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BEAM CORRECTION FOR MULTI-PASS ARCS IN FFA@CEBAF: STATUS UPDATE

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Abstract

As design and simulation studies for the energy upgrade at the Continuous Electron Beam Accelerator Facility progress, both static and dynamic errors must be addressed. The current upgrade design introduces a pair of Fixed-Field Alternating-Gradient (FFA) recirculating arcs: one in the East recirculating arc, and one in the West. In the present design, each FFA arc supports six concurrent beam energies in the same beam pipe; these must be concurrently corrected for both static and dynamic errors. This document discusses the present beam correction strategies applied in simulation.

INTRODUCTION

There are a number of challenges to overcome in correcting the beam dynamics in an FFA accelerator, most importantly that each corrector magnet affects all of the beam energies present[1]; in the current design at CEBAF, the energy ranges present in the East and West FFA arcs are (respectively) 10.55–21.55 GeV and 11.65–22.65 GeV [2]. Since these energies span approximately a factor of two, from the definition of magnetic rigidity the lowest energy beams are twice as susceptible to corrector fields as the highest energy beams.

The beam quality and position diagnostics in these FFA lattices are expected to be button BPMs. There is not currently a scheme to multiplex button BPMs in the arcs: that is while CEBAF is in continuous wave (CW) operation, individual beams in the FFA arcs will not be distinguishable. Therefore detailed beam position information will only be available in 'tune mode' or pulsed, diagnostic operation of CEBAF. For this reason there is no obvious way to integrate the FFA arcs with the CEBAF 1 Hz 'orbit lock' [3] or online beam correction system.

In this document a method to use detailed diagnostic information from tune mode to set corrector magnets with AC dipole and quadrupole fields is presented. Furthermore, evidence from simulations is presented which shows that a neural network trained on information produced by the detailed correction scheme may allow for online controls.

METHODOLOGY

To design a detailed correction scheme for FFA@CEBAF, first the method employed at CBETA was examined: since in concept CBETA had similar requirements to FFA@CEBAF, the correction method described in the design report [4] was taken as a starting place. As such, the algorithm for detailed corrections is based on SVD.

Multi-Pass SVD

The algorithm used to correct the FFA arcs in FFA@CEBAF is an iterative SVD, which changes the objectives of the algorithm after correcting each pass. All of the simulations used to test this algorithm were performed using Bmad and Tao.[5]

The basis of this algorithm is the SVD routine packaged with Bmad. Each of the BPMs in the arc are weighted equally, except for the exit of the arc: taking cues from techniques used at CBETA[6], the exit of the arc is weighted heavily such that the SVD considers the exit coordinates the most important. The final multi-pass correction algorithm is an iterative process, the basics of which are shown below:

1. Remove from consideration detailed diagnostic information from higher energy passes;
2. Increase the weight of the final BPM for the current energy;
3. Correct the current energy subject to constraints imposed by all lower energies;
4. Repeat for each energy.

It's important to note that the SVD algorithm is also tuned to value the survival of *all* beam energies more than any BPM value for any energy.

Steering with a Neural Network

Once the SVD algorithm was shown to be an effective method to steer six energies through each of the East and West FFA arcs designed for CEBAF, attempts to reduce the amount of diagnostic information necessary to set the corrector magnets were undertaken. While the precise nature of readings from button BPMs during six pass operation is unknown, a linear combination of simulated readings from six passes is a possible approximation. Using several different such linear combinations: *eg* the sum of the readings, the mean of the readings, and a sum with each pass weighted differently: a densely connected feed forward neural network [7] constructed with Tensorflow and Keras packages for Python [8, 9] was trained on the association between the BPM readings and the final corrector strengths given by the multi-pass SVD algorithm.

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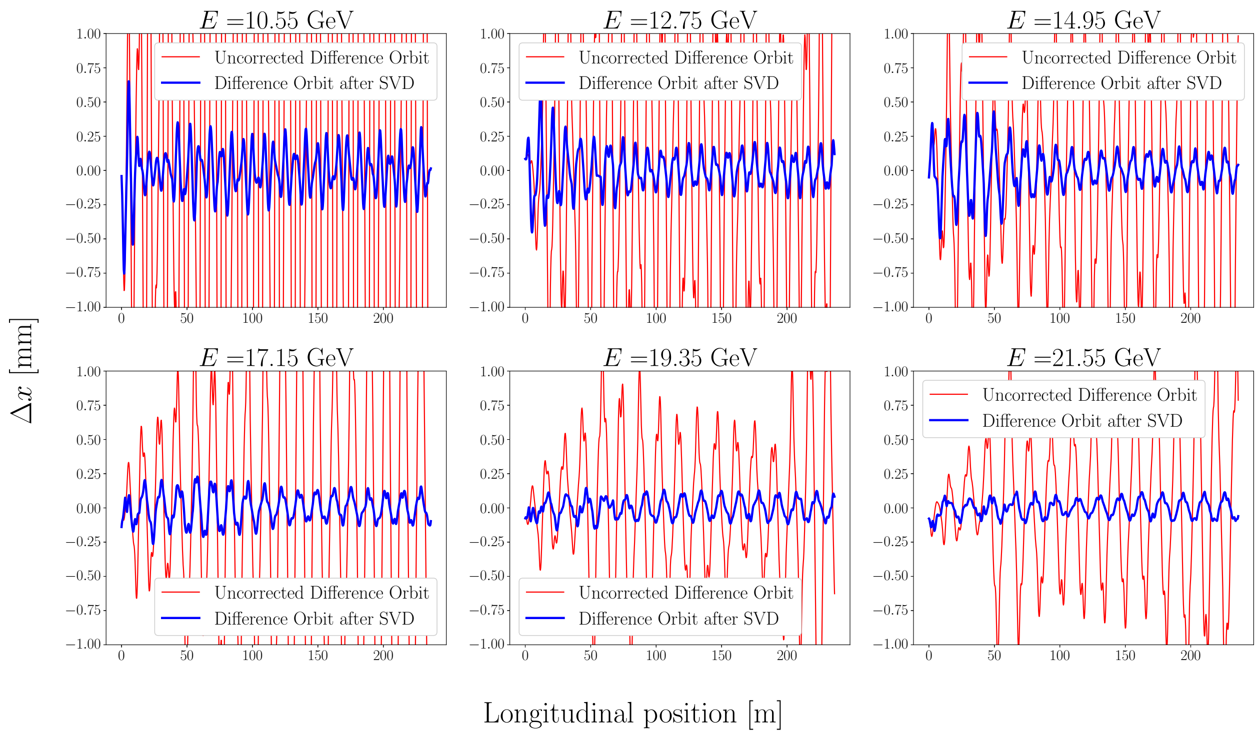

