# Using AI to Predict Calibrations for the Central Drift Chamber in GlueX at Jefferson Laboratory

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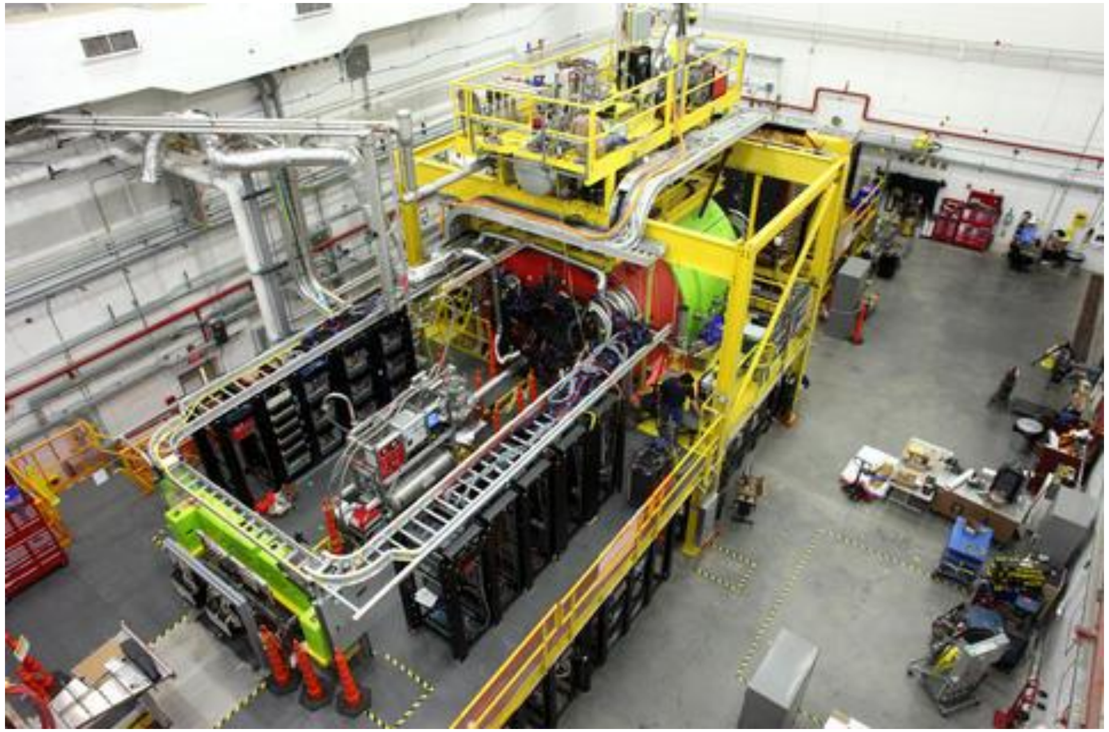
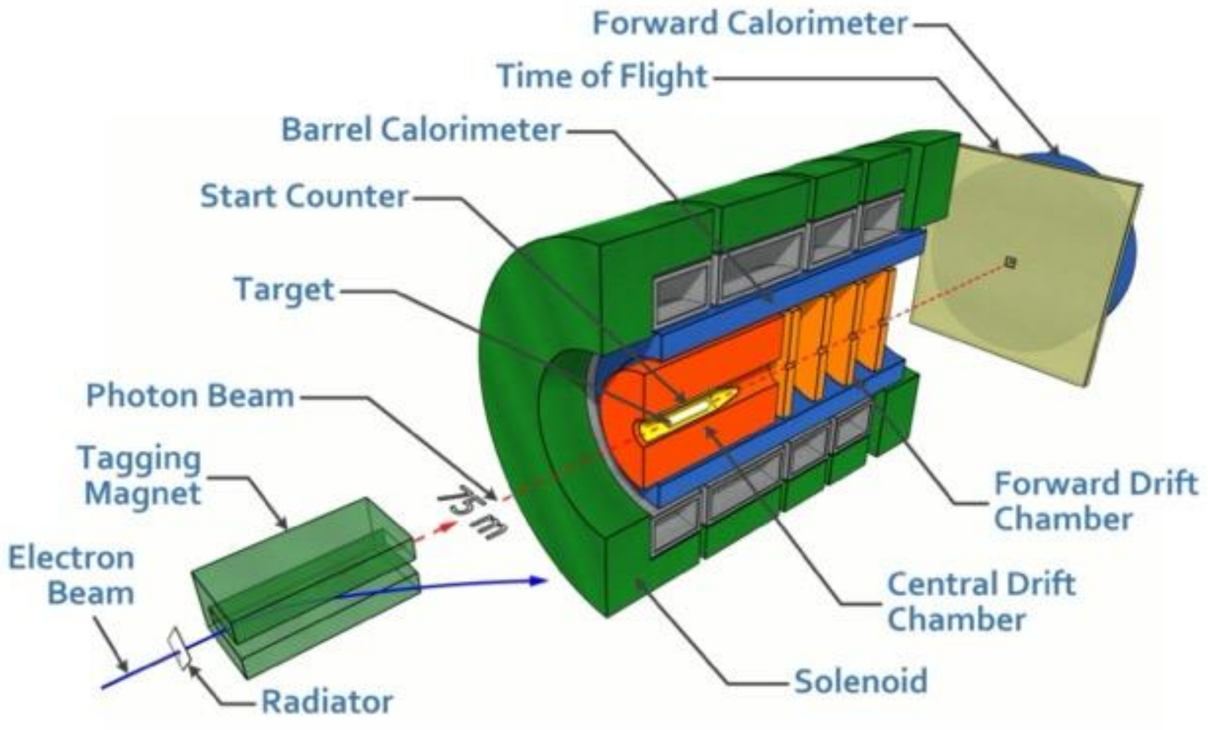
# GlueX Experiment at Jefferson Lab

