Gaussian process for calibration and control of GlueX Central Drift Chamber

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

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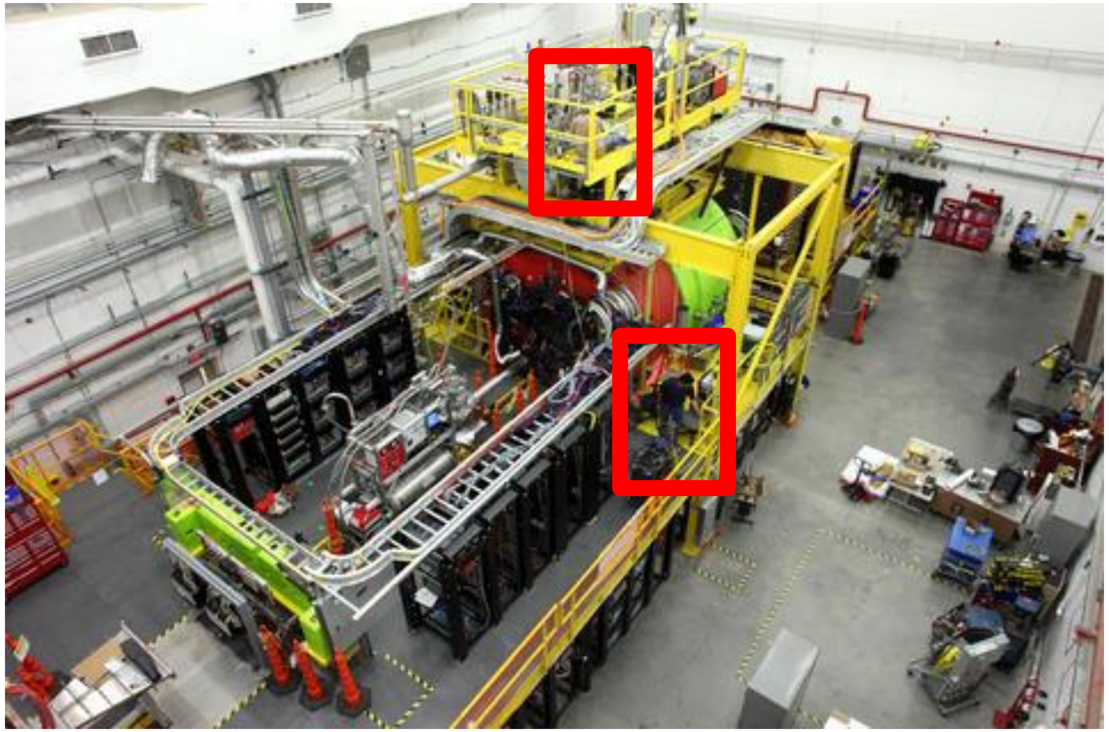
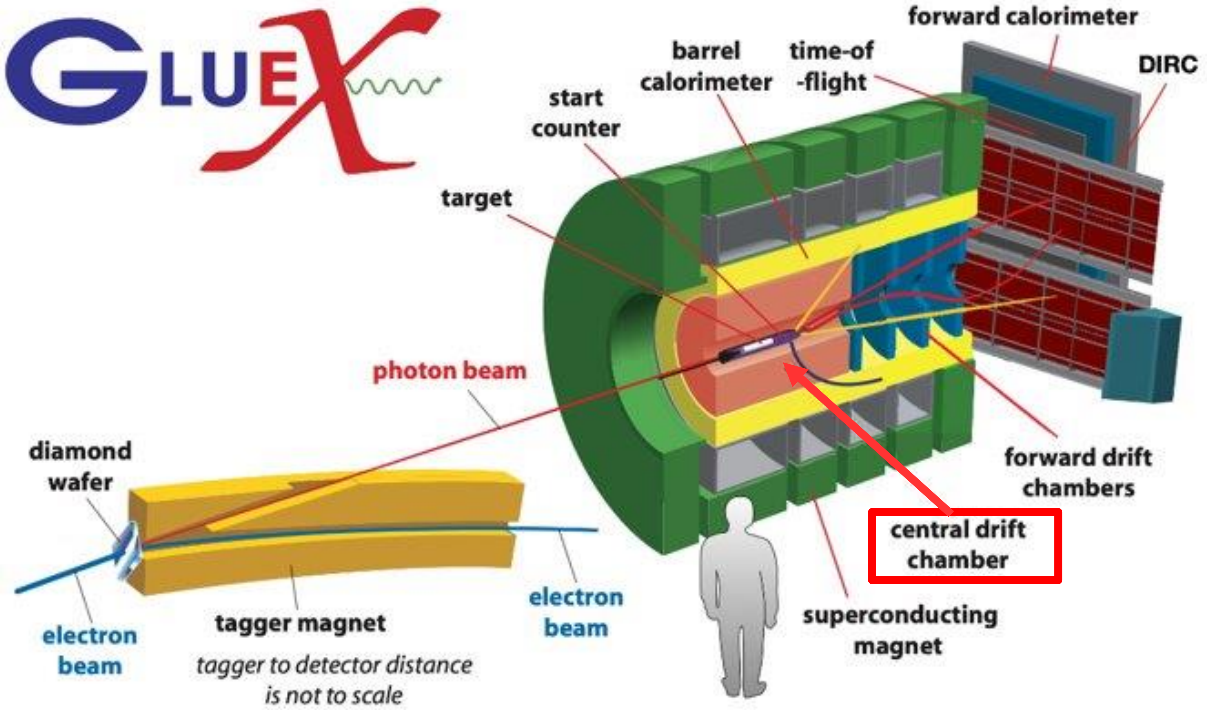
ACAT 2022

Jefferson Lab
EPSCI Experimental Physics Software and Computing Infrastructure
Carnegie Mellon University
U.S. Department of Energy Office of Science
JSA

GlueX Experiment at Jefferson Lab

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

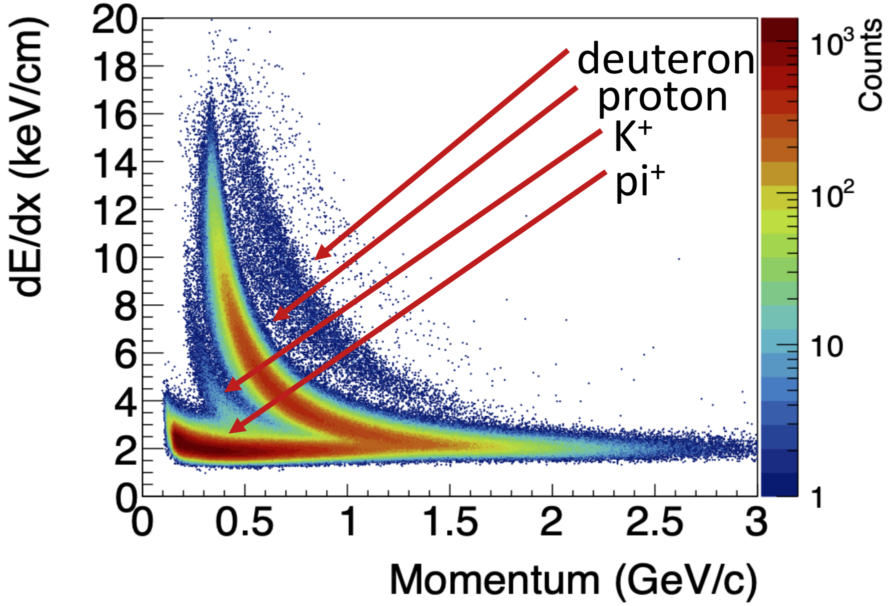




GlueX Central Drift Chamber (CDC)

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

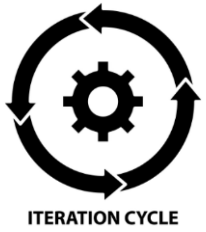
- **Used to detect and track charged particles with momenta p > 0.25 GeV/c**
- **Use for particle identifcation**
- **dE/dx**: measure of deposited energy per unit of track length
  - 1.5 m long x 1.2 m diameter cylinder
  - 3522 anode wires at 2125 V inside 1.6 cm diameter straws
  - 50:50 Ar/CO_2 gas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



Motivation: Conventional vs. Online, ML Calibration Paradigms

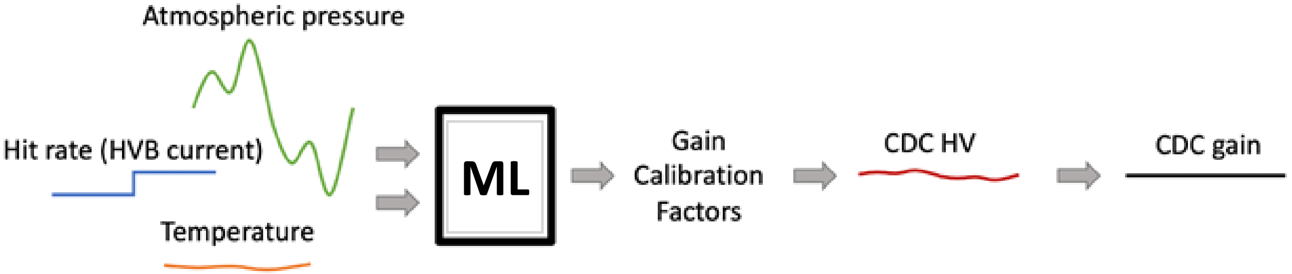
Conventional

- **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



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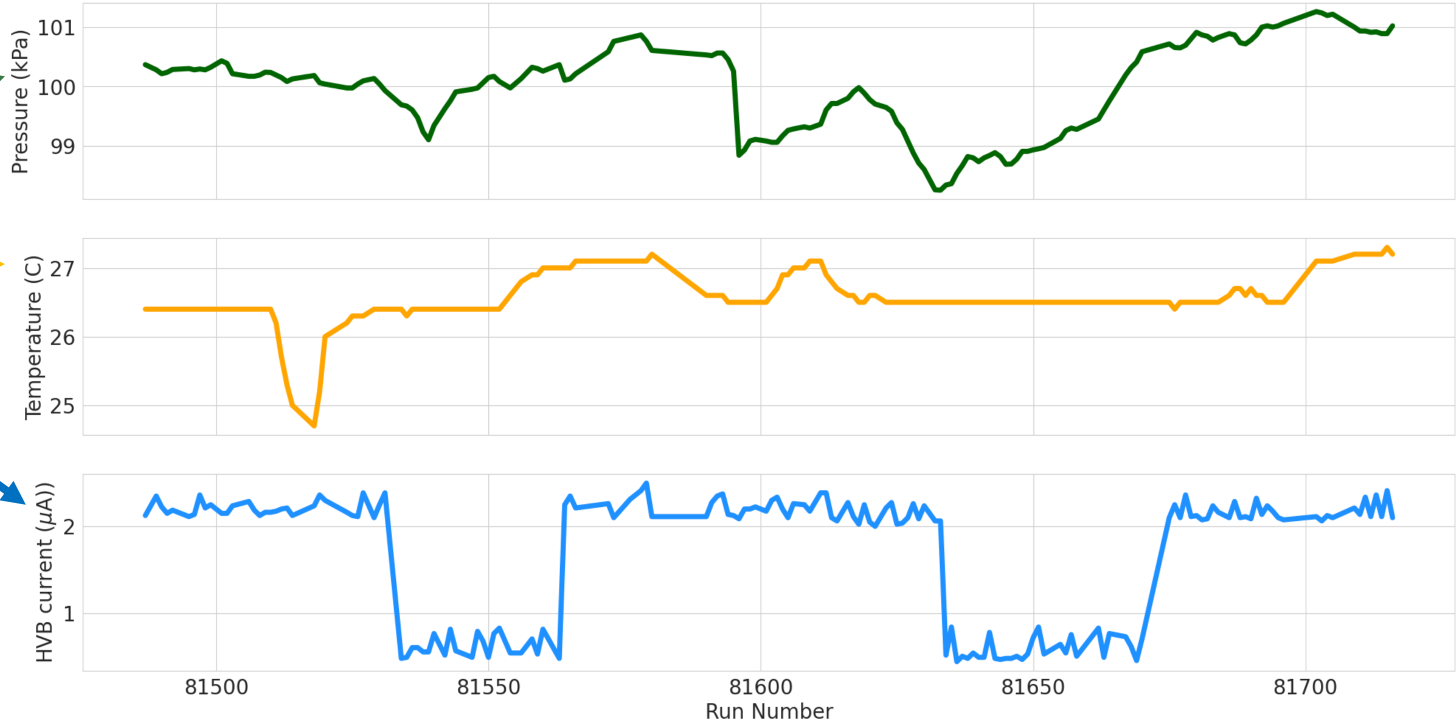
Q1: Can we predict GCFs? Input variables

