Scheduling Heterogeneous Delay Tolerant Tasks in Smart Grid with Renewable Energy

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***Abstract*—The smart grid is the new generation of electricity grid that can efficiently facilitate new distributed sources of energy (e.g., harvested renewable energy), and allow for dynamic electricity price. In this paper, we investigate the cost minimization problem for an end-user, such as a home, community, or a business, which is equipped with renewable energy devices when electrical appliances allow different levels of delay tolerance. The varying price of electricity presents an opportunity to reduce the electricity bill from an end-user's point of view by leveraging the flexibility to schedule operations of various appliances and HVAC systems. We assume that the end user has an energy storage battery as well as an energy harvesting device so that harvested renewable energy can be stored and later used when the price is high. The energy storage battery can also draw energy from the external grid. The problem we formulate here is to minimize the cost of the energy from the external grid while usage of appliances are subject to individual delay constraints and a long-term average delay constraint. The resulting algorithm requires some future information regarding electricity prices, but achieves provable performance without requiring future knowledge of either the power demands or the task arrival process.**

I. Introduction

The next-generation electricity grid, known as the "smart grid", provides both suppliers and consumers with full visibility and pervasive control over their assets and services in order to achieve economy and sustainability [1]. Being able to incorporate renewable energy sources (e.g., solar or wind) is one of the key objectives of the smart grid [2]. In addition, the utility companies are allowed to dynamically adjust the electricity price in order to control the power usage. For example, prices of electricity increase during high demand periods, and decrease during low demand periods. Consumers thus can avoid the premium for using electricity at high price periods when they are aware of the price for some future period.

In this paper, we consider an end-user equipped with renewable energy devices in smart gird, where the electricity price is time varying. The renewable energy devices consist of an energy storage battery and an energy harvesting device. Renewable energy can be harvested and stored in the battery. We assume that the arrivals of demands for electrical appliances is a stochastic process (from now on, we use the terms appliance and task interchangeably). Fig. 1 shows some typical appliances at an end user. We assume that some tasks are delay tolerant, that is, they do not need to be activated immediately upon their arrival, such as washer and dish washer. They can be opportunistically scheduled when the electricity price is relatively low in order to reduce cost. For instance, if the price is high around 7pm and low around 2am, then some delay-tolerant tasks, such as dish washer, can be postponed to be scheduled around 2am. The power demand is met by drawing energy from the battery, or purchasing extra energy from the outside grid. We also allow the battery to charge energy from the grid, because the battery can purchase and store energy when the price is low, and discharge when the price is high.

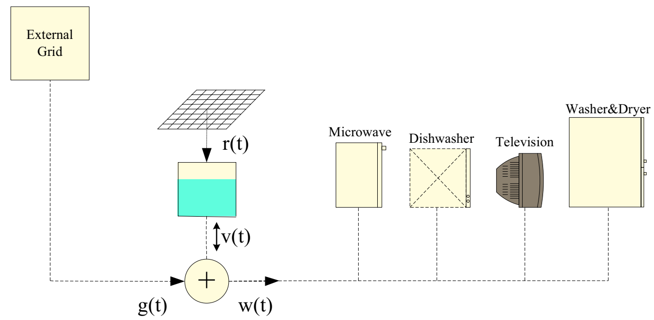

Fig. 1. Demand and Supply

In this work, we are interested in developing an optimal task scheduling algorithm that minimizes the total price cost of the energy drawn from the external grid subject to delay constraints. The customer has full control over all electricity appliances. The algorithm can exploit the delay flexibility and take advantage of time-varying prices.

A. State-of-the-art

In power networks, there have been some literature that has focused on scheduling delay-tolerant tasks. Koutsopoulos and Tassiulas [3] investigate an off-line version and an on-line version of the task scheduling problem. The authors propose two algorithms under these two cases, respectively, and provide a provable performance bound. However, these finite-horizon problems are proven to be NP-hard, and the algorithms only achieve optimality when the delay constraint is arbitrarily loose. In [4], the authors develop an energy allocation algorithm to minimize the total electricity cost. However, they do not allow renewable energy to be saved for

