EIC USER GROUP & EPIC JOINT COLLABORATION MEETING

Autonomous Monitoring and Calibration Workflows

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Motivation

Analysis-ready data often takes months to years to become available due to offline, manual, and iterative calibration and validation processes.

There is significant effort to streamline and optimize calibration procedures, metrics, and workflows to reduce the delay between data taking and analysis.

EXISTING EFFORTS AT JLAB

CLAS12 Calibration Task Force (~late 2024)

Objective of making calibrations more efficient, i.e. (more) automatic, faster, using fewer resources.

CLAS12 CALCOM

Organize and coordinate calibration and commissioning for all experiments

GlueX Calibration and Production Working Group (~late 2023)

Organize and coordinate calibration and production workflows for all experiments

ePIC calibrations

Aim to have rapid turnaround time (2-3 weeks max) from data to full calibrated/reconstructed data

Calibration requirements and metrics need to be defined per subsystem

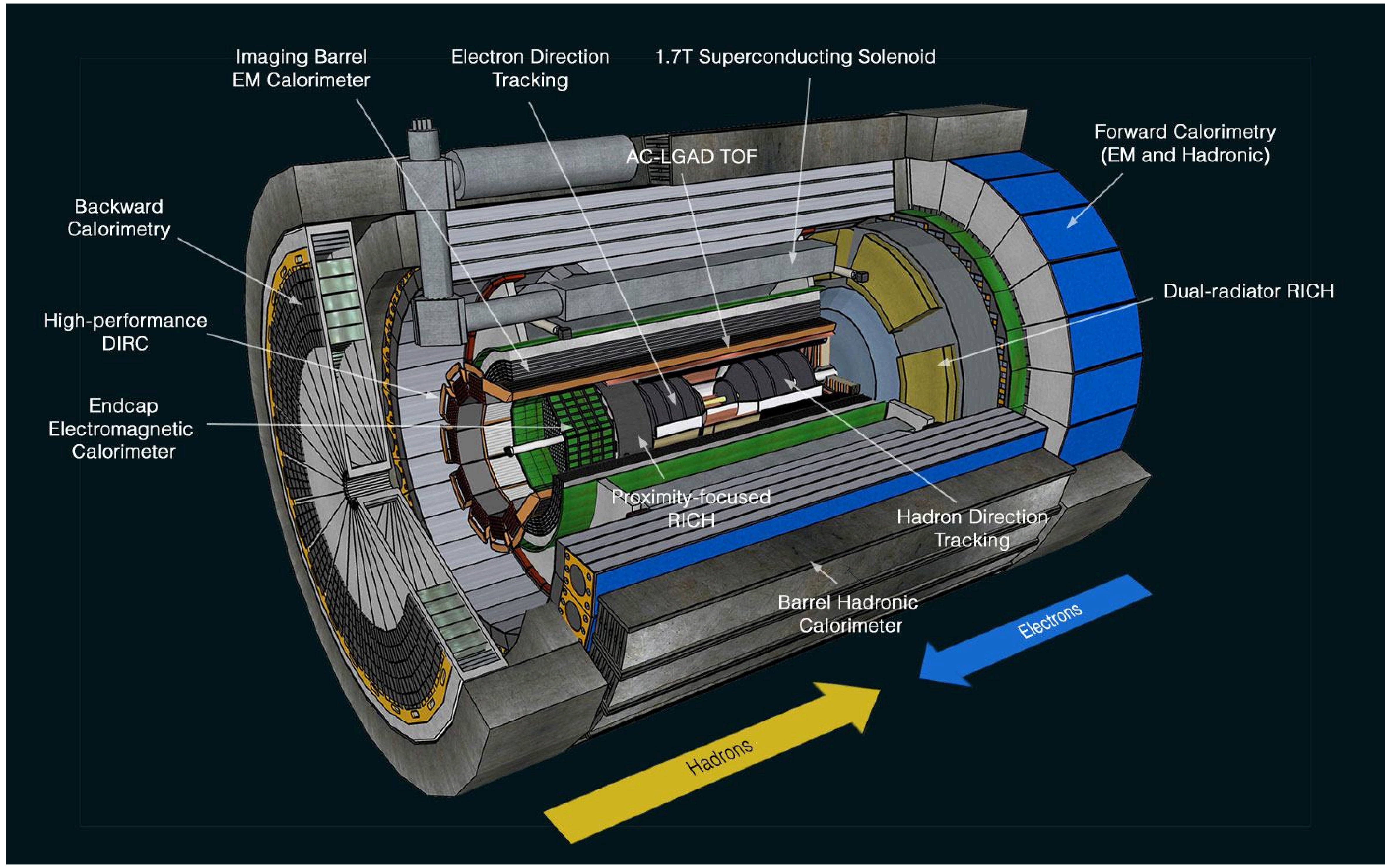
This is not too early to think about!

Iterations and dependencies

What calibration depends on another, how many iterations until convergence?

Automatic and/or Autonomous

Develop calibration procedures with with automation in mind



Requirements for autonomous detectors

1

Monitoring

Real-time data from detectors, beam conditions, and environmental sensors. Early anomaly detection through statistical or ML-based methods.

2

Calibration

Automated alignment and calibrations that supports both parasitic updates and dedicated calibration “runs”

3

Intelligent Decision-Making/Control

ML or rules-based approach for dynamic optimization, coordination across subsystems, safe interaction with control systems

4

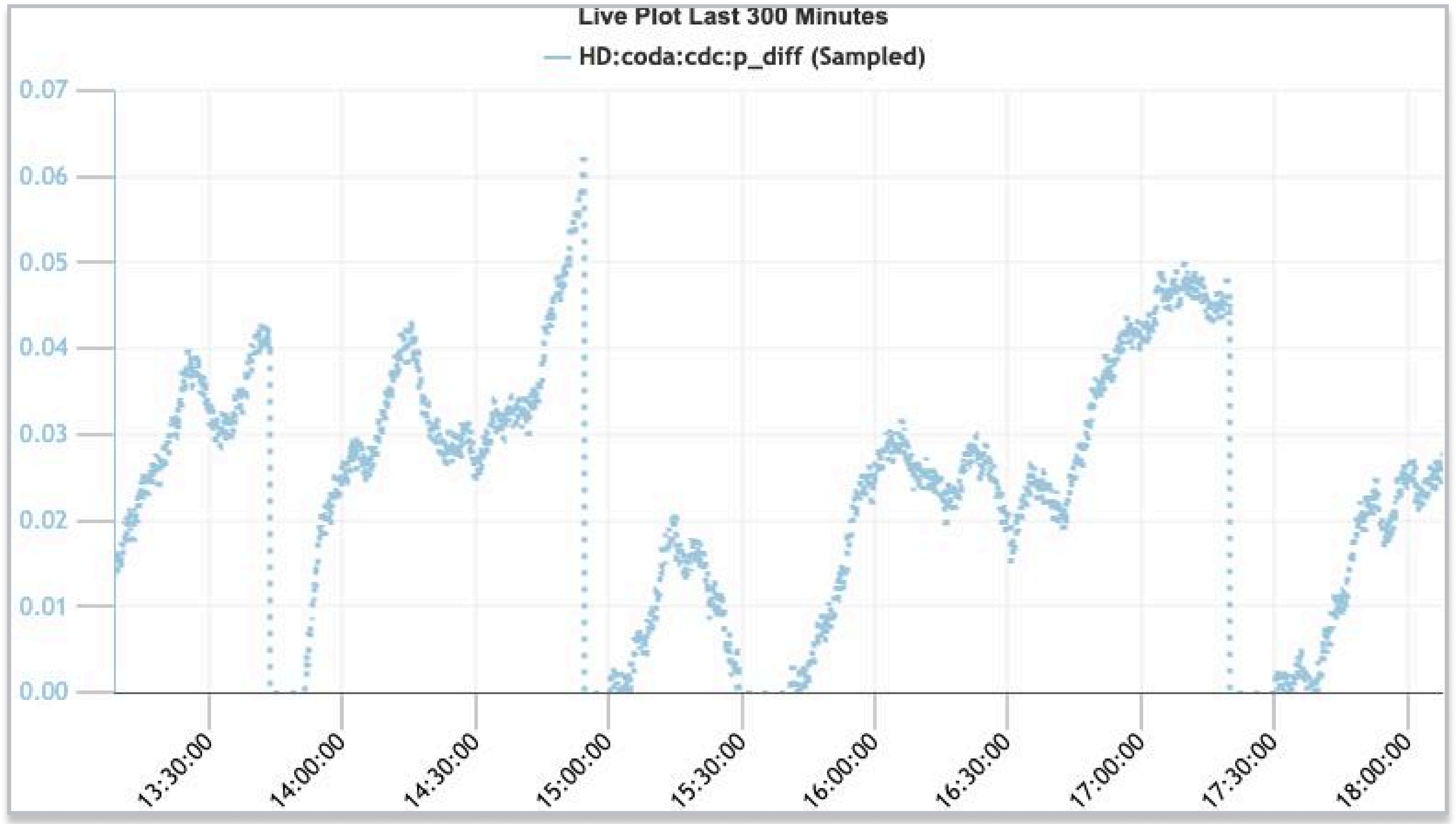
Human-in-the-Loop Interface

Transparent logs and reasoning behind autonomous decisions, tools for experts to validate, override, or tune behavior, dashboard views of system state and performance