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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Q1: Can we predict GCFs? The Gaussian process model

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

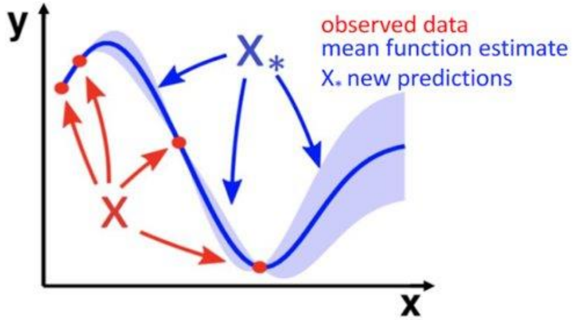


Illustration training a Gaussian process

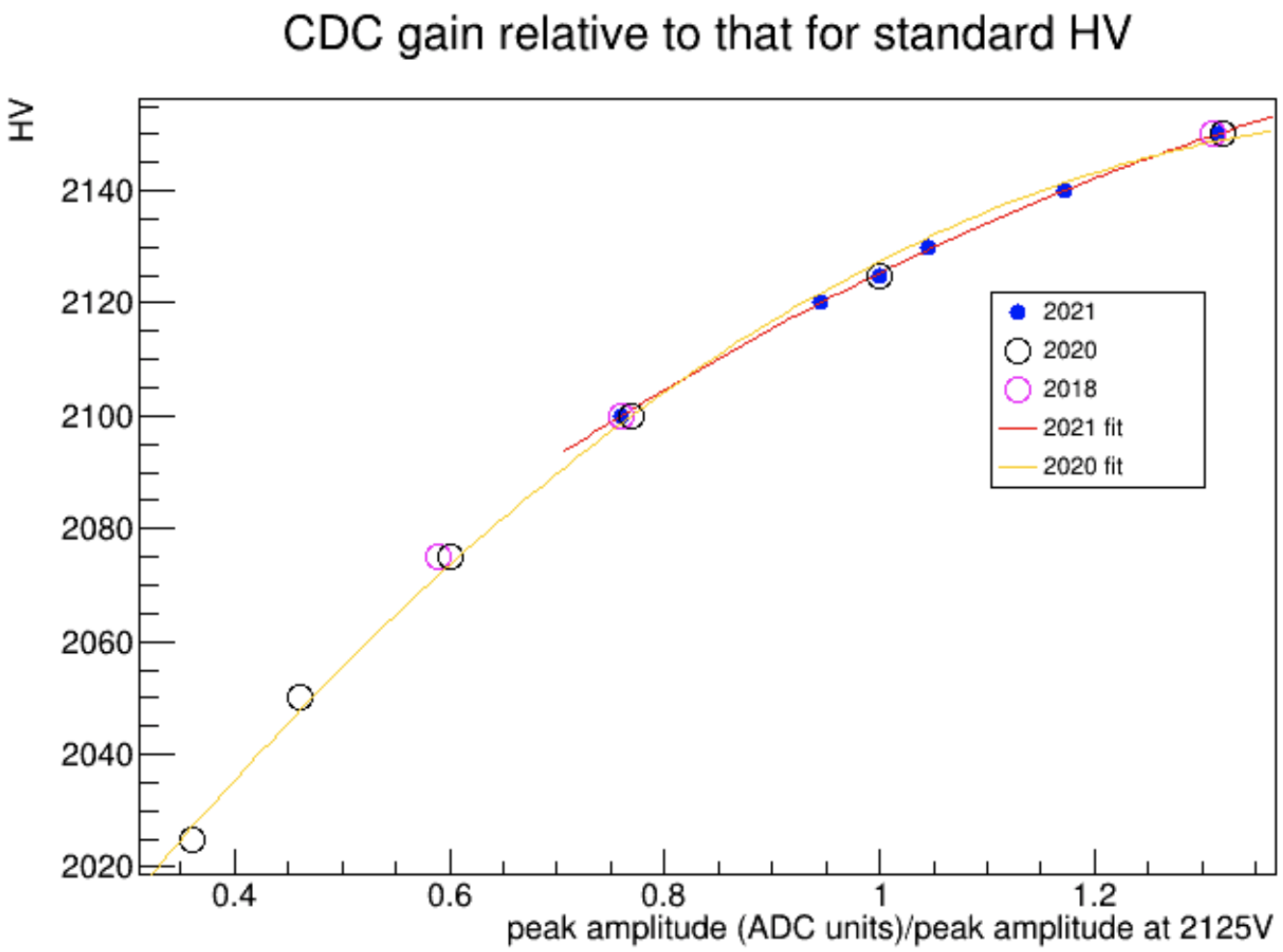
We can exploit the standard deviation for uncertainty quantification (UQ).

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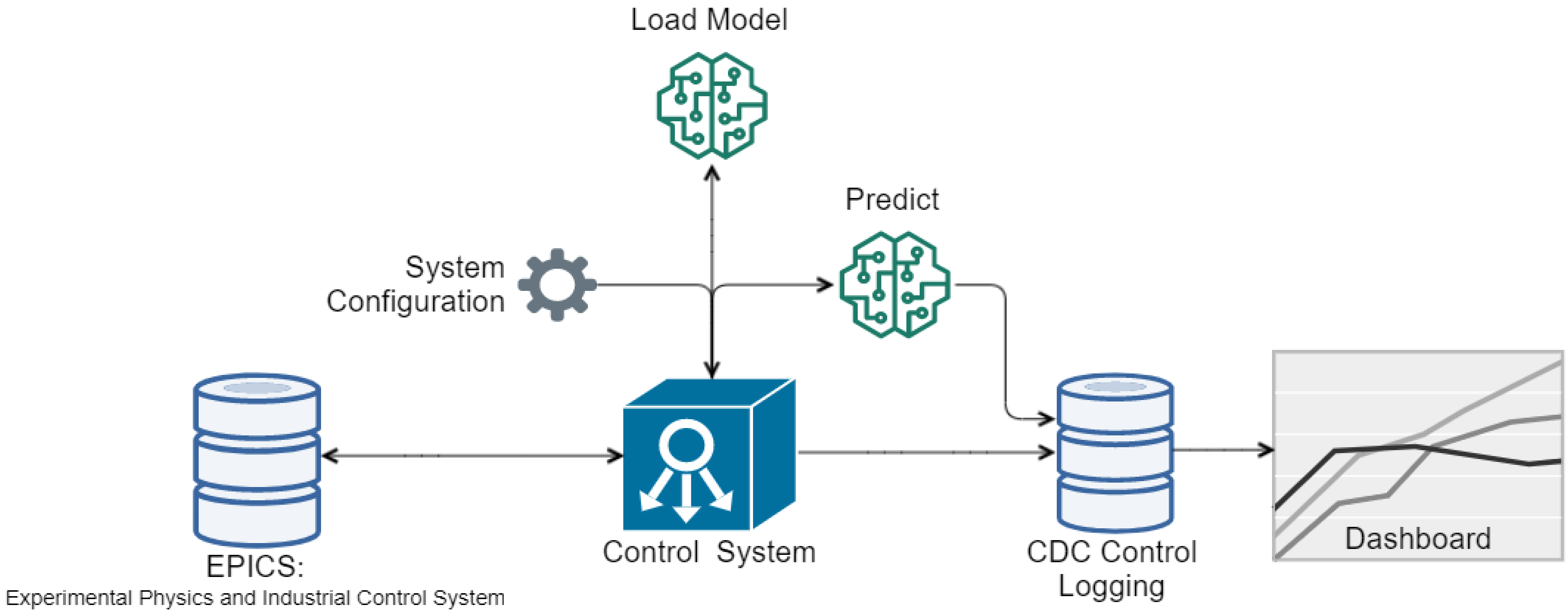
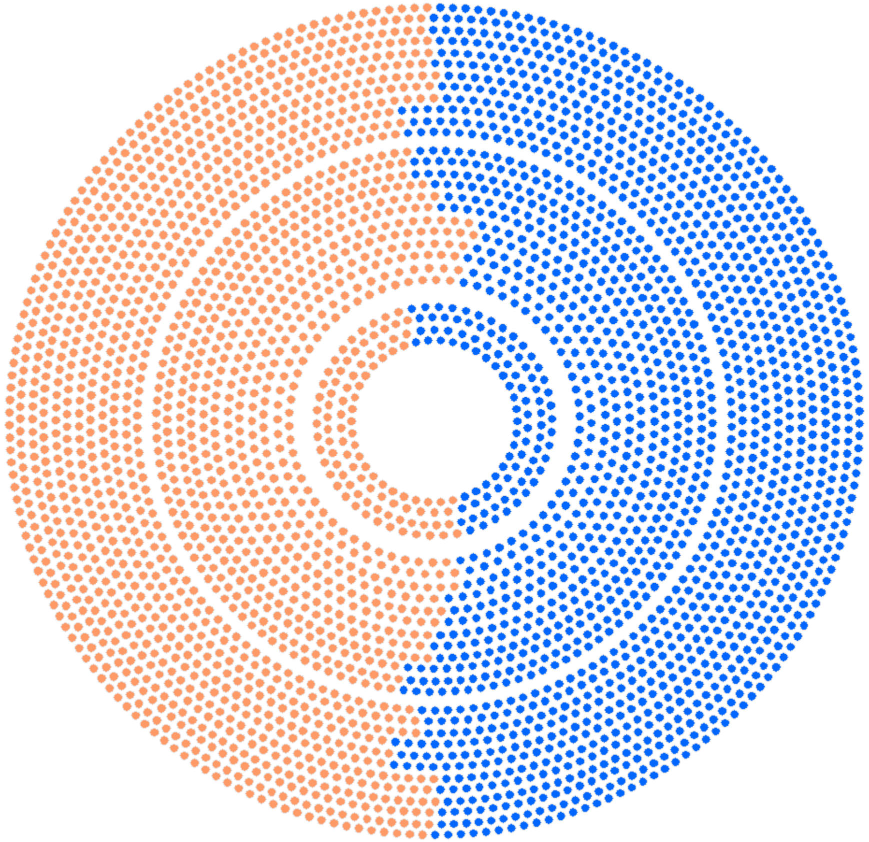
Q2: Can we control HV to stabilize gain? RoboCDC, a modular ML system for control



Q2: Can we control HV to stabilize gain? Does RoboCDC work?

