Distributed Model Predictive Control for energy management in buildings

Ph.D. thesis presented by:
Mohamed Yacine Lamoudi

Supervised by:
Mazen Alamir - Directeur de recherche CNRS
Patrick Béguery - Schneider-Electric / Strategy & Innovation

November 29th 2012
Introduction

Energy consumption in the world - the facts

The challenge ...

Energy demand x2

Now → 2050
Introduction

Energy consumption in the world - the facts

The challenge ...

Energy demand $\times 2$

CO$_2$ emission $\div 2$

Now 2050

Now 2050
Introduction

Energy consumption in the world - the facts

The challenge ...

Energy demand $\times 2$

CO$_2$ emission $\div 2$

$= x 4$

More efficient
Introduction

Energy consumption in the world - the facts 🌍
Introduction

Energy consumption in the world - the facts 🌍
Introduction

Energy consumption in the world - the facts

40% of world-wide primary energy consumption is due to buildings
Introduction

Energy consumption in the world - the facts 🌍

- **40%** of world-wide primary energy consumption is due to buildings

Towards smart grid

- Nuclear plants
- Thermal plants
- Electrical Grid
- Power
Introduction

Energy consumption in the world - the facts 🌍

40% of world-wide primary energy consumption is due to buildings

Towards smart grid

- Solar plants
- Wind farms
- Nuclear plants
- Thermal plants
- Electrical Grid
- Power
Introduction

Energy consumption in the world - the facts 🌍

- **40%** of world-wide primary energy consumption is due to buildings

Towards smart grid

- Solar plants
- Wind farms
- Nuclear plants
- Thermal plants
- Electrical Grid
- Power
Introduction

Energy consumption in the world - the facts 🌍

40% of world-wide primary energy consumption is due to buildings

Towards smart grid

- Solar plants
- Wind farms
- Nuclear plants
- Thermal plants
- Electrical Grid
- Power
- D/R signals
**Introduction**

Energy consumption in the world - the facts 🌍

1. 40% of world-wide primary energy consumption is due to buildings
2. Buildings play a key role in smart grid

![Diagram showing energy sources and demand-side management](image-url)
Introduction

Energy consumption in the world - the facts 🌍

1. **40%** of world-wide primary energy consumption is due to buildings
2. Buildings play a key role in smart grid

Objectives

1. Reduce Buildings energy consumption
2. Make them smart grid ready
The HOMES program

Largest funded program on buildings **active energy efficiency** in Europe ...
The HOMES program

Largest funded program on buildings **active energy efficiency** in Europe ...

“Equip each building with Active Energy Efficiency solutions, to achieve the best possible energy performance”

September 2008 > September 2012
26 Work Packages – 80 M€
39 M€ funded by OSEO (French Agency) incl. Schneider 26 M€
Thesis objectives

Design control algorithms able to improve energy management in buildings

1. **Reduce energy and maintain comfort**
2. Make buildings "smart grid ready" (variable energy prices, power limitations)
3. Design generic, scalable and modular solutions
Distributed Model Predictive control for energy management in buildings

1. MPC for energy management in buildings
2. Zone Model Predictive Control
3. Distributed Model Predictive Control
4. Conclusion
Distributed Model Predictive control for energy management in buildings

1. MPC for energy management in buildings
2. Zone Model Predictive Control
3. Distributed Model Predictive Control
4. Conclusion
Energy management in buildings

An introduction

**Comfort indicator**
Ensure comfort by maintaining outputs in a given set

**Energy criterion**
Find the best way to achieve comfort given constraints on inputs

![Diagram showing Comfort indicator and Energy criterion](chart.png)
Conventional control in buildings

Rule-based control

Rule-based control

Rule1: if condition[params] then action[params]
Rule2: if condition[params] then action[params]
...

Many issues

- Coherence of the process of decision
- Parameters tuning ?
- complex situations ?
Conventional control in buildings

Rule-based control

Rule1: \textit{if} condition[params] \textit{then} action[params]
Rule2: \textit{if} condition[params] \textit{then} action[params]
...

Many issues

- Coherence of the process of decision
- Parameters tuning ?
- \textit{complex situations} ?

To sum up ...

- Difficult to generalize
- Must be fully adapted for a given scenario
- Difficult to handle economical objectives
- Difficult to ensure coherence of the decision
- Extremely simple to implement on BEMS!
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles

Initial state
Avoid Obstacles
Target
Compute the Optimal Trajectory
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles

Initial state

Target

Avoid Obstacles

Apply the first part
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles

Initial state
Avoid Obstacles

Target

Compute the Optimal Trajectory
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles

Initial state

Avoid Obstacles

Target

Apply the first part
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles

Avoid Obstacles

Target

Initial state

Compute the Optimal Trajectory
Model Predictive Control (I)
An intuitive concept...

