LCWS2024

2024-07-10

Design of the ILC electron-driven positron source and utilization of black-box optimization

Shunpei Kuroguchi, Masao Kuriki, Tohru Takahashi, Zachary Liptak, Hiroki Tajino,

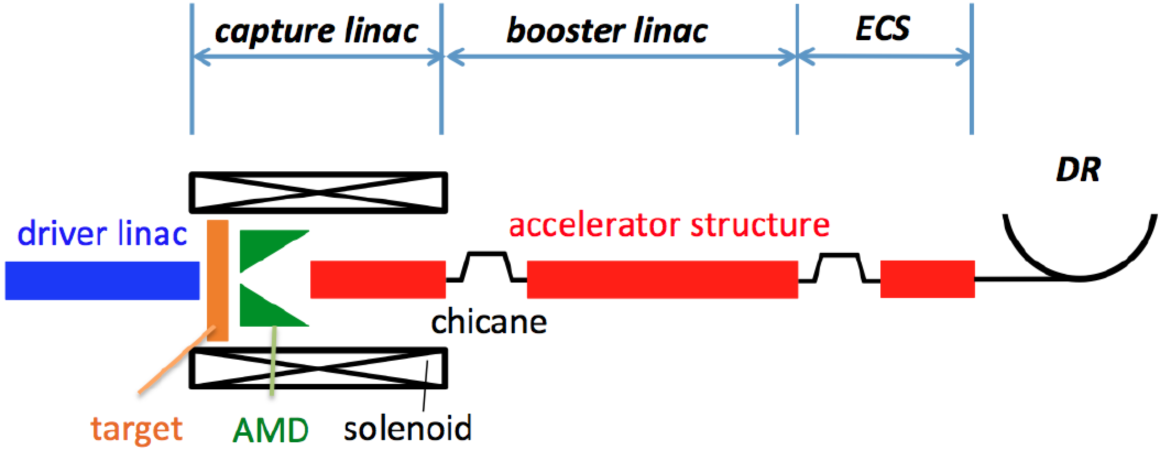
Junji Urakawa, Yoshinori Enomoto, Tunehiko Omori, Masafumi Fukuda, Yu Morikawa, Kaoru Yokoya

(Hiroshima Univ. & KEK)

Contents

Design of the ILC E-Driven Positron Source

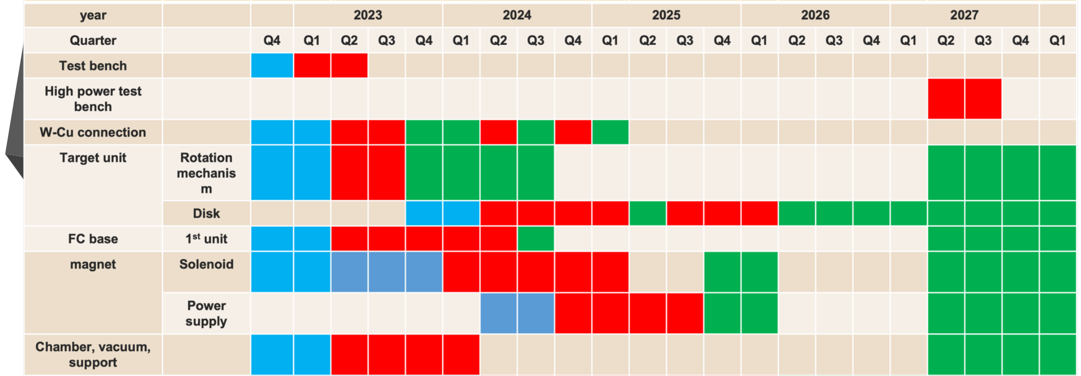
- In the ILC E-Driven positron source (positrons are generated by pair production and bremsstrahlung), it is important to increase the positron capture rate to prevent the destruction of the arroy target.
  - Here, the **positron yield η** is defined as the number of captured positrons N_{e^+} at the exit per incident electron N_{e^-}
  - given by $\boldsymbol{\eta} = \frac{\boldsymbol{N_{\mathrm{e}^+}}}{\boldsymbol{N_{\mathrm{e}^-}}}$



- **Driver Linac**: drive electron beam 3 GeV
- **Target**: Generate positrons with a W-Re alloy target, 16mm, at a tangential speed of 5 m/s
- **FC**: Suppress the transverse momentum of positrons
- **Capture Linac**: Capture positrons in an RF bucket with L-Band SW cavities and accelerate them to about 250 MeV
- **Chicane**: Remove electrons and shorten the bunch length
- **Booster Linac**: Accelerate up to about 5 GeV with L-band and S-band TW cavities
- **ECS**: Suppress energy spread with chicanes and L-Band TW cavities

