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AN EVOLUTIONARY ALGORITHM APPROACH TO MULTI-PASS ERL OPTICS DESIGN*

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Abstract

An Energy Recovery Experiment at CEBAF (ER@CEBAF) is aimed at demonstrating high energy, low current, multi-pass energy recovery at the existing 12 GeV CEBAF accelerator. The beam break-up instability, limiting the maximum beam current, can be controlled through minimizing beta functions for the lowest energy pass, which gives a preference to strongly focusing optics, e.g. a semi-periodic FODO lattice. On the other hand, one needs to limit beta function excursions, caused by under focusing, at the higher energy passes, which in turn favors weakly focusing linac optics. Balancing both effects is the main objective of the proposed multi-pass linac optics optimization. Here, we discuss an optics design process for ER@CEBAF transverse optics using evolutionary algorithms.

INTRODUCTION

The Continuous Electron Beam Accelerator Facility (CEBAF) accelerator at Jefferson Lab consists of two superconducting linacs connected by 10 recirculating arcs in a racetrack design. Polarized electrons are accelerated for up to 5 passes through the machine, achieving up to 12 GeV [1].

The energy recovery (ER) concept "recycles" bunch energy by recirculating accelerated bunches through the linacs at the decelerating RF phase, before delivering them to a dump at injection energy. As bunches decelerate, energy is returned to the RF cavities to further accelerate new bunches.

Jefferson Lab has demonstrated 1-pass ER in 2003 [1], and the ER@CEBAF experiment intends to extend this to 5-passes. CEBAF will require an additional path length chicane and low energy extraction line to set up the ER@CEBAF experiment.

MULTIPASS LINAC OPTICS

This work evaluates the beta functions for 5 accelerating and 5 decelerating passes through the CEBAF north linac. For decelerating passes, the linac direction is treated as reversed to preserve symmetry. The resulting beamline is an interleaving of the accelerating and decelerating linac lattices connected using an inverting matrix (**M**), as illustrated in Fig. 1. This is to match the optics at the entrance/exit of arcs.

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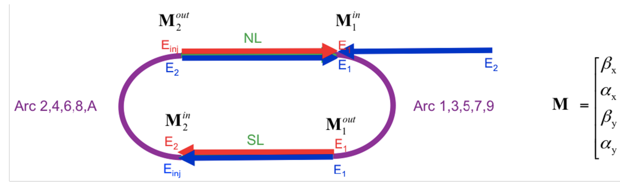

Figure 1: Matching conditions at the linac ends [2].

The optics of the 10-pass north linac is shown in Fig. 2. It consists of a FODO-like arrangement using a 60 degree phase advance per cell. This is the best-known optics solution which fulfills the multi-pass requirements for an energy gain of 750 MeV per linac [3].

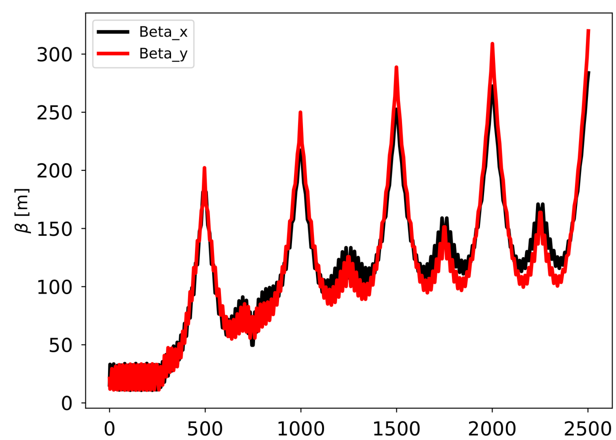

Figure 2: Multipass optics for 60 degree FODO-like linac.

