Physics Informed and Bayesian Machine Learning for Maximization of Beam Polarization at RHIC

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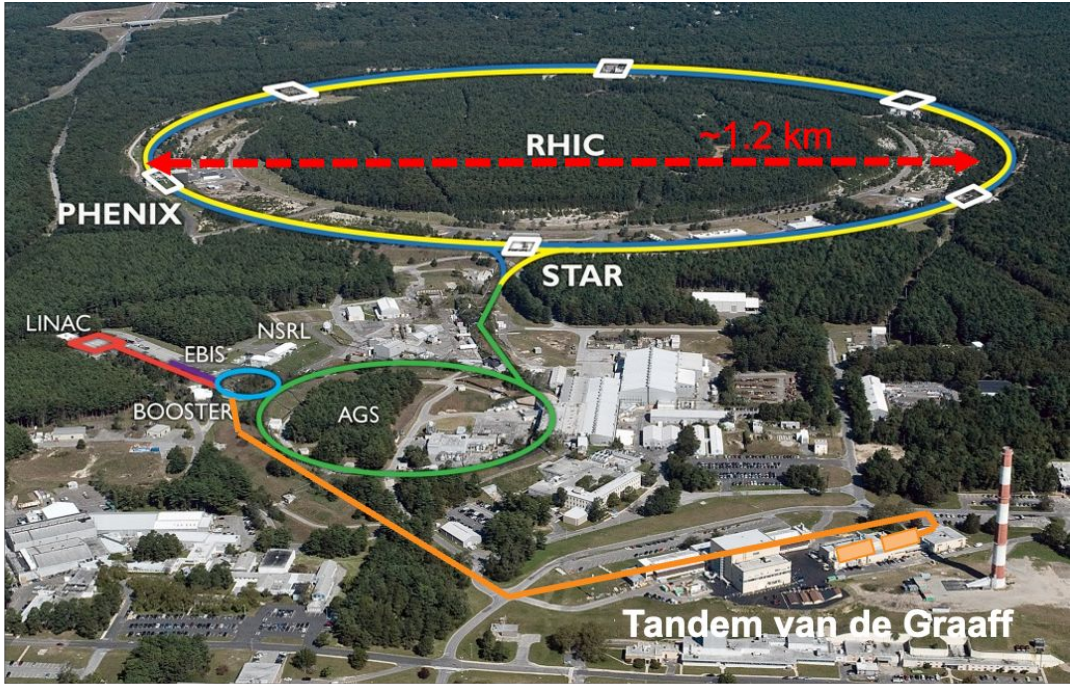
Outline

- Introduction to RHIC/EIC and project goals
- Current areas of work
  - Booster and AGS injection
  - Booster and AGS model calibration
  - Bunch splitting/merging and timing
  - Resonance minimization
- Conclusion/Outlook

Relativistic Heavy Ion Collider (RHIC): world's only high-energy polarized proton beam and largest operating accelerator in the US
→ *unique opportunities to study from where nuclei obtain their spin*

Electron Ion Collider (EIC): new successor to RHIC; will collide polarized proton and electron beams

Increase in instrument complexity for EIC will require new tools to optimize accelerator performance and maximize the utility of polarized beam experiments



Heavy Ions	Protons
E-beam Ion Source (EBIS)	OPPIS (polarized)
Tandem Van de Graaf	High-intensity H^- (unpolarized)

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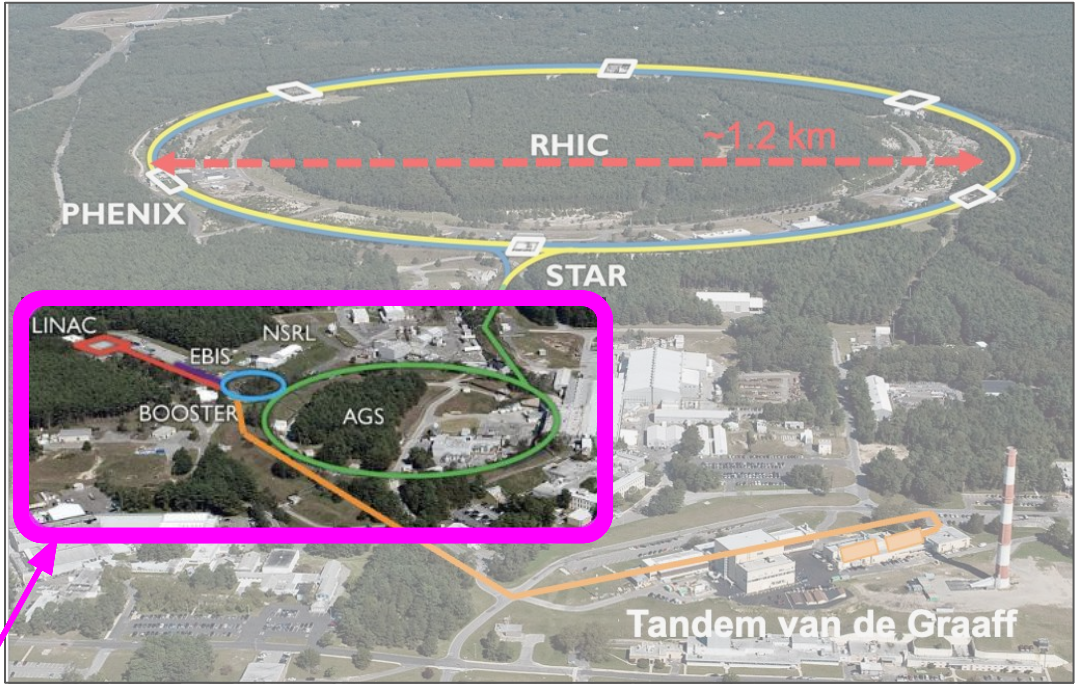
<u>Alternating Gradient Synchrotron</u> (AGS) and its **<u>Booster</u>** serve as part of the **<u>injector compound</u>** for RHIC and future EIC

Bright ion beams in AGS / Booster are required for optimal luminosity and highest polarization in RHIC and EIC



Heavy Ions	Protons
E-beam Ion Source (EBIS)	OPPIS (polarized)
Tandem Van de Graaf	High-intensity H^- (unpolarized)

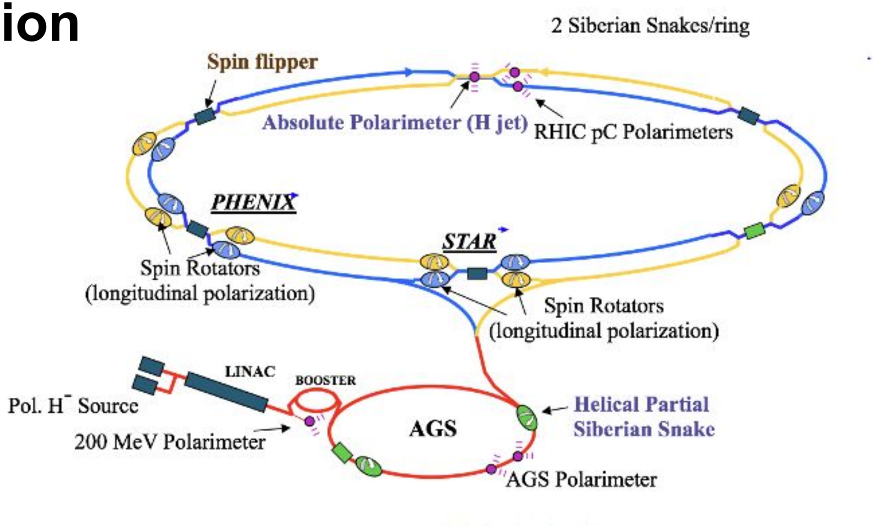
Desired Result: higher proton polarization

From the source to high energy RHIC experiments, 20% polarization is lost.

Polarized luminosity for longitudinal collisions scales with P^4 (a factor of 2 reduction!)

The proton polarization chain depends on delicate accelerator settings form Linac to the Booster, the AGS, and the RHIC ramp.

Currently, the injector compound is largely hand-tuned by operators



Polarimetry available at:
- Source
- End of Linac (200 MeV)
- AGS extraction
- RHIC injection energy
- RHIC flattop

Polarization is a high-impact challenge to address

Even 5% more polarization would be a significant achievement!

	Max Energy [GeV]	Pol. At Max Energy [%]	Polarimeter
Source+Linac	1.1	82-84	
Booster	2.5	~80-84	
AGS	23.8	67-70	p-Carbon
RHIC	255	55-60	Jet, full store avg*

Loss in polarization along the chain

	Relative Ramp Polarization Loss (Run 17, full run avg)
AGS	17 %
RHIC	8 %

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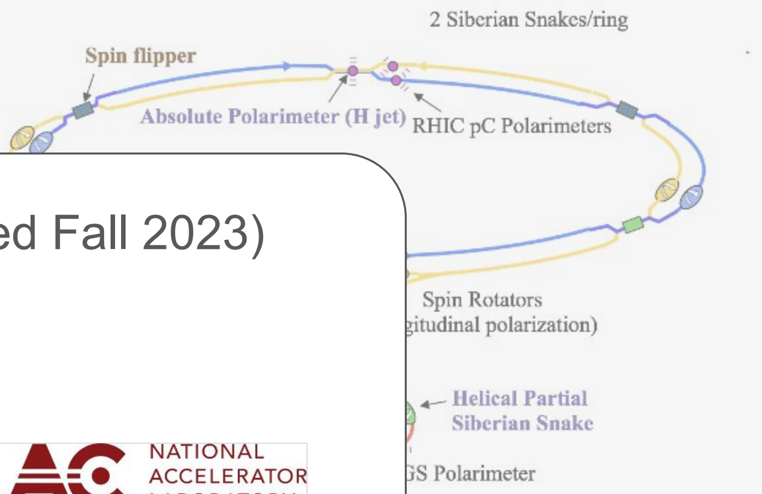

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New project to tackle this! (started Fall 2023)

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Stony Brook University

Jefferson Lab Thomas Jefferson National Accelerator Facility

Rensselaer

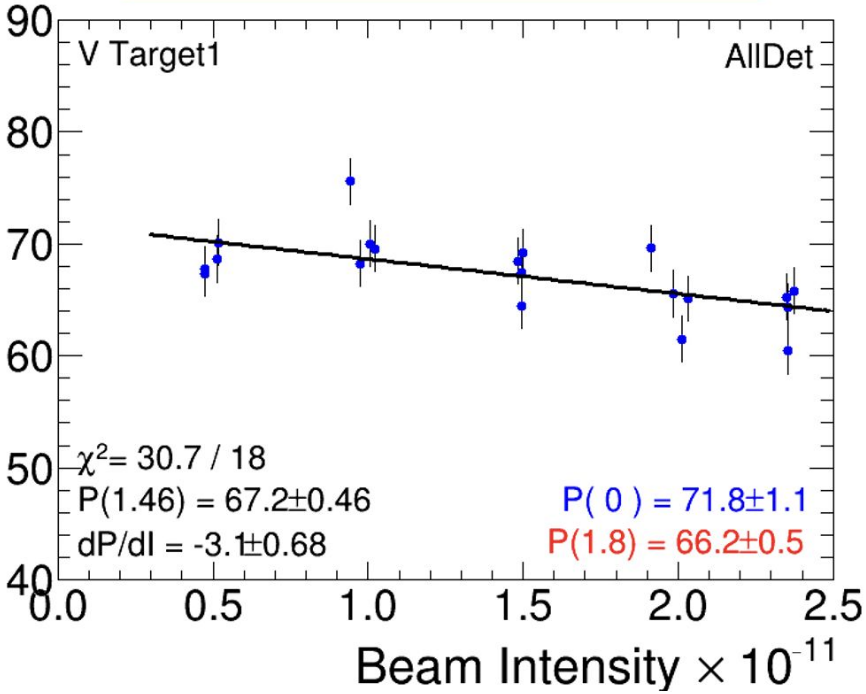
radiasoft

Combined team of accelerator physicists, controls experts, and ML researchers

What is needed to improve polarization?

