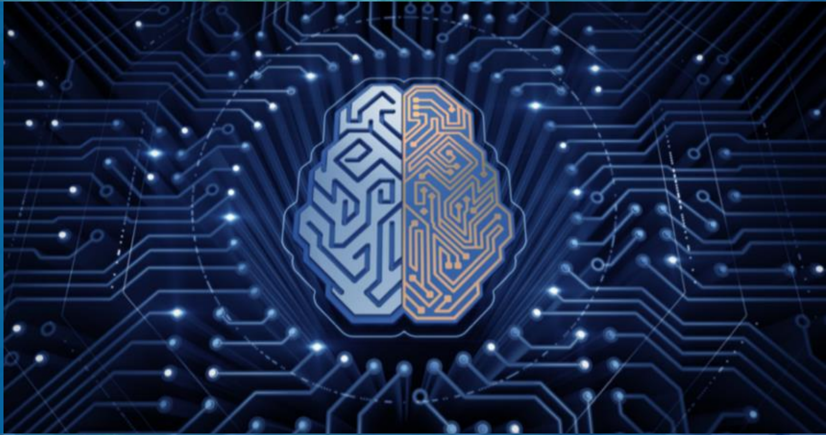
4TH ICFA BEAM DYNAMICS MINI-WORKSHOP ON MACHINE LEARNING APPLICATIONS FOR PARTICLE ACCELERATORS
GYEONGJU, SOUTH KOREA, MARCH 5-8, 2024

MACHINE LEARNING TOOLS FOR HEAVY-ION LINAC OPERATIONS



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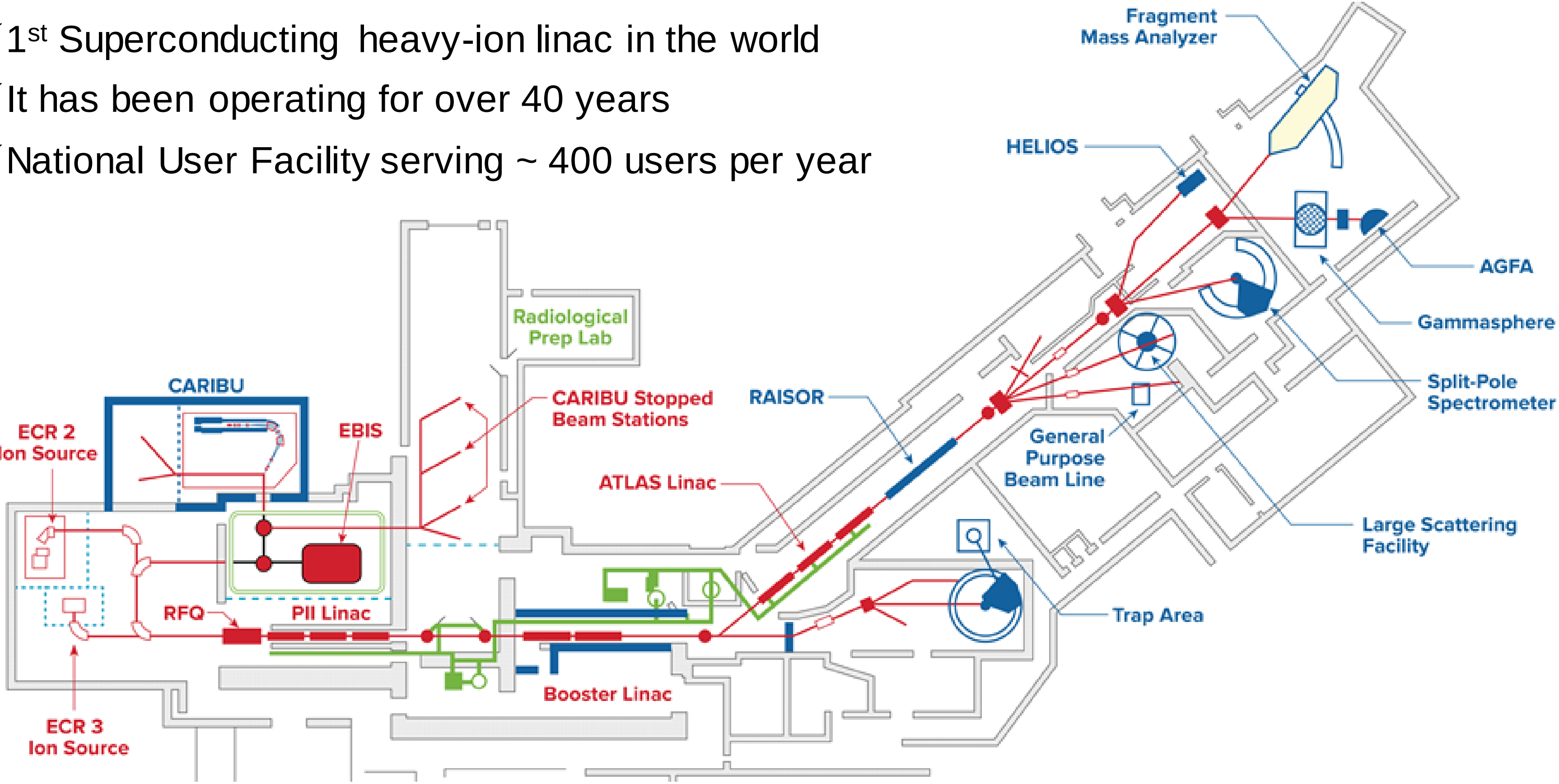
OUTLINE

- ❑ Brief Overview of the ATLAS Facility and AI-ML Project
- ❑ Project Status and Summary of Progress
- ❑ Progress & Highlights
- ❑ Future Plans – New Project …

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



BRIEF OVERVIEW OF THE ATLAS 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
- The main project goals are:
  - **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**
    … completed for several sections of the linac
  - **Virtual model to enhance understanding of machine behavior to improve performance and optimize particular/new operating modes** ... progress

