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Cornell Laboratory for Accelerator-based ScienceS & Education

Brookhaven National Laboratory

U.S. Department of ENERGY

Machine Learning Applications for Improving Accelerator Operations

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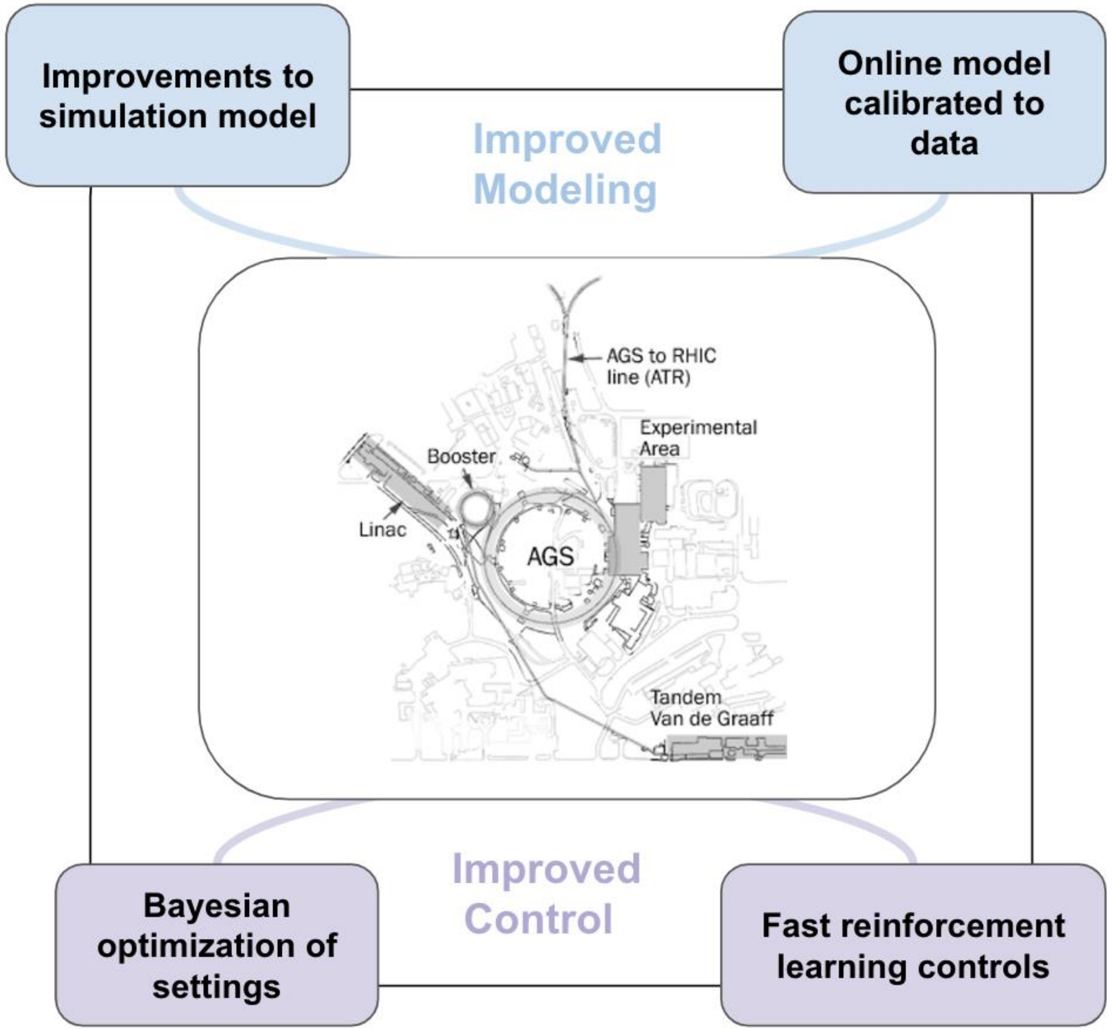
Improve Accelerator Operations with ML

