Exploring machine learning techniques to improve cooling performance at RHIC

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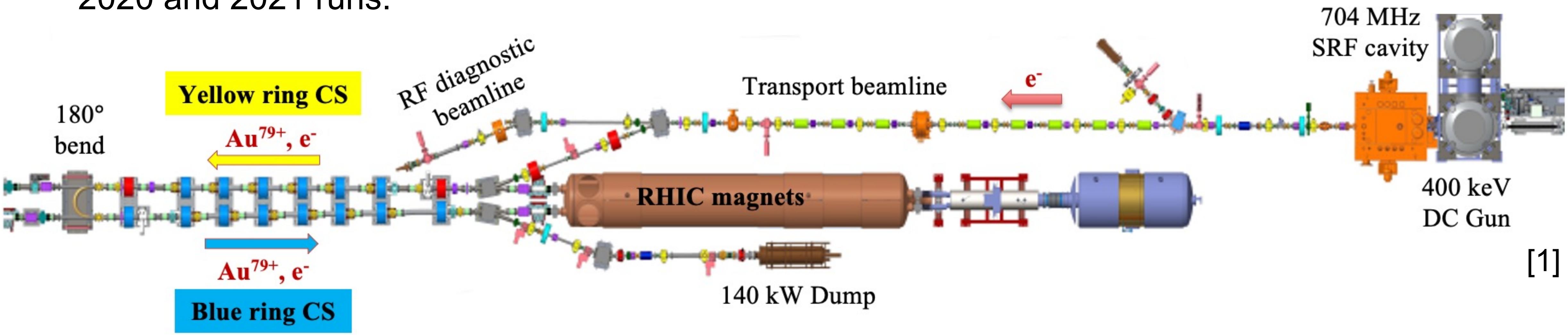
Summary

- Experiment of Bayesian Optimization for Trajectory Alignment at Low Energy RHIC electron Cooling (LEReC)

- Machine Learning for improving Coherent electron Cooling (CeC) operations

Low Energy RHIC electron Cooling

- Designed to increase luminosity of ion beam in RHIC, successful luminosity improvement in 2020 and 2021 runs.



[1]

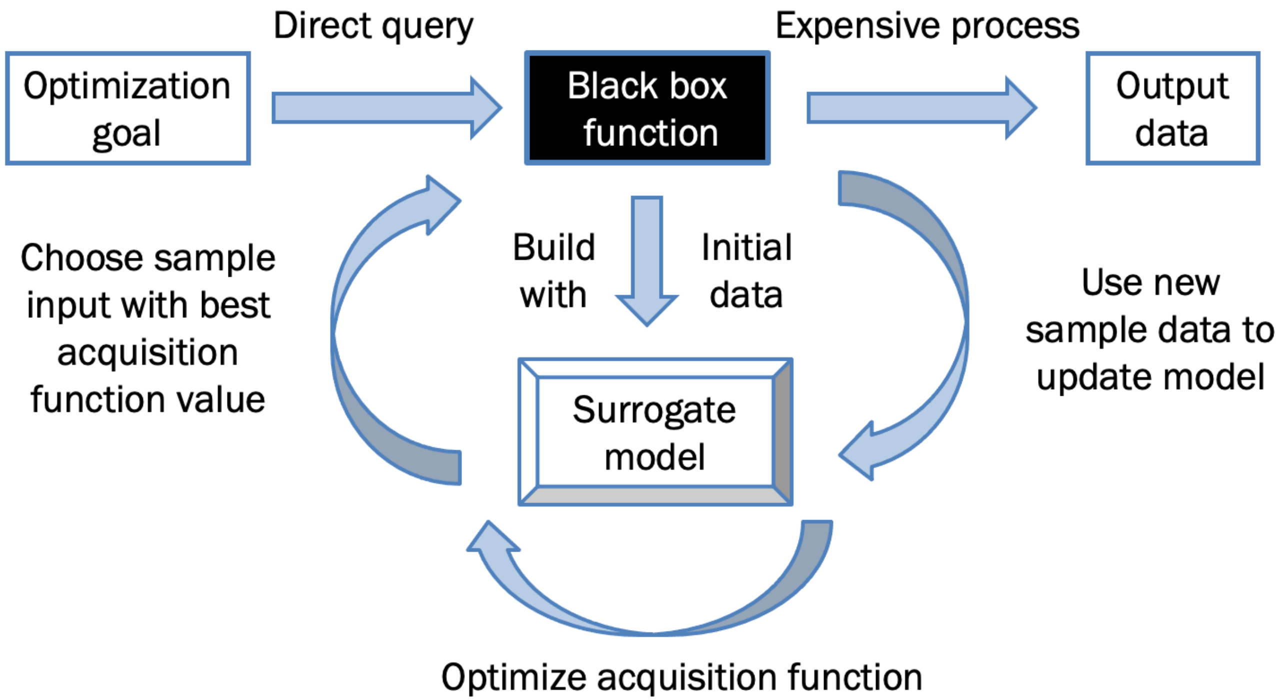
- 704 MHz electron bunches (grouped into 9 MHz macro-bunches) are produced from the photocathode and accelerated in the SRF cavity to the designed energy (1.6 MeV, 2 MeV).
- Those e-bunches are delivered to the two cooling sections (20 meter each) in RHIC's yellow and blue rings, where they co-travel with ion bunches.
- Ions experience a friction force from the co-propagating electrons, reducing momentum and angular spread.

Motivations

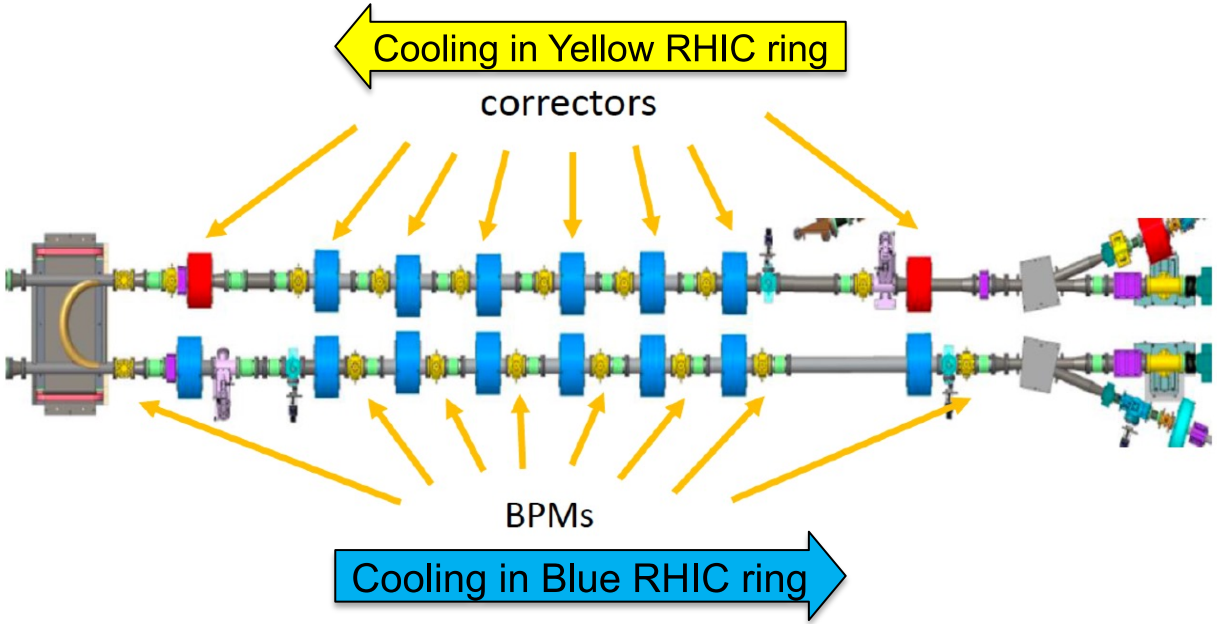
- Account for possible errors in BPM Measurement
- An independent way to optimize the cooling performance

Method

- Bayesian Optimization (BO): a powerful tool for finding the extrema of objective functions that are expensive to evaluate. [2]



LEReC Experiment Settings

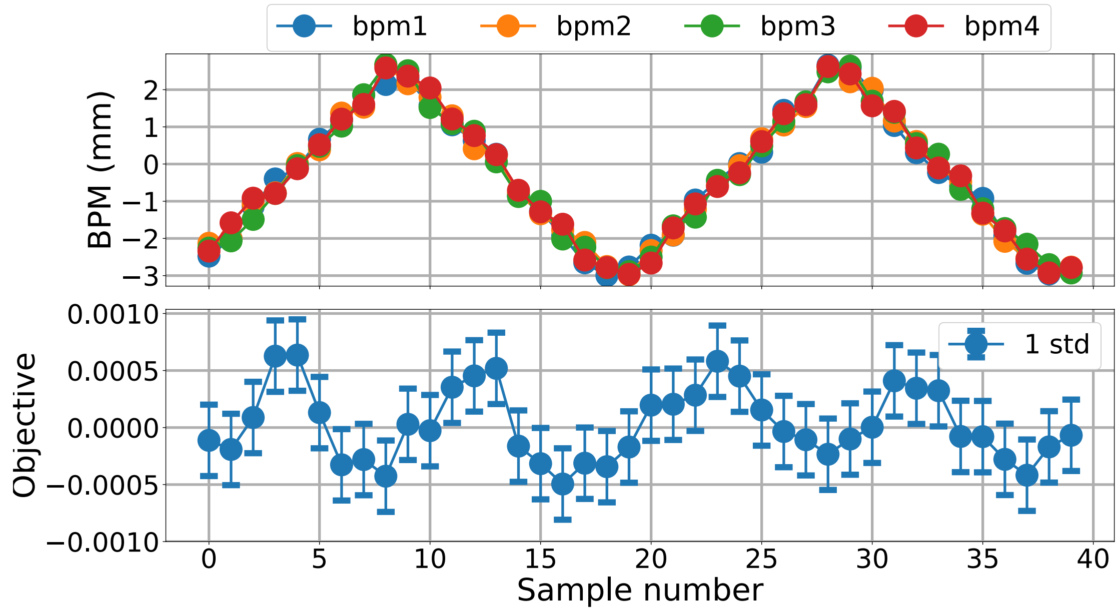


- Only the first 4 BPMs in the Yellow cooling section are considered
- Cooling rate is defined as the decreasing speed of transverse ion beam size δ :

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

- Ions are assumed to stay in the center position (x=0, y=0)
- More negative λ → faster cooling rate → **use BO to maximize $-\boldsymbol{\lambda}$**

Initial Sampling



[1]

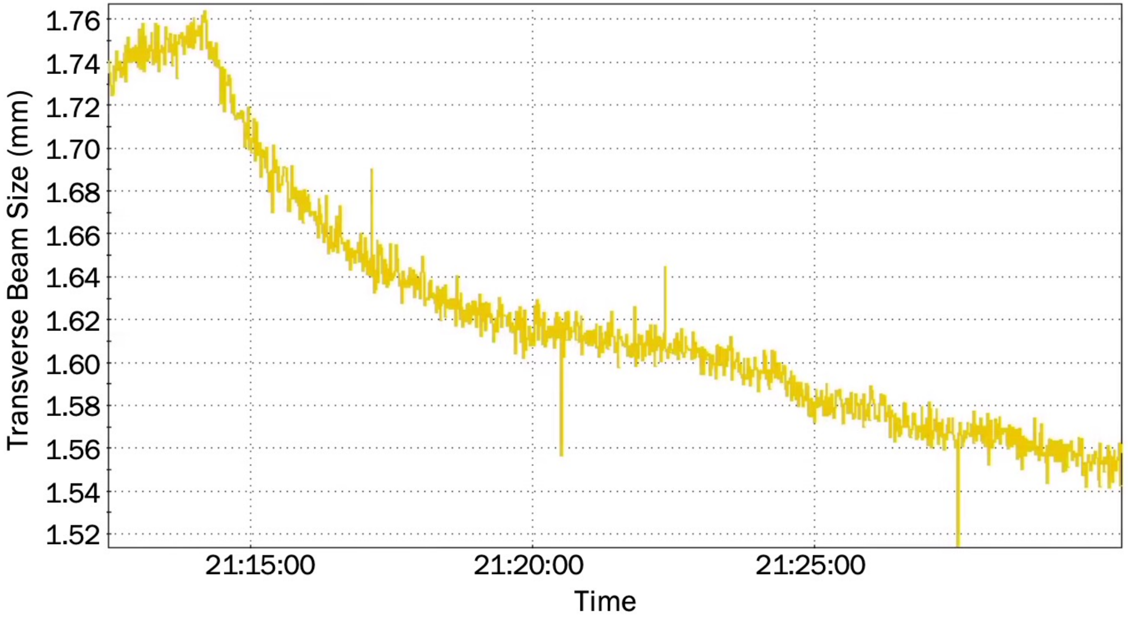
- Input: readings of 4 BPMs, each has a range of [-3, 3] mm
- Objective: cooling rate $-\lambda$
- 40 initial samples were taken, the inputs go through the entire range in incremental steps with added randomness
- The objective exhibits a pattern, it favors input positions around 0

Noise in Signals

- The objective contains division by a point value δ :

