C-AD AI/ML Activities, Results, and Plans

Kevin Brown (C-AD)

Collaborations with Cornell, RPI, CMU, JLab, SLAC, Fermilab, LBNL, PNNL, and growing.

11 December 2025 2025 C-AD MAC Review

Outline

- Overview of AI/ML funded projects to date
- Genesis Mission Connections
- EIC-BeamAI
- NARAD project
- polarization improvements project
- Longitudinal emittance monitor
- Transverse emittance
- Optics measurements and ORM analysis
- Summary
- List of publications (including submitted or in-progress) and Presentations

Overview of AI/ML funded projects to date

- **Higher RHIC polarization by Physics-informed Bayesian Learning**
  - NP funded, $1.5M, duration 2 years, start 09/01/2023
  - BNL, Cornell, JLAB, SLAC, RPI
  - Plans presented in 2023 C-AD MAC
- **Toward higher brightness and polarization of hadron beams: Digital-Twin-based autonomous control of BNL's hadron accelerator chain**
  - NP funded, $1.5M, 2 years, continuation/renewal
  - BNL, Cornell, JLAB, SLAC, FNAL, RPI
- **Developing AI-Ready Data Framework for DOE NP Particle Accelerators**
  - Now called **NARAD =** NP AI-Ready Accelerator Data
  - ASCR/NP funded, $4M, duration 2 years, start 10/1/2025
  - JLAB (lead), BNL, Cornell, LBNL, PNNL (+ informally, FNAL and SLAC)

Additional collaborations

- **Particle Accelerator Lattice Standard (PALS)**
- **python Accelerator Middle Layer (pyAML)**
- **Multi-Office particle Accelerator Team (MOAT)**

Genesis Mission Connections

Genesis Mission is a national initiative to build the world's most powerful scientific platform to accelerate discovery science, strengthen national security, and drive energy innovation.

- MOAT aims to build national accelerator physics knowledge into a national AI infrastructure that can be used across all platforms to inform on accelerator design and operation.
- PALS aims to build a standard language for describing particle accelerators.
- NARAD aims to build a standard framework for streaming accelerator data to AI agents.

Our aim is to build infrastructure that will benefit EIC.

EIC will be one of the first large-scale collider-based programs in which AI/ML is integrated from the start.

EIC-BeamAI

Our growing collaboration has joined the **EIC Accelerator Collaboration (EICAC)**, as a working group named **EIC-BeamAI**.

We have been participating in the AI4EIC workshops each year since they started. For the next workshop we will have a special session on AI in accelerators.

2021 – Auralee Edelen, **Accelerator control**

2022 – Todd Satogata, **AI/ML overview for accelerator design activities**

2023 – 1st year with Accelerator session: Led by K. Brown, Elena Fol

7 talks on community efforts that relate to the EIC

Lucy Lin, **Machine learning for digital twin development and polarization optimization at BNL hadron injectors**

2025 - AI/ML for Accelerators session: led by K. Brown and B. Mustapha

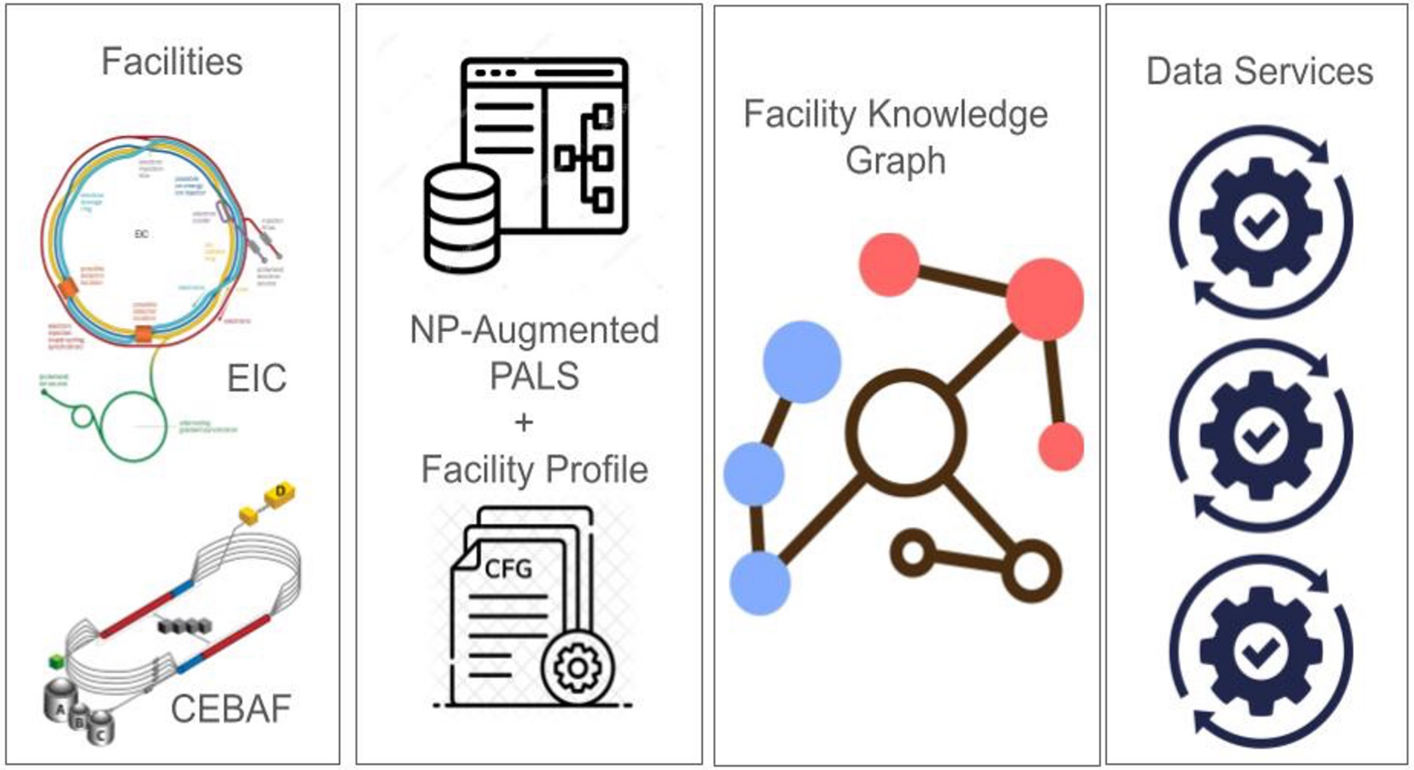
Eiad Hamwi, **Use of AI/ML for higher brightness and higher polarization of hadron beams**

Chris Kelly, **Machine-Learning–Accelerated Bayesian Uncertainty Quantification for Digital Twin Modeling …**

Chris Hall, **Machine Learning Approaches to Improved Ion Profile Monitor Measurements**

K. Rajput, **Explainable and Differential Reinforcement Learning for Multi Objective Optimization in Particle Accelerators**

NP AI-Ready Accelerator Data (NARAD)

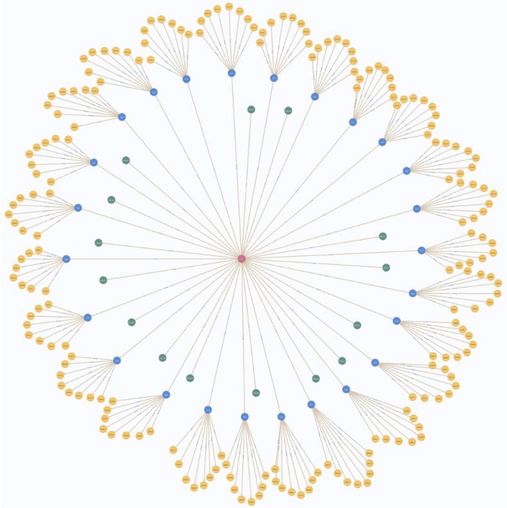


Local Machine Description

PALS Description

American Science Cloud, Foundation Models, AI systems, ModCon

Example Workflow



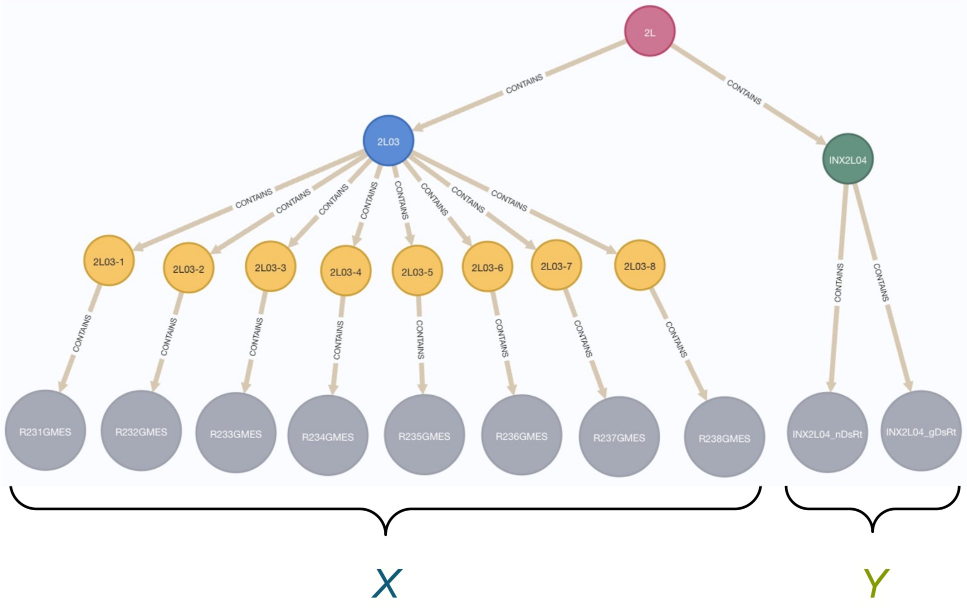
Facility Knowledge Graph

Example Query:
Estimate the radiation level at radiation detector "INX2L04" using PVs of the previous CryoModule "2L03"

Some Query Method

```
MATCH (l:Linac)-[:CONTAINS]->(m:CryoModule {name: "2L03"})-
[:CONTAINS]->(c:CryoCavity)-[:CONTAINS]->(pc:PV)
WHERE pc.name ENDS WITH "GMES"
MATCH (l)-[:CONTAINS]->(d:NeutronDetector {name: "INX2L04"})-
[:CONTAINS]->(pd:PV)
RETURN l, m, c, pc, d, pd
```

Contextual Subgraph Extraction



Temporal Data Extraction

AI Supervised Learning:

Y = NN(X) ⇒ Traditional

or

Y = GNN(X) ⇒ Advanced

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Why is this useful? EIC as an example

- We are developing AI/ML methods at the AGS and AGS Booster, learning experimentally how to get these tools to work in operations.

