The EIC-BeamAI Collaboration: Preparing Machine Learning for the Electron-Ion Collider

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For the EIC-BeamAI collaboration

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05/11/2026

Goal of the EIC-BeamAI collaboration

Improve EIC accelerator performance by ML/AI

Probably the most complex accelerator ever built:

- Polarized protons and electrons.
- Beam cooling (Rf, e, and photon based)
- Superconducting RF acceleration
- Superconducting magnets

- Too complex to be operated with traditional operator control

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AI/ML funded projects for the EIC

AI / ML is not part of the EIC construction project
(partly because AI for accelerator operations is so now.)

Subsequent (off-project) funding:

- **Higher RHIC polarization by Physics-informed Bayesian Learning**
  BNL, Cornell, JLAB, SLAC, RPI (DOE-NP funding 2023 – 2025)
- **Toward higher brightness and polarization of hadron beams: Digital-Twin-based autonomous control of BNL's hadron accelerator chain**
  BNL, Cornell, JLAB, SLAC, FNAL, RPI (DOE-NP funding 2025 – 2027)
- **Developing AI-Ready Data Framework for DOE NP Particle Accelerators**
  Now called **NARAD =** NP AI-Ready Accelerator Data
  JLAB (lead), BNL, Cornell, LBNL, PNNL (ASCR/NP funding 2025-2027)
- **National collaboration: Multi Organization Accelerator Team (MOAT)**
  To prepare for AI/ML in accelerators funding through the US Genesis mission.

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What is the EIC-BeamAI collaboration

Grown out of the DOE-NP funded AI/ML projects for the EIC, we have …

- Worked on the funded projects
- Contributed to workforce development for AI/ML in the EIC.

- Connected to related work from other collaborations
  - AI/ML optimization of electron gun commissioning
  - Osprey for LLM aided accelerator operations
  - Topics of the Multi Office Accelerator Team (MOAT) – US collaboration for AI in accelerators

Zoom meetings are open to all (Tuesdays 11am, Friday 3pm EST)

➔ **We are requested to expand to the International EIC accelerator collaboration**

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The US Genesis mission

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 (9 DOE labs and universities) prepares the particle accelerator community for the Genesis Mission. It 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.

Several of the **MAOT-related proposals** are applicable to or focused **on the EIC**, e.g.,

- AI-Driven, Self-Learning Digital Twins for Robust Operation of Particle Accelerators *(focused on EIC pre-accelerators)*
- AI-reform of legacy codes in Accelerator modeling and operations *(focused on Bmad and SciBmad that models EIC)*
- AI-driven Accelerator Operations Prototyping with Cornell's Electron Test Beams *(with implementation at EIC pre-accel.)*
- Robust Diagnostic Comprehension for Facilitation of Large Scale Digital Twins *(with examples form BNL, e.g., IPMs)*
- Robust and Safe Deep Agent for Optimization and Control of Particle Accelerators *(Collaboration with BNL)*
- And more …

The EIC-BeamAI collaborations aim as part of the Genesis Mission is to build infrastructure that will benefit EIC.

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

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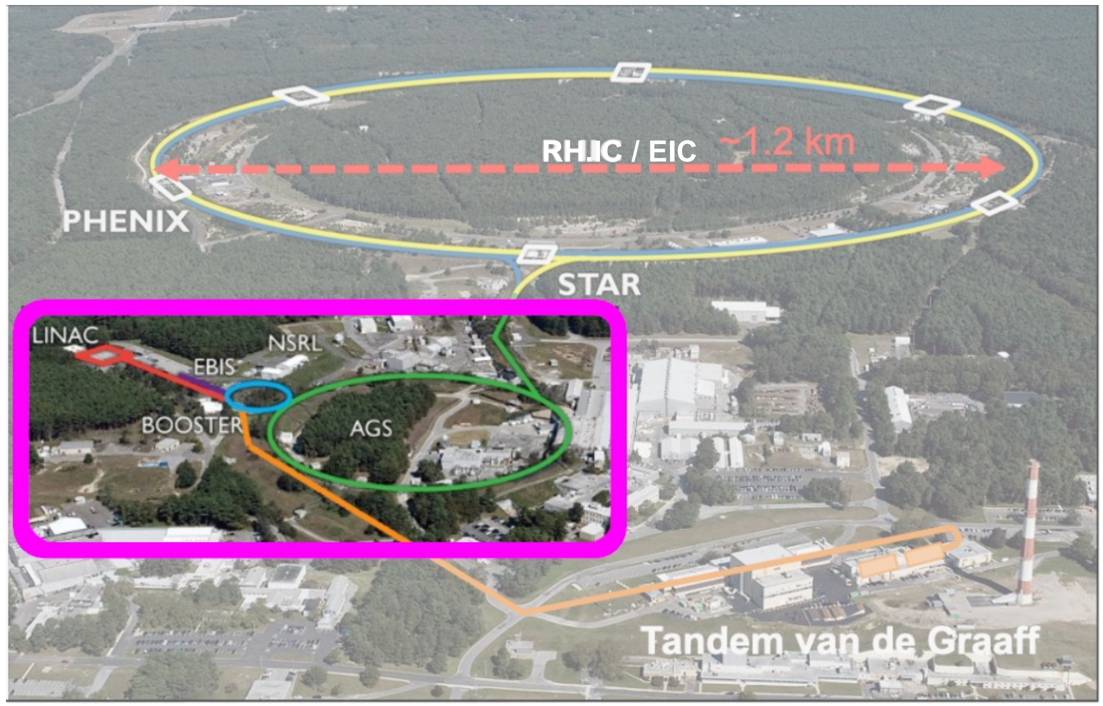
Development at existing EIC systems

Accelerator Rings

	Circumference [m]
Booster	201
AGS	807
RHIC	3833

Typical Top Energies [Total, GeV/N]

	Au	Pol. Protons
Linac (H^-)	--	1.1
Booster	1	2.3
AGS	10	23.8
RHIC	100	255



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Improving polarized collider performance

Collider luminosity, $\mathcal{L}$

$$\mathcal{L} \propto \frac{N^2}{\varepsilon}$$

N = intensity/ bunch
ε = tran. emittance

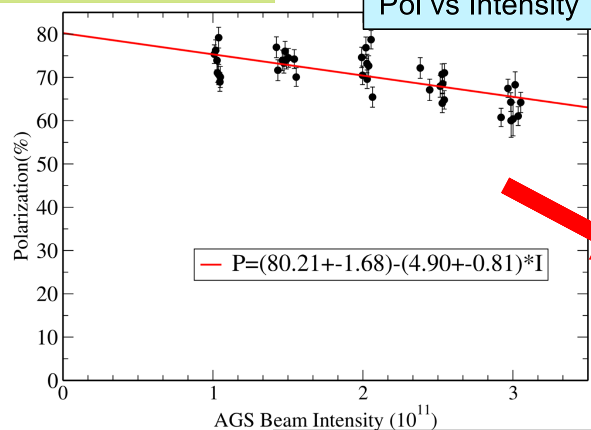
Polarized collider figure of merit (for polarization P):

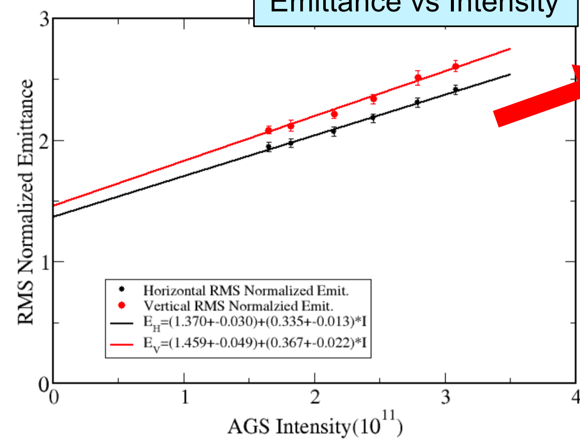
$$\text{FoM} = \begin{cases} \mathcal{L}\,P^2 & \text{transverse spin} \\ \mathcal{L}\,P^4 & \text{longitudinal spin} \end{cases}$$

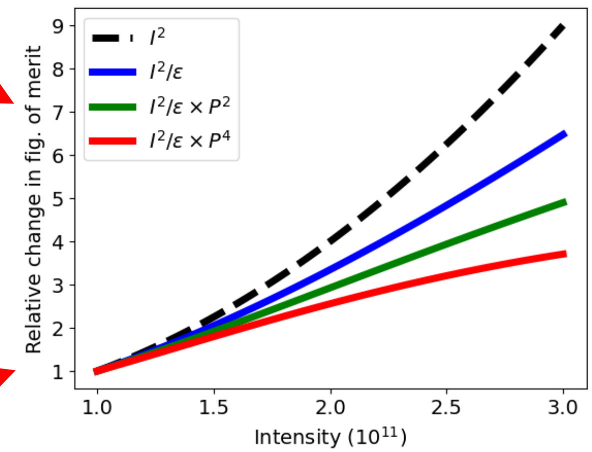
Since both emittance and polarization degrade with intensity figure of merit decreases rapidly

FoM dependence on intensity closer to linear in N than quadratic.

