Machine learning for high current beam operation at cERL

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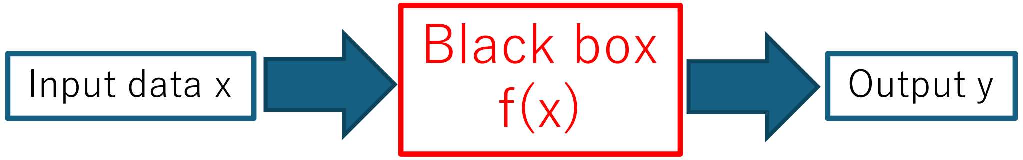
Auto-tuning using Machine Learning

- Realization of automatic beam–tuning
  - Minimize the number of tuning parameter searches: Reduce tuning time
  - Simultaneous optimization of multiple parameters: Better tuning including correlation
- Optimization of the beam = "Black-box Optimization"
  - Looking for the global maximum point in situations where only the input-output relationship is known



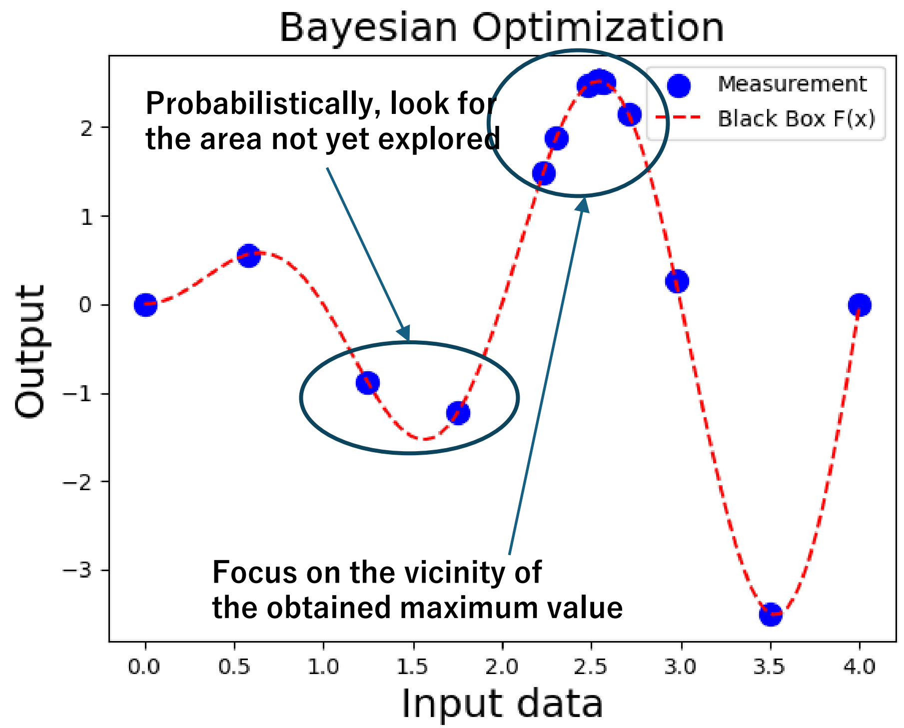
  - Auto-tuning using "Bayesian Optimization"

Using the trial results so far, predict

- Parameter space not yet explored
- Parameter space close to maximum value

and search efficiently

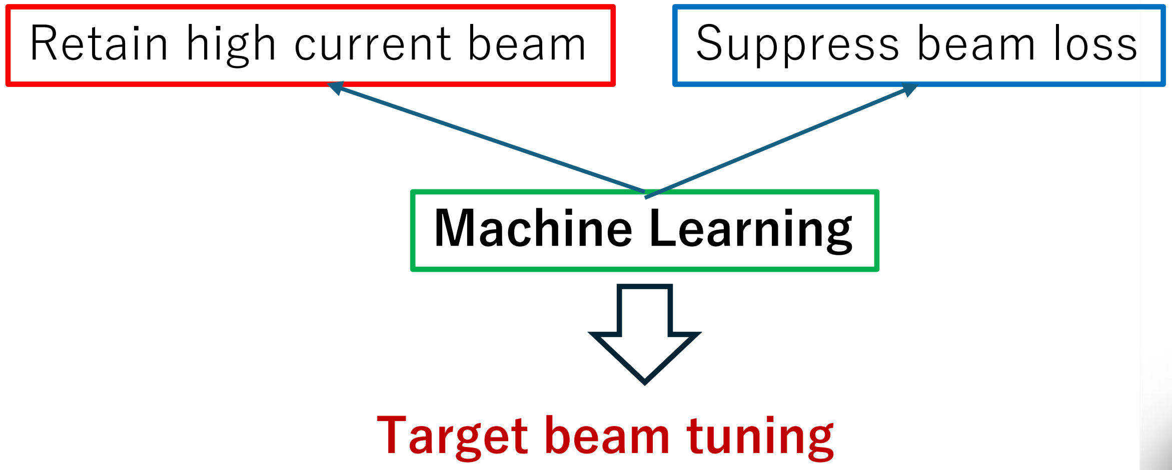
Do not need "training", like neural-network

