MACHINE LEARNING TO SUPPORT THE ATLAS LINAC OPERATIONS AT ARGONNE

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Abstract: The use of artificial intelligence can significantly reduce the time needed to tune the ATLAS heavy ion linac. After establishing automatic data collection procedures and analyzed the data, we have developed, and tested machine learning models to tune and control the machine. Models based on Bayesian Optimization (BO) and Reinforcement Learning (RL) will be presented and their performance compared and discussed. RL and BO are well known AI techniques, often used for control systems. The results will be presented for a subsection of ATLAS that contains complex elements such as the radio-frequency quadrupole. The models will be later generalized to the whole ATLAS linac, and similar models can be developed for any accelerator with a modern control system.

Project Description & Data Collection

Brief Description of Project

- ❑ 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 automatic and electronic data collection for both machine and beam data

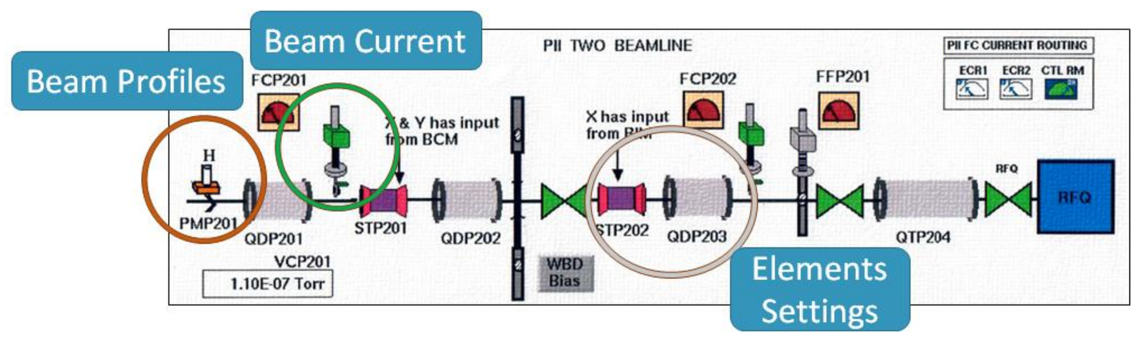
✓ **Online tuning model** to optimize operations and shorten beam tuning time and make more beam time available for the experimental program

✓ **Virtual machine model** to enhance our understanding of the machine behavior, improve machine performance and optimize particular and new operating modes

Available Data & Its Collection

~ 80% of a Data Scientist's time is Collecting Data, Cleaning, Organizing and Labelling Data. Kind of data? How much data? Is it Accessible? Is it Automated?