- Figure-of-merits (FOM) for the project ("experimental outputs"): emittance, beam intensity, polarization
- Trade-offs in optimizing **FOMs**:
  - Emittance ↓ Beam intensity ↑ Polarization ↑
- Trade-offs between **controls**:
  - Beam intensity ↑ → Emittance ↑
  - Emittance ↑ → Polarization ↓
- Main areas to optimize:
  - Booster injection / capture
  - AGS bunch splitting / merging scheme
  - AGS spin resonance compensation

AGS Polarization vs. Beam Intensity



Tasks that can aid polarization:

(1) Emittance reduction (beam density preservation)

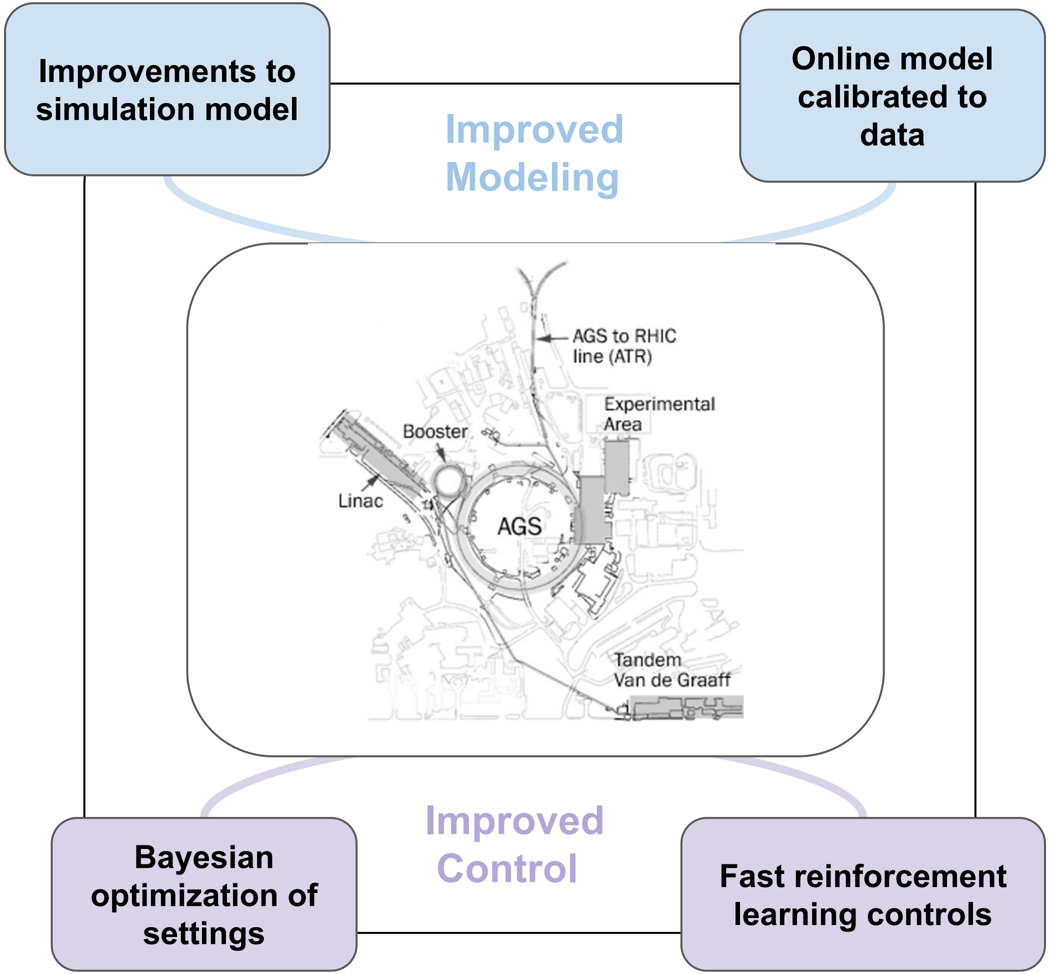
(2) Synchronize accelerator components at depolarizing resonance crossings

(3) Minimize depolarizing resonance strengths

Strategy:
Establish more accurate models for Booster and AGS to better understand and predict how beam behaves in the rings.

Develop more streamlined tuning routines so desirable beam status can be obtained more efficiently.

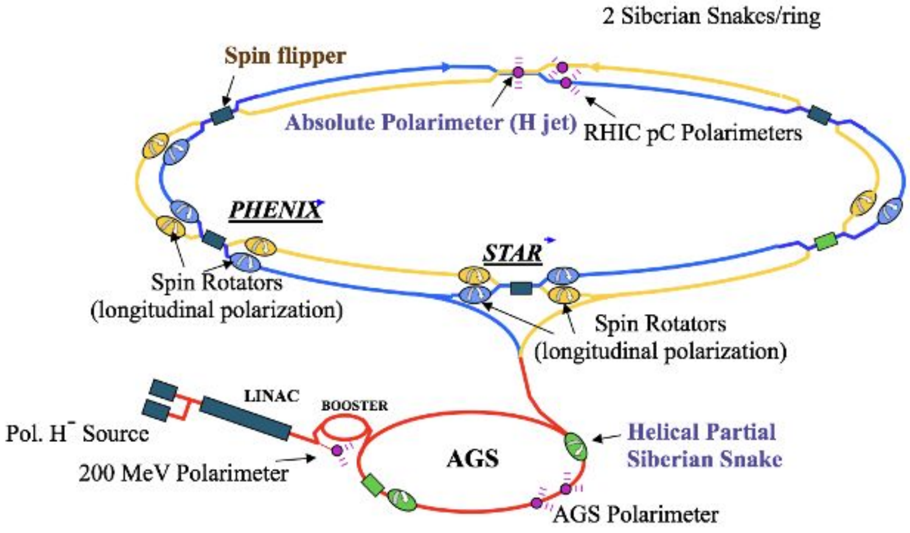
Project brings together techniques in AIML to target the key areas where polarization can be improved



Different sub-systems have different needs (e.g. fast corrections vs. high-level optimization of settings)

Emittance reduction → less depolarization

- Optimize Linac to Booster transfer
- Optimize Booster to AGS transfer
- Optics and orbit correction in Booster and AGS
- Beam-based alignment & calibration from orbit response in Booster and AGS
- Bunch splitting in the Booster for space charge reduction and bunch re-coalescing at AGS top energy

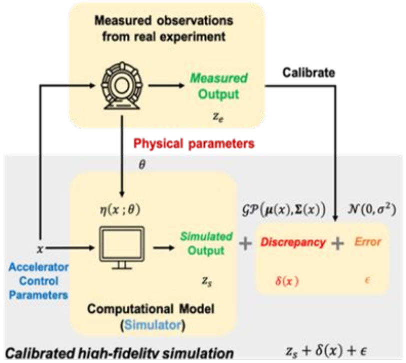


Integrated ML Approach for Polarization Improvement

Data-model Integration

Solve inverse problem for unknown model parameters

Learn data-driven model



Scientific Machine Learning

Include constraints for physics process in surrogate model training

"Soft" constraints as an objective penalty

Optimization with linear constraints

$$min_{\boldsymbol{x}\in D_{\boldsymbol{x}}}\ f(\boldsymbol{x})\quad s.t.\ \ c_r(\boldsymbol{x}) \le 0\quad \forall\, r \in [1,..,R]$$

Objective and constraints as GPs

$$f(\boldsymbol{x}) \sim \mathcal{GP}(\mu,\Sigma)\ \text{ and }\ c_r(\boldsymbol{x}) \sim \mathcal{GP}(\mu_r,\Sigma_r)$$

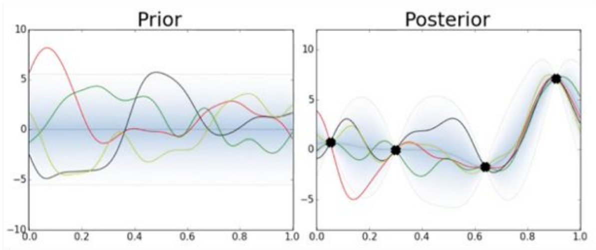
Integrate the feasibility through the CDF

$$cEI(\boldsymbol{x}) = EI(\boldsymbol{x}) \times \prod_{r=1}^{R} \Phi(\frac{\mu_r}{\sigma_r})$$

Optimization Under Uncertainty and Fast ML-based Control

Bayesian optimization with priors from system models

Reinforcement learning trained with system model



Target Areas and Sub-projects

(a) Optimize Booster injection
(b) Optimize AGS injection

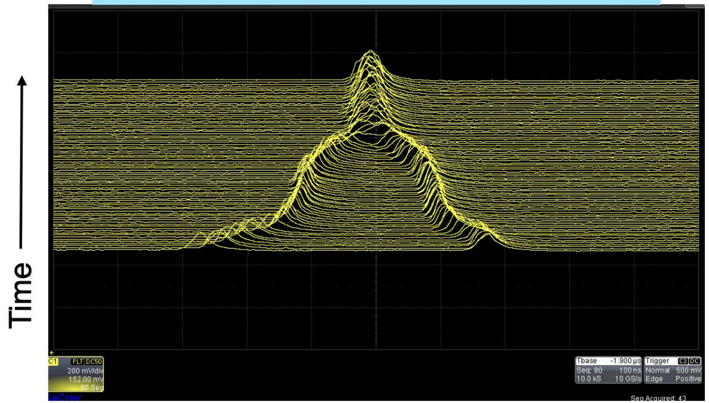
(c) Booster model calibration
(d) AGS model calibration

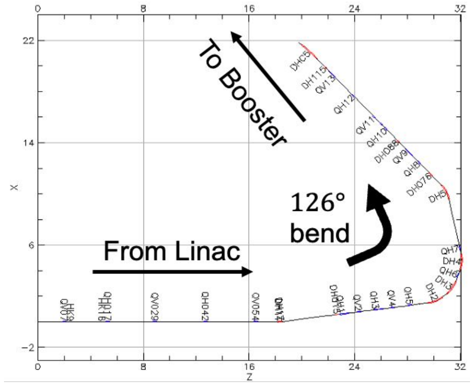
(e) Bunch splitting/coalescing
(f) Timing

(g) Resonance minimization

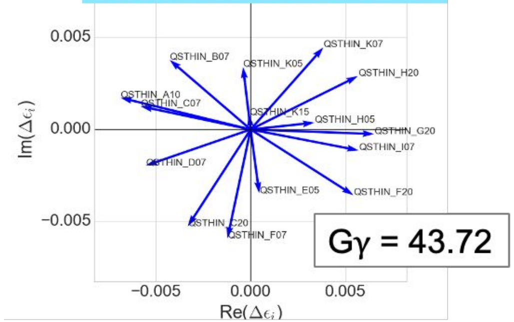
(h) Combined and verified evaluation of existing emittance measurements

Merge of AGS proton bunches at flattop





Spin resonance terms from skew quads in AGS

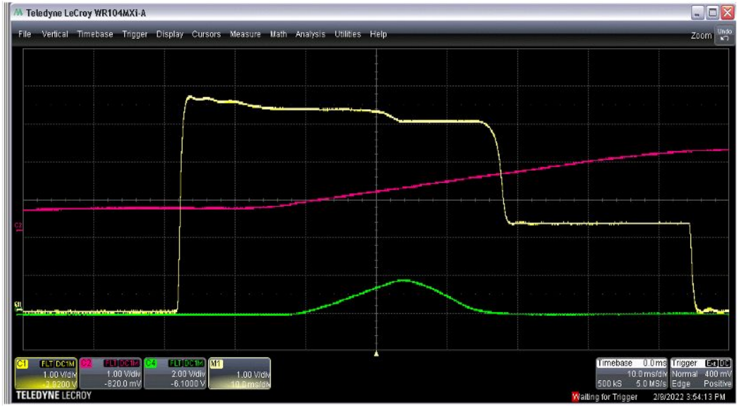


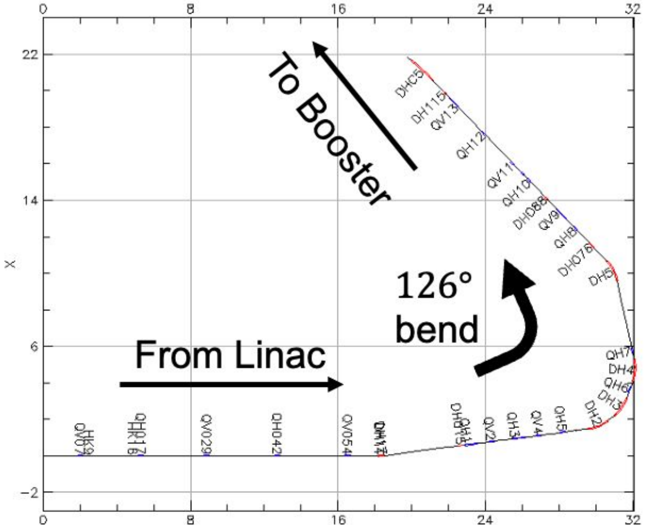
Tasks range from being highly approachable with existing AIML techniques to challenging new use cases requiring R&D

Booter injection/capture optimization

- Booster injection/early acceleration process sets maximum beam brightness for rest of acceleration though RHIC
- Linac pulse of 300 us, H- beam ~6-9x10^{11} protons, strip through a carbon foil. Intentional horizontal and vertical scraping reduce emittance (and intensity) to RHIC requirements ~2.5x10^{11} protons
- Controls: Linac to Booster (LtB) transfer line optics, beam size on ionization foil
- Goal: minimize beam loss at scraper
- Method: Bayesian Optimization

Progress: Set up injection model including foil, create interface for optimization





Linac to Booster transfer

Parameters to vary:

• Transfer line steers

• Main Booster dipole field

• Booster beta wave (stop-band quadrupoles) for tune toward ½ and minimum on the foil

• Last two linac phases

• Injection bump elements and their time profile

• Scraper amplitudes

Observables to optimize:

• Transfer efficiency linac → Booster early ramp

• Emittance from multi wires of the AGS transfer line

AGS injection optimization

Parameters to vary:

• Transfer line steerers

• Main AGS dipole field, RF phase, injection bumps, tunes.

