Gaussian process for calibration and control of GlueX Central Drift Chamber

The AI for Experimental Controls (**AIEC**) Team:

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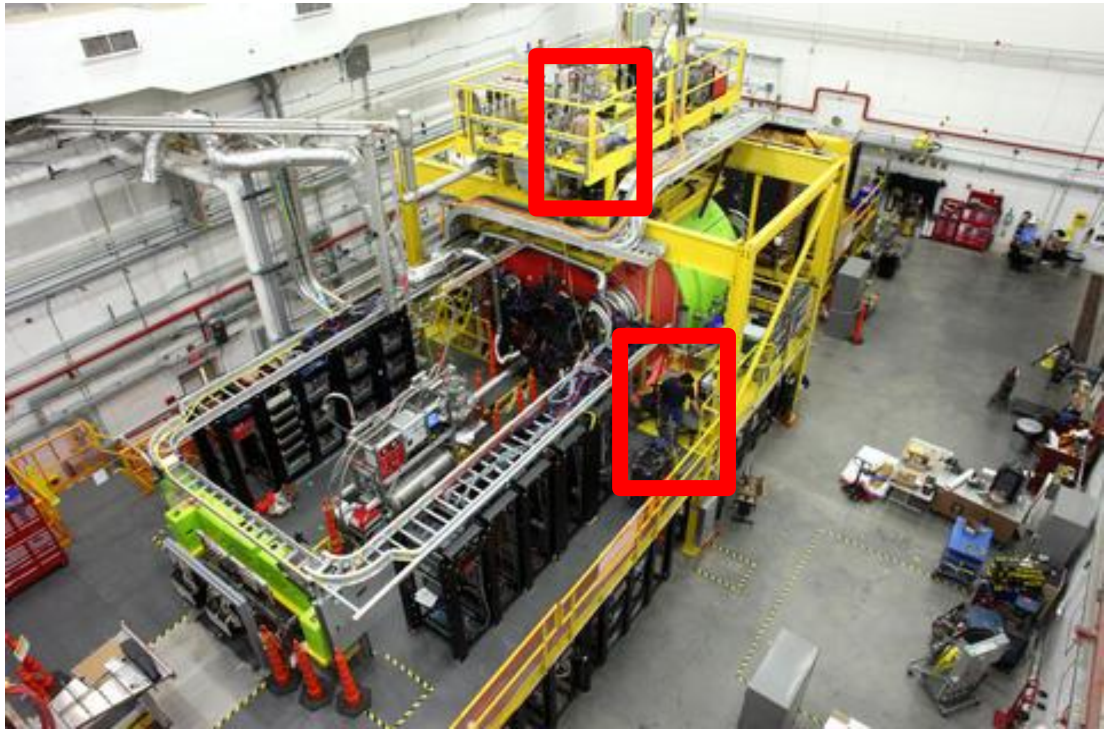
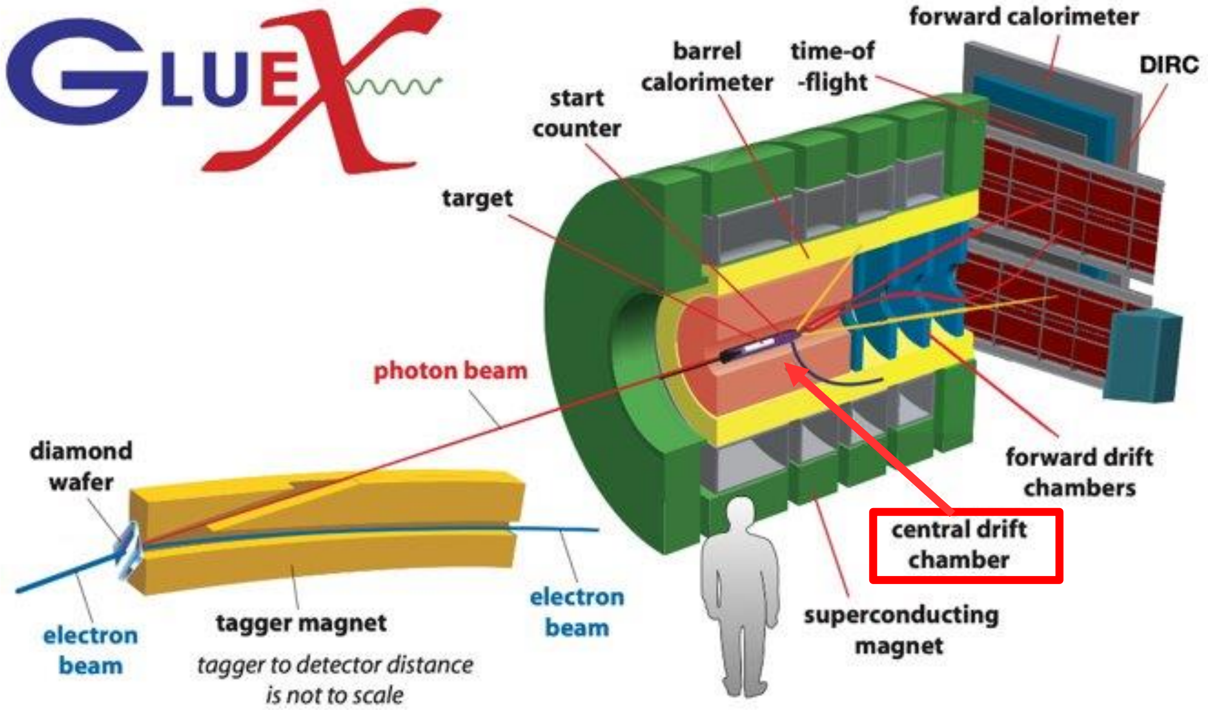
ACAT 2022

GlueX Experiment at Jefferson Lab

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

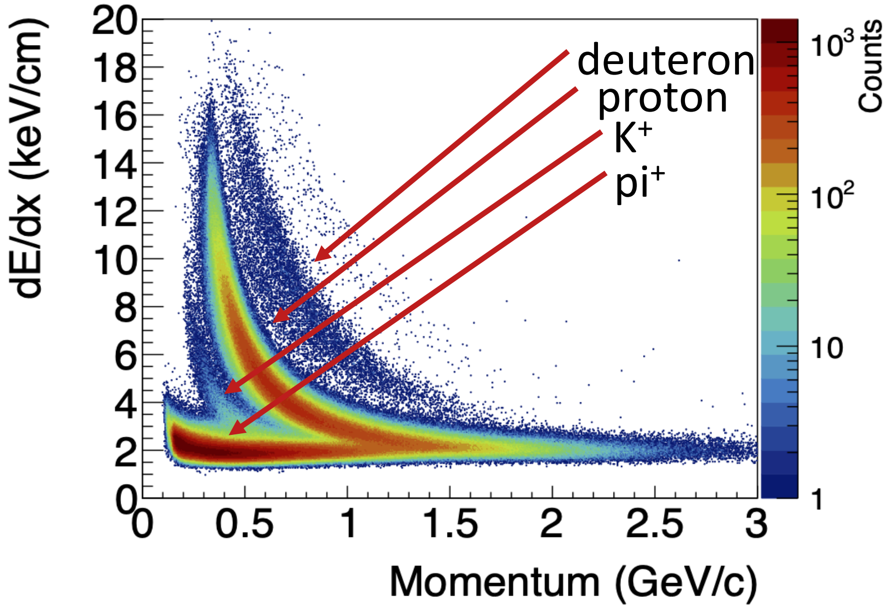




GlueX Central Drift Chamber (CDC)

- Requires two calibrations: **gain** and drift time-to-distance
  - **Gain Correction Factor (GCF)**:
    - GCF calibrations have most variation +/- 15%
- Has **one** control: **operating voltage**

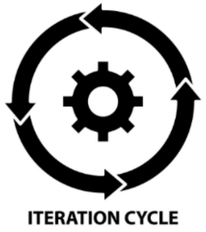
- **Used to detect and track charged particles with momenta p > 0.25 GeV/c**
- **Use for particle identifcation**
- **dE/dx**: measure of deposited energy per unit of track length
  - 1.5 m long x 1.2 m diameter cylinder
  - 3522 anode wires at 2125 V inside 1.6 cm diameter straws
  - 50:50 Ar/CO_2 gas mix



Motivation: Conventional vs. Online, ML Calibration Paradigms

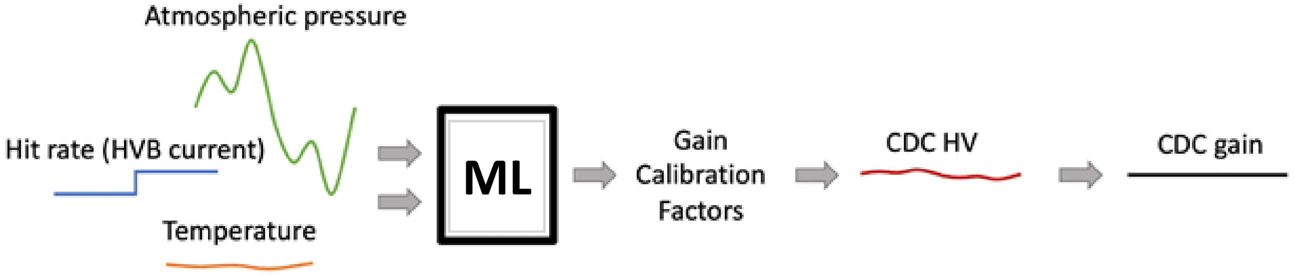
Conventional

- **Calibrate**: calibration values **iteratively,** produced after the experiment
  - **~2 hour runs**
- **~~Control~~**: CDC operating voltage is ***fixed*** at 2125 V



Online and ML

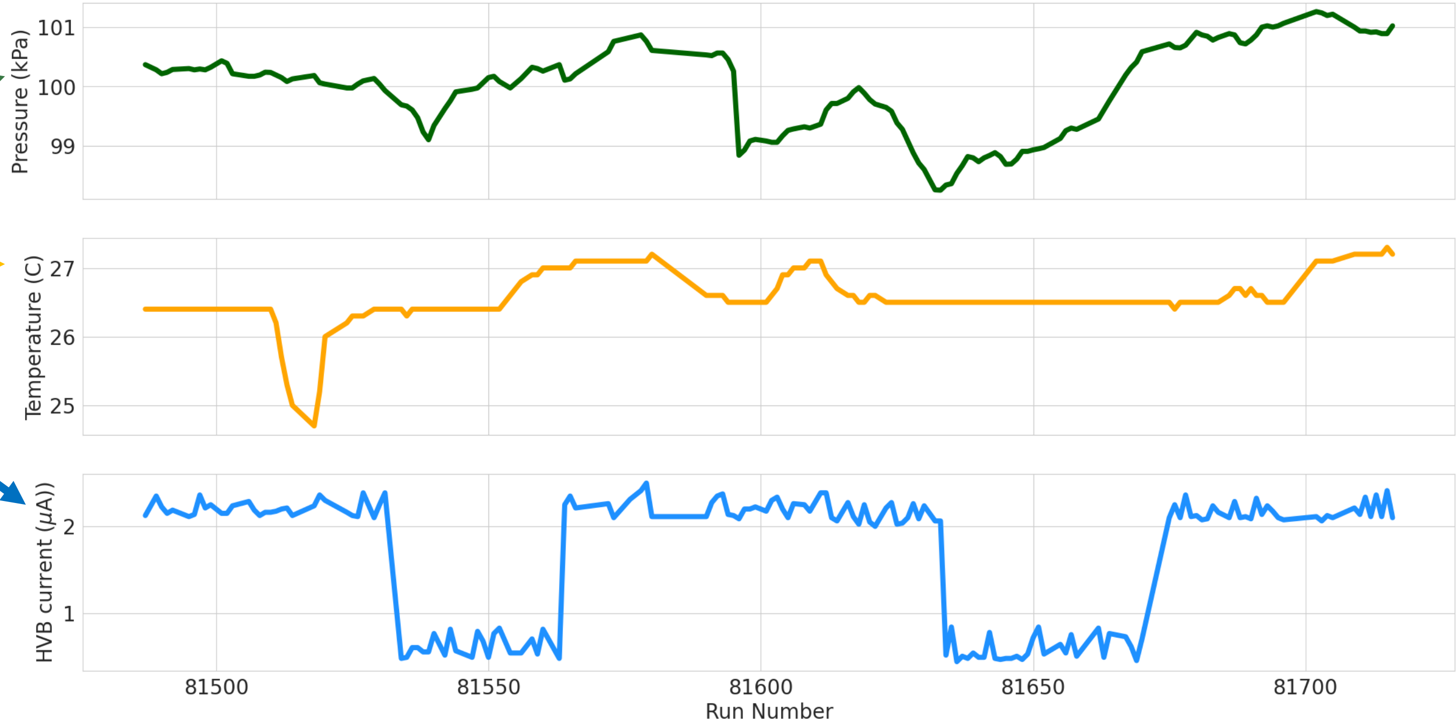
- **Control**: Stabilize detector response to changing environmental/experimental conditions by ***adjusting*** CDC HV
- **Calibrate**: **online** calibration values produced during the experiment



Q1: Can we predict GCFs? Input variables

Can we predict GCFs using data that are **readily available as a run begins**?

