

Model Predictive Control in Buildings: from Model-Centric to Data-Centric

Sicheng (James) Zhan

szhan@nus.edu.sg



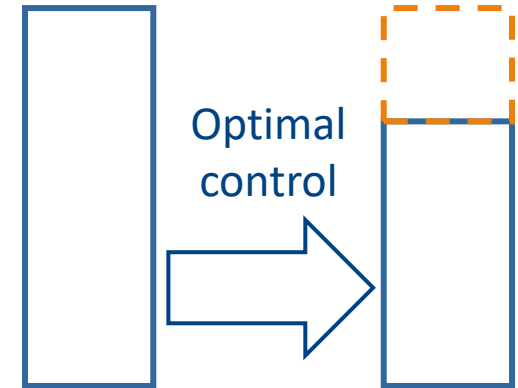
The need of optimal control in buildings



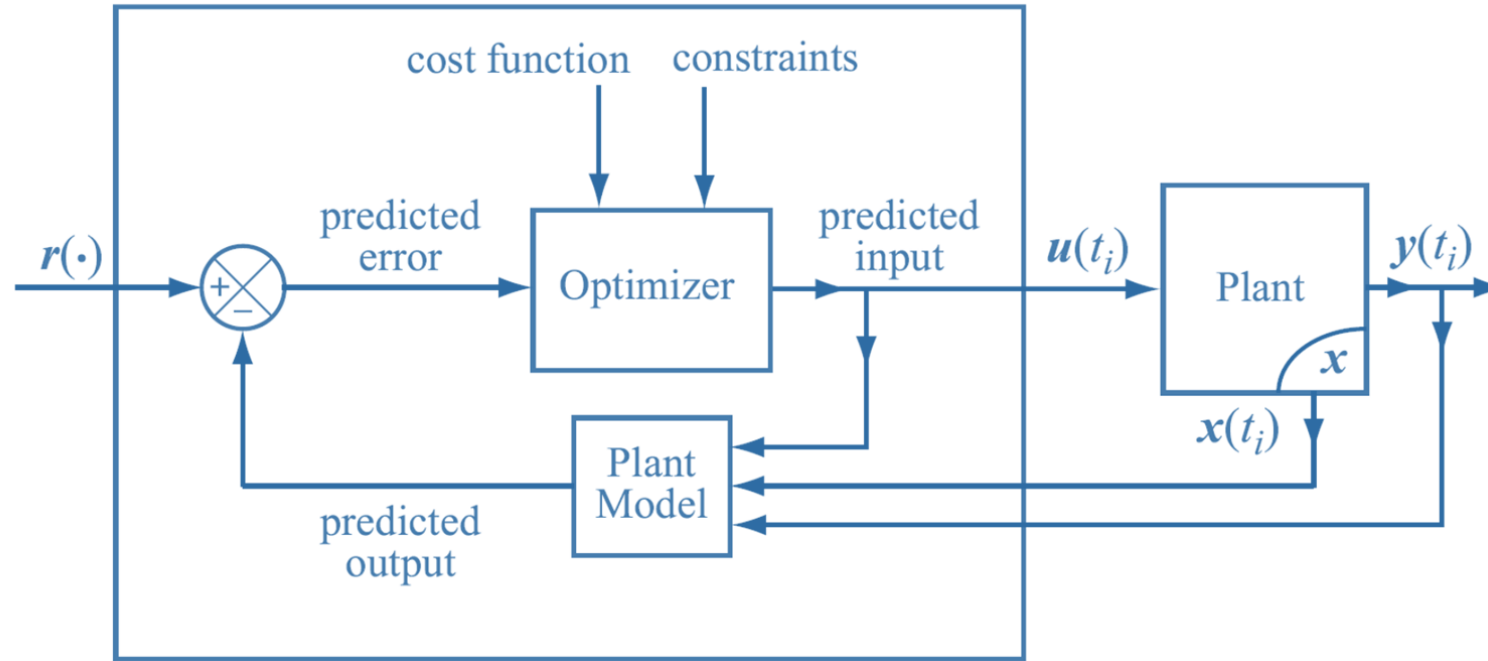
Buildings contribute **30-40%** global GHG emission and energy consumption, where **~90%** is consumed in the operation phase



Buildings take up **~50%** of electricity consumption in Singapore, where **50-70%** goes to Air-conditioning & Mechanical Ventilation (ACMV) systems



Generally, **~30%** of energy saving can be expected by applying optimal control (**10-20% in the tropics**)



