Application of Machine Learning to Collision Parameter Tuning in the SuperKEKB Accelerator

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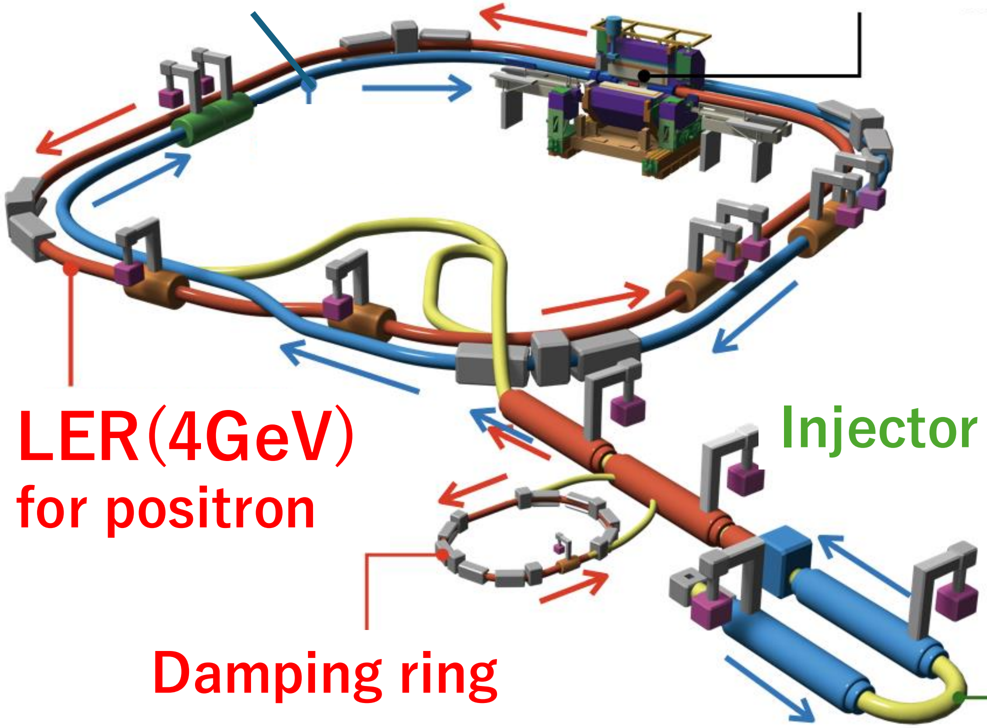
Tokyo University[A], KEK IPNS[B], SOKENDAI[C], Nara Woman's University[D]

Belle II Experiment and SuperKEKB Accelerator



Belle II experiment searches new physics using **SuperKEKB Accelerator** which records the highest luminosity in the world.

$$N = \sigma \int L \, dt$$

Number of event

Cross section

Luminosity

Target Luminosity before Long shutdown:

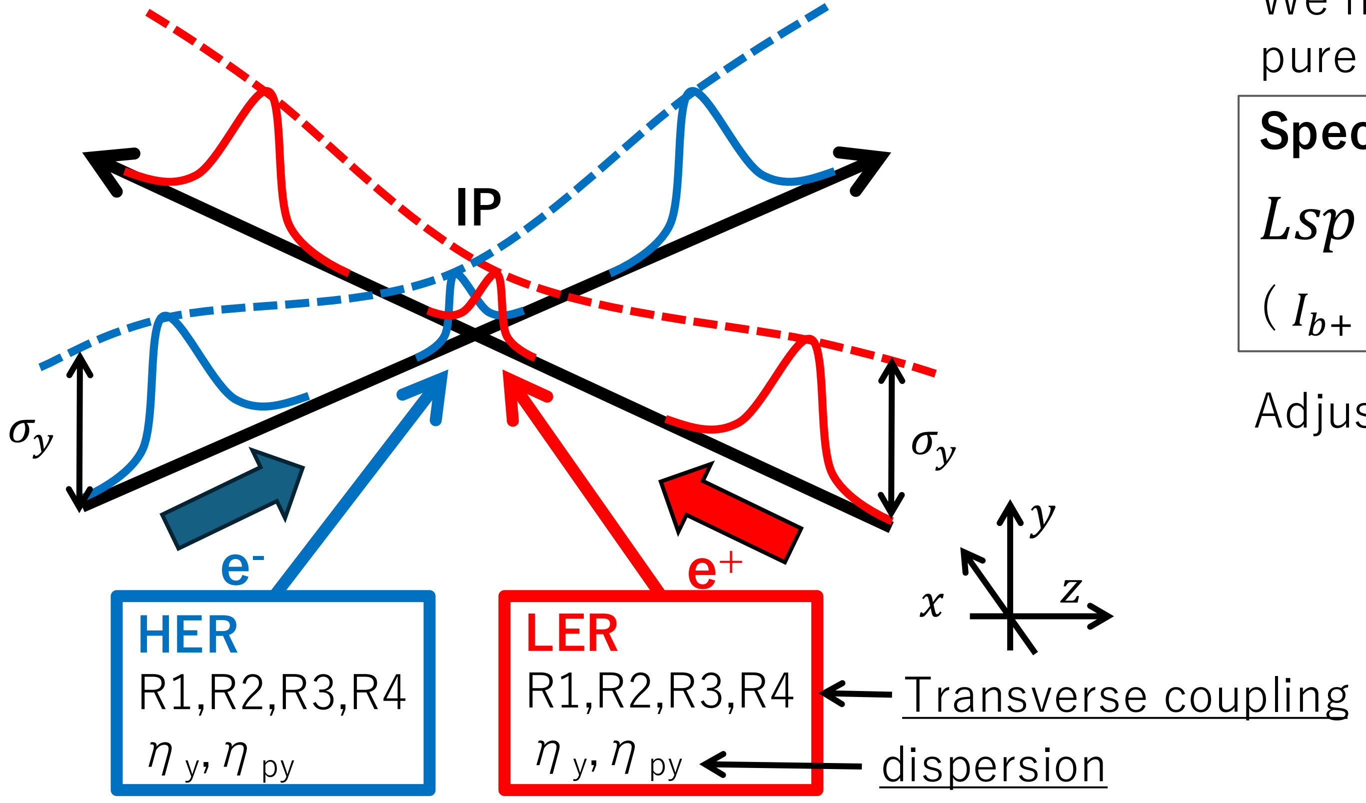
$$\mathbf{2 \times 10^{35} [cm^{-2} s^{-1}]}$$

Achieved Highest Luminosity:

$$\mathbf{5.3 \times 10^{34} [cm^{-2} s^{-1}]}$$

Beam Collision Parameter Tuning at SuperKEKB

- **There is 12 tuning parameters.**
- **These parameters change beam size at IP**



Beam collision parameters

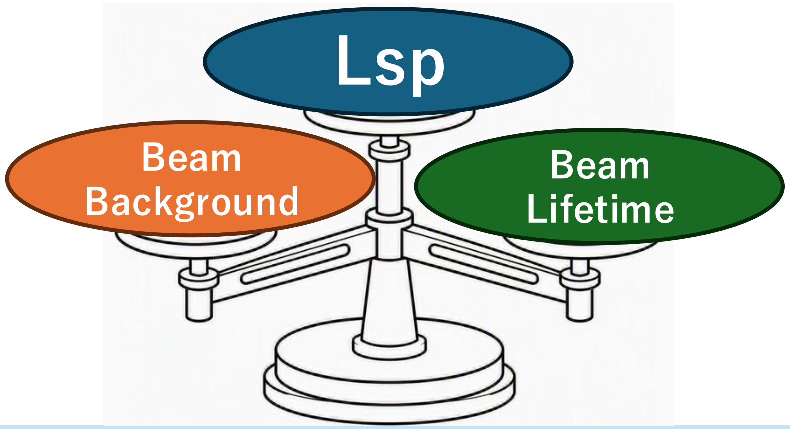
Luminosity itself depends on Beam Current and Number of bunches.
We need to use **Specific Luminosity** to monitor pure collision status.

Specific Luminosity(Lsp) :

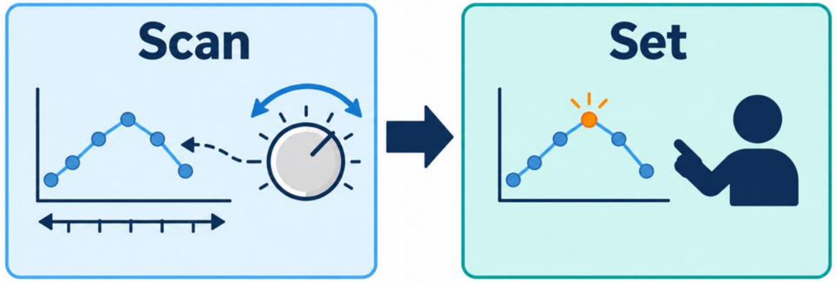
$$Lsp := \frac{L}{I_{b+} I_{b-} N_b}$$

(I_{b+} / I_{b-} : bunch current N_b : number of bunch)

Adjusting beam size at IP be like…



Why Do We Need ML for Beam Collision Tuning?



Scan Part

Current situation
- **Manual linear scan for each parameters**

Problems
- Consuming a lot of time.
- Scanned parameter space is too small.

Solution
- **Bayesian Optimization**

- Optimization by using **Gaussian Process** which is surrogate model.