- Data extracted from Experimental Physics Industrial Controls System (EPICS)
  - Atmospheric pressure
  - Gas temperature
  - Current drawn from CDC HV boards (proxy for beam current)
- Readily available during the experiment
- Not dependent on other detectors
- No reconstruction!



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ML Technique

Gaussian Process (GP)

- 3 input features
- **1 target**: the traditional Gain Correction Factor (**GCF**)
- GP calculates PDF over admissible functions that fit the data
- GP provides the standard deviation
- We used a popular GP kernel:
    - Radial Basis Function + White

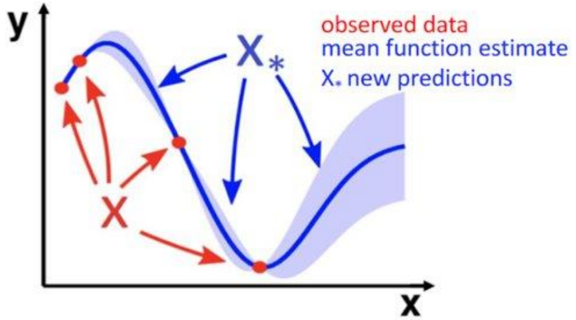


Illustration training a Gaussian process

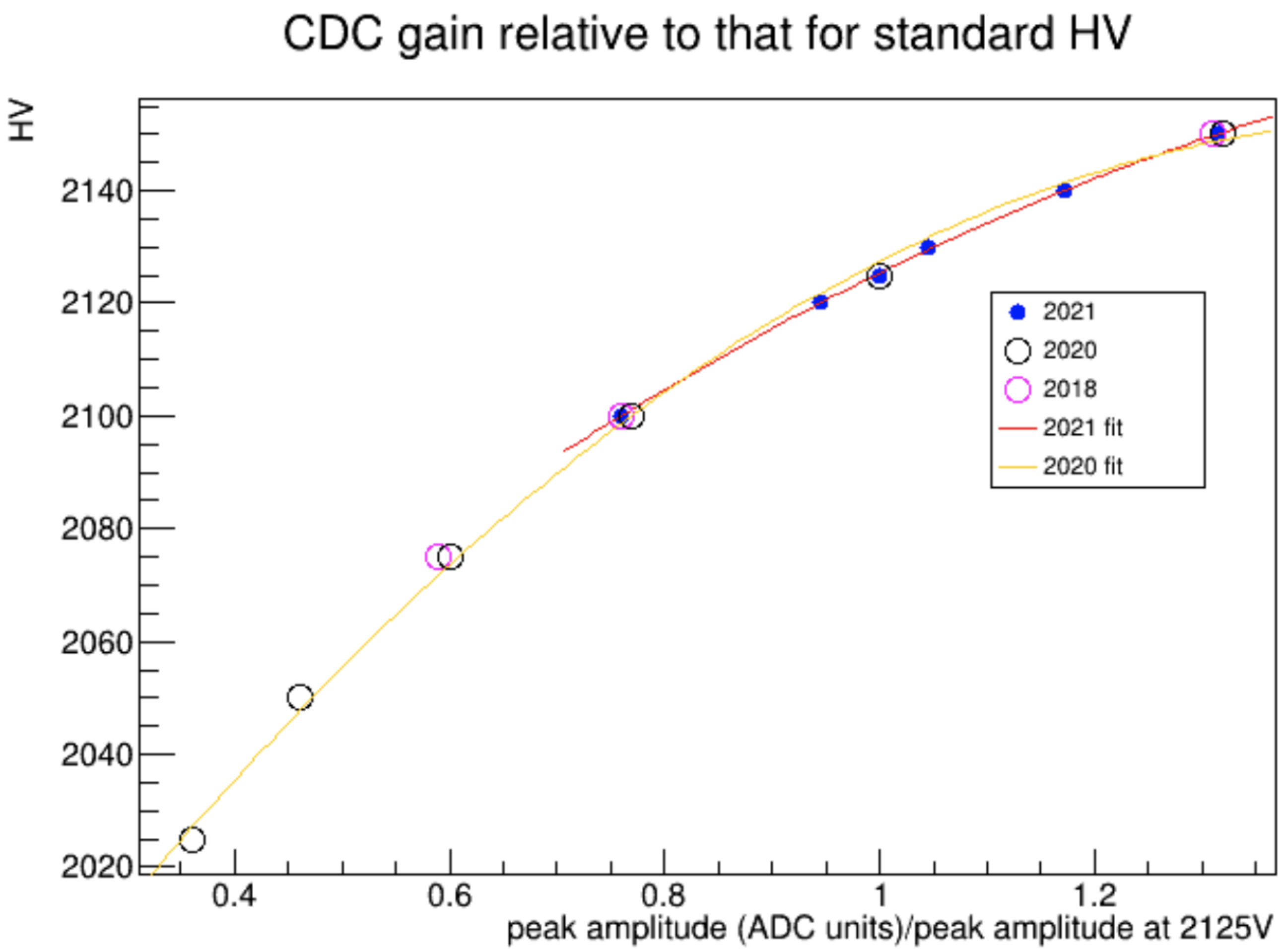
We can exploit the standard deviation for uncertainty quantification (UQ).

Our goal was better than a 5% error

RBF kernel (length scale(s))	R^2	RMSE	Mean |% err|
Isotropic (1.412)	0.97	0.002	**0.8%**
Anisotropic (1.4,1.17,.171)	0.97	0.002	0.8%

Q1: Can we predict GCFs? HV Recommendation

- GCF is related to HV
- Recommended HV setting obtained from fit to HV as a function of relative peak amplitude



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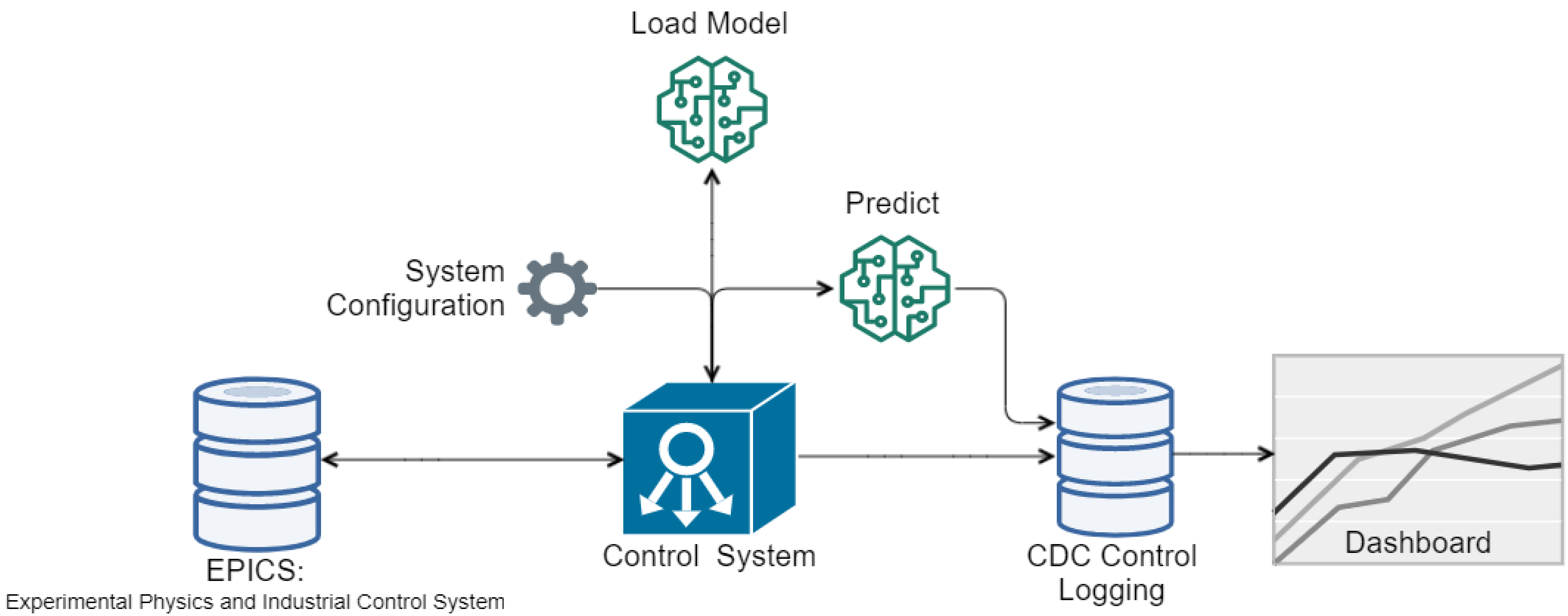
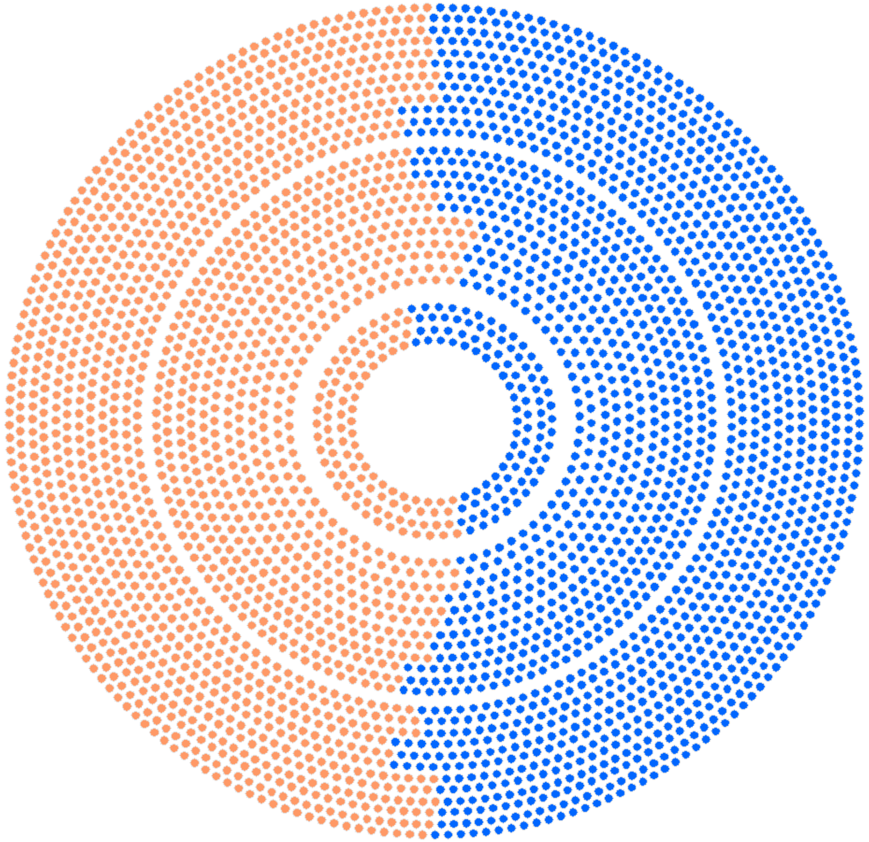
Q2: Can we control HV to stabilize gain? RoboCDC, a modular ML system for control