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

- Large noise presents in real-time measurement of δ



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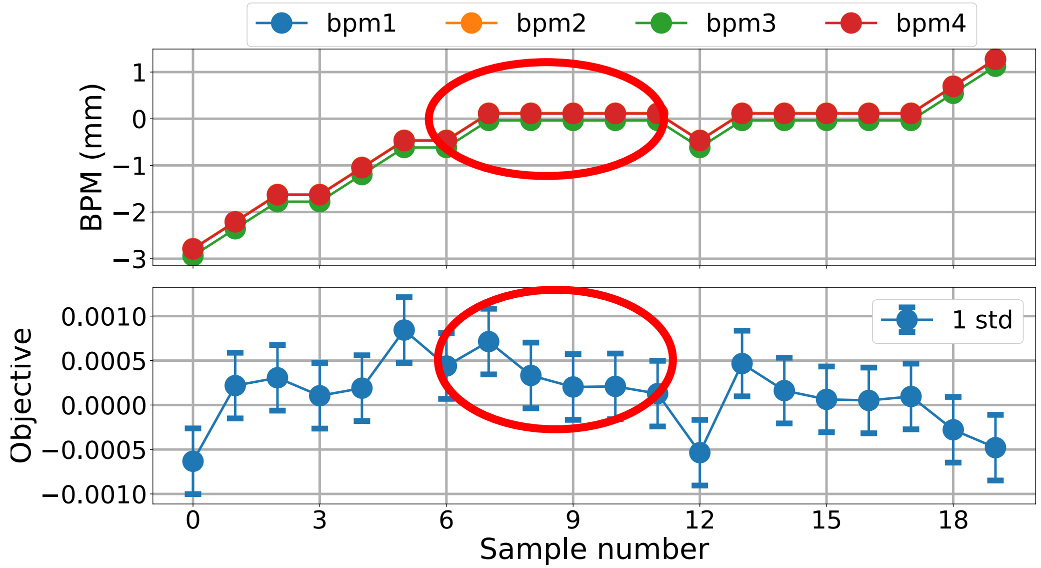
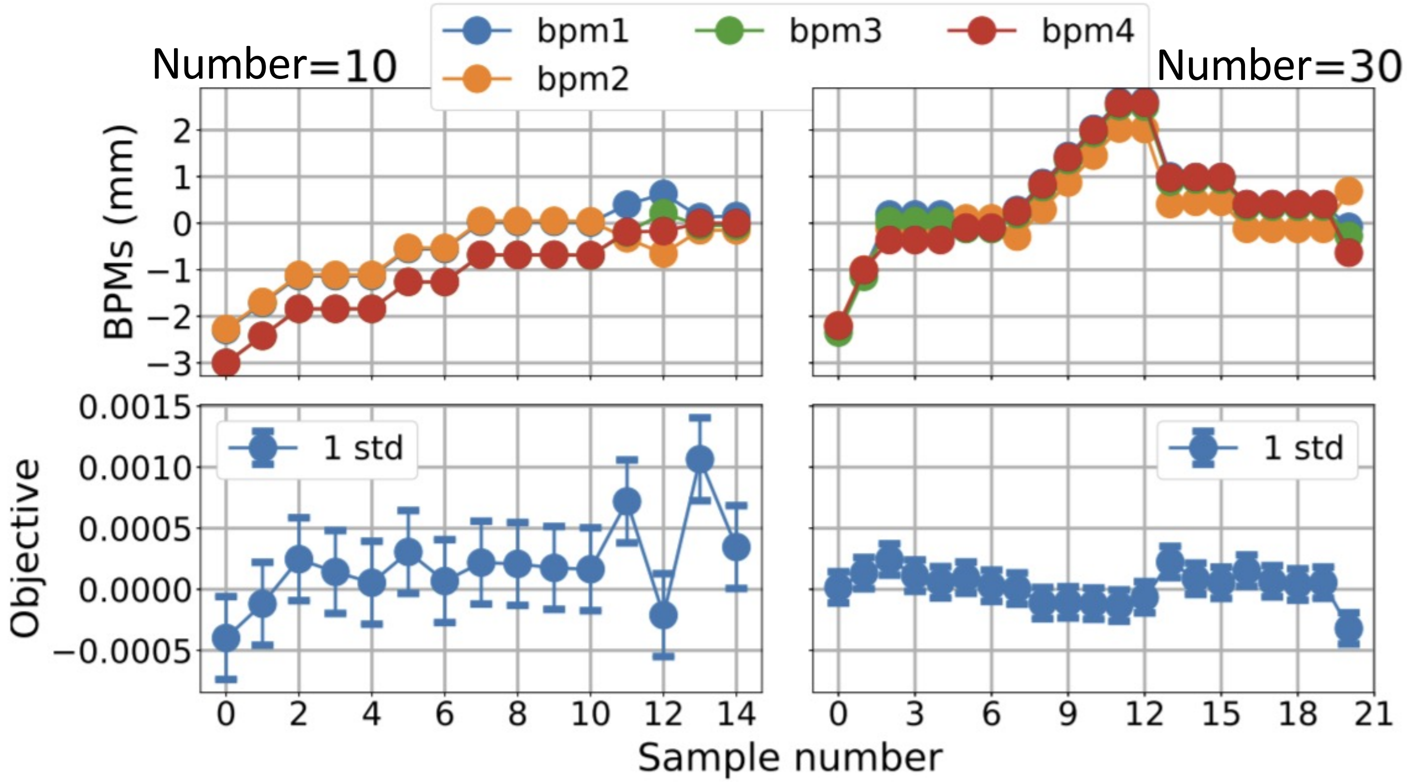


- The objective is unstable even when inputs stay constant
- The BO algorithm had trouble converging

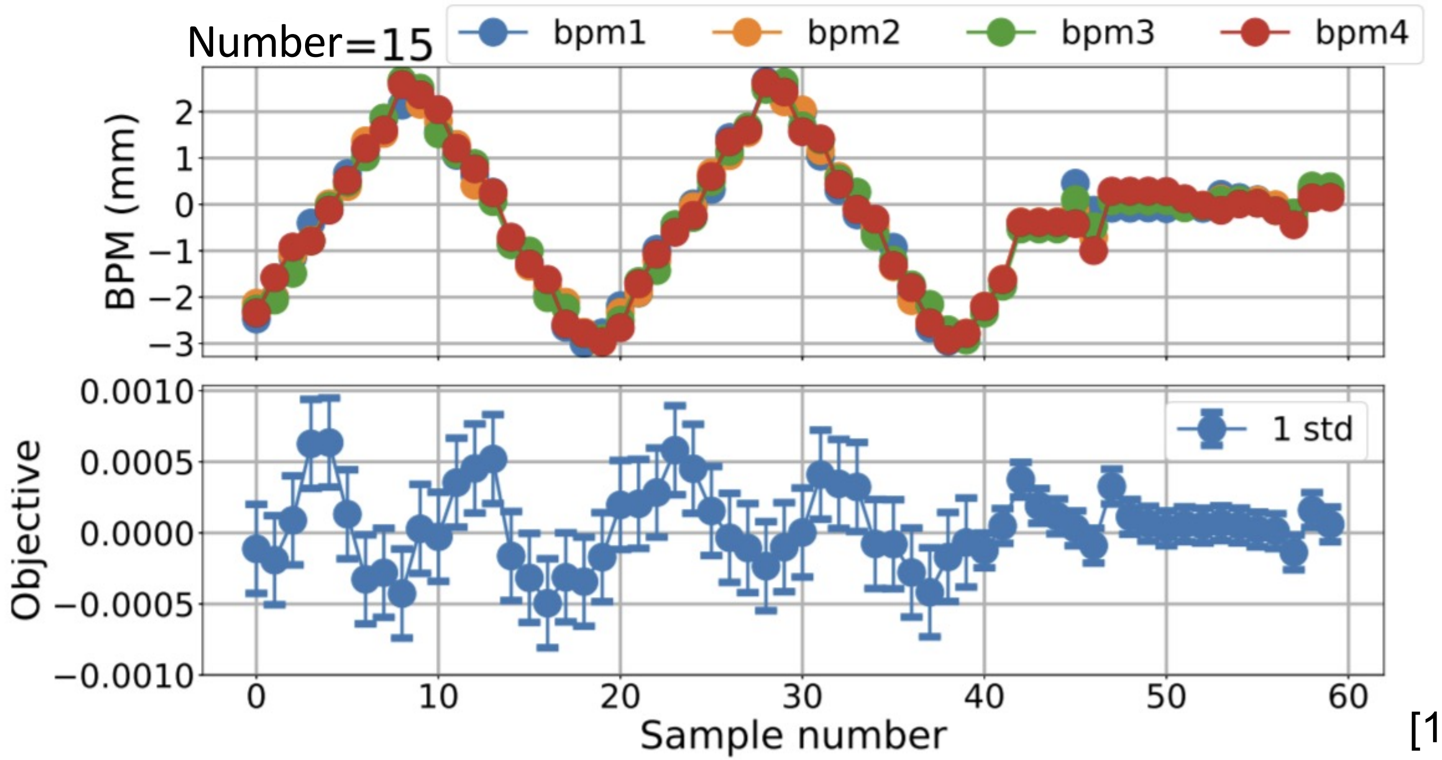
Smoothing by Moving Average



[1]

- New definition for cooling rate: $\lambda' = (1/\bar{\delta})(\overline{d\delta}/dt)$
- A new parameter: number of points to average
- Different number produce different algorithm behaviors

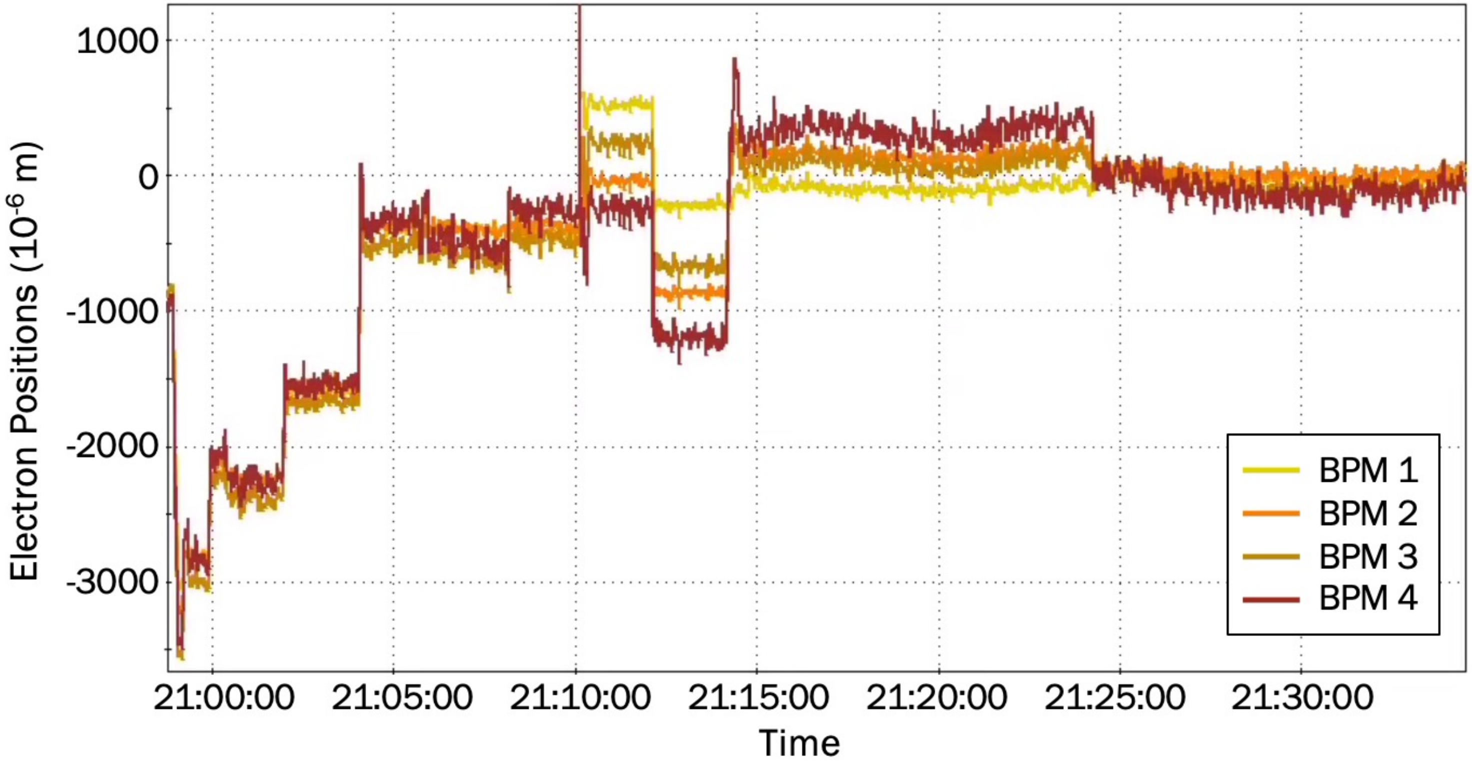
Experiment Results



[1]

- Results are generated using an average window of 15 points
- BO algorithm converged quickly (reaches a close neighborhood after 3 steps) to an optimum solution, which corresponds to the center position of ($x = 0, y = 0$)

Electron trajectory optimization



[1]

- The algorithm can tune electrons from the farthest positions to the center and maintain the trajectories

Conclusion

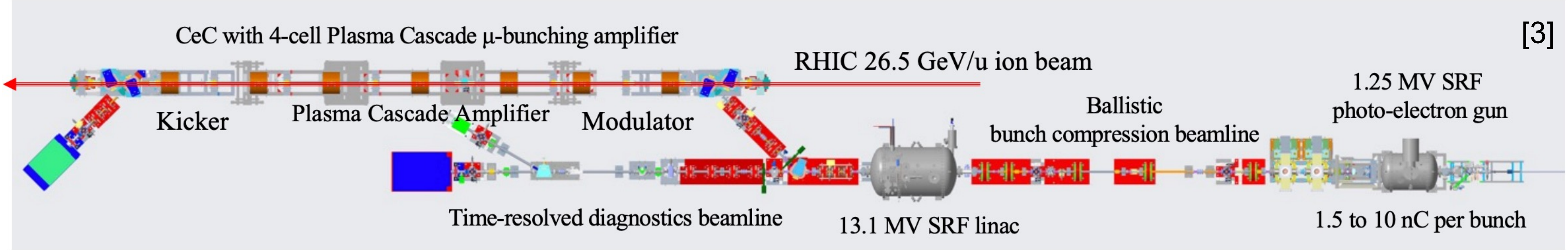
- The BO method is very effective in optimizing the cooling performance at LEReC.

- It also verifies the correctness of the traditional orbit correction program and the BPM calibrations.

- 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.

Coherent electron Cooling

- Designed to cool 26.5 GeV/u ion beam circulating in RHIC's yellow ring.



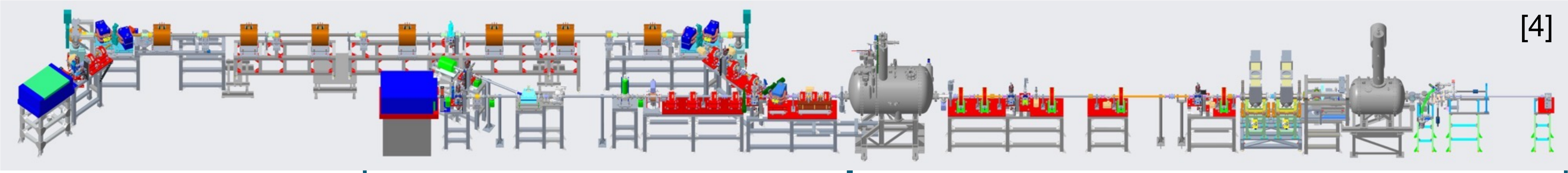
- CeC CW SRF accelerator with unique SRF electron gun generates electron beams with quality sufficient for the current experiment and for the future EIC cooler.
- Electron bunches are compressed to peak current of 50 – 100 A and accelerated to 14.5 MeV.
- Accelerated electron beam is transported through an achromatic dogleg to merge with ion beam in RHIC.
- Interaction between ions and electron beam occurs in the common section.

