Demo Abstract: CityLearn v1.0 - An OpenAI Gym Environment for Demand Response with Deep Reinforcement Learning

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ABSTRACT

Demand response has the potential of reducing peaks of electricity demand by about 20% in the US, where buildings represent roughly 70% of the total electricity demand. Buildings are dynamic systems in constant change (i.e. occupants' behavior, refurbishment measures), which are costly to model and difficult to coordinate with other urban energy systems. Reinforcement learning is an adaptive control algorithm that can control these urban energy systems relying on historical and real-time data instead of models. Plenty of research has been conducted in the use of reinforcement learning for demand response applications in the last few years. However, most experiments are difficult to replicate, and the lack of standardization makes the performance of different algorithms difficult, if not impossible, to compare. In this demo, we introduce a new framework, CityLearn, based on the OpenAI Gym Environment, which will allow researchers to implement, share, replicate, and compare their implementations of reinforcement learning for demand response applications more easily. The framework is open source and modular, which allows researchers to modify and customize it, e.g., by adding additional storage, generation, or energy-consuming systems.

CCS CONCEPTS

• Software and its engineering • Virtual worlds software • Virtual worlds training simulations

KEYWORDS

Building Energy Control, Smart Buildings, Smart Grid

1 Introduction

Buildings account for approximately 70% of the electricity consumption in the US [1]. However, this demand for electricity is not evenly distributed. Urban areas are growing rapidly, increasing the magnitude and the density of the demand for electricity in these territories. This rapid growth not only increases the constraints in power lines, and consequently the cost of electricity, but also represents a problem for the current power grid, which needs to grow as well. Although extremely high peaks of electricity consumption do not occur frequently, they are used to size the equipment of the power grid (i.e., transformers, power lines) and the loads it is capable to sustain. These additional investments in the power grid are then reflected in the electricity bills of the consumers. Being able to effectively shave the peaks of electricity can help increase the reliability of the power grid and reduce the average cost of electricity.

Demand response (DR) provides electricity consumers with the ability to modify their consumption patterns in order to adapt to changing electricity prices or other incentives they may be offered. Some estimates point out that DR has the potential of shaving peaks of electricity up to 20%, on average [2], in the US. However, for DR to be effective, loads must be controlled in a responsive, adaptive and intelligent way. When all the electrical loads react simultaneously to the same price signals, electricity peaks could be shifted rather than shaved. Therefore, there is a need for more effective ways of coordinating the multiple agents that constitute a part of the electrical system. Some advanced control approaches, such as model-predictive controllers (MPC), can provide good results when properly designed. However, they require a deep understanding of the physical behavior of the systems being controlled, as well as developing a model of such systems. Due to the lack of information, resources (the modeling process can be costly), or because the system is to complex, it is often not feasible to develop a model. Other times, despite the feasibility of developing a model, the system under control changes over time, and therefore, the models must be updated.

Reinforcement learning (RL) is an adaptive and potentially model-free control algorithm that can take advantage of both real-time and historical data to provide DR capabilities. As Figure 1 illustrates, RL agents learn through interaction with their environment (the system being controlled), by taking actions under certain states and observing the actions and future states that result from such interaction [3].

The use of RL in DR, and to control urban energy systems in general, is a field that has received a lot of attention in the past few years [4]. However, despite this interest and the increasing amount of research being devoted to this topic, there has been an overall lack of standardization in the problems being solved [5]. This lack of standardization makes it difficult to compare different RL

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algorithms with each other, replicate the experiments, share the code or the results, or even understand what has been done. While there is some previous work that aims towards the standardization [6], it is mostly focused on the building level. In this paper, we introduce CityLearn, a simulation framework for testing RL algorithms in DR scenarios at the urban scale.

2 CityLearn

CityLearn is a simulation environment for demand response that allows researchers to easily implement their own RL agents, or other RL agents from the computer science community, which are often written to be implemented in OpenAI Gym Environments. CityLearn is written in Python and can be downloaded from our GitHub repository [7]. It can be loaded with data of the heating and cooling loads from buildings or with surrogate models. CityLearn has multiple models of energy storage and supply devices that can be controlled: version v1.0 is released with models of air-to-water heat pumps, thermal energy storage, and batteries. Further developments will include additional energy storage and supply devices, more detailed models.

The heating and cooling demands for the buildings are obtained from CitySim, a building energy simulator for urban scale analysis [8]. CitySim uses geometrical 3D and physical reduced order models to estimate the heating and cooling loads in the buildings. It accounts for the internal heat gains due to solar irradiance, activities of the occupants, and the thermal losses. We modelled the buildings as a single-thermal zones that are provided with various heating and cooling supply devices, and energy storage devices.

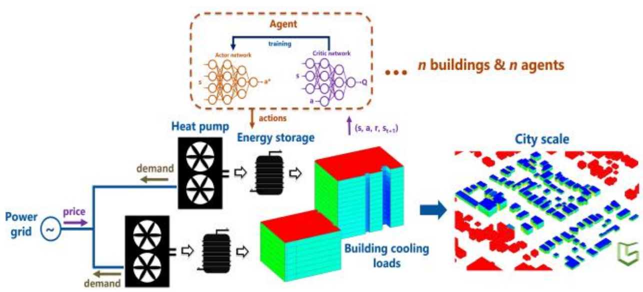

Figure 1: Demand response environment with RL agents

To develop CityLearn, we first defined the main components of any DR problem. As illustrated in Figure 1, these components are the energy demand or electrical loads, the energy storage systems, and the energy supply systems, which are connected to the power grid. In addition to these physical models, the RL agents coordinate the various energy supply and storage devices and make them responsive to electricity prices. CityLearn follows a modular bottom-up structure. At the bottom, energy storage and supply devices constitute the simplest objects or classes of this environment, which are instantiated and controlled by the Building class. On the top of this hierarchy, the CityLearn class enables buildings to run within the simulation, and inherits methods and attributes from the OpenAI Gym Environment super class. OpenAI Gym is a toolkit for developing and comparing RL algorithms. It makes no assumptions about the structure of the agents, and is compatible with machine learning libraries such as TensorFlow, Theano, or PyTorch [9]. There are currently various Gym environments for robotics, classic control problems, or Atari games among others. These environments have been widely used in the research community in order to test different RL implementations, perform benchmarking, and compare different algorithms with each other [10].

3 Demo description

CityLearn allows the easy implementation of RL algorithms for demand response in a simulated environment. During the demo, we will explain its different modules and functions. We will also run a sample urban model of 10 buildings, each of them with its own RL agent (using the deep deterministic policy gradient algorithm: DDPG). The buildings will interact and learn from each other, trying to minimize the total cost of the electricity they consume and flattening the overall curve of demand in the district.

During the demo, attendees will be able to download CityLearn, run examples, or implement their own RL algorithms in the environment.

4 Conclusion

Reinforcement learning, because of its adaptive and model-free nature, can take advantage of the increasing availability of data and provide demand response capabilities in a cost-effective way. However, reinforcement learning has multiple challenges it needs to overcome for its practical implementation. These challenges include robustness, reliability and efficiently from limited amounts of data and in changing environments. Simulation environments serve as a way of testing reinforcement learning and ensuring their reliability before their implementation in real physical systems. The objectives of CityLearn are to improve reproducibility of future research, allow for the comparison of different reinforcement learning algorithms with each other, and make them easier to implement and share. In the future, we plan to organize a competition for different researchers to test their RL algorithms on CityLearn.

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