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Reinforcement Learning based Control of Integrated Energy Systems Using OpenAI Gym

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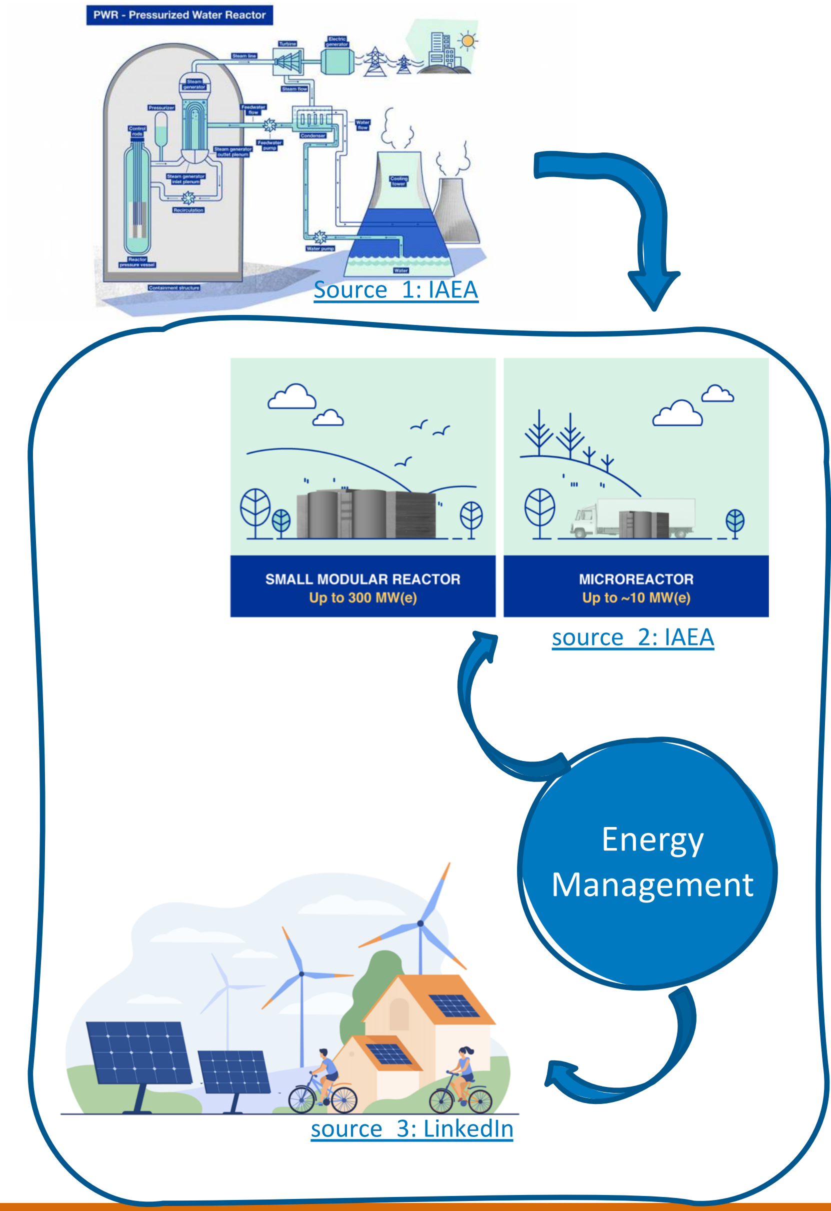
Background Introduction

- Nuclear power plants have traditionally served as centralized plants for base supply.
- The development of **advanced small modular reactors (SMRs)** in recent years has brought nuclear utilization for microgrids closer, together with other forms of green energy, such as solar and wind.
- Given the interaction of multi-domain systems, the Modelica language is an appropriate tool for developing multi-physics models.
- For this study, we used open-source packages such as **HYBRID (by INL)** and a **TRANSFORM** (by ORNL) library to create the Integrated Energy System (IES).
- What is the suitable way to control such a complex system, artificial intelligence or a traditional controller like PID, or both?



