

# Grid-Responsive Heating in Buildings Saves Cost

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## Motivation

- The **decarbonization** of the energy sector **requires energy flexibility**, which is incentivized with **dynamic pricing**.
- Space heating** constitutes **27%** of the **final energy consumption** in the EU.
- Advanced controls can **minimize energy cost** while providing energy flexibility

## Setup

- District heating + Floor heating
- Control values: supply temperature, valve openings per room
- A variable price signal incentivizes **load shifting**.
- Indoor air temperature bounds for comfort. [2]
- Fully automated disturbances**, such as window openings.



Fig. 1: Controlled buildings under nearly identical conditions: (1) Benchmark; (2) MPC; (3) FLC [1]

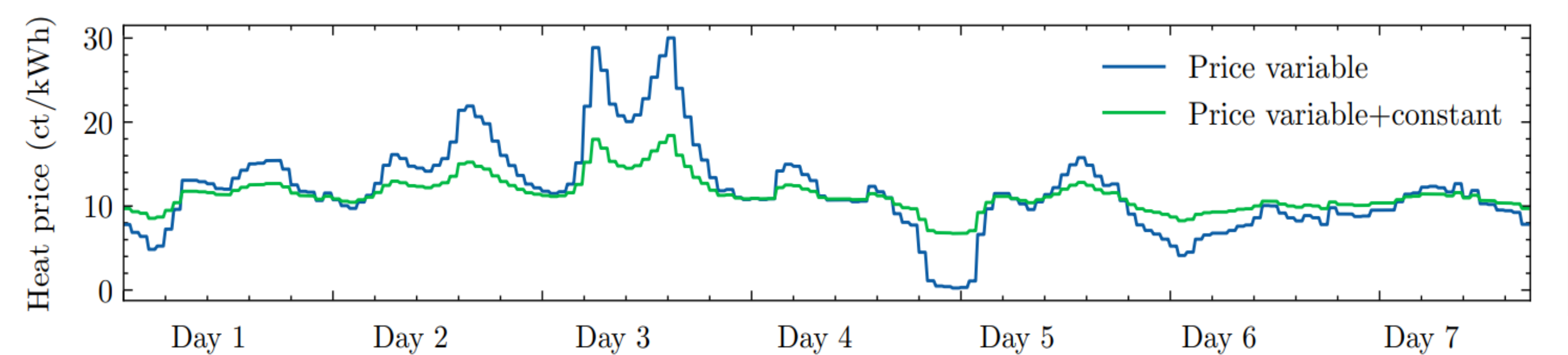


Fig. 2: The seven-day heat price signals used throughout the experiments. [1]

## Model Predictive Control (MPC)

- MPC **predicts** the building's temperatures using a **dynamic model**.

