A meta-learning approach to enable autonomous buildings

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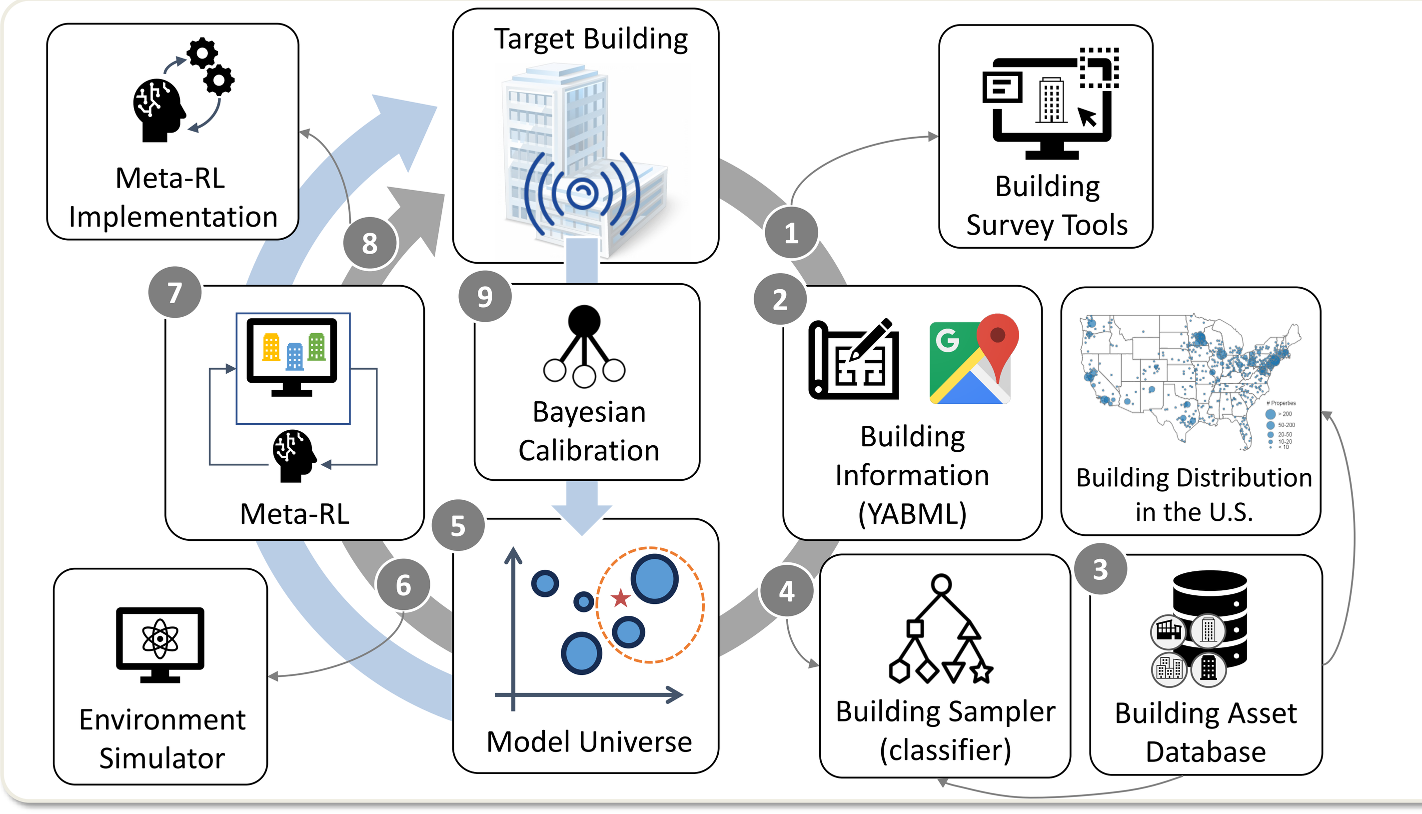
Challenge

Intelligent building controls require engineering customized, site-specific and costly solutions

