

# Data-Driven Feedback Optimization

Application for Particle Accelerators

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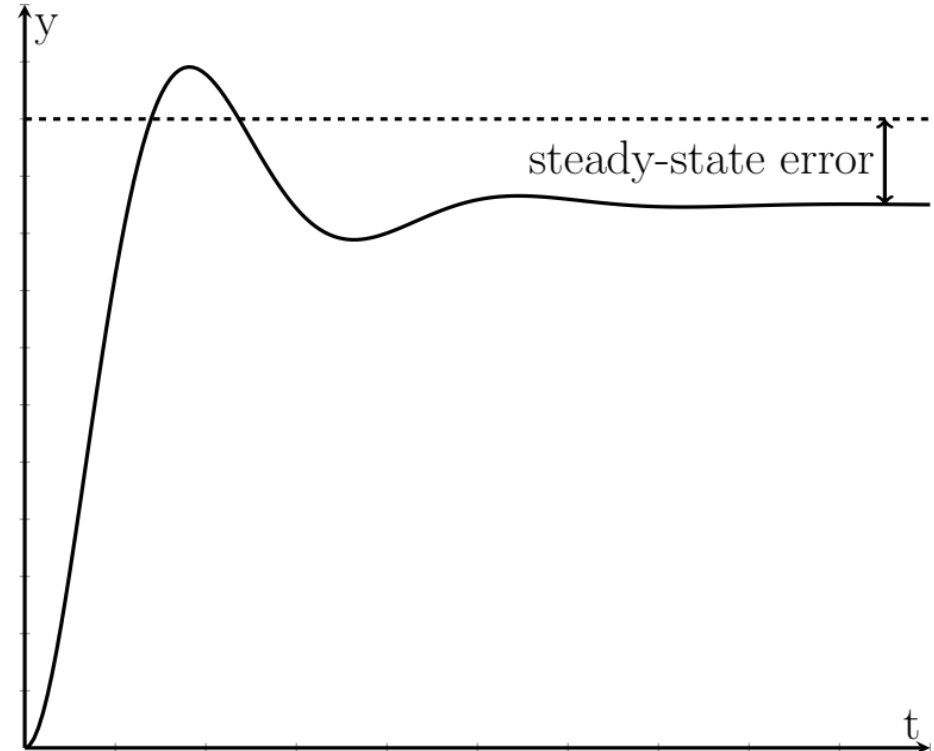
5<sup>th</sup> MaLAPA Workshop, CERN, 08.04.2025

# Steady-State Control

## Differential equations, steady-states, and transients

### Scenario

- Dynamic system
  - Described by differential equation
  - Mapping  $u \rightarrow y$
- Here: operating in steady-state
  - Transients have faded
  - Input determines operating point
- Task: Find optimal input-output pair
  - Defined by cost function



# Data-Driven Feedback Optimization

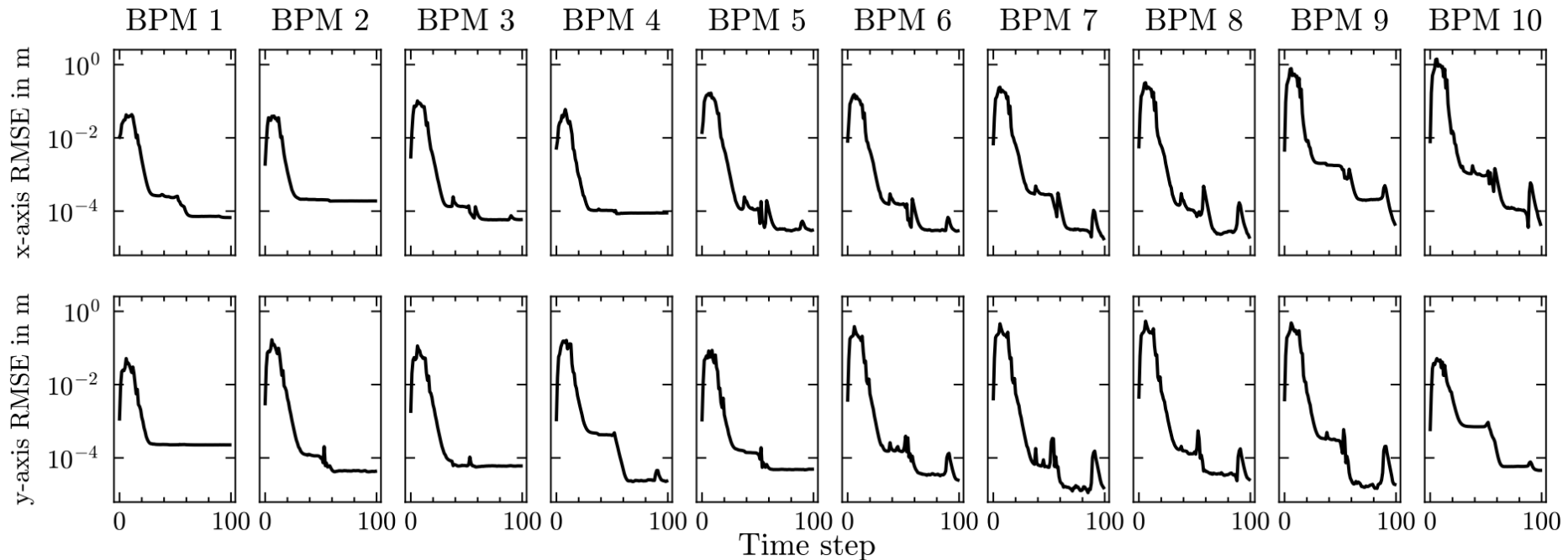
## Why apply this method?