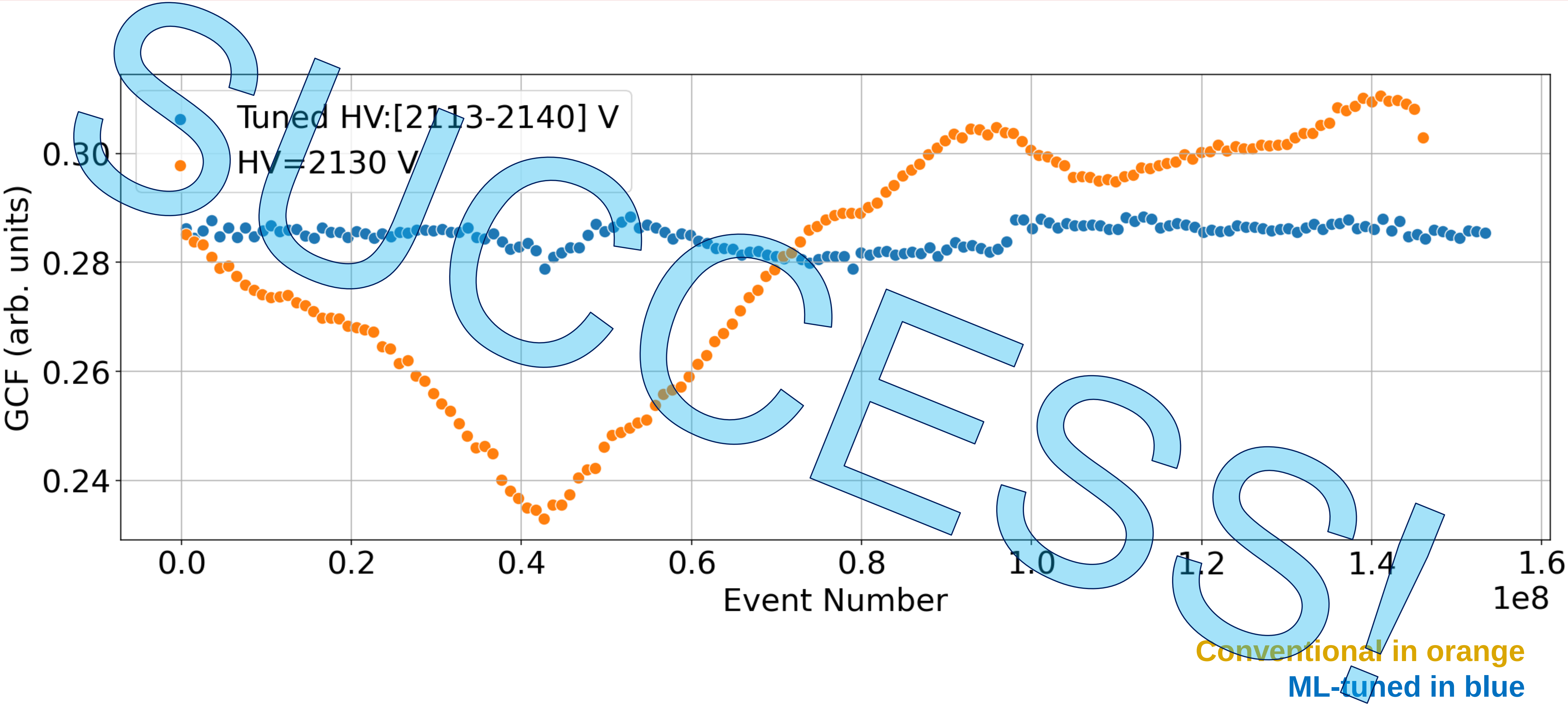
Cosmic Ray Experiment

- Split the CDC into **2 halves**
  - Leave one side at a **fixed HV (conventional)**
  - Let the **ML control the other**
    - **Autonomously** adjust HV every 5 min



Should see the ML system side's gains stabilized

Q2: Can we control HV to stabilize gain? Cosmic Ray Test Results



Conventional in orange
ML-tuned in blue

Trust and Uncertainty Quantification

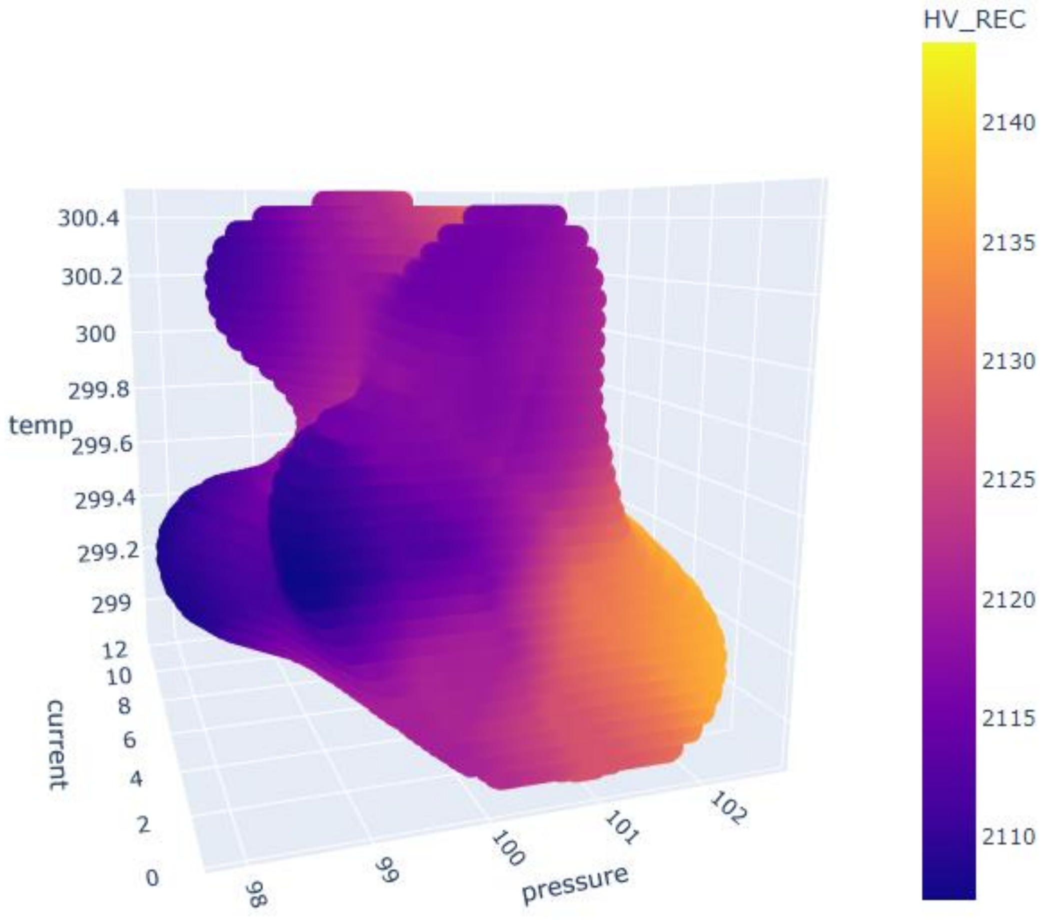
- Does the system **generalize for differing conditions**?
  - Do we **trust** interpolations and extrapolations?
  - First self-driving particle detector we know of – it **must be trusted**
  - **Uncertainty quantification (UQ)**
  - **Uncertainty quantification (UQ)**
  - **Uncertainty quantification (UQ)**
  - **…**

Uncertainty
by craiyon.com

Q3: Does the system generalize for differing conditions? An experiment

- **Charged Pion Polarizability (CPP)**
  - Used RoboCDC at the start of each run in the experiment (summer 2022)

- At the start of each run:
  - the HV setting was **predicted**, and CDC HV **controlled**.
  - Used Recommended HV
    - when standard deviation <= 3% ideal GCF
  - Used the closest “certain” HV in Euclidean distance on the uncertainty mesh
    - when standard deviation > 3% of GCF



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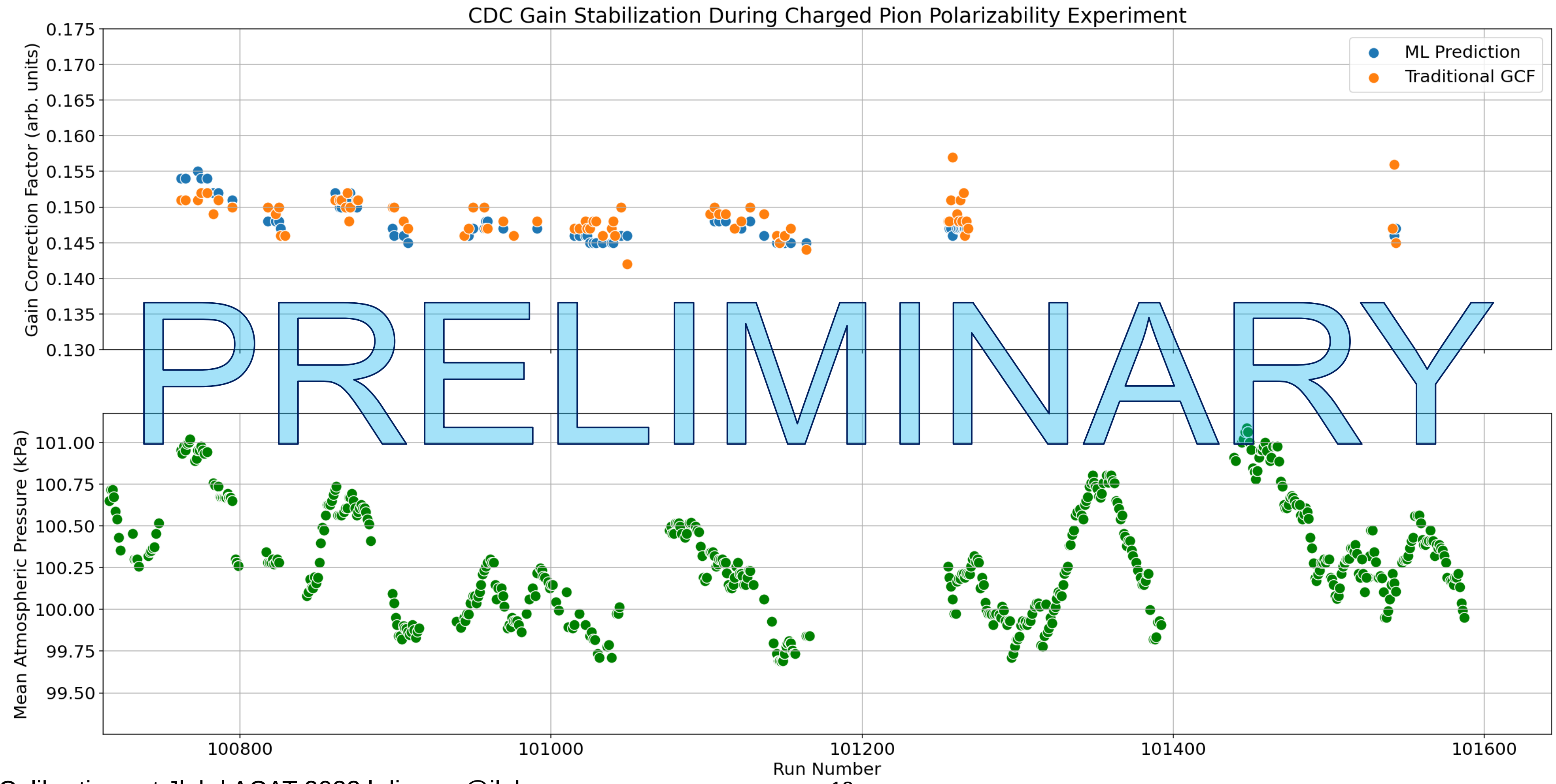

