# AI for Experimental Control

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### Certain aspects of experiments are costly and error prone.

### **Calibration**

Usually done after data taking, with a timescale on the order of months to years. As a result, there is a significant delay between data collection and publication.

#### Subsystem operation

Can require human attention and manual intervention.





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#### Detector/Data Monitoring

Requires constant human attention.



## Can we develop and deploy an AI system to autonomously adjust detector controls during data acquisition in order to reduce or eliminate the need for offline calibrations?

[AI for Experimental Controls Proposal](https://wiki.jlab.org/epsciwiki/images/e/e6/20200824_AI_Experiment_Controls_Proposal.pdf) 





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## Main objectives

### Uniform gain

Can we train a model to determine calibration constants as quickly as possible? From those calibration constants, can we recommend a HV setting to stabilize the chamber gain?

#### Reduced expert time

Reduce the number of offline iterations required for satisfactory dE/dx and timing resolution





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#### Extend to other detector systems

Build an overall control system that can be used for other detector components





## Challenges with deploying ML based software

### Higher technical risk

How to define "good enough" performance? What model architecture to use? Variable data needs and quality? Limitations of AI/ML based solutions

#### Expanded skill set/workforce

Introducing ML based solutions for NP tasks requires a broader set of skills and team members





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#### Require change

The control system we develop would change the standard operation of the detector



## Gluonic Excitations Experiment

Located in Hall-D at Jefferson Lab, GlueX was designed to search for and measure exotic hybrid mesons produced in photo-production reactions





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## **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

### **Calibrations (run-by-run):**

- Chamber gain
- Drift time to drift distance





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## Chamber gain

The gain determines the size of the avalanche and, therefore, the height of the pulse recorded.

This affects both the measured amplitude used in particle identification and the measured drift time used to determine the particle's momentum.





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## ML Control System Design

There are several design choices and requirements that determine what the ML system might look like

For our use case, we want quick inference times and readily accessible input features. For monitoring purposes, we want to clearly convey input features, inferences, and control decisions to the shift crew and detector experts.





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### ML system status

#### **Observations**

Balanced for High, Medium, and Low pressure runs 80/20 train test split

#### Model architectures

LR, ANNs, XGBoost, GPs Offline training Online inference

### Iterations of control system

Actively maintained by EPSCI group





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601

5

5

Dashboard

## Architectures + Performance

GlueX has an extensive calibration and conditions database which can be used for training models to predict calibration values

Initial feature set included slow controls data, reconstructed quantities, and engineered features









## **Gaussian processes**

Gaussian process was chosen based on

- Performance
- Quick training and inference times
- "Out-of-the-box" uncertainty quantification





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### **Training**

## **Gaussian process**

Input features: environmental and experimental data from EPICS archive

- Gas temperature
- Current drawn from the HV boards
- Atmospheric pressure

**Target: Gain calibration constants from** previous experiments

**Kernel:** Radial basis function + White **Noise** 





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## **Control Policies**

Having an uncertainty estimate on our predictions is a requirement

- Control policies
	- when model is uncertain
	- when HV setting is detected outside of allowed operational zone
- Informs when the model may need to be retrained

From an operations standpoint, we do not distinguish between epistemic or aleatoric uncertainty





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High voltage scans are conducted at regular intervals during each operational period.

This data is used to establish the optimal HV setting required to maintain chamber gain stability and performance.





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#### CDC gain relative to that for standard HV

#### Control

## High Voltage Recommendation

Shift takers are able to toggle the control aspect ON/OFF

Even when control is OFF, we record the actions the system would take.





