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# IMPROVE BEAM BRIGHTNESS WITH BAYESIAN OPTIMIZATION AT THE AGS BOOSTER INJECTION AT BNL*

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*Abstract*

Alternating Gradient Synchrotron (AGS) and its Booster serve as part of the injector compound for RHIC and the future EIC at Brookhaven National Laboratory. Injection and early acceleration processes set maximum beam brightness for the collider rings. Such processes have many control parameters and are traditionally optimized empirically by operators. In an effort to streamline the injection processes with machine learning (ML) techniques, we develop and test a Bayesian Optimization (BO) algorithm to automatically tune the Linac to Booster (LtB) transfer line magnets to maximize beam brightness after injection into the Booster. We present experimental results that demonstrate BO can be applied to optimize Booster injection efficiency.

## INTRODUCTION

For polarized proton operation at the Relativistic Heavy Ion Collider (RHIC), 200 MeV $H^-$ beam is created in the Linac and transported to the Booster through the Linac to Booster (LtB) transfer line. The LtB line is 114 feet in length and includes three main sections [1]. The first section starts from the Linac High Energy Beam Transport (HEBT) line to the 126° bend region. The second section is the 126° bend region with four identical dipoles. The third section starts from the exit of the last 126° dipole and continues into the Booster through the backleg iron of the C5 main ring dipole. $H^-$ particles are fully stripped to protons at a carbon foil after the C5 magnet. Figure 1 shows the layout of the Booster injection region, with the LtB line outlined in red.

Proton beam in the Booster is scraped in both planes to reduce the emittance and intensity to RHIC requirements. The operation efficiency of Booster injection is characterized by three quantities: the input intensity, the early intensity, and the late intensity. The input intensity is measured when beam leaves the Linac, and this value usually stays relatively constant throughout normal operations. The early intensity is measured when beam first enters the Booster, and the late intensity is measured right before extraction to the AGS, after acceleration and scraping in the Booster. Figure 2 shows how beam changes during a typical Booster acceleration cycle. Timestamps when early and late intensities are measured are shown with red arrows.

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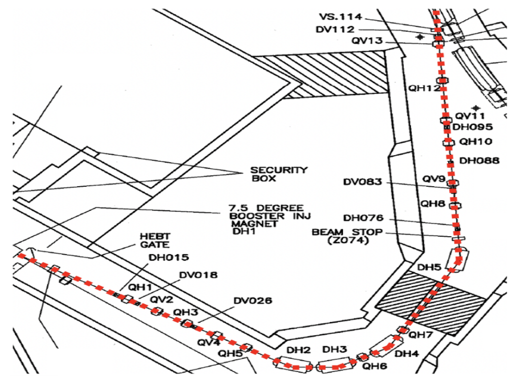


Figure 1: Layout of the Linac to Booster (LtB) transfer line (outlined with red dashed line).

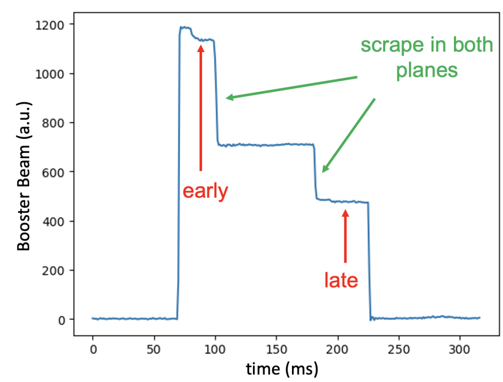


Figure 2: Booster beam intensity in one Booster cycle. Horizontal and vertical scrapings are visible as sharp decreases.

There are 13 quadrupoles and 16 correctors in the LtB line used to optically match the incoming beam both at the entrance of the 126° bend region and into the Booster ring. Traditionally Booster injection is hand tuned by experienced operators to increase the Booster early and late intensities.

In this work, we use Bayesian optimization (BO) to optimize Booster injection efficiency. BO has been widely implemented to solve complex particle accelerator control problems [2], because it is sample efficient and needs no existing model. Accurate models for transfer lines are difficult to construct due to their complicated geometry, so we choose BO for fast real-time optimization.

## SIMULATION RESULTS

In order to study the sensitivity of injection efficiency to the correctors, a corrector scan was performed where all 16 correctors were changed individually until the Booster late intensity dropped by 50 %. Figures 3 and 4 show the

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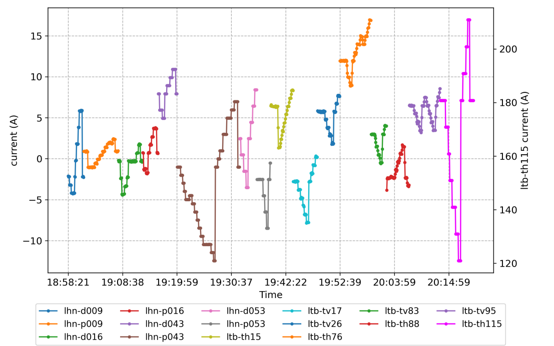


Figure 3: Corrector power supply currents for all 16 correctors during LtB corrector scan.

