Massachusetts Institute of Technology

Decision-oriented Digital Twins for Intelligent and Sustainable Urban Energy Systems

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26/3/6

At the intersection of architectural engineering and computational science

2016, BS in Energy and Environment Systems Engineering, Zhejiang University

2017, MS in Civil Engineering, Carnegie Mellon University

2022, PhD in the Built Environment, National University of Singapore

2022-24, Research fellow, National University of Singapore

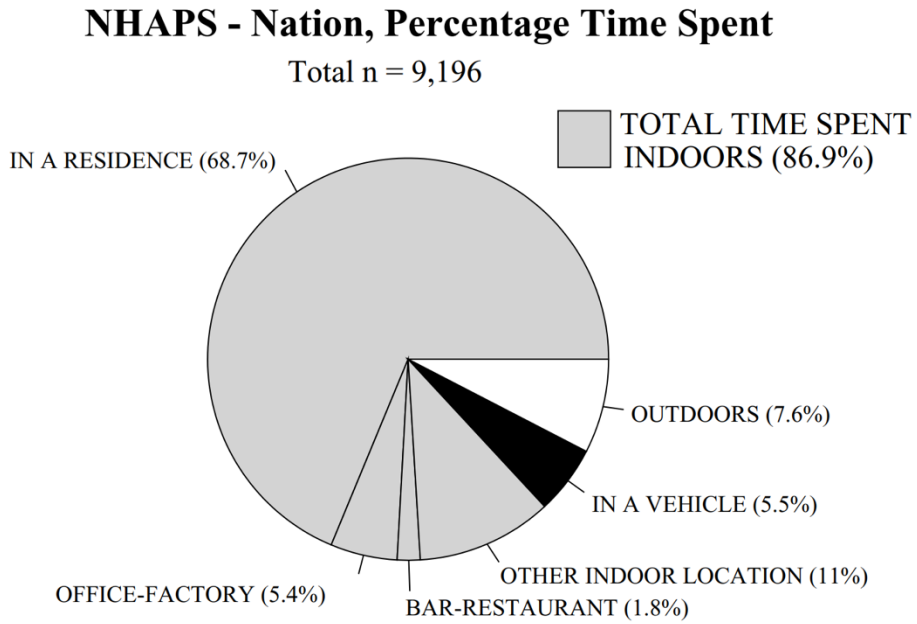
2024-, Postdoctoral Associate in Building Technology, Massachusetts Institute of Technology

Research interest

Building energy modeling, optimal control, digital twin, carbon reduction, energy flexibility, scientific machine learning, optimization

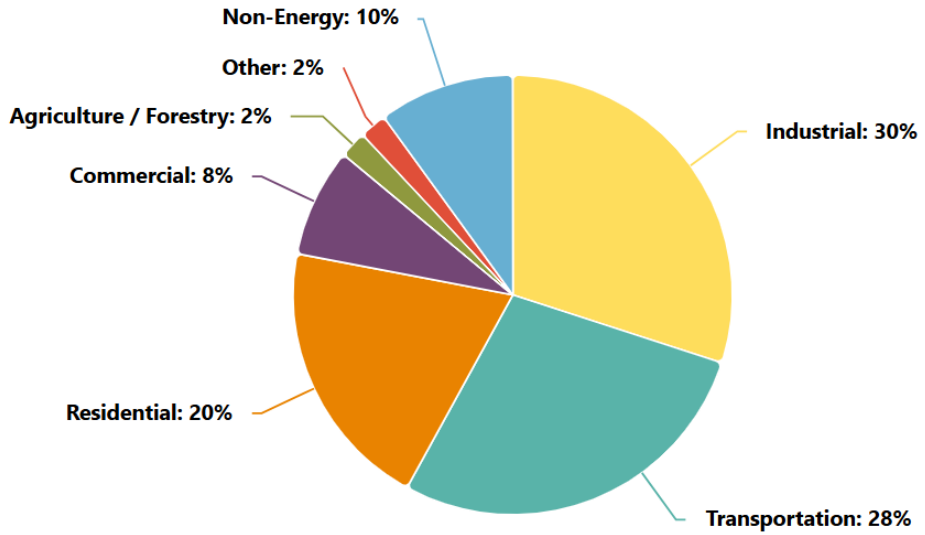
Data-centric Scientific Machine Learning for Intelligent and Sustainable Urban Energy Systems

People spend ~90% of daily lives indoor

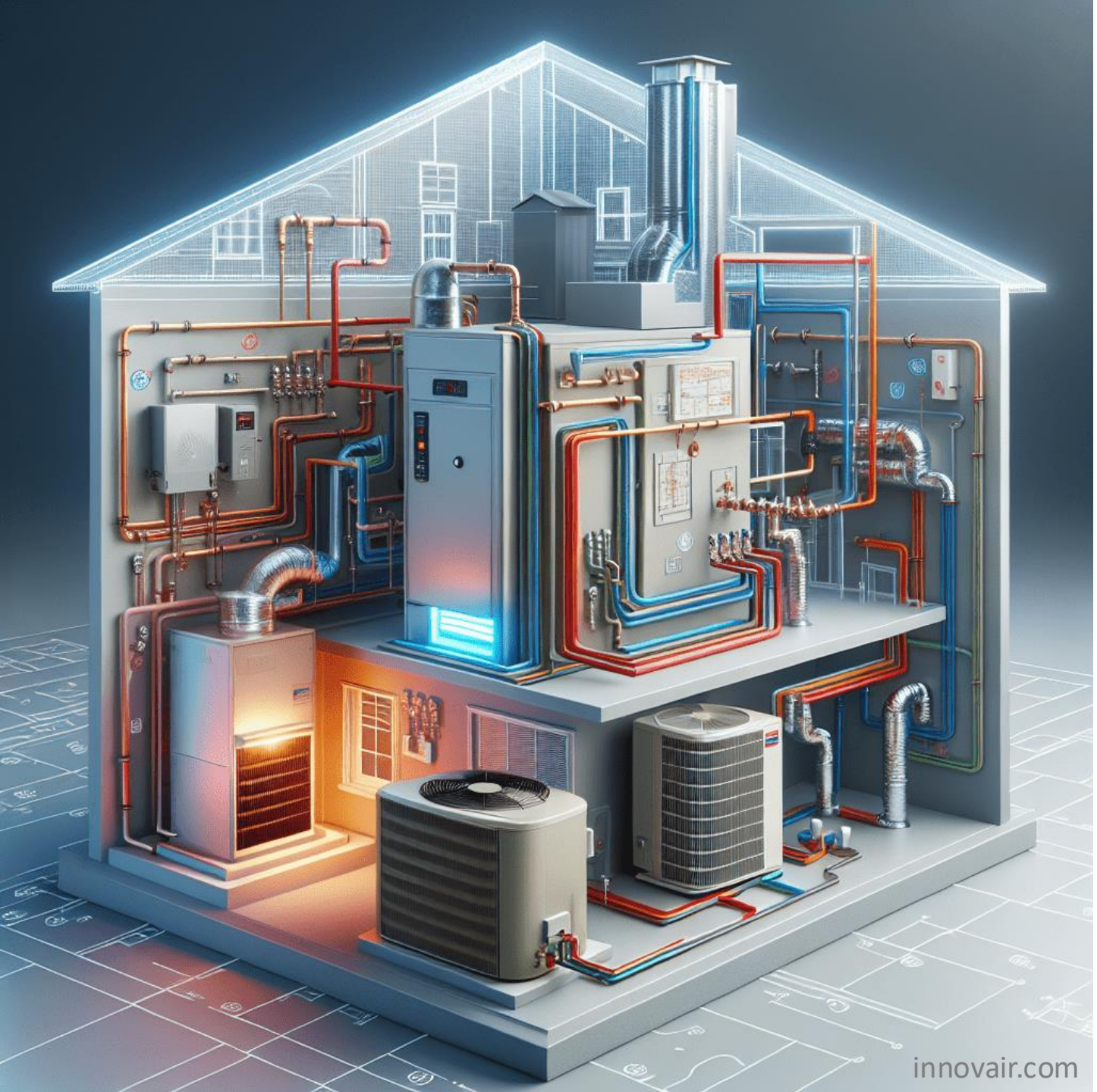


Klepeis, N. E. *et al. J. Expo. Sci. Environ. Epidemiol.* **11**, 231–252 (2001).

