CREST Center for Research in Energy Systems Transformation

iCyPhy industrial cyber~physical systems

TerraSwarm

Co-design of Control Algorithm and Embedded Platform for Building HVAC Systems

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Sponsored by CREST, iCyPhy, and TerraSwarm Research Consortiums.
A collaboration of UC Berkeley, UC Riverside, Future Cities Lab of ETH Zurich, and NTU of Singapore.

industrial cyber-physical systems

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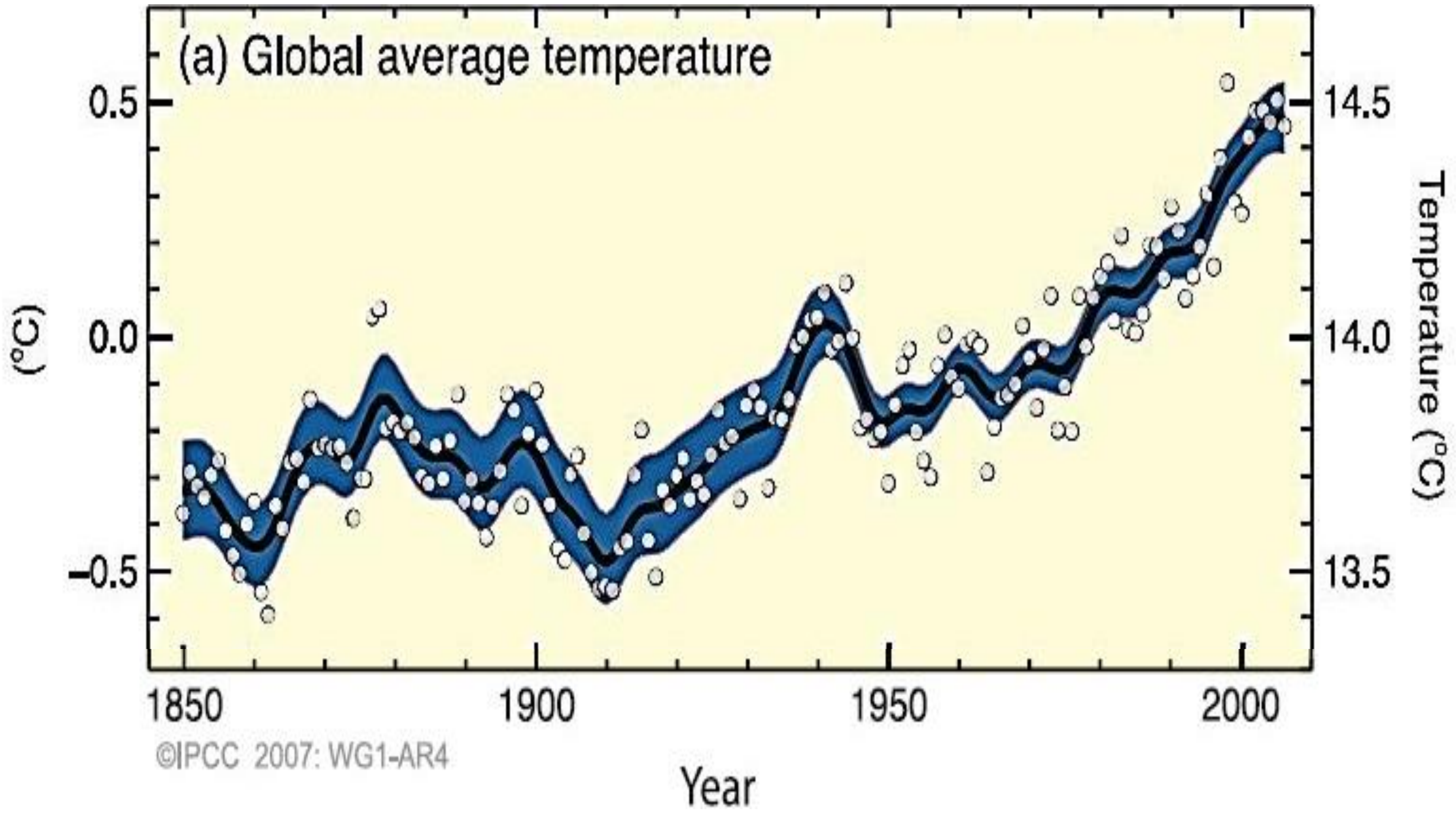
Global Climate Change

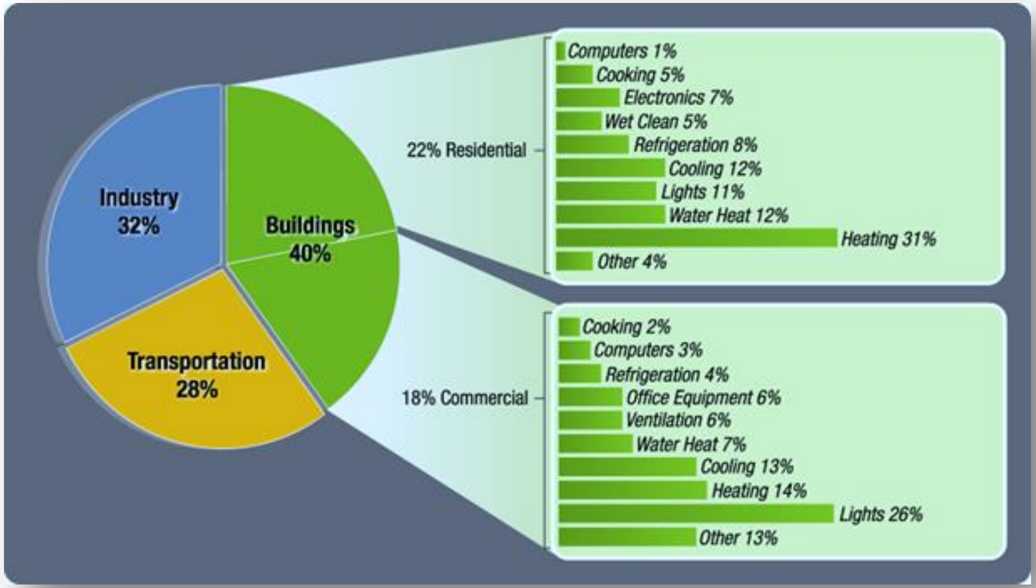


Energy Systems *must* Change

- **California Global Warming Solutions Act:**
  - Reduce greenhouse gas emissions to **1990** levels by **2020** (30% below the forecasts).
  - A further 80% cut below **1990** threshold by **2050**.
- **European Union Renewables Directive:**
  - Member states to produce a pre-agreed % of energy consumption from renewable sources
  - EU as a whole shall obtain at least 20% of total energy consumption from renewables by **2020**.
- **Singapore Energy Conservation Bill:**
  - Reduce its greenhouse gas (GHG) emissions by 16% from the **2020** business-as-usual scenario.
  - Reduce its energy intensity by 35% from **2005** levels by **2030**.

...

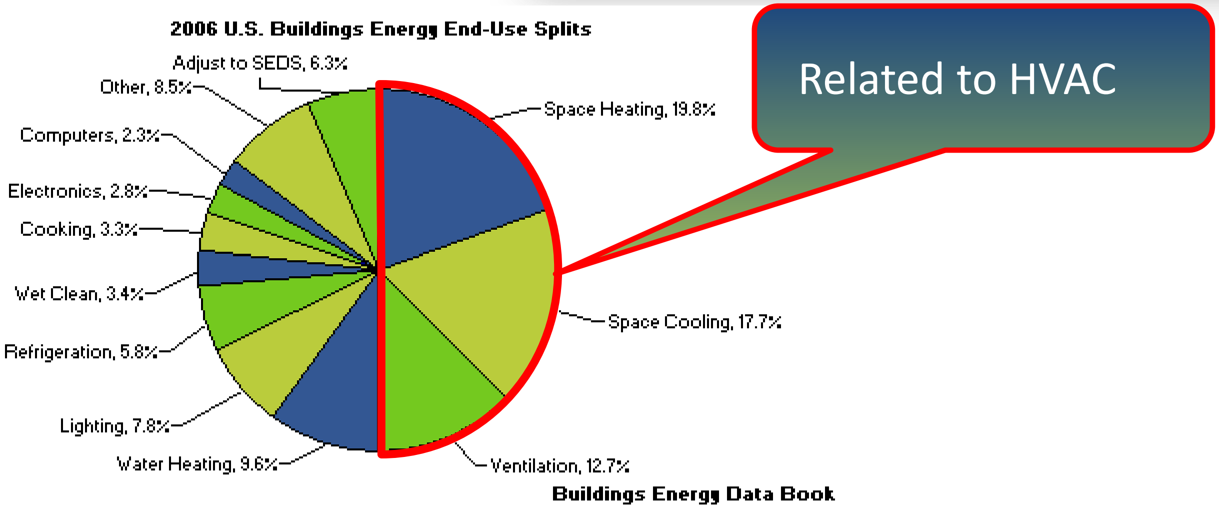
What's the biggest contributor?



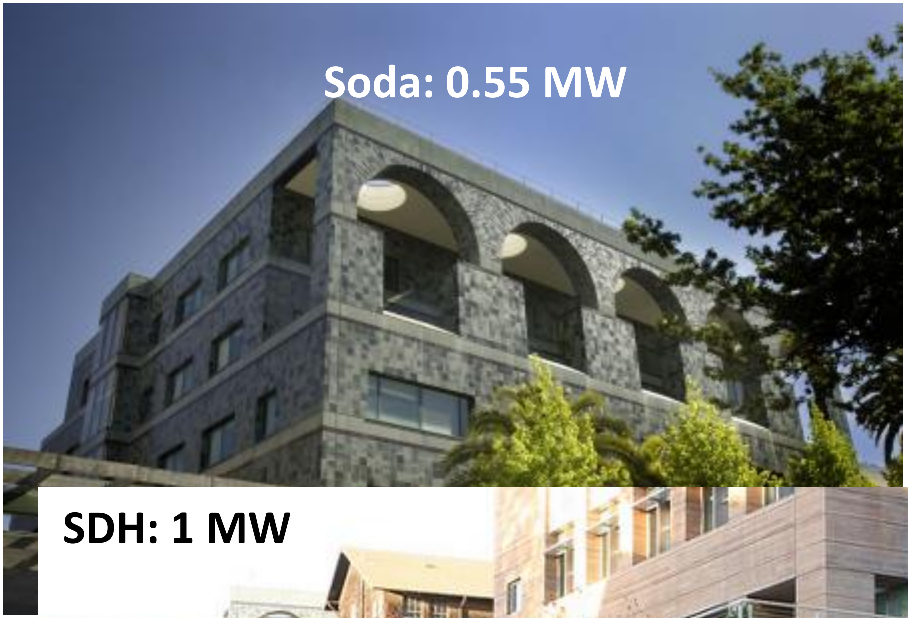
Buildings Consume Significant Energy:

- **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



Some Statistics… (courtesy of sMAP)



