Modeling And Predictive Control Of High Performance Buildings With Distributed Energy Generation And Thermal Storage

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OUTLINE

Introduction
  Objectives
  Overview

Integrated modelling
  Solar System
  Building Model

System Identification
  Gray-Box
  Subspace Algorithm (Black-Box)

Results and Analysis
  MPC Simulation
  Energy Saving Potential

Conclusions
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Objectives

- **Develop models** that capture the relevant system dynamics and are computationally efficient for subsequent use within model-predictive control (MPC) algorithms.

- Investigate the **energy saving potential** of the integrated system and the predictive controller in comparison with baseline operation strategies.
Overview

Utility price ➔ Grid

Heat pump ➔ Building

BIPV/T ➔ HVAC, Ventilation, Heating load

Thermal storage ➔ BIPV/T

$T_{BIPV/T}$, $T_{HP}$, $q_{HP}$, $T_{tank}$

Solar irradiance

Environmental disturbances

Electricity energy flows
Thermal flow

Occupancy, Weather
Overview

Utility price → Grid

Heat pump → Thermal storage

q_{HP} → T_{BIPV/T}

BIPV/T → Radiant floor heating

T_{tank} → Solar irradiance

Ventilation → Heating load

Occupancy Weather

Electricity energy flows
Thermal flow
Environmental disturbances
Overview

Approach

- CFD simulation
- Experiments
- Energy simulation – thermal network
- Parametric study
- Nu correlations
- Airflow and thermal field analysis

Test-bed: Living Lab

- Building systems integration & Model-predictive Control
- Validate

Input

- Assumptions

Weather data

Integrated energy model

Coupled with TRNSYS

Weather forecast uncertainty
Overview

- Simulation test-bed: the Hydronic Living Lab
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Solar System

The corrugated transpired solar collector (without (left) and with (right) PV panels)
Building Model

- Simulation test-bed: the Hydronic Living Lab
# Building Model

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Room Temperature</strong></td>
<td>18 – 26 °C, 8:00 am – 10:00 am</td>
</tr>
<tr>
<td></td>
<td>21 – 26 °C, 10:00 am – 18:00 pm</td>
</tr>
<tr>
<td></td>
<td>&gt;15 °C, 18:00 pm – 8:00 am</td>
</tr>
<tr>
<td><strong>Floor Temperature</strong></td>
<td>19 – 29 °C (ASHRAE Standard 55)</td>
</tr>
<tr>
<td><strong>Blind control</strong></td>
<td>ON, when the incident solar radiation on the window exceeds 180 W/m²</td>
</tr>
<tr>
<td></td>
<td>OFF, when the incident solar radiation on the window drops below 160 W/m²</td>
</tr>
<tr>
<td><strong>BIPV/T design</strong></td>
<td>Total area: 65 m²</td>
</tr>
<tr>
<td></td>
<td>PV area: 58.5 m², around 6.32 kWp</td>
</tr>
<tr>
<td></td>
<td>Air flow rate: 5,600 m³/hr, corresponding suction velocity: 0.024 m/s</td>
</tr>
</tbody>
</table>
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Gray-Box

Identification

- State Space
- 4th order
- Linear
- Time-invariant
- Discrete

\[ x_{k+1} = Ax_k + Bu_k \]
\[ y_k = Cx_k + Du_k \]

- \( x \): state vector (= \( y \))
- \( u \): input vector
- \( y \): output vector
- \( A, B, C, D, K \): unknowns need to be identified
Gray-Box

Identification

Cost Function: \[ J(P) = \sum_{i=1}^{K} \left[ \sqrt{\frac{\left(T_{\text{env}}(i) - \hat{T}_{\text{env}}(i)\right)^2}{k}} + \sqrt{\frac{\left(T_{\text{roo}}(i) - \hat{T}_{\text{room}}(i)\right)^2}{k}} + \sqrt{\frac{\left(T_{\text{floor}}(i) - \hat{T}_{\text{floor}}(i)\right)^2}{k}} + \sqrt{\frac{\left(T_{\text{tank}}(i) - \hat{T}_{\text{tank}}(i)\right)^2}{k}} \right] \]

Subject to: \begin{align*}
10^1 &\leq U_{ea} \leq 10^2 \\
10^2 &\leq U_{re} \leq 10^3 \\
10^1 &\leq U_{rf} \leq 10^3 \\
10^1 &\leq U_{ft} \leq 10^3 \\
10^1 &\leq U_{ta} \leq 10^3 \\
10^1 &\leq U_{ra} \leq 10^3 \\
10^1 &\leq U_{ef} \leq 10^3 \\
10^2 &\leq U_{fa} \leq 10^3 \\
10^3 &\leq C_e \leq 10^4 \\
10^3 &\leq C_r \leq 10^4 \\
10^3 &\leq C_f \leq 10^5 \\
10^3 &\leq C_t \leq 10^5 
\end{align*}

Optimization algorithm: GA

- Training data set: 49 days (Jan 3rd – Feb 24th)
- Calibration data set: 7 days (Feb 25th- Mar 3rd)
## Gray-Box Results

<table>
<thead>
<tr>
<th></th>
<th>$T_{\text{env}}$</th>
<th>$T_{\text{room}}$</th>
<th>$T_{\text{floor}}$</th>
<th>$T_{\text{tank}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Data-RMSE (°C)</td>
<td>0.48</td>
<td>0.62</td>
<td>0.84</td>
<td>0.39</td>
</tr>
<tr>
<td>Calibration Data-RMSE (°C)</td>
<td>0.59</td>
<td>0.61</td>
<td>0.98</td>
<td>0.55</td>
</tr>
</tbody>
</table>

