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USE OF DIMENSION-REDUCTION TECHNIQUES WITH MULTI-OBJECTIVE GENETIC ALGORITHMS TO IMPROVE THE VERTICAL EMITTANCE AND ORBIT AT CESR

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Abstract

In order to reduce the vertical emittance at the Cornell Electron Storage Ring (CESR), we first measure and correct the vertical orbit, dispersion, and coupling. However, due to the finite resolution of our optics measurements, we still retain a significant residual emittance. In order to correct this further, we made use of the theory of sloppy models, according to which certain high-dimensionality systems can be modeled with significantly fewer "eigenparameters" that still contain most of the effect on the desired objective, in this case, the emittance. However, we noted that using these knobs for tuning often resulted in increased vertical orbit errors. In an attempt to constrain these, we have applied multi-objective genetic algorithms to this problem. We have found that it can be more efficient to run such algorithms using our eigenparameters as the genes to be varied, as opposed to the raw magnet values. When running with the first 8 such knobs as genes, we can get either orbits or beam sizes as good as we obtain with our regular emittance-tuning algorithm which uses all the corrector magnets.

INTRODUCTION

Our current procedure for minimizing the vertical emittance at CESR is to measure and correct the vertical orbit and dispersion and the coupling, and has been quite successful [1]. However, the ability of this method to further reduce the emittance is limited by the finite resolution of our vertical dispersion measurements. We therefore have been exploring other methods of doing the task, in particular, a dimension-reduction technique coupled with the RCDS algorithm [2–5]. This method, however, has only made modest improvements in the vertical emittance. Additionally, the emittances that our tuning procedures have been able to achieve are significantly larger than those which our simulations imply we should be able to reach. This leads us to suspect that our emittance source is not present in our models, so we have begun exploring the applicability of genetic algorithms to our problem, since they are less sensitive to the model used. In particular, since we had seen that fixing the vertical emittance often introduced vertical orbit errors when using our emittance-tuning knobs, we wished to explore multi-objective genetic algorithms which use orbit information as an objective along with the beam size.

Huang and Tian have explored the applicability of genetic algorithms to particle accelerator optimization, finding that it is possible to obtain noticeable improvements in the emittance and dynamic aperture [6, 7]. However, they had concluded that such algorithms tend to perform more slowly than other options, and are sensitive to noise. We have therefore looked for ways to get improved convergence, and have found that it is often useful to reparameterize our search space in terms of the eigenparameters we had obtained from our dimension-reduction techniques. Applying this algorithm to the physical machine has enabled us to see significant improvements in the emittance when starting from an uncorrected lattice.

Genetic algorithms work analogously to evolution in organisms: a population of solutions is evaluated to obtain some merit function, and the best individuals become parents for the next generation. These algorithms are particularly amenable for use in multi-objective optimization because, by returning a population of individuals in the final state rather than single solution, running the algorithm once permits one to obtain a representative sampling of the Pareto front [8].

Our dimension-reduction is based on the theory of sloppy models, which states that certain systems with a large number of free parameters may be reparameterized such that the relative importance of these new ordered eigenparameters drops exponentially [9, 10]. This serves as an efficient dimension-reduction technique since one may use only the first few eigenparameters in the optimization and still retain most of the ability to fix the desired objective. Moreover, the eigenparameters for our problem are orthogonal in the emittance, so that optimization using one eigenparameter will not affect the optimal setting of a second eigenparameter.

CESR is a storage ring for electrons and positrons operating at 5.3 GeV. It has nominal horizontal emittance of 97 nm-rad and vertical emittance of 0.04 pm-rad, although, in practice, the vertical emittance is roughly 20 pm-rad. It is equipped with roughly 100 beam position monitors (BPMs), in addition to a visible-light beam size monitor (VBSM) [11]. All of its magnets are individually powered, and so can be tuned independently. We had found that our 57 vertical kickers and 24 skew quadrupoles had a significant impact on the vertical emittance, and so used them as our base tuning parameters.

ALGORITHM USED

We have used SPEA2 as the selector for our genetic algorithm, the code for which may be obtained in an open-source format from PISA [12, 13]. SPEA2 ranks the individuals in a population primarily using a dominance relation, where one individual dominates another if it is better in at least one objective and not worse in any of the other objectives.

