Abstract (95 words)

* Battery dispatch is an important and current problem. Optimization, reinforcement learning, among other approaches, have been used to solve these problems, but, a method to rigorously compare these methods hasn’t been developed. By evaluating optimization and different reinforcement learning algorithms against a ‘perfect dispatch strategy’ (as developed by Pimm et al, 2018), under a range of commercial and residential load profiles, I will seek to provide a robust comparison of these methods. I also hope to see how a wider state space, such as including weather, can impact the performance of reinforcement learning approaches.

Problem Definition

* Battery storage is a rapidly commercializing technology, that can be used both at the edge of the grid by end consumers to reduce their costs, and at substations and hubs by the utilities to avoid more expensive reinforcement options. Batteries are inherently limited resources and must be charged in order to be available; the choice of when to charge or discharge is therefore an important problem. Reinforcement learning is a possible avenue for batteries to best meet the needs of their owners with minimal intervention in a wide range of contexts.

Data Set

* The US Government, through the Apps for Energy competition, posted a range of example 15-minute interval data from small, medium, and large residential and commercial customers. This data provides a range of datasets against which we can run algorithms, and compare results across algorithms and contexts.

Research Question

* There are a few different methods I have read about, based on both reinforcement learning and optimization methods. There are also papers that have developed methods that calculate, based on perfect knowledge of the problem, the maximum possible benefit achievable from a battery (effectively giving us a benchmark ‘perfect dispatch’ strategy). There does not appear to be a lot of work rigorously comparing these methods, so a possible research question is to compare these methods, and to evaluate how more complicated reinforcement learning, considering a bigger state space such as weather, might improve results.

References (see my DS8012 presentation on Battery Dispatch Strategies for Peak Shaving for further elaboration):

* Zheng, Menglian, Christoph J. Meinrenken, and Klaus S. Lackner (2015). Smart households: Dispatch strategies and economic analysis of distributed energy storage for residential peak shaving.
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* Joshi, Lapesh A. Joshi, Naran M. Pindoriya, and Anurag K. Srivastava (2018). A Two-Stage Fuzzy Multiobjective Optimization for Phase-Sensitive Day-Ahead dispatch of Battery Energy Storage System.
* Palensky, Peter (2011). Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads.