Impact of the controller model complexity on MPC performance evaluation for building climate control

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STU FCHPT

KU LEUVEN

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Problem: EU spends 400 billion EUR/year on energy.

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Solution: Thermal comfort control

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Model Predictive Control

Pros:

- Satisfy thermal comfort constraints
- Minimize energy consumption
- Obey technological restrictions

Cons:

- Implementation in early stages
- Need for a good controller model

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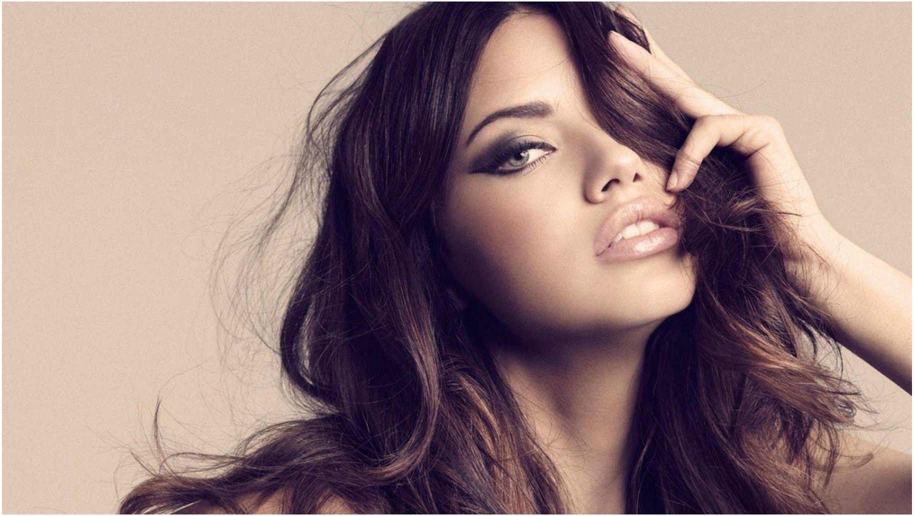
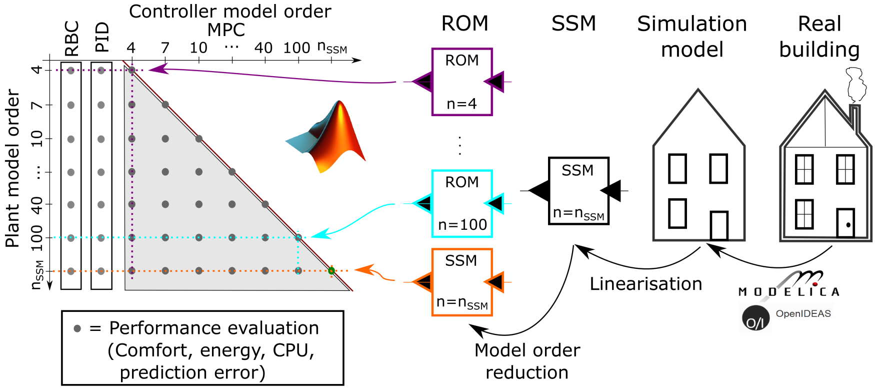
What is the Best Model?




COMPLEXITY


simplicity


Controller model order
RBC
PID
MPC
4 7 10 ⋯ 40 100 nSSM
Plant model order
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ROM
SSM
Simulation model
Real building
ROM n=4
ROM n=100
SSM n=nSSM
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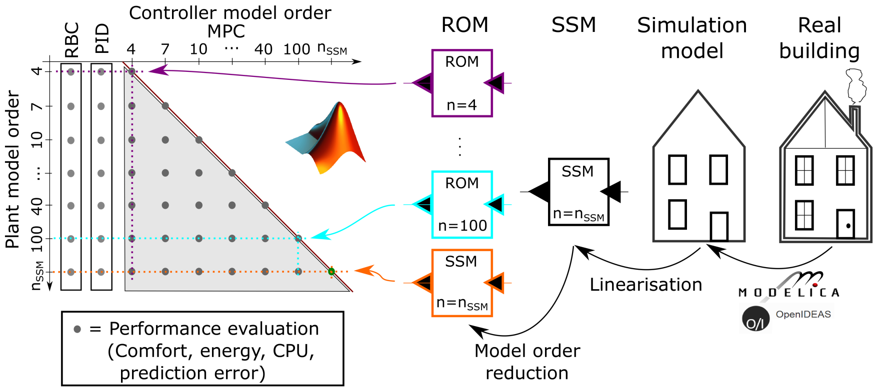
Linearisation
Model order reduction
MODELICA
OpenIDEAS
O/I
• = Performance evaluation (Comfort, energy, CPU, prediction error)