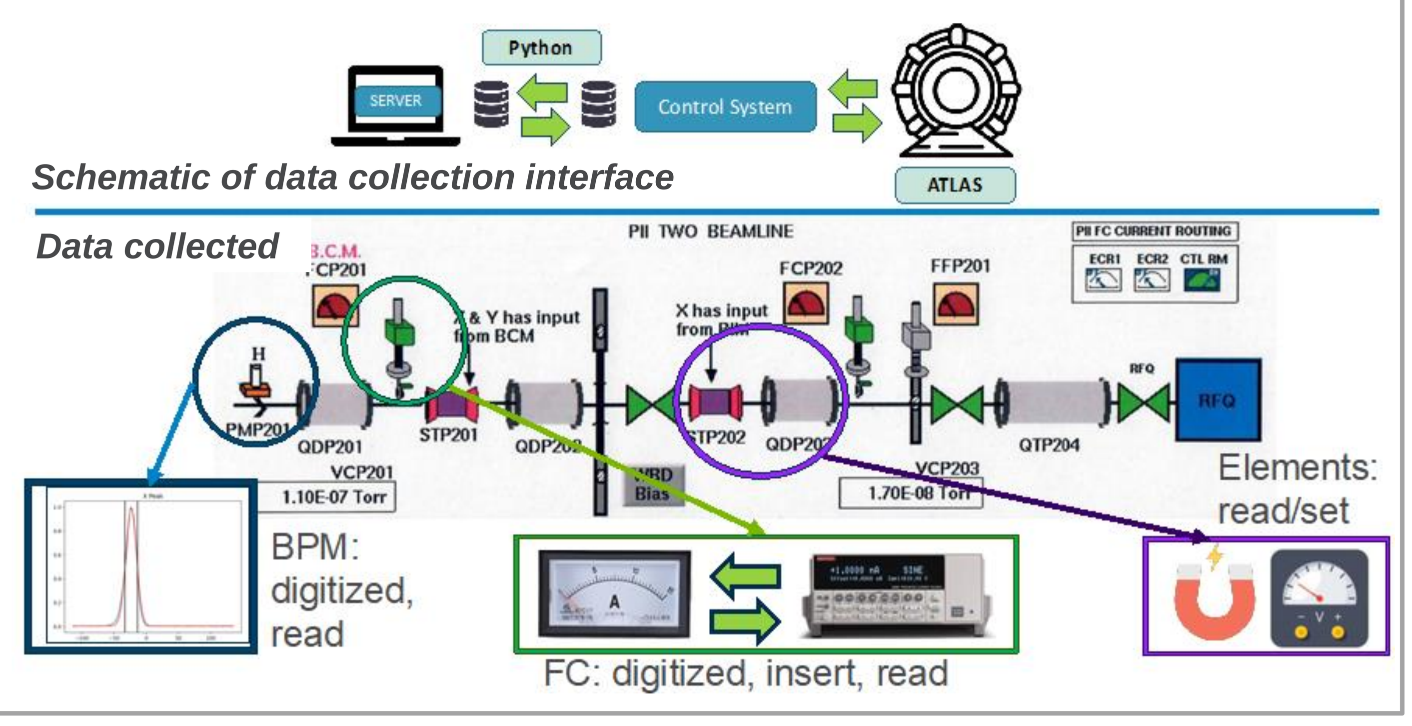
Typical Data Available at ATLAS



- ○ Only elements settings could be saved on-demand using an interface to the Control System (Vsystem)
- ○ Faraday cup readings and beam profiles were not digitized or saved
- ➢ Digitize and collect the data required for beam tuning