AGS extraction







Impact of intensity increase on FoM given emittance and polarization dependence at AGS extraction

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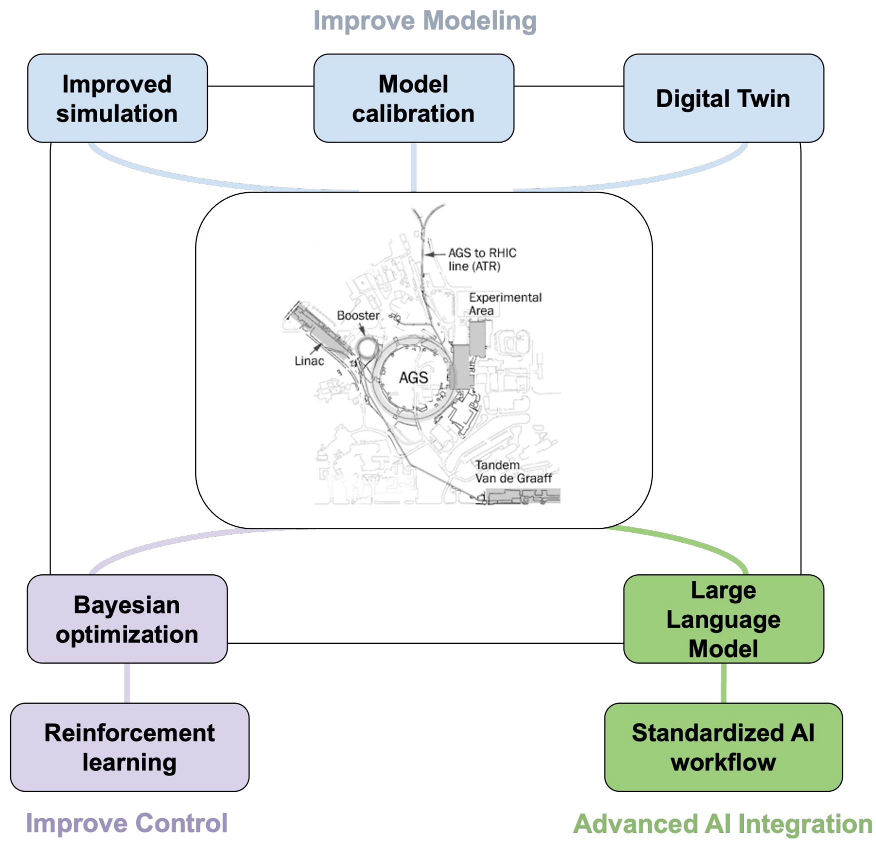
Preparation of AI for the EIC

Goal: Improve beam quality (brightness and polarization) and operational efficiency for the EIC.



Focus areas

- Automated beam tuning
- Operational Digital Twins
- Data-driven model calibration
- Fast adaptive control

Case studies: **BNL hadron injector complex**

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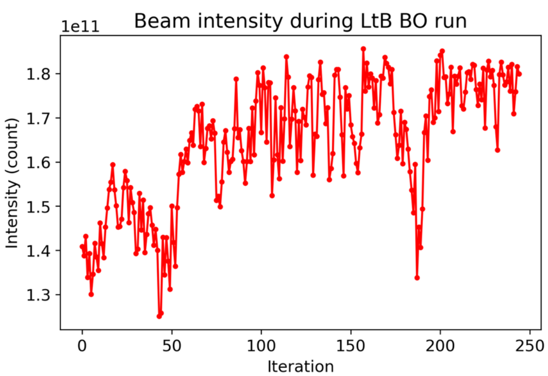
Booster injection optimization with BO

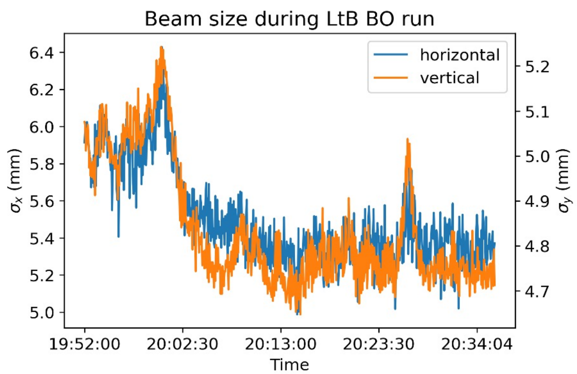
LtB Injection Optimization

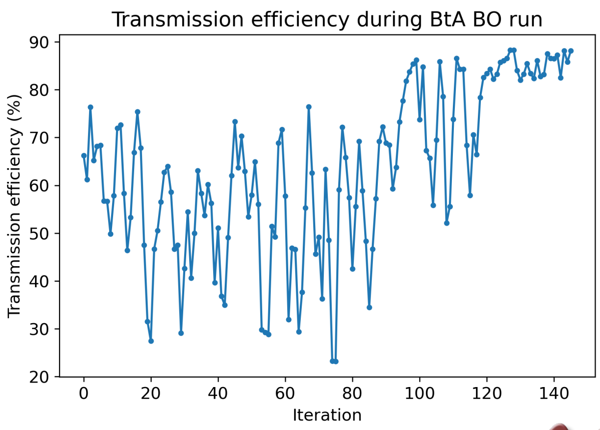
- BO maximizes Booster beam intensity using LtB optics.
- Beam size decrease in both planes during LtB optimization.

BtA Injection Optimization

- BO maximizes beam transmission efficiency using using BtA optics.
- 20% improvement from operational settings.







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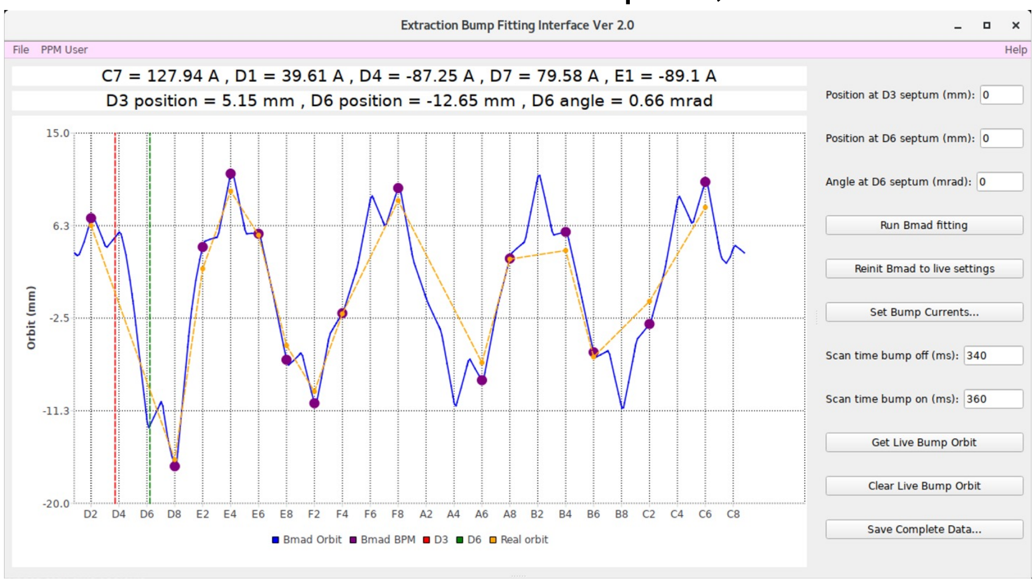
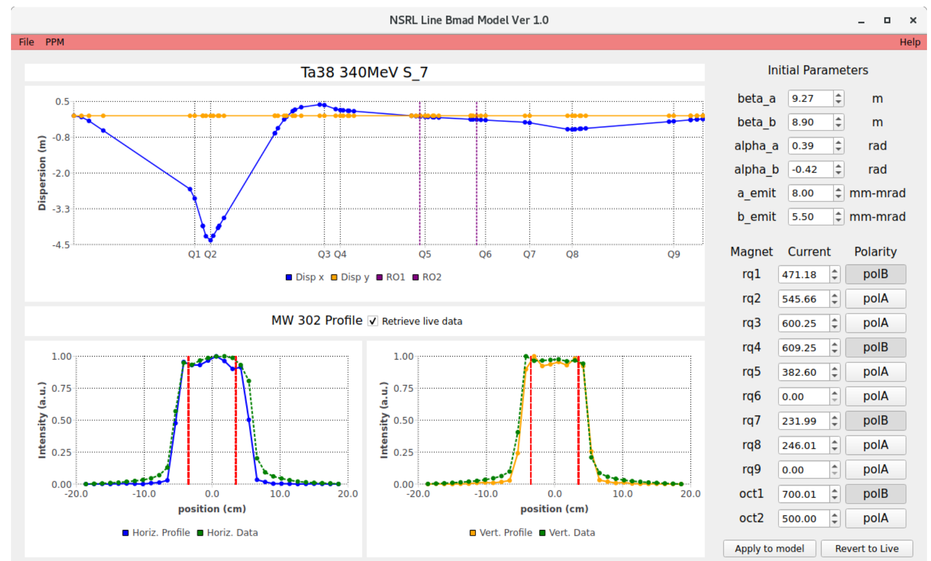
Digital Twin for NSRL