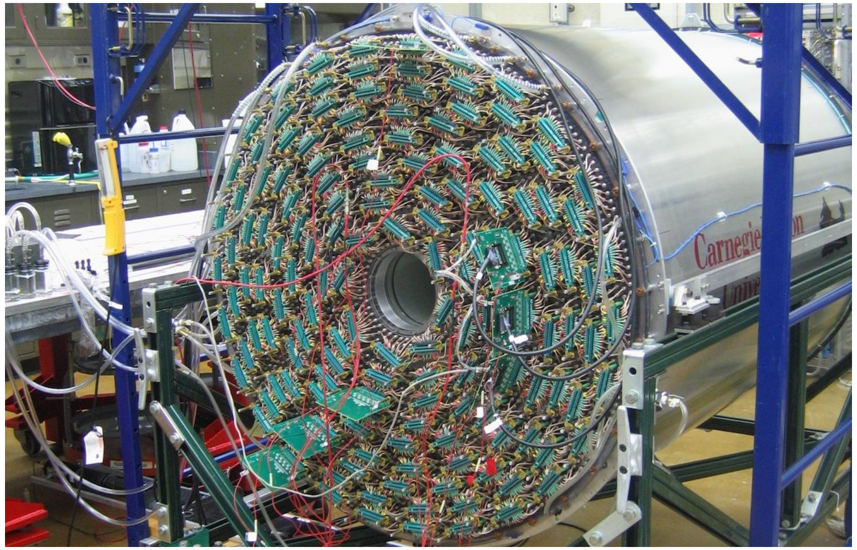
Designed to search for exotic hybrid mesons produced in photoproduction reactions and study the hybrid meson spectrum





# GlueX Central Drift Chamber

- 1.5 m long x 1.2 m diameter cylinder
- 3522 anode wires at 2125 V inside 1.6 cm diameter straws
- 50:50 $Ar/CO_2$ gas mix
- Used to detect and track charged particles with momenta p > 0.25 GeV/c
- **Requires two calibrations: chamber gain and time-to-distance**





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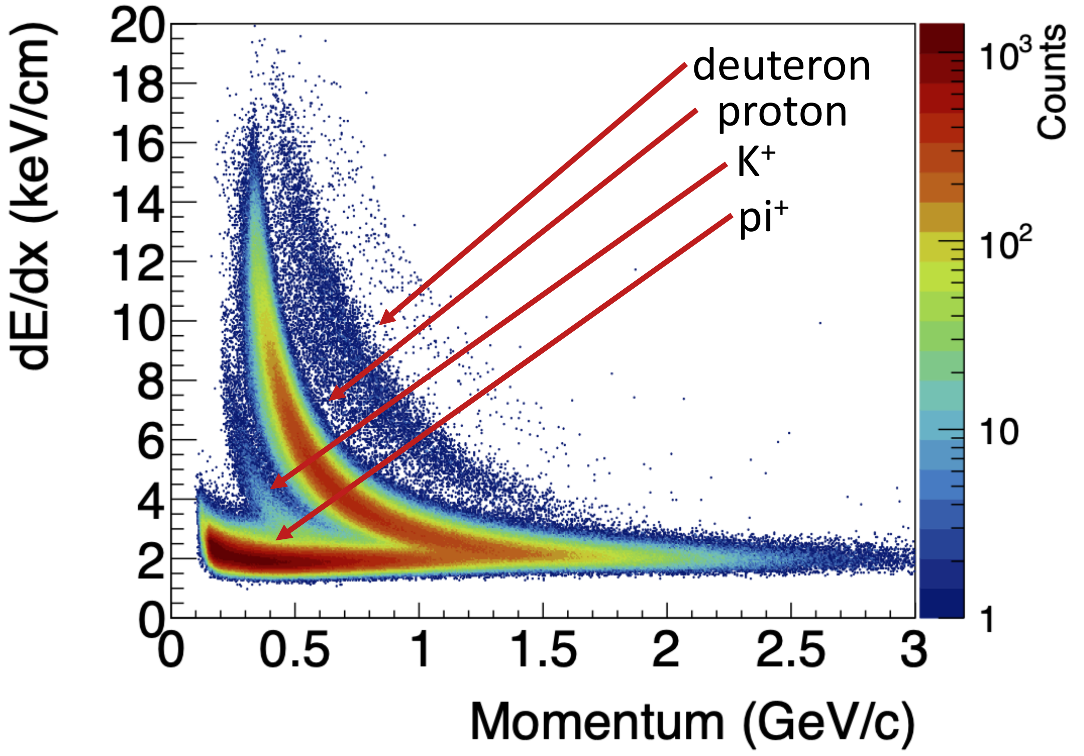
# CDC Calibrations

- Gain: affects PID selections in analysis
  - Sensitive to environmental conditions
  - Beam conditions change with the experiment
  - Gain correction factor obtained from Landau fit to amplitude
- Time to distance: track fitting, vertex and dE/dx resolution
  - Non-analytic fit function generates 6 unique calibration constants
- Calibration constants are generated per run