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



Conventional in orange
ML-tuned in blue

Should see the **ML side's** gains stabilized

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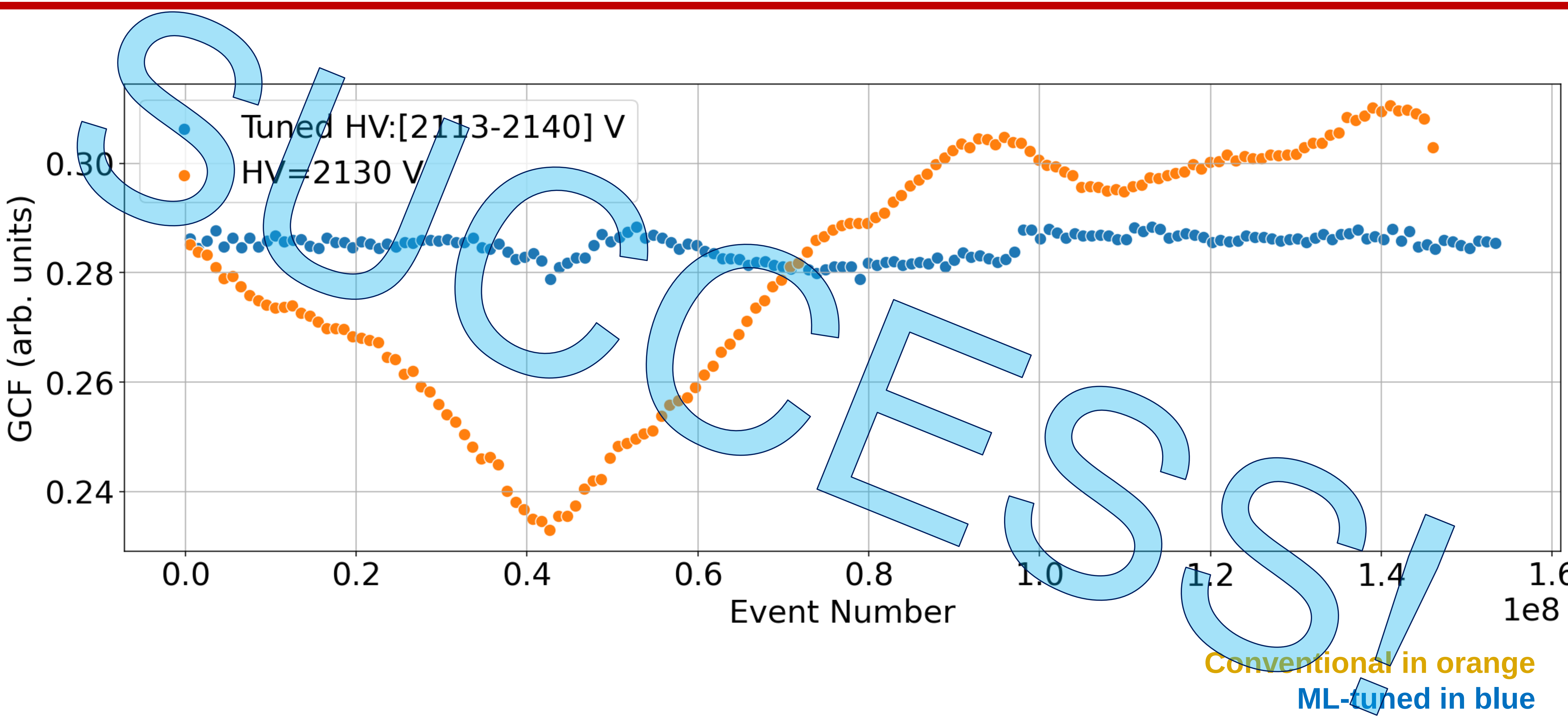
Q2: Can we control HV to stabilize gain? Cosmic Ray Test Results



Conventional in orange
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Trust and Uncertainty Quantification

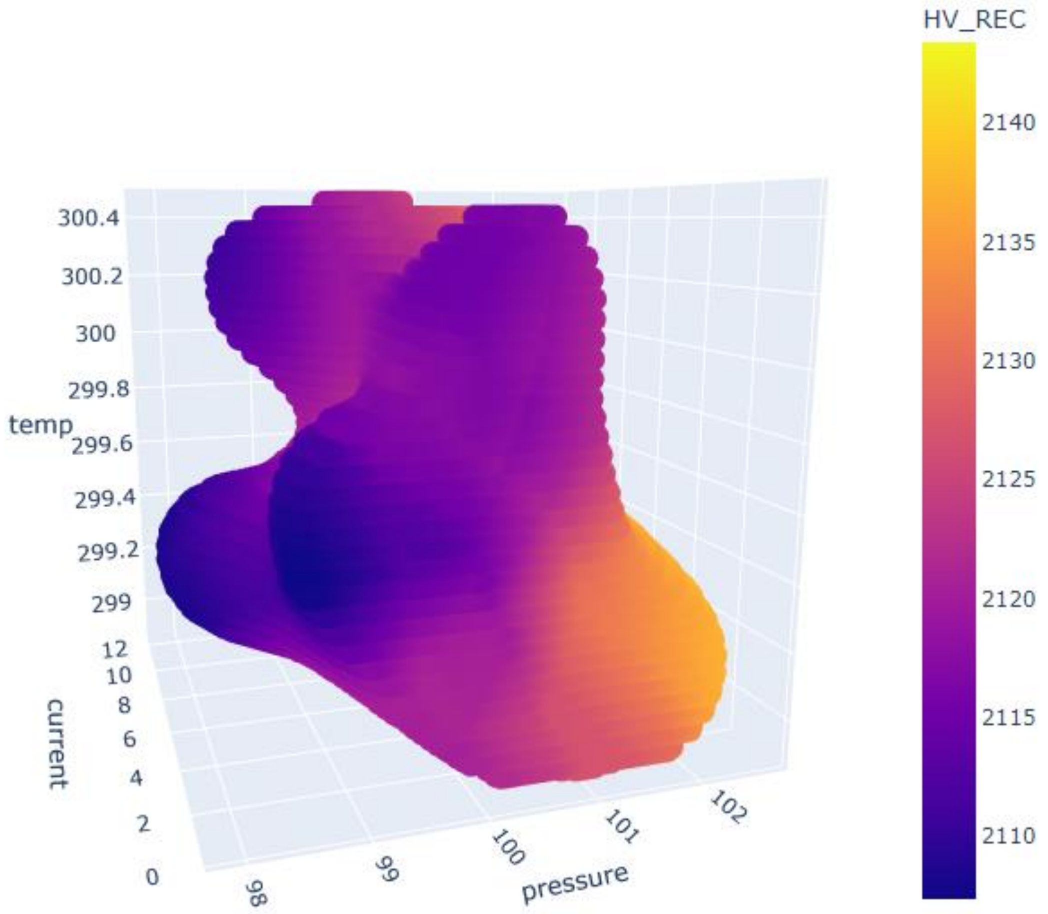
- Does the system **generalize for differing conditions**?
  - Do we **trust** interpolations and extrapolations?
  - First self-driving particle detector we know of – it **must be trusted**
  - **Uncertainty quantification (UQ)**
  - **Uncertainty quantification (UQ)**
  - **Uncertainty quantification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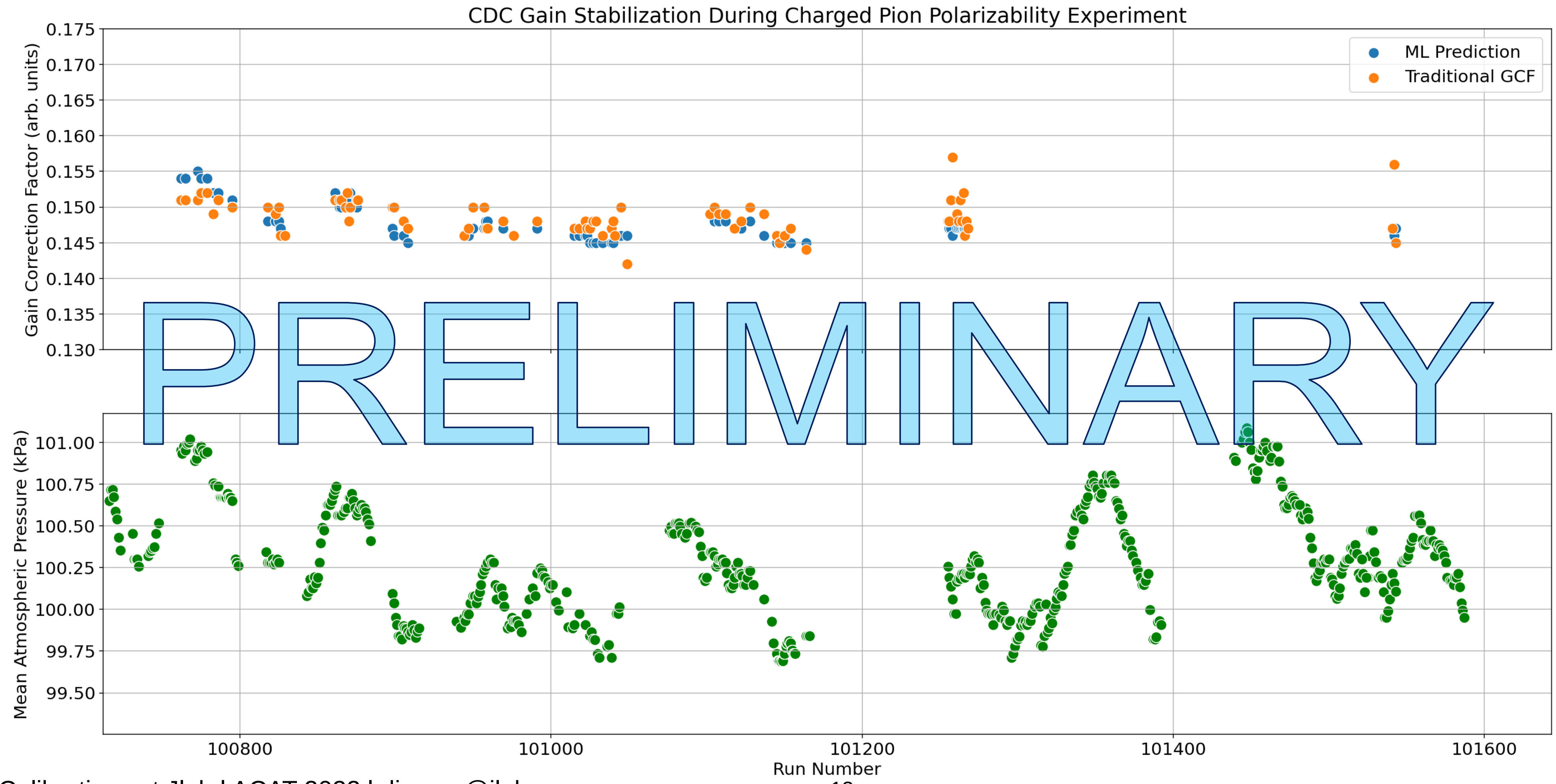