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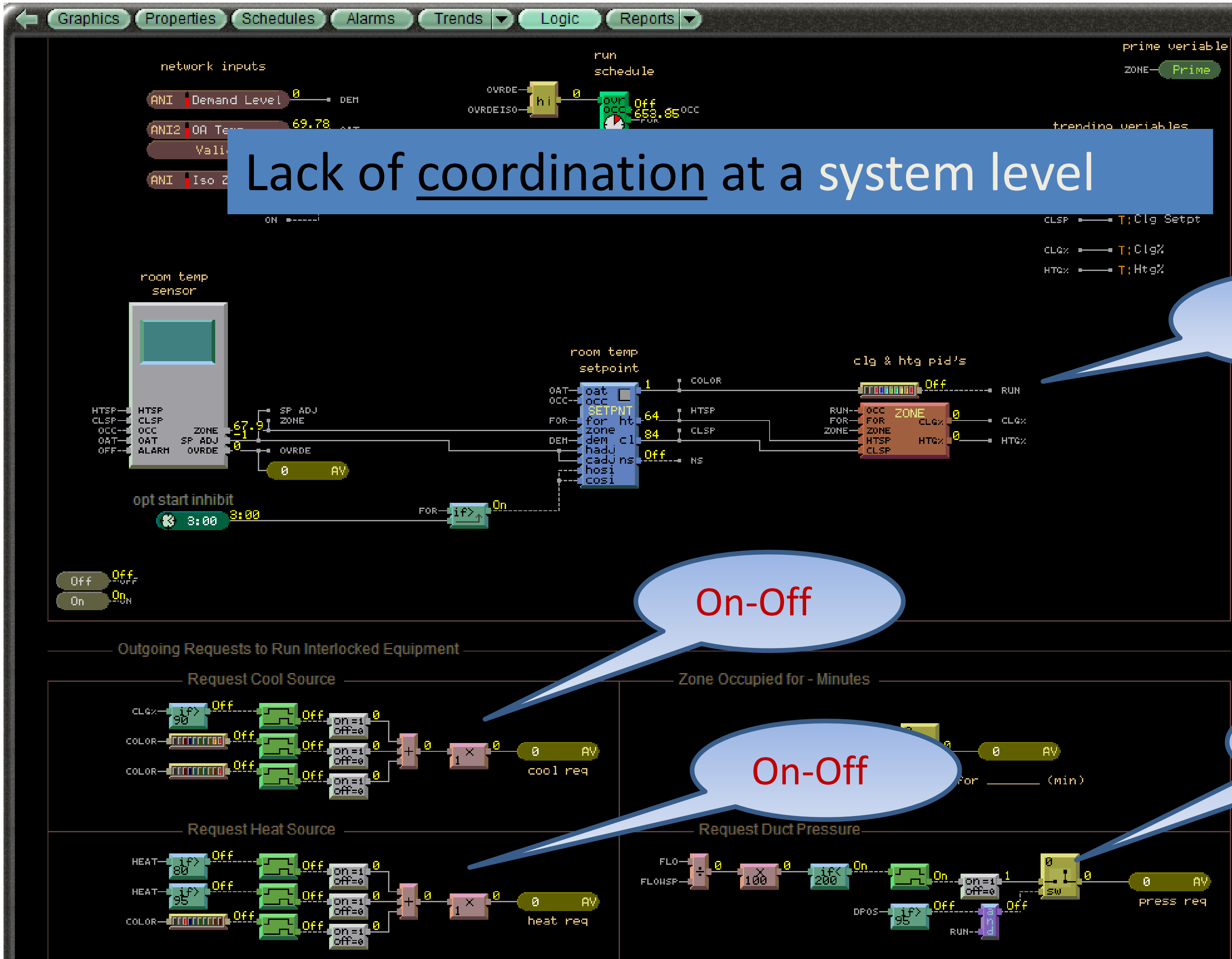
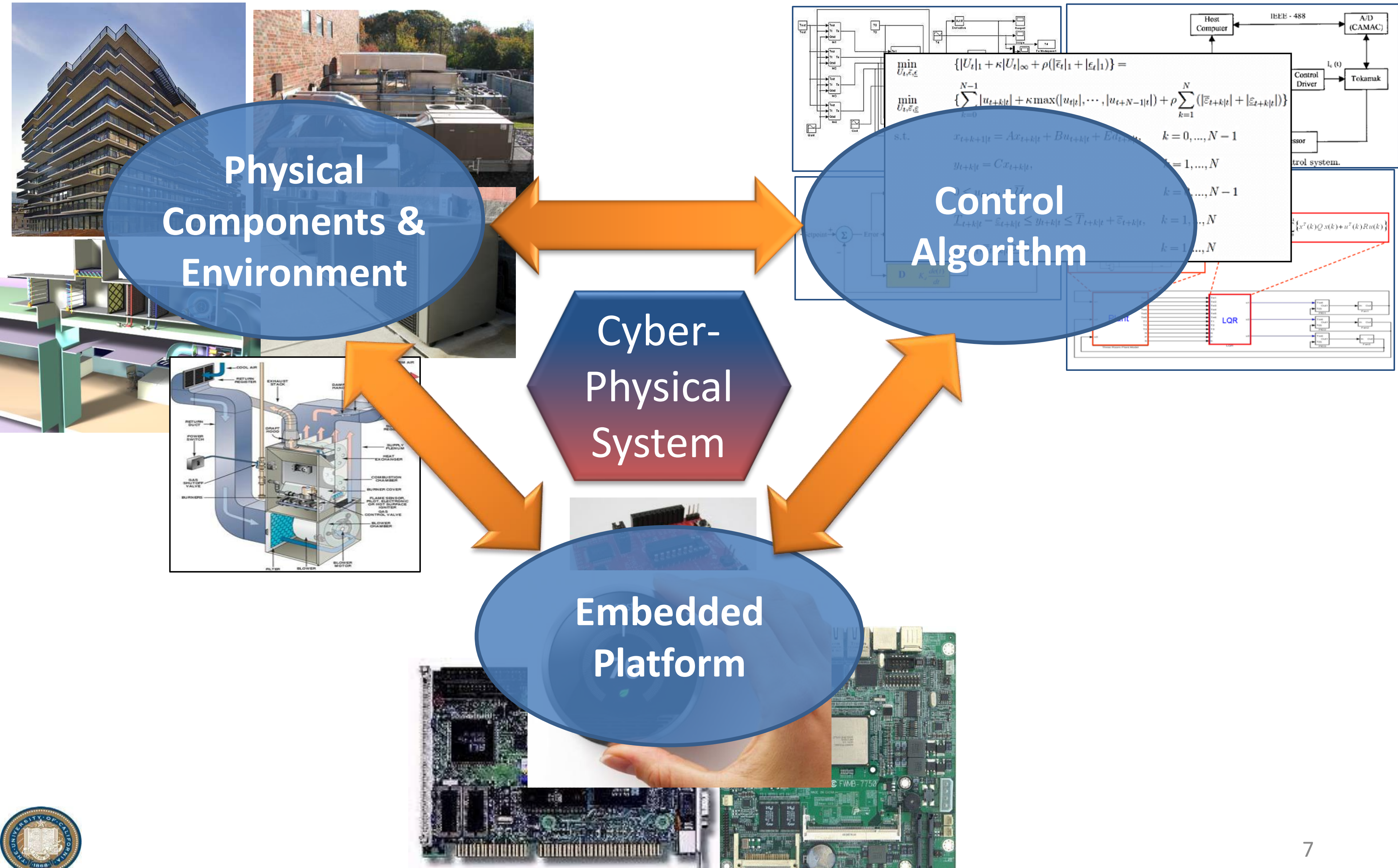
Existing HVAC Control Algorithms



UC Berkeley,
Bancroft Library

HVAC System as Significant Cyber-Physical System



Previous works

2008
DB Crawley, (**Simulation**)

2009
M. Wetter, (***modeling and simulation***)

2010
- Y. Ma, (**MPC**)
- F. Oldewurtel, (**SMPC**)
- K Deng, (**Model Reduction**)
- C Liao, (**Occupancy Modeling**)

2011
- Y. Ma, (**DMPC**)
- M. Maasoumy, (**Hierarchical**)
- TX Nghiem, (**Scheduling**)

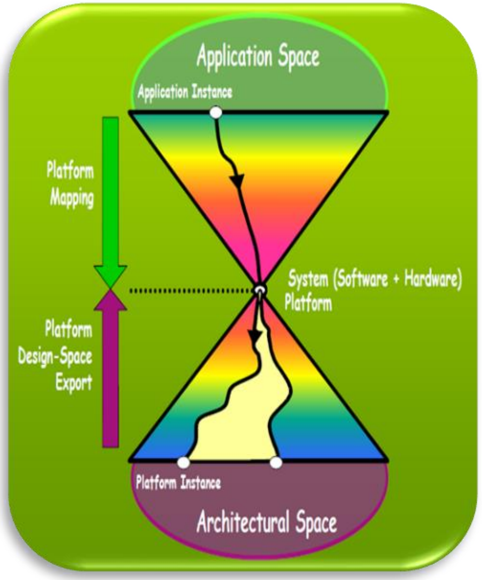
2012
- B. Hencey, (**Estimation**)
- M. Maasoumy (**RMPC**)
- Y. Yang (**BAS**)

2013
…

None of which explicitly address the Cyber-Physical aspect of buildings!

Necessity of Co-design

- Design of HVAC system involves:
  - Physical components and environment
  - Control algorithm
  - Embedded platform
- In the traditional *top-down approach*, the design of the HVAC control algorithm is done without explicit consideration of the embedded platform.



With…
- *More complex HVAC control algorithms*
- *Distributed networked platforms*
- *Tighter requirements for user comfort*

Assumption:
Embedded platform will always be sufficient for any control mechanism

No longer valid

… **Sensor accuracy** and **availability**, **communication** channel **reliability**, and **computation power** of embedded processors, may have a significant impact on the BAS quality and cost.

Outline

- Co-design problem
- Plant Modeling
- Interface variables
- Control Design
- Embedded Platform
- Simulation Results

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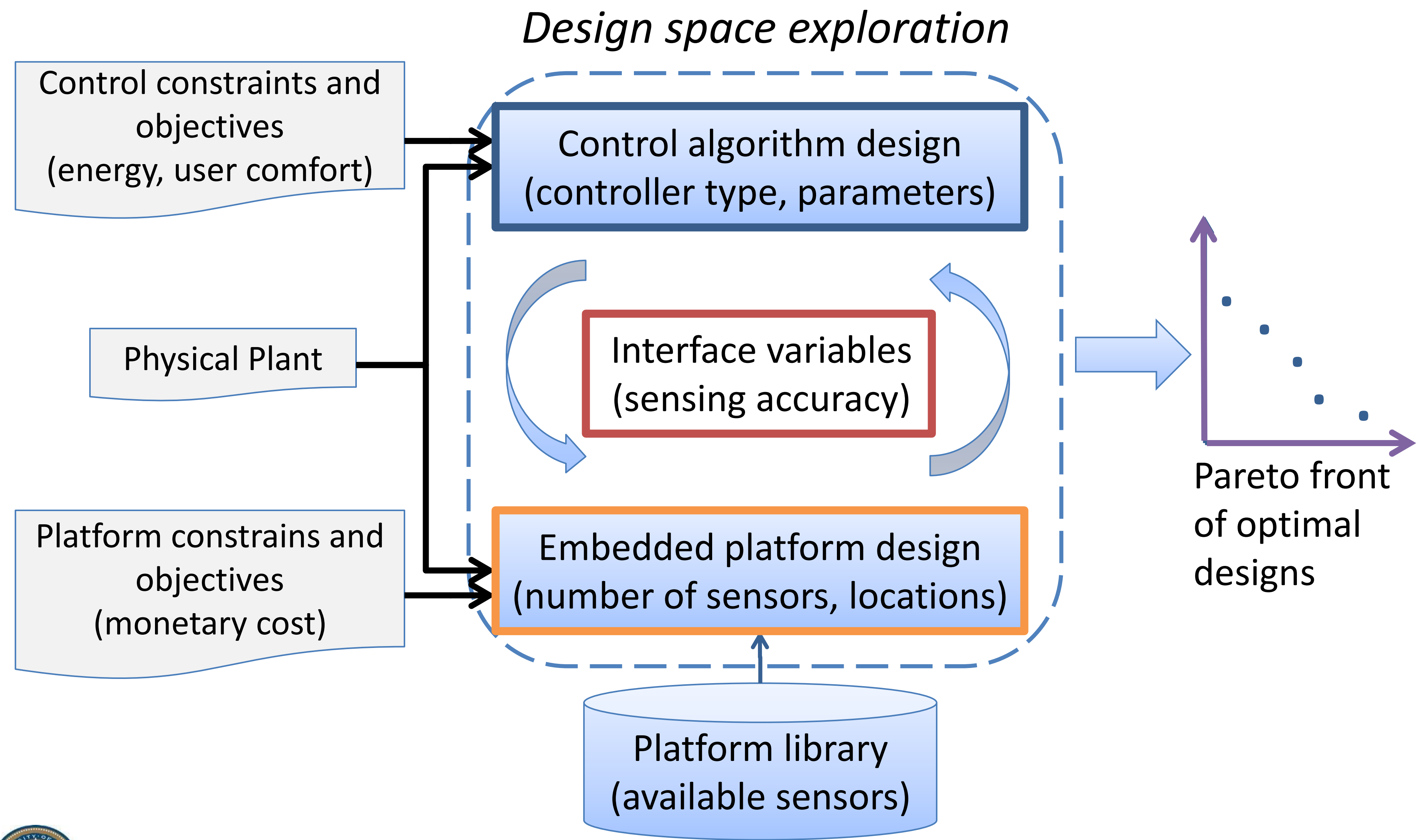
Co-design Framework for HAVC Systems



