AI for Optimized SRF Performance of CEBAF Operations

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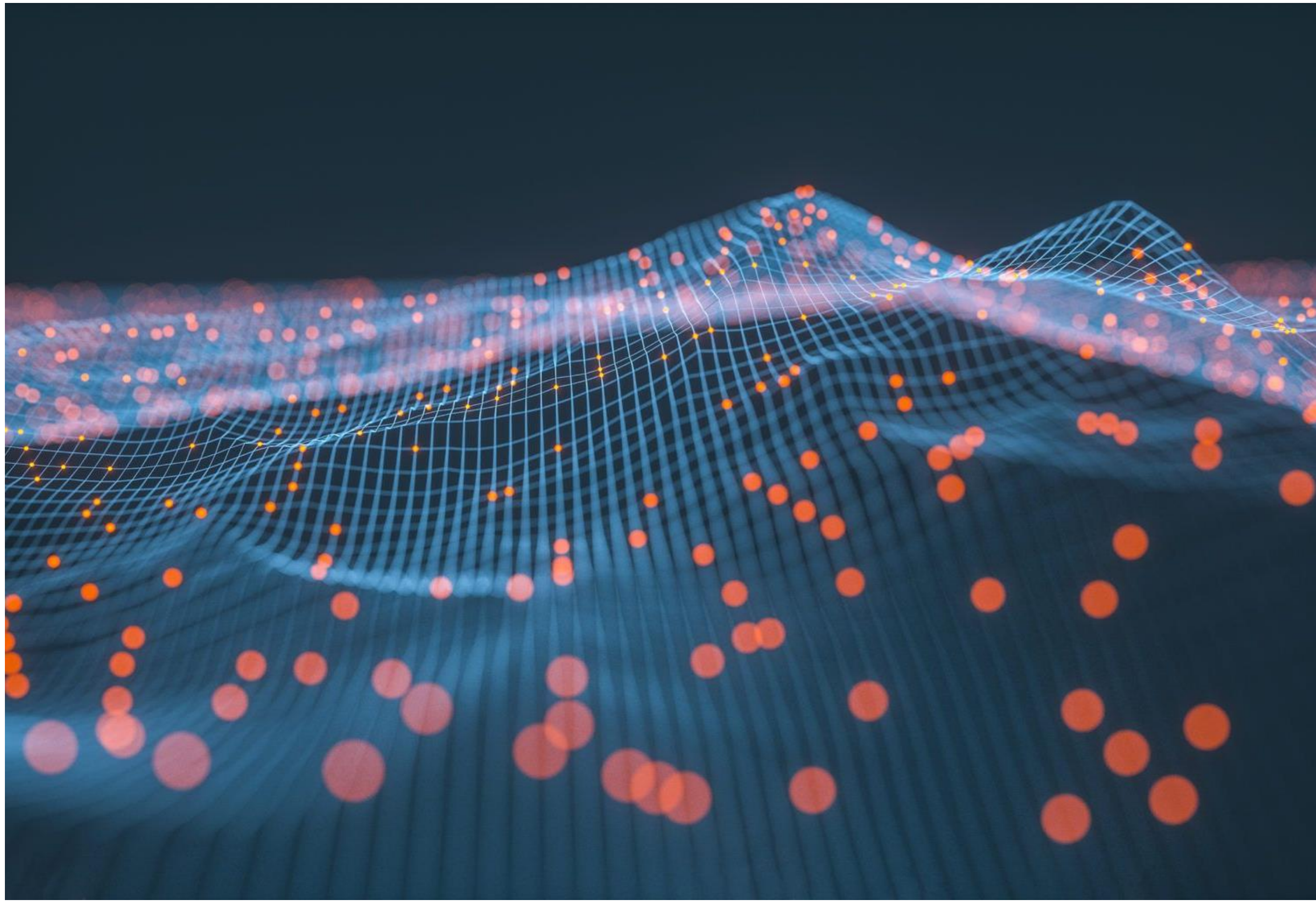
for the Jefferson Laboratory Team

DOE PI AI/ML Exchange Meeting | November 30, 2021



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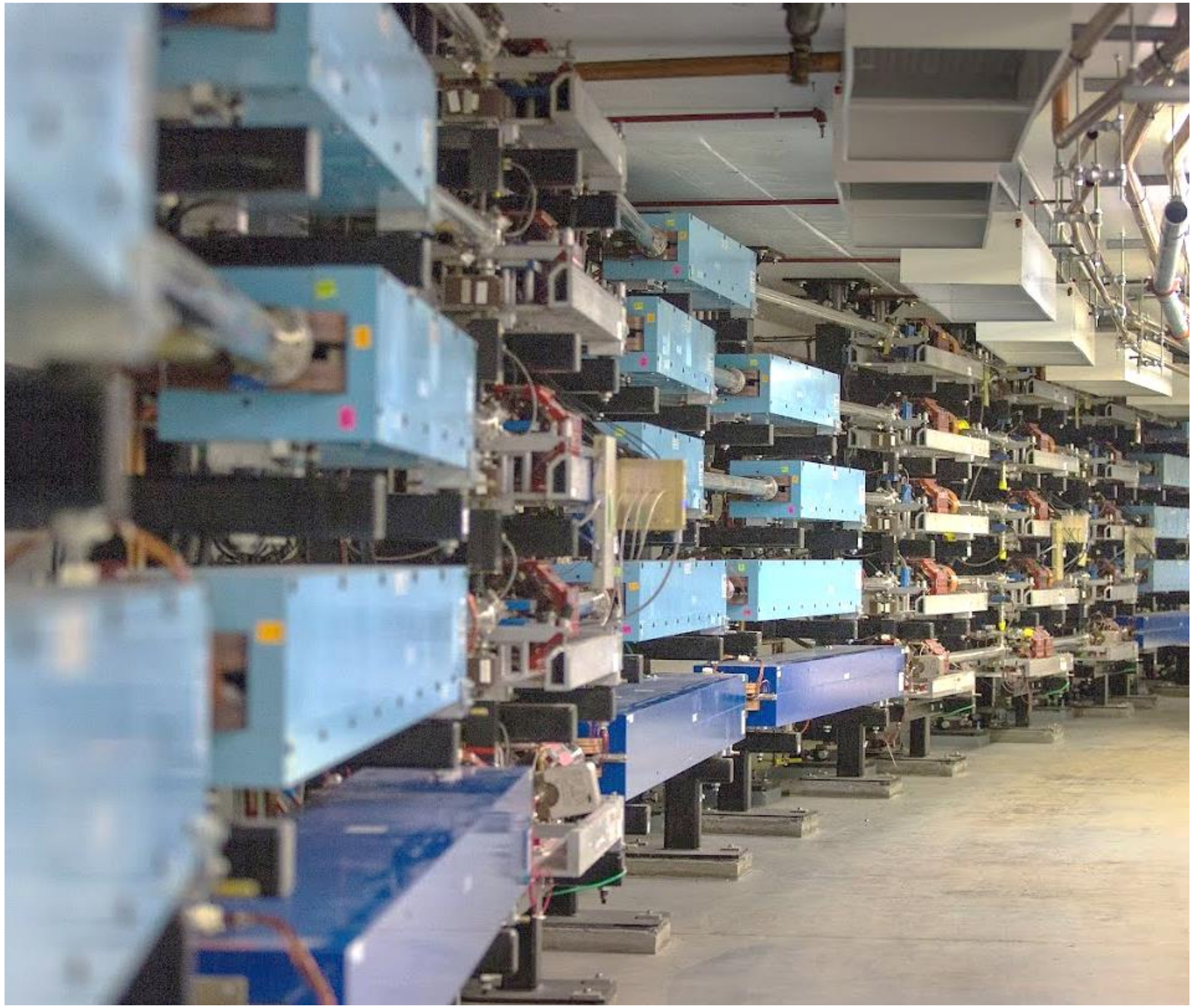
Outline

- **Jefferson Laboratory**
- **FOA LAB 20-2261: Year 1 Status**
  - ✓ *Cavity Instability Detection*
  - ✓ *C100 Fault Prediction*
  - ✓ *Field Emission Management*
- **Project Summary**
  - ✓ *Deliverables and Schedule*
  - ✓ *Budget*



"AI for Optimized SRF Performance of CEBAF Operations"

This proposal 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.

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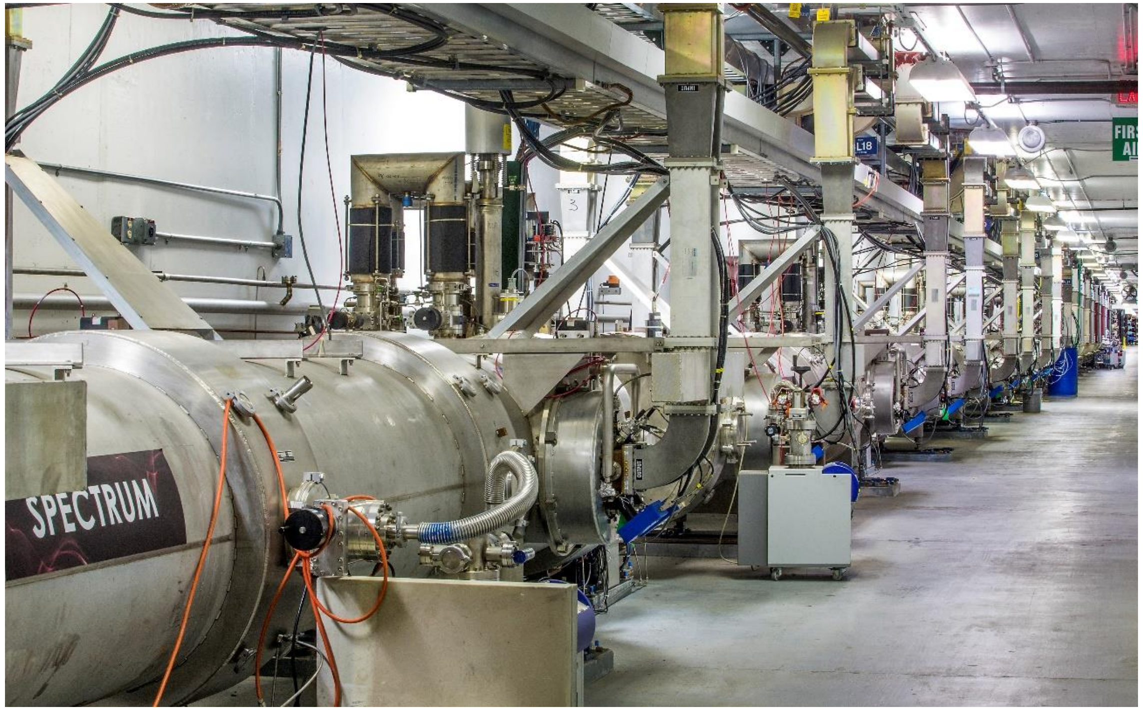
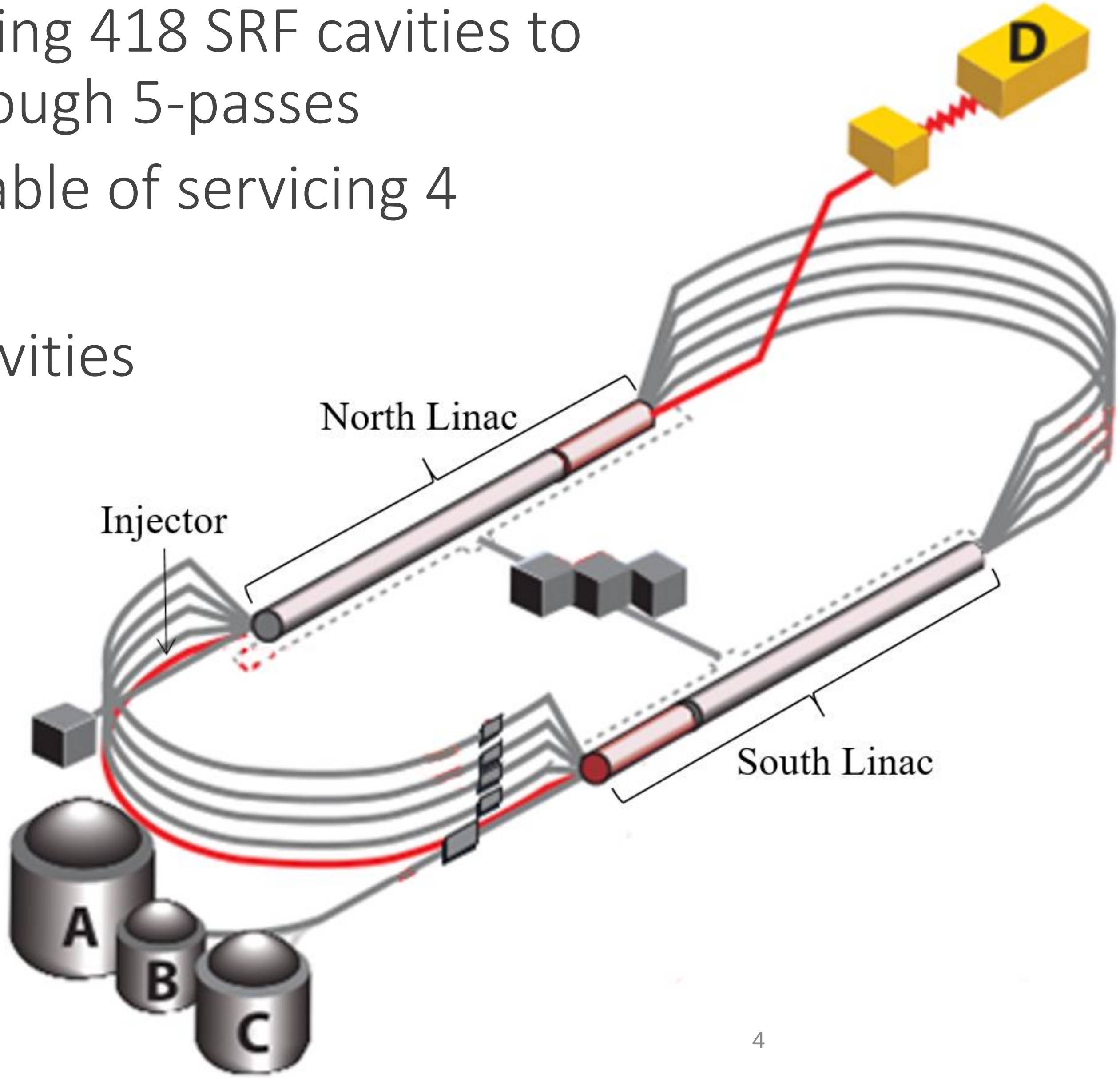
DATA, ARTIFICIAL INTELLIGENCE, AND MACHINE LEARNING AT DOE SCIENTIFIC USER FACILITIES

