NUS National University of Singapore

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Digital twin for buildings: identification, calibration, and applications

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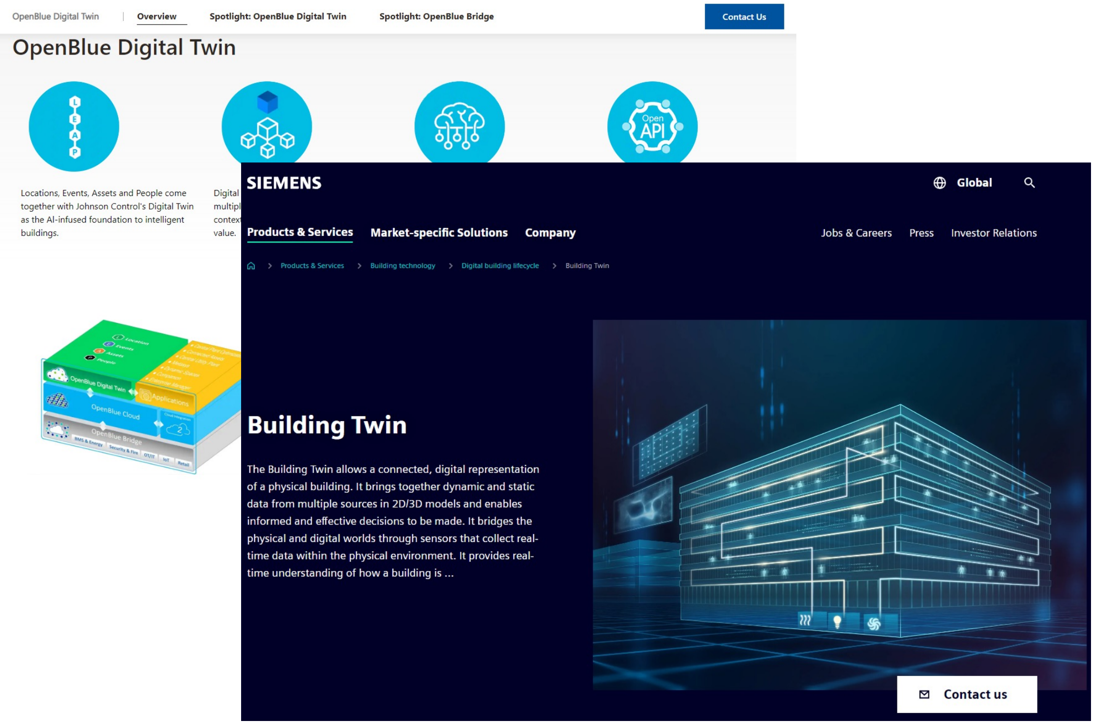
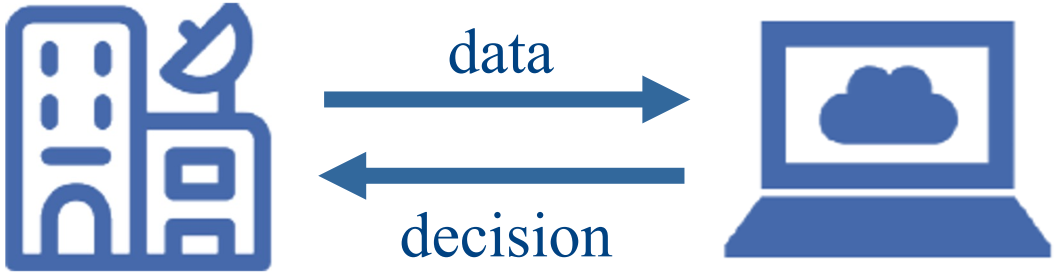


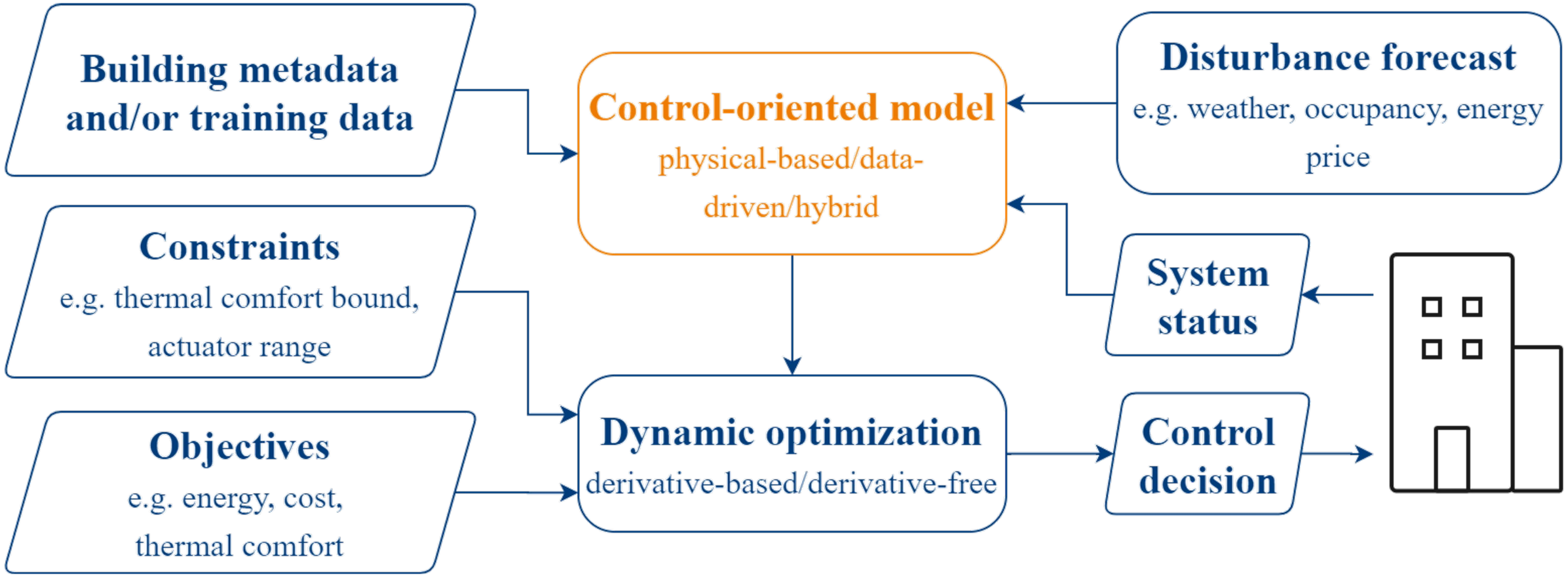
Existing digital twin solutions

- 3D BIM model
- Data acquisition
- Data visualization
- Energy prediction & evaluation

Computational models that replicate the behaviour of real-world systems and support decision-making by conducting virtual experiments.



