Estimation of beam parameters with the bunch-shape monitor using the machine learning

- Introduction
- Concept of the parameter estimation
- Architecture of the Neural Network
- Estimation result by the training dataset
- Prospect and summary

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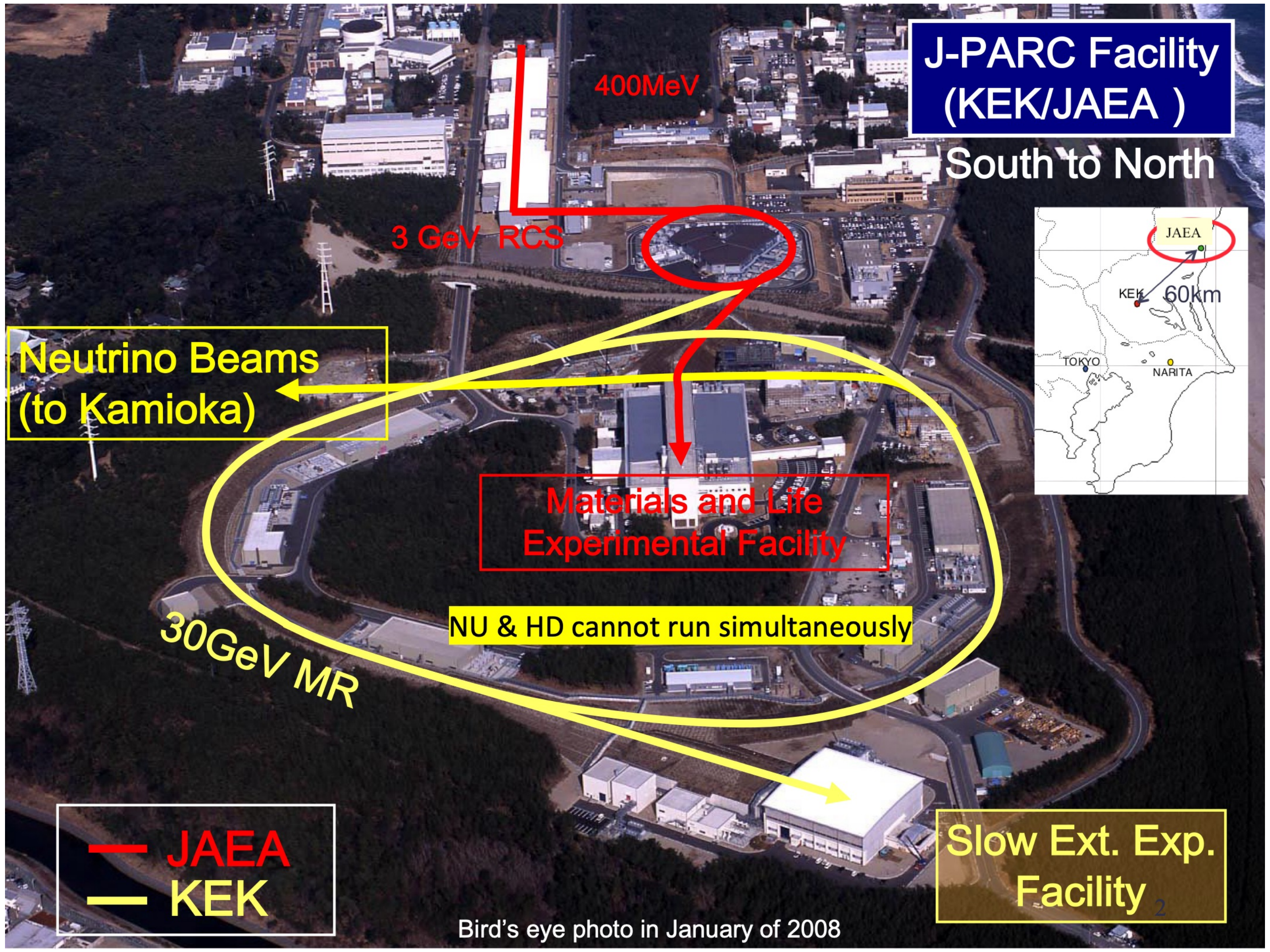
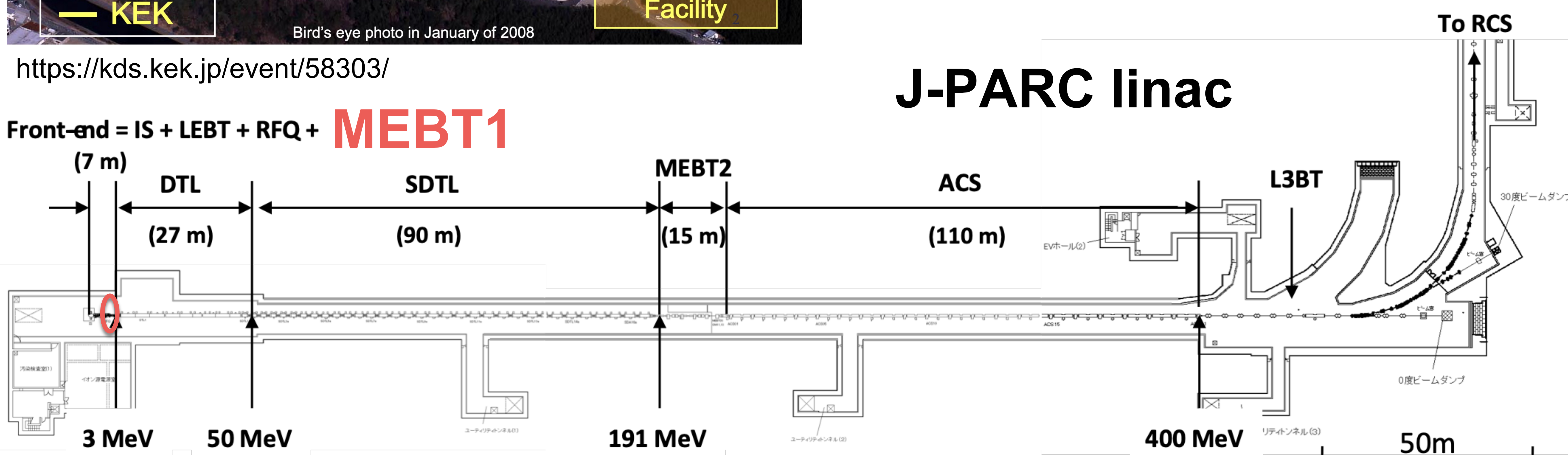
Introduction: J-PARC linac

