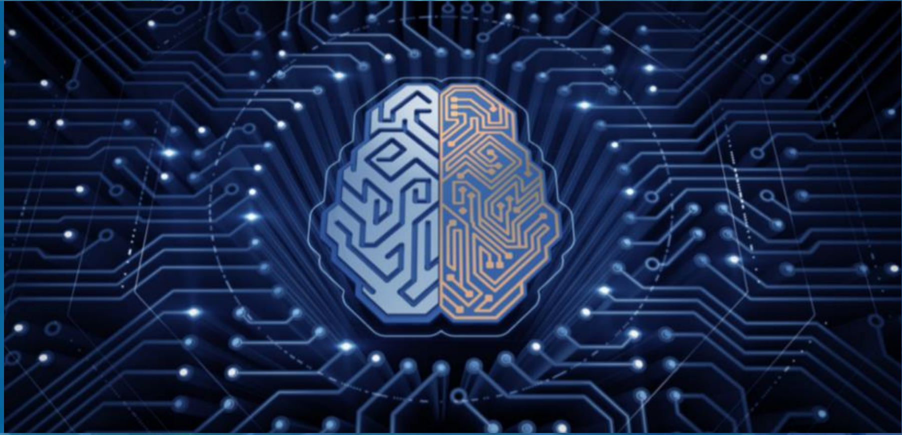
2024 DOE/NP ARTIFICIAL INTELLIGENCE/MACHINE LEARNING
PRINCIPAL INVESTIGATOR EXCHANGE MEETING
GAITHERSBURG, MD, DECEMBER 4-5, 2024

USE OF AI-ML TO OPTIMIZE ACCELERATOR OPERATIONS & IMPROVE MACHINE PERFORMANCE



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OTHER CONTRIBUTORS
Calem Hoffman, Physicist
Adwaith Ravichandran, Postdoc
Sergio Lopez-Caceres, Postdoc

OUTLINE

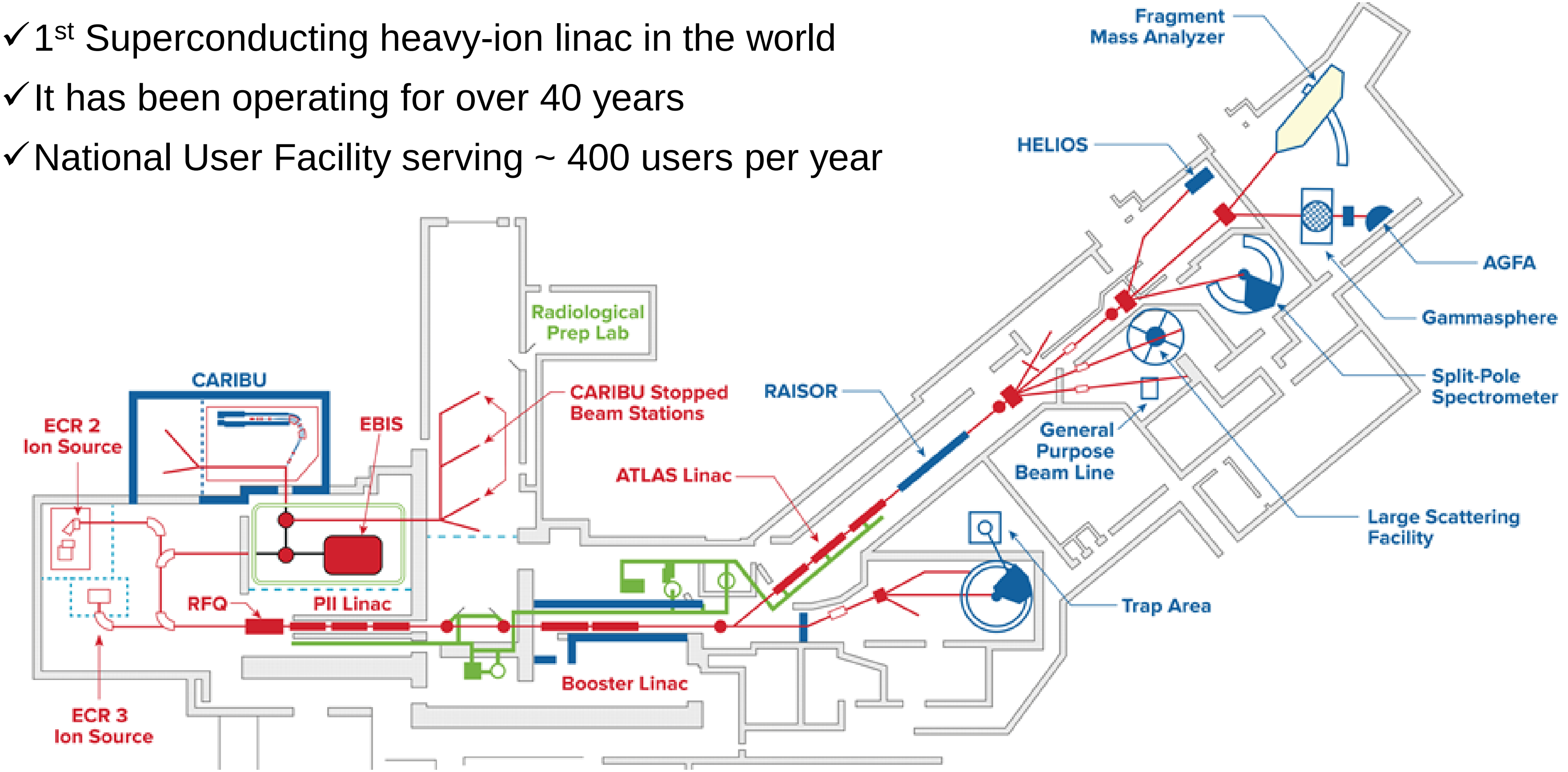
- ❑Completion of the Original ATLAS AI-ML Project
- ❑Accomplishments & Main Conclusions
- ❑The New AI-ML Project – Overview & Objectives
- ❑Development and Testing of AI-ML User Interface(s)
- ❑Recent Progress & Highlights – ATLAS & CARIBU

ATLAS: ARGONNE TANDEM LINEAR ACCELERATOR SYSTEM

✓1st Superconducting heavy-ion linac in the world

✓It has been operating for over 40 years

✓National User Facility serving ~ 400 users per year



ATLAS BY THE NUMBERS

In FY24, served 400+ unique users

300+ unique users in a typical year

60% from U.S. national labs and universities

40% from international labs and universities

25% of users are students

USERS FROM

15+ states

15+ countries

The ATLAS accelerator at Argonne National Laboratory is a DOE/SC/NP national user facility that supports forefront nuclear physics research, national security applications, and studies of the origin of chemical elements.

6,000+ hours of beam time delivered annually

40% of requested beamtime approved as high priority

1–2 calls for proposals per year

30 scientific and user support staff

AVAILABLE PARTICLE BEAMS

250 heavy ion beams provided by ATLAS

- **2,500** heavy ion beams added through the N=126 Factory
- **500** heavy ion beams added through CARIBU and nuCARIBU
- **130** heavy ion beams added through RAISOR

Our heavy ion acceleration capability is **10–20%** the speed of light*

*Speed depends on the ion used.

https://www.anl.gov/atlas

OVERVIEW OF ORIGINAL ATLAS AI-ML PROJECT

Use of artificial intelligence to optimize accelerator operations and improve machine performance

- ❑ At ATLAS, we switch ion beam species every 3-4 days … → Using AI could streamline beam tuning & help improve machine performance
- ❑ Project objectives and approach:
  - **Data collection, organization and classification, towards a fully automated and electronic data collection for both machine and beam data**
  - **Online tuning model to optimize operations and shorten beam tuning time in order to make more beam time available for the experimental program**
  - **Virtual model to enhance understanding of machine behavior to improve performance and optimize particular/new operating modes**

ACCOMPLISHMENTS VS. ORIGINAL OBJECTIVES

- **Data collection, organization and classification, towards a fully automated and electronic data collection for both machine and beam data**… established

- **Online tuning model to optimize operations and shorten beam tuning time in order to make more beam time available for the experimental program**… achieved for short beam lines, commissioning of a new beamline

- **Virtual model to enhance understanding of machine behavior to improve performance and optimize particular/new operating modes** … good progress, a long-term goal…

MAIN CONCLUSIONS FROM ORIGINAL PROJECT

- Developed and used Bayesian Optimization (BO) for multiple beamlines. BO is very effective for beam tuning even with no prior data.
- BO typically converges in 50 iterations or less for a few parameter problem (< 10). With every iteration taking ~15 s, that’s 10-15 min, this is comparable to operators’ time.
- Used BO to support the commissioning of a new beamline (AMIS), it was more competitive and helpful in this task (new to operators). Also, for multi-objective optimization MOBO, it’s not an easy task for the operators.
- Demonstrated transfer learning: We were able to save a BO model from one beam and used it as starting point (prior knowledge) to tune another beam leading to faster accelerated convergence.
- Transfer from a simulation model was not as successful due to discrepancy between the model and the actual machine. We need a more realistic simulation or surrogate model.
- Developed and used Reinforcement Learning (RL) for the AMIS line with different parameter combinations. RL requires a lot of prior data and training, which is very expensive to perform online.
- We were able to train RL models with 3, 5 & 7 parameters in ~1000 iterations which took ~ 4 hours each. Once trained, an RL model converges in 2-3 iterations, less than 1 min!
- We made good progress on the virtual machine model based on TRACK simulations. Once ready, it will be very helpful to train BO & RL models offline, then apply them directly to the machine with no or minimal further online training…

THE NEW ATLAS AI-ML PROJECT (2023 FOA)

THE NEW CONSOLIDATED PROJECT (2023 FOA) – THREE SUBPROJECTS

- Stable beams in ATLAS – Brahim Mustapha
- Inflight radioactive beams from RAISOR – Calem Hoffman
- Radioactive beams from CARIBU – Daniel Santiago

- Consolidation: close collaboration, exchange of ideas, codes and effort…
- Two new postdocs joined the ATLAS and CARIBU projects
  - Adwaith Ravichandran, started in December'23
  - Sergio Lopez-Caceres, started in June'24

ATLAS NEW PROJECT: DEPLOYMENT…

Same project title: Use of artificial intelligence to optimize accelerator operations and improve machine performance

- The main objectives of the phase II project are:
  - Deploy the autonomous beam tuning tools developed during our previous project, evaluate their impact on both automating the tuning process and saving on tuning time.
  - Develop tools for new operating modes such as multi-user operation of the ATLAS linac and high-intensity beams, as well as developing virtual diagnostics to supplement existing ones.

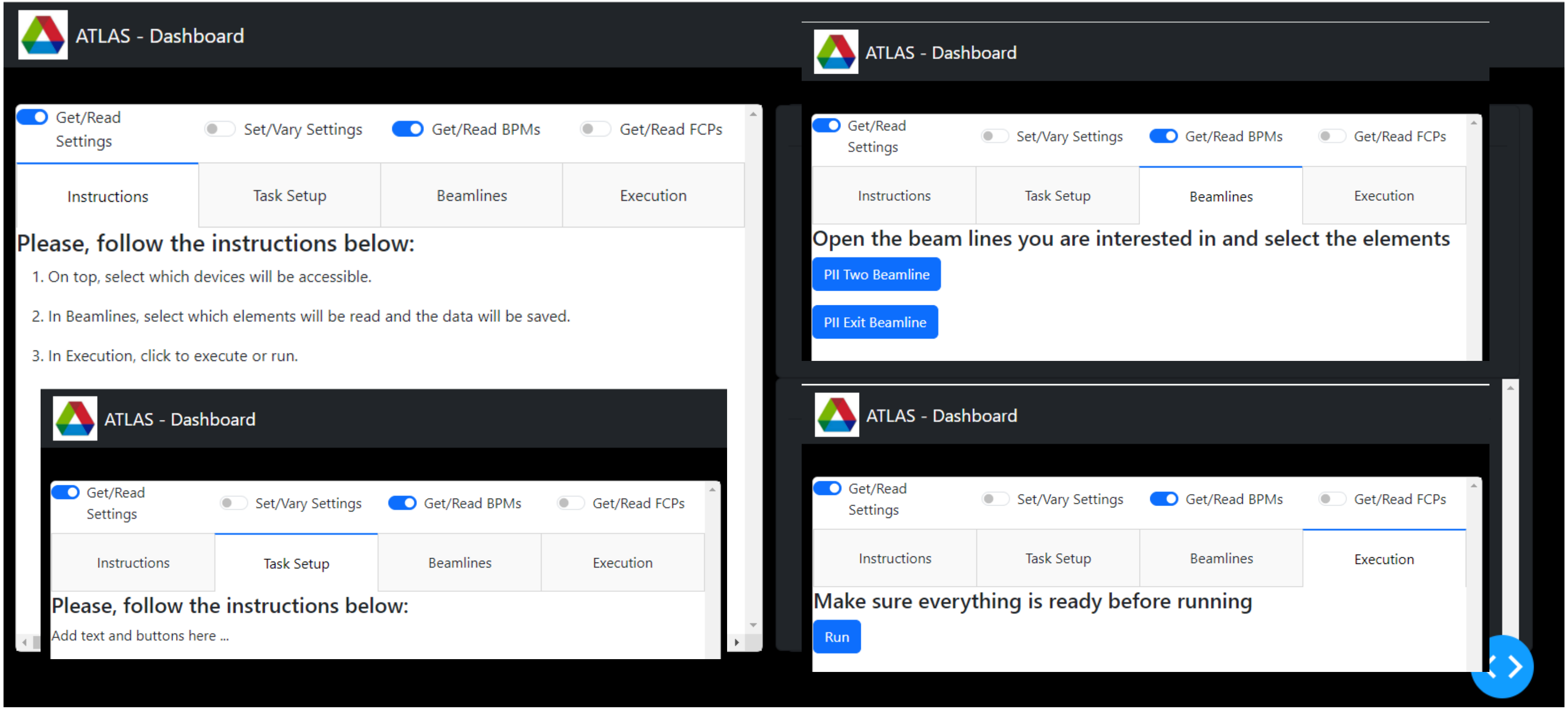
PROGRESS - MOST RECENT DEVELOPMENTS…

- ❑ Development of an AI-ML Graphics User Interface – ATLAS Dashboard
  - Offline tests using simulation model – successful
  - Online tests at ATLAS – not yet successful, but promising
- ❑ Adapted the existing AI-ML GUI, Badger from SLAC, for use at ATLAS
  - Well supported and offers more options / optimization algorithms
  - Not as friendly or customized as the ATLAS Dashboard GUI
- ❑ Tuning the beam to an end target station
  - Issues with tuning intermediate sections using only beam transmission
- ❑ Re-tuning the beamline after an energy change
  - A time-consuming process when done manually

DEVELOPMENT & TESTING OF AI-ML USER INTERFACE(S)

