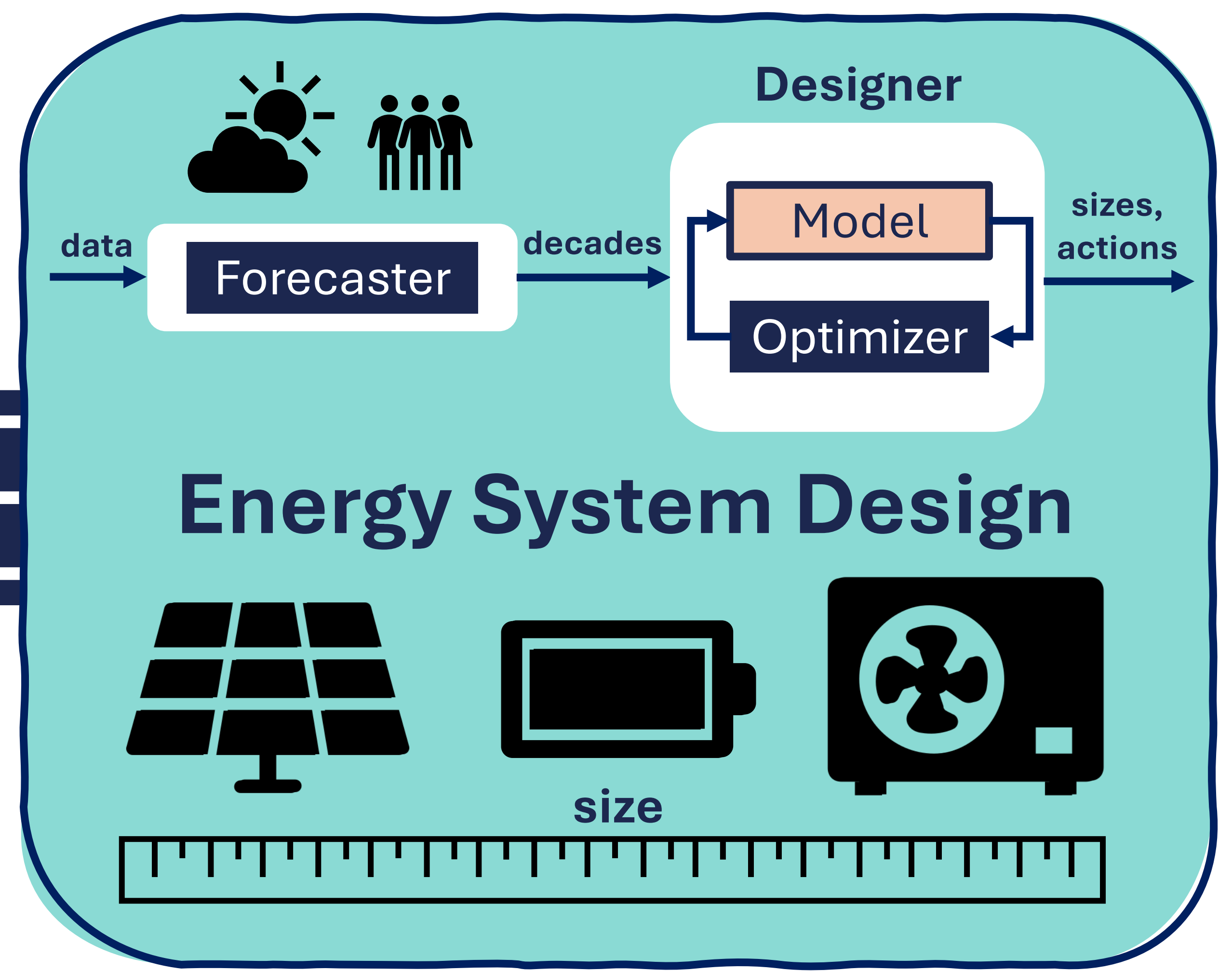


Bridging the gap



# Can we consider the *intended* energy system operation to get a superior design?

Cara Koepele<sup>a,b</sup>, Georgios Mavromatidis<sup>b</sup>, John Lygeros<sup>a</sup>

## Goal: Find the energy system plan with the lowest cost over its lifetime, $T$

We can cast this as a **bilevel optimization problem** with a design upper level and operation lower level

If we ignore the controller behavior, we risk over- or under-sizing components!

How can we solve this bilevel problem with **MPC operation**?

