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EXPLAINABLE RL AND RULE REDUCTION FOR BETTER BUILDING CONTROL

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ABSTRACT

Although it is widely acknowledged that reinforcement learning (RL) can be beneficially used for better building control, many RL-based control actions still remains unexplainable for daily practice of facility managers. This study reports the development of explainable RL for cooling control of an existing office building. A decision tree is applied to trained DQN agent and then a set of reduced-order control rules were suggested. Compared to the DQN agent, the rules are proved to be good-enough and the difference in energy savings between the two is marginal, resulting in 2.8%.

1 INTRODUCTION

Recently, reinforcement learning (RL) based control of building systems has been attracting significant attention in the building simulation domain. Although many recent studies have proved that RL can contribute to optimal control of building thermal systems, e.g. chiller, heat pumps, two challenges still remain unsolved: (1) because most RL agents rely on neural network model or a black box, an RL-based controller is often not interpretable for building operators. In other words, it is difficult for the operators to prevent and predict errors of the controller. (2) Many buildings still do not have automatic building control systems that RL based control can be directly applied to. This means that a novel concept enabling the collaboration between humans and artificial agents should be introduced. With these in mind, this study aims to develop explainable RL (DQN + decision tree) control for cooling system of an existing building. It is hypothesized that even a shallow decision tree model can interpret the decisions made by DQN and be further used to develop a set of reduced-order explainable control rules.

2 PROJECT SCOPE

An existing office building located in Gyeongsangbuk-do, South Korea is chosen as a target building (Fig.1). The building is cooled in summer by two parallel heterogenous systems (an ice-based thermal storage supported by two turbo chillers + 18 geo-thermal heat pumps). A federated model is proposed to find optimal control strategies of the systems. The federated model is an integrated data-driven model that consists of several modules based on physical causality. The model is composed of six modules and used for training of an agent of deep Q-learning. A reward function is defined to lead the agent to learn control strategies to reduce energy consumption while providing cold for the target building. Then, a decision tree model is trained using state-action pairs out of the pre-trained agent. Four important features are captured based on calculated feature importance of states. Finally, the reduced order 'if-then' rules that building operators can interpret and directly apply to building control are developed (Fig. 1).

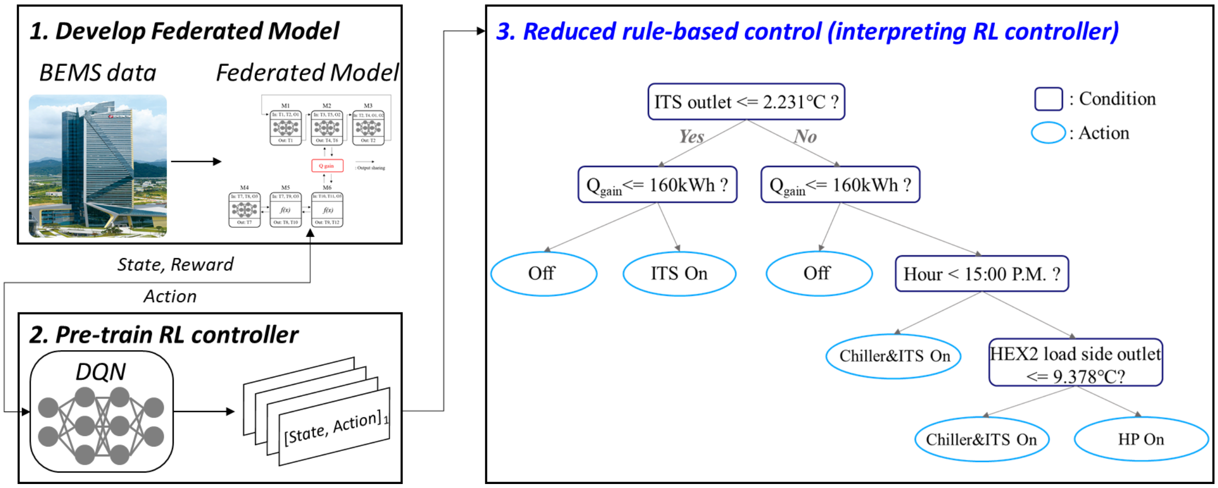

Figure 1: Development process of explainable RL and reduced control rules from deep Q-network.

3 RESULTS AND CONCLUSION

The DQN agent was iteratively trained for 500 episodes using data gathered for 21 days (July 22-August 11). The reduced rules were extracted from state-action pairs generated during episodes 451-500 with a decision tree (maximum depth: 4, minimum samples of leaves: 100). Both the DQN controller and the reduced control rules were compared for three days (August 12- 14). The DQN controller could save 31.9% of energy consumption compared to the existing baseline control. The rule-based controller could save energy consumption by 29.1% (Table 1). It is found that the reduced-order control rules are good enough in terms of energy savings and more explainable and practical for facility managers than the DQN.

Table 1. Comparison between DQN and reduced-order control rules.

	Baseline	**DQN**	**Reduced rule**
Chiller energy consumption (kWh)	14,440	6,464	7,272
Heat pump energy consumption (kWh)	0	3,372	2,957
Total energy consumption (kWh)	14,440	9,836	10,229
Energy saving rate (%)	-	31.9%	29.1%
Return	3.4	27.5	23.1

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