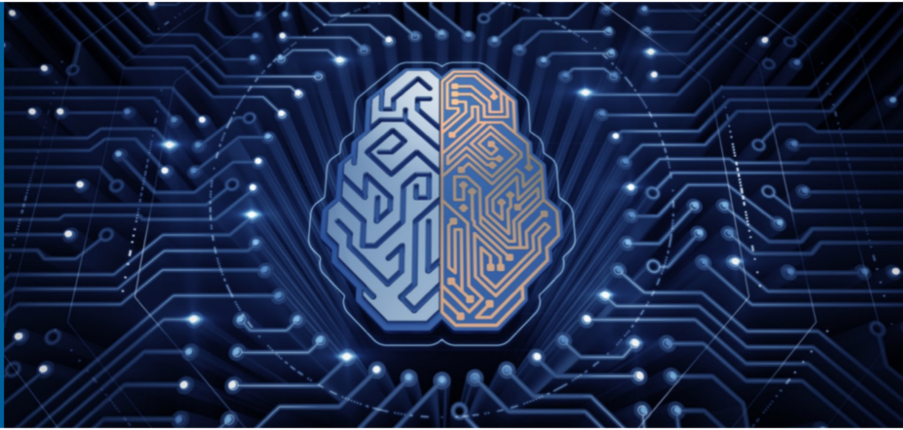
3RD ICFA BEAM DYNAMICS MINI-WORKSHOP ON
MACHINE LEARNING APPLICATIONS FOR PARTICLE ACCELERATORS

Argonne NATIONAL LABORATORY | 75 1946–2021

MACHINE LEARNING TOOLS TO SUPPORT THE ATLAS ION LINAC OPERATIONS AT ARGONNE



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Physics Division
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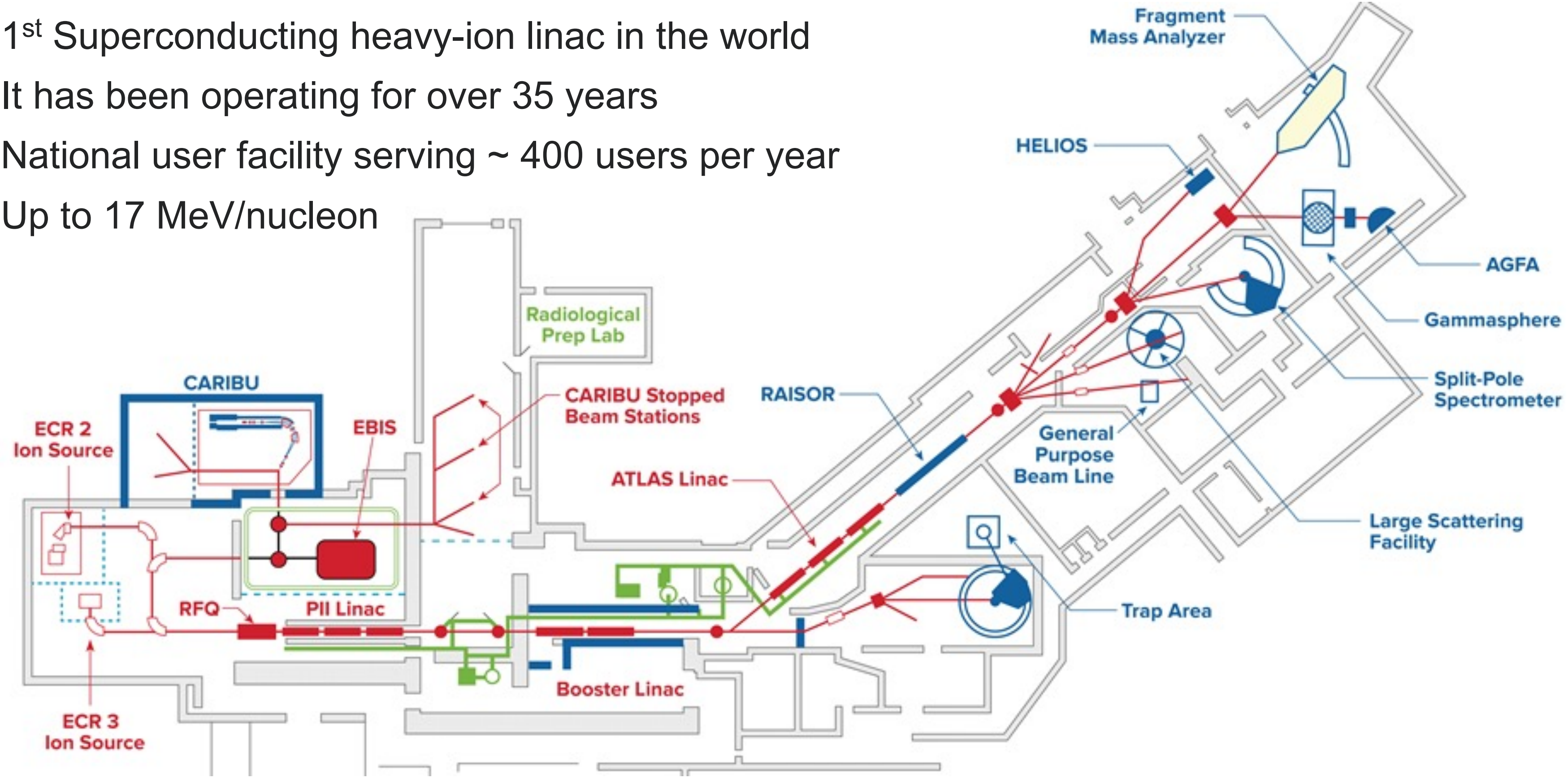
November 2nd, 2022

OUTLINE

- ❑Progress on the ATLAS AI/ML Project.
- ❑Automated data collection established.
- ❑Bayesian Optimization used for online beam tuning.
- ❑AI / ML supporting the commissioning of the new AMIS beamline.
- ❑BO from one beam to another.
- ❑BO with Deep Kernel Learning.
- ❑Reinforcement Learning for online beam tuning.

