Applying Bayesian Optimization to Achieve Optimum Cooling at the Low Energy RHIC Electron Cooling System

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Introduction

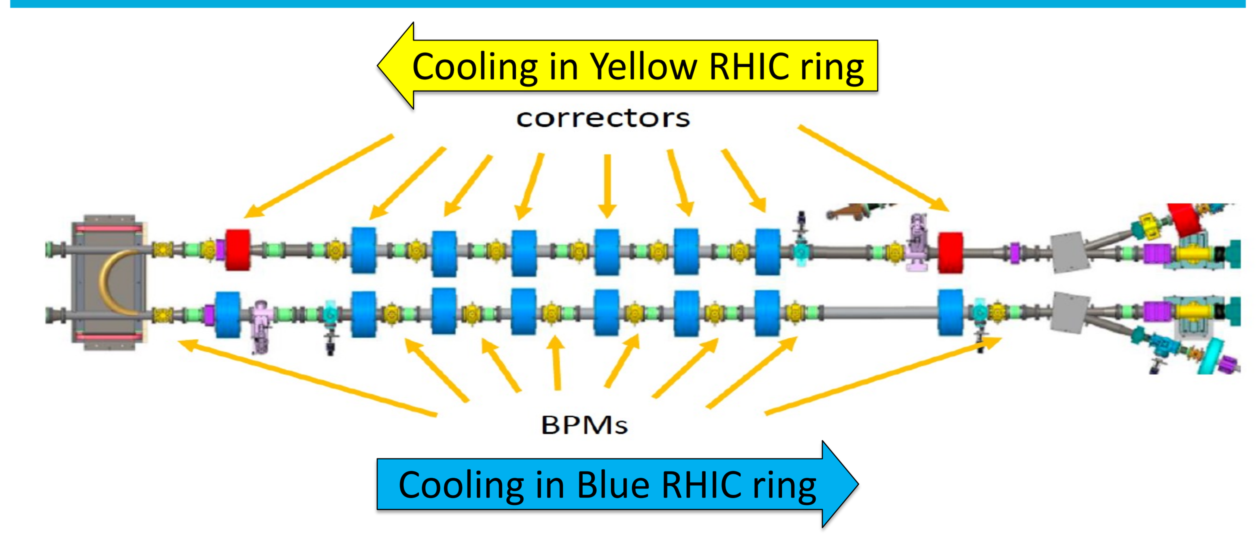

Figure 1. LEReC cooling section layout.

- Low Energy RHIC Electron Cooling (LEReC) improves luminosity for operation of the Relativistic Heavy Ion Collider (RHIC).
- LEReC is the world's first electron cooler using radio frequency (RF) accelerated electron bunches.
- Higher luminosity ion beams result in more collision in interaction region, generating more useful data.
- Historical data shows LEReC mainly cools at small transverse cooling rate.

Algorithm

- Goal: tune correctors automatically to produce and maintain best electron-ion alignment for maximum cooling rate.
- Bayesian optimization (BO) is used to optimize an unknown/expensive function with as few samples as possible [1].
- Gaussian Process (GP) builds a surrogate model for the objective function.
- Acquisition function determines which inputs are most likely to generate optimal output.

System Simulator

- LEReC system simulator takes electron beam positions and generate simulated transverse cooling rate, assuming ion beam is at the center $x = 0, y = 0$.

Simulation Results [2]

- The algorithm is trained on 60 random samples and produced 15 samples.

