APPLICATIONS OF ONLINE OPTIMIZATION ALGORITHMS FOR INJECTION AT THE AUSTRALIAN SYNCHROTRON

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Abstract

Accelerators have hundreds of design parameters that makeup the design space. The optimization of complex nonlinear systems (like accelerators) is not straightforward. Trade-offs between competing nonlinear design variables means that optimizing a target objective (such as optics matching) can lack any obvious deterministic method.

At the Australian Synchrotron, accelerator tuning predominantly occurs via manual optimization or traditional optimization techniques such as the Linear Optics from Closed Orbits (LOCO) algorithm. While we have had distinct success with the implementation of LOCO [1] and manual tuning, these strategies are not without their downsides. Some situations (such as the optimization of synchrotron beam dynamics) produce a design space too large and multifaceted for manual tuning while implementing LOCO can be computationally expensive. Also, without sufficient diagnostic systems, both LOCO and manual tuning do not necessarily guarantee that the optimal solution will be found.

Motivated by the successful implementation of online optimization algorithms at SPEAR3 [2], this paper outlines the application of online optimization algorithms to improve the performance of the Australian Synchrotron injection system. We apply the efficient Robust Conjugate Direction Search (RCDS) Algorithm to reduce beam size in the storage ring.

THE CHALLENGES TO THE OPTIMIZATION OF ACCELERATORS

Particle accelerators are complex machines that rely on thousands of components and design variables. Accelerators also contain a multitude of subsystems that often act at cross-purposes to one another. For example, adjusting magnet strength can improve beam-size but cause issues with injection efficiency downstream. Additionally, demands placed on accelerator performance (such as the number of hours of availability and beam emittance) necessitates that stringent performance demands must be met.

TRADITIONAL METHODS OF IMPROVING BEAM PERFORMANCE

The traditional approach to tuning the machine has been to either manually tune or use of orbit response matrix (ORM) techniques such as the Linear Optics from Closed Orbits (LOCO) algorithm [3]. Manual tuning has traditionally involved selecting a parameter to vary, making a change to that parameter and then waiting to observe the machine response

before making other changes. However, this approach assumes that the parameter change scales linearly, does not cause any unintended consequences in other parts of the machine and that the tuner already knows what the desired solution will look like. The LOCO method is very powerful but requires a good model of the machine.

THE ONLINE OPTIMIZATION SOLUTION

Machine learning has been successfully implemented to improve performance and design of accelerators at many facilities; for example, SLAC [4], APS [5], Cornell [6]. Motivated by these successes, we have formed a machine learning working group at the Australian Synchrotron.

The Australian Synchrotron is moving into its second phase of development: delivering 7 beamlines under the auspices of the BRIGHT accelerator program. These new beamlines require a finely tuned machine to provide peak performance under exact specifications for the expanded user base. Machine learning and online optimization algorithms will be of significant benefit to the design and deployment of these new beamlines. For example, work is underway to produce predictive algorithms to diagnose beam dumps and reduce user beam downtime [7]. Our group has also used optimization algorithms to aid the design of a single nonlinear injection kicker to be constructed and commissioned at the Australian Synchrotron (see [8,9]). In this paper, we will outline an illustrative example of the power of optimization algorithms to improve beam performance at the Australian Synchotron.

THE RCDS ALGORITHM

The RCDS algorithm, kindly provided by Dr Xiaobaio Huang [2] has been shown to be an effective and efficient algorithm for online optimization of accelerators. RCDS uses Powell's method (Conjugate Directional Search) to iteratively search along the conjugate directions. The line search is fit to a parabolic minimum while taking into account the RMS noise of the measurement. Many facilities have shown RCDS to be robust against the noise of a real life accelerator and those without sufficient diagnostics (see e.g. [10]). As an illustrative example, we use the RCDS algorithm to optimize the vertical beam size along the BTS.