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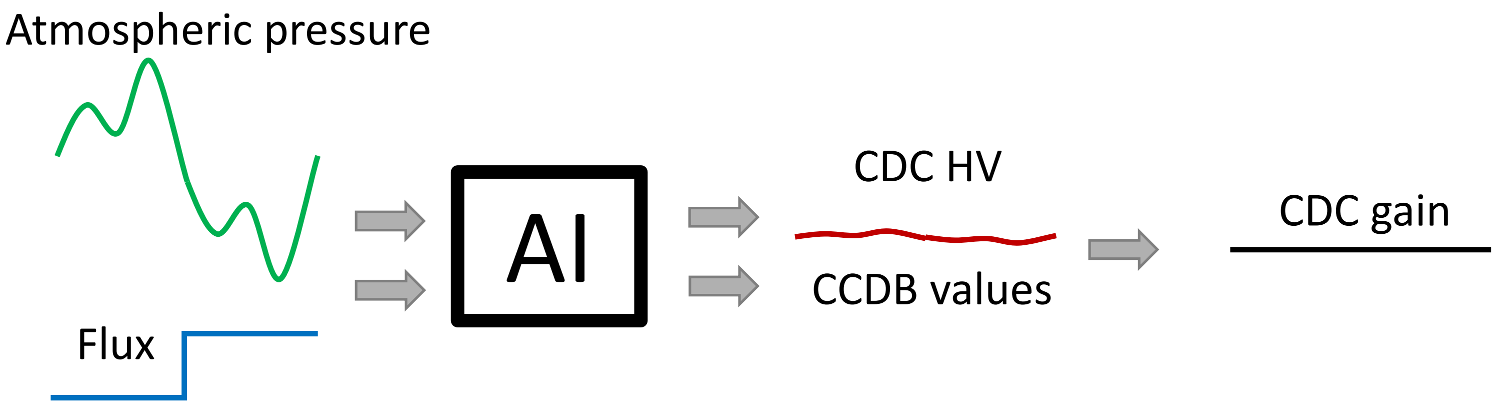
# Conventional Calibrations vs AI

## Conventional

- CDC operating voltage set at 2125 V
- Calibrations are fine tuned in an offline setting
- Current method is relatively slow, requires multiple iterations
- *Time scale to complete all calibrations is a few months*

## AI

- Maintain consistent detector response to changing environmental/experimental conditions by adjusting CDC HV
- Produce calibration constants online

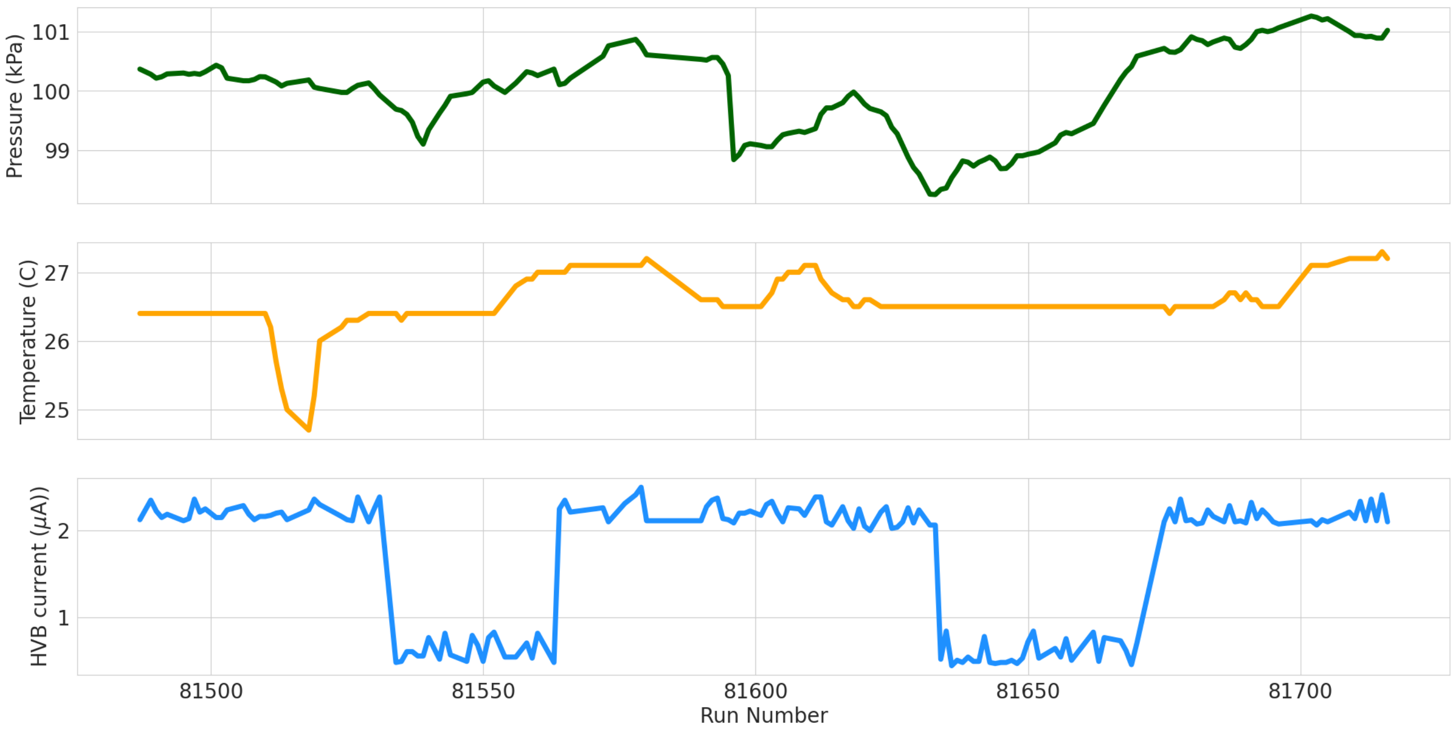


# Approach

- Can we predict existing calibration constants that exist for both calibrations?
- Can we control the CDC and predict calibration constants during an experiment?
- How do the AI generated calibration constants compare to those generated using the conventional approach?
- Can we apply this to other detector systems at the lab?

