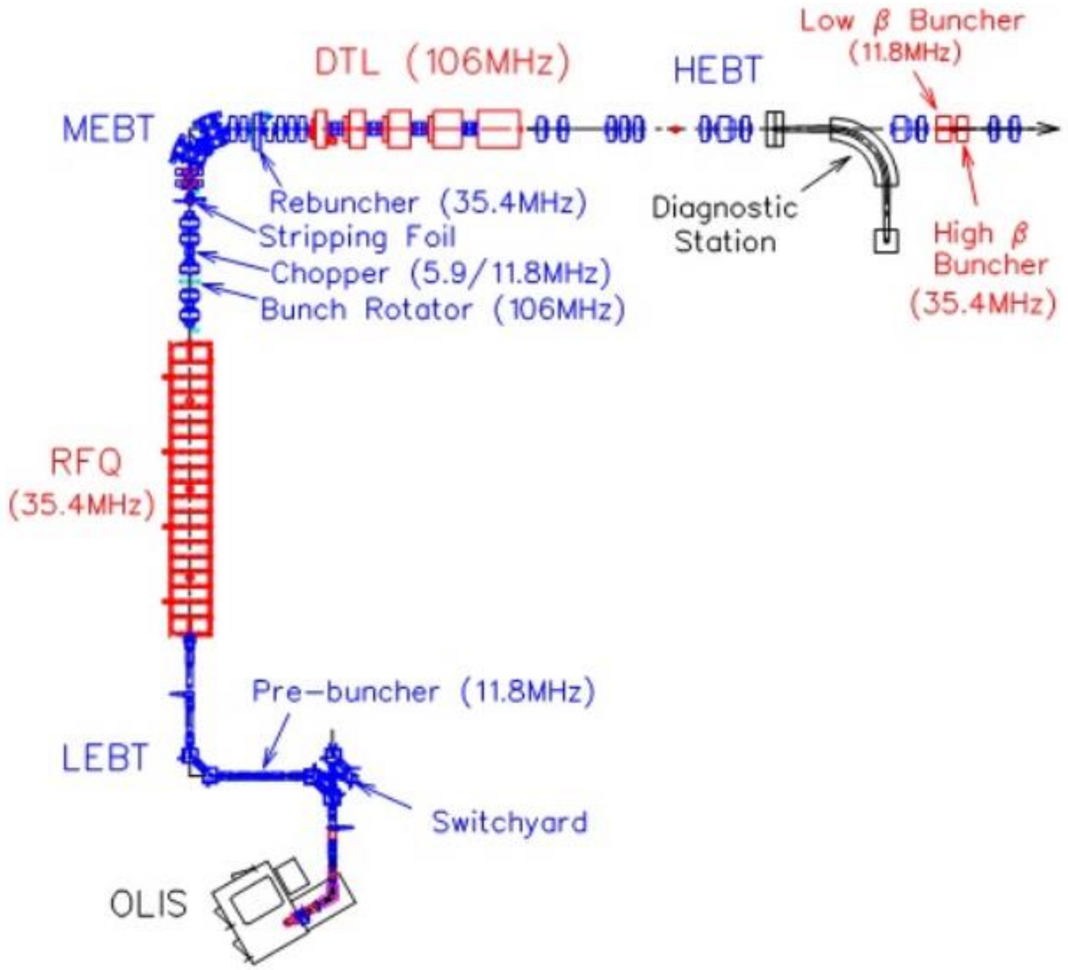
LLRF and event recognition

Ramona Leewe, Ken Fong

Outline

- What is LLRF and why do we need it?
- Importance of an event recognition system in LLRF
- Event recognition through Machine Learning/ Machine Learning in the field of particle accelerator
- First steps: Spark detection in TRIUMF’s cyclotron

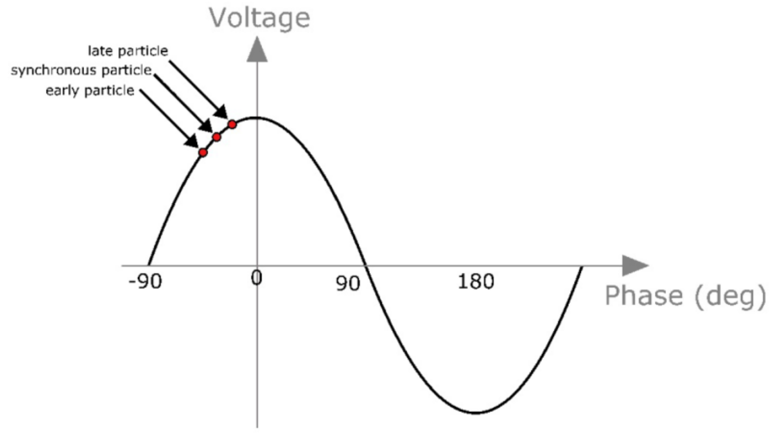
What is LLRF and why do we need it?



Beam travelling along the beam pipe from the low energy section to the high energy section and gains its energy in the different acceleration structures such as he RFQ or DTL

Field needs to be synchronized with the travelling particles

What is LLRF and why do we need it?



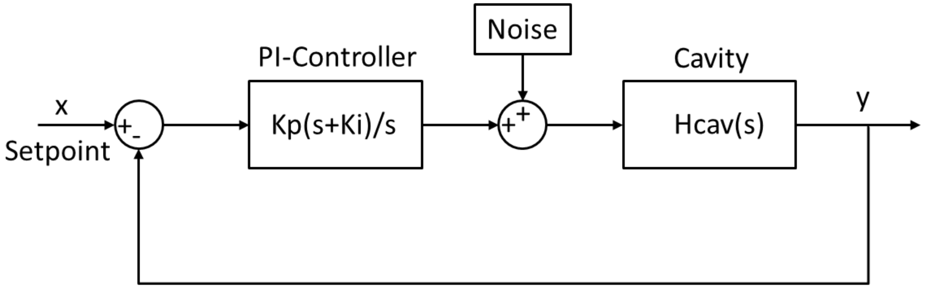
- **Main goal:** maintain the stability of the RF field, and minimize the required overhead power. RF field depends on:
  - Amplitude
  - Phase
  - Frequency

  Field stabilization

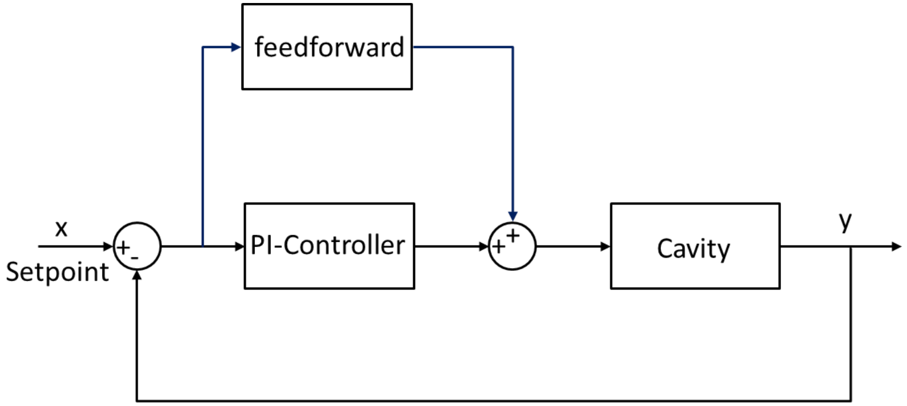
  Cavity tuning

- Perturbations can be seen everywhere in an accelerator and affect the Amplitude, Phase and Frequency
  - Power supply
  - Temperature drifts
  - Microphonics
  - ect.
  - Beam loading
  - Lorentz force detuning
  - ect.

