REAL-TIME JOINT ENERGY STORAGE MANAGEMENT AND LOAD SCHEDULING WITH RENEWABLE INTEGRATION

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ABSTRACT

We consider joint design of energy storage management and load scheduling with integrated renewable energy. We aim at optimizing the energy flows and load scheduling simultaneously in order to minimize the overall system cost over a finite time horizon. Our model incorporates battery operational costs and assumes unknown arbitrary dynamics of renewable source, load, and pricing information. Loads are modeled by individual tasks with their own intensities, requested service durations, and maximum and average delay constraints. We use a sequence of problem modification and transformation and employ Lyapunov optimization technique to design the real-time joint control and scheduling policy. Our policy provides an closed-form solution for load scheduling and storage energy management. We show that our proposed algorithm guarantees a bounded performance from an optimal non-causal T-slot look-ahead control policy.

Index Terms— Energy Storage Management, Load Scheduling, Renewable Generation, Lyapunov Optimization

1. INTRODUCTION

Integrating renewable energy sources into the grid system has become a vital green solution to reduce the energy cost [1]. As the renewable generation becomes widely adopted, energy storages are used to reduce the power grid instability caused by renewable integration. Another attractive solution to stabilize the power grid and reduce energy cost is the flexible load scheduling. The demand of smart appliances can be shifted from the high-peak period to the low-peak period. Combining both energy storage and flexible loads will be the most promising future solution for the grid and the consumers. To achieve these benefits, developing an effective joint energy storage management and load scheduling solution is important, but faces unique challenges. These include the stochastic nature of renewable sources, the double effects of cost reduction by energy storage and the operation cost of storage, and the coupling of control decisions over time due to the finite battery capacity. Furthermore, the scheduling delay of each load and the energy usage are coupled with each other. As a result, it is particularly challenging for a joint design of storage management and load scheduling.

Load scheduling and storage management have attracted growing interests recently for future energy system designs. For the load scheduling, dynamic pricing problems to reduce peak-load are considered in [2]–[4]. In [2], [3], multi-timescale scheduling is proposed assuming the statistics of renewable energy are known ahead of time. While [4] proposes a real-time scheduling algorithm, no energy storage is considered. A real-time storage control policy is studied in [5]. However, a prediction for each user's load is required. Without statistical information and prediction, Lyapunov optimization framework [6] has been applied to design real-time solutions for storage management with inflexible loads [7]–[10] and with flexible loads [8], [11]–[14]. From the storage management perspective, renewable energy is not considered in [11], [12], and battery operation cost for storage is not modeled in [8], [13]. For demand management, [8], [11]–[14] impose certain delay constraints on loads to guarantee the worst delay, while the actual scheduling for each user's load tasks is not considered. Load scheduling is considered in [15], assuming electricity price is known beforehand. Except for [9], all the above works consider the long-term average system cost.

In this paper, we design a real-time control solution for joint energy storage management and load scheduling with integrated renewable energy. We aim at optimizing the energy flows and load scheduling simultaneously to minimize the overall system cost *within a finite time period*. We consider a storage battery with finite capacity, and model battery operational costs and delay requirements for each load scheduling. Unlike existing works, we assume unknown arbitrary dynamics of renewable source, load, and pricing. To tackle this difficult stochastic problem, we develop techniques through a sequence of problem modification and transformation. This enables us to employ Lyapunov optimization to design a real-time algorithm, in which we show that the storage management and load scheduling are decoupled to be solved sequentially with closed-form solutions. We further show that our algorithm guarantees a bounded performance from an optimal non-causal T-slot look-ahead control policy.

2. SYSTEM MODEL

We consider an energy storage management system as shown in Fig. 1. A power consuming entity (user) can draw electricity to supply its loads from available power sources and an energy storage unit (battery). Two types of power sources are considered: the conventional grid and the renewable generator. The battery is used to store energy from both power sources and to supply electricity to the user. As a part of the management system, a load scheduling mechanism is implemented to schedule the user's loads within their delay requirements. We assume the system operates in discrete time slots with $t \in \{0, 1, \cdots\}$, and all operations are performed per time slot.

