AI-ML DEVELOPMENTS FOR THE ATLAS ION LINAC FACILITY

B. Mustapha, C. Dickerson, B. Blomberg, C. Peters and J. Martinez
Physics Division, Argonne National Laboratory, Argonne, IL, USA

Abstract: ATLAS is a DOE/NP User Facility for the study of low-energy nuclear physics with heavy ions. It operates ~6000 hours per year. In addition to delivering any stable beam from proton to uranium, the facility also provides radioactive beams from the CARIBU source or via the in-flight radioactive ion separator, RAISOR. The facility uses 3 ion sources and services 6 target areas at energies from ~1-15 MeV/u. To accommodate the large number and variety of approved experiments, ATLAS reconfigures once or twice per week over 40 weeks of operation per year. The startup time varies from ~12 – 48 hours depending on the complexity of the tuning, which will increase with the upcoming Multi-User Upgrade to deliver beam to two experimental stations simultaneously. DOE/NP has recently approved a project to use AI/ML to support ATLAS operations. The project aim is to significantly reduce the accelerator tuning time and improve machine performance by developing and deploying artificial intelligence methods. These improvements will increase the scientific throughput of the facility and the quality of the data collected. Our recent developments and future plans will be presented and discussed.

Project Plan & Objectives

Project Motivation & Goals

❑ At ATLAS, we switch ion beam species every 3-4 days → **Using AI could streamline beam tuning & help improve machine performance**

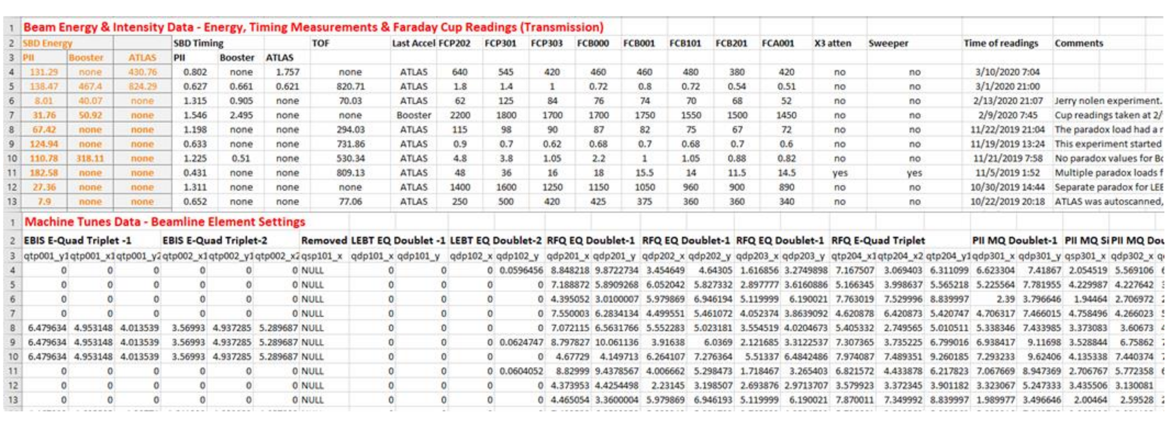
❑ The main project goals are:

✓ **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

Data Collection / Online Tuning Model / Virtual Machine Model



❑A sample of historic machine tunes and beam data

❑Some of the data is collected manually in paper form!

❑Part of the project is to move to fully automatic and electronic data collection → A new e-logbook is added

❑The online tuning model consists of an initial tune model based on machine tunes data and a set of optimization and feedback loops fed by online data

❑ A first version of the online tuning model leverages already existing machine and beam data, the model will be further enhanced with new data and specific measurements

❑The virtual machine model will be particularly useful for multi-beam transport and acceleration as part of the upcoming ATLAS multi-user upgrade, as well as for high-intensity beams

