AI-Driven Occupant-Centric Control in University Buildings: Lessons Learned and Carbon Impacts

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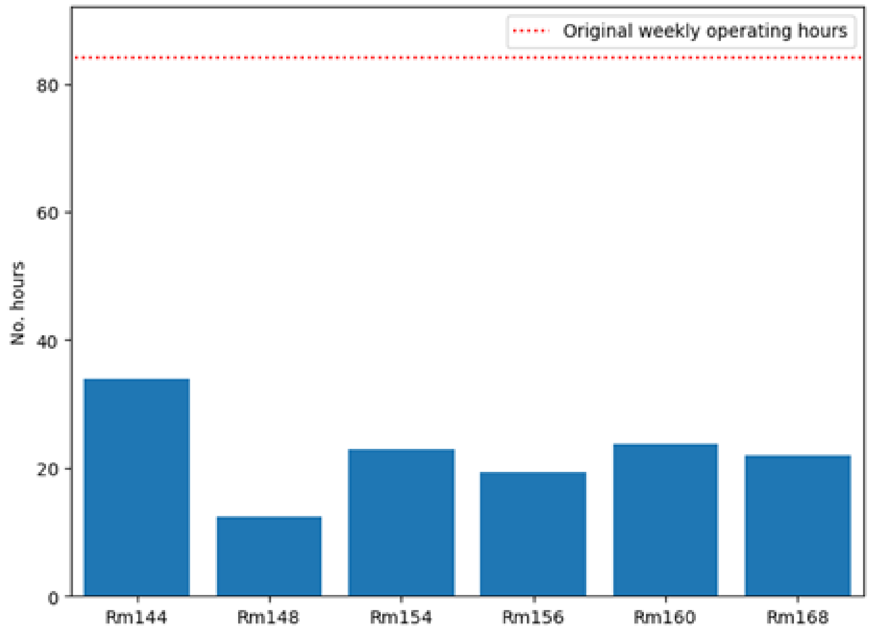
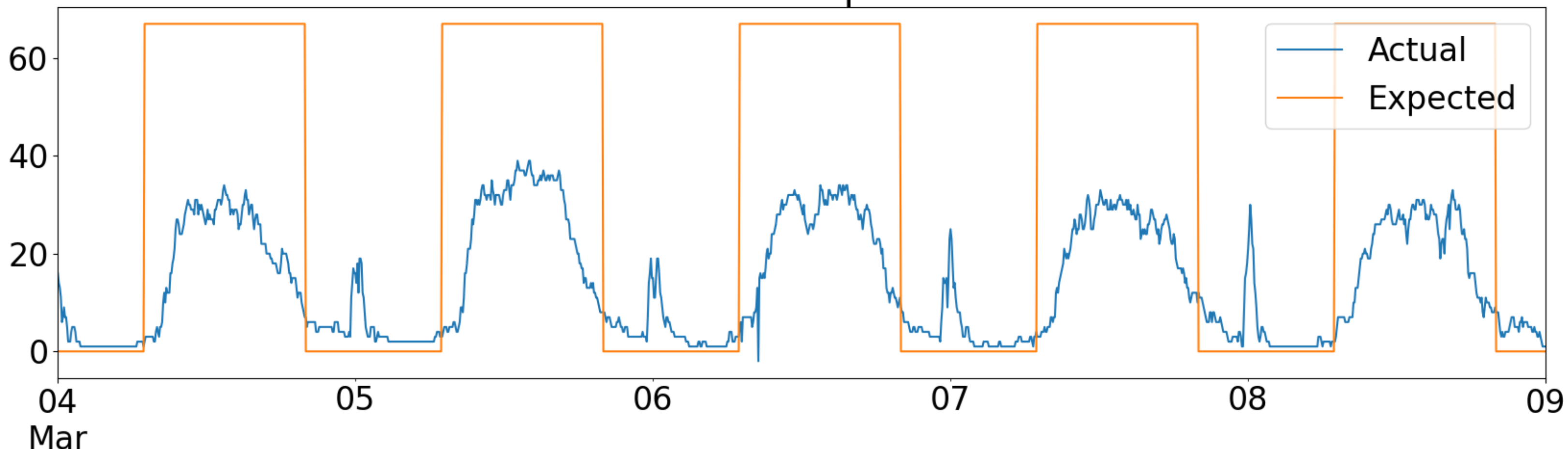
Significant energy waste in campus buildings

- Every room on campus was conditioned from 7am to 7pm (or 11pm, sometimes 7 days a week)
- On average, classes are only scheduled during 26.8% of these hours during semesters
- At maximum around half of the offices were occupied