- Once EIC is built, we will use what we learned to efficiently apply to EIC systems.
  - NARAD: by making EIC data AI ready, existing workflows can be used to implement AI based automation
  - MOAT: by adopting frameworks and connecting data, expertise, and innovation across the DOE complex, we will ensure the EIC is at the forefront of AI-enabled scientific infrastructure, and that next-generation accelerators achieve unprecedented performance, efficiency, scientific, and societal impact.

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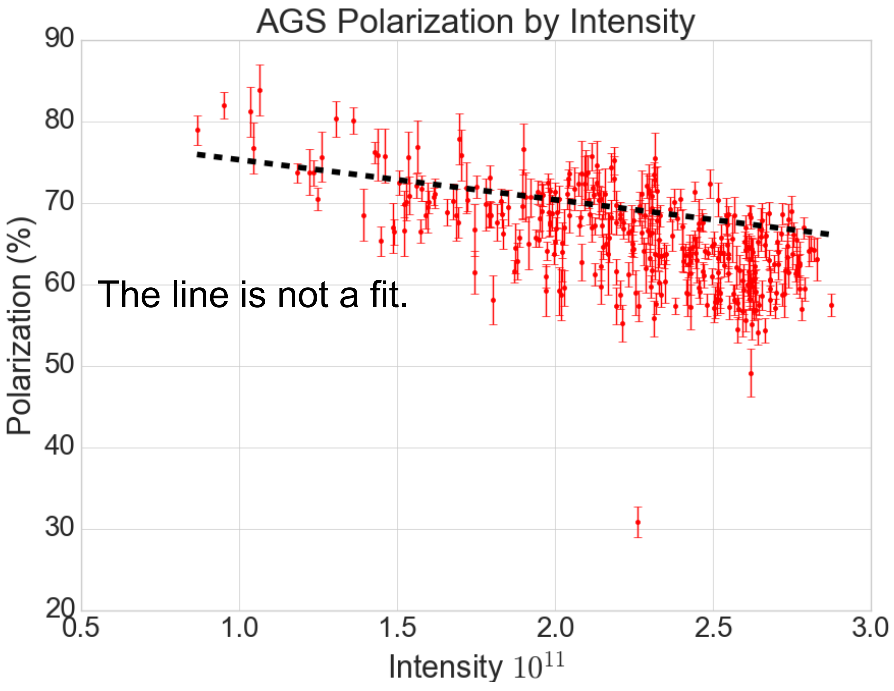
Polarization Improvement Projects

1. NP AI-Ready Accelerator Data
2. LINAC models, magnetized beams
3. Diagnostic for measuring coupling in LtB
4. LtB injection optimization
5. NSRL Digital twins (bumps and beam line optics)
6. BtA injection optimization

High polarization through brighter beams and AI enabled corrections

- Making polarization measurements is slow, so we instead focus on indirect measurements to optimize polarization
  - Make smaller emittance, brighter beams
  - Reduce coupling to minimize vertical emittance
  - Reduce space charge blow-up
  - Automate to maintain optimum states
  - Improved physics models to better inform improvements. Provide virtual diagnostics
  - Improve existing diagnostics



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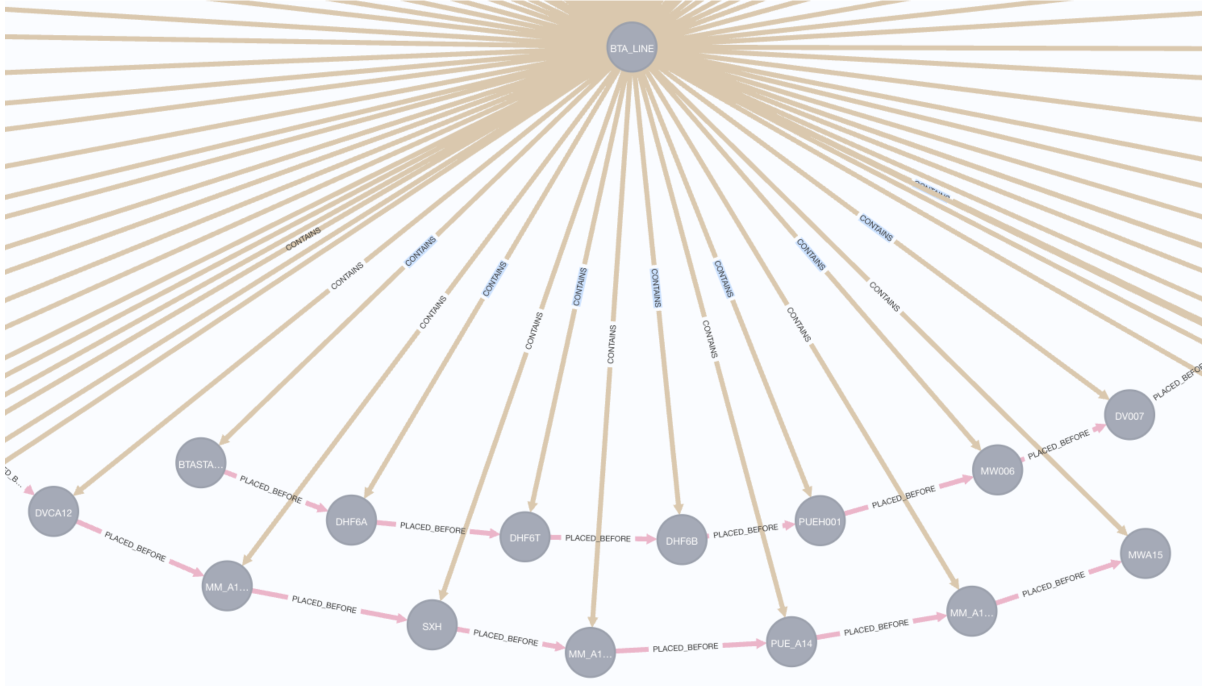
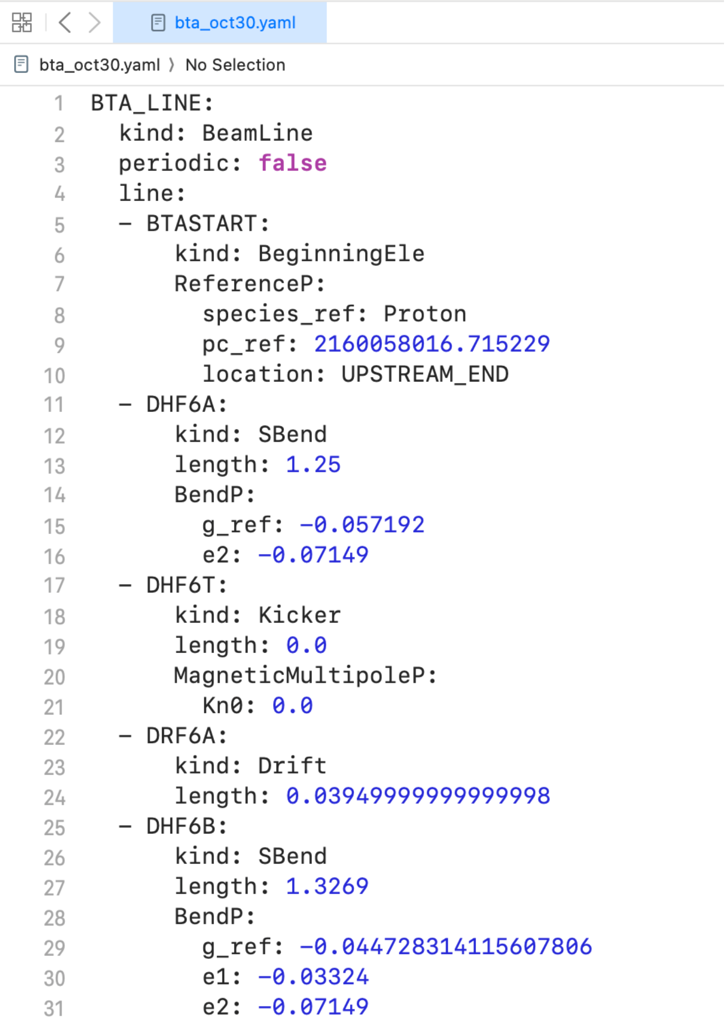
NP AI-Ready Accelerator Data (NARAD)

- The BNL use case focuses on the Booster to AGS (BtA) transfer line. The use case demonstrates how a standardized, AI-ready lattice and data representation can support modeling, diagnostics, and optimization workflows.
- We have produced a complete PALS representation of the BtA line and built corresponding parsers between PALS and Bmad to enable consistent simulation studies.




