Multi-Agent Reinforcement Learning for Distributed Solar-Battery Energy Systems

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Research goal

The aims of the thesis are in several folds:

First, I aim to achieve the sustainable development goals (SDG-7) in ensuring access to affordable and clean energy. In this thesis, I aim to raise the efficiency of using renewable energy sources for local residences.

Second, I aim to explore solutions for designing distributed intelligent agents in the energy management sector. I aim to see how reinforcement learning (RL) methods could be applied to single-house and multi-house systems.

Finally, I aim to improve the effective operation of the energy grid systems in determining the optimal use of distributed generations to feed the electrical loads and to find what factors would influence the performance.

Methods

The local direct current open energy system (DCOES) at the OIST faculty housing area allows energy exchange among houses under communication. However, current sharing energy protocols have to be manually modified and fixed for each house. As solar energy production varies in time and space depending on weather conditions, how to combine it with distributed energy storage and exchange systems with intelligent control is an important research issue. Therefore, it is necessary to involve some adaptive methods as an artificial intelligence (AI) base to raise the efficiency of the grid. I applied reinforcement learning methods to the system to tackle these problems. In the energy management sector, I first test multiple RL algorithms for energy storage control of single houses with the linear battery model I create. I then extend the Autonomous Power Interchange System (APIS) from SONY to combine it with reinforcement learning algorithms in each house. I consider different design decisions in applying RL: whether to use centralized or distributed control, at what level of detail actions should be learned, what information is used by each agent, and how much information is shared across agents. Based on these considerations, I implemented the deep Q-network (DQN) and prioritized DQN to set the parameters of the real-time energy exchange protocol of APIS and tested it using the actual data collected from OIST DCOES.

Result

For single-house system, the simulation results indicate that charge and discharge coefficients and the decay value can be obtained with the battery model for individual houses. In addition, the tabular method can control the current of energy storage. But it has limitations in structuring the state representations. The deep RL method converges faster in learning than the tabular method. Also, having time-of-day information in the state can reach smoother learning in the early days, but this cyclic value slower the performance.

For multi-house systems, the simulation results showed that DQN agents outperform rule-based control on energy sharing and that prioritized experience replay further improves the performance of DQN. Simulation results also suggest that sharing average energy production, storage, and usage within the community helps the performance.

Conclusion

I have Verified that RL methods could tackle energy management problems in DCOES. For multiple houses, RL methods outperform fixed rule-based controllers. In addition, the Prior-DQN method outperforms the DQN method. Having community average information could further improve the performance. Also, trained agents can perform better in different data sets.