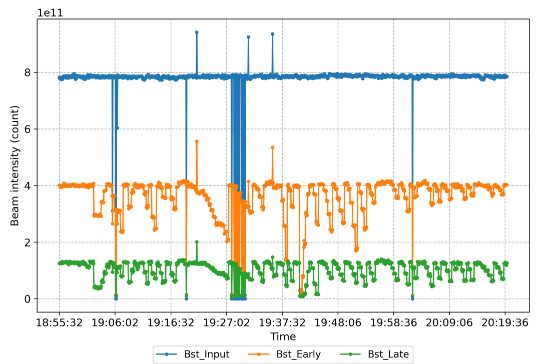


Figure 4: Input, early, and late Booster intensities during LtB corrector scan.

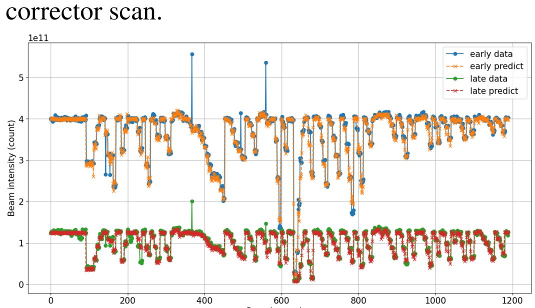


Figure 5: Comparison between beam intensity measurements and NN model predictions.

corrector power supply currents and the corresponding beam intensities during the LtB corrector scan.

We constructed a neural network (NN) model using the corrector scan data to test the performance of Bayesian optimization (BO) algorithm. One corrector (lhn-d009) is ignored due to its minimal effects on beam intensities. Thus, the NN model takes 15 corrector currents as inputs and returns 2 intensities (early and late) as outputs. The points when the input intensity goes to zero is caused by a misfired shot from the Linac, and are ignored during model training.

The NN model is a fully connected feed-forward neural net- work (FFNN). It has two hidden layers, with Rectified Linear Unit (ReLU) and Hyperbolic Tangent (Tanh) as activation functions [3]. The model was trained on 893 samples, and reached an accuracy of 85% when tested on 297 samples. Figure 5 shows the testing results on all samples.

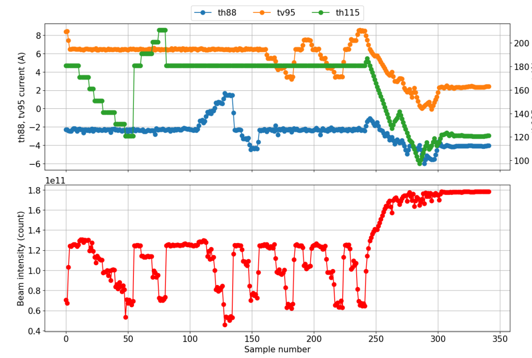


Figure 6: Bayesian optimization results on the LtB NN model. The algorithm converges within 50 samples.

The test BO algorithm developed with Xopt [4] mimics the empirical tuning method by taking the last two horizontal correctors (th88, th115) and the last one vertical corrector(tv95) as control variables, and Booster late intensity as target objective. Upper confidence bound (UCB) was used as the acquisition function, and the algorithm is trained using 242 data points from the LtB scan. Figure 6 shows the testing results. The BO algorithm was able to converge and increase the Booster late intensity using three LtB correctors.

## EXPERIMENTAL RESULTS

After successfully test of the Xopt BO algorithm on the LtB NN model, we apply the algorithm to the real LtB system. In order to speed up convergence, we utilized Bayesian Optimization with interpolated samples. When adjustments to accelerator parameters are frequent like our case, it is beneficial to augment the dataset by sampling multiple times with input changes smaller than the predefined step size. Quick measurements of the objective are done for these small intermediate steps in between the sample changes guided by the BO algorithm's acquisition function. This approach is more efficient than measuring the same inputs multiple times in a noisy environment. In our case, we added 3 interpolation steps between each sample step.