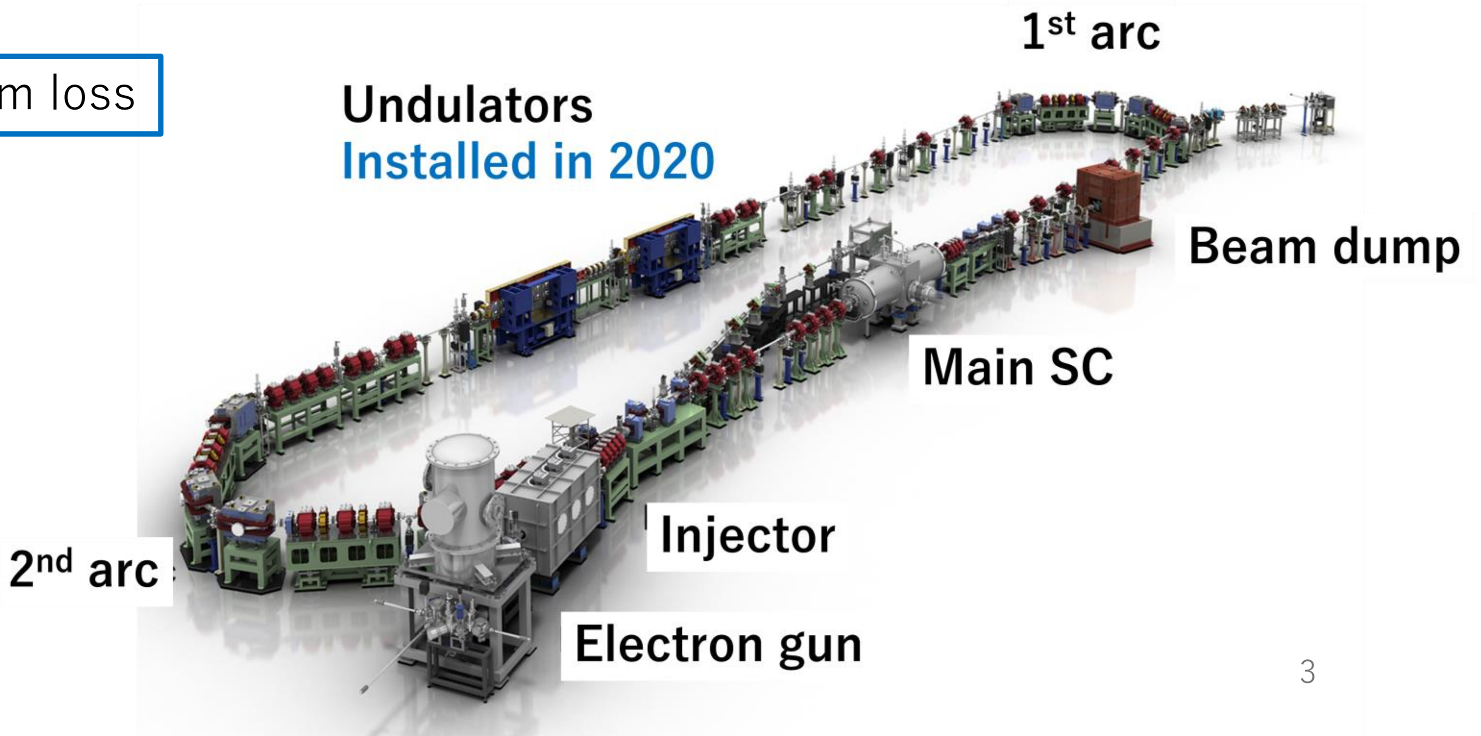


ML application for beam tuning @ cERL

- Compact ERL (cERL)
  - cERL is exploring the possibility of auto-tuning for high current operation with Machine Learning
  - Target: High current CW operation while suppressing beam loss
    - Beam loss leads to severe radiation due to CW operation

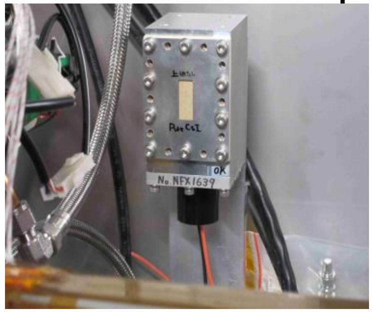
    → go to termination
  - Realize beam tuning aiming for compatibility between the two conditions





