

AI Research in Accelerators in Japan

Global Trends and Cutting-Edge Initiatives Towards
Intelligent & Autonomous Accelerators

2026/10/5 M. Iwasaki

Osaka Metropolitan U., Osaka U. RCNP



Motivation & Outline

Motivation

- **Complexity:**

Modern accelerators require tuning thousands of coupled parameters under complex physical constraints.

- **Limit of Human Capability:**

Conventional expert-based manual tuning is reaching its operational limits.

- **Paradigm Shift:**

AI/ML provides a transformative solution for real-time control, predictive modeling, and beam optimization.

Talk Outline

1. **Global Trends in Accelerator AI/ML**
(Insights from MaLAPA 2026)
2. **Japanese Major Initiatives**
(SACLA/SPRING-8, KEK, J-PARC, RIKEN RIBF)
3. **Deep Dive: OMU & UO RCNP Project**
(GNN, XAI, and KEK Linac / SACLA Applications)
4. **Summary & Future Outlook**

Global Trends (Insights from MaLAPA 2026)

MaLAPA — Machine Learning Applications for Particle Accelerators

An international ICFA-sponsored community connecting researchers to advance AI/ML deployment across particle accelerator facilities worldwide.

Global Mission

Fostering international collaboration between accelerator physicists, computer scientists, and facility operators to accelerate scientific discoveries

Core FOCUS Areas

Bayesian optimization, surrogate modeling, digital twins, phase-space reconstruction, and real-time failure prognosis.

Workshop History

Hosted worldwide: SLAC ('18), PSI ('19), BNL ('22), PAL ('24), CERN ('25), **SPRING-8 ('26)**, and LBNL ('27).



MaLAPA 2026

Global Trends (Insights from MaLAPA 2026)



6th Workshop on Machine Learning Applications for Particle Accelerators

Apr 21 – 24, 2026
Acrea Himeji
Asia/Tokyo timezone

- Welcome
- Important Dates
- Venue
- Scientific Program
- Call for Abstracts
- Timetable
- Contribution List
- Fees & Payment
- Registration
- Accommodation
- Code of Conduct
- Contact

Welcome



~100 or more oral/poster presentations there

86. [Intelligent scientific facility operations via active learning algorithms: AI/ML developments at SLAC MeV-UED](#)
Fuhao Ji (SLAC National Accelerator Laboratory)
4/22/26, 9:50 AM

Optimisation and Control oral Optimisation and Control

SLAC MeV-UED is part of LCLS scientific user facility and has enabled unprecedented opportunities in the studies of ultrafast structural dynamics in a variety of gas, liquid and solid-state systems. To remain at the scientific and technical forefront, continuing enhancements to the facility and operations are needed. In this talk, we will describe developments

96. [Meta Learning assisted Bayesian Optimisation for Accelerator Tuning](#)
Xingchi Liu (Science and Technology Facilities Council)
4/22/26, 10:10 AM

Optimisation and Control oral Optimisation and Control

Bayesian optimisation (BO) has become a well-established approach for efficient particle-accelerator tuning and optimisation. However, BO with a standard Gaussian Process (GP) prior can require a substantial number of measurements in cold-start settings, which limits its practical value in operational environments with tight measurement

93. [End-to-End Emittance Optimization at EuXFEL: Differentiable-Model-Based Laser Pulse Shaping](#)
Denis Ilia (DESY)
4/22/26, 11:00 AM

Optimisation and Control oral Optimisation and Control

Free-electron laser (FEL) performance critically depends on electron-beam emittance. At the European XFEL (EuXFEL), stringent emittance requirements are essential for accessing higher photon energies and advanced operational modes such as high-duty-cycle running. Achieving such beam quality requires solving a nonlinear optimization problem spanning

135. [SPRING-8/SACLA](#)
Eito Iwai (SPRING-8)
4/22/26, 11:20 AM
Others (AI for facility de...)

98. [AI for Particle Accelerators: French and European Efforts](#)
Adnan GHRIBI (CNRS - GANIL)
4/22/26, 11:40 AM

Others (AI for facility de... oral Others (AI for facility de...)

ARTIFACT (ARTificial Intelligence For Accelerators, user Communities and associated Technologies) is the European open-science network coordinating a concerted strategy for AI across particle accelerator research infrastructures. ARTIFACT has assembled 40+ partners across 14 countries around a FAIR-by-design federated ecosystem

Global Trends (Insights from MaLAPA 2026)

Key Paradigm Shifts in Worldwide Accelerator AI/ML

From Offline Analysis to Closed-Loop Control

Real-time online optimization directly interfacing with accelerator hardware.

4 Main Pillars of Current Research:

- **Autonomous Tuning & Multi-Objective Optimization:**

Bayesian Optimization (BO) and Reinforcement Learning (RL) for acc. control.

- **Surrogate Modeling & Digital Twins:**

Ultra-fast neural network surrogates enabling real-time simulation and predictive control.

- **Anomaly Detection & Trip Prediction:**

Early interlock detection in ACC system to minimize facility downtime.

- **High-Dimensional AI & Explainability:**

Overcoming huge parameter spaces using DR / NN / XAI.

AI/ML in Acc. Physics vs Pure Science

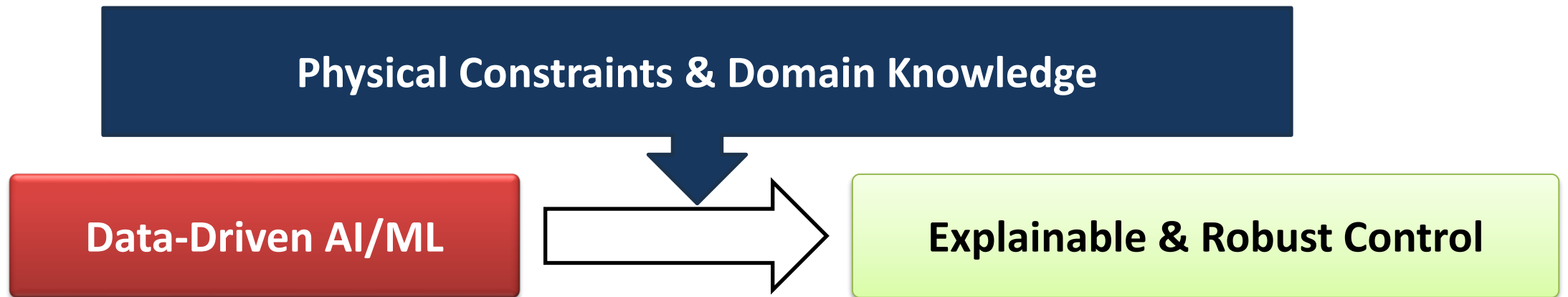
Unique Advantages of Accelerator AI Applications

- **Clear Operational Goals:**

Unlike pure physics search where targets can be ambiguous, accelerators have clear metrics (beam energy, intensity, transmission rate, stability, beam loss, ..).

- **Addressing the "Black-Box" Problem:**

Pure black-box models are insufficient for accelerator control; physics-informed AI and XAI are essential to uncover underlying beam dynamics.



Japanese Initiatives Across Major Facilities

Nationwide R&D Ecosystem for Accelerator AI

Application Purpose	Representative Methods	Major Facilities / Key R&D
Auto-tuning	Bayesian Optimization	SACLA (X-ray intensity optimization & tuning time reduction) RIBF (Optimization of the beam transport system) SuperKEKB (Automated tuning of orbits and chromaticities)
Fast Prediction / Surrogate Modeling	Deep Neural Networks	J-PARC (Real-time prediction of beam loss and distribution including space-charge effects) SACLA, KEK Linac
Autonomous Operation & Commissioning	Digital Twin, Reinforcement Learning	NanoTerasu (Accelerated commissioning & virtual diagnostics)
Accelerated Data Analysis	CNN, Phase Retrieval	SACLA / NanoTerasu (Image screening & ultra-high-resolution analysis)

Japanese ML forums: 加速器機械学習フォーラム

加速器への機械学習に関して情報共有 (Mattermost, 研究会) を行っています

Sharing information on machine learning applications for particle accelerators (via Mattermost and Workshops).