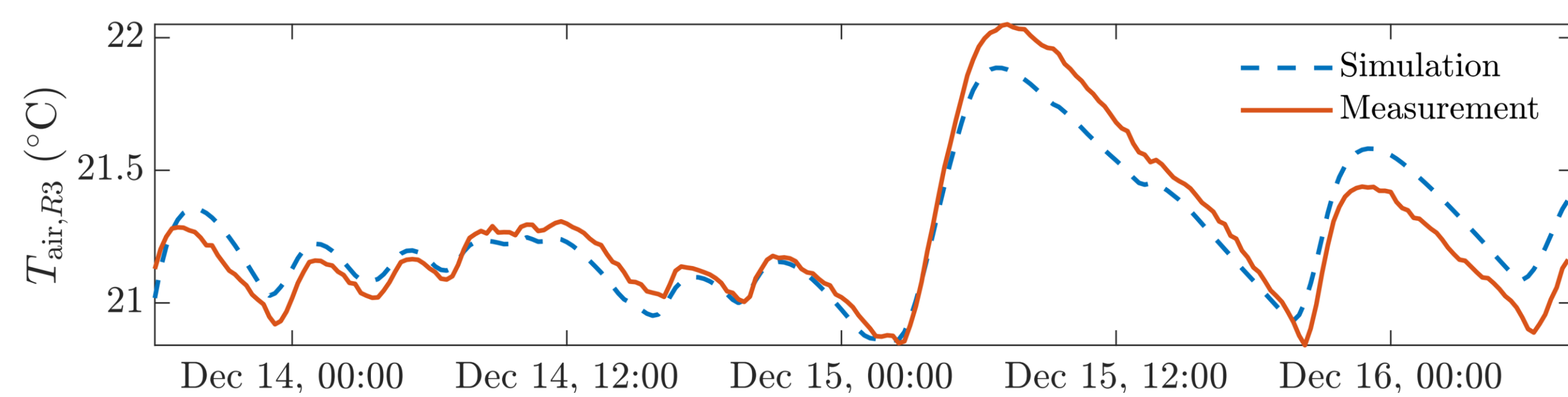


Fig. 3: Validation results of the thermal model in room R3. [1]

- Based on the model predictions and current measurements, **optimal control values** are determined to **minimize cost** while respecting constraints.

$$\min_{v, T_{\text{supply}}} \left( \sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{J}} (p_{\text{buy},k} \cdot \dot{Q}_{h,j,k} + \gamma \cdot \|\xi_{j,k}\|_2) \right)$$

subject to

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k$$

Thermal model

$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k$$

$$\underline{T}_{j,k} - \xi_{j,k} \leq T_{\text{air},j,k} \leq \bar{T}_{j,k} + \xi_{j,k} \quad \forall k \in \mathcal{K}, \forall j \in \mathcal{J}$$

Temperature bounds

## Fuzzy Logic Control (FLC)

- FLC is a **rule-based controller** using **expert knowledge**.
- The input data are converted into fuzzy membership values, and control inputs are calculated by activating **If-Then rules**.

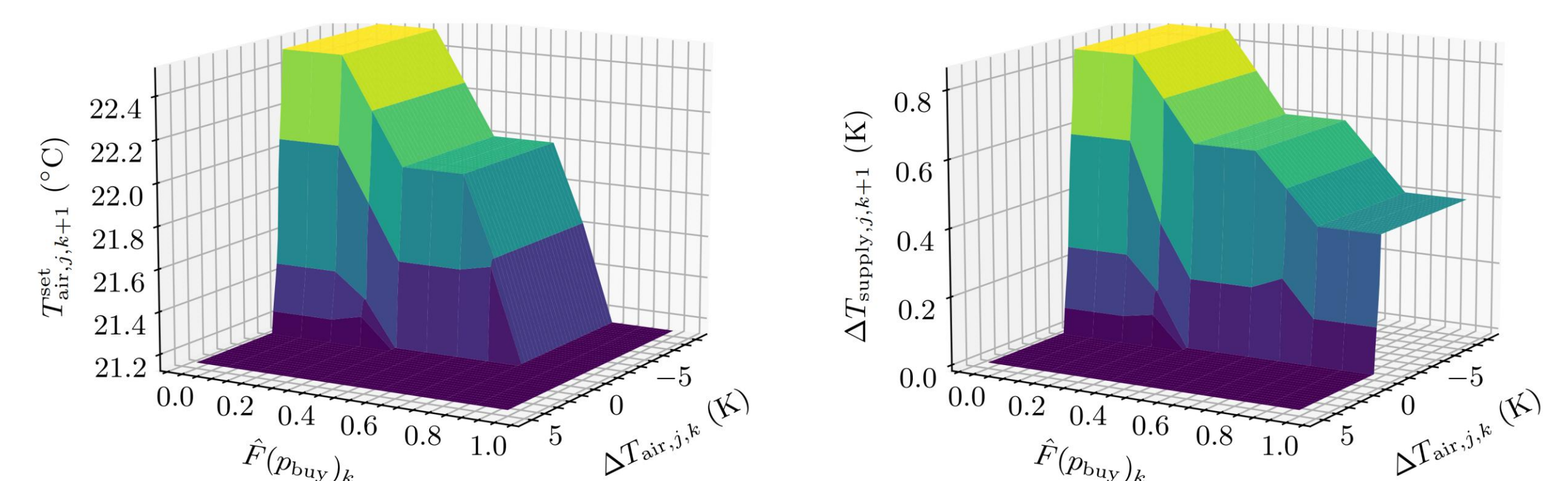


Fig. 4: The FLC graph mapping the inputs to the outputs. [1]

- Utilized information:** (i) indoor air temperature; (ii) lower temperature bound for the next 6 hours; (iii) change in indoor air temperature; (iv) empirical cumulative distribution function of the heat price for the next 24 hours.