In multipass linacs, lower energy passes should have smaller transverse beta variations to avoid transverse beam break-up (BBU) instabilities. For a single cavity in TM110 mode, the threshold beam current, I_{th}, is given by

$$I_{th} = \frac{2pc}{e\omega \frac{R}{Q} Q} \frac{1}{|T_{12}| \sin \omega t_{tr}}, \tag{1}$$

where Q is the cavity quality factor, p/e is beam rigidity, ω is the RF higher order mode angular frequency, and t_{tr} is the arc time of flight. The term $T_{12} = \sqrt{\beta_1 \beta_2} \sin \phi$ is the transport matrix element for displacement at the second pass. This equation suggests an optics optimization to suppress BBU in linacs [4] is to minimize the average ratio of the beta function, β, to instantaneous beam total energy, E:

$$\left\langle \frac{\beta}{E} \right\rangle = \int \frac{\beta}{E} ds. \tag{2}$$

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Along with minimizing (β/E) for the 1^{st} pass, transverse beta variations in higher passes must be controlled, and symmetry between the accelerating/decelerating passes needs to be preserved. β values at the end of the 10 passes should be the same order of magnitude as the length of the linac; not to exceed 300 m. Furthermore, only the quadrupole fields should be adjusted when tuning the optics.

Performing such minimization manually takes a considerable effort, since it considers multiple objectives simultaneously. Hence, the need for a multi-objective approach.

DEFINITION OF THE MULTI-OBJECTIVE OPTIMIZATION PROBLEM

The optimization of the 10-pass north linac's optics involves multiple conflicting objectives [2]. Without loss of generality, we consider all of these objectives to be minimized, leading to the following multi-objective problem definition [5]:

$$\begin{aligned} &\underset{x}{\text{Minimize}}\, F(x) = [F_1(x), F_2(x), ..., F_k(x)]^T \\ &\text{subject to} \quad g_j(x) \leq 0, \quad j = 1, 2, ..., m \\ &h_l(x) = 0, \quad l = 1, 2, ..., e, \end{aligned}$$

with k, m, and e referring to the number of objective functions, inequality constraints, and equality constraints, respectively. In general, a solution to such a problem cannot optimize all objectives at once, and instead, one must investigate a set of solutions that fit a predetermined definition for an optimum [5, 6]. A Pareto optimal solution cannot be improved with regard to any objective without worsening at least one other objective [6].

The set of Pareto optimal solutions is called the *Pareto optimal set*, for which the corresponding objective functions in the objective space form the *Pareto front*. Since the number of Pareto optimal solutions to a given problem is enormous, our goal is to define a multi-objective optimization algorithm that computes the best-known Pareto front, which should ideally be as close as possible to the true front with solutions being uniformly distributed over this front.

EVOLUTIONARY ALGORITHMS

Evolutionary algorithms (EA) are particularly suited to solving multi-objective optimization problems. In contrast to aggregating approaches that combine multiple objectives, EAs simultaneously optimize all these objectives to directly generate the Pareto front [7]. We use a class of EAs, Genetic Algorithms (GA), which represent solutions as an evolving population of individuals according to the natural selection process [6]. The finer details are beyond the scope of this work, but the reader is encouraged to learn more in [6, 7].

GAs offer the advantage of evaluating multiple solutions in a single run, leading to an increased flexibility in problems where background knowledge is not available [7]. In addition, GAs are well suited to problems with complex shapes of Pareto fronts (e.g. non-convex, discontinuous and multi-modal solution spaces [6]). In this work, we consider the well tested Non-dominated Sorting Genetic Algorithm II (NSGA-II) [8] to handle multiple objectives. We use the python module Pymoo [9] as an implementation of NSGA-II.

OBJECTIVE DEFINITION

Multipass linac optics optimization involves two main goals. To minimize and tighten β variation of the lowest pass, the (β/E) ratio at each focusing (qf) and defocusing (qd) quadrupole is used. Twiss parameter characterization uses focusing and defocusing quads for horizontal and vertical planes, respectively. The average (β/E) for each pass is calculated for each plane separately, and then these 10 values are averaged. To couple both planes, the first objective function is defined as the mean of these two average values, where sums are taken over ten passes and quadrupole instances:

$$F_1 = \frac{\frac{1}{10}\Sigma_{i=1}^{10}\left[\frac{1}{n}\Sigma_{i=1}^{n}\left(\frac{\beta_x}{E}\right)_i^{\text{qd}}\right] + \frac{1}{10}\Sigma_{i=1}^{10}\left[\frac{1}{n}\Sigma_{i=1}^{n}\left(\frac{\beta_y}{E}\right)_i^{\text{qf}}\right]}{2}. \quad (3)$$