Monitoring

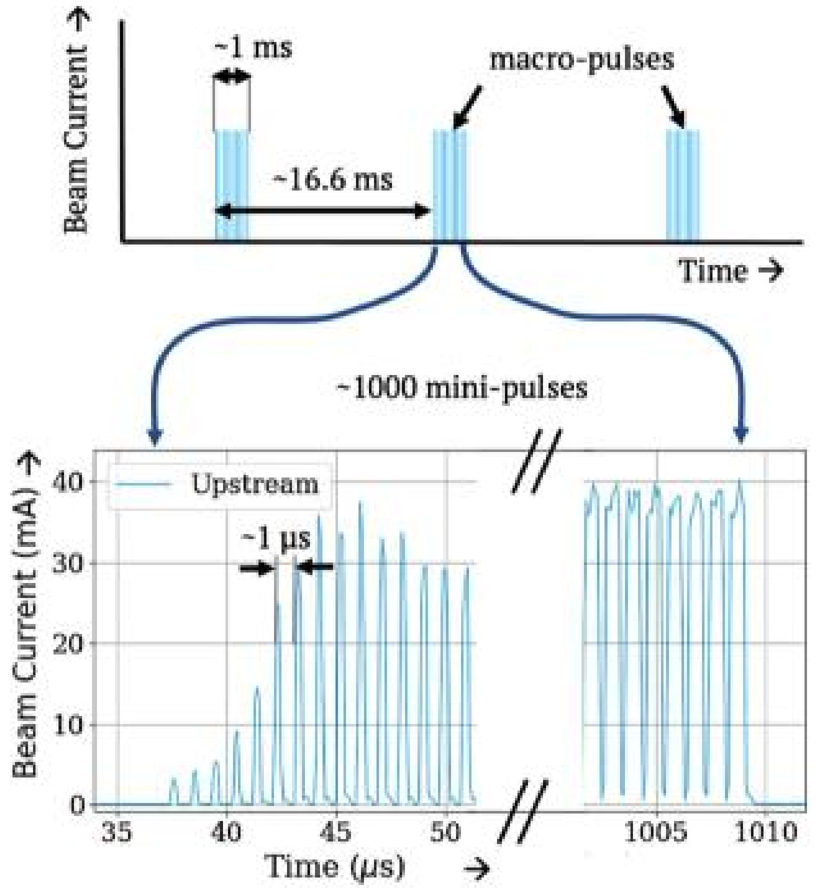
Rules-based monitoring

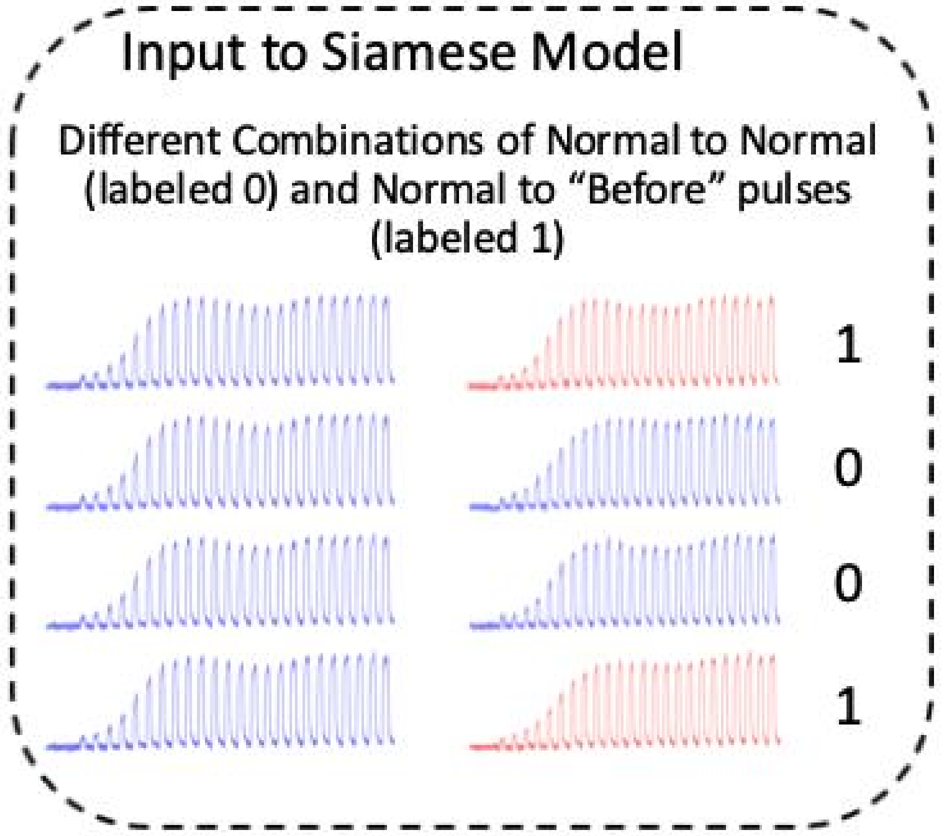
Alarm if the atmospheric pressure has changed by 0.1 kPa since the start of the run

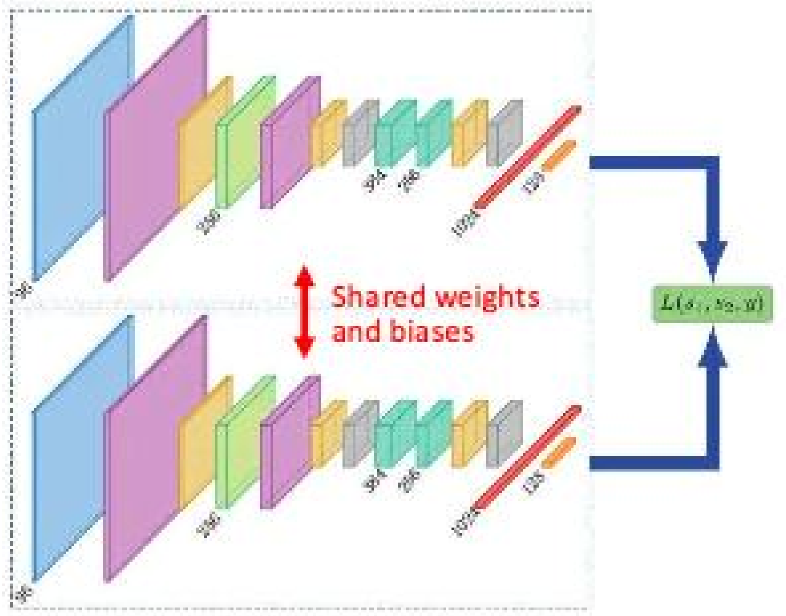


Advanced monitoring techniques

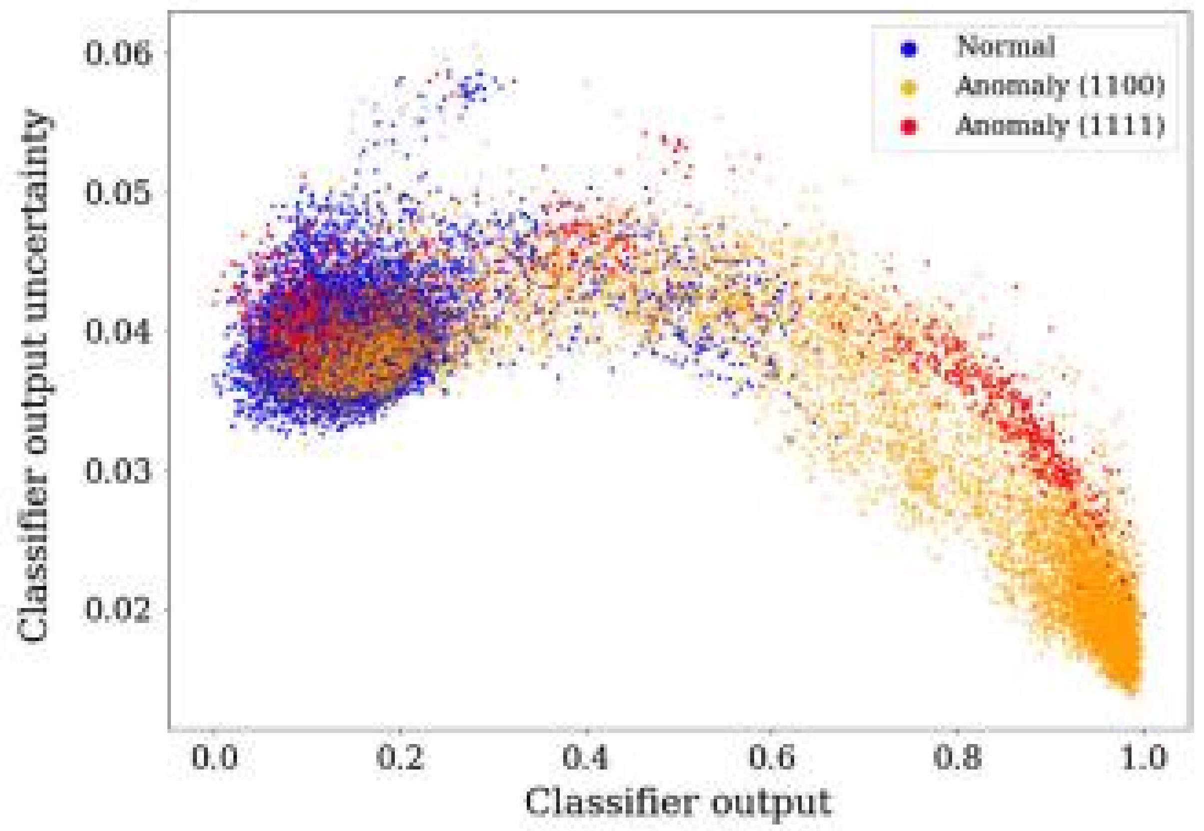
Fault Prediction at ORNL's Spallation Neutron Source using an uncertainty-aware Siamese model