Optimization while avoiding IL and corruption

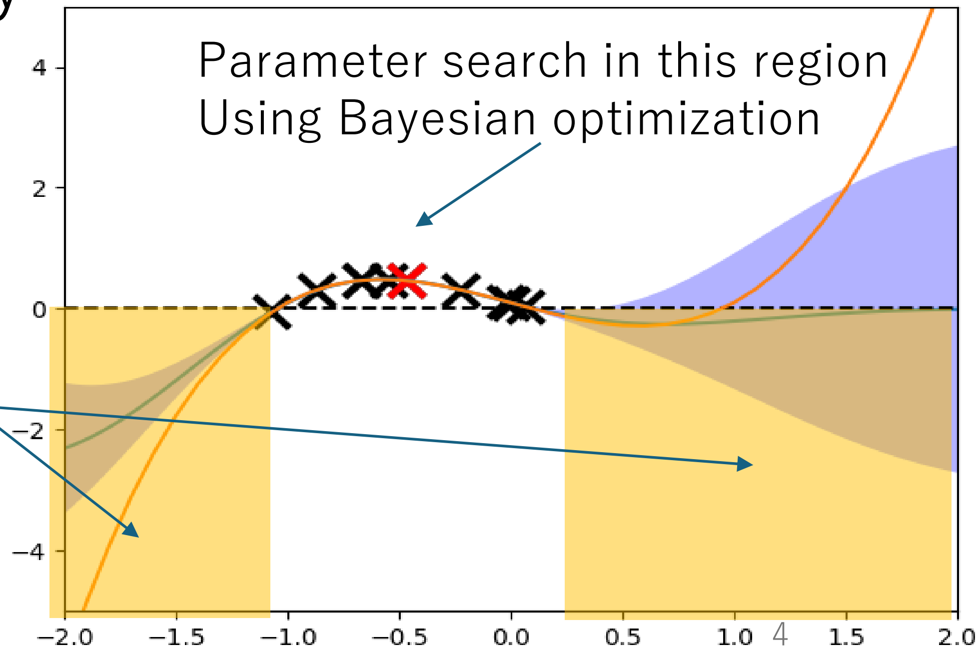
- Find loss: watching by loss monitors


Loss monitor on the beam line


Loss monitor undulator section

- If the beam are lost during ML, PMT with HV near the loss point can lead to IL, or be BROKEN
- Therefore, optimization while avoiding "dangerous" parameter searches
- Now applying the algorithm to automatically estimate the "safe" parameter space
- And then, do Bayesian optimization within that parameter space

Do not watch this region
If these areas are the region with IL



"Safeopt"
F. Berkenkamp, A. P. Schoellig, A. Krause, Safe Controller Optimization for Quadrotors with Gaussian Processes in Proc. of the IEEE International Conference on Robotics and Automation (ICRA), 2016, pp. 491-496.

Designing Evaluation function

- The design of the evaluation function represents a fundamental aspect of Bayesian optimization
- Achieve a balance between the two conditions
  - Linear combination of 2 parts

$$f = a \cdot \overbrace{I_{Dump}}^{\text{High current}} + b \cdot \overbrace{\frac{1}{Max(loss)}}^{\text{Reduce loss}}$$

H_{Dump}: beam current @Dump
$Max(loss)$: maximum peak signal of all the loss monitors
a,b: balancing 2 conditions
Large a: maintain high current Large b: suppress loss strongly

    - Determine carefully of parameter a and b

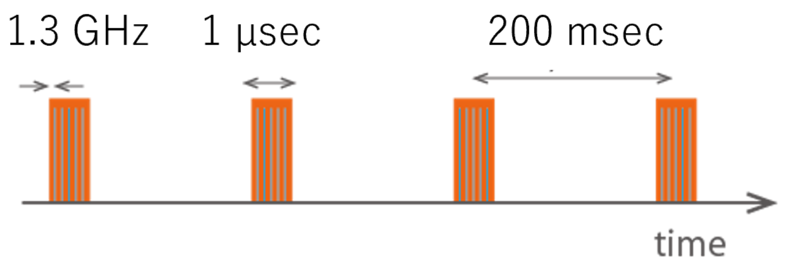
  - Look for the parameter set which can maximize this function:

Input data x → Evaluation function f → Output y

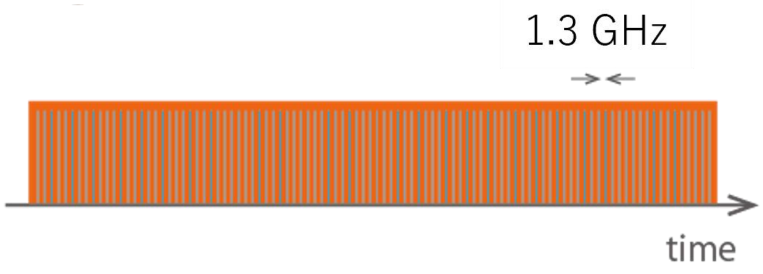
Beam tuning @cERL

- Tackling radiation level reduction: successive trials of both
    - Beam & collimator tuning in burst mode ⇔ Beam operation in CW mode
- Equipment to struggle beam loss:
    - **Loss monitors** - located anywhere on the beam line
    - **Collimators** - at the entrance & middle of the merger

Burst (5Hz)



