Massachusetts Institute of Technology

2026 CMU BPD

When simulation meets reality: model calibration ~~and~~ for downstream applications

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26/03/26

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

2024-26, Postdoctoral Associate in Building Technology, Massachusetts Institute of Technology

2026.7-, Assistant Professor, The University of Hong Kong

Research interest

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

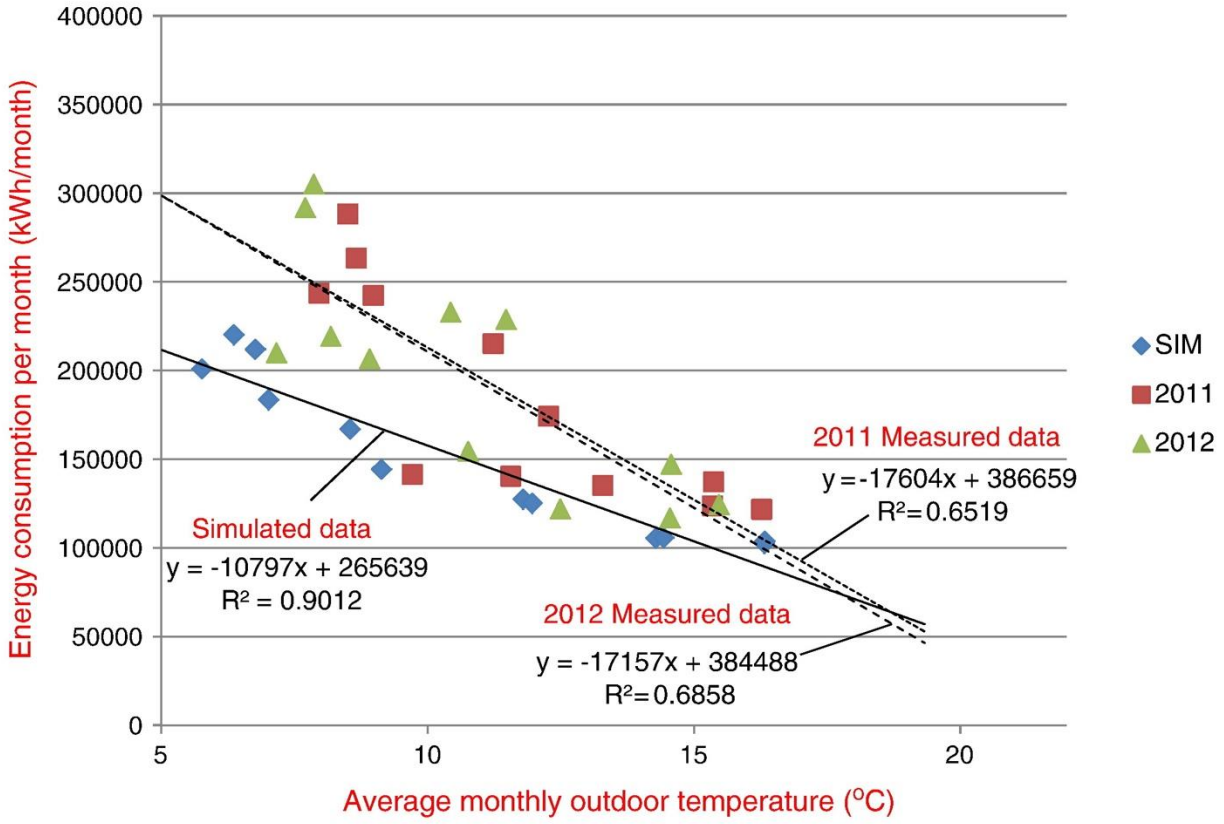
Building performance gap

Actual building performance deviate from prediction results

Design - simplified model, unrealistic assumptions

Construction - built quality quality, human-driven commissioning

Operation - untracked settings, human behavior, system aging



De Wilde, P. *Autom. Constr.* **41**, 40–49 (2014).

Calibration - matching model to reality

Drawings
Submittals
Energy bill
Operational data
…

Typical workflow of automated calibration

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

Ground truth of model output(s)

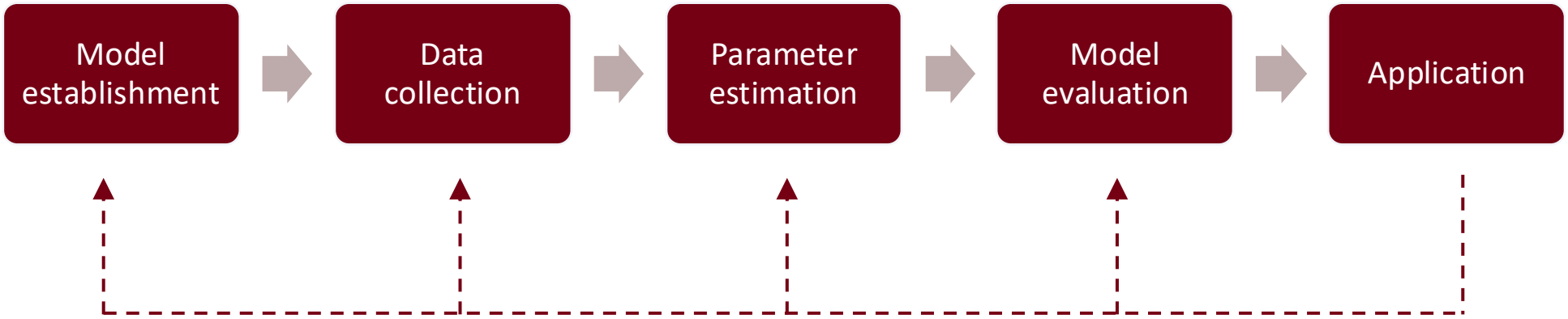
$$s.t. \quad y = \mathcal{M}(x, u, \theta)$$

