Artificial Intelligence for Climate Change Mitigation through Efficient Electrical Storage Policies

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Abstract

While large-scale AI deployment can perpetuate the problem of climate change through large electricity demands for computation, we seek use ML to attack the problem. With buildings beginning to have more and more electrical resources, we look to apply AI to manage these resources more effectively, and thereby reduce GHG emissions. We do this by training an RL agent which learns an electrical management policy that manages the electricity in a more efficient way therefore reducing the GHG emissions made by the power grid and reducing the overall cost of electricity.
[1]

1 Introduction

In the US, more than 70% of the electrical needs are met by Residential and Commercial buildings where Residential buildings account for more than half of them utilizing about 1.48 Trillion kWh. With such an increase in electricity consumption increase in energy efficiency can reduce energy costs and reduce the emission of Greenhouse gases (GHG) significantly. Energy Efficiency can be brought on by Demand Response which is a measure for reducing energy load in response to supply constraints, generally during periods of peak demand. Unlocking this potential requires control systems that operate on distributed systems, ideally data-driven and model-free . For this, Artificial Intelligence (AI) algorithms especially Reinforcement Learning (RL) algorithms are used. We have used the comprehensive dataset from CityLearn to perform various AI algorithms to achieve energy efficiency.

1.1 Related Work

We look for work that deals with real-time data management that focuses on optimization processes. The most prominent example comes from Guan et al [3]. They used TD(Λ) learning on data created from a model of battery storage systems with the aim at using this on residential data someday. They demonstrated a 59.8 improvement in energy cost reduction with the policy generated from their TD(Λ) generated policy as opposed to conentional methods. However this also meant they needed to clearly define the state and action spaces, and reward function in the TD(Λ)-learning algorithm such that the objective of the reinforcement learning algorithm coincides with the goal of electric bill minimization for the residential consumer. This is distinct from our project in a few ways. First we care about multiple metrics not just the consumers cost for electricity second we have a large dataset to test our model on.

Another related work was done by Aljohani [2] Where they use double deep Q learning network and a markov chain model to optimize a route to minimize energy cost of an electric vehicles travel.

[1] https://gitlab.aicrowd.com/CHUF/citylearn-project-cs-640/-/tree/master

Results obtained for two geographically different drives show that the proposed energy consumption minimization framework reduced the energy utilization of the EVs to reach its intended destination by 5.89 percent and 11.82 percent, compared with Google's proposed routes originally. Their framework could still prove useful as a way for us to tackle our problem.

1.2 Problem

Kaack et al. explains that ML has a "multi-faceted relationship" with climate change [4]. On one side of this relationship, large-scale deployment of ML applications leads to an increase in GHG emissions due to the electric load that is required for training models and computations. On the other side, there are ML applications that can serve to reduce GHG emissions as well. One such application, is to apply ML to optimize the electrical storage policies of buildings.

The problem faced in the NeurIPS 2022: CityLearn Challenge, is to manage the resources such as home batteries and solar panels which are increasingly present in buildings. The CityLearn environment is a gym environment that is designed to simulate this resource management. The goal of the challenge is to learn a policy that will reduce district electricity costs and CO2 emissions in this environment. Specifically, the goal is to efficiently route power during peak loads on the grid and route power from solar panels to help lessen this load while at the same time maintaining the operating capacity for all buildings. This means the agents must learn when to use electricity directly from the on-site solar panels, when to charge/discharge the battery, and when to rely on the grid. If they rely on the grid, they should learn to use it when it's cheap and/or with low carbon content. Due to this complicated relationship and real-time changes this problem is best tackled through deep reinforcement learning

2 Methods

2.1 Rule-based Policies

For this milestone report, we submitted a baseline rule based policy provided in the starter kit. Rule-based policies may have a lot of merit in this application, as a lot of easily quantifiable data is provided in the observation data. Each observation has features such as the hour of the day which may be a large factor in what action we should take, especially for a building with solar panels for instance. If we can learn an effective rule-based system, it may perform relatively well.

Additionally, the observations provided contain continuous features, and for a continuous state space, rule-based methods will be generally more appropriate.

2.2 DQN & DDQN

Q-learning is not feasible for this specific problem because the state space is very large as it's based on a great number of observations which would have to be discretized. Q-Learning would take a large amount of memory and data to store and learn the Q values respectively. A DQN would only need to store the model, and would learn patterns in the data that would generalize well to unseen Q-values. However, given the continuous state space, this might not be a strong architecture

We can also use a double deep Q learning scheme which would utilize two neural networks which update each other which can avoid maximization bias by disentangling our updates from biased estimates.

3 Results

3.1 Evaluation Criteria

In order to evaluate our policy, we made submissions to the NeurIPS 2022: CityLearn Challenge [1]. The submissions are evaluated based on the average of three metrics:

1. The average electricity cost
2. The average CO_2 emissions

3. The average grid cost

The metrics are normalized against the metrics of an environment where there are no batteries. The average is taken over the buildings in the environment, of which there are 5/17 for training, 5/17 for validation, and 7/17 for testing. The training score, validation score, and testing score are weighted by 20%, 30%, and 50% respectively.

The competition has now ended, and has not yet released the validation and testing sets, so for the time being we will split our training set so that we have data to test on moving forward.

3.2 Baseline Model

We submitted the baseline rule-based model given in the competition, and obtained a local evaluation and a final evaluation on the testing set:

Evaluation	Average Price Cost	Average Emissions Cost	Average Grid Cost	**Average Score**
Local	1.069	1.179	1.074	1.107
Testing	1.065	1.164	1.063	1.097

We seek to improve on these baseline scores by trying different architectures, and tuning them appropriately for the final report.

References

[1] Neurips 2022: Citylearn challenge, 2022.

[2] T. M. Aljohani, A. Ebrahim, and O. Mohammed. Real-time metadata-driven routing optimization for electric vehicle energy consumption minimization using deep reinforcement learning and markov chain model. *Electric Power Systems Research*, November 2020.

[3] C. Guan, Y. Wang, X. Lin, S. Nazarian, and M Pedram. Reinforcement learning-based control of residential energy storage systems for electric bill minimization. *IEEE Xplore*, 2019.

[4] Lynn H. Kaack, Priya L. Donti, Emma Strubell, George Kamiya, Felix Creutzig, and David Rolnick. Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, 12(6):518–527, Jun 2022.

[4, 1, 3, 2].