Summary of Recent Results: Crowd-Sourced Storage-Assisted Demand Response in Microgrids

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ABSTRACT

This paper studies the problem of utilizing energy storage systems to perform demand-response in microgrids. The objective is to minimize the operational cost while balancing the supply-and-demand mismatch. The design space is to select and schedule a subset of heterogeneous energy storage devices that arrive online with different availabilities. Designing a performance-optimized solution is challenging due to the existence of mixed packing and covering constraints in a combinatorial problem, and the essential need for online design. We devise an online algorithm and show that it achieves logarithmic bi-criteria competitive ratio. Experimental results demonstrate the effectiveness of our algorithm.

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1 INTRODUCTION

We study crowd-sourced storage-assisted demand response in microgrid. In this approach, hundreds of electric vehicles and residential storages, residing in a microgrid, with huge aggregate capacity can actively participate in microgrid demand response through reducing their charging demand or even discharging and selling back the electricity to the microgrid, e.g., through *vehicle-to-grid* scheme for EVs. In this way, not only the microgrid can reduce its electricity usage from main grid, but also, the customers can benefit by participating in this scheme.

We consider a scenario in which the microgrid operator solicits contribution of heterogeneous energy storage systems (or sources), such as EVs and residential batteries, in demand response through storage crowd-sourcing paradigm. After receiving all the information of the available sources, the operator selects a subset of sources and schedules their participation volume, by either reducing their charging rate or even discharging, to (i) fulfill the supply shortage of microgrid, for reliable operation, and (ii) minimize total cost of involving the chosen sources, for economic operation.

Challenges. It turns out that achieving the above objectives is a formidable task since it requires solving a joint Source Selection and Scheduling Problem (S3P), which is uniquely challenging to solve because of two critical challenges:

Heterogeneity of the sources, in terms of cost, capacity, and availability in time leads to a combinatorial problem with both packing constraints, i.e., capacity constraint of the sources, and covering constraints, i.e., supply shortage of the microgrid. It turns out that a simplified version of the S3P can be re-expressed as the Capacitated Facility Location Problem (CFLP) [4], which is known to be as a fundamental theoretical CS problem [5]. The S3P is more complicated than the CFLP as it involves a topological constraint caused by the availability of sources.

The second challenge is the essential need for online solution design. In practice, the supply shortage as well as the availability of sources reveal online. The underlying problem, however, is coupled over the time, i.e., the current decision depends on input of future slots, thereby it is challenging to make online scheduling decisions without knowing future input. It turns out that in online setting, achieving a bounded performance against offline optimum without violating either packing or covering constraints is infeasible [1]. Therefore, we follow bi-criteria competitive online algorithm design paradigm [5] which jointly minimizes both cost and the amount of packing constraint (capacity) violation.

Contributions. We focus on designing an online fractional algorithm for the linear-relaxed version of the S3P. Note that even linear version of the problem is still difficult in online scenario, because the input to the time-coupled linear problem is not known in advance. By adapting the recently proposed framework for online mixed packing and covering problems [1], we propose an online fractional algorithm called OnFrc. In the OnFrc at each slot, we obtain a fractional solution for the S3P by constructing a potential function that is linear in cost and exponential in violating the capacity constraint of the storage sources.

We analyze the performance of the OnFrc using bi-criteria competitive ratio analysis[1] and demonstrate that the OnFrc is a bi-criteria $O(\log n, \log n)$-competitive online algorithm, where n is the number of sources. By experiments using real-world data traces, we

[1]In context of our problem, a bi-criteria (α, β)-competitive online algorithm produces a solution at cost of at most α times of the offline optimum, while violating the capacity constraints by no more that a β factor.

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investigate the performance of the algorithm. Note that although the proposed algorithm is logarithmic competitive, this is a worst-case bound and our results demonstrate much better performance in practical settings.

