OPTIMIZATION OF ONE AND TWO-PLANE MULTI-TURN INJECTION IN THE SIS18 SYNCHROTRON

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Abstract

In the SIS18 heavy-ion synchrotron at GSI, loss-induced vacuum degradation and reduced beam lifetime limit high-intensity operation with uranium ions. During multi-turn injection (MTI), even small localized losses can trigger pressure bump instabilities, making optimized injection control essential to reach FAIR intensity goals. We present a comprehensive study on optimizing the MTI process in the SIS18 at GSI, combining experimental measurements and simulations. Online optimization using the derivative-free BOBYQA algorithm enabled direct improvement of machine performance. Multi-objective Bayesian optimization (BO) was applied to reconstruct the Pareto front experimentally between injection efficiency and beam losses, providing insight into the best achievable performance. On this basis, we introduce a multi-fidelity BO framework that integrates prior knowledge from low-fidelity models with high-fidelity experimental measurements, achieving improved sample efficiency. Complementary simulation studies on two-plane injection indicate a further potential for loss reduction. The results demonstrate effective, adaptive MTI optimization and support future autonomous tuning strategies.

INTRODUCTION

The Facility for Antiproton and Ion Research (FAIR) is an international center of heavy-ion accelerators, designed to advance research in heavy-ion and antimatter physics [1]. The facility's complexity demands a high degree of automation for future operations [2]. As part of this effort, we developed a framework called Generic Optimisation Frontend and Framework (*Geoff*) [3], which allows machine experts and operators to solve concrete optimization problems and reuse these solutions in an operational context.

A critical challenge for FAIR is the MTI into SIS18, which serves as a booster for SIS100 synchrotron. The MTI is a major bottleneck for achieving target beam intensities. Losses during injection can degrade the vacuum and limit the intensity of intermediate charge-state beams, and so must be minimized [4–6]. To address this challenge, online optimization campaigns were performed using classical algorithms such as BOBYQA, as well as advanced methods including BO and multi-fidelity BO. These approaches leverage simulations and machine measurements to efficiently reduce beam losses.

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MULTI-TURN INJECTION

The MTI of the SIS18 is central for reaching target intensities of FAIR without exceeding acceptable beam losses of a few percent. Individual beamlets are stacked in a horizontal phase space until machine acceptance is reached. A time-dependent closed-orbit bump, generated by four bumper magnets, guides each incoming beamlet into the free phase space near the previous ones, typically using an exponential bump decay. After injection, the beamlets undergo betatron oscillations with horizontal tune Q_x and pass the injection point again after each turn. If the orbit bump decays too slowly, the beamlets may hit the inner septum and be lost; losses can also occur at limited acceptance [7, 8]. The **loss fraction** η quantifies the particles lost during injection:

$$\eta = \frac{N_{\text{lost}}}{N_{\text{inj}}} = \frac{I_{\text{TK}}n - I_{\text{SIS18}}}{I_{\text{TK}}n}, \tag{1}$$

where averaged $I_{\text{TK}}n$ is the ideal injected current and I_{SIS18} is the actual accumulated current. "TK" stands for the injection beamline to the SIS18. Low η indicates a more efficient injection. The effective number of accumulated turns is then $m = n(1 - \eta)$. In [9], the ideal injected current is defined more precisely as the sum of TK pulses per turn, which accounts for fluctuations and local variations. For optimal phase-space filling [10], injected emittances can be mapped to upright ellipses and the lattice functions mismatched so that the curvature of the incoming beamlets matches the acceptance. Previous studies demonstrate that horizontal emittance is a key factor for MTI performance: smaller emittance leads to reduced losses and higher accumulation. Experimental measurements and simulations confirm this trend, increasing confidence in the MTI simulation model implemented in Xsuite [7, 8, 11].