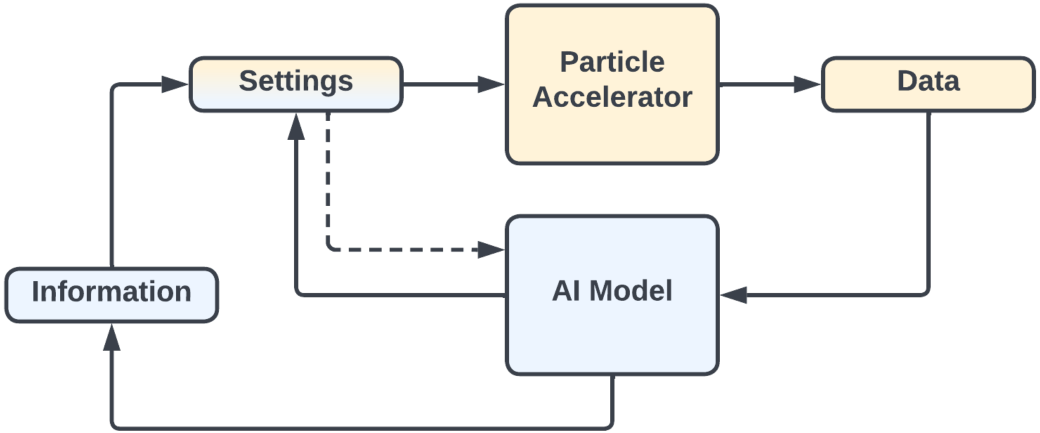
ARGONNE TANDEM LINEAR ACCELERATOR SYSTEM

- ✓1st Superconducting heavy-ion linac in the world
- ✓It has been operating for over 35 years
- ✓National user facility serving ~ 400 users per year
- ✓Up to 17 MeV/nucleon



THE ATLAS AI / ML PROJECT

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



- ✓Surrogate Models
- ✓Virtual Diagnostics
- ✓Tuning Control Model
- ✓…

PROGRESS ON THE 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

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- Virtual model to enhance our understanding of the machine behavior in order to improve performance and optimize particular and new operating modes

ATLAS – FIRST STEPS IN DATA COLLECTION

~80% time of a Data Scientist is Collecting Data, Cleaning and Organizing Data

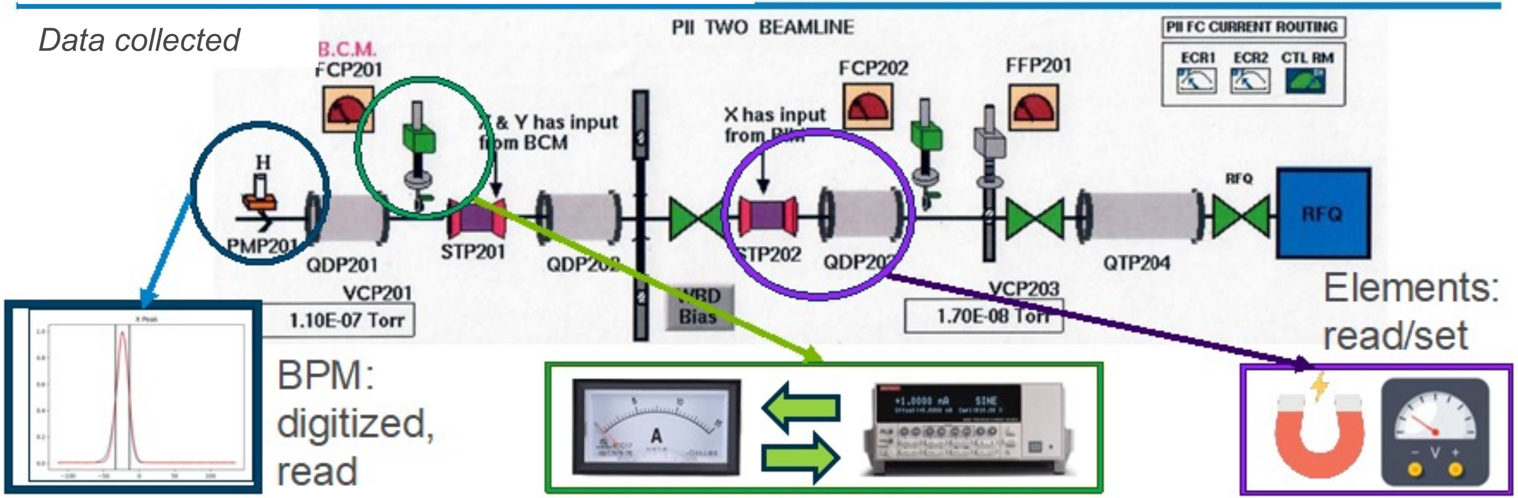
- ✓ Kind of data?
- ✓ How much data?
- ✓ Accessible?
- ✓ Automated?