Set Part

Current situation
- **Set Optimal setting by operator's decision**

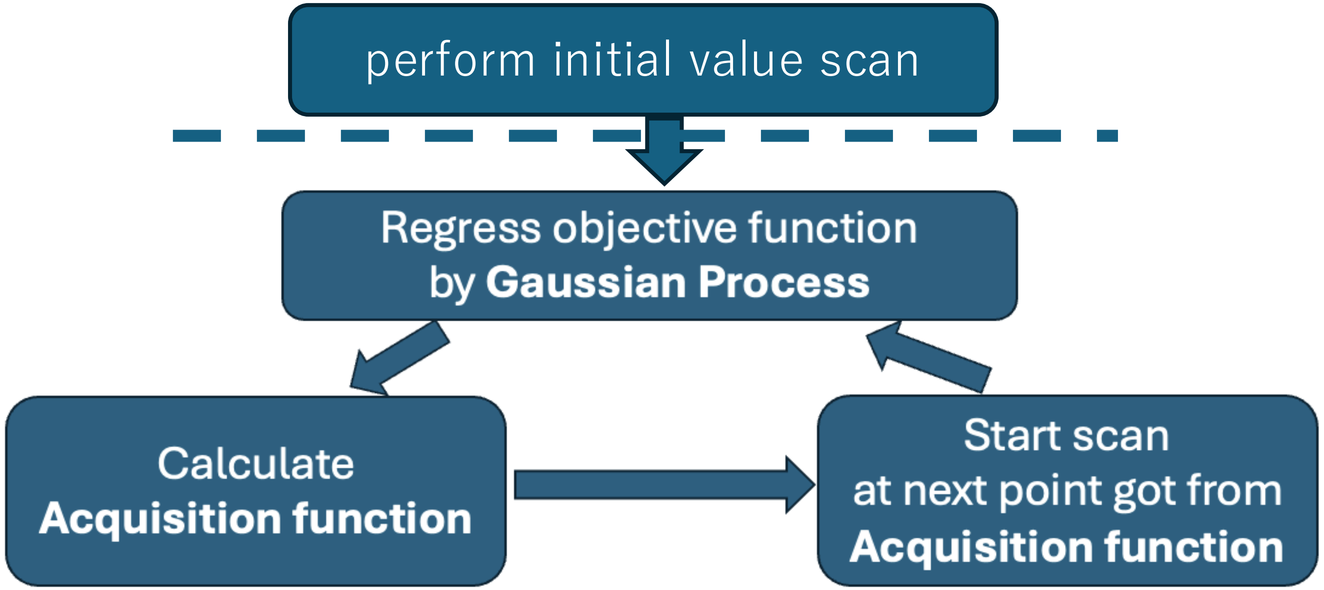
Problems
- No obvious criteria.
- Various purpose.
(Increase Luminosity, Suppress Background...)

Solution
- **Machine Learning**

[Scan] Overview of the Bayesian Optimization Tool

Concept of Bayesian Optimization :

1. Regress objective function using Gaussian Process.
2. Calculate Acquisition function to decide next scan point.
3. Scan at next scan point.
4. Iterate 1.-3.



Iterate this loop until converges

There are various parameters to monitor.
But…

For simplicity, we defined
Objective function: Lsp

Acquisition function: $\mu + \alpha\sigma$
(μ, σ : prediction, dispersion from GP
α : exploration parameter)

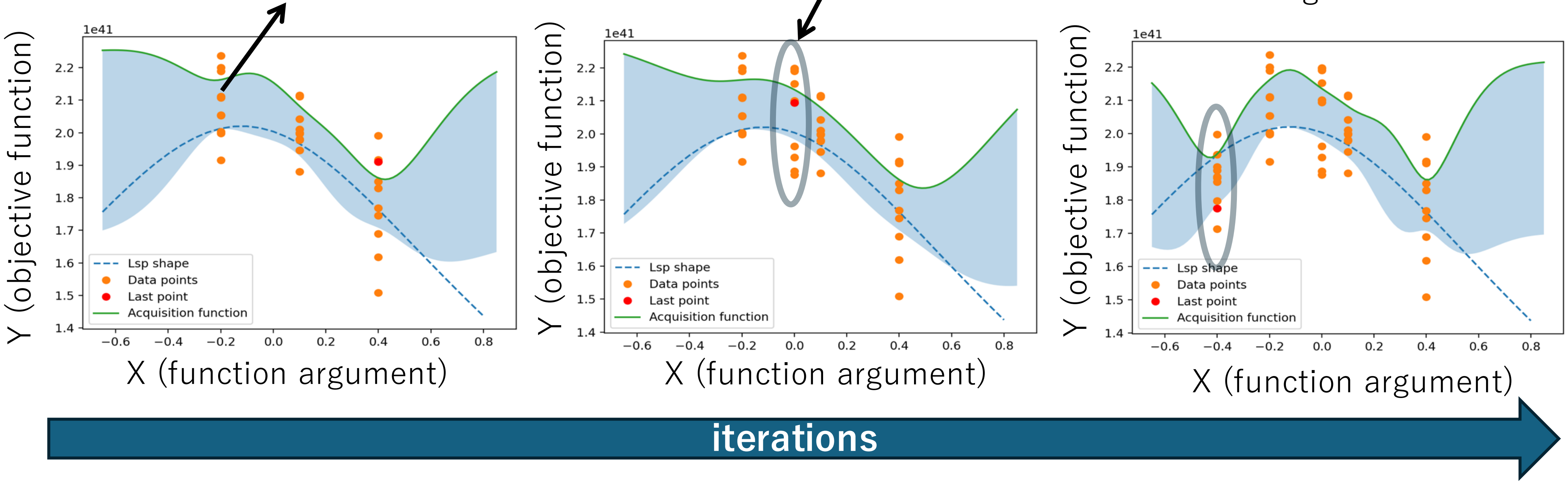
Convergence Criterion:
the next point is within 0.1 step
(manual linear scan step) from the current point.

[Scan] Example of Bayesian Optimization

1. Gaussian Process Regression
2. Calculate Acquisition function

3. Scan at next scan point.

Gaussian process output changing through iterations

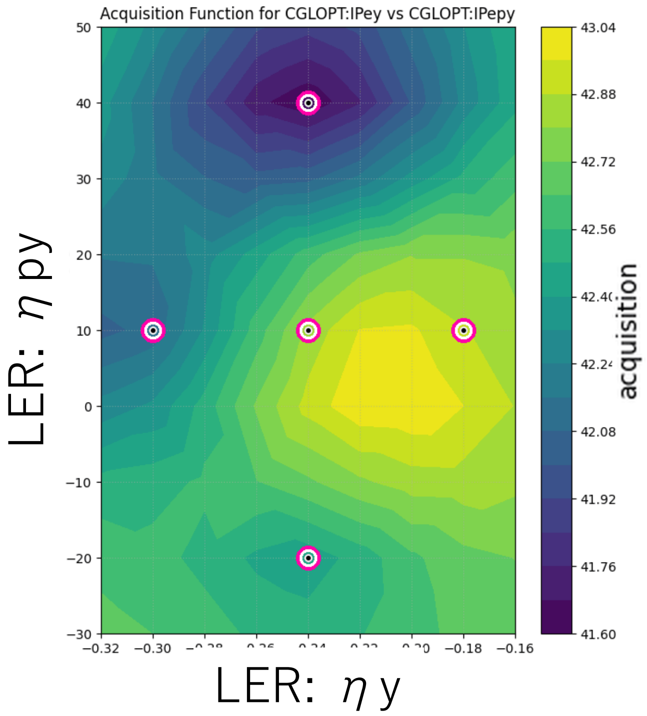


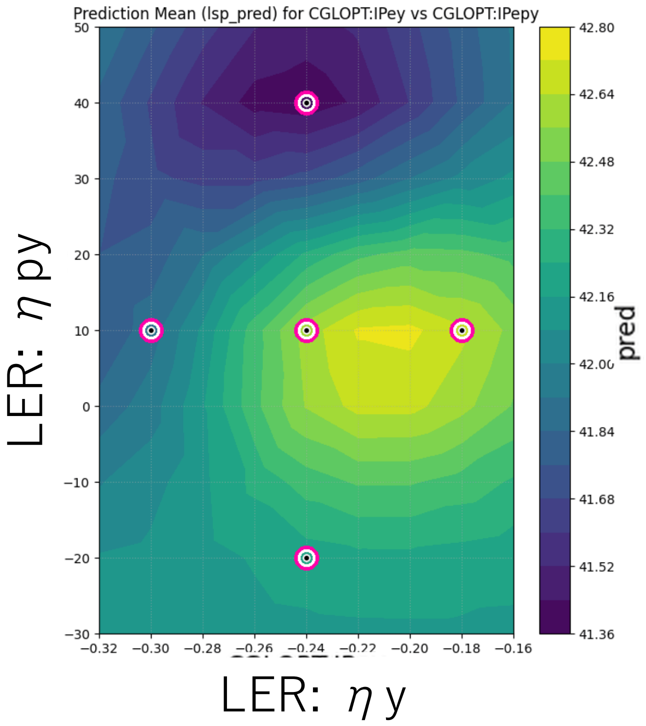
Advantages of using Bayesian Optimization

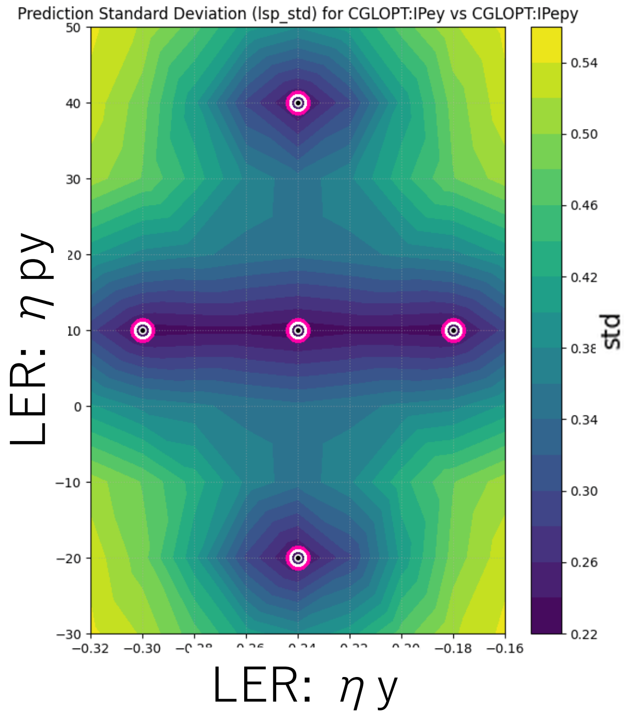
- No prior training required
- Several previous studies have applied Bayesian optimization to accelerator tuning.