Machine Learning for improving CeC operation

- Motivation
  - Tuning of system parameters (i.e. solenoids and trims) are currently done blindly to obtain desirable beam status
  - Optimization is currently done by genetic algorithm (GA), which takes too long
- Goals for ML algorithms
  - <u>Virtual diagnostics</u>: establish mapping between tuning parameters and YAG screen images for image prediction and analysis
  - <u>Multi-objective optimization</u>: optimize peak current, slice emittance, and slice energy spread of the beam at the same time
- Useful techniques
  - <u>Neural network</u>: surrogate model trained with history data to provide direct, accurate mapping between specified input parameters and output results
  - <u>Bayesian optimization</u>: optimize analytically intractable/computationally intensive objective with as few steps as possible, can be used for single-objective and multi-objective problems

CeC Beamline & Current Projects

Common Section with RHIC



[4]

Time-Resolved Diagnostic Beamline (TRDBL)

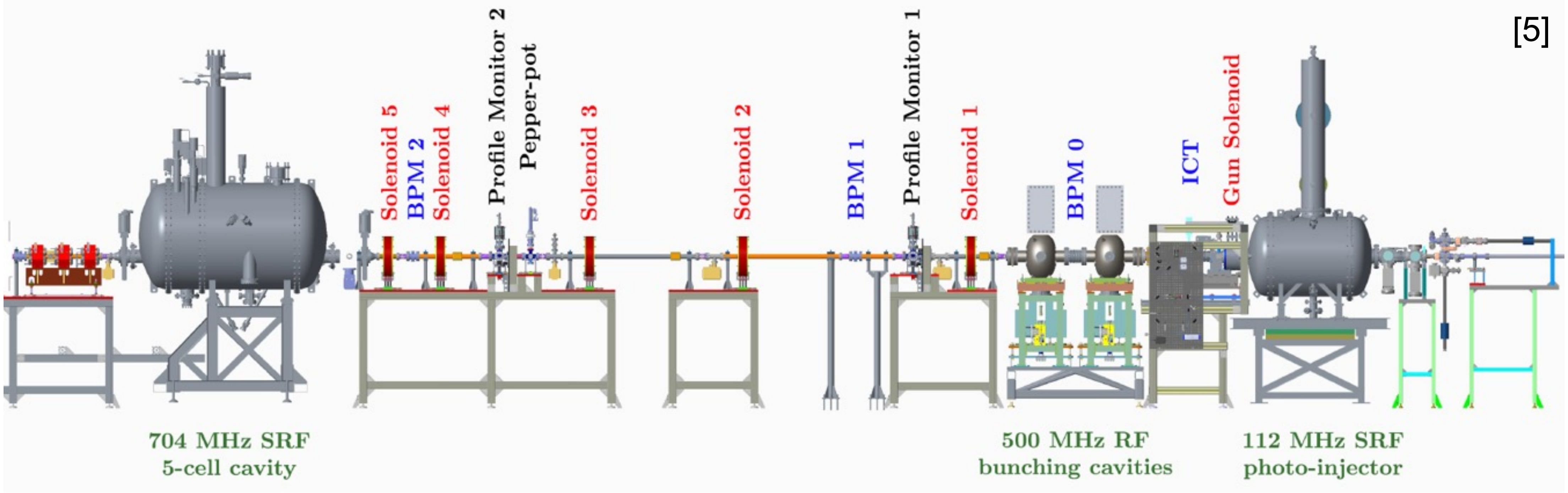
CeC accelerator / Low Energy Beam Transport (LEBT)

2. Establish beamline model with Bmad/Tao and develop emittance measurement algorithm

1. Input scan for emittance profile with Impact-T simulation

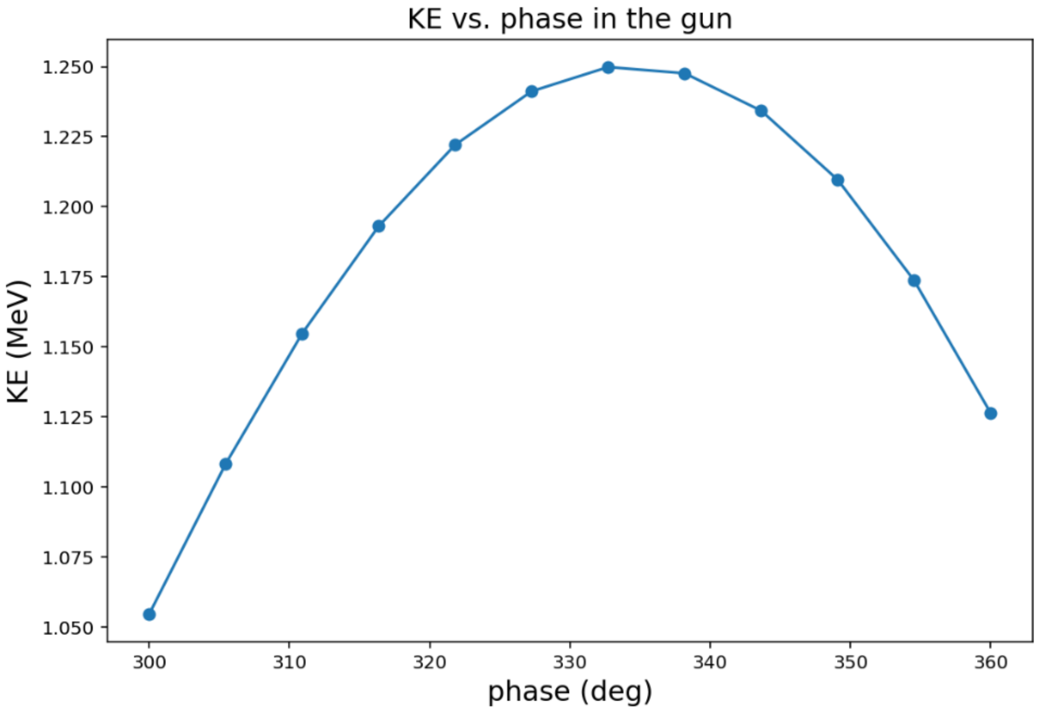
Low Energy Beam Transport (LEBT)

Beam line: 3 cavities (Gun, Buncher, SRF Linac), 6 solenoids, 1 final drift
Monitors: 2 Profile Monitors (Yag 1, Yag 2), 2 BPMs (BPM 1, BPM 2)

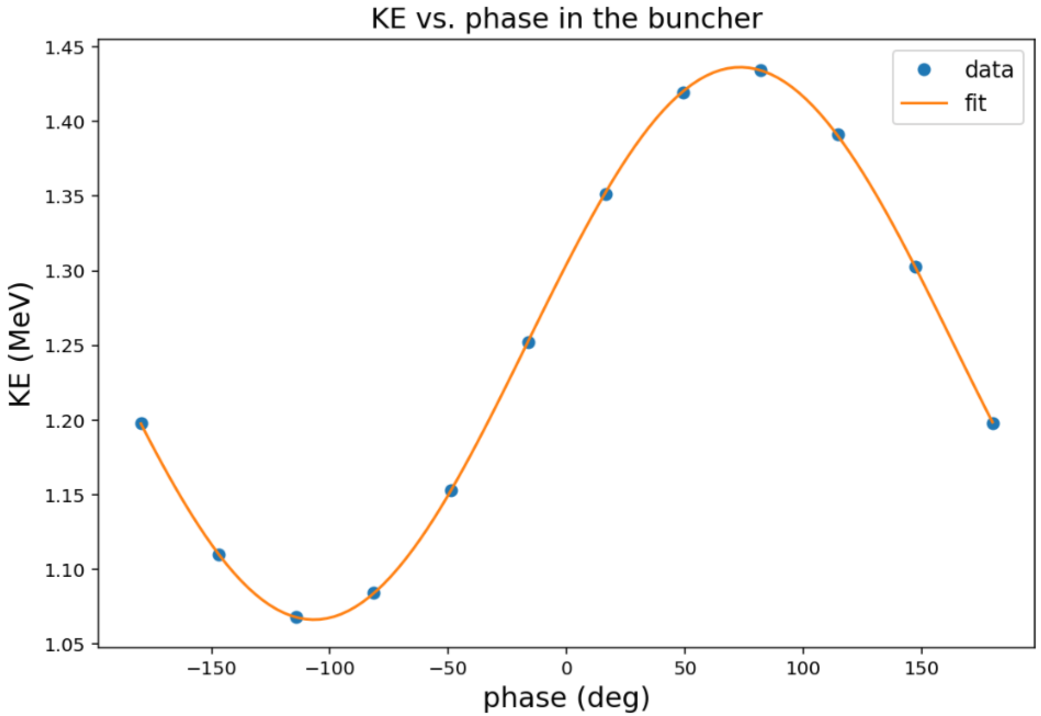


LEBT Gun and Buncher

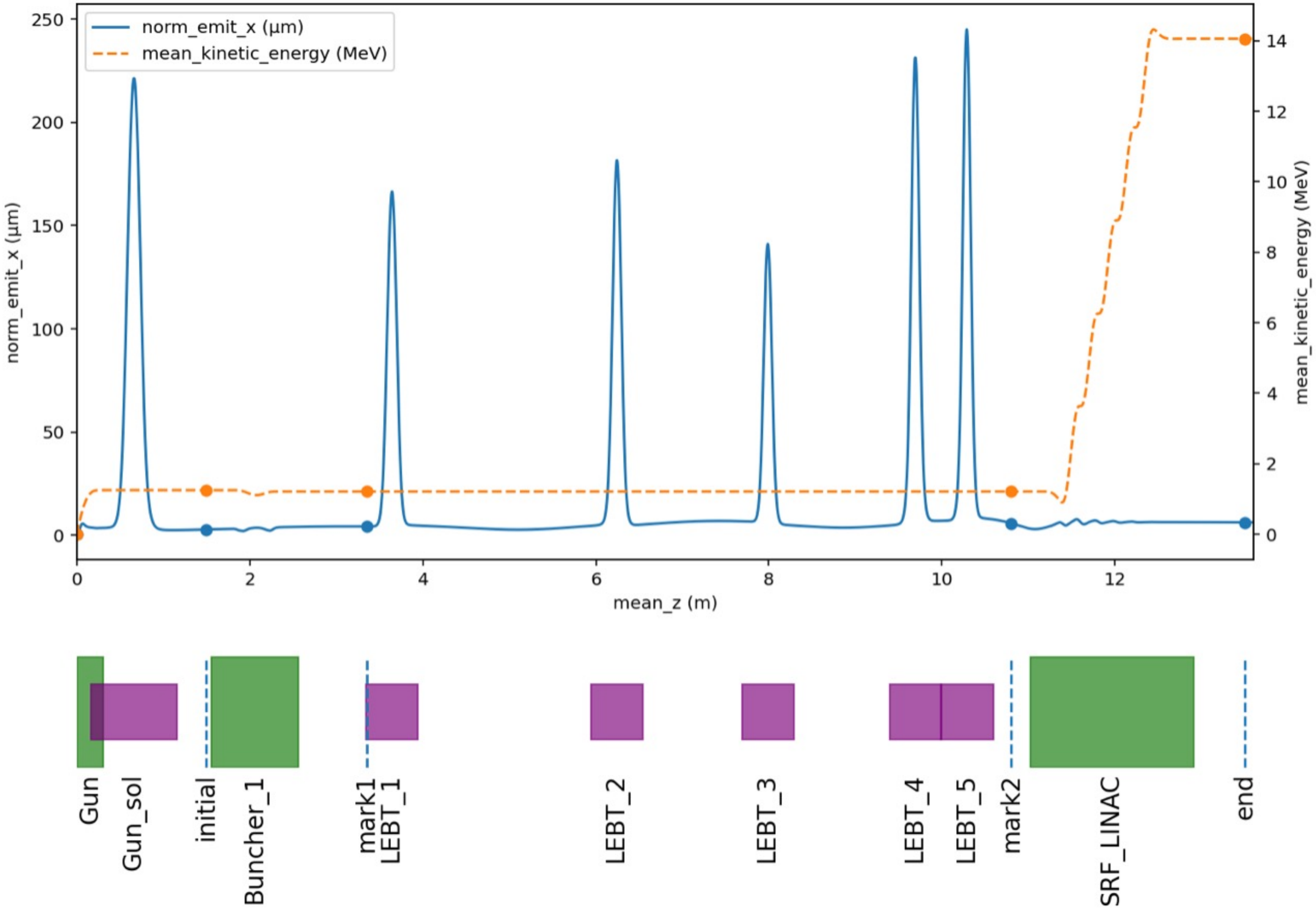
Target final KE: 1.25 MeV



Target energy (amplitude): 168 kV
Target phase: -13° from zero crossing
Final KE: ~ 1.21 MeV