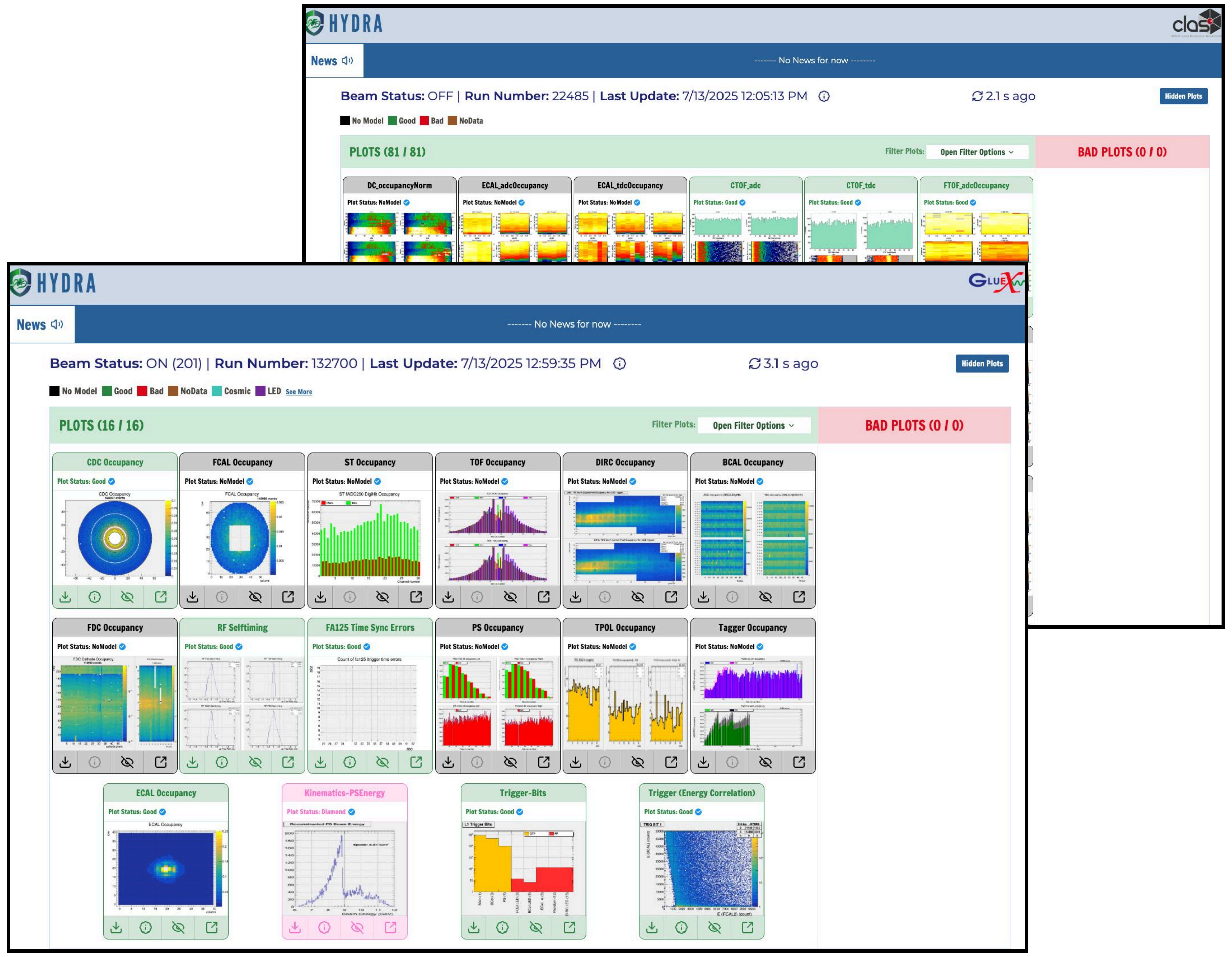


Siamese Model



Data Quality Monitoring

Shift crews cannot monitor everything, at the same time, all of the time.



Utilize both supervised and unsupervised learning

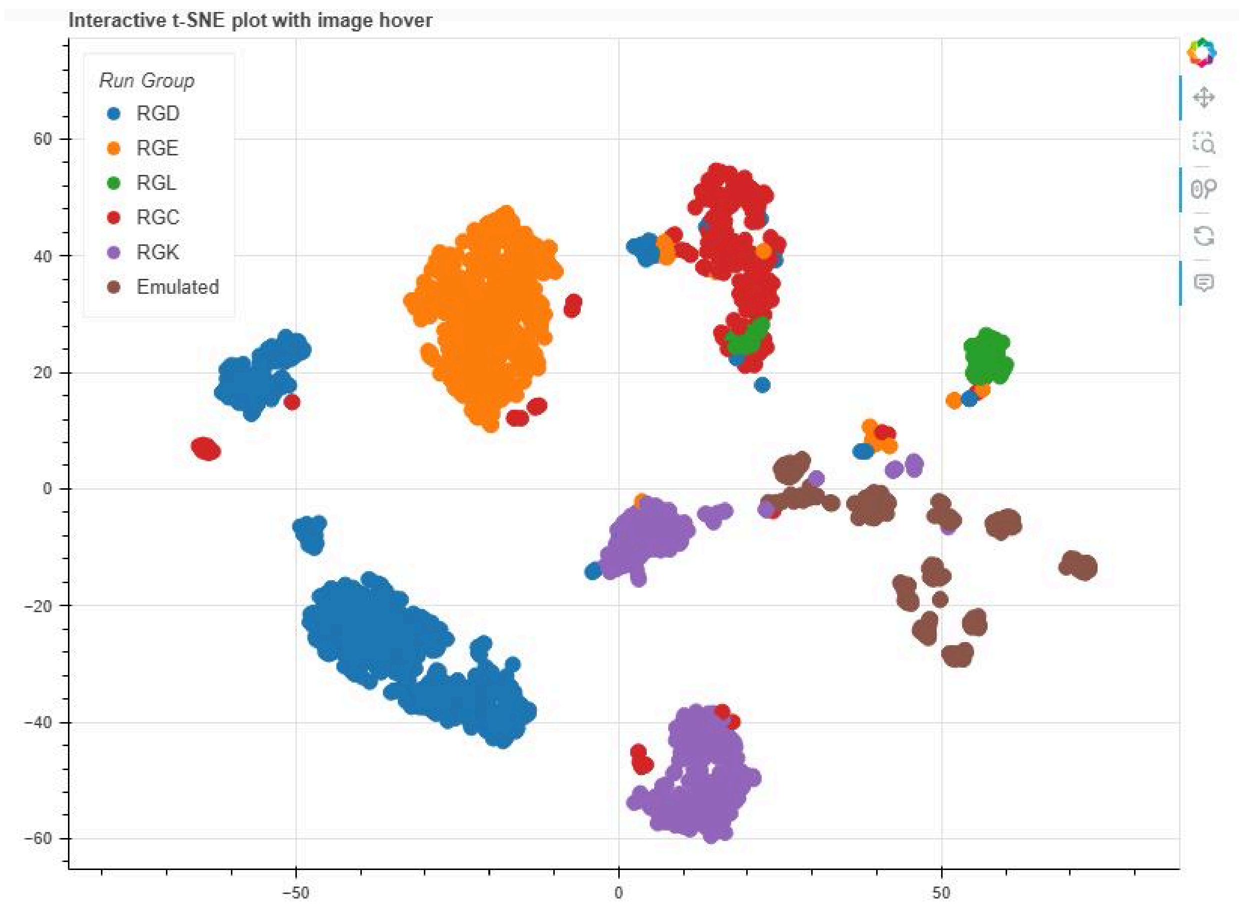
Classify anomalies quickly, reliably, and more consistently. Clustering algorithms separate monitoring histograms from different run periods, experiments, and configurations.

