Scenario-based Model Predictive Control Applied to Building Automation Systems

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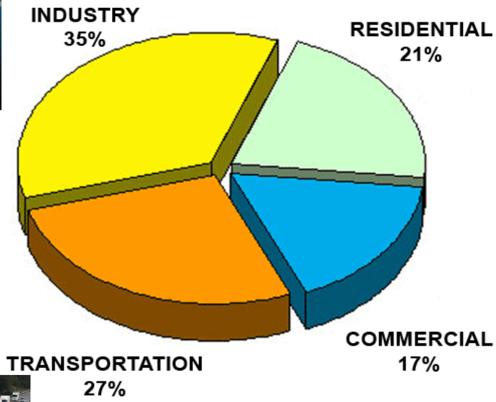
Damiano Varagnolo (Luleå TU)
Afrooz Ebadat, Marco Molinari (KTH)
Giulio Bottegal (KU Leuven)

and other collaborators

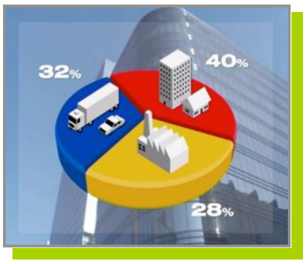
Funding sources:

Energy Consumption



US Energy Information Administration

Energy Consumption and Enabling Technologies

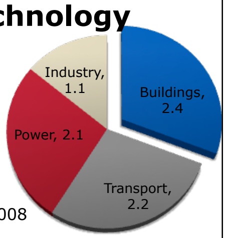


Energy consumption in Europe

- 40% of total energy use is in buildings
- 76% of building energy is for comfort

Enabling Information and Communication Technology

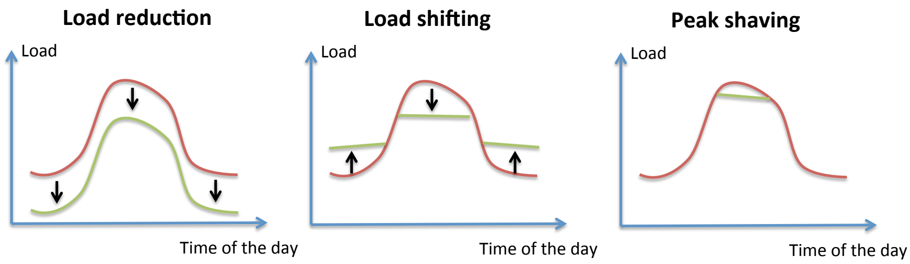
- Total energy savings of up to 15% by 2020
- Buildings can save 2.4 $GtCO_2e$
- Enormous potential for control and optimization



Energy efficiency requirements in building codes, International Energy Agency, Report, 2008

SMART 2020: Enabling the low carbon economy in the information age, The Climate Group, Report, 2008

How to Achieve Energy Efficiency?



Stockholm Royal Seaport

2010
- Oil depot
- Container terminal
- Ports
- Gas plant

2030
- 10,000 new homes
- 30,000 new work spaces
- 600,000 m2 commercial space
- Modern port and cruise terminal
- 236 hectares sustainable urban district
- Walking distance to city centre

From a brown field area to a sustainable city district

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From a brown field area to a sustainable city district

Project Goals
- CO_2 emissions <**1.5** tons per person by 2020 (today **4.5**)
- Fossil fuel-free by 2030