Current Status of the E-Driven Positron Source

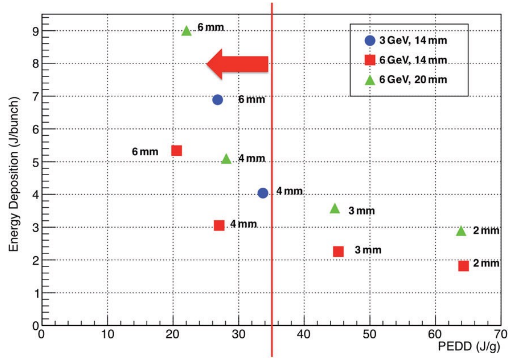
- The safe operating threshold of **PEDD** (Peak Energy Deposition Density) is considered to be **35 J/g**, which is already met in the initial overall design of the E-Driven positron source.
  - However, **further technical margins (consideration of transient beam loading, thermal loads, manufacturability, further positron yield, etc.)** are necessary.
- Currently, we are **refining and improving the design through simulations, structural design, prototyping, and testing.**



FY		2022		2023				2024				2025				2026				2027			
year			2023				2024				2025				2026				2027				
Quarter		Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1
Test bench		🟦	🟥	🟥																			
High power test bench																				🟥	🟥		
W-Cu connection		🟦	🟦	🟥	🟥	🟩	🟩	🟥	🟩	🟥	🟩												
Target unit	Rotation mechanism	🟦	🟦	🟥	🟥	🟩	🟩	🟩	🟩											🟩	🟩	🟩	🟩
	Disk					🟦	🟦	🟥	🟥	🟥	🟥	🟩	🟥	🟥	🟥	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩
FC base	1st unit	🟦	🟦	🟥	🟥	🟥	🟥	🟥	🟩											🟩	🟩	🟩	🟩
magnet	Solenoid	🟦	🟦	▦	▦	▦	🟥	🟥	🟥	🟥	🟥			🟩	🟩					🟩	🟩	🟩	🟩
	Power supply							▦	▦	🟥	🟥	🟥	🟥	🟩	🟩					🟩	🟩	🟩	🟩
Chamber, vacuum, support		🟦	🟦	🟥	🟥	🟥	🟥													🟩	🟩	🟩	🟩
Acc. structure	1st unit	🟦	🟦	🟦	🟦	🟦	🟦	🟥	🟥	🟥	🟥	🟥	🟥	🟥	🟥	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩
FC power supply						🟦	🟦	🟦	🟦	🟥	🟥	🟥	🟥	🟥	🟥	🟥	🟥	🟥	🟥	🟩	🟩	🟩	🟩

Number of Bunches	1320 = (33 + 33) × 20
Repetition	5 Hz
Charge per Bunch	3.2 nC/bunch
Beam Current Average	21 μA

Yield in the initial overall simulation



Y. Seimiya et al., 2015, https://doi.org/10.1093/ptep/ptv136

Background / Traditional Design Optimization Process and Ideal

- We have been **optimizing sequentially for each part** so far.
  - It takes time because human intervention is required.
  - Precise physical simulations are slow.
  - It cannot be said to be overall optimization.
  - Once parameters are set, they are difficult to change.

Current State

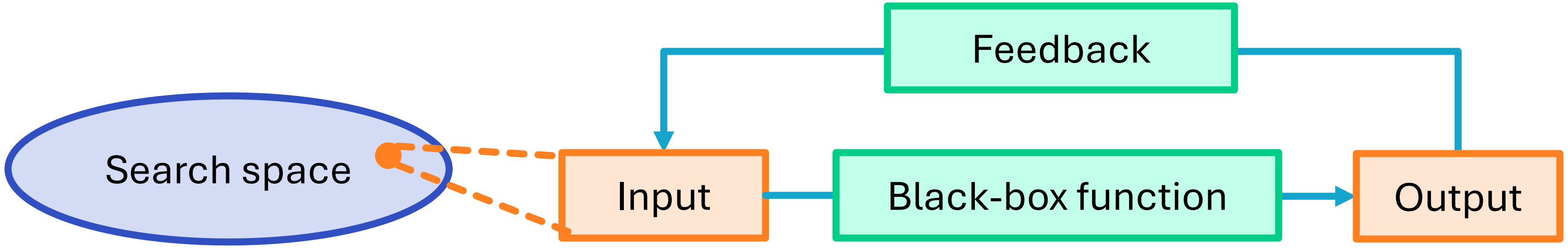
Slow, Partial Optimization, (Partially) Manual