[Scan] Evolution of the Acquisition Function During a 2D Scan

The tool was tested during BelleII data taking.
In this test, we performed 2D scan for LER's beam collision parameters η y and η py







- **2D scan was successfully converged to best Lsp point**
- For stable convergence, we needed to adjust distance correlation in Gaussian Process.

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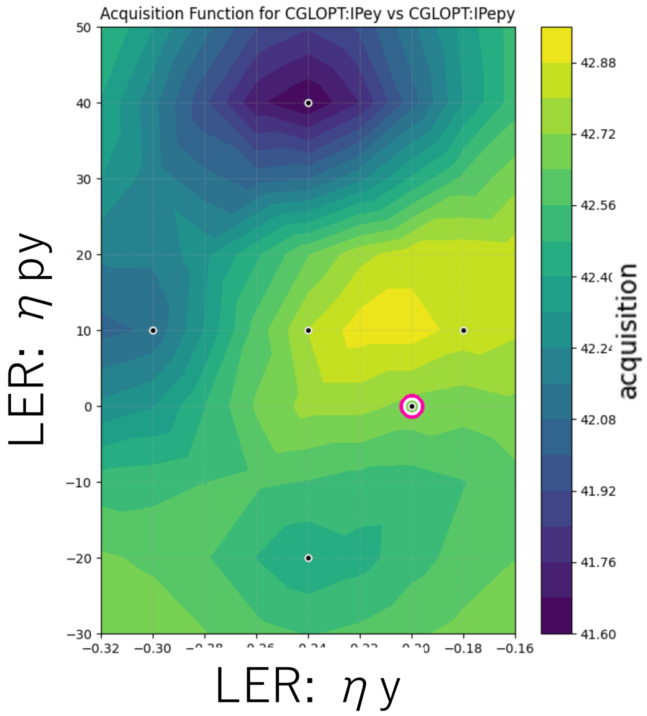

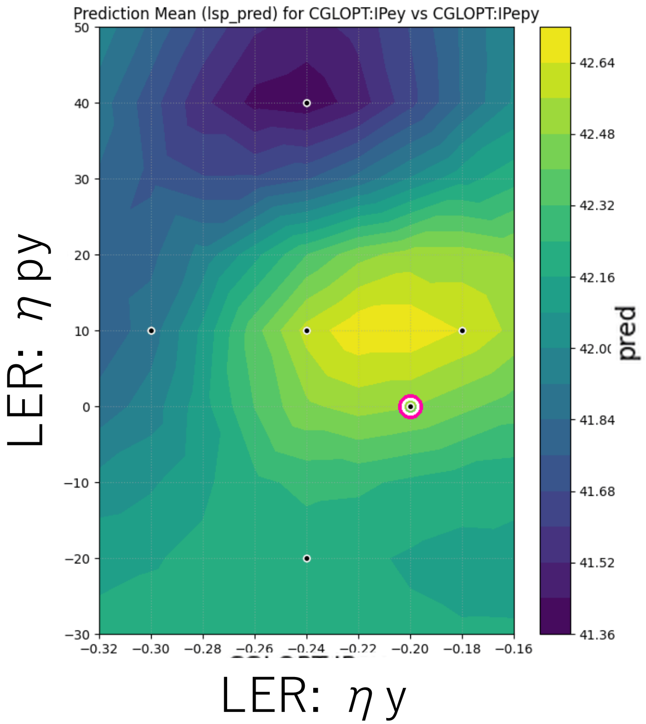

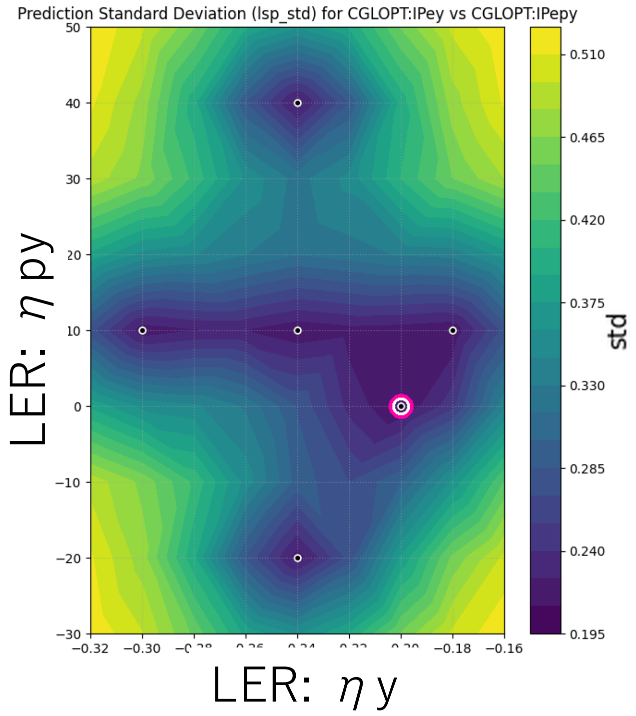

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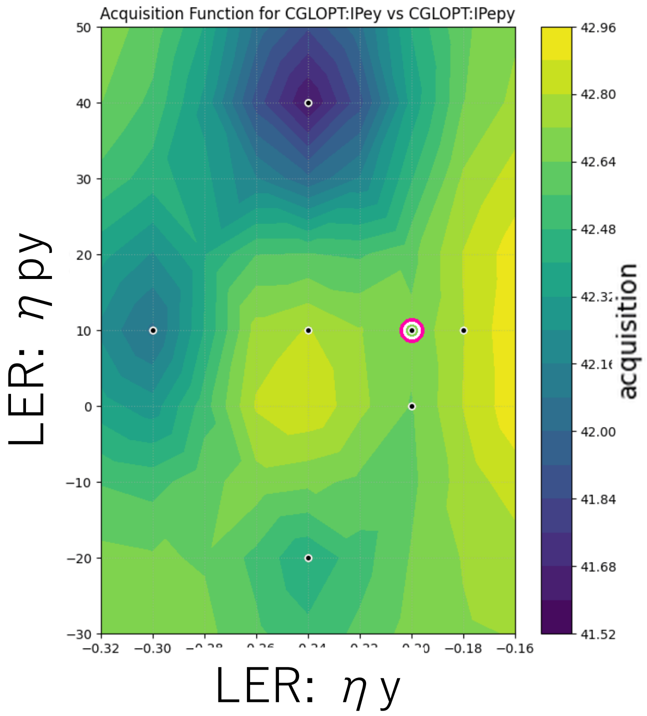

