Active Reinforcement Learning for Robust Building Control

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RL for Optimal HVAC Control

HVAC (Heating, Ventilation and Air Conditioning) systems are critical components of building infrastructure, consuming significant **energy** resources.

Optimizing their **control** presents challenges due to :

- ***Dynamic*** environmental conditions
- ***Diverse*** building *usage* ***patterns***
- Occupant ***comfort*** requirements

Reinforcement Learning offers a promising approach by enabling the HVAC system to **learn optimal control** strategies through interaction with its environment, ultimately leading to *adaptive* and *efficient* operation.

RL for Optimal HVAC Control

Several studies have explored the **application** of Reinforcement Learning (RL) techniques for optimizing **HVAC** control in buildings.

While these approaches have shown **promise**, they often face challenges in **adapting** to sudden **environmental changes**, such as *extreme* weather conditions.

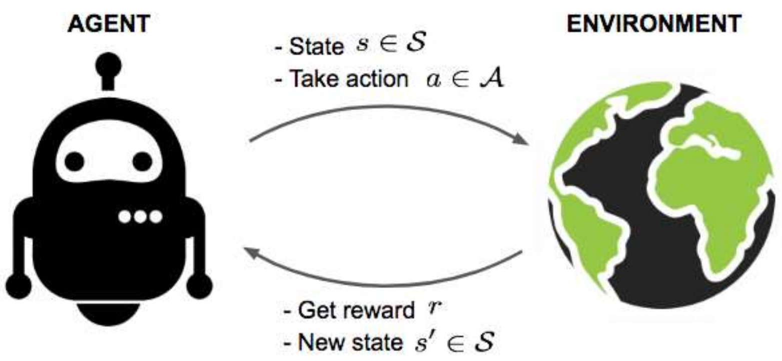
Is this really a problem?

Climate Change

The answer is… **YES, it is**

Active RL for Robust Building Control

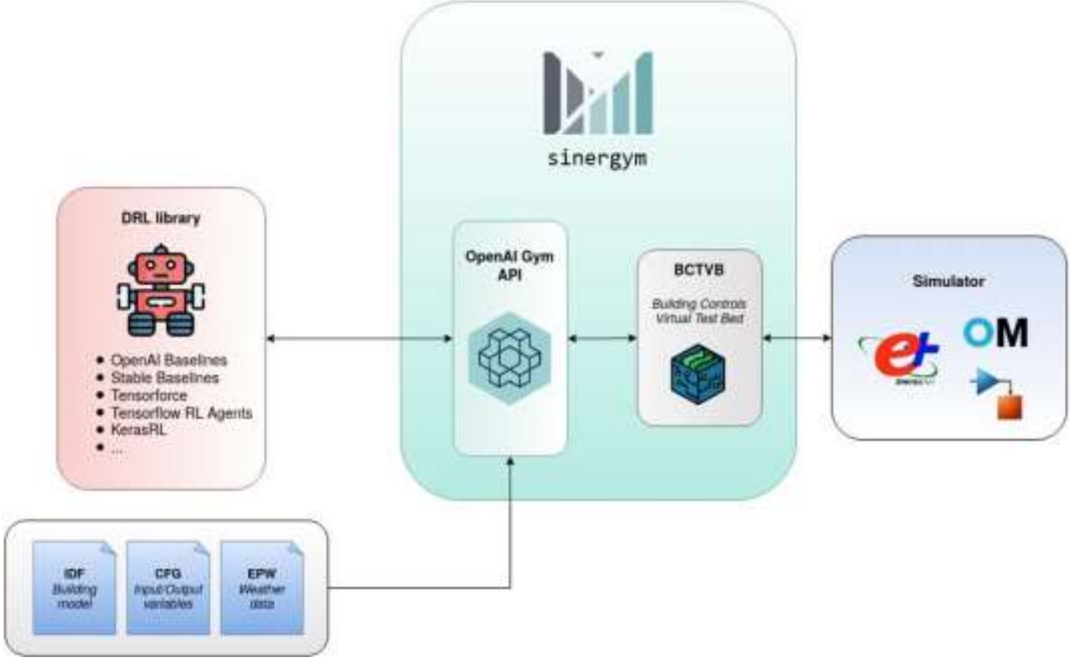
- RL **agents** can get too used to their training and **struggle** with **new situations**.
- Unsupervised Environment Design (**UED**) **helps** by training these agents in *specially* **crafted environments**.
- Not all UED approaches fit well when we need the agent to do well in one specific environment, especially under different conditions like normal or extreme weather.
- In this work, I introduce a new UED method called **ActivePLR**. It smartly creates training scenarios that challenge the RL agent just enough, focusing on **maintaining** a building's energy **efficiency** and **comfort** during *various* **weather** conditions in a chosen environment.



