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EFFICIENT ACCELERATOR OPERATION WITH ARTIFICIAL INTELLIGENCE BASED OPTIMIZATION METHODS

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Abstract

This work presents a simulation-based beam tuning study for the Karlsruhe Research Accelerator (KARA) injection line, combining model-free optimization strategies with beam diagnostics. This is the first application of such a machine learning-driven tuning framework to this part of the accelerator. The study is carried out entirely within Cheetah, a differentiable Python-based simulation code, with steering correction performed using Bayesian Optimization (BO) and quadrupole tuning conducted via the Bayesian Algorithm Execution (BAX), a multi-objective optimization tool. The simulation includes realistic beam dynamics and screen-based diagnostics to evaluate tuning performance. The beam measurements at KARA show a clear transverse misalignment, further motivating the need for automated tuning strategies. These results provide a foundation for future experimental deployment and demonstrate the potential of machine learning techniques to improve tuning efficiency and robustness in accelerator operations.

INTRODUCTION

Accurate steering of particle beams through magnetic elements is a fundamental aspect of accelerator operation, particularly in low-energy sections such as injection lines. When a beam travels off-axis through magnets like quadrupoles or solenoids, it experiences non-linear effects such as feed-down from higher-order multipole fields, which manifest as effective dipole kicks. These unintentional deflections complicate tuning procedures, as changes to individual magnet settings can induce further misalignments downstream. This is especially problematic in beamline sections with small apertures or limited diagnostics, where misalignments can lead to beam loss or degradation in beam quality due to interactions with non-ideal field geometries and fringe fields. Beam-based alignment (BBA) methods have been developed to identify and correct beam misalignments in such cases. Traditional BBA approaches rely on beamline models to relate magnet displacements and strengths to observable beam deflections, allowing correction through iterative scans and orbit fitting [1]. Although effective, these model-dependent methods can be time-consuming and sensitive to inaccuracies in the lattice description. Alternatively, model-free strategies have been proposed that iteratively probe the response of the system using steering magnets and beam position monitors (BPMs) or profile screens [2]. Although these methods avoid explicit dependence on the beamline model, they typically require a large number of measurements and offer limited scalability to higher-dimensional tuning spaces.

In this study, we present a simulation-based approach for automated beam tuning based on machine learning techniques, applied to the KARA injection line. The approach combines realistic beamline modeling with Bayesian optimization strategies and is implemented entirely within Cheetah, a lightweight, Python-based, simulation-differentiable code developed by DESY and KIT [3, 4]. The tuning campaign is structured in two stages: in the first, the beam steering is optimized using Gaussian process (GP) regression and acquisition functions to minimize beam centroid offsets; in the second, the quadrupole magnet settings are tuned using the BAX, which is integrated into Cheetah to handle multi-objective, model-aware optimization and incorporate prior knowledge to guide the search [5].

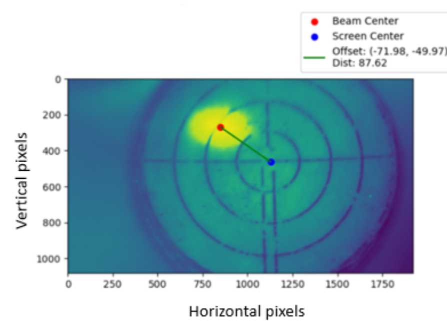

Figure 1: The injection line beam position analysis on the screen image. Units are in pixels.

Beam position measurements at KARA (see Fig. 1) show the injected beam centroid (red) offset from the screen center (blue) by approximately 88 pixels, corresponding to a physical displacement of ~ 0.88 mm (assuming 10 µm/pixel). This transverse misalignment may be caused by incorrect quadrupole strengths arising from effects such as hysteresis, calibration errors, or deviations from the modeled lattice.

OPTIMIZATION SIMULATION SOFTWARE AND TOOLS

Cheetah

Cheetah is a modular and extensible simulation environment developed for modeling and optimizing particle accelerator systems in support of data-driven control strategies [3,4]. It provides a flexible interface for simulating beam dynamics through various accelerator components, including

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quadrupoles, dipoles, and diagnostic elements. Cheetah enables rapid prototyping and evaluation of control algorithms in a virtual accelerator setting prior to experimental deployment. It has been successfully employed in the development and testing of surrogate-based tuning workflows.

Bayesian Optimization

In case of steering magnet tuning, we are not solving a matrix-based orbit correction. Instead, we treat the orbit error as a black-box function of magnet settings, avoiding reliance on an accurate response matrix and enabling the capture of nonlinear effects. Bayesian Optimization (BO) models an unknown objective function $f : \mathbb{R}^d \to \mathbb{R}$ using a probabilistic surrogate model. A Gaussian Process (GP) is commonly used:

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')), \tag{1}$$

where $m(\mathbf{x})$ is the mean (often zero), and $k(\mathbf{x}, \mathbf{x}')$ is the covariance kernel function.

