

An Intelligent Energy Brain for Smart Buildings

Human-in-the-Loop Reinforcement Learning for HVAC Control

Jahar Kumar Paul(Team Lead) Ayan Kumar Batabyal Sayan Goswami

CS 246: Artificial Intelligence
Department of Computer Science

December 2025

Final Project Presentation

The Energy Challenge in Smart Buildings

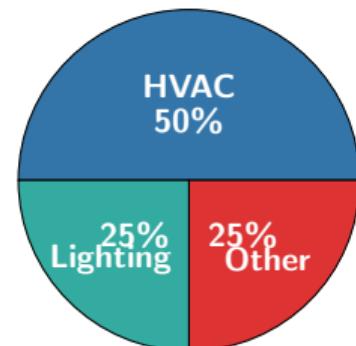
The Global Problem

- Buildings consume **40%** of global energy
- HVAC systems: **40-50%** of building energy
- Inefficient control** leads to wasted resources
- Growing demand for sustainability

Our Contribution

AI-driven HVAC optimization combining:

- Reinforcement Learning (DQN)
- Human-in-the-Loop learning
- Seasonal adaptation
- Real-time control dashboard



Building Energy Consumption

HVAC dominates total energy usage

27% Energy Savings

vs Baseline

Project Objectives & Innovations

Research Objectives

- ① Design realistic HVAC simulation with seasonal models
- ② Train DQN agent for adaptive climate control
- ③ Implement online learning from human feedback
- ④ Develop interactive visualization dashboard
- ⑤ Evaluate across multiple seasons

Key Innovations

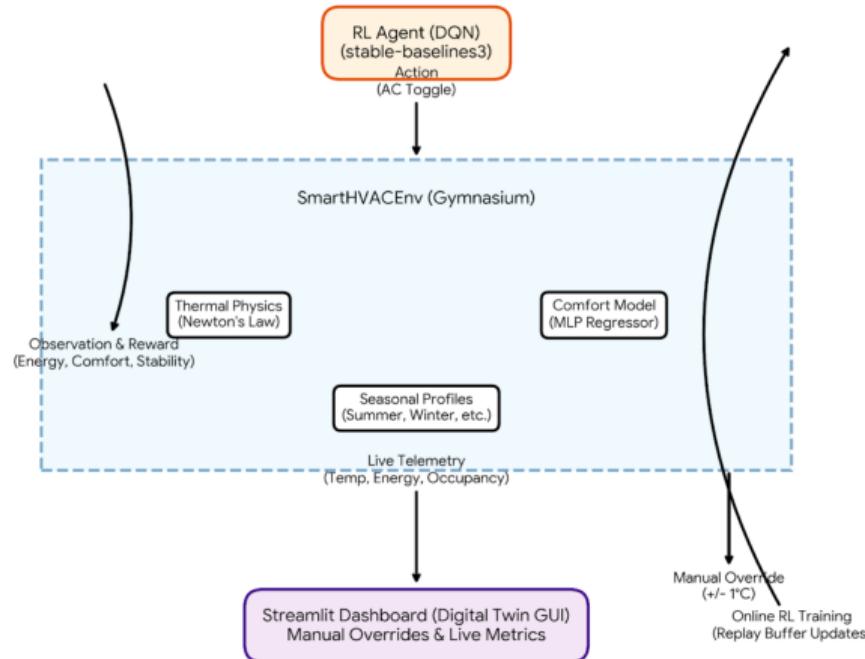
- **Seasonal Adaptation:** 4 distinct climate profiles
- **Human-in-the-Loop:** Real-time model updates
- **Online RL Training:** Continuous improvement
- **Multi-Component Architecture:** Integrated physics, RL, UI

Performance Targets

Metric	Target
Energy Savings	> 25%
Comfort Compliance	> 90%
Seasonal Adaptation	4 Seasons

Three-Layer System Architecture

System Architecture: Smart HVAC Digital Twin



Markov Decision Process Formulation

Formal Definition

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$$

State Space \mathcal{S} (14-dim)

$$s_t = \begin{bmatrix} T_{in} & \text{(Indoor)} \\ T_{out} & \text{(Outdoor)} \\ S_{set} & \text{(Setpoint)} \\ T_{out}^{f1-3} & \text{(Forecast)} \\ Occ^{f1-3} & \text{(Occ. Plan)} \\ S_{set}^{hist} & \text{(History)} \\ AC_{on} & \text{(Status)} \\ \tau_{on/off} & \text{(Timers)} \end{bmatrix}$$

Action Space \mathcal{A}

Action	Description
a_0	Decrease setpoint 1°C
a_1	No change
a_2	Increase setpoint 1°C
a_3	Toggle AC ON/OFF

