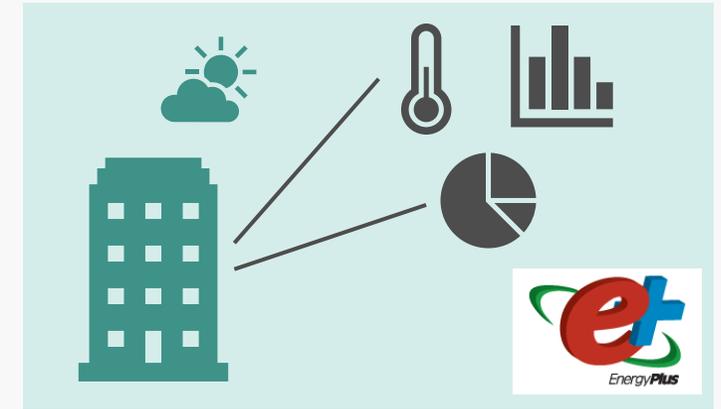


LLM Driven Agent-Based Evaluation Framework for Occupant-Centric HVAC Control Considering Individual Differences and Movement Behavior

[Shinnosuke Sasaki](#), Nattaon Techasarntikul, Yuichi Ohsita, Hideyuki Shimonishi

Graduate School of Information Science and Technology, The University of Osaka

- **Building Performance Simulation (BPS)** is the tool to analyze and predict the environmental performance and energy consumption of a building during the design phase.
- **Performance gap** exists due to unmodeled occupant dynamics.



Cause of Performance Gap Between Prediction and Operation

Fixed occupancy schedules

Occupancy and behavior typically treated as exogenous and homogenous inputs.

Population-average indices

Population-average metrics such as PMV/PPD, cannot adequately represent individual thermal preferences.

Building Performance Simulation (BPS) must internalize both individual thermal sensations and the behaviors they induce.

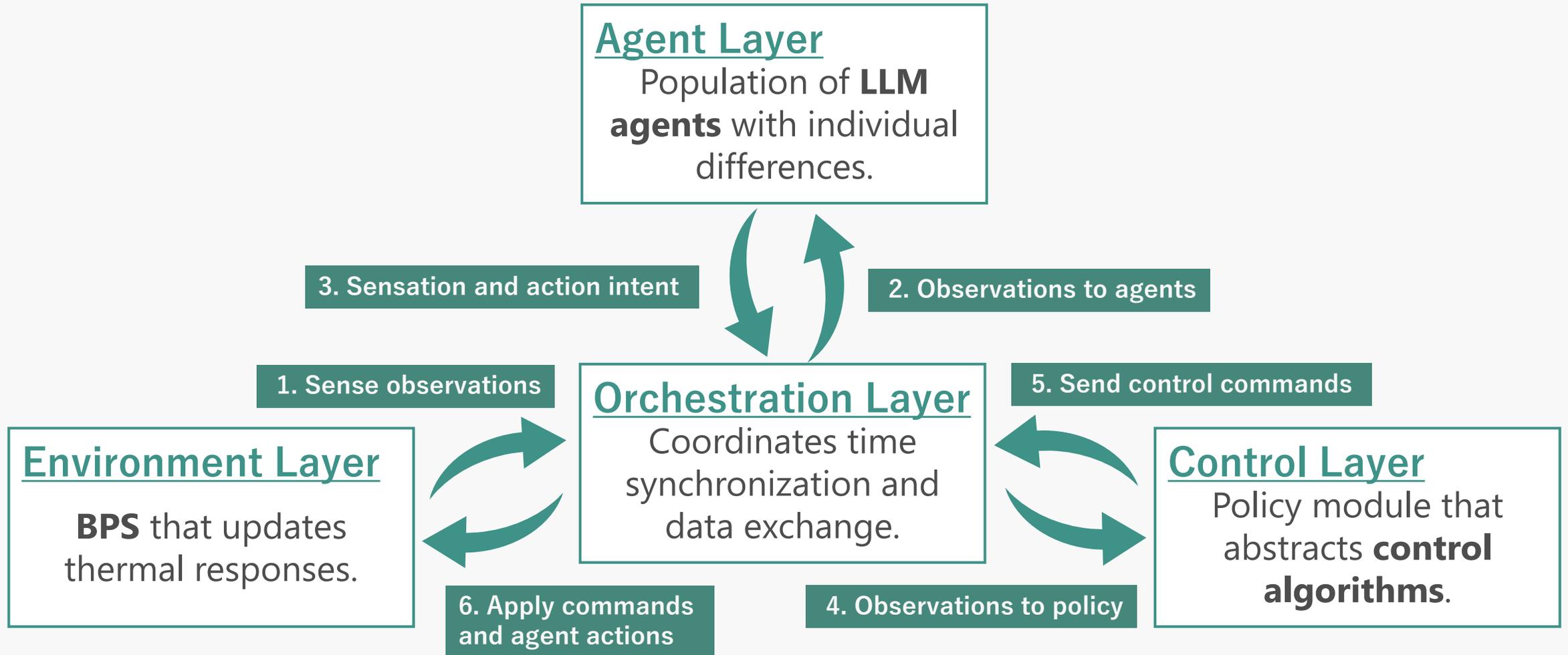
Conventional Solution: Agent-Based Modeling (ABM)

- ABM is computational approach that models explicit individual, autonomous agents.
- ABM can capture heterogeneity, decision making, and interactions.
- Achieving realistic, subjective sensation and context-dependent judgements is a challenge in traditional ABM.