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Plant Modeling

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

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

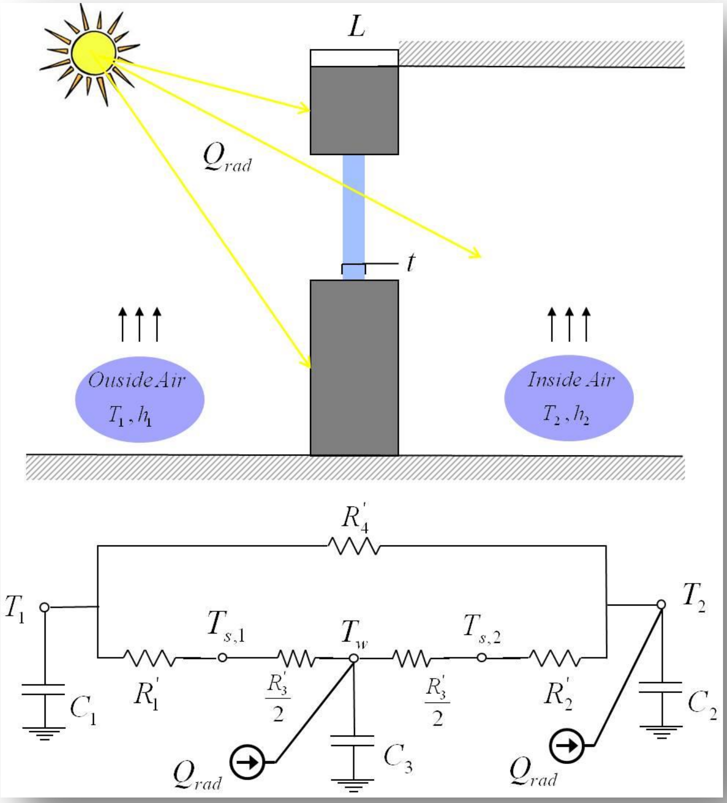
$$r_i = \begin{cases} 0 & \text{internal wall} \\ 1 & \text{peripheral wall} \end{cases}$$

Unmodeled dynamics

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

$$C_{r_i}\frac{dT_{r_i}}{dt} = \sum_{j\in\mathcal{N}_{r_i}} \frac{T_j - T_{r_i}}{R'_{ij}} + \dot{m}_{r_i} c_a (T_{s_i} - T_{r_i}) + w_i\tau_{w_i} A_{w_i} q''_{rad_i} + \dot{q}_{int_i}$$

$$w_i = \begin{cases} 0 & \text{wall } i \text{ doesn't have window} \\ 1 & \text{wall } i \text{ has window} \end{cases}$$



Thermal and circuit model of a wall with window

Plant Modeling:
Unmodeled Dynamics

- External heat gain $$q''_{rad_i}(t) = \tau \hat{T}_{out}(t) + \zeta$$
- Internal heat gain $$\dot{q}_{int}(t) = \mu \Psi(t) + \nu$$

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

Disturbance:

$$\hat{d}_t = a q''_{rad_i}(t) + b \dot{q}_{int}(t) + c \hat{T}_{out}(t) + e$$

which results to:

$$\begin{aligned} \hat{d}_t &= (a\tau + c)\hat{T}_{out}(t) + b\mu\hat{\Psi}(t) + a\zeta + b\nu + e \\ &= \bar{a}\hat{T}_{out}(t) + \bar{b}\hat{\Psi}(t) + \bar{e} \end{aligned}$$

where $\bar{a} = a\tau + c$, $\bar{b} = b\mu$, and $\bar{e} = a\zeta + b\nu + e$.

Leading to the LTI system:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + E\hat{d}_k \\ y_k &= Cx_k \end{aligned}$$

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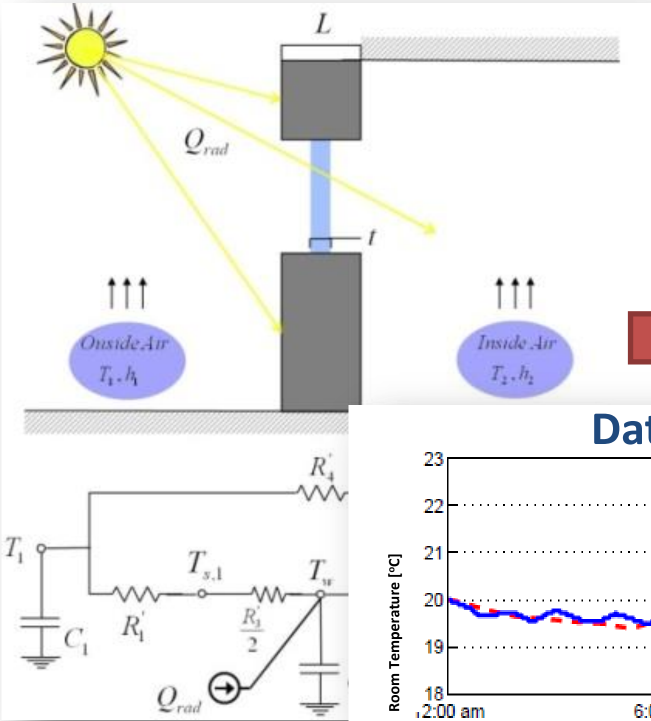
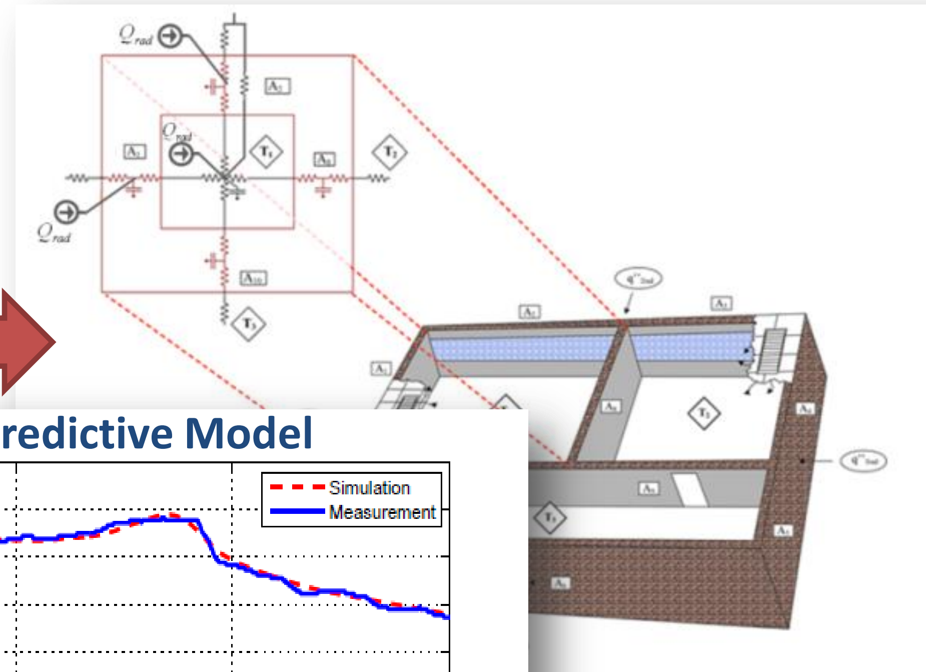
Data driven modeling

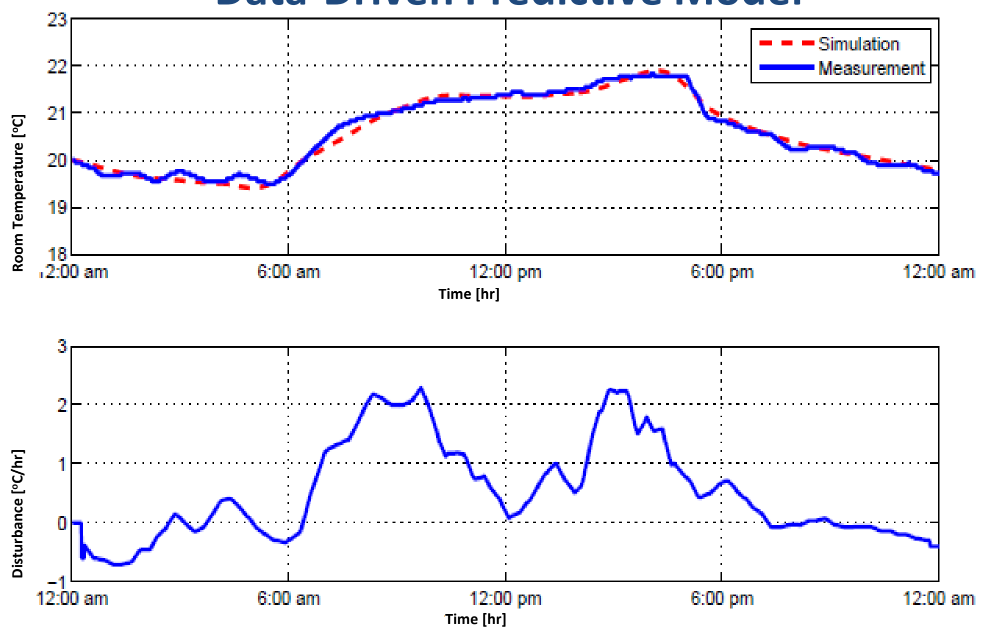
Mathematical Model



Scale-up to Building Level



Data-Driven Predictive Model



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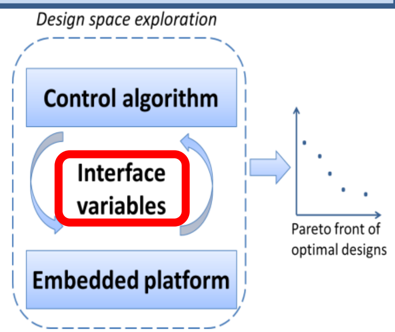
Interface Variables



- **Sensing inaccuracy:**
  - Error of indoor temperature estimation:

ϵ^{rt} = *f* (*accuracy of individual sensors, number and locations of sensors*)

Extracted from historical data

- **Prediction inaccuracy:**

$$\begin{aligned}\hat{d}_k &= \bar{a}\hat{T}_{out}(k) + \bar{b}\hat{\Psi}(k) + \bar{e} \\ &= \bar{a}(T_{out}(k) - \epsilon_k^{ot}) + \bar{b}(\Psi(k) - \epsilon_k^{c}) + \bar{e} \\ &= d_k - (\bar{a}\epsilon_k^{ot} + \bar{b}\epsilon_k^{c})\end{aligned}$$

$$\begin{aligned}x_{k+1} &= Ax_k + Bu_k + E(d_k - w_k) \\ z_k &= Cx_k + Fv_k\end{aligned}$$

Linear Stochastic Model

where: $w_k = -\xi(\bar{a}\epsilon_k^{ot} + \bar{b}\epsilon_k^{c})$ and $v_k = \epsilon_k^{rt}$

with variance:
$$\begin{aligned}\sigma_w^2 &= \mathbb{E}[(w - \hat{w})(w - \hat{w})^T] \\ &= \mathbb{E}\left\{[-\xi(\bar{a}\tilde{\epsilon}^{ot} + \bar{b}\tilde{\epsilon}^{c})][-\xi(\bar{a}\tilde{\epsilon}^{ot} + \bar{b}\tilde{\epsilon}^{c})]^T\right\} \\ &= \xi^2(\bar{a}^2\sigma_c^2 + \bar{b}^2\sigma_{ot}^2)\end{aligned}$$