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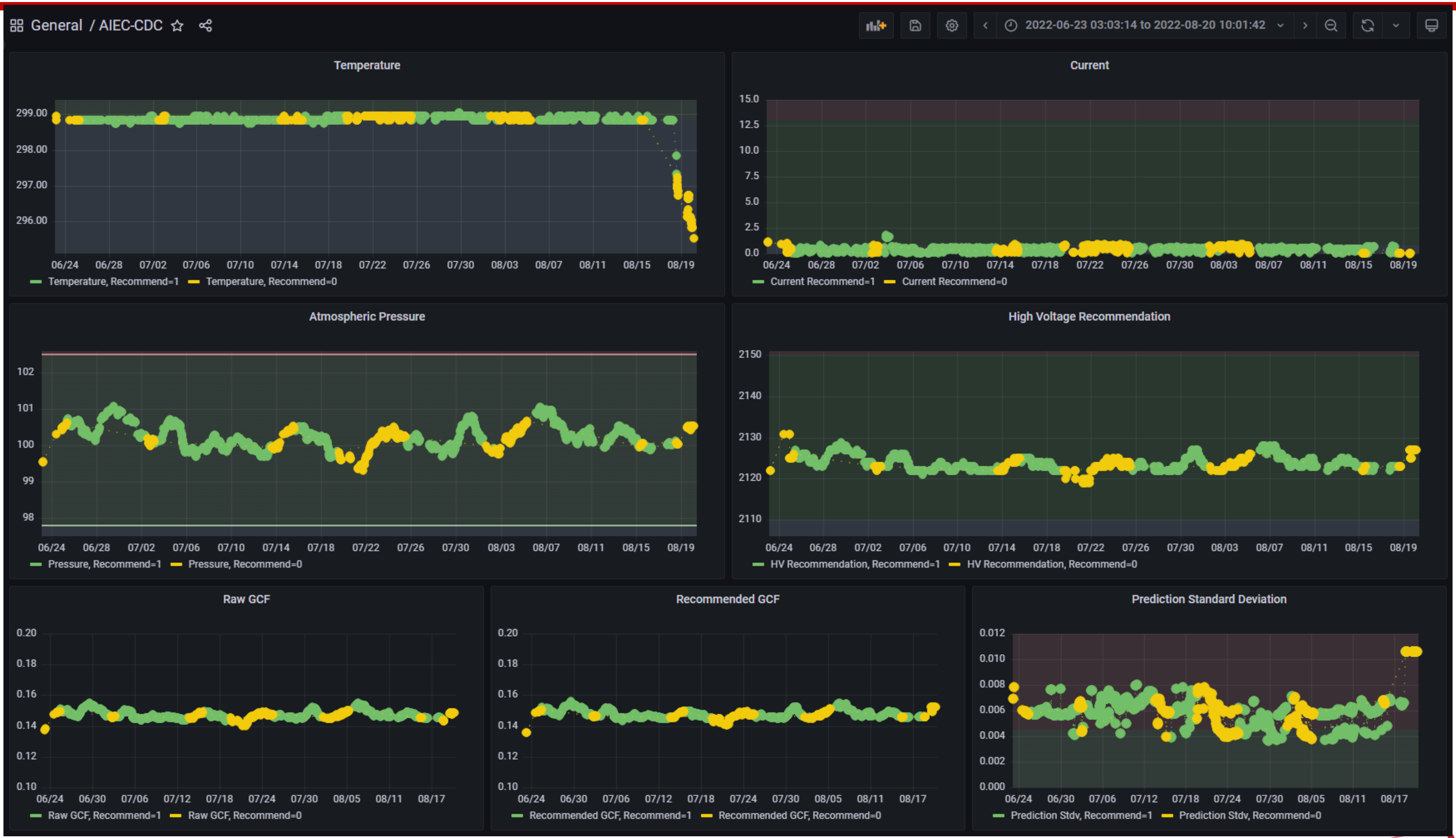

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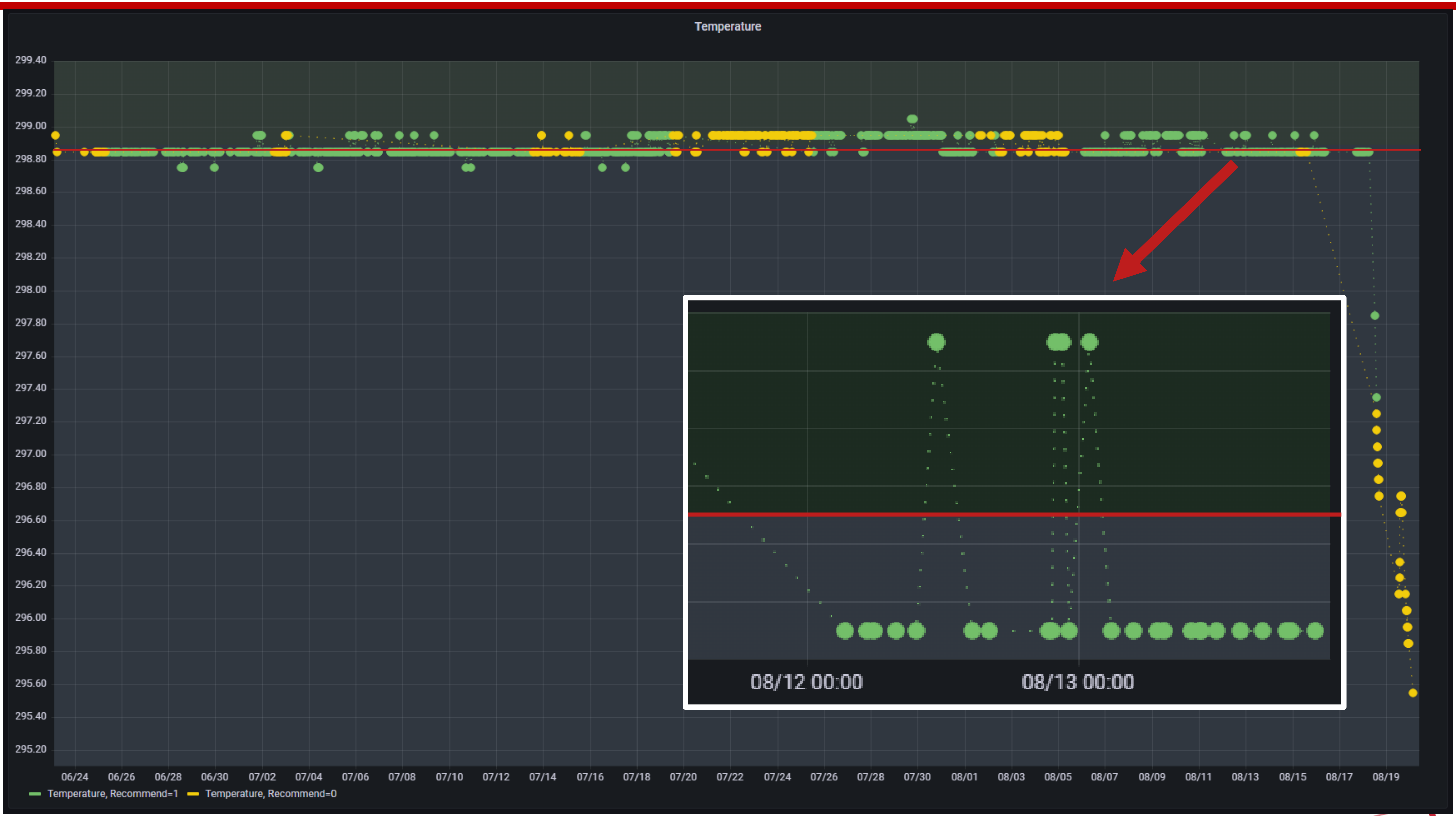

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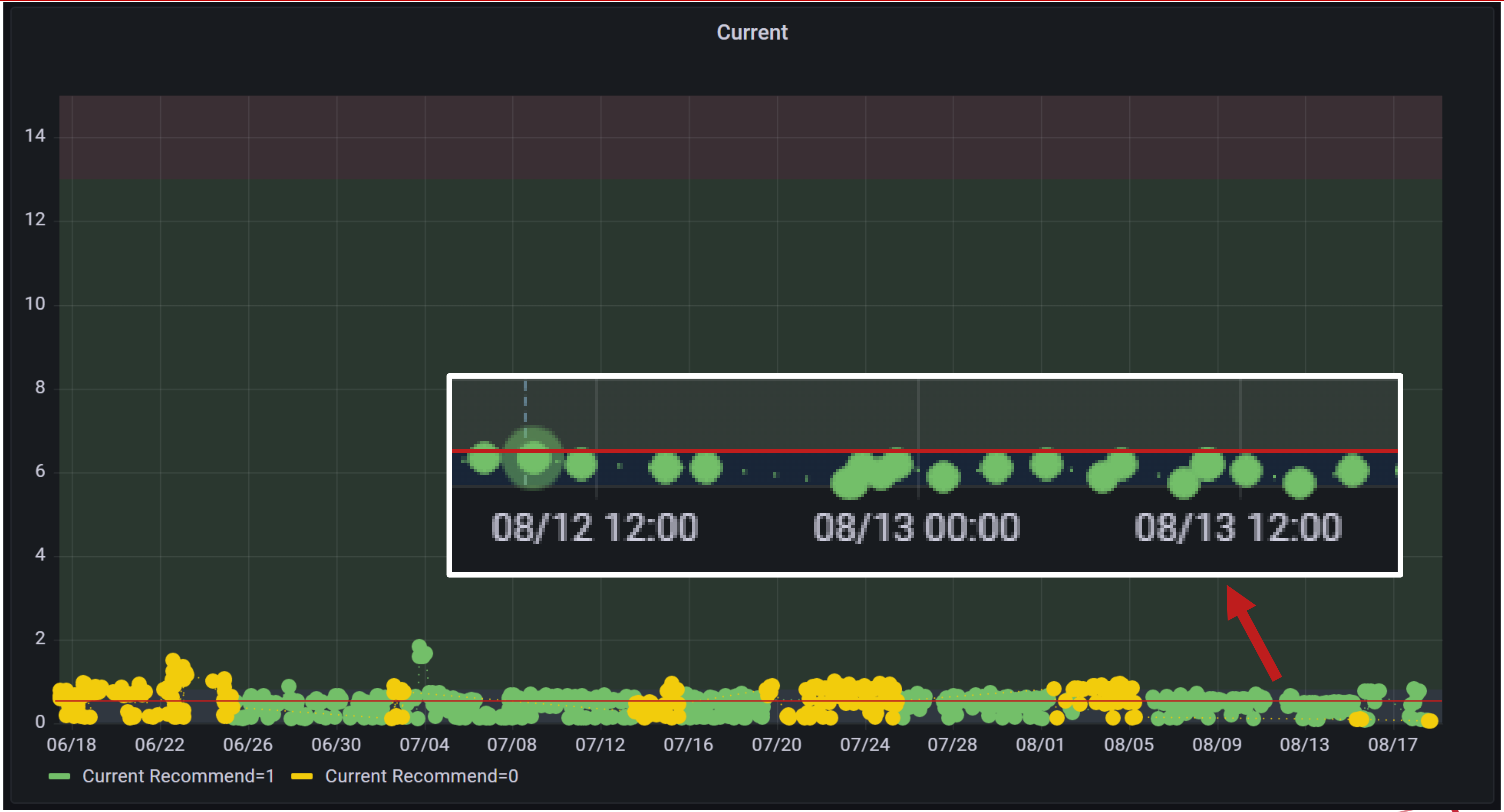

