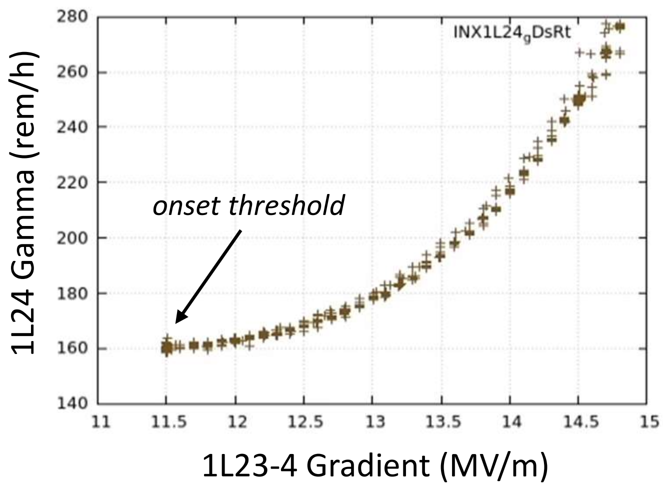


Field Emission

- FE is a notorious problem in SRF cavities resulting in component damage, RF faults, material activation, and neutron and gamma radiation production
- a single cavity produces FE electrons with a non-linear response to gradient above a threshold (FE onset)
- the C100 cryomodules present pronounced FE-related operational challenges
- we are developing a surrogate model of radiation as a function of SRF cavity gradients within a linac that can be optimized offline for a more optimal distribution of real world cavity gradients

hazards due to activation

radiation-damaged valve



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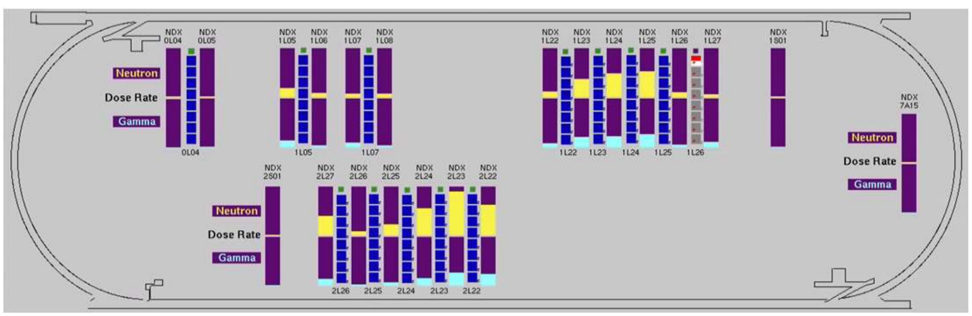
Field Emission Management: Data Requirements

- Jefferson Lab designed, installed, and commissioned a new neutron and gamma radiation detection system* focused on FE radiation
  - ✓operational August 2021
  - ✓measure neutron dose rates correctly in the presence of photon radiation
  - ✓detectors are “blind” to low energy photons and electrons
  - ✓integrated into EPICS with signals for gamma and neutron dose rates
  - ✓wide dynamic range
  - ✓currently have 32 detectors installed