2.1. Load Scheduling

An example of load scheduling time line is shown in Fig. 2. Let W_t denote a load arriving at the beginning of time slot t. We have $W_t \triangleq \rho_t \lambda_t$, where ρ_t and λ_t are the load intensity per slot and duration associated with W_t, respectively. We assume the load duration is an integer in multiple of time slots, and the minimum duration for any load is 1, *i.e.,* $\lambda_t \in \{1, 2, \ldots\}$.

Let $d_t^{\max}$ denote the maximum allowed delay for W_t before it is served (in multiple of time slots), and let d_t denote the actual

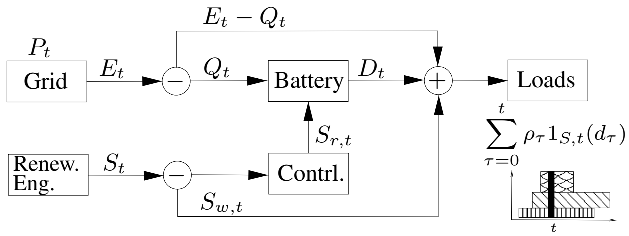

Fig. 1. An energy storage management system.

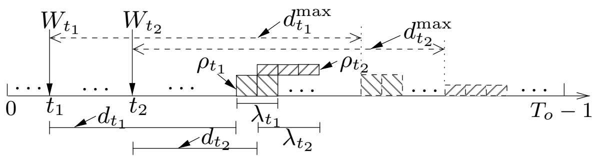

Fig. 2. An example of load scheduling.

scheduling delay incurred for W_t. We have

$$d_t \in \{0, 1 \ldots, d_t^{\max}\}, \ \forall t. \tag{1}$$

We define an indicator function $1_{S,t}(d_\tau) \triangleq \{1 : \text{if } t \in [\tau + d_\tau, \tau + d_\tau + \lambda_\tau); \ 0 : \text{otherwise}\}$, for $\forall \tau \leq t$. It indicates whether or not the load W_τ is being served at time slot t. Consider a T_o-slot period. We define $\overline{d_w}$ as the average scheduling delay of all arrived loads within this T_o-slot period, given as $\overline{d_w} \triangleq \frac{1}{T_o}\sum_{\tau=0}^{T_o-1} d_\tau$.

Besides the per load maximum delay constraint in (1), we impose a constraint on the average delay $\overline{d_w}$ as

$$\overline{d_w} \in [0, d^{\max}] \tag{2}$$

where $d^{\max}$ is the maximum average delay for the loads within the T_o-slot period. The average delay $\overline{d_w}$ reflects the quality of service (QoS) for the loads within the T_o-slot period. Let $C_d(\overline{d_w})$ be the cost function associated with $\overline{d_w}$. A longer delay reduces the QoS and incurs a higher cost. Thus, we assume $C_d(\cdot)$ to be a continuous, convex, non-decreasing function with derivative $C'_d(\cdot) < \infty$.

2.2. Energy Storage and Supply

1) Power Sources: The user can purchase energy from the *conventional grid* with a real-time price. Let E_t be the amount of energy bought per slot. It is bounded by

$$E_t \in [0, E_{\max}] \tag{3}$$

where $E_{\max}$ is the maximum amount of energy can be bought from the grid per slot. This amount can either be used to supply the user's loads and/or be stored into the battery. The real-time price P_t is bounded as $P_t \in [P_{\min}, P_{\max}]$, where $P_{\min}$ and $P_{\max}$ are the minimum and maximum electricity prices at time slot t. We assume the value of P_t is known to the user and is kept unchanged during the slot t. The average cost for the purchased energy from the grid over a T_o-slot period is defined by $\overline{J} \triangleq \frac{1}{T_o}\sum_{t=0}^{T_o-1} E_t P_t$.

