Meta-learning to enable autonomous buildings

Panagiota Karava
Jack and Kay Hockema Professor
Lyles School of Civil Engineering
Center for High Performances Buildings
Purdue University

CHPB CENTER FOR HIGH PERFORMANCE BUILDINGS AT PURDUE

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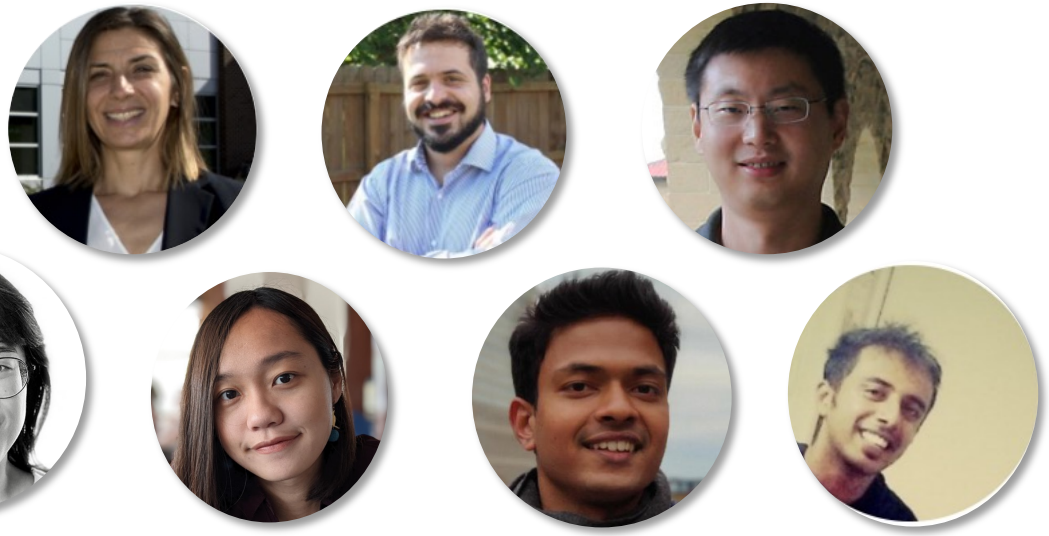
PURDUE UNIVERSITY

Team

Principal Research Investigators
• *Panagiota Karava*
• *Ilias Bilionis*
• *Jianghai Hu*

Researchers
• *Xiaoqi Liu*
• *Ting-Chun Kuo*
• *Sreehari Manikkan*
• *Hemanth Devarapalli*