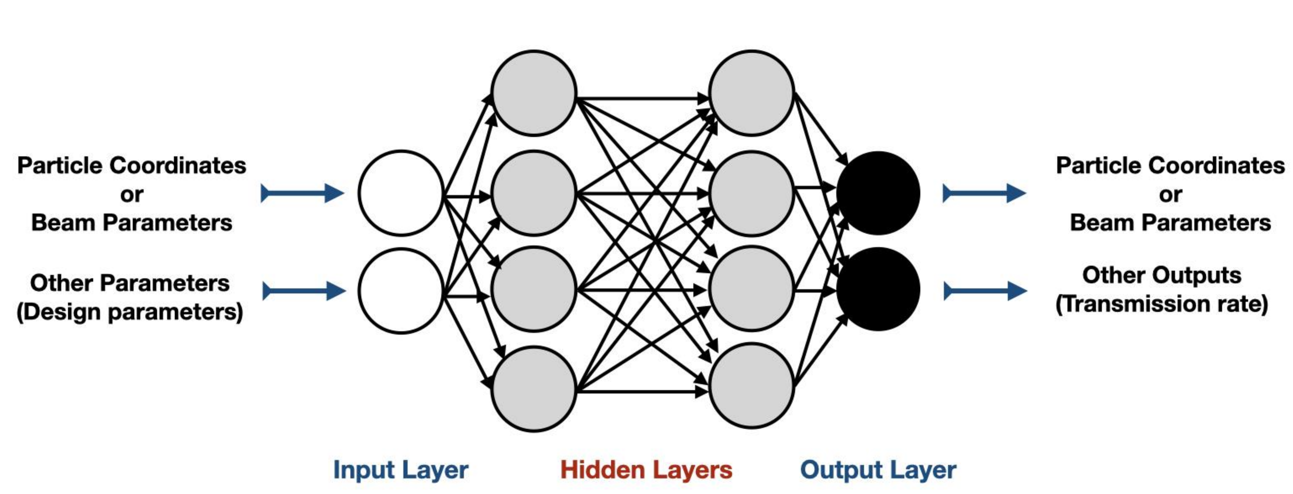
❑Since full beam physics models, which usually include particle tracking in 3D fields, are slow and not very useful to support online accelerator operations, we are developing a surrogate AI models for different sections of the linac.

❑A surrogate model can be trained on beam simulation data to reliably reproduce the physics results in very short time, then be enhanced with experimental data