Renewable generator: Let S_t be the amount of renewable energy harvested at time slot t. We assume the priority of using S_t is to first supply the user's loads. Denote this portion by $S_{w,t}$, we have

$$S_{w,t} = \min\left\{\sum_{\tau=0}^{t} \rho_\tau 1_{S,t}(d_\tau), S_t\right\}. \tag{4}$$

The remaining portion of S_t, if any, can be stored into the battery. Since there is a cost associated to the battery charging activity, we use a controller to determine whether or not the remaining portion can be stored into the battery. Let $S_{r,t}$ be the amount of renewable energy charged into the battery at time slot t. It is bounded by

$$S_{r,t} \in [0, S_t - S_{w,t}]. \tag{5}$$

2) Battery Operation: The battery can be charged from either the grid, the renewable generator, or both. Let Q_t denote the portion of E_t charged into the battery. The total charging amount at time slot t is bounded by

$$Q_t + S_{r,t} \in [0, R_{\max}] \tag{6}$$

where $R_{\max}$ is the maximum charging amount for the battery. Similarly, let D_t denote the discharging amount from the battery. It is bounded by

$$D_t \in [0, D_{\max}] \tag{7}$$

where $D_{\max}$ is the maximum discharging amount allowed from the battery. We assume there is no simultaneous charging and discharging activities at the battery. This means

$$(Q_t + S_{r,t}) \cdot D_t = 0. \tag{8}$$

Let B_t denote the state of battery (SOB) at time slot t. With a finite capacity, B_t is bounded by

$$B_t \in [B_{\min}, B_{\max}] \tag{9}$$

where $B_{\min}$ and $B_{\max}$ are the minimum energy required and maximum energy allowed in the battery. The dynamics of B_t due to charging and discharging activities evolve as

$$B_{t+1} = B_t + Q_t + S_{r,t} - D_t. \tag{10}$$

We consider two types of battery degradation costs caused by the (dis)charging activities: *entry cost* and *usage cost*. The entry cost is a fixed cost incurred due to each (dis)charging activity. Define two indicator functions to represent charging and discharging activities: $1_{R,t} \triangleq \{1 : \text{if } Q_t + S_{r,t} > 0; \ 0 : \text{otherwise}\}$ and $1_{D,t} \triangleq \{1 : \text{if } D_t > 0; \ 0 : \text{otherwise}\}$. Denote C_{rc} as the entry cost for each charging activity and C_{dc} for each discharging. Define $x_{e,t} \triangleq 1_{R,t}C_{\text{rc}} + 1_{D,t}C_{\text{dc}}$ as the entry cost at time slot t. We have the time-averaged entry cost over T_o-slot period defined as $\overline{x_e} \triangleq \frac{1}{T_o}\sum_{t=0}^{T_o-1} x_{e,t}$. The usage cost is the cost associated with the (dis)charging amount. Define $x_{u,t} \triangleq |Q_t + S_{r,t} - D_t|$ as the battery net changing amount at time slot t due to (dis)charging. From (6) and (7), $x_{u,t}$ is bounded by $x_{u,t} \in [0, \max\{R_{\max}, D_{\max}\}]$. We define the time-averaged usage over T_o-slot period as $\overline{x_u} \triangleq \frac{1}{T_o}\sum_{t=0}^{T_o-1} x_{u,t}$. It is straightforward to see that $\overline{x_u}$ is bounded by

$$\overline{x_u} \in [0, \max\{R_{\max}, D_{\max}\}]. \tag{11}$$

We model the usage cost as a function of $\overline{x_u}$, denoted by $C_u(\overline{x_u})$. It is known that fast (dis)charging, *i.e.,* a large value of $x_{u,t}$ has more detrimental effects on the life time of a battery. Let $C_u(\overline{x_u})$ be the cost function associated with the average net charging amount $\overline{x_u}$. We assume $C_u(\cdot)$ is a continuous, convex, and non-decreasing function with derivative $C'_u(\overline{x_u}) < \infty$. Overall, we have the average battery degradation cost over the T_o-slot as $\overline{x_e} + C_u(\overline{x_u})$.

