Land Model and Biogeochemistry Working Groups

Local Urban Climate-Aware HVAC Control via Reinforcement Learning

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Urbanization changes land surface processes

Radiation

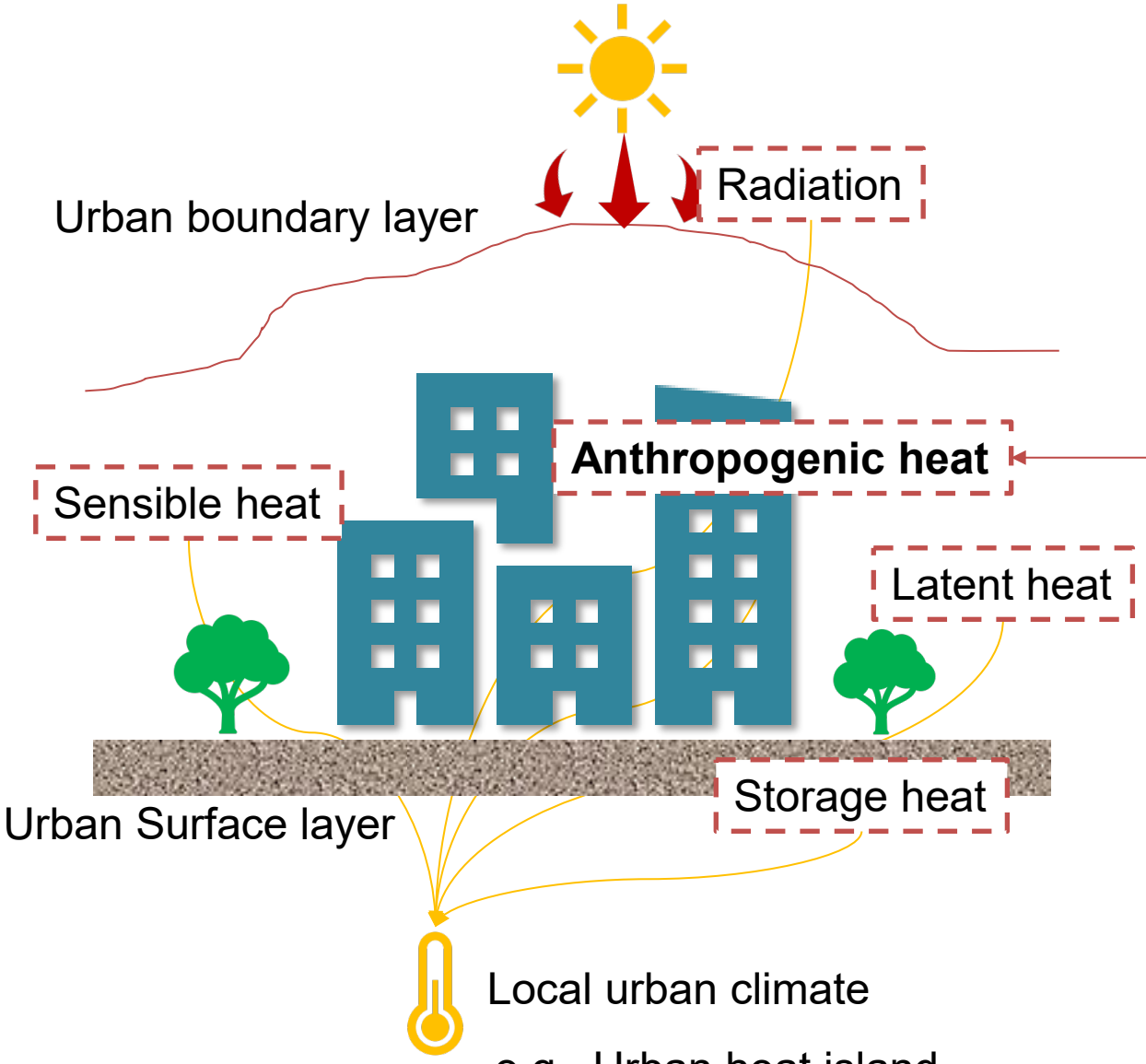
Turbulence

Anthropogenic emission

…

Source: Urban Climates (Cambridge University Press)

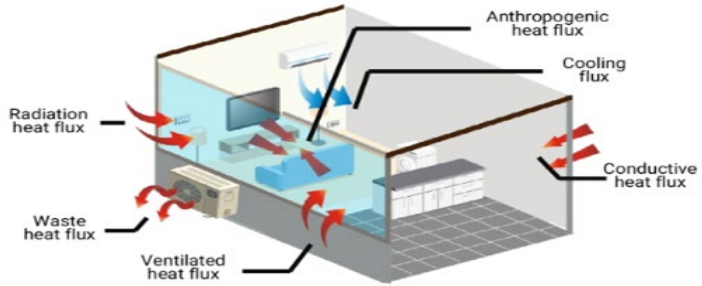
Heat from HVAC is important for urban climate