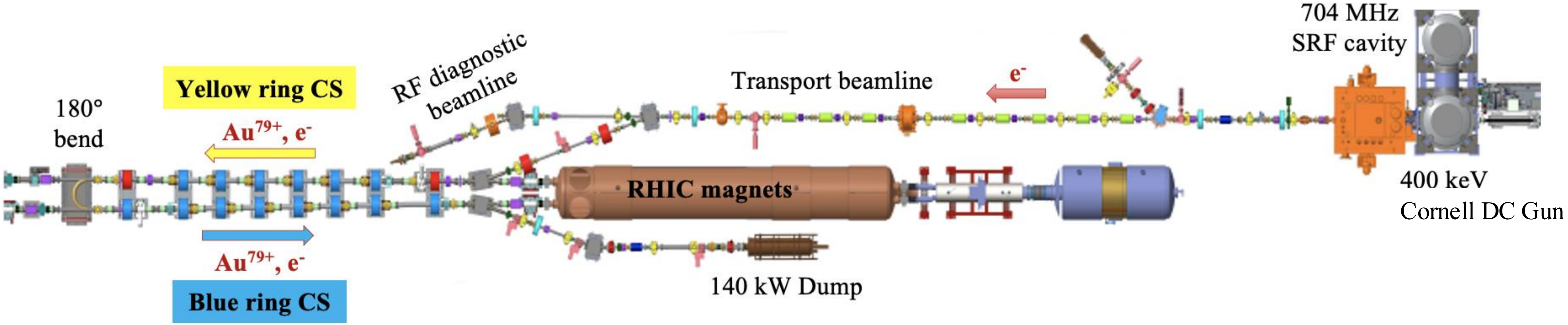
- Figure-of-merits (FOM) for machine learning (ML) algorithms ("experimental outputs"): <u>beam size</u>, <u>emittance</u>, <u>beam intensity</u>, <u>polarization</u>
- Possible areas where ML is useful:
  - Cooling optimization
  - Injection optimization
  - Digital-twin & Error detection
- Useful ML methods:
  - Bayesian Optimization (BO)
  - Neural Network (NN)
  - Reinforcement Learning (RL)



Cooling Optimization

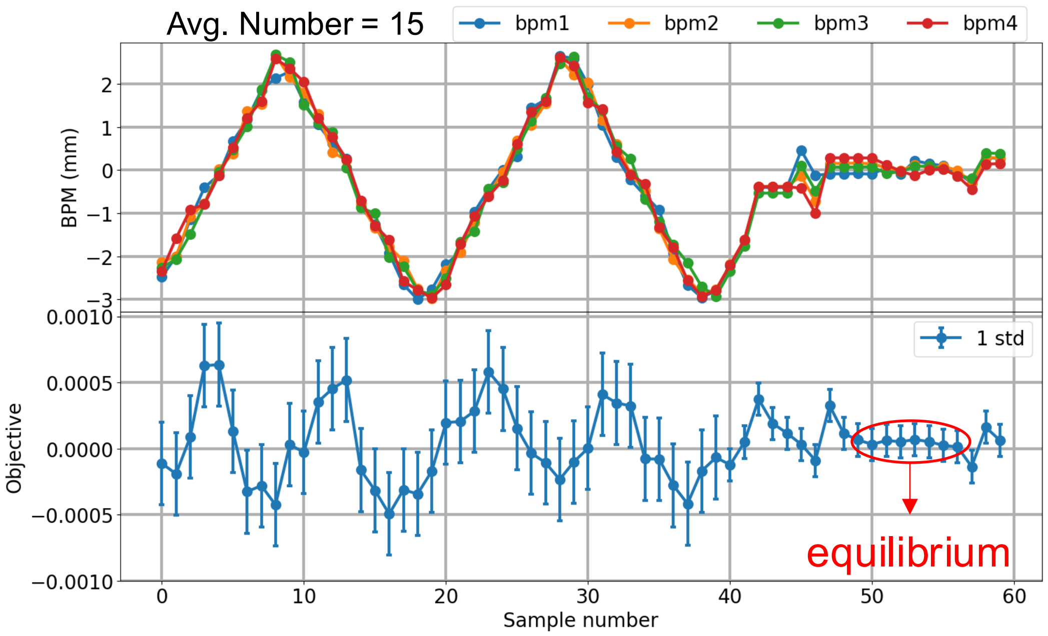
- Low Energy RHIC electron Cooling (LEReC)
- Coherent electron Cooling (CeC)

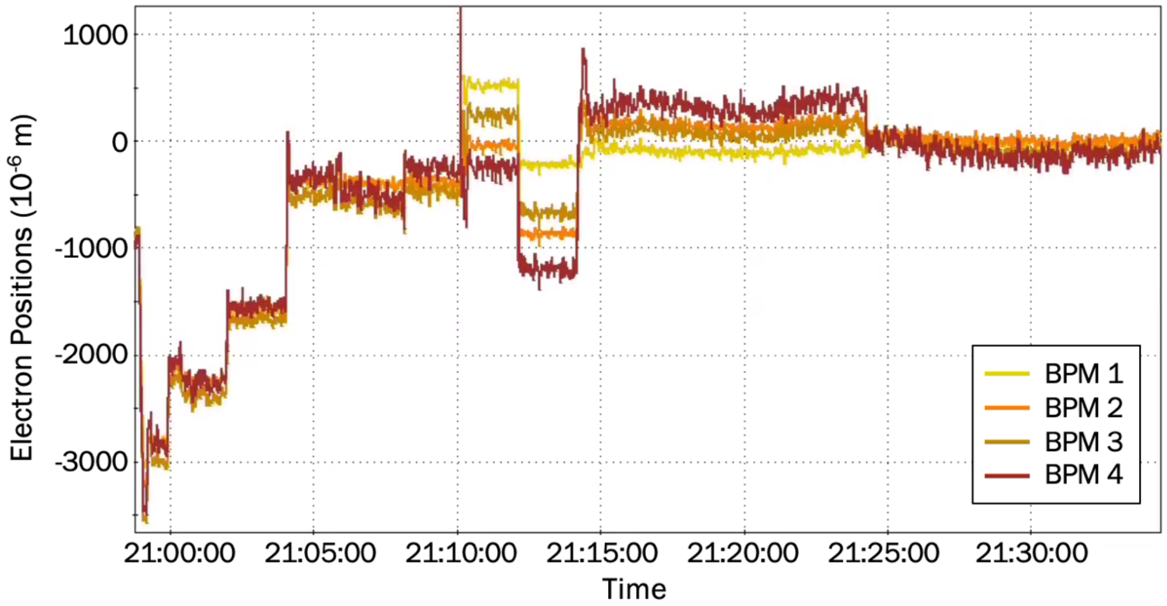
Low Energy RHIC electron Cooling (LEReC)