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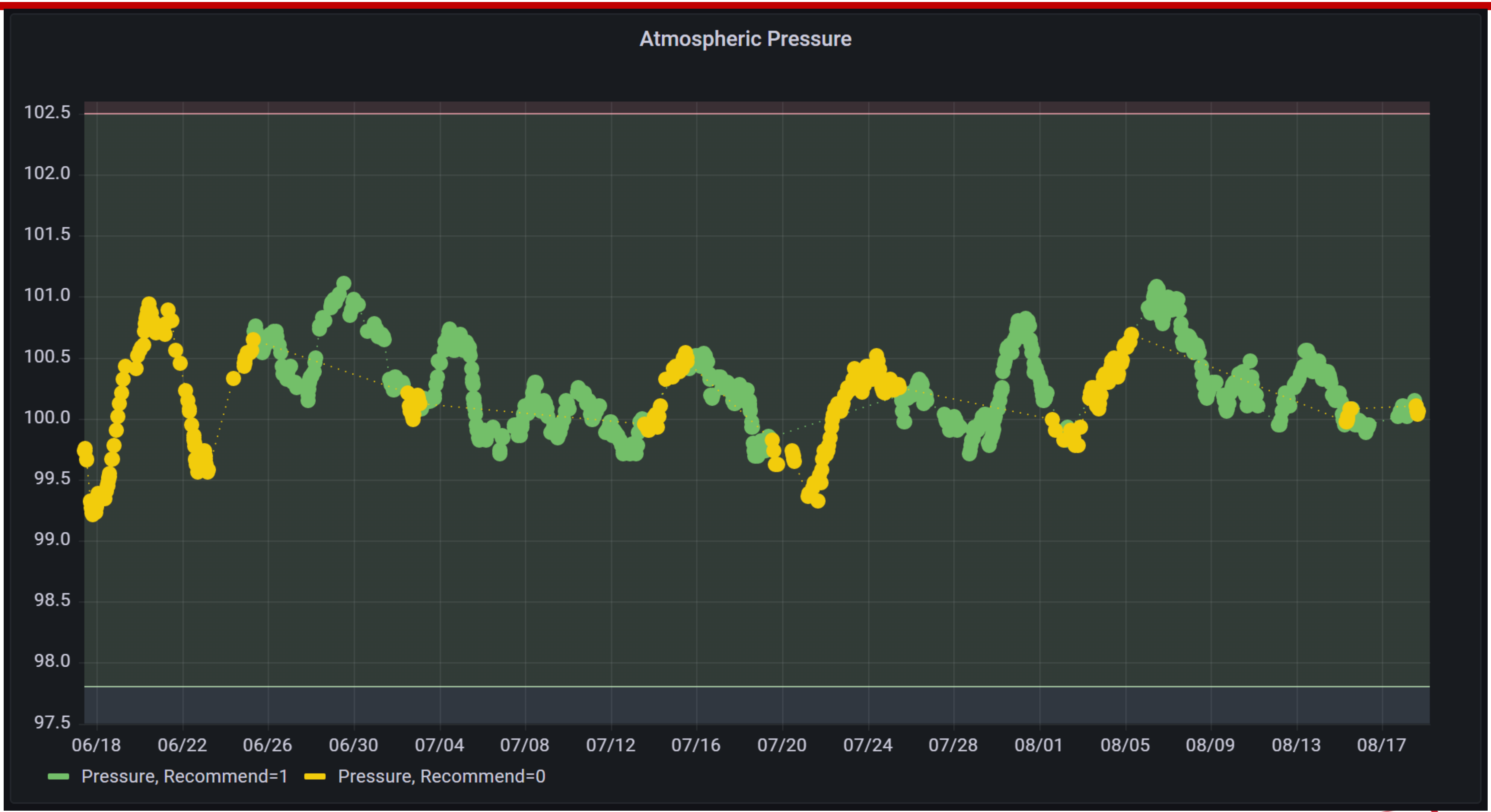

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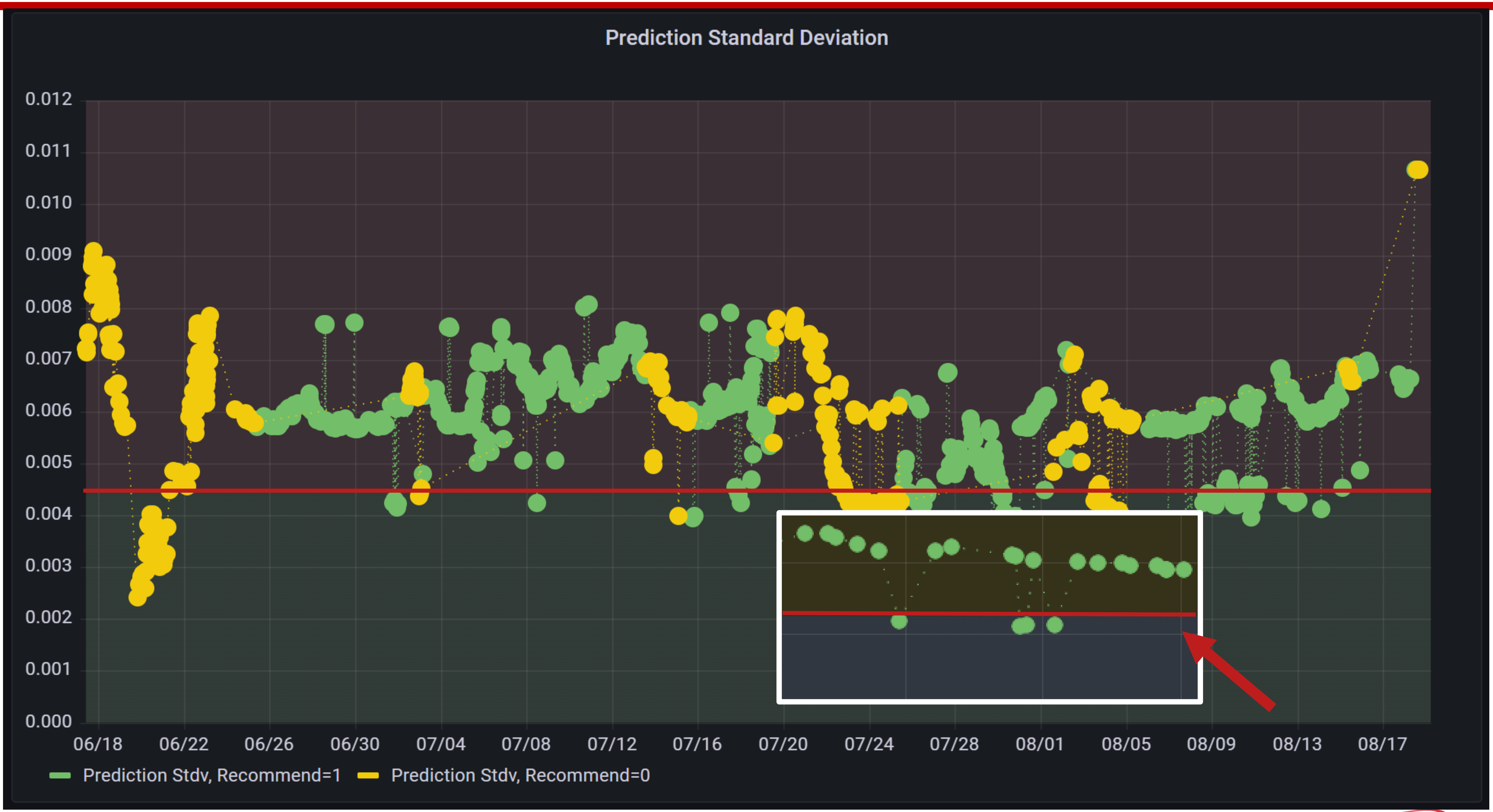

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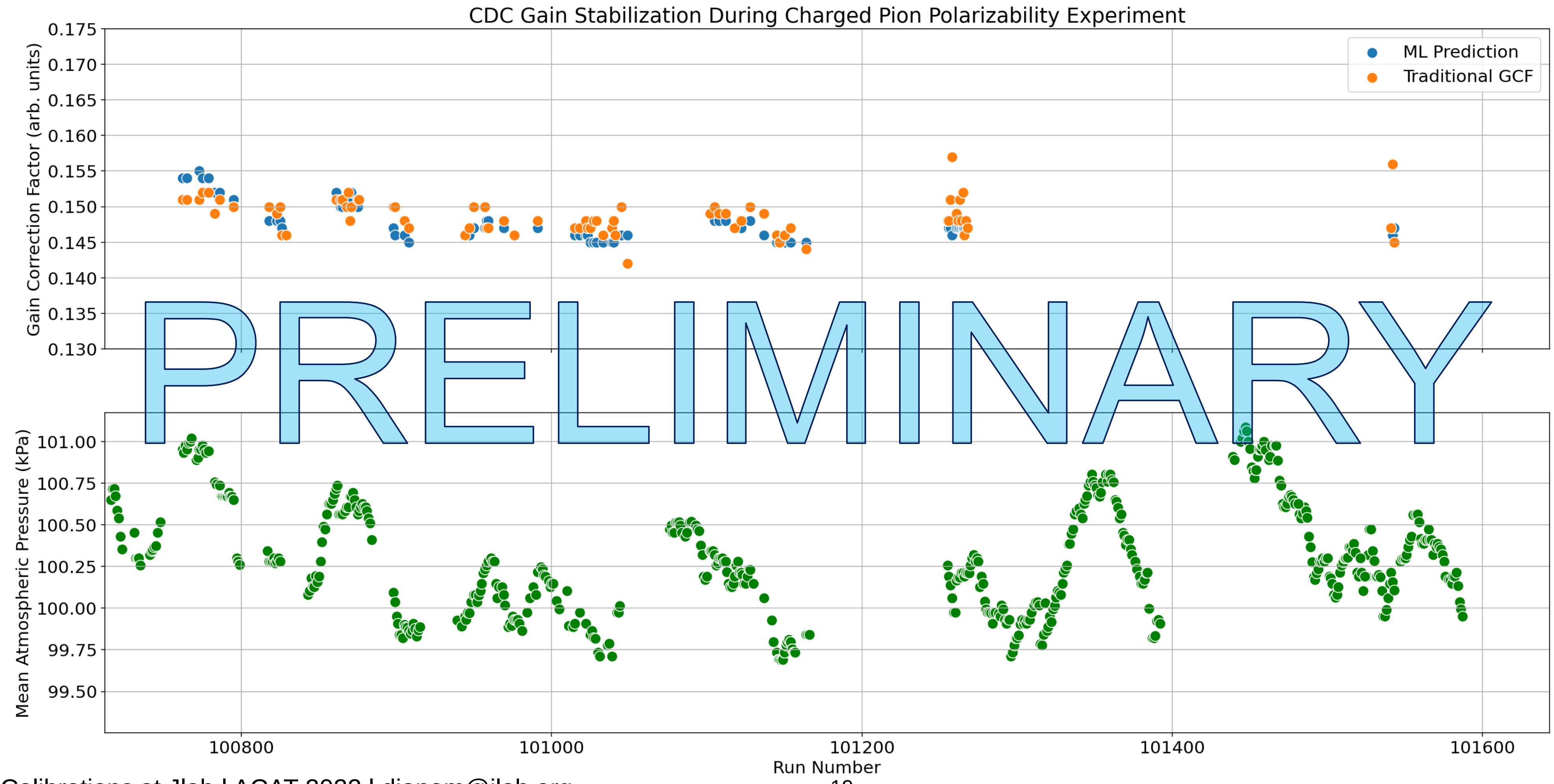

Acknowledgements

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GlueX acknowledges the support of several funding agencies and computing facilities: www.gluex.org/thanks.