WS will be held on 2027 Nov @ Hiroshima



加速器・ビーム物理の機械学習ワークショップ 2026

Nov 16-17, 2026
広島大学東広島キャンパス
Asia/Tokyo timezone

Enter your search term

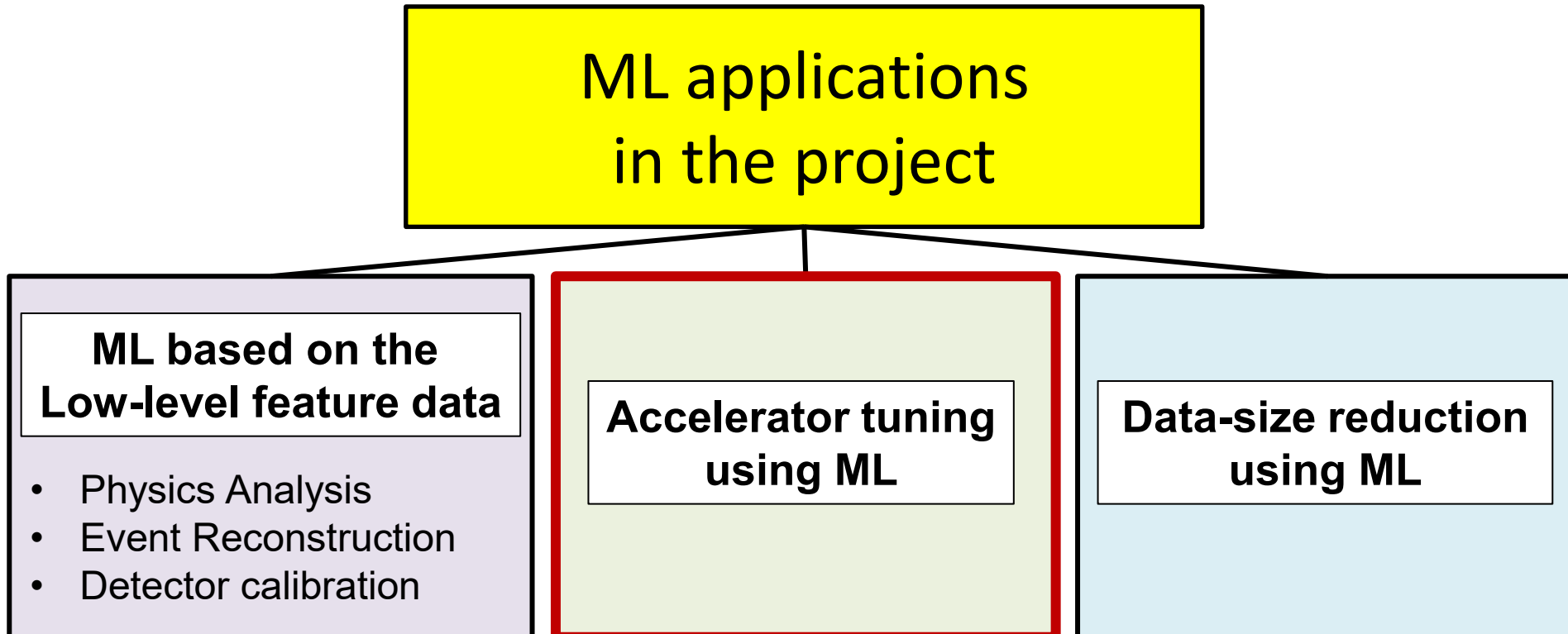


Deep Drive : OMU & UO RCNP Project

Since 2018, we form a group to proceed

“Application of DL for Accelerator Experiments”

→ As RCNP project / D3C(IDS) project



Deep Drive : OMU & UO RCNP Project

Initiative: DL Application Group for Accelerator Experiments.

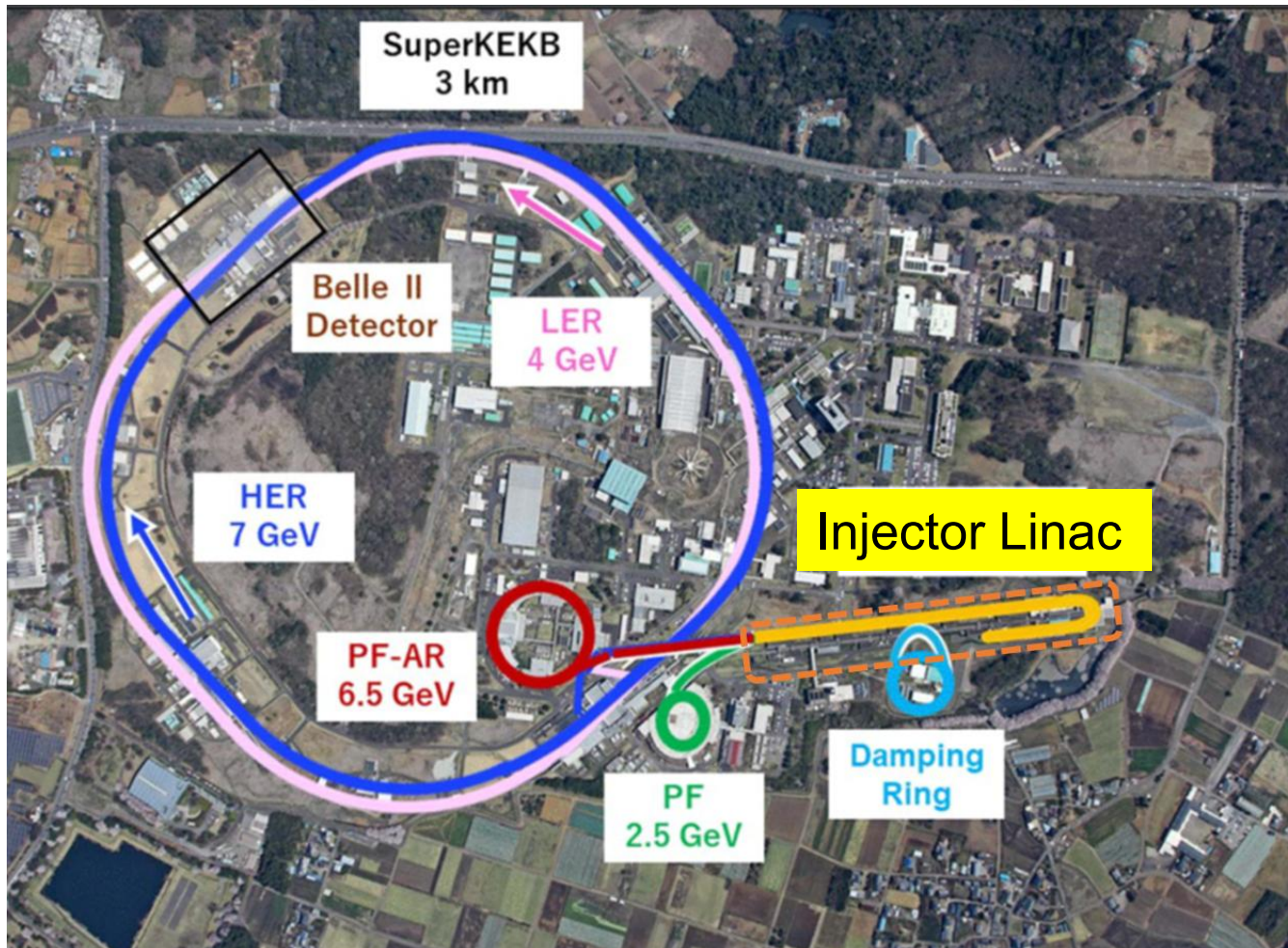
Target Facility: KEK Injector Linac, and SPring-8/ SACLA

Key Focus Areas:

1. Acc. monitoring based on Dimensionality Reduction
2. Beam transmittance (Q_{ratio}) / Beam loss / Pulse energy prediction from high-dimensional acc. data. (1st step of the Surrogate Modeling)
3. Overcoming overfitting in large-scale accelerators using Graph Neural Networks (GNNs).
4. Physical interpretation of machine parameters using Explainable AI (XAI / SHAP).
5. Continual learning for dynamic model construction

KEK Injector Linac Operation Tuning using ML

OMU, KEK, UOsaka RCNP/D3

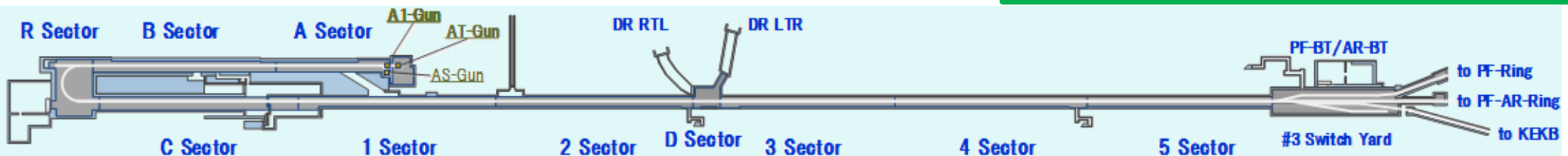


We have developed the KEK Injector Linac Operation Tuning using ML to get

- **Higher injection efficiency** (SuperKEKB, EBES)
- **Lower Beam loss** (EBES)

We use the Linac operation data (Accumulated 2018 Nov. -)

100 Beam Position Monitors (BPM)
200 Steering Magnets, 60 RF monitors



Linac Operation Tuning using ML

Problems on the operation tuning

1. **Operation system becomes much complicated**
due to the large number of the control points $O(\sim 1000)$

→ Visualization of the accelerator status

by **Dimensionality Reduction**

to model and monitor the accelerator status

2. **Accelerator condition (environment) vary**

due to ground motion, tidal force, temperature, etc.