Figure 1: SVD correction for initial and survey errors drawn from normal distributions.

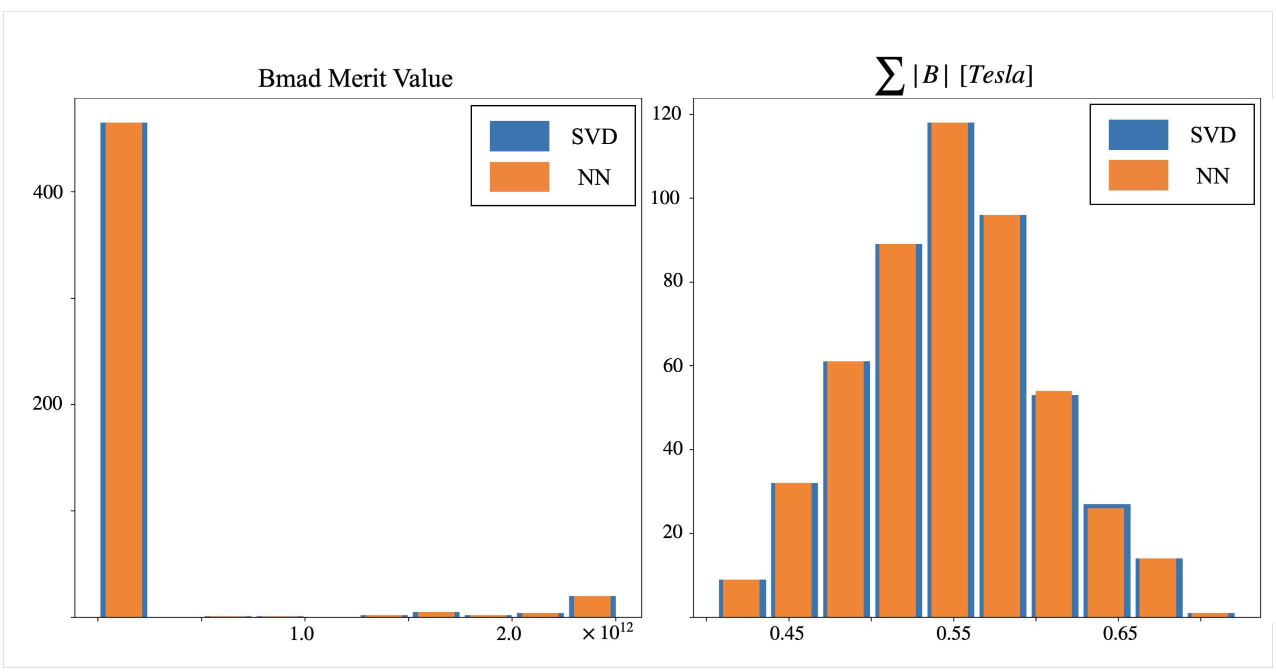

Figure 2: Histograms showing the Bmad internal figure of merit (left) and the sum of corrector field magnitudes (right) for 500 FFA@CEBAF lattices with randomly generated errors.

RESULTS

These results are preliminary: not all direct results have been independently confirmed, and there is more confidence in some than others.

Multi-Pass SVD Correction

The algorithm described in the methodology section is shown to give good results under many conditions. Figure 1 shows the difference orbits (actual minus design) of each pass through the West FFA arc with errors. The initial position of each beam is shifted horizontally, the initial hor-

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izontal momentum is offset, and each magnet in the lattice is misaligned. Each of these error are drawn from normal distributions: initial position and momentum errors have a mean of zero and a standard deviation of 1×10^{-4}, while misalignment errors have a mean of zero and a standard deviation of 6×10^{-5}.

Neural Network Steering

In this section, a direct statistical comparison to SVD steering is made. The neural network used was trained on 1500 SVD corrected lattices, and all of the comparisons come from randomly generated, new error configurations. Several hundred quantitatively different error configurations were generated, and direct comparisons on all of them are shown in Fig. 2

CONCLUSIONS AND BROADER IMPLICATIONS

This work shows that it is possible for a neural network to learn a numerical correction algorithm such as SVD. Moreover, it has been shown here that training a neural network on a linear combination of BPM readings for different passes in a multi-pass line might be effective. It is concluded that a multiplexed system of BPMs may not be necessary to implement a fast orbit-lock in the lattice presently under consideration for FFA@CEBAF.

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