

ONLINE OPTIMIZATION ALGORITHMS FOR ACCELERATORS AND EXPERIMENTAL RESULTS *

X. Huang[†], J. Corbett, J. Safranek, J. Wu, SLAC, Menlo Park, California

Abstract

Online accelerator optimization is generally a multi-variant nonlinear problem with considerable noise which require efficient and robust algorithms. In this study we evaluate the viability of several optimization algorithms and demonstrate the strength of the recently proposed RCDS method for online application with both simulations and experiments.

Automated tuning is basically a multi-variable optimization problem. It differs from usual optimization problems in that the function values contain noise. In this study we attempted to explore optimization algorithms that are suitable for online application. We proposed an algorithm that is effective in a noisy environment. Simulation and experimental studies were conducted to demonstrate the strength of this algorithm [2].

INTRODUCTION

The performance of an accelerator depends on the cooperation of all its subsystems which in turn may consist of many components that are individually controlled. For best performance, ideally the subsystems and components are monitored and the optimal target values of the monitors are known, and, if the monitors deviate from the target values, a deterministic procedure can be taken to make corrections. Orbit correction is an example of this ideal scenario.

However, in some cases the diagnostics cannot provide sufficient information to guide the move of the knobs toward the target. One example is the steering of the beam in a transport line prior to injection into a storage ring. The launching angle and position of the injected beam are usually not very well determined with the transport line BPMs because they are too close to the last few steering magnets. It is also possible that the necessary diagnostics do not exist at all.

In other cases the ideal target of a subsystem itself may be unknown or not very well known, or there does not exist an effective way to relate the knobs to the target. An example is the optimization of the nonlinear dynamics of storage rings with harmonic sextupoles. There is no direct way to determine the desired parameter adjustment for the harmonic sextupoles to compensate the discrepancies between the model and the real machine caused by calibration errors of the sextupole magnets and nonlinear components in the other magnets. The fact that the nonlinear motion detected by BPMs is usually weak and is plagued by the nonlinear response of the BPMs themselves makes it very challenging to calibrate lattices with a response-matrix approach.

When there is no direct method to predict the desired changes to the knobs, we usually tune the machine manually by turning the knobs to improve machine performance such as output power, injection efficiency, beam lifetime, or luminosity, *etc.*, depending on the application. This approach can be automated, as was done in Ref. [1], which employed the Nelder-Mead simplex method and iterative 1-dimensional scans.

GENERAL CONSIDERATIONS AND THE RCDS METHOD

Two basic requirements for an online optimization algorithm are high efficiency and robustness. High efficiency means that it is able to find the optimum with as few function evaluations as possible. Robustness in this context means the algorithm can find the optimum despite noise in measured function values (and occasional function value outliers) and that the algorithm behaves properly under machine failures.

One candidate algorithm is an iterative parameter scan that basically automates the manual approach. At each iteration parameters are scanned within a specific range while the other parameters are fixed at the previous best values. This method may be inefficient because each scan gains only a small amount if the downhill direction is not lined up with the unit vector [3]. Another candidate is Powell's conjugate direction method [3, 4], which is an iterative line search algorithm that updates the search direction set to make an efficient search. It also employs bracketing and an advanced line optimizer (golden section or quadratic interpolation). A third candidate we considered is the well known Nelder-Mead simplex method [3, 5]. We also included multi-objective genetic algorithms (MOGA) for comparison even though they may not be promising candidates for online optimization since usually it takes many function evaluations for genetic algorithms to work.

The algorithm we propose is called robust conjugate direction search (RCDS) [2]. It combines Powell's conjugate direction method with a new line optimizer that is robust against random noise and occasional outliers. The line optimizer first brackets the minimum (for a minimization problem) by going both directions along the line until hitting the boundary of the valid parameter region or finding a solution whose objective function value is higher than the present minimum by a significant amount as compared to the noise level. It then evaluates extra points within the bracketed zone for global sampling. Finally the sample points are fitted to a parabola from which the line minimum is determined.

* Work supported by DOE Contract No. DE-AC02-76SF00515

[†] xiahuang@slac.stanford.edu

COMPARISON OF ALGORITHMS IN SIMULATION

The candidate algorithms are applied to two realistic accelerator optimization problems in simulation for a comparison of performance. The two problems are coupling correction of the SPEAR3 ring and optimization of the SPEAR3 Booster-to-SPEAR (BTS) transport line optics.

Coupling correction

The goal of coupling correction in a storage ring is to minimize the vertical emittance caused by vertical dispersion inside dipole magnets and linear horizontal to vertical coupling, both of which can be mitigated with skew quadrupole magnets.