AUTOMATED DATA COLLECTION ESTABLISHED

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

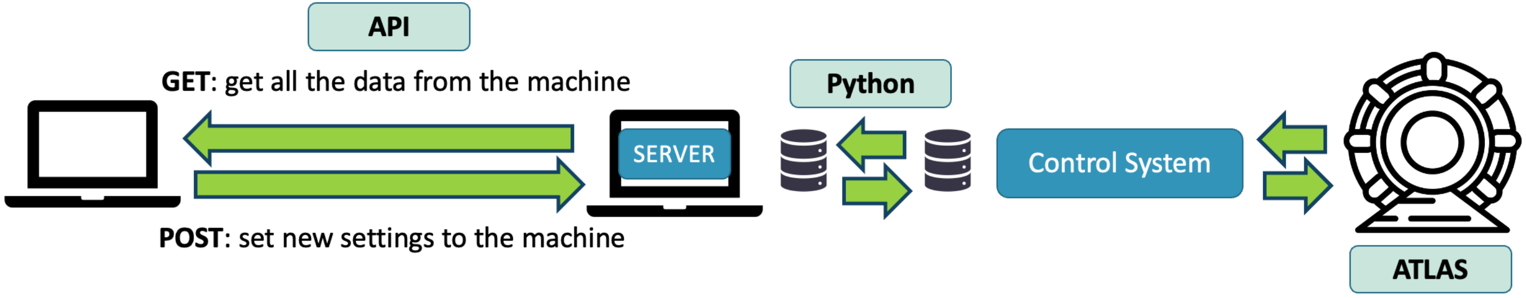
Schematic of data collection interface

Data collected



Now focused on reducing reading times…

ATLAS - DATA COLLECTION



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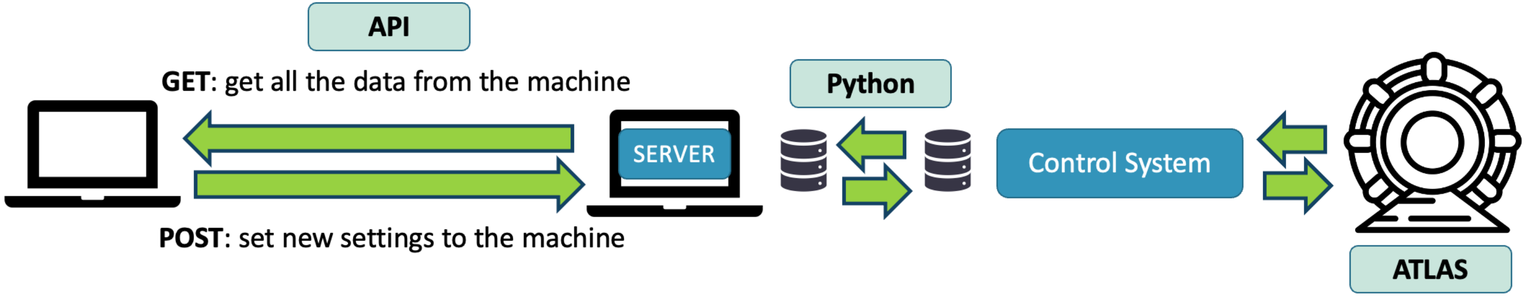
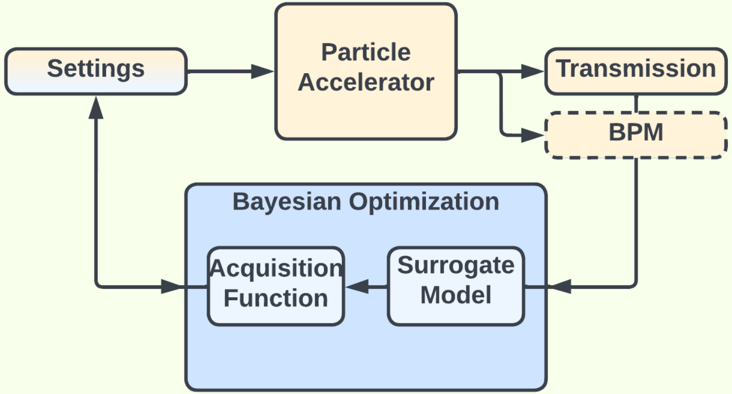


SIMULATION - DATA COLLECTION

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

BAYESIAN OPTIMIZATION USED FOR BEAM TUNING



- **<u>Surrogate Model</u>: A probabilistic model approximating the objective function** [Gaussian Process with RBF Kernel and Gaussian likelihood]

- **<u>Acquisition Function</u> tells the model where to query the system next for more likely improvement** [EI]

- **Bayesian Optimization with Gaussian Processes gives a reliable estimate of uncertainty and guides the model**

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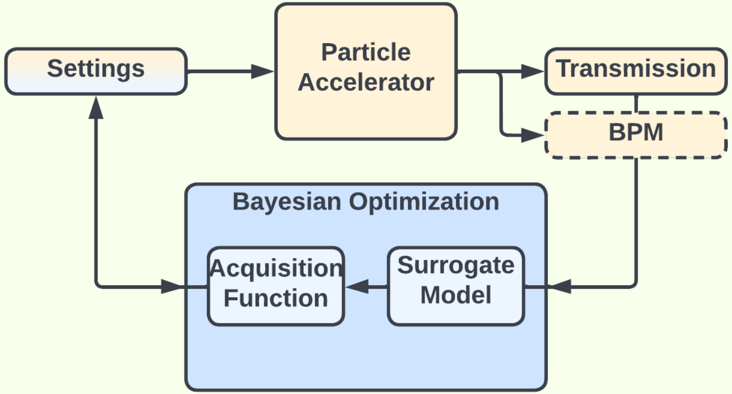

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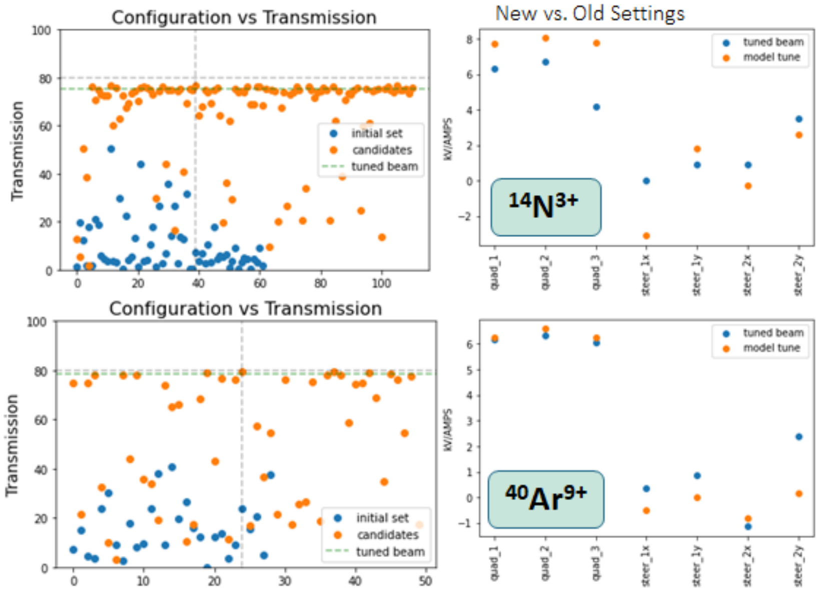
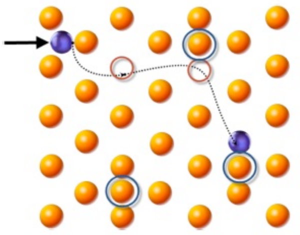
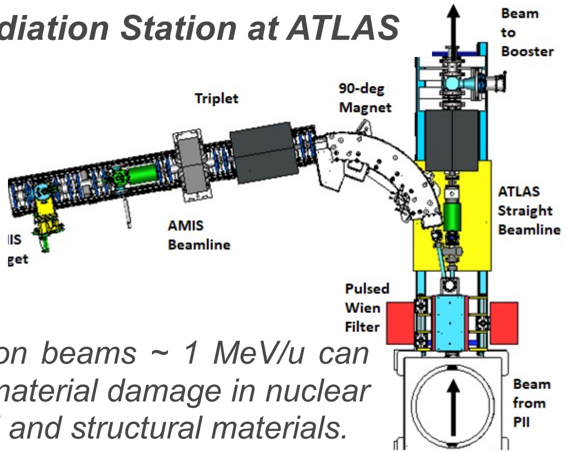


- **7 varied parameters (3 quads + 2 steerers)**
- **Optimization of beam transmission**
- **Case of $^{14}N^{3+}$: 29 historical + 33 random tunes**
- **Case of $^{40}Ar^{9+}$: 29 historical tunes**

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.