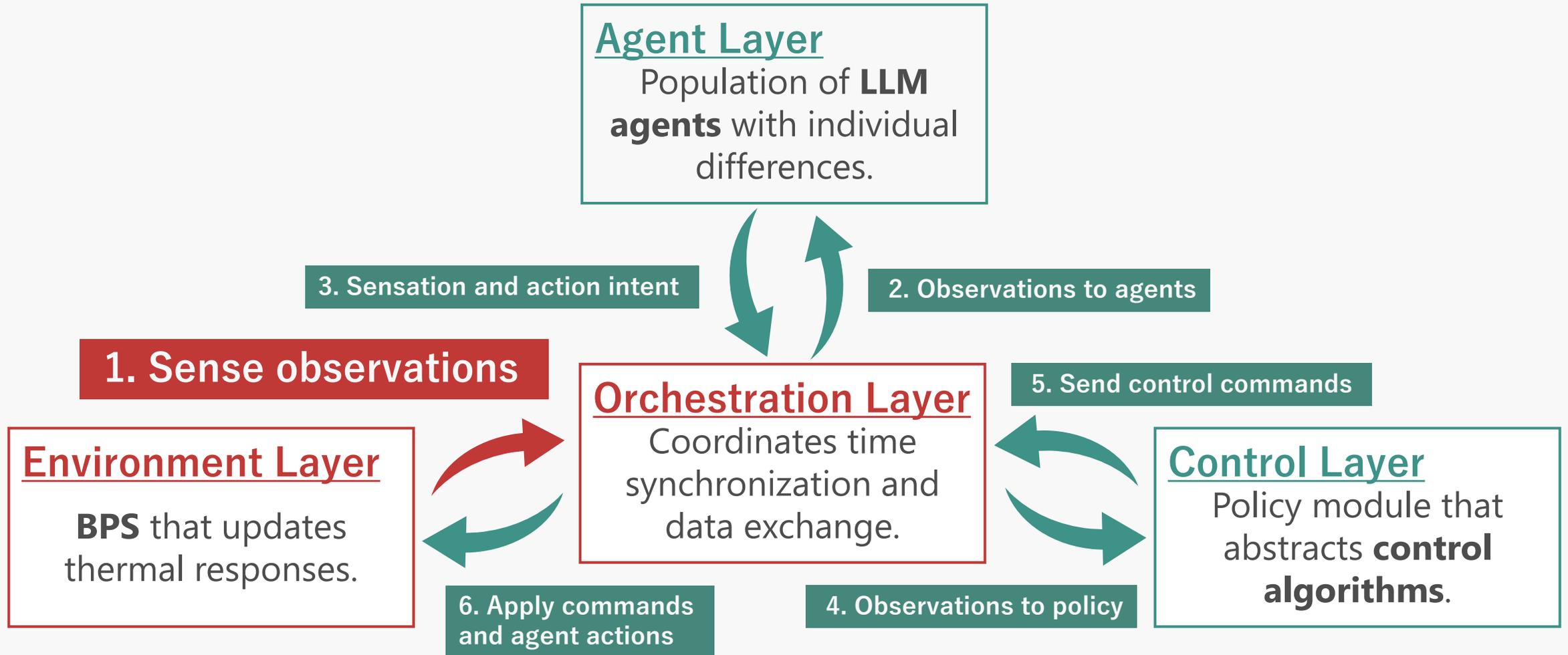
Our Solution: Large Language Model (LLM) Driven ABM

- Delegate agent's decision-making to an LLM.
- LLMs enable agents to express individuality and context-dependent judgements.

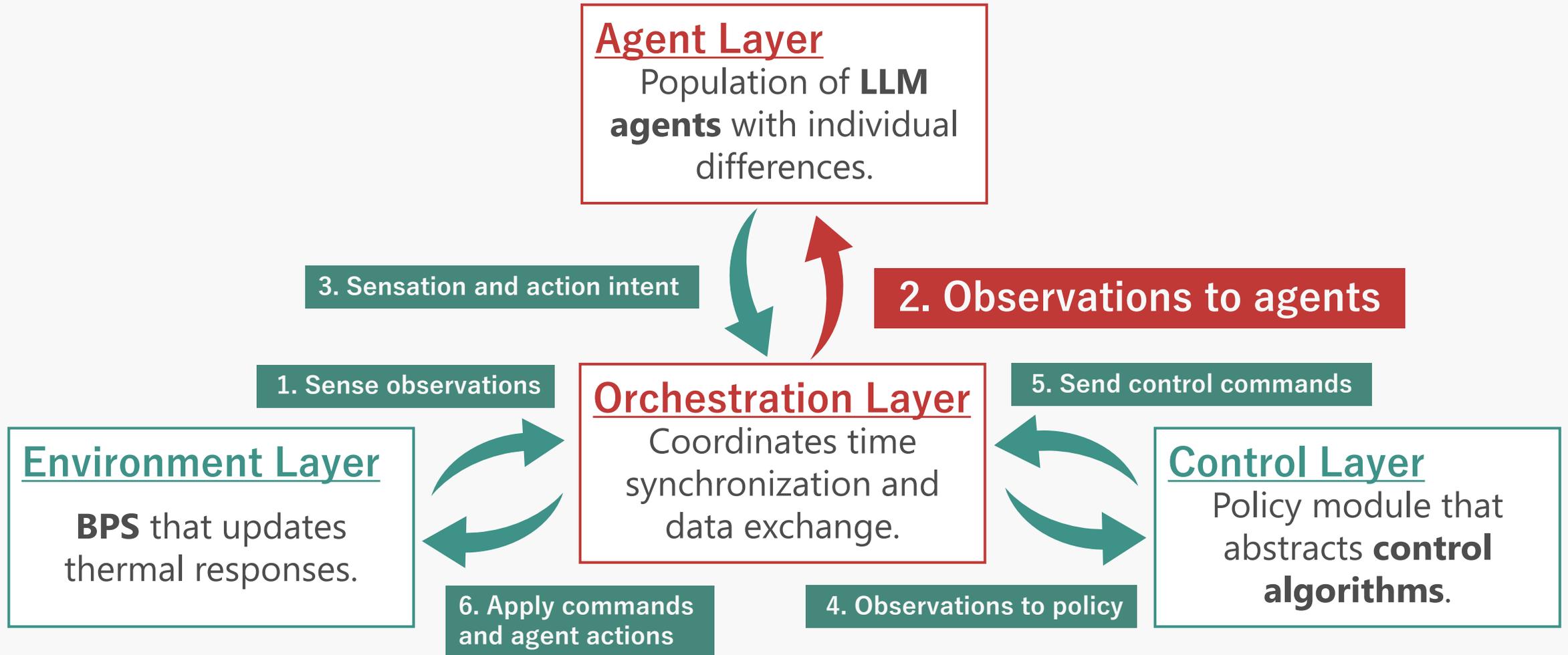
We propose a framework that models occupants' subjective thermal sensations and movement behaviors as LLM agents, and couples them with a Building Performance Simulation (BPS).