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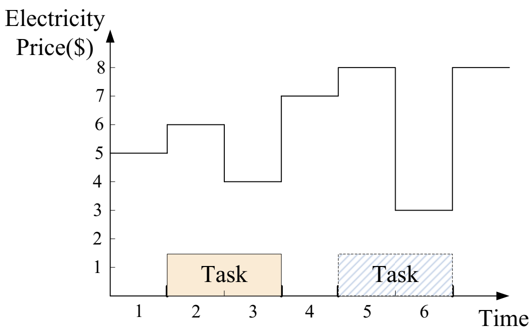

Fig. 2. An example of battery's influence on task scheduling

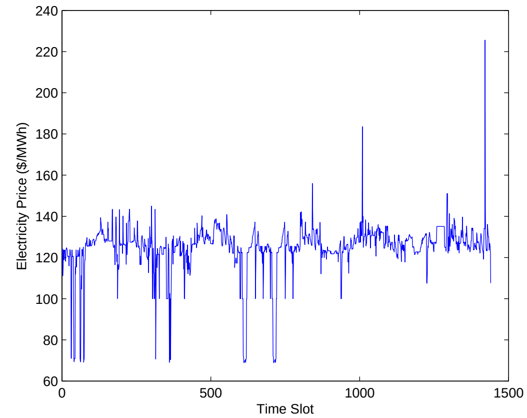

Fig. 3. 5-minute average spot market price during the week of 10/10/2011-10/14/2011 for Columbus Area from CAISO [9]

future use, which our work takes into account. In addition, we provide individual delay constraints to all tasks, instead of the universal worst-case delay constraint which is likely to be very large. Some works adopt dynamic programming techniques, e.g. [5]. They can achieve optimality only if the distribution of the power demand is known a priori. There are also some other works that have formulated problems using game theory, e.g., [6]. The authors in [7] [8] develop a scheduling scheme to achieve an optimized upper bound on the power peak load.

B. Our Contributions

In this paper, we address the task scheduling problem while tasks are subject to individual hard delay constraints and average delay constraints. To the best of our knowledge, it is the first work that takes into account these two different types of delay constraints in the area of smart grid. If there is no average delay constraint, a greedy algorithm could achieve the optimal solution. We, however, also take into account the average delay constraint, which is an important quality of service metric, but makes the problem challenging. Further, having a battery brings about significant differences. The reason is that the battery can draw energy from external grid when the electricity price is low and discharges energy when the price is high. Fig. 2 shows a simple example, where a task (the boxes illustrated in the figure) requires a service period of two slots. If there is no battery, we can see that the optimal way is to schedule during time slot 2 and slot 3 (the red box), resulting in a total cost of 10 dollars. However, with the help of a battery, we can store some energy in time slot 3 since the electricity price is low during this time slot. For simplicity of exposition, we assume that the maximum energy that is stored in one slot can be used to support up to one-slot service. Now, let us consider an alternate schedule, where the power demand during time slot 5 is met from the stored energy in slot 3 and the demand during time slot 6 is met from the external grid, as shown by the shadowed blue box. It can be seen that the total cost under this scheduling policy is 7 dollars, which is the optimal.

We summarize our main contributions as follows:

1) We consider different types of delay constraints in our model. First, each task has a hard delay constraint, which cannot be violated. Further, there is a "dissatisfaction" function of delay for each task, and we require the long-term average dissatisfaction to be less than a threshold. This is a generalization of the average delay constraint.
2) We propose a simple algorithm that can achieve provable performance, which is within a bounded distance of the optimum. Note that our algorithm does not require future knowledge of the power demand and the task arrival process.
3) We validate our algorithm using real electricity price traces to compute realistic savings. We show that our algorithm can indeed reduce cost under various system parameter settings.

Our paper is organized as follows: In Section II, we discuss our system model. In Section III, we formulate our cost minimization problem with various delay constraints. In Section IV, we develop our task scheduling algorithm and show its performance. After presenting simulation results in Section V, we conclude our paper in Section VI.

II. System Model

We consider a set of appliances connected to the external smart grid. Time is assumed to be slotted. The price of electricity is time varying and denoted by $P(t)$ in time slot t. As an example, Fig. 3 shows the average five-minute spot market prices for the Columbus area obtained from CAISO [9]. Let N_t represent the set of tasks that arrive in time slot t, while n_t represents the number of tasks in N_t, i.e., $n_t = |N_t|$, where $|\cdot|$ denotes the cardinality of a set. For simplicity of exposition, we assume that all tasks arrive at the beginning of each slot.