## Results

- The **savings** ranges from **2.1% to 8.6%** for **FLC** and from **7.8% to 33.4%** for **MPC**.
- Both controllers almost completely **eliminate thermal discomfort**.
- MPC chooses **high supply temperatures**, as it **preheats** the building at maximum capacity while energy **prices are low**.
- FLC also selects higher supply temperatures than baseline (BAU), as it computes a correction factor that increases the supply temperature obtained from the heating.

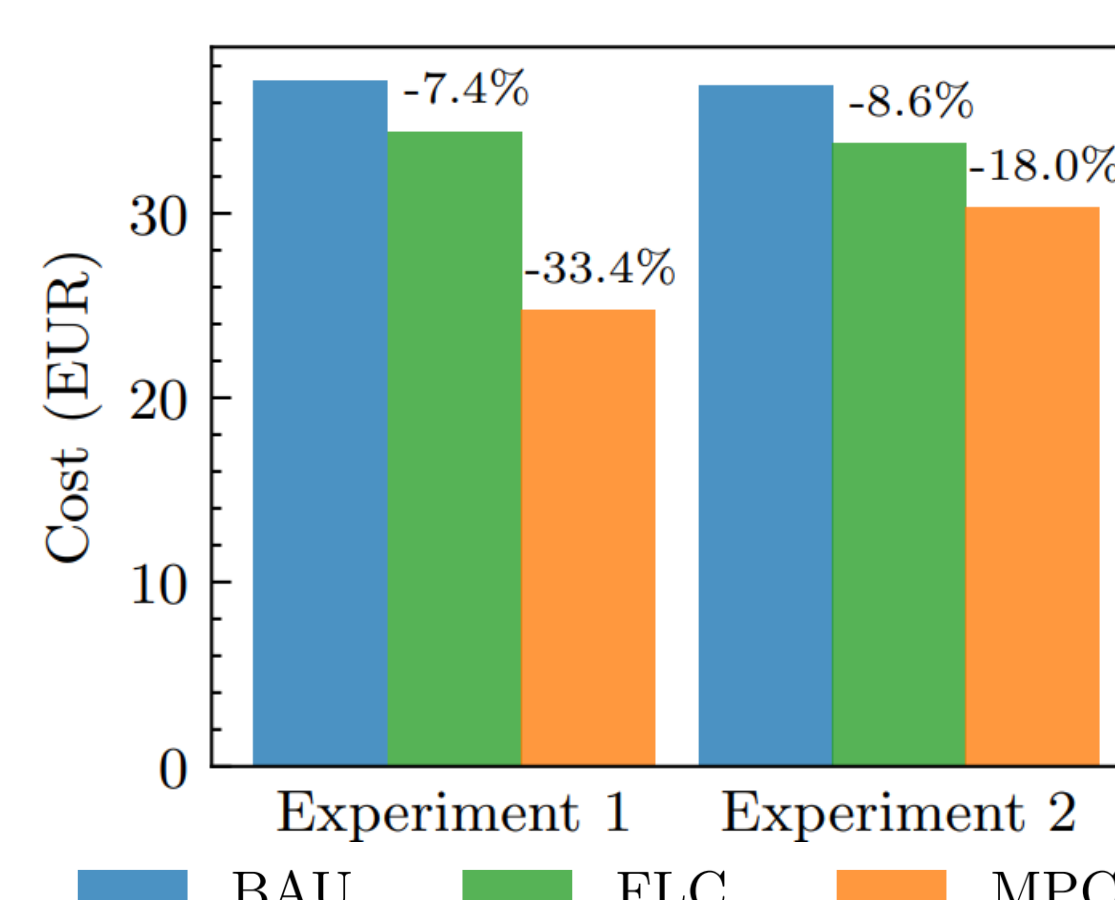


Fig. 5: Savings of FLC and MPC for two experiments. [1]

- FLC **uniformly** preheats all rooms, while MPC utilizes **room-individual control**.

