Control and Optimization of Cyber-Physical Energy Systems:

Smart Buildings within Smart Grid

(A Platform-Based Design Approach)

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Outline

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

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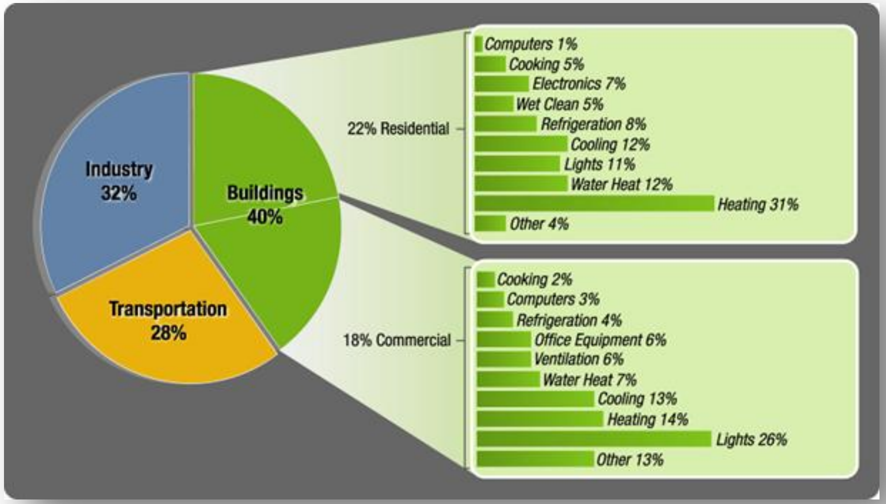
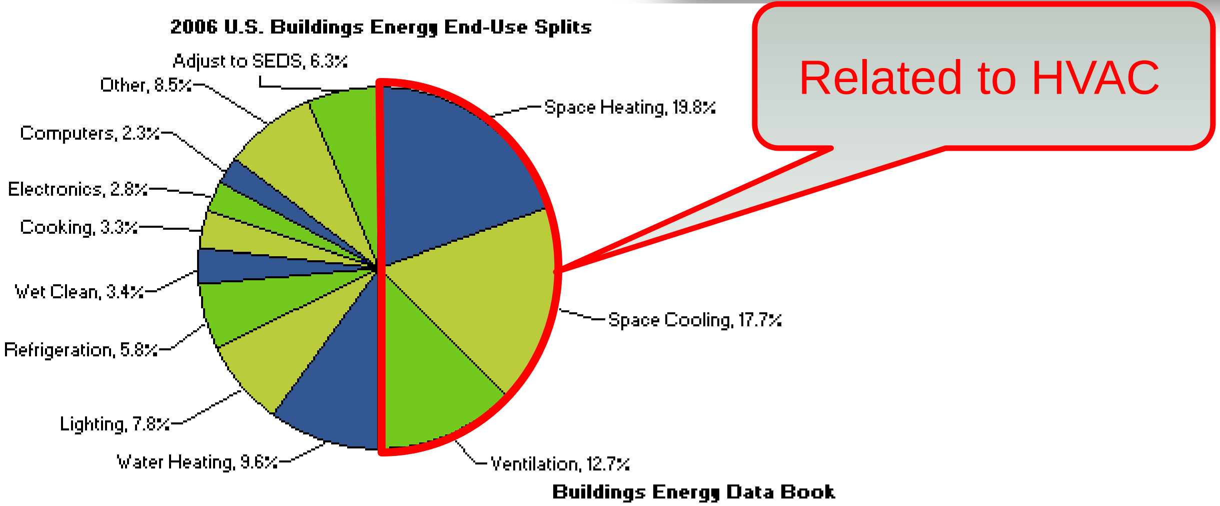
Motivation

Buildings Consume Significant Energy

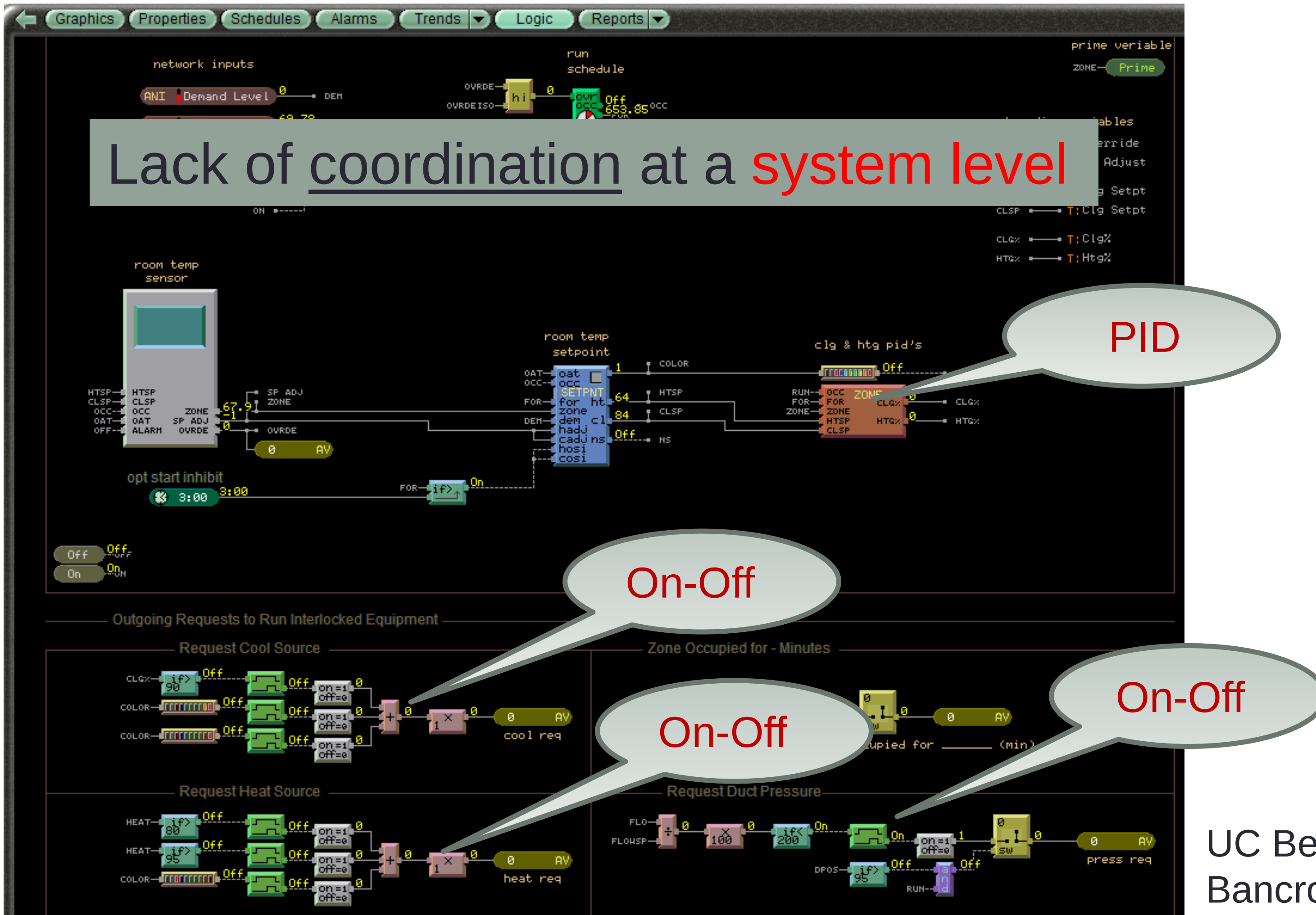
- 40% of total US energy consumption
- 72% of total US electricity consumption
- 55% of total US natural gas consumption
- Total US annual energy cost $ 370 Billion
- Increase in US electricity cons. since 1990: 200%

Source: Buildings Energy Data Book 2007





Current HVAC Control Systems



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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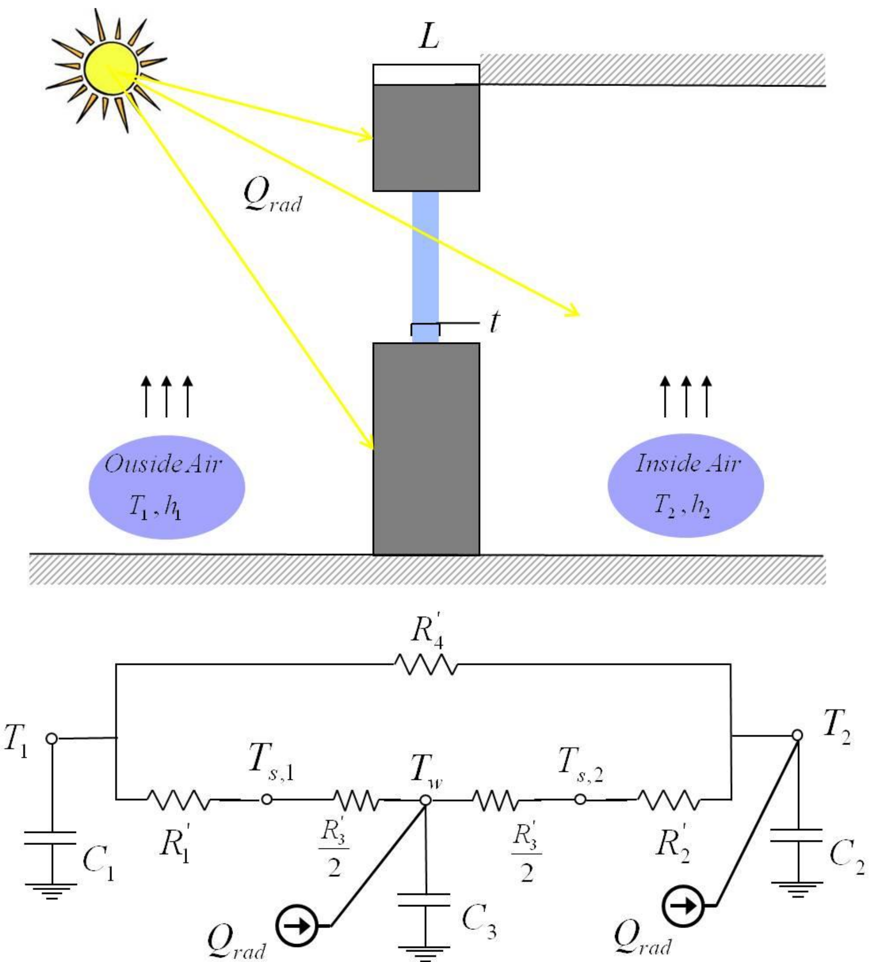
First approach

Physical Buildings

- Modeling
- Parameter & Unmodeled dynamics estimation
- Online state estimation and parameter adaptation
- Model-based Control

courtesy of smartgeometry.com

Thermal Modeling



Thermal and circuit model of a wall with window

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

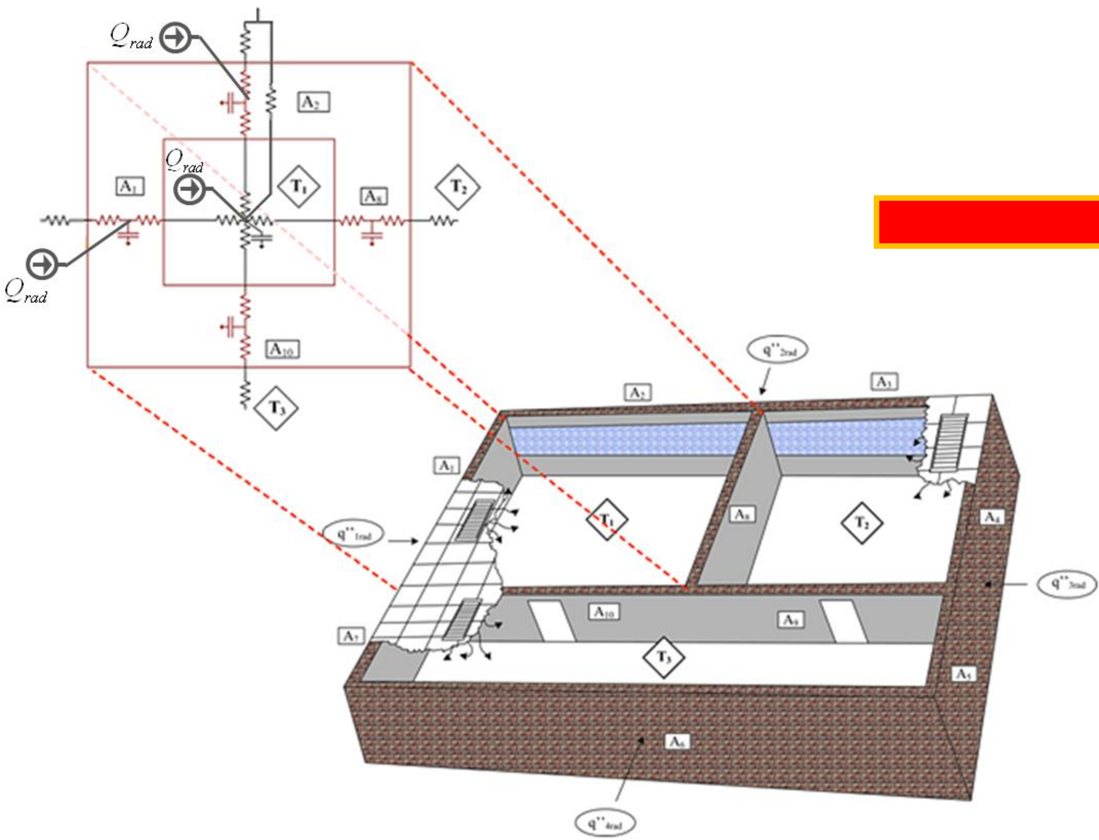
$$\frac{dT_{w_i}}{dt} = \frac{1}{C_{w_i}} \left[\sum_{j \in \mathcal{N}_{w_i}} \frac{T_j - T_{w_i}}{R'_{ij}} + r_i \alpha_i A_i q''_{rad_i} \right]$$

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

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

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

Building Thermal Dynamics



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

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

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.

