Comparative Study of Deep Reinforcement Learning Algorithms for Residential HVAC Control

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Machine Learning Project

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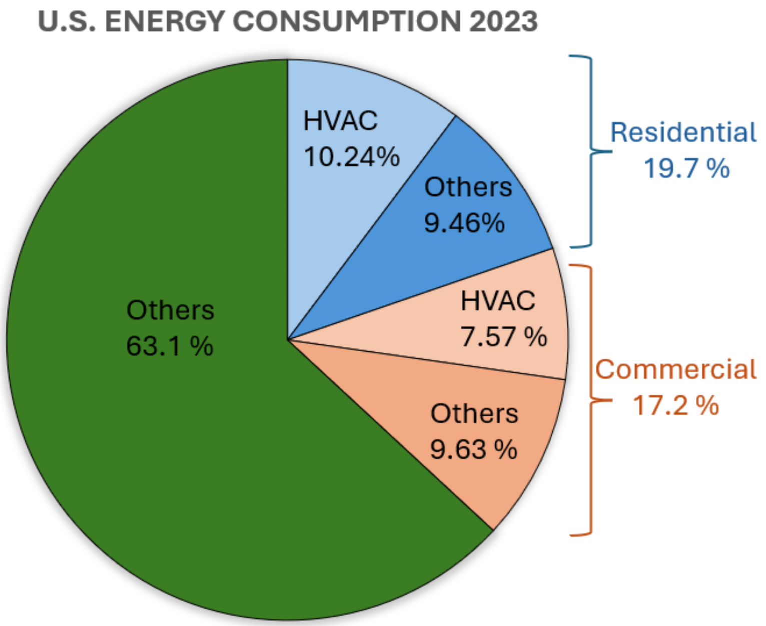
1. Motivation

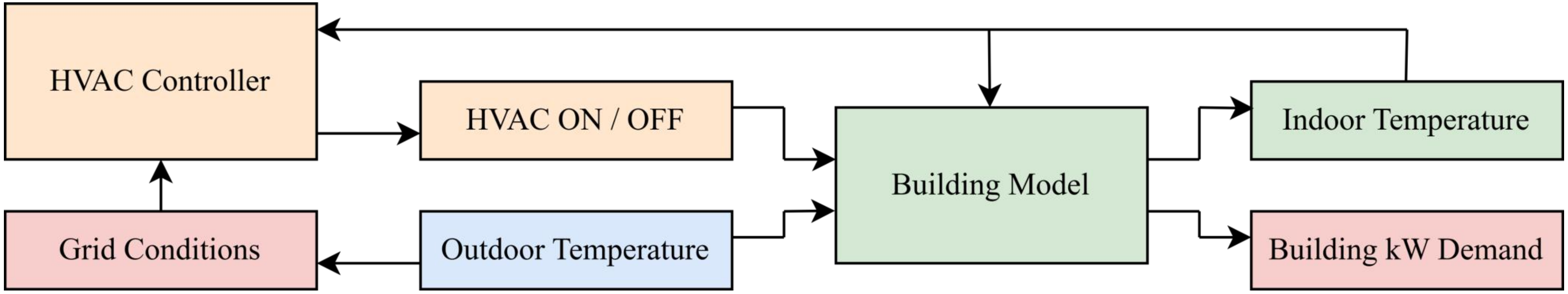
Motivation

- Right now, electricity demand is increasing faster than supply.
- Building new capacity, such as Generators and Transmission Lines, is slow and difficult.
- Energy storage can relieve some stress on the grid, but batteries are still too expensive to deploy at scale.
- Because of their thermal inertia, buildings can serve as energy storage.
- Buildings can adapt their energy consumption to grid needs. This is known as Demand Response (DR).
- Buildings already exist at scale on the grid.
- Buildings can make use of HVAC for DR.



Research Challenge

- Traditional thermostats use basic on/off control at fixed setpoints, functioning only to keep the indoor temperature within a predefined comfort band.
- Many regions are adopting dynamic electricity pricing that changes throughout the day.
- Smart HVAC controller: responds to price signals and shifts energy usage accordingly.
- Model Predictive Control: requires accurate system models, computationally heavy.
- To address these challenges, we use Reinforcement Learning to learn an effective control policy.