Goal: Operational digital twin framework with **bidirectional interaction** between the physical and virtual machines.

Outcome: Enable non-interruptive, model-based routine tuning for NSRL operations.





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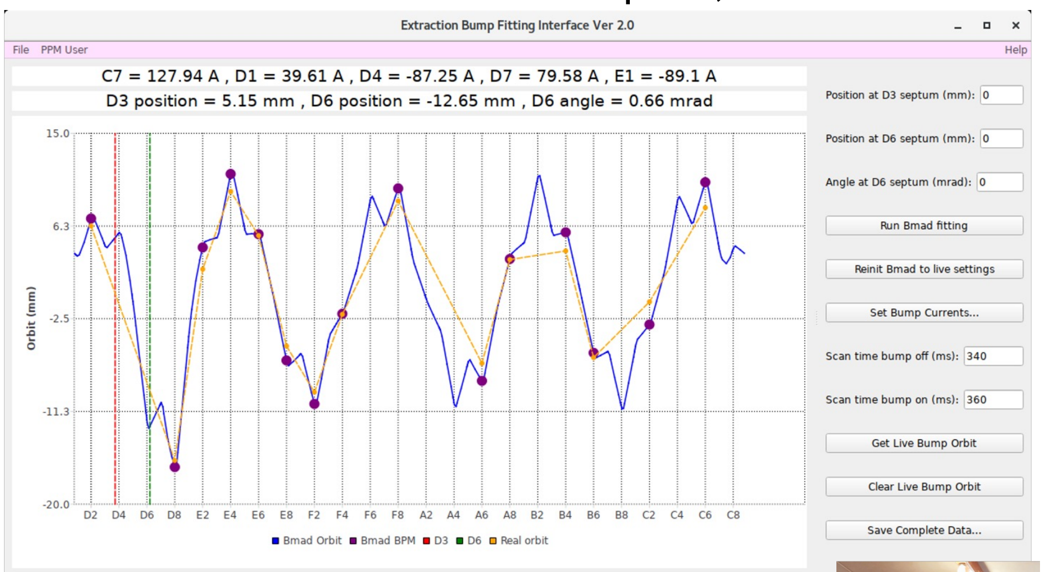

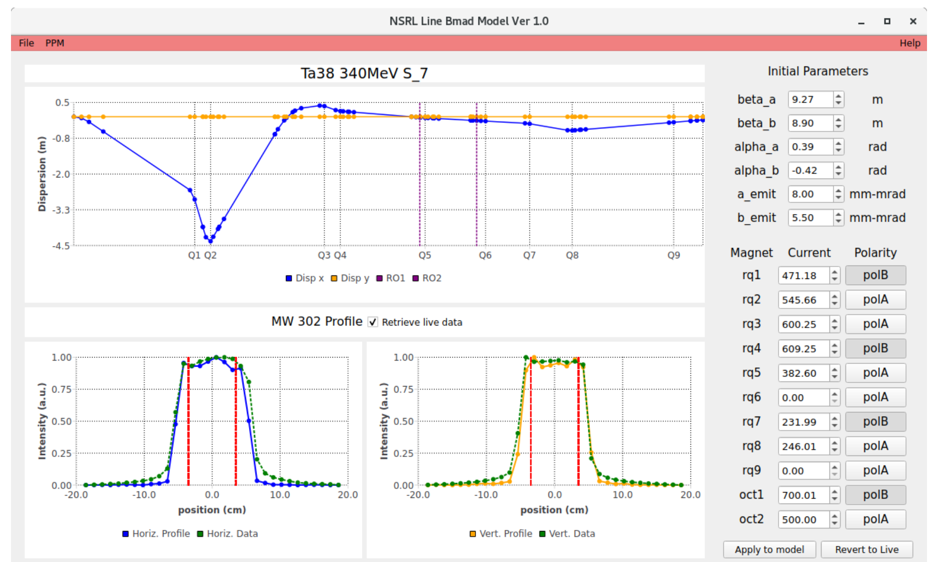

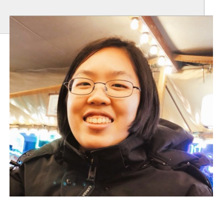

Weijian (Lucy) Lin
BNL postdoc

Brookhaven National Laboratory

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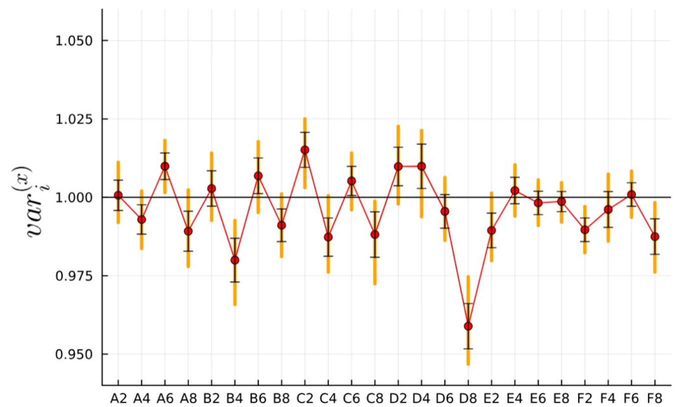
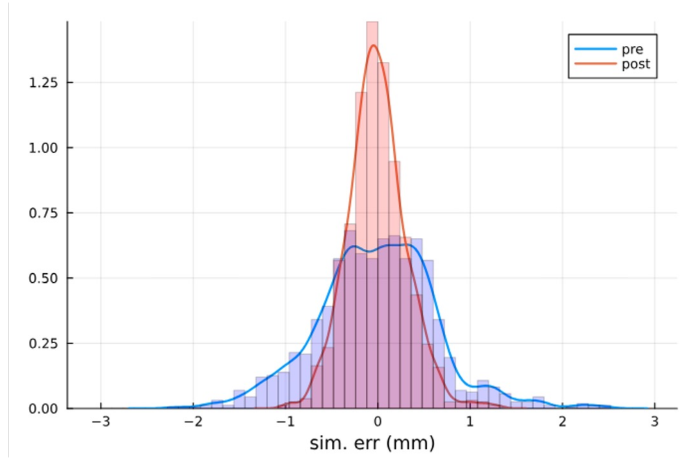
UQ to improve the Booster Model

Goal: Use Bayesian Uncertainty Quantification (UQ) to characterize and reduce model-data mismatches, assisting Digital Twin development.



Approach

- Bayesian UQ analyzes orbit response discrepancies.
- Neural network surrogate model accelerates UQ process.



Outcome

- UQ analysis investigates quadrupole field errors as possible sources of errors.
- Incorporating UQ results improves agreement between simulation and measurement.