A simplistic example
minimize path length and avoid obstacles

Avoid Obstacles
Initial state
Target

Apply the first part
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles

Initial state

Target

Avoid Obstacles

Compute the Optimal Trajectory
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles

Initial state

Target

Avoid Obstacles

Closed loop trajectory
Model Predictive Control (I)

An intuitive concept...

A simplistic example

minimize path length and avoid obstacles

Initial obstacles positions
Final obstacles positions

Target

Initial state

First Optimal Trajectory
Closed loop trajectory
Model Predictive Control (II)

Receding Horizon Principle
Why Model Predictive Control in buildings?

- Thermal inertia
- Coupled dynamics
- Constraints (comfort, actuators, power consumption, etc.)
- Multi-source: several power sources (thermal, electrical, etc.)
- Economic objectives (varying energy tariffs)
MPC for building Energy management

The ingredients ...

Model
MPC for building Energy management

The ingredients ...

Model + Predictions
MPC for building Energy management

The ingredients ...

Model + Predictions + Objective
MPC for building Energy management

The ingredients ...
MPC for building Energy management

The ingredients ...

Model + Predictions + Objective + Solver

Optimization Problem
MPC for building Energy management

The ingredients ...

Model + Predictions + Objective + Solver

Optimization Problem

Optimal solution
Building control layers

Decomposition approach
Building control layers

Decomposition approach
Building control layers

Decomposition approach

MPC for energy management in buildings

Model Predictive control
Building control layers

Decomposition approach

Energy layer

Storage and transformation

Gas

Supply

Grid

Local prod.

Electrical storage

Boiler

Pump

Heat Storage

Energy cons. / ensure comfort

Zone layer
Building control layers
Decomposition approach
Building control layers

Decomposition approach

Energy layer

Supply

Grid

Gas

Storage and transformation

Electrical storage

Boiler

Pump

Heat Storage

Local prod.

Energy cons. / ensure comfort

Zone layer
Building control layers

Decomposition approach

Energy layer

Storage and transformation

Information exchange

Zone layer

Energy cons. / ensure comfort
Distributed Model Predictive control for energy management in buildings

1. MPC for energy management in buildings

2. Zone Model Predictive Control
   - Zone modeling
   - The control problem
   - Simulation and real-time implementation
   - Yearly simulation
   - Roombox implementation

3. Distributed Model Predictive Control

4. Conclusion
Zone Model Predictive Control

zone presentation

Objective

(a) Control comfort parameters (temperature, CO$_2$ level, lighting),
(b) Minimize operational costs (energy, invoice).
Zone Model Predictive Control

Zone presentation

Objective

(a) Control comfort parameters (temperature, CO$_2$ level, lighting),
(b) Minimize operational costs (energy, invoice).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_W$</td>
<td>FCU valve opening</td>
<td>[−]</td>
</tr>
<tr>
<td>$u_f$</td>
<td>FCU fan speed</td>
<td>[−]</td>
</tr>
<tr>
<td>$u_h$</td>
<td>Elec. heating control</td>
<td>[−]</td>
</tr>
<tr>
<td>$u_v$</td>
<td>Ventilation control</td>
<td>[−]</td>
</tr>
<tr>
<td>$u_l$</td>
<td>Lighting control</td>
<td>[−]</td>
</tr>
<tr>
<td>${u_{bi}}_{i=1, \ldots, N_f}$</td>
<td>Blind ctrl facade $i$</td>
<td>[−]</td>
</tr>
<tr>
<td>$T_W$</td>
<td>Inlet FCU water temp.</td>
<td>[°C]</td>
</tr>
<tr>
<td>$T_{ex}$</td>
<td>Outdoor temperature</td>
<td>[°C]</td>
</tr>
<tr>
<td>$T_{adj}$</td>
<td>Adjacent zones temp.</td>
<td>[°C]</td>
</tr>
<tr>
<td>${\phi_g}_{i=1, \ldots, N_f}$</td>
<td>Global irr. flux facade $i$</td>
<td>[W/m$^2$]</td>
</tr>
<tr>
<td>Occ</td>
<td>Number of occupants</td>
<td>[−]</td>
</tr>
<tr>
<td>$C_{ex}$</td>
<td>Outdoor CO$_2$ level</td>
<td>[ppm]</td>
</tr>
<tr>
<td>$T$</td>
<td>Indoor air temperature</td>
<td>[°C]</td>
</tr>
<tr>
<td>$C$</td>
<td>Indoor CO$_2$ level</td>
<td>[ppm]</td>
</tr>
<tr>
<td>$L$</td>
<td>Indoor illuminance</td>
<td>[Lux]</td>
</tr>
</tbody>
</table>