• Horizontal orbit in the snakes and their optics and orbit correction.

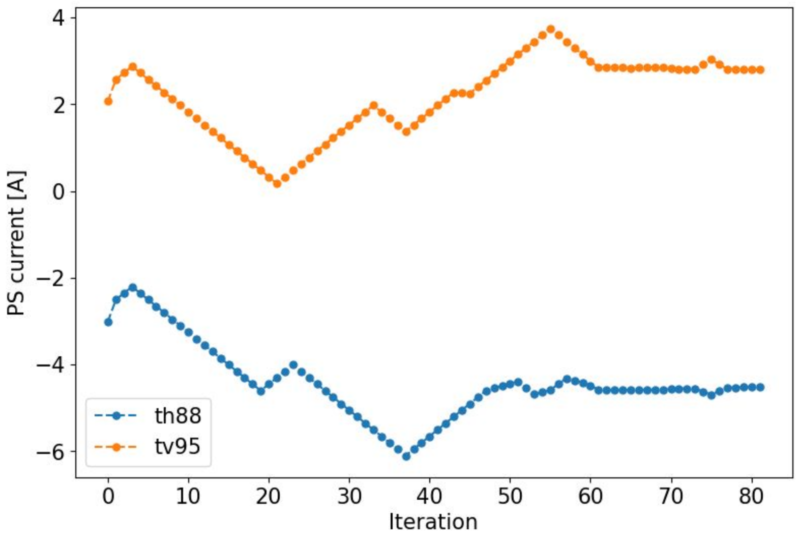
Observables to optimize:

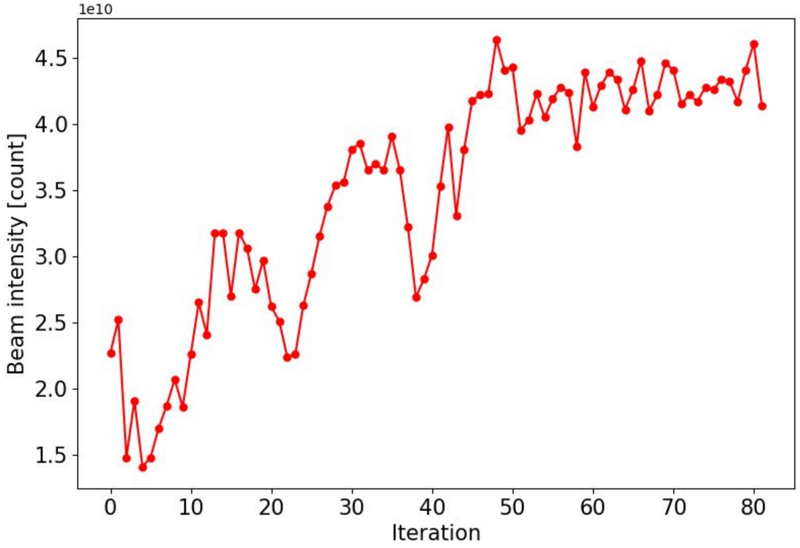
• Transfer efficiency Booster → AGS early ramp

• Emittance from two IPMs

Booster injection optimization using Xopt

- BO algorithm to maximize beam intensity after scraping by tuning Linac to Booster (LtB) magnets
- Preliminary study done using two correctors at the end of LtB, algorithm was able to converge and maximize beam intensity

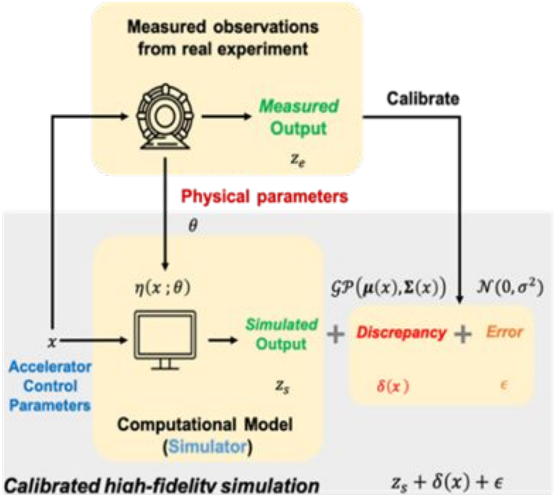




Booster Model Calibration

$$(I_{quad}, I_{corr}, \theta) \overset{model}{\Longleftarrow\!=\!=\!=\!\Longrightarrow} \left(X_{BPM}^{(I_{quad}^{(1)}, I_{corr}^{(1)})}, X_{BPM}^{(I_{quad}^{(2)}, I_{corr}^{(2)})}, \dots\right)$$

- Control: power supply currents of quadrupoles and correctors
- Parameter θ: parameters that affect the orbit but not in our control → (<u>magnet misalignments</u>, <u>magnet transfer functions</u>, etc.)
- Output: orbit at the BPMs with certain current configuration
- Invert from measured BPM data to simulation model parameters
- Update beliefs on model parameters with real data → calibrated model *m* can be used to optimize beam quality (objective *F*)



$$X_{BPM} = m(I_{quad}, I_{corr}; \theta) + \epsilon, \qquad \epsilon \sim N(0, \sigma)$$

$$I_{quad}^*, I_{corr}^* = \mathrm{argmax}\, F(m(I_{quad}, I_{corr}; \theta))$$

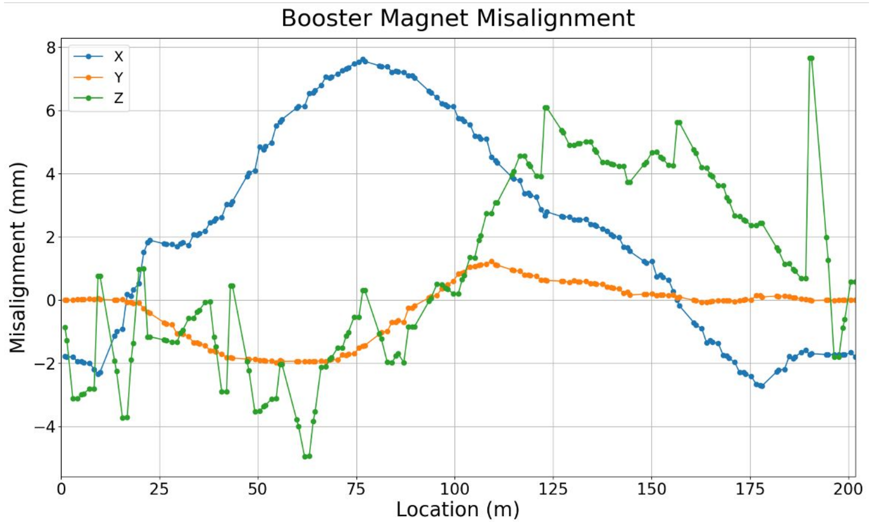
Challenge: How well can we determine the alignment by orbit-response evaluation?

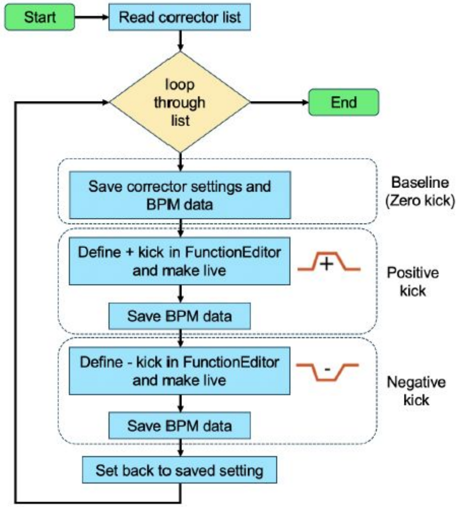
Booster magnet misalignment

- Simulation studies using Bmad to see how magnet misalignments affect orbit; survey misalignments from 2015 used as the baseline values in the model

- Misalignment data gathered for quadrupoles and dipoles → *trouble with making physics simulation with misalignment agree with real orbit data*

- Use Bayesian optimal experimental design (BOED)-based approach to determine magnet settings which are expected to return orbit data that most reduces uncertainty in the magnet misalignment parameters





Booster magnet misalignment

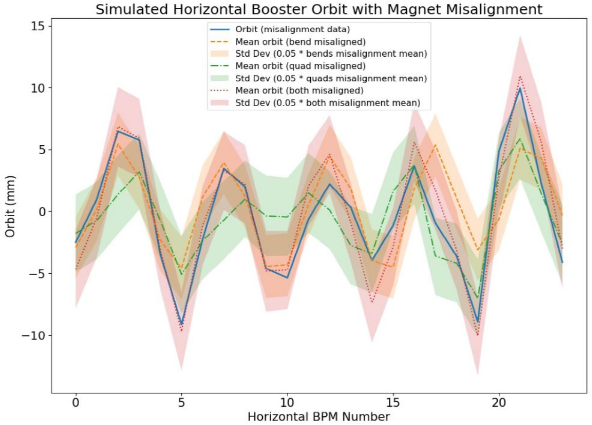
See poster by Lucy Lin

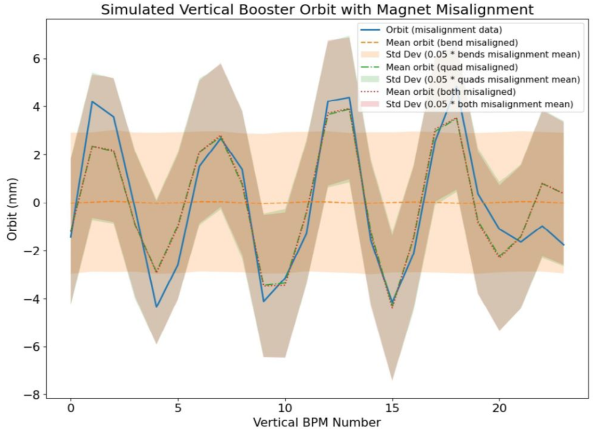
Initial comparison of the differential orbit (orbit difference between positive, zero, and negative corrector settings) shows good agreement, validating the status and calibration of real Booster BPMs.

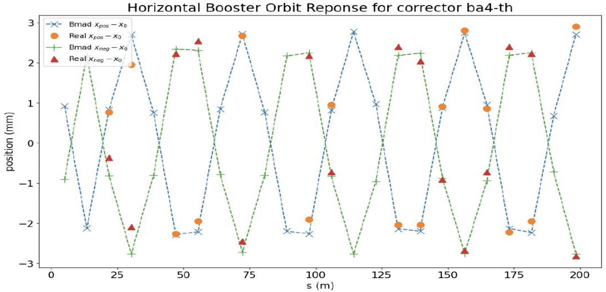
Current/future steps:
More factors need to be added:
- Radial steering
- Time-dependent fields induced by magnet ramps

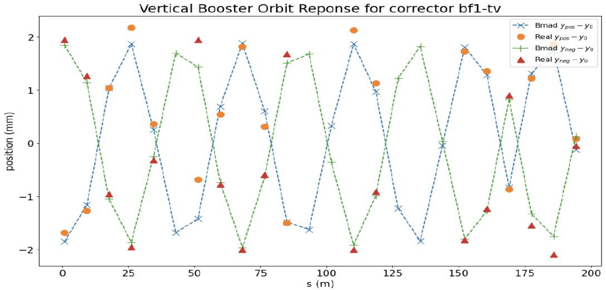
Will then perform Bayesian inference

May use differentiable simulation (Bmad-X / Bmad-Julia) to aid model calibration









AGS bunch splitting/merging

• Emittance increase is from space charge → bunch splitting can help reduce space charge

• Peak current (space charge) at AGS injection can be reduced by splitting the bunch into 2 longitudinally in Booster before transferring to AGS

• Bunches are later merged at AGS extraction

• Requires expert tuning of many parameters, often done ‘by eye’