Model outputs

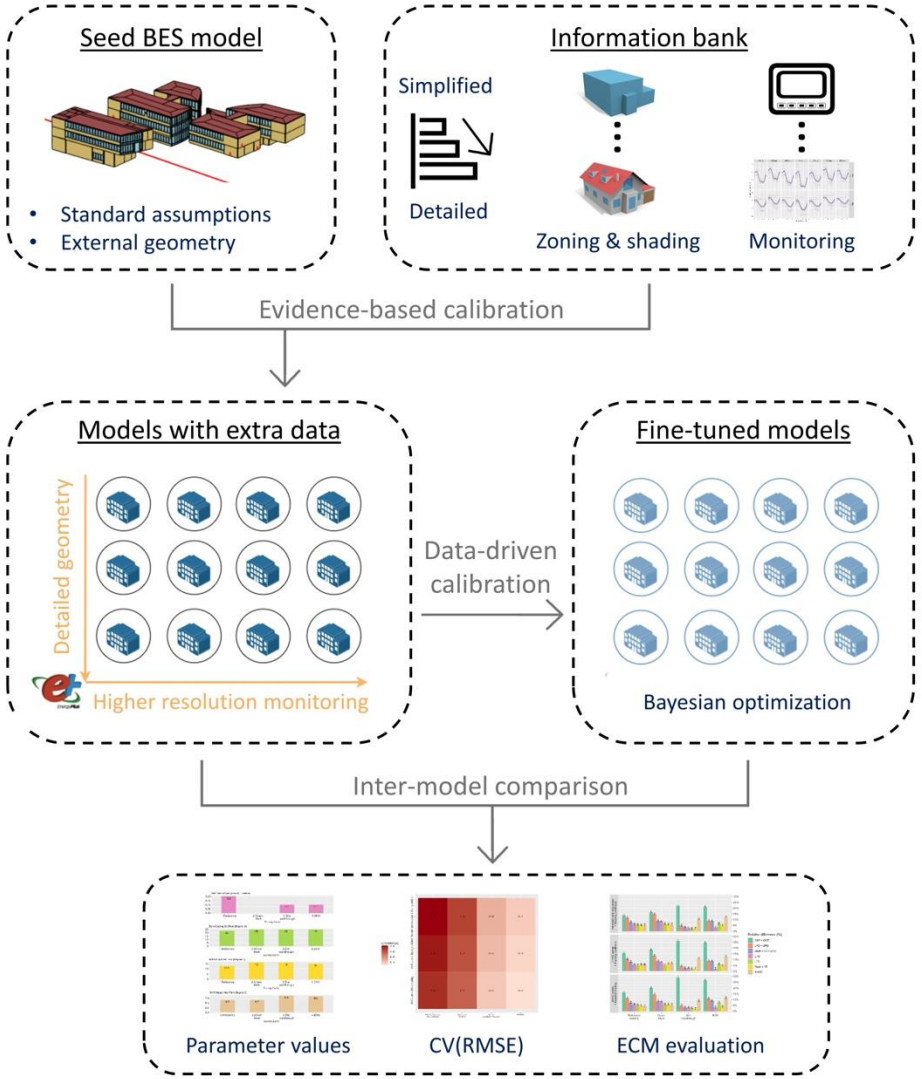
Model inputs

Disturbances

Model parameters

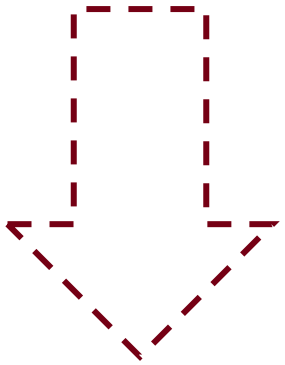


Energy model calibration for building retrofit



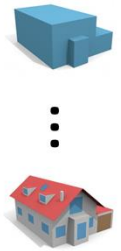
Zhan, S. *et al. Build. Simul. 18, 123–140 (2025).*

Manual (bottom-up)



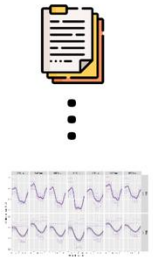
Automated (top-down)

Building Geometry



	Zoning	Shading
Simplified zoning + Simplified shading	5 zones per floor	Shading coefficient
Detailed zoning + Simplified shading	Actual HVAC zones	Shading coefficient
Detailed zoning + Detailed shading	Actual HVAC zones	Shading devices

Operating conditions



	Load density	Operating schedules	HVAC system
Reference building	Reference values (average from survey)		
Energy certification	Submissions	Reference schedules	System specifications
One day site walk-through	Manual calculation	Interviewing	Eyeballing values
Historical BMS data	Monthly maximum	Average daily profile	Monthly average

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

Ground truth of model output(s)