Solution

Develop the AI-Enabled Building Energy Expert (AI-BEE) integrates data-driven and model-based learning and fuses different sources of information to automate the discovery of optimal policies for building control



1. Survey Tool
2. Information Schema
3. Asset Database
4. Prior Knowledge Sampler
5. Model Universe
6. Environment Simulator
7. Meta-Reinforcement Learning (Meta-RL)
8. Meta-RL Implementation
9. Bayesian Update of Model Universe

Scientific Impact

- Novel TD-based meta-RL algorithm for smaller-scale control problems
- Novel gradient-based meta-RL algorithm for complex control problems
- Automatic generation of differentiable building models sampled from the model universe
- Automated Bayesian update of model structure and parameters using building data

Broader Impacts

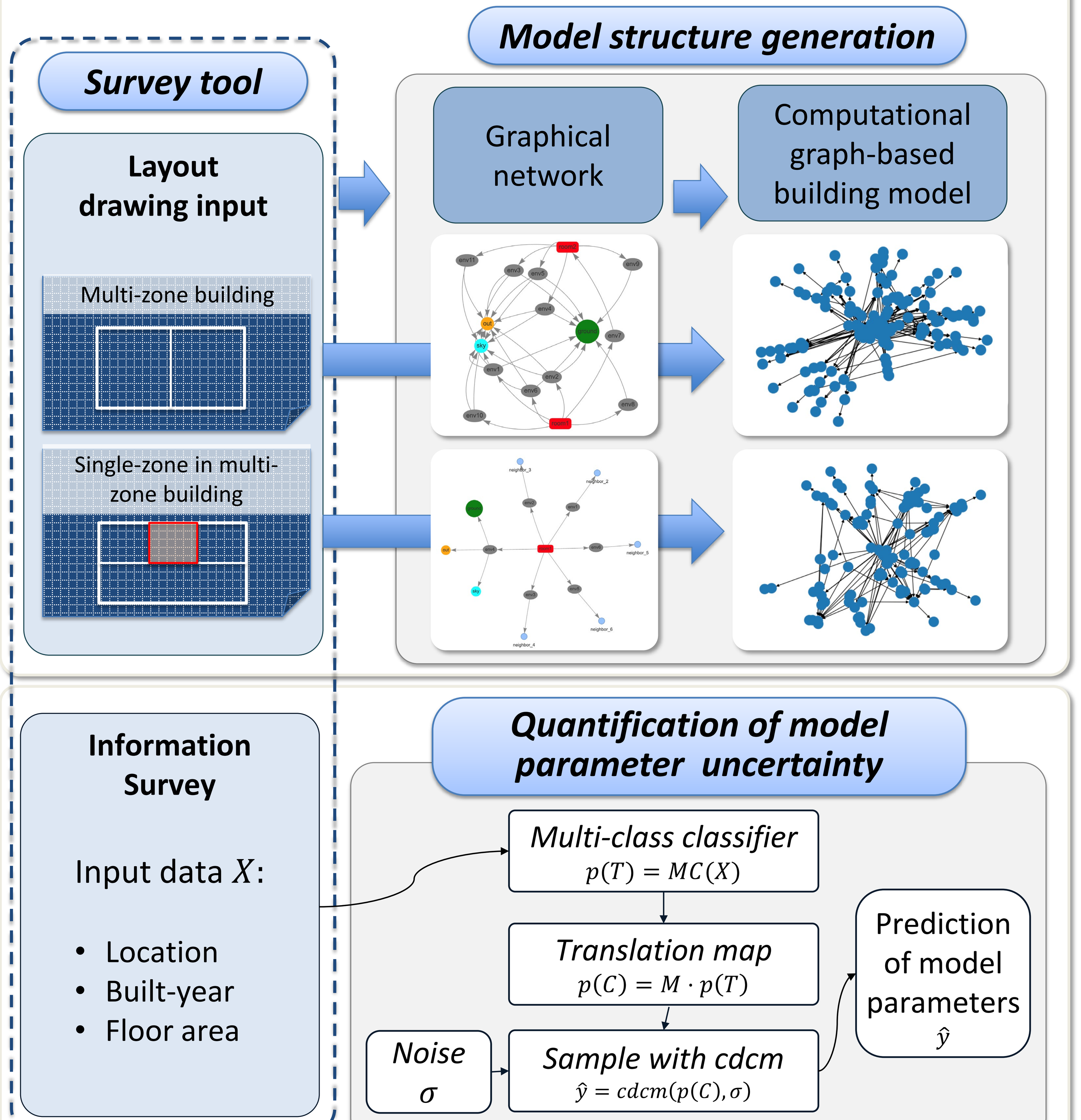
- CPS solution for autonomous buildings enabling deployment of asset-specific smart control policies by non-experts
- Field deployment and outreach through Purdue's Industry Consortium on Center for High Performance Buildings