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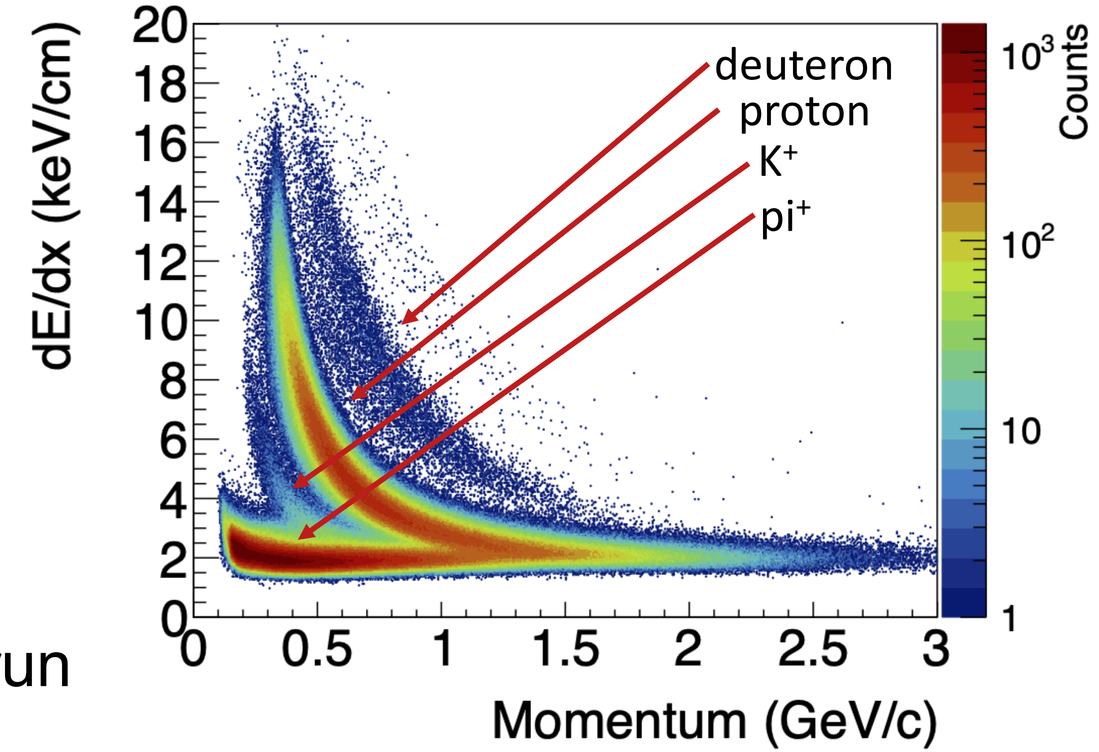
Thank you

Backup slides

CDC Calibrations

- Gain affects PID selections in analysis
  - Sensitive to environmental conditions
    - Atmospheric pressure
    - Temperature
  - Sensitive to experimental conditions
    - Beam conditions change with the experiment



- **Traditionally**:
  - GCF obtained from Landau fit to dE/dx
  - Calibration constants are generated per run
    - Approximately 2 hours of beam time

Q1: Can we predict GCFs? The Gaussian process model

ML Technique

Gaussian Process (GP)

- 3 features:
  - **atmospheric pressure** within the hall
  - **Gas temperature** within CDC
  - **CDC high voltage board current** -> a measure of charged particle track rate within the CDC
- 601 runs from 2020 and 2021 run periods
  - 536 and 65 respectively
  - Pressure balanced for low, medium and high pressure
  - 80 / 20 train test split
- **1 target**: the traditional Gain Correction Factor (**GCF**)
- GP calculates PDF over admissible functions that fit the data
- GP provides the standard deviation
  - we can exploit for uncertainty quantification (UQ)
- We used a popular GP kernel:
  - Radial Basis Function + White
  - Compared isotropic (1 length scale) and anisotropic (length scale per input variable) kernels

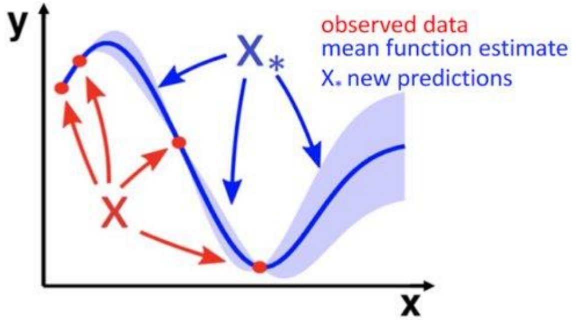


Illustration training a Gaussian process

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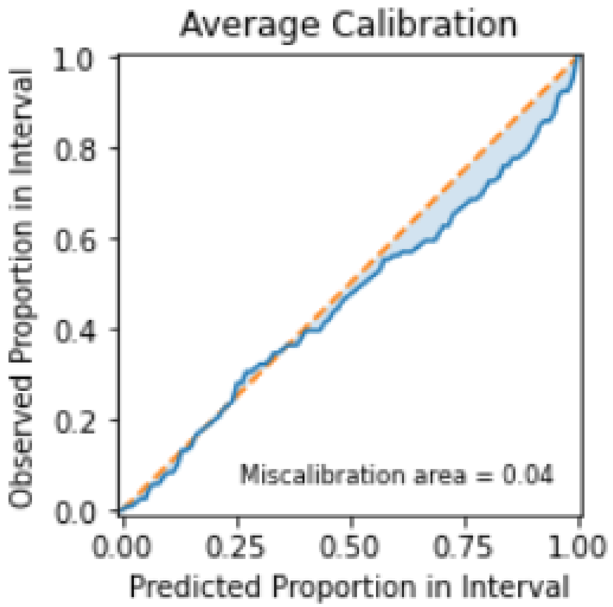
Q3: Does the system generalize for differing conditions? Evaluating Uncertainty

Do we trust our uncertainties?

- We checked our "uncertainty calibration" using **Uncertainty Toolbox**

https://github.com/uncertainty-toolbox/uncertainty-toolbox



- Predicted proportion of the test data expected to lie inside the prediction interval (x-axis)
- Proportion of the test data observed inside the prediction interval (y-axis)
- We are marginally underconfident with a 4% global miscalibration area.

For example, the 0.75 prediction interval aims to include observed values 75% of the time.

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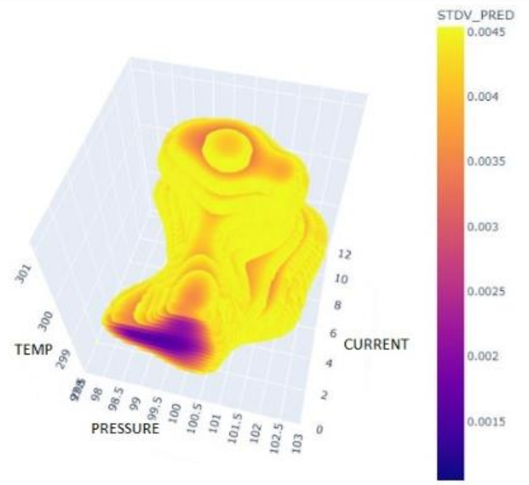
Table 1: Uncertainty Toolbox accuracy and average calibration metrics for GP models. Metrics were similar for both the isotropic and the anisotropic kernel.

RBF kernel (length scale(s))	noise kernel variance	R^2	RMSE	MACE	RMSCE
isotropic (1.412)	0.0154	0.97	0.002	0.040	0.051
anisotropic (1.400,1.17,1.71)	0.0153	0.97	0.002	0.038	0.049

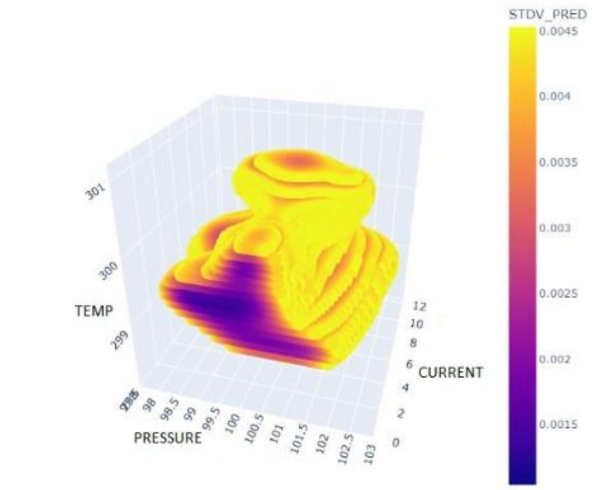
Q3: Does the system generalize for differing conditions? Uncertainty quantification

- The Gaussian process provides uncertainty quantification.
  - Important not to set the HV when uncertain, but how do we use uncertainty?
- First, we thought of an uncertainty threshold "surface".

Few low current training runs

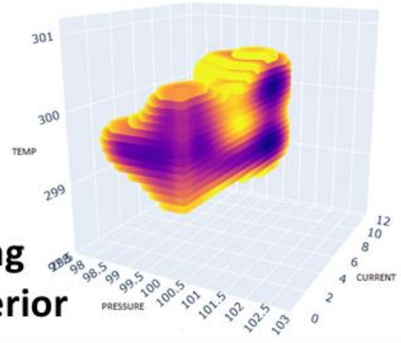


Added low current training runs



Plots of a grid mesh of the input feature space for predictions with Gaussian process standard deviation <= 3% of the ideal GCF:

- As expected, the "surface" increases for low current runs, when more low current runs were added to training data.