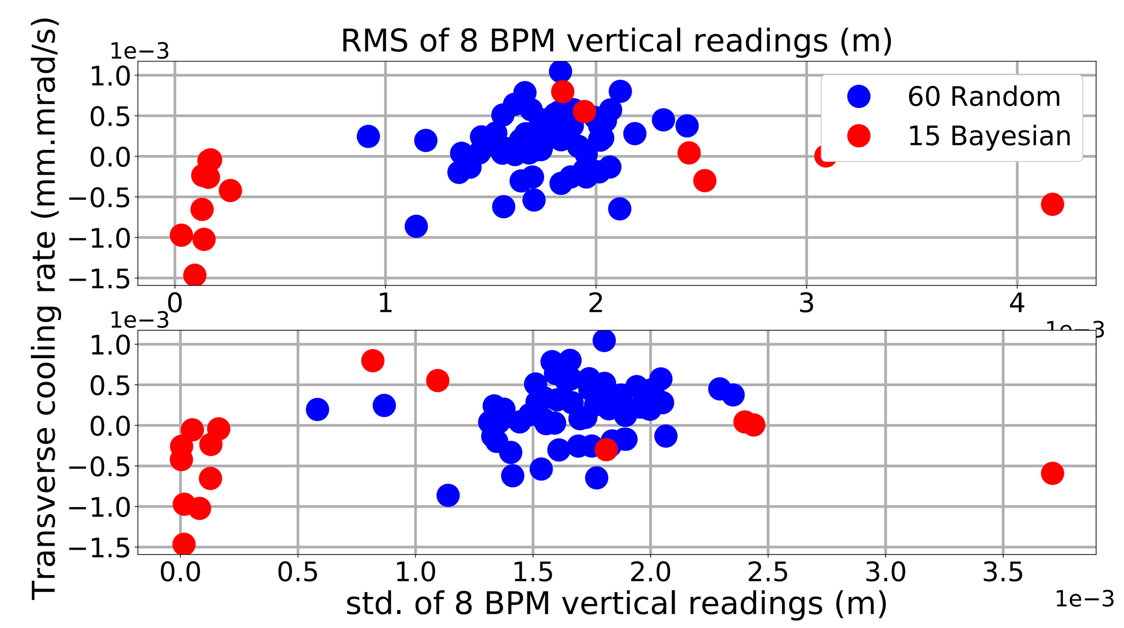

Figure 2. Comparison of rms and std values of BPM values from random samples (blue) and Bayesian samples (red).

- The Bayesian samples are more centered around optimal solution 0, with smaller root mean square (rms) and standard deviation (std) values (Fig. 2), thus having higher percentage of faster cooling rate (Fig. 3).

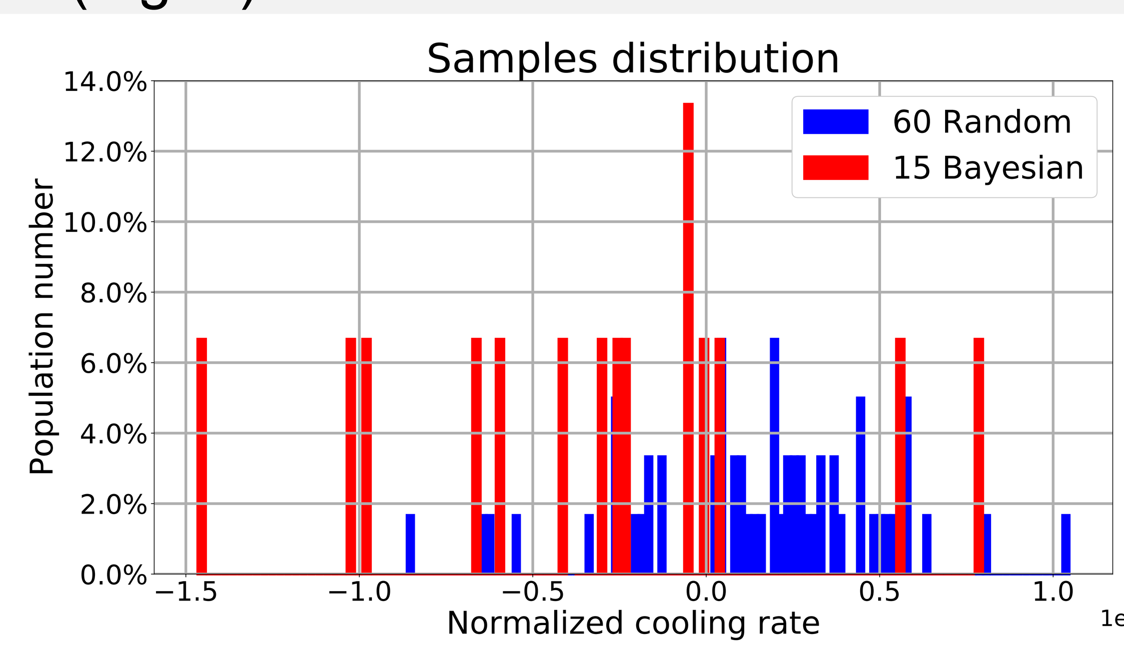

Figure 3. Comparison of statistical distribution of random sample outputs (blue) and Bayesian sample outputs (red).

