ONLINE TUNING OF THE NSLS-II INJECTOR USING BAYESIAN OPTIMIZATION WITH DIFFERENT PACKAGES

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Abstract

The injector of the NSLS-II consists of a linear accelerator (LINAC) that accelerates the electron beam to 170 MeV, followed by a linac-to-booster (LTB) transport line and a booster synchrotron that further increases the beam energy to 3 GeV. The performance of LINAC and LTB is critical to achieve efficient and stable beam injection. Automated online tuning is an effective method to improve injector performance. In this paper, we present an automated tuning approach based on Bayesian optimization, using different software packages to optimize the LINAC and LTB. We evaluate and compare these packages based on their ability to improve injection efficiency. Our results demonstrate that Bayesian optimization can significantly enhance injector performance and show differences in performance between different packages.

INTRODUCTION

The injector of a storage ring light source typically consists of an electron gun, a linear accelerator (LINAC), a LINAC-to-booster (LTB) transport line, a booster synchrotron, and a booster-to-storage ring (BTS) transport line. It is the upstream accelerator system that generates, accelerates, and transports electrons to the storage ring, where they are stored to produce synchrotron radiation. The injector directly determines the quality of the injected beam, including emittance, energy spread, and injection efficiency. In practice, even if the same machine settings are reloaded after a shutdown, the system does not behave exactly the same. Small changes in magnet calibration, temperature variations, and slow drifts over time introduce deviations. These effects accumulate and lead to suboptimal beam conditions. Because the injector is a complex and nonlinear system, existing physics models cannot fully capture all real-world variations and coupling between components. As a result, model-based prediction alone is not sufficient to achieve optimal performance. Therefore, online tuning is necessary to restore and optimize injector performance.

Online tuning is an effective approach to recover and improve machine performance by iteratively adjusting machine parameters based on real-time beam measurements. To reduce the need for manual effort, automated online tuning has emerged as a powerful method to efficiently optimize accelerator performance. It has been successfully applied using traditional optimization algorithms [1, 2]. However, these algorithms are often inefficient, as they typically require a large number of objective function evaluations to reach a global optimum. Given the limited machine study time available, this becomes a practical limitation. To address this, machine learning–based optimization methods have been introduced to improve efficiency. These approaches have been successfully applied in storage ring light sources [3], free-electron lasers [4].

The goal of this work is to deploy a Python-based Bayesian optimization framework to the control room input/output controller (IOC) for routine NSLS-II injector tuning. To support this effort, we also implemented a MATLAB-based version as a benchmark and compared optimization performance across platforms. Because these packages implement Bayesian optimization with different configurations and settings, their performance can vary. Therefore, a systematic comparison is necessary to provide practical guidance for automated online tuning of the NSLS-II injector [5]. This paper presents optimization results for the LINAC and LTB using both Python- and MATLAB-based Bayesian optimization packages. The results demonstrate that injector performance can be significantly improved through automated online tuning.

BAYESIAN OPTIMIZATION PACKAGES

There are many Bayesian optimization packages available in different programming languages, with varying features and implementations. In this work, we used both Python- and MATLAB-based packages for NSLS-II injector online tuning.

For the Python-based package, we employed `Xopt` [6], which is specifically developed for accelerator optimization applications. It provides flexible interfaces for defining optimization problems, supports Gaussian process–based surrogate models, and allows easy integration with control systems, making it well suited for online real-time tuning.

For the MATLAB-based package, we used the built-in Bayesian optimization function (`bayesopt`) from the MATLAB Machine Learning Toolbox [7]. This implementation offers a well-documented and standardized framework with robust default settings, making it convenient for quick testing and benchmarking.

Using both packages, we compared their performance in terms of convergence behavior, robustness, and optimization efficiency, and assessed their suitability for practical deployment in the NSLS-II injector tuning workflow.

BAYESIAN OPTIMIZATION SETTINGS

In this work, we used the default settings for `Xopt` and `bayesopt`. For both implementations, a Gaussian process (GP) model [8] was used as a surrogate to approximate the objective function.

For Bayesian optimization using `Xopt`, the GP used a radial basis function (RBF) kernel [8], which assumes the

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smooth variation of the objective with respect to the input parameters. For Bayesian optimization using `bayesopt`, the GP also employed the RBF kernel but allowed different length scales for each input variable. In both cases, kernel hyper-parameters, such as length scales, signal variance, and noise level, were automatically optimized during training using the observed data.

The acquisition function in `Xopt` was set to expected improvement (EI), while `bayesopt` used the expected improvement plus acquisition function (EI+). EI evaluates the expected amount of improvement in the objective function, ignoring values that cause an increase in the objective. In contrast, EI+ introduces an additional mechanism to reduce overexploitation: when the model uncertainty at a candidate point is too low, indicating that the search is focusing too narrowly, the algorithm increases the surrogate model variance to encourage exploration of new regions. This behavior is controlled by an exploration parameter and helps avoid getting trapped in local optima. In the study, the exploration parameter was set to 0.6 to balance exploration and exploitation.

The optimization was initialized with five random samples in `Xopt` and four random samples in `bayesopt`, which were used to train the initial GP models. After initialization, the models were iteratively updated as new measurements were collected. At each iteration, the acquisition function was optimized to propose the next evaluation point and the corresponding measurement was added to the dataset to update the model.

OPTIMIZATION RESULTS

The optimization of injection efficiency from the LINAC to the booster was performed in two stages. First, the LINAC was optimized to maximize injection efficiency from the LINAC to the LTB. Second, the LTB was optimized to maximize injection efficiency from the LTB to the booster.

During the experimental study, the LINAC and LTB transport lines were loaded with their normal settings, and the booster beam was directed to a beam dump.