With low current training runs, displaying the interior of certainty "surface"

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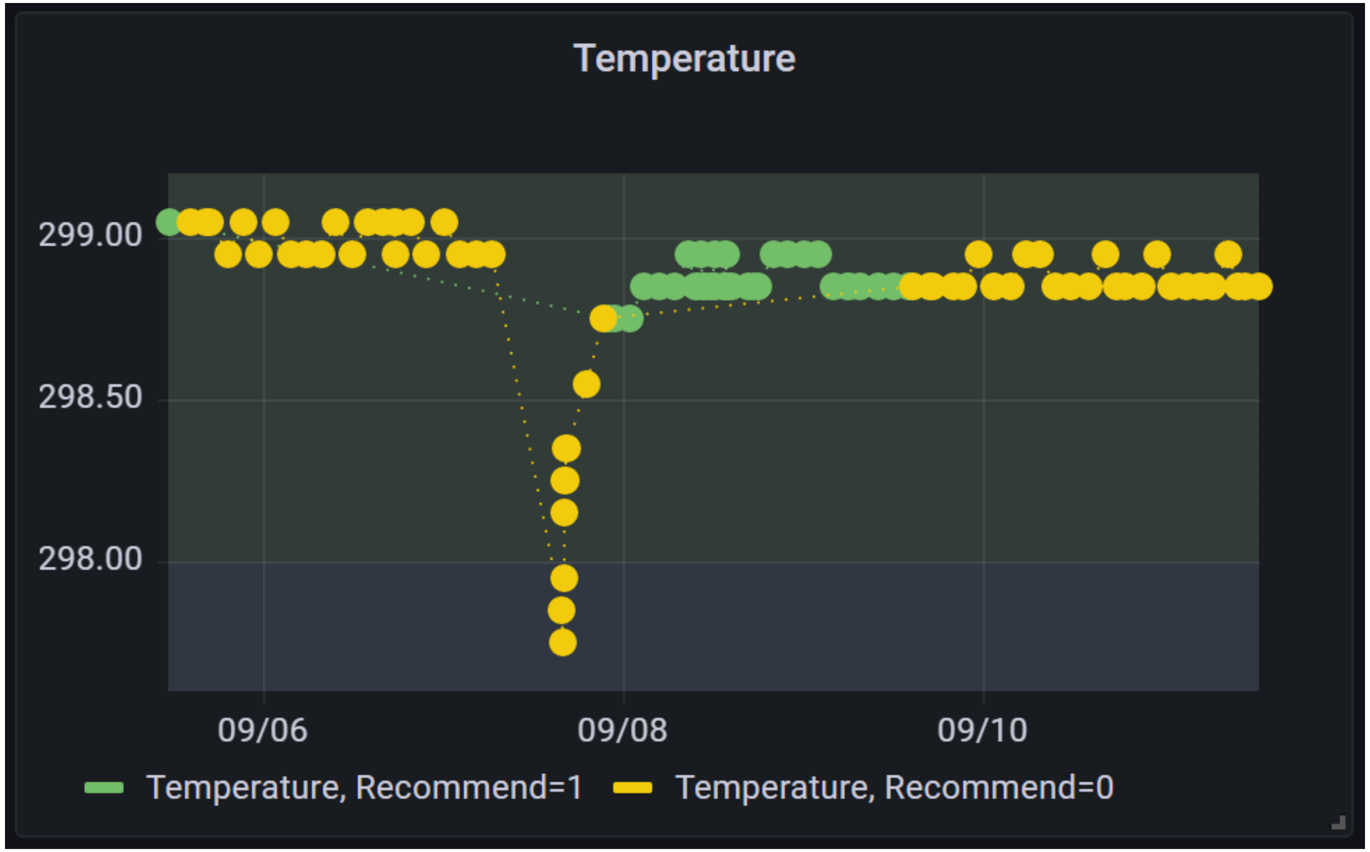
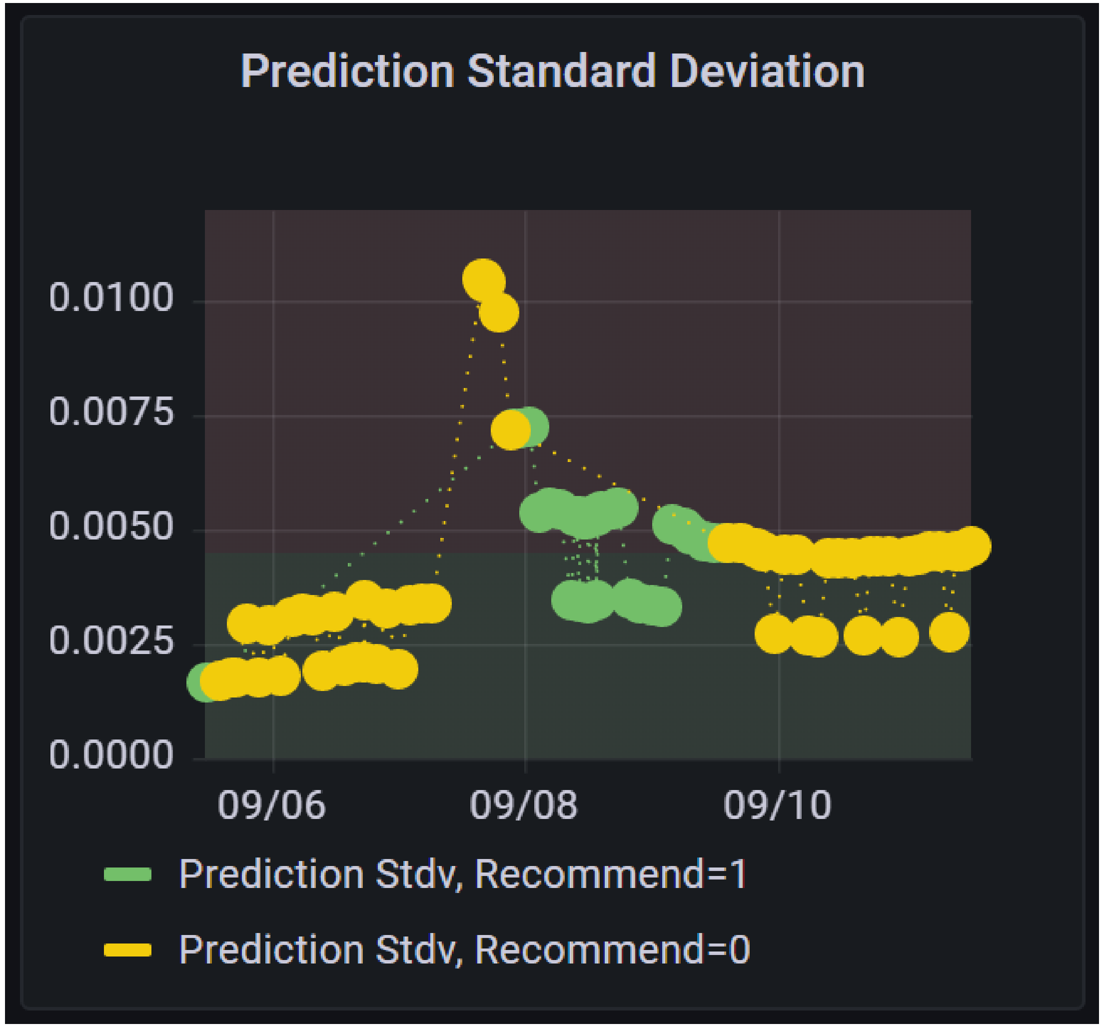
Q3: Does the system generalize for differing conditions? CPP