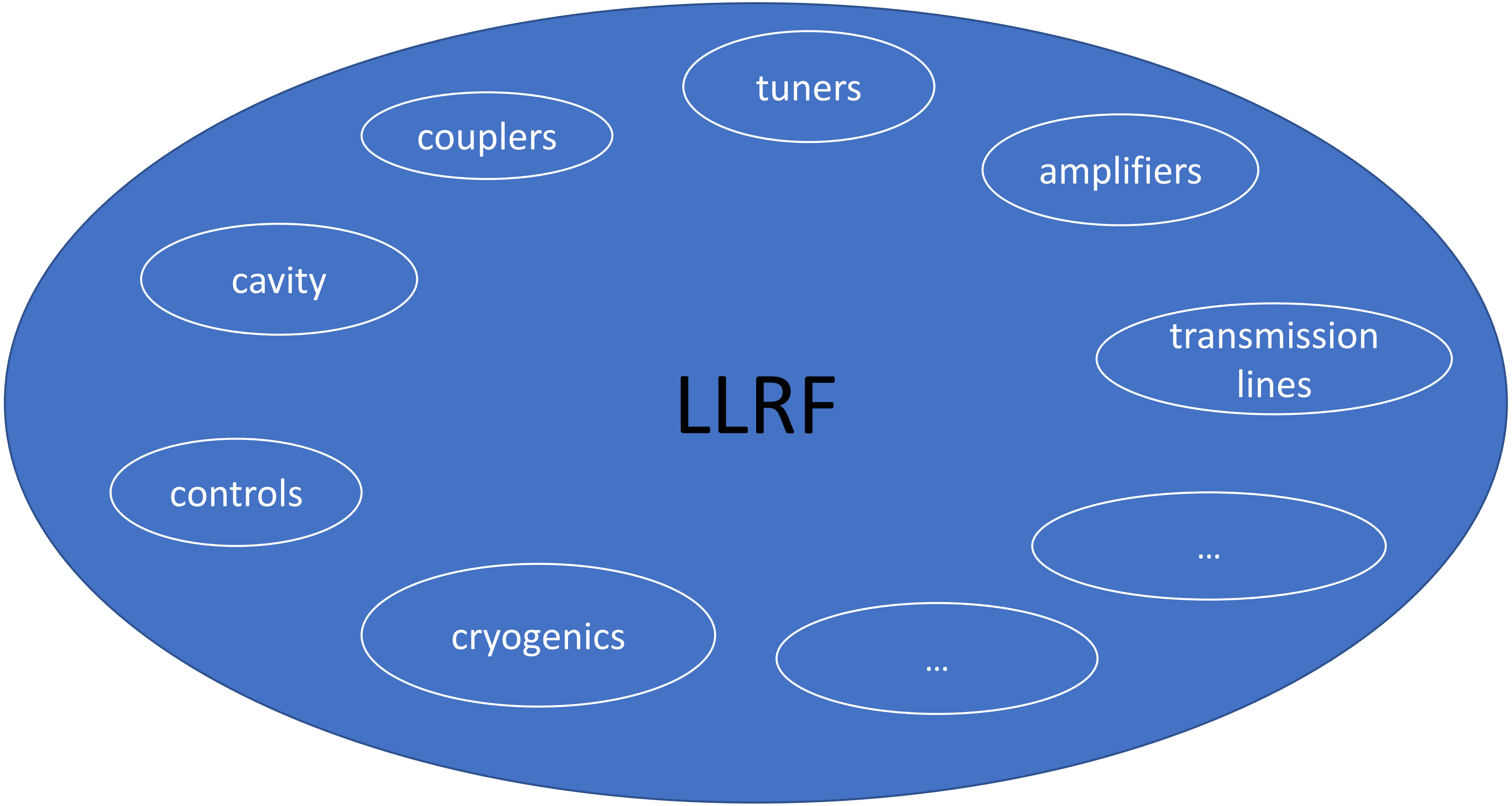
PI feedback is the classical way to deal with random perturbation



Feedforward is the classical way to deal with repetitive perturbations



Components involved in a LLRF system



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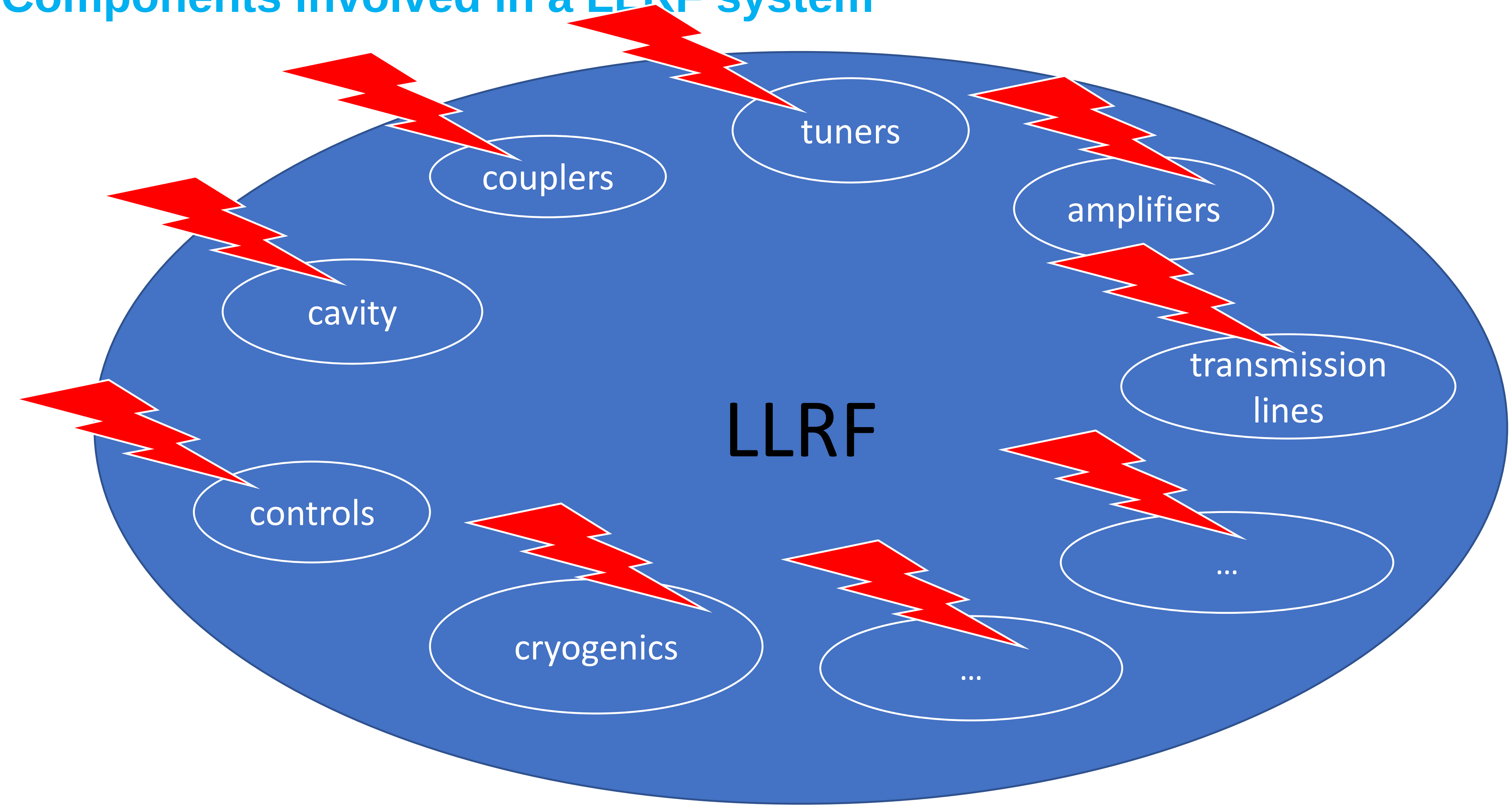