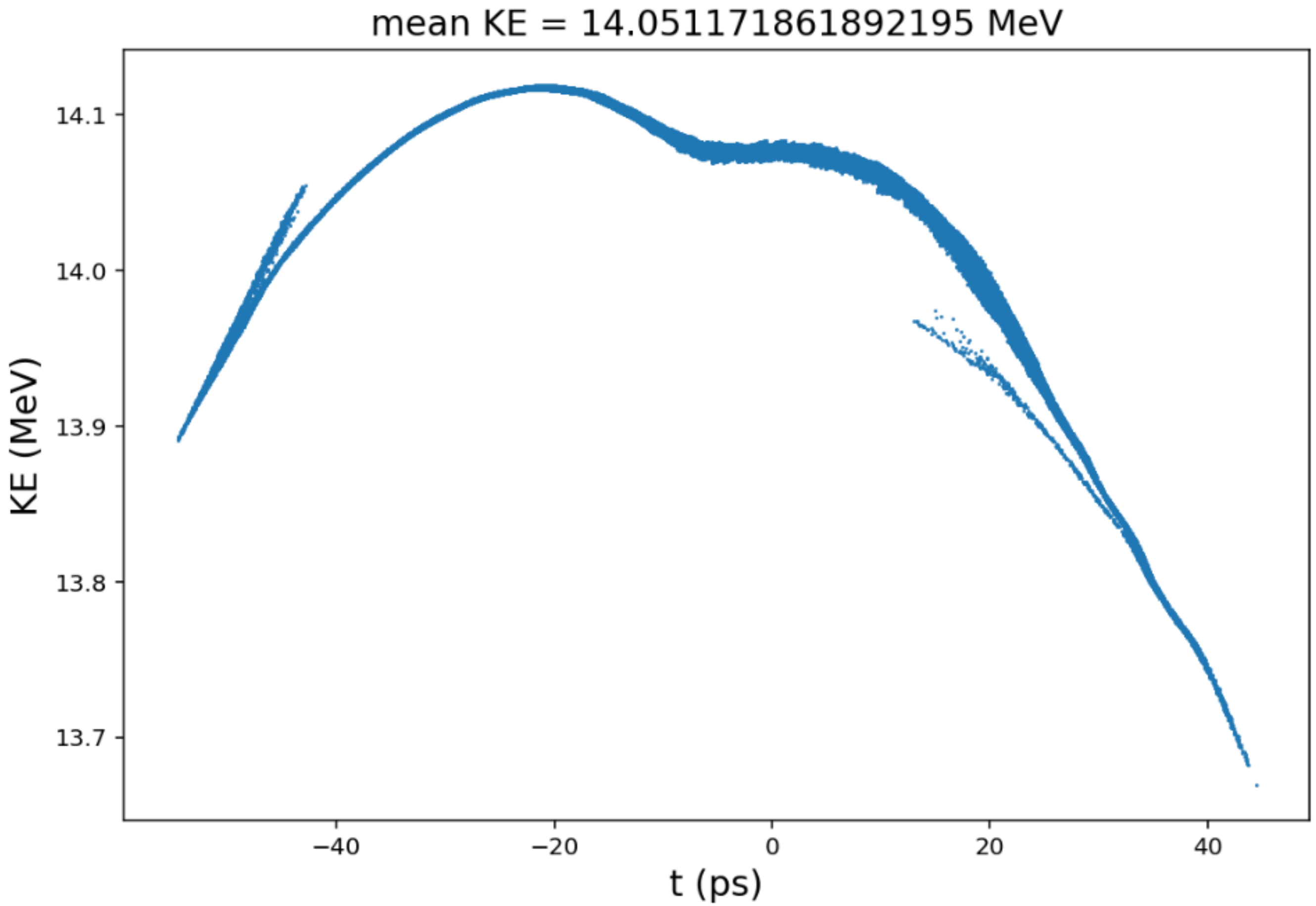


Optimized beam: emittance and energy



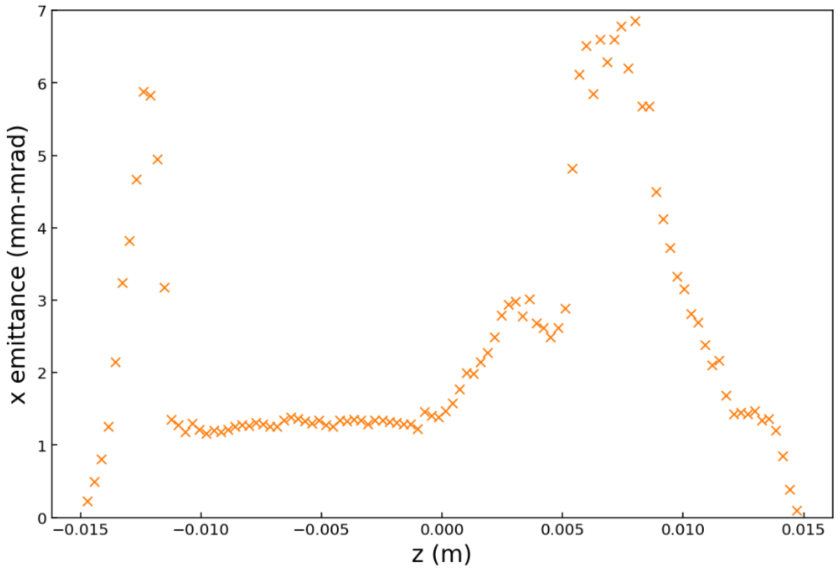
Optimized beam: long. phase space

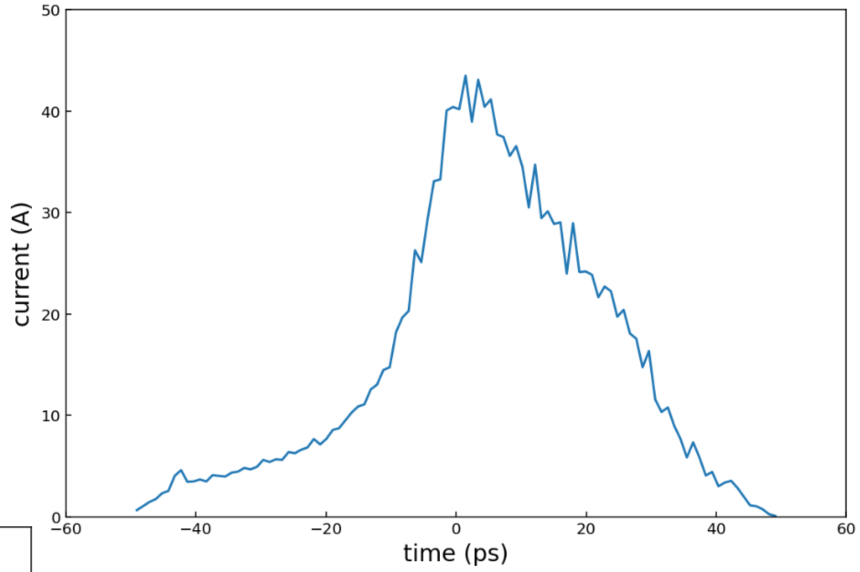
Phase 704 MHz cavity to produce final beam with target KE = 14.0525 MeV, γ = 28.5, and core section with small energy spread (flat center)

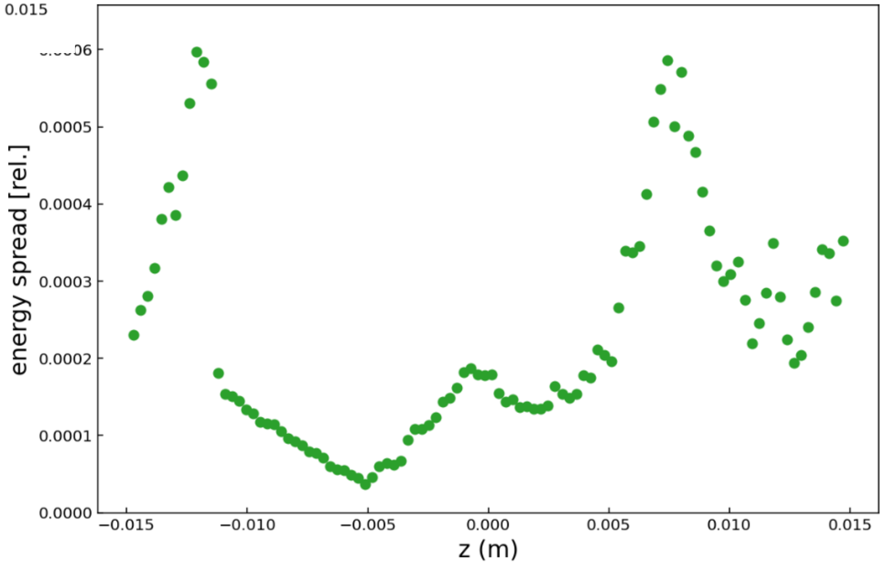


Optimized beam: slice statistics

Core part of the beam has < 1.5 um emittance, ~ 1e-4 slice energy spread, ~ 40 – 50 A peak current

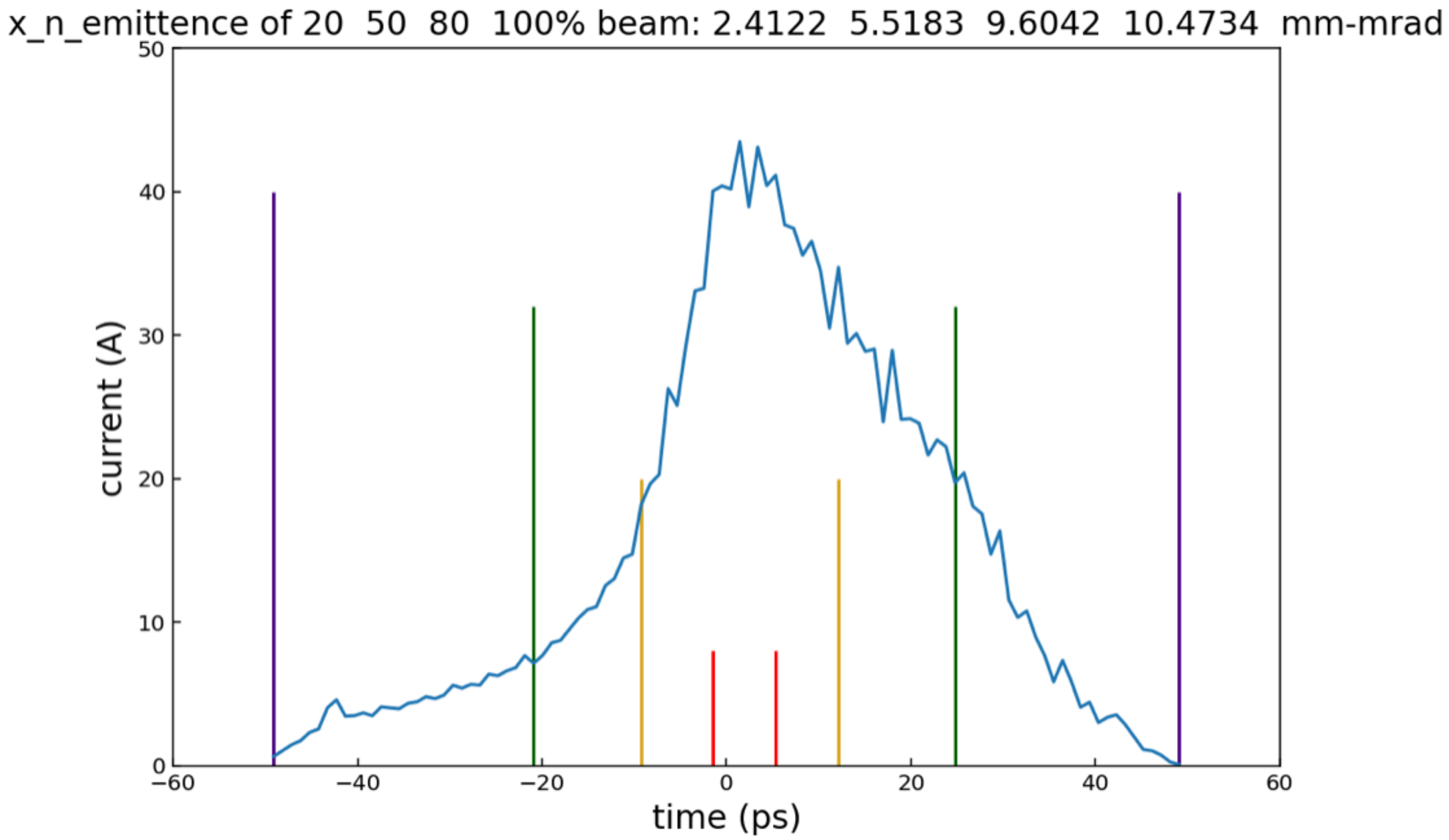






Core emittance calculation

- Python script groups beam from the center into 20%, 50%, 80%, and 100% of total particles, then calculate rms emittance for each group



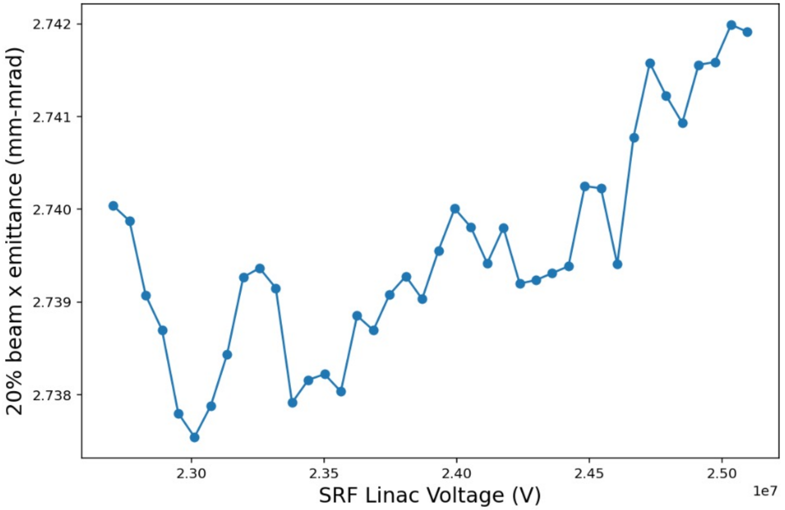
LEBT Input scan: parameters

Name	Unit	Range	Low	High
SRF Linac voltage	V	$\pm$ 5%	2.278e7	2.518e7
SRF Linac phase	deg	$\pm$ 1.5°	288.6	291.6
LEBT solenoid 1 strength	T	$\pm$ 1%	0.033 $\pm$ 1%	
LEBT solenoid 2 strength	T	$\pm$ 1%	-0.036 $\pm$ 1%	
LEBT solenoid 3 strength	T	$\pm$ 1%	0.035 $\pm$ 1%	
LEBT solenoid 4 strength	T	$\pm$ 1%	-0.038 $\pm$ 1%	
LEBT solenoid 5 strength	T	$\pm$ 1%	0.047 $\pm$ 1%	
SRF Linac displacement	mm	[-5, 5] in x, y direction		

