

Comparing model predictive control and reinforcement learning for the optimal operation of building-PV-battery systems

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IAQVEC 2023

Indoor Air Quality Ventilation
and Energy Conservation





- Microgrids: energy consumers (buildings), distributed energy generation (renewable), energy storage
 - Potential of carbon reduction, cost saving, etc.
 - Schedule-based rules: unsatisfactory performance (**uncertain boundary conditions**)
 - Optimized energy management needed
- Control strategies
 - Model predictive control (MPC): dependent on model reliability, unscalable
 - Reinforcement learning (RL): long period of training, uninterpretable
 - **Pros and cons are theoretical and general**

Phase I (Warm Up Round): Completed




Phase II: Completed

Phase III: Completed

NeurIPS 2022

CityLearn Challenge

Using AI For Building's Energy Management

 15,000 USD Cash Prizes + 3 Travel Grants Co-authorship in Competition Solutions PaperBy Intelligent Environments Lab &  Alcrowd 35.3k 679 111 1806 33

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**Overview**

Leaderboard

Notebooks




Discussion

Insights

Resources

Rules

My Team

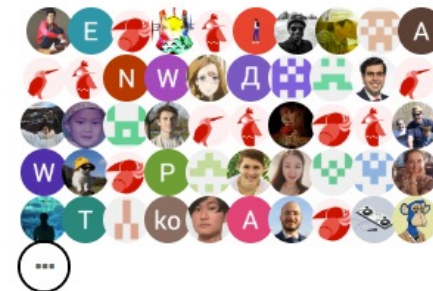
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Introduction

Buildings are responsible for 30% of greenhouse gas emissions. At the same time, **buildings are taking a more active role in the power system** by providing benefits to the electrical grid. As such, buildings are an unexplored opportunity to address climate change. Energy storage devices such as home **batteries** can reduce peak loads of the grid by shifting the energy use of buildings to different times.

Solar photovoltaic generation can reduce the overall demand to the grid while also