We note that there are two types of tasks, delay-tolerant and delay-intolerant tasks. Let c_i^t denote the required service time for each task $i \in N_t$. Also, there is a deadline associated with each task $i \in N_t$, i.e., the maximum number of time slots allowed for finishing the job from its arrival time t, denoted by d_i^t. The deadline is a hard constraint, namely the task needs to be completed before time $t + d_i^t$. We call the task delay-intolerant if $c_i^t = d_i^t$, and delay-tolerant if $c_i^t < d_i^t$. For a delay-intolerant task, the only choice that we have is to activate it immediately upon its arrival. However, for delay-tolerant tasks, we can opportunistically schedule them in order to make use of the fluctuating nature of the electricity price. Our goal here is to find the optimal “postponing” time s_i^t so that the total cost is minimized subject to the delay constraints. Clearly, for the delay-intolerant tasks, we have to set $s_i^t = 0$. Let d_{max} denote the maximum delay allowed for any task, i.e., $d_{max} \triangleq \max_{t,i} d_i^t$. Notice that $(c_i^t, s_i^t, d_i^t), \forall t, \forall i$ are integers. It is assumed that we have an accurate short-term estimation of the electricity price. More precisely, we know $\vec{P}_t \triangleq P(t), P(t+1), \cdots, P(t+d_{max})$. It is worth pointing out that this is a reasonable assumption because the short-term estimation of electricity price can be obtained from the history [10].

Let $h(t)$ denote the harvested renewable energy in time slot t, and let $r(t)$ denote our energy storage decision, i.e., the actual energy that is stored into the battery. For simplicity of exposition, we assume that $r(t)$ amount of energy is stored in the battery at the end of slot t. First, it is convenient for us to assume that battery has infinite capacity. We will show later that our algorithm only requires a reasonably sized finite battery. A natural constraint of $r(t)$ is

$$r(t) \leq h(t). \tag{1}$$

The reason that we keep $r(t)$ and $h(t)$ different is due to some technical issues used in our proof. We assume that $[n_t, c_i^t, h(t)]$ is i.i.d. over slots.

Let $w(t)$ represent the total power demand in time slot t. We assume that each task $i \in N_t$ consumes energy at a constant rate π_i^t, namely the power consumption for task i stays the same during its activation period. In this paper, we only consider the case where the activation period of any task is a contiguous chunk of time, and we do not consider the case where the activation period of tasks can be interrupted and resumed. We notice that part of $w(t)$ is met by utilizing energy from the battery, while the other part will be drawn from the grid. Let $g(t)$ and $v(t)$ represent the amounts of energy that are drawn from the outside grid and the battery in time slot t, respectively. Because the supply always needs to balance the demand, we have $w(t) = g(t) + v(t)$ as shown in Fig. 1. In addition, we also allow the battery to charge energy from the grid, which means that $v(t)$ could be negative. In particular, the battery discharges/charges energy if we have $v(t) \gtrless 0$. We denote v_{max} as a maximal rate of either charging or discharging from the battery. We use $B(t)$ to denote the battery level at the beginning of time slot t, and the energy dynamics can be formulated as follows:

$$B(t+1) = B(t) + r(t) - v(t). \tag{2}$$

Since we have $g(t) \geq 0$, it follows that $v(t) \leq w(t)$.

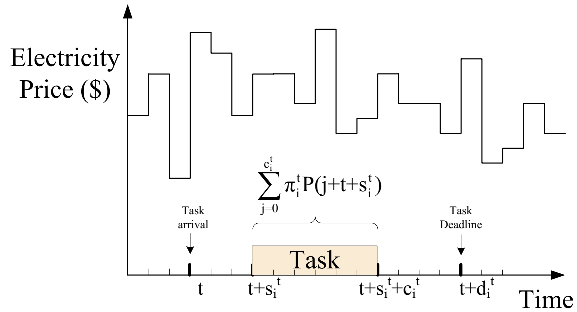

Fig. 4. Example of the scheduling of one task $i \in N_t$

Therefore, the constraints on $v(t)$ are given by

$$|v(t)| \leq v_{max} \tag{3}$$

$$v(t) \leq B(t), \tag{4}$$

$$v(t) \leq w(t), \tag{5}$$

where the second constraint means that the allocated energy from the battery should be less than or equal to the current available energy in the battery.