Description of Input/Output and exogenous variables
Zone Modeling

electrical analogy

Thermal model

Heat transfer phenomena are essentially linear, varying resistors depending on controlled inputs make the system bilinear.
Zone Modeling

electrical analogy

CO₂ accumulation model

Heat transfer phenomena are essentially linear, varying resistors depending on controlled inputs make the system bilinear.
Zone Modeling

**electrical analogy**

Indoor illuminance model

\[ c_4 \cdot u_b \cdot \phi_g \]

Shaded part

\[ c_5 \cdot (1 - u_b) \cdot \phi_g \]

Window

\[ c_6 \cdot u_l \]
Zone Model
Bilinear state-space representation

Zone model - bilinear system

\[
\begin{align*}
  x^+ &= A \cdot x + [B(y, w)] \cdot u + F \cdot w \\
  y &= C \cdot x + [D(w)] \cdot u
\end{align*}
\]

- \(x\) state, \(y\) output, \(w\) disturbance, \(u\) input.
- The matrices \([B(y, w)]\) and \([D(w)]\) are affine in their arguments.
Zone Model

Bilinear state-space representation

Zone model - bilinear system

\[
\begin{align*}
\dot{x}^+ &= A \cdot x + [B(y, w)] \cdot u + F \cdot w \\
y &= C \cdot x + [D(w)] \cdot u
\end{align*}
\]

- \( x \) state, \( y \) output, \( w \) disturbance, \( u \) input.
- The matrices \([B(y, w)]\) and \([D(w)]\) are affine in their arguments.
Zone Model

Bilinear state-space representation

Zone model - bilinear system

\[
\begin{cases}
    x^+ &= A \cdot x + [B(y, w)] \cdot u + F \cdot w \\
    y &= C \cdot x + [D(w)] \cdot u
\end{cases}
\]

- \( x \) state, \( y \) output, \( w \) disturbance, \( u \) input.
- The matrices \([B(y, w)]\) and \([D(w)]\) are affine in their arguments.

Simulator form

\[
y_k := Z(u_k, w_k, x_k)
\]

boldfaced vectors are predicted profiles (e.g. \( u_k := [u_k^T, u_{k+1}^T, u_{k+N-1}^T] \)).
The control problem

Problem description

Comfort indicator + Energy criterion

Ensure comfort by maintaining outputs in a given set

Find the best way to achieve comfort given constraints on inputs
The control problem

The comfort indicator

- Comfort is only required during presence
- Comfort constraints are relaxed to ensure feasibility of the problem
The control problem

The comfort indicator

- Comfort is only required during presence
- Comfort constraints are relaxed to ensure feasibility of the problem
The control problem

Mathematical formulation

NMPC-related optimization problem

\[
\text{Minimize } \quad J := J^E(p) + J^C(y) \quad (1)
\]

where:

- the boldfaced vectors stand for predicted profiles (e.g. \( y := [y^T_k, \ldots, y^T_{k+N-1}]^T \)),
- \( p \in \mathbb{R}^{n_p} \) is the power consumption,
- \( J^C \) is the discomfort criterion,
- \( J^E \) is the energy criterion.
The control problem

Optimization problem - explicit form:

\[
\text{NLP}_k: \quad \text{Minimize} \quad J_k(u_k, y_k)
\]

Subject To:

\[
[\Phi(y_k, w_k)] \cdot u_k + \delta^-_0 + \delta^-_1 \geq y_k - \psi x_k - \Xi w_k \tag{2b}
\]

\[
[\Phi(y_k, w_k)] \cdot u_k - \delta^+_0 - \delta^+_1 \leq \bar{y}_k - \psi x_k - \Xi w_k \tag{2c}
\]

\[
D \cdot u_k - \delta^+_d + \delta^-_d = a \tag{2d}
\]

\[
0 \leq u_k \leq 1 \tag{2e}
\]

\[
\delta_0 \geq 0, \delta_d \geq 0, 0 \leq \delta_1 \leq \begin{bmatrix} \delta_y^+ \\ \delta_y^- \end{bmatrix} \tag{2f}
\]
The control problem

Optimization problem - explicit form:

\[ \text{NLP}_k: \text{Minimize } J_k(u_k, y_k) \]