$$s.t. \quad y = \mathcal{M}(x, u, \theta)$$

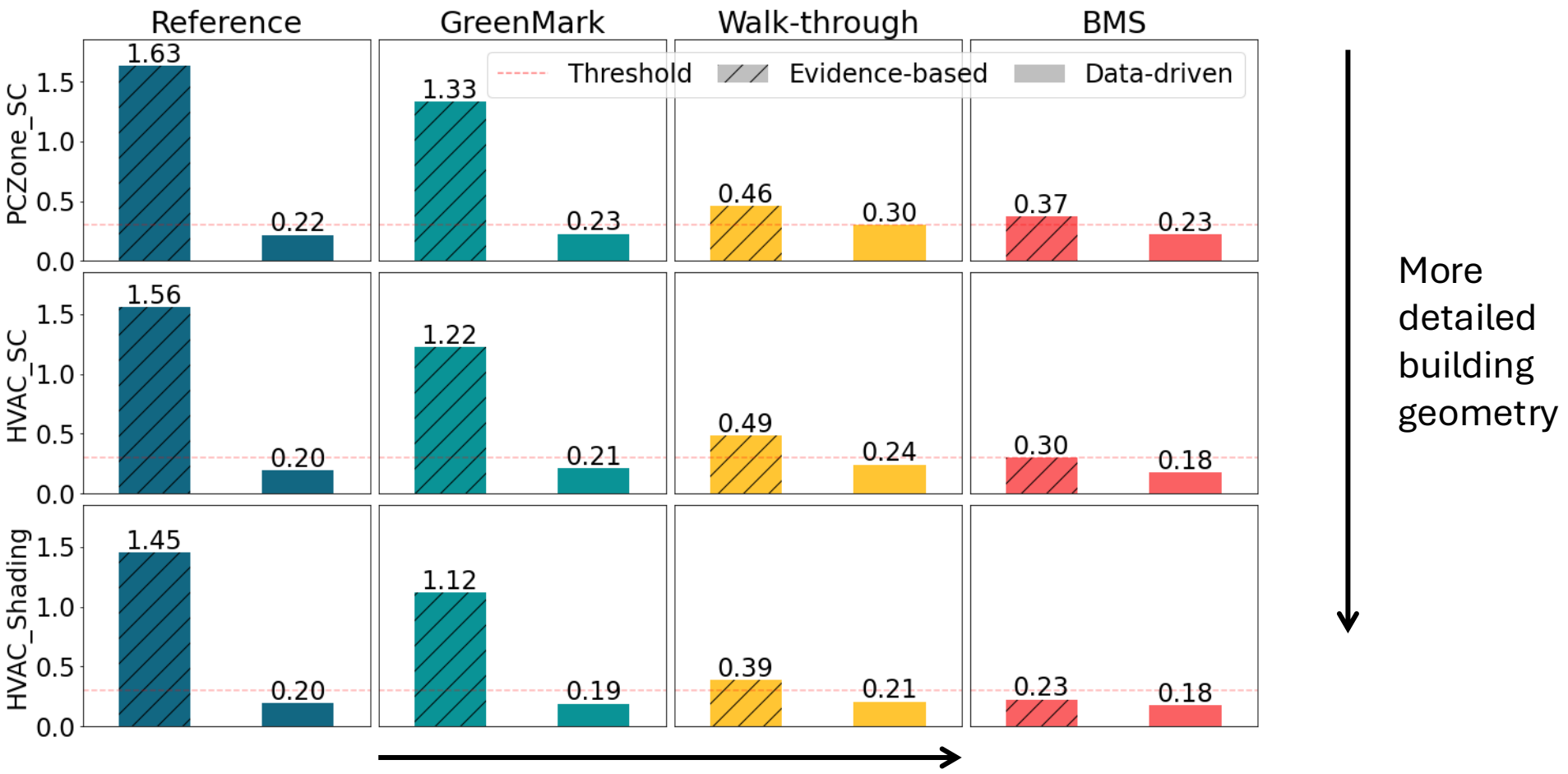
Model outputs

Model parameters

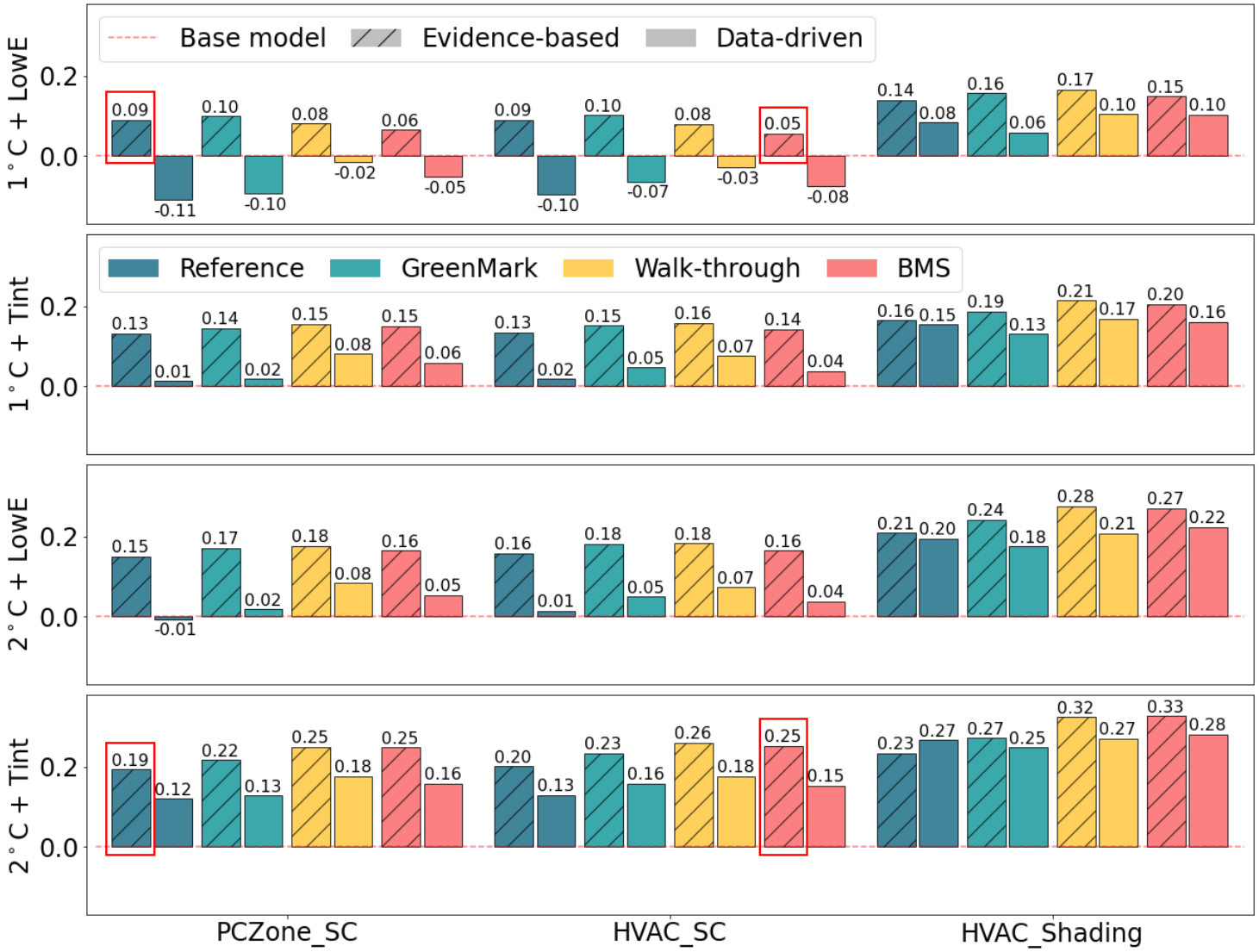
Model inputs

Disturbances

All base models achieved satisfactory accuracy after optimization



ECM evaluation using calibrated models

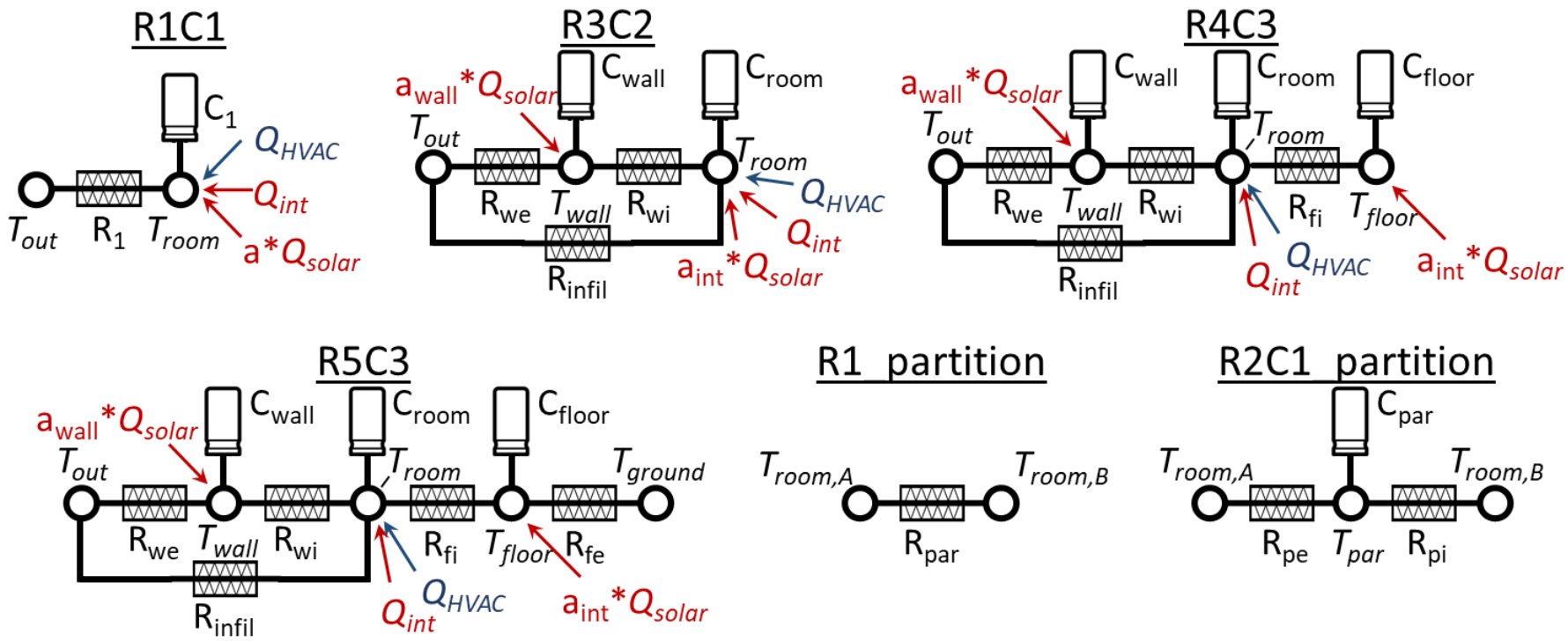


Models with similar accuracy could have distinct results

A good-enough base model is essential

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

Resistor-capacitor model identification for optimal control

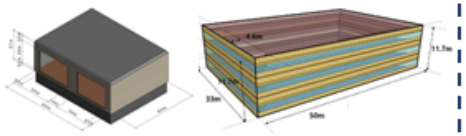


Zhan, S. *et al. Appl. Energy* **323**, 119580 (2022).

Simulation experiments to link prediction and control

Emulator setup

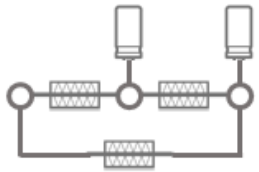
Measured disturbance inputs
- Actual meteorology year
- Occupant and electricity (office and classroom)