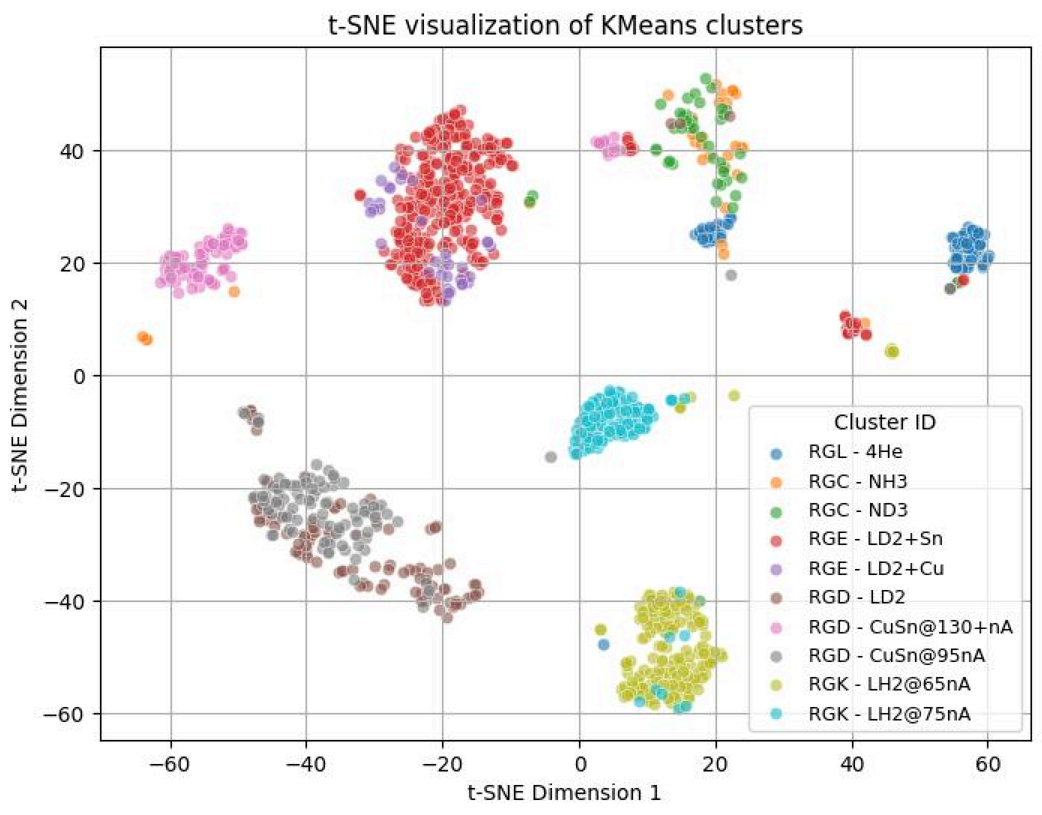
Automatic Logging

Inferences and associated images are recorded automatically

Customizable

Monitoring histograms can be easily added or removed depending on experiment needs.





GlueX Central Drift Chamber

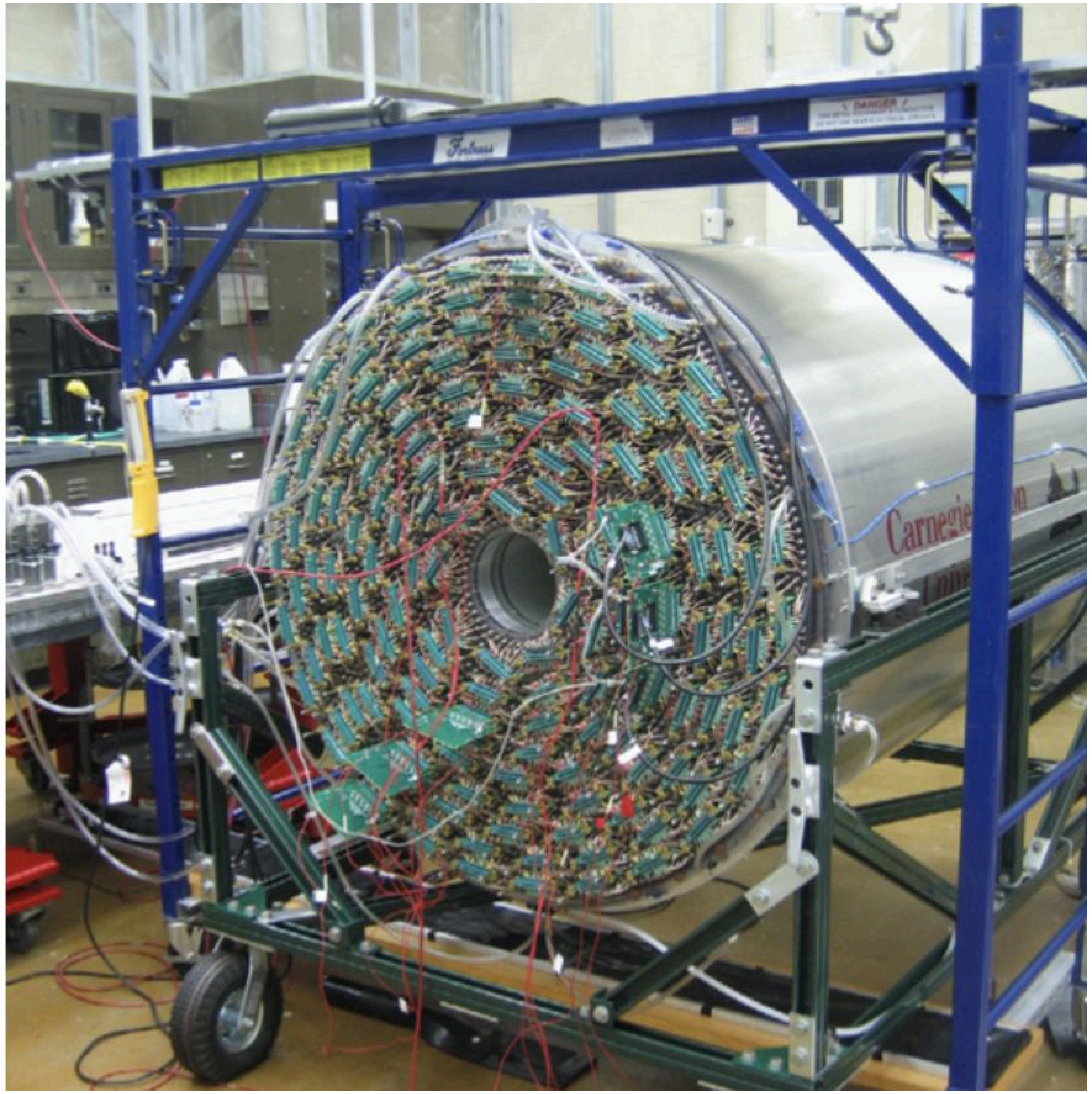
Used to detect and track charged particles as they traverse the detector.

Specs

- 1.5 m long x 1.2 m diameter, cylindrical straw tube chamber
- 3522 anode wires traditionally held at 2125 V
- 50:50 Ar:CO2 gas mixture at 30 Pa above atmospheric pressure