bta_oct30.yaml

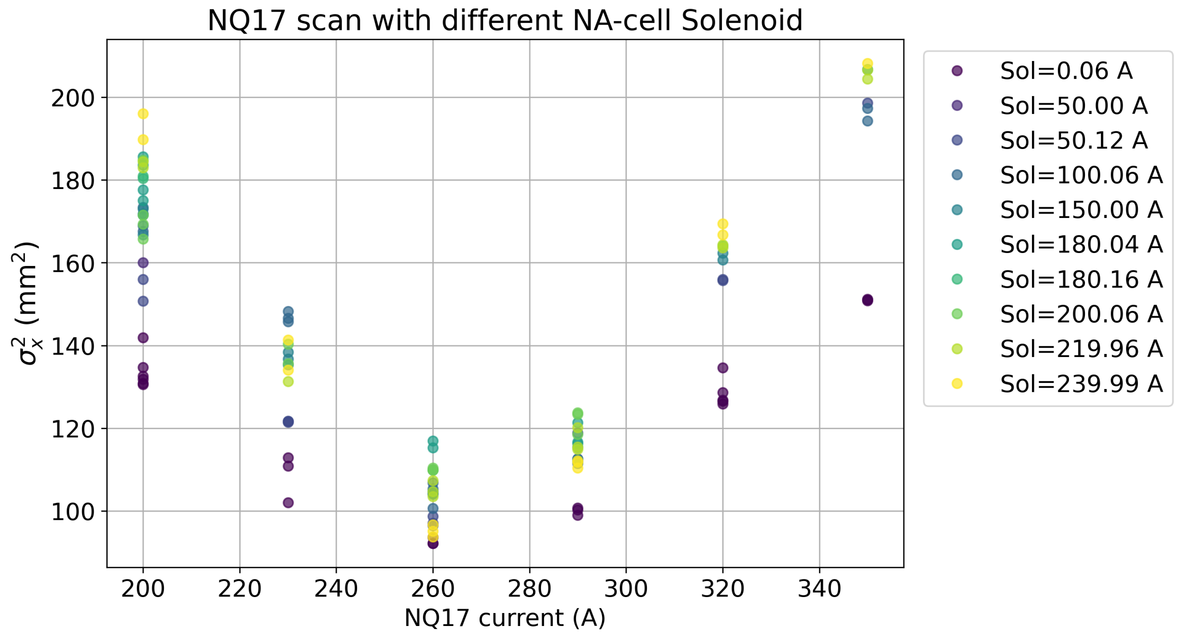
bta_oct30.yaml 〉 No Selection

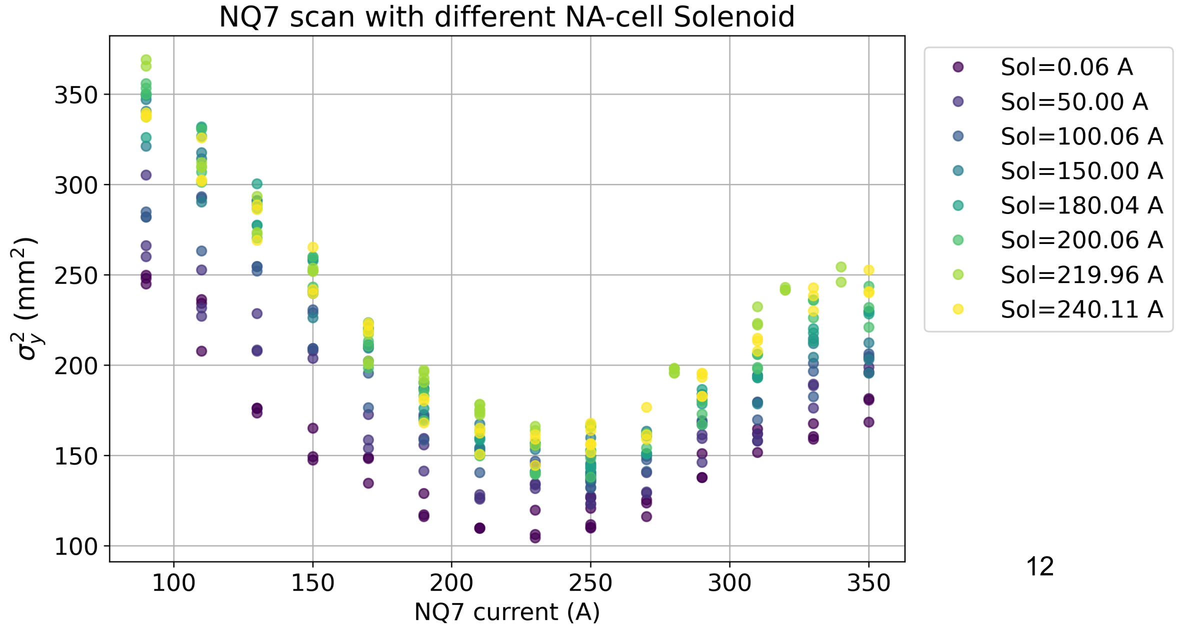

```yaml
BTA_LINE:
  kind: BeamLine
  periodic: false
  line:
  - BTASTART:
      kind: BeginningEle
      ReferenceP:
        species_ref: Proton
        pc_ref: 2160058016.715229
        location: UPSTREAM_END
  - DHF6A:
      kind: SBend
      length: 1.25
      BendP:
        g_ref: -0.057192
        e2: -0.07149
  - DHF6T:
      kind: Kicker
      length: 0.0
      MagneticMultipoleP:
        Kn0: 0.0
  - DRF6A:
      kind: Drift
      length: 0.03949999999999998
  - DHF6B:
      kind: SBend
      length: 1.3269
      BendP:
        g_ref: -0.044728314115607806
        e1: -0.03324
        e2: -0.07149
```

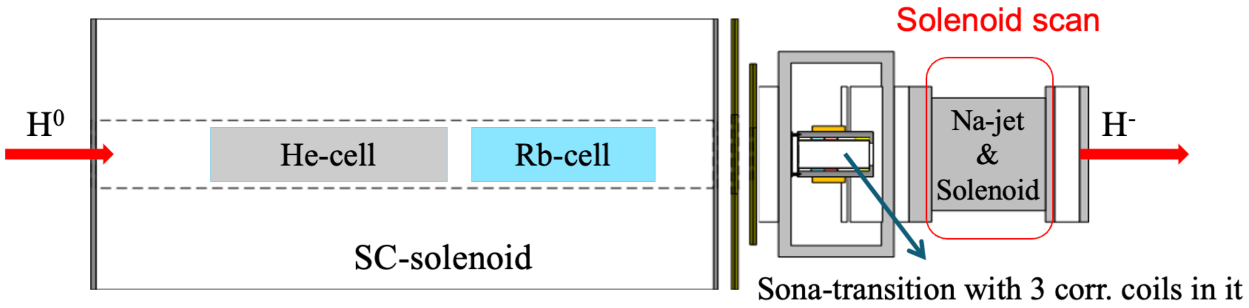

- We have also begun reviewing operational data sources to identify format gaps and required metadata for integration into the NARAD framework.

Coupling measurement in LtB

- H- beam is born inside a solenoid in OPPIS as transversely coupled beam
- Multiple quadrupole scans have been performed at various locations of the LtB beam line, while changing the solenoid strength
- Data analysis and simulation studies to quantify coupling is in progress



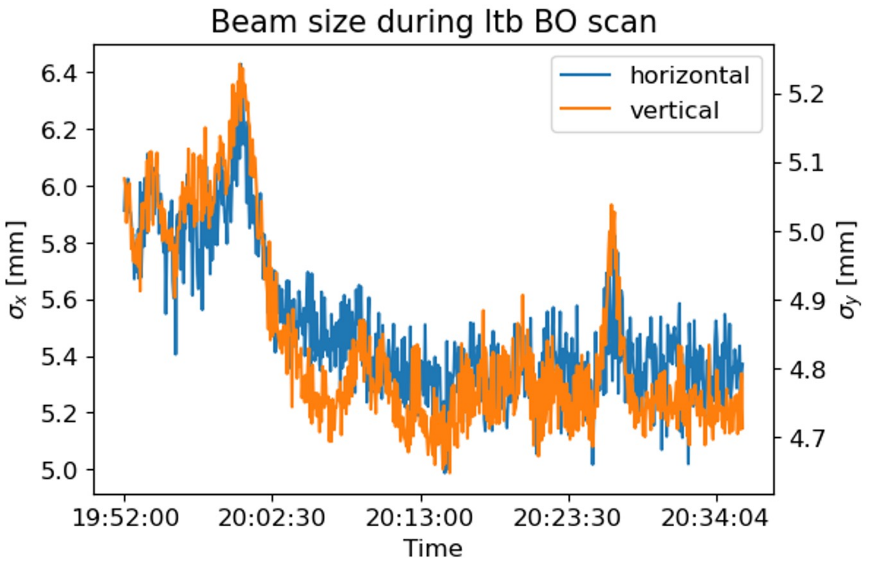


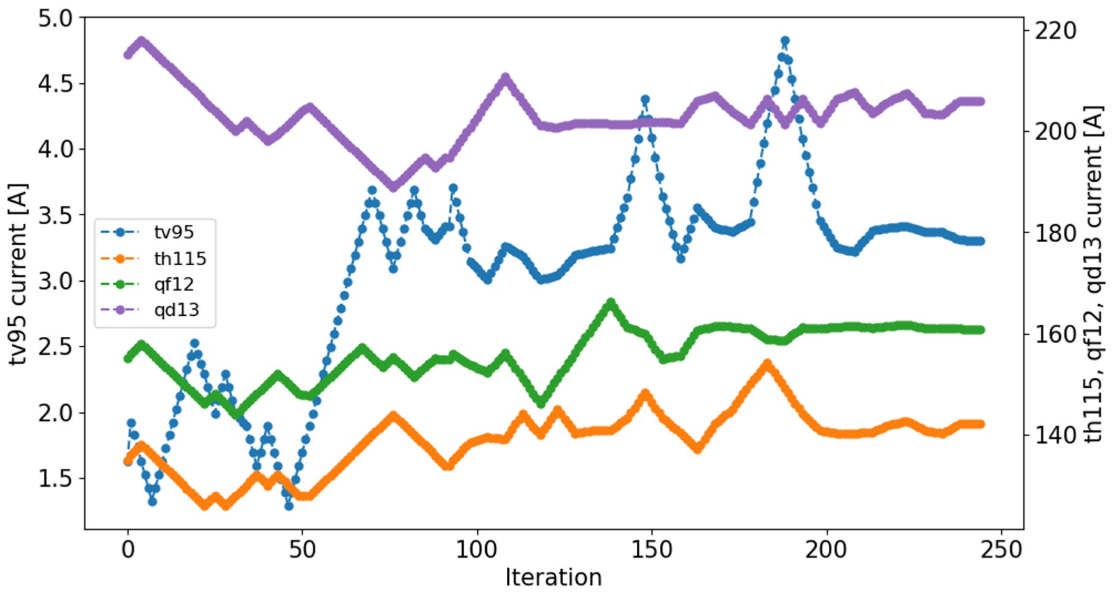


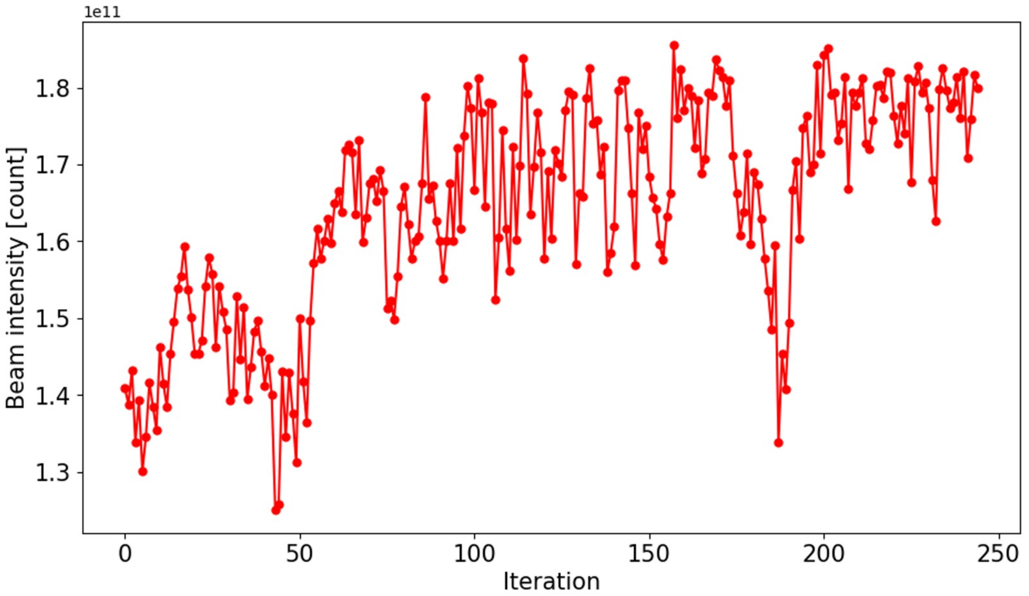
LtB Injection Optimization with BO

- Bayesian Optimization algorithm automatically maximizes Booster beam intensity using LtB optics
- Higher intensity after fixed scrapers → smaller beam size → higher luminosity L
- Beam size decrease observed in both planes in the BtA line corresponds to intensity increase

