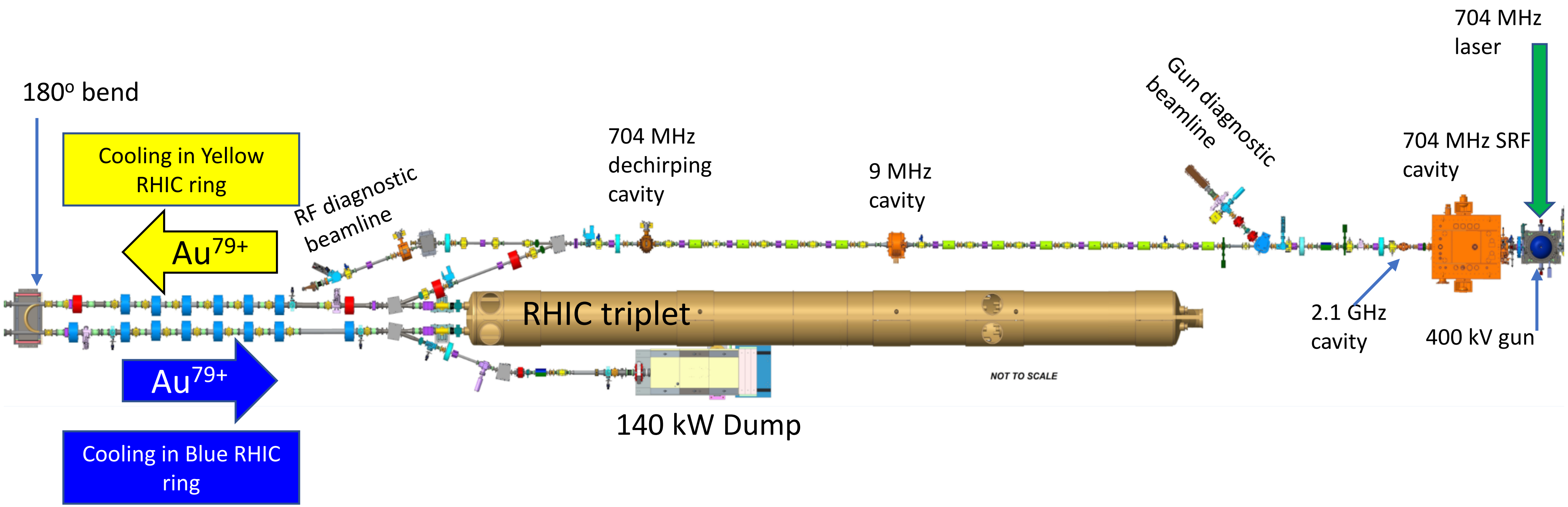
# Applying Machine Learning to Optimization of Cooling Rate at Low Energy RHIC Electron Cooler

Y. Gao, K. A. Brown, P. Dyer, S. Seletskiy, H. Zhao

Collider-Accelerator Department, Brookhaven National Laboratory,

Upton, NY 11973, USA

# LEReC System Overview




- 704 MHz e-bunches (grouped into 9 MHz macro-bunches) are produced from photocathode and accelerated in SRF cavity to design energy (1.6 MeV, 2 MeV).
- Those e-bunches are brought to Yellow and Blue RHIC cooling sections (20 meter) where they co-travel with ion bunches with the same average velocity.
- Cooling is fully operational right now, part of RHIC run, at 2 MeV energy.
- Longitudinal cooling was easy to obtain, transverse cooling was obtained but it was more challenging.