*P. Degtiarenko, US Patent 10,281,600

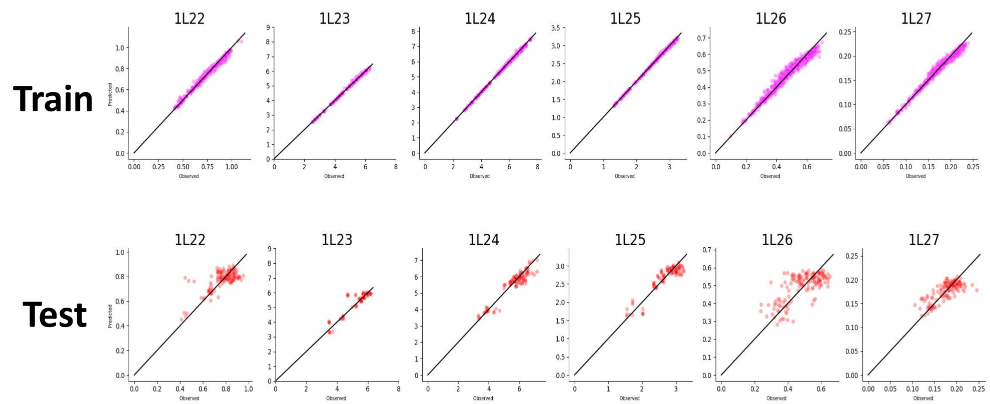
Baseline Model

- need a model that is capable of estimating radiation levels for a given gradient configuration
- demonstrated model effectiveness using accelerator development periods on a section of a linac (32 cavities, 6 detectors)
- demonstrated proof-of-concept with simple optimizer
  - ✓ applied model-optimized gradient distribution to the 32 cavities with reasonable success
- requires hours-long invasive gradient scan for initial dataset
  - ✓ custom software to control entire linac gradient settings

XGBoost, 09-07-022, C100 Data

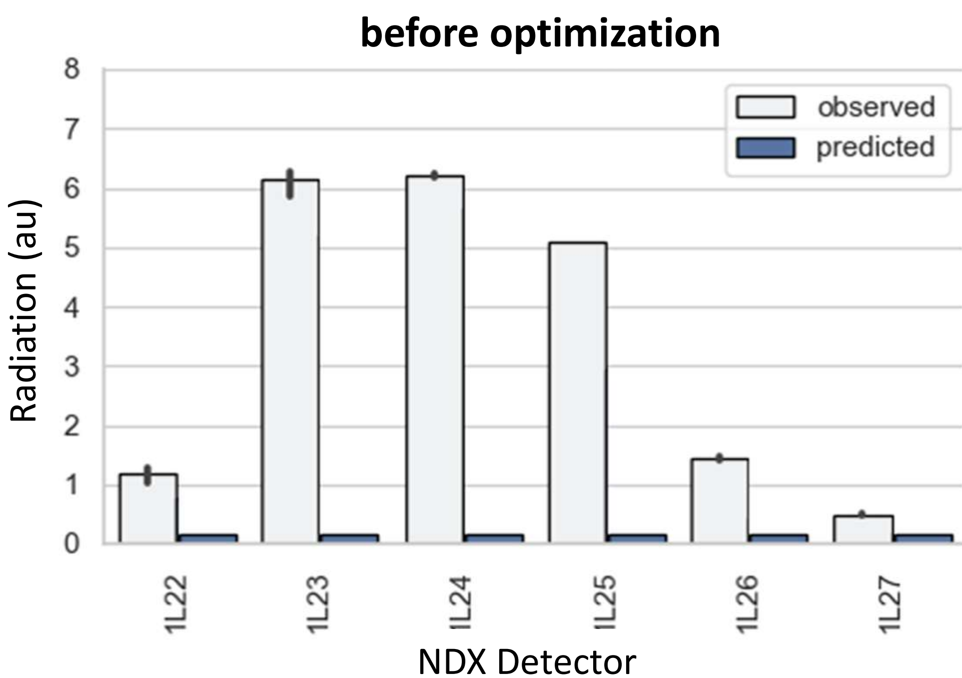
	R-Sq	MSE	MAE	MAPE
Train	0.981	0.062	0.133	0.012
Test	0.652	1.815	0.701	0.062

