Machine Learning Applications for Improving Accelerator Operations for the EIC

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Probing the frontiers of nuclear physics with AI at the EIC (II)

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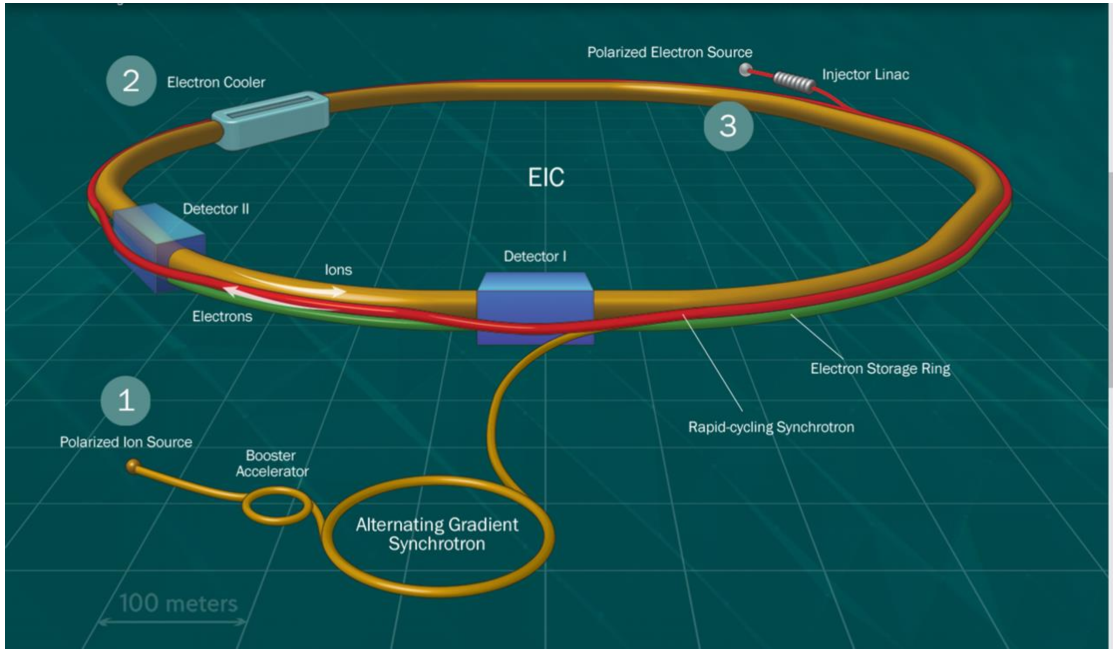
Motivation

- Particle accelerator – kilometer-scale machine with thousands of coupled components to generate and preserve beam with very precisely defined qualities (e.g., energy, emittance, luminosity etc.)

- Traditionally maintained with many hours of manual tuning, taking time away from data collection

- Constantly varying complex system – no constant set of routine, needs real-time adjustments

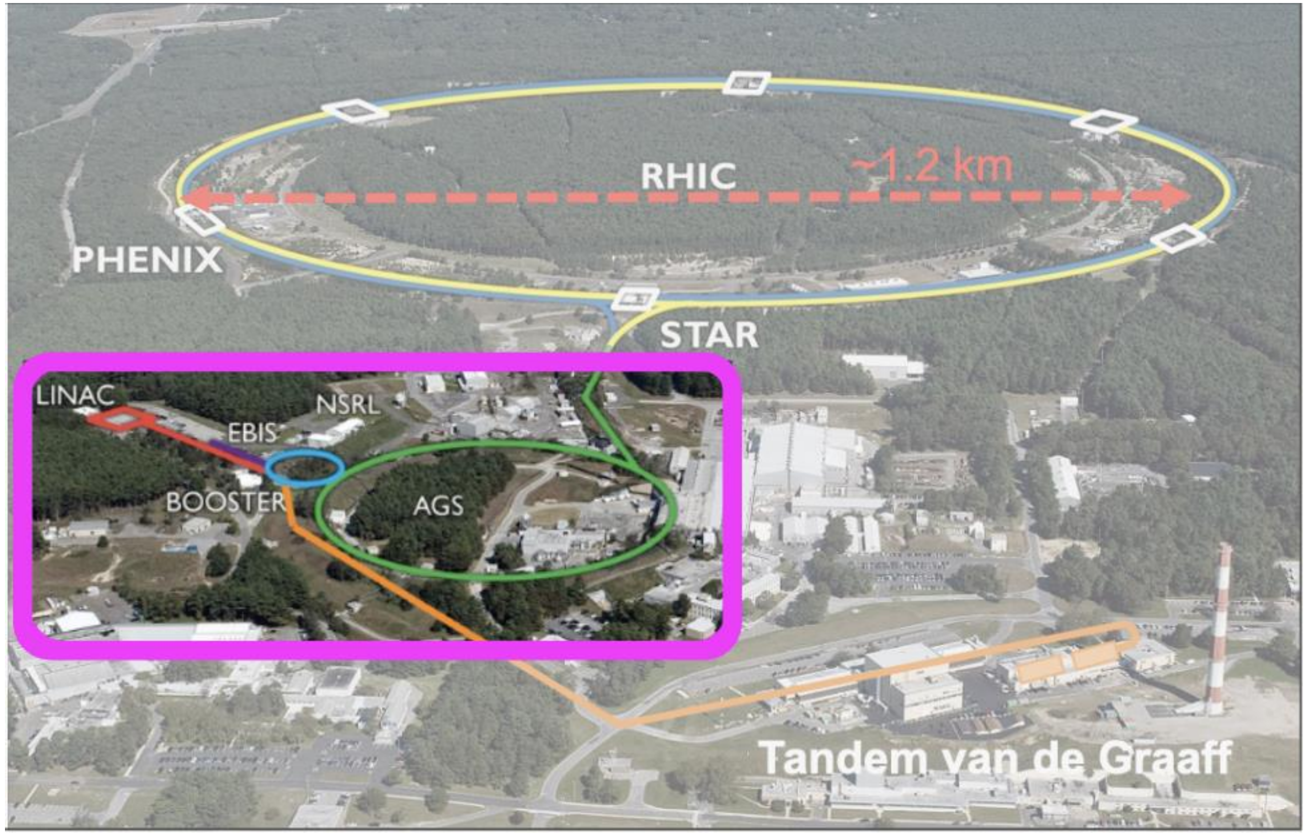


Motivation

<u>Alternating Gradient Synchrotron</u> (AGS) and its **<u>Booster</u>** serve as part of the **<u>injector compound</u>** for RHIC and future EIC

	Max Energy [GeV]	Pol. At Max Energy [%]
Source+Linac	1.1	82-84
Booster	2.5	~80-84
AGS	23.8	67-70
RHIC	255	55-60

Loss in polarization along the chain



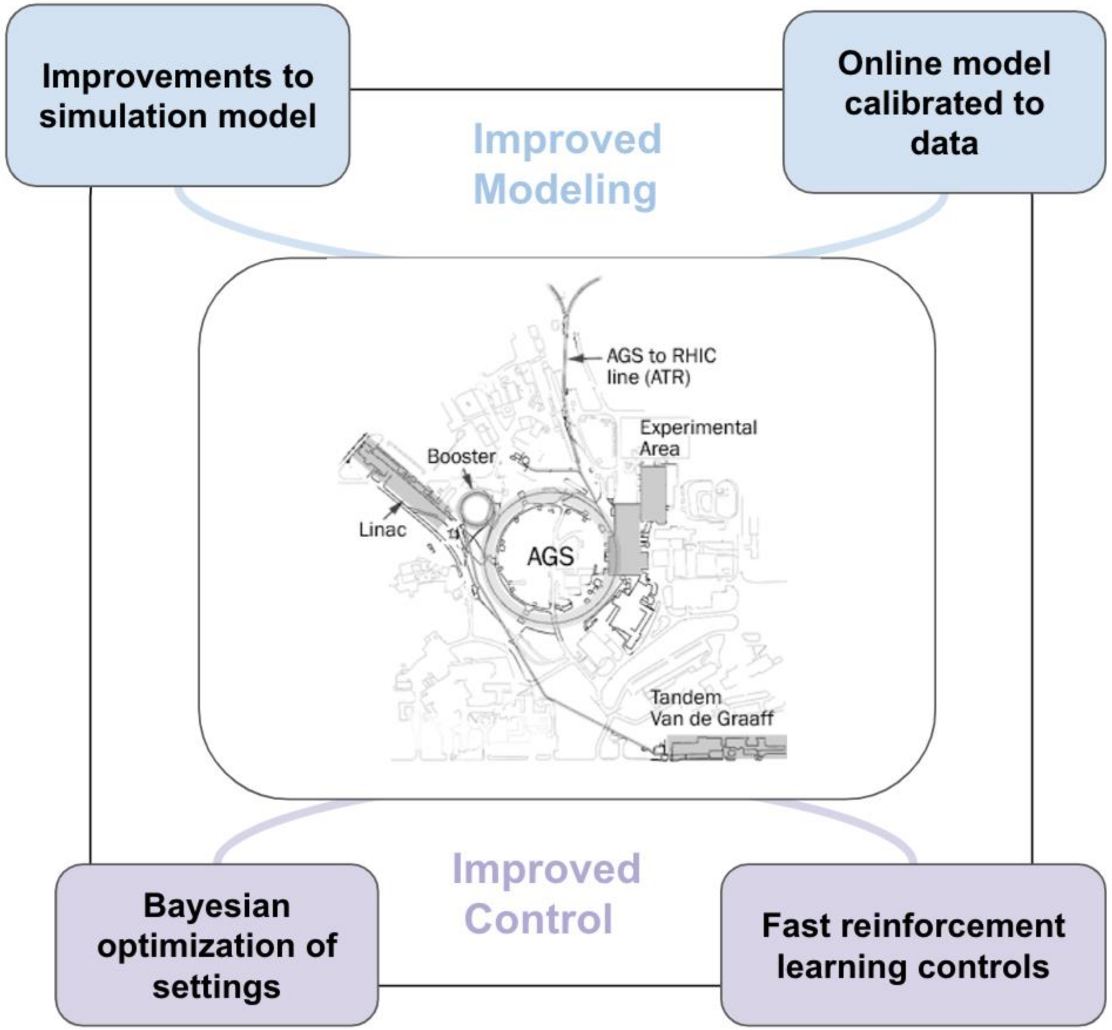
Difficulty in improving beam quality:

1) polarimeter measurement is slow and has big error bars
2) tuning involves many control parameters and is mostly done by hand

Machine Learning (ML) techniques can be used to optimize beam luminosity, quality, and polarization in RHIC and EIC

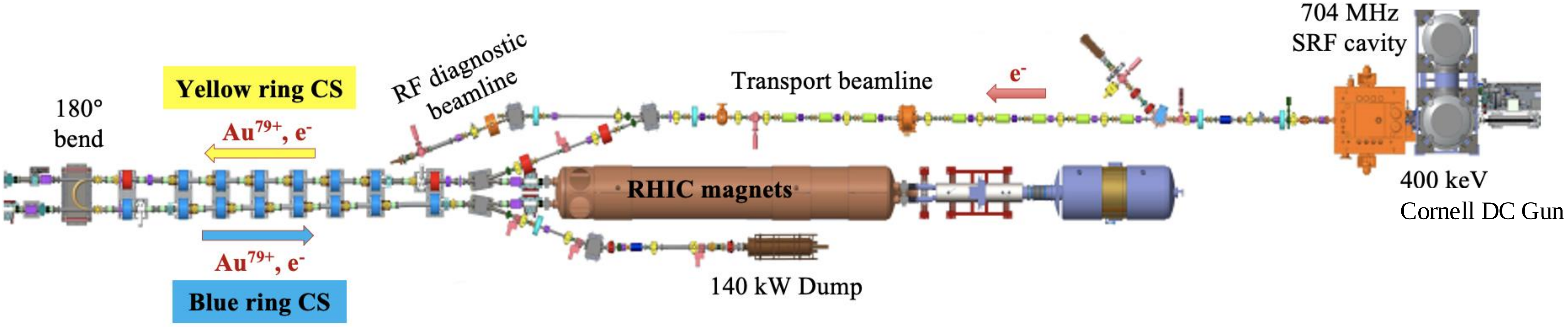
Improve Operations with ML

- Figure-of-merits (FOM) for ML algorithms ("experimental outputs"): emittance, beam intensity, polarization
- Possible areas where ML is useful:
  - Cooling optimization
  - Injection optimization
  - Digital-twin & Error detection
  - Electronic Logbook upgrade
- Useful ML methods:
  - Bayesian Optimization (BO)
  - Neural Network (NN)
  - Reinforcement Learning (RL)
  - Natural Language Processing (NLP)