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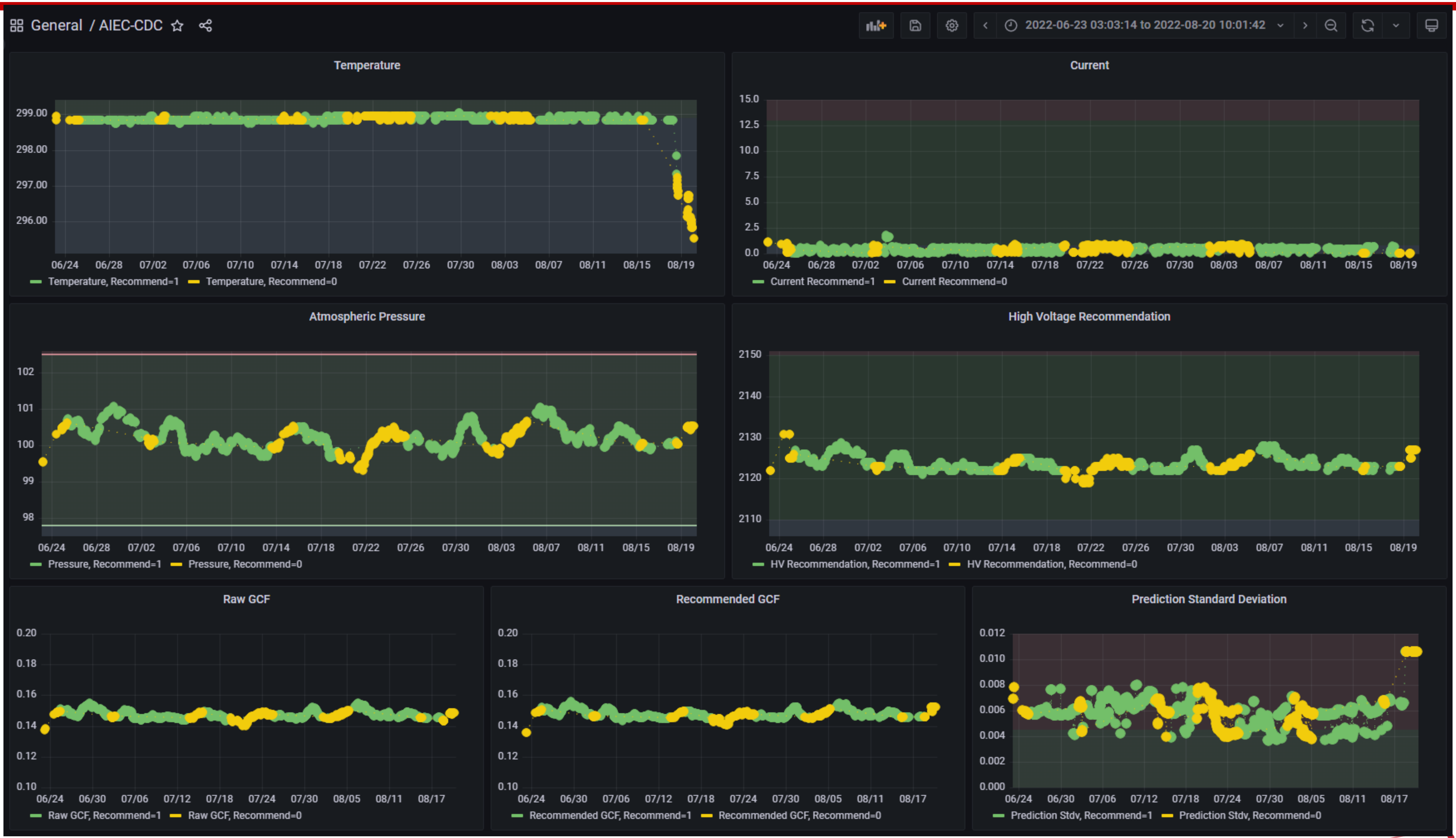

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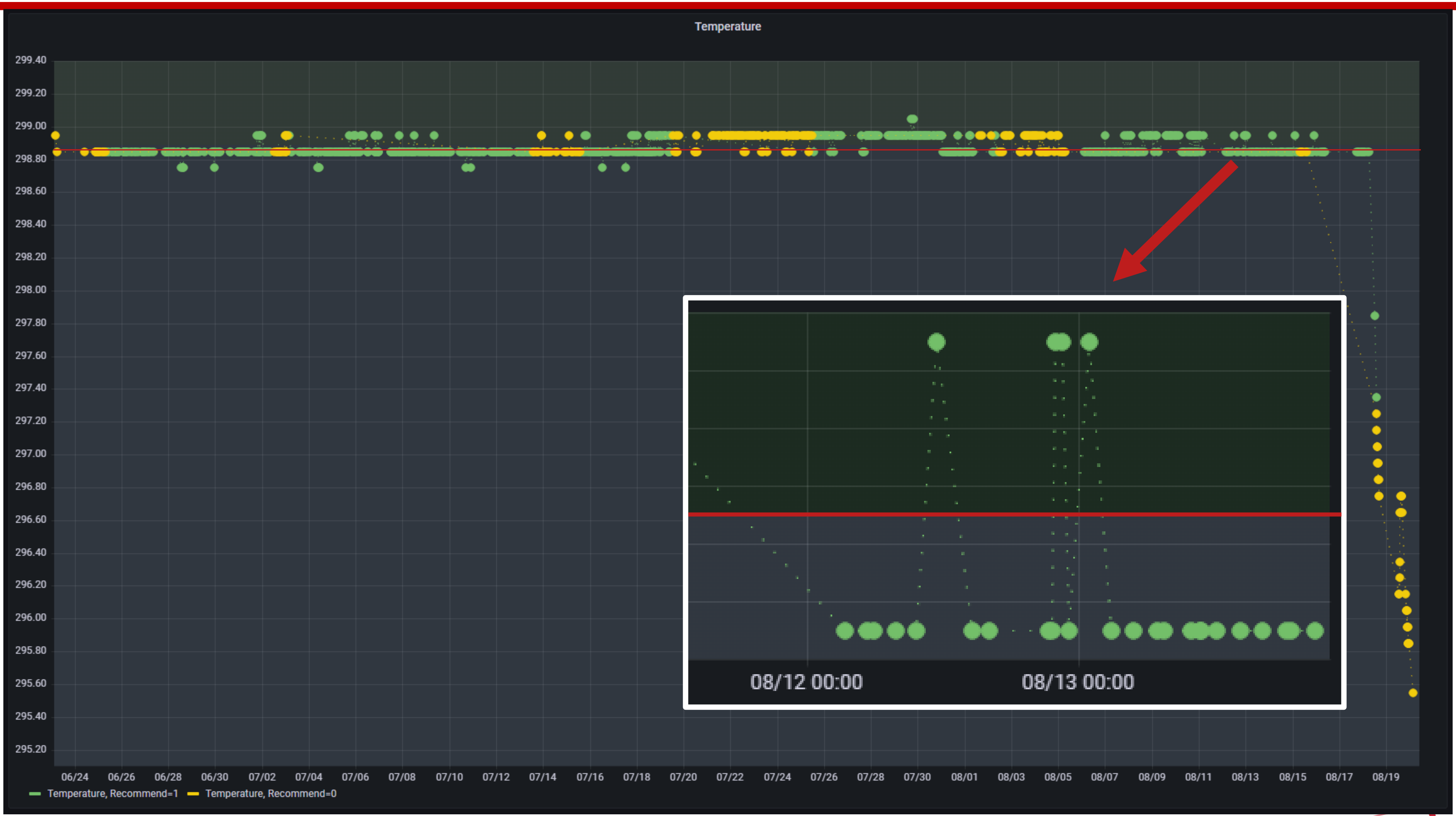

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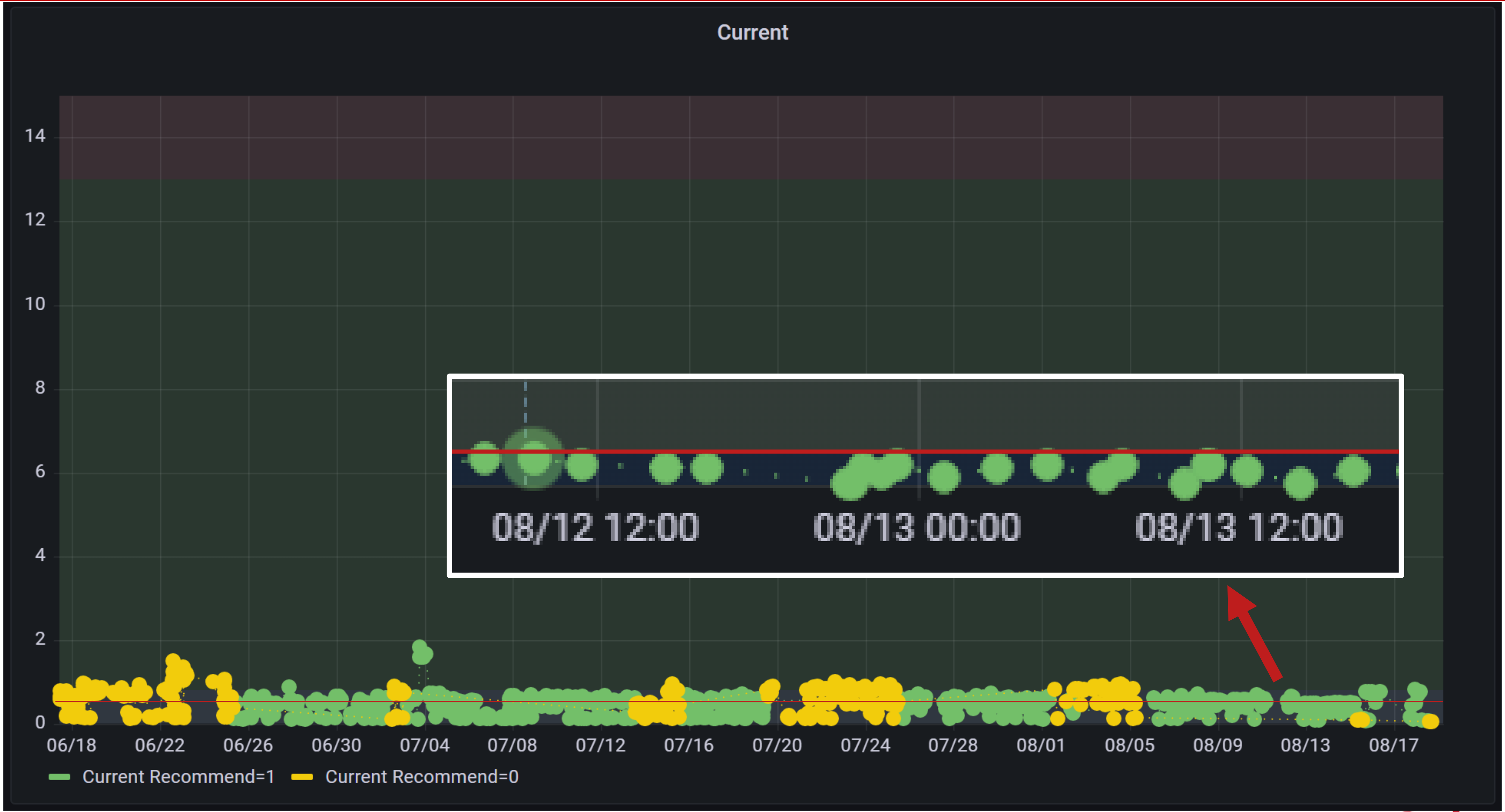

