Decarbonizing Household CO2 Emissions with a Battery Storage System

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Terminology

- BSS → Battery Storage System
- PV → Photovoltaic (i.e Solar Panels)
- Carbon Intensity → amount of CO2 Emitted per kWh
- RL → Reinforcement Learning
- PPO → RL agent
- DQN → RL agent

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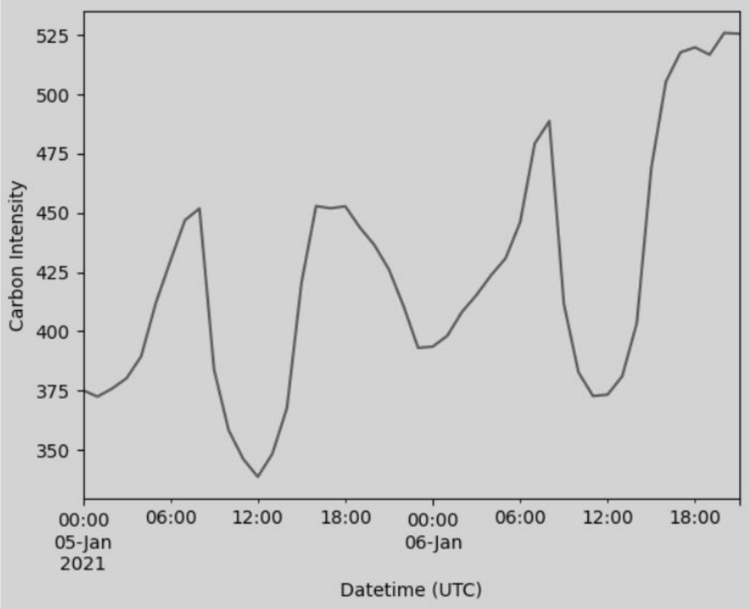
Introduction

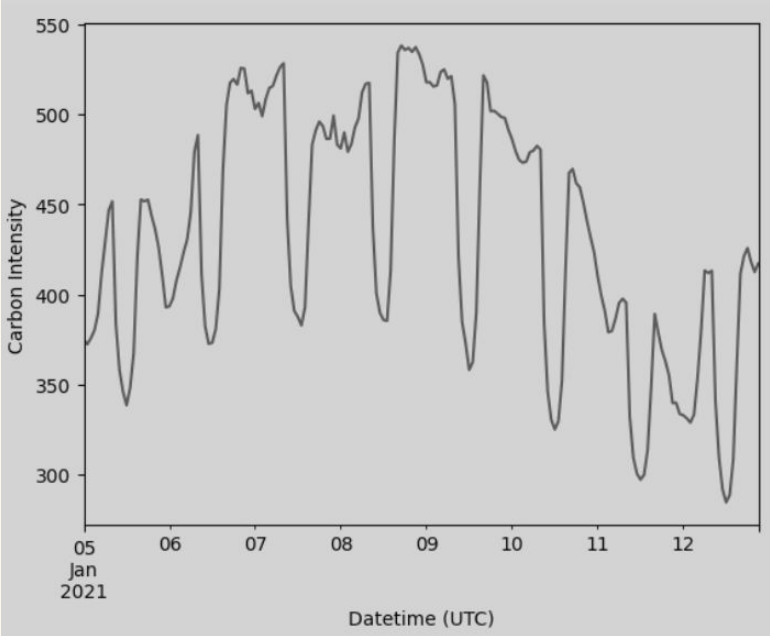
Household Decarbonization, Why?

- Transitioning to ‘greener’ energy mixes does not resolve the human-caused high-demand patterns.
- Carbon Intensity peaks coincide with energy demand ones, the latter causing the former (Zhang, 2019).
- As such, the Dutch electrical grids’ carbon intensity varies drastically every day.



Household Decarbonization, How?

- A BSS could shift a household’s energy demand.
- The BSS should charge when carbon intensity is low and discharge when high.
- The system takes advantage of carbon intensity variability.



Why not rely on photovoltaics?

- PV systems **can** save up to 21% of household emissions (Khowaja et al., 2022).

However, compared to grid-connected BSSs:

- They are more expensive.
- They are more complex systems.
- They can only be installed on detached houses, which leaves out 46% of Europeans who live in apartments (Eurostat, 2021).

Research Question

“To what extent can a grid-connected BSS reduce household CO_2 emissions?”

Our Plan

1. Create a simulated environment of the CO_2 emitted by a Dutch house with and without a BSS.
2. In this environment, train two RL agents to control the BSS' charge/discharge strategy.
3. Evaluate the CO_2 savings across **seasons** and multiple **battery sizes**.
4. Compare results to existing literature and assess the real-world feasibility of a BSS.

