On Designing Prediction-Aware Online Algorithms for Energy Generation Scheduling in Microgrids

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ABSTRACT

In the critical problem of energy generation scheduling for microgrids, one needs to decide when to switch energy supply between a cheaper local generator with startup cost and the costlier on-demand external grid, considering intermittent renewable generation and fluctuating demands. In this paper, we exploit the structure of information in the prediction window to design a novel prediction-aware online algorithm that makes more competitive decisions. Our algorithm achieves the best competitive ratio to date for this important problem, which is at most $3 - 2/(1 + \mathcal{O}(\frac{1}{w}))$, where w is the prediction window size. This competitive ratio keeps decreasing as the window size increases, and it is upper bounded by a constant that is independent of the start-up cost. We also characterize a non-trivial lower bound of the competitive ratio and show that the competitive ratio of our algorithm is only 9% away from the lower bound, when a few hours of prediction is available. Simulation results based on real-world traces corroborate our theoretical analysis and highlight the advantage of our new design.

1 INTRODUCTION

The advances of machine learning and big data analytics enable relatively accurate forecasting and provide the missing information for optimal decision-making in online algorithms. In this paper, a novel prediction-aware online algorithm is provided for energy generation scheduling in microgrids that considers a parameterized prediction window with any window size. While the previous study [6] focuses on a homogeneous setting of local generators, in this paper we consider a more general setting where local generators can be heterogeneous with different capacities.

Our algorithm not only solves the online energy generation scheduling problem but also paves the way for tackling more general Metrical Task System (MTS) problems [1] with limited predicted information. MTS considers general online decision-making processes for state changes with uncertain future switching costs among the states. We note that the online energy generation scheduling problem belongs to a class of scalar MTS problems, where the states are the number of generators being on (or off). However, there is no prediction-aware online algorithm for MTS in the literature so far, to the best of our knowledge. We summarize our main contributions as follows:

(1) We propose CHASEpp as a novel prediction-aware online algorithm that can further improve the competitive ratio of the state-of-the-art CHASElk. This algorithm achieves competitive ratio of $3-\big(2\alpha+2(1-\alpha)/(1+\mathcal{O}(\frac{1}{w})\big) \leq 3-2/(1+\mathcal{O}(\frac{1}{w}))$, where $\alpha \in [0, 1]$ is the system parameter that captures price discrepancy between using local generation and external sources to supply energy. Our algorithm achieves the best competitive ratio to date with up to 20% improvement than the state-of-the-art CHASElk. This competitive ratio also decreases twice faster with respect to w than CHASElk.

(2) We explore a new design space in our algorithm called cumulative differential cost in the prediction window, to better utilize the prediction information in making more competitive decisions. We also characterize a non-trivial lower bound of the competitive ratio, and show that the competitive ratio of our algorithm is close to the lower bound. For example, they only differ by 9% (i.e., 1.94 vs. 1.75) when we have a few hours of predictions.

Reference	Structure Exploitation	Competitive Ratio	Lower Bound	Heterogeneous Generators
Lin *et al.* [5]	✗	arbitrarily large (in a more general setting)	✗	✗
Hajiesmaili *et al.* [2]	✗	heuristic	✗	✗
Lu *et al.* [6]	✗	sub-optimal (partial use of the information)	✗	✗
Menati *et al.* [7]	✓	reduces twice faster than [6] with w	✓	✓

Table 1: Summary and comparison of existing works.

2 RELATED WORK

In recent years, online convex optimization (OCO) has emerged as a foundational topic in a variety of computer systems. There are some similarities between OCO with switching costs for dynamic scaling in datacenters [4] and the one of energy generation [7]. However, the inherent structures of both problems and solutions are significantly different. In their recent work [5], the competitive ratio increases linearly by increasing the switching cost, while our algorithm's competitive ratio is always upper bounded by a constant that is independent of the switching cost [7]. Other prediction-aware online algorithms like the one in [3] also produce competitive ratios that grow unbounded as the switching cost increases. Some recent works [8] tried to solve this issue by designing online algorithms with bounded competitive ratios. Still, their algorithm can only leverage prediction for large enough window sizes $w \geq r_{co}$, where r_{co} is a constant that grows unbounded as the switching cost increases. Meanwhile, the competitive ratio of our algorithm always keeps decreasing as the window size increases.

In [6], a competitive algorithm design approach is used to solve the problem of energy generation scheduling in microgrids, and in [2] a randomized online algorithm is proposed to solve this problem. In [6], a prediction-aware online algorithm has been proposed to this end, but it fails to utilize all the given predicted information. Here we propose a novel competitive online algorithm that will further improve both theoretical and practical performance over the previous algorithm. There are several aspects, both in algorithm design and theoretical analysis, that make our work different from other online solutions. We compare the most important aspects of these works and our work in Table 1.

