Multi-Agent Reinforcement Learning For Building Energy Flexibility

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Abstract

- Developed a novel algorithm for coordinated demand response: A multi-agent RL algorithm with predicted information sharing.
- Applied our algorithm in groups of five buildings for electrical storage (battery) charge and discharge control of the buildings with the goal of reducing electricity cost and CO2 emissions.

Motivation

Buildings account for over 70% of the electricity consumption and 30% of greenhouse gas emissions in the US. Energy storage devices such as home batteries can reduce peak loads of the grid by shifting the energy use of buildings to different times. Solar photovoltaic generation can reduce the overall demand to the grid while also reducing emissions.

However, all these resources must be carefully managed simultaneously in many buildings to unlock the full energy potential and reduce homeowners' costs.

We want to develop energy management agent(s) and their reward function for battery charge and discharge control in each building to minimize the monetary cost of electricity drawn from the grid and the CO2 emissions when electricity demand is satisfied by the grid.

Dataset

- One year of actual meteorological weather data for the buildings' location used to provide observation valuesto the environment.
- One year of actual CO2 emission rate from grid mix.
- One year of Time-of-Use electricity cost.
- One year of each building's time series data including, there are five buildings in total.
- temporal variables, end-use demand, solar generation and indoor environment variables.

Method

➤ Multi-agent RL Model:

- Agents: Actor–critic
- Estimator: Linear Regression

➤ Reward Design:

$$r_i^1\colon min\{0, e_i\} \quad r_i^2\colon sign(e_i)\cdot min\{0, e_i\}^2$$

$$r_i^3\colon min\{0, e_i\}^3 \quad r_i^4\colon -sign(e_i)\cdot e_i^2 \cdot min\left\{0, \sum_{i=0}^{n} e_i\right\}$$

Fig 1. Reward functions compared

➤ Information sharing:

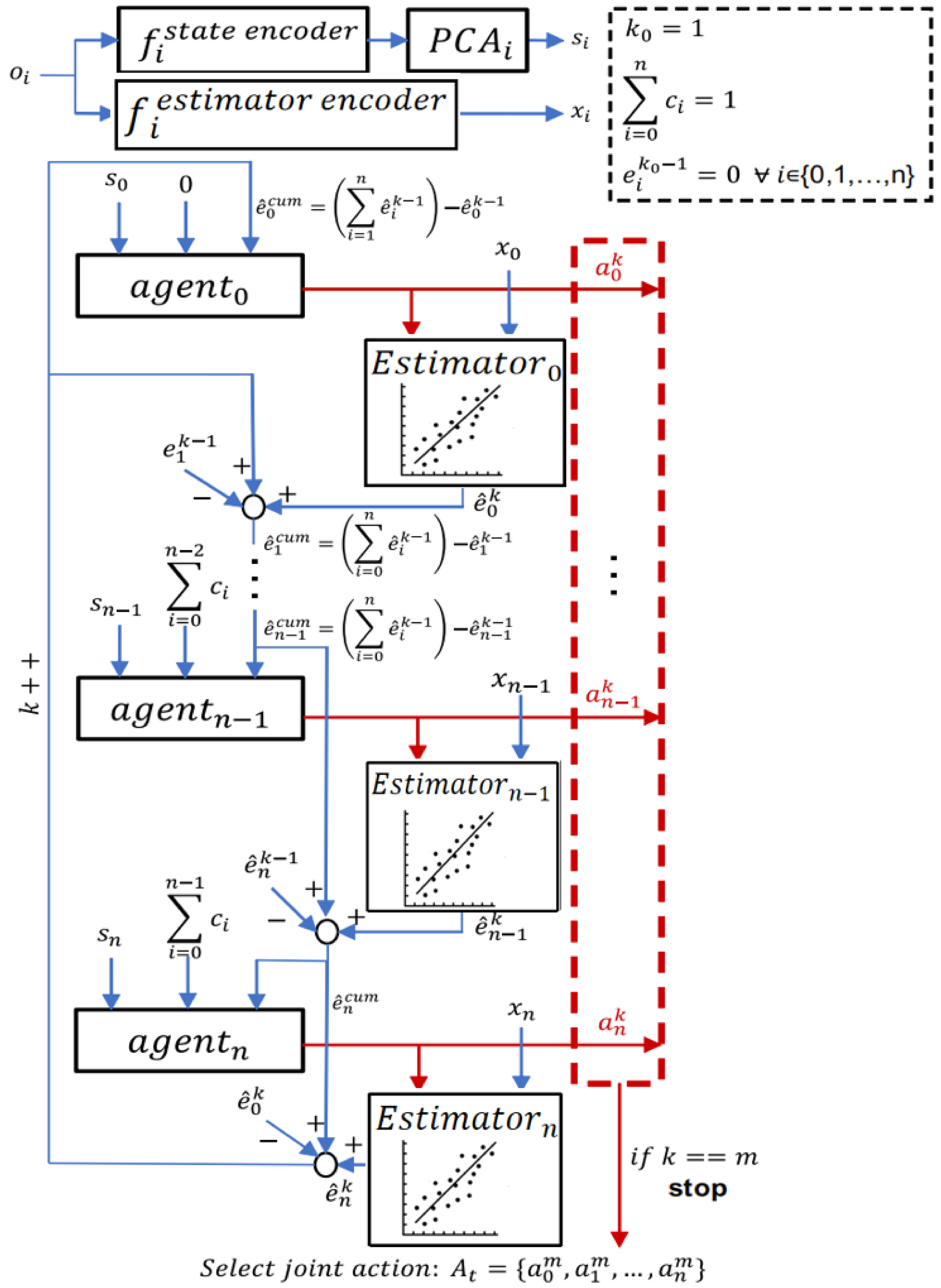
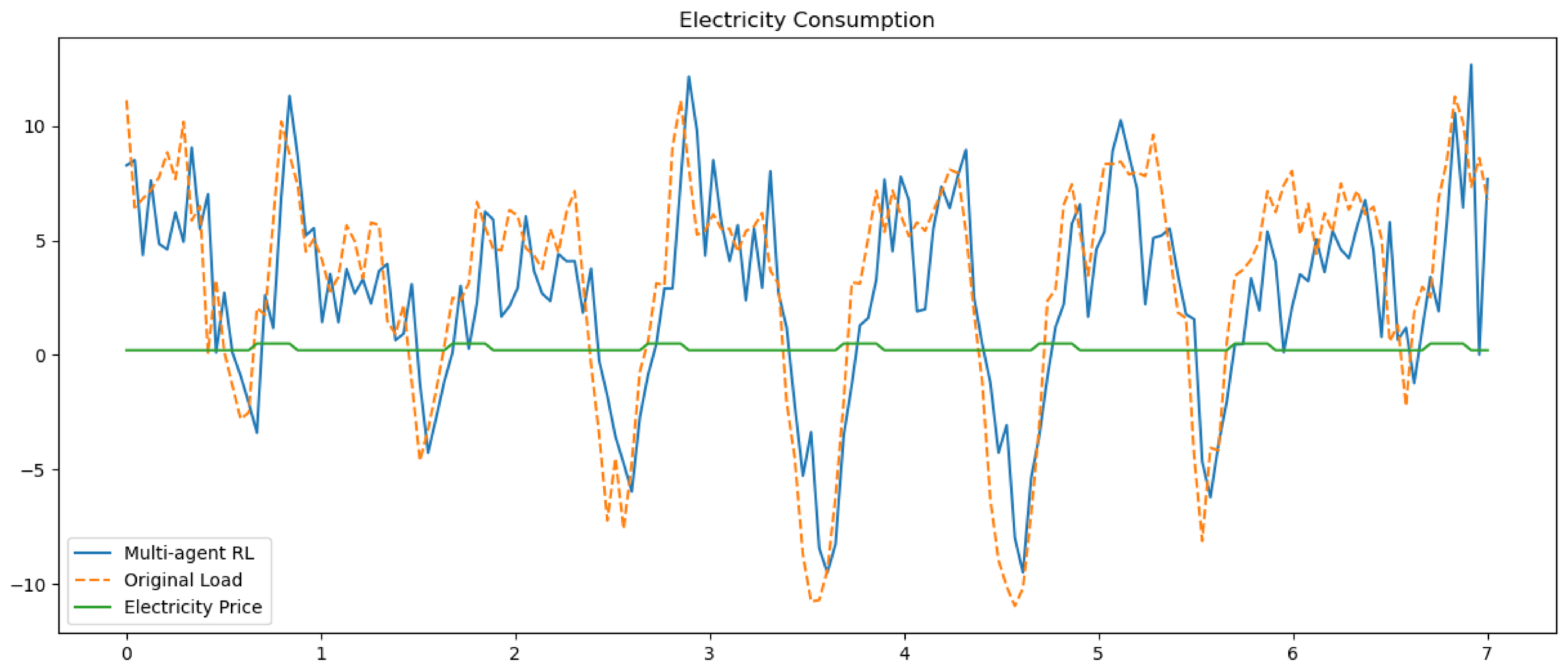
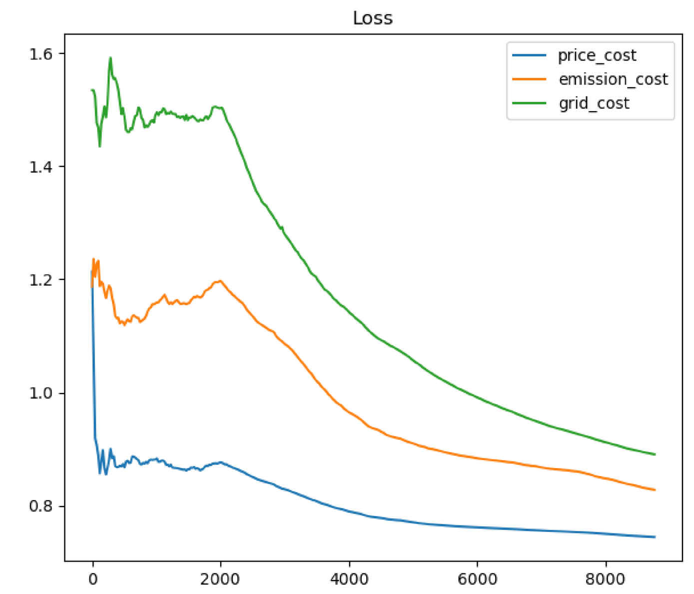