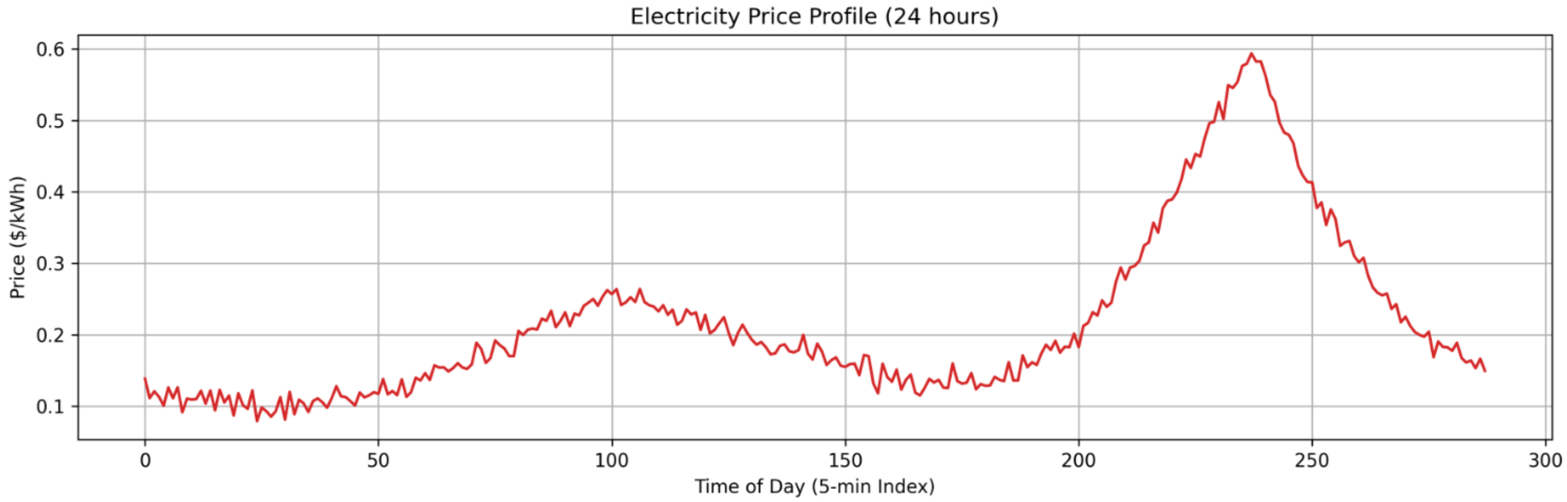


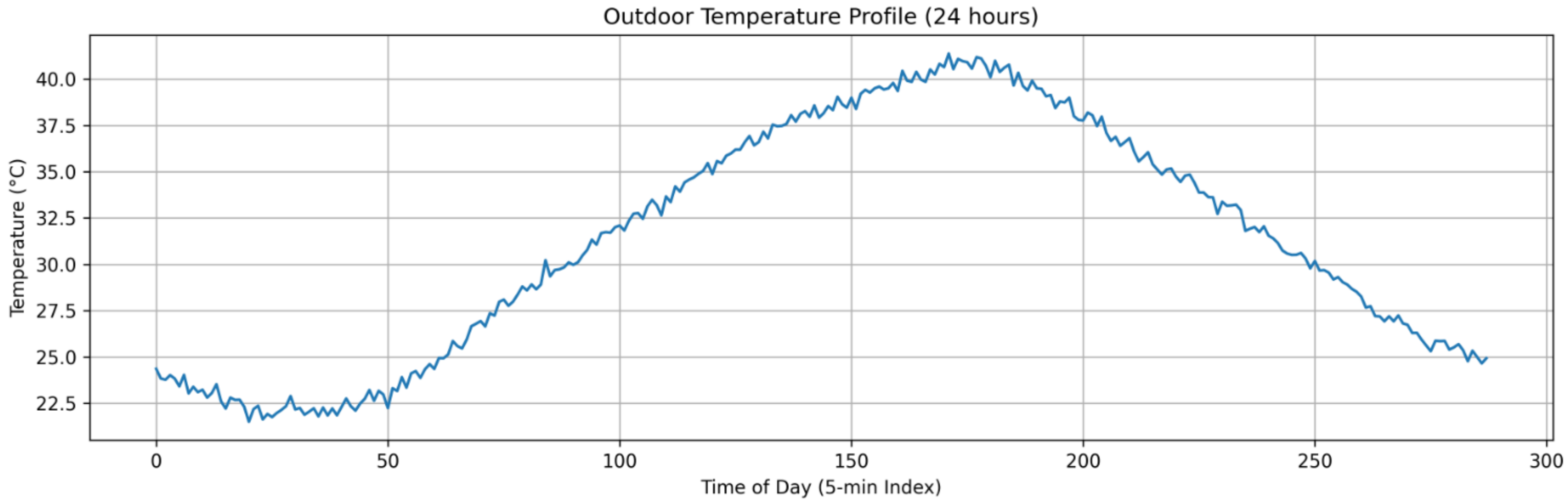
Why Deep Reinforcement Learning?

- Reinforcement Learning acts as a natural framework for sequential decision-making.
- The agent discovers optimal HVAC policies through interaction with the building environment.
- Handles multi-objective tradeoffs between cost, comfort, and equipment wear.
- Leverages deep RL with neural networks to scale to continuous state spaces.
- To evaluate different RL algorithms, we need computationally efficient models and a Gymnasium for a standardized environment.