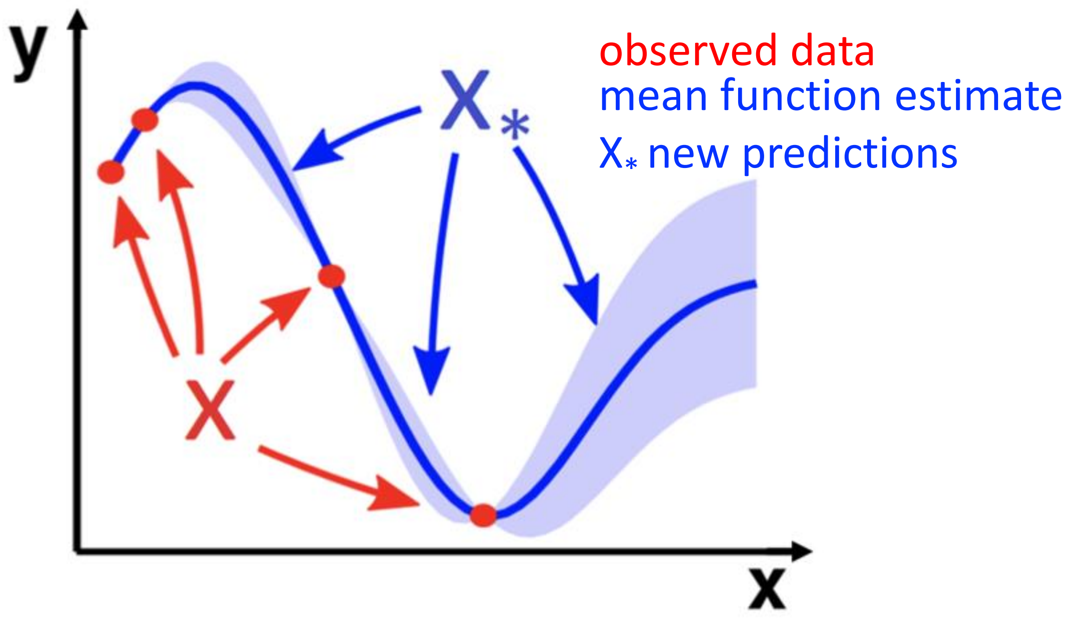
# Input Features

- Data extracted from Experimental Physics Industrial Controls System (EPICS)
- Initial features generated from:
  - Atmospheric pressure
  - Gas temperature
  - Current drawn from CDC HV boards
- Readily available during the experiment



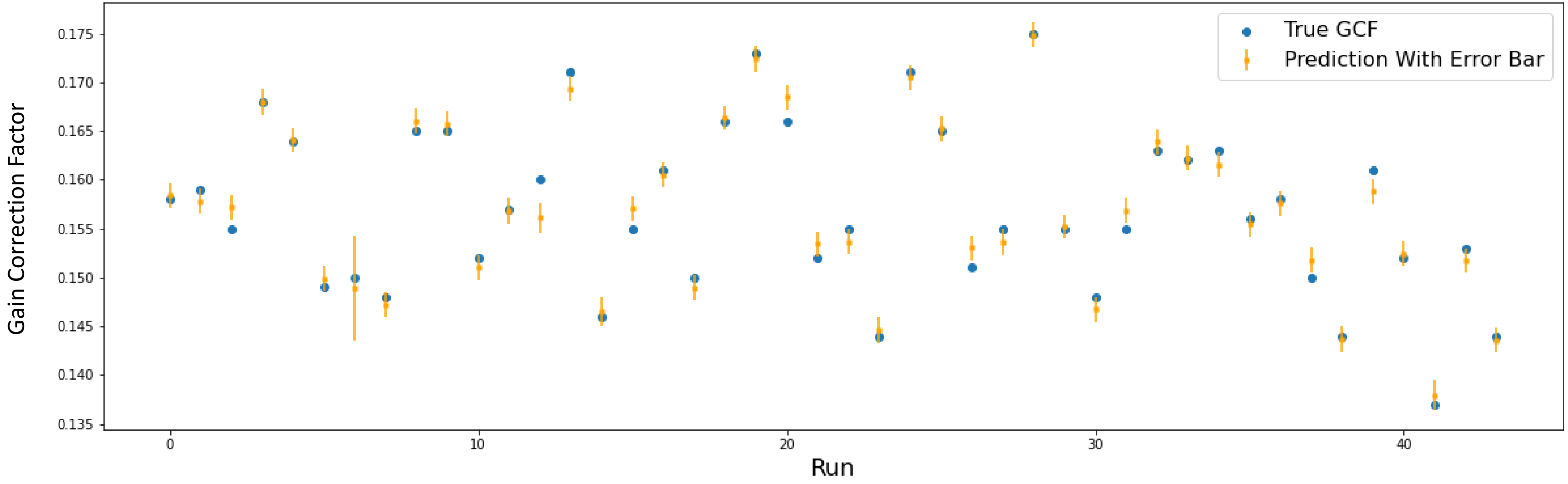
# *Current Model*: Gaussian Process Regression

- Gaussian process model: probability distribution over possible functions that fit a set of points
- Suited to small data set:
  - 430 training runs
  - 106 testing runs
- Provides uncertainty quantification
- Implemented using SciKit Learn



# GPR Model Predictions: Gain Correction Factor

- Targets: existing Gain Correction Factor (GCF) from GlueX 2020 run period
- Evaluation Metric: % error between model prediction and existing GCF
- Results for test set:
  - Mean Absolute Percent Error: 0.7%
  - Max Percent Error: 1.95%
  - Count Runs Over 1% Error: 10 of 44



