Quantitative Comparison of Data-Driven and Physics Based Models for Commercial Building HVAC Systems

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Background

Energy Consumption of Buildings

- $\approx 40\%$ of total energy consumption in developed countries[1]
- HVAC Systems are major source of this consumption

Frequency Regulation and Demand-Side Management

- Use *elasticity* of buildings' energy consumption
- Exploit inherent thermal inertia to shift consumption in time
- Aggregate buildings thermal capacities to offer as ancillary service in energy markets[2]

Models for Temperature Evolution

- Traditionally: High-dimensional, physics-based models
  - Resistance-Capacitance Models[3]
  - TRNSYS[4], EnergyPlus[5]
- New approach: Lower-dimensional, purely data-driven models
  - Semi-parametric regression[6]

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Identifying Temperature Dynamics

Goals

- Identify a state-space model amenable to HVAC control:

$$x(k+1) = Ax(k) + Bu(k) + Cv(k) + q_{IG}(k) + \epsilon(k)$$

- $q_{IG}(k)$: Internal gains due to occupancy and electric devices
- Estimate $q_{IG}(k)$ from one year of temperature data of the 4th floor of SDH
  - Daily Variation?
  - Seasonal Variation?
- Implement energy-efficient controller based on identified state space model
- Testbed: 4th floor of Sutardja Dai Hall, UC Berkeley office building

Methodology

1. Simple, low-dimensional model:
   Semiparametric Regression
2. Complex, high-dimensional, physics-based model:
   Resistance-Capacitance

How do the models compare to each other?

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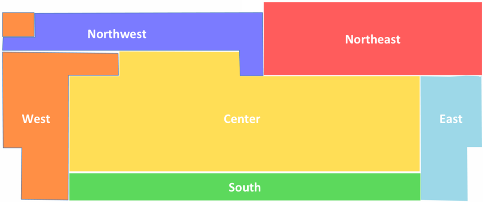

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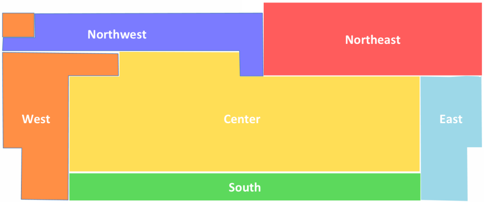

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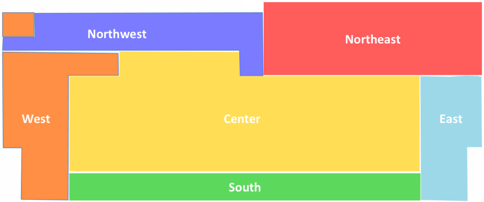

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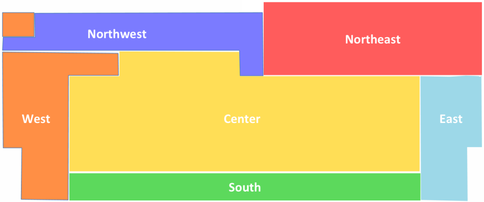

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Model 1: Semiparametric Regression

Lumped Zone Model

- Discrete time state space model:

$$x(k+1) = ax(k) + bu(k) + c^\top v(k) + q_{IG}(k) + \epsilon(k) \tag{1}$$

- v is vector of *known disturbances*: Ambient air temperature, HVAC supply air temperature, solar radiation (4 cardinal directions)
- *Smoothing* of (1) yields

$$x(k+1) - \hat{x}(k+1) = a(x(k) - \hat{x}(k)) + b(u(k) - \hat{u}(k)) + c^\top(v(k) - \hat{v}(k)) + \epsilon(k)$$

- Coefficients a, b, c can be found with linear regression, using an additional prior:

$$\begin{aligned}(\hat{a}, \hat{b}, \hat{c}) = \arg\min_{a,b,c} \;\; & (J_\mathcal{F} + J_\mathcal{W} + J_\mathcal{S}) + \|\Sigma_a^{-1/2}(a - \mu_a)\|^2 + \|\Sigma_b^{-1/2}(b - \mu_b)\|^2 \\ \text{s.t. } & J_\mathcal{X} = \textstyle\sum_{i \in \mathcal{X}} \|x_i(k+1) - \hat{x}_i(k+1) - a\left(x_i(k) - \hat{x}_i(k)\right) \\ & \quad - b\left(u_i(k) - \hat{u}_i(k)\right) - c^\top\left(v_i(k) - \hat{v}_i(k)\right)\|^2 \\ & \text{for } \mathcal{X} \in \{\mathcal{F}, \mathcal{W}, \mathcal{S}\}, \; 0 < a < 1, \; b \le 0, \; c \ge 0.\end{aligned} \tag{2}$$

- Collect observational data from fall ($\mathcal{F}$), winter ($\mathcal{W}$), spring ($\mathcal{S}$) period
- Insuffcient excitation of SDH motivates use of Bayesian priors
  - μ_a from (2) without priors
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Model 1: Semiparametric Regression (cont'd.)