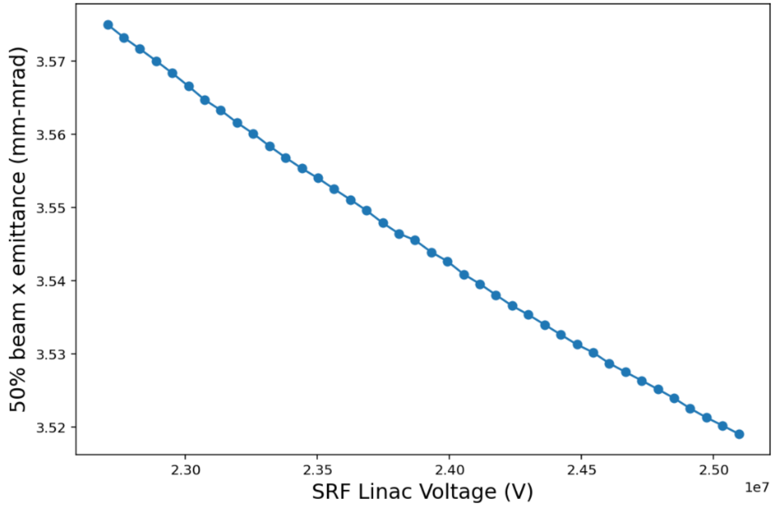
Input scans: SRF linac voltage

Name	Unit	Range	Low	High
SRF Linac voltage	V	$\pm$ 5%	2.278e7	2.518e7

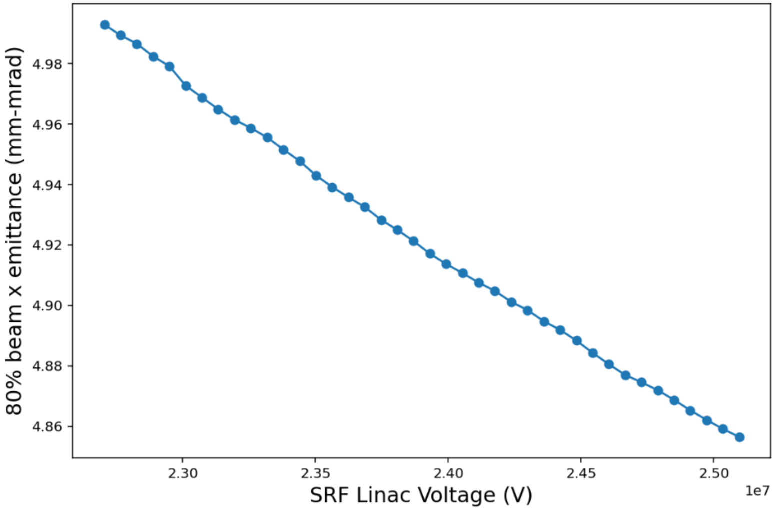
20%



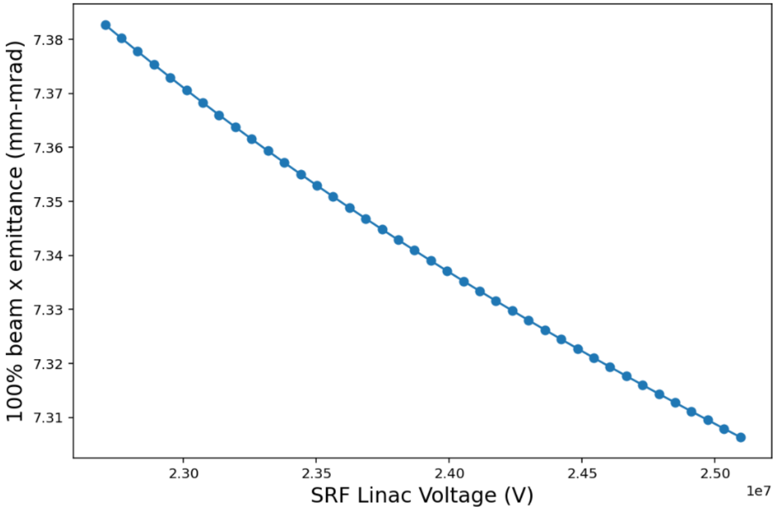
50%



80%

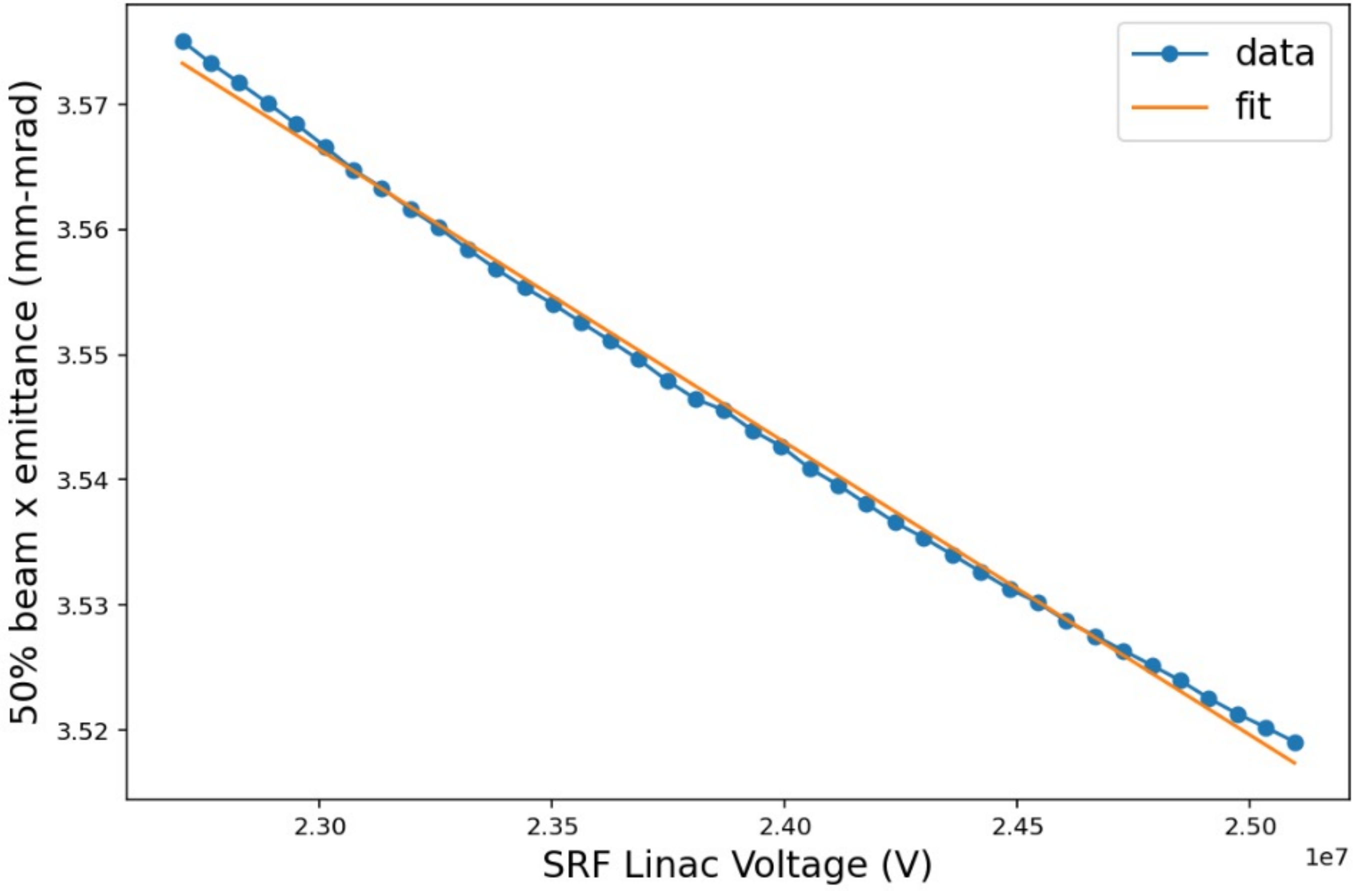


100%



Sensitivity: SRF linac voltage

$$fit = -2.3378\times10^{-8}\, x + 4.104$$

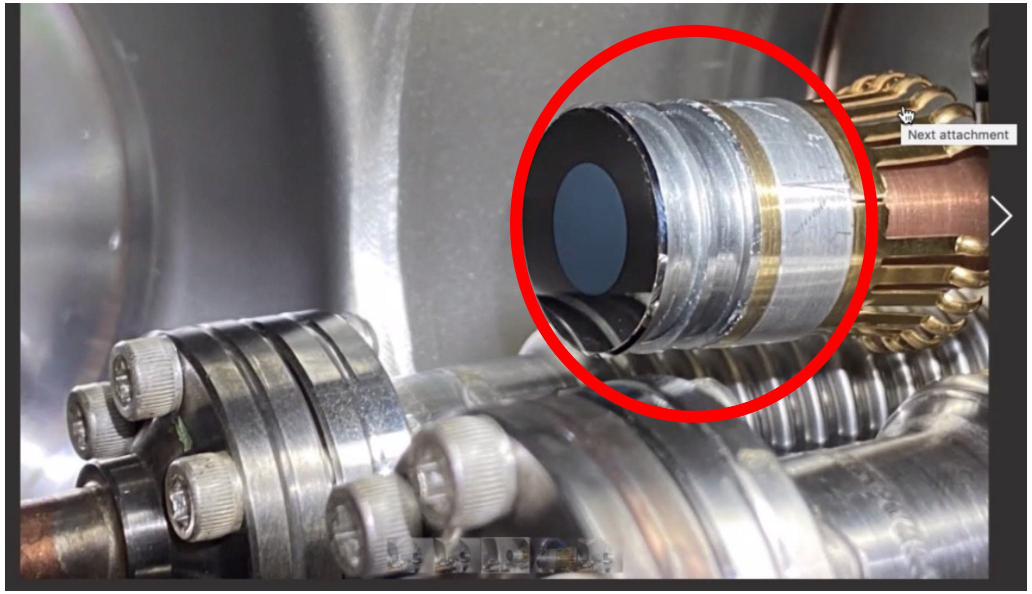


LEBT input scan: emittance sensitivity

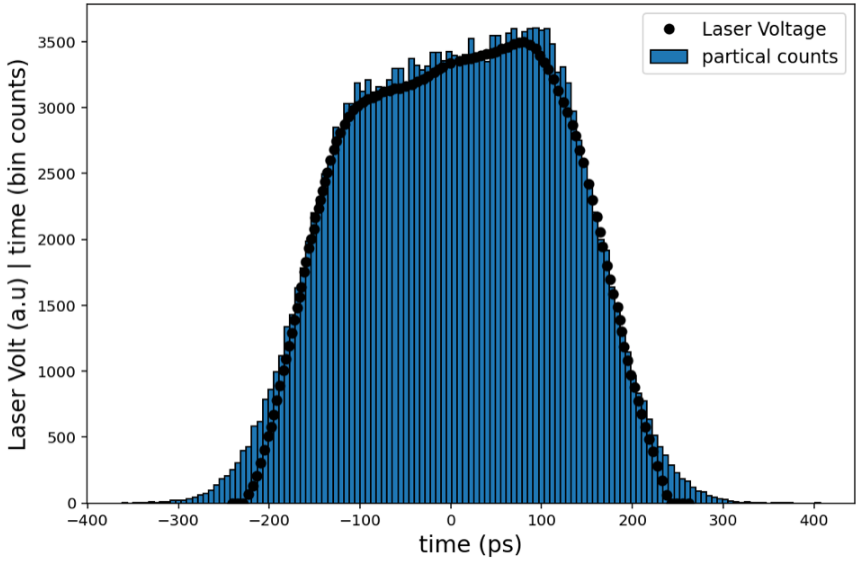
$$\text{Slope} = \frac{d\ (\text{emittance})}{d\ (\text{parameter})}$$

Name	Slope
SRF Linac voltage	-2.3378e-8 mm-mrad/V
SRF Linac phase	-0.03085 mm-mrad/deg
LEBT solenoid 1 strength	559 mm-mrad/T
LEBT solenoid 2 strength	-304 mm-mrad/T
LEBT solenoid 3 strength	-444 mm-mrad/T
LEBT solenoid 4 strength	-314 mm-mrad/T
LEBT solenoid 5 strength	499 mm-mrad/T
SRF Linac x displacement	-0.0233 mm-mrad/mm
SRF Linac y displacement	0.0284 mm-mrad/mm

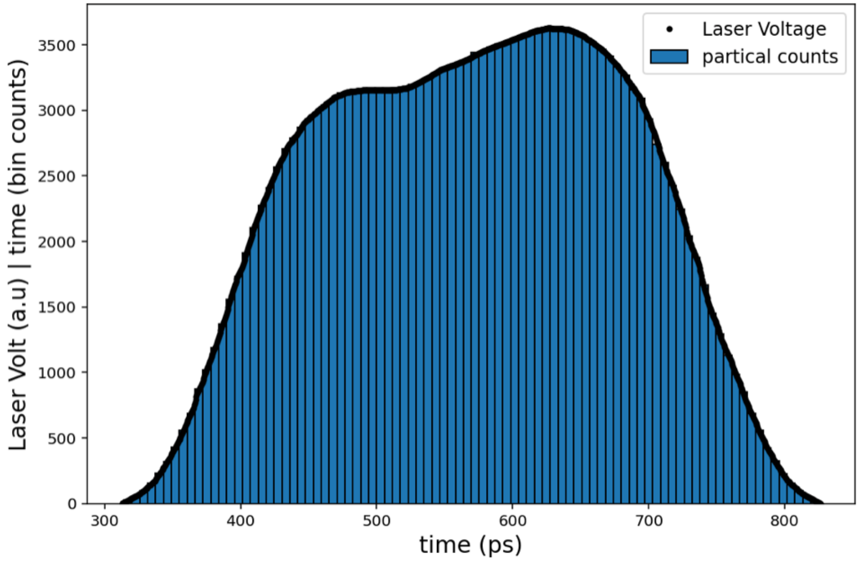
Problem with gun, new laser profile…



Version 1



Version 2



Time-resolved Diagnostic Beamline (TRDBL)

Beam line: 7 quadrupoles (3 + 4), 2 trims, 1 transverse deflecting cavity, 1 dipole
Monitors: 2 Profile Monitors, 4 BPMs

