VAEとベイズ最適化によるビーム輸送系の最適化

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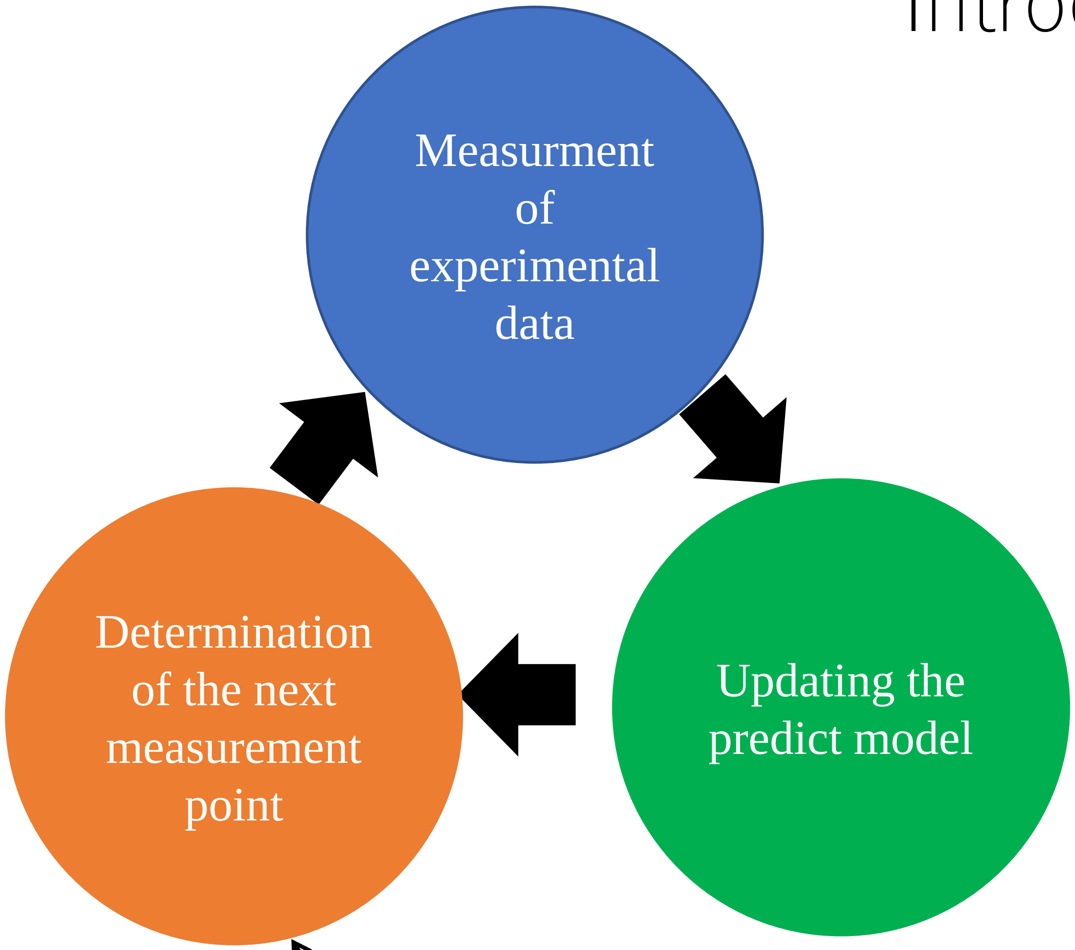
Outline

- Introduction
  - Motivation
  - Methods
- Demonstration in simulation
- Experiments
  - Beamline
  - Training data
  - VAE Learning
  - Tuning experiment results

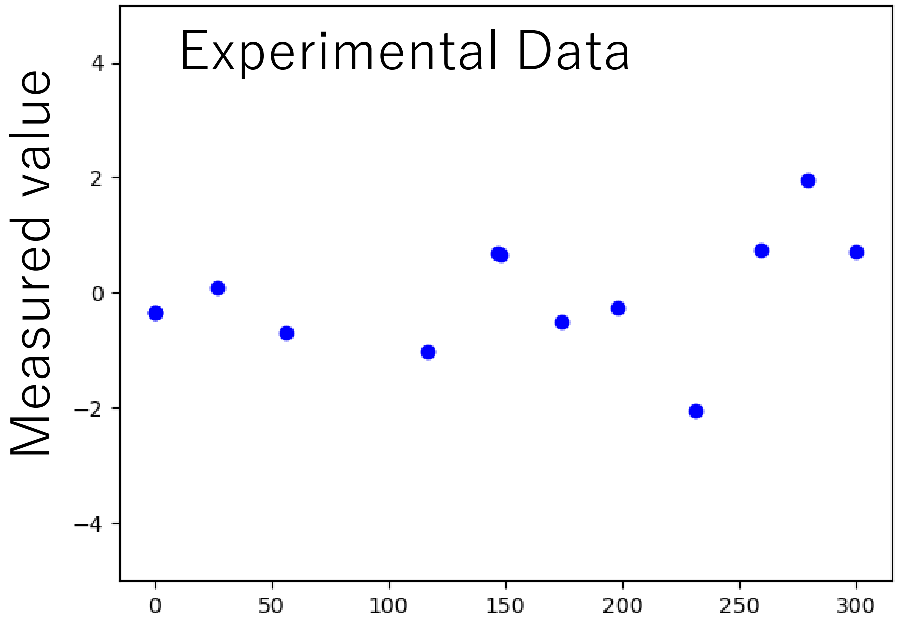
Introduction

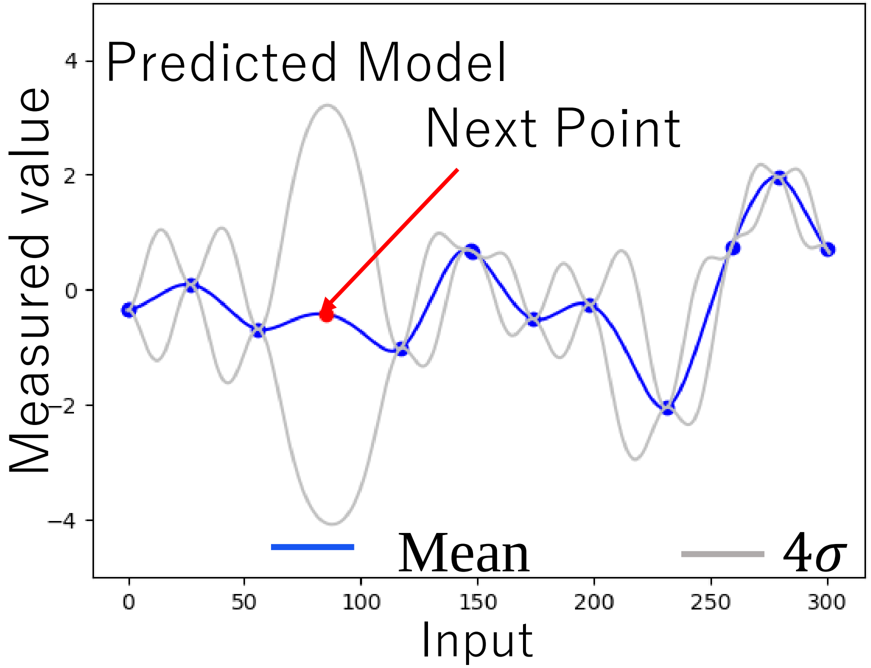


Predicted value(Mean) and dispersion (σ) are calculated by Gaussian Process

Determine next measurement point using Acquisition function

Acquisition function: $L = Mean + \alpha \times \sigma$





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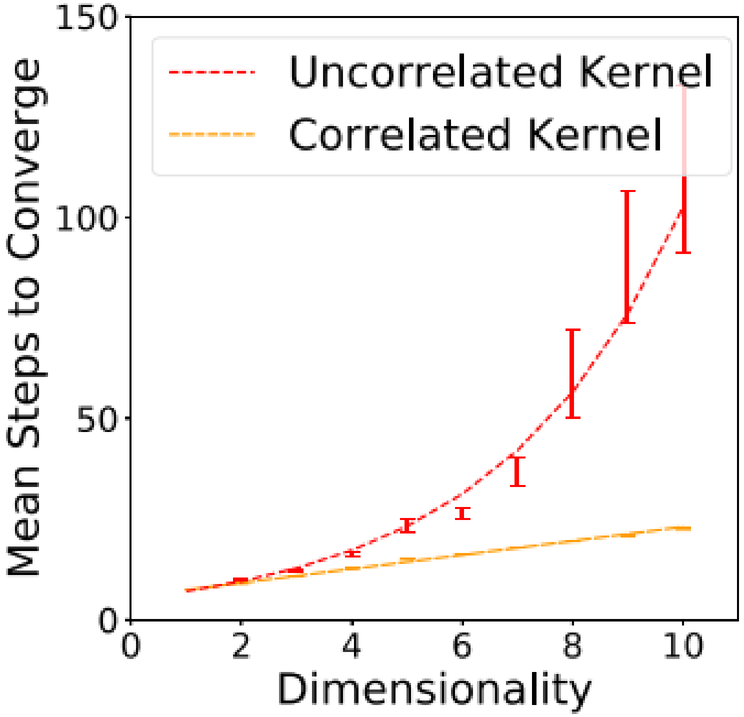


J. Duris, J. et al. Bayesian Optimization of a Free-Electron Laser. Phys. Rev. Lett. 124, 124801 (2020).

As the number of parameters to be tuned increases,
the number of adjustment steps required increases exponentially.

