

Feedback Optimization on the EuXFEL Electron Dump Beamline

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Steady-State Control of Dynamic Systems

- Nonlinear dynamic system

$$\dot{x} = f(x, u)$$

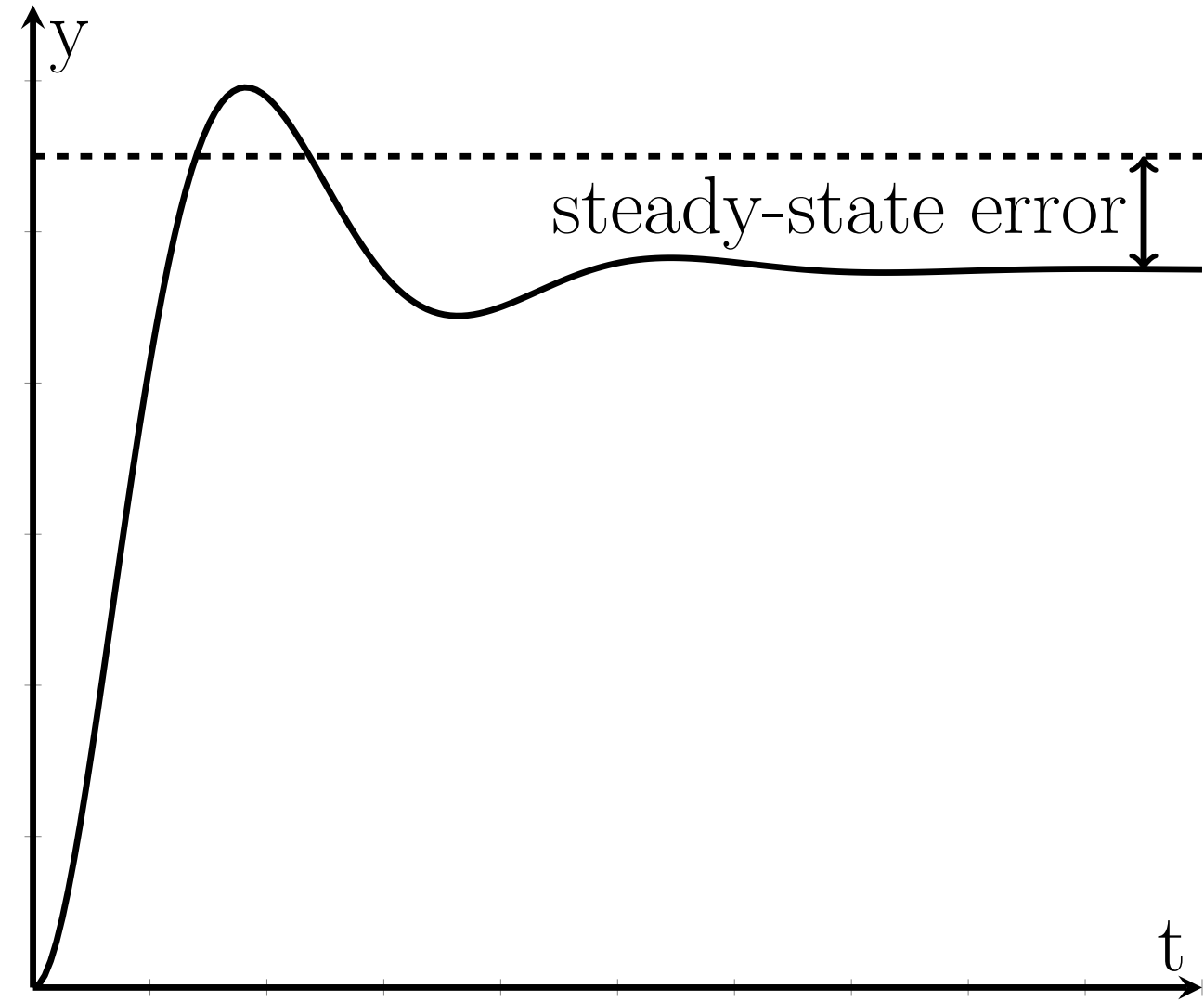
$$y = g(x)$$

- Steady-state map

$$0 \stackrel{!}{=} f(\bar{x}, \bar{u})$$

$$\bar{x} = \hat{h}(\bar{u})$$

$$h(u) := g(\hat{h}(u))$$



Optimization Problem

- Cost function $\Phi(u, y)$