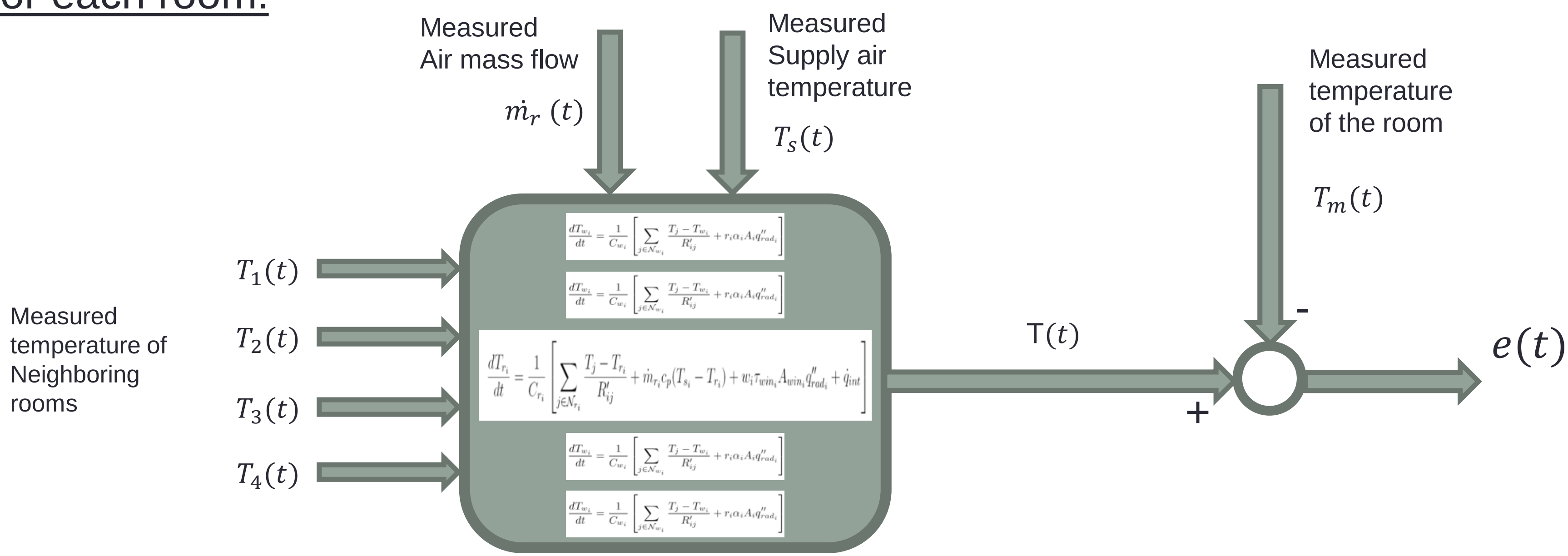
- Internal heat gain

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

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

Parameter & Unmodeled Dynamics Identification

For each room:



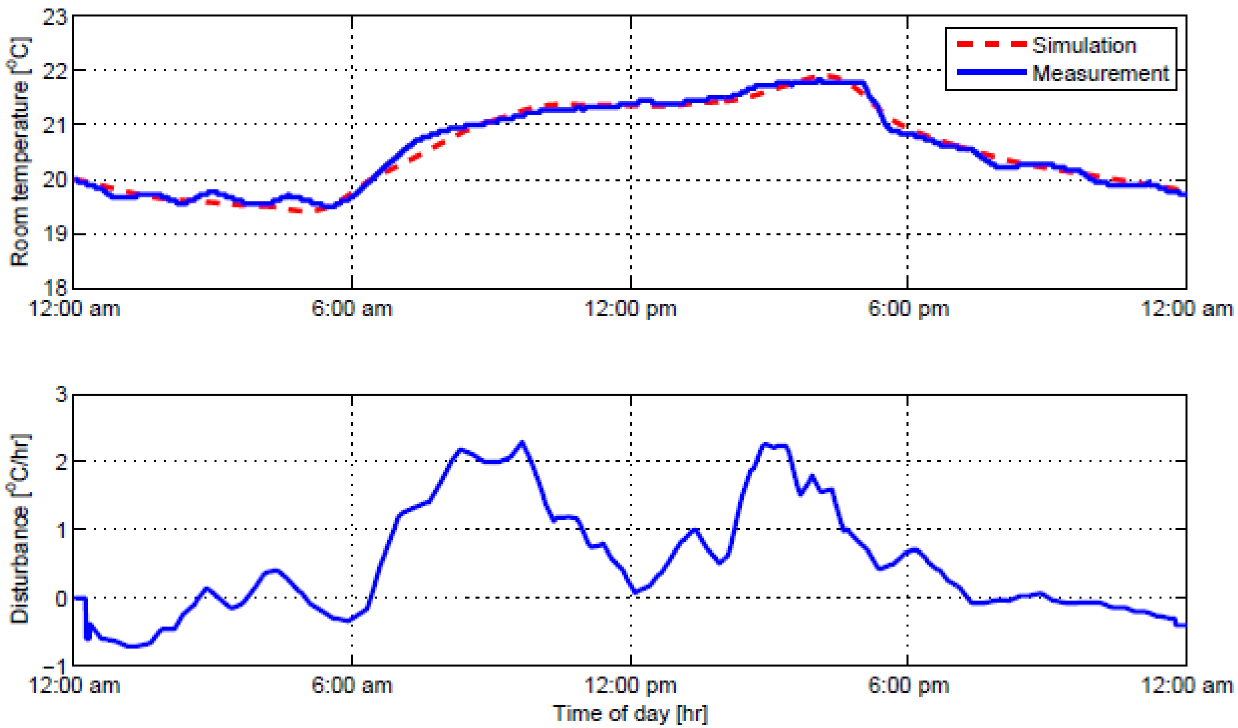
$$T(t) = f(C_r, C_{w1}, C_{w2}, C_{w3}, C_{w4}, R_1, R_2, R_3, R_4)$$

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

Unmodeled Dynamics Estimation

- Initial guess (ASHRAE Handbook)

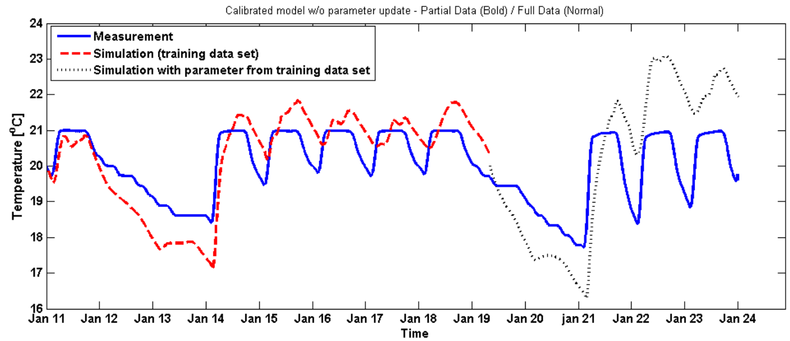
- Data of UC Berkeley
- Bancroft library, Conference room



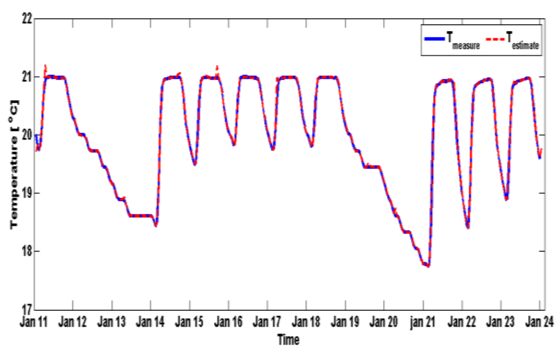
More details at: Maasoumy et al., IEEE D&T, SI on Green Buildings, July/Aug 2012

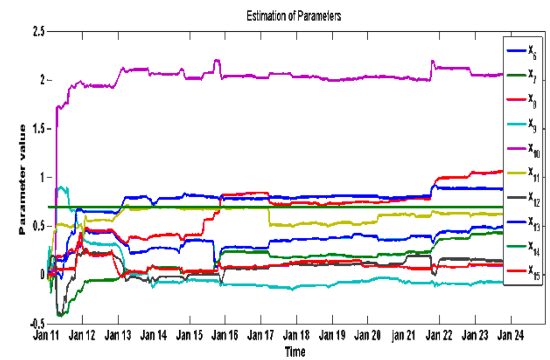
Online State Estimation and Parameter Adaptation

Offline parameter identification

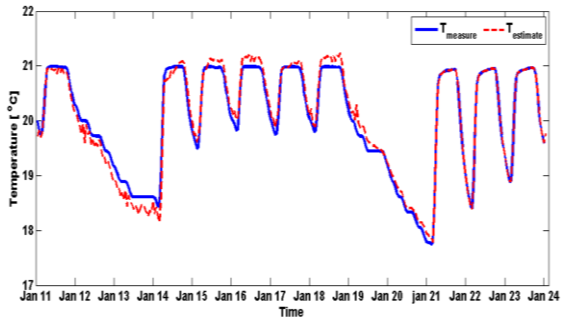


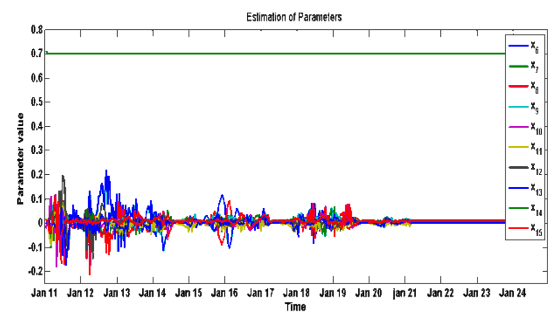
Online Parameter Adaptation using EKF





Online Parameter Adaptation using UKF



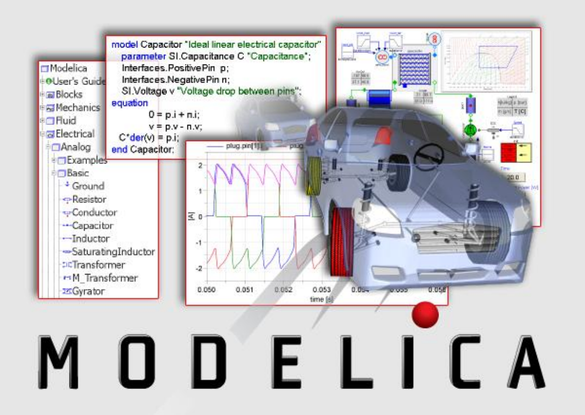


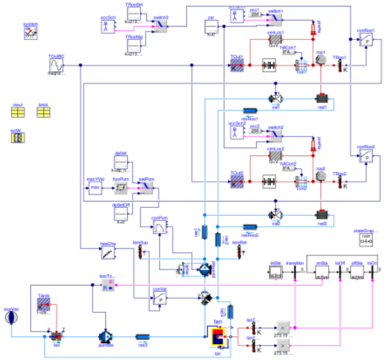
More details at: Maasoumy et al. DSCC 2013, Submitted.

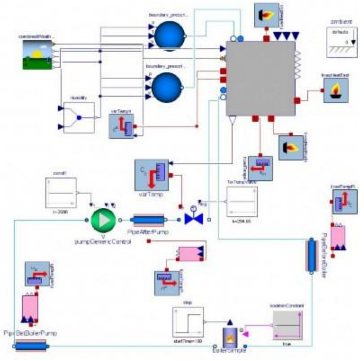
Second approach

Simulation Models

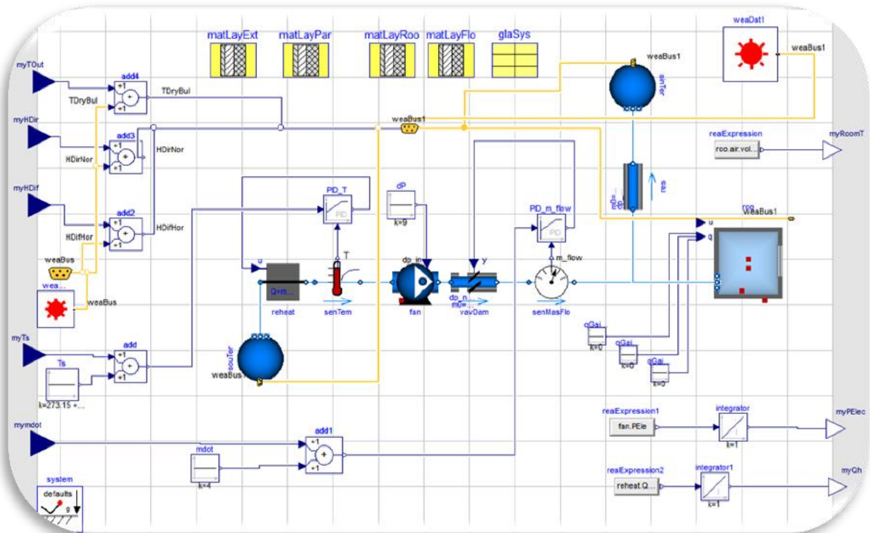
- Family of linear systems:
  - Linearized models at each operating point
  - Obtain adequate number of models for a given tolerance
  - Switched or Hybrid Models
  - Balanced realization
  - Model order reduction