Then the operation tuning is continuously done by operators.

→ Operation tuning based on Reinforcement ML

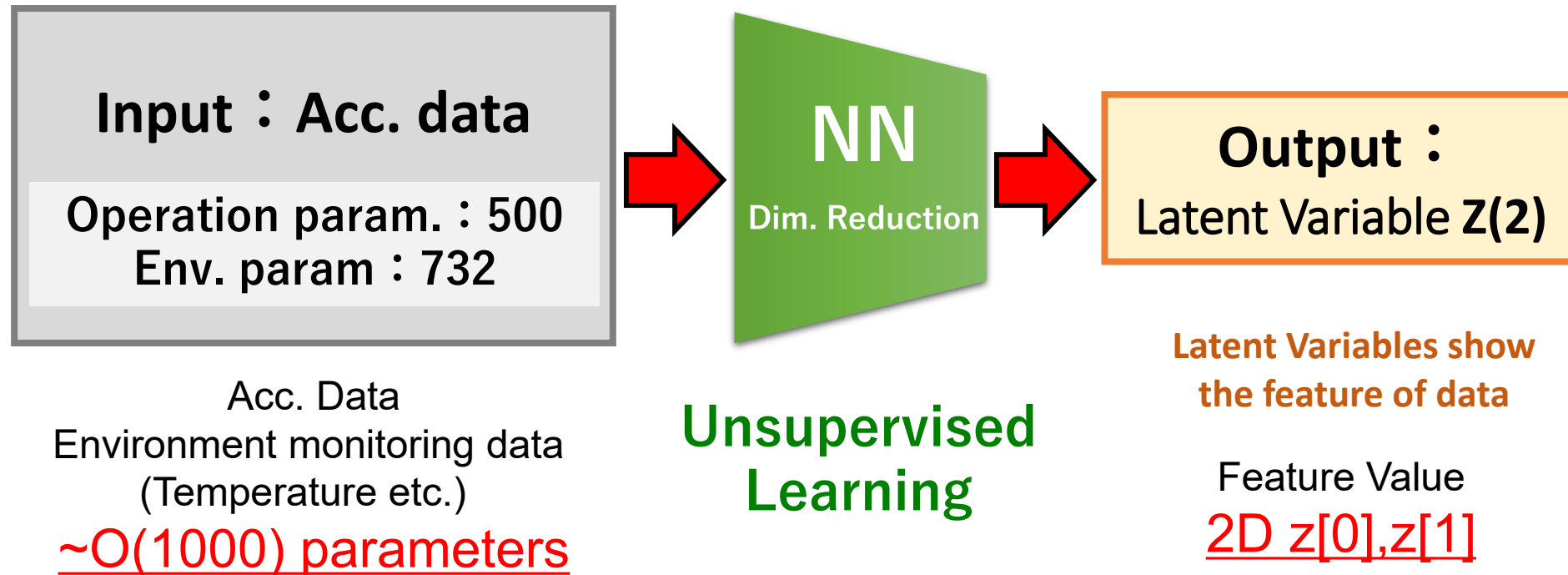
to continuously optimize the parameters

to maximize the injection efficiency

1. Acc. Monitoring based on Dimensionality reduction

To visualize the acc. Status,
we use Dimensionality Reduction
based on the unsupervised learning

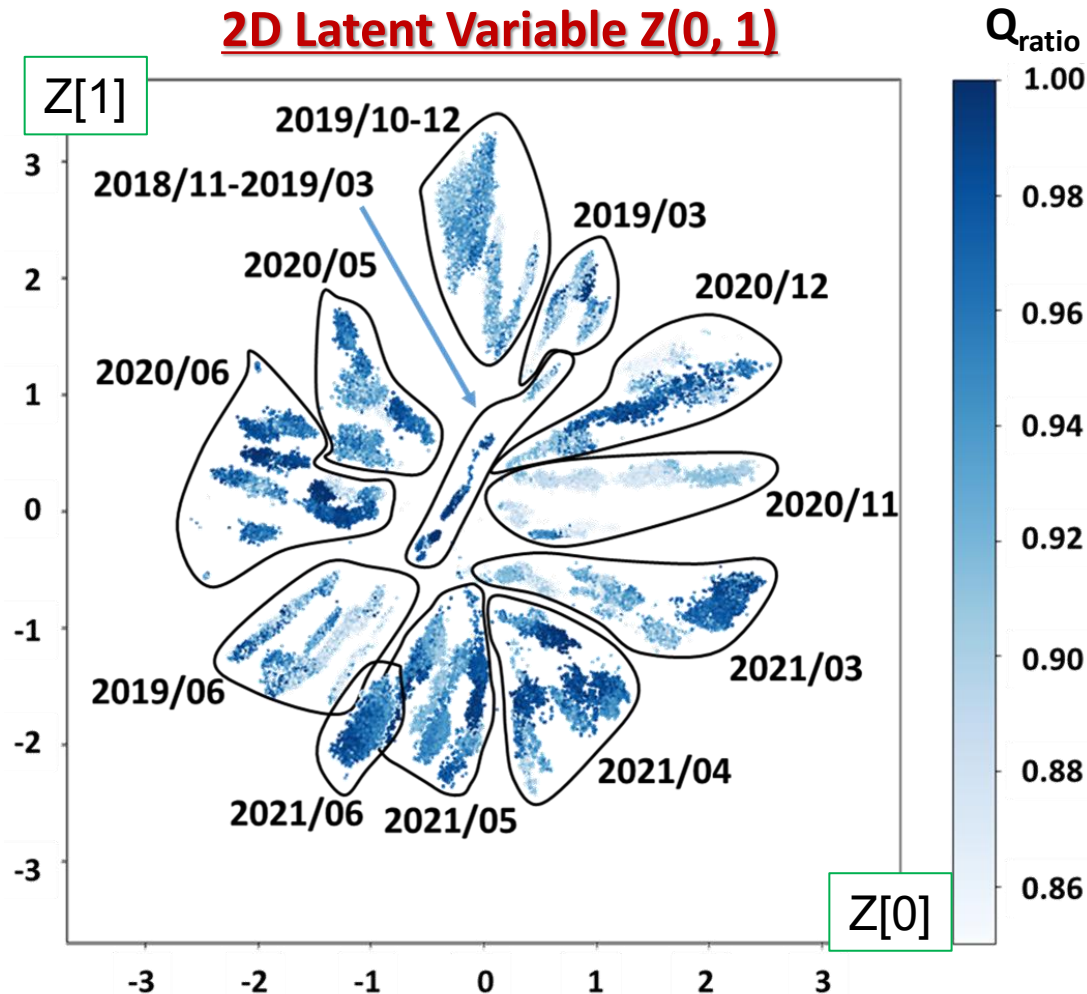
NN (VAE, Variational Auto Encoder)



1. Acc. Monitoring based on Dimensionality reduction

We did dimensionality reduction
1295 accelerator parameters $\rightarrow$ 2 parameter Latent Variable

A.Hisano (Osaka-City U.)