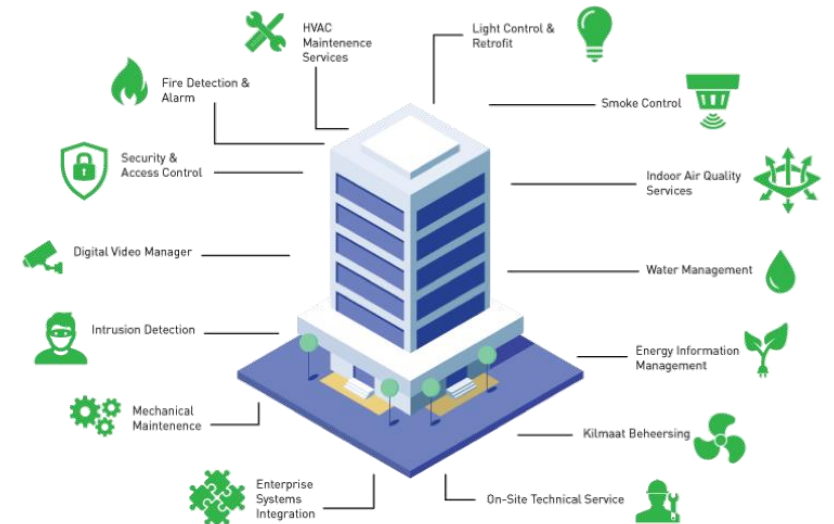
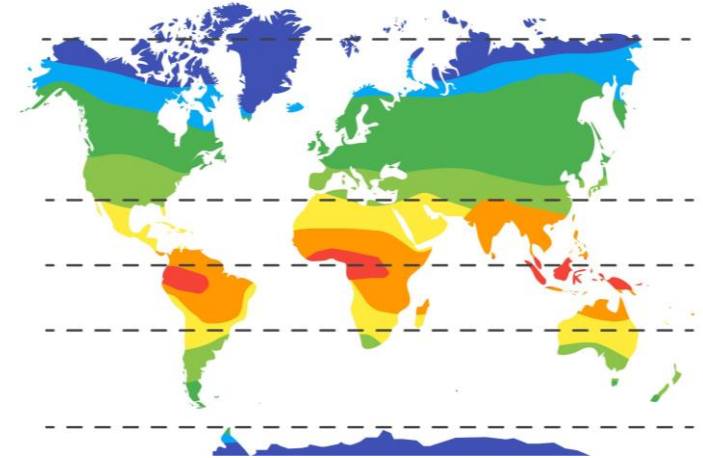
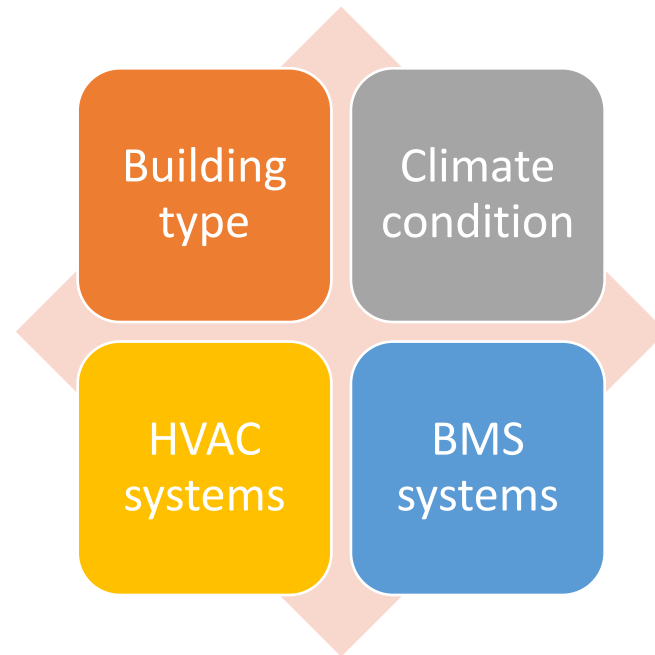
Model predictive control

in buildings

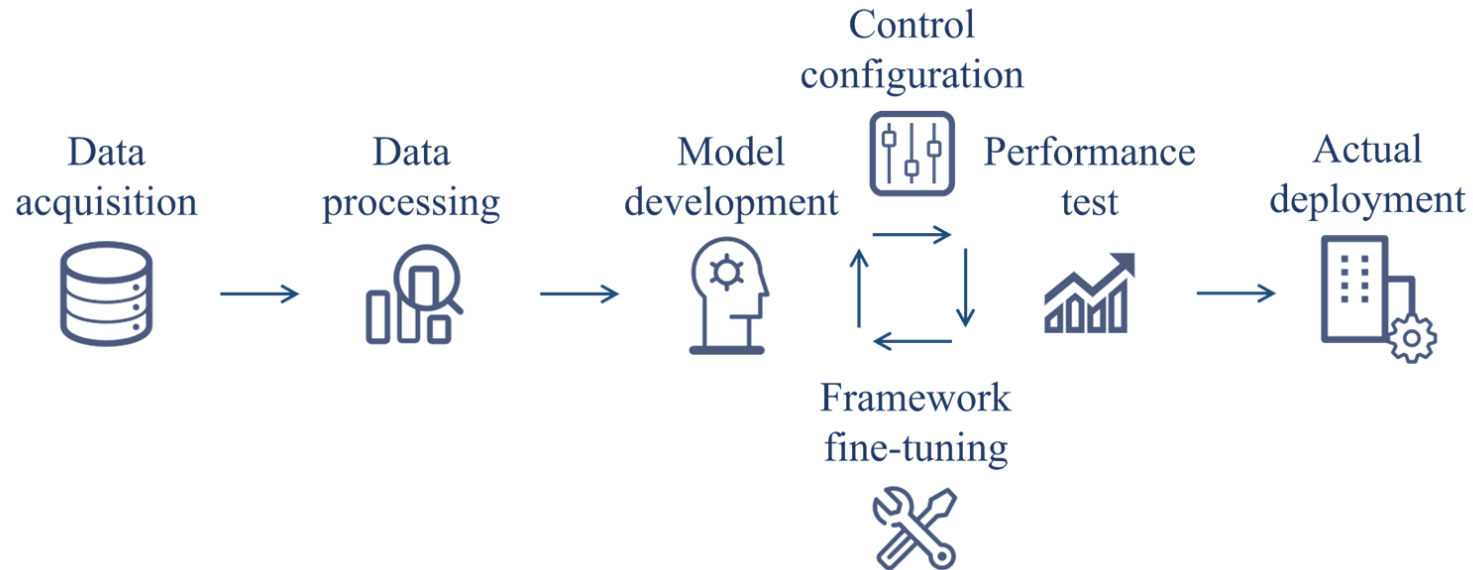
- ✓ Well-established optimal control framework
- ✓ Successfully implemented in places such as industrial process control

- Research since the 90s
- >70% studies were simulation
- >60% studies less than 5 zones
- Why?