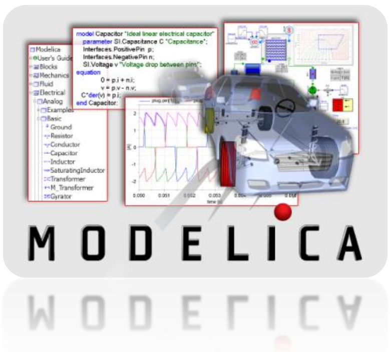




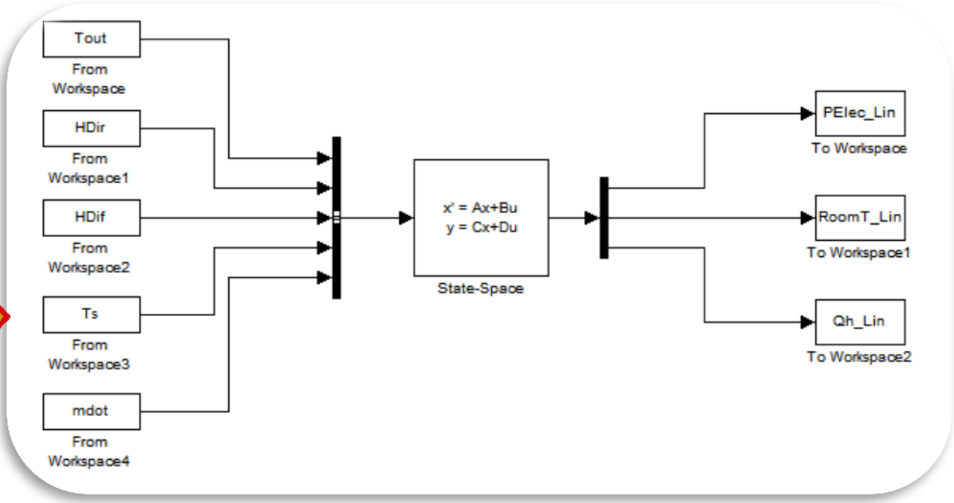
Family of linear systems



Modelica model

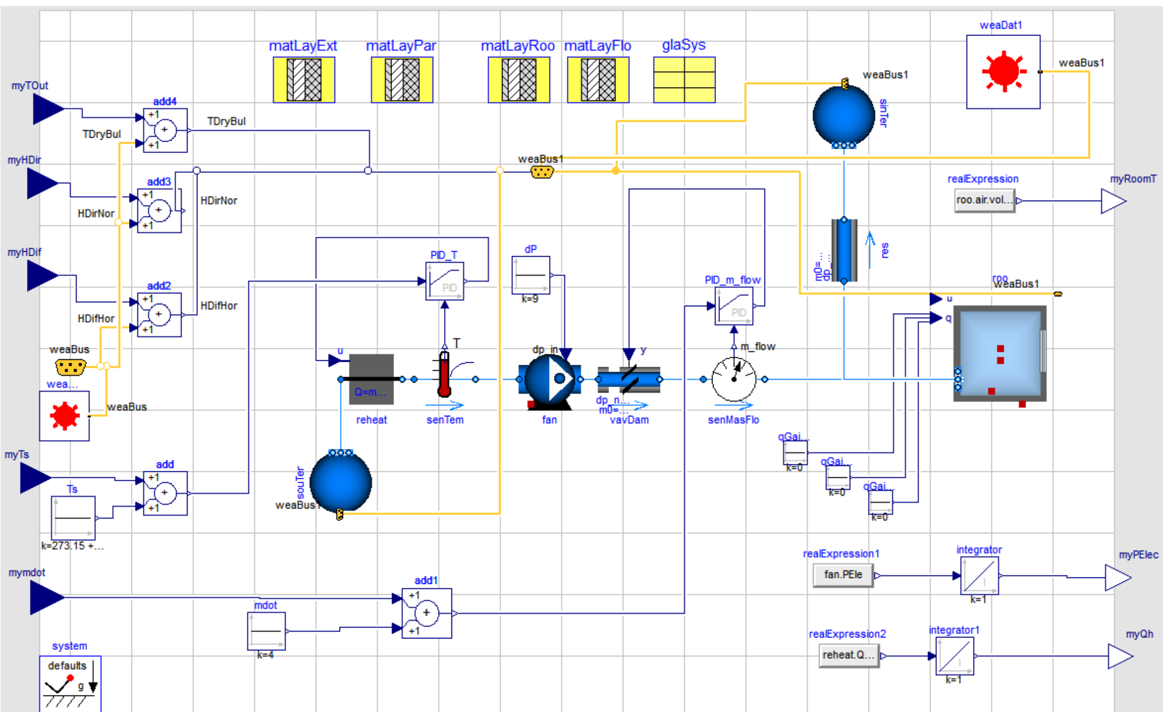


Extract linearized model



Simulink model

MOR Procedure



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

Linearize

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

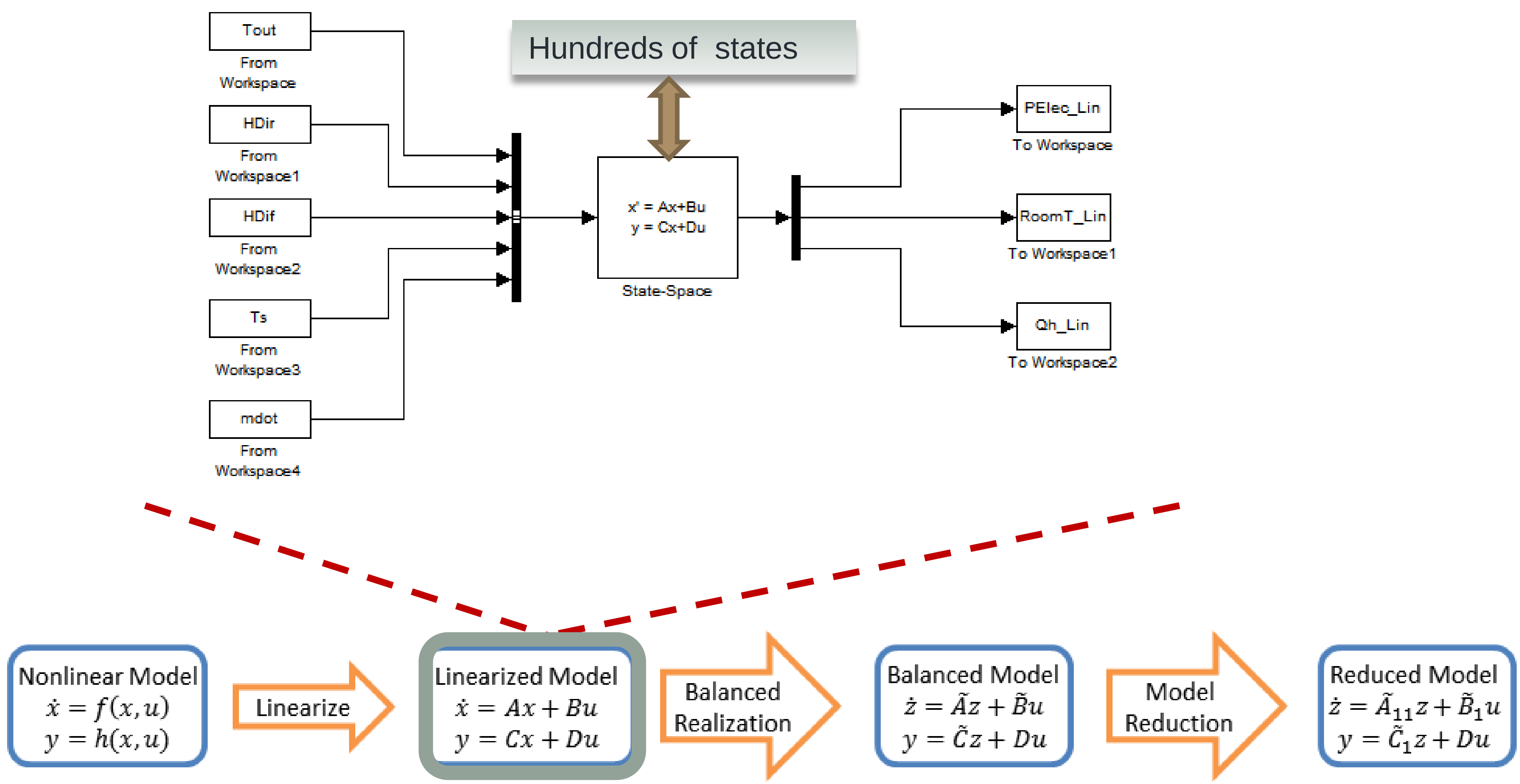
Balanced Realization

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

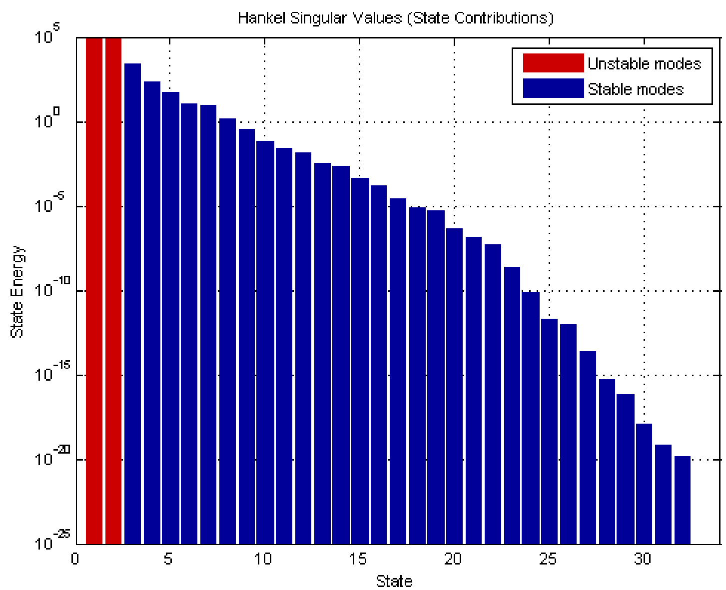
Model Reduction

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

MOR Procedure



MOR Procedure



Hankel singular values:
Relative amount of energy per state

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
$\dot{z} = \tilde{A}z + \tilde{B}u$
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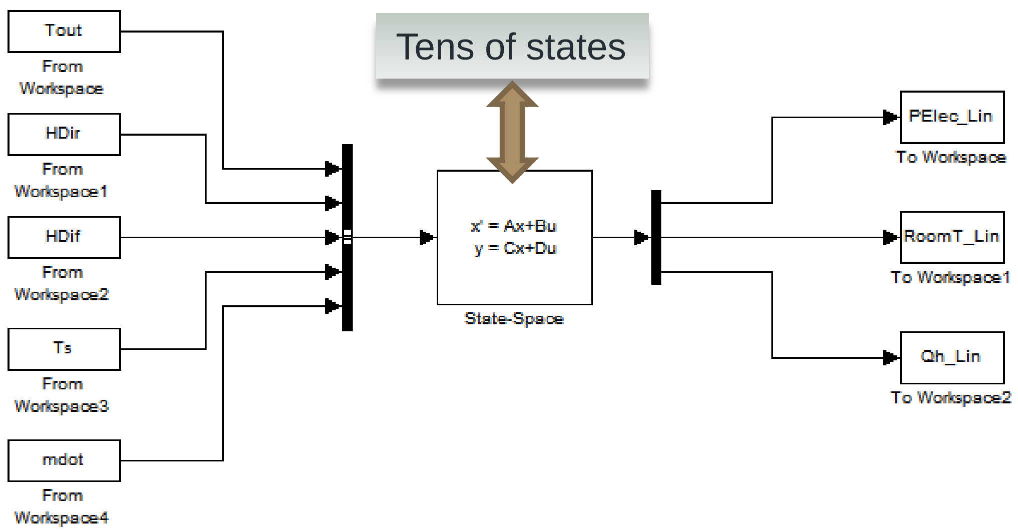
MOR Procedure



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

Linearize

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

Balanced Realization

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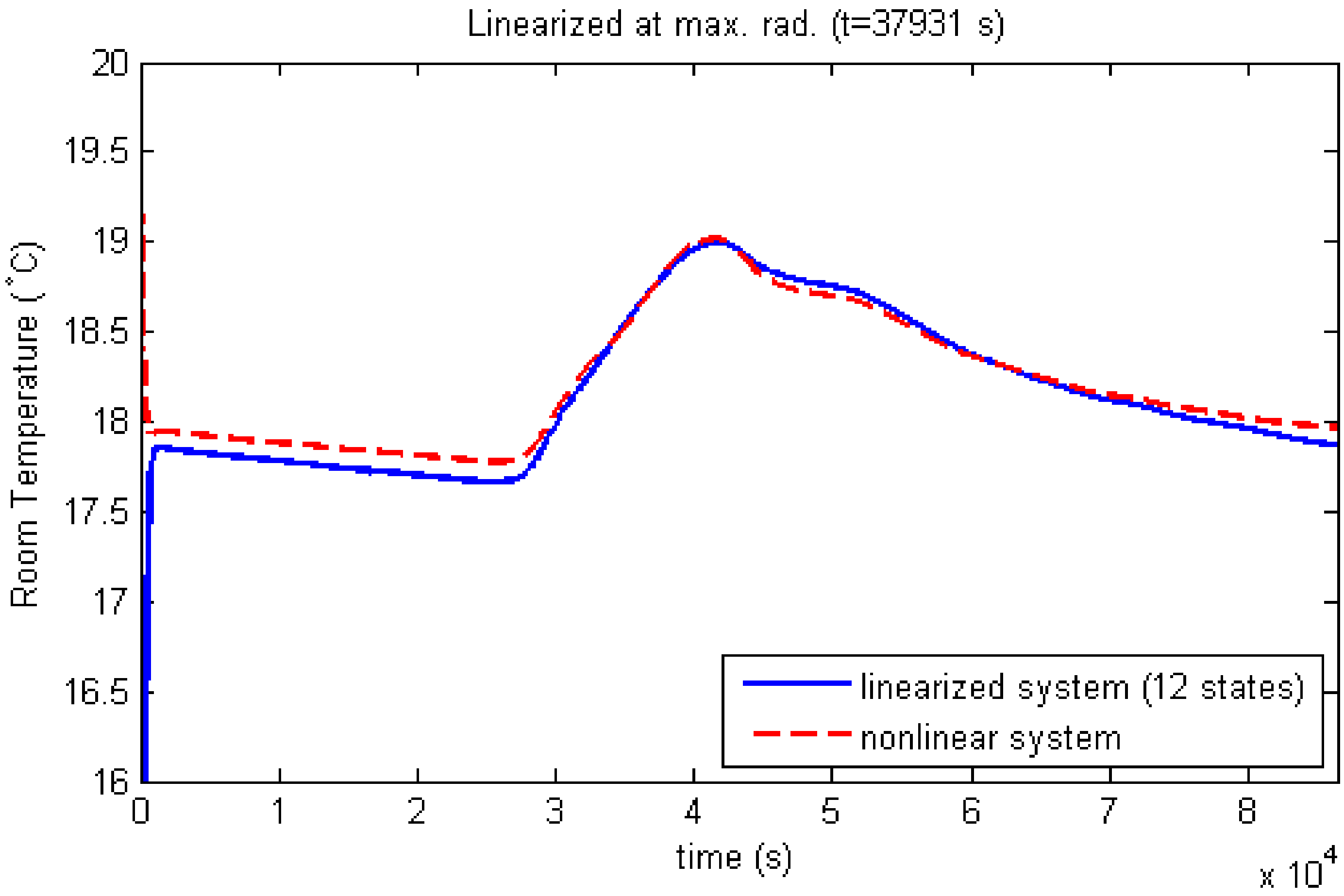
$\dot{z} = \tilde{A}z + \tilde{B}u$
$y = \tilde{C}z + Du$