**Visualize the accelerator status with
2 parameters**

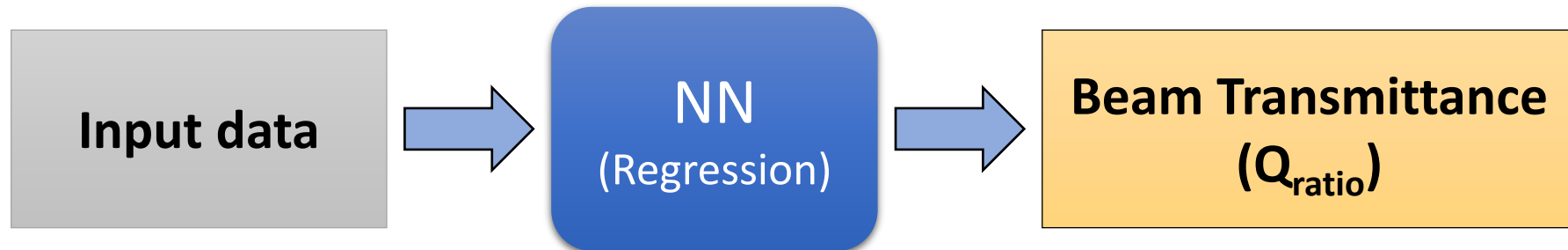
**In short term (~ 1 month)
acc. status does not drastically
change**

**In long term (> 6 month)
acc. parameters vary
over a wide range**

2. Beam Transmittance prediction using DNN

KEK, Osaka-City U., Osaka U. IDS, RCNP

We use DNN regression to predict the beam transmittance from acc. parameters.
The DNN is trained with the past acc. operation data.



Accelerator Operation parameters /
Environment monitoring data
(Temperature etc.)

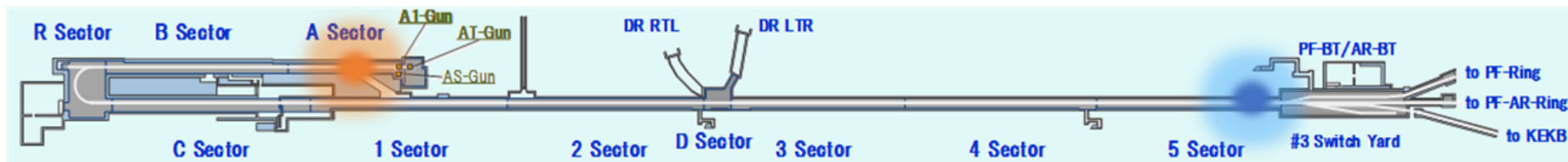
~O(1000) Parameters

Hidden Layers : 4
Optimizer: Adam
Activation Function: Relu

We use the Linac operation
data accumulated in
2018 Nov. - 2021 June

Beam transmittance

$$Q_{ratio} = \frac{\text{Charge of the Linac downstream BPM(SP_58_0)}}{\text{Charge of the Linac upstream BPM(SP_A1_M)}}$$



2. Beam Transmittance prediction using DNN

KEK, Osaka-City U., Osaka U. IDS, RCNP

Result : 1

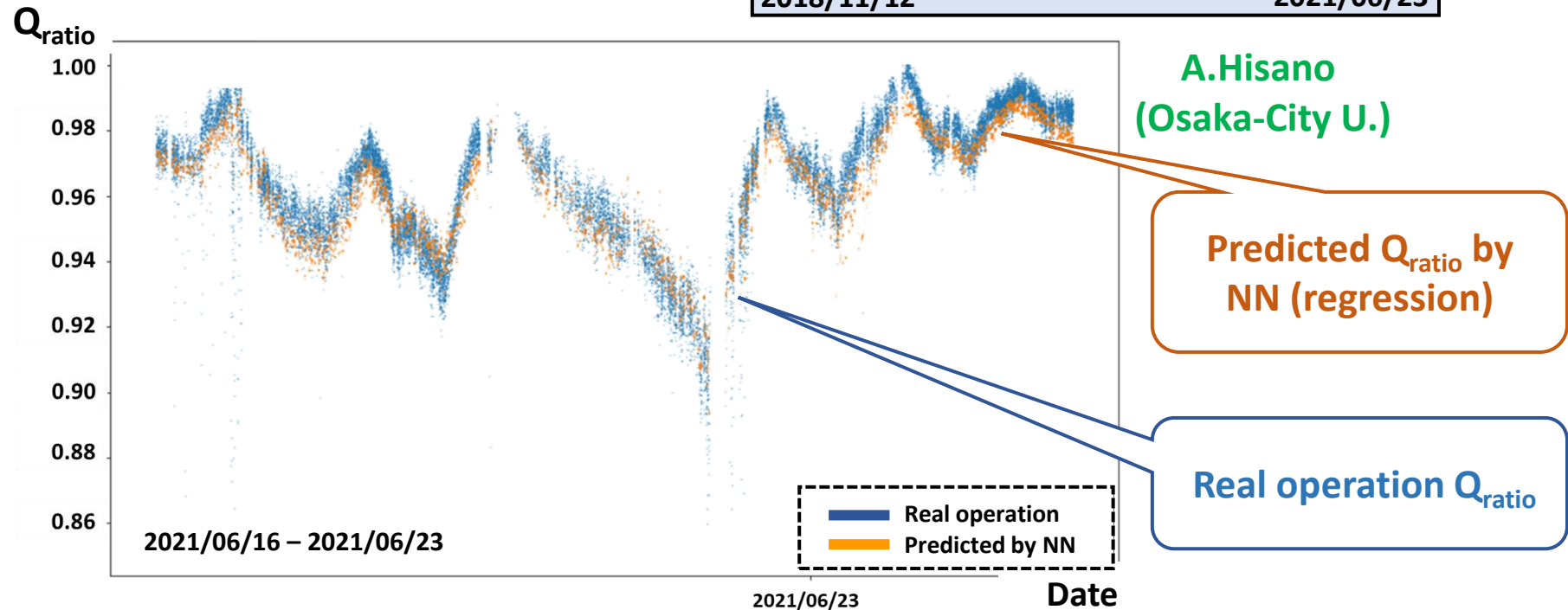
Training / Validation data → Accumulated in 2018/11 to 2021/06

Training data : 150K events

Validation data : Except for the training data

2018/11/12 **Training data** 2021/06/23

2018/11/12 **Validation data** 2021/06/23



DNN can predict the beam transmittance

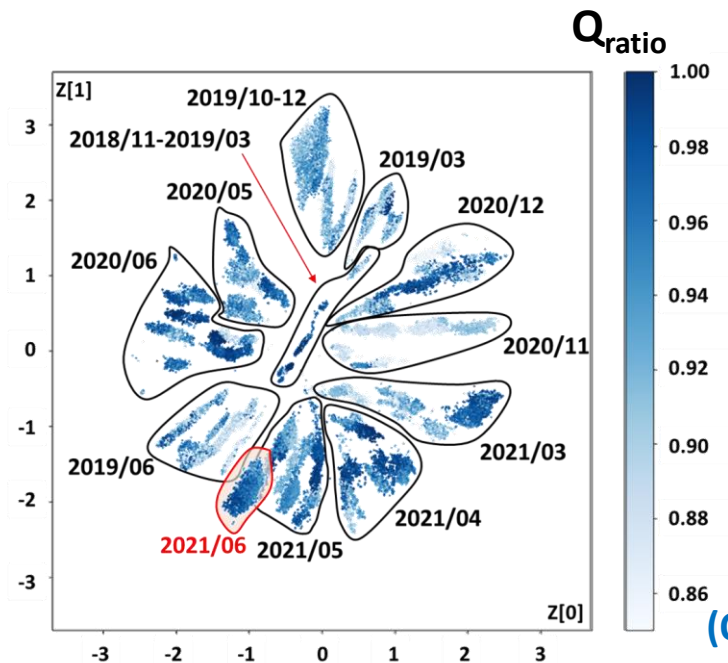
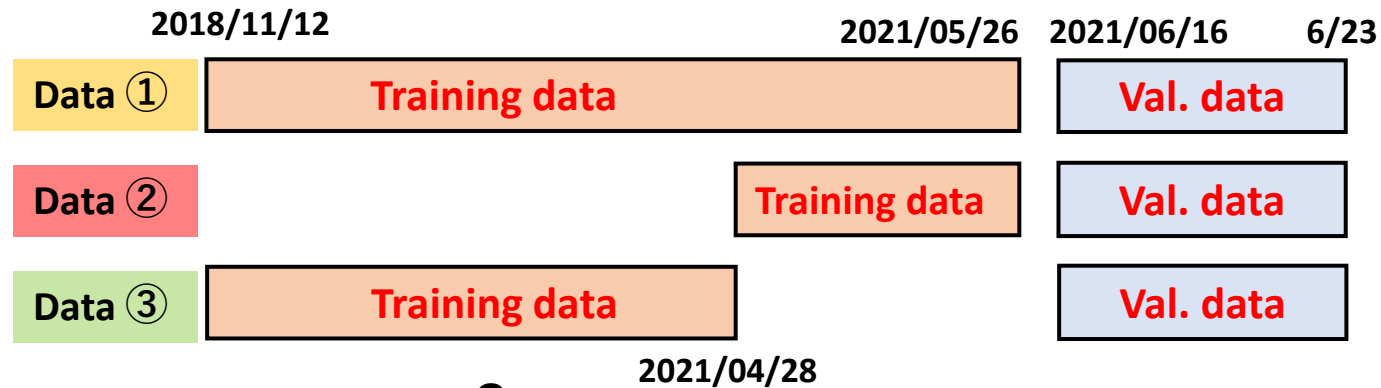
→ DNN can express the relationship btw acc. parameters and beam transmittance

2. Beam Transmittance prediction using DNN

KEK, Osaka-City U., Osaka U. IDS, RCNP

Result : 2

DNN is trained with the “past data”



2D Latent value for 2021, June is close to 2021, May

→ 2021, June injection efficiency might be predicted using the DNN trained with 2021, May data.

