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U.S. DEPARTMENT OF ENERGY

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

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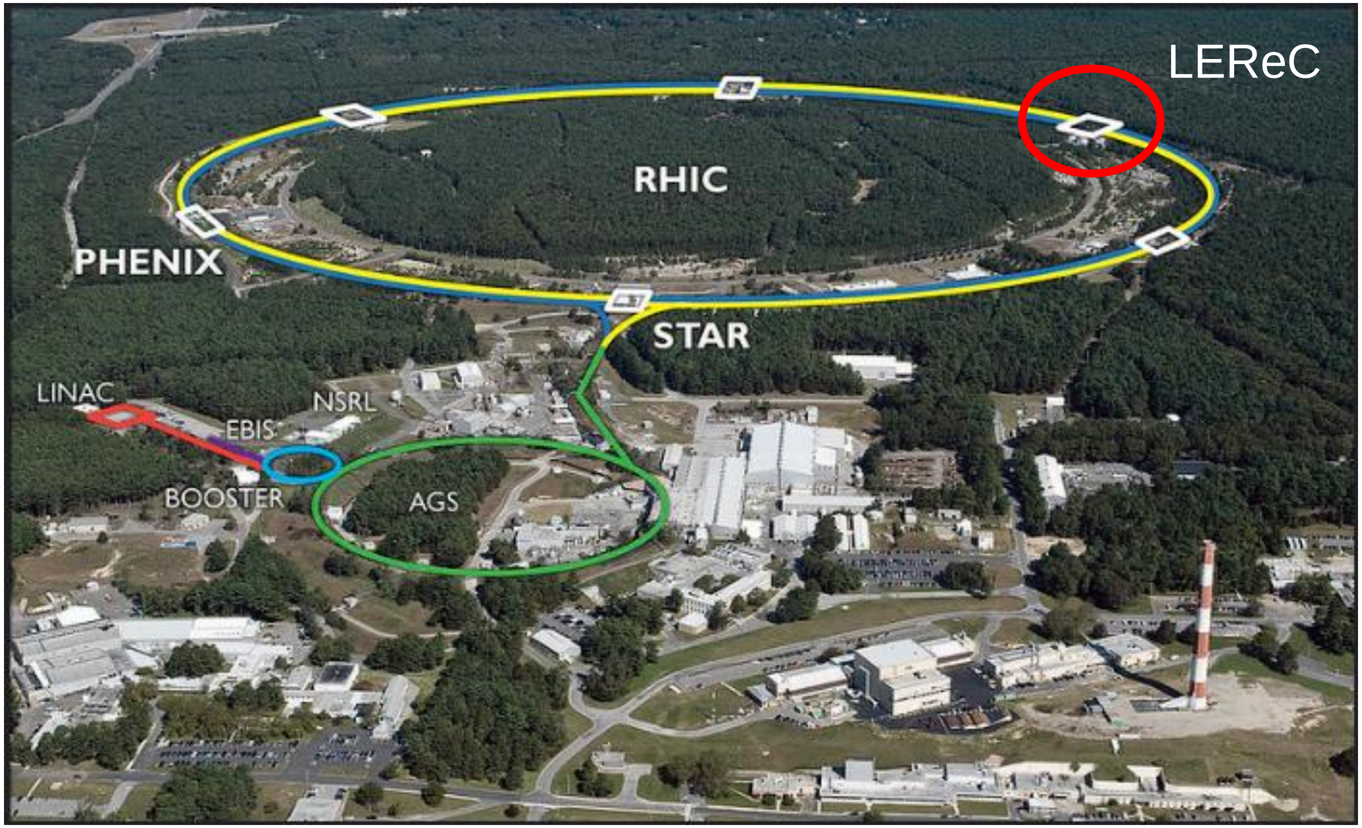
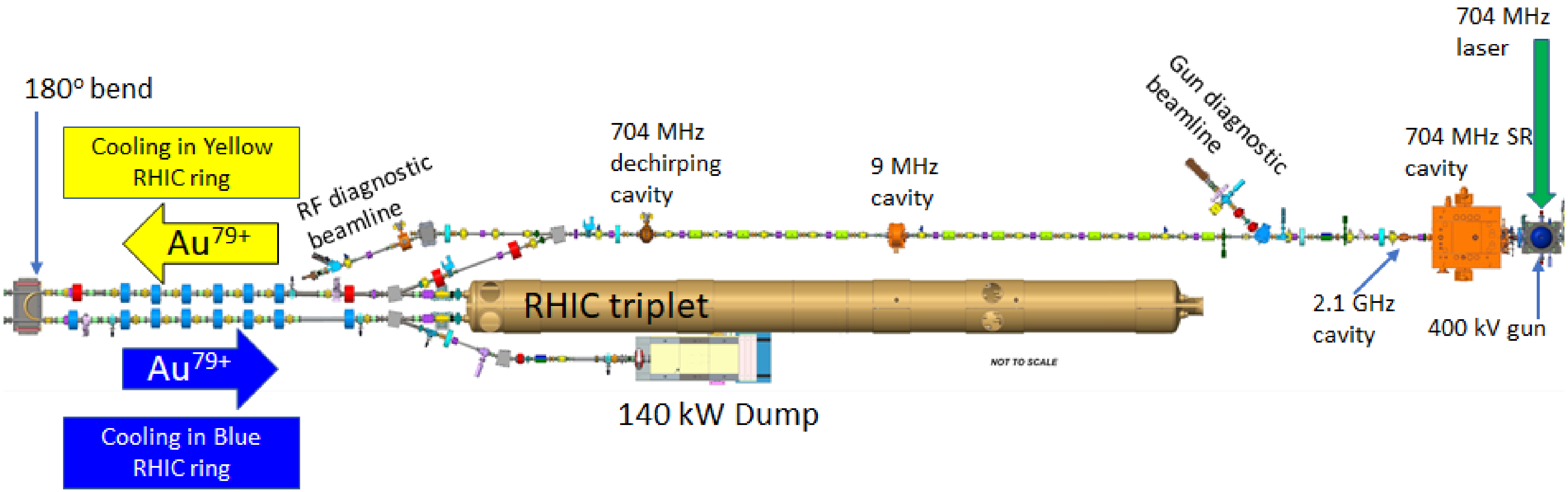
Relativistic Heavy Ion Collider



- Two 3.8 km counter-rotating supper-conducting rings;
- Six Interaction Regions (IR), LEReC is at IR2;

LEReC System Overview



- LEReC is used to increase the luminosity, it was successfully improved the luminosity multifold in 2020 and 2021 runs;
- 704 MHz e-bunches (grouped into 9 MHz macro-bunches) are produced from the photocathode and accelerated in the SRF cavity to the designed energy (1.6 MeV, 2 MeV);
- Those e-bunches are delivered to the cooling sections (20 meter), where they co-travel with ion bunches.