PARTICIPANTS



NOTEBOOKS

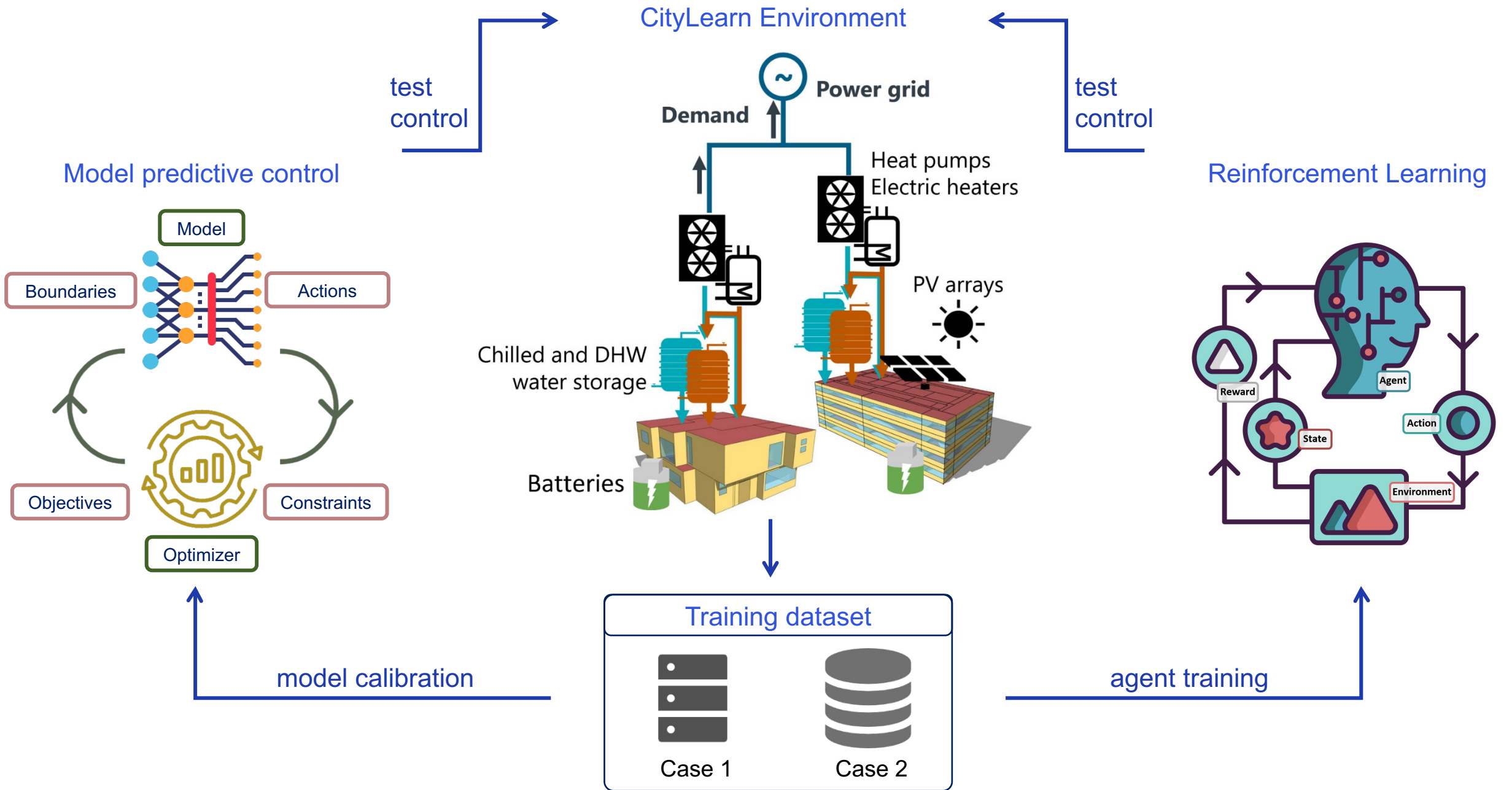
See all

9

**Going below 1.0 score with stablebaseline3**

4

By adrian_ferby 7 months



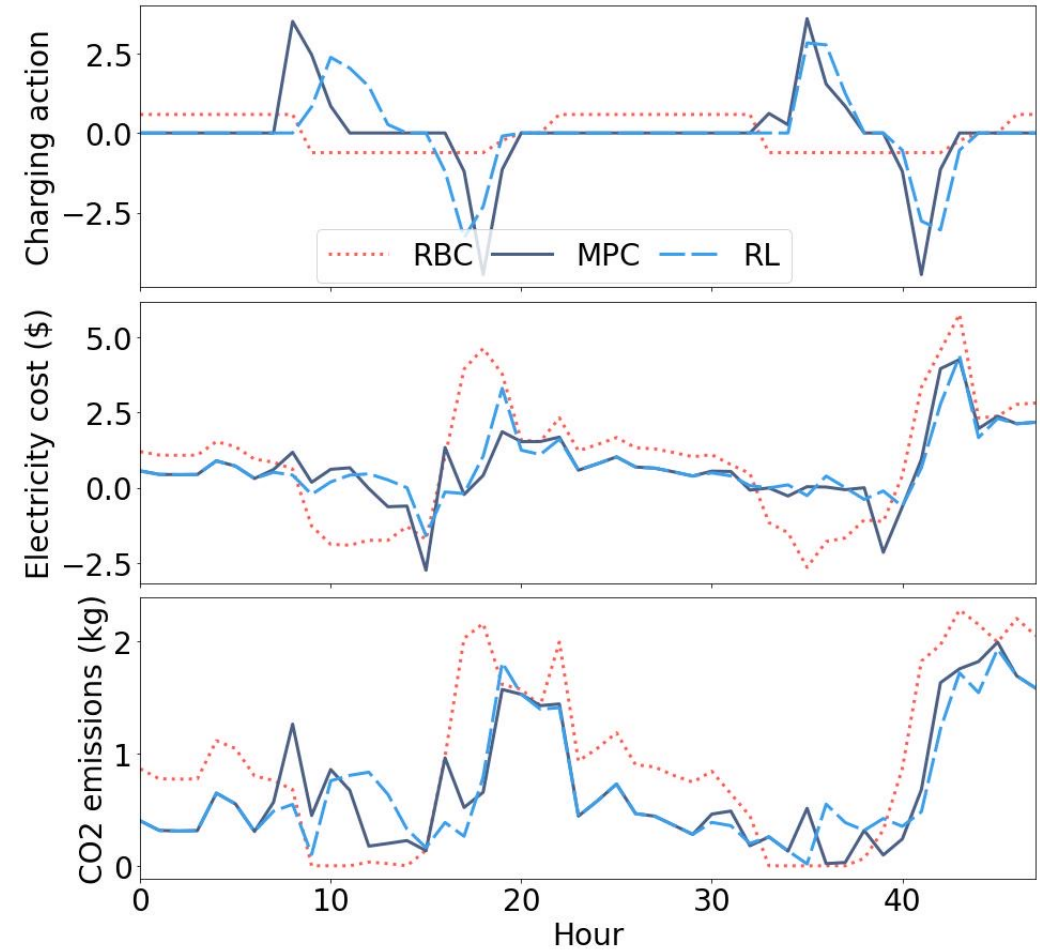
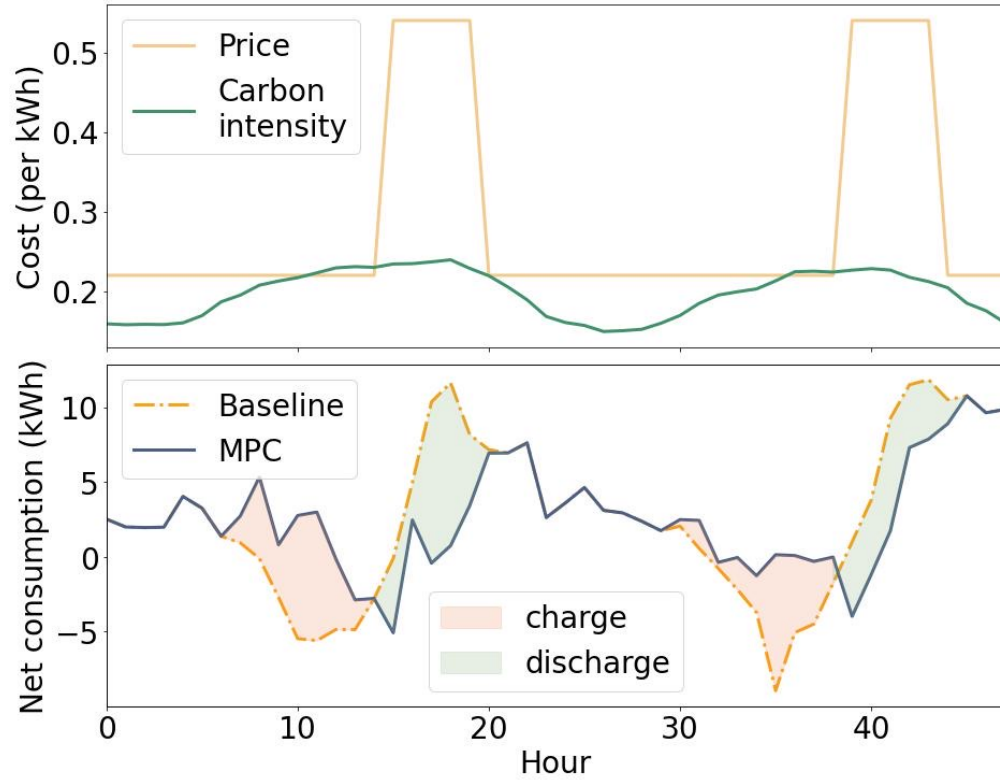


	Case 1 (CA)	Case 2 (IL)
<i>Buildings</i>	5 different single-family houses	9 with different types
<i>Batteries</i>	All buildings have, different capacity and nominal power	
<i>PV</i>	All have	Only 4 have
<i>Training data</i>	1 year	1 year
<i>Testing condition</i>	Training data	Unseen 3 years