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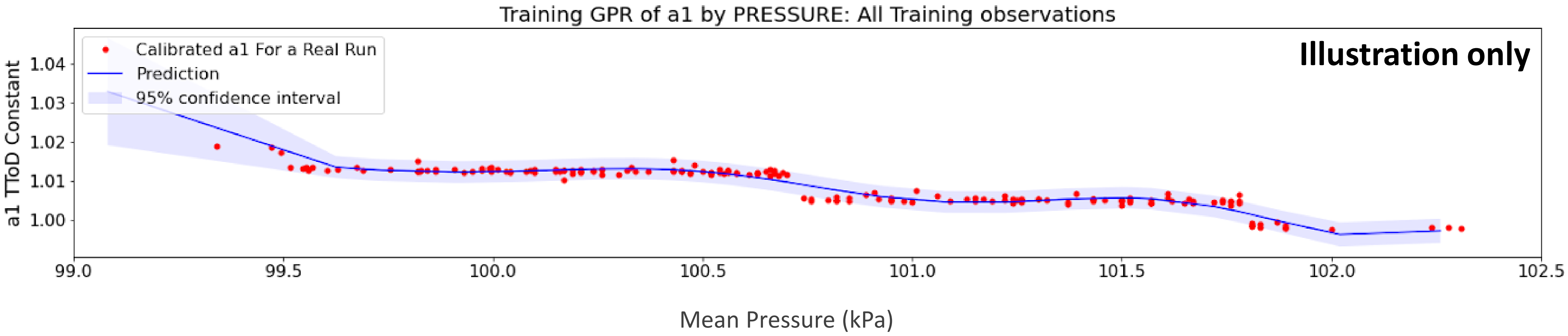
# *Current* TToD Model: Gaussian Process Regression

- Same input features as GPR for gain
- Targets: Existing TToD calibration constants from GlueX 2020 run period
- Evaluation metric:

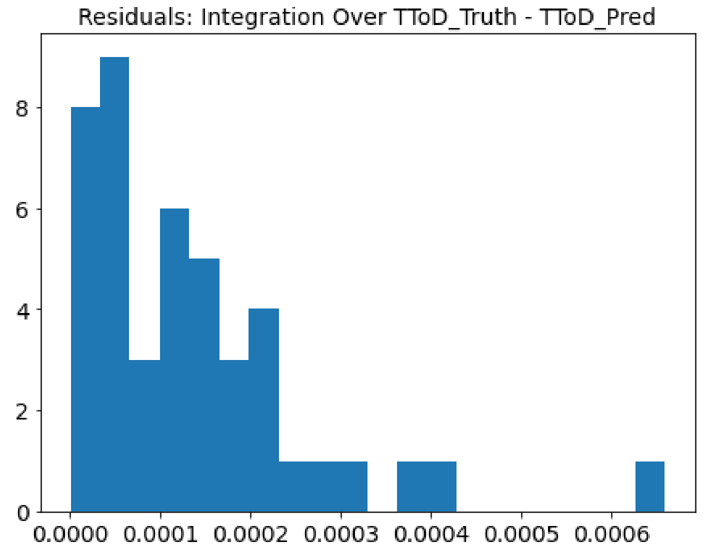
$$\mathcal{L} = \int_0^{1\mu s} \int_{-0.2cm}^{+0.2cm} \left| f\{t, \delta, B : \mathbf{k}_{label}\} - f\{t, \delta, B : \mathbf{k}_{model}\} \right| d\delta dt$$

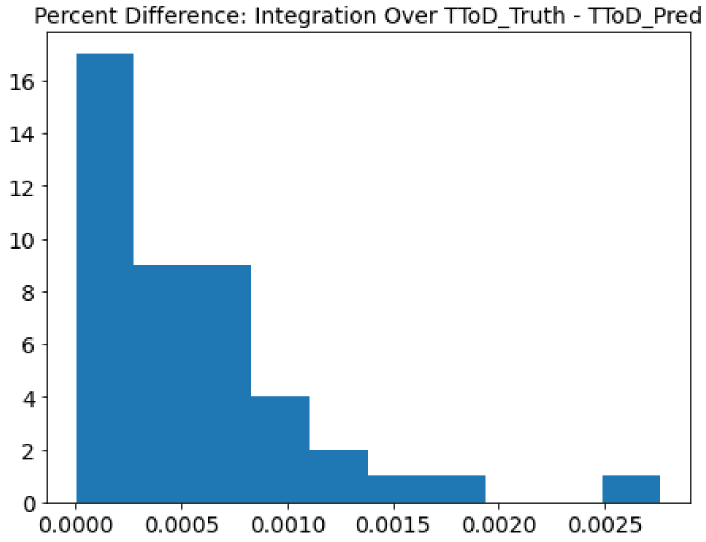


# Predictions: Time to Distance Parameters

- Predict each constant individually using 3 EPICS features: atmospheric pressure, HV board current, and gas temperature
- Cascading predictions: use preceding constant(s) in addition to EPICS features