MPC as an example

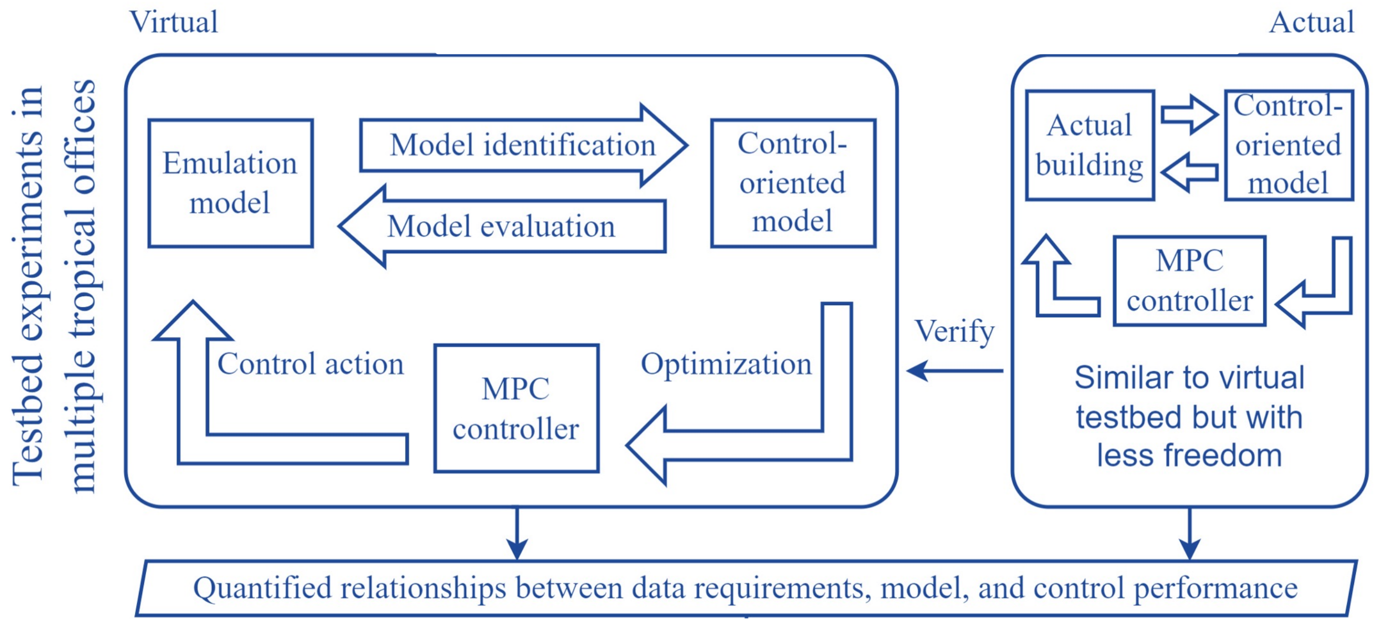


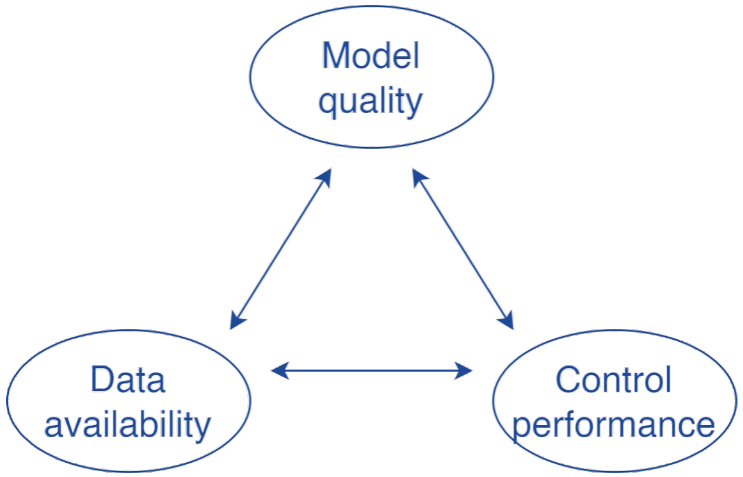
- Three main processes: disturbance forecast, control-oriented model, dynamic optimization
- Control-oriented model is the cornerstone, data required for model establishment
- Up to 70% of total effort is attributed to model construction and calibration

Impact of data on model identification

Zhan, S., Lei, Y., Jin, Y., Yan, D., & Chong, A. (2022). Impact of occupant related data on identification and model predictive control for buildings. Applied Energy, 323, 119580.

Research question





What is the impact of data on downstream model and control performance?

- Virtual and actual testbeds
- Series of factorial experiments
- Quantified relationship

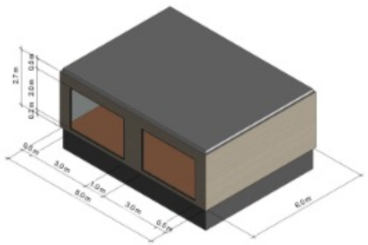
Emulator configurations

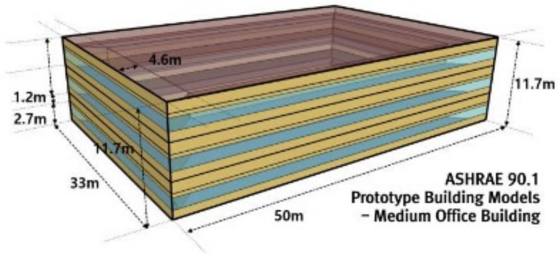
Single-zone experiment

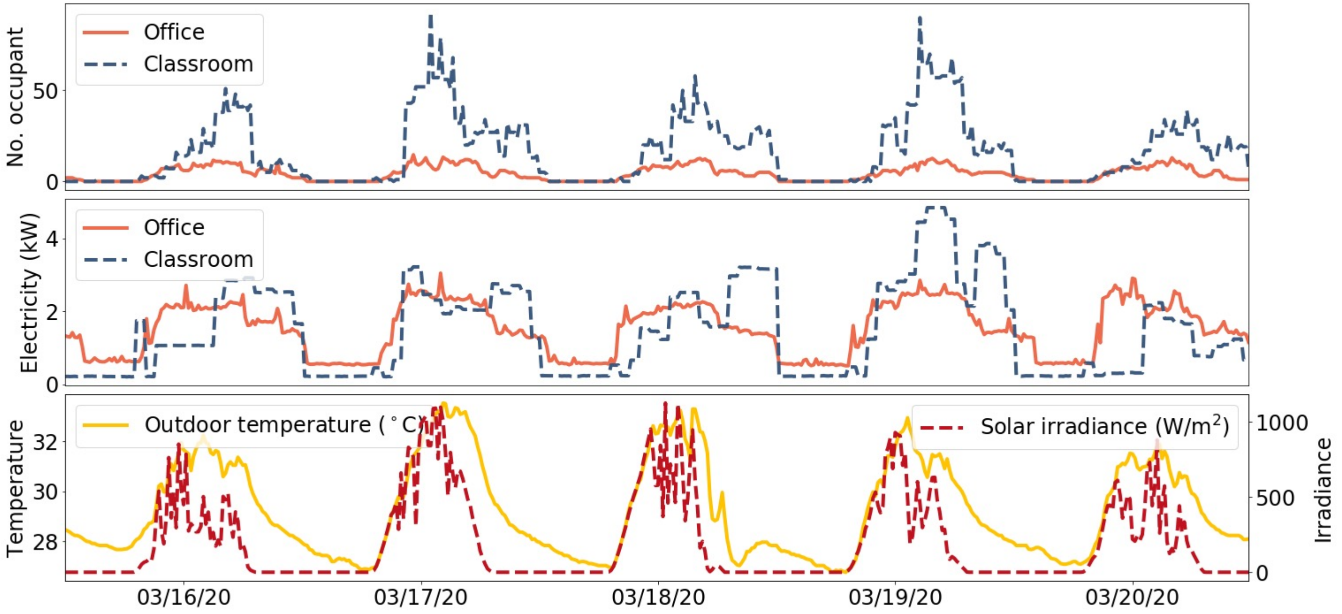
- BESTEST Case 600
- Fan coil unit with PI local control
- No. occupant and electricity load from an actual office and classroom