- Constraint sets $\mathcal{U}, \mathcal{Y}$

$$\min_{u, y} \Phi(u, y)$$

$$\text{subject to } y = h(u)$$

$$u \in \mathcal{U}$$

$$y \in \mathcal{Y}$$

- Find optimal steady-state pair u, y

Obtaining Gradient Information

- 1) Rely on model knowledge
- 2) Approximation by sampling & heuristics
- 3) Recursive estimation

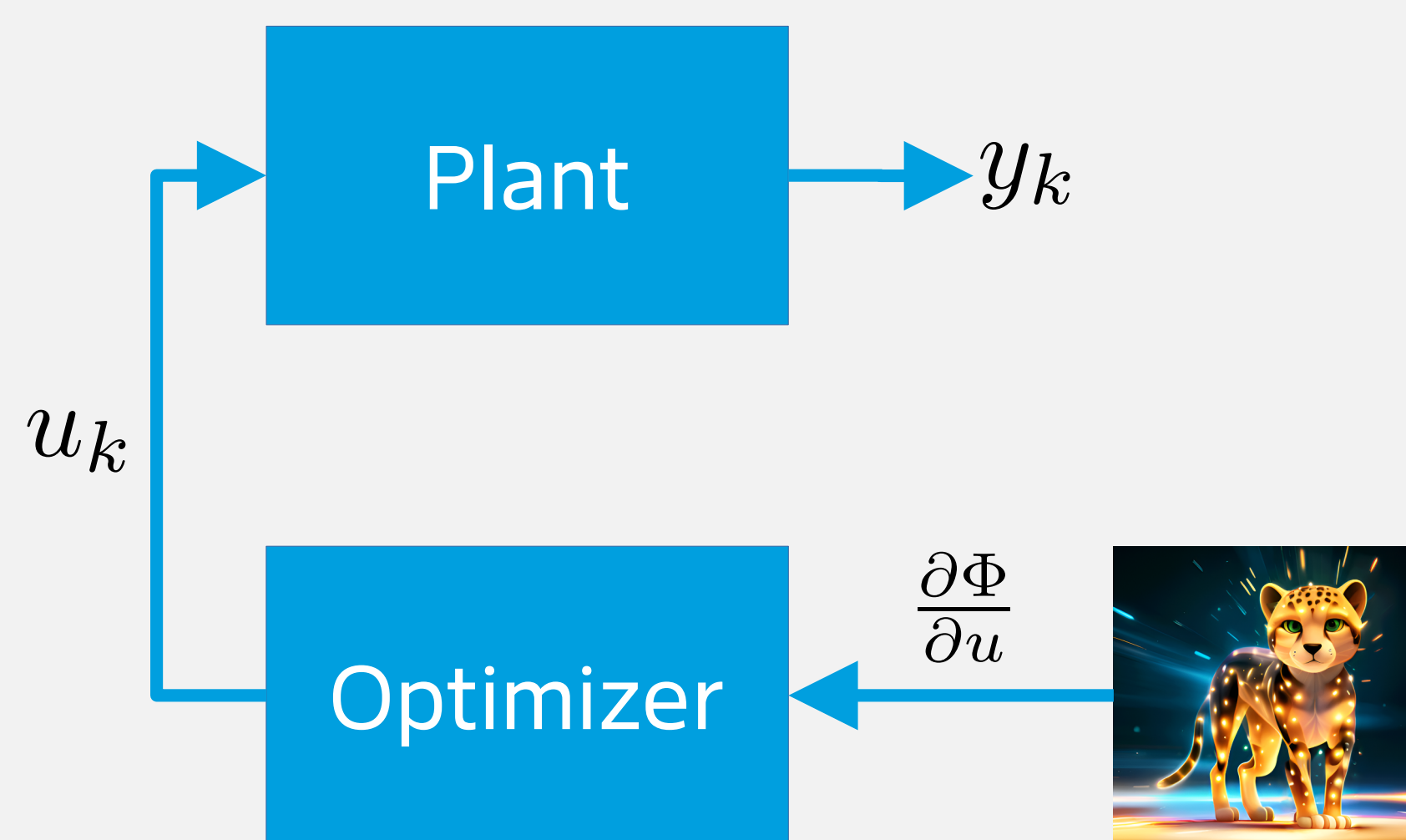
Chosen here: Recursive least-squares [Picallo et al.]