# Motivation

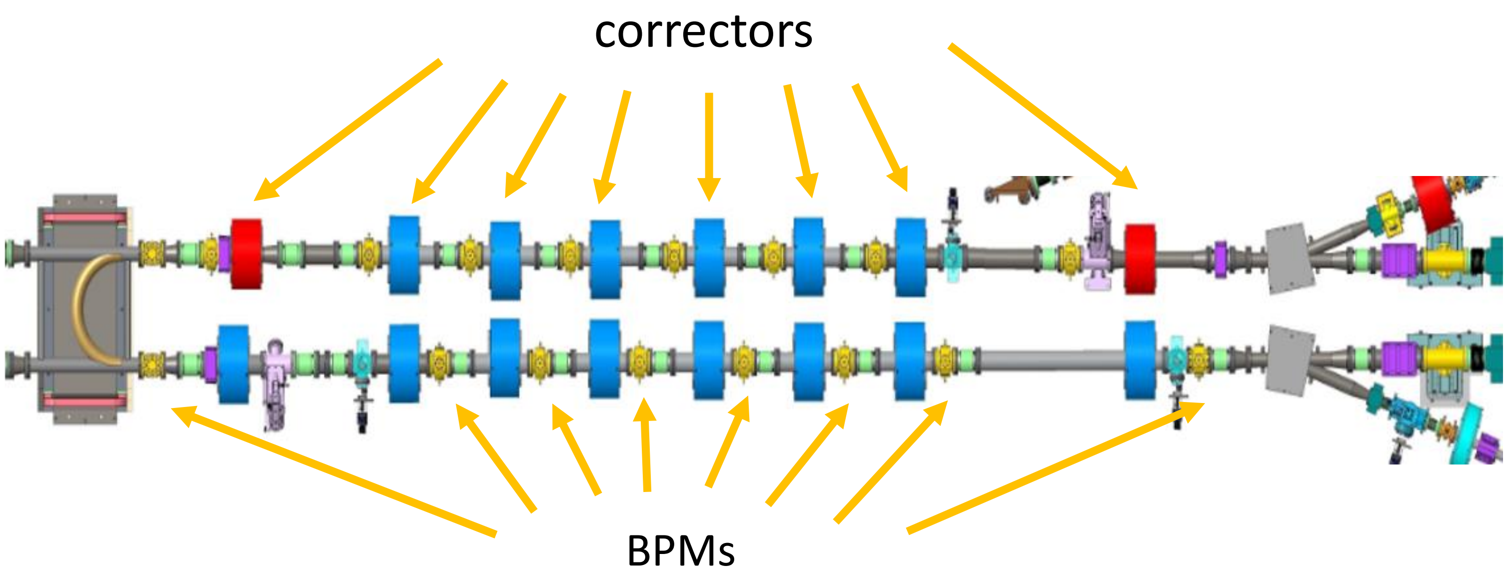
- LEReC increases at least 50% luminosity.

- Cooling rate strongly depends on how electrons and ions align; Although good alignment and functional cooling are already obtained, we believe better cooling can still be achieved.

- The **goal** is to demonstrate Machine Learning techniques can be useful to optimize the cooling performance.

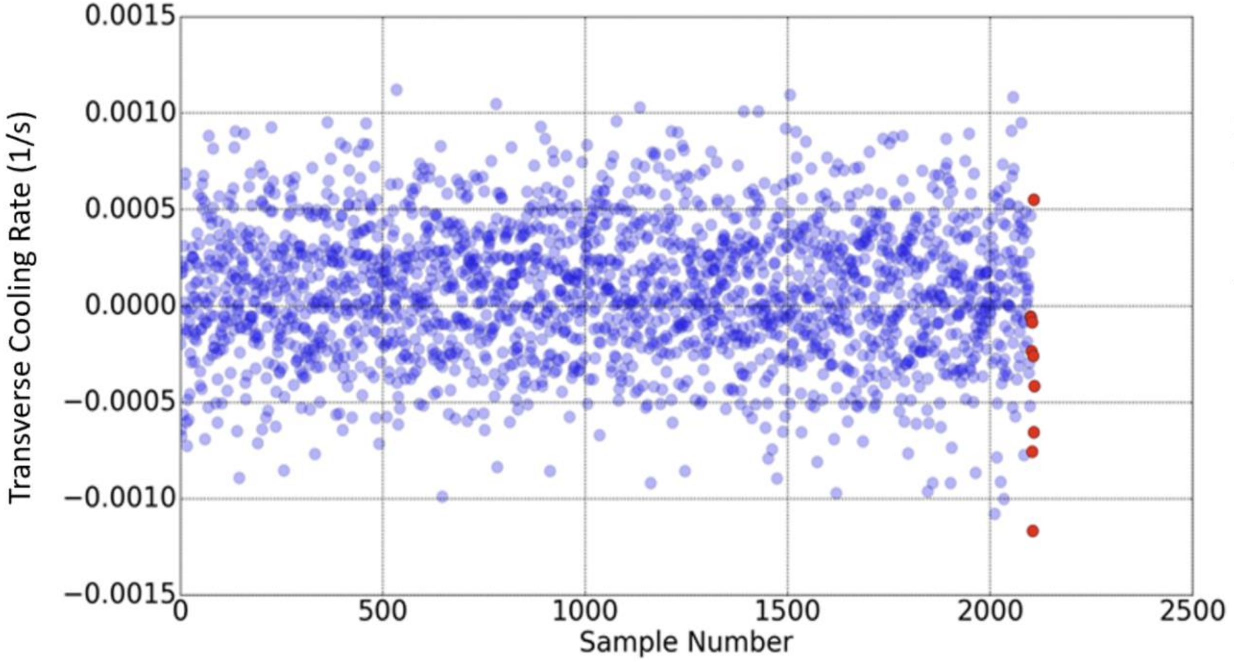
- It also serves the purpose of experimenting with machine learning techniques in order to prepare for the transition from simulation to implementation in the live LEReC system.