2.3. Supply and Demand Balance

For each load W_τ arriving at time slot τ, if it is scheduled to be served at time slot $t \geq \tau$, the energy supply needs to meet the energy demand ρ_τ per slot. The overall energy supply must be equal to the total energy demand from those loads being served at time slot t. Thus, we have the following supply-demand balance

$$E_t - Q_t + S_{w,t} + D_t = \sum_{\tau=0}^{t} \rho_\tau 1_{S,t}(d_\tau), \quad \forall t. \tag{12}$$

3. JOINT LOAD SCHEDULING AND ENERGY STORAGE MANAGEMENT

Our design objective is to minimize the system cost averaged over a period of T_o slots. We model the overall system cost as a weighted sum of the cost from energy purchase and battery degradation, and the cost of scheduling delay. Define $\mathbf{a}_t \triangleq [E_t, Q_t, D_t, S_{w,t}, S_{r,t}]$ as the energy control action vector at time slot t. Our goal is to determine $\{\mathbf{a}_t, d_t\}$, based on current and past system inputs $\{W_\tau, S_\tau, P_\tau\}_{\tau=0}^t$, to minimize the time-averaged system cost. This stochastic optimization problem is formulated by

$$\textbf{P1:} \min_{\{\mathbf{a}_t, d_t\}} \quad \overline{J} + \overline{x_e} + C_u(\overline{x_u}) + \alpha C_d(\overline{d_w})$$

$$\text{s.t. } (1) - (5), (8), (11), (12), \text{and}$$

$$0 \le S_{r,t} + Q_t \le \min\{R_{\max}, B_{\max} - B_t\} \tag{13}$$

$$0 \le D_t \le \min\{D_{\max}, B_t - B_{\min}\}. \tag{14}$$

where α is the relative weight between energy related cost and delay incurred in load scheduling in the joint optimization.

Problem Modification: **P1** is a difficult stochastic optimization problem. The (dis)charging constraints (13) and (14) are functions of the current SOB B_t, making the control actions coupled over time. To remove the time coupling, we see that the change of battery energy level over the T_o-slot period is $B_{T_o} - B_0 = \sum_{t=0}^{T_o-1}(Q_t + S_{r,t} - D_t)$. We now set this change to be a desired value Δ_u, *i.e.,*

$$\sum_{t=0}^{T_o-1} (Q_t + S_{r,t} - D_t) = \Delta_u. \tag{15}$$

Note that Δ_u is only a desired value we set, which may not be achieved by an control algorithm at the end of T_o-slot period. With constraint (15), we now modify **P1** to the following problem

$$\textbf{P2:} \min_{\{\mathbf{a}_t, d_t\}} \quad \overline{J} + \overline{x_e} + C_u(\overline{x_u}) + \alpha C_d(\overline{d_w})$$

$$\text{s.t } (1) - (8), (11), (12), (15).$$

From **P1** to **P2**, we impose constraint (15) on the net change of SOB over the T_o-slot period. By doing so, we remove the dependency of B_t in (13) and (14), and replace them by (6) and (7).

Problem Transformation: In the objective of **P2**, the battery average usage cost $C_u(\overline{x_u})$ and scheduling delay cost $C_d(\overline{d_w})$ are functions of time-averaged quantities, which complicate the problem. Using the technique introduced in [16], we transform the problem into one that only contains the time-average of the functions. Specifically, we introduce auxiliary variables $\gamma_{u,t}$ for $x_{u,t}$ and $\gamma_{d,t}$ for d_t, and impose the following constraints