2. Setup

Generated Data





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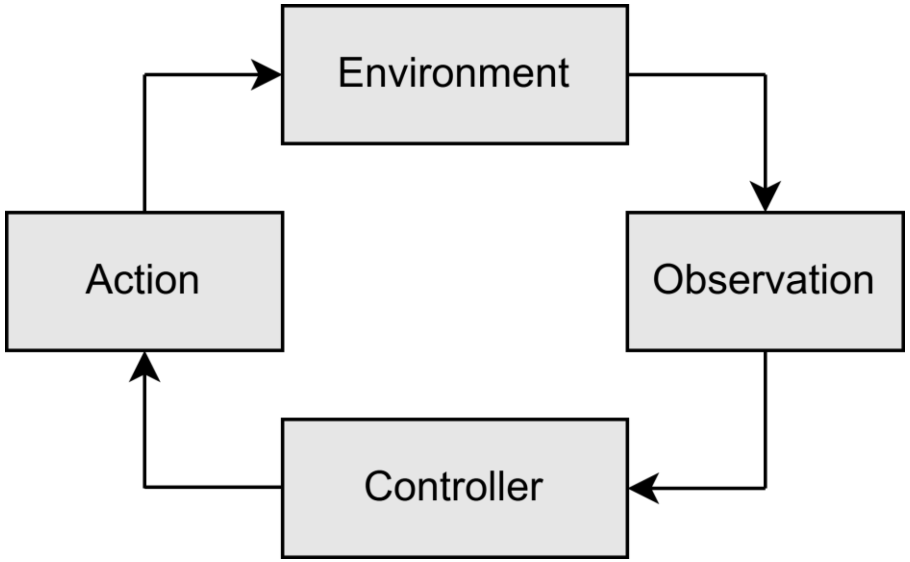
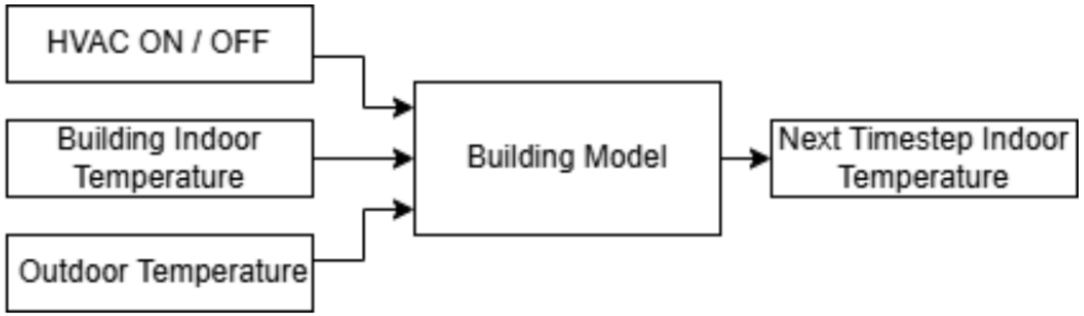
3. Environment

Gymnasium Environment Design

- Gymnasium provides agent-environment interaction loop for RL training.
- Agent observes indoor temperature, outdoor temperature, electricity price, and time of day.
- Agent controls HVAC with binary actions: turn ON or turn OFF.
- Each episode runs for 24 hours at 5-minute intervals, totaling 288 timesteps.
- The building model is implemented as part of the environment.





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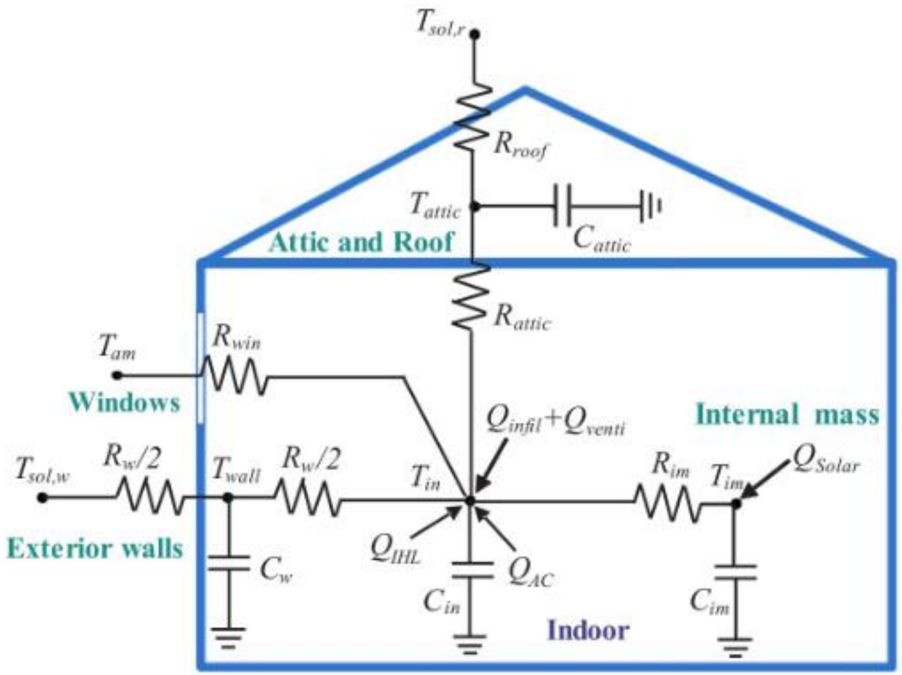
RC Modelling

