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EXPERIENCE WITH COMPUTER-AIDED OPTIMIZATIONS IN LINAC4 AND PSB AT CERN

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Abstract

Currently, accelerator optimizations are routinely performed with the help of computer algorithms that allow to fully automatize these tasks. However, their efficiency, speed, and implementation time largely vary among them. In LINAC4, a few optimization tasks were targeted using different algorithms found by conducting a comparative analysis. We present the problems for which computer algorithms were used and the results of our comparative study.

INTRODUCTION

Numerical methods in accelerator performance optimization have become a standard. A dedicated framework, called GeOFF [1], has been developed at CERN to facilitate the exploitation of optimizing algorithms. This generic optimization framework acts as a high-level interface between the CERN accelerator control system and different algorithms, such that only the problem-specific code needs to be developed. Another advantage is the possibility to choose from a wide range of different conventional optimizers, and, if needed, switch between them. In this article we describe the tools and the achieved results for LINAC4 and for the PSB extraction recombination line.

In 2020 LINAC4 replaced LINAC2 as the Proton Synchrotron Booster (PSB) injector. It accelerates negative hydrogen ions (H^-) to the kinetic energy of 160 MeV [2]. It is a normal conducting linear accelerator operating at a frequency of 352 MHz. The linac was constructed and commissioned in stages between 2013 and 2016 [3–6]. Reliability runs took place in 2017 and 2018 [7, 8]. The commissioning of the transfer line connecting it to the PSB took place in 2019 and of the charge exchange injection in 2020 [9].

The PSB is a synchrotron made of four superimposed rings. At injection, each (H^-) beam pulse is vertically distributed over the rings, and at ejection the proton bunches are recombined vertically to follow the same trajectory when sent to the PS or the ISOLDE experimental facility.

For the problems described in this document, it was not practical to build a model through simulation, nor was it efficient to employ full-scale approximation using, e.g., neural networks. Some of the optimized quantities depend on factors that cannot easily be controlled and eventually change with time, making it difficult to model these phenomena reliably. Alternatively, the model could be learned from accelerator data. However, this approach would require extensive beam time. Therefore, for the studies presented here, we opted for efficient algorithms for handling cases with limited data, like numerical optimizers and linear correction via Singular Value Decomposition (SVD) [10, 11].

MACHINE SAFETY

Computer-driven optimizations must be carefully programmed because, in most cases, the beams have destructive potential. An algorithm may decide to test settings corresponding to significant beam losses, which could lead to accelerator failure. Particle accelerators such as LINAC4 and the PSB are protected with multiple interlock systems, but one cannot afford to rely solely on them when running an optimization algorithm. Instead, the allowed parameter ranges and step sizes must be set such that any increase in beam losses stays within the acceptable ranges, and the penalty for the beam loss is significantly higher than the other terms in the objective function. It should be ensured that losing the beam is not a way to find an optimum value.

Because of the aforementioned safety considerations and the importance of the speed in finding an optimum, we concentrated on Derivative-Free Optimization (DFO) methods that use a deterministic approach and discarded Bayesian optimizers for initial tests. There exist different machine-specific limits for the elements in the accelerators. Suppose the parameter space breaches one of the element's machine-specific limits. If an out of range settings is attempted then, in the best case, an exception is thrown halting the program or the device stops with a fault. To ensure that this does not happen, the program changes a given parameter scale s_{max} to be within the allowed range $s_{max} = |c - s_0|$, where c is the machine constraint and s_0 initial condition for this parameter. Every parameter has its own s_{max}. The same applies for s_{min}. As a result, the relative parameter change will be smaller than it initially would be, but inconsequential for the algorithm's performance.

DERIVATIVE-FREE ALGORITHMS

For the studies presented here, we focused on a branch of DFOs called model-based methods. Here a surrogate model of the objective function is constructed, defining the next iteration by seeking to minimize this model inside a trust region. One such method is COBYLA [12] and it employs linear approximations of the objective and constraint functions. The approximations are formed by linear interpolation at $n + 1$ points in the space of the parameters and are regarded as vertices of a simplex. The model is equivalent to a 1st-order Taylor expansion and at each step its accuracy is improved asymptotically. By extending this to a 2nd-order Taylor expansion, the trust-region minimization can now take curvature into account. An example of such an algorithm is BOBYQA [13]. However, the quadratic model comes at the price of making the model construction and the trust-region minimization more difficult.

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The CERN GeOFF framework has been implemented in Python, using the SciPy implementation of COBYLA and the Py-BOBYQA of BOBYQA. Py-BOBYQA is an open-source package, which includes robustness to noise strategies and many other parameters that can be adjusted for optimal performance.