KTH Live-In Lab

KTH Live-in Lab

Smart living

Green living

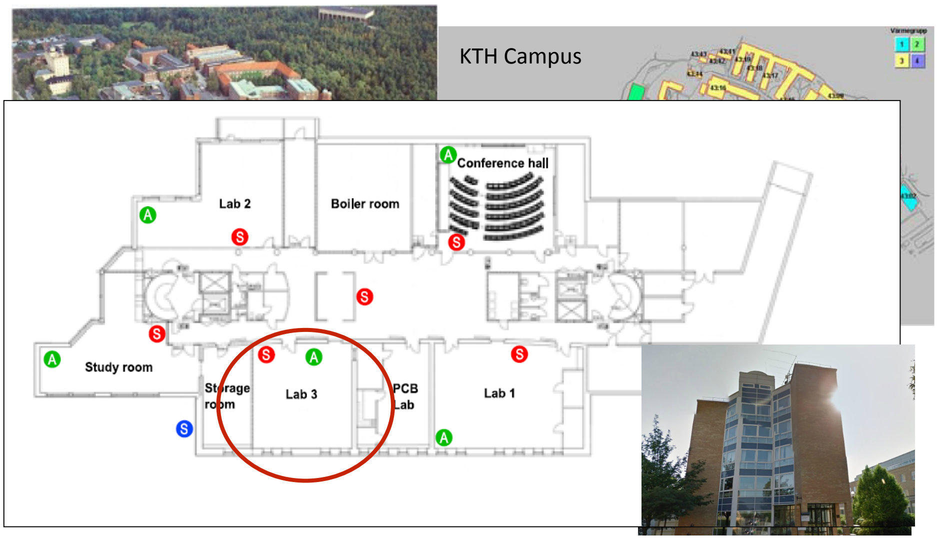
ICT living

Energy living

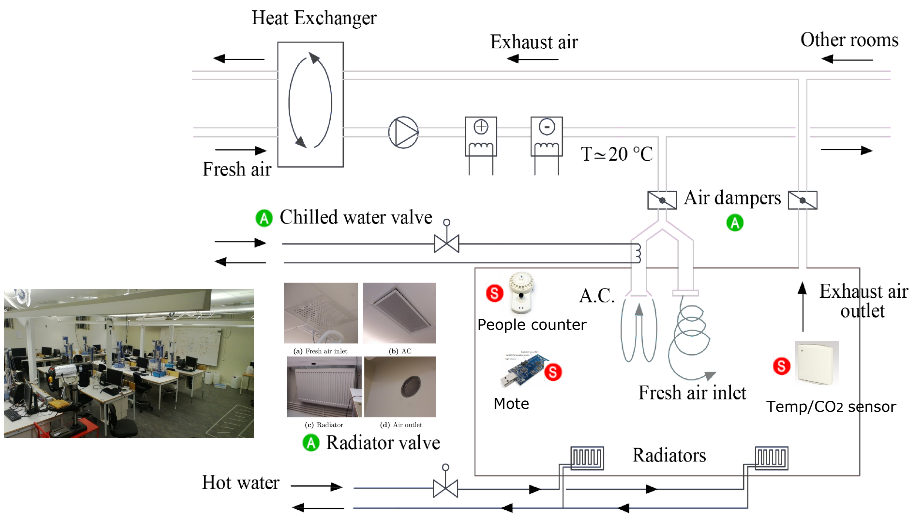
- 270 student apartments
- Reconfigure apartments according to research projects
- Extensive data gathering