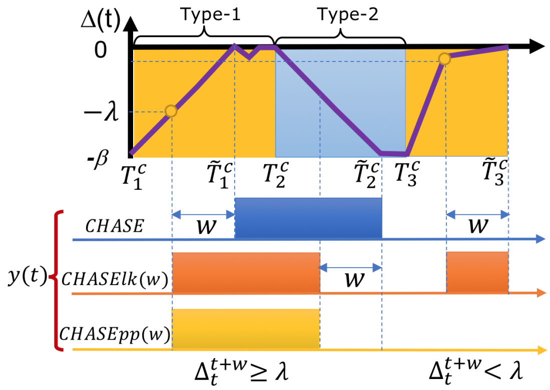

Figure 1: An example of $\Delta(t)$ and the online algorithms CHASE, CHASElk, and CHASEpp. The prediction-aware online algorithms detect the segment type w time slots before CHASE.

3 ALGORITHM DESIGN

We first review state-of-the-art online solutions and the optimal offline solution, providing the necessary understanding for designing a new algorithm later. In the offline setting, we define

$$\delta(t) \triangleq \psi(\sigma(t), 0) - \psi(\sigma(t), 1), \qquad \textit{and} \tag{1}$$

$$\Delta(t) \triangleq \min\left\{0, \max\{-\beta, \Delta(t-1) + \delta(t)\}\right\}, \tag{2}$$

where $\delta(t)$ captures the single-slot cost difference between using or not using the local generation. When $\delta(t) > 0$ (resp. $\delta(t) < 0$), we tend to turn on (resp. off) the generator. To avoid turning on/off the generator too frequently, the cumulative cost difference $\Delta(t)$ is also defined, where β is the start up cost of the generator. Using $\Delta(t)$, we divide the time horizon $\mathcal{T}$ into several disjoint sets called critical segments. As shown in Fig. 1, each segment corresponds to an interval where $\Delta(t)$ goes from -β to 0 (type-1) or from 0 to -β (type-2). In the offline setting, we can detect the beginning of each critical segment right after the process enters them and set $y(t)$ as one for the type-1 segments (turn on the generator) and zero for type-2 segments (turn off the generator). However, in the online setting, with no future information, it is impossible to do so. So an online algorithm called CHASE [6] is proposed to track the offline optimal in an online manner. This algorithm turns on (off) the generator as soon as it detects that it is already in a type-1 (type-2) segment and its competitive ratio satisfies CR(CHASE) $\leq 3 - 2\alpha$. A prediction-aware online algorithm called CHASElk(w) is also proposed, which behaves similar to the prediction-oblivious CHASE, but it can detect segment types w time slots sooner.

In our paper [7], we define a new parameter called cumulative differential cost in the prediction window $\Delta_t^{t+w} \triangleq \sum_{s=t}^{t+w} \delta(s)$ that captures the benefit of using the generator in the coming window. Our new algorithm called CHASEpp(w) tracks the offline algorithms, checks the cumulative differential cost, and turns on the generator only if it is larger than a certain threshold ($\Delta_t^{t+w} \geq \lambda$). Unlike CHASElk($w$), which simply imitates the offline algorithm in an online fashion, our new algorithm ensures that there is enough benefit in turning on the generator for the prediction window. This new design space helps improve the performance of the online algorithm and achieve the worst-case competitive ratio of $3 - \left(2\alpha + 2(1-\alpha)/(1+O(\frac{1}{w})\right) \leq 3 - 2/(1+O(\frac{1}{w}))$.

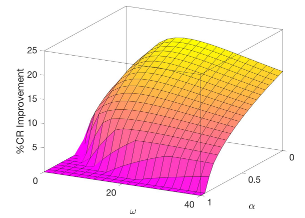

Figure 2: CR improvement as a function of α and w.

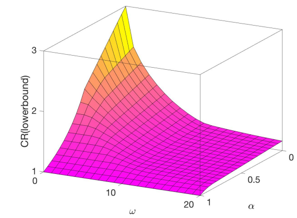

Figure 3: Lower bound of CR as a function of α and w.

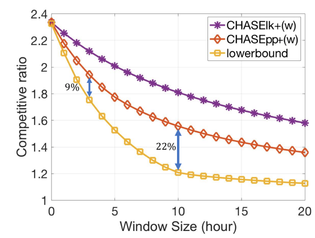

Figure 4: Competitive ratio as a function of w.

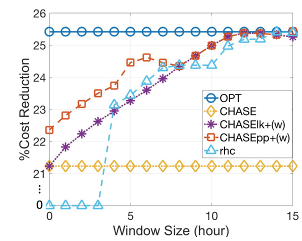

Figure 5: Cost reduction as a function of w.

4 NUMERICAL EXPERIMENTS

As shown in Fig. 2, our algorithm improves the competitive ratio by up to 20%. We also present, for the first time, a lower bound of the competitive ratio shown in Fig. 3. In Fig. 4, it can be seen that the competitive ratio of our algorithm is only 9% away from the lower bound when a few hours of prediction is available. We also use real-world traces to compare the performance of our algorihtm with the optimal offline algorithm OPT, CHASE, CHASElk, CHASEpp, and RHC, which is a popular algorithm widely used in the control literature. It can be seen that our algorithm outperforms all other algorithms and is able to make more competitive online decisions.

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