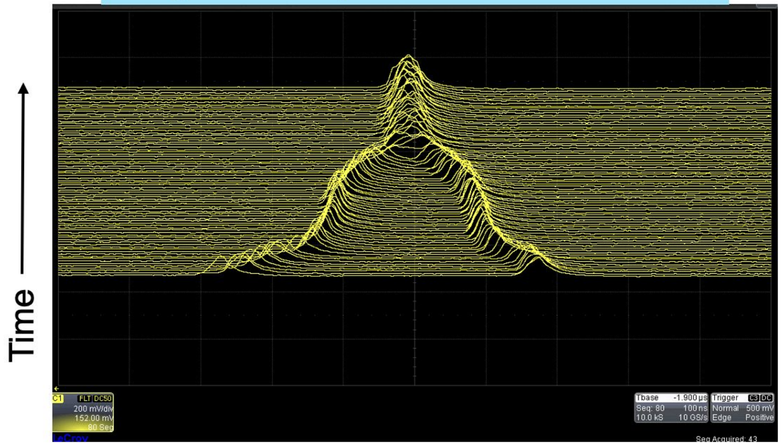
• Prone to drift over time

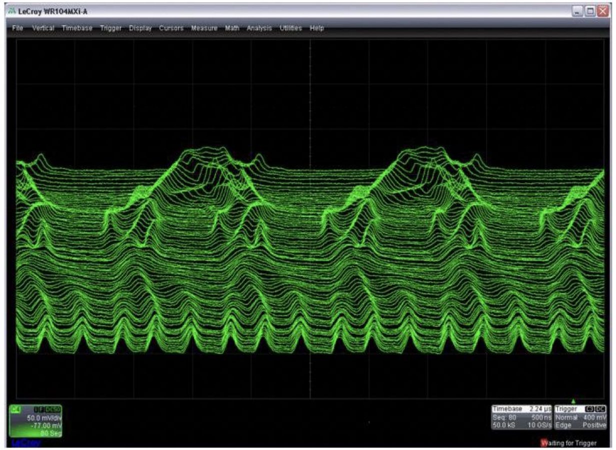
• Controls: RF voltages, phases

• Goal: minimize longitudinal emittance

• Method: Reinforcement Learning

Merge of AGS proton bunches at flattop





Real mountain range data showing 6-to-1 bunch merge in Booster

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

Bunch Merge Controls

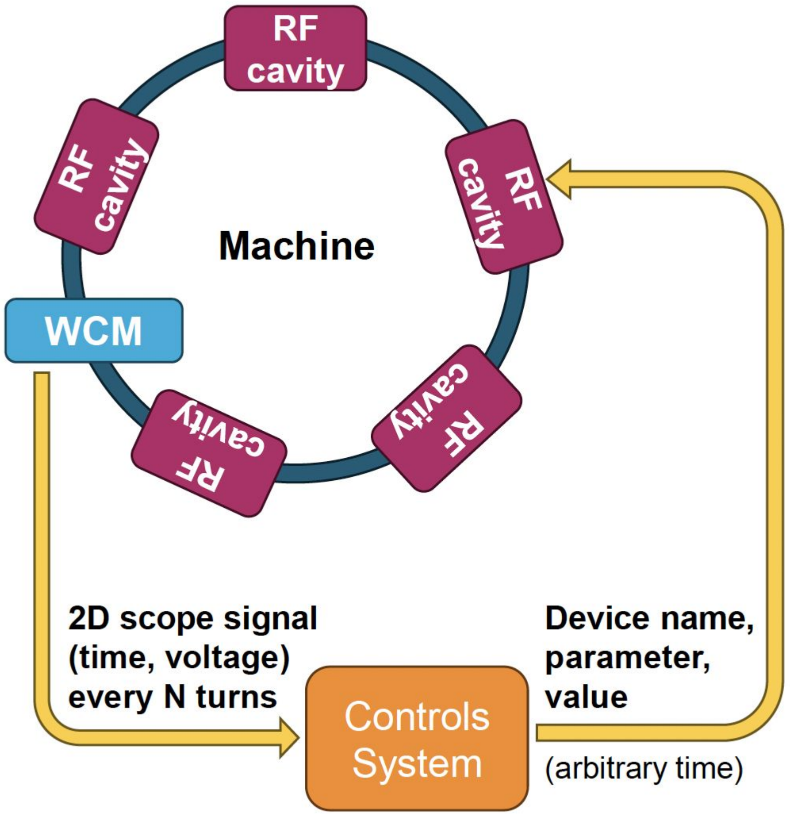
Good bunch merging essential for operations but not trivial to achieve.

- For the merge, RF gymnastics are performed via different RF harmonics—but not necessarily different physical cavities.

- Booster & AGS differ in number of physical cavities and can differ in harmonics and merge pattern. They naturally differ in energy, slip factor, and other beam/accelerator qualities.

Voltage and phase are the available knobs for a given RF harmonic.

Real machine time is limited for development: Booster and AGS part of accelerator chain with multiple programs → need a simulator



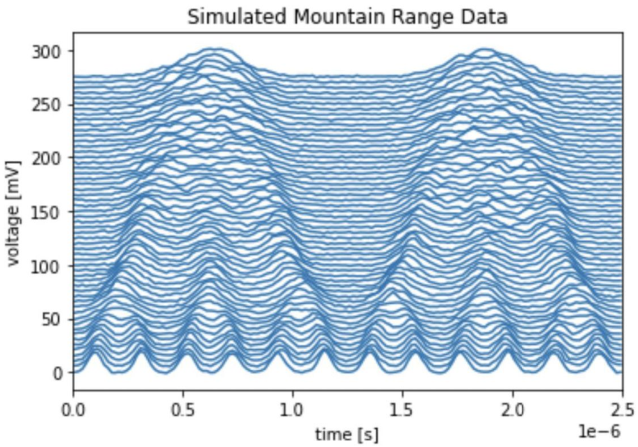
Cartoon representation of accelerator with WCM, RF cavities (arbitrary number), and input/output

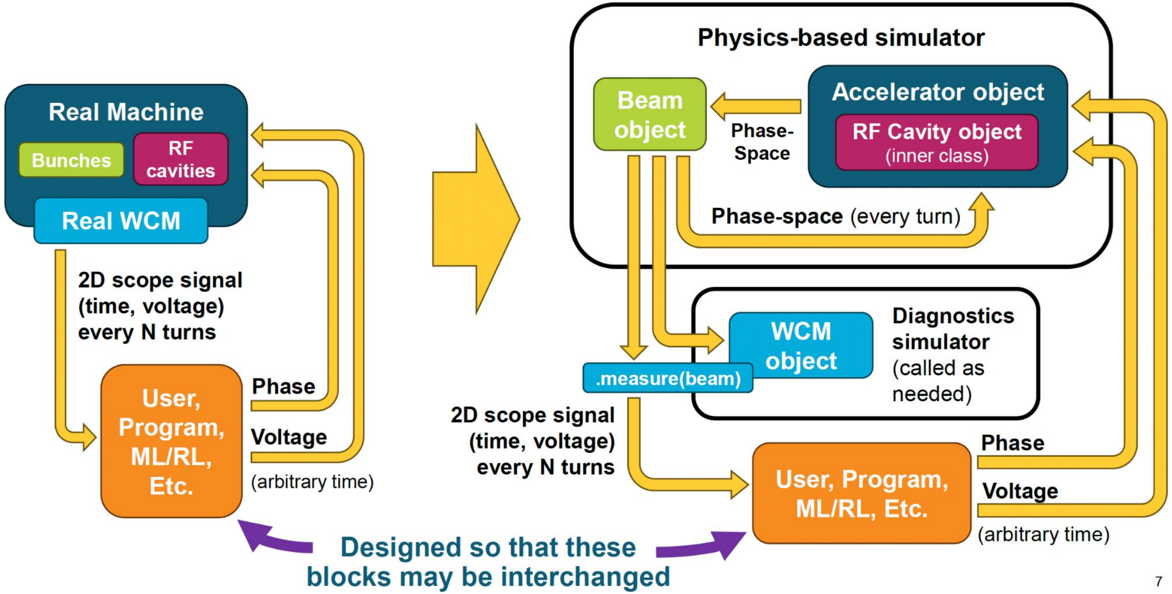
Bunch Merge Simulator

Object-Oriented Programming

Created a physics-based simulator in Python for bunch merge environment and diagnostics

Combines longitudinal phase-space mapping and phase-space projection for time signal replication





The simulator will be used for RL development for improving bunch merges

Nguyen, Linh, et al., ICALEPCS '23
10.18429/JACoW-ICALEPCS2023-FR2AO04

Bunch Merge Control

- Plan to use Reinforcement Learning (RL) to optimize the bunch merge process in AGS
  - First validate in a simulator, then test in the real system: *Bmad model provides initial training platform for the agent*

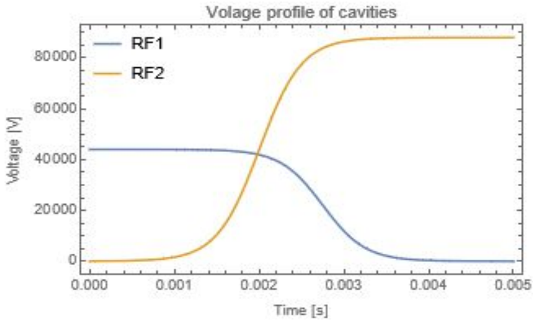
  - A few candidates being examined: TD3, SAC, PPO

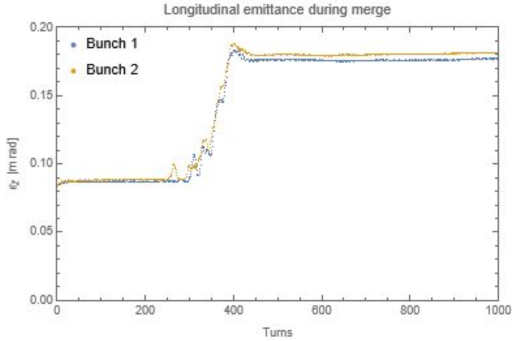
- A Bmad simulator was built based on the run 22 merge data → still in the development stage

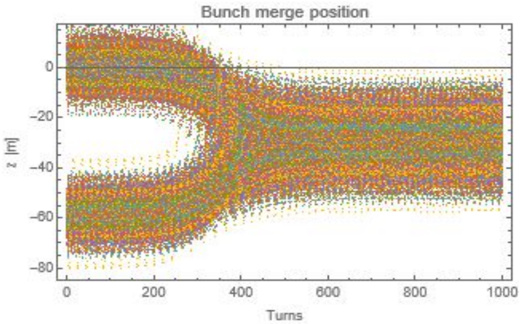
- May use Inverse Reinforcement Learning (IRL)

  - Not easy to quantify good merge results, i.e., bunch width/intensity, center oscillation, shape oscillation, etc.

  - Instead of learning the objective directly, IRL learns a reward function from expert’s demonstrations that best explain the experts’ behaviors → could be useful for bunch merge







Bunch Merge Control: Future Work

Algorithm side:

- Add more intermediate control points in Bmad simulator, work out parameter constraints
- Link components to make full simulator
- Explore RL/IRL approaches

Deployment side (FPGA):

- We have a Zynq Ultrascale FPGA evaluation board and an FMC expansion card to digitize the WCM signals: 12-bit conversion at 1,000 Megasamples per second, with an analog range of +=2.5V
- Working on basic demonstration (FPGA) code to acquire input signals
- Still at the step of talking to the digitizer card with the FPGA board
- Next steps after this is completed:
  - Work on configurable trigger logic
  - Work on buffer memory implementation (to store multiple turns)

AGS resonance compensation

• Partial snakes in the AGS keep the spin tune away from the integer (>0.96), avoiding vertical resonances

• Horizontal resonances remain, currently ‘jumped’ by moving the horizontal tune through the resonance

• Each resonance is weak (~0.1% p loss), but there are many of them (82), and measurements are slow

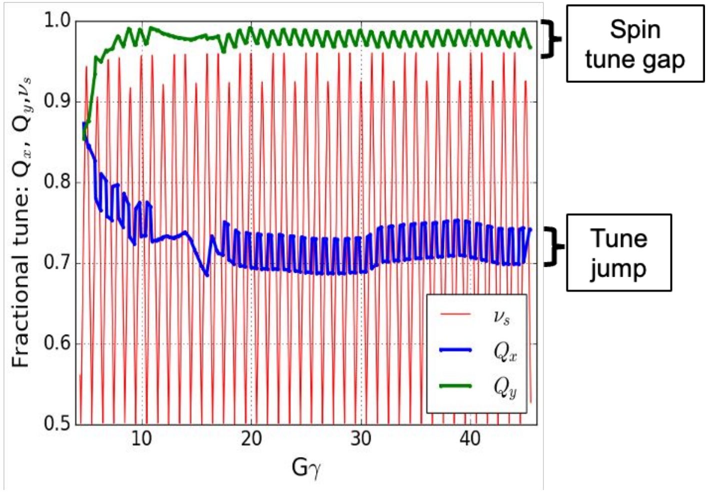
• **Proposal to use 15 pulsed skew quadrupoles to eliminate residual resonances**

• Goal: minimize resonance strengths by timed skew quads

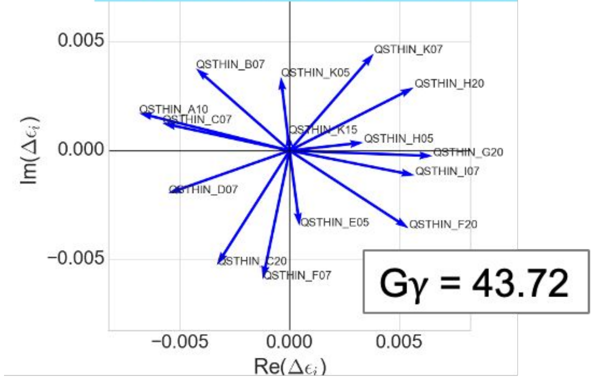
• Method: Reinforcement Learning / Bayesian Optimization

Progress: detailed Bmad model incl. differentiable snake model, symplectic tracking, orbit and optics correction, and various methods of resonance strength evaluation.