High-fidelity models
- BESTEST case600
- DOE medium office prototype

Evaluated against the emulators

Model identification

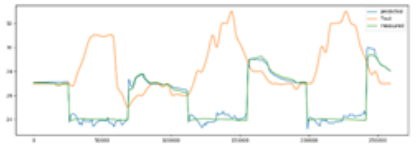


$$\theta = argmin \int_{t0}^{t1} \sum_{i}^{k} (T_{room,i} - \hat{T}_{room,i})^2$$

Control-oriented models
- RC model complexities
- Inputs for internal heat gain
- Open-loop prediction error

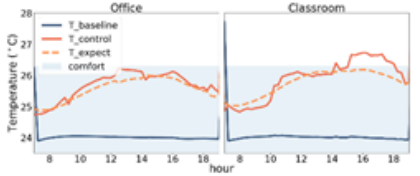
Evaluated against the emulators

Predictive evaluation



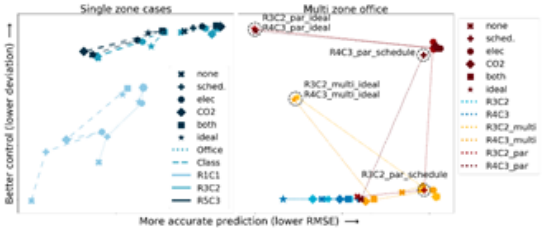
- Root mean square error
- Tested under multiple operating conditions

Control evaluation



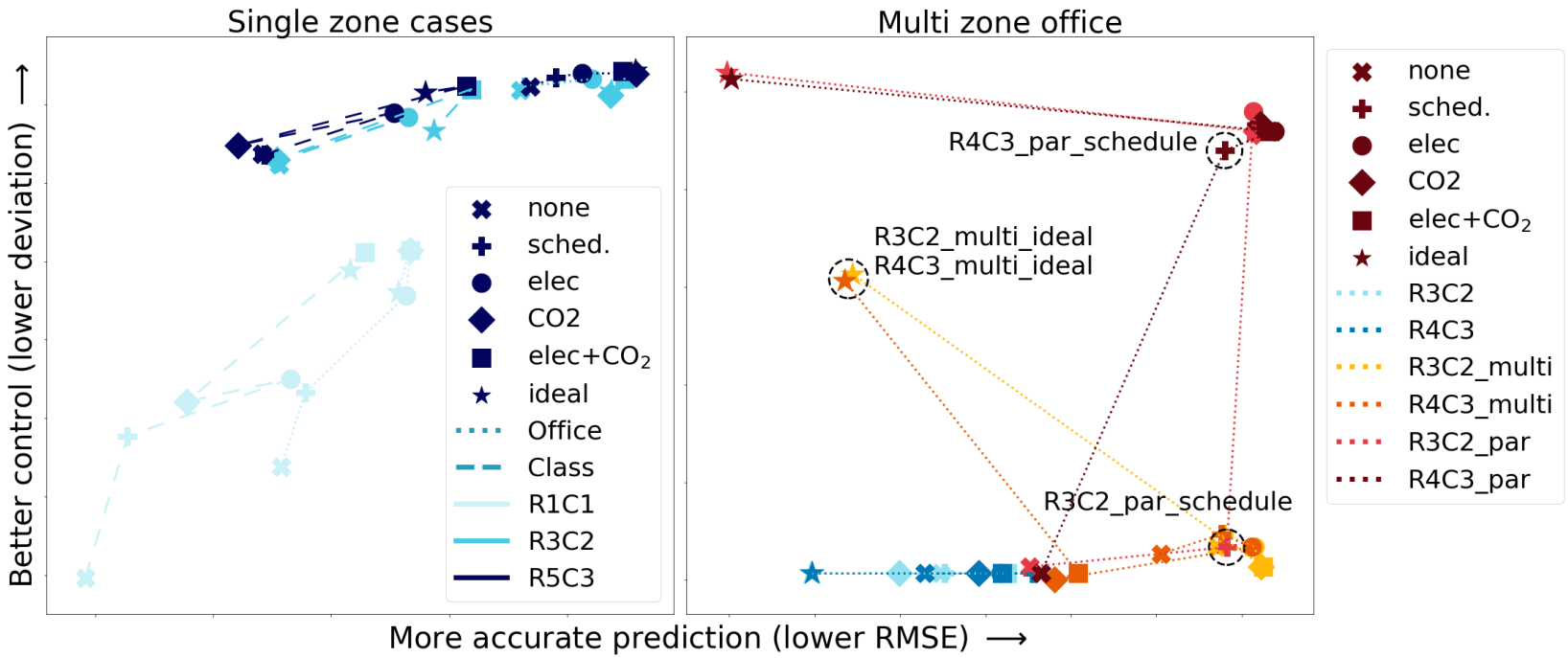
- Minimize overall penalty of energy and comfort
- Track multiple setpoints

Post analysis



- Affecting factors of data usefulness
- The interaction between data and model in identification
- Heterogeneous requirements of prediction and control