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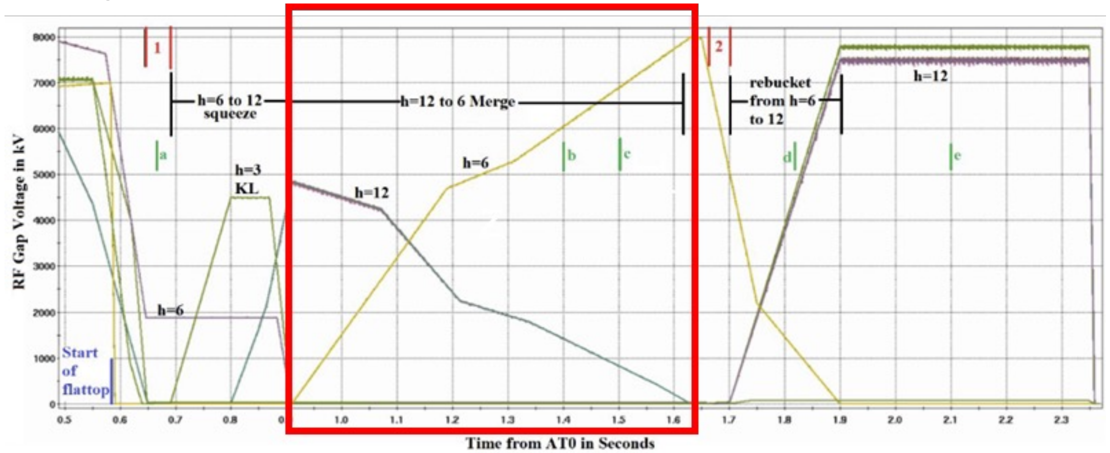
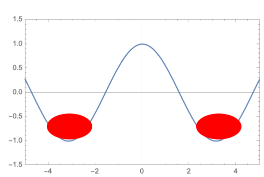
Bunch splitting and merging at BNL

Splitting in the Booster and merging after AGS accelerator reduces space charge and emittance growth ➔ more polarization

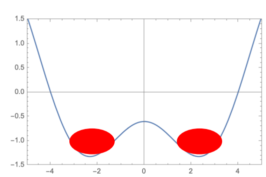


Three RF amplitudes (h=3, 6, 12) in the AGS during bucket manipulation and merging.

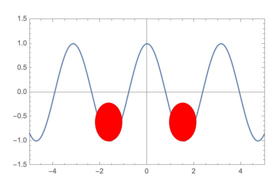
➔ We have set up Reinforcement Learning for the merging section.



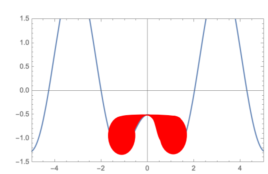
Accelerating RF h=6



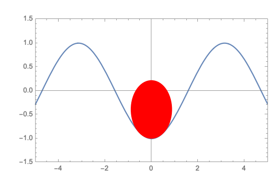
Attracting RF h=3



Close bucketing h=12



Combining h=6



Final bucketing h=6

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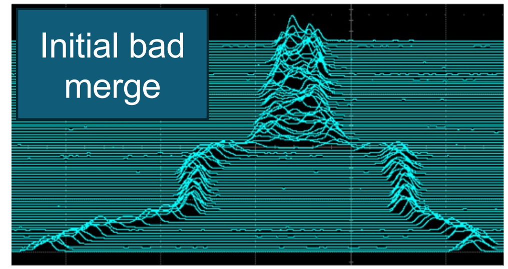
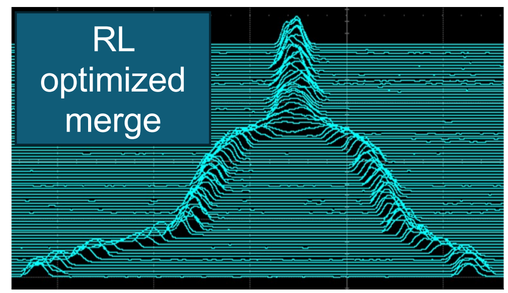
LLM optimized RL for Bunch Merging

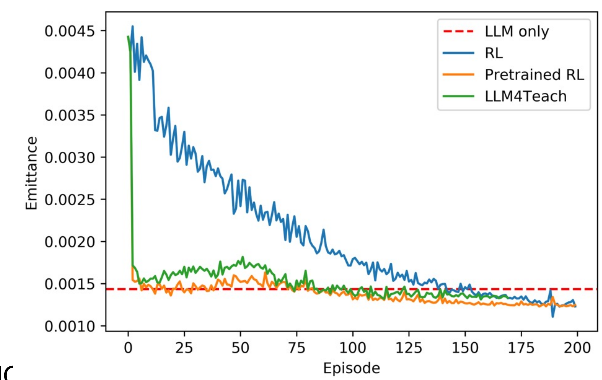
Goal: Obtain a good merged bunch profile – low emittance growth, no loss, centered and stable.





RL Optimization

- RL agent trained to minimize emittance growth.
- Begins from poor merge conditions; finds good RF settings after one step.
- Comparable performance to operational settings.
- LLM-based policy teacher for RL agent in development, leads to faster convergence and better performance.



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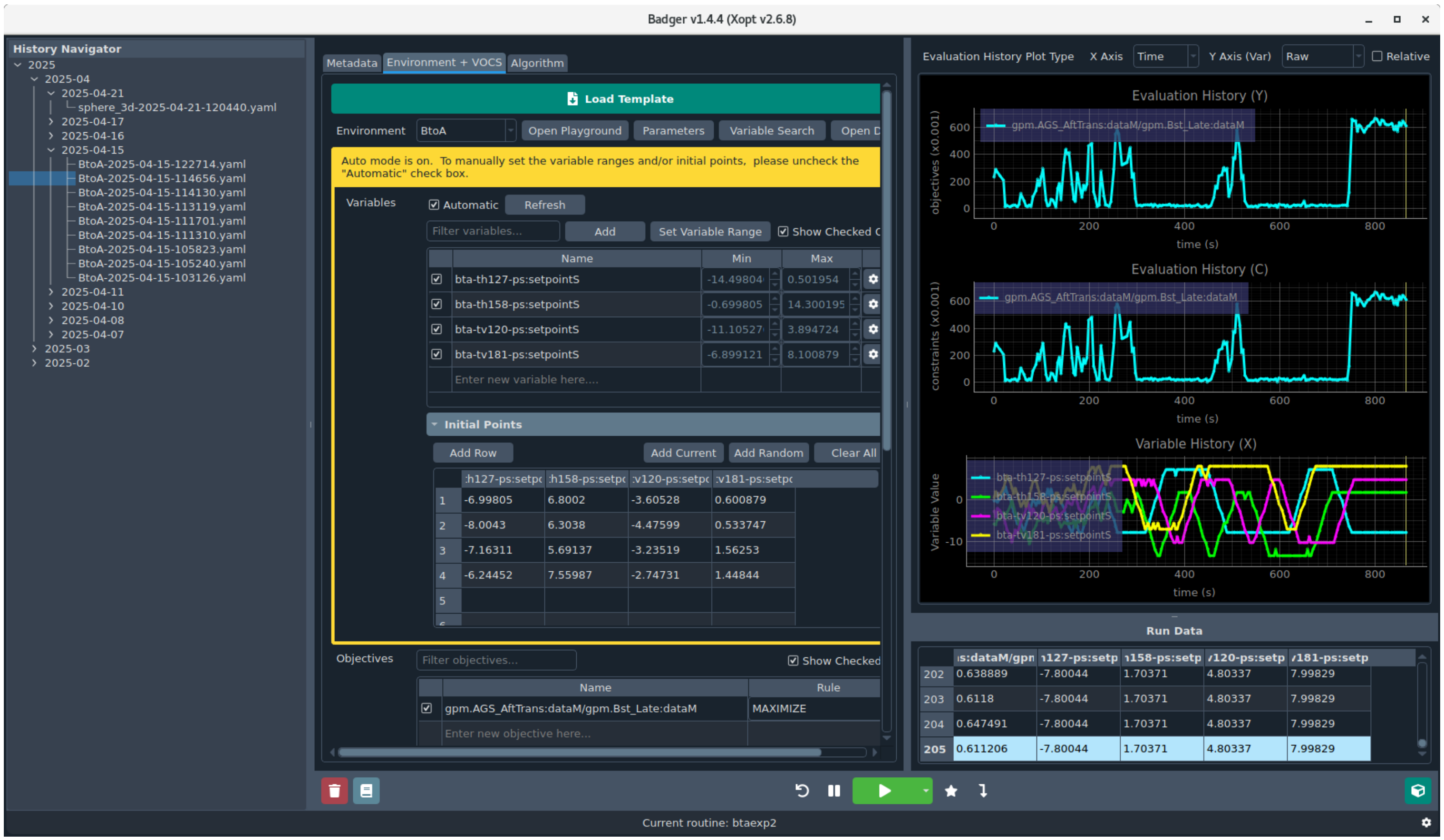
Badger: GUI for BO in the control room