Betatron and spin tunes during AGS ramp

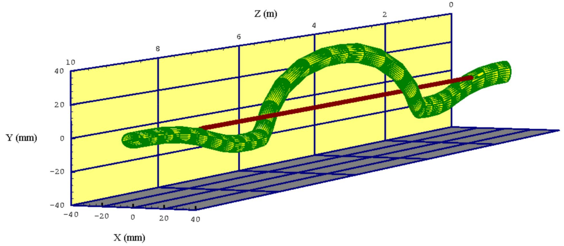


Spin resonance terms from skew quads in AGS

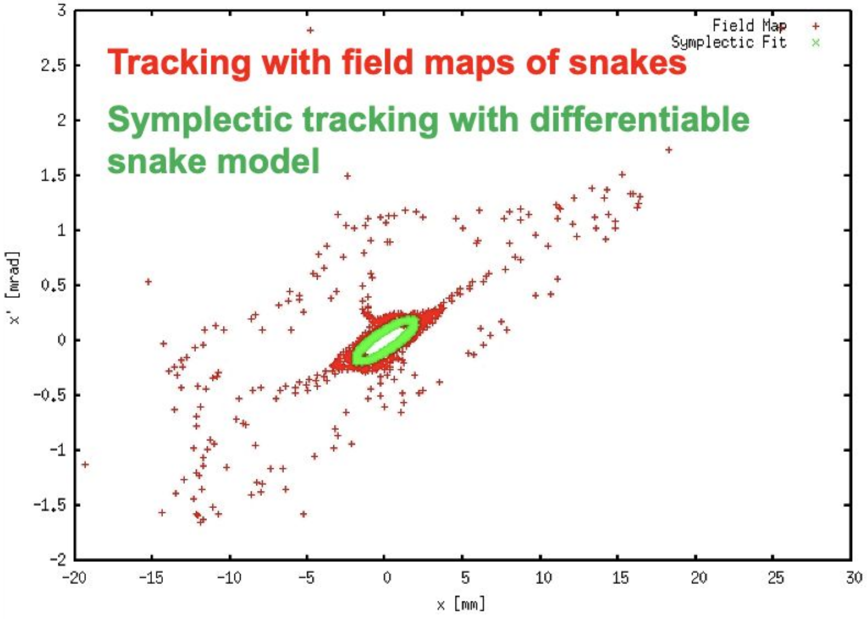


Importance of Snake Modeling

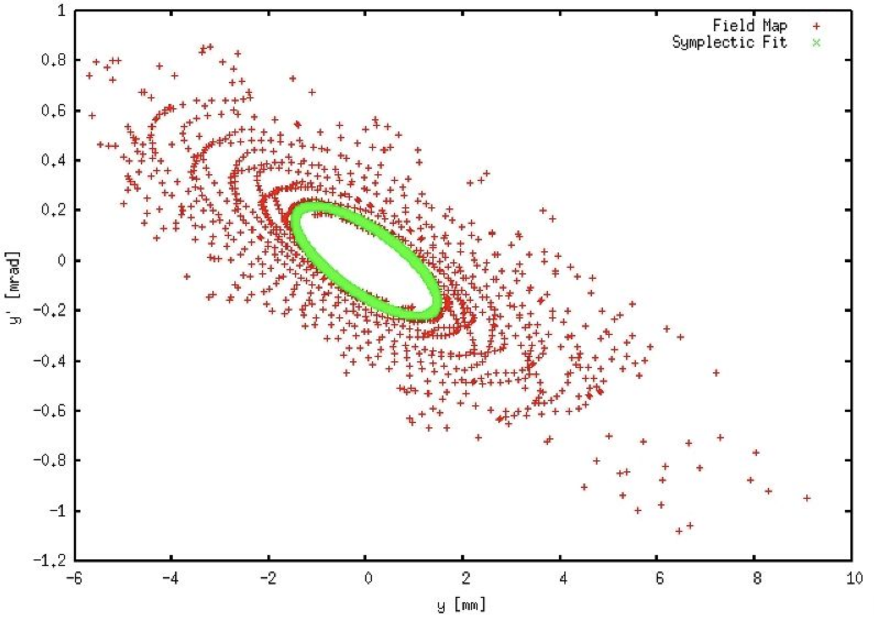
Careful modeling is essential toward understanding the system behavior



Horizontal Phase Space



Vertical Phase Space



AGS Model Calibration

Parameters to vary:

• Corrector coils (24 per Booster plane)

• Corrector coils (48 per AGS plane)

Observables to optimize:

• BPM readings (24 x&y in the Booster) (100um accuracy)

• BPM readings (72 x&y in the AGS) (100um for 2mm size at 25GeV)

Progress:

• Detailed model of AGS incl. differentiable snakes, symplectic tracking, orbit and optics compensation of snakes for all energies.

Summary and Conclusion

- **New project to improve polarization for RHIC and EIC (started Fall 2023)**
  → ***even 5% improvement would be significant***

- **Aim to do high-level optimization and control throughout the polarization chain in the injector complex**

- **Taking an integrated approach**:
  - Modeling: improve models of the Booster and AGS by combining physics simulations and data; use Bayesian approaches to help calibrate models

  - Optimization and control: use models to aid training of RL controllers, form priors for Bayesian optimization where possible

- Challenges range from use of standard ML techniques on many parts of machine (e.g. BO for injection optimization), to complicated new problems that require more R&D (e.g. RL for bunch merge)

- Much initial work on physics modeling!

- **Steadily making progress on building out tools for testing and deploying ML on target tasks!**

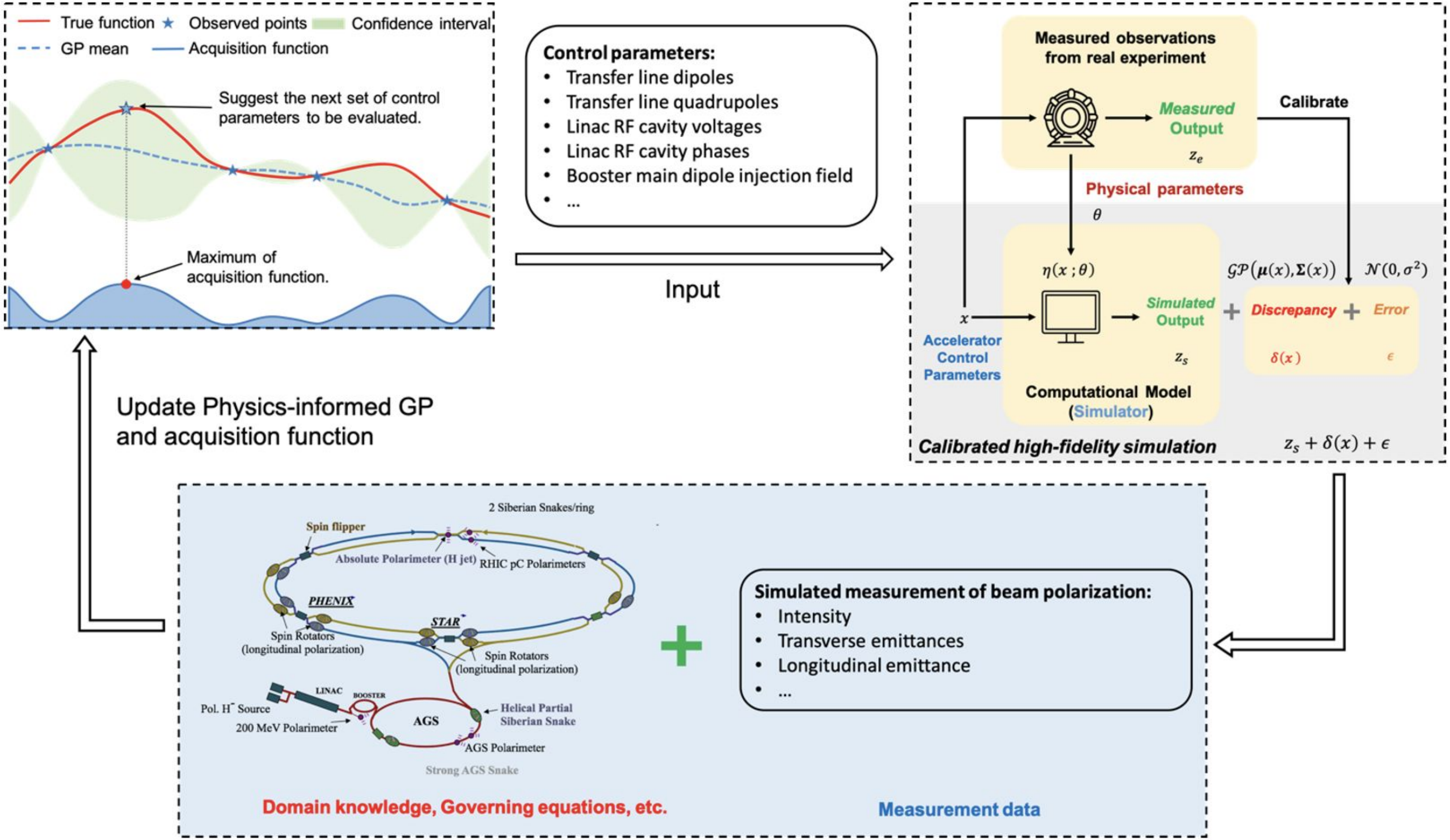
Main Project Participants

Advice and collaborations welcome!

- Kevin Brown, Yuan Gao, Levente Hajdu, Kiel Hock, Natalie Isenberg, Linh Nguyen, Vincent Schoefer, Nathan Urban, Keith Zeno
- Eiad Hamwi, Lucy Lin, Georg Hoffstaetter de Torquat, David Sagan, Jonathan Unger
- Weining Dai, Bohong Huang, Thomas Robertazzi
- Yinan Wang
- Auralee Edelen, Ryan Roussel
- Malachi Schram, Kishansingh Rajput
- Nathan Cook, Jon Edelen, Chris Hall

This funding for ML-based polarization increase comes from DOE Nuclear Physics through Manouchehr Farkhondeh

Backups

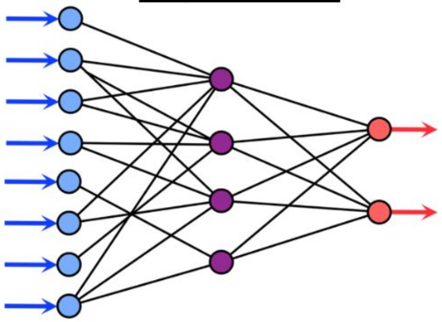


True function
Observed points
Confidence interval
GP mean
Acquisition function
Suggest the next set of control parameters to be evaluated.
Maximum of acquisition function.
Control parameters:
• Transfer line dipoles
• Transfer line quadrupoles
• Linac RF cavity voltages
• Linac RF cavity phases
• Booster main dipole injection field
• ...
Input
Measured observations from real experiment
Measured Output
z_e
Calibrate
Physical parameters
θ
$\eta(x\,;\theta)$
$\mathcal{GP}(\boldsymbol{\mu}(x), \boldsymbol{\Sigma}(x))$
$\mathcal{N}(0, \sigma^2)$
x
Simulated Output
Discrepancy
Error
Accelerator Control Parameters
z_s
$\delta(x)$
ϵ
Computational Model (Simulator)
Calibrated high-fidelity simulation
$z_s + \delta(x) + \epsilon$
Update Physics-informed GP and acquisition function
2 Siberian Snakes/ring
Spin flipper
Absolute Polarimeter (H jet)
RHIC pC Polarimeters
PHENIX
STAR
Spin Rotators (longitudinal polarization)
Spin Rotators (longitudinal polarization)
LINAC
BOOSTER
Pol. H$^-$ Source
200 MeV Polarimeter
AGS
Helical Partial Siberian Snake
AGS Polarimeter
Strong AGS Snake
Simulated measurement of beam polarization:
• Intensity
• Transverse emittances
• Longitudinal emittance
• ...
Domain knowledge, Governing equations, etc.
Measurement data

Future: Digital twin and Optimal control

Control parameters + Environmental factors

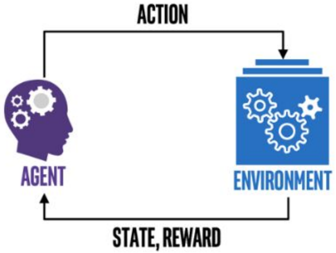
Digital Twin

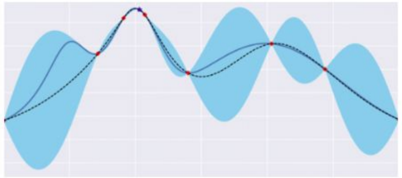


Evaluation / Analytic Metric (e.g., agreement with real measurements)

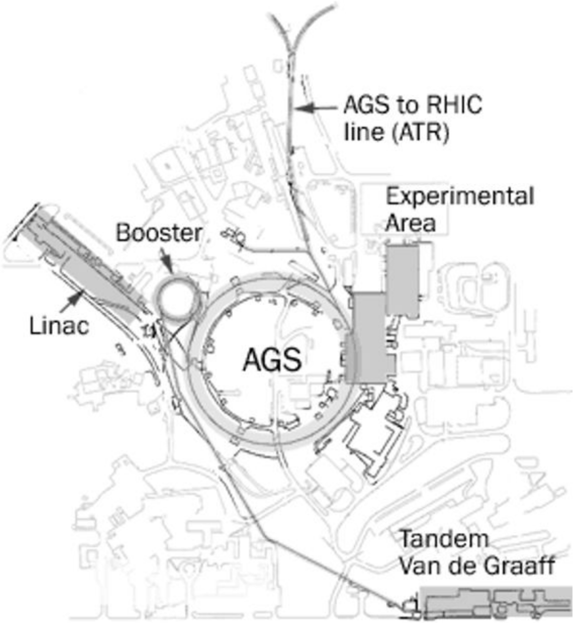
Find best settings for desired machine state

AI/ML Methods (RL, BO, etc.)