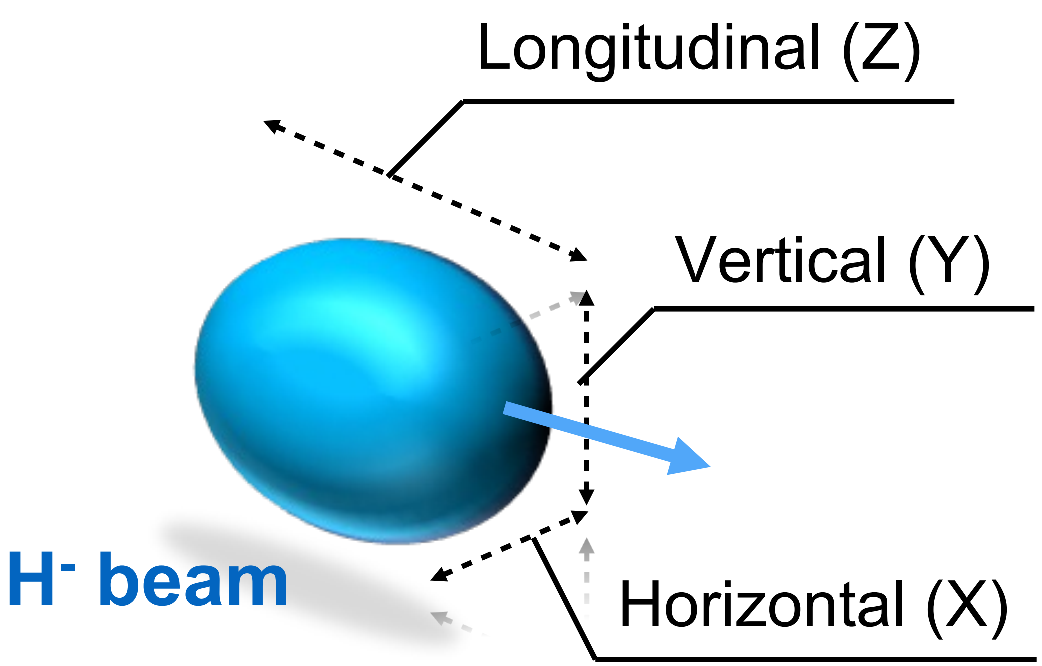


https://kds.kek.jp/event/58303/

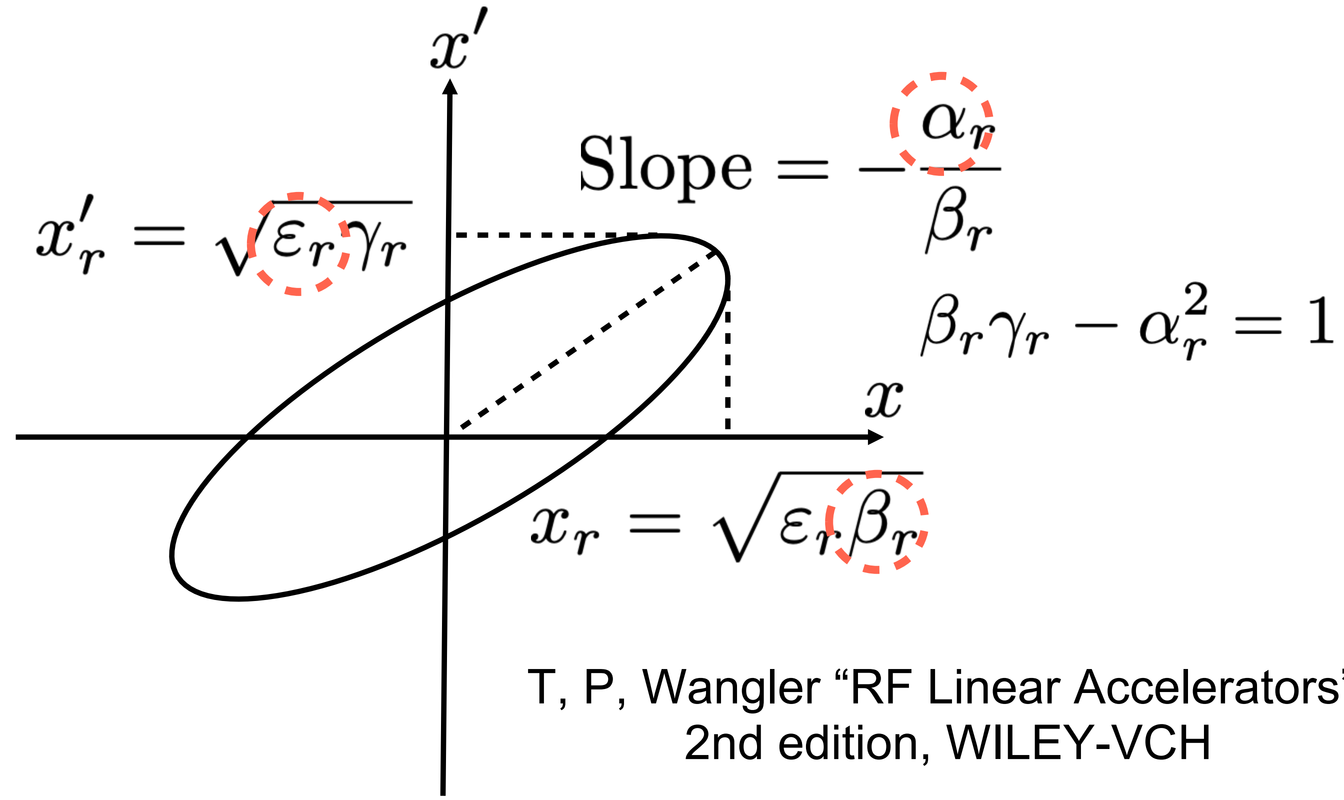
- J-PARC accelerators
- Linac : H^- ion beam is delivered to 3-GeV synchrotron
  - Peak current : 50 mA
  - Repetition : 25 Hz
  - Output energy : 400 MeV
- Beam parameters: Twiss parameters and emittance are measured in the Medium-Energy Beam Transport1 (MEBT1) to identify an initial condition of the linac.



Definition of beam parameters



Phase space distribution



T, P, Wangler “RF Linear Accelerators”
2nd edition, WILEY-VCH

RMS envelope eq. w/ space charge

$$a_x'' + k_x(s)a_x - \frac{\varepsilon_{r,x}^2}{a_x^3} - \frac{3\boxed{K_3}(1-f)}{(a_x+a_y)a_z} = 0$$

$$a_y'' + k_y(s)a_y - \frac{\varepsilon_{r,y}^2}{a_y^3} - \frac{3\boxed{K_3}(1-f)}{(a_x+a_y)a_z} = 0$$

$$a_z'' + k_z(s)a_z - \frac{\varepsilon_{r,z}^2}{a_z^3} - \frac{3\boxed{K_3}f}{a_x a_y} = 0$$

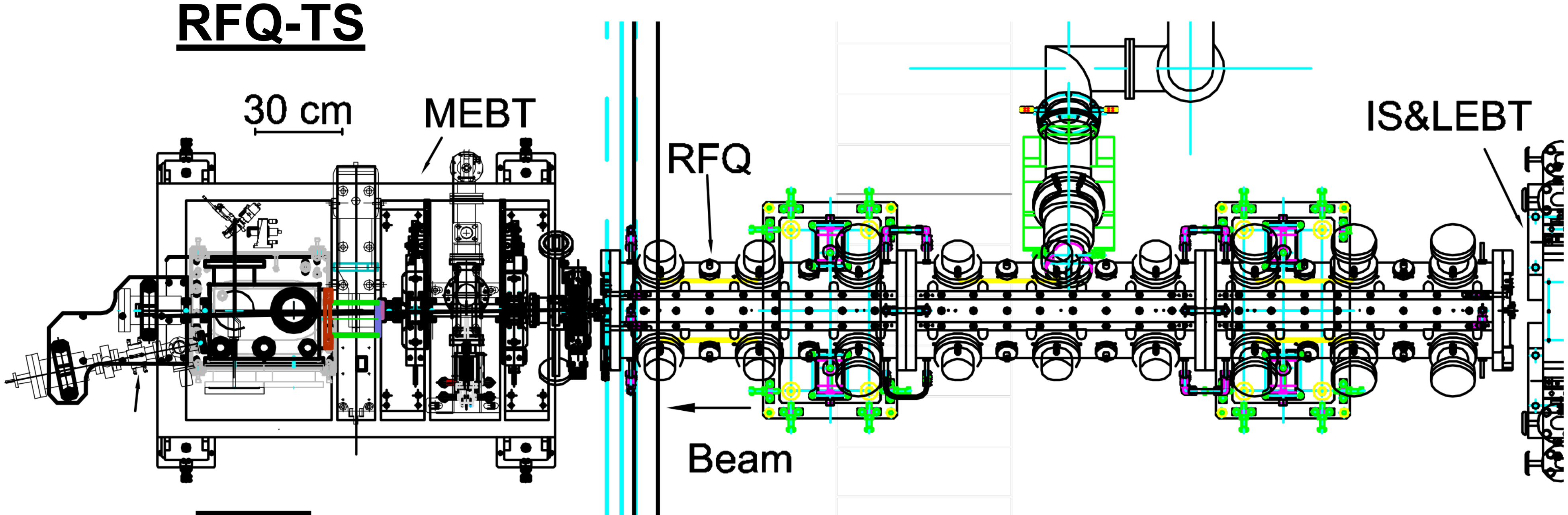
$$\text{where } K_3 = \frac{q\boxed{I}\lambda}{20\sqrt{5}\pi\varepsilon_0 m c^3 \gamma^3 \beta^2}$$

Beam parameters→(α, β, ε)