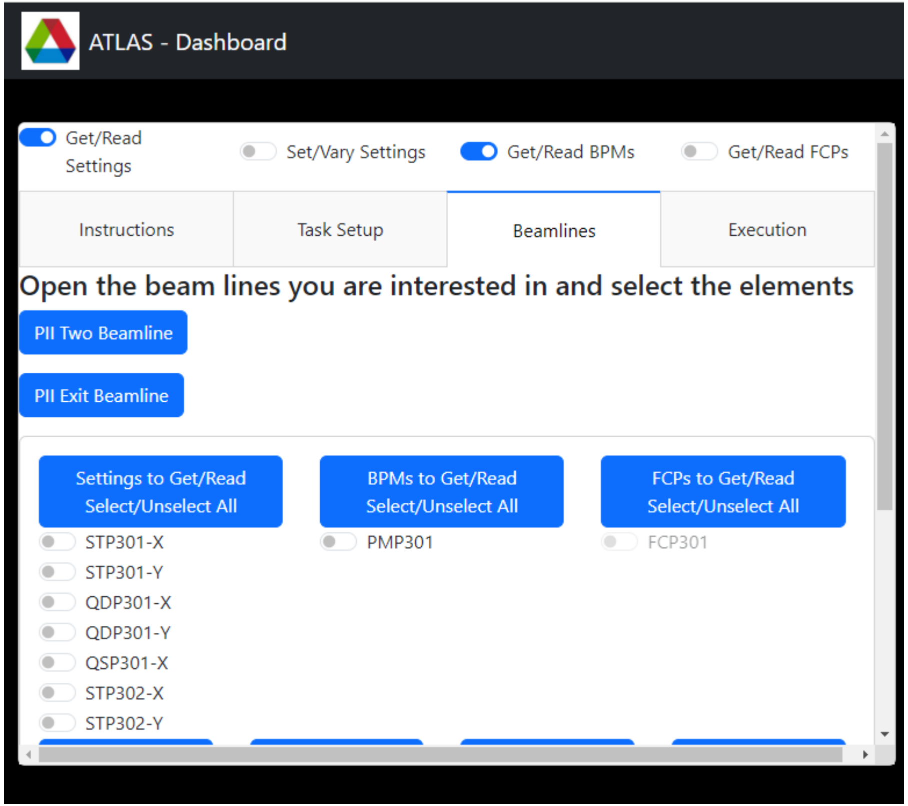
NEW ATLAS DASHBOARD INTERFACE

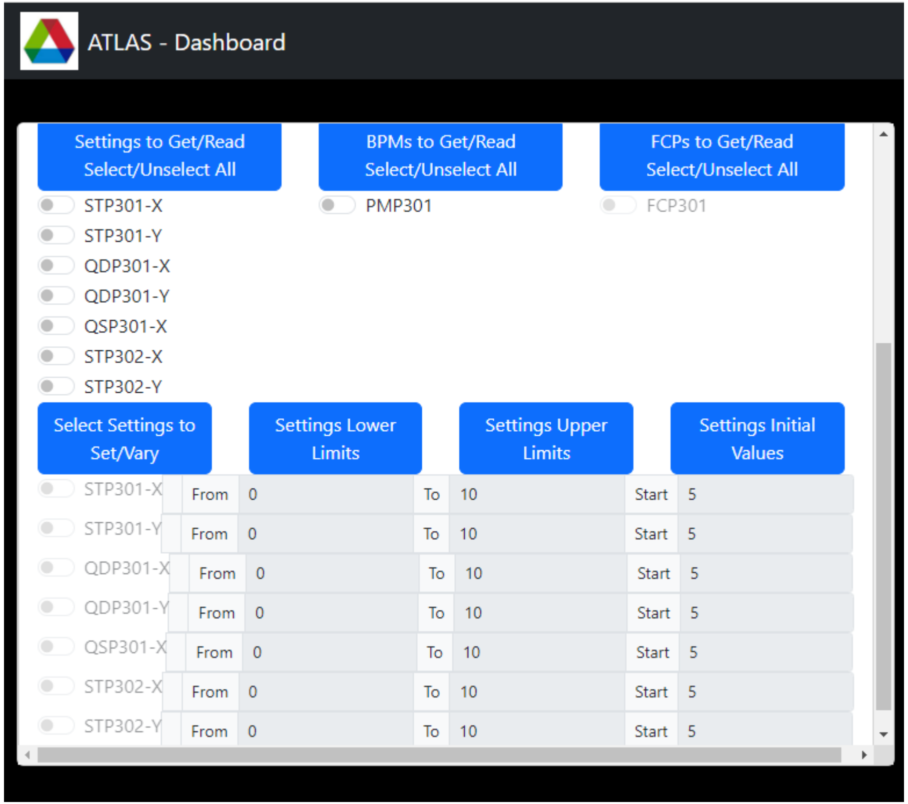
Development of a User Interface for the Operators



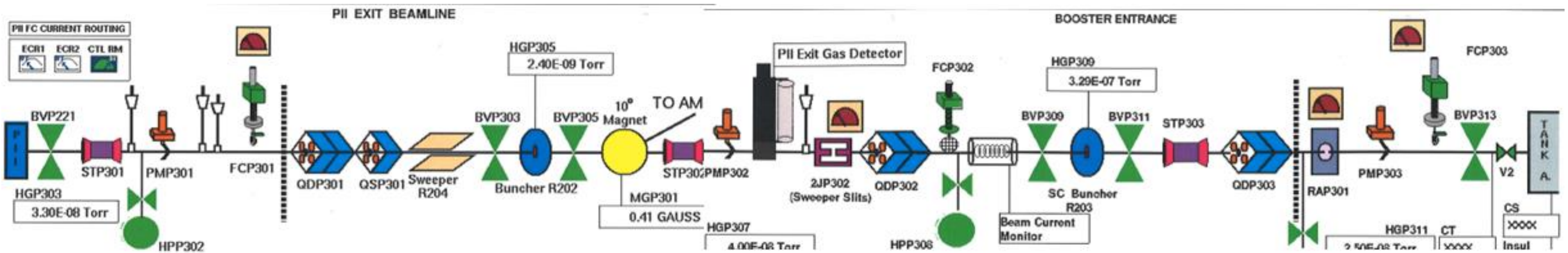
NEW ATLAS DASHBOARD INTERFACE (2)

Development of a User Interface for the Operators



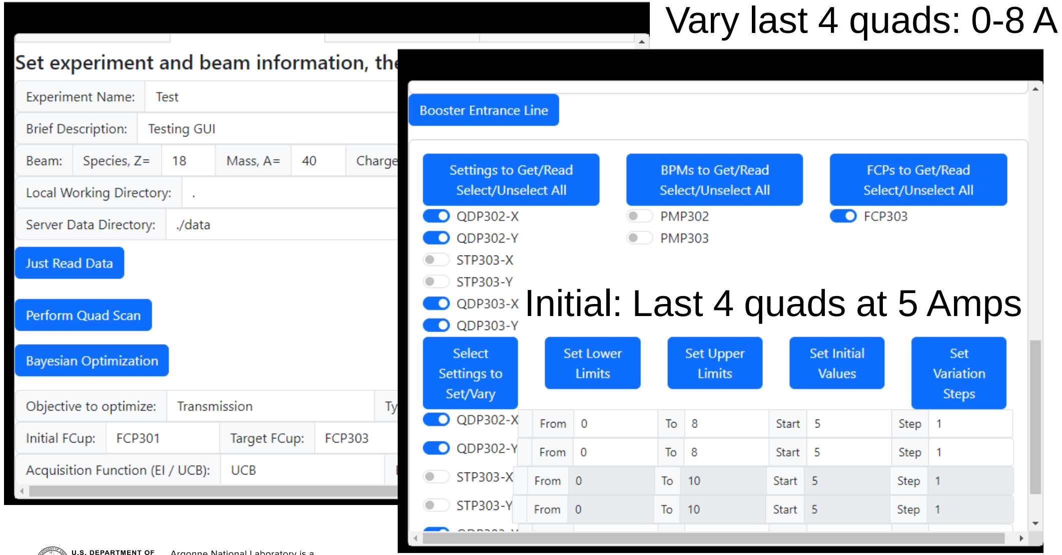


GUI ONLINE TEST #1: PII TO BOOSTER LINE



Task Setup (Op#1 – Henry)

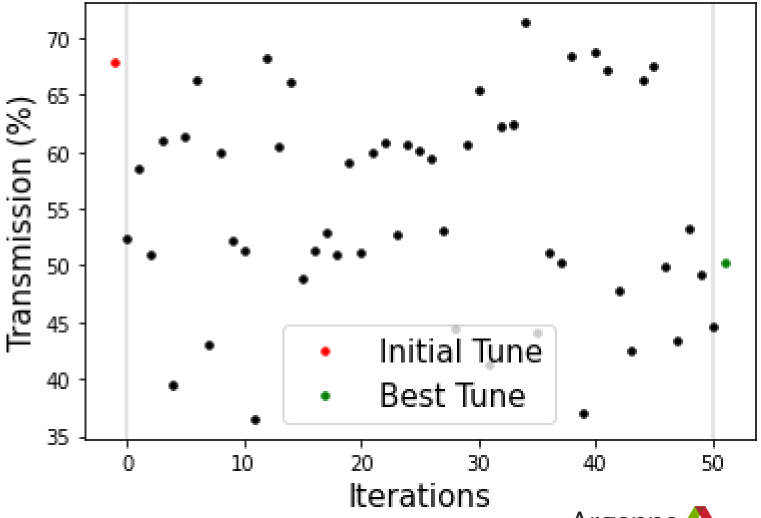
Vary last 4 quads: 0-8 A



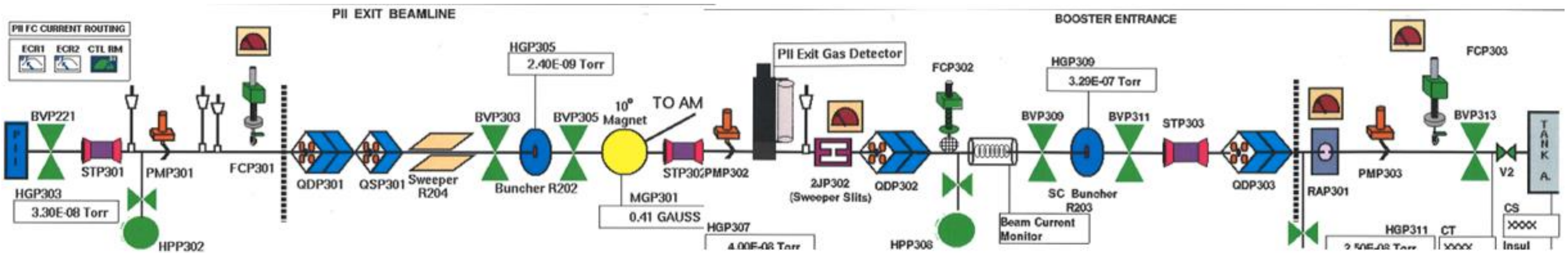
Initial: Last 4 quads at 5 Amps

Results

(Not yet successful, issue with FC reading!)

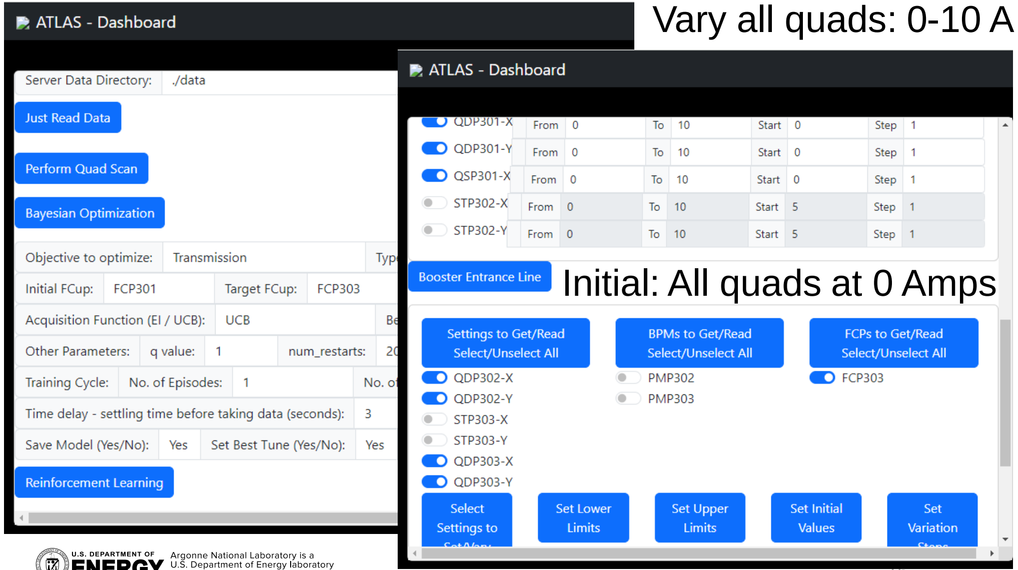


GUI ONLINE TEST #2: PII TO BOOSTER LINE



Task Setup (Op#2 – Raul)

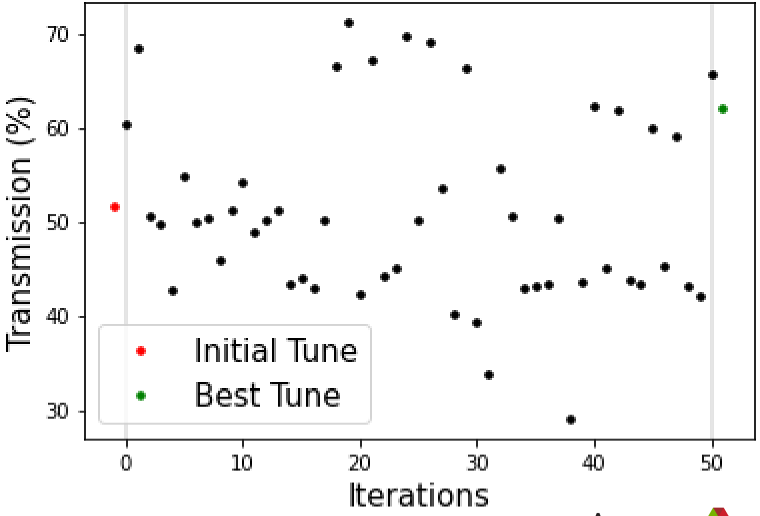
Vary all quads: 0-10 A



Initial: All quads at 0 Amps

Results

(Not yet successful, issue with FC reading!)