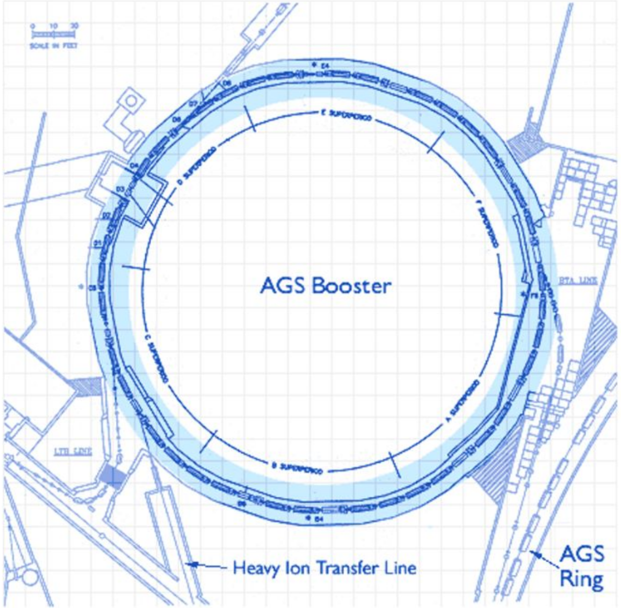


Alternating Gradient Synchrotron (AGS)



- Alternating gradient / strong focusing principle: achieve strong vertical and horizontal focusing of charged particle beam at the same time
- Accelerates proton to 33 GeV in 1960
- 12 super-periods (A to L), 240 main magnets, 810 m circumference
- Now serves as injector for Relativistic Heavy Ion Collider (RHIC)

Alternating Gradient Synchrotron (AGS) Booster



- Pre-accelerate particles entering the AGS ring
- Accepts heavy ions from EBIS or protons from 200 MeV Linac
- Serves as heavy ion source for NASA Space Radiation Laboratory (NSRL)
- 6 super-periods (A to F), 72 main magnets

RL technique: Soft Actor-Critic (SAC)

- An entropy-based Reinforcement Learning (RL) aims to not only maximize total rewards, also to maximize the entropy of the policy

$$J(\pi) = \sum_{t=0}^{T} \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t) \sim \rho_\pi} \left[r(\mathbf{s}_t, \mathbf{a}_t) + \alpha \mathcal{H}\big(\pi(\cdot\,|\mathbf{s}_t)\big) \right]$$

Final objective is weighted between a reward term r and an entropy term H by α

- SAC makes use of three networks: a state value function V parameterized by ψ, a soft Q-function Q parameterized by θ, and a policy function π parameterized by ϕ

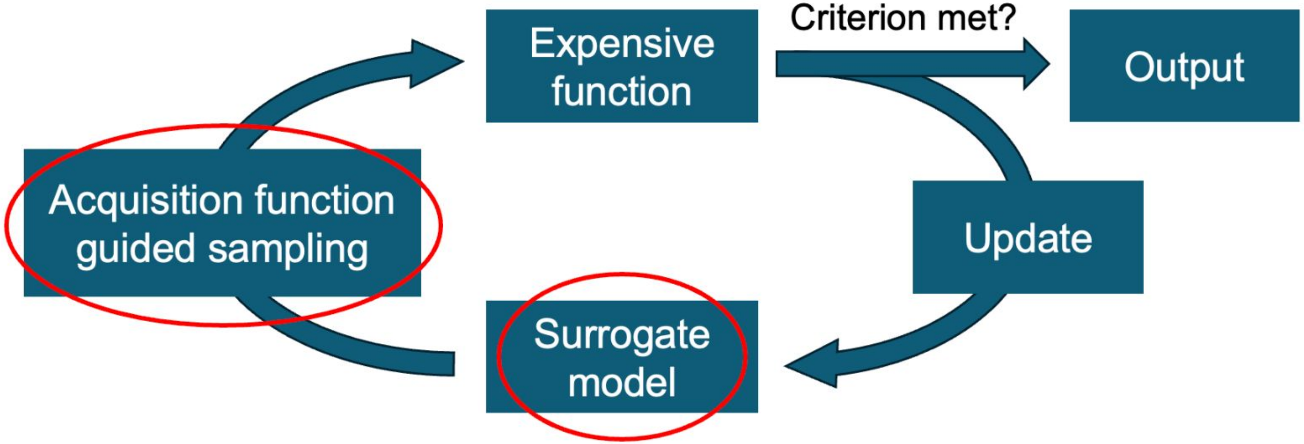
- We can apply SAC to automatically tune RF phases and voltages so that a balanced beam profile can be achieved after bunch merge

ML Method: Bayesian Optimization

- A powerful tool for finding the extrema of objective functions that are expensive to evaluate
- Bayes' theorem: probability of event based on previous knowledge of conditions

$$P(f|\mathcal{D}_{1:t}) \propto \boxed{P(\mathcal{D}_{1:t}|f)} P(f)$$

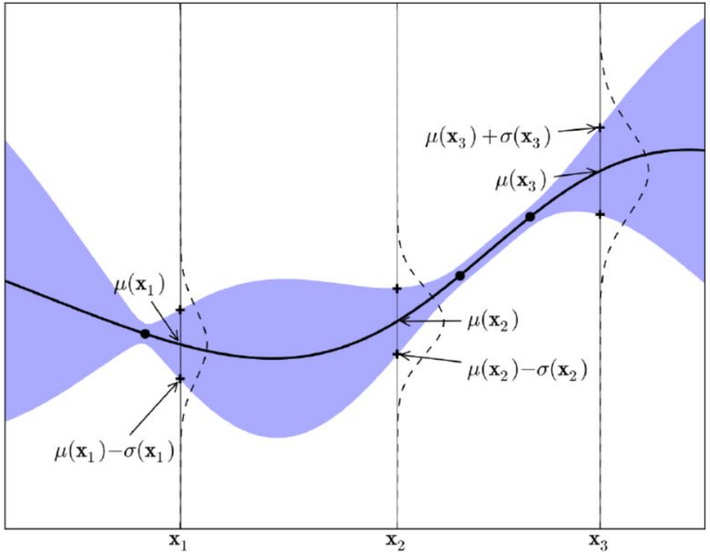
Tune hyperparameters of f to maximize likelihood of getting data $D_{1:t}$



BO technique: Gaussian Process

- A probability distribution over possible functions that fit a set of points
- Mean function + Covariance function

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$$



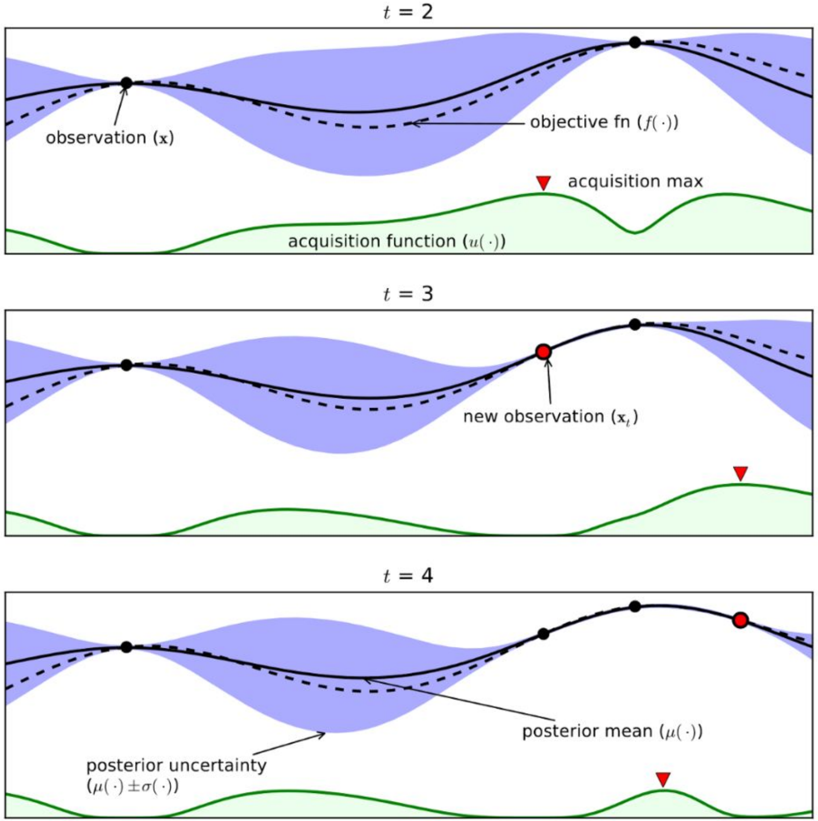
- Kernel: covariance function $k(x_i, x_j)$ of the input variables
- Covariance matrix $\mathrm{K} = k(X, X) = \begin{bmatrix} k(x_1, x_1) & \cdots & k(x_1, x_t) \\ \vdots & \ddots & \vdots \\ k(x_t, x_1) & \cdots & k(x_t, x_t) \end{bmatrix}$
- At a sample point x_i, Gaussian process returns mean $\mu(x_i|X) = m(x_i) + k(x_i, X)K^{-1}\big(f(X) - m(X)\big)$ and variance $\sigma^2(x_i|X) = k(x_i, x_i) - k(x_i, X)K^{-1}k(X, x_i)$

BO technique: Acquisition Function

- Guide how input space should be explored during optimization

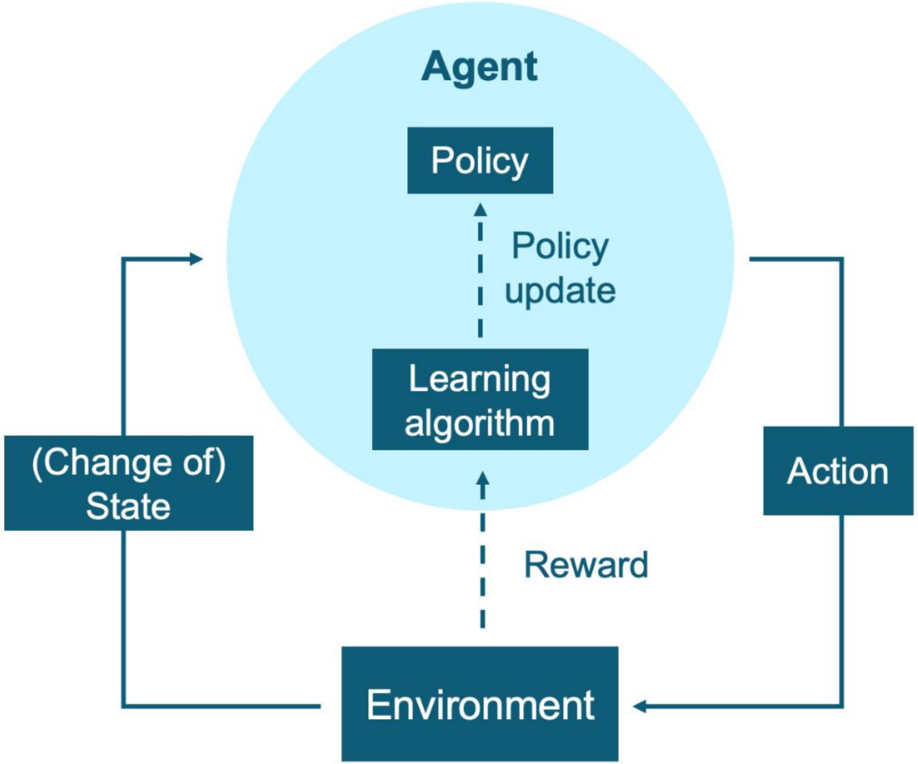
- Combine predicted mean and variance from Gaussian Process model
  - Probability Improvement (PI)
  - Expected Improvement (EI)
  - **Upper Confidence Bound (UCB)**

$$\mathbf{UCB}(\boldsymbol{x}) = \boldsymbol{\mu}(\boldsymbol{x}) + \boldsymbol{\kappa\sigma}(\boldsymbol{x})$$