Given n observations, the posterior mean $\mu_n(\mathbf{x}_*)$ and variance $\sigma_n^2(\mathbf{x}_*)$ at a test point $\mathbf{x}_*$ are given by:

$$\mu_n(\mathbf{x}_*) = \mathbf{k}_*^T(\mathbf{K} + \sigma_n^2\mathbf{I})^{-1}\mathbf{y}, \tag{2}$$

$$\sigma_n^2(\mathbf{x}_*) = k(\mathbf{x}_*, \mathbf{x}_*) - \mathbf{k}_*^T(\mathbf{K} + \sigma_n^2\mathbf{I})^{-1}\mathbf{k}_*, \tag{3}$$

where $\mathbf{K}$ is the kernel matrix of the training points, $\mathbf{k}_*$ is the vector of covariances between the test point and training points, and σ_n^2 is the noise variance.

To decide where to sample next, BO maximizes an acquisition function. In this work, we use the Upper Confidence Bound (UCB) acquisition function:

$$\alpha_{\text{UCB}}(\mathbf{x}) = \mu_n(\mathbf{x}) + \kappa \cdot \sigma_n(\mathbf{x}), \tag{4}$$

where $\kappa > 0$ is a tunable hyperparameter that controls the trade-off between exploration and exploitation.

Beam Alignment Using BAX

Quadrupole magnet tuning is not just a black-box optimization problem. It involves physics, constraints, safety, and a rich structure in parameter space. BAX gives flexibility to reason analytically and structurally about decisions. Let $\mathbf{x} = [s_1, s_2, \ldots, s_k, q]$ represent the upstream steering magnet settings s_i and the quadrupole strength q. A GP is used to model the beam centroid position $y(\mathbf{x})$ on a downstream screen [6].

Using a degree-1 polynomial product kernel:

$$k(\mathbf{x}, \mathbf{x}') = \prod_{i=1}^{k+1}(1 + x_i x_i'), \tag{5}$$

we ensure that the surrogate model reflects the approximately linear and independent influence of each magnet.

To compute beam deflection for fixed steering settings $\mathbf{s}$, the slope with respect to q is evaluated as:

$$\Delta y = \frac{y([\mathbf{s}, q_2]) - y([\mathbf{s}, q_1])}{q_2 - q_1}. \tag{6}$$

Here, q_1 and q_2 represent two slightly different strengths of the same quadrupole magnet, used to evaluate the beam's sensitivity to quadrupole variations. By measuring the downstream beam position y at both strengths, we approximate the derivative of the beam position with respect to quadrupole strength. The alignment objective becomes:

$$\mathbf{s}^* = \arg\min_{\mathbf{s}} \left| \frac{y([\mathbf{s}, q_2]) - y([\mathbf{s}, q_1])}{q_2 - q_1} \right|. \tag{7}$$

RESULTS

We performed two simulations to evaluate the effectiveness of Bayesian optimization techniques in aligning and steering an electron beam from microtron to booster in the injection line of KARA. The first simulation focused on using Bayesian Optimization (BO) to identify optimal settings for two steering magnets, M_1 and M_2, followed by a triplet of quadruple magnets with the goal of centering the beam on a downstream screen (see Fig. 2). As shown in Fig. 3,

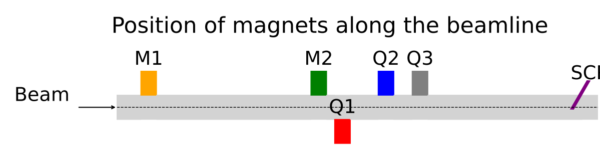

Figure 2: The positions of steering magnets M_1 and M_2, as well as quadrupole magnets Q_1, Q_2, and Q_3, are shown along the beam path in the injection line.

the initial beam image (left) reveals a clear offset from the screen center. After running the optimization, the beam is successfully centered.

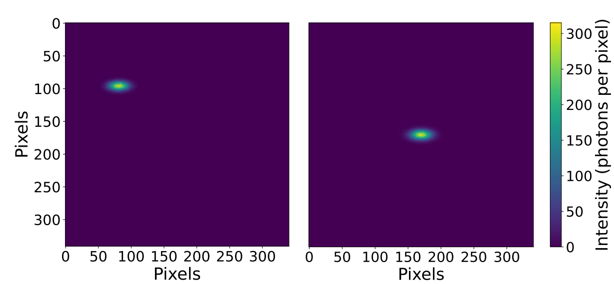

Figure 3: Beam position before (left) and after (right) Bayesian Optimization, showing successful centering.