Human affected

1. **Building heat**
2. Transportation heat
3. Human bio
4. …

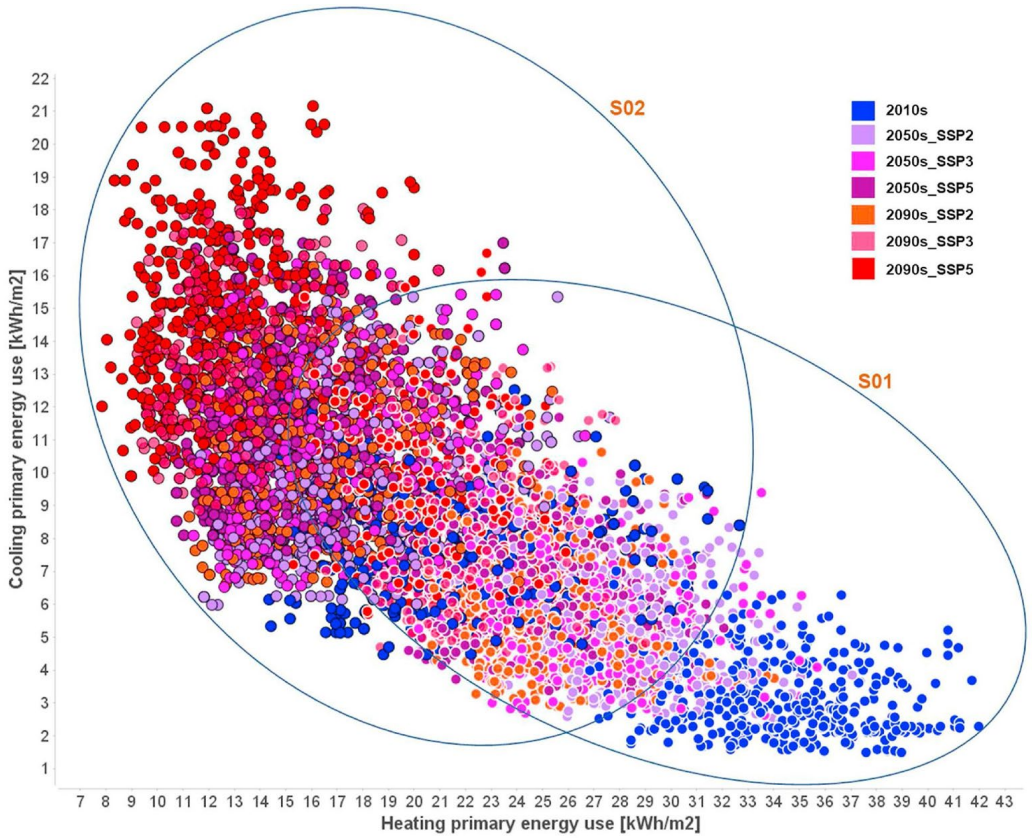
HVAC of Building heat



40%

HVAC system
among building energy

We need dynamic HVAC control



Source: j.buildenv.2022.109397

Climate Change Challenges the HVAC Systems

heating-dominated

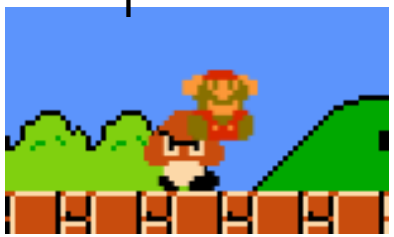
↓

cooling-dominated

We need dynamic HVAC control.

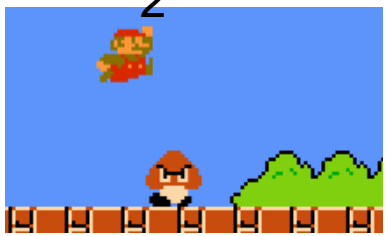
Reinforcement Learning (RL)

Try 1



Game over

Try 2



Live

But 0 PTS

Try 3

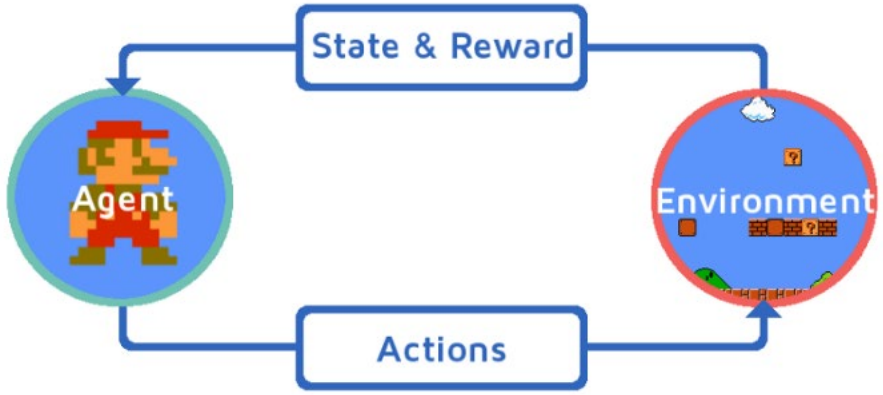
We learn how to kill the mushroom with rewards

Learned

If we see  , Jump to kill to get 

State | Action | Reward

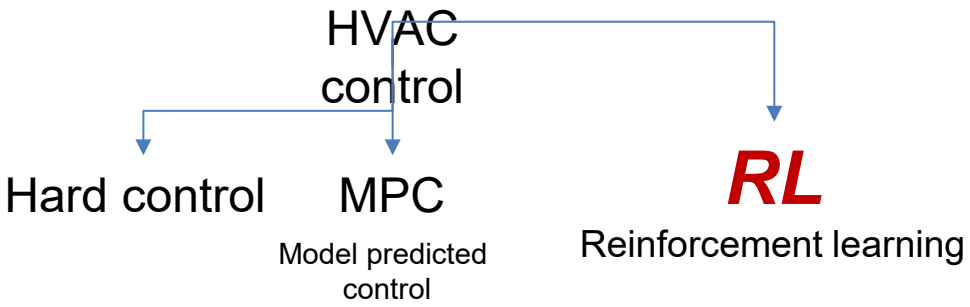
Reinforcement Learning



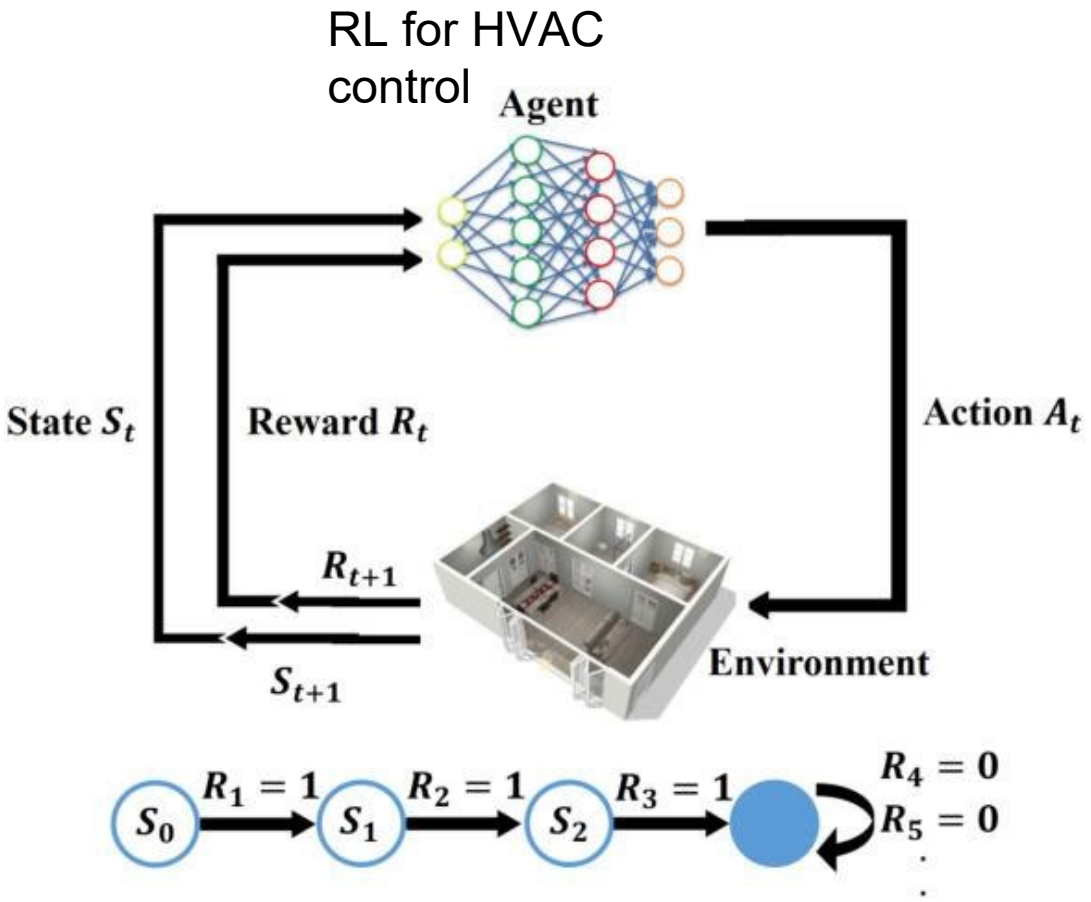
Source: https://imgtec.eetrend.com/blog/2019/100017372.html

