Development of Building Automation and Control (BAC) Systems:

Modeling and Controller Design
(A Platform-Based Design Approach)

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11/15/2012

Outline

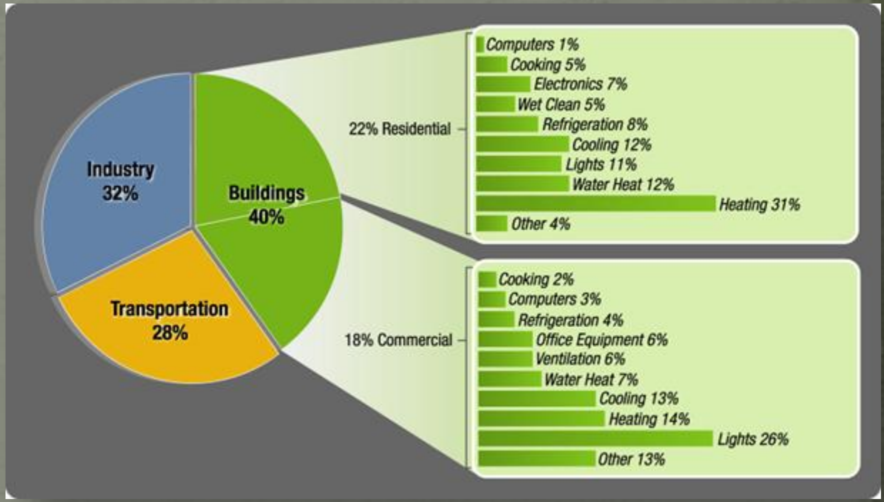
- Motivation
- Thermal Modeling
  - First approach (Physical Buildings)
  - Second Approach (Simulation Models)
- Model-Based Optimal Control Design
- Robust MPC
- Comparing Different Control Strategies
- Co-design of Control Algorithm and Embedded Platform
- Buildings and Smart Grid

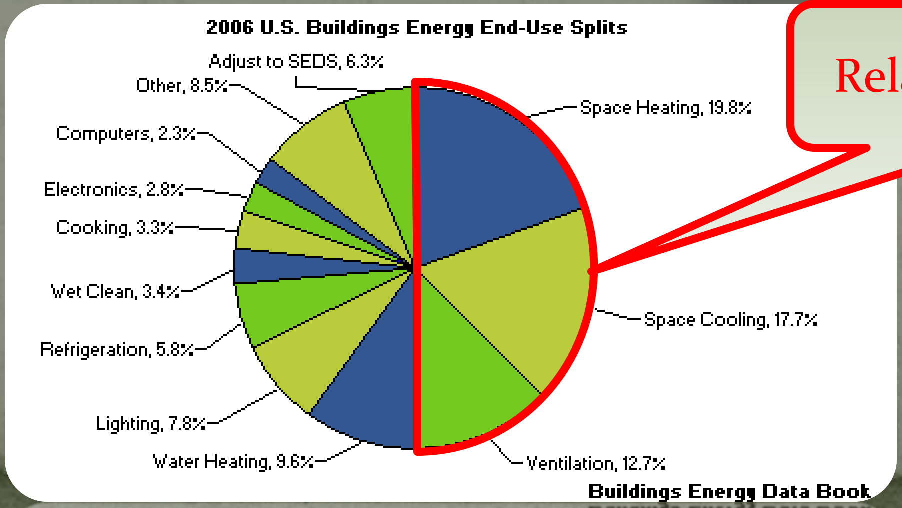
Motivation

Buildings Consume Significant Energy

- 40% of total US energy consumption
- 72% of total US electricity consumption
- 55% of total US natural gas consumption
- Total US annual energy cost $ 370 Billion
- Increase in US electricity cons. since 1990: 200%

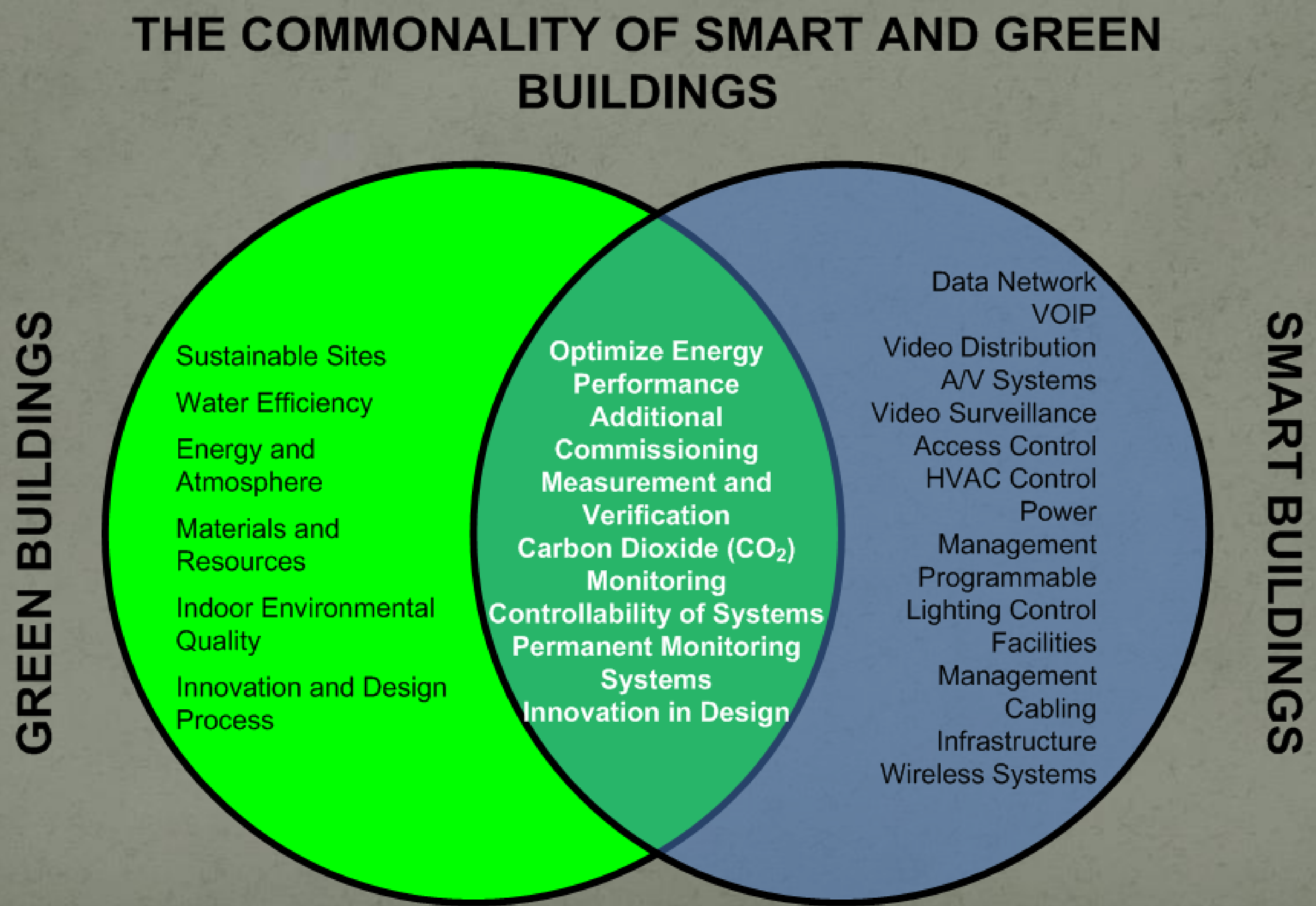
Source: Buildings Energy Data Book 2007





Related to HVAC

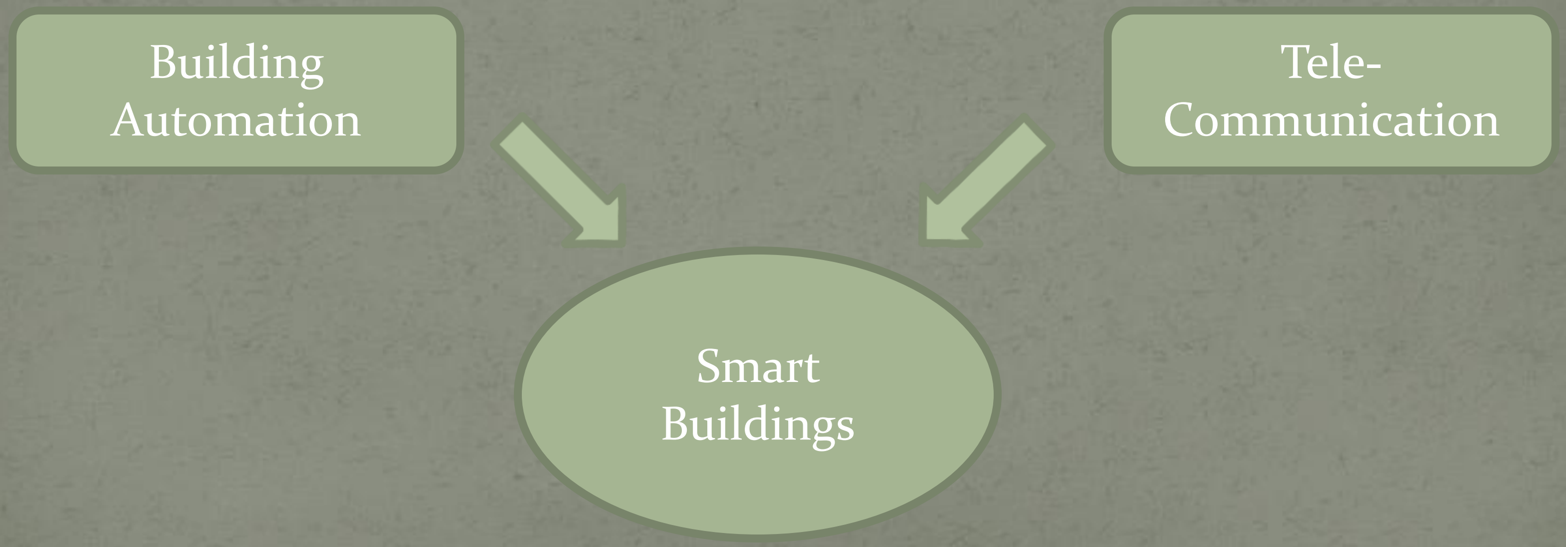
Smart vs. Green Buildings



Source: http://www.smart-buildings.com

Smart Buildings

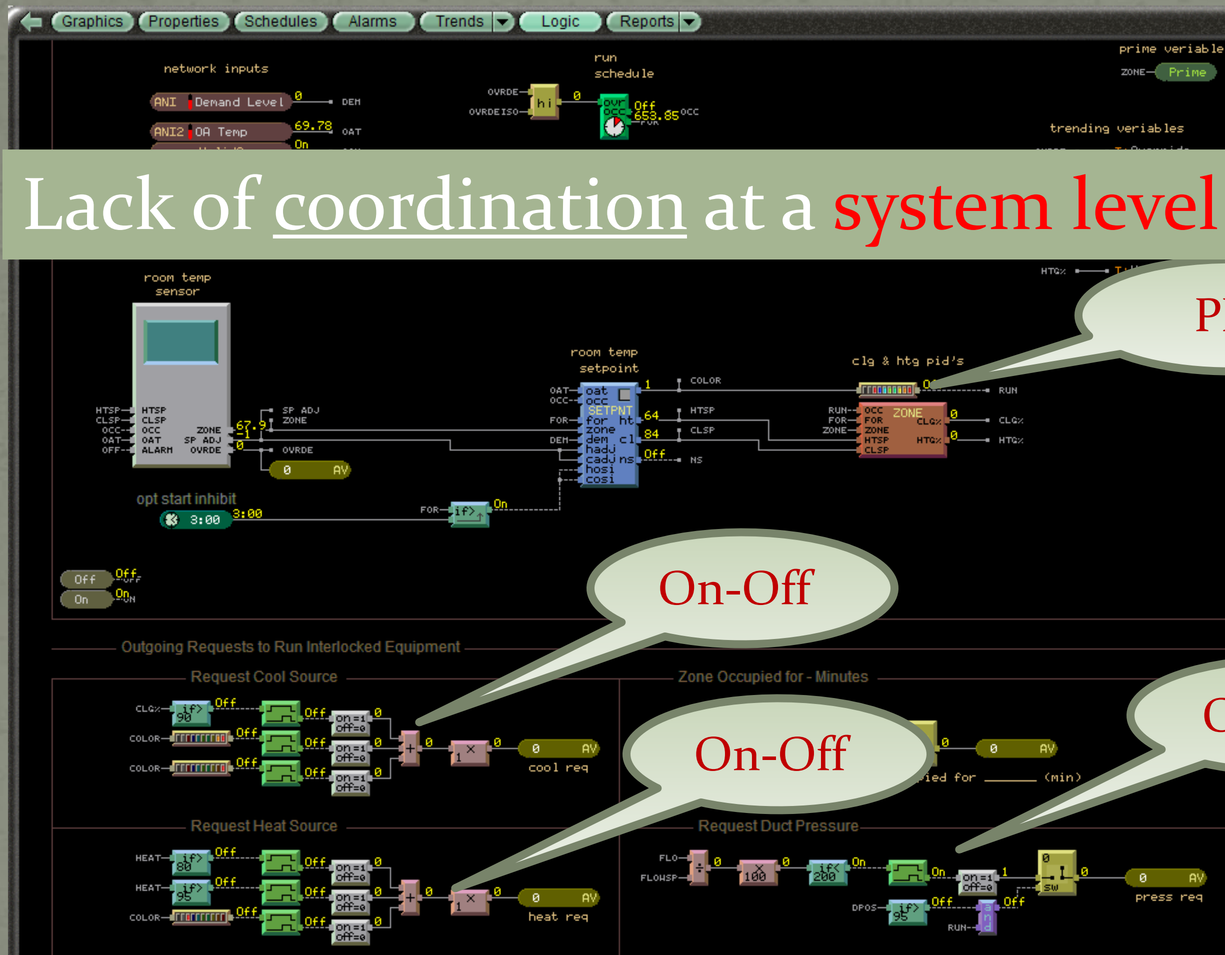
- First mention of Smart buildings: 25 years ago upon advent of PC and deregulation of tele-communication industry, and advances in building automation



Smart buildings idea:

... get more functionality out of system when integrated and tied to each other

Current HVAC Control Systems



Lack of <u>coordination</u> at a system level

PID

On-Off

On-Off

On-Off

UC Berkeley, Bancroft Library

Observations

- Control logic governing today's buildings uses simple control schemes dealing with one subsystem at a time…

- Local actions are determined without taking into account the interrelations among:

    - **Outdoor weather conditions**
    - **Indoor air quality**
    - **Cooling demands**
    - **HVAC process components**

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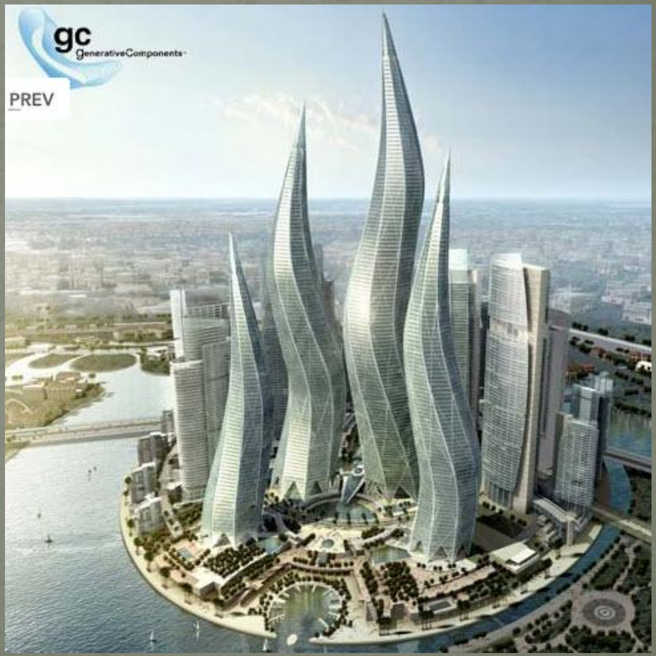
First approach