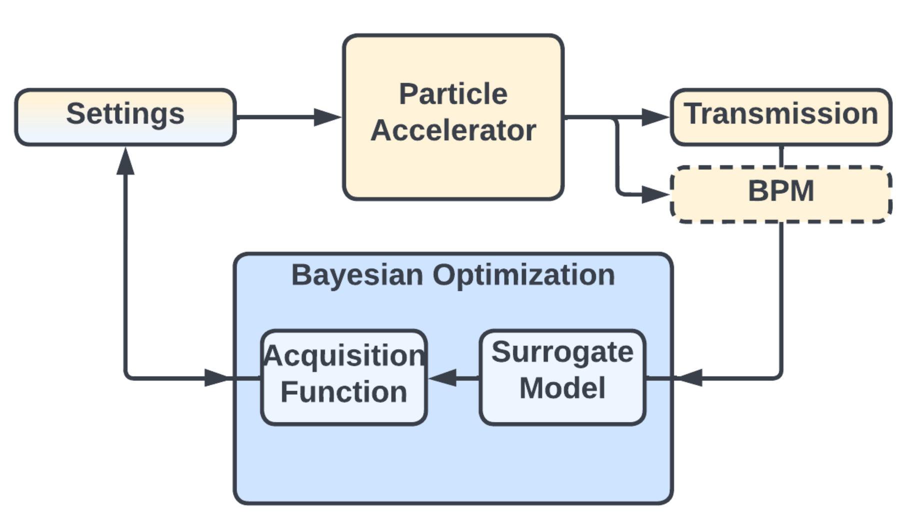
Establishing Automated Data Collection

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

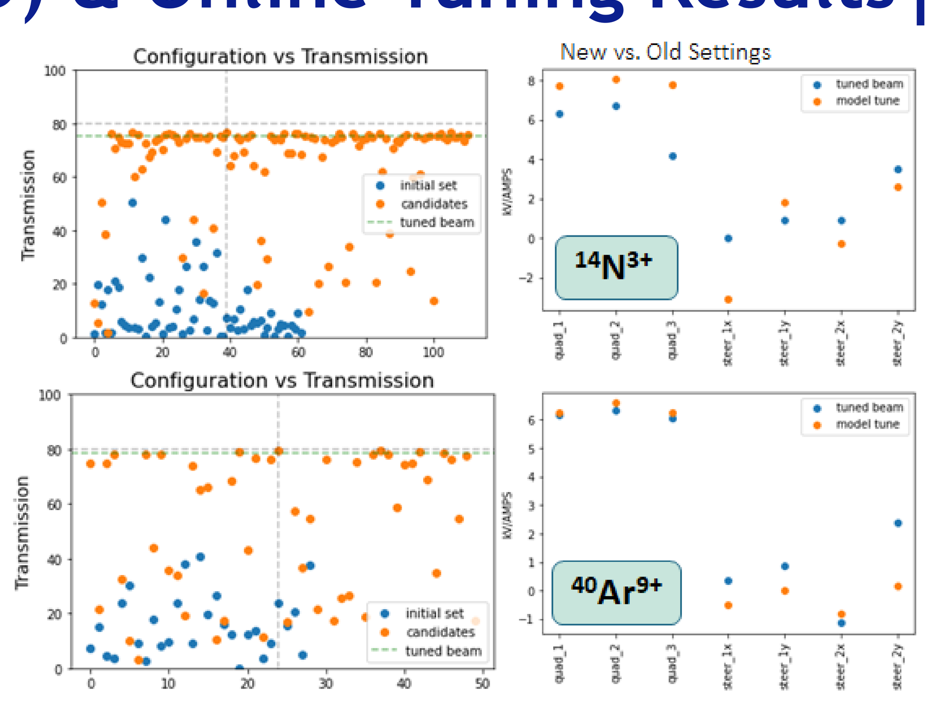


BO and RL for Beam Tuning and Accelerator Control

Bayesian Optimization (BO) & Online Tuning Results

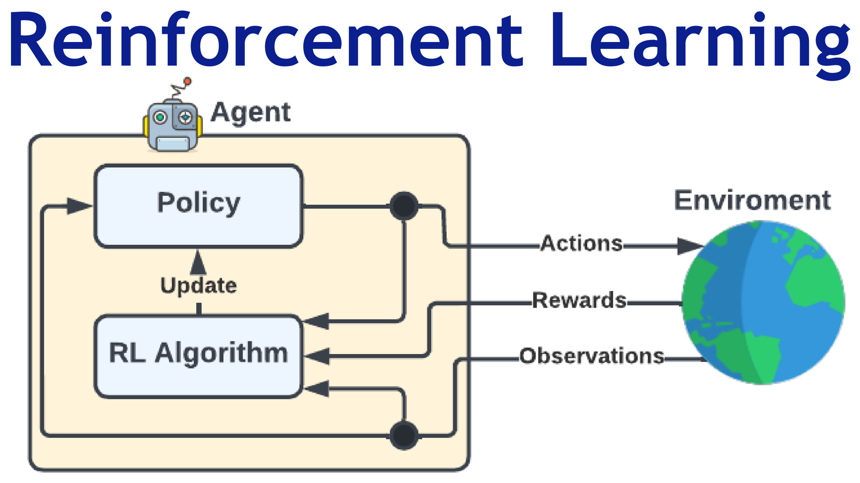


- ○ <u>Surrogate Model</u>: A probabilistic model approximating the objective function
- ○ <u>Acquisition Function</u> tells the model where to query the system next for more likely improvement
- ○ BO with Gaussian Process (GP) gives a reliable estimate of uncertainty and shapes the model's prior belief via the choice of the kernel