RL is an efficient and scalable solution for HVAC control

No additional infrastructure



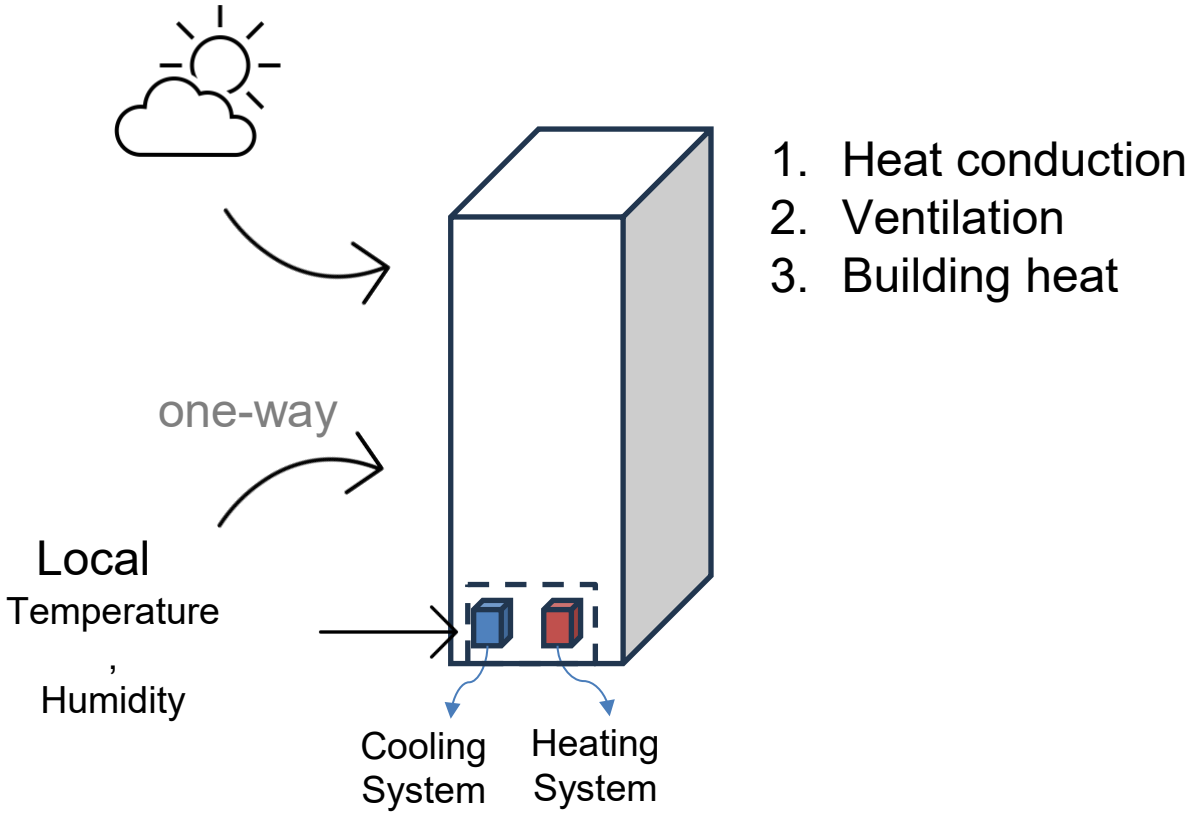
Effective, low cost, keep indoor comfort



Source: 10.1016/j.jobe.2024.110085

HVAC Control ⇄ Local Urban Climate ?