DOE NATIONAL LABORATORY PROGRAM ANNOUNCEMENT NUMBER: LAB 20-2261

Continuous Electron Beam Accelerator Facility

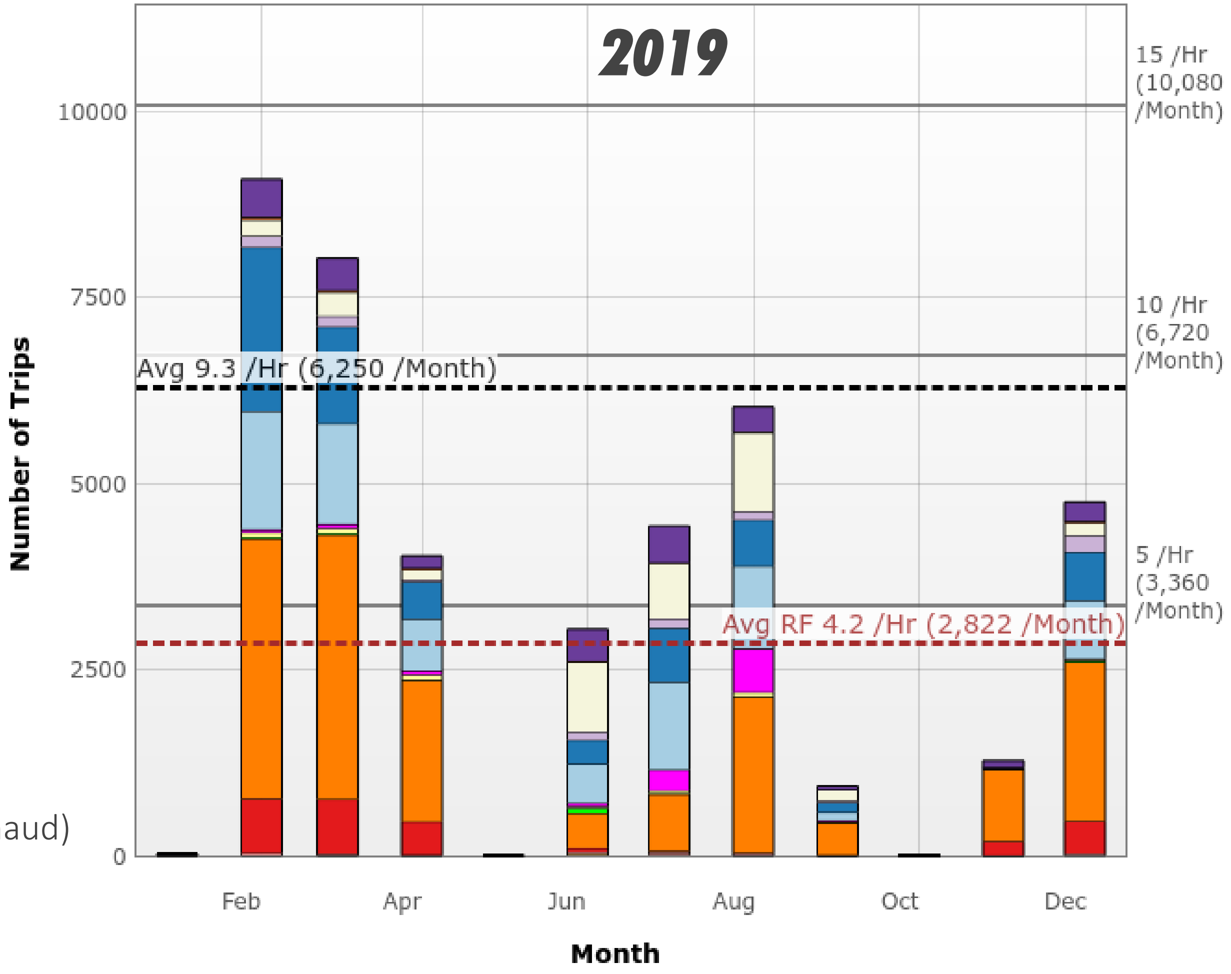
- CEBAF is a CW recirculating linac utilizing 418 SRF cavities to accelerate electrons up to 12 GeV through 5-passes
- it is a nuclear physics user-facility capable of servicing 4 experimental halls simultaneously
- the heart of the machine is the SRF cavities





CEBAF Down Time Manager

- CEBAF short machine downtime trips (< 5 min.) in 2019



(courtesy R. Michaud)

	Trips /Hr	Lost Hrs	Mins /Trip
Dump (Insert.)	0.6	12.7	0.3
Dump (Station.)	0.0	0.0	0.3
Gun/Laser	0.0	1.5	0.5
Hall	0.8	17.7	0.3
MPS (BCM/BLA)	0.2	4.9	0.3
MPS (BLM)	1.4	35.9	0.3
MPS (Multi/Other)	1.6	39.7	0.3
Magnets	0.0	0.1	1.2
Multiple/Other	0.2	5.6	0.3
Unknown/Missing	0.1	2.3	0.4
Vacuum	0.0	1.9	0.8
RF (C25/C50)	3.5	109.2	0.4
RF (C100)	0.6	75.2	1.7
RF (Multi/Other)	0.0	3.0	1.0
RF (Separator)	0.0	1.1	1.3
Total:	**9.3**	**310.7**	**0.4**

- Max Trip Duration: 5 Minutes
- Rate from Program (4492.47 hrs)
- SAD Trips excluded

Project A: Cavity Instability Detection

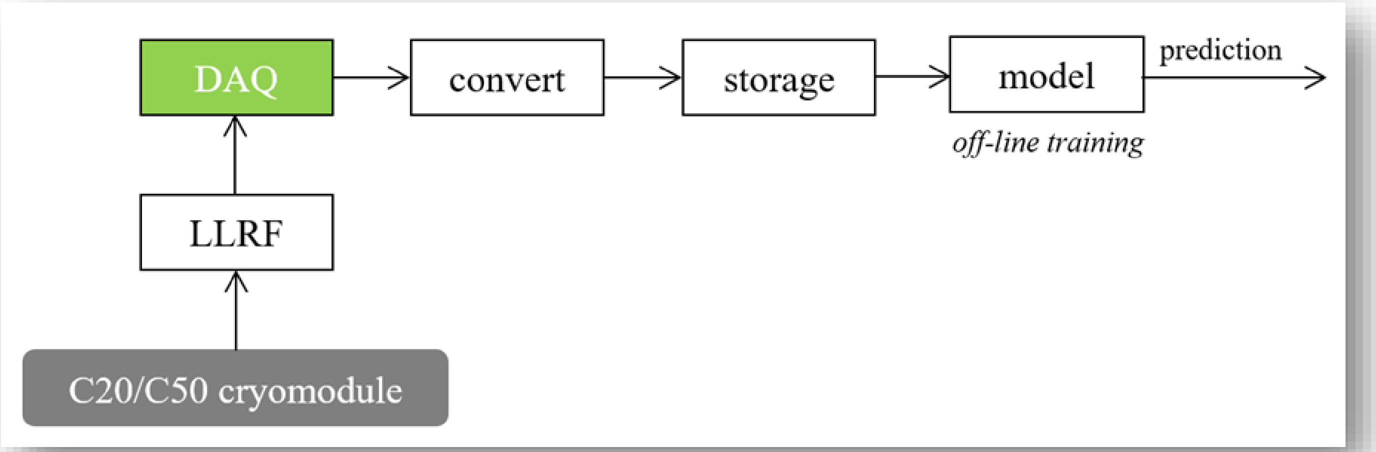
- **Goal:**

  Develop a DAQ for collecting RF signals from *legacy* cryomodules

  Improve beam availability by automating the process of identifying unstable RF cavities

- **Description:**

  Use the strength of machine learning's ability for pattern recognition (particularly in noisy data sets) to identify RF cavities that go unstable by analyzing recorded signals and therefore improve beam quality and availability



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Project A: Cavity Instability Detection

Problem

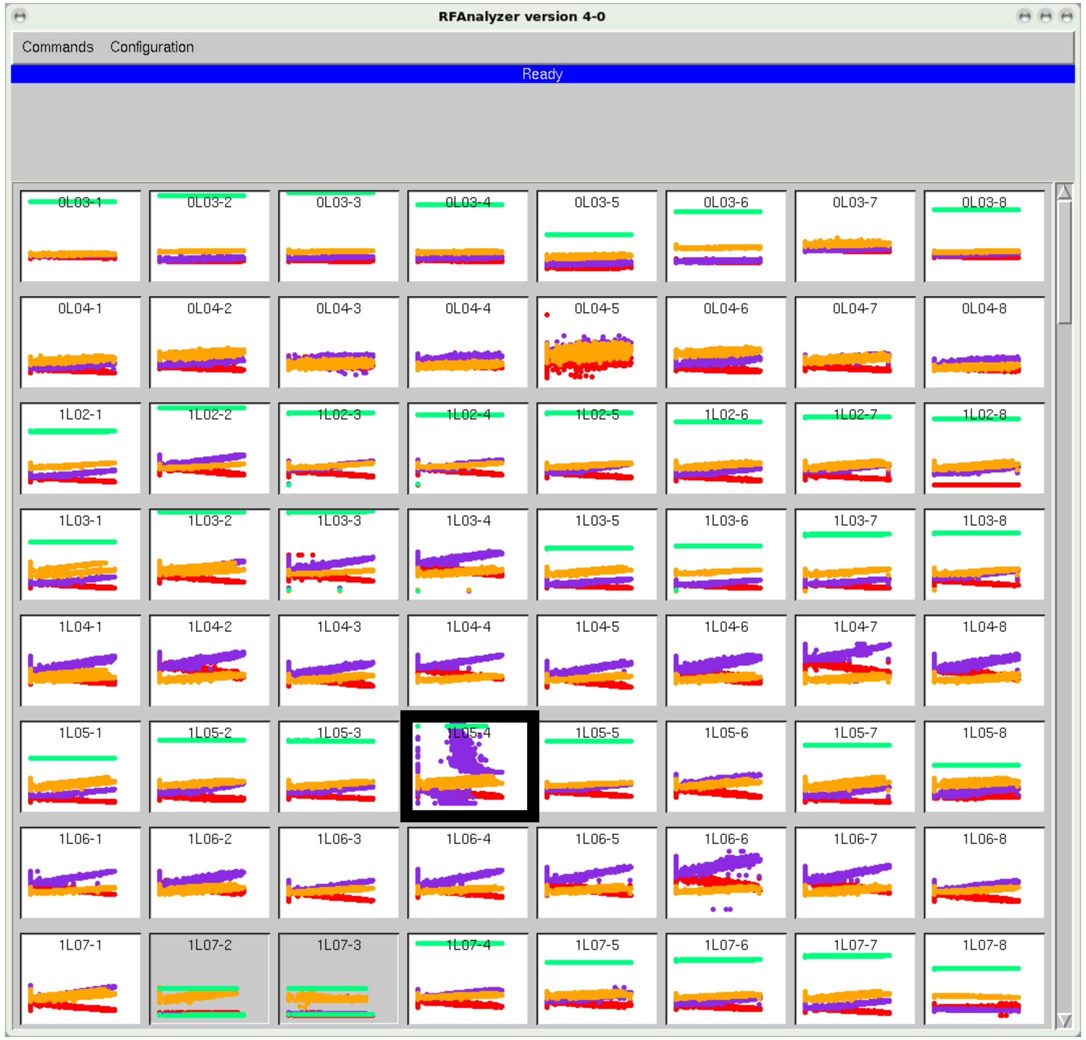
- ✓SRF cavities can become unstable without presenting faults
- ✓cavity instability causes beam energy instability, which can lead to beam loss and limited availability of beam for experiments
- ✓identifying an unstable SRF cavity with the present diagnostics at CEBAF is difficult and time-consuming
  - *present SRF diagnostics for the legacy cavities are not fast enough to record fast transient instabilities*