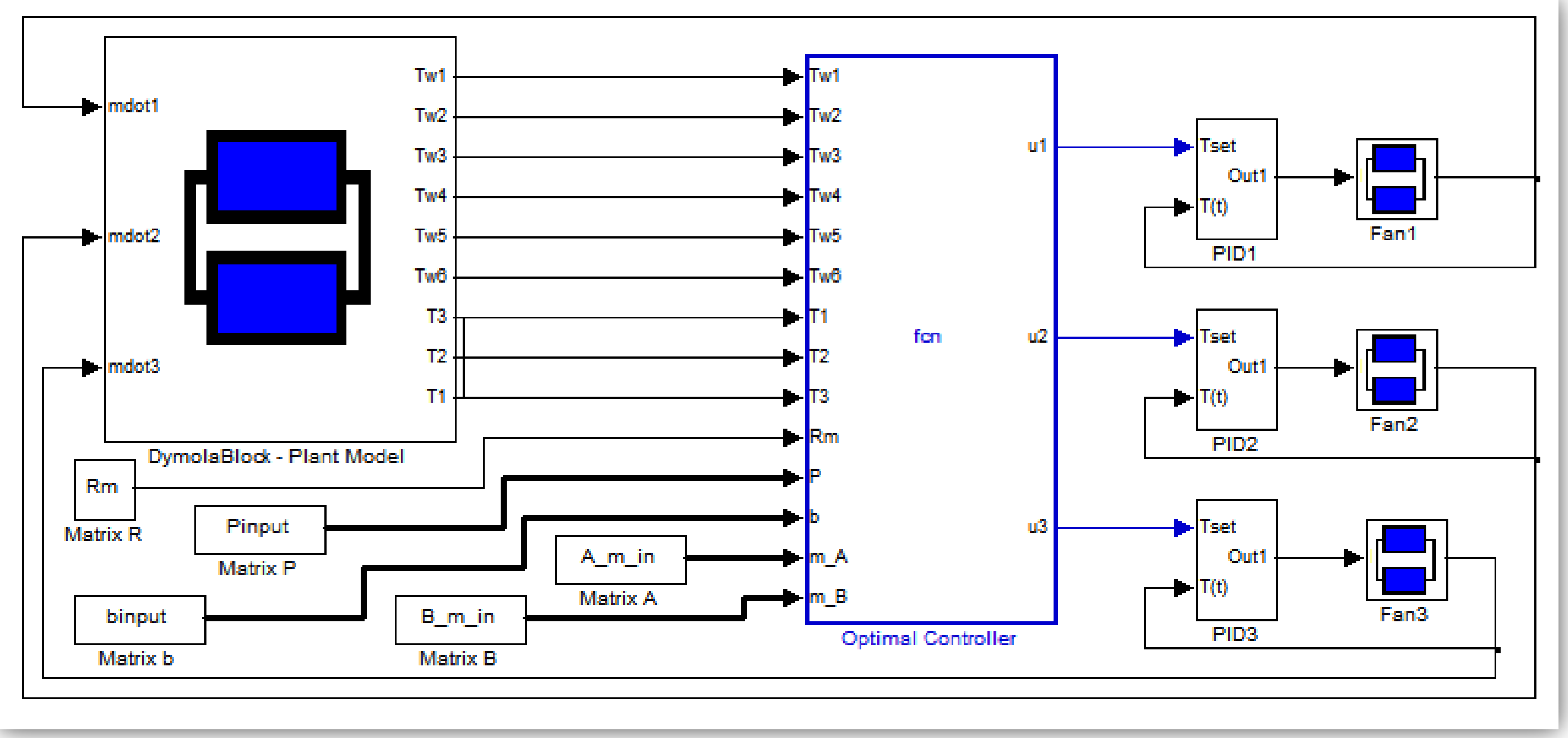
Model Reduction

Reduced Model
$\dot{z} = \tilde{A}_{11}z + \tilde{B}_1u$
$y = \tilde{C}_1z + Du$

Reduced Order Model



Heterogeneous Modeling and Control



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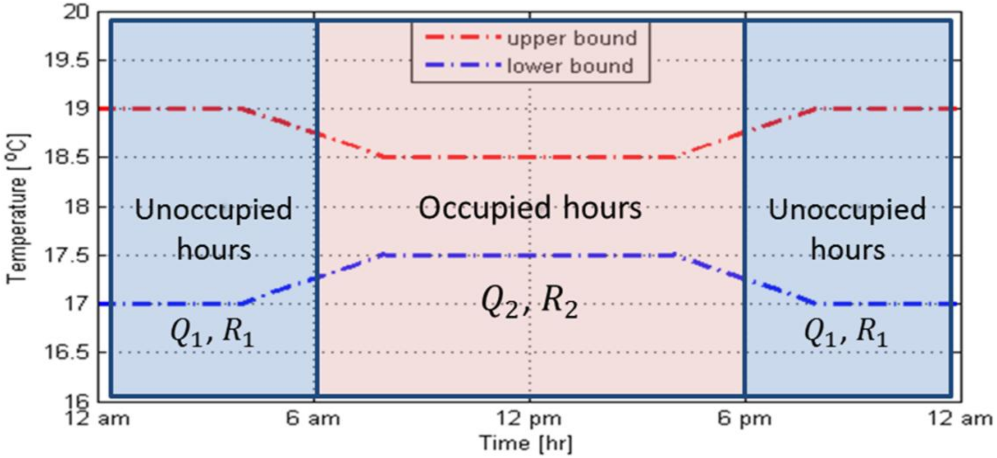
Model Predictive Control

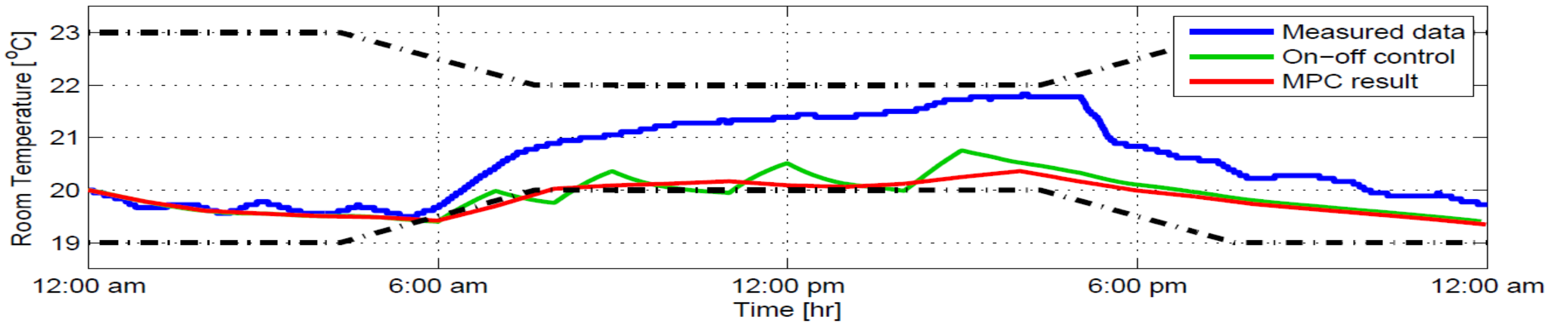
$$\min_{U_t,\bar{\epsilon},\underline{\epsilon}} \quad \{|U_t|_1 + \kappa |U_t|_\infty + \rho(|\bar{\epsilon}_t|_1 + |\underline{\epsilon}_t|_1)\} =$$

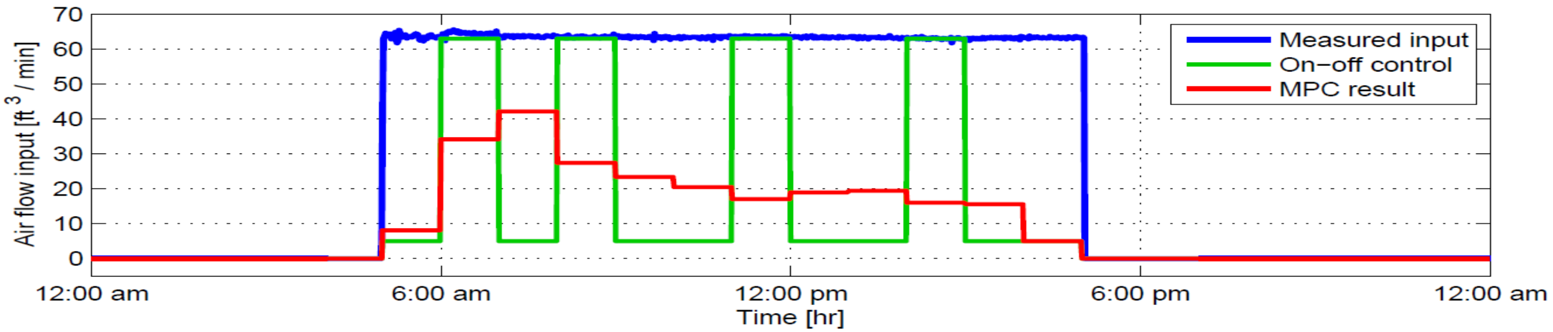
$$\min_{U_t,\bar{\varepsilon},\underline{\varepsilon}} \quad \{\sum_{k=0}^{N-1} |u_{t+k|t}| + \kappa \max(|u_{t|t}|, \cdots, |u_{t+N-1|t}|) + \rho \sum_{k=1}^{N} (|\bar{\varepsilon}_{t+k|t}| + |\underline{\varepsilon}_{t+k|t}|)\}$$