- We model Building Internal Dynamics by the principle of “Heat-flow”.
- Resistors represent resistance to heat flow.
- Capacitors represent the building capacity to store thermal energy.

$$C_z \frac{dT_z}{dt} = \sum_{i=1}^{N} \frac{T_{w_i} - T_z}{R_{zw_i}} + \frac{T_a - T_z}{R_{za}} + A_z Q_{HVAC} + B_z Q_{Int} + D_z Q_{Solar},$$

$$C_{w_i} \frac{dT_{w_i}}{dt} = \sum_{\substack{j=1 \\ j \neq i}}^{N} \frac{T_{w_j} - T_{w_i}}{R_{w_{ij}}} + \frac{T_z - T_{w_i}}{R_{zw_i}} + \frac{T_{am} - T_{w_i}}{R_{wa_i}} + B_{w_i} Q_{Int} + D_{w_i} Q_{Solar}.$$



$$\dot{\underline{x}} = A(\underline{\theta})\underline{x} + B(\underline{\theta})\underline{u} + D(\underline{\theta})\underline{w}$$
$$y = C\underline{x}.$$

4. Algorithms

RL– Algorithms

DQN

- Learns Q-values: How good each action is in a given state
- Uses replay buffer to break data correlation, improving stability.
- Explores with ε-greedy strategy: Random actions early, optimal actions later.
- Ideal for discrete action spaces like binary HVAC control

PPO

- Directly learns a policy: which actions to take.
- Uses clipped objective to prevent overly large policy updates.
- Collects experience batches and performs multiple training passes.
- Known for stability and robustness in control problems.

SAC

- Actor-critic method: learns both policy and value function.
- Encourages exploration through entropy regularization.
- Stays uncertain early in training to avoid local optima.
- Typically used for continuous control.