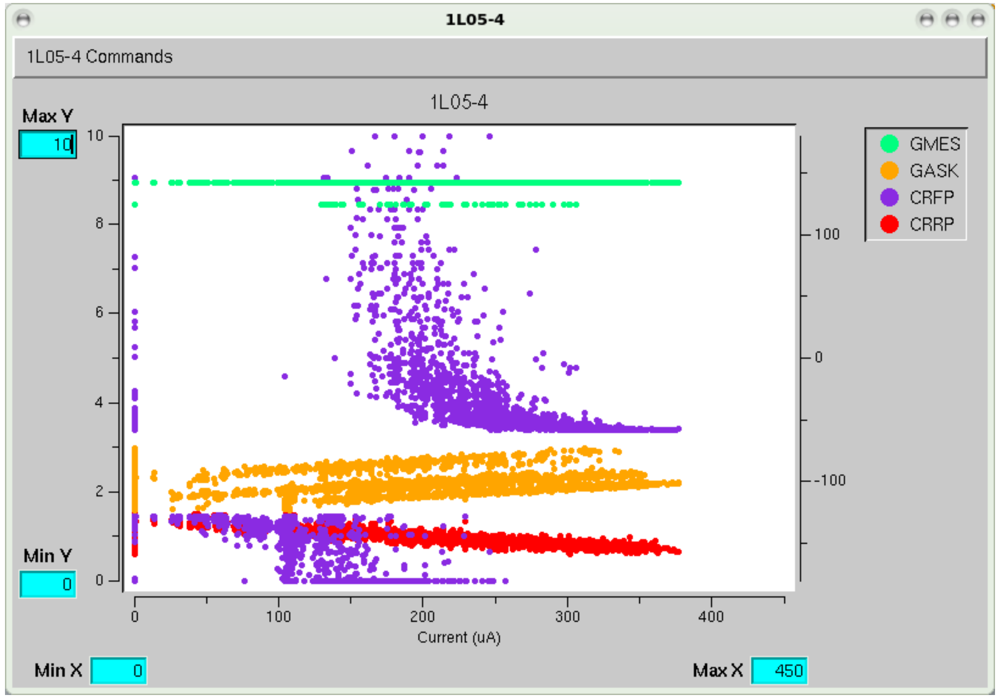
Solution

- ✓develop and install a new fast DAQ system for the legacy SRF cavities
- ✓apply AI to the data acquired by the new DAQ to identify unstable cavities
- ✓the goal is to quickly identify misbehaving cavities and therefore improve beam quality and availability

Cavity Instability Detection: Current Approach

RF Analyzer Tool

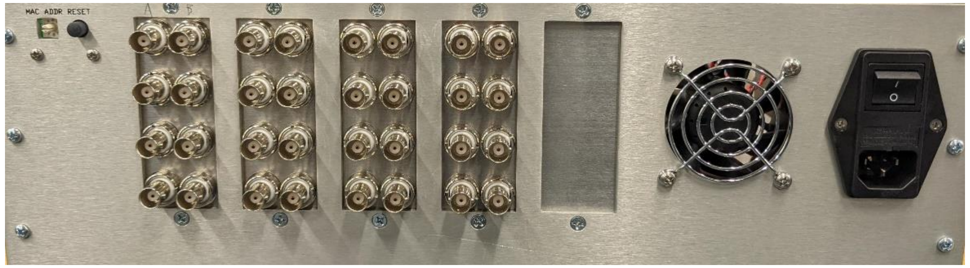


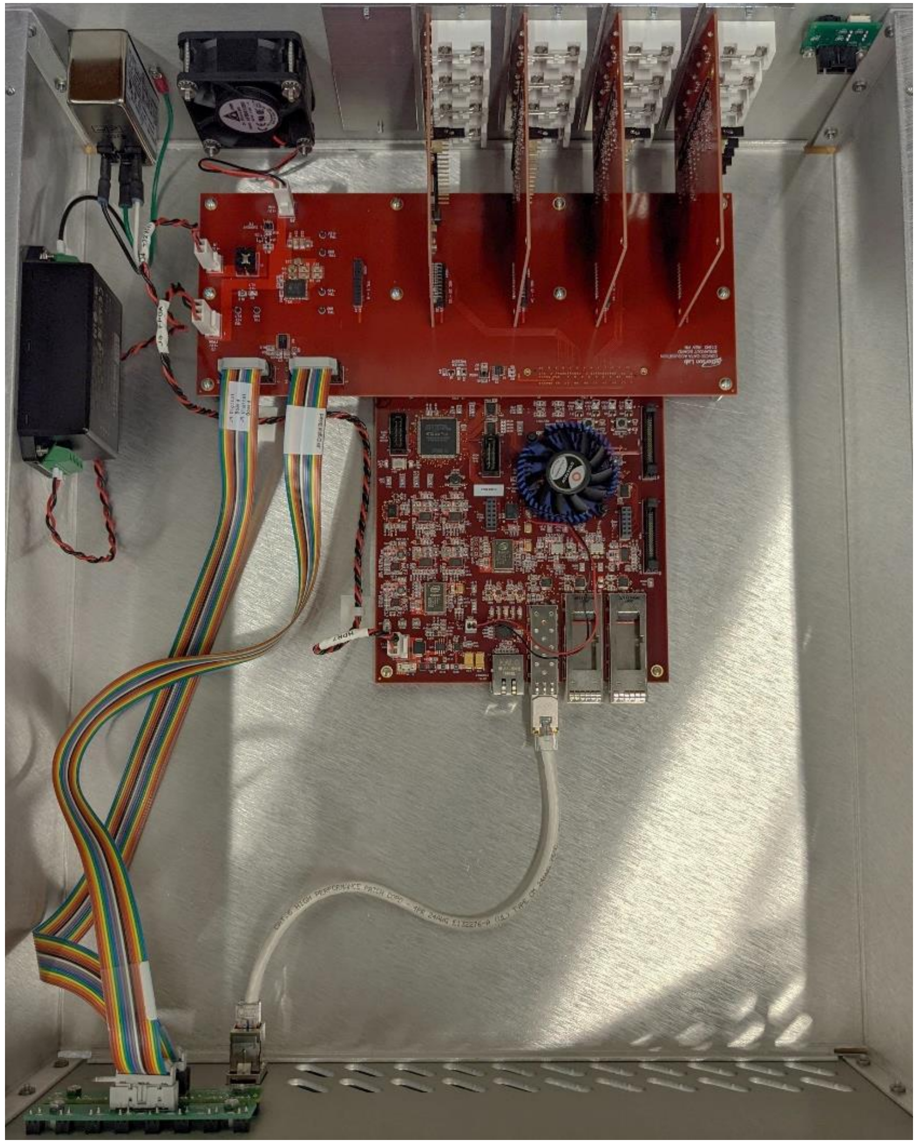


- note, this represents an obvious example
- not all instances are so easily detectable by an operator

Cavity Instability Detection: Data Collection

- one chassis per zone
  - ✓ 32 input signals (8 cavities × 4 signals/cavity)
    - *gradient, phase, drive amplitude and phase*
  - ✓ based on Cyclone 10 GX FPGA design
  - ✓ gigabit ethernet interface
  - ✓ prototype chassis ready and testing in progress





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Cavity Instability Detection: Software Development

- absent data from the DAQ, we are constrained by how much progress we can make on the software development
- started developing high-level software filter
  - ✓only store waveforms when there is an FSD trip of interest → reduce data storage requirements
- started collecting and labeling archived RF data (linac current, GMES, PMES, GASK, PASK) to develop an ML model
  - ✓these represent the same signals that will be captured by DAQ – only much faster (kHz vs Hz)

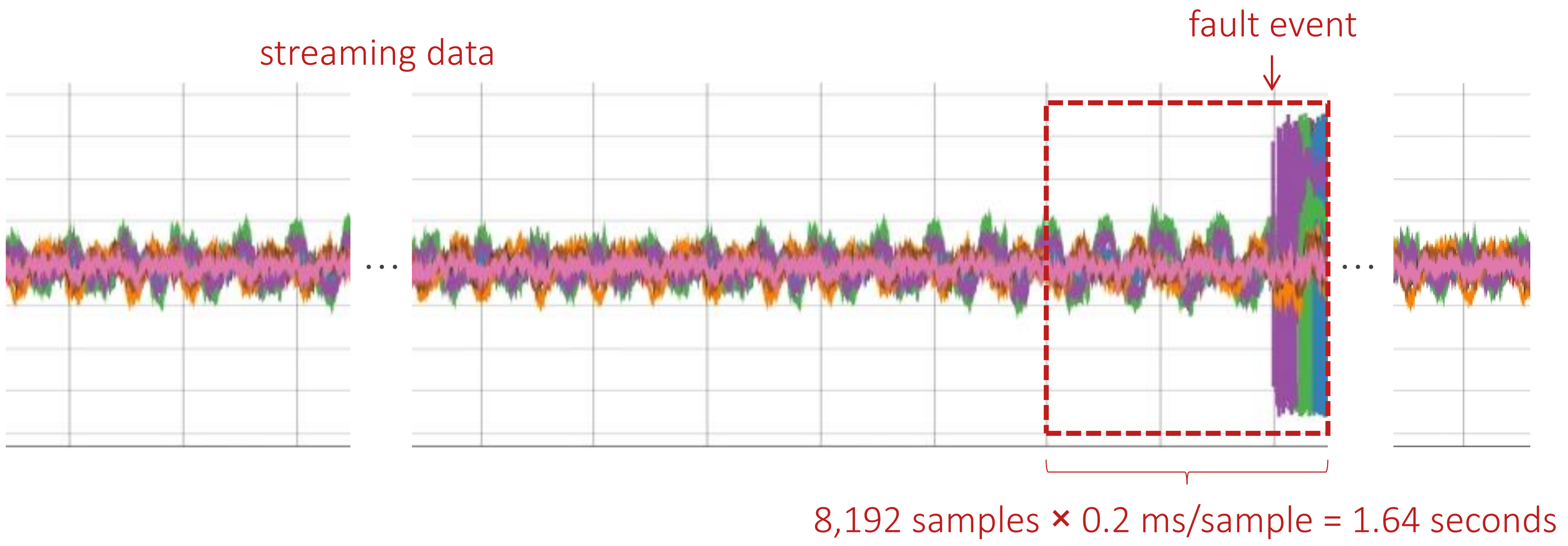
Project B: C100 Fault Prediction

- **Goal:**

  Proactively *predict* if a C100 cavity fault will occur

- **Description:**

  Currently deployed ML models analyze data *after* a fault has occurred. Investigate the use of machine learning to predict if a fault will occur.



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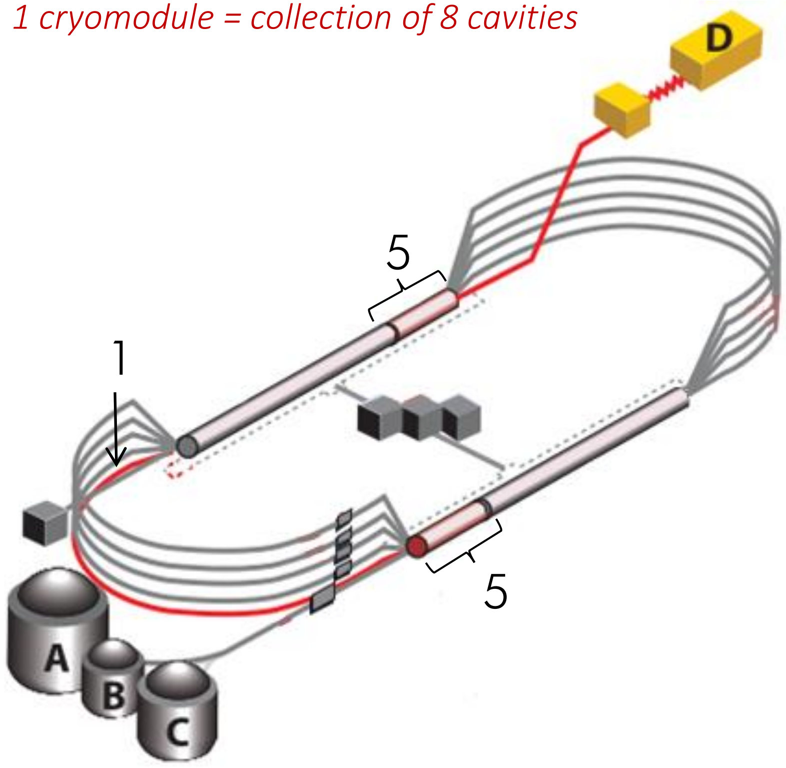
C100 Fault Isolation and Identification: Present

have the ability to record high-fidelity data from 11 cryomodules

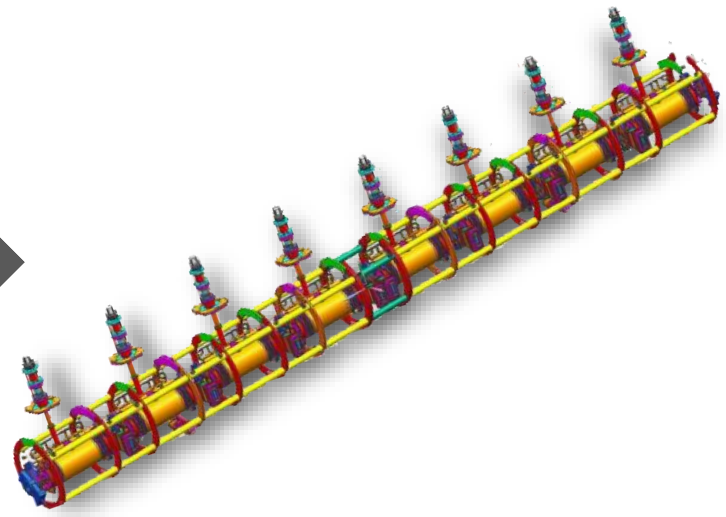
1 cryomodule = collection of 8 cavities



FAULT ISOLATION

Which of the 8 cavities faulted first?