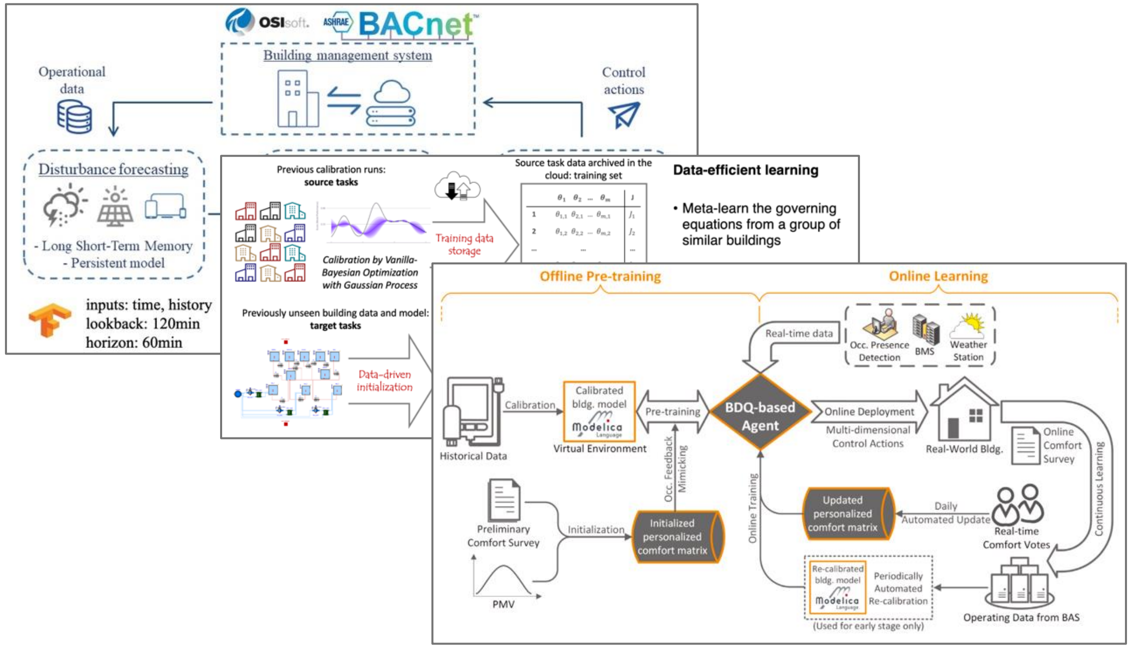
Number of hours for each room



Number of occupied offices



Pilot tests of AI-driven control



- Thermal response models for optimal predictive control
  - Calibrated physics-based model (white/gray)
  - Data-driven machine learning (black)
  - Physics-informed ML (dark gray)

- Optimizing the heating and cooling setpoints in real-time
  - Minimize energy consumption given occupant-centric comfort constraints

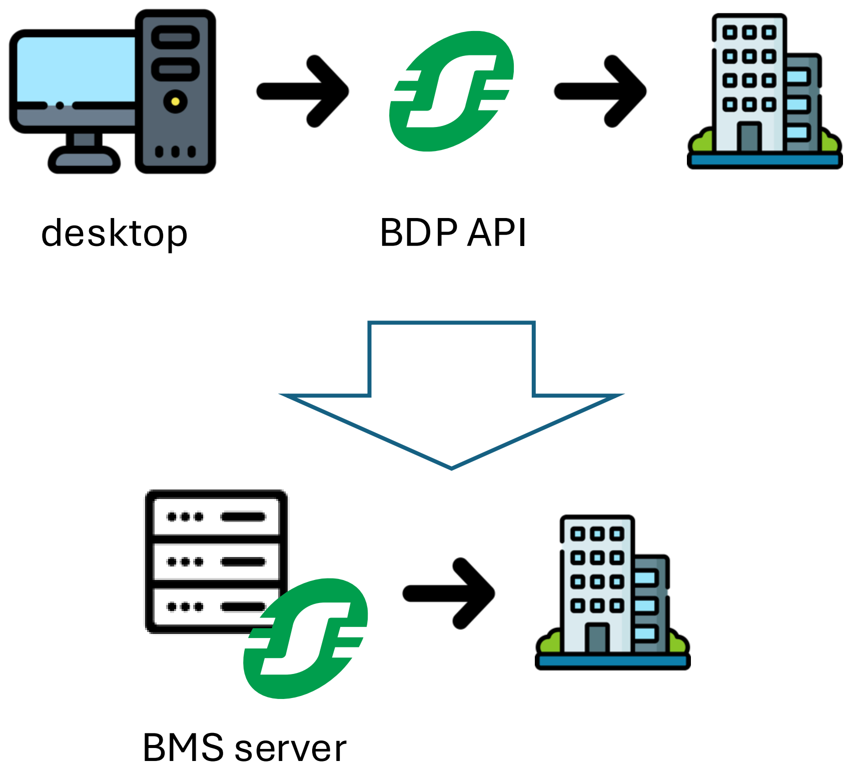
- Pilot test demonstrated over 30% of energy saving[1]

MPC/RL SE BDP API

[1] Pilot experiments conducted by Daisy Green (MIT ECE) and You Lin (MIT LIDS).

