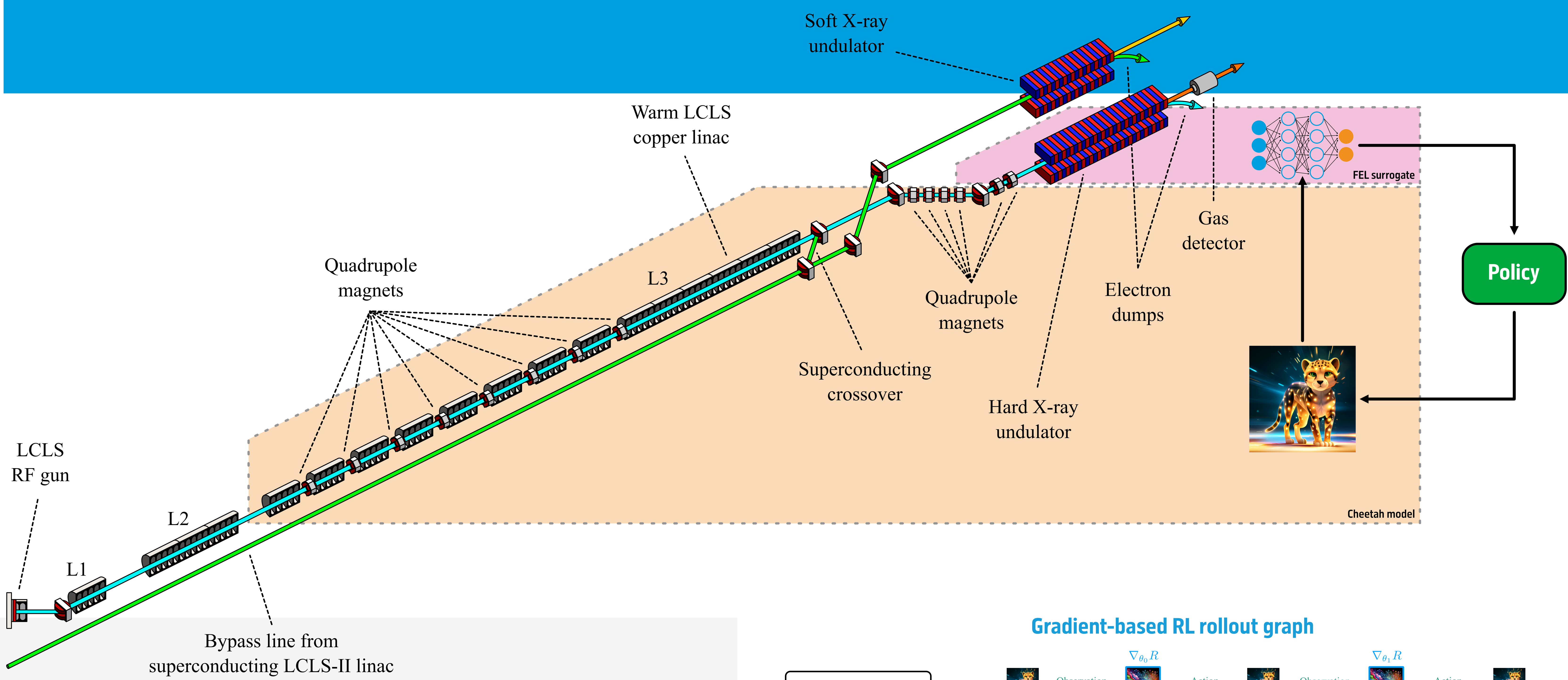
The **fast differentiable beam dynamics simulator Cheetah** coupled with neural network surrogate models enables **gradient-based RL** in **minutes** on complex high-dimensional tasks like FEL tuning.



High-Speed Differentiable Simulations as an Enabler for Reinforcement Learning-based FEL Tuning Agents.