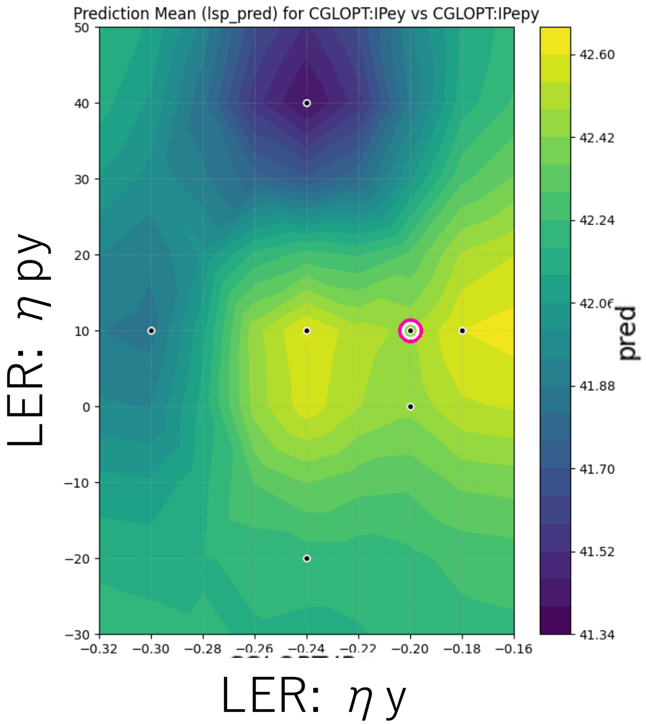

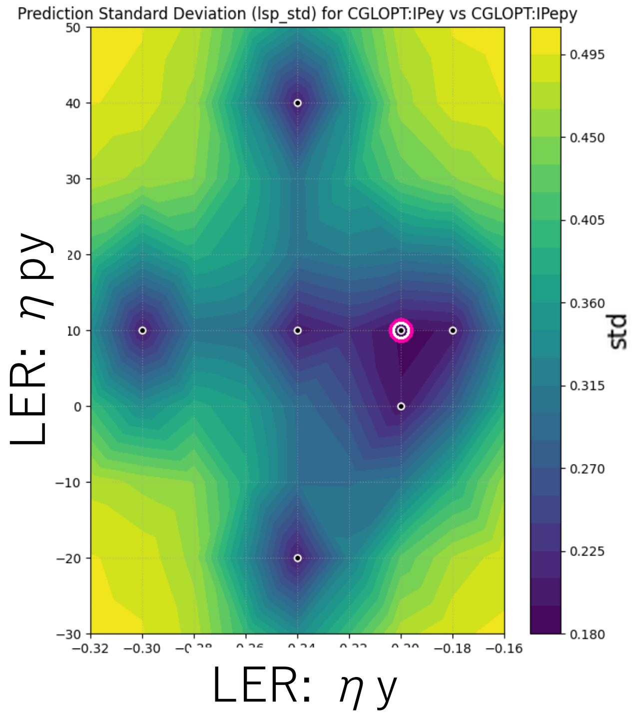

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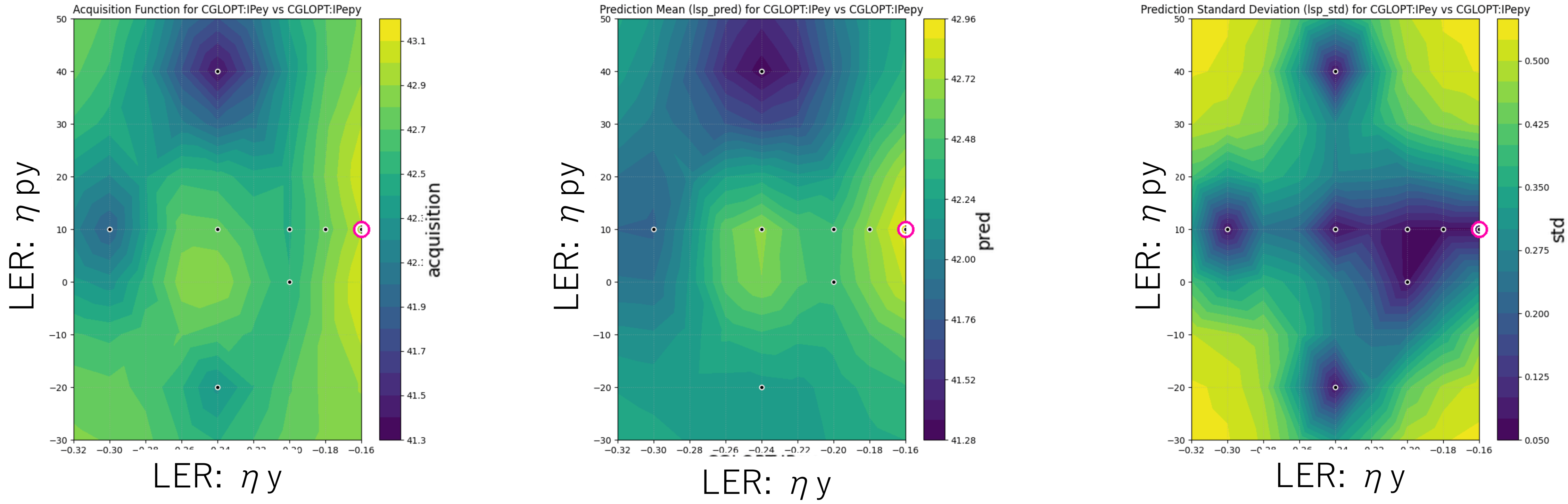

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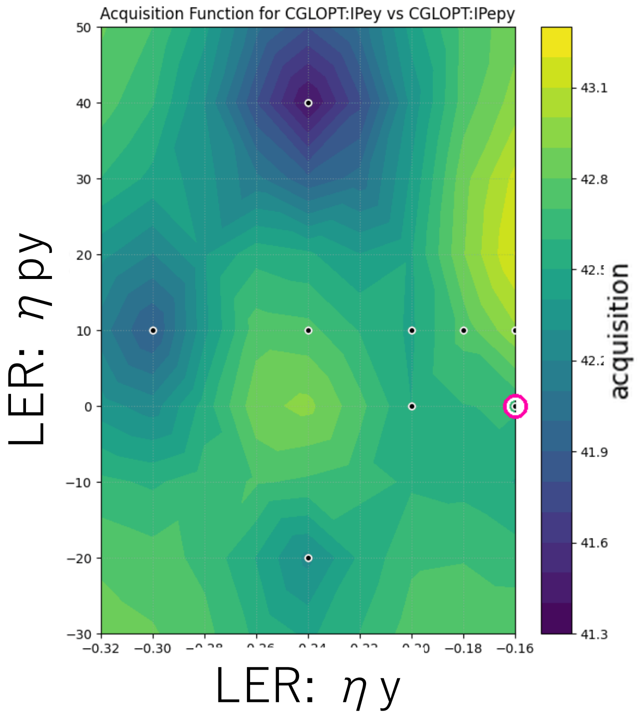

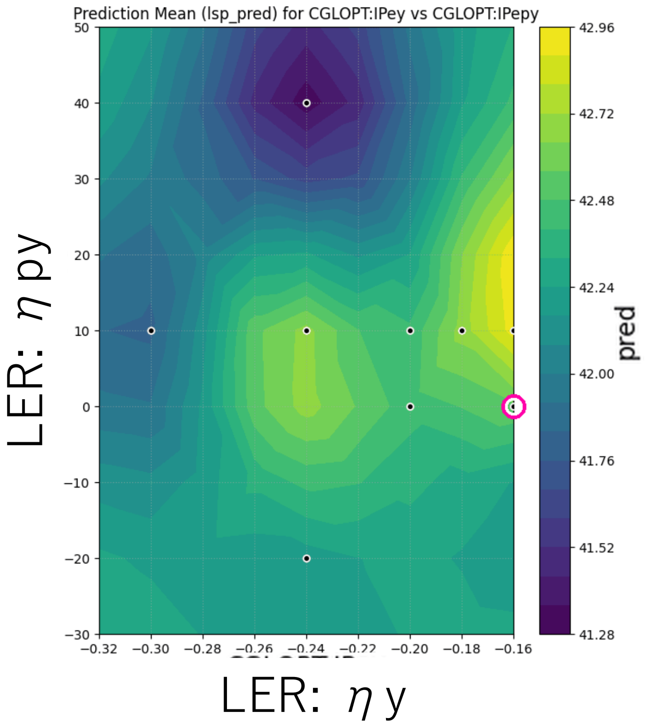

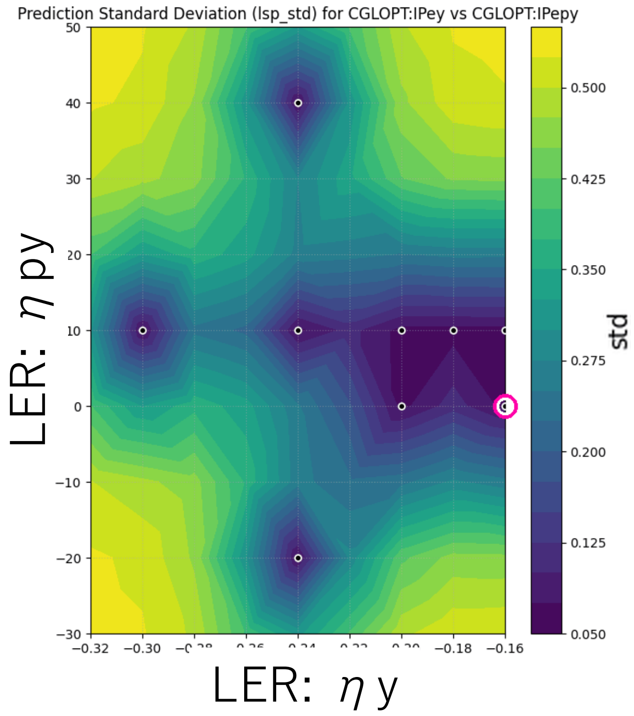

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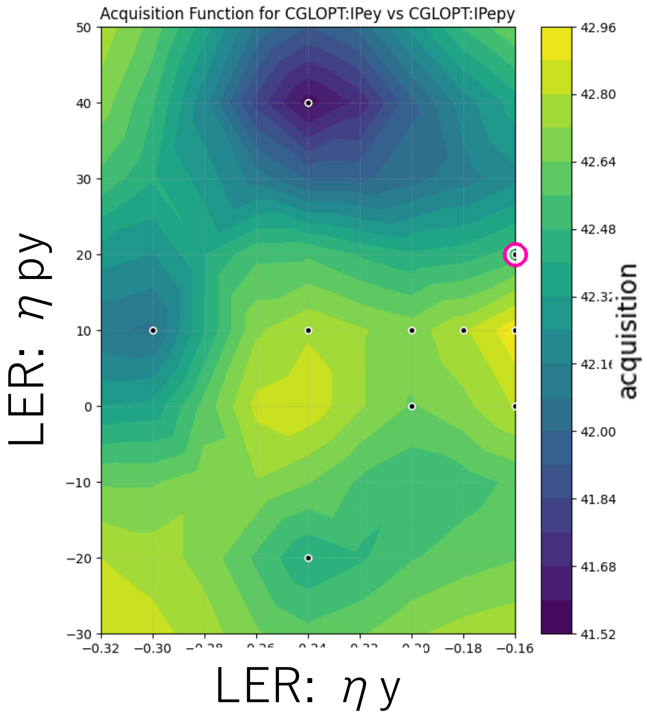