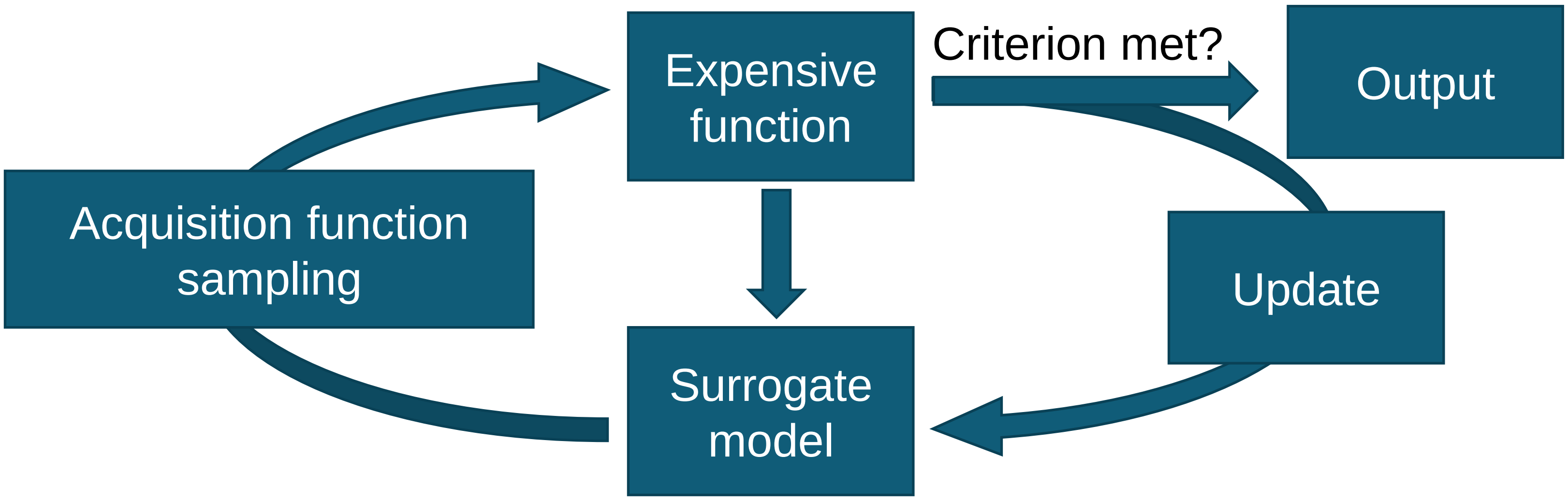
Motivations

- BPM Measurement errors;
- An independent way to optimize the cooling performance.

Method

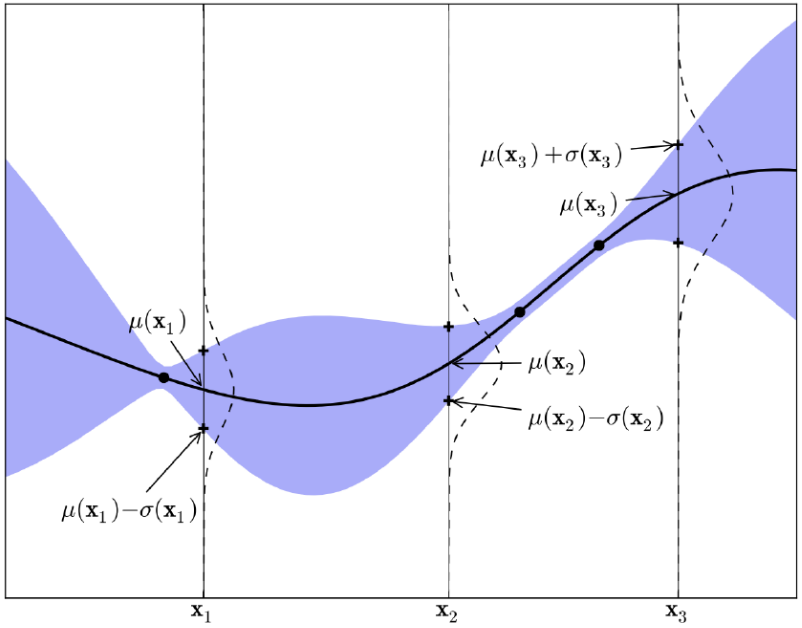
- Bayesian Optimization (BO): a powerful tool for finding the extrema of objective functions that are expensive to evaluate;
- It is called Bayesian because it uses the famous “Bayes’ theorem”.

$$P(f|\mathcal{D}_{1:t}) \propto P(\mathcal{D}_{1:t}|f)P(f)$$



Gaussian Process

[Brochu et al, 2010]



- A probability distribution over possible functions that fit a set of points

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$$

- The kernel function $k(x_i, x_j)$ describes how closely two points are related.

- The function value at a new sample point x_{t+1} follows $\mathcal{N}\left(\mu_t(\mathbf{x}_{t+1}), \sigma_t^2(\mathbf{x}_{t+1})\right)$ where

$$\begin{aligned}\mu_t(\mathbf{x}_{t+1}) &= \mathbf{k}^T\mathbf{K}^{-1}\mathbf{f}_{1:t}\\ \sigma_t^2(\mathbf{x}_{t+1}) &= k(\mathbf{x}_{t+1}, \mathbf{x}_{t+1}) - \mathbf{k}^T\mathbf{K}^{-1}\mathbf{k}\end{aligned}$$

and the covariance matrix $\mathrm{K} = k(X, X) = \begin{bmatrix} k(x_1, x_1) & \cdots & k(x_1, x_t) \\ \vdots & \ddots & \vdots \\ k(x_t, x_1) & \cdots & k(x_t, x_t) \end{bmatrix}$