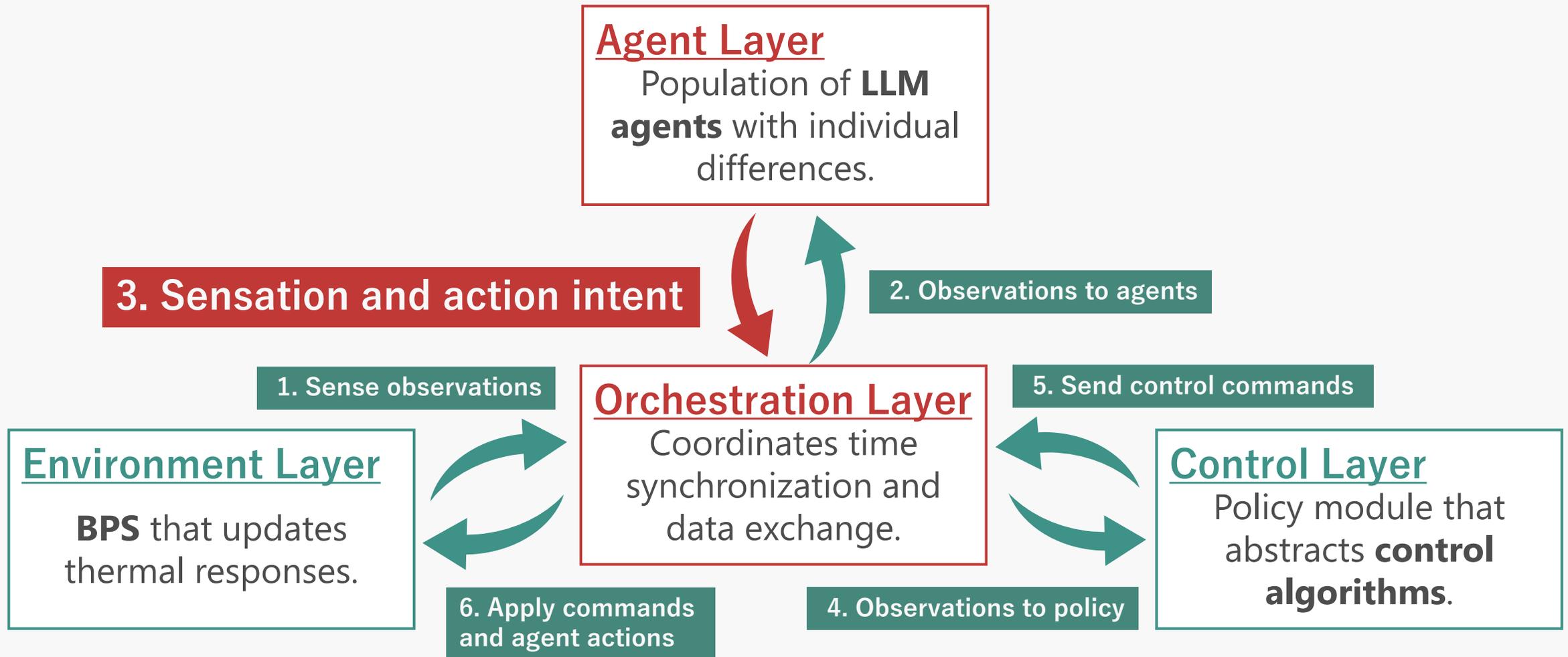
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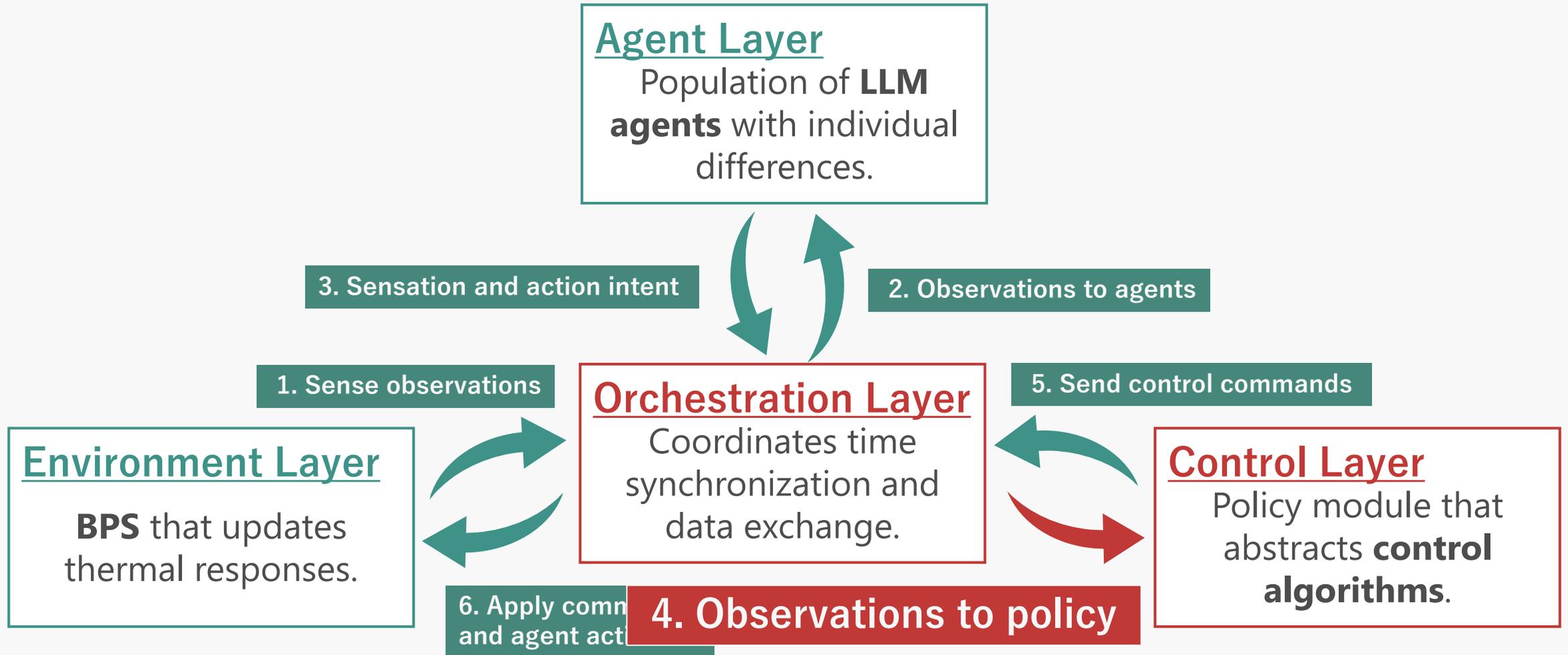
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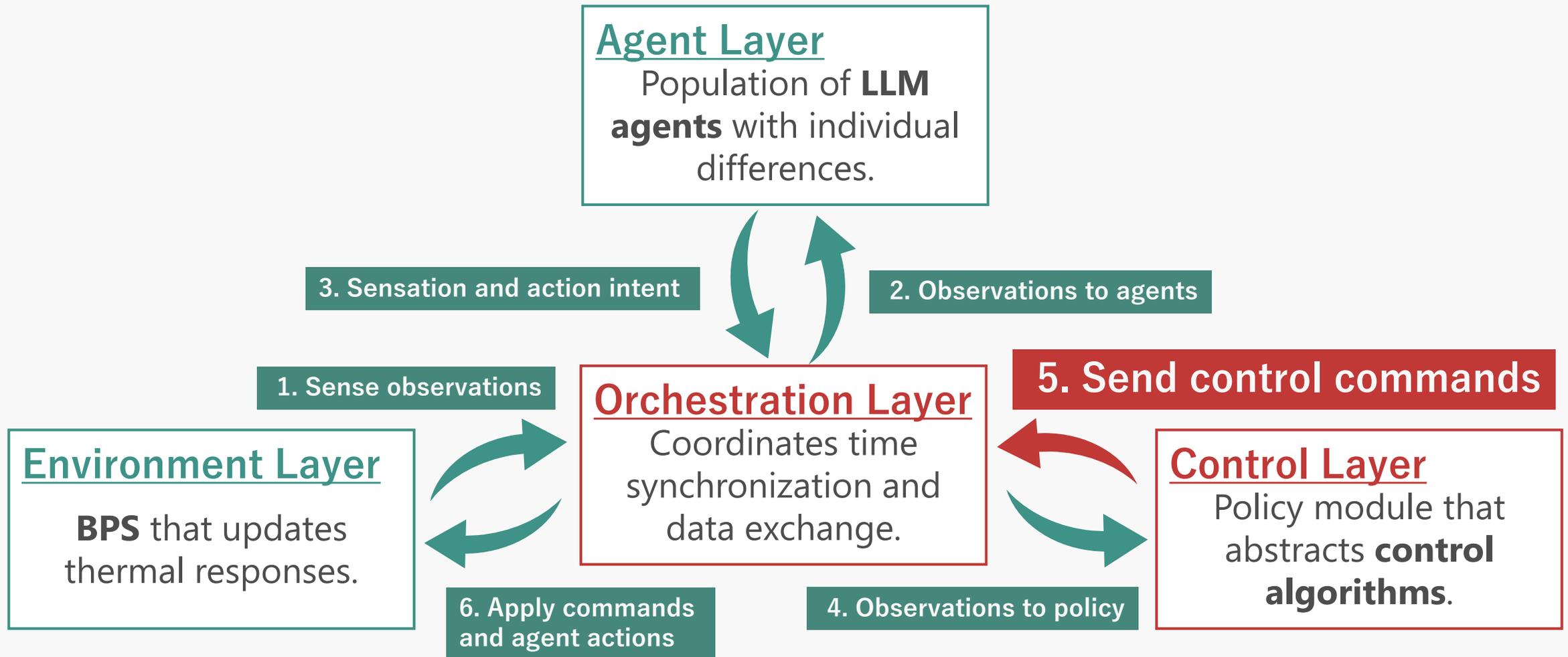
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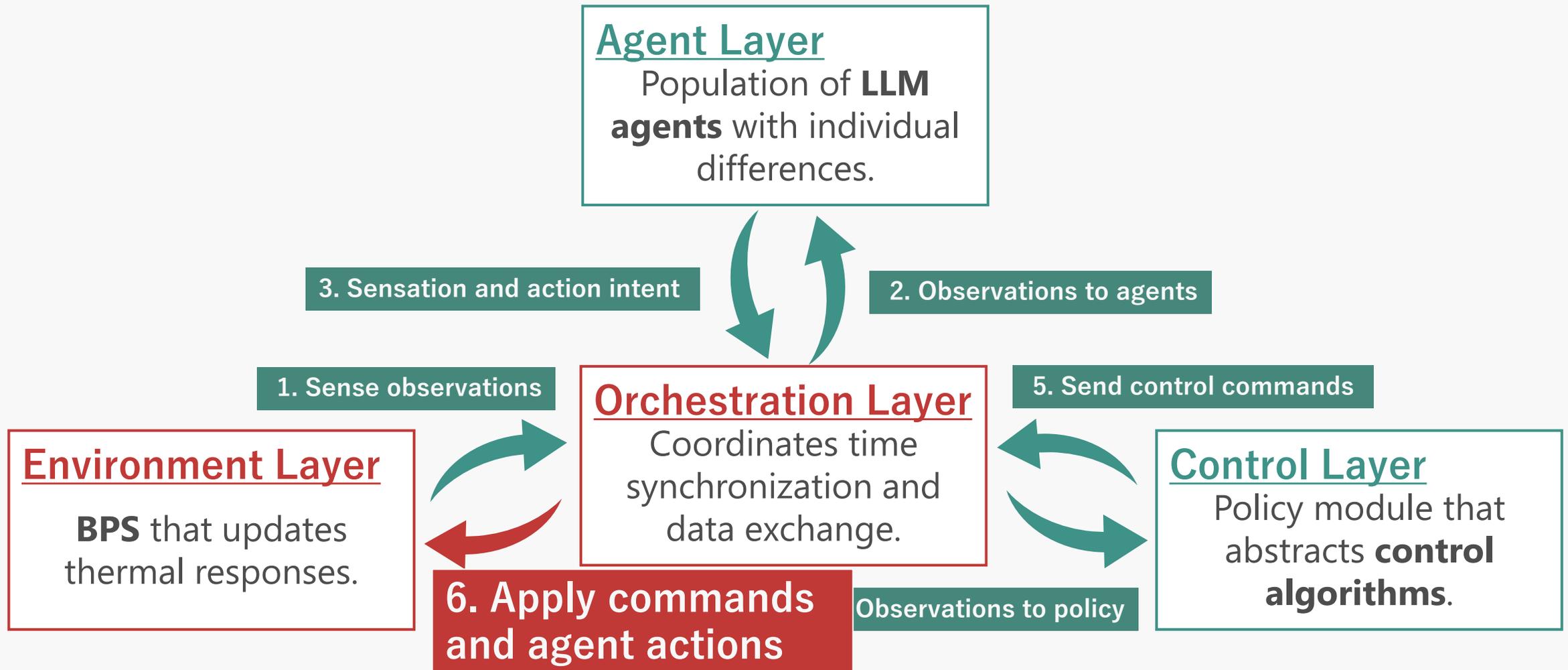
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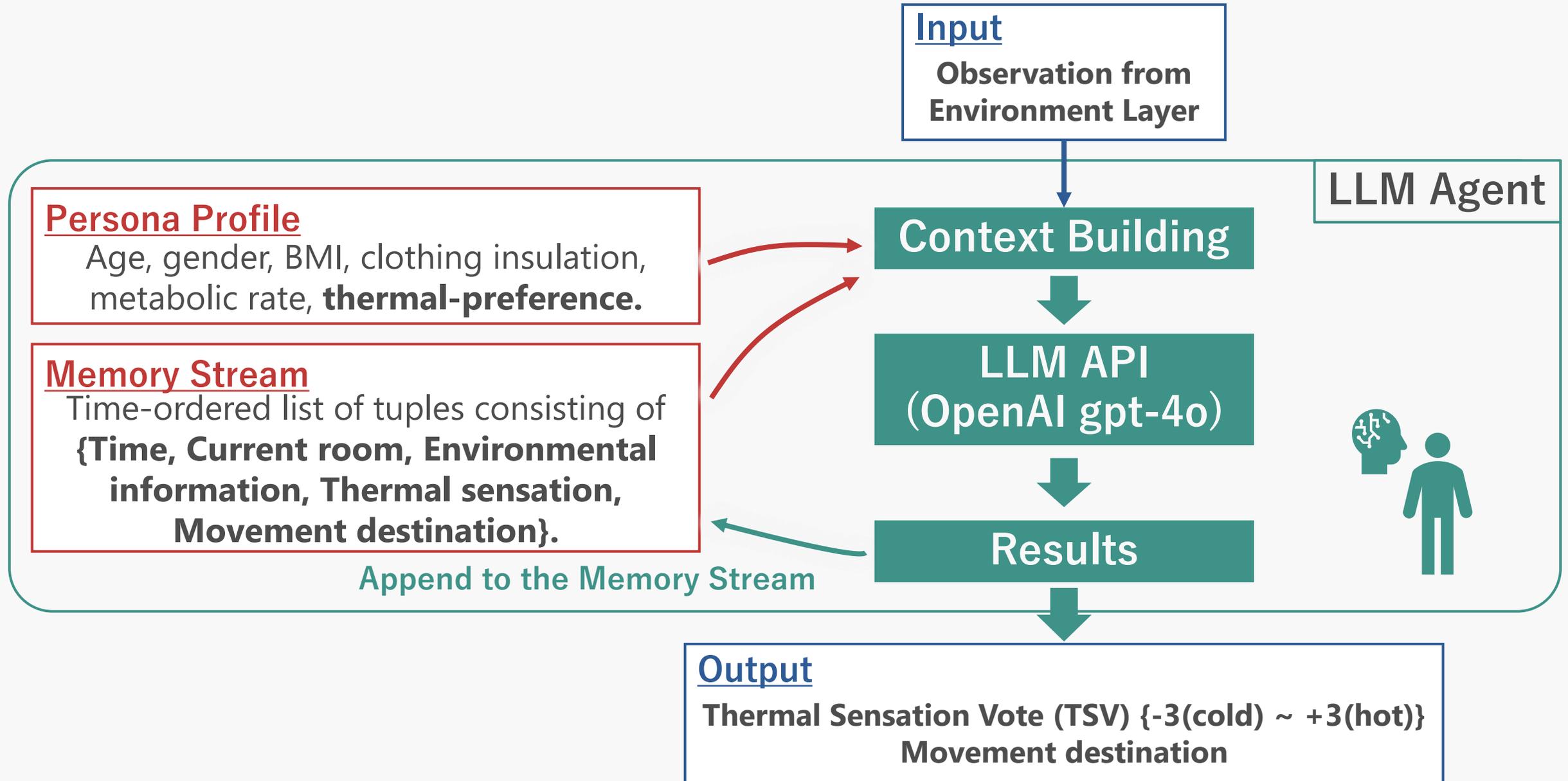