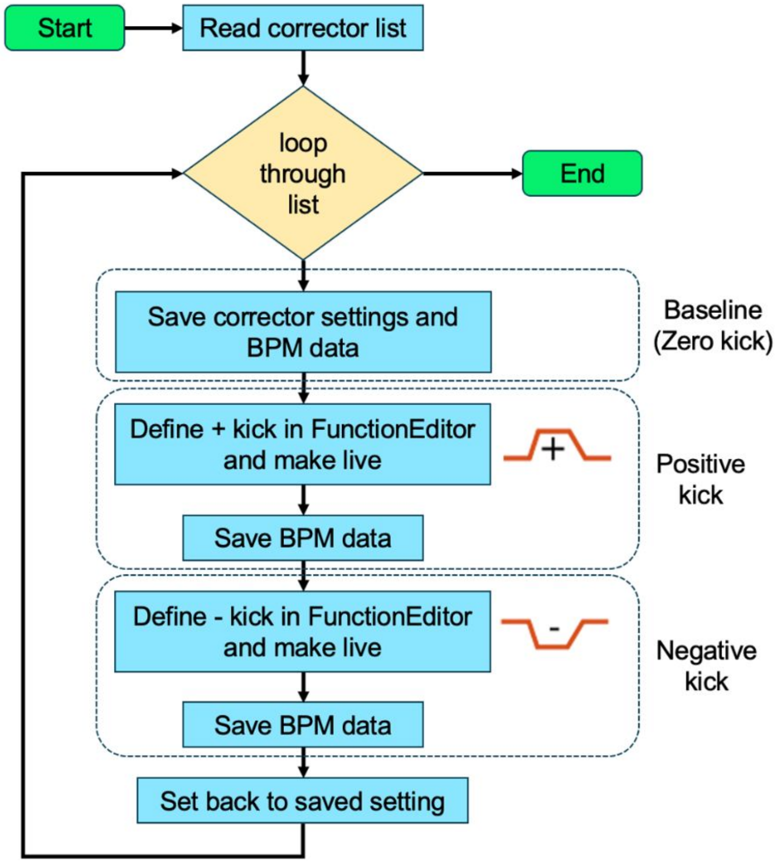
ML Method: Reinforcement Learning

- Learn optimal behavior in an environment to obtain maximum reward (e.g., highest polarization)
- Agent: controller, determine sampling policy
  - Action A: change control values
- Environment: controlled system
  - State S: representation of environment
  - Reward R: numerical evaluation of action
- Sequence of experience and agent forms trajectory $(S_0, A_0, R_0), (S_1, A_1, R_1), \cdots$



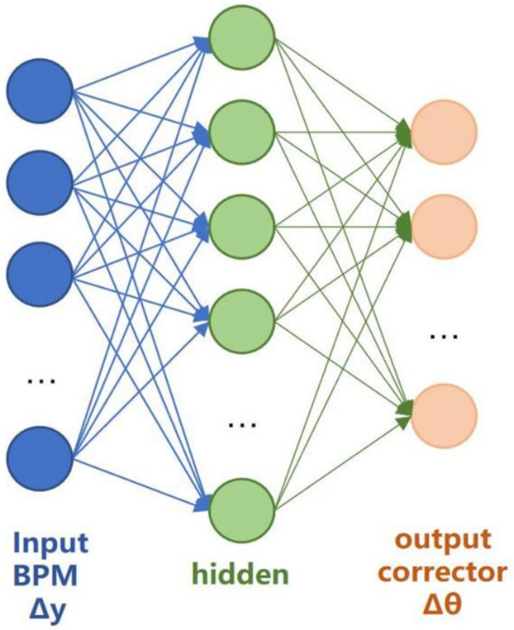
Script to get Booster orbit responses

- Script development with Collider Accelerator Department (CAD) Controls Group
- FunctionEditor: send trapezoid-like time-dependent function to corrector power supplies
- Script sets three corrector settings: positive, zero, negative; and save corresponding orbits



Orbit Correction at the AGS

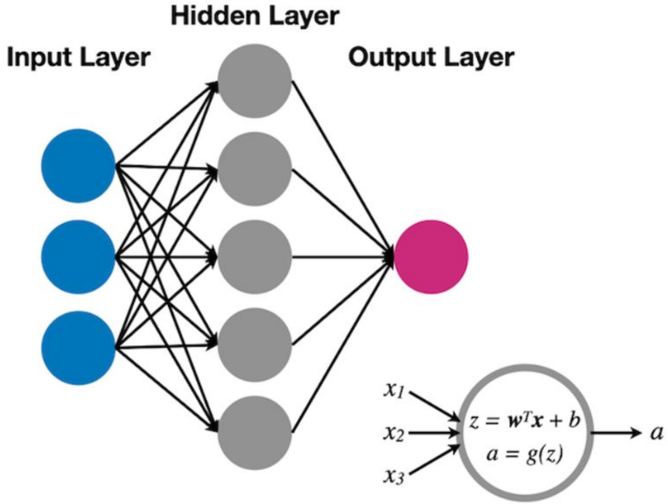
$$\begin{pmatrix} \Delta\vec{x} \\ \Delta\vec{y} \end{pmatrix} = \underline{R} \begin{pmatrix} \Delta\vec{\theta}_x \\ \Delta\vec{\theta}_y \end{pmatrix}$$

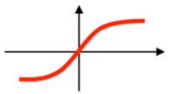


- Traditional orbit correction
  - obtain mapping $\underline{R}$ (orbit response matrix) from corrector settings $\vec{\theta}$ to orbit measurements $\vec{y}$
  - inverse mapping to get corrector settings $\Delta\vec{\theta}$ needed to cancel orbit deviations $\Delta\vec{y}$
- Orbit correction with NN
  - train directly to get inverse mapping, no need for extra calculation
  - easily update with new data and stay accurate

ML method: Neural Network (NN)

- Establish mapping between a given set of inputs $\vec{X}$ and corresponding outputs $\vec{Y}$
- Fully connected layers: output = activation(dot(input, weight) + bias)
- Activation function: Hyperbolic Tangent (Tanh) and Rectified Linear Unit (ReLU)
- Feed forward neural network (FFNN): most common, no feedback route

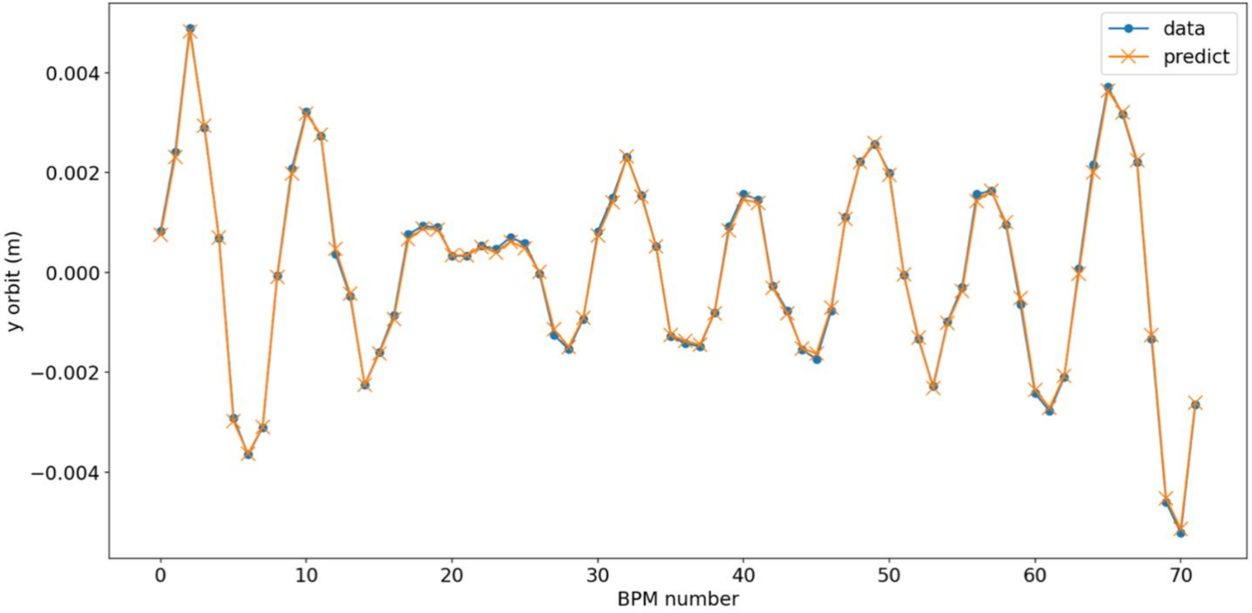


Hyperbolic tangent	$\phi(z) = \dfrac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = max(0, z)$	Multi-layer Neural Networks	

AGS ORM NN model: training results

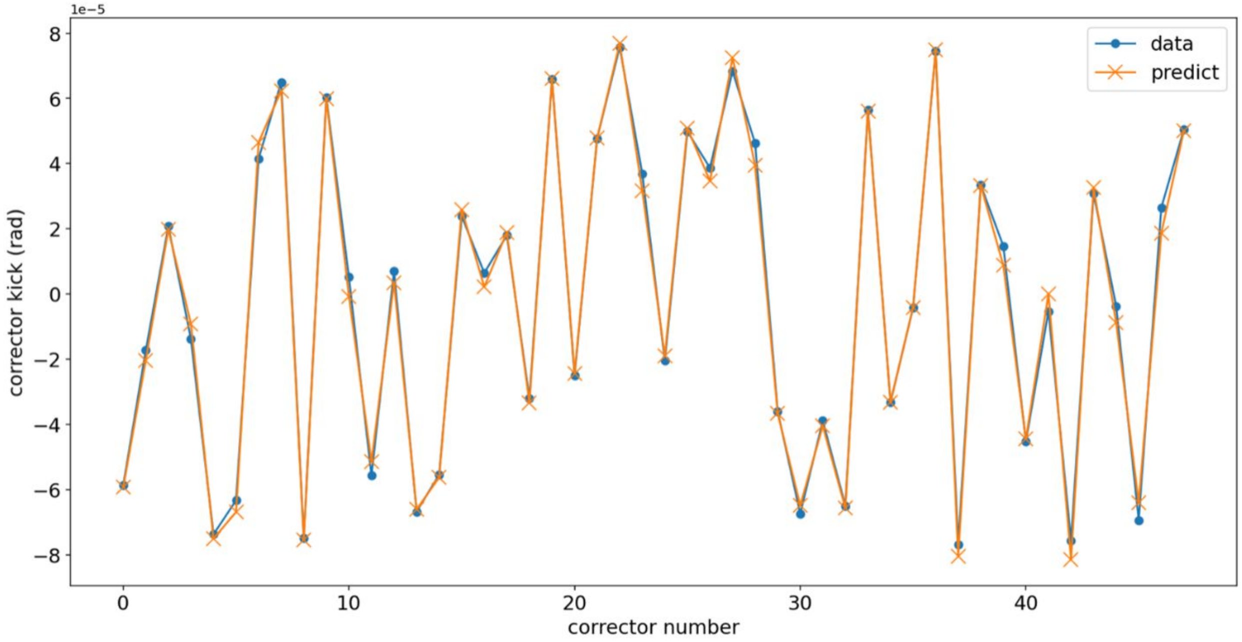
- Input 48 vertical corrector kick → Output 72 y orbit measured at BPM
- Trained on 800 data pairs, tested on 200 data pairs: R^2 score = 0.998

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \overline{y}_i)^2}$$



Inverse AGS ORM NN model: training results

- Input 72 y orbit measured at BPM → Output 48 vertical corrector kick
- Trained on 800 data pairs, tested on 200 data pairs: R^2 score = 0.993