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Hyperparameter tuning

DQN

1. Learning Rate: 0.001
2. Discount Factor: 0.98
3. Better Buffer Size: 100,000
4. Exploration Fraction: 0.05

PPO

1. Learning Rate: 5e-5
2. Discount Factor: 0.95
3. Batch Size: 256
4. Rollout Horizon: 256

SAC

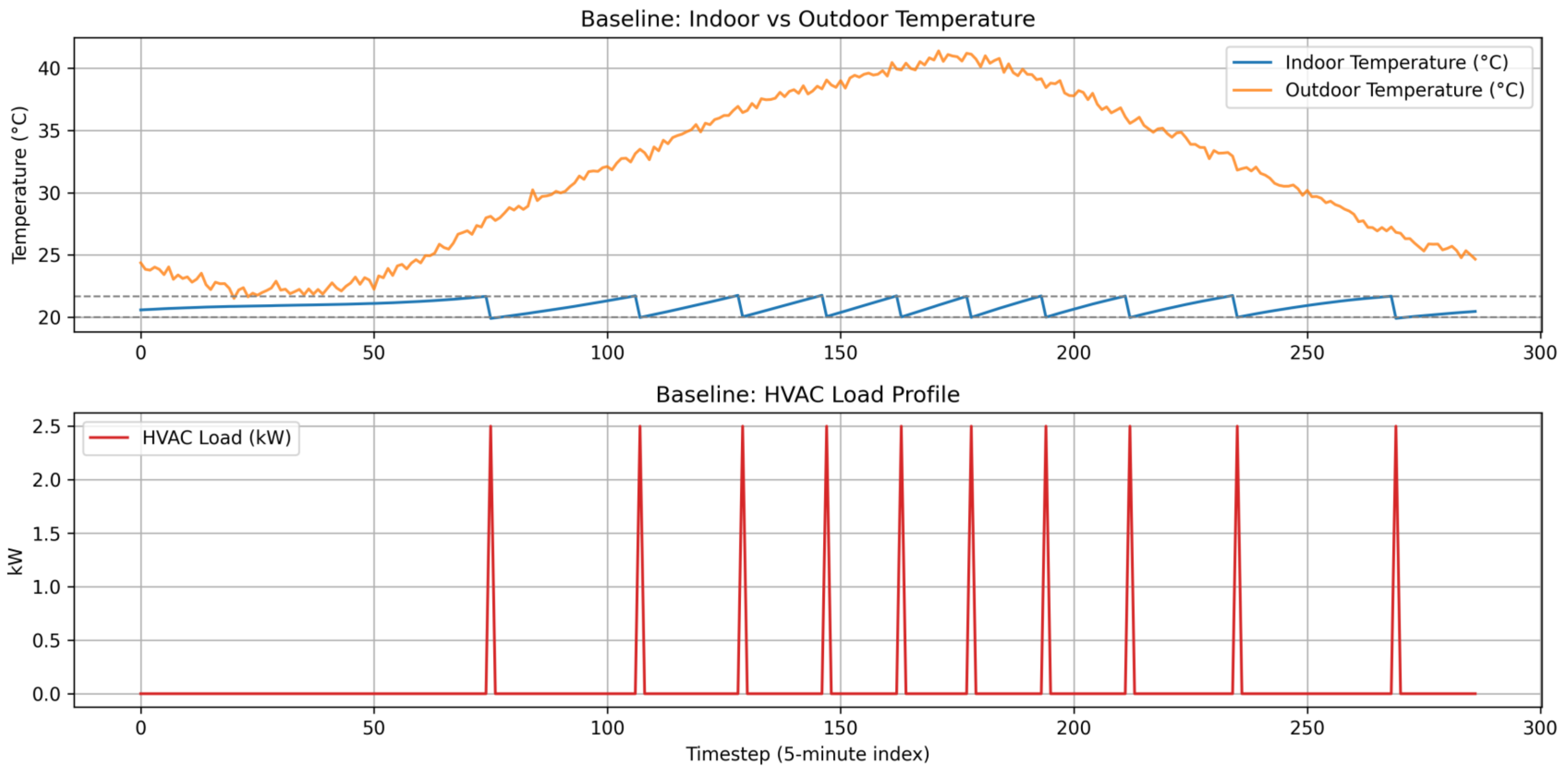
1. Learning Rate: 3e-4
2. Discount Factor: 0.98
3. Batch Size: 128
4. Polyak smoothing coefficient: 0.01
5. Entropy coefficient setting: auto

- Parameter Optimization was performed for each algorithm.
- The models were trained for 50,000 timesteps with different hyperparameters.
- We chose the hyperparameters resulting in the lowest loss.