ONLINE OPTIMIZATION

Building on promising optimization results in simulation [7, 12], online MTI optimization campaigns were performed at SIS18 to reduce beam losses, as shown in Fig. 1. In the November 2023 and May 2024 campaigns, five injection parameters[1] and four beamline steerers were optimized using *Geoff* and **classical algorithms**. The parameter values were randomized before each run to avoid bias from favorable initial states. BOBYQA performed robustly when fluctuations were reduced by taking the median of three measurements for each iteration. Losses decreased from approximately 45 % (manual tuning) to 15 % in 2023 and

[1] Orbit bump amplitude and decay, two septum steerers, and a timing offset.

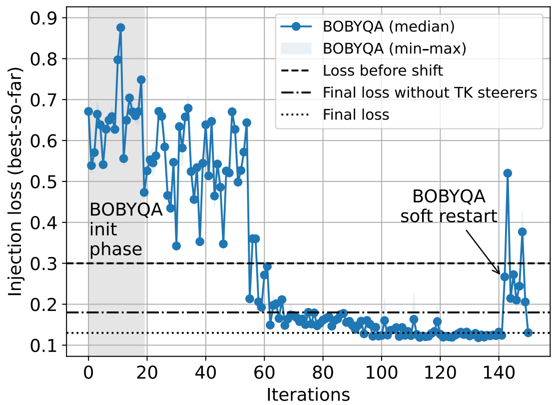

Figure 1: SIS18 MTI online optimization with BOBYQA (measurements). Gray area: initialization; final point: extra evaluation at optimum.

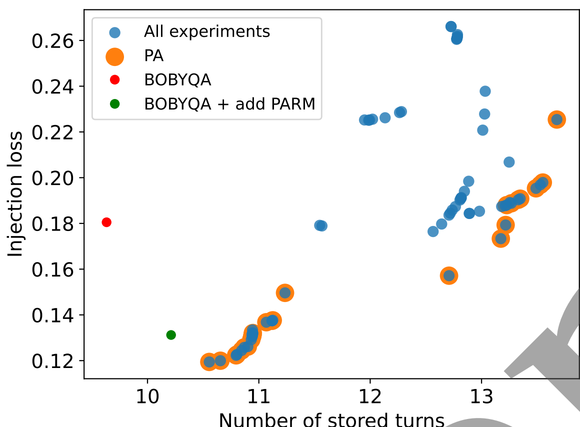

Figure 2: Pareto front for MTI losses vs. stored turns (measurements). Blue: all measurements; orange: Pareto front; red/green: BOBYQA results.

from 30 % to 15 % in 2024, with each run lasting 15–20 minutes [13].

Classical algorithms are efficient and reliable for many tasks but can struggle in high-dimensional or highly nonlinear parameter spaces. **Bayesian optimization** constructs a probabilistic surrogate (typically a Gaussian process) and selects candidate evaluations via an acquisition function that balances exploration and exploitation [14, 15].

Single-objective BO minimizes injection losses, while **multi-objective Bayesian optimization (MOBO)** trades losses against injected current and approximates the Pareto front [6]. A key metric in this process is the hypervolume, which measures the volume in objective space dominated by the current Pareto front relative to a reference point. The optimization algorithm uses this metric, particularly the expected increase in hypervolume, to guide the search for better trade-offs [16]. MOBO identifies more solutions and achieves better trade-offs than BOBYQA (Fig. 2). The measured Pareto front agrees with previous simulation studies [7]. The expected increase in injection loss with a higher number of stored turns can also be observed.