Building Description

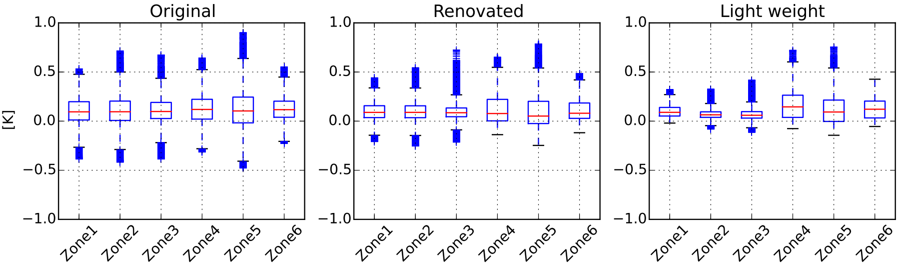
Floor area	[m^2]	48.3
Conditioned volume	[m^3]	130.6
Total exterior surface area	[m^2]	195
Windows	[-]	5
Walls	[-]	22
Roof and floor surfaces	[-]	12
Thermal zones	[-]	6

Linearisation[1]



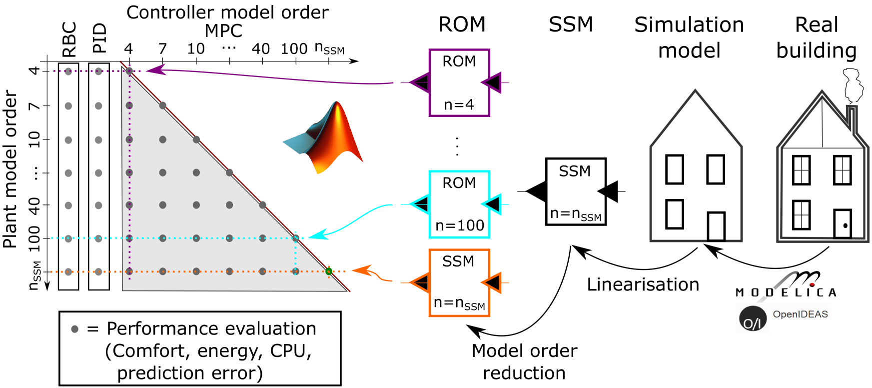
[1] Picard, D., Jorissen, F., and Helsen, L. 2015. Methodology for Obtaining Linear State Space Building Energy Simulation Models. In 11th International Modelica Conference, pages 51–58, Paris

Linearisation Error



Full year open-loop simulation linearization error below 1 K.

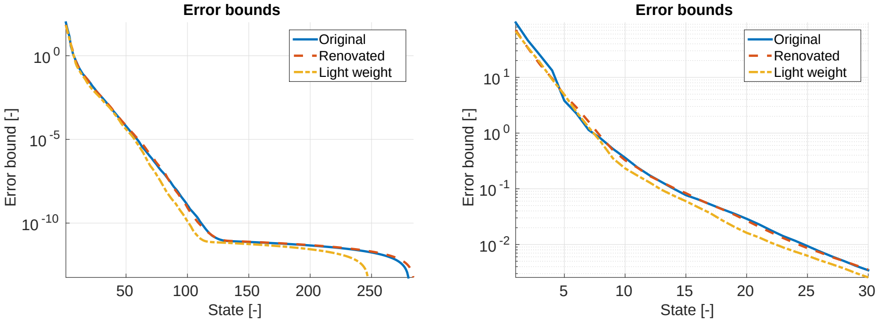
Model Order Reduction[2]