SUMMARY OF PROGRESS & HIGHLIGHTS

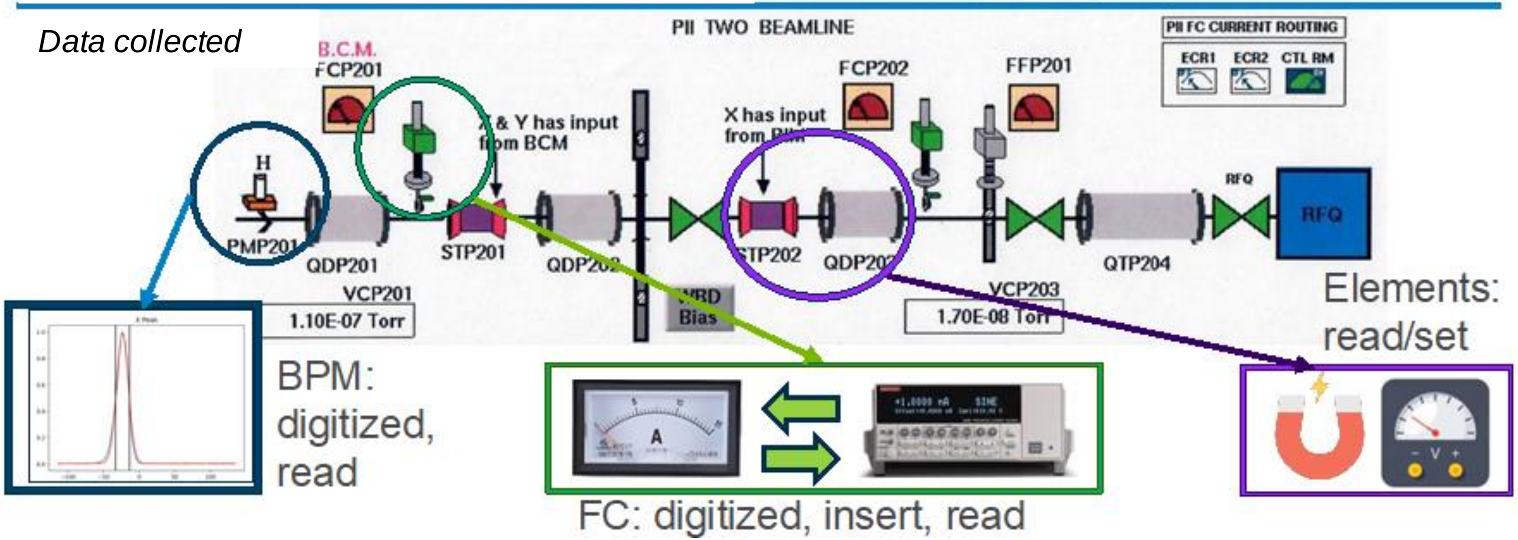
- ❑ Automated data collection and two-way communication established
- ❑ Bayesian Optimization (BO) successfully used for online beam tuning
- ❑ Multi-Objective BO (MOBO) to optimize transmission and beam size
- ❑ AI-ML supporting the commissioning of a new beamline (AMIS)
- ❑ Transfer learning from one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