The Environment

Sinergym is a powerful tool for modeling building **environments** and simulating HVAC systems' behavior within those environments.

It serves as an interface to **EnergyPlus**, a widely used building energy **simulation engine**, providing a user-friendly environment for HVAC control experimentation and analysis.

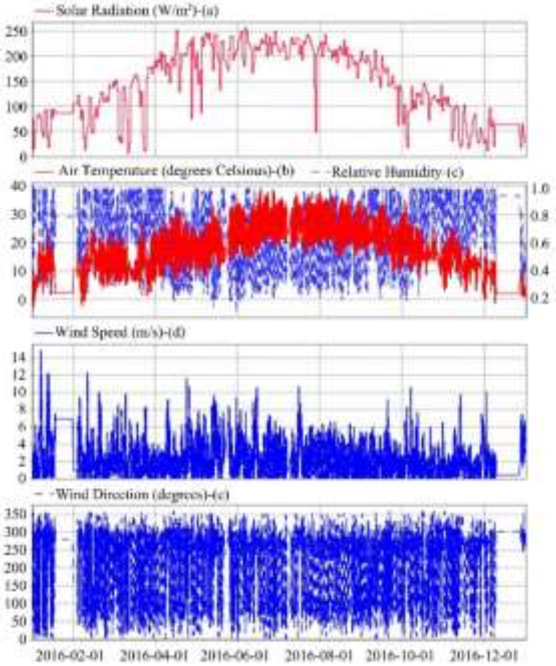


Unsupervised Environment Design

To make the agent more robust to changes in the environment, an environment **wrapper** must be created.

By default, synergym varies only the external temperature based on (**mu**, **sigma**, **theta**) specified. With this wrapper, you can now specify parameters of (mu, sigma, theta) for **5** environment **factors**:

- Outdoor temperature (**drybulb**)
- Relative humidity (**relhum**)
- Wind direction (**winddir**)
- Wind speed (**windspd**)
- Solar irradiance (**dirnorrad**)



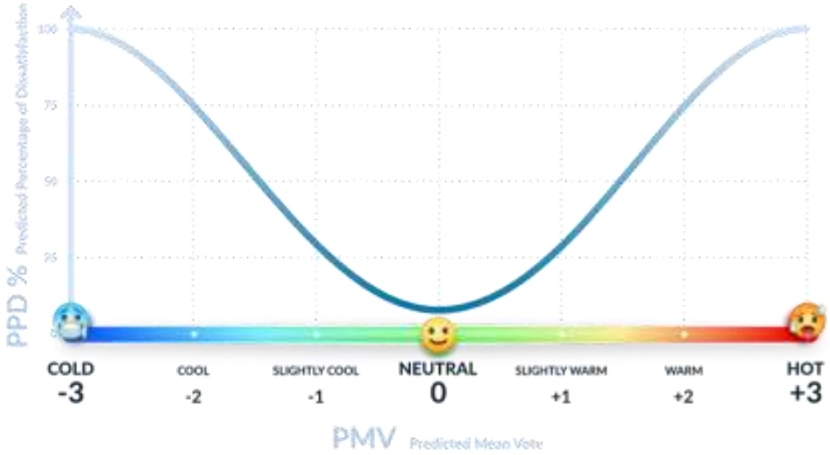
In order to make these changes, it was necessary to **override** default sinergym functions.

The Reward Function

Linear **reward** function using **Fanger** PPD thermal comfort is also created. This considers the **energy consumption** and the **PPD** (Percentage of People Dissatisfied) thermal comfort metric, as well as occupancy:

$$R_t = -\rho \cdot \lambda_E \cdot P_t - (1-\rho) \cdot \lambda_p \cdot PPD_t \;\cdot\; \mathbb{I}_{occupancy_t > 0} \cdot \mathbb{I}_{PPD_t > 20}$$

Sinergym offers the ability to define *custom reward* functions very easily. This reward is derived from a standard **linear reward** by modifying the **comfort** factor only.



RAY

Ray is an open-source framework designed to **simplify** and **scale** up machine learning and other intensive computation tasks. It provides a simple, universal API to build distributed applications.
RLlib is a reinforcement learning library built on top of Ray.