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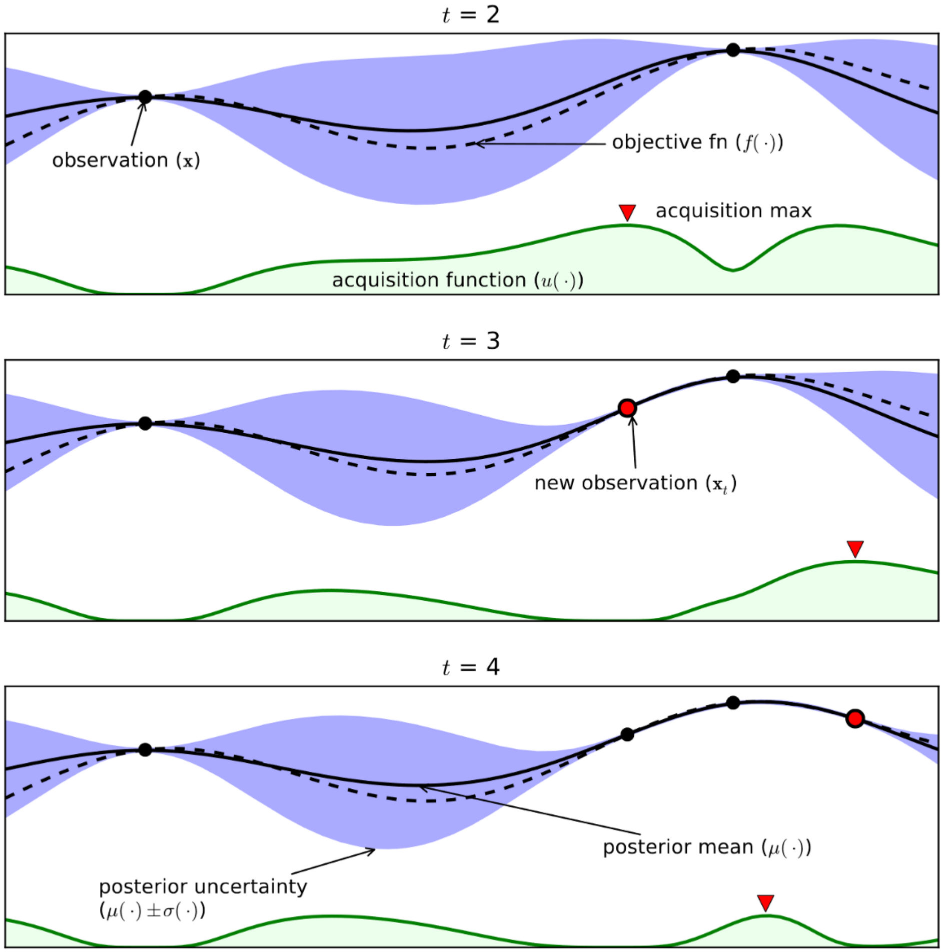
Acquisition Function

- Guide how input space should be explored during optimization;
  - Probability Improvement (PI)
  - Expected Improvement (EI)
  - Upper Confidence Bound (UCB)

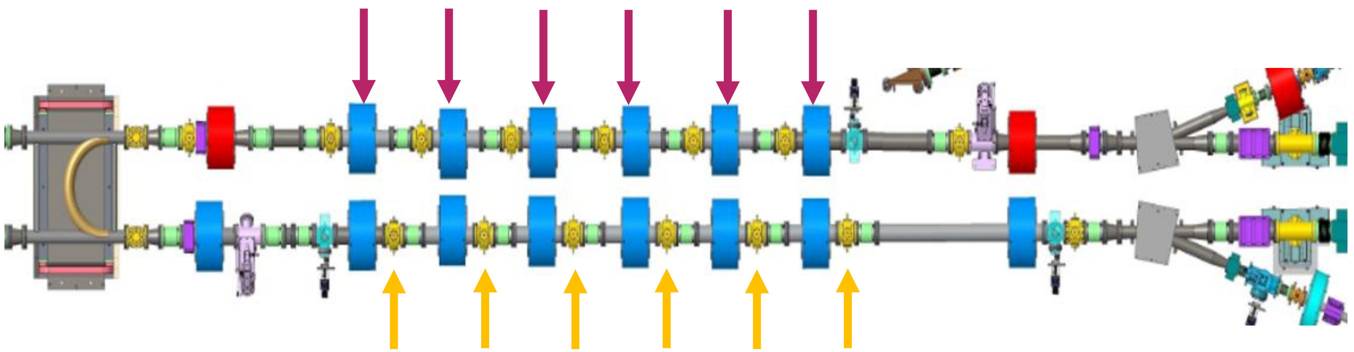
- A combination between predicted mean and variance;

$$\mathbf{UCB}(\boldsymbol{x}) = \boldsymbol{\mu}(\boldsymbol{x}) + \boldsymbol{\kappa\sigma}(\boldsymbol{x})$$

[Brochu et al, 2010]



Experiment Settings



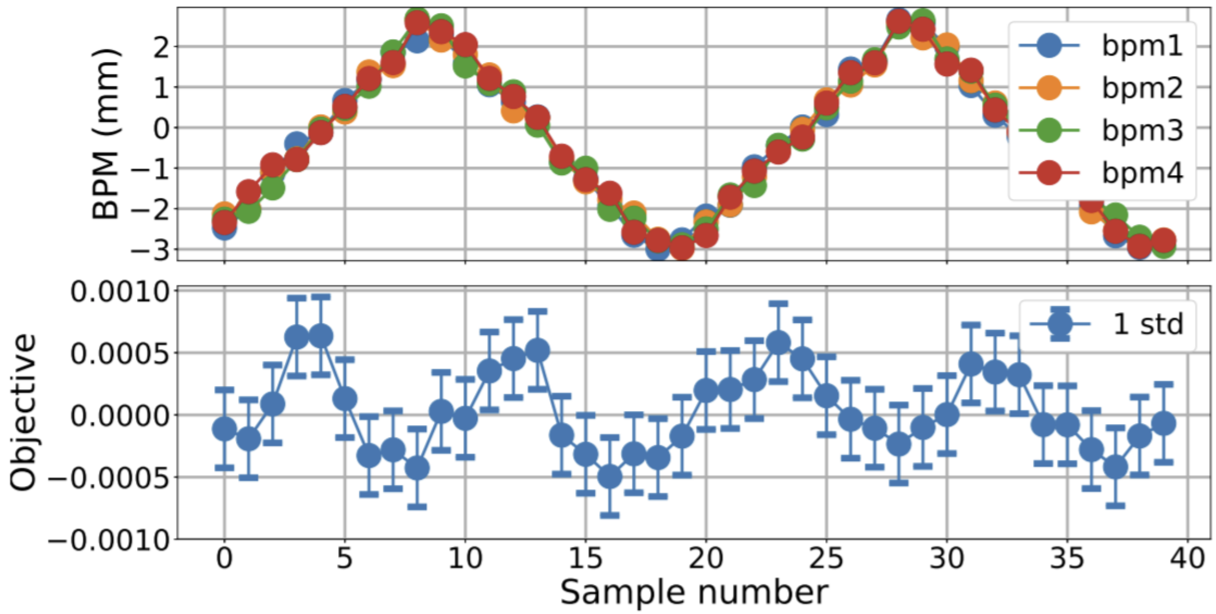
The <u>Goal</u> is to use BO to tune electron trajectories to maximize the ion cooling rate.