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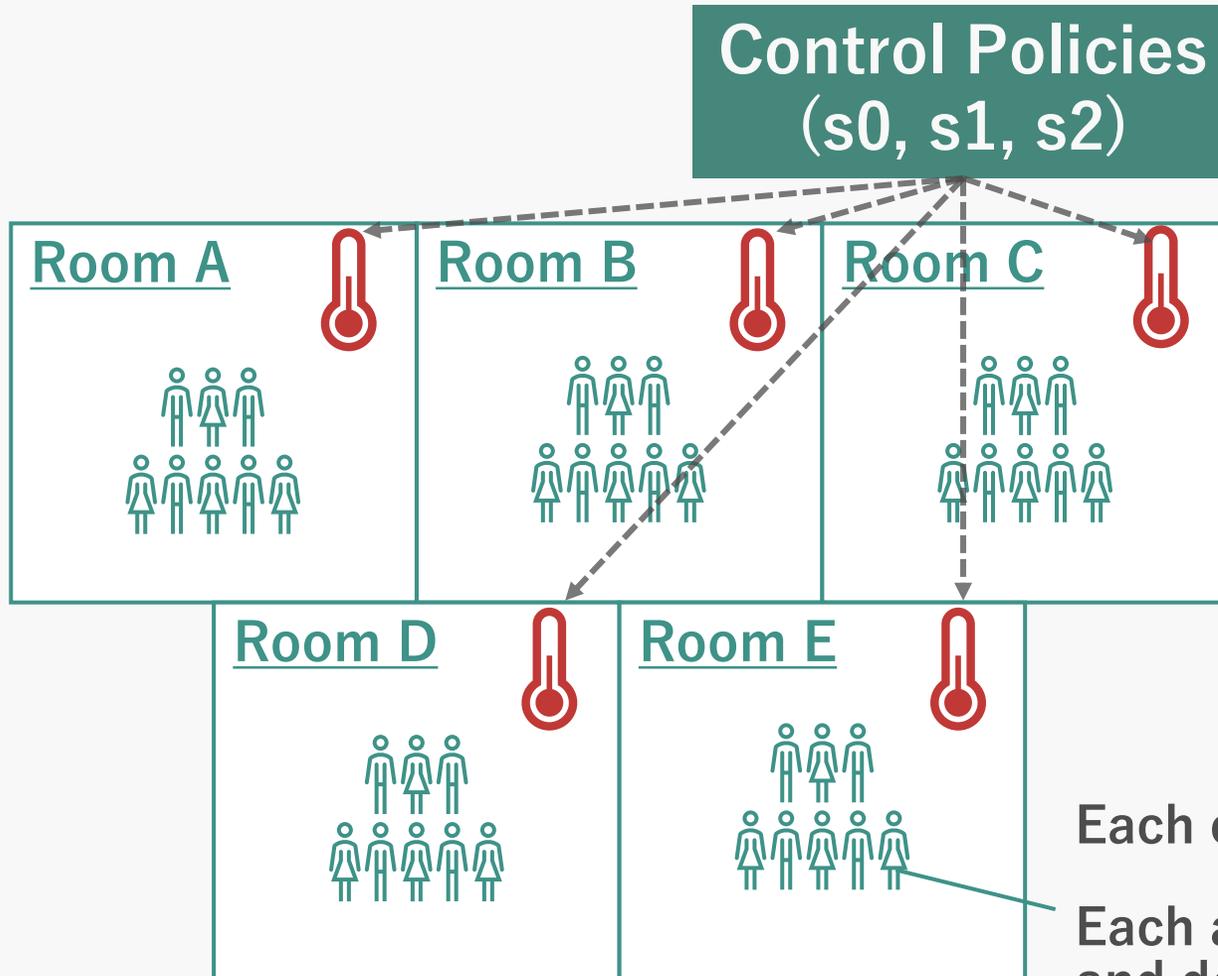