Charging decision in the coming 12 hours to minimize **energy cost** and **carbon emissions**

- MPC: energy models based on metadata, LSTM forecast, Powell's method for optimization
- RL: MARLISA, soft actor-critic (SAC) agents

Case I

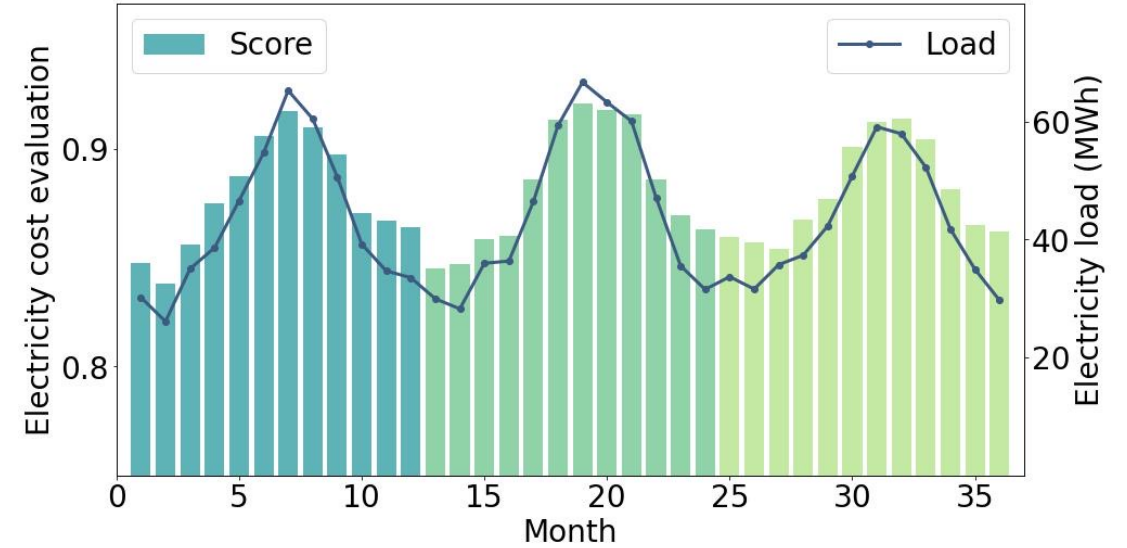
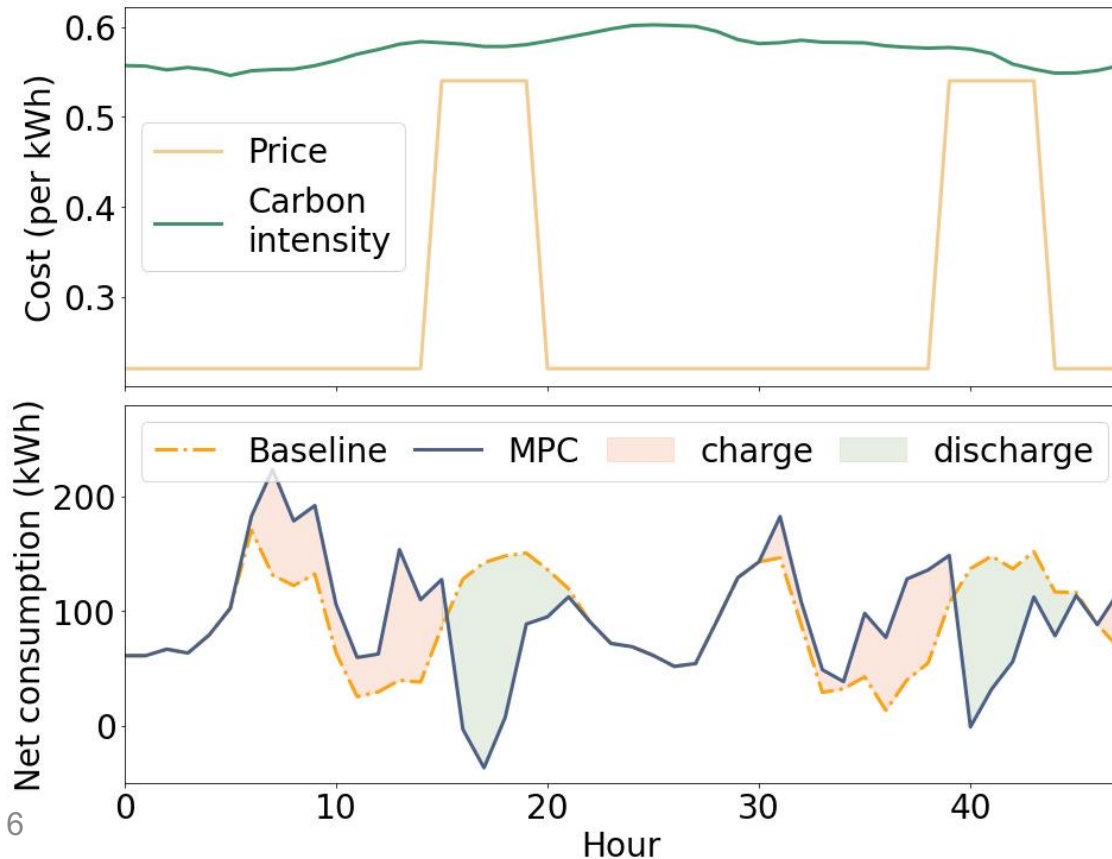