Challenges to scaling up the optimal control

- Computational resource (maintenance)
  - From 1 building to 100 buildings
  - Data exchange costs and risks
- Sensor/data availability
  - Existing outdated infrastructure
  - Lack of historical data (additional data server needed)
- Do we need AI to save energy?

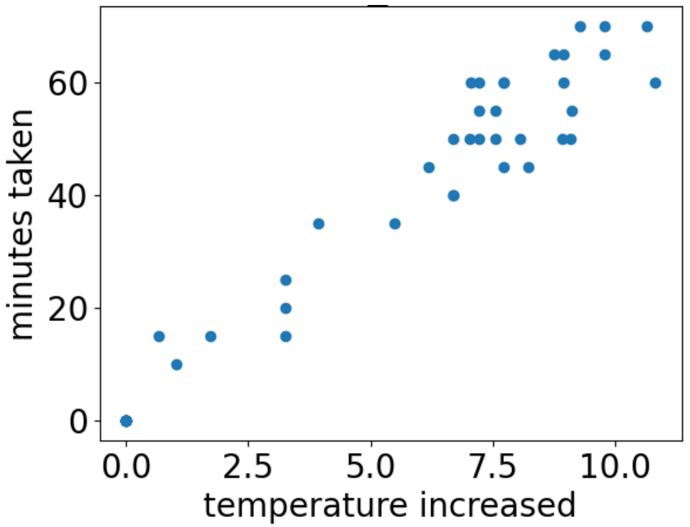


Rule-based occupant-centric control for classrooms

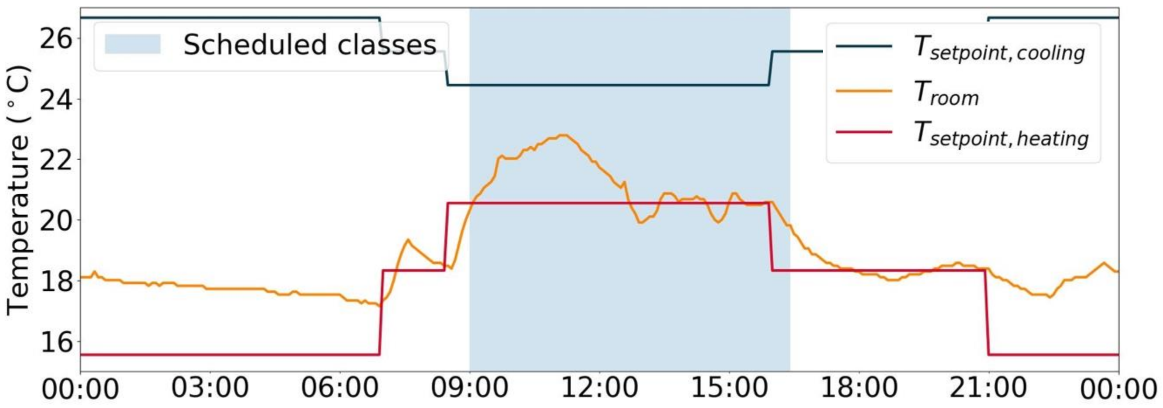
- Operating schedule informed by class registration

Modes	**Setback**	**Standby**	**Occupied**
Cooling setpoint	26.6°C (80°F)	25.5°C (78°F)	23.9°C (75°F)
Heating setpoint	15.5°C (60°F)	18.3°C (65°F)	20.5°C (69°F)

- Pre-conditioning set by historical data
  - Start from X hours before the first class
  - Comfortable environment when peoples come in
  - More free-floating during unoccupied operating hou