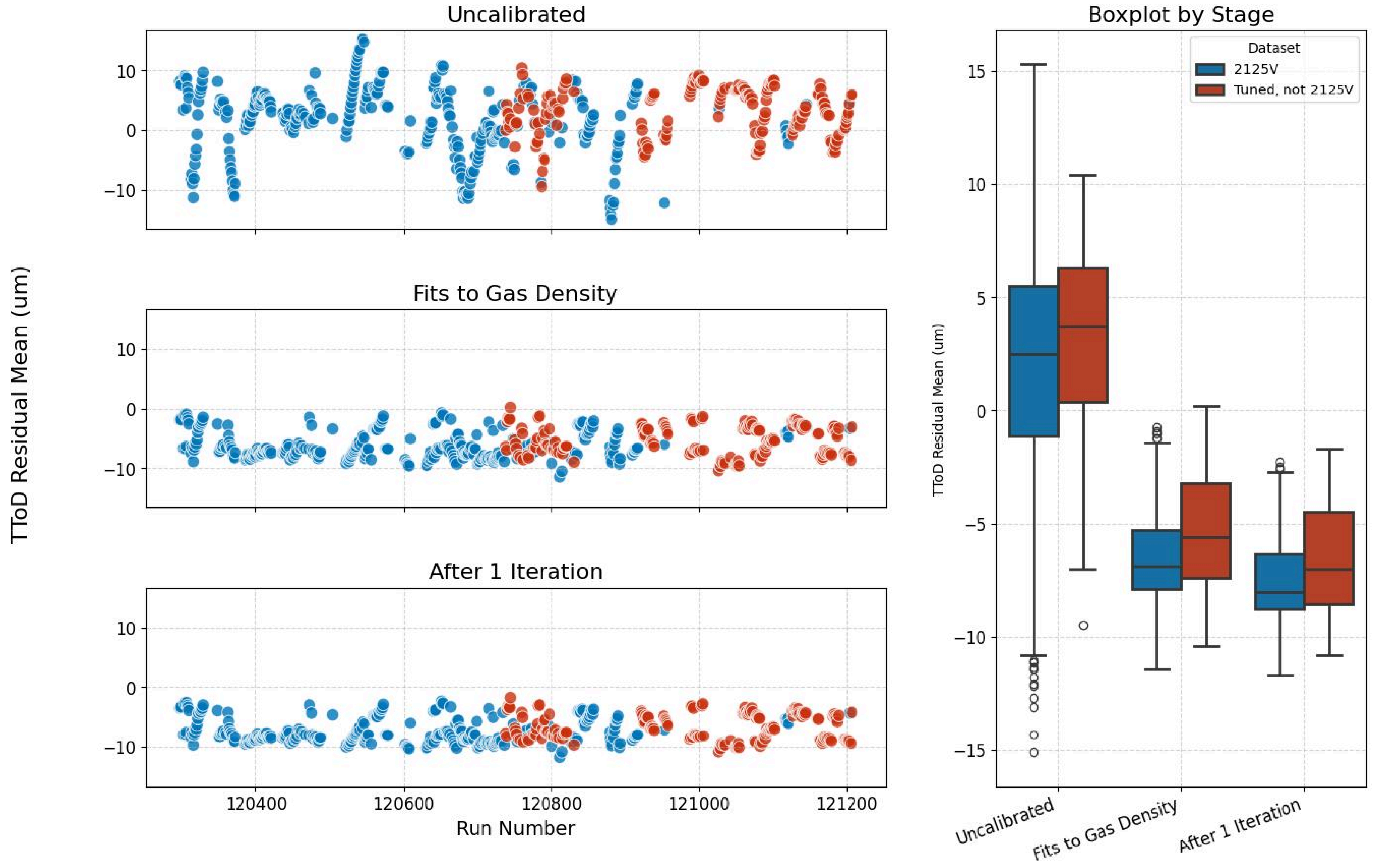
Run-by-run calibrations

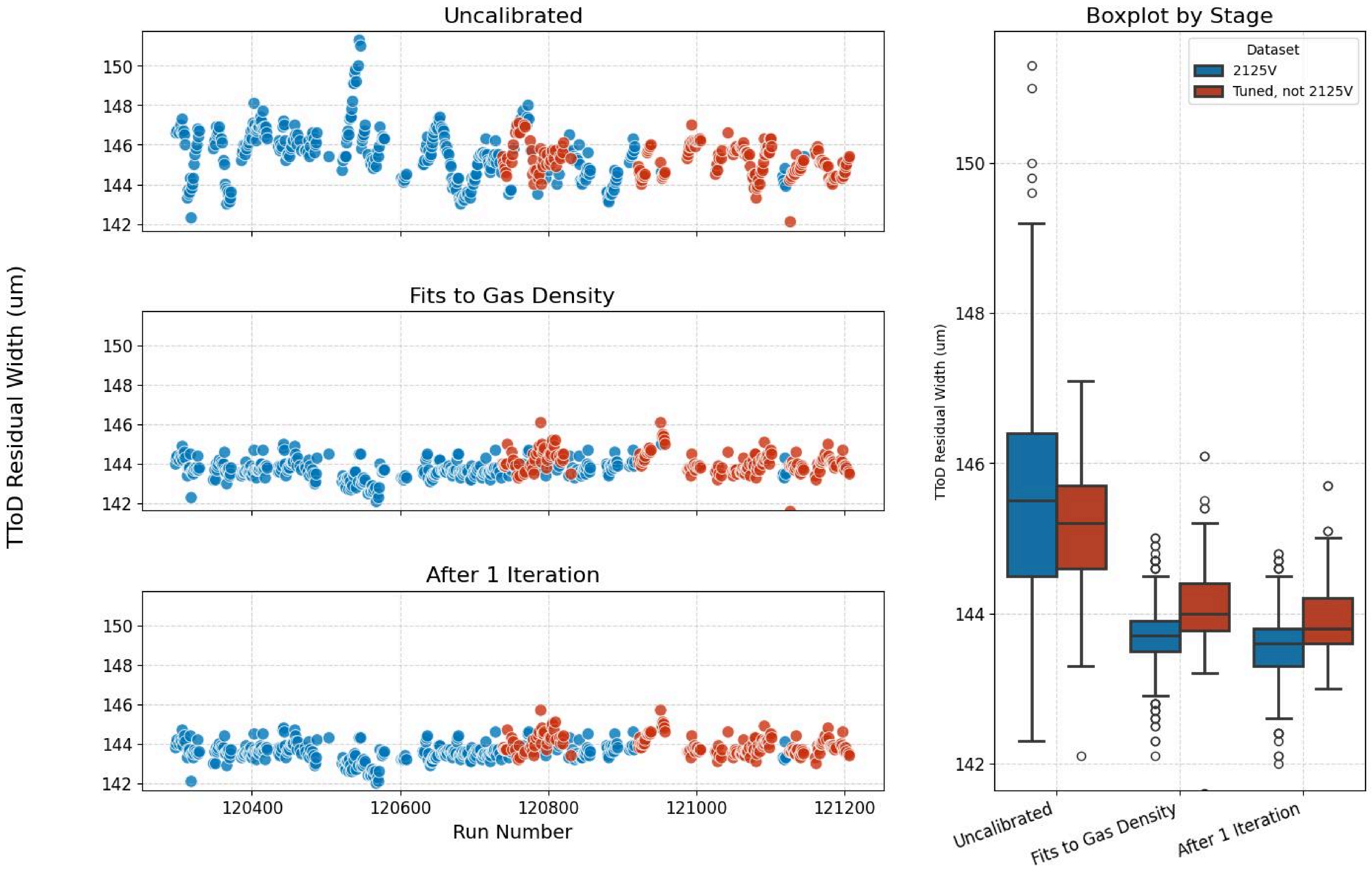
Chamber gain and drift time to drift distance



Automated Calibrations

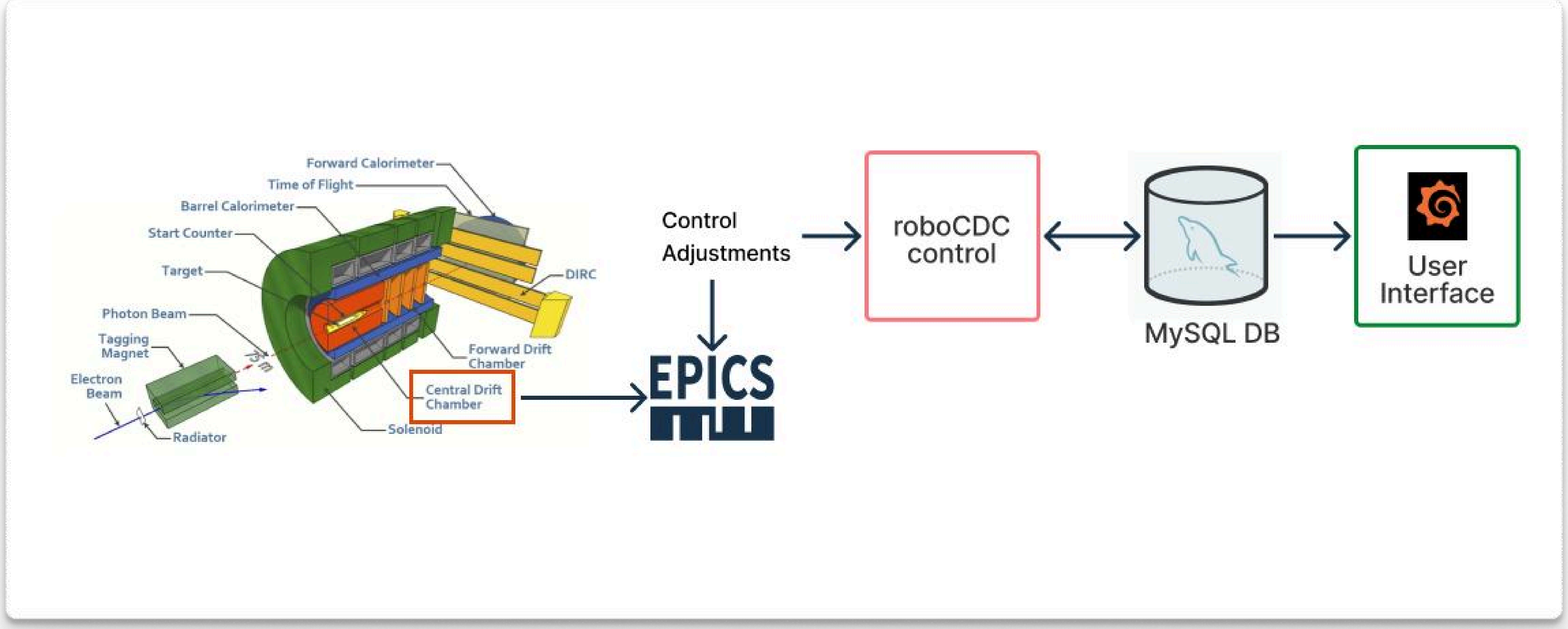
Calculating initial drift time to drift distance calibration constants using the gas density significantly reduces the number of iterations required. **Constants can be calculated and uploaded at the start of each run period.**





Dynamic HV Control

RoboCDC **adjusts the anode high-voltage settings** in response to environmental conditions, **stabilizing the chamber gain** and reducing our dependence on offline calibrations.

