XFEL Accelerator R&D Status Report
Learning-based Methods Towards an Autonomous European XFEL

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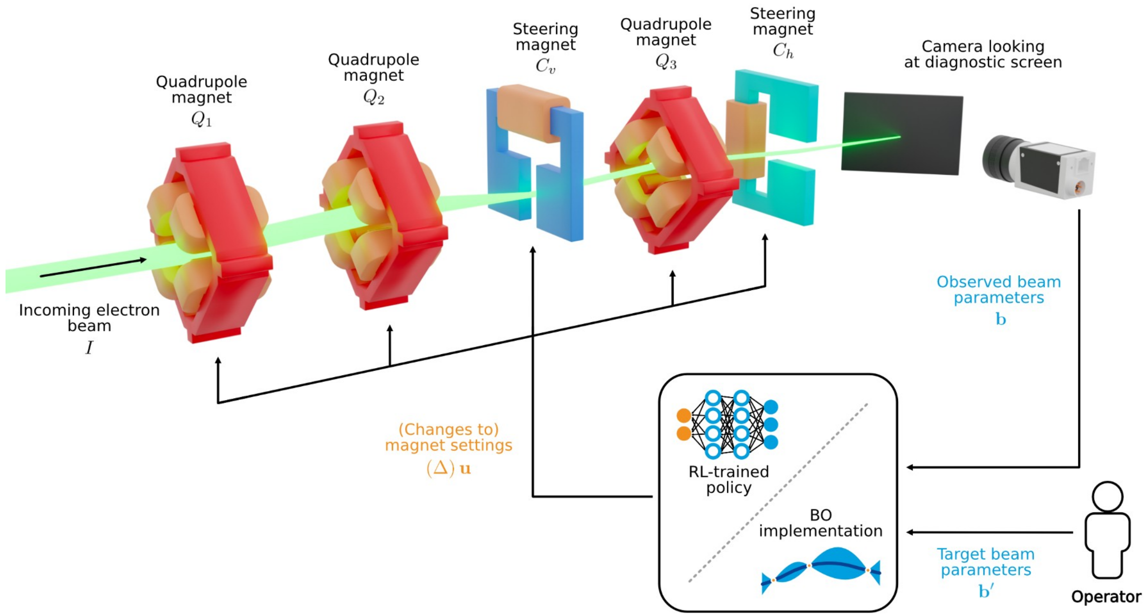
Scope of the R&D activity