2 PROBLEM FORMULATION

We assume that the system is time-slotted, where each time slot $t \in \mathcal{T}$, $(T \triangleq |\mathcal{T}|)$ has a fixed length (e.g., 1 hour). At slot t, the microgrid has a shortage $d_t \geq 0$ in supply whose value is revealed at the beginning of the slot.[2] For the future slots, we have no assumptions on the exact or stochastic modeling of d_t. Let $\mathcal{I}$, $(n \triangleq |\mathcal{I}|)$, be the set of energy storage systems (sources, used interchangeably) in the microgrid that are available to contribute in demand response scheme. By storage system, we mean any devices like EVs and residential batteries that can be connected to the microgrid and participate in demand response by either reducing their charging rate or discharging back to the microgrid. The sources are heterogeneous in terms of availability over time horizon, capacity, and operating cost. Source i is available in interval $\mathcal{T}_i \subseteq \mathcal{T}$, where $\mathcal{T}_i = [a_i, b_i]$ and a_i and b_i are the arrival and departure slots. This captures the availability of sources, e.g., EVs are available in different intervals in parking lots. In our model, we also assume sources arrive online. Source i announces total capacity c_i which can be used arbitrarily in its availability window for demand response scheme. Cost model of source i is: (i) a fixed cost f_i as the participation cost, which is fixed value regardless of the amount of energy that is solicited, and (ii) a unit cost u_i which must be multiplied by the volume of energy that is contributed by source i.

Given the set of heterogeneous sources, the objective is to use the potentials of the available sources by *selecting* a subset of them such that by a proper *scheduling*, the supply shortage during time horizon is covered, and at the same time the aggregate fixed and unit costs are minimized. The optimization problem is a joint *source selection and scheduling problem* (S3P) that is formulated as

$$\text{S3P}: \min \quad \sum_{i \in \mathcal{I}} \left(f_i x_i + u_i \sum_{t \in \mathcal{T}_i} y_i(t) \right)$$

$$\text{s.t.} \quad \sum_{t \in \mathcal{T}_i} y_i(t) \leq c_i x_i, \quad \forall i \in \mathcal{I}, \tag{1a}$$

$$\sum_{i \in \mathcal{I}: t \in \mathcal{T}_i} y_i(t) \geq d_t, \quad \forall t \in \mathcal{T}, \tag{1b}$$

$$\text{vars.} \quad x_i \in \{0,1\}, \quad \forall i \in \mathcal{I},$$

$$y_i(t) \geq 0, \quad \forall i \in \mathcal{I}, t \in \mathcal{T}_i,$$

where optimization variables are x_i and $y_i(t)$. $x_i = 1$, if source i is selected; $x_i = 0$, otherwise. In addition, $y_i(t)$ denotes the amount of energy that is covered by source i at time t. Constraint (1a) is the capacity (packing) constraint of the sources. Constraint (1b) is the covering constraint that guarantees that total acquired energy by the chosen sources covers the shortage at each slot. Finally, note that the S3P is an NP-hard mixed integer linear program which is difficult to solve, in general, even in offline setting. Recall that the S3P without availability limit of the sources is equivalent to the CFLP, which is generally difficult to tackle even in offline setting.

Our design is even more challenging since the S3P requires online solution design. The online inputs in our problem are two-fold. First, supply shortage d_t is revealed in slot-by-slot fashion. Second, the sources arrive online. In this way, all the characteristics (cost, capacity, and departure time) of *available* sources reveal at the beginning of each time slot. In terms of underlying optimization problem, both packing and covering constraints arrive online.