XGBoost (Neutron, C100s Only)
Observed vs Predicted Plots



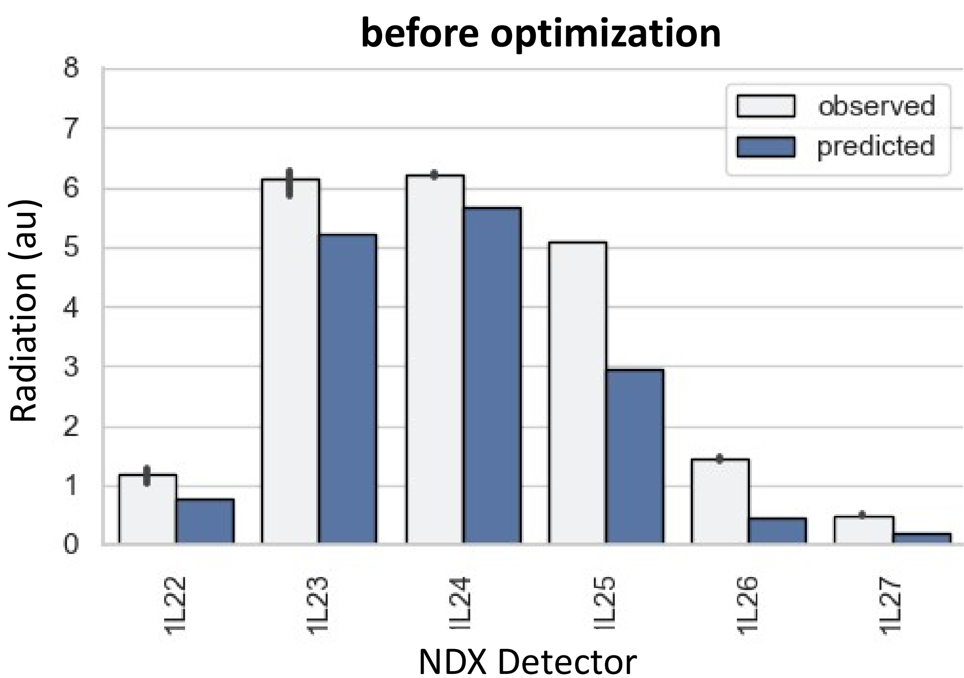
Proof-of-Concept Demonstration

1. observe NDX readings in the NL for a given gradient distribution



Proof-of-Concept Demonstration

1. observe NDX readings in the NL for a given gradient distribution
2. input gradient distribution to ML surrogate model of NDX detectors to predict radiation