- Idea: First-order Taylor expansion

$$y_{k+1} = h(u_{k+1}) \approx y_k + \frac{\partial h}{\partial u}(u_k)[u_{k+1} - u_k]$$

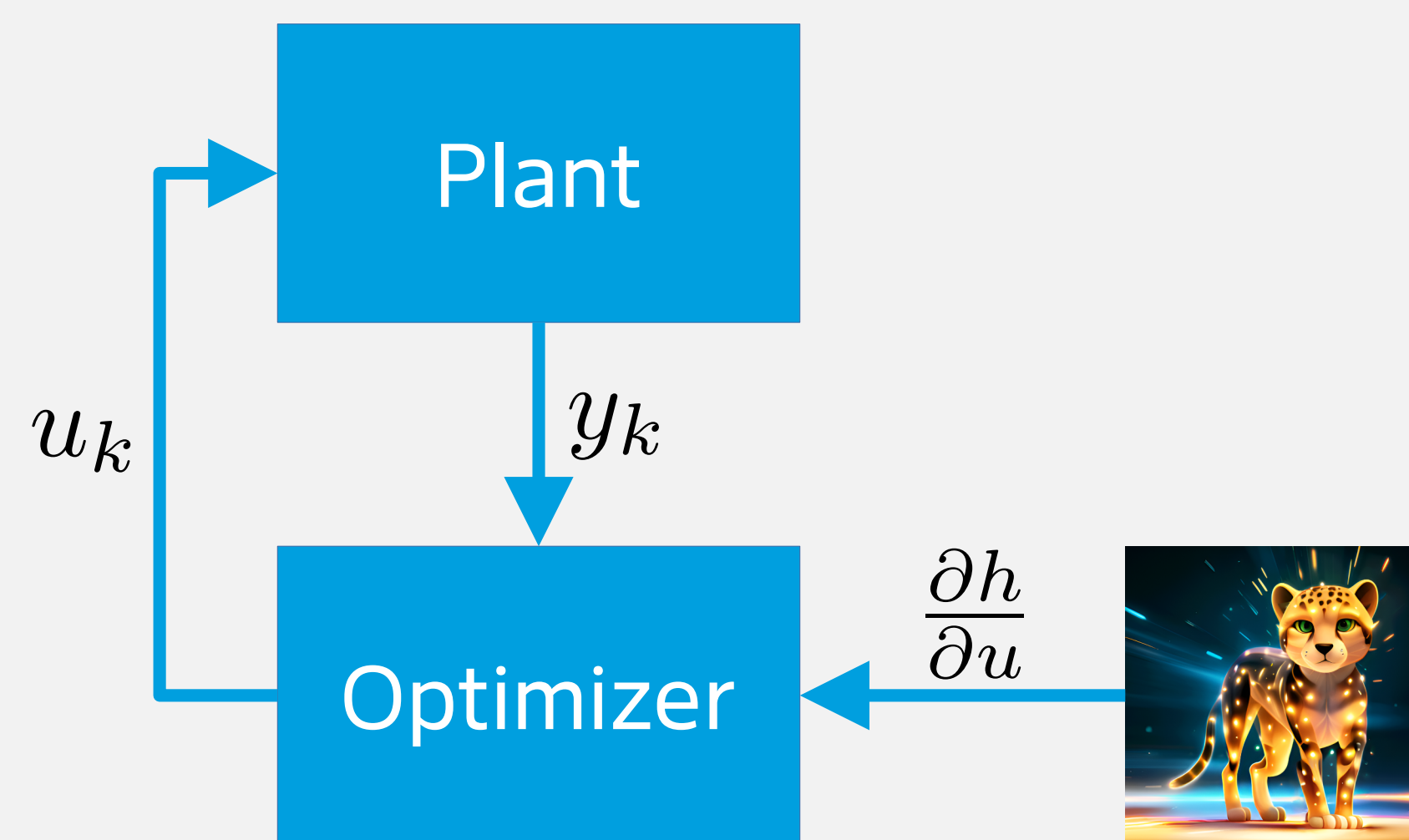
- Reformulate as linear dynamic system
- Estimation using Kalman filter