For physical buildings

- Modeling
- Parameter estimation
- Unmodeled dynamics estimation
- Model-based Control



courtesy of smartgeometry.com

Modeling

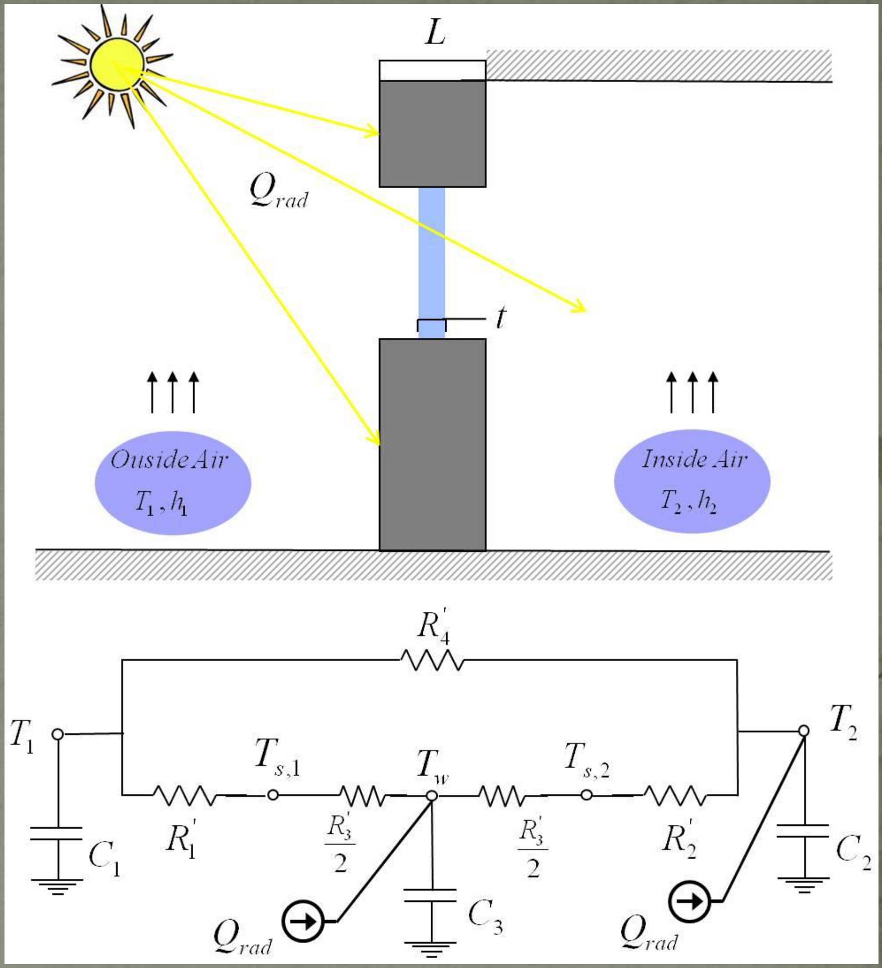
- Energy balance for a **wall** node:

$$\frac{dT_{w_i}}{dt} = \frac{1}{C_{w_i}}\left[\sum_{j\in\mathcal{N}_{w_i}} \frac{T_j - T_{w_i}}{R'_{ij}} + r_i\alpha_i A_i q''_{rad_i}\right]$$

$$r_i = \begin{cases} 0 & \text{internal wall} \\ 1 & \text{peripheral wall} \end{cases}$$

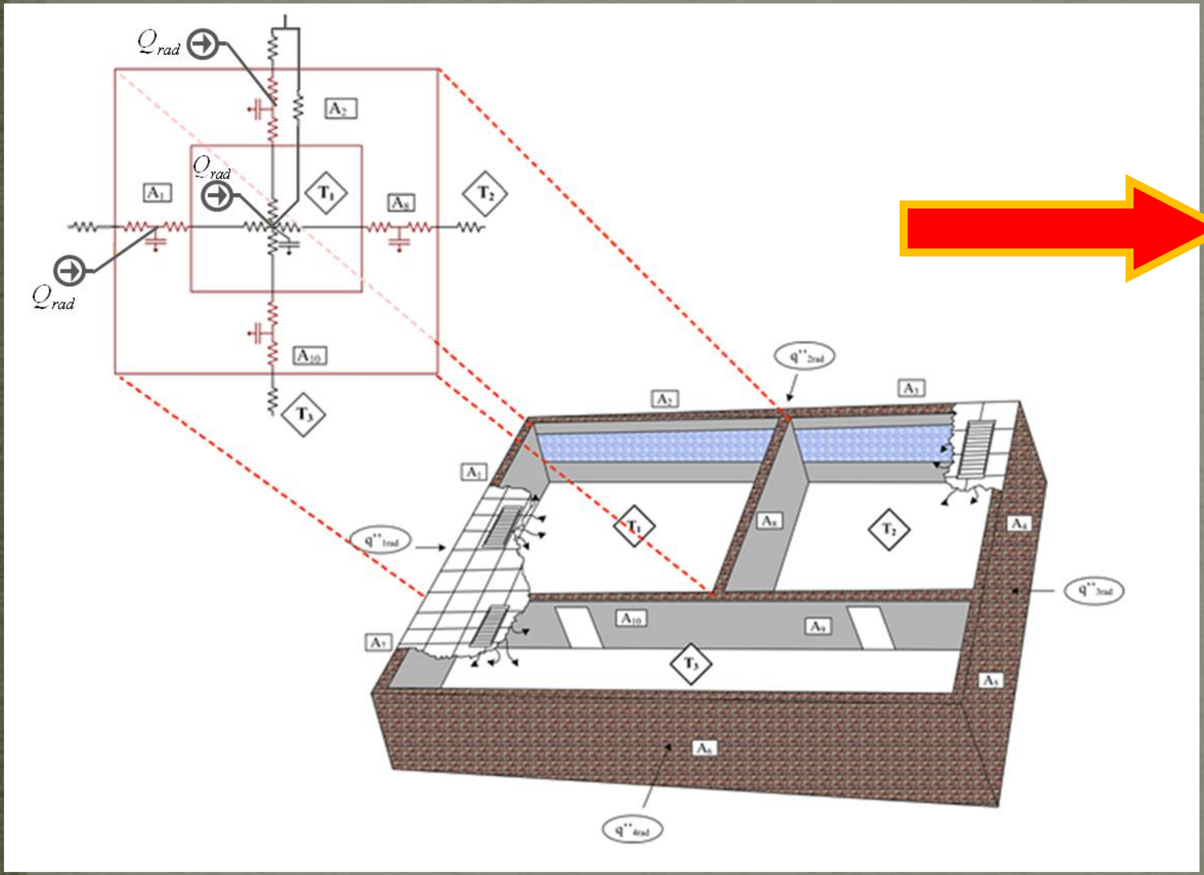
- Energy balance for a **room** node:

$$\frac{dT_{r_i}}{dt} = \frac{1}{C_{r_i}}\left[\sum_{j\in\mathcal{N}_{r_i}} \frac{T_j - T_{r_i}}{R'_{ij}} + \dot{m}_{r_i}c_p(T_{s_i} - T_{r_i}) + w_i\tau_{win_i}A_{win_i}q''_{rad_i} + \dot{q}_{int}\right]$$



Thermal and circuit model of a wall with window

Building Thermal Model



q''_{rad_i} $\dot{q}_{int}$

$$\dot{x}(t) = Ax(t) + Bu(t) + d(t)$$
$$y(t) = Cx(t)$$

More details at: Maasoumy et al. DSCC 2011.

Parameterizing Unmodeled Dynamics

- External heat gain

$$q''_{rad_i}(t) = \lambda T_{out}(t) + \gamma$$

Note: other quantities such as **global horizontal irradiance (GHI)** data can be used here as well.

- Internal heat gain

$$\dot{q}_{int}(t) = \mu \Psi(t) + \nu$$

$\Psi(t)$ is the CO_2 concentration in the room in (ppm).

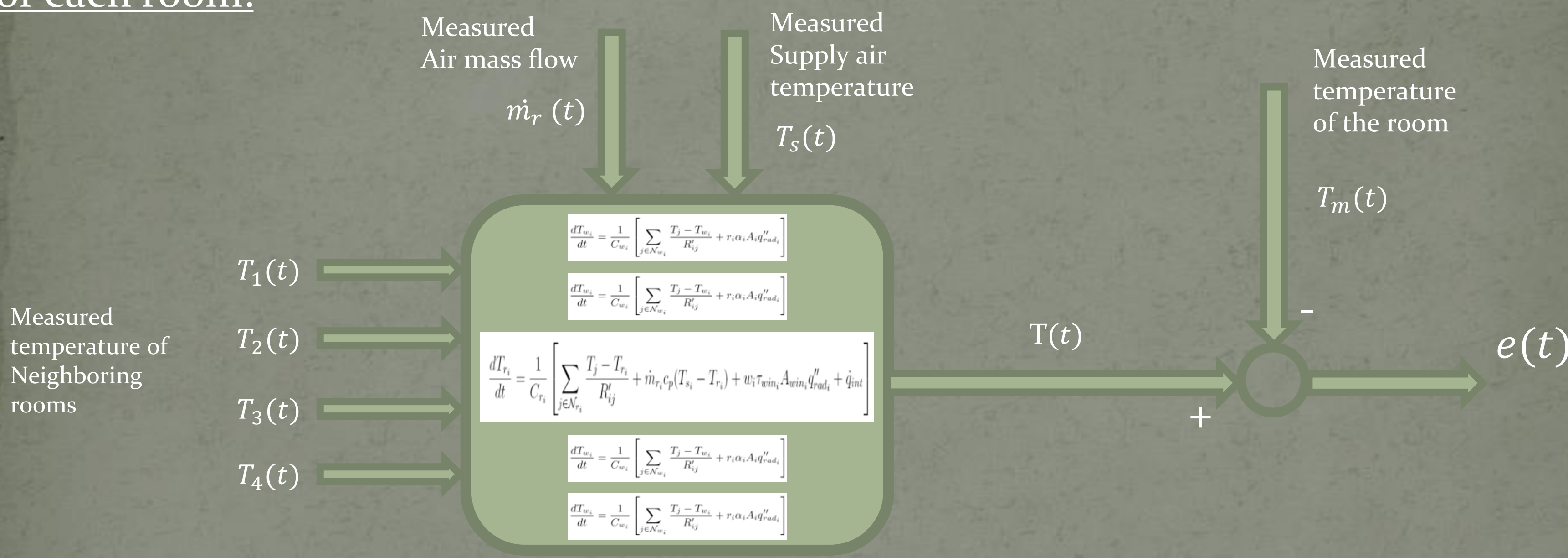
Parameter Identification

$$\min_{C_{[.]},R_{[.]},\lambda,\gamma,\mu,\nu} \|Y^m - Y^s\|_2^2$$

$$\text{s.t.} \begin{cases} x_{t+1}^s = Ax_t^s + f(x_t^s, u_t^m, d_t^m) & t = 0, \ldots, N-1 \\ y_t^s = Cx_t^s & t = 0, \ldots, N \end{cases}$$

Parameter Identification

<u>For each room:</u>



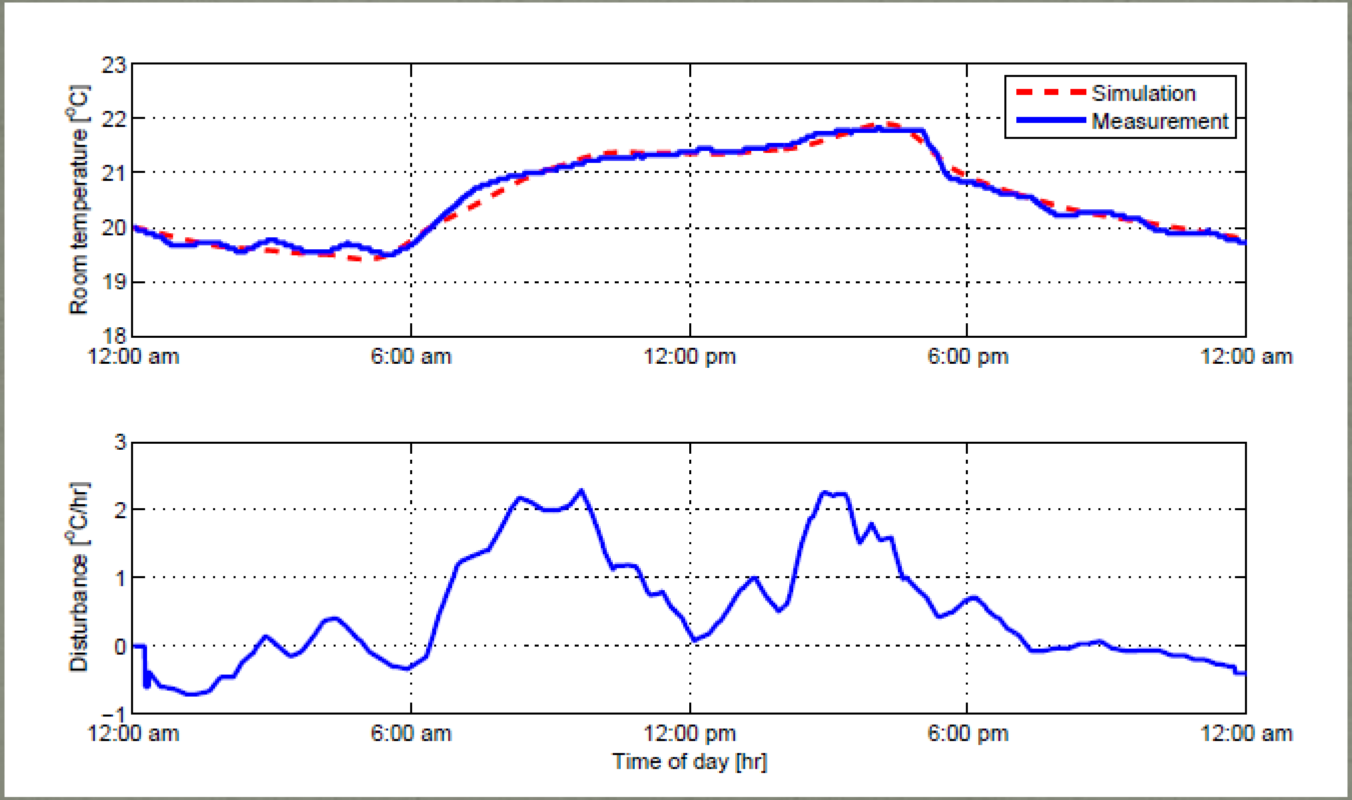
$$T(t) = f(C_r, C_{w1}, C_{w2}, C_{w3}, C_{w4}, R_1, R_2, R_3, R_4)$$

$$[C_r, C_{w1}, C_{w2}, C_{w3}, C_{w4}, R_1, R_2, R_3, R_4]^* = arg \min_{C_r, C_{wi}, R_i} \sum_t [e(t)]^2$$

Unmodeled Dynamics Estimation

- Initial guess (ASHRAE Handbook)

- Data of UC Berkeley
- Bancroft library, Conference room

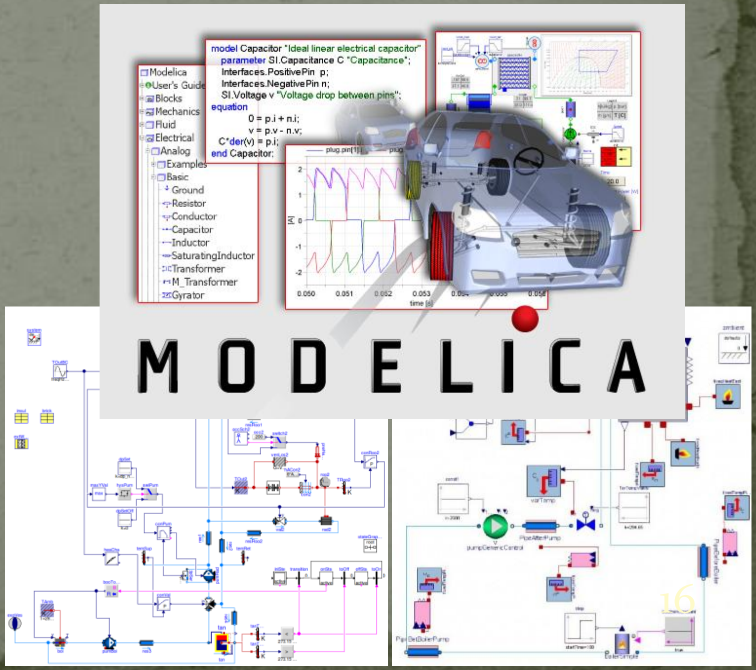


More details at: Maasoumy et al., IEEE D&T, SI on Green Buildings, July/Aug 2012

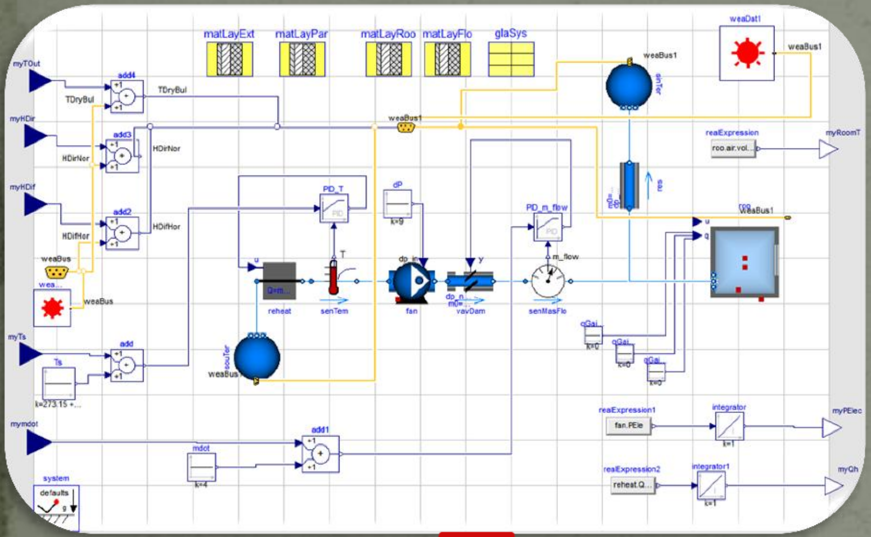
Second approach

For simulation models

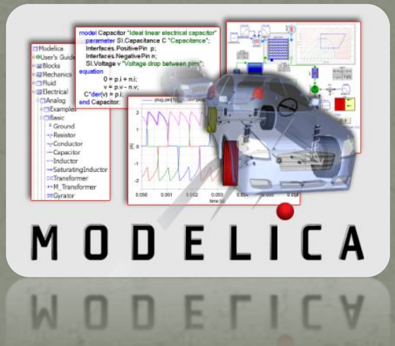
- Family of linear systems:
  - Linearized models at each operating point
  - Obtain adequate number of models for a given tolerance
  - Balanced realization
  - Model order reduction