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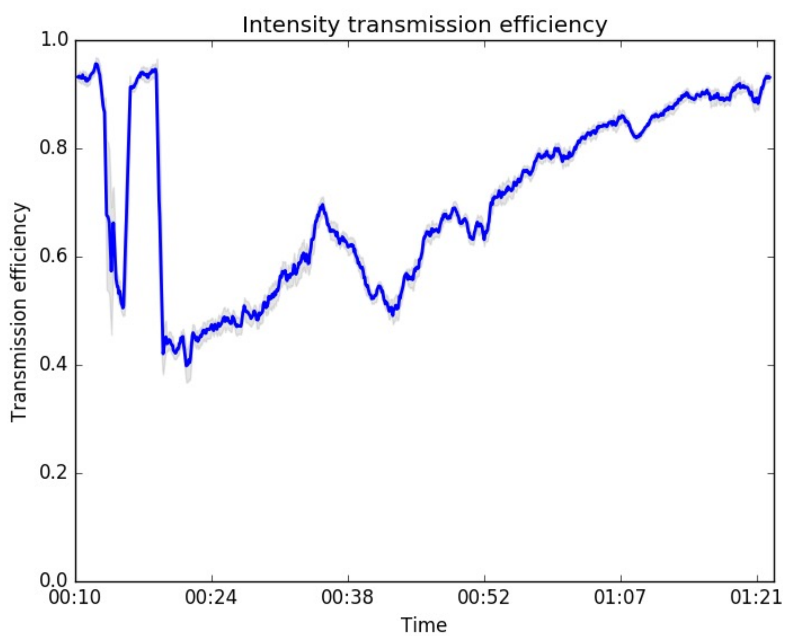
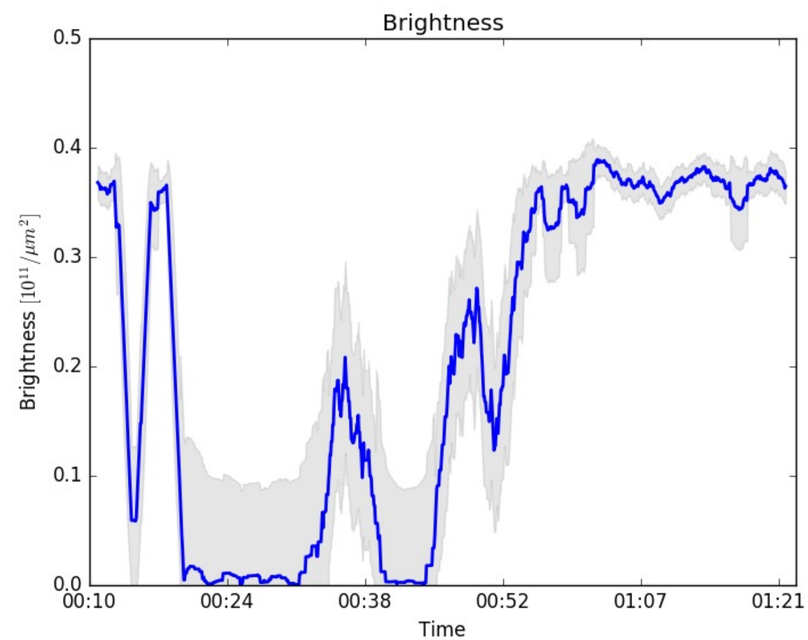
Automated AGS injection by BO

Algorithm efficiently found settings that were different, but at least as good as the previously optimized ones, automatically maintain the AGS injection at optimal performance without human intervention.





➔ Optimization of current while observing the brightness.

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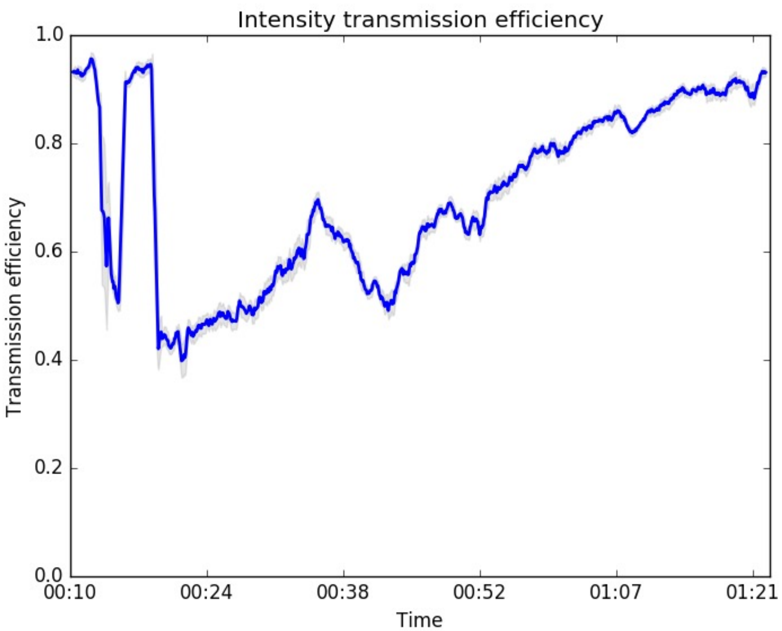

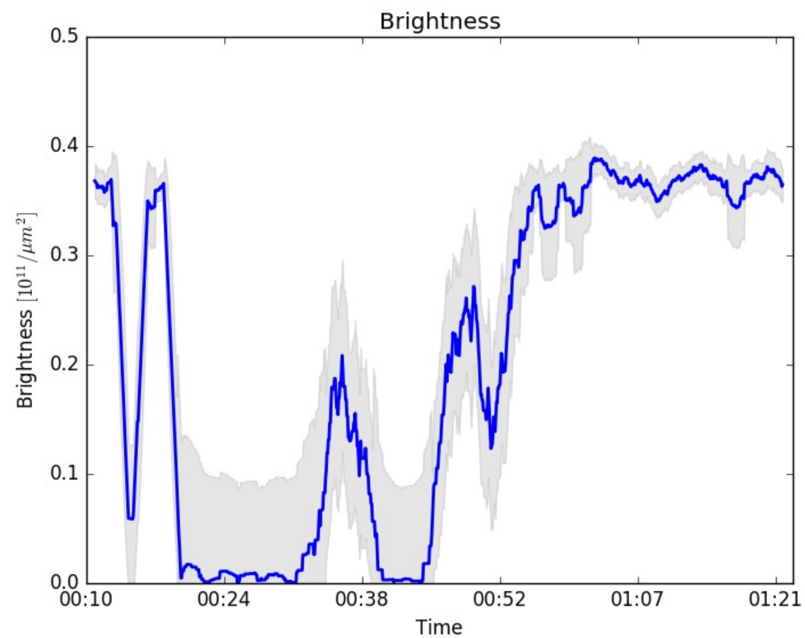

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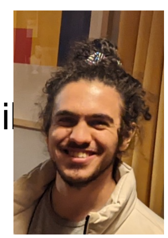

Eiad Hamwi, BNL postdoc

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ML-improved AGS IPM

Goal: Improve emittance reconstruction accuracy and robustness of AGS Ion Profile Monitor.

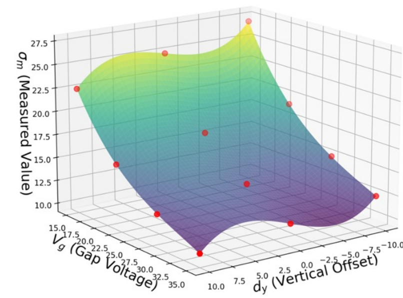
Approach

- Gaussian process based surrogate model for fast IPM profile inference.
- Unsupervised anomaly classifier to detect atypical IPM profiles.