Buildings account for ~30% of global energy end uses



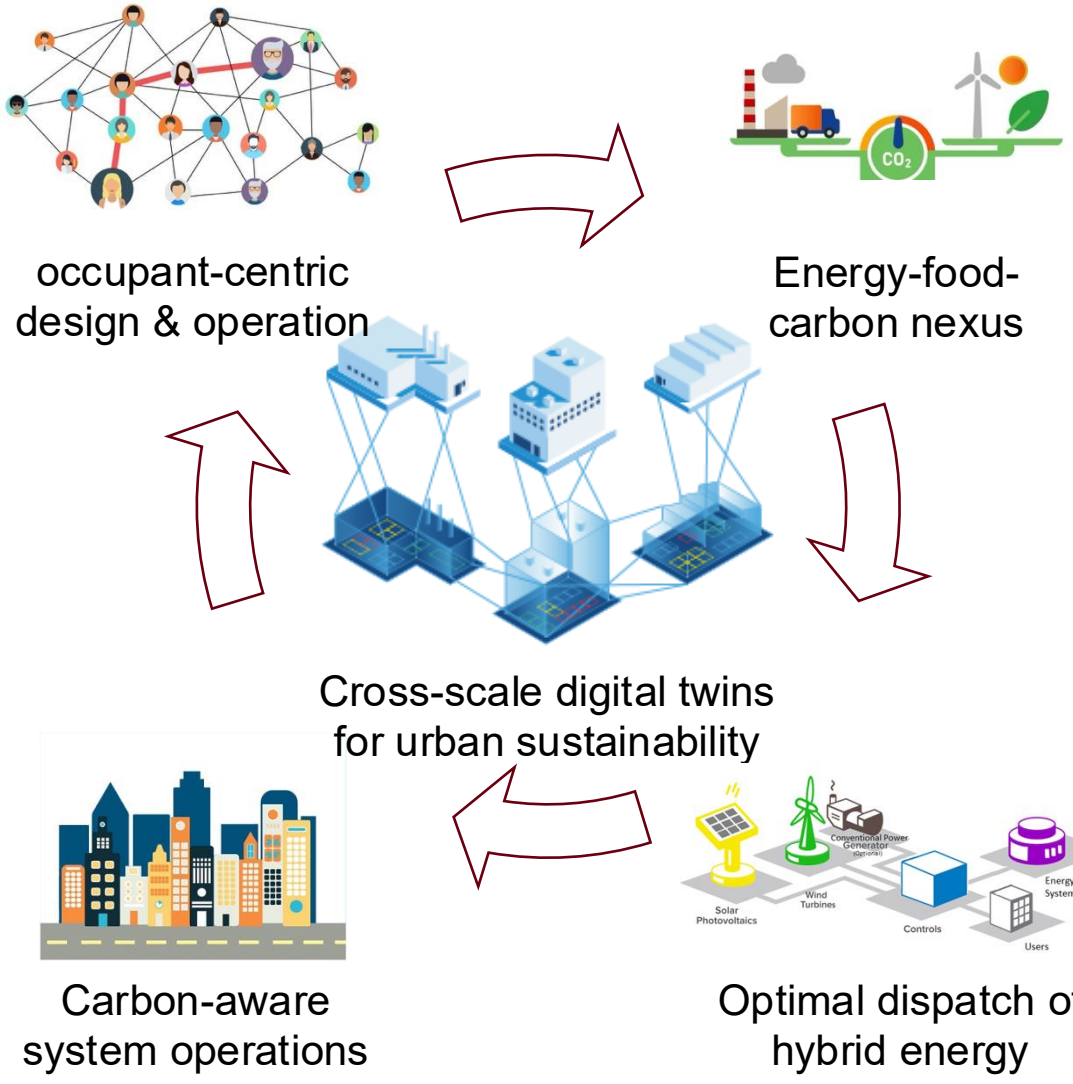
IEA (2023).



Most life-cycle energy use occurs during operations, consumed by building service systems: HVAC, lighting, and equipment

Over 40% energy saving potential in intelligent and efficient building operations[1]

Ding, C. *et al. Nat. Commun.* **15**, 5916 (2024).



Centered around building operations

- Energy-efficient supervisory control
- Grid-interactive buildings for energy transition

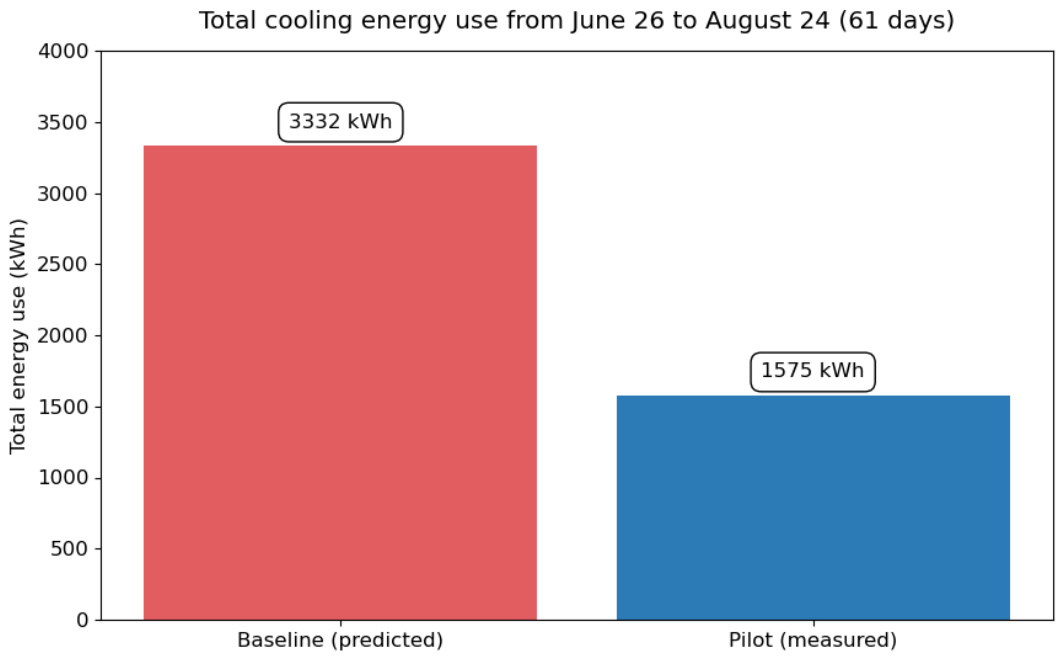
Bridging operations and design

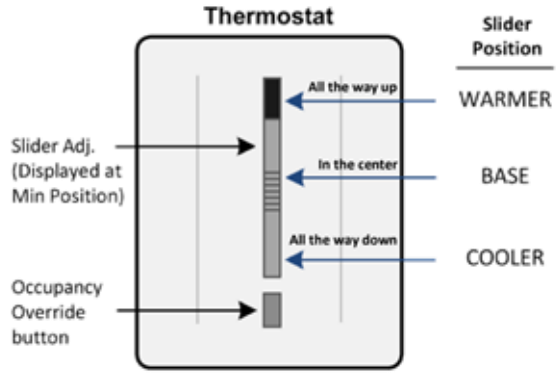
- Track and minimize performance gap
- Operation-informed design decisions

What's the easiest way to save energy?

Avoid unnecessary heating and cooling

Smart thermostat at your home

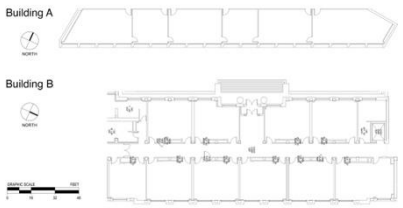




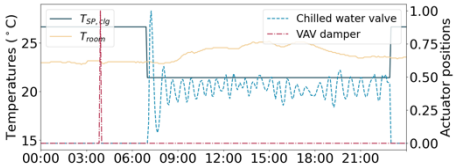
Legacy thermostat at MIT offices
learnable occupant behavior -> over 50% savings