Note that $w(t)$ depends on the decisions made during time slot t up to time slot $t - d_{max} + 1$, we have

$$w(t) = \sum_{\tau=t-d_{max}+1}^{t} \sum_{i=1}^{n_\tau} \pi_i^\tau \mathbf{1}(\tau + s_i^\tau + c_i^\tau > t \,\&\, \tau + s_i^\tau \leq t), \tag{6}$$

where $\mathbf{1}(\tau + s_i^\tau + c_i^\tau > t \& \tau + s_i^\tau \leq t)$ is the indicator function.

Our goal is decide $(r(t), s_i^t, v(t))$ at each time slot such that the total price cost of the energy drawn from the external grid is minimized. We do not explicitly consider some practical issues, such as energy leakage in the battery or DC/AC conversion loss, but we can readily incorporate them into our model. We summarize the notations in Table I.

TABLE I
NOTATIONS

c_i^t	Required service time for task $i \in N_t$
d_i^t	Deadline for task $i \in N_t$
s_i^t	Delay for task $i \in N_t$
$P(t)$	Electricity price in time slot t
$w(t)$	Power demand in time slot t
$g(t)$	Energy drawn from the grid in time slot t
$v(t)$	Energy drawn from the battery in time slot t
$h(t)$	Harvested renewable energy in time slot t
$r(t)$	Actual energy stored into battery in time slot t
$B(t)$	Battery level in time slot t

III. Problem Formulation

Suppose that there is an increasing convex function $U_i^t(s)$, satisfying $U_i^t(0) = 0$, which reflects the dissatisfaction associated with delay s for task $i \in N_t$. The convexity models a typical user for whom the rate of increase in dissatisfaction increases with delay. Notice that $U_i^t(\cdot)$ is different for heterogeneous tasks. We assume that the long-term average dissatisfaction should be no greater than some threshold α, that is,

$$\limsup_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{n_t} U_i^t(s_i^t) \le \alpha. \tag{7}$$

For any task $i \in N_t$, since we have to finish it before the deadline, it yields

$$s_i^t + c_i^t \le d_i^t.$$

Therefore, the constraint for the postponing time s_i^t is given by

$$0 \le s_i^t \le d_i^t - c_i^t. \tag{8}$$

Hence, the cost minimization problem can be formulated as

$$\text{Problem } \mathbf{A}: \quad \min_{r(t),s_i^t,v(t)} \quad \lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}\big[g(t)P(t)\big] \tag{9}$$
$$s.t. \quad (1),(3),(4),(5),(7),(8),$$

where $P(t)g(t)$ represents the total price of the energy drawn from the grid during time slot t.

Since $g(t) = w(t) - v(t)$, we can rewrite Problem **A** as follows:

$$\min_{r(t),s_i^t,v(t)} \quad \lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}\big[w(t)P(t) - v(t)P(t)\big] \tag{10}$$
$$s.t. \quad (1),(3),(4),(5),(7),(8).$$

Notice that $\lim_{T\to\infty}\sum_{t=1}^{T} w(t)P(t)$ represents the total cost of the power demand, which is equal to the summation of the cost for all tasks. That is,

$$\lim_{T\to\infty}\sum_{t=1}^{T} w(t)P(t) = \lim_{T\to\infty}\sum_{t=1}^{T}\sum_{i=1}^{n_t}\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+t+s_i^t), \tag{11}$$

where $\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+t+s_i^t)$ is the cost of task $i \in N_t$ as depicted in Fig. 4.

Now, we can reformulate the optimization problem as follows:

$$\text{Problem } \mathbf{B}: \min_{r(t),s_i^t,v(t)} \lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}\Big[\sum_{i=1}^{n_t}\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+s_i^t+t) - P(t)v(t)\Big] \tag{12}$$
$$s.t. \quad (1),(3),(4),(5),(7),(8).$$

Now we aim at finding the optimal solution to Problem **B**. We adopt the Lyapunov optimization approach [4] to solve it.

IV. Task Scheduling Policy

In this section, we propose a task scheduling policy and show that its performance is within a bounded distance of the optimum as T tends to infinity.