- LEReC is used to increase the luminosity, it was successfully improved the luminosity in 2020 and 2021 runs ➔ The new EIC pre-cooler layout follows the same principle
- Cooling rate: velocity of decrese in ion beam size $\lambda = (1/\bar{\delta})(\overline{d\delta}/dt)$
- Ions are assumed in the center position (x=0, y=0)
- **Goal**: use Bayesian optimization (BO) to maximize $-\lambda$ by aligning electron orbit with ion orbit

LEReC experiment result

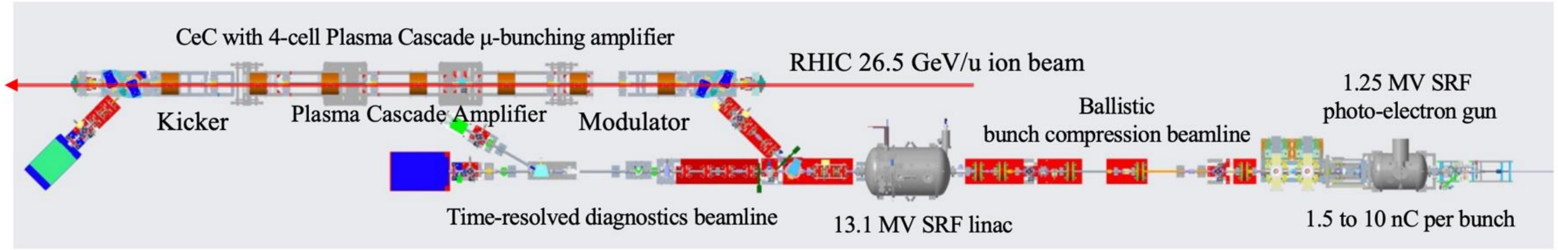


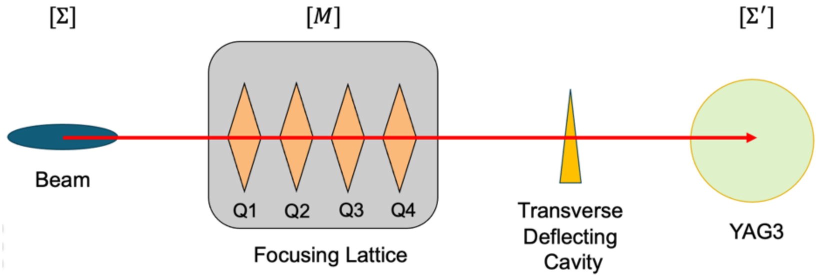


- Bayesian optimization algorithm trained with 40 initial samples to optimize transverse cooling rate λ
- The system reaches optimal status when cooling balances growth from intra-beam scattering (IBS), so λ approaches 0 once the system reaches equilibrium
- Algorithm converged quickly (reach close neighborhood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

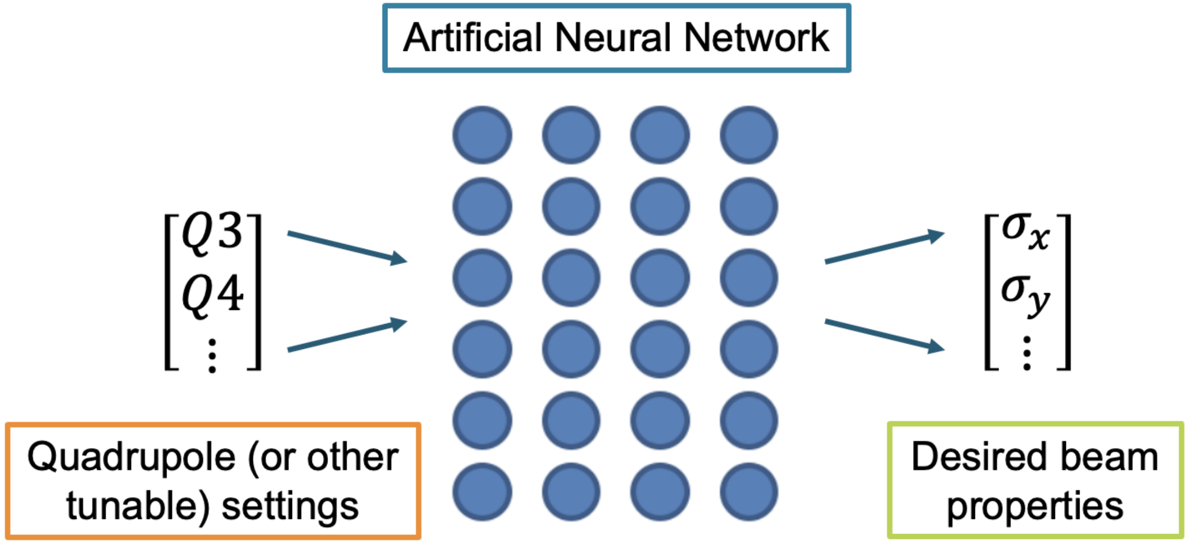
Coherent electron Cooling (CeC)