Experiment

- 40 initial samples (using first 4 BPMs in the yellow cooling section) that explore the entire input domain incrementally are obtained from the real LEReC system.
- After training with initial samples, the algorithm is used to control electron trajectories in the yellow cooling section.

Experimental Results [2]

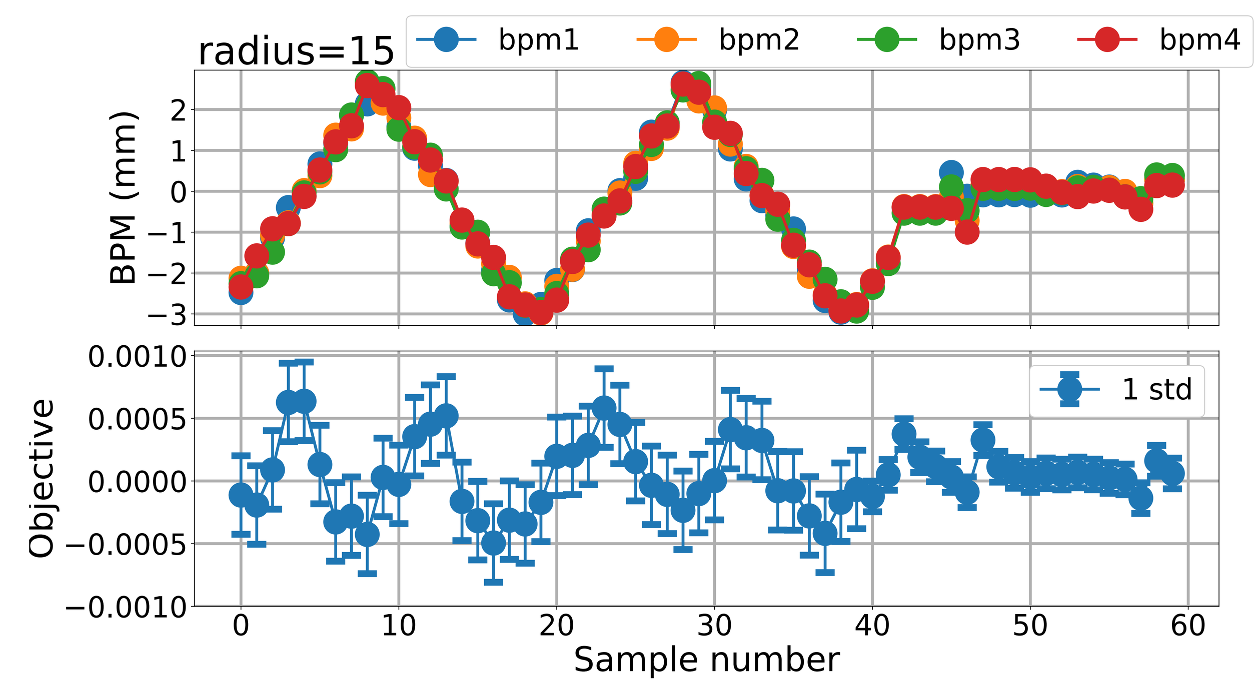

Figure 4. Experimental results with 40 training samples and 20 optimization steps.

- The trained algorithm quickly (in 3 steps as shown in Fig. 4) tunes the electron positions to the center (correct optimal solution) and maintains them there (as shown in Fig. 5).