Avoiding unnecessary heating, cooling, and ventilation

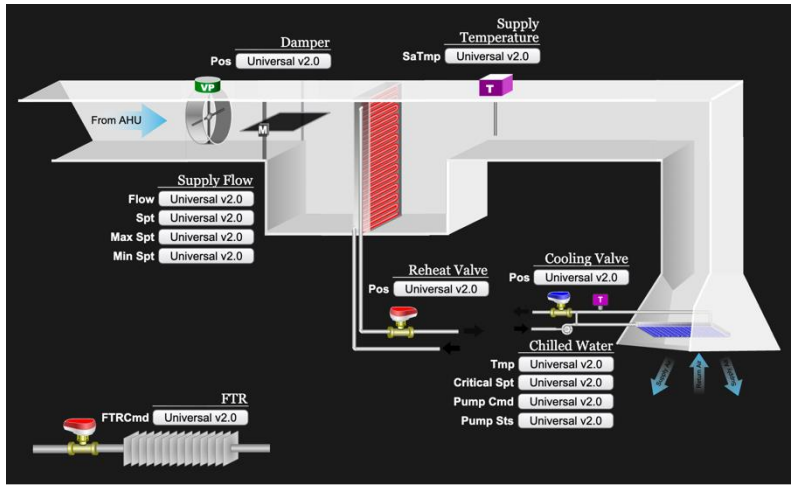
Class schedules



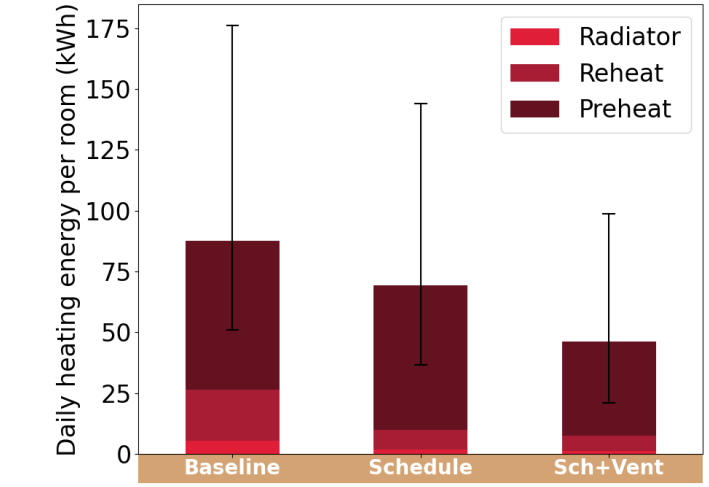
Drawings



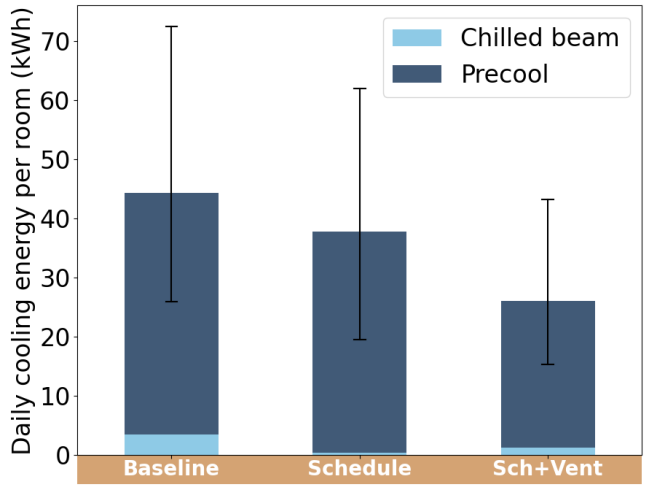
Historical data



Building management system



	Baseline	Schedule	Sch+Vent
Total kWh	87.66	69.34	46.05
Saved kWh	/	18.32	41.61
Saved ratio	/	**0.21**	**0.47**



	Baseline	Schedule	Sch+Vent
Total kWh	44.27	37.75	25.98
Saved kWh	/	6.52	18.29
Saved ratio	/	**0.15**	**0.41**

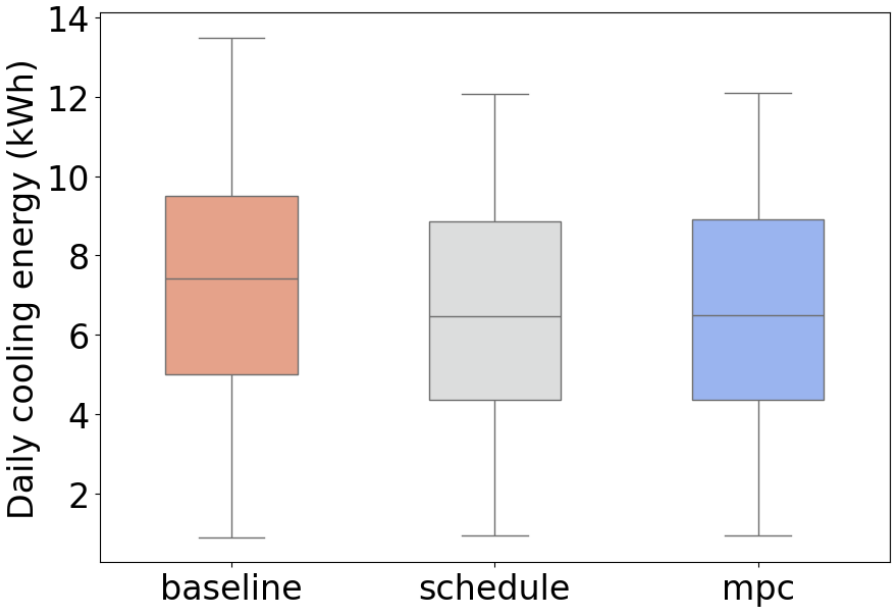
Towards cost-effective implementation

Comparative simulation over a summer (simulation testbed)

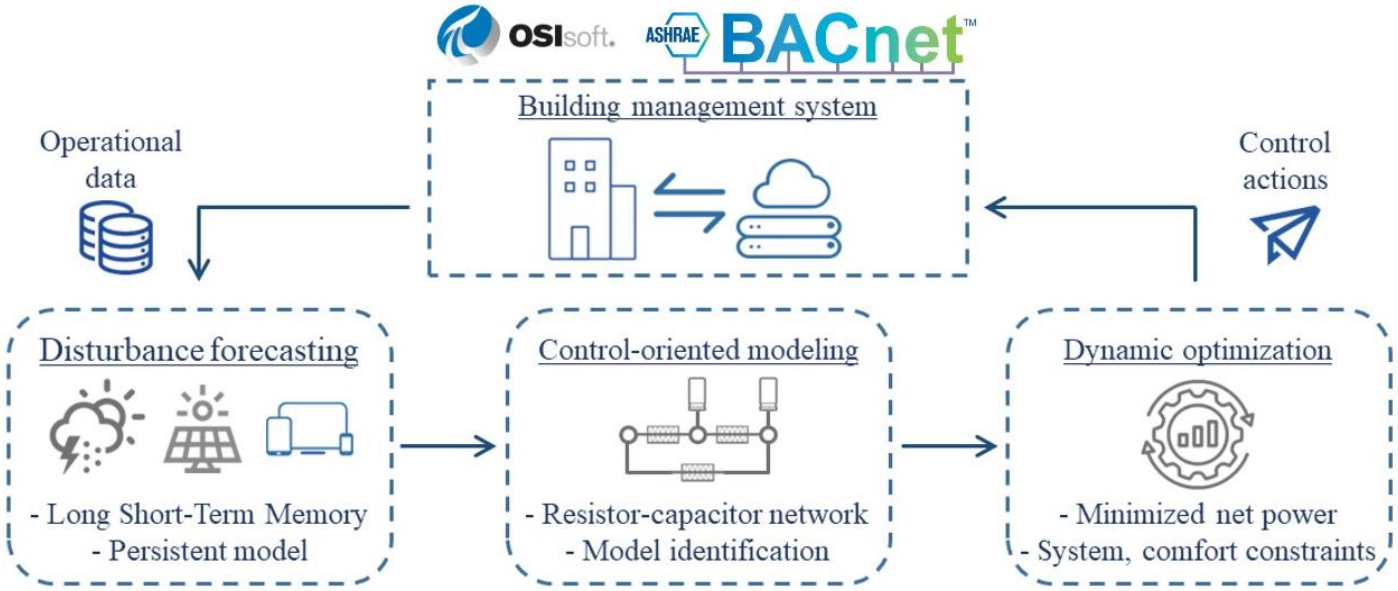
- Baseline: static day-to-day schedule
- Schedule: mode switching based on actual schedules
- MPC: minimize energy with the same comfort constraint

Similar energy savings of 11.2% (schedule) and 10.8% (MPC)

- Given the same information, only minor differences in control actions
- Much lower computational and implementation costs