### Feedback Optimization

- Robust to model uncertainties
- Can enforce problem constraints
- Can be applied model-free

### Result Preview

- EuXFEL beam orbit feedback
- Without model knowledge
- Partially evaluated on the dump beamline



# Agenda

Subheading, optional

**01 Feedback Optimization**

**02 Data-Driven Response Estimation**

**03 The EuXFEL Electron Dump Beamline**

# Feedback Optimization

# Problem Setup: Steady-State Optimization

Slow dynamics, fast dynamics

## Problem Context

- Nonlinear dynamic system

$$\begin{aligned}\dot{x} &= f(x, u) \\ y &= g(x)\end{aligned}$$

- Assume steady-state

$$\begin{aligned}0 &\stackrel{!}{=} f(\bar{x}, \bar{u}) \\ \bar{x} &= \hat{h}(\bar{u})\end{aligned}$$

- Steady-state map

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

## Problem Statement

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

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

$$\begin{aligned}\text{subject to } & y = h(u), \\ & u \in \mathcal{U}, \\ & y \in \mathcal{Y}\end{aligned}$$

# Gradient-Based Iterative Optimization

Ignoring the constraints, for now

$$\begin{array}{l} \min_{u,y} \Phi(u, y) \\ \text{subject to } y = h(u) \end{array} \quad \longleftrightarrow \quad \min_u \Phi(u, h(u))$$

## Gradient Descent

- First-order method

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

- Linear convergence with good step size tuning

## How to Obtain Gradient Information

- Sampling-based approximation
  - Sample  $\Phi$  around current input
  - Approximate the gradient
- Model-based
  - Fully rely on the model
  - No feedback from measurements

# Adding Feedback

## Becoming robust against uncertainties

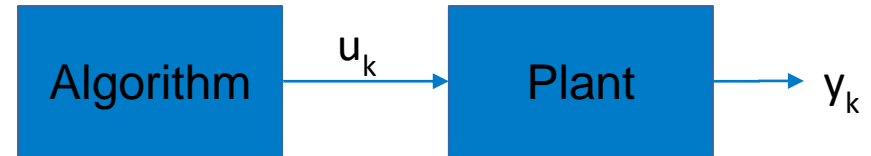
- Take advantage of chain rule

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

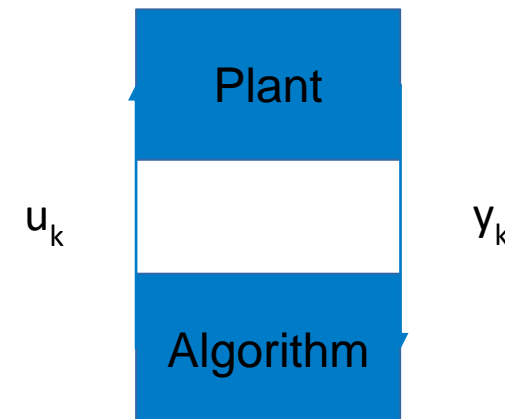
- **Cost function:** Known, depends on  $h(u_k)$
- **Plant sensitivity:** Uncertain, independent of  $y_k$

Idea: Replace  $h(u_k)$  by measured  $y_k$

### “Feedforward” Optimization



### Feedback Optimization



A. Hauswirth, Z. He, S. Bolognani, G. Hug, and F. Dörfler, “Optimization algorithms as robust feedback controllers,” Jan. 2024