Heterogeneity across buildings



Model-centric/data-driven configuration procedure

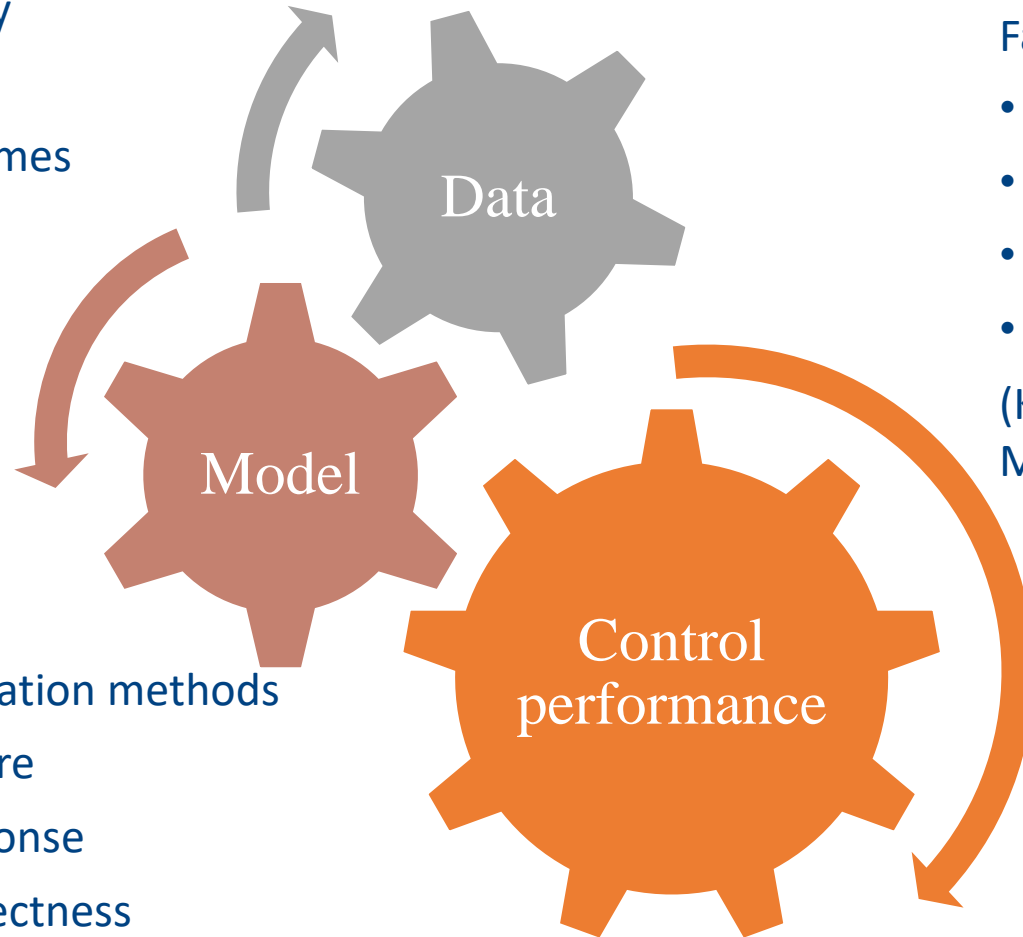


- Work with the given data
 - New models developed in each study
 - White/gray/black box models
 - Expert-driven procedure to be repeated every time
- x Ungeneralizable experimental results
 - x Key data points missing, many unused
 - x Unpredictable implementation cost and control performance

Unclear relationships between data, model, and control

Prediction accuracy

- Metrics
- Prediction schemes
- Testing data



Other model evaluation methods

- Physical structure
- Frequency response
- Parameter correctness

(Picard et al. 2017, Lin et al. 2012 , Reynders et al. 2014)

Unknown before implementation

Factors affecting the control performance

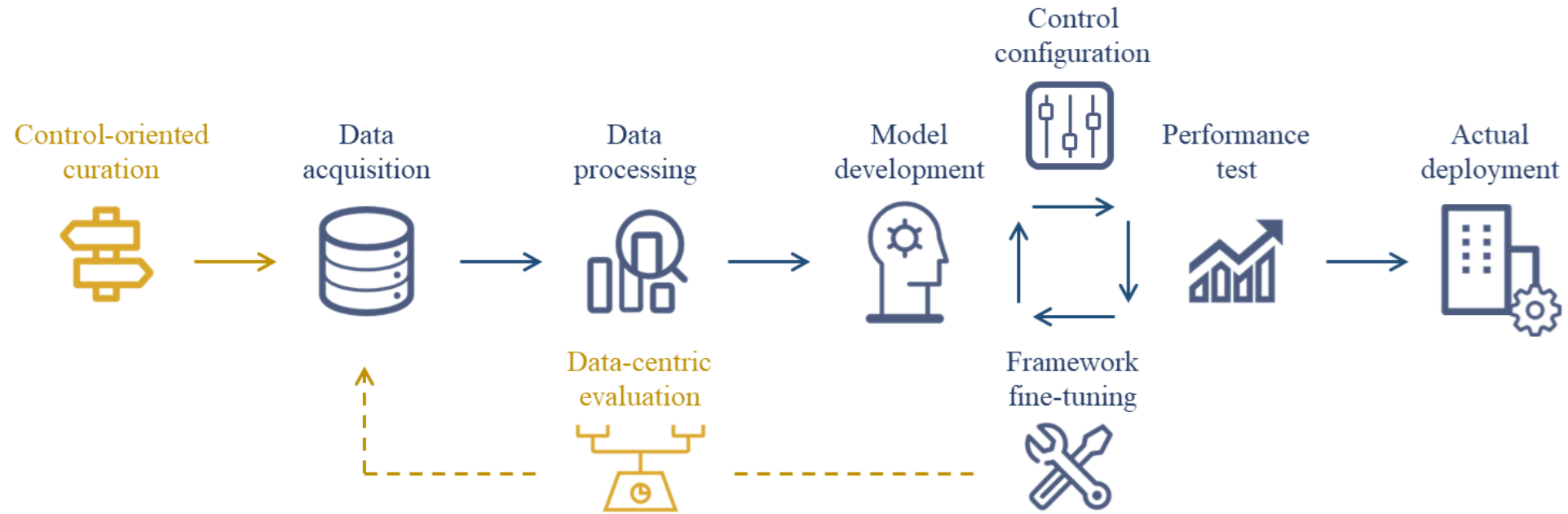
- Model quality
- Building characteristics
- Ambient conditions
- Control formulation

(Kavgic et al. 2015, Sturzenegger et al. 2015, Maasoumy et al. 2014, Ma et al. 2014)

Interrelated factors require explicit experiments to isolate the effect of data and model

Buildings have potential, and data decides how much can be realized.

