

Advanced Control Strategy for Building Energy Management Systems

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AIM

Develop a **building model** suitable for **control development, optimisation and assessment**.

BACKGROUND

Building Energy Management Systems (BEMS) are centralised control systems that supervise the **energy services** in buildings, mainly Heating, Ventilation and Air Conditioning (HVAC). Today, the **control strategy** in BEMS are feedback loops, not exceeding the complexity of Proportional-Integral Controllers.

Advanced control implementation in buildings would have a **multitude of benefits**:

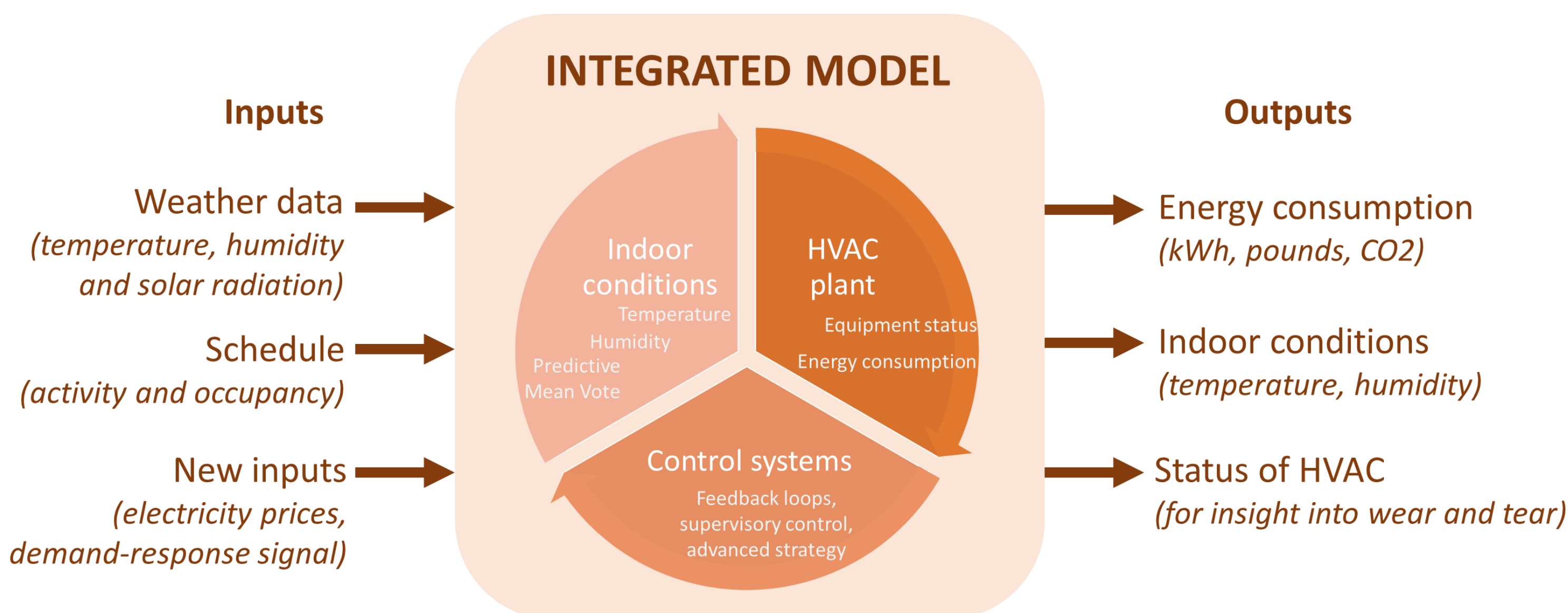
- Energy services and comfort improvement
- Energy savings, operating cost and carbon footprint reduction
- Increase of the assets' values

Yet, advanced control have a **low penetration** in the buildings sector. A limiting factor identified is the **need for a building model**.

METHODOLOGY

An **integrated** approach is adopted.