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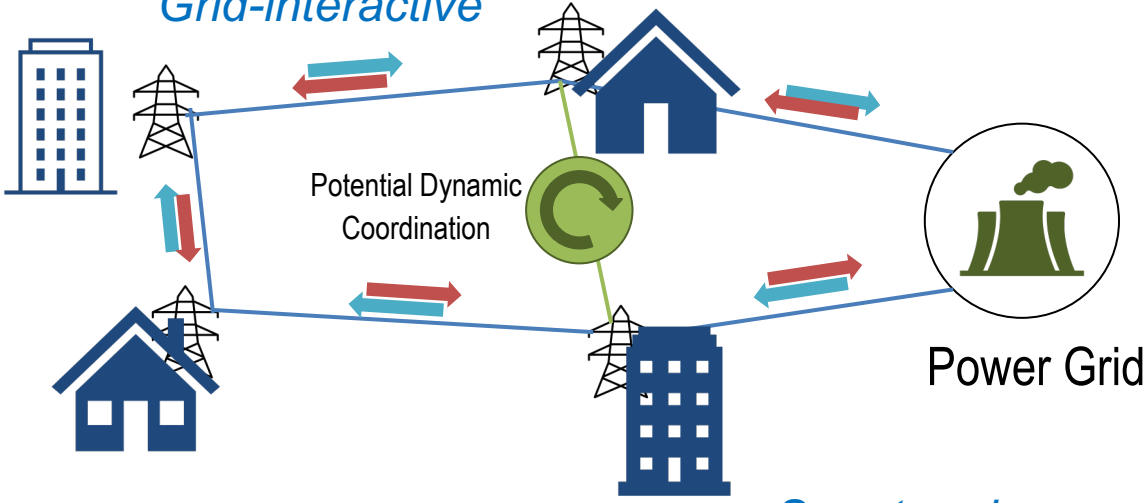
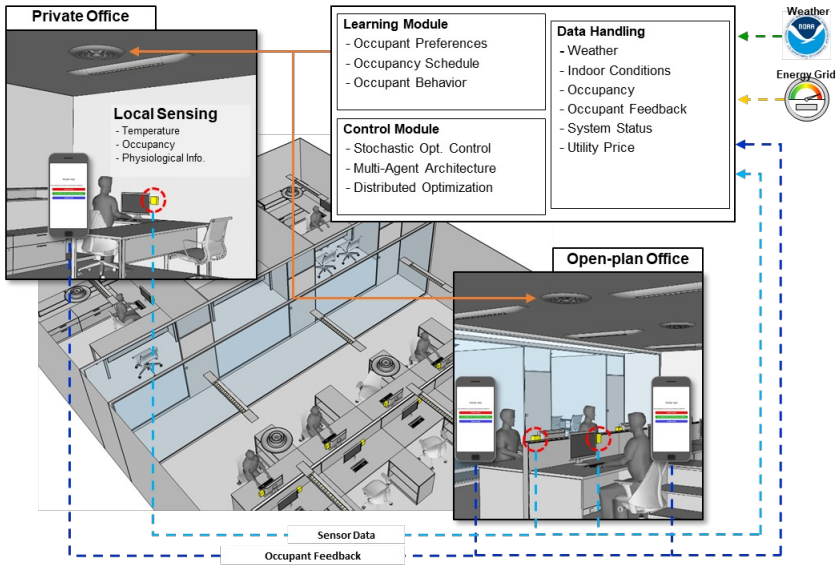
Societal need for smart and autonomous CPS – high performance buildings

