

From Models to Data: Smarter Predictive Control in Buildings

Introduction

Buildings are major energy consumers, with heating systems playing a significant role. Traditional control strategies often rely on fixed rules or detailed physical models, which can be complex, costly to develop, and inflexible in real-world applications.

Data-driven predictive control offers an alternative. Instead of explicitly modeling system dynamics, this approach uses historical input-output data—structured as Hankel matrices—to forecast future behavior. This method is grounded in the fundamental lemma of behavioral systems theory [1], which shows that, under controllability and sufficient excitation, future trajectories can be expressed as combinations of past data [2].

Emerging research further suggests that additional energy savings can be achieved by accounting for occupant behavior and preferences directly. Rather than treating occupants as disturbances, a shift toward occupant-centric control emphasizes personalized comfort and adaptive energy use.



Figure 1: NEST, Dübendorf Switzerland. Vision wood residential living lab.

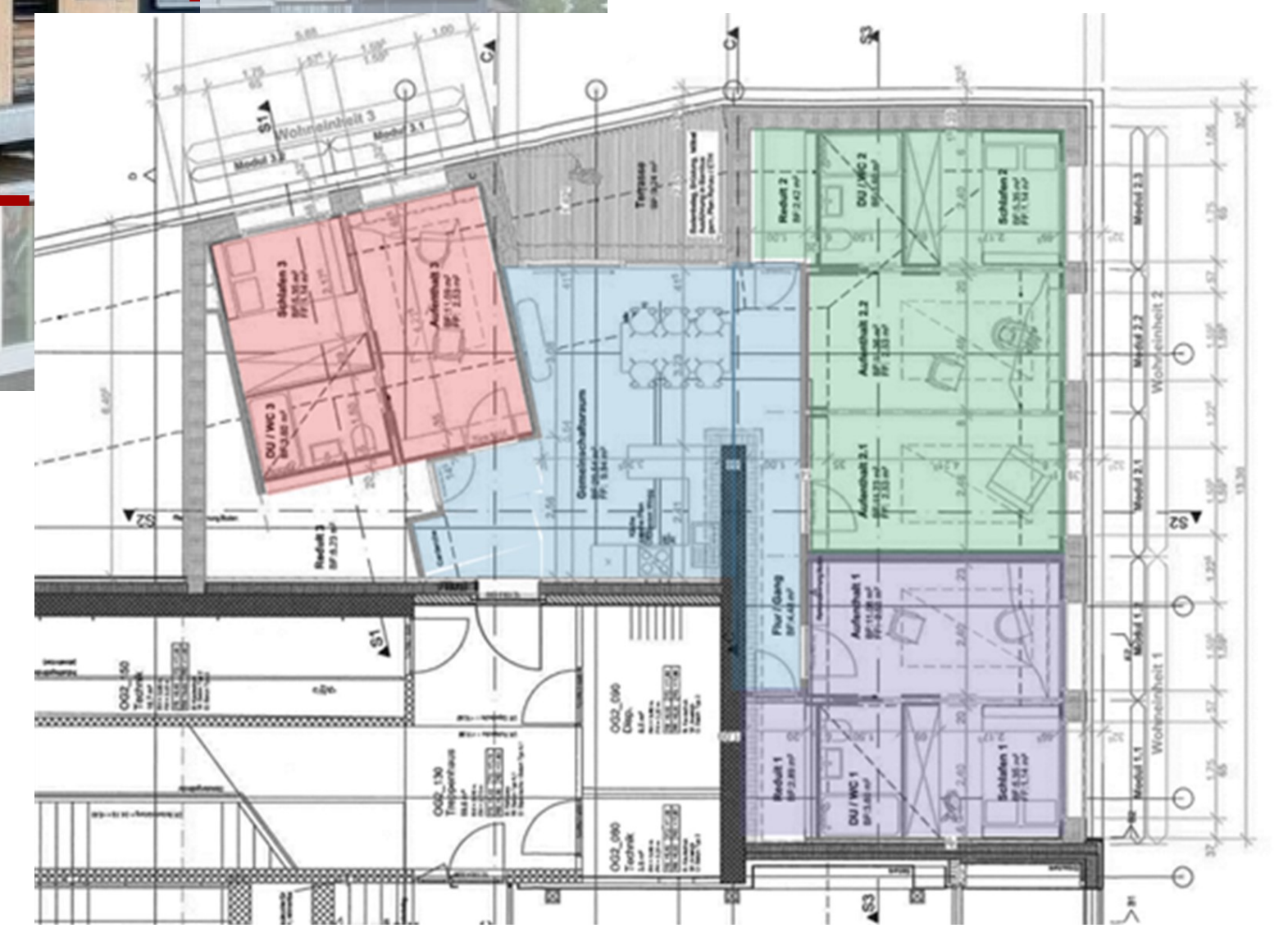


Figure 2: Floor plan of vision wood.

$$\min_{u,x,y} \sum_{k=0}^{N-1} (\|y_k - r_{t+k}\|_Q^2 + \|u_k\|_R^2)$$

$$\text{Subject to } \begin{aligned} x_{k+1} &= Ax_k + Bu_k, \forall k \in \{0, \dots, N-1\}, \\ y_k &= Cx_k + Du_k, \forall k \in \{0, \dots, N-1\}, \\ x_0 &= \hat{x}(t), \\ A_{ineq} y_k &\leq b_{ineq}, \\ A_{eq} y_k &= b_{eq}, \\ lb &\leq u_k \leq up \end{aligned}$$

MPC

$$\min_{u,y} \sum_{k=0}^{N-1} (\|u_k\|_R^2 + \|y_k - r_{t+k} + c\|_Q^2 + \|g\|_{\lambda_g} + \|u_{k+1} - u_k\|_{y_{regu}})$$

$$\text{Subject to } \begin{pmatrix} U_p \\ Y_p \\ U_f \\ Y_f \end{pmatrix} g = \begin{pmatrix} u_{ini} \\ y_{ini} \\ u \\ y \end{pmatrix}$$

$$lb \leq u_k \leq up$$

SM-MPC

Methodology

The two control strategies were implemented in a single-zone building simulation with internal heat gains and occupancy-driven setpoint changes.