Q3: Does the system generalize for differing conditions? PrimeX

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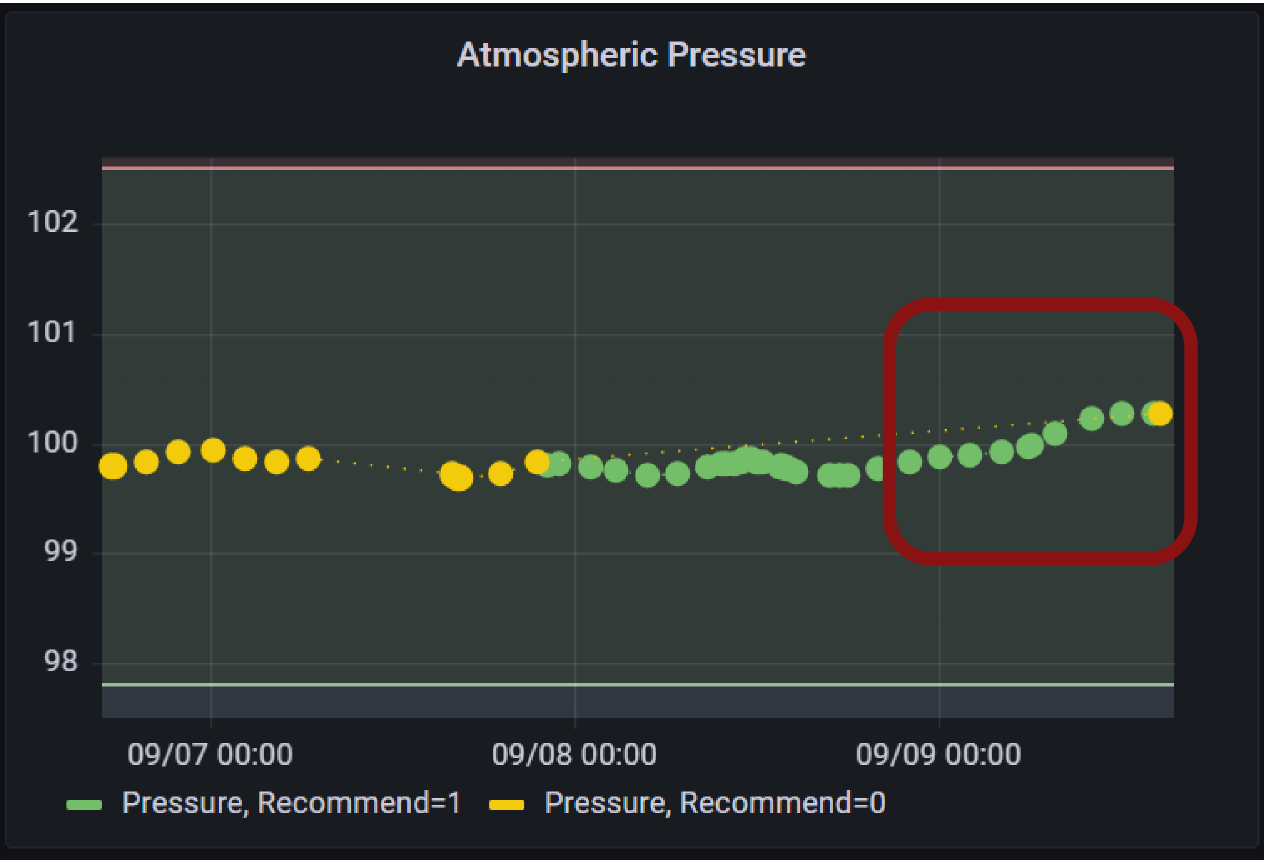
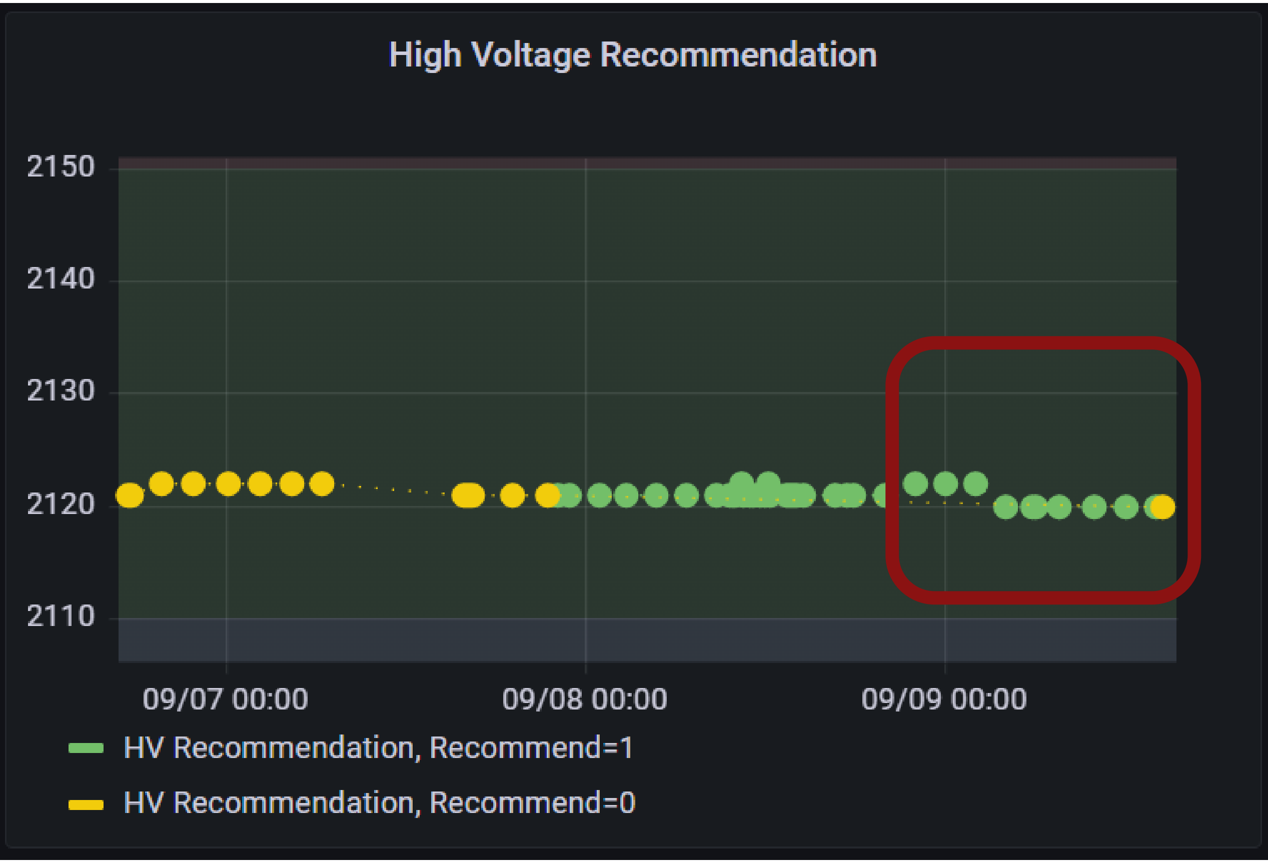
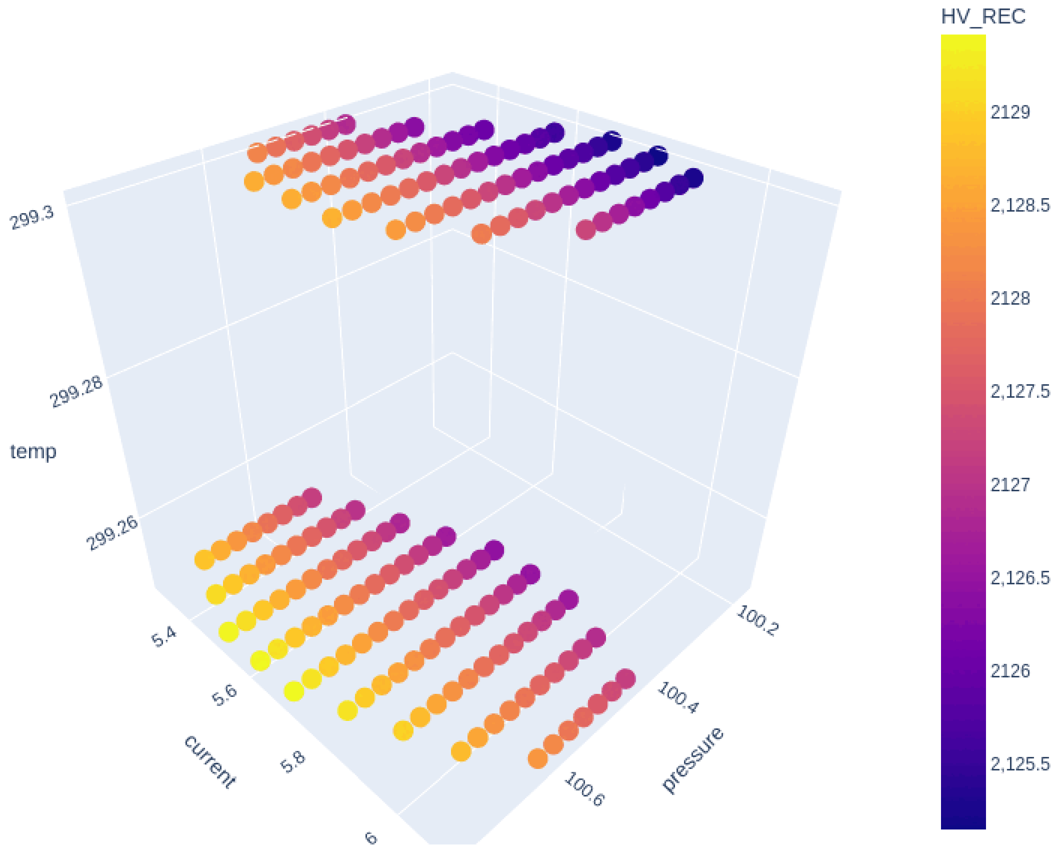




How Can We Use Uncertainty Quantification?

Can we use uncertainty to guide new data acquisition?

Temp vs. Current vs. Pressure for different uncertainties



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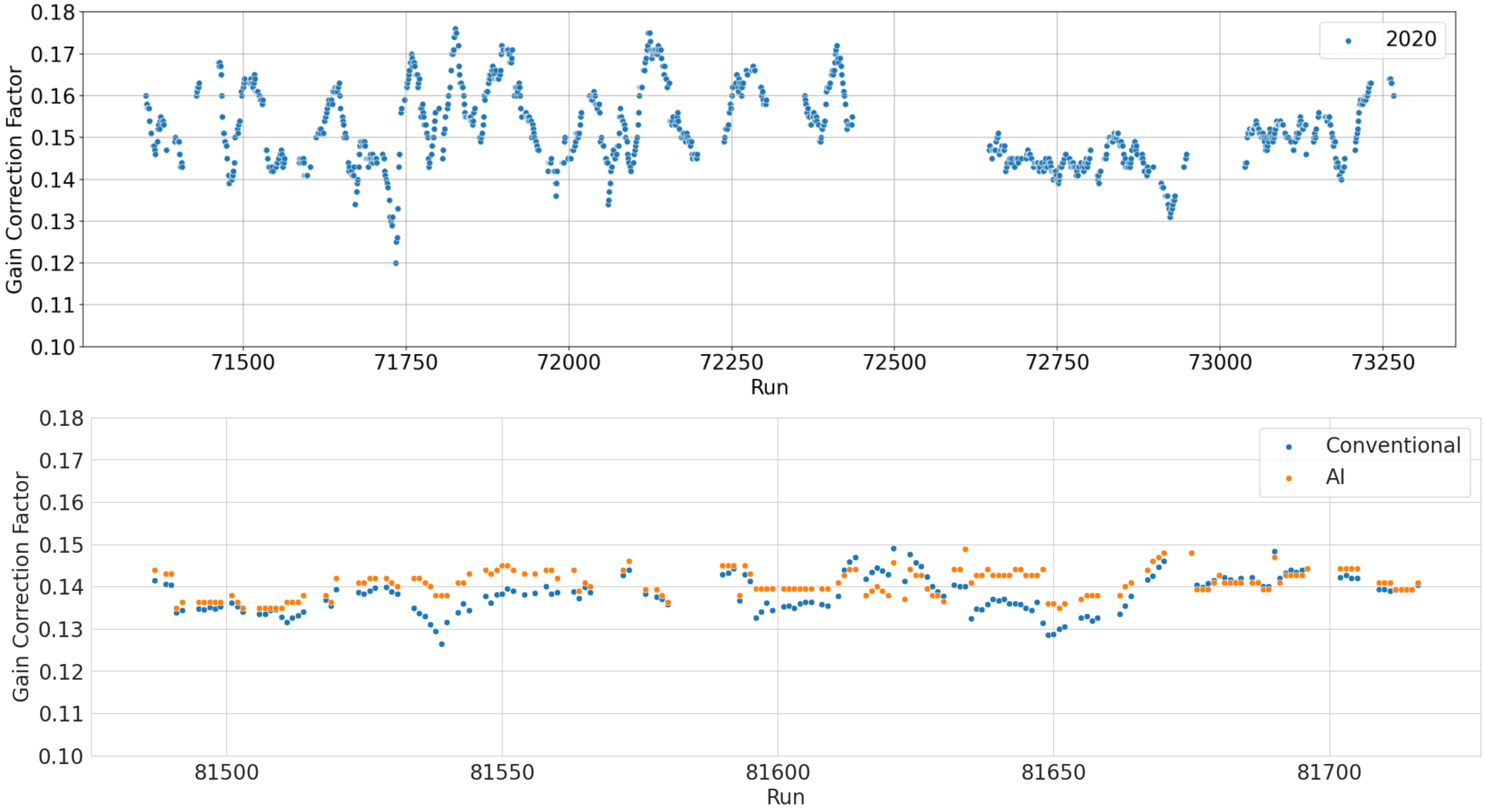
Calibrations with AI: Gain

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



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Summary and Outlook

- Ability to predict existing calibration constants using GPR models using environmental and detector specific data
- Compared calibrations with conventional and AI-generated starting values
- System is implemented and has been used for 3 experiment run periods.
- Application to additional drift chambers in progress

This work was supported by the US DOE as Lab 20-2261

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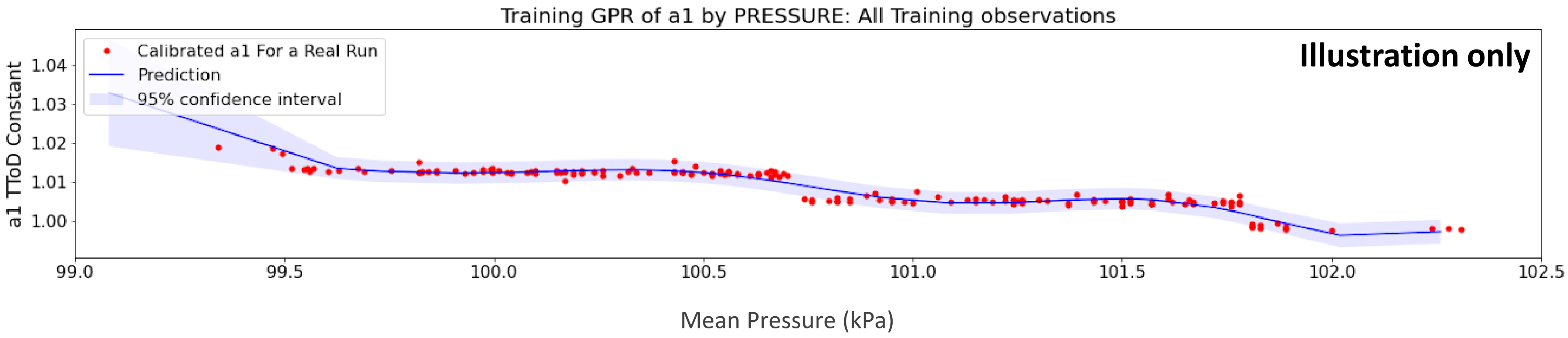
GlueX acknowledges the support of several funding agencies and computing facilities: www.gluex.org/thanks

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:

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



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

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

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

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

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

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