Multi-zone experiment

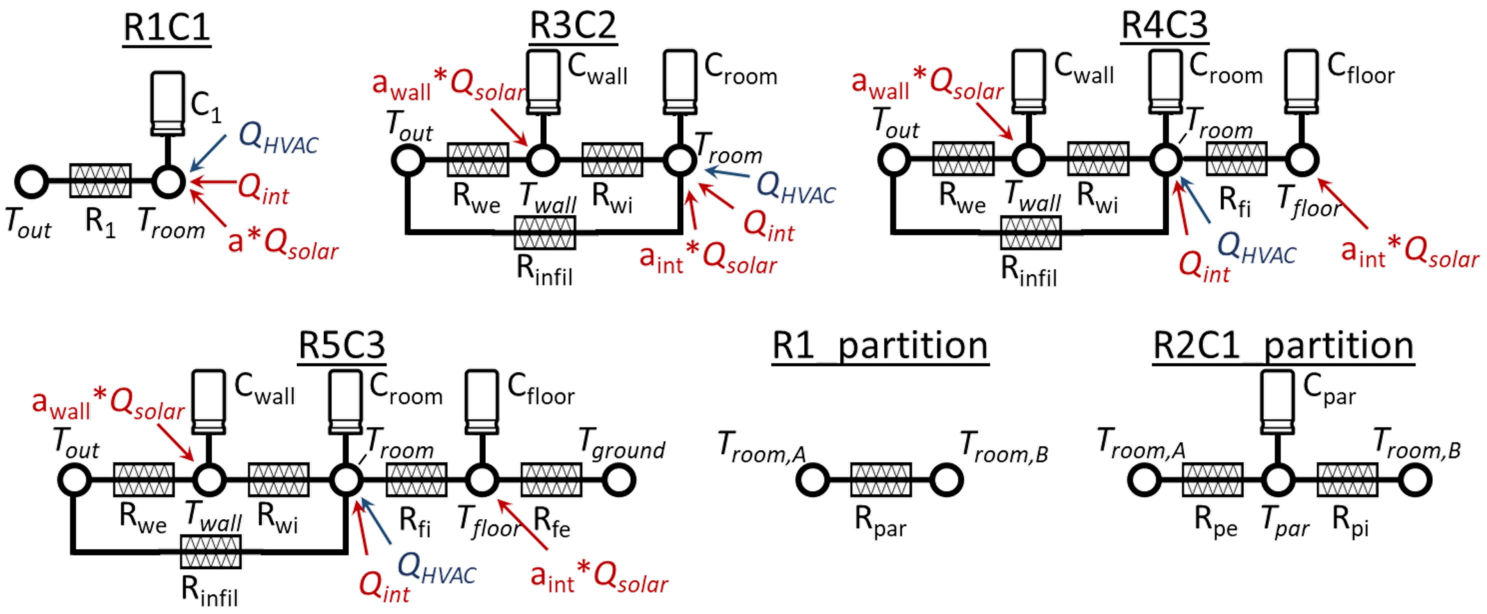
- A floor of DOE medium office
- Internal disturbance profiles randomly sampled for each room on each day







Model identification



- Increasing RC model complexity
- 6 alternative inputs for occupant-related disturbances
    - none, schedule, plug, CO_2, plug+CO_2, ideal
- Identified with the same dataset through non-linear programming

$$\theta = argmin \int_{t0}^{t1} \sum_{i}^{k} (T_{room,i} - \hat{T}_{room,i})^2 dt$$
$$s.t. \quad \hat{T}_{room} = f(x, u, d, \theta)$$
$$\theta^{lb} \leq \theta \leq \theta^{ub}$$

- Tested under different conditions (extrapolation capability)

Control performance evaluation

Two control tasks designed for comprehensive evaluation

1. Typical MPC task of balancing energy and thermal comfort
2. Simpler setpoint tracking to examine the control capability of RC models

$$J = \int_{t_0}^{t_0+30min} \sum_{i}^{k} \left(q_u (m_{flow,i})^2 + q_t (PMV_i)^2 \right) dt$$