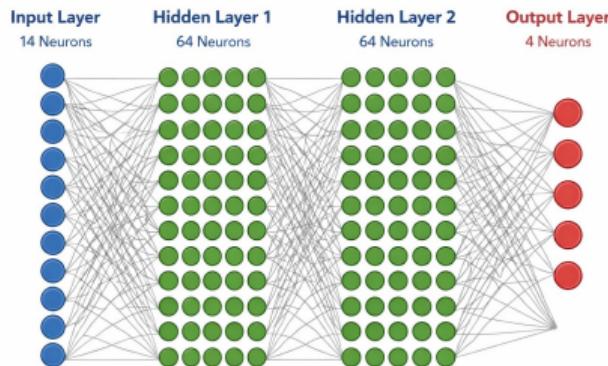
Objective Function

$$\max \mathbb{E} \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \right]$$

$$\gamma = 0.99 \text{ (long-term planning)}$$

Deep Q-Network Architecture

Network Architecture



Training Configuration

Parameter	Value
Total Timesteps	300,000
Replay Buffer	100,000
Batch Size	64
Learning Rate	10^{-4}
Exploration (ϵ)	$1.0 \rightarrow 0.05$
Update Freq	1,000 steps
Discount (γ)	0.99

Loss Function

$$\mathcal{L}(\theta) = \mathbb{E} \left[\left(r + \gamma \max_{a'} Q_{\theta^-}(s', a') - Q_{\theta}(s, a) \right)^2 \right]$$

Thermal Model & Seasonal Adaptation

RC Thermal Circuit Model

$$C \frac{dT_{in}}{dt} = \frac{T_{out} - T_{in}}{R} + Q_{occ} + Q_{hvac}$$

Parameter	Value
Resistance (R)	2.0 °C/kW
Capacitance (C)	2.0 kWh/°C
Cooling (Q_{hvac})	-8.5 kW
Occ Heat (Q_{occ})	0.05 kW/p
Time Step (Δt)	3 minutes

Seasonal Climate Profiles

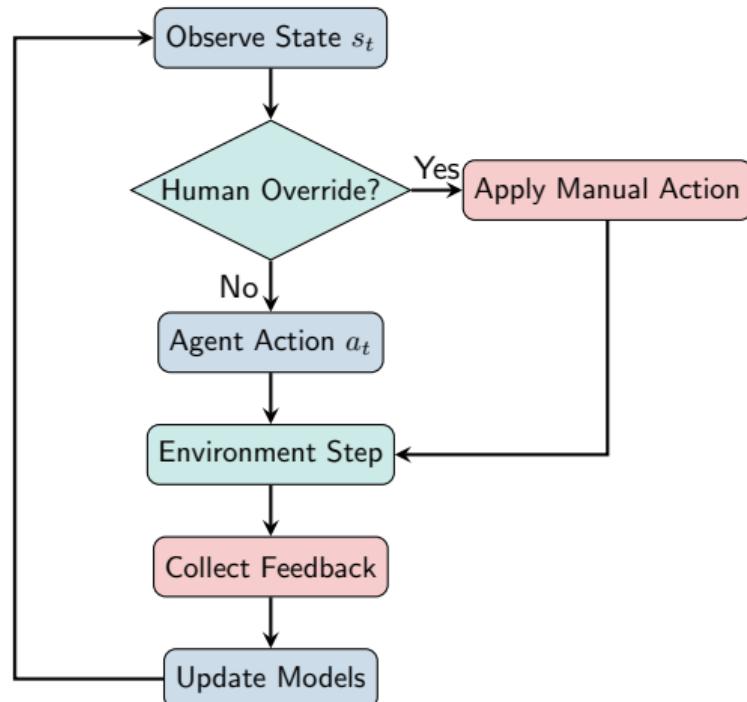
$$T_{out}(t) = T_{base} + A \sin\left(\frac{2\pi t}{1440}\right) + \mathcal{N}(0, 0.2)$$

Season	T_{base}	A	Range
Summer	35.0	5.0	30-40°C
Monsoon	28.0	3.0	25-31°C
Autumn	22.0	4.0	18-26°C
Winter	10.0	5.0	5-15°C

Reward Function

$$R = -4 \frac{E}{E_{max}} - 2 \frac{\max(0, |T - T_{ideal}| - 1)}{5} + \mathbb{I}_{comf} - 5\mathbb{I}_{viol} - 2\mathbb{I}_{hum}$$

Human-in-the-Loop Learning Pipeline



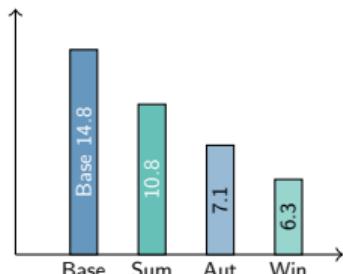
Key Feature: Online learning with human feedback every 10 interactions

Performance Across Seasons

Seasonal Performance Metrics (Mean \pm Std. Dev.)