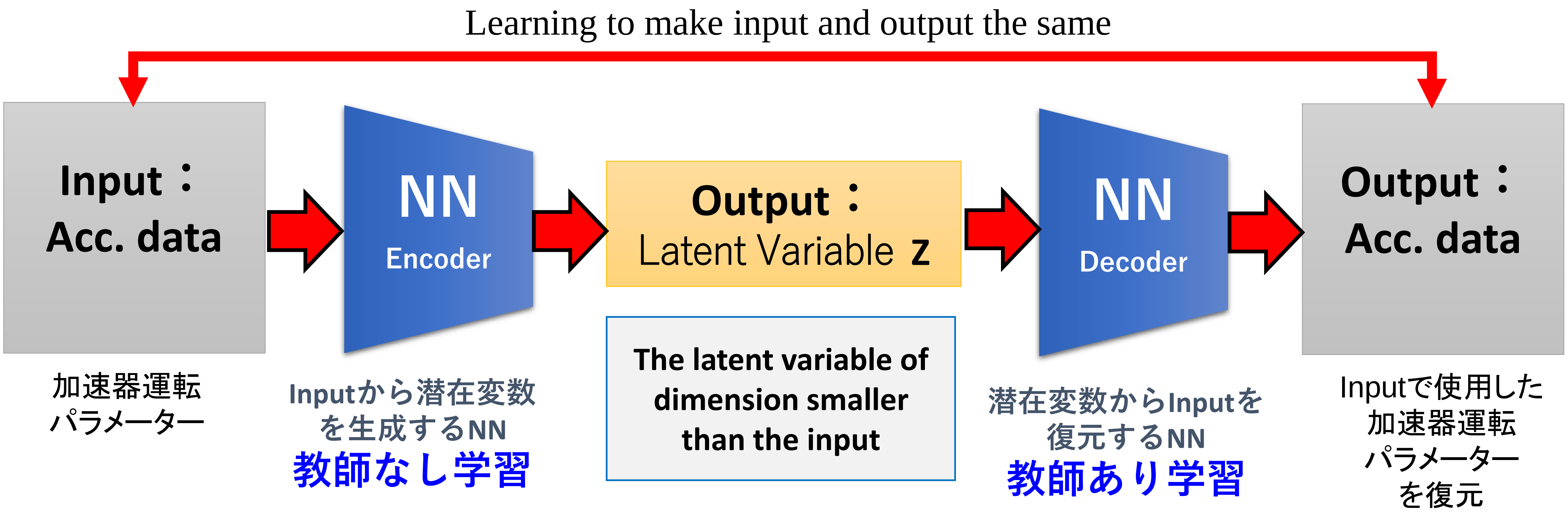
- <u>Tuning time increases as the number of parameters increases.</u>
- <u>If the number of parameters is too large, the system may not work.</u>

Tuning by dividing beamlines into sections
Or
Tuning by reducing the dimension of parameters

The dimensionality reduction technique allows for quick tuning of a large number of parameters!

Dimensionality reduction

Attempt dimensionality reduction using Autoencoder (AE) and Variational Autoencoder (VAE).



Dimensionality reduction

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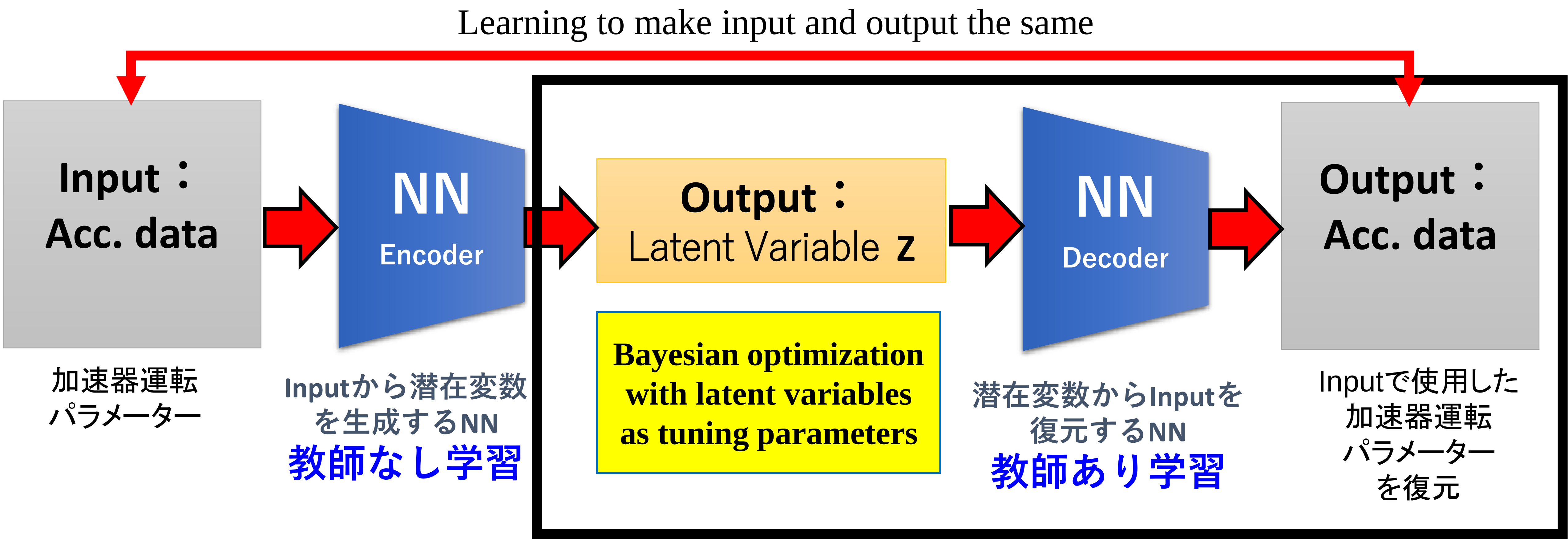