Data-centric MPC research framework



Control-oriented curation



- Data acquisition based on the need of control scenario

Data-centric evaluation



- Well-designed experiments conducted to support control-oriented curation for one kind of control scenario

Virtual and actual testbed



Emulation model

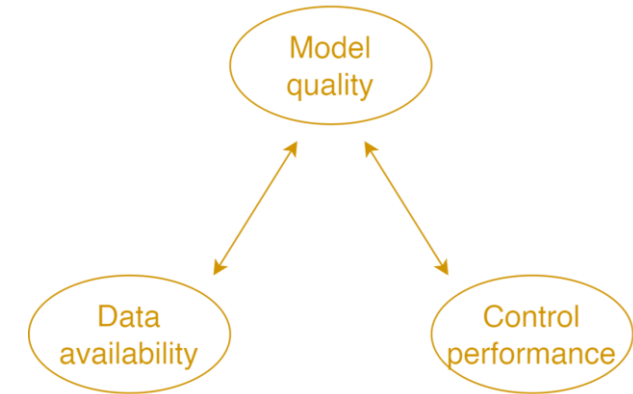
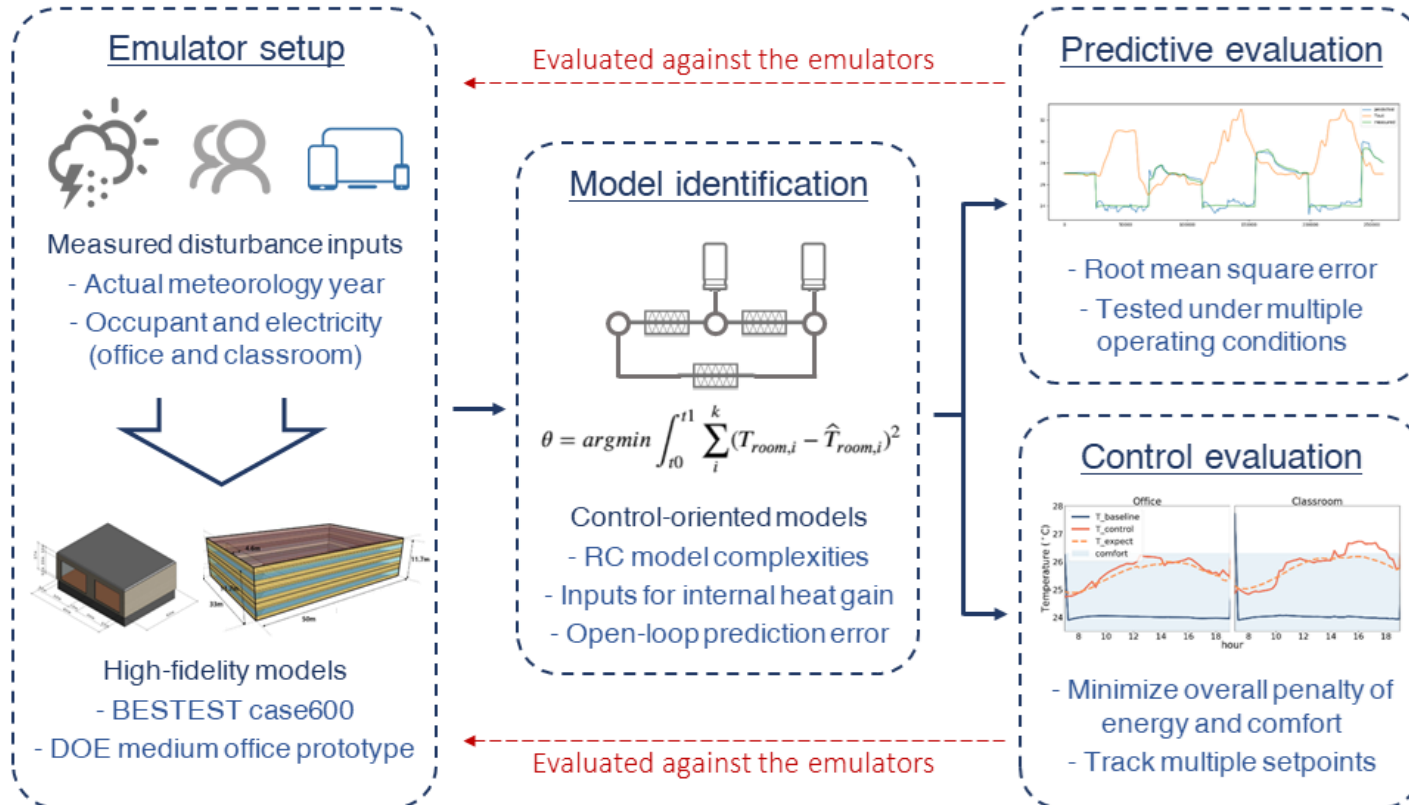
- Lower experimental costs
 - **Full flexibility** of experimental design
- All variables attainable