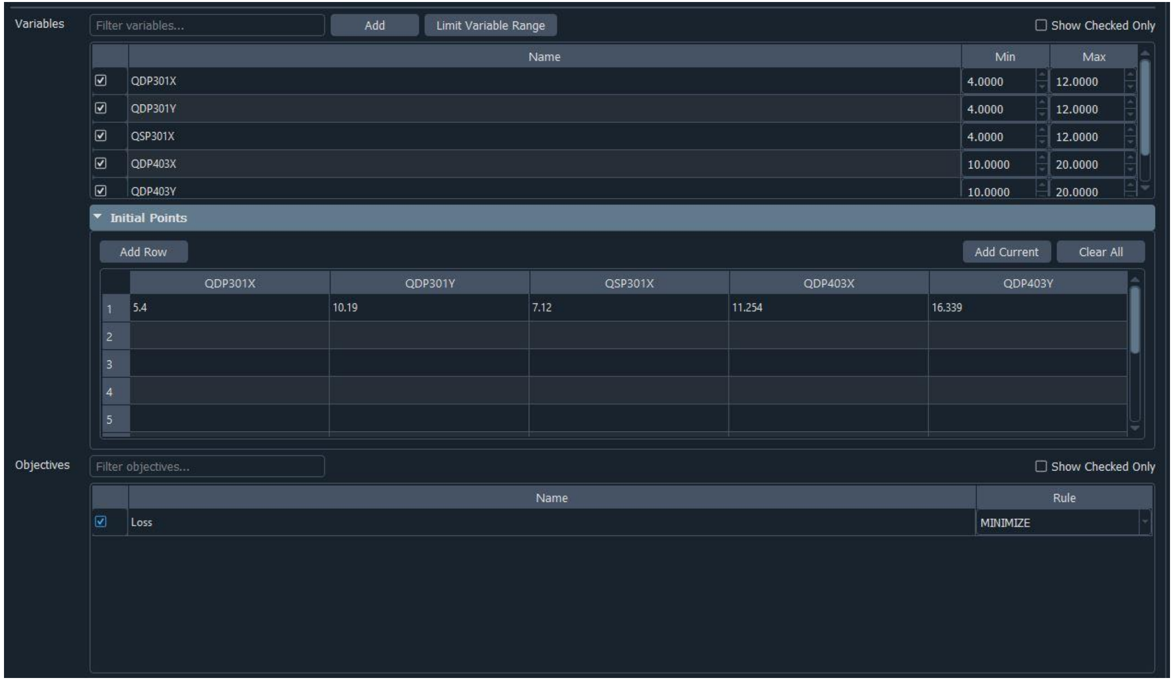


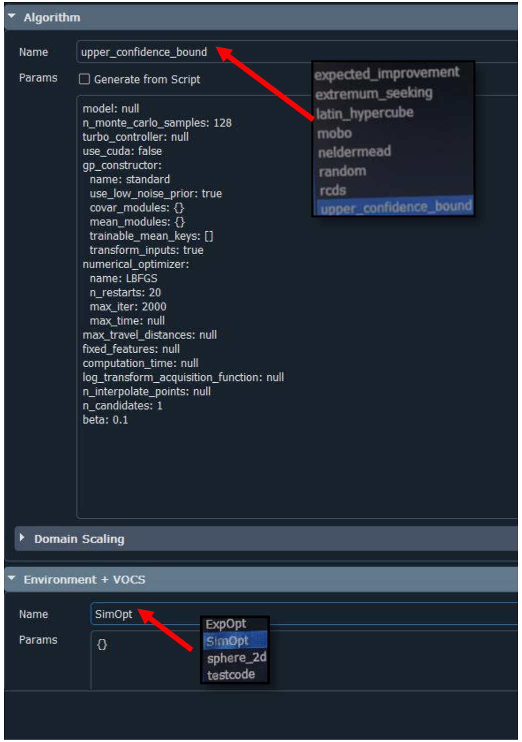
NEW ATLAS BADGER INTERFACE

Development of a Developer Interface for the Experts

Select Algorithm & Parameters

Setup the problem's variables and objectives





NEW ATLAS BADGER INTERFACE (2)

Developer Interface testing using simulations with different setups

```
|    iter    |    Loss    |  QDP301X  |  QDP301Y  |  QDP403X  |  QDP403Y  |  QSP301X  |
-------------------------------------------------------------------------------------------
system:  Windows
.
.\TRACKv39C.exe
  Task begin at  Jun 10,2024,11:46:29
 MNINIT UNABLE TO DETERMINE ARITHMETIC PRECISION. WILL ASSUME:  0.40E-06
  MINUIT RELEASE 95.03  INITIALIZED.   DIMENSIONS 500/250  EPSMAC=  0.80E-06
    Task end at  Jun 10,2024,11:46:32
|  1         |  0.3588    |  5.4      |  10.19    |  11.25    |  16.34    |  7.12     |
system:  Windows
.
.\TRACKv39C.exe
  Task begin at  Jun 10,2024,11:46:33
 MNINIT UNABLE TO DETERMINE ARITHMETIC PRECISION. WILL ASSUME:  0.40E-06
  MINUIT RELEASE 95.03  INITIALIZED.   DIMENSIONS 500/250  EPSMAC=  0.80E-06
    Task end at  Jun 10,2024,11:46:35
|  2         |  0.7815    |  12.0     |  4.906    |  19.43    |  17.07    |  4.151    |
system:  Windows
.
.\TRACKv39C.exe
  Task begin at  Jun 10,2024,11:46:36
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    Task end at  Jun 10,2024,11:46:39
|  3         |  0.5918    |  4.683    |  10.76    |  10.37    |  16.26    |  7.443    |
system:  Windows
.
.\TRACKv39C.exe
  Task begin at  Jun 10,2024,11:46:40
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  MINUIT RELEASE 95.03  INITIALIZED.   DIMENSIONS 500/250  EPSMAC=  0.80E-06
    Task end at  Jun 10,2024,11:46:44
|  4         |  0.05418   |  6.158    |  9.583    |  12.19    |  16.42    |  6.779    |
system:  Windows
.
.\TRACKv39C.exe
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    Task end at  Jun 10,2024,11:46:51
|  5         |  0.07961   |  6.893    |  8.994    |  13.1     |  16.51    |  6.448    |
system:  Windows
.
.\TRACKv39C.exe
  Task begin at  Jun 10,2024,11:46:51
 MNINIT UNABLE TO DETERMINE ARITHMETIC PRECISION. WILL ASSUME:  0.40E-06
  MINUIT RELEASE 95.03  INITIALIZED.   DIMENSIONS 500/250  EPSMAC=  0.80E-06
    Task end at  Jun 10,2024,11:46:56
|  6         |  0.04901   |  6.532    |  9.518    |  12.73    |  16.12    |  6.737    |
system:  Windows
.
.\TRACKv39C.exe
  Task begin at  Jun 10,2024,11:46:57
 MNINIT UNABLE TO DETERMINE ARITHMETIC PRECISION. WILL ASSUME:  0.40E-06
  MINUIT RELEASE 95.03  INITIALIZED.   DIMENSIONS 500/250  EPSMAC=  0.80E-06
    Task end at  Jun 10,2024,11:47:02
|  7         |  0.000184  |  6.251    |  8.999    |  12.44    |  16.71    |  6.554    |
system:  Windows
.
.\TRACKv39C.exe
```
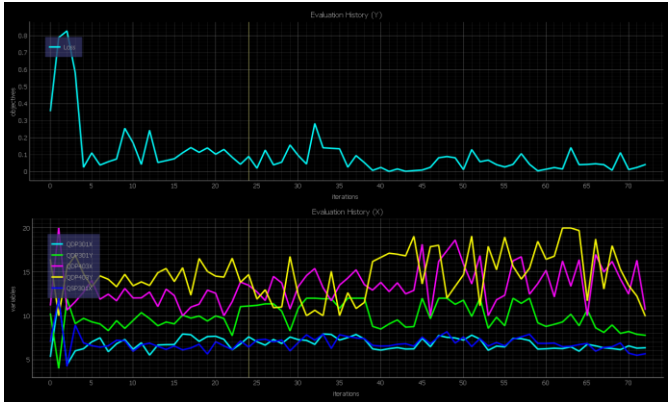
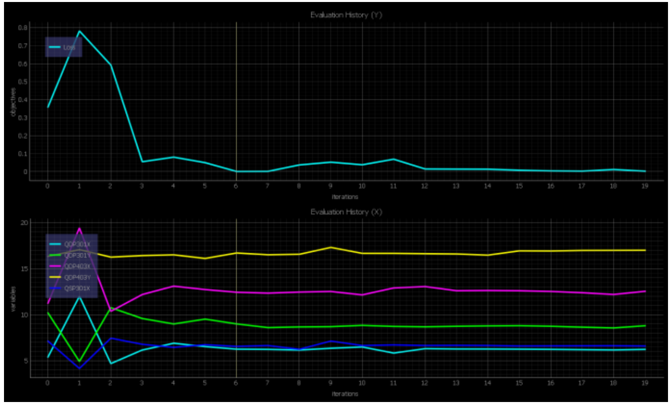

BO Model Hyperparameters:

- Beta : 2.0
- No of candidates: 1
- No of restarts: 20
- Max Iterations: 2000
- No of Monte Carlo Samples: 128



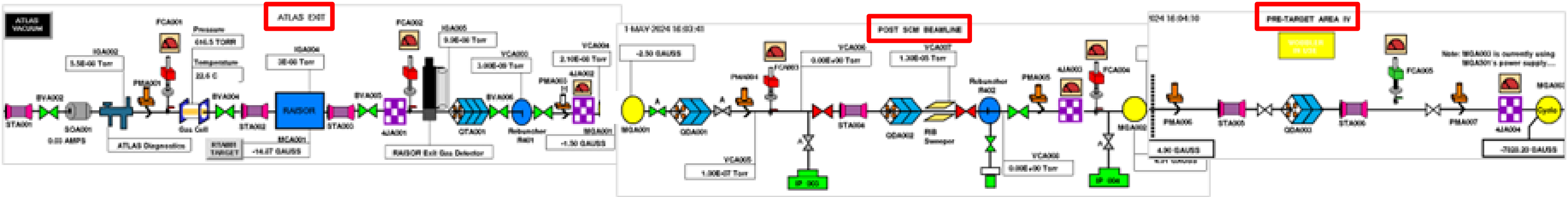
BO Model Hyperparameters:

- Beta : 0.1
- No of candidates: 1
- No of restarts: 20
- Max Iterations: 2000
- No of Monte Carlo Samples: 128

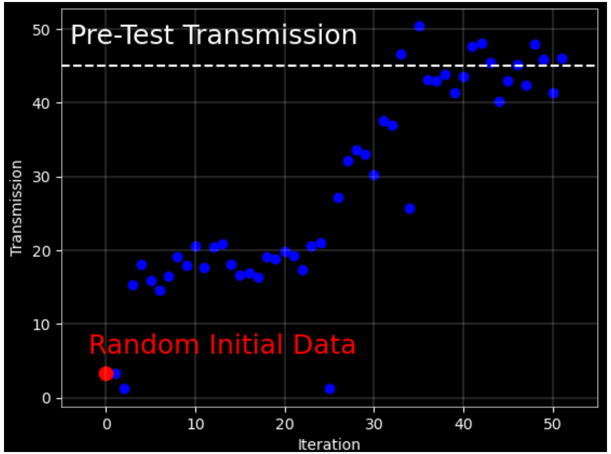


RECENT PROGRESS & HIGHLIGHTS - ATLAS

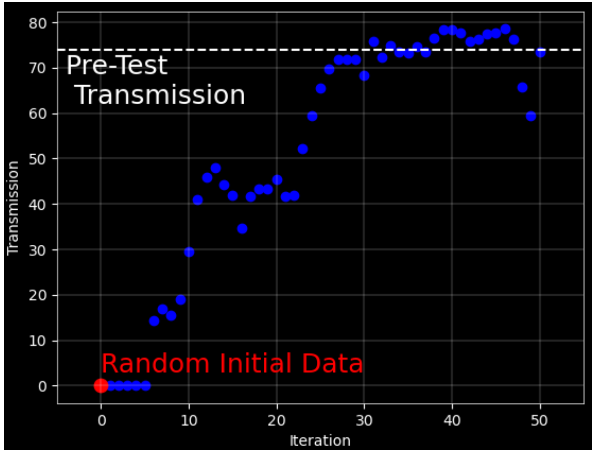
TUNING THE BEAM - ATLAS EXIT TO FMA TARGET



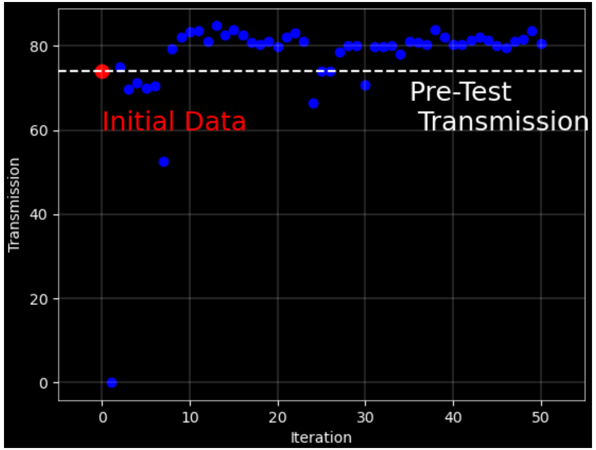
Problem: Maximize transmission, use BO **Tuning parameters**: up to 9 quads & 6 steerers (v&h)
Method: Don't vary all parameters at once, find the most sensitive set of parameters…
Iterations & Time: Typically, 50 iterations x 15 sec (reading two FCs), x 8 sec (reading one FC)