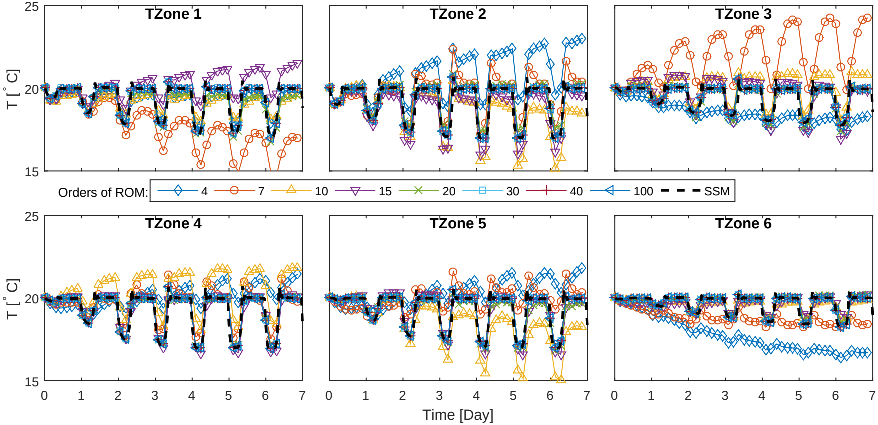
Square root balanced truncation algorithm, based on Hankel singular values.

[2] Antoulas, A. C. and Sorensen, D. C. 2001. Approximation of large-scale dynamical systems: An overview. Applied Mathematics and Computer Science.

Reduced Order Models – Error Bounds

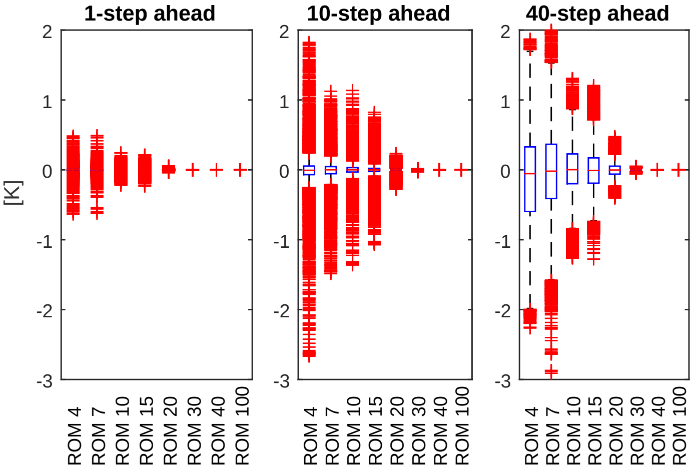


Guarantees of an error bounds and preserves most of the system characteristics in terms of stability, frequency, and time responses.

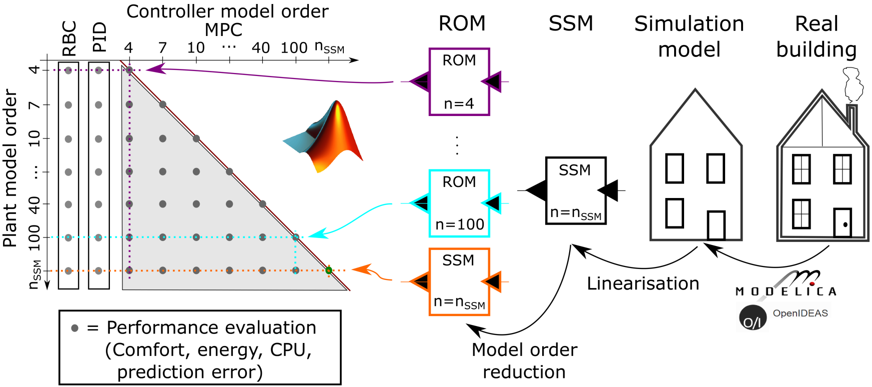


Single week open loop simulation with realistic control inputs and disturbances.

Reduced Order Models – Prediction Errors



The central line is the median, the box gives the 1st and 3rd quartiles, the wiskers contain 99.5% of the data, the crosses are the outliers.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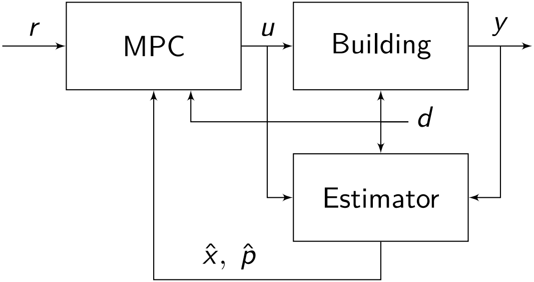
Control Scheme