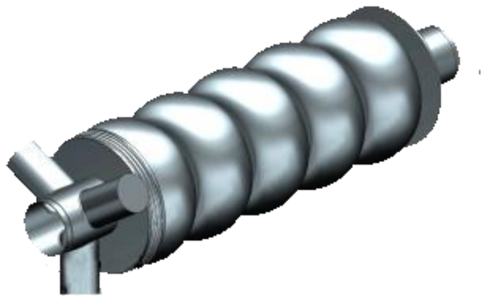
17 signals/cavity × 8 cavities = 136 signals



FAULT IDENTIFICATION

What kind of trip was it?

17 signals



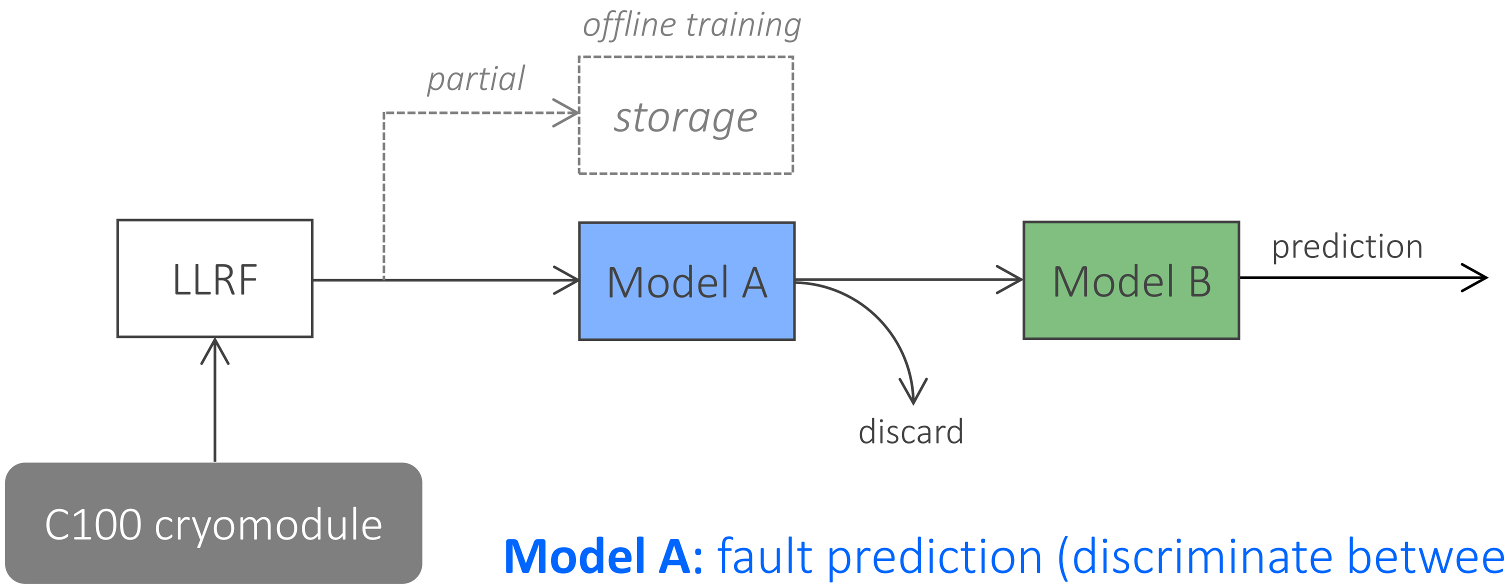
train a model to correctly classify the <u>cavity</u> and <u>type</u> of RF fault given waveform data

machine learning

multi-class classification

time-series data

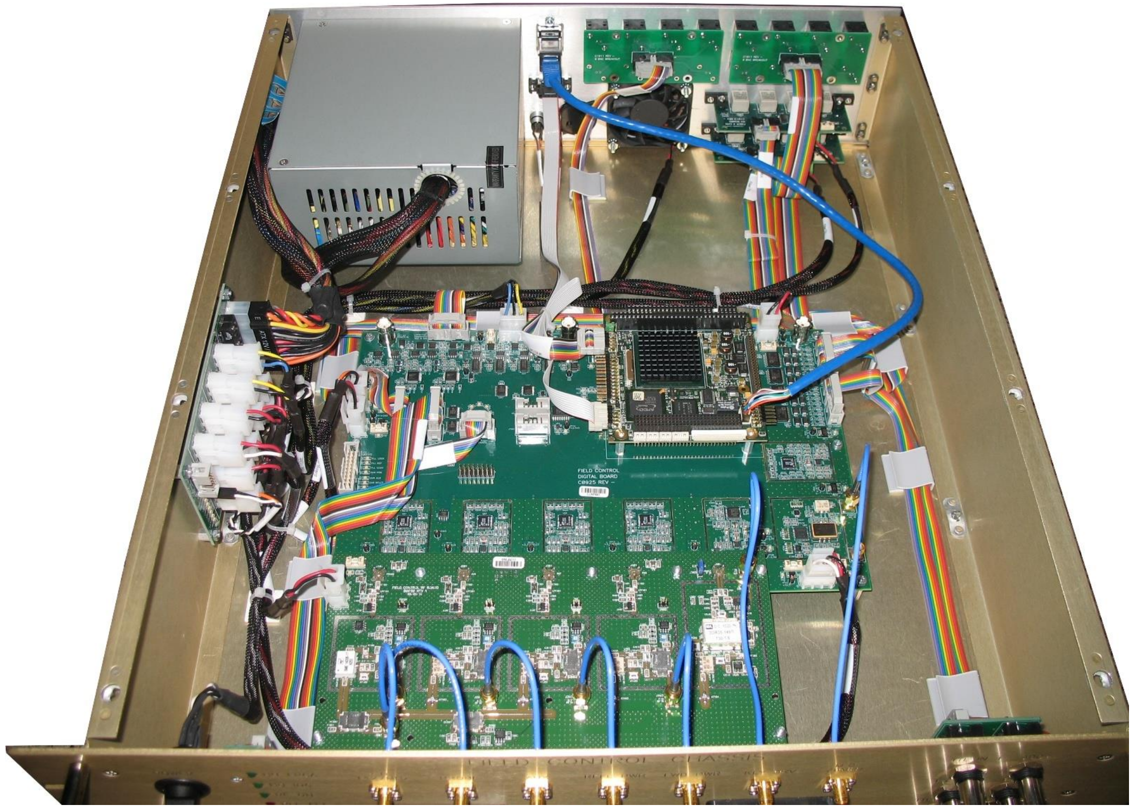
C100 Fault Prediction: Future



Model A: fault prediction (discriminate between "stable" and "impending")
Model B: fault-type prediction (classify fault)

- learning from data streams requires
  1) the ability to process an example, inspect it only once, after which the data is discarded
  2) using a limited amount of memory
  3) the ability of models to predict at any point

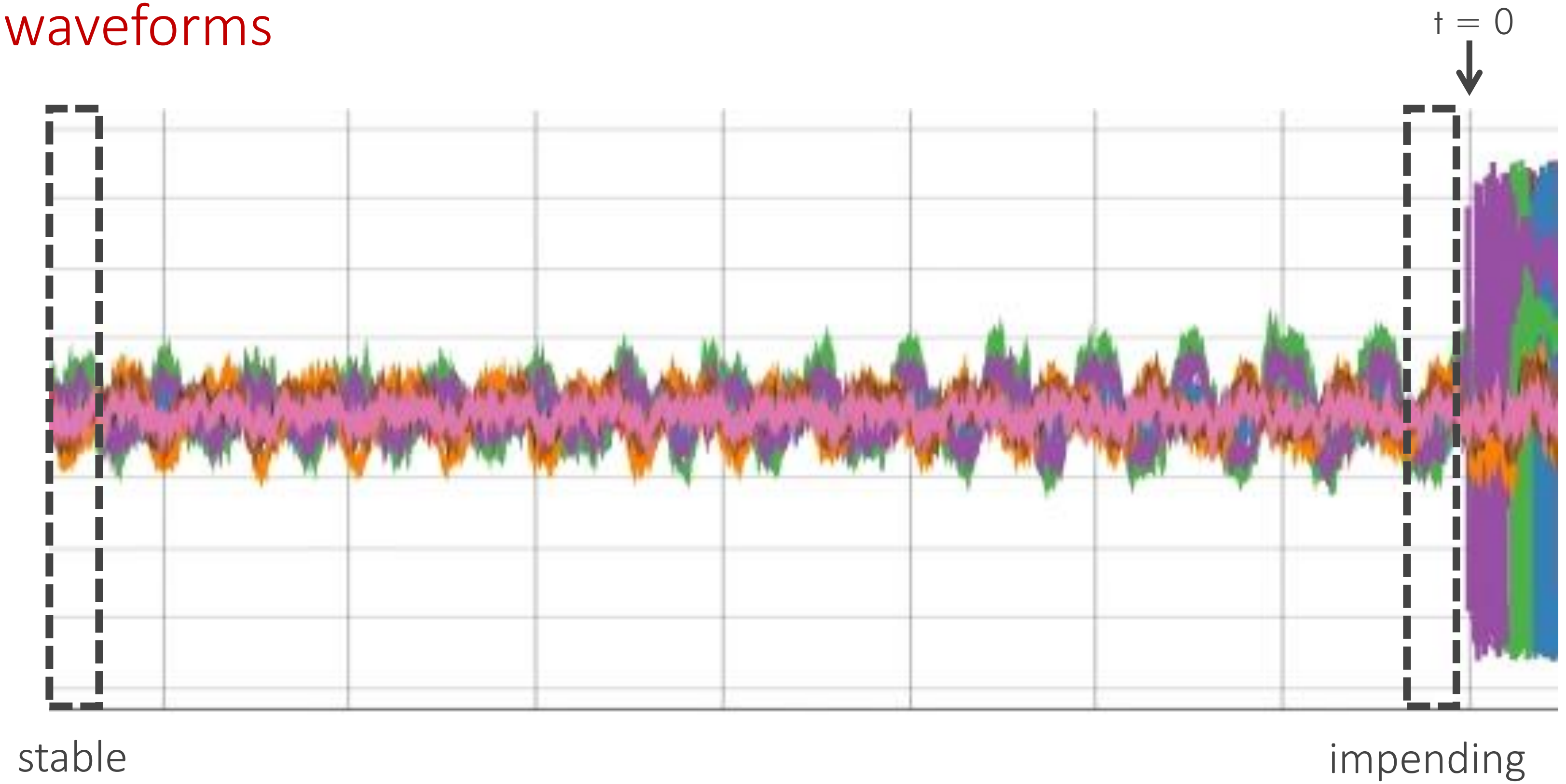
C100 Fault Prediction: Data Requirements



- Cyclone III FPGA (digital system)
- one IOC per chassis (PC/104)
  - ✓ installed in 12 zones
  - ✓ operational for few years
- *continuous data* available in EPICS
  - ✓ gradient and phase
  - ✓ forward power
  - ✓ reverse power
  - ✓ detune angle
  - ✓ amplifier drive
- *trip data* available in EPICS
- both not available at the same time → dual-buffer implementation is forthcoming

From Isolation and Identification to Prediction

- fault prediction
  - ✓ near-term: fault avoidance
  - ✓ longer-term: predictive maintenance/prognostics
- initial step: discriminate between “stable” and “impending” fault conditions
  - ✓ use saved waveforms