![Graph showing temperature trends over time](image_url)
Subspace State-Space System Identification (4SID)

- State vector: \( x_{k+1} = Ax_k + Bu_k + Ke_k \)
- Output vector: \( y_k = Cx_k + Du_k + e_k \)

- Orders: 20
- Inputs: 6; Outputs: 5;
- Training data set: 49 days (Jan 3rd – Feb 24th)
- Calibration data set: 7 days (Feb 25th– Mar 3rd)

\( x: \) state vector  
\( u: \) input vector  
\( y: \) output vector  
\( A, B, C, D, K: \) unknowns need to be identified
Subspace State-Space System Identification (4SID)

**Results**

<table>
<thead>
<tr>
<th></th>
<th>$T_{enve}$</th>
<th>$T_{room}$</th>
<th>$T_{floor}$</th>
<th>$T_{wr}$</th>
<th>$T_{tank}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Data-Fit factor (%)</td>
<td>89.20</td>
<td>91.39</td>
<td>94.98</td>
<td>96.39</td>
<td>93.71</td>
</tr>
<tr>
<td>Training Data-RMSE (°C)</td>
<td>0.37</td>
<td>0.31</td>
<td>0.12</td>
<td>0.08</td>
<td>0.37</td>
</tr>
<tr>
<td>Calibration Data-RMSE (°C)</td>
<td>0.38</td>
<td>0.31</td>
<td>0.11</td>
<td>0.08</td>
<td>0.35</td>
</tr>
</tbody>
</table>

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![Graph showing temperature variations over time](image)

- Troom-Reduced-order SS model
- Troom-TRNSYS model
- Ttank-Reduced-order SS model
- Ttank-TRNSYS model
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MPC Simulation

Read the TMY3 data as the weather forecast

Input the initial states of the building (5 temperatures)

Model-predictive controller

Propose a heuristic initial guess for the control variable $q_{hp}$

Substitute the control variable into the simplified model and apply the optimization algorithm to explore and assess the potential solutions for $q_{hp}$

- Ensure no violations of the environmental (temperatures) or equipment constraints
- Calculate the cost function for different sequences of the control variable

Select the sequence of the control variable with lowest cost function and output the corresponding set points of the tank temperature

For online MPC, send the tank set point trajectory to the building automation system over the next 2 hours. Recalculate the final states for the building and repeat the process every 2 hours.
MPC Simulation

Cost Function: \[ J_{tot} = \sum_{t=0}^{N} \left[ \frac{q_{hp}(t)}{COP(t)} + P_{heater}(t) \right] \]

\[ \text{COP} = c_0 + c_1 T_{bipvt} + c_2 T_{tank} + c_3 T_{bipvt}^2 + c_4 T_{tank}^2 + c_5 T_{bipvt} T_{tank} \]

Subject to: \[ q_{hp} \in [0, \text{HeatPumpCapacity}] \]
\[ T_{tank} \in [25, 55] \]
\[ T_{floor} \in [19, 29] \]
\[ T_{room} \in \begin{cases} [18, 26] \, (08:00 \sim 10:00) \\ [21, 26] \, (10:00 \sim 18:00) \\ [15, 26] \, (18:00 \sim 08:00) \end{cases} \]

Optimization algorithm: Pattern search
MPC Simulation

Scenario 1

- Three consecutive sunny days
- Total electrical energy consumption: 84 kWh
- Corresponding heating load: 690.3 kWh
- Equivalent COP: 8.22
Two sunny days and one cloudy day

Total electrical energy consumption: 116 kWh (38% more than scenario1)

Corresponding heating load: 491.3 kWh

Equivalent COP: 4.24
Energy Saving Potential

- Two optimal trajectories for scenario one
- Total electrical energy consumption:
  116 kWh vs. 84 kWh (34.5% more for red line)
Energy Saving Potential - One month Simulation

Building heating load: 3896 kWh (February)
Conclusions

- The developed low-order models capture the control-relevant system dynamics
  - Gray-box model: RMSE of 0.61°C and 0.55 °C for the zone and tank temperature
  - Black-box model: RMSE of 0.31°C and 0.35 °C for the zone and tank temperature

- Model-predictive control is an efficient solution for the proposed solar system with hydronic floor and thermal storage
  - Significant energy savings can be achieved (up to 34.5% based on the analysis for scenario 1 and 2)
  - The total energy saving of the proposed system with MPC can be up to 45.4% compared to baseline RFH operation.
Future Work

- Improve the solution algorithm for the nonlinear optimization problem.

- Incorporate the water flow rate as a control variable to have a more precise control of the room temperature.

- Investigate the weather forecast uncertainty modeling and propagation over the planning horizon.

- Investigate the energy efficiency of the integrated system using other solar collectors.
Acknowlegdements

- Purdue Research Foundation.
- ASHRAE (New Investigator Award).
Thank You!
Weather Forecast Uncertainty

Prediction: *sunny* day
Reality: *cloudy* day

The energy consumption difference is small.
The impact on thermal comfort can be significant.

The MPC results for the 70% less case is 76 kWh, requires 43% more energy.
Control In TRNSYS

Tank set-point temp = \( \min(T_{\text{out}} + 50, 55) \)