Actual building

- Real-world implementation
 - Realistic disturbances
 - Occupant in the loop



Impact of occupant-related data

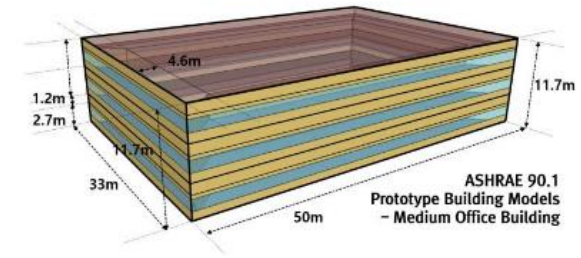
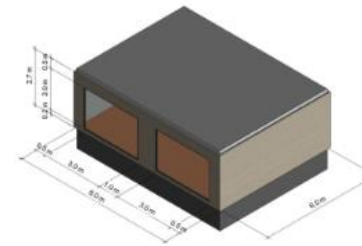


- How data inputs interact with model complexity and affect the performance through identification
- Occupant-related data as the primary focus

Emulator configurations

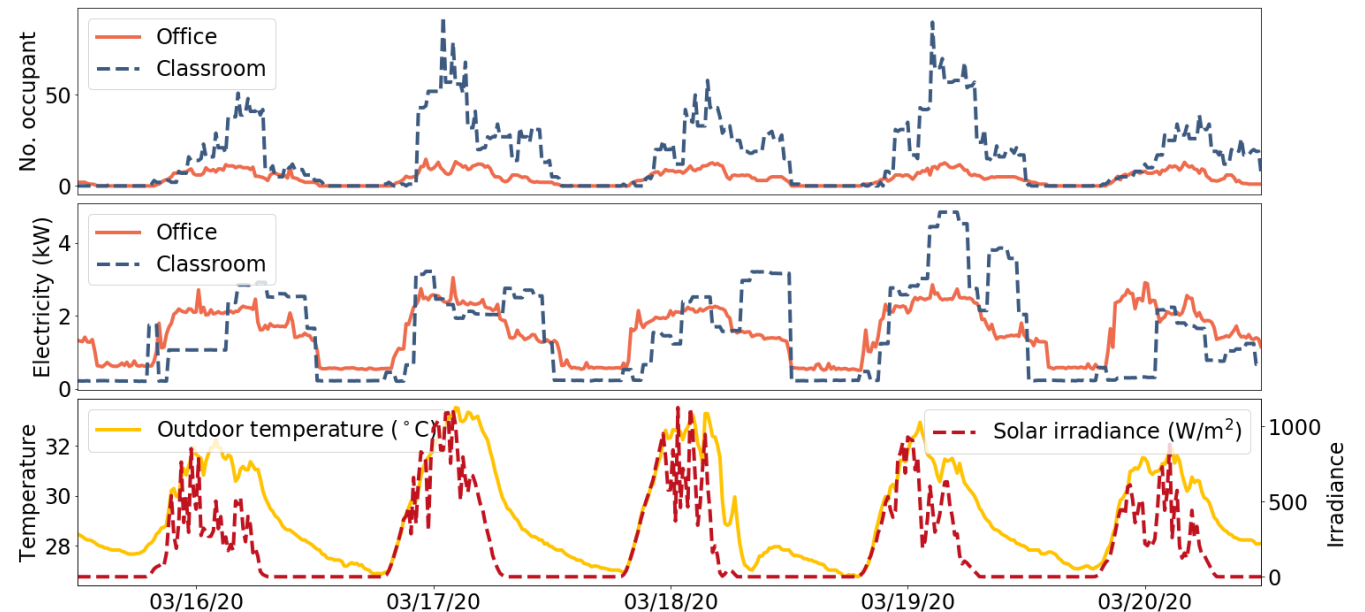
Single-zone experiment

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

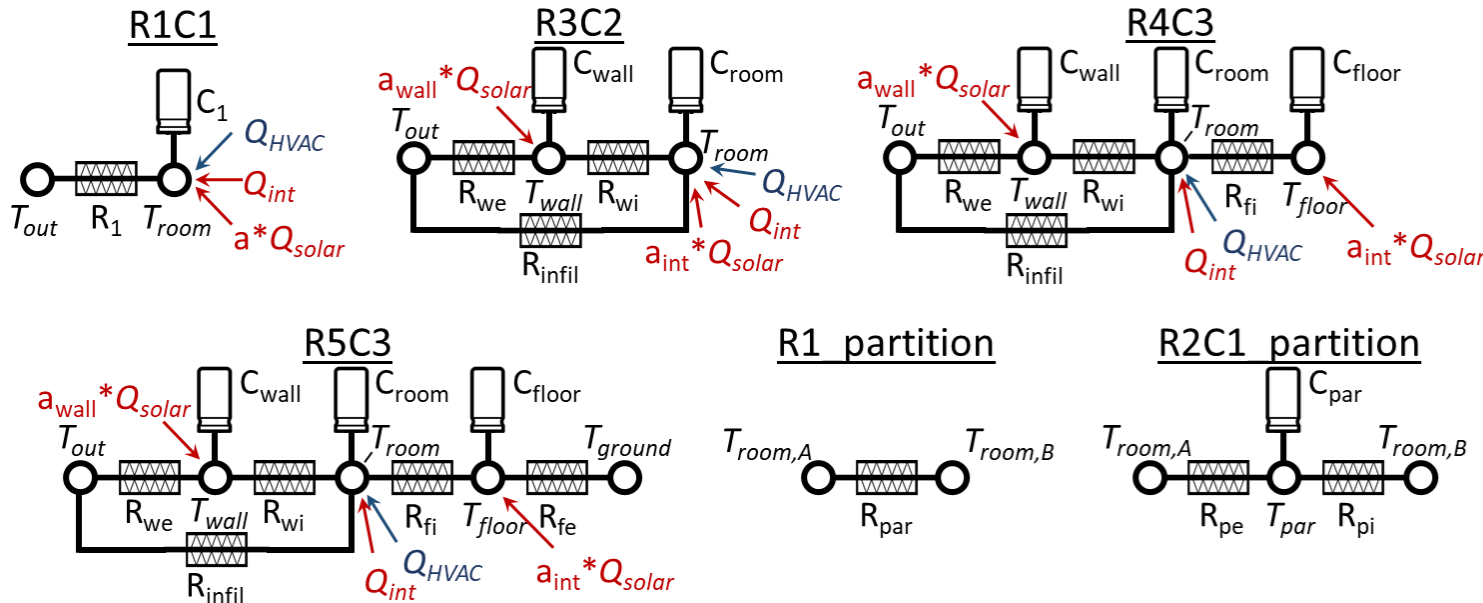


Multi-zone experiment

- A floor of DOE medium office (5 zones, VAV)
- Internal disturbance profiles randomly sampled for each room on each day



RC model identification



- Increasing RC model complexity
- 6 alternative inputs for occupant-related disturbances
 - none, schedule, plug, CO₂, plug+CO₂, ideal
- Identified with the same dataset through non-linear programming