EINAR MATTSSON Semrén+Månsson

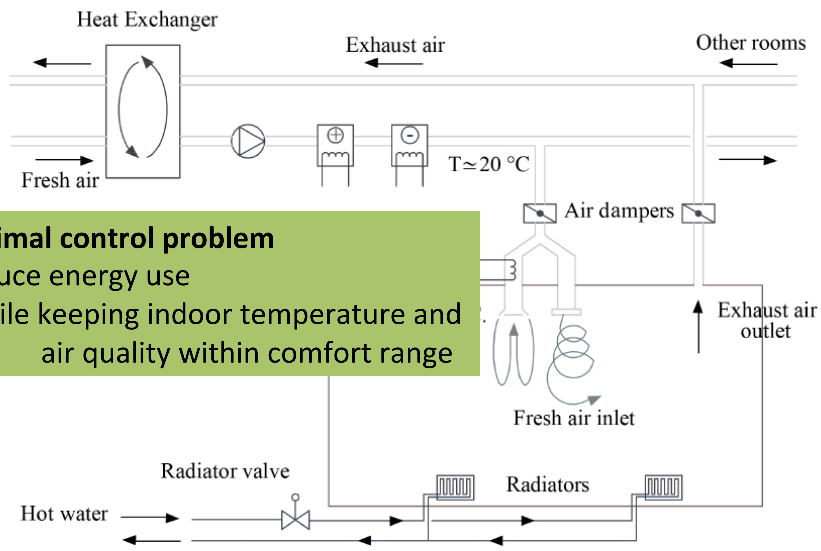
KTH Smart Building Testbed



KTH Smart Building Testbed

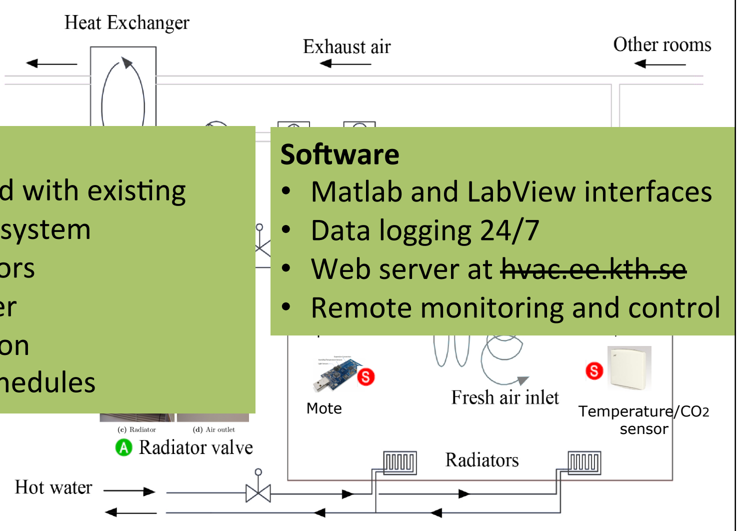


Heating, Ventilation, and Air Conditioning



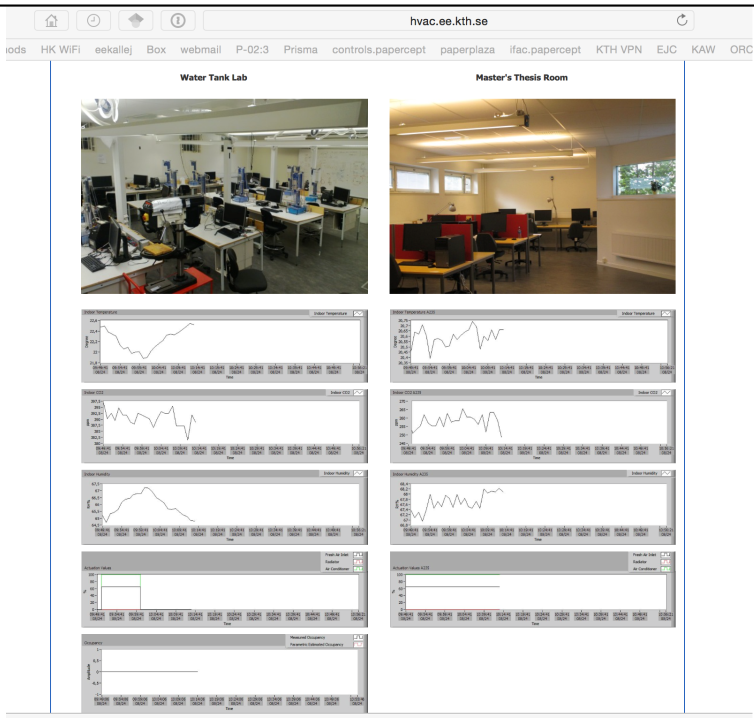
Optimal control problem
Reduce energy use
while keeping indoor temperature and air quality within comfort range

Testbed Implementation



Hardware
- PLC integrated with existing HVAC SCADA system
- Wireless sensors
- People counter
- Weather station
- Occupancy schedules

Software
- Matlab and LabView interfaces
- Data logging 24/7
- Web server at ~~hvac.ee.kth.se~~
- Remote monitoring and control