# Data-Driven Response Estimation

# Sensitivity Estimation

How to obtain the necessary model knowledge

$$\begin{aligned} \min_{u, y} \quad & \Phi(u, y) \\ \text{subject to} \quad & y = h(u) \end{aligned}$$

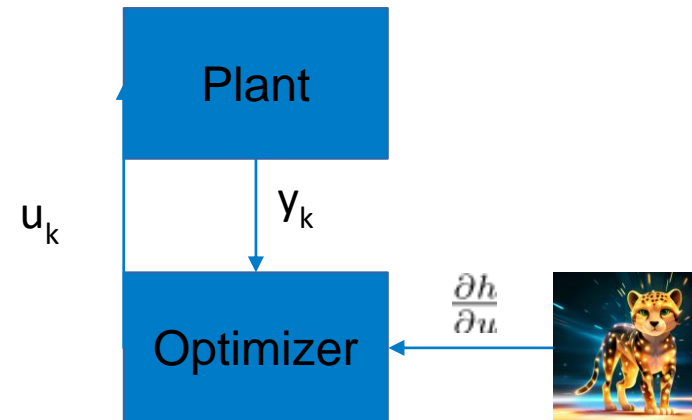


$$u_{k+1} = u_k - \alpha_k \left( \frac{\partial \Phi}{\partial u}(u_k, y_k) + \frac{\partial \Phi}{\partial y}(u_k, y_k) \frac{\partial h}{\partial u}(u_k) \right)$$

## How to apply the idea

- Calculate gradient steps
  - Partially with respect to  $y_k$
- Constraints via projection
- Problem: **plant sensitivity**

## Model-Based Implementation



# Online Optimization and Estimation

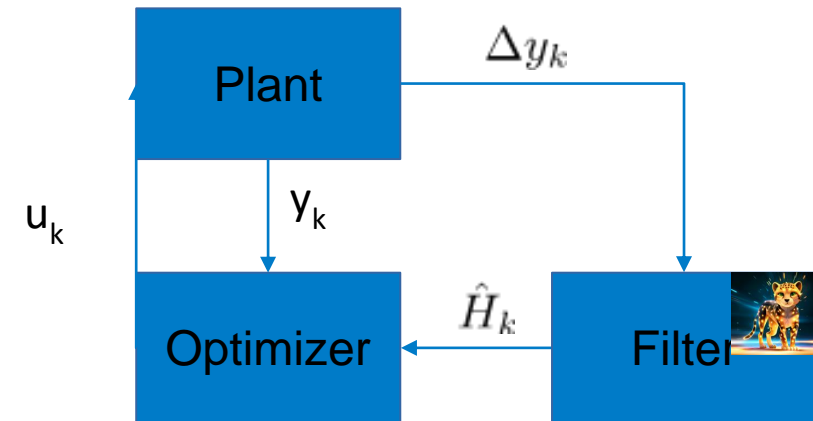
## Model-free gradient-based optimization

### Closed-Loop Sensitivity Estimation

- Online estimation using Kalman filter
- Feed estimated sensitivity to optimization algorithm
- Learn while steady-state is optimized

### Modified Algorithm

- Rely on **estimated sensitivity**
- Add random **excitation signal**



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

M. Picallo et al., "Adaptive real-time grid operation via Online Feedback Optimization with sensitivity estimation," Nov. 2022