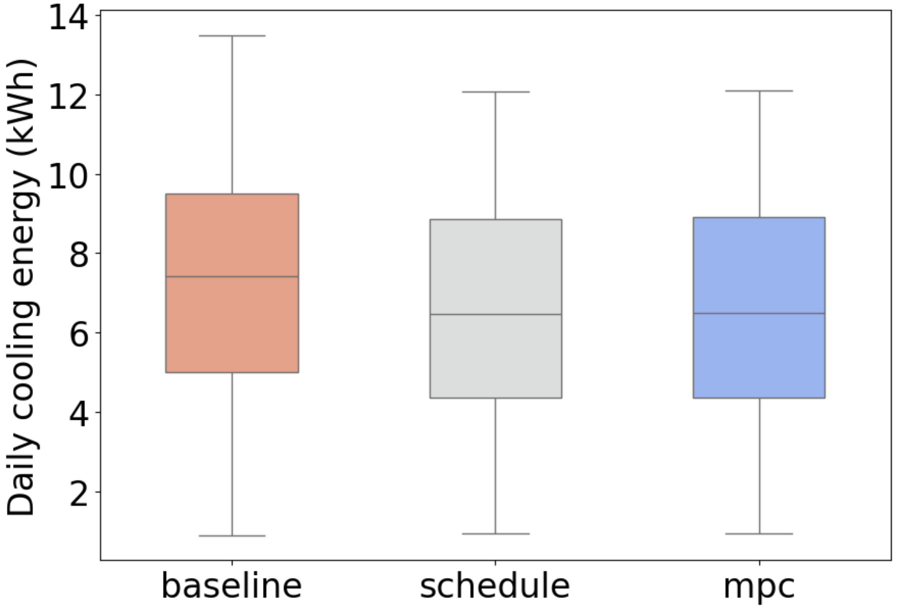
Example of schedule-based control

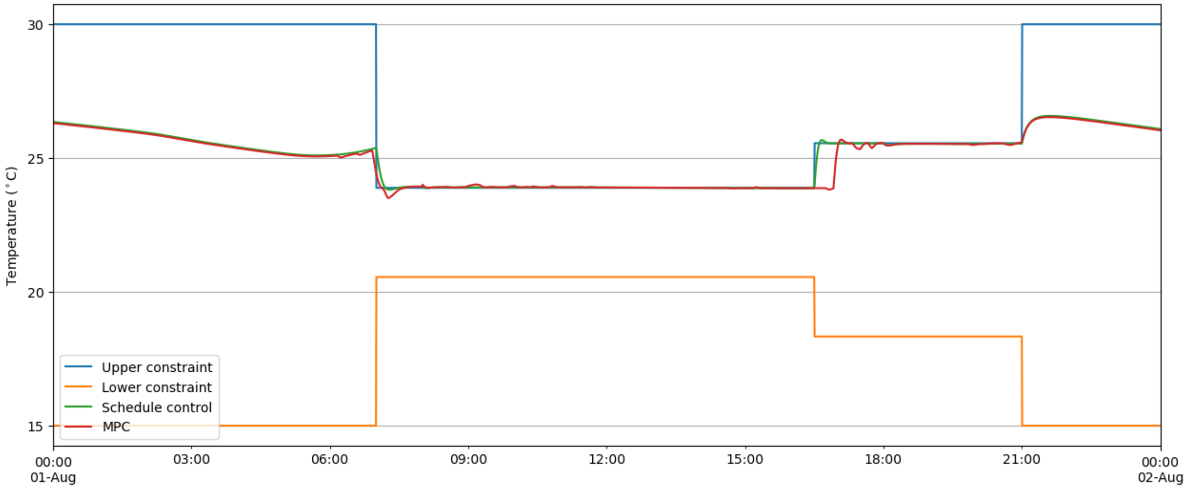


Performance comparison using BOPTEST (bestest_air)

- Comparison of energy performance over a summer
  - Baseline: static day-to-day schedule
  - Schedule: mode switching based on actual schedules
  - MPC: minimize energy with occupancy-based comfort constraint

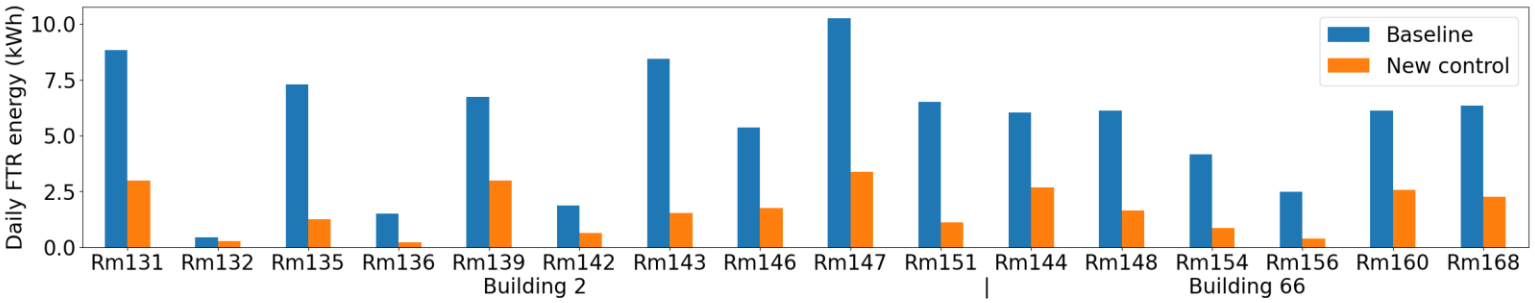
- Close energy saving of 11.2% (schedule) and 10.8% (MPC)
  - Given the same information, only minor differences in control actions

