

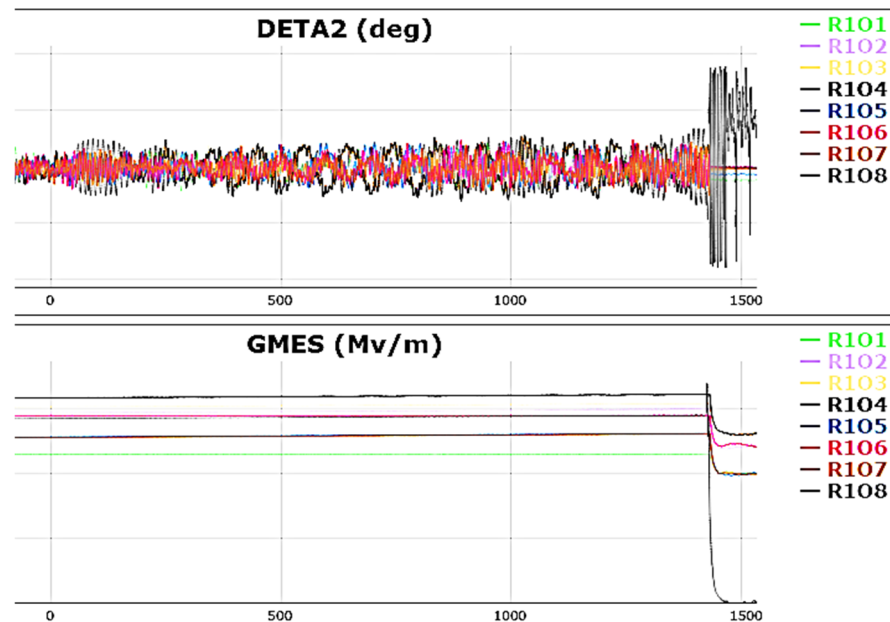
SRF Cavity Fault Classification Using Machine Learning At CEBAF

IPAC19

Anna Solopova¹, A. Carpenter¹, T. Powers¹,
Y. Roblin¹, C. Tennant¹, K. Iftekharuddin²,
L. Vidyaratne²

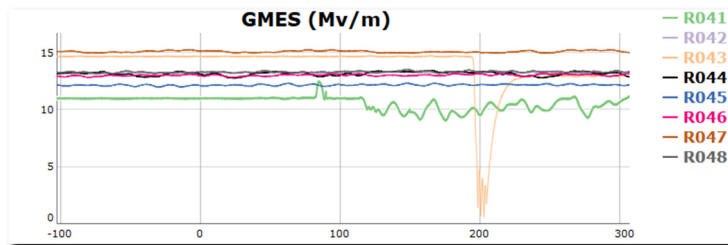
¹Jefferson Lab ²Old Dominion University

 Jefferson Lab



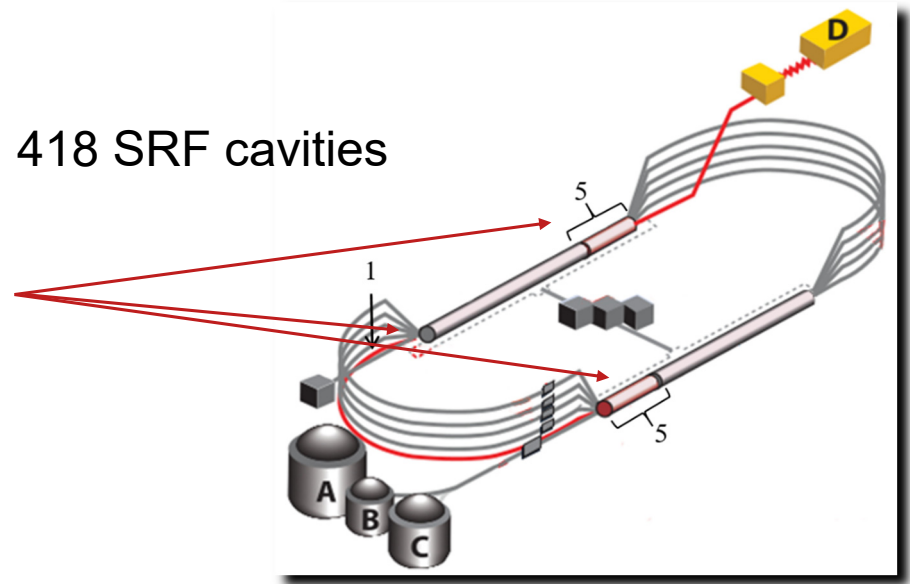
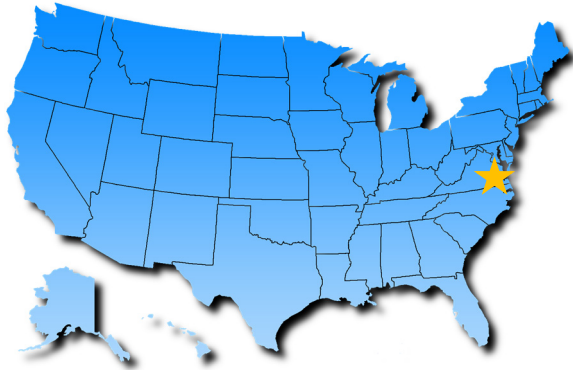
Outline