RCDS OPTIMIZATION OF VERTICAL BEAM SIZE IN THE AS STORAGE RING

To optimize the vertical beam size (σ_y) we vary the quadrupole magnetic strengths. All skew quads were normalized, set to zero and the RCDS algorithm was deployed

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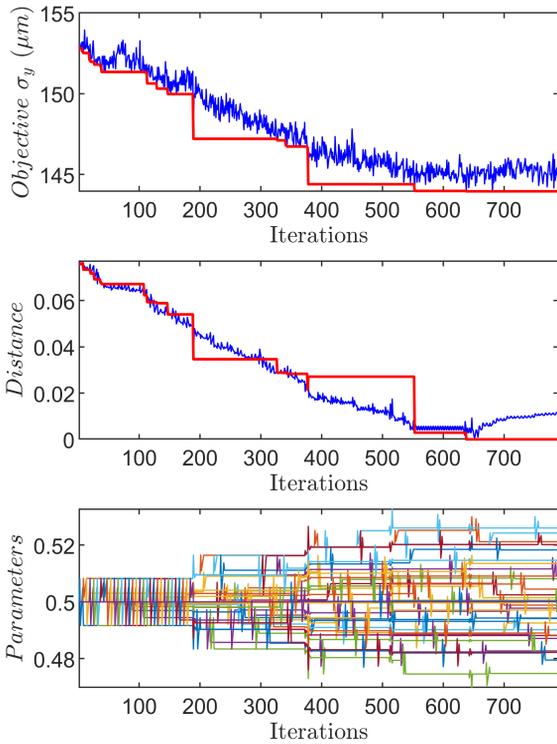
Figure 1: RCDS optimization of all skew quadrupoles to minimize the vertical beam size.

Figure 2: Second pass of the RCDS algorithm to minimize the vertical beam size.

to optimize the cost function (minimize the vertical beam size). Figure 1 shows the first run of the RCDS algorithm to optimize all variables of the parameter space. Parameters were normalized to [-1,1] over the domain for plotting comparison. The vertical beam-size was been optimized from 152.8 μm to 144 μm over 790 iterations. The LOCO method was then implemented to further refine the beam size before deploying the RCDS algorithm again. The second pass of the RCDS algorithm reduced σ_y to 94.7 μm in another 1097 iterations; as shown in Figure 2.

SENSITIVITY ANALYSIS

As mentioned, an accelerator can have thousands of parameters that have an impact on the beam size. Rather than optimize 100 variables over a long period of time, one can complete a sensitivity analysis. Sensitivity analyses investigate the cost function response of a parameter to determine what variable is the most sensitive to the objective. This allows one to discard any irrelevant or ineffectual features from the list of parameters. If you have 100 magnets that impact the beam size and 80 of the magnets do not correlate with the desired target, you can eliminate 80% of the computational time by selecting only those parameters that have a distinct impact on the target.
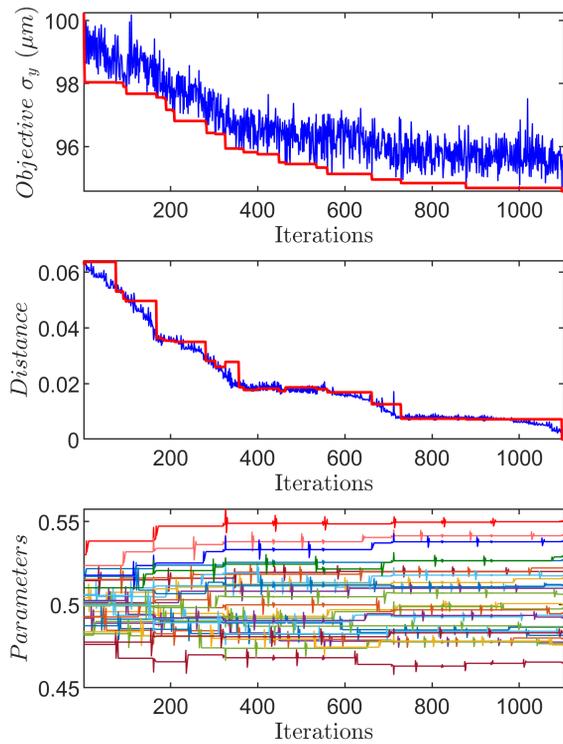
SENSITIVITY ANALYSIS OF THE BTS QUADRUPOLES

To illustrate how a sensitivity analysis can aid optimization efforts, an example of minimizing the vertical beam size using quadrupole strengths was conducted. The vertical beam size response as a function of 12 quadrupole current strengths were investigated using the Accelerator Toolbox (AT) and Matlab Middle Layer (MML) [11]. For 12 quadrupoles, 400 random distributions of quadrupole strengths were generated as inputs to the model. The Twiss parameters, horizontal beam size (σ_x) and vertical beam size (σ_y) were calculated at 4 screens at different points along the BTS. Figure 3 shows the Pearson correlation heatmap for all 12 individual quadrupoles as a function of vertical beam size.