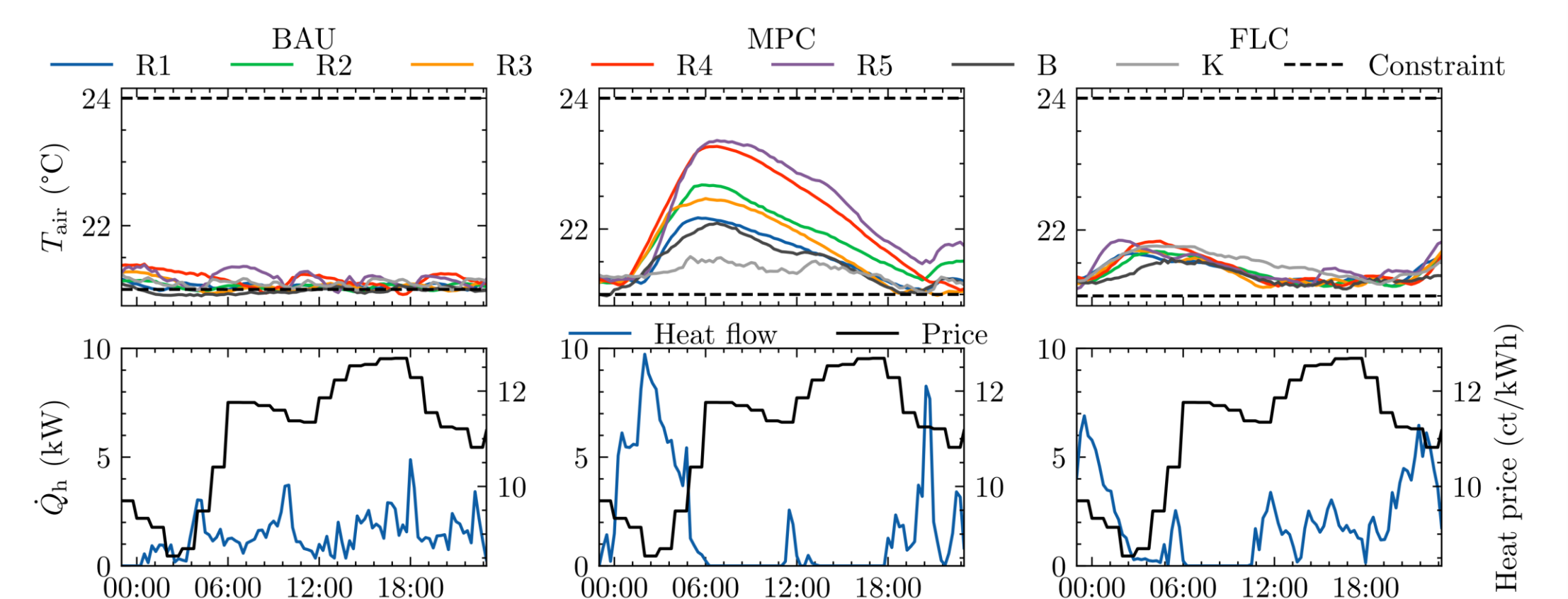


Fig. 6: Indoor air temperatures, total heat flow and price signal for each building for one day. [1]

## Conclusions

- Controlling **three architecturally identical buildings** in a real-world experiment enables direct evaluation of the controllers' performances under nearly identical conditions.
- Both controllers can **activate energy flexibility** by shifting demand from high-heating-price periods to low-heating-price periods.
- MPC achieves substantially **greater savings** in experiments characterized by either **high-price spreads** or high flexibility potentials.
- Focusing solely on **cost minimization** is **insufficient** to achieve substantial **emission reductions**.

[1] F. Langner et al., "Experimental evaluation of model predictive control and fuzzy logic control for demand response in buildings", Manuscript under revision, Applied Energy.

[2] T. Ueno, A. Meier, "A method to generate heating and cooling schedules based on data from connected thermostats", Energy and Buildings 228 (2020)