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ENHANCING BEAM INTENSITY IN RHIC EBIS BEAMLINE VIA GPTUNE MACHINE LEARNING-DRIVEN OPTIMIZATION*

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Abstract

The application of machine learning techniques to accelerator research has led to significant breakthroughs in optimization strategies. This paper presents a pioneering study using a novel machine learning algorithm, GPTune, to optimize beam intensity by adjusting parameters in the EBIS injection and extraction beamlines. Our research demonstrates substantial improvements, achieving a remarkable 22% and 70% increase in beam intensity at two separate measurement locations.

Furthermore, the XGBoost package is employed for offline data analysis to evaluate the individual impact of each parameter on beam intensity. This analysis provides valuable insights to guide us toward optimal parameter settings, paving the way for further beam intensity enhancements.

INTRODUCTION

Brookhaven National Lab has successfully developed the Electron Beam Ion Source (EBIS) [1], a compact and versatile heavy ion accelerator. EBIS serves as the pre-injector system for both the Relativistic Heavy Ion Collider (RHIC) and NASA Space Radiation Laboratory (NSRL). It utilizes an electron beam ionization source followed by a radiofrequency quadrupole linac and an interdigital H linac.

One of EBIS's key advantages is its ability to produce short, high-intensity pulses of ions. These pulses are ideally suited for single or few-turn injection into synchrotrons like RHIC, where ions need to be injected quickly and efficiently. Additionally, EBIS offers significant operational benefits compared to traditional injector systems. Its lower energy consumption translates to reduced operating costs, while its ability to quickly switch between different ion beams within one second enhances operational flexibility. This, in turn, allows for the simultaneous feeding of beams of different ions to RHIC and NSRL, enabling quick transitions between various ion species for diverse research programs.

Figure 1 shows the layout of the EBIS system. The system comprises several beamline sections, and they are LION (Laser Ion Source), EBIS Injection Line, EBIS, EBIS Extraction Line, RFQ, MEBT, Linac, and HEBT. Each beamline section has numerous parameters that can influence beam performance. These operational parameters can affect beam performance simultaneously, making it challenging to isolate their individual effects.

Furthermore, the beam intensity signal exhibits significant noise at xf14 (current transformer). Optimizing these parameters individually based solely on the intensity signal would be a time-consuming task. This is due to the instability of the beam intensity when the system is not optimized, necessitating the collection of multiple data cycles to obtain representative intensity values. This is particularly true after certain parameters have already reached their optimal values.

To address the aforementioned issues and optimize EBIS beam intensity online, a machine learning algorithm, GPTune [2], was implemented on the EBIS beam injection and extraction lines at the conclusion of the RHIC 2023 run.

Concurrently, following the online optimization with GPTune, we applied a machine-learning algorithm, XGBoost [3–6], to the same operational data for offline analysis. Upon acquiring the data for these parameters and constructing a model using XGBoost, the beam intensity as a function of individual parameters can be plotted separately for distinct parameters. This enables the identification of optimized operational parameters.

GPTUNE OPTIMIZATION

Experimental Setup

During the optimization, the ion beam species was Si^{+11}. The beam injection system (Booster-AGS) has a supercycle time of 6.6 seconds. Although within a single supercycle, up to 12 pulses of EBIS beam could be injected into the Booster-AGS ring, while only one pulse was injected into the Booster-NSRL target room. Only one pulse of the ion beam was then used for subsequent processes.

Meanwhile, some power supplies require two supercycles for their outputs to settle. After the power supplies stabilize, the script takes four measurements for averaging, each separated by the supercycle time, to obtain more robust statistics.

The Faraday-cup FC96 measurement was used for injection optimization, employing 9 control parameters with 70 iterations. Similarly, the current transformer XF14 measurement was used for extraction optimization, utilizing 10 control parameters with 60 iterations. The conversion factors from raw integral to beam charge vary depending on the