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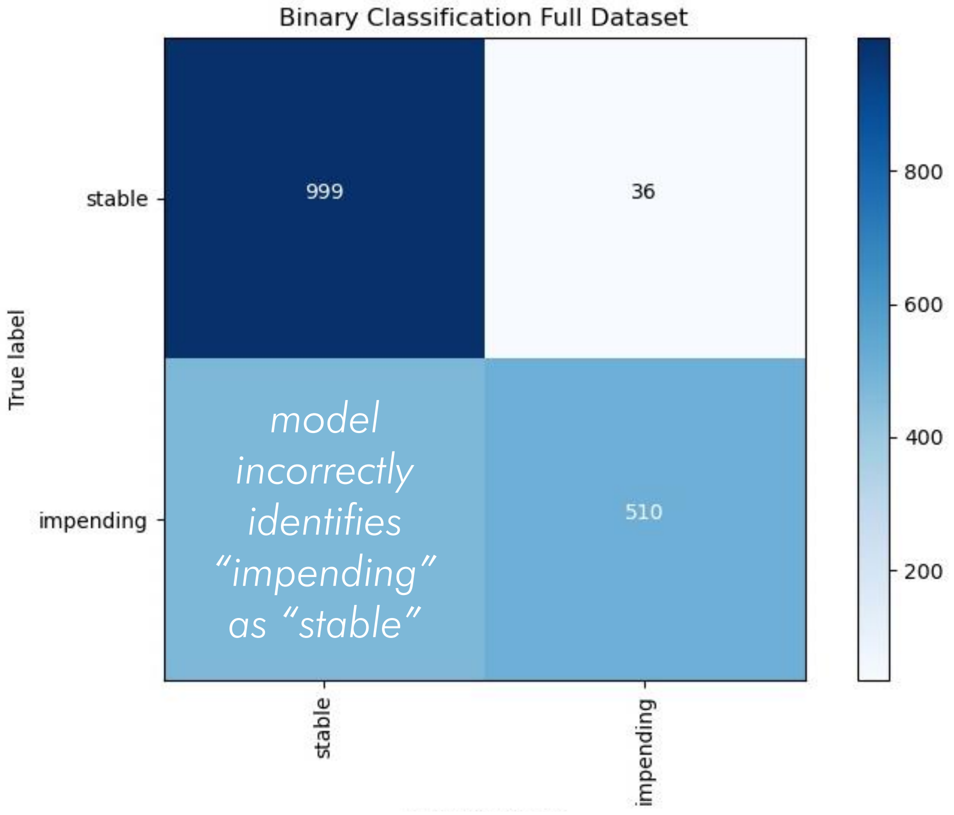
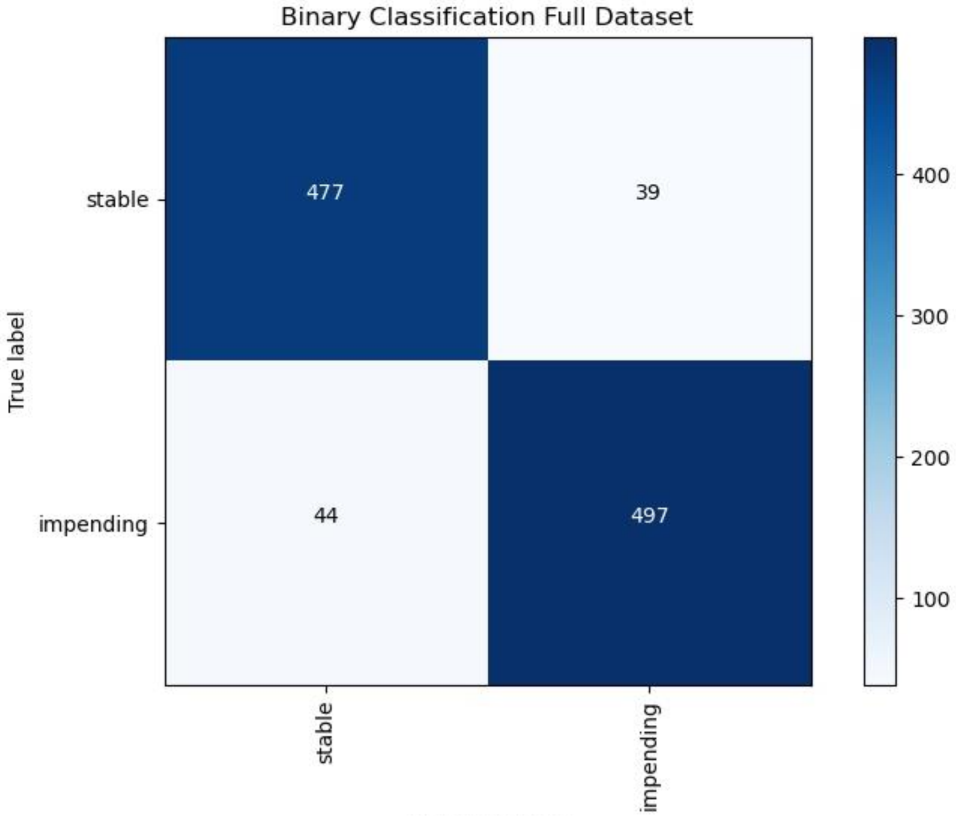
Initial Step: Binary Classifier



accuracy = 74.74%



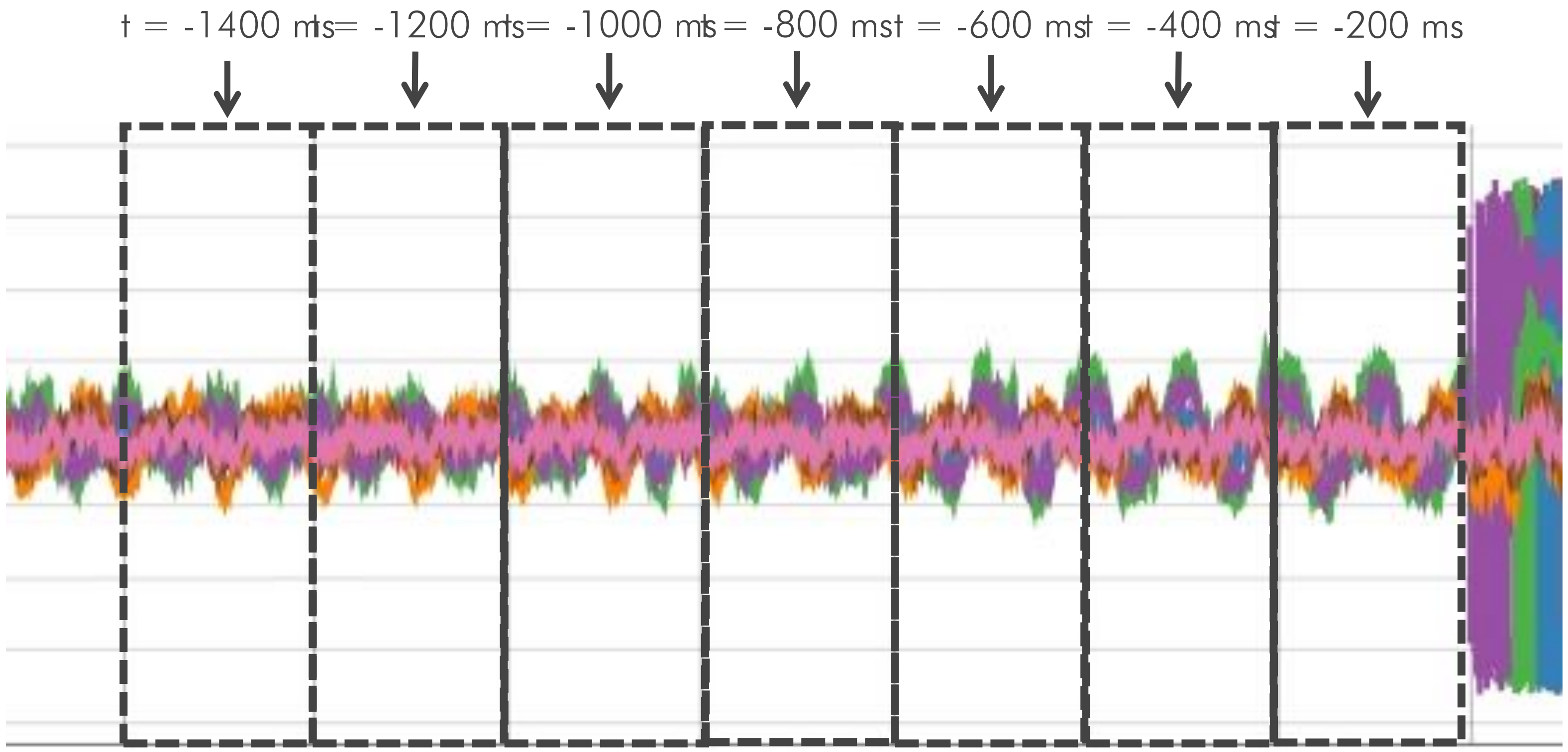
accuracy = 92.13%

- remove fault types which do not show any precursors

	Precision	Recall	f1-score	Support
Stable	0.9155	0.9244	0.9199	516
Impending	0.9272	0.9186	0.9229	541
Accuracy	0.9213			

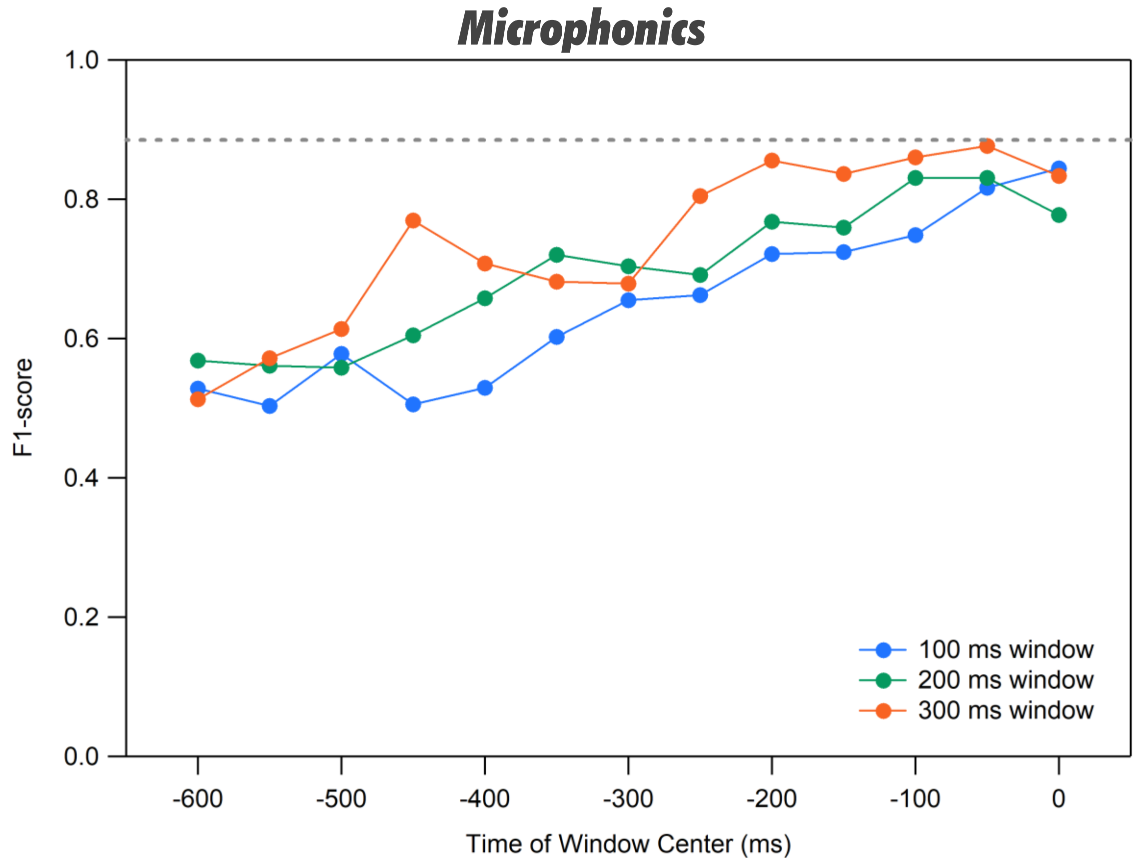
Intermediate Step: Sliding Window

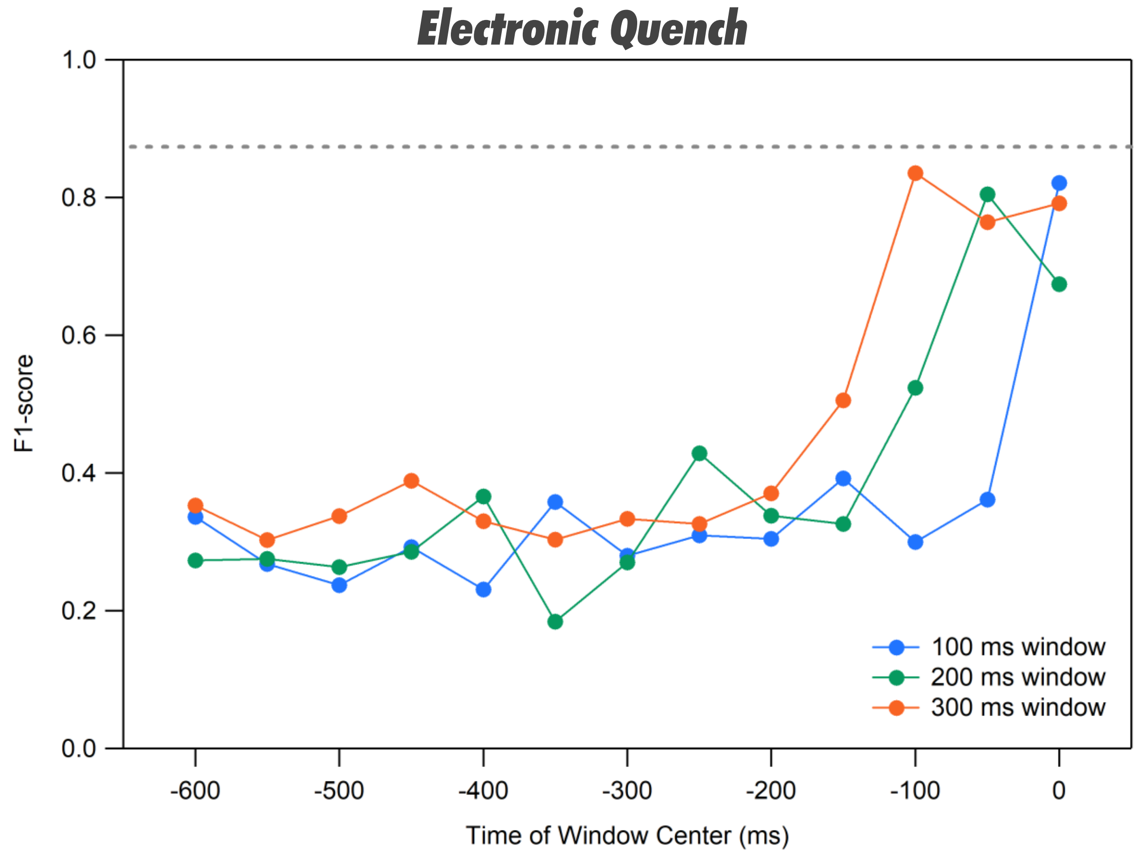
- use saved waveforms
- can data prior to event accurately predict the fault type?