- CEBAF operations
 - C100 cryomodules
 - Energy reach
- Fault data collection and analysis
 - DAQ
 - Fault types
 - Offending cavity
- Applying Machine Learning
- Plans
- Conclusions



CEBAF

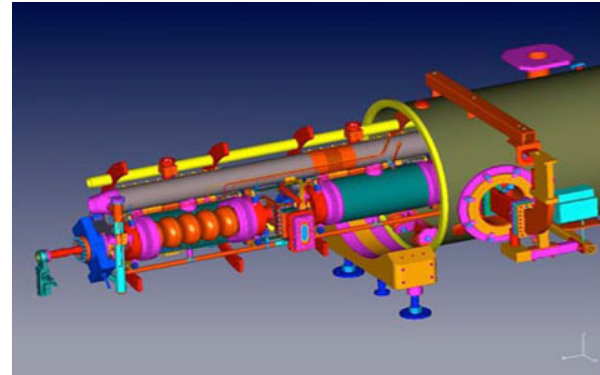
- Continuous Electron Beam Accelerator Facility (CEBAF) at Jefferson Lab is the first large high power SRF machine
- Over 25 years in operation
- 4 experimental halls, injector, 2 linacs, 418 SRF cavities
- 12 GeV design energy
- 11 new cryomodules added in 2013



C100 cryomodules

- Each cryomodule contains a string of eight 7-cell SRF cavities
- After commissioning:
 - Average Max Operating Gradient = 19.6 MeV
 - Average energy gain = 110 MV/m
- C100 cavities are strongly mechanically coupled, instability in one cavity causes other cavities to trip
 - Hard to determine which one was responsible for a trip
- Operators only have one parameter to adjust – decrease cavity gradient.

Gradient reach and availability of the machine suffer.

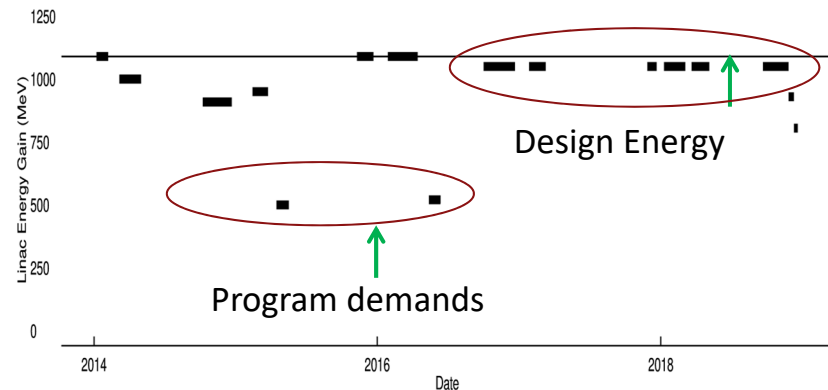


Gradient reach, trips, unhappy users

- CEBAF energy degradation is a big problem
- C100 are not quite reaching 100MeV*
- Average 6 RF trips an hour
 - 0.5 minute to recover
 - 1.5 minutes of bad experimental data per trip
 - **15% of an hour lost just to the RF!**
- “Gradient recovery” program for C100 modules started in Spring 2018
 - Balance gradient reach and trip rate
 - Optimize C100 performance
 - Guide operators