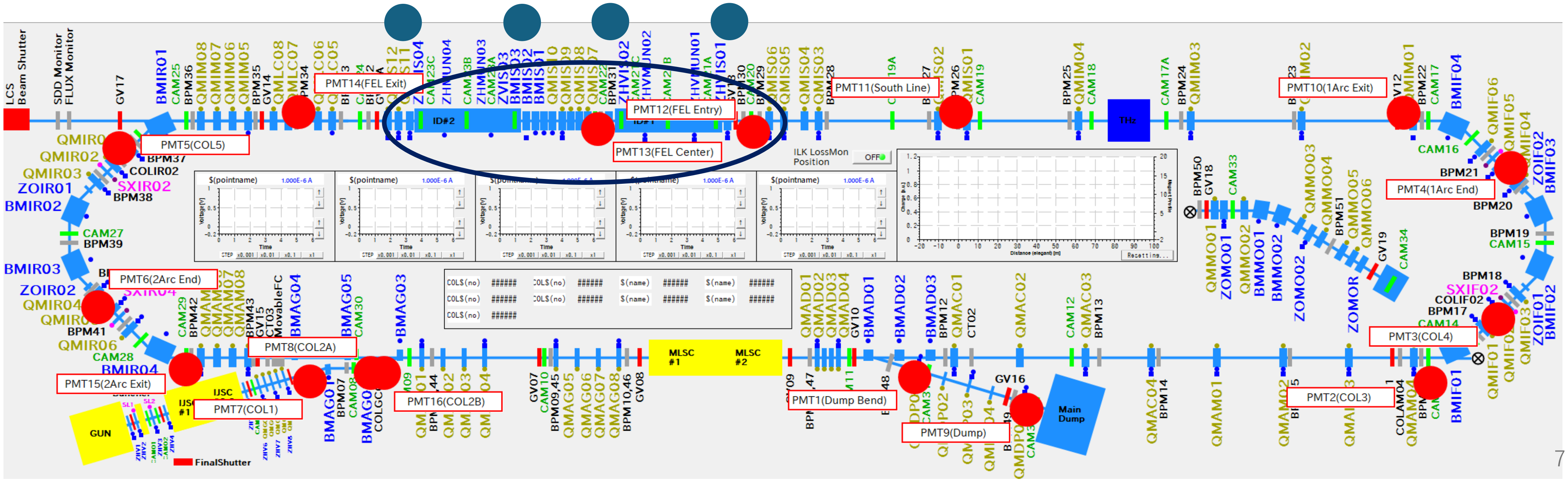
CW



One example of the auto-tuning @Burst mode

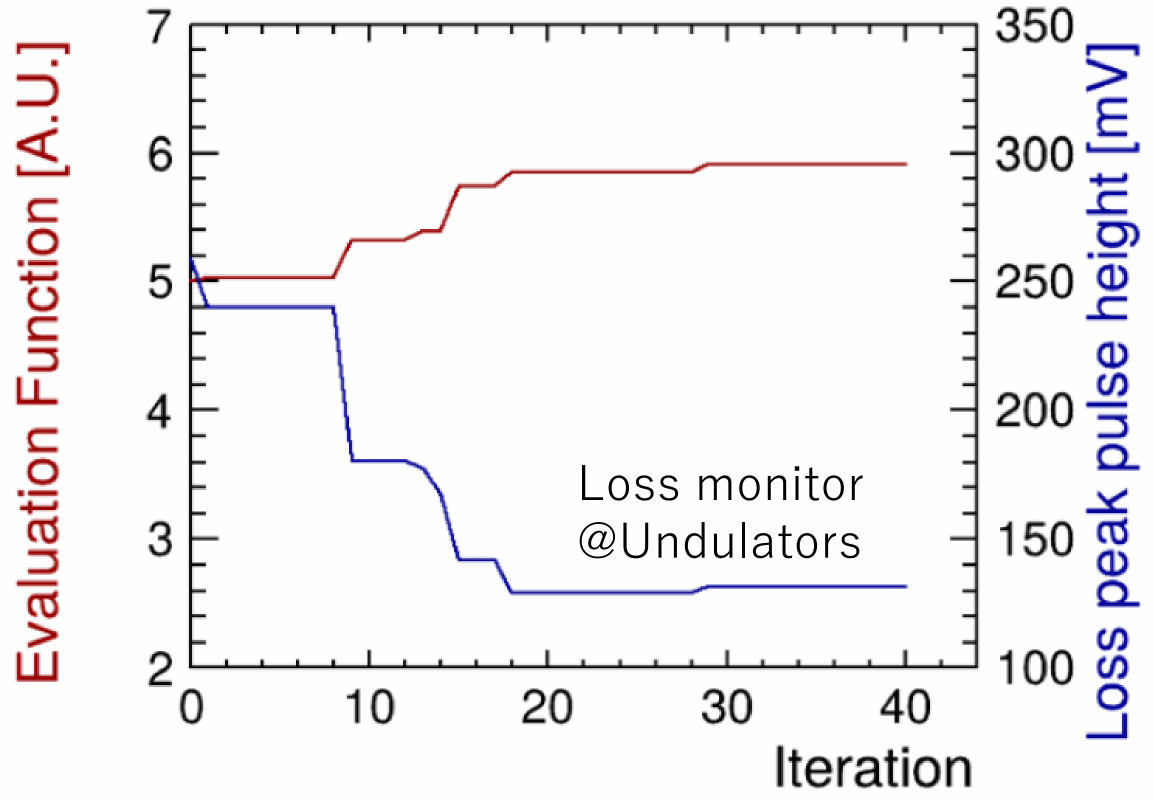
- @Undulator section
  - Dedicated beam tuning is necessary due to narrow chamber size
    - Oval shape with
      - 50mm major axis(horizontal) & 8mm minor axis (vertical)
  - Radiation level reduction around this region is essential for CW operation
- Watch 16 IL loss monitors & 4 loss monitors at undulator section