$$0 \le \gamma_{u,t} \le \max\{R_{\max}, D_{\max}\}, \ \forall t \tag{16}$$

$$0 \le \gamma_{d,t} \le \min\{d_t^{\max}, d^{\max}\}, \ \forall t \tag{17}$$

$$\overline{\gamma_u} = \overline{x_u}, \quad \overline{\gamma_d} = \overline{d_w} \tag{18}$$

where $\overline{\gamma_i} \triangleq \frac{1}{T_o}\sum_{\tau=0}^{T_o-1}\gamma_{i,t}$, for $i = u, d$. Define $\overline{C_i(\gamma_i)} \triangleq \frac{1}{T_o}\sum_{t=0}^{T_o-1} C_i(\gamma_{i,t})$ as the time-averaged value of $C_i(\gamma_{i,t})$ over T_o slots, for $i = u, d$. Replacing $x_{u,t}$ and d_t by $\gamma_{u,t}$ and $\gamma_{d,t}$, we transform **P2** into the following problem

$$\textbf{P3:} \min_{\{\boldsymbol{\pi}_t\}} \quad \overline{J} + \overline{x_e} + \overline{C_u(\gamma_u)} + \alpha\overline{C_d(\gamma_d)}$$

$$\text{s.t } (1) - (8), (12), (15) - (18)$$

where $\boldsymbol{\pi}_t \triangleq [\mathbf{a}_t, d_t, \gamma_{u,t}, \gamma_{d,t}]$. It can be shown that the two problems **P2** and **P3** are equivalent. The proof is omitted here.

Transforming **P2** to **P3** enables us to propose a real-time joint storage management and load scheduling policy by adopting Lyapunov optimization technique [6]. The control actions $\{\mathbf{a}_t\}$ for **P3** may not be feasible to **P1** due to the modification from **P1** to **P2**. However, by properly designing our control parameters, we will ensure the produced solution $\{\mathbf{a}_t\}$ are still feasible to **P1**.

4. REAL-TIME ALGORITHM

4.1. Lyapunov Function and Drift

For the time-averaged scheduling delay $\overline{d_w}$ in (2), we introduce a virtual queue X_t whose dynamics are given by

$$X_{t+1} = \max(X_t + d_t - d^{\max}, 0). \tag{19}$$

The relation between (2) and (19) is that, by averaging (19) over T_o slots, we have $\overline{d_w} \le d^{\max} + \frac{X_{T_o} - X_0}{T_o}$, and (2) is approximately satisfied by (19) with mismatch $\frac{X_{T_o} - X_0}{T_o}$.

For the time-averaged constraint (15), we introduce a virtual queue Z_t with dynamics given by

$$Z_{t+1} = Z_t + Q_t + S_{r,t} - D_t - \frac{\Delta_u}{T_o}. \tag{20}$$

From the dynamics of Z_t above and B_t in (10), we can show that $Z_t = B_t - A_t$ with $A_t \triangleq A_o + \frac{\Delta_u}{T_o}t$. Later, we design A_o to ensure our storage control solution $\{\mathbf{a}_t\}$ by our real-time algorithm satisfies the battery capacity constraint (9) imposed in **P1**.

Finally, to meet constraints in (18), we establish virtual queues $H_{u,t}$ and $H_{d,t}$ as follows

$$H_{u,t+1} = H_{u,t} + \gamma_{u,t} - x_{u,t}, \ H_{d,t+1} = H_{d,t} + \gamma_{d,t} - d_t. \tag{21}$$

Let $\boldsymbol{\Theta}_t \triangleq [Z_t, X_t, H_{u,t}, H_{d,t}]$ be the vector of the virtual queues defined above. The quadratic Lyapunov function $L(\boldsymbol{\Theta}_t)$ for $\boldsymbol{\Theta}_t$ is defined as $L(\boldsymbol{\Theta}_t) \triangleq \frac{1}{2}(Z_t^2 + H_{u,t}^2 + X_t^2 + H_{d,t}^2)$. To design a real-time control algorithm, we define a one-slot sample path Lyapunov drift as $\Delta(\boldsymbol{\Theta}_t) \triangleq L(\boldsymbol{\Theta}_{t+1}) - L(\boldsymbol{\Theta}_t)$, which can be shown to only depend on the current system inputs $\{W_t, S_t, P_t\}$.