$$s.t. \quad 0 \leq m_{flow,i} \leq m_{flow,norm}$$

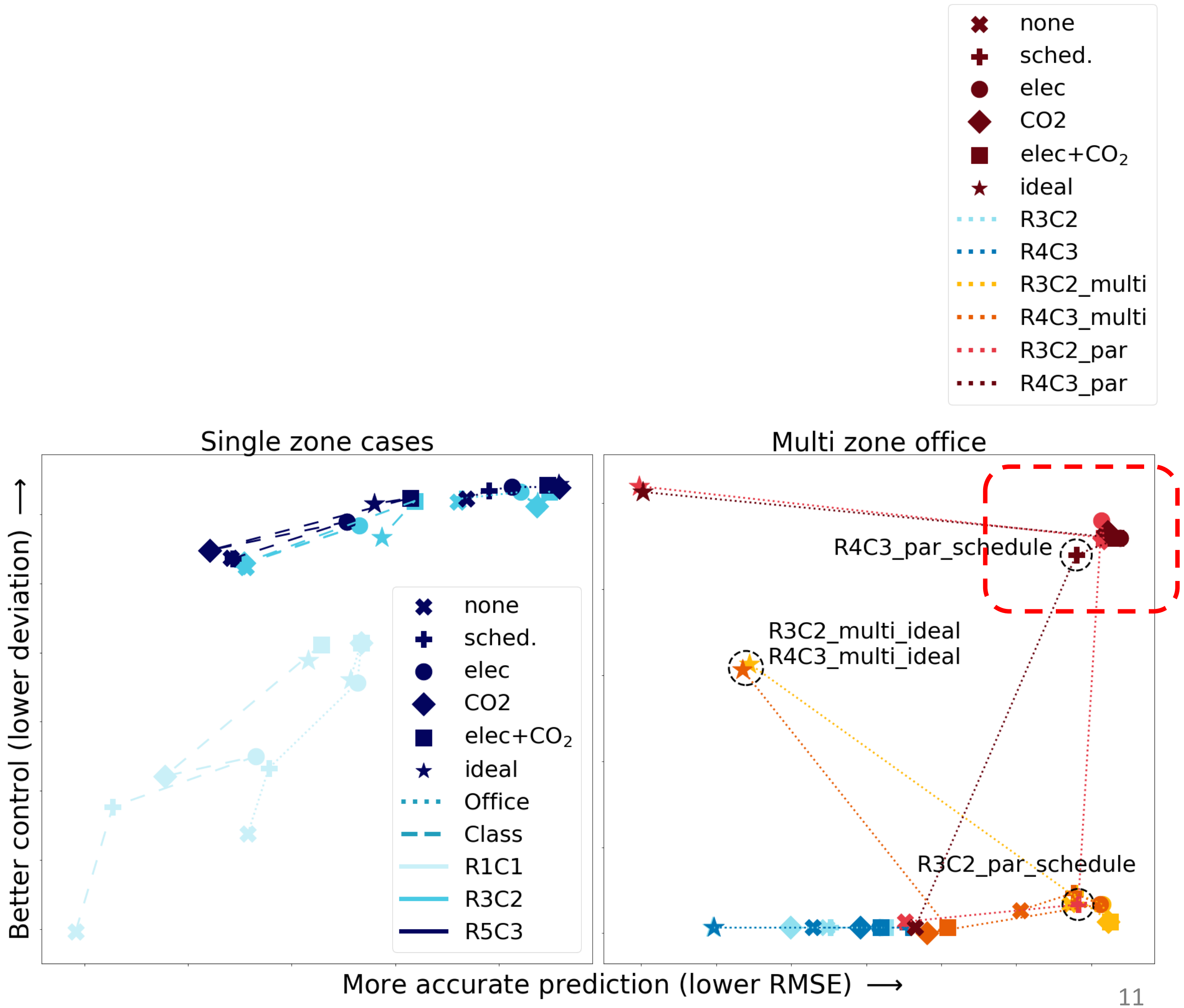
$$-0.5 \leq PMV_i \leq 0.5$$

$$J = \int_{t_0}^{t_0+30min} \sum_{i}^{k} (T_{room,i} - T_{setpoint,i})^2 dt$$

$$s.t. \quad 0 \leq m_{flow,i} \leq m_{flow,cap}$$

Summary of results

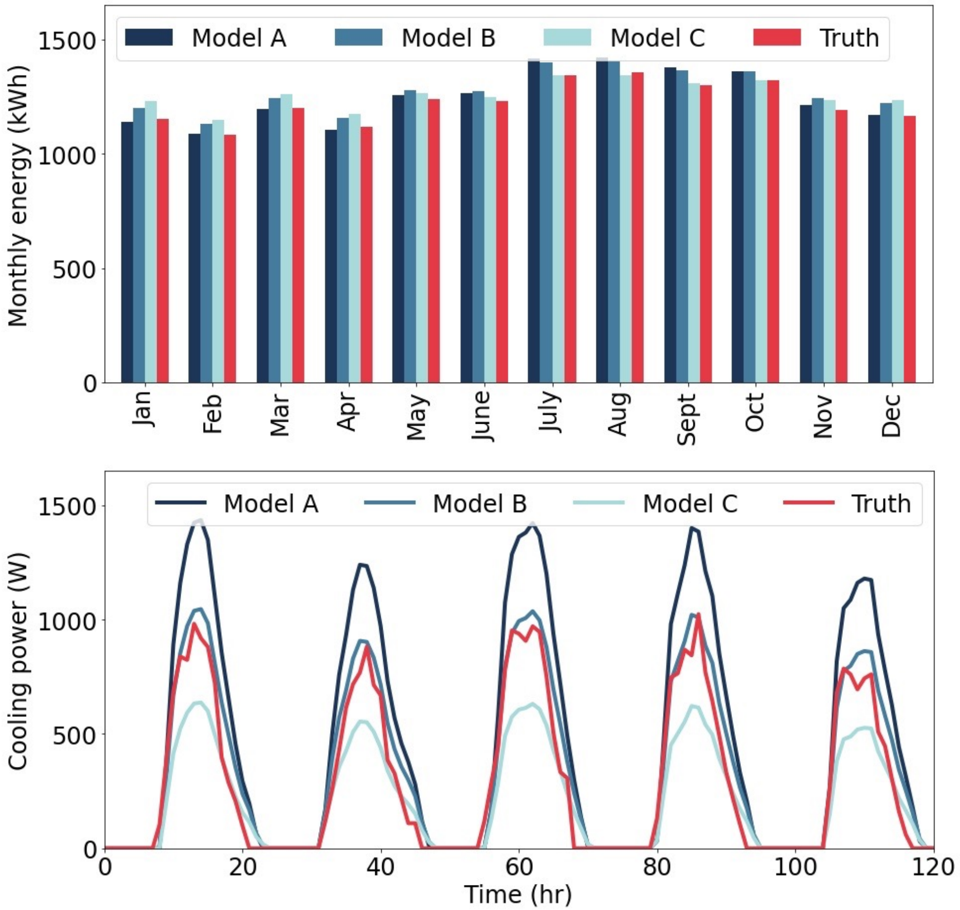
- Model adequacy and data informativeness are both essential
  - More informative data generally reduce prediction error
  - Only led to better control with adequate model
  - Critical physical component should be preserved (partition capacitor here)



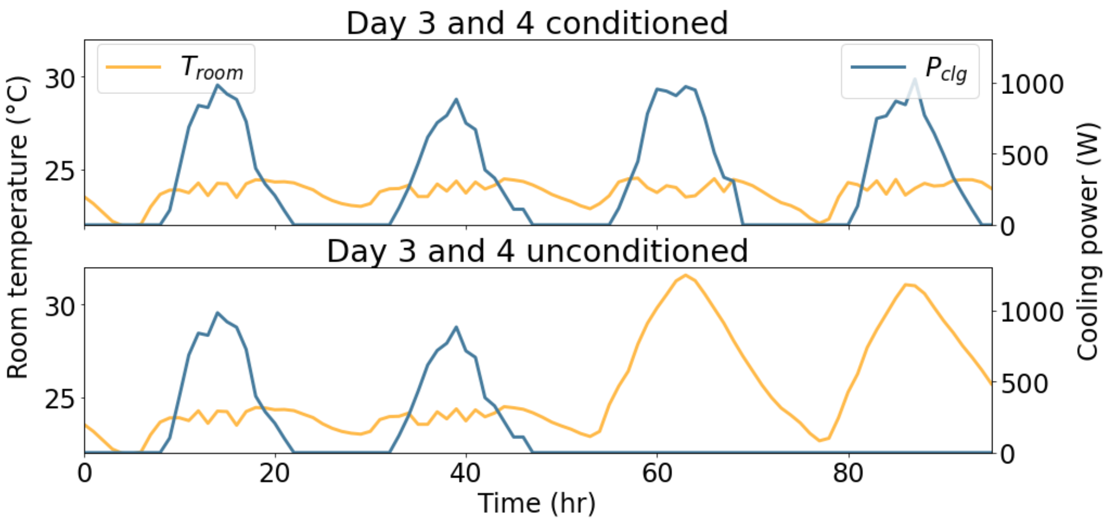
Robust evaluation of model calibration

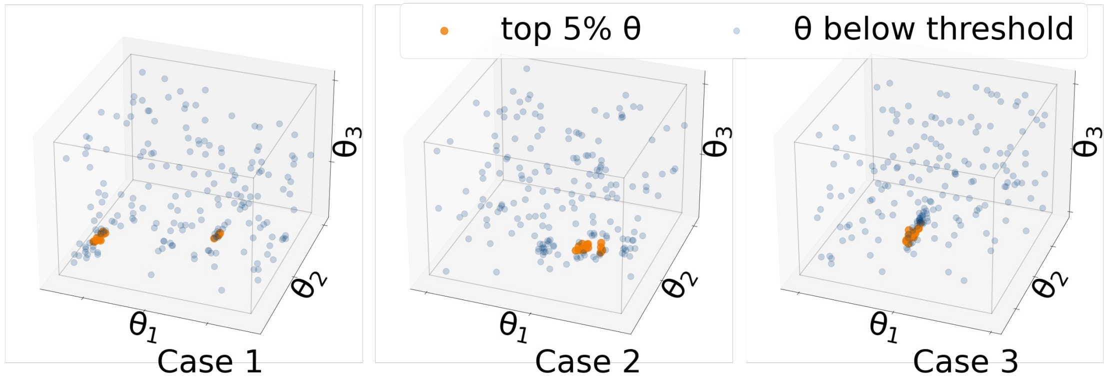
Zhan, S, Chakrabarty, A, Laughman, C, Chong, A. (2022). A virtual testbed for robust and reproducible calibration of building energy simulation models. Building Simulation 2023.