*Mostly due to microphonics and field emission

Cryomodule	Commissioned Energy, MV, 2013	Operational Energy 2016	Delta, MV
C100-1	104	77.2	-26.8
C100-2	122	89.7	-32.3
C100-3	108	91.4	-16.6
C100-4	93	91.6	-1.4
C100-5	121	91.9	-29.1
C100-6	111	91.9	-19.1
C100-7	103	91.9	-11.1
C100-8	110	86.9	-23.1
C100-9	105	83.7	-21.3
C100-10	106	77.3	-28.7

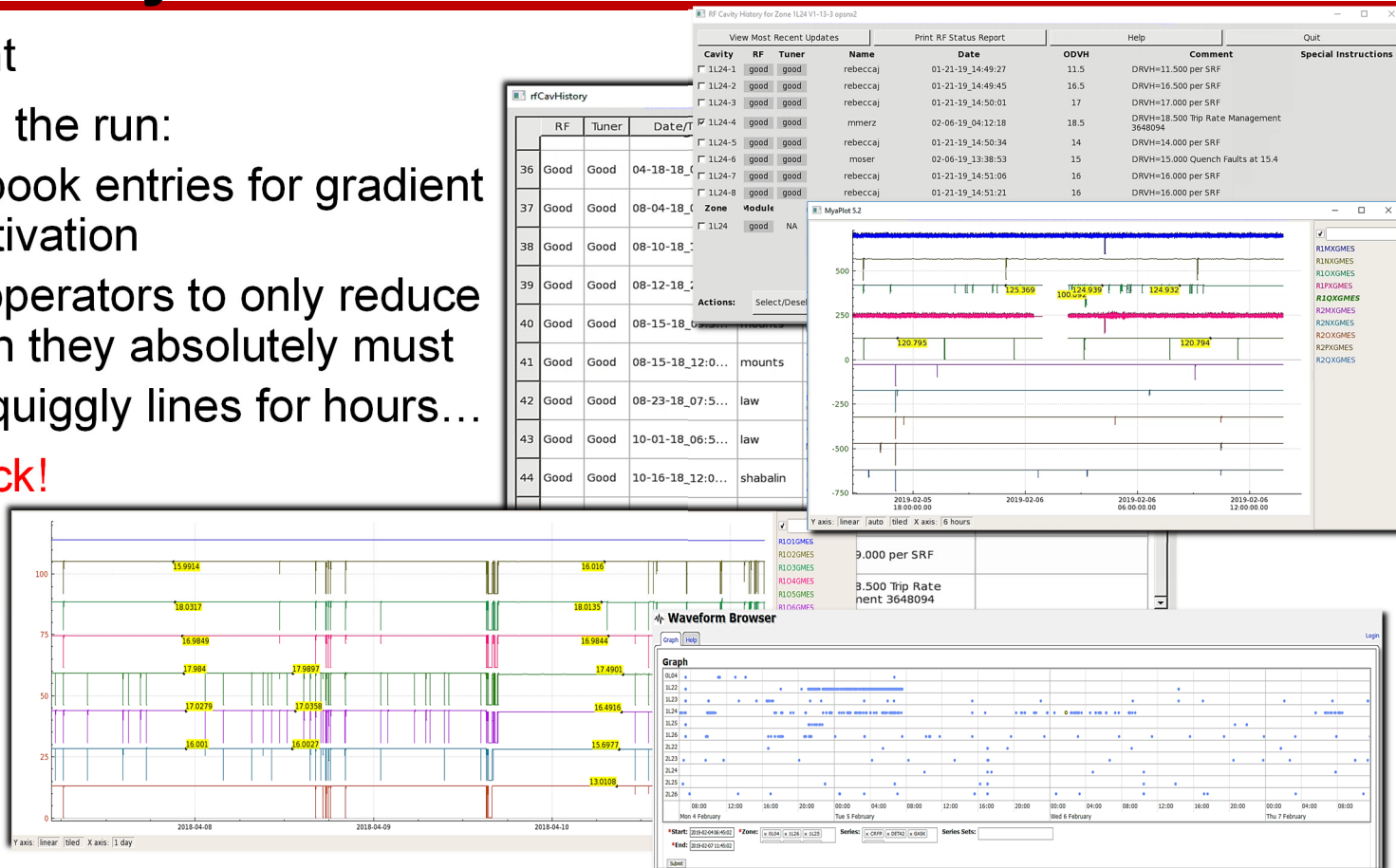


Motivation – why do I care?



