Plasma control system of QUEST and fast plasma shape recognition with Machine Learning

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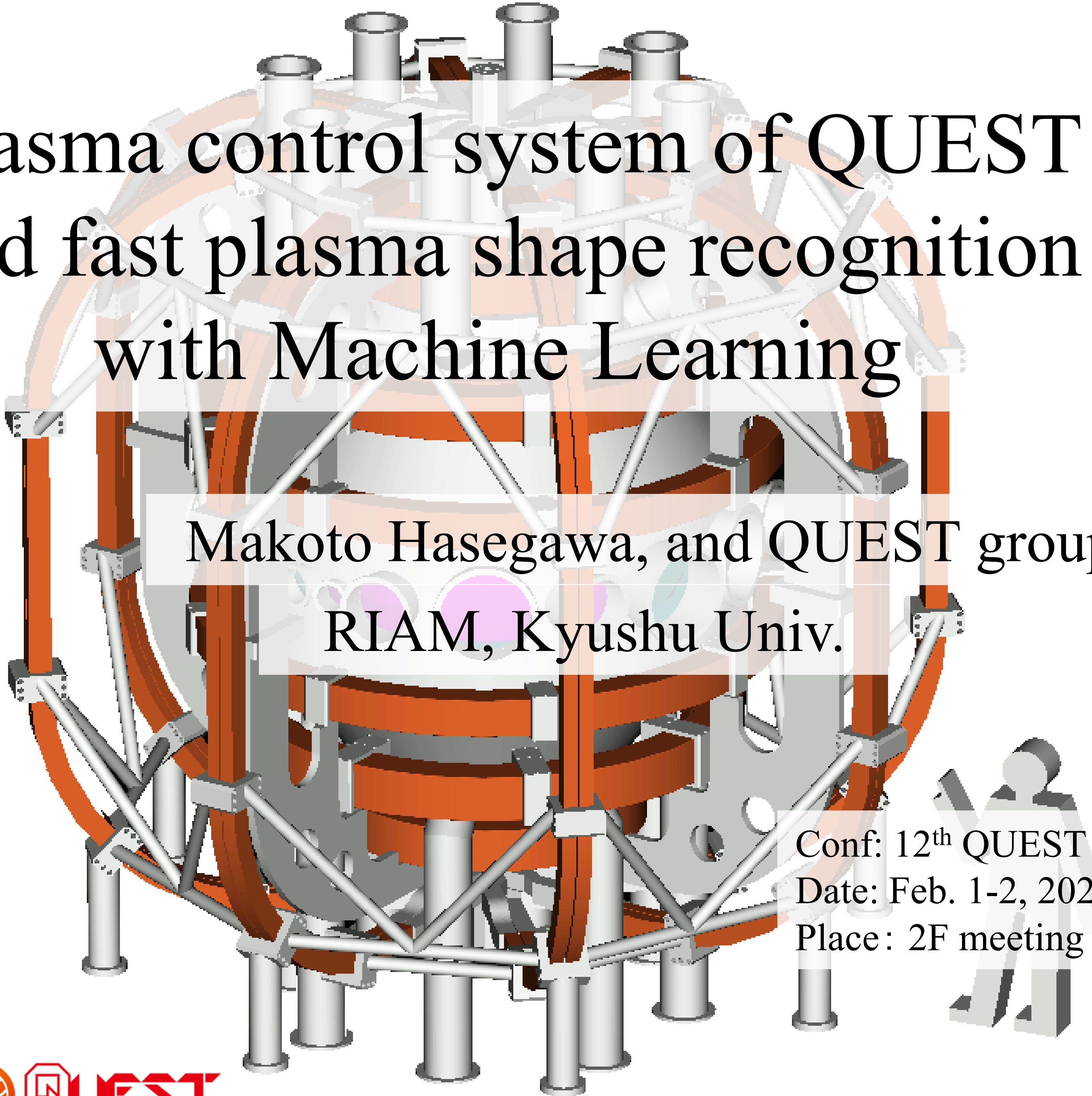

Makoto Hasegawa, and QUEST group

RIAM, Kyushu Univ.

Conf: 12th QUEST Workshop
Date: Feb. 1-2, 2023
Place： 2F meeting room, QUEST building

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- Motivation for fast plasma shape recognition
- Introduction to plasma control system of QUEST
- Dataset for machine learning
- Machine learning model structure and data processing
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Motivation for fast plasma shape recognition

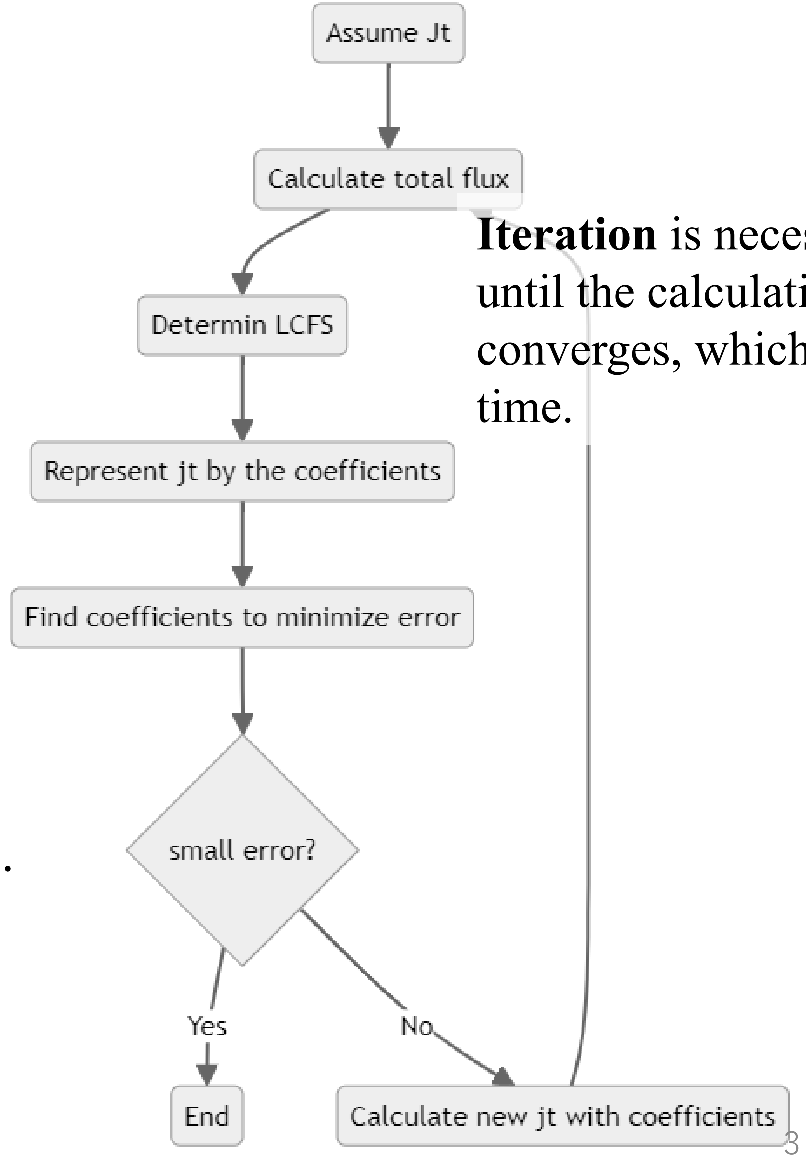
- For **steady-state operation** with QUEST, particle control and heat load control are important.
- In order to perform these controls, it is necessary to control the position and shape of the plasma and maintain the **divertor configuration**, and **fast recognition of plasma shape** is also required.