4.2. Real-Time Algorithm

Solving **P3** is still difficult. Instead of minimizing the system cost objective of **P3**, we intend to minimize a *drift-plus-cost* metric given by $\Delta(\boldsymbol{\Theta}_t) + V[E_tP_t + x_{e,t} + C_u(\gamma_{u,t}) + \alpha C_d(\gamma_{d,t})]$, where $V > 0$ is the relative weight between the drift and the system cost. We use the upper bound of this drift-plus-cost function to design our real-time algorithm. By removing all constant terms independent of control action $\boldsymbol{\pi}_t$, we arrive at the following per slot optimization problem

$$\begin{aligned}\textbf{P4}: \min_{\boldsymbol{\pi}_t} \ & Z_t\left[E_t + S_{r,t} + S_{w,t} - \rho_t 1_{S,t}(d_t)\right] - |H_{u,t}|S_{w,t} \\ & + H_{u,t}[\gamma_{u,t} - (E_t + S_{r,t})] + |H_{u,t}|\rho_t 1_{S,t}(d_t) + X_t d_t \\ & + H_{d,t}(\gamma_{d,t} - d_t) + V\left[E_tP_t + x_{e,t} + C_u(\gamma_{u,t}) + \alpha C_d(\gamma_{d,t})\right] \\ \text{s.t } & (1), (3) - (8), (12), (16), (17).\end{aligned}$$

Denote the optimal control action of **P4** by $\boldsymbol{\pi}_t^* \triangleq [\mathbf{a}_t^*, d_t^*, \gamma_{u,t}^*, \gamma_{d,t}^*]$. Regrouping the terms in the objective of **P4** with respect to the control variables, we can split **P4** into sub-problems and solve them sequentially. The steps are described below.

(i) Determine d_t^* and $\gamma_{d,t}^*$ by solving $\mathbf{P4_{a1}}$ and $\mathbf{P4_{a2}}$ as below.

$$\mathbf{P4_{a1}}: \min_{d_t} \ d_t(X_t - H_{d,t}) - \rho_t 1_{S,t}(d_t)\left(Z_t - |H_{u,t}|\right) \ \text{ s.t. } (1).$$

$$\mathbf{P4_{a2}}: \min_{\gamma_{d,t}} \ H_{d,t}\gamma_{d,t} + V\alpha C_d(\gamma_{d,t}) \quad \text{s.t. } (17).$$

(ii) Determine $S^*_{w,t}$ in (4) using d^*_t obtained in (i).

(iii) Using $S^*_{w,t}$ obtained in (ii) in (12), determine $\gamma^*_{u,t}$ and $\mathbf{a}^*_t$ by solving the following $\mathbf{P4_{b1}}$ and $\mathbf{P4_{b2}}$, respectively.

$$\mathbf{P4_{b1}}: \min_{\gamma_{u,t}} \; H_{u,t}\gamma_{u,t} + VC_u(\gamma_{u,t}) \quad \text{s.t. } (16).$$

$$\mathbf{P4_{b2}}: \min_{\mathbf{a}_t} \; E_t(Z_t - H_{u,t} + VP_t) + S_{r,t}(Z_t - H_{u,t}) + V\left(1_{R,t}C_{\text{rc}} + 1_{D,t}C_{\text{dc}}\right) \quad \text{s.t. } (3)-(8), (12).$$

We now solve each subproblem to obtain a closed-form solution.