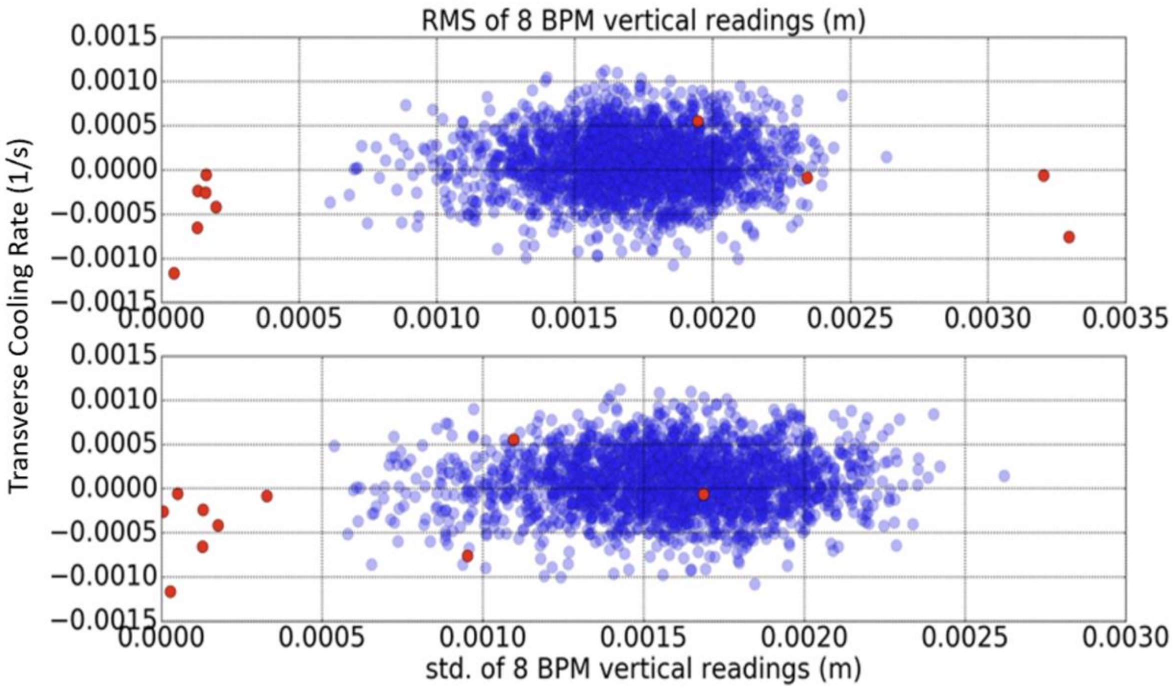
# Simulation Settings




- Only electron positions are studied, all other parameters are fixed, such as beam energy, number of particles, magnet strength, etc.
- Ion beam is assumed to be centered with respect to the cooling section.
- To avoid disrupting the normal operations of the real system, a system simulator is used to output the cooling rate.