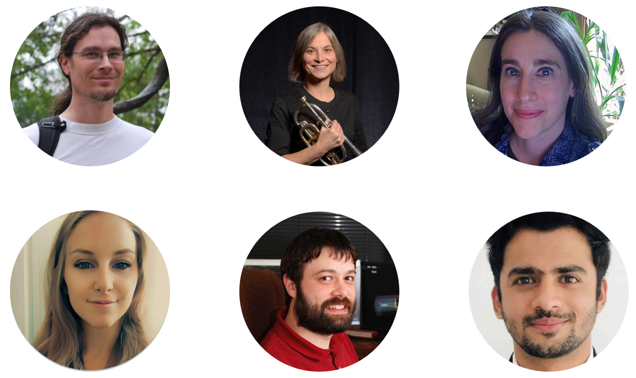


INSIGHTS

5
active deployments

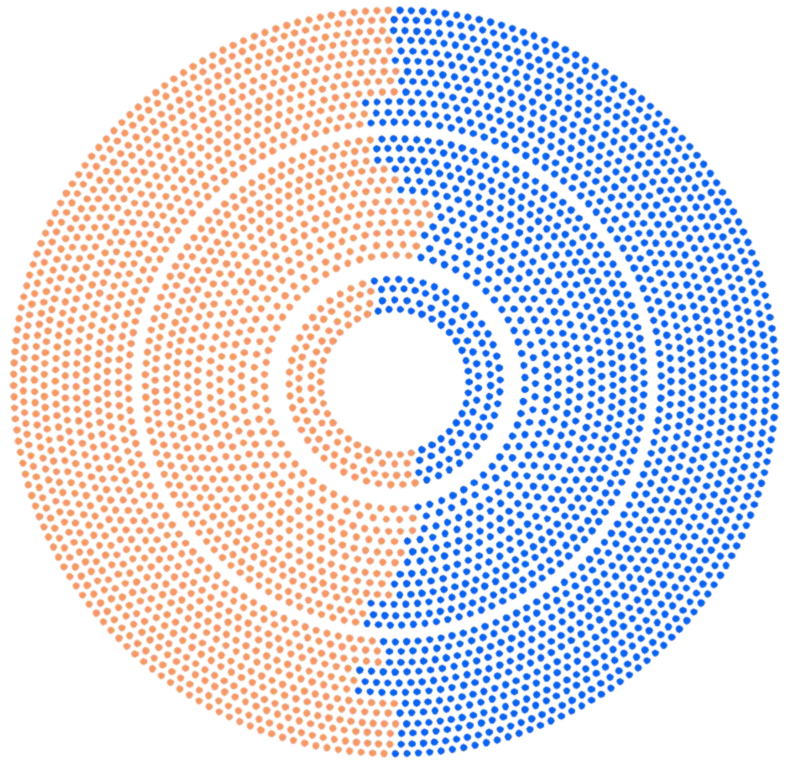
2128 runs
Active control: HV adjusted

3399 runs
Passive control: HV not adjusted

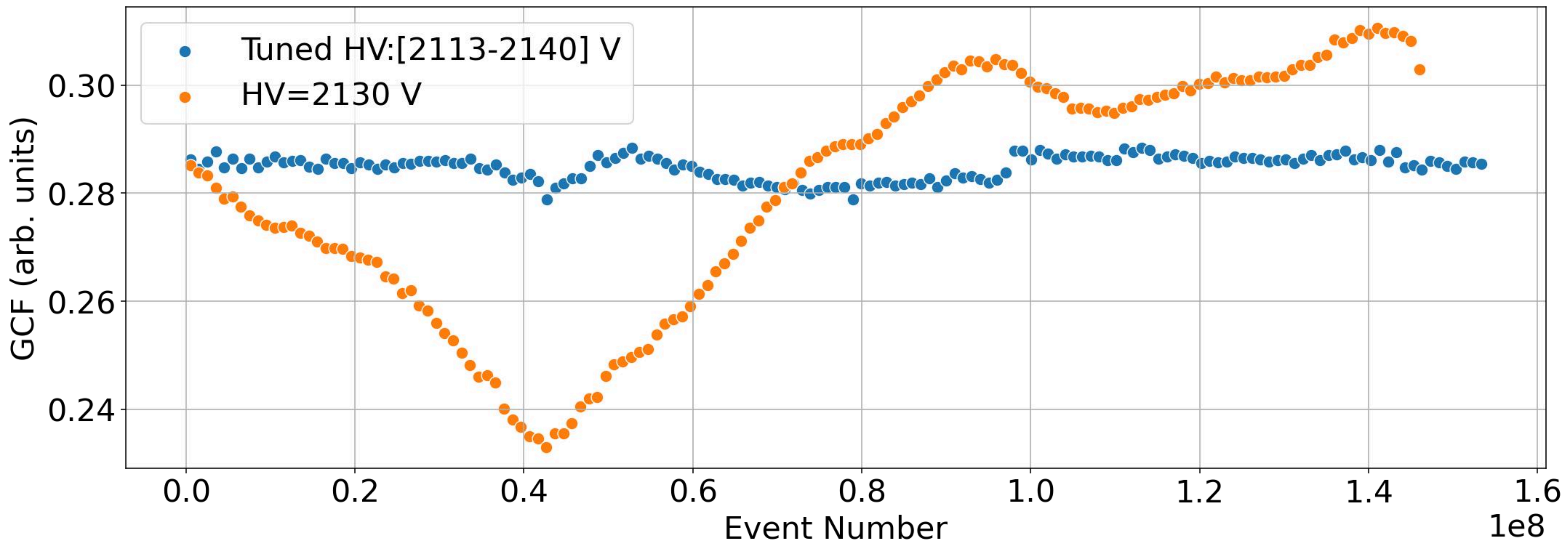


Stabilized chamber gain despite changing environmental conditions.

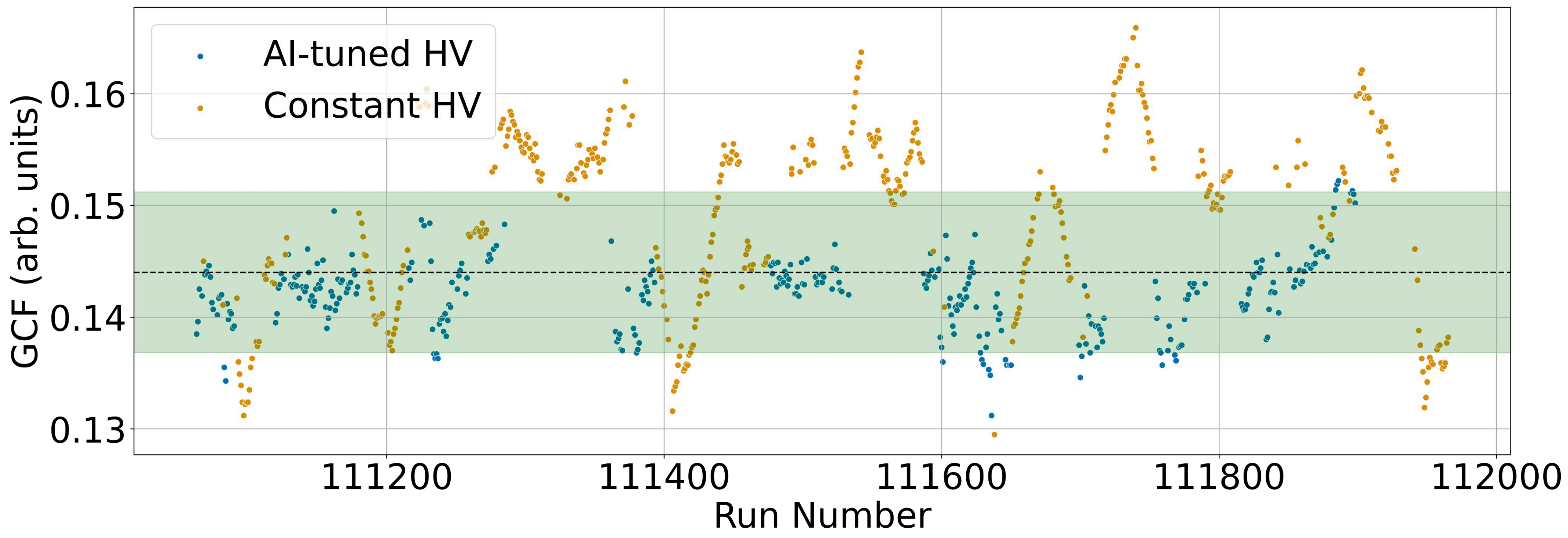
First tested with cosmics data *before* deploying to production.