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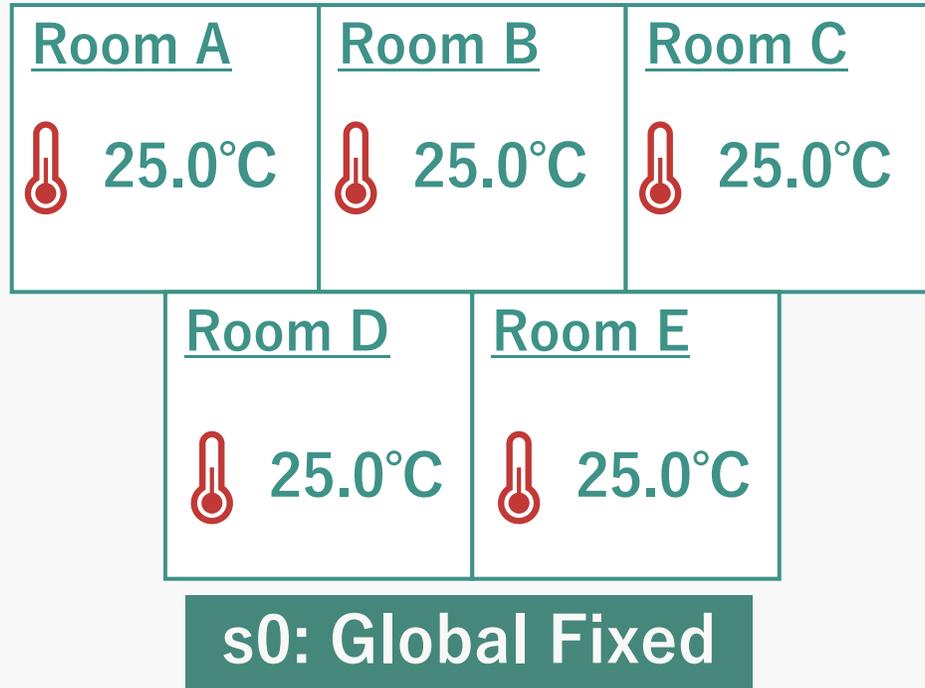
Adjusting per-room setpoints using control policies to maximize occupant comfort.