Algorithm 1: OnFrc- Online Fractional Algorithm, at time t

Initialization
$\mathcal{I}_t \leftarrow$ an ordering of sources that are available in t in ascending order of $v_i(t)$ in Eq. (2)
$\mathcal{P}_t \leftarrow$ the maximal subset of $\mathcal{I}_t$ such that $\sum_{i \in \mathcal{P}_t} x_i < 1$
$l_t \leftarrow$ the first source in $\mathcal{I}_t$ that is not in $\mathcal{P}_t$
while $\sum_{i \in \mathcal{P}_t \cup \{l_t\}: t \in \mathcal{T}_i} z_i(t) < 1$ **do**
  foreach $i \in \mathcal{P}_t \cup \{l_t\}$ **do**
    if $i \in \mathcal{P}_t$ **or** $(i = l_t$ **and** $x_i < 1)$ **then**
      $x_i \leftarrow \min\left\{x_i + x_i/\hat{f}_i T, 1\right\}$
      $z_i(t) \leftarrow \min\left\{2x_i, \frac{x_i - 1/n}{d_i(t) + \hat{u}_i(t)/\hat{f}_i}\right\}$
    end
    if $i = l_t$ **and** $x_i = 1$ **then**
      $z_i(t) \leftarrow z_i(t) + 1/v_i(t)T$
    end
  end
end

3 ONLINE SOLUTION DESIGN

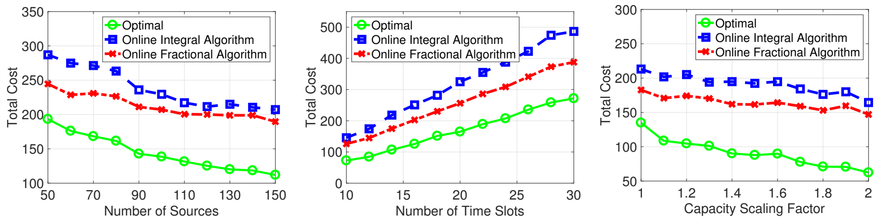
Since the S3P encounters mixed packing and covering constraints, to achieve a competitive ratio better than $O(n)$ in online scenario, it is inevitable that either packing or covering constraint is violated [3]. In demand response, however, it is critical that the shortage is fulfilled by the chosen sources. Hence, in our online algorithm design, we force the covering constraint to be respected, and as a result, violation of capacity constraints of the sources is permitted. As such, our goal is to minimize the capacity violation of selected sources, in addition to total cost minimization.

In this work, we briefly explain our online algorithm design for the linear version of the S3P. In [3], we propose a randomized rounding approach to find an integral solution based on the fractional solution obtained from linear S3P. We skip the details of randomized integral solution due to space limit and refer to [3].

We assume that the number of time slots (T) is known in advance and the optimal offline cost Opt is given.[3] We assume that $f_i \leq$ Opt, $\forall i \in \mathcal{I}$, otherwise, we exclude the sources with fixed cost greater than Opt. Now, we introduce $\hat{f}_i$ as the scaled fixed-cost of source i as $\hat{f}_i = \max\{(f_i n)/\text{Opt}, 1\}$, and $\hat{u}_i(t)$ as the normalized unit cost of the source i at time t as $\hat{u}_i(t) = (u_i d_t n)/\text{Opt}$. Finally, we

[2]In general, d_t could be either negative or positive, in which negative value corresponds to the case that there is extra supply in microgrid that could be absorbed by the storage systems. In this paper, however, we focus on the cases where $d_t \geq 0$.

[3]These assumptions are reasonable since T is fixed usually. The optimal offline cost also can be estimated based on historical data. Nevertheless, the algorithm can be extended to the case that the optimal offline cost is not known at the expense of adding a multiplicative logarithmic order in competitive ratio [1].



(a) (b) (c)

Figure 1: Impact of input parameters on total cost of different algorithms

define $d_i(t) = d_t/c_i$. Note that by multiplying fixed and unit cost parameters by n/Opt, the optimal value of the problem changes to $O(n)$, facilitating the competitive analysis. Let $x_i \geq 0$ be the relaxed integer source selection variable. Moreover, $z_i(t) \in [0, 1]$ is the portion of supply shortage d_t that is fulfilled by source i, provided that $t \in \mathcal{T}_i$. Indeed, $y_i(t) = d_t z_i(t)$.