Fixed HV | Tuned HV

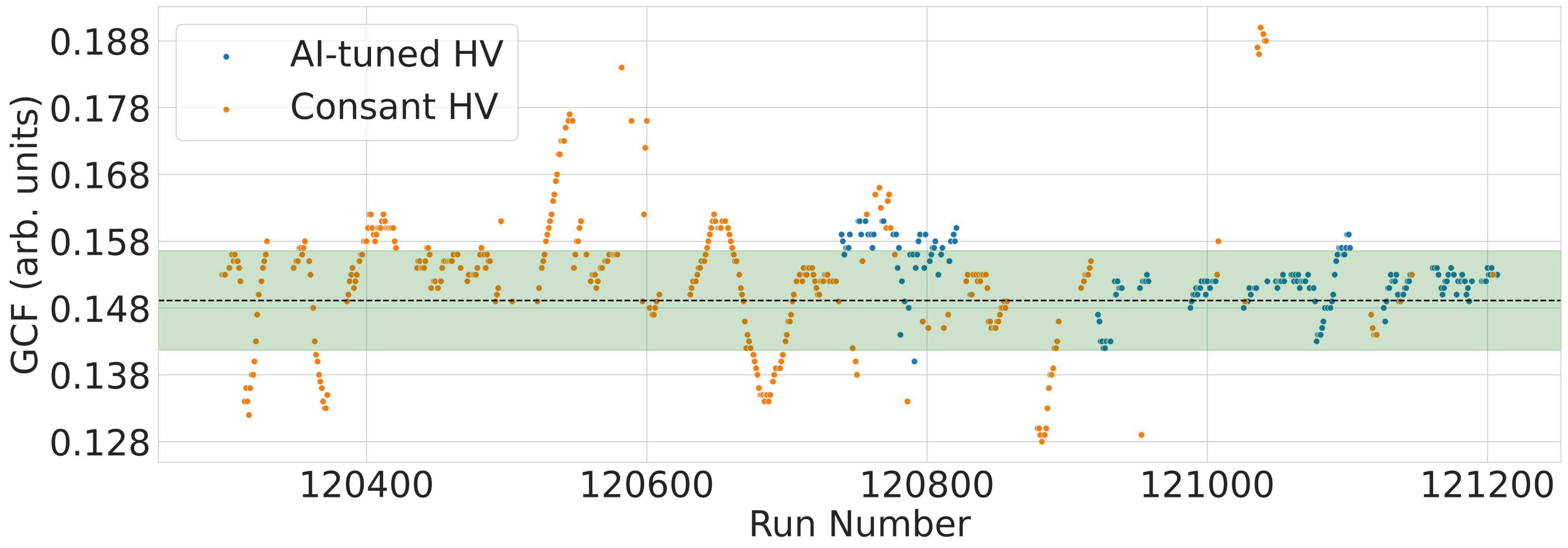


Stabilized chamber gain despite changing environmental conditions.



PrimEx II - 2022

Nearly all controlled runs fall within our 5% threshold.



GlueX 2023

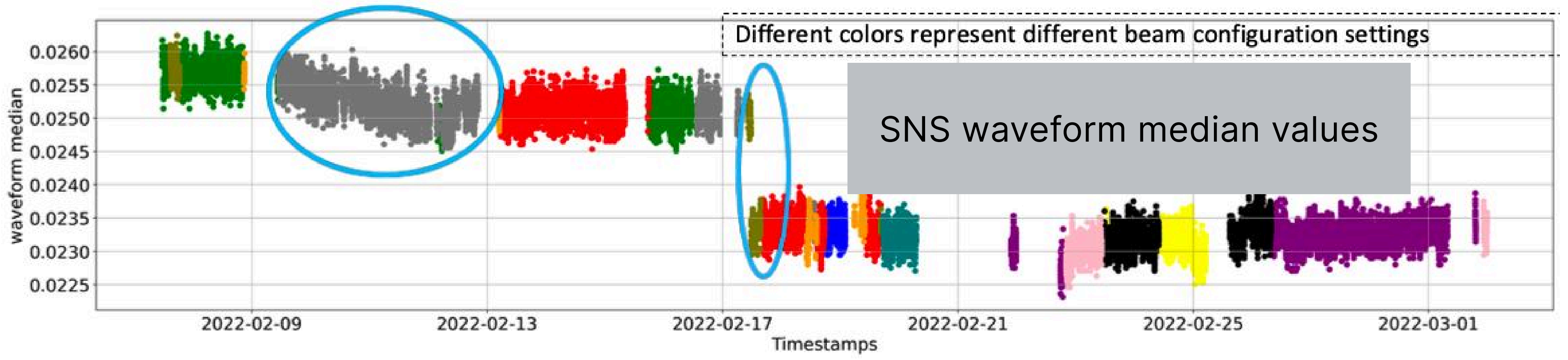
Faulty pressure sensor, nearly all controlled runs were within our 5% threshold.

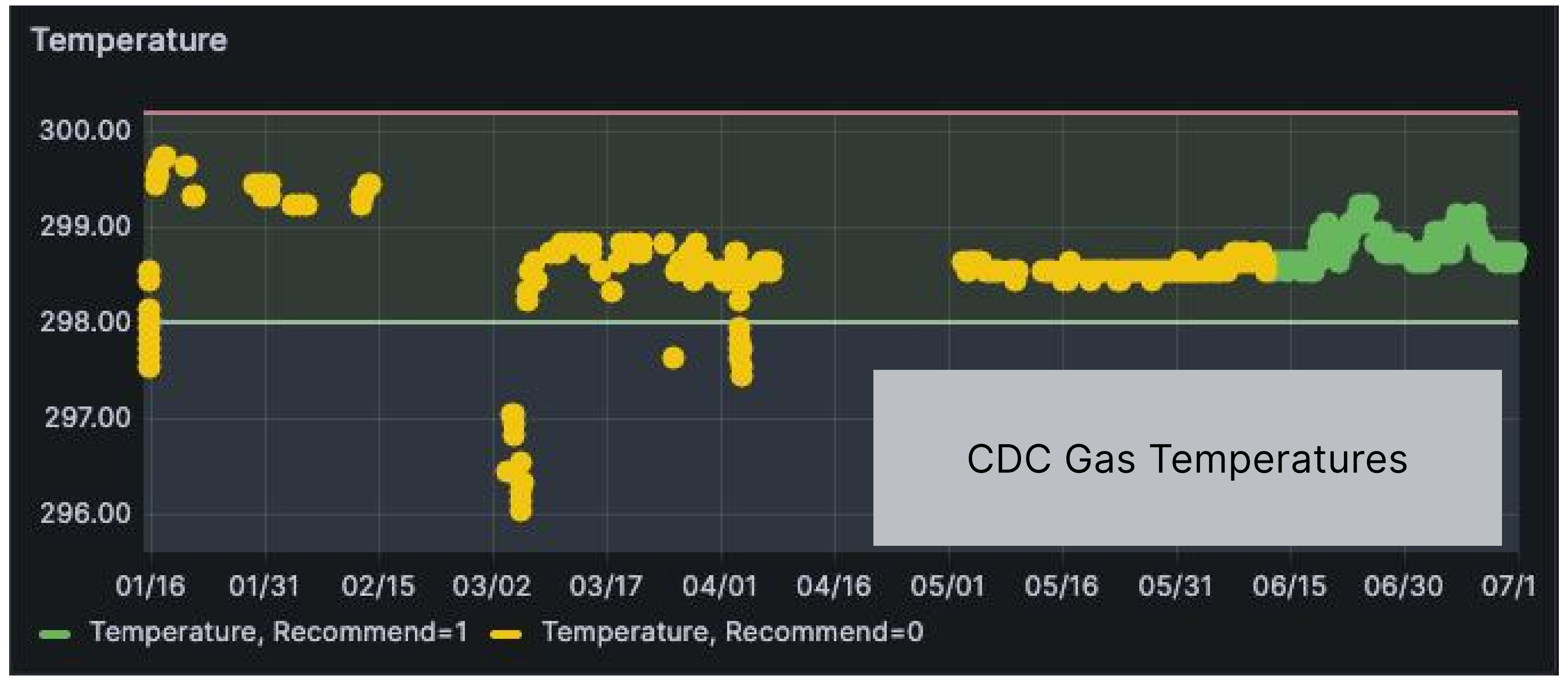
ML Operations

MLOps is a set of practices, tools, and processes designed to streamline and manage the lifecycle of ML models. We can all build and train models, but not all of them will make it into production.

Data drifts and model degradation

Data drifts and model degradation will happen! Automated monitoring and alerts for significant drifts or degradation.





Model repositories and storage

Structured repositories to manage and version ML models
Easy access for rapid updates or rollbacks

Dataset Tracking

Tools to track datasets used in model training to ensure reproducibility

Intelligent Decisions, Policies, and Constraints

Use data and models to propose actions

Intelligent Decisions

Adaptive, data-driven, and predictive actions based on real-time (or near real-time) conditions.