Simulation experiments to link prediction and control

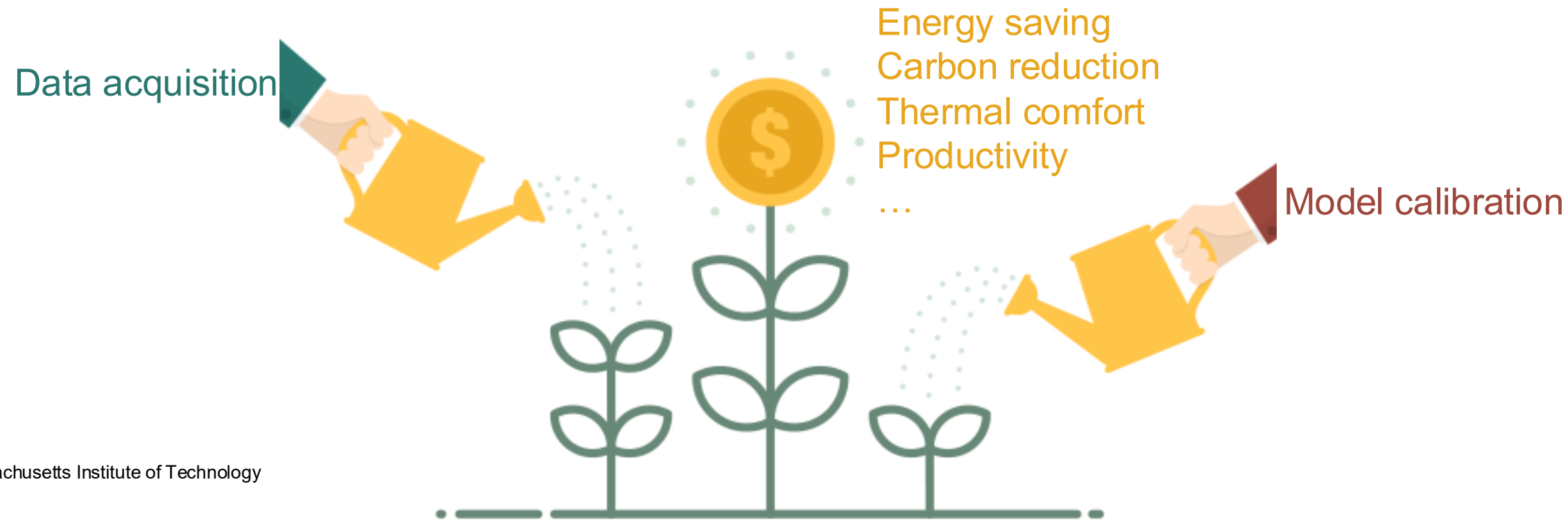


- Lower prediction error means better control for simple dynamics
- For complex buildings, more data only led to lower predictive errors
- Better control requires physically-representative models

Key takeaways

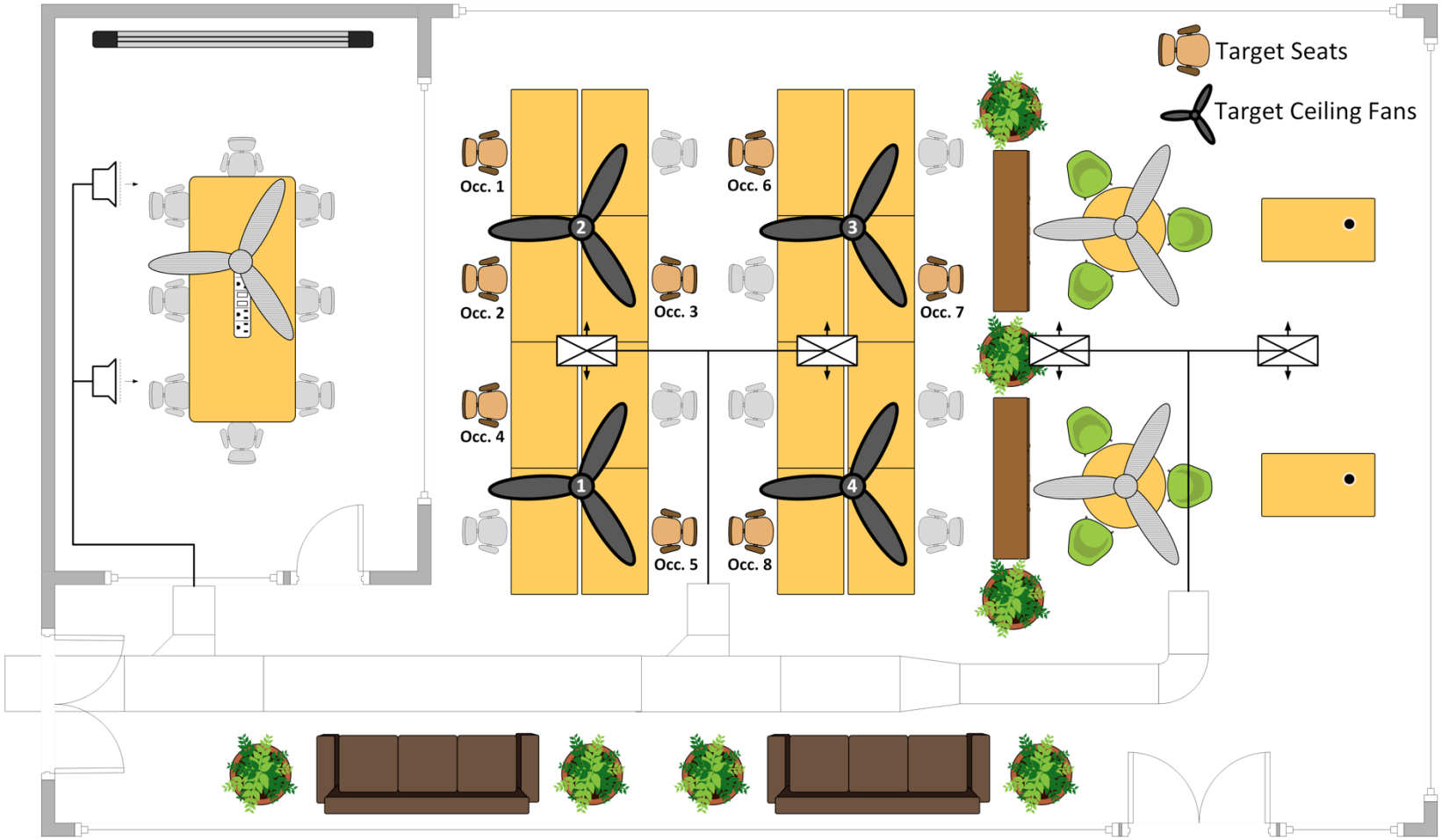
From chasing lower error to decision-oriented calibration.