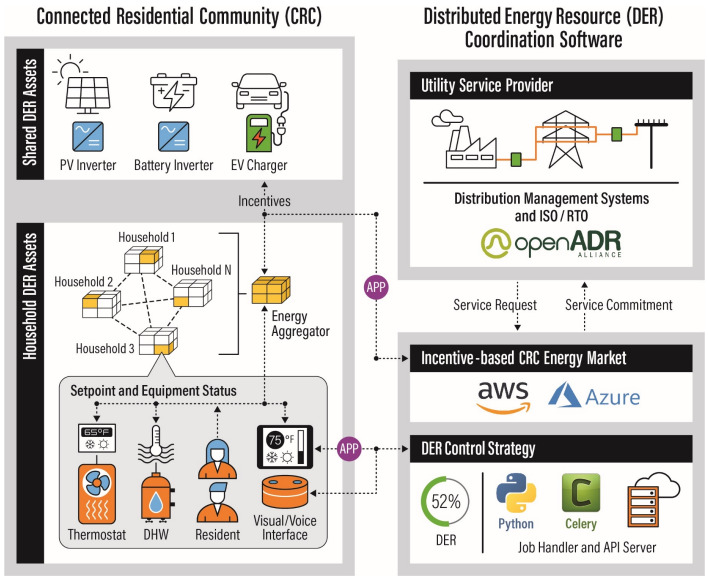
Grid-interactive



Human-centered



Smart and connected



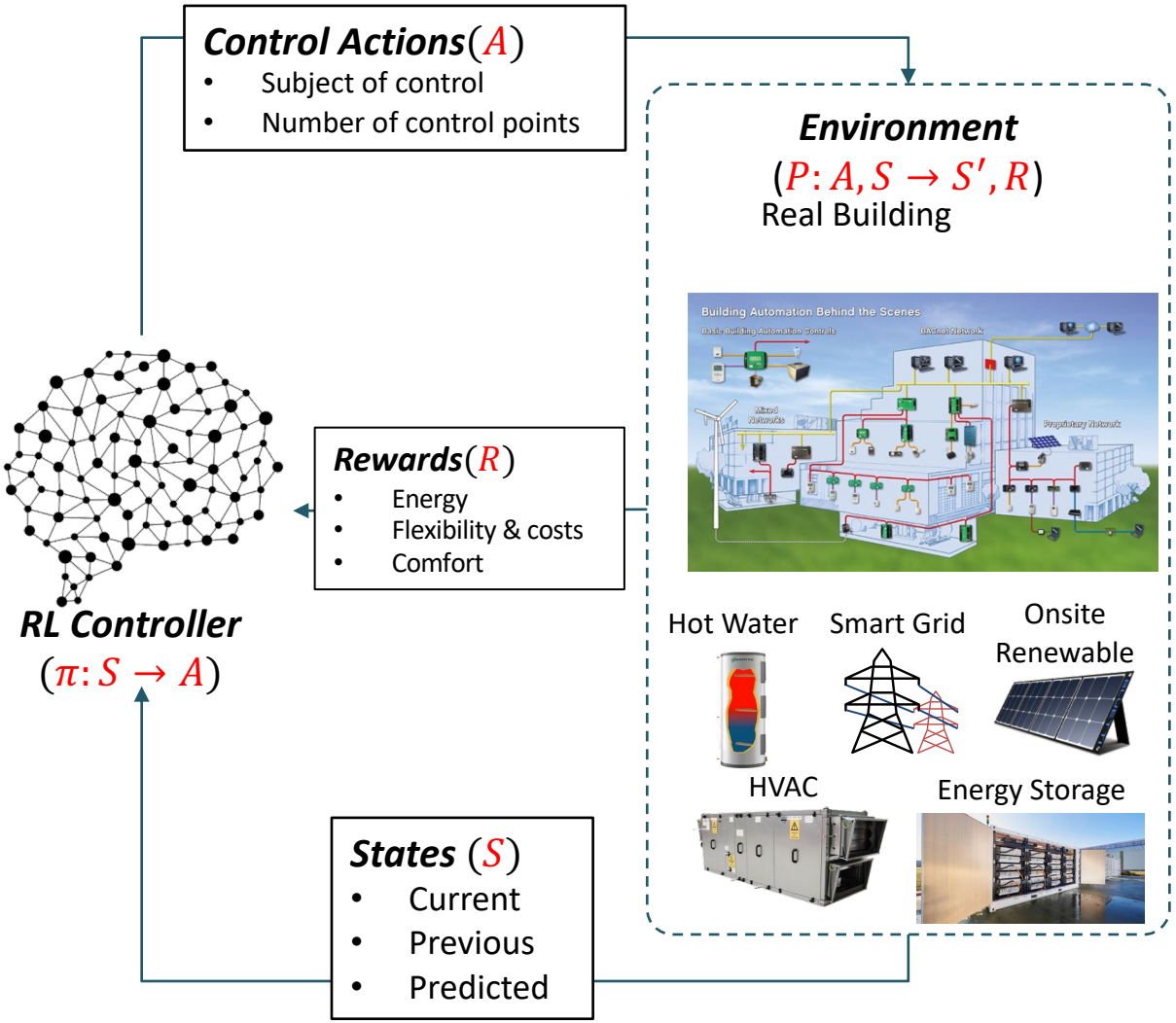
Challenges and opportunities for smart and autonomous CPS

- How to leverage data availability and AI/ML?
- How to combine data-driven machine leaning and model-based learning to automate the discovery of optimal policies for real-time control?