1) The optimal d^*_t: Let $\omega_o \triangleq -\rho_t(Z_t - |H_{u,t}|)$, $\omega_1 \triangleq (X_t - H_{d,t})$, and $\omega_{d^{\max}_t} \triangleq d^{\max}_t(X_t - H_{d,t})$. Solving $\mathbf{P4_{a1}}$, we have i) If $X_t - H_{d,t} \geq 0$: $d^*_t = \{0 : \text{if } \omega_o \leq \omega_1;\; 1: \text{ otherwise}\}$; ii) If $X_t - H_{d,t} < 0$: $d^*_t = \{0 : \text{if } \omega_o \leq \omega_{d^{\max}_t};\; d^{\max}_t: \text{ otherwise}\}$.

2) The optimal $\gamma^*_{d,t}$ *and* $\gamma^*_{u,t}$: Let $C'^{-1}_i(\cdot)$ denote the inverse function of $C'_i(\cdot)$, which is the derivative of $C_i(\cdot)$. The optimal solution $\gamma^*_{i,t}$, for $i = u, d$, is given by $\gamma^*_{i,t} = \{0 : \text{if } H_{i,t} \geq 0;\; \Gamma_i : \text{if } H_{i,t} < -V\beta_i C'_i(\Gamma_i); \text{ and } C'^{-1}_i\left(-\frac{H_{i,t}}{V\beta_i}\right) : \text{otherwise}\}$, where $\beta_u = 1$, $\beta_d = \alpha$, $\Gamma_u \triangleq \max\{R_{\max}, D_{\max}\}$, and $\Gamma_d \triangleq \min\{d^{\max}_t, d^{\max}\}$.

3) The optimal $\mathbf{a}^*_t$: Using d^*_t in 1), we determine the schedules for the loads. Consequently, the optimal $S^*_{w,t}$ is obtained. The optimal storage control solution $\mathbf{a}^*_t$ is obtained by using the similar approach in [9]. We omit the details due to space limitation.

4.3. Feasible Solution and Performance Bound

1) Feasible solution: Since the battery capacity constraint (9) on B_t is not imposed in $\mathbf{P4_{b2}}$, our real-time algorithm may not provide a feasible control solution $\{\mathbf{a}^*_t\}$ for $\mathbf{P1}$. To ensure our solution is feasible to $\mathbf{P1}$, we design A_o and V as $A_o = \{A'_o : \text{if } \Delta_u \geq 0;\; A'_o - \Delta_u : \text{if } \Delta_u < 0\}$, where $A'_o = B_{\min} + VP_{\max} + VC'_u(\Gamma_u) + \Gamma_u + D_{\max} + \frac{\Delta_u}{T_o}$, and $V \in [0, V_{\max}]$ with $V_{\max} = \frac{B_{\max} - B_{\min} - R_{\max} - D_{\max} - 2\Gamma_u - |\Delta_u|}{P_{\max} + C'_u(\Gamma_u)}$. We can show that with the above values, the resulting B_t satisfies the battery capacity constraint (9), and $\{\mathbf{a}^*_t\}$ is feasible to $\mathbf{P1}$.

2) Performance bound: Denote $u^*(V)$ as the objective value of $\mathbf{P1}$ achieved by our real-time algorithm over T_o-slots. Partition T_o slots into T frames with $T_o = MT$, for $M, T \in \mathbb{N}^+$. Let u^{opt}_m be the minimum T-slot average cost over the mth frame obtained by an optimal non-causal T-slot look-ahead solution (*i.e.,* $\{W_t, S_t, P_t\}$ are known ahead of time). The following theorem provides a bound of the cost performance of our proposed real-time algorithm to u^{opt}_m of the T-slot look-ahead optimal solution.

Theorem 1. *For any $T > 0$ that $T_o = MT$, and $\{W_t, S_t, P_t\}$ being any arbitrary processes over time, the T_o-slot average system cost under the real-time algorithm is bounded by*

$$u^*(V) - \frac{1}{M}\sum_{m=0}^{M-1} u^{opt}_m \leq \frac{GT}{V} + \frac{L(\Theta_0) - L(\Theta_{T_o})}{VT_o} + \frac{C'_u(\Gamma_u)(H_{u,0} - H_{u,T_o}) + \alpha C'_d(\Gamma_d)(H_{d,0} - H_{d,T_o})}{T_o}$$

where $G > 0$ is a constant, and the above upper bound is finite.