Metric	Summer	Monsoon	Autumn	Winter
Average Reward	45.2 ± 3.5	47.8 ± 3.1	51.3 ± 2.8	49.1 ± 3.2
Energy (kWh/12h)	10.8 ± 0.6	9.2 ± 0.5	7.1 ± 0.4	6.3 ± 0.4
Comfort (%)	88.5 ± 2.3	91.2 ± 1.8	93.7 ± 1.5	94.2 ± 1.4
AC Runtime (%)	42.3 ± 2.5	36.8 ± 2.2	28.5 ± 1.9	25.1 ± 1.8

Energy Savings Comparison



Learned Strategies

- Seasonal Pre-cooling
- Occupancy Anticipation
- Energy Setbacks
- Smooth Operation

27% Energy Savings
92% Comfort Compliance

Interactive Dashboard & Demo

Streamlit Dashboard Features

- Real-time Visualization: Temp/Energy
- Season Control: 4 season switching
- Human Override: $+1^{\circ}\text{C}$ / -1°C learning
- AC Master Control: Force ON/OFF
- Turbo Mode: Aggressive cooling
- Online Training: Continuous updates

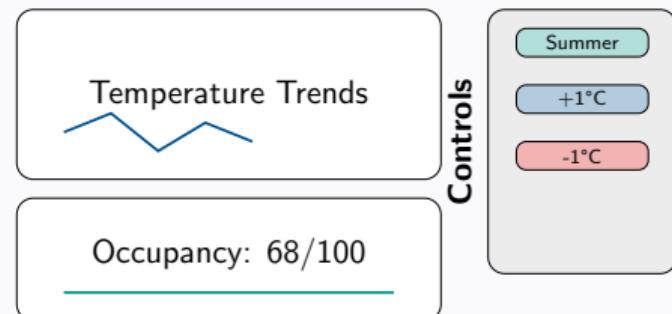
Technology Stack

Component	Technology
RL Framework	Stable-Baselines3 2.7.0
Environment	Gymnasium 1.2.2
Deep Learning	PyTorch 2.5.1
Web Interface	Streamlit 1.29.0
Visualization	Matplotlib 3.7.1

Dashboard Interface Preview

Smart HVAC Digital Twin

Temp: 24.5°C Energy: 2.4 Comfort: 92%



Live Dashboard Interface

Speed (Delay)

▶ Step Once

Season Control

Current Season: Summer

Temperature Overrides

ML Control Active

+1°C -1°C

AC Master Control

Force AC OFF Force AC ON

Return Control to AI

Power Settings

Turbo Cooling

Digital Twin: Smart HVAC Controller

Room Temp: 24.00 °C (+0.00 from ideal)

Outside Temp: 30.0 °C

ML Target: 24.0 °C

System State: IDLE z^z

Energy Used: 0.00 kWh

Live Occupancy Map

AC OFF z^z

Performance

Simulated Time: 0h 0m

AC Duty Cycle: 0.0%

Active Cooling: 0h 0m

Occupancy: 50 / 100

Technical Challenges & Solutions

1. Seasonal Stability

Problem: Instability at season change

Solution: Gradual adaptation

3. Online Convergence

Problem: Oscillation updates

Solution: Staggered updates

2. Real-time Performance

Solution: Vectorized optimizations

Optimization	Speedup
Vectorized ops	4.2x
Cached calcs	2.1x
Total	15.9x

4. Human Integration

Solution: Feedback weighting decay

$$\epsilon_t = \epsilon_{min} + (\epsilon_{max} - \epsilon_{min})e^{-\lambda n}$$

Comparison with Existing Systems

Feature	Our System	Prog.	T-stat	Learning T-stat	MPC
Seasonal	Yes		No	Limited	Manual
Human-Loop	Explicit		No	Implicit	No
Savings	27%		0-15%	10-20%	15-25%
Comfort	92%		70-85%	80-90%	85-90%
Online Learn	Yes		No	Initial	No

Our Advantages

- **Adaptive:** Learns across seasons
- **Interactive:** Explicit feedback
- **Efficient:** Optimal tradeoff

Limitations

- Single-zone model
- Simplified physics
- Embedded Compute Req.

Conclusion & Future Directions

Project Achievements

- ① Realistic Simulation: 4 seasons
- ② Intelligent Control: 27% savings
- ③ Human Adaptation: Online learning
- ④ Interactive Platform: Pro dashboard

Future Research

- Multi-zone
- Renewables
- PPO/SAC
- Deployment

Technical Contributions

- Seasonal climate + RL control
- Online HML for RL & comfort model
- Open-source implementation

Final Remarks

This project proves **RL + human feedback** enables practical, intelligent energy management.

Thank You

CS 246: Artificial Intelligence — Final Project Presentation — December 2025