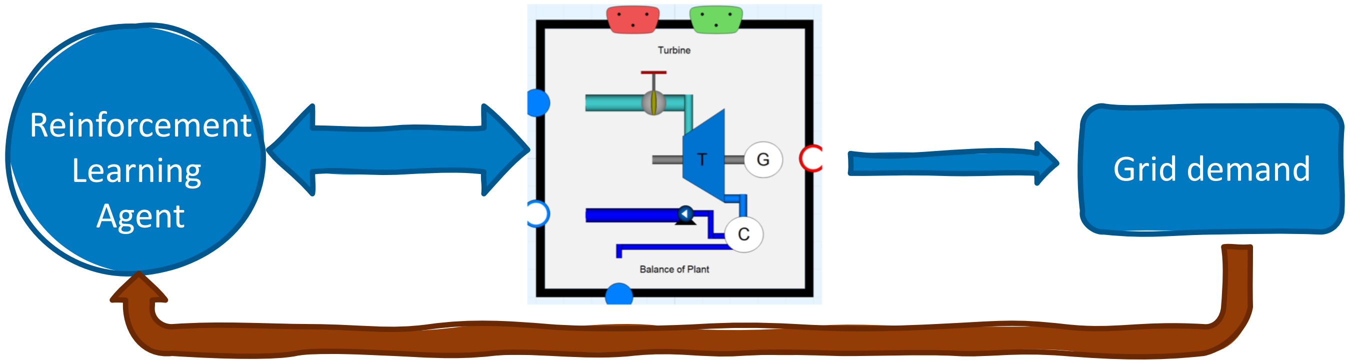
Motivation and Objective

Motivation:

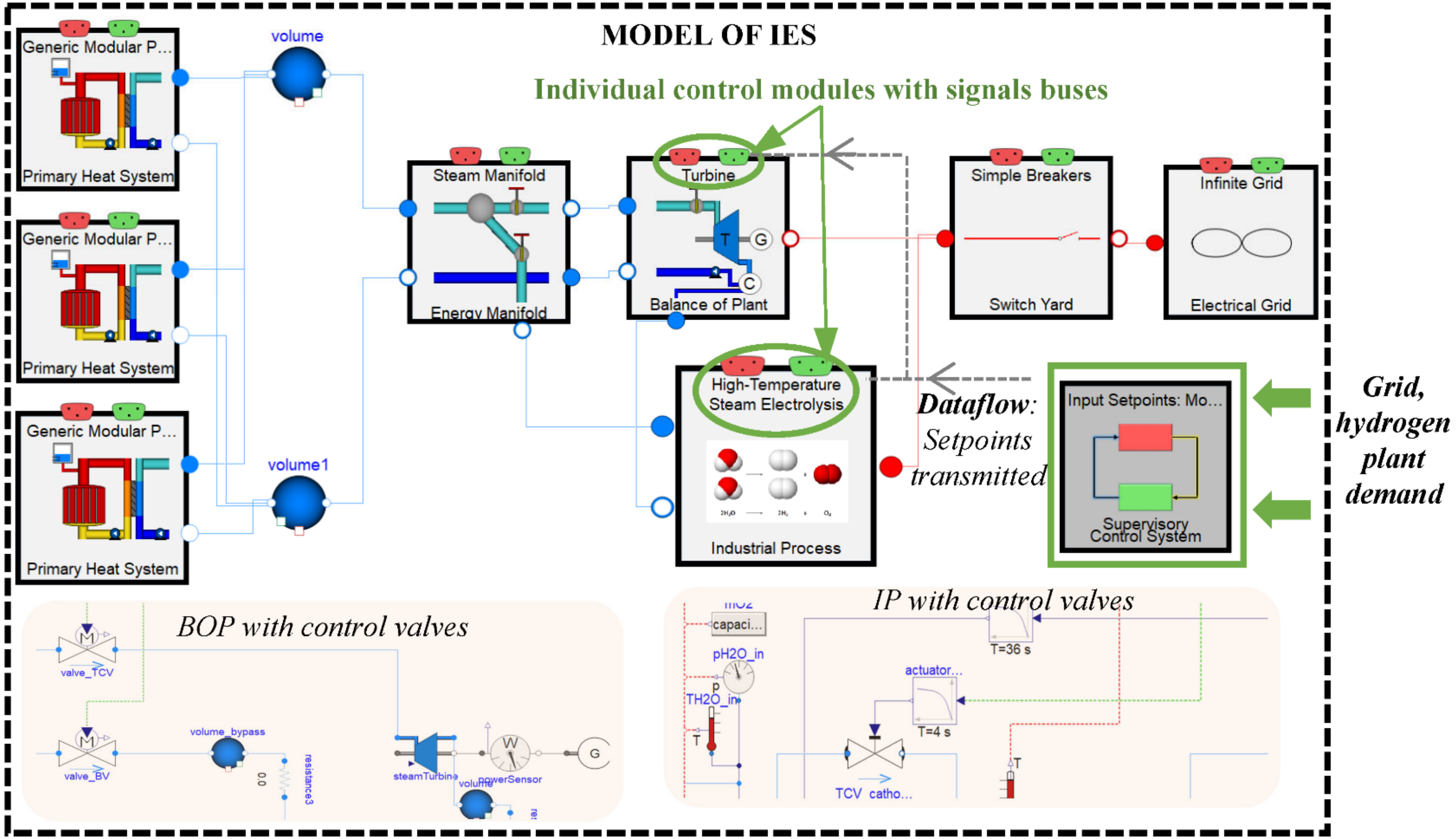
- When a variety of renewable energy systems combine to form a complex integrated energy system (IES), the benefit of reinforcement learning could be leveraged to control the IES with associated uncertainties.