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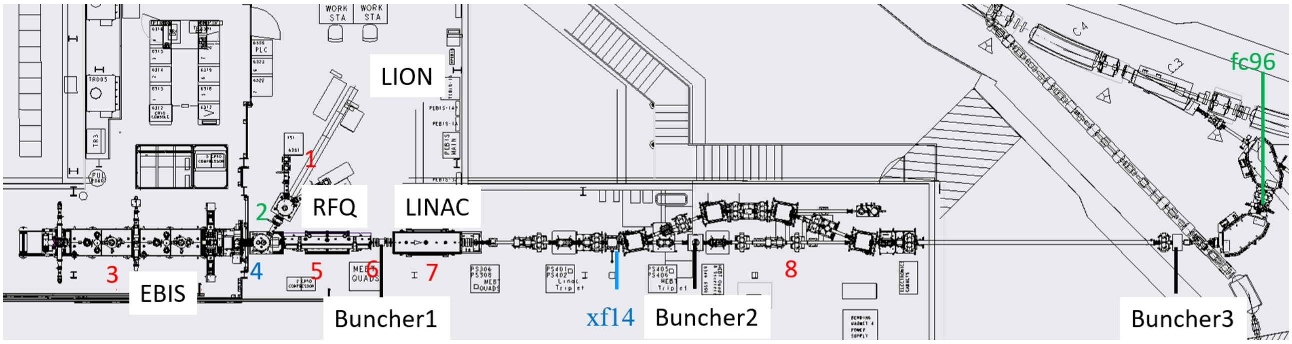

Figure 1: The Layout of the EBIS.

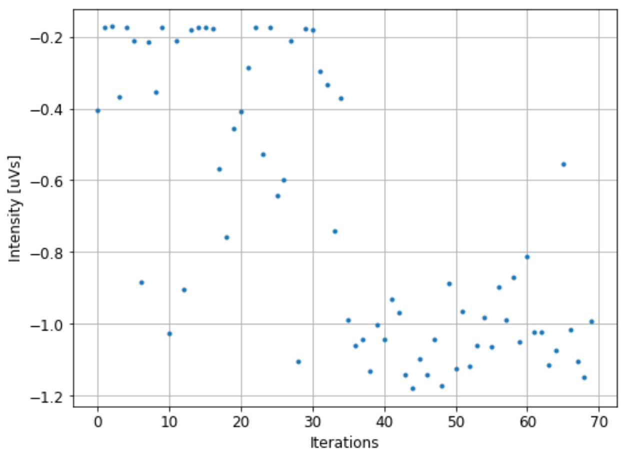

Figure 2: 30 mA CW electron beam current test in 2018.

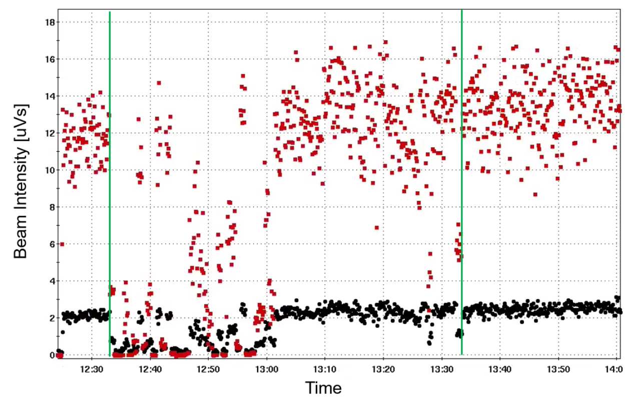

Figure 3: Injection Line Optimization Result. Red dots represent the fc96 signals, and black dots represent the xf14 signal.

location. At xf14, 1 µVs corresponds to 1.43 nC, while at fc96, the same signal translates to 0.109 nC.

Injection Line Optimization

During the optimization, the injection and extraction beam lines were initially optimized separately. When optimizing the injection line, the current transformer fc96 was used to measure the ion beam intensity.

Figure 2 shows the progress of the injection line optimization using GPTune. The horizontal axis represents the iteration number of the GPTune script, while the vertical axis represents the normalized and averaged signal of fc96. As mentioned earlier, GPTune aims to minimize the signal to achieve maximum output; therefore, a more negative value indicates a better optimization result. As Fig. 2 demonstrates, GPTune finds a significantly improved result after approximately 45 iterations for the 9 variable parameters.

Figure 3 displays the fc96 beam intensity signal during the optimization process (between the two vertical green lines). Following the optimization, the average beam intensity increased from 11.5 uVs to 14.0 uVs, representing an improvement of approximately 22 %.

Extraction Line Optimization

Figure 4 depicts the progress of injection line optimization using GPTune. It's evident that GPTune identifies a superior outcome after approximately 45 iterations with 10 control variable parameters.

Figure 5 illustrates the xf14 beam intensity signal during the optimization process (delineated by the two vertical green lines). Post-optimization, the average beam intensity exhibited a substantial increase from 1.4 uVs to 2.0 uVs, translating to a remarkable 43 % improvement.