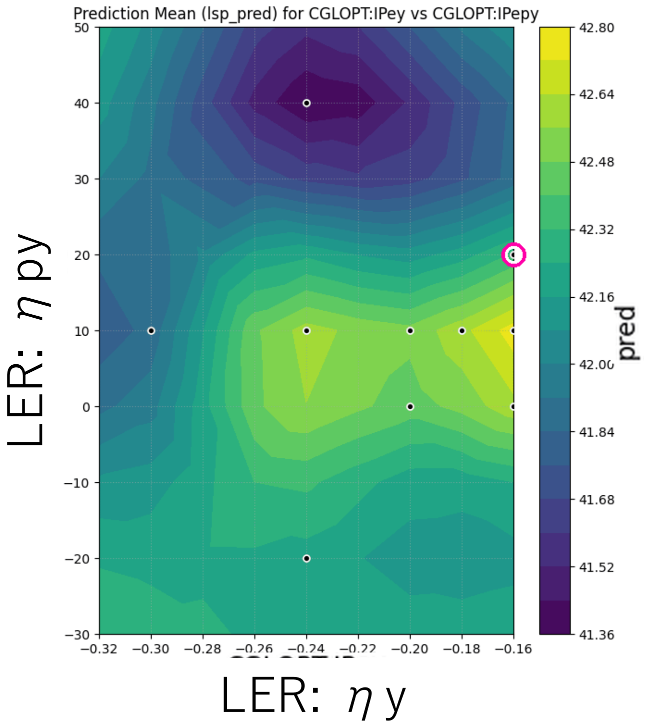

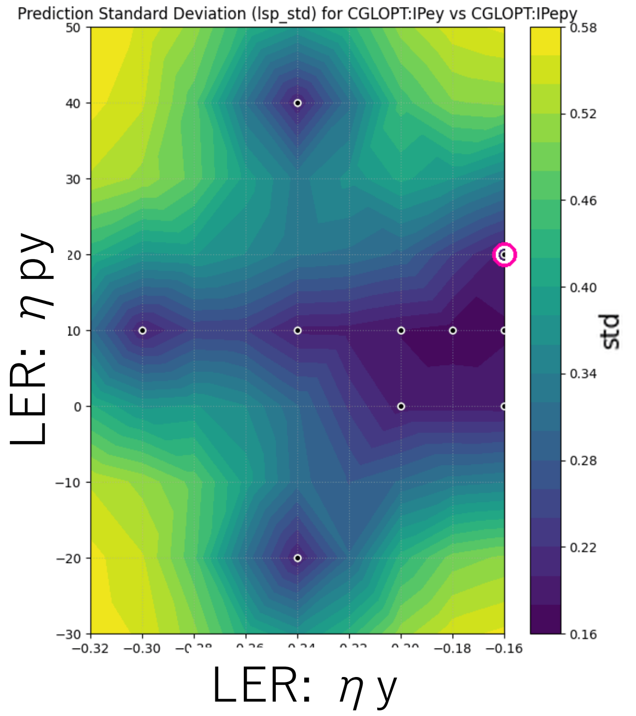

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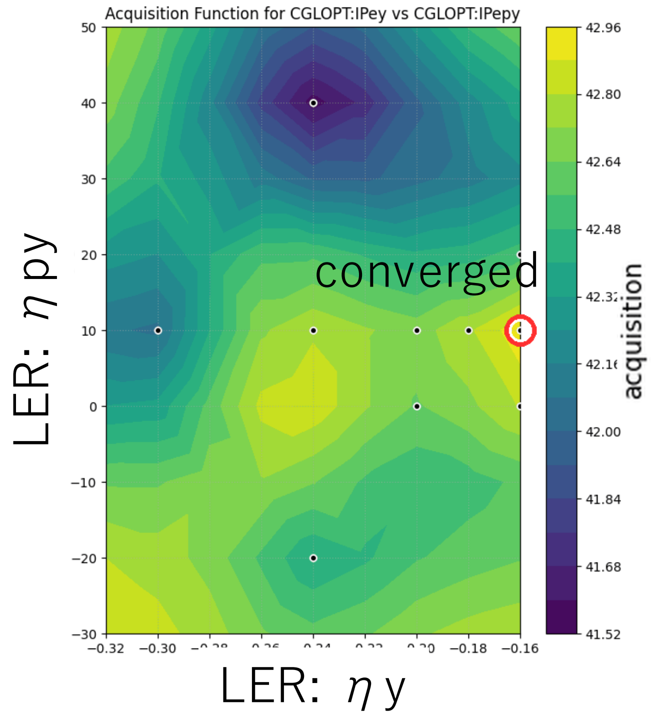

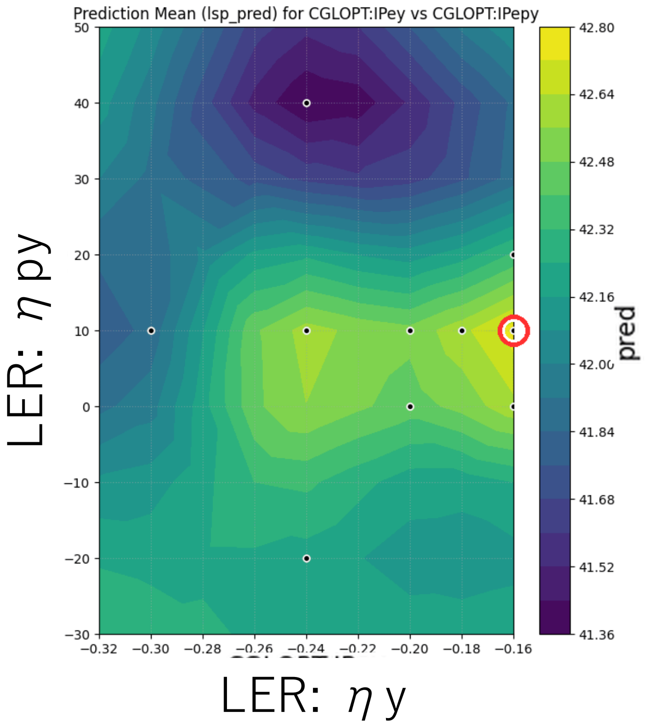

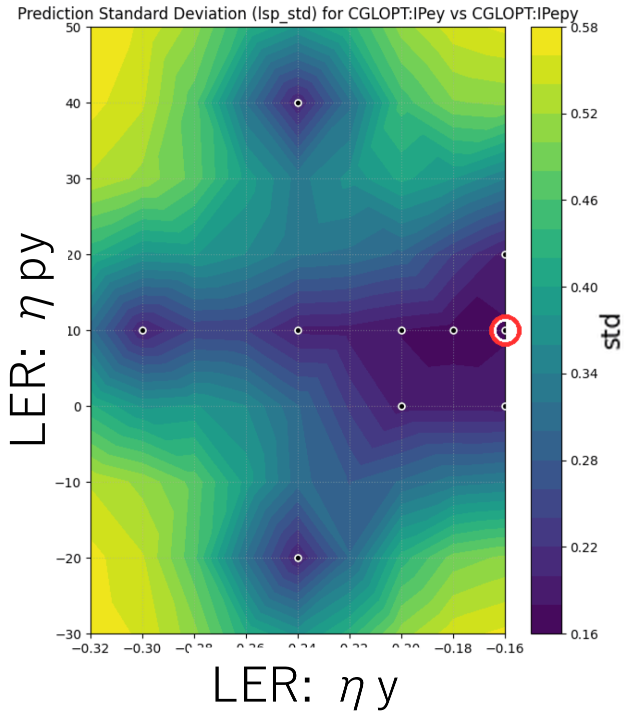

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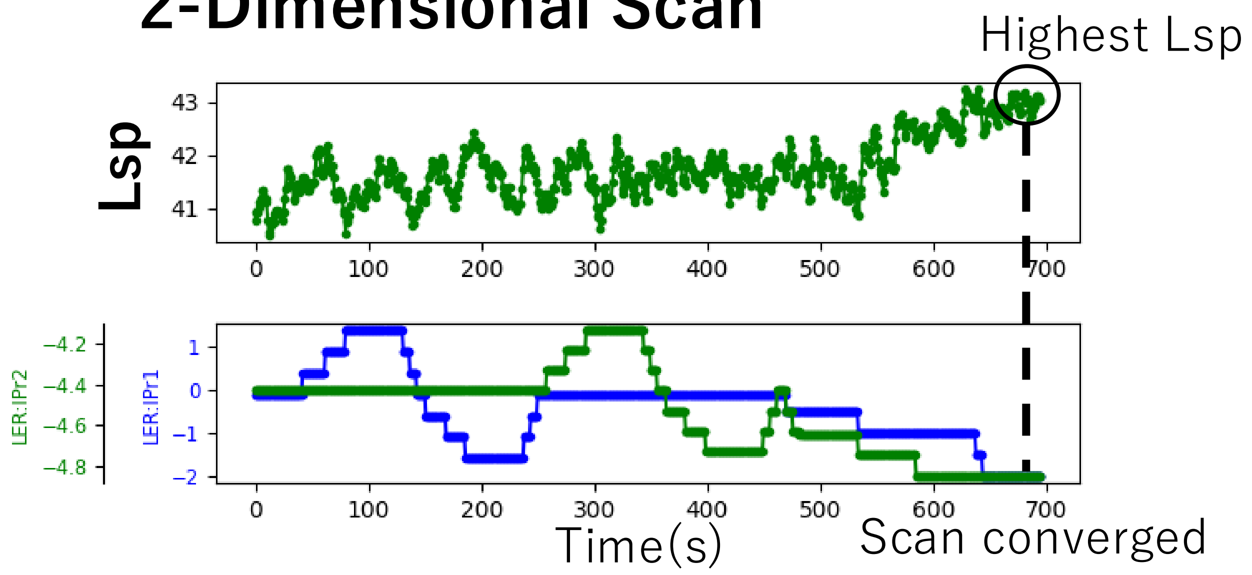
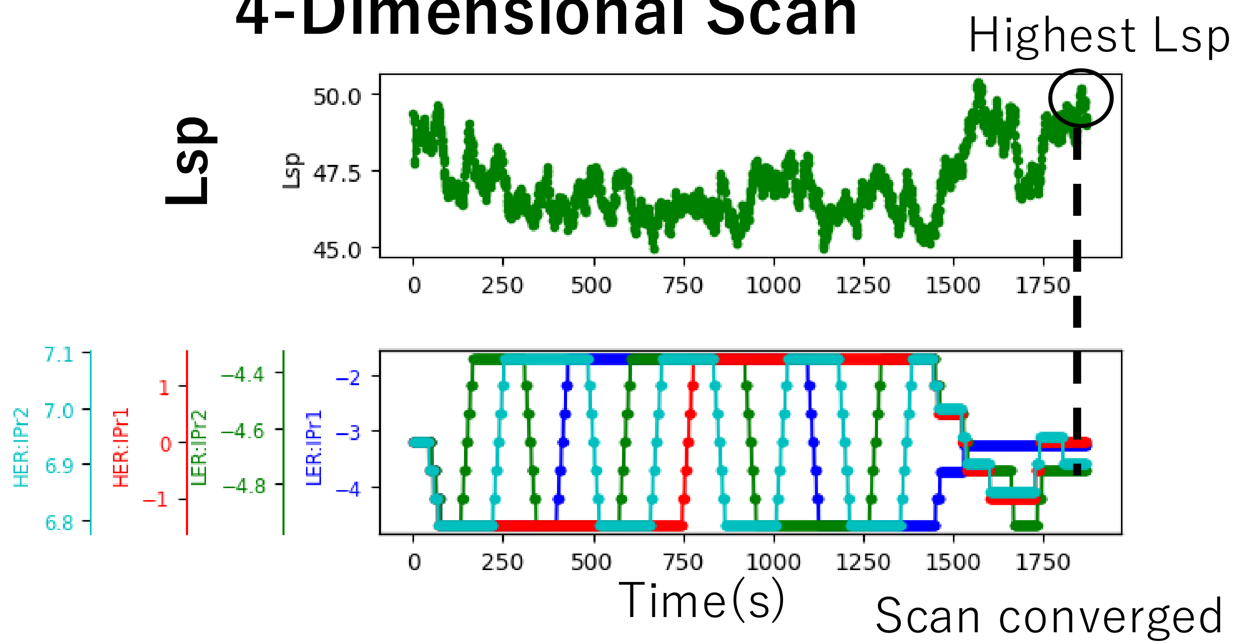
[Scan] Multi-dimensional Scan Using the BO Tool

