MACHINE LEARNING–DRIVEN OPTIMIZATION OF POSITIVE ION BEAMS ON THE LUTEX IRRADIATION FACILITY

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Abstract

LUTEX (Ligne pour UTilisateurs EXternes) is a high-performance irradiation facility providing the world's largest testing area ($400 \times 700\,\mathrm{mm}^2$). It delivers light-ion beams with very high fluxes at 300 keV/u (~5000 km/s) for H^+ up to 4×10^9 protons/cm^2/s. This enables rapid reproduction of extreme exposure conditions and allows for short time qualification of a material lifetime. For comparison, a typical solar storm reaches only 3 keV/u (~600 km/s) and 0.2 protons/cm^2/s.

Operating a continuous accelerator such as LUTEX requires achieving beam stability conditions on energy and current over a long period of time tailored to experimental needs. The difficulty resides in the change of a large number of input parameters, in their nonlinear interactions and in the variability of irradiation conditions.

Pantechnik is developing a Machine Learning model designed to facilitate beam tuning, to optimize beam quality, and to predict parameters required for production of continuous beam. The model exploits data collected from plasma generation, extraction, transport, separation, and dose measurements to learn the relationship between machine settings and resulting beam performances. After data preprocessing and feature extraction, several approaches, including Bayesian optimization and nonlinear regression methods, will be benchmarked to predict and optimize the beam current as a function of operating parameters.

INTRODUCTION

Particle accelerators must meet strict beam performance requirements in terms of energy, homogeneity, and reproducibility. However, their optimization faces major challenges: a variety of parameters, nonlinear interactions, strict operational constraints, and costly, noisy experimental measurements.

Bayesian optimization has already proved its effectiveness in various fields, particularly for accelerator optimization [1–3]. This method has been successfully applied to ion sources, the Nanogan [4], and the Venus [5]. Based on probabilistic models, it enables efficient exploration of the parameter space while integrating uncertainties from experimental measurements. Its ability to converge rapidly toward optimal solutions with a reduced number of samples makes it a tool of choice for optimizing complex systems.

The LUTEX facility (Ligne pour UTilisateurs EXternes), provides an ideal framework to apply and evaluate Bayesian optimization. The objective is to optimize key beam parameters, such as current, from a probabilistic model fed by experimental data (generation, extraction, transport, and dose measurements). Several Bayesian optimization strategies, including different acquisition functions and regression methods, are evaluated to determine the most effective configuration.

Applying Bayesian optimization at LUTEX's system aims to significantly reduce tuning time, improve beam quality, and demonstrate the potential of this method for particle accelerators. The results obtained could also be extended to other complex systems facing similar multi-parameter optimization challenges.

SYSTEM SETUP

LUTEX uses an ECR (Electron Cyclotron Resonance) Monogan 1000 source from Pantechnik, with an extraction and transport beam line, which comprises a dipole magnet for ion selection. Gas, typically H_2 for protons, is injected into the source to generate a plasma, from which the ion beam is extracted and shaped. The dipole magnet sorts ions by their mass-to-charge ratio, delivers mainly H^+ to the irradiation table. Figure 1 illustrates the conceptual layout of the LUTEX's irradiation line.

In this study, beam diagnostics will focus on varying three key input parameters: extraction puller electrode voltage, focus electrode voltage, and the dipole current which correlates to the magnetic field. These parameters will be adjusted to analyze their impact on beam performance. The Faraday Cup current will serve as the primary objective measurement, providing a quantitative assessment of the beam's characteristics under different conditions. To isolate the effects of the selected variables, all other experimental parameters will be kept constant throughout the experiments. This controlled approach will enable an evaluation of the relationship between the input parameters and the resulting beam current.

SIMULATION RESULTS

For each system, Pantechnik is looking for the optimal parameters required to reach the customer's specifications. This process relies on theoretical calculations to refine and validate the expected performance of the system. Prior to this phase, a comprehensive simulation was conducted using