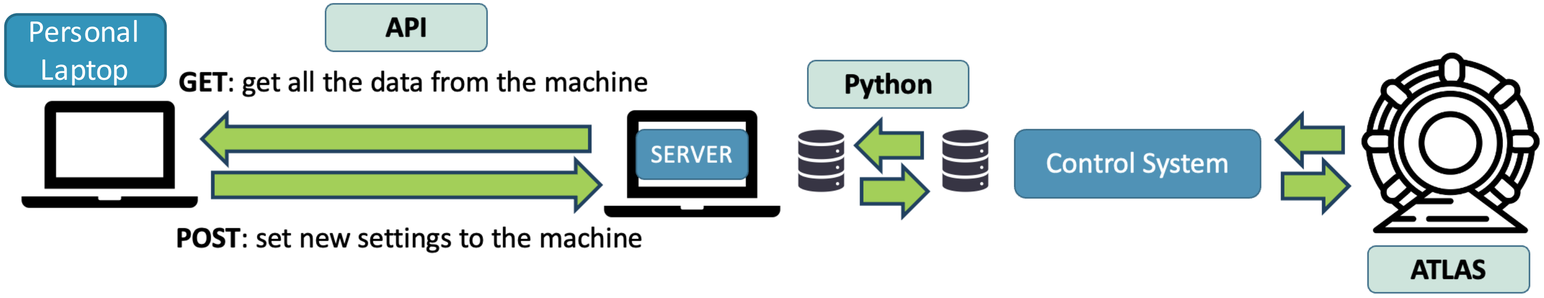
Schematic of data collection interface

Data collected



Now working on reducing acquisition time …

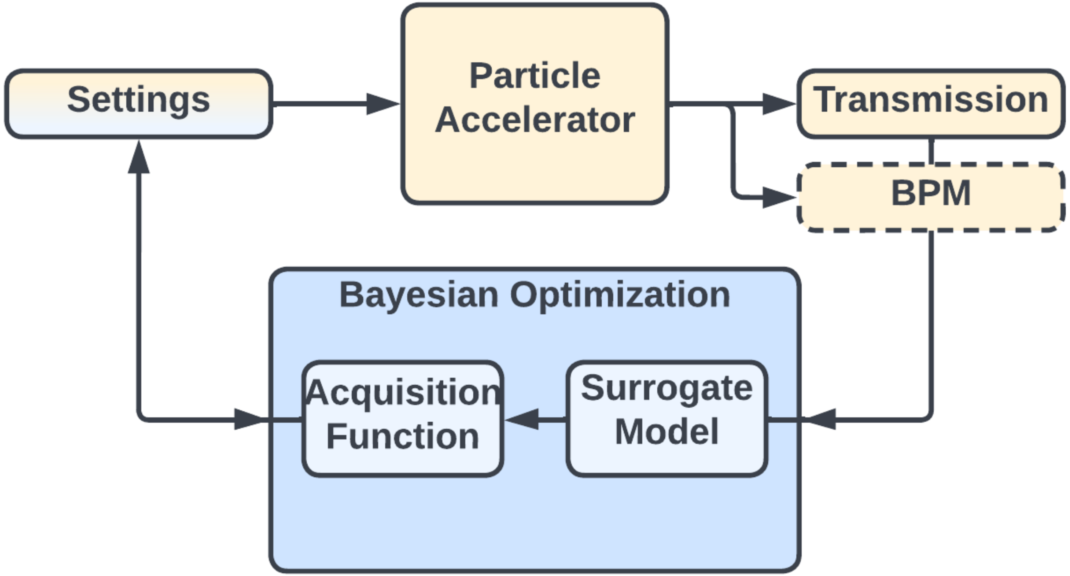
ONLINE – INTERFACE WITH CONTROL SYSTEM



OFFLINE – INTERFACE WITH BEAM SIMULATION

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

BRIEF DESCRIPTION OF BAYESIAN OPTIMIZATION

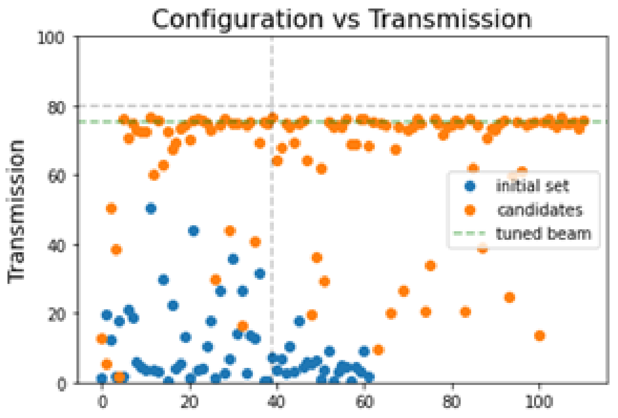


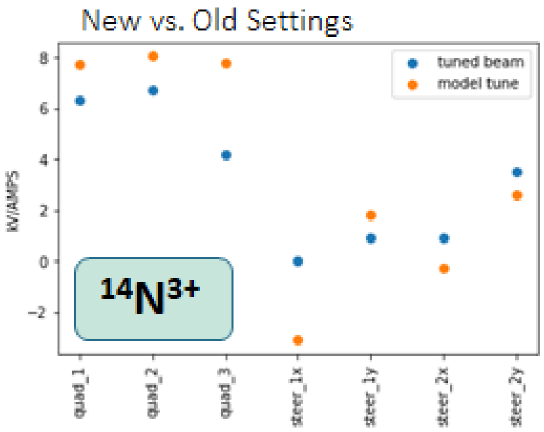
- ✓ <u>**Surrogate Model**</u>**: A probabilistic model approximating the objective function**
  [Gaussian Process with Radial Basis Function (RBF) Kernel and Gaussian likelihood]
- ✓ <u>**Acquisition Function**</u> **tells the model where to query the system next for more likely improvement**
- ➢ **Bayesian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

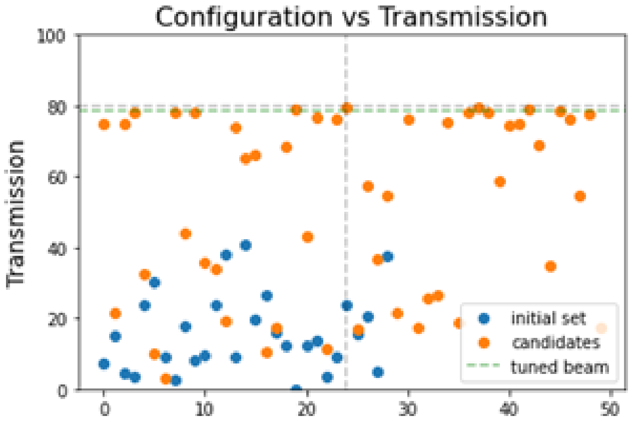
BAYESIAN OPTIMIZATION USED FOR BEAM TUNING

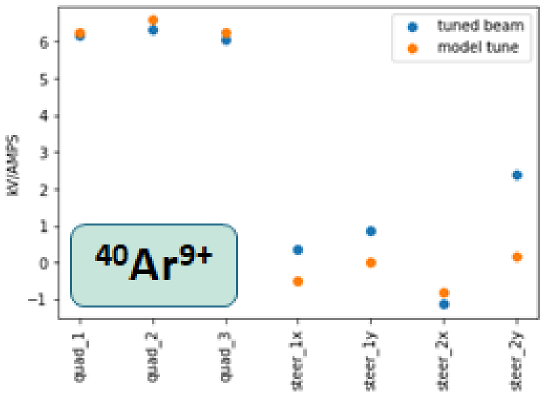
Beamline under study

- 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



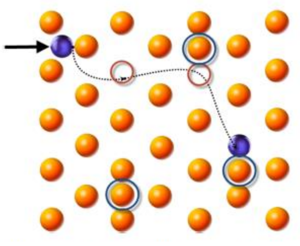


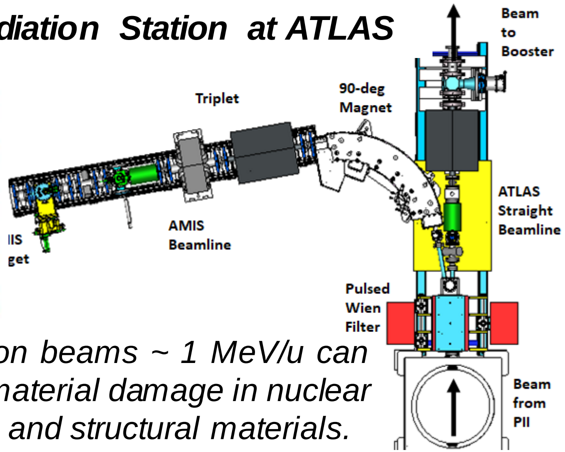




AI/ML SUPPORTING AMIS LINE COMMISSIONING

New Material Irradiation Station at ATLAS

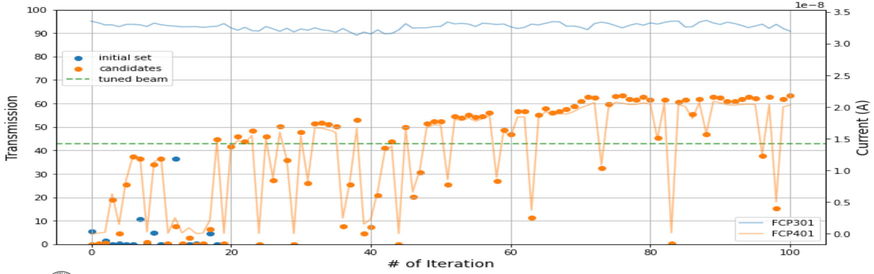




Low-energy heavy-ion beams ~ 1 MeV/u can effectively emulate material damage in nuclear reactors, in both fuel and structural materials.