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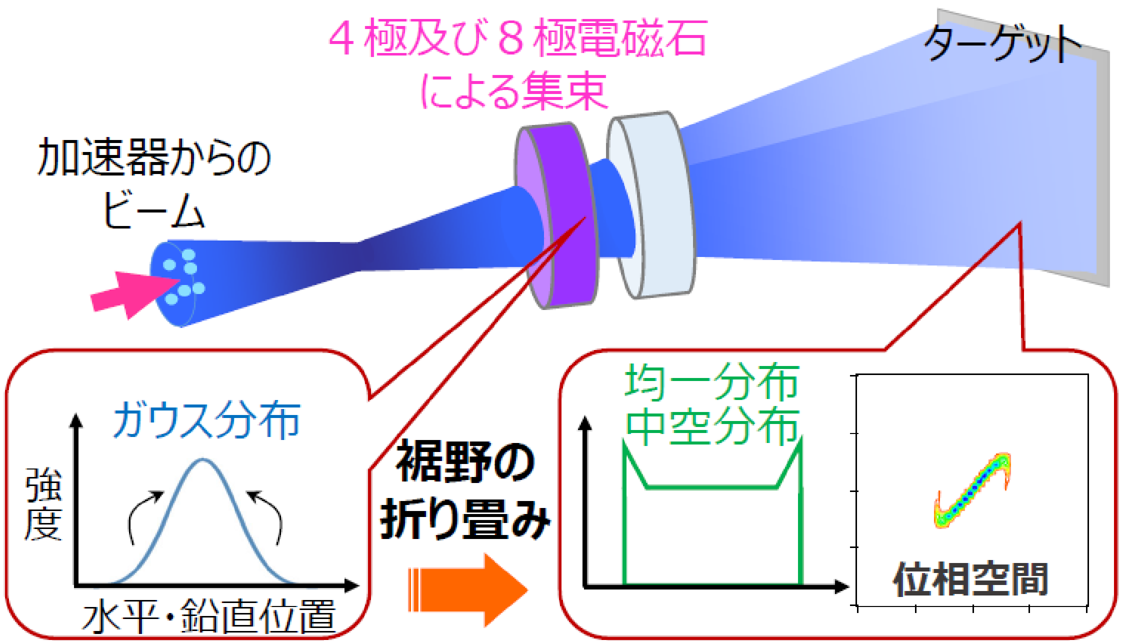
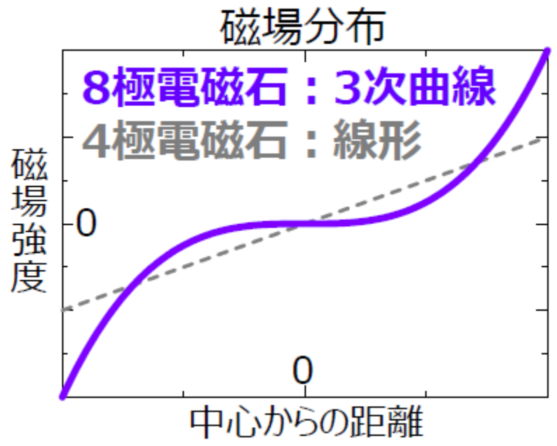
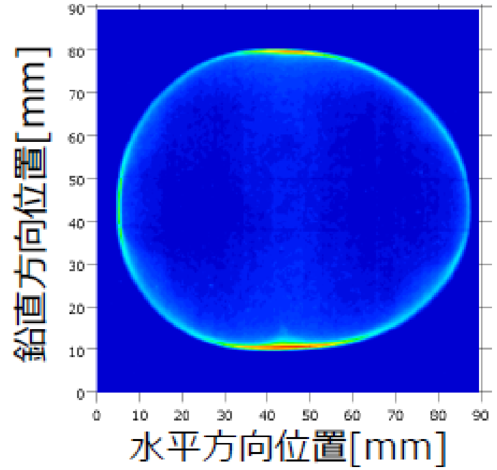
Hollow Beam used to test method



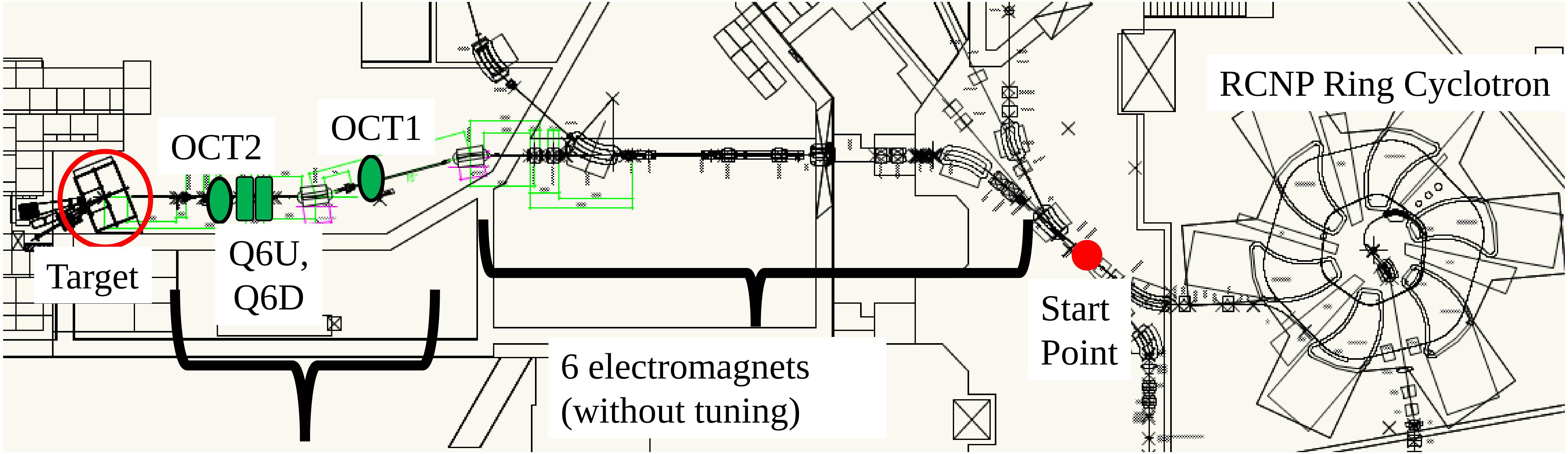




Equation of motion

$$\begin{cases} x'' + K_Q(s)x + \dfrac{K_{SXT}(s)}{2!}(x^2 - y^2) + \dfrac{K_{OCT}(s)}{3!}(x^3 - 3xy^2) + \cdots = 0 \\ y'' \underbrace{- K_Q(s)y}_{\text{Quadrupole}} \underbrace{- \dfrac{K_{SXT}(s)}{2!}(2xy)}_{\text{Sextupole}} \underbrace{+ \dfrac{K_{OCT}(s)}{3!}(y^3 - 3x^2y)}_{\text{Octupole}} + \cdots = 0 \end{cases}$$

Beam transport simulation



Tuning test combining autoencoder and Bayesian optimization

- Only OCT1, OCK2, Q6U, and Q6D are tuned. Beam conditions, other magnets are completely fixed.

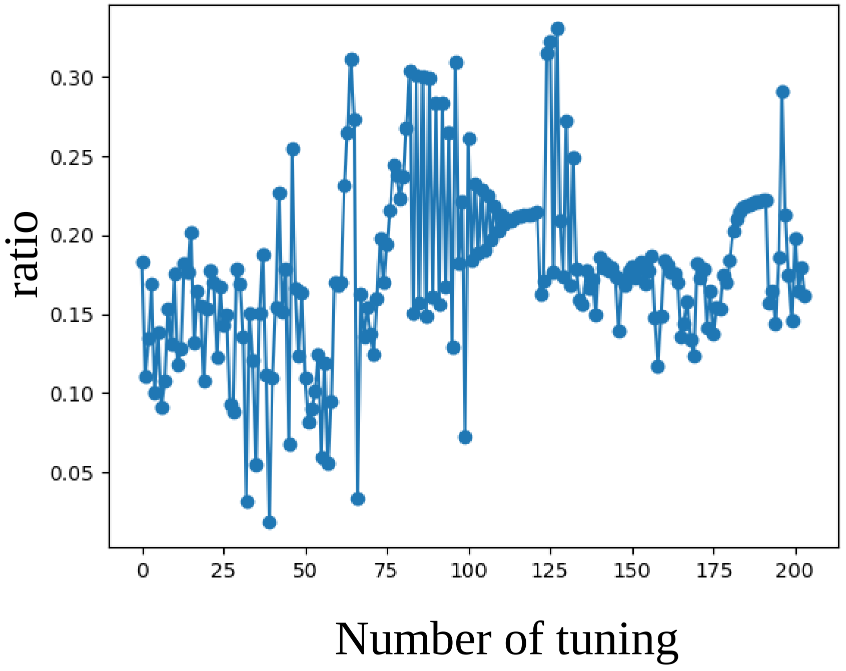
<u>Target is cylindrical with a radius of 20 mm</u>

- <u>Maximize the ratio of the range 17.5mm ≤ r ≤ 20.0mm out of the total beam.</u>

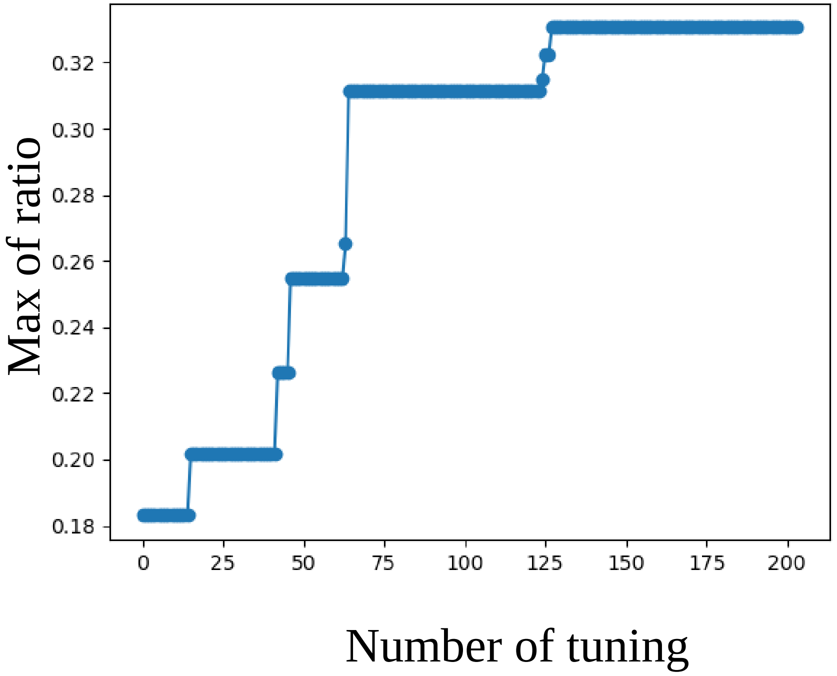
In Simulation

Converts 4 parameters into 2-dimensional latent variables using AE.