Control policies

Rules and thresholds guiding how decisions are made

Operational Constraints

Boundaries and safeguards ensuring safety, stability, and integrity of detector operation

What do we do if the model is uncertain?

Revert back to 2125 V and get more training data

What should we do if the HV set point is outside of our operational range?

Automatically email the development team that passive mode is being enabled.

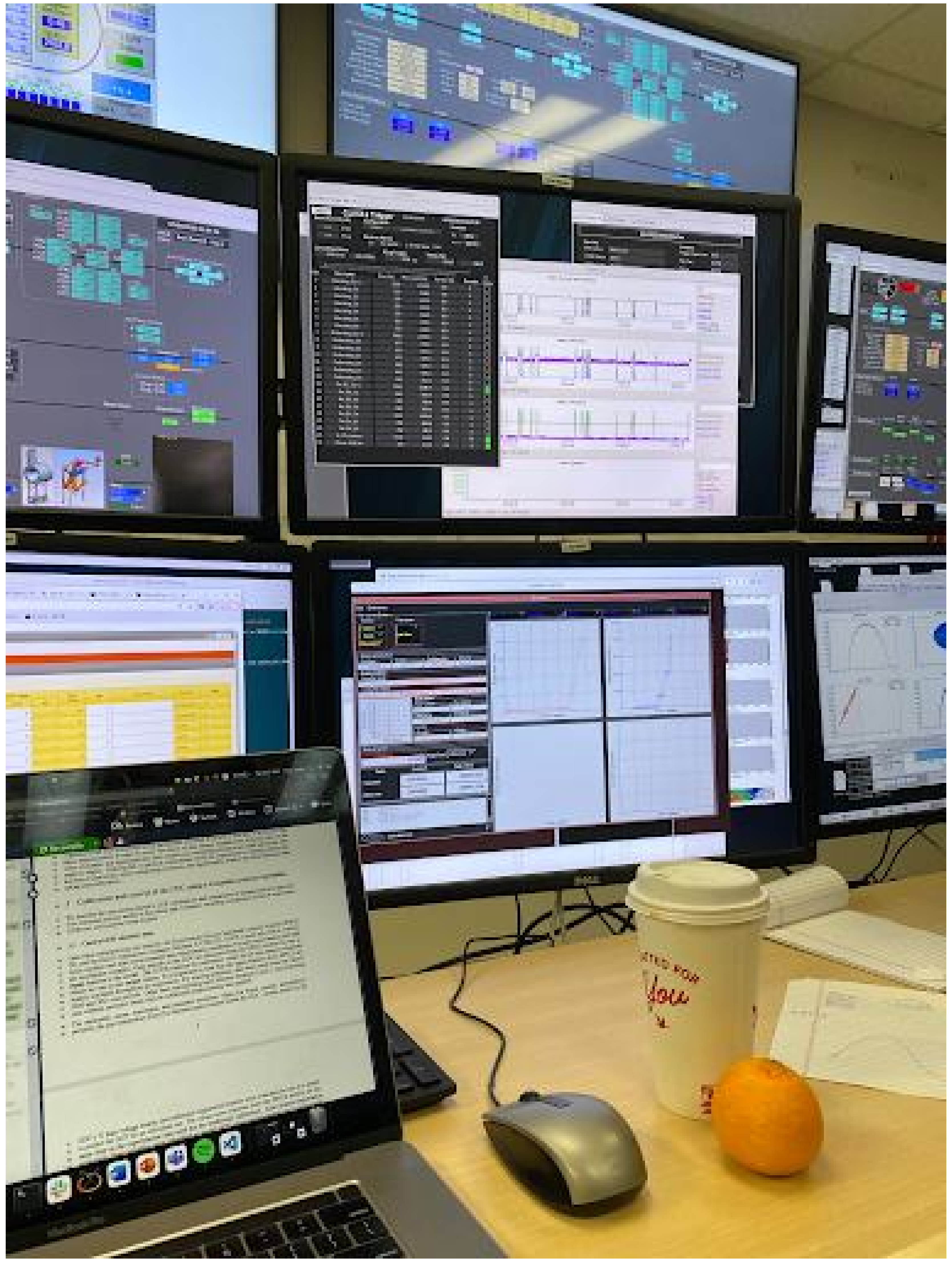
What do we do if EPICS data is unavailable?

Revert to 2125 V.

These are developed with the detector experts!

User Interface/Experience Design

Autonomous detector systems will necessitate new user interfaces and experiences.



Standard Monitoring

Shift crews monitor detector occupancies, time-series data, environmental sensors, alarms, etc

Autonomous System Monitoring

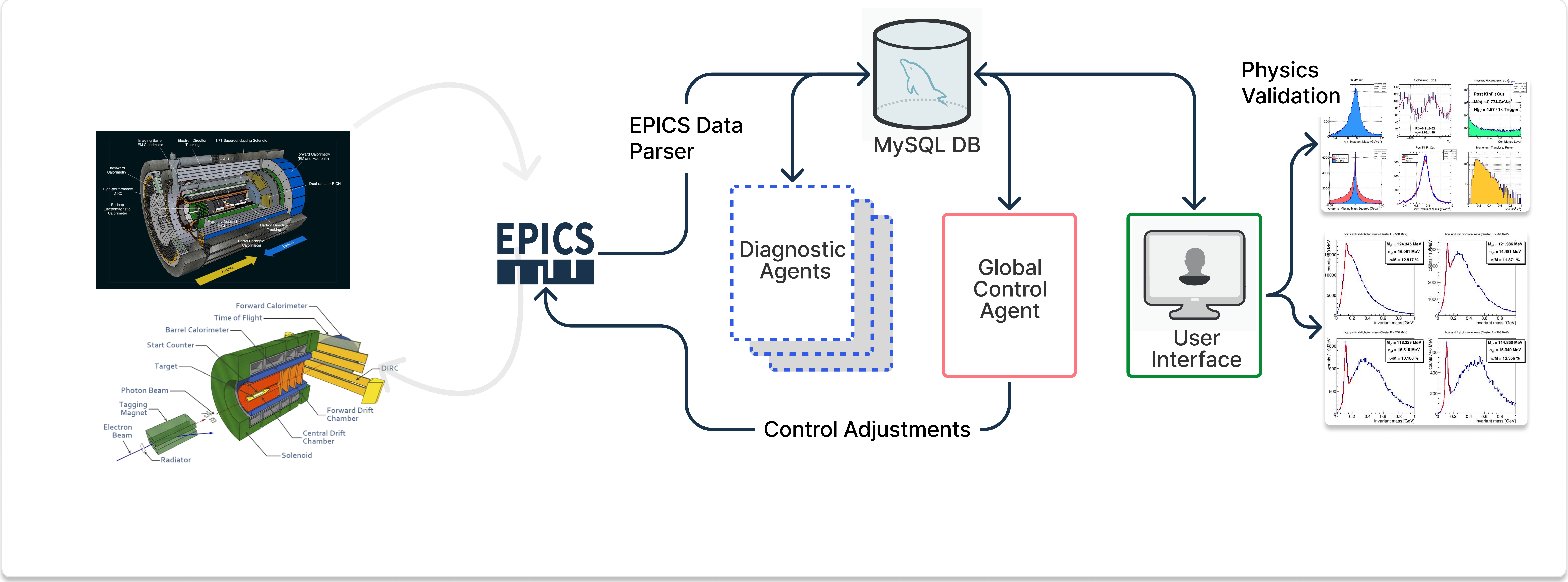
Shift crews will need to monitor any automated and/or autonomous system operating during an experiment

AI/ML Operations

Shift crews and detector experts will need to monitor any deployed models for performance degradation and data drifts.

A multi-agent approach to autonomous detector systems

Submitted to DOE Early Career Research Program



Conclusions

Monitoring

Real-time, advanced monitoring with anomaly detection and fault prediction essential for early issue detection

Decision Making

Intelligent, data-driven decision policies can enhance detector stability and reduce manual overhead

Calibration

Automated calibration significantly reduces offline calibration resources

Design

New UI/UX designs crucial for effective human-in-the-loop interactions and oversight

This work requires collaboration across physics, computer science, data science, and design.

Thinking about the necessary requirements and infrastructure *now* will give us a much needed head start for the future.

People

EPSCI

Experimental Physics Software and Computing Infrastructure

David Lawrence

EPSCI LEAD, ACTING HEAD OF SCIENTIFIC DATA AND COMPUTING DEPARTMENT

Torri Jeske

STAFF SCIENTIST

Thomas Britton

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Data Science Department

Malachi Schram

DEPARTMENT HEAD

Armen Kasparian

DATA SCIENTIST

Diana McSpadden

FORMERLY DATA SCIENCE, NOW PART OF CHIEF DATA OFFICE

Physics Division + User Community

Naomi Jarvis, Will Imoehl, Jiawei Guo

CARNEGIE MELLON UNIVERSITY

Cristiano Fanelli, Patrick Moran

WILLIAM & MARY

Hovanes Egiyan

HALL D STAFF SCIENTIST

Chris Keith, James Maxwell

JLAB POLARIZED TARGET GROUP

References

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