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



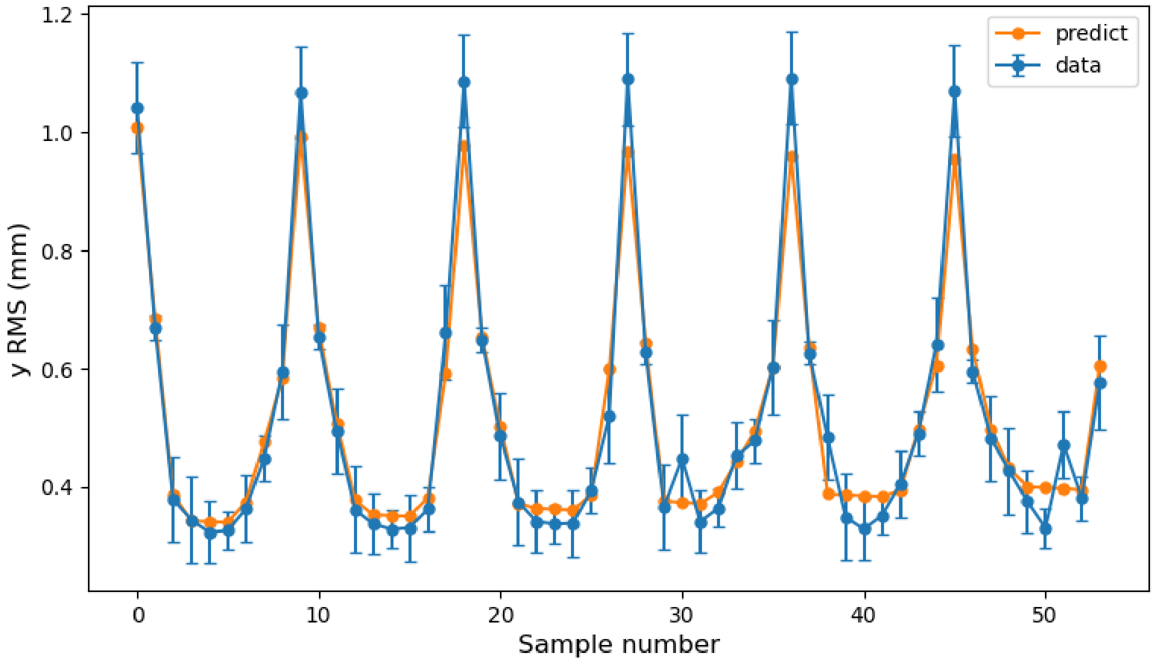


- Scan two quads (Q3, Q4) with opposite polarity to measure electron beam slice emittance: > 1 hour for entire scan routine
- Train a ML model to establish mapping between quadrupole settings and beam size
- Trained ML model predicts best Q3-Q4 combinations without additional scans
- Useful for faster general beam tuning & as starting point of optimization