In Fig. 4, the evolution of steering magnet settings and beam position during the Bayesian optimization process is shown. It displays the recorded angles for magnets M_1 and M_2 over 70 iterations, with initial fluctuations reflecting the exploration phase. Around iteration 30, both angles stabilize, indicating convergence to values that achieve beam centering. In Fig. 5 we can see the total beam displacement as a function of these angular settings. A pronounced minimum region appears where the beam approaches the optical axis. This behavior highlights the strong sensitivity of the trajectory

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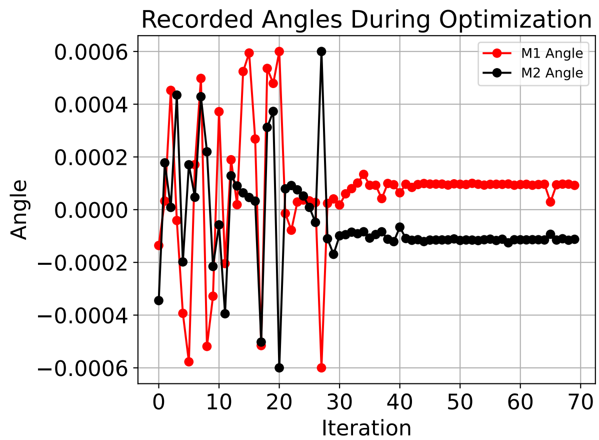

Figure 4: Steering magnet angles M_1 (red) and M_2 (black) recorded over successive optimization iterations.

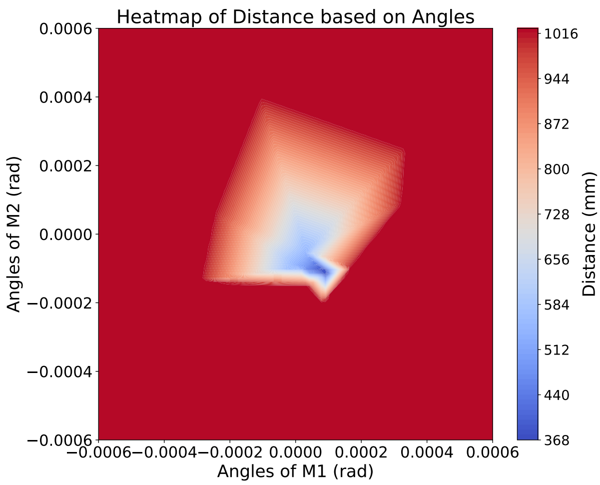

Figure 5: Beam centroid displacement on the screen (in mm) as a function of steering angles applied by magnets M_1 and M_2.

to small steering deviations and defines a low-displacement region that would serve as an ideal starting point or prior for downstream optimization.

In the second simulation, we applied the BAX alignment algorithm to identify the optimal steering parameter M_1 required to align the beam through the magnetic center of a quadrupole magnet Q_1. This was achieved by minimizing a virtual objective defined as the finite-difference slope in the position of the beam, calculated by varying the quadrupole strength Q_1.

In Fig. 6, in the top panel is illustrated the beam displacement in the horizontal x-direction as a function of both M_1 and Q_1. The red vertical line marks the optimum value of M_1, where the beam remains minimally displaced across varying quadrupole strengths, indicating ideal alignment. The left plot in the lower panel shows the beam x-displacement as a function of quadrupole strength Q_1 for the optimal M_1 value found by BAX which is near zero, confirming flat response and effective decoupling. The right plot shows the virtual objective function — defined as the slope of beam displacement vs. quadrupole strength — along with its 95 % confidence interval. The global minimum of this curve corresponds to the optimal alignment, where the beam is least sensitive to changes in Q_1, validating the BAX algorithm's ability to infer optimal alignment from indirect measurements with high confidence.

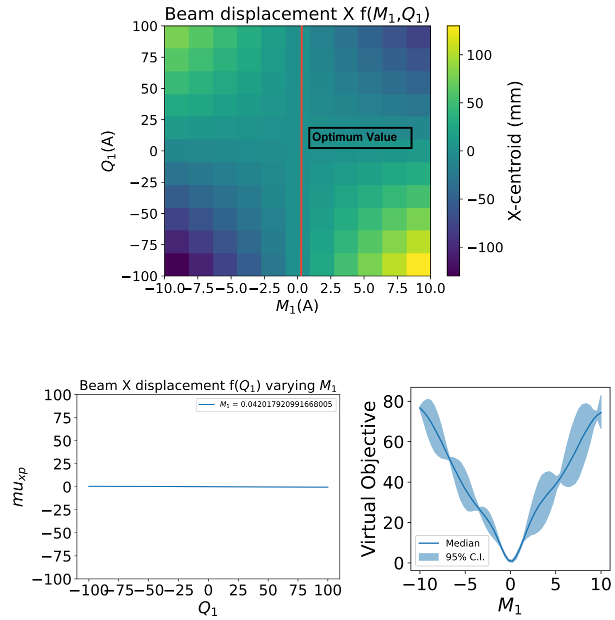

Figure 6: BAX alignment results: optimum steering value (top), flat beam response (bottom left) and virtual objective minimum (bottom right).

CONCLUSION

In this study, we demonstrated that Bayesian Optimization and the BAX algorithm can effectively automate beam alignment tasks at KARA. These methods accurately centered the beam and aligned it through key magnetic elements, significantly reducing the need for manual intervention. Future work will involve experimental validation on the live machine and the extension of the approach to multi-parameter, high-dimensional tuning problems in real time.

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