Fig 2. Information sharing and shared predictions

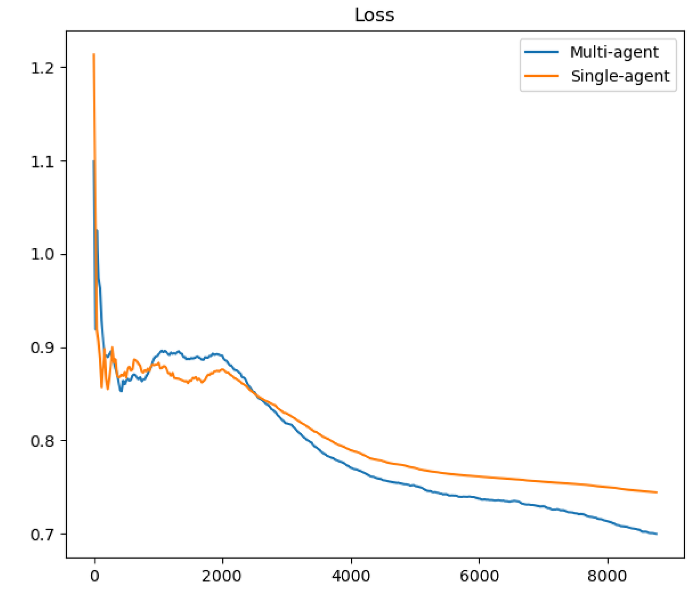
Training Results



Electricity Cost



Training Loss



Multi-agent V.S. Single-agent

Fig 3. Training results

Conclusion

- Multi-agent RL works well on reducing the total electricity cost and CO2 emissions of 5 buildings in the district.
- Compared to official Rule based agent, RL agent outperforms 6.7% on electricity cost and 8.3% on CO2 emissions.
- Multi-agent works better than Single-agent because of the information sharing algorithm.
- The reward functions need to be further discussed since it sometimes fall into the result of doing nothing.

Reference

[1] Vázquez-Canteli, J.R., Henze, G.P., & Nagy, Z. (2020). MARLISA: Multi-Agent Reinforcement Learning with Iterative Sequential Action Selection for Load Shaping of Grid-Interactive Connected Buildings. Proceedings of the 7th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation.
[2] Mason, K., & Grijalva, S. (2019). A review of reinforcement learning for autonomous building energy management. Computers & Electrical Engineering, 78, 300-312.