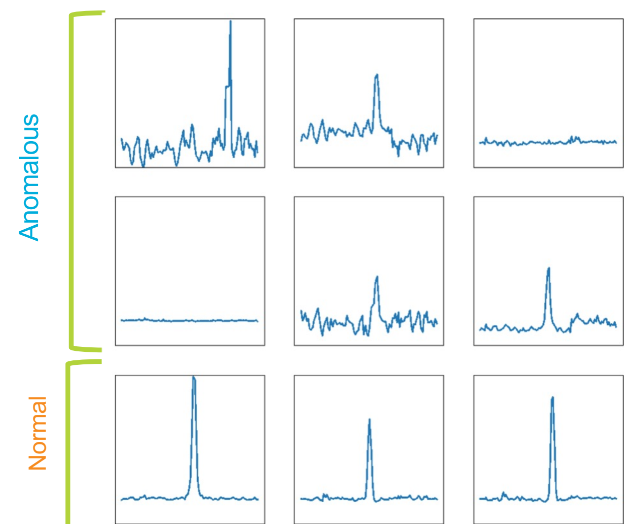
Outcome

- Improved accuracy in reconstructed bunch size and automated detection of anomalous IPM signals.

Simulated scan with surface fitting



Classifier predictions on archive data



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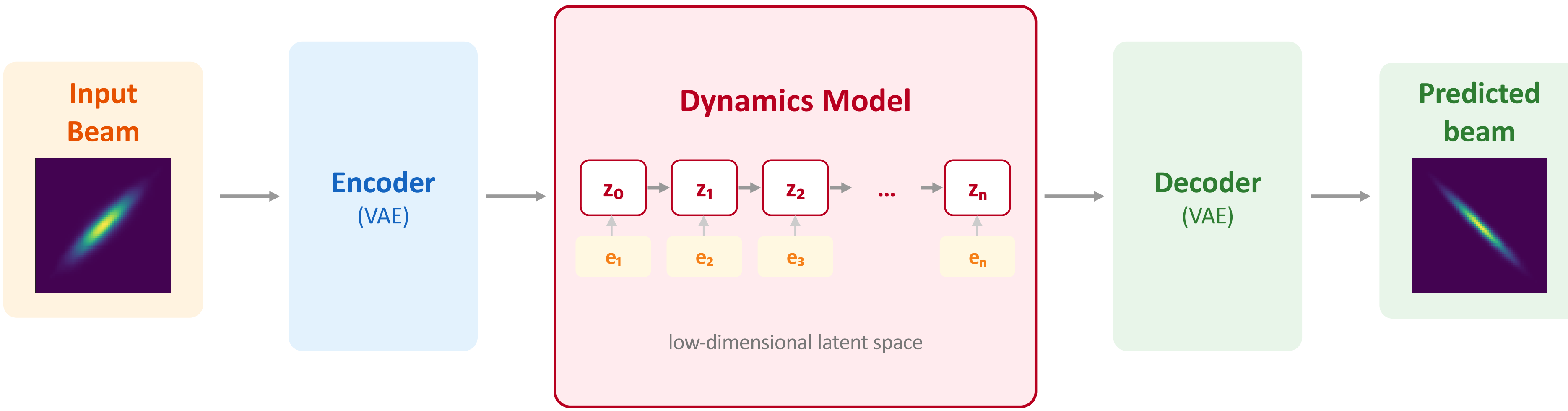
Fast Beam Propagation in Latent Space

Compress beam distributions into a learned latent space, then predict dynamics there.



Fast: dynamics in low-dimensional latent space, not full beam.

Application: collective effect (space charge, etc.) dominated regimes where tracking is computationally expensive.

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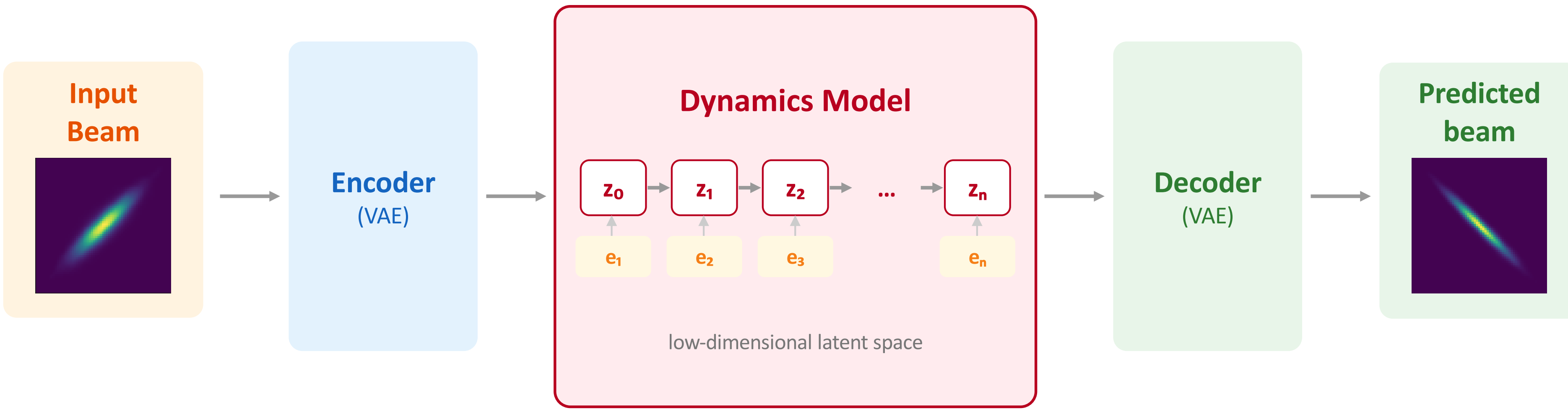

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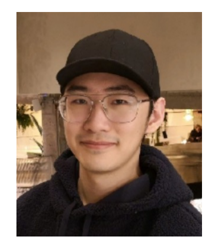

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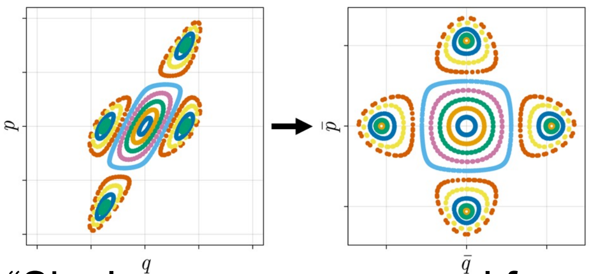
SciBmad – ML oriented beam modeling

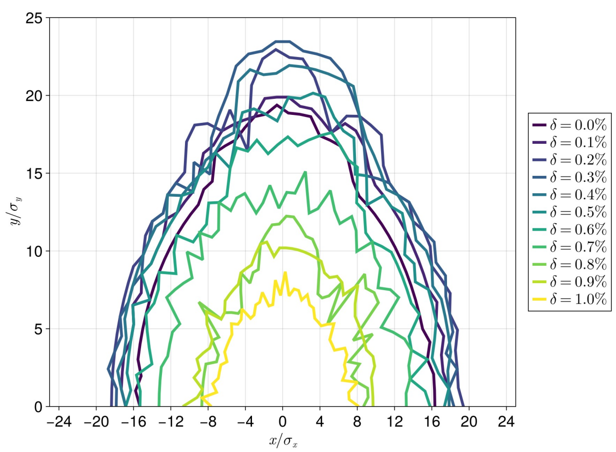
New accelerator modeling library *SciBmad* for nonlinear dynamics **simulation, analysis + optimization**:

SciBMAD



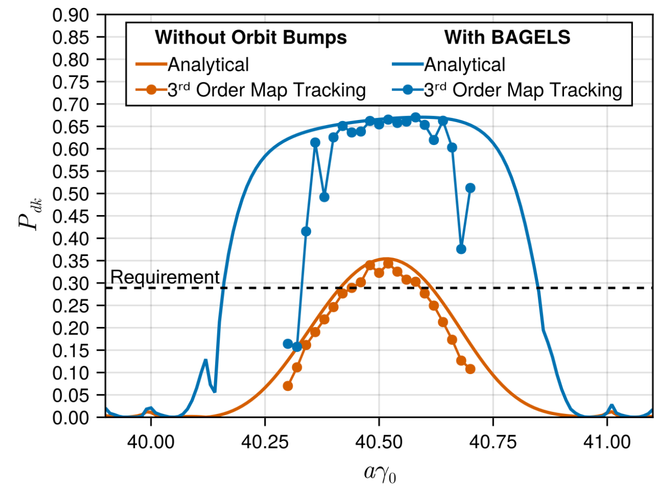
"Single resonance normal form"

