Machine Learning in Accelerator Physics

S. Kötter, A. Santamaria Garcia, C. Xu

August 19, 2022

1 Optimization

1.1 Bayesian Optimization

1. Johannes Kirschner et al., *Tuning particle accelerators with safety constraints using Bayesian optimization*, Phys. Rev. Accel. Beams 25 (2022). DOI: `10.1103/PhysRevAccelBeams.25.062802`

2. Y. Gao et al., *Bayesian optimization experiment for trajectory alignment at the low energy RHIC electron cooling system*, Phys. Rev. Accel. Beams 25 (2022). DOI: `10.1103/PhysRevAccelBeams.25.014601`

3. C. Xu et al, *Optimization Studies of Simulated THz Radiation at FLUTE*, Proc. 13th International Particle Accelerator Conference, Bangkok, Thailand (2022). DOI: `10.18429/JACoW-IPAC2022-WEPOMS023`

4. Ryan Roussel, Adi Hanuka, and Auralee Edelen, *Multiobjective Bayesian optimization for online accelerator tuning*, Phys. Rev. Accel. Beams 24 (2021). DOI: `10.1103/PhysRevAccelBeams.24.062801`

5. S. Jalas et al, *Bayesian Optimization of a Laser-Plasma Accelerator*, Phys. Rev. Let. 126 (2021). DOI: `10.1103/PhysRevLett.126.104801`

6. R. Roussel et al, *Turn-key constrained parameter space exploration for particle accelerators using Bayesian active learning*, nature communications 12 (2021). DOI: `10.1038/s41467-021-25757-3`

7. Auralee Edelen et al., *Machine learning for orders of magnitude speedup in multiobjective optimization of particle accelerator systems*, Phys. Rev. Accel. Beams 23 (2020). DOI: `10.1103/PhysRevAccelBeams.23.044601`

8. R. J. Shalloo et al., *Automation and control of laser wakefield accelerators using Bayesian optimization*, nature communications 11 (2020). DOI: `10.1038/s41467-020-20245-6`

9. J. Duris et al., *Bayesian Optimization of a Free-Electron Laser*, Phys. Rev. Lett. 124 (2020). DOI: `10.1103/PhysRevLett.124.124801`

10. Johannes Kirschner et al., *Adaptive and Safe Bayesian Optimization in High Dimensions via One-Dimensional Subspaces*, Proc. 36th International Conference on Machine Learning, Long Beach, USA (2019). DOI: `10.48550/arXiv.1902.03229`

11. J. Kirschner et al., *Bayesian Optimization for Fast and Safe Parameter Tuning of SwissFEL*, Proc. 39th Free Electron Laser Conf. Hamburg, German, pp. 707–710 (2019). DOI: `10.18429/JACoW-FEL2019-THP061`

12. M. McIntire et al., *Bayesian optimization of FEL performance at LCLS*, Proc. 7th International Particle Accelerator Conference, Busan, Korea, pp. 2972–2975 (2016). DOI: `10.1103/PhysRevLett.124.124801`

1.2 Misc

1. C. Xu et al., *Machine Learning Based Spatial Light Modulator Control for the Photoinjector Laser at FLUTE*, Proc. 12th International Particle Accelerator Conference, Campinas, Brazil, pp. 3332–3335 (2021). DOI: `10.18429/JACoW-IPAC2021-WEPAB289`

2. Alexander Scheinker et al., *Online multi-objective particle accelerator optimization of the AWAKE electron beam line for simultaneous emittance and orbit control*, AIP advances 10 (2020). DOI: `10.1063/5.0003423`

1.2.1 Orbit

1. D. Schirmer, *Orbit Correction with Machine Learning Techniques at the Sychrotron Light Source DELTA*, Proc. 17th International Conference on Accelerator and Large Experimental Physics Control Systems, New York, USA, pp. 1426–1430 (2019). DOI: `doi:10.18429/JACoW-ICALEPCS2019-WEPHA138`

2. E. Meier, G. LeBlanc, and Y. E. Tan, *Orbit Correction Studies using Neural Networks*, Proc. 3rd International Particle Accelerator Conference, New Orleans, USA, p. 28372839 (2012).