In addition to the low-hanging fruits



Predictive control to resist internal/external disturbances

Better thermal comfort with over 10% additional savings

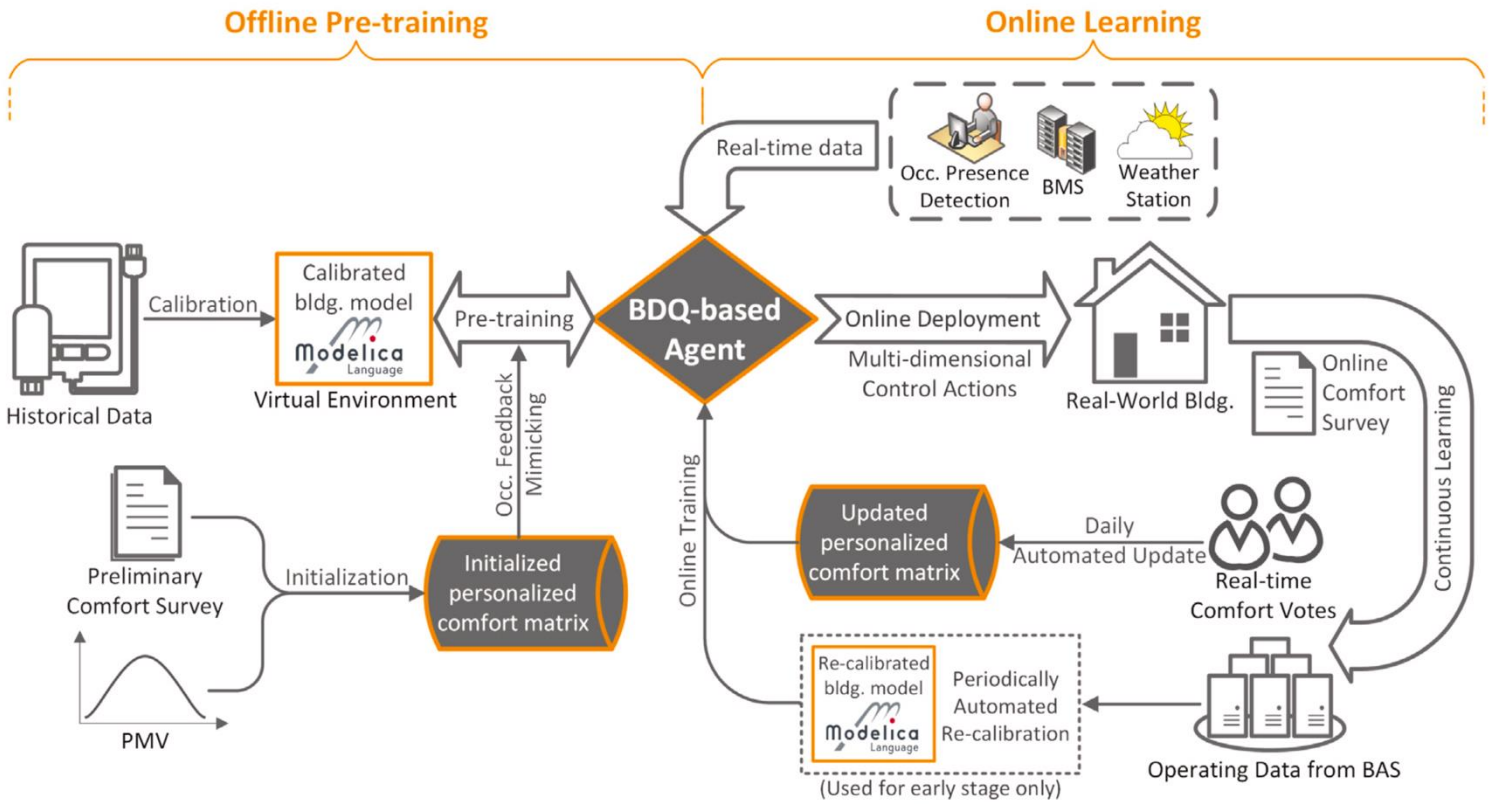
Zhan, S. *et al. Appl. Energy* **323**, 119580 (2022).

Accommodate personal preferences through RL

Coordinated multi-agent RL

10% better individual thermal sensation

14% cooling energy reduction



Lei, Y. *et al. Appl. Energy* **324**, 114920 (2022).

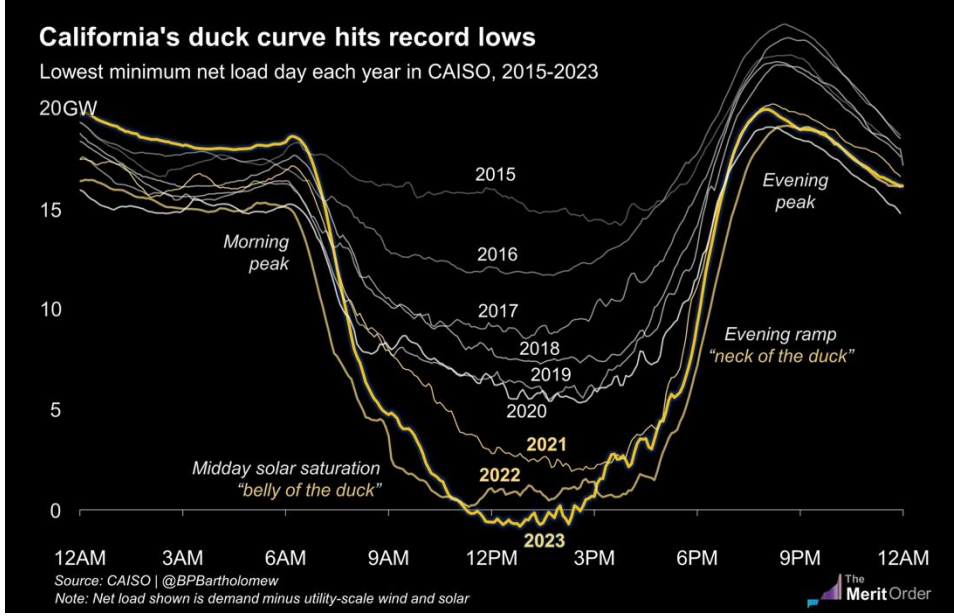
Towards a zero-carbon future

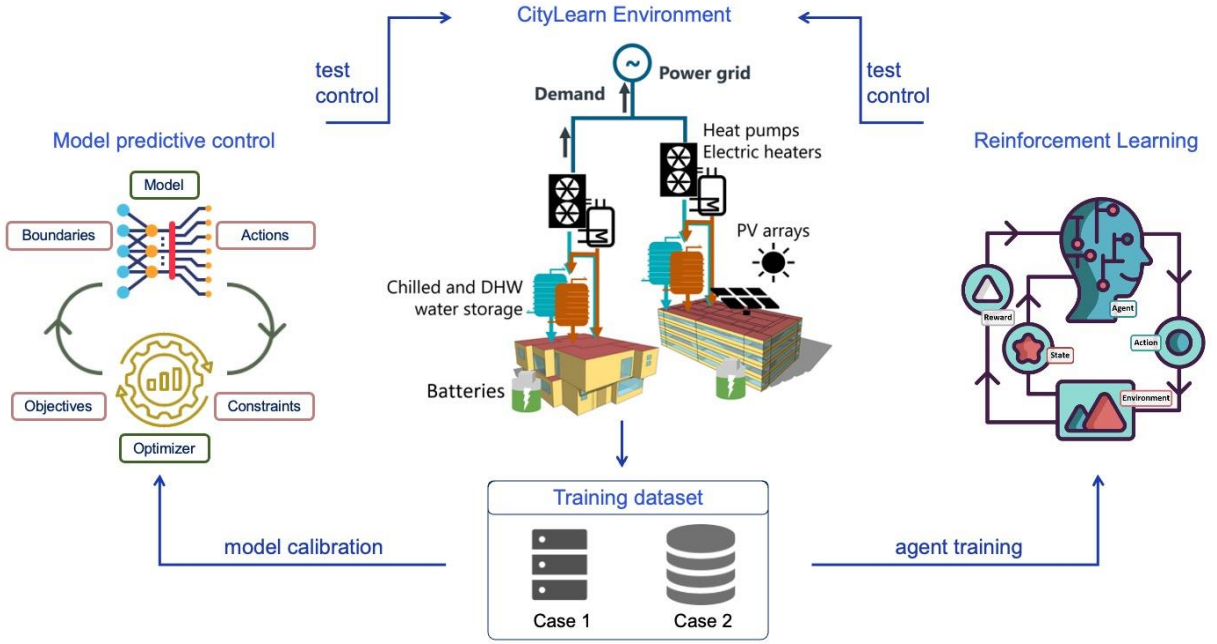
Increasing renewable integration

Demand/generation forecasting

Multi-system coordination

10-35% reduction in energy and carbon (CapEx as well)





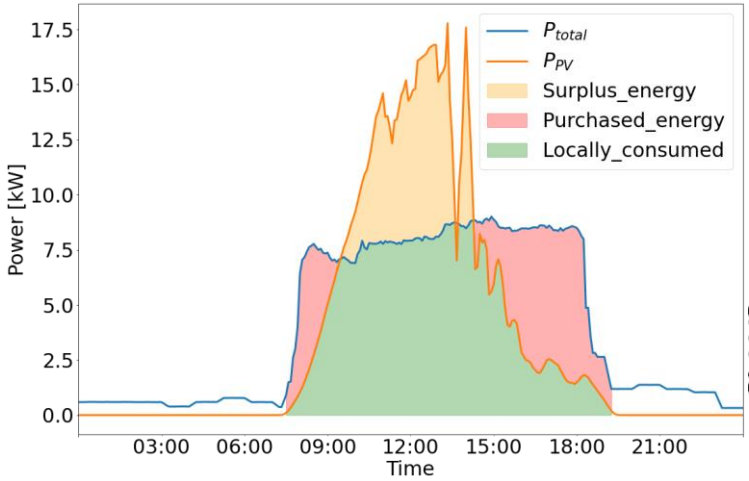
Zhan, S. *et al. IAQVEC.* (2023).