Estimator and Augmented Model

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + L\left(y_{m,k} - \hat{y}_{k|k-1}\right)$$
$$\hat{x}_{k+1|k} = A\hat{x}_{k|k} + Bu_{k|k} + Ed_{k|k}$$
$$\hat{y}_{k|k} = C\hat{x}_{k|k} + Du_{k|k}$$

$$\underbrace{\begin{bmatrix} \hat{x}_{k+1} \\ \hat{p}_{k+1} \end{bmatrix}}_{\tilde{x}_{k+1}} = \underbrace{\begin{bmatrix} A & \mathbf{0} \\ \mathbf{0} & I \end{bmatrix}}_{\tilde{A}} \underbrace{\begin{bmatrix} \hat{x}_k \\ \hat{p}_k \end{bmatrix}}_{\tilde{x}_k} + \underbrace{\begin{bmatrix} B \\ \mathbf{0} \end{bmatrix}}_{\tilde{B}} u_k + \underbrace{\begin{bmatrix} E \\ \mathbf{0} \end{bmatrix}}_{\tilde{E}} d_k$$

$$\hat{y}_k = \underbrace{\begin{bmatrix} C & F \end{bmatrix}}_{\tilde{C}} \begin{bmatrix} \hat{x}_k \\ \hat{p}_k \end{bmatrix} + \underbrace{\begin{bmatrix} D \\ \mathbf{0} \end{bmatrix}}_{\tilde{D}} u_k$$

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MPC Formulation

$$
\begin{aligned}
\min_{u_0,\ldots,u_{N-1}} \sum_{k=0}^{N-1} & \left(||s_k||^2_{Q_\text{s}} + ||u_k||^2_{Q_\text{u}} \right) \\
\text{s.t. } & x_{k+1} = Ax_k + Bu_k + Ed_k \\
& y_k = Cx_k + Du_k \\
& lb_k - s_k \le y_k \le ub_k + s_k \\
& \underline{u} \le u_k \le \overline{u} \\
& x_0 = \hat{x}(t) \\
& \forall k \in \{0, \ldots, N-1\}
\end{aligned}
$$

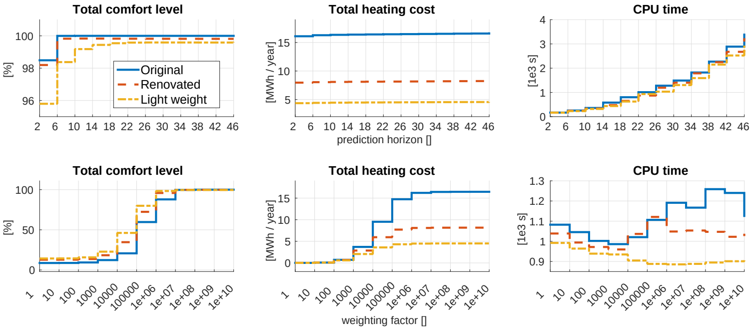
State Condensing

$$
\begin{aligned}
x_1 &= Ax_0 + Bu_0 + Ed_0 \\
x_2 &= A\left(Ax_0 + Bu_0 + Ed_0\right) + Bu_1 + Ed_1 \\
&\vdots \\
x_{k+1} &= A^{k+1}x_0 + \dots \\
&\left[A^k B \dots AB\ B\right]\left[u_0^T \dots u_k^T\right]^T + \dots \\
&\left[A^k E \dots AE\ E\right]\left[d_0^T \dots d_k^T\right]^T \\
y_k &= CA^k x_0 + \dots \\
&C\left[A^{k-1} B \dots AB\ B\right]\left[u_0^T \dots u_{k-1}^T\right]^T + \dots \\
&C\left[A^{k-1} E \dots AE\ E\right]\left[d_0^T \dots d_{k-1}^T\right]^T + Du_k + Fp_0
\end{aligned}
$$

Significantly reduces the number of the optimization variables.

Simulation Setup

One year performances of RBC, PID, MPC.
Three types of 6-zone buildings, with 300 states.



$T_s = 900$, $N = 40$ steps (i.e., 10 hours), $\frac{Q_s}{Q_u} = 10^8$.