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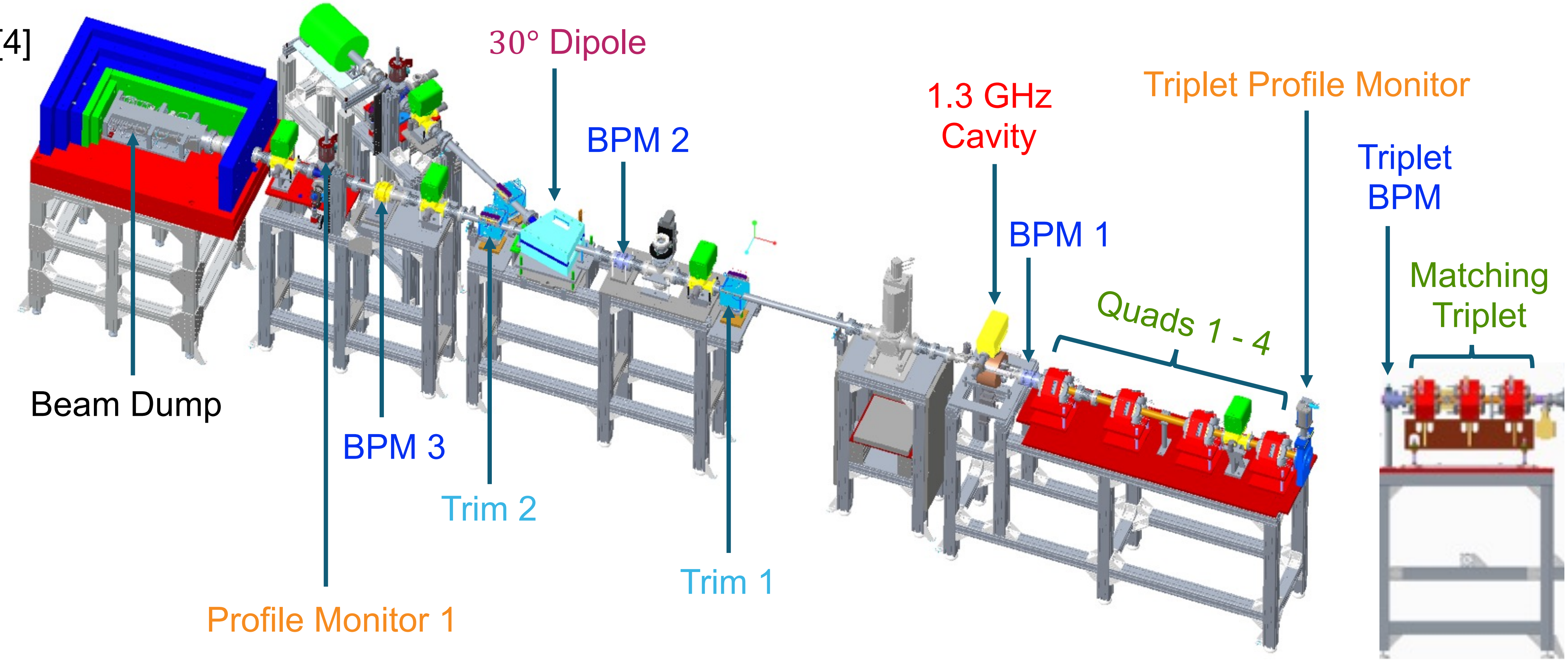
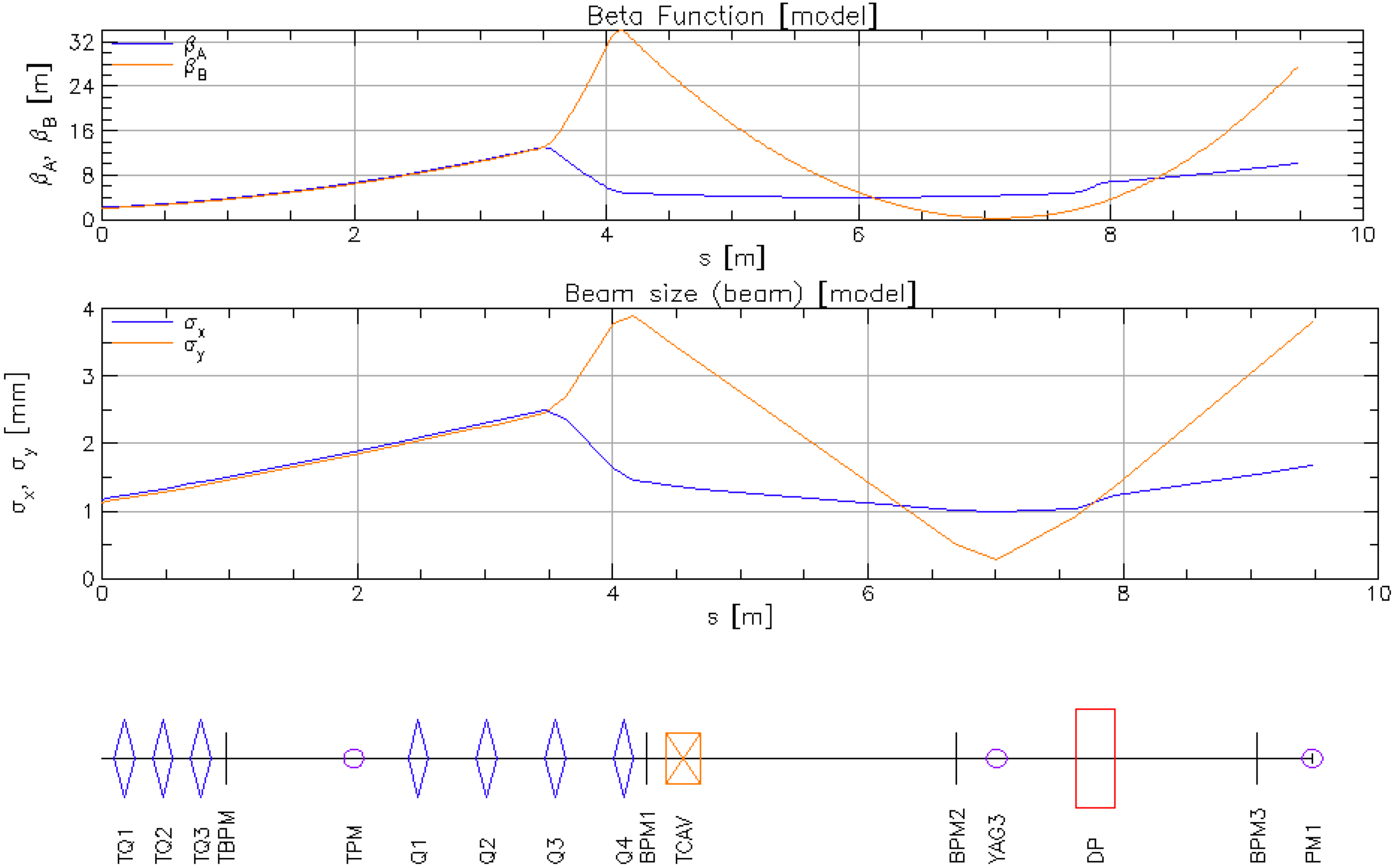
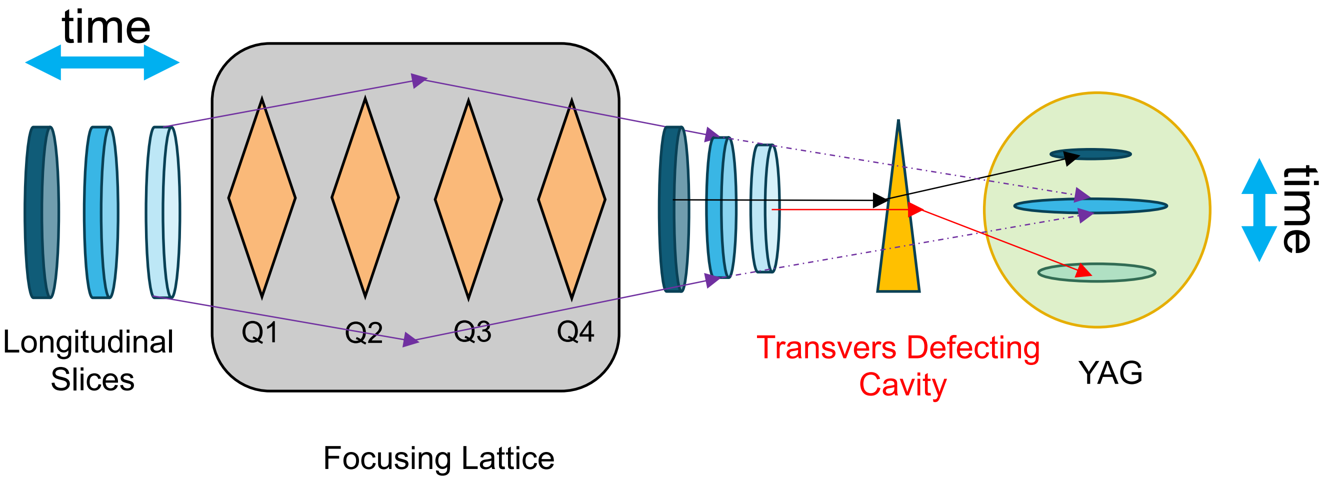


Bmad simulation of TRDBL



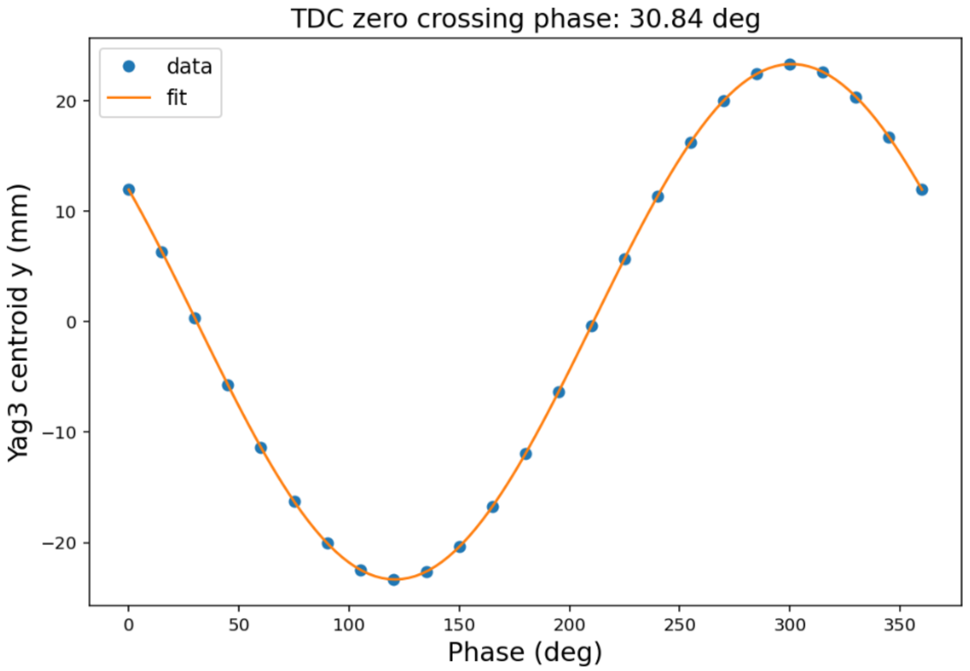
Transverse deflecting cavity (TDC)

- A TDC converts the beam's longitudinal distribution to transverse distribution which is measurable



[7]

Phase TDC to zero crossing phase

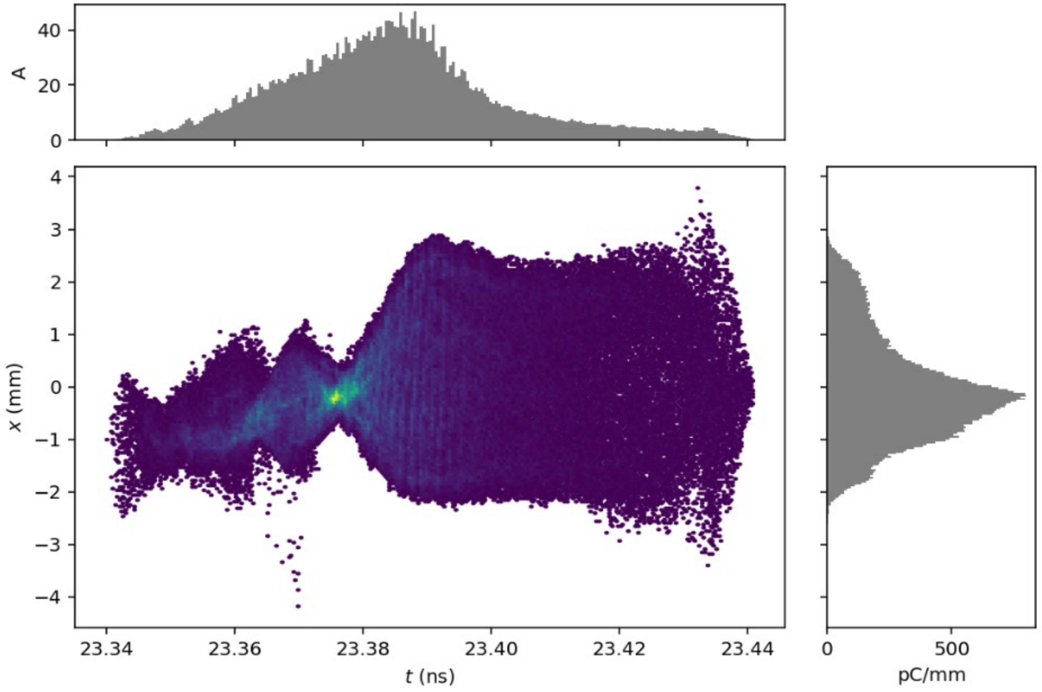


Parameter	Value
TDC RF frequency	1.3 GHz
TDC RF voltage	100 – 140 kV
Bunch length	~ 70 ps
Beam energy	14.56 MeV
Beam size σ_y at Yag without TDC	~ 0.2 – 0.4 mm

TDC simulation results: time profile

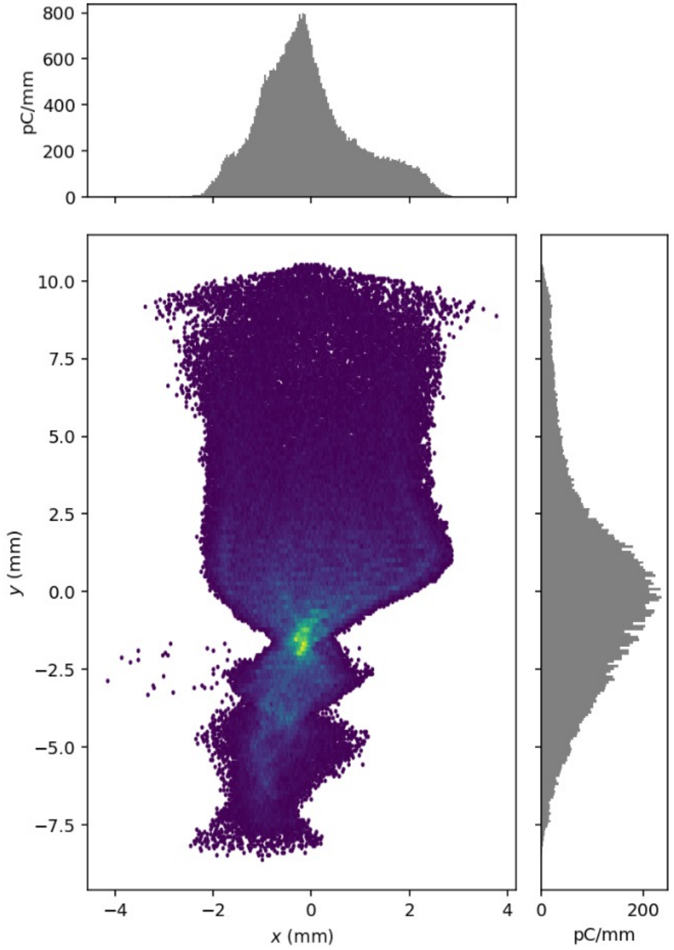
- TDC provide a time dependent transverse kick to the beam
- After TDC, the beam's time information convert to Y direction
- In Bmad, a crab cavity with tilt = pi/2 is used