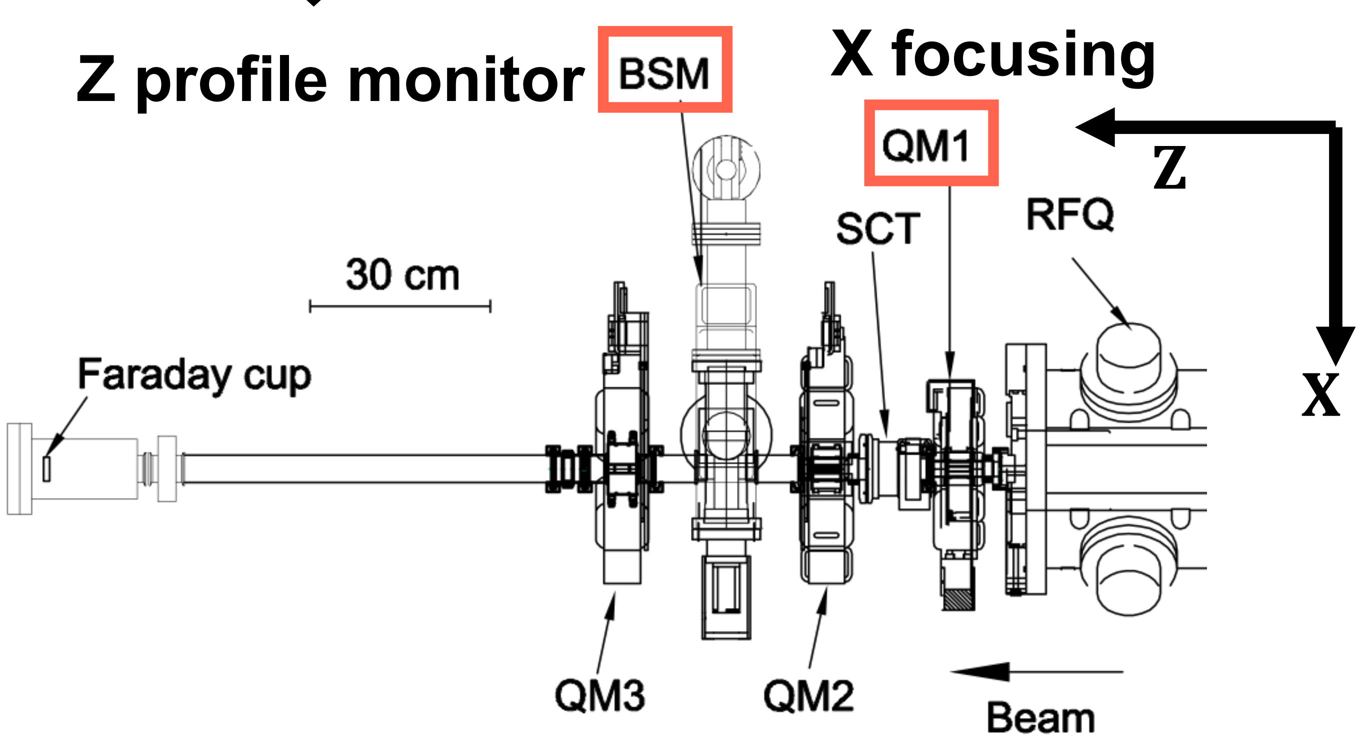
- Beam parameters in the phase space are correlated in terms of X, Y, and Z directions by the space-charge effect in the high-intensity beam.
- The parameters are evaluated with Particle-In-Cell (PIC) simulation in the J-PARC linac to consider the space-charge effect.

Experimental setup

RFQ-TS



R. Kitamura *et al.*, Proc. of IPAC'26, Deauville, France, May 2026, WEP4722, pp.2769–2772.



R. Kitamura *et al.*, PRAB **26**, 032802 (2023).

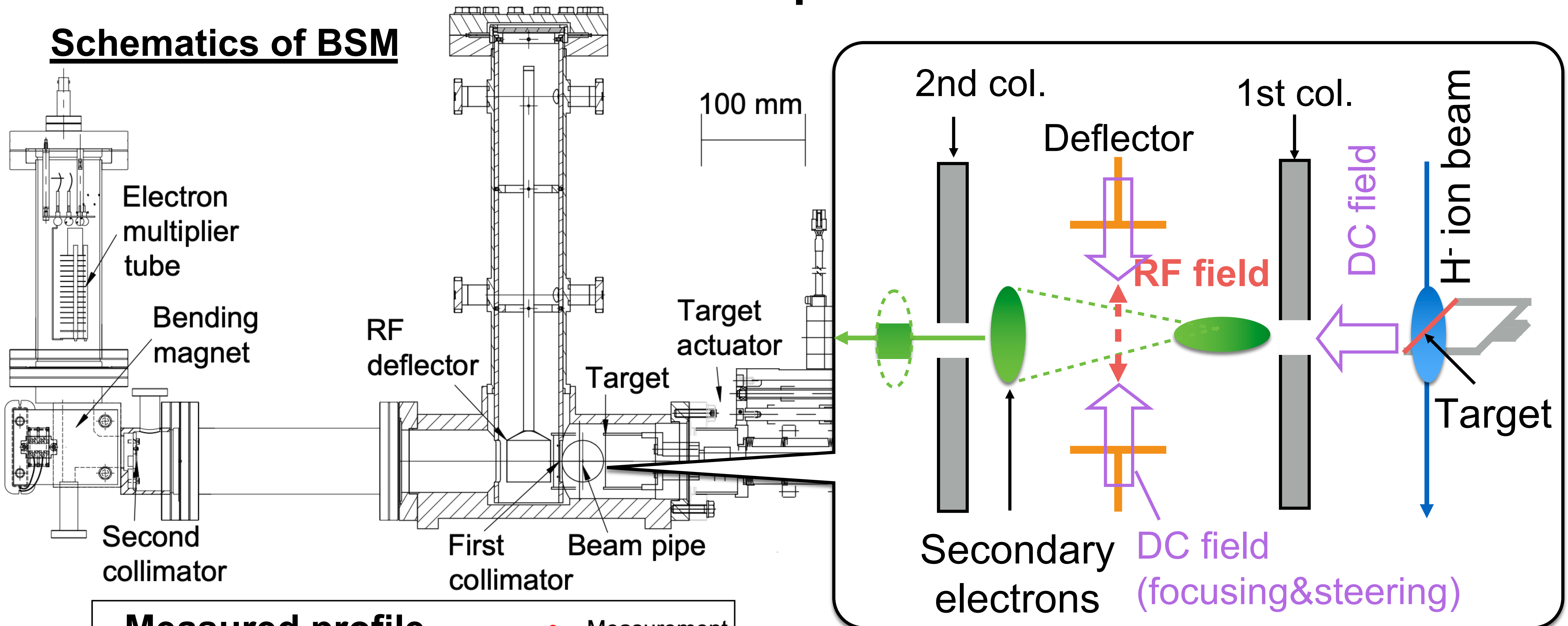
Beam condition

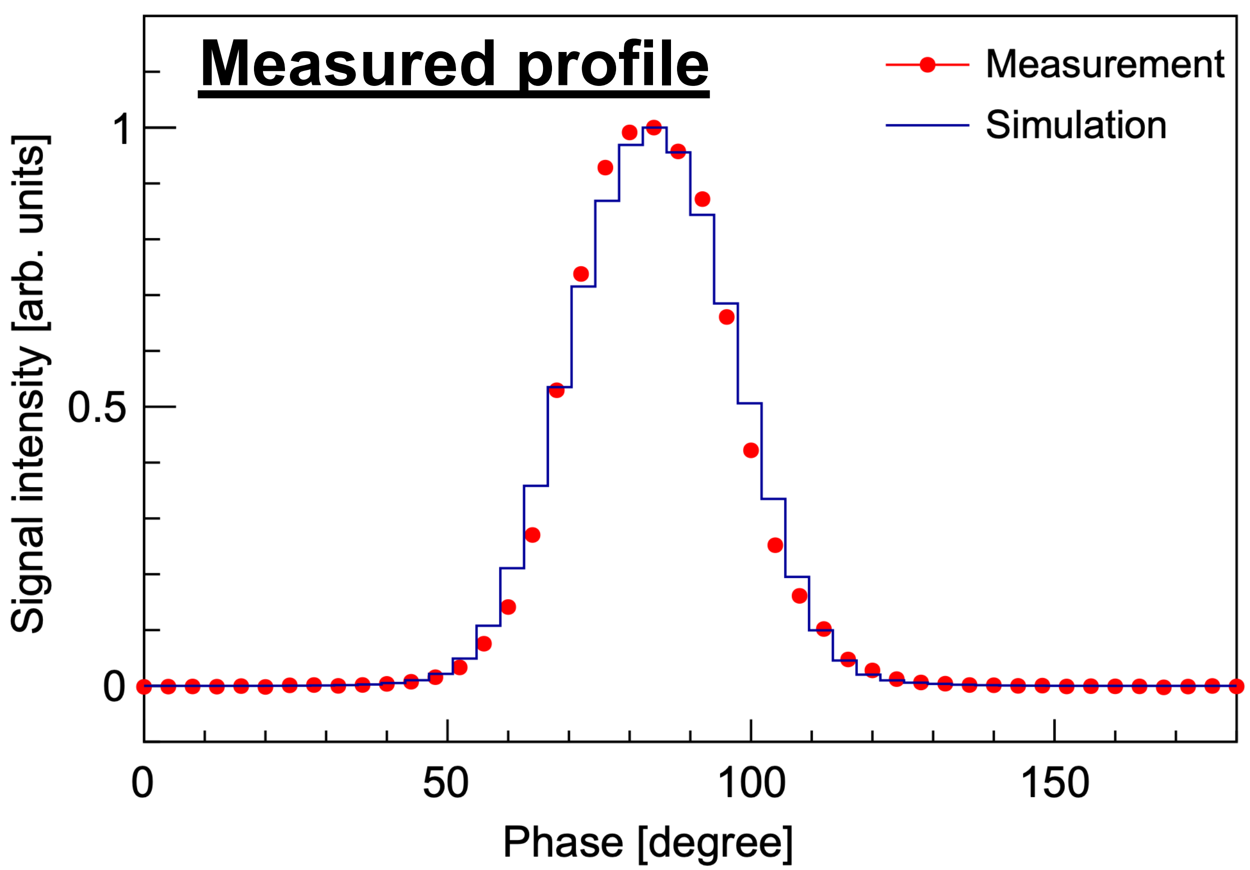
Peak current	~50 mA
Energy	3 MeV
Pulse length	50 μs
Repetition	1 Hz