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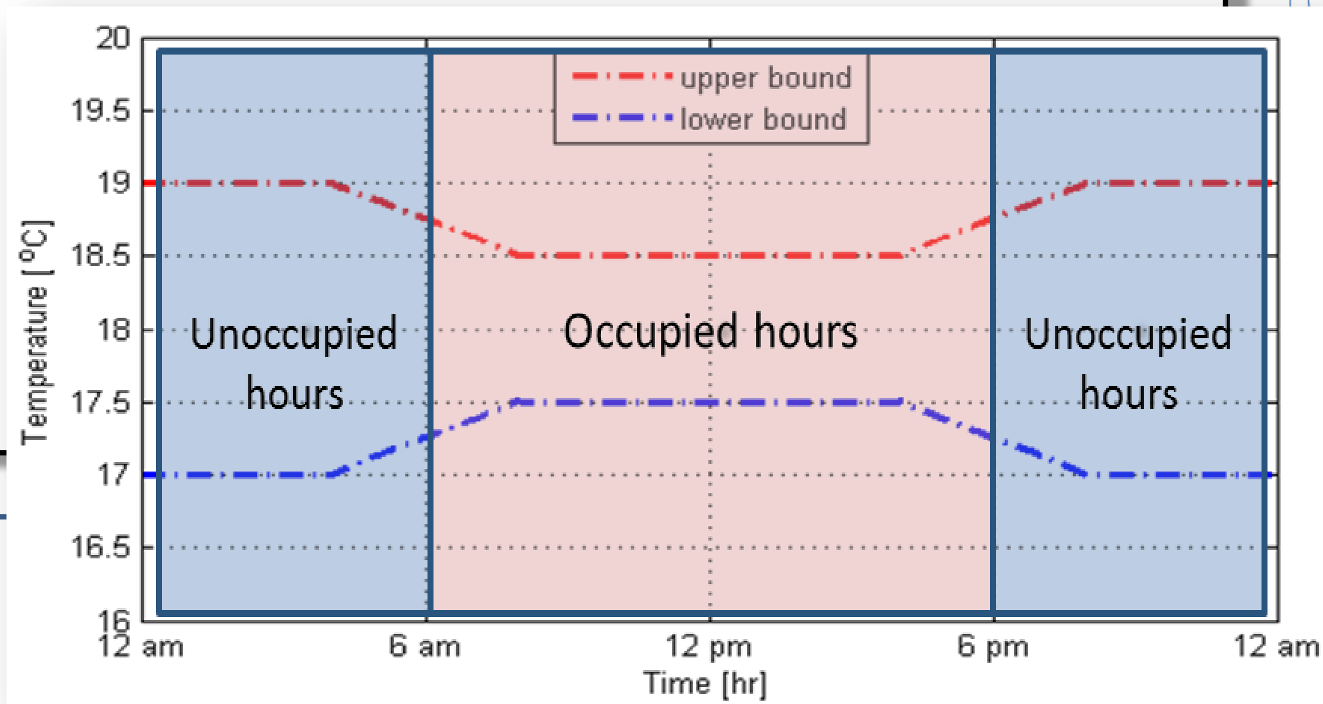
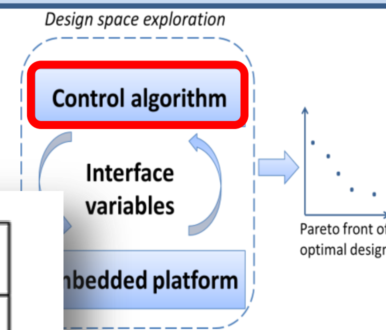
Control Algorithm:
Model Predictive Control

$$\min_{U_t, \overline{\Theta}_t, \underline{\Theta}_t} \quad \{|U_t|_1 + \kappa |U_t|_\infty + \rho(|\overline{\Theta}_t|_1 + |\underline{\Theta}_t|_1)\}$$

s.t.





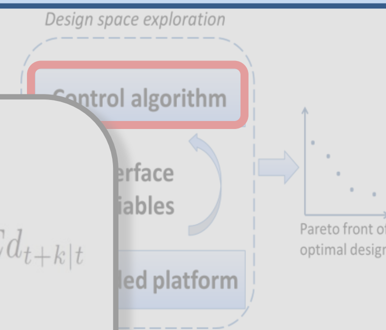
U_t :

$\underline{\Theta}_t, \overline{\Theta}_t$:

$\underline{\mathcal{U}}_t, \overline{\mathcal{U}}_t$: Lower and upper bounds on control input

$\underline{T}_t, \overline{T}_t$: Lower and upper bounds on temperature

Control Algorithm:
Robust Model Predictive Control



Open Loop

$$J_t(x(t),U_t) \triangleq \max_{w_{[\cdot]}}\{\|Pz_{t+N|t}\|_p + \sum_{k=0}^{N-1} \|Qz_{t+k|t}\|_p + \|Ru_{t+k|t}\|_p\}$$

$$\text{s.t.} \quad x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t} + E(d_{t+k|t} - w_{t+k|t})$$
$$z_{t+k|t} = Cx_{t+k|t} + Fv_{t+k|t}$$
$$w_{t+k|t} \in \mathcal{W} \quad \& \quad v_{t+k|t} \in \mathcal{V}$$
$$\forall \quad k = 0,1,\cdots,N-1$$

Too Conservative!

$$J_t^*(x(t)) \triangleq \min_{U_t} \quad J_t(x(t),U_t)$$
$$\text{s.t.} \quad x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t} + Ed_{t+k|t}$$
$$z_{t+k|t} = Cx_{t+k|t} + Fv_{t+k|t}$$
$$u_{t+k|t} \in \mathcal{U} \quad \& \quad x_{t+k|t} \in \mathcal{X}$$
$$\forall \; w_{t+k|t} \in \mathcal{W} \quad \& \quad \forall \; v_{t+k|t} \in \mathcal{V}$$
$$\forall \quad k = 0,1,\cdots,N-1$$

Closed Loop

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

Intractable Problem

Feedback Predictions

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

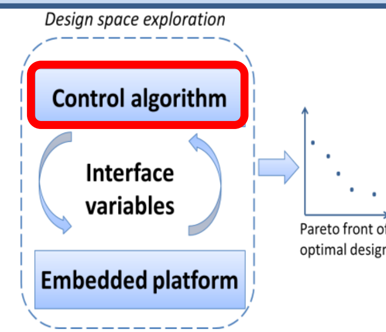
$$u_i := m_{i,i-2}w_{i-2} + m_{i,i-1}w_{i-1} + v_i$$
$$= \sum_{j=i-2}^{i-1} m_{i,j}\omega_j + v_i \qquad \forall i = 1,\ldots,N-1$$

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

$$\mathbf{M} := \begin{bmatrix} 0 & 0 & \cdots & 0 & 0 & 0 \\ m_{21} & 0 & 0 & \cdots & 0 & 0 \\ m_{31} & m_{32} & & & \vdots & \vdots \\ 0 & m_{42} & \ddots & 0 & & \vdots \\ \vdots & & \ddots & m_{1,2} & 0 & 0 \\ 0 & \cdots & 0 & m_{N,N-2} & m_{N,N-1} & 0 \end{bmatrix}, \quad \mathbf{v} := \begin{bmatrix} v_0 \\ \vdots \\ \vdots \\ v_{N-1} \end{bmatrix}$$

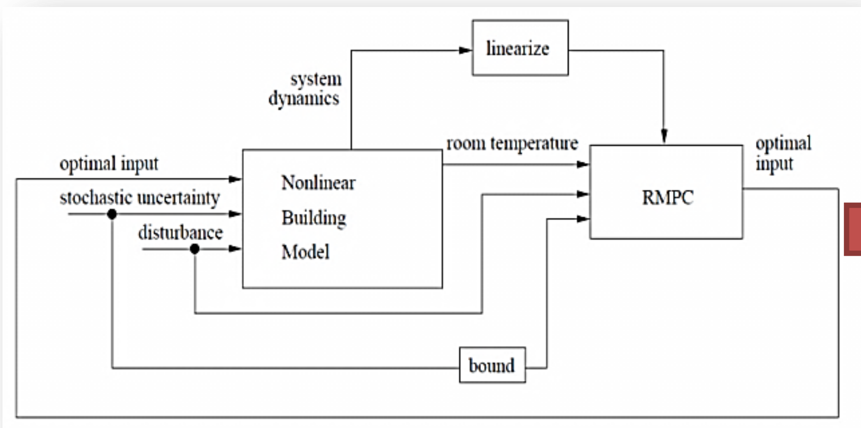
M. Maasoumy, et al., (2012)