❑A preliminary surrogate model was developed for the ATLAS RFQ

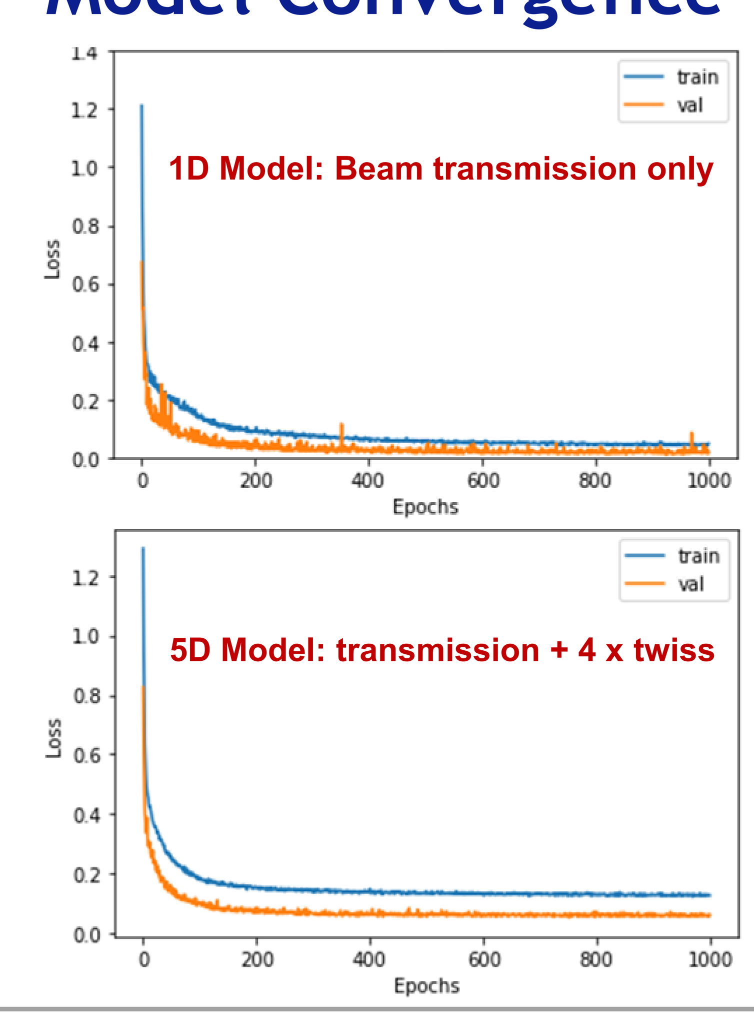
Surrogate Models for ATLAS RFQ

Neural Network Model

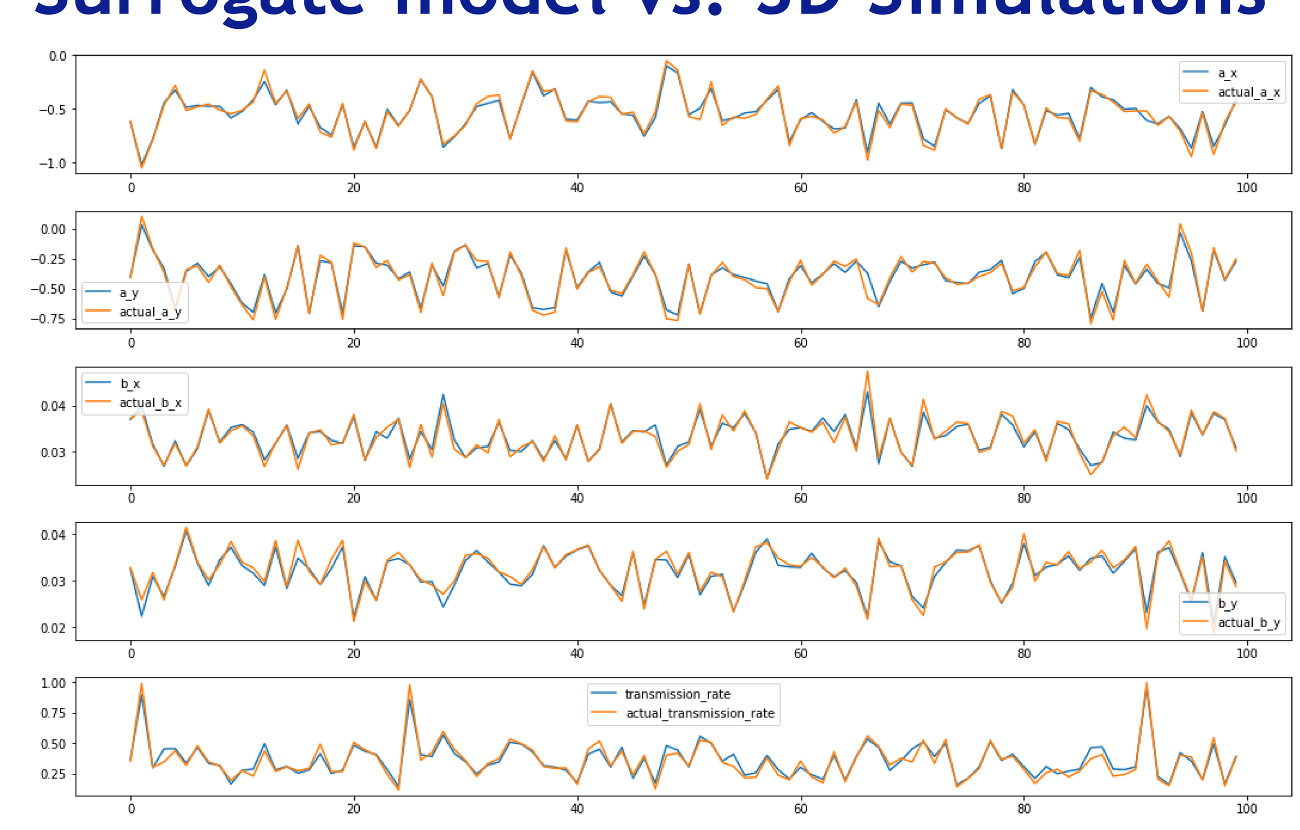


✓ We used a neural network for this model, which is fully based on simulations data
✓ Excellent convergence for 1D results, will need more data for the 5D case!
✓ Excellent agreement with TRACK 3D beam simulations, similar to results form different codes!
✓ Much much faster than TRACK, speed-up factor ~ 30,000 → **can be used to support online operation**