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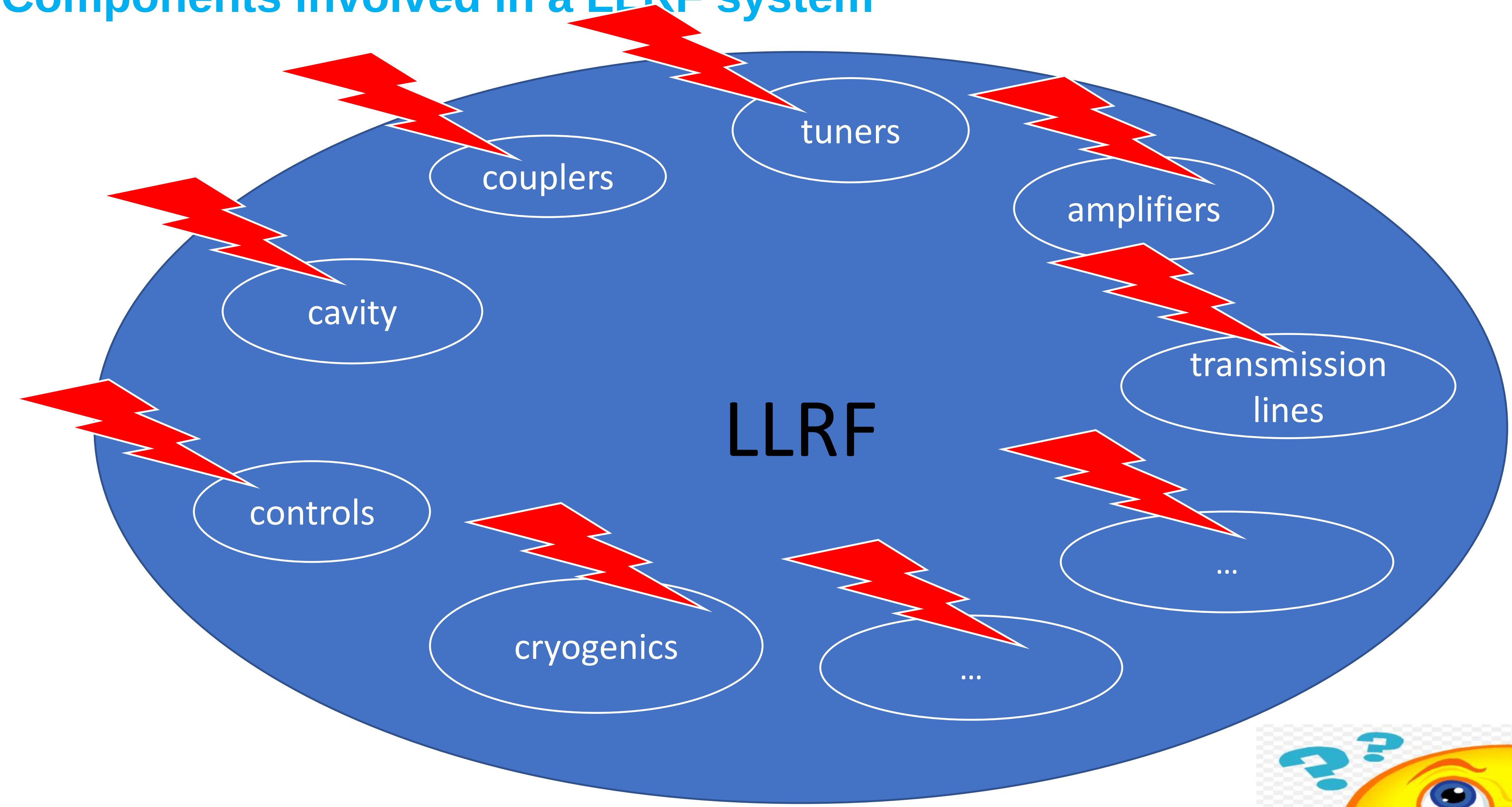

Machine learning in the field of particle accelerators

Neural Networks for Modeling and Control of Particle Accelerators

A. L. Edelen, *IEEE Student Member*, S.G. Biedron, *IEEE Senior Member*, B.E. Chase, *I*
D. Edstrom Jr., S.V. Milton, *IEEE Senior Member*, P. Stabile, *IEEE Member*

Paper Appearing in the Proceedings of the 2016 International Particle Accelerator Conference (IPAC), May 8-13, 2016

NEURAL NETWORK MODEL OF THE PXIE RFQ COOLING SYSTEM AND RESONANT FREQUENCY RESPONSE*

A.L. Edelen[†], S.G. Biedron[1], S.V. Milton, Colorado State University, Fort Collins, CO
D. Bowring, B.E. Chase, J.P. Edelen, J. Steimel, Fermilab, Batavia, IL
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APPLYING ARTIFICIAL INTELLIGENCE TO ACCELERATORS*

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INTELLIGENT CONTROLS AND MODELING FOR PARTICLE ACCELERATORS AND OTHER RESEARCH AND INDUSTRIAL INFRASTRUCTURES

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Opportunities in Machine Learning for Particle Accelerators

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Anomaly Detection for the European XFEL using a Nonlinear Parity Space Method

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Fault detection and prevention through machine learning; example

EUXFEL: so far quench detection realized through loaded Q measurement

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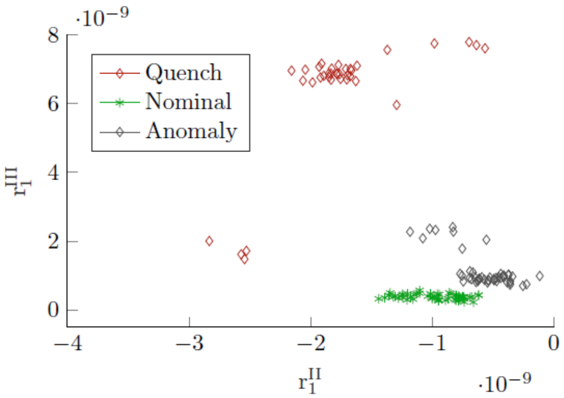
*** *University of Luebeck (e-mail: philipp.rostalski@uni-luebeck.de)*

$$Q_L < threshold$$

- Problem: Quench detection after it happened

- New idea: Anomaly detection of the field to prevent a quench from happening?