Results of Applying the Tool to 2-Dimensional Scan



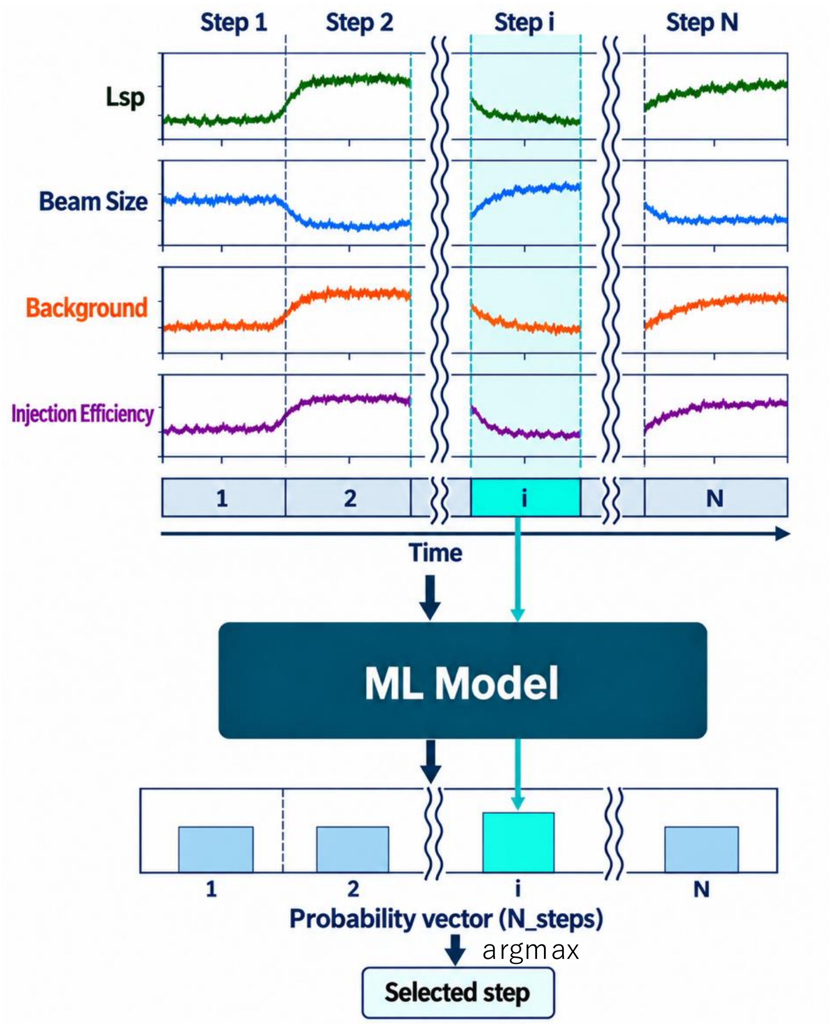
4-Dimensional Scan



- Extreme tuning can destabilize the beam, but this behavior was not observed in tests.

We confirmed that the tool supports multidimensional BO up to four dimensions.

[Set] ML Framework and Training Data for reproducing Operator’s decision



Set : Set Optimal setting by operator’s decision

- No obvious criteria.
- Various purpose.

→ We want to reproduce operator’s decision using ML

- One (scan+set) is one data.

Input features：

{collision parameters, Lsp, BackGround, BeamSize, inj eff}$_i$ $(1 \leq i \leq N_{steps})$

Output：

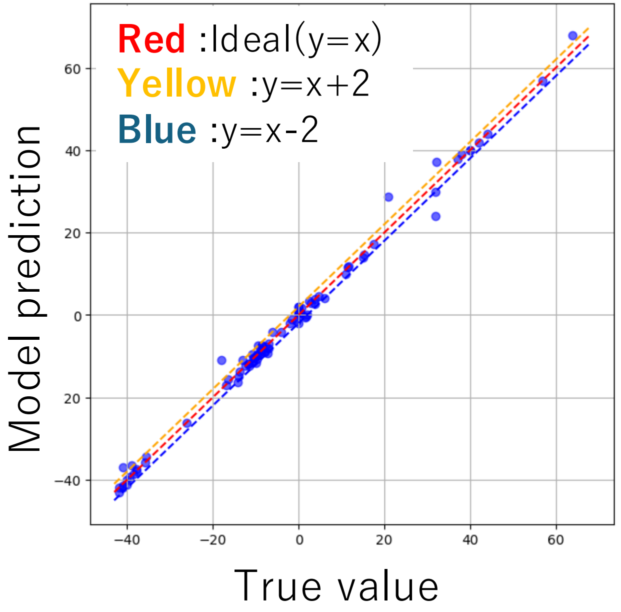
One parameter value within the scan range.

Training data set：

All collision parameter tuning during 2024 and 2025

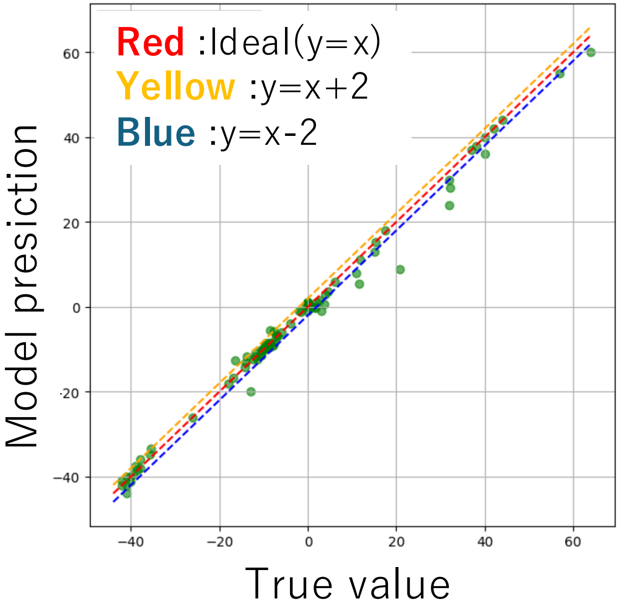
[Set] Validation of ML Models on the Test Data

Encoder model



Within 1step: 72.73% , count:64
Within 2step: 89.77% , count:79

NN model



Within 1step: 72.73% , count:64
Within 2step: 84.09% , count:74

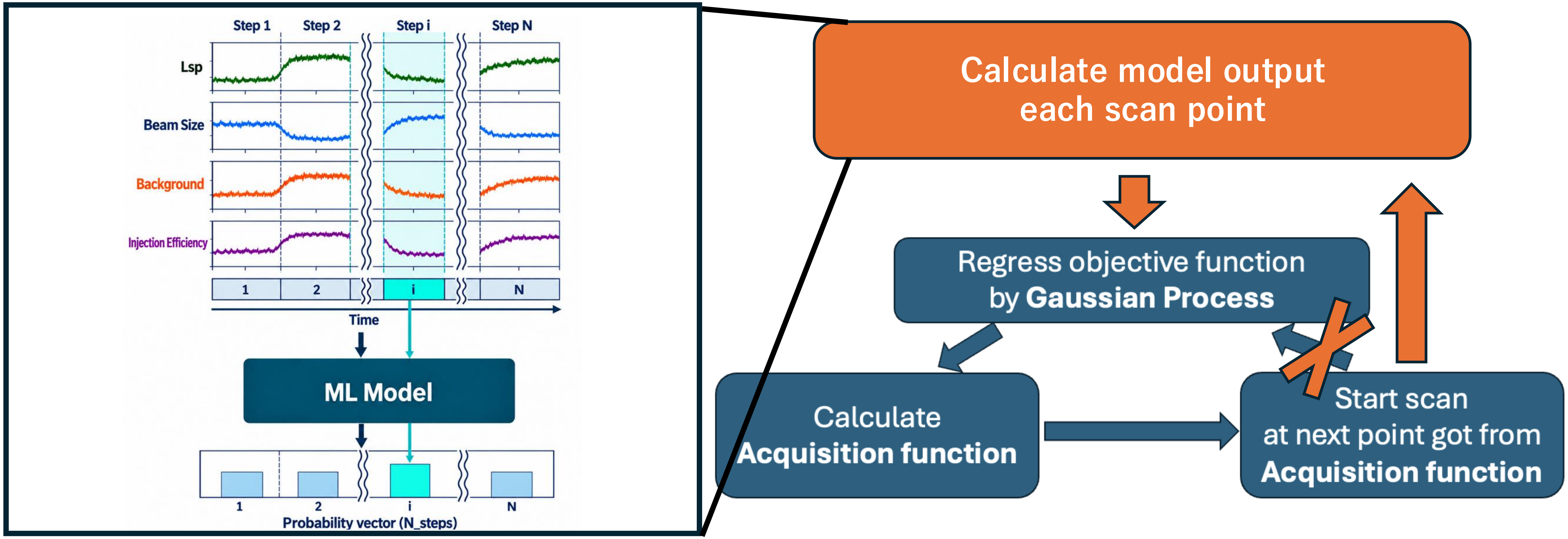
Plots of Reproducing 2024 and 2025 operator's decision
(collision parameters are normalized.)

- The NN achieved slightly higher average accuracy but produced more outliers.
- The encoder model produced fewer outliers.

80–90% of predictions were within ±2 steps of the operators' selections.

