Development of Building Automation and Control (BAC) Systems:

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

Mehdi Maasoumy
PhD Candidate, UC Berkeley
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

THE COMMONALITY OF SMART AND GREEN BUILDINGS

GREEN BUILDINGS
- Sustainable Sites
- Water Efficiency
- Energy and Atmosphere
- Materials and Resources
- Indoor Environmental Quality
- Innovation and Design Process

SMART BUILDINGS
- Data Network
- VOIP
- Video Distribution
- AV Systems
- Video Surveillance
- Access Control
- HVAC Control
- Power
- Management
- Programmable
- Lighting Control
- Facilities
- Management
- Cabling
- Infrastructure
- Wireless Systems

Source: http://www.smart-buildings.com
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 coordination at a system level
Control logic governing today’s buildings uses simple control schemes dealing with one subsystem at a time...

Local actions are determined \textit{without} taking into account the interrelations among:

\begin{itemize}
  \item Outdoor weather conditions
  \item Indoor air quality
  \item Cooling demands
  \item HVAC process components
\end{itemize}
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
First approach

For physical buildings

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

• Energy balance for a **wall** node:

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

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

• Energy balance for a **room** node:

\[
\frac{dT_{ri}}{dt} = \frac{1}{C_{ri}} \left[ \sum_{j \in N_{ri}} \frac{T_j - T_{ri}}{R'_{rij}} + m_{ri} c_p (T_{si} - T_{ri}) + w_i T_{win_i} A_{win_i} q''_{rad_i} + \dot{q}_{int} \right]
\]
Building Thermal Model

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

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

$$\min_{C, R, \lambda, \gamma, \mu, \nu} \| Y^m - Y^s \|^2_2$$

s.t. \[ \begin{aligned}
  x_{t+1}^s &= Ax_t^s + f(x_t^s, u_t^m, d_t^m) & t = 0, \ldots, N - 1 \\
  y_t^s &= Cx_t^s & t = 0, \ldots, N
\end{aligned} \]
Parameter Identification

For each room:

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

\[ [C_r, C_{w1}, C_{w2}, C_{w3}, C_{w4}, R_1, R_2, R_3, R_4]^* = \arg \min_{C_r, C_{wi}, R_i} \sum_t [e(t)]^2 \]
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
\[ \dot{x} = Ax + Bu \]
\[ y = Cx + Du \]

Balanced Realization
\[ \dot{z} = \tilde{A}z + \tilde{B}u \]
\[ y = \tilde{C}z + Du \]

Model Reduction
\[ \dot{\hat{z}} = \tilde{A}_{11}\hat{z} + \tilde{B}_1 u \]
\[ y = \tilde{C}_1 \hat{z} + Du \]
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
\[ \dot{\hat{z}} = \tilde{A}_{11}\hat{z} + \tilde{B}_1u \]
\[ y = \tilde{C}_1\hat{z} + Du \]
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
\[ \dot{z} = \tilde{A}z + \tilde{B}u \]
\[ y = \tilde{C}z + Du \]

Model Reduction

Reduced Model
\[ \dot{z} = \tilde{A}_{11}z + \tilde{B}_1u \]
\[ y = \tilde{C}_1z + Du \]
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
\[ \dot{\tilde{z}} = \tilde{A}_{11}z + \tilde{B}_1 u \]
\[ y = \tilde{C}_1 z + Du \]

Tens of states
Reduced Model

![Graph showing linearized and nonlinear system temperatures over time](image-url)
Heterogeneous Modeling and Control
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
Controller Design - Linearization