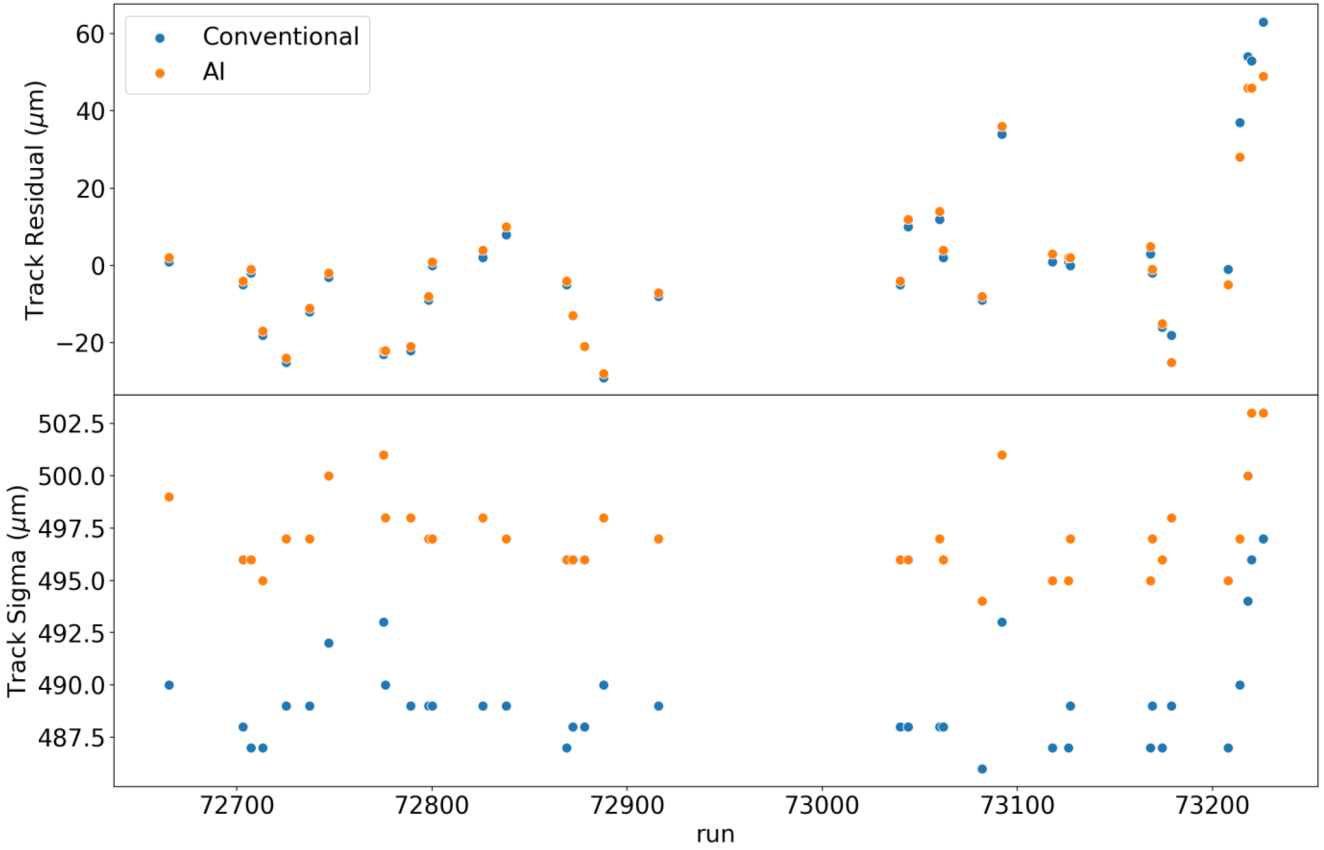
$$\mathcal{L} = \int_0^{1\mu s} \int_{-0.2cm}^{+0.2cm} \left| f\{t, \delta, B : \mathbf{k}_{label}\} - f\{t, \delta, B : \mathbf{k}_{model}\} \right| d\delta dt$$



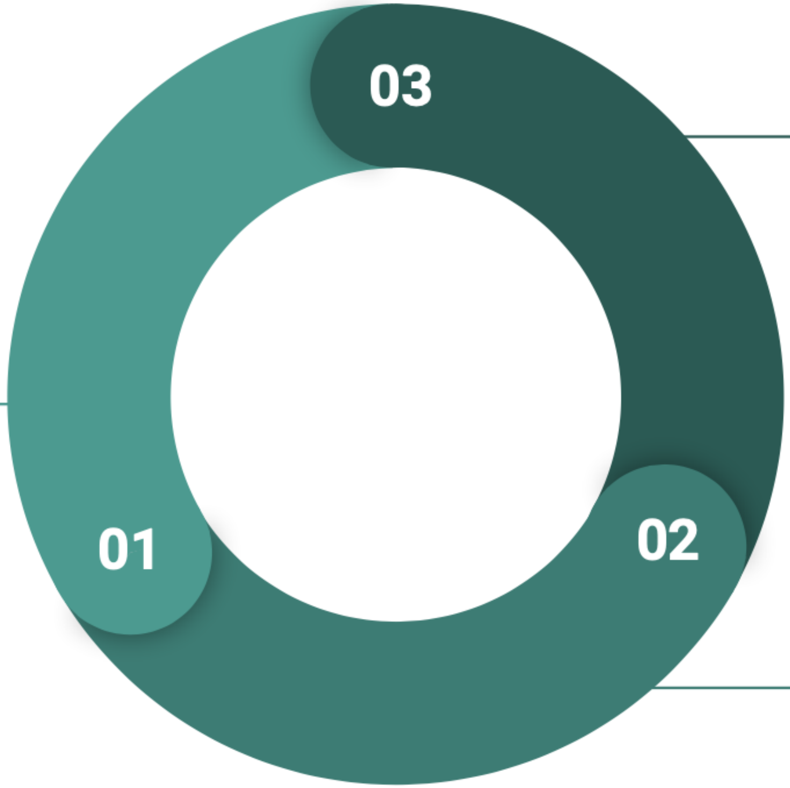



# Calibrations with AI: Time to Distance

- Use AI generated constants as starting values for calibrations
- Traditional calibrations take multiple iterations (~8 hours/iteration) to achieve satisfactory track residuals
- Performing TToD calibrations with AI generated start values achieved similar track residuals at **one** iteration



# Experiment Control with AI: Initial test, GCF only




**Establish target gain for run period**

Run AI with: desired beam current, radiator and target, temperature, board current, and standard pressure