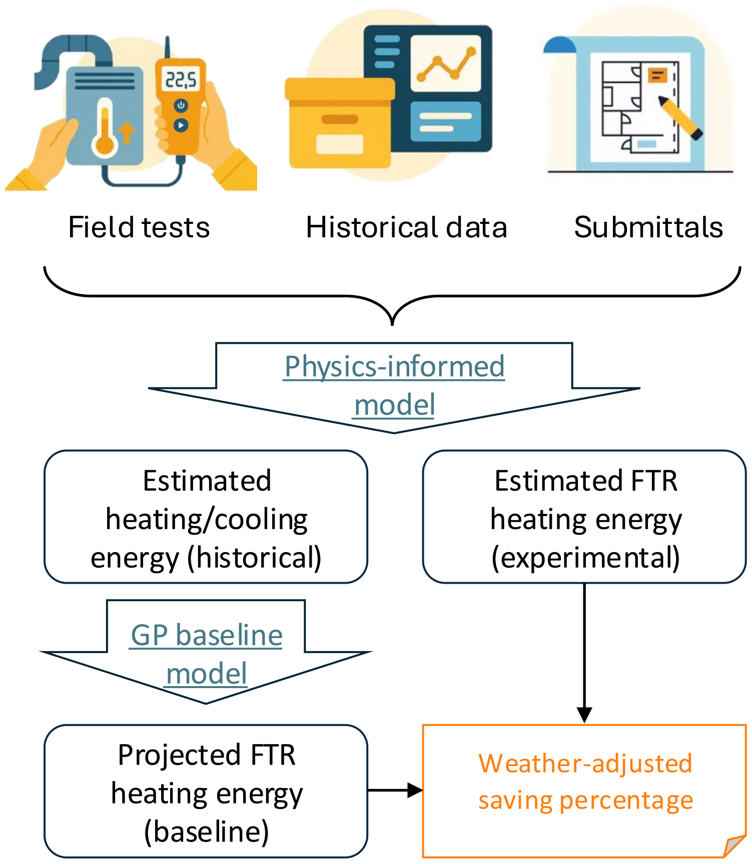




Field implementation of OCC in classrooms

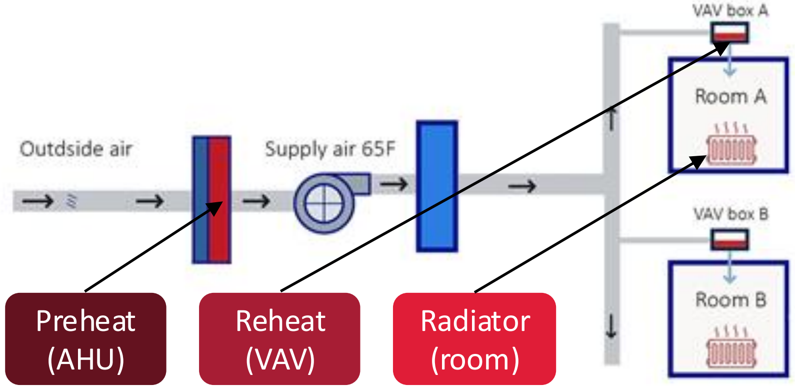
- Long-term pilot since November 2024[1]
- Energy saving estimation given limited data
  - Physics-informed model to map valve position to power
  - Uncertainty-aware baseline model trained with historical data
- 70% percent of radiator energy saving (3.9kWh/room/day)