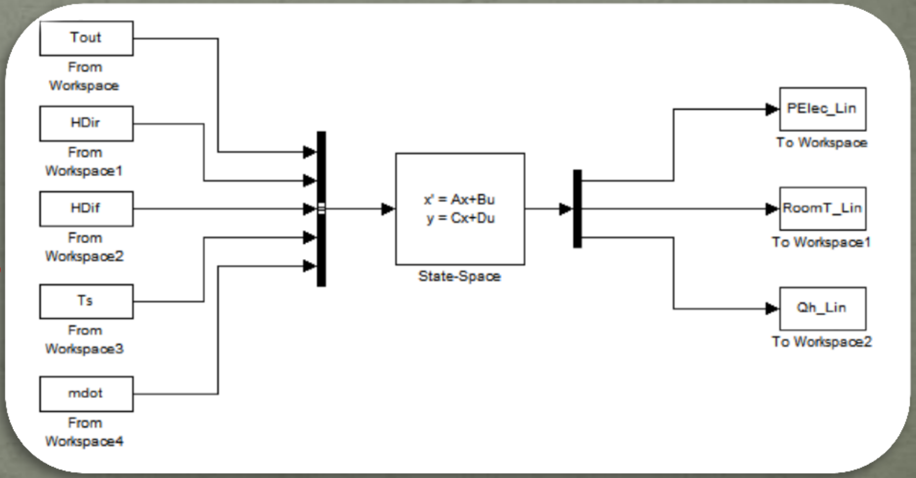
Family of linear systems



Modelica model

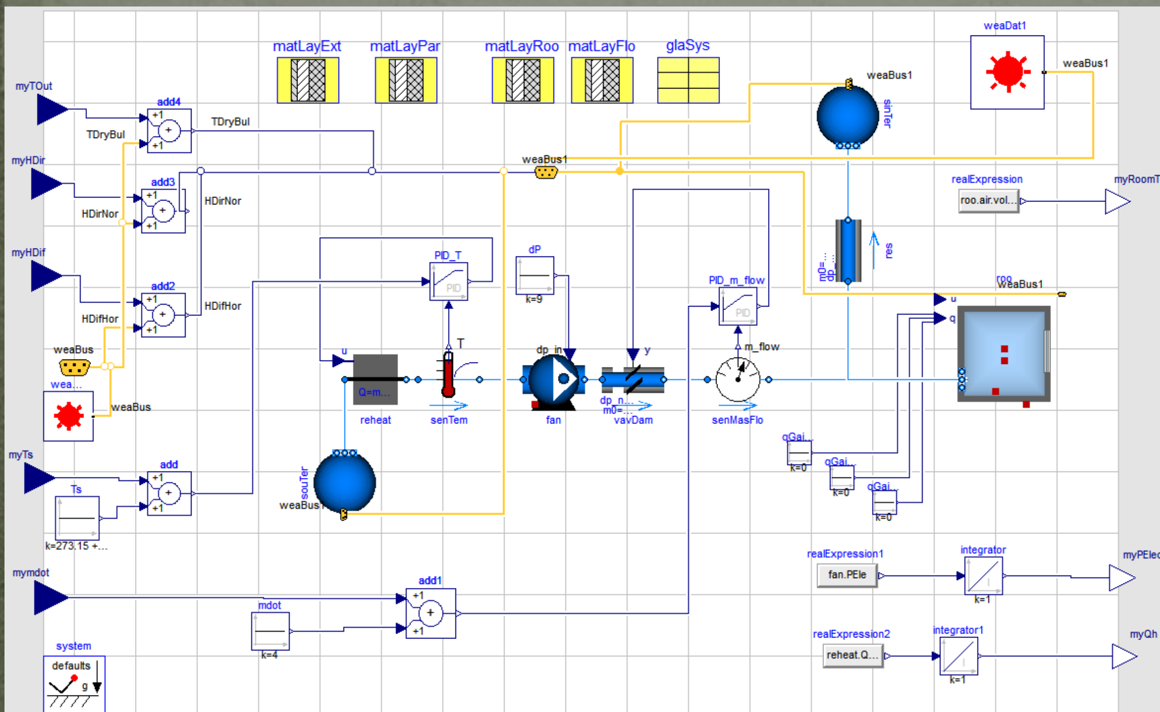


Extract linearized model



Simulink model

MOR Procedure



Nonlinear Model
$\dot{x} = f(x,u)$
$y = h(x,u)$

→ **Linearize** →

Linearized Model
$\dot{x} = Ax + Bu$
$y = Cx + Du$

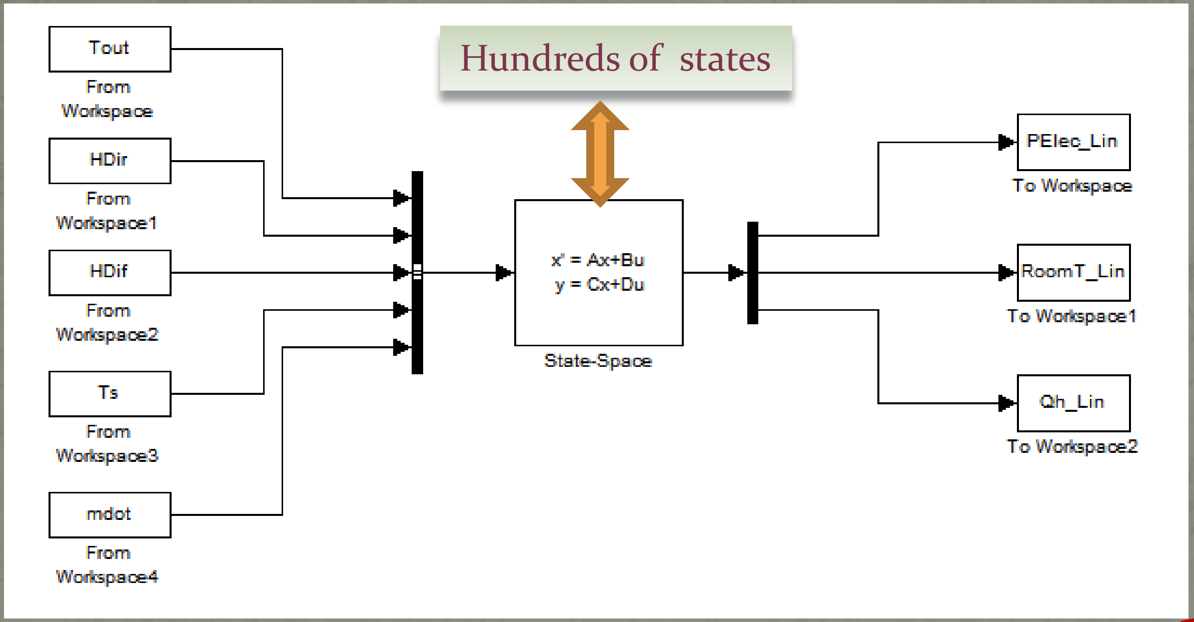
→ **Balanced Realization** →

Balanced Model
$\dot{z} = \tilde{A}z + \tilde{B}u$
$y = \tilde{C}z + Du$

→ **Model Reduction** →

Reduced Model
$\dot{z} = \tilde{A}_{11}z + \tilde{B}_1 u$
$y = \tilde{C}_1 z + Du$

MOR Procedure



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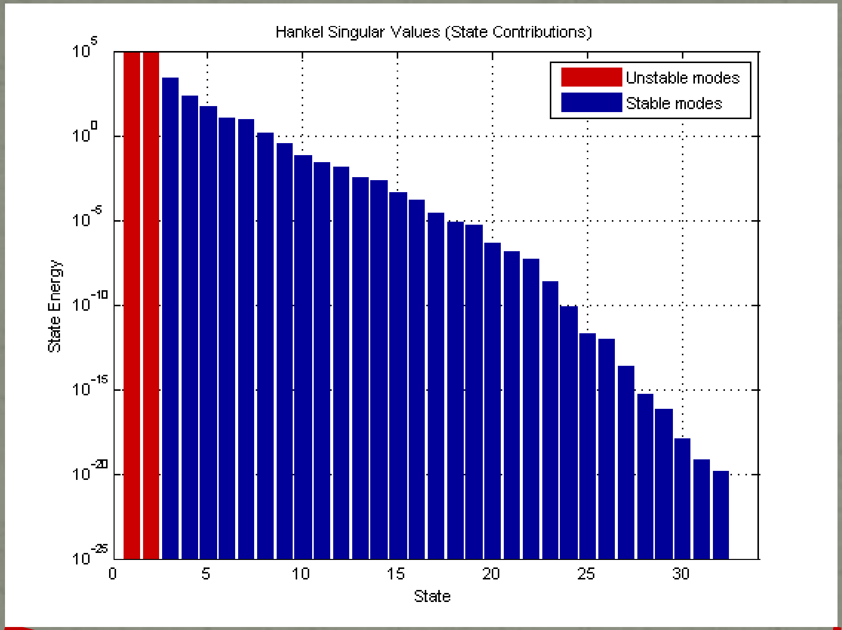
MOR Procedure



Hankel singular values: Relative amount of energy per state

Nonlinear Model
$\dot{x} = f(x,u)$
$y = h(x,u)$

→ Linearize →

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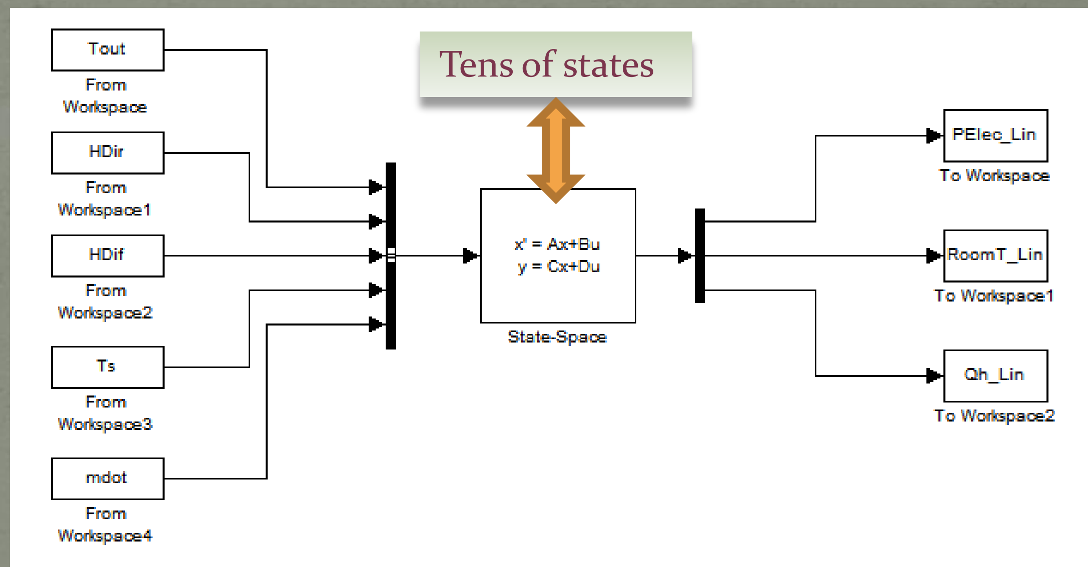

Nonlinear Model
$\dot{x} = f(x,u)$
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→ Linearize →

Linearized Model
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Balanced Model
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→ Model Reduction →

Reduced Model
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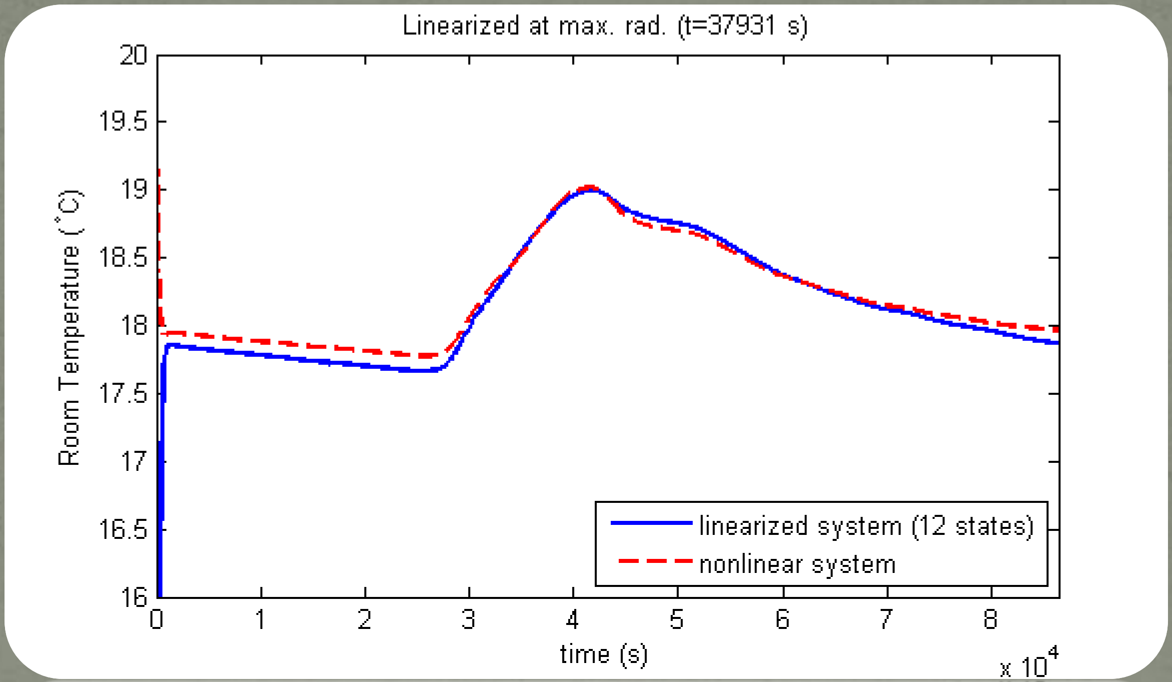
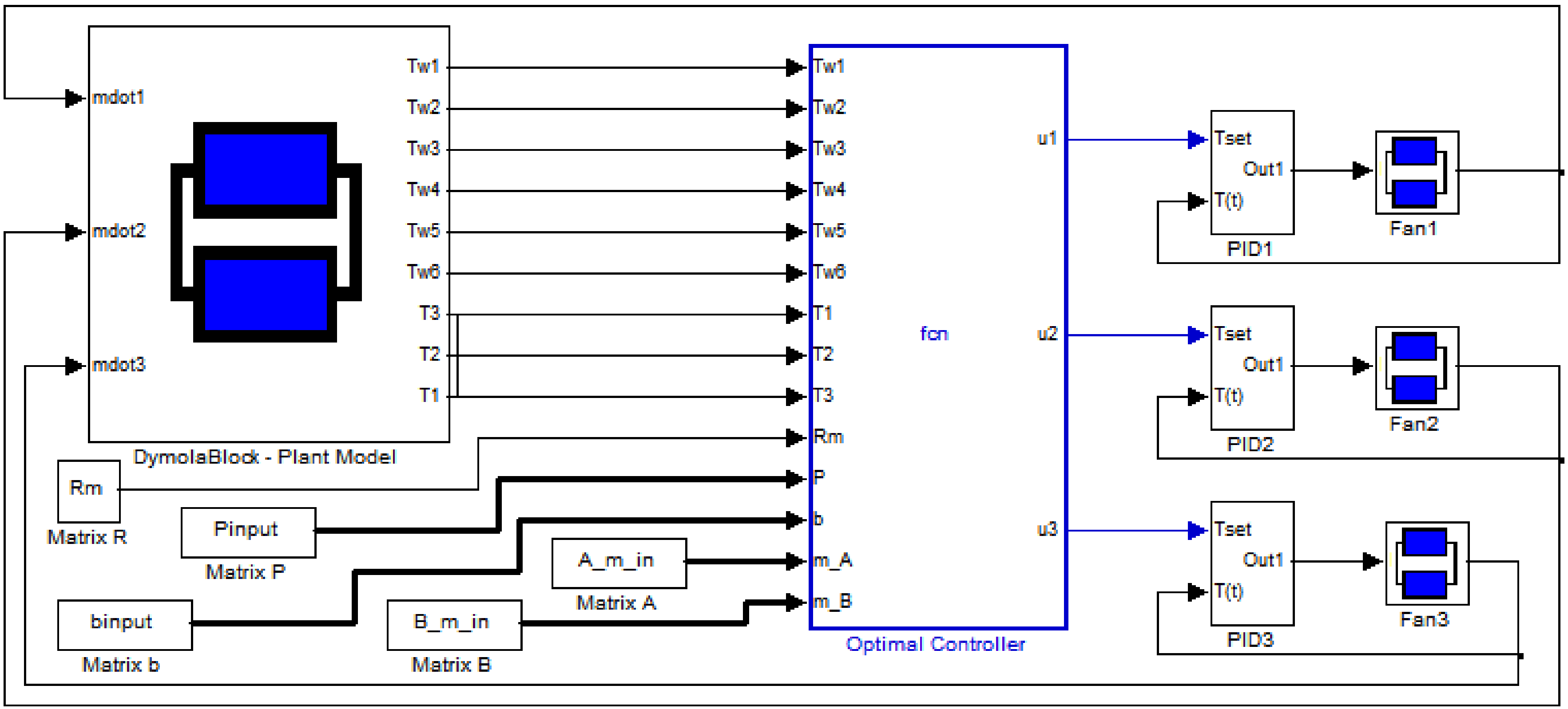
Reduced Model