Objective:

- Develop an artificial intelligence module (**reinforcement learning** agent) in conjunction with a physics-based model.
- Control the valves **to meet electricity generation and pressure balancing.**



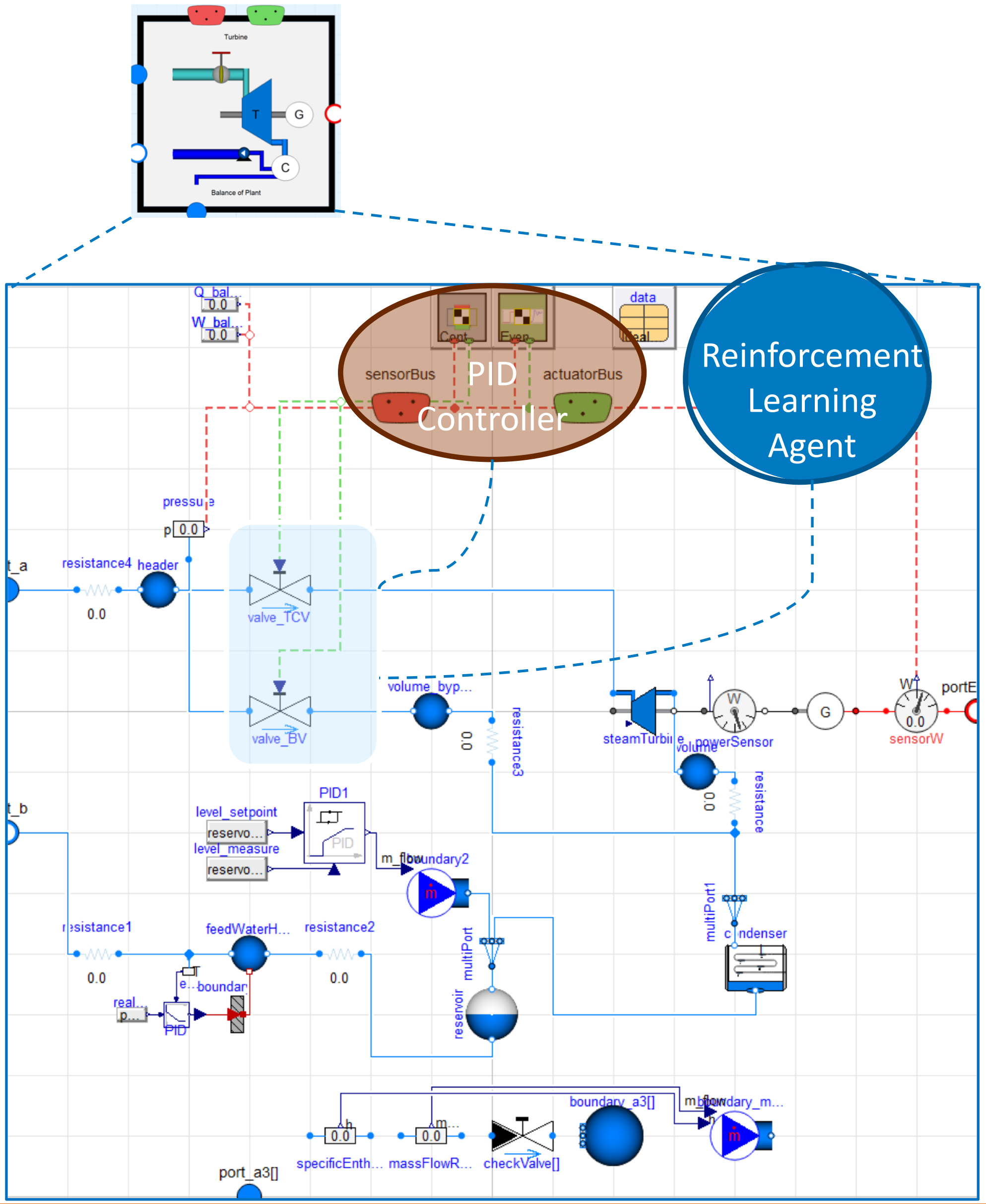
Environment: Modelica based Integrated Energy Systems