- Realization:
  - Build a cavity model including Lorentz force and beam loading
  - Create residuals/error signal through comparison of simulation and measurement (database with quenches must be available)
  - Plot the residuals with respect to each other
  - Clusters within the plot suggest decision boundaries for online operation
- Results:
  - Anomalies could be detected on an example set successfully
  - So far online operated offline, real time anomaly detection to be tested

Fault detection for TRIUMF's cyclotron/ spark detection
Part of the cyclotron LLRF system upgrade

Spark detection so far:

- Spark indication:
  - Abrupt fall of the Dee voltage, increase in reversed power
- Spark detection through rate of change of the Dee voltage:
  - the rate of change of the Dee voltage is measured
  - Categorized in
    - Small - RF drive unchanged
    - Medium - RF drive switched off + quick start
    - Large - RF drive switched off + normal start

Classification problematic, system can be damaged if not switched off

Idea:

Can we use machine learning to identify a spark?

Can we detect where it occurred in the system?

- Different approaches:
  - Model based
    - Requires good knowledge of the system, exact modelling is important
  - Non model based
    - Supervised machine learning requires manual classification of each event and then trains a neural network

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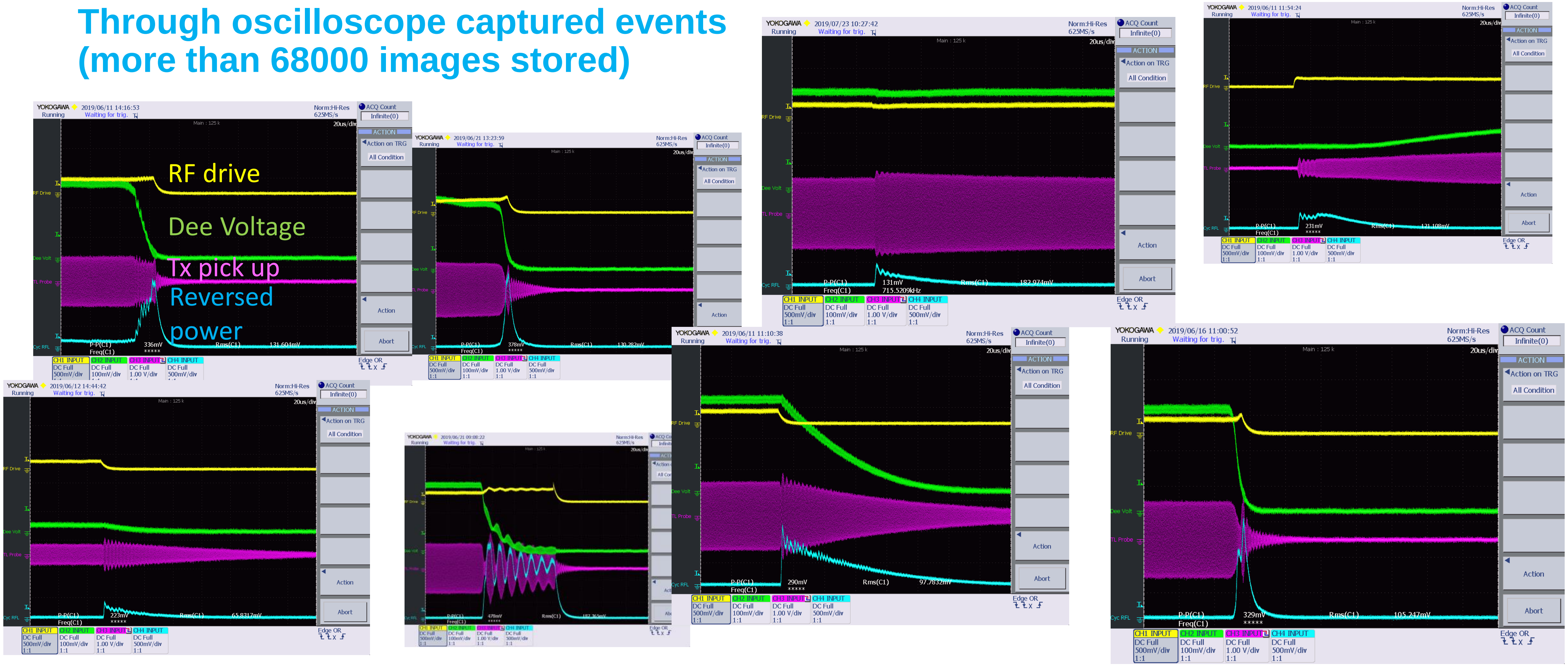
Model-based Spark Classification/ available data from TRIUMF's cyclotron

Through oscilloscope captured events (more than 68000 images stored)



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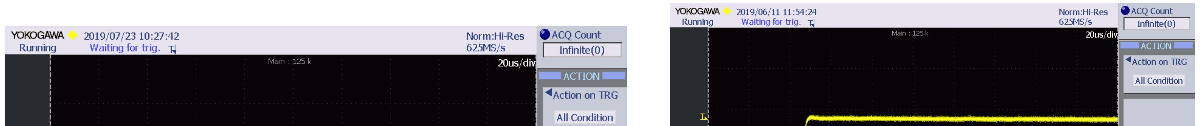