Heterogeneous Modeling and Control



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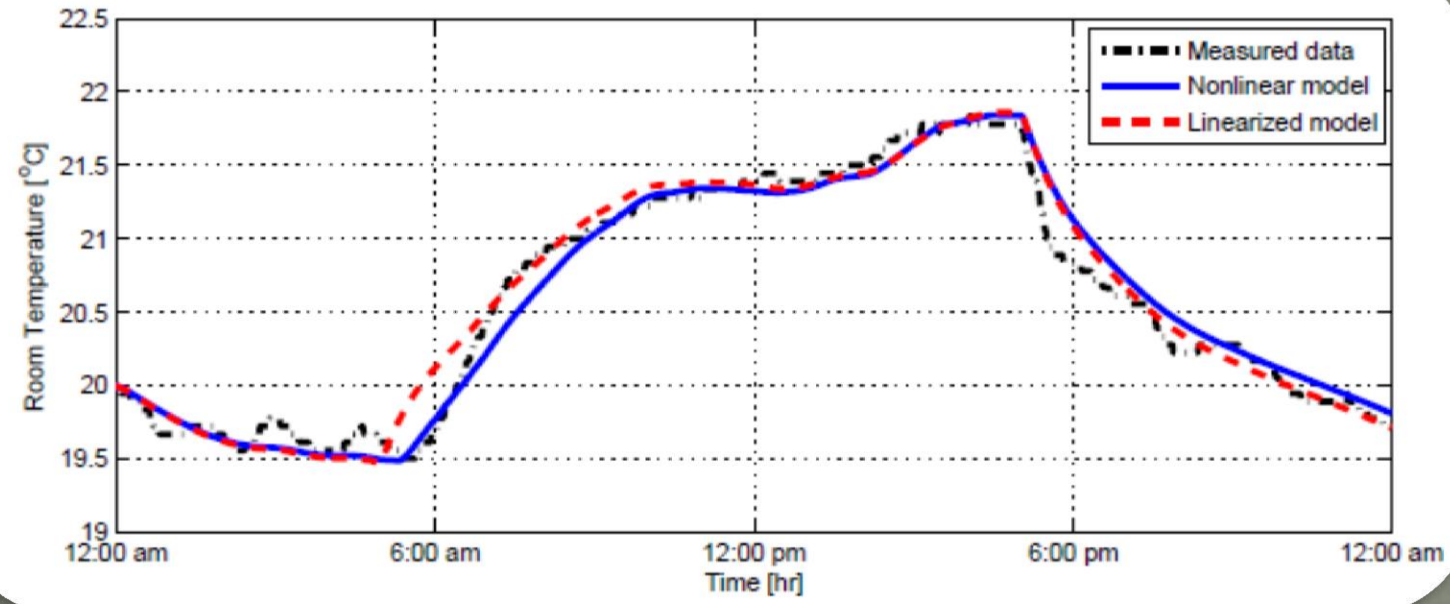
Controller Design - Linearization

Find an operating point of the system → Find the closest equilibrium point → Linearize about the equilibrium point



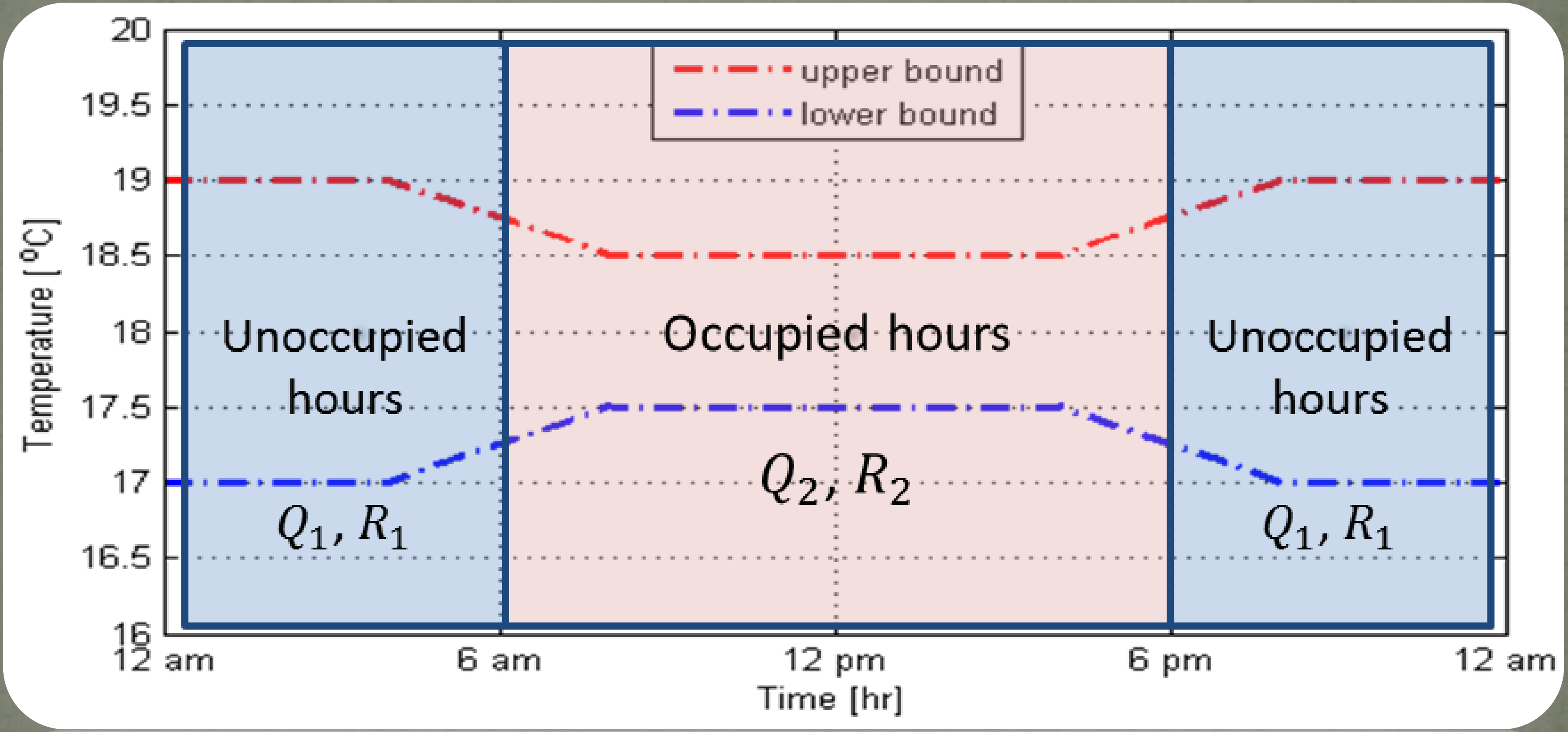
Model Predictive Control

$$\min_{U_t,\bar{\epsilon},\underline{\epsilon}} \quad \{|U_t|_1 + \kappa |U_t|_\infty + \rho(|\bar{\epsilon}_t|_1 + |\underline{\epsilon}_t|_1)\} =$$

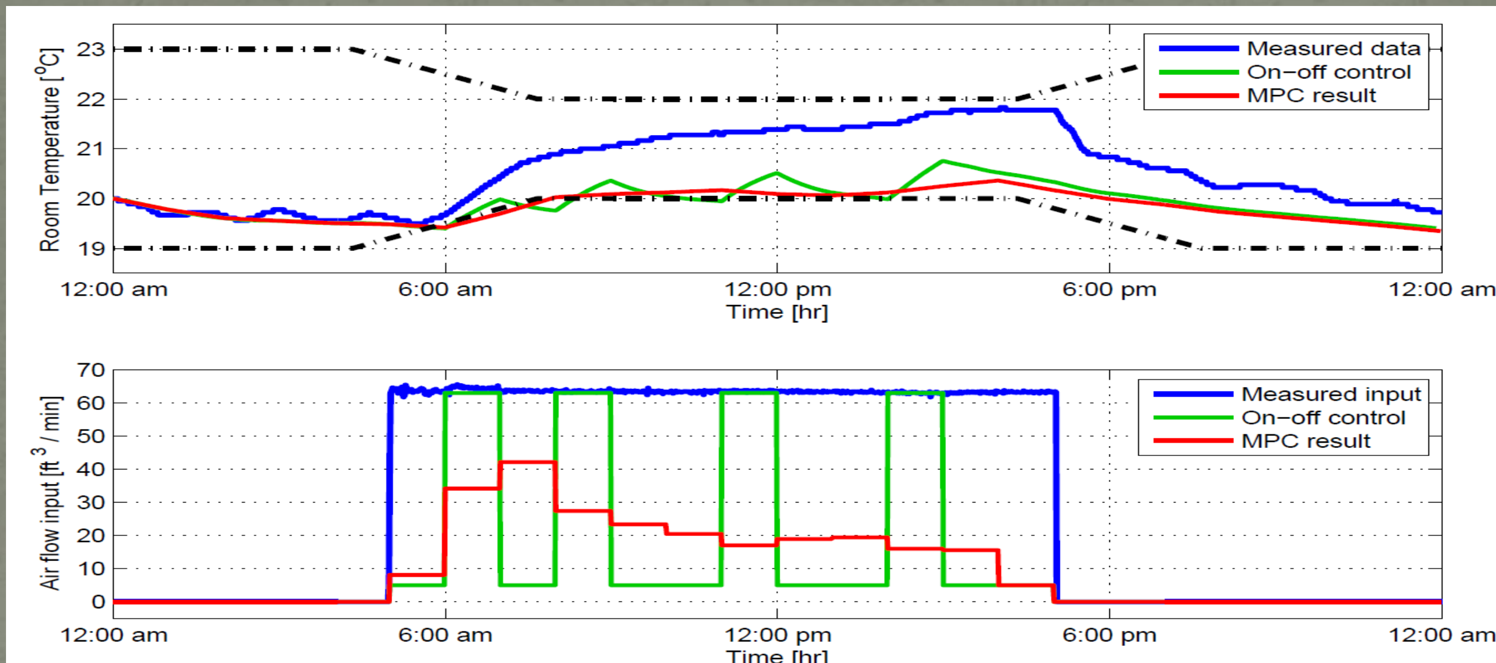
$$\min_{U_t,\bar{\varepsilon},\underline{\varepsilon}} \quad \{\sum_{k=0}^{N-1} |u_{t+k|t}| + \kappa \max(|u_{t|t}|, \cdots, |u_{t+N-1|t}|) + \rho \sum_{k=1}^{N} (|\bar{\varepsilon}_{t+k|t}| + |\underline{\varepsilon}_{t+k|t}|)\}$$

$$\begin{aligned}
\text{s.t.} \quad & x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t} + Ed_{t+k|t}, && k = 0, ..., N-1 \\
& y_{t+k|t} = Cx_{t+k|t}, && k = 1, ..., N \\
& 0 \le u_{t+k|t} \le \overline{\mathcal{U}}, && k = 0, ..., N-1 \\
& \underline{T}_{t+k|t} - \underline{\varepsilon}_{t+k|t} \le y_{t+k|t} \le \overline{T}_{t+k|t} + \bar{\varepsilon}_{t+k|t}, && k = 1, ..., N \\
& \underline{\varepsilon}_{t+k|t}, \bar{\varepsilon}_{t+k|t} \ge 0, && k = 1, ..., N
\end{aligned}$$

Comfort Zone Definition



"MPC" and "On-off" Control Results



Controller	Total input $[ft^3]$	Peak input $[ft^3/min]$	Total energy $[kWh]$	Running time $[s]$
Original control	45360	63	12.46	-
On-off control	17520	63	4.62	1.8
MPC	14870	42	3.33	102.4