To identify the most promising features (quadrupoles) to focus on for minimization of the vertical beam size at the fourth screen (σ_y^4) at the end of the BTS, feature variables can be combined in a meaningful way using domain-specific information. As a proof of concept, we group the quadrupoles into 4 sets of 3 quadrupoles (Table 1) to reduce complexity of the model and allow us to zero-in on the most prominent set of quadrupoles that impact the beam size. The Pearson correlation heatmap and a pairplot of the most statistically significant quadrupole groupings are shown in Figures 4 and 5. After identifying the most significant quadrupole groups (in this case, Group 4: quadrupoles
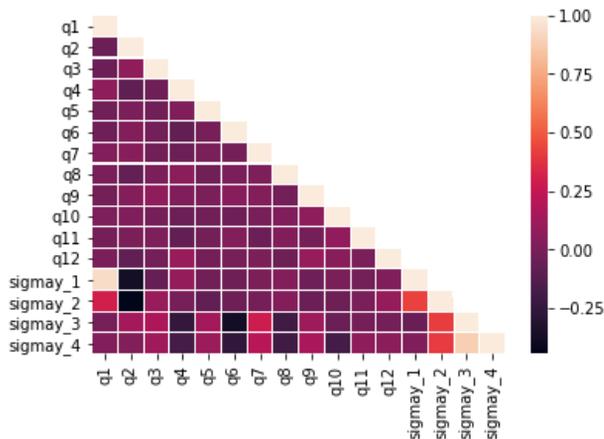
Figure 3: Pearson Correlation Heatmap of all 12 quadrupoles as a function of vertical beam size at 4 screens along the BTS. For readability, the exact Pearson coefficients are omitted.

Q10, Q11, Q12), these quadrupoles would be selected as the parameters for optimization algorithms. As a demonstrative case and for simplicity sake, a simple summation of the grouped responses of each magnet was taken in this example. Realistically, the magnetic contributions may not be a linear case, but each magnet will have differently weighted responses and combinations of groupings that need to be explored.
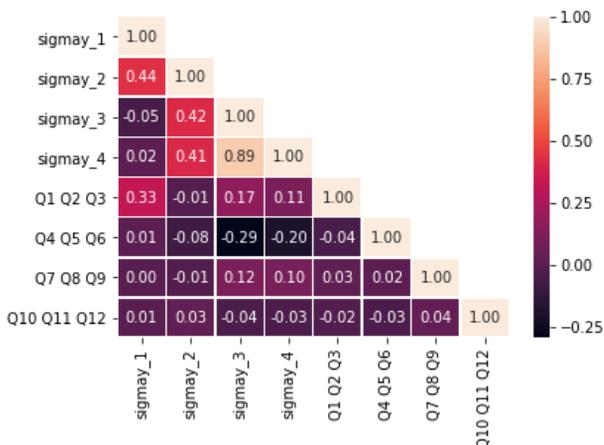

Figure 4: Pearson Correlation Heatmap of the four groups of quadrupoles as a summed function of vertical beam size at 4 screens along the BTS.

Table 1: Quadrupole Grouping for Reduction of Features for Sensitivity Analysis with the Pearson Correlation Coefficient (Pearson-r).

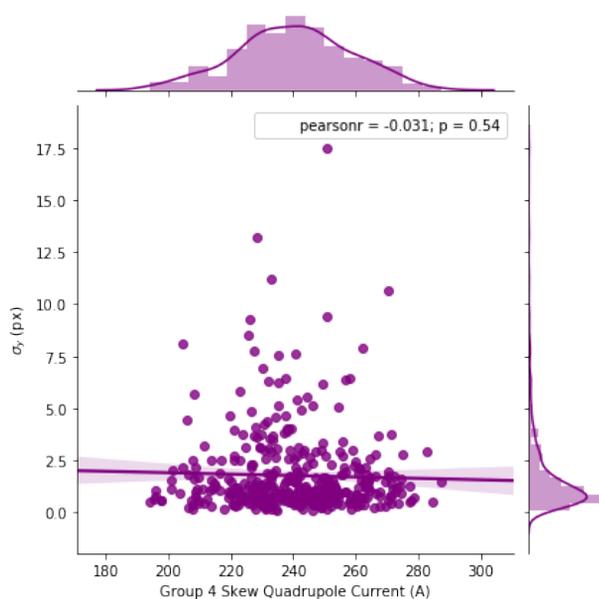| Group Number	Quadrupoles	Pearson-r
1	Q1, Q2, Q3	0.11
2	Q4, Q5, Q6	-0.2
3	Q7, Q8, Q9	0.097
4	Q10, Q11, Q12	-0.031

Figure 5: Pairplot with correlation coefficients of the most statistically significant group of skew quadrupoles as a summed function of vertical beam size at 4 screens along the BTS.