OPTIMIZATIONS

LINAC4 Chopping Efficiency

The chopper is composed of a pair of electrostatic kickers installed in the Mid Energy Beam Transport (MEBT), between the Radio Frequency Quadrupole (RFQ) and the first Drift Tube Linac (DTL1) accelerating cavity. It removes unwanted bunches by deviating them towards a dedicated in-vacuum dump. This includes the pulse head, i.e., the first 200 µs where the pulse intensity is not yet constant, the 2 µs gaps in the pulse corresponding to the rise time of the kickers at the PSB distribution and the bunches that would fall outside the PSB longitudinal acceptance. The chopping efficiency is important because any remaining particles would be accelerated by the RF system and lost at higher energies. For the head of the LINAC4 beam pulse, there is a dedicated in-vacuum dump installed in the device distributing the beam to the 4 PSB rings, however, it can only tolerate maximum 70 W of beam power.

The efficiency optimization involves setting eight trajectory correctors and ten quadrupoles to minimize the intensity of the unwanted bunches and maximize the intensity of the wanted ones. The intensity is measured with a Beam Current Transformer (BCT) located just behind the chopper dump and the sum signal of a Beam Position Monitor (BPM) downstream of DTL1. The BPM has a much higher bandwidth compared to the BCT and, therefore, provides more accurate time-resolved measurements. Three pulses are measured for each tested setting, and the average values are used in the penalty function evaluation.

To ensure that the algorithm does not generate any dangerous beam losses the penalty function has a special term. If the beam loss is bigger than 1% then then the square of the intensity difference is added with a weight of 10^6. Additionally, the maximum step size is kept small and the algorithm is allowed to change the settings in a limited range close to the initial values.

We compared the performance of COBYLA and BOBYQA, with and without the noise switch enabled. The best result was obtained using BOBYQA with the noise flag on. On the other hand, it needed 120 iterations versus 30 iterations of COBYLA. While both managed to increase the beam intensity by the same amount, BOBYQA reduced the remaining intensity of the pulse head after the chopper dump by almost a factor of two.

PSB Extraction and Recombination

The bunches from the four PSB rings are extracted sequentially and after the recombination they need to have the same trajectory. In the first step of this process three bending magnets (BE) create a closed orbit bump in the horizontal plane. The kickers (KE) send the beam towards the septum (SE). SE has one common power supply for all four beams, and the same applies for the three BE magnets. Each of the rings has only two high energy orbit corrector magnets to regulate position and angle at extraction independently for each ring. However, these create orbit oscillations all around the ring, which should be avoided.

This optimization problem is complex partly because of the relatively large number of parameters (>20) and because some are common to all beams. Naturally, the aim is to minimize signals of the Beam Loss Monitors (BLM). The BPMs position reading should also be as small as possible. There are several vertical correctors installed in the recombination system. On the other hand, due to lack of space, there is only one horizontal corrector per beam.

The quality of the trajectory overlap at each BPM is quantified as $q = \sum_{r=1}^{4} (p_r - \overline{p_r})^2$, where p_r is position reading for beam from ring number r and $\overline{p_r}$ is the mean value. The penalty function is a sum of four main components, each having separate weights: the sum of q's for all BPMs in the transfer line, the sum of BLM signals squared, the sum of position readings squared in the rings and in the transfer lines. The highest weight was put on the BLM signals and then on the recombination quality.

For this case, both COBYLA and BOBYQA were compared. The algorithms had to be rerun a few times to reach a satisfactory solution. This was most probably related to the initial step size being small. It was always set to a minimum value that changed observed quantities by a measurable amount to minimize the risk that the tested settings provoked significant beam losses and induced interlocks. In the automatic optimization, the trajectories were successfully overlapped without increasing the BLM signals. However, it failed to reduce loss and improve overlap simultaneously, even in cases when the weight for the BLM part was increased. The poor shot-to-shot stability of these signals, reaching 20% of the amplitude, could be one of the reasons.

In the final optimized configuration the beam losses were reduced by ten-fold with respect to the operational setting in 2021. Observing the trajectory evolution during the optimization allowed us to understand relations that the algorithm eventually failed to capture. For example, by changing the ejection position for two beams simultaneously, one could avoid losses when adjusting the septum at the second recombination stage. In these cases, we applied the correction and restarted the optimization program.

Due to the high number of parameters, COBYLA optimized by a factor four more quickly than BOBYQA. However, the final result was worse. It seems that the knowledge of the nominal settings and certain correlations between the parameters were important factors for the final result, most likely related to the high non-linearity of the problem.