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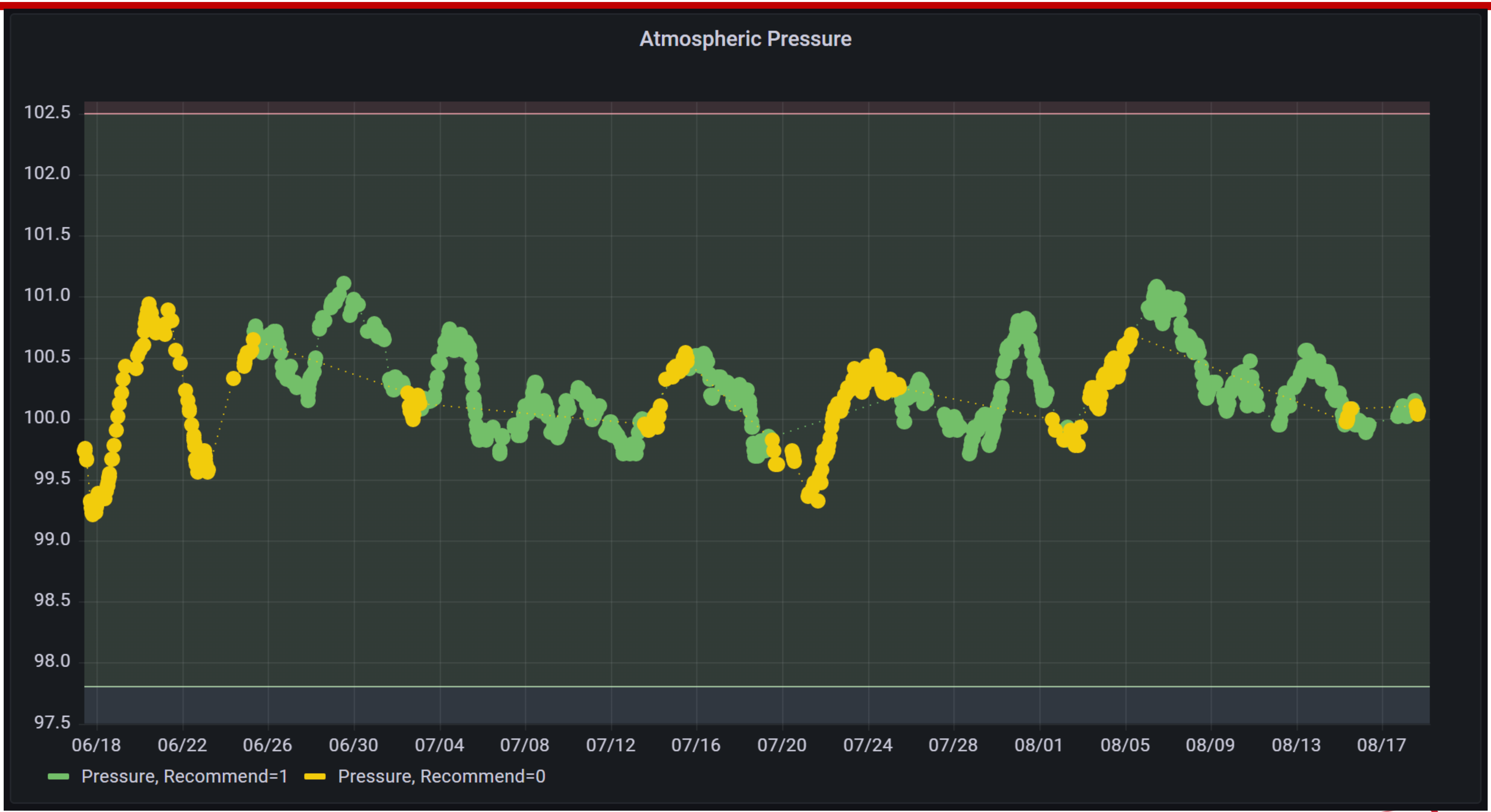

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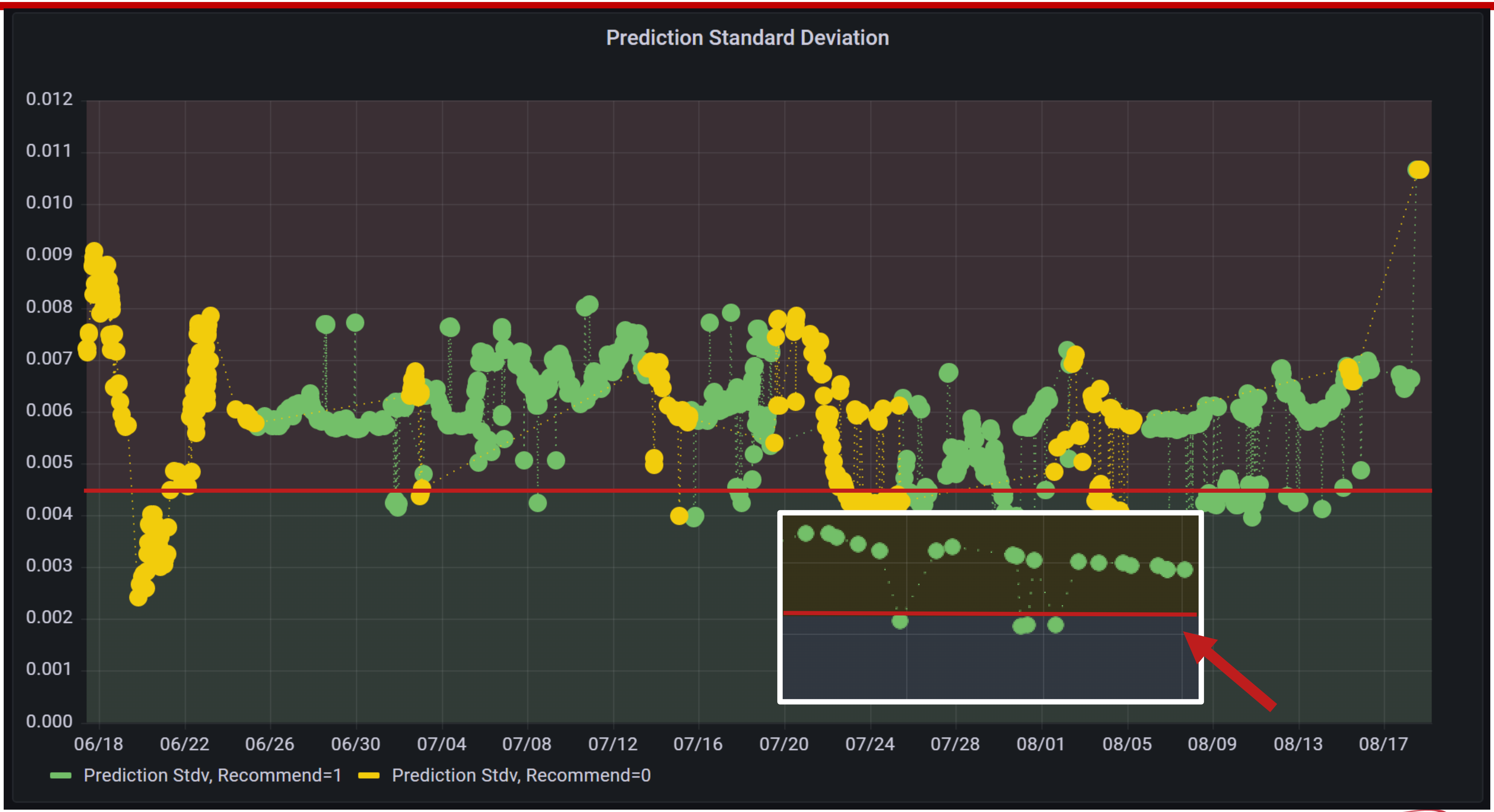

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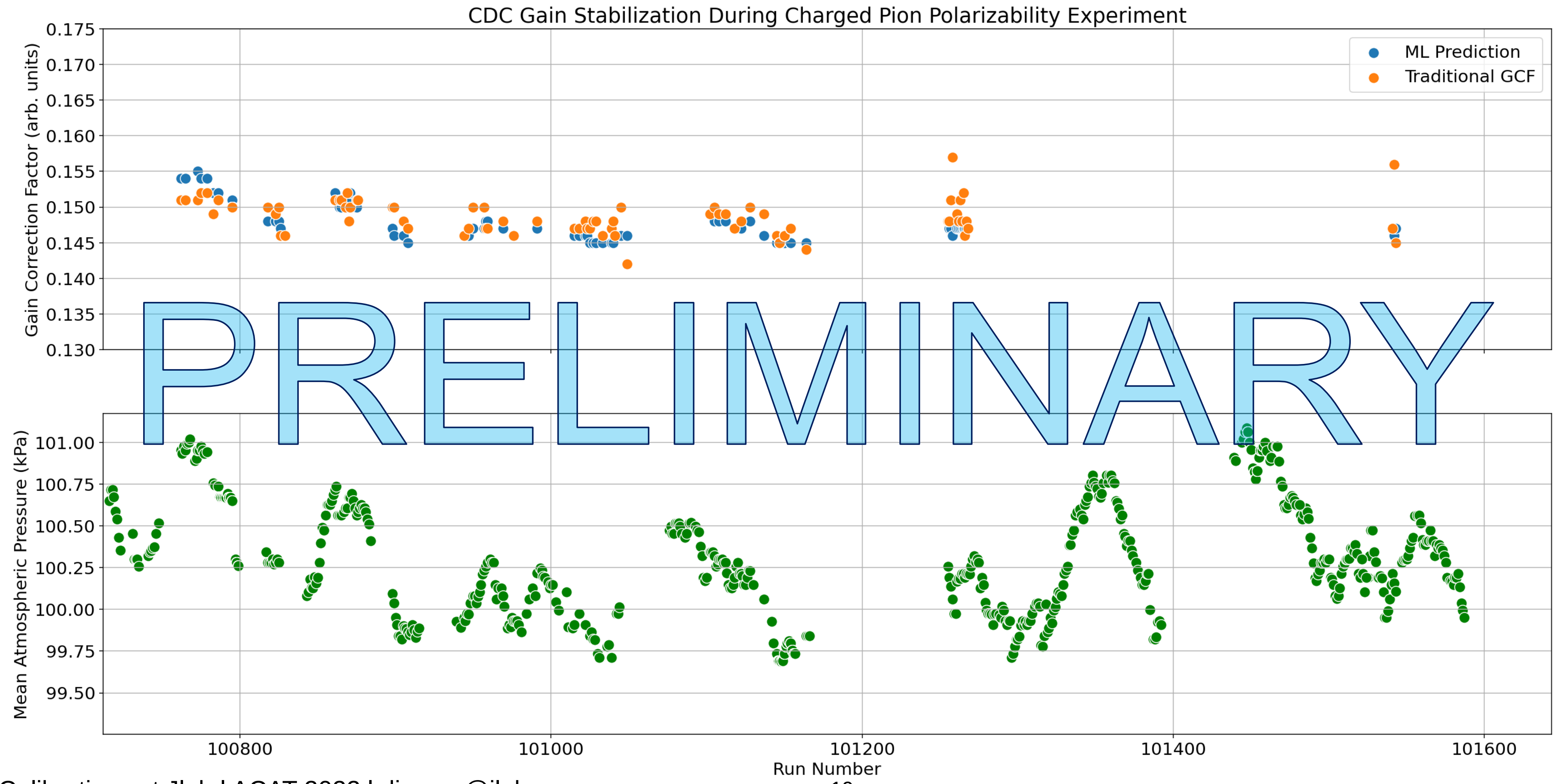

Acknowledgements

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

References

S. Adhikari et al. The GlueX beamline and detector. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, 987:164807, jan 2021. doi:10.1016/j.nima.2020.164807.