**Run AI before each run**

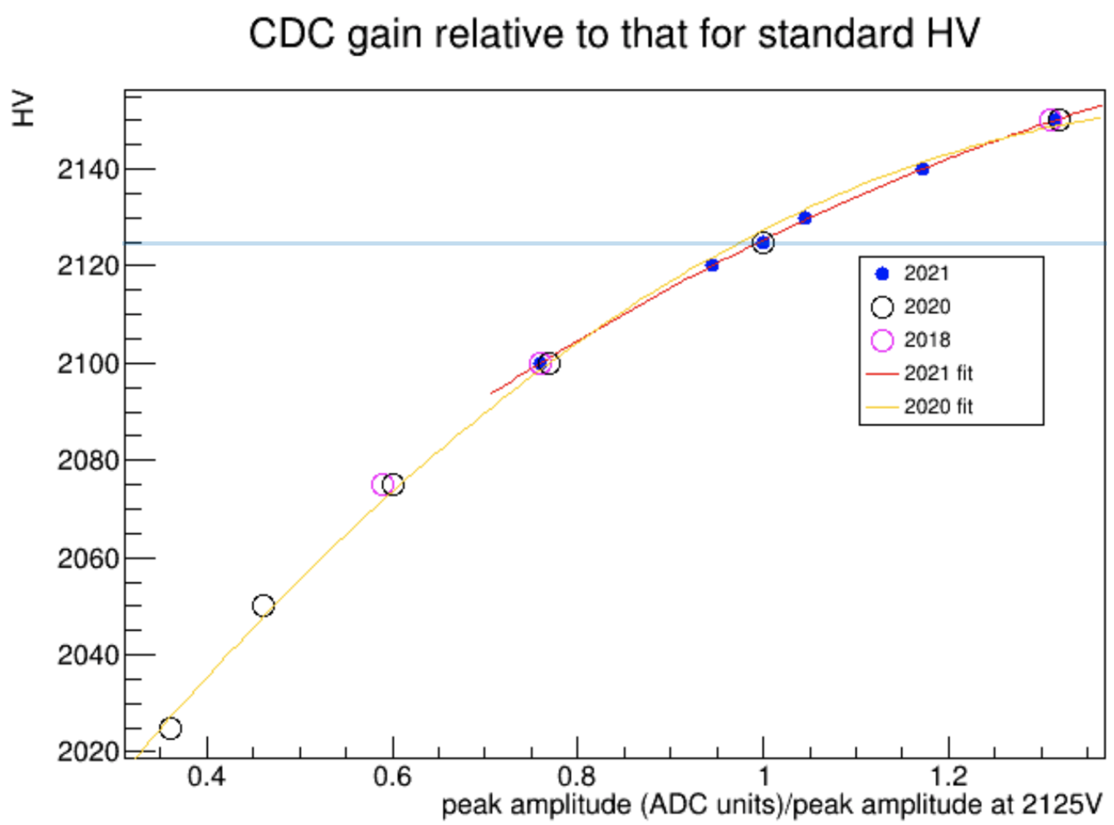
Use input features from EPICS for previous minute while beam current is steady. Use AI predictions to determine HV needed to produce relative gain

**Shift takers approve and adjust HV before starting new run**

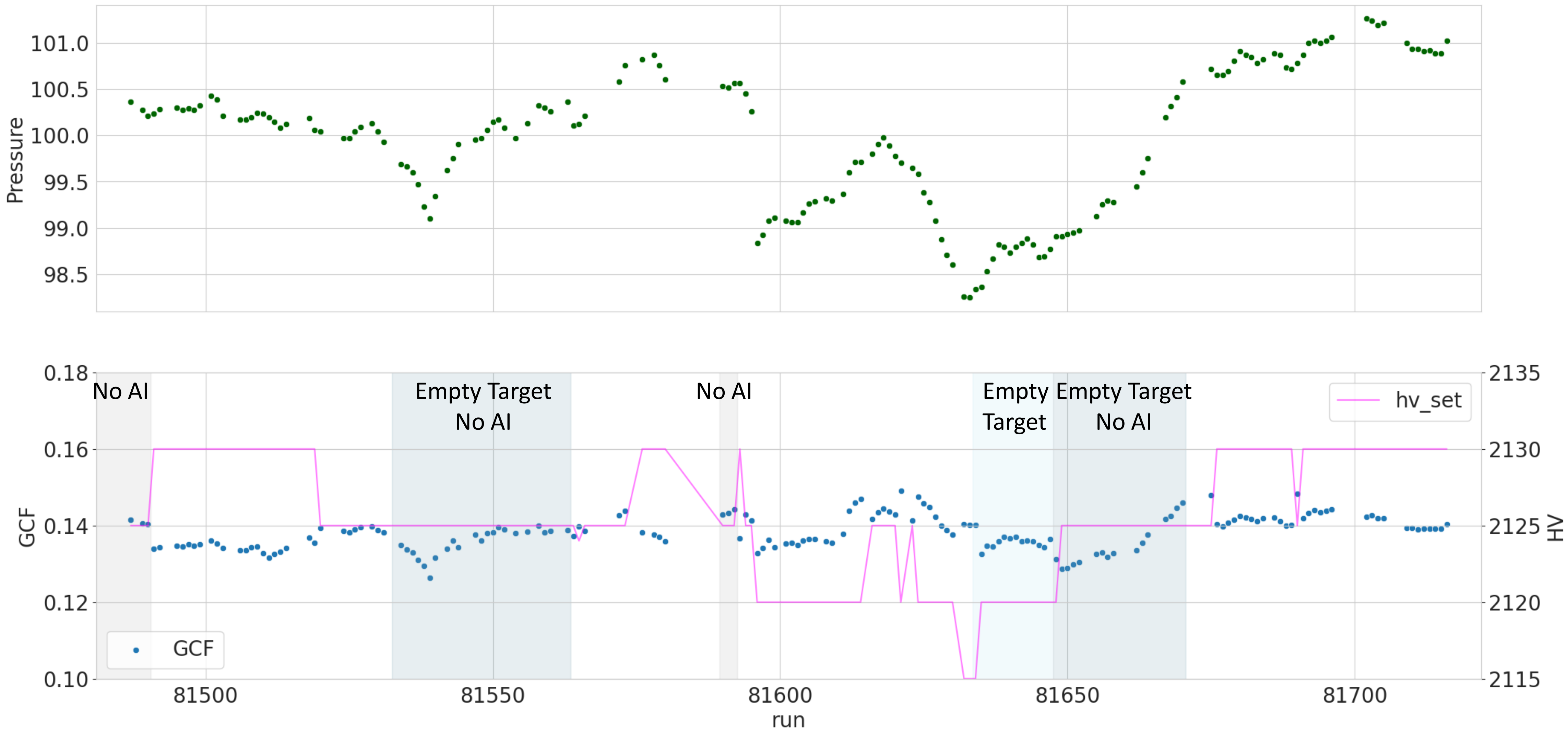
Default to standard 2125 V for empty target runs.