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1. observe NDX readings in the NL for a given gradient distribution
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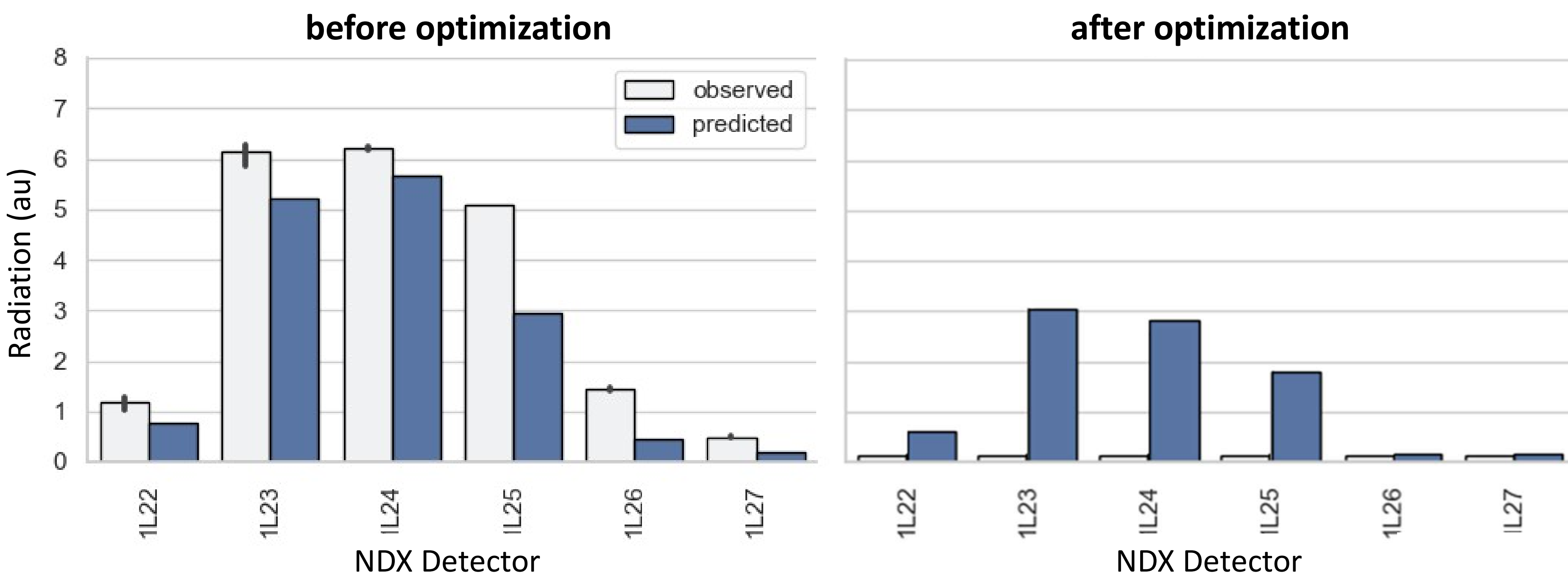
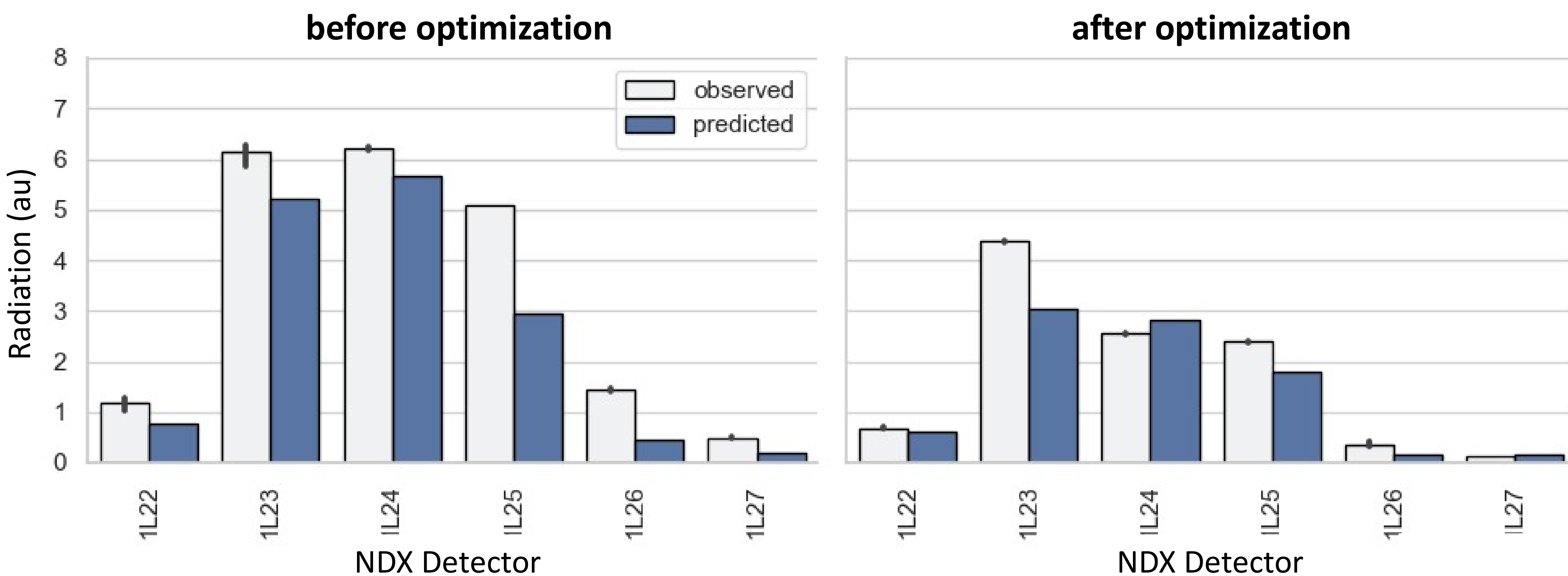
3. use surrogate model (off-line) to redistribute gradients so as to minimize radiation