„Feedforward“ Optimization



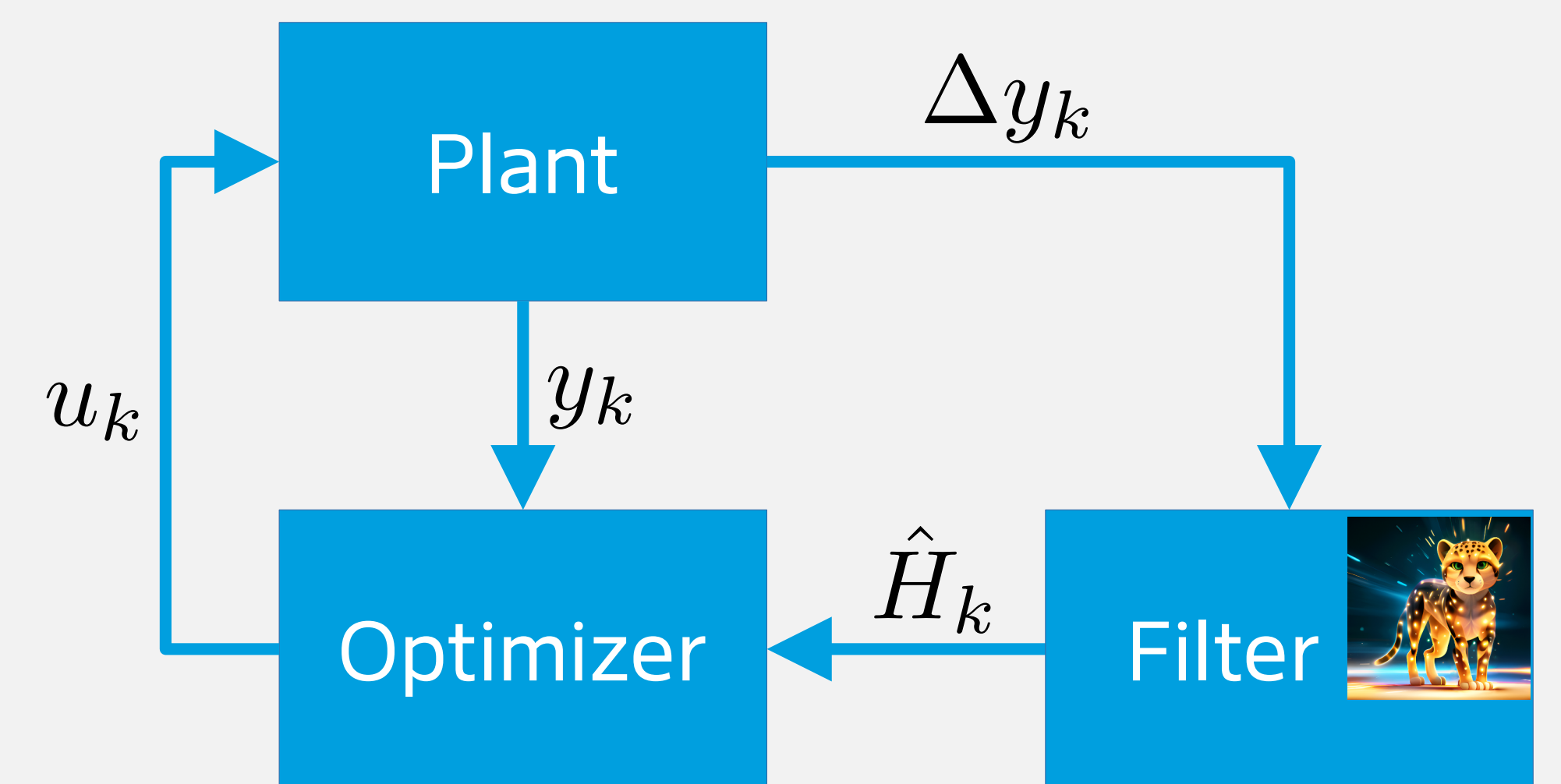
$$u_{k+1} = u_k - \alpha_k \frac{\partial \Phi(\cdot, h(\cdot))}{\partial u}(u_k)$$