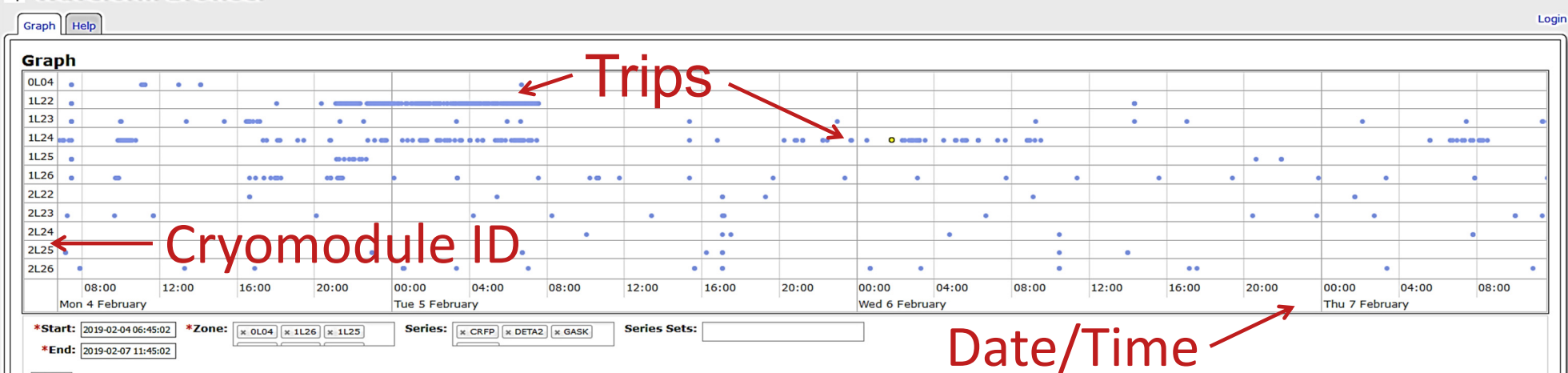
To recover gradient

- Every day during the run:
 - Chasing logbook entries for gradient reduction motivation
 - Convincing operators to only reduce gradient when they absolutely must
 - Looking at squiggly lines for hours...
- I want my life back!
- Maybe there is a better way...