68%
66%
35%
73%

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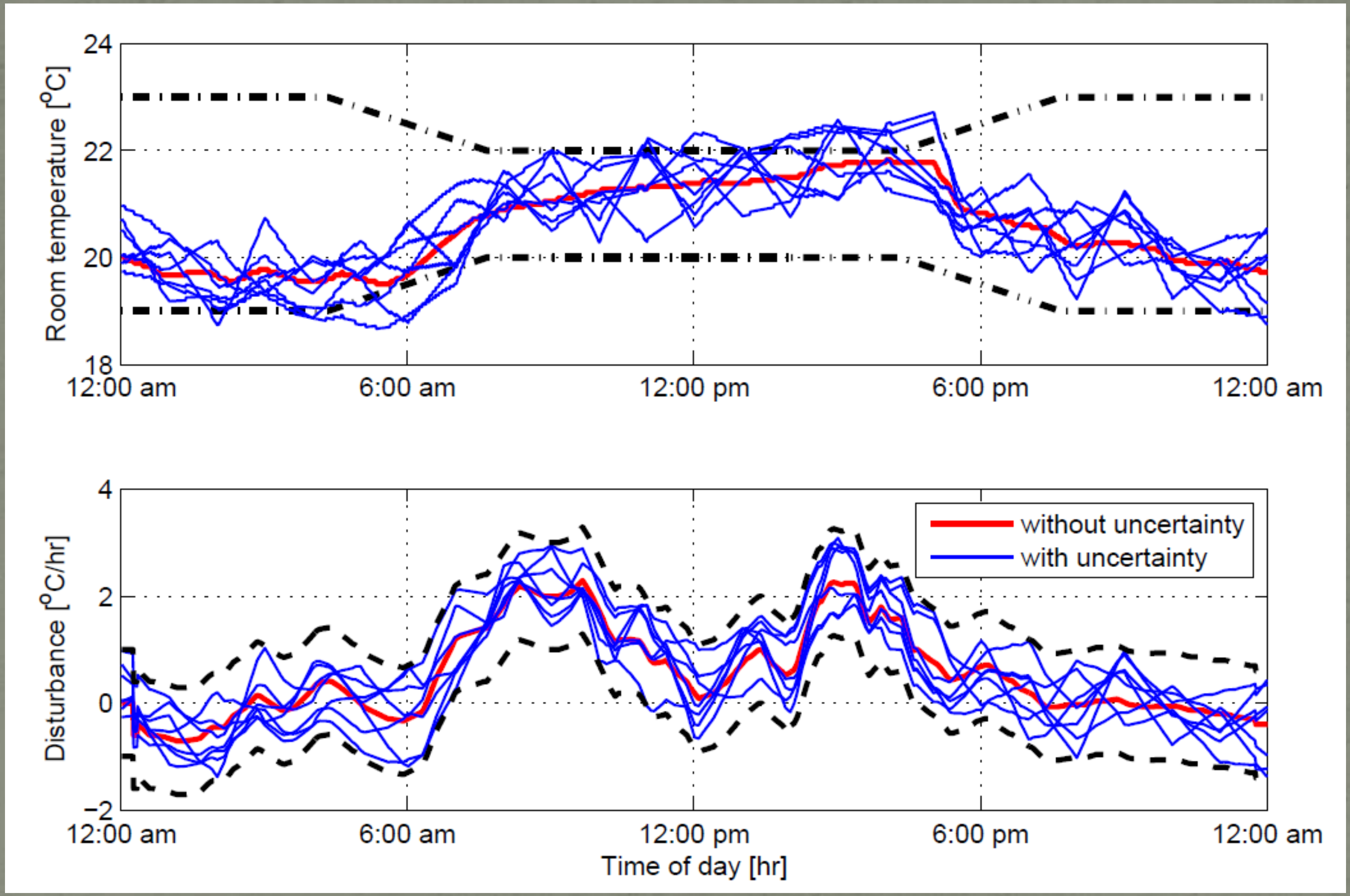
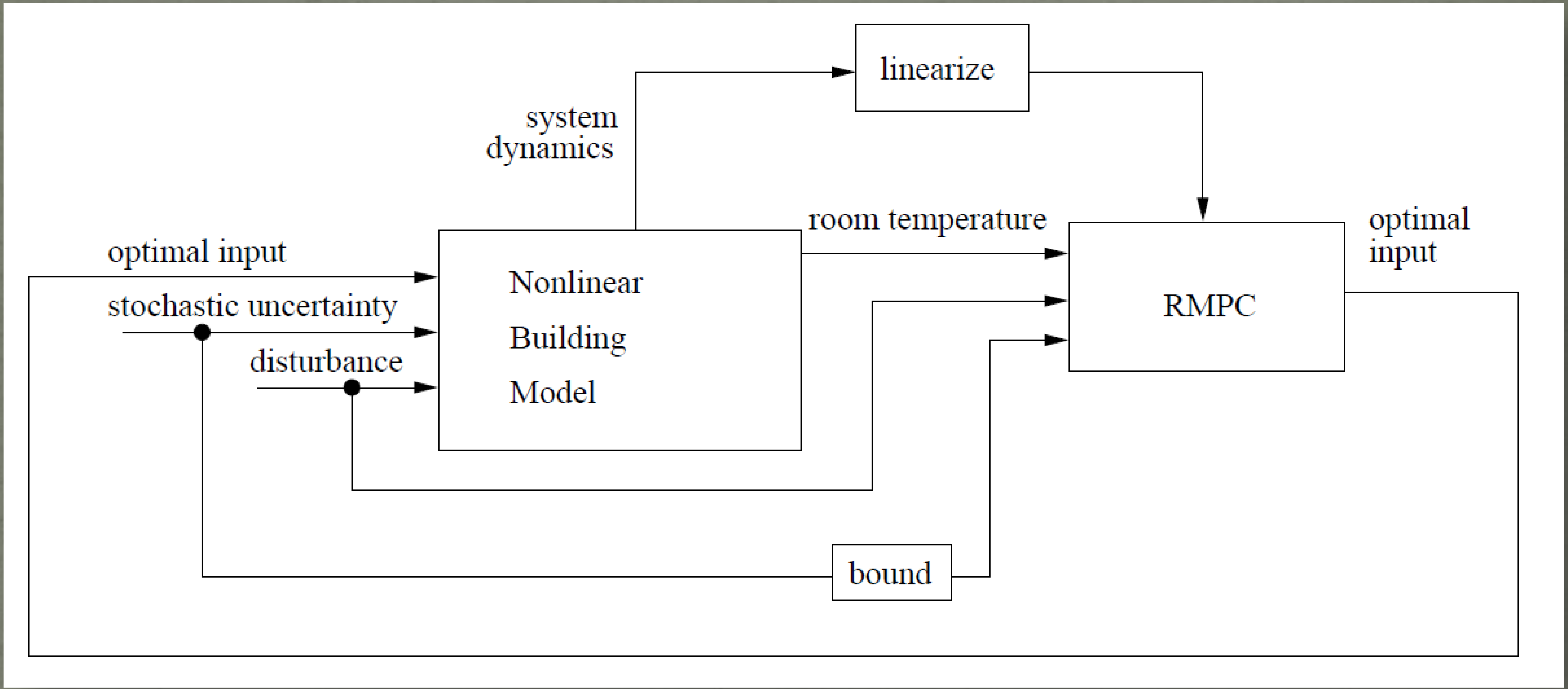
Robust Model Predictive Control
(against model and measurement uncertainties)

Original Control with Uncertainty



for $\lambda = 1$

Schematic of RMPC Implementation



$$x^+ = Ax + Bu + Ed + Fw$$

State update equation

$$\mathcal{W}_\lambda = \{w : ||w||_\infty \leq \lambda\}$$

Additive uncertainty

More details at: Maasoumy, et al. DSCC 2012

Min-Max Strategy (Open-Loop) for RMPC

$$
\begin{aligned}
& J_0(x(t), U_t) \triangleq \\
\max_{w_{[\cdot]}} \quad & \Big\{ \sum_{k=0}^{N-1} |u_{t+k|t}| + \kappa \max(|u_{t|t}|, \cdots, |u_{t+N-1|t}|) + \\
& \rho \sum_{k=1}^{N} (|\overline{\varepsilon}_{t+k|t}| + |\underline{\varepsilon}_{t+k|t}|) \Big\} \\
\text{s.t.} \quad & x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t} + Ed_{t+k|t} + Fw_{t+k|t} \\
& w_{t+k|t} \in \mathbb{W} \\
& k = 0, \cdots, N-1
\end{aligned}
$$

TOO CONSERVATIVE!!!

Robust counterpart of an uncertain optimization problem

$$
J_0^*(x(t)) \triangleq \min_{U_t} \quad J_0(x(t), U_t)
$$

subject to

$$
\begin{aligned}
& x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t} + Ed_{t+k|t} + Fw_{t+k|t} \\
& y_{t+k|t} = Cx_{t+k|t} \\
& \underline{T}_{t+k|t} - \underline{\varepsilon}_{t+k|t} \leq y_{t+k|t} \leq \overline{T}_{t+k|t} + \overline{\varepsilon}_{t+k|t} \\
& \underline{\varepsilon}_{t+k|t}, \overline{\varepsilon}_{t+k|t} \geq 0 \\
& \forall \;\; w_{t+k|t} \in \mathbb{W} \qquad \forall \;\; k = 0, \cdots, N-1
\end{aligned}
$$

CL-RMPC: Feedback Predictions

- Closed-loop min-max problem:

$$\min_{u_{k|k}} \max_{w_{k|k}} \cdots \min_{u_{k+N-1|k}} \max_{w_{k+N-1|k}} \sum_{j=0}^{N-1} p(x_{k+j|k}, u_{k+j|k})$$

Intractable Problem

Feedback Predictions

- State feedback prediction: $U = \mathbf{M}X + \mathbf{v}$

The mapping from **M** and **v** to *X* and *U* is nonlinear!

- New decision variables: $\mathbf{v} = [v_{k|k}, v_{k+1|k}, \ldots, v_{k+N-1|k}]$
- Parameter matrix **M** is *causal*:

in the sense that $u_{k+j|k}$ only depends on $x_{k+i|k}$, $i \leq j$.

- Sometimes **M** is incorporated as a **decision variable**...

Lower Triangular Structure (LTS)

- Disturbance Feedback Policy:
  - **parameterize future inputs as affine functions of past disturbances.**

$$U = \mathbf{M}\mathbf{w} + \mathbf{v}$$

i.e.

$$u_i := \sum_{j=0}^{i-1} m_{i,j}\omega_j + v_i \qquad \forall i = 1, \ldots, N-1$$

Where $M_{i,j} \in \mathbb{R}^{m \times p}$ and $v_i \in \mathbb{R}^m$.

$$\mathbf{M} := \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ m_{1,0} & 0 & \ddots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ m_{N-1,0} & \cdots & m_{N-1,N-2} & 0 \end{bmatrix}, \mathbf{v} := \begin{bmatrix} v_0 \\ \vdots \\ \vdots \\ v_{N-1} \end{bmatrix}$$

Drawback:

- Main **problem** with the *min-max formulations* based on these parameterizations is:

the **excessive** number of decision variables and constraints

To resolve this issue

we study some other parameterizations

Toeplitz Structure

- *Lower Triangular Toeplitz* (diagonal-constant) structure:

$$U = \mathbf{M}\mathbf{w} + \mathbf{v}$$

$$\mathbf{M} = \begin{pmatrix} k_1 & & & & & \\ k_2 & k_1 & & & & \\ k_3 & k_2 & k_1 & & & \\ \vdots & & \ddots & \ddots & & \\ k_{N-1} & \cdots & \cdots & k_2 & k_1 & \\ k_N & k_{N-1} & \cdots & \cdots & k_2 & k_1 \end{pmatrix}$$

- was shown to deteriorate the performance of the CL-RMPC in our simulations!

Two Lower Diagonal Structure (TLDS)

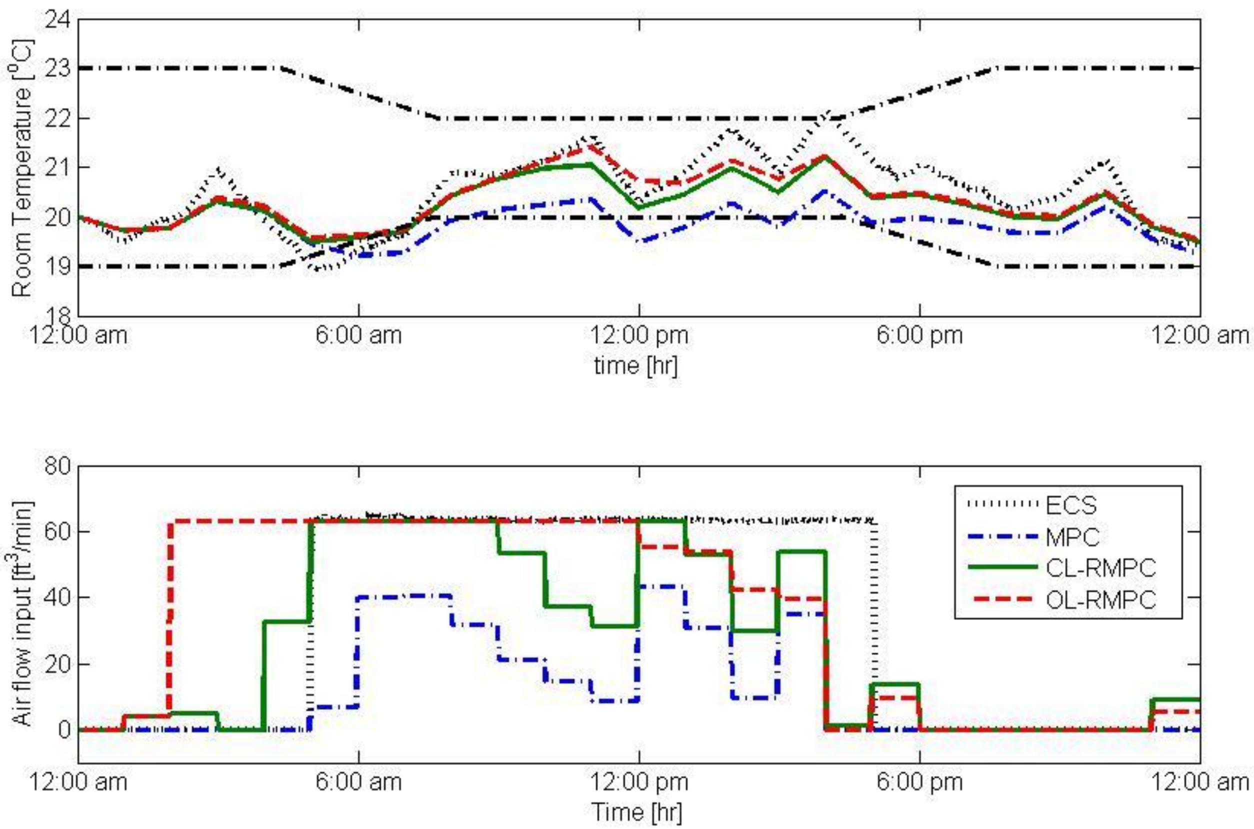
- By analyzing the structure of the optimal matrix **M**, we observed:
  - the parameterization of the input need not consider feedback of more than past <u>two</u> values of *w* at each time.

$$
\begin{aligned}
u_i &:= m_{i,i-2} w_{i-2} + m_{i,i-1} w_{i-1} + v_i \\
&= \sum_{j=i-2}^{i-1} m_{i,j} \omega_j + v_i \qquad \forall i = 1, \ldots, N-1
\end{aligned}
$$

we exploit the **sparsity** of the **M** matrix to enhance the <u>computational cost</u> of the optimization problem

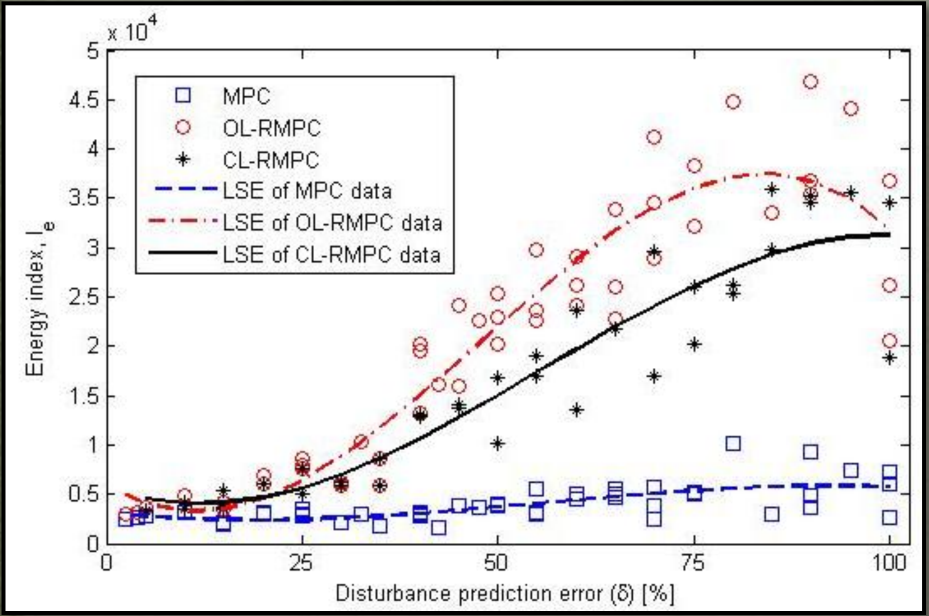
$$
\mathbf{M} = \begin{bmatrix}
0 & 0 & \cdots & 0 & 0 & 0 \\
m_{21} & 0 & 0 & \cdots & 0 & 0 \\
m_{31} & m_{32} & \ddots & \vdots & \vdots & \vdots \\
0 & m_{42} & \ddots & 0 & \vdots & \vdots \\
\vdots & \ddots & \ddots & m_{1,2} & 0 & 0 \\
0 & \cdots & 0 & m_{N,N-2} & m_{N,N-1} & 0
\end{bmatrix}
$$

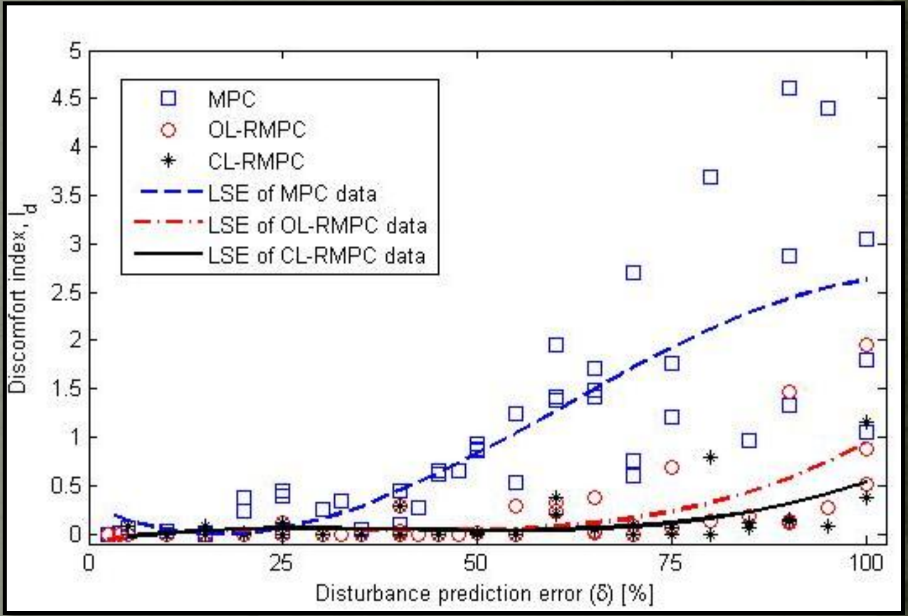
Simulation Results



Comparison of ECS, MPC, OL-RMPC and CL-RMPC

RMPC: Energy vs. Comfort





$$P_c(t) = \dot{m}_c(t) c_p [T_{out}(t) - T_c(t)]$$

$$P_h(t) = \dot{m}_h(t) c_p [T_h(t) - T_{out}(t)]$$

$$P_f(t) = \alpha \dot{m}^3(t)$$

$$I_E = \int_{t=0}^{24} [P_c(t) + P_h(t) + P_f(t)]\, dt$$

$$I_D = \int_{t=0}^{24} \left[\min\left\{\left|T(t) - \overline{T}(t)\right|, \left|T(t) - \underline{T}(t)\right|\right\} .\mathbf{1}_{\mathcal{B}(t)^c}(T(t))\right] dt$$

Simulation Results

- Comparison of **LTS** and **TLDS** uncertainty feedback parameterizations and Open Loop min-max results for the case of $\delta = 50\%$.