- Ions are assumed in the center position, only the first 4 BPMs are considered;
- Decreasing speed of transverse ion beam size:

$$\lambda = (1/\delta)(d\delta/dt)$$

- Cooling performance is measured by (- λ), a more negative λ means a faster cooling rate;

Initial Sampling



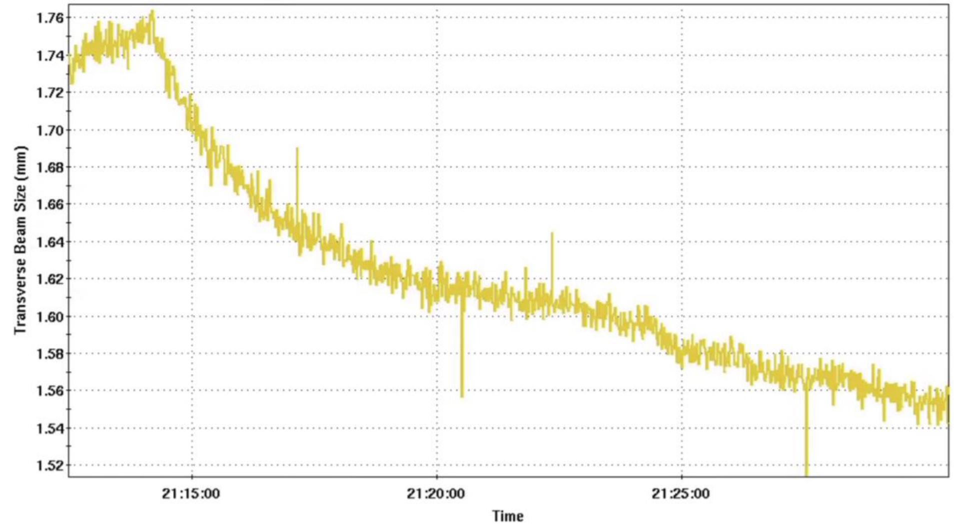
- Input (Top): 4 BPMs, go through the entire [-3, 3] mm range;
- Objective (Bottom): cooling rate (- λ), exhibits a pattern, favors input positions around 0.

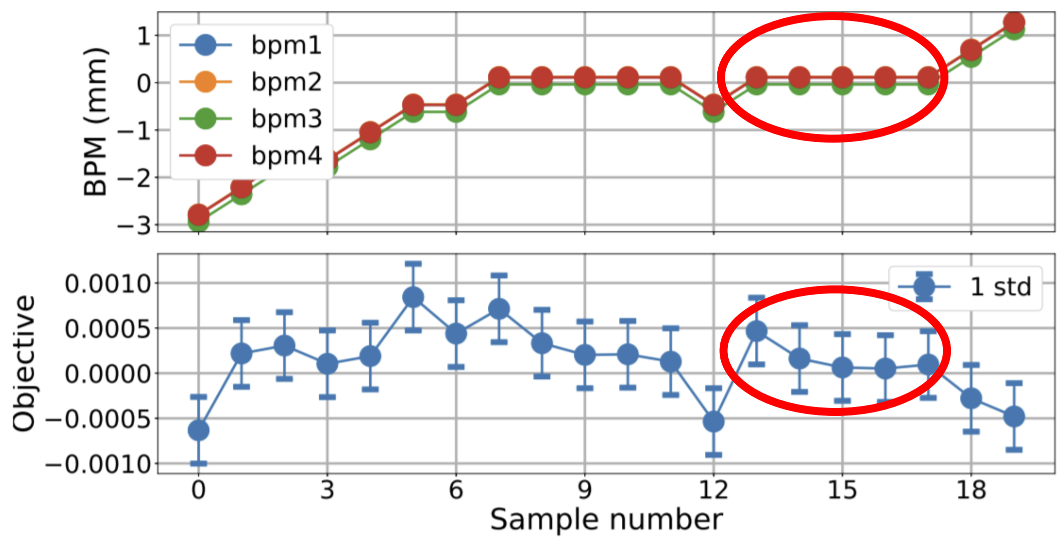
Optimization Strategy in the Presence of Noise

Large noise presents in δ (Top), makes the objective:

- $\lambda = -(1/\delta)(d\delta/dt)$

unstable and unable to converge.





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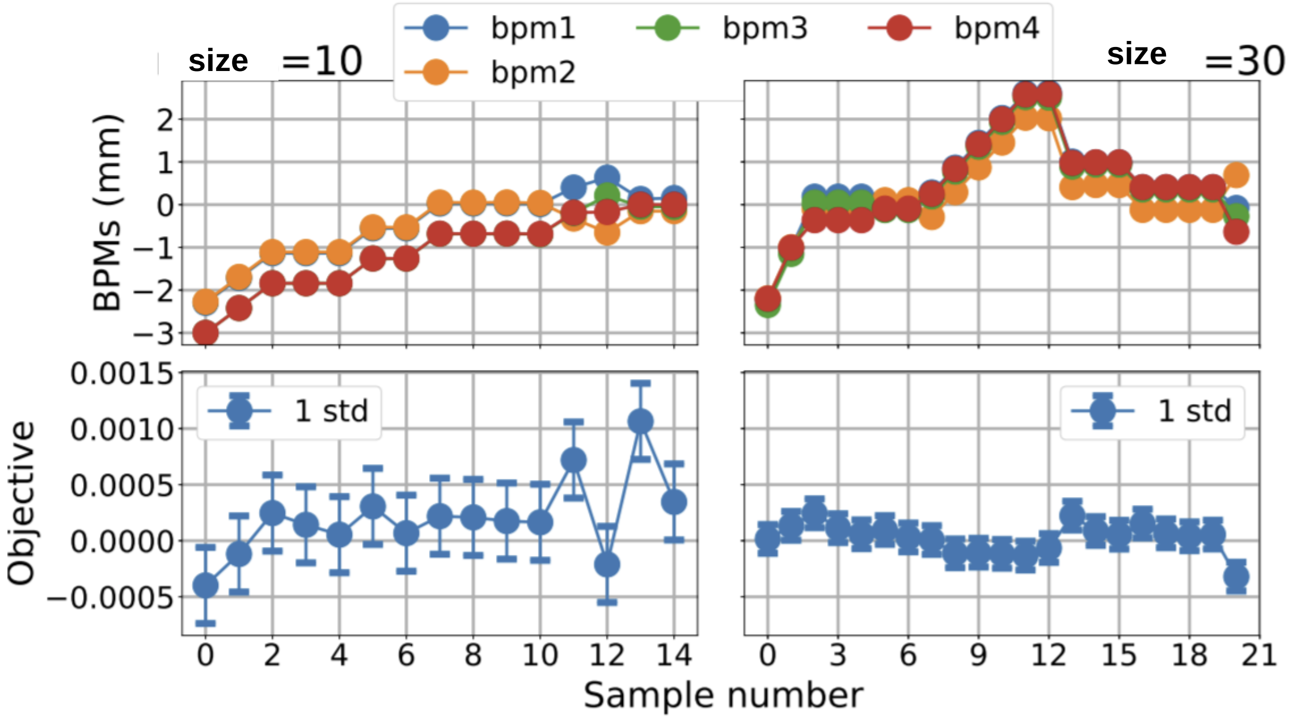
Smoothing the Noise