- **Flexible**: easy integration with various *environments*.
- **Scalable**: Designed to scale from a single CPU to large clusters with minimal effort.
- **Comprehensive**: supports a *wide variety* of RL algorithms, including ***PPO***, DQN, and A3C.

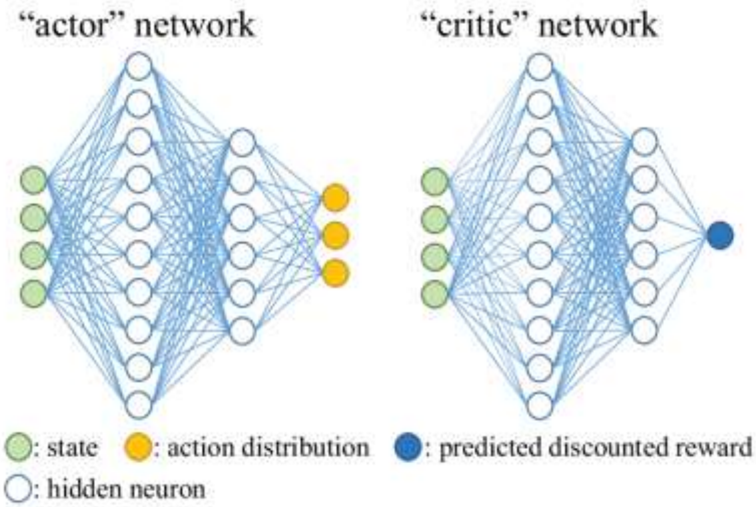
Chosen for its flexibility with the goal of testing the modeled environment.

The Agent

Proximal Policy Optimization (**PPO**) is a type of **policy gradient method** for training deep reinforcement learning algorithms.

PPO achieves this through a novel **objective function** that balances the *exploration-exploitation* trade-off more effectively than its predecessors.

This method **limits** the size of policy updates, reducing the likelihood of performance degradation due to **large**, destabilizing **updates**.

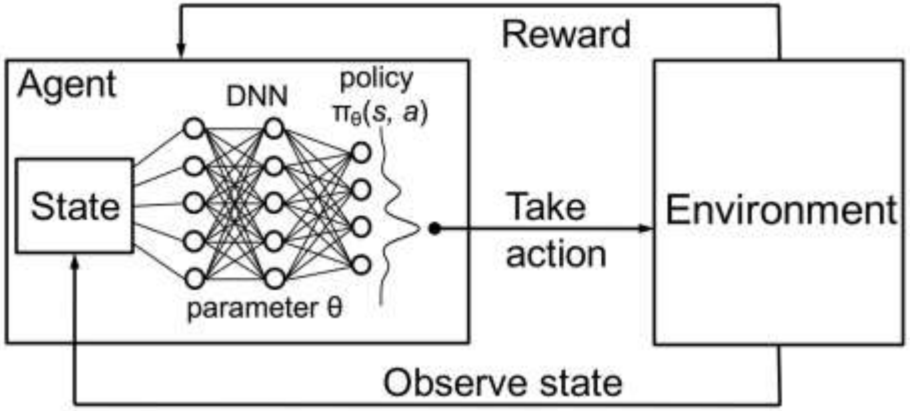


Training

Agent training took place in each test over a total of **500** training **episodes**. The **goal** of the training was to **understand** what **factors** were **significant** in improving agent performance.

I started from a **baseline** using the **default** configurations of RLlib, and made changes to the training setup with the goal of achieving improvements.

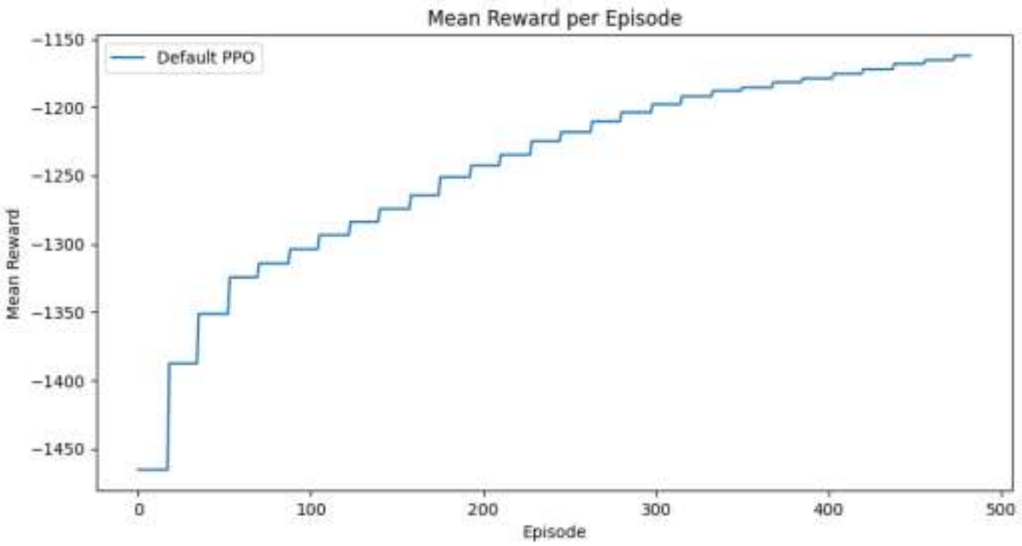
To evaluate an agent's performance, the **mean reward** obtained at each **episode** during training was considered as a metric.