A. Virtual Queue

Let us construct an auxiliary virtual queue $Q(t)$, whose input and output are $\sum_{i=1}^{n_t} U_i^t(s_i^t)$ and α respectively. The queueing dynamics is depicted as

$$Q(t+1) = \max\{Q(t) + \sum_{i=1}^{n_t} U_i^t(s_i^t) - \alpha, 0\} \tag{13}$$

***Lemma 1**: **Lemma 1**:* If the virtual queue is rate stable, i.e., $\limsup_{T\to\infty} Q(t)/t = 0$ with probability 1, then the constraint (7) is satisfied.

Proof: The proof is similar to Lemma 1 in [11], we refer to our technical report [12] for the proof. ■

B. Lower Bound the Minimum Cost

In this subsection, we will obtain a lower bound on the minimum cost of Problem **B**. The following lemma shows that the performance achieved by using a stationary and randomized algorithm forms a lower bound.

Let c^{opt} be the minimum cost to Problem **B**. And let $\tilde{c}$ be the minimum cost to the following Problem **C**.

$$\text{Problem } \mathbf{C}: \min_{r(t),s_i^t,v(t)} \lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}\Big[\sum_{i=1}^{n_t}\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+s_i^t+t) - P(t)v(t)\Big]$$
$$s.t. \quad (1),(3),(7),(8).$$

***Lemma 2**:* c^{opt} is lower bounded by $\tilde{c}$, i.e., $\tilde{c} \le c^{opt}$. Further, $\tilde{c}$ can be achieved by an optimal stationary and randomized policy, that is, the control action $(\tilde{r}(t), \tilde{s}_i^t, \tilde{v}(t))$ in each time slot is only a function of $[n_t, c_i^t, h(t)]$. In particular, we have

$$\mathbb{E}\Big[\sum_{i=1}^{n_t}\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+t+\tilde{s}_i^t) - P(t)\tilde{v}(t)\Big] = \tilde{c}, \tag{14}$$
$$\mathbb{E}\Big[\sum_{i=1}^{n_t} U_i^t(\tilde{s}_i^t) - \alpha\Big] \le 0, \tag{15}$$
$$\mathbb{E}\big[\tilde{r}(t) - \tilde{v}(t)\big] \ge 0, \tag{16}$$

Proof: The proof argument is similar to the one in [4], We refer to our technical report [12] for the proof. ■

In the lemma, Eqn. (15) means that the long-term average dissatisfaction achieved by the stationary policy is no greater than α. Eqn. (16) implies that the average allocated energy from the battery is no greater than the stored energy.

C. HTSA: Heterogeneous Task Scheduling Algorithm

We define the Lyapunov function $L(t) = \frac{1}{2}(Q(t)^2 + (B(t) - \theta)^2)$, where θ is a parameter specified later. The intuition behind it is that, by minimizing the drift of the Lyapunov function, we force $B(t)$ to approach θ. We also define several constants $n_{max} = \max_t n_t$, $h_{max} = \max_t h(t)$, $c_{max} = \max_{t,i} c_i^t$, and $U_{max} = \max_{t,i} U_i^t(d_i^t)$, where U_{max} reflects the maximum dissatisfaction among all tasks.

Let $Z(t) = (Q(t), B(t))$. The conditional Lyapunov drift is given by $\mathbb{E}\{(L(t+1) - L(t)|Z(t)\}$. We will show some properties of the drift via the following lemma.

Lemma 3: The conditional Lyapunov drift satisfies that

$$\begin{aligned}&\mathbb{E}\{(L(t+1) - L(t)|Z(t)\} \leq \\ &D + Q(t)\mathbb{E}\big[\sum_{i=1}^{n_t} U_i^t(s_i^t) - \alpha|Z(t)\big] \\ &\quad + (B(t) - \theta)\mathbb{E}\big[r(t) - v(t)|Z(t)\big], \end{aligned} \tag{17}$$

where $D \triangleq \frac{1}{2}(n_{max}^2 U_{max}^2 + \alpha^2 + r_{max}^2 + v_{max}^2)$.