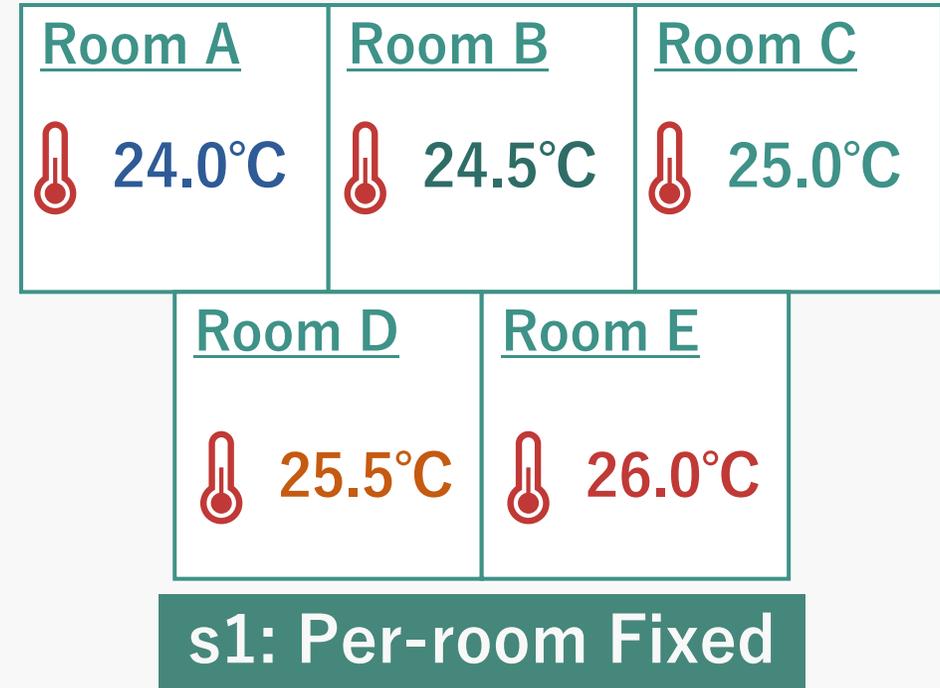
- Environment: A five-room building.
- Season: Summer
- Population: 50 occupants overall.
- Horizon: 10 hours (8 am to 6 pm).
- BPS : EnergyPlus 24.1.0