36 **A.Hisano**
(Osaka-City U.)

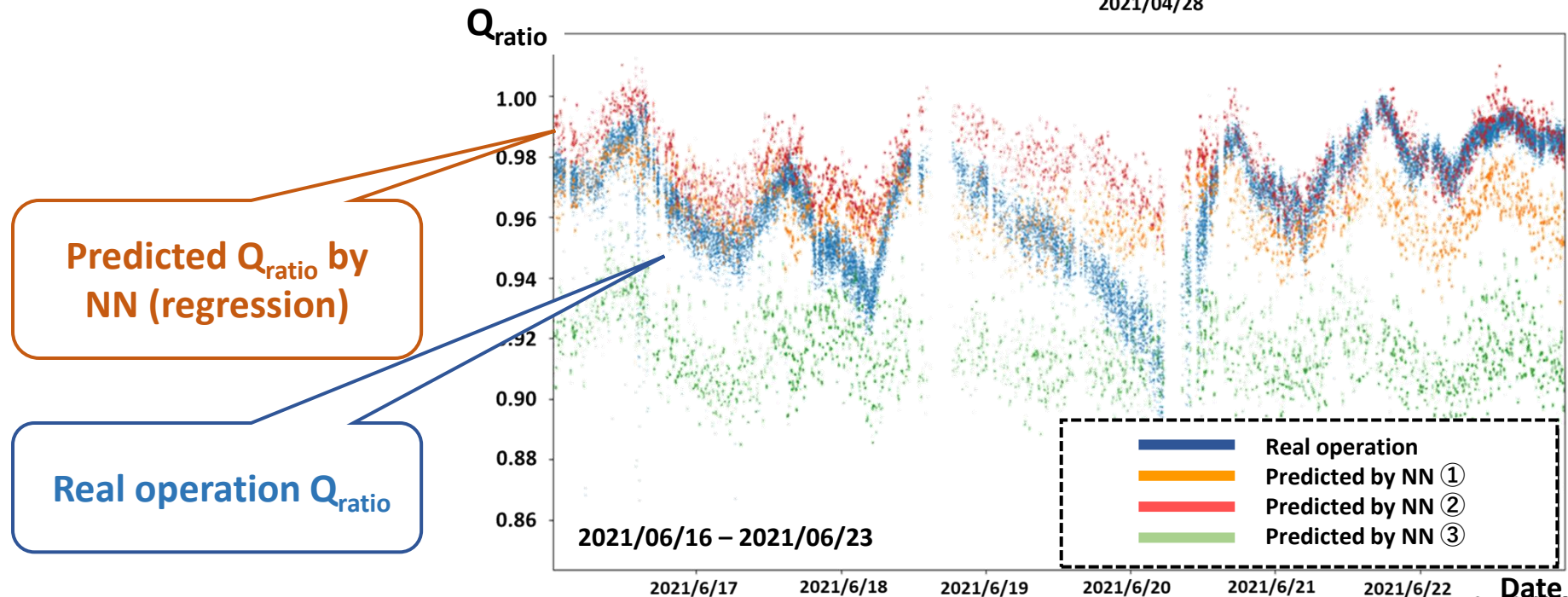
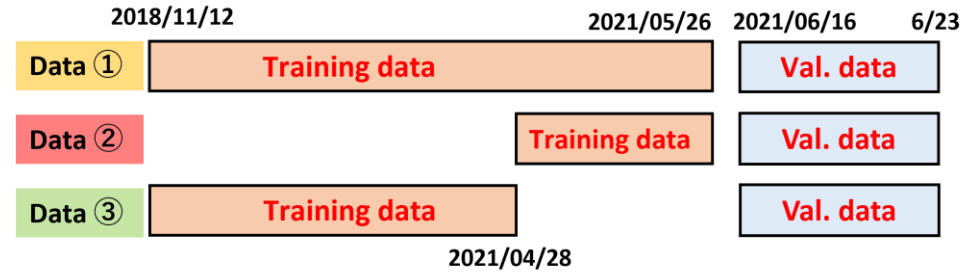
2. Beam Transmittance prediction using DNN

KEK, Osaka-City U., Osaka U. IDS, RCNP

Result : 2

Validation data → 2021, June

Training data : 150K events each



A.Hisano
(Osaka-City U.)

DNN trained with 2021, May data (①②)
can predict 2021, June injection eff.

**Training based on the current
recent data is important**

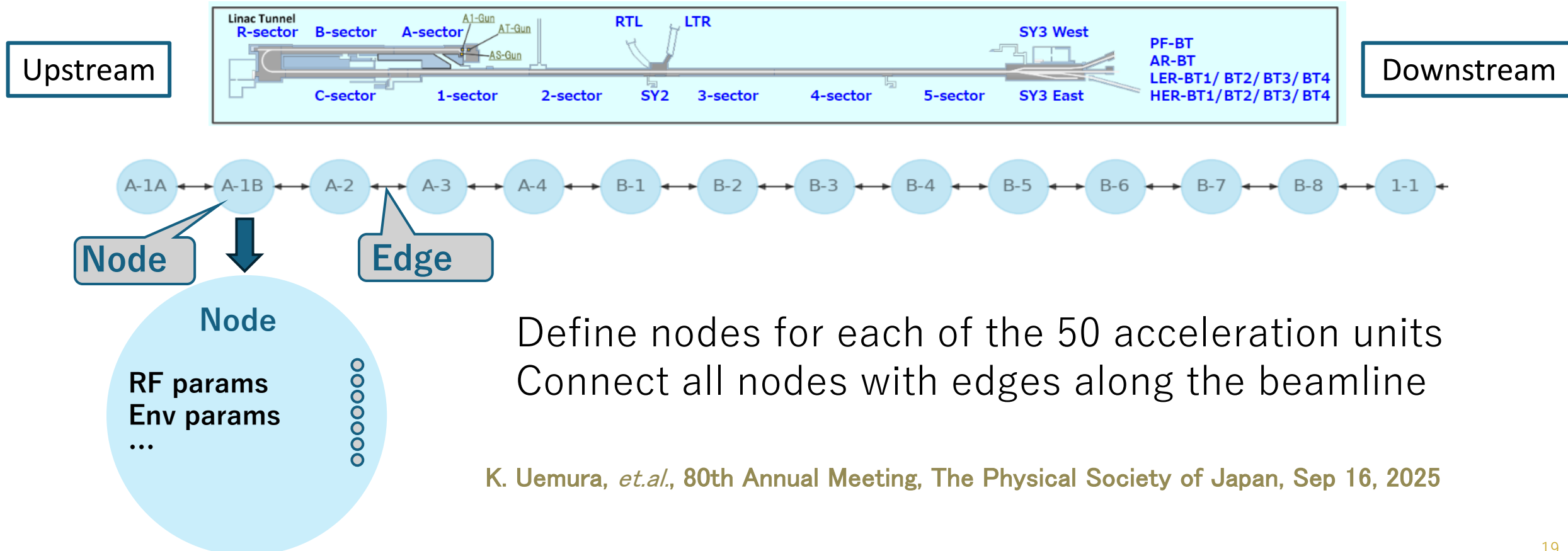
ML Application to the Accelerator Tuning 2