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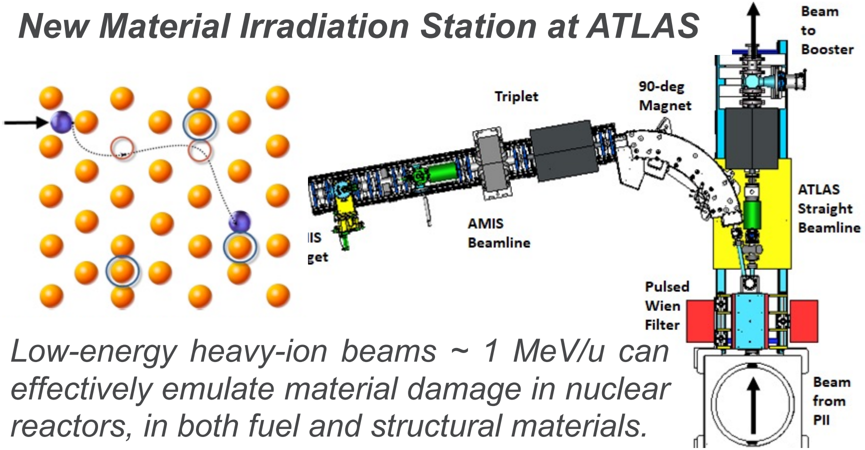

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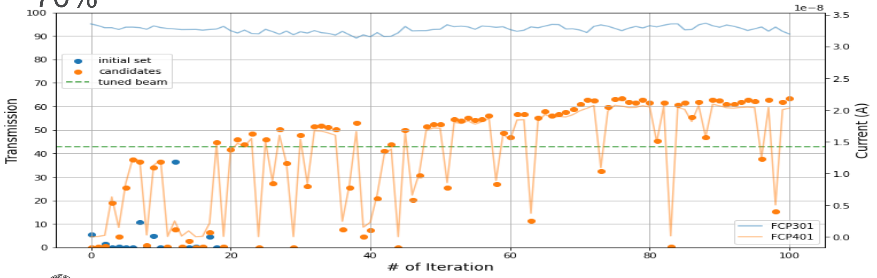
Improving Beam Transmission

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



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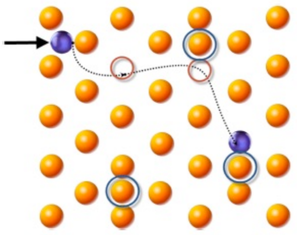

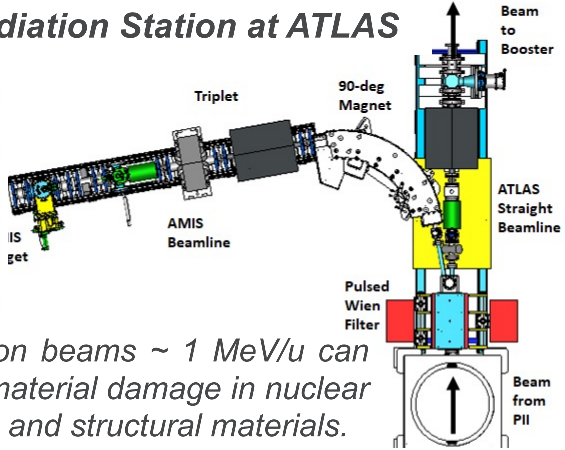

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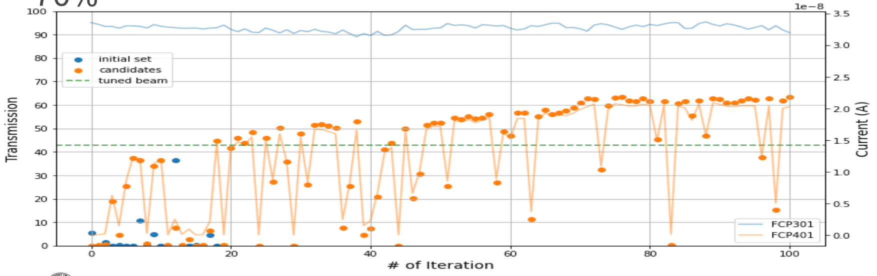
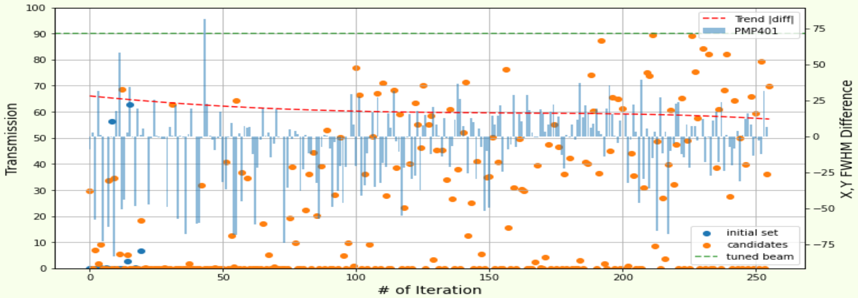
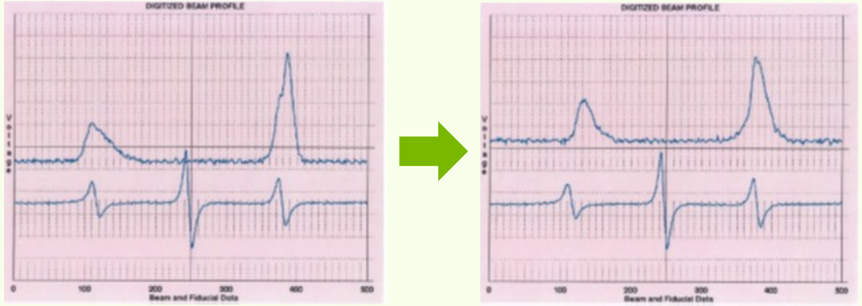


Improving Beam Profiles

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!