**The EuXFEL**

**Electron Dump Beamline**

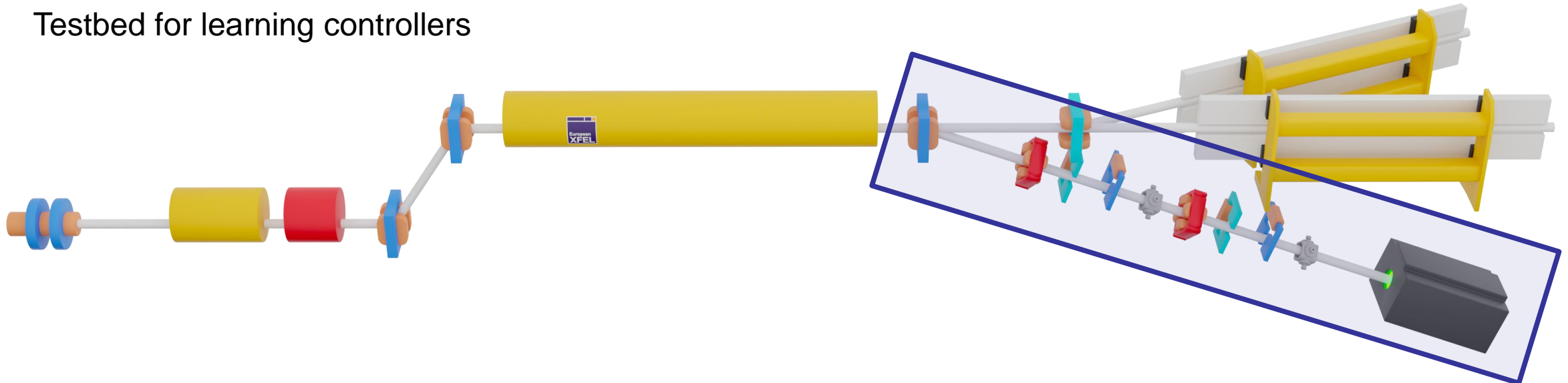
# The EuXFEL Electron Dump

## The Setup

- Beam orbit in dump beamline is drifting
  - Unreliable sweeping on the dump surface
  - Occasional temperature issues
- Counteract with continuous feedback
- Testbed for learning controllers

## The Scenario

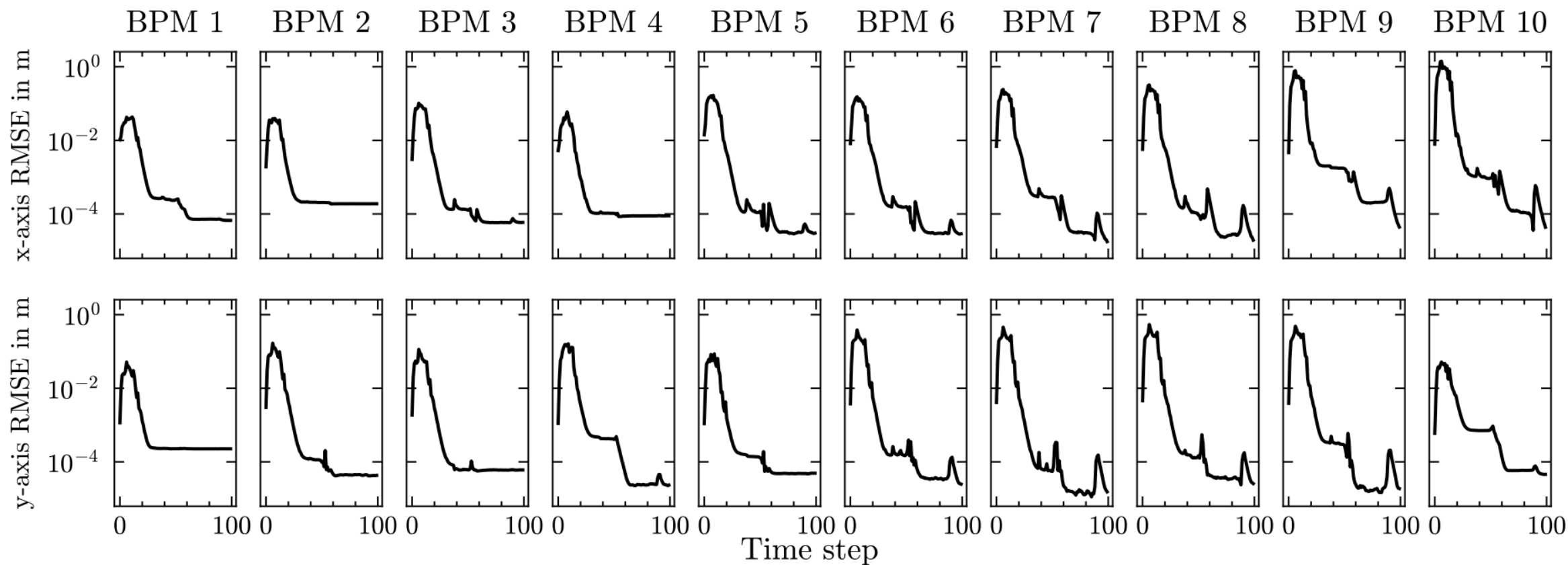
- Find optimal settings for the 12 corrector magnets
- Feedback from 10 beam position monitors
- Differentiable model available from Cheetah



# Model-Free Optimization in Simulation

## Learning by doing

- Simultaneous learning and tuning, starting without model information
- In practice: initialize estimator with approximated model