J. Kaiser*, A. Eichler, J. Morgan, Z. Zhu, R. Roussel, A. Edelen, D. Ratner, M. Schram, K. Rajput

Motivation

- Tuning and control tasks at accelerators can be very complex, with high-dimensional input spaces ,complex physics and sparse objective signals, which make them difficult to solve with conventional methods.
- Reinforcement learning (RL) can train policies capable of solving such difficult tasks, but **RL training is notoriously sample-inefficient**, which can result in intractable training times.
  - We consider as one such task a setup, where **14 quadrupoles are tuned to maximise the FEL pulse intensity** at *LCLS*.
  - This tasked is performed frequently as the FEL has to switch between energies and phase space shapes.
  - Similar tasks need to be solved at **other facilities like *European XFEL* and *FLASH***.
  - Training **on the real machine or with conventional simulators takes on the order of weeks to months**, and even with a high-speed simulator (not using gradients) it requires two days to train a good policy using the PPO algorithm.

Gradient-based reinforcement learning using Cheetah

- The sample-inefficiency of most RL algorithms results from the need to estimate stable gradients from large sample sizes because environments are considered to be black boxes with unknown gradients.
- We developed ***Cheetah*, a high-speed differentiable beam dynamics simulator**. In addition to **orders of magnitude faster compute**, Cheetah can provide gradients of beam dynamics with **automatic differentiation**.
- Cheetah enables us to compute the exact gradient of the episodic return with respect to the policy parameters from just a few samples instead of having to collect an enormous amount of samples to smooth out a noisy estimate.

AI/ML coupling to include complex dynamics

- Some physical effects like the FEL process are **inherently expensive** to compute, and remain too time-consuming even when implementations are extensively optimised.
- Here, **neural network surrogate models** and **Cheetah's native integration with PyTorch** enable the intuitive inclusion of such effects in gradient-based RL training, while **preserving both the computational speed and the ability to compute gradients**.

Results

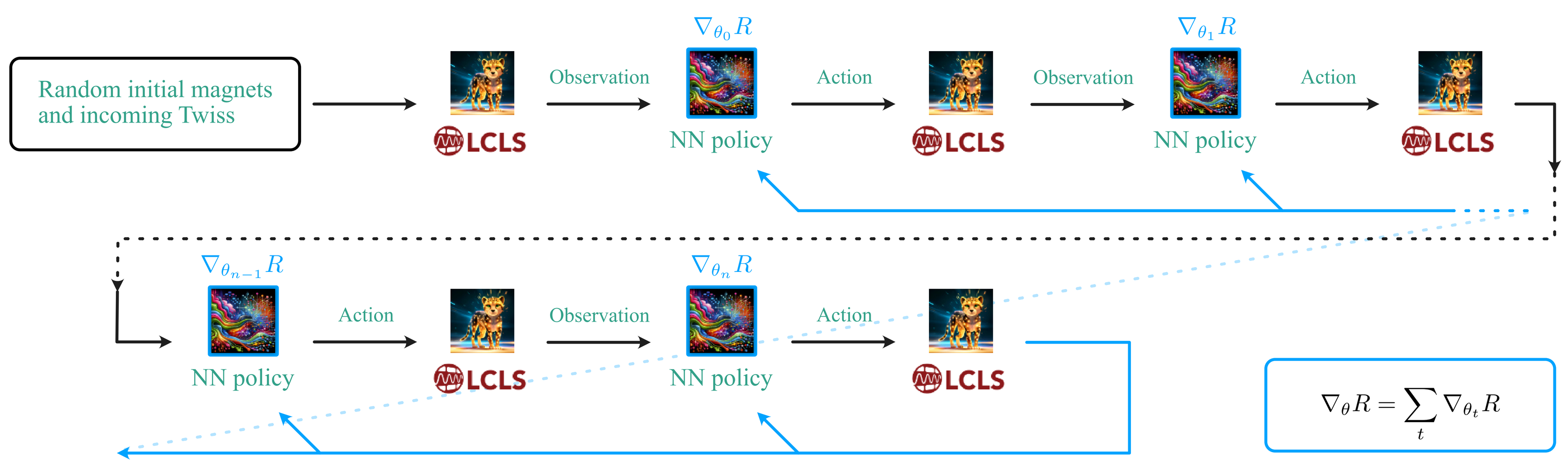
- Our implementation of gradient-based policy optimisation using Cheetah and *PyTorch Lightning* reaches the same reward threshold as PPO in at least **45x fewer samples**. The resulting policy performs just as well.
- The result is the ability to train an RL policy on a complex high-dimensional FEL intensity tuning task **in a matter of minutes**.