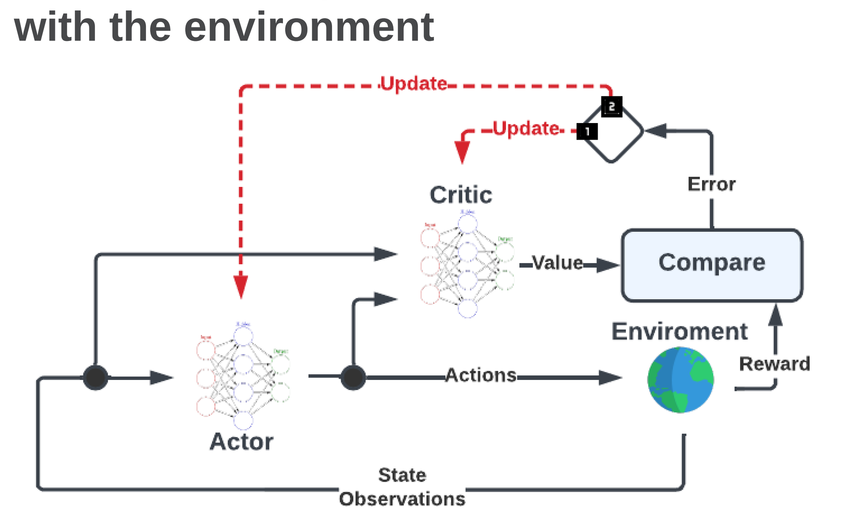


- ○ 7 input parameters (3 quads + 2 steerers)
- ○ Optimization of beam transmission
- ○ Case of 14N3+: 29 historical tuned beams + 33 random configurations
- ○ Case of 40Ar9+: 29 historical tuned beams

Reinforcement Learning (RL) & Preliminary Results



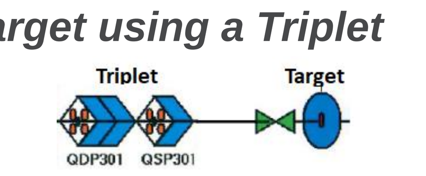
Reinforcement learning is learning what to do based on experience and interaction with the environment



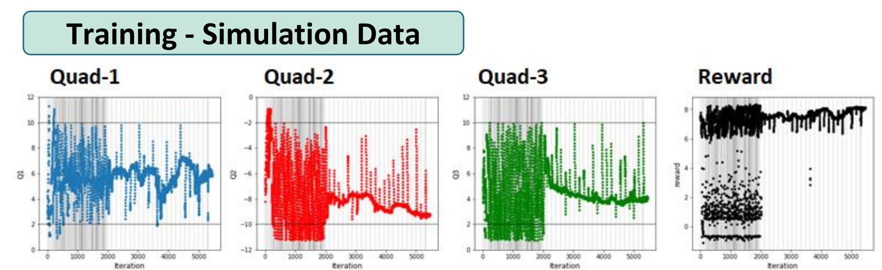
Deep Deterministic Policy Gradient (DDPG)

Focusing Beam on Target using a Triplet

- 3 electrostatic quads
- Voltage limits: 2 – 10 kV
- Max. action: +/- 0.25 kV

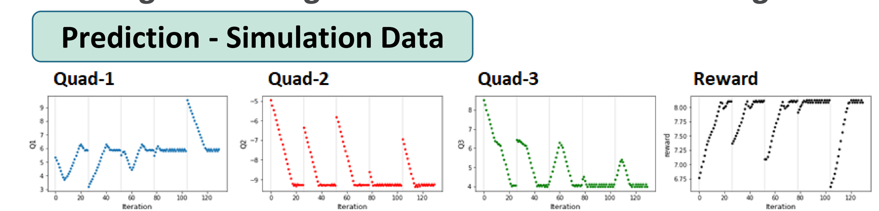


Training - Simulation Data



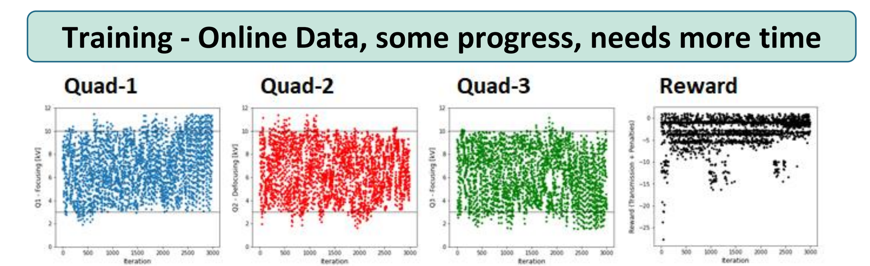
After learning the quad setting limits the model starts learning the voltages to focus the beam on target