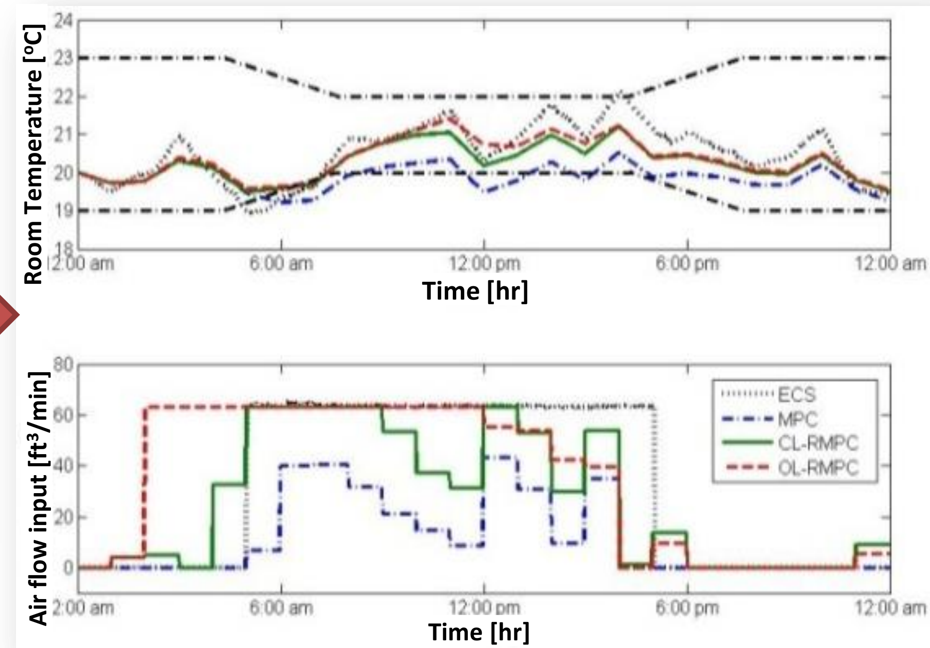
Robust Model Predictive Control



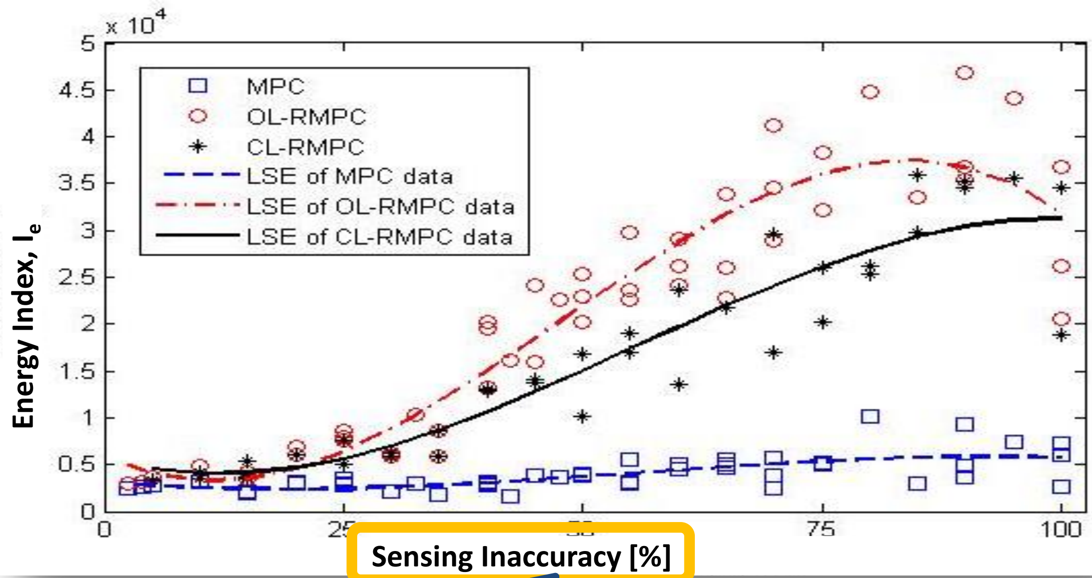
Control Performance

Robust Control Architecture

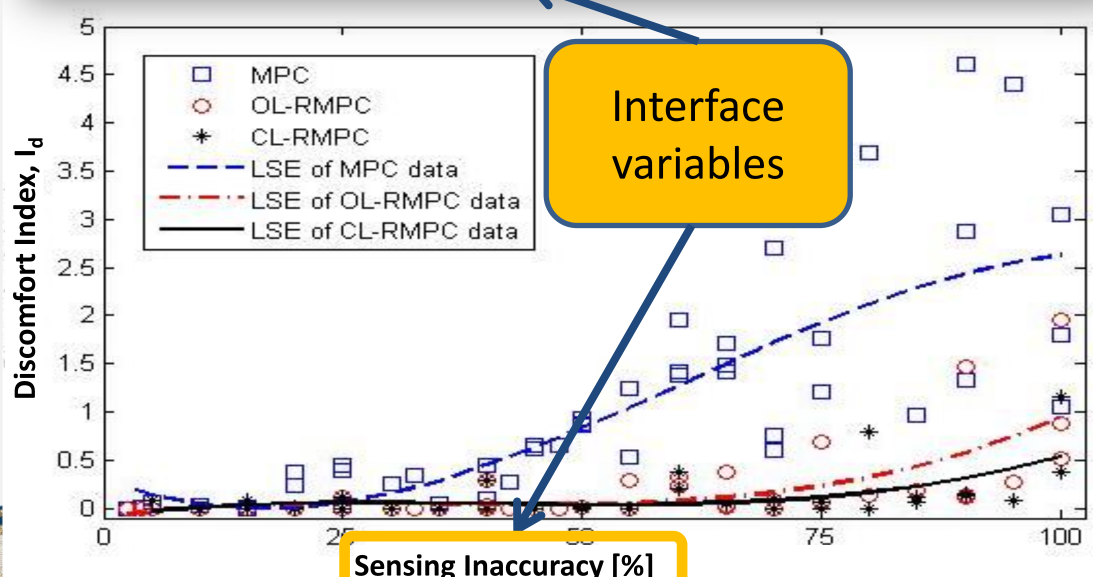


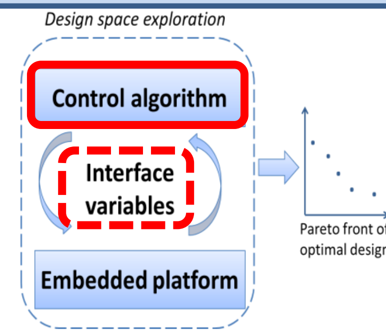


MPC versus RMPC



Interface variables



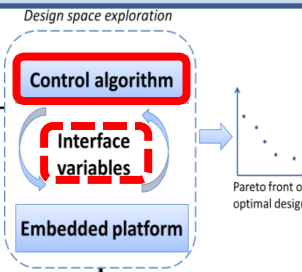


$$P_c(t) = \dot{m}_c(t) c_p [T_{out}(t) - T_c(t)]$$
$$P_h(t) = \dot{m}_h(t) c_p [T_h(t) - T_{out}(t)]$$
$$P_f(t) = \alpha \dot{m}^3(t)$$

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

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

Control Algorithm:
Extended & Unscented Kalman filtering



Extended Kalman Filter Algorithm

Prediction:

A-priori state estimate: $\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_{k-1}, d_{k-1}, 0)$

State transition and observation matrices:

$$F_{k-1} = \frac{\partial f}{\partial x}\Big|_{\hat{x}_{k-1|k-1}, u_{k-1}} \qquad H_k = \frac{\partial h}{\partial x}\Big|_{\hat{x}_{k|k-1}}$$

A-priori state estimation error covariance:

$$P_{k|k-1} = F_{k-1} P_{k-1|k-1} F_{k-1}^T + W_{k-1}$$

Update:

A-priori output estimation error: $\tilde{y}_k = z_k - h(\hat{x}_{k|k-1})$

Innovation or residual covariance: $S_k = H_k P_{k|k-1} H_k^T + V_k$

Near-optimal Kalman gain: $K_k = P_{k|k-1} H_k^T S_k^{-1}$

A-posteriori state estimate: $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{y}_k$

A-posteriori state estimation error covariance: $P_{k|k} = (I - K_k H_k) P_{k|k-1}$

Unscented Kalman Filter Algorithm

Prediction:

Calculate sigma points:

$$\mathcal{X}_{k-1} = [\hat{x}_{k-1} \quad \hat{x}_{k-1} + \gamma\sqrt{P_{k-1}} \quad \hat{x}_{k-1} - \gamma\sqrt{P_{k-1}}]$$

Propagate each column of $\mathcal{X}_{k-1}$ through time:

$$(\mathcal{X}_k)_i = f((\mathcal{X}_{k-1})_i) \qquad i = 0, 1, \ldots, 2L$$

A-priori state estimate: $\hat{x}_k^- = \sum_{i=0}^{2L} W_i^{(m)} (\mathcal{X}_k)_i$

A-priori error covariance:

$$[illegible] \sum^{2L} [illegible])_i - \hat{x}_k^-][(\mathcal{X}_k)_i - \hat{x}_k^-]^T + W_{k-1}$$

[illegible]

$$(\mathcal{Z}_k)_i = h((\mathcal{X}_k)_i) \quad i = 0, .., 2L$$

$$\hat{z}_k^- = \sum_{i=0}^{2L} W_i^{(m)} (\mathcal{Z}_k)_i$$

A-posteriori state estimate: $\hat{x}_k = \hat{x}_k^- + K_k(z_k - \hat{z}_k^-)$

where: $K_k = P_{\hat{x}_k \hat{z}_k} P_{\hat{z}_k \hat{z}_k}^{-1}$

A-posteriori estimate of the error covariance: $P_k = P_k^- - K_k P_{\hat{z}_k \hat{z}_k} K_k^T$

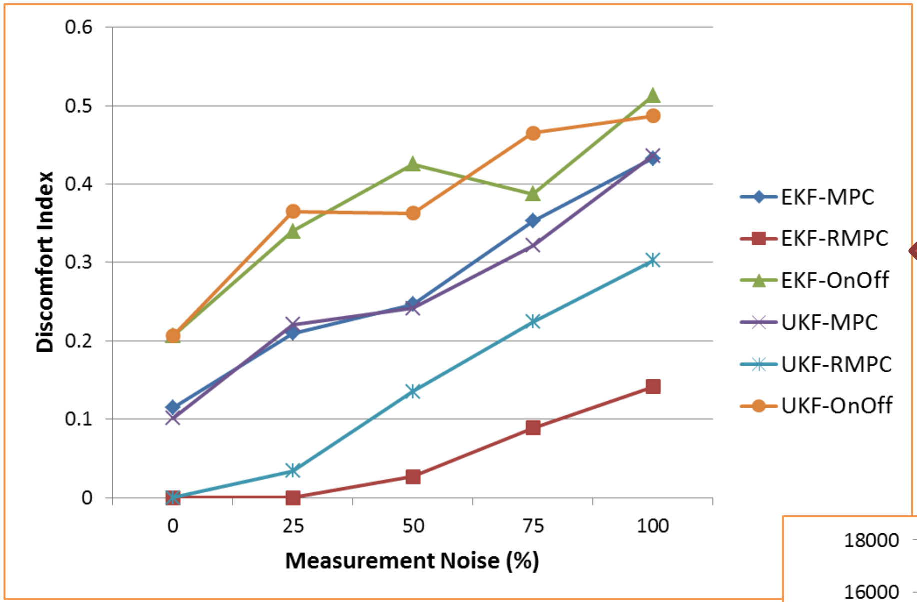
where:

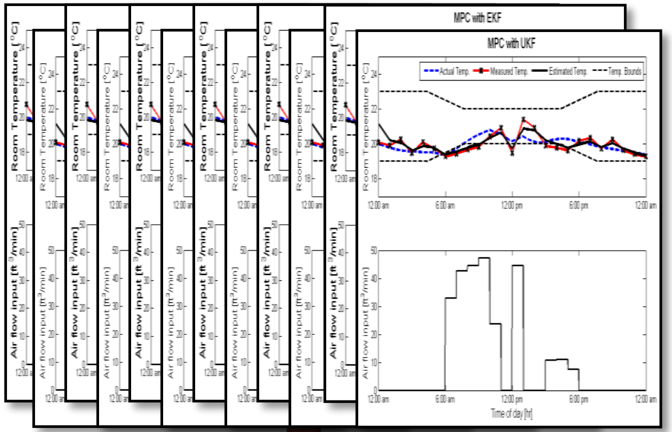
$$P_{\hat{x}_k \hat{z}_k} = W_i^c [(\mathcal{X}_k)_i - \hat{x}_k^-][(\mathcal{Z}_k)_i - \hat{z}_k^-]^T$$

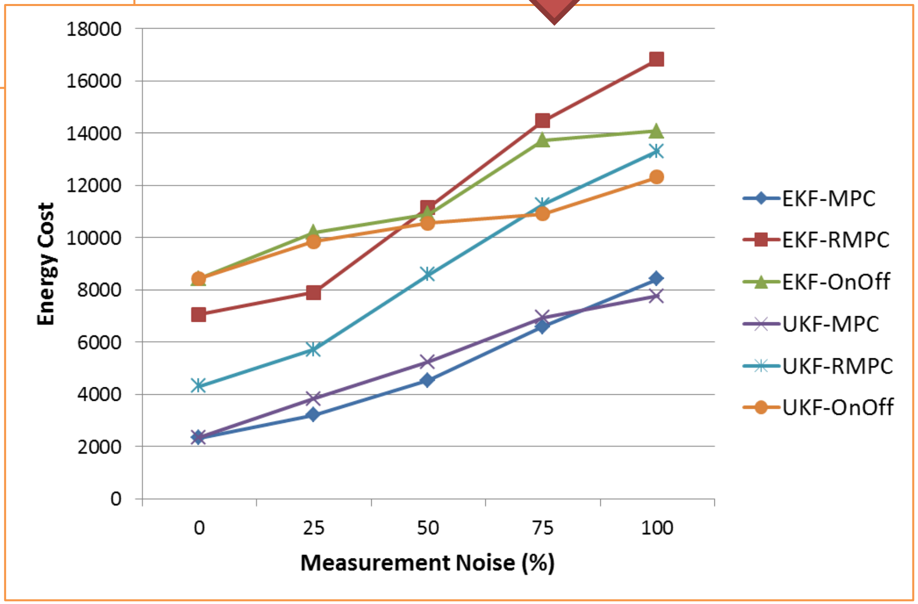
$$P_{\hat{z}_k \hat{z}_k} = \sum_{i=0}^{2L} W_i^c [(\mathcal{Z}_k)_i - \hat{z}_k^-][(\mathcal{Z}_k)_i - \hat{z}_k^-]^T + V_k$$