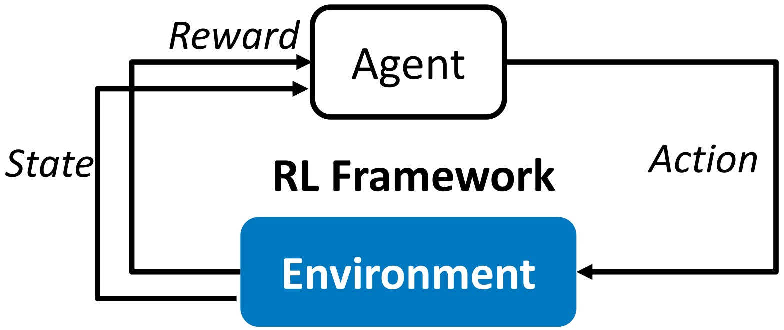
- Conventional PID controllers are used in these models.
- The RL control mechanism is autonomous, and can be deployed online for real-time control of the IES.

Experiment on the Balance of Plant

- **Model environment:** Dymola 2022
- **Model to invest with RL algorithm:** Balance of Plant (From the HYBRID library developed by Idaho National Lab)
- **Model Details:**
  - An ideal turbine model, a condenser a feedwater system for reheating.
  - Several **valves** that allow steam to flow to the turbine or as a bypass to the condenser.
    - Original control method: **PID controller** to meet electricity generation and pressure balancing.
    - Investigated Method: **RL algorithm** to control valves
  - From a modeling standpoint, test the viability of co-simulation with an artificial agent and a complex physics model, as well as comprehend the effort of training the agent with such a system.
  - From the control point of view, to compare the PID performance and intelligent agent.



