Artificial Intelligence for Climate Change Mitigation through finding Efficient Electrical Storage Policies

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Abstract

While large-scale ML 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 ML 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.

The Problem

Kaack et al. explains that ML has a "multi-faceted relationship" with climate change [2]. 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

Dataset

We will use the dataset given in the NeurIPS 2022: CityLearn Challenge [1]. This dataset consists of: the operational electricity demand for 17 modern single-family style homes in California, The meteorological data around the homes during the year, the carbon intensity or C02 emissions rate from the grid, the time of use electricity costs for the homes, and finally the buildings time series data which includes the end-use demand, solar generation, and other indoor variables. Each of these data sets has 8,760 observations. Out of the 17 houses, 5 are allocated for the training dataset. The whole dataset is used to evaluate submissions as described below.

Evaluation Criteria

In order to evaluate our policy, we will submit to the NeurIPS 2022: CityLearn Challenge [1]. The submissions are evaluated based on the sum of two metrics:

1. The district electricity cost, called C_{entry}
2. The district CO_2 emissions called G_{entry}

The metrics are normalized against the metrics of an environment where there are no batteries, $(C_{\text{no battery}}, G_{\text{no battery}})$. For these metrics, district means 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.

We can compare these scores across multiple submissions to evaluate the performance of various approaches in our final project.

Project Milestone

For our project milestone, we will make at least two submissions to the competition so that we can analyze and compare two approaches to the problem.

References

[1] AIcrowd. 2022. NeurIPS 2022: CityLearn Challenge.

[2] Kaack, L. H.; Donti, P. L.; Strubell, E.; Kamiya, G.; Creutzig, F.; and Rolnick, D. 2022. Aligning Artificial Intelligence with Climate Change Mitigation. *Nature Climate Change*, 12(6): 518–527.

[2, 1].