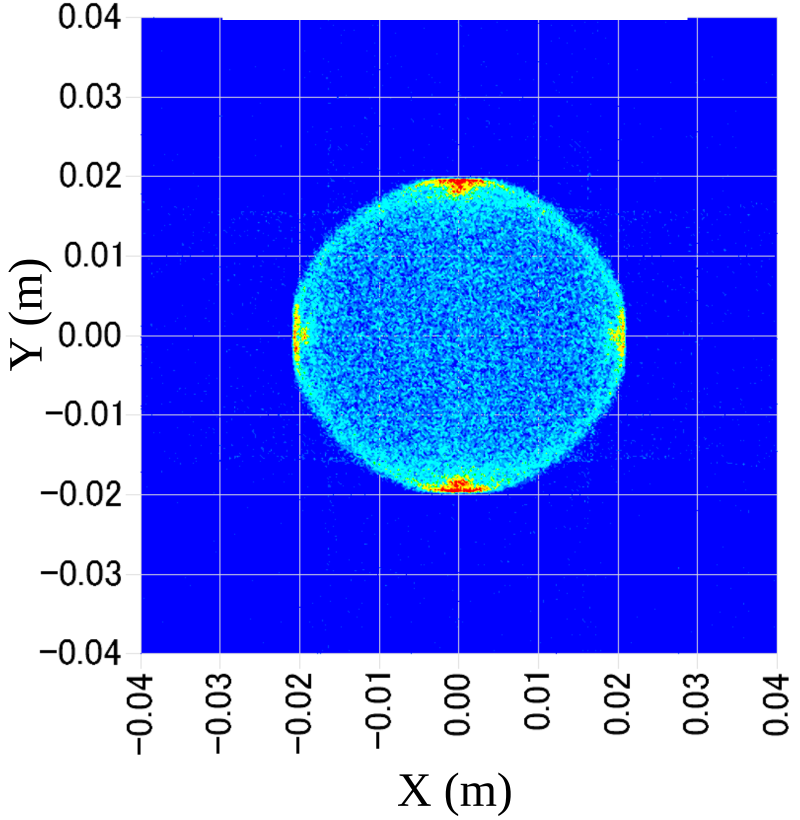
Parameter change and
ratio variation



Parameter change and
Maximum value of ratio



Beam distribution



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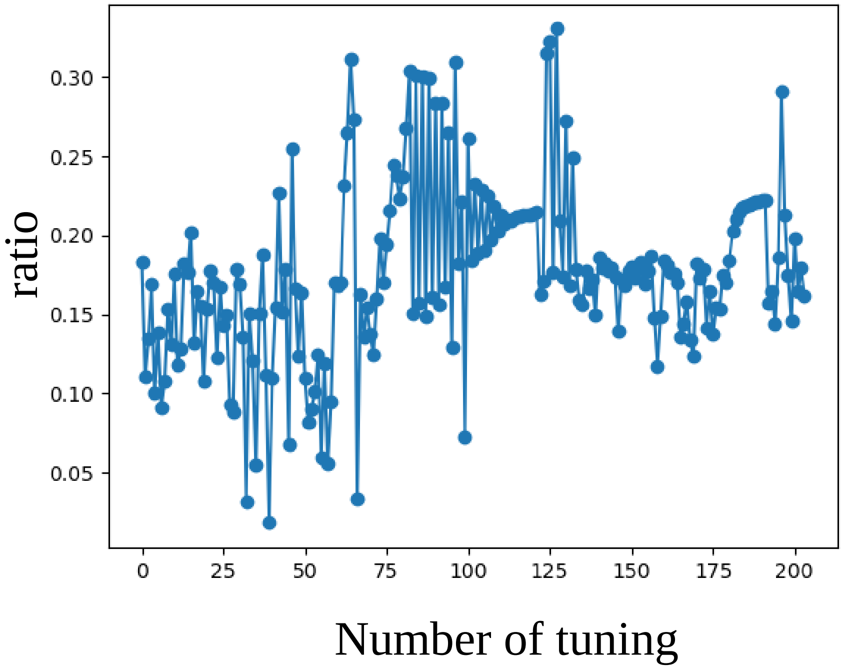
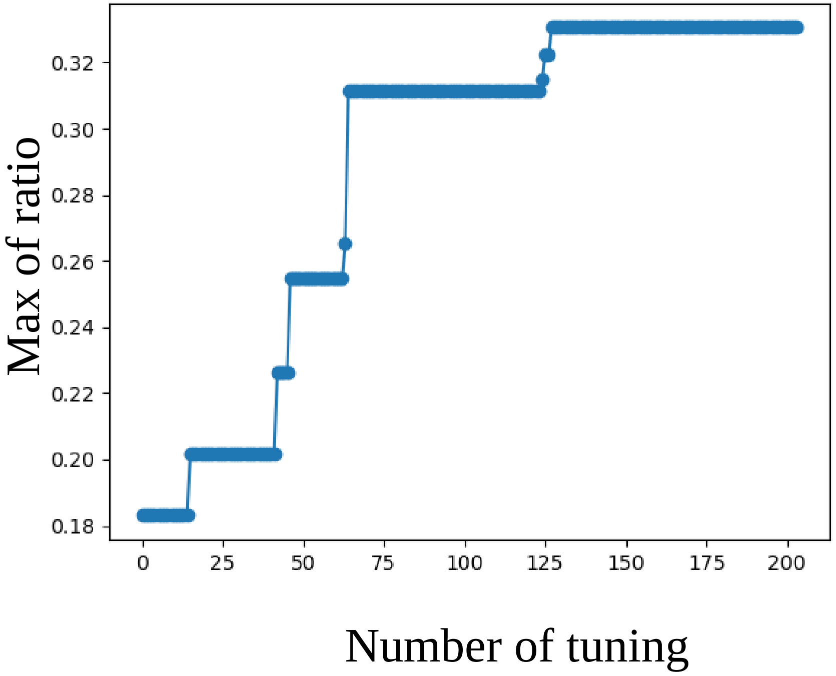
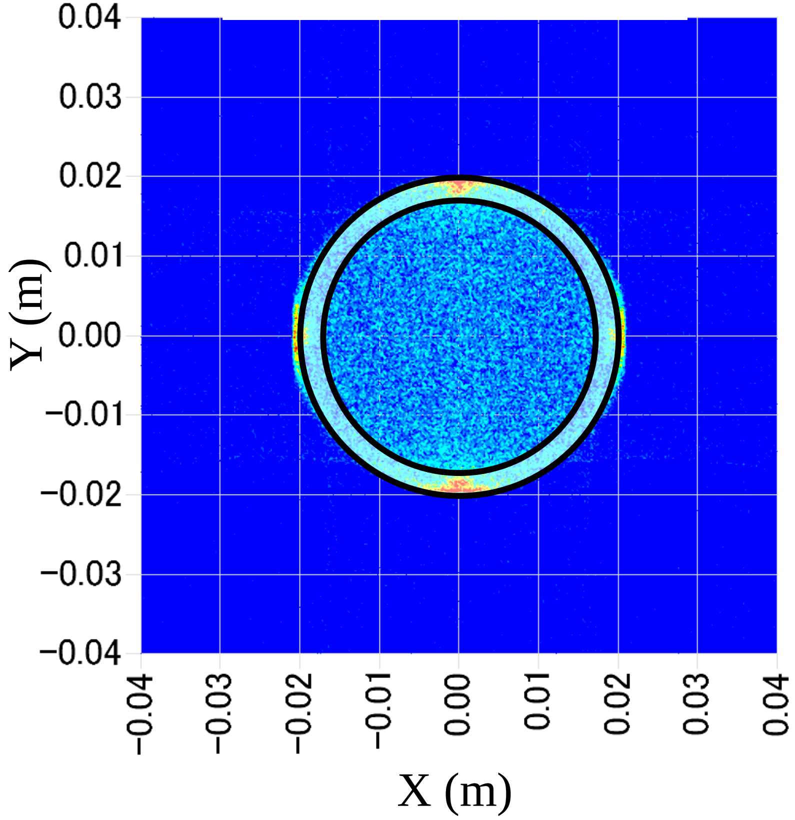