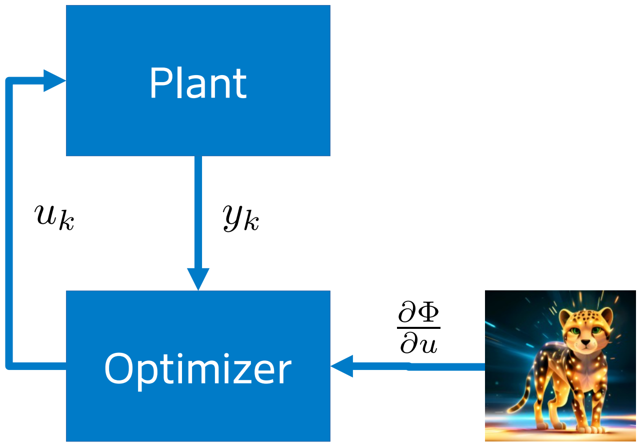


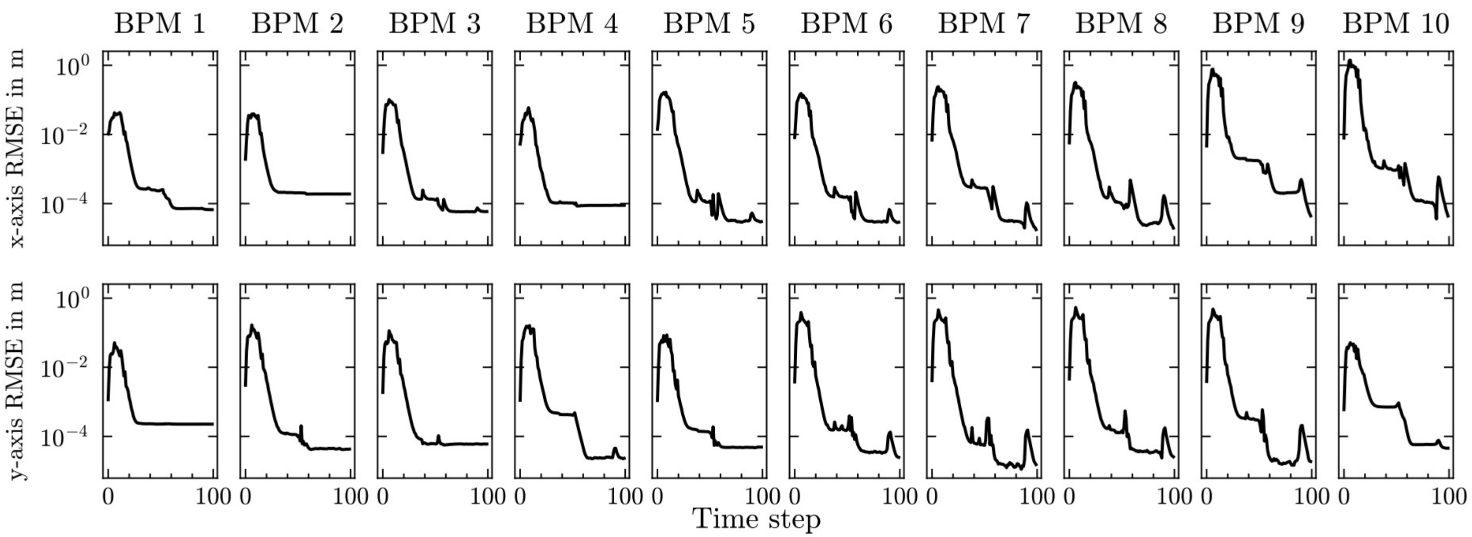
- Accelerator and FEL tuning
  - requires human expertise
  - is lengthy and tedious
  - involves more than hundreds of tuning knobs
- Deliverables
  - Reinforcement Learning for beam dump line & FEL intensity tuning
  - Hierarchical optimization for global performance improvements
- Synergies
  - Collaboration with EuXFEL GmbH Data Analysis Group

Achievements — *Feedback Optimization* for Beam Orbit Control

- Feedback Optimization → Optimization method with feedback loop
- Successful transfer to TLD beam orbit control
  - TLD as testbed for learning-based algorithms
- Implemented as python DOOCS server, control panel integration next