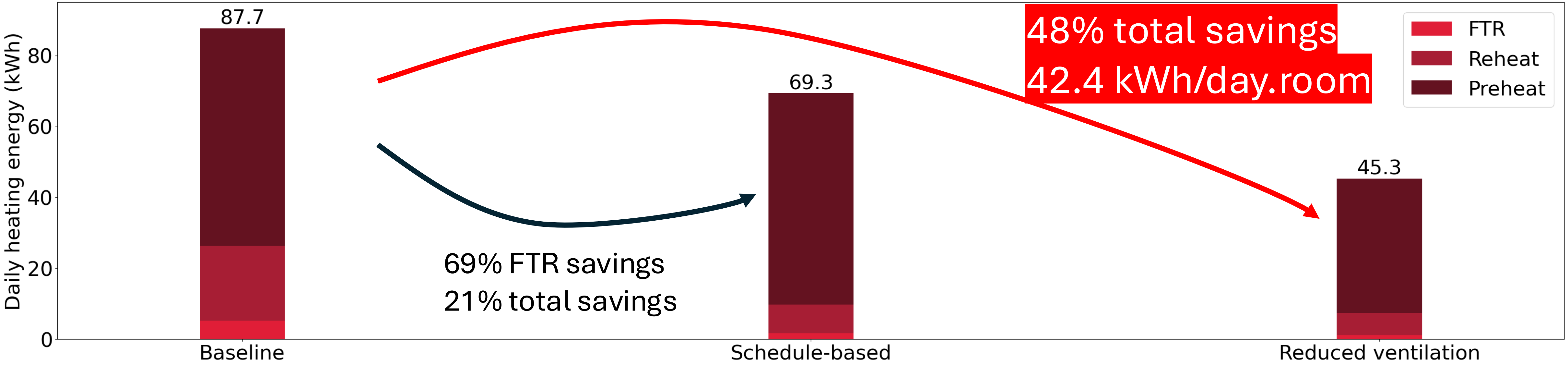


[1] Data from November-December 2024 were collected from experiments conducted by You Lin, MIT LIDS.

The critical role of ventilation

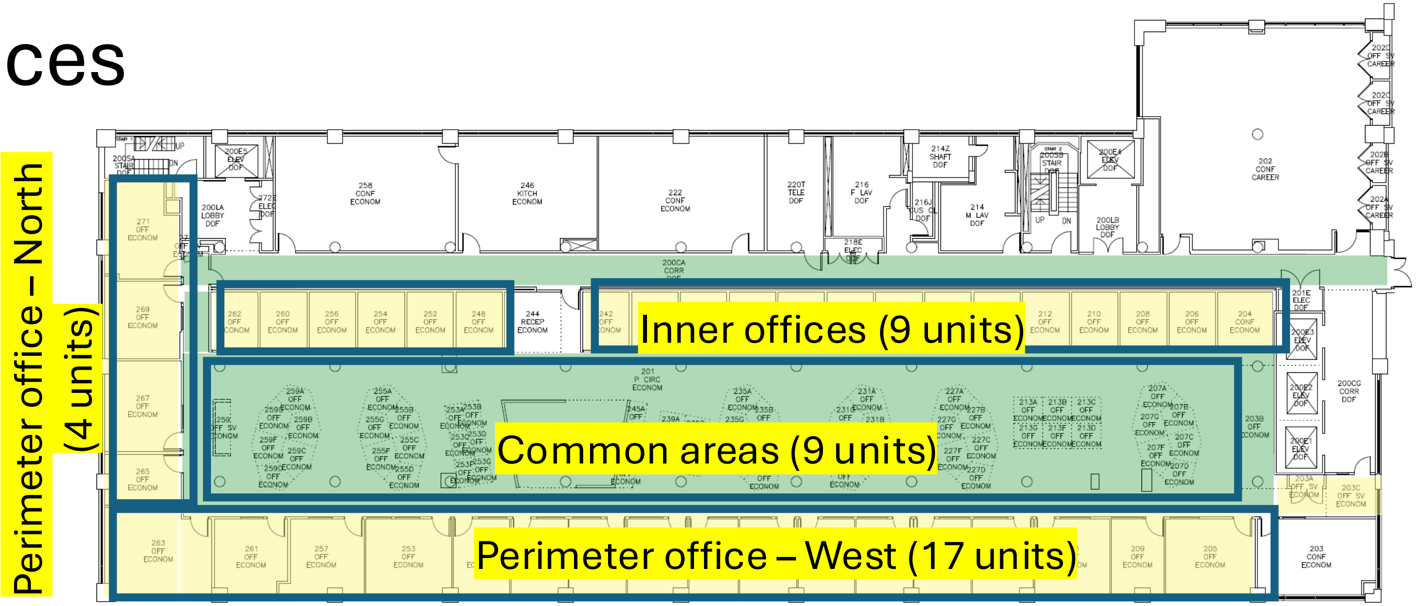


- Majority of heating energy consumed by supply air, savings amplified after reducing the supply airflow rate
- 35% energy saving in the cooling season mostly came from avoiding over-ventilation