N.S. Jarvis, C.A. Meyer, B. Zihlmann, M. Staib, A. Austregesilo, F. Barbosa, C. Dickover, V. Razmyslovich, S. Taylor, Y. Van Haarlem, G. Visser, and T. Whitlatch. The Central Drift Chamber for GlueX. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, 962:163727, May 2020. doi:10.1016/j.nima.2020.163727.

AJ Kozubal, LR Dalesio, JO Hill, and DM Kerstiens. Experimental Physics and Industrial Control System. In ICALEPCS89 *Proceedings*, volume 288, 1989.
[

JeffersonLab. Jefferson Lab Calibration Constants Database Wiki. URL: https://github.com/JeffersonLab/ccdb/wiki.

Sean Gillies et al. Shapely: manipulation and analysis of geometric objects, 2007–. URL: https://github.com/shapely/shapely.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

David Barber. *Bayesian Reasoning and Machine Learning*. Cambridge University Press, 2012.

Youngseog Chung, Ian Char, Han Guo, Jeff Schneider, and Willie Neiswanger. Uncertainty toolbox: an open-source library for assessing, visualizing, and improving uncertainty quantification. *arXiv preprint* arXiv:2109.10254, 2021.

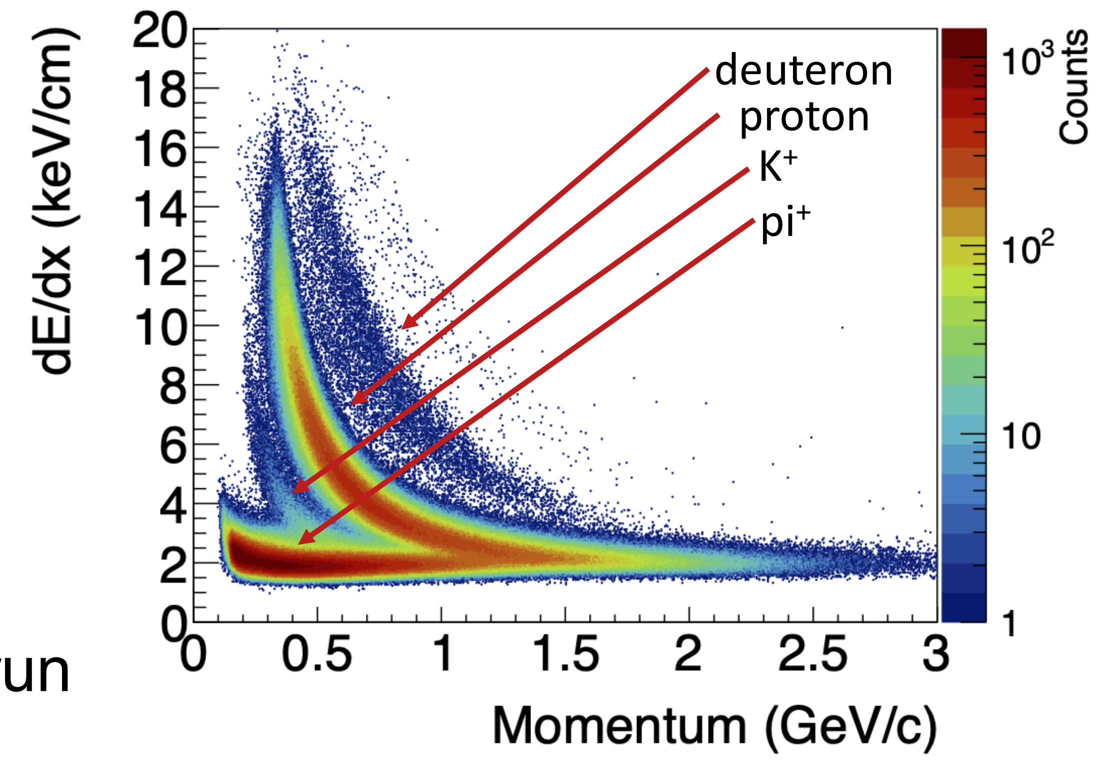
Edmon Begoli, Tanmoy Bhattacharya, and Dimitri Kusnezov. The need for uncertainty quantification in machine-assisted medical decision making. *Nature Machine Intelligence*, 1(1):20–23, 2019.

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

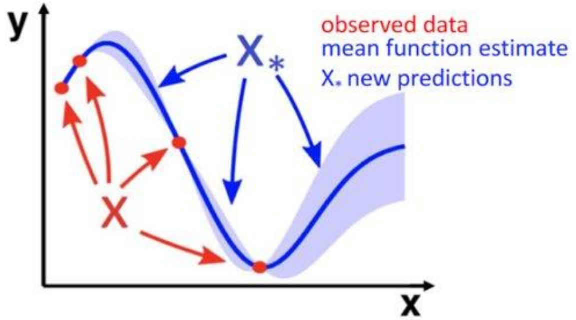


Illustration training a Gaussian process

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Isotropic (1.412)	0.97	0.002	**0.8%**
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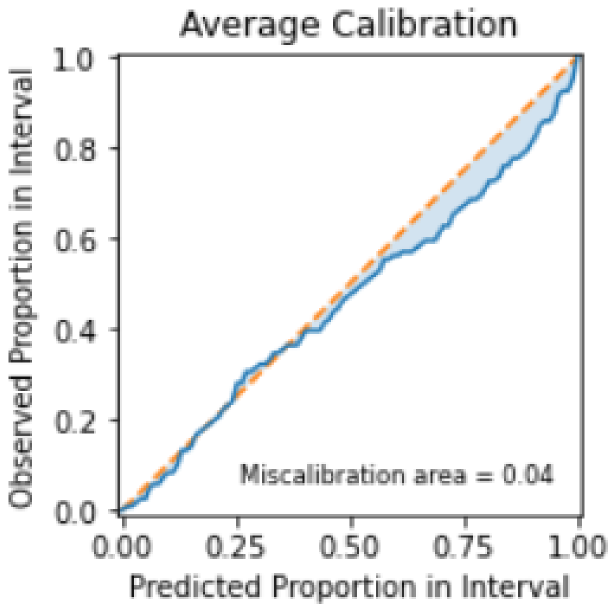
Q3: Does the system generalize for differing conditions? Evaluating Uncertainty

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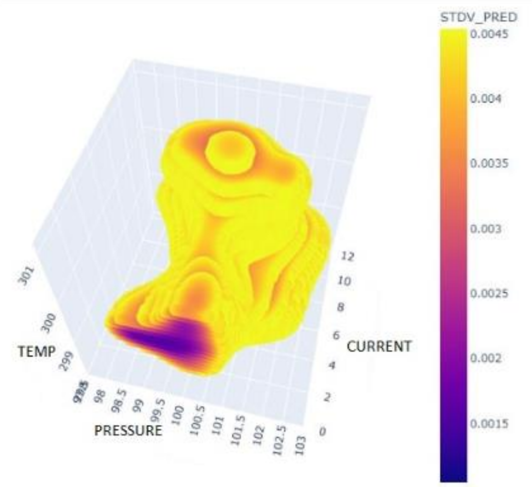
Table 1: Uncertainty Toolbox accuracy and average calibration metrics for GP models. Metrics were similar for both the isotropic and the anisotropic kernel.

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

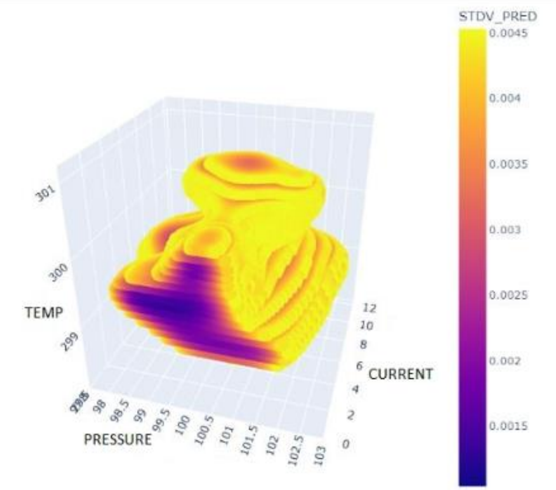
Q3: Does the system generalize for differing conditions? Uncertainty quantification