Key Innovations

AI-BEE Generate Model Universe

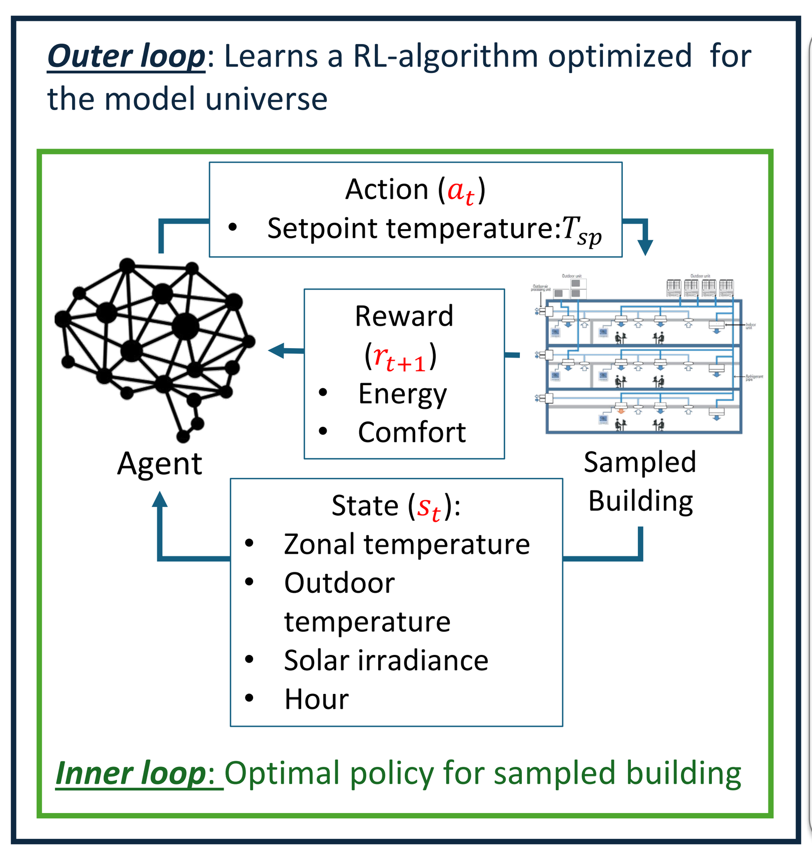
Scalability in Model Structure

Generate model structure for any building layout



Meta-Reinforcement Learning

Building Control Task Formulation



Algorithm 2: Gradient-based Meta-RL

- Inner loop: policy gradient approach
- High-dimensional control problems
- More computationally expensive