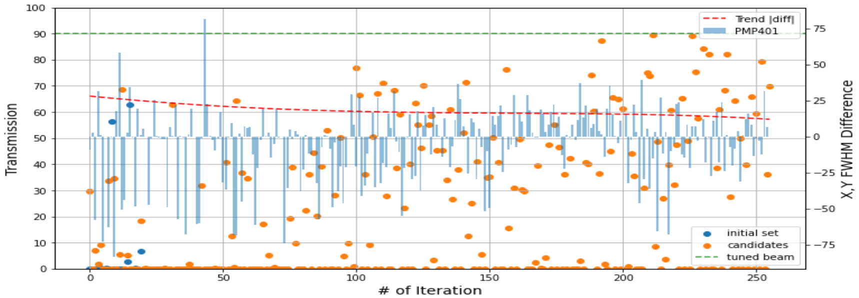
Improving Beam Transmission

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

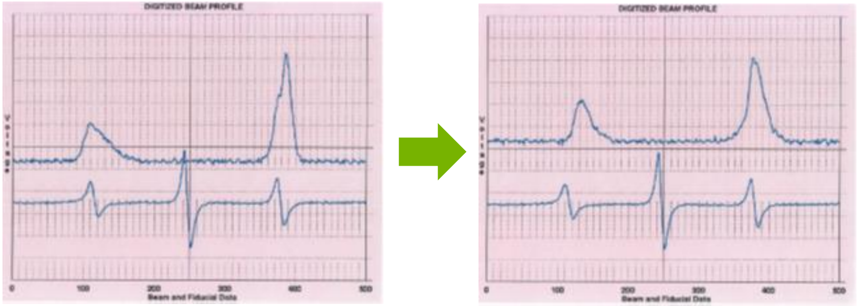


Improving Beam Profiles

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!



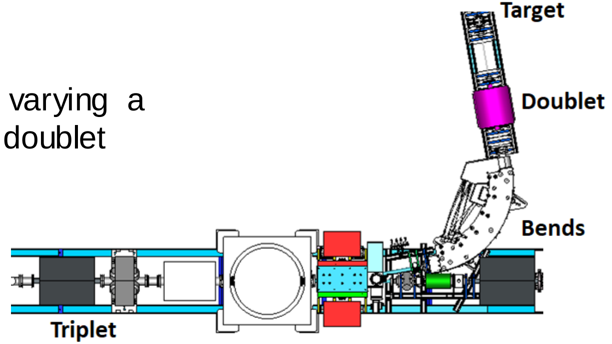
Very encouraging first results!

MULTI-OBJECTIVE BAYESIAN OPTIMIZATION

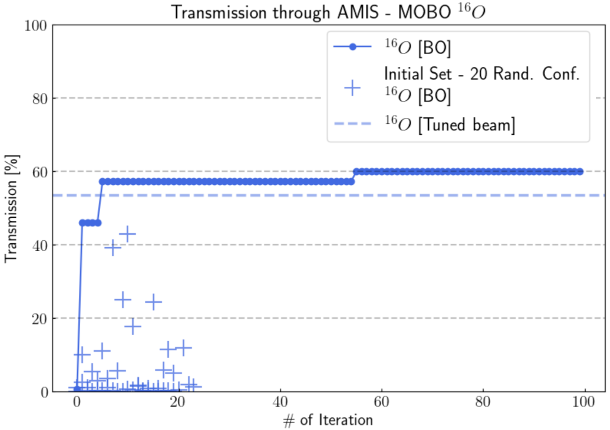
Multi-Objective Problem: Optimize transmission and beam profiles on target - Not easy for an operator!

Improving Beam Transmission & Improving Beam Profiles

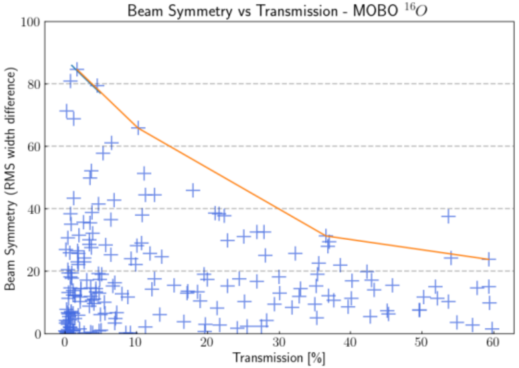
AMIS line: varying a triplet and a doublet



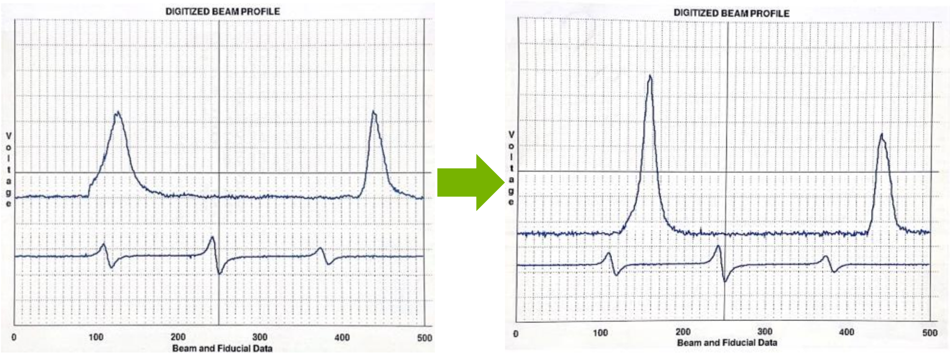
MOBO Results:
53→ 60%
Beam transmis.