Pitfalls in model calibration



Prediction error of a single output

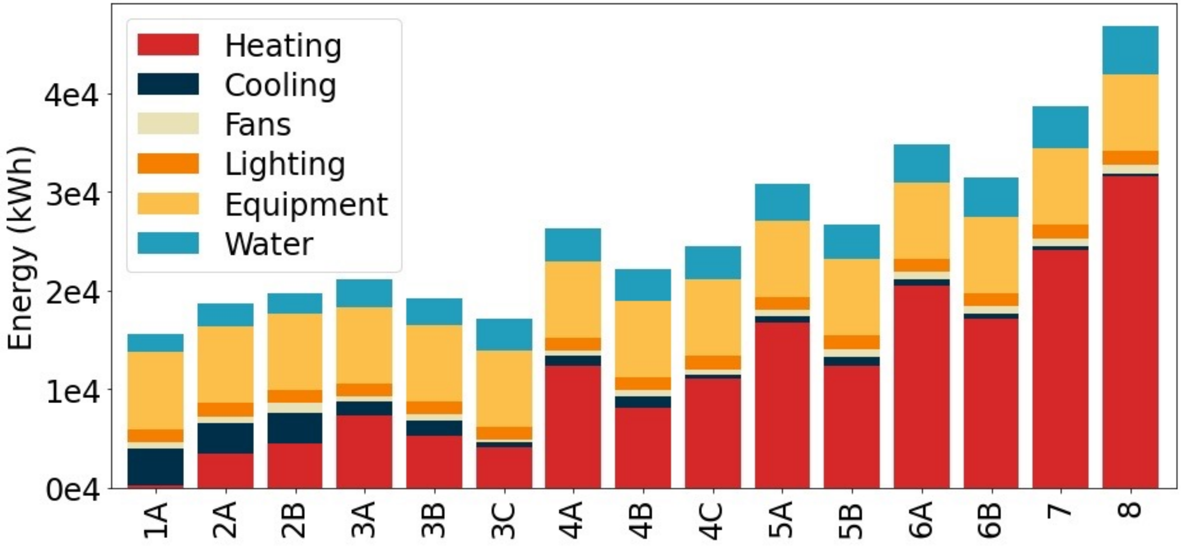


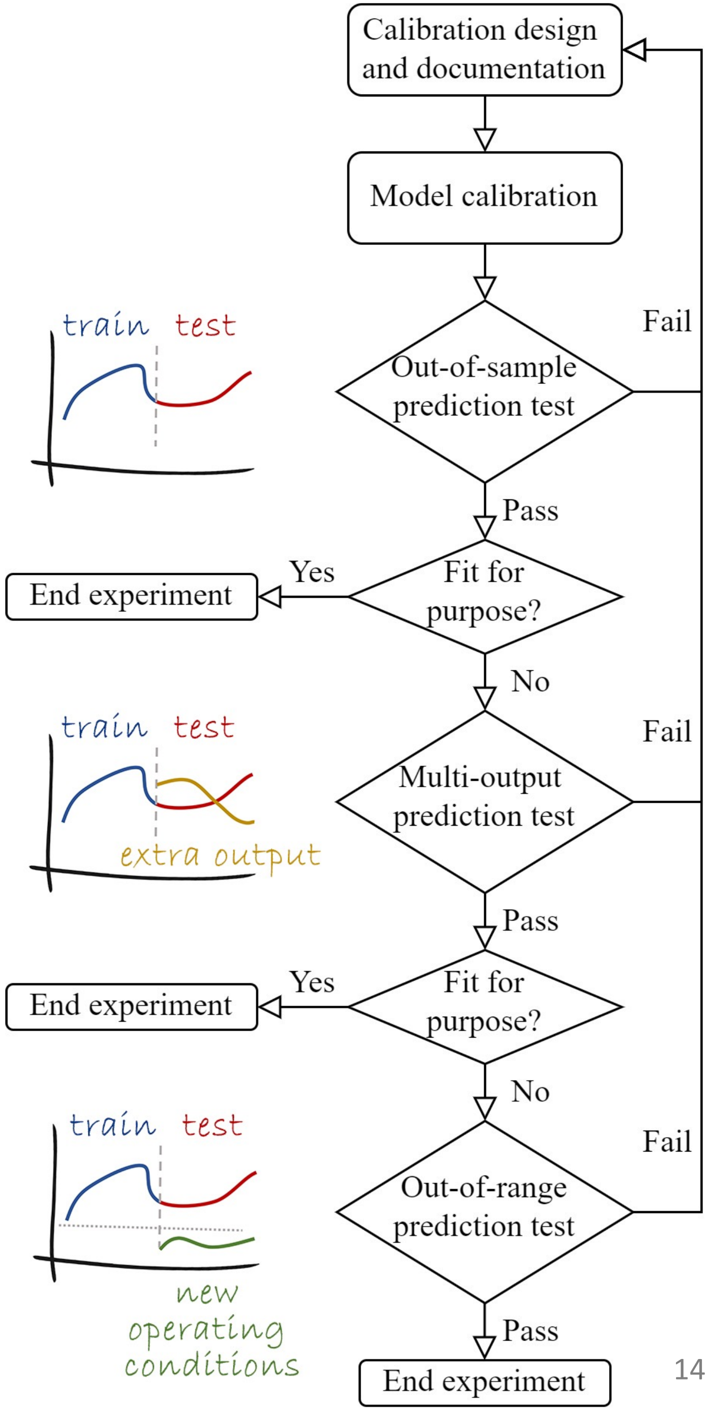


Identifiability issues

Virtual testbed for robust evaluation

- Residential and commercial cases across different climate zones
- Various levels of extrapolation tests according to the application scenarios



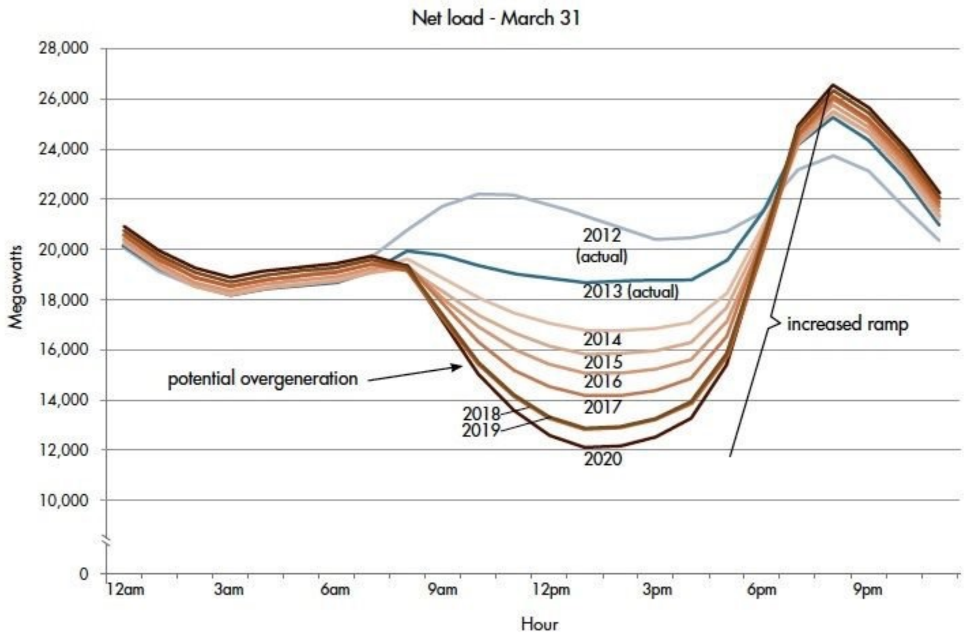


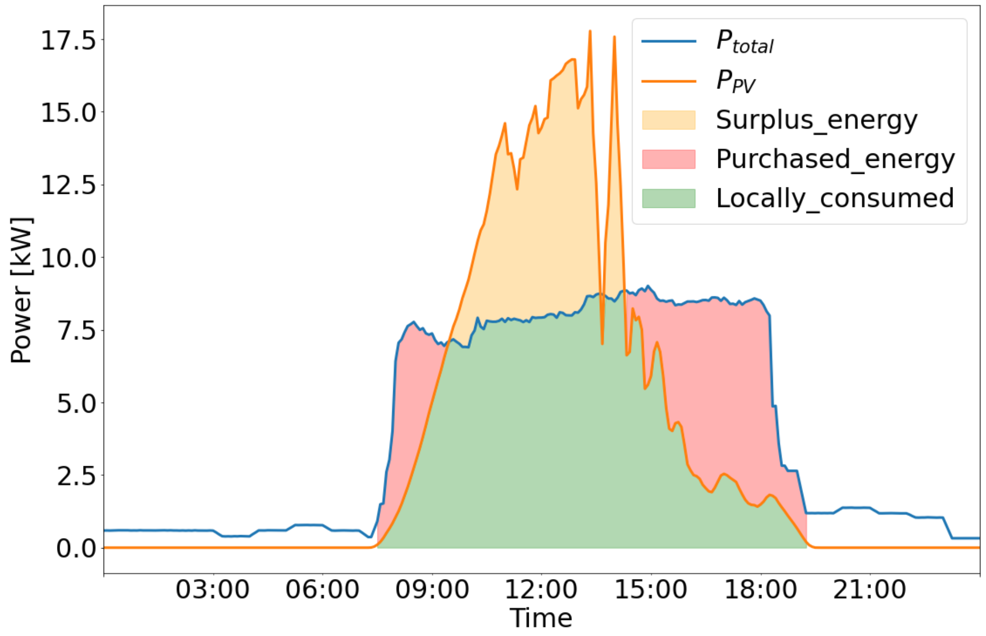
An energy flexibility use case

Zhan, S., Dong, B., & Chong, A. (2022). Improving energy flexibility and pv self-consumption for a tropical net zero energy office building. Energy and Buildings, 112606.