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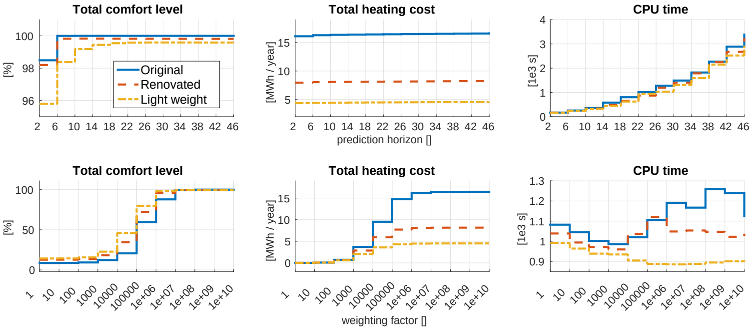

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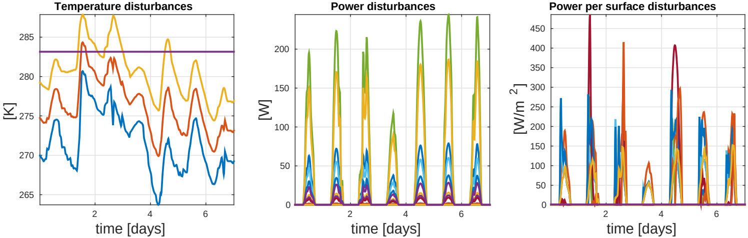
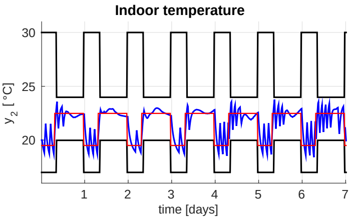
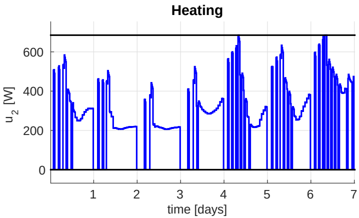
Disturbance Profiles



52 disturbances

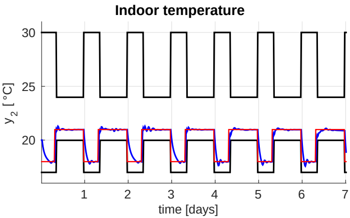
Control Profiles – RBC

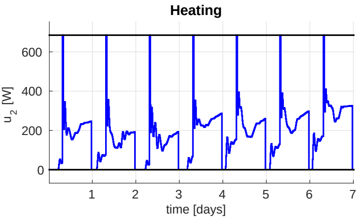




Comfort satisfaction, spanning from 93.9% to 95.2%.

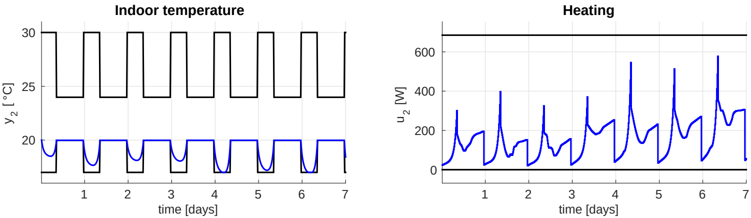
Control Profiles – PID





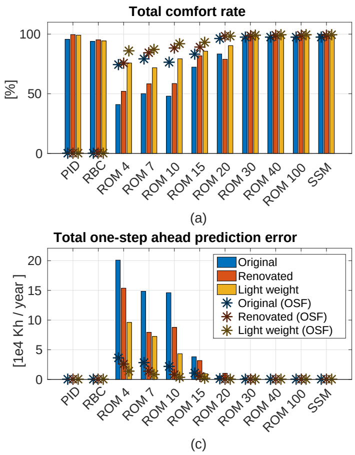
Comfort satisfaction, spanning from 95.6% to 99.6%.
Energy savings around 6%.

Control Profiles – MPC



Comfort satisfaction, close to 100.0%.
Energy savings around 13%.

Performance Evaluation



Conclusions

1. Influence of controller model accuracy on controller performance.
2. Minimum of 30 states was necessary for 6-rooms house.
3. When a dense formulation is used a CPU time becomes independent of the number of states of the controller model.
4. Use a controller model which emulates the real building as accurately as possible!

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