- Generally, **equilibrium calculations** are used to recognize plasma shapes, but the calculation load is high and **time consuming** (～sec).

Purpose:
Creation of a model that enables **fast plasma shape recognition**.

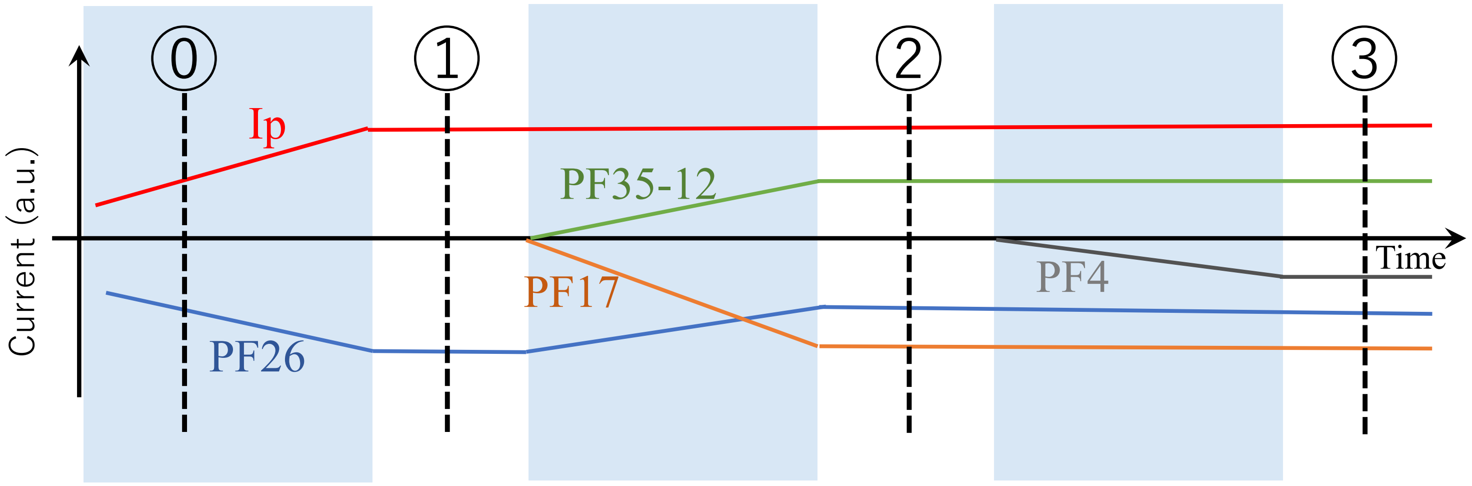
- Creation of a **huge data set** for equilibrium calculations
- Machine learning with **neural network model**

Procedure of equilibrium calculation



Iteration is necessary until the calculation converges, which takes time.

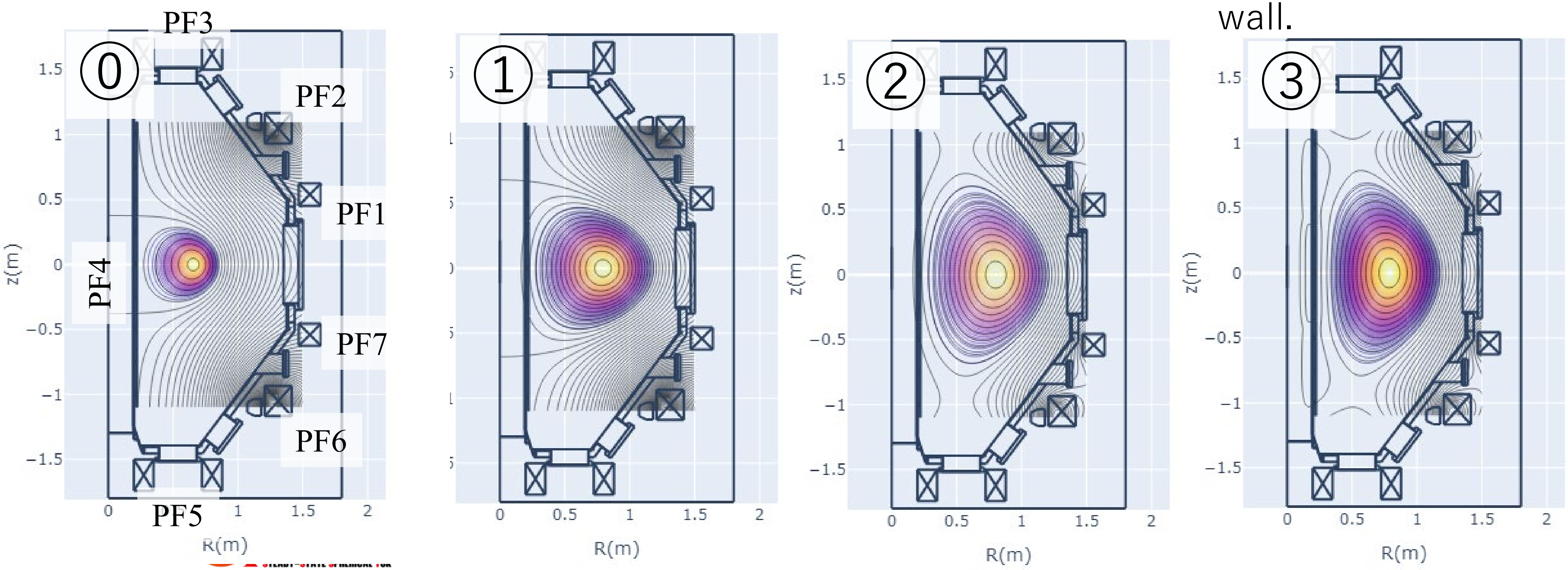
Procedure to form a divertor configuration