Cooling Optimization

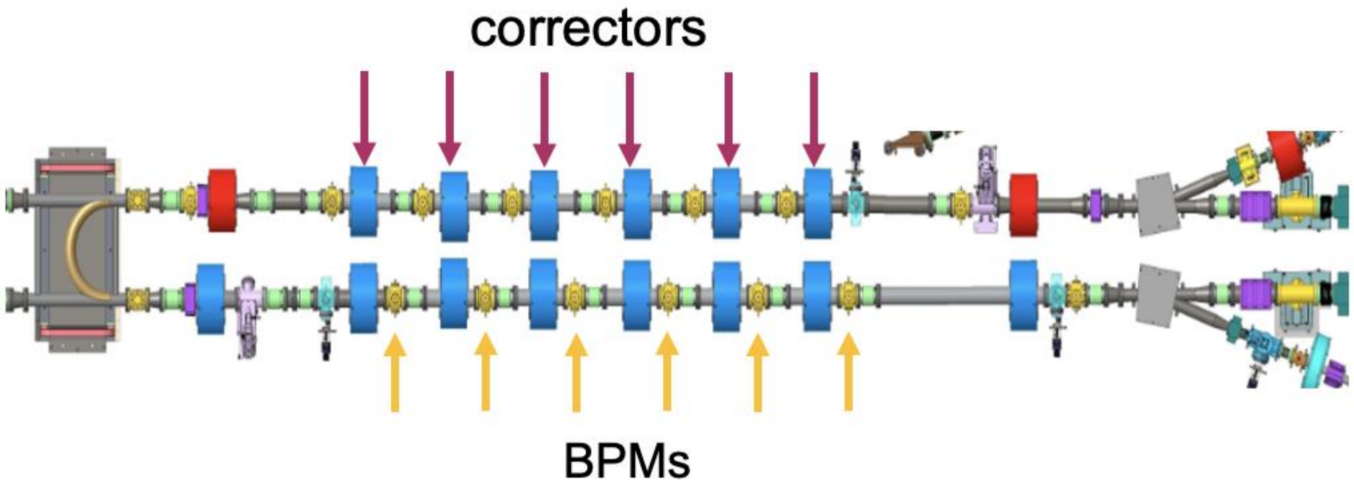
Low Energy RHIC electron Cooling (LEReC)



- LEReC is used to increase the luminosity, it was successfully improved the luminosity in 2020 and 2021 runs
- 704 MHz e-bunches are created in the 400 keV Cornell gun, and delivered to the cooling sections (20 meter), where they co-travel with ion bunches

➔ The new EIC pre-cooler layout follows the same principle, profiting form the same ML techniques

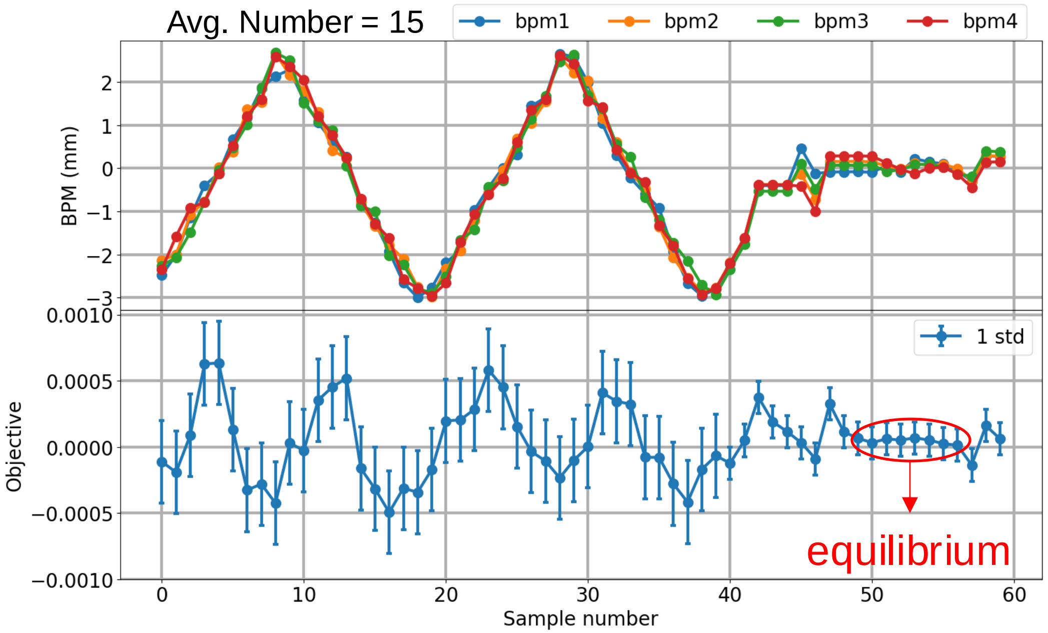
LEReC experiment settings

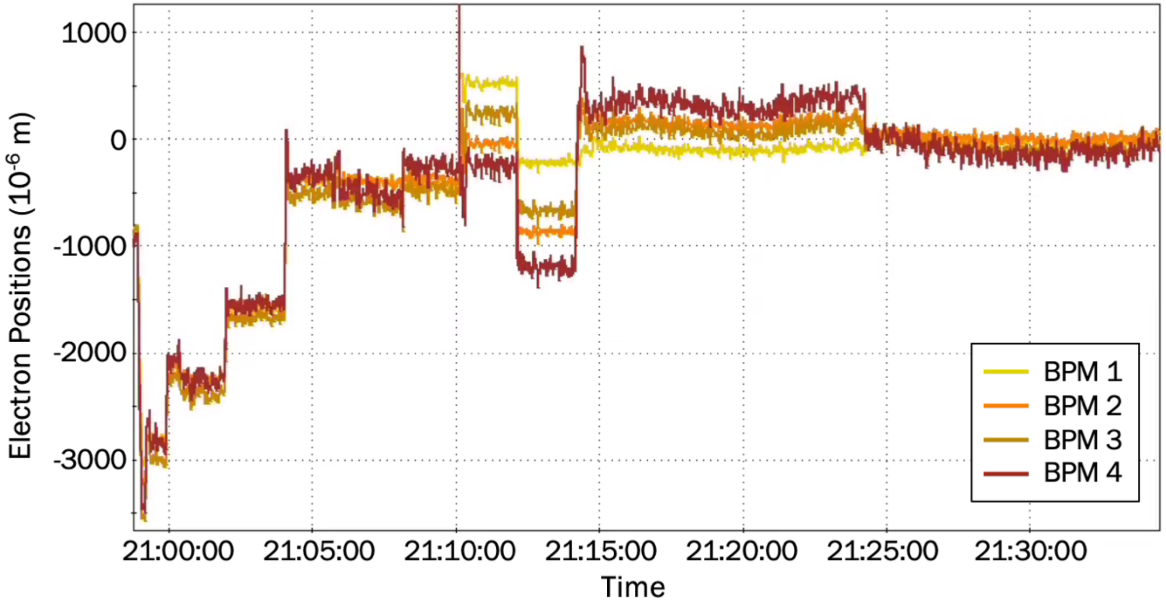


- Only the first 4 BPMs are considered due to limited machine time
- Cooling rate:$\lambda = (1/\bar{\delta})(\overline{d\delta}/dt)$
- Ions are assumed in the center position (x=0, y=0)

- **<u>Goal</u>**: use Bayesian optimization (BO) to maximize $-\lambda$ by aligning electron orbit with ion orbit

LEReC experiment results

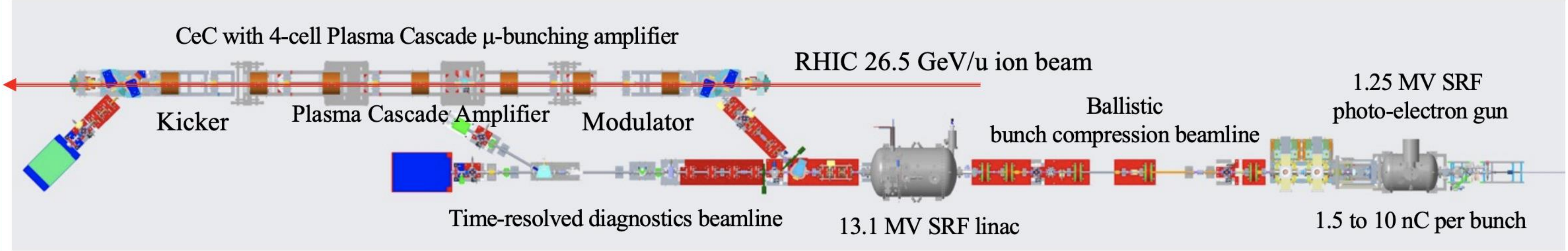




- Bayesian optimization algorithm trained with 40 initial samples to optimize transverse cooling rate λ
- The system reaches optimal status when cooling rate balances the IBS-driven growth rate, so λ approaches 0 once the system reaches equilibrium
- Algorithm converged quickly (reach close neighborhood in 3 steps)
- Tune electrons from the farthest positions to the center and maintain the trajectories

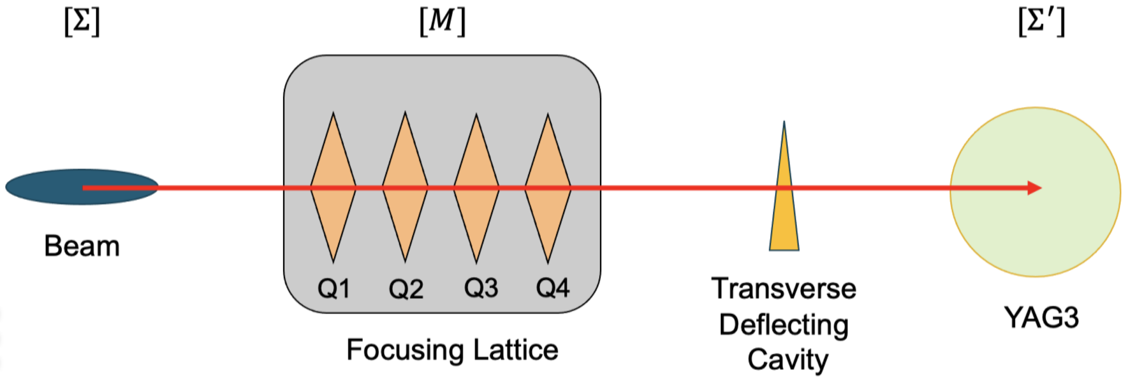
Coherent electron Cooling

- Designed to cool 26.5 GeV/u ion beam circulating in RHIC’s yellow ring.