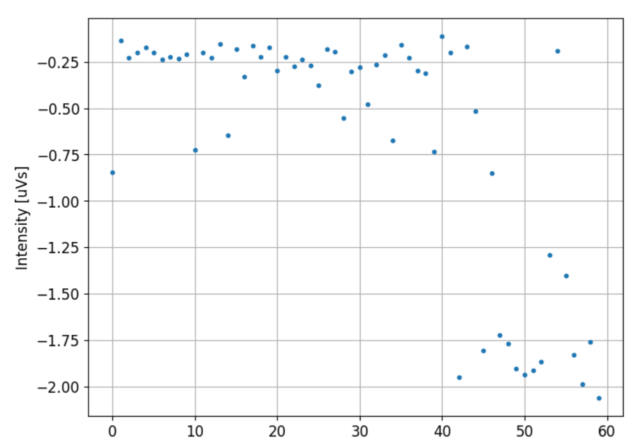

Figure 4: Extraction Line Optimization using GPTune.

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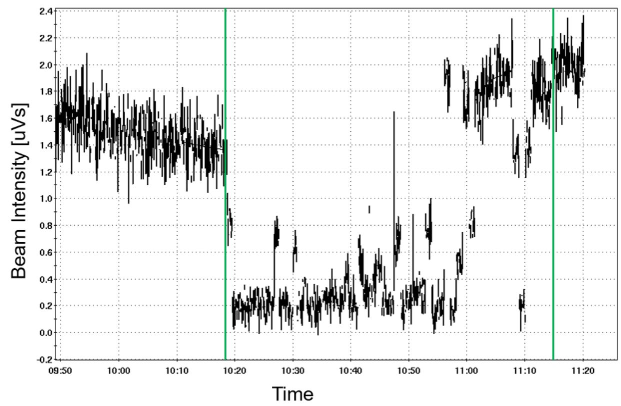

Figure 5: Extraction Line Optimization result.

While xf14 and fc96 share the same unit, direct comparison of their results is not feasible due to the utilization of different normalization factors during post-measurement data processing.

Injection and Extraction Combined Optimization Settings

In the previous sections, we optimized the injection and extraction lines separately. Their power supply settings were also saved individually. To evaluate their combined contribution to beam intensity, we compared the intensity under three settings:

- Inj + Ext: Power supplies optimized for both injection and extraction lines
- Ext: Power supplies optimized only for extraction with original injection settings
- Original: Original settings without any optimization

The optimization results for the three different settings are shown in Fig. 6. In Fig. 6, the red and black dots represent

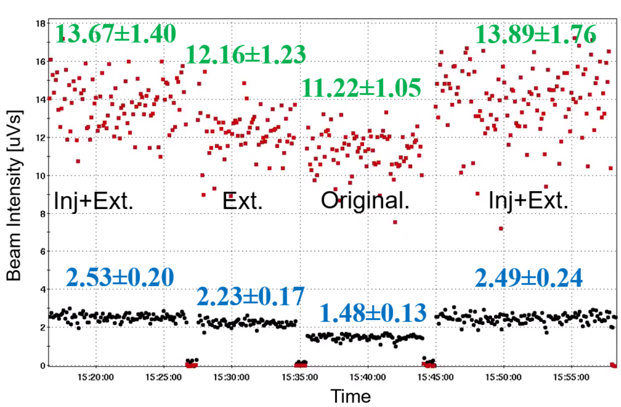

Figure 6: Optimization results with different settings: Inj + Ext, Ext only, and Original.

the measurements from fc96 and xf14, respectively. The green and cyan numbers represent the average beam intensity with their deviations for the fc96 and xf14 measurements.

Figure 6 reveals a characteristic of the beam intensity signal: substantial noise. The standard deviation is $\pm 10\,\%$, and the peak-to-peak deviation is $\pm 15\,\%$. This demonstrates GPTune's outstanding capability to handle noisy signals, a valuable feature for many experimental settings.

From Fig. 6, we observe significant intensity gains:

- xf14 measurement: 42 % for extraction-only optimization and 68 − 71 % for combined optimization.
- fc96 measurement: 8.4 % for extraction-only optimization and 22 − 24 % for combined optimization.

SUMMARY AND DISCUSSION

In this paper, we demonstrate the power of GPTune as an optimization tool. We applied it to EBIS intensity optimization and achieved a 22 to 24 % intensity improvement at fc96 (reaching 70 % with xf14 CT). This was achieved despite the presence of noisy signals with $\pm 10\,\%$ standard deviation and involving 19 variables. We plan to expand GPTune's use to other beamlines in the RHIC complex.

Meanwhile, XGBoost exhibits excellent model construction capabilities. Combined with model interpretation algorithms like SHAP, it can provide valuable insights into setting operation parameter ranges.

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