A Data-driven Storage Control Framework for Dynamic Pricing

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Abstract

Dynamic pricing is both an opportunity and a challenge to the demand side. It is an opportunity as it better reflects the real time market conditions and hence enables an active demand side. However, demand's active participation does not necessarily lead to benefits. The challenge conventionally comes from the limited flexible resources and limited intelligent devices in demand side. The decreasing cost of storage system and the widely deployed smart meters inspire us to design a data-driven storage control framework for dynamic prices. We first establish a stylized model by assuming the knowledge and structure of dynamic price distributions, and design the optimal storage control policy. Based on Gaussian Mixture Model, we propose a practical data-driven control framework, which helps relax the assumptions in the stylized model. Numerical studies illustrate the remarkable performance of the proposed data-driven framework.

Related work

The investigation on storage control policy for dynamic pricing only emerges recently. Jin *et al.* propose a heuristic algorithm using Mixed Integer Linear Programming to optimize the electric vehicle charging schedules in [1]. Oudalov *et al.* focus on conducting peak load shaving and introduce a sizing methods as well as an optimal operational scheme in [2]. Wang *et al.* design an optimal control policy and solve the optimal investment problem for general ToU scheme using dynamic programming in [3]. Chau *et al.* assume the knowledge of future demand and the bounds of prices, and illustrate a threshold cost minimizing online algorithm with worst-case performance guarantee in [4]. To deal with limited information and uncertainty, Qin *et al.* introduce an online modified greedy algorithm for storage control in [5]. Vojvodic *et al.* design a forward threshold algorithm to manage storage operation in real-time market, where stages are decomposed using integer programming and heuristic search [6].

Model Formulation

Consider the interaction between consumers and the grid as shown in Fig. 1. The grid operator sets dynamic price $p(t)$ at each time t. Facing such a pricing scheme, the consumer wants to satisfy its demand $d(t)$ in different ways: directly purchases energy $g(t)$ from the grid, saves energy $b(t)$ in the storage system, or uses the energy in the storage system ($c(t)$ out of $s(t)$ in the storage) to meet its demand.

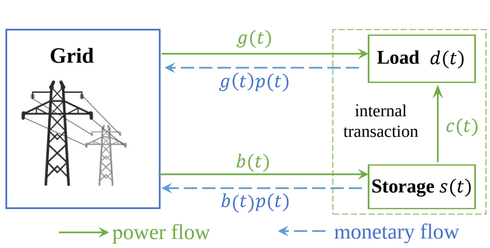

Figure: System model

Major Contributions

The data-driven storage control framework is show in Fig. 2. We provide the theoretical basis for the optimal *online* threshold based storage control policy and derive its regret bound, comparing with the *offline* optimal policy. From the practical perspectives, we take a data-driven approach and employ GMM[7] to accurately characterize the price distribution, and use extensive numerical studies to assess the performance of our proposed framework. In summary, we highlight our principal contributions as follows:

- *Optimal Online Threshold Policy*: Based on the one-shot load decomposition technique, we propose a simple yet effective online threshold policy to minimize the consumers' expected electricity bills. We prove its optimality and derive its regret bound.
- *Data-driven Framework with* GMM: We adopt GMM to relax the assumption of knowing exact price distribution in deriving the threshold policy. With historical price data, we illustrate how to customize the Expectation-Maximization (EM) algorithm for the parameter estimation in GMM, yielding our data-driven storage control framework.
- *Bridge theory and practice*: Our data-driven framework and its heuristic variants enable us to relax many assumptions on the price distributions, including the knowledge of its exact form and the *i.i.d.* assumption. Such relaxations significantly improve the practical feasibility of our framework.

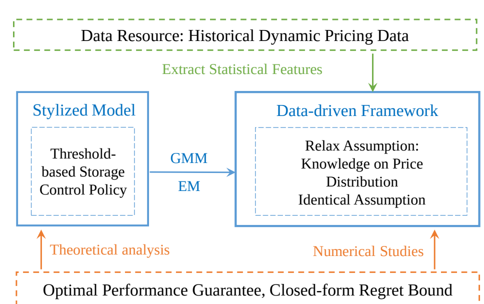

Figure: Major Contributions

Regret Bound Analysis

Theorem 1: ETA is the optimal storage control policy for the *one-shot load serving problem*.
Lemma 1: Denote the solution space of general load serving problem by $\mathcal{S}$. Assume this problem can be decomposed into a sequence of k one-shot load serving problems and denote the corresponding solution spaces by $\mathcal{S}_1, \ldots, \mathcal{S}_K$, respectively. It holds:

$$\mathcal{S} = \bigcup_{i=1}^{k} \mathcal{S}_i. \tag{1}$$

Proposition 1: ETA is the optimal storage control policy for the general load serving problem.
Theorem 2: Assume the dynamic price $p(t)$ is non-negative, then,

$$R(T) \leq \frac{2}{\sum_{i=2}^{T} \beta_i} - T\alpha^{T-1}\mathbb{E}[p]. \tag{2}$$

Numerical Studies

We use the hourly real-time price data to characterize the stochastic nature in dynamic price. The data is collected from AEP during August, 2019. To align with the *i.i.d.* assumption of the price distribution in our stylized model, we first use synthetic data (generated by the fitted GMM) to evaluate ETA's performance. Then, we use real price data to evaluate the performance of DETA and its heuristic variants.As for load dataset, we randomly sample a period from the AEP users' load data, during 2019. The simulation studies show the remarkable performance of DETA and its variants in Fig. 3.

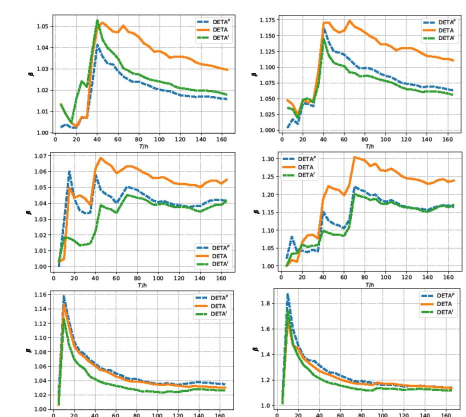

Figure: Performance of heuristic variants.

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