3. Eva Bozoki and Aharon Friedman, *Neural network technique for orbit correction in accelerators/storage rings*, AIP Conference Proceedings 315 (1994). DOI: `10.1063/1.46759`

4. Eva Bozoki and Aharon Friedman, *Neural networks and orbit control in accelerators*, Proc. 4th European Particle Accelerator Conference, pp. 1589–1591 (1994).

1.3 Reinforcement Learning

1. Jason St. John et al., *Real-time artificial intelligence for accelerator control: A study at the Fermilab Booster*, Phys. Rev. Accel. Beams 24 (2021). DOI: `10.1103/PhysRevAccelBeams.24.104601`

2. Weija Wang et al., *Accelerated Deep Reinforcement Learning for Fast Feedback of Beam Dynamics at KARA*, IEEE Transactions on Nuclear Science 68 (2021). DOI: `10.1109/TNS.2021.3084515`

3. Xiaoying Pang, Sunil Thulasidasan, and Larry Rybarcyk, *Autonomous Control of a Particle Accelerator using Deep Reinforcement Learning*, arXiv (2020). DOI: `10.48550/arXiv.2010.08141`

4. F. H. O'Shea, N. Bruchon, and G. Gaio, *Policy gradient methods for free-electron laser and terahertz source optimization and stabilization at the FERMI free-electron laser at Elettra*, Phys. Rev. Accel. Beams 23 (2020). DOI: `10.1103/PhysRevAccelBeams.23.122802`

5. Niky Bruchon et al., *Basic Reinforcement Learning Techniques to Control the Intensity of a Seeded Free-Electron Laser*, Electronics 9 (2020). DOI: `10.3390/electronics9050781`

6. Simon Hirlaender and Niky Bruchon, *Model-free and Bayesian Ensembling Model-based Deep Reinforcement Learning for Particle Accelerator Control Demonstrated on the FERMI FEL*, arXiv (2020). DOI: `10.48550/arXiv.2012.09737`

7. Verena Kain et al., *Sample-efficient reinforcement learning for CERN accelerator control*, Phys. Rev. Accel. Beams 23 (2020). DOI: `10.1103/PhysRevAccelBeams.23.124801`

8. T. Boltz et al., *Feedback Design for Control of the Micro-Bunching Instability based on Reinforcement Learning*, Proc. 10th International Particle Accelerator Conference, Melbourne, Australia, pp. 104–107 (2019). DOI: `doi:10.18429/JACoW-IPAC2019-MOPGW017`

9. T. Boltz et al., *Studies of Longitudinal Dynamics in the Micro-Bunching Instability Using Machine Learning*, Proc. 9th International Particle Accelerator Conference, Vancouver, Canada, pp. 3277–3279 (2018). DOI: `doi:10.18429/JACoW-IPAC2018-THPAK030`

1.4 Surrogate Model

1. C. Xu et al, *Surrogate Modelling of the FLUTE Low-Energy Section*, Proc. 13th International Particle Accelerator Conference, Bangkok, Thailand (2022).

2. Auralee Edelen et al., *Machine learning for orders of magnitude speedup in multiobjective optimization of particle accelerator systems*, Phys. Rev. Accel. Beams 23 (2020). DOI: `10.1103/PhysRevAccelBeams.23.044601`

3. C. Emma et al., *Machine learning-based longitudinal phase space prediction of particle accelerators*, Phys. Rev. Accel. Beams 21 (2018). DOI: `10.1103/PhysRevAccelBeams.21.112802`

2 Classification

2.1 Anomaly Detection

1. E. Fol et al., *Detection of faulty beam position monitors using unsupervised learning*, Phys. Rev. Accel. Beams 23 (2020). DOI: `10.1103/PhysRevAccelBeams.23.102805`