- Test experiment was conducted in the Radio-Frequency Quadrupole linac Test Stand (RFQ-TS), which was a test facility to prepare the spare equipment and investigate the performance of the instrumentation.
- Although the bunch-shape monitor (BSM) was developed, there was no buncher cavity to measure longitudinal beam parameters.
- It is considered that beam parameters are estimated with XZ profiles with the BSM using ***the machine learning (ML)***.

Bunch-shape monitor

Schematics of BSM



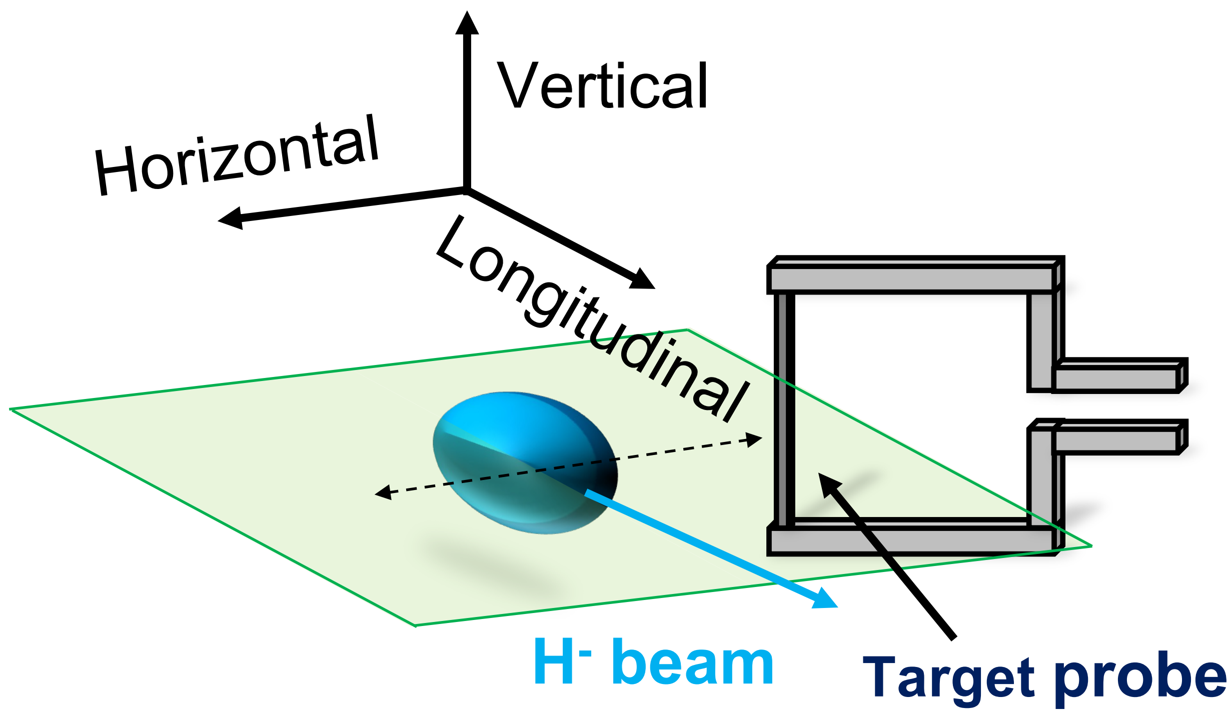


- The Bunch-Shape monitor (BSM) in the linac is a powerful tool to measure a longitudinal profile.
- The dedicated BSM was developed to measure the 3-MeV H^- ion beam using the HOPG (Highly Oriented Pyrolytic Graphite) target probe.

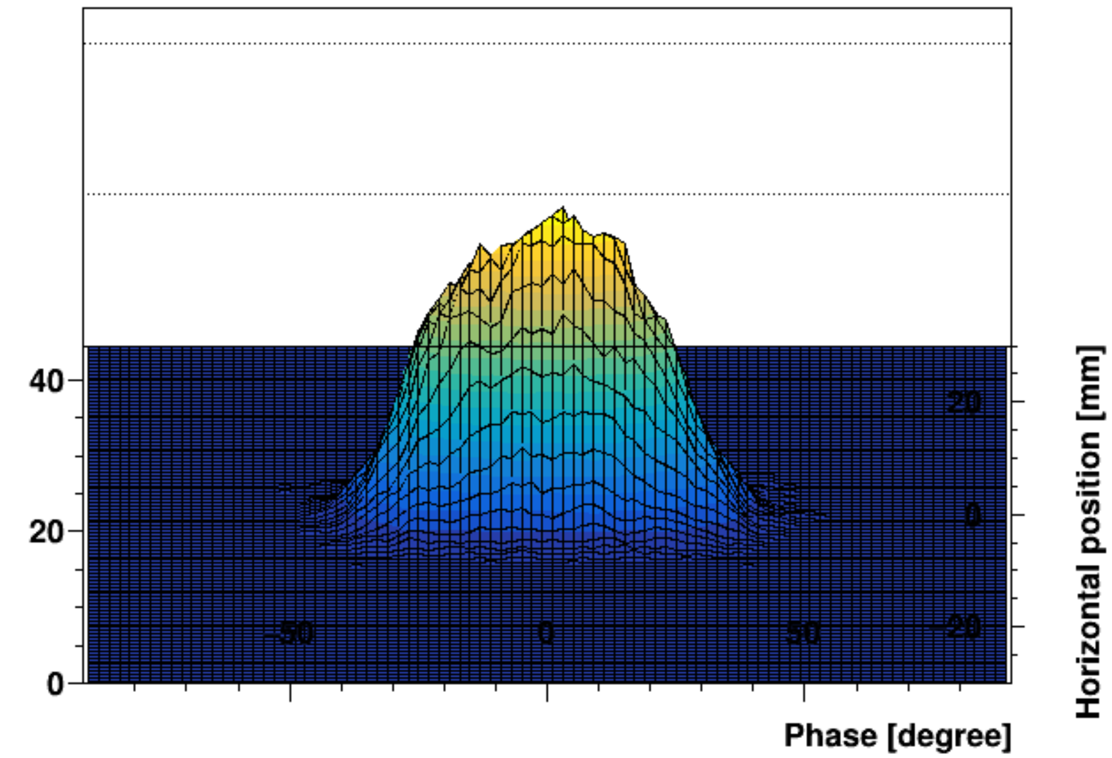
R. Kitamura *et al.*, PRAB **26**, 032802 (2023).

Concept of parameter estimation

XZ profile measurement w/ BSM



Simulated beam profile at BSM



	Resolution
X	0.3 mm
Z	0.9deg.@324MHz

Flowchart of the estimation

Space-charge effect

Beam (or simulation)

Monitor resolution

Beam parameters @RFQ exit

Profile monitor

What we want to know

Measurement data

Reverse procedure of the normal beam tracking by ML

- Input: a series of profile images under the single quadrupole scan in terms of X direction.
- Output: 9 parameters of Twiss and emittance in the X, Y, and Z directions.

ML method to estimate beam parameters

- **Normal method**

$f(a_x, k_x) \rightarrow \alpha_x,\ \beta_x,\ \varepsilon_x$

$g(a_y, k_y) \rightarrow \alpha_y,\ \beta_y,\ \varepsilon_y$

$h(a_z, k_z) \rightarrow \alpha_z,\ \beta_z,\ \varepsilon_z$

$\Rightarrow$ **6D phase space distribution** $J(x, y, z, p_x, p_y, p_z)$

※a: beam size, k: focusing factor

- **ML method**

- Training data are generated by the PIC simulation.
- Assuming the geometry of the beam line, the electromagnetic field such as focusing magnets, and the beam condition such as the peak current.