Parameter change and Maximum value of ratio

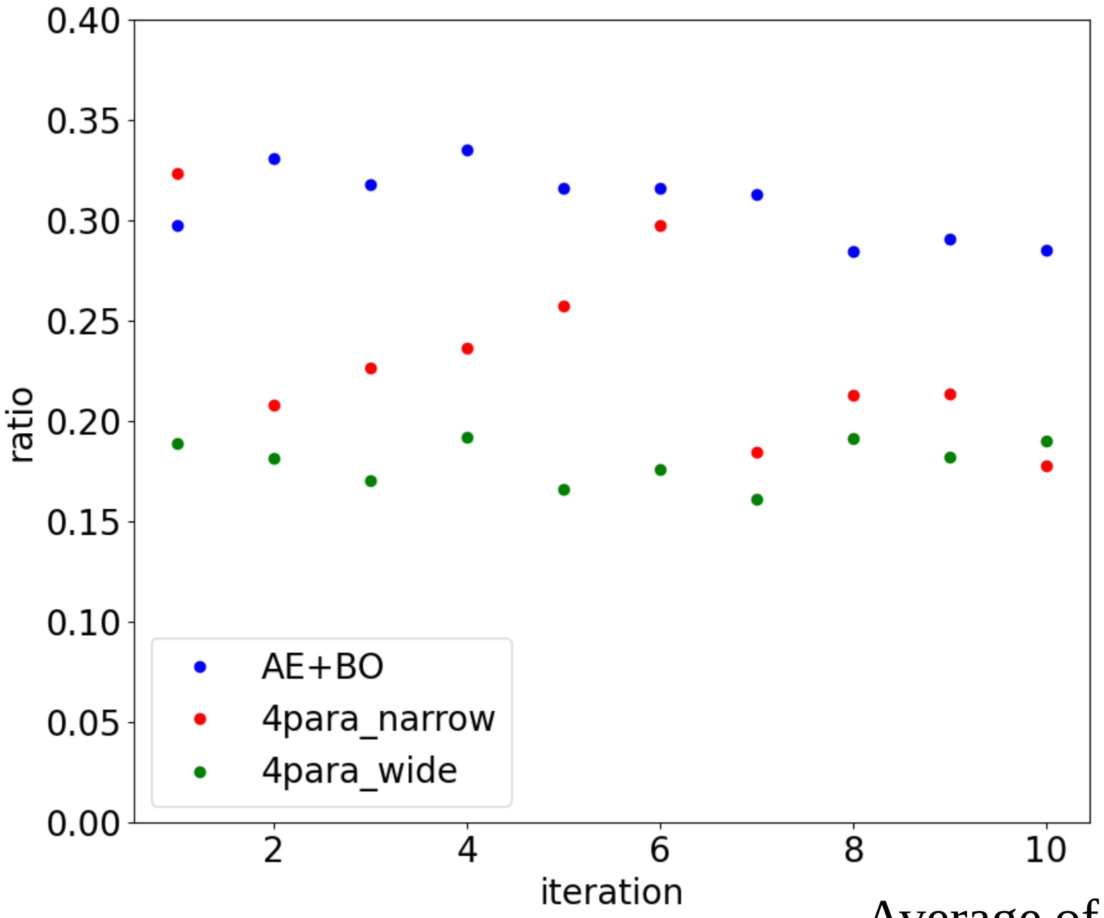


Beam distribution



The beam distribution is not perfect, but it is good enough in a short time.

Comparison with direct tuning of 4 parameters



- <u>4 parameter (narrow)</u>
  Octupole -> Same range as AE (but discrete)
  Quadrupole -> Only 4 values can be selected

- <u>4 parameter (wide)</u>
  Octupole -> Same range as AE (but discrete)
  Quadrupole -> Same range as AE (but discrete)

It is more stable and higher ratios can be obtained than by adjusting the four parameters directly.

➢ More effective tuning than tuning a narrower range of parameters!

Average of ratio for each tuning

AE+BO	4 parameter BO (narrow)	4 parameter BO (wide)
0.309	0.234	0.180

ELSEVIER

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment

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Full Length Article

Accelerator tuning method using autoencoder and Bayesian optimization

Yasuyuki Morita [a], Takashi Washio [b], Yuta Nakashima [c]

https://doi.org/10.1016/j.nima.2023.168730

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Beam line Tuning

In simulation, it was effective in speeding up the tuning process.

- Does it work in real?

Beam line Tuning

In simulation, it was effective in speeding up the tuning process.

➢ Does it work in real?

Problem

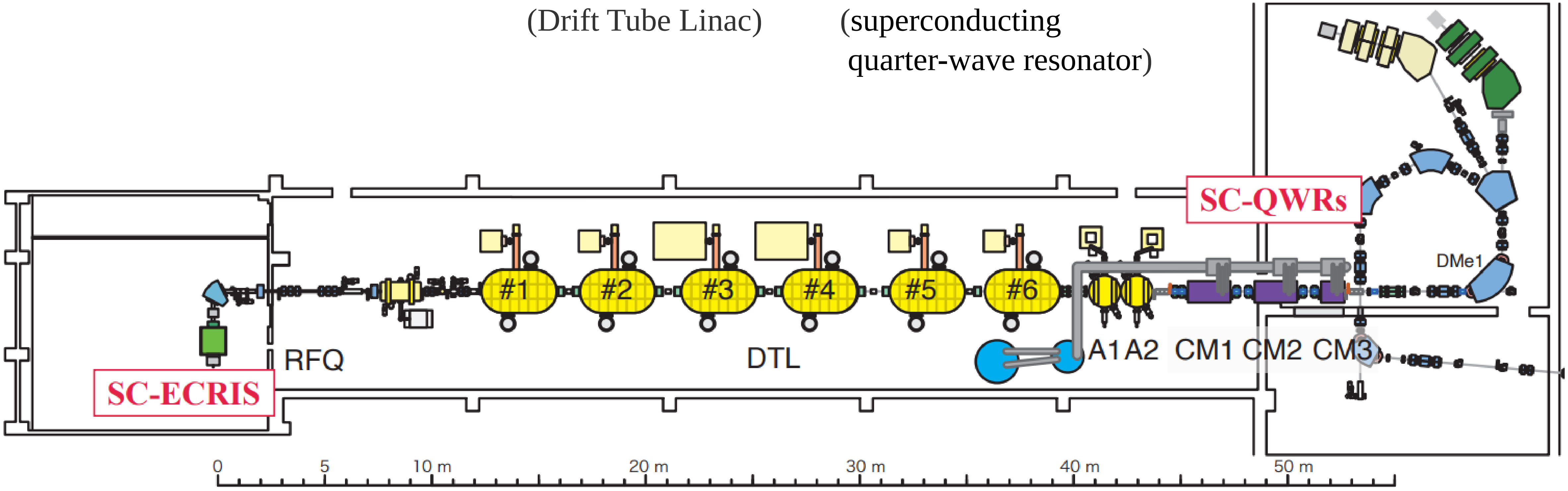
- Number of data : It is difficult to secure the number of data for tuning
- Variations of data : Tuning data is biased because it is based on past performance

➢ **Use simulation to learn VAE and use it for tuning.**

RIKEN Heavy Ion LINAC (RILAC)

28GHz SCECRIS + *f*-tunable RFQ + 8 DTLs (#1-#6, A1,A2) + 10 **SC-QWR** (Fixed *f* = 73 MHz)

(Drift Tube Linac) (superconducting quarter-wave resonator)



Various experiments using heavy ion beams are conducted.