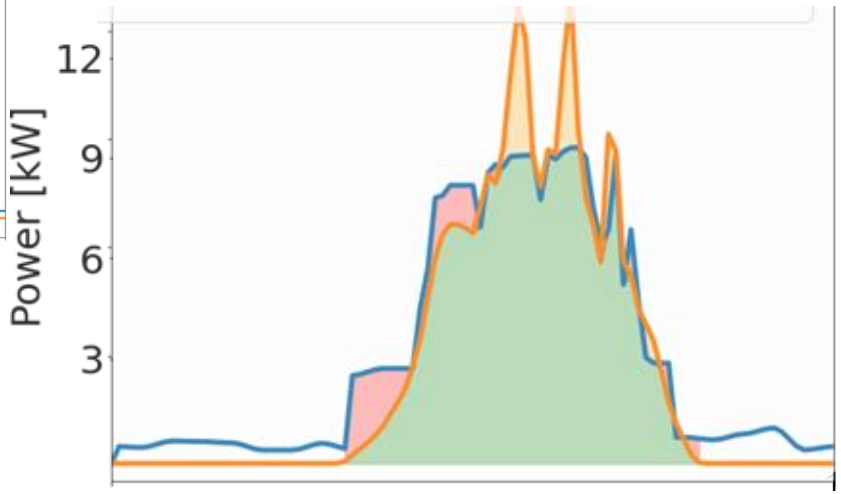
Net zero energy buildings

Buildings with rooftop PV

MPC to provide energy flexibility

20% more self-consumption
10% more self-sufficiency

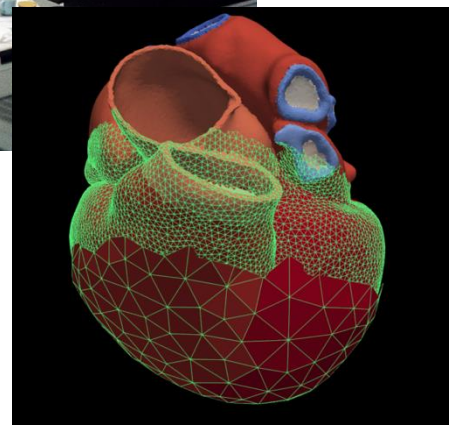


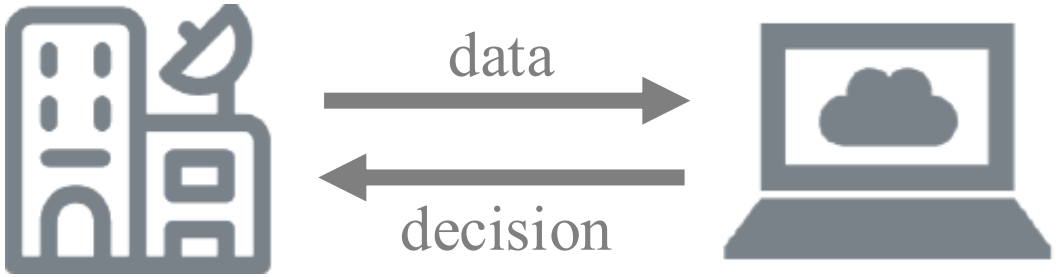


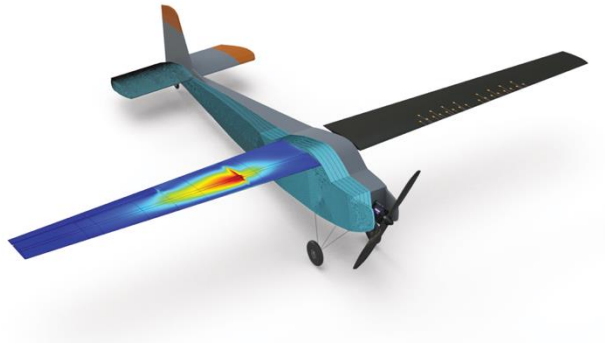
Zhan, S. *et al. Energy Build.* **278**, 112606 (2023).

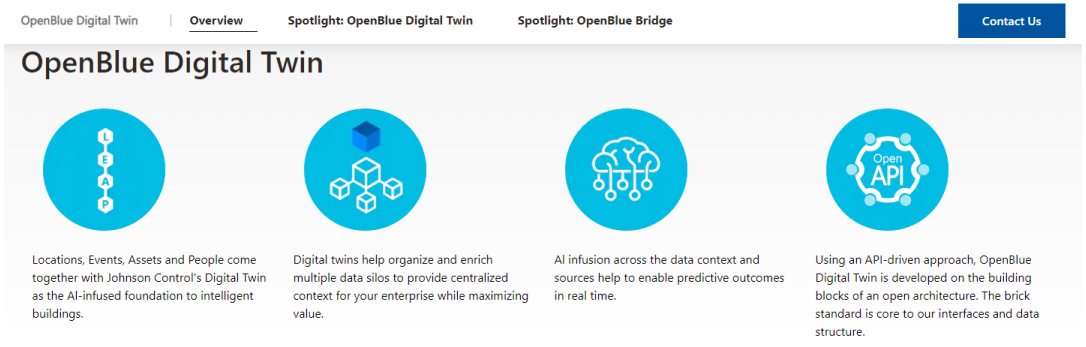
Data-centric Scientific Machine Learning for Intelligent and Sustainable Urban Energy Systems

Digital twins - Computational models that replicate the behaviour of real-world systems, conducting virtual experiments in unseen scenarios and supporting decision-making



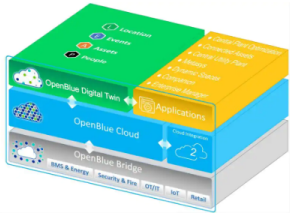






Existing DT solutions are decision-lacking

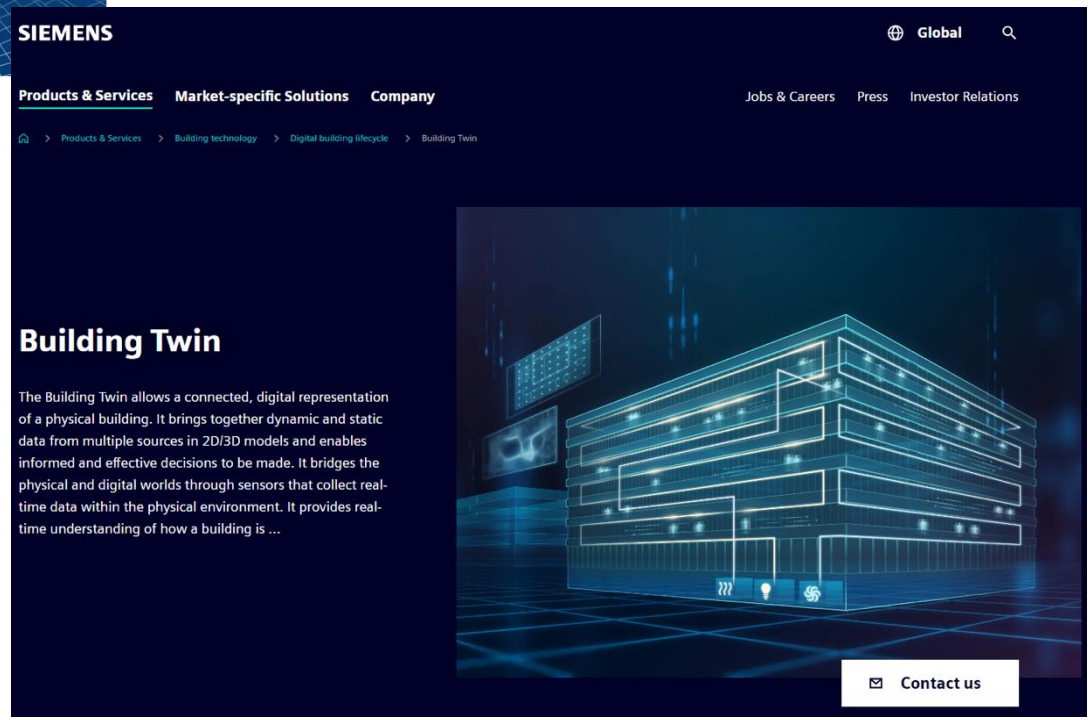
- Data aggregation, 3D visualization, KPI
- Accurate predictions, but without action



3D BIM

Digital Twin Visualization

Digital Twinning is integrated into the 3D BIM for contextual visualization, enabling an immersive analysis of your locations, events, assets and people in the context of the physical building.