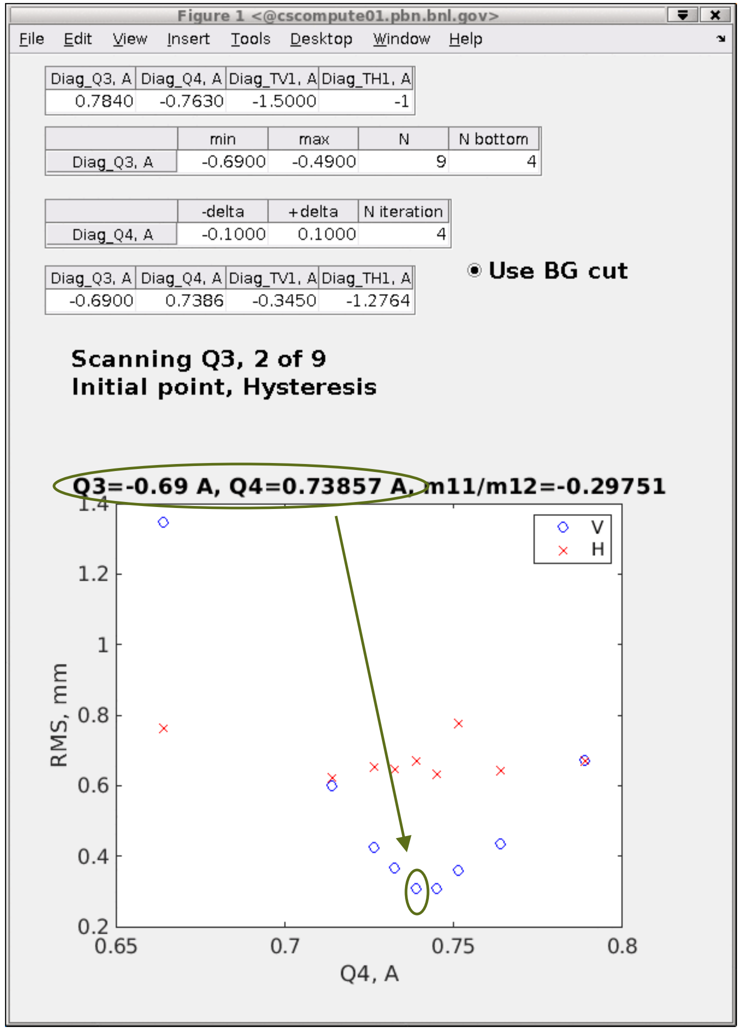


- CeC CW SRF accelerator with unique SRF electron gun generates electron beams with quality sufficient for the current experiment and for the future EIC cooler
- Time-resolved diagnostics beamline is used to provide high precision measurements of electron beam quality

Quadrupole scan with two quads

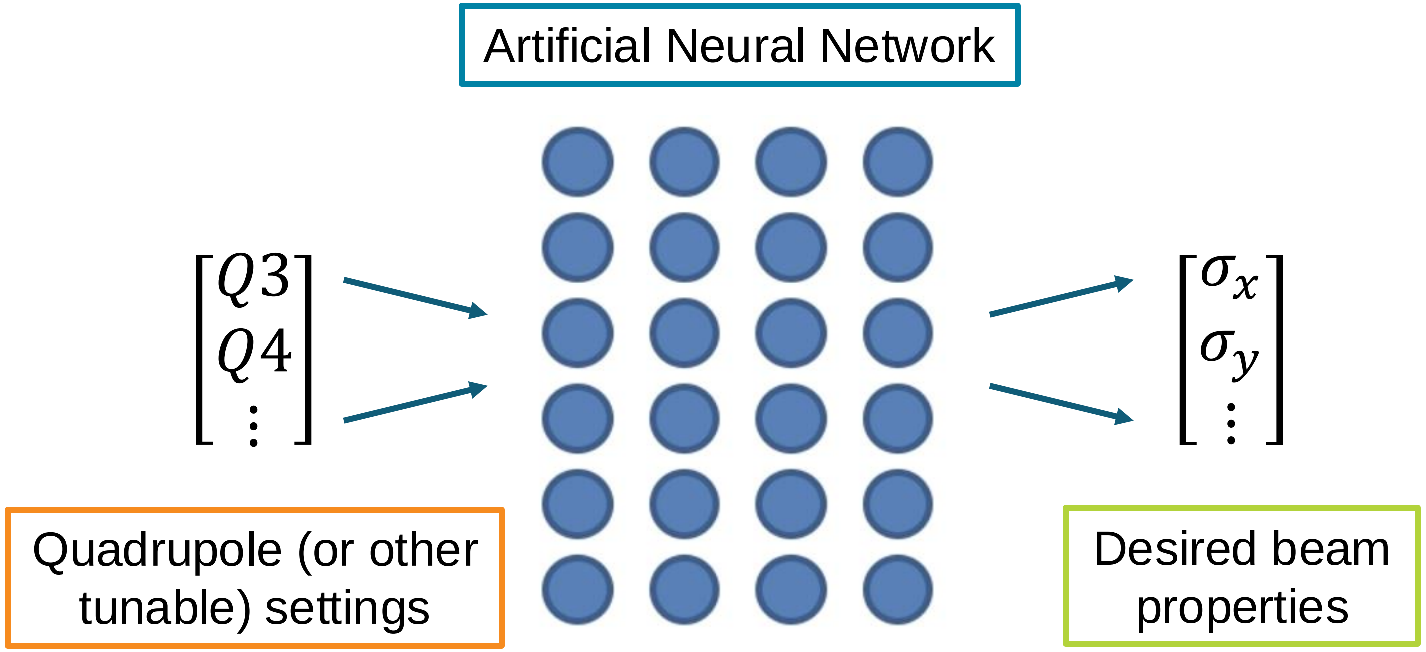


- Scan two quads (Q3, Q4) with opposite polarity → keep beam focused vertically
- Find quad combination settings that gives best vertical focusing
- Find best Q3-Q4 combinations with sequential scans: 1) scan 13 Q3 settings; 2) for each Q3 setting, scan 9 Q4 settings
- Time taken: ~ 5 minutes for each Q3 setting, > 1 hour for an entire scan routine



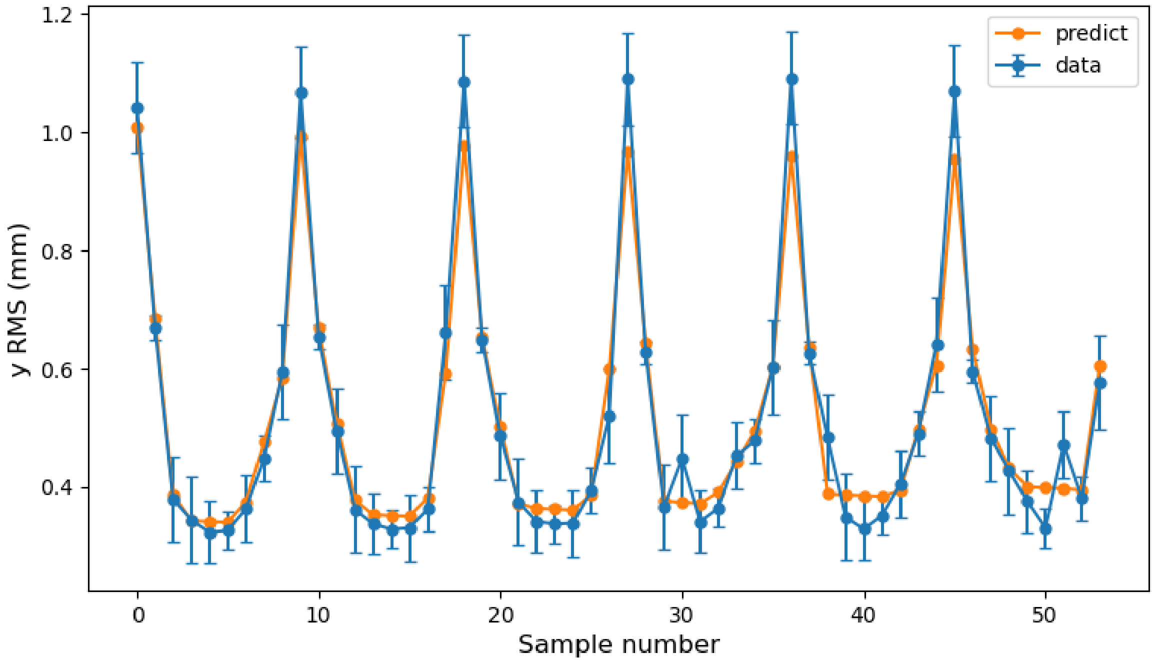
Speed up quad scan with Neural Network

- Time consuming sequential scans
- Train a ML model to establish mapping between quadrupole settings and beam size
- Trained ML model predicts best Q3-Q4 combinations without additional scans
- Useful for faster general beam tuning & as starting point of optimization



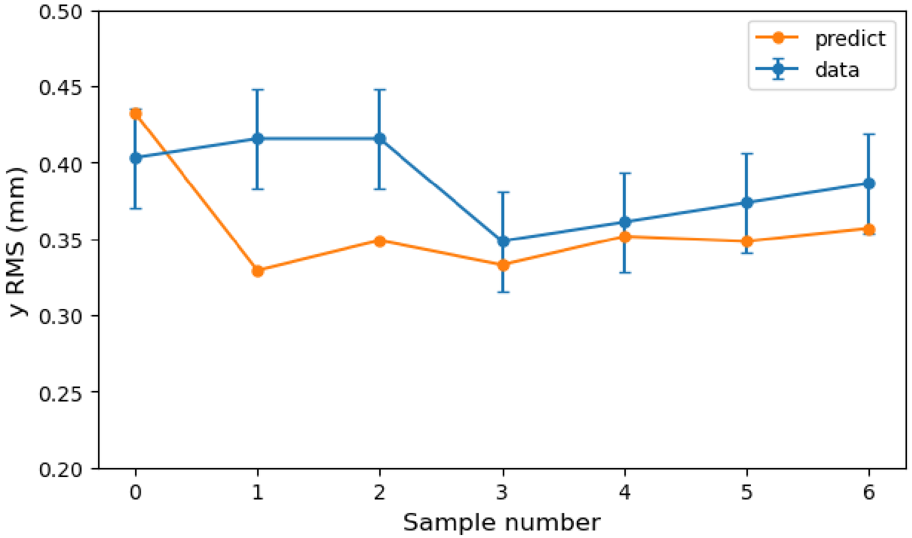
New CeC routine test results

First 6 rounds: 54 saved data points



Remaining 7 rounds: 7 data points using Q3-Q4 settings predicted by NN model

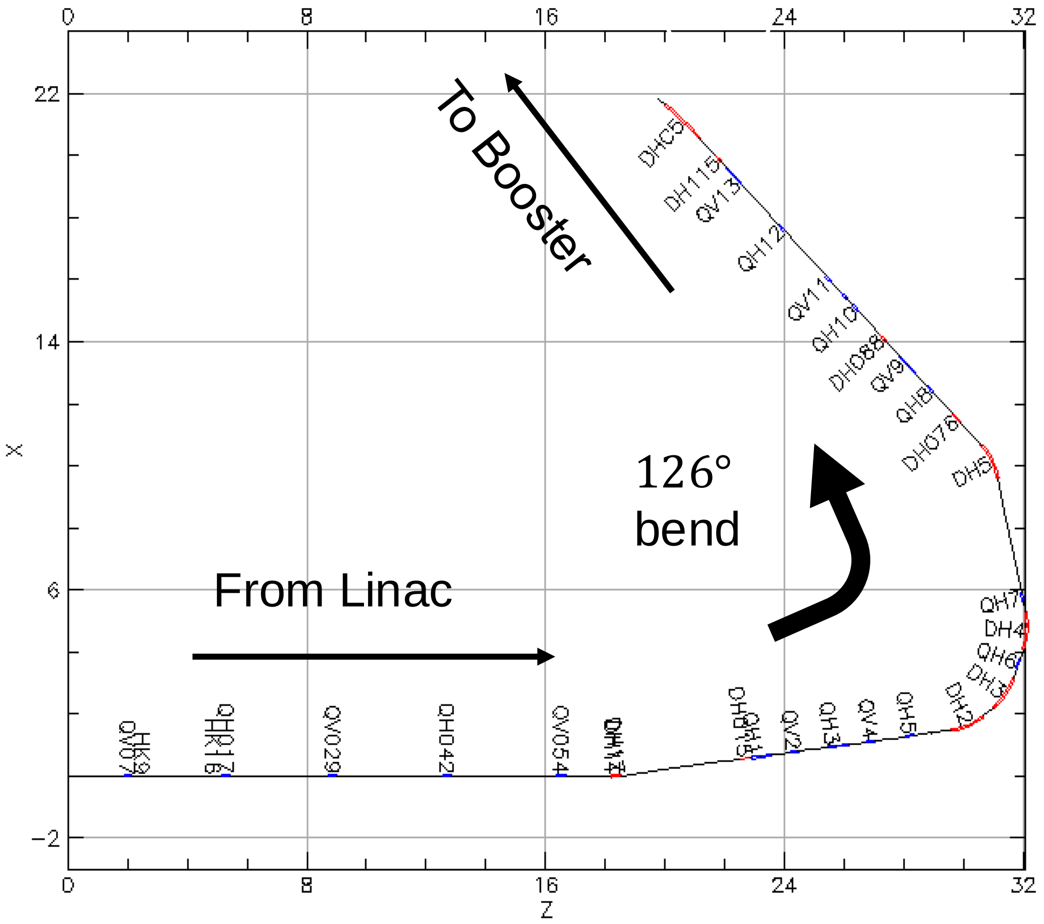
- Trained NN accuracy on 54 data points: 93.65%
- Tested 7 proposed Q3-Q4 combo settings
- Obtained Y RMS values around 0.3 – 0.4 mm range: satisfactory preliminary results
- Successfully cut scan time by 50%