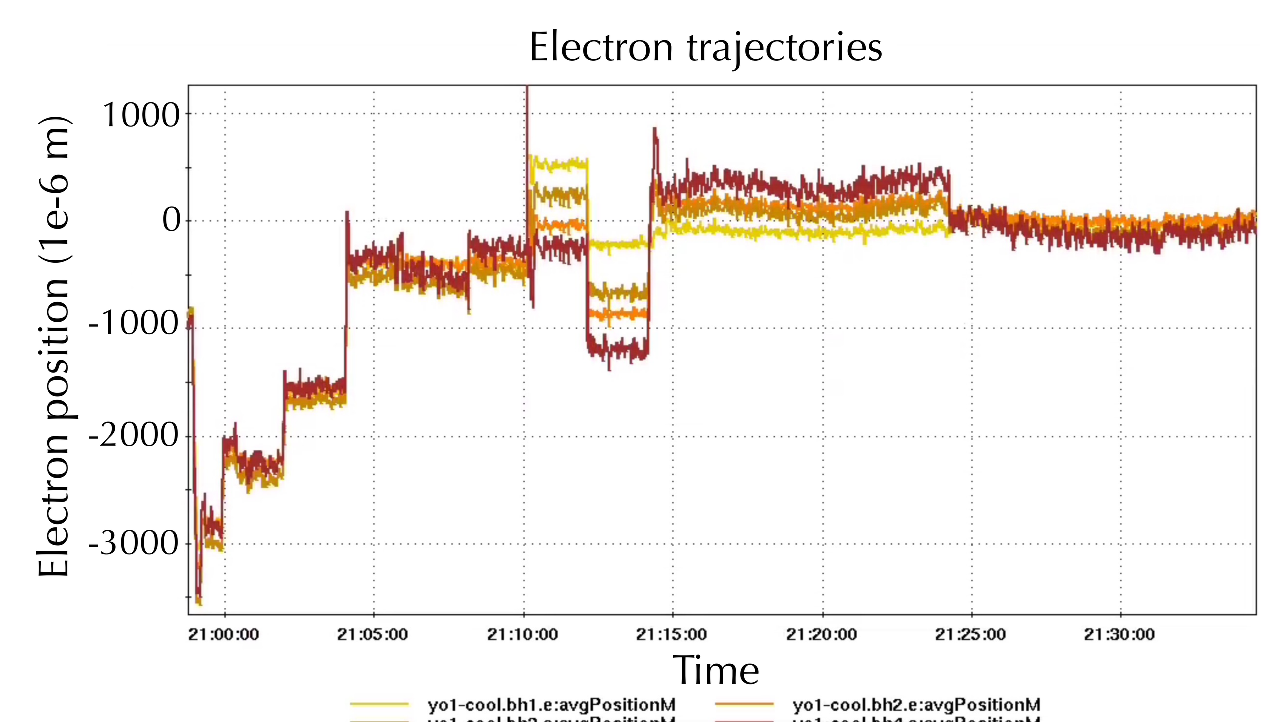

Figure 5. Electron positions are quickly tuned to the center and maintained there by the trained BO algorithm.

Future Work

- Physics-informed BO (Fig. 6) uses Hessian matrix calculated around historical optimum as the covariance function for the GP, so it is more efficient and needs less data during optimization.
- Contextual GP (Fig. 7) uses composite covariance function so it can handle varying environmental factors that affect objective function value.