Proof: We refer to our technical report [12] for the proof. ■

By adding $V\mathbb{E}[\sum_{i=1}^{n_t}\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+s_i^t+t) - P(t)v(t)|Z(t)]$ on both sides of Eqn. (17), we have

$$\begin{aligned}&\mathbb{E}[(L(t+1) - L(t)|Z(t)] \\ &+ V\mathbb{E}[\sum_{i=1}^{n_t}\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+s_i^t+t) - P(t)v(t)|Z(t)] \\ &\leq D + Q(t)\mathbb{E}\big[\sum_{i=1}^{n_t} U_i^t(s_i^t) - \alpha|Z(t)\big] \\ &+ (B(t) - \theta)\mathbb{E}\big[r(t) - v(t)|Z(t)\big] \\ &+ V\mathbb{E}\big[\sum_{i=1}^{n_t}\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+s_i^t+t) - P(t)v(t)|Z(t)\big] \\ &= D - \alpha Q(t) + (B(t) - \theta)\mathbb{E}\big[r(t)|Z(t)\big] + \\ &\sum_{i=1}^{n_t}\mathbb{E}\big[Q(t)U_i^t(s_i^t) + V\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+s_i^t+t)|Z(t)\big] \\ &+ (\theta - B(t) - VP(t))\mathbb{E}\big[v(t)|Z(t)\big], \end{aligned} \tag{18}$$

where V is a control parameter.

We now describe our scheme, *heterogeneous task scheduling algorithm (HTSA)*. The idea of *HTSA* is to minimize the right-hand side (RHS) of Eqn. (18) subject to the energy-availability constraint (4) and (5).

Heterogeneous task scheduling algorithm (*HTSA*):

- In each time slot t, the harvested energy $r^*(t)$ is determined by

$$r^*(t) = \begin{cases} h(t), & \text{if } B(t) - \theta < 0, \\ 0, & \text{otherwise.}\end{cases} \tag{19}$$

- In each time slot t, the postponing time s_i^t for task $i \in N_t$ is determined by:

$$s_i^{t*} = \arg\min_{0\leq s_i^t \leq d_i^t - c_i^t} Q(t)U_i^t(s_i^t) + V\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+t+s_i^t). \tag{20}$$

- In each time slot t, the battery charge/discharge is given by:

$$v^*(t) = \begin{cases} \min\{v_{max}, w(t)\}, & \text{if } \theta - B(t) - VP(t) < 0, \\ -v_{max}, & \text{otherwise,}\end{cases} \tag{21}$$

where $w(t)$ is determined by Eqn. (6).

Define a constant P_{max} as the highest electricity price, i.e., $P_{max} = \max_t P(t)$. By setting $\theta = v_{max} + VP_{max}$, from Eqn. (21), we can see that when $B(t) < v_{max}$, it always has $\theta - B(t) - VP(t) > 0$. In other words, the battery always draws energy from the grid, namely $v(t) = -v_{max}$, when the battery level is less than v_{max}. This implies that when the battery discharges, there is always enough energy in the battery, i.e., $B(t) > v_{max}$. Therefore, the energy constraint of Eqn. (4) is indeed *redundant*.

D. Performance Analysis

In this subsection, we will prove that *HTSA* achieves a performance that is within a bounded distance of the optimum via the following theorem.

Theorem 1: By setting $\theta = v_{max} + VP_{max}$ and $B(0) = \theta$, *HTSA* has the following property:

1) The battery level $B(t)$ satisfies:

$$B(t) \leq \theta + v_{max} + h_{max}. \tag{22}$$

2) There exists $M > 0$, such that $Q(t)$ is bounded by M for all t, where M is a constant.
3) The cost achieved by *HTSA* satisfies:

$$\begin{aligned}&\limsup_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}\Big[\sum_{i=1}^{n_t}\sum_{j=0}^{c_i^t-1}\pi_i^t P(j+s_i^*+t) - P(t)v^*(t)\Big] \\ &\leq c^{opt} + P_{max}v_{max} + \frac{D + (v_{max}+h_{max})^2}{V}.\end{aligned}$$

Proof: We refer to our technical report [12] for the proof. ■

From part (2) in Theorem 1, since $Q(t)$ is bounded, combining with lemma 1, we can see that the average delay constraint, i.e., Eqn. (7), is satisfied. Part (3) in Theorem 1 shows that the cost induced by our algorithm is within a bounded distance of the optimum by setting the parameter V to be sufficiently large. It is worth pointing out that the algorithm does not require the future knowledge of the statistics of power demand and the task arrival process.