6. Results

RESULTS

Baseline Controller



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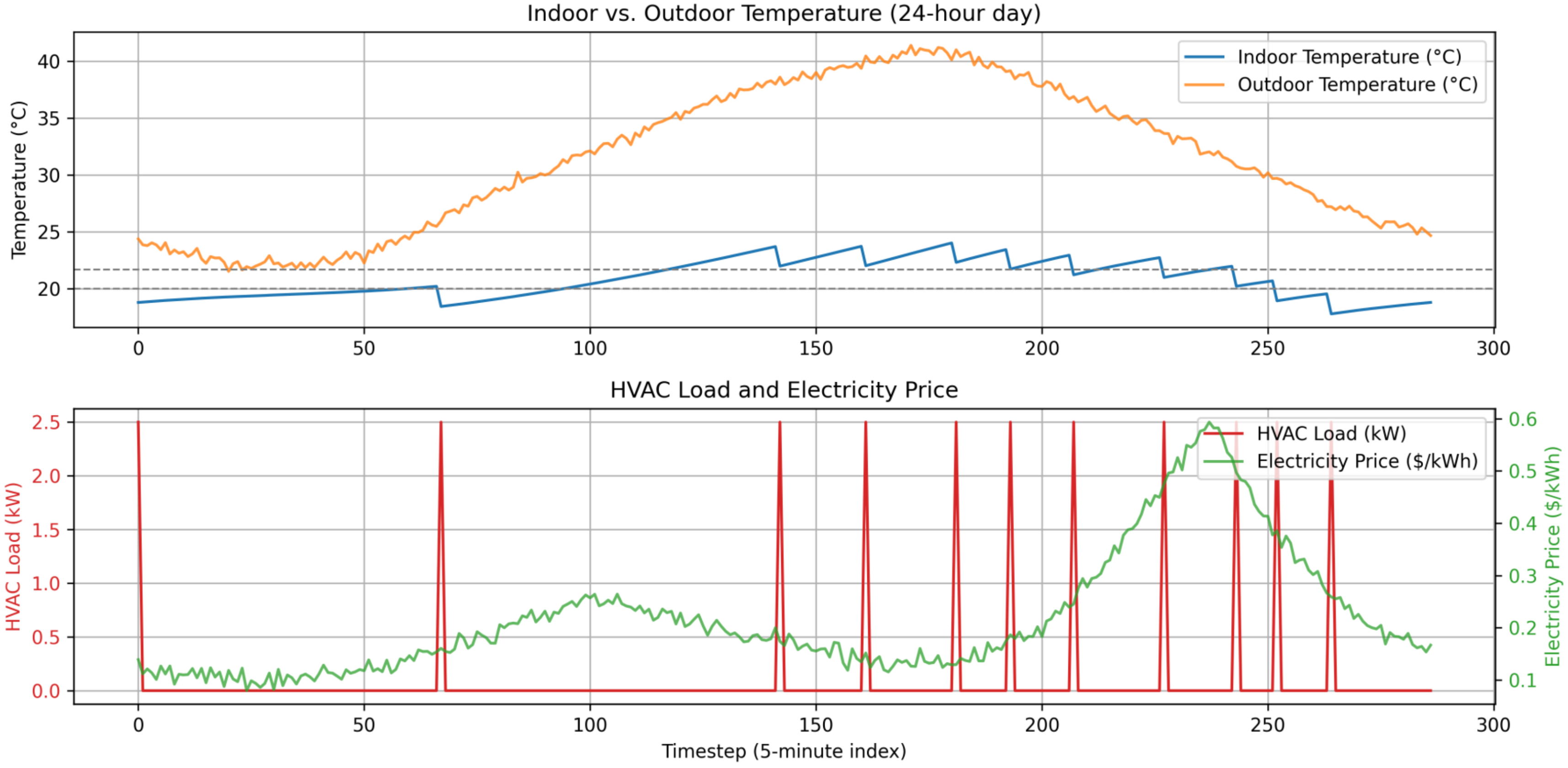
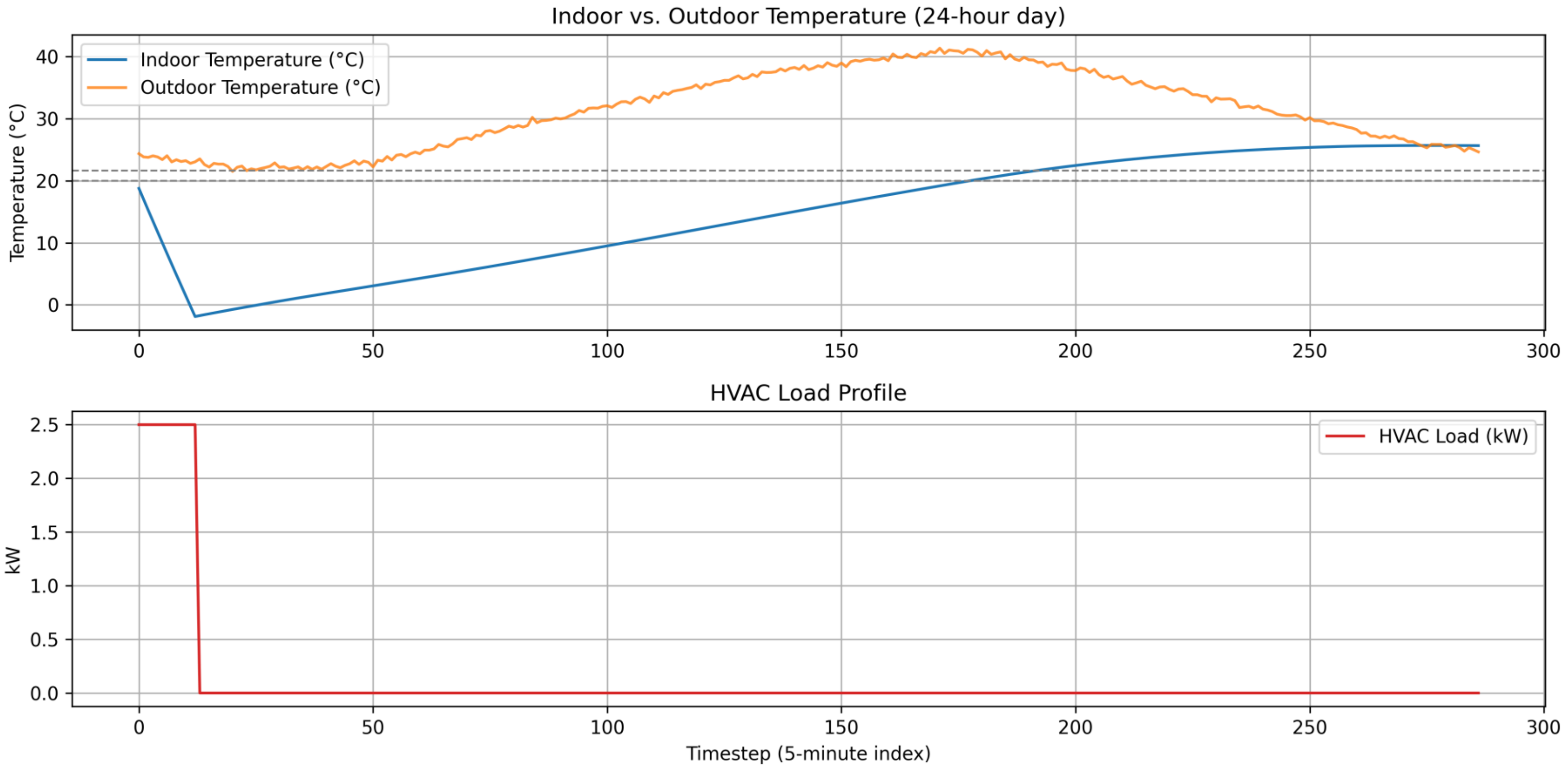
RESULTS