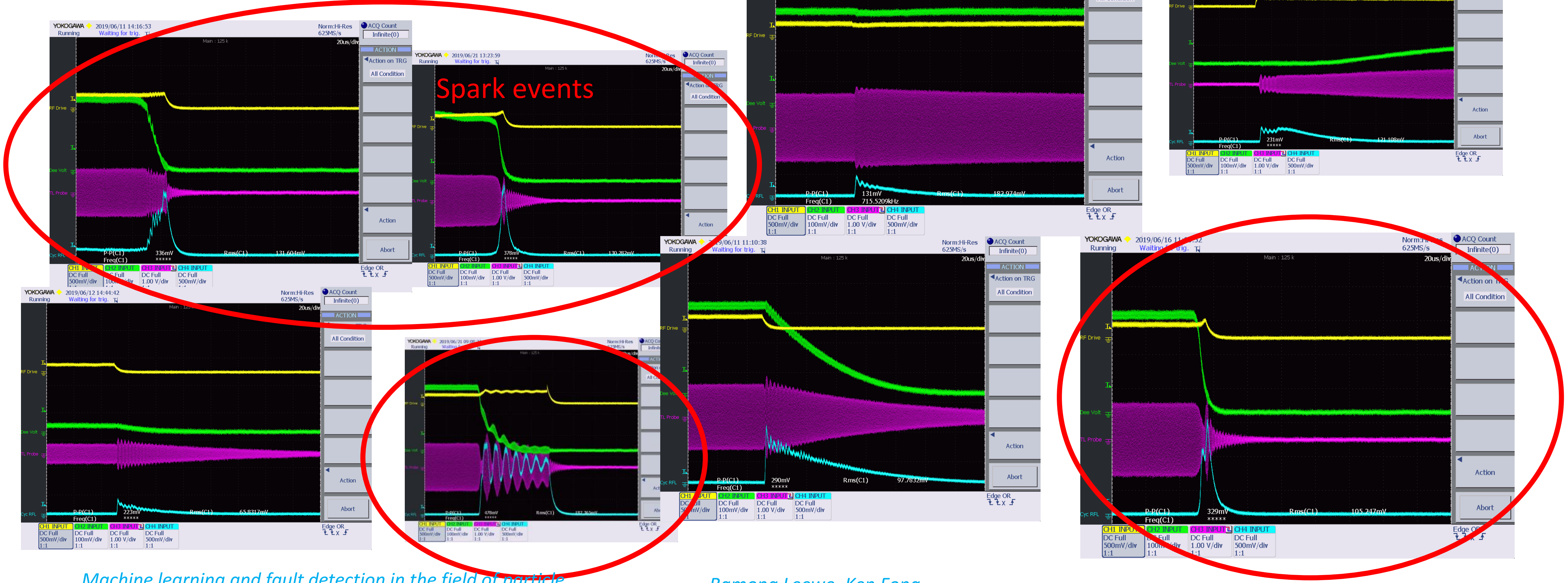

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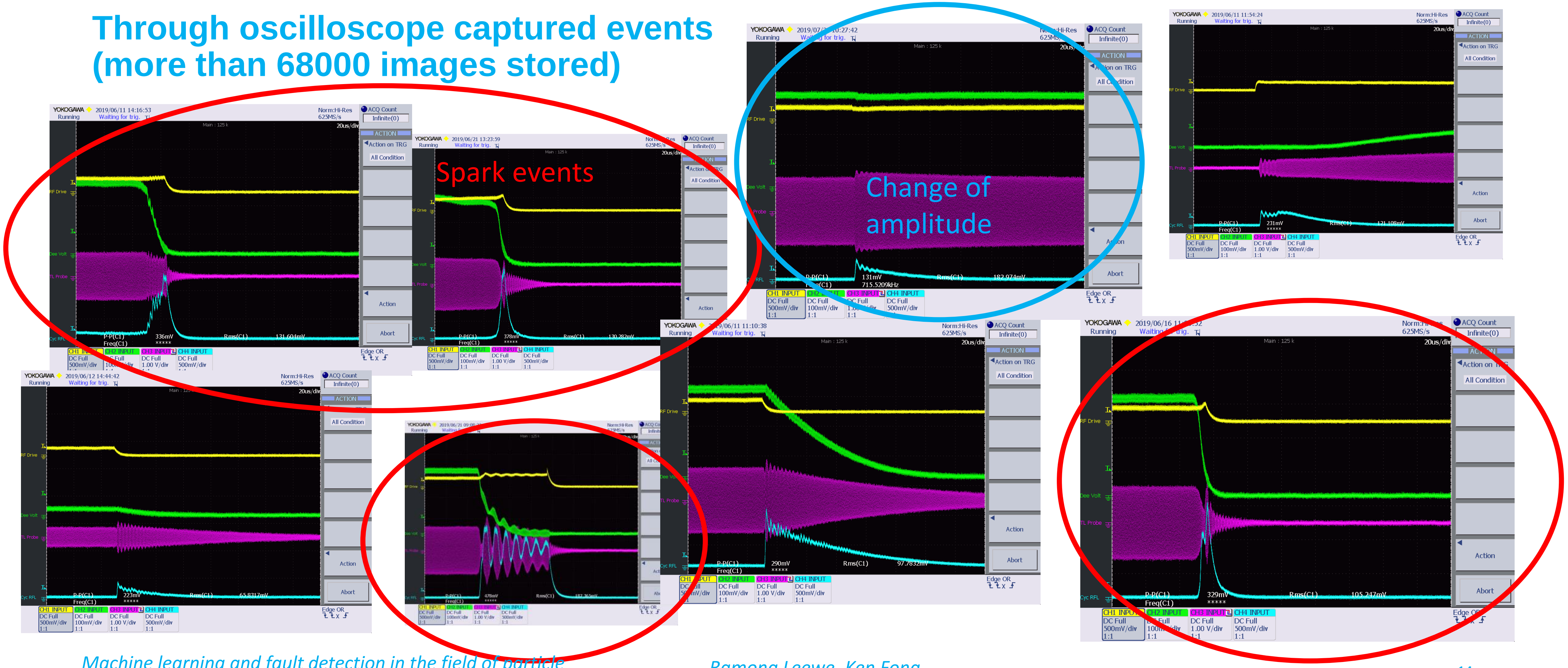

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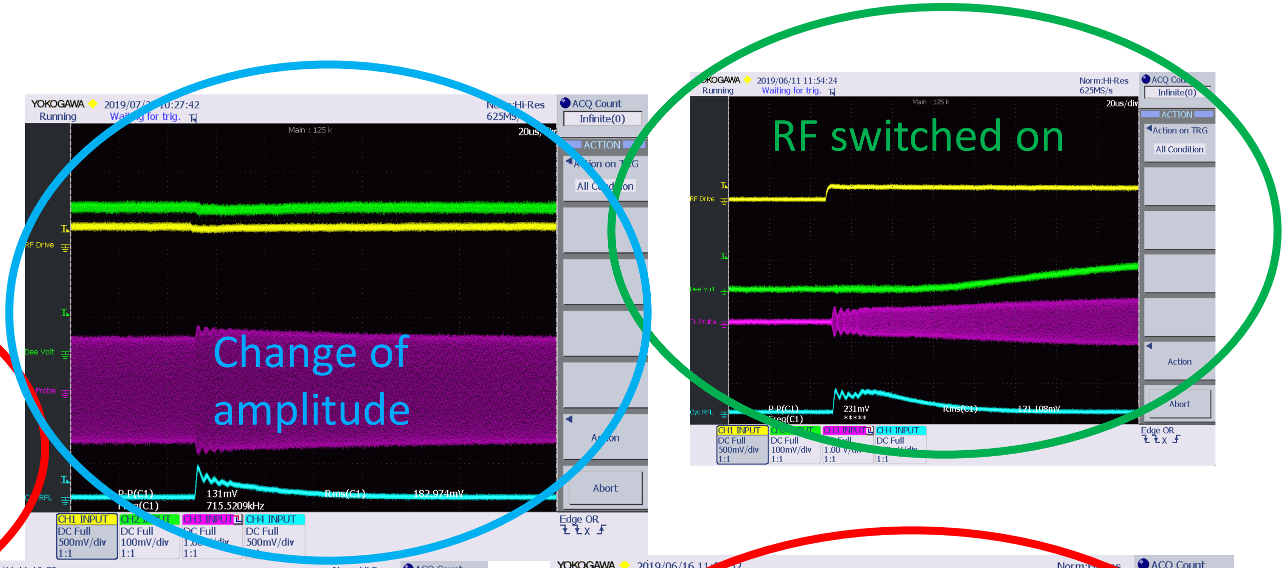