Default PPO

With the goal of setting a **baseline** from which to start, the first tests performed were with the **default** configuration of **RLlib**'s PPO.

Some of these default parameters include the use of the **hyperbolic tangent** as a trigger function for fully connected layers, and a discount factor **gamma** of 0.99.

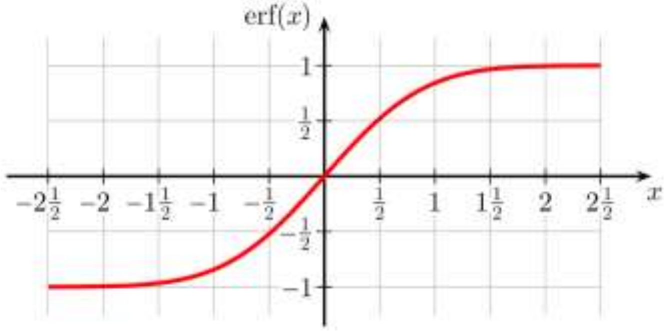


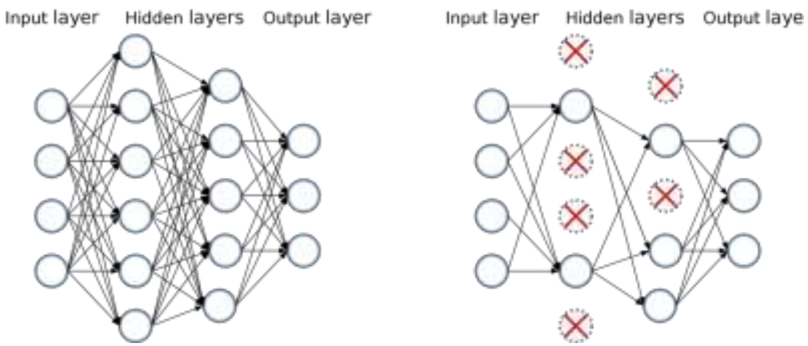
Activation function

One of the factors that influenced performance significantly was changing the **activation function** of the PPO.

By default, this is a simple **hyperbolic tangent**, but adding a **dropout** to it (**p=0.3**) resulted in improvements.

This is because the *dropout* acts as a **regularizer**: with a certain **probability** p, some of the **information** at each layer is **masked**, forcing the model to rely on only a reduced part of the network, thus **improving generalization** performance.