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



“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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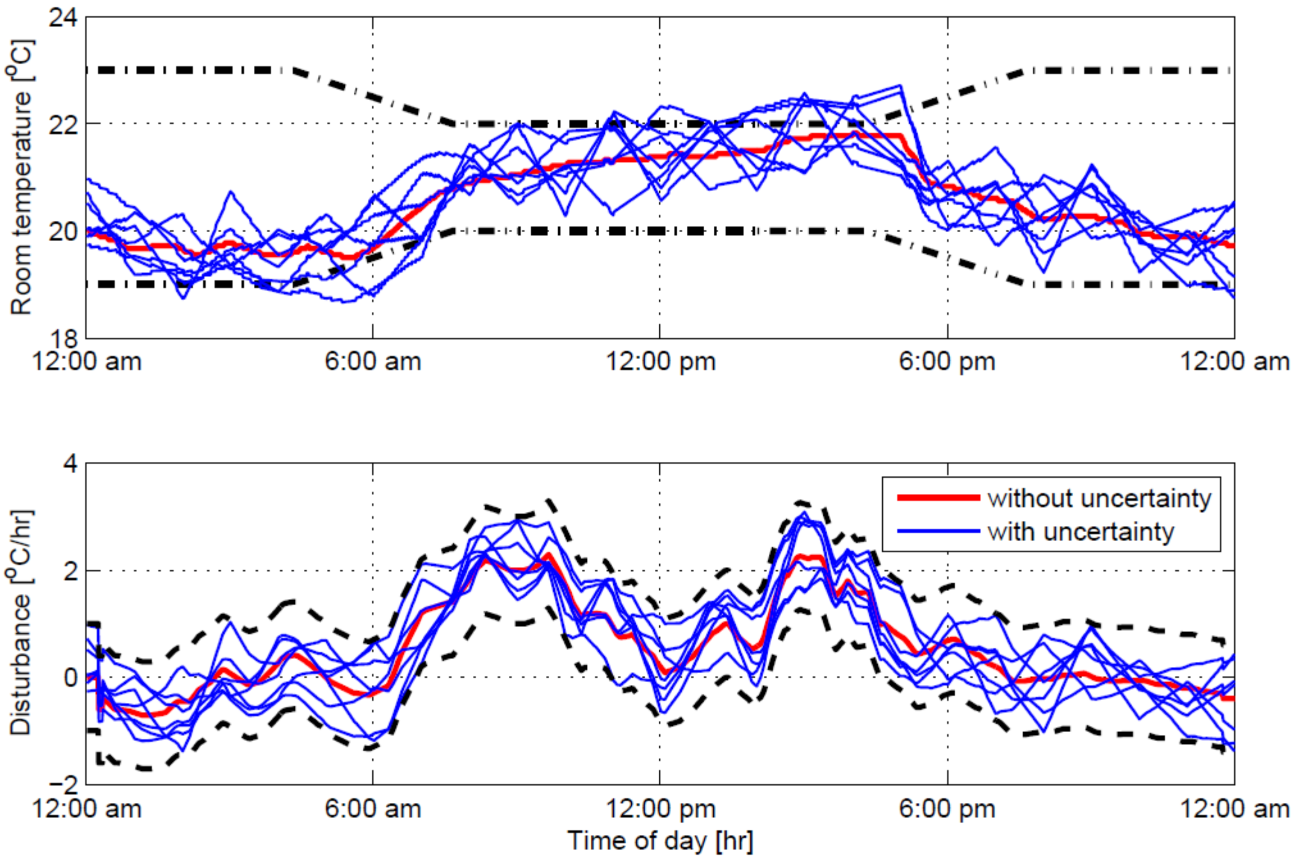
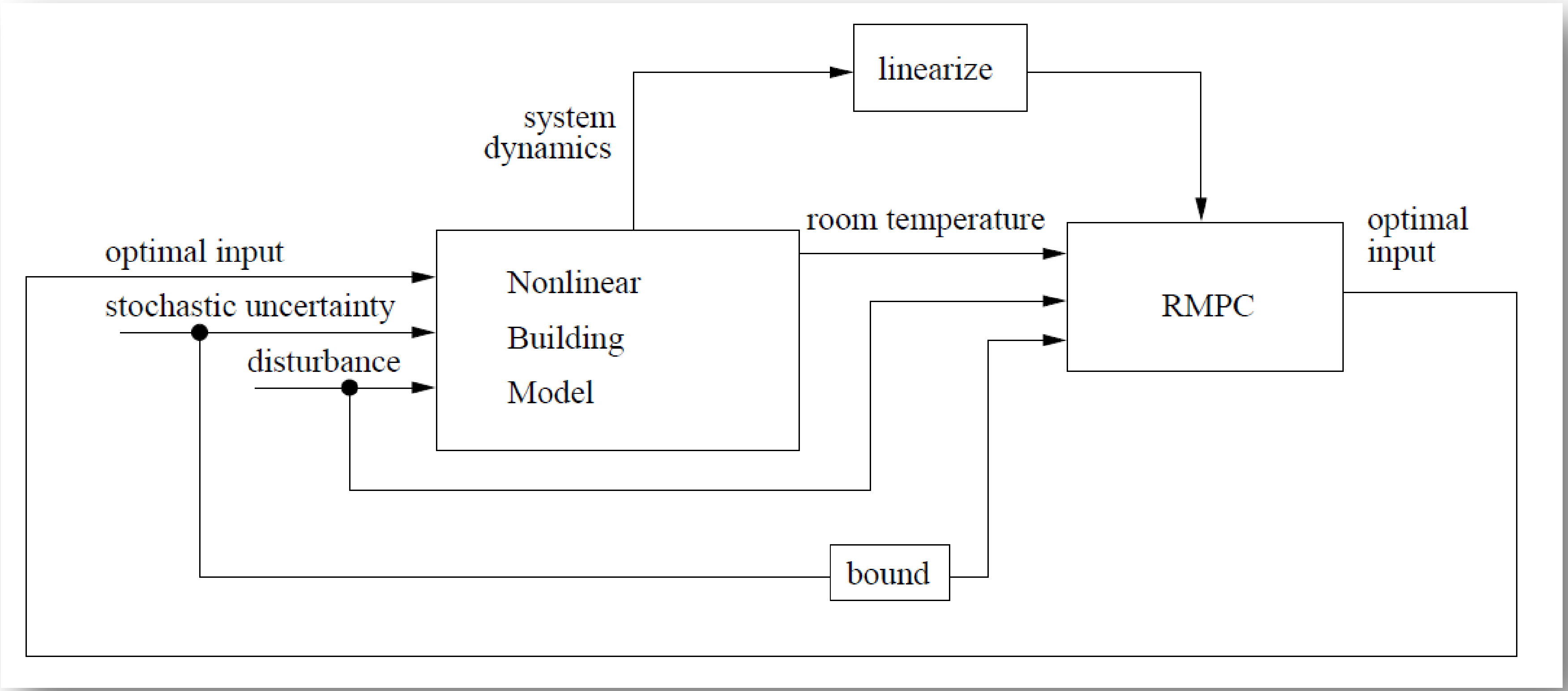
ROBUST MODEL PREDICTIVE CONTROL
(AGAINST MODEL AND MEASUREMENT UNCERTAINTIES)

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

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

TOO CONSERVATIVE!!!

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

subject to

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

Robust counterpart of an uncertain optimization problem

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*:

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

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

Lower Triangular Structure (LTS)

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

$$U = \mathbf{M}\mathbf{w} + \mathbf{v} \quad \text{i.e.} \quad u_i := \sum_{j=0}^{i-1} m_{i,j}\omega_j + v_i \qquad \forall i = 1, \ldots, N-1$$

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 other parameterizations

Toeplitz Structure

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

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

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

Two Lower Diagonal Structure (TLDS)

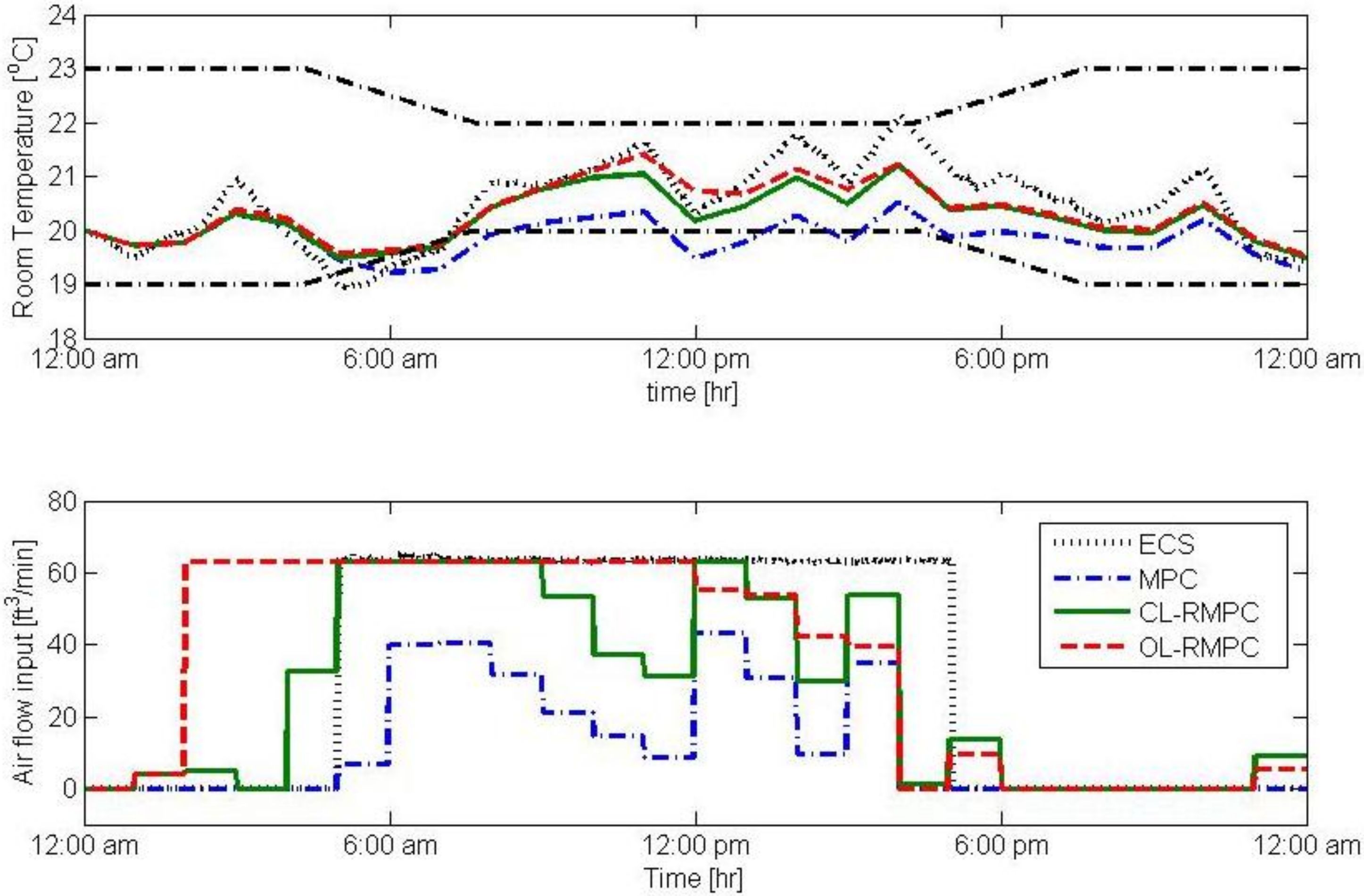
- By analyzing the structure of the optimal matrix **M**, we observed:
  - the parameterization of the input need not consider feedback of more than past two values of *w* at each time.

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

we exploit the **sparsity** of the **M** matrix to enhance the computational cost of the optimization problem

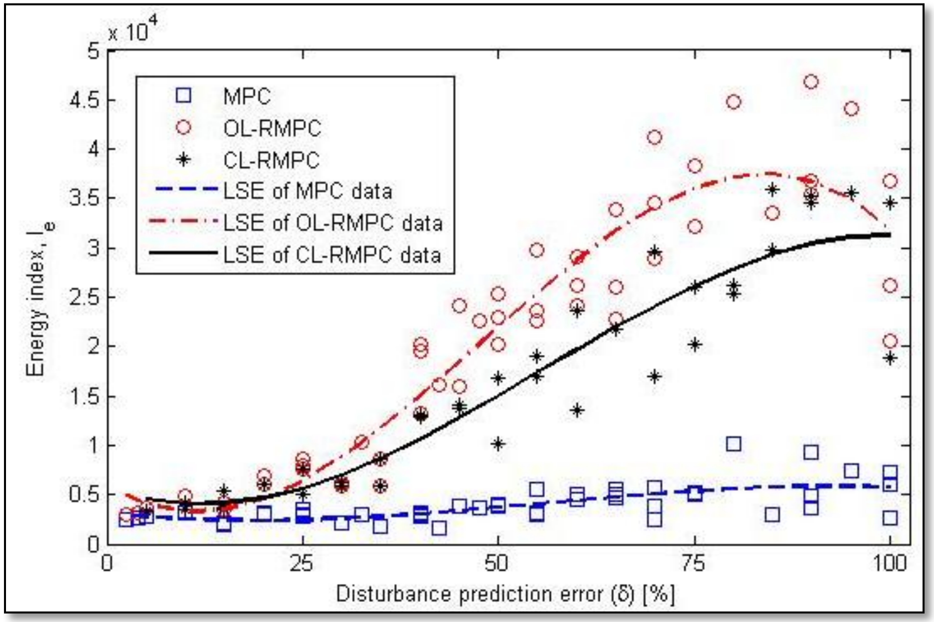
$$\mathbf{M} = \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 & 0 \\ m_{21} & 0 & 0 & \cdots & 0 & 0 \\ m_{31} & m_{32} & \ddots & \vdots & \vdots & \vdots \\ 0 & m_{42} & \ddots & 0 & \vdots & \vdots \\ \vdots & \ddots & \ddots & m_{1,2} & 0 & 0 \\ 0 & \cdots & 0 & m_{N,N-2} & m_{N,N-1} & 0 \end{bmatrix}$$

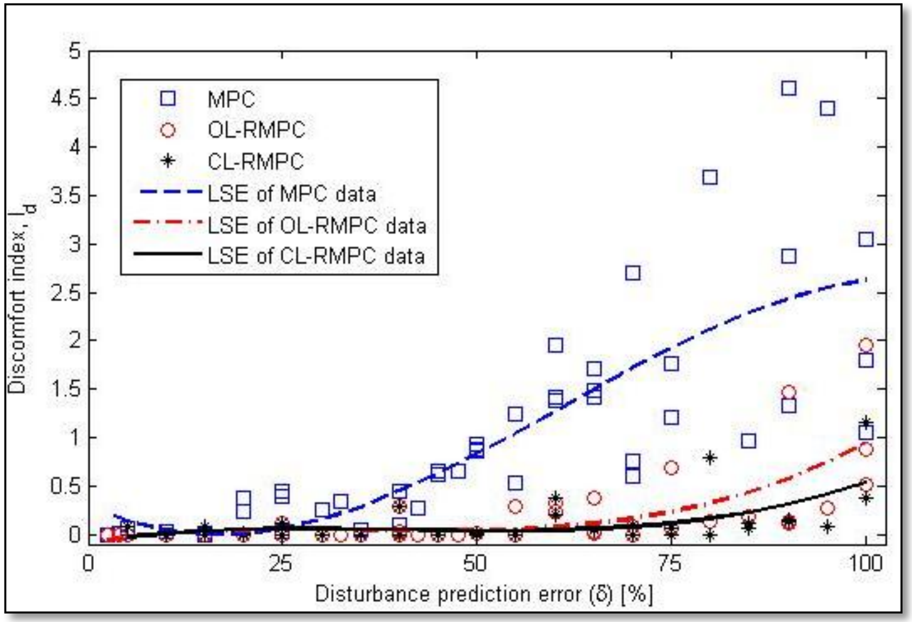
Simulation Results



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

RMPC: Energy vs. Comfort





$$P_c(t) = \dot{m}_c(t) c_p [T_{out}(t) - T_c(t)]$$
$$P_h(t) = \dot{m}_h(t) c_p [T_h(t) - T_{out}(t)]$$
$$P_f(t) = \alpha \dot{m}^3(t)$$

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

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

Simulation Results

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

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

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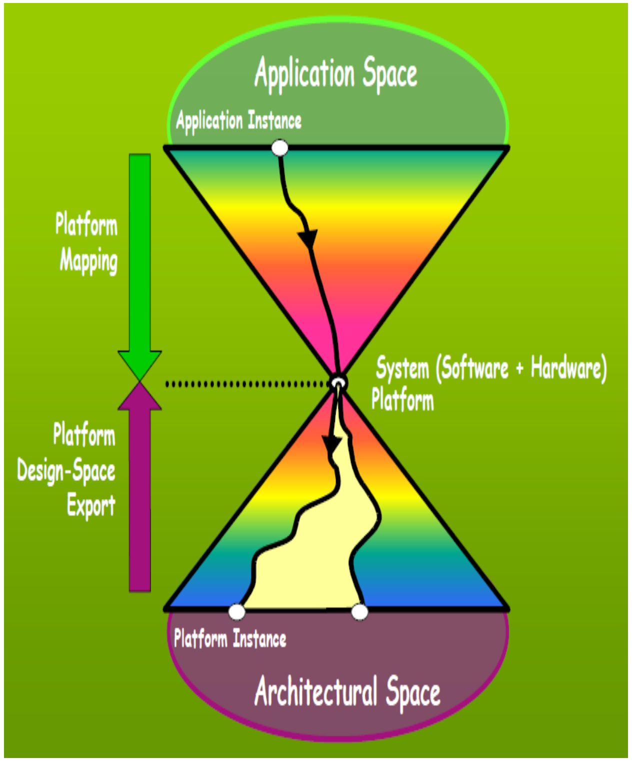
Observations

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!!!