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Individuals are preferred if they are dominated by no or few other individuals. In order to promote diversity in the population, the algorithm prefers individuals which are in more sparsely-populated regions of objective space if they have equal scores in the dominance relation. Importantly, SPEA2 is an elitist algorithm, meaning that any solutions with good fitness values will be preserved in the population through multiple generations until they are out-competed. This poses challenges for applications which use experimental measurements, because an individual which is only considered good due to to a measurement error could continue to adversely influence subsequent generations indefinitely. In order to mitigate this effect, we reduced the measurement error for each individual by averaging ten measurements of its objectives. Additionally, we remeasured the value of the objective functions for an individual every seven generations. We used recombination with simulated binary crossover, symmetric recombination, and a binary tournament selection process. Additional parameters are shown in Table 1.

Table 1: Algorithm Parameters

Variable Swap Probability	0
Variable Mutation Probability	0.1
Individual Mutation Probability	1
Individual Recombination Probability	1
Eta Mutation	20
Eta Recombination	15

SIMULATION RESULTS

In order to test our tuning algorithm we made use of the BMAD lattice simulation software [14]. This provides an accurate model of the CESR lattice, and also includes the possibility to input realistic magnet misalignment errors and corrections according to our usual emittance-tuning procedures [1]. For all cases shown here, we ran the genetic algorithm with a population of 30 for 30 generations. Experiments with different population sizes showed convergence after similar numbers of function evaluations. The initial population contained the starting lattice without corrections as one of the individuals, with the values of the correctors of the other members of the population centered at zero with a random uniform distribution.

To construct the eigenparameters, we used the BMAD simulation to obtain the Hessian matrix of the emittance with respect to all 81 corrector magnets, then took its singular value decomposition. The eigenparameters are the singular vectors.

In order to measure the emittance of the beam in the storage ring, we used the vertical beam size as a proxy, and so we have taken the same approach in simulation. Although the beam size will also depend on the local beta function and the local dispersion and coupling, the magnets which we are changing do not have a significant effect on the beta function and reductions in the local coupling and dispersion are also desirable, since they ought to be zero. The orbit measurement is provided by taking the sum of the squares of the vertical displacement as measured by 3 BPMs near the undulators, since this is where the orbit constraint is most important.

We first used the 81 raw magnet settings as our genes, and obtained the results shown in Fig. 1 after 30 generations. These may be compared with the results of the optimization obtained when using the first 8 eigenparameters as our genes, as seen in Fig. 2. We see that the latter method allows us to converge to a superior Pareto front in the same amount of time. We attribute this improvement to some mixture of two factors. First, it is easier in general to search a space with a smaller number of dimensions. Additionally, since the eigenparameters are orthogonal in the emittance, there is a definite sense in which one value of a particular gene is "better" than another value, regardless of the values of the other genes, enabling more efficient transmission of genetic information.

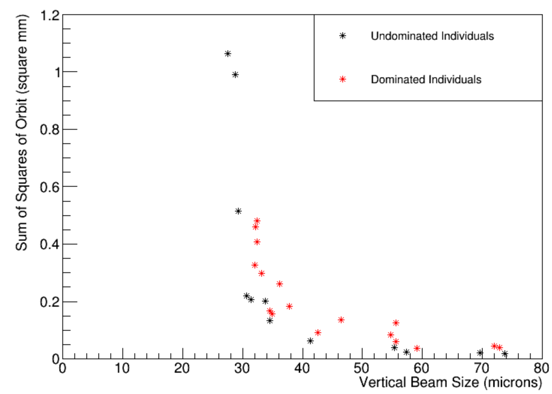

Figure 1: Population in simulation after 30 generations when using the raw magnets as our genes.

