

TOWARDS THE AUTOMATIC SETUP OF LONGITUDINAL EMITTANCE BLOW-UP IN THE CERN SPS

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Abstract

Controlled longitudinal emittance blow-up in the CERN SPS is necessary to stabilize high-intensity beams for the High-Luminosity LHC (HL-LHC) by increasing the synchrotron frequency spread. The process consists of injecting bandwidth-limited noise into the main RF phase loop to diffuse particles in the core of the bunch. The setting up of the noise parameters, such as frequency band and amplitude, is a non-trivial and time-consuming procedure that has been performed manually so far. In this preliminary study, several optimization methods are investigated to set up the noise parameters automatically. We apply the CERN Common Optimization Interfaces as a generic framework for the optimization algorithm. Single-bunch profiles generated with the BLoND simulation code have been used to investigate the optimization algorithms offline. Furthermore, analysis has been carried out on measured bunch profiles in the SPS to define the problem constraints and properly formulate the objective function.

INTRODUCTION

Ensuring the longitudinal stability of high-intensity LHC-type beams in the CERN SPS is mandatory. This is achieved by using the fourth harmonic RF system in combination with controlled longitudinal emittance blow-up. Both techniques enhance Landau damping by increasing the synchrotron frequency spread within the bunch [1, 2].

For the controlled longitudinal blow-up, bandwidth-limited phase noise is injected into the beam phase loop locking the bunch phases to the main RF system operating at 200 MHz. The noise generation is critical: it requires a band-limited excitation spectrum (pink noise) which follows the variation of the small-amplitude synchrotron frequency f_{s0} during the acceleration ramp [3]. The input parameters for the noise generation algorithm are the low and high cutoff frequencies (normalized with respect to f_{s0}) that define the excitation band, f_{low} and f_{high} respectively, and the desired amplitude, a , of the noise. The frequencies f_{low} and f_{high} are ideally chosen to target the core of the bunch without affecting the tails. Beam stability can be reached by finding the optimal values of these three settings during the time the blow-up is active.

Adjusting the blow-up settings was done manually in the past, and it needed to be reviewed when significant changes in beam parameters occurred, e.g. increased bunch intensity. Therefore, a study of the feasibility of applying automatic

optimization methods to provide longitudinal stabilization of the beam was performed.

For this purpose, the search for proper noise settings is defined as an optimization problem integrated into the CERN Machine Learning (ML) project [4]. This activity aims at bringing numerical optimization, machine learning, and reinforcement learning into day-to-day operation at the CERN accelerator complex. In addition, we propose an objective function based on the width at different heights of the longitudinal bunch profile, as a means to quantify its shape.

In this paper, after briefly presenting the generic optimization tool employed, the implementation of an automatic procedure to optimize the longitudinal emittance blow-up in the CERN SPS is described. The novel objective function is applied, and results from offline and online optimization runs are shown and analyzed.

GENERIC OPTIMIZATION TOOLS AT CERN

Optimization is fundamental to improve the performance of the accelerator facilities [5]. From this wide experience, a tool for generic optimization has been developed.

The Common Optimization Interfaces (COI) aims at unifying multiple approaches into a single generic optimization application supported by a graphical user interface, the Generic Optimization Frontend and Framework (GeOFF). COI is the software running numerical optimization and reinforcement learning on CERN accelerators facilities. Currently, several algorithms are already implemented in the application, e.g. Bound Optimization BY Quadratic Approximation (BOBYQA) [6], Constrained Optimization BY Linear Approximation (COBYLA) [7], Nelder Mead [8], and Powell's conjugate direct method [9].

Ideally, the COI can manage every optimization problem encapsulated in an appropriate structure, as described in [4]. This means that it is sufficient to properly formulate the problem, and COI dynamically selects this implementation of classical single-objective optimization, reinforcement learning, or both, depending on the supported approaches.

LONGITUDINAL BLOW-UP CONTROL

The goal is to ensure the desired bunch emittance and distribution at the SPS flat-top, by exciting the core of the bunch with a band-limited noise, without exciting the bunch tails. Often, the settings are kept constant for the entire duration of the noise injection for simplicity, while in principle they could be defined by time-dependent functions.

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The blow-up takes place during the acceleration ramp, and the time available is limited: the blow-up can only start when the size of the bucket is sufficient. It has to be large enough to avoid losing particles when the bunch is excited. Additionally, it must finish before the start of the transverse scraping close to the arrival at flat-top.

Each parameter of the blow-up can be scanned only in a limited range. The noise is ineffective if the amplitude is too small, while, if the noise amplitude is too high, there is a risk of excessive losses. A well-targeted frequency band increases the emittance as it excites the core of the bunch only. A wrong frequency band (e.g. f_{low} too low) might excite the tails of the bunch and degrade the longitudinal beam quality. Similarly, f_{high} too high might excite quadrupolar single-bunch or coupled-bunch oscillations.