Prediction - Simulation Data



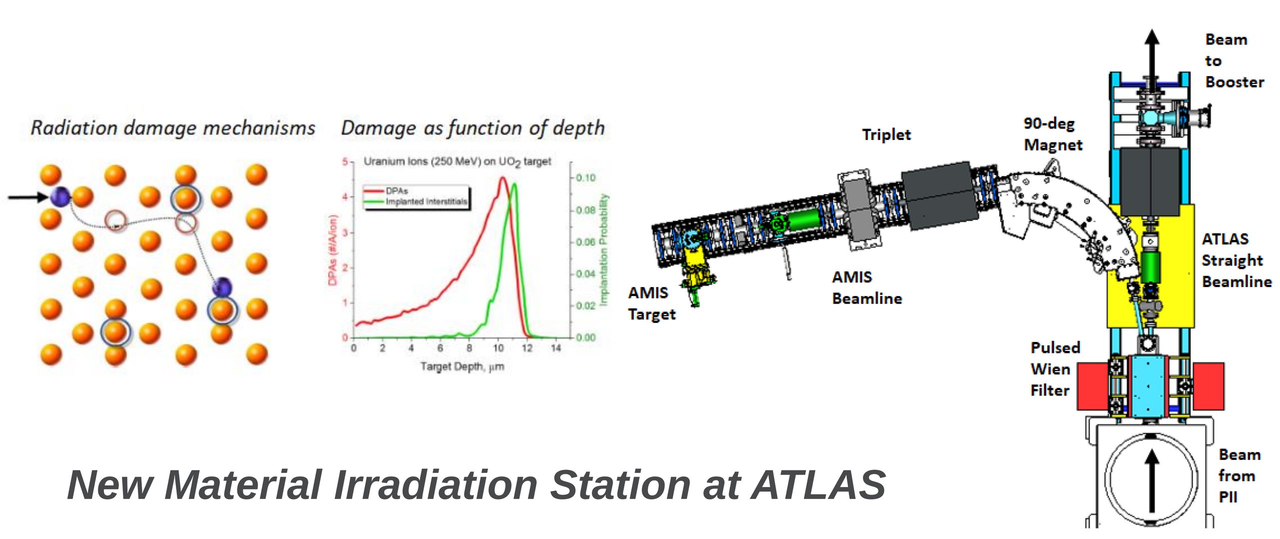
Model converges from 5 random initial configurations, convergence speed depends on maximum action