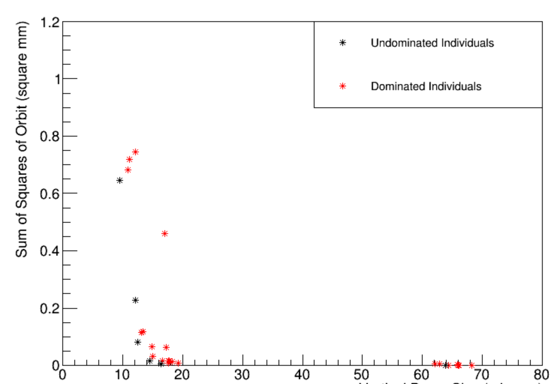

Figure 2: Population in simulation after 30 generations when using the first 8 eigenparameters as our genes.

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EXPERIMENTAL RESULTS

In order to have the most visible improvement in the beam size, we started our optimization procedure from an uncorrected lattice. As with the simulations, we ran with populations sizes of 30. However, due to time constraints and the appearance of some convergence, we only ran for 10 generations. We first used the first 8 eigenparameters as our genes. The uncorrected lattice was chosen as one individual in the starting population, with the rest having uniform distributions in the values of the eigenparameters, centered at 0. The widths of the distributions were correlated with the expected strengths of the knobs, as obtained from simulations. The population after 10 generations is shown in Fig. 3. For comparison, the standard emittance-tuning procedure permits us to obtain a beam size of 27 microns and orbit error of 0.6 mm^2. The starting lattice had a beam size of 60 microns and orbit error of 1 mm^2. In order to test the efficacy of our knobs, we also ran the algorithm using the eight eigenparameters numbered 9-16 as our genes, with the results shown in Fig. 4.

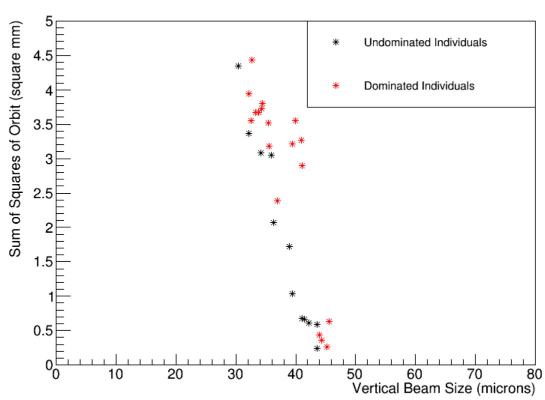

Figure 3: Population in data after 10 generations when using the first 8 eigenparameters as our genes.

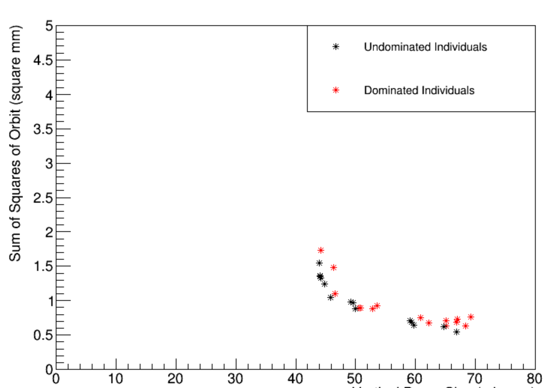

Figure 4: Population in data after 10 generations when using the eigenparameters numbered 9-16 as our genes.

It is immediately clear that the first eight knobs are significantly more useful than the next eight at reducing the beam size, as would be expected. We also note that, on average, the latter knobs have fewer orbit errors. This seems sensible, since the first eight knobs are efficient at reducing beam size at the expense of the orbit, and so some will do so, while the next eight do not have as much impact on the beam size, and so have much less reason to sacrifice orbit. We are unsure why the first eight knobs reach lower minimum orbit errors than the next eight, since no orbit information was incorporated in the knobs' creation.

CONCLUSIONS

We have demonstrated that our dimension-reduction techniques enable us to use only eight free parameters to reduce the vertical emittance at CESR by as much as the standard correction technique which relies on the use of all the magnets. However, since our knobs rely mainly on vertical steerings, this forces us to also introduce orbit errors. By using a multi-objective genetic algorithm we are able to map out the Pareto front showing the trade-off of these two objectives. By limiting ourselves to 8 carefully-chosen knobs, we obtain faster convergence than if we had used all available steerings in our genetic algorithm. This dimension-reduction capability also offers the possibility of applying other algorithms in storage rings which would hitherto have been considered unsuitable for such high-dimensional problems.

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