Injection Optimization

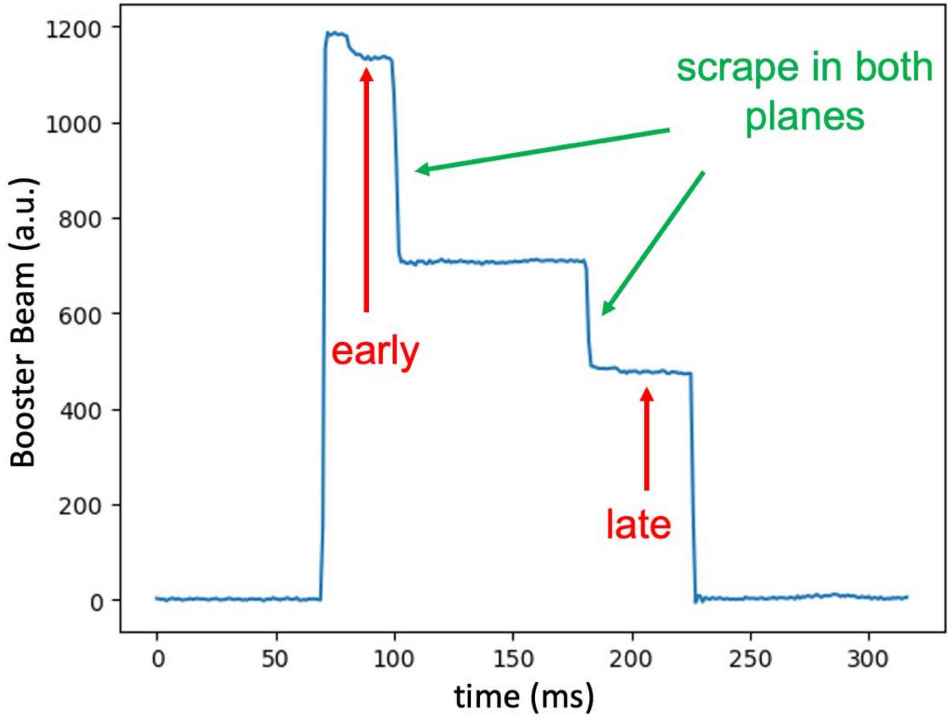
Booter injection

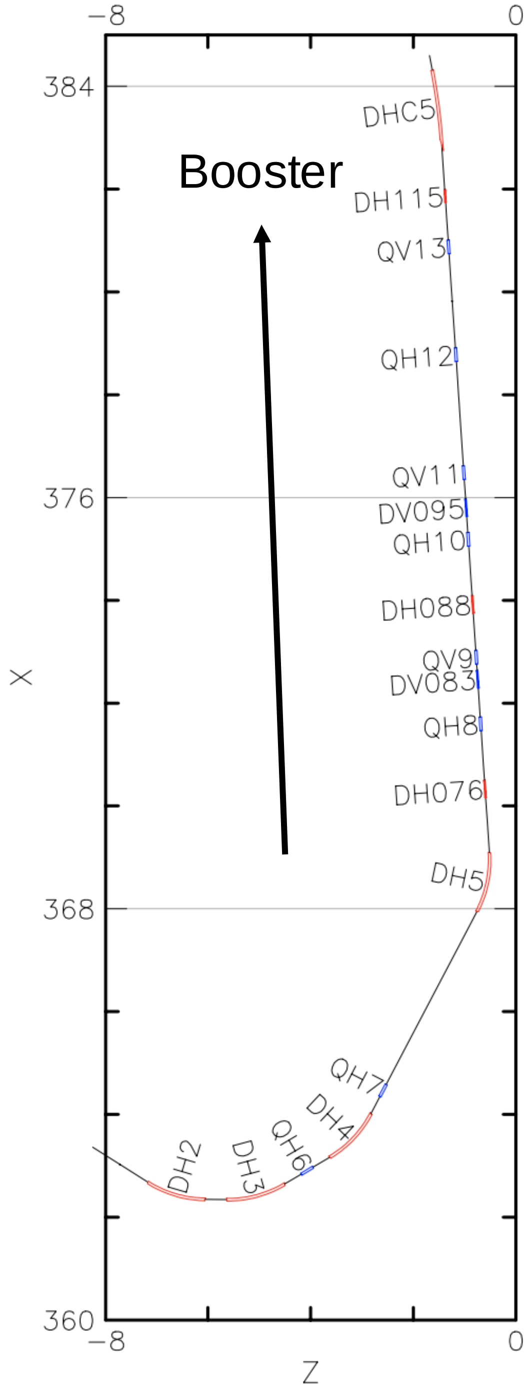
- Booster injection process sets maximum beam brightness for rest of acceleration through RHIC
- Known emittance effect on polarization loss
- Intentional horizontal and vertical scraping reduce emittance to RHIC requirements
- **<u>Goal</u>**: minimize emittance / maximize beam intensity after scraping
- Controls: Linac to Booster (LtB) transfer line optics
- Method: Bayesian optimization (BO)



LtB controls and measurement

- 13 quadrupoles and 16 correctors between Linac and Booster
- Common practice to improve Booster injection efficiency: tune last few correctors at the end of the LtB line
- Criteria to check injection efficiency: Booster early and late intensity

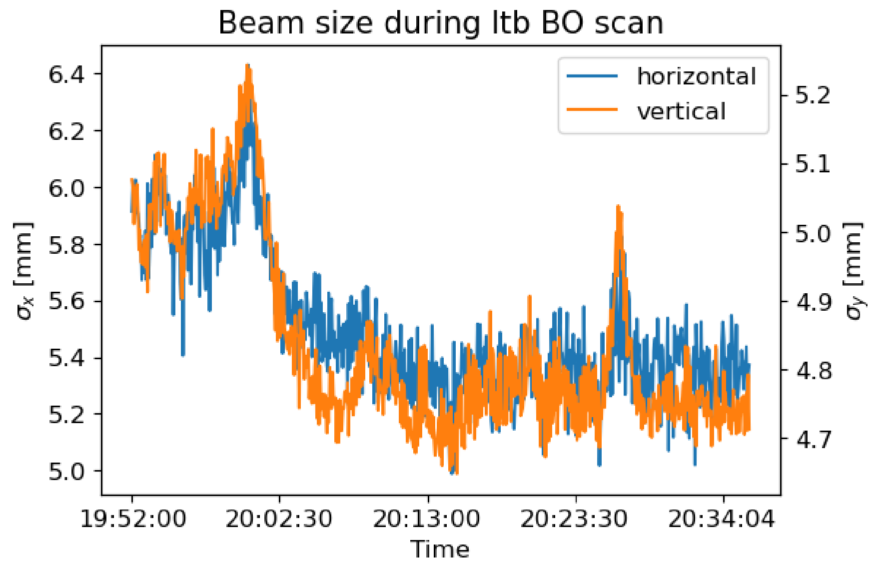


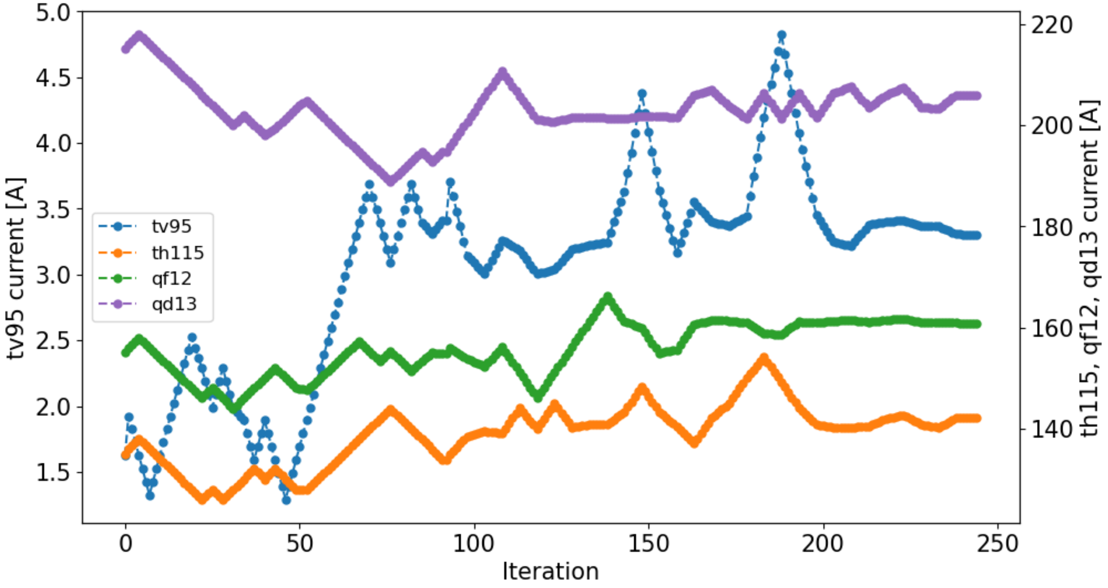


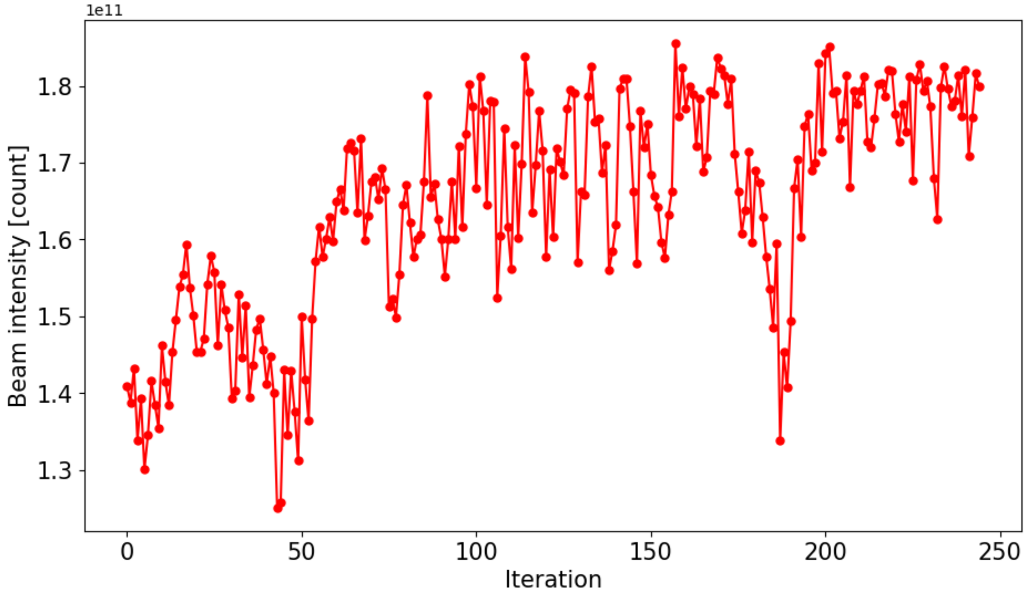
LtB optimization: 2 correctors + 2 quadrupoles

- Controls: Power supply currents of two correctors and two quadrupoles at the end of the LtB line