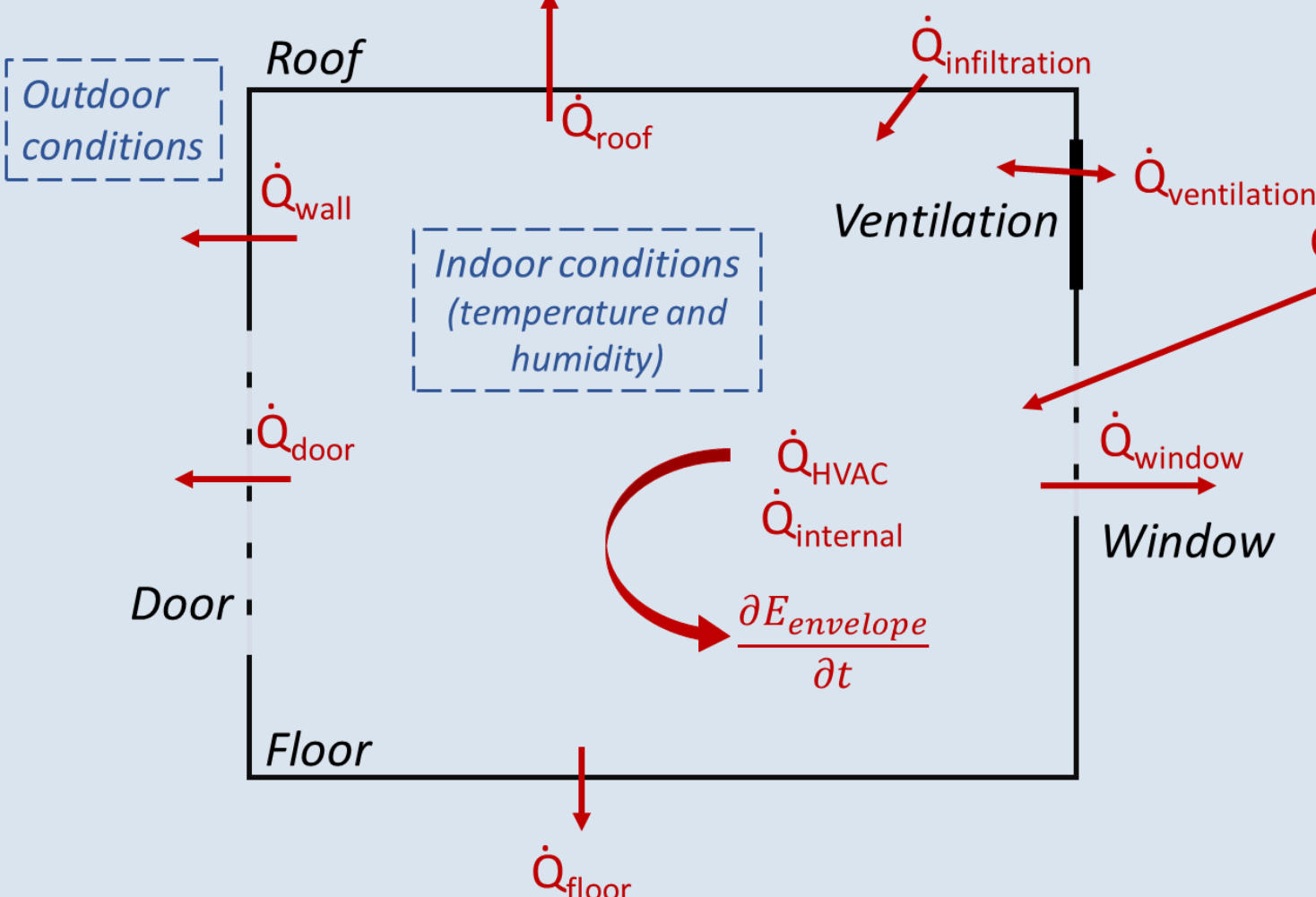
Figure 1: The model's structure



THE THERMAL MODEL

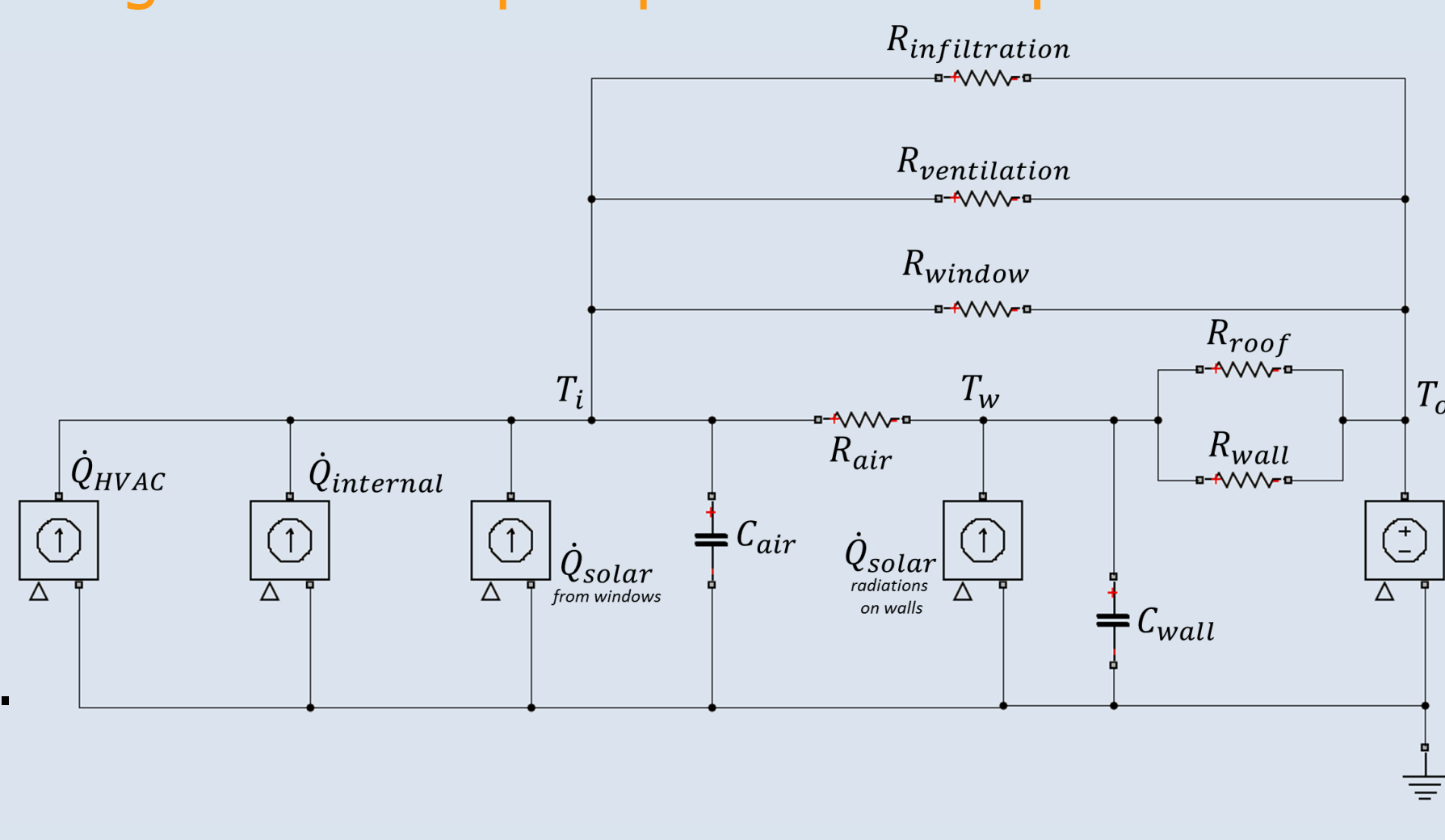
A **difficulty lies in the indoor-conditions unit** of the integrated model. The indoor conditions are determined by the heat balance equations. A thermal model is developed.

Figure 1: Heat balance in buildings



Among the existing building thermal models, **the thermal network** (cf. figure 2) appears to be the most suitable. It is a low-order model, thus it has a **short running time** which is convenient for control optimisation. The model is **flexible** in terms of space granularity: the space granularity corresponds to the number of nodes of the network.

Figure 2: Lumped-parameter representation



The **structure of the network** is determined by the heat gains and the thermal mass that **have the greater impacts** on the indoor conditions and the number of thermal zones modelled.

The values of the resulting **parameters** (thermal resistance and capacitance values) are **identified** thanks to **training data**.

CASE STUDY: A SUPERMARKET

A 3,300-square-meter supermarket in Kent (England) was modelled and different control strategies for the heating system were simulated.