⓪→① : **Stable startup** of plasma current using PF26 with large decay index

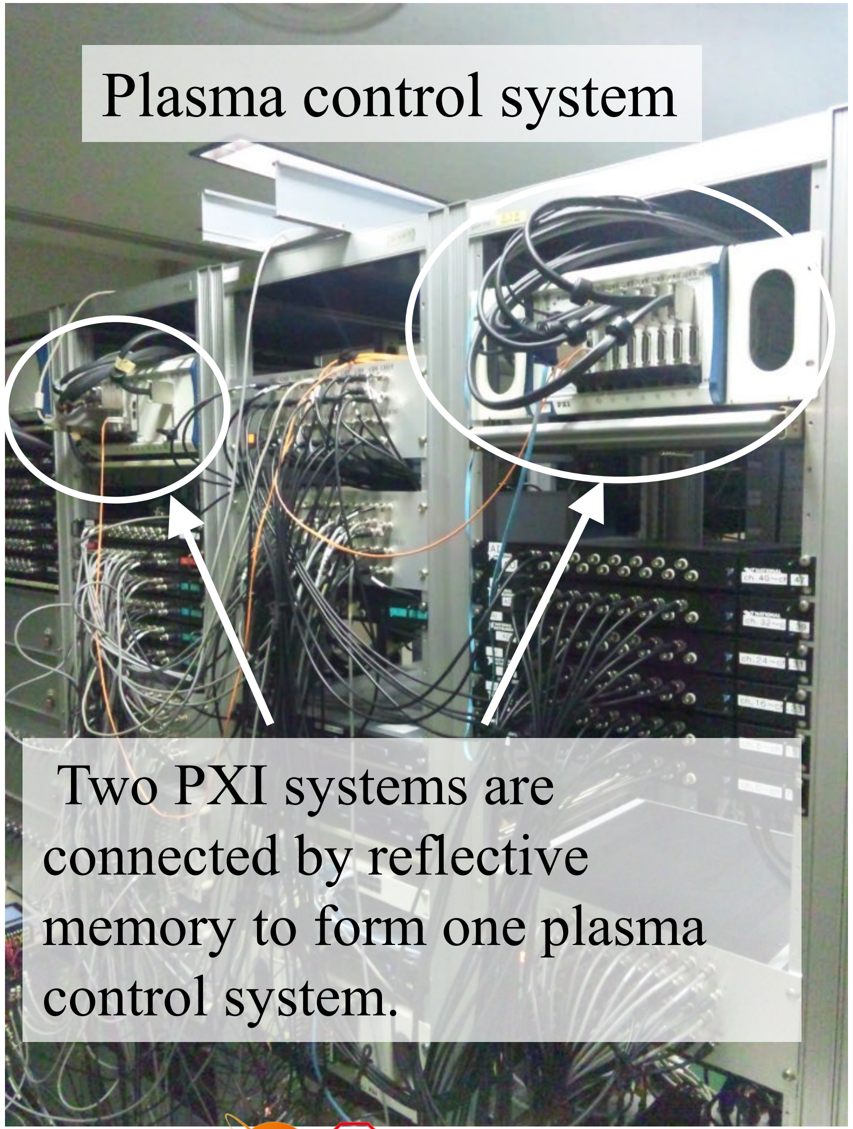
①→② : **High elongation configuration** by pushing from the outside with PF17 and pulling up and down with PF35 coils.

②→③ : **Divertor configuration** by pushing from the inside with PF4 coils and detaching plasma from vacuum vessel wall.



The PF4 coil current is kept within a range where the vertical position is controllable.

Introduction to plasma control system of QUEST

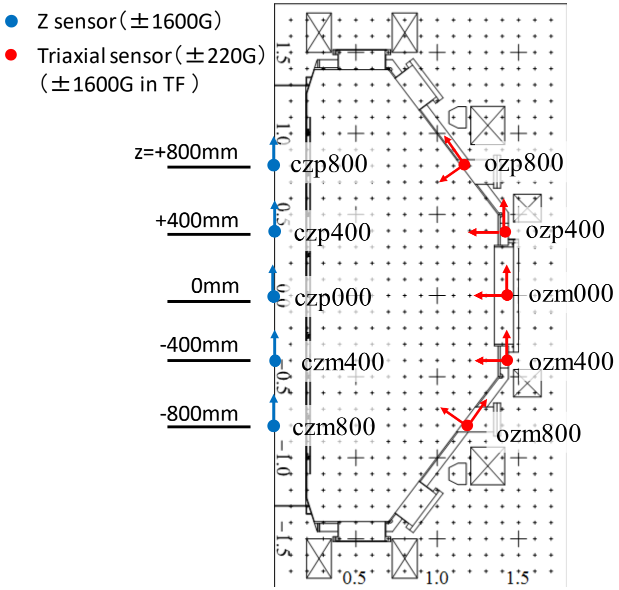


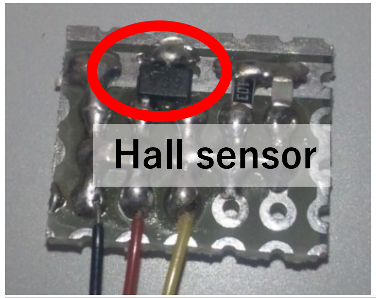
Name	Value
OS	LabVIEW Realtime OS
Control frequency	4 kHz
Input Items	TF&PF currents, magnetics (**Hall sensors**), visible, etc.
Control Items	TF coil, PF coils, Particle fuel, Heating power

Purpose of QUEST project: achievement of **steady state operation** using high-temperature walls.

Installation of Hall sensors *outside the vessel* that allows **steady magnetic measurement**.

Installed location of hall sensors





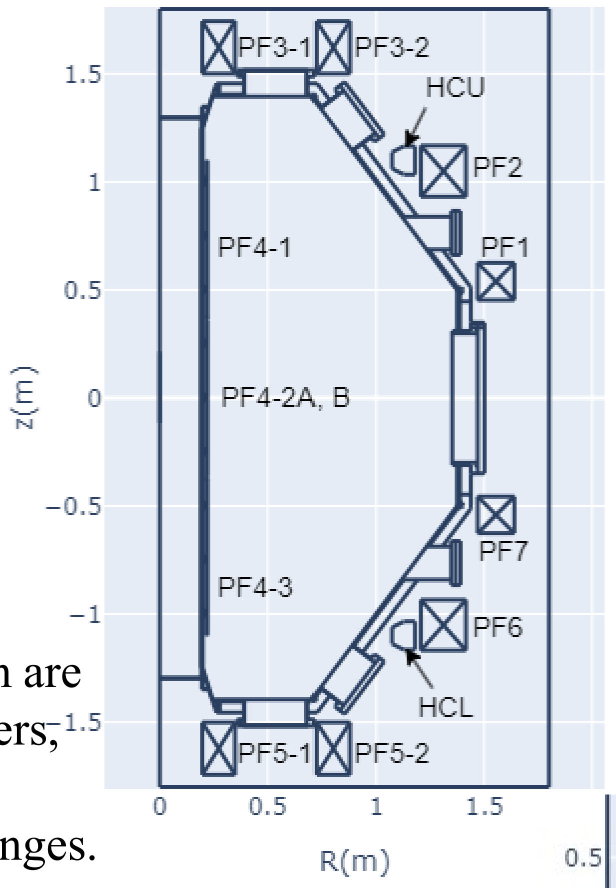
(left): prototype sensor
(below): current triaxial sensor