Individual Zone Model

- Discrete time state space model:

$$x(k+1) = Ax(k) + Bu(k) + Cv(k) + q_{\mathrm{IG},\mathcal{X}}(k) \text{ for } \mathcal{X} \in \{\mathcal{F}, \mathcal{W}, \mathcal{S}\} \tag{3}$$

- Newton's Law of Cooling:

$$A_{ij} = \begin{cases} \neq 0, & \text{if } i = j \text{ or } (i,j) \text{ adjacent} \\ 0, & \text{otherwise.} \end{cases}$$

Model 1: Semiparametric Regression (cont'd.)

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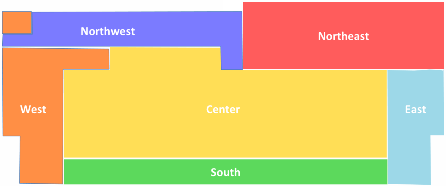

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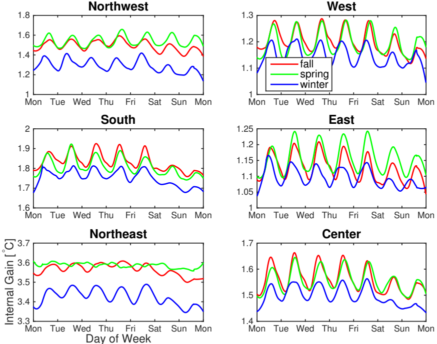
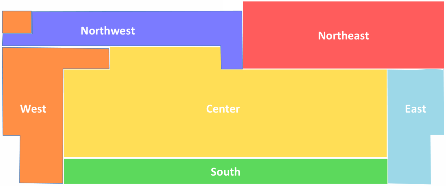
Optimization Results





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Model Setup

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$$y = Cx(k)$$

- $x \in \mathbb{R}^{289}$ represents temperatures of building walls, ceilings, floors, zone air
- $y \in \mathbb{R}^{6}$ represents average zone temperatures

Two Step Parameter Estimation[7]

1. Set $f_{IG}(k) \equiv 0$ in (4) to estimate A, B_v, B_{xu_i}, B_{vu_i}
   - Use Kalman Filter to estimate unmeasurable states (wall, ceiling, floor temperatures)
2. Identify internal gains $CB_{IG} f_{IG}(k)$

[7] Q. Hu et al. "Model Identification of Commercial Building HVAC Systems During Regular Operation - Empirical Results and Challenges". In: *American Control Conference* (2016), pp. 605–610.

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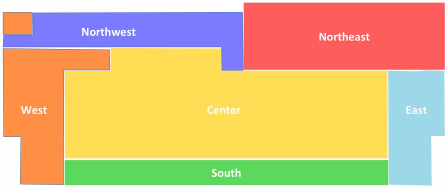

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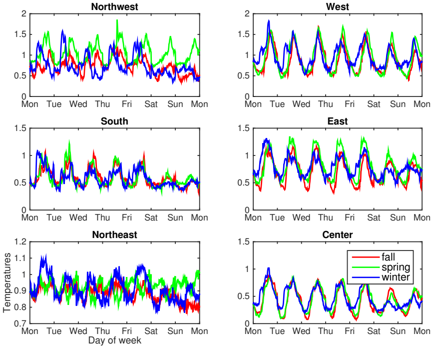

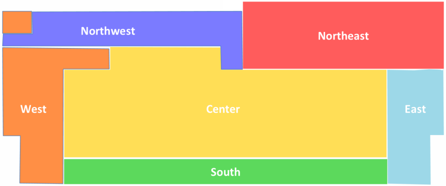

Comparison of Models

Prediction Accuracy

Root Mean Square Error:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left[\bar{x}(k) - x(k)\right]^2}$$