Each occupant is represented by an LLM agent.

Each agent outputs a Thermal Sensation Vote (TSV) and decide whether to move.



- Conventional uniform-control.
- No agent-derived information is used, and actions do not change over time.



- Deliberately creates spatial thermal diversity.
- Passively leverages autonomous agent relocation for comfort improvement.

s2 adapts each room's setpoint temperature " t " using the UCB() algorithm.

UCB algorithm

$$UCB_t = \bar{R}_t + c \sqrt{\frac{2 \ln n}{n_t}}$$

- Play the arm " t " that maximizes UCB_t



- Update UCB_t score

\bar{R}_t : The empirical mean reward of arm " t "

n : The total number of trials

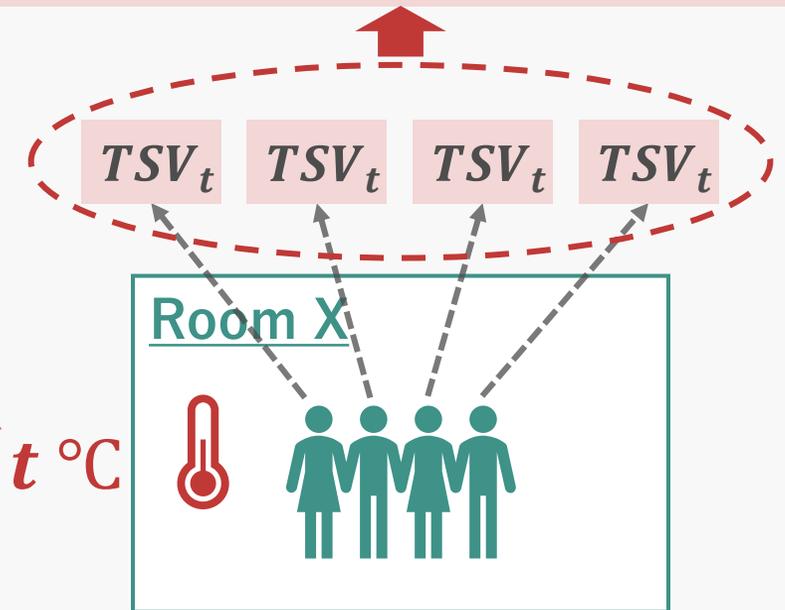
n_t : The number of pulls of arm " t "

c : A tunable parameter ($c \in \{1.0, 0.5, 0.3, 0.1\}$)

A larger c prioritizes exploration.