- Convolutional Neural Network is trained by the simulated beam profile images to evaluate beam parameters.

2D profiles
+1D focusing scan

$\boxed{F(x, z, k_x)}$ $\Rightarrow$ ML $\Rightarrow$

Direct

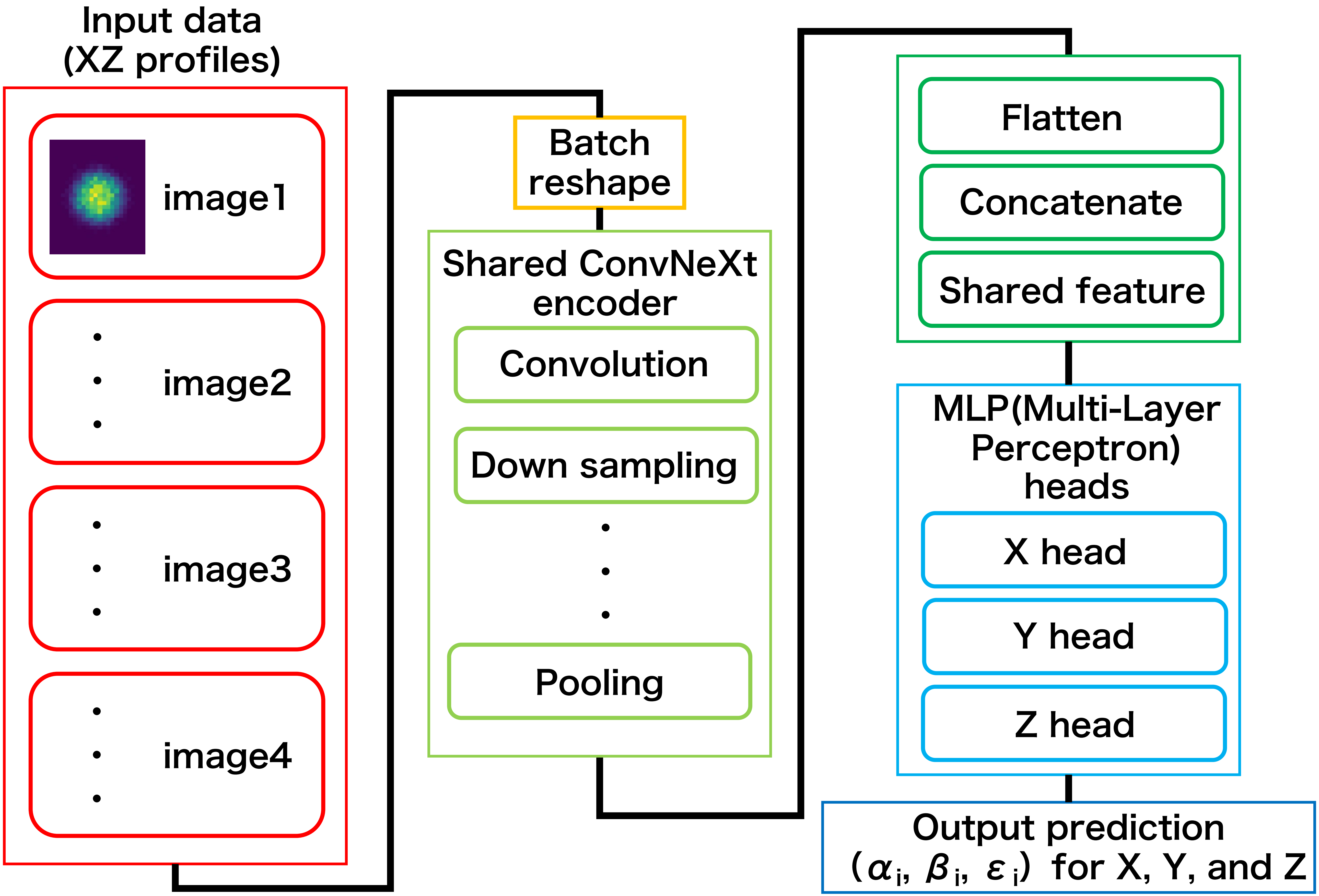
$\alpha_x,\ \beta_x,\ \varepsilon_x$

$\alpha_z,\ \beta_z,\ \varepsilon_z$

Indirect

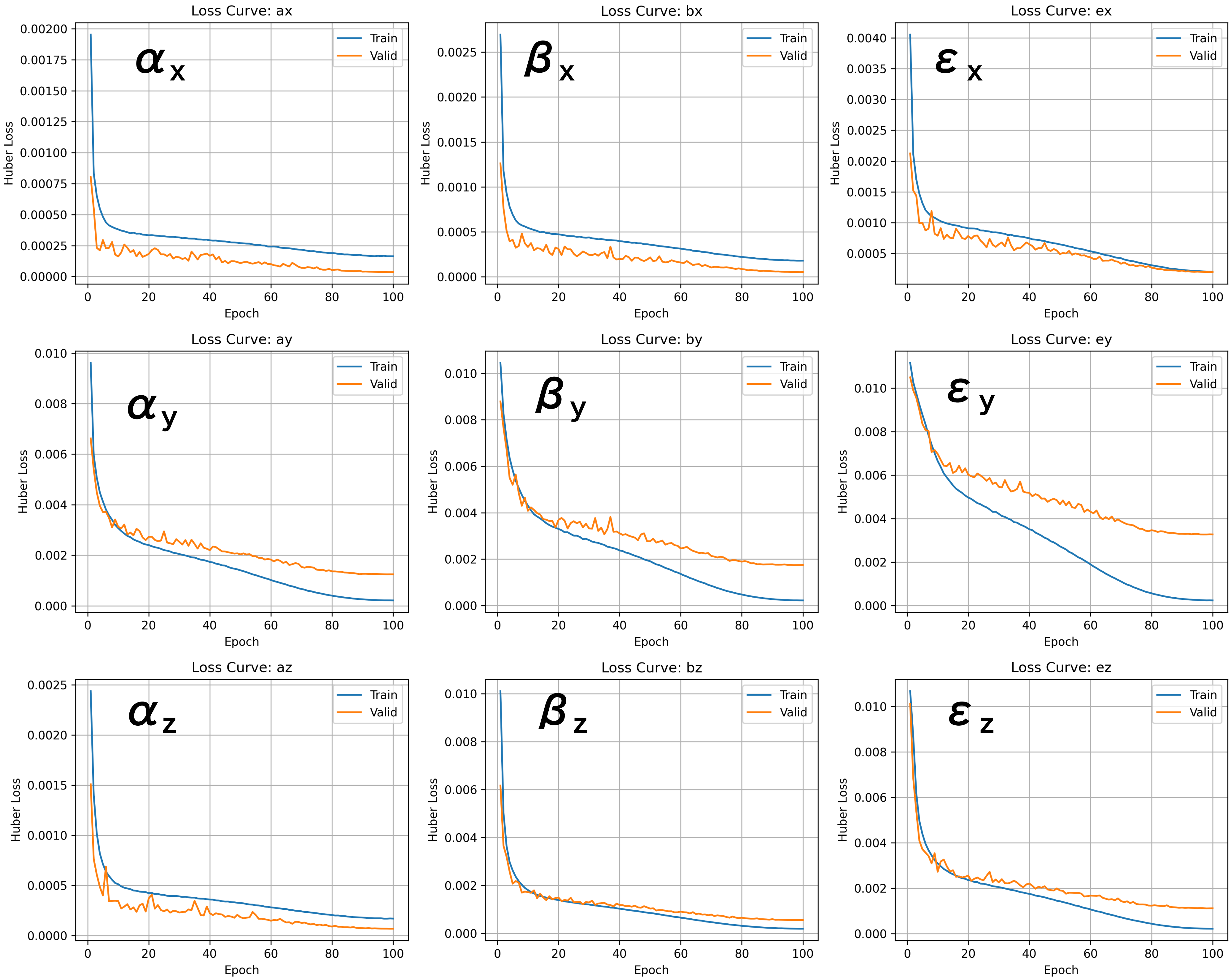
$\alpha_y,\ \beta_y,\ \varepsilon_y$

Architecture of the Neural Network