$$\mathcal{L} \sim \frac{N^2}{\beta^* \varepsilon} \sim \frac{N^2}{beam\ size}$$

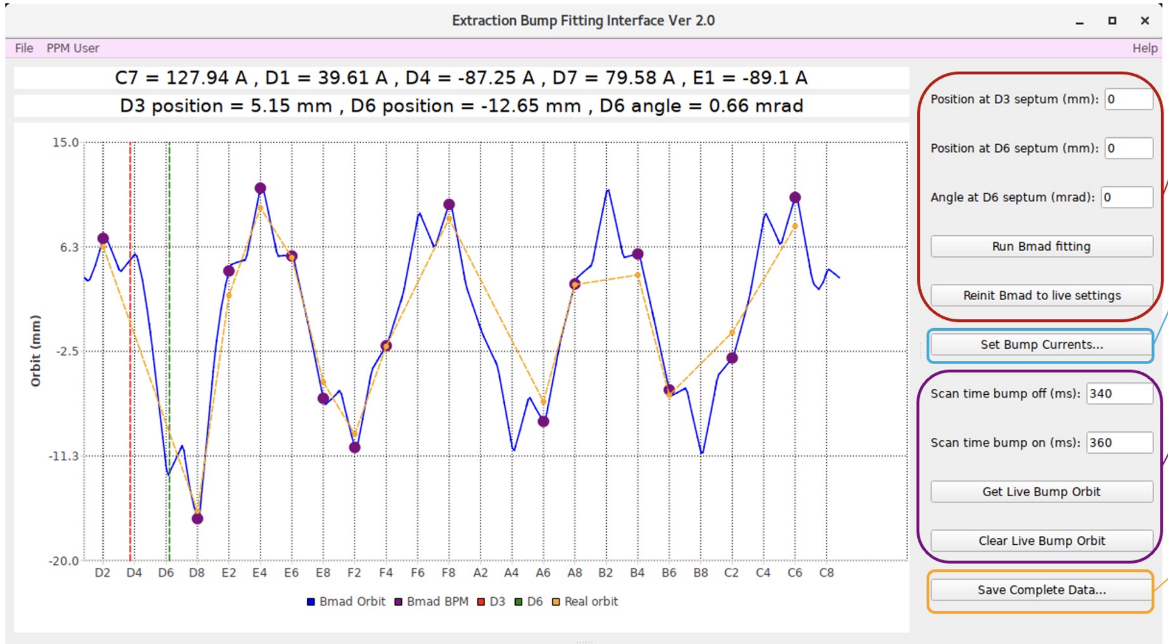






Digital Twin for NSRL

- We developed and tested a complete digital twin (DT) system for the Booster extraction bumps, with bidirectional interaction between physical and virtual accelerators.
- DT for NSRL line also under development, will facilitate beam uniformity optimization
- Future NSRL tuning will be easier and more streamlined with the help of DT applications

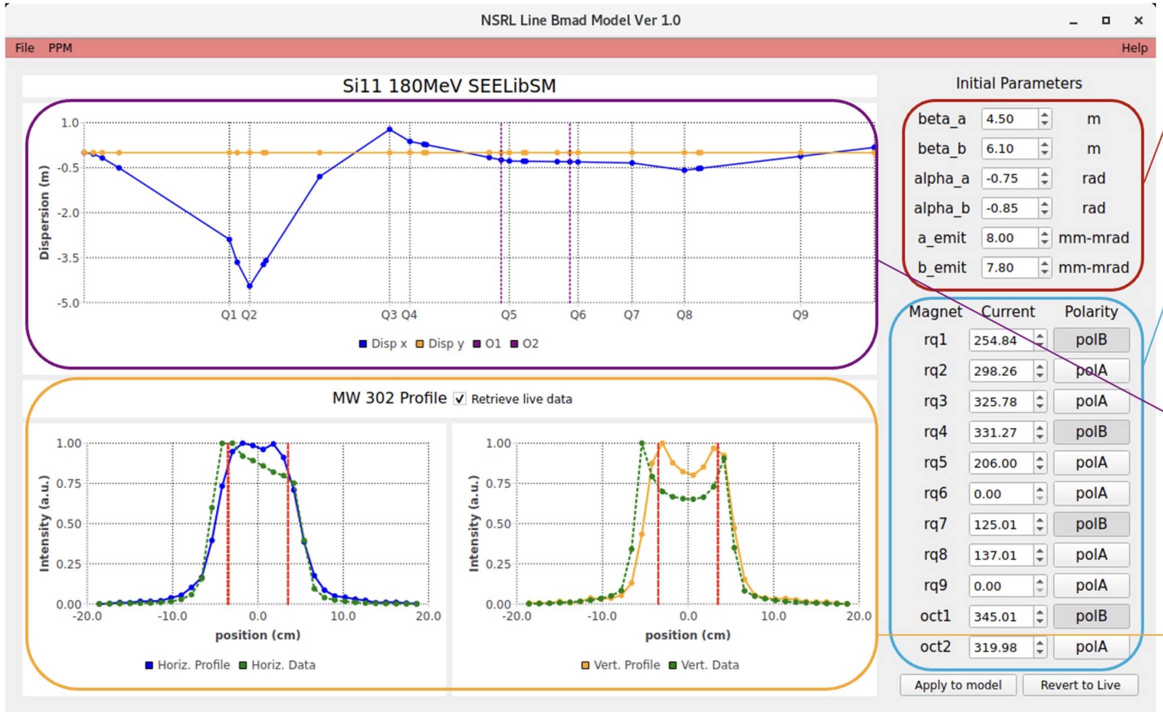


Use Bmad to fit any design bump shape

Send calculated bump currents to real machine

Time stamps in Booster cycle used to measure bump orbit

Save simulated and measured data



Initial beam parameters used by model

Currents and polarities of quadrupoles from live machine

Simulated dispersion of NSRL line using live machine info

Simulated vs. real transverse beam profile at MW302

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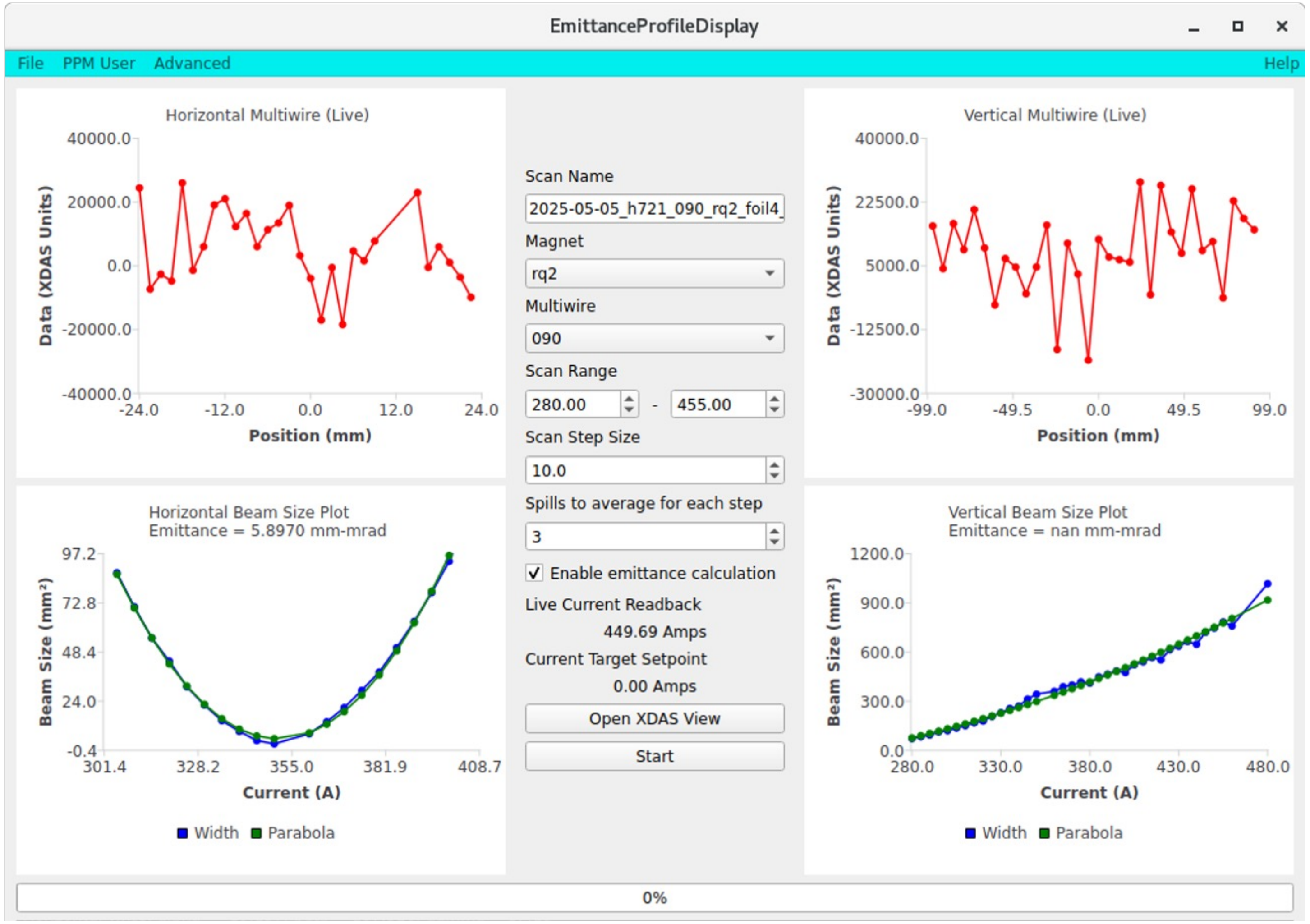
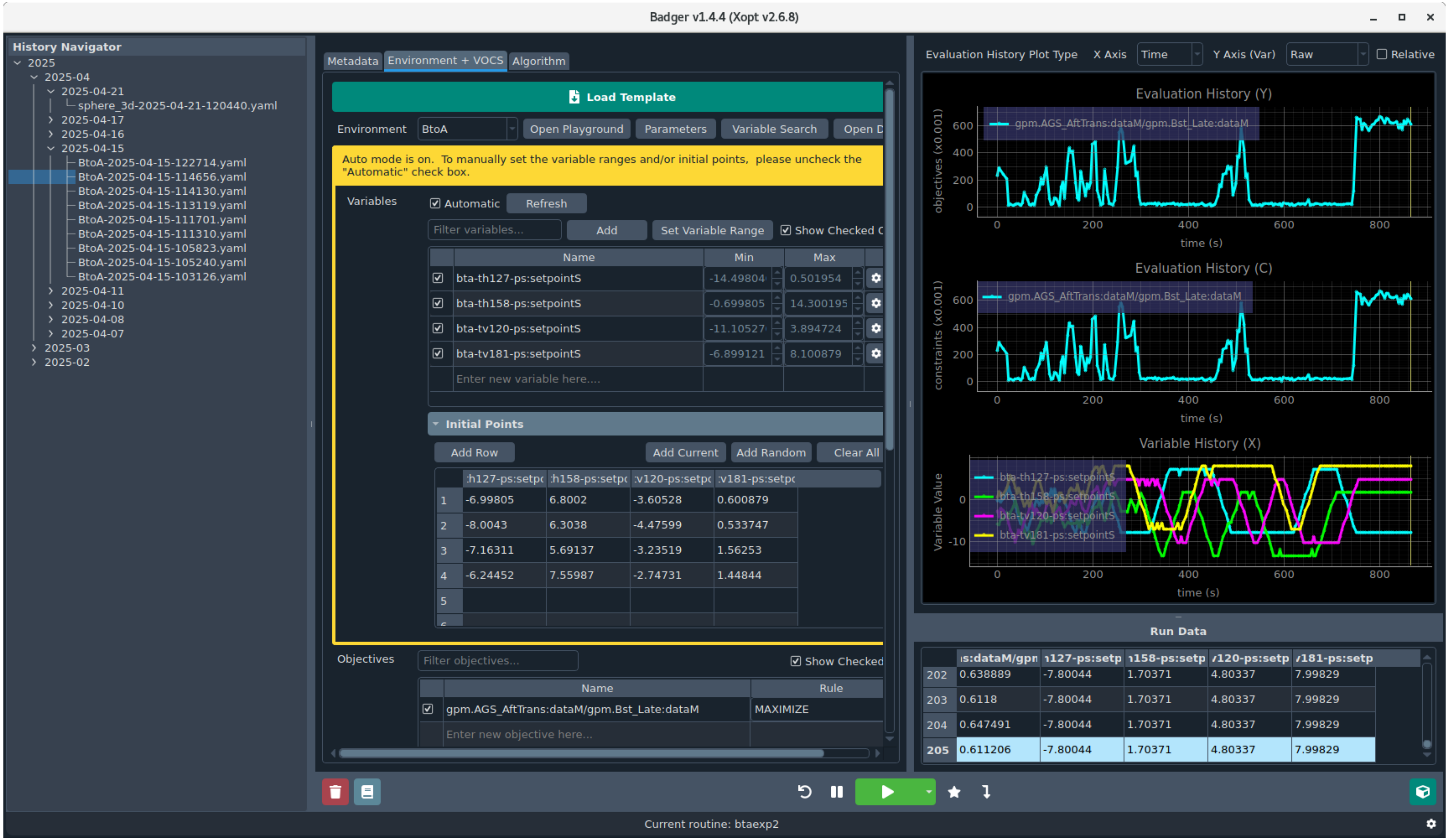
In operation: quad scan application