Reward $R_t \in [0, 1]$

$$(R_t = \bar{S}_t, S_t = \max \left\{ 0, 1 - \frac{|TSV_t|}{2} \right\})$$



Thermal Sensation Vote (TSV)
 $\in \{-3, -2, -1, 0, +1, +2, +3\}$

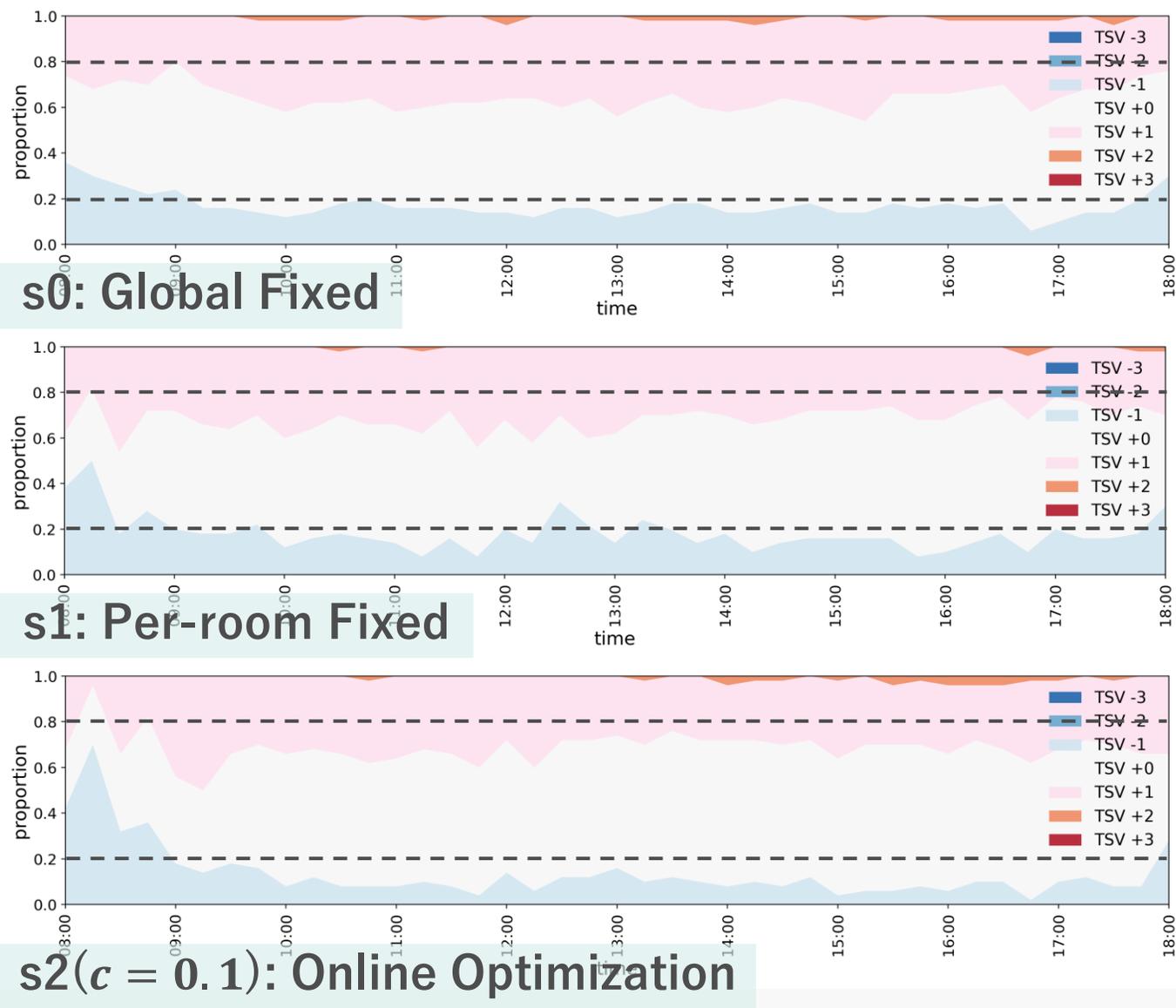
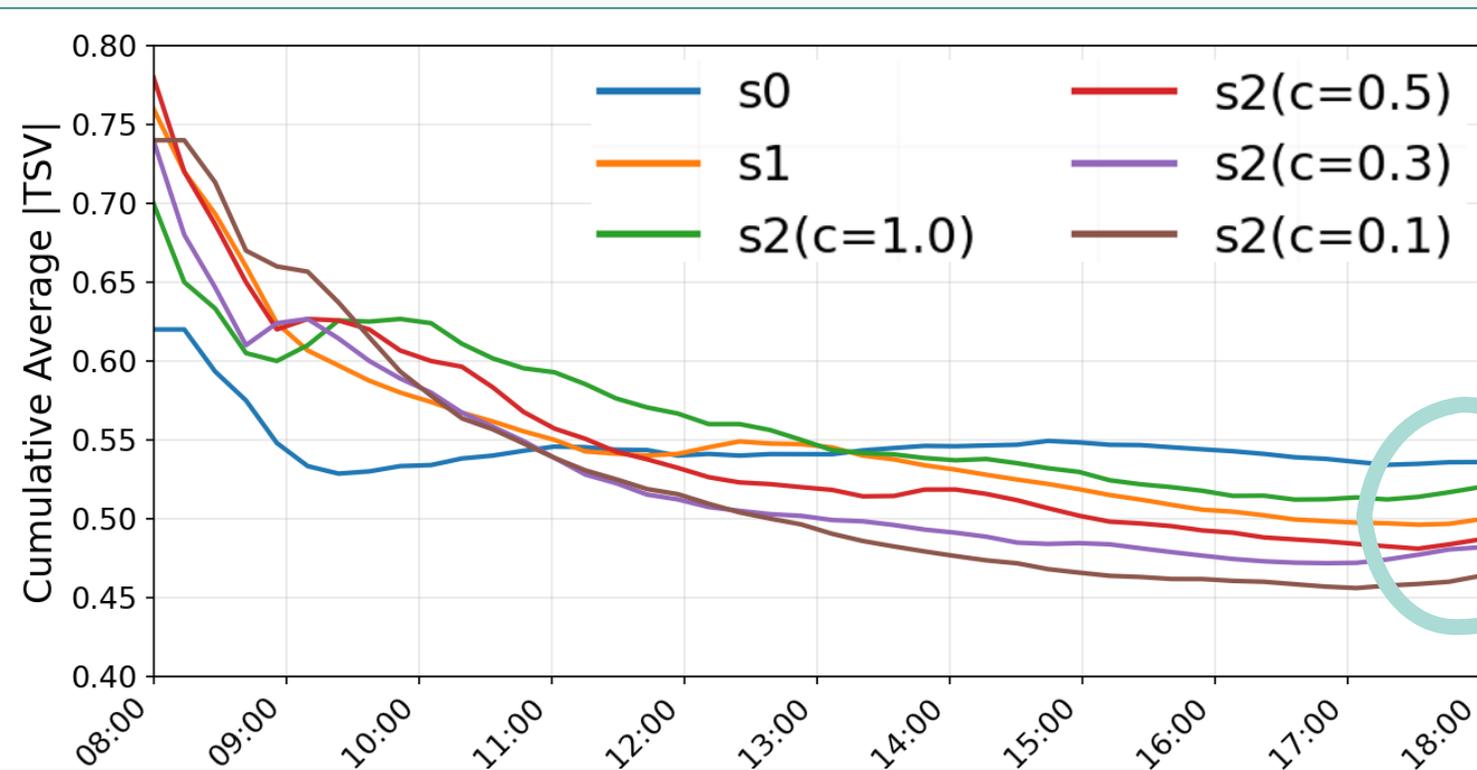


Fig: TSV distribution over time

- **s0: Lowest neutral share; extreme votes frequent (e.g., $TSV \geq 2$).**
 - Occupants have different thermal preferences.
- **s1: Yields larger neutral ($TSV = 0$) share and fewer extreme votes than s0.**
 - Occupants autonomously move between rooms in search of comfort.
- **s2($c = 0.1$): Achieve highest neutral share.**
 - Online optimization improves occupant comfort.

* c : exploration coefficient

- s0: discomfort persists due to occupant heterogeneity.
- s1: improves comfort via spatial diversity and passive self-selection.
- s2: decline in discomfort, but slow initial gains.



s2, with a tuned " c " and sufficient horizon, improves cumulative comfort.

s0: Global Fixed
s1: Per-room Fixed
s2($c \in \{1.0, 0.5, 0.3, 0.1\}$): Online Optimization

Fig: Cumulative average |TSV| by policy.

Conclusion

- Proposed framework successfully couples LLM agents with BPS.
- It establish a policy-agnostic evaluation testbed that allows for fair comparison of HVAC control strategies.
- It has the potential to be applied to real-world HVAC operation.

Future Work

- Extend scenarios (multiple buildings, climates, longer horizons).
- Conduct multi-objective studies (optimizing comfort, energy, fairness).
- Validate external validity using real occupant data.