CO_2 model

$$x_{CO_2}(k+1) = a x_{CO_2}(k) + b u_{CO_2}(k) + e w_{CO_2}(k)$$
$$y_{CO_2}(k) = x_{CO_2}(k)$$

$w_{CO_2}(k) =$ occupancy at k, $u_{CO_2}(k) = \dot{m}_{\mathrm{vent}}(k) x_{CO_2}(k)$

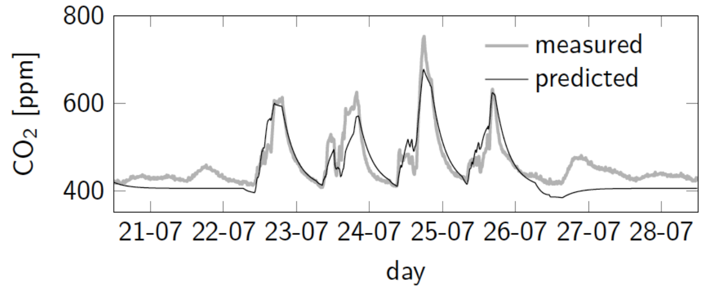
Temperature model

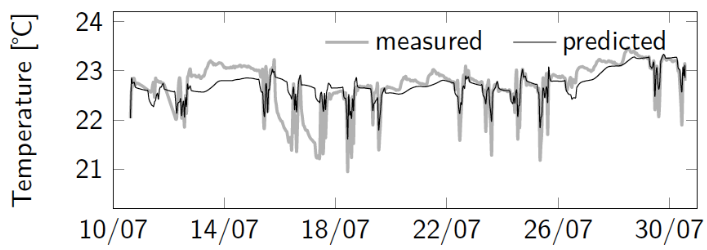
$$x_{\mathrm{T}}(k+1) = A_{\mathrm{T}} x_{\mathrm{T}}(k) + B_{\mathrm{T}} u_{\mathrm{T}}(k) + E_{\mathrm{T}} w_{\mathrm{T}}(k)$$
$$y_{\mathrm{T}}(k) = C_{\mathrm{T}} x_{\mathrm{T}}(k)$$

$w_{\mathrm{T}}(k) =$ (outside temperature, solar radiation, internal heat gain)
$u_{\mathrm{T}}(k) \rightarrow \left|Q_{\mathrm{venting}}\right|, Q_{\mathrm{heating}} \rightarrow \left(\dot{m}_{\mathrm{vent}}(k), T_{\mathrm{sa}}(k), T_{\mathrm{rad}}(k)\right)$

Parisio et al., 2013

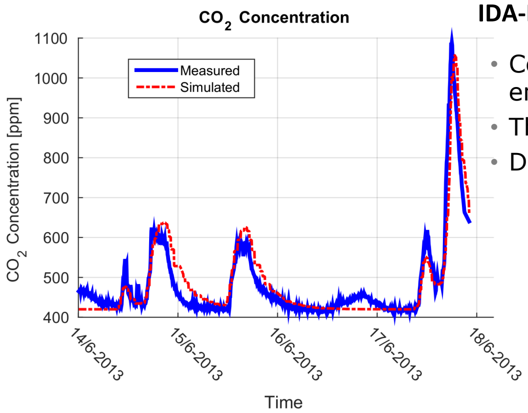
Model Validation of Low-Order Models





Parisio et al., 2013

Model Validation of High-Order Models



IDA-ICE Building Performance Simulator

- Commercial software for multi-zone energy flow dynamic modeling
- Thermal comfort simulations
- Daylight and solar gains