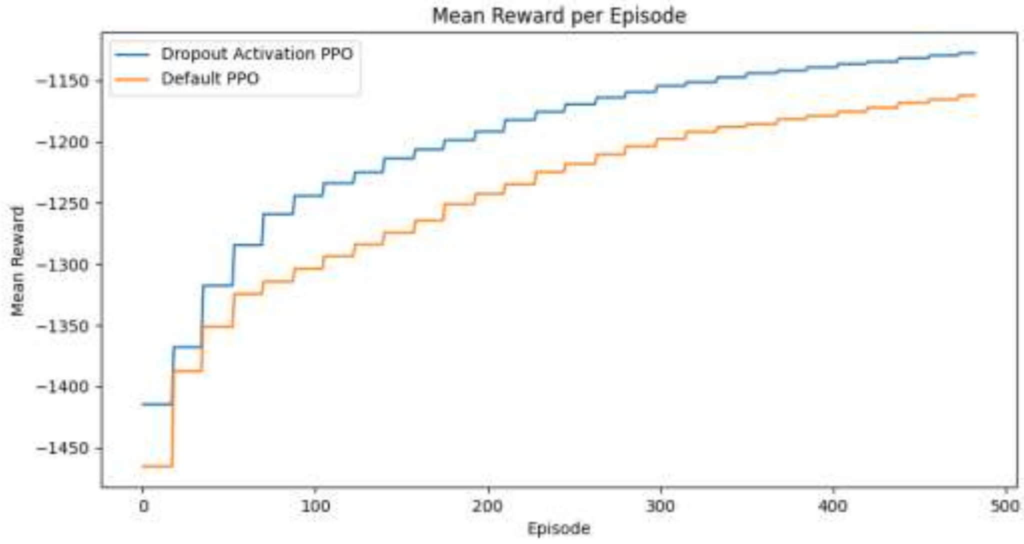




Activation function

After changing the default activation function, one can see a slight **improvement** of the agent on the rewards obtained.

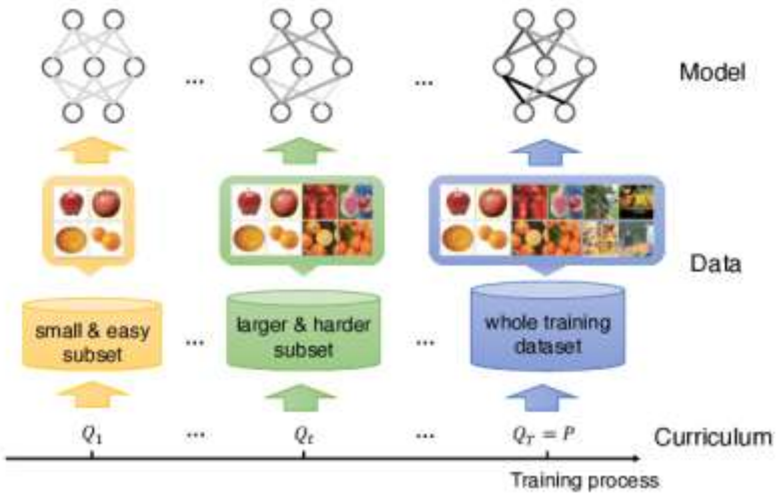
This is because as the surrounding environment is more **variable**, adding a **dropout** increases the **generalization** ability of the model.



Curriculum Learning

Another strategy I decided to test is **Curriculum Learning**: start with an easier task and **gradually increase** the **difficulty**.

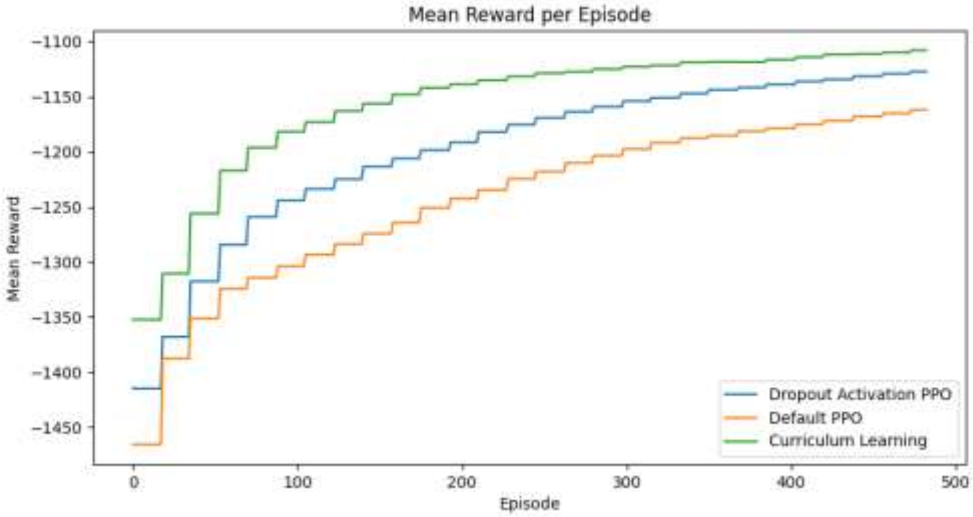
As described earlier, the defined environment allows 5 environmental factors to vary significantly. Instead of starting the training in a more complex environment in which all variables are active, a new **variable** is **introduced at** a **fixed cadence**, performing for *75%* of the training a gradual learning, and for *25%* a learning at maximum difficulty.



Curriculum Learning

In the **initial stages**, when the environment is less *complex*, it's easier for the agent to **understand** the relationship between its **actions** and the resulting **rewards**.