Model Convergence



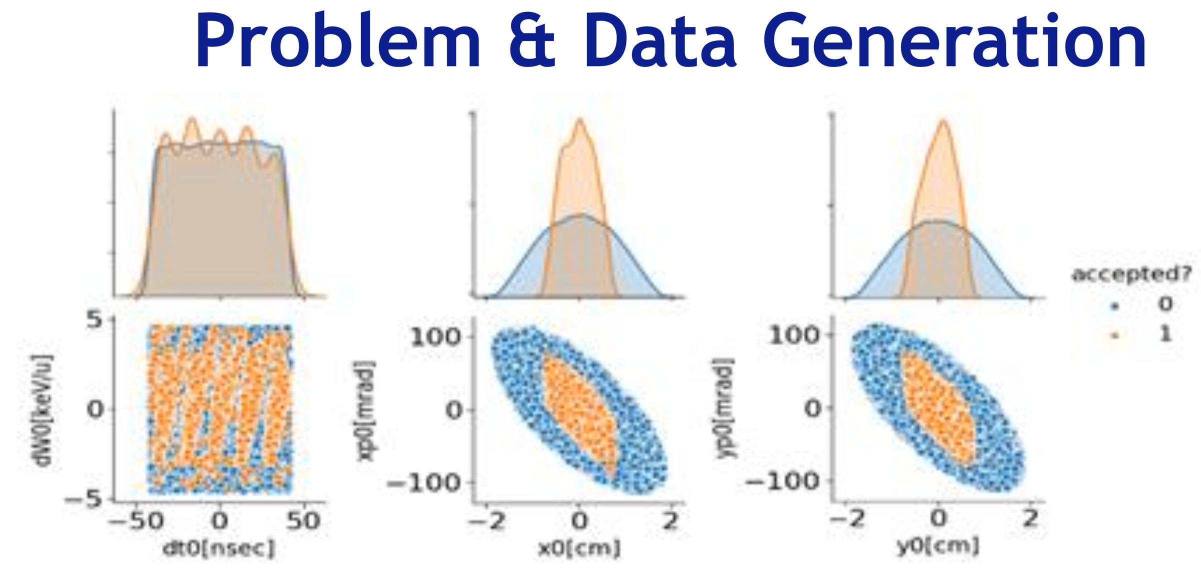
Surrogate model vs. 3D Simulations



Plots comparing the 5D surrogate model results to actual 3D simulation results. From top to bottom are twiss parameters: αx, βx, αy, βy, and beam transmission for a DC beam (no MHB)