- MPC used a third order RC-model identified from data.
- SM-MPC was built using input-output data directly, structured as Hankel matrices, with no explicit system model.

Both controllers ran with a 24-hour horizon and 1-hour steps, minimizing heating demand while keeping indoor temperature within comfort bounds.

Constraints and cost functions were kept consistent for fair comparison.

Conclusion

MPC	SM-MPC
<ul style="list-style-type: none"> + Well-established method + Intuitive with physical insight + Predictive capability based on known dynamics 	<ul style="list-style-type: none"> + No need for detailed system model + Fast deployment + Naturally handles varying system behavior
<ul style="list-style-type: none"> - Requires accurate system modeling - Time-consuming model development - Sensitive to model mismatch 	<ul style="list-style-type: none"> - Requires quality data - May struggle with extrapolation

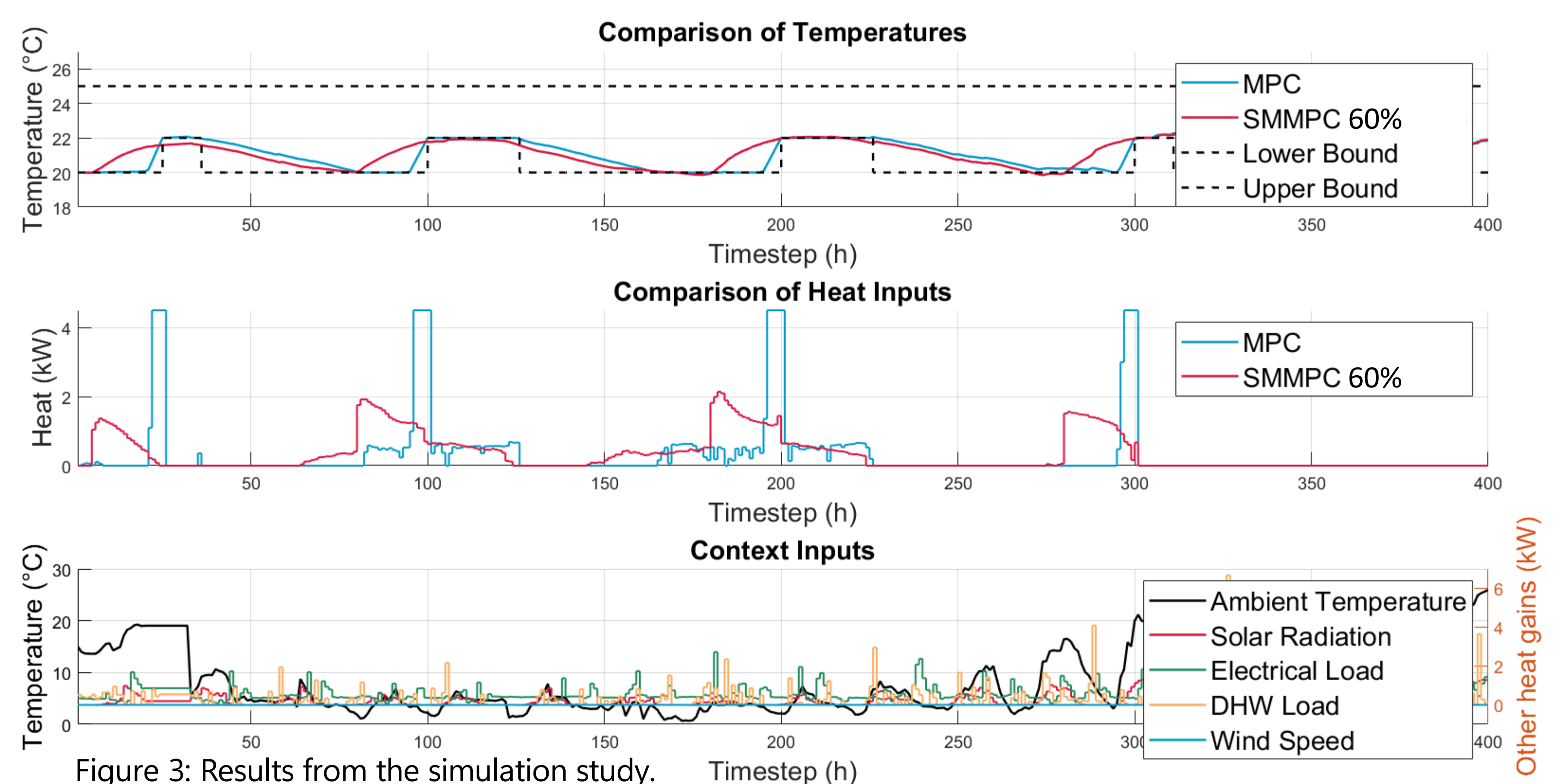


Figure 3: Results from the simulation study.

Control solution	Total heat consumption	Degree hours	Occurrences below
MPC	132,96 kWh	0	1,75%
SM-MPC confidence 95%	155,44 kWh	0,03	0,75%
SM-MPC confidence 60%	138,83 kWh	10,81	18,45%