1. Find an operating point of the system
2. Find the closest equilibrium point
3. Linearize about the equilibrium point

![Graph showing room temperature over time with measured data, nonlinear model, and linearized model.](image)
Model Predictive Control

\[
\begin{align*}
\min_{U_t, \varepsilon, \xi} & \quad \left\{ |U_t|_1 + \kappa |U_t|_\infty + \rho (|\varepsilon_t|_1 + |\xi_t|_1) \right\} = \\
\min_{U_t, \varepsilon, \xi} & \quad \left\{ \sum_{k=0}^{N-1} |u_{t+k}|_t + \kappa \max( |u_t|_t, \ldots, |u_{t+N-1}|_t ) + \rho \sum_{k=1}^{N} (|\varepsilon_{t+k}|_t + |\xi_{t+k}|_t) \right\} \\
\text{s.t.} & \quad x_{t+k+1|t} = A x_{t+k|t} + B u_{t+k|t} + E d_{t+k|t}, \quad k = 0, \ldots, N - 1 \\
& \quad y_{t+k|t} = C x_{t+k|t}, \quad k = 1, \ldots, N \\
& \quad 0 \leq u_{t+k|t} \leq \bar{U}, \quad k = 0, \ldots, N - 1 \\
& \quad T_{t+k|t} - \varepsilon_{t+k|t} \leq y_{t+k|t} \leq \bar{T}_{t+k|t} + \varepsilon_{t+k|t}, \quad k = 1, \ldots, N \\
& \quad \varepsilon_{t+k|t}, \bar{\varepsilon}_{t+k|t} \geq 0, \quad k = 1, \ldots, N
\end{align*}
\]
Comfort Zone Definition

![Diagram showing temperature over time with unoccupied and occupied hours highlighted, along with different bounds for Q1, R1, Q2, R2]
"MPC" and "On-off" Control Results

<table>
<thead>
<tr>
<th>Controller</th>
<th>Total input $[\text{ft}^3]$</th>
<th>Peak input $[\text{ft}^3/\text{min}]$</th>
<th>Total energy $[\text{kWh}]$</th>
<th>Running time $[\text{s}]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original control</td>
<td>45360</td>
<td>63</td>
<td>12.46</td>
<td>-</td>
</tr>
<tr>
<td>On-off control</td>
<td>17520 $68%$</td>
<td>63 $66%$</td>
<td>4.62 $35%$</td>
<td>73% 1.8</td>
</tr>
<tr>
<td>MPC</td>
<td>14870</td>
<td>42</td>
<td>3.33 $73%$</td>
<td>102.4</td>
</tr>
</tbody>
</table>
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
Robust Model Predictive Control
(against model and measurement uncertainties)
Original Control with Uncertainty

for $\lambda = 1$
Schematic of RMPC Implementation

State update equation

\[ x^+ = Ax + Bu + Ed + Fw \]

Additive uncertainty

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

More details at: Maasoumy, et al. DSCC 2012
Min-Max Strategy (Open-Loop) for RMPC

\[ J_0(x(t), U_t) \triangleq \]

\[
\max_{w_{[\cdot]}} \{ \sum_{k=0}^{N-1} |u_{t+k}|_t + \kappa \max(|u_t|_t, \cdots, |u_{t+N-1}|_t) + \\
\rho \sum_{k=1}^{N} (|\varepsilon_{t+k}|_t + |\xi_{t+k}|_t) \}
\]

s.t.

\[
x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t} + Ed_{t+k|t} + Fw_{t+k|t}
\]

\[ w_{t+k|t} \in \mathbb{W} \]

\[ k = 0, \cdots, N - 1 \]

Robust counterpart of an uncertain optimization problem

\[ J^*_0(x(t)) \triangleq \min_{U_t} J_0(x(t), U_t) \]

subject to

\[
x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t} + Ed_{t+k|t} + Fw_{t+k|t}
\]

\[ y_{t+k|t} = Cx_{t+k|t} \]

\[ T_{t+k|t} - \xi_{t+k|t} \leq y_{t+k|t} \leq \overline{T}_{t+k|t} + \xi_{t+k|t} \]

\[ \xi_{t+k|t}, \overline{\varepsilon}_{t+k|t} \geq 0 \]

\[ \forall \ w_{t+k|t} \in \mathbb{W} \quad \forall \ k = 0, \cdots, N - 1 \]
CL-RMPC: Feedback Predictions

- Closed-loop min-max problem:

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

- Feedback Predictions

- State feedback prediction:
  \[U = MX + v\]

- New decision variables:
  \[v = [v_k|k, v_{k+1}|k, \cdots, v_{k+N-1}|k]\]

- Parameter matrix \(M\) is causal:

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

- Sometimes \(M\) is incorporated as a decision variable...
Disturbance Feedback Policy:

- parameterize future inputs as affine functions of past disturbances.

\[
U = Mw + v
\]

i.e.