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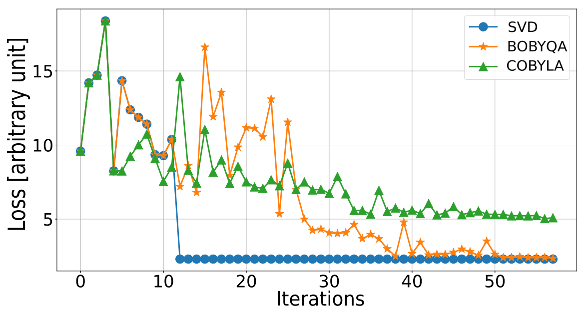

Figure 1: Comparison of optimization speed between SVD, COBYLA and BOBYQA.

Dispersion Free Steering

In LINAC4, the vertical position variation along the pulse is much more pronounced than the horizontal one and can exceed 1 mm. The origin of this effect is not yet clear. It could be related to imperfections in the chopper amplitude or to vertical alignment issues. In the LINAC4 accelerator hall the floor has risen by about 4 mm over the years and the alignment of the RFQ is extremely delicate to perform. The downstream elements were aligned to create a smooth transition and the resulting beam performance is now within the accepted range.

In an attempt to minimize the position variation, Dispersion Free Steering (DFS) [14, 15] was implemented. This consists of a simultaneous correction of the trajectories and of the measured dispersion. We look for the trajectory corrector setting such that a cavity phase change does not change BPM readings. The beam energy was changed by varying phases in selected cavities at the beginning of the linac. This unfortunately did not change the energy uniformly all along the linac, but rather created a beating pattern.

In a simulation we compared COBYLA, BOBYQA and SVD [11], see Fig.1. For this particular problem, we concluded that SVD is by far the quickest method among the ones tried out. This is due to the practicability of describing the problem linearly by performing linear mapping between trajectories measured at BPMs to the change in corrector strength in the form of a matrix. This linear equation can further be solved in a least-square sense via SVD. An additional advantage is that we can archive the response matrix and reuse it in the future.

The measured dispersion and trajectory was successfully minimized in single iteration in both planes. Figure 2 shows the achieved improvement in the horizontal plane. We could then confirm that with the obtained steering the trajectory sensitivity to phase changes in all cavities was reduced. However, the vertical position variation along the pulse was not improved indicating that it has a different origin than dispersion. The measured emittance was also not significantly improved.

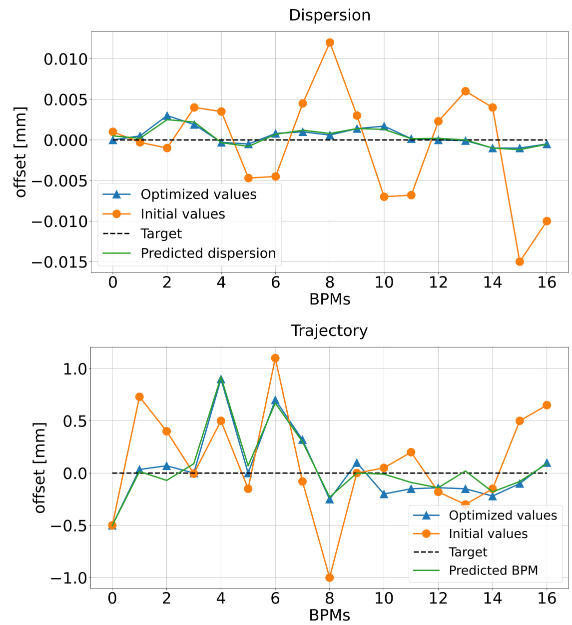

Figure 2: Horizontal position variation upon buncher cavity phase change (top) and trajectory (bottom) along LINAC4. Orange circles illustrate initial values and blue triangles optimized ones. Green line represent the algorithm prediction for the corrected values.

CONCLUSIONS

Automatic optimization tools have been implemented for chopping and dispersion-free steering in LINAC4, as well as for beam extraction and recombination in the PSB. In all the cases they successfully improved the performance.

For the problems that are linear, or nearly linear, such as trajectory steering and Dispersion Free Steering, SVD is the fastest algorithm. Additionally, the SVD response matrix can be saved and reused on the next occasion if the conditions do not change in time. For other applications, such as extraction and recombination, we found that Derivative-Free Optimization methods are the most suitable ones and we used COBYLA and BOBYQA algorithms.

The consistently better performance of BOBYQA in comparison to COBYLA is due to the higher number of interpolation points required by BOBYQA ($2n + 1$) to approximate the Hessian. Meanwhile, for COBYLA, it is sufficient with $n + 1$ for the Jacobian. The number of interpolation points for BOBYQA can be adjusted to a minimum of $n + 1$ interpolation points to achieve quicker convergence, at the expense of a less satisfactory result.

COBYLA, being a re-framing of steepest descent, starts optimizing already in the discovering phase. That is, while constructing the full simplex, if one of the vertices yields better results, this setting is put immediately. Due to the lack of curvature information in this model, the result is not as satisfactory as with BOBYQA.

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