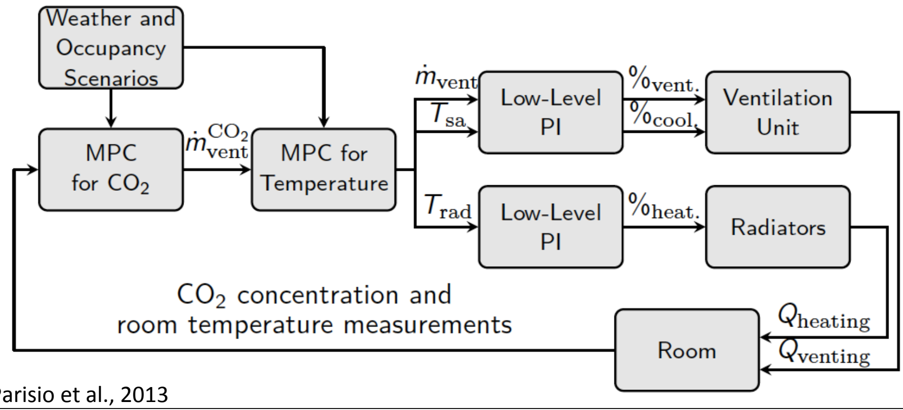
Molinario, 2013

HVAC Control Architecture

Goal: Minimize energy use while satisfying comfort constraints

Approach: Scenario-based Model Predictive Control

- CO_2 MPC generates constraints for temperature MPC
- Probabilistic models of occupancy and weather forecasts errors
- Learn statistics from building operation to generate scenarios
- Air flow and temperature control from scenario-based optimization



Parisio et al., 2013

Scenario-based **CO_2** MPC

Chance Constraints

$$\mathbb{P}\left[\dot{m}_{\mathrm{vent}}^{\min} x_{CO_2}(k) \leq u_{CO_2}(k) \leq \dot{m}_{\mathrm{vent}}^{\max} x_{CO_2}(k)\right] \geq 1-\alpha \quad \textit{\textbf{(flow rate)}}$$

$$\mathbb{P}\left[y_{\min} \leq y_{CO_2}(k) \leq y_{\max}\right] \geq 1-\alpha \quad \textit{\textbf{(air quality)}}$$

Inputs Constraints

$$u_{\min} \leq u_{CO_2}(k) \leq u_{\max}$$

Cost Function

$$\sum_{k=0}^{N-1} c'\left(u(k)\Delta k\right) \qquad \textit{\textbf{(minimize energy use)}}$$

Compute Control Inputs

$$\dot{m}_{\mathrm{vent}}^{CO_2}(k) = \frac{u_{CO_2}(k)}{x_{CO_2}(k)}$$

Parisio et al., 2013

Scenario-based **Temp** MPC

Chance Constraints

$$\mathbb{P}\left[y_{\min} \leq y_{\mathrm{T}}(k) \leq y_{\max}\right] \geq 1-\alpha_T \qquad \textit{\textbf{(thermal comfort)}}$$

Inputs Constraints

$$u_{\min} \leq u_{\mathrm{T}}(k) \leq u_{\max}$$

Cost Function

$$\sum_{k=0}^{N-1} c_T'\left(u_{\mathrm{T}}(k)\Delta k\right) \qquad \textit{\textbf{(minimize energy use)}}$$

Compute Setpoints for the Low-level Controllers

$$\left(\dot{m}_{\mathrm{vent}}(k), T_{\mathrm{sa}}(k), T_{\mathrm{rad}}(k)\right) = f\left(\dot{m}_{\mathrm{vent}}^{CO_2}(k), u_{\mathrm{T}}(k)\right)$$

Parisio et al., 2013

How to Handle Chance Constraints

$\omega :=$ random variable (weather, occupancy, ...)

Uncertainty Modeling

$$\omega(k) = \bar{\omega}(k) + \tilde{\omega}(k)$$

- $\bar{\omega}(k) :=$ forecast
- $\tilde{\omega}(k) :=$ forecast error

How to Handle Chance Constraints

$\omega :=$ random variable (weather, occupancy, ...)