Model-Based Feedback Optimization



$$u_{k+1} = u_k - \alpha_k \left(\frac{\partial \Phi}{\partial u}(u_k, y_k) + \frac{\partial \Phi}{\partial y}(u_k, y_k) \frac{\partial h}{\partial u}(u_k) \right)$$

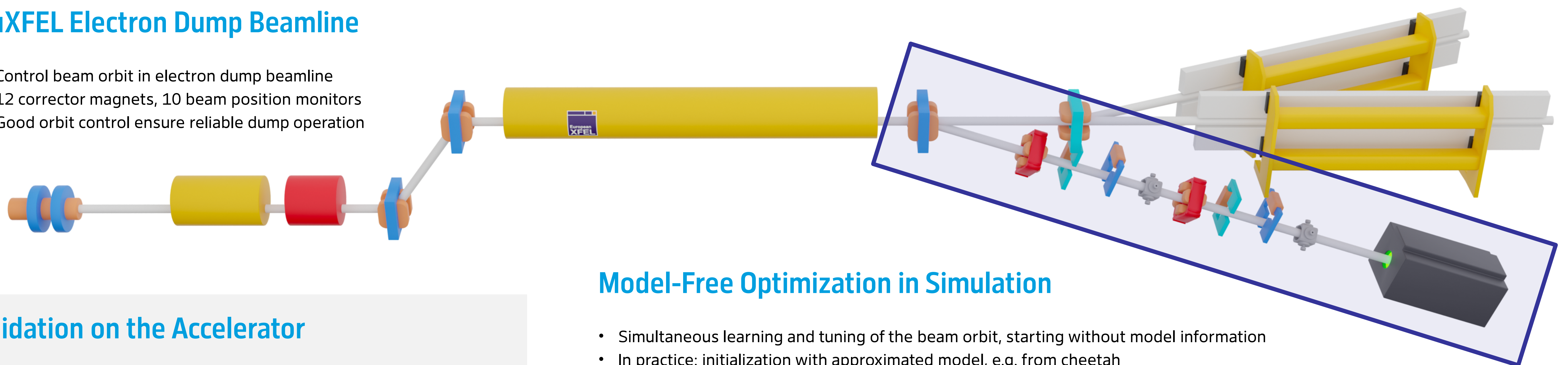
Learning-Based Feedback Optimization



$$u_{k+1} = u_k - \alpha_k \left(\frac{\partial \Phi}{\partial u}(u_k, y_k) + \frac{\partial \Phi}{\partial y}(u_k, y_k) \hat{H}_k \right) + \nu_k$$