In the first stage of optimization (LINAC to LTB), the optimization variables included the phases of the pre-buncher, buncher, and two RF cavities, as well as the amplitude of one RF cavity. The objective was to maximize the charge while applying a constraint to keep the horizontal position on one monitor within the range of [-6 mm, -4 mm]. During optimization, if a candidate solution satisfied the constraint, the measured charge was used as the objective value. Otherwise, the objective value was set to zero.

For this optimization problem, both `Xopt` and `bayesopt` were used and compared. As shown in Fig. 1, the best objective value achieved so far is plotted as a function of the number of evaluations for both methods. The optimization process was completed after 110 evaluations. Both `Xopt` and `bayesopt` converged to a similar level of performance. After applying the best solution, the injection efficiency from LINAC to LTB exceeded 90%.

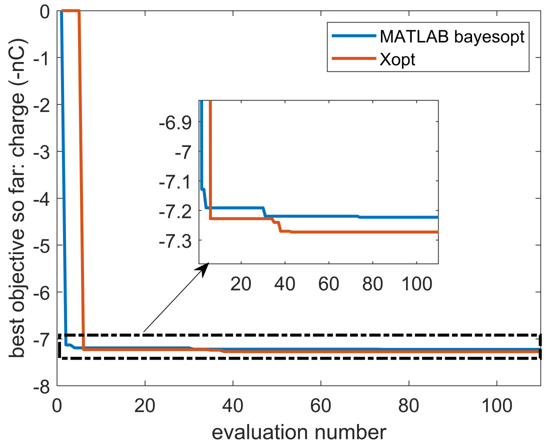

Figure 1: Comparison of the best objective value achieved so far as a function of evaluation number during the LINAC optimization using `Xopt` and `bayesopt`.

However, the injection efficiency into the booster remained below 90%. To address this, further optimization of the LTB was performed. Starting from the best solution obtained from the LINAC optimization, we continued to optimize the LTB using both `Xopt` and `bayesopt`.

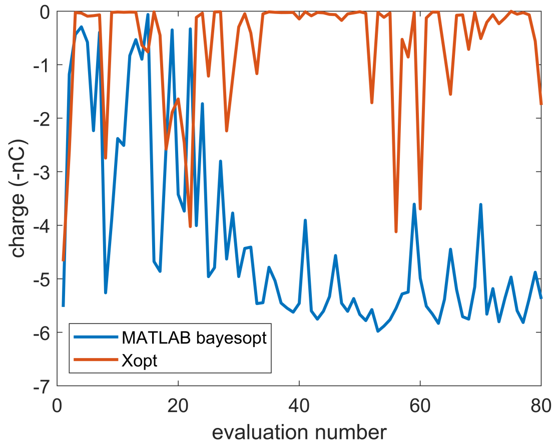

Figure 2: Comparison of the best objective value achieved so far as a function of evaluation number during the LTB optimization using `Xopt` and `bayesopt`.

In the LTB optimization procedure, eight tuning knobs were used, including the amplitude of the RF cavity, corrector magnets along the LTB transport line, as well as the injection system power supply and timing delays of the booster. The objective was to maximize the booster extraction charge. In this optimization, both `Xopt` and `bayesopt` were used with the same settings as in the LINAC optimization.

Figure 2 shows the best objective value achieved so far as a function of the number of evaluations for both methods. As observed in Fig. 2, `bayesopt` converged rapidly and found a good solution after approximately 40 evaluations. In contrast, `Xopt` did not show steady convergence, where the objective values fluctuated significantly, and many sampled points were located in regions that yielded low injection efficiency, suggesting inefficient exploration of the high-performance parameter space. After applying the best LTB settings obtained by `bayesopt`, the booster injection efficiency reached approximately above 90%, as shown in Fig. 3. These results demonstrate the effectiveness of the optimization using `bayesopt`.

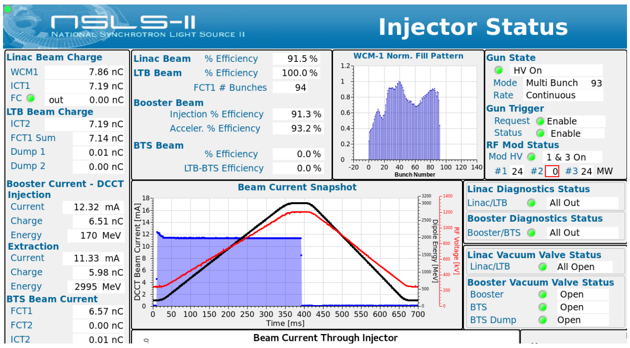

Figure 3: Injector status after LINAC and LTB optimization, as displayed on the NSLS-II Control System Studio (CSS) page.

CONCLUSION AND DISCUSSION

In this study, we performed online tuning for a critical problem: maximizing the injection efficiency from the LINAC to the booster. Bayesian optimization was applied using both a Python-based package (`Xopt`) and a MATLAB-based package (`bayesopt`). The experimental results demonstrate that `bayesopt` effectively improved the performance of both the LINAC and the LTB. In contrast, `Xopt` did not reliably converge during LTB optimization. The failure of convergence in `Xopt` may be attributed to differences in the choice of acquisition function. For example, `bayesopt` uses the expected improvement plus acquisition function, which includes mechanisms to mitigate overexploitation and encourage exploration when the search becomes too localized. In contrast, `Xopt` used the standard expected improvement, which may lead to premature focus on suboptimal regions, especially in noisy or constrained optimization problems.

These results suggest that the choice of Bayesian optimization settings plays a critical role in practical accelerator tuning. Using more robust exploration strategies or optimal kernel and acquisition function configurations in `Xopt` may improve its performance for complex, noisy optimization tasks such as LTB tuning.

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