MOBO Results: Pareto Front



MOBO Results: More symmetric beam profiles



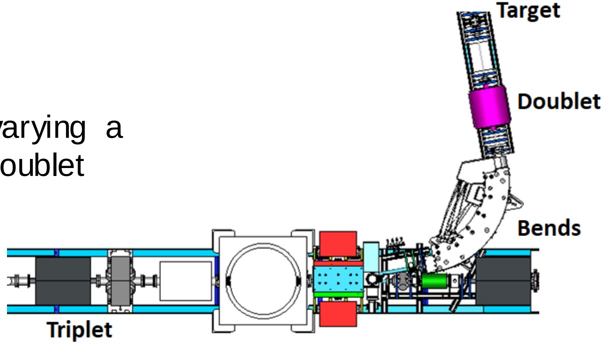
TRANSFER LEARNING FROM ^{16}O TO ^{22}NE - BO

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

Training model on ^{16}O

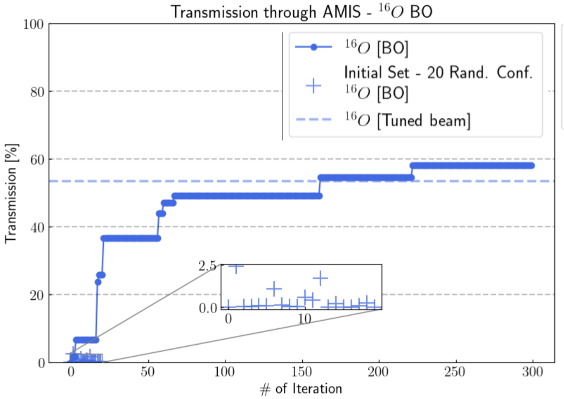
Applying same model to ^{22}Ne

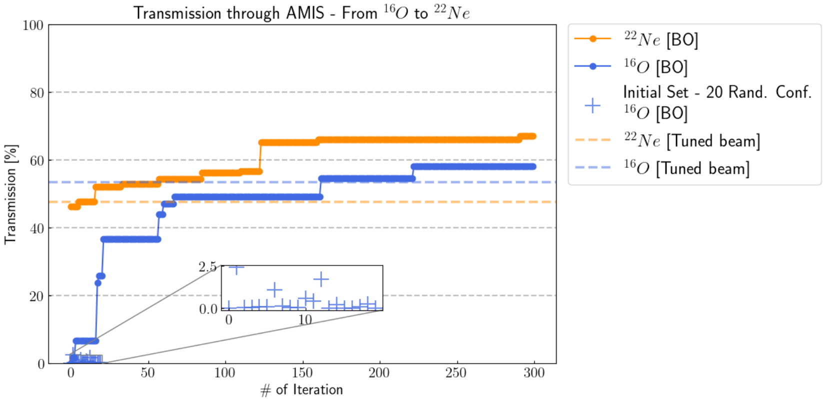
AMIS line: varying a triplet and a doublet



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 %

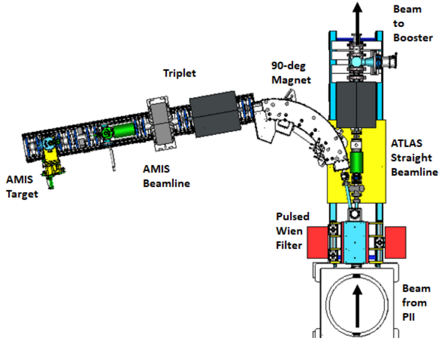
With more training for 22Ne: 48 → 67%

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

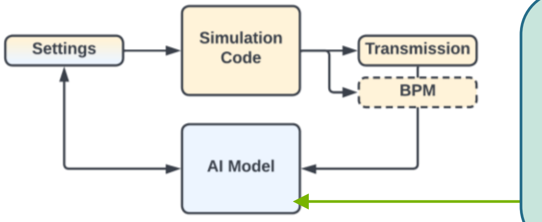
TRANSFER LEARNING FROM SIMULATION TO ONLINE

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

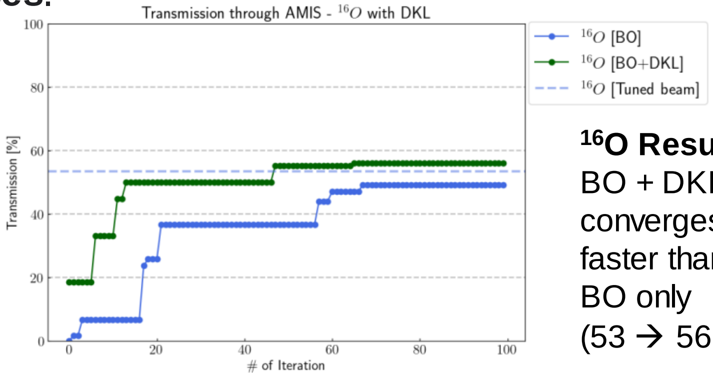
Method: Deep kernel learning (DKL) to **combine the representational power of neural networks with the reliable uncertainty estimates of Gaussian processes**.