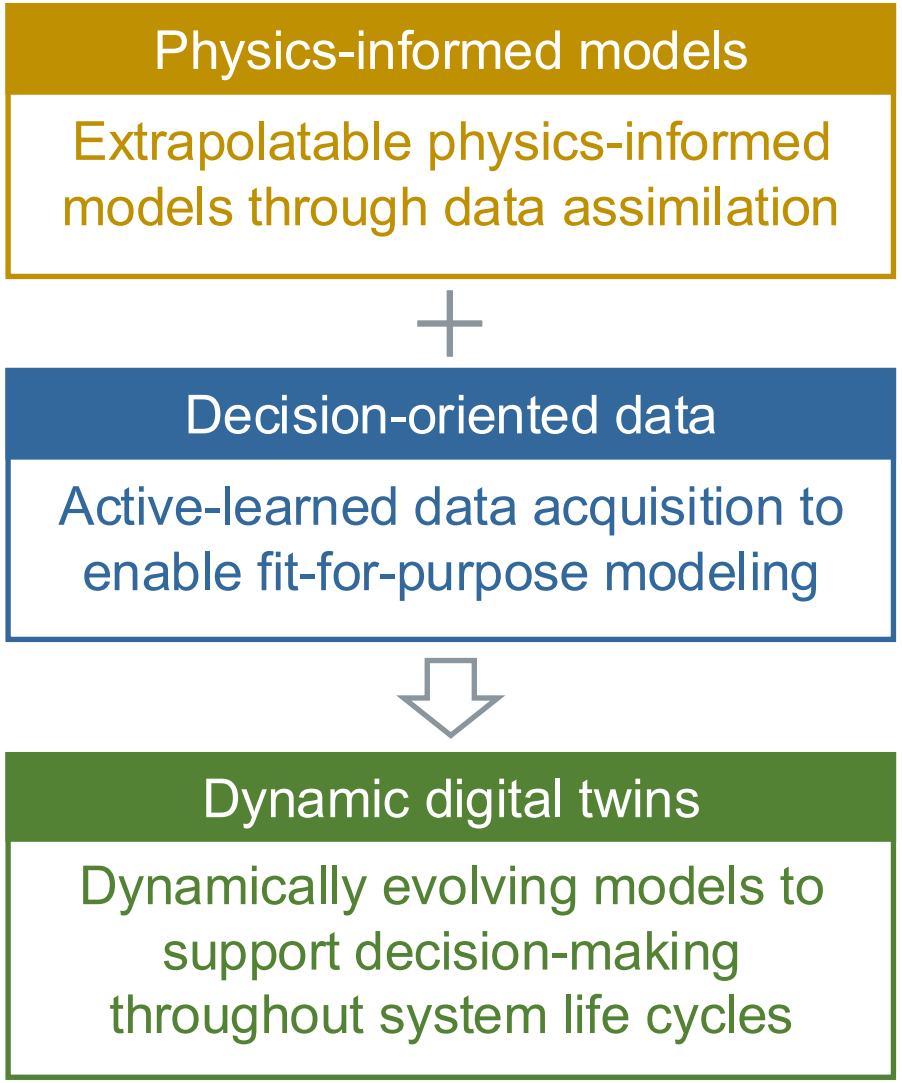


Heterogeneous and data-poor buildings

- Lack of scalable and extrapolatable model
- Absence of key information

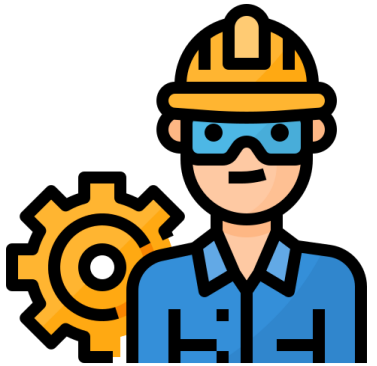
Combine domain knowledge and operational data to enable extrapolatable models

- Robust decision-making in new scenarios
- Data-efficient active learning



Thermal response model for optimal control

V.S.



What research papers highlight

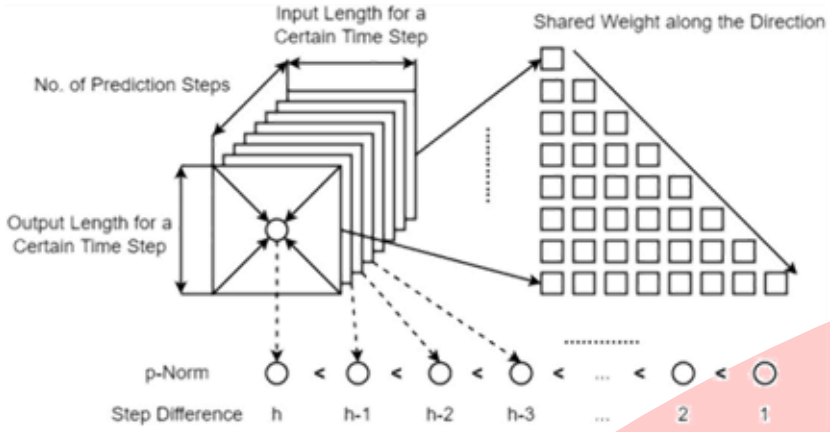
- X% higher predictive accuracy
- Y kWh energy saving based on simulation/experiments
- Z% reduction in data requirements/ computational costs

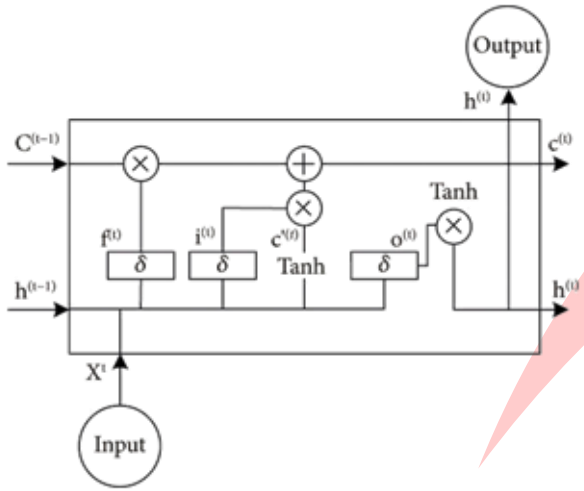
What facility managers care about

- What's the payback period?
- Is it easy to set up, with few additional requests?
- **Does it offer robust control under all conditions?**

Royapoor, M. *et al. Energy Build.* **158**, 453–465 (2018).

The role of physics in model development





LSTM

PINN

$$\mathcal{L}_{PINN} = \mathcal{L}_{MSE} + \lambda \mathcal{L}_{grad},$$

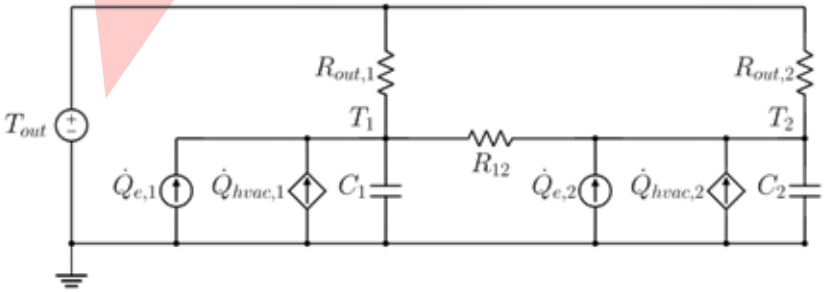
$$\mathcal{L}_{grad} = \frac{1}{l}\sum_{k=0}^{l-1}\left[\frac{1}{m}\sum_{z=1}^{m} g_k^z\right],$$

$$g_k^z = \sum_{y=1}^{m} ReLU(-\frac{\partial \hat{T}_l^z}{\partial u_k^y}) + ReLU(-\frac{\partial \hat{T}_l^z}{\partial T_k^{out}})$$