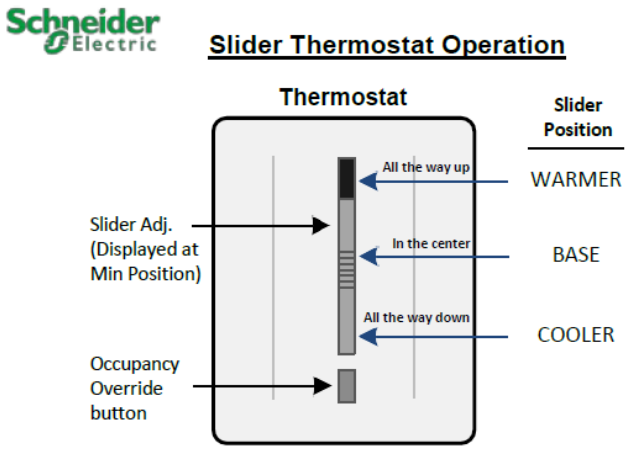


OCC implementation in offices

- No pre-determined schedule, but faster thermal response
- Hardware-driven solutions
  - Restricted by HVAC configurations
  - Customized based on zone type

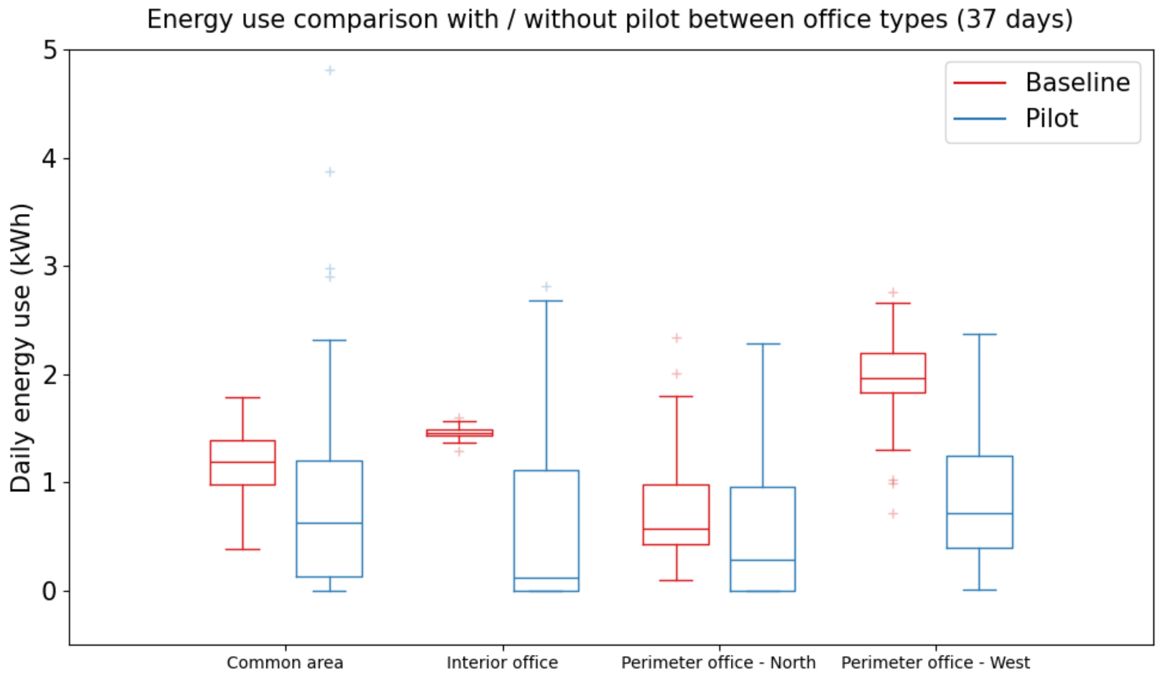


Occupancy signal	User override	Occupancy sensor
Occupied setpoints	21.1°C / 23.3°C 4 Hr timer	21.1°C / 23.3°C 2 Hr timer
Unoccupied setpoints	18.3°C / 26.6°C	18.3°C / 26.6°C