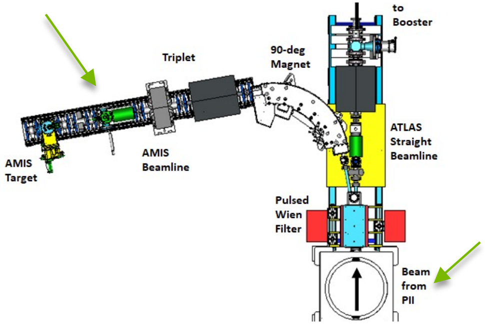


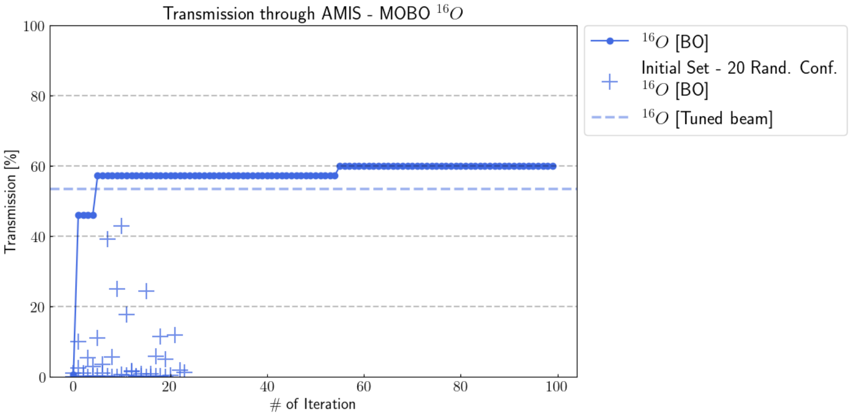
Very encouraging first results!

MULTI-OBJECTIVE BAYESIAN OPTIMIZATION

Improving Beam Transmission

Problem: Maximize beam transmission by varying a triplet, and a doublet [MOBO]; **Results**: 53 → 60%





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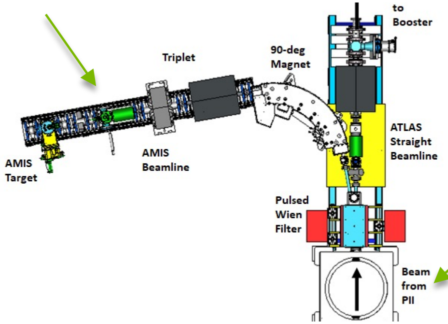

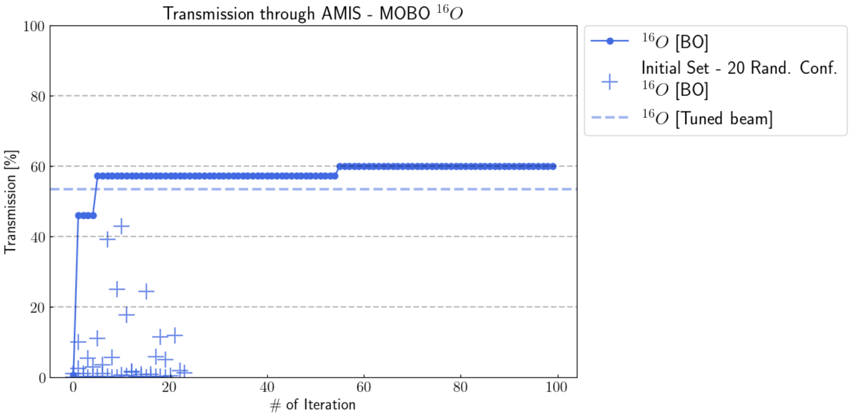

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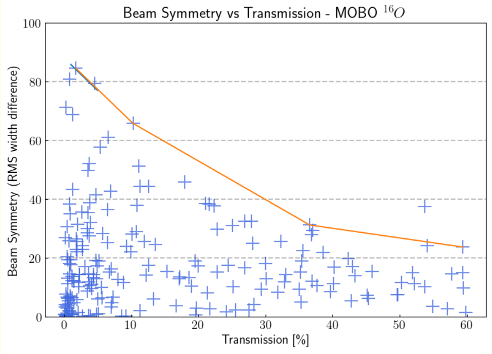