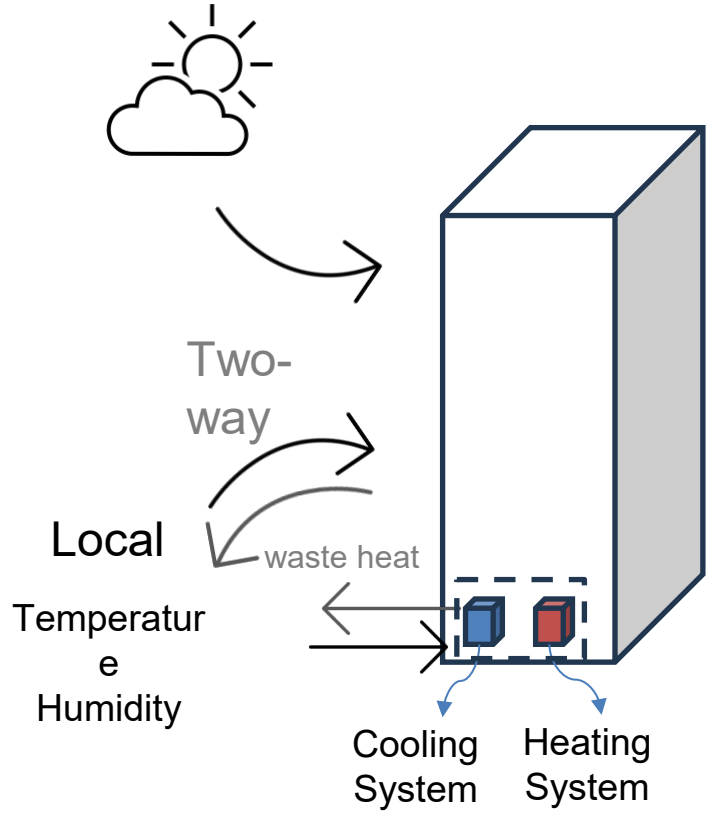
one-way simulation



1. Heat conduction
2. Ventilation
3. Building heat

Previous paradigm for RL HVAC control

two-way simulation



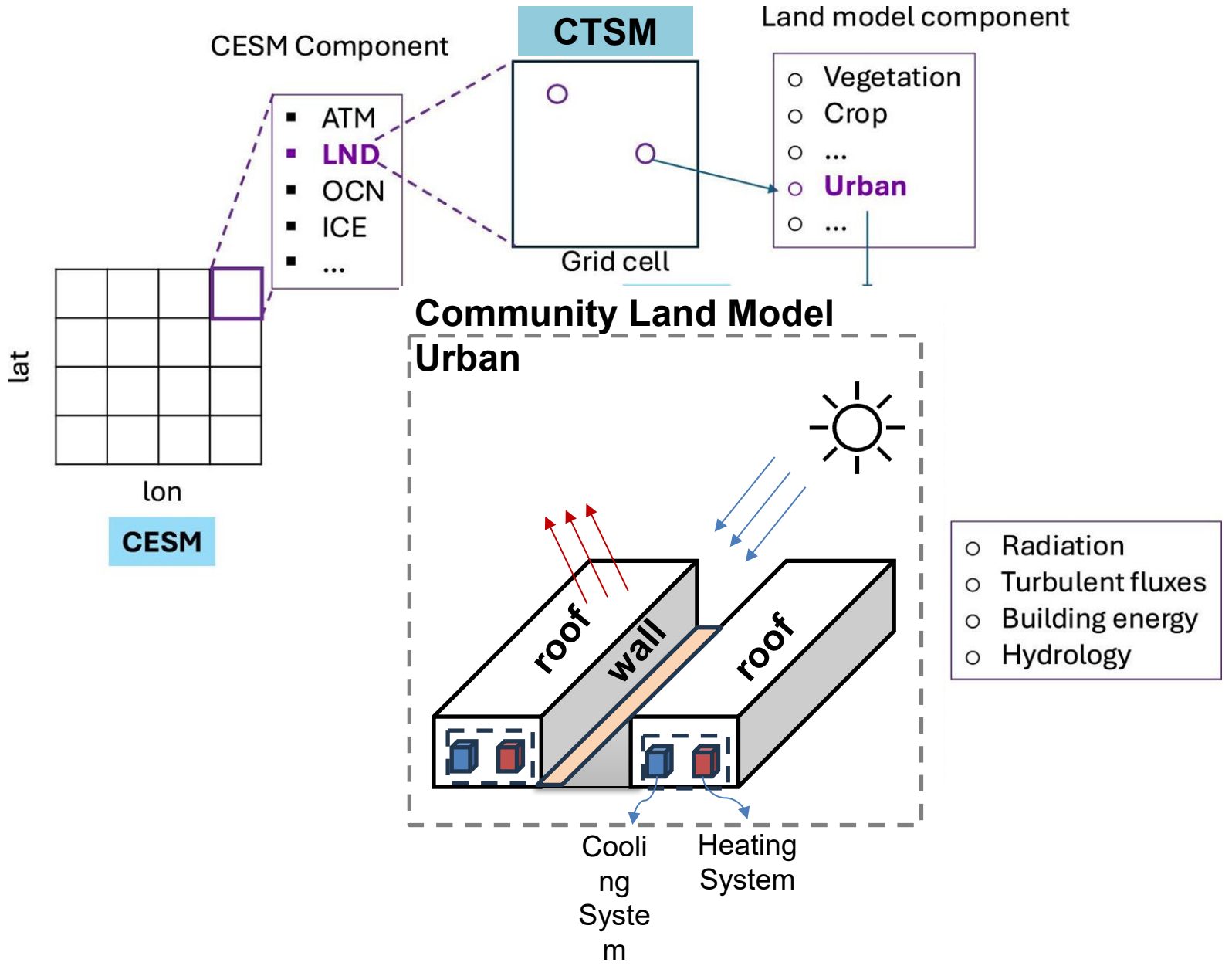
40%
underestimation of cooling

10%
overestimation of heating

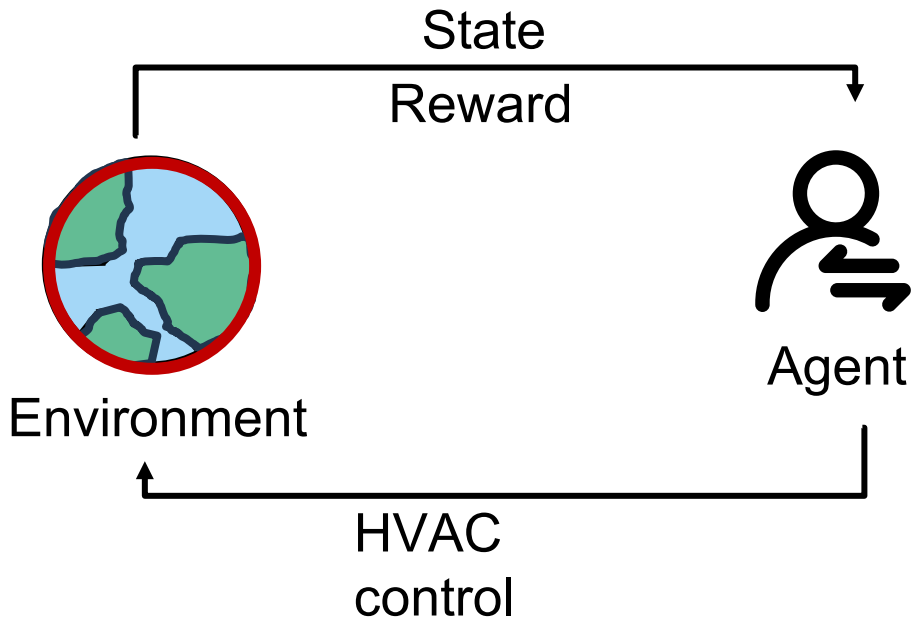
0.5°C
reduction in local air temperature (heat pump)