Preparing dataset for machine learning

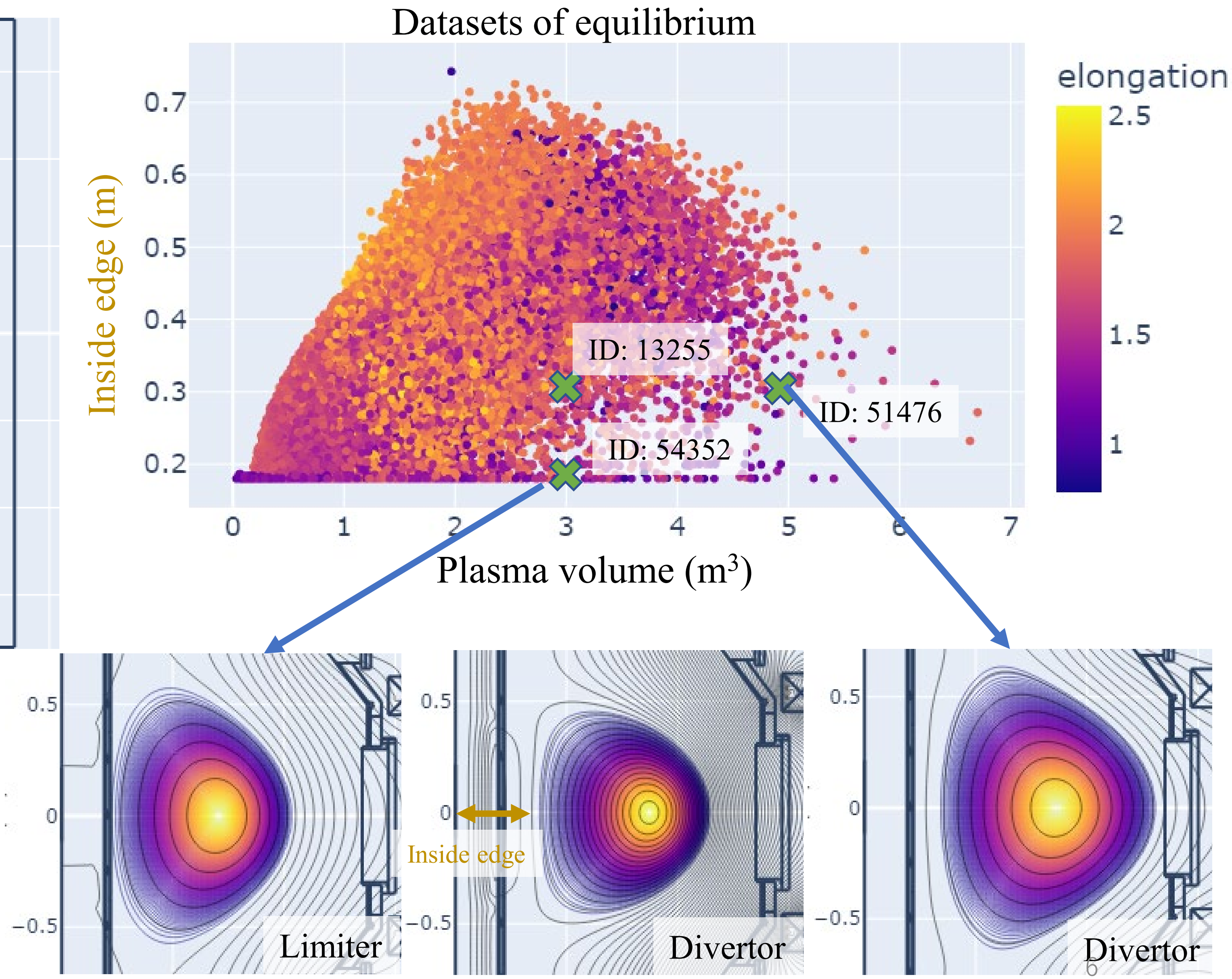
Parameter range

Plasma current:
Ip: 100kA (Fix)
Rp: 0.5～1.0m

PF coils:
PF17: -8.0～0.0 kA
PF26: -8.0～0.0 kA
PF4: -8.0～0.0 kA
PF351: 0.0～8.0 kA
PF352: 0.0～8.0 kA



Equilibrium calculation are executed with parameters, which are randomly extracted from these ranges.



Out of 95,000 pieces of data, 3,900 pieces of data converged with limiter or diverter configuration.

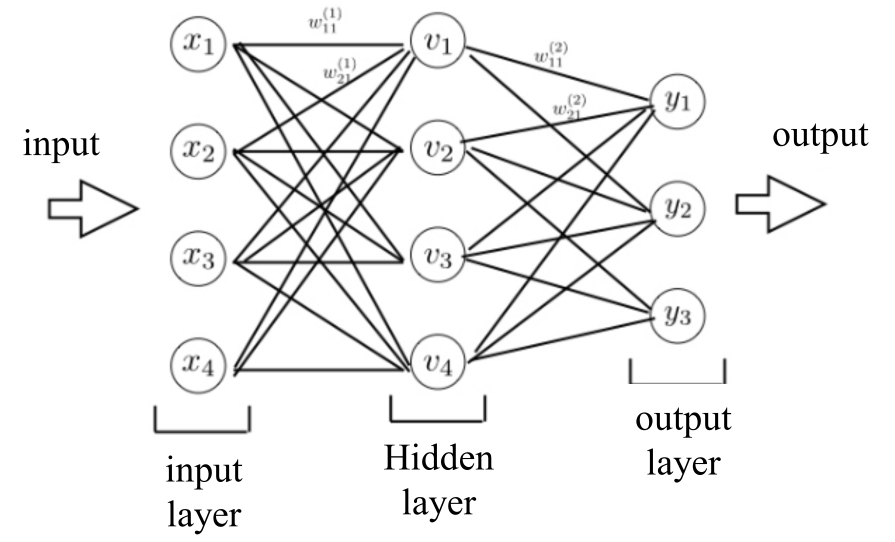
Total data points: ～39000

Machine learning procedure to recognize plasma shape

Neural network regression is used to recognize the plasma shape.

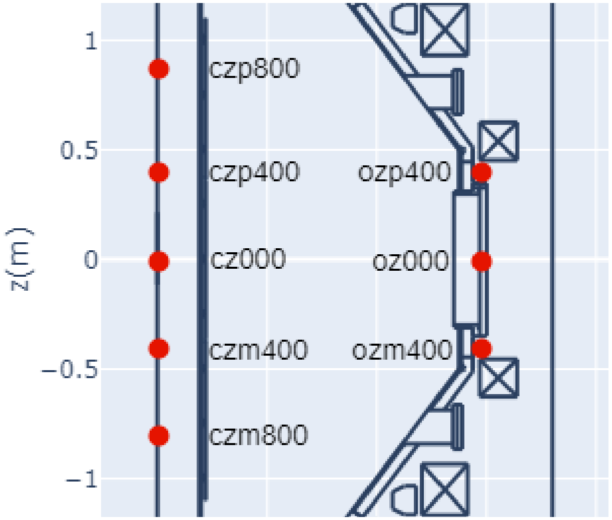
Model of neural network

Number of input: 13
(5 PF currents, 8 hall sensors)
Number of output: 15
(Ip, 4 shape parameters, and 5 points (R, z))
Hidden layer: 2 layers
Nodes per layer: 32 nodes



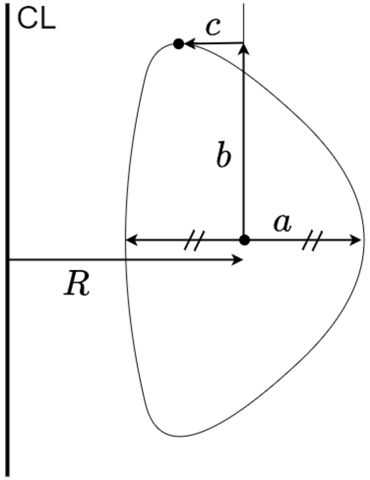
$$v_1' = w_{11}^{(1)}x_1 + w_{21}^{(1)}x_2 + w_{31}^{(1)}x_3 + w_{41}^{(1)}x_4 + b_1^{(1)}$$
$$v_1 = h^{(1)}(v_1')$$

https://atmarkit.itmedia.co.jp/ait/articles/1811/20/news012.html



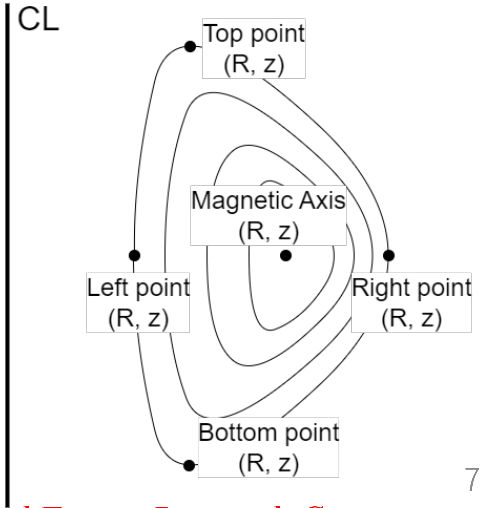
8 hall sensor position to measure Bz

Shape parameters



Shape parameters
Major Radius: R
Minor Radius: a
Elongation: κ $(=b/a)$
Triangularigy: δ $(=c/a)$