Our goal is to minimize beam size dependent luminosity loss during Booster injection. Maximizing the Booster late intensity means more particles from the initial beam distribution survived the scraping, which has roughly constant number of total particles. For a Gaussian beam, an increase in particles $N$ after fixed scrapers indicates a decrease in its waist value, which can be observed on beam profile monitors as a decrease in the beam size $\sigma$. The decrease in beam size in turns signals a decrease in the beam luminosity, as shown in Eq. (1) [5].

$$\mathscr{L} \sim \frac{1}{4\pi} \cdot f_{rev} \cdot \frac{N^2}{\sigma_x \sigma_y}. \quad (1)$$

Figure 7 shows the BO results using two correctors and two quadrupoles in both planes as control parameters. Figure 8 shows the beam sizes measured at the first beam profile monitor in the Booster to AGS transfer line (BtA) during the optimization. We did observe decreases in beam size in

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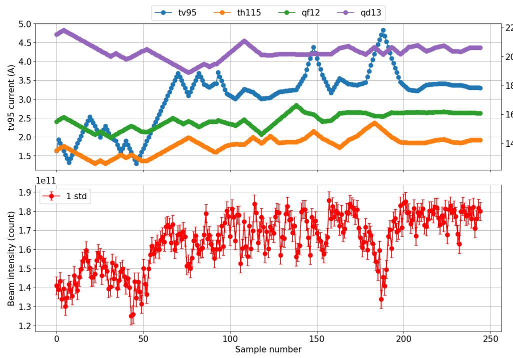


Figure 7: Bayesian optimization results on the LtB line using two correctors and two quadrupoles as control variables.

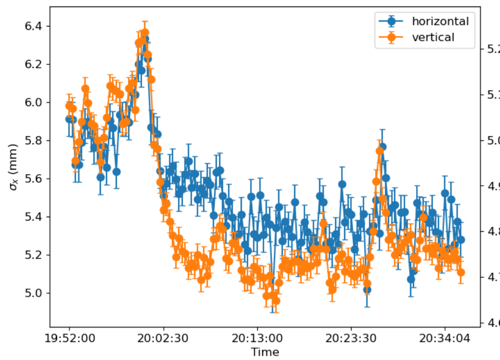


Figure 8: Beam size measurements in the Booster to AGS transfer line during Bayesian optimization on the LtB line using two correctors and two quadrupoles as control variables.

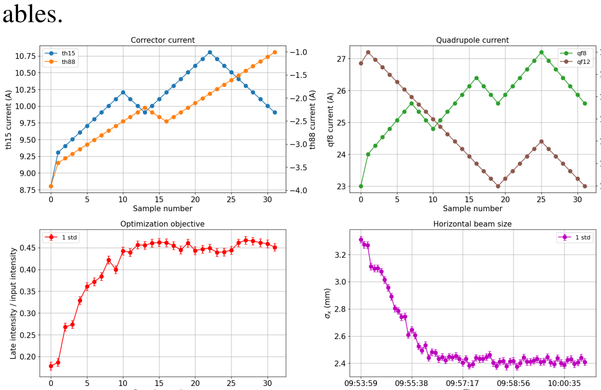


Figure 9: Bayesian optimization results on the LtB line using two correctors and two quadrupoles in the horizontal plane as control variables.

both planes as the Booster late intensity increases, which correspond to an increase in beam luminosity.

As we can see in Fig. 7, the Booster late intensity is quite noisy. We changed the BO objective from late intensity to the ratio of late intensity and input intensity so that the objective function is less noisy, since the input intensity is basically constant according to Fig. 4.

To further test the effectiveness of the BO algorithm, we also changed how we sabotage the beam quality before the experiment starts. Initial beam was sabotaged by changing magnets in the middle of LtB line, and the control parameters

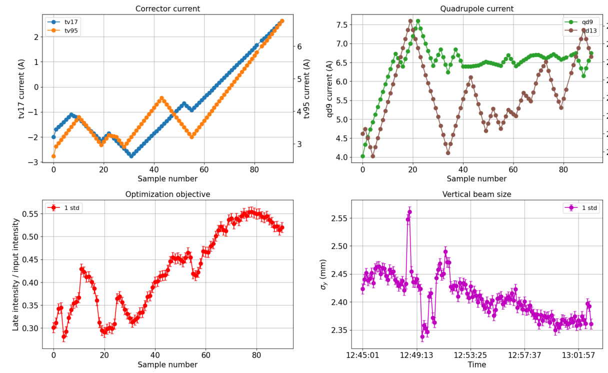


Figure 10: Bayesian optimization results on the LtB line using two correctors and two quadrupoles in the vertical plane as control variables.

are two pairs of magnets, one upstream and one downstream of the changed magnets. The algorithm has no knowledge of what caused the beam to degrade, but as shown in both Fig. 9 and Fig. 10, it was able to compensate and undo the damages occurred in the other parts of the beam line. However, we did encounter a degeneracy problem for these two cases, as shown in the top two graphs in Figs. 9 and 10. The control parameters failed to converge but the objective value did approach convergence. This could be a result of the limited time we had to run the algorithm, as we had less beam time for the fourth and fifth cases than the previous cases, but it may need further investigation.

## CONCLUSION

In this work, we developed and tested Bayesian optimization algorithms in the Linac to Booster transfer line. Experimental results show that BO algorithm is able to automatically improve Booster injection performance and beam luminosity, making it a powerful tool for complicated tuning tasks in real time.

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