Ideal State

Fast, Holistic Optimization, Automated

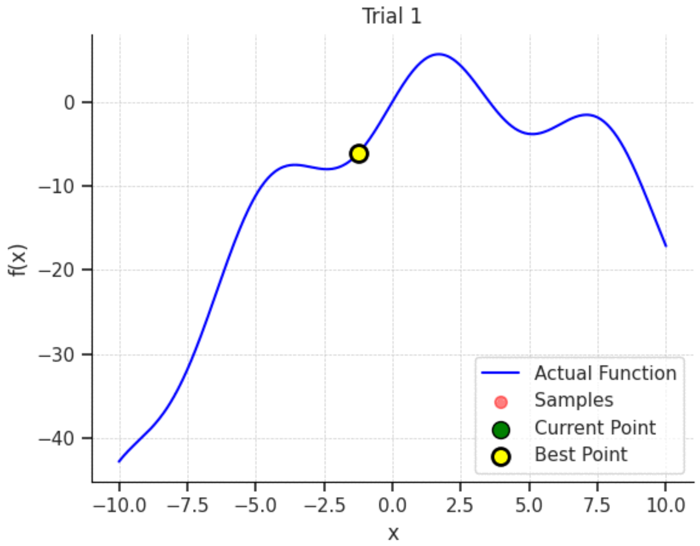
Methods / Utilizing black box optimization

- The function to obtain the desired values (such as positron yield) for various parameters in an **accelerator is complex**, and we want to optimize it with as few simulations as possible.
- For this purpose, **black-box optimization (BBO)**, which does not require knowledge of the objective function, is suitable.

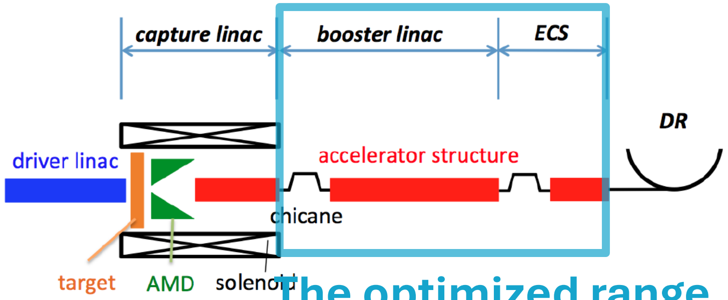


Methods / the TPE algorithm

- In this study, we used the **Tree-structured Parzen Estimator (TPE) algorithm**.
- It is one of the methods that perform parameter search using probability density functions.
- We considered and tested several methods, and chose TPE because it is **applicable and stable even with a large number of parameters and trials**.
- It is also used for hyperparameter optimization of neural networks.
- Time complexity: $\mathcal{O}(dn\log n)$
  - d is the dimension of the search space, n is the number of finished trials
  - Compared to optimization by Gaussian process regression (typically $\mathcal{O}(n^3)$), the computational complexity is smaller.



Methods / Optimization



The optimized range

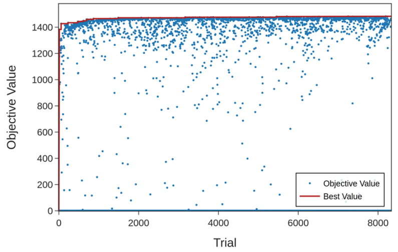
- We optimized only the part of the SAD simulation **from the chicane at the exit of the Capture Linac to the exit of the ECS**.
- The **input consists of 10 parameters**, and the **output is the captured positron count**.
- Using a general desktop computer (considering the use of HPC in the future), I utilized 15 out of 16 logical threads for concurrent processing, achieving a **10-fold speedup** compared to using a single thread.
- I further refined the optimization by narrowing the range of each parameter (while keeping the number of parameters fixed) and performed another round of optimization (**local parameter search**)
  - Since this involves human intervention, it is considered a Human-in-the-Loop (HITL) optimization.