Training - Online Data, some progress, needs more time



AI/ML Supporting the Commissioning of a New Beamline

New AMIS Beamline



New Material Irradiation Station at ATLAS

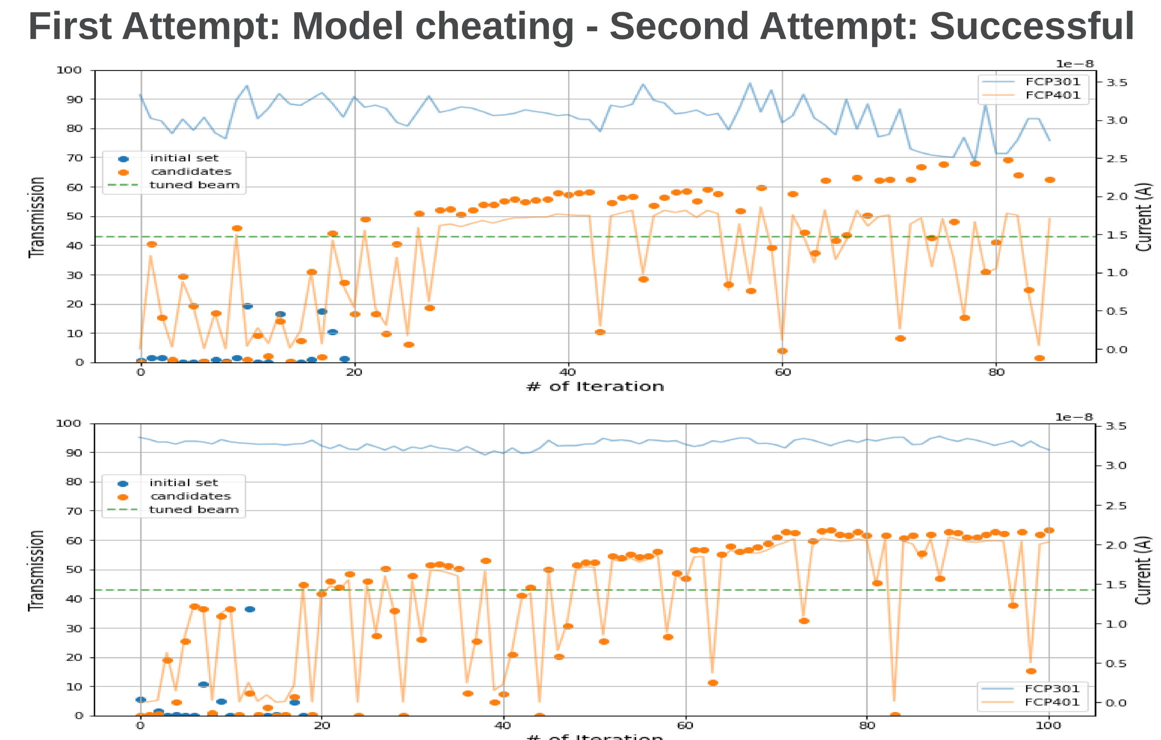
- ✓ Low-energy heavy-ion beams ~ 1 MeV/u can effectively emulate material damage in nuclear reactors, in both fuel and structural materials
- ✓ Damages that could take years in a reactor environment could in principle be reproduced in few days or hours using an ion accelerator
- ✓ Following irradiation, materials are analyzed and their robustness and adequacy for nuclear reactor environment is evaluated

Ref: M. Pellin et al, Journal of Nuclear Materials 472 (2016) 266-271

Improving Beam Transmission

Problem: Maximize beam transmission by varying a triplet, two dipoles and two steerers

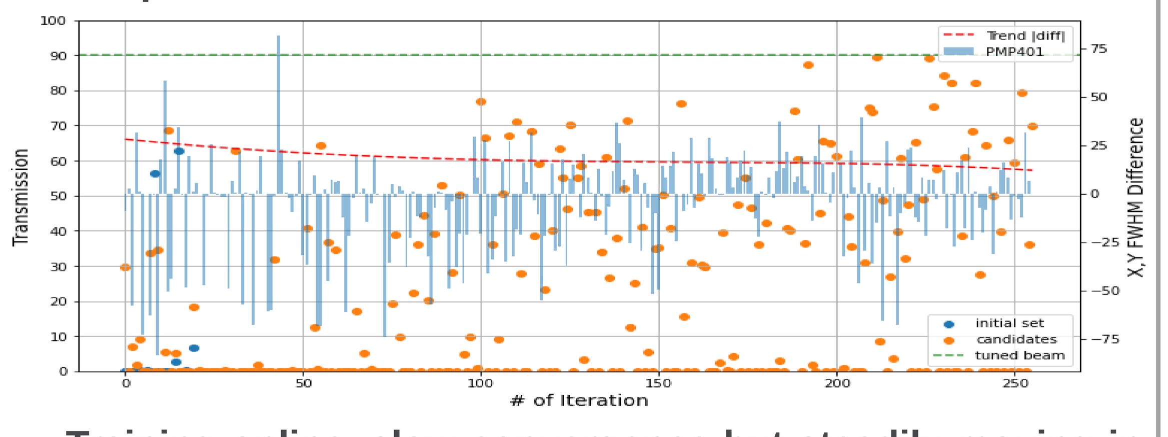
First Attempt: Model cheating - Second Attempt: Successful



Best initial tune by operator ~ 40 % beam transmission
Best achieved by ML model ~ 70 % beam transmission

Improving Beam Profiles

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



Training online, slow convergence but steadily moving in the desired direction. There is competition between nice profiles and beam transmission!

Very encouraging first results!

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