Intermediate Step: Sliding Window

- initial results suggests that for some fault types, prediction is possible

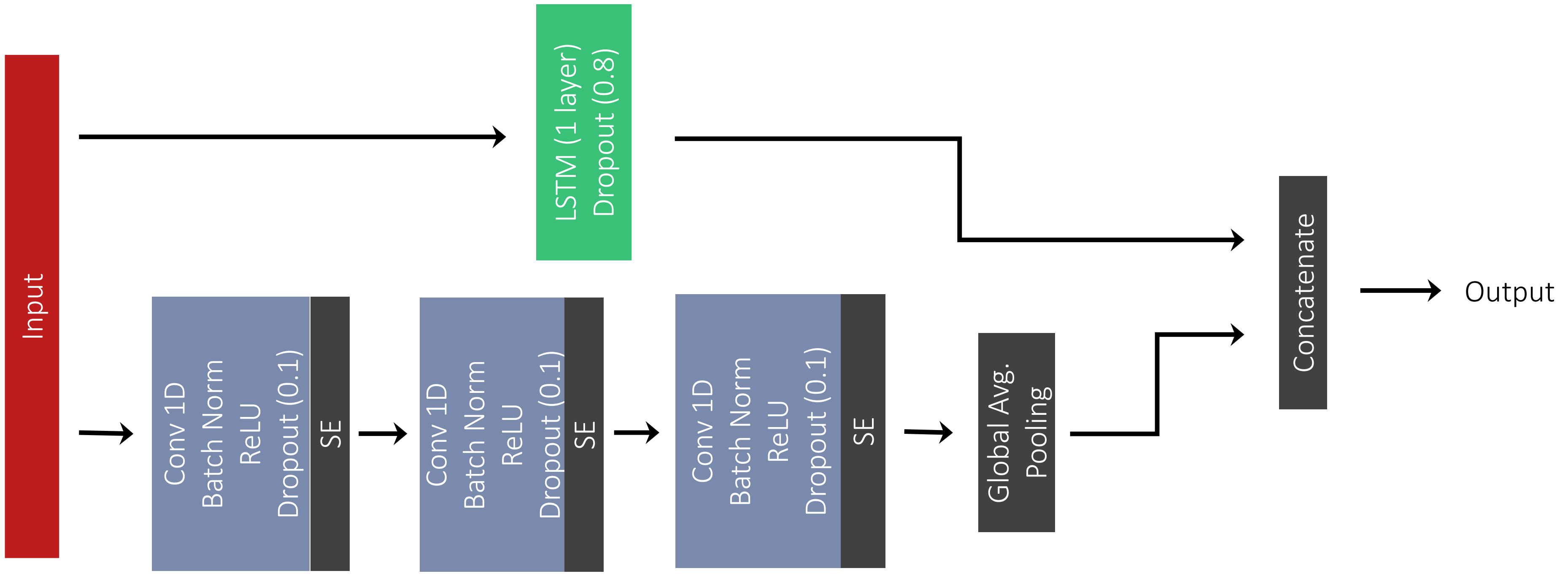




- motivates continued study
  - ✓ what kind of targeted mitigations could be implemented in those time-scales?

Hybrid Deep Learning Model for Fault-type Prediction

- 1D FCN – LSTM Model Architecture
- "squeeze and excitation" (SE) module
  - ✓ builds channel wise attention



Project C: Field Emission Management

- **Goal**:

  Maintain low levels of field emitted (FE) radiation without invasive interruptions to physics, reduce personnel radiation dose and prevent damage to beamline components

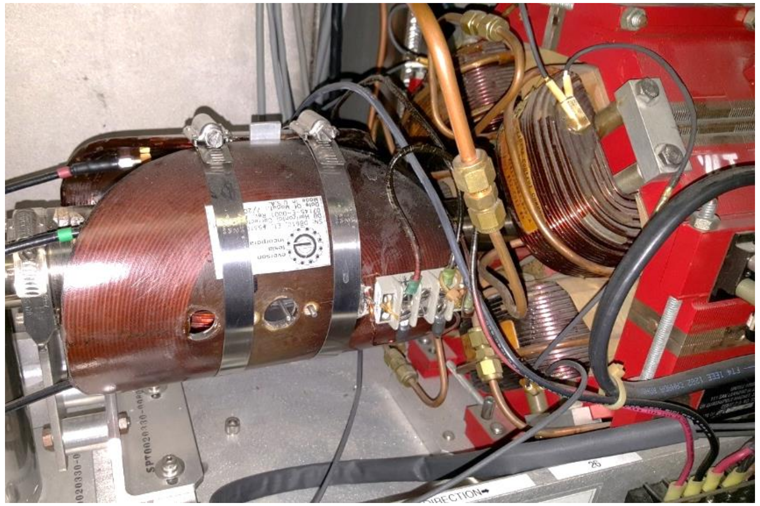
- **Description:**

  Use machine learning models – trained on data acquired with newly installed radiation monitors – to model radiation levels, identify cavities that are the source of excessive FE and/or cavities where field emission onsets have changed

radiation area

damaged beamline valve

damaged magnet and cables



Project C: Field Emission Management

Problem

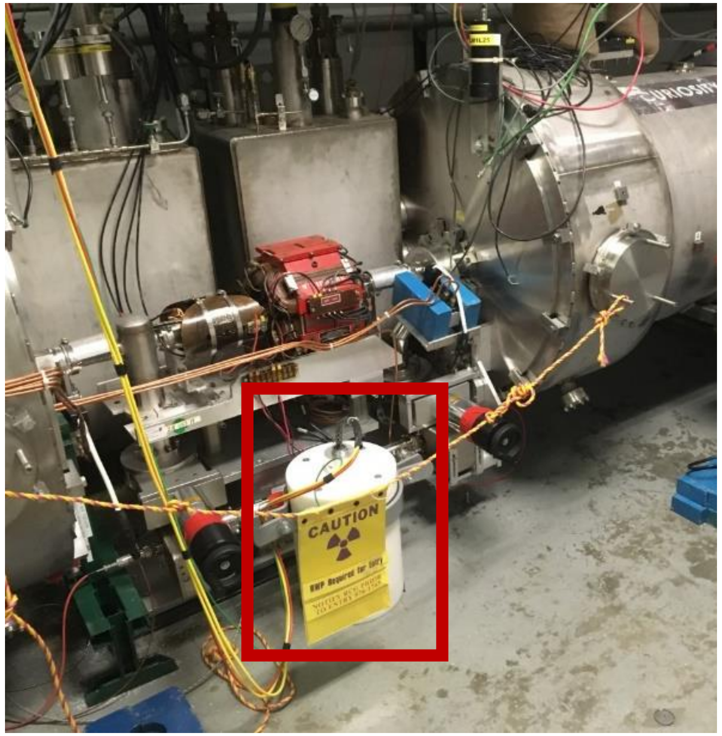
- ✓ field emission is a notorious problem resulting component damage, trips, activation, etc.
- ✓ a single cavity produces field emitted electrons with a non-linear response to gradient above a threshold (FE onset)
  - *these may change over time due to various factors*
- ✓ FE electrons can have complicated interactions with neighboring cavities/cryomodules and can be transported substantial distances up or downstream

Solution

- ✓ use machine learning models to help manage this radiation problem non-invasively
  - *can we model radiation levels given an RF configuration (GSETs, etc.)?*
  - *can we identify cavities that are the source of lots FE-related radiation?*
  - *can we identify cavities with changed radiation onset thresholds?*
  - *can we identify new field emitters and localize them in a linac?*

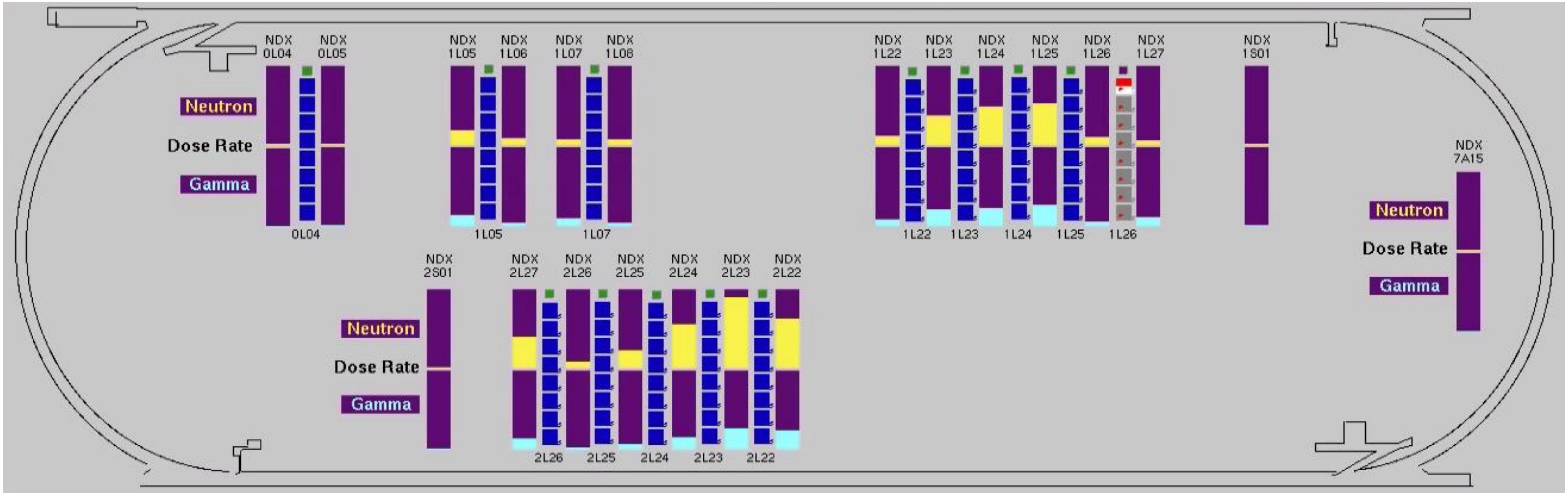
Field Emission Management: Data Requirements

- 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 21 detectors installed



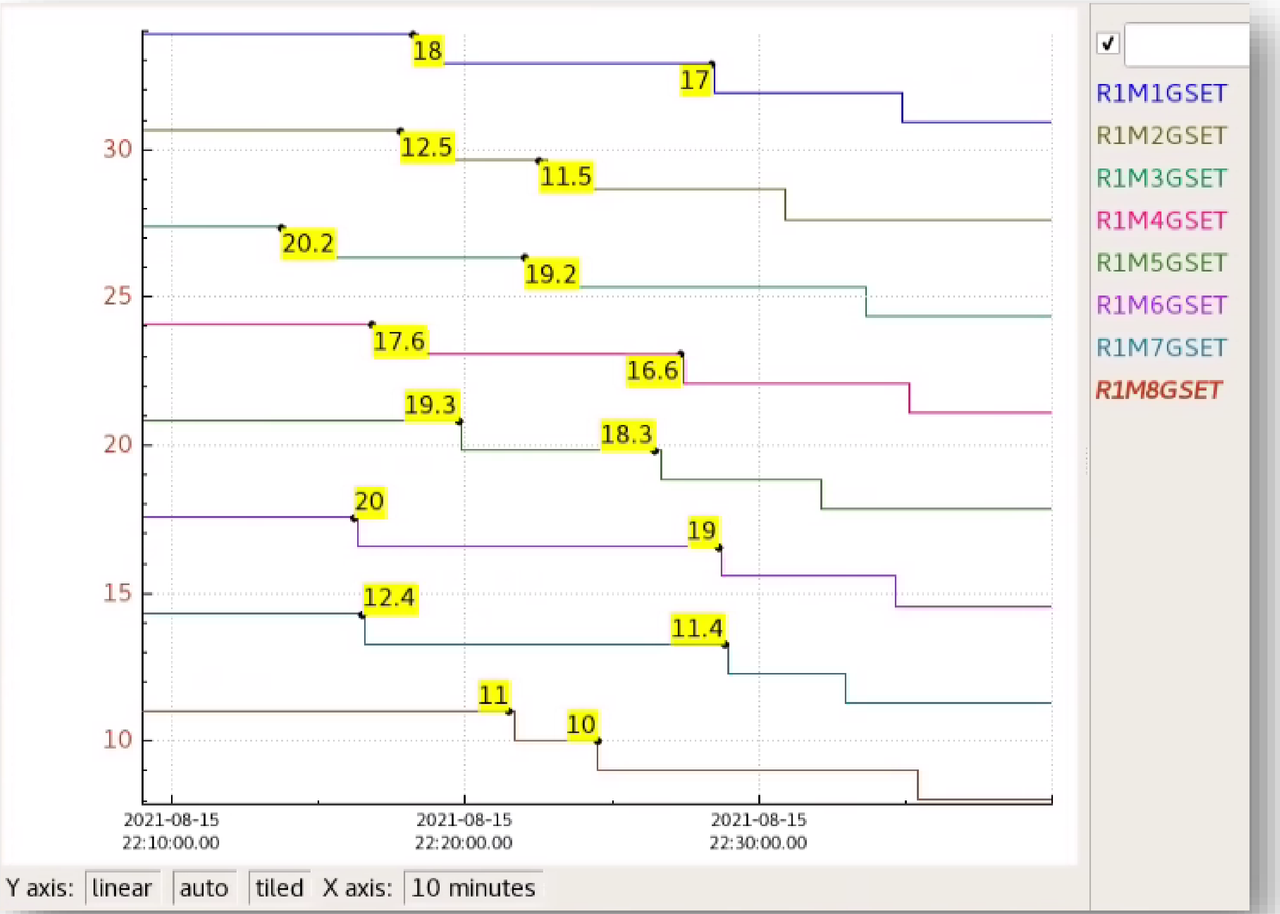
Field Emission Management: Data Requirements