Metrics	RBC	MPC	RL
Electricity cost	1.033	0.652	0.678
CO ₂ emissions	1.156	0.842	0.834

Case II - MPC



- › Adjust objective weighting based on training data
- › Update energy models based on metadata
- › LSTM models for solar and building loads



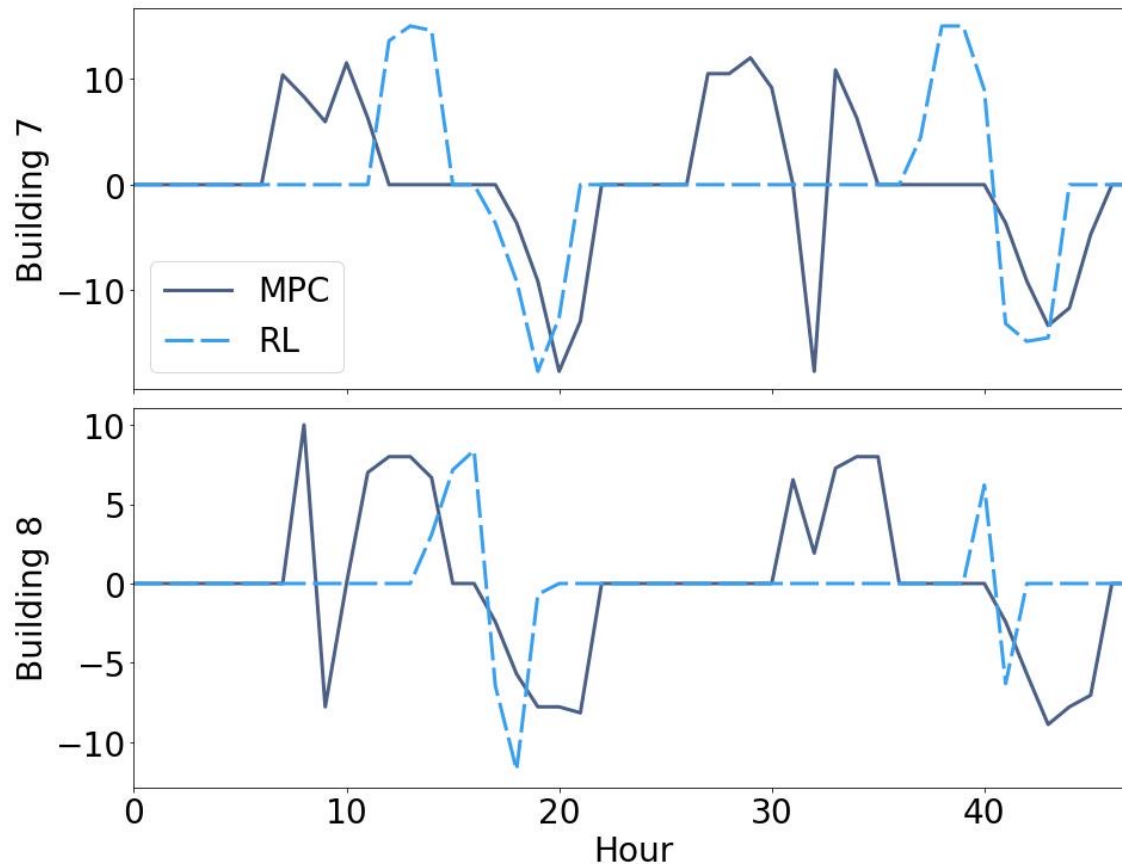
- Evaluation: 0.887 for electricity cost and 1.009 for CO₂ emissions (irregular short-term carbon intensity)
- Absolute saving decided by the PV/battery capacities, larger load (denominator) yielded smaller percentage