PCNN

RC

Increasing levels of physics

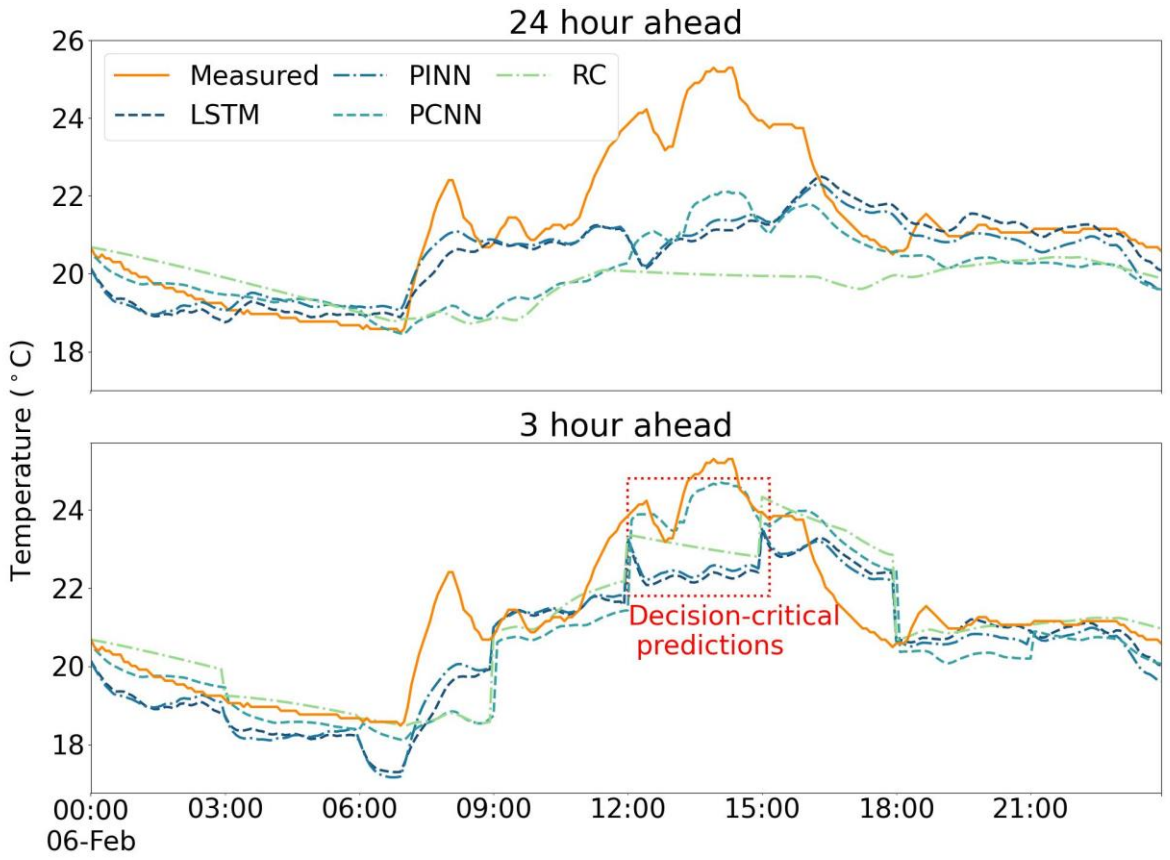


RMSE (°C)

	Traditional test		Extrapolation test	
	std	*avg*	*std*	*avg*
LSTM	0.21	0.89	0.44	1.21
PINN	0.23	0.89	0.51	1.12
PCNN	0.22	0.88	0.27	0.87
RC	0.15	1.39	0.13	1.78

Proper level of physics constraints

- Balance fitting and extrapolation capability
- Physics-consistency more important than predictive accuracy

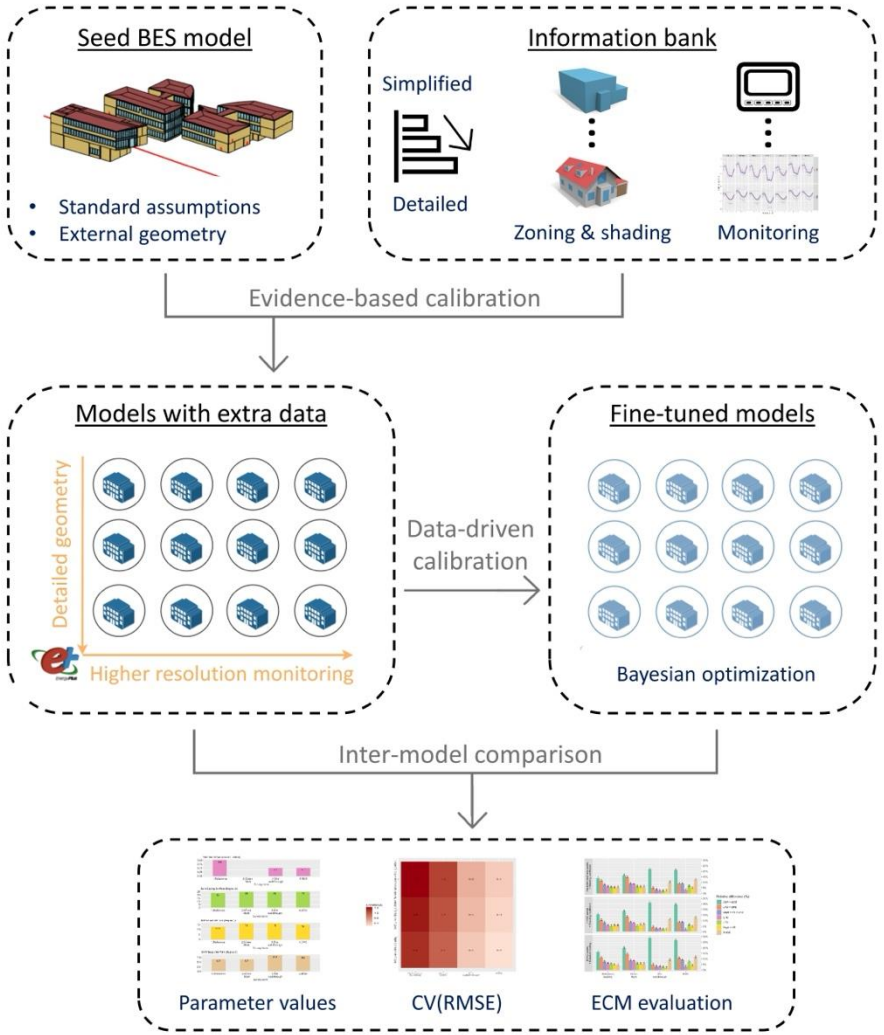


Zhan, S. *et al. Building Simulation 2025.*

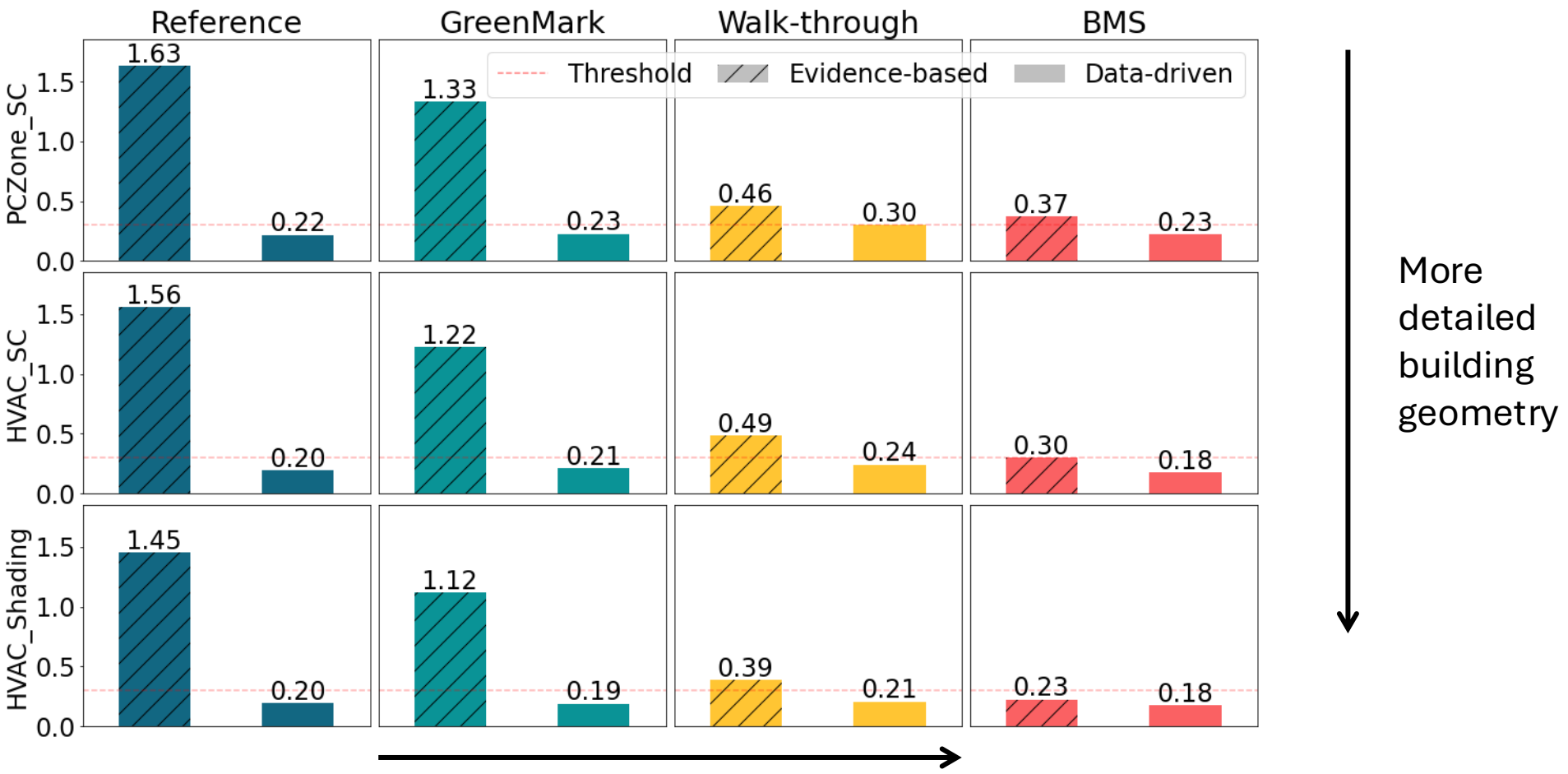
Energy model calibration to capture performance gap