Representative 5 points



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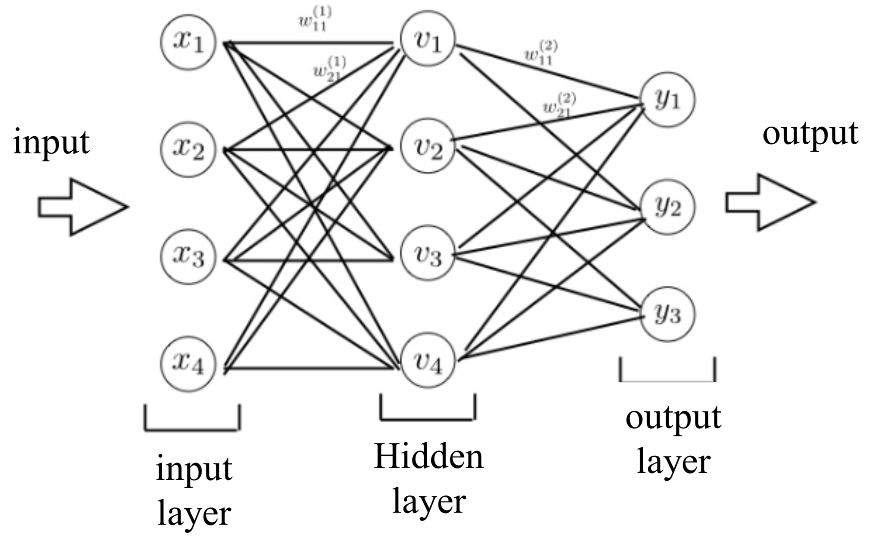


$$v_1' = w_{11}^{(1)}x_1 + w_{21}^{(1)}x_2 + w_{31}^{(1)}x_3 + w_{41}^{(1)}x_4 + b_1^{(1)}$$
$$v_1 = h^{(1)}(v_1')$$

https://atmarkit.itmedia.co.jp/ait/articles/1811/20/news012.html

Forward propagation of neural network

- Weighting factor: $w_{j,k}^{(i)}$

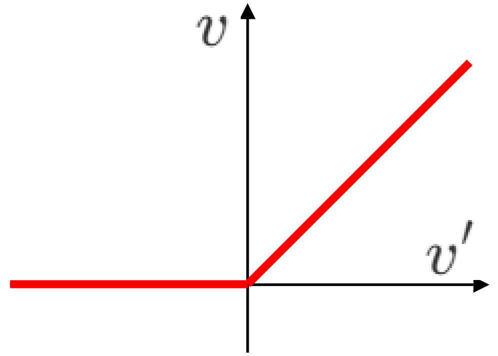
  from k-th node of (i-1)-th layer to j-th node of i-th layer

- Propagated value: $v_j'^{(i)} = \sum_k w_{j,k}^{(i)} v_k^{(i-1)}$

  to j-th node of i-th layer

- Output value: $v_j^{(i)} = \phi(v_j'^{(i)})$

  of j-th node of i-th layer (ϕ: activation function)



For 2 hidden layers,
ϕ : Rectified Linear Unit (ReLU) is used

Machine learning procedure to recognize plasma shape

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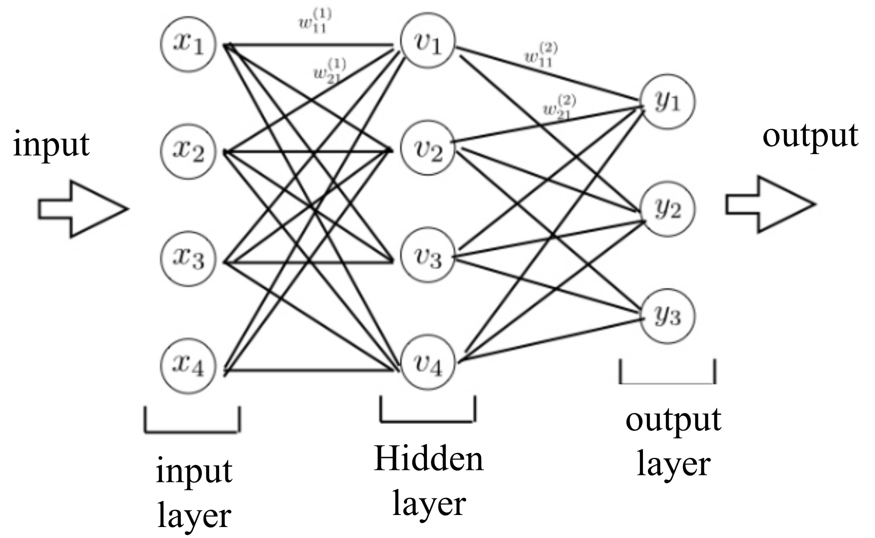

$$v_1' = w_{11}^{(1)}x_1 + w_{21}^{(1)}x_2 + w_{31}^{(1)}x_3 + w_{41}^{(1)}x_4 + b_1^{(1)}$$
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https://atmarkit.itmedia.co.jp/ait/articles/1811/20/news012.html

Data pre-processing before machine learning

0. Prepare data set

1. Normalization

Normalize to the value per unit PF coil current.

- Normalization Factor *nf*
  = Sum of 5 PF abs. coil currents $\left(nf = \sum_{i=1}^{5} |I_{PFi}| \right)$
- Normalize values:
  5 PF coils, 8 hall sensors, Ip
  $\left(ex.\ I_{PFi\_normalized} = I_{PFi}/nf \right)$

2. Standardization

- Standardize all parameters so that the mean is zero and the standard deviation is one.

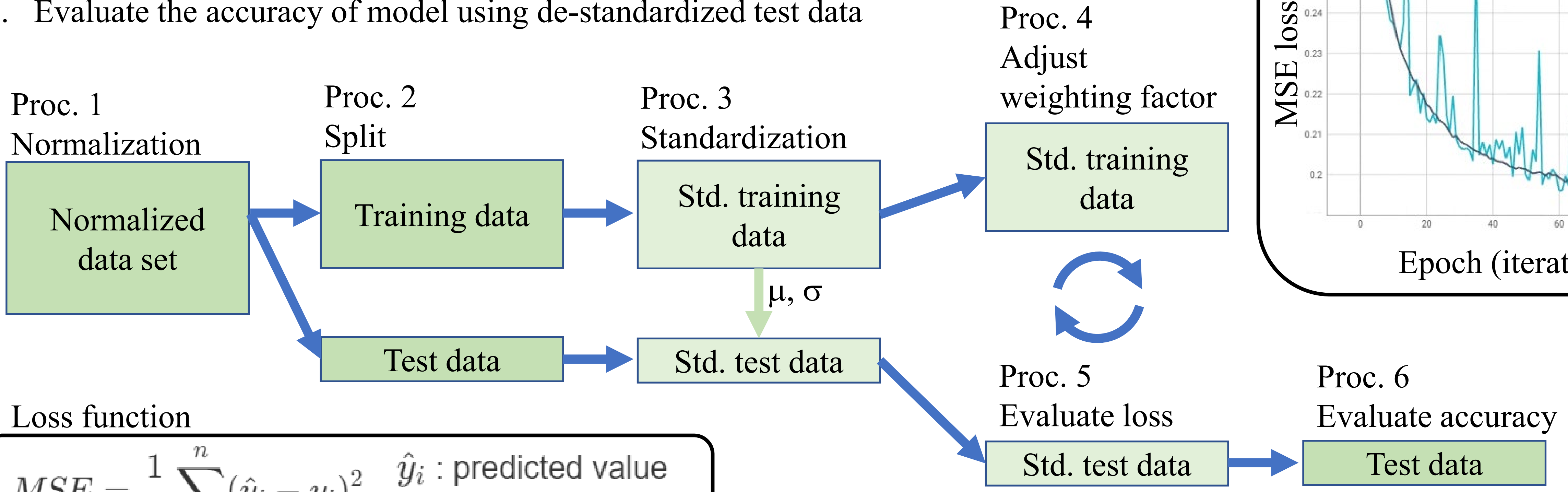
$$\left(z = \frac{x-\mu}{\sigma} \right)$$
x: original param.
z: standardized param.
μ: mean of x
σ: std. dev. of x