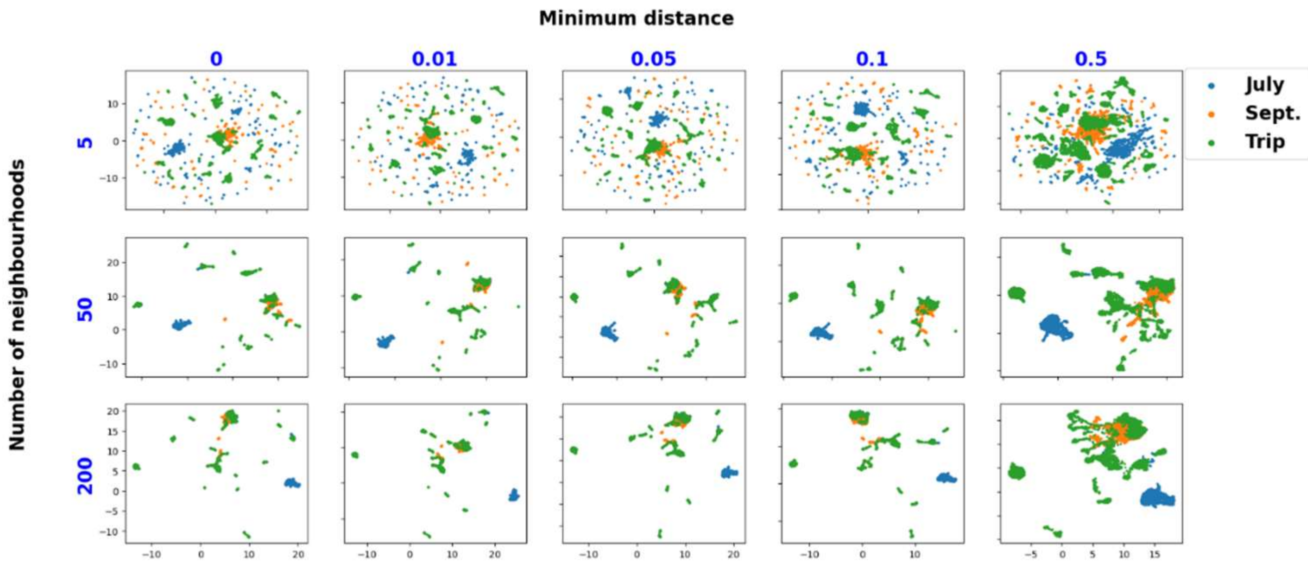
Proof-of-Concept Demonstration

1. observe NDX readings in the NL for a given gradient distribution
2. input gradient distribution to ML surrogate model of NDX detectors to predict radiation
3. use surrogate model (off-line) to redistribute gradients so as to minimize radiation
4. load optimized gradients into NL → *12 rem/hour decrease for 5 MV/m reduction in gradient*



CEBAF Drift

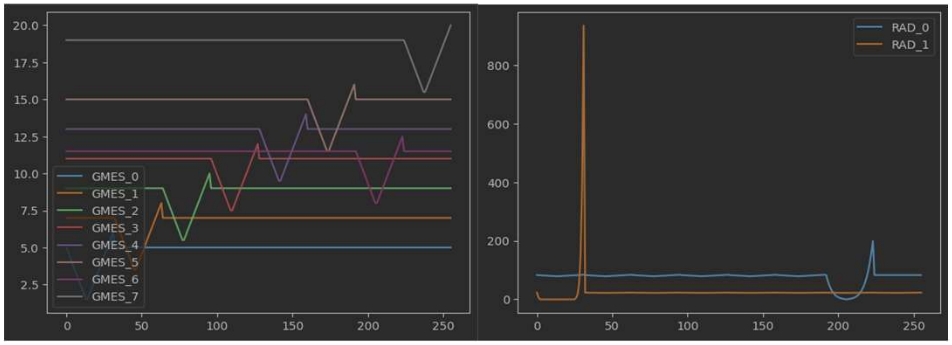
- CEBAF and SRF cavity FE changes over time
  - ✓model must track linac energy, gradient redistribution, and new/changed field emitters
- accelerator time is limited, and invasive data collection takes hours
  - ✓continuously taking data to retrain not an option
- investigating fine tuning using passive data sources such as RF trips
- dimensionality reduction techniques suggest trip data share commonalities with future scan data
- fine-tuning studies suggest this approach has merit