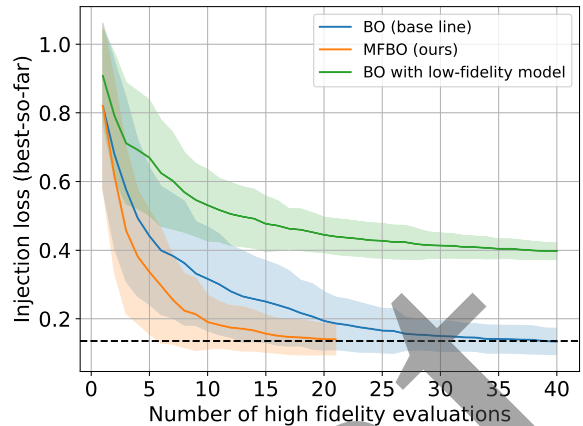

Figure 3: Blue and green show standard BO on the high- and low-fidelity models, respectively; orange shows MFBO using both models. Curves indicate the mean best-so-far injection loss versus the number of high-fidelity evaluations (shaded areas are one standard deviation over 50 runs).

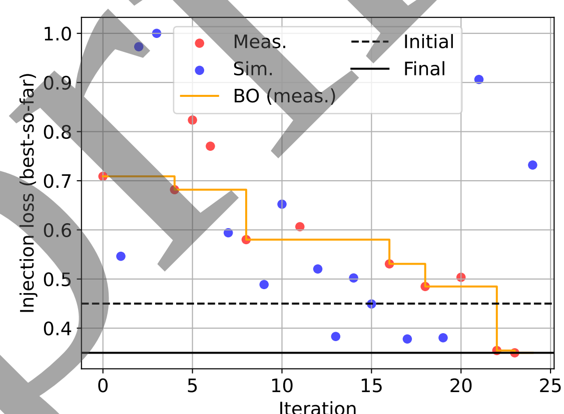

Figure 4: Multi-fidelity MTI optimization (measurements): interactions reduced from 25 to 11 using high-fidelity (red) and low-cost simulations (blue).

Multi-fidelity Bayesian optimization (MFBO) further accelerates online optimization by combining low-cost simulations with high-fidelity machine measurements [17]. In this setting, simulations guide the search, while machine measurements are used selectively to validate and refine promising regions, thereby reducing the number of costly machine interactions. Figure 3 compares standard BO using only the high-fidelity model (blue), standard BO using only the low-fidelity model (green), and the MFBO approach (orange). The results indicate that MFBO reaches competitive loss values with significantly fewer high-fidelity evaluations while showing a more consistent convergence behavior. Initial proof-of-concept experiments combining 14 low-fidelity simulations with 11 high-fidelity machine measurements within a total budget of 25 iterations (time constrain) reduced losses from about 45 % (manual tuning) to about 35 %, see Fig. 4. Remote execution via *Remote Geoff* enables computationally intensive MFBO to run on external HPC resources while securely interfacing with the accelerator [18].

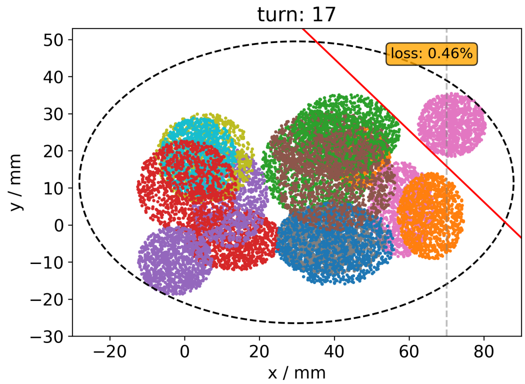

Figure 5: Two-plane injection (simulation). Red: tilted septum; gray: conventional horizontal septum; beamlets can overlap in this projection while remaining separated in full transverse phase space.

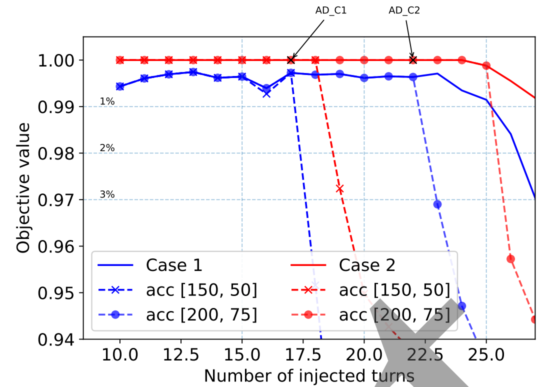

Figure 6: Loss dependence for two-plane MTI (simulation). Case 1 (blue): $\epsilon_{x,y} = 5$ mm mrad; Case 2 (red): $\epsilon_{x,y} = 3.5/5$ mm mrad. Vertical dashed lines indicate loss constraints. "AD" markers: [20].