The second objective function aims to control the β peaks with mirror-symmetric variation. For this, β values at the beginning of each pass (i.e. at the arc ends) are considered, where the sums are taken over quadrupole instances:

$$F_2 = \frac{\frac{1}{n}[\Sigma_{i=1}^{n}\beta_x + \Sigma_{i=1}^{n}\beta_y]}{2}. \quad (4)$$

RESULTS AND DISCUSSION

The optimization of 10-pass north linac optics involves the tuning of 26 quadrupoles (L02-L27). Due to computational limitations, and the complexity of these stochastic search methods, the initial studies used only 4 degrees of freedom (DOF). The last 4 quadrupole fields (L24-L27) were varied in the north linac and 3 constraints were used to preserve the quality of the optics of the individuals in the Pareto front. The constraints used are:

$$G_{1,2} = \beta_{x-max,y-max}^{\text{first pass}} - 40 \text{ m} \quad (5)$$

$$G_3 = (\Sigma\beta_{yi} - \Sigma\beta_{xi})^{\text{arc}} - 30 \text{ m}. \quad (6)$$

The same population was used and run through different numbers of generations to make sure the Pareto front converged.

For a population of N = 100 and for 200 generations, the Pareto front consisted of 23 individuals. For this, 20000 Elegant [10] simulations were performed. 4 individuals were chosen from the Pareto front and are marked with different colors in Fig. 3.

The corresponding Twiss plots of the 4 chosen individuals are shown in Fig. 4. β_x curves are represented by black and β_y curves are represented by red. The resulting Twiss variations are in agreement with the expectations.

With this success, we began to increase the number of DOF by adding in pairs of quadrupoles. For the 6D problem, where we varied the quadrupole fields for 6 quadrupoles

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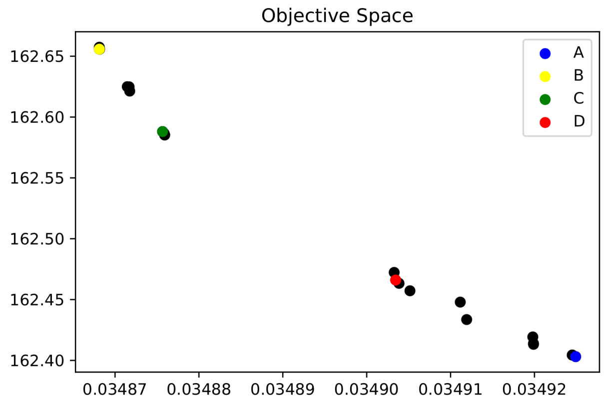

Figure 3: Pareto front for N = 100, Gen = 200 for 4-variables.

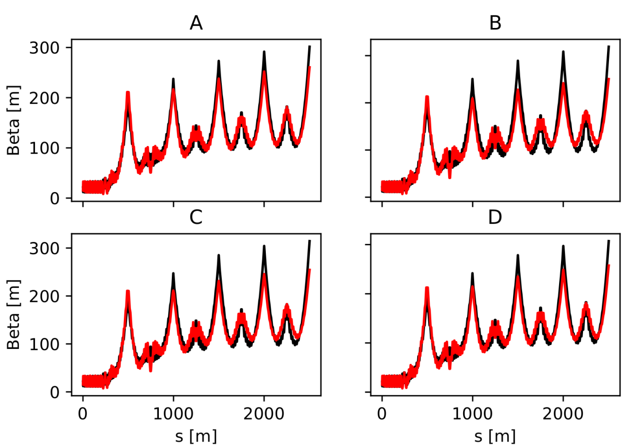

Figure 4: 4D: Beta functions for individuals A-D (Fig. 3). β_x is shown in black and β_y is shown in red in this and following figures.