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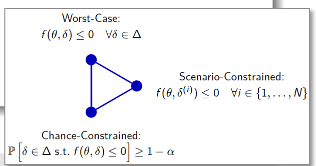


Approximating Chance Constraints

- extract a limited number $S = \frac{2}{\alpha}\left(\ln\left(\frac{1}{\beta}\right) + N \cdot n_u\right)$ of i.i.d. outcomes (called ***scenarios***)
- approximate $\mathbb{P}[y_{\text{min}} \leq y(k) \leq y_{\text{max}}] \geq 1 - \alpha$ with $y_{\text{min}} \leq y\left(\hat{\omega}^j(k)\right) \leq y_{\text{max}}, \quad \forall j = 1, \dots, S$
- remove redundant constraints: $\max_j \left\{y\left(\hat{\omega}^j(k)\right)\right\} \leq y_{\text{max}}$

Calafiore & Campi, 2006; Calafiore, 2010

Controller Computation

Chance-constrained problem approximated with deterministic problem:

$$\begin{aligned} \min_{\boldsymbol{u}} \quad & \boldsymbol{c}^{\mathrm{T}}\boldsymbol{u}\Delta k \\ \text{s.t.} \quad & \boldsymbol{G}_{xk}x(k) + \boldsymbol{G}_u\boldsymbol{u} \leq \boldsymbol{g} - \max_{i=1,\dots S} \boldsymbol{G}_w\boldsymbol{w}_i \\ & \boldsymbol{F}\boldsymbol{u} \leq \boldsymbol{f}, \end{aligned}$$

Multi-parametric linear problem with x being vector of parameters and w representing S scenarios

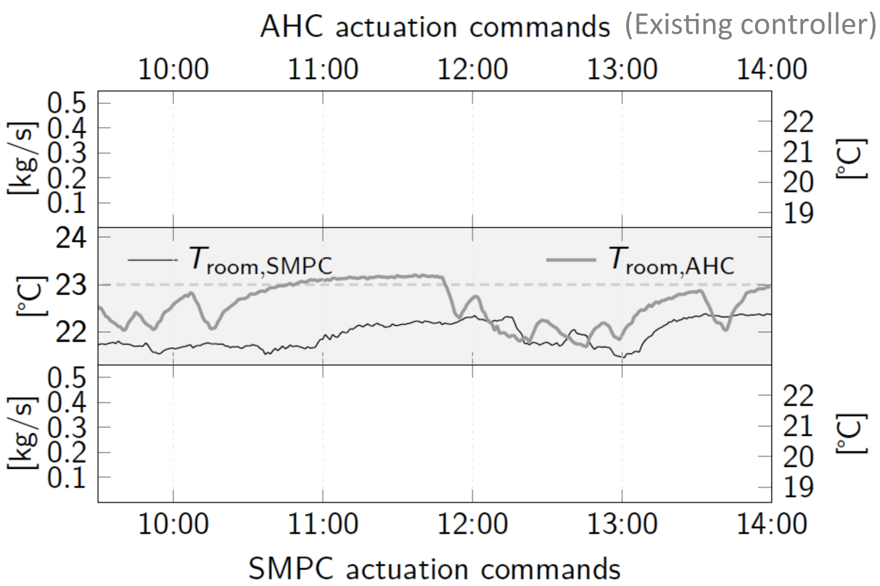
Possible to solve off-line using the Multi-Parametric Toolbox

Leads to a piecewise affine state-feedback control law:

$$u(k) = Q_i x(k) + q_i \quad \text{if} \quad H_i x(k) \leq K_i$$

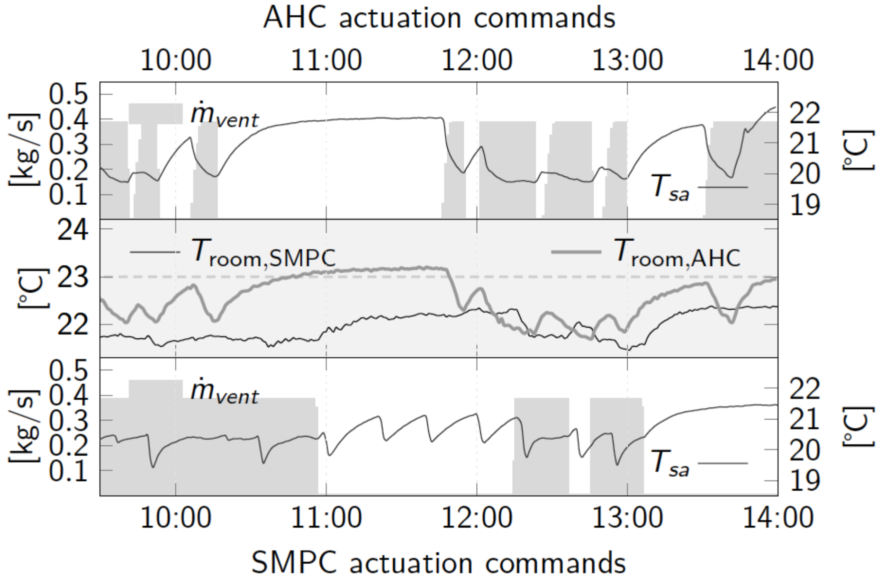
Schildbach et al., 2013; Bemporad et al., 2002; Kvasnica et al., 2004; Parisio et al., 2013

Evaluations on HVAC Testbed



Parisio et al., 2013

Evaluations on HVAC Testbed

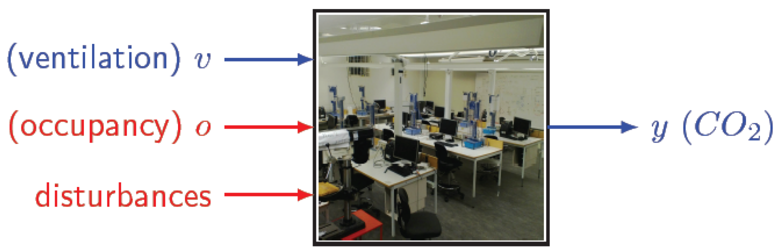


$E_{SMPC} = 1.27$ **kWh**, $E_{AHC} = 1.39$ **kWh** (savings: 8.4%)

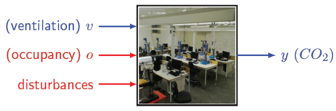
Occupancy Estimation

Estimate occupancy using only available measurements

- No additional sensors or other hardware
- No a priori knowledge of physical parameters



Blind Identification Problem



$$y(t) = [g_y * y](t) + [g_v * v](t) + [g_o * o](t) + e(t)$$

Measurements are CO_2 level y and HVAC actuation v

Approach

1. Estimate impulse responses g_y, g_v, g_o and occupancy o

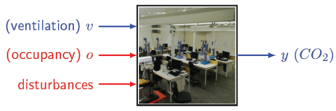
2. Estimate best scaling factor α with $\tilde{g}_o = \alpha^{-1} g_o$ and $\tilde{o} = \alpha o$

Assumptions

- $o(t) - o(t-1)$ is sparse
- $|o(t) - o(t-1)| \leq \gamma_{\max}$ for known $\gamma_{\max}$

Ebadat et al., 2015

Blind Identification Problem



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Approach

1. Estimate impulse responses g_y, g_v, g_o and occupancy o

- Maximum likelihood identification of parametric first-order model

$$y(t) = ay(t-1) + b_v v(t-1) + b_o o(t-1) + e(t)$$

- Marginal likelihood maximization using expectation maximization

$$\hat{\theta} = \arg\max_{\theta} \log p(y;\theta)$$

$$\theta = \text{distributions parameters and } o$$

2. Estimate best scaling factor α with $\tilde{g}_o = \alpha^{-1} g_o$ and $\tilde{o} = \alpha o$

Ebadat et al., 2015

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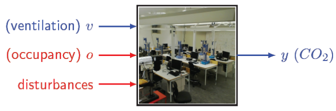

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Approach

1. Estimate impulse responses g_y, g_v, g_o and occupancy o
2. Estimate best scaling factor α with $\tilde{g}_o = \alpha^{-1} g_o$ and $\tilde{o} = \alpha o$

$$\alpha^* = \arg\min_{\alpha > 0} \sum_{t=2}^{N} (\alpha \hat{\delta}(t) - \gamma_\alpha(t))^2$$