OpenAI and Modelica Environment Interface

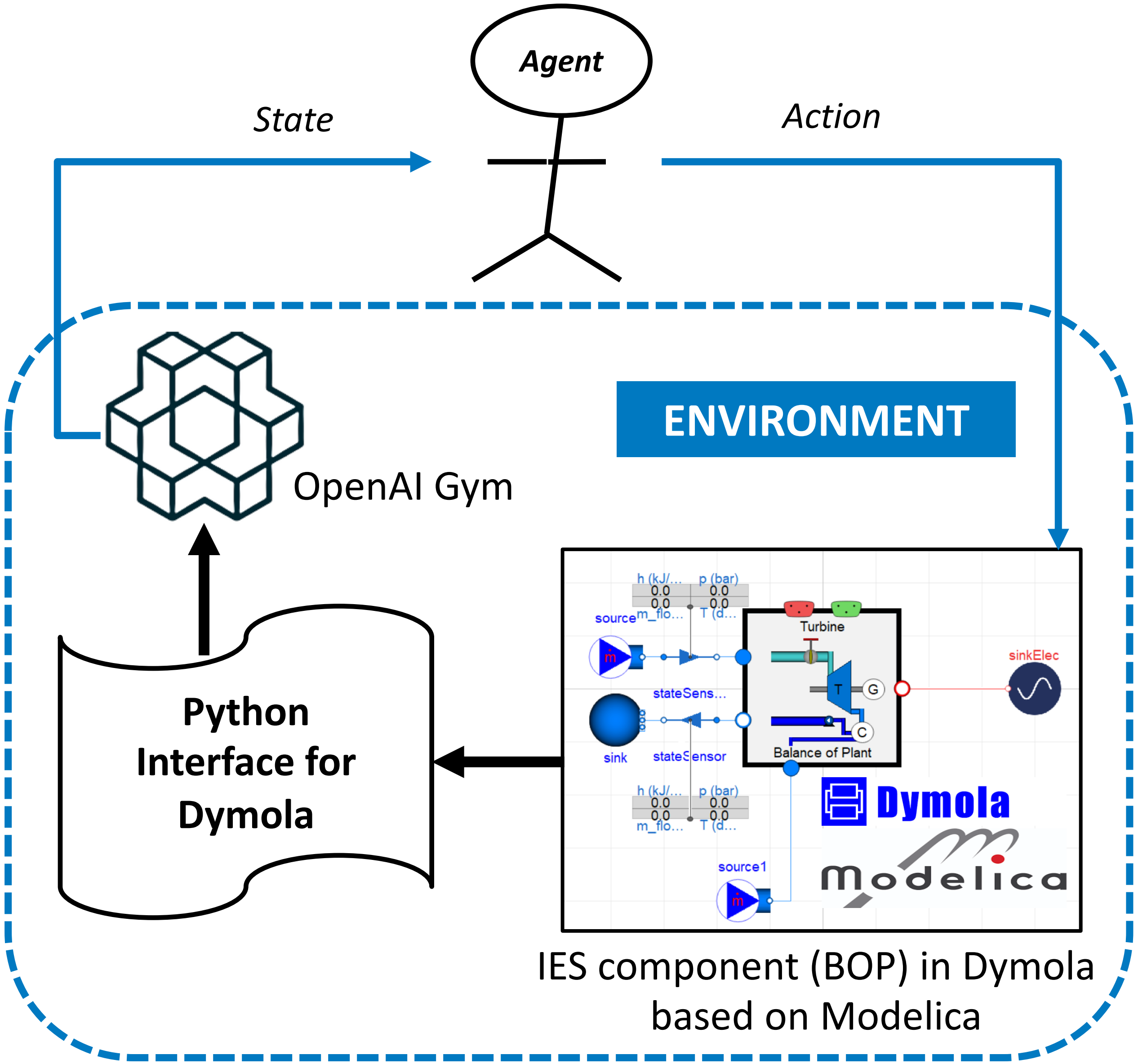


<u>State</u>:
Power produced by the BOP.
$s = \frac{P_{BOP}}{P_{BOP}^{max}}$

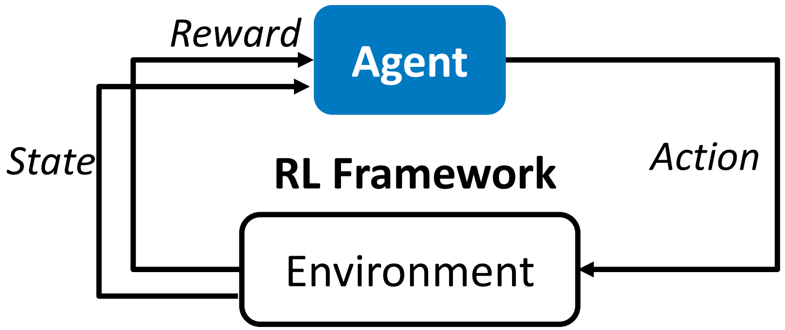
<u>Action</u>:
Turbine control valve (TCV) and
Bypass valve (BV) positions (0 to 1).

<u>Reward</u>:
$e = |s - \frac{P_{BOP\_demand}}{P_{BOP}^{max}}|$; minimize error.
$r = \frac{1}{e + \delta}$