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## Monitoring CDC Control GUI

## **Monitoring** Grafana Interface

All input features, inferences, and actions are logged for further analysis regardless of whether control is ON or OFF





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#### **三** Home > Dashboards > AIEC-CDC cc

#### 



**Atmospheric Pressure** 





Recommended GCF (Raw, or UQ-Corrected GCF)



2140

 $07/03$ 

**Prediction Standard Deviation** 

07/11

HV Recommendation, Recommend=



07/13

07/15

High Voltage Recommendation (Based on Recommended GCF)

**Current (Scaled and Unscaled)** 





## First deployments

#### PrimEx - 2021

Shift crews ran script to run model inference and adjusted HV (rounded to nearest 5V) manually before starting new run.







### Charged Pion Polarizability - 2022

Script was run via DAQ GO. Experimental conditions (beam current, target type and position) were quite different from our training data.

5% threshold



### Cosmic ray tests



#### Split chamber in half via software

One side held at fixed HV, other side adjusted every 5 minutes





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### Stabilized gain

The variation in the gain for the "constant HV" side was caused by a well-timed thunderstorm.

### More deployments

#### GlueX 2023

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

### PrimEx II - 2022

Nearly all controlled runs fall within our 5% threshold.





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5% threshold





### Time-to-distance

Existing drift time to drift distance parameters are strongly correlated with the gas density

We can automatically generate these calibration values from fits to the gas density and reduce the number of iterations required





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### Time-to-distance

Tuning HV to stabilize the gain results in comparable performance to those runs taken at 2125 V

This alleviates any concern that adjusting the HV to stabilize the gain might negatively impact the timing resolution

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### Extensions to other detector systems

### GlueX Forward Calorimeter

### GlueX Forward Drift **Chambers**

Aimed to generate calibration values using the light monitoring system, unsuccessful due to lack of correlations between existing gain values and amplitudes

Chamber gain is also strongly correlated with atmospheric pressure. Can use linear regression or a GP to obtain calibration values at the start of each run.





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#### CLAS12 Drift Chambers

Not pursued due to lack of enough historical calibration data



### In Summary

#### Predict calibration values without relying on track reconstruction

This enables us to generate calibration values during data taking while ensuring stable detector operation and performance

### An UQ-aware control system is now standard operation for GlueX

MLOps becomes critical to ensure model performance, detect data drift, and performance degradations





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### A team of scientists with complementary skills is critical

Continued collaboration will be essential for new AI/ML based solutions for current and future experiments



"The mostly uniform gain is great because it ensures that the yields in our monitoring plots don't change drastically because the proton band moved below the analysis selection, and also because it ensures that minimum ionizing particles stay above the detection threshold. The biggest effect of data quality is not having hits from the same type of tracks disappear below threshold or saturate the adc depending on the weather of the day"

Naomi Jarvis · CDC Expert









### Resources





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### AIEC Final Report

Extensive paper covering entire project: [https://arxiv.org/](https://arxiv.org/pdf/2402.13261) [pdf/2402.13261](https://arxiv.org/pdf/2402.13261)

### AI4EIC2023 Proceedings

Shorter description:<https://arxiv.org/pdf/2403.13823>



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### AIEC

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### AIEC Team

Work started in April 2021

Torri Jeske **EPSCI** 



Strong ties to Data Science Department and Physics Division





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Diana McSpadden

Data Science



Nikhil Kalra Data Science



Thomas Britton

**EPSCI** 



Naomi Jarvis

David Lawrence

**EPSCI** 



Full automation tests with half of detector HV adjusted autonomously every 5 min

Observed stable gain for ML controlled side of CDC

#### PrimEx-II 2022

Added an "auto-off" function to roboCDC to detect empty target runs and human tests

#### CPP 2022

RoboCDC run from DAQ "GO" processes without intervention from shift crew

Stable performance despite out of domain input features

Control ON/OFF toggle added to CDC HV GUI





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#### GlueX 2023

Problems with atmospheric pressure sensor resulted in less controlled runs.

Stable performance was achieved with new pressure sensor installation.

#### PrimEx 2021

Shift crew manually ran roboCDC script and adjusted HV

#### Deployment timelines

#### **Cosmics**