Osaka Metropolitan U., KEK,
OU RCNP/IDS, Kyutech, UT ICEPP

Large acc. Facilities: Huge number components ($O(1000) \sim O(10000)$)

→ Preventing overfitting is key

To apply machine learning to large-scale accelerators, we have developed a novel machine learning method using Graph Neural Networks (GNNs)



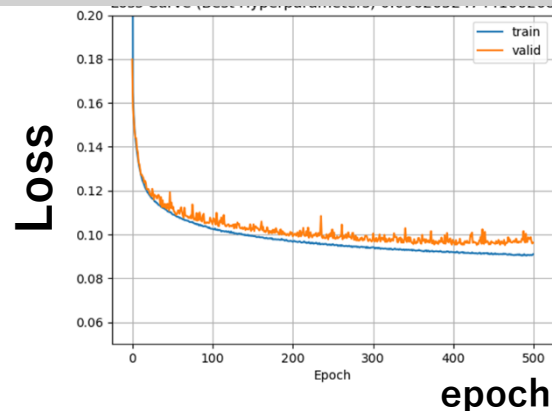
K. Uemura, *et.al.*, 80th Annual Meeting, The Physical Society of Japan, Sep 16, 2025

ML Application to the Accelerator Tuning 2

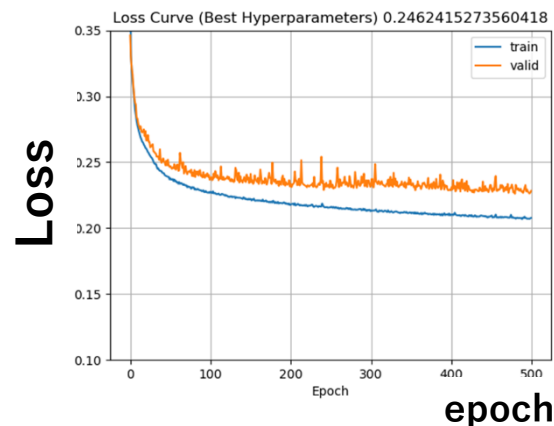
Osaka Metropolitan U., KEK,
OU RCNP/IDS, Kyutech, UT ICEPP

K.Uemura (OMU)

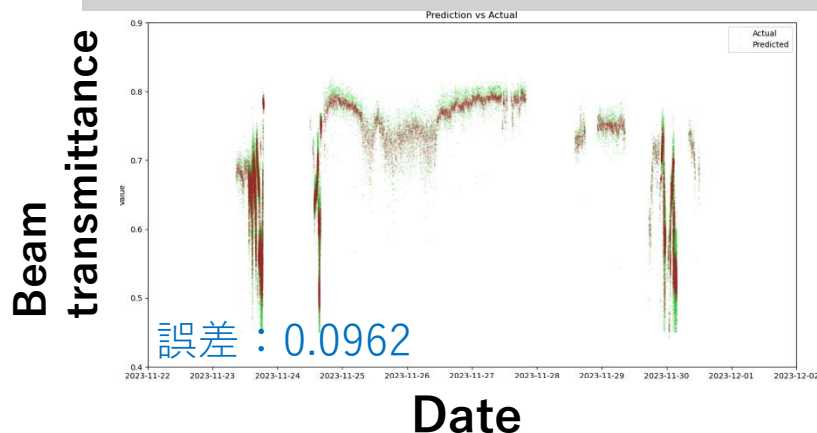
Beam transmittance:
Learning Curve



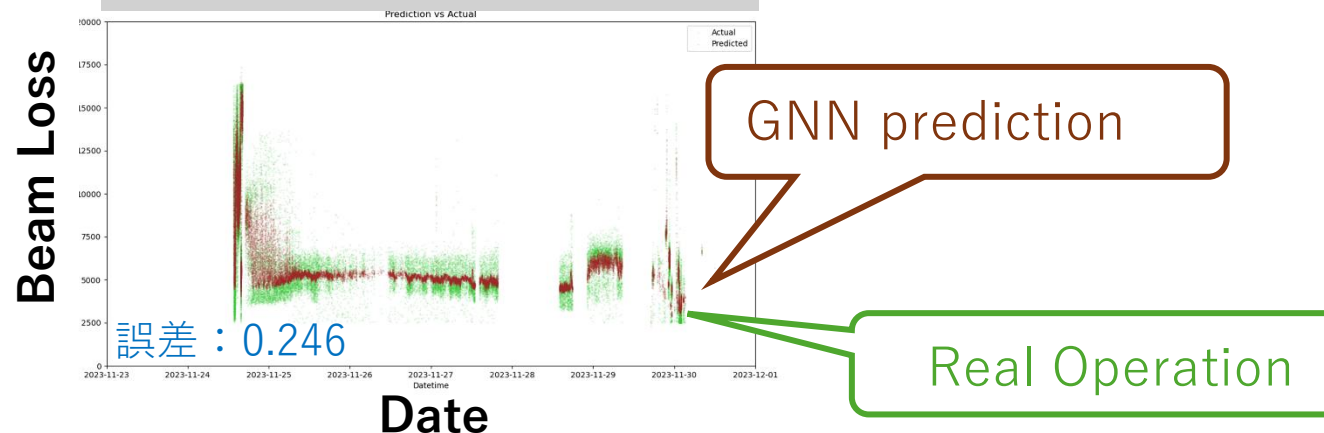
Beam Loss: Learning Curve



Prediction of Beam transmittance



Prediction of Beam Loss



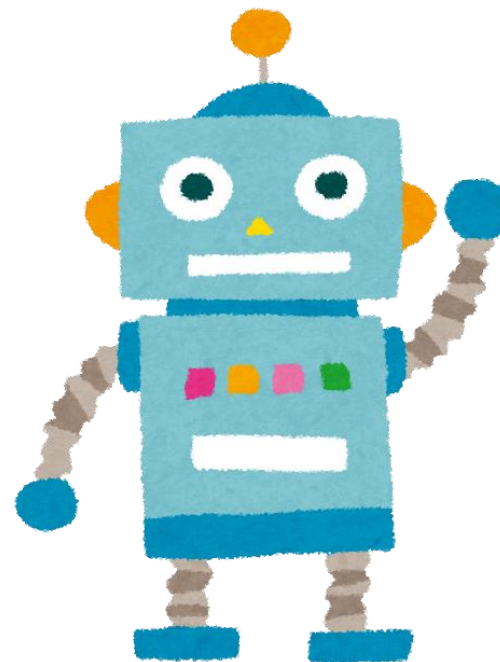
Machine learning using GNN successfully predicted beam transmittance and beam loss (Input: ~2,000 parameters) without overfitting

4. Physical interpretation of acc. parameters using Explainable AI (XAI / SHAP)

Osaka Metropolitan U., Osaka U. RCNP D3, KEK,
KyuTech, U Tokyo ICEPP

Using the Accelerator model constructed with Machine Learning(DNN)
XAI (Explainable AI) predicts the important parameters
for the accelerator tuning

Explainable AI
XAI



XAI(Explainable AI)

Important param estimation with XAI



SHAP

We use SHAP(**SH**apley **A**dditive ex**P**lanations) as XAI

In a ML model, create a linear model of input params and prediction results for each data instance, then evaluate the influence of the input params on the prediction.

$$\begin{array}{c} \text{ML model} \\ f(x) \end{array} = \begin{array}{c} \text{Linear model} \\ g(x') \end{array} = \phi_0 + \sum_{i=1}^M \phi_i x'_i$$

$g(x')$ is a linear model of
SHAP values ϕ_i

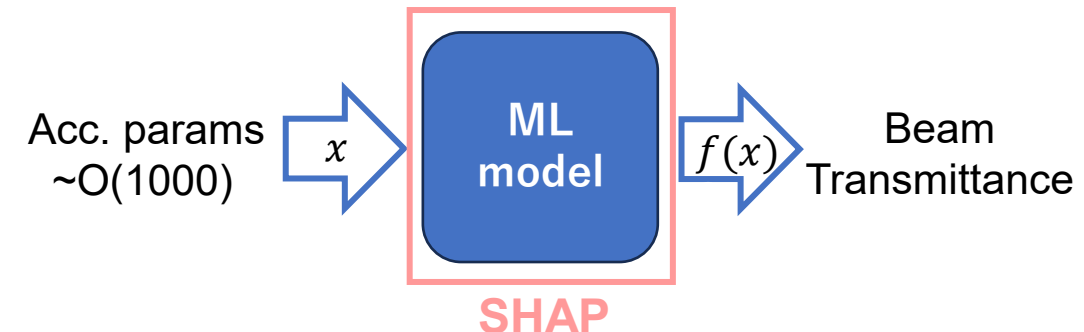
x'_i : binary value (0 or 1) for input parameter x_i