SPEAR3 have 13 skew quadrupole magnets for coupling correction. Since beam loss is usually dominated by Touschek scattering, we can use the beam loss rate (or lifetime) as an indirect measure of vertical emittance. In the simulation, errors are seeded to 42 skew quadrupoles (including the 13 that are used for correction) in the lattice. The vertical emittance is computed with the code Accelerator Toolbox [6]. The coupling ratio when the 13 correcting skew quadrupoles are turned off is 0.9%, which corresponds to a loss rate of 0.6 mA/min for a 500 mA beam. The loss rate is calculated according to the coupling ratio, with random noise seeded through beam current, which is assumed to have an rms uncertainty of $\sigma_I = 0.03$ mA. The loss rate evaluated with the change of beam current over an interval of 6 seconds corresponds to a 0.06 mA/min rms uncertainty in the loss rate. Increasing the interval reduces the noise level.

We applied Powell's method, the simplex method, NSGA-II [7] and RCDS to this problem several runs with noise or without noise. The evolution of the best solution are shown in Figure 1. The initial solution for Powell's method is the all-zero solution. This solution is also seeded to the initial NSGA-II population and is one initial vertex of the simplex method. The initial conjugate direction set of the RCDS algorithm is obtained by singular value decomposition of the Jacobian matrix of the orbit response matrix (ORM) with respect to the 13 skew quadrupoles. This makes convergence much faster than starting from the unit vectors (not shown).

With noise, both the simplex method and Powell's method perform poorly. This is especially true for Powell's method. This is understandable because the original Powell's method uses a line optimizer that is very sensitive to noise. The simplex method fails to work when the noise affects the comparison results of the objectives on the simplex vertices. Without noise the simplex method works nicely. The convergence of Powell's method without noise would be much faster if the initial conjugate direction set derived from the ORM Jacobian matrix is used. The NSGA-II method converges slowly, with or without noise. And a detailed look of the population shows that the solutions which are favored by noise (i.e., noise makes

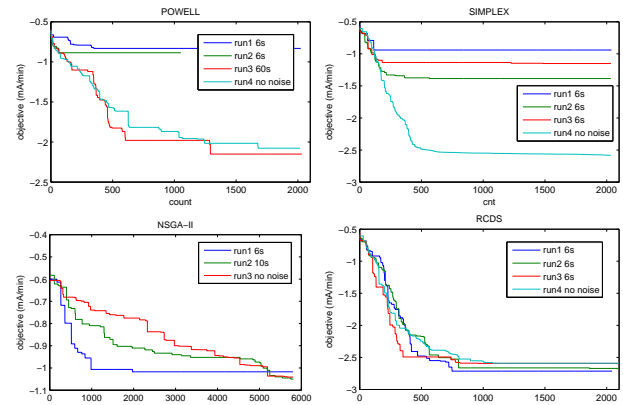


Figure 1: Evolution of best solution for Powell's method, simplex method, NSGA-II and RCDS.

their objectives smaller) unfairly dominate the population and prevents convergence. The RCDS method, however, demonstrates good convergence with or without noise.

Figure 2 compares the evolution of the coupling ratio of the best solution during the courses of the candidate algorithms. The coupling ratio has no noise added in and is hence a true measure of the quality of the solutions. Also shown is the IMAT method which uses the robust line optimizer of the RCDS method but its direction set is fixed as the unit vectors. Clearly the conjugate direction set approach is the reason for fast convergence and the robust line optimizer leads to the ability to steer through noise.

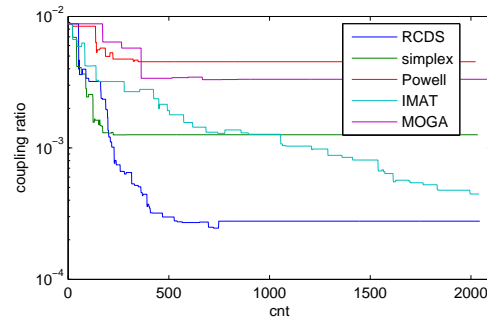


Figure 2: Comparison of the coupling ratio of the best solution for various algorithms.

Transport line optics

A second simulation problem is matching the BTS optics to the SPEAR3 ring. The last six quadrupole magnets in the BTS line are used to modify the optics functions at the injection point. Injection optics matching for the horizontal plane is illustrated in Figure 3. For the demonstration purpose we intentionally reduced the dynamic aperture of SPEAR3 to 12.5 mm in the simulation. Only particles that are inside the ellipse and to the left side of the septum line will be captured.

The injection efficiency is calculated by counting the number of surviving particles among 1000 particles that are randomly generated according to the optics functions, including the dispersion effect. Because of the finiteness of the total particles, the injection efficiency has a random

noise level of 1.6%. The left plot in Figure 3 shows the situation for the initial, present BTS optics with a simulated injection efficiency of 61.7%, while the right plot shows the best solution found by RCDS for an injection efficiency of 85%.