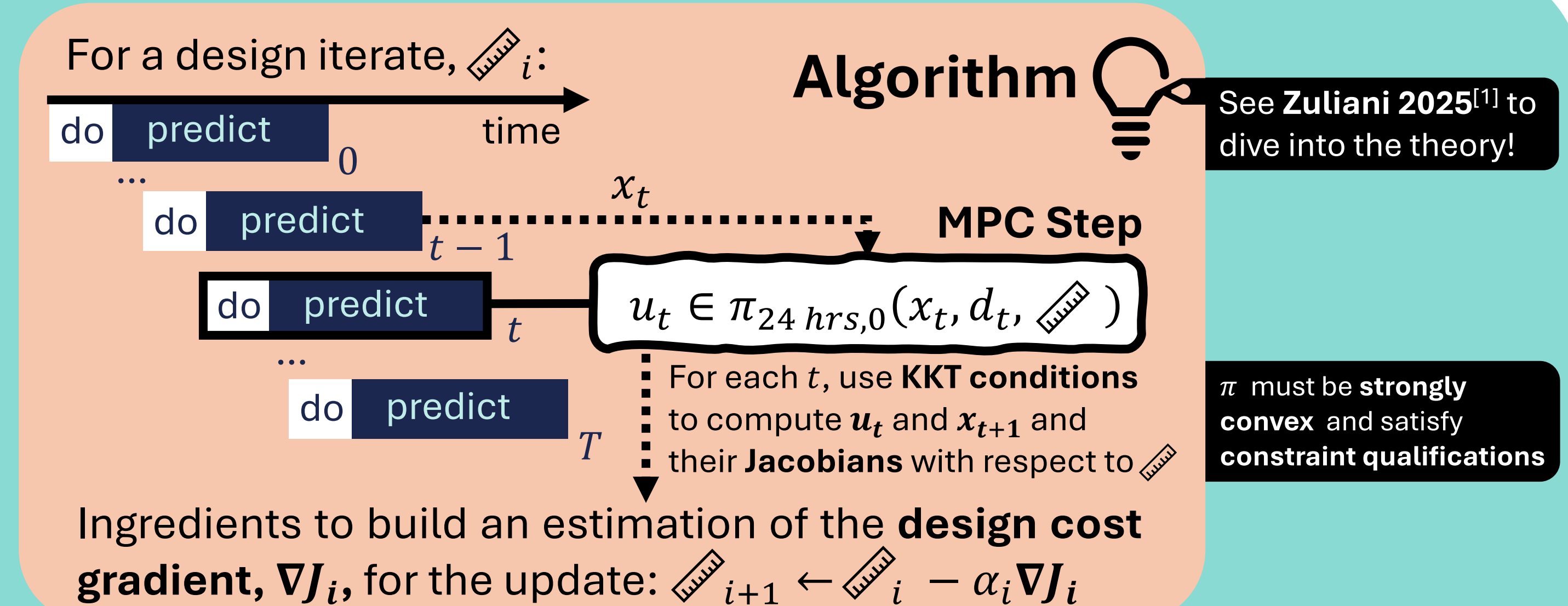
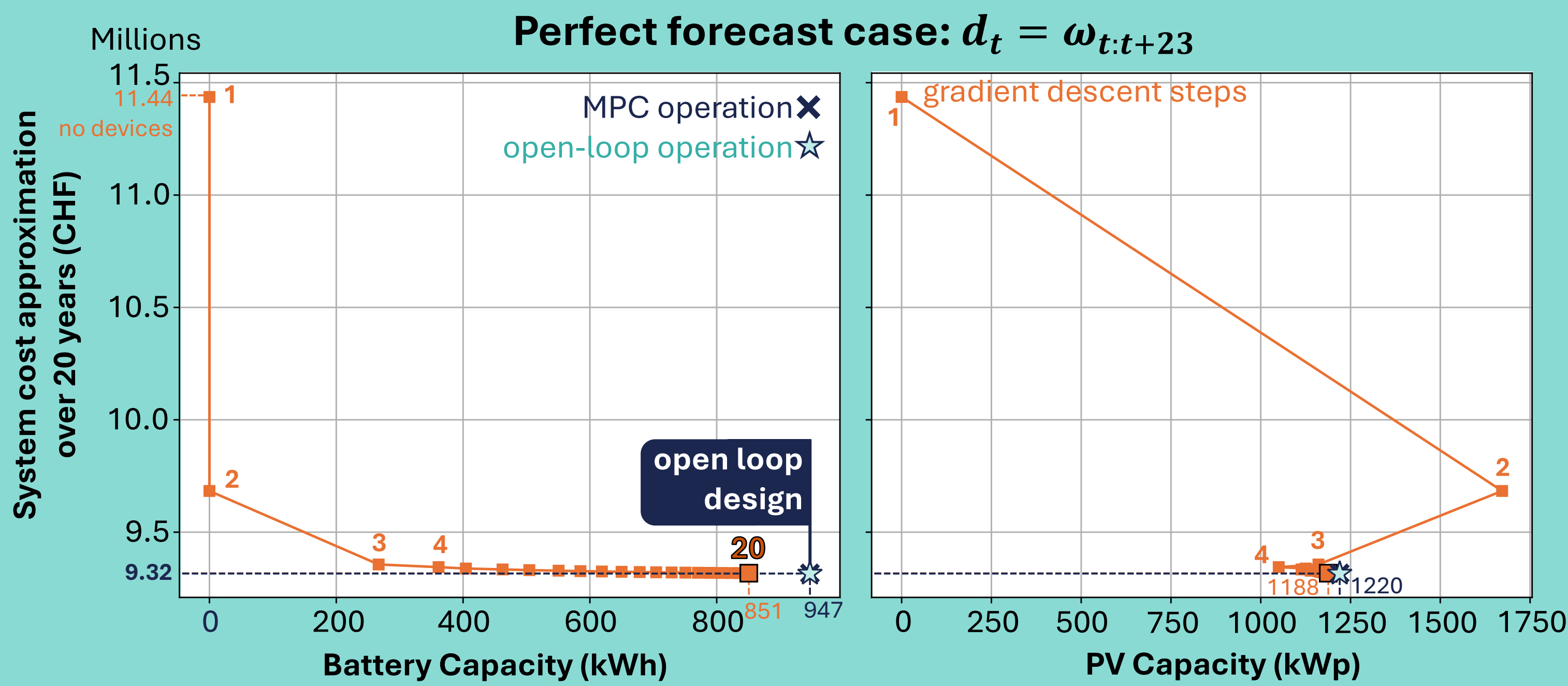
$$\begin{aligned} & \underset{\text{design}}{\operatorname{argmin}} \sum_{t=0}^T \text{Device investments} + \sum_{t=0}^T \text{Operation cost} \\ & \text{s.t. } \begin{cases} \text{design constraints} \\ x_{t+1} \in f(x_t, u_t, \omega_t), \text{ storage dynamics} \\ d_t \in \psi_t(\omega_{t-1}, \dots), \text{ disturbance forecast} \\ u_t \in \pi_{T,t}(x_t, d_t), \text{ controller model} \end{cases} \end{aligned}$$