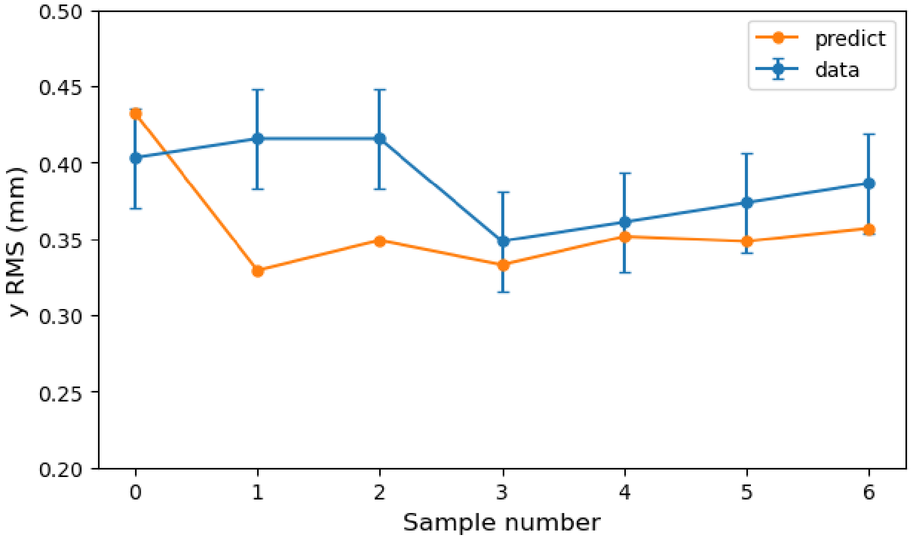
Test new routine on CeC system

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%

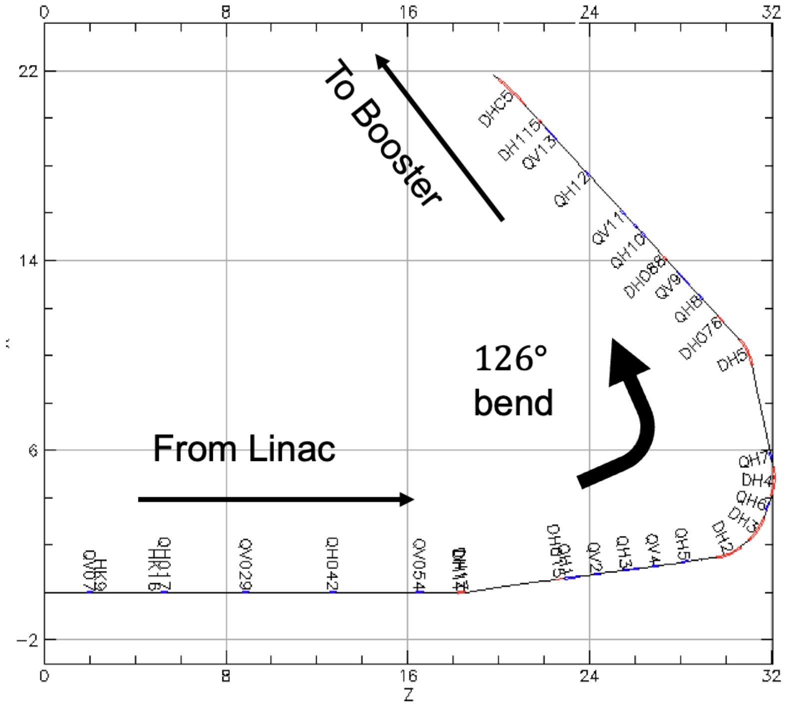


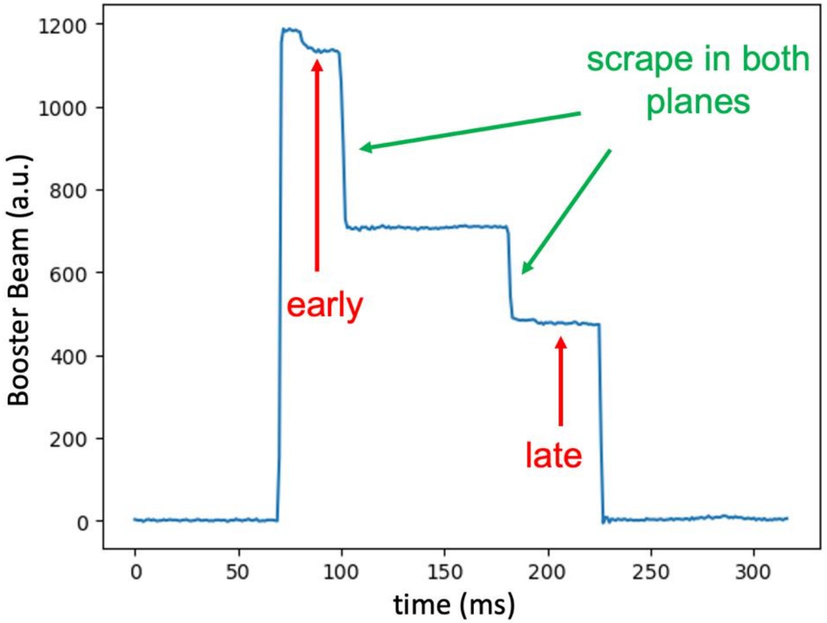
Injection Optimization

◇ Linac to Booster (LtB) Transfer Line

AGS 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
- Goal: minimize emittance / maximize beam intensity after scraping
- Controls: Linac to Booster (LtB) transfer line optics
- Method: Bayesian optimization (BO)