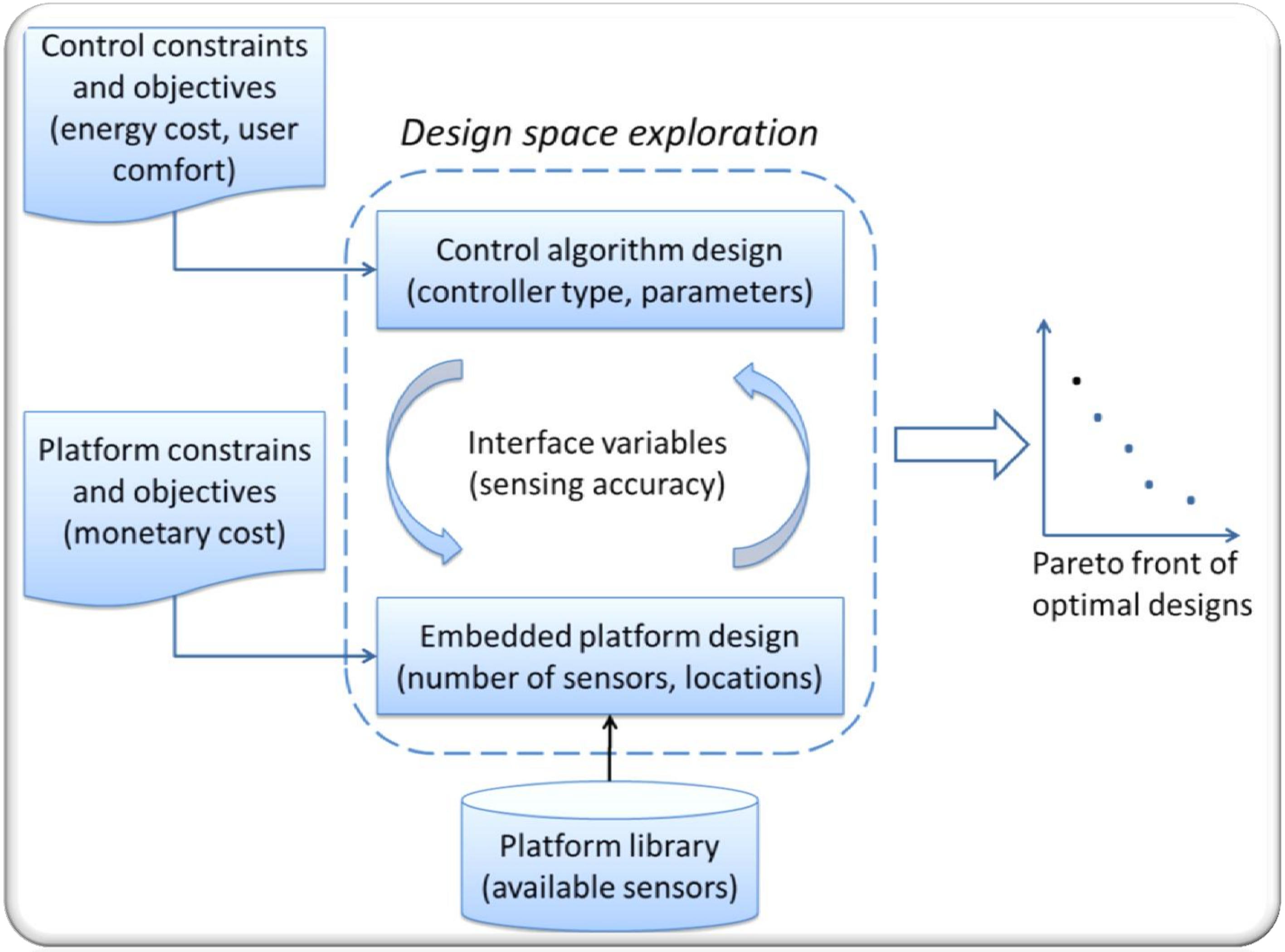
Problem

With…

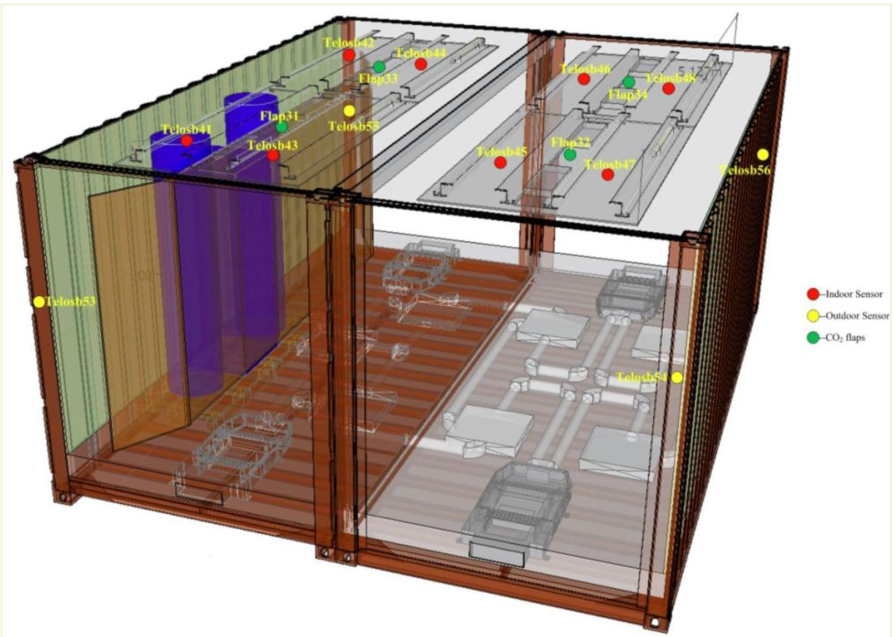
- *Employment of more complex HAVC control algorithms*
- *use of distributed networked platforms*
- *imposing of tighter requirements for user comfort*

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

Co-design framework for HVAC systems



Sensing System Set-up



BubbleZERO Research Setup

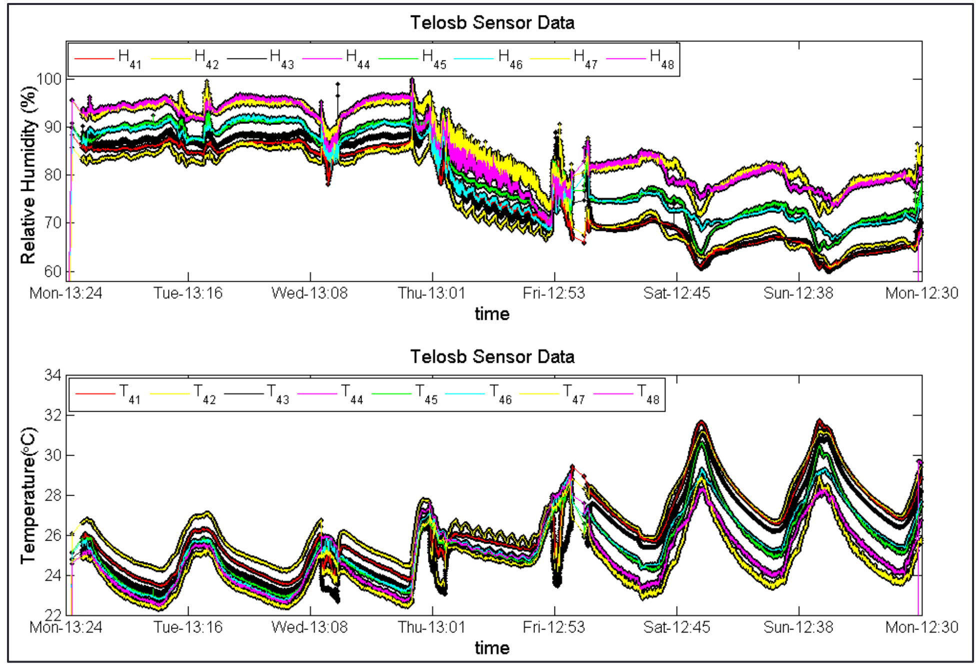
Which is conceived as part of the Low Exergy Module development for Future Cities Laboratory (FCL)

The environment sense system includes:

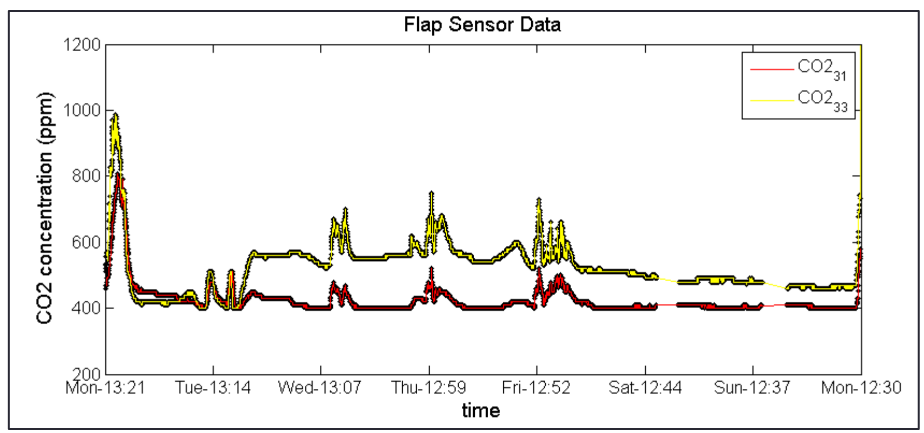
- 8 indoor sensors (Telosb41-48)
- 4 CO2 concentration sensors (flap31-34)
- 4 outdoor sensors (Telosb53-56)

Sensor Reading from the Set-up

Temperature measurements from 8 sensors located spatially at different locations in the room.

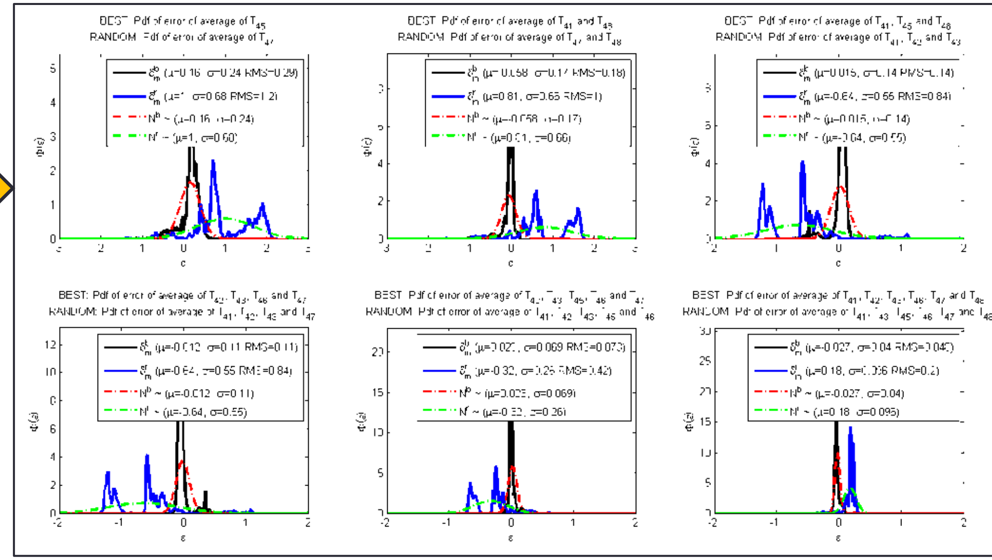


CO2 measurements from 2 sensors located spatially at different places in the room.