# Accelerator Experiment

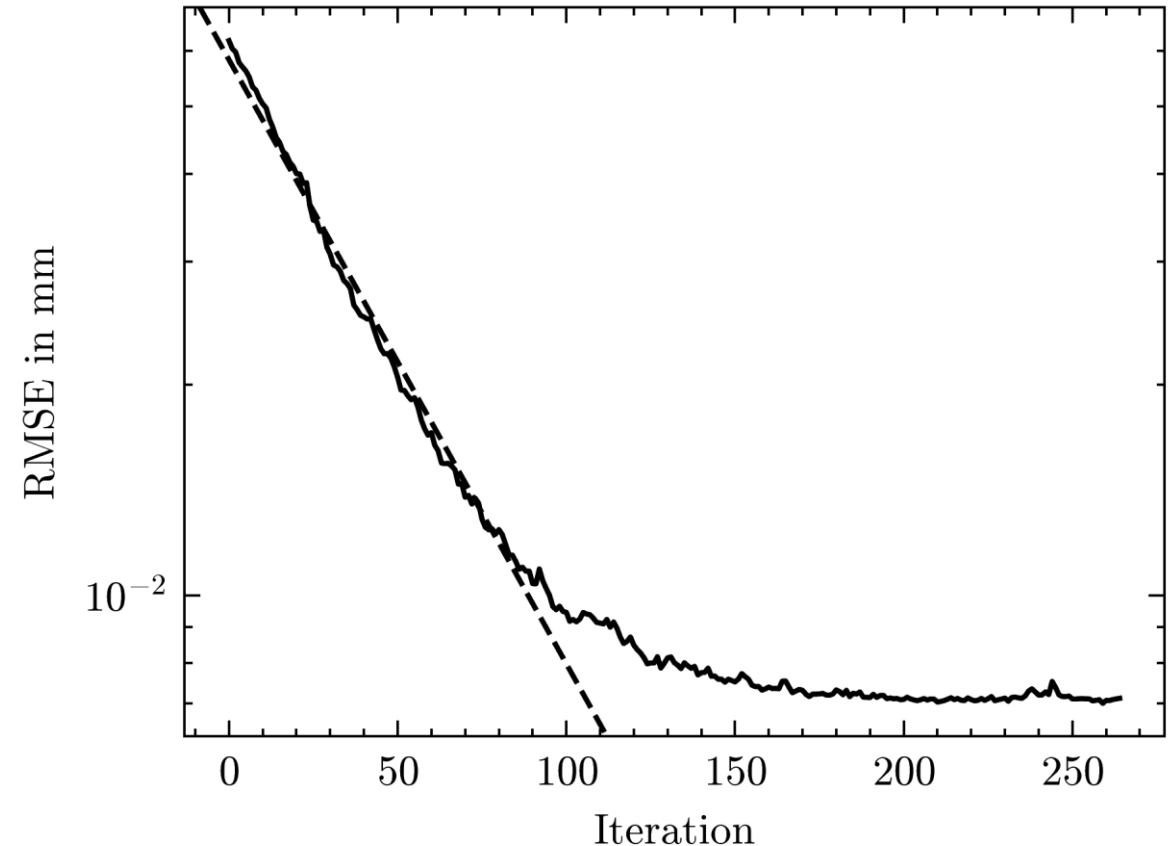
## Putting the algorithm to test in practice

### Restrictions

- Only model-based feedback tested
  - Algorithm robust enough
- Single bunch operation tested
- Approximately 1 Hz update rate

### Highlights

- Reliably converged for different starting points
- Takes magnet current limits into account
- Convergence rate  $\approx 0.02$ 
  - Expected, deliberately slowed down



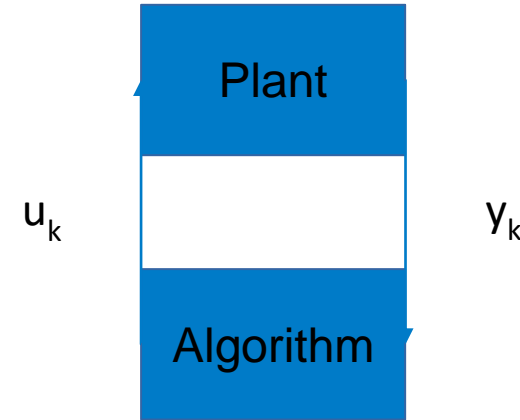
# Conclusion

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## Feedback!

### Summary

- Presented feedback optimization
  - Solve steady-state optimization problems
  - Robust, gradient-based
- Online response matrix estimation
  - Recursive least-squares method
  - Enable model-free feedback optimization
- Validated in simulation and experiment



### Outlook

- Evaluate response estimation on the machine
- Implement in the accelerator control panel
- Apply to other control problems on the accelerator

# Thank you

## Contact

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