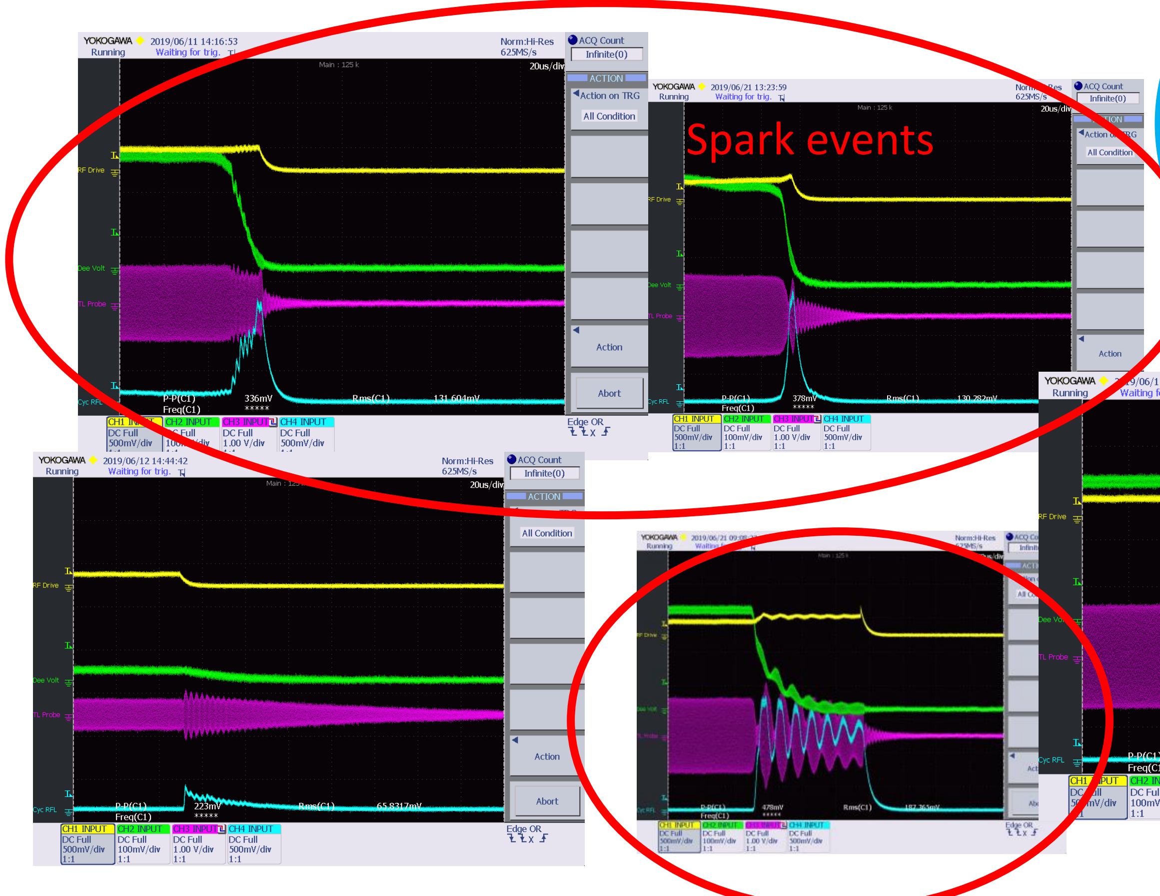

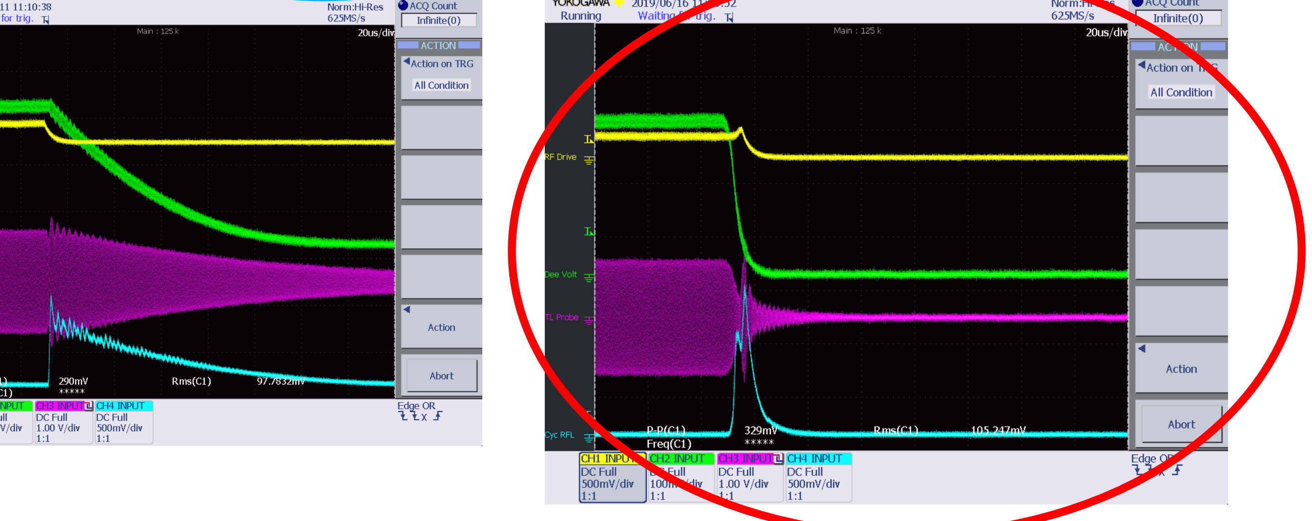

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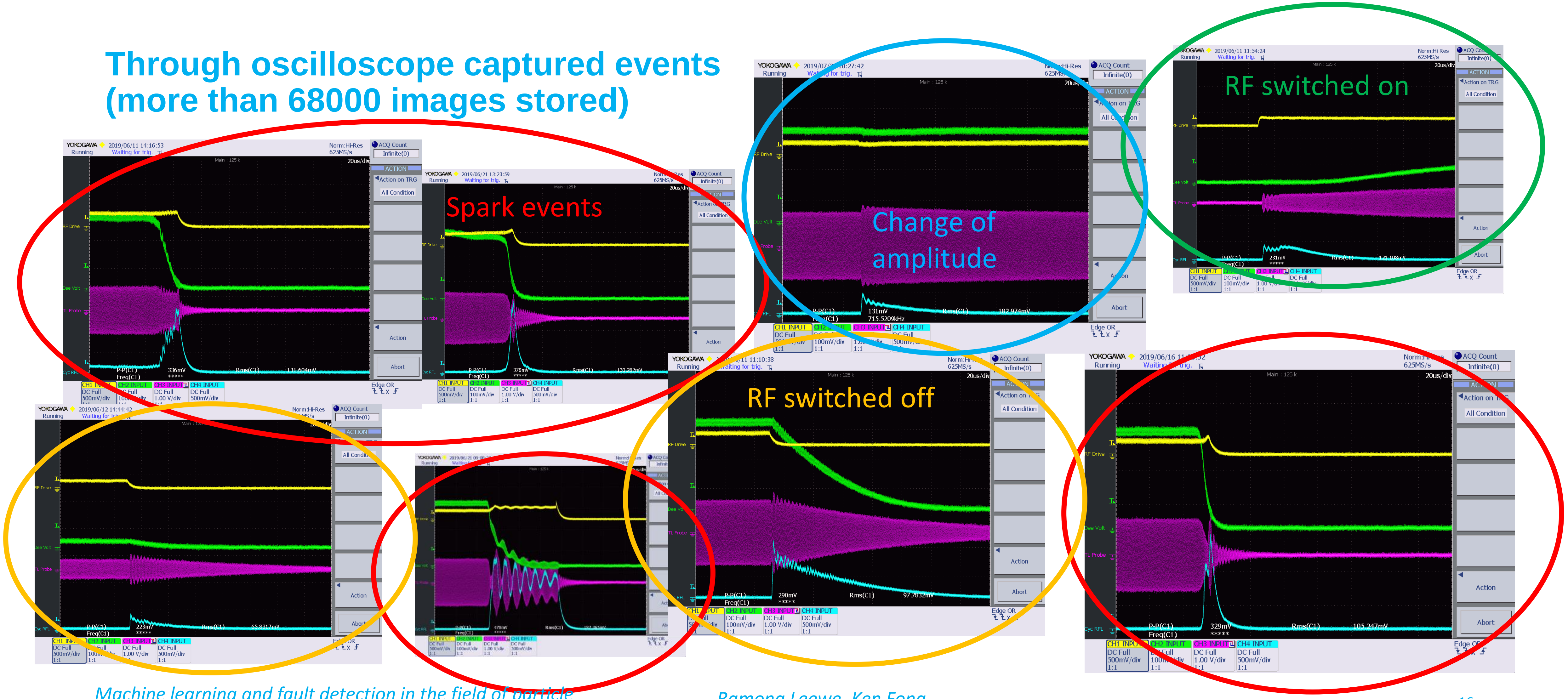