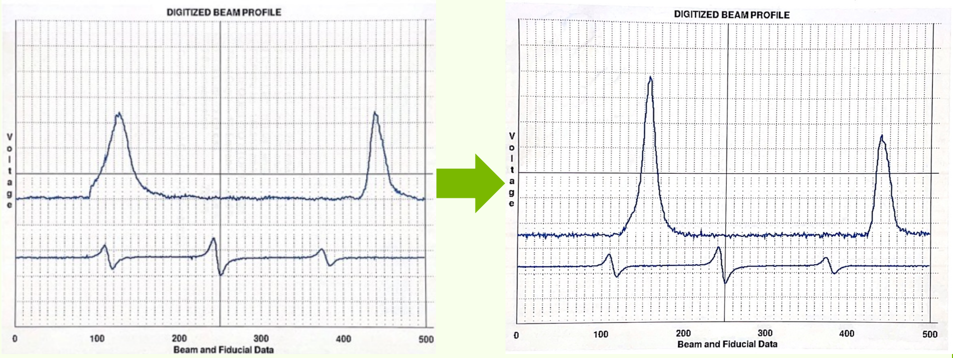

BO – TRANSFER FROM 16O BEAM TO 22NE BEAM

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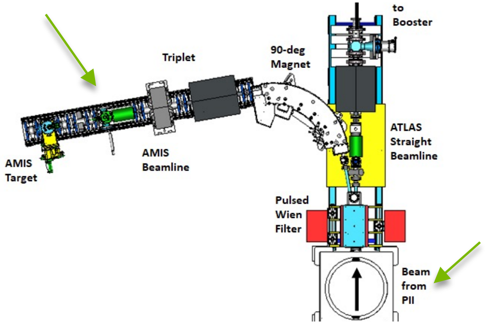
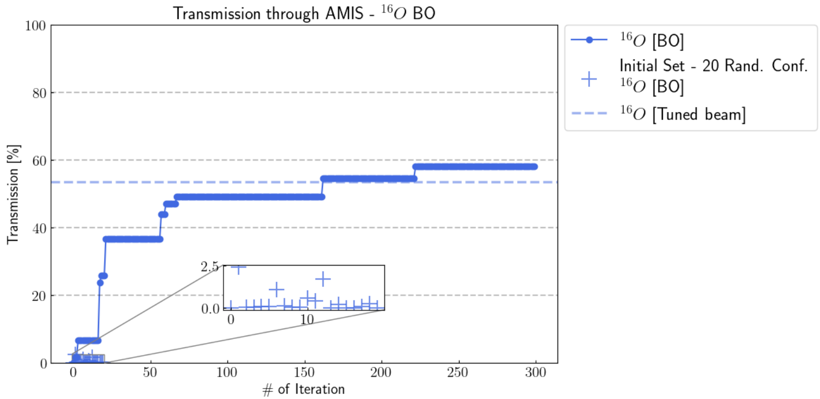
Problem: Maximize beam transmission by varying a triplet, and a doublet [BO]; **Results**: 53 → 58%





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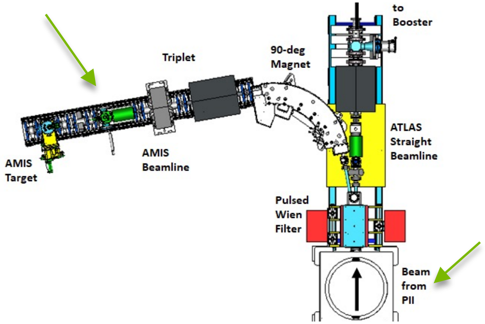
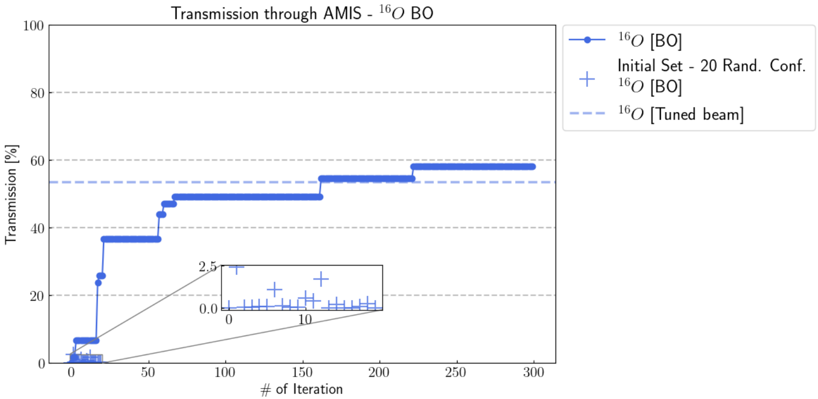
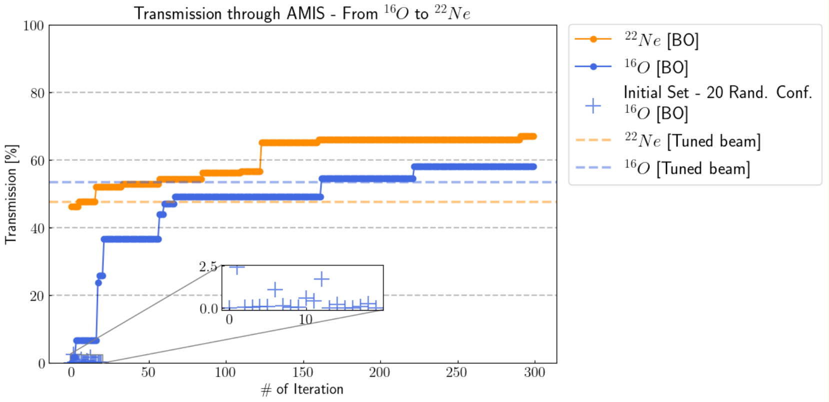




Improving Beam Transmission

Problem: Maximize beam transmission by varying a triplet, and a doublet [BO]; **Results**: 48 → 67%

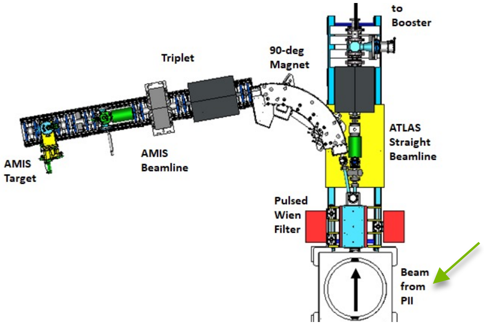


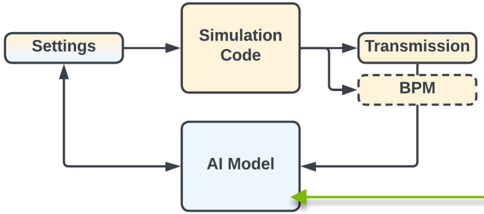
BO WITH DEEP KERNEL LEARNING AT AMIS

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

Improving Beam Transmission

Problem: Maximize beam transmission by varying a triplet [BO+DKL]; **Results**: 53 → 60%





NN trained offline with TRACK [4k simulations train set /1k simulations for val set]

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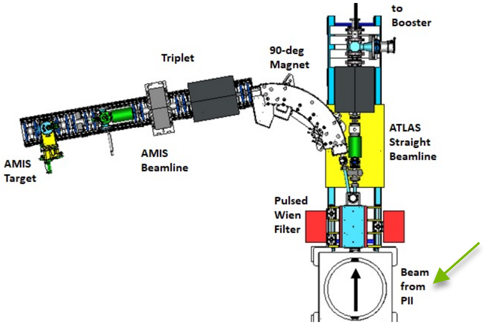