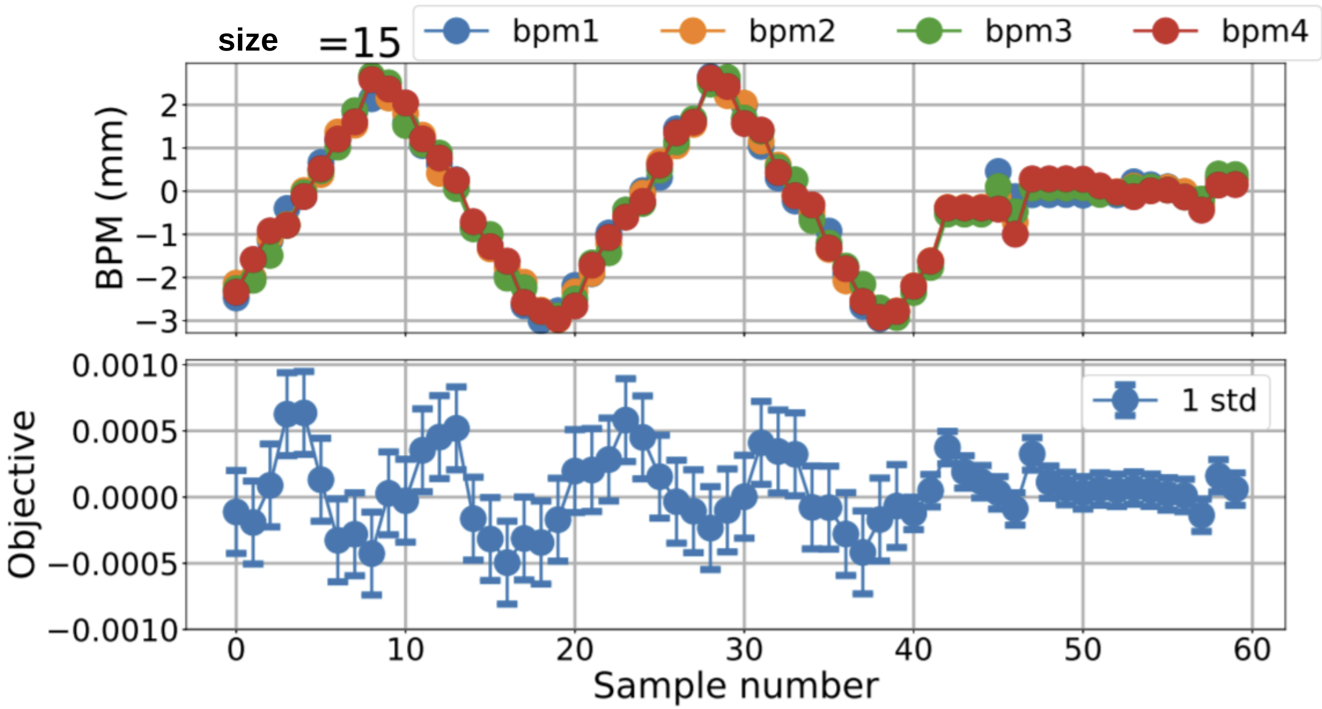


- Use moving average windows, instead of point δ values:

$$\lambda' = (1/\bar{\delta})(\overline{d\delta/dt})$$

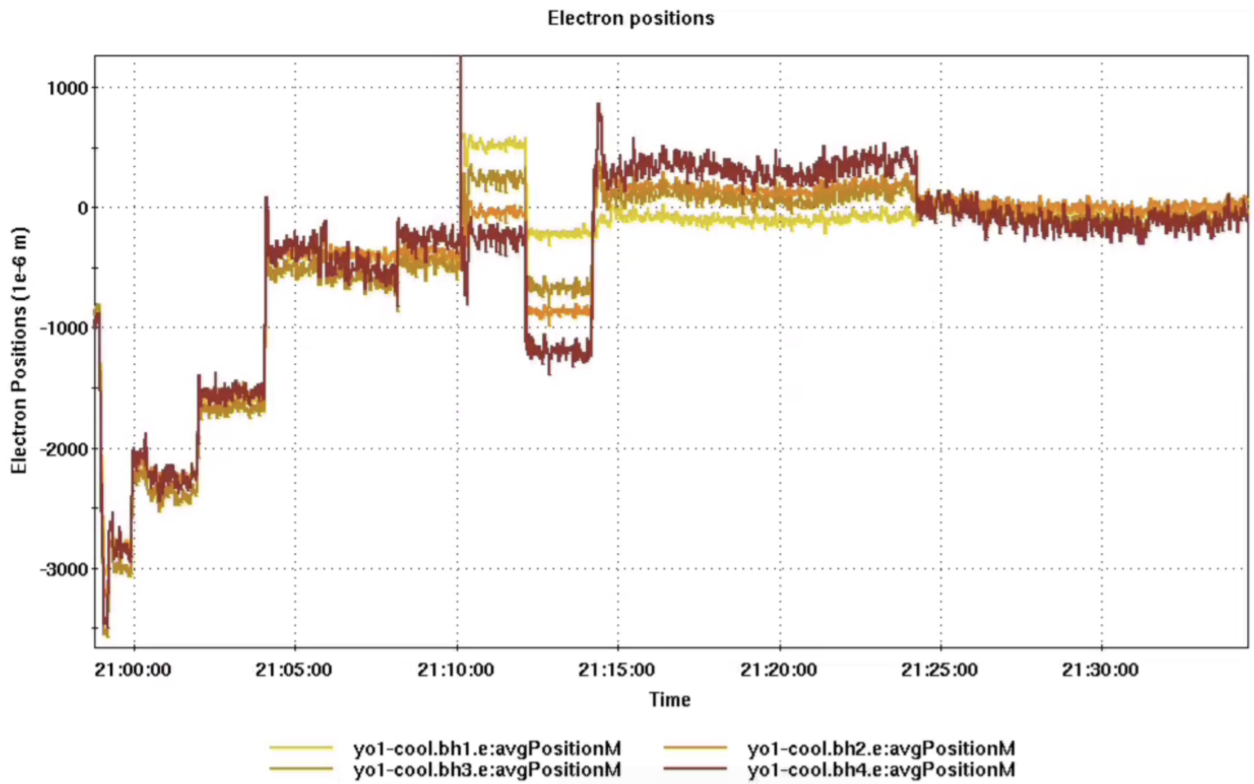
- The window sizes affect how algorithm behaves;

Results



- The final tuning algorithm uses a window size of 15;

Electron Positions Controlled by the BO



- Electron trajectories reported by 4 BPMs;
- The algorithm can tune the trajectories from the farthest points (-3 mm) to the center position and maintain them.