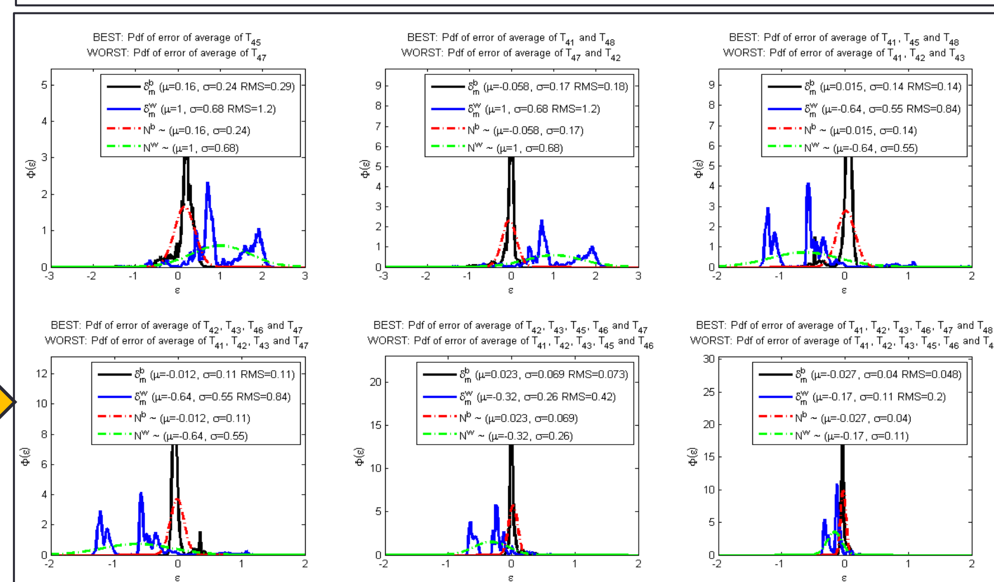
Analysis of Sensor Readings

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

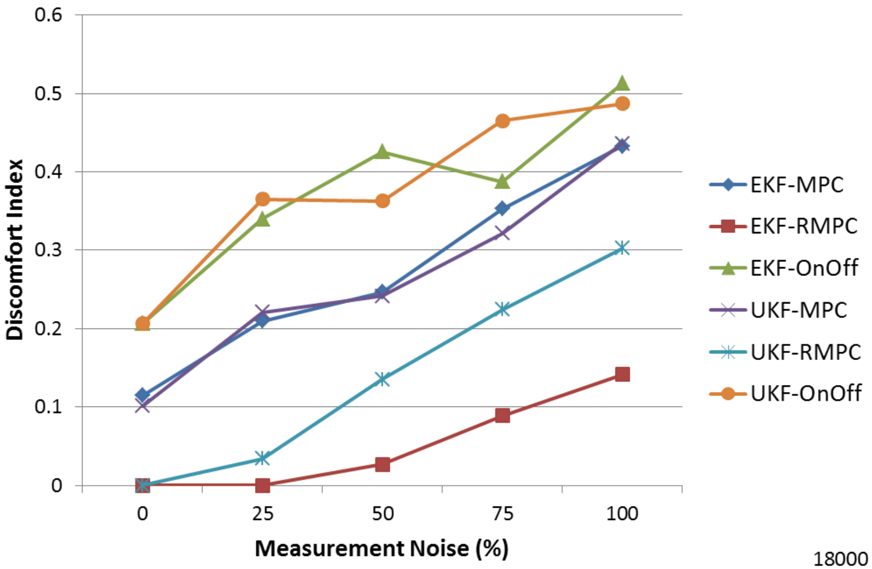


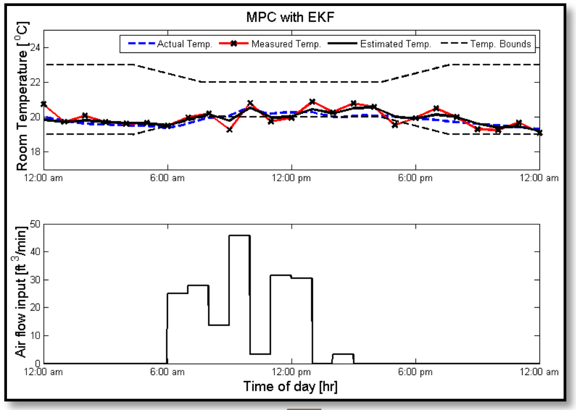
The pdf of the difference of the average of k sensor readings with the average of all nts=7 sensor readings.
The best, worst and random set of sensors are selected based on their resulting Δ_{rms} error.

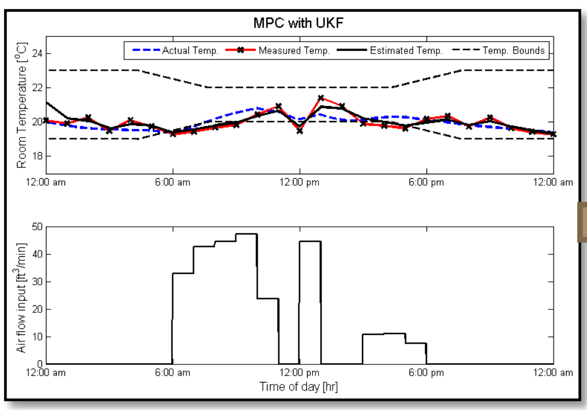
Average error of k sensors for the Minimal error set of sensors and the worst choose of sensors.

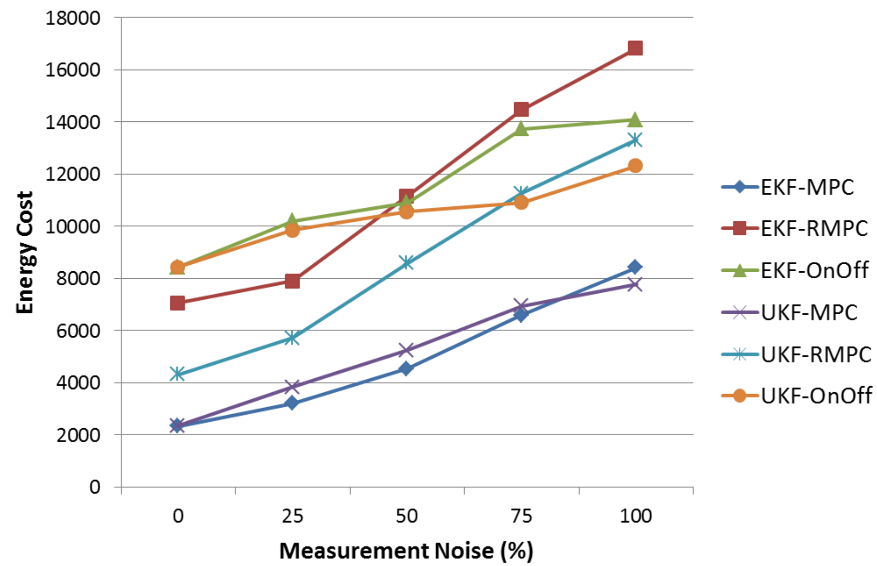


Simulation Results

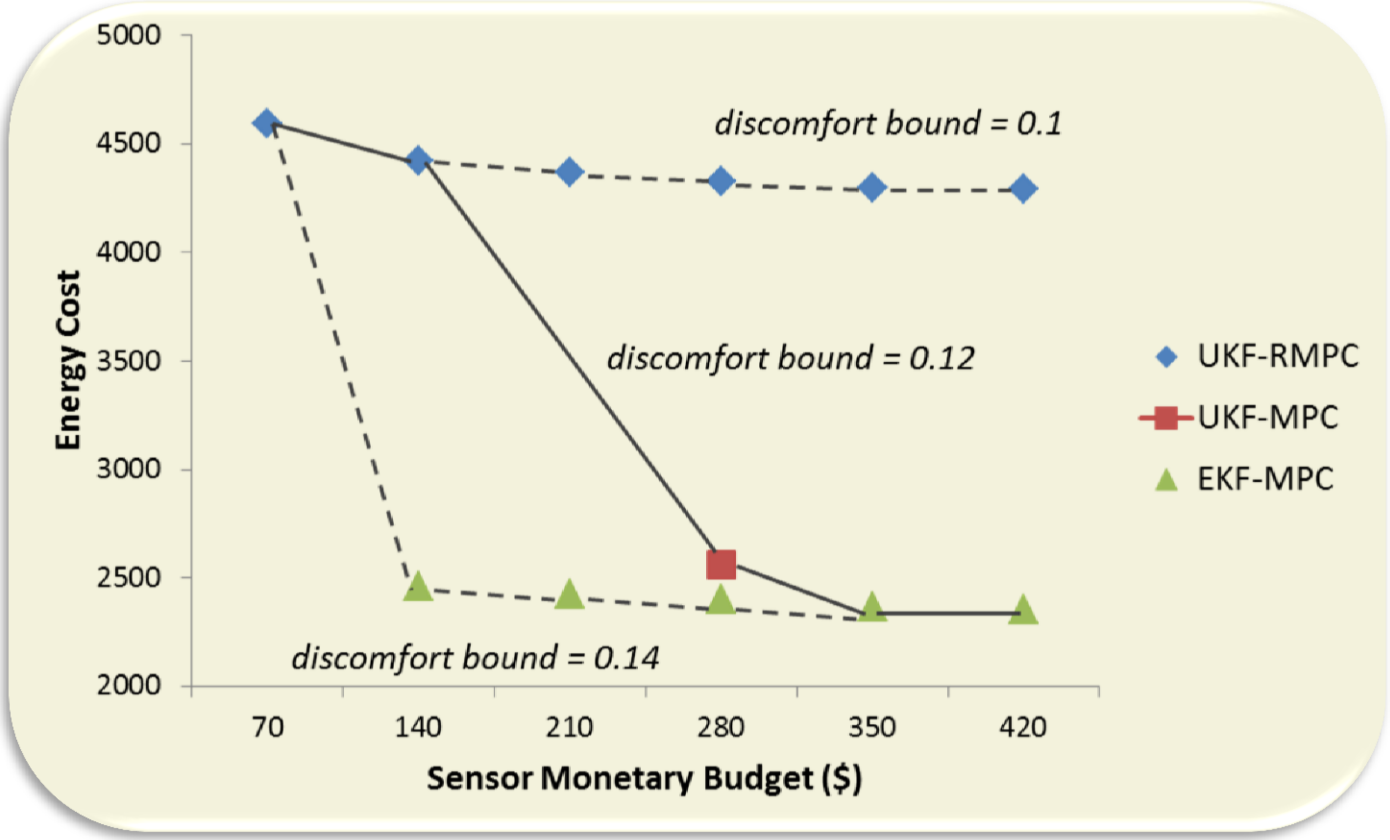








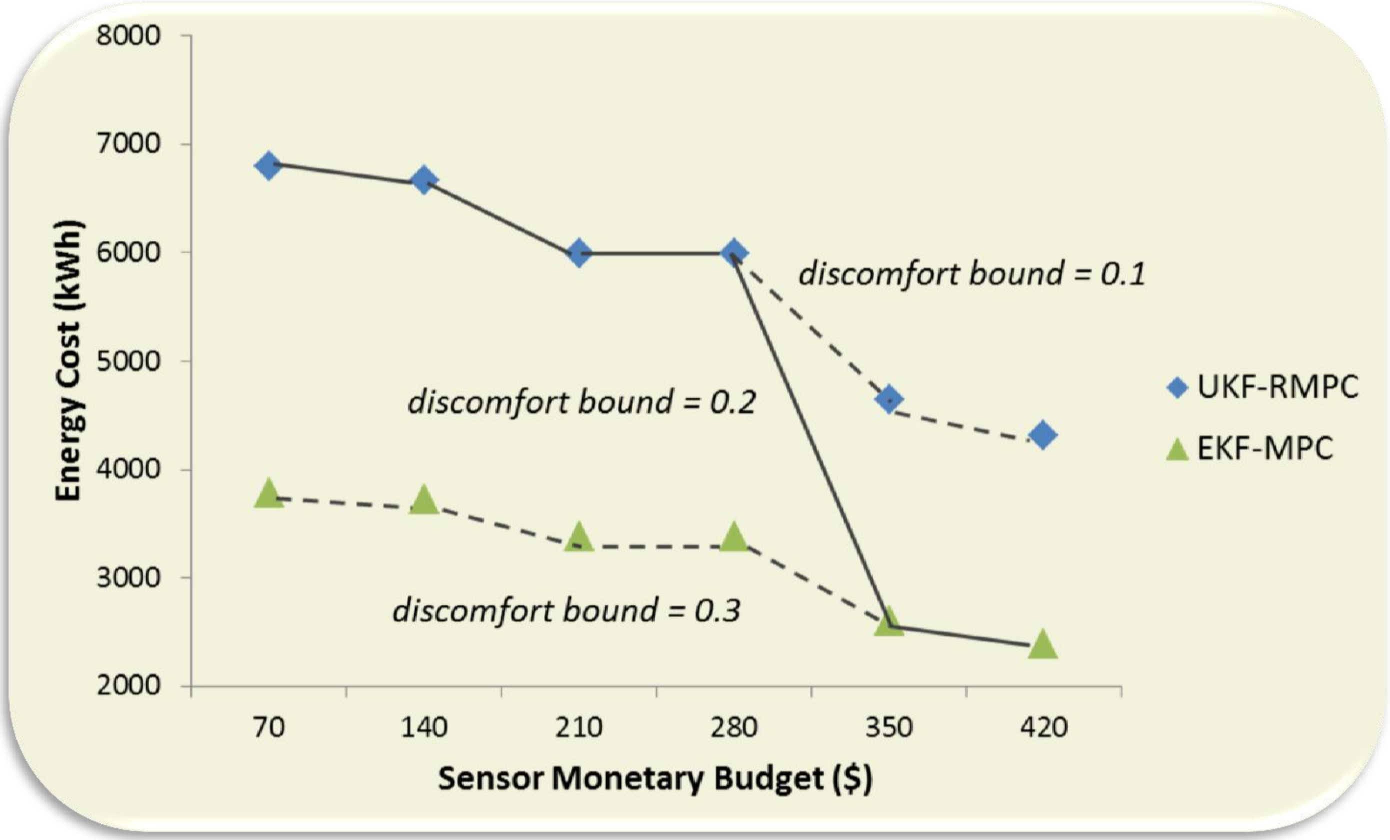
Pareto front Under Discomfort index Contraints