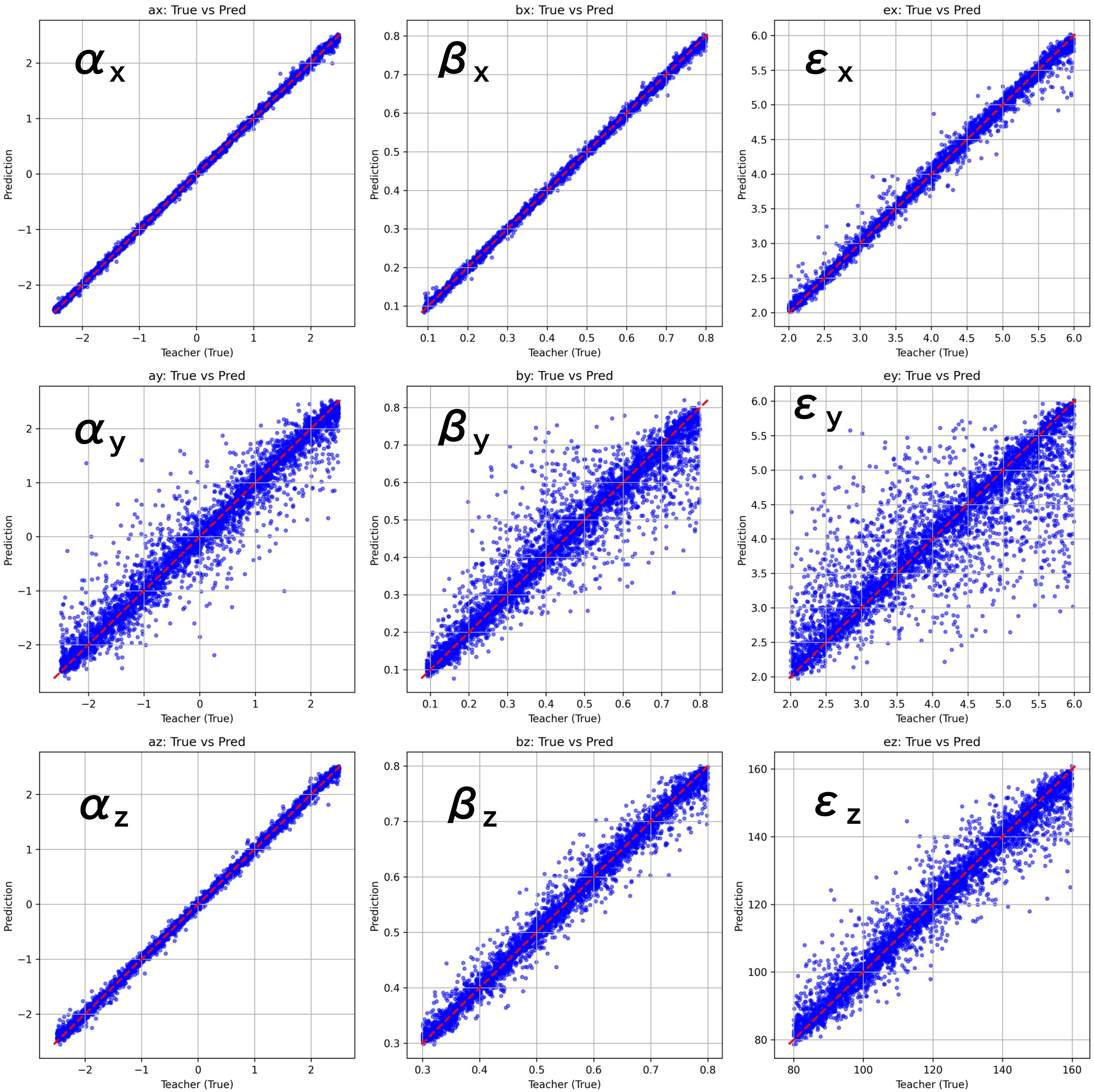
Z. Liu *et al.*, arXiv:2201.03545 (2022).

Loss curve in the training



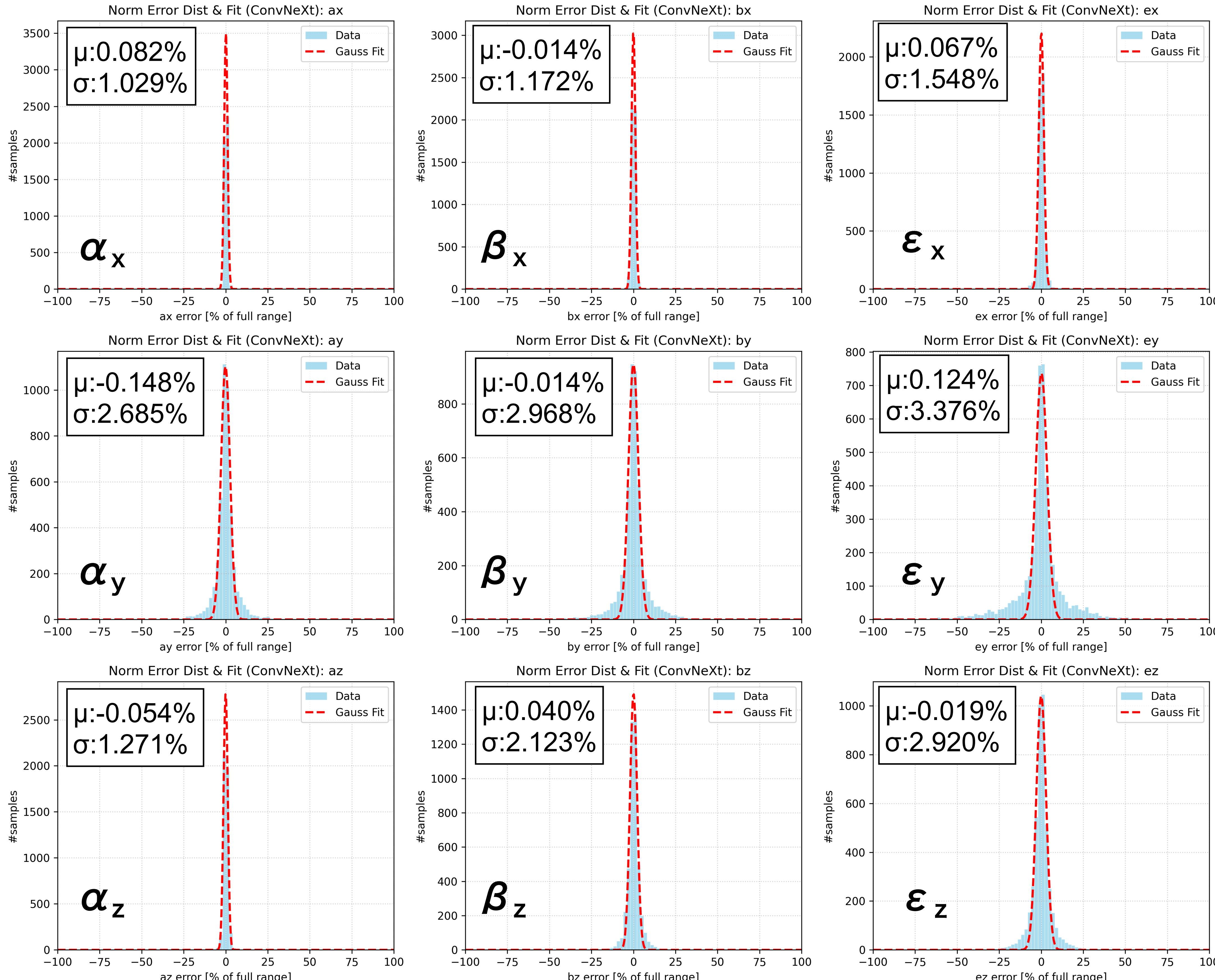
- 90k profile sets are prepared for the training of the ML, which are generated by the PIC simulation.
- Training samples are 90% for all data. The validation and the test are 5% each, respectively.
- The NN was trained well and there was no over training from the loss curve of each parameter.