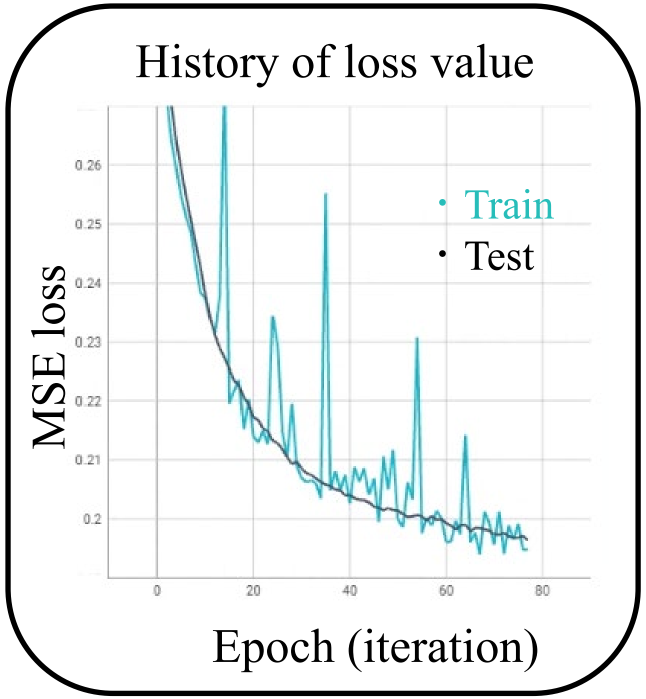
Reason:
- To make all weighting factors similar in size.
- To evaluate all outputs with equal importance.

Machine learning procedure to recognize plasma shape

Typical data processing steps for machine learning

0. Prepare dataset
1. Normalization to value per unit PF current.
2. Split all data into training data and test data at a ratio of 8:2
3. Standardization of training and test data from statistical information of training data
4. Adjustment of the weighting factors to make the MSE loss function smaller using test data
5. Repeat step 4 until the test data loss value is sufficiently small
6. Evaluate the accuracy of model using de-standardized test data





Loss function

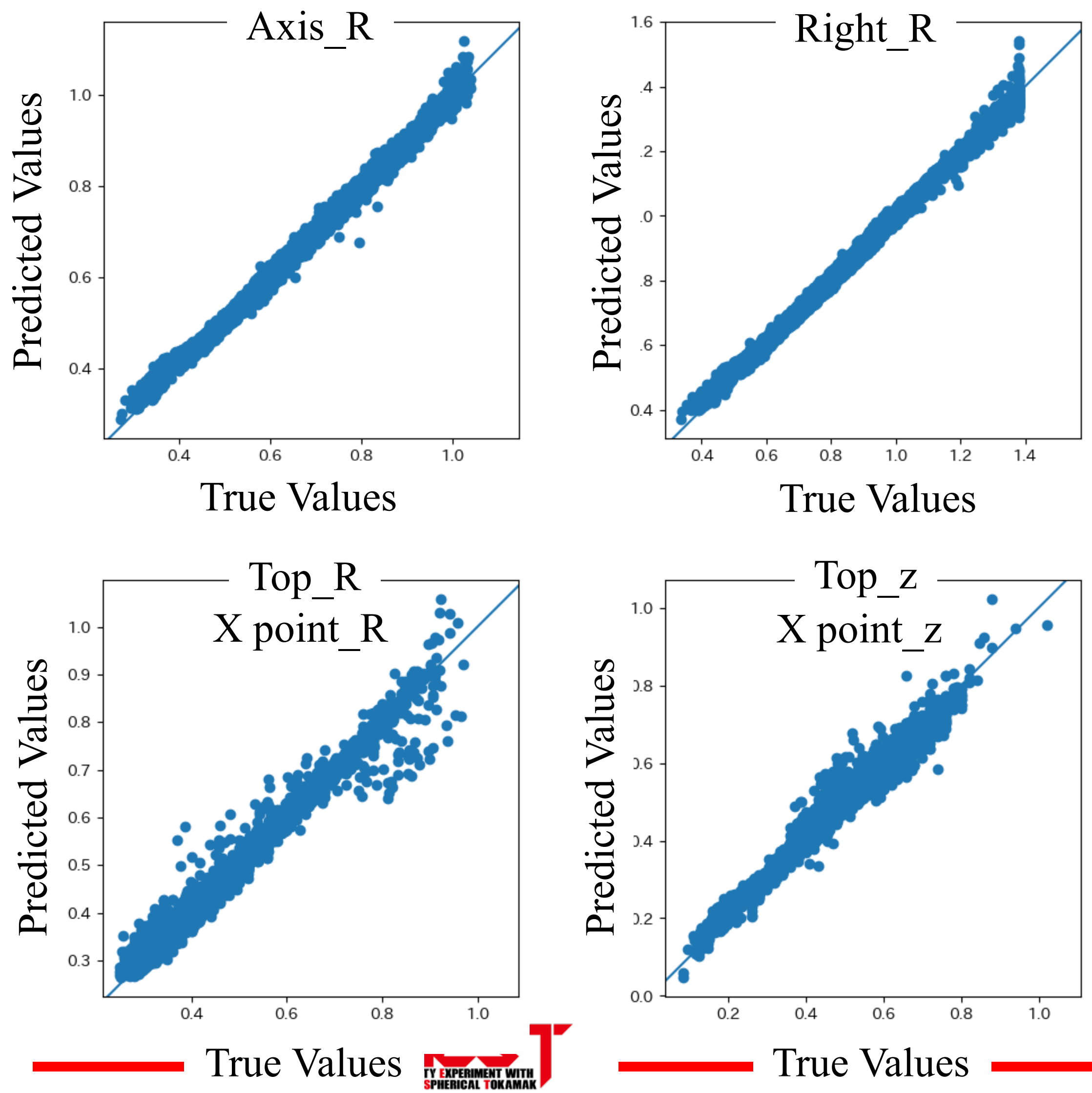
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