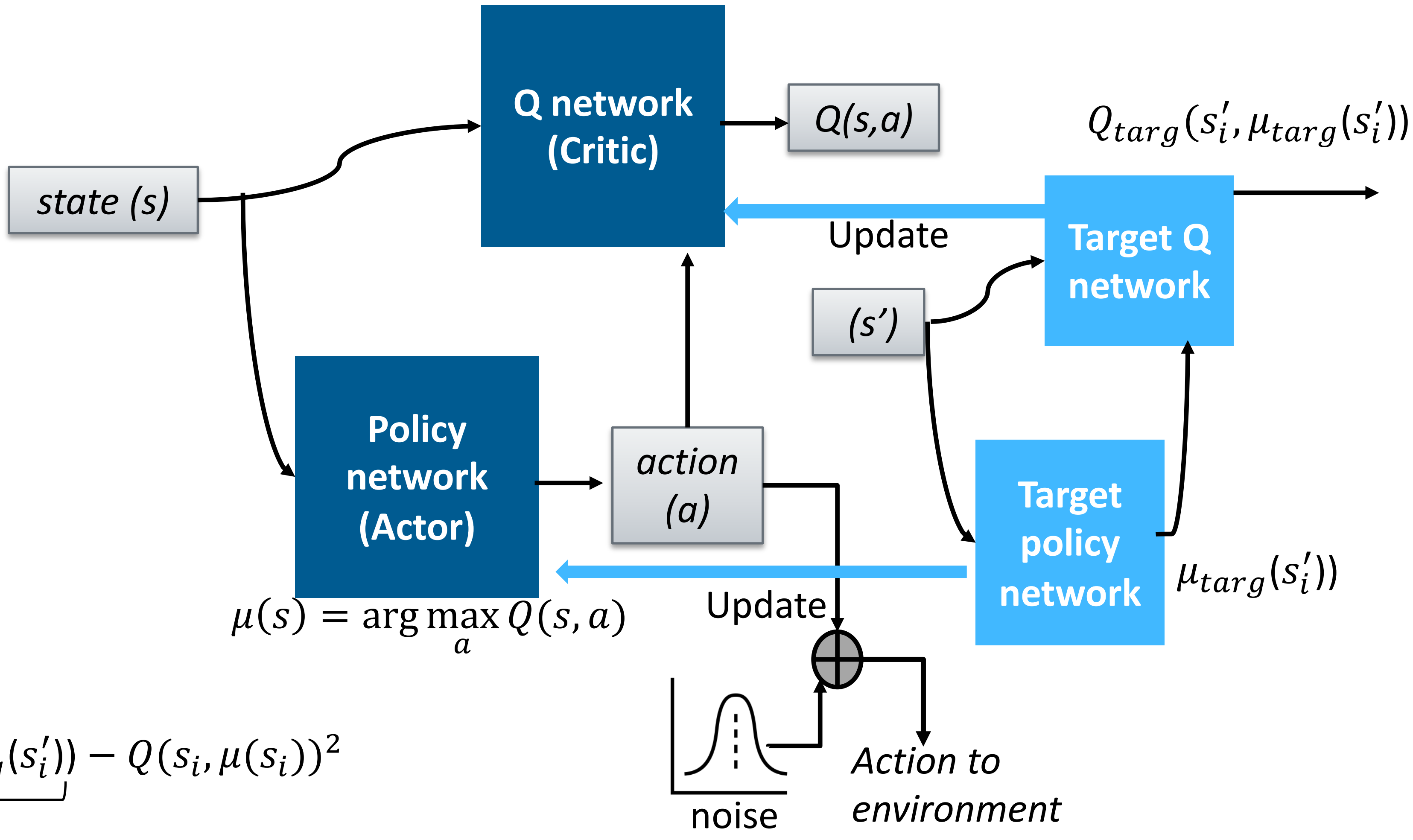
Episode
varying
power
profiles



Learning Framework



Deep Deterministic Policy Gradient (DDPG) algorithm



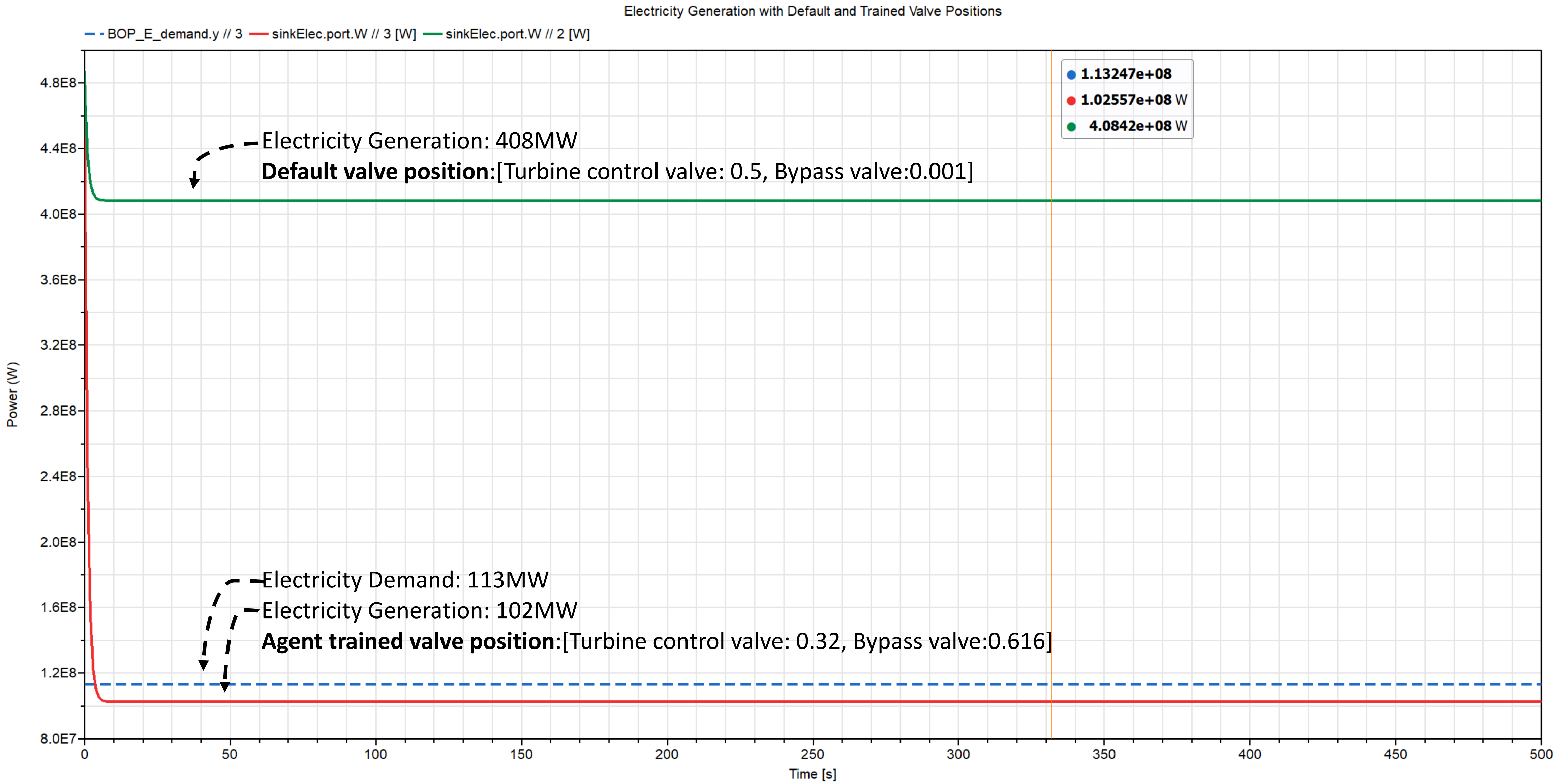
- Four feedforward neural networks are used.
- The target networks are delayed networks compared to main networks.
- The weights of targets are updated periodically based on the main networks.