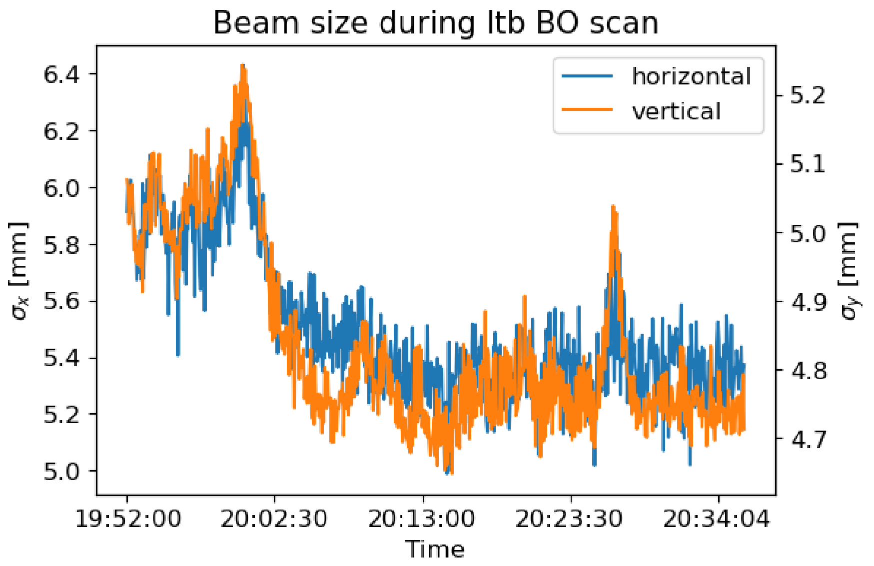


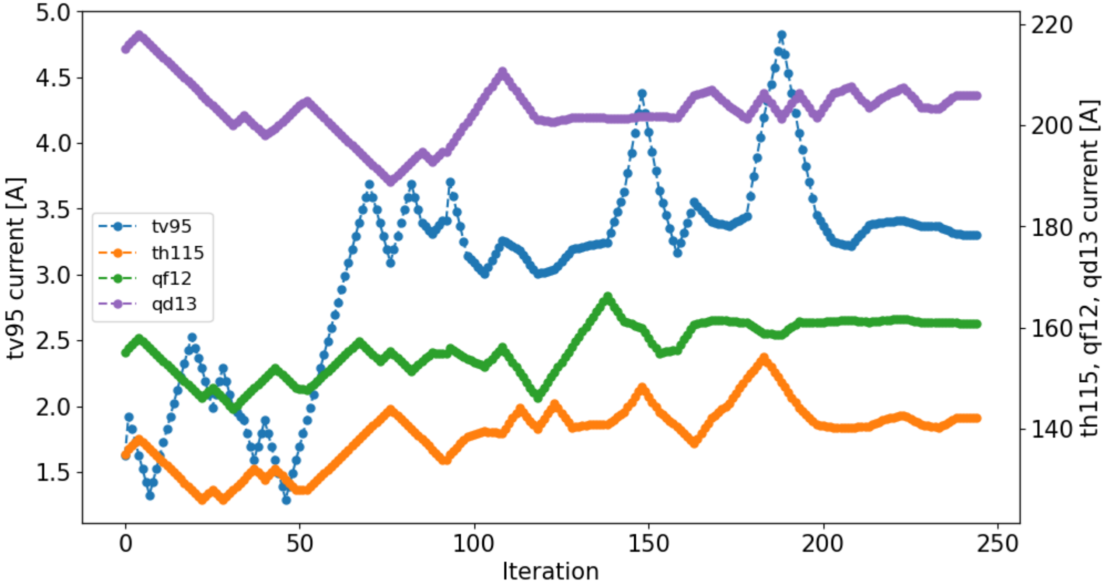


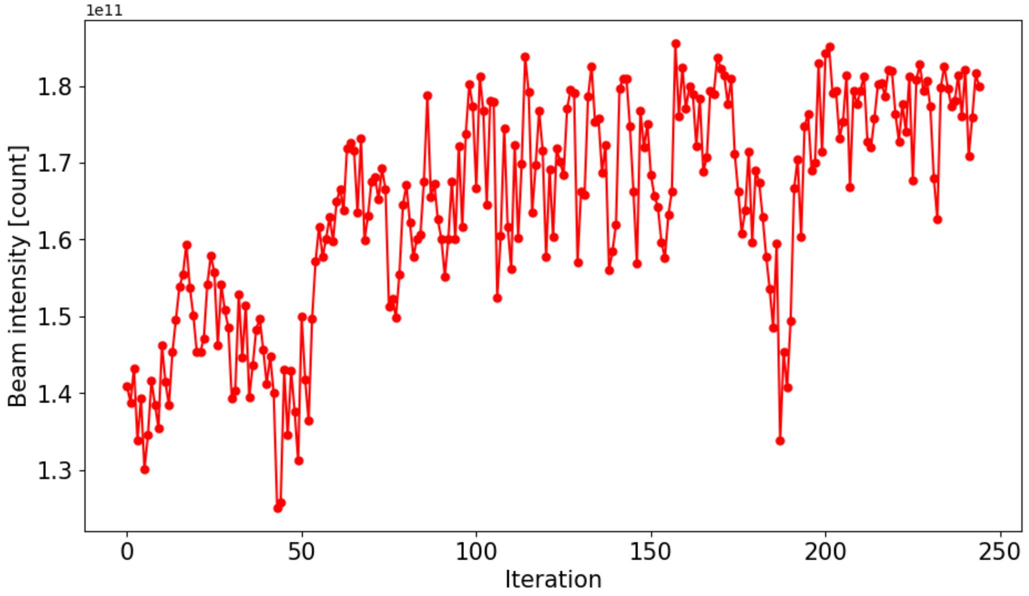
LtB optimization result

- 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

$$\mathcal{L} = \frac{1}{4\pi} \cdot N_b f_{rev} \cdot \frac{N^2}{\beta^* \varepsilon} \sim \frac{N^2}{beam\ size}$$