Closed-loop

Controller	Number of feedback decision variables	Average simulation time for $N = 24$ [s]	I_e $[kWh]$	I_d $[^oCh]$
LTS	$lmr(\frac{N(N+1)}{2})$	200	16467	0
TLDS	$3lmr(N-1)$	138	16467	0
OL	-	159	22592	0.84

Conclusion

- Presented a:
  - **MPC** strategy that is ***robust*** against additive uncertainty.
- Study the performance of two robust optimal control strategies, i.e.
  - Open-loop (OL-RMPC)
  - Closed-loop (CL-RMPC)
- Proposed (*TLDS*): a **new uncertainty feedback parameterization** for the CL-RMPC which results in:
  - Same **energy** and **discomfort** indices as *LTS*.
  - Fewer **decision variables**, (*linear in* N, as opposed to *quadratic* for *LTS)*.
  - Average **simulation time** of 30% less than LTS.

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- Buildings and Smart Grid

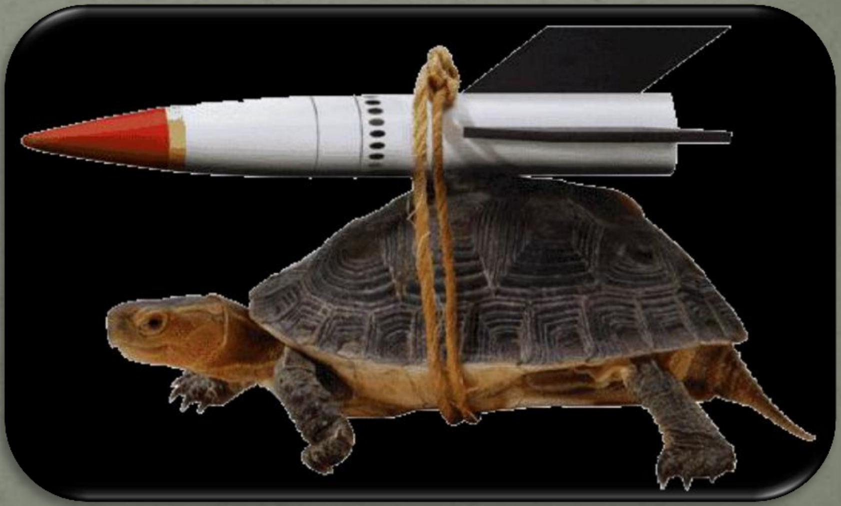
Comparative Analysis of Different Model-Based Optimal Controllers

Problem Statement

Computation (and Communication) constraints

ask for …

Faster Controllers!!!



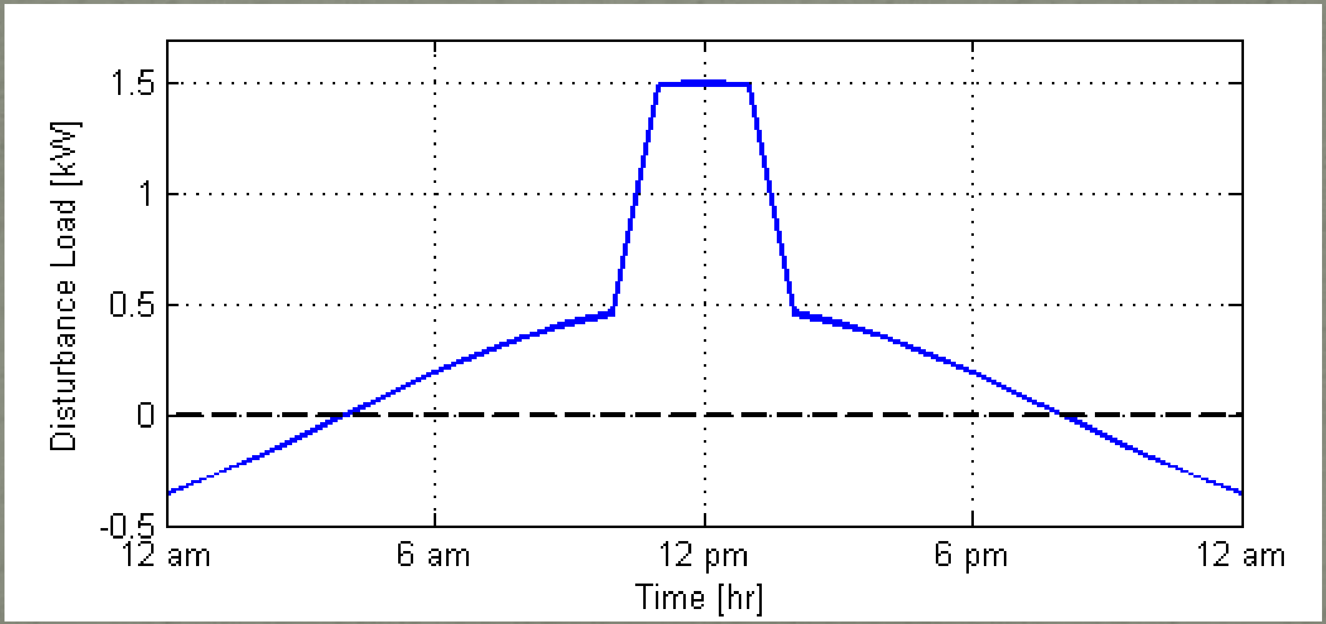
Controllers

- P Control: fast, not optimal. (baseline)
- LQR: fast (closed form solution); NO hard constraints handling
- AQR: fast (closed form solution); NO hard constraints handling; more accurate than LQR
- MPC: slower (online optimization problem solving); hard constraints handling

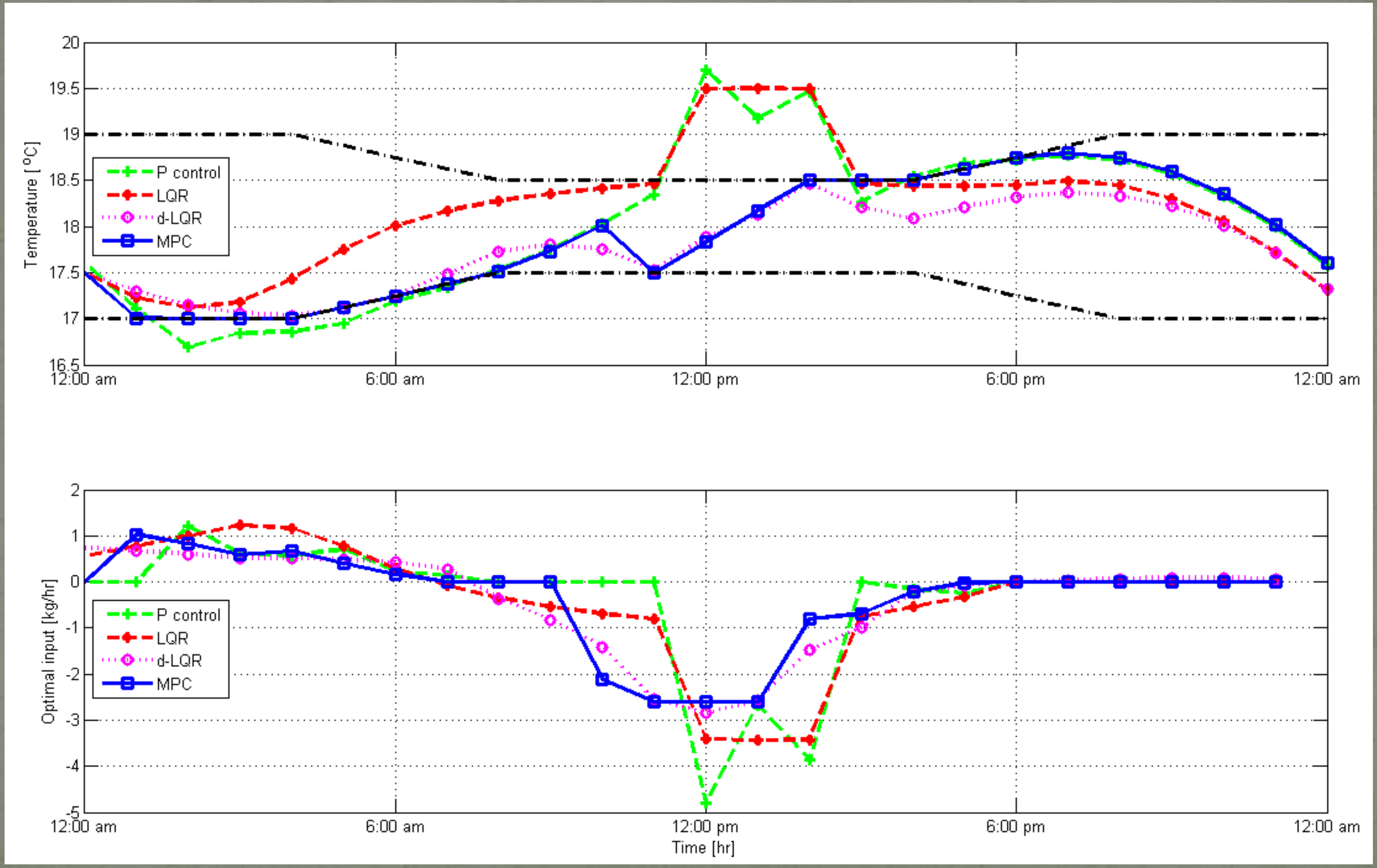
Disturbance Model

Assume:

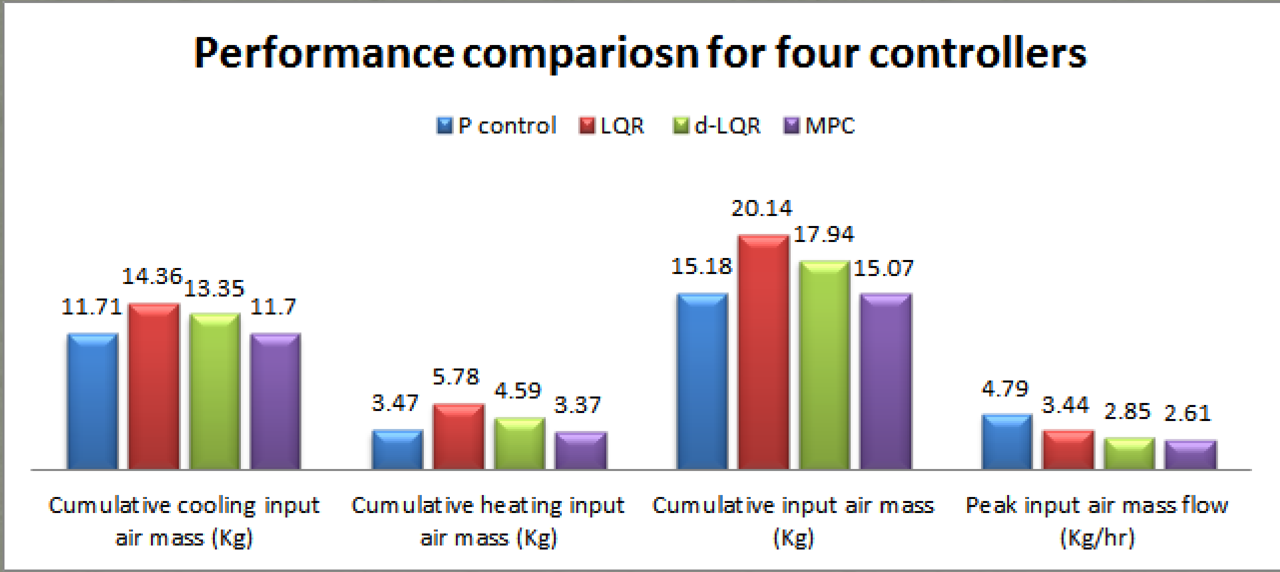
- Meeting in the considered room from 11 am to 1 pm.
- The disturbance load would be like:



Comparative Analysis of controllers : LQR, d-LQR (AQR), MPC and P control

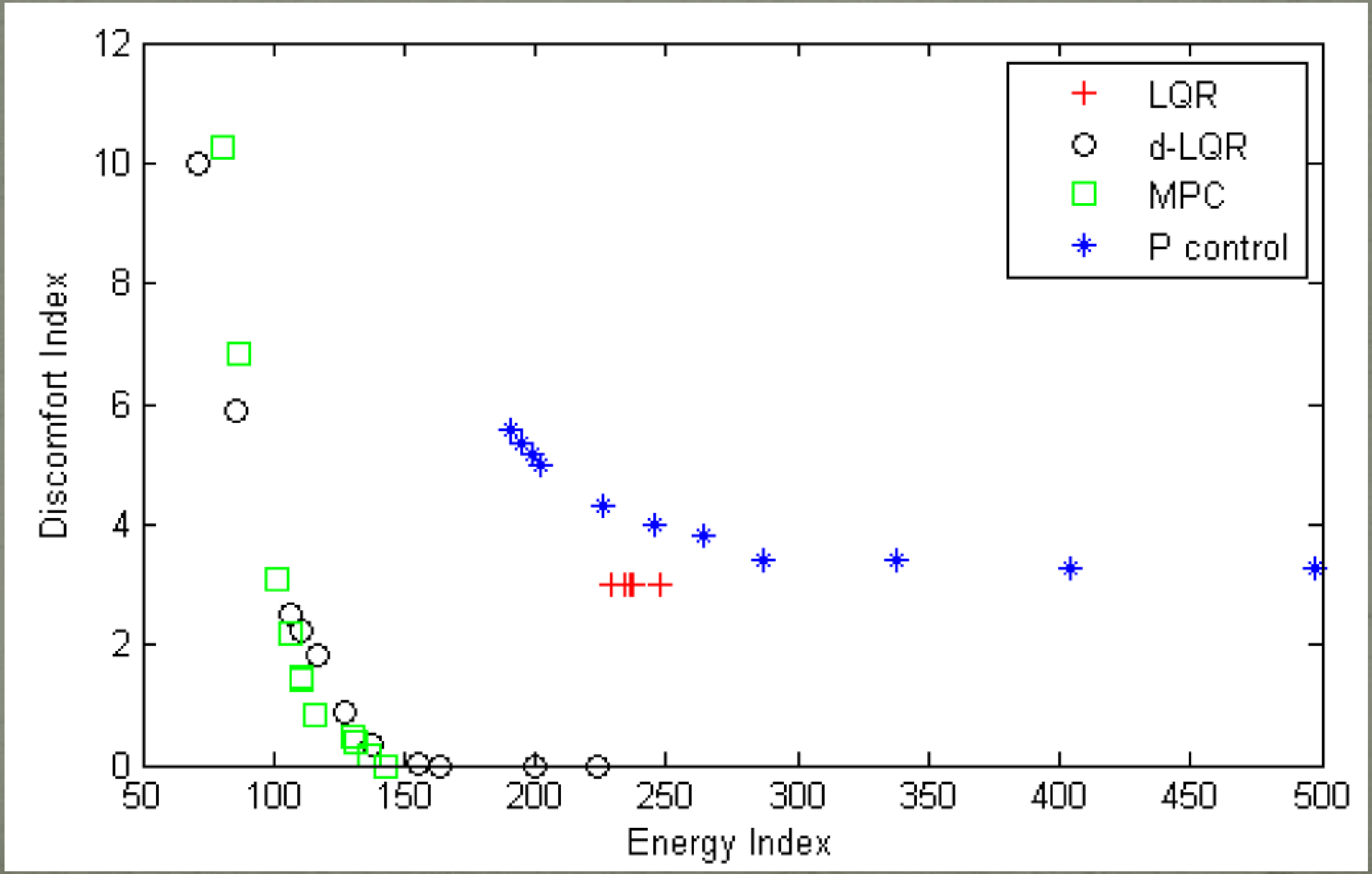


Performance Comparison



Controller	Parameters	Simulation time $[s]$
P control	$K_p = 4$	0.187
LQR	$Q_1 = 0.01,\ Q_2 = 100$ $R_1 = 10\ R_2 = 0.02$	0.057
d-LQR	$Q_1 = 0.24,\ Q_2 = 0.54$ $R_1 = 1\ R_2 = 0.09$	0.009
MPC	$\kappa = 2,\ \rho = 1000$	95.098

Comfort vs. Cost



Outline

- Motivation
- Thermal Modeling
  - First approach (Physical Buildings)
  - Second Approach (Simulation Models)
- Model-Based Optimal Control Design
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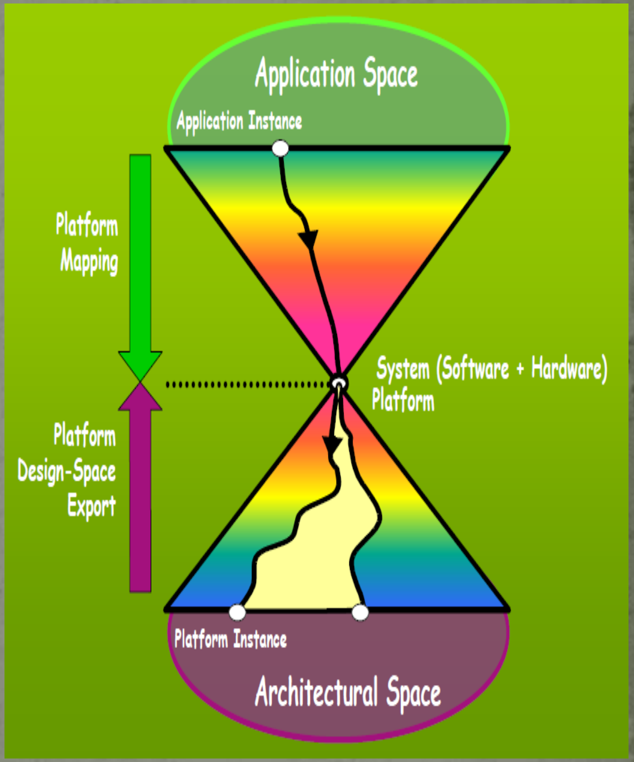
Co-design of Control Algorithm and Embedded Platform for HVAC Systems

Observations

The design of HVAC systems involves three main aspects:

I. Physical components and environment
II. Control algorithm that determines the system operations based on sensing inputs,
III. Embedded platform that implements the control algorithm.