- 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

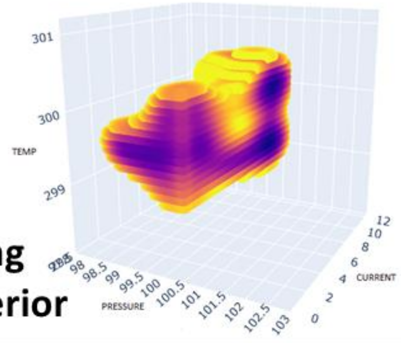


Added low current training runs



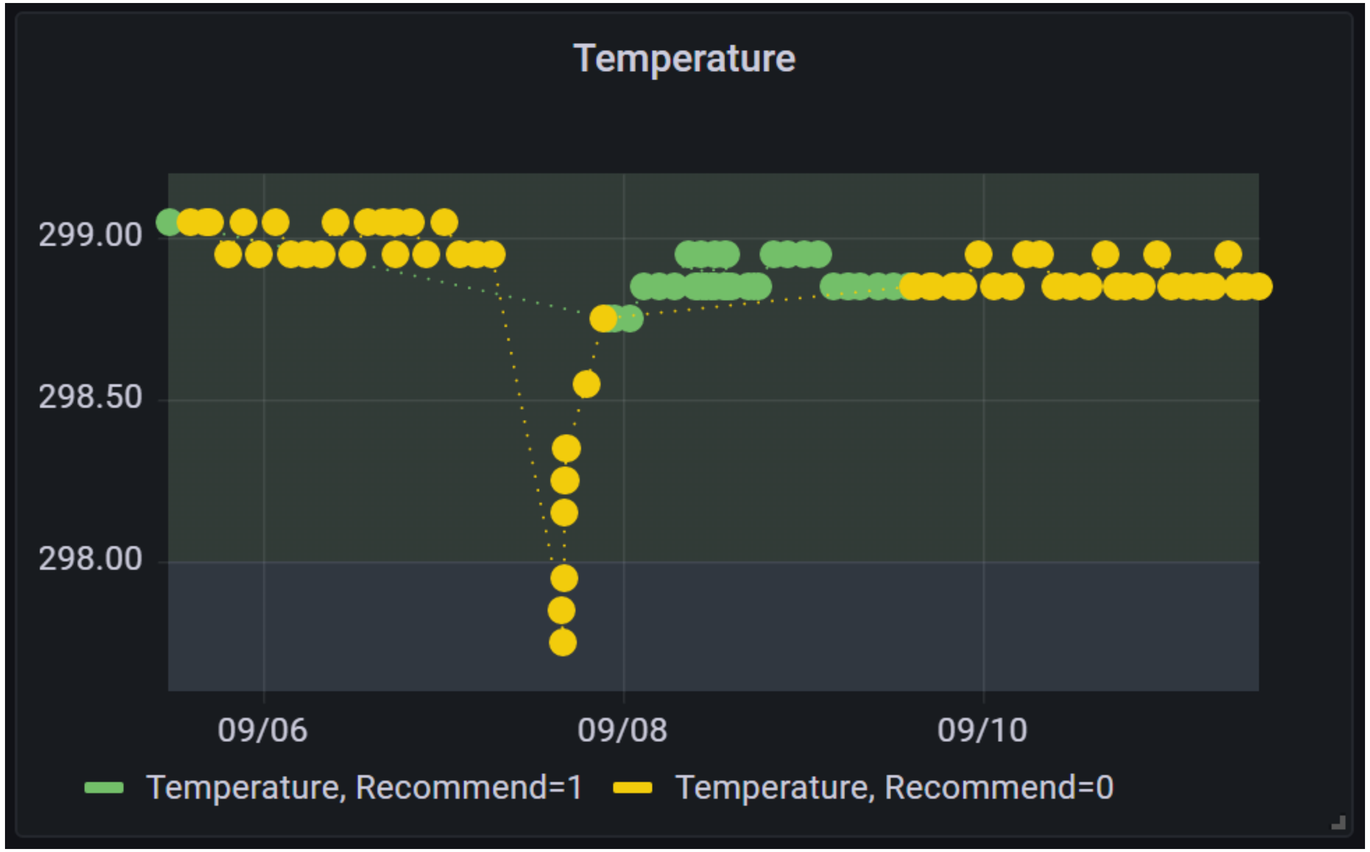
Plots of a grid mesh of the input feature space for predictions with Gaussian process standard deviation <= 3% of the ideal GCF:

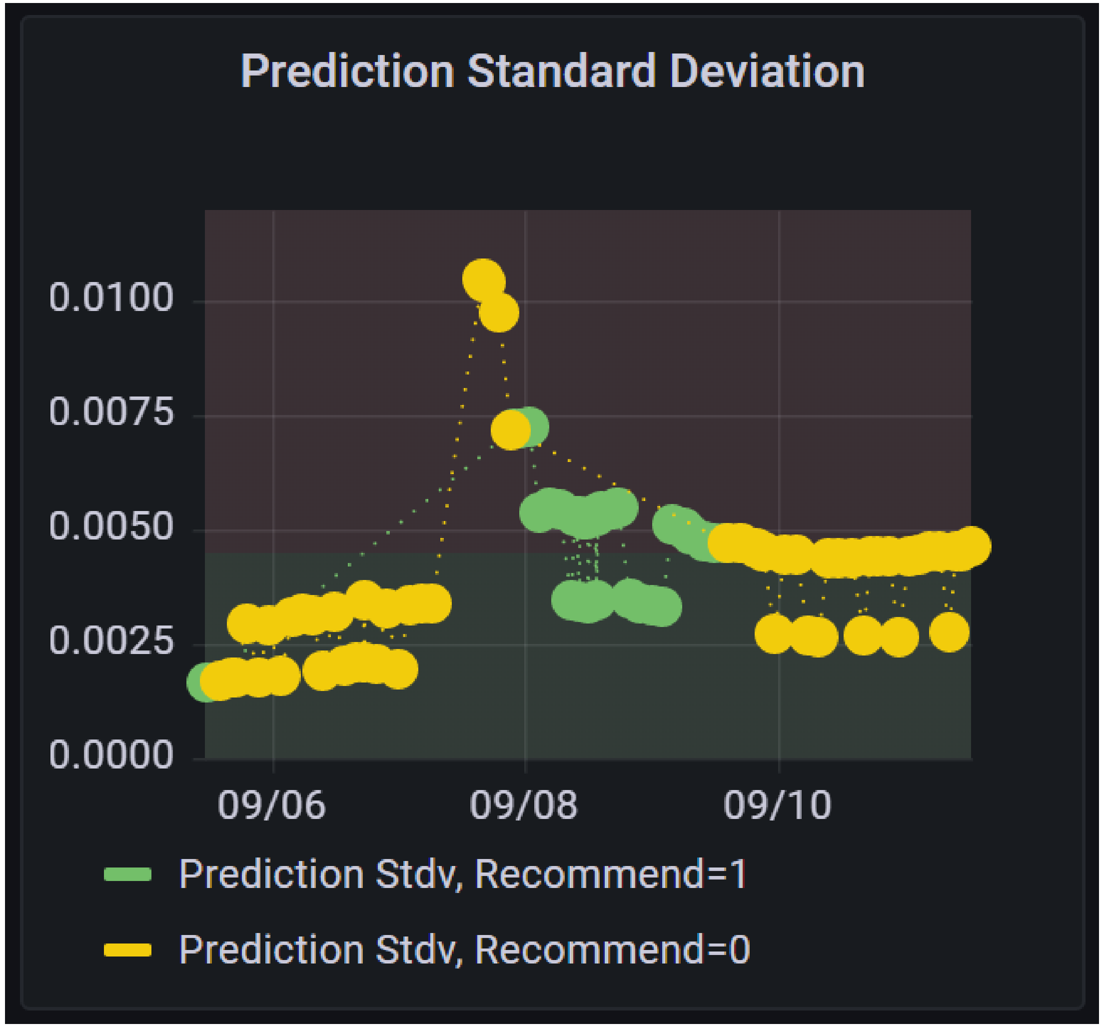
- As expected, the "surface" increases for low current runs, when more low current runs were added to training data.