Subject To :

\[ \Phi(y_k, w_k) \cdot u_k + \delta_0 + \delta_1 \geq y_k - \psi x_k - \Xi w_k \] \hspace{1cm} (2b)

\[ \Phi(y_k, w_k) \cdot u_k - \delta_0 - \delta_1 \leq \bar{y}_k - \psi x_k - \Xi w_k \] \hspace{1cm} (2c)

\[ D \cdot u_k - \delta_d^+ + \delta_d^- = a \] \hspace{1cm} (2d)

\[ 0 \leq u_k \leq 1 \] \hspace{1cm} (2e)

\[ \delta_0 \geq 0, \delta_d \geq 0, 0 \leq \delta_1 \leq \left[ \begin{array}{c} \delta_y \\ \delta_y \end{array} \right] \] \hspace{1cm} (2f)

Nonlinear optimization problem due the product terms \( u \cdot y \)
The control problem

Optimization problem - explicit form:

\[ \text{LP}_{k}^{(s)}: \begin{array}{c}
\text{Minimize} \\
J_{k}(u_{k}, y_{k}^{(s)})
\end{array} \]

Subject To:

\[ \begin{align*}
[\Phi(y_{k}^{(s)}, w_{k})] \cdot u_{k} + \delta_{0}^{-} + \delta_{1}^{-} & \geq y_{k} - \psi x_{k} - \Xi w_{k} \\
[\Phi(y_{k}^{(s)}, w_{k})] \cdot u_{k} - \delta_{0}^{+} - \delta_{1}^{+} & \leq y_{k} - \psi x_{k} - \Xi w_{k} \\
D \cdot u_{k} - \delta_{d}^{+} + \delta_{d}^{-} & = a \\
0 & \leq u_{k} \leq 1 \\
\delta_{0} & \geq 0 , \delta_{d} \geq 0 , 0 \leq \delta_{1} \leq \begin{bmatrix} \delta_{y} \\ \delta_{y} \end{bmatrix}
\end{align*} \]
The control problem

Optimization problem - explicit form:

\[ u_k^{(s)} \leftarrow \text{LP}^{(s)}: \text{Minimize } J_k(u_k, y_k^{(s)}) \]  

Subject To:

\[ \Phi(y_k^{(s)}, w_k) \cdot u_k + \delta^-_0 + \delta^-_1 \geq y_k - \psi x_k - \Xi w_k \]  
\[ \Phi(y_k^{(s)}, w_k) \cdot u_k - \delta^+_0 - \delta^+_1 \leq \bar{y}_k - \psi x_k - \Xi w_k \]  
\[ D \cdot u_k - \delta^+_d + \delta^-_d = a \]  
\[ 0 \leq u_k \leq 1 \]  
\[ \delta_0 \geq 0, \delta_d \geq 0, 0 \leq \delta_1 \leq \begin{bmatrix} \delta_y \\ \delta_y \end{bmatrix} \]  

Update the output trajectory \( y_k^{(s+1)} \) by simulating the NL system:

\[ y_k^{(s+1)} = Z(u_k^{(s)}, w_k, x_k) \]
The control problem

Problem resolution

Optimization problem - explicit form:

\[ u_k^{(s)} \leftarrow \text{LP}_{k}^{(s)} : \text{Minimize } J_k(u_k, y_k^{(s)}) \]  \hspace{1cm} (2a)

Subject To:

\[ \Phi(y_k^{(s)}, w_k) \cdot u_k + \delta_0^- + \delta_1^- \geq y_k - \psi x_k - \Xi w_k \]  \hspace{1cm} (2b)

\[ \Phi(y_k^{(s)}, w_k) \cdot u_k - \delta_0^+ - \delta_1^+ \leq y_k - \psi x_k - \Xi w_k \]  \hspace{1cm} (2c)

\[ D \cdot u_k - \delta_d^+ + \delta_d^- = a \]  \hspace{1cm} (2d)

\[ 0 \leq u_k \leq 1 \]  \hspace{1cm} (2e)

\[ \delta_0 \geq 0, \delta_d \geq 0, 0 \leq \delta_1 \leq \begin{bmatrix} \delta_y^1 \\ \delta_y^1 \end{bmatrix} \]  \hspace{1cm} (2f)

Update the output trajectory \( y_k^{(s)} \) by simulating the NL system:

\[ y_{k}^{(s+1)} = Z(u_k^{(s)}, w_k, x_k) \]