DAQ: Waveforms

Waveform Browser

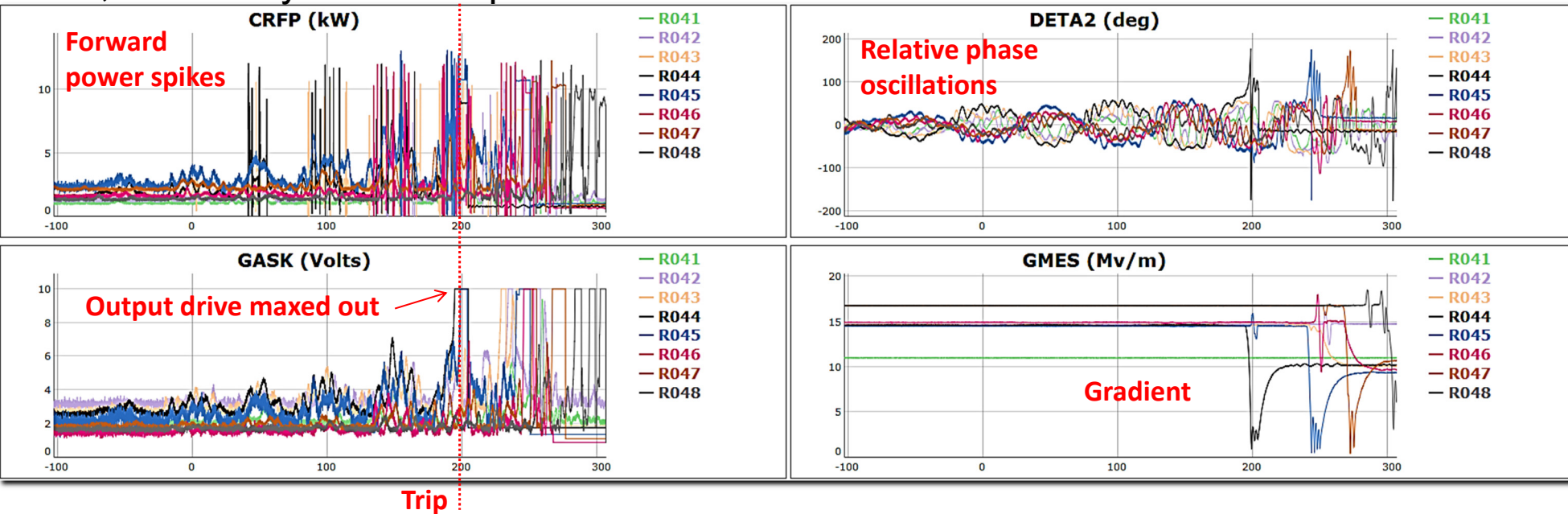


- Digital LLRF system for C100 provides live waveforms for each cavity
 - Now reconfigured to collect 17 RF signals from each of 8 cavities when a fault occurs
- At 5 kHz sample rate signals span ~1.6 seconds including several hundreds of milliseconds before the event
- Allows an insight into fault mechanisms

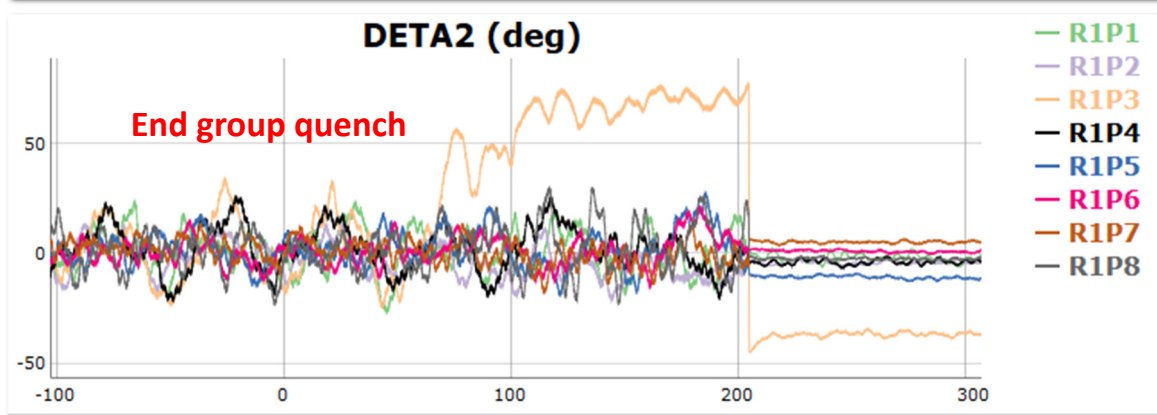
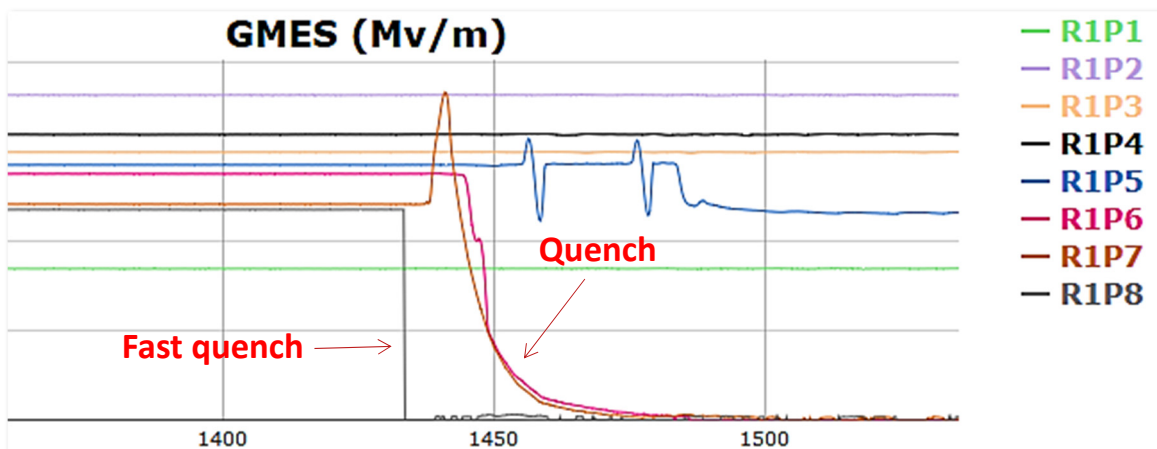
What does a trip look like - Microphonics

Each fault type has distinctive features subject matter experts (SME) are able to identify by looking at the graphs.