M : Number of the input params

ϕ_0 : Expected output value

ϕ_i : **SHAP value** for i-th parameter

← Shows how much impact it has on the final output



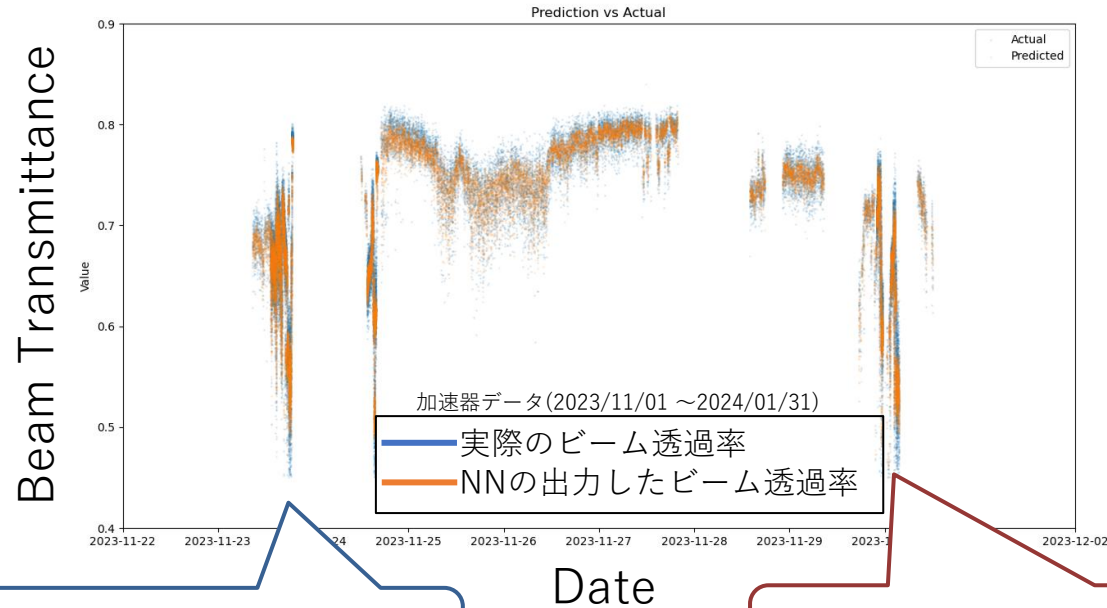
Important param estimation with XAI

Osaka Metropolitan U., KEK,
UO RCNP/IDS, Kyutech, UT ICEPP

1. Prediction by NN Regression (for EBES experiment)

K.Uemura (OMU)

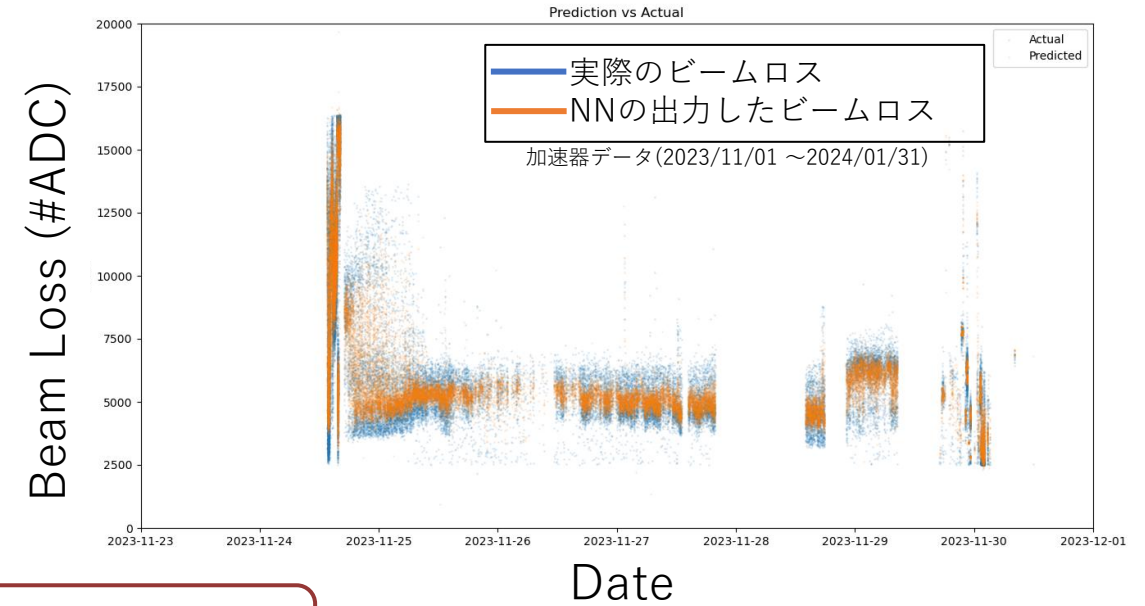
① Beam Transmittance



Real Operation

Predicted by NN (regression)

② Beam Loss



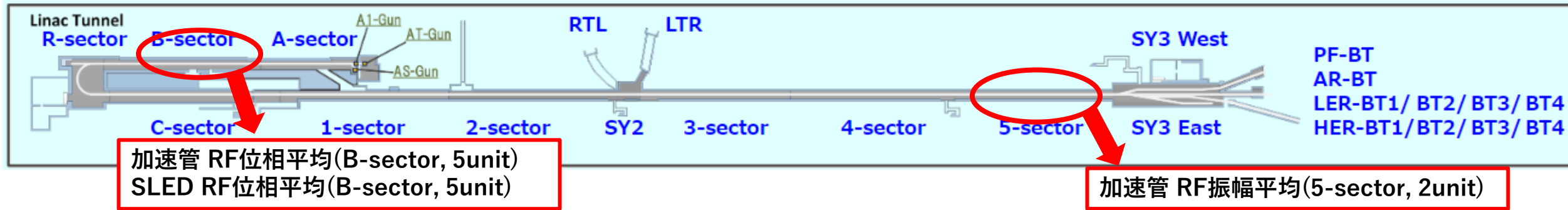
ML model to predict beam transmittance or beam loss is constructed

Important param estimation with XAI

Osaka Metropolitan U., KEK,
UO RCNP/IDS, Kyutech, UT ICEPP

2. Estimated important params by XAI

K.Uemura (OMU)



① Params affecting beam transmittance

Rank	Parameter	Place
1	RF-system av. phase (klb5apa)	B-sector
2	SLED RF av. phase (klb5spa)	B-sector

② Params affecting beam loss

Rank	Parameter	Place
1	RF av. amplitude (kl52aaa)	5-sector
2	RF-system av. phase (klb5apa)	B-sector

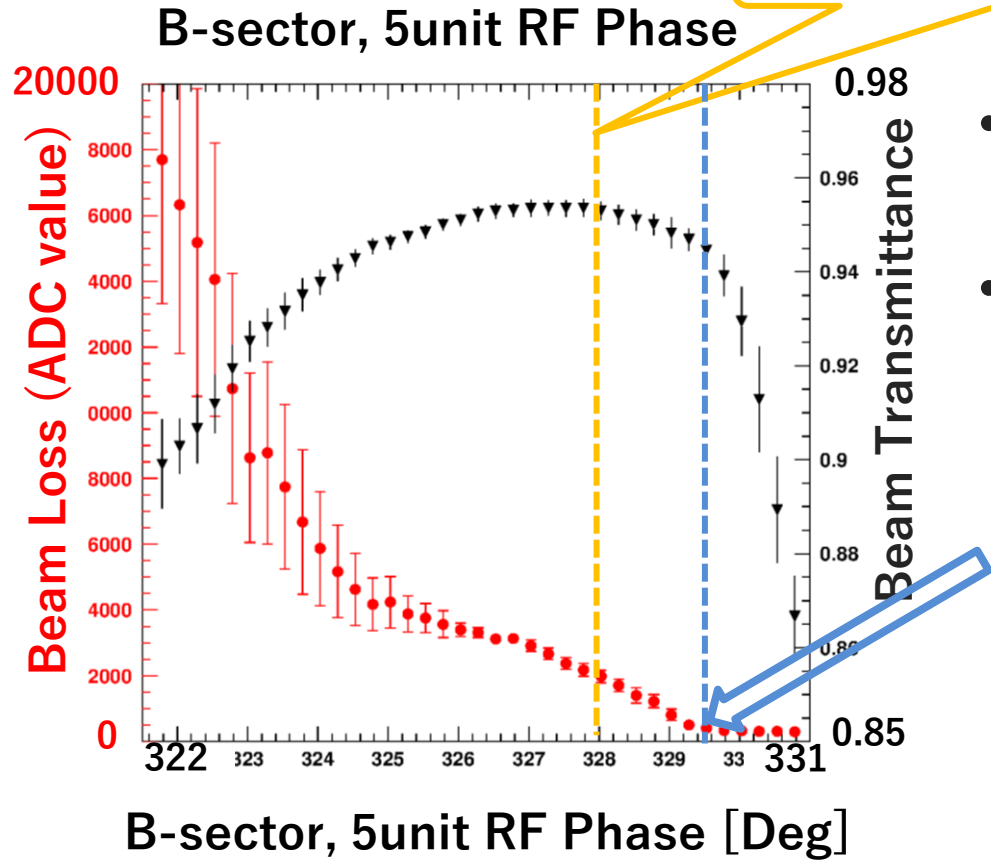
We found that the RF phase in the upstream (B-sector) of the KEK Linac affects to both beam Transmittance and beam loss.