# HV Recommendation

- Script calculates expected GCF/ideal GCF
- Recommended HV setting obtained from fit to HV as function of relative peak amplitude

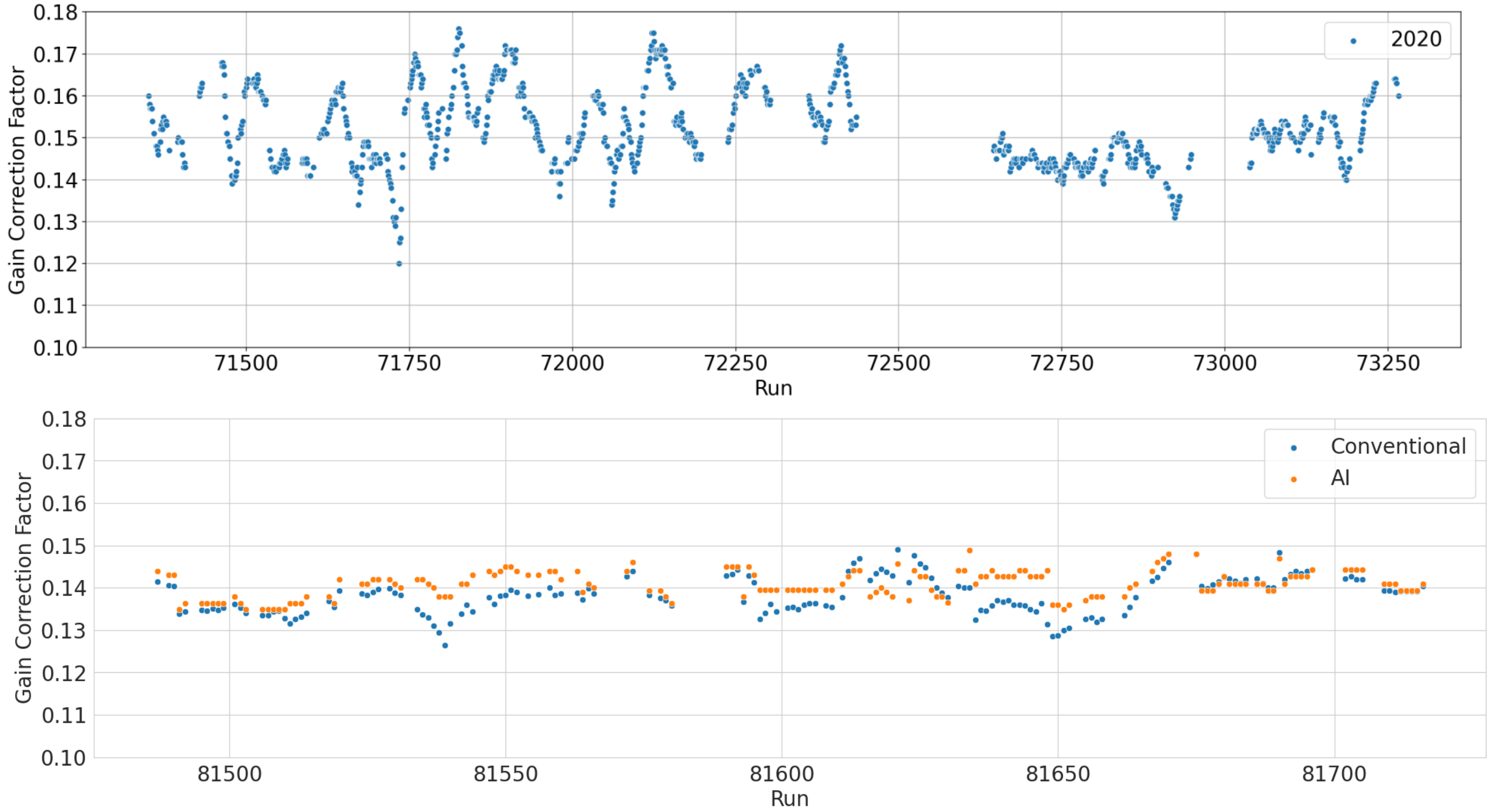


# Experiment Control with AI: Initial Test Results



# Calibrations with AI: Gain

- AI generated calibration constants agree with conventional gain calibration results
- GCF are more stable compared to GlueX 2020 run period



# Summary and Outlook

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- Ability to predict existing calibration constants using GPR models using environmental and detector specific data
- Compared calibrations with conventional and AI-generated starting values
- Automation of control aspect is under way
- Application to CLAS12 drift chambers in progress

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# References


- GlueX detector: https://doi.org/10.1016/j.nima.2020.164807
- CDC: https://doi.org/10.1016/j.nima.2020.163727
- GPR: https://arxiv.org/pdf/2009.10862.pdf

Backup slides

# TToD Fit function

- $d(t) = f_\delta \left( \frac{d_0(t)}{f_0} P + 1 - P \right)$

- $d_0(t)$ comes from table of time to distance for an ideal straw

- $P = \begin{cases} 0 & t > T \\ \frac{T - t}{T} & t \leq T \end{cases}$

  - Drift times less than 250 ns are not affected significantly by the distortion of the electric field from straw sag

$$f_\delta = a\sqrt{t} + bt + ct^3$$

$$f_0 = a_1\sqrt{t} + b_1 t + c_1 t^3$$

$$a = a_1 + a_2|\delta|$$

$$b = b_1 + b_2|\delta|$$

$$c = c_1 + c_2|\delta|$$