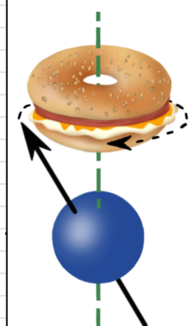
Optimization by GPU lattice parallelization



Dynamic aperture for the EIC

- **Fully forward, backward, and Taylor differentiable.**
- **Fully GPU and CPU parallelized.**
- **Spin dynamics optimized "BAGELS"**





Phys. Rev. Accel. Beams **28**, 031002, ***Editor's Suggestion***

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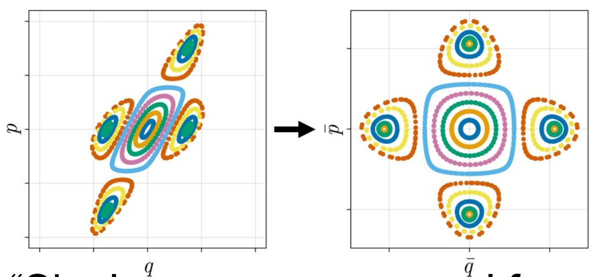

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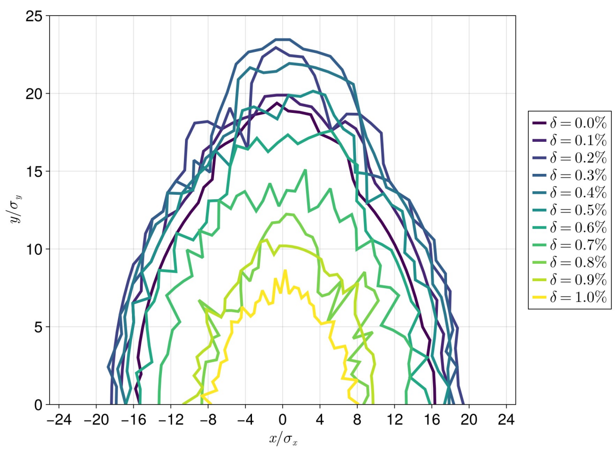

Dynamic aperture for the EIC

Brookhaven National Laboratory

EIC-BeamAI

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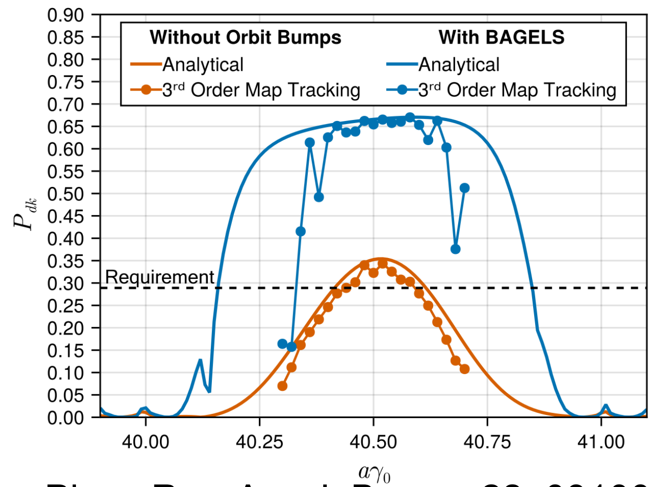

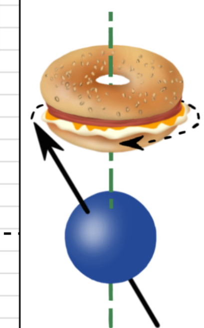

Phys. Rev. Accel. Beams **28**, 031002,

Suggestion

Matt Signorelli
EIC Postdoc

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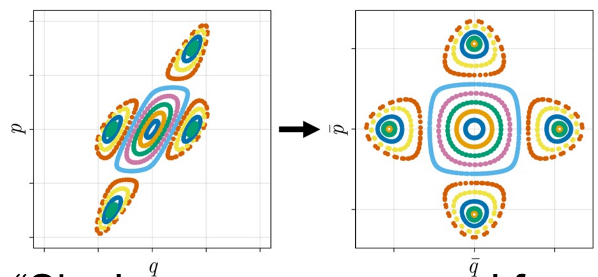

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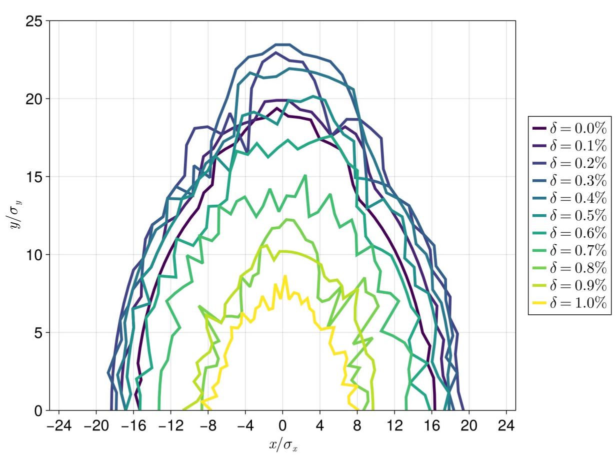

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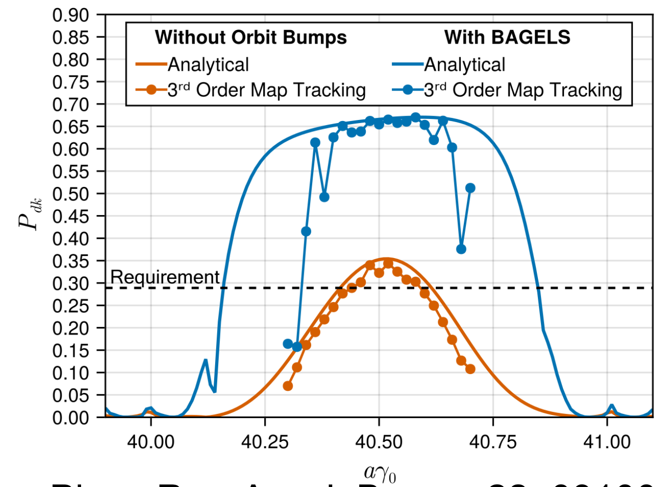
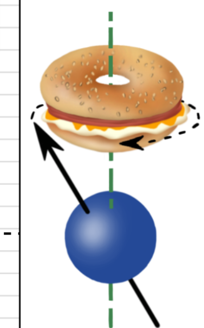