$$\theta = \operatorname{argmin} \int_{t_0}^{t_1} \sum_i^k (T_{room,i} - \hat{T}_{room,i})^2 dt$$

$$s.t. \quad \hat{T}_{room} = f(x, u, d, \theta)$$

$$\theta^{lb} \leq \theta \leq \theta^{ub}$$

- 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



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

s.t. $0 \leq m_{flow,i} \leq m_{flow,norm}$
 $-0.5 \leq PMV_i \leq 0.5$



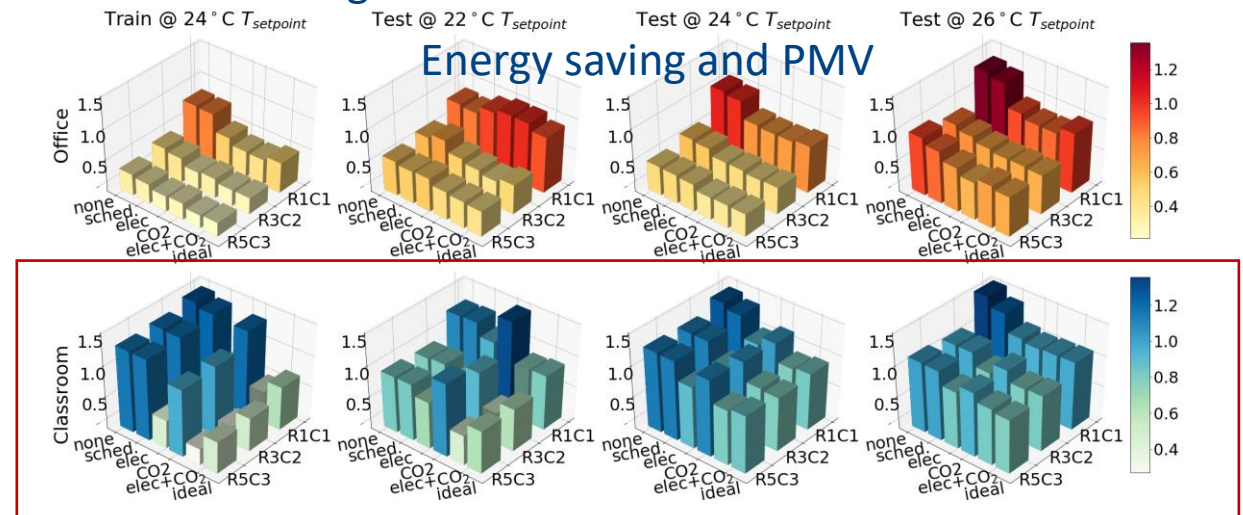
$$J = \int_{t_0}^{t_0+30min} \sum_i^k (T_{room,i} - T_{setpoint,i})^2 dt$$

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

Impact of internal disturbance data

- More impactful in the classroom scenarios than in offices
 - Larger portion of internal gain, higher variability, and more irregular patterns
- The performance of balancing energy and comfort not affected
 - Deviations corrected every step by the state feedback
- Design **schedule** is typically sufficient for offices
 - Model complexity as a more important factor