Motivations

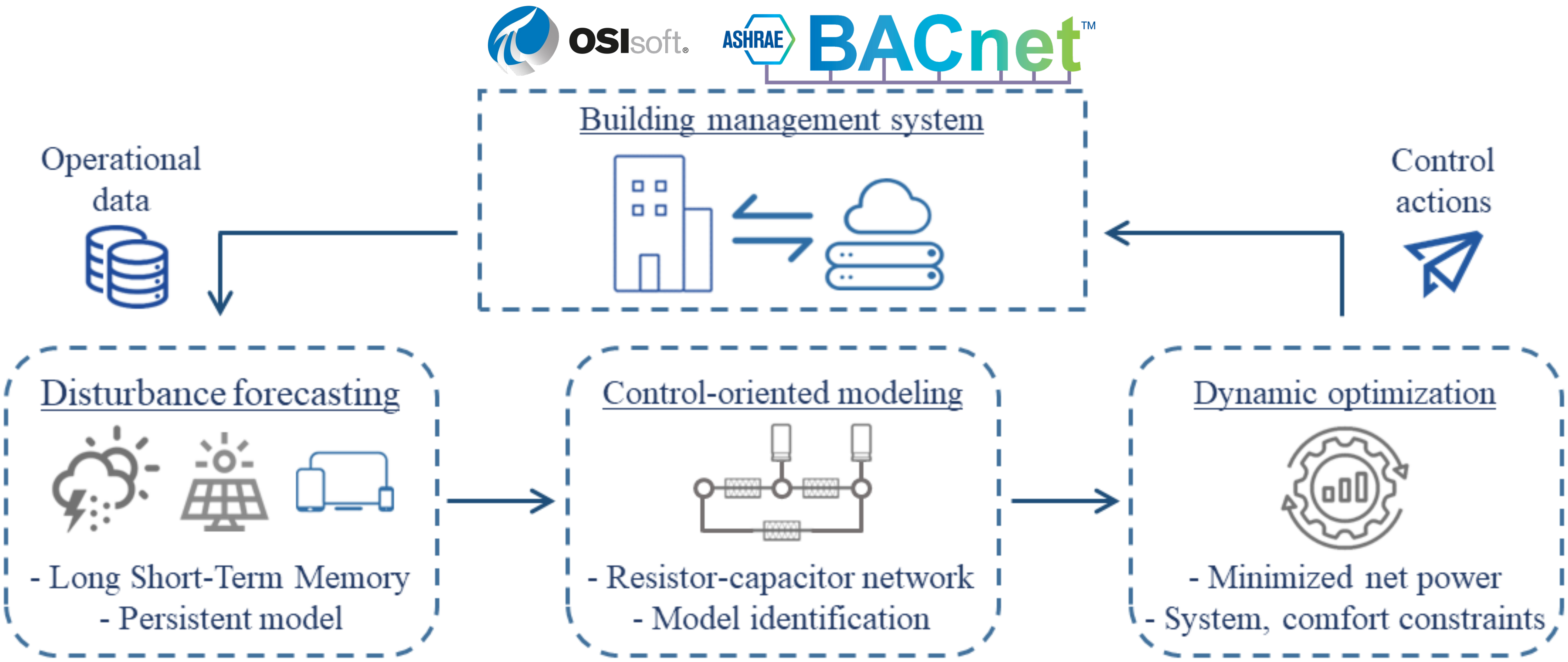
- The integration of renewable energy exerts pressure on grid operation (e.g. the “duck” curve)
- Demand side management requires buildings to be energy flexible[1]
- Great solar power potential to be exploited in the tropics, self-consumption and self-sufficiency to be improved
- Operating with constant setpoints yields considerable surplus and purchased energy



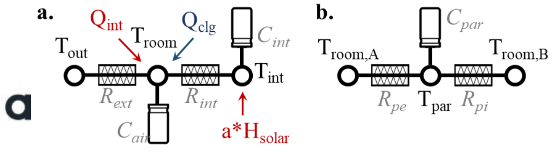


1. Annex 67: the ability to manage its demand and generation according to local climate conditions, user needs, and energy network requirements

The MPC framework



inputs: time, history
lookback: 120min
horizon: 60min



R2C2 room　　R2C1 partition

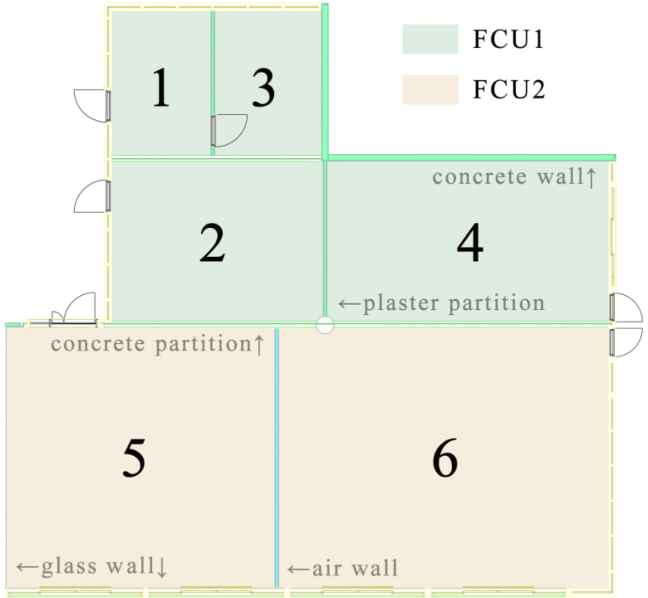
$$J = \int_{t_0}^{t_0+60min} (P_{PV} - P_{total})^2 + q_c \sum_{i}^{k} (T_{RM,i} - 26)^2$$