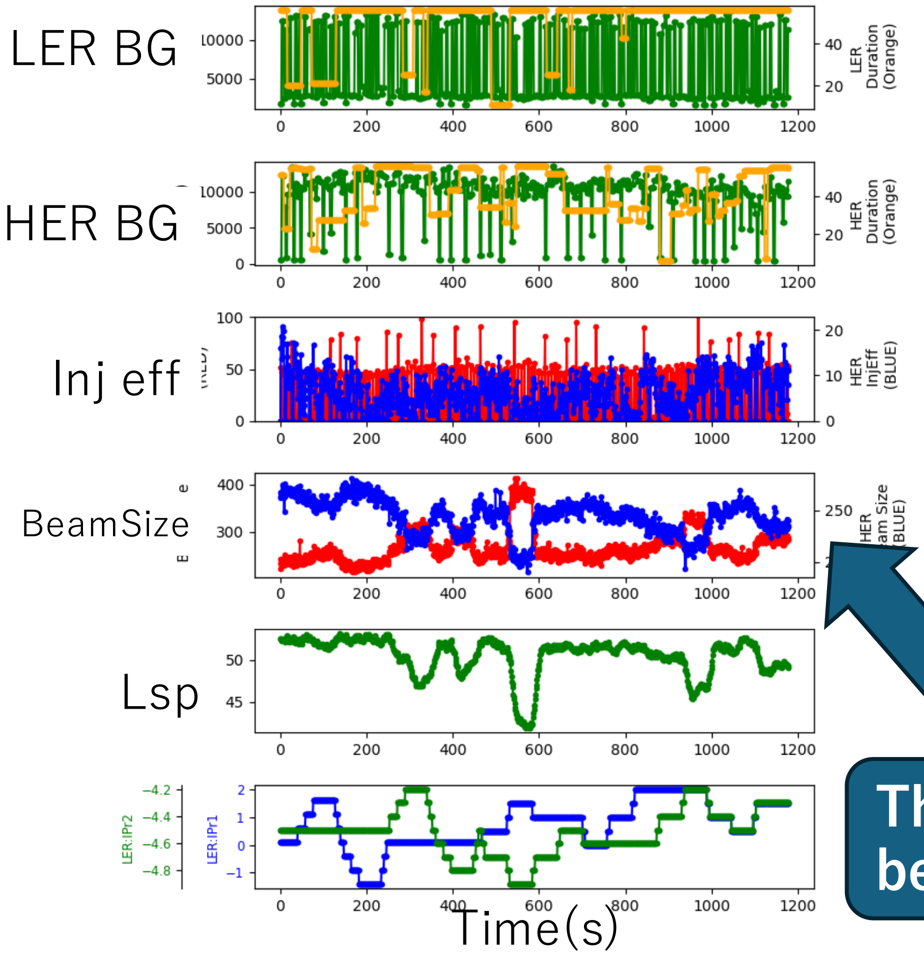
[Scan+Set] Structure of BO + ML model

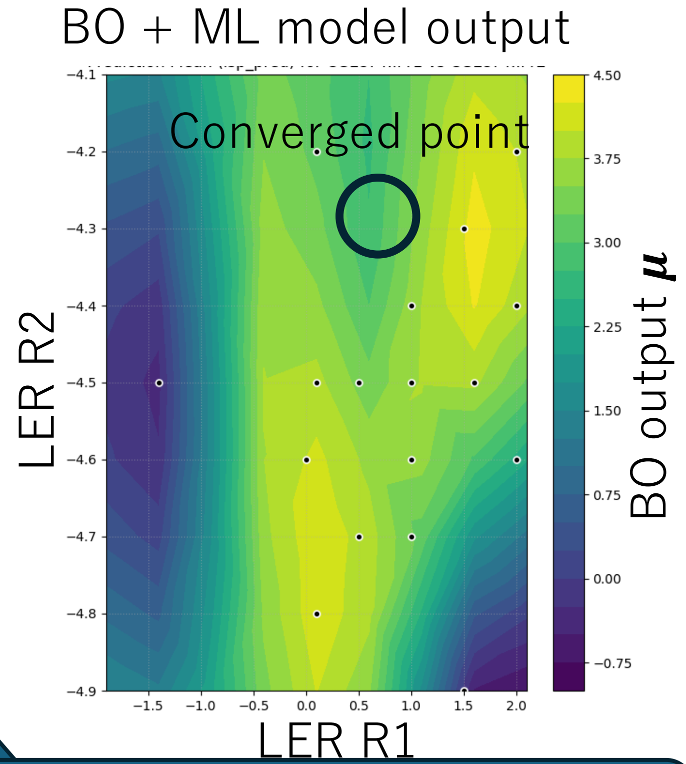
- We combine BO and ML model to bring the tool closer to operator's scan.

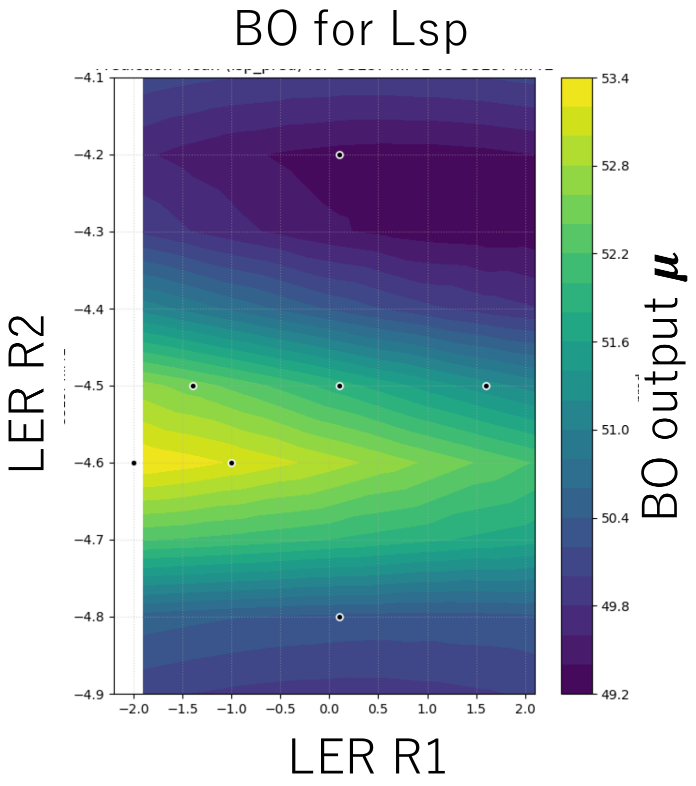


[Scan+Set] Applying BO + ML model to 2-dimensional scan

The tool was tested during physics data taking.







The model tends to reduce both beam sizes regardless of Lsp.

Remaining Challenges

The tool is operational, but two major challenges remain.

1. Scan:
Parameters such as Lsp fluctuate by several percent, independently of the scan.

Plan
- Development of an Lsp Extrapolation Model to Mitigate Fluctuations Caused by External Factors

2. Set:
The limited number of scans makes machine-learning training difficult.

Plan
- Development of Unsupervised learning.
- Development of beam collision simulation.

Summary and Future prospects

- We developed a tool to automate beam collision parameter tuning for higher luminosity.

- During the 2025 and 2026 operations,
  we tested multidimensional scans using Bayesian optimization.

- We also used machine learning
  to reproduce parameter settings selected by operators in past tuning operations.

- After that we combined the Bayesian optimization and Machine learning
  to make this optimization close to actual scan.

Future Prospects

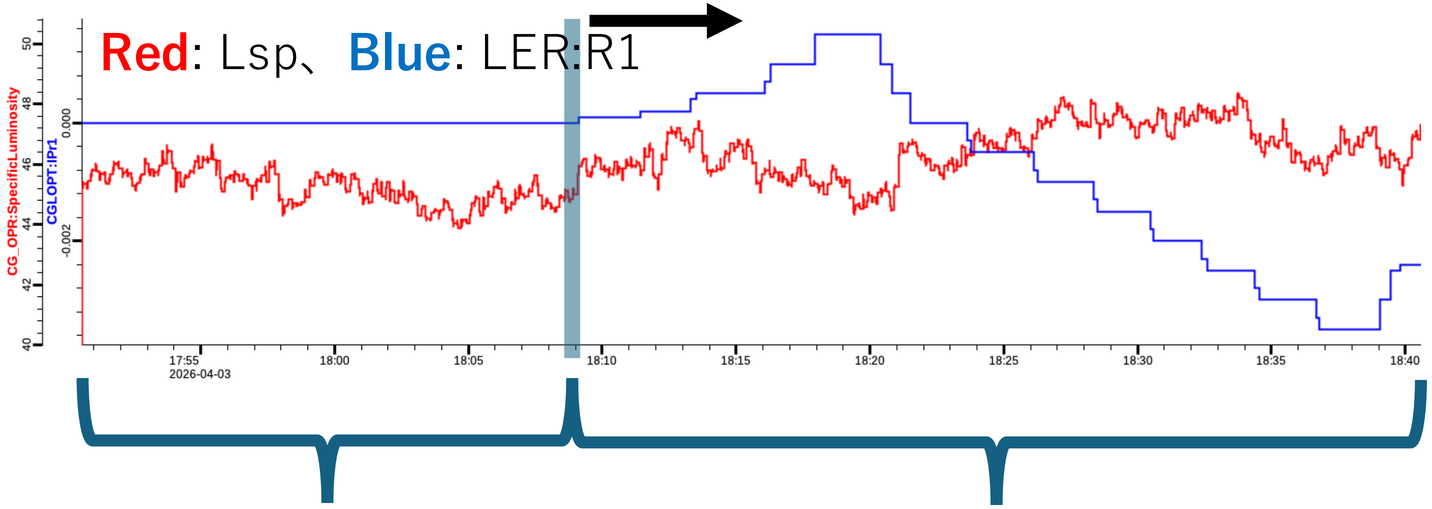
- Development of an Lsp Extrapolation Model
  to Mitigate Fluctuations Caused by External Factors.

- Development of Unsupervised learning.

Back up

Development of an Lsp Extrapolation Model to Mitigate Fluctuations Caused by External Factors

IP knob tuning



Selecting input parameter
Regression Model Training

Regression Model Extrapolation
Extract IP knob effect

Selecting input parameter

- approximately 30 parameters that are strongly correlated with Lsp, excluding IP knob-tuning parameters.