Varying 6 quads only

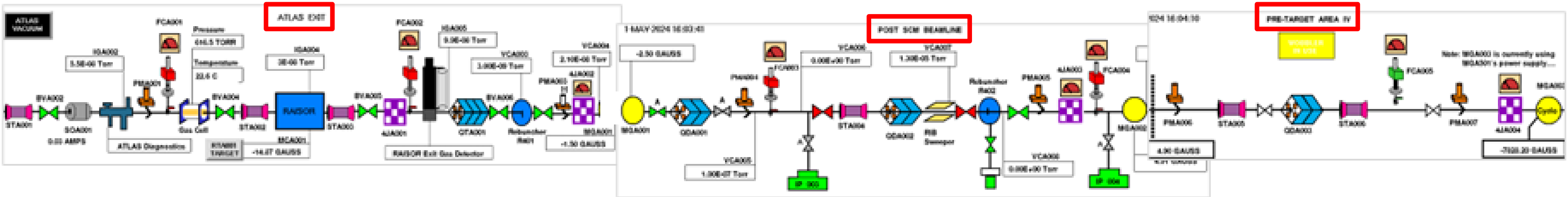


Varying 6 quads + 2 steerers

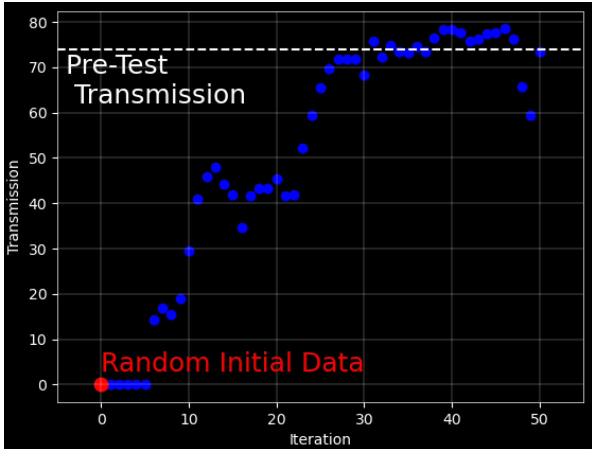


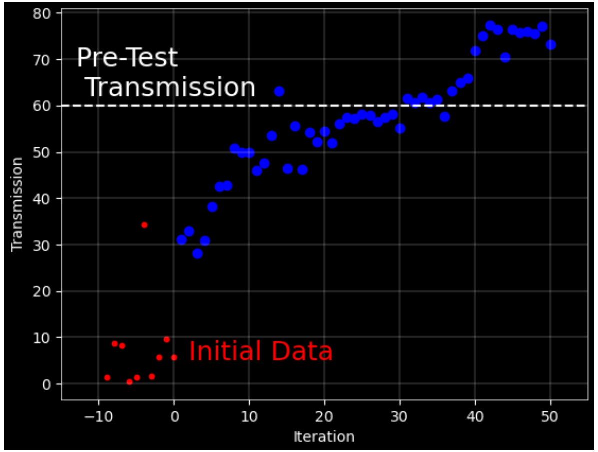
→ Change initial data point

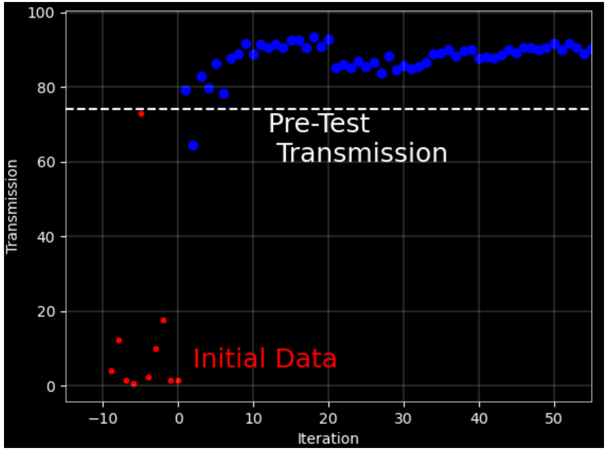
TUNING THE BEAM - ATLAS EXIT TO FMA TARGET (2)



Problem: Maximize transmission, use BO **Tuning parameters**: up to 9 quads & 6 steerers (v&h)
Method: Change number of initial data points for BO model, also explore more β = 0.1 → 1.5
Iterations & Time: Best transmission 95% in less than 50 iterations x 8 sec ~ 7 min



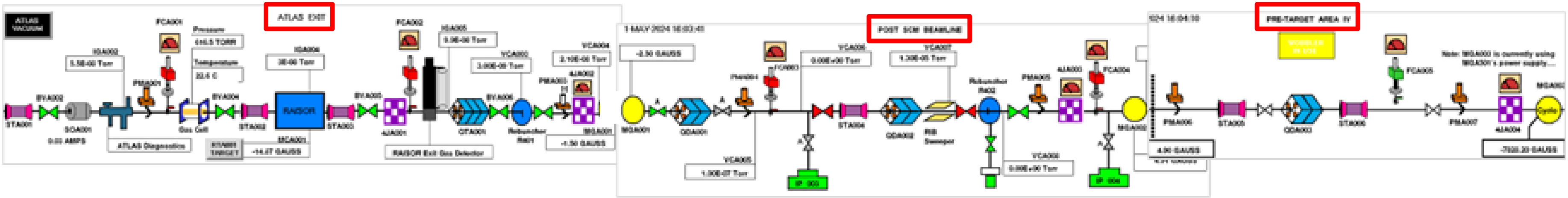




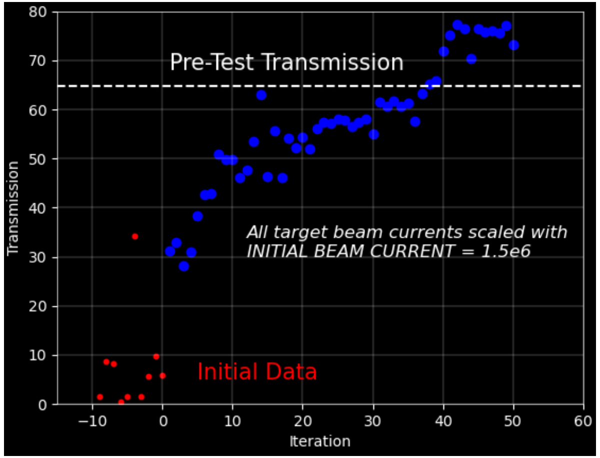
Varying 6 quads + 2 steerers → Using 10 initial data points

Varying 6 quads + 4 steerers

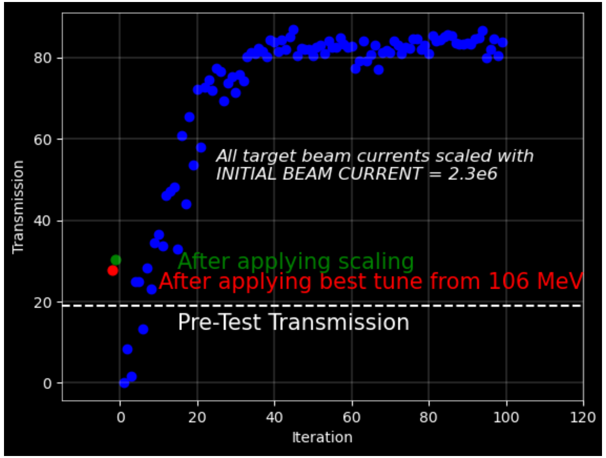
RE-TUNING THE BEAMLINE AFTER ENERGY CHANGE



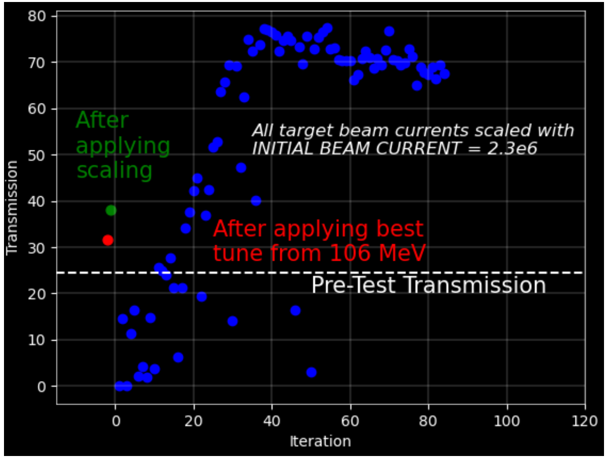
Problem: Switch to a lower energy tune, 106 MeV → 71 MeV, retune for max. transmission
Method: Load 106 MeV tune after energy change, scale to 71 MeV and re-optimize…
Iterations & Time: Best transmission ~ 85% in ~ 50 iterations x 8 sec ~ 7 min



106 MeV [Best Tune]



71 MeV [Trial 1]



71 MeV [Trial 2]

RECENT PROGRESS & HIGHLIGHTS - CARIBU

DECEMBER 4TH, 2024

THE CARIBU-MATIC PROJECT

AUTOMATION FOR THE TRANSPORT OF RADIOACTIVE BEAMS FROM THE CARIBU/NUCARIBU SOURCE

DANIEL SANTIAGO-GONZALEZ
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Physics Division
Argonne National Laboratory

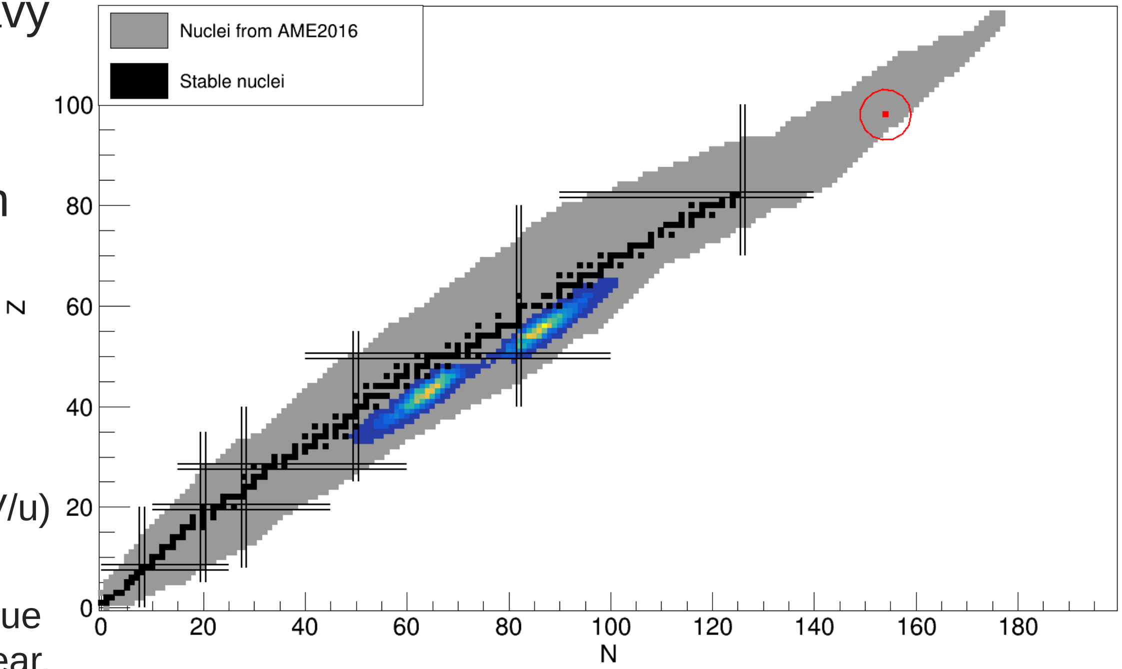
U.S. DEPARTMENT OF ENERGY
Argonne National Laboratory is a U.S. Department of Energy laboratory managed by UChicago Argonne, LLC.

Argonne NATIONAL LABORATORY

WHAT IS CARIBU?

A radioactive ion source part of the ATLAS national user facility

- CARIBU provides beams of heavy ions made from ^{252}Cf fission fragments ($10^2 – 10^4$ pps, few keV/u)
- **nuCARIBU** - a major upgrade in progress to increase beam intensities via neutron induced fission
- Essential for ATLAS multi-user upgrade (post-accel. beams, 3-10 MeV/u)
- User statistics: in FY24, ATLAS enabled research directly impacting over 430 unique users (many come more than once per year, about 25 are students)



https://www.anl.gov/atlas/caribu-beams

SCIENCE ENABLED BY THE CARIBU SOURCE

Selected highlights

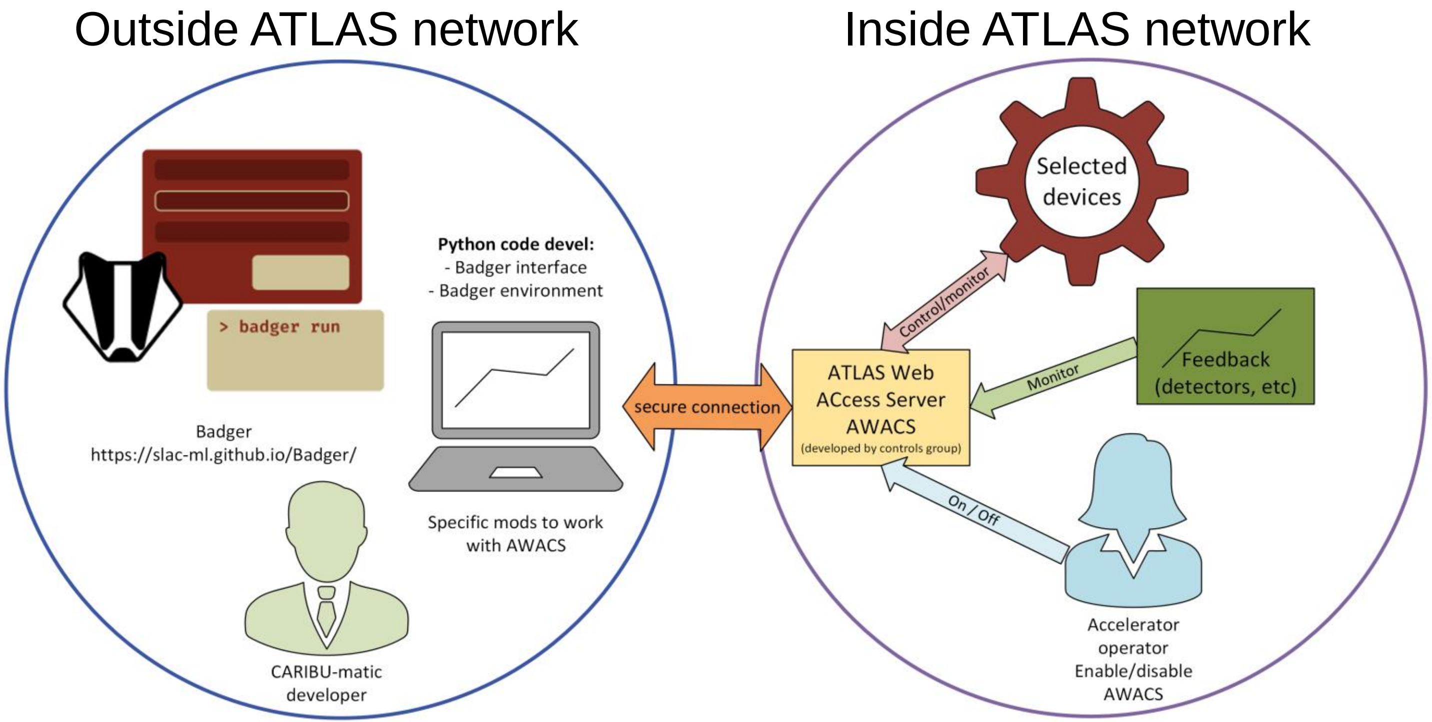
- CARIBU beams enable a diverse user program that produces cutting-edge scientific publications with impact in the fields of:
  - nuclear structure
  - nuclear astrophysics
  - national nuclear security, and others

- Selected publications include:
  - Mass measurements that help us better understand how the chemical elements were produced in stellar environments – Van Schelt et al. PRL 111, 061102 (2013)
  - First direct experimental evidence of a “pear-shaped” nucleus - Bucher et al. PRL 116, 112503 (2016)
  - First study of the $^{139}Ba(n,\gamma)^{140}Ba$ reaction to constrain the conditions for the astrophysical i process – Spyrou et al. PRL 132, 202701 182502 (2024)