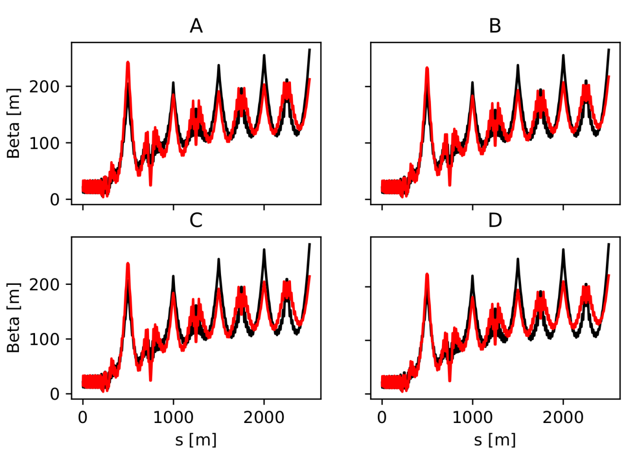

Figure 5: 6D: Beta functions for individuals A-D .

(L22-L27), we had N = 100 and 250 generations (25,000 Elegant simulations). These results are shown in Fig. 5.

The Twiss plots obtained for the chosen individuals from the Pareto front show better variations in higher passes maintaining $\beta_{x,y}$ < 250 m. But a disruptive behavior for β_y was observed at the end of the first decelerating pass.

For the 8D (L20-L27, N=150, 250 generations, 37,500 Elegant simulations) in Fig. 6 and 10D (L18-L27, N = 200, 400 generations) problem in Fig. 7, we achieved similar results. The β_y problems of the 6D trial have faded for the 8D trial. This persists for the 10D trial, which continues to improve overall.

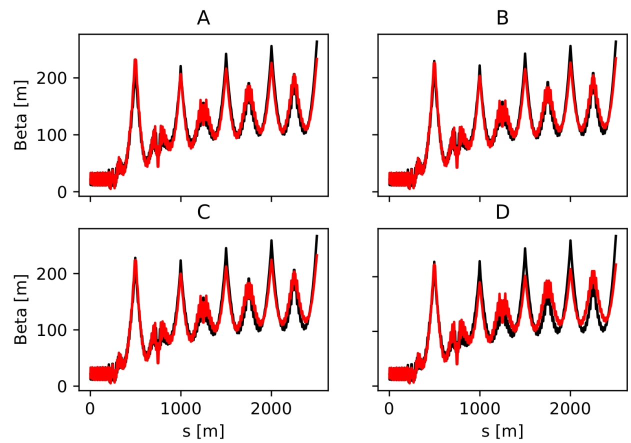

Figure 6: 8D: Beta functions for individuals A-D.

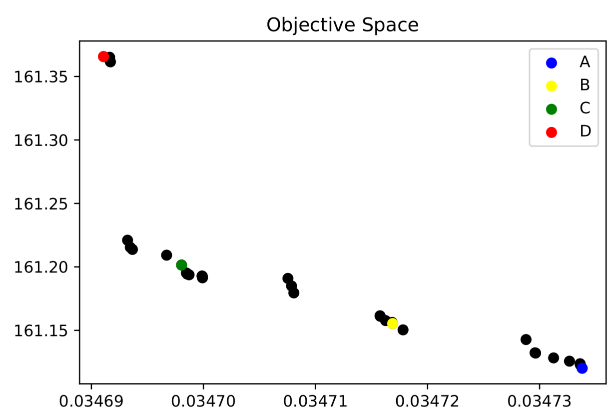

Figure 7: 10D: Beta functions for individuals A-D .

CONCLUSIONS

The optics show a promising agreement with the expected outcome. The lowest energy pass optics is preserved well in all cases studied due to the influence from constraints. The population size needs to be increased, as well as the number of generations, as we increase the search space. This makes the problem become a more computationally complex one.

FUTURE WORK

A complete the 30-dimensional search will require larger computational time. This procedure will be modified to utilize the scientific computing cluster at Jefferson Lab.

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