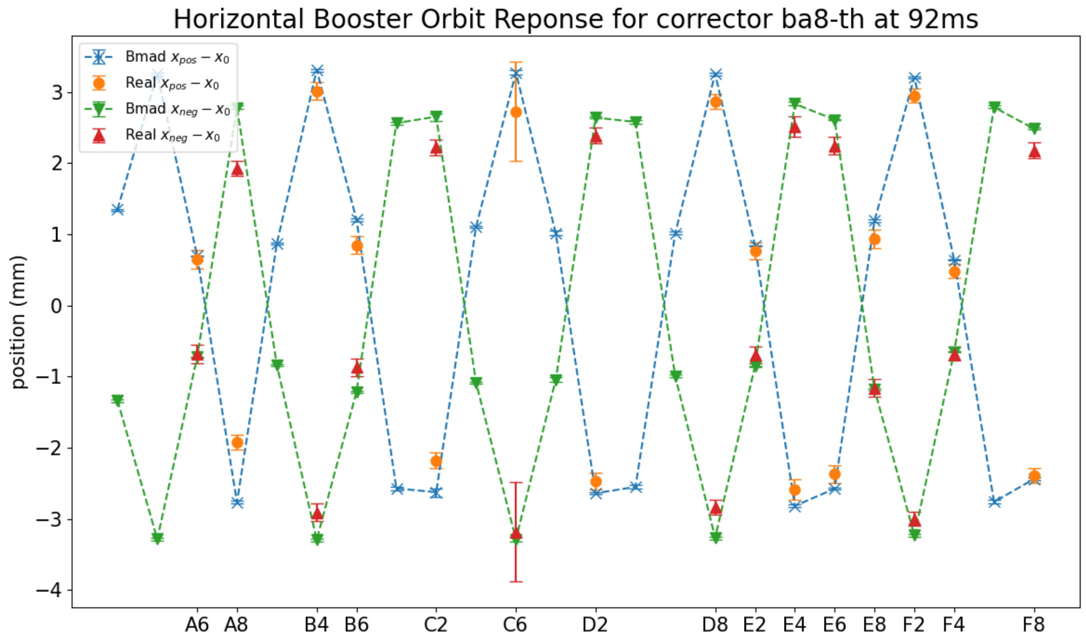


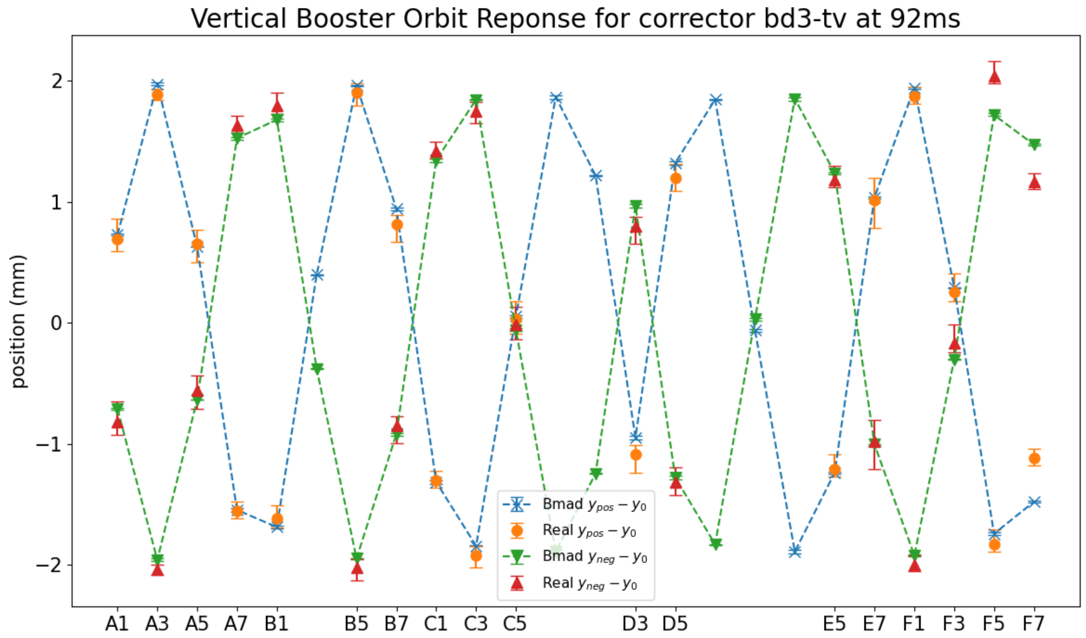




Digital-twin and Error Detection

- Alternating Gradient Synchrotron (AGS) Booster
- NASA Space Radiation Laboratory (NSRL)