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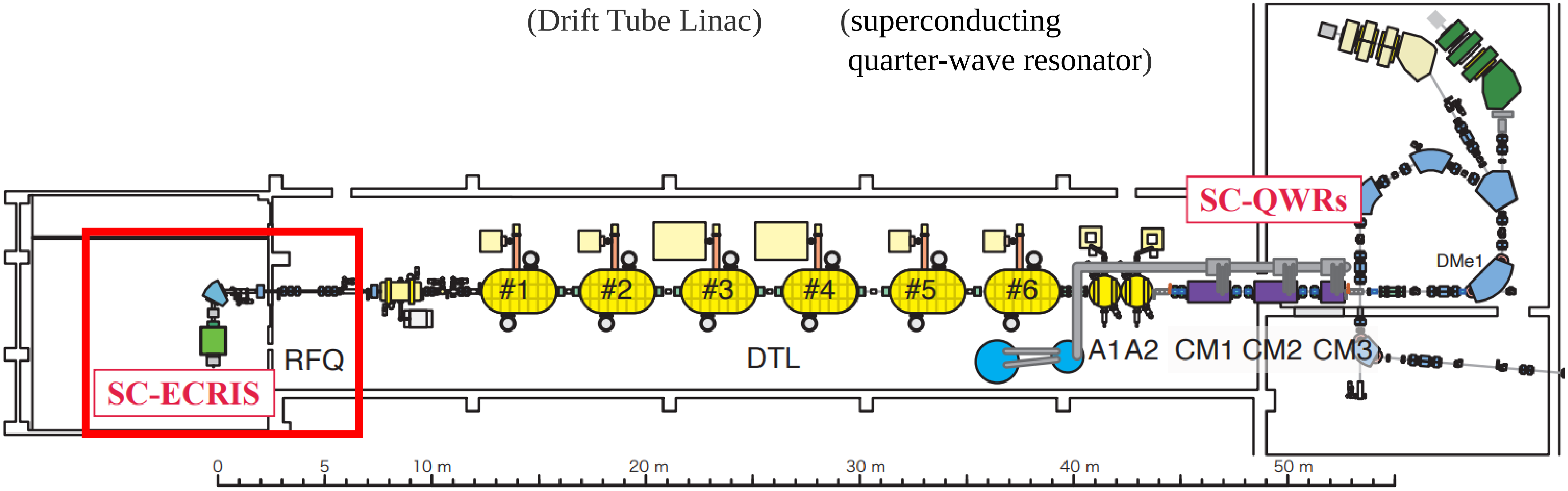


Various experiments using heavy ion beams are conducted.

Low Energy Beam Transport (LEBT)

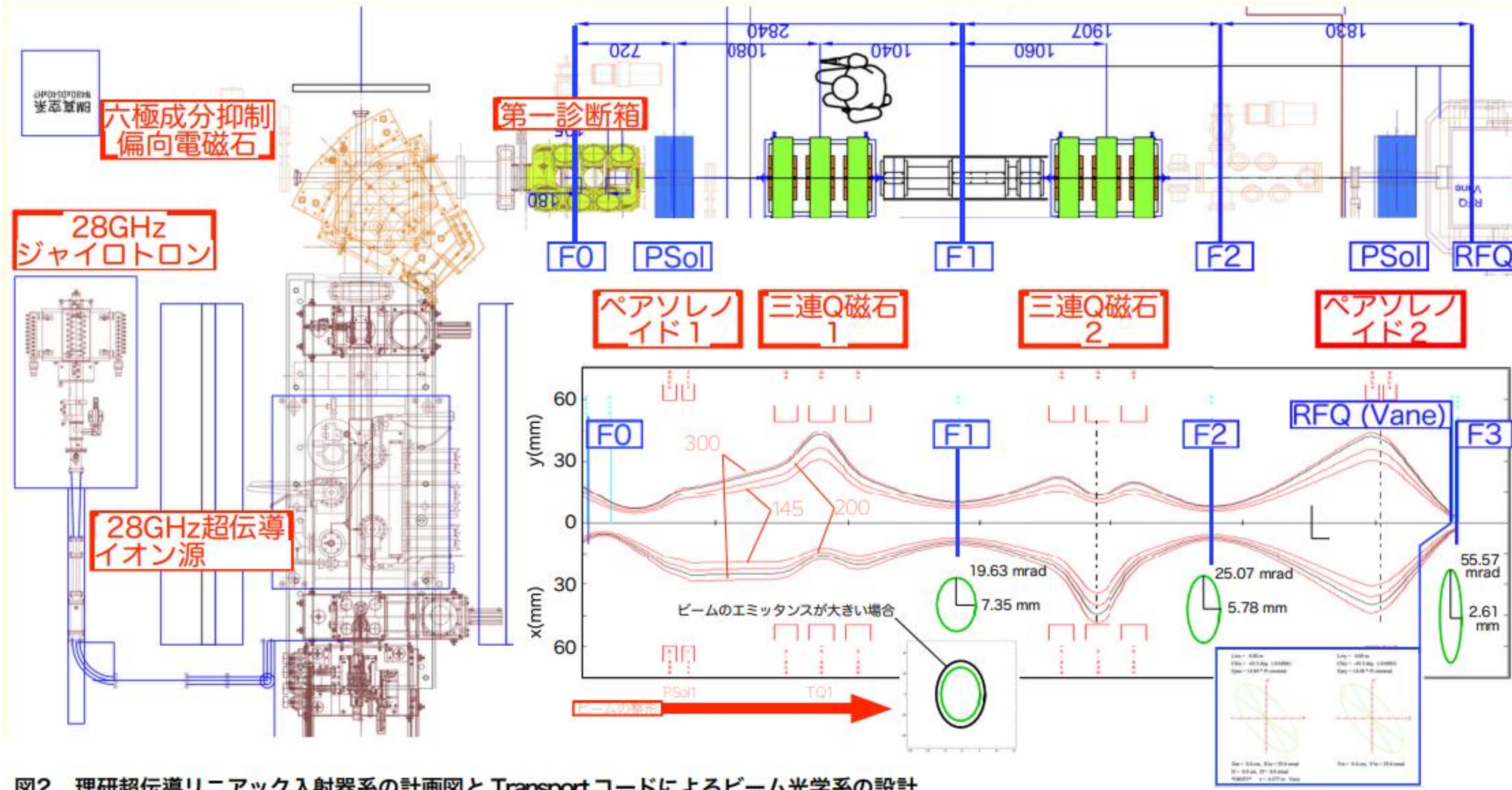


表1 ビーム光学レンズの磁場

Qはx=50mmでの磁場のy成分

$^{54}Cr^{9+}$, 20 kV引出し

Name	Transport (T)	G4BL(T)
P-Sol1	0.29979	0.33700
Q11	0.02139	0.02352
Q12	-0.04175	-0.04484
Q13	0.03252	0.03508
Q21	-0.04141	-0.04436
Q22	0.06389	0.06842
Q23	-0.04060	-0.04299
P-Sol2	0.35503	0.39914