$$s.t.\quad \dot{V}_{SA,min,i} \le \dot{V}_{SA,i} \le \dot{V}_{SA,max,i}$$

$$25 \le T_{RM,i} \le 28$$

Building description

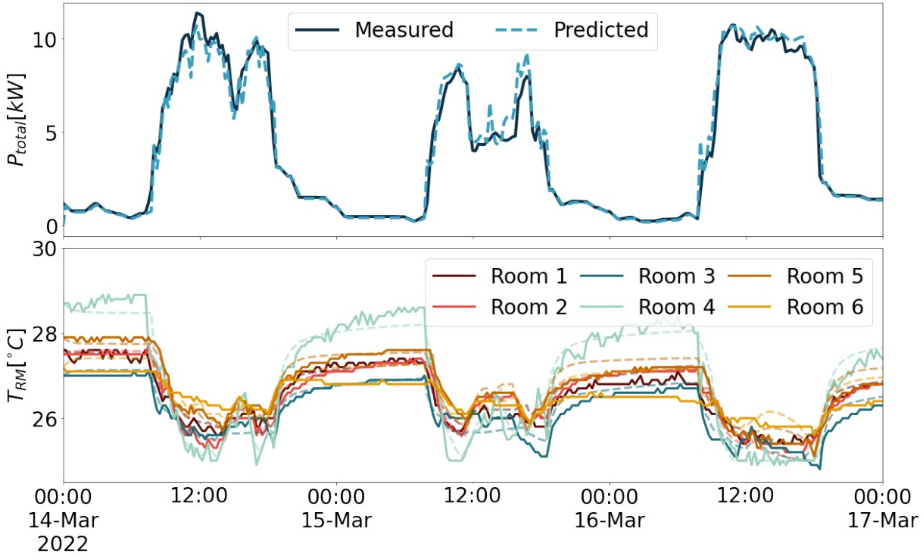
6-zone offices in a NZEB



data points used in the experiments

Data category[a]	Point name	Symbol	Unit	Data source
Energy consumption	chilled water power	P_{clg}	kW	BTU meters of each FCU[b]
	supply air fan power	P_{fan}		power meters of each FCU
	PV power	P_{PV}		smart meter for the entire building[c]
	electric power	P_{elec}		power meters for all zones under each FCU[d]
Indoor condition	room temperature	T_{RM}	°C	thermostats of each room
	CO_2 concentration	C_{CO_2}	ppm	
Internal disturbance	operating schedule	Ope	on/off	building design specifications
	occupant number	Occ		indirect estimation guided by site visit[e]
External disturbance	airport outdoor temperature	$T_{airport}$	°C	airport weather station (~20km away)
	airport solar irradiance	$H_{airport}$	W/m^2	
	local outdoor temperature	T_{local}	°C	rooftop weather station
	local solar irradiance	H_{local}	W/m^2	
System condition	room temperature setpoint	$T_{RM,SP}$	°C	thermostats of each room
	damper position	k_{VAV}	%	VAV boxes of each room
	supply airflow rate	$\dot{V}_{SA}$	m^3/h	airflow meter of each VAV box
	supply air temperature	T_{SA}	°C	off coil temperature sensor of each FCU
	supply air temperature setpoint	$T_{SA,SP}$	°C	PID loop of each cooling coil

Validated virtual testbed



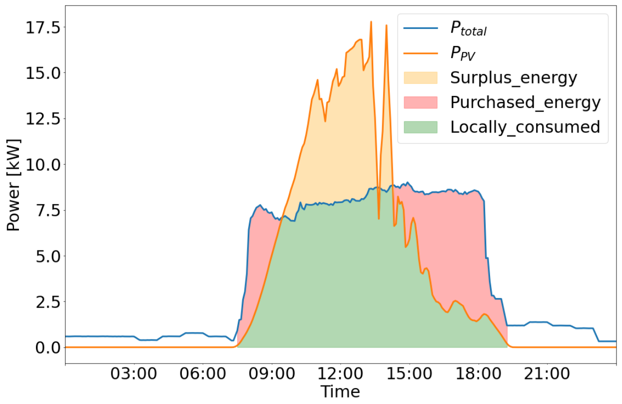
Experiment design

2 baselines (constant setpoint 26/27.5°C) and 4 MPC configurations (virtual and actual)

Case name	Data points involved in the MPC framework: Disturbance forecast (input)	Control-oriented model (initial state/input)	Dynamic optimization (constraint/control action)
MPC_main	$T_{local}, H_{local}, P_{PV}, P_{elec}$	$T_{RM}/T_{local}, H_{local}, \dot{V}_{SA}, T_{SA}$	$Ope/T_{RM,SP}$
MPC_occ	$T_{local}, H_{local}, P_{PV}, P_{elec}$	$T_{RM}/T_{local}, H_{local}, Occ, \dot{V}_{SA}, T_{SA}$	$Occ/T_{RM,SP}$
MPC_sat	$T_{local}, H_{local}, P_{PV}, P_{elec}$	$T_{RM}/T_{local}, H_{local}, \dot{V}_{SA}, T_{SA}$	$Ope/T_{RM,SP}, T_{SA,SP}$
MPC_airport	$T_{airport}, H_{airport}, P_{PV}, P_{elec}$	$T_{RM}/T_{airport}, H_{airport}, \dot{V}_{SA}, T_{SA}$	$Ope/T_{RM,SP}$

Evaluation metrics

- Self-consumption $$SC = \frac{E_{locally\_consumed}}{E_{PV}}$$
- Self-sufficiency $$SS = \frac{E_{locally\_consumed}}{E_{total}}$$