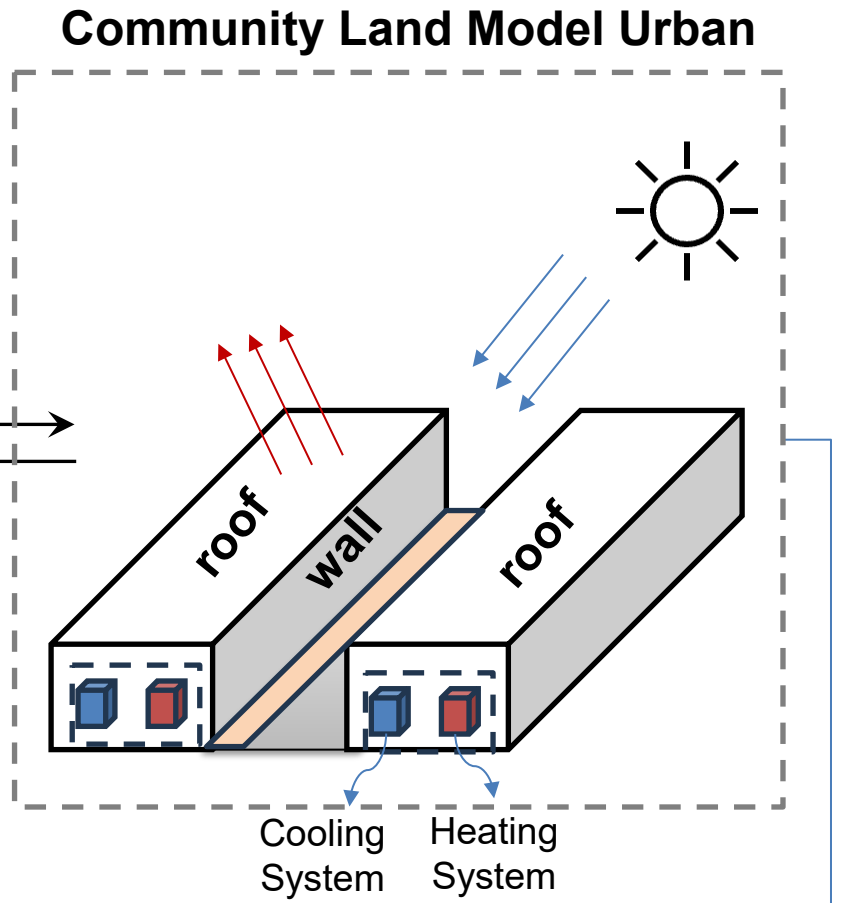
HVAC control ⇄ local urban climate

Modelling urban and building energy in CTSM



Reinforcement Learning (RL) Framework





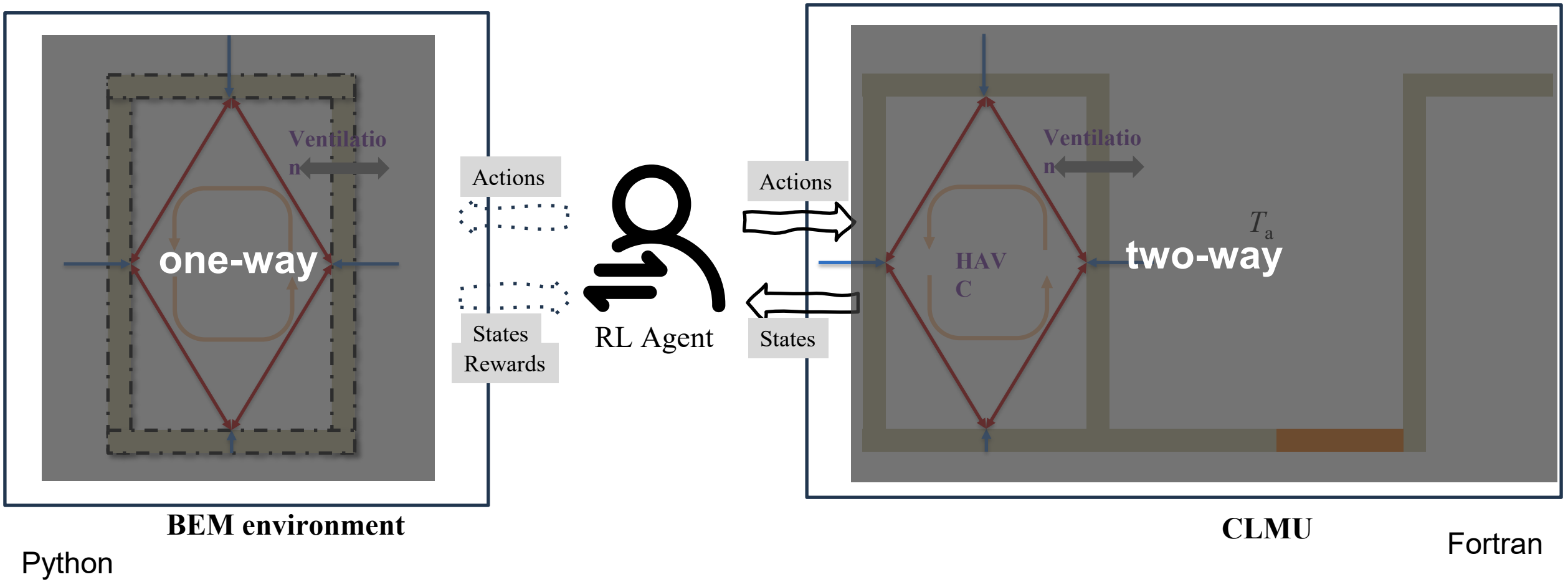
Consider current and future to get the maximum reward

- Modeling local urban climate
- Modeling building energy and HVAC

Training Framework

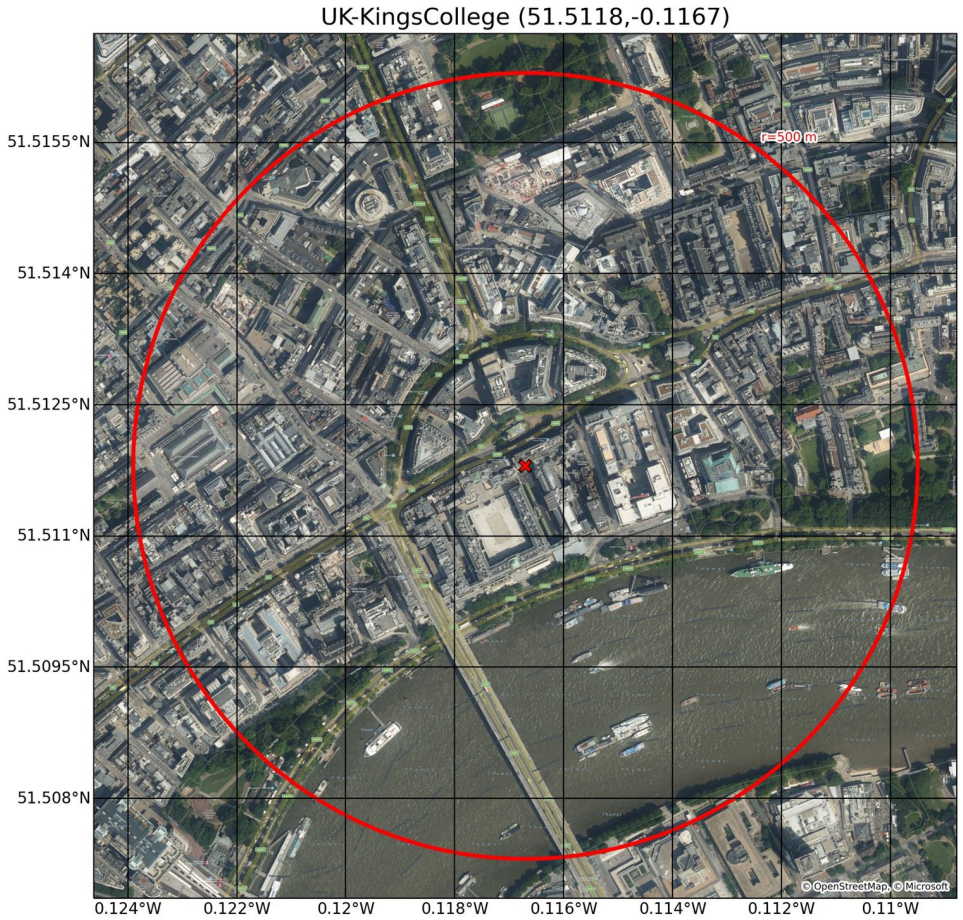
Surrogate model

- Time consuming simulation
- Fortran based model



Agent Objective: using less cost to maintain indoor thermal comfort

Case study: heat-pump retrofit and RL heating control in London



UK London

Heating system of **heat-pump**

Waste heat from heating system will put into urban canyon

$$Q_{waste} = F_{heating} * (COP^{-1} - 1)$$

$$COP = 0.07 * T_{ac} + 3.2$$

Determine the performance of heating system

heating set point temperature
indoor air temperature
local urban air temperature
electricity prices (n, n+4) intervals
sin and cos time embedding