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



Model calibration meets AI/ML

Accommodate personal preferences through RL



Open plan shared office in a net zero building

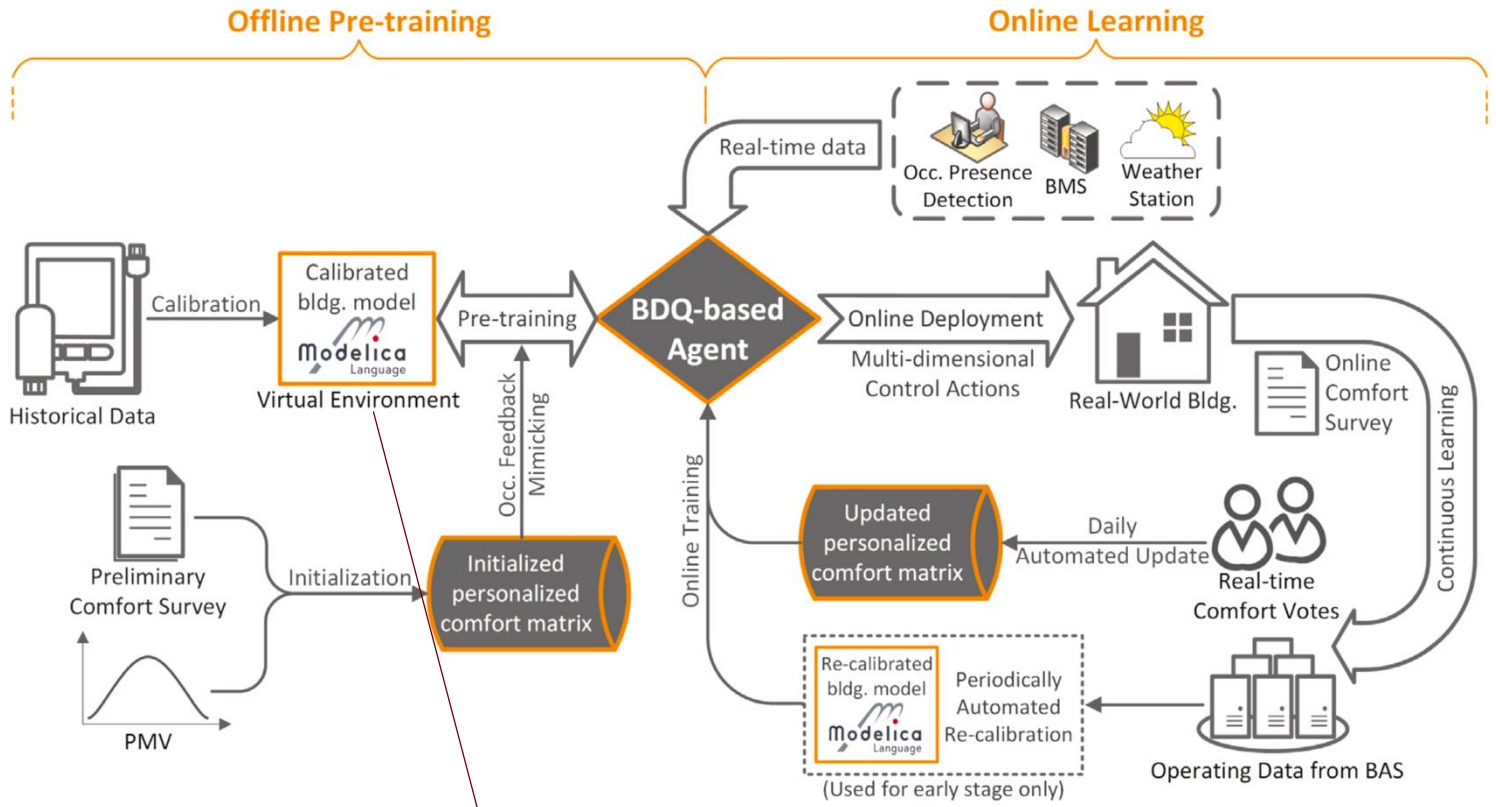
Hybrid cooling to saving energy

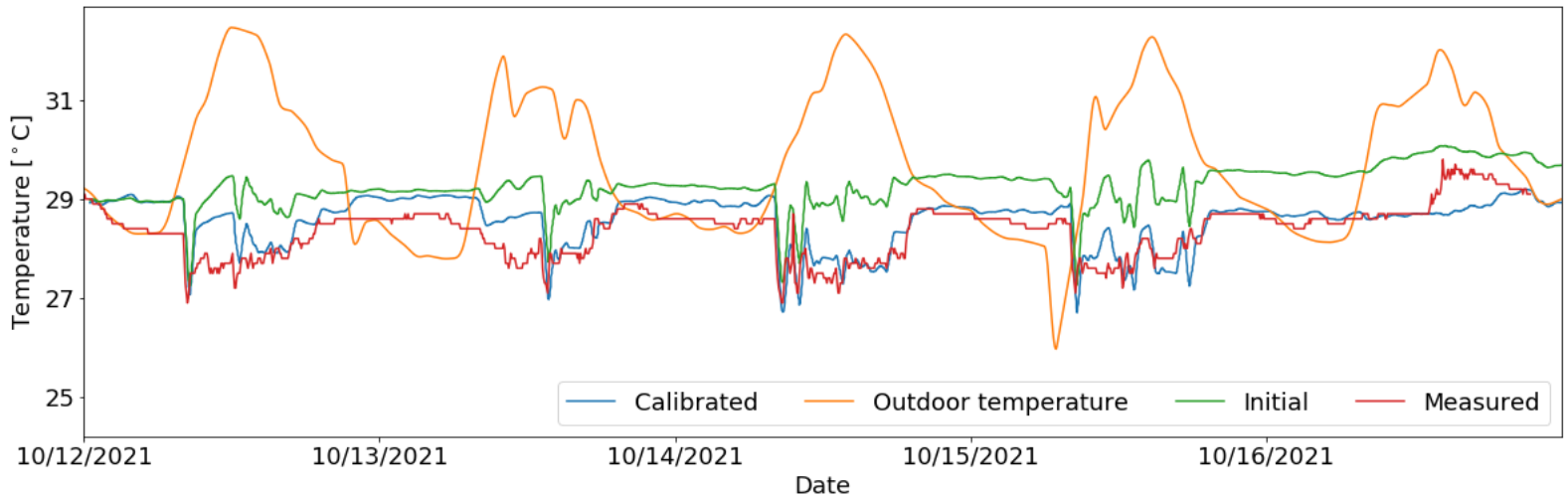
Diversified thermal comfort
-> Multiple control actions