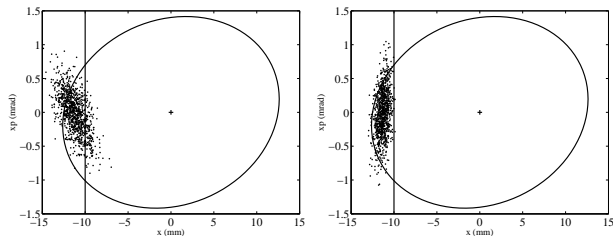


Figure 3: Optics match at the septum for the initial optics (left) and the RCDS solution (right).

Figure 4 shows the injection efficiency of the best solution for the algorithms. The same convergence behavior is demonstrated for these algorithms. The RCDS and IMAT methods are robust against noise while the former converges fast due to the high efficiency of the conjugate direction method. In this case the initial direction set is from the SVD of the Jacobian matrix of the distribution moments with respect to the six quadrupoles.

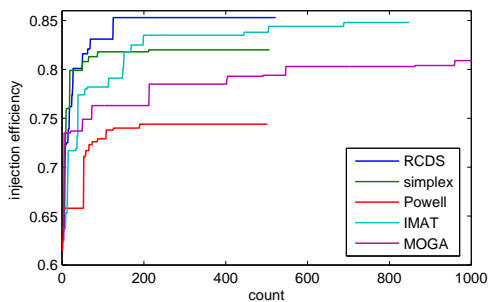


Figure 4: The history of the best injection efficiency during optimization for the various algorithms.

EXPERIMENTS

We have applied the RCDS method in experiments for several optimization problems, including coupling correction, kicker bump matching for SPEAR3 and injection beam steering for BTS.

The coupling correction problem is almost the same as the simulation problem discussed in the previous section. The ring is filled to 500 mA and maintains that level with frequent fill at 5-min interval. The beam loss rate is measured by observing the beam current change over a 6-second interval. The noise level is found to be 0.04 mA/min. Figure 5 shows the history of the objective of all evaluated solution during an experiment with the RCDS method which started from the all-zero solution. The final loss rate was higher than that of the solution found with the orbit response matrix method.

The goal of kicker bump matching is to minimize the orbit disturbance of the injection kick bump to the stored

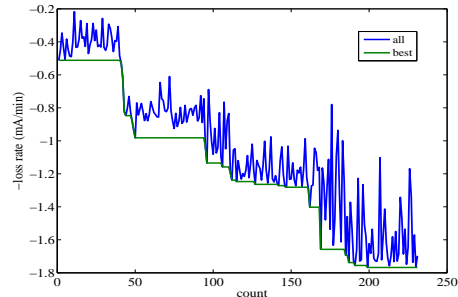


Figure 5: Beam loss rate of all evaluated solutions.

beam after injection. SPEAR3 has three injection kickers. The kick amplitude, kick pulse delay and width of the two side kickers K1 and K3 are varied. Also varied are strengths of two skew quadrupoles inside the kick bump. The orbit disturbance is measured by a turn-by-turn BPM. The objective function is the sum of the horizontal and vertical rms orbit of 100 turns after the kick. In experiments the RCDS method reduced the orbit oscillation amplitude to below $50 \mu\text{m}$ for the low emittance lattice with less than 100 evaluations. Figure 6 shows the history of the objective for the optimization of the low alpha lattice.

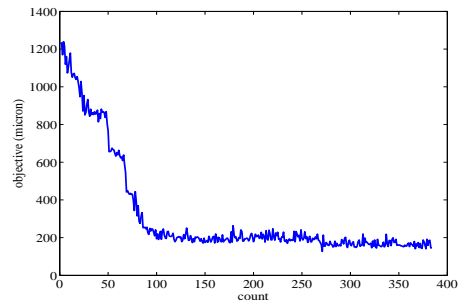


Figure 6: Kicker bump matching experiment with RCDS for the low-alpha lattice.

CONCLUSION

Simulation and experiments demonstrated that the RCDS method we proposed is suitable for experimental optimization of accelerators or other complex systems.

REFERENCES

- [1] L. Emery, *et al*, Proceedings of PAC'03, Portland, Oregon (2003)
- [2] X. Huang, J. Corbett, J. Safranek, J. Wu, submitted to Nuclear Intr. and Methods, section A (2013), SLAC-PUB-15414
- [3] W. H. Press, *et al*, Numerical Recipes, 3rd ed, Cambridge University Press, (2007)
- [4] M.J.D. Powell, *Computer Journal* **7** (2), 155-162 (1964)
- [5] J. Nelder, R. Mead, *Computer Journal*, **7**, 308 (1965)
- [6] A. Terebilo, Proceedings of PAC'01, Chicago, IL (2001)
- [7] K. Deb, *IEEE Trans. on Evolutionary Computation*, vol 6, no 2, (2002).