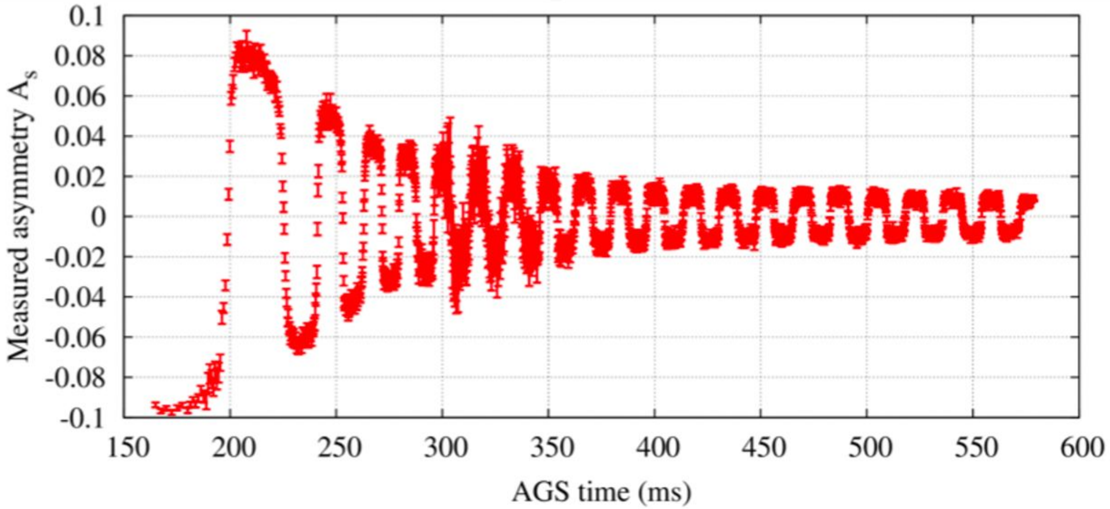
Future project: Timing of tune jumps

The G-gamma meter and accurate energy vs. time

(1) Measure the energy by orbit + revolution frequency measurement

(2) Measure of energy by field + revolution frequency measurement

(3) Measure energy by spin flip at every integer spin tune



Combined optimization

➔ better timing

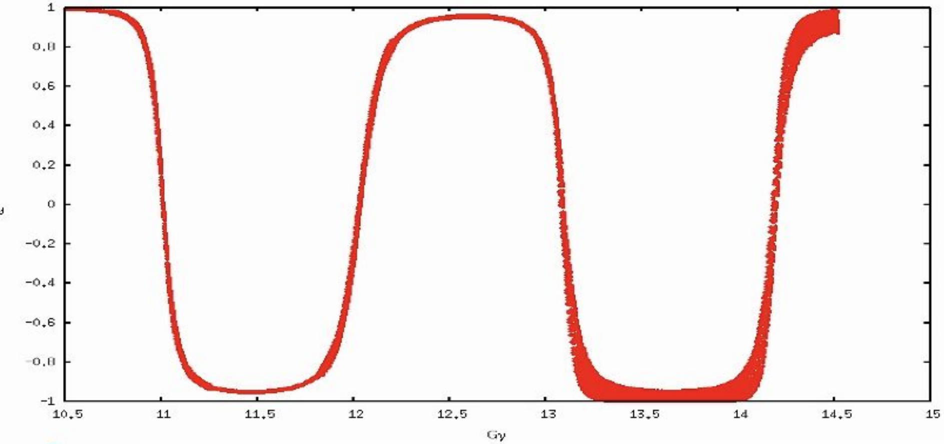
➔ higher polarization

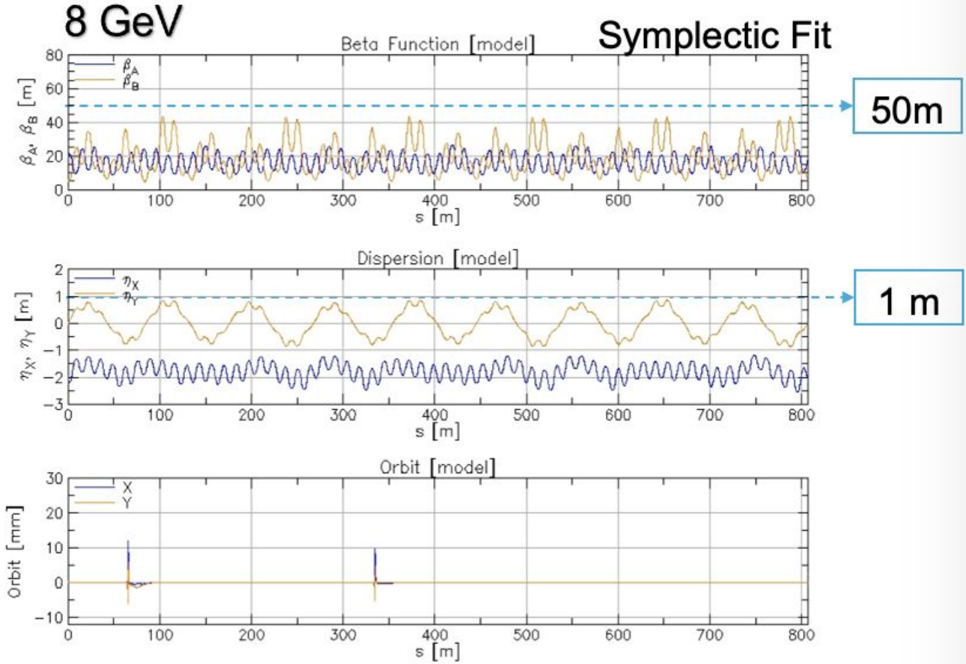
For ongoing project (g): Need of optics correction

In the following, we track through a few resonances with realistic transverse emittance before transition energy (at Gγ~15).

The transverse emittance blows up due to vertical dispersion and optics errors after Gγ~13, decreasing polarization.

In response to yesterday's question, no problem has yet been observed at 1/3 spin tune.

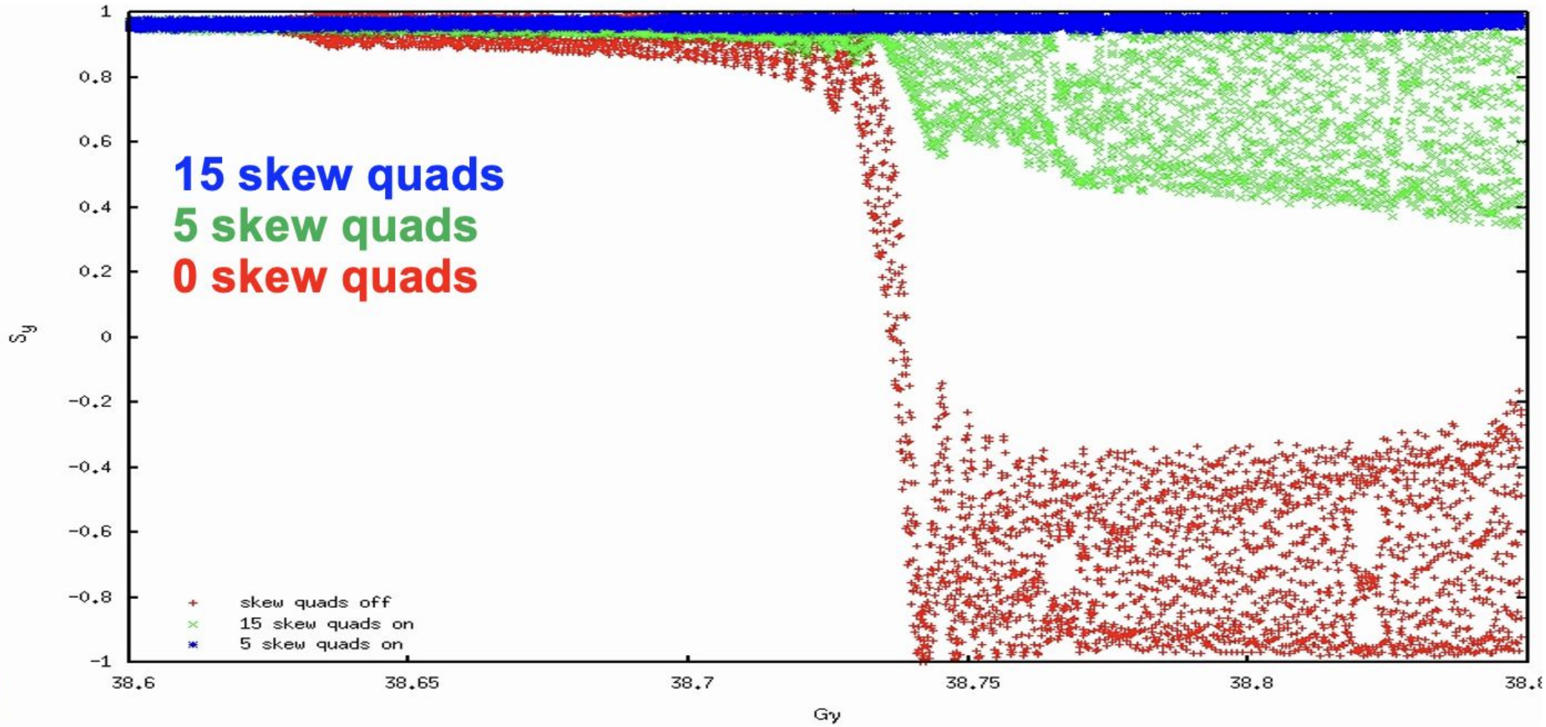




Brookhaven National Laboratory

For ongoing project (g): AGS polarization tracking

Tracking through a single horizontal spin resonance with very large emittance to visualize depolarization. *This is not the real case since each resonance is much weaker and causes less than 0.1% depolarization*:



I used a series expansion of solutions to Maxwell's equations such that each term is an exact solution.

This allows me to truncate the expansion at any order and still precisely satisfy Maxwell's equations.

The following is an example of 1 term in such a series solution:

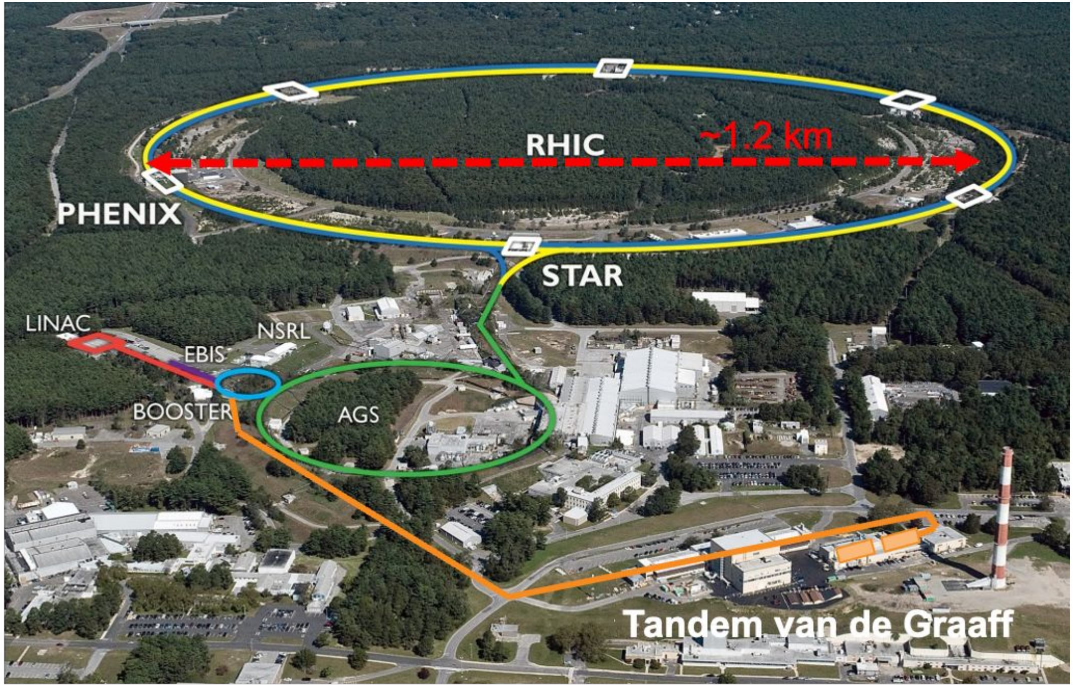
$$
\begin{aligned}
B_x &= \quad A \qquad \cosh(k_x(x+x_0))\cos(k_y(y+y_0))\cos(k_z z+\phi_z) \\
B_y &= -A\,\frac{k_y}{k_x}\sinh(k_x(x+x_0))\sin(k_y(y+y_0))\cos(k_z z+\phi_z) \\
B_s &= -A\,\frac{k_z}{k_x}\sinh(k_x(x+x_0))\cos(k_y(y+y_0))\sin(k_z z+\phi_z)
\end{aligned}
$$

By fitting the field data to 300 such terms, I recover an expression that exactly solves Maxwell's equations (i.e. satisfies symplecticity for any particle trajectory) and agrees with the simulated data with an RMS deviation of 0.02 T in the relevant region. Max field is 2T.

With a differentiable model, TPSA (DA) techniques become available, e.g. normal forms

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



Heavy Ions	Protons
E-beam Ion Source (EBIS)	OPPIS (polarized)
Tandem Van de Graaff	High-intensity H^- (unpolarized)

Measurements

- ORM will give us
  - BPM and Corrector Anomalies (Trust Analysis)
  - Gradient errors for given conditions
  - Beta-deviations from model
- Dispersion measurements give us
  - BPM Consistency check for given dp/p (BPM Anomalies)
  - Coupling through longitudinal motion (very slow, typically)
- Tune measurements
  - Betatron tune and coupling = destructive measurement in Booster/AGS
  - Tune, Chrom, coupling, emittance, dp/p from RHIC Schottky
- Chromaticity measurements – need to change energy and measure tune
- Orbit Measurements – parasitic = most are time averaged, some turn by turn
- Linear model + small nonlinearities with NN model