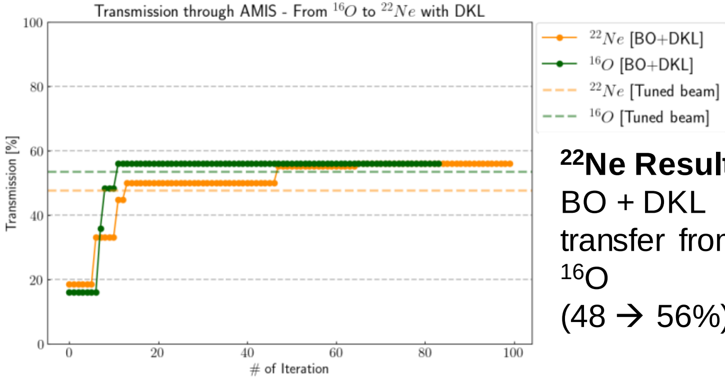
AMIS Line: Maximize beam transmission by varying a triplet [BO+DKL]



NN trained offline with TRACK simulations [4k training set /1k evaluation set]



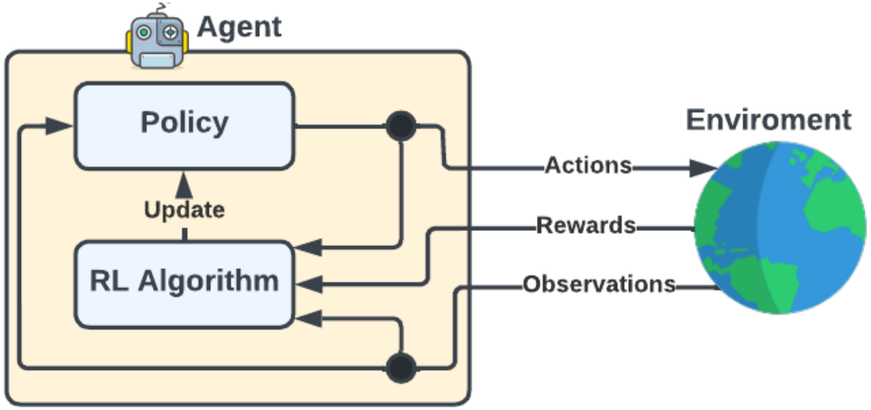
^{16}O Results: BO + DKL converges faster than BO only (53 → 56%)



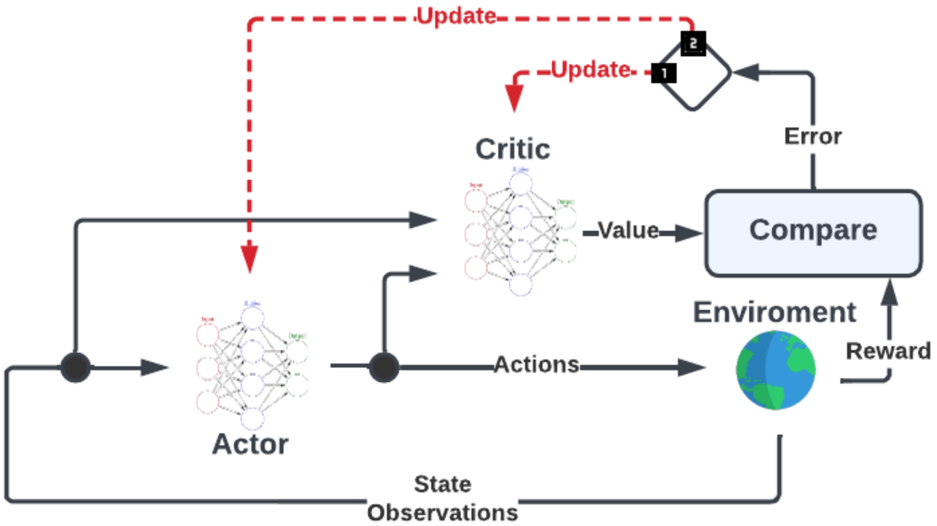
^{22}Ne Results: BO + DKL transfer from ^{16}O (48 → 56%)

BRIEF DESCRIPTION OF REINFORCEMENT LEARNING

Basic Concept



Implementation Example

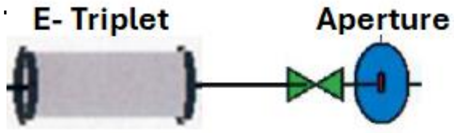


- ✓ **Essence:** Learning from experience based on interaction with the environment
- ✓ **Action:** Varies the parameters/variables of the problem
- ✓ **Reward:** Measures the goal function to maximize/optimize
- ✓ **Policy:** How the process evolves/learns
- ✓ **Algorithm used:** Deep Deterministic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

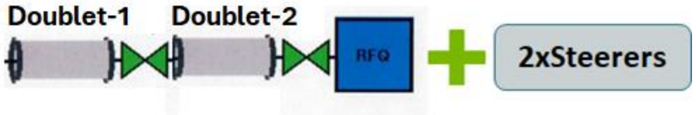
REINFORCEMENT LEARNING: FIRST ATTEMPT…

Simulation Case

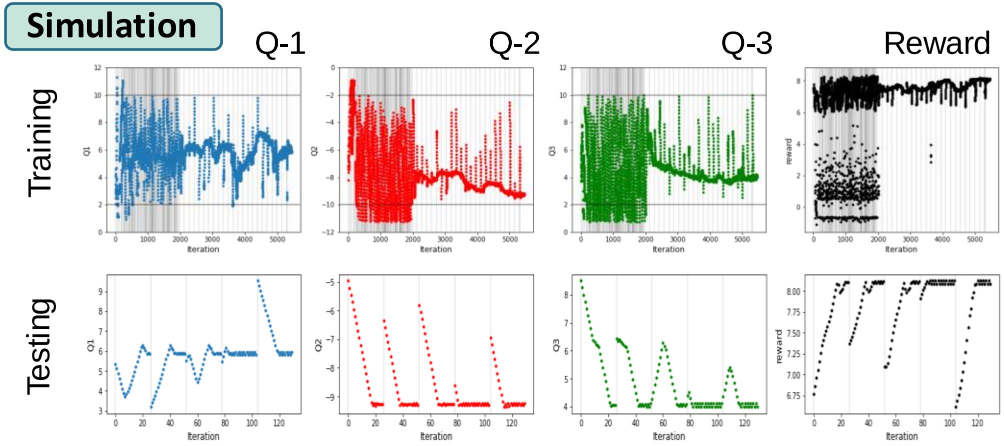
- ✓ Focusing the beam through an aperture using an electrostatic triplet (3 Quadrupoles)
- ✓ Voltage limites: 2 – 10 kV
- ✓ Max. action: +/- 0.25 kV