Case II - RL



- › Adjust reward weighting based on training data
- › Hyperparameter tuning by trial-and-error

	Runtime (Hr)		Performance	
	Y1	Y2-4	Y1	Y2-4
MPC	2	7	0.855	0.887
RL	15	1	0.933	0.949



- Longer training but faster decision
- Sub-optimal control performance

- Batteries not fully charged given smaller state values

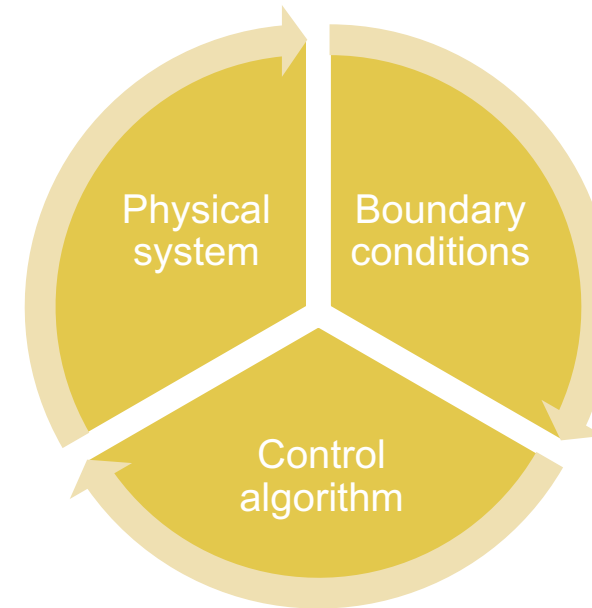
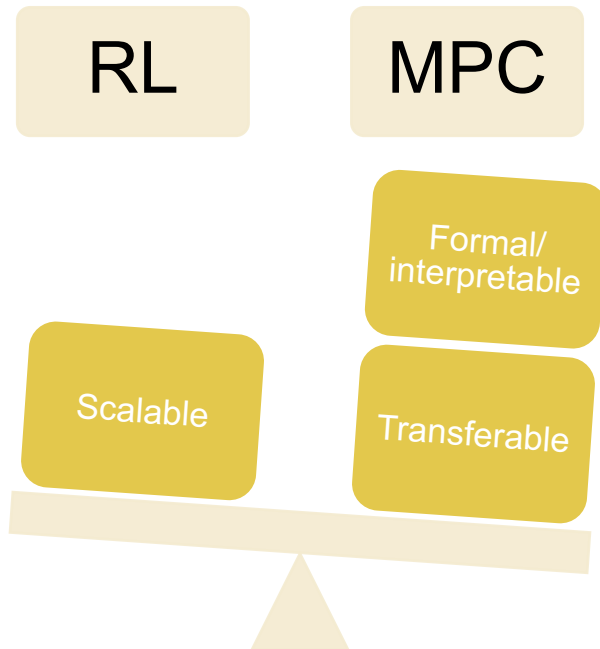
- Further engineering effort required to exploit the potential



Different factors jointly affect the control performance



The need of standardized benchmark



- Lower data and modeling requirements for both in grid-scale applications
- MPC more suitable in most practical settings



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