Microphonics-induced trip is caused by mechanical vibrations. Cavities start to lose tune, eventually run out of power.



What does a trip look like - Quenches

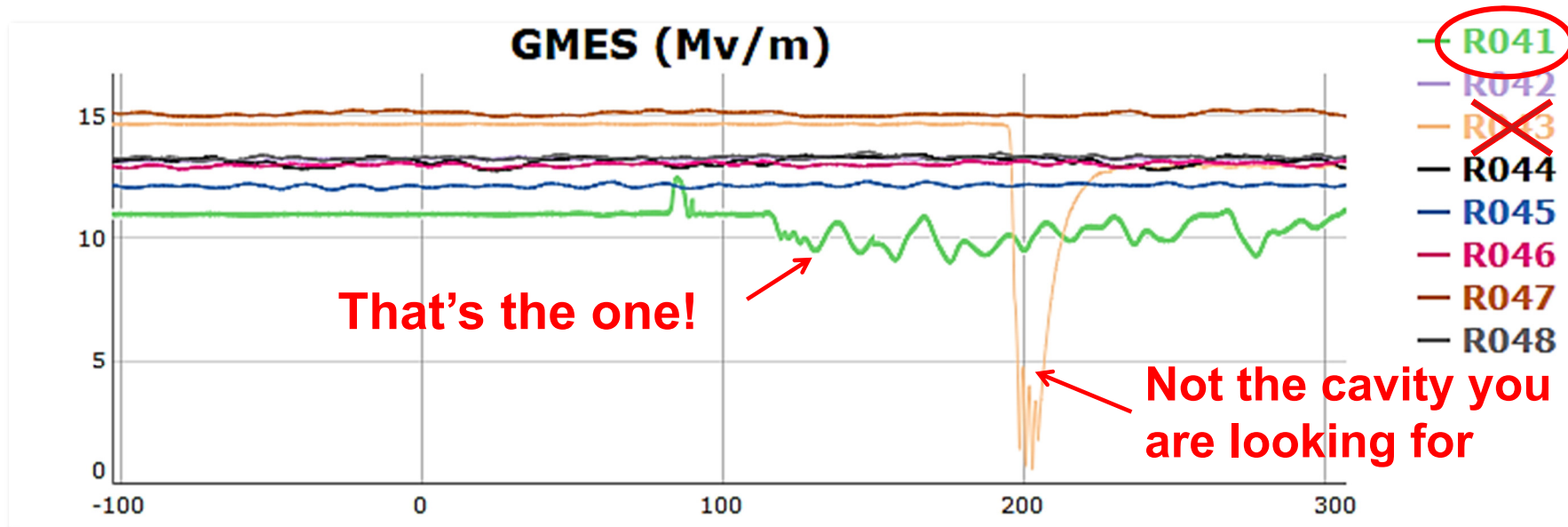


- Fast quench
 - Gradient fall appears instant
 - Often accompanied by a pressure spike seen in the beam line ion pump
 - May indicate gas loading
- Thermal quench (in cell)
 - No indicators of previous instability
 - Gradient fall time 2-3ms
- End group quench
 - 1 cavity slowly loses tune

To the operator they're all the same
But they should be treated differently

Harder question – which one was first?

Cavity losing gradient first is not always the offending one!