DQN Controller



RESULTS

PPO Controller



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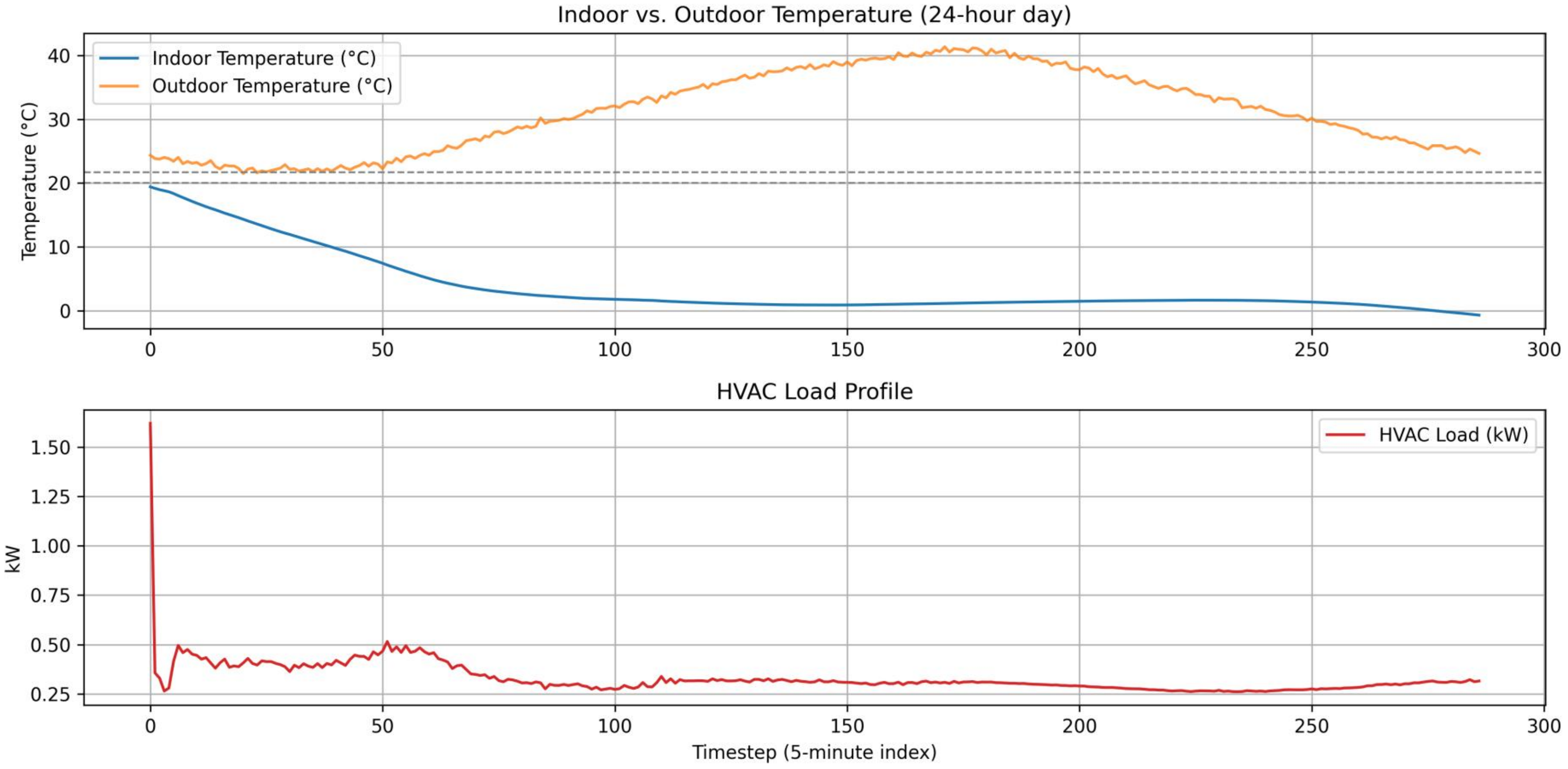
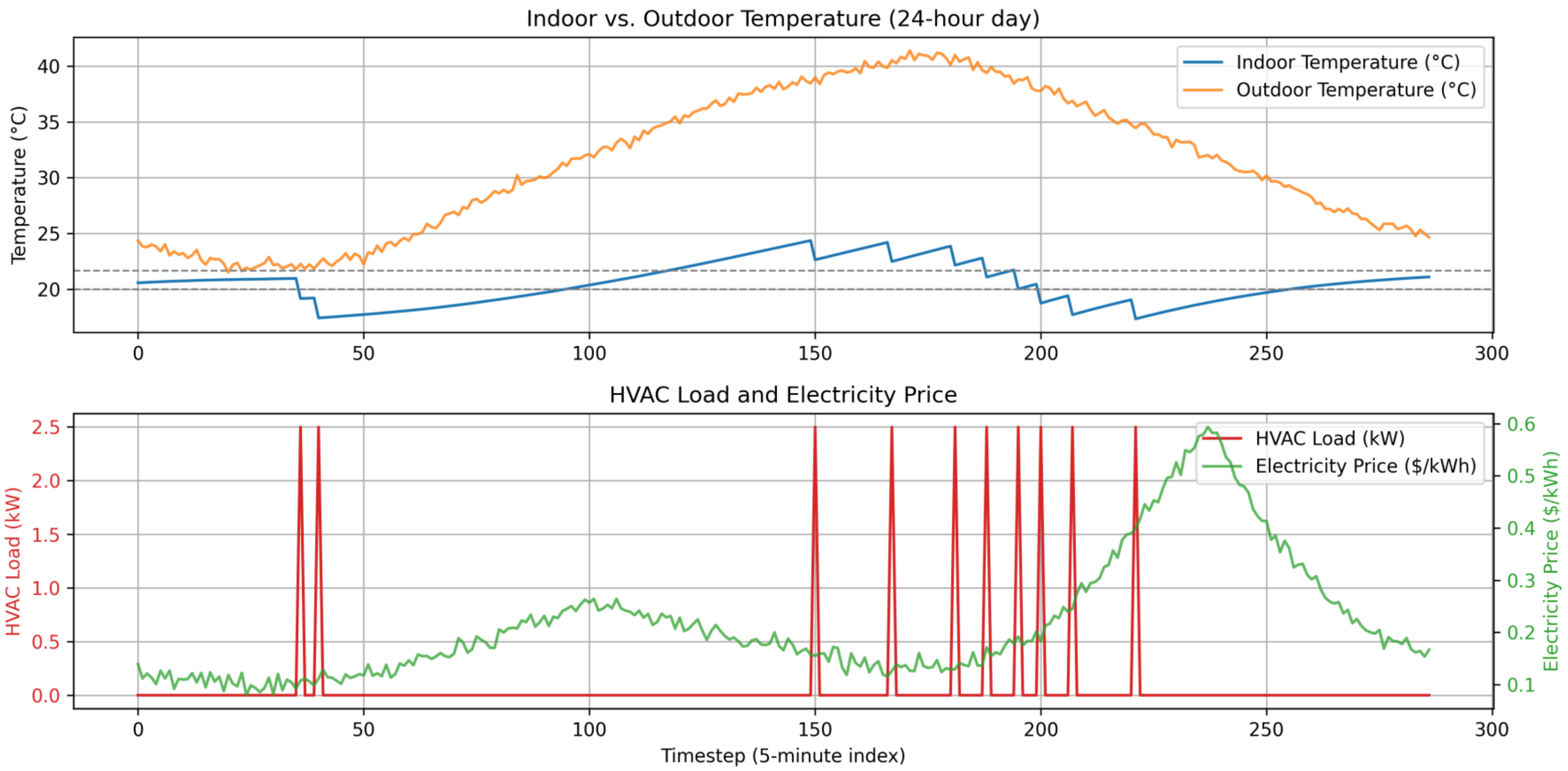
RESULTS

SAC Controller



RESULTS

Cost-Aware DQN Controller



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6. Conclusion and Future Work

Conclusion

- DQN successfully learned duty-cycle HVAC control after 500,000 timesteps with optimized hyperparameters.
- DQN outperformed PPO and SAC because it naturally matches discrete ON/OFF actions and handles low-dimensional state spaces.
- DQN learned to pre-cool buildings before price peaks, demonstrating cost-aware load shifting.
- Deep RL is feasible for residential HVAC control and opens new paths for grid-interactive buildings.
- Future Work: Extend to multi-day training, increased environmental variability, and refined reward tuning for improved comfort reliability.

THANK YOU