- detectors mostly installed around C100s



Data Collection: Gradient Scans

- all models need lots of data representing the future prediction space to have accurate outputs → **gradient scans**
- measured radiation signals via NDX as combination of North Linac C100 gradients were varied across a range of operational values
  - ✓ collected 17,610 samples across 1,794 gradient combinations
- each cavity step
  - ✓ jiggle cavity phase
  - ✓ step cavity
  - ✓ wait for gradient ramp and settle time
  - ✓ wait for data collection



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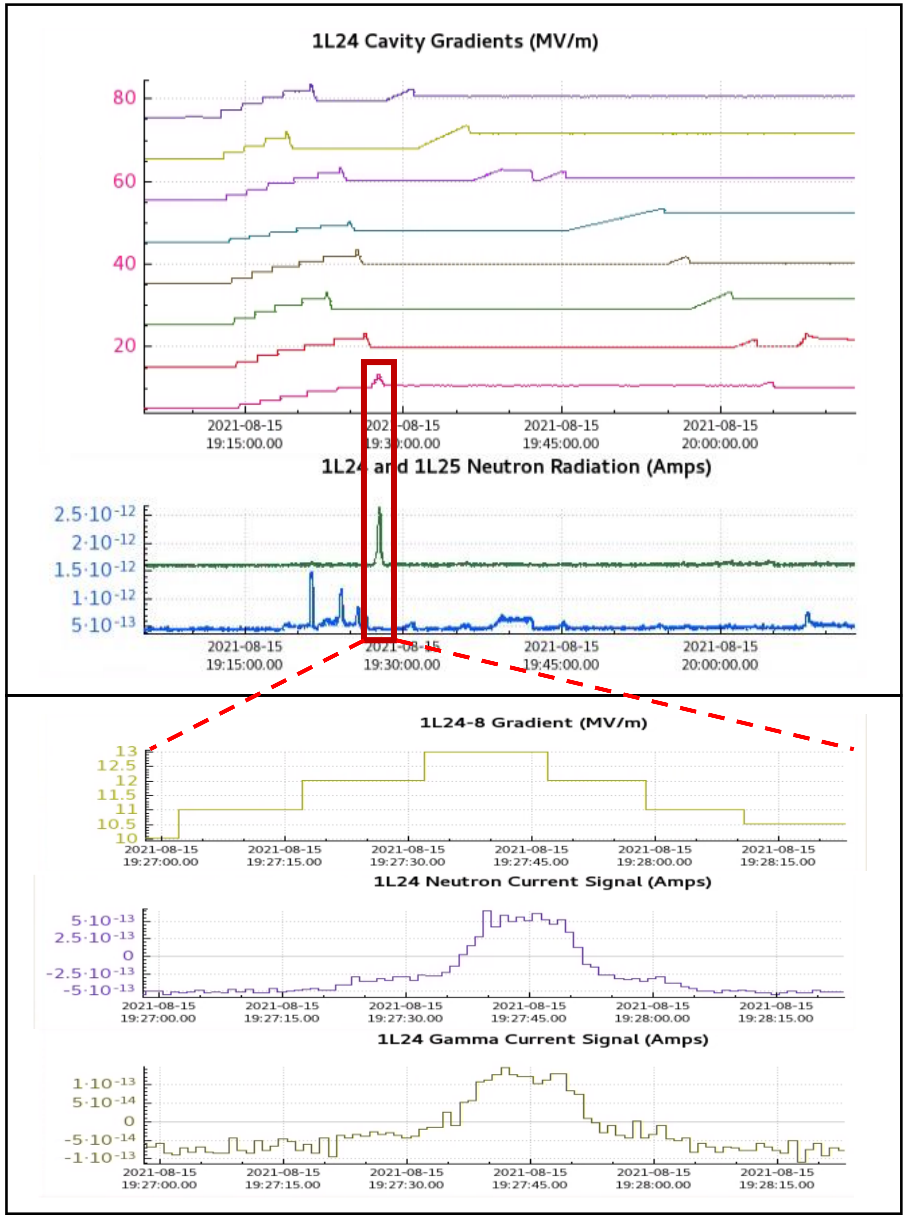
Data Collection: Radiation Onset Scans

- knowing at what gradient a cavity is producing radiation at levels detectable by the NDX system is useful to a variety models → **radiation onset scans**
- use NDX to detect small increases in radiation above background when a cavity's gradient is increased
  - ✓ use radiation detection as a proxy for FE onset
- developed code to automate FE scan data acquisition
  - ✓ all cavities baselined at 5 MV/m when not being scanned
  - ✓ background radiation measured before scanning each cavity
  - ✓ walk individual cavities up in big steps until we see radiation
  - ✓ walk down from there in small steps until we don't see radiation

Radiation Onset Scans

- used NDX to identify radiation onset for every C100 cavity
  - ✓ *radiation onset*: highest gradient without radiation detected by NDX under operational conditions
  - ✓ closely related to FE onset
- measure one C100 at a time
  - ✓ turn off four zones up- and down-stream
  - ✓ establish a high, no radiation, baseline gradient to amplify the radiation signal from each onset
  - ✓ walk each cavity up in 0.125 MV/m steps until a statistically significant increase in radiation is measured over a 10 second interval

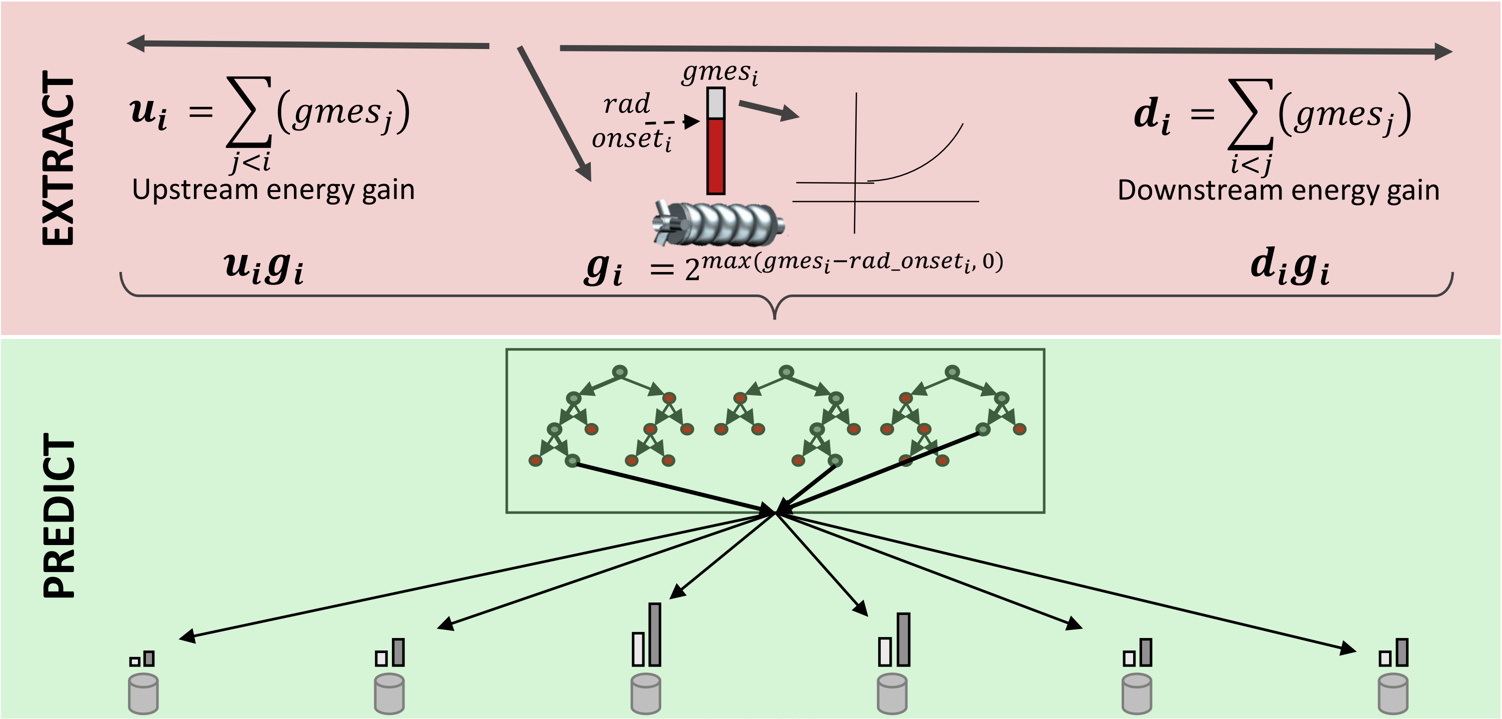


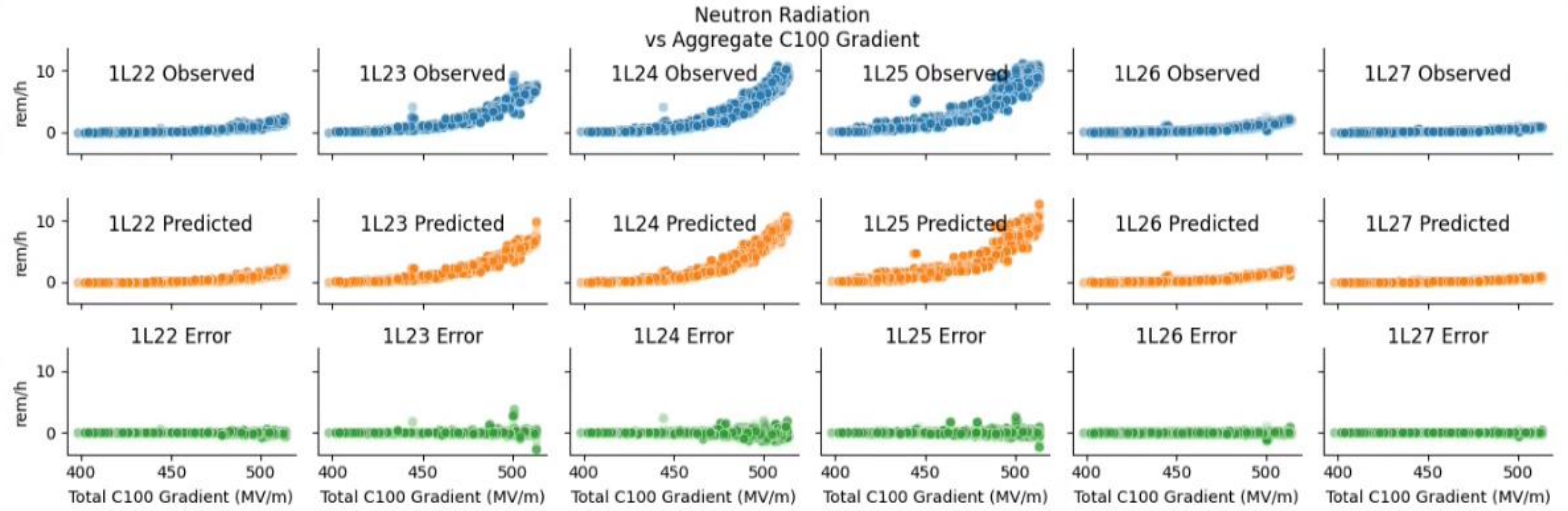
Model Development: Machine Learning

- model the NDX radiation around NL C100 cryomodules using cavity functions of gradients and radiation onsets as input
  - ✓ multi-output RF regressor
  - ✓ 5 features/cavity × 8 cavities/module × 4 modules (=160 features total)
- five per-cavity features
  - ✓ surface FE
  - ✓ upstream energy gain
  - ✓ downstream energy gain
  - ✓ upstream interactions
  - ✓ downstream interaction