- These state-of-the-art investigations are possible in part because the CARIBU staff scientists deliver close to 2500 hours (or about 100 days) of beam time per year to our users

CARIBU-MATIC PROJECT

Our approach for secure radioactive beams tuning automation

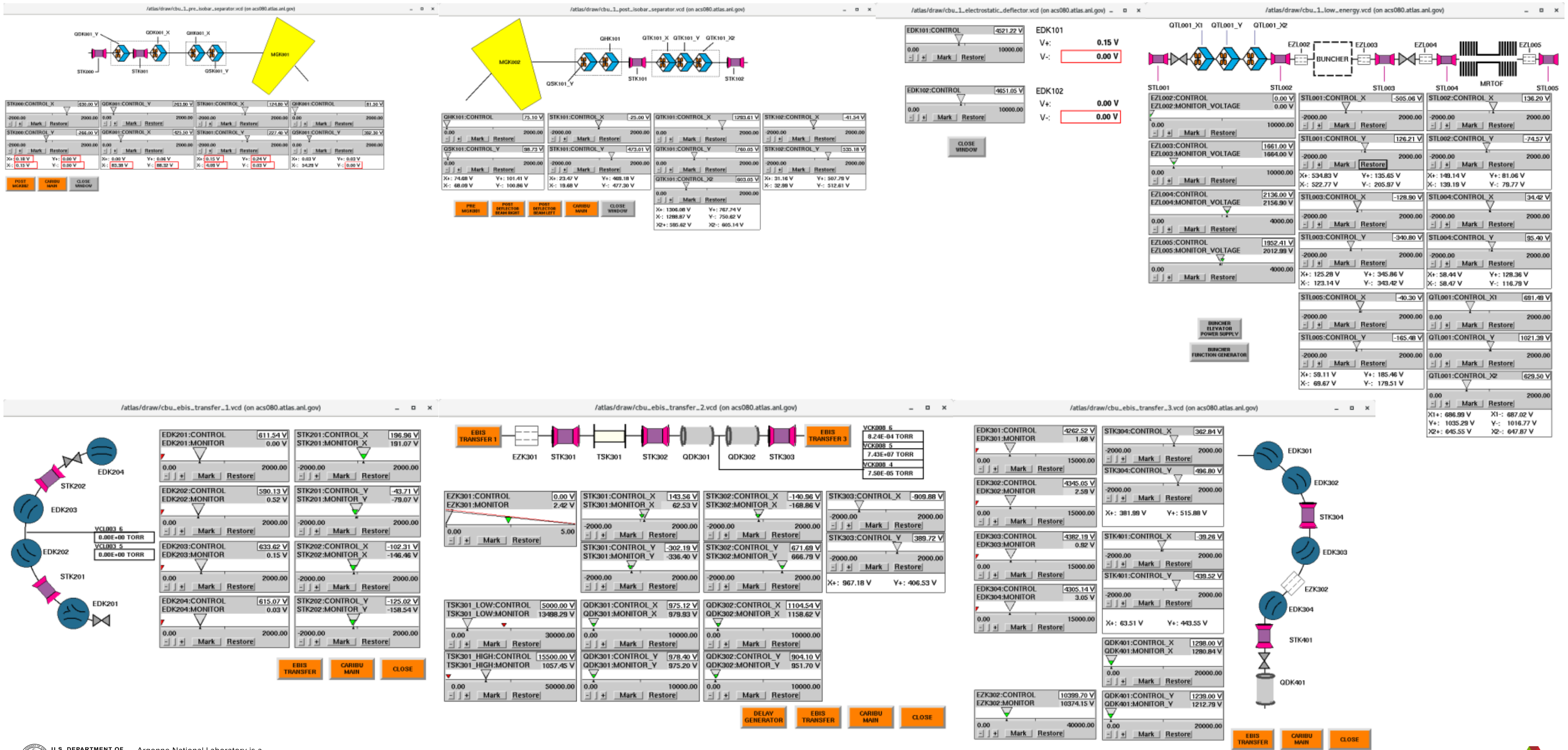


RECENT MILESTONES
- JUL/2024 FOUNDATIONAL WORK COMPLETED
- AUG/2024 CARIBU-MATIC LIVE OPTIMIZATION

TASK: IN A SINGLE SESSION, TRANSPORT A RADIOACTIVE BEAM USING BAYESIAN OPTIMIZATION (60+ CONTROL PARAMS)

CARIBU CONTROLS FOR THIS TEST

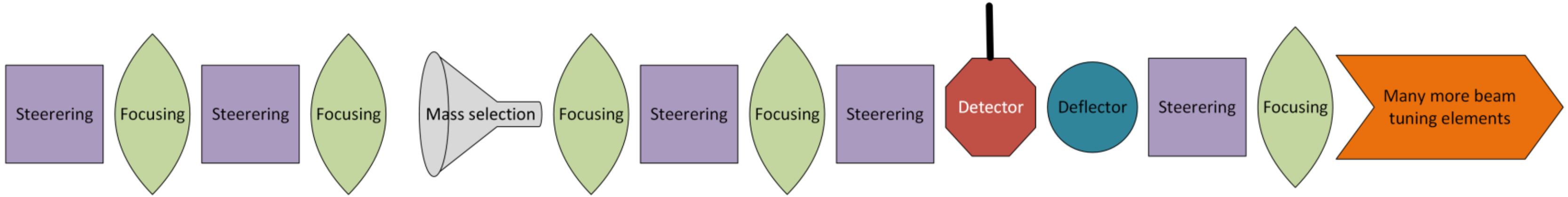
60+ control parameters to transport beam from start to finish



CARIBU CONTROLS – SIMPLIFIED VIEW

60+ control parameters to transport beam from start to finish

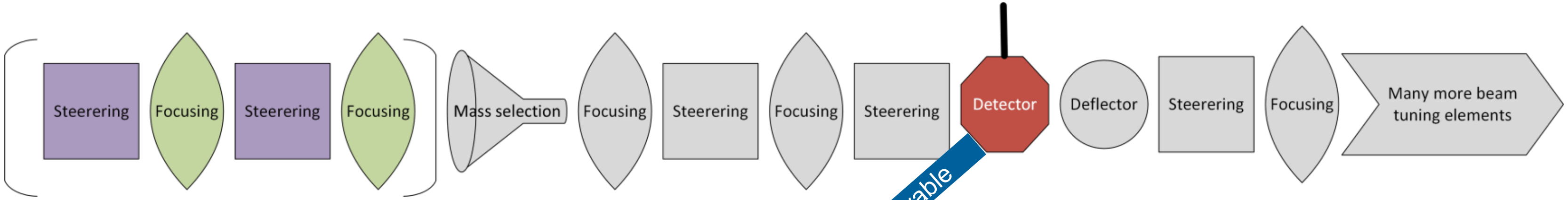
inactive



CARIBU CONTROLS – SIMPLIFIED VIEW

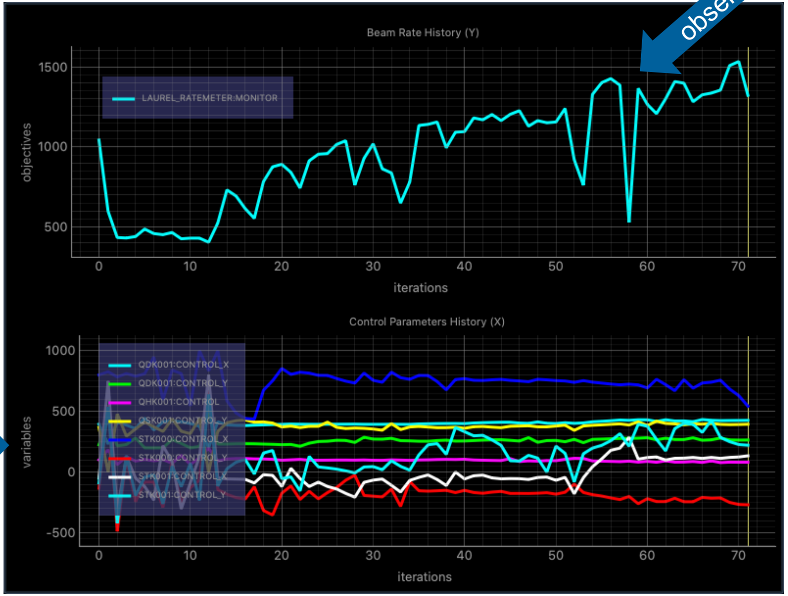
Splitting in sections, each with 10 or less control parameters

inactive



8 control params

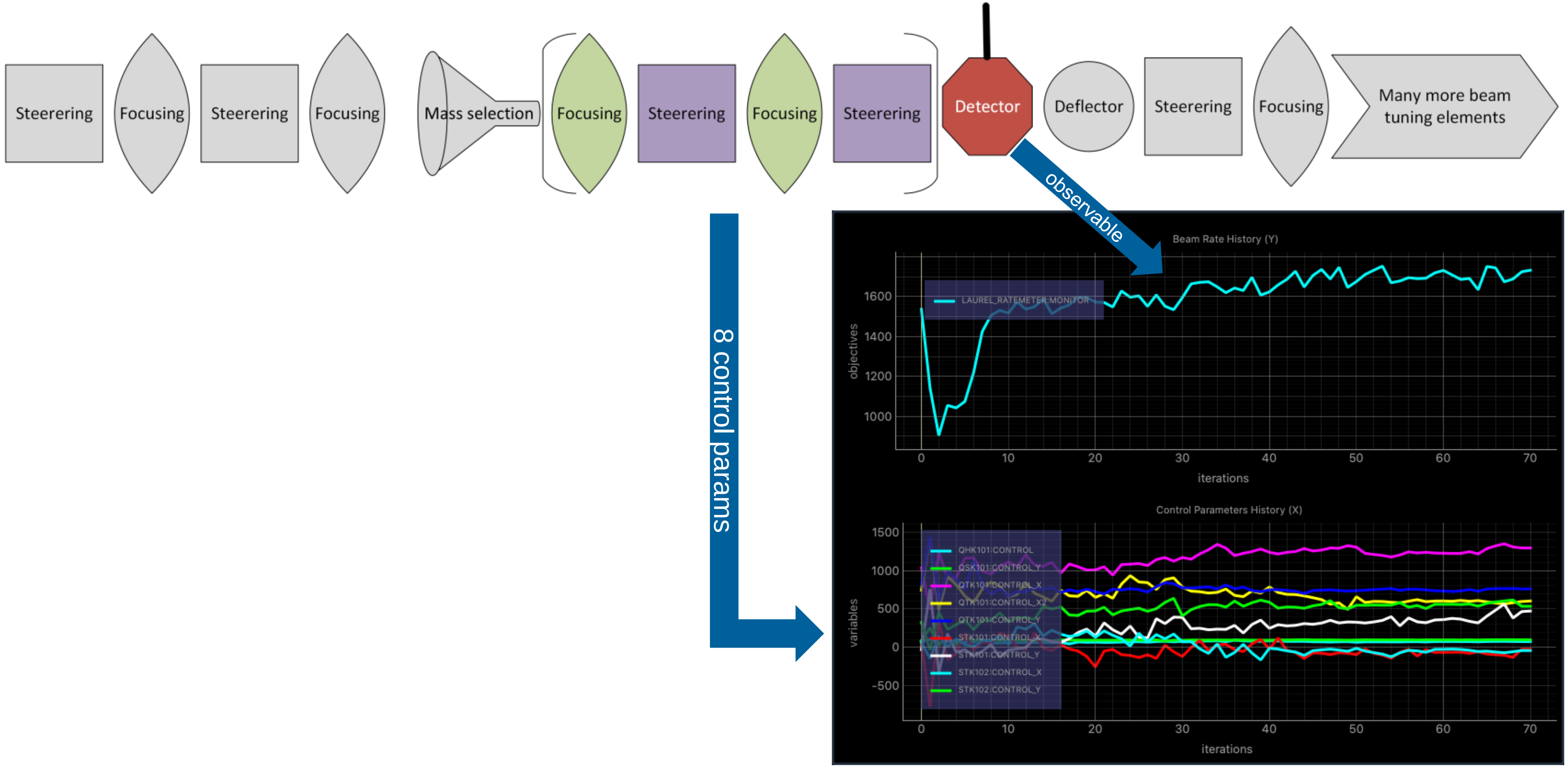
observable



CARIBU CONTROLS – SIMPLIFIED VIEW

inactive

Splitting in sections, each with 10 or less control parameters



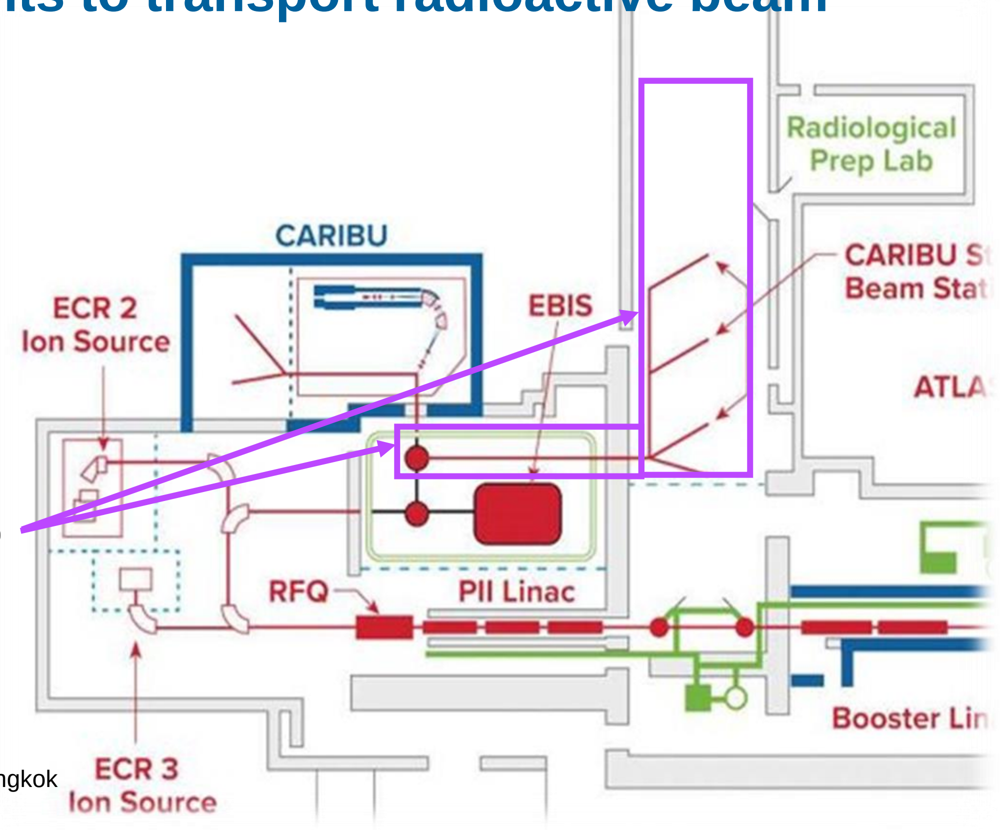
CARIBU-MATIC TEST RESULTS (NOT A SIMULATION)