- Quadrupole scan application to automate quad scans and emittance calculations

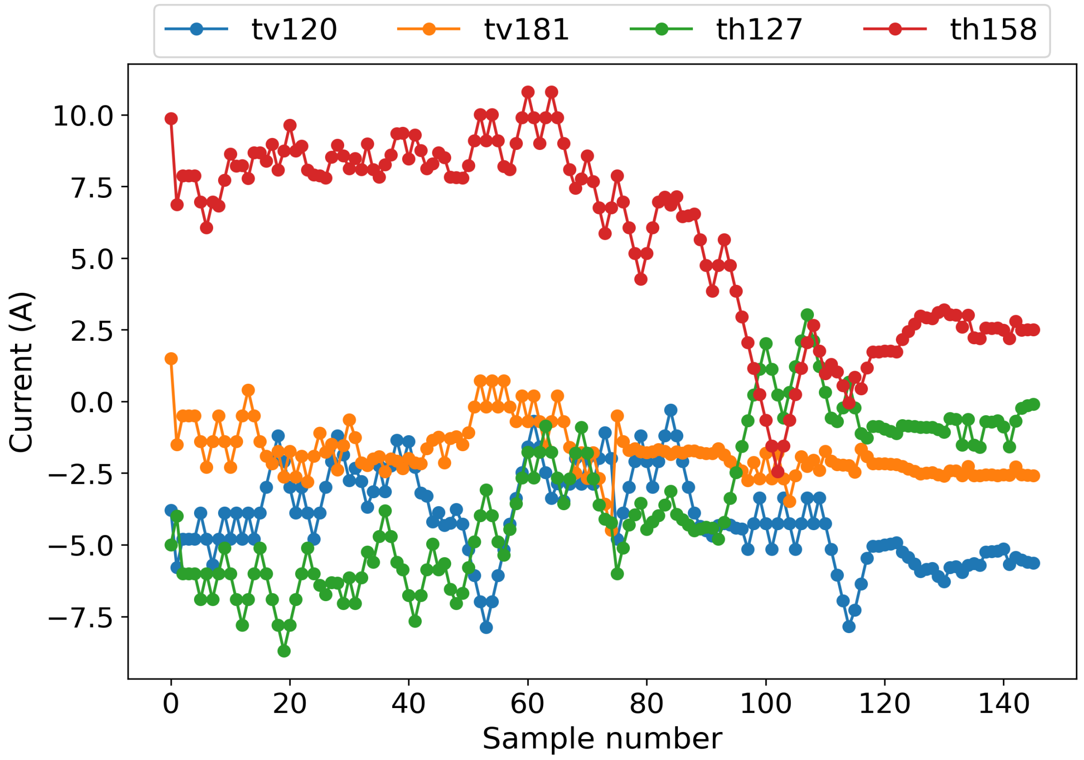


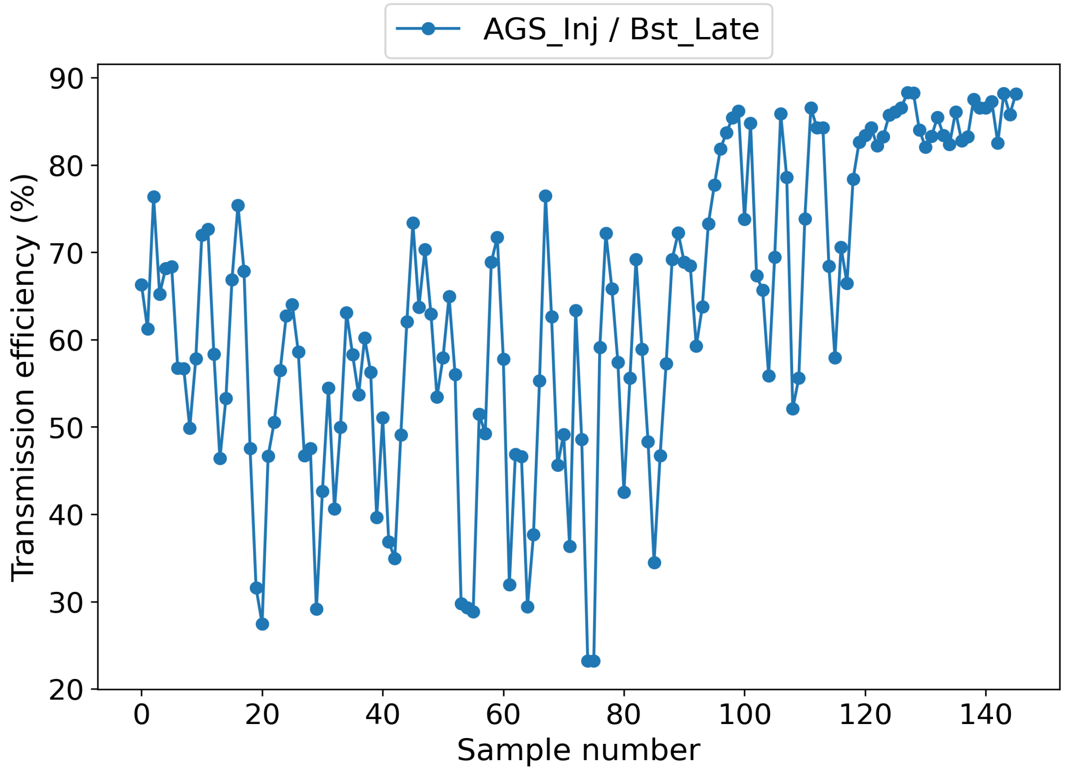
Badger: GUI for Bayesian Optimization



BtA Injection Optimization with BO

- Bayesian Optimization algorithm automatically maximizes beam transmission using BtA optics
- Measure transmission efficiency via DCCT and emittance growth via IPM
- Real-world test starting from operational settings show 20% improvement





Digital Twin and Polarization

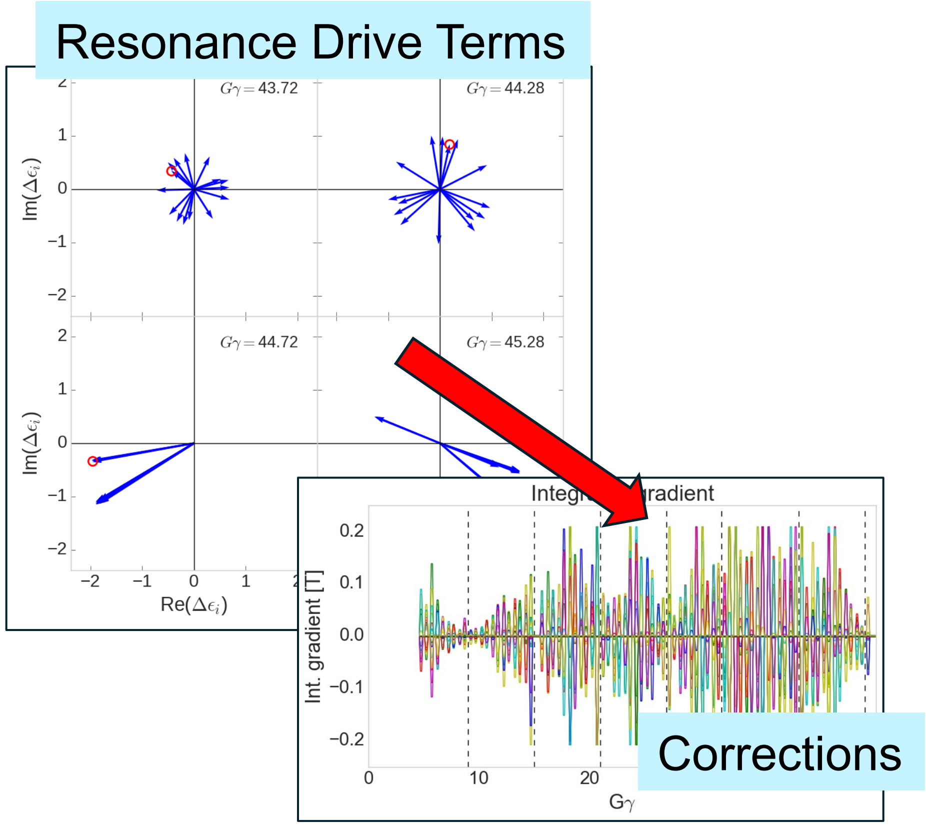
Correcting and avoiding depolarizing resonance is heavily model dependent