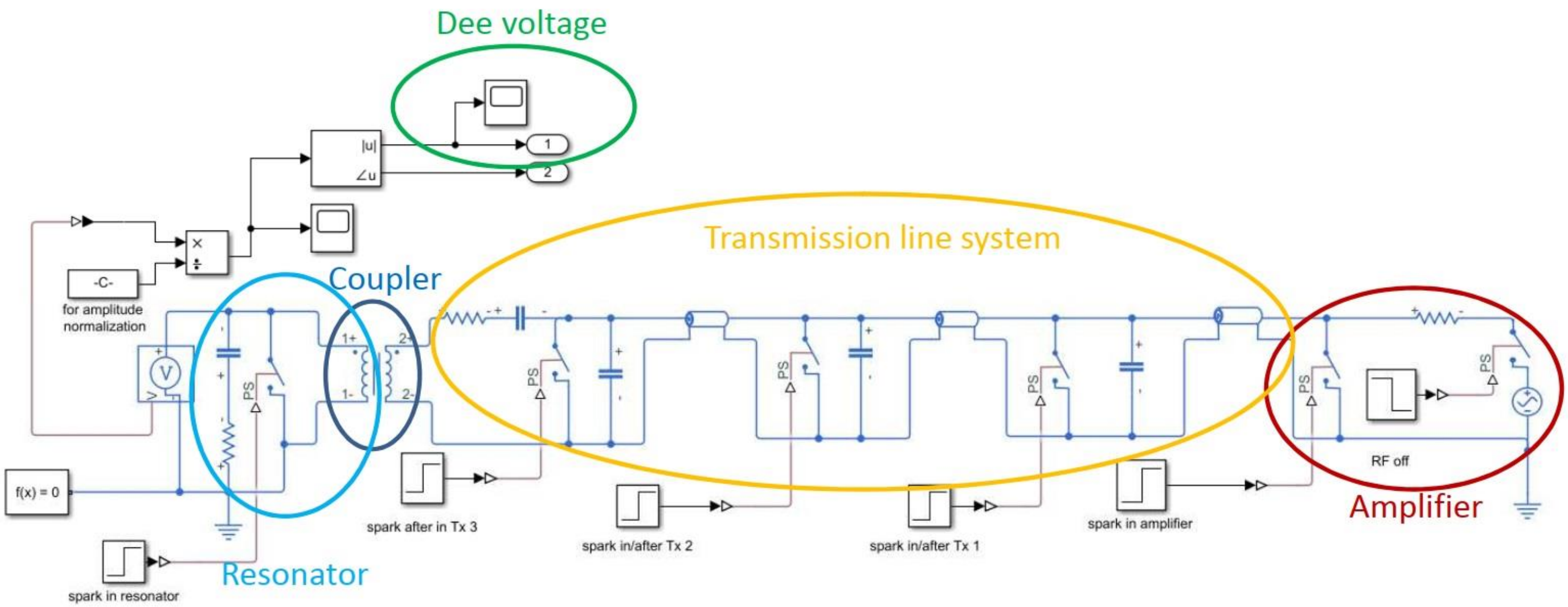


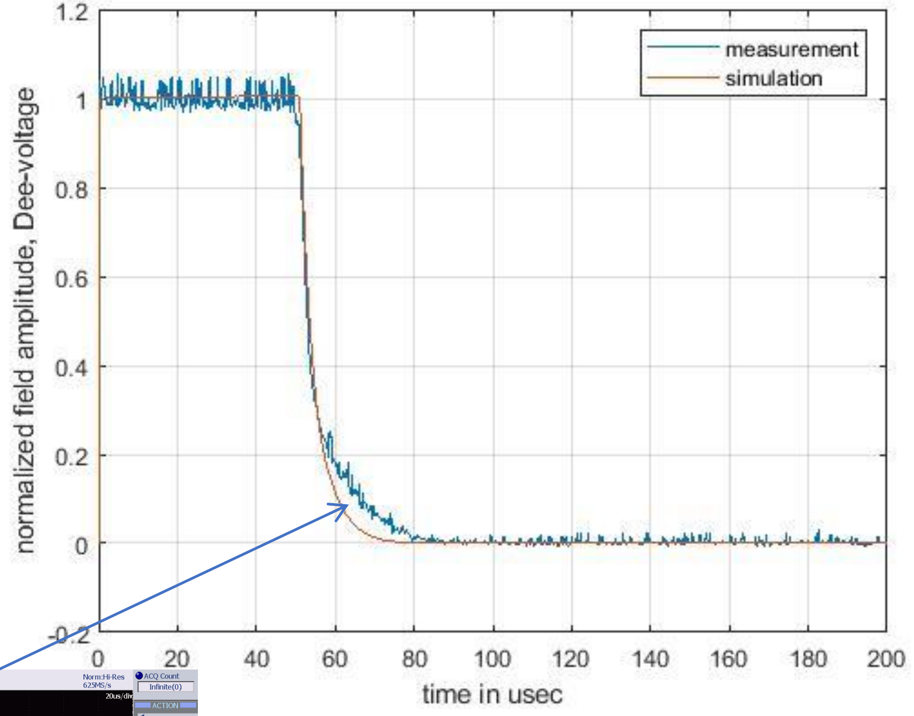
Model-based spark identification/ cyclotron model