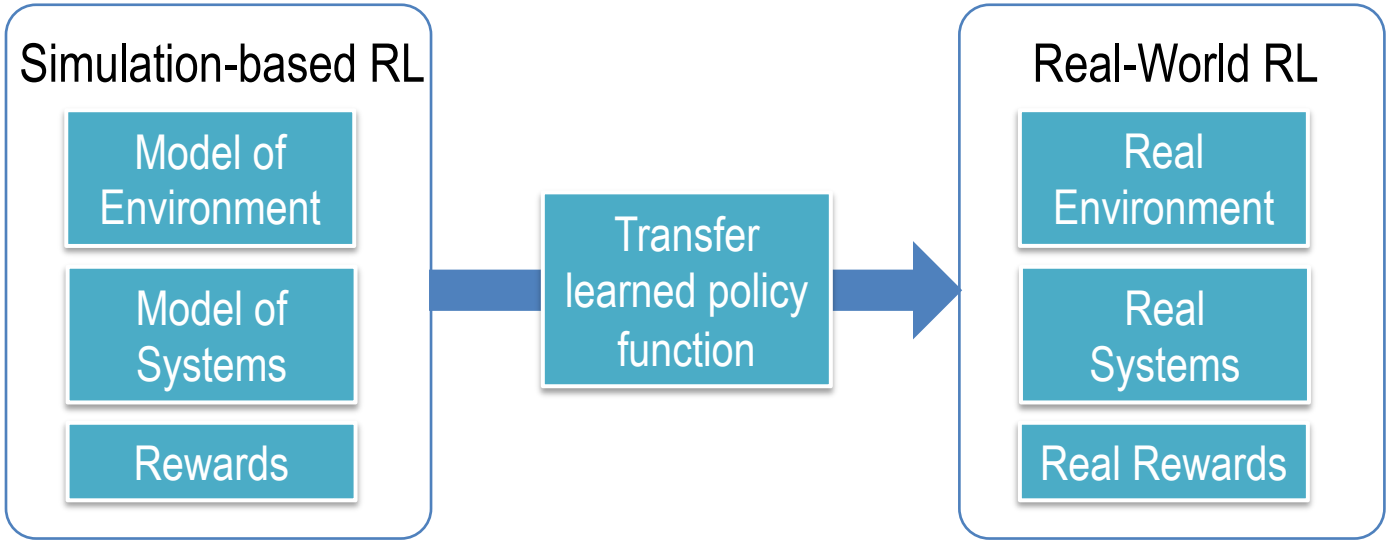
Use of traditional RL to build smart controllers

Real-World Challenges

- ❑ Learn from live systems
- ❑ Partially observable systems
- ❑ Learning in high-dimensional spaces
- ❑ Learning multiple objectives
- ❑ Deal with unknown delays
- ❑ Full system constraints
- ❑ Provided explainable policies



Use of traditional RL to build smart controllers



Challenges

- ❑ System, environment, rewards models do not match reality
- ❑ Policy function may be over-optimized for the wrong models
- ❑ RL in real system takes very long time
- ❑ Hard to guarantee good RL performance in real system

