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ADVANCED ALGORITHMS FOR LINEAR ACCELERATOR DESIGN AND OPERATION

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Abstract

In this paper, we investigate the usage of advanced algorithms, specifically Bayesian optimization, adapted for optimizing the design and operation of different linear accelerators (LINACs). The aim is to enhance the design efficiency and operational reliability and adaptability of linear accelerators. Through simulations and case studies, we demonstrate the effectiveness and practical implications of these algorithms for optimizing LINAC performances across diverse applications.

INTRODUCTION

The field of accelerator physics has advanced significantly, driven by the demand for higher performance in particle accelerators used in research, medical, and industrial applications. Conventional methods for designing and operating these complex systems, such as Nelder-Mead Simplex [1] and robust conjugate direction search [2], often rely on extensive simulations and expert knowledge due to the large and varied accelerator components and parameters needed to be tuned. Therefore, developing more efficient ways to solve complex optimization problems through advanced machine learning (ML) based algorithms are being explored.

Among the advanced algorithms, Bayesian Optimization (BO) has been gaining popularity within the accelerator community for both offline and online tuning due to its flexibility, low initialization effort, fast convergence, and robustness to noisy environments [3–5]. BO builds a probabilistic surrogate model, typically a Gaussian process [6], of the objective function. This model predicts the function's behavior and quantifies uncertainty. The optimization process iteratively selects new evaluation points based on this model, balancing exploration of the search space with exploitation of known high-performing regions. An acquisition function guides the selection of points by considering both predicted performance and uncertainty. This efficient approach finds optimal parameters with a limited number of evaluations.

In this paper, we explore the application of Bayesian Optimization in the design of the ANTHEM MEBT line and the operation of the TAP accelerator complex at INFN-LNL. We discuss the challenges in accelerator optimization, review current techniques, and present case studies demonstrating the effectiveness of Bayesian optimization.

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THE ANTHEM MEBT LINE

The AdvaNced Technologies for Human-centrEd Medicine (ANTHEM) project aims to develop technologies for the healthcare of chronic patients. One of its main proposals is the construction of an Accelerator-based Boron Neutron Capture Therapy (A-BNCT) facility in Caserta, Campania, Italy. This facility will utilize a high-intensity proton source with the TRASCO RFQ as the proton accelerator, operating at a frequency of 352 MHz and an output beam energy of 5 MeV at a 30 mA beam current [7]. The medium energy beam transport (MEBT) line, located after the RFQ, is responsible for transporting and manipulating the spatial distribution of the beam to the target for optimal neutron production. As presented in Fig. 1, the MEBT line design includes various magnetic elements, such as quadrupoles, a dipole, and a pair of octupoles, which utilize the tail folding technique to achieve a uniform beam distribution at the target [8]. Good beam uniformity at the target with an area of 120 × 120 mm^2 is necessary to maintain the beam power deposition at around 1 kW/cm^2 for optimal neutron production and target operation.

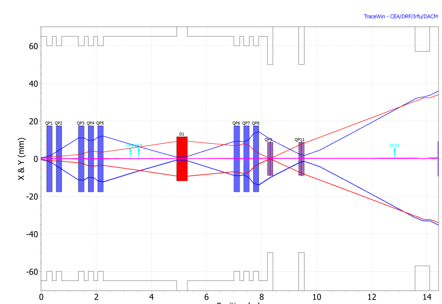

Figure 1: ANTHEM MEBT line beam envelopes with quadrupoles, dipole and octupoles being the blue, red, and purple elements respectively. Blue line: x. Red line: y.

Bayesian Optimization for Shaping the Beam Uniformity at the Target

The manipulation of the beam distribution is performed through the activation and optimization of the octupole strengths and the addition of a collimator. However, before proceeding with this step, the MEBT line was first optimized to transport the beam without losses to the target using TraceWin, a tracking program that utilizes a PIC technique to calculate the beam dynamics and exploit the space charge-induced behavior of the beam [9]. Additionally, the

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beam envelope was shaped to create beam waists at the octupole positions, decoupling their effects in the transverse plane (refer to Fig. 1).

To optimize beam uniformity at the target, we chose to use a Bayesian Optimization (BO) Python package [10] paired with TraceWin (for particle transport and tracking) to tune the magnetic field strengths of the last three quadrupoles and the two octupole magnets (5 parameters). Before performing the optimization, the octupoles were activated and a collimator of 114 × 114 mm^2 was added to shape the beam as seen in the last part of MEBT line. The objective function of the BO was designed to balance both uniformity and transmission of the beam, with a constraint that the beam transmission should be higher than 85%, which is important for maintaining neutron production yield above a certain threshold and facilitating easier collimator cooling design. The algorithm was given 60 random points to map the search space and 100 iterations for BO.