Scatter plots for teacher and prediction



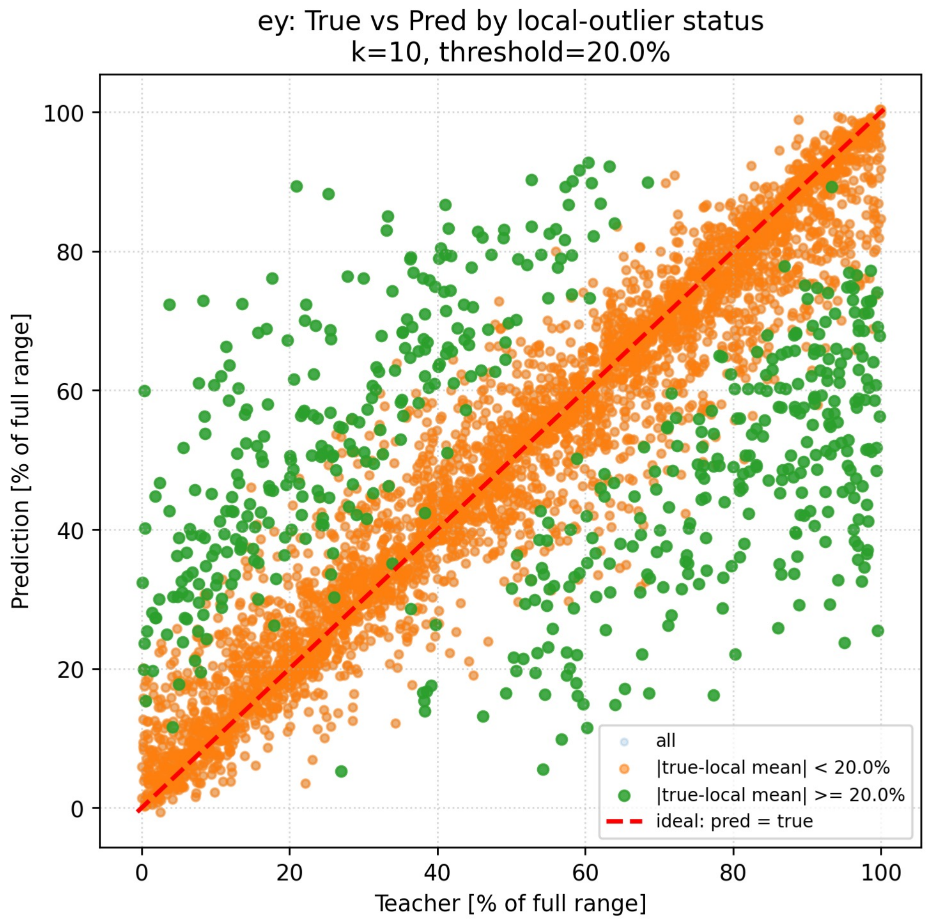
- Scatter plots for the teacher and the prediction by the test data set describes a good linear correlation as expectation.
- Although the direct measurements for the X and Z directions show the relative precise prediction, the indirect measurement for the Y direction shows the rough prediction.
- The difference about the precision of the prediction between α, β, and ε in one direction may describe the geometrical difference of the beam profile as the slice in the phase space.

Estimation result by the training dataset



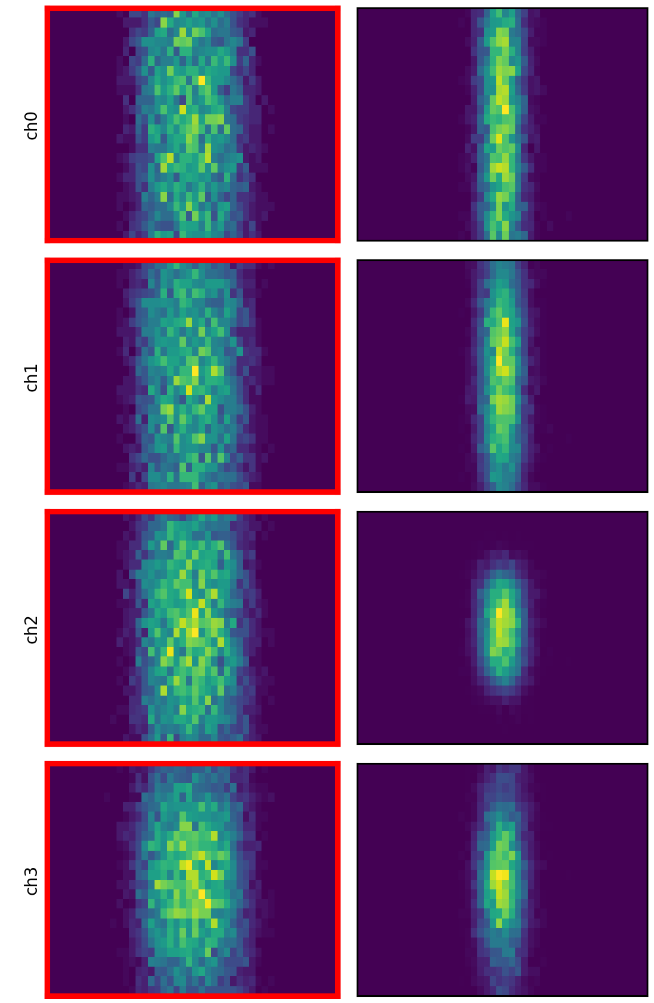
- Relative error histograms show the precision of the trained model.
- The mean and the sigma fitted by the gaussian function describe the bias and the precision, which show the good estimation for each direction.
- The developed ML model can well applicable to the real profile data.

Consideration of tail samples



$$S_{local} = |y_{true} - \bar{y}_{NN}|$$

Query



Nearest neighbor

ε_y True:3.7 Prediction:72.4 T:89.8 P:79.4

- Since the prediction for ε_y is slightly worse than others, the cause is investigated for its outliers.
- While "local outliers" are defined as S_{local}≥20%, it is expected that the normalized norm for the feature value in terms of the local outliers becomes minimum.
- Although the neighbor samples are close to a certain query in the learned feature space, their beam profiles looks different each other.
- Next: Improving the feature representation and increasing the amount of the training data.