Find a good policy from a model universe - Meta-RL

Universe of possibilities with quantified uncertainties

Sample environments $E_1, E_n \cdots, E_N$

for episode $m = 1, \cdots, M$

for $n = 1, \cdots, N$

Inner loop: Traditional RL

Initialize the parameters of π_{θ_n}: $\theta_n = \theta_{e,m}$

Update θ_n with DDPG for $t = 1, \cdots, T$

Sample transitions $\mathcal{O}_n = \{(s_t, a_t, r_t, s')\}$ using π_{θ_n}

$n = n + 1$

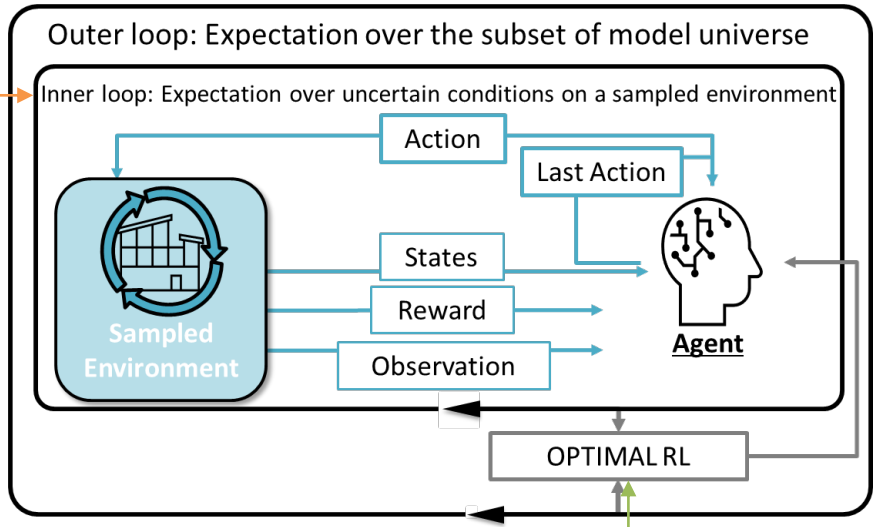
end for

Update θ_e using all trajectories $\mathcal{O}_{1:N}$ by gradient ascent:

$$\theta_{e,m+1} = \theta_{e,m} + \beta_3 \nabla_{\theta_{e,m}} \sum_n \mathbb{E}\left[\sum_{t=1}^{T} r(s_{n,t}, \pi(o_{n,t}|\theta_n))\right]$$