Phys. Rev. Accel. Beams **28**, 031002,

Suggestion

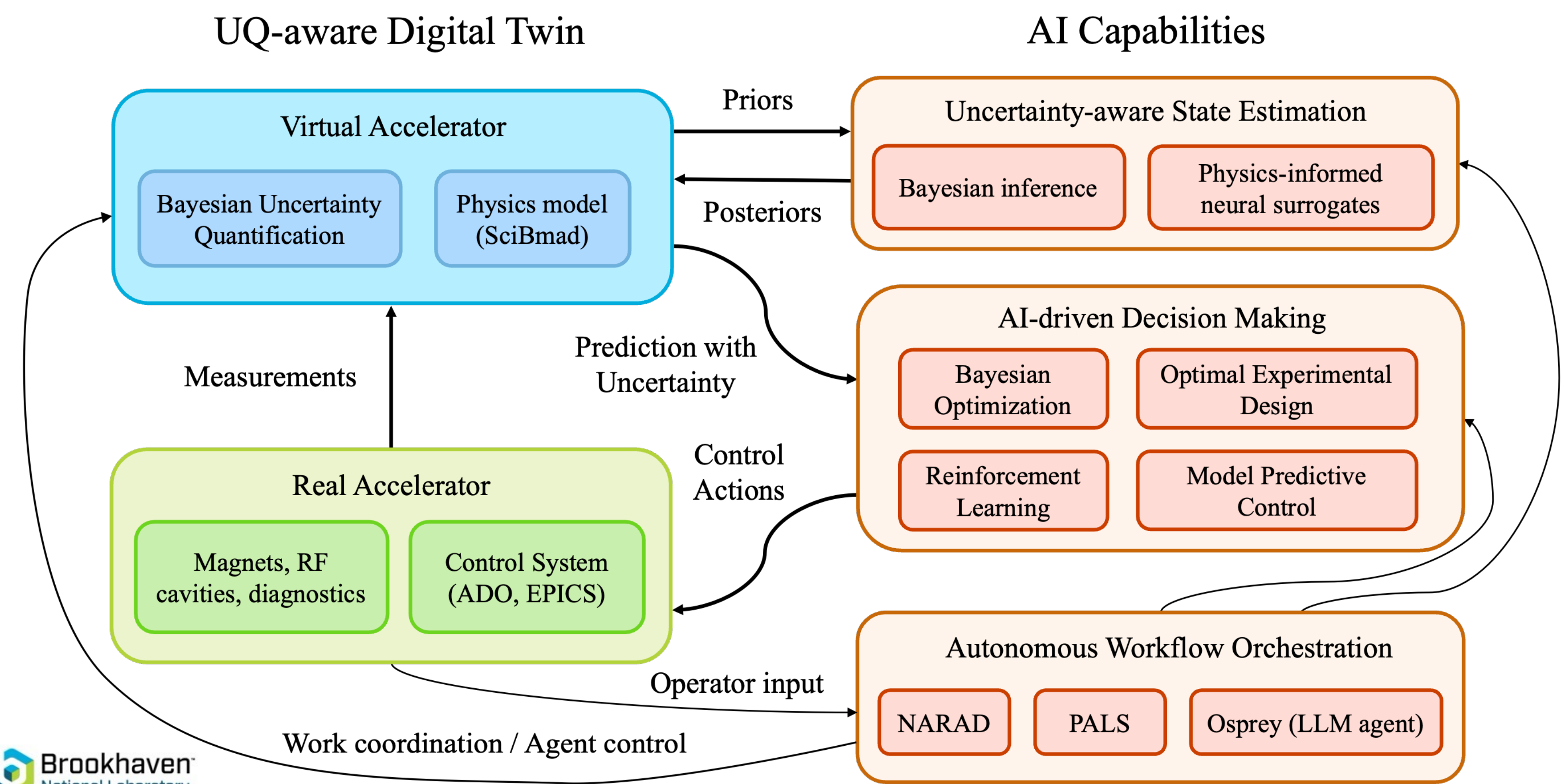
Matt Signorelli
EIC Postdoc

Arrow,
Matt's puppy

Cornell University

AI integration in EIC operations

Closed-Loop AI and Digital Twin Framework for Accelerator Operations



NP AI-ready Accelerator Dada (NARAD)

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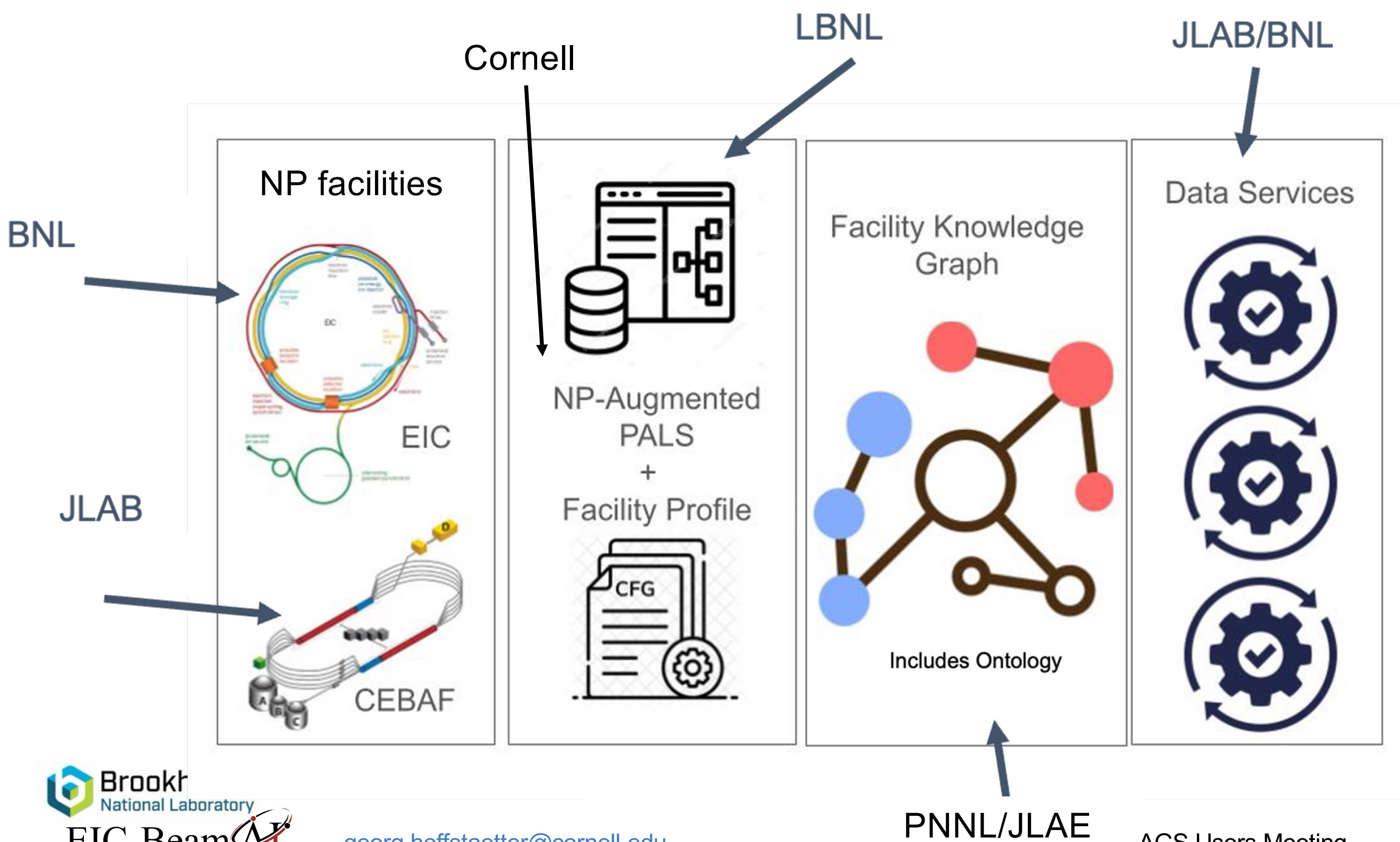
NP-focused, but facility independent



American Science Cloud (AmSC) integration

JLab/PNNL

- Strategic alignment of NARAD artifacts/demos with AmSC infrastructure
- Definition of AI-ready semantic contracts for NARAD data

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Participants

- Brookhaven National Laboratory: Kevin Brown, Yuan Gao, Eiad Hamwi, Levente Hajdu, Christopher Kelly, Trevor Olsen, Vincent Schoefer, Nathan Urban
- CLASSE (Cornell Laboratory for Accelerator-based ScienceS & Education): Georg Hoffstaetter de Torquat, David Sagan
- Fermilab: Tia Miceli
- Jefferson Lab (Thomas Jefferson National Accelerator Facility): Armen Kasparian, Kishansingh Rajput, Todd Satogata
- radiasoft: Christopher Hall
- Rensselaer: Yinan Wang, Yue Zhao
- SLAC National Accelerator Laboratory: Auralee Edelen, Ryan Roussel

+ Unfunded collaborators

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Publications

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- [4] W. Lin et al., “AGS Booster model calibration and digital-twin development”, in *Proc. IPAC’24*, Nashville, TN, May 2024, pp. 3449-3452.
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- [13] L. Hajdu et al., “Image processing with ML for automated tuning of the NASA Space Radiation Laboratory beam line”, in *Proc. ICALEPCS2025*, Chicago, Sep. 2025, pp. 1008-1011.
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Summary

The EIC-BeamAI collaboration has the goal to utilize AI/ML for EIC design and operation.

The collaboration was formed around DOE-NP funded proposals

- Bayesian Optimization for increased proton polarization from the AGS
- Using ML for brighter & more polarized beams in the EIC's hadron injectors.
- NARAD to develop cross-facility AI-ready workflow
- Utilize MOAT goal by connecting to US-wide AI/ML accelerator work

Key Outcomes

- Automated beam-tuning routines
- Operational bidirectional Digital Twins with differentiable accelerator models
- Streamlined and automated model calibration
- Robust anomaly detection and diagnostics
- Workforce development