Data-Driven Model							
Season	NW	W	S	E	NE	C	Mean
Fall	0.98	0.61	0.28	0.42	0.28	0.36	0.488
Winter	1.41	0.34	0.29	0.26	0.25	0.21	0.460
Spring	0.56	0.25	0.31	0.71	0.17	0.34	0.390

Physics-Based Model							
Season	NW	W	S	E	NE	C	Mean
Fall	0.61	0.46	0.39	0.39	0.20	0.32	0.396
Winter	0.55	0.39	0.34	0.32	0.18	0.24	0.338
Spring	0.45	0.28	0.24	0.33	0.09	0.19	0.263

- Physics-Based Model (M2) more accurate than data-driven model (M1)
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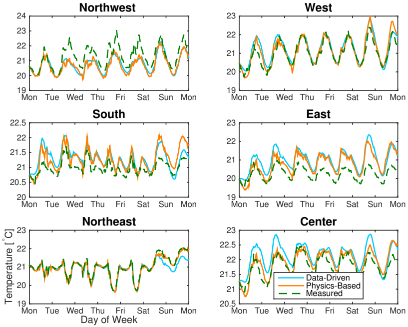

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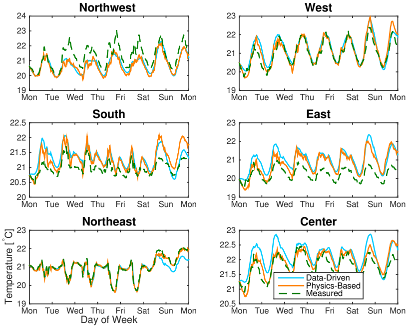

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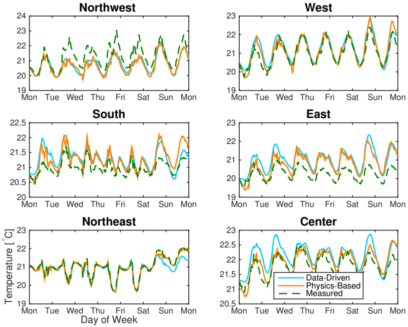

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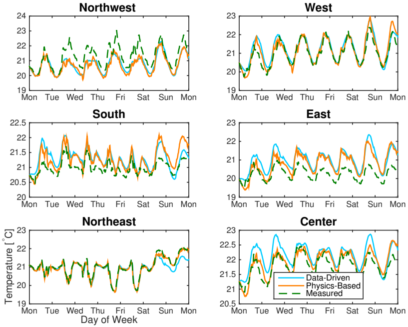

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Comparison of Models (cont'd.)

Model Predictive Control for Energy Efficiency

- Use state space models in energy efficient control scheme

$$\min_{u,\varepsilon} \sum_{k=1}^{N} u(k)^2 + \rho\|\varepsilon\|_2$$

$$\text{s.t. } x(0) = \bar{x}(0)$$

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- Soft constraints on VAV flow
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&\min_{u,\varepsilon} \sum_{k=1}^{N} u(k)^2 + \rho\|\varepsilon\|_2 \\
&\text{s.t. } x(0) = \bar{x}(0) \\
&\quad x(k+1) = \begin{cases} Ax(k) + Bu(k) + Cv(k) + q_{IG}(k), & \text{M1} \\ Ax(k) + B_v v(k) + B_{IG} f_{IG}(k) + \sum_i (B_{xu_i} x(k) + B_{vu_i} v(k)) u_i(k), & \text{M2} \end{cases} \\
&\quad u_{\min} - \varepsilon \leq u(k) \leq u_{\max} + \varepsilon \qquad \forall k \in [0, N-1] \\
&\quad \begin{cases} T_{\min} \leq x(k) \leq T_{\max}, & \text{M1} \\ T_{\min} \leq Cx(k) \leq T_{\max}, & \text{M2} \end{cases} \quad \forall k \in [1, N]
\end{aligned}
$$

- Soft constraints on VAV flow
- Comfort bounds: $T_{\min} = 20^{\circ}\mathrm{C}$, $T_{\max} = 22^{\circ}\mathrm{C}$[8]
- Strategy: Use control effort only when "close" to comfort bounds

[8] Shirley J. Hansen and H.E. Burroughs. *Managing Indoor Air Quality*. Lulu Press, Inc., 2013.

Comparison of Models (cont'd.)