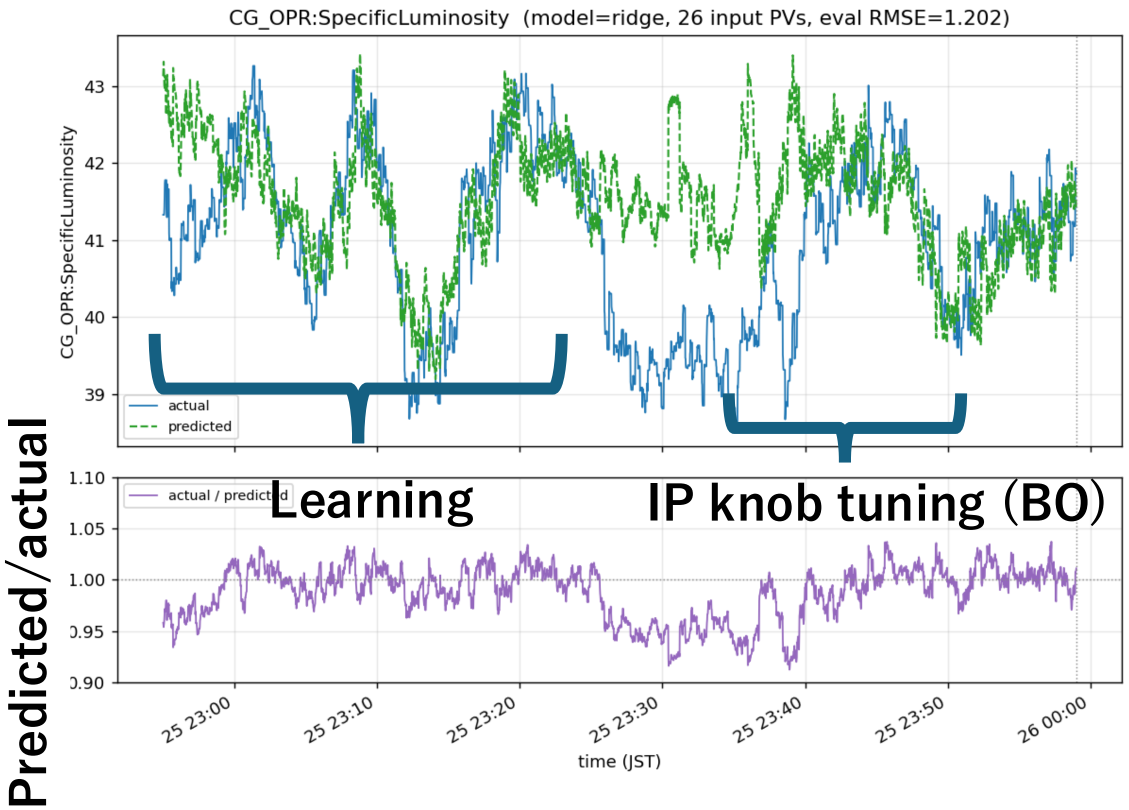
Regression Model Training

- Using the selected parameters, we performed linear regression (ridge regression) to predict Lsp.

we expect it to predict the Lsp that would have been obtained without changing the IP knobs.

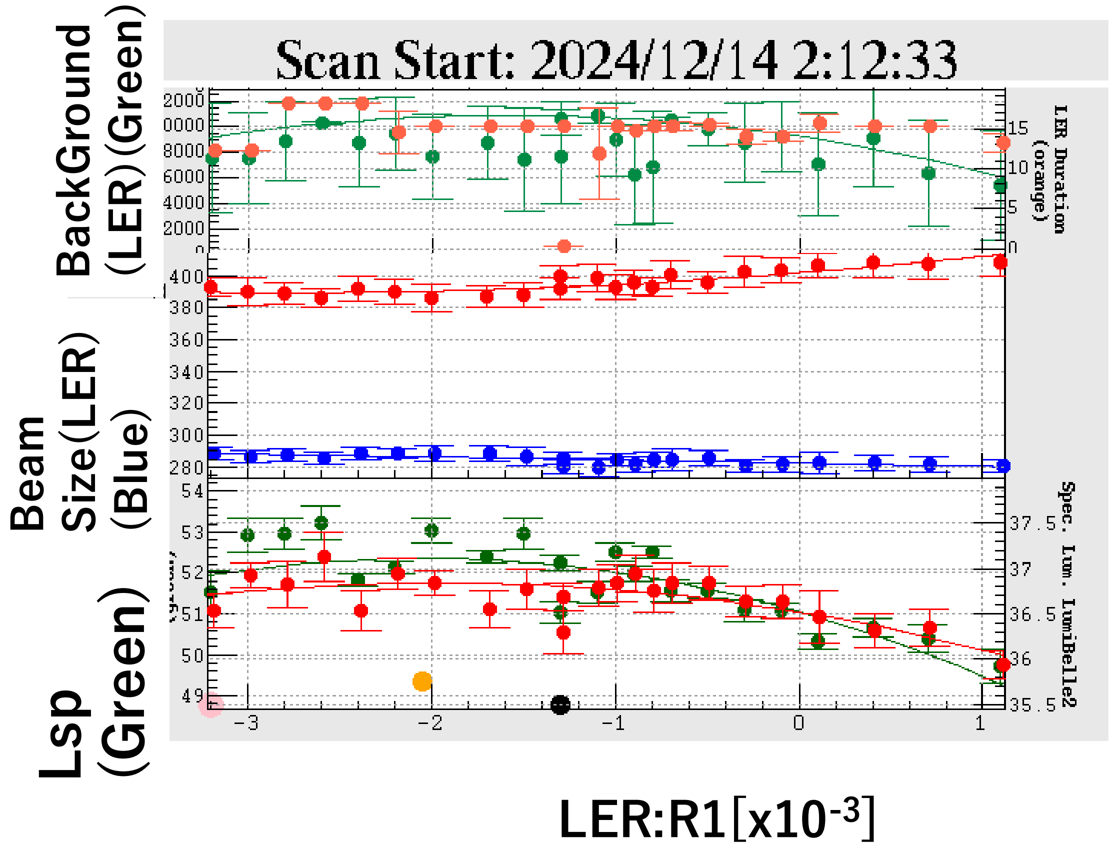
Model Training and Application Results

- we test this Lsp regression model in final operation of 2026.

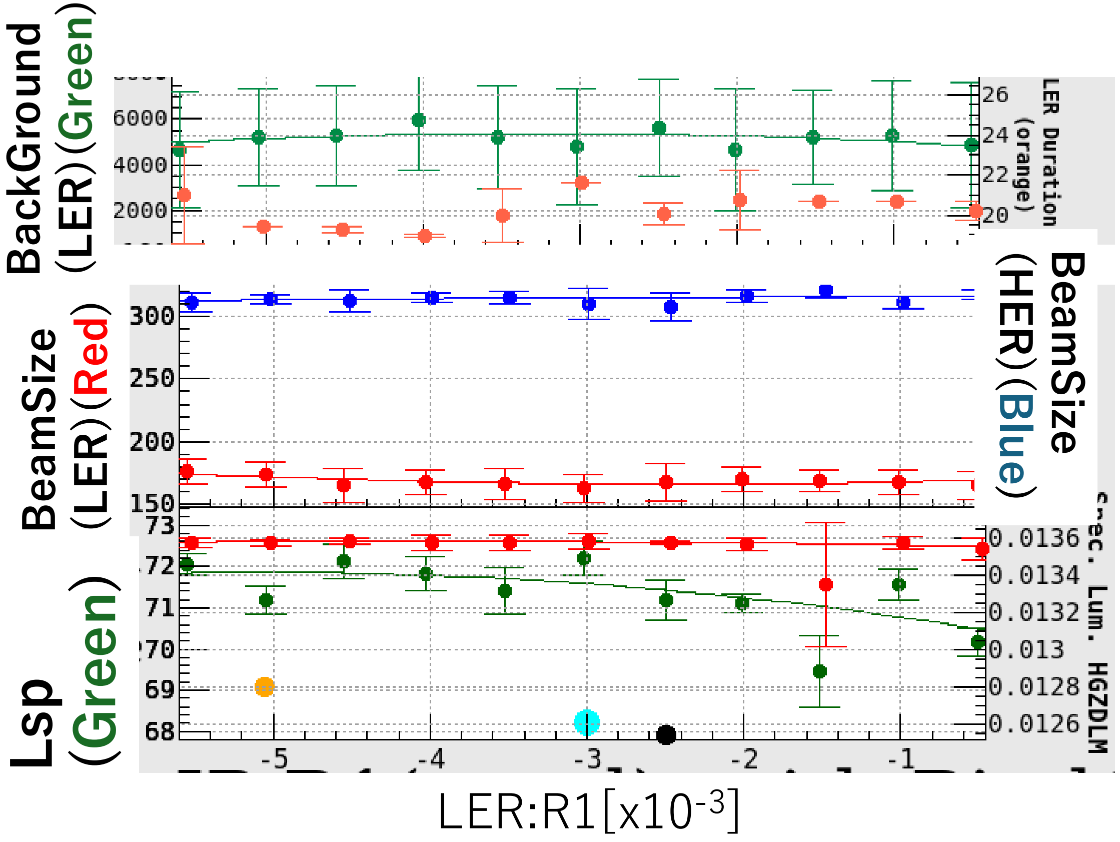


- Before changing the IP knobs, we compared the predicted and measured Lsp and found an error of approximately ±5%.
- We performed BO for actual/predicted
- The BO didn't stop at the maximum Lsp;

For next period, we will build more precise model.



Scan Start: 2024/12/14 2:12:33
BackGround (LER)(Green)
Beam Size(LER) (Blue)
Lsp (Green)
LER Duration (orange)
Spec. Lum. LumiBelle2
LER:R1[x10^{-3}]



BackGround (LER)(Green)
LER Duration (orange)
BeamSize (LER)(Red)
BeamSize (HER)(Blue)
Lsp (Green)
Spec. Lum. HGZDLM
LER:R1[x10^{-3}]