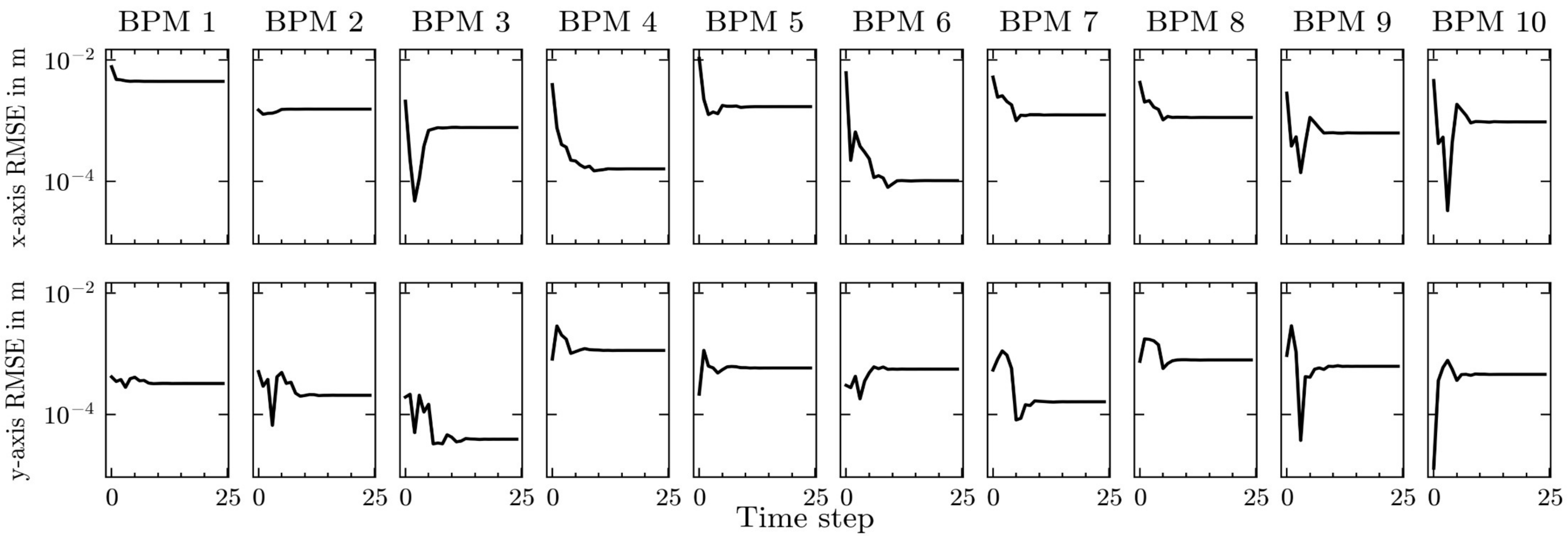
Feedback Optimization





Achievements — Reinforcement Learning

- Learn to solve TLD orbit task in simulation -> then deploy to the real machine
  - Experience equivalent of 7 hours of beam time in 20 minutes of a laptop
- Converged after ~10-15 steps
- A lot of software infrastructure work (based on code developed at ARES)



Achievements — Cheetah DOOCS Server

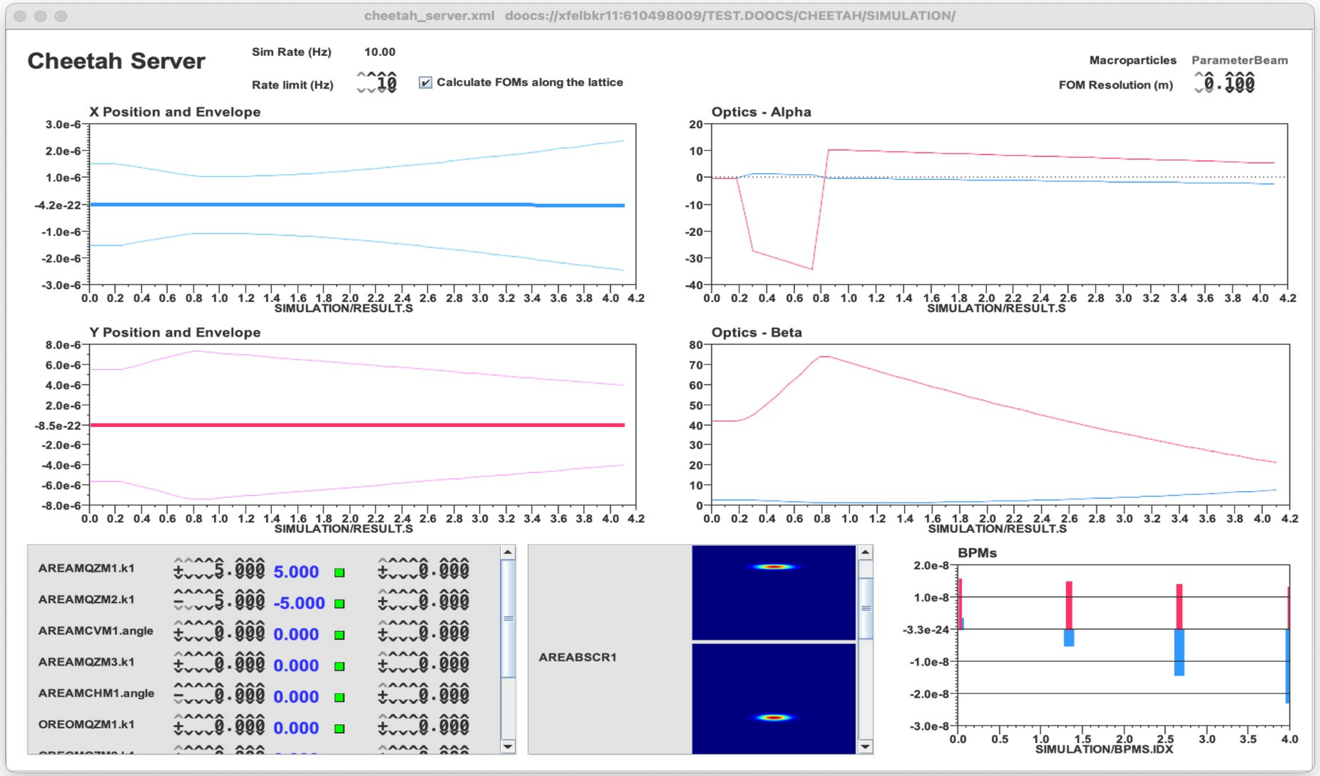
- Turns any **Cheetah** simulation setup into a DOOCS server using **doocs4py**
- Automatically exposes adjustable lattice element parameters and calculated figures of merit as standard DOOCS addresses
- Dynamically generates its own jddd panel components
- Simulates jitter, camera noise, magnet ramping, etc.
- Motivation: local instance, virtual diagnostics

```python
import cheetah
from cheetah_doocs_server import CheetahServer

# Load beam e.g. from ASTRA
beam = cheetah.ParameterBeam.from_astra("input_beam.astra")

# Load lattice e.g. from Elegant
lattice = cheetah.Segment.from_elegant("tld_reduced.lte", "tld")

# Start the server
server = CheetahServer(lattice, beam, update_rate_hz=10)
server.run()
```