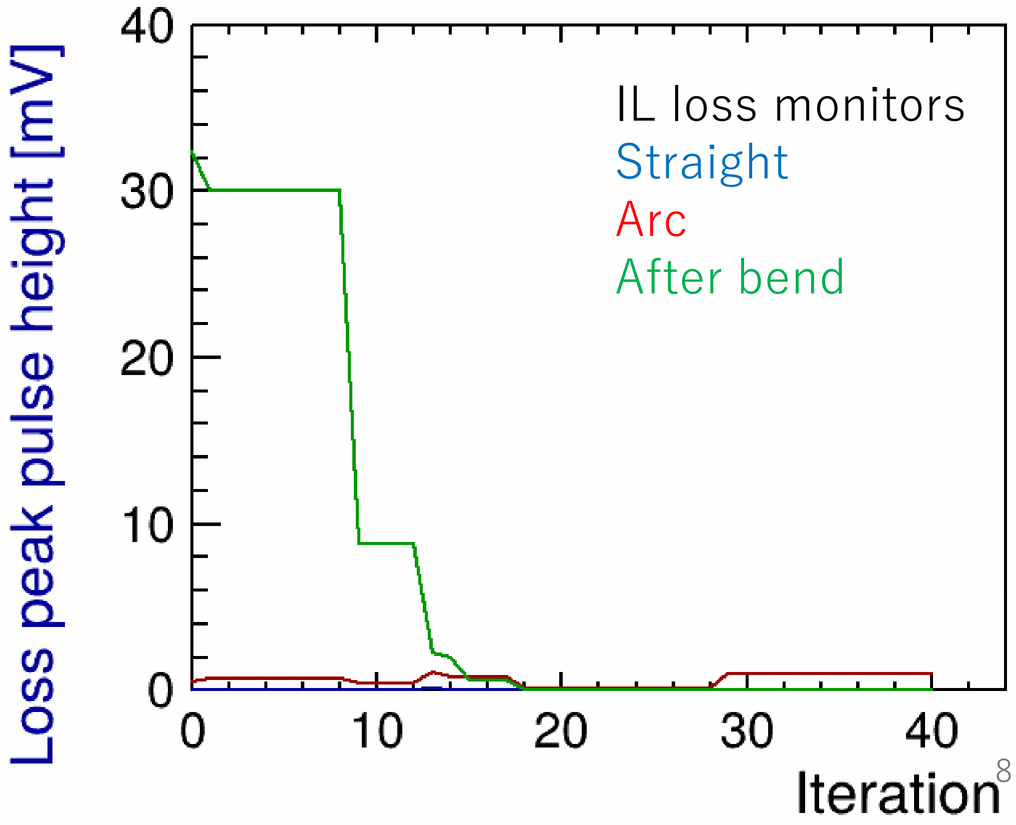
FEL04 FEL03 FEL02 FEL01



Beam tuning

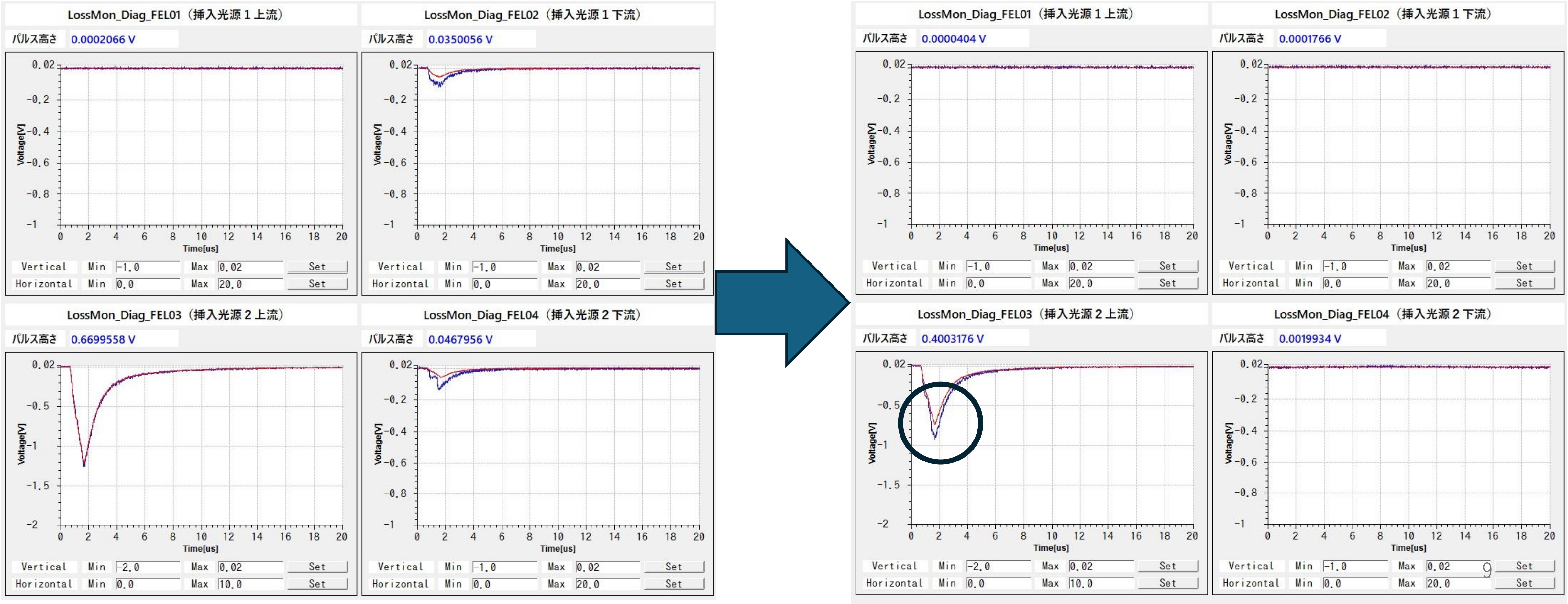
- Choose 8 Q & steer magnets combination around undulators
- Increase Evaluation function & decrease loss signal @Undulators
  - ML tuning goes better direction
- Did not occur loss signal explosion at IL loss monitors
  - ML just steps safe parameter space: Optimization without IL from loss monitors