V. CASE STUDY

We adopt the 5-minute average spot market prices for Columbus Area from CAISO [9]. The profile depicted in Fig. 3 shows the electricity price for the period 10/10/2011-10/14/2011. The arrival process of all tasks here are assumed to be Poisson process with different intensity λ_i, although Theorem 1 holds for any general arrival process. Without loss of generality, we consider four types of appliances in our simulations. The first three tasks are delay-tolerant, while the last one is delay-intolerant. The arrival intensities for these tasks are set to be 2, 0.5, 0.035 and 100, respectively. And the energy consumption rate for these tasks π_i^t are set to be 5.2kw, 3.5kw, 2.4kw and 60w. The "dissatisfaction" functions are assumed to be $U(x) = x^2$. The average delay constraint threshold α is set to be 1000, and the parameter V is set to be 100.

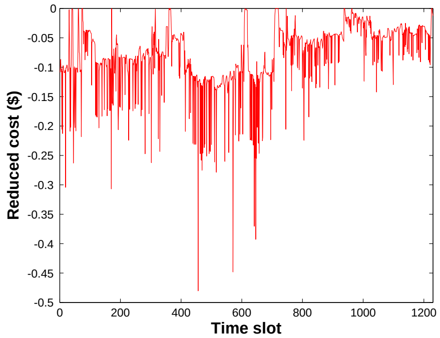

Fig. 5. Reduction in cost for Class I appliances

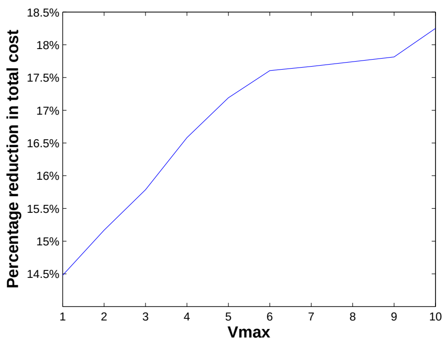

Fig. 6. Reduced cost versus the battery size

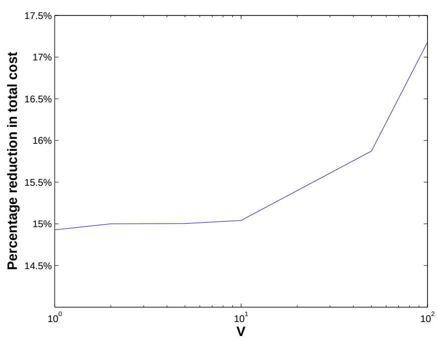

Fig. 7. Reduced Cost versus parameter V

We start by comparing our algorithm and a naive scheme, which activates the task immediately upon its arrival. Consider the first type of delay-tolerant task, which has a deadline of 100 slots, while the required service time is two slots. Fig. 5 shows the cost reduced for scheduling this type of task using our algorithm. The total cost saved in these five days is $\$35.4033$, which is 19.82% of the total cost. If we extend the hard delay deadline to 200 slots, the corresponding percentage of saved cost increases to 27.20%. This is because if we have a less stringent delay constraint, we can gain more benefit.

Next, we will show how the battery influences the performance. The deadline for other two types of delay-tolerant tasks are set to be 10 and 20, respectively. We set the battery size to be $2v_{max} + VP_{max} + h_{max}$. Fig. 6 depicts the percentage reduction in cost versus v_{max}. We can see that the percentage reduction in cost increases as v_{max} grows, i.e., the battery size grows. This is because a large battery can lead to a higher shaved cost.

In Fig. 7, we illustrate the relationship between the percentage of reduced cost and the parameter V. It can be seen that when V is small, the reduced cost is less than the counterpart when V is large. The reason is that the term $\frac{D+(v_{max}+h_{max})^2}{V}$ in Theorem 1 cannot be neglected when V is small.

VI. Conclusion

In this paper, we investigate the cost minimization problem for an end-user, which is equipped with renewable energy devices when electrical appliances allow different levels of delay tolerance. The problem we formulate here is to minimize the cost of the energy from the external grid while usage of appliances are subject to individual delay constraints and a long-term average delay constraint. Our proposed algorithm, *HTSA*, requires some future information of the electricity price, but achieves provable performance without requiring future knowledge of either the power demands or the task arrival process.

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