Agent

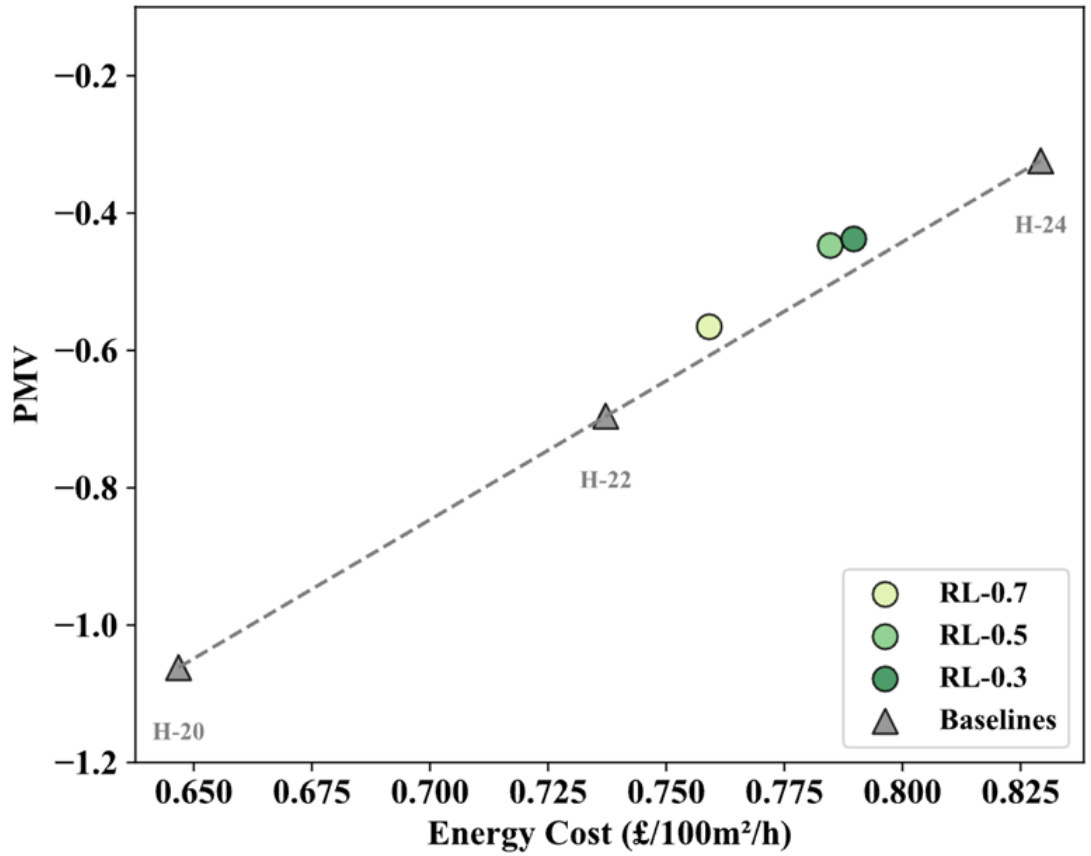
heating set point temperature

RL balances the thermal comfort and energy cost

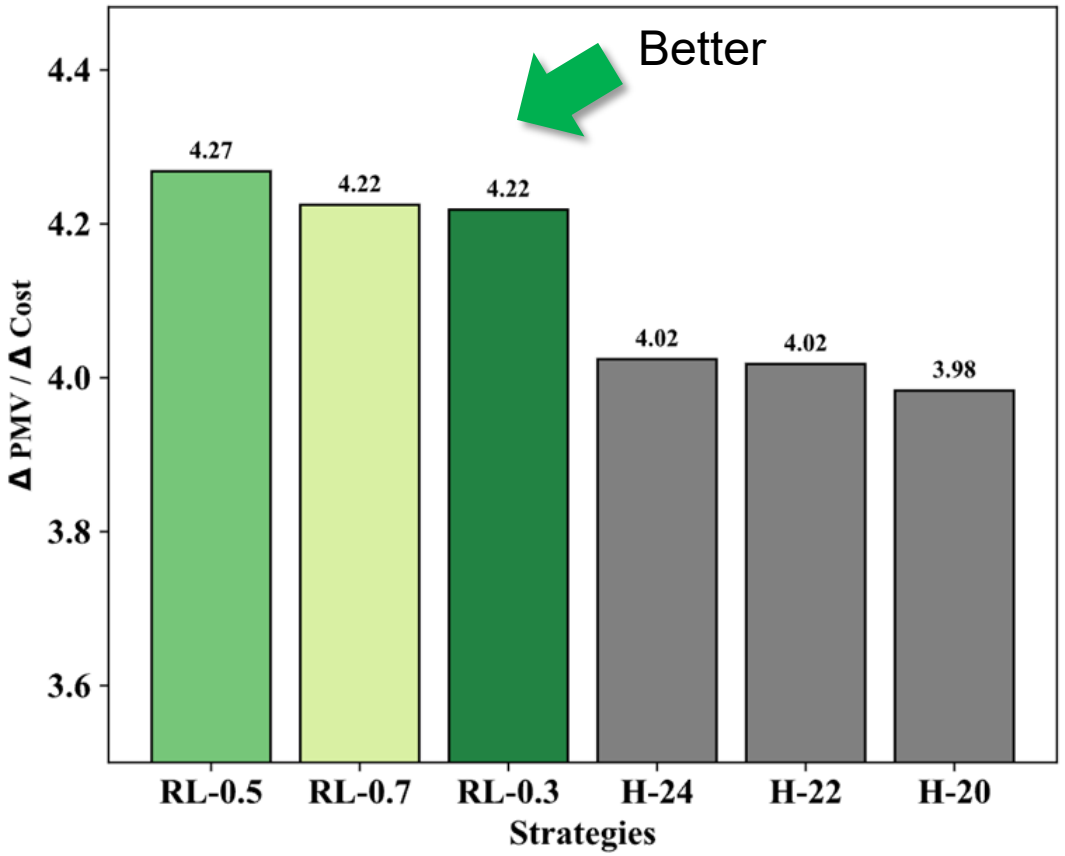
Comfortable (close to 0)