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Methodology

Household Emissions Simulation

- Real-world data of carbon intensity and a homes' electricity consumption was used (Electricity Maps, 2024; Uttama Nambi et al., 2015).
- The simulation was custom-built, following OpenAI's Gymnasium framework (Brockman et al. 2016).
- Its interface is directly compatible with any StableBaselines3 RL agent.
- Lastly, the environment follows the Markovian assumption.

Reinforcement Learning Agents

DQN

- Heavily discounted future rewards
- Relatively sample inefficient
- Low exploration after initial period
- Primitive design

(Watkins & Dayan, 1992; Minh et al., 2013; Jin et al., 2018)

PPO

- Emphasis on long-term cumulative reward
- Increased sample efficiency and complexity
- Comprehensive exploration in all stages
- Hyperparameter tuning research unavailable

(Schulman et al. 2017)

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Results

Disclaimer

The environment is, ultimately, a real-world simulation so:

1. Above-expectation results can be caused by unaccounted-for inefficiencies.
2. Below-expectation results can be caused by inadequacies in the RL agents.
3. The RL agents are stochastic at nature, so results will vary.

Seasonal Comparison

	Spring	Summer	Fall	Winter	Total
PPO	3.02%	2.14%	1.20%	1.73%	2.04%
DQN	0.06%	N/A	N/A	N/A	N/A

- Battery size of 5 kWh and charge rate of ¼ of battery size.
- Five models of each were trained, the one with largest mean episodic reward chosen.
- Results obtained from averaging 30 episodes from each model.

Battery Size Comparison

RL Agent	1 kWh	3 kWh	5 kWh	7 kWh	10 kWh
PPO	0.61%	1.81%	1.93%	0.97%	1.17%
DQN	N/A	N/A	N/A	N/A	N/A

- Charge rate of ¼ of battery size.
- Selected season for the simulation is summer.
- Five models of each were trained, the one with largest mean episodic reward chosen.
- Results obtained from averaging 30 episodes from each model.

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Discussion

DQN Inadequacies

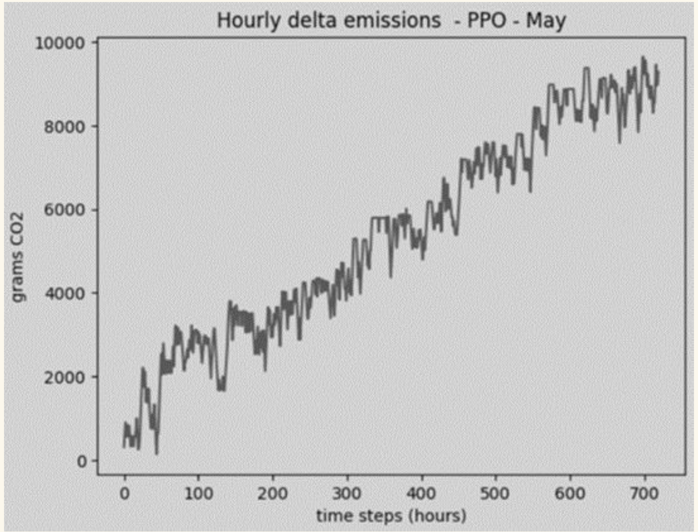
“N/A” values explained:

1. DQN **never** performed **enough exploration**.
2. Exploration is done with completely random steps.
3. Most times, choosing random actions was better than using DQN.

“N/A” is more appropriate than negative CO_2 savings

Interpreting Seasonal Results

- **Best** performance: March to May at **3.02%**
- **Worst** performance: September to November at **1.20%**
- **Total** savings: **2.04% yearly**, or **70kg** out of **3534kg** of CO_2



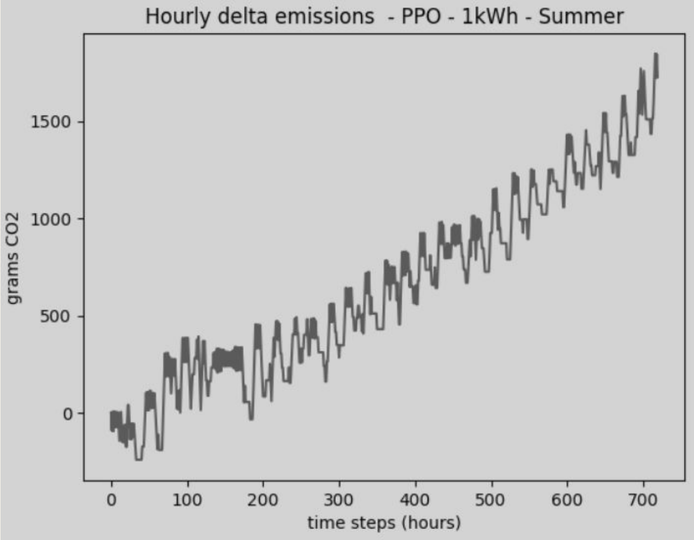
The PPO models trained and performed well throughout each of the four tests.