Input:
the entrance momentum at the first chicane, chicane bending angle, Two types of chicane bending K, Booster initial phase, Booster peak voltage, ECS initial phase, ECS peak voltage, ECS chicane bending angle, and the z-center of the damping ring

Threads	Time (s/trial)	Speedup
1	57.8	-
15	5.79	9.98x

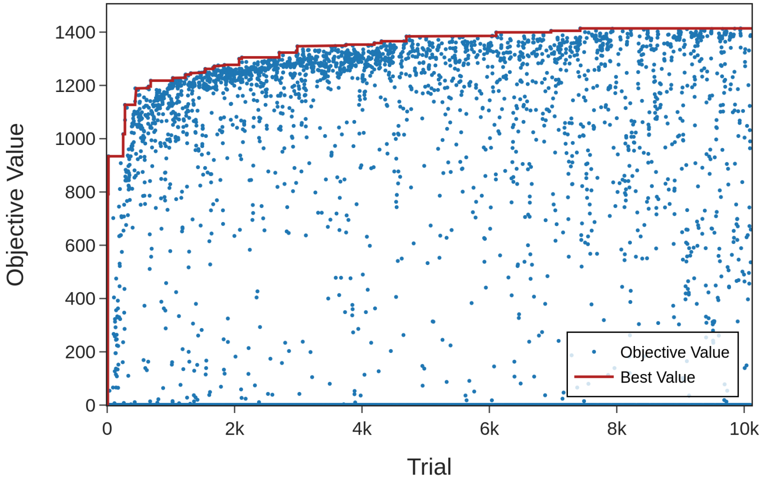
Results / Yield and Optimization Time

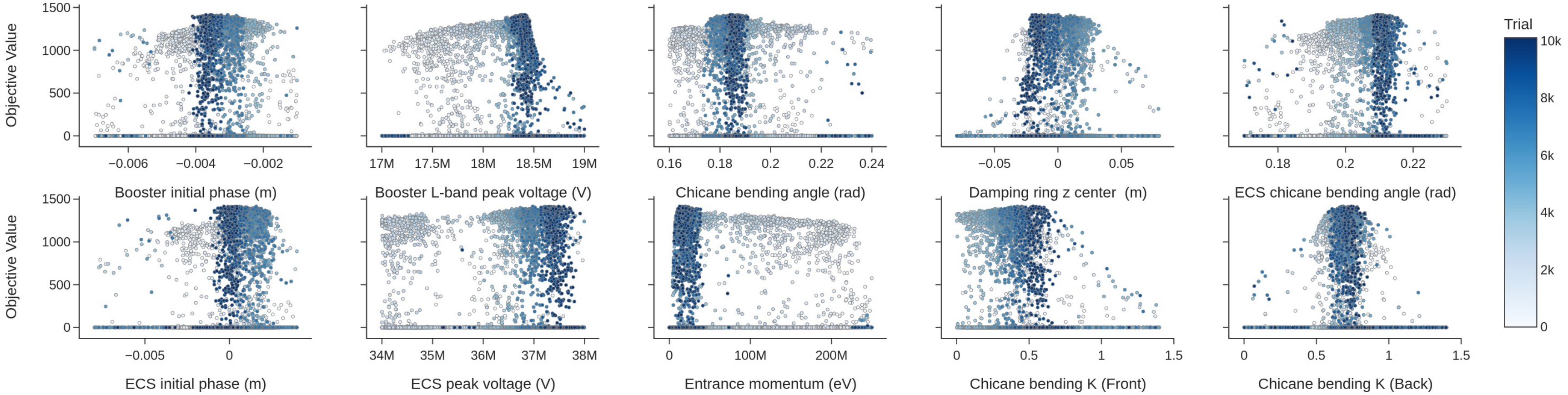
Local parameter search



- The optimization **achieved** a yield (η) of **1.48**, which is **significantly higher than** the **1.20** rate obtained through manual optimization.
  - Further local search optimization after optimization **increased** the yield by approximately **0.05** on average.
- The optimization time was **reduced** from approximately **one week to half a day** (including local search, it took **about one to two days**).