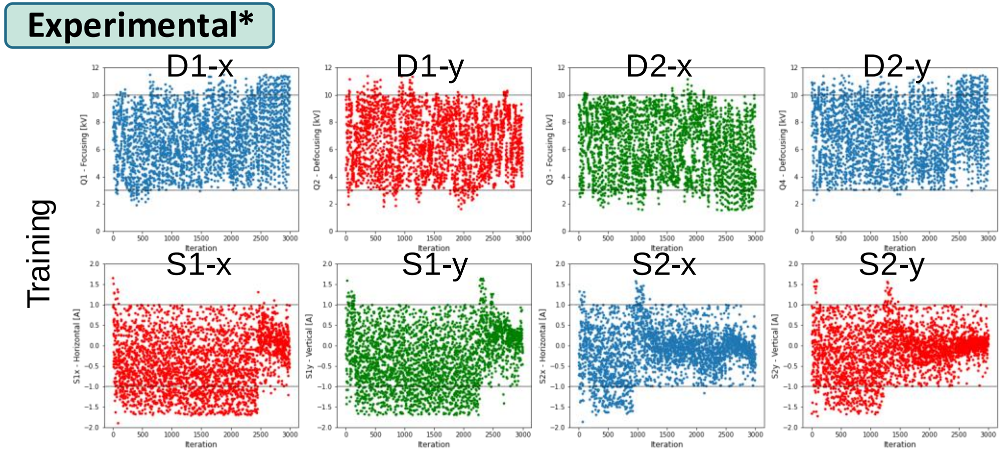


Actual Experiment



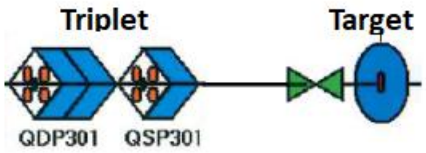
- ✓ Maximizing beam transmission using 2 doublets (4 quads) and 2x2 steerers
- ✓ Electrostatic Quadrupoles :
  - 2 kV to 10 kV
  - Max action +/- 0.25 kV
- ✓ Steering Magnets:
  - -1 A to 1 A
  - Max action +/- 0.25 A





REINFORCEMENT LEARNING: FIRST EXP. SUCCESS

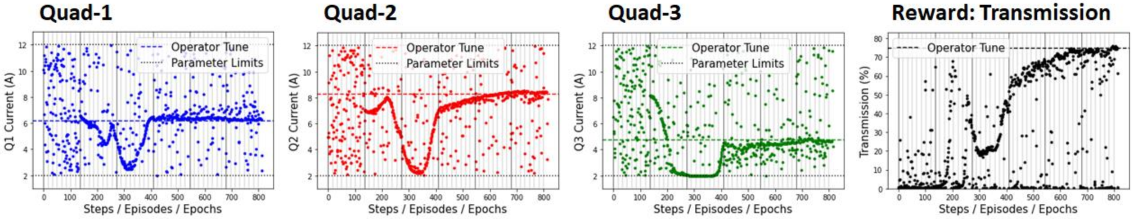
Beamline under study



Objective: Maximize beam transmission to target

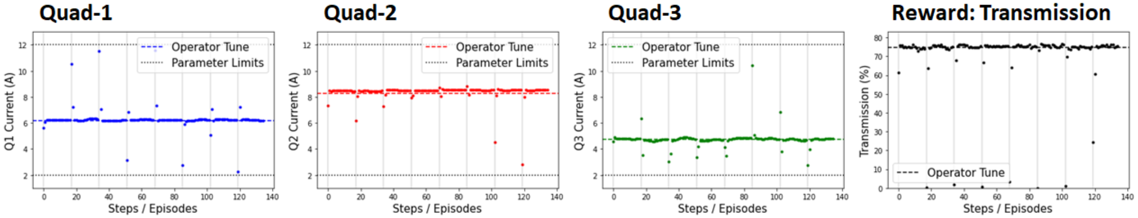
- Varying 3 magnetic quads
- Quadrupole Current limits: 2 – 12 Amps
- Max. Action: Full range

Training - Online



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

Testing - Online



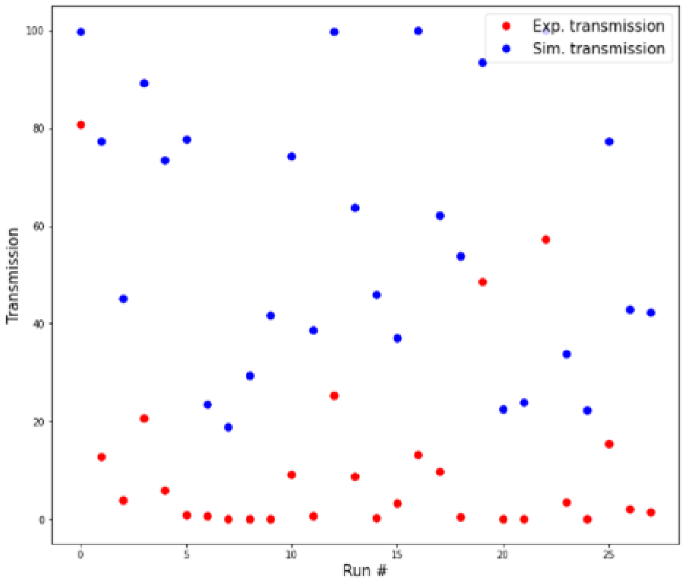
➢ Testing done for 8 episodes (16 steps/episode)

➢ Model converges in 2-3 steps, starting from random conf.