CONCLUSION

In this work, we have shown how one can use sensitivity analysis for dimension reduction and application of the RCDS algorithm to minimize beam size at the Australian Synchrotron. Using the RCDS and LOCO algorithms, we demonstrated the effectiveness of using the two algorithms to reduce the vertical beam size of the BTS from 152 μm to 94.7 μm. We will continue to develop our machine learning capabilities and approach in operations and facility projects.

ACKNOWLEDGEMENTS

REFERENCES

[1] R. Dowd, M. Boland, G. Leblanc, and Y. R. E. Tan, "Achievement of ultralow emittance coupling in the Australian Synchrotron storage ring", in *Phys. Rev. Spec. Top. - Accel. Beams*, vol. 14, no. 1, p. 12804, Jan. 2011.

[2] X. Huang, J. Safranek, "Online optimization of storage ring nonlinear beam dynamics", in *Phys. Rev. Spec. Top. - Accel. Beams.*, 18 (2015) 84001.

[3] J. Safranek, G. Portmann, and A. Terebilo, "Matlab-Based LOCO", in *Proc. 8th European Particle Accelerator Conf. (EPAC'02)*, Paris, France, Jun. 2002, paper WEPLE003, pp. 1184–1186.

[4] X. Huang and J. A. Safranek, "Beam-Based Optimization of Storage Ring Nonlinear Beam Dynamics", in *Proc. 8th Int. Particle Accelerator Conf. (IPAC'17)*, Copenhagen, Denmark, May 2017, pp. 3627–3630. doi:10.18429/JACoW-IPAC2017-THXA1

[5] Y. P. Sun, "Multi-Objective Online Optimization of Beam Lifetime at APS", in *Proc. North American Particle Accelerator Conf. (NAPAC'16)*, Chicago, IL, USA, Oct. 2016, pp. 913–915. doi:10.18429/JACoW-NAPAC2016-WEPOB12

[6] Bergan, W. F. and Bazarov, I. V. and Duncan, C. J. R. and Liarte, D. B. and Rubin, D. L. and Sethna, J. P. "MOnline storage ring optimization using dimension-reduction and genetic algorithms", in *Phys. Rev. Accel. Beams*, 22, 5, p. 054601.

[7] M. C. Chalmers, "Machine Learning Algorithms for a Predictive Tool to Reduce Beam Down Time", presented at the 10th Int. Particle Accelerator Conf. (IPAC'19), Melbourne, Australia, May 2019, paper THPRB003, this conference.

[8] R. Auchettl and Y. E. Tan, "Proposed Nonlinear Injection Kicker for the Australian Synchrotron", presented at the 10th

Int. Particle Accelerator Conf. (IPAC'19), Melbourne, Australia, May 2019, paper WEPMP001, this conference.

[9] R. Auchettl, R. T. Dowd, and Y. E. Tan, "Beam Dynamics, Injection and Impedance Studies for the Proposed Single Pulsed Nonlinear Injection Kicker at the Australian Synchrotron", presented at the 10th Int. Particle Accelerator Conf. (IPAC'19), Melbourne, Australia, May 2019, paper TUZ-ZPLS2, this conference.

[10] T. Pulampong, P. Klysubun, S. Kongtawong, S. Krainara, and P. Sudmuang, "Online Optimisation Applications at SPS", in *Proc. 8th Int. Particle Accelerator Conf. (IPAC'17)*, Copenhagen, Denmark, May 2017, pp. 4086–4088. doi:10.18429/JACoW-IPAC2017-THPAB151

[11] A. Terebilo, "Accelerator Modeling with MATLAB Accelerator Toolbox", in *Proc. 19th Particle Accelerator Conf. (PAC'01)*, Chicago, IL, USA, Jun. 2001, paper RPAH314, pp. 3203–3205.