The transverse beam distributions at the target before and after the uniformity optimization are presented in Fig. 2. Through the tail folding technique of the octupole magnets and BO, we achieved a beam homogeneity of $\pm$12.5% in x and $\pm$15.02% in y for a 120 × 120 mm^2 beam area with a high beam transmission of 88% (refer to Table 1). There is a clear asymmetry in the x-plane for both beam distributions due to the uncorrected dispersion caused by the dipole. Target cooling simulations must be performed to determine if this asymmetry will cause problems in target operation and maintenance. The entire optimization run lasted about 30 minutes.

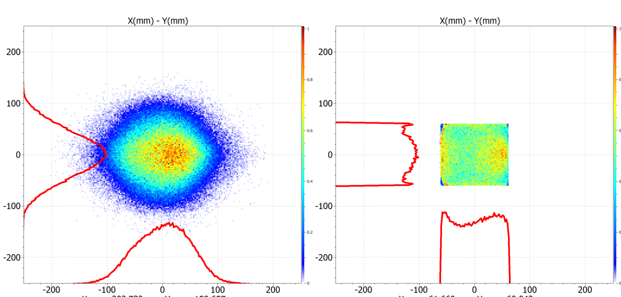

Figure 2: Transverse beam distributions at the target. Left: octupoles inactive, without collimator. Right: octupoles active, with collimator.

Table 1: Beam Transmission and Transverse Uniformity at the Target

Uniformity x	Uniformity y	Transmission
$\pm$ 12.5%	$\pm$ 15.02%	87.51%

THE SUPERCONDUCTIVE LINAC ALPI

The ALPI linac consists of 20 cryostats (CR), each housing four Quarter Wave Cavities (refer to Fig. 3). At the start of each ion-specific run, each cavity must be independently tuned to the beam. The superconducting cavities were originally engineered to reach 3 MV/m with a bore aperture of 10 mm. The linac period was designed to include one triplet for transverse focusing and two cryostats (eight cavities) to optimize the machine's real estate. Currently, ALPI has two injectors for stable ions: the electrostatic accelerator TANDEM, which accelerates light ions, and the PIAVE superconducting RFQ, with an output energy of 587.5 keV/u [11]. Both injectors suffer from low transmission to ALPI due to the machine's low longitudinal acceptance. The ALPI PIAVE accelerator complex has a design transmission of 60%, with real transmission of around 15 - 20%.

In recent years, advancements in superconducting cavity technology have nearly doubled the accelerating fields of the cavities compared to the original design values. However, this improvement in energy gain has resulted in a trade-off with transmission efficiency. To help minimize these losses, especially in the low beta regime, the Alternate Phase Focusing technique at $\pm$ 20° synchronous phase was adapted [12]. This technique reduced the longitudinal phase advance from around 160° to below 120°, which helped control the defocusing and steering effects but further reduced the longitudinal acceptance of ALPI.

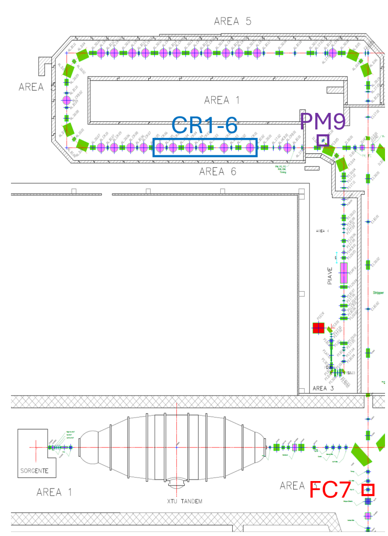

Figure 3: TANDEM ALPI PIAVE (TAP) accelerator complex at INFN-LNL. Blue rectangle: CR1-6. Purple square: PM9. Red square: FC7.

Bayesian Optimization for Shaping the Longitudinal Acceptance

A beam of $^{129}Xe^{25+}$ was accelerated to 950 MeV through the PIAVE-ALPI setup with cryostats 1 to 17 activated. The TAP accelerator complex is equipped with several diagnostics stations, including a beam profiler and a Faraday cup. Additionally, all the components (quadrupoles, dipoles, steerers, cavities, bunchers, and diagnostics) apart from the superconducting RFQ PIAVE are controllable by EPICS. The beam current is the main characteristic we monitor for setting up the beam for the users. At first, the beam was manually transported from the source to the faraday cup FC7 (refer

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to Fig. 3) and the cavities activated and tuned according to the APF technique for 1-2 days. The beam current reached through manual tuning and transport was 122 nA.