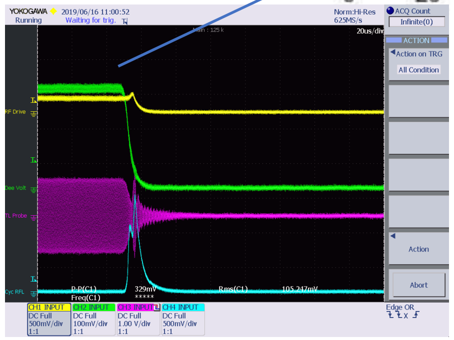
Matlab/Simulink toolbox simscape



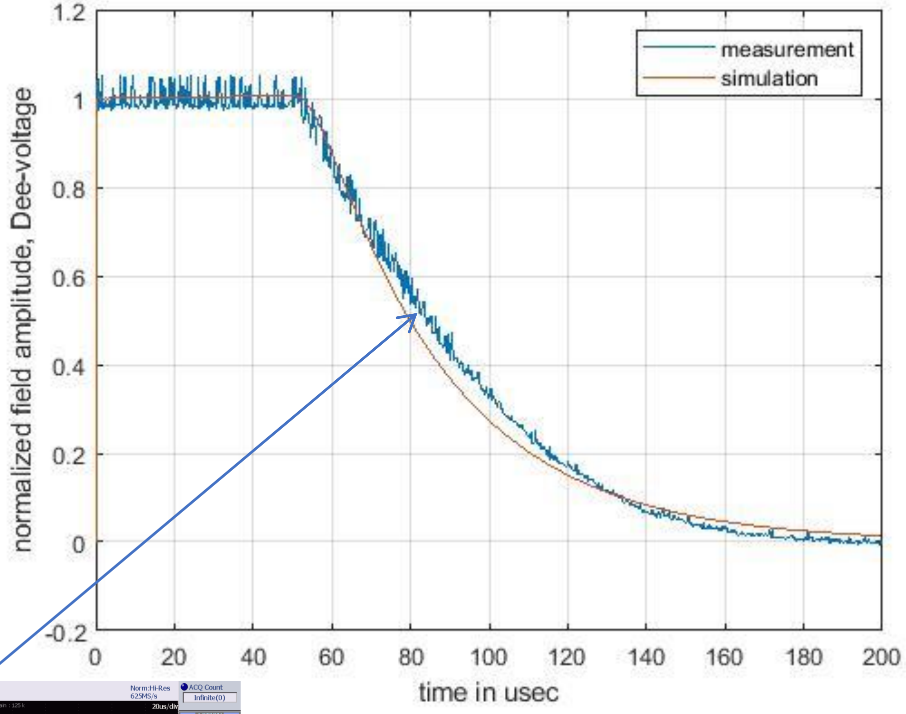
Model verification

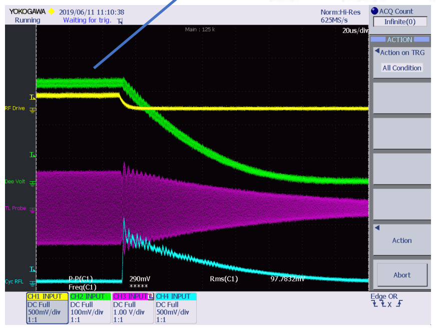
Spark within the resonator





RF drive being switched off



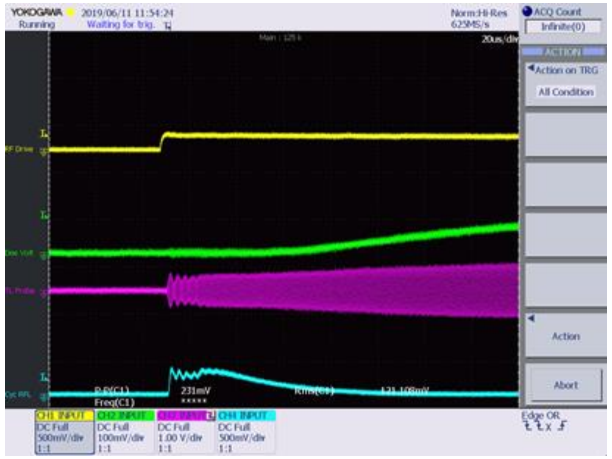


Measurement signals are reconstructed from scope images through a Matlab script

Residual generation

Yellow data trace used for pre classification

- Pre – classification based on the RF drive in
  - RF on
  - RF off



Residual calculation

- For in increase of the RF drive

$$r_1 = \left(y - ysim_{RFon}\right)^2$$

$$r_2 = \left(y - ysim_{RFonfailed}\right)^2$$

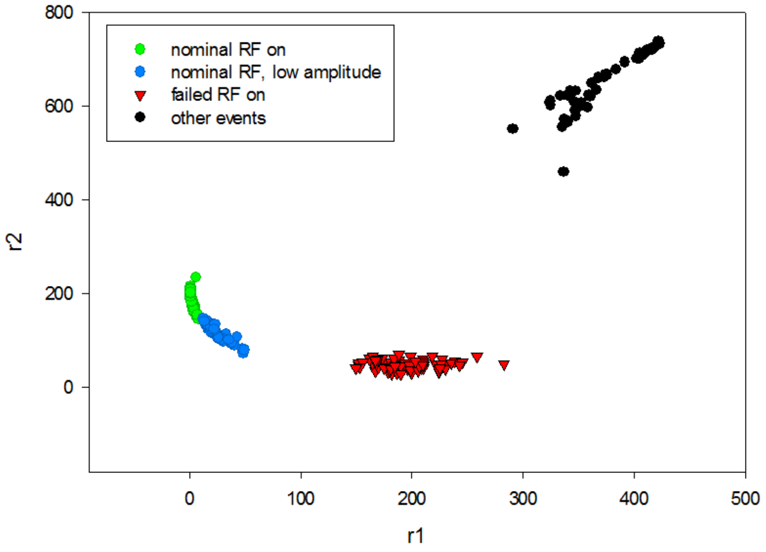
- For a decrease of the RF drive

$$r_3 = \left(y - ysim_{RFoff}\right)^2$$

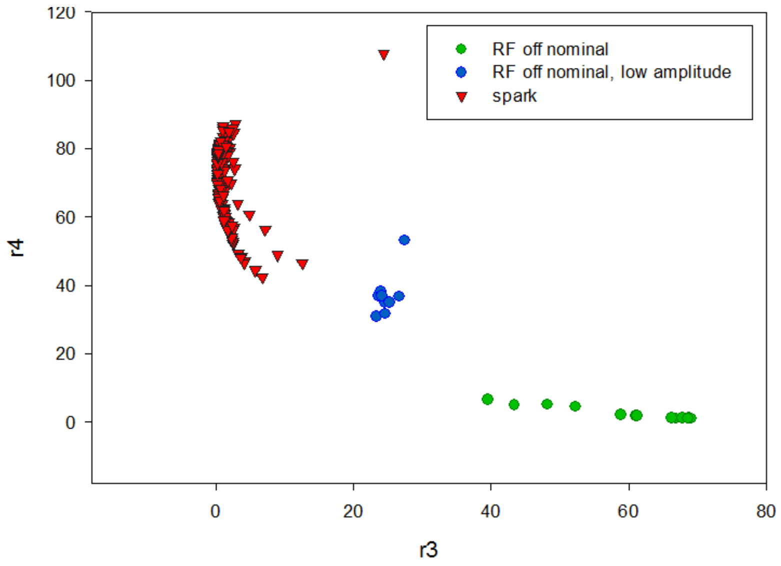
$$r_4 = \left(y - ysim_{spark}\right)^2$$

Residuals for 400 captured events

Increase of RF drive



Decrease of RF drive



- Clear cluster separation for both plots
- The cyclotron event image database can be categorized in terms of the event
- All ‘other events’ are located in the upper plot. Other events include:
  - Increase in reversed power due to frequency mismatch (e.g. temperature changes)
  - Change of operating field amplitude
- Builds the foundation for a deeper analysis for spark events or failed RF on events

Summary and Outlook

Summary

- The existing images can be categorized with respect to
  - RF on successful
  - RF on failed
  - RF off events
  - Sparks
  - Other events

Outlook, next steps

- Analysis of spark diagnostic with respect to the location where they occurred
  - How does a spark develop in vacuum?
  - Add signals like the reversed power or the transmission line signal
- Long term goal: Online classification and real time reaction system
- Other Machine Learning application within LLRF, e.g.
  - Failed cyclotron start up events
  - Improved start up sequence
- …

Thank you for your attention!