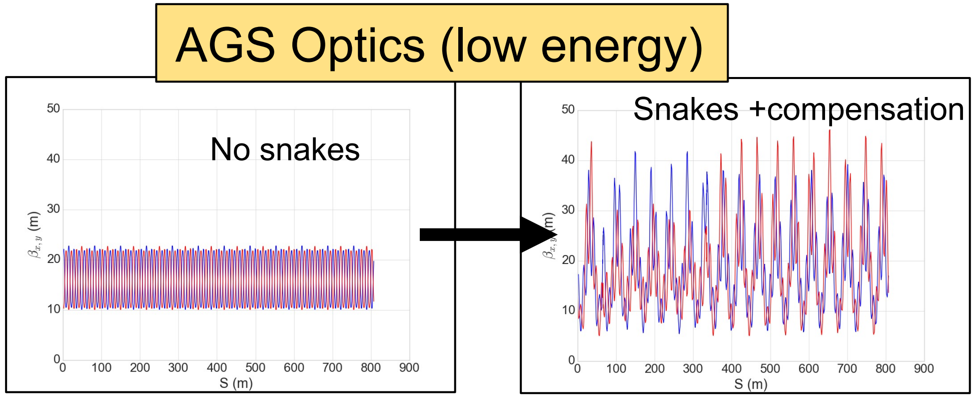
Polarization often requires challenging configurations
- Near resonance tune
- Complicated helical dipole magnets

Spin-related interventions like tune jumps/spin matching have impact on beam motion like tune and orbit

Polarization measurements are costly in time

Digital twin allows
- Predicting/compensating for side effects immediately
- Real time viewing of model/machine discrepancy
- Trial of hypothetical situations (e.g. proposed gradient error)





List of operational tools / applications

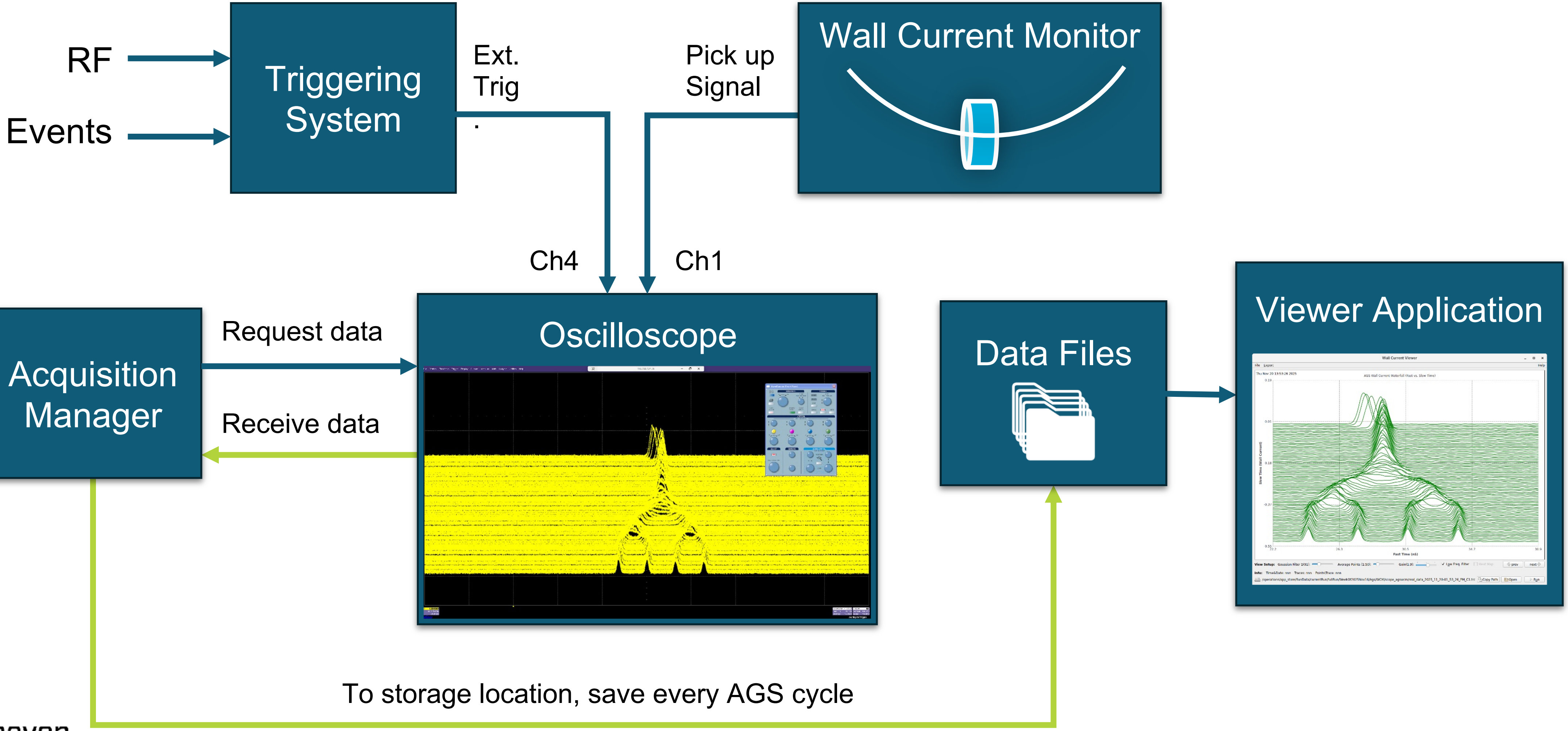
- Badger (Xopt) for Bayesian Optimization, available for LtB, BtA, NSRL
- Booster extraction bump fitting interface
- NSRL line tuning interface
- Quadrupole scan application, available for BtA and NSRL, in development for LtB and TtB
- Orbit response measurement script, available for Booster and AGS

Emittance

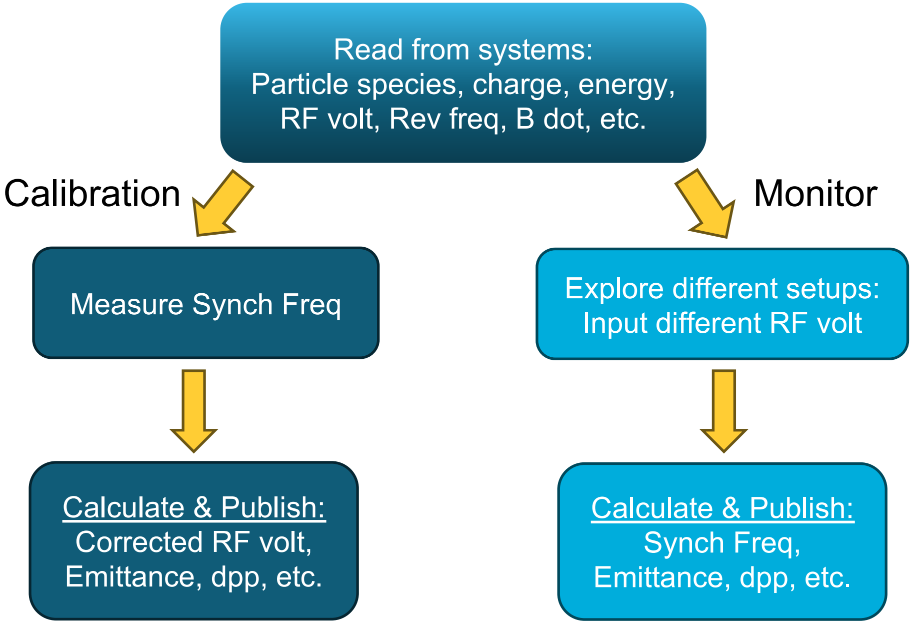
1. Longitudinal Profile Data Acquisition
2. Longitudinal Emittance Manager
3. Bunch merging
4. Transverse Emittance in AGS
5. Optics Measurements

Line Current Profile Data Acquisition

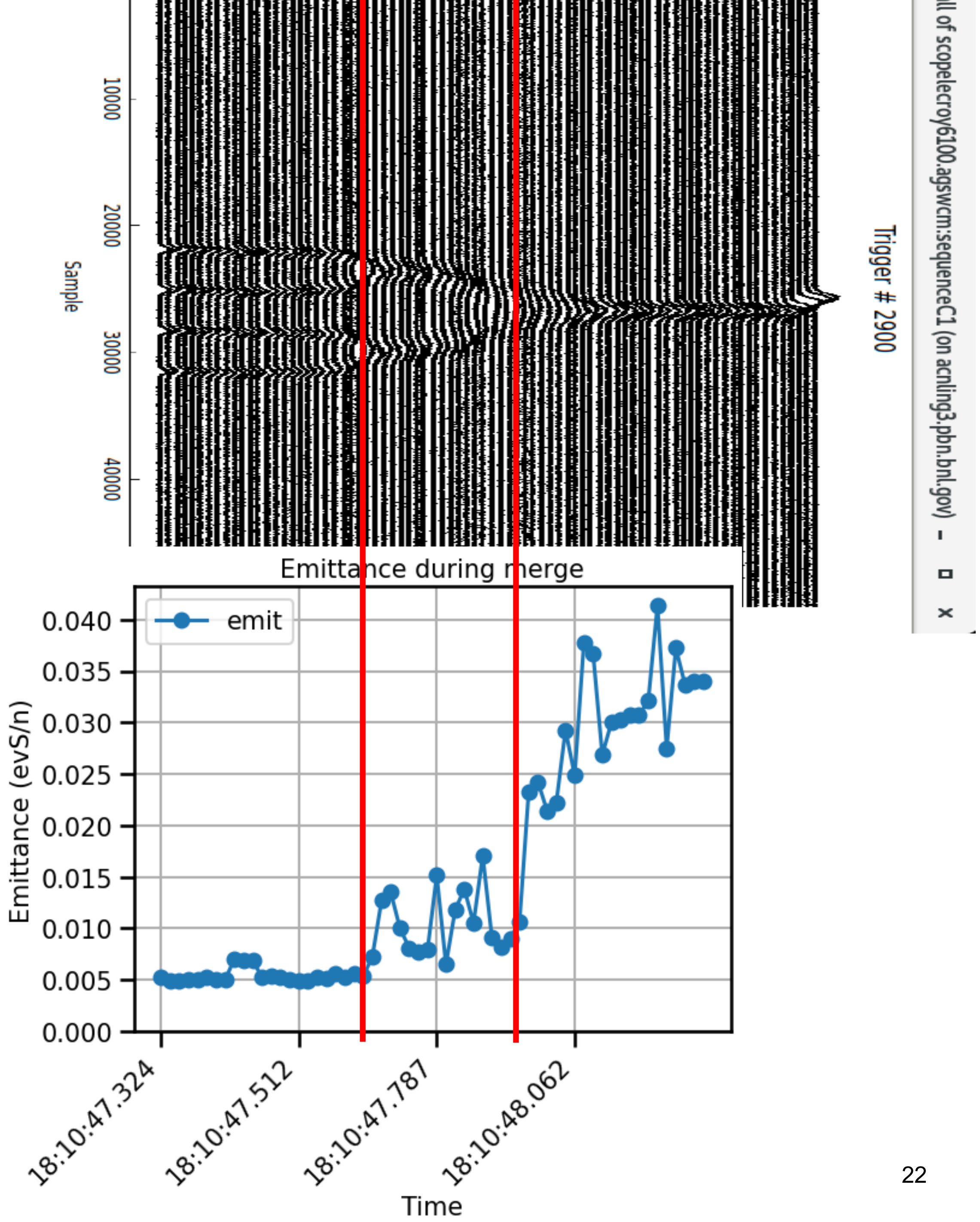
A dedicated longitudinal profile monitor for dedicated longitudinal emittance measurements.