Surrogate Models for Particle Tracking

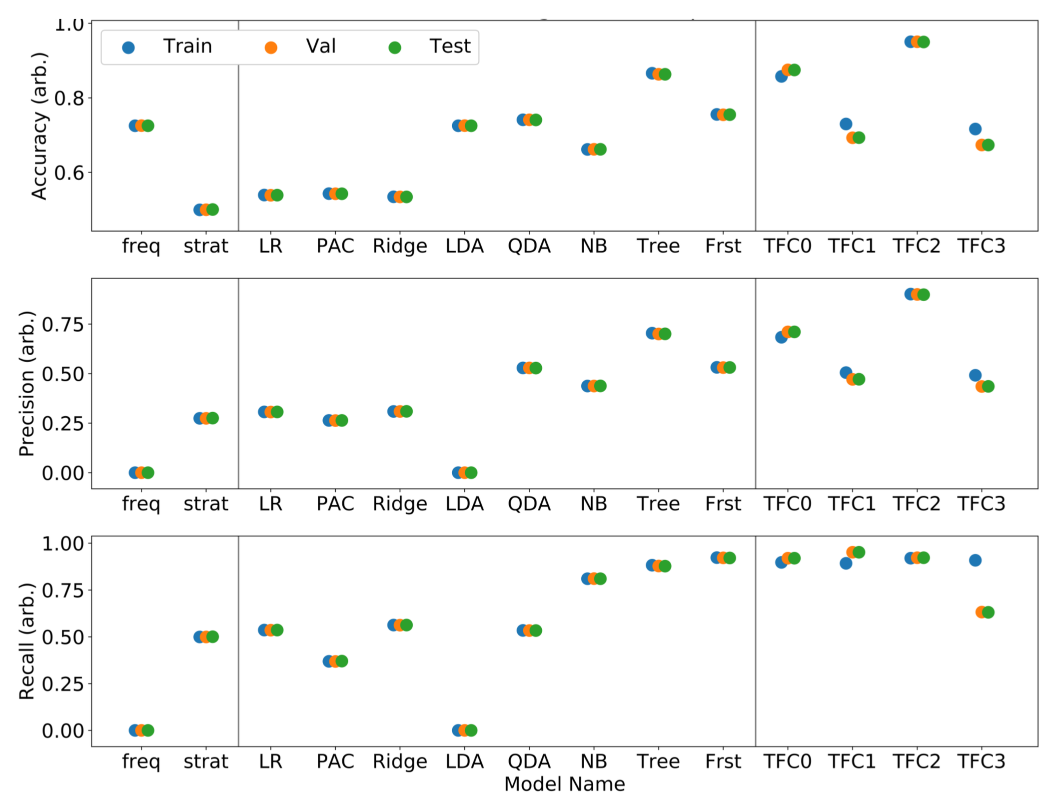
Problem & Data Generation



Data generated using the TRACK code for ATLAS RFQ: Output particle coordinates and acceptance flag tagged with input particle coordinates, 10M particles used.

Two problems are addressed, knowing input coordinates:
1) Classification problem: Is particle accepted or not?
2) Regression problem: Can we predict output coordinates?
→ **Different ML and DL models were developed & compared**

Classification Models



Definitions & Metrics:

– $Accuracy = \frac{correct}{total\ examples}$

– $Precision = \frac{true\ positives}{predicted\ positives}$

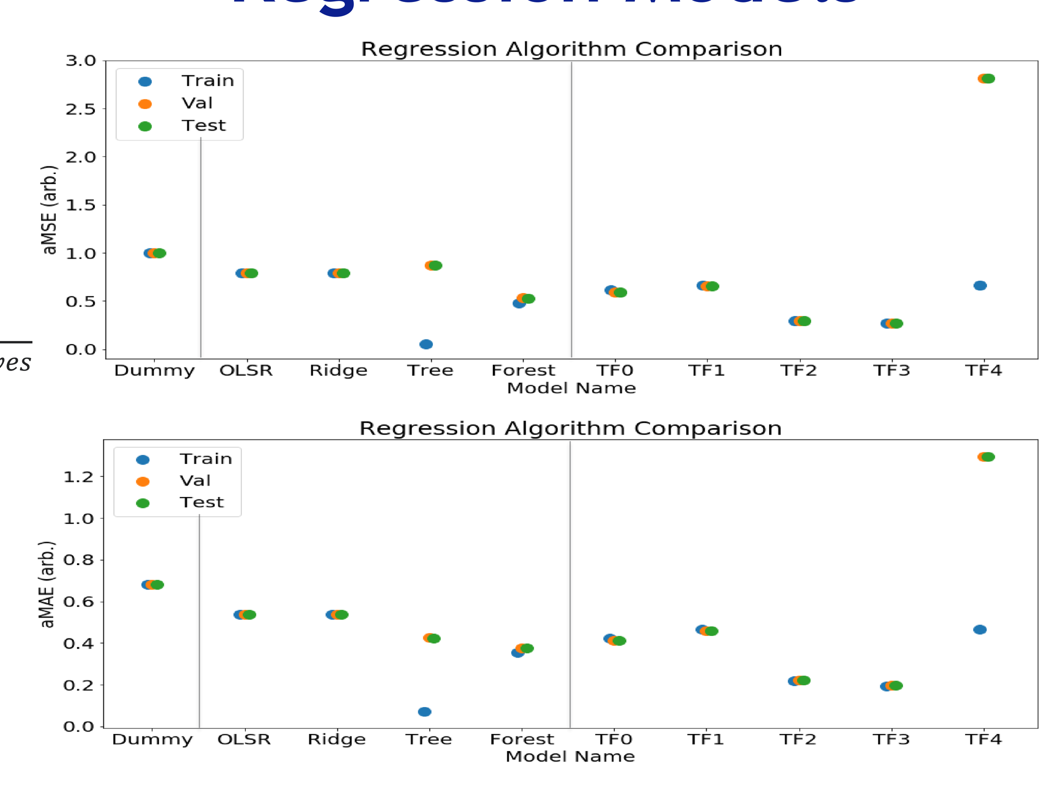
– $Recall = \frac{true\ positives}{real\ positives}$

– aMSE: Average Mean-Squared-Error

– aMAE: Average Mean-Absolute-Error

Comparison criteria: higher Accuracy, precision and Recall → **TFC0, TFC2 and Tree are the best performer for predicting particle acceptance**

Regression Models



Nonlinear model architectures; ResNet, Forest, and Tree performed well on both problems → can be the basis for an ML model for particle tracking