Serial optimization of 60+ elements to transport radioactive beam

- **Transport efficiency**
  - 40% from first detector to last detector
  - On par with typical hand tune
- **Optimization time**
  - About 10-15 minutes per section
  - Comparable to hand tune approach

Next steps

- Refine code
- Extend to **target stations** (100+ different elements)
- Automate multi-section optimization



Badger web sites and reference

https://slac-ml.github.io/Badger/
https://github.com/SLAC-ML/Badger
Zhang, Z., et al. "Badger: The missing optimizer in ACR", Proc. IPAC'22, Bangkok

THANK YOU

MANY THANKS TO

- Students & Postdocs:

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  Daniel Stanton, Kenneth Bunnell and David Novak

- ATLAS Operations Group:

  Ben Blomberg, Eric Letcher, Gavin Dunn, Henry Brito and Raul Patino

BACK-UP SLIDES

ORIGINAL PROJECT – PROGRESS & HIGHLIGHTS

SUMMARY OF PROGRESS & HIGHLIGHTS

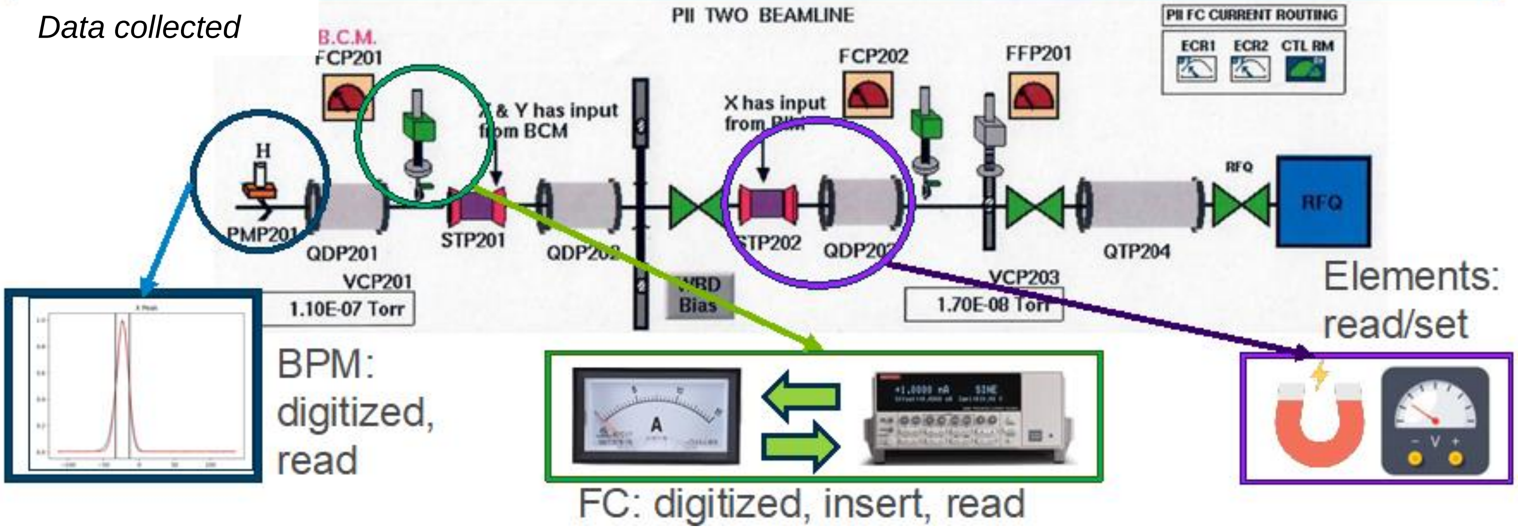
- ❑ Automated data collection and two-way communication established
- ❑ Bayesian Optimization (BO) successfully used for online beam tuning
- ❑ Multi-Objective BO (MOBO) to optimize transmission and beam size
- ❑ AI-ML supporting the commissioning of a new beamline (AMIS)
- ❑ Transfer learning from one ion beam to another (BO)
- ❑ Transfer learning from simulation to online model (BO with DKL)
- ❑ Reinforcement Learning (RL) for online beam tuning – Exp. Success
- ❑ Good progress on the virtual machine model / physics model

AUTOMATED DATA COLLECTION - ESTABLISHED

- ✓ Beam currents and beam profiles digitized
- ✓ A python interface developed to collect the data automatically

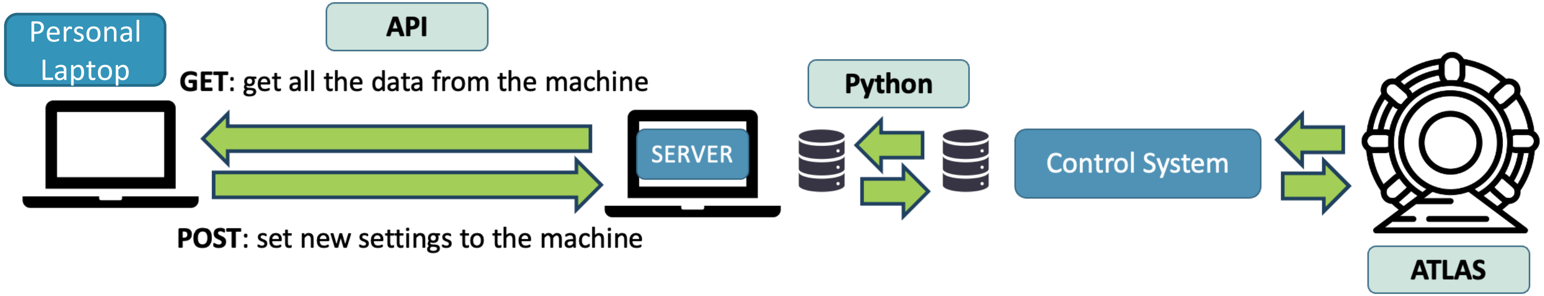
Schematic of data collection interface

Data collected



Now working on reducing acquisition time …

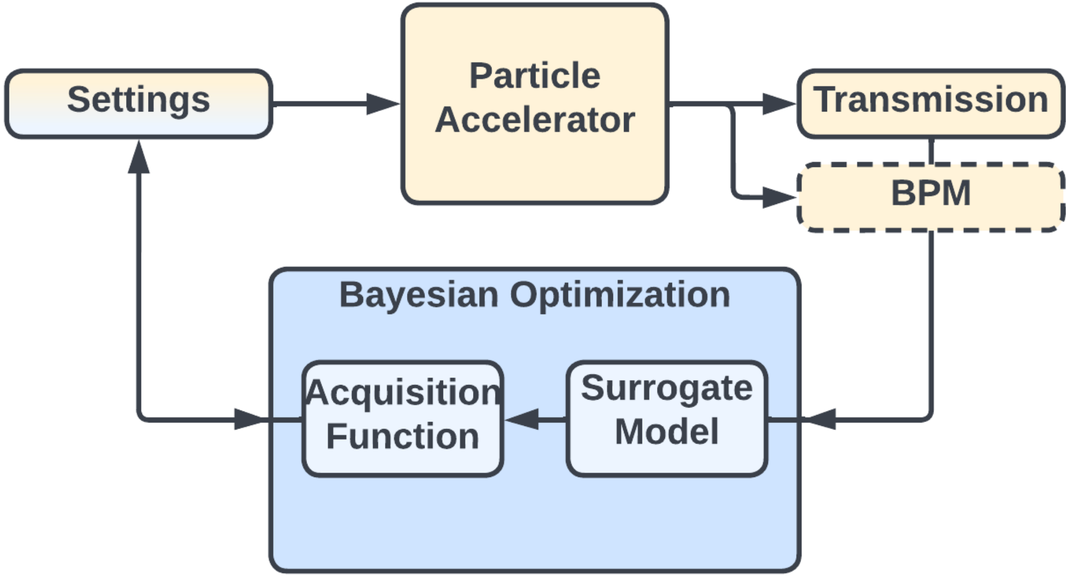
ONLINE – INTERFACE WITH CONTROL SYSTEM



OFFLINE – INTERFACE WITH BEAM SIMULATION

- ✓ Python wrapper for TRACK (Simulation Code)
- ✓ Generation of simulation data
- ✓ Different conditions and inputs
- ✓ Integration with AI/ML modeling

BAYESIAN OPTIMIZATION – A BRIEF DESCRIPTION

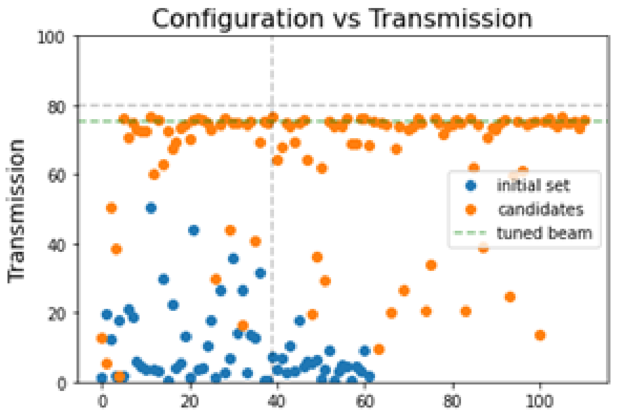


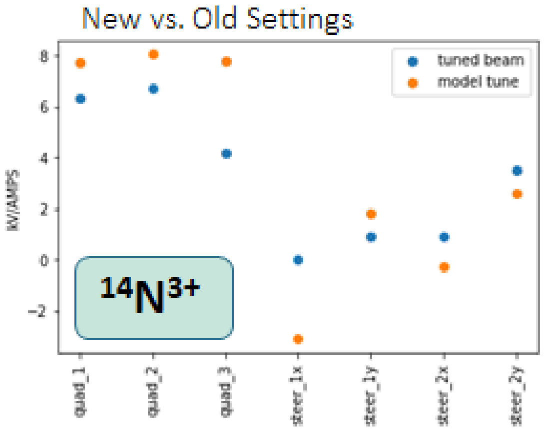
- ✓ **<u>Surrogate Model</u>: A probabilistic model approximating the objective function**
  [Gaussian Process with Radial Basis Function (RBF) Kernel and Gaussian likelihood]
- ✓ **<u>Acquisition Function</u> tells the model where to query the system next for more likely improvement**
- ➢ **Bayesian Optimization with Gaussian Processes guides the model and gives a reliable estimate of uncertainty**

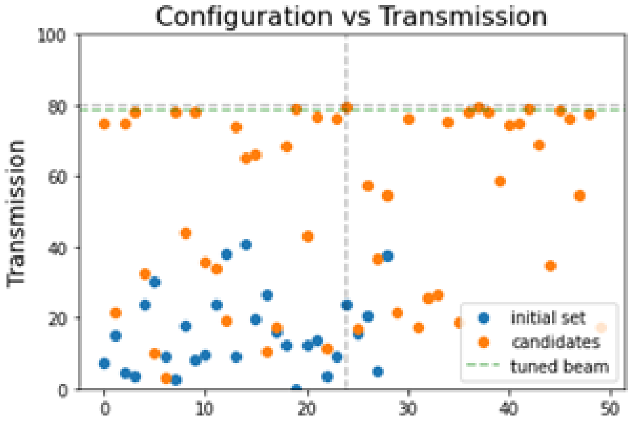
BAYESIAN OPTIMIZATION USED IN ONLINE TUNING

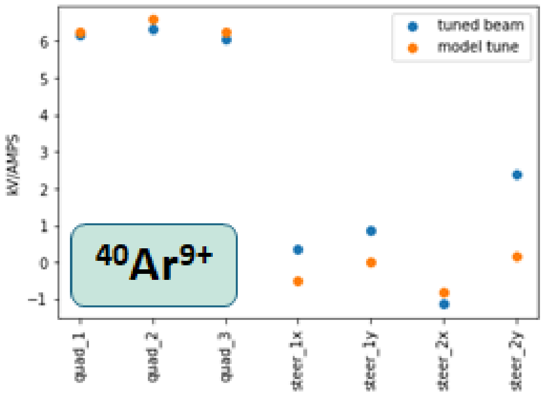
Beamline under study

- **7 variable parameters (3 quadrupoles + 2x2 steerers)**
- **Optimization of beam transmission**
- **Case of $^{14}N^{3+}$: 29 historical + 33 random tunes**
- **Case of $^{40}Ar^{9+}$: 29 historical tunes**







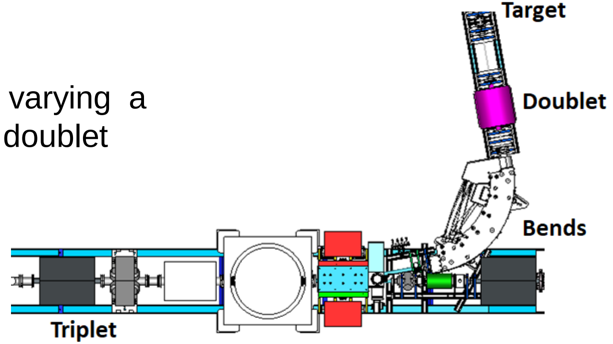


MULTI-OBJECTIVE BAYESIAN OPTIMIZATION

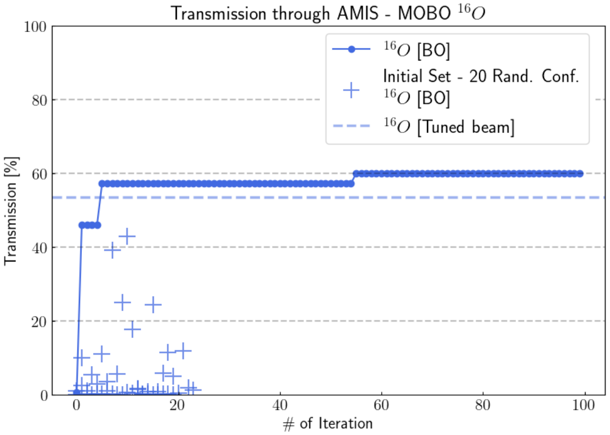
Multi-Objective Problem: Optimize transmission and beam profiles on target - Not easy for an operator!