$m = m + 1$

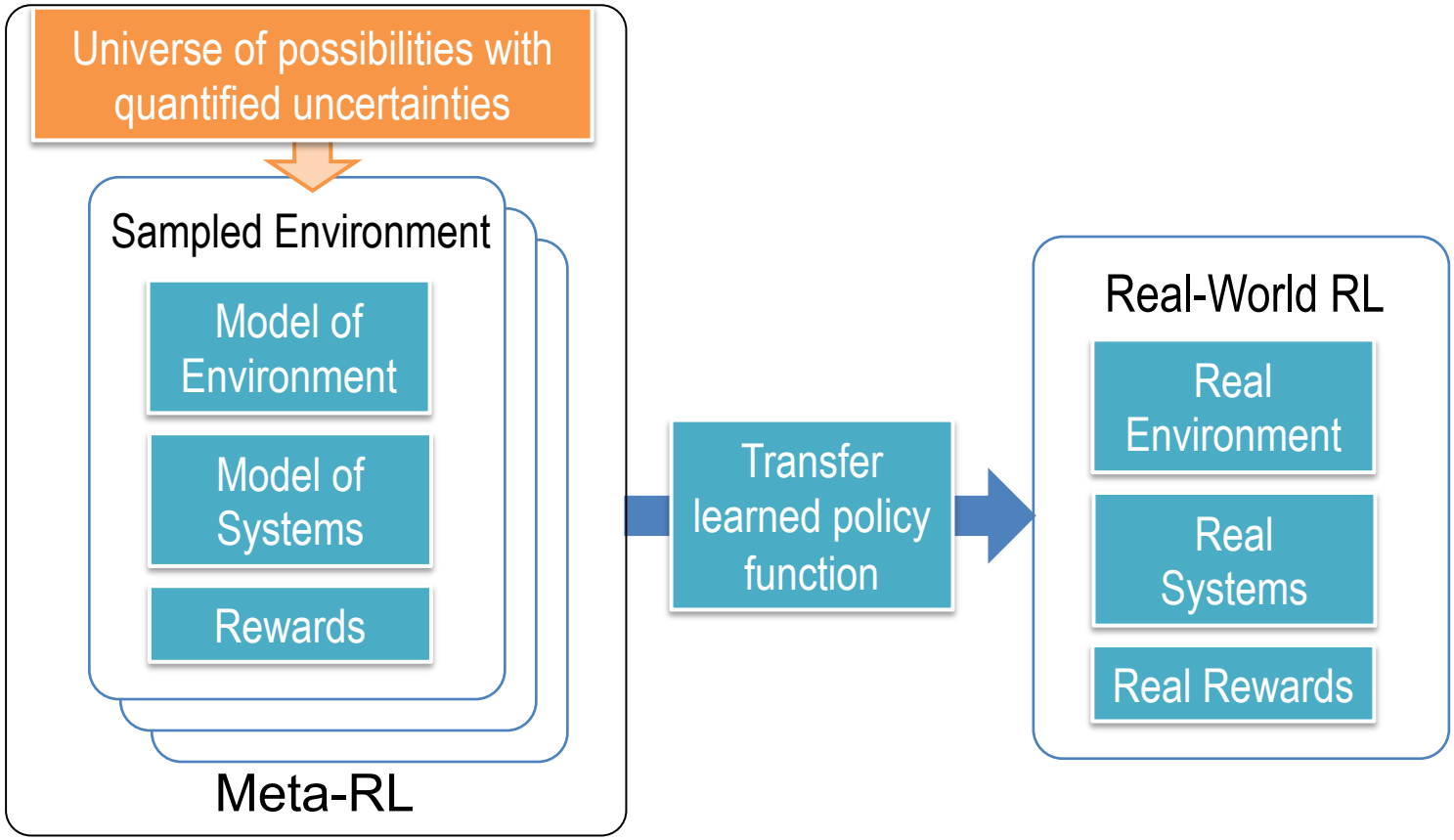
end for



Outer loop: Find optimal RL

MAML by Finn et al. (2017)

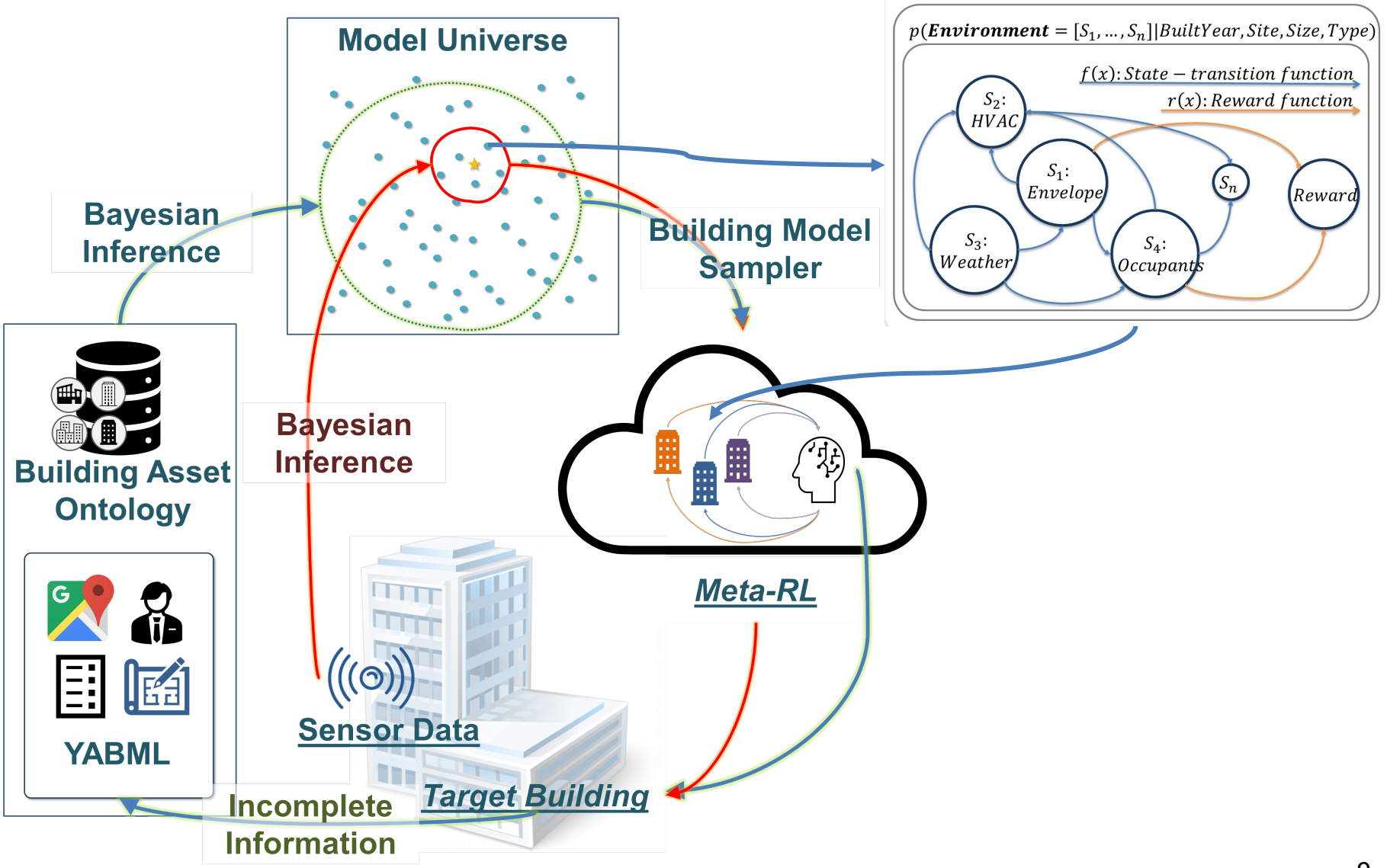
Find a good policy from a model universe - Meta-RL