The proposed online competitive algorithm, summarized as Algorithm 1, accomplishes source selection and scheduling by providing an ascending ordering among the available sources at each slot. In this way, our main endeavor is to construct a metric to be used to sort the sources. The sorting metric $v_i(t)$ which we refer to it as *virtual cost* of source i at time t is defined as follows.

$$v_i(t) = \begin{cases} \hat{f}_i \theta^{\gamma_i(t)-1} d_i(t) + \hat{u}_i(t), & \text{if } x_i = 1, \\ \hat{f}_i d_i(t) + \hat{u}_i(t), & \text{otherwise,} \end{cases} \quad (2)$$

where $\theta > 1$ is a constant factor and $\gamma_i(t) = \sum_{\tau \in \mathcal{T}_i : \tau \leq t} d_i(\tau) z_i(\tau)$ is the current congestion level of source i. Hence, we call θ the congestion parameter. By this definition, when source i is not fully chosen ($x_i < 1$), the cost is linear in both normalized fixed and unit cost. On the other hand, if source i is already fully chosen ($x_i = 1$) in the fractional solution due to the scheduling in the previous time slots, the virtual cost is linear in fixed cost, however exponential in the congestion level $\gamma_i(t)$. The following theorem characterizes the competitive ratio of the OnFrc.

Theorem 3.1. *[3] Given $1 < \theta < 1.5$, OnFrc generates a fractional schedule that is $O(\log n, \log n)$-competitive.*

4 PERFORMANCE EVALUATIONS

In this section, we report a selected set of results of the online fractional algorithm (in Sec. 3) and the randomized rounding algorithm in [3] that is built on top of the fractional one and leads to an integral solution. The electricity data traces are from [2] and we assume that on average 10% of the demand is regarded as supply shortage in each slot. The unit cost for each source follows a uniform distribution over [\$0, \$1]. The fixed cost is chosen in order of ×20 of the unit costs, which is roughly around 1/3 of the volume cost. The available capacity c_i is randomly generated in $[10, 70]$kWh. We set $T = 12$ and the length of each slot to 1 hour. We compare the result of online algorithms to the offline optimum.

In Fig. 1, we report the total costs of offline optimal solution and our fractional and integral algorithms as a function of different input parameters. The result in Fig. 1(a) shows that as the number of sources increases, total cost of all algorithms decreases, which is reasonable since with the increase in sources, there is more freedom to pick more cost-effective sources. The average cost ratios, i.e., the cost of the algorithms over the offline optimums cost, for the fractional and integral algorithms are 1.56 and 1.71, respectively which demonstrate sound performance of our algorithms. The obtained empirical cost ratios demonstrate that our algorithms can achieve much better results than those obtained in theoretical analysis. The difference between the cost of fractional and integral algorithms is due to the integrality gap made by randomized rounding [3]. Fig. 1(b) shows that as the number of slots increases, total cost increases for all solutions. This is reasonable since with fixed number of sources as the number of slots increases, more demand must be covered and hence total cost increases. The results in Fig. 1(c) show that as the capacity of sources scales, total cost decreases since each source can cover more supply shortage.

5 CONCLUSIONS AND FUTURE DIRECTIONS

This paper advocates the idea of using the potentials of existing sources in a microgrid to perform crowd-sourced storage-assisted demand-response. It formulates a joint problem of source selection and scheduling with the goal of minimizing the cost, while respecting mixed packing and covering constraints. An efficient online competitive algorithm for the problem is devised and experiments show that the performance of the algorithm is near optimum. The underlying problem could be imagined as a natural expansion of the minimum knapsack problem over time, and one can find several applications rather that demand-response in microgrids. In fact, our formulation makes sense in any application in which different sources can contribute in fulfilling a service that arrives in time.

An interesting direction is to consider the scenario as an online combinatorial reverse auction problem and try to design dominant strategy incentive compatible algorithms. The problem is different from the existing problems in the sense that the design space in the current auction problems are usually just winner determination (or source selection). In the new setting, the design space is both winner determination and resource allocation (scheduling).

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