Future Work

- Increase the convergence rate to implement the full control routine on 16 BPMs;

- Physics-model informed GP [1]:
  An alternative way to estimate the kernel function.

- Contextual GP [2]:
  Handle the environmental factors by using separate kernels to model the inputs and contexts.

[1] A. Hanuka, X. Huang, J. Shtalenkova, et al., Physics model-informed gaussian process for online optimization of particle accelerators, Phys. Rev. Accel. Beams 24, 072802 (2021).
[2] A. Krause and C. Ong, Contextual gaussian process bandit optimization, in Advances in Neural Information Processing Systems (NIPS), Vol. 24, (Curran Associates, Inc., 2011).

Data-informed GP, Physics model-informed GP

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$$

- For convenience, we usually assume the prior mean is the zero-function m(x)=0. A very popular choice for the kernel is the squared exponential function:

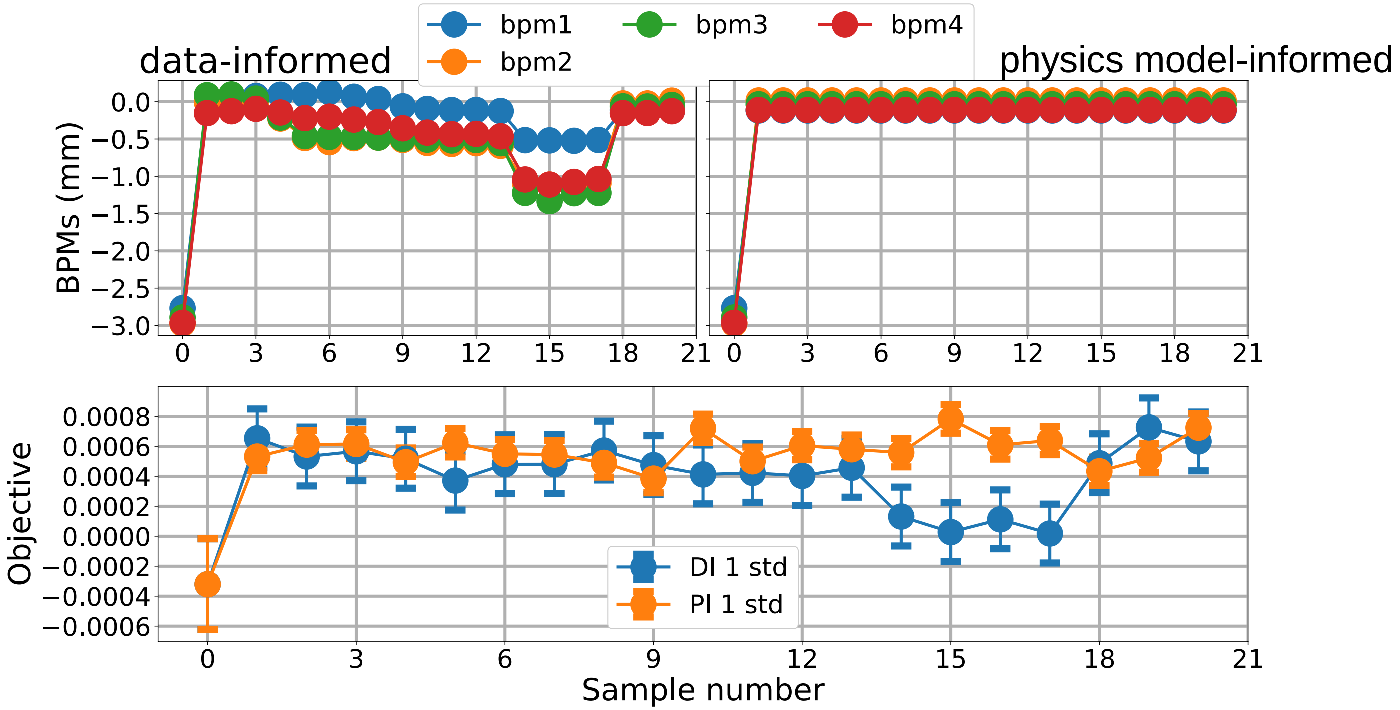
$$k_{\mathrm{RBF}}(\boldsymbol{x}, \boldsymbol{x}') = \sigma_f^2 \exp\left[-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{x}')^T \Sigma (\boldsymbol{x} - \boldsymbol{x}')\right]$$

- Accurately estimate of the precision matrix ∑ is very important.

- Data-informed GP estimates the Sigma matrix by fitting the data repeatedly.

- Physics model-informed GP, by evaluating the Hessian matrix around the optimal point (could be obtained by physics model/simulation), then calculate the Sigma directly: $\Sigma = -H/2$