Improving Beam Transmission & Improving Beam Profiles

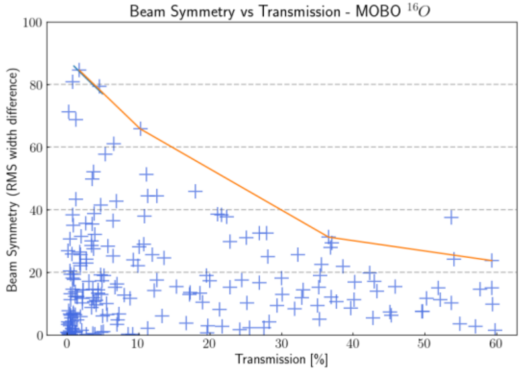
AMIS line: varying a triplet and a doublet



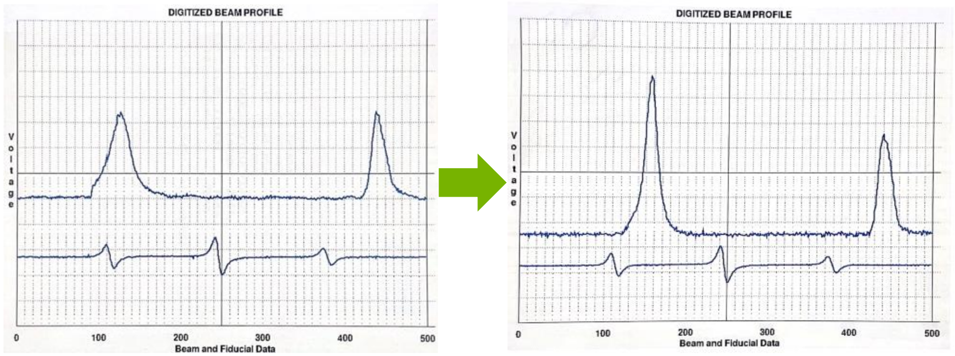
MOBO Results: 53→ 60% Beam transmis.



MOBO Results: Pareto Front

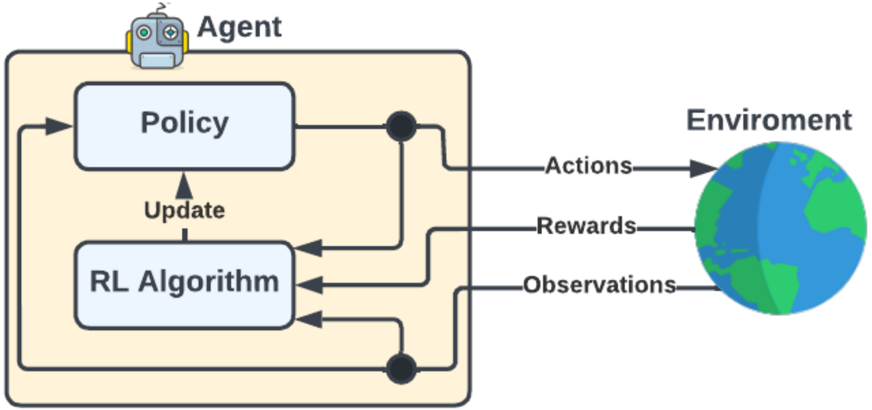


MOBO Results: More symmetric beam profiles

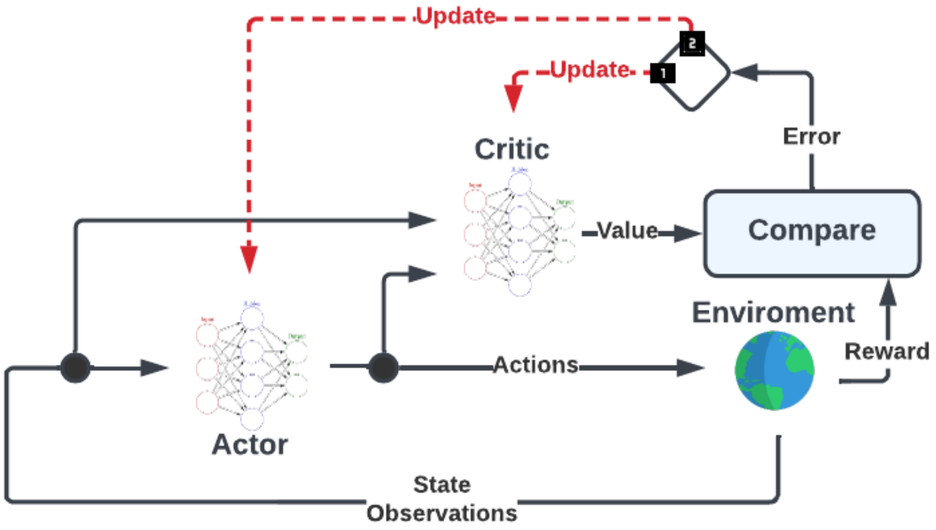


REINFORCEMENT LEARNING – A BRIEF DESCRIPTION

Basic Concept



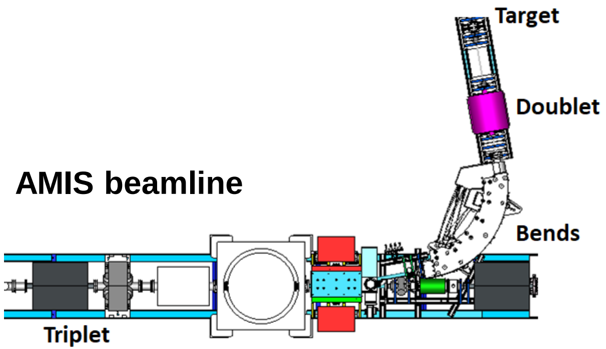
Implementation Example



- ✓ **Essence:** Learning from experience based on interaction with the environment
- ✓ **Action:** Varies the parameters/variables of the problem
- ✓ **Reward:** Measures the goal function to maximize/optimize
- ✓ **Policy:** How the process evolves/learns
- ✓ **Algorithm used:** Deep Deterministic Policy Gradient (DDPG); Actor-Critic Approach

REINFORCEMENT LEARNING: FIRST EXP. SUCCESS

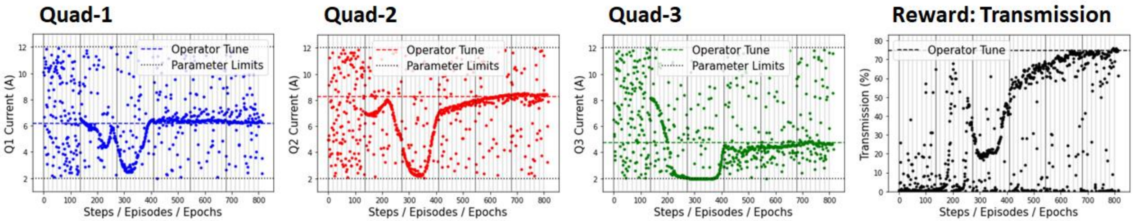
Beamline under study



Objective: Maximize beam transmission

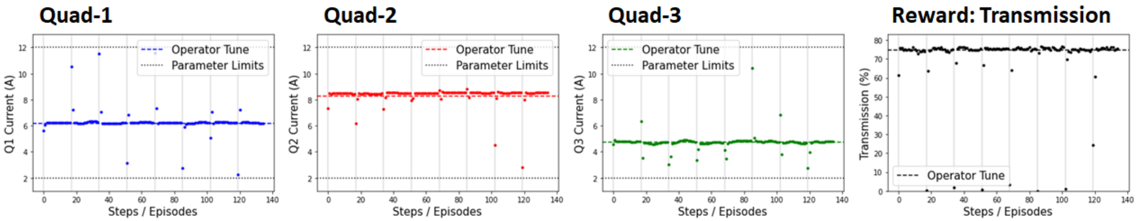
- Varying 3 magnetic quads
- Current limits: 2 – 12 Amps
- Max. Action: Full range

Training - Online



➢ Training done in 816 total steps/evaluations (48 episodes)

Testing - Online

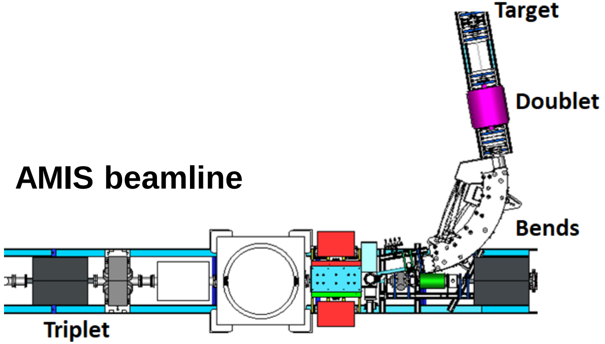


➢ Testing done for 8 episodes (16 steps/episode)
➢ Model converges in 2-3 steps, starting from random config.

➢ **RL is much slower than BO, requiring significantly more data → more iterations to train, but once trained, it takes fewer steps to converge to the best solution …**

REINFORCEMENT LEARNING: MORE PARAMETERS

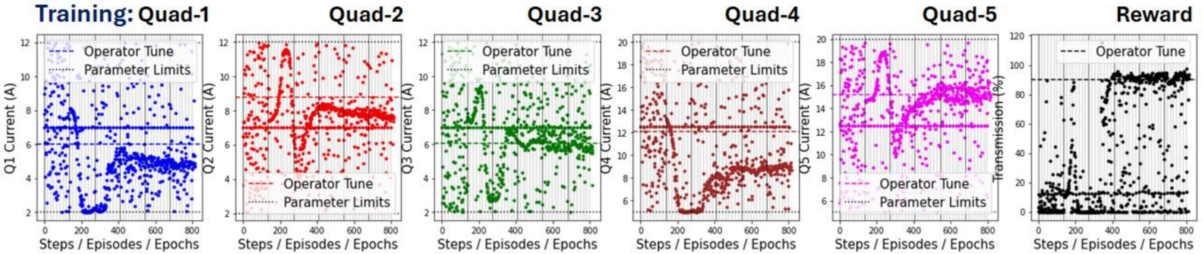
Beamline under study



Objective: Maximize beam transmission

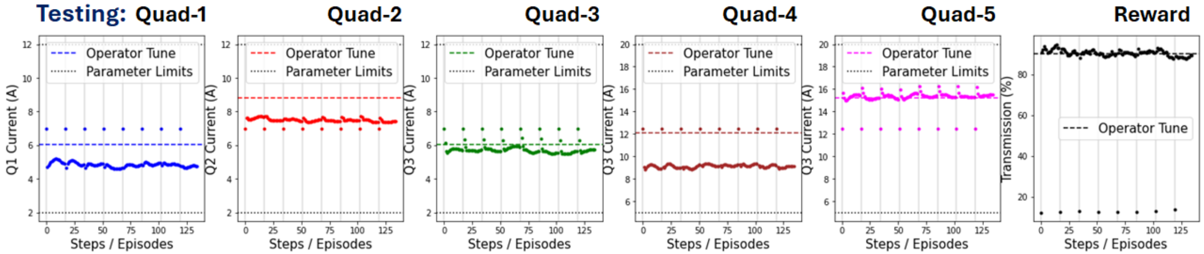
- Varying 5 magnetic quads
- Triplet 2–12 A, Doublet 5-15 A
- Max. Action: Full range

Training - Online



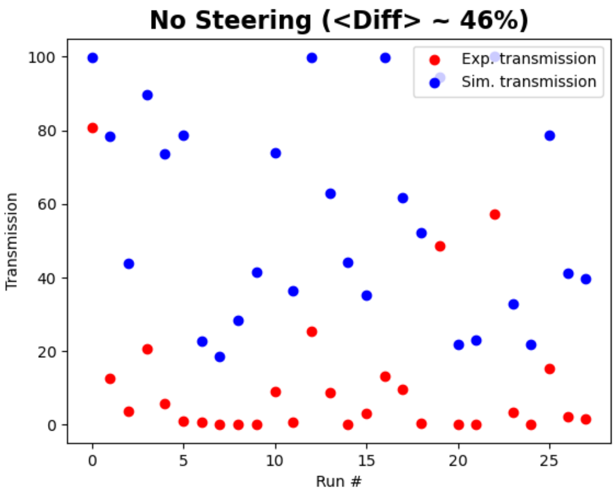
- ➢ Training done in 816 total steps/evaluations (48 episodes)

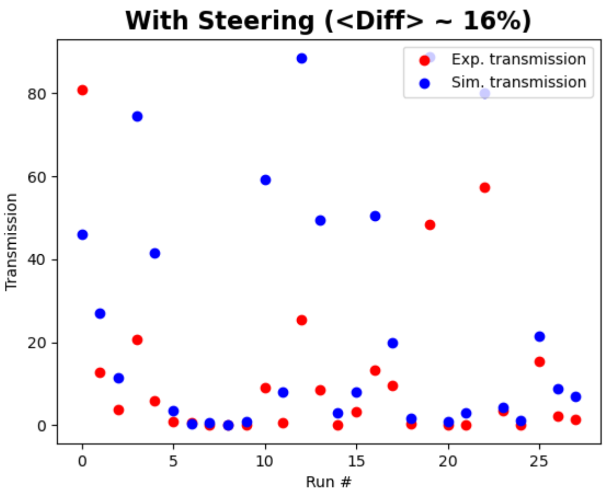
Testing - Online

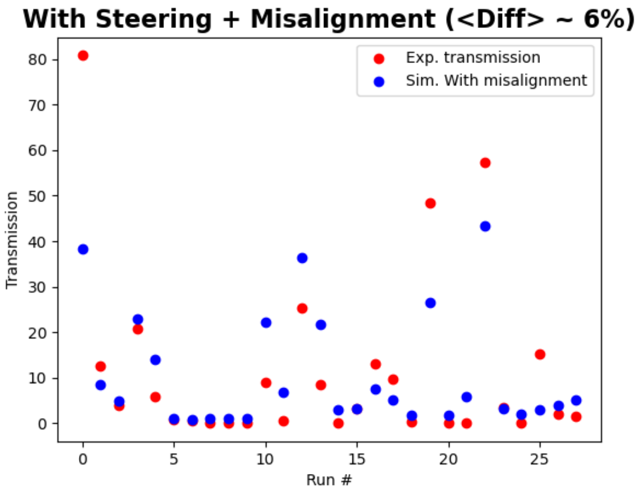


- ➢ Testing done for 8 episodes (16 steps/episode)
- ➢ Model converges in 2-3 steps, starting from same config.