In the traditional *top-down approach*, the design of the HVAC control algorithm is done without explicit consideration of the embedded platform.

NOT PLATFORM-BASED!!!

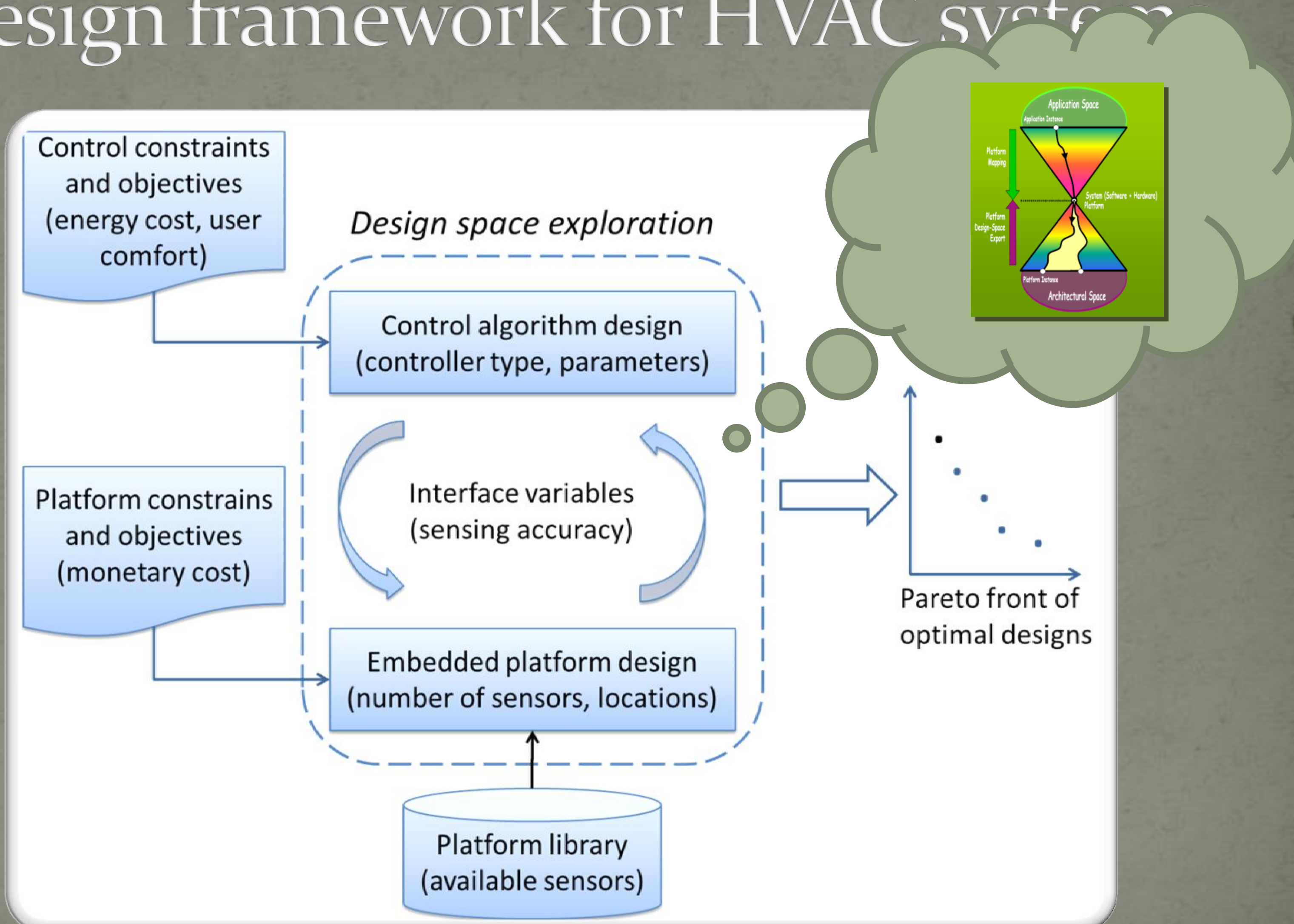
Problem

With…

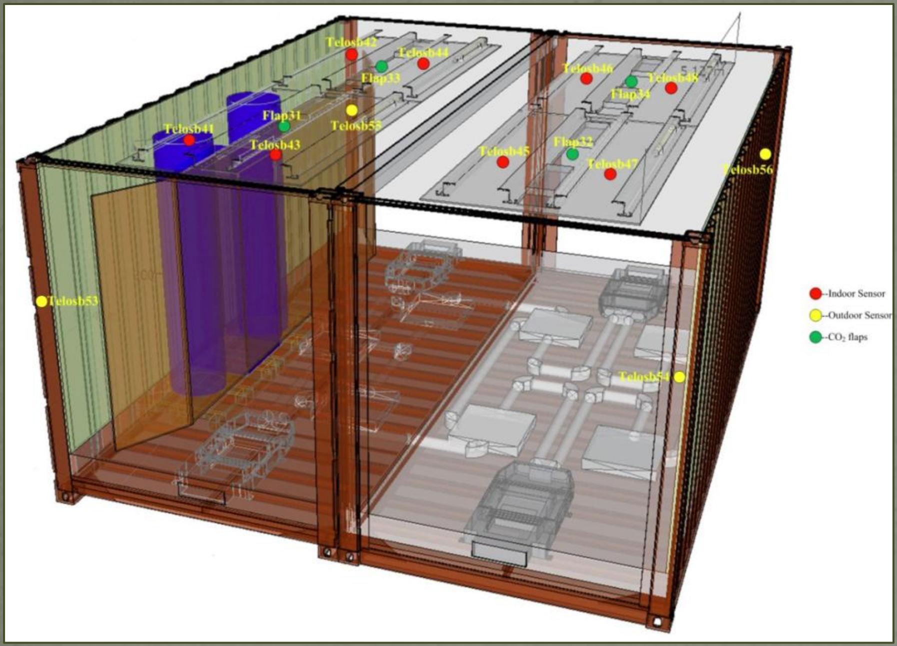
- *the employment of more complex HAVC control algorithms*
- *the use of distributed networked platforms, and*
- *the imposing of tighter requirements for user comfort*

the assumption that…
the embedded platform will always be sufficient for any control mechanism
is no longer true.

Co-design framework for HVAC system



Sensing System Set-up



BubbleZERO Research Setup

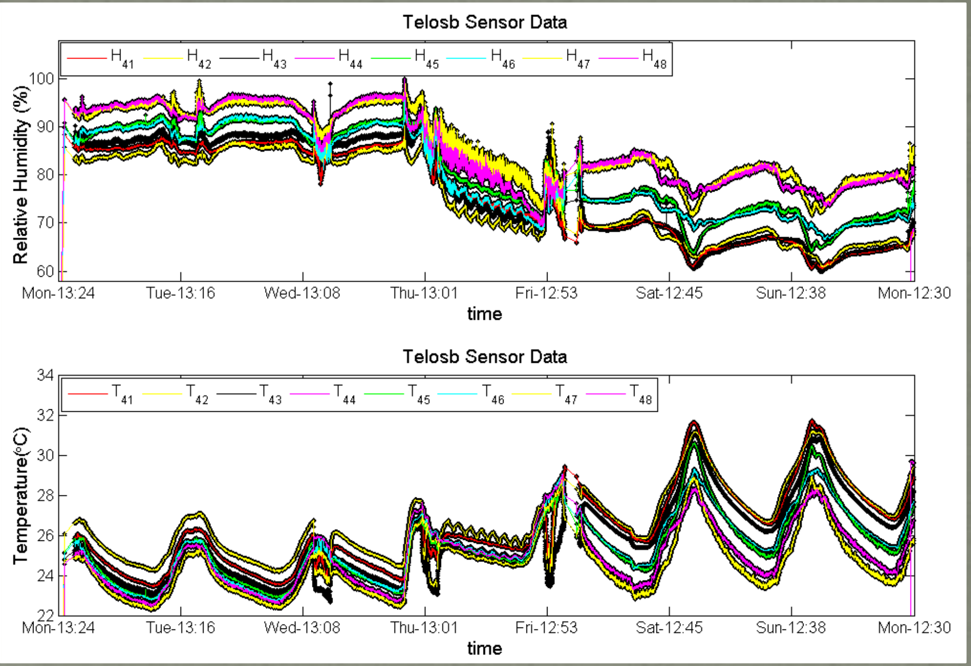
Which is conceived as part of the Low Exergy Module development for Future Cities Laboratory (FCL)

The environment sense system includes:

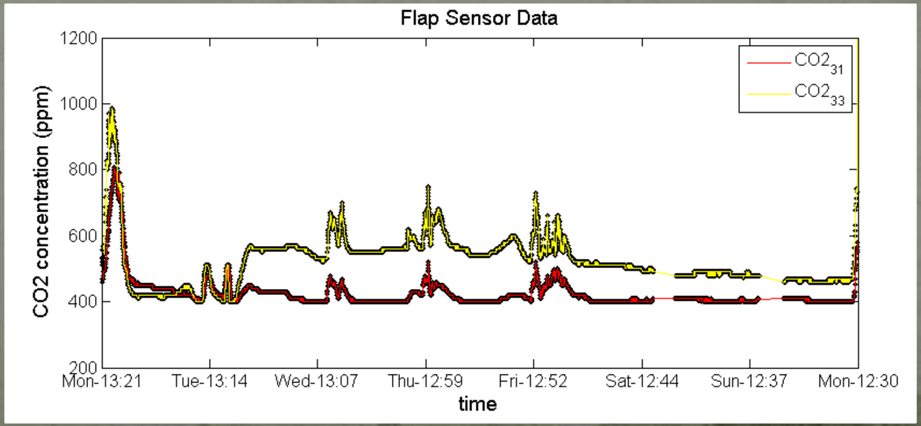
- 8 indoor sensors (Telosb41-48)
- 4 CO2 concentration sensors (flap31-34)
- 4 outdoor sensors (Telosb53-56)

Sensor Reading from the Set-up

Temperature measurements from 8 sensors located spatially at different places in the room. The statistics of the sensor measurement error is extracted from this set of data.

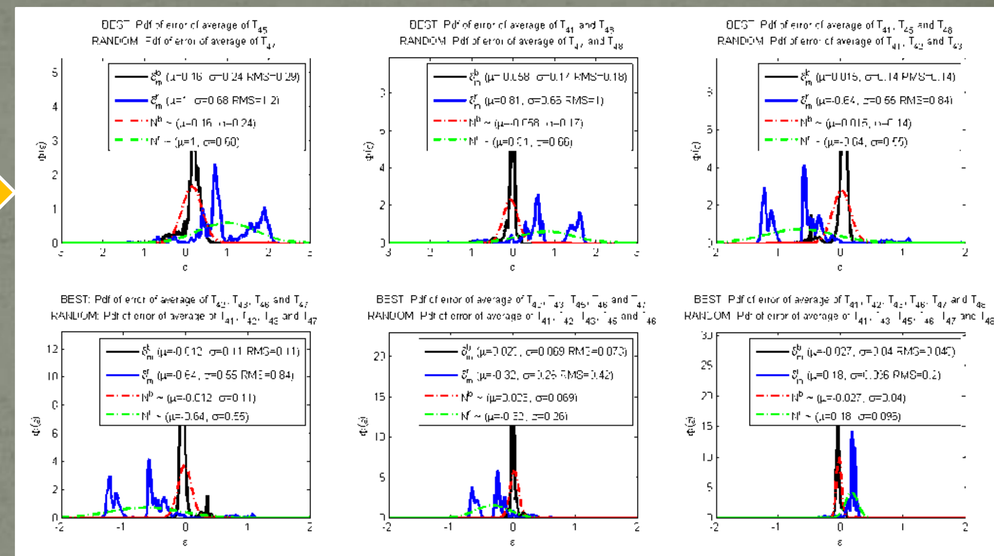


CO2 measurements from 2 sensors located spatially at different places in the room.



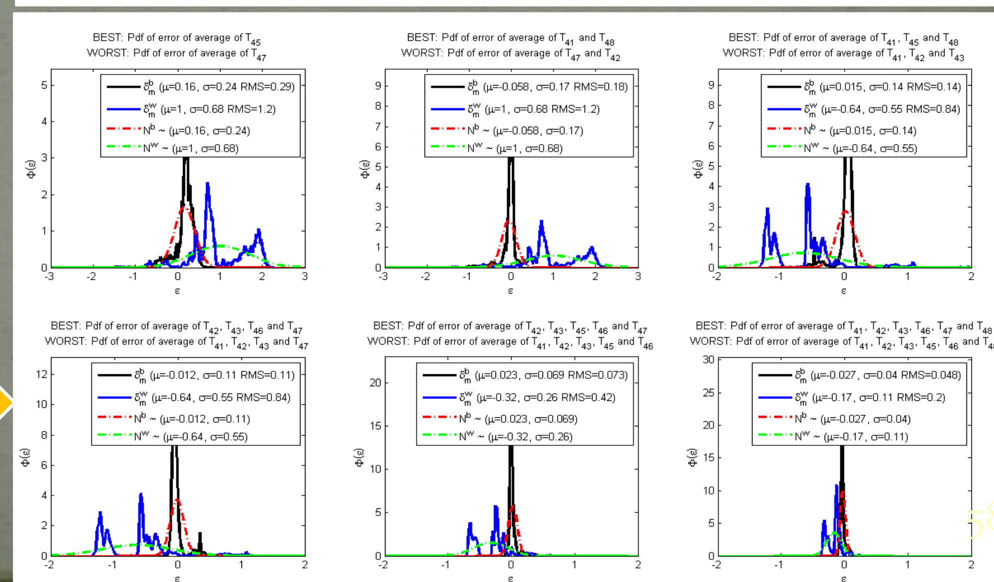
Analysis of Sensor Readings

Average error of k sensors for the Minimal error set of sensors and a random choose of sensors.