MPC_main performance: typical behavior

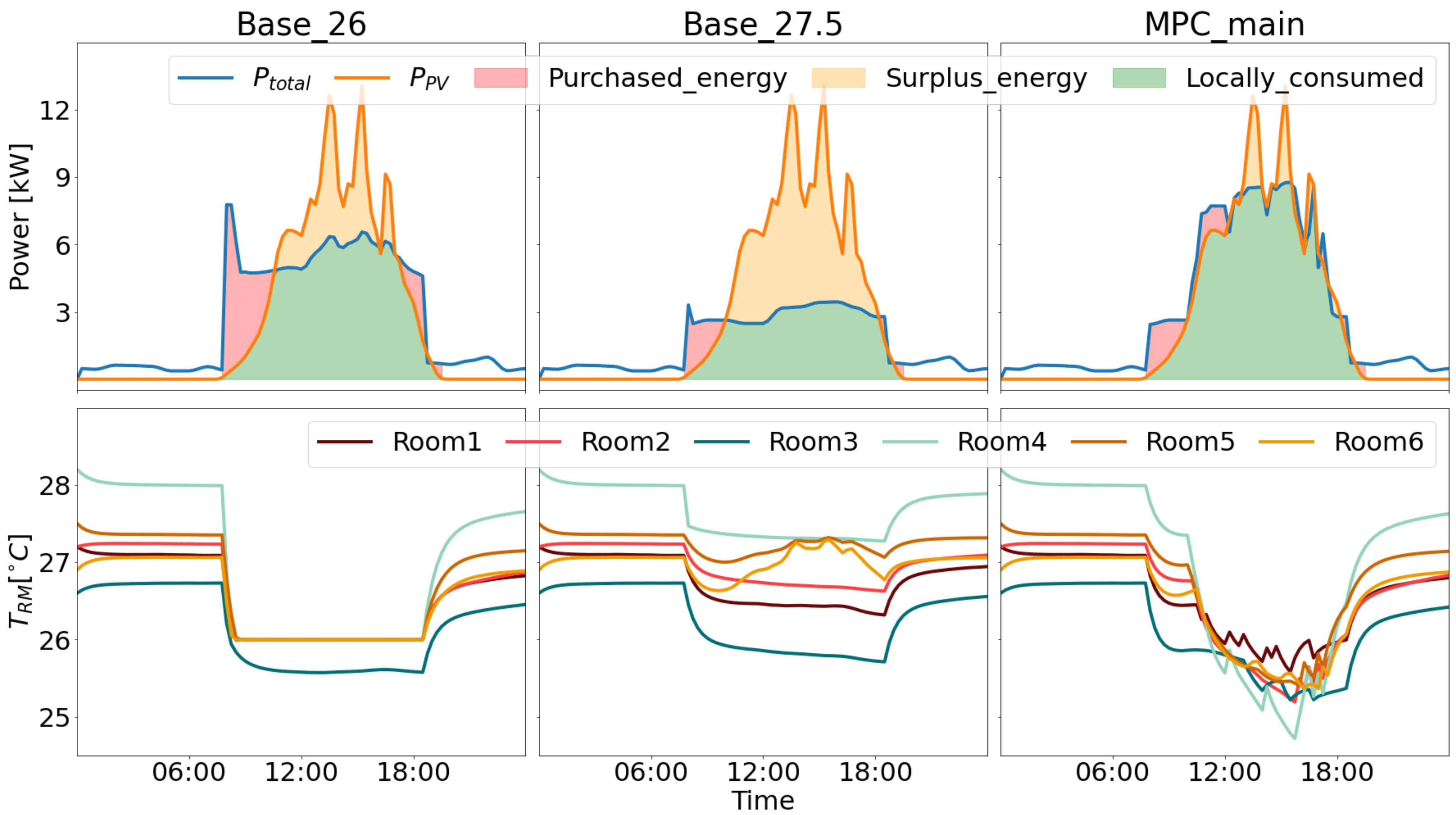
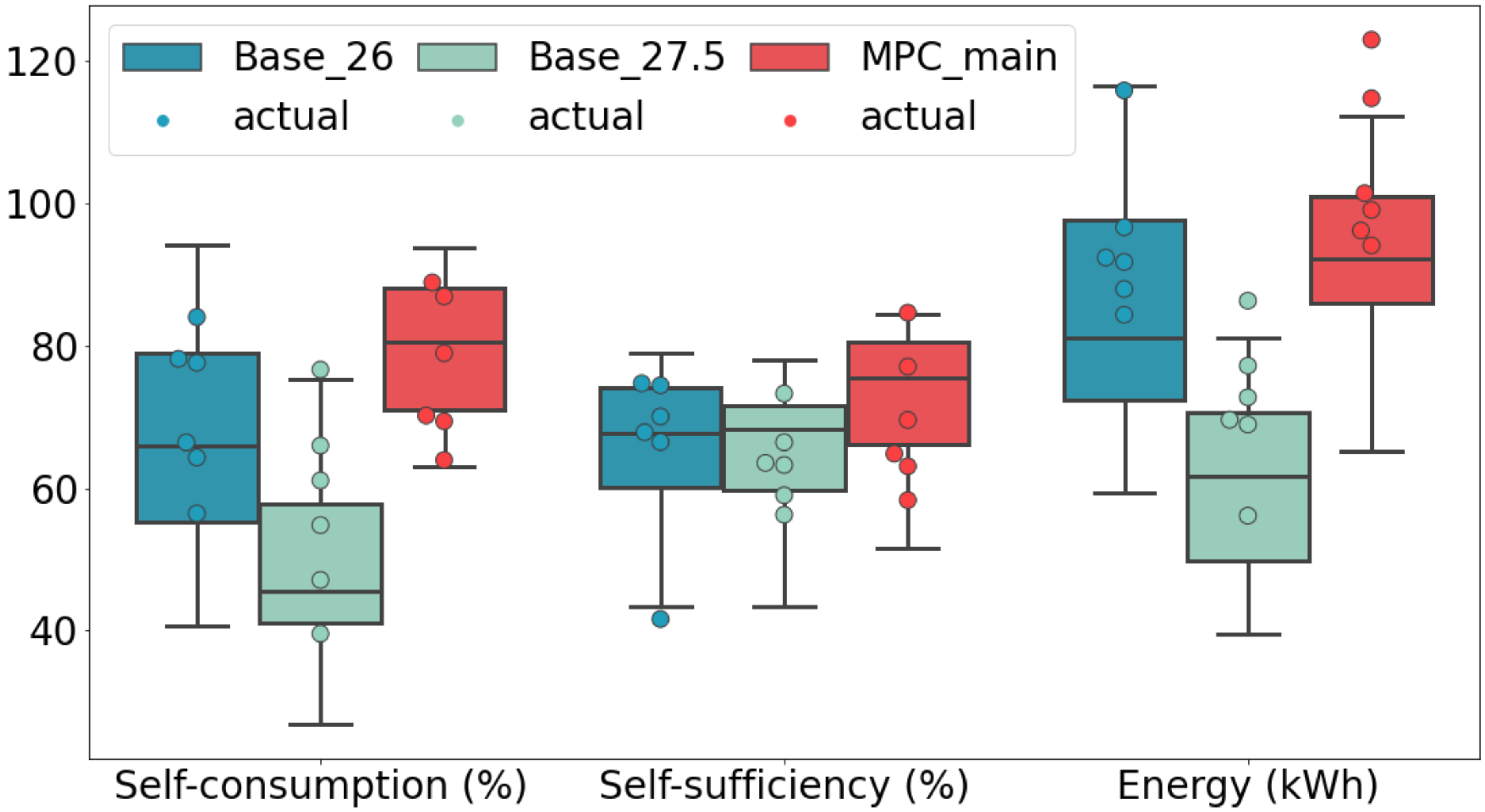


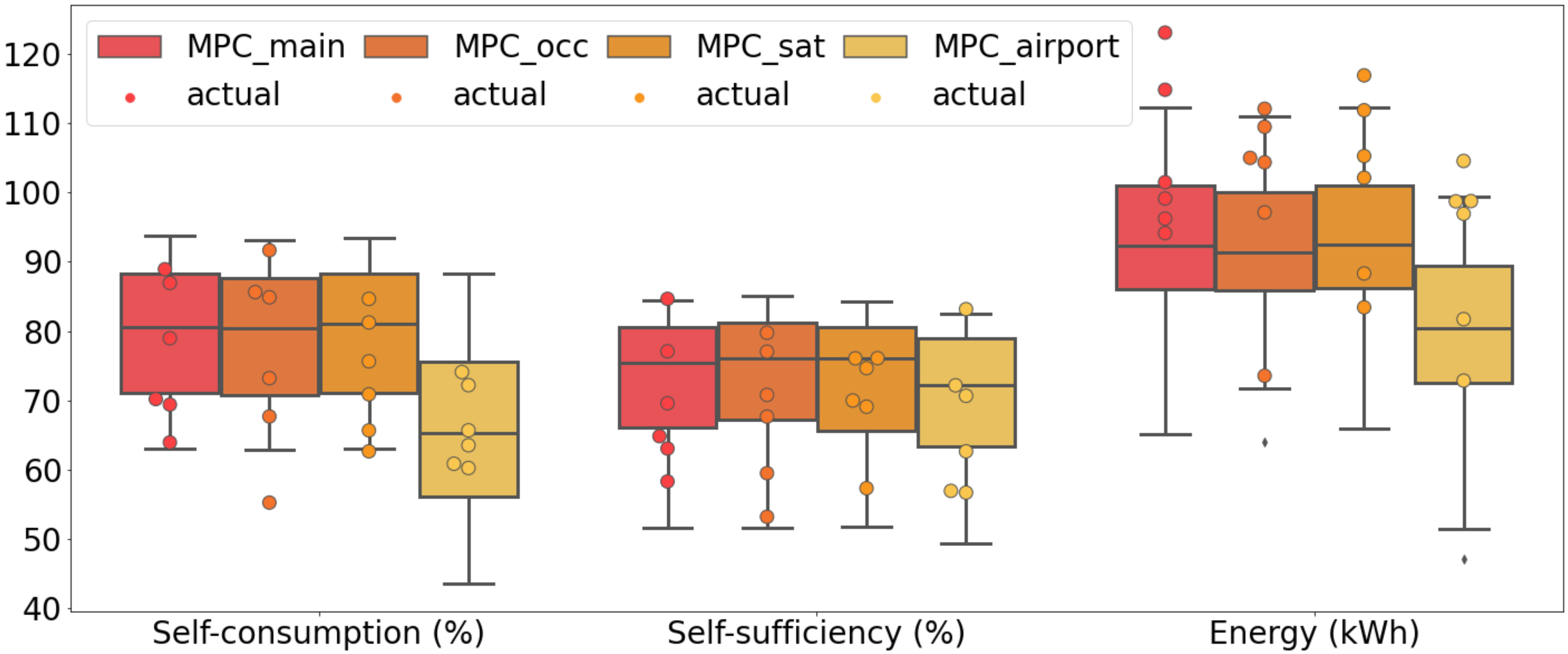
Figure: simulation results of two baselines and MPC_main on a typical day

MPC_main performance: evaluation metrics



Compared with 26°C: SC improved by 19.5%, SS improved by 10.6%

Comparing alternative data availability



Discussion

- The MPC framework successfully leveraged energy flexibility, improving the PV self-consumption and building self-sufficiency
- Physical systems set the upper bound of control performance, data availability determines the actual performance
- Data as the fuel: towards data-centric digital twins

Thank you!

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