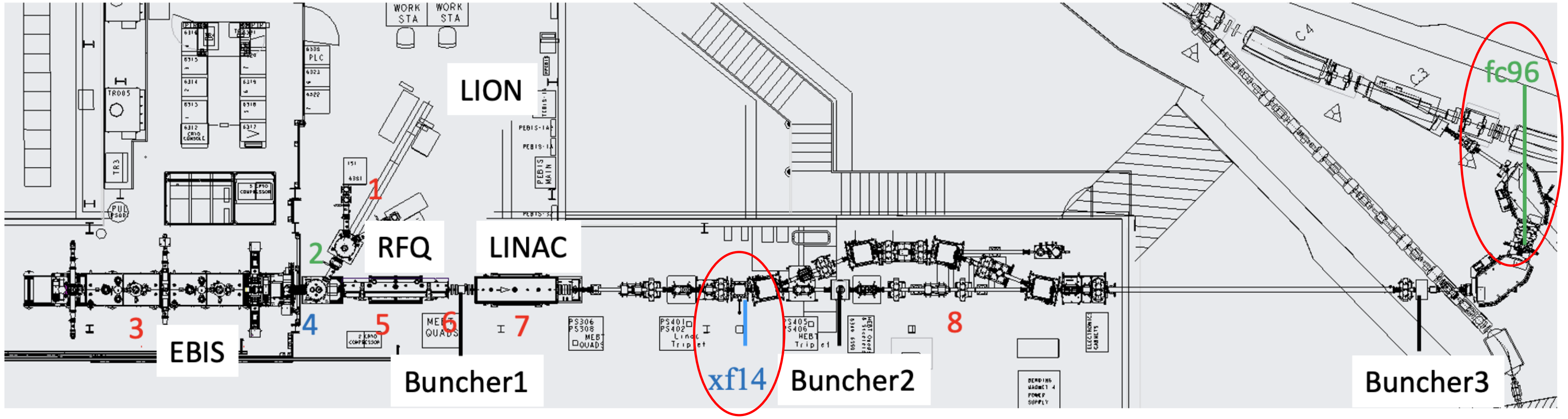
- Beam size decrease in both planes in the BtA line in correspondence with intensity increase







Electron Beam Ion Source

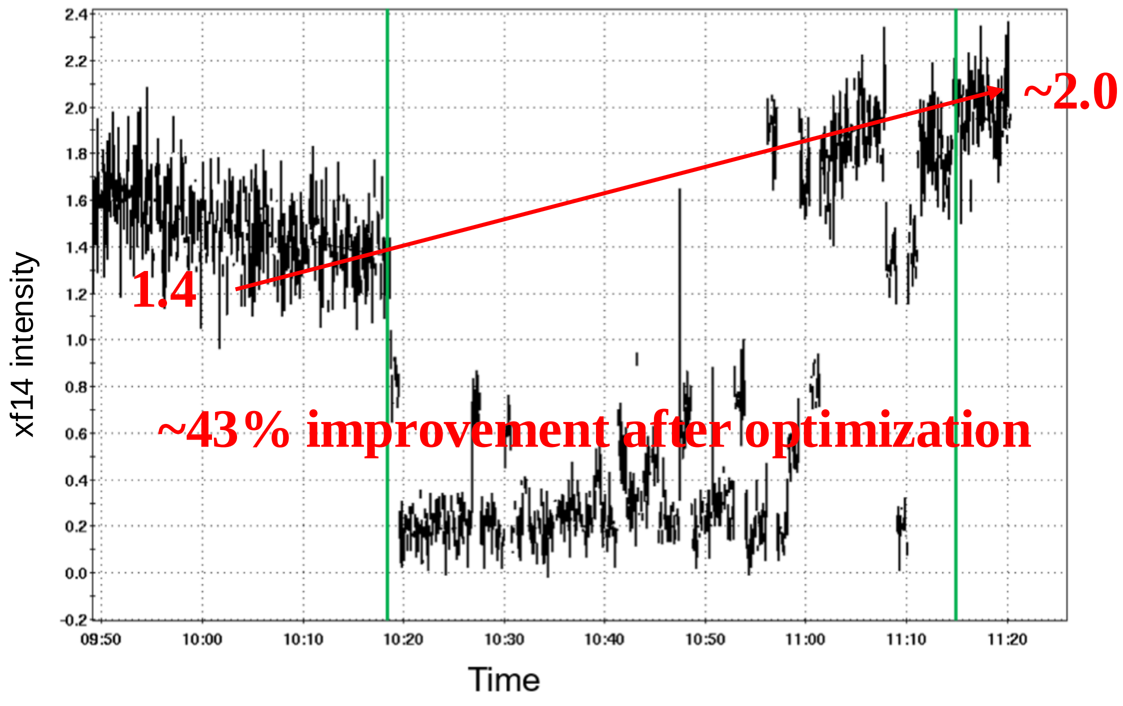


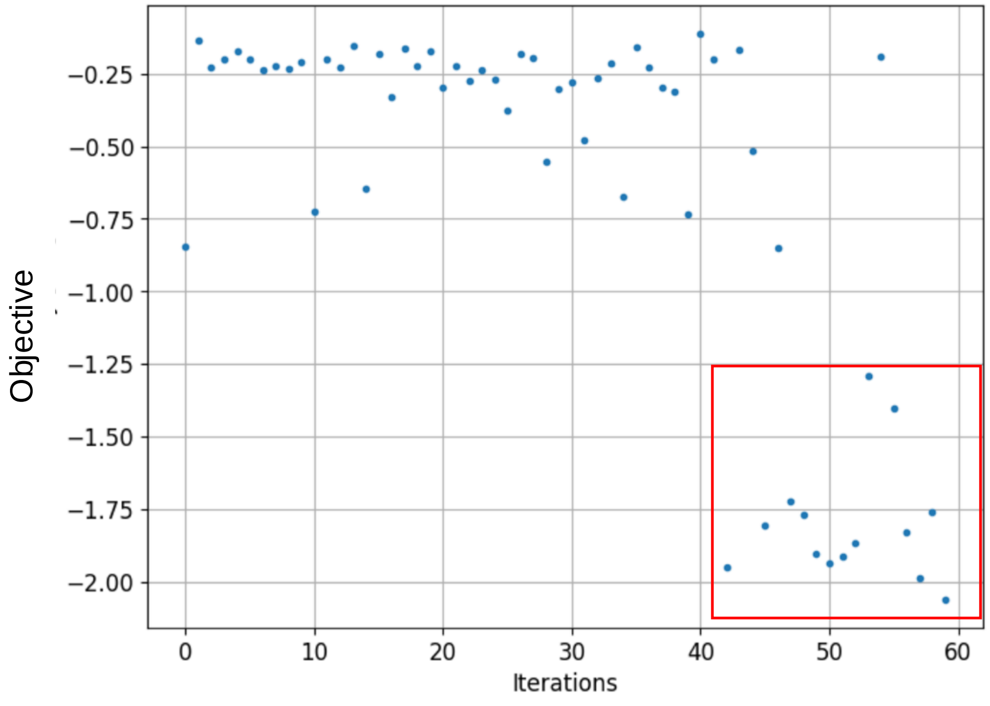
- Heavy ion source to replace Tandem as pre-injector for RHIC

1. LION
2. EBIS Injection Line (fc96)
3. EBIS
4. EBIS Extraction line (xf14)
5. RFQ
6. MEBT
7. Linac
8. HEBT

		Injection [fc96]	Extraction [xf14]
1	IonLens20-40kV	✓	✓
2	DeflPlatBias	✓	✓
3	16PoleX	✓	✓
4	16PoleY	✓	✓
5	Gridded_Lens	✓	✓
6	Horiz_Bend_Defl	✓	✓
7	Inter_Vert_Defl	✓	✓
8	Inter_Vert_Defl_Lower	✓	✓
9	Horiz_Sphere_Bend	✓	×
10	RFQ_Horiz_Bend	×	✓
11	LEBT_Solenoid	×	✓
	Total Variables	**9**	**10**

EBIS extraction line optimization

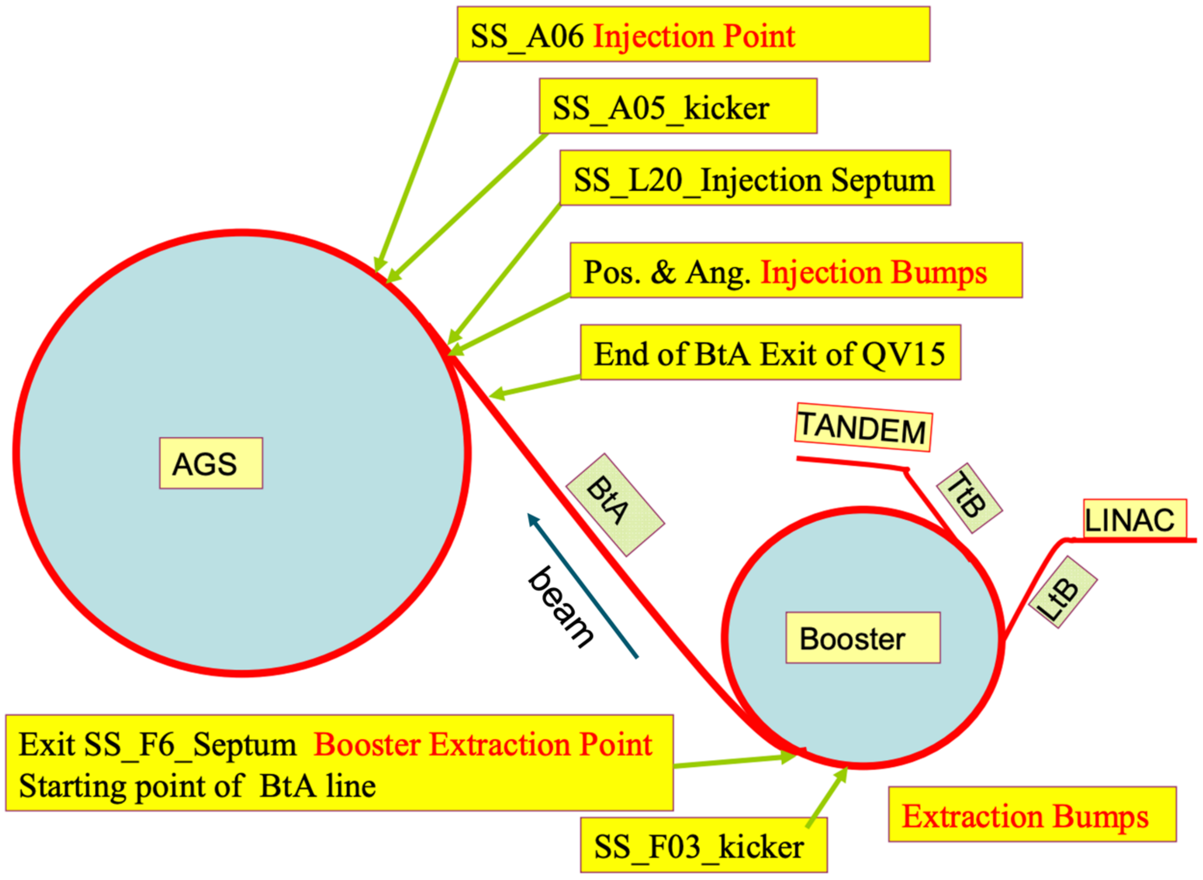




- 10 control parameters measured at xf14 were used to maximize ion beam intensity
- Objective is average intensity over 4 super-cycles (6.6 sec per cycle), multiplied by a negative scaling factor, BO algorithm aims to minimize objective
- 43% improvement observed after 60 iteration (~57 minutes)

AGS injection

- Extraction septum at F6 in Booster, injection septum at L20 in AGS, no scraping
- Multi-wires MW006, MW060, MW125, MW166
- Emittance measured by AGS Ionization Profile Monitor (IPM)
- **Goal**: maximize beam brightness in the AGS
- Controls: Booster to AGS (BtA) transfer line optics