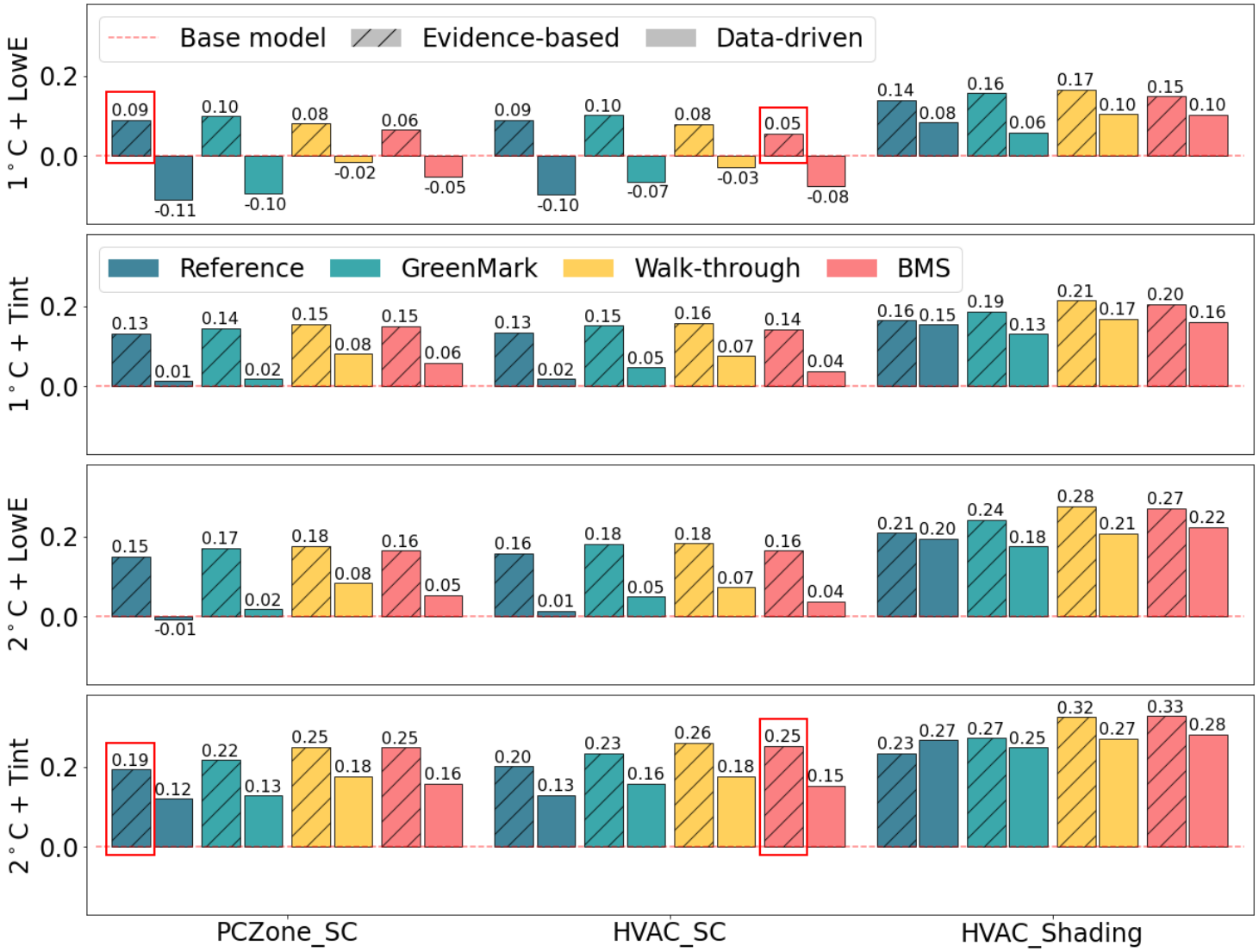
$$\boldsymbol{\theta}^* = arg\min_{\theta \in \Theta}(J(\hat{Y}, Y))$$

$$s.t. \quad \hat{Y} = \mathcal{M}(X, \boldsymbol{\theta})$$



All base models achieved satisfactory accuracy after optimization

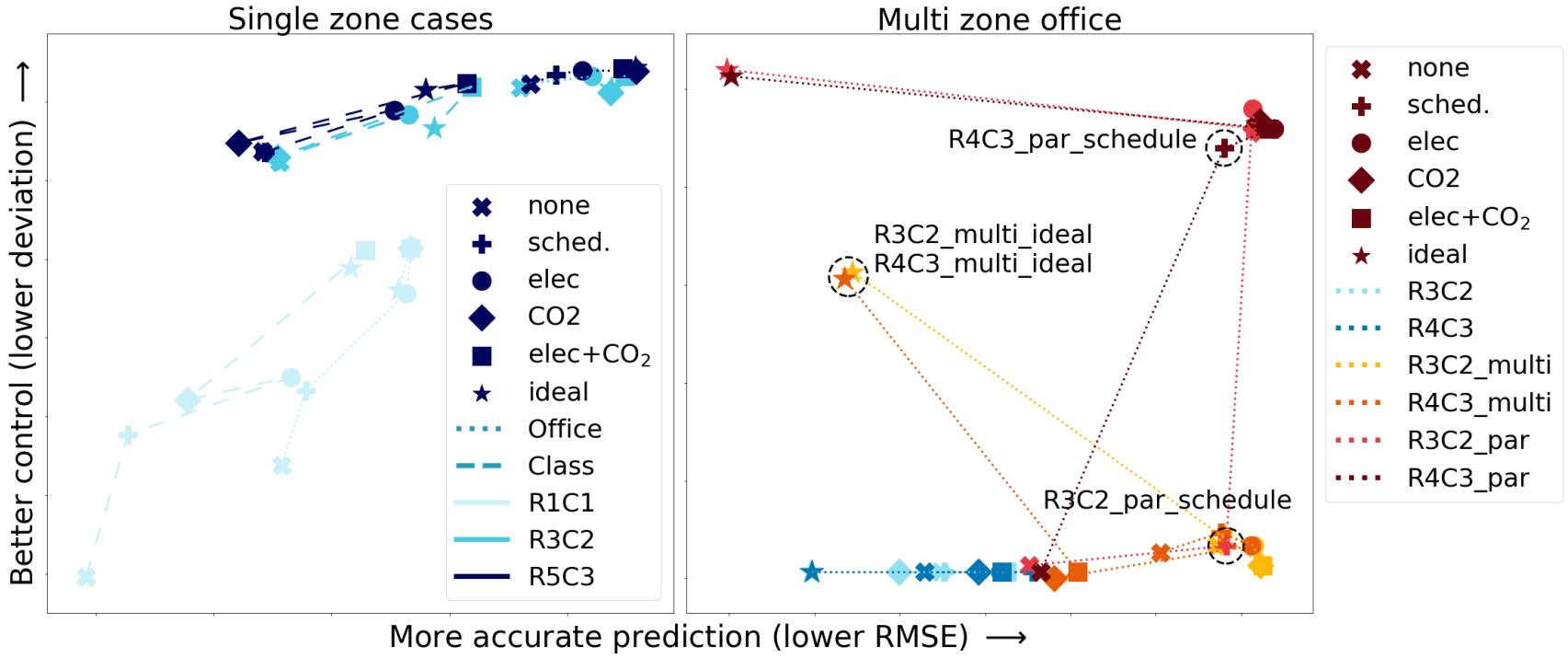




Models with similar accuracy could have distinct ECM evaluation

The key to informed decision-making is a good estimate of the relevant parameter

Zhan, S. *et al. Build. Simul. 18, 123–140 (2025).*



From chasing accuracy to decision-oriented digital twins

Data is like minerals, everywhere but few are useful. You need to know where to drill.

Zhan, S. *et al. Appl. Energy* **323**, 119580 (2022).

Thank you!

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