Example jddd panel, which uses dynamically generated control components provided by the server

Deviations from plan

- Learning-based feedback optimization in addition to reinforcement learning
  - Approached from a control theory viewpoint
  - Promising results, in simulation and on the machine
- Reinforcement learning not yet transferred to the machine
  - Significant investments in surrounding architecture were necessary
  - Agents not ready before LIMP
- FEL intensity optimization delayed
  - Surrogate modeling in preparation

Timeline of this R&D activity

- Hiring delays shifted the project start by three quarters
  - Transfer of RL agent will start after LIMP
  - FEL intensity optimization will be approached afterwards

Proposed	Milestone Description	Updated
Q2 2024	RL agent trained for the beam dump line in simulation	Q1 2025
New	(Learning based) feedback optimization on dump line	Q1 2025
New	Integrated the dump line feedback optimization as DOOCS server	Q3 2025
Q4 2025	Reviewed hierarchical optimization and RL	Q3 2025
New	Implemented Cheetah digital twin DOOCS server	Q4 2025
Q1 2025	FEL intensity surrogate model trained	Q4 2025
Q2 2025	Trained RL agent for FEL intensity optimization in simulation	Q1 2026
Q3 2024	Transferred the RL agent to the beam dump line of the European XFEL	Q1 2026
Q4 2024	Integrated the RL dump line feedback as DOOCS server	Q1 2026
Q3 2025	Transferred the RL agent to FEL intensity optimization on EuXFEL	Q3 2026
Q4 2025	Integrated FEL intensity optimisation into Ocelot Optimizer / Badger	Q3 2026

Risks to R&D Project

- FEL intensity surrogate modeling
  - Accurate FEL simulation expensive, surrogate modeling is key
  - Initial attempts have shown difficulties
  - Reinforcement learning prone to exploiting deficits

Outlook / Summary

- Planned activities
  - Transfer of reinforcement learning agent to machine
  - FEL intensity optimization
- Expected risks
  - Anticipated challenges when developing the FEL surrogate model
- Publications
  - Hespe, C., Kaiser, J., Lübsen, J., Mayet, F., Scholz, M., & Eichler, A. (2025). Data-driven feedback optimization for particle accelerator application. At - Automatisierungstechnik, 73(6), 429–440. https://doi.org/10.1515/auto-2024-0170
  - Posters at the MT-ARD-ST3, MaLAPA, and RL4AA workshops this year