$\hat{y}_i$: predicted value

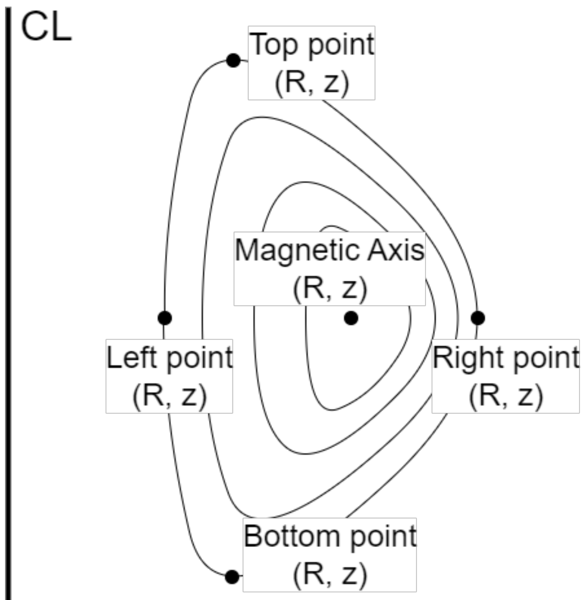
y_i : correct value

Prediction accuracy of trained model for representative points

Evaluation of the prediction accuracy of representative points (right point, top point, magnetic axis, and etc.).



Definition of points

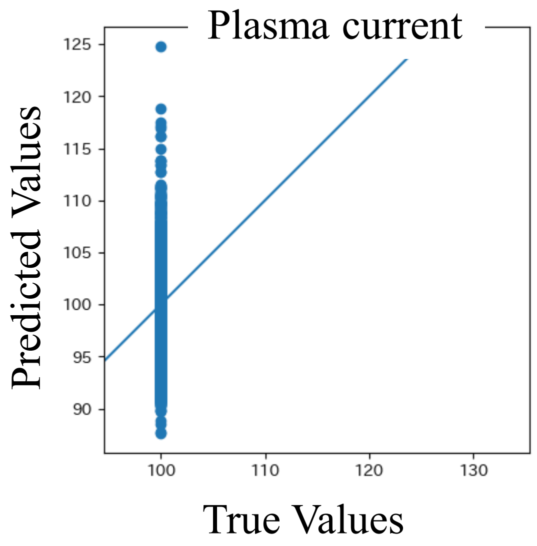


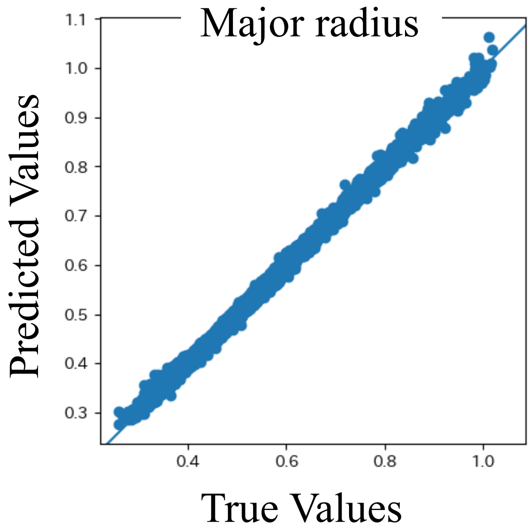
Standard deviation between true values and predicted values

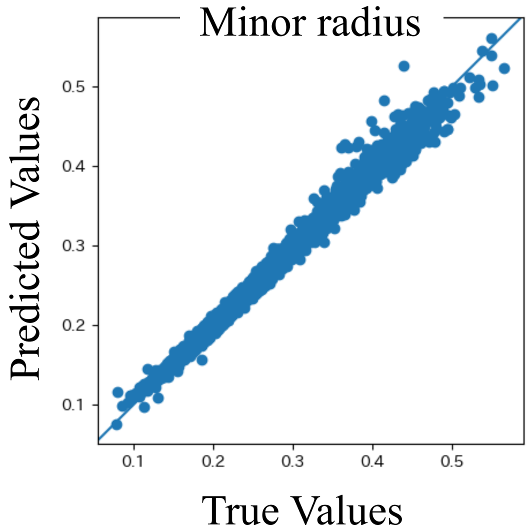
	R (mm)	z (mm)
Magnetic axis	12.28	0.14
Right point	14.26	0.38
Left point	10.76	7.55
Top point	18.61	18.65
Bottom point	18.42	18.57

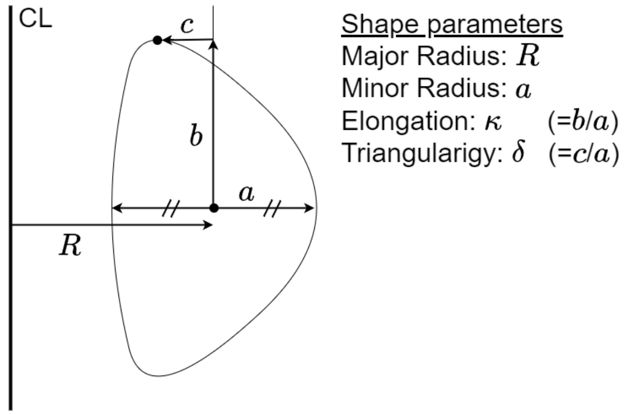
The accuracy of the top and bottom points is slightly poor.
The top and bottom points are a **null points (x point)** whose position is essentially difficult to evaluate because of saddle point.

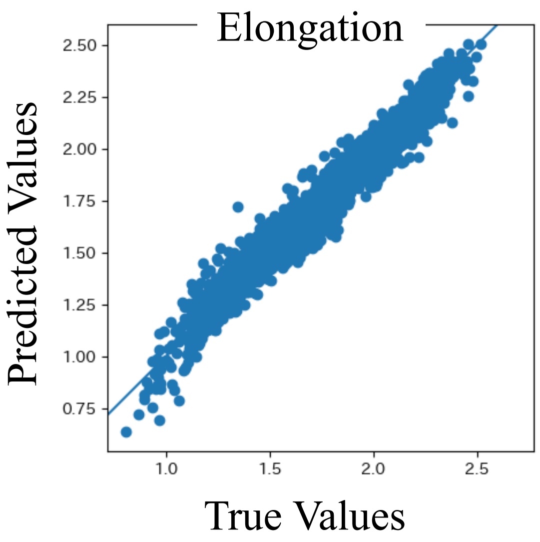
Prediction accuracy of trained model for Ip & shape parameters

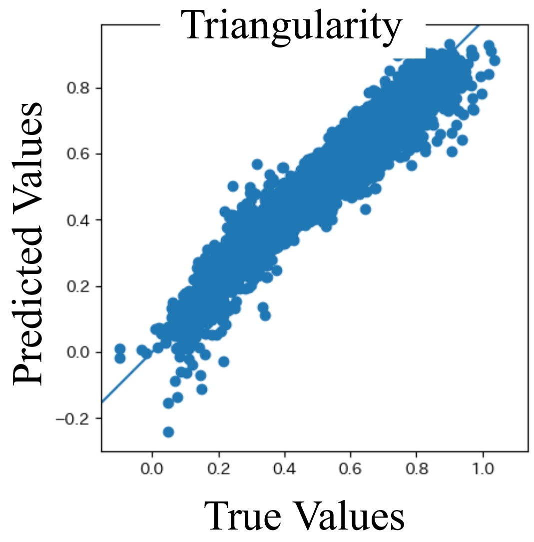












Standard deviation between true values and predicted values

Name		Std. dev.
Plasma current	Ip	3.3 kA
Major radius	R	7.65 mm
Minor radius	a	6.33 mm
Elongation	κ	0.048
triangularity	δ	0.049

- Although the deviation of Ip appears large from the plot, the standard deviation is sufficiently small.
- The deviation of κ and δ is about 5 % from the typical range (κ: 1 ~ 2, δ: 0 ~ 2).