An automatic procedure to speed up the process of finding the optimal frequency band and amplitude, and to guarantee the final result, is investigated.

OBJECTIVE FUNCTION

The objective function is the core of every optimization problem as it provides the evolution of the controlled system to the optimizer. It is called loss function if an optimization problem seeks to minimize the objective function, while it is called reward function if the aim is to maximize it. In this section, we propose an objective function that easily adapts to minimization and maximization problems just by changing its sign.

A simplified description of the bunch profile is given by its width w at different relative heights with respect to the peak, which are defined as percentages of the peak value. Figure 1 shows a profile with the widths at 20%, 50%, and 80%. The values are calculated by a custom algorithm that is called Full Width at Different Levels (FWDL) by similarity with the conventional Full Width at Half Maximum (FWHM).

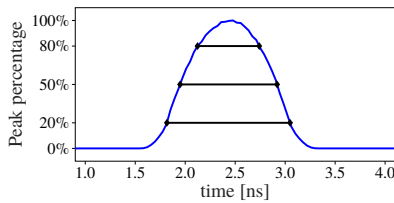


Figure 1: Example of widths (black) at different percentages of the normalized peak of a simulated bunch profile (blue).

Moreover, functions of the width can provide a partial representation of the bunch profile. Each one is a feature of the bunch, and we will name it a factor, or $f(w)$. It is possible to determine the quality of the factor, or Q_f , by providing the desired width values, w^* , and an allowed tolerance, k . The modularity of the approach allows combining multiple factors to quantify the bunch profile in terms of bunch length and shape. Therefore, the objective function, named Bunch Factor (BF), is given by the sum of the qualities taken into consideration for the optimization, $BF = \sum_f Q_f$, while the

quality Q_f is calculated as follows:

$$Q_f = \begin{cases} \log_2 \left(\frac{k}{2} \times \left(\frac{f(W)}{f(W^*)} - 1 \right)^2 \right), & \text{if } \left(\frac{f(W)}{f(W^*)} - 1 \right)^2 > \frac{2}{k} \\ 0, & \text{otherwise} \end{cases}$$

where $f(W)$ can be a function of multiple widths w .

The minimum of the quality function is zero by definition since it is the default result when the factor satisfies half of the tolerance required. This ensures a well-defined optimal region regardless of the optimization method. Only half of the tolerance is considered to define a threshold for the maximum value which fulfills the requirements. As an example, Fig. 2 shows the quality of the Bunch Length Factor (BLF) which corresponds to the width at 50% of the peak. This is actually used in combination with the quality of the Bunch Shape Factor (BSF), the ratio between the widths at 80% and 20%, to provide the objective function.

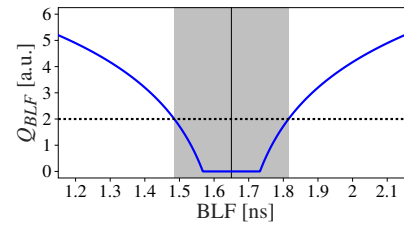


Figure 2: Q_{BLF} (blue) as a function of BLF. The vertical black line indicates the target value of 1.65 ns. The area shaded in grey corresponds to the $\pm 10\%$ tolerance. The dashed horizontal line is the threshold to fulfill the given tolerance.

The proposed objective function was validated by comparison with the Root Mean Square Error (RMSE) over a dataset of 16065 simulated profiles. Similarly to [10], each simulation started 200 ms before the start of the ramp with a 2.9 ns long matched (4σ) bunch and ended at extraction. The accelerator and RF programs were those of the high-intensity (1.5×10^{11} protons) single-bunch LHC-type beam in the SPS at the end of the 2021. The phase noise setting used in the simulation setup are listed in Table 1.

Table 1: Phase Noise Parameters Range used in Simulation

Parameter	Min.	Max.	Step
a	0.00	5.00	0.10
f_{low}	0.50	0.90	0.02
f_{high}	0.80	1.10	0.02

Both metrics identify the best simulated profile as the one obtained by applying the following blow-up settings: amplitude 0.40, margin low 0.74, and margin high 1.02 (see Fig. 3). The maps for amplitude 0.40 are shown in Fig. 4, where BF objective function provides a more constrained optimal region. The tolerance for both Q_{BLF} and Q_{BSF} was set to 0.1%.