***Corresponding author:** jan.kaiser@desy.de

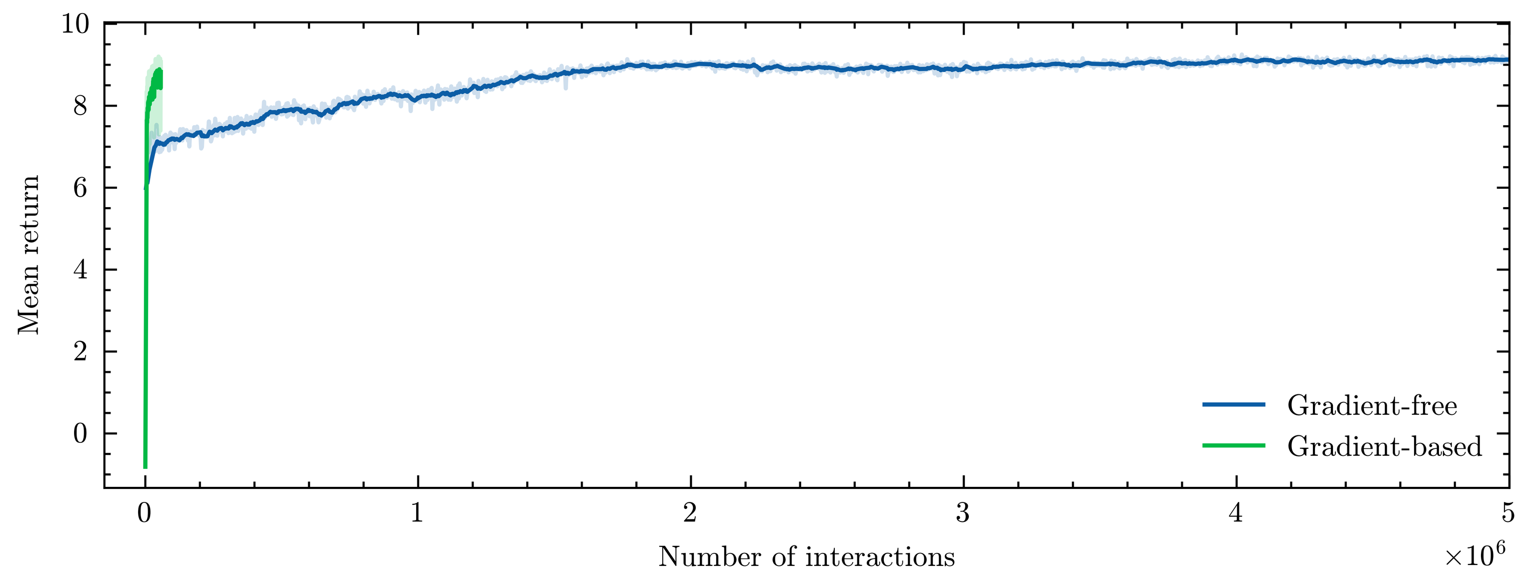
Scan me to download the poster!