Lastly, my results align with those of Khowaja et al. (2022), despite large differences in methodology. Overall savings at around 2%, with best and worst performance in spring and fall respectively.

Interpreting Battery Size Results

Battery sizes 1-5 kWh:

- The 1 kWh test could not save much, as full discharge barely covers one hour of consumption.
- The 3 and 5 kWh battery sizes could reliably cover the household's energy needs for more extended periods of time; within 5-10% of the overall results.
- The 5kWh test is the same as the 'summer' investigation in the seasonal investigation. The mismatch between 2.14% and 1.93% is explained by the stochastic nature of PPO.



Considering the household has a **low energy intensity**, and our findings indicate a **5 kWh battery is most appropriate**, then **our results align** with those of Leadbetter & Swan (2012).

Interpreting Battery Size Results

For battery sizes 7-10 kWh we encountered an issue with RL agents:

- A larger battery should result in more CO_2 savings, but the agent could not deal with with the large short-term increases in CO_2 emissions.
- The battery must be charged at first, which always leads to short-term emission losses.
- Then one discharge cycle would always cover the energy demand of the house, with a lot to spare. Thus, the added complexity hindered the training.

The observed savings of 0.97% and 1.17% fit with the case of sub-par training of the PPO agent.

Limitations

1. Roundtrip efficiency of the batteries stands at around 90% (Bistline & Young; 2020); we assumed 100%.
2. Unavailability of newer and more varied data on household energy consumption.
3. Non-custom implementation of PPO.

Points 1 and 3 would **decrease** observed **performance**.
Point 2 could **increase** observed **performance and** improve **generalizability** of the study.

Real–World Feasibility of BSSs

On **just CO2 emission** savings: BSSs **perform worse** than PV systems (2% compared to 21% annually).

However, **BSSs have some advantages:**

1. Considerably lower up-front cost.
2. Can be installed in any home-type.
3. Can be used as backup power storage.
4. Can also be used for energy arbitrage.

To answer the RQ: Grid-connected BSSs can slightly reduce household CO2 emissions, with average savings of around 2% annually for a low energy intensity Dutch household.

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References

Bistline, J. E. T., & Young, D. T. (2020). Emissions impacts of future battery storage deployment on regional power systems. *Applied Energy*, *264*, 114678. https://doi.org/10.1016/j.apenergy.2020.114678

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., & Zaremba, W. (2016). OpenAI Gym. *Computing Research Repository*. https://arxiv.org/abs/1606.01540

Electricity Maps. (2024). Netherlands 2021 Hourly Carbon Intensity Data (Version January 17, 2024). In *Electricity Maps Data Portal*. https://www.electricitymaps.com/data-portal/netherlands

Eurostat. (2021). *House or flat: where do you live?* https://doi.org/10.2908/ILC_LVHO01

Jin, C., Allen-Zhu, Z., Bubeck, S., & Jordan, M. I. (2018). Is Q-learning Provably Efficient? *International Conference on Machine Learning*. https://arxiv.org/abs/1807.03765

Khowaja, A., Dean, M. D., & Kockelman, K. M. (2022). Quantifying the emissions impact of repurposed electric vehicle battery packs in residential settings. *Journal of Energy Storage*, *47*, 103628. https://doi.org/10.1016/j.est.2021.103628

Leadbetter, J., & Swan, L. (2012). Battery storage system for residential electricity peak demand shaving. *Energy and Buildings*, *55*, 685–692. https://doi.org/10.1016/j.enbuild.2012.09.035

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing Atari with Deep Reinforcement Learning. *International Conference on Machine Learning*. https://arxiv.org/abs/1312.5602

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., & Klimov, O. (2017). Proximal Policy Optimization Algorithms. *Computing Research Repository*. https://arxiv.org/abs/1707.06347

Uttama Nambi, A. S. N., Reyes Lua, A., & Prasad, V. R. (2015). LocED. *Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments*, 45–54. https://doi.org/10.1145/2821650.2821659

Watkins, C. J. C. H., & Dayan, P. (1992). Q-learning. *Machine Learning*, *8*(3–4), 279–292. https://doi.org/10.1007/BF00992698

Zhang, H. (2019). Effects of electricity consumption on carbon intensity across Chinese manufacturing sectors. *Environmental Science and Pollution Research*, *26*(26), 27414–27434. https://doi.org/10.1007/s11356-019-05955-9