Pareto front under comfort constraints with best sensor locations

More details at: Maasoumy, et al. ICCPS 2012

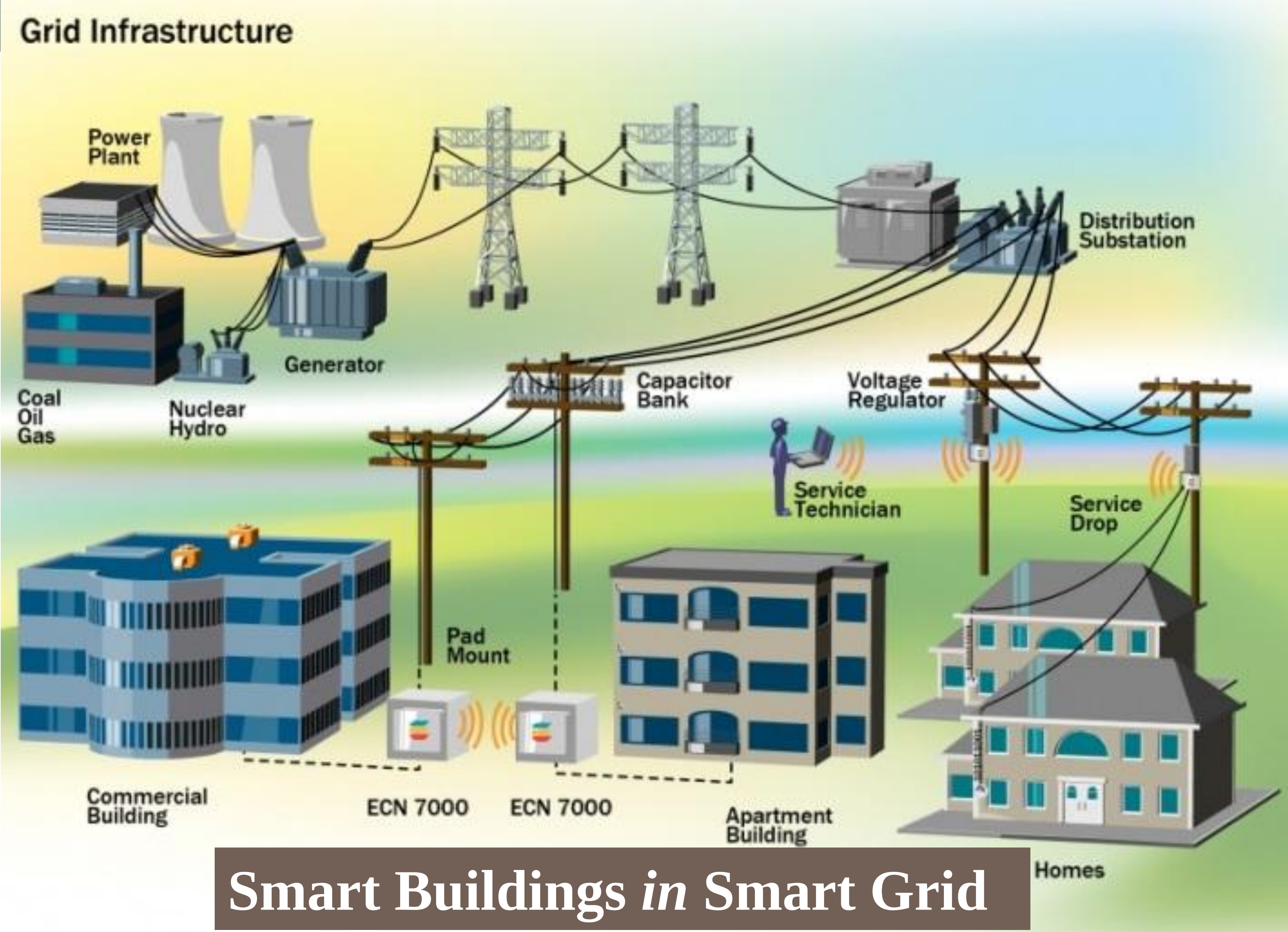
Pareto front Under Discomfort index Contraints



Pareto front under comfort constraints with random sensor locations

Outline

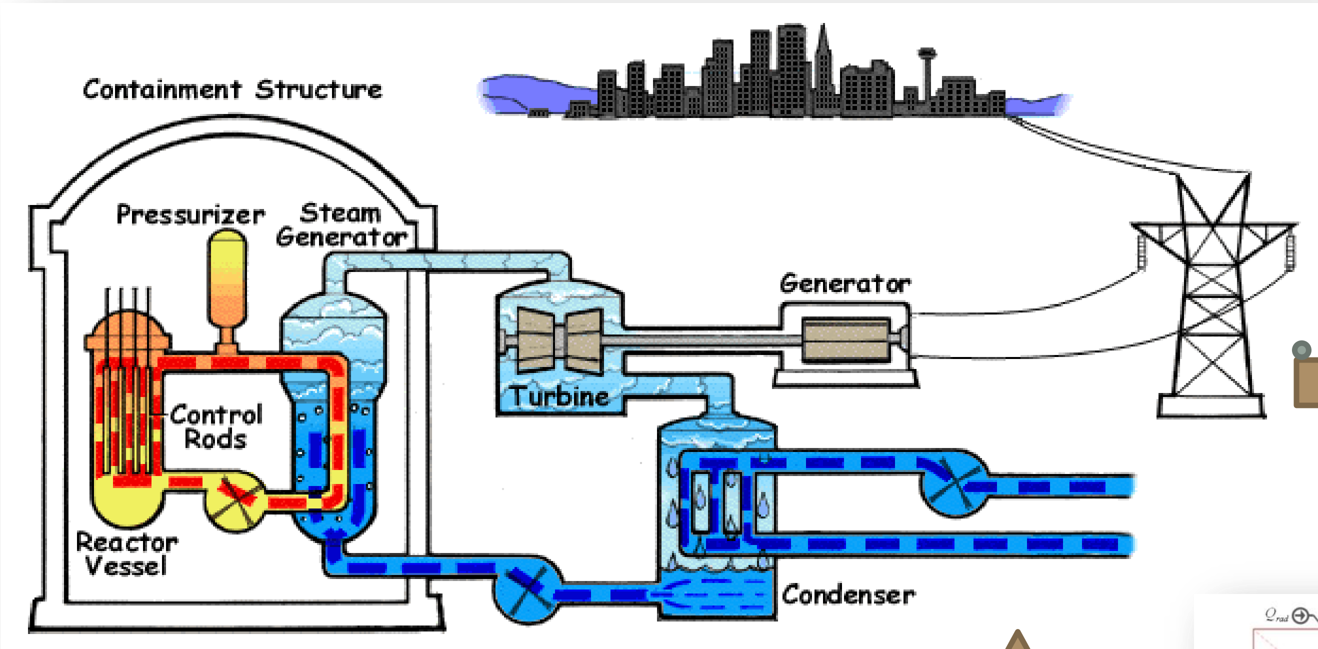
- Motivation
- Thermal Modeling
  - First approach (Physical Buildings)
  - Second Approach (Simulation Models)
- Model-Based Optimal Control Design
- Robust MPC
- Co-design of Control Algorithm and Embedded Platform
- Buildings and Smart Grid



Smart Buildings *in* Smart Grid

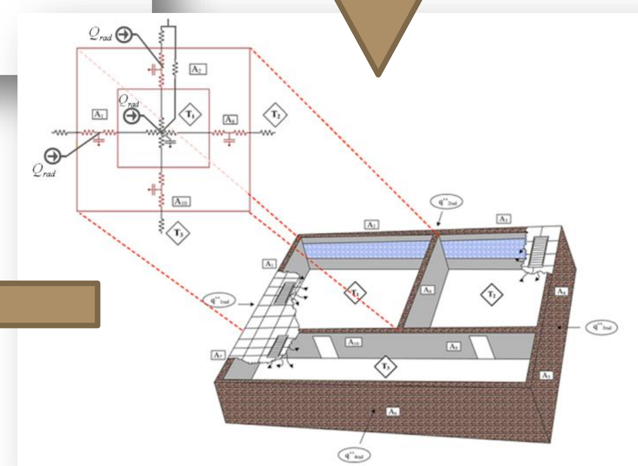
Source: www.engineerlive.com

Smart Grid & Smart Buildings



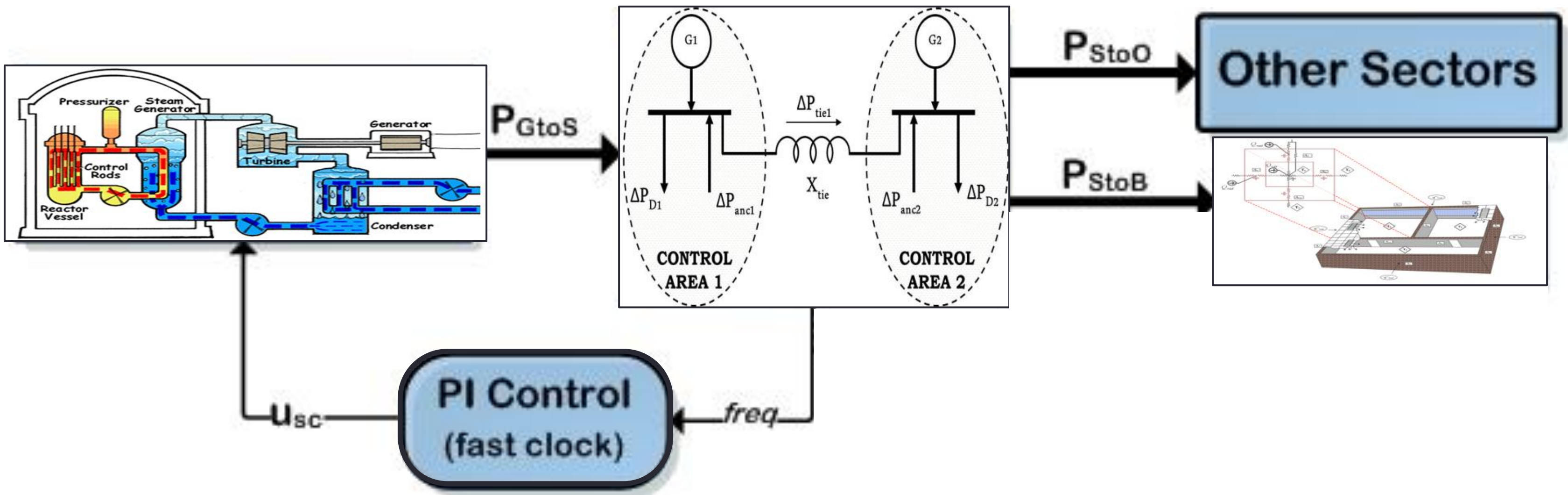
Source: http://evergreennuclear.blogspot.com/2011/08/primer-on-how-pressurized-water-reactor.html

Cyber-Physical System



Main idea:
Ancillary Service for the Grid via Control of HVAC Systems

Ancillary service to Grid from Buildings



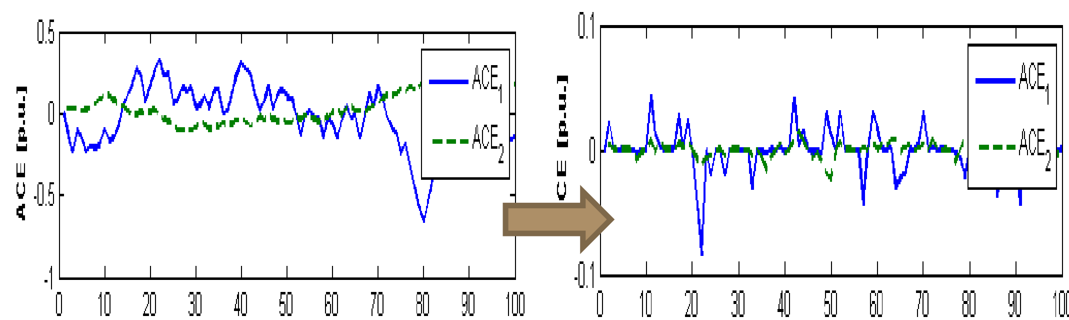
$$\min_{u_{anc}} \quad \sum_{i=1}^{n} \int (ACE^i(t))^2 \, dt$$

$$\text{s.t.} \quad x(k+1) = Ax(k) + B_2 u_{anc}(k) + Ed(k)$$

$$U_{anc}^{min}(k) \le u_{anc}(k) \le U_{anc}^{max}(k)$$

$$|u_{anc}(k) - u_{anc}(k+1)| \le L_{anc}^{max}(k)$$

Where: $ACE_i = \Delta P_{tie}^i + \beta^i x_1^i$



ACE(rms)=1.06
No Ancillary

20X reduction

ACE(rms)=0.05
With Ancillary

Thank You!

Questions?

More information at:

eecs.berkeley.edu/~maasoumy

References

- **Mehdi Maasoumy**, Barzin Moridian, Meysam Razmara, Mahdi Shahbakhti and Alberto Sangiovanni-Vincentelli, *"Online Simultaneous State Estimation and Parameter Adaptation for Building Predictive Control"*, Dynamic System and Control Conference (DSCC 2013), Stanford, CA, USA. *Submitted*

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- **Mehdi Maasoumy**, Alberto Sangiovanni-Vincentelli, "*Total and Peak Energy Consumption Minimization of Building HVAC Systems Using Model Predictive Control*", IEEE Design & Test of Computers, Special Issus on Green Buildings, July/Aug 2012

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- **Mehdi Maasoumy**, "*Modeling and Optimal Control Algorithm Design for HVAC Systems in Energy Efficient Buildings*,” Master's Thesis, University of California, Berkeley. Feb. 2011.