Interface variables

Interface Variables and Control Algorithm







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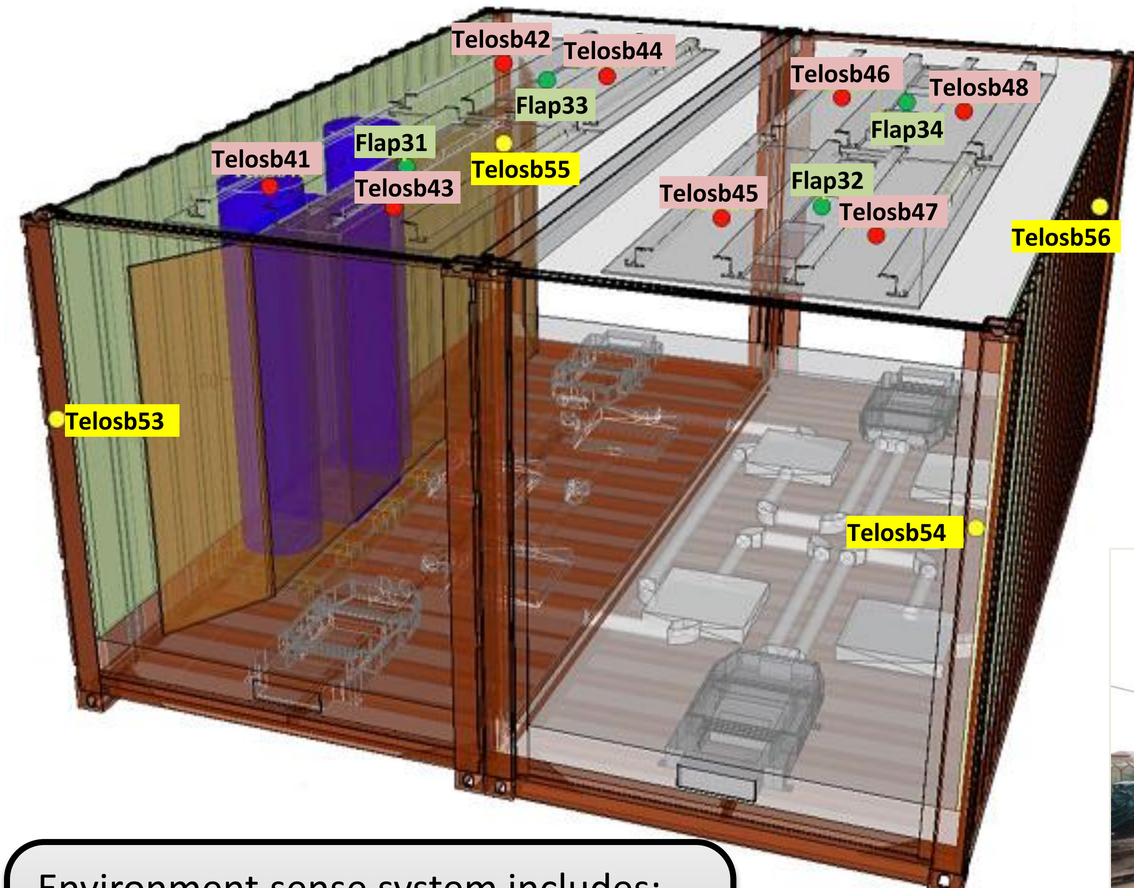
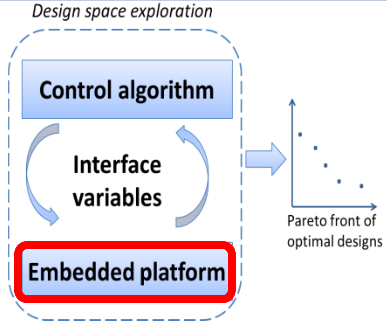
Platform:
BubbleZERO Setup - Singapore



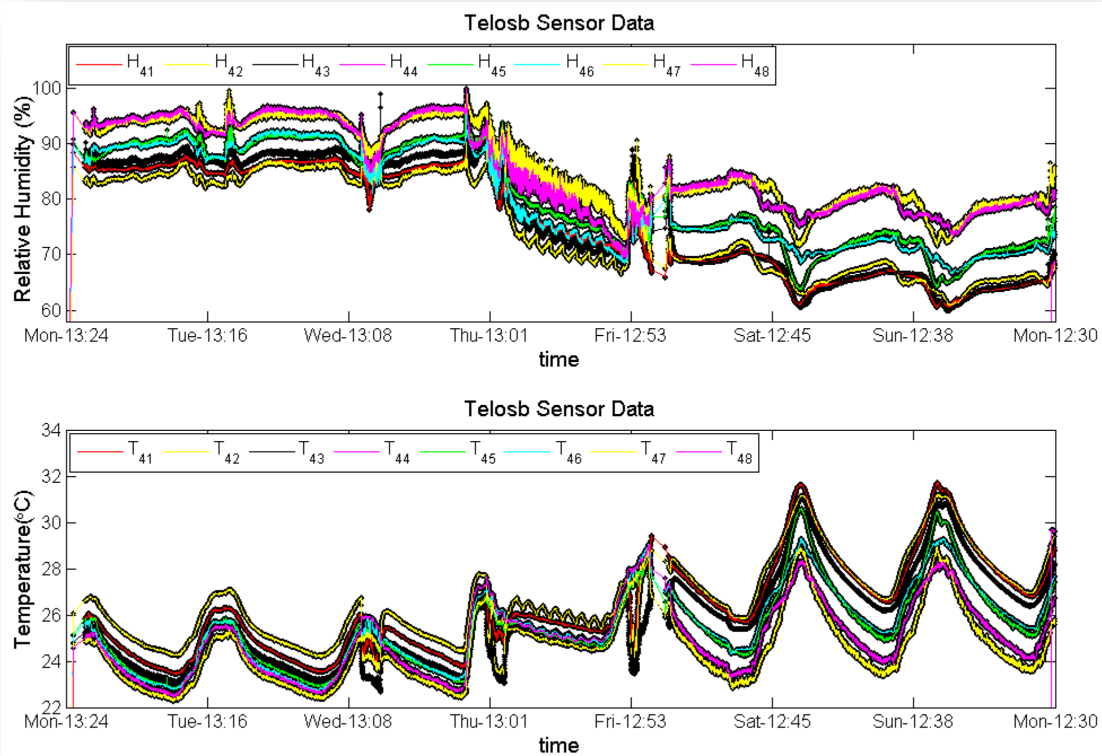


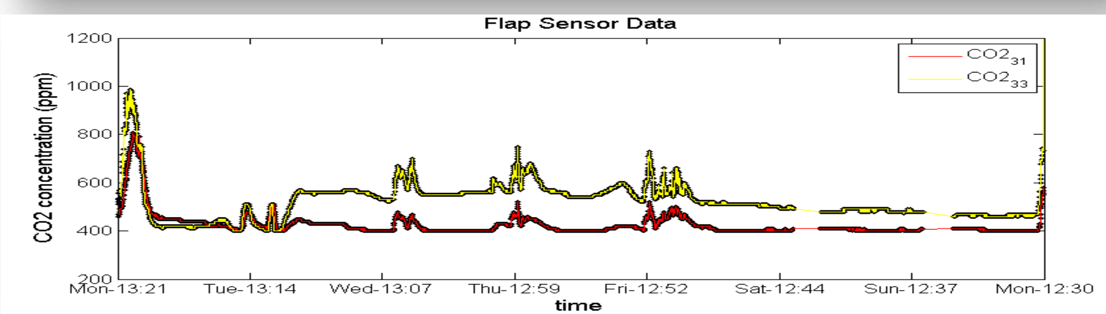
- Indoor Sensor
- Outdoor Sensor
- CO_2 Flaps

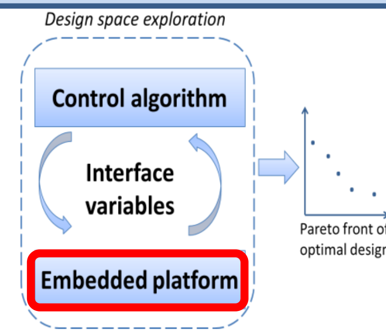
Environment sense system includes:
- **8 indoor sensors (Telosb41-48)**
- **4 CO2 concentration sensors (Flap31-34)**
- **4 outdoor sensors (Telosb53-56)**

Platform:

Sensor Readings from the Set-up







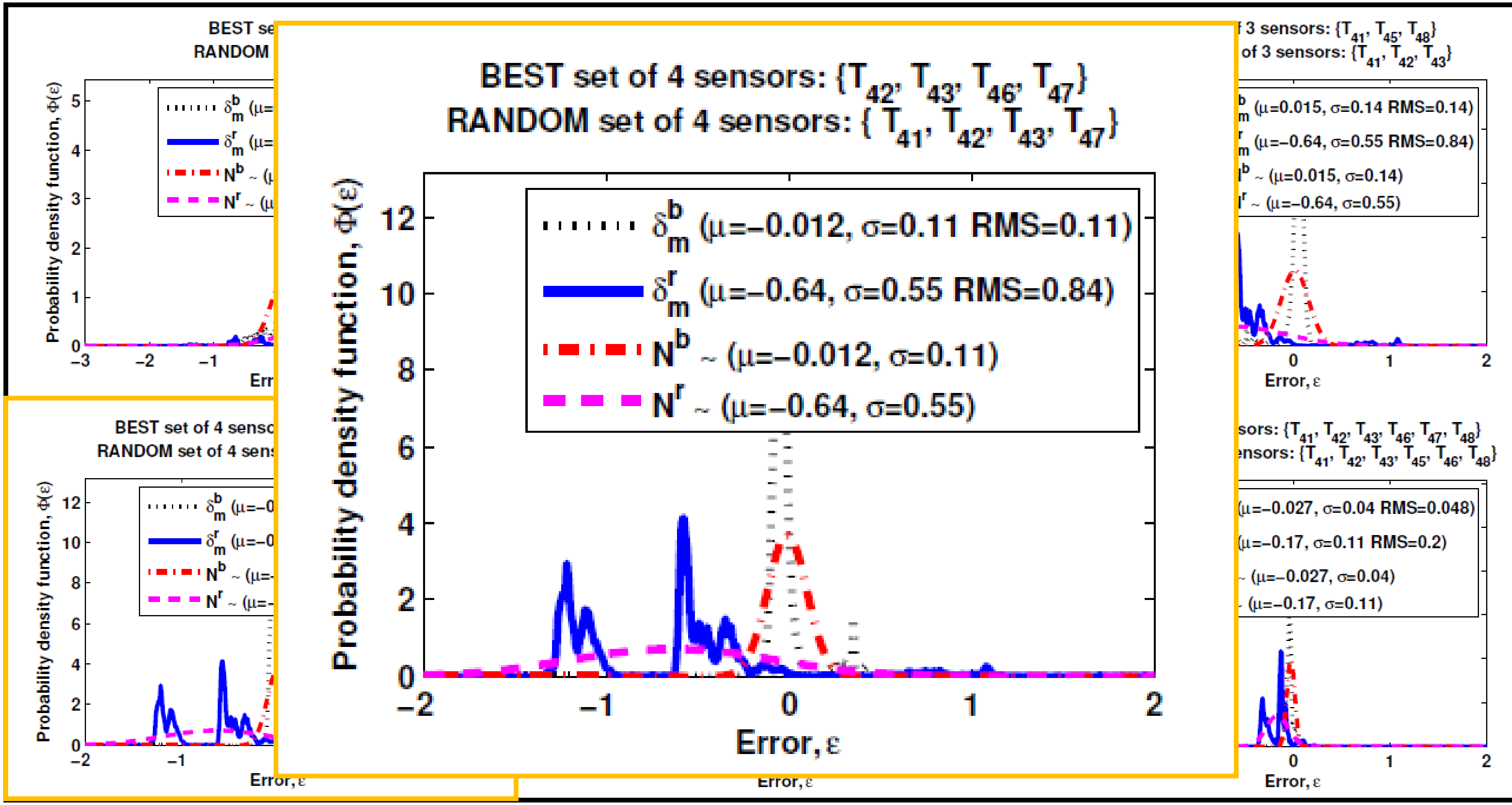
Telosb sensors:
- Relative Humidity
- Temperature measurements

from 8 sensors.