Indoor thermal comfort index

Higher cost, greater thermal comfort



RL has higher cost-effectiveness

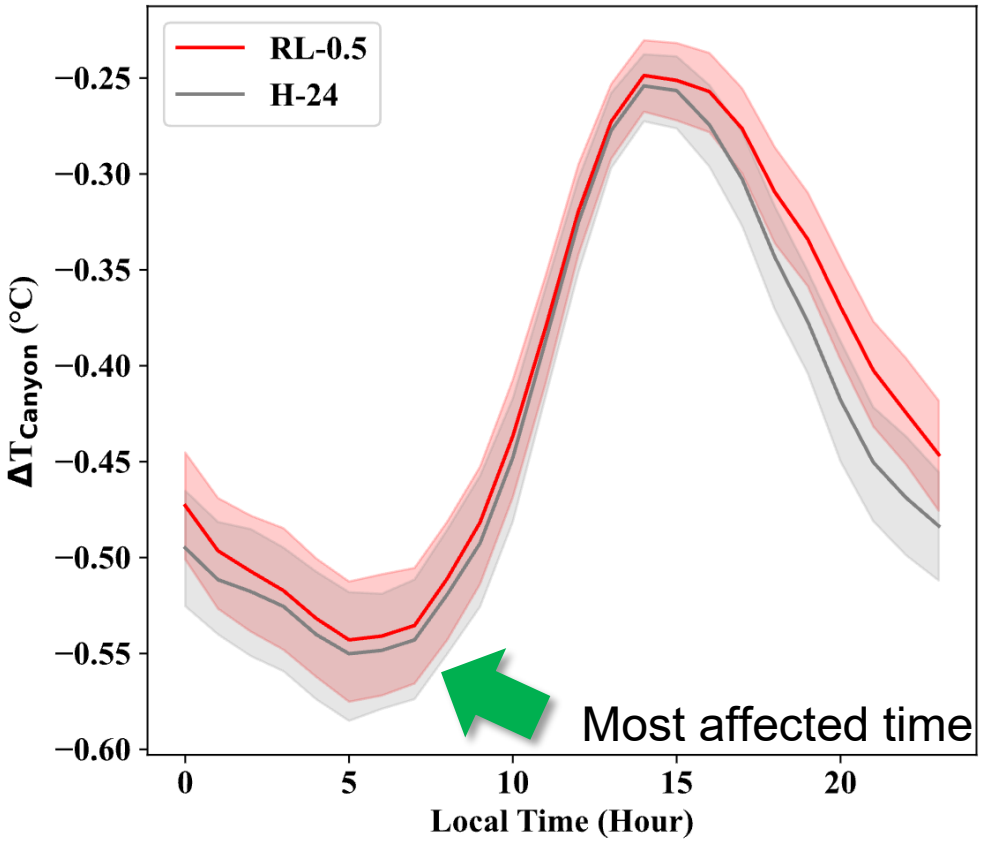


~6% improvement in cost-effectiveness

Weight: index for balancing the cost and thermal discomfort, higher means more concern about the cost

Two-way interaction affects outdoor thermal environment

Less energy use □ less environmental footprint induced by two-way interaction



Two-way interaction makes a cooler and wetter environment

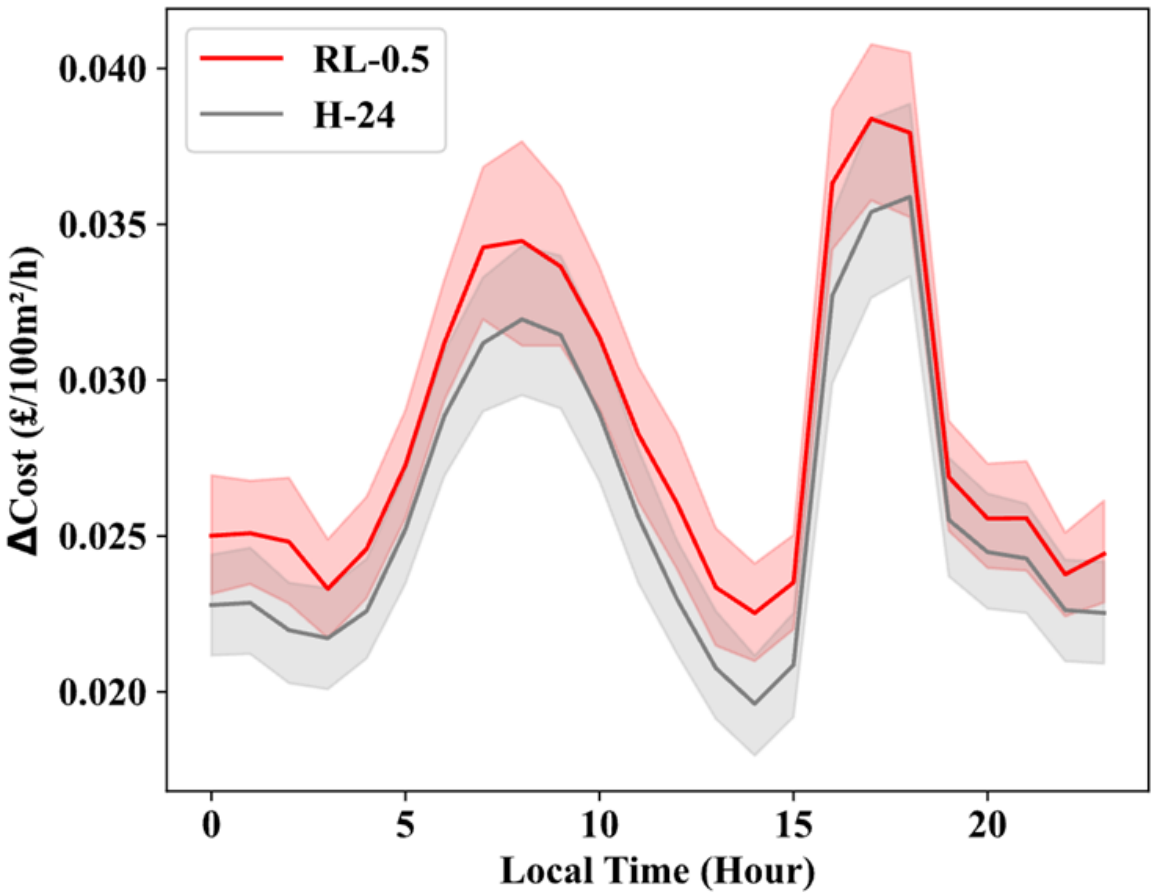
	T_{canyon}(°C)			RH (%)		
	OFF	**ON**	**Δ**	**OFF**	**ON**	**Δ**
H-20	6.913	6.552	-0.361	71.293	72.916	1.623
H-22	6.983	6.585	-0.398	70.868	72.680	1.812
H-24	7.055	6.625	-0.430	70.451	72.415	1.964
RL-0.3	7.021	6.605	-0.416	70.651	72.473	1.822
RL-0.5	7.017	6.606	-0.411	70.676	72.480	1.804
RL-0.7	6.997	6.591	-0.406	70.793	72.579	1.786

Improve efficiency!!!