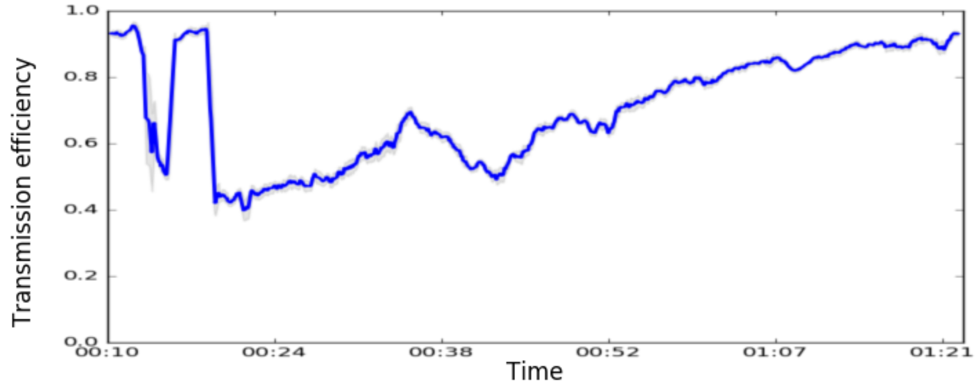
BtA optimization: 4 correctors

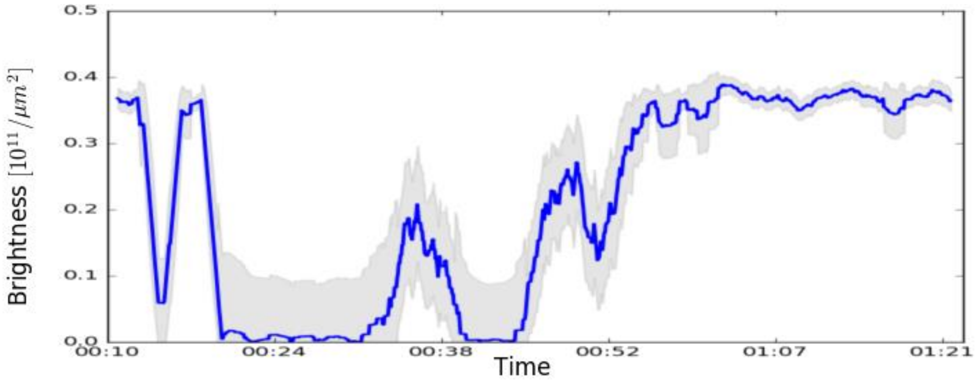
- Controls: Power supply currents of two vertical and two horizontal correctors.

- Target: Increase brightness. Increase intensity and decrease beam size.

- Method: Ruin initial settings, use Bayesian optimization to re-optimize settings.

- Results: Automatically achieved previous maximum brightness and intensity in < 130 iterations with new settings

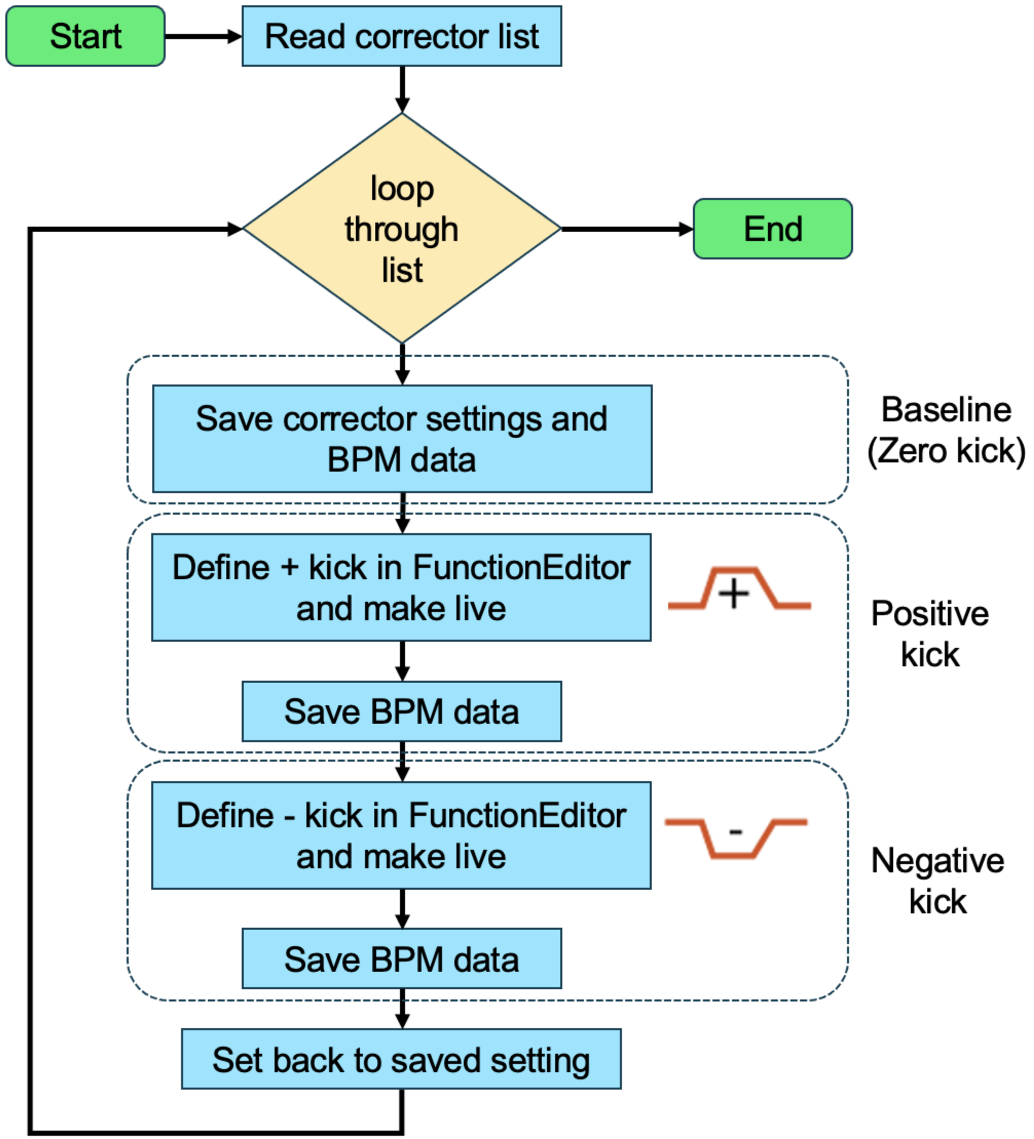


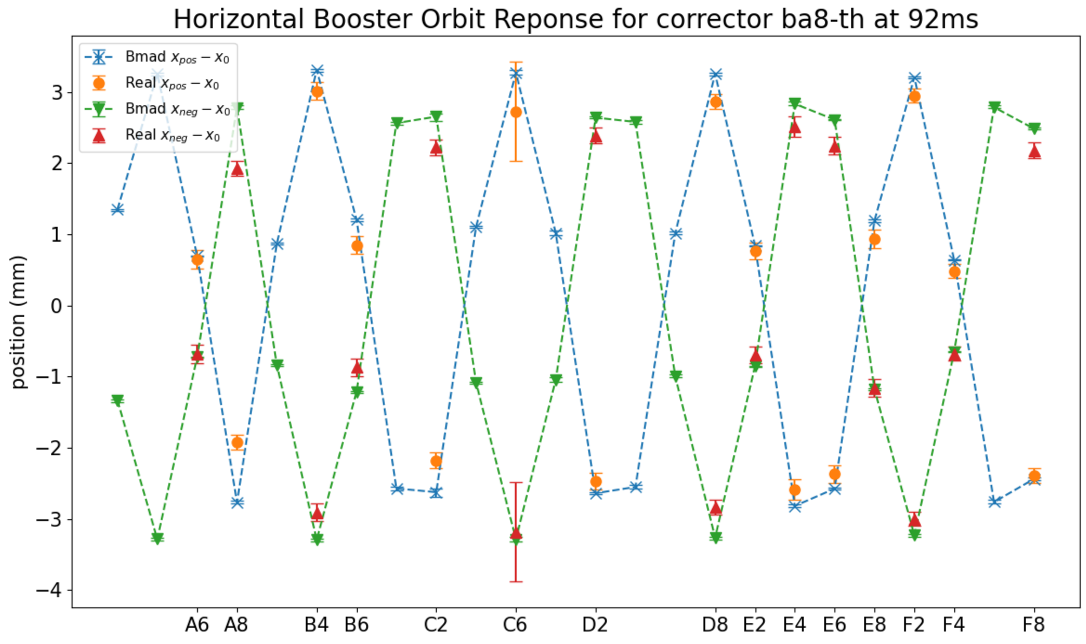


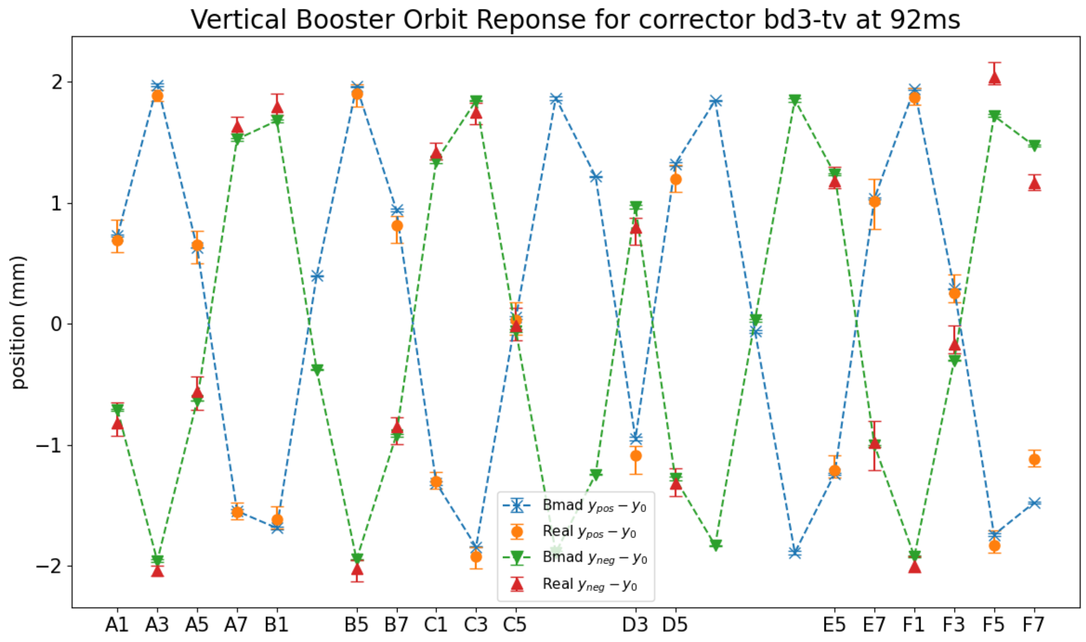
Digital-twin and Error detection

Orbit responses measurement script

- Script development with Collider Accelerator Department (CAD) Controls Group
- Can be easily adapted to other accelerators at BNL
- Script sets three corrector settings: positive, zero, negative; and save corresponding orbits
- All magnet settings (including dipoles and quadrupoles etc.) are saved for model calibration for digital-twin