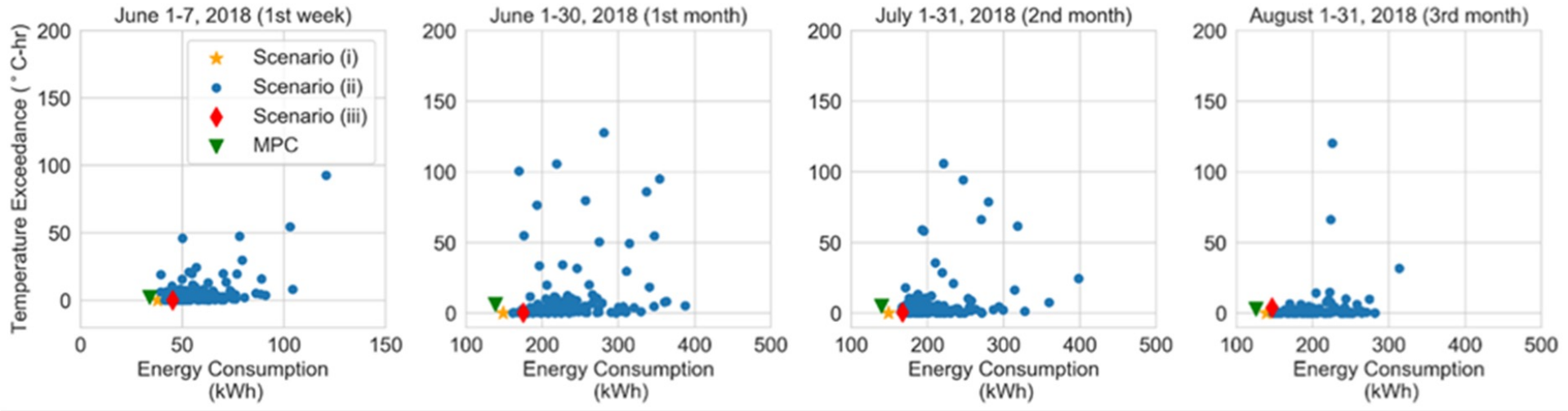
Open research questions

- How do we automate the construction of model universe with uncertainty quantification?
- How do we guarantee the performance of RL algorithm?

Use case: AI-Enabled Building Energy Expert



AI-Enabled Building Energy Expert: Impact



- Optimal policies without an accurate building model or a large amount of data
- Large-scale deployment of asset-specific smart control policies by non-experts → >$18 billion in annual energy savings

Foundational Research needs

- **Automated configuration** of digital twins from incomplete information
- **Formal knowledge representation** of the space of dynamical systems based on computational graphs
- Optimal **decision making** from limited information and data