<u>Loss functions :</u>

$$J_\mu = \frac{1}{N} \sum_{i=1}^{N} Q(s_i, \mu(s_i))$$

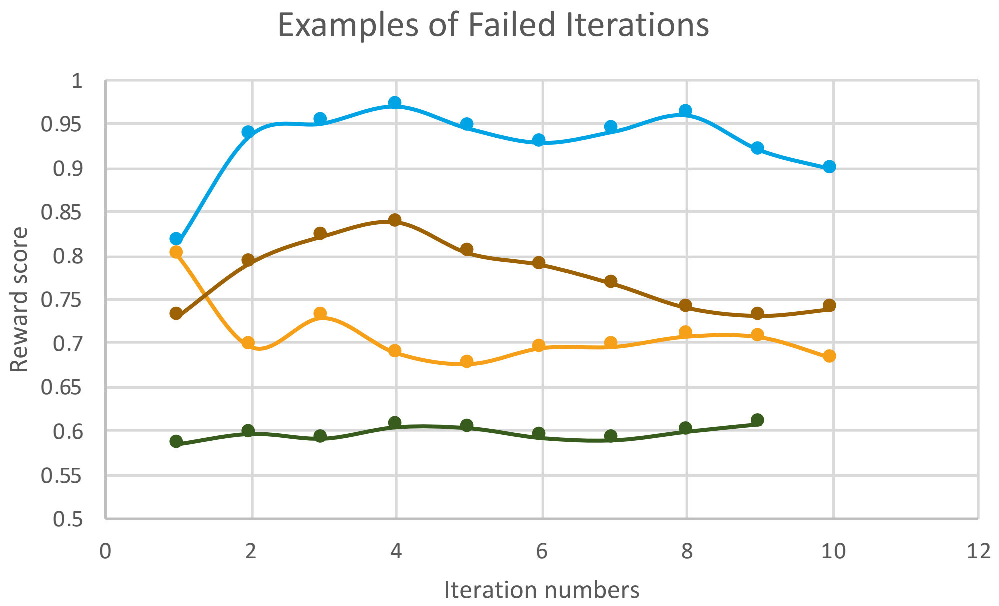
$$J_Q = \frac{1}{N} \sum_{i=1}^{N} \underbrace{r_i + \gamma(1-d)\, Q_{targ}(s_i', \mu_{targ}(s_i'))}_{\text{Bellman equation}} - Q(s_i, \mu(s_i))^2$$

Electricity Generation with Default and Trained Valve Positions



Reinforcement Learning Agent Training Progress (On-going)

- **The agent generates normalized electricity demand while learning how to control valves to meet the power demand.**
- **Performed training with multi step multi episodes**



- **Multiples episodes indicated general trend during iterations, but not for every episode.**

Conclusion and Challenges

- **The RL agent training process revealed a trend in which the agent can learn both turbine control and bypass valve positions based on electricity demand.**
- **There is still work to be done before the agent is fully trained.**
  - During training, the agent became stuck at the boundary conditions.
  - The working range of the action item does not completely match the working zone of the agent. By fixing this issue, the agent can be trained more sufficiently.

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