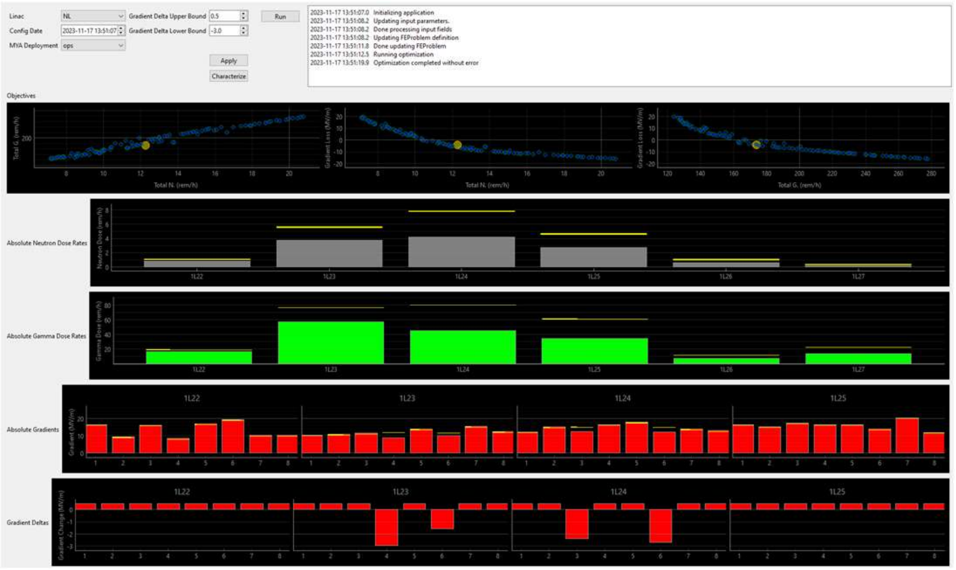
UMAP applied to cavity gradients and radiation measurements at a variety of hyperparameter settings.

Ongoing Work

- synthetic data generator for controlled studies on UQ, data collection, and fine tuning
- developing UQ-capable model for entire linac
  - ✓needed for robust optimization
- developing software for optimizing gradient redistribution
- refining data collection software
- planning a full linac demonstration in Spring 2024



Physics-based model producing synthetic data



Genetic algorithm optimization run on a 32 cavity, 6 detector model

SUMMARY

Project Summary: Major Deliverables and Schedule

Project	Deliverable	Date
Cavity Instability Detection	Installation of 17/20 production DAQs	07/2023
	Deployment of user interface	09/2023
	Training and testing of ML model using *fast* data	02/2024
	Deploy ML model in CEBAF	03/2024
C100 Fault Prediction	Optimize cryomodule-level binary classifier	12/2024
	Demonstrate performance on collected data	01/2024
	Investigate data drift with model	03/2024
Field Emission Management	Develop whole (NL) linac surrogate model	01/2024
	Develop model with UQ	02/2024
	Develop optimization software for use with surrogate model to optimize gradients	03/2024
	Full linac demonstration	05/2024

Project Summary: Annual Budget

	FY 2020	FY2021	FY2022	Total
a) Funds allocated	$450,000	$450,000	$450,000	$1,350,000
b) Actual costs to date	$450,000	$450,000	$226,387	$1,126,387
c) Uncosted commitments	$0	$0	$0	$0
d) Uncommitted funds (d=a-b-c)	$0	$0	$223,613	$223,613