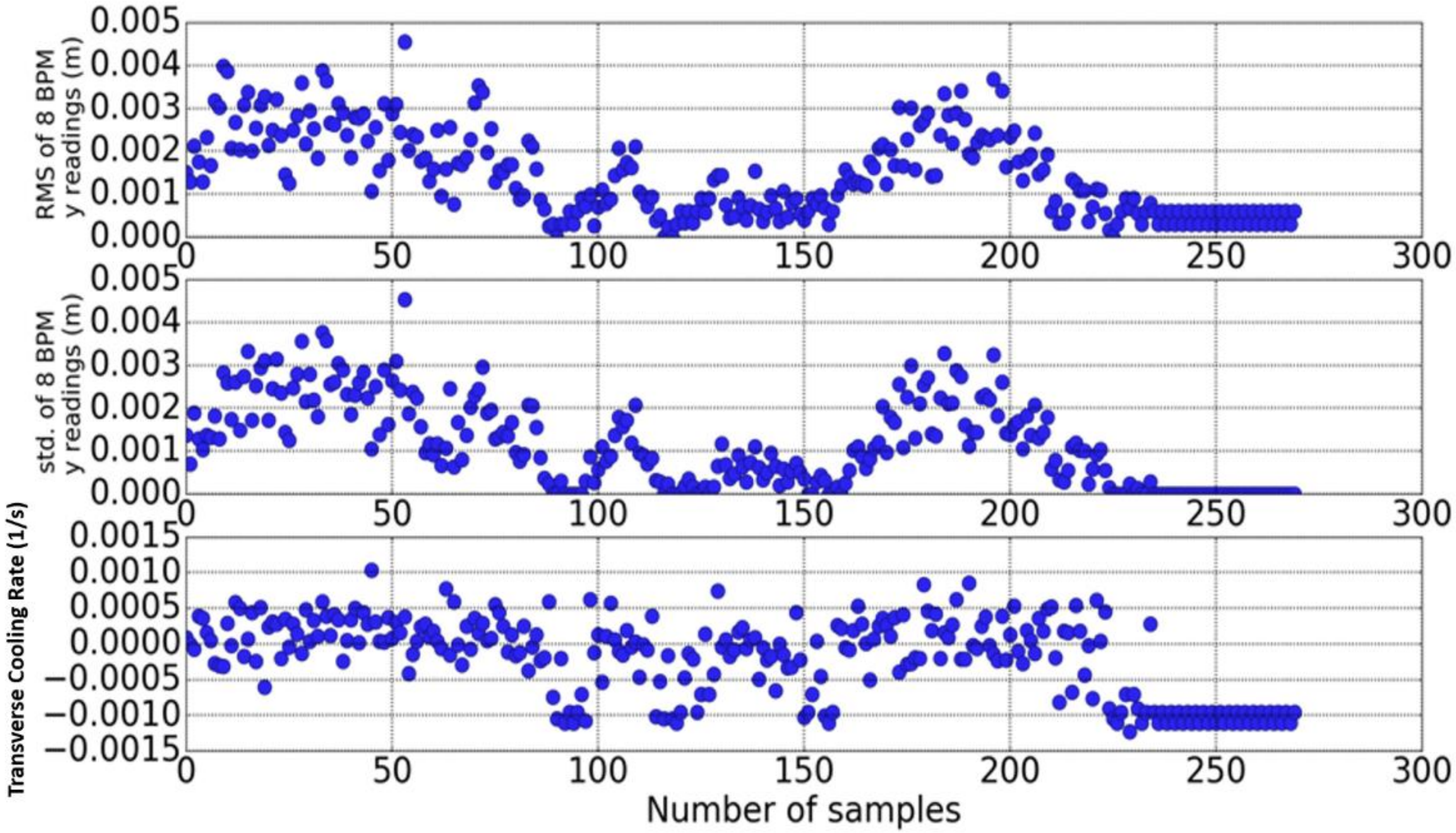
# Simulation Results – Bayesian Optimization




- The cooling rate is defined as the decreasing speed of the transverse beam size.
- Bayesian samples (red) clearly have a better cooling rate.
- 2 features are examined, rms and std.
- Bayesian method (red) tends to sample toward 0, which means it learns a pattern to optimize the goal.