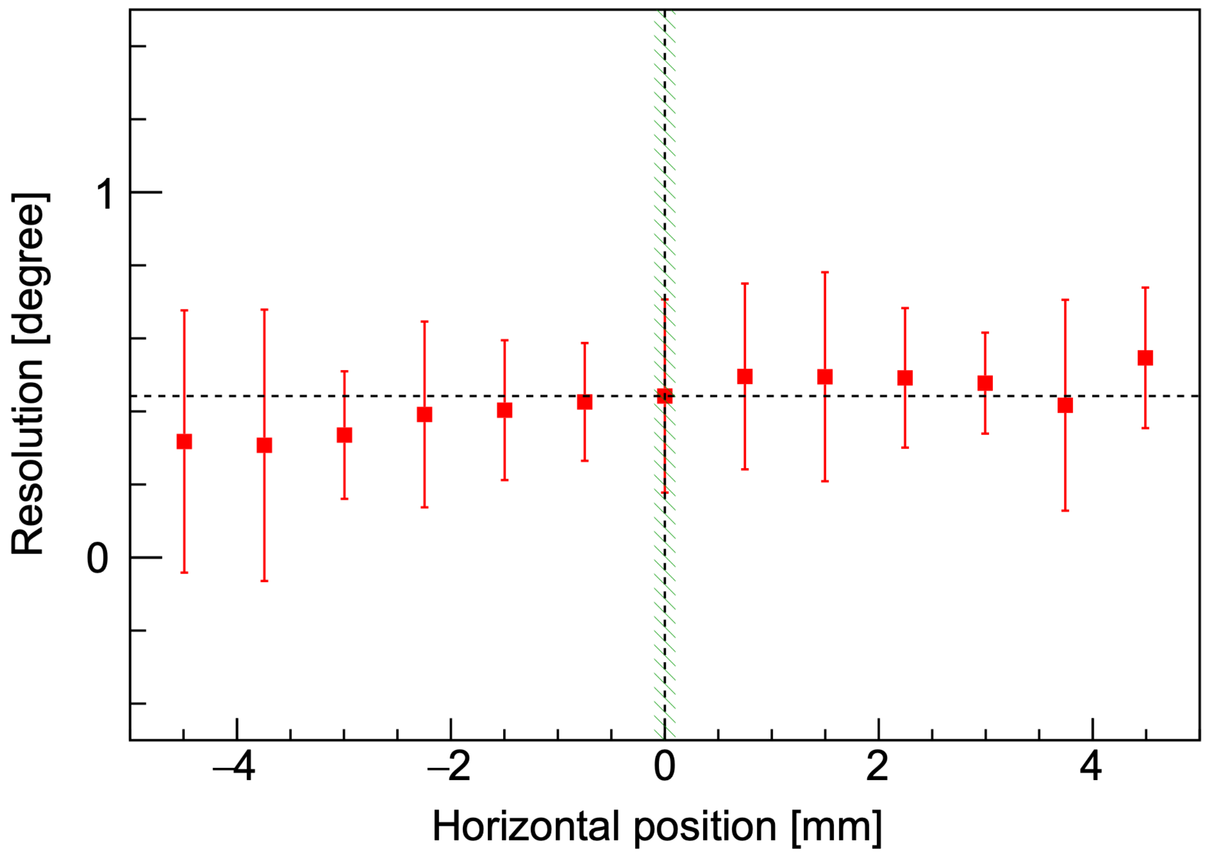
Prospect and summary

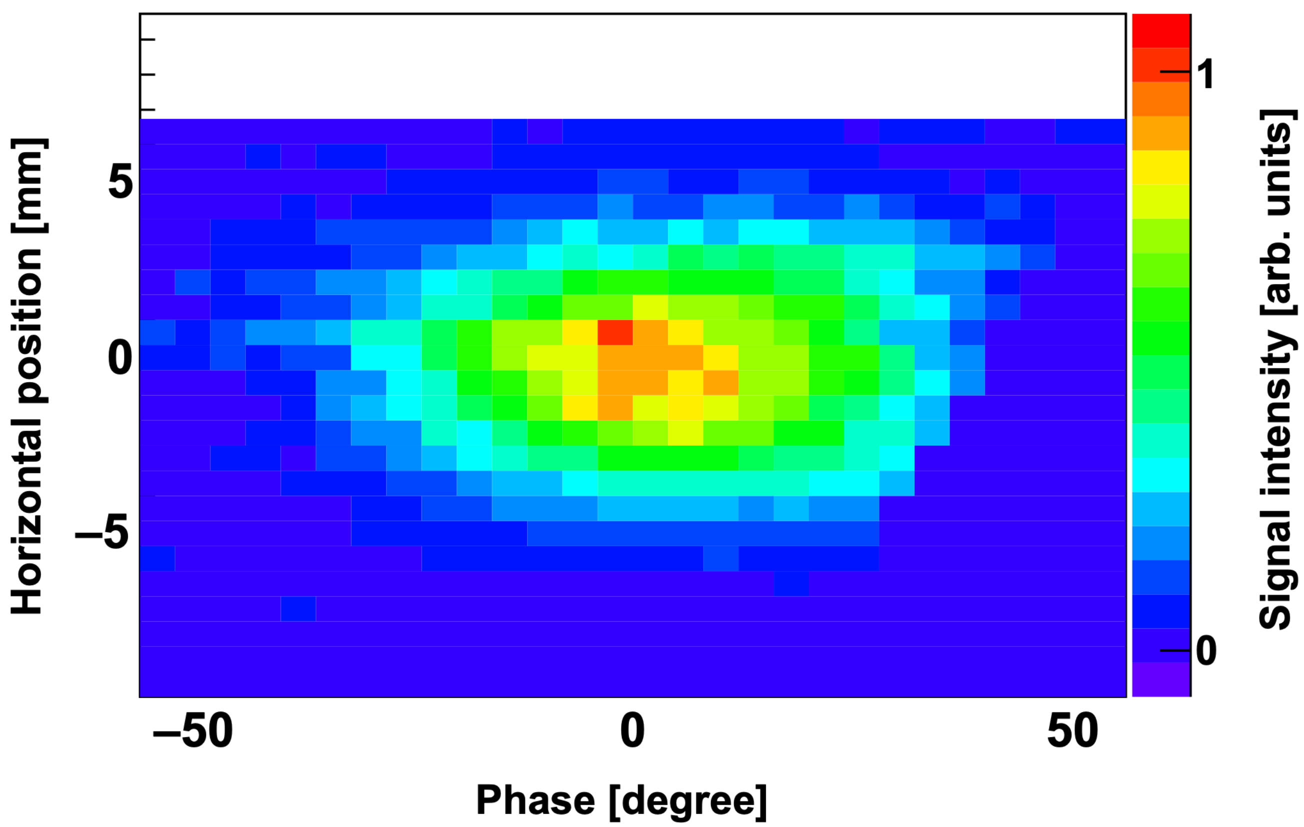
- New method is being developed to evaluate beam parameters using the machine learning for the beam measurement in the J-PARC linac.
- All Twiss parameters and emittance in the X, Y, and Z direction can be evaluated from the XZ profile images from the BSM.
- Since the current framework shows a good prediction so far, the real profile data is being introduced to measure the beam parameters.

- ***Acknowledgements***
- We would like to deeply thank the J-PARC linac group for their significant support.
- This work was supported by JSPS KAKENHI Grant Number JP25K00160.

BACK UP

Resolution depending on the target position

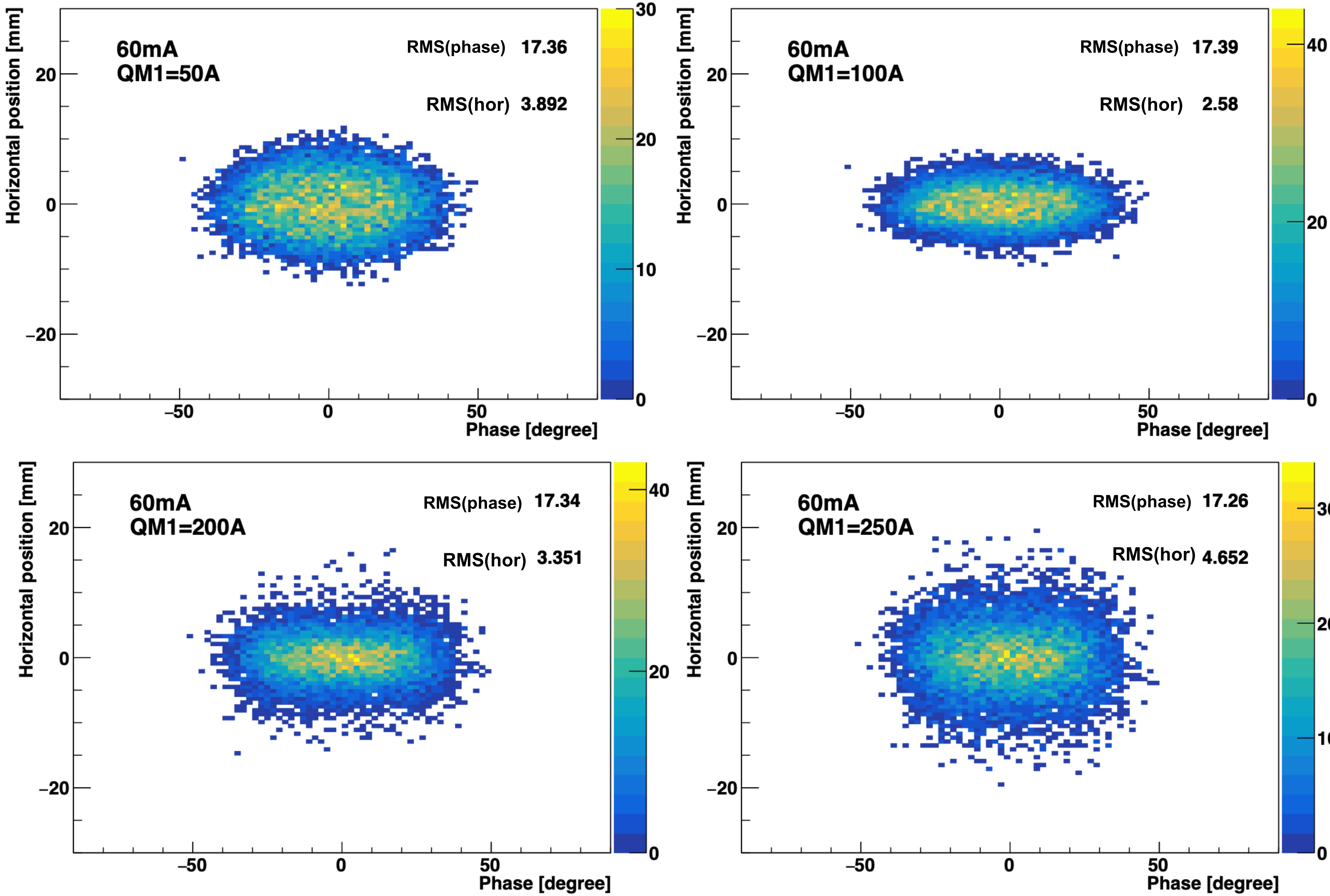




R. Kitamura *et al.*, PRAB **26**, 032802 (2023).

- The resolution depending on the target position is considered.
- The improper focus setting of the lens voltage results in the broadening of the longitudinal bunch shape.
- However, the small difference in the focus setting is not so serious in the RFQ-TS.

Simulated XZ profiles



- Initial phase-space distributions are assumed as 6-d gaussian function.