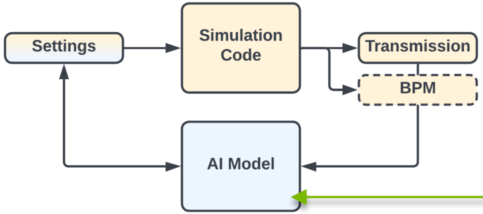

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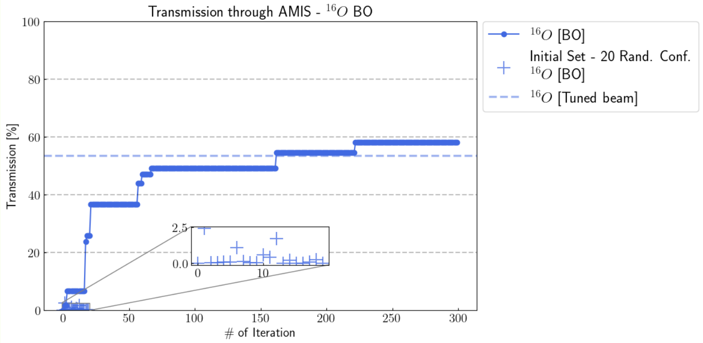

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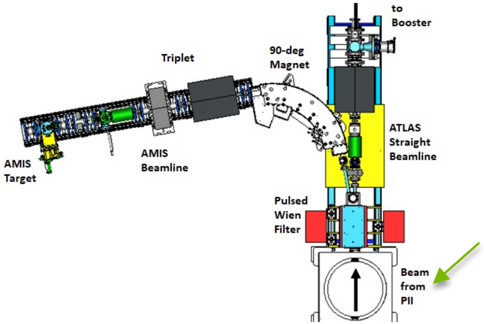

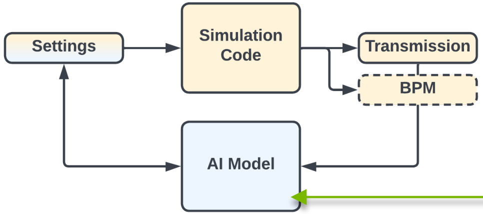

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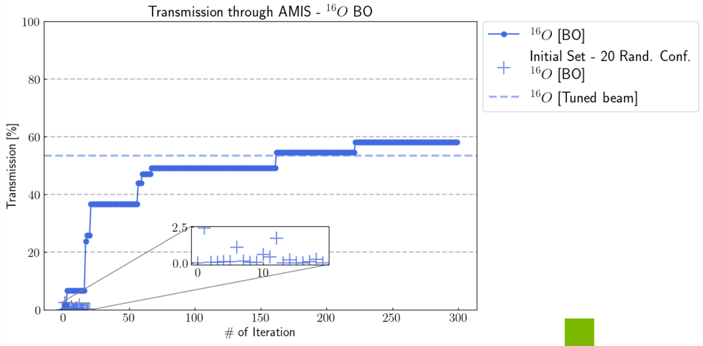

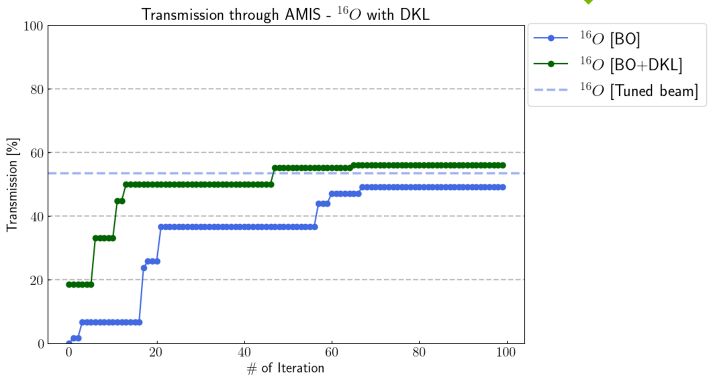

BO+DKL – TRANSFER FROM 16O TO 22NE BEAM

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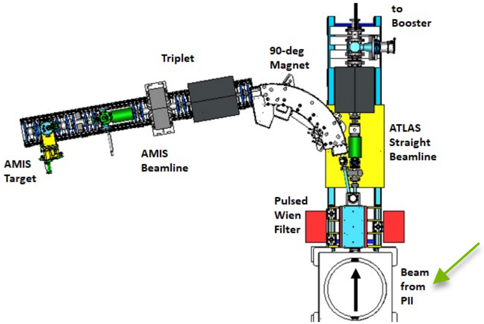

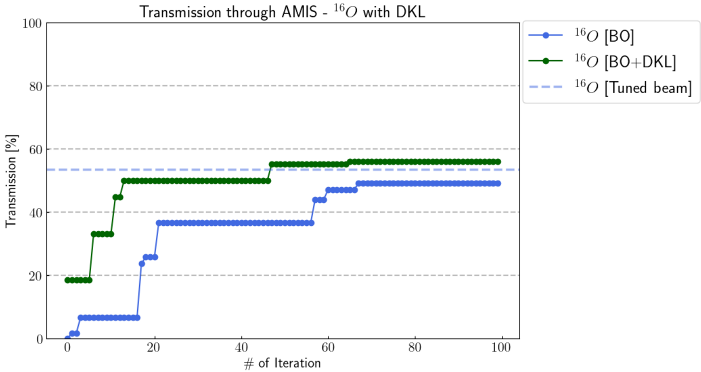

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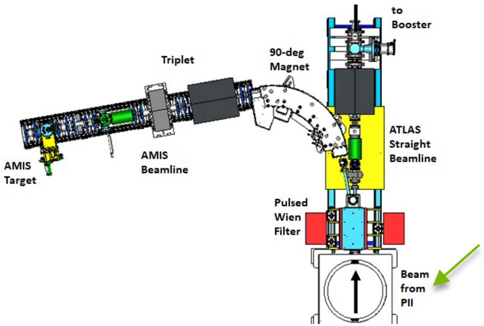