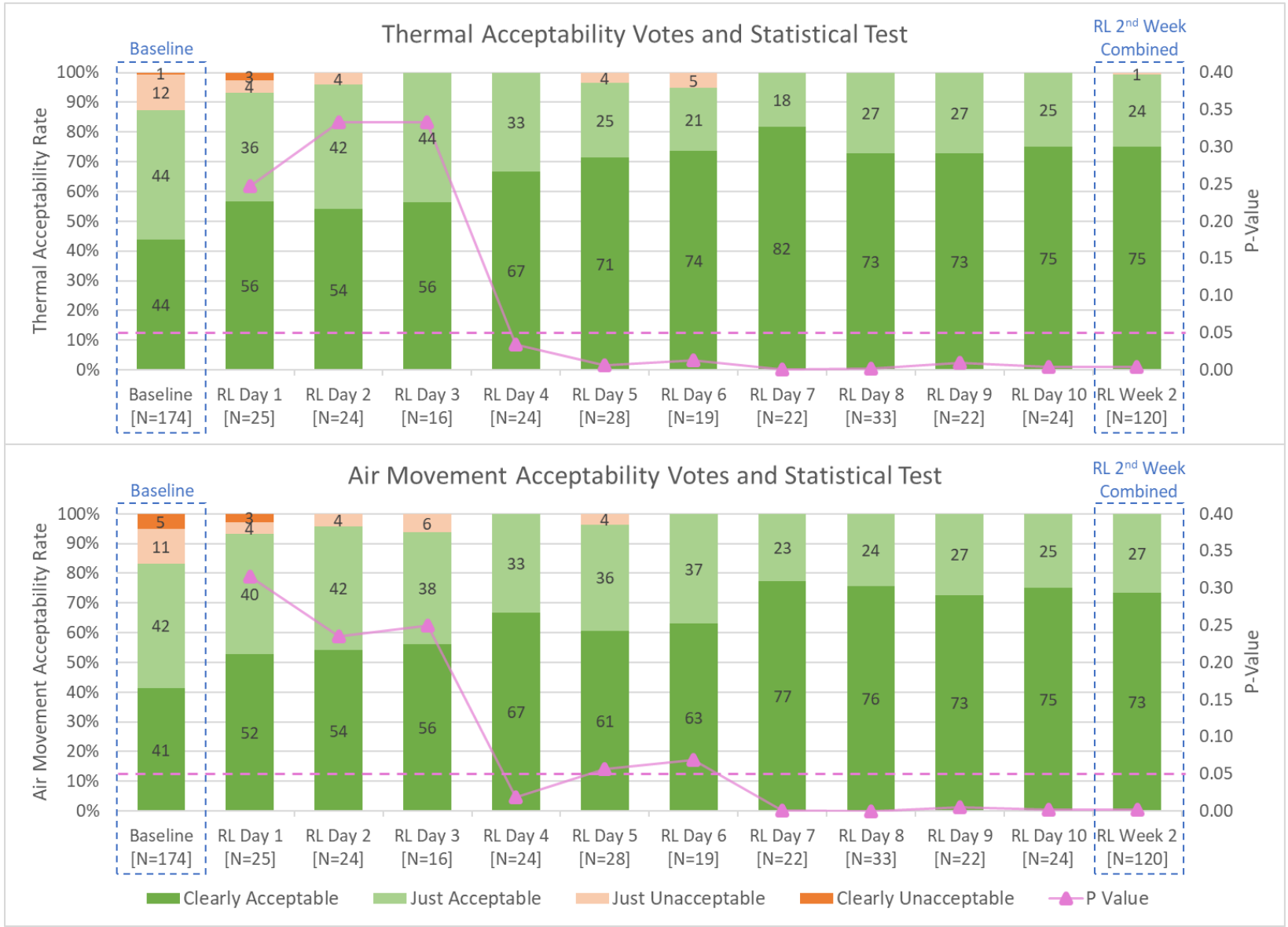
Lei, Y. *et al. Appl. Energy* **324**, 114920 (2022).

Calibrated high-fidelity model for RL training

Few-shot learning after online deployment



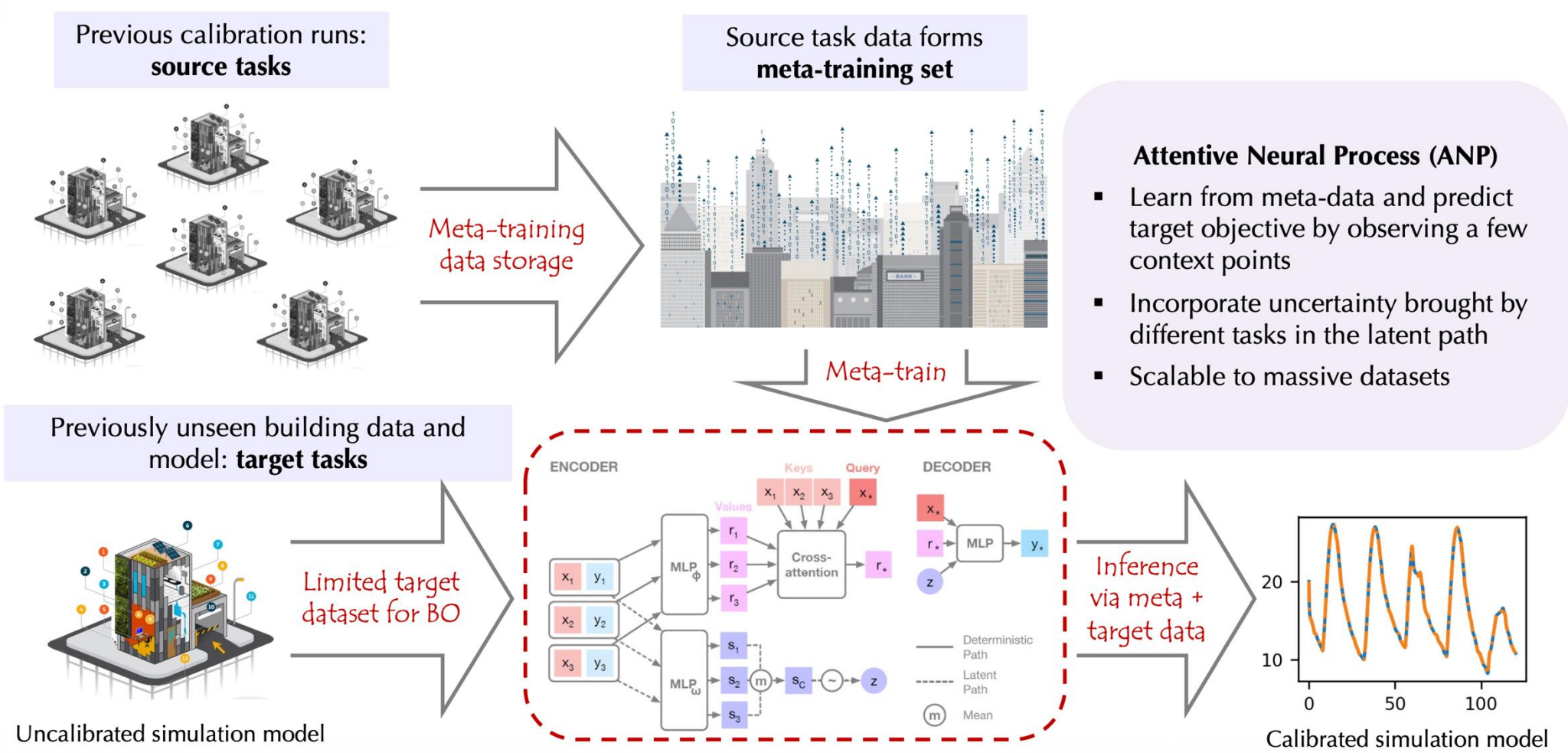




10% better individual thermal sensation

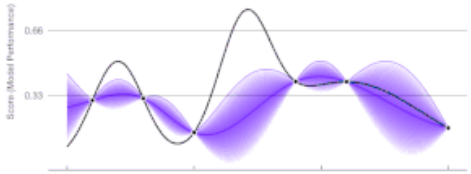
14% cooling energy reduction

How to accelerate a target calibration task by learning from related but not identical tasks?