Fixed-point algorithm:

\[ y_k^{(s)} \xrightarrow{\text{LP}} u_k^{(s)} \xrightarrow{\text{SIM}} y_k^{(s+1)} \]
Convergence analysis

- No formal convergence proof of the algorithm is provided,
- Run the algorithm starting from 100 random (unrealistic) initial guesses.
Computational burden

Computation time for $N = 720$, $N_u^{par} = 20$, $N_y^{par} = 20$ (Intel® Xeon® @ 2.67 GHz, 3.48 Go RAM - ILOG CPLEX 12.1 for LPs)
The case study
small business building

- Typical French small business building built in 2006, 20 zones, 540 (m²),
- Electrical heater,
- Local dampers for ventilation control,
- Automated blinds,
- Location *Trappes* (near Paris),
- Modeled using the SIMBAD toolbox.
MPC integration in SIMBAD

Configuration step

1. Build the structure of the building (.xml),
2. Identify the dynamical models of each zone,
3. Generate automatically C code able for zones and energy layer representations,
4. Instantiate MPCs for the whole building (observers, powers estimators, available forecast, occupancy schedule, available equipments, etc.)
MPC integration in SIMBAD

Example: 20 zones building:
- ≈70 inputs / ≈60 outputs / ≈160 states

Simulation
- Refreshing period: 5 min.
- ≈2,102,400 optimization problems (600-900 d.v × 1000 con.) solved during the whole year simulation.
- Simulation time ≈ 18 (h)
**MPC integration in SIMBAD**

**Example:** 20 zones building:
- ≈70 inputs / ≈60 outputs / ≈160 states

**Simulation**
- Refreshing period: 5 min.
- ≈2,102,400 optimization problems (600-900 d.v × 1000 con.) solved during the **whole year simulation**.
- Simulation time ≈ 18 (h)

→ **need for efficient code to perform a yearly simulation**
  - use of C code when appropriate
  - vectorized m-code
  - logical matrix indexation
Simulation results (I)
Zone MPC illustration - an office

48 (h) simulation - office # 1
Simulation results (II)

Yearly simulation results

1. Perfectly known forecast ($\alpha = 1$)
2. Errors on forecast ($\alpha = 0$)
3. Rule-based control

<table>
<thead>
<tr>
<th></th>
<th>Energy cons. (kWh/m$^2$/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule based*</td>
<td>142</td>
</tr>
<tr>
<td>MPC ($\alpha = 1$)</td>
<td>119 ($-16%$)</td>
</tr>
<tr>
<td>MPC ($\alpha = 0$)</td>
<td>122 ($-14%$)</td>
</tr>
</tbody>
</table>

Energy consumption / Comfort - Rule-based vs. MPC

*: more advanced RB control strategy ($\approx$-50% compared to current practice)
Simulation results (II)

Yearly simulation results

1. Perfectly known forecast ($\alpha = 1$)
2. Errors on forecast ($\alpha = 0$)
3. Rule-based control

<table>
<thead>
<tr>
<th></th>
<th>Energy cons. (kWh/m²/year)</th>
<th>GTC (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule based*</td>
<td>142</td>
<td>91.6</td>
</tr>
<tr>
<td>MPC ($\alpha = 1$)</td>
<td>119 ($-16%$)</td>
<td>91.8</td>
</tr>
<tr>
<td>MPC ($\alpha = 0$)</td>
<td>122 ($-14%$)</td>
<td>88.1</td>
</tr>
</tbody>
</table>

*: more advanced RB control strategy ($\approx$-50% compared to current practice)
Simulation results (II)

Yearly simulation results

1. Perfectly known forecast \((\alpha = 1)\)
2. Errors on forecast \((\alpha = 0)\)
3. Rule-based control

<table>
<thead>
<tr>
<th></th>
<th>Energy cons. (kWh/m(^2)/year)</th>
<th>GTC (%)</th>
<th>TCV (k(\cdot)°C(\cdot)h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule based*</td>
<td>142</td>
<td>91.6</td>
<td>322</td>
</tr>
<tr>
<td>MPC ((\alpha = 1))</td>
<td>119 ((-16%))</td>
<td>91.8</td>
<td>295</td>
</tr>
<tr>
<td>MPC ((\alpha = 0))</td>
<td>122 ((-14%))</td>
<td>88.1</td>
<td>310</td>
</tr>
</tbody>
</table>

Energy consumption / Comfort - Rule-based vs. MPC

*: more advanced RB control strategy \((\approx -50\% \text{ compared to current practice})\)
Other features (I)

Handling fan coil units

The FCU model is a static nonlinear heat emission characteristic:

\[ \phi^{th}(u_w, u_f, T, T_w) = (T_w - T) \cdot \phi^N(u_w, u_f) \]

Thermal emission characteristic
Other features (I)

Handling fan coil units

The FCU model is a static nonlinear heat emission characteristic:

\[
\phi^{th}(u_w, u_f, T, T_w) = (T_w - T) \cdot \phi^N(u_w, u_f)
\]

PWA approx.