UPGRADE: TWO-PLANE INJECTION

The performance of the MTI strongly depends on machine acceptance and beam emittance. Exploiting both transverse phase spaces increases the number of stored beamlets from $m = A/(d\epsilon)$ for single-plane injection to $m = A_x A_y/(d\epsilon_x \epsilon_y)$, allowing roughly 30–60 injection for SIS18 parameters [19]. Early layout studies of a two-plane injection for SIS18, including a transfer line redesign, were presented in [20], with updated results in [21].

Figure 5 illustrates a simulated two-plane injection, showing the transverse phase spaces together with the septum (red: tilted, gray: conventional horizontal). Using the vertical phase space allows beamlets to overlap in this projection while remaining separated in full 4D space. Compared to single-plane injection, the number of tuning parameters doubles due to the additional vertical bumper system and the need to adapt vertical beam parameters. Following [22], linear and exponential segments are used for orbit bump reduction to optimize injection while respecting acceptance limits.

For SIS18 with uranium beams, loss-free injection is critical to prevent vacuum degradation. The feasibility of two-plane injection for **loss-free injection** is analyzed. To account for acceptance uncertainty ($A_x \approx 150$ mm mrad to 200 mm mrad, $A_y \approx 50$ mm mrad to 70 mm mrad [20]), a penalty term p for the stored emittance is subtracted from the BO objective together with injection loss (since BO is a maximization procedure):

$$\text{objective} = 1 - \eta - \sum_{i \in \{x,y\}} \lambda_{\text{eff},i} \ln(1 + p_i). \qquad (2)$$

The results of the BO optimization study are summarized in Fig. 6. Approaching the Pareto front, small deviations or acceptance limitations increase emittance or losses. For $\epsilon_{x,y} = 5$ mm mrad and acceptance 150/50 mm mrad (blue), losses below 1 % over 17 turns are achievable. Under more relaxed conditions ($\epsilon_{x,y} = 3.5$ mm mrad, acceptance 200/75 mm mrad, red), up to 25 turns can be stored nearly loss-free. Points labeled "AD" correspond to previous results [20]. Lower emittance combined with larger acceptance shifts the Pareto front to more favorable values, consistent with analytical estimates.

SUMMARY AND OUTLOOK

This work presents a successful optimization of SIS18 injection using BOBYQA, MOBO, and MFBO. Experimental studies reveal that injection losses were reduced from 45 % demonstrating the advantages of online optimization. The experimentally determined Pareto front shows that the best reachable performance corresponds to 12 % losses for 11 stored turns. MFBO improved the efficiency of the sample by incorporating MTI simulations. Additional two-plane injection investigations suggest that losses below 1 % over 17 turns are feasible for $\epsilon_{x,y} = 5$ mm mrad and machine acceptance of 150/50 mm mrad. Under more relaxed conditions, up to 25 turns can be accumulated without losses.

The effectiveness of MTI optimization validates **future autonomous** tuning concepts at FAIR [23]. Model Predictive Control is being investigated for the injection of SIS18 [9]. New approaches are being developed for automated setup procedures and to improve the performance of the next-generation fragment separator Super-FRS at FAIR [24, 25].

GSI supports TU Darmstadt in automating the **PUMA** (antiProton Unstable Matter Annihilation) experiment at CERN. A dedicated setup in Darmstadt confirmed that automated operation is feasible and yielded promising initial results for improved automation with the *Geoff* framework [26]. Thanks to the flexibility of both EPICS and *Geoff*, *Geoff* was integrated into the EPICS control system without any major difficulties.

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