Simulation Results

- Set up MPC with prediction horizon $N = 3$
- Simulate 7 days without state feedback

- Very similar performance in terms of control cost
- If state feedback employed, expect differences between M1 and M2 to become minor
- M1 fast (5 minutes), M2 slow (20 hours) on 2 GHz Intel Core i7, 16 GB MHz DDR3

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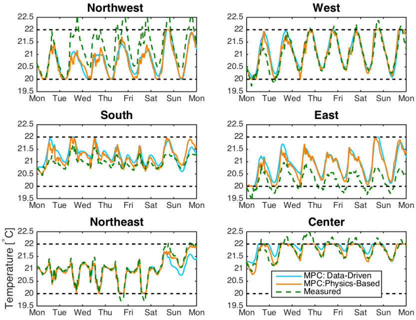
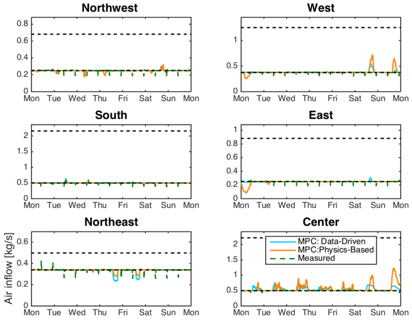


Figure: Temperature profiles



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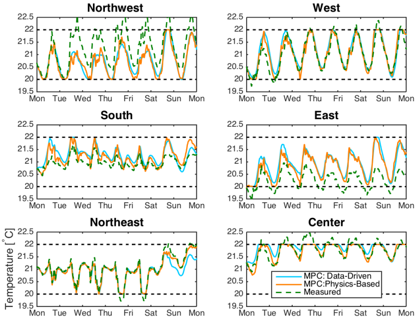

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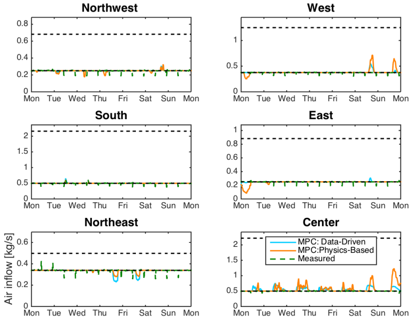

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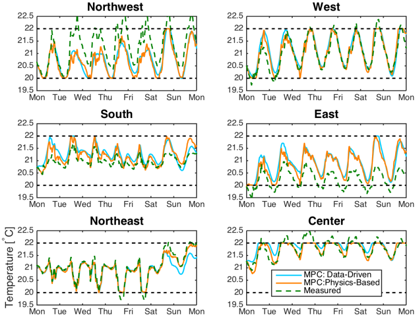

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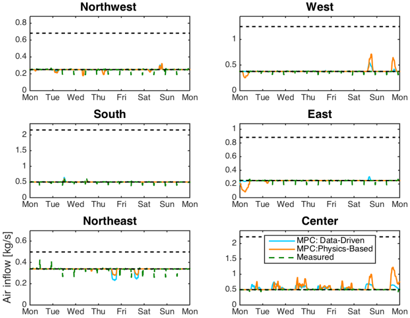

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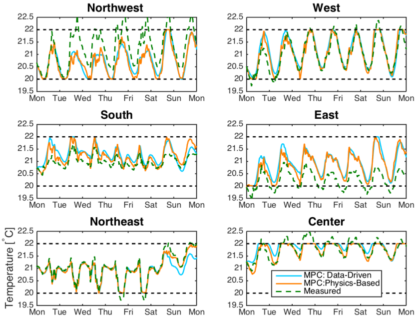

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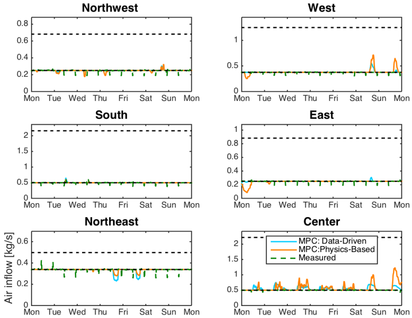

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- Model 1: Low dimensional, data-driven model (semiparametric regression)
- Model 2: High fidelity, physics-based model (BRCM Toolbox)
- Comparison of both models on the *same* testbed under *regular* operation

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- Model 1 and Model 2 yield similar control strategy
- Model 1 precise enough for most real-time control applications

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Thank You!
Questions?