Average RMSE of alternative RC models

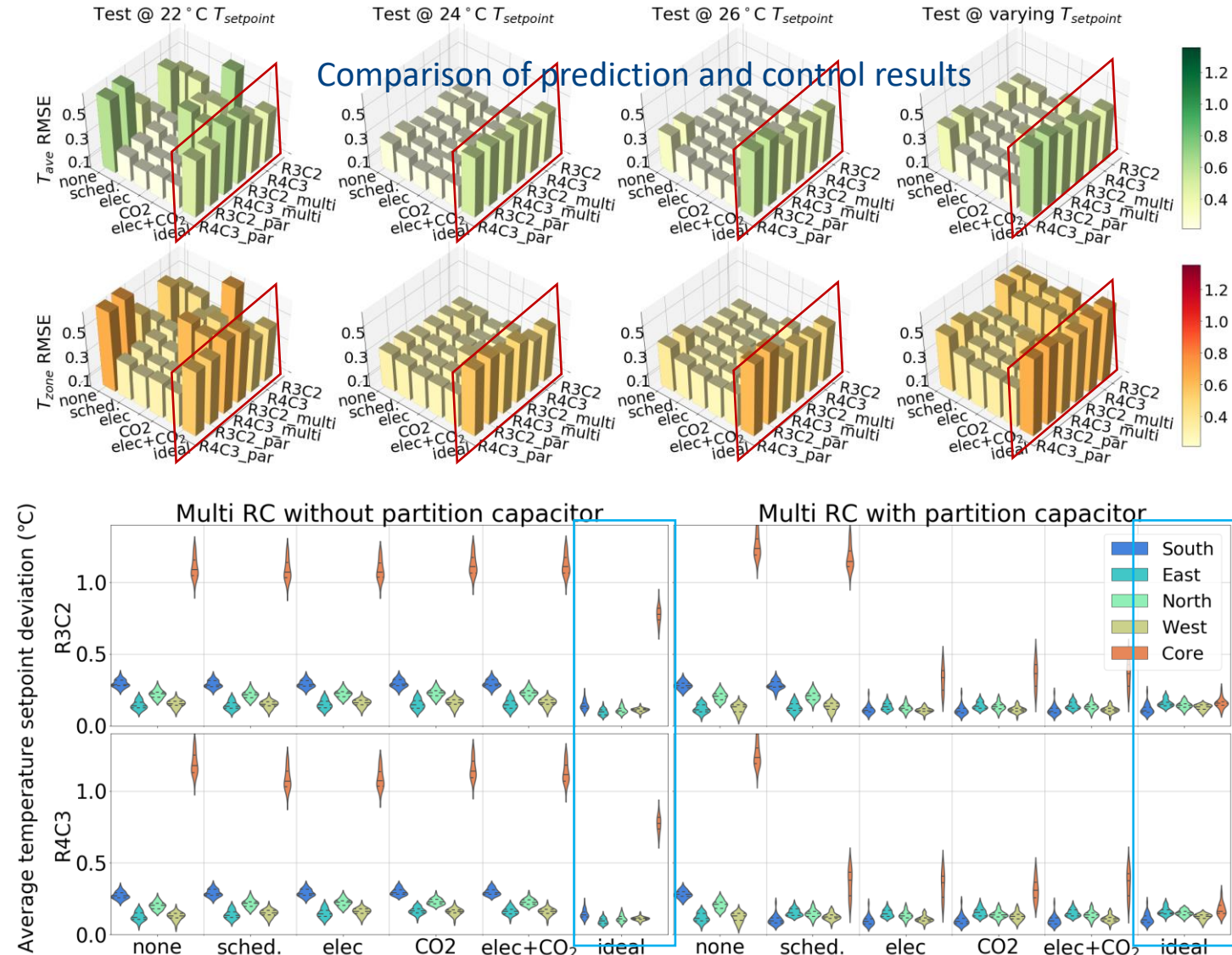


Temperature deviations in control



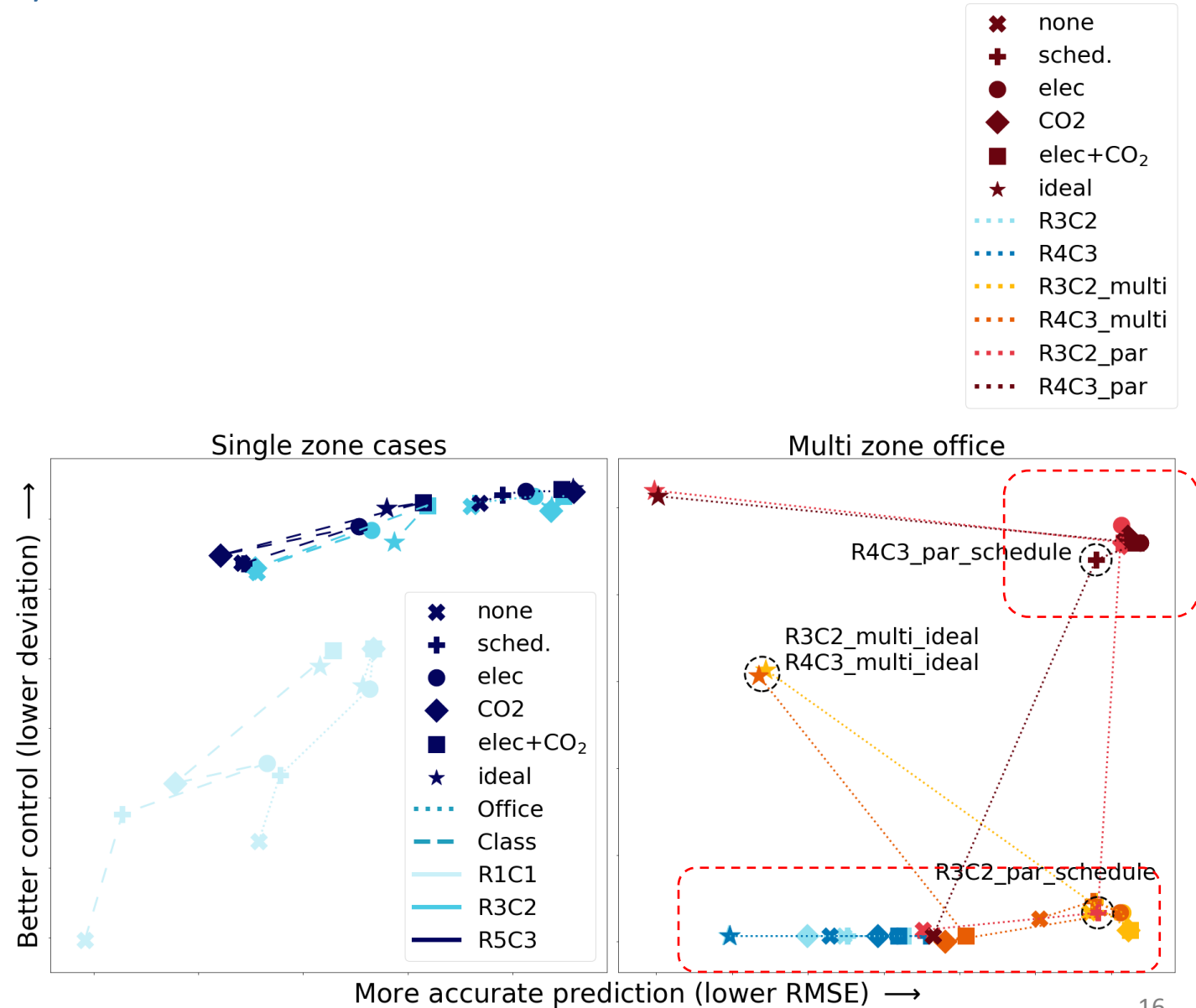
Mismatch between model and control performance