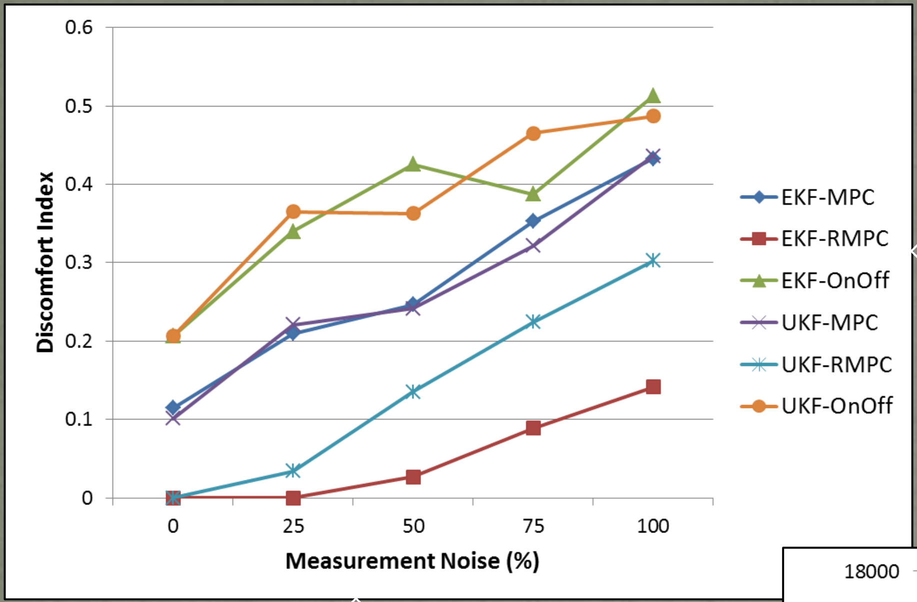


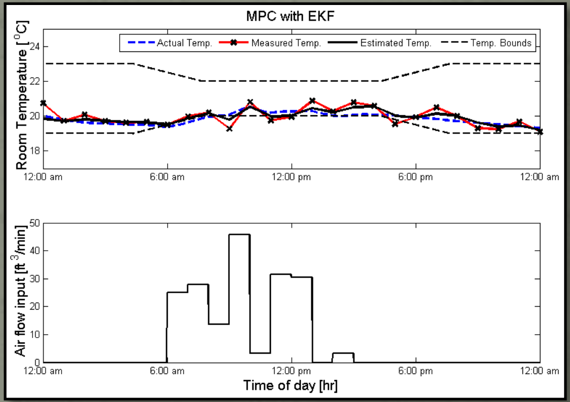
The *pdf* of the difference of the average of k sensor readings with the average of all $n_{ts}=7$ sensor readings.
The best, worst and random set of sensors are selected based on their resulting Δ_{rms} error.

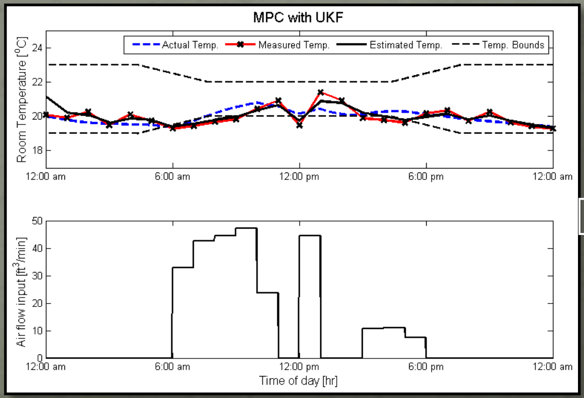
Average error of k sensors for the Minimal error set of sensors and the worst choose of sensors.

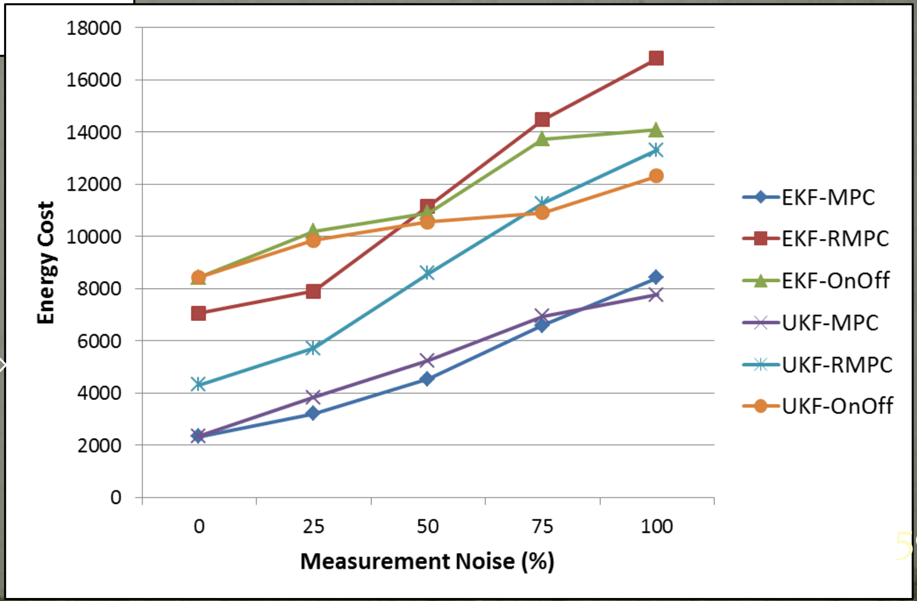


Simulation Results

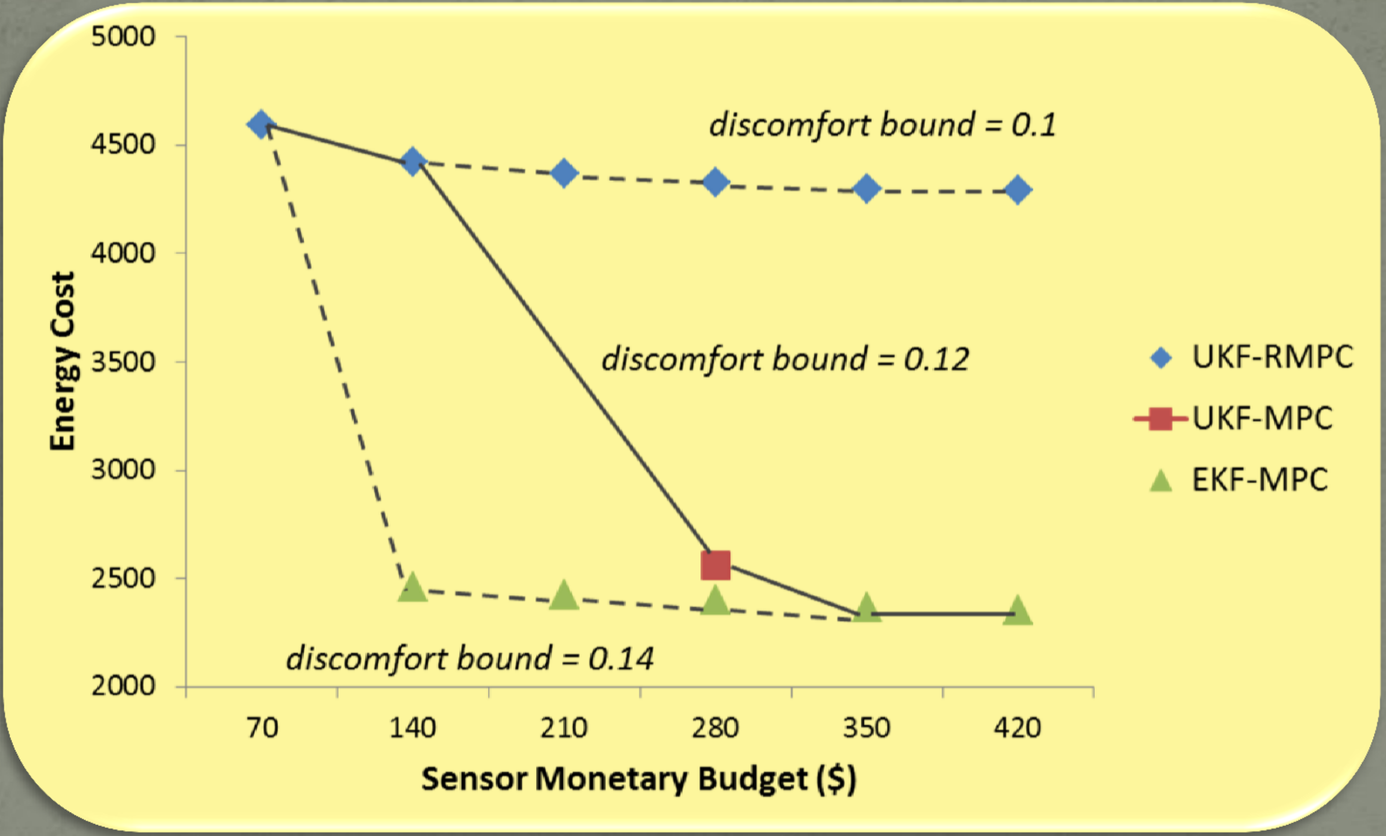






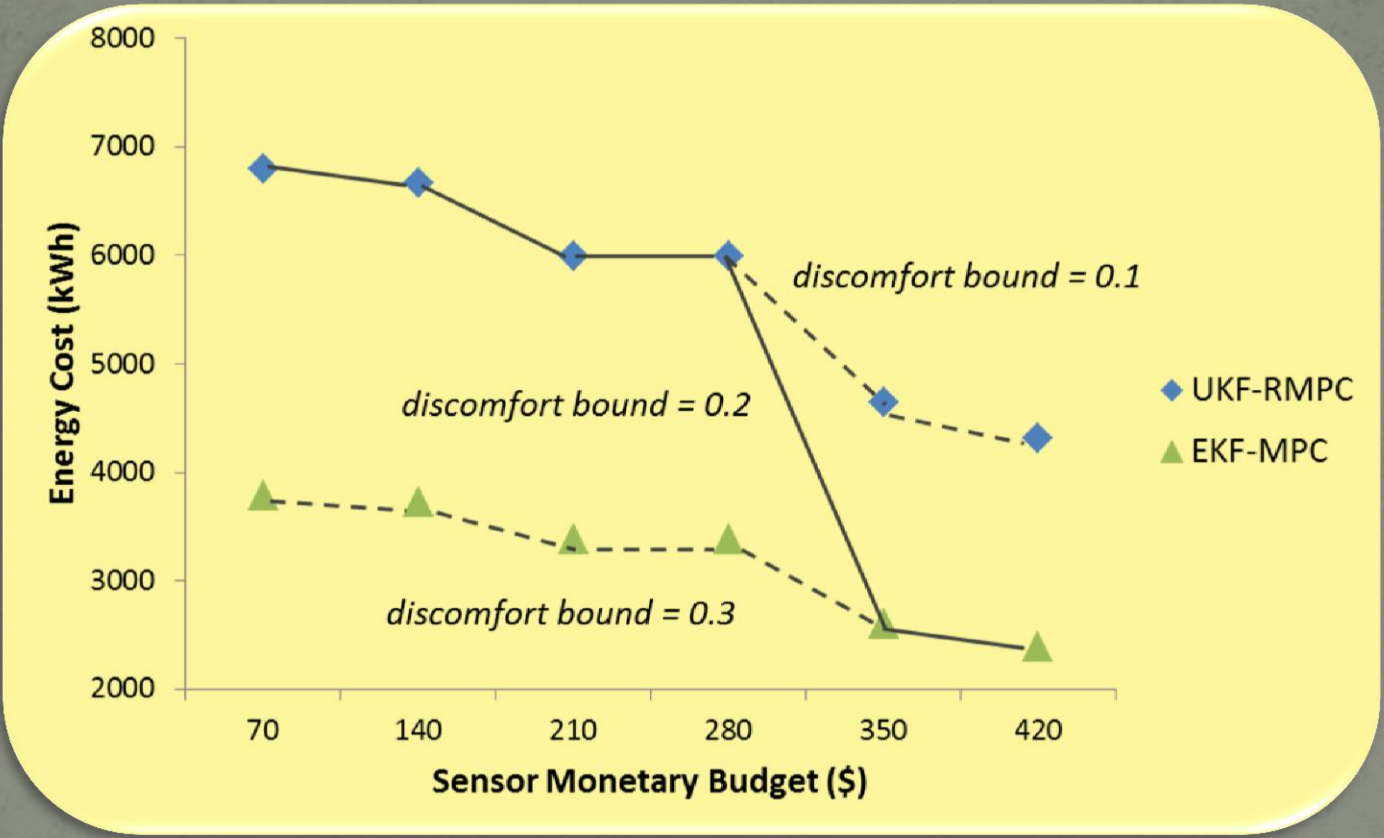


Pareto front Under Discomfort index Contraints



Pareto front under comfort constraints with best sensor locations

Pareto front Under Discomfort index Contraints



Pareto front under comfort constraints with random sensor locations

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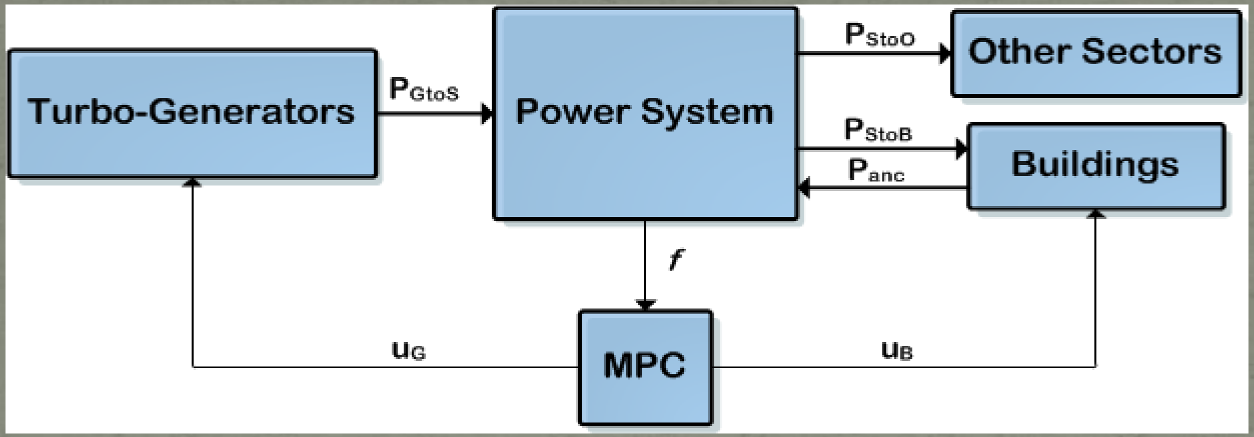
Ongoing Research…

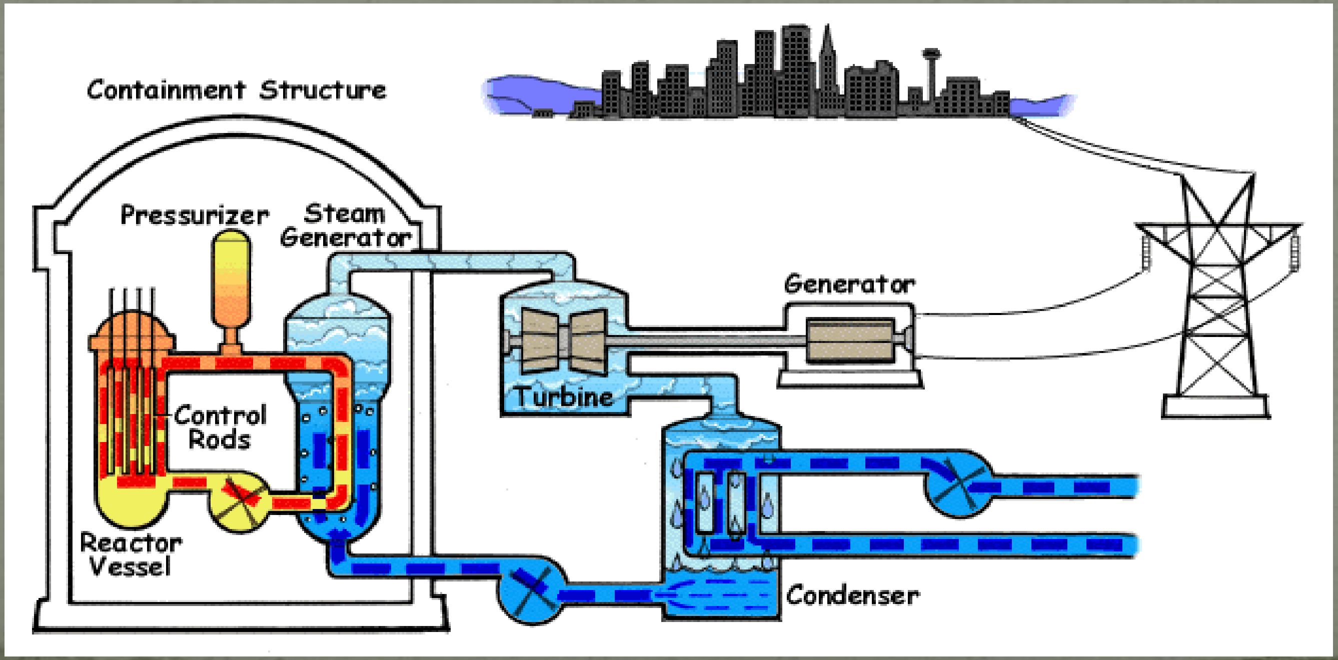
Cyber-Physical System

Buildings and Smart Grid

Ancillary Services via Control of HVAC Systems

Ancillary Services via Control of Building HVAC Systems





Source: http://evergreennuclear.blogspot.com/2011/08/primer-on-how-pressurized-water-reactor.html

Thank You!

Questions?

More information at: eecs.berkeley.edu/~maasoumy

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