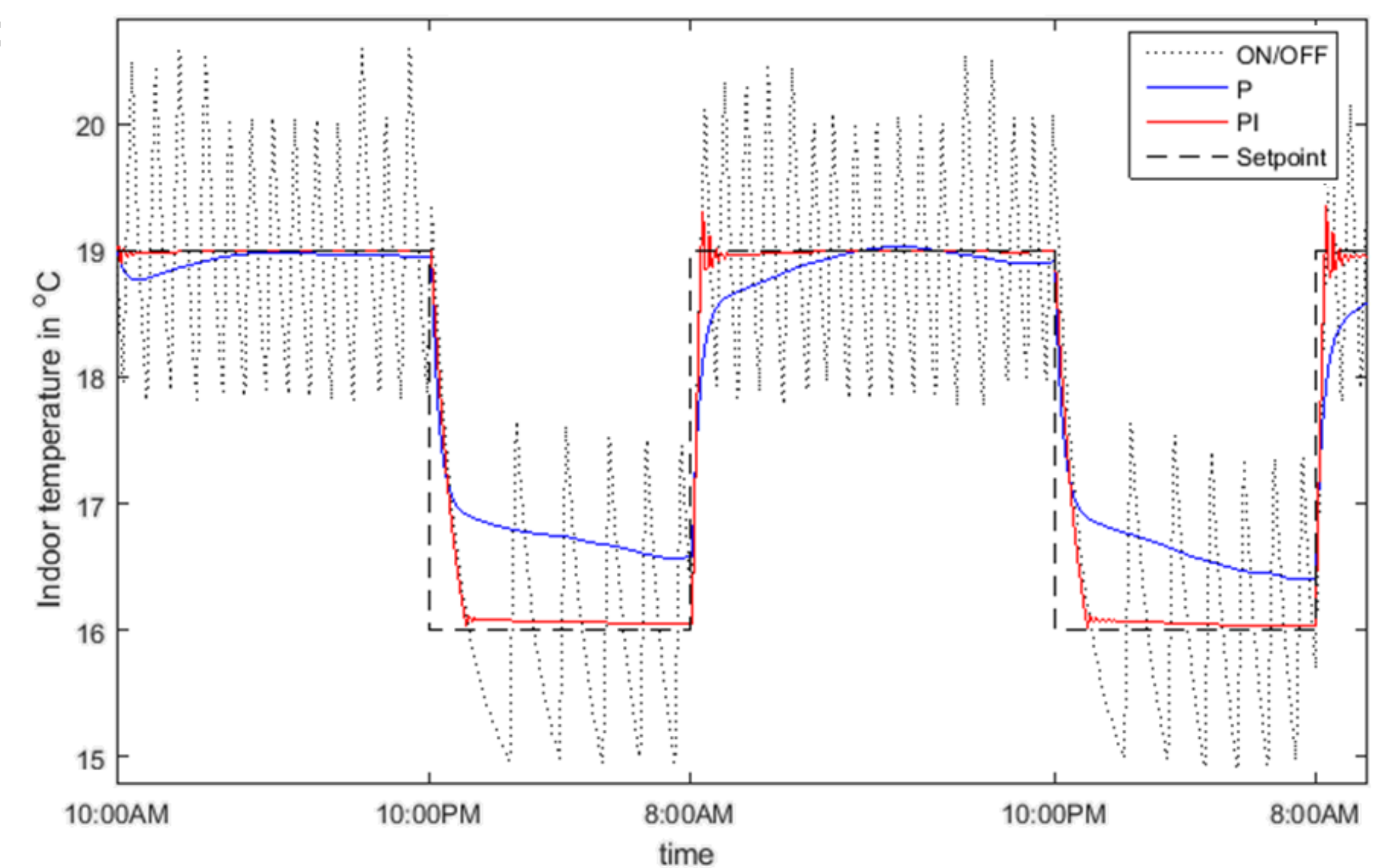
Figure 3: Comparison of basic control strategies

Three feedback loops:

- **On/Off**
- **Proportional**
- **Proportional-Integral**

are **tuned** for the supermarket thanks to the integrated model.

The performances of the tuned controllers are **compared**.