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

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

\[
M := \begin{bmatrix}
0 & \cdots & \cdots & 0 \\
m_{1,0} & 0 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
m_{N-1,0} & \cdots & \cdots & 0 \\
\end{bmatrix}, \quad v := \begin{bmatrix}
v_0 \\
\vdots \\
v_{N-1}
\end{bmatrix}
\]
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:

\[
U = Mw + v
\]

\[
M = \begin{pmatrix}
k_1 & & &  \\
k_2 & k_1 & &  \\
k_3 & k_2 & k_1 &  \\
& \ddots & \ddots & \ddots  \\
k_{N-1} & \cdots & \cdots & k_2 & k_1  \\
k_N & k_{N-1} & \cdots & \cdots & k_2 & k_1
\end{pmatrix}
\]

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

$$u_i := m_{i,i-2}w_{i-2} + m_{i,i-1}w_{i-1} + v_i$$

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

we exploit the sparsity of the $M$ matrix to enhance the computational cost of the optimization problem.
Simulation Results

Comparison of ECS, MPC, OL-RMPC and CL-RMPC
RMPC: Energy vs. Comfort

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

\[ I_D = \int_{t=0}^{24} \min \{ |T(t) - \bar{T}(t)|, |T(t) - \overline{T}(t)| \} \cdot 1_{B(t)c}(T(t)) \, dt \]

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

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

<table>
<thead>
<tr>
<th>Controller</th>
<th>Number of feedback decision variables</th>
<th>Average simulation time for $N = 24$ [s]</th>
<th>$I_e$ [kWh]</th>
<th>$I_d$ [$^\circ Ch$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>LTS</td>
<td>$l\text{mr}(\frac{N(N+1)}{2})$</td>
<td>200</td>
<td>16467</td>
<td>0</td>
</tr>
<tr>
<td>TLDS</td>
<td>$3l\text{mr}(N-1)$</td>
<td>138</td>
<td>16467</td>
<td>0</td>
</tr>
<tr>
<td>OL</td>
<td>-</td>
<td>159</td>
<td>22592</td>
<td>0.84</td>
</tr>
</tbody>
</table>
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.
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
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

![Performance comparison for four controllers](image)

<table>
<thead>
<tr>
<th>Controller</th>
<th>Parameters</th>
<th>Simulation time [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>P control</td>
<td>$K_p = 4$</td>
<td>0.187</td>
</tr>
<tr>
<td>LQR</td>
<td>$Q_1 = 0.01$, $Q_2 = 100$, $R_1 = 10$, $R_2 = 0.02$</td>
<td>0.057</td>
</tr>
<tr>
<td>d-LQR</td>
<td>$Q_1 = 0.24$, $Q_2 = 0.54$, $R_1 = 1$, $R_2 = 0.09$</td>
<td>0.009</td>
</tr>
<tr>
<td>MPC</td>
<td>$\kappa = 2$, $\rho = 1000$</td>
<td>95.098</td>
</tr>
</tbody>
</table>
Comfort vs. Cost
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
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!!!**
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 systems

Design space exploration

Control constraints and objectives (energy cost, user comfort)

Platform constraints and objectives (monetary cost)

Control algorithm design (controller type, parameters)

Interface variables (sensing accuracy)

Embedded platform design (number of sensors, locations)

Platform library (available sensors)

Pareto front of optimal designs
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)
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 \( \Delta_{rms} \) error.

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

![Graphs showing simulation results for different noise levels and algorithms.](Image)
Pareto front under comfort constraints with \textit{best} sensor locations
Pareto front under discomfort index constraints

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
- Comparing Different Control Strategies
- Co-design of Control Algorithm and Embedded Platform
- Buildings and Smart Grid
Ongoing Research...

Buildings and Smart Grid

Ancillary Services via Control of HVAC Systems
Ancillary Services via Control of Building HVAC Systems

Thank You!

Questions?

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