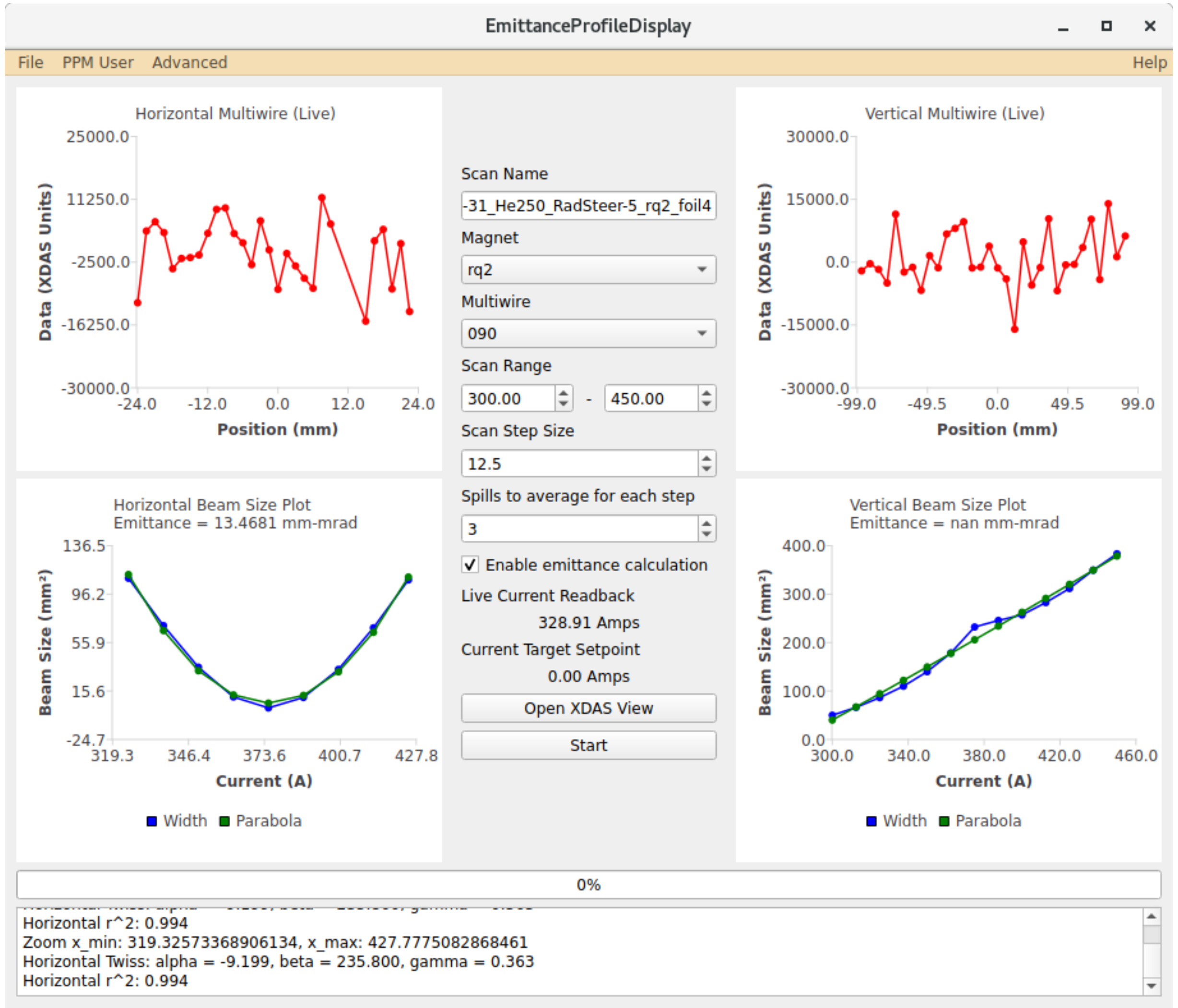


Orbit response data in AGS Booster

- Good agreements between AGS Booster data and physics simulation (Bmad) model are reached, despite some faulty BPMs
- Bayesian Uncertainty Quantification (UQ) is being used to probe and quantify sources of errors that could lead to the discrepancies between simulation and measurement
- <u>**Goal**</u>: produce accurate real-time predictions for operators and give tuning suggestions to improve beam quality

Automated quad scan software for NSRL

- Script package with GUI interface for fast and easy emittance measurement in the NSRL line
- User sets quadrupole, beam profile monitor, scan current range, and step size
- Measured data will be used to calibrate simulation model
- Can be adapted for other beam lines at BNL: Booster to AGS (BtA) and Tandem versions in progress



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

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Thank you!

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