Beam Property Manager



- The goal is to publish beam parameters, such as bunch length, dpp, emittance, etc., in real time, for any beam.
- Those parameters will also be logged, so they can be accessed later for further analysis.
- Analyze the bunch profile evolutions.
- This system has just been developed and is still under test. It is being integrated with operations, but improvements are still being made.



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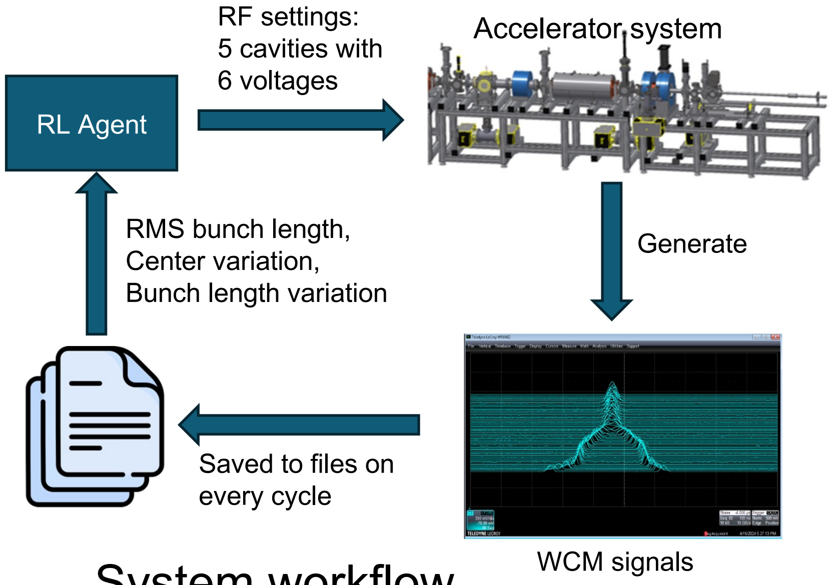
Reinforcement Learning in AGS Bunch Merging

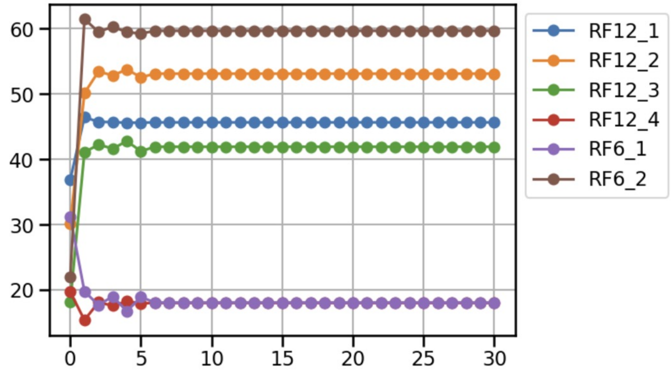
RL is trained using (Julia) simulations of the bunch merge.

- RL agent regulates AGS bunch merging by tuning RF voltages; The observable is the WCM signals, which is saved to files on every AGS cycle.
- RL agent is able to achieve the optimal merge in one step from a bad state; The result is comparable to the operational merge.

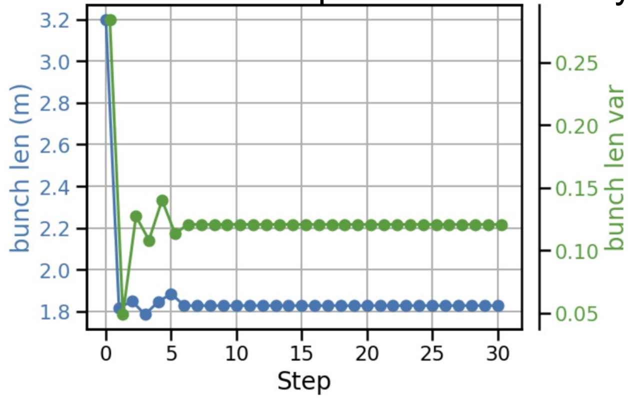


System workflow

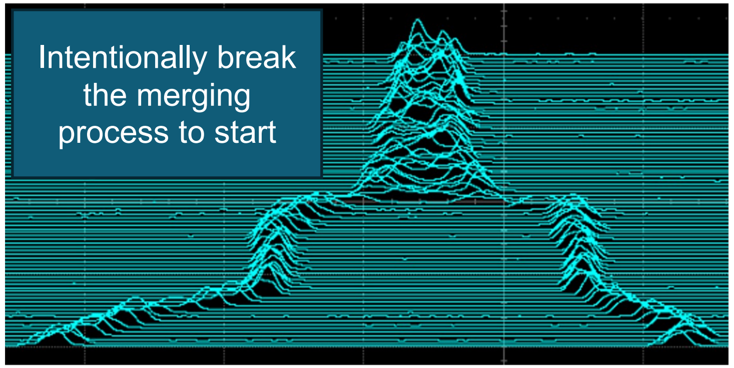
All actions converge in one step

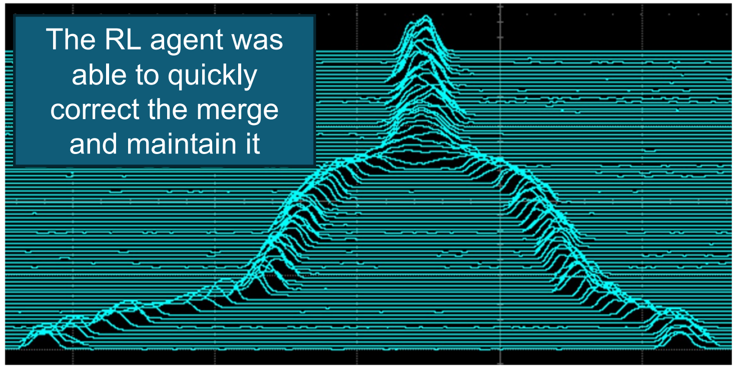


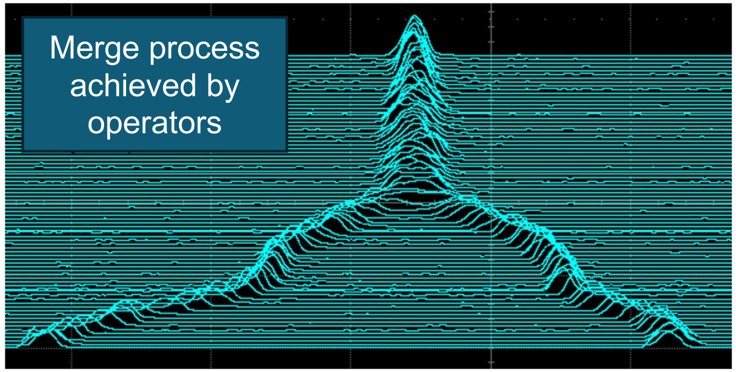
Both the bunch length and bunch variations were optimized effectively



	Initial	**RL**	**System**
bunch length	3.2	1.83	2.12
bunch length var	0.28	0.12	0.09







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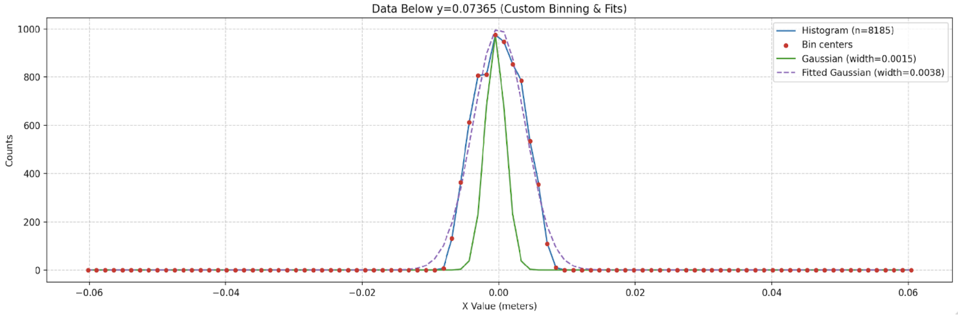
Improving IPM Emittance Measurements with ML

Developed 3D PIC model of AGS IPM operation

Exploring use of Gaussian Process-based surrogate for fast evaluation

- Infer true beam size from short scans of IPM operating points without other beam measurements

IPM profile at collector wires in simulation

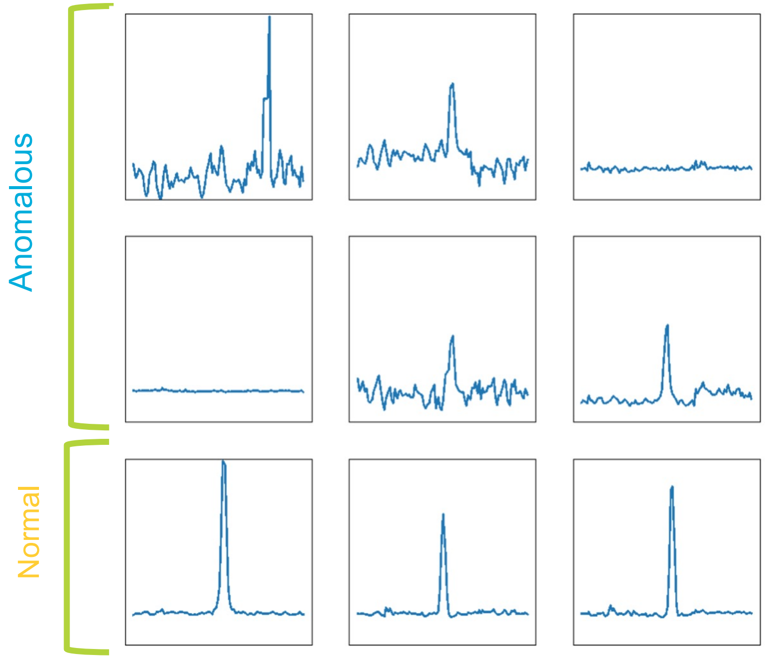


Unsupervised anomaly classifier from transformer-encoder embeddings to detect atypical IPM profiles