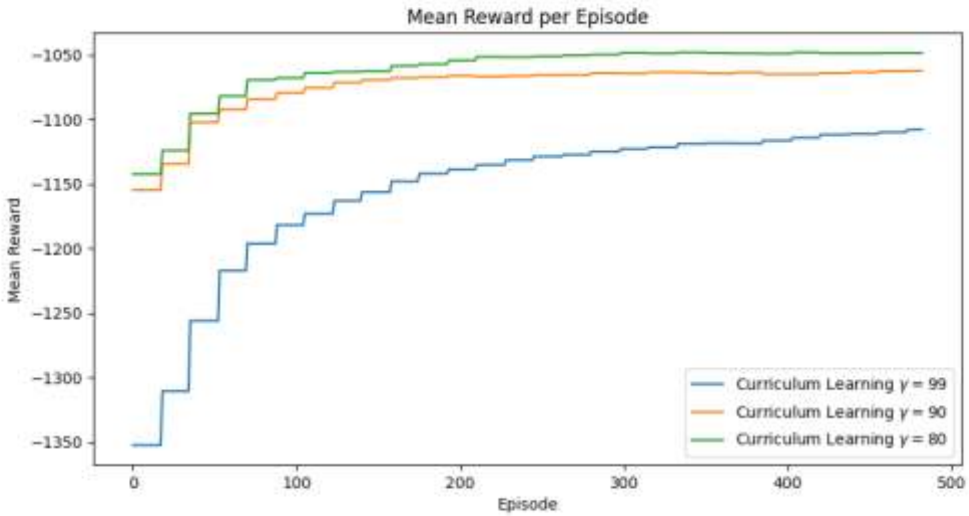
Incremental learning **encourages** the development of a more **robust policy**, and by the time the agent is exposed to the full complexity of the environment, it has already learned to **adjust** its strategy in **response** to changes in **one variable** at a **time**.



Gamma

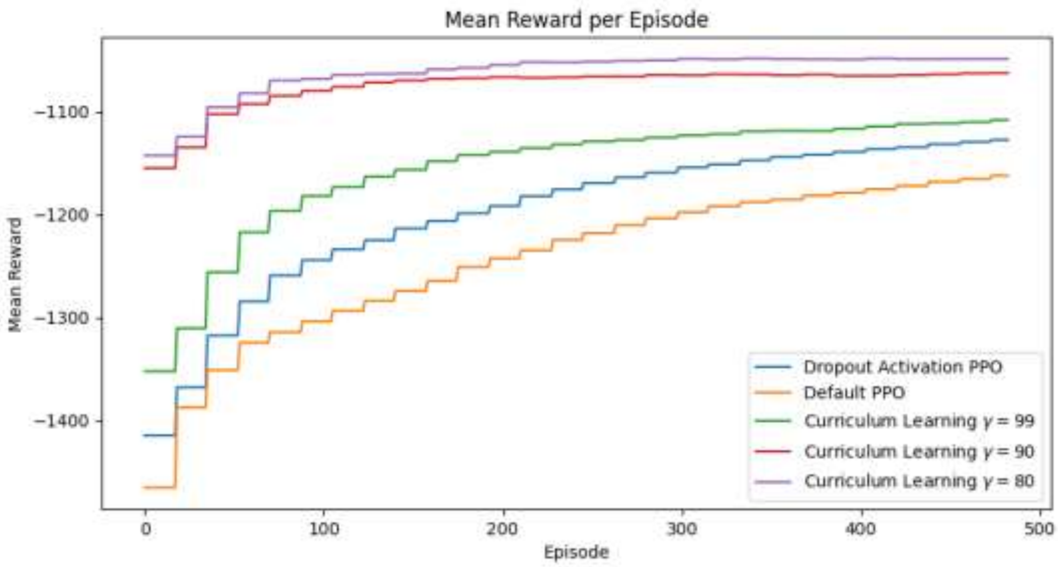
The **discount factor** gamma, that determines the **importance** of **future rewards** in the total expected rewards for an agent's actions.

After testing various values, the optimal one is **0.8**. This indicates that **immediate** or short-term **decisions** have a **more significant** impact on performance than long-term strategies.
That’s because the **benefits** of adjusting HVAC settings might **diminish** over time due to *external factors* like weather changes or occupancy variations.



Improvements overview

Through strategic modifications, including **dropout** regularization, **Curriculum Learning**, and **gamma** adjustment, our RL agent now achieves **higher rewards**, indicating enhanced adaptability and efficiency in building control.



Thanks for your attention