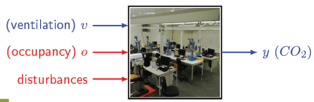
$$\delta(t) := o(t) - o(t-1), \qquad \hat{\delta}(t) := \hat{o}(t) - \hat{o}(t-1),$$

$$\delta(t) \in \Gamma := \{-\gamma_{\max}, \dots, +\gamma_{\max}\} \subset \mathbb{N}.$$

$$\gamma_\alpha(t) = \begin{cases} -\gamma_{\max} & \text{if } \alpha\hat{\delta}(t) \leq -\gamma_{\max} \\ \lceil \alpha\hat{\delta}(t) \rfloor & \text{if } \lceil \alpha\hat{\delta}(t) \rfloor \in \Gamma \\ \gamma_{\max} & \text{if } \alpha\hat{\delta}(t) \geq \gamma_{\max} \end{cases}$$

Ebadat et al., 2015

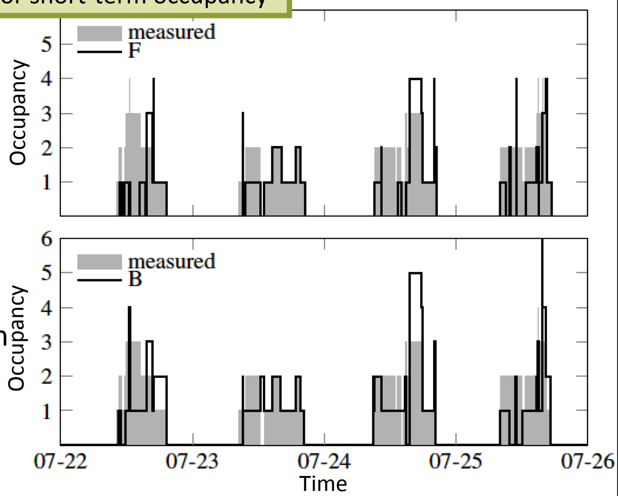
Experimental Results



- Good detection of occupation intervals
- Inaccurate estimates for short-term occupancy

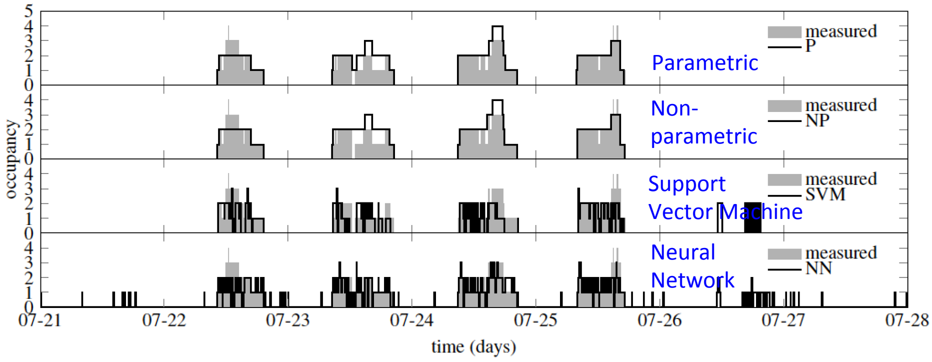
Parametric approach

Non-parametric approach



Ebadat et al., 2015

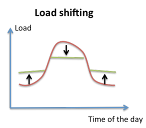
Comparison with Other Approaches



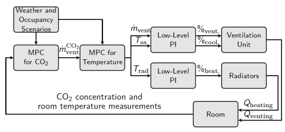
Ebadat et al., 2013

Conclusions

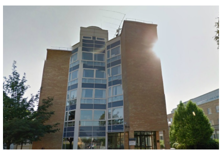
- Buildings are **large energy consumers** and **buffers**
  - Potential for more flexible use of energy



- New **scenario-based MPC** for **HVAC** systems
  - Optimizes air flow and temperature
  - Utilizes occupancy and weather information



- **Testbed evaluations**
  - Integration with people behavior at individual and social scale



people.kth.se/~kallej

Literature

people.kth.se/~kallej

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