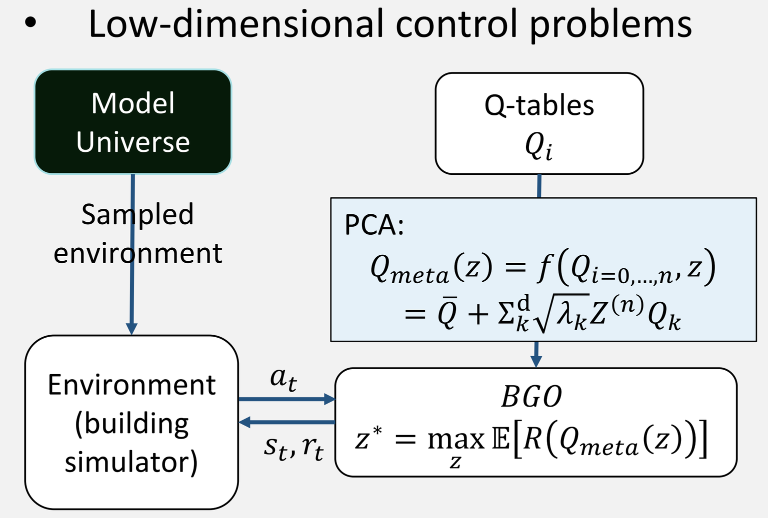
Algorithm2: Adapted version of MAML for Reinforcement Learning

Setup $p(\mathcal{M})$: distribution over tasks (i.e. Model Universe)
Setup hyperparameters: $\omega = \theta_0$;
external reward function $R(\mathcal{M}_i, f_{\theta^*}, \omega)$

1: *External Loop*:
2: **while** not done **do**
3: Randomly initialize $\theta = \theta_0$
4: *Internal Loop*:
5: **while** not done **do**
6: Sample batch of tasks $\mathcal{M}_i \sim p(\mathcal{M})$
7: **for** all $\mathcal{M}_i$ **do**
8: Sample K trajectories $\mathcal{D} = \{(x_1, a_1, \ldots, x_H)\}$ using f_θ in $\mathcal{M}_i$
9: Optimize f_θ with gradient descent $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{M_i}(f_\theta)$
10: **end for**
11: **Update** $\omega' \leftarrow \omega + \alpha \frac{\partial \mathbb{E}_{\tau \sim \mathcal{M}, f_{\theta^*}}[R_\tau]}{\partial \omega}$

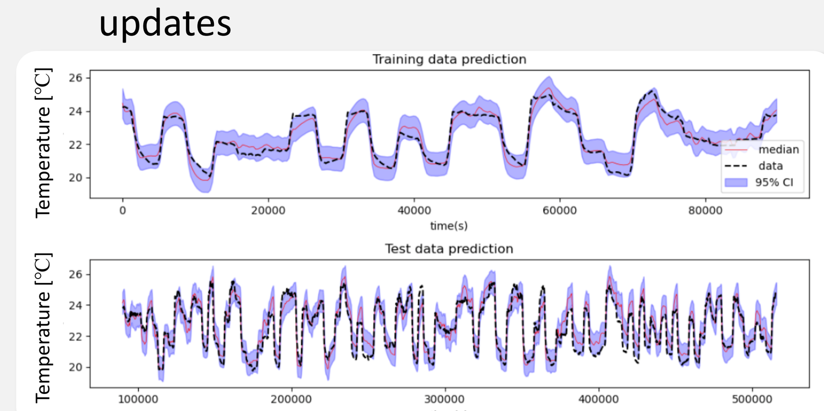
Algorithm 1: TD-based Meta-RL

- Inner loop: tabular Q-learning
- More computationally efficient
- Low-dimensional control problems