Deutsches Elektronen-Synchrotron DESY
A Research Centre of the Helmholtz Association

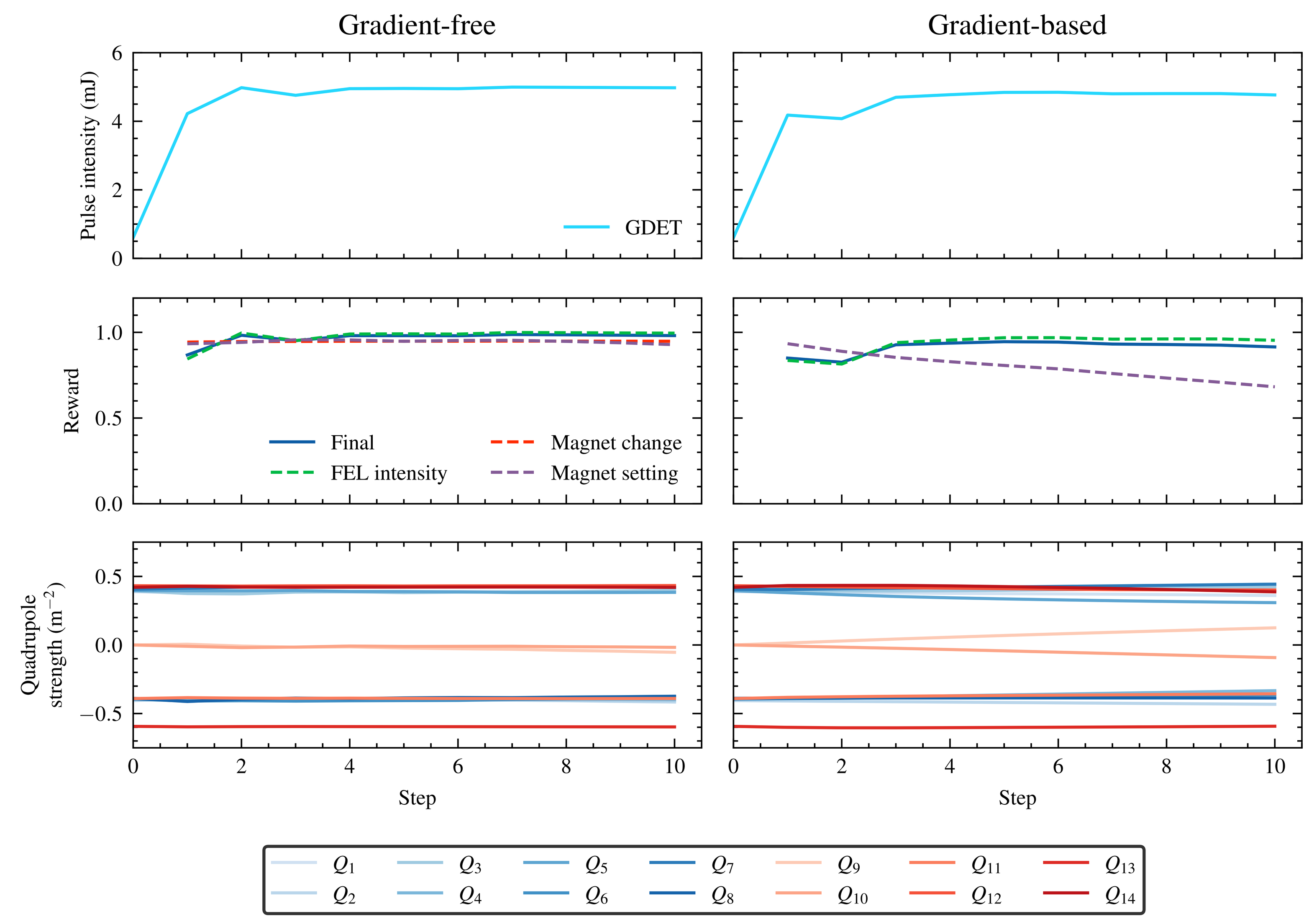
Gradient-based RL rollout graph



Mean return curves of gradient-free vs. gradient-based training



Example FEL tuning run by a trained policy



HIR³X Jefferson Lab SLAC NATIONAL ACCELERATOR LABORATORY DESY.