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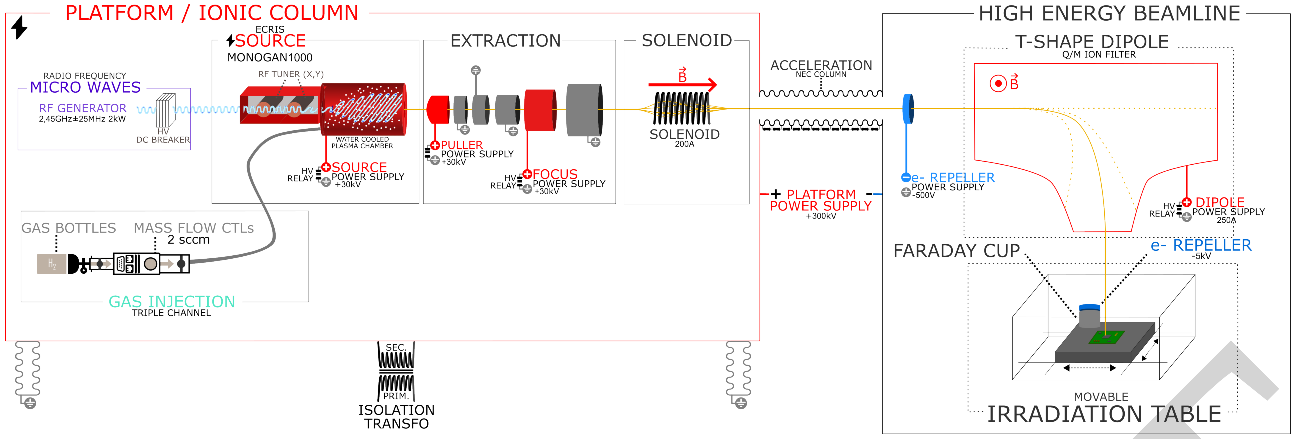

Figure 1: Conceptual layout of the LUTEX's irradiation line.

the IBSimu software to identify and fine-tune the relevant parameters. The results of this effort are illustrated in Fig. 2, which presents a simulation of the extraction process fully compliant with the dimensional constraints of the LUTEX's system. The beam depicted in this simulation is generated by injecting hydrogen into the ion source, with a platform voltage of 100 kV, a source voltage of 15 kV, a puller voltage of 9.5 kV, and a focus voltage of 10.5 kV. At this acceleration, these settings are expected to maximize the beam current for the extracted hydrogen beam. This simulation verifies that the proposed parameters satisfy both theoretical expectations and practical constraints, ensuring a solution that fits the customer's needs.

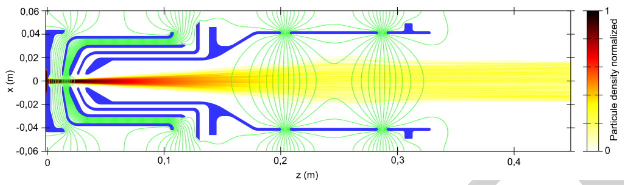

Figure 2: IBSimu extraction result used as a reference for beam tuning.

BAYESIAN OPTIMIZATION

Bayesian optimization is an iterative, probabilistic method designed to solve expensive optimization problems where direct evaluation of the objective function is limited by experimental or computational constraints. It relies on two key components: a probabilistic surrogate model (typically a Gaussian process) that approximates the objective function $f : \mathscr{X} \to \mathbb{R}$ by providing both an estimate of its mean value $\mu(x)$ and associated uncertainty $\sigma^2(x)$, and an acquisition function $\alpha(x)$ that determines the next evaluation points by balancing exploration (uncertainty reduction) and exploitation (optimum seeking) [6]. Unlike traditional methods such as grid searches or genetic algorithms, Bayesian optimization efficiently converges to optimal solutions with fewer evaluations while naturally incorporating measurement uncertainties and system constraints. Its iterative process (updating the model, optimizing the acquisition function, performing experimental evaluation, and enriching the dataset) makes it particularly suitable for complex systems where evaluations are costly, noisy, or subject to strict operational constraints. Bayesian optimization has proven especially effective for optimizing physical systems with nonlinear parameter interactions and limited experimental measurements, as is commonly encountered in particle accelerator optimization problems.

METHODOLOGY

The Bayesian optimization pipeline was implemented using the Ax library [7] in conjunction with BoTorch [8], leveraging their integrated capabilities for efficient Gaussian process modeling and acquisition function optimization. The optimization problem was defined over three key parameters described above while all other system settings were held constant. The objective function was established as the Faraday Cup current measurement, serving as an indicator of beam intensity.

A Python-based automation software was developed to interface with the LUTEX's control system, executing a closed-loop optimization process for each iteration:

1. receiving suggested parameter values from the Bayesian optimizer,
2. applying these settings to the system,
3. allowing a 20-second stabilization period to ensure steady-state beam conditions,
4. recording the Faraday Cup current, and
5. feeding the measurement back into the optimization pipeline.

This automated workflow eliminated manual intervention, ensuring consistency and reproducibility in data collection.