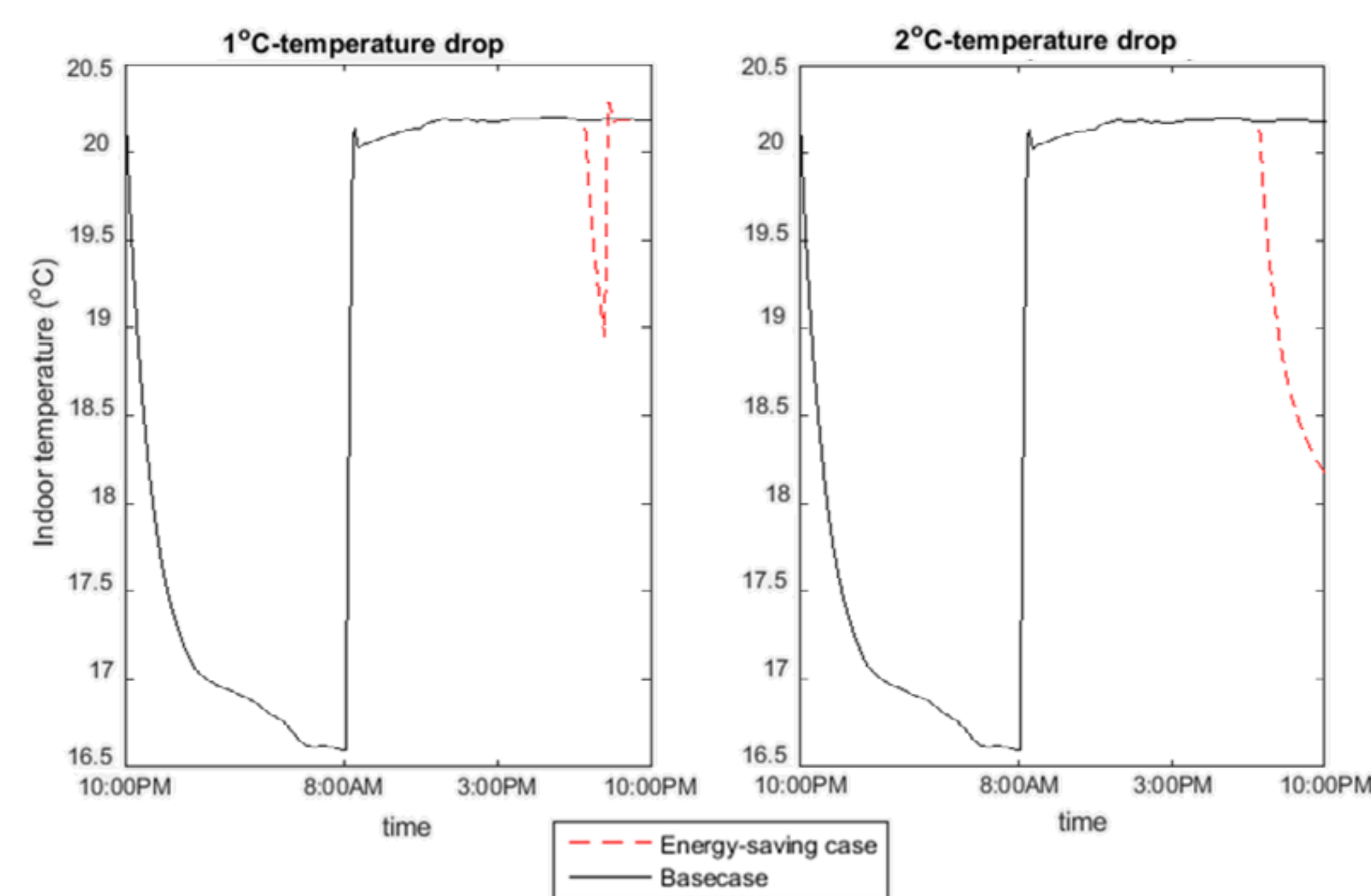


The PI controller performs the best with respect to the chosen indicators.

Indicators	ON/OFF	P	PI
Thermal energy consumption (kWh)	4,173	4,245	4,165
Temperature range* (°C)	3.34	1.73	1.82
Discomfort hours*	6h25	55min	30min

*during opening hours

Figure 4: Implementation of energy-saving measure



Advanced control consists in either **complex algorithms** or the use of **new inputs** in feedback loops.

The strategy investigated here is the use of additional inputs: **occupancy** and **closing hour**, in a PI controller. The BEMS can decide, once a day, to let the temperature drop from the setpoint, when the occupancy is lower or the closing hour is imminent.

In the 1°C-drop scenario, some energy savings are observed without jeopardising comfort.

Indicators	0°C	1°C	2°C
Time without heating	0	55 min	3 h
Temperature range* (°C)	1.70	1.76	2.01
Discomfort hours*	3%	4%	18%
Energy savings	0%	3%	13%

*during opening hours

CONCLUSION

The modelling approach developed was used to assess, tune and compare control strategies. Advanced control is often associated with complex algorithms. Yet, the integration of additional inputs in feedback loops is also able to improve the overall performance of the control system.

ACKNOWLEDGEMENT The case study was conducted thanks to the data made available by Sainsbury's.