EuXFEL Electron Dump Beamline

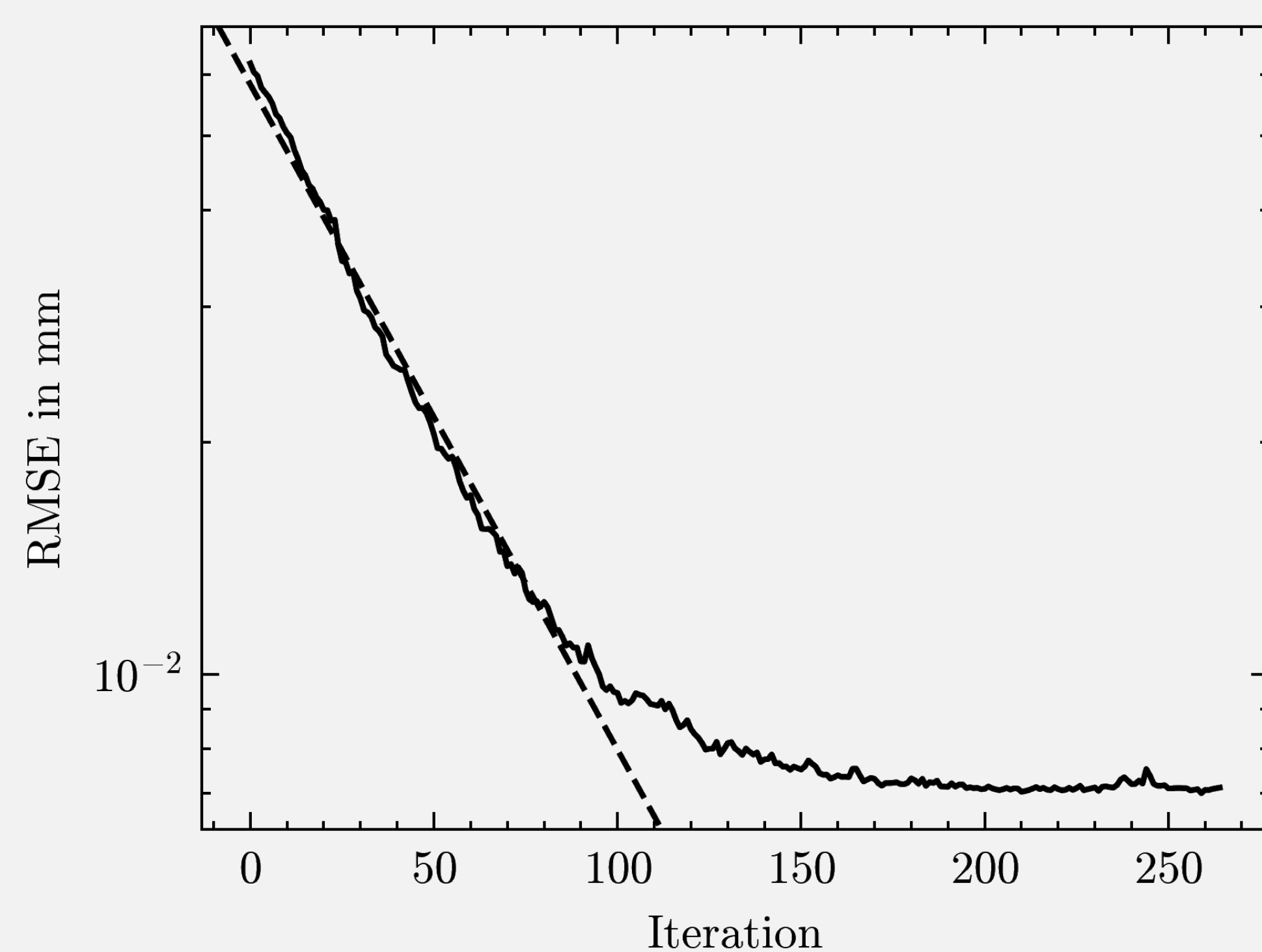
- Control beam orbit in electron dump beamline
- 12 corrector magnets, 10 beam position monitors
- Good orbit control ensure reliable dump operation