Evaluation of model validity etc.

Calculation time for prediction

The time taken to normalize, standardize, and predict was evaluated.

Calculation condition

- Batch processing
  (265ms to predict 7835 of data)
  ⇒ 34 usec/data
- Call python language directly
  (not a compiler language)

Detailed time evaluation is required.
However, it seems to be fully applicable to real-time shape recognition, since the calculation speed is **sufficiently fast**.

Normalization issues

As mentioned earlier, to reduce the amount of the dataset, the following normalization is performed.

Normalize to the value per unit PF coil current.

- Normalization Factor nf
  = Sum of 5 PF abs. coil currents $\left(nf = \sum_{i=1}^{5} |I_{PFi}|\right)$
- Normalize values:
  5 PF coils, 8 hall sensors, Ip
  $\left(ex.\, I_{PFi\_normalized} = I_{PFi}/nf\right)$

Case 1.		Case 2.
Ip: 100kA	×1/100 →	Ip: 1kA
PF17: 1.0kA		PF17: 0.01kA
PF26: 1.0kA		PF26: 0.01kA

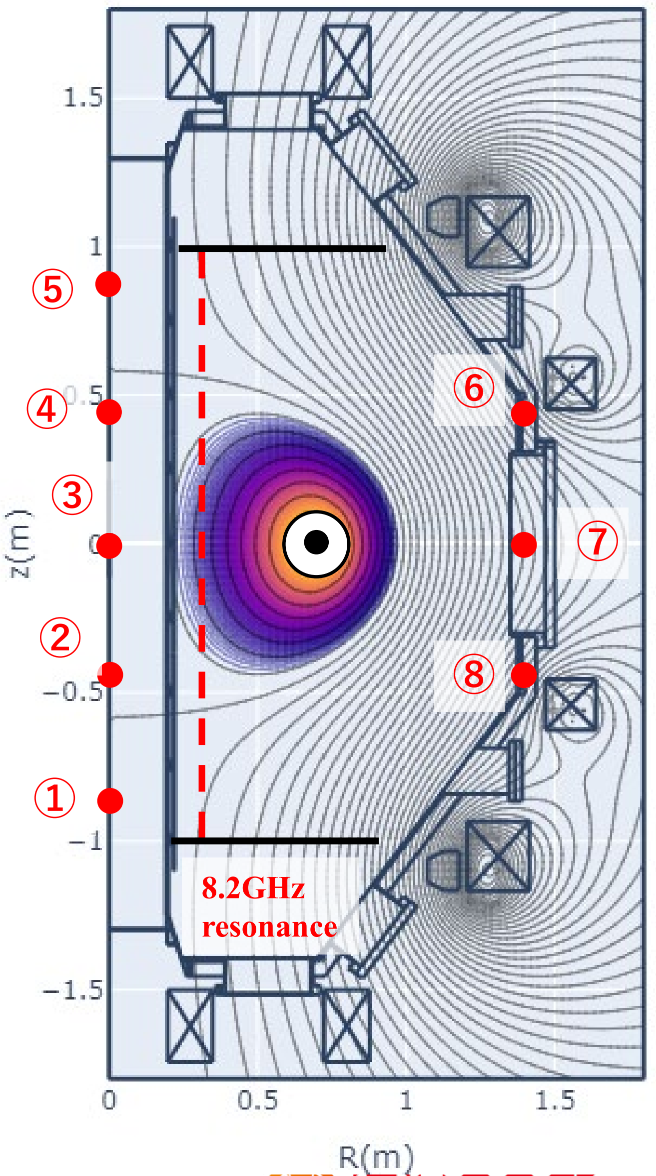
The data in these two cases are **treated as the same data** by this normalization.

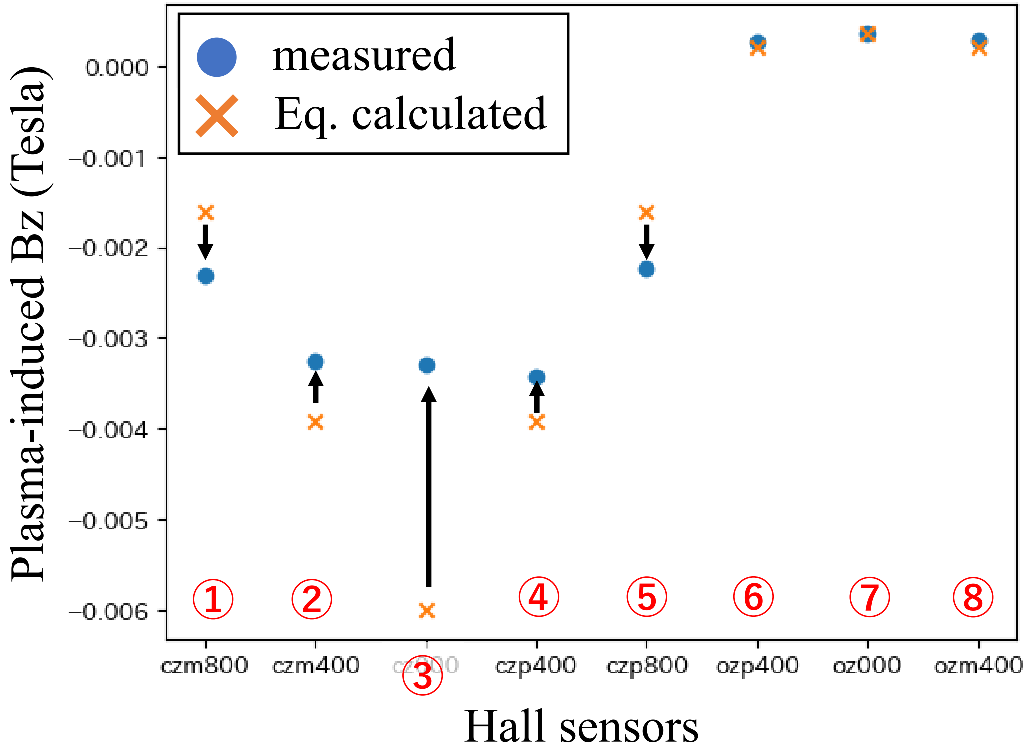
- This normalization is useful for the plasma shape recognition with a small amount of dataset.
- It cannot be applied when dealing with plasma pressure, beta value, etc.

⇒ Other methods are being considered to account for other equilibrium quantities.

Difference between measured and equilibrium values of Bz

#27207 @t=2.0sec





Equilibrium cal. to obtain the inner limiter configuration.

- Outer hall sensors: match well
- Inner hall sensors: systematic difference

Large positive: ③
Small positive: ②, ④
Small negative: ①, ⑤

- This suggests that there is a local toroidal current near the Hall sensors, namely current profile in the z direction.
- The difference between the measured and the calculated values appears to depend on the value of Bz.

→ Machine learning to recognize the plasma shape needs to take these systematic differences into consideration.

Summary

- Using Deep Neural Network (DNN), plasma shapes can be predicted quickly and with high accuracy.
- It is necessary to consider new methods that handle not only plasma shape but also plasma pressure, beta value, etc.
- For practical applications, it is necessary to incorporate the effect of local toroidal current distributed in the z direction.