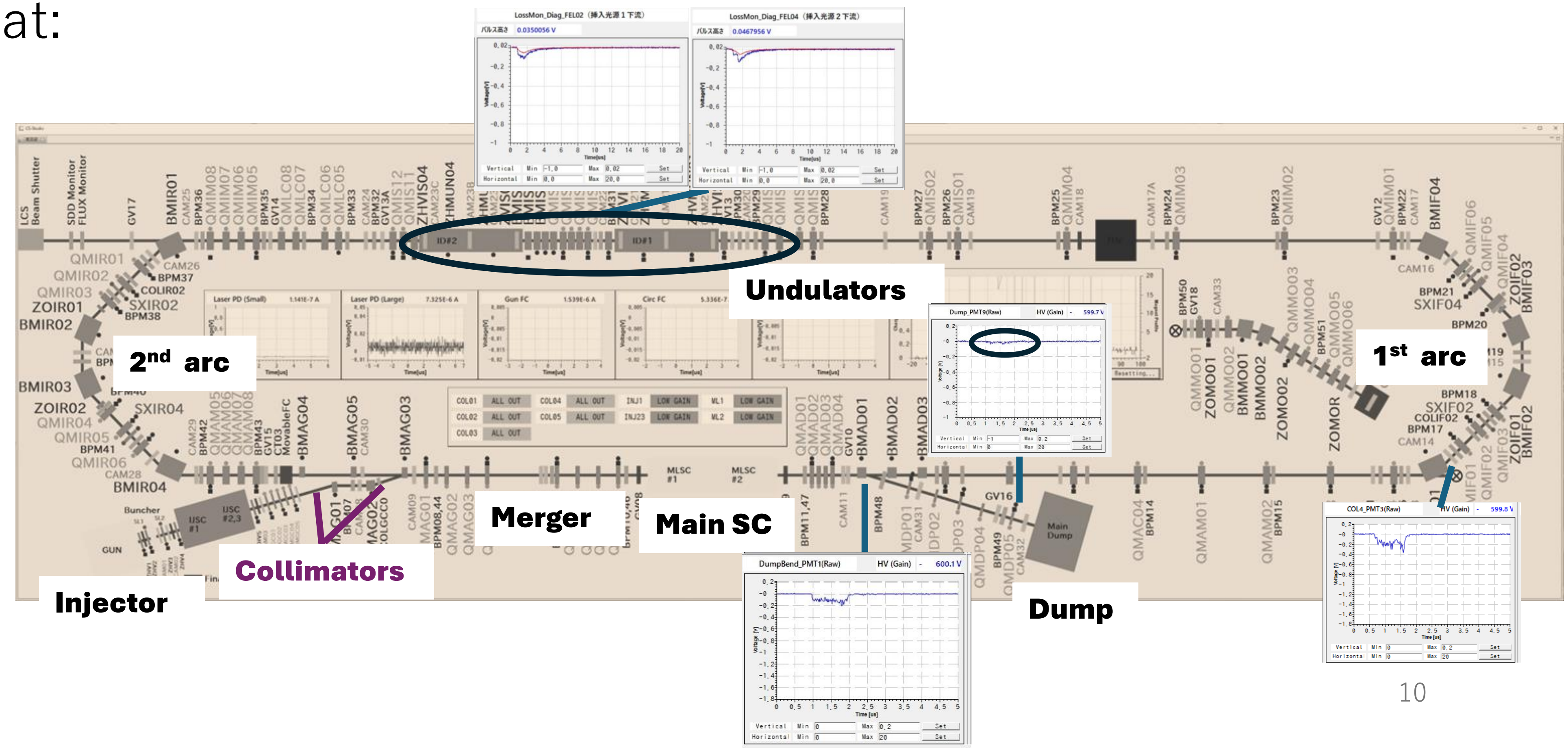
Tuning around Undulator section

- Tuning
  - Loss signal reduced
    - except chicane between undulators
  - Rest signal contains the component which can only be rejected by collimators
    - Needs optimization over the whole beamline & collimators



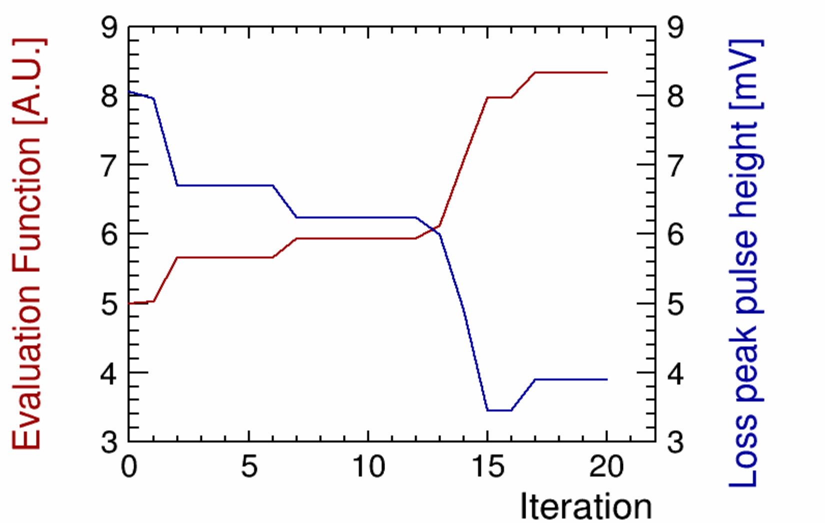
Trial of auto-beam tuning for CW operation