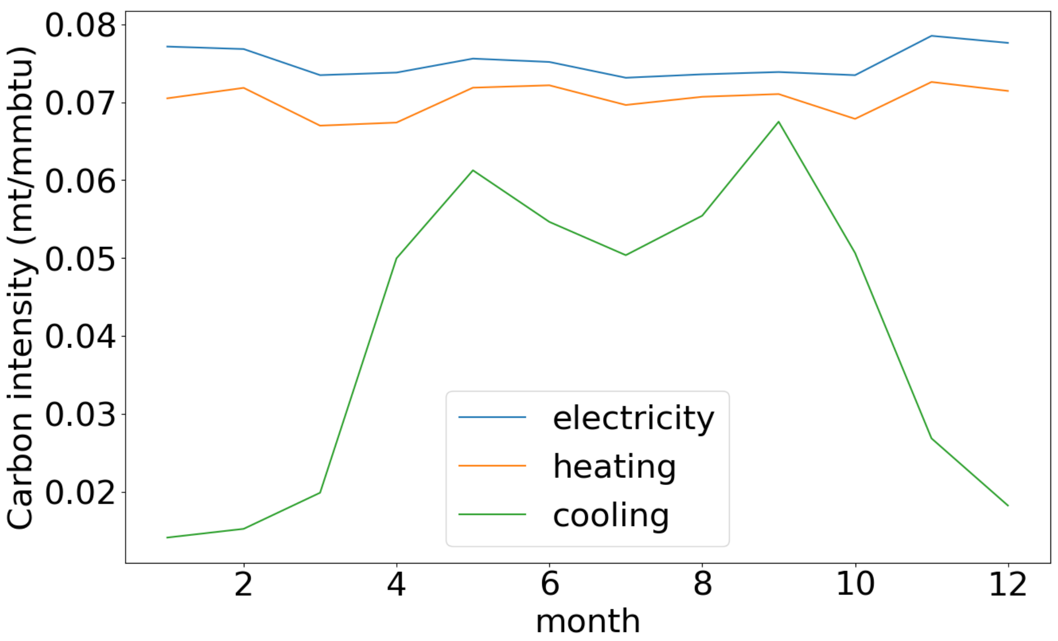
OCC implementation in offices

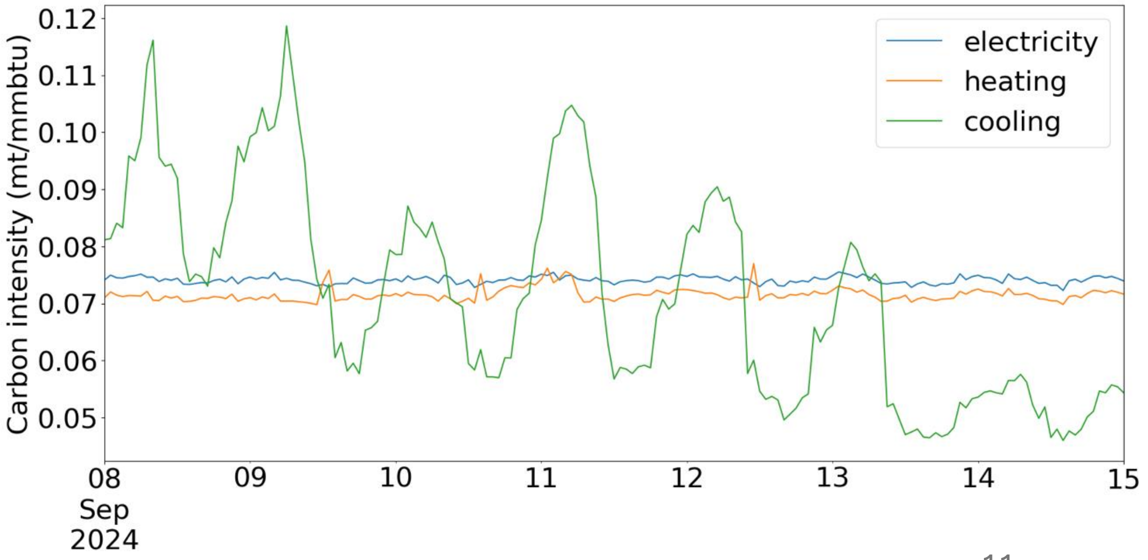
- In total 50% of cooling energy reduction
- Zone level savings affected by many factors
  - More savings in individual offices
  - Larger saving potential when exposed to sunshine
  - More interaction with thermostats led to lower setpoints, therefore larger variance and less saving
- Gradually integrate schedule adaptation to balance comfort



Impact on carbon emissions

- Most heating energy comes from waste heat of electricity generation
  - Supplemental duct burner activated when needed
- Non-linear mapping from energy to carbon reduction in heating season shrunk from 48% to 32.3%
- AI method could be advantageous to leverage short-term variation in cooling carbon intensity





Final remarks

- Significant savings can be achieved WITHOUT AI
- Ventilation is more critical than heating/cooling setpoints
- Major factors affecting energy saving potential
    - More significant potential in winter than summer (larger temperature difference, countering supply air)
    - Effects of orientation, window area, etc. and constraints from HVAC equipment
    - Occupants react differently to occupant-centric control
- AI may bring potential for better thermal comfort and further carbon reduction

Thank you!