Validation on the Accelerator

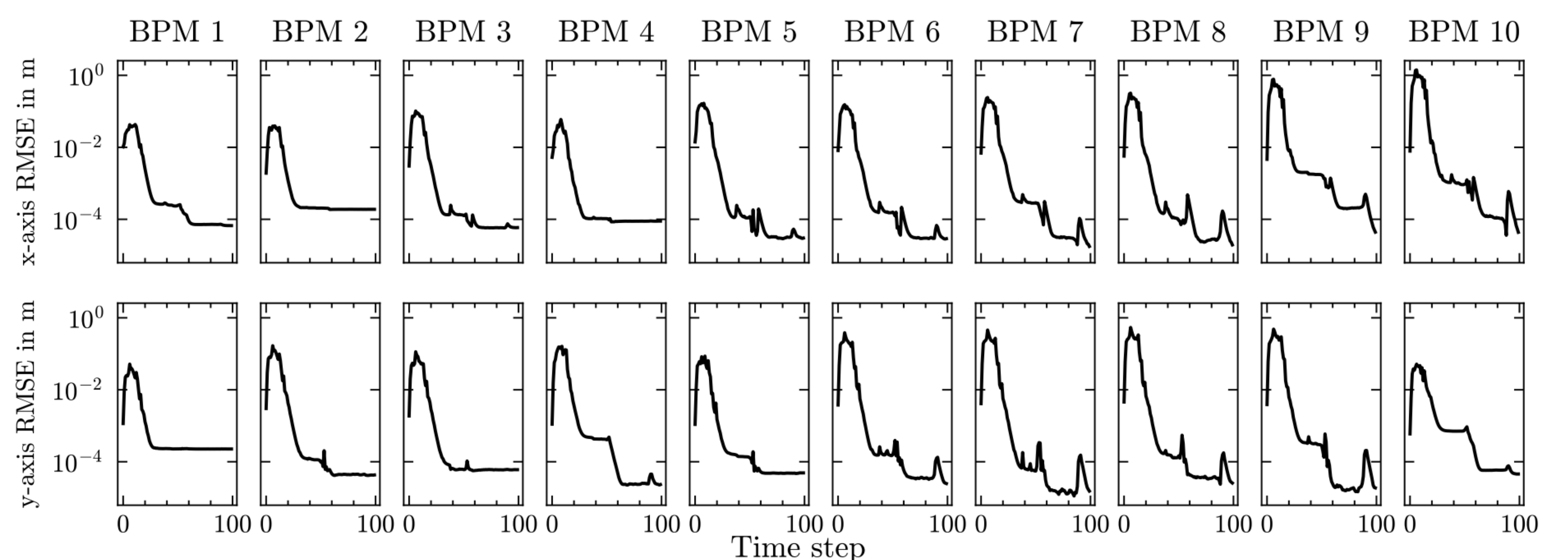
- Only model-based feedback tested - Algorithm is sufficiently robust
- Single bunch operation tested, 1 Hz update rate of the algorithm

- Reliably converged for different initial conditions
- Magnet current limits respected
- Convergence rate ≈ 0.02 , deliberately slowed down



Model-Free Optimization in Simulation

- Simultaneous learning and tuning of the beam orbit, starting without model information
- In practice: initialization with approximated model, e.g. from cheetah



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A. Hauswirth, Z. He, S. Bolognani, G. Hug, and F. Dörfler, "Optimization algorithms as robust feedback controllers," Annual Reviews in Control, vol. 57, p. 100941, Jan. 2024, doi: 10.1016/j.arcontrol.2024.100941.

M. Picallo, L. Ortmann, S. Bolognani, and F. Dörfler, "Adaptive real-time grid operation via Online Feedback Optimization with sensitivity estimation," Electric Power Systems Research, vol. 212, p. 108405, Nov. 2022, doi: 10.1016/j.eprsr.2022.108405.

C. Hespe, J. Kaiser, J. Lübsen, F. Mayet, M. Scholz, A. Eichler, "Data-Driven Feedback Optimization for Particle Accelerator Application", at – Automatisierungstechnik, vol. 73, no. 6, pp. 429-440, May 2025, doi: 10.1515/auto-2024-0170.