- ML automatic beam tuning was performed like beam tuning by hand
- Initial condition: Some loss signals @Burst mode
  - 1st arc: suppressed by collimator adjustment
  - Magnet tuning at:
    - Undulators
    - Dump bend
    - Before dump

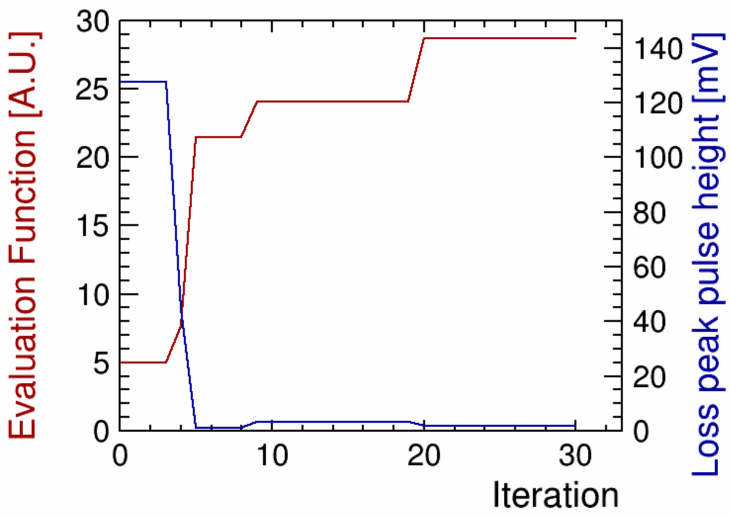


ML optimization

- Auto tuning by machine learning in burst mode
  - Choose Q & steer magnet's sets to suppress loss at a loss monitor to be controlled
  - 2 collimators optimization at the same time
- Well optimized under loss signal suppression condition
  - Keeps beam transmission to the dump ～100% @Burst mode
  - Reduce loss monitor signal well