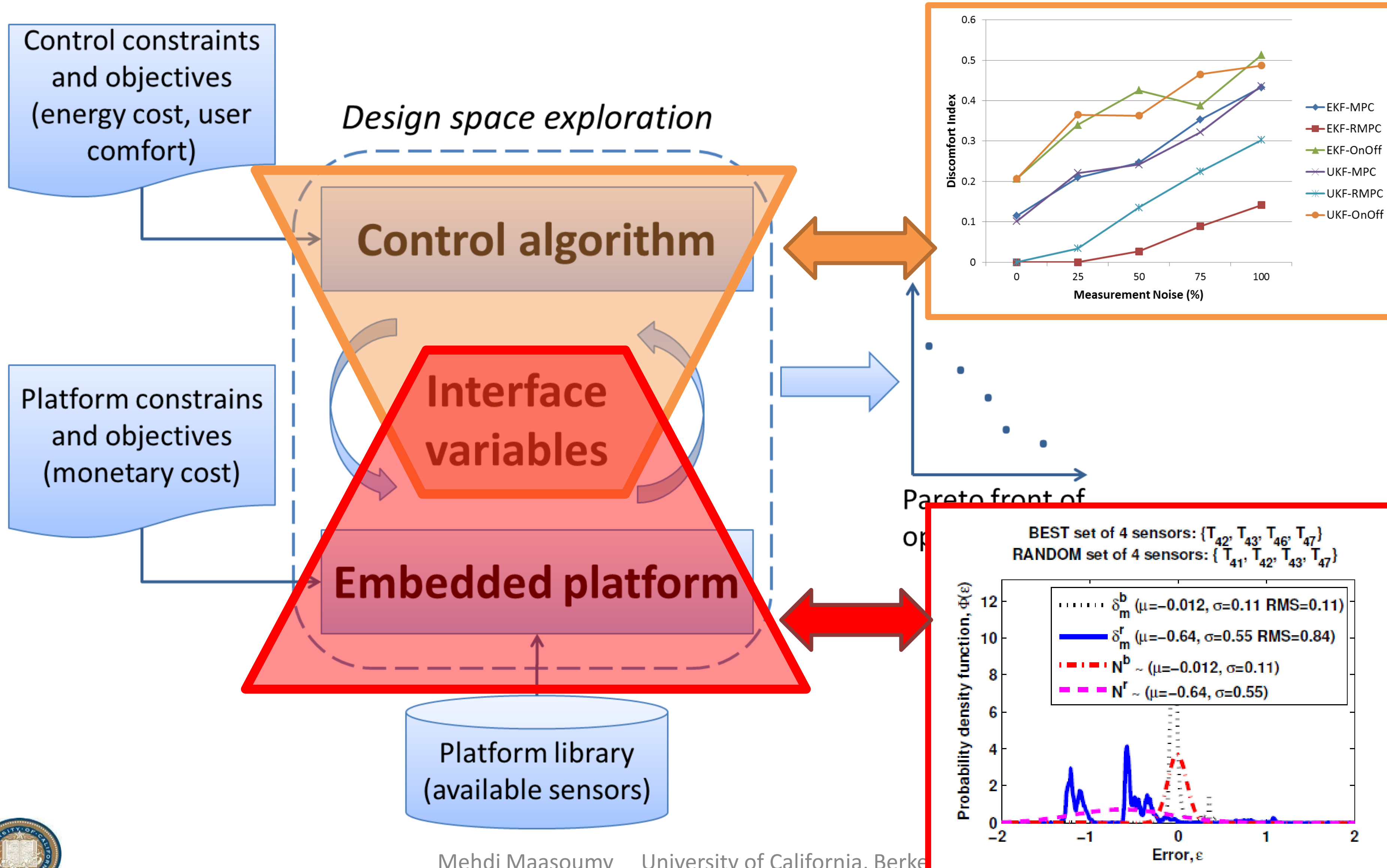
Flap sensors:
- CO2 measurements

from 2 sensors.

Interface variable and Embedded Platform



Design tools are ready…



Outline

- ❑ Co-design problem
- ❑ Plant Modeling
- ❑ Interface variables
- ❑ Control Design
- ❑ Embedded Platform
- ❑ Simulation Results

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- ❑ Co-design problem
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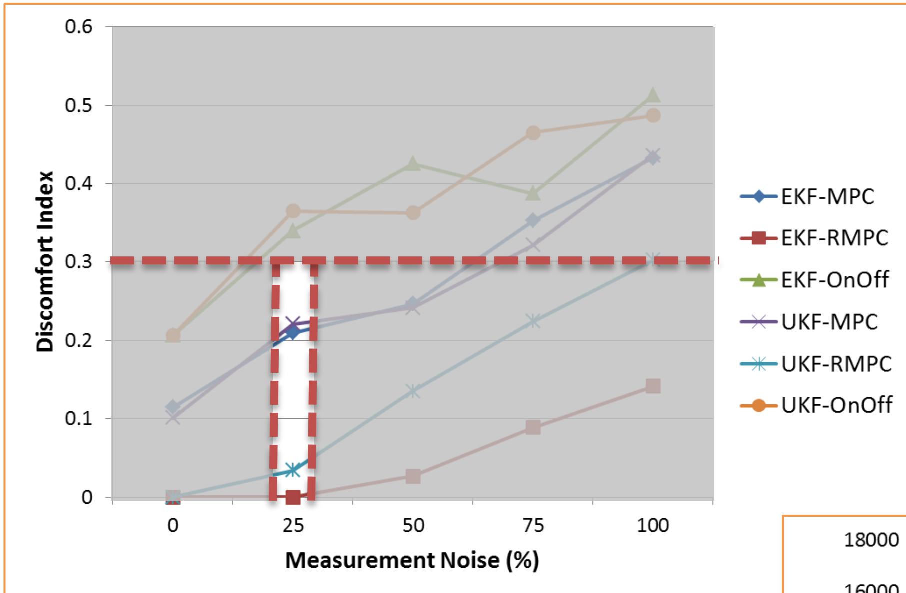
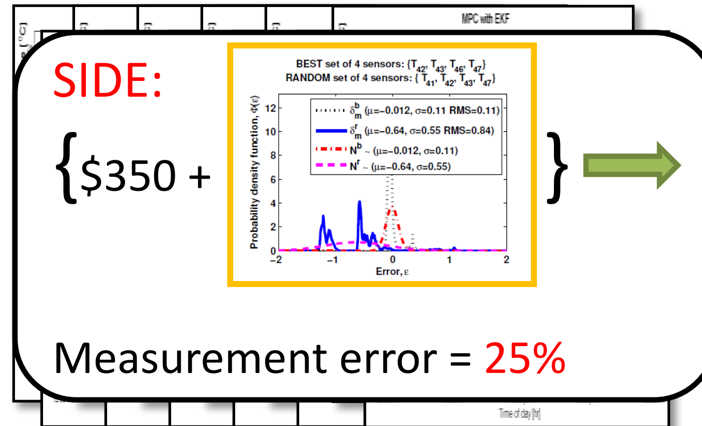
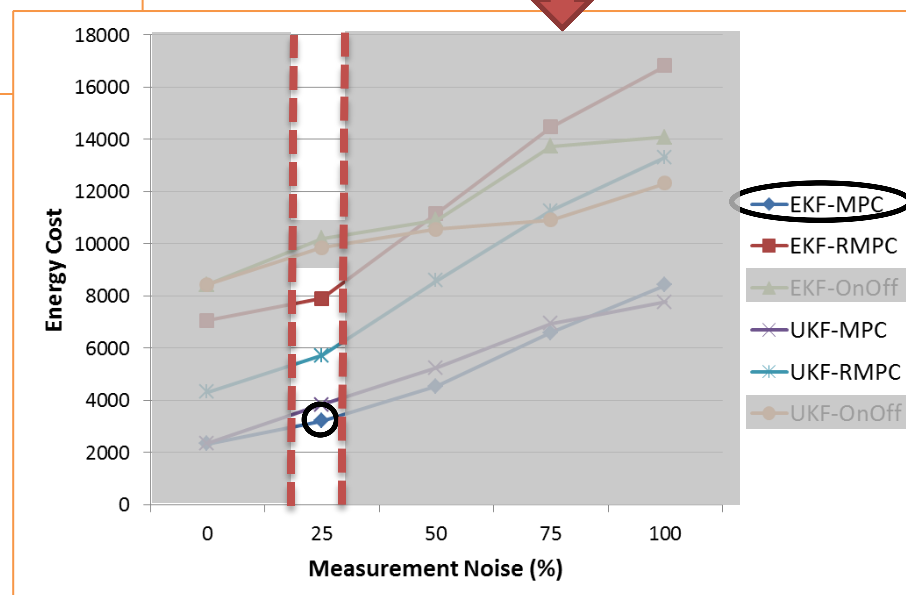
Co-Design Illustration:
Example 1





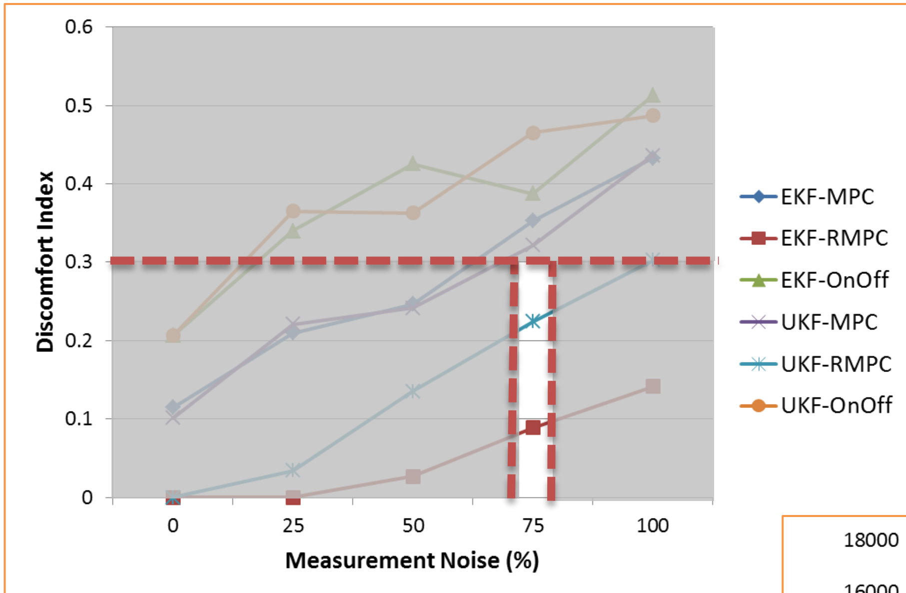


Example 1:

- Discomfort index < 0.3
- Monetary cost = $ 350

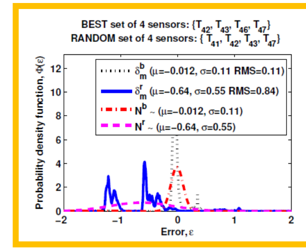
Design Choice: EKF-MPC

Co-Design Illustration:
Example 2



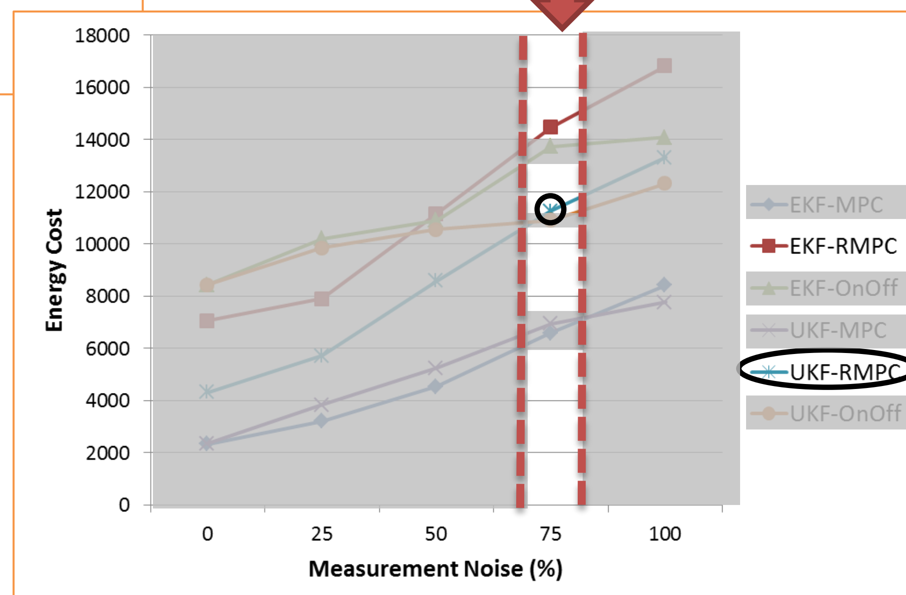
SIDE:

{$70 +



}

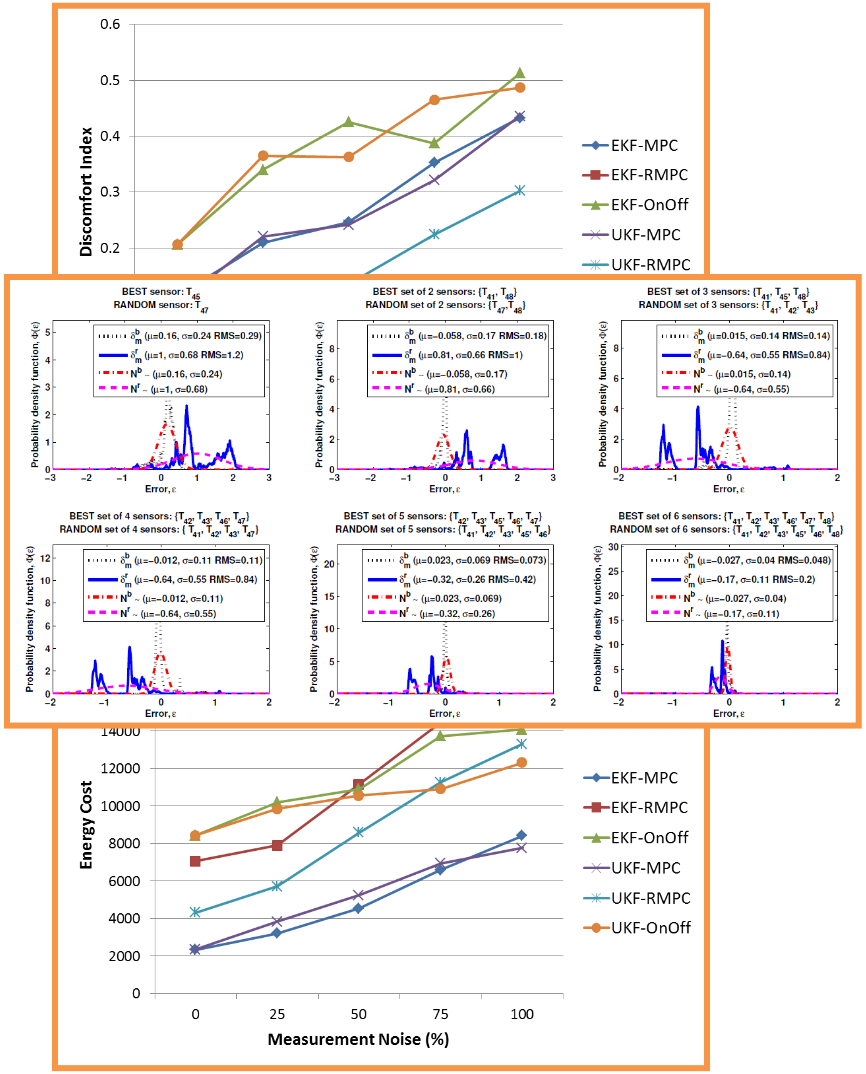
Measurement error = 75%

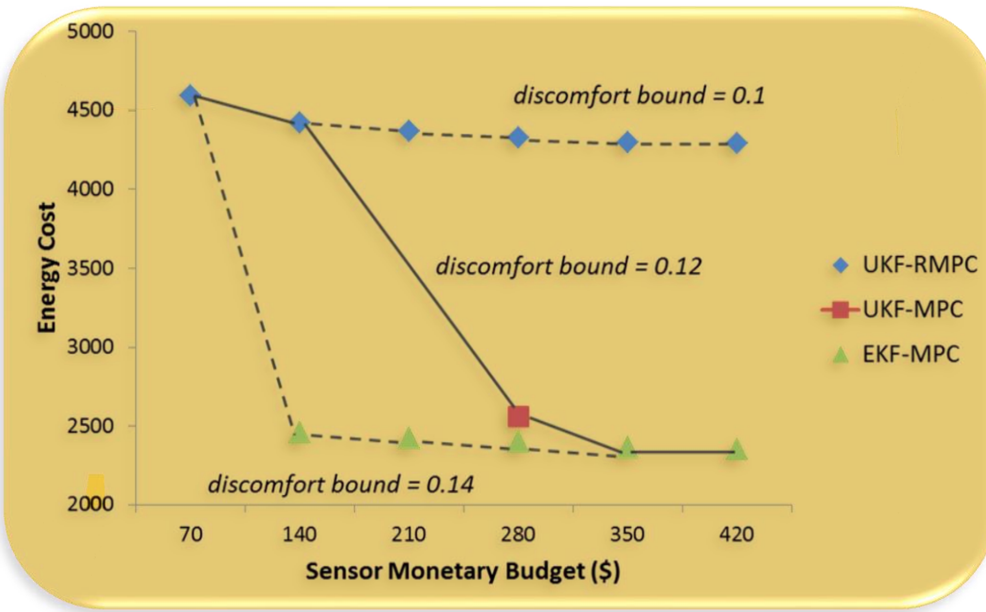


Example 2:
- Discomfort index < 0.3
- Monetary cost= $70

Design Choice: UKF-RMPC

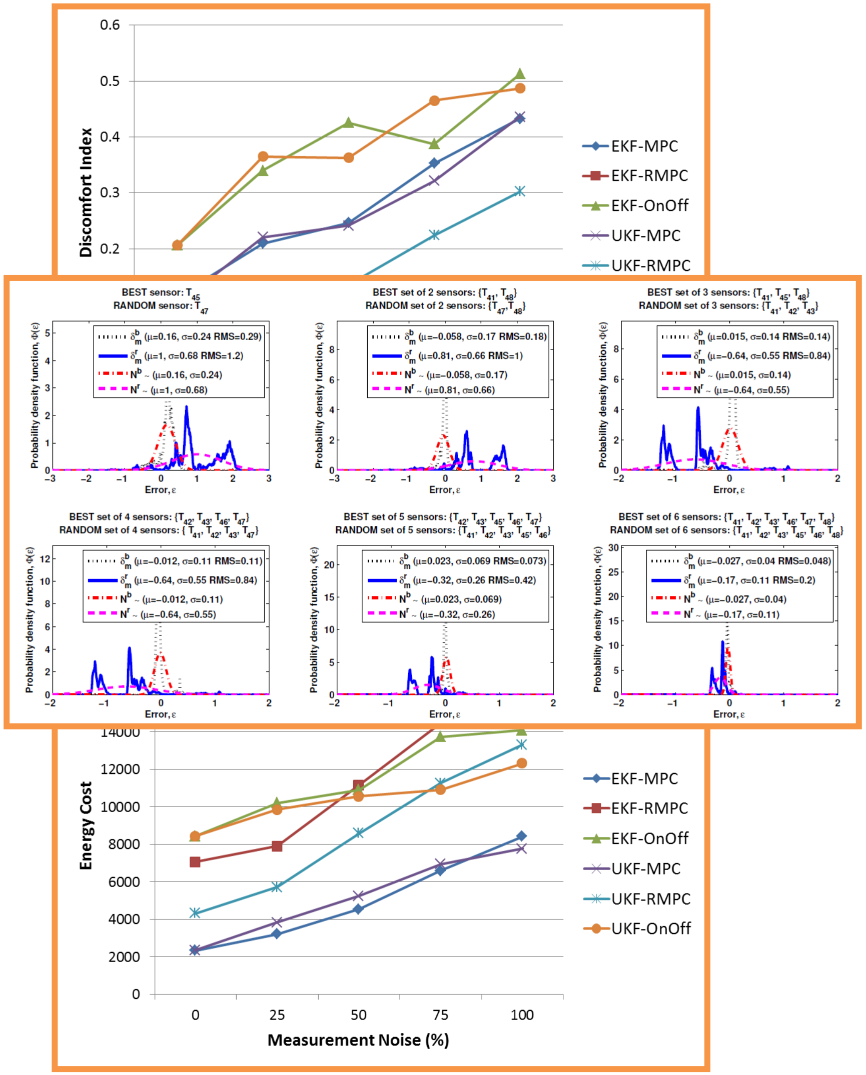
Pareto front
Under Discomfort index Contraints

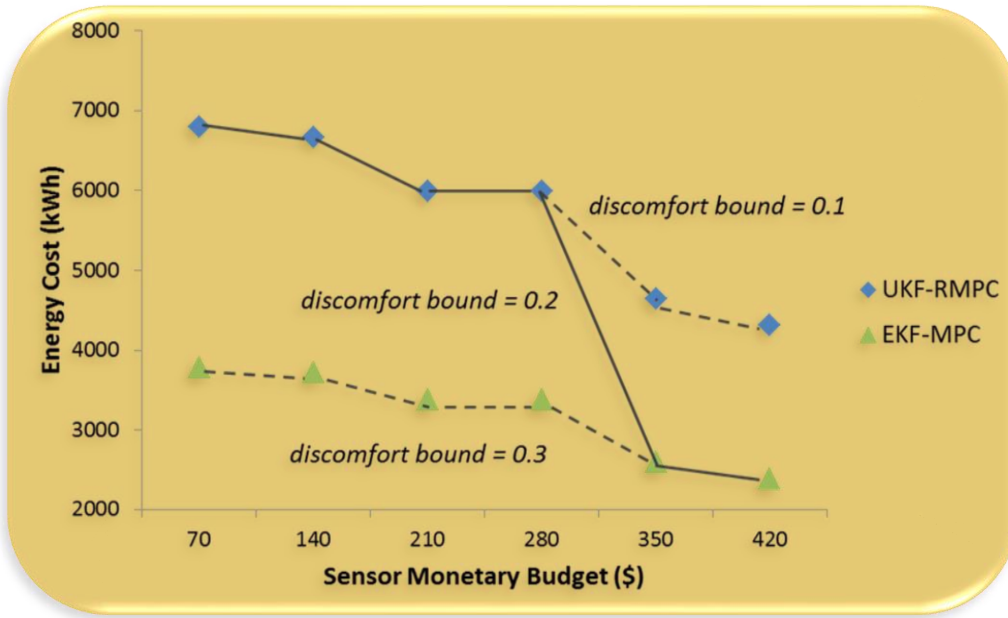




Pareto front under comfort constraints with best sensor locations

Pareto front
Under Discomfort index Contraints





Pareto front under comfort constraints with random sensor locations

Summary

Proposed a **framework for co-designing** the control algorithm and the embedded platform:

- Identify the interface variables.
- Designed six different controllers with consideration of interface variables. Captured the relation between the sensing accuracy and control performance.
- Captured the relation between sensing accuracy and the number and locations of sensors.
- Performed the **co-design** with constraints on the control performance and monetary constraints.

Future Work

1. Analyze the relation between the prediction error and the design of the embedded platform.

2. Broaden our consideration of the embedded platform design from the sensing system to the **computation** and **communication** components, such as the impact of **communication reliability** on the control algorithm.

Thanks for your attention!

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Questions?

References

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