Energy Storage in the Smart Grid: a Multi-Agent Deep Reinforcement Learning Approach

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Introduction

This poster introduces a novel RL-controlled energy storage system for households in the smart grid (SG). It optimizes electricity trading in variable tariff settings, showcasing substantial consumer savings without altering consumption patterns. The system is evaluated in both singleagent and Multi-Agent System (MAS) simulations, in the latter the price depends on total demand. Simulation results underscore storage's positive influence on the energy market, benefiting consumers and network

Key Results

- Variable tariffs lead to significant (up to 35.7%) annual electricity bill reductions for most households (98%), as compared to flat tariff.
- My system offers substantial savings (average of 20.91% as compared to variable tariff for extended DQL with 3kWh battery) for all households, including these negatively affected by tariff change.
- Combining my storage system with PV results in increased savings (26.49% for 1kW PV and 90.47% for 4kW PV with 3kWh battery).

operators alike. We also explore varied storage sizes and agent complexities, offering valuable insights into the system's potential and benefits.

Methodology



Figure 1: Reinforcement Learning cycle. Agent in state s_1 takes action a_1 , altering the environment to s_2 and receiving reward r_1 , then process repeats.

Agent operations are illustrate in Figure 1. In each half-hour episode, agents evaluate environment state, including factors like price, storage level, and stored electricity value, and then select one action like waiting, purchasing, using, or selling energy. The range of environment states varies from 110 in single-agent scenarios to infinity in MAS simulations. The experiments used consumption data from the Low Carbon London project alongside Octopus Energy's variable pricing tariff. Three algorithms were tested: a simple rule-based approach, tabular Q-learning, and Deep Q Learning (DQL). An extended DQL agent with a fourth action (selling) was also investigated. Later, a custom-made simulation of PV generation, with results shown in Figure 2, was incorporated into the DQL agent to simulate prosumers.

- In single-agent simulations with PV, immediate self-use, surplus storage, and excess energy sales prove the most efficient scheme, outperforming the direct storage and surplus sale approach. Contrarily, MAS favor the latter scheme.
- Steep price-demand functions in MAS lead to higher savings. Thus exponential function offers the largest savings, yet variable tariff pattern aligns more with logarithmic function.
- Households in MAS benefits from widespread adoption of my storage system, but even non-adopters benefit from its presence.
- My storage system eases stress on the power grid by leveling demand peaks as can be seen in Figure 3.
- In MAS, each agent's savings depend on their storage and decisions, as well as those of others in the community
- Higher total yearly household consumption reduces system savings.
- Savings rise with higher battery capacity, plateauing around 4kWh.
- DQL agent rarely uses high currents, thus increasing battery lifetime.





Figure 3: Comparison of a total usage in a community of 3 consumers without and with our 0.5kWh storage system installed in each household.

Conclusion

In summary, our innovative agent-controlled energy storage system provides benefits for both consumers and suppliers, contributing to ongoing research in the field. All households benefit, including those initially disadvantaged by variable tariffs. Thus my system boosts social acceptance of changes in the energy sector, further promoting SG development.

Future Work

¹⁰ Time of the day¹⁵ ²⁰

Figure 2: An example of solar energy generation patterns of 2nd June (Blue), and 1st January (Orange) for 1 kW system.

In MAS simulations, DQL agents represented a community of three consumers/prosumers. Various price-demand functions (linear, logarithmic, exponential) were tested. As agents' actions influence demand, the price varies, posing a challenge as agents base decisions on the initial price, which differs from the final price used for bill calculations. Selling price was set at 80% of the import price, or 0 if import price was negative, mirroring the variable tariff behaviour.

Future work can include:

- Implementing a continuous action space.
- Analyzing the effect of agent count on savings.
- Studying bigger energy storages and PV panels.
- Accounting for battery, transmission, and inverter losses.
- Using real PV generation data or refining the simulation.
- Adjusting the simulation to reflect current consumption patterns and electricity pricing influenced by the COVID-19 pandemic and economic crisis.