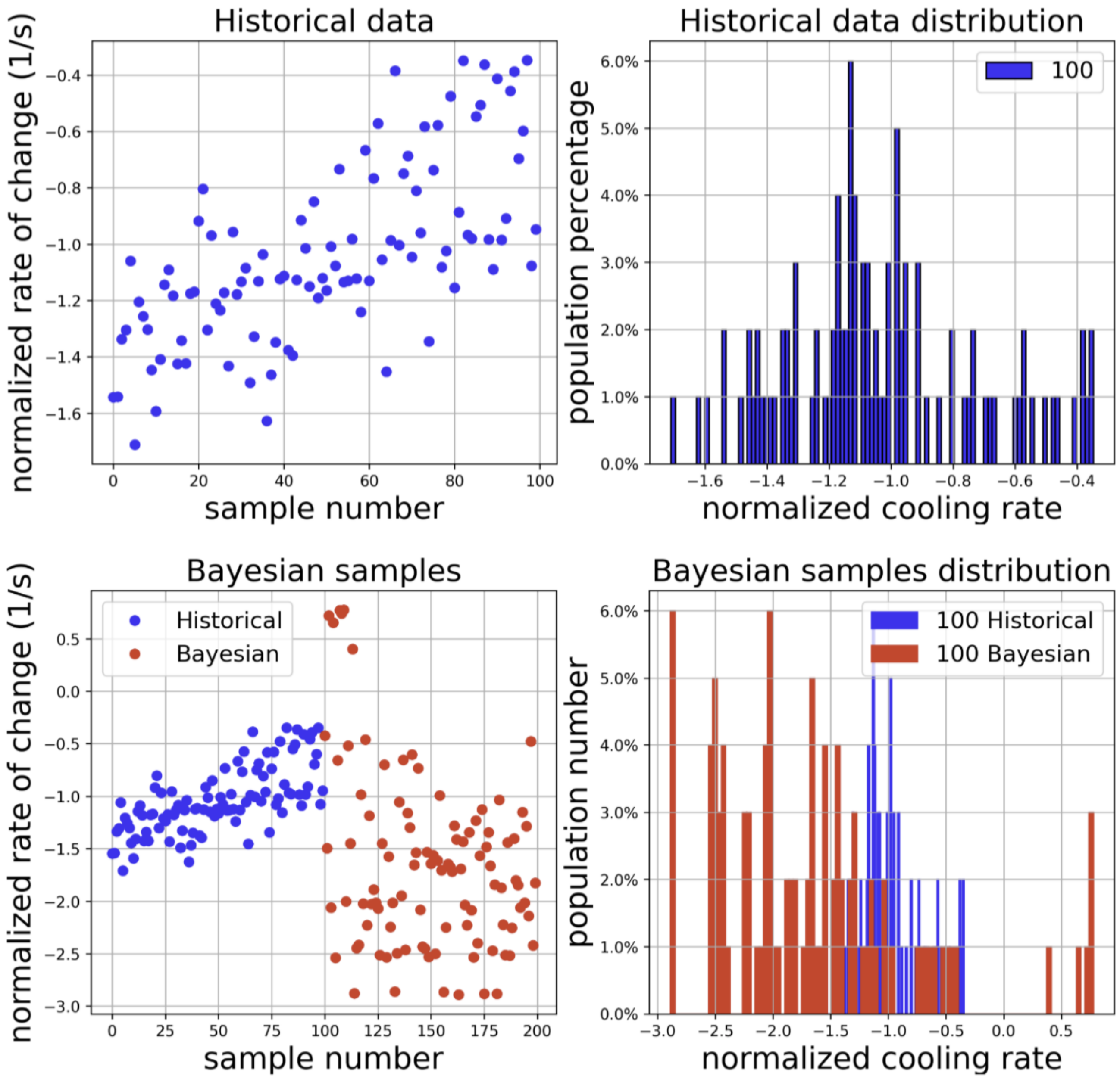
# Simulation Results – Q-learning




- Q-learning also exhibits a similar behavior.
- We can see Bayesian method takes fewer samples to converge.

# Experiment Results on Real Cooling Data

- The Bayesian method was trained on the real historical data.
- Then it was used to make 100 samples (red).
- As we can see, the number of population of larger cooling rates is greatly enhanced.



# Summary

- In this work we present machine learning methods, Bayesian optimization and Q-learning, can be used to optimize the cooling rate.
- It serves the purpose of making preparation for implementations in the live system.