Adapt the algorithm to handle FCUs and preserve the LP formulation
Other features (II)

variable energy prices

1. Preheat the first day during off-peak hours,
2. Optimal start the second day during on-peak hours,
Other features (II)

variable energy prices

Sensitivity of the solution to the ratio between high and low energy price periods ($\beta_p$)

\[
\beta_p \cdot \gamma_{off}
\]

\[
\gamma_{off}
\]

\[
\Gamma_e [\text{\euro}]
\]

Time [h]
Other features (II)

variable energy prices

![Graph showing energy prices and temperature changes with increasing $\beta_p$.](image)
Other features (II)

variable energy prices

Heater half dimensioned
Other features (II)

variable energy prices

+ another zone (more inertia)
Other features (II)

variable energy prices

Heater half dimensioned + another zone (more inertia)
Other features (II)
variable energy prices

The optimal behavior is linked to the dynamical characteristics of each zone
Roombox implementation

Main features:
- Power output: lighting, shutters and blinds, HVAC
- Network connection to BMS
- Ethernet port for local PC
- Inputs for switches and window contacts 24 Vcc
- Output protection (SC protection, overload ...)

Roombox
Main features:

- Power output: lighting, shutters and blinds, HVAC
- Network connection to BMS
- Ethernet port for local PC
- Inputs for switches and window contacts 24 Vcc
- Output protection (SC protection, overload ...)

Roombox
Roombox implementation

**Objective**
Implement the MPC algorithm on the Roombox →
- To study the real-time implementation
- To identify the main related issues

**Validation**
→ Virtual signals sent via the ethernet port (measures and forecast)
Roombox implementation

Zone Model Predictive Control

- Roombox implementation

Matlab®

C/C ++

MPC

Solver
(LP)

Matrix
library

Code compilation

Code translation

human

C/C ++

Matrix
library

C/C ++

Code compilation

ecplise®

Roombox

Roombox implementation

Conditions

- Prediction horizon 12 h.
- Sampling period 2 min.
- Zone: $n_u = 6$, $n_y = 3$
- GLPK (GNU MILP solver)
Roombox implementation

Results

- ≈ 6 (s) / iteration
- 8.2% of memory usage
- Able to run more than one thread of the algo. on one Roombox
Distributed Model Predictive control for energy management in buildings

1. MPC for energy management in buildings
2. Zone Model Predictive Control
3. Distributed Model Predictive Control
   - Problem presentation
   - Distributed MPC design
4. Conclusion
Building control layers

Decomposition approach

**Objective**

Coordinate the energy layer and the zone layer → Manage resource coupling constraints

- **Energy layer** → energy supply, storage and transformation

- **Zone layer** → consume energy to provide comfort
Building control layers

Decomposition approach

Objective

Coordinate the energy layer and the zone layer → Manage resource coupling constraints

- **Energy layer** →
  energy supply, storage and transformation

- **Zone layer** →
  consume energy to provide comfort
Building control layers

Decomposition approach

Objective

Coordinate the energy layer and the zone layer → Manage resource coupling constraints

- **Energy layer** → energy supply, storage and transformation

- **Zone layer** → consume energy to provide comfort
Handling coupling resource constraints

Objectives:
- Power limitation constraint on the whole building cons.
  \[ p_g^+ + \sum_{\ell \in \mathbb{Z}} p_{\ell} \leq P_g \]
- Manage the storage capability (elec. battery)
Handling coupling resource constraints

Objectives:

- Power limitation constraint on the whole building cons.

\[ p_D^+ + \sum_{\ell \in Z} p_\ell \leq P_g \]

- Manage the storage capability (elec. battery)
Handling coupling resource constraints

Objectives:
- Power limitation constraint on the whole building cons.
  \[ p^+ + \sum_{\ell \in \mathbb{Z}} p_\ell \leq P_g \]
- Manage the storage capability (elec. battery)
Zone Predictive controller

Slight modifications ...

Each zone controller controls local variables

\[
\text{MPC}_\ell : \text{Minimize } L_\ell \cdot z_\ell \\
\text{s.t. } z_\ell \leq z_\ell \leq \bar{z}_\ell
\]

Subject To:
\[
A_\ell \cdot z_\ell \leq b_\ell
\]
Zone Predictive controller

Slight modifications ...