- Different story about the quality of RC model with ideal input
 - Same conclusion with other evaluation metrics tested
- The identification underestimate partition capacitor for lower RMSE
 - **Not** detected by prediction tests
 - Prevented by the ideal input as a constraint of optimization
- The **predictive and control** capability of control-oriented models should be carefully examined

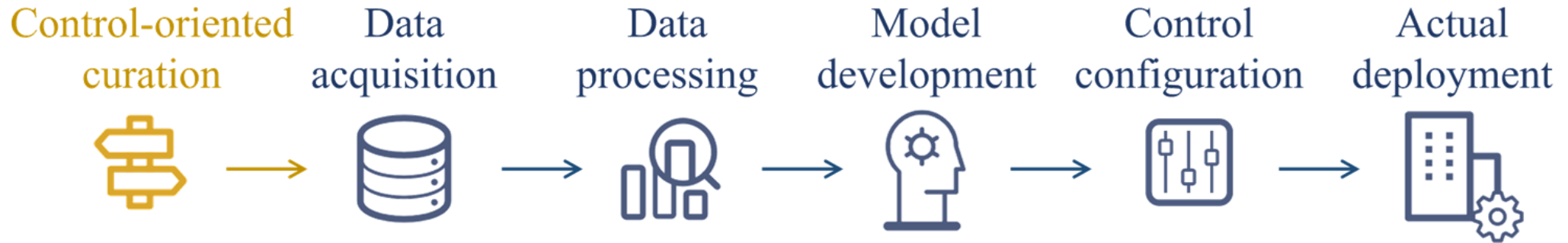


Model adequacy and data informativeness

- Better control is the ultimate goal
 - Unknown in practice until field implementation
 - Lack of robust indicator
- 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)



Data-centric configuration procedure



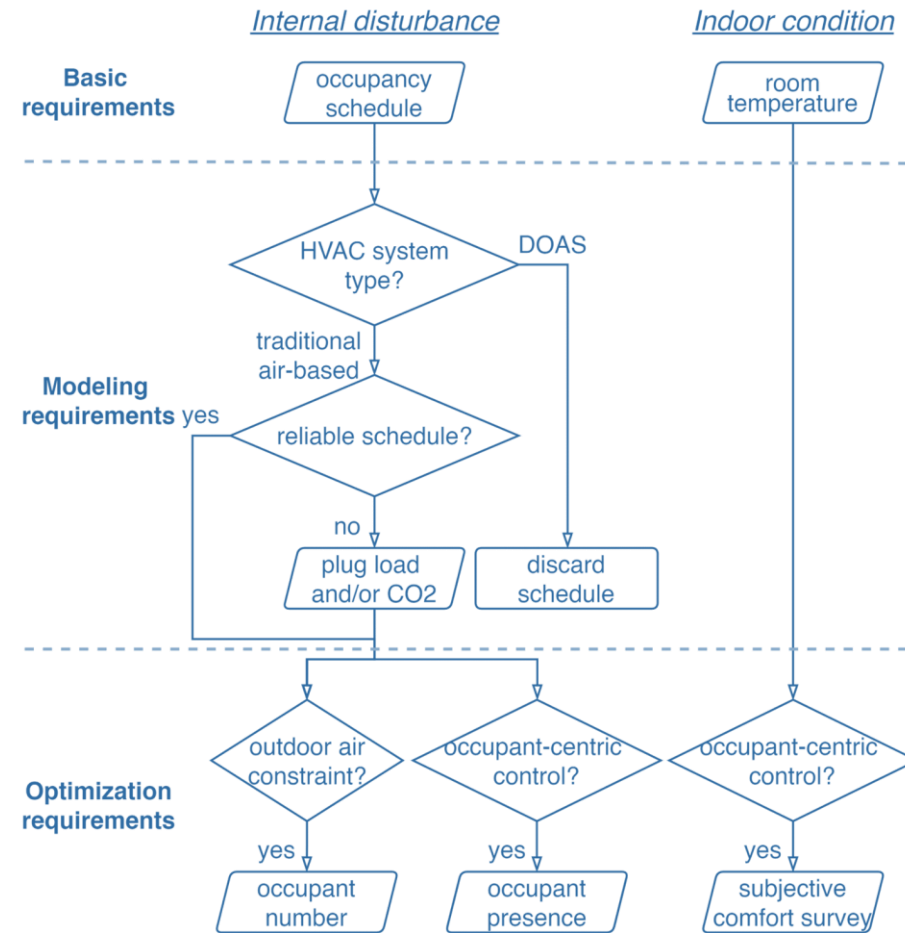
- Systematically acquire data according to the control scenario
- Performance decided by data availability
- Smoother model and control configuration
- Reproducible for a certain type of buildings

Control-oriented data curation

Control-oriented curation



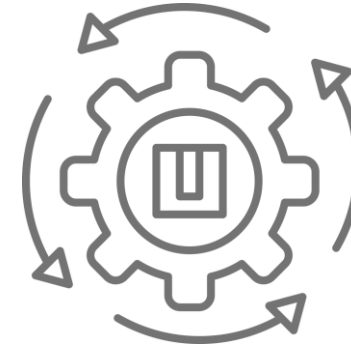
- Data acquisition based on the need of control scenario
- Established relationship between data and performance



Ongoing work



Absolute quantification of
data informativeness



Automation of active
data acquisition

Thank you!