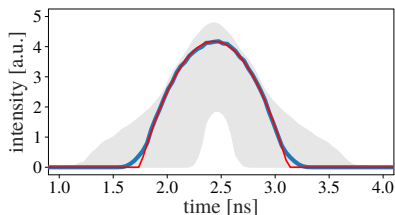
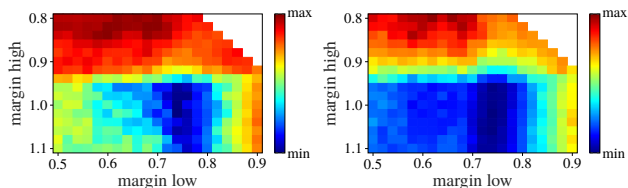


Figure 3: Best-simulated profile (blue) compared to the target one (red) and all grid scan profiles (grey area).



(a) Bunch Factor

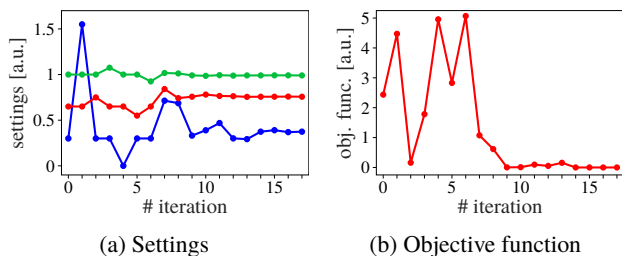
(b) RMSE

Figure 4: Map of objective functions for 0.40 amplitude. Bunch Factor (a) and the RMSE (b) are comparable in the distribution of minima and maxima.

RESULTS

Initially, the optimization was performed on the simulated dataset introduced previously by running the different algorithms available within the COI. BOBYQA was selected for the beam tests in the SPS, thanks to its better performance in terms of convergence and number of iterations. In the simulated dataset, the settings available are defined by the discrete values shown in Table 1. However, in reality, settings can have much finer granularity. For this reason, data interpolation is needed every time settings between the grid points are required. Given the desired setting values, the returned profiles are linearly interpolated by averaging according to the closest discrete settings.

Figure 5 shows an example optimization run using simulated data. The settings converge to their optimal values that minimize the objective function. BF is calculated at two times during the SPS cycle, i.e. the end of the noise injection, and at extraction, and the sum of the two values is the total cost. The desired bunch factors are based on target parabolic profiles with bunch lengths of 1.80 ns and 1.65 ns respectively within $\pm 5\%$ tolerance.



(a) Settings

(b) Objective function

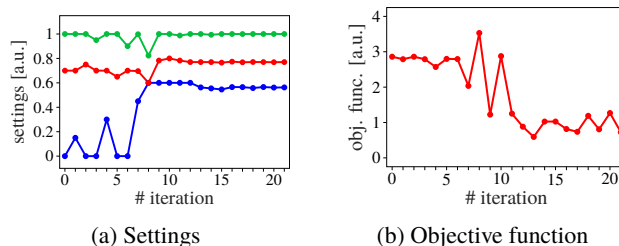
Figure 5: One scan example of automatic blow-up optimization in the simulation: amplitude (blue), margin low (red), and margin high (green) in (a); objective function in (b).

The promising results obtained in simulations prove the feasibility of solving the problem with the generic optimization tool of the CERN ML project. Therefore, the next step was to apply the same approach with beam in the SPS, based on the online acquisition of bunch profiles.

Table 2: Phase Noise Parameters Range used in the SPS

Parameter	Min.	Max.
a	0.00	0.60
f_{low}	0.60	0.80
f_{high}	0.80	1.00

As shown in Table 2, settings ranges are more restricted than for the simulated data, e.g. to avoid excessive beam losses. Nevertheless, the objective function and the tolerances were maintained as in the simulation. Due to the operating cycle, the target bunch lengths were set to 1.90 ns and 1.85 ns respectively. One example of optimisation with BOBYQA in the real machine is shown in Fig. 6.



(a) Settings

(b) Objective function

Figure 6: One scan example of the automatic blow-up optimization in the SPS: amplitude (blue), margin low (red), and margin high (green) in (a); objective function in (b).

Despite the difference between simulations and real-world measurements, BOBYQA has been able to optimize the bunch profile by controlling the blow-up parameters. Both in simulation and in the SPS, the objective function has been minimized bringing the bunch profile closer to the desired one.

CONCLUSIONS

The feasibility of controlling the longitudinal blow-up in the CERN SPS by automatically optimizing the bandwidth-limited noise injected in the phase loop has been proven. Based on the studies on a simulated dataset, a novel objective function, the Bunch Factor, has been defined, validated, and used for the preliminary optimization tests. By showing the best performance between the optimization algorithms available in the Common Optimization Interfaces, BOBYQA has been selected for online tests in the SPS where the bunch profile has been successfully optimized. Further steps in these studies include: e.g. multi-staged optimization (where the injected noise varies in subsequent time intervals), the use of reinforcement learning, and the application to multi-bunch beams.

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