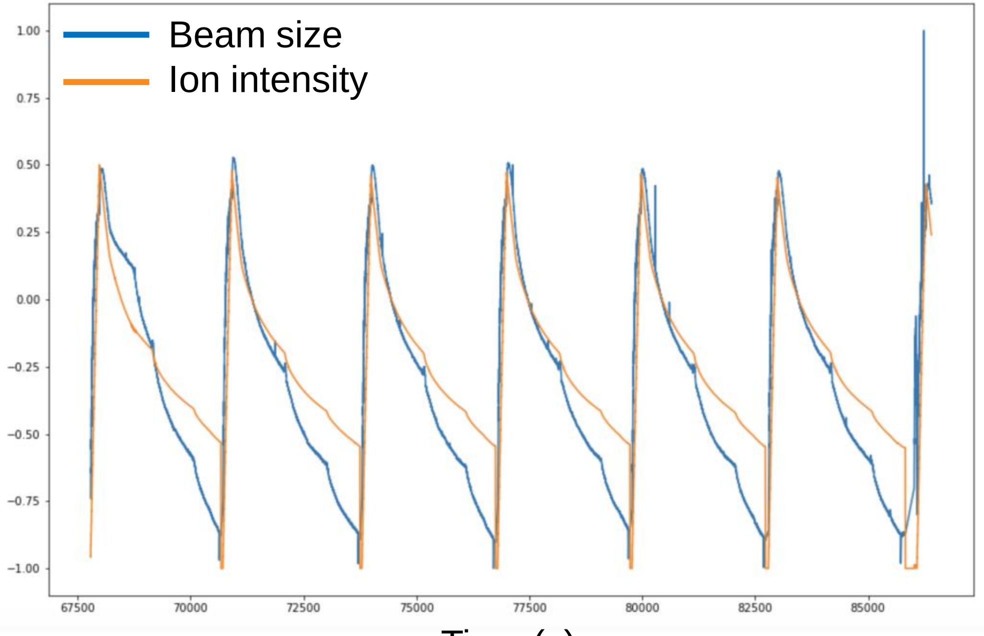
Simulation Comparisons



- Objective function: 4-dimensional Gaussian-like function centered at the origin;
- Physics model-informed GP converges faster and is more stable.

Contextual GP (CGP)

Normalized ion intensity and beam size vs. time



Time (s)

$$k = k_S \otimes k_Z = k_S(s, s') \cdot k_Z(z, z')$$

$$k = k_S \oplus k_Z = k_S(s, s') + k_Z(z, z')$$

- Contexts – <u>uncontrollable</u>, <u>varying</u> environmental conditions that affect objective function value;
- In our case – **<u>ion beam intensity</u>** decreases with time and can be treated as an environmental variable;
- Construct a composite kernel – one describes input-specific trend (k_S), the other describes context-specific trend (k_Z):
  - Multiplication
  - Summation

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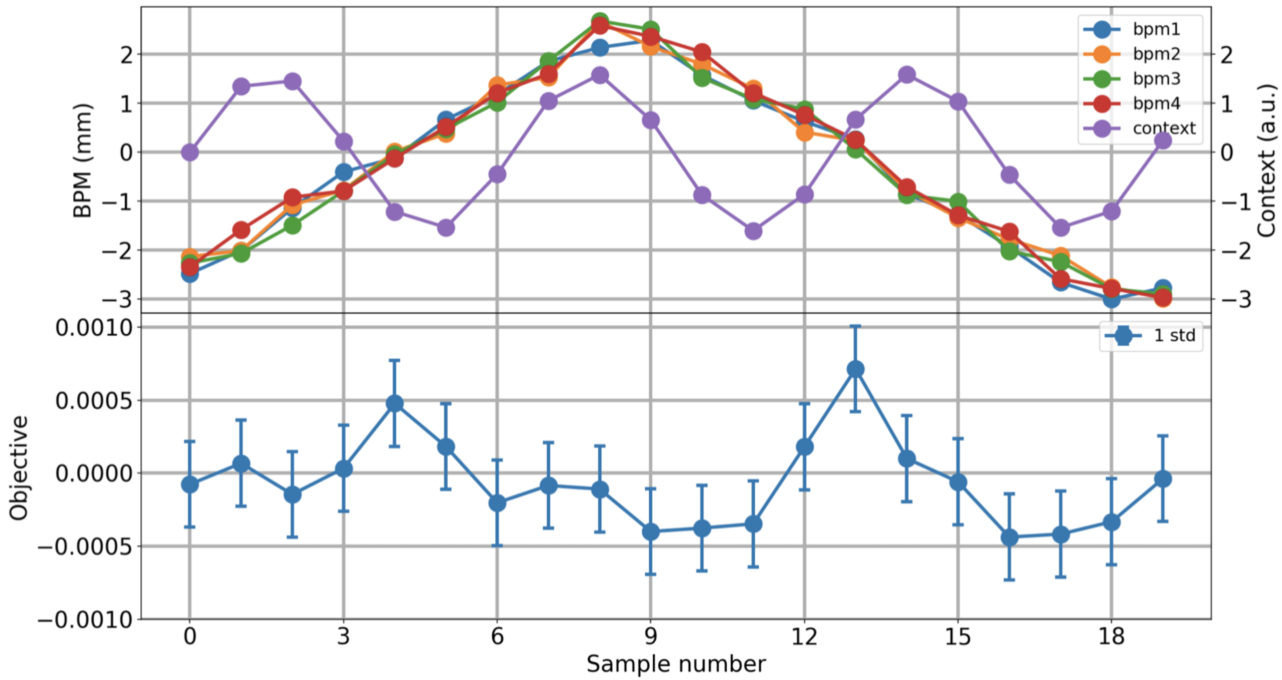
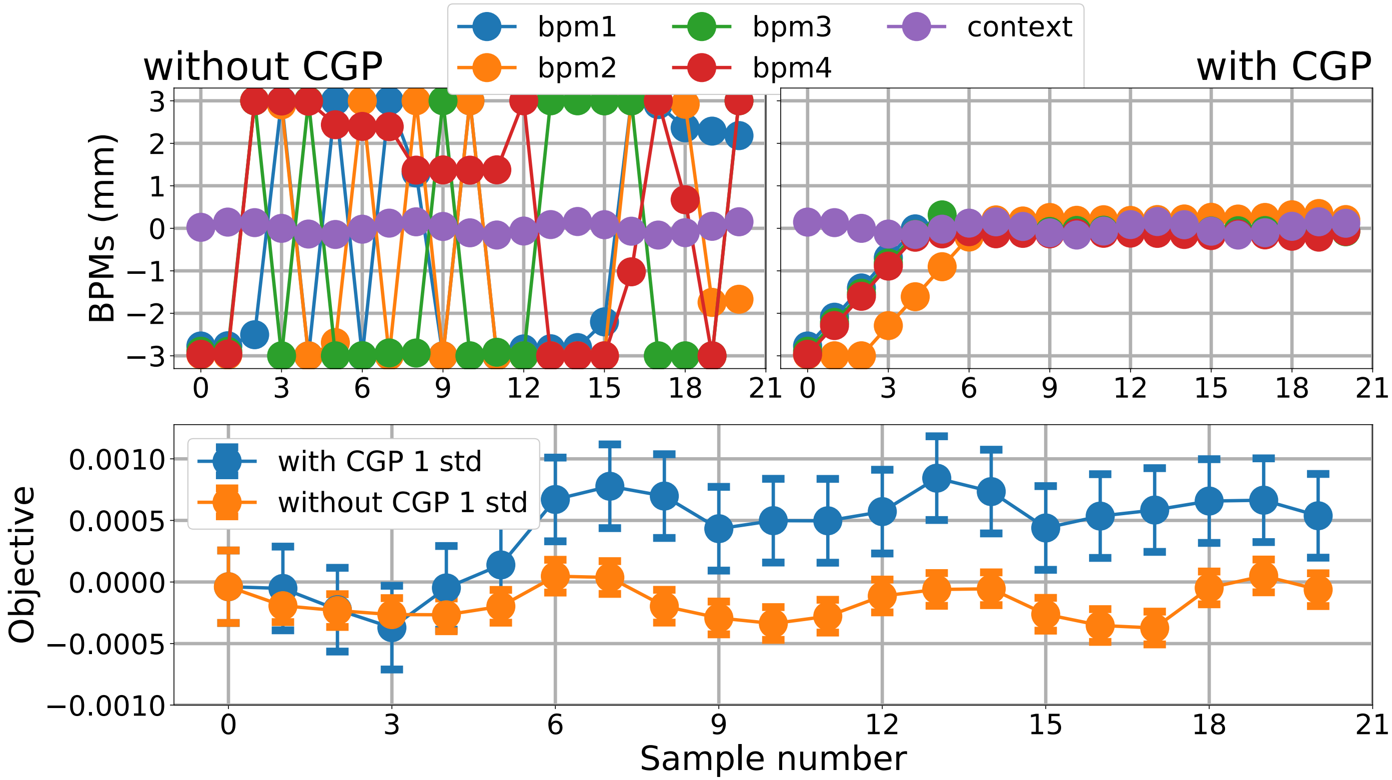
CGP Simulation