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

Q3: Does the system generalize for differing conditions? CPP





Q3: Does the system generalize for differing conditions? PrimeX

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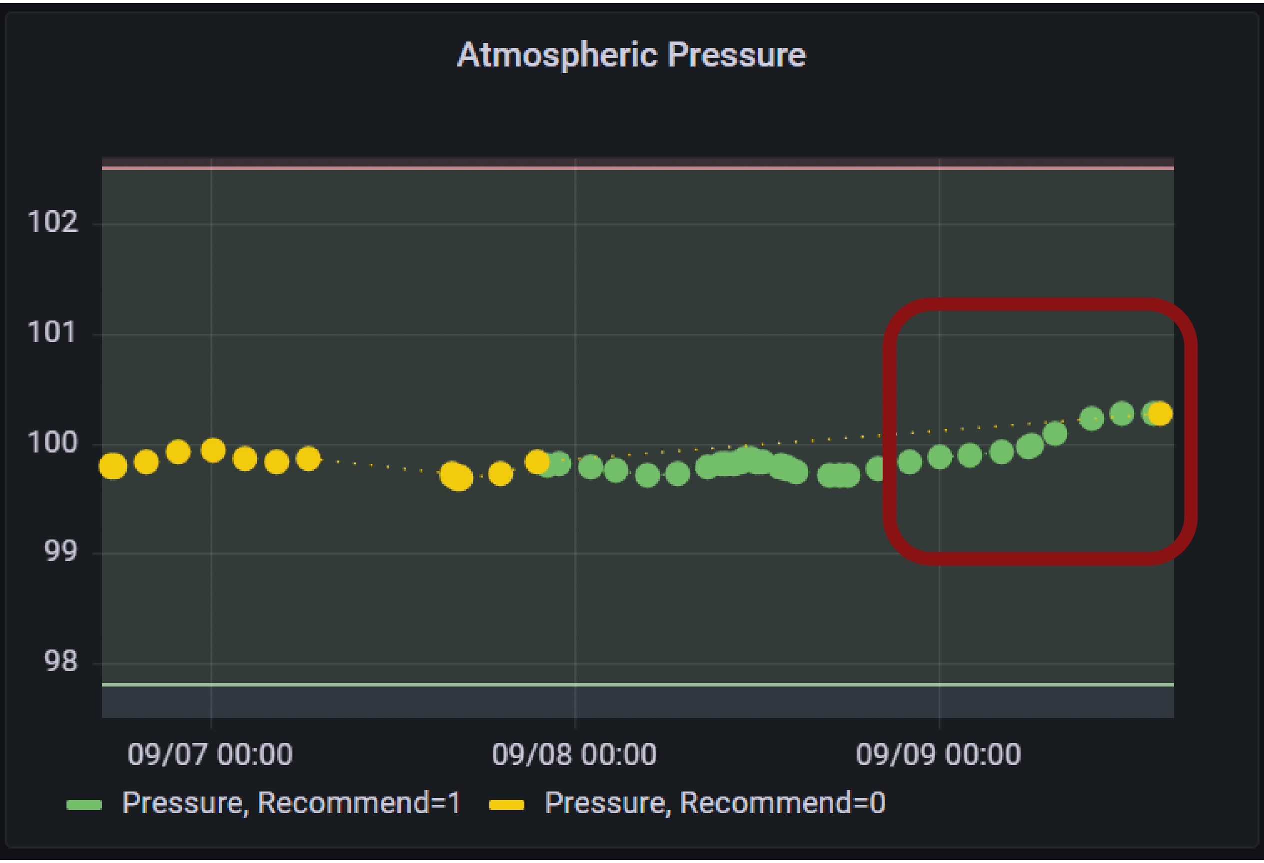
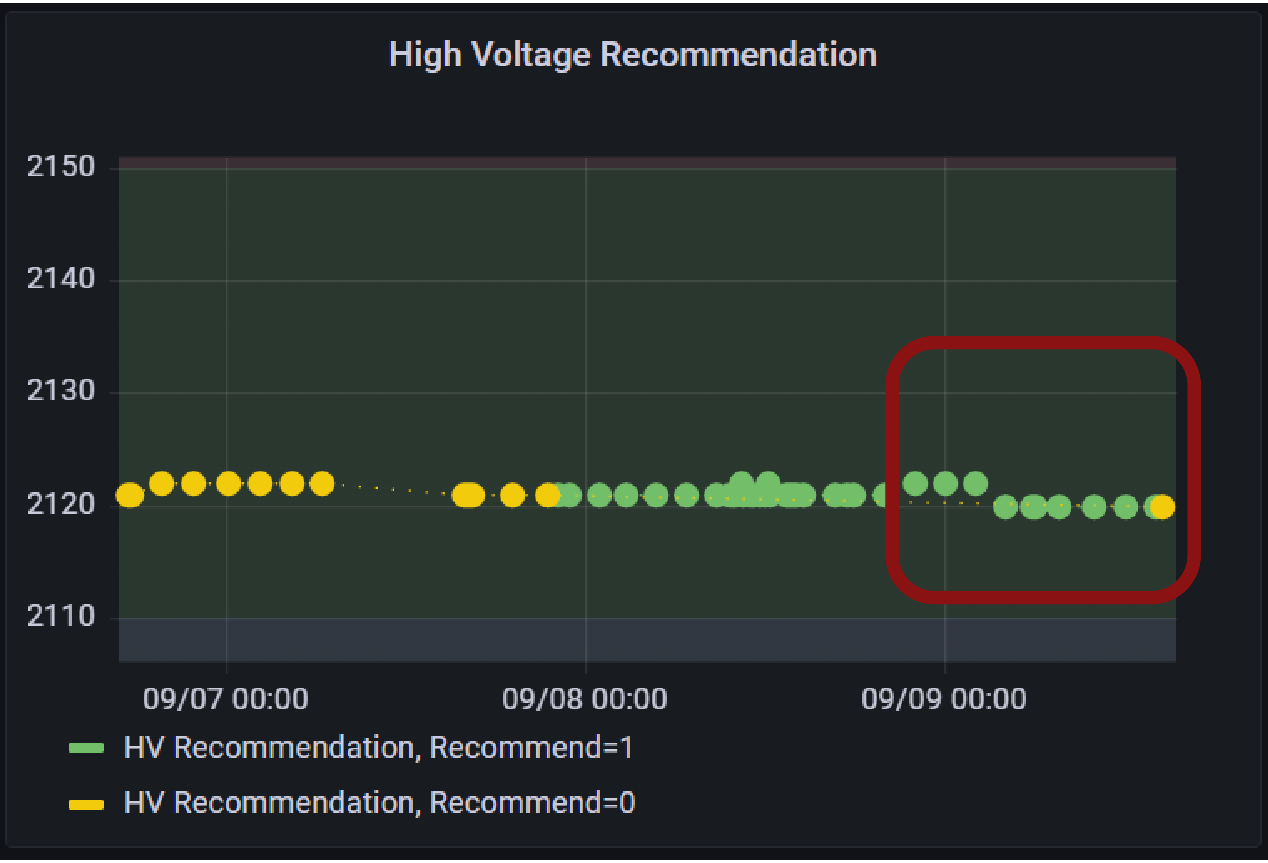
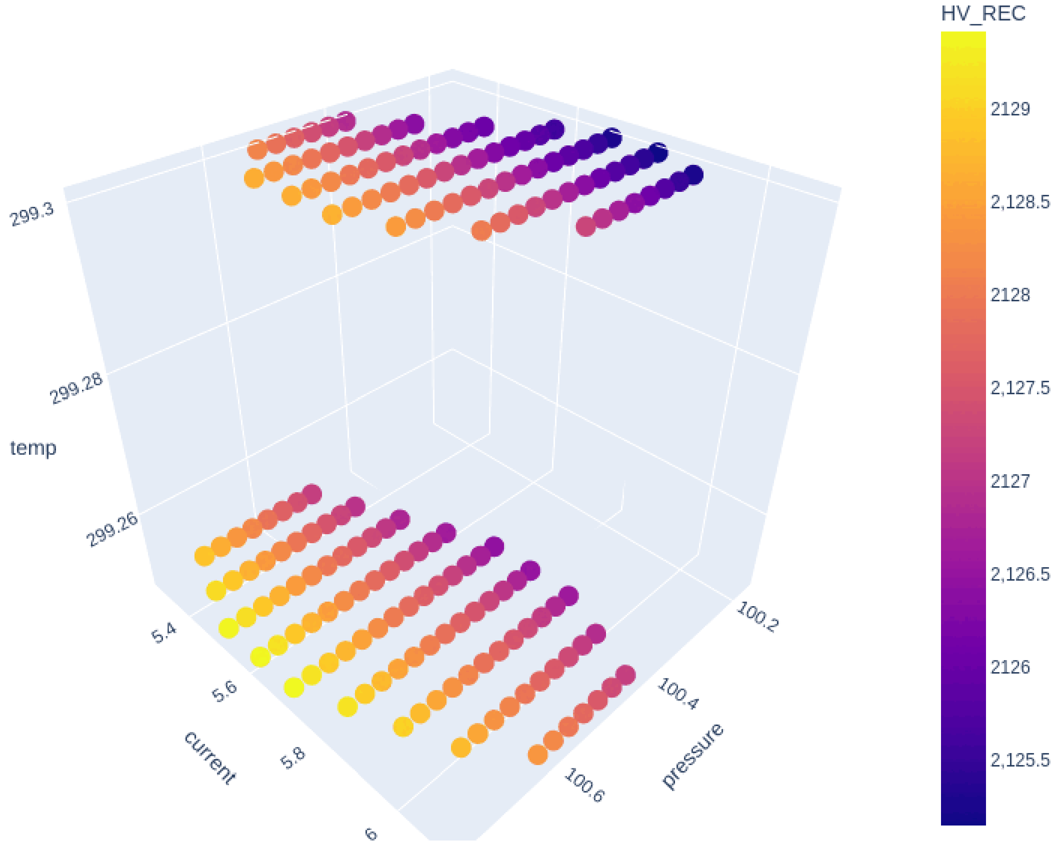




How Can We Use Uncertainty Quantification?

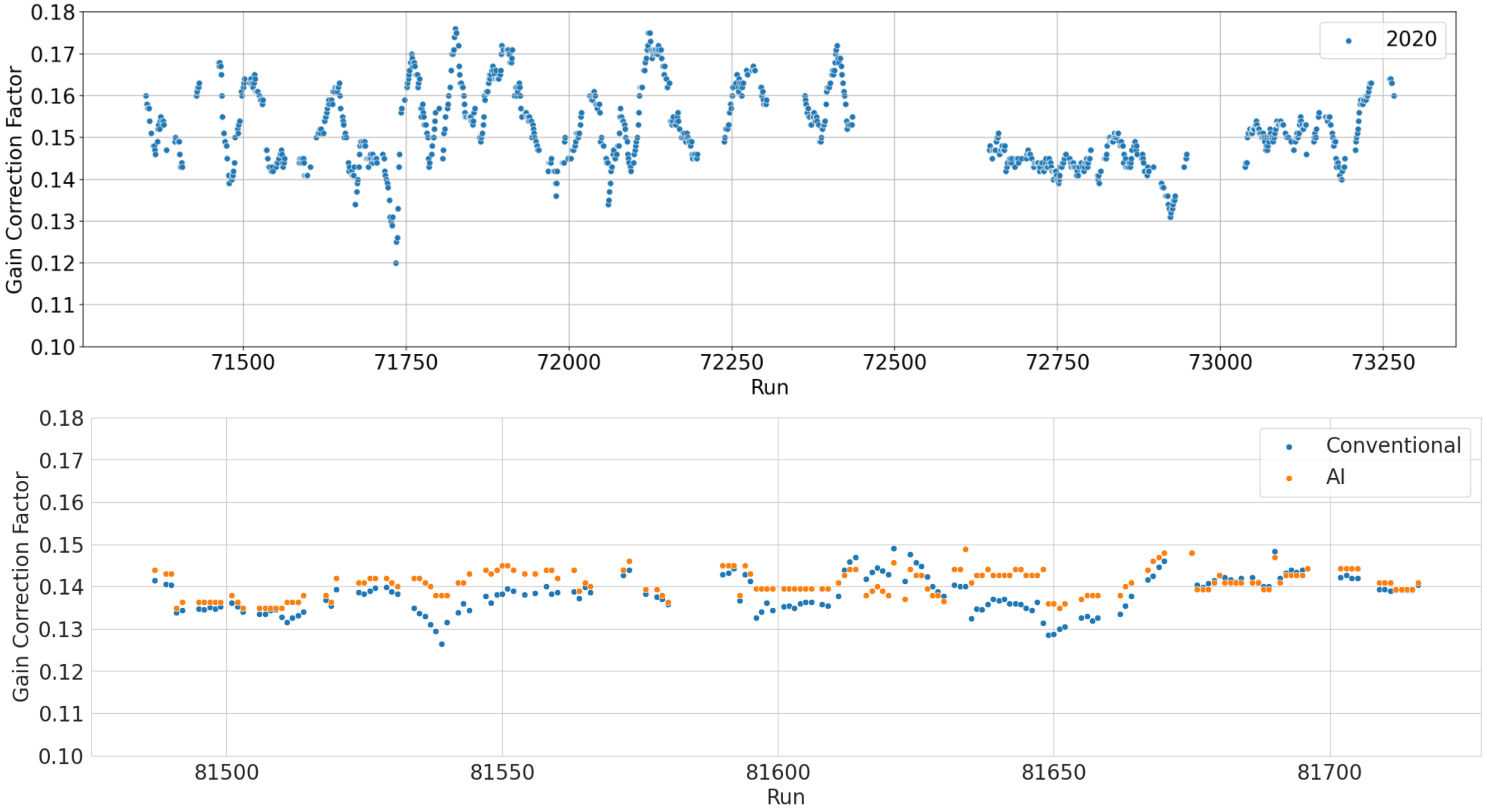
Can we use uncertainty to guide new data acquisition?

Temp vs. Current vs. Pressure for different uncertainties



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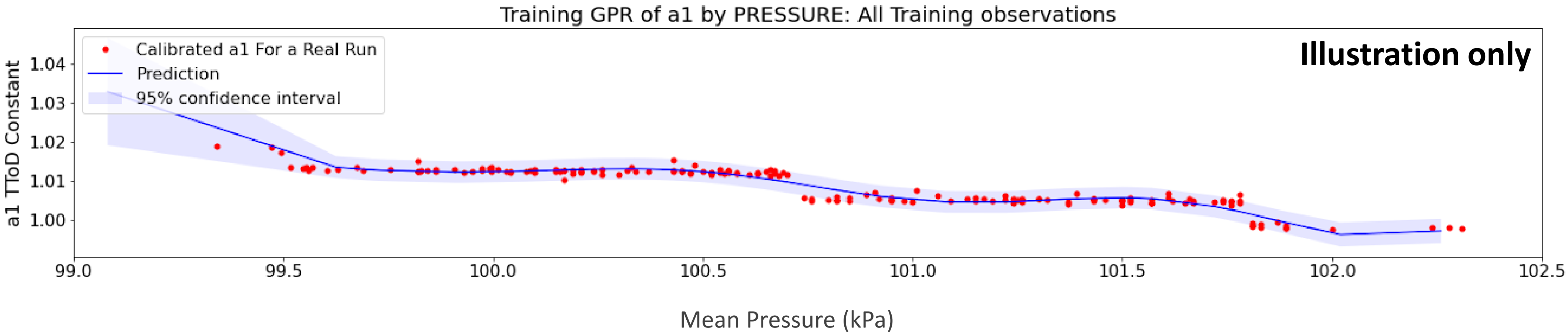
GlueX acknowledges the support of several funding agencies and computing facilities: www.gluex.org/thanks

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:

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



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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

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

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

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

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

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