Zhan, S. *et al. Energy Build.* **270**, 112278 (2022).

Previous calibration runs:
source tasks



Calibration by Vanilla-Bayesian Optimization with Gaussian Process

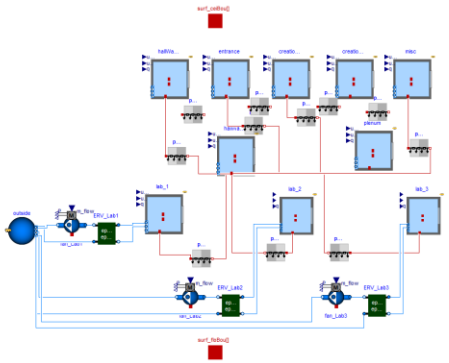
Training data storage

Source task data archived in the cloud: training set

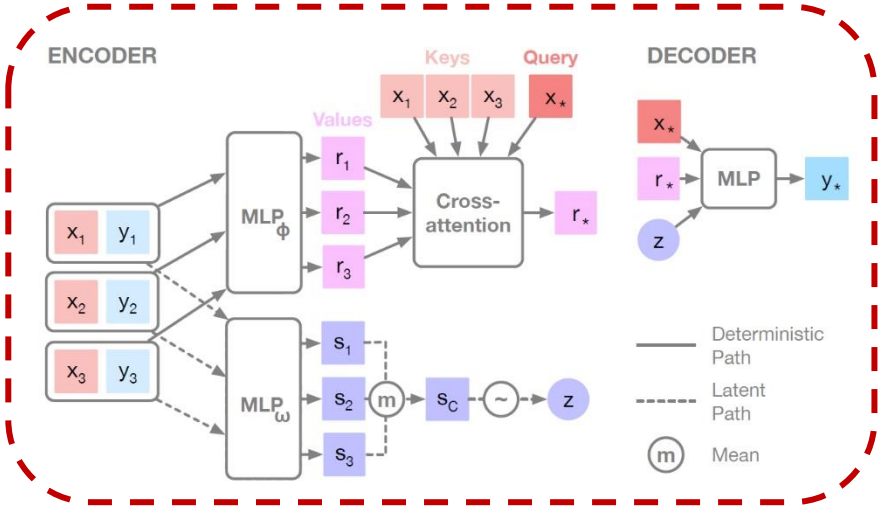
	θ_1	θ_2	...	θ_m	J
1	$\theta_{1,1}$	$\theta_{2,1}$	...	$\theta_{m,1}$	J_1
2	$\theta_{1,2}$	$\theta_{2,2}$	...	$\theta_{m,2}$	J_2
...		...			...
n	$\theta_{1,n}$	$\theta_{2,n}$	...	$\theta_{m,n}$	J_n

Meta-train

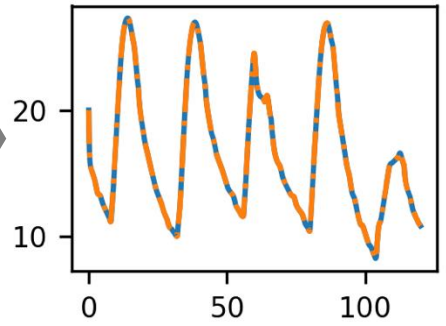
Previously unseen building data and model:
target tasks



Data-driven initialization



Meta-ANP-BO



Data-efficient learning

- Meta-learn the governing equations from a group of similar buildings
- Fastened target task with limited data
- 50% reduction in computational costs

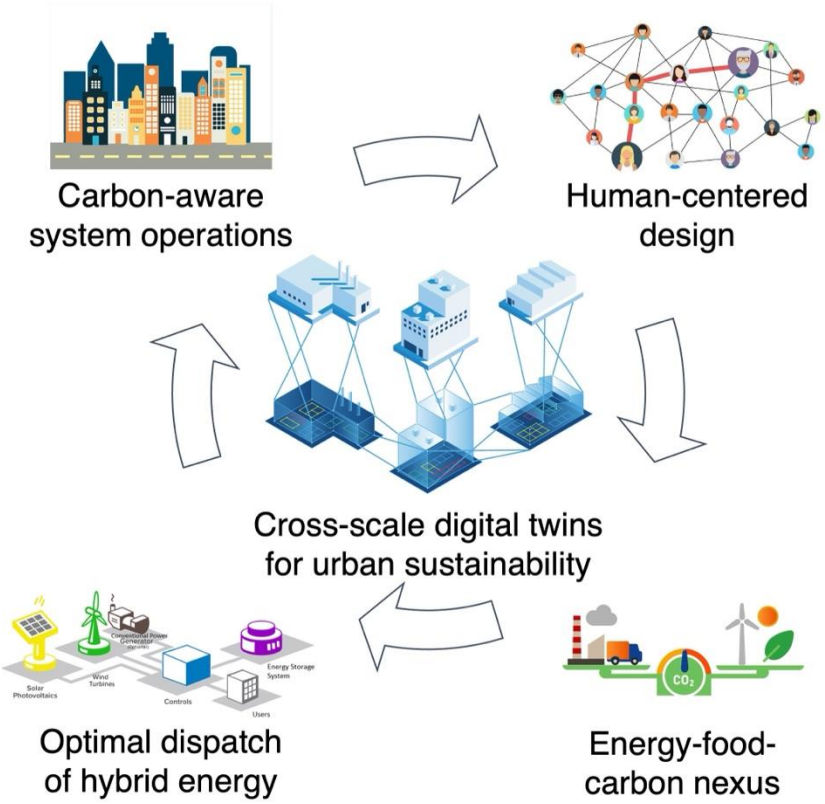
Sustainable Intelligence Nexus Lab @ HKU

Fully-funded PhD students

- 2026 Fall
- 2027 Spring/Fall

Postdoc

- Sustainable data center
- Energy audit intelligence
- Other topics



Decision-oriented data

Active-learned data acquisition to enable fit-for-purpose modeling

+

Physics-informed models

Extrapolatable physics-informed models through data assimilation

Dynamic digital twins

Dynamically evolving models to support decision-making throughout system life cycles

https://jamescheng21.github.io/

Questions?

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