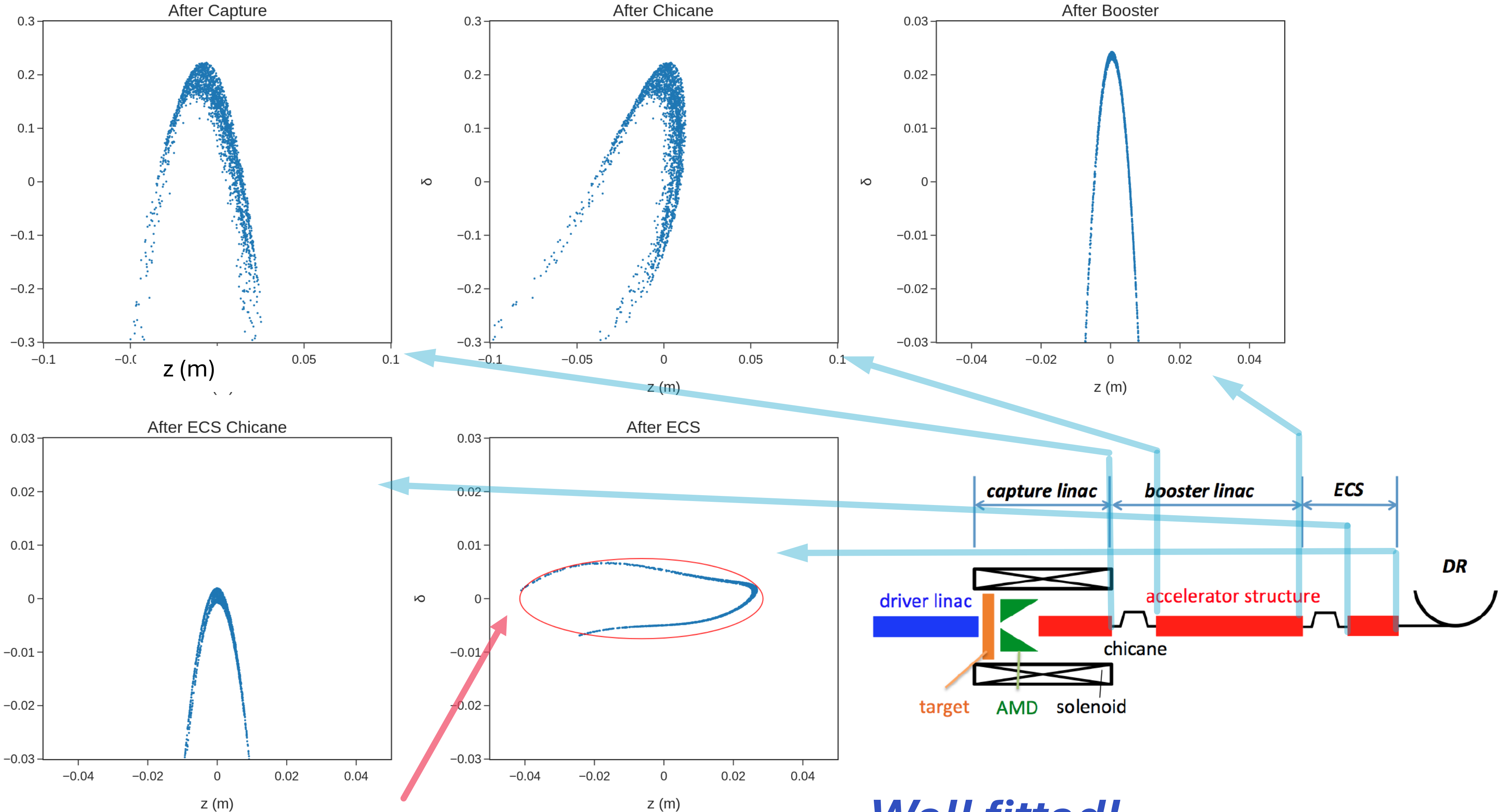
Parameter search





Results / Longitudinal Phase Space Distribution

$$\delta = \frac{\gamma - \bar{\gamma}}{\bar{\gamma}}$$



Acceptance of the Damping Ring

Well fitted!

Conclusions

- By using the TPE algorithm, a type of black-box optimization, **we were able to significantly improve the positron yield (η)** through parameter optimization from the Capture Linac onwards.
- Simultaneously, **the optimization period was greatly reduced,** allowing more time to be allocated to other design processes.
- This improvement is attributed to performing a holistic optimization rather than partial optimization, and the automation and parallel processing enabled exploration of parameters that would be difficult to achieve manually.
- This method will likely be **beneficial for optimizing various other designs**.

Future Work

- Based on the optimization results, we will work on physical understanding and design review.
- Optimization including beam loading of the Booster Linac.
- Simulation of multi-bunches.
- Start-to-end automatic optimization.
- Holistic optimization including detailed parameters.

Thank you for your attention

Appendix

Conditions for This Simulation and Optimization

- This study includes single bunch simulations of beam loading compensation in the Capture Linac using an iterative method with phase modulation and amplitude modulation calculations.
- The Capture Linac part was not included this time because the optimization of the Capture Linac uses GPT, which takes longer to evaluate compared to SAD for beam loading compensation.
- The beam loading in the Booster is not considered.
- The TPE algorithm uses the TPESampler of Optuna.