2. Chris Tennant et al., *Superconducting radio-frequency cavity fault classification using machine learning at Jefferson Laboratory*, Phys. Rev. Accel. Beams 23 (2020). DOI: `10.1103/PhysRevAccelBeams.23.114601`

3. A. Nawaz et al., *Anomaly Detection for the European XFEL using a Nonlinear Parity Space Method*, IFAC-PapersOnLine 51 (2018). DOI: `10.1016/j.ifacol.2018.09.554`

3 Misc

1. Alexander Scheinker, *Adaptive Machine Learning for Robust Diagnostics and Control of Time-Varying Particle Accelerator Components and Beams*, Information 12 (2021). DOI: `10.3390/info12040161`

2. Sichen Li et al., *A Novel Approach for Classification and Forecasting of Time Series in Particle Accelerators*, Information 12 (2021). DOI: `10.3390/info12030121`

3. A. Eichler et al., *First Steps Toward an Autonomous Accelerator, a Common Project Between DESY and KIT*, Proc. 12th International Particle Accelerator Conference, Campinas, Brazil, pp. 2182–2185 (2021). DOI: `10.18429/JACoW-IPAC2021-TUPAB298`

4. Ayla Nawaz et al., *Probabilistic model-based fault diagnosis for the cavities of the European XFEL*, at - Automatisierungstechnik 69 (2021). DOI: `10.1515/auto-2020-0064`

5. Andrei Ivanov and Ilya Agapov, *Physics-based deep neural networks for beam dynamics in charged particle accelerators*, Phys. Rev. Accel. Beams 23 (2020). DOI: `10.1103/PhysRevAccelBeams.23.074601`

6. Jared Willard et al., *Integrating Physics-Based Modeling with Machine Learning: A Survey*, arXiv (2020). DOI: `10.48550/arXiv.2003.04919`

7. Andreas Adelmann, *On Nonintrusive Uncertainty Quantification and Surrogate Model Construction in Particle Accelerator Modeling*, SIAM/ASA Journal on Uncertainty Quantification 7 (2019). DOI: 10.1137/16M1061928

8. T. Boltz et al., *Accelerating Machine Learning for Machine Physics (an AMALEA-project at KIT)*, Proc. 17th International Conference on Accelerator and Large Experimental Physics Control Systems, New York, USA, pp. 2226–0358 (2019). DOI: 10.18429/JACoW-ICALEPCS2019-TUCPL06

9. Giuseppe Carleo et al., *Machine learning and the physical sciences*, Rev. Mod. Phys. 91 (2019). DOI: 10.1103/RevModPhys.91.045002

10. E. Fol et al., *Optics Corrections Using Machine Learning in the LHC*, Proc. 10th International Particle Accelerator Conference, Melbourne, Australia, pp. 3990–3993 (2019). DOI: doi:10.18429/JACoW-IPAC2019-THPRB077

11. K.A. Brown et al., *Experience with Machine Learning in Accelerator Controls*, Proc. of 16th International Conference on Accelerator and Large Experimental Control Systems, Barcelona, Spain, pp. 258–264 (2018). DOI: 10.18429/JACoW-ICALEPCS2017-TUCPA03

12. E. Fol et al., *Machine Learning Methods for Optics Measurements and Corrections at LHC*, Proc. 9th International Particle Accelerator Conference, Vancouver, Canada, pp. 1967–1970 (2018). DOI: doi:10.18429/JACoW-IPAC2018-WEPAF062

13. Auralee Edelen et al., *Opportunities in Machine Learning for Particle Accelerators*, arXiv (2018). DOI: 10.48550/arXiv.1811.03172

14. A. L. Edelen et al., *Neural Networks for Modeling and Control of Particle Accelerators*, IEEE Transactions on Nuclear Science 63 (2016). DOI: 10.1109/TNS.2016.2543203