Each zone controller controls local variables \textbf{while meeting local constraints on resources:}

\[
\text{MPC}_\ell(r_\ell) : \ \text{Minimize} \ \mathbf{L}_\ell \cdot \mathbf{z}_\ell \quad \text{subject to:} \\
\mathbf{A}_\ell \cdot \mathbf{z}_\ell \leq \mathbf{b}_\ell \\
\mathbf{A}'_\ell \cdot \mathbf{z}_\ell \leq r_\ell
\]
Zone Predictive controller

Slight modifications ...

Each zone controller controls local variables while meeting local constraints on resources:

\[
\text{MPC}_\ell (r_\ell) : \text{Minimize } L_\ell \cdot z_\ell
\]

Subject To:

\[
A_\ell \cdot z_\ell \leq b_\ell \\
A'_\ell \cdot z_\ell \leq r_\ell
\]

One gets:

\[
(J_\ell, g_\ell) \leftarrow \text{MPC}_\ell (r_\ell)
\]

- \(J_\ell := J_\ell (r_\ell) : \text{optimal value}\)
- \(g_\ell := g_\ell (r_\ell) : \text{sub-gradient at } r_\ell\)
Zone Predictive controller

Slight modifications ...

Each zone controller controls local variables while meeting local constraints on resources:

\[
\text{MPC}_\ell (r_\ell) : \text{Minimize } L_\ell \cdot z_\ell \\
\text{Subject To:} \\
A_\ell \cdot z_\ell \leq b_\ell \\
A'_\ell \cdot z_\ell \leq r_\ell
\]

One gets:

\[(J_\ell, g_\ell) \leftarrow \text{MPC}_\ell (r_\ell)\]

- \(J_\ell := J_\ell (r_\ell)\) : optimal value
- \(g_\ell := g_\ell (r_\ell)\) : sub-gradient at \(r_\ell\)
The coordination layer

At the coordination layer, the problem is the following:

How to affect optimally resource profiles \( r := \{ r_\ell \}_{\ell \in \mathbb{Z}} \) to minimize the total cost function?

\[
\begin{align*}
\text{Solve the master problem:} \\
\text{Minimize} & \quad \mathbf{z}_e, \mathbf{r}, \sum_{\ell \in \mathbb{Z}} J_\ell(r_\ell) \\
\text{S.t.} & \quad C(r, \mathbf{z}_e) \leq b_e,
\end{align*}
\]

\( J_\ell \) are not available!

\( \rightarrow \) built-up approximations of \( J_\ell \)

\( \rightarrow \) Bundle method
The coordination layer

At the coordination layer, the problem is the following:

How to affect optimally resource profiles \( r := \{ r_\ell \}_{\ell \in \mathcal{Z}} \) to minimize the total cost function?

→ Solve the master problem:

\[
\begin{align*}
\text{Minimize} \quad & \quad [ \quad L_e \cdot z_e \quad + \quad \sum_{\ell \in \mathcal{Z}} J_\ell (r_\ell) \quad ] \\
\text{S.t.} \quad & \quad C(r, z_e) \leq b_e
\end{align*}
\]

- Energy layer cost fct.
- Zone cost fct.
- Global constraints
At the coordination layer, the problem is the following:

How to affect optimally resource profiles \( r := \{ r_{\ell} \}_{\ell \in \mathbb{Z}} \) to minimize the total cost function?

→ Solve the master problem:

\[
\begin{align*}
\text{Minimize} & \quad L_e \cdot z_e + \sum_{\ell \in \mathbb{Z}} J_{\ell}(r_{\ell}) \\
\text{subject to} & \quad C(r, z_e) \leq b_e
\end{align*}
\]

→ \( J_{\ell} \) are not available!
The coordination layer

At the coordination layer, the problem is the following:

How to affect optimally resource profiles \( r := \{ r_\ell \}_{\ell \in \mathbb{Z}} \) to minimize the total cost function?