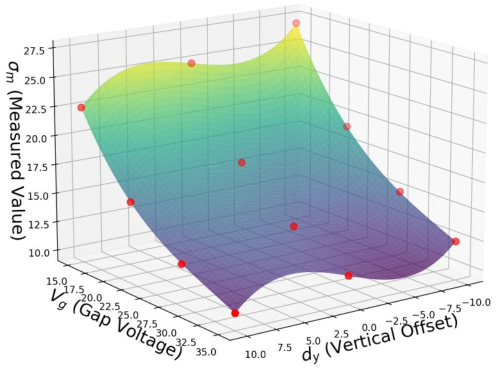
Model prediction accuracy for true bunch size

Approach	Model	R^2	MAE (mm)
Gaussian Noise ($\sigma = 0.75$ mm)			
Surface-Fit	RandomForest	0.4291	0.6503
	XGBoost	0.4222	0.6466
	GaussianProcess	**0.8089**	**0.3736**
Voltage-Fit	RandomForest	0.2038	0.7983
	XGBoost	0.0598	0.8413
	GaussianProcess	0.7233	0.4573
Point by Point	RandomForest	-0.1094	0.9040
	XGBoost	0.0015	0.8725
	GaussianProcess	0.1199	0.8270
No Noise			
Surface-Fit	RandomForest	0.8827	0.3060
	XGBoost	0.8858	0.2956
	GaussianProcess	0.9885	0.0890
Voltage-Fit	RandomForest	0.8922	0.2835
	XGBoost	0.9025	0.2544
	GaussianProcess	**0.9908**	**0.0683**
Point-by-Point	RandomForest	-0.0533	0.9697
	XGBoost	0.0266	0.9452
	GaussianProcess	0.0996	0.9363

Classifier predictions on logger data



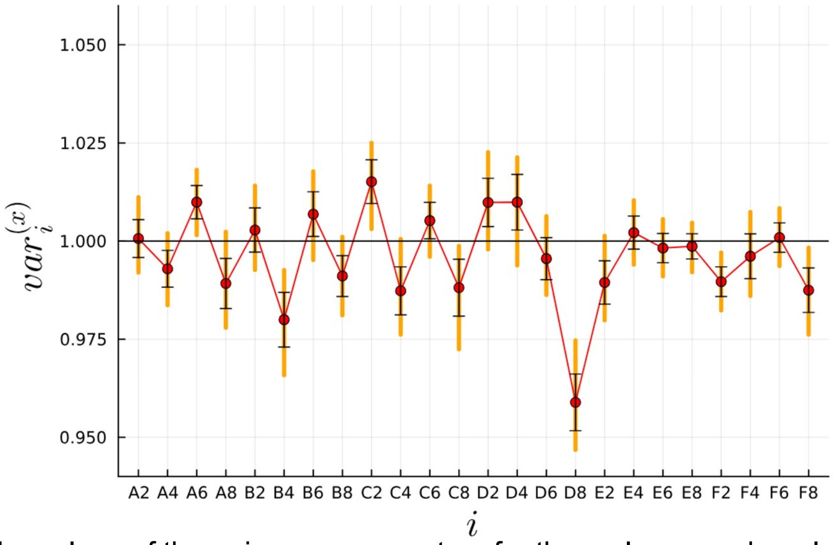
Simulated scan with surface fitting



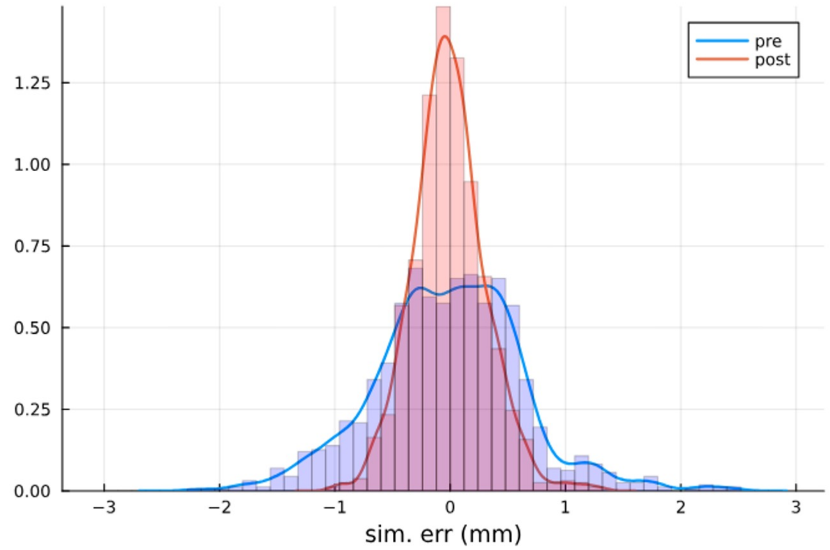
Machine-Learning–Accelerated Bayesian Uncertainty Quantification for Digital Twin Modeling and Control of the AGS Booster

- A precise Digital Twin for AGS Booster would enable more reliable beam control, improving beam quality for RHIC and EIC.
- Comparison of existing Digital Twin (Bmad) to real beam orbit data shows discrepancies of unknown origin.
- **We used Bayesian Uncertainty Quantification (UQ) to study the discrepancies.**

- We introduced quadrupole-dependent nuisance parameters to the Bmad simulation.
- UQ provides estimates of those parameters and their uncertainties by combining orbit-response data with expert foreknowledge.
- A machine-learned surrogate was employed to obtain a fast, differentiable model required for the UQ procedure.
- We find strong evidence of position-dependent deviations from the null result.
- **Including these nuisance parameters in the simulation significantly improved the model errors.**



The values of the nuisance parameters for the x-plane quadrupoles. A value of 1.0 represents the null result. We observe clear deviations from null for, in particular, the D8 quadrupole.



A comparison of the absolute simulation error for a subset of our data with and without including the nuisance parameters (central values only), showing a significant improvement in simulation error.

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Summary

- Polarized Proton work
  - Optimizing injection to Booster and AGS to increase beam brightness to reduce intensity dependent polarization. Experiments show we can reduce emittances by 20%. 4 times faster than an operator.
  - Bunch Merge: Aimed at reducing space charge at AGS injection. Reduced transverse emittance by 15%. A well-trained RL model makes the correction in just a handful of steps.
  - Still looking to understand the emittance evolution in the injectors. Much depends on quality of measurements in AGS IPMs
  - ORM measurements with new analysis is helping build better models. We are eager to get turn-by-turn BPM electronics installed in AGS & Booster to improve things even more!
- Operations Tools
  - New Diagnostics: Quad scanning, new ORM analysis, longitudinal emittance monitor
  - AI tools: Badger (Xopt) for Bayesian optimization, digital twins for Booster slow extraction bumps and NSRL beamline, RL optimization for bunch merging
  - Ongoing work on digital twins and emittance diagnostics
- Community work
  - AI/ML Collaborations, NARAD, MOAT, EIC-BeamAI
  - Workshops: AI4EIC, MaLAPA, RL4AA

Publications

- [1] Y. Gao et al., “Applying Bayesian Optimization to Achieve Optimum Cooling at the Low Energy RHIC Electron Cooling System”, Physical Review Accelerators and Beams 25, 014601 (2022).
- [2] W. Lin et al., “Simulation Studies and Machine Learning Applications at the Coherent electron Cooling experiment at RHIC”, in *Proc. IPAC'22*, Bangkok, Thailand, Jun. 2022, pp. 2387-2390.
- [3] W. Lin et al., “Machine learning applications for orbit and optics correction at the Alternating Gradient Synchrotron”, in *Proc. IPAC'23*, Venice, Italy, May 2023, pp. 4460-4463.
- [4] W. Lin et al., “AGS Booster model calibration and digital-twin development”, in *Proc. IPAC’24*, Nashville, TN, May 2024, pp. 3449-3452.
- [5] R. Roussel et al., “Bayesian Optimization Algorithms for Accelerator Physics”, Physical Review Accelerators and Beams 27, 084801 (2024).
- [6] T. Balasooriya et al., “Reinforcement Learning for Charged Particle Beam Control to Minimize Injection Mismatch in Particle Accelerators”, *ICASSP 2025 - 2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Hyderabad, India, 2025, pp. 1-5.
- [7] W. Lin, “Maintaining optimal beam brightness and luminosity using machine learning”, in *Proc. HIAT2025*, East Lansing, MI, Jun. 2025, pp. 79-84.
- [8] W. Lin et al., “Improve beam brightness with Bayesian optimization at the AGS Booster injection at BNL”, in *Proc. NAPAC’25*, Sacramento, CA, Aug. 2025, pp. 157-159.
- [9] E. Hamwi et al., “Application of Bayesian optimization to BtA injection at BNL”, in *Proc. NAPAC’25*, Sacramento, CA, Aug. 2025, pp. 58-60.
- [10] W. Lin et al., “Machine learning assisted Bayesian calibration of accelerator digital twin from orbit response data”, in *Proc. NAPAC’25*, Sacramento, CA, Aug. 2025, pp. 177-180.
- [11] Y. Gao et al., “Exploring Reinforcement Learning for Optimal Bunch Merge in the AGS”, in *New York Scientific Data Summit 2025*, pp. 13-16 (2025).
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Presentations / Talks

- [1] A. Edelen, *“Physics Informed and Bayesian Machine Learning for Maximization of Beam Polarization at RHIC”*, presentation at the 4th ICFA Beam Dynamics Mini-Workshop on Machine Learning Applications for Particle Accelerators (MaLAPA 2024), Gyeongju, South Korea, March 5, 2024.
- [2] W. Lin, *“Maintaining optimal beam brightness and luminosity using machine learning”*, presentation at the 16th International Conference on Heavy Ion Accelerator Technology (HIAT 2025), East Lansing, MI, USA, June 24, 2025.
- [3] W. Lin, *“Extraction bump digital twin for NSRL slow extraction”*, presentation at the 6^{th} Slow Extraction Workshop (SX 2025), Stony Brook, NY, USA, October 8, 2025.
- [3] E. Hamwi, *“Use of AI/ML for higher brightness and higher polarization of hadron beams”*, presentation at the Artificial Intelligence for the Electron Ion Collider (AI4EIC 2025), Boston, MA, USA, October 27, 2025.
- [4] C. Kelly, *“Machine-Learning–Accelerated Bayesian Uncertainty Quantification for Digital Twin Modeling and Control of the AGS Booster”*, presentation at the Artificial Intelligence for the Electron Ion Collider (AI4EIC 2025), Boston, MA, USA, October 27, 2025.
- [5] C. Hall, *“Machine Learning Approaches to Improve Ion Profile Monitor Measurements”*, presentation at the Artificial Intelligence for the Electron Ion Collider (AI4EIC 2025), Boston, MA, USA, October 27, 2025.