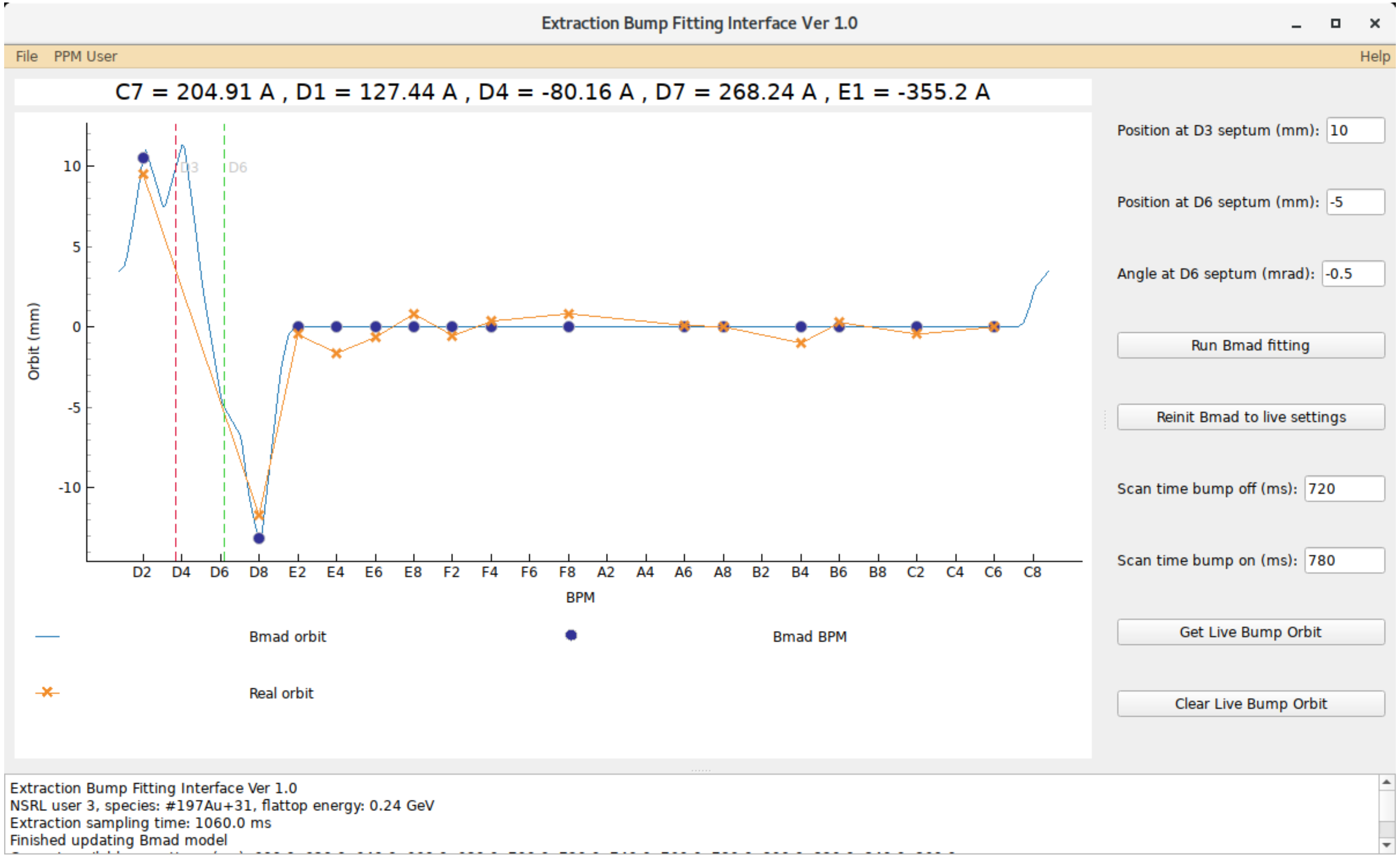




Orbit response data in AGS Booster

- Good agreements between AGS Booster data and Bmad model are reached, despite some faulty BPMs
- Small discrepancies (within 1 mm) beyond error bars is being investigated to better calibrate model to real machine
- **Goal**: produce accurate real-time predictions for operators and give tuning suggestions to improve beam quality

Extraction bump fitting interface

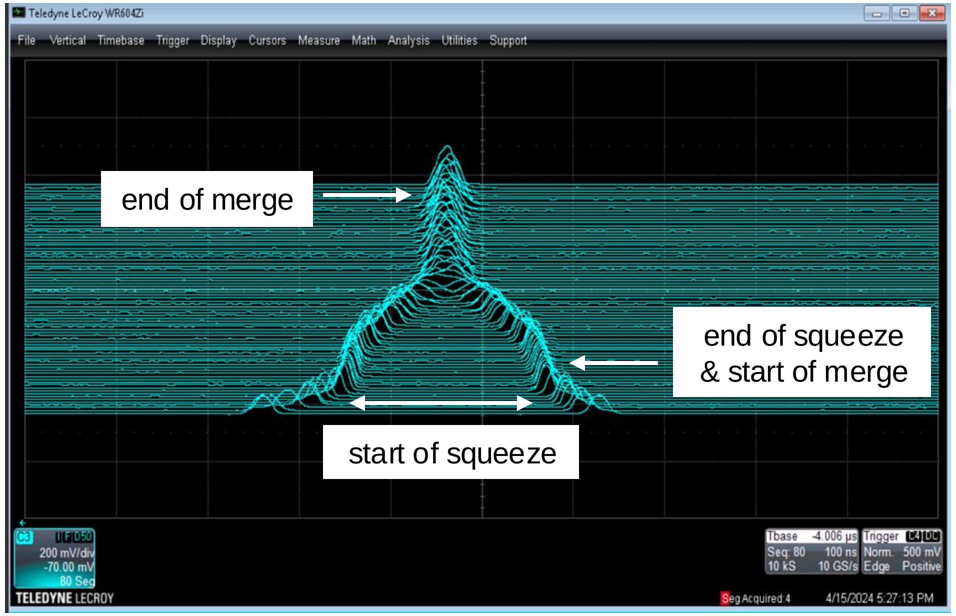


- NASA Space Radiation Laboratory (NSRL) takes beam from AGS Booster via slow extraction
- Current extraction bump gives large residual orbit
- **Goal**: tune bump setting by specifying desired beam position and angle at extraction septum

Bunch Merging

AGS bunch merging

- Before transferring to AGS, beam bunch is split into 2 longitudinally to reduce the space charge effect → reduce emittance → improve polarization
- Bunches are later merged in the AGS
- Tuning requires expert knowledge, is time consuming, and tend to drift over time
- Controls: RF voltages & phases
- **<u>Goal</u>**: Obtain good merged bunch profile
  - Emittance preservation
    - No particle lost, Gaussian, no baby bunches
  - Stable final bunch profile
    - Merged in the center, not shifting left/right or bouncing up/down

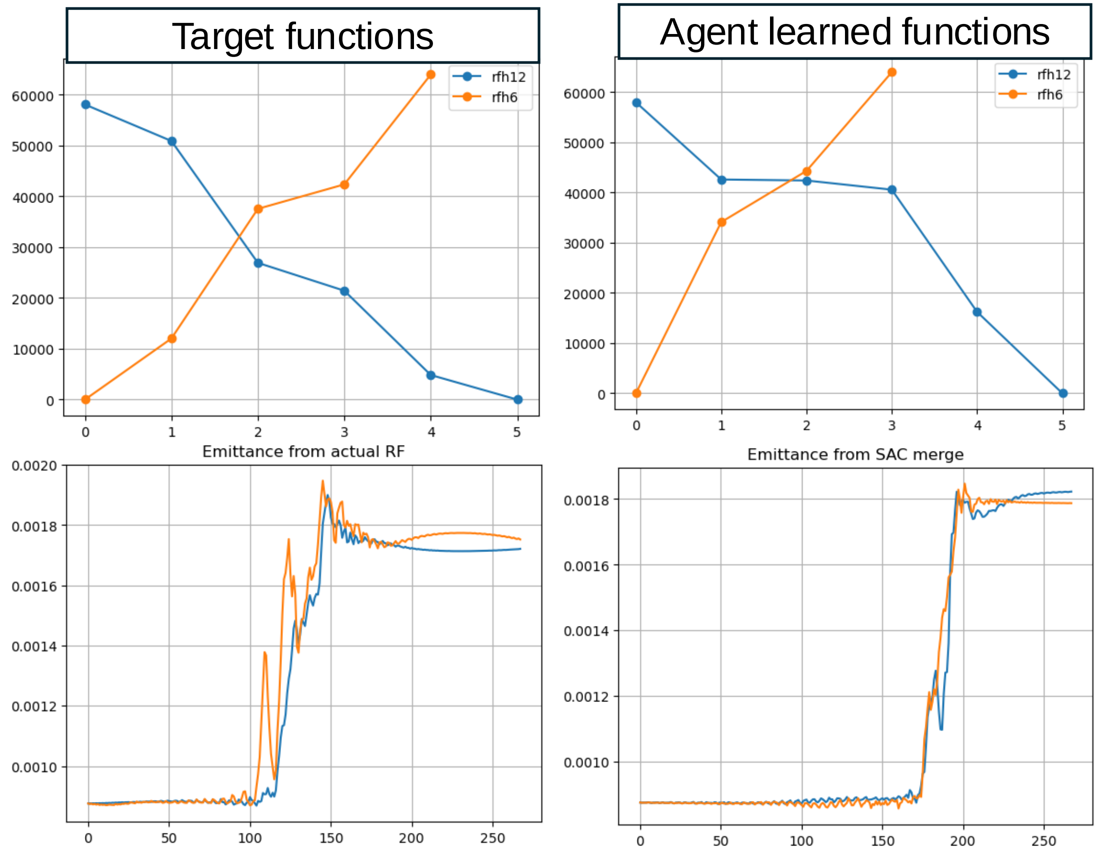


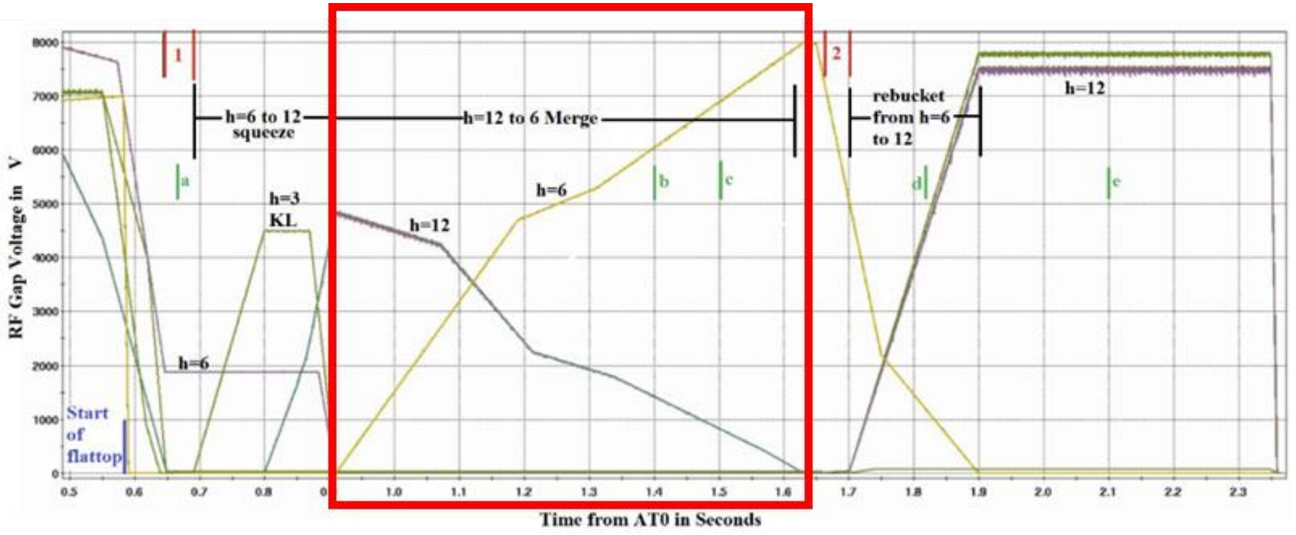
Real mountain range data showing 2-to-1 bunch merge in AGS