→ Solve the master problem:

\[
\begin{align*}
\text{Minimize} \quad & \quad L_e \cdot z_e + \sum_{\ell \in \mathbb{Z}} J_\ell(r_\ell) \\
\text{Energy layer cost fct.} & \quad \text{Zone cost fct.} \\
\text{S.t.} & \quad C(r, z_e) \leq b_e \\
\text{Global constraints}
\end{align*}
\]

problem:
→ \( J_\ell \) are not available!
→ built-up approximations of \( J_\ell \) → Bundle method
The bundle method

1. The coordinator affects local resources
2. Each zones gives:
   - The value of the cost function $J_\ell(r_\ell)$
   - A sub-gradient $g_\ell(r_\ell)$ (sensitivity)
The bundle method
Cutting plane approximation

Unknown at the coordination layer
The bundle method
Cutting plane approximation
The bundle method

Cutting plane approximation
The bundle method
Cutting plane approximation
The bundle method

Cutting plane approximation
The bundle method

Cutting plane approximation
The bundle method
Cutting plane approximation
Distributed MPC scheme

- Process of decision is distributed among several agents
- The coordinator manages only the shared resources
- A restricted number of negotiation iterations is allowed

Now Distribute the optimization problem solving over time
Distributed MPC scheme

- Process of decision is distributed among several agents
- The coordinator manages only the shared resources
- A restricted number of negotiation iterations is allowed

Now Distribute the optimization problem solving over time
Distributing the optimization over time
The memory mechanism

The idea is simply to keep a certain part of the information (approximation) from one decision instant to next one...

\[ J_{\ell}^{(k-1)} \]
Distributing the optimization over time

The memory mechanism

The idea is simply to keep a certain part of the information (approximation) from one decision instant to next one...

\[ J^{(k)} \]
Distributing the optimization over time

The memory mechanism

The idea is simply to keep a certain part of the information (approximation) from one decision instant to next one...
Distributing the optimization over time

The memory mechanism

The idea is simply to keep a certain part of the information (approximation) from one decision instant to next one...

...by introducing a memory factor.
Memory mechanism

Illustration

$J^{(s_{\text{max}})}_\ell$ is given at decision instant $k - 1$
Memory mechanism

Illustration

- Decrease it (memory factor $m_{\ell,k}$)
Memory mechanism

Illustration

- First iteration (exchange between zone layer and coordinator)
Memory mechanism

Illustration

- Iterate (exchanges between zone layer and coordinator)
Memory mechanism

Illustration

- One gets the latest approximation at decision instant $k$
Memory mechanism

Illustration

► And so on ...
DMPC simulation

Closed-loop trajectories

DMPC - 3 iterations with memory

$p_b^+$ and $p_b^-$

Zones Temp. [°C]

Zones cons. [kW]

$b$ [kWh]

$p_e$ [kW]

Time [h]

Effect of the memory mechanism

Achieve better solutions faster with memory!
Distributed Model Predictive Control

Other features

1. Handling shared variables
2. Including local production
Distributed Model Predictive Control

Other features

1. Handling shared variables
2. Including local production
Distributed Model Predictive control for energy management in buildings

1. MPC for energy management in buildings
2. Zone Model Predictive Control
3. Distributed Model Predictive Control
4. Conclusion
Conclusion

Summary

1. Zone MPC design (Bilinear model, MIMO)
   - generic framework
   - energy savings
   - Moderate computational burden
   - Real-time implementation
Conclusion

Summary

1. Zone MPC design (Bilinear model, MIMO)
   - generic framework
   - energy savings
   - Moderate computational burden
   - Real-time implementation

2. Build a distributed solution based on local controllers
   - Handle global power limitations (multi-sources)
   - Handle storage equipment
   - Manage shared actuators
   - Distributed-in-time optimization
Conclusion

Benefits

- A generic and coherent framework
- Modular $\rightarrow$ scalable, maintenance concerns
- Represents a good answer for smart-grid connectivity
Conclusion

Benefits

- A generic and coherent framework
- Modular → scalable, maintenance concerns
- Represents a good answer for smart-grid connectivity

Issues

- Availability of the model of the building
- Availability of forecast
- Much more computationally demanding
For future ...

Projects

1. **First MPC prototype** in North-Andover (USA) starting in few weeks
2. Extend the current framework to manage **smart districts** (building ← zone, district ← building): **Ambassador** project (Europe)
Conclusion

For future ...

Projects

1. **First MPC prototype** in North-Andover (USA) starting in few weeks
2. Extend the current framework to manage **smart districts** (building $\leftarrow$ zone, district $\leftarrow$ building): **Ambassador** project (Europe)

but also ...

1. **Deployment tools** for large scale penetration
2. **MPC commissioning**
3. **Code certification** for large deployment
This work is part of HOMES collaborative program.

The HOMES program is funded by OSEO (http://www.oseo.fr).
Conferences


Publications II


Book chapter


Schneider-Electric white papers

Publications III

Patents


Thank you for your attention

Questions ?