[6]



Time

TDC on



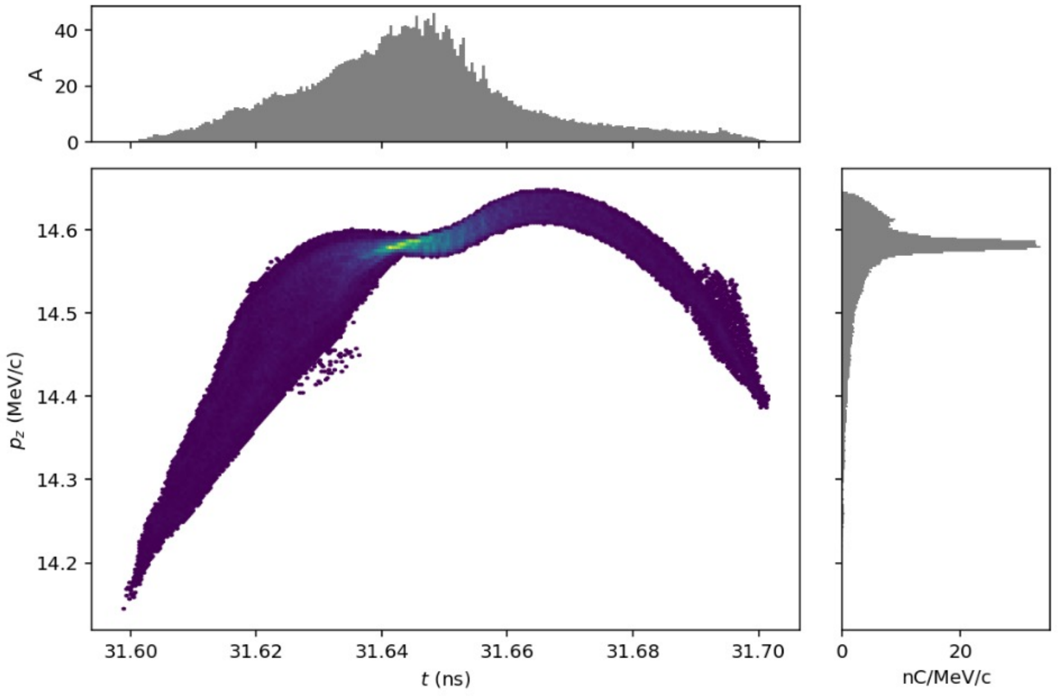
Time

Dipole simulation results: energy profile

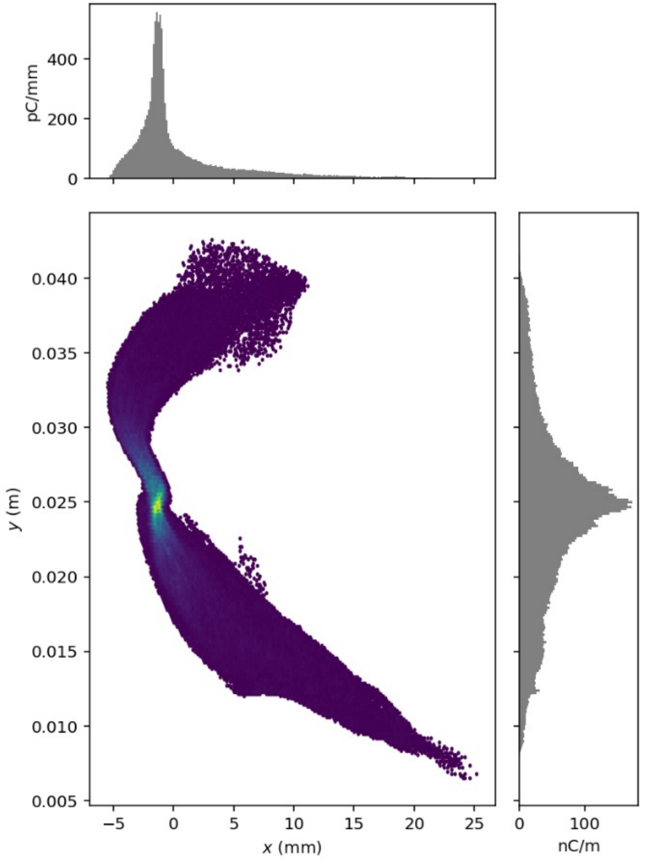
- Dipole provide an energy dependent bend to the beam
- After dipole, the beam’s longitudinal phase space information convert to X direction

[6]

Energy Spread

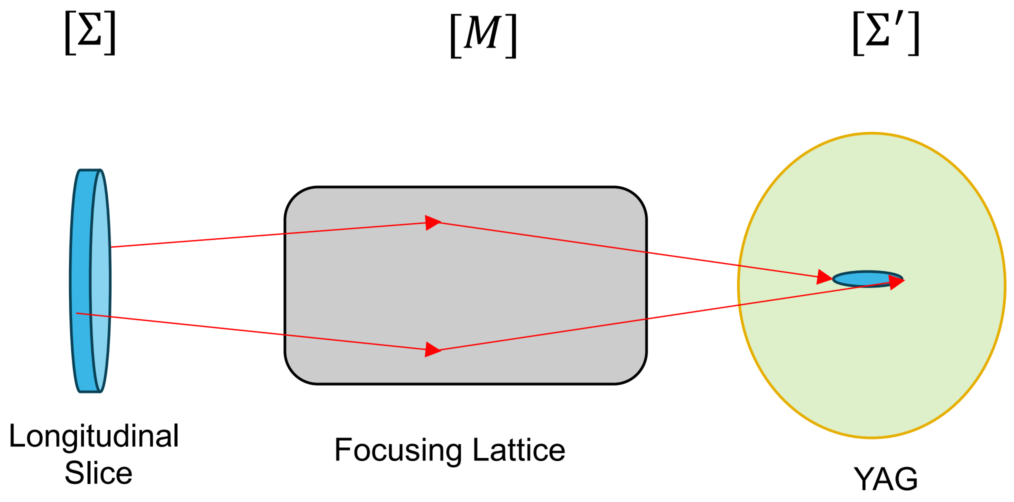


After DP



Energy Spread

Emittance measurement



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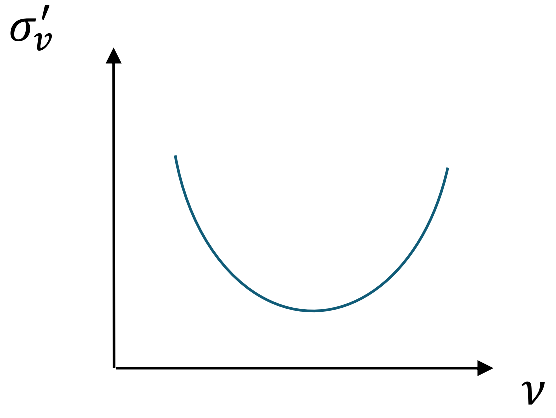


$$[\Sigma] = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{bmatrix} \qquad [M] = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix}$$

$$\because \ [\Sigma'] = [M][\Sigma][M]^T$$

$$\therefore \ \sigma'_{11} = m_{11}^2\sigma_{11} + m_{11}m_{12}2\sigma_{12} + m_{12}^2\sigma_{22}$$

Define $\nu = \frac{m_{11}}{m_{12}^2}$, $\sigma'_v = \frac{\sigma'_{11}}{m_{12}^2}$

$$\sigma'_v(\nu) = \sigma_{11}\nu^2 + 2\sigma_{12}\nu + \sigma_{22}$$

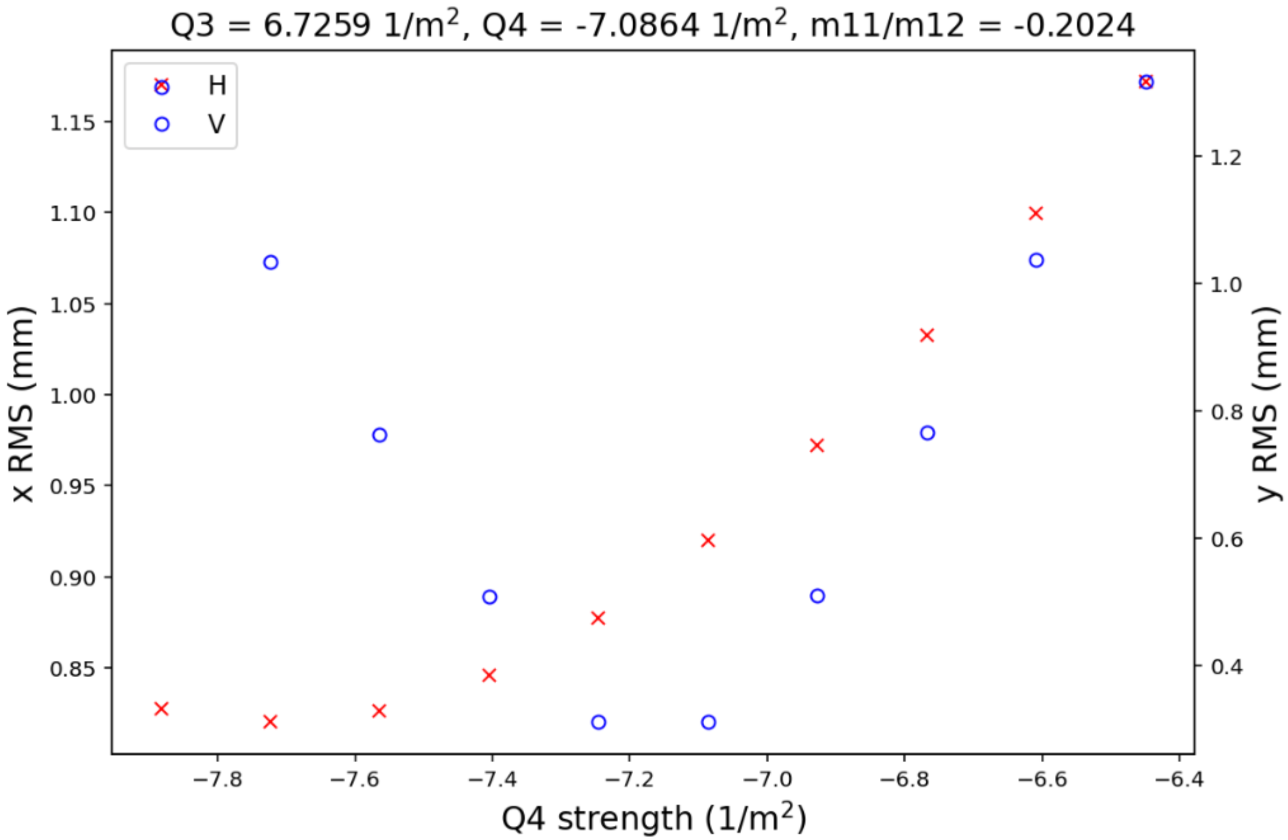
Calculate emittance with parabola fit parameters

$$\varepsilon = \sqrt{\sigma_{11}\sigma_{22} - \sigma_{12}^2}$$

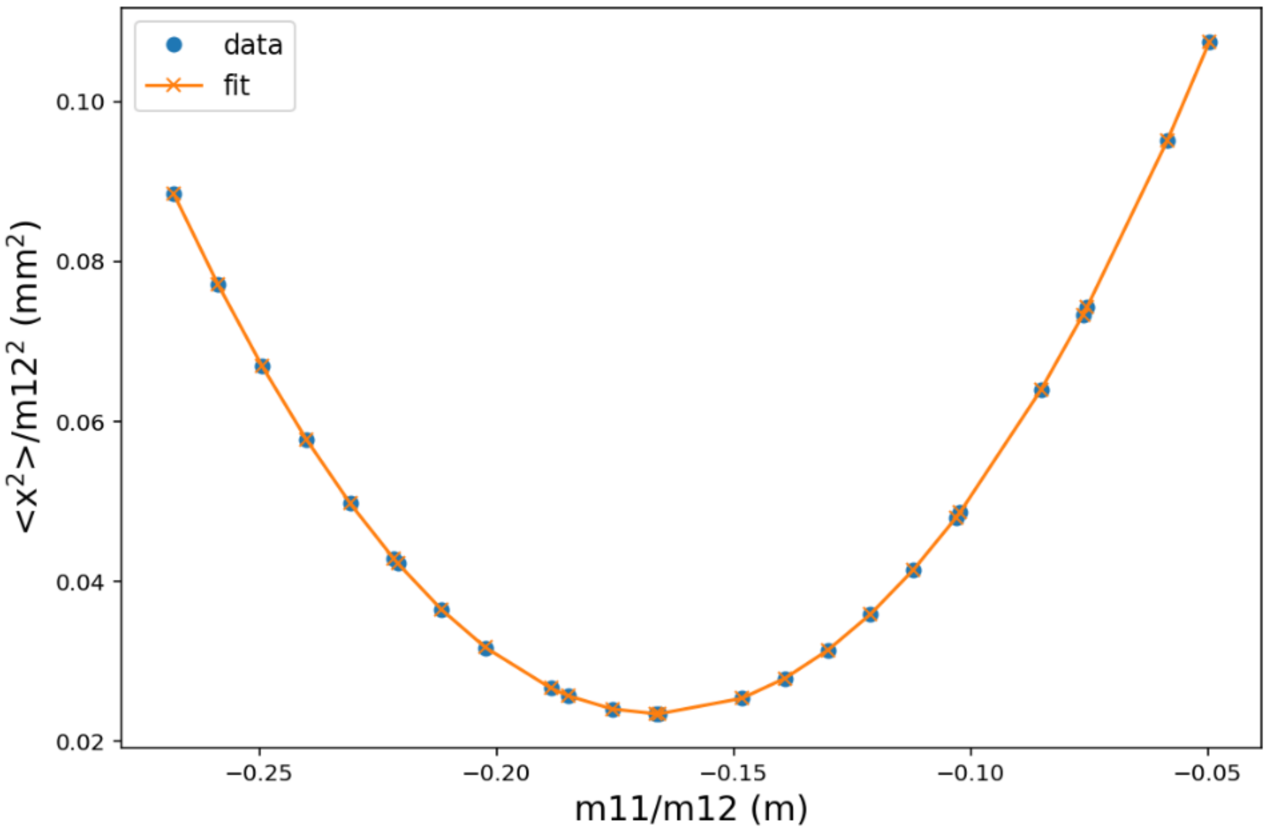
Quadrupole scan

- Scan diagnostic Q3 and Q4 together, observe beam at Yag3
- For each Q3 value, find Q4 value that gives best vertical focusing at Yag3