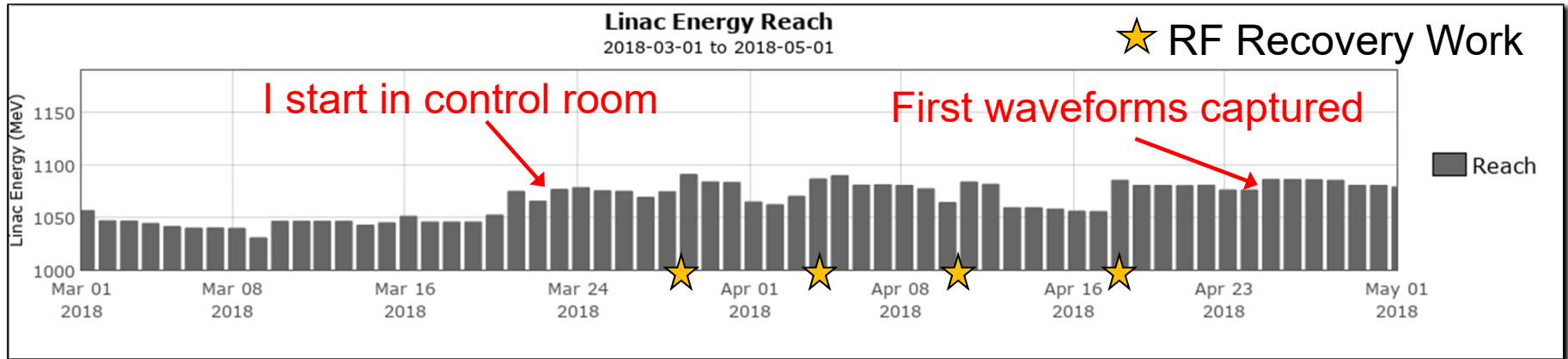
Losing energy in the wrong cavities.

Success is expensive

Eventually we reached intermediate success: recovered some gradient, trip rate approximately the same

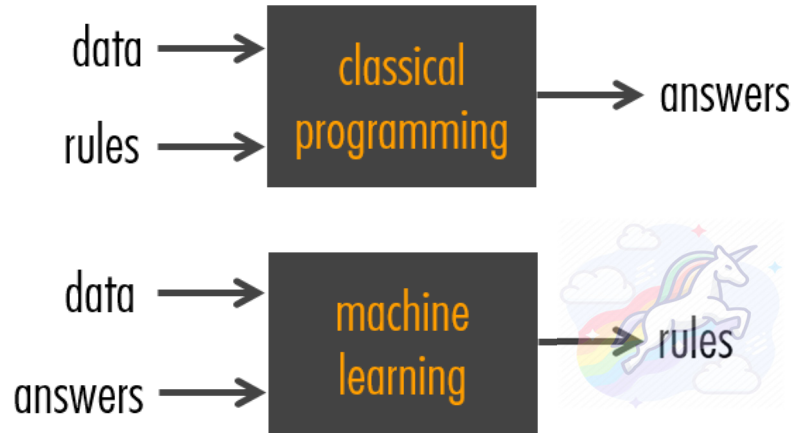
- Several hours each day to look through last night's data
- Even more hours from others to classify faults, find and apply mitigations

We could have been doing something else



Machine Learning

Machine learning (ML) can be used to recognize images and patterns, may be applied in real time.