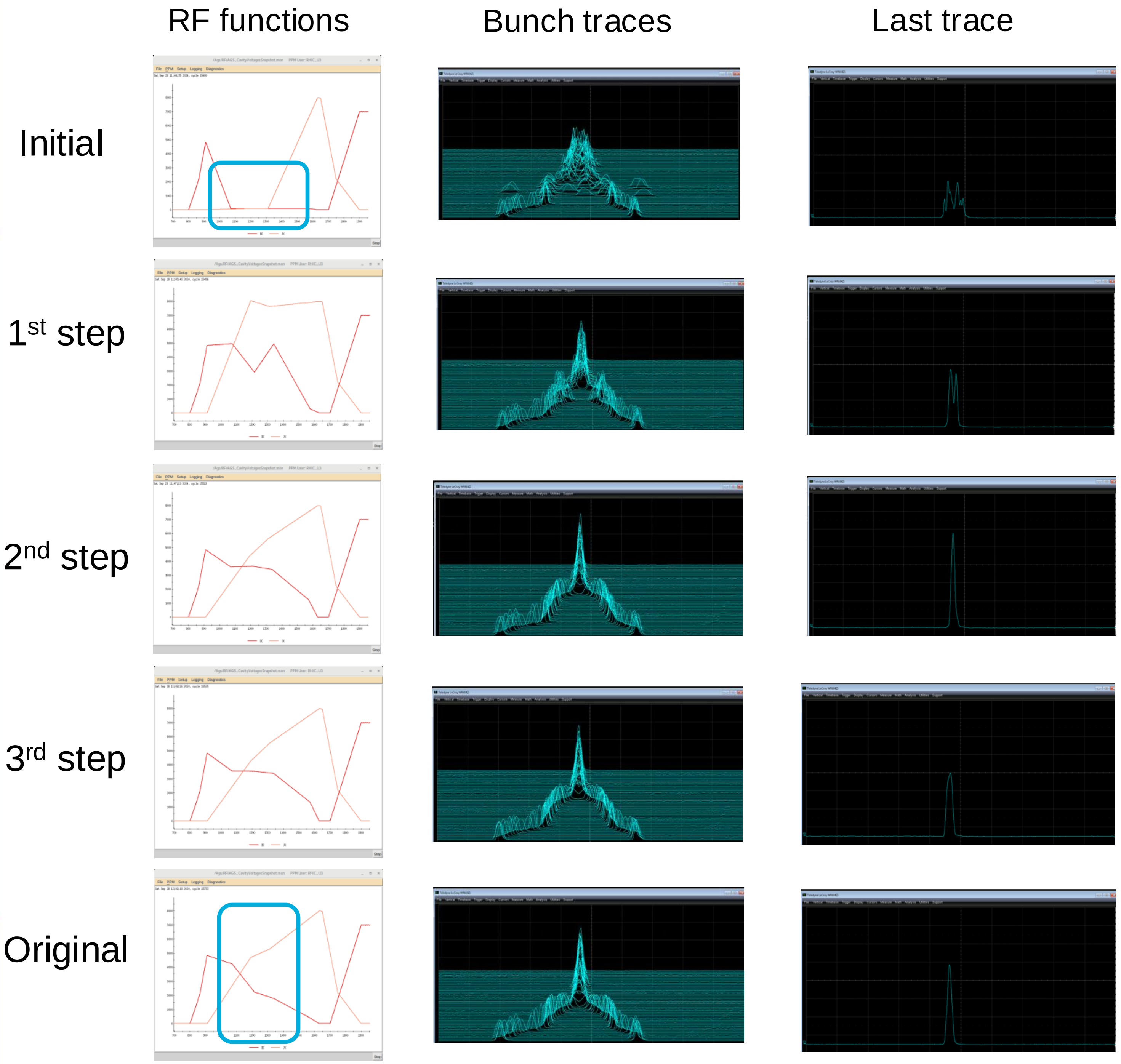
Wall current monitor (WCM) generates voltage vs time signal. Each separated in time by N turns (N accelerator periods)

Bunch merge simulation results

- Julia simulator of the bunch merge process
- Soft Actor-Critic (SAC) agent to minimize emittance growth: 10,000 initial samples + 4,000 training steps
- Able to learn target functions pretty well







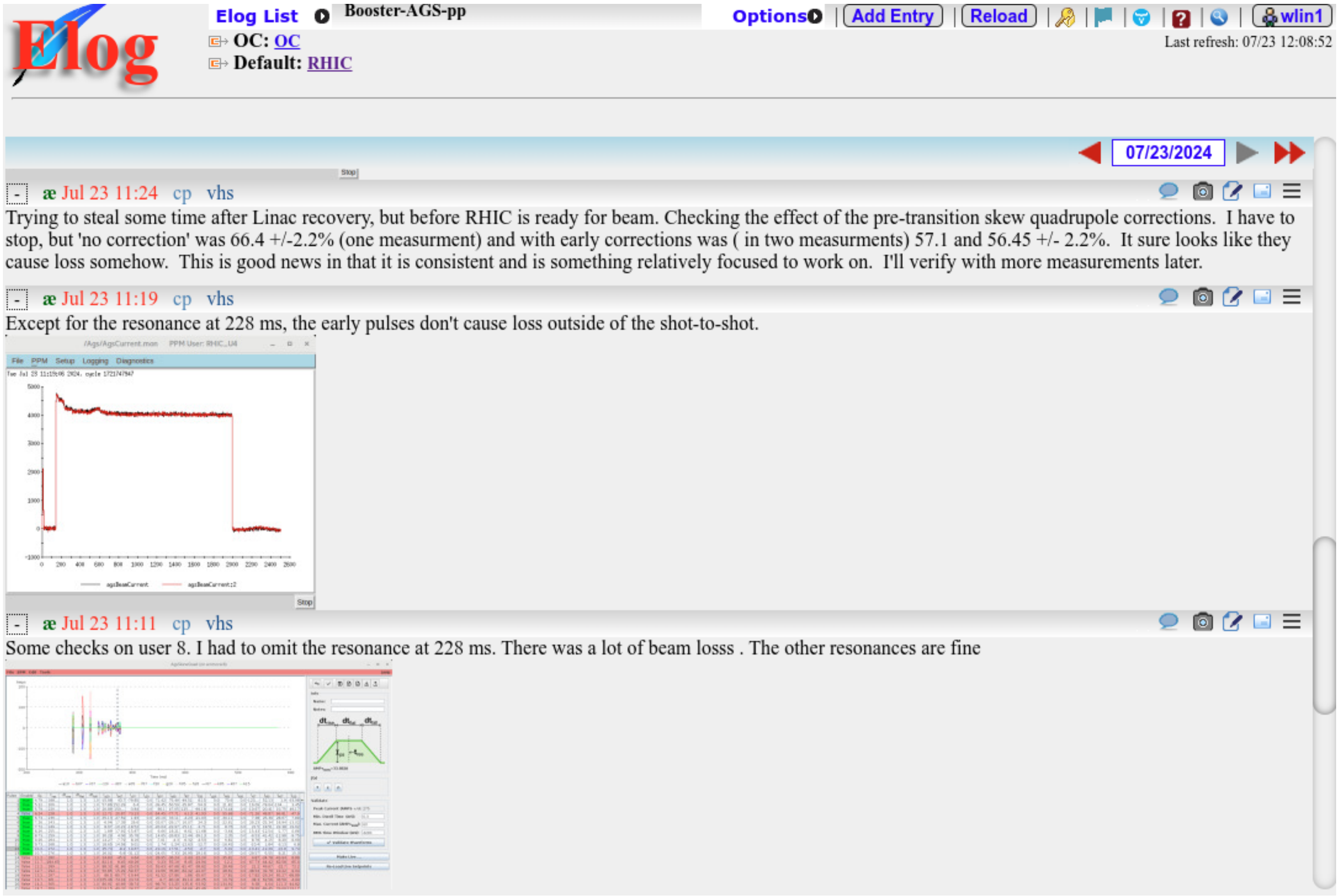
Machine test – Julia agent

- RF cavities voltages are initially set to close to 0 during merge period to intentionally decrease merge quality
- RL agent trained on the Julia simulator is applied to correct RF settings
- RL agent manage to find good RF settings, produce result similar to established machine optimum

Electronic Logbook Upgrade

Electronic Logbook

- Record information ranging from meeting notes, to do lists, and critical operations
- Current search feature only provides exactly what a user enters, difficult to find related entries without the exact words
- **Goal**: provide custom sets of entries based on users' interactions with the system



Elog search upgrade workflow

Elog Database	This assumes we have ALL entries from ALL elogs (e.g., RHIC, Machine Learning, personal elogs etc.)
NLP Preprocessing	Removes any punctuation, stop words, and empty entries. Tokenize each entry & save this information.
Doc2Vec Model	Gensim Doc2Vec model trains 100 epochs. Returns the top few similar elog entries.
Classification	SKLearn MultinomialNB classifier predicts any entry's tag.
Similar Entries	Return similar entries in order by most similar.

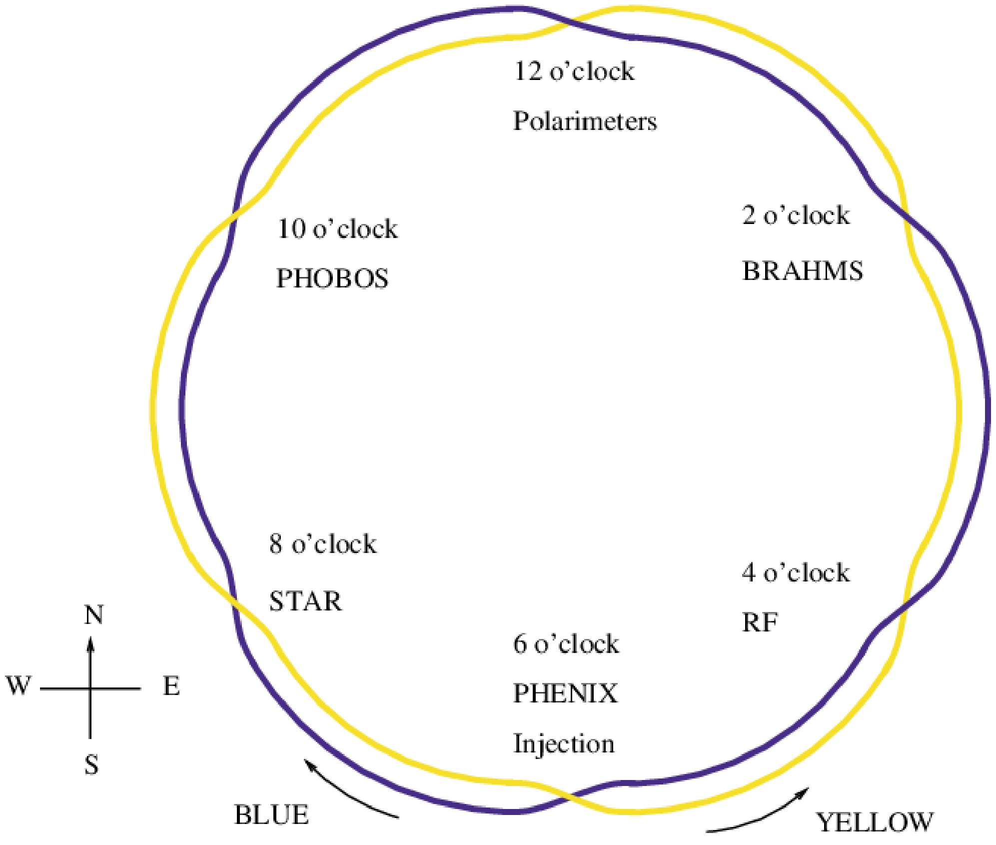
Similarity by word

Polarization

- Background ~ 70%
- Beta ~ 69%
- Polarimeter ~ 64%
- Bunch ~ 63%
- Excitation ~ 63%
- Coherence ~ 62%
- Emittance ~ 60%

Blue

- Yellow ~ 94%
- RHIC ~ 87%
- Ramp ~ 84%
- Power ~ 84%
- Run ~ 82%
- Fill ~ 80%
- Delay ~ 79%



Summary

- Machine learning methods have been developed and tested at multiple experiments and accelerators at the RHIC complex

- Promising results indicate that ML algorithms can be powerful tools for various optimization problems, suitable for fast and complicated tuning in real time

- Digital-twin development is underway to establish accurate models for different accelerators, with a focus on the injection compound, which will remain for the EIC
  - Better understanding of beam behavior in the early stages of the acceleration chain
  - Facilitate offline development of optimization routines

- Important beam qualities such as emittance and polarization will benefit from incorporation of ML algorithms in the control system

Publications

- [1] Y. Gao, W. Lin 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] Y. Gao et al., “Bayesian optimization calibration of ionization profile monitor at the AGS complex”, in *Proc. IPAC'23*, Venice, Italy, May 2023, pp. 4444-4447.
- [4] 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.
- [5] W. Lin et al., “AGS Booster model calibration and digital-twin development”, in *Proc. IPAC’24*, Nashville, TN, May 2024, pp. 3449-3452.
- [6] R. Roussel, W. Lin et al., “Bayesian Optimization Algorithms for Accelerator Physics”, arXiv:2312.05667 [physics.acc-ph]
- [7] X. Gu et al., “Enhancing beam intensity in RHIC EBIS beamline via GPTune machine learning-driven optimization”, in *Proc. IPAC'24*, Nashville, TN, May 2024, pp. 118-120.
- [8] J. Maldonado et al., “Towards unlocking insights from logbooks using AI”, in *Proc. IPAC'24*, Nashville, TN, May 2024, pp. 3579-3582.

Thank you!

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