Simulation for Future Work

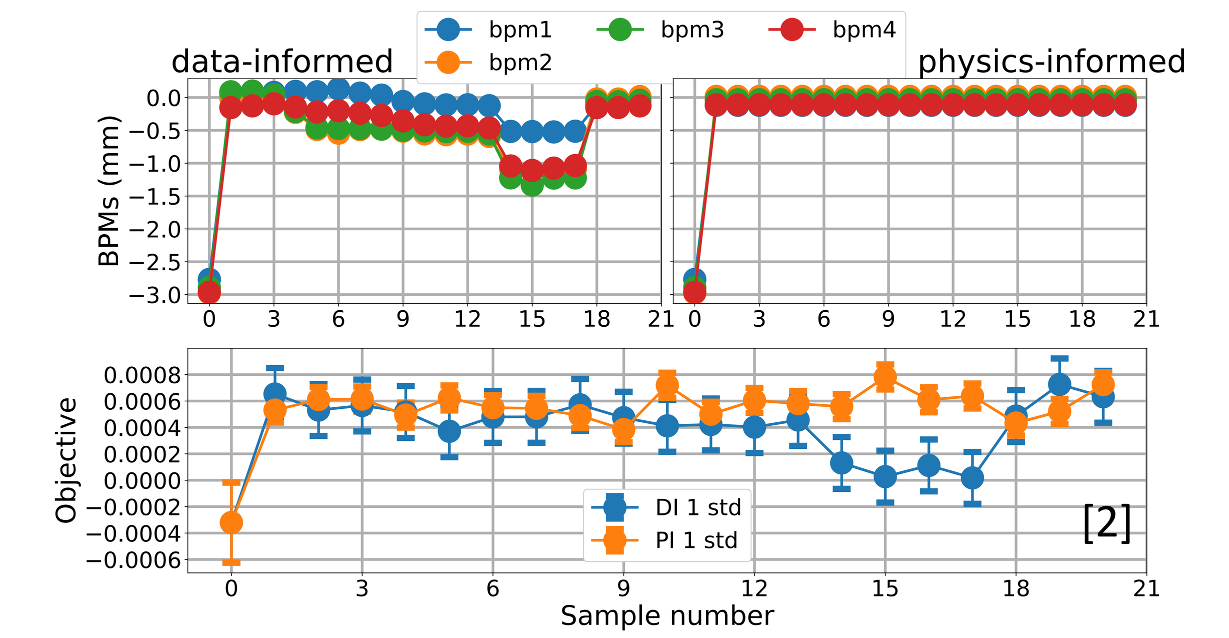

Figure 6. Comparison of simulation results from data-informed BO (top left) and physics-informed BO (top right).

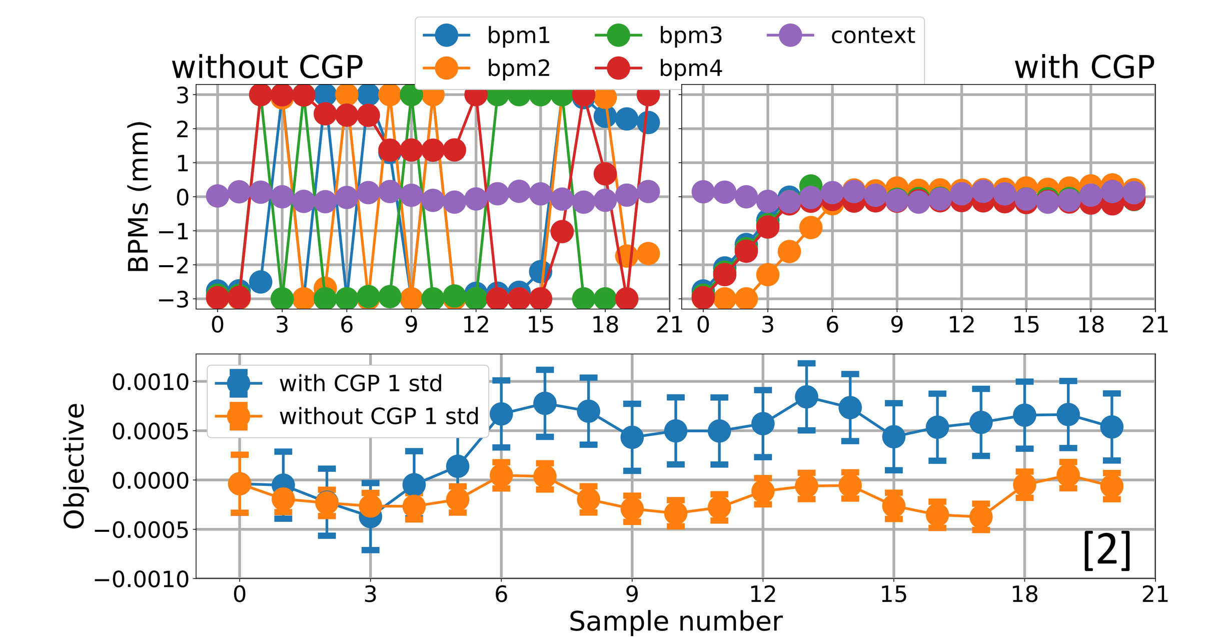

Figure 7. Comparison of simulation results from physics-informed BO without contextual GP (top left) and with contextual GP (top right).

Conclusion

- Bayesian optimization (BO) is effective in finding and maintaining good electron and ion alignment that optimizes cooling performance in the LEReC system.
- Optimal solution found by the algorithm verifies the traditional orbit correction program and the BPM calibrations.

Bibliography

[1] E. Brochu, V. M. Cora, and N. de Freitas, A Tutorial on Bayesian Optimization of Expensive Cost Functions, with Application to Active User Modeling and Hierarchical Reinforcement Learning (2010), arXiv:1012.2599.

[2] Y. Gao, W. Lin, et al., Applying Bayesian Optimization to Achieve Optimum Cooling at the Low Energy RHIC Electron Cooling System, Manuscript submitted to Phys. Rev. Accel. Beams, Sept. 2021.