$$[M] = [M_{Q4\ to\ YAG3}][M_{Q4}][M_{Q3\ to\ Q4}][M_{Q3}]$$



Quadrupole scan data fitting



Use numpy.polyfit to find fitting parameters

$$fit = [\sigma_{11}\,, 2\sigma_{12}\,, \sigma_{22}]$$

$$\varepsilon = \sqrt{fit[0] * fit[2] - (\frac{fit[1]}{2})^2}$$

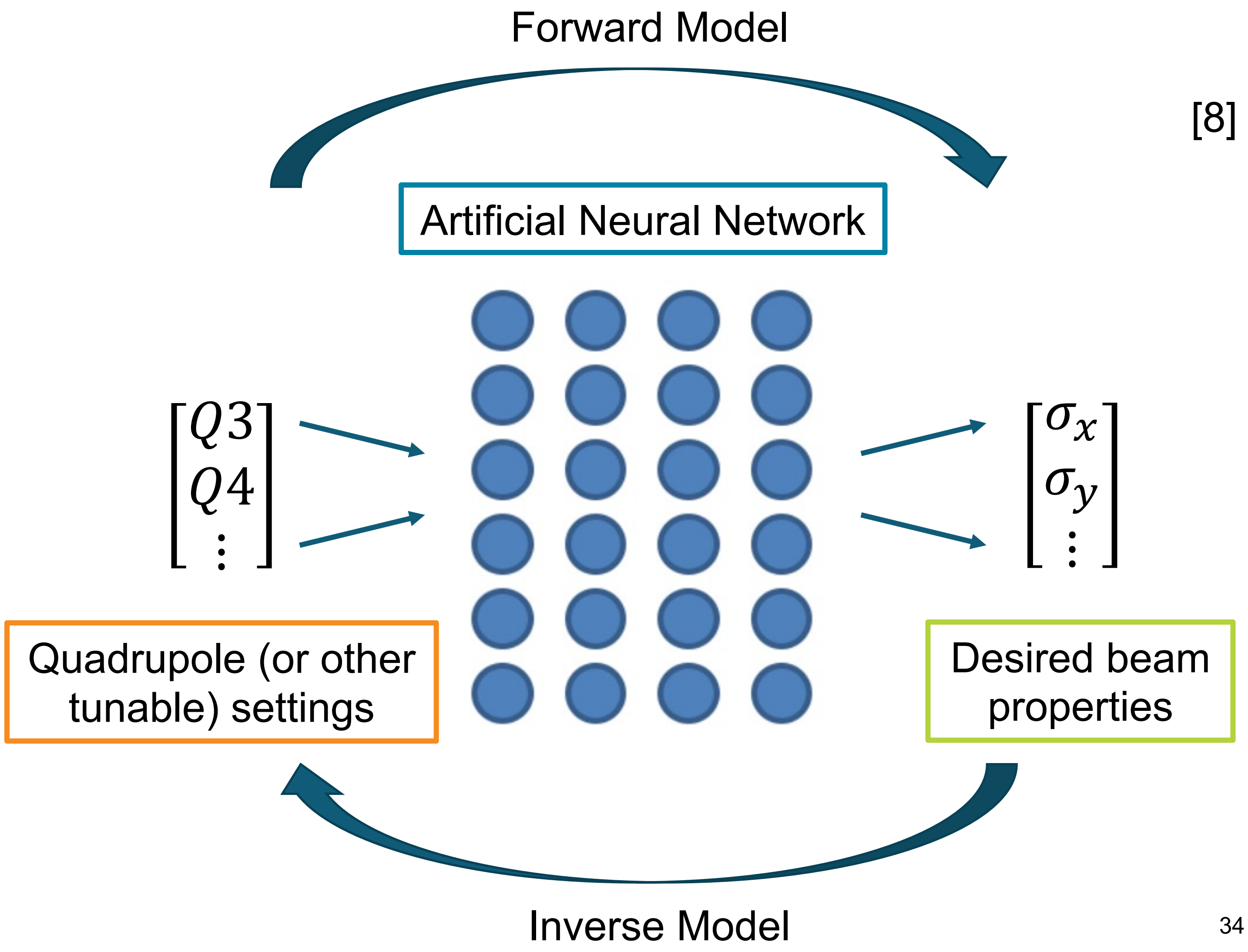
$$\varepsilon = 0.382 \text{ mm}-\text{mrad}$$

$$\gamma = 28.5$$

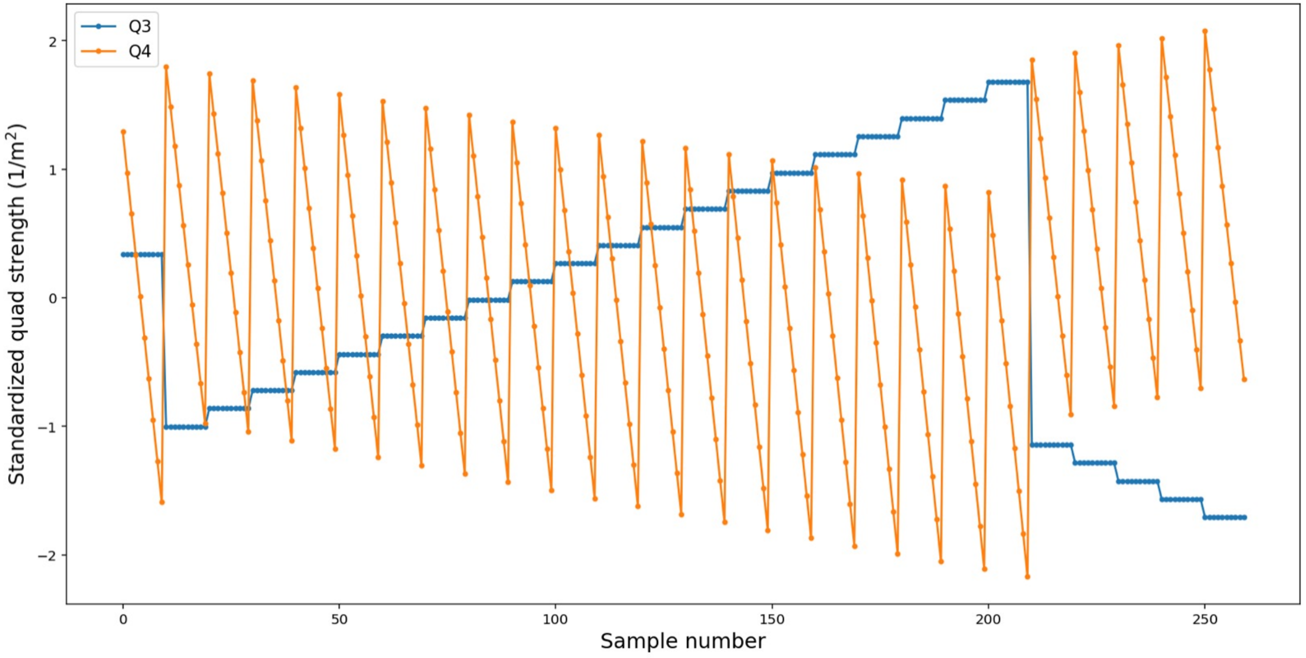
$$\varepsilon_n = \gamma\varepsilon = 10.887 \text{ mm}-\text{mrad}$$

Ongoing: speed up quad scan with ML

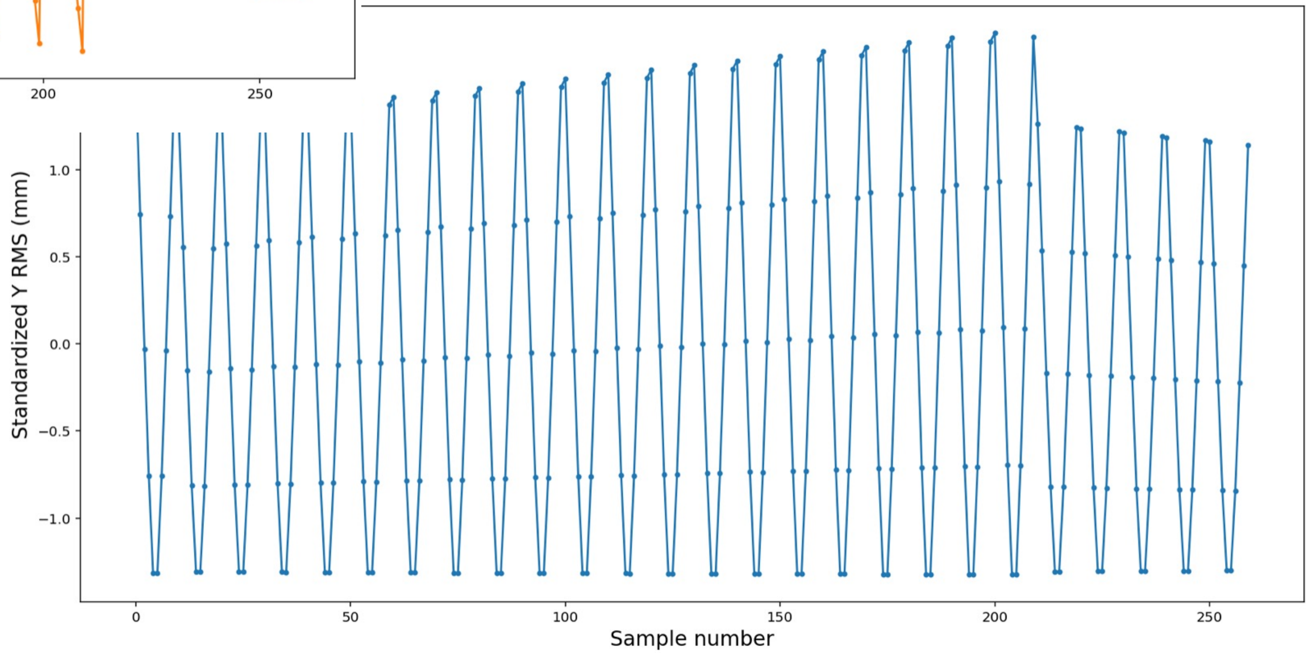
- Time-consuming quad scan: 9 points for each Q3 value, 13 rounds for parabola fitting → > 100 measurements
- Possibility of training a model to establish mapping between quadrupole settings and beam size
- Useful for faster general beam tuning & as starting point of optimization
- Forward vs. Inverse model



Quadscan model: simulation data

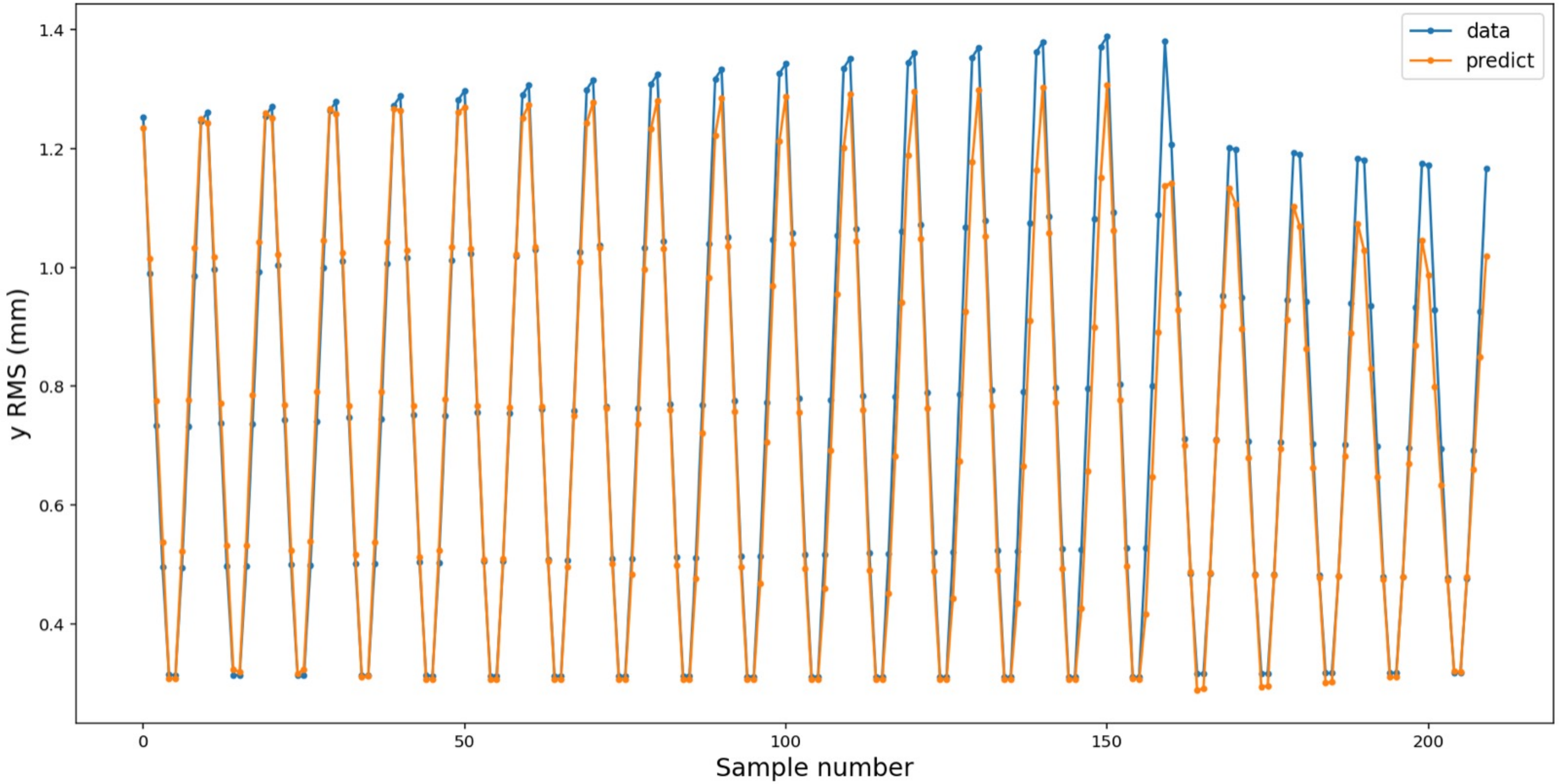


- Forward model: three layers with ReLU and Tanh activation functions
- Input: Q3, Q4 strength (k1 values)
- Output: RMS beam size, focus on y direction



Quadscan model: training results

Training: 50 out of 260 data pairs, testing (shown below): 210 out of 260 data pairs



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