The optimization started without prior experimental data, allowing the algorithm to explore the parameter space from scratch. The training protocol used a two-phase approach: an initial exploration with 30 evaluation points to build a surrogate model, followed by an exploitation phase with 10 additional points to refine the optimum. The Expected Improvement (EI) acquisition function guided the search, balancing exploration and exploitation. The Gaussian process surrogate model used default parameters from the Ax library.

RESULTS

The Bayesian optimization procedure successfully identified an improved parameter configuration that significantly enhanced beam performance compared to the initial reference settings. Under the reference simulation conditions, with a dipole current set to 49.3 A, the system produced a measured Faraday Cup current of 3.85 µA. Through systematic exploration of the parameter space, the optimization algorithm converged to a superior configuration characterized by a Puller voltage of 10.3 kV, a Focus voltage of 8.5 kV, and a dipole current of 48.9 A. This optimized parameter set produced a predicted Faraday Cup current of 4.94 µA, representing a substantial 28.3 % improvement (+1.09 µA) over the original reference configuration. These settings have been successfully tested on the accelerator.

To analyze the relationships between control parameters and beam performance, visualization techniques were used. Figure 3 shows a slice plot of the predicted Faraday Cup current as a function of Focus voltage, with the other parameters fixed at their optimized values. This plot reveals a clear optimal region around 8.5 kV, where the current reaches its maximum. The curve shows a nonlinear response, with a sharp increase in current between 7.5 to 9.0 kV, followed by a gradual drop at higher voltages. This suggests complex interactions in the focusing system, where too much focusing can lead to beam divergence or losses.

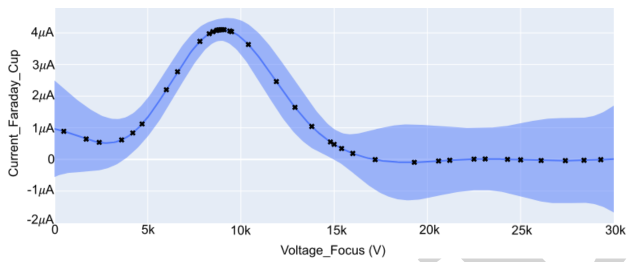

Figure 3: Slice plot showing predicted Faraday Cup current (dark blue) and its uncertainty (light blue) as a function of Focus voltage.

Figure 4 displays a contour plot illustrating the predicted Faraday Cup current as a joint function of both Puller and Focus voltages, while maintaining the dipole current at its optimized value. Several important observations emerge from this visualization:

1. a well-defined optimal region exists around the coordinate (Puller voltage: 10.3 kV, Focus voltage: 8.5 kV),
2. the contour lines indicate cross-interaction between these parameters, and
3. the current shows sensitivity to variations in both voltages within the optimal region.

These results collectively demonstrate that Bayesian optimization can effectively navigate the nonlinear parameter space of particle accelerator systems to achieve substantial performance improvements with minimal experimental evaluations.

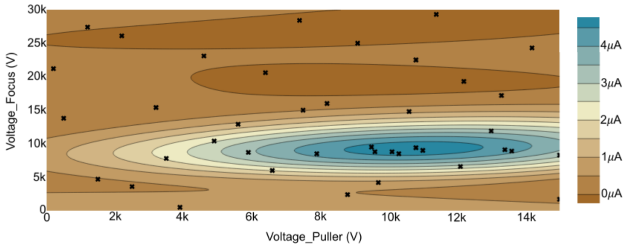

Figure 4: Contour plot showing predicted Faraday Cup current as a function of Puller and Focus voltages.

FUTURE DEVELOPMENTS

The future development of the LUTEX optimization framework aims at establishing a comprehensive machine learning-based control system. This includes progress in data infrastructure, such as structured databases and systematic data collection, to support more sophisticated optimization approaches. The framework will be expanded to include additional parameters and multi-objective optimization, incorporating beam quality metrics, such as beam size and homogeneity. Ultimately, this will lead to real-time, adaptive control systems for Pantechnik's particle accelerators and ECR ion sources.

CONCLUSION

This study demonstrates the application of Bayesian optimization to optimize beam parameters in the LUTEX's irradiation line. Using a surrogate model based on Gaussian processes, the optimization varied three key parameters. An optimal configuration was identified, achieving a 28 % improvement in predicted Faraday Cup current compared to the simulation-based reference settings. Experimental validation, including beam profile analysis, confirmed the effectiveness of the approach, highlighting its potential for efficient parameter tuning in complex accelerator systems.

The work also establishes elements for data-driven control, including automated data collection and preprocessing pipelines. These developments support the transition toward intelligent, adaptive control systems for particle accelerators and ECR sources.

Future research will explore multi-objective optimization and real-time adaptation to further enhance beam performance and operational efficiency [9].

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