Actions are typically modeled as optimal **open-loop** over the entire lifetime.

$$\begin{aligned} \pi_T(\bar{x}, d, \text{design}) = & \underset{u_0, \dots, u_{T-1}}{\operatorname{argmin}} \sum_{t=0}^T \text{Operation cost} \\ \text{s.t. } & \begin{cases} x_{t+1} = f(x_t, u_t, d_t), \text{ storage dynamics} \\ x_t \in \mathbb{X}(d_t), \text{ storage constraints} \\ u_t \in \mathbb{U}(d_t, \text{design}), \text{ action constraints} \\ 0 = H_u u_t + H_d d_t, \text{ energy balance} \\ x_0 = \bar{x}, \text{ initial storage level} \end{cases} \end{aligned}$$

This allows for a **single-level** optimization problem, but the recommended MPC operation is **closed-loop!**

## Backpropagation MPC (BPMPC) unlocks gradient descent for bi-level energy system design problems with an MPC lower-level

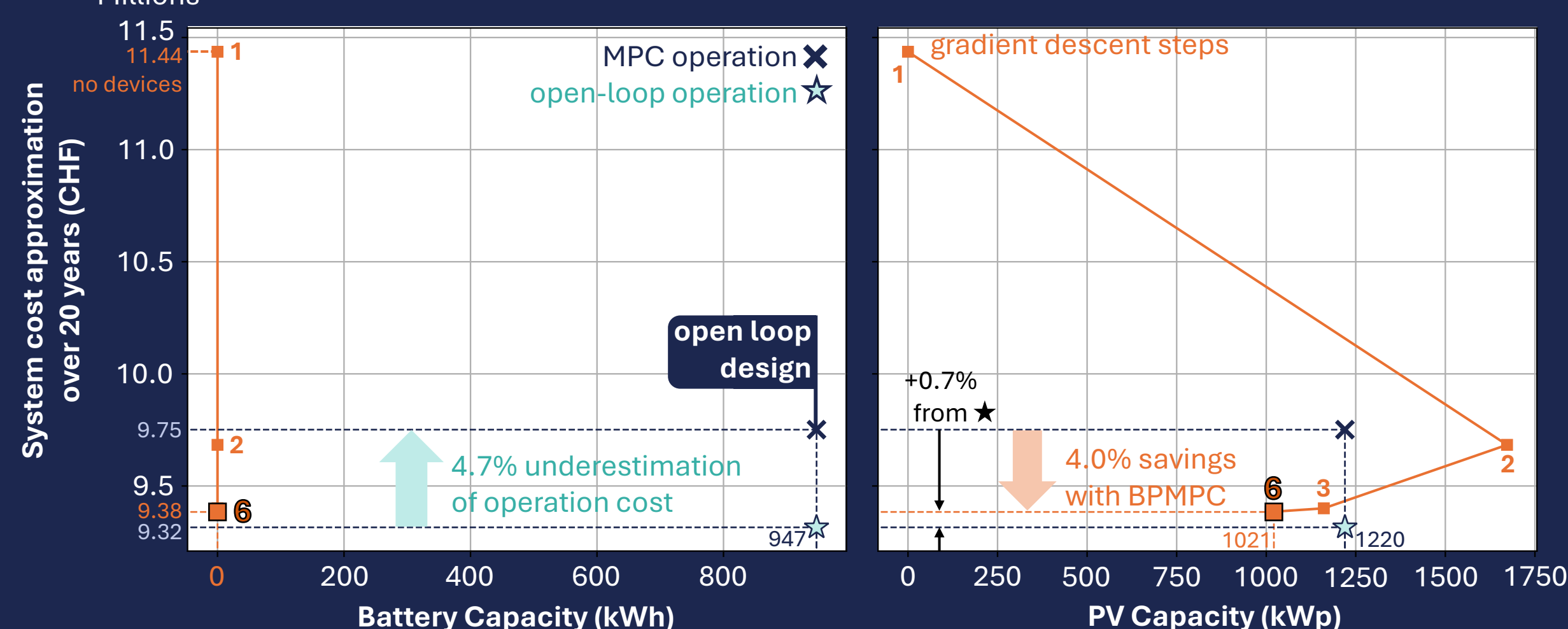


Energy Device Models	System Cost Model	Simulation Data
<ul style="list-style-type: none"> <li>All <math>x</math> and <math>u</math> are continuous and nonnegative</li> <li>battery: <math>x_{t+1} = \eta_{\text{store}} x_t + \eta_{\text{ch}} u_t^{\text{ch}} - \eta_{\text{dc}} u_t^{\text{dc}}</math></li> <li>solar: <math>u_t^{\text{pv}} \leq d_t A_t^{\text{pv}}</math></li> <li>heat pump: <math>u_t^{\text{hp}} \leq \text{COP}^{\text{hp}} u_t^{\text{hp}}</math> (fixed design)</li> </ul>	<ul style="list-style-type: none"> <li>Purchase and annual maintenance costs of each device</li> <li>Grid purchases, sales, and heat slack based on energy balance</li> <li>Linear Cost! (+ Regularization)</li> </ul>	<ul style="list-style-type: none"> <li>Demand and weather data from ETH buildings and weather center</li> <li>1 representative year of data for 20 years with a 1 hr resolution</li> <li>Approximated system costs account for interest rate</li> </ul>

## BPMPC finds the superior cost-effective design considering imperfect forecasts

1-day persistence forecast for weather and load

$$d_t = \omega_{t-24:t-1}$$



Optimal device sizes are smaller than those of the open-loop solution since operation is less efficient with incorrect forecasts.

## What is next?

### Work-in-progress

- Designing more devices: heat pumps and thermal storage
- Improving algorithm convergence with, e.g., momentum
- Implementing high performance forecasters and uncertainty-awareness

### Long-term interests

- Codesigning device sizes and controller parameters
- Considering upper-level uncertainties and degradation
- Pivoting to methods such as Bayesian Optimization to handle mixed-integer models