Differentiable building models

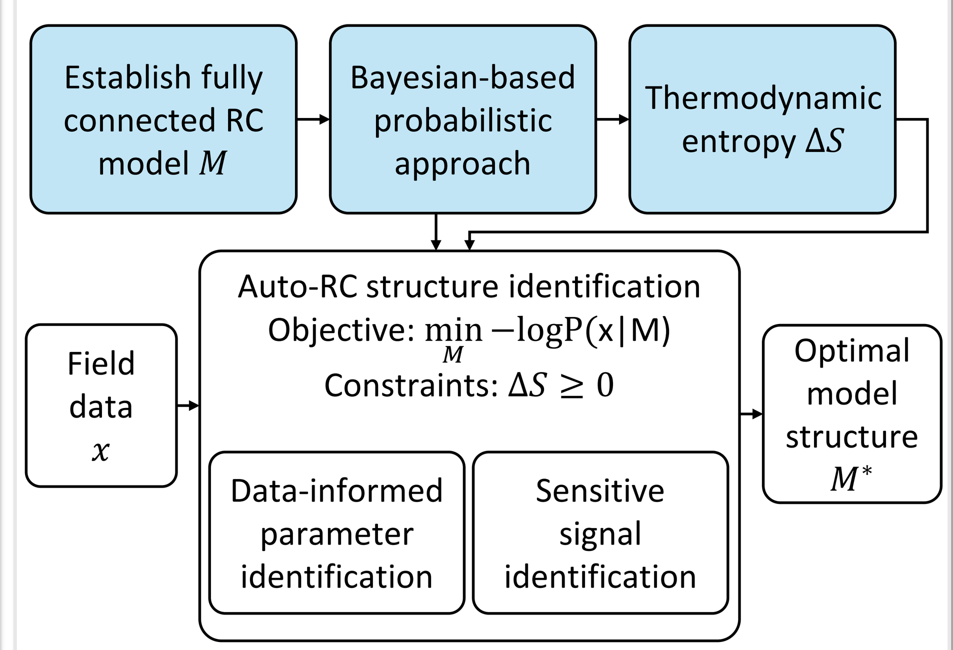
- Gradient-based meta-RL requires a differentiable reward function
- JAX-based implementation of building model
- Automatic differentiation enables Bayesian updates



Field Study

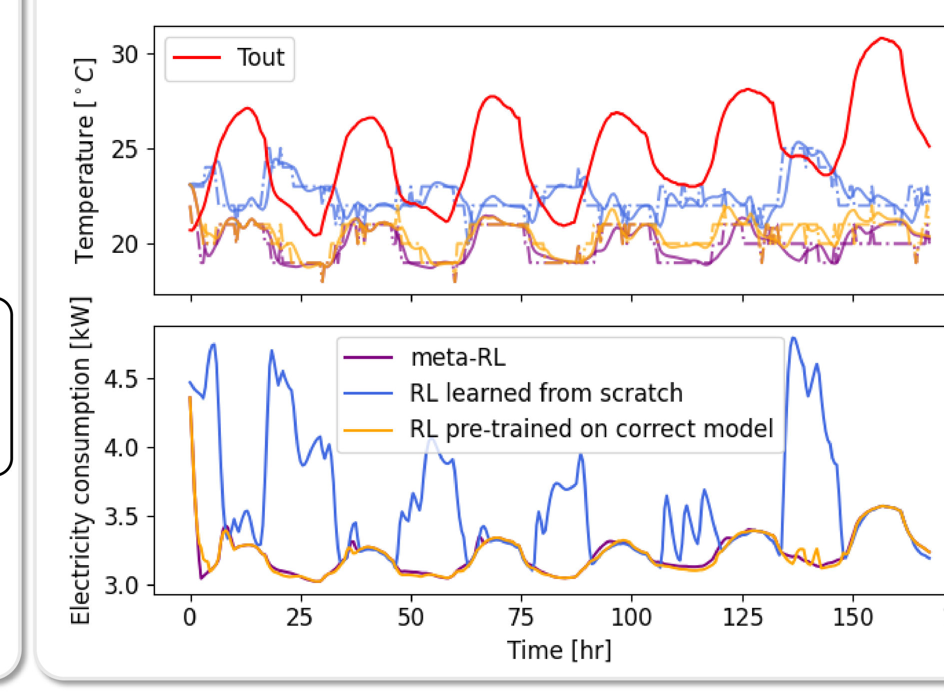
Model Update

- Model structure selection via field data



Simulation results

- Meta-RL outperforms RL learned from scratch and performs close to RL pretrained on correct model



Future Goal

Field implementation of autonomous control

- Deploy and validate meta-RL on a real building
- Verification of Bayesian update using synthetic building data
- Validation of Bayesian updates in a real building
- Couple Bayesian updates of the model universe with meta-RL (referred to as BUMRL)
- Verify BUMRL using synthetic building data
- Deploy and validate BUMRL

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