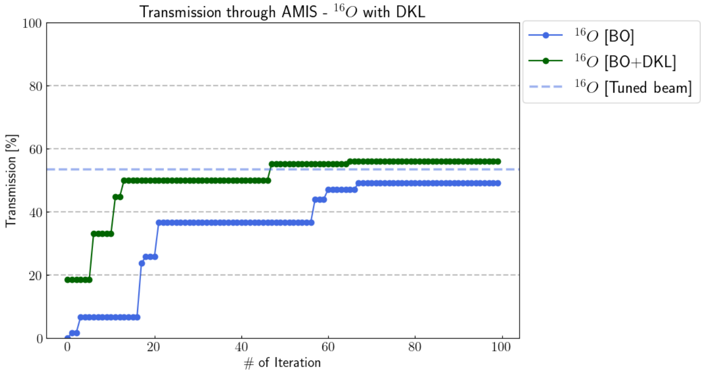

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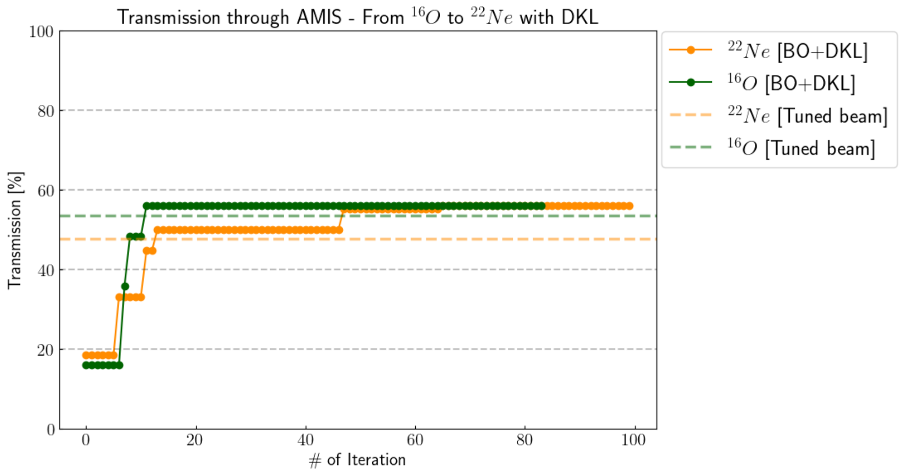
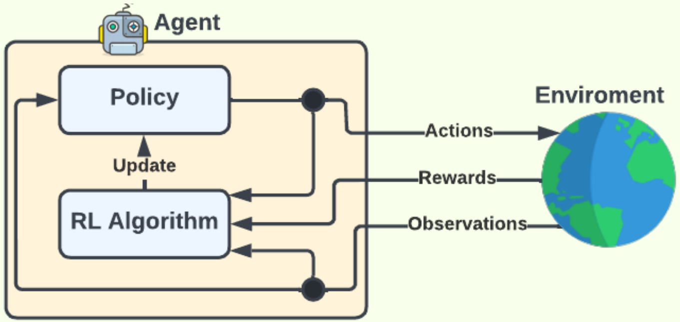
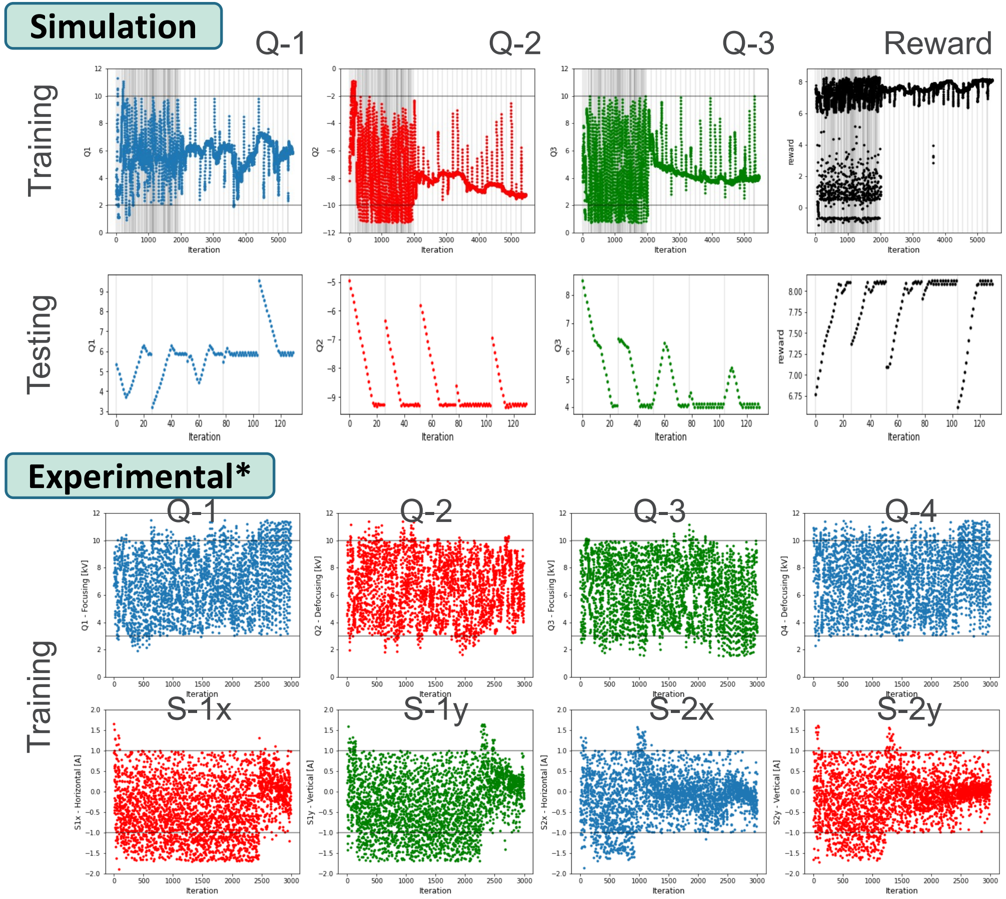


REINFORCEMENT LEARNING FOR FINE TUNING



- ✓ **Method**: Deep Deterministic Policy Gradient (DDPG); Actor-Critic Approach
- ✓ **Simulation Case**: Focusing beam on target using a triplet (3 Quadrupoles)
- ✓ **Experimental Case**: Maximizing beam transmission using 4 quads and 2 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



CONCLUSIONS AND NEXT STEPS

✓**Automated data collection** and testing the integration of new devices as the pepper pot and functionalities such as automated quad scan procedure.

✓**Successfully trained and deploy a BO with GP on real machine for a subsection of ATLAS.**

✓**Transfer model from one beam to another beam.**

✓**Integration of RL model with the real machine.**

✓ Misalignments and Steerers added into TRACK code.

✓ Next Steps:

- Improve existing models (ex. acquisition function).
- Better offline training (misalignments and steerers added), online tuning.

✓Current Challenges:

- Possible damage to devices when beam is lost during model training.

ACKNOWLEDGMENTS

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