PROGRESS ON THE VIRTUAL MACHINE MODEL





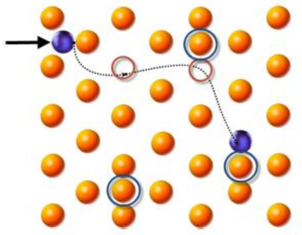


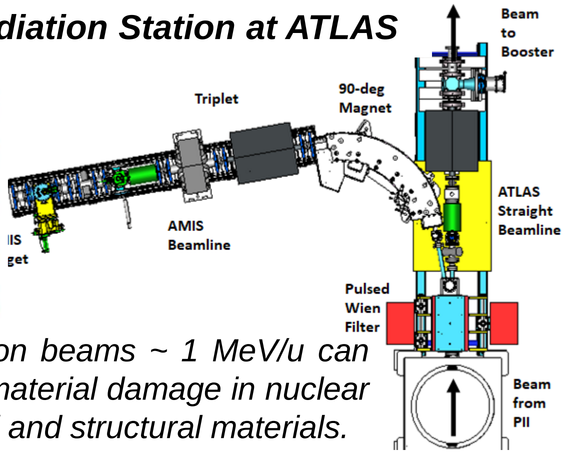
- ✓ In order to develop a realistic virtual machine model, we need first to improve the predictability of the physics model based on beam dynamics simulations (using TRACK code)
- ✓ Significant improvement was realized by adding steering effects, using steerers settings
- ✓ Further improvement achieved by adding misalignment effects, obtained using BO inference
- ✓ Adding information about the initial beam distribution should close the gap even further
- ✓ Once the agreement is ~ 1%, a surrogate model will be developed based on the simulations

MORE SLIDES

AI/ML SUPPORTING AMIS LINE COMMISSIONING

New Material Irradiation Station at ATLAS

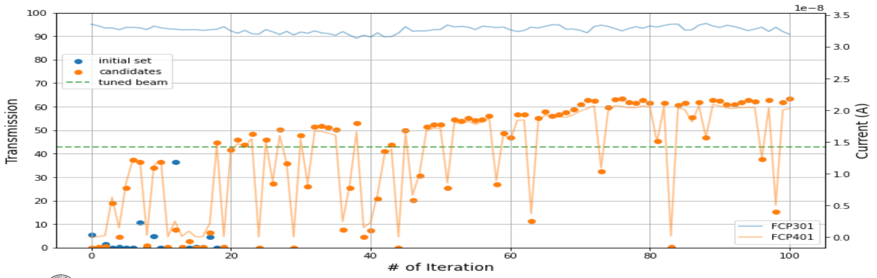




Low-energy heavy-ion beams ~ 1 MeV/u can effectively emulate material damage in nuclear reactors, in both fuel and structural materials.

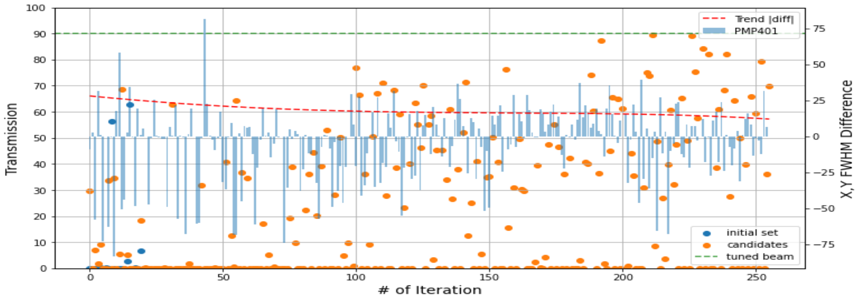
Improving Beam Transmission

Problem: Maximize beam transmission by varying a triplet, two dipoles and two steerers [BO]; **Results**: 40 → 70%

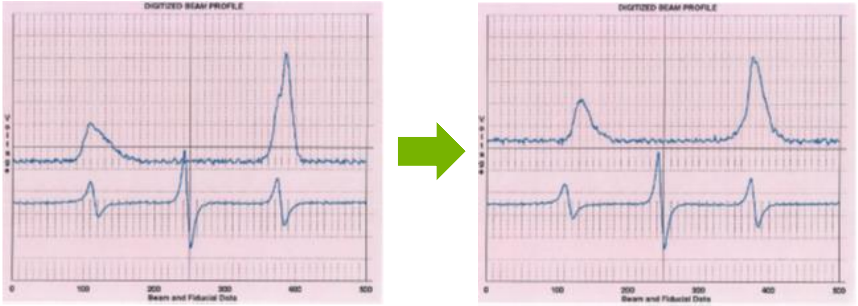


Improving Beam Profiles

Problem: Produce symmetric beam profiles by varying a triplet and a steerer [BO]



Training online, slow convergence but steady progress. Competition between nice profiles and beam transmission!



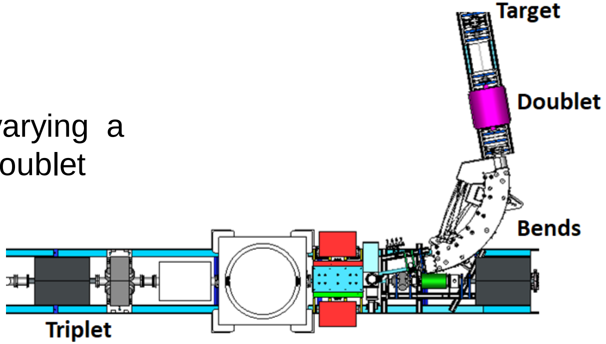
Very encouraging first results!

TRANSFER LEARNING FROM ^{16}O TO ^{22}NE - BO

Goal: Train a model using one beam then transfer it to tune another beam → Faster switching and tuning

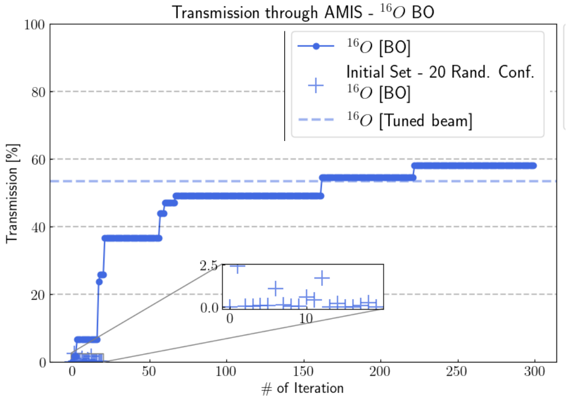
Training model on ^{16}O → Applying same model to ^{22}Ne

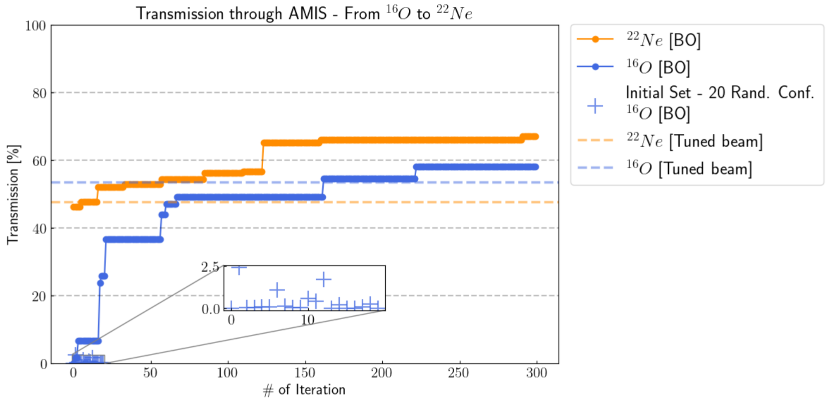
AMIS line: varying a triplet and a doublet



BO Training: Over 300 iterations 53 → ~ 60% Beam transmis.

Model saved & exported





16O Model loaded for 22Ne: Initial transmission improved in 7 iterations: 48 → 55 %

With more training for 22Ne: 48 → 67%

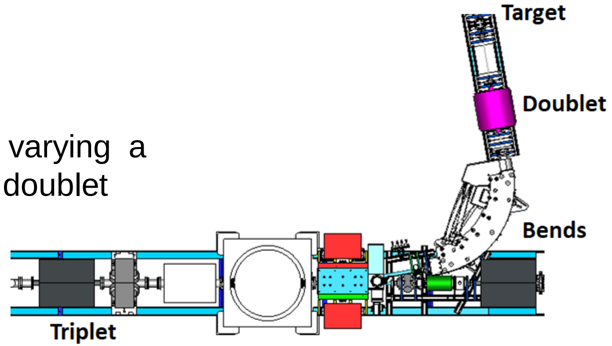
Scaling was applied from 16O to 22Ne, re-tuning is often needed because of different initial beam distributions

TRANSFER LEARNING FROM SIMULATION TO ONLINE

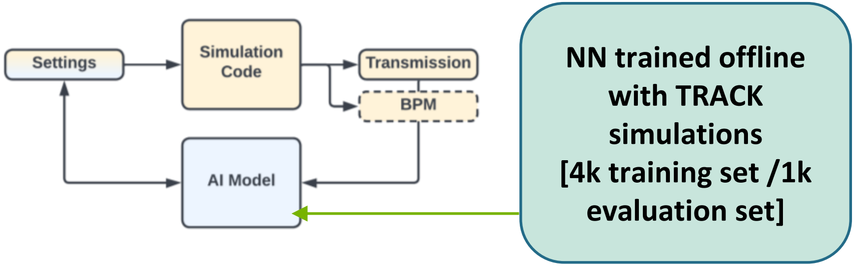
Goal: Train a model using simulations then use it for online tuning → Less training & faster convergence online

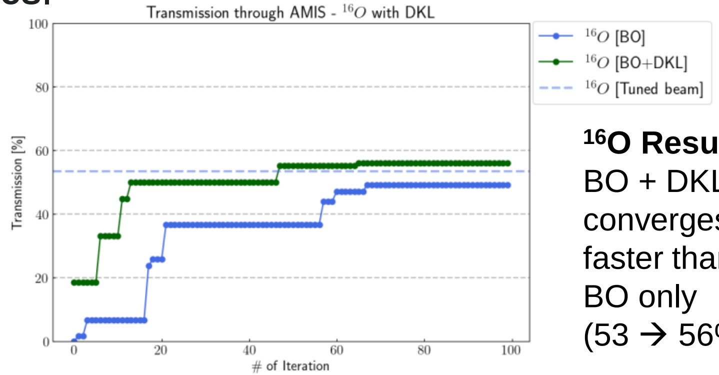
Method: Deep kernel learning (DKL) to **combine the representational power of neural networks with the reliable uncertainty estimates of Gaussian processes**.

AMIS line: varying a triplet and a doublet

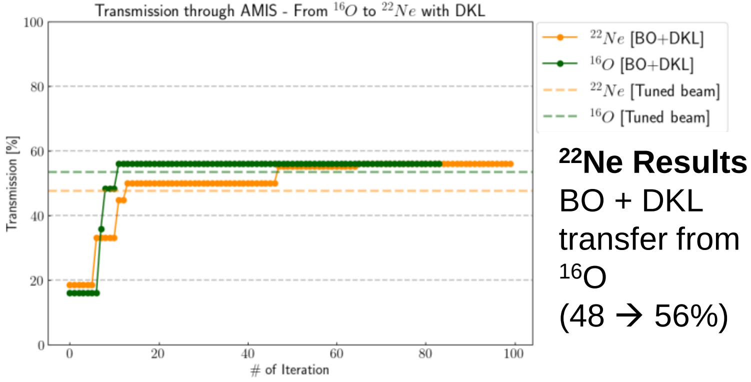


AMIS Line: Maximize beam transmission by varying a triplet [BO+DKL]





^{16}O Results: BO + DKL converges faster than BO only (53 → 56%)

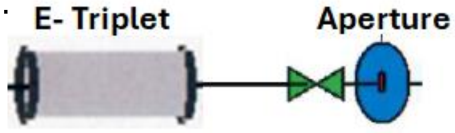


^{22}Ne Results: BO + DKL transfer from ^{16}O (48 → 56%)

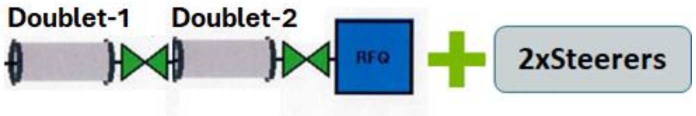
REINFORCEMENT LEARNING: FIRST ATTEMPT…

Simulation Case

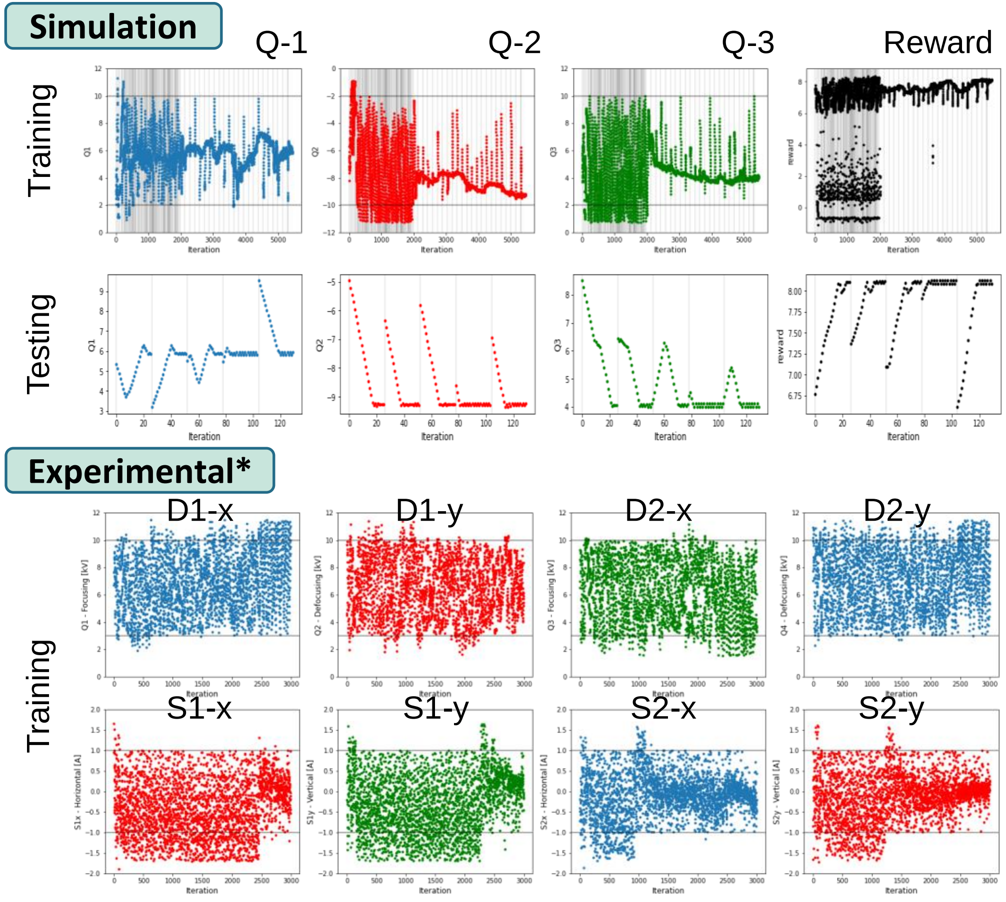
- ✓ Focusing the beam through an aperture using an electrostatic triplet (3 Quadrupoles)
- ✓ Voltage limites: 2 – 10 kV
- ✓ Max. action: +/- 0.25 kV



Actual Experiment



- ✓ Maximizing beam transmission using 2 doublets (4 quads) and 2x2 steerers
- ✓ Electrostatic Quadrupoles :
  - 2 kV to 10 kV
  - Max action +/- 0.25 kV
- ✓ Steering Magnets:
  - -1 A to 1 A
  - Max action +/- 0.25 A



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