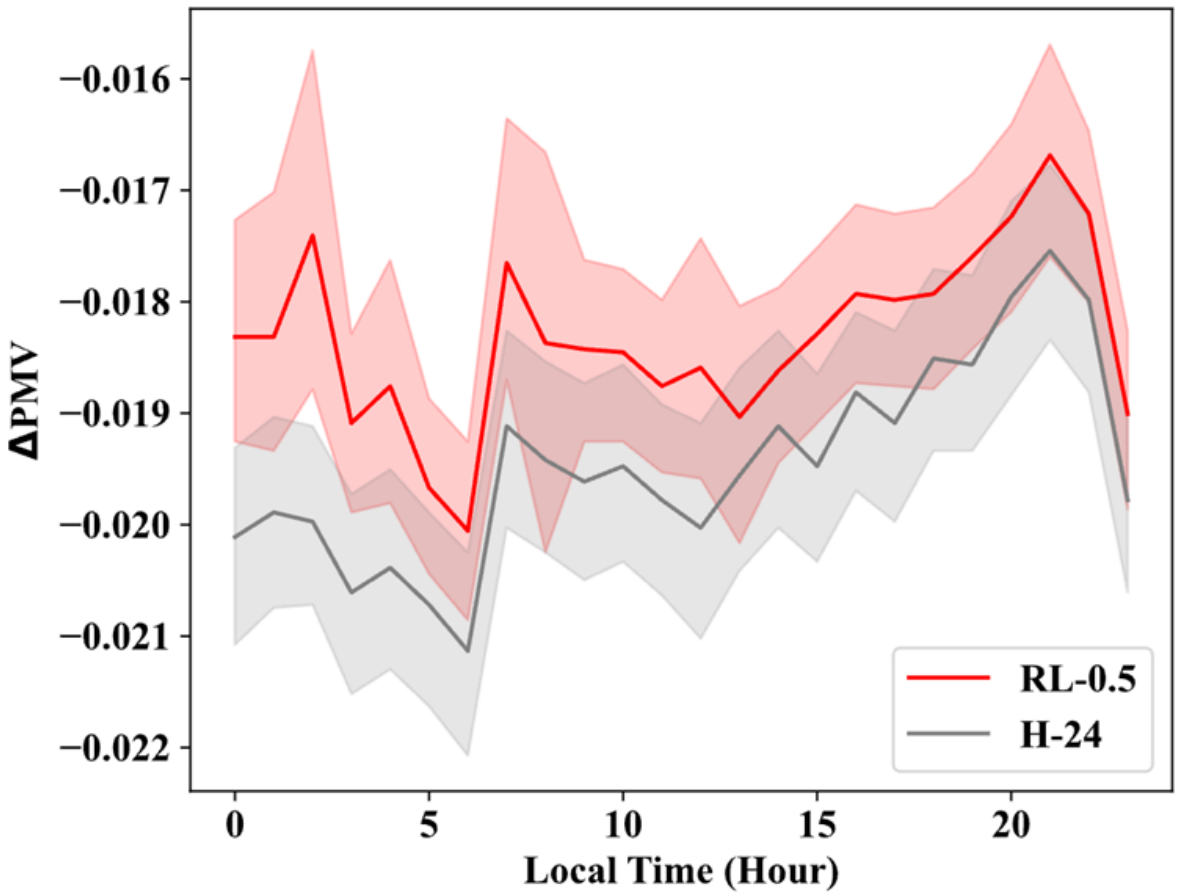
Δ = Simulation(with waste heat) - Simulation(no waste heat)

Cost and thermal comfort affected by two-way interaction

RL cost is more affected

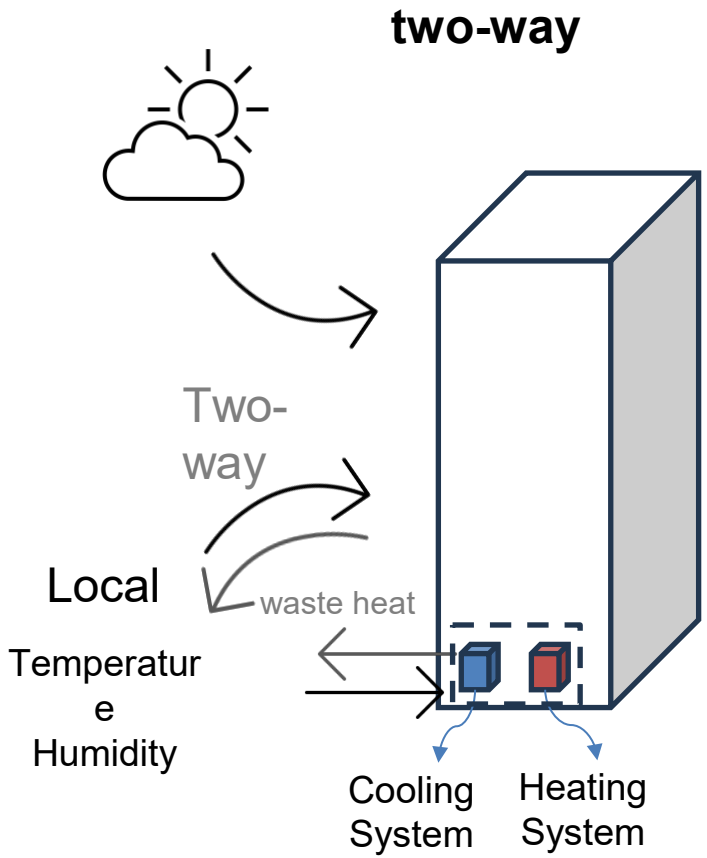


RL PMV is less affected



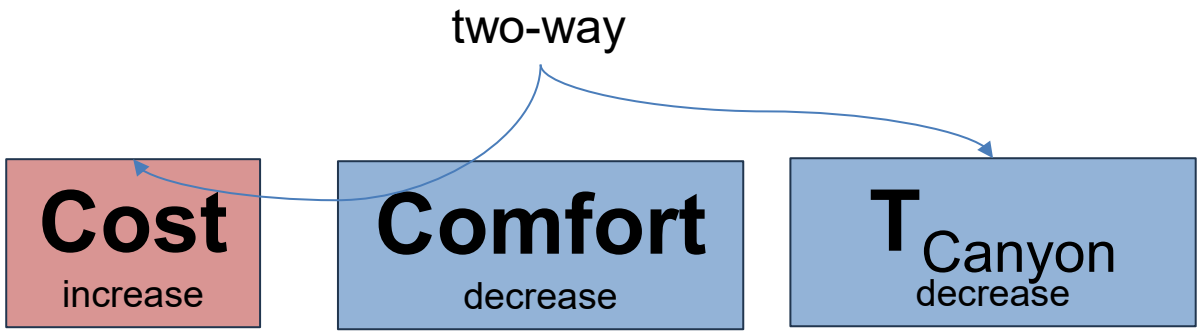
3.60% difference in cost of RL
2.95% difference in cost of H-24

Conclusions



RL Higher cost-effectiveness

RL avoids extreme cost



Next step: regional simulations

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