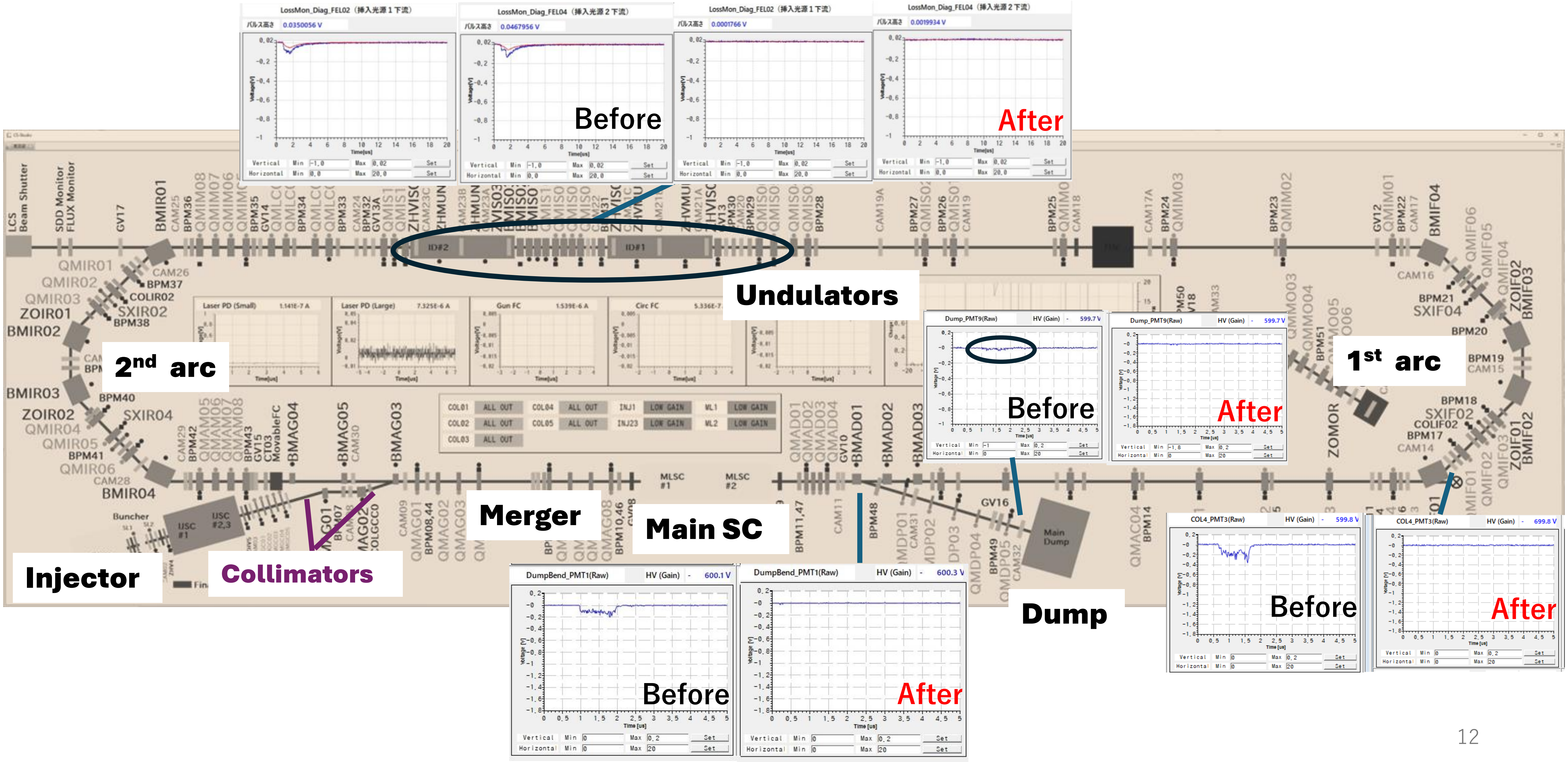
Machine learning tuning before the dump



Machine learning tuning of the collimators

Results

- Reduction of loss signals



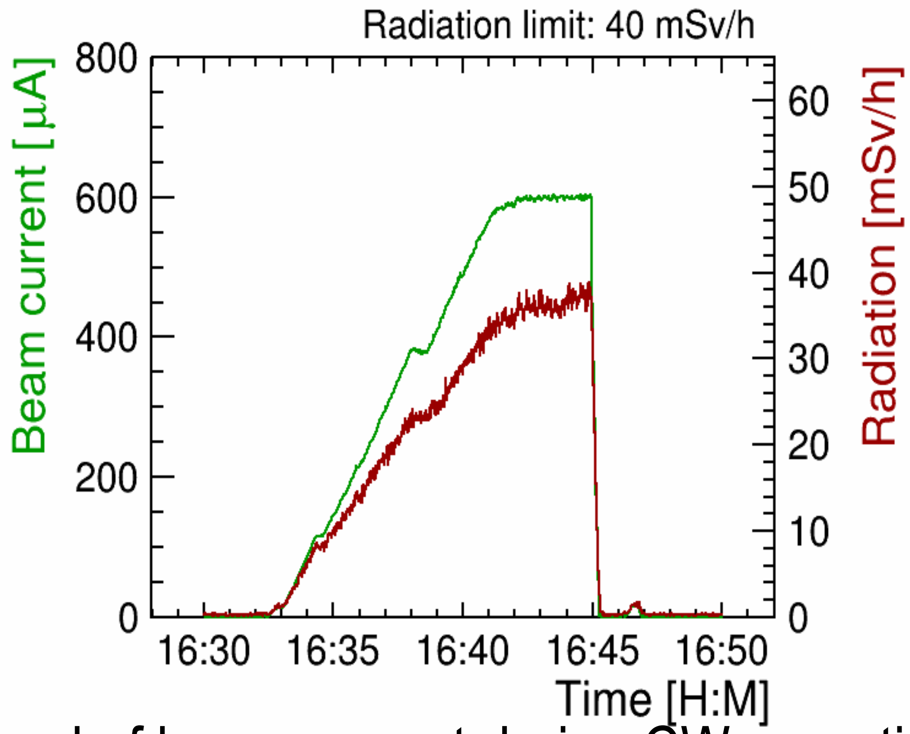
Results

- Obtained current for CW operation
  - Improved!

	Before ML	After ML
CW current [μA]	140	**600**

  - Target CW current: ~1 mA: not yet reached

- In this study, loss reduction before the dump was not enough
  - ALOKA IL was limited
  - Needs thoroughly loss reduction
    - Even tiny loss signal is prohibited
    - Detailed study of hyperparameters
    - Strategy of combining the loss monitor information
    - Application to more realistic situation



Trend of beam current during CW operation

Next step

- Speed up
  - For this study, sequential loss monitor reading and magnet (collimators) setting
    - 16 IL loss monitors + 4 undulator loss monitors + 1 current
    - This was a bottleneck during optimization
  - Parallel signal reading & magnet setting

Collimator movement is one of bottlenecks

Collimators	sequential	parallel
30 iteration	52’ 00’’	8’ 44’’

Q & steer	sequential	parallel
20 iteration	22’ 42’’	4’ 32’’

    - Drastic speed up can be realized!
  - Just check the time for optimization: Need detail study of beam tuning
- More efficient integration of each loss monitor signal
  - If number of loss monitors are increased, loss monitor signal integration is more important
  - $\mathcal{O}(100)$ loss monitors will be necessary for higher current operation(e.g. 10mA)
  - Need precise consideration

Summary and outlook

- cERL: explore the possibility of auto-tuning for high current & low beam loss operation
  - Looks promising: balance the high current & loss reduction condition
  - Thorough beam loss reduction is important for high current beam
    - Detailed study of hyper parameters
    - Strategy for efficient beam tuning
  - Next step:
    - Speed up the optimization
    - Signal integration for large number of loss monitors
    - Apply for more realistic situation
- This is for beam tuning feature
  - Flexible construction for any kinds of the targets
  - ML is suitable for other tasks
    - e.g.) Anomaly detection for machine protection
Tomography of phase space

Backups