図2 理研超伝導リニアック入射器系の計画図と Transport コードによるビーム光学系の設計

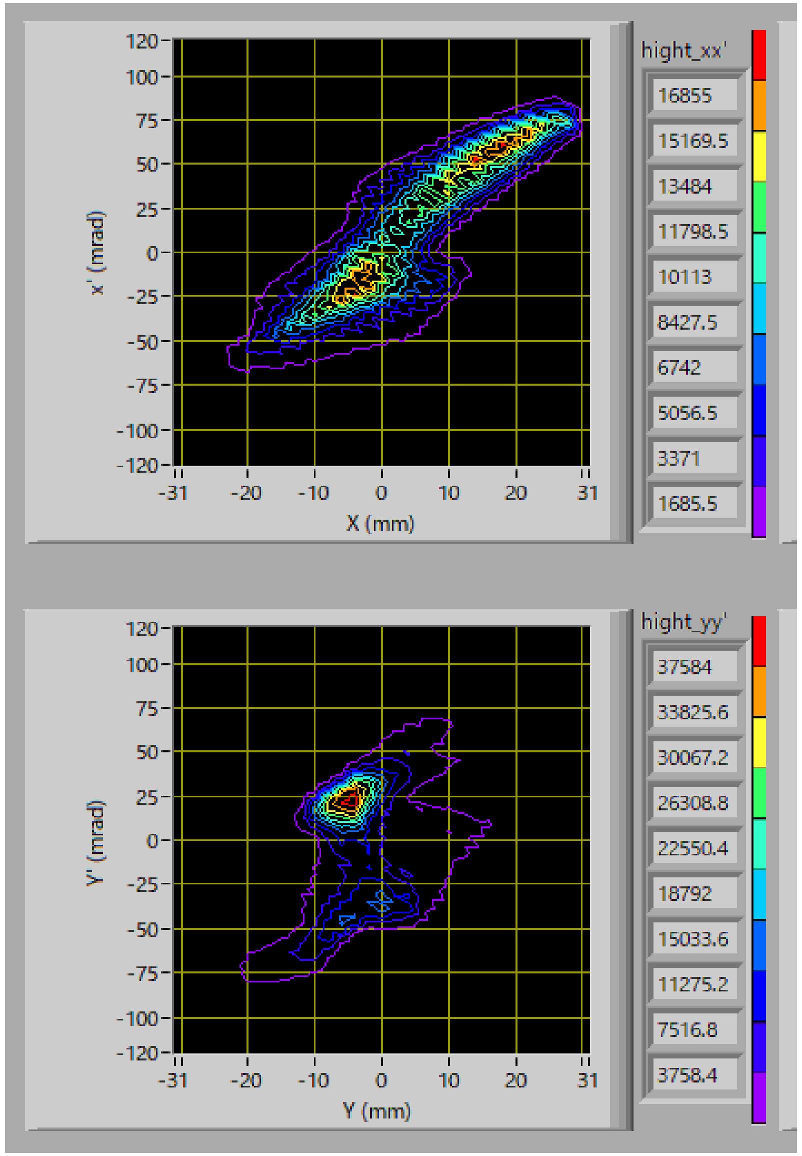
Simulation condition for training data

Ion	$^{51}V^{13+}$
Extraction voltage	11.8 kV (~3 keV/u)
Emittance(x-x’)	221.4 π mm mrad
Emittance(y-y’)	209.6 π mm mrad
Beam duct	40 mm

Magnetic field of each electromagnet (kG)

Pear solenoid	0.29979
Triplet Q magnets 1	0.02139, -0.04175, 0.03252
Triplet Q magnets 2	-0.04141, 0.06389, -0.35503

Dispersion of each magnet 25% / 1σ

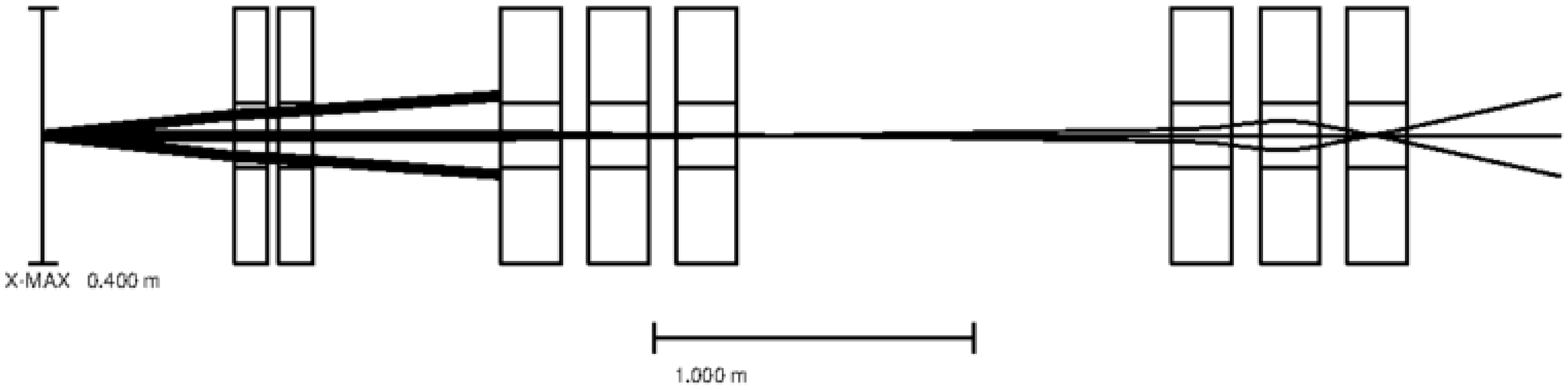


Beam Transport Simulation

Simulations were performed using GICOSY and MOCADI.

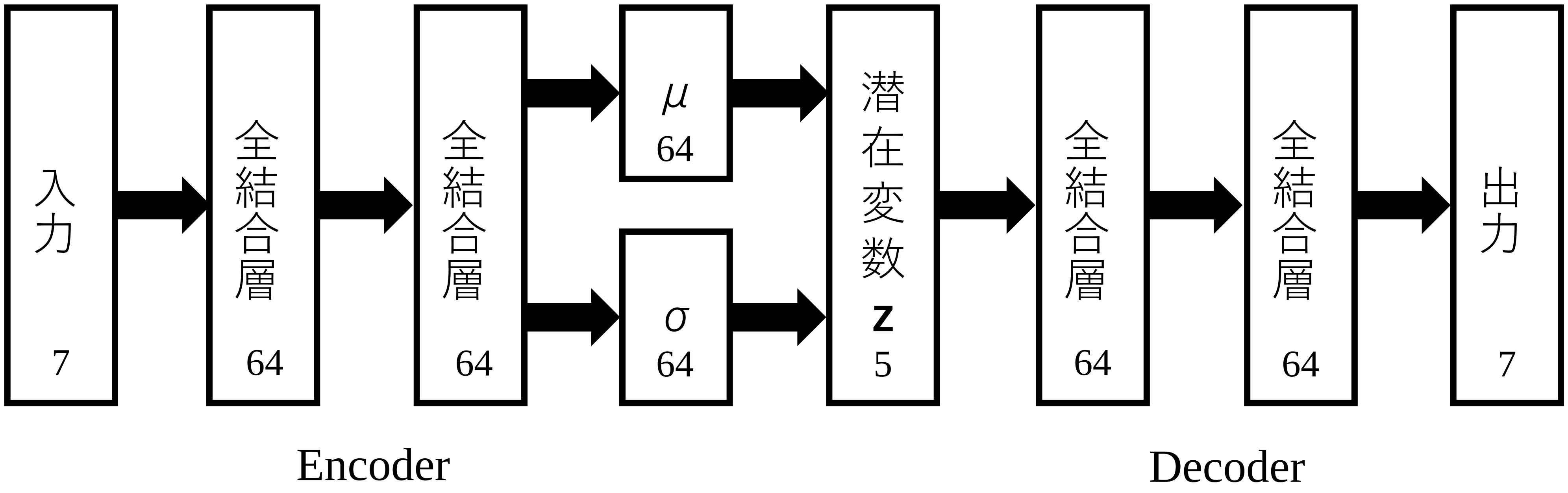
5×10^5 simulations were performed. of which those with beam transmission greater than Only results with transmission greater than 21.5% were used in the study.

- Only 97 data can be used for learning.
  (Due to the wrong magnetic field strength referenced.)