Important param estimation with XAI

Osaka Metropolitan U., KEK,
UO RCNP/IDS, Kyutech, UT ICEPP

3. Verification using the Test Beam

F. Miyahara (KEK)



- We performed the beam test and change the RF phase of the B-sector.
- As predicted by XAI, both the beam transmittance and beam loss changed significantly.

New Setting Value

We can find the new RF parameter value that minimized beam loss while achieving high beam transmittance!

Important param estimation with XAI

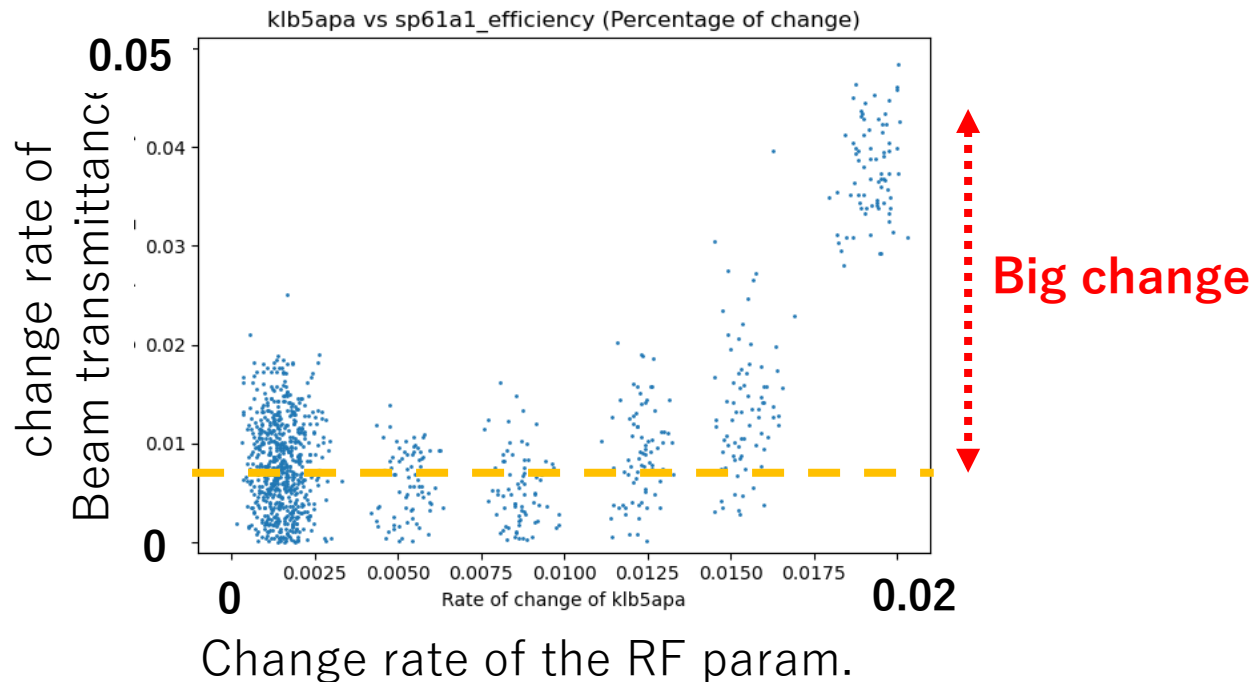
Osaka Metropolitan U., KEK,
UO RCNP/IDS, Kyutech, UT ICEPP

3. Verification using the Test Beam

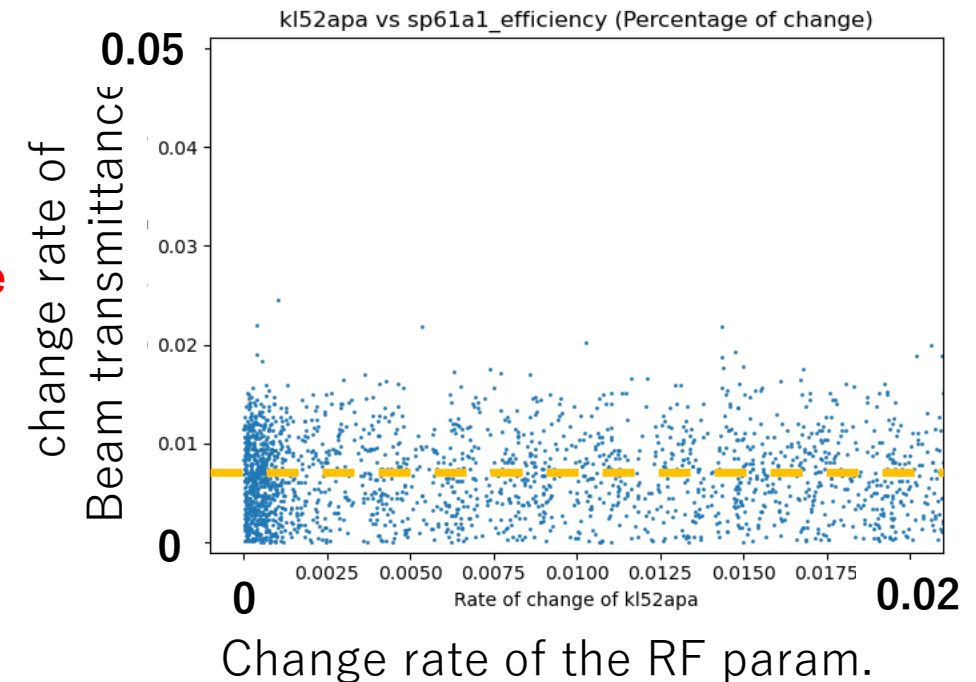
We varied parameters that were predicted to be important and parameters that were predicted to be unimportant.

K.Uemura (OMU)

RF param. predicted to be **important**



RF param. predicted to be **unimportant**



→ **Parameters predicted as important by XAI are actually important.**

5. Continual learning for dynamic model construction

Osaka Metropolitan U., Riken / JASRI

Building a model adaptable to accelerator environmental changes
(dynamic model) requires rapid updates

→ **Developed continual learning to reduce training time**

- Predicted pulse energy using machine learning with SACLA data at SPring-8
- Compared continual learning using historical data against standard training
- Confirmed that continual learning reduces training time

K.Kinoshita (OMU)

Training data size (Recent data)	Standard training	Continual learning
3 hrs.	Loss = 0.314	0.279
6	0.307	0.297
12	0.272	0.255
24	0.260	0.255

Summary & Outlook: AI/ML in Acc. Science

- **Superior Performance**

ML methods consistently outperform conventional manual trial-and-error tuning.

- **Real-Time Adaptation**

Dynamic continuous learning models track environmental drift in facilities like SACLA.

- **Explainable AI (XAI)**

Tools like SHAP isolate high-impact variables from thousands of inputs.

- **Shared Community**

MaLaPa workshops and Japanese ML forums accelerate nationwide collaboration.

The Future of Accelerator Physics is AI-Driven

Automating routine operations empowers operators to focus on breakthrough discovery.

FAIRS 2026

ありがとう
ございました