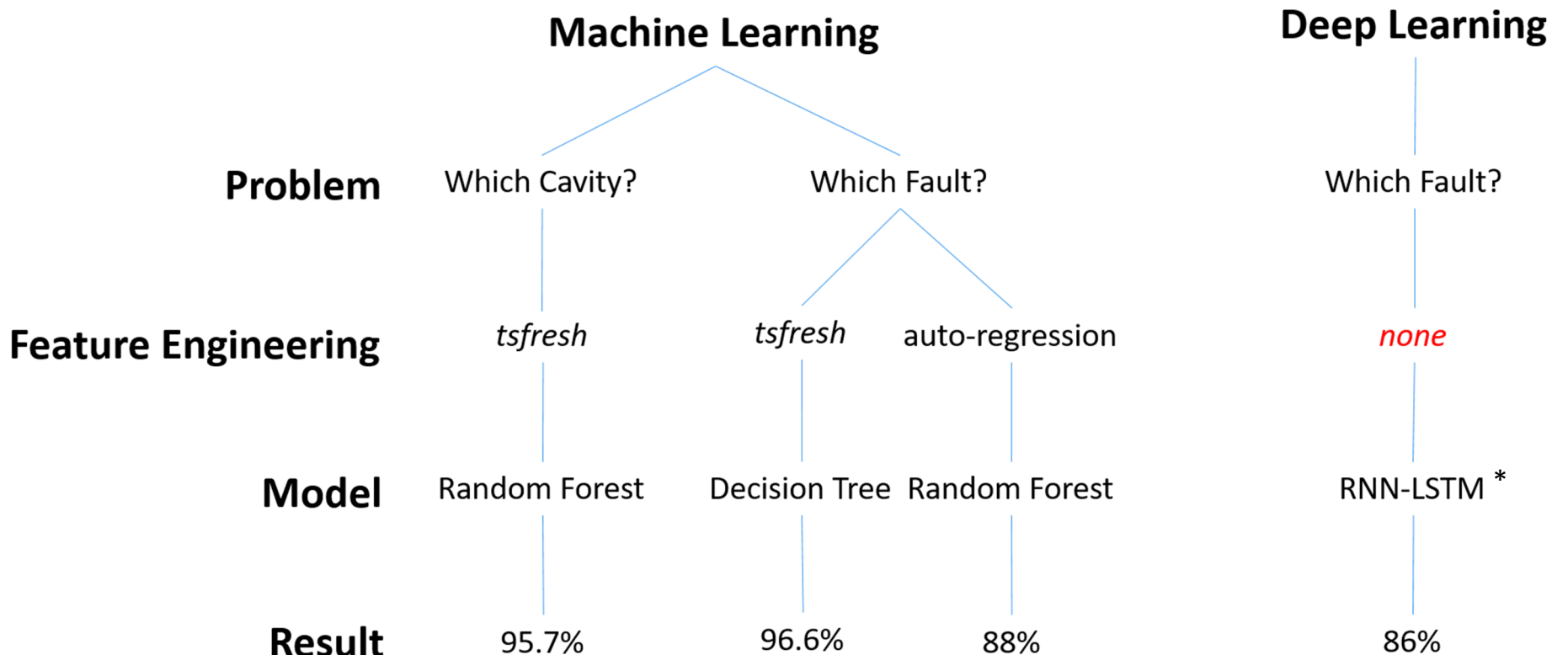


Data and answers – we got that!

But what is the question?

1. Which cavity caused the trip?
2. What was the fault type?
3. What is the proper response?

Results



*Recurrent Neural Network - Long Short Term Memory type

Results

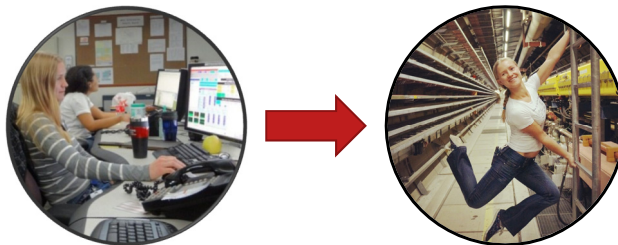
- Conventional machine learning is accurate, but computationally expensive
 - Performs well even with limited data sets
- Deep learning can be used on raw data
 - One step closer to a real-time control room application
 - Requires more data for training

Plans

- Apply Deep Learning to fault classification problem
- Recent collaboration with Old Dominion University provides expertise and resources to focus on more complex problems:
 - First unstable cavity identification
 - Trip prediction and avoidance
 1. Predict if a fault may occur
 2. Predict a type of a fault
- Create an application for the operators to suggest action based on fault classification and cavity identification
- New collaboration with SLAC will tie our trip prediction mechanism into a ML based modeling and control project for LCLS-II
- Other SRF machines will join in?

Conclusions

- Real-time continuous data collection and intelligent analysis may lead to developing new fast trip avoidance mechanisms to compensate for cavity detuning and power starving
 - Piezo tuners
 - Short bursts of additional power
- Automation of cavity fault analysis frees up valuable expert's time
- Gathered information and statistics will help improve future cryomodule design and guide us in how we operate and set up the machine
- **Understanding the origins and the nature of cavity faults increases accelerator reliability and availability**
- I *sort of* got my life back



Questions?

Talks and posters to consider

- **S. Biedron**, “Machine Learning, Data Mining and Big Data Handling for Accelerators” – **Today at 14:00**
- **G. Azzopardi**, “Operational Results of LHC Collimator Alignment Using Machine Learning” – **Today at 15:00**
- **Posters:** MOPGW017, MOPGW023, MOPGW026, THPRB003, THPRB011, THPRB040, THPRB077, THPRB102, THPRB106, THPTS047, TUPGW094, WEPGW045, WEPGW049, WEPGW058, WEPGW081, WEPGW081, SUSPF076, ...

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Thank you!