- Objective function: 4-dimensional Gaussian-like function centered at the origin plus a sinusoidal function;

- 20 initial samples;

Results comparison: Contextual GP



- Without CGP: algorithm is unable to converge due to the varying context;
- With CGP: algorithm converges in 7 steps and is stable;

Conclusion & Outlook

- The BO method can be very effective in control tasks at accelerator control systems;

- It opens many possibilities of trying different machine learning methods on optimizing performance for control tasks in the RHIC complex, as well as the future EIC.
  - Instrument calibration: Ionization Profile Monitor (IPM) at AGS;
  - Coherent electron Cooling (CeC) experiment at RHIC

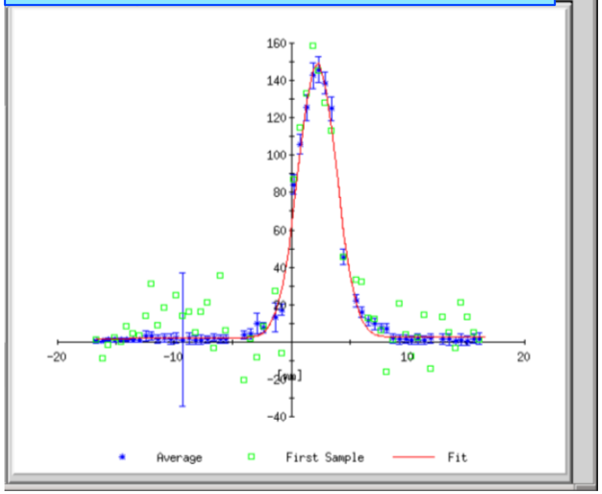
IPM Calibration

- Ionization profile monitor: measures transverse profile of the beam
  - Circulating beam ionizes residual gas in the beampipe;
  - An electric field forces electrons onto a microchannel plate (MCP);
  - Forms a projection of the beam profile;

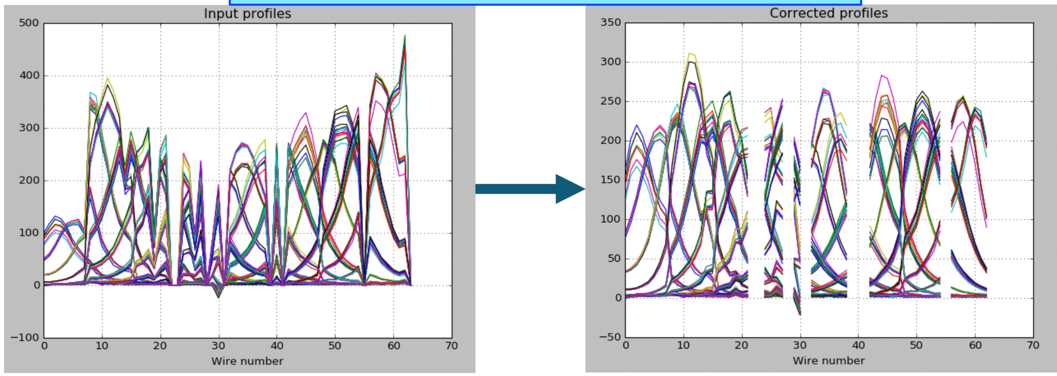
- Beam profile measurement depends on position because of systematic errors in channel gains from
  - Initial channel-to-channel gain variation;
  - Depletion of channel gains over time (systematically faster in region of high beam intensity);
  - Variation in ADC performance;
  - Usually addressed with position scans and offline calibration factors;

- Machine learning/BO opportunities:
  - Confidence intervals for channel gains, profile fit parameters;
  - Identification, imputation of data of ‘bad’ channels;
  - Data assimilation, slow calibration for aging MCPs;

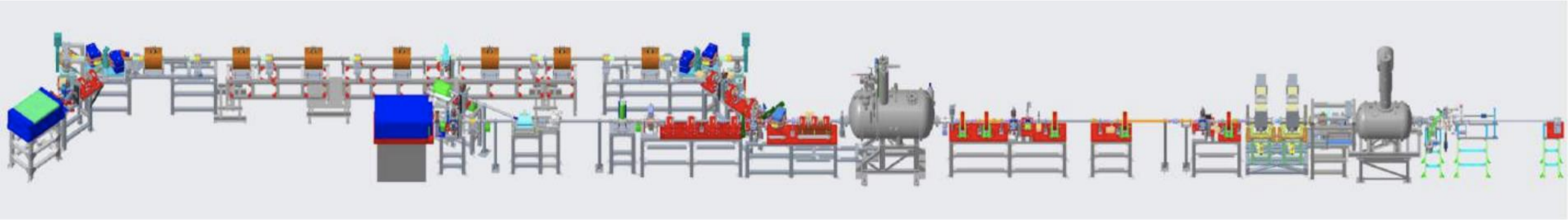
AGS IPM measurement



Position scan for calibration



Improving CeC Operations



- Motivation
  - Tuning of system parameters (i.e. solenoids and trims) are done blindly to obtain desirable beam status
  - Optimization is done by time-consuming genetic algorithm (GA)
- Goal
  - Virtual diagnostics: tuning parameters ↔ YAG screen images
  - Multi-objective optimization: peak current, emittance, energy spread etc.

Thank you !