Model performance metrics

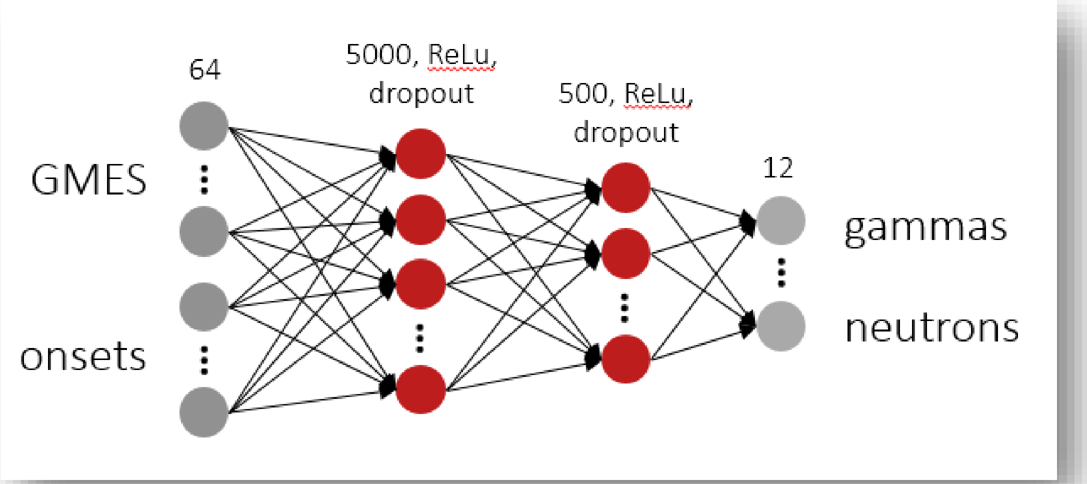
	Training	Testing
R-Squared	0.999	0.978
MSE	0.001	0.052
MAE	0.013	0.115

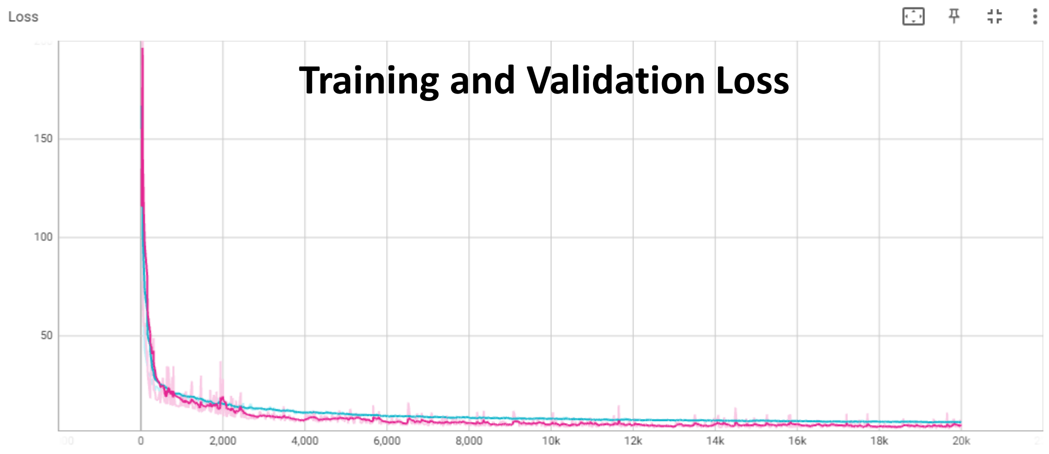




Model Development: Deep Learning

- develop deep learning models that *do not rely on feature engineering*
  - ✓ getting similar performance as ML model
- create optimization software to suggest gradient distribution
  - ✓ genetic algorithm, etc.
  - ✓ investigate reinforcement learning as an alternative
- develop models to address changing field emitters, and (dis)appearance of emitters
  - ✓ model changes in radiation onset via MLP
  - ✓ anomaly detection via AutoEncoder





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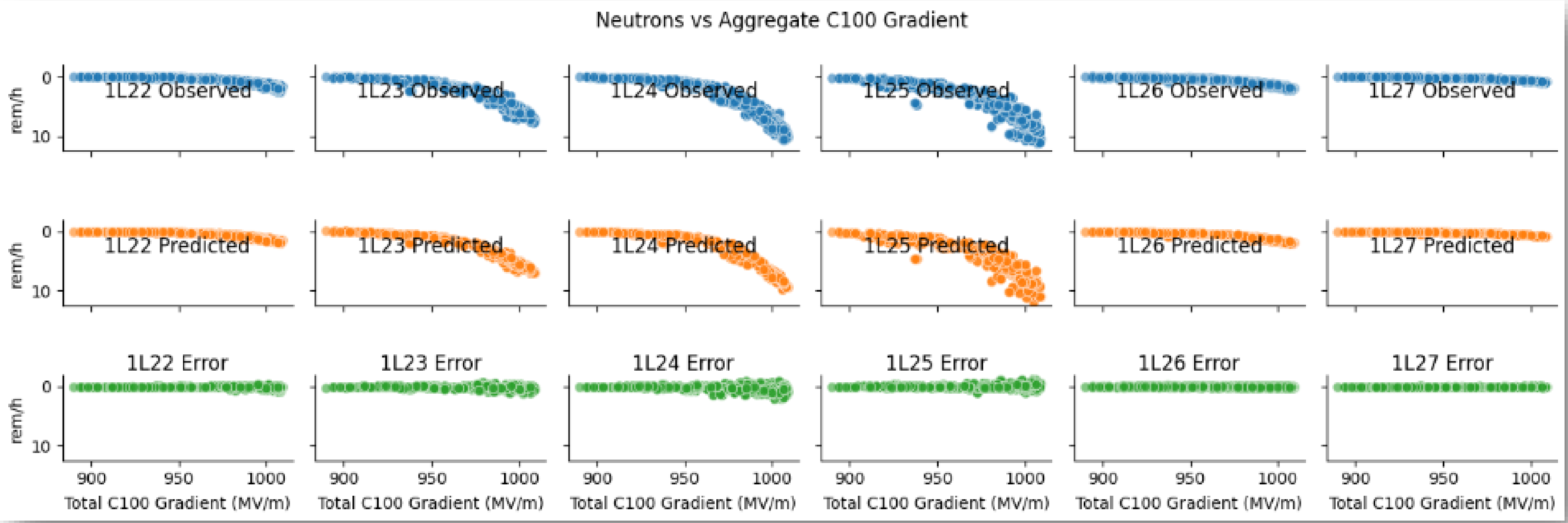
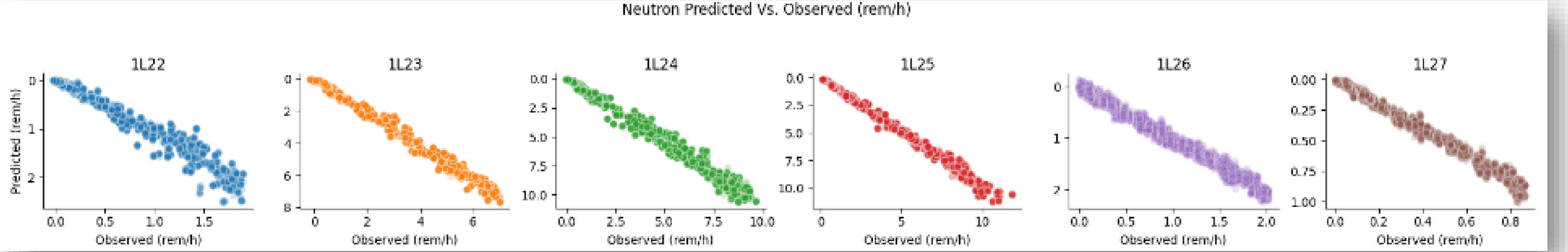
Deep Learning Model Output: Neutrons

Note: vertical scales are reversed





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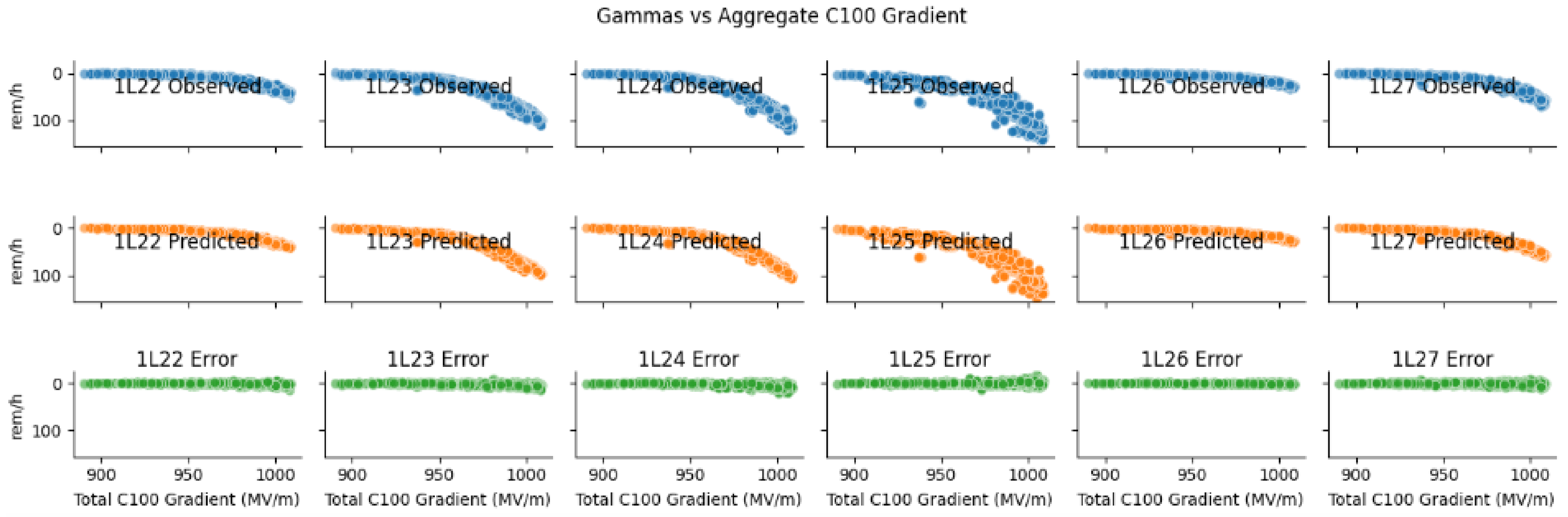
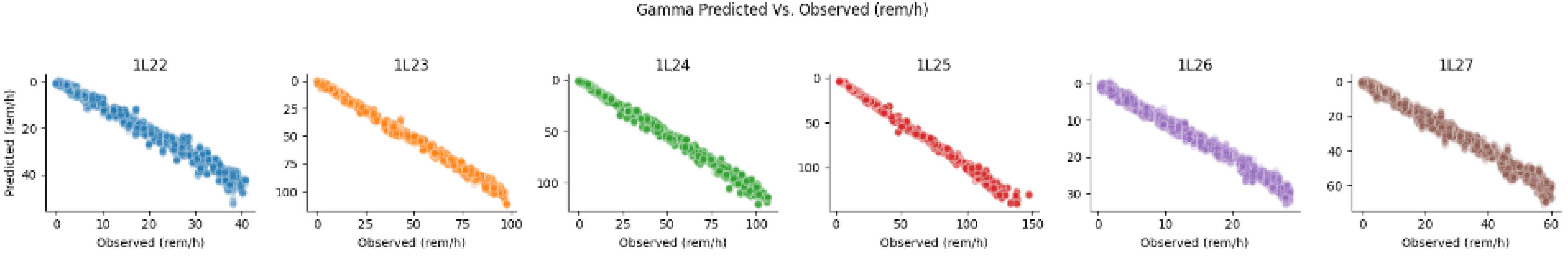
Deep Learning Model Output: Gammas

Note: vertical scales are reversed





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Data: The Fuel for Machine Learning

- focus in Year 1 was getting systems in place to collect information-rich data
  A. cavity instability detection: DAQ system
     - 🚩 *supply chain issues causing delays (12-18 months)*
     - *redesign of DAQ to be more flexible (i.e. be able to use components that are available)*
  B. C100 fault prediction: dual-buffer firmware upgrade
     - 🚩 *bench tests ongoing, however at least 1-year delay from expected deployment*
     - *developing software to collect 1.6 second snapshots of data on-demand*
  C. field emission management: NDX detectors
     - *built, tested, commissioned, installed, and operational*
- focus of Year 2 will be to continue making progress in getting systems in place to collect data required for developing machine learning models
- two posters presented at 2021 ICALEPCS conference
  - ✓ "Initial Studies of SRF Cavity Fault Prediction at Jefferson Laboratory"
  - ✓ "Using AI for Management of Field Emission in SRF Linacs"

Project Summary: Major Deliverables and Schedule

Project	Deliverable	Date
Cavity Instability Detection	Prototype DAQ installation	01/2022
	Procurement of production DAQ parts	02/2022
	DAQ driver development, software development for data harvesting and filtering	06/2022
	Installation of 40 production DAQs	TBD
C100 Fault Prediction	Collect snapshots of (not continuous) data as a temporary work around	02/2022
	Firmware upgrade to C100 modules (partial)	06/2022
	Develop deep learning models for streaming data (by training on snapshot data)	06/2022
Field Emission Management	Develop deep learning models of NDX radiation around C100s	02/2022
	Develop optimization software to suggest gradient distribution	06/2022

Project Summary: Annual Budget

	FY20 ($k)	FY21 ($k)	Totals ($k)
a) Funds allocated	450,000	450,000	900,000
b) Actual costs to date	149,599	0	149,599

- *unspent $200K: DAQ-related*

🚩 *unspent $100K: student-related*

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Thank You