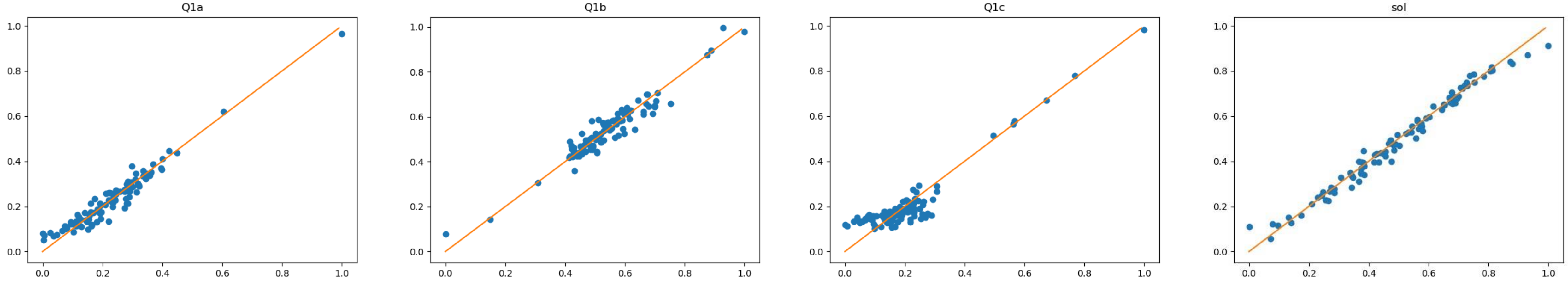
Variational Autoencoder (VAE) model

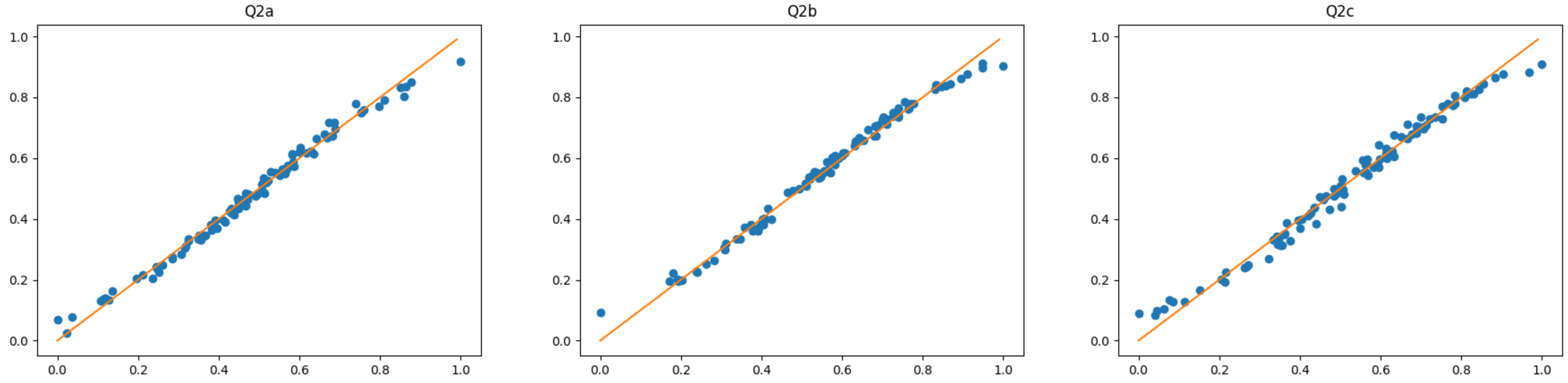
- VAE consisting of 2 fully-connected layers,
- The input layer was normalized to be 0 to 1.
- The latent variable **z** was set from -1 to 1 for all parameters using the **hyperbolic tangent function**.



Input/output reproducibility

The relationship between VAE input and output was checked for each parameter.
Reproducibility looks good there.





Loss: 0.0097 (MSE)

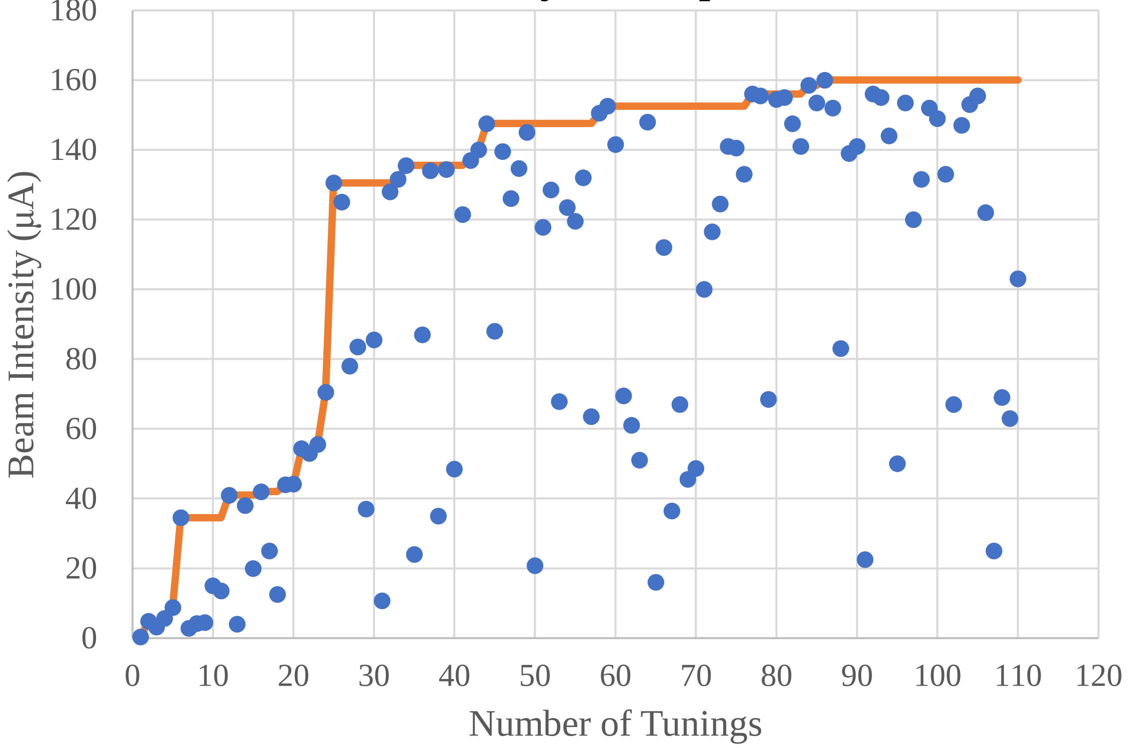
Tuning results

- The methods using VAE and Bayesian optimization were tested on a LEBT.
  - Beam: N^{4+}
  - Extraction voltage: 13.066 kV

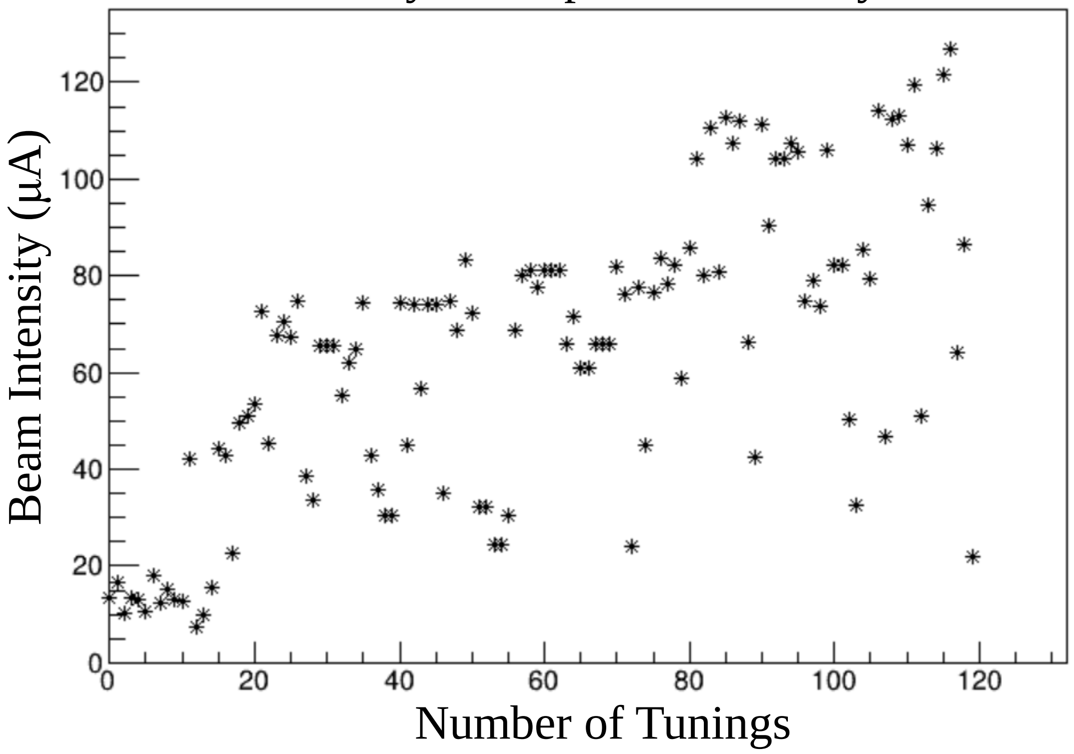
Set up by correcting the magnetic field

- This method was compared to an experiment with Bayesian optimization only.

VAE + Bayesian optimization



Bayesian optimization only



Conclusion

- A new tuning method combining VAE, AE, and Bayesian optimization is proposed.
- This method worked effectively on simulation.
- For use in actual tuning, we experimented with VAE learned by simulation.
- The VAE learned by simulation worked well in the actual beamline tuning.

Future Work

- Modify simulation conditions.
- Developing the system closer to the actual tuning, such as adding optimization conditions.