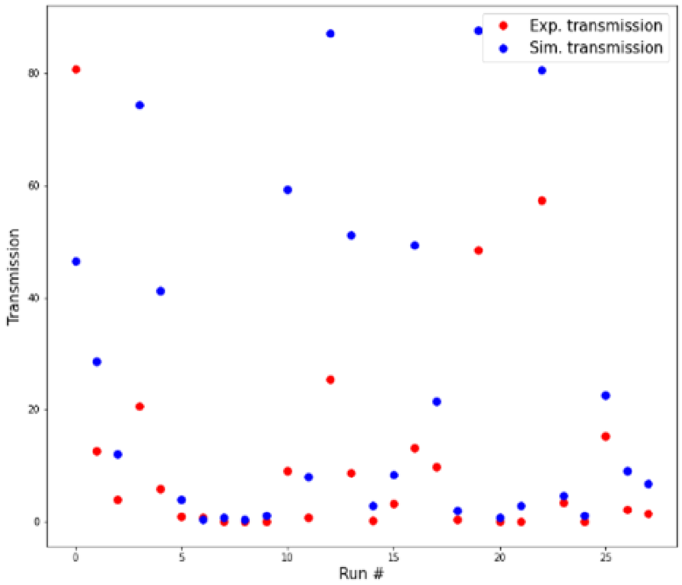
➢ **RL is much slower than BO, requiring significantly more data → more iterations to train, but once trained, it takes fewer steps to converge to the best solution …**

PROGRESS ON THE VIRTUAL MACHINE MODEL

No Steering (<Diff> ~ 46%)



With Steering (<Diff> ~ 16%)



- ✓ In order to develop a realistic virtual machine mode, we need first to improve the predictability of the physics model based on beam dynamics simulations (using TRACK).
- ✓ Significant improvement was realized by adding the steering effects, adding information on misalignments and initial beam distribution should close the gap further.
- ✓ Once the agreement is ~ 1%, a surrogate model will be developed based on the simulations.

NEW AI-ML PROJECT: BRIEF OVERVIEW

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

- The main objectives of the new 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.

MANY THANKS TO

- ❑ Jose Martinez: He was the project postdoc and did most of the work …

- ❑ ATLAS Controls Team:

  Daniel Stanton and Kenneth Bunnell

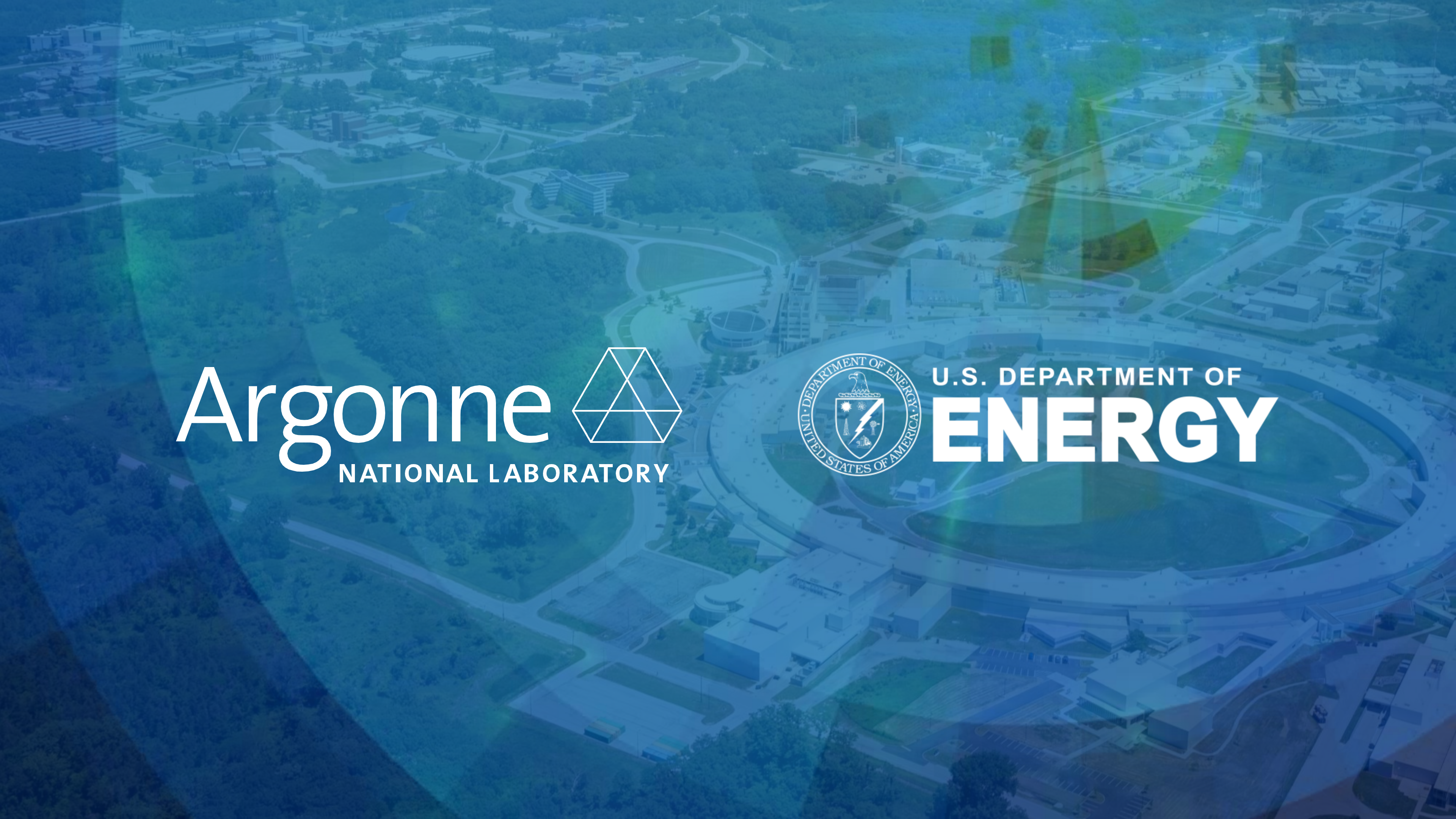
- ❑ ATLAS Operations Team:

  Ben Blomberg, Eric Letcher and Gavin Dunn

- ❑ ATLAS Users Liaison and beam time schedular:

  Daniel Santiago

THANK YOU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