To test if the BO can improve the beam transmission of ALPI, the algorithm was tested on the first six cryostats (24 cavities) while looking at the current reading at Faraday cup FC7. The phases of the cavities were allowed to explore $\pm$ 3.5° from the original phase setting. The objective function of the BO depended solely on the current measurement, as it was the only diagnostic available. The algorithm was set to have 40 random points and 80 BO iterations.

Table 2: Initial and Optimized Current Measurement at Faraday Cup 7 (FC7) and the Corresponding Measurement Increase

Diagnostic	Initial	Optimized	% Increase	Time Elapsed
FC7	122 nA	180 nA	47.54 %	5 min

The results of the optimization are presented in Table 2, which shows the initial and final current readings at FC7, and Fig. 4(a), which shows the synchronous phases of the cavities for AFP (black) and BO (red). We observed an increase of 47.54% in transmission in just under 5 minutes. To understand the observed increase in transmission and correlate it to changes in the beam dynamics of the accelerator, we plotted the longitudinal acceptance of ALPI before (black) and after (red) the optimization, as shown in Fig. 4(b). The longitudinal acceptance was obtained in TraceWin by transporting a beam with large longitudinal emittance and number of particles through ALPI and tracking the surviving particles at the end back to the start. The synchronous phases of the cavities were adjusted to simulate the optimized phases obtained by the BO. The resulting longitudinal acceptances show that with the BO, we are distorting the shape of the acceptance to increase the acceptance towards $+\phi$. This could be due to the input beam having a phase drift induced by timing differences between PIAVE and ALPI or by temperature fluctuations throughout the accelerator operation.

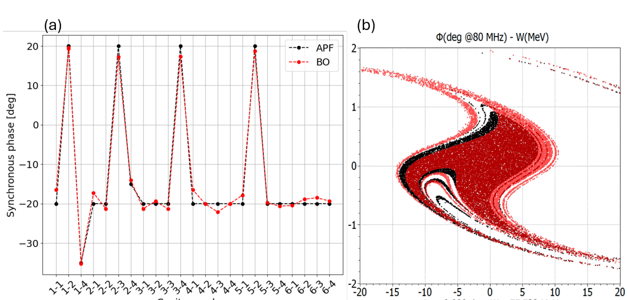

Figure 4: (a)Synchronous phases of the accelerating cavities CR1-6. (b) Longitudinal acceptance. Black: Alternate Phase Focusing (APF). Red: Bayesian optimized (BO).

We also observed an increase in longitudinal emittance from ϵ_{APF} = 2.942 π.deg.MeV to ϵ_{BO} = 3.212 π.deg.MeV accounting for an almost 9% increase in acceptance. In addition, we determined that there is no significant change in the output beam energy by changing the phases of the accelerating cavities.

Bayesian Optimization for Improving the Transverse Optics

Another BO test at the TAP facility was performed with the same beam of $^{129}Xe^{25+}$ to improve the transmission by optimizing the transverse optics of PIAVE, looking at Faraday cup PM9 (refer to Fig. 3), which is just before the entrance on ALPI. In this case, the elements included in the algorithm were quadrupole lens averages and imbalances and steerers totaling 37 parameters. The quadrupole lenses were allowed to vary by $\pm$2 (average) and $\pm$0.5 (imbalance) while the steerers varied by $\pm$0.003 with respect to the starting point settings. Adaptive boundaries were also applied to the test run, allowing the bounds to expand if the best settings were close to the set boundaries.

Table 3: Beam Transmission at Faraday Cup PM9 after Optimizing the Transverse Optics of PIAVE

Optimizer	Transmission	Time Elapsed
Best operator	62 %	1 hour
BO	64.5 %	30 min

To compare the effectiveness of BO with manual tuning, we gave the best operator in the laboratory one hour to optimize the PIAVE transverse optics for maximum beam transmission, starting from the same initial settings. Then, we run the BO until it surpassed the beam transmission set by the best operator. The results of the test are listed in Table 3. Through BO, we obtained a transmission of 64.5% through PIAVE, which is the highest ever recorded since its operation. It is also the first time the transmission approached the theoretical values of PIAVE, which are around 65 - 70%. Comparing this result to the manual tuning (62%), the algorithm achieved the same transmission in half the time (240 iterations).

CONCLUSIONS

In this paper, we present an innovative method applied to both accelerator design and operation. We utilized BO to optimize the design of the spatial beam manipulation segment of the ANTHEM MEBT line for obtaining a uniform beam distribution at the target with minimal losses. From a practical perspective, we also employed BO to enhance the performance of both transverse and longitudinal elements at the TAP facility, thereby improving the machine's transmission efficiency. Our findings suggest that ML has the potential to enhance accelerator physics, providing opportunities to improve performance and operational efficiency. In the future, our goal is to optimize all elements of the TAP facility simultaneously, enabling fully automatic machine settings.

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