Acknowledgements

Kawser Ahammed

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Steven Goldenberg

Khan Iftekharuddin

James Latshaw

Jiang Li

Theo McGuckin

Md. Monibor Rahman

Riad Suleiman

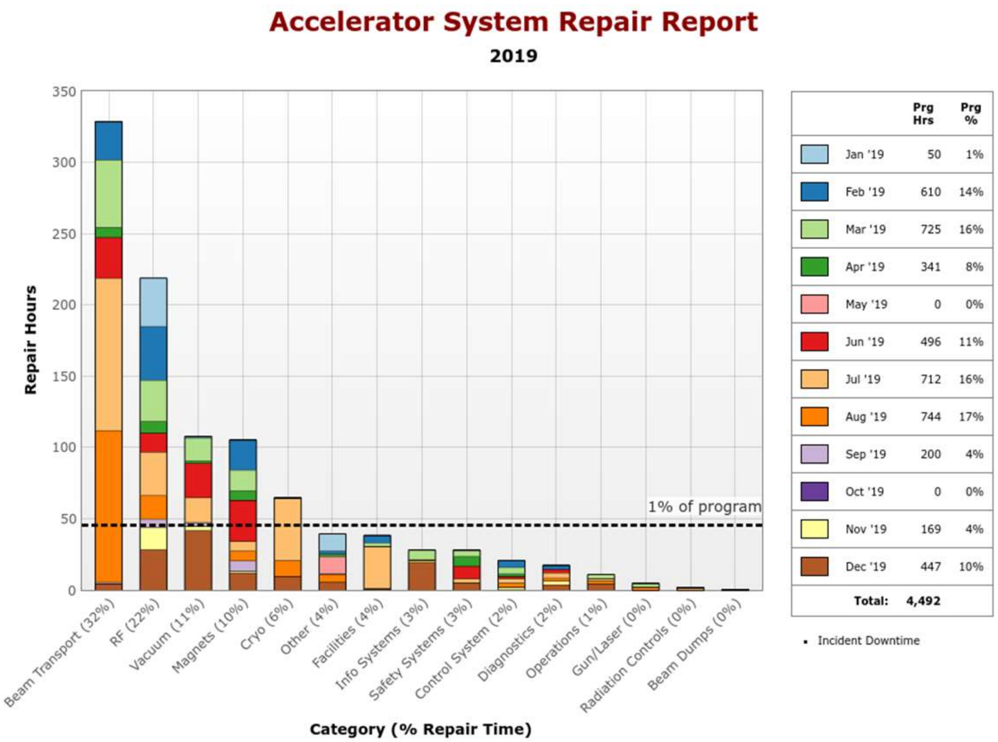
Dennis Turner

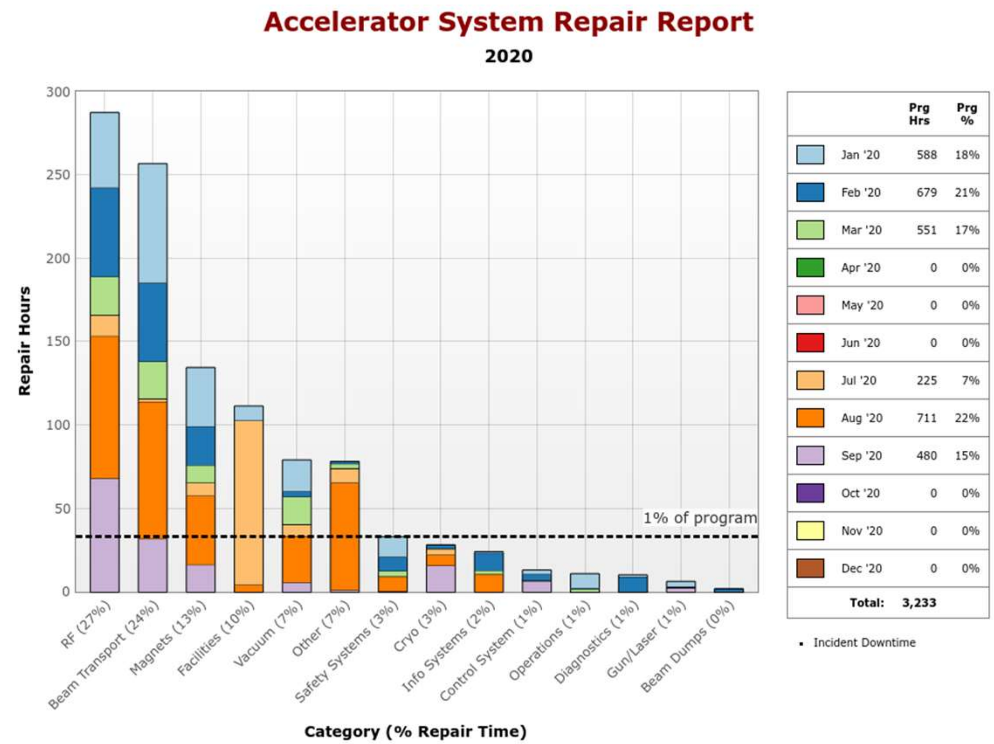
And others!

Thank You

CEBAF Down Time Manager

- RF related issues are consistently one of the biggest contributors to downtime





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Hybrid Deep Learning Model for Fault-type Prediction

- 1D CNN – LSTM model architecture for *both* model A and B