5. SIMULATION RESULTS

We set each slot duration to be 5 minutes and consider a 24-hour duration. Thus $T_o = 288$ slots. We use price P_t in [17] as shown in Fig. 3 top. We consider both solar energy $\{S_t\}$ and load $\{W_t\}$ being non-stationary processes, with the mean amount $\overline{S}_t = \mathbb{E}[S_t]$ and $\overline{W}_t = \mathbb{E}[W_t]$ changing periodically over 24 hours, following three-stage values as shown in Fig. 3 middle and bottom, where the standard deviations are $\sigma_{S_i} = 0.4\overline{S}_i$ and $\sigma_{W_i} = 0.2\overline{W}_i$, for $i = h, m, l$. Other parameters are set as follows: $R_{\max} = D_{\max} = 0.165$ kWh, $E_{\max} = 0.3$ kWh, $C_{\text{rc}} = C_{\text{dc}} = 0.001$, $B_{\min} = B_0 = 0$, $B_{\max} = 3$ kWh and $\Delta_u = 0$. We set $V = V_{\max}$ and $d^{\max}_t$ to be identical for $\forall t$. We assume the battery usage cost and the delay cost are both quadratic functions, given by $C_u(\overline{x_u}) = k_u\overline{x_u}^2$ and $C_d(\overline{d_w}) = k_d\overline{d_w}^2$, where the constants $k_u = 0.2$ and $k_d = 1/(d^{\max})^2$.

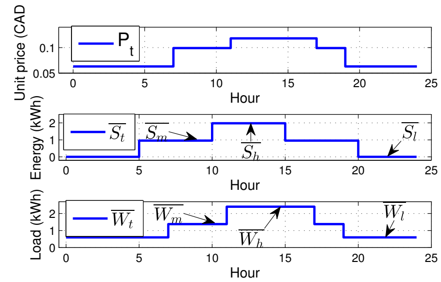

Fig. 3. System inputs $\overline{W}_t, \overline{S}_t$, and P_t over 24 hours.

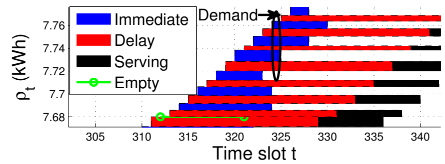

Fig. 4. A trace of scheduling results over time ($d^{\max}_t = d^{\max} = 18$, $\alpha = 0.005$).

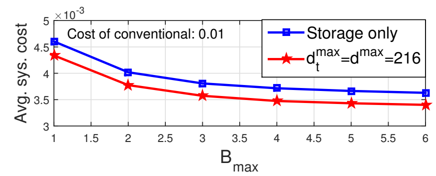

Fig. 5. Average system cost vs. $B_{\max}$ ($\alpha = 0.001$).

Under our proposed algorithm, we first show a section of load scheduling results over time slots in Fig. 4. Each load is shown by ρ_t (y-axis) and λ_t (x-axis). For example, the total amount of load scheduled at time slot $t = 324$ is the summation over the region circled in the plot. Fig. 5 shows the system cost vs. battery capacity. The system cost reduces as $B_{\max}$ increases. This is because a larger battery capacity allows more flexible (dis)charging to reduce the cost. Also, we compare our result with two other algorithms: 1) *conventional*: where there is neither storage nor load scheduling; 2) *storage only*: where storage management is provided, but loads are scheduled immediately without delay. Since the conventional approach does not use a battery, the system cost is unchanged over $B_{\max}$ and is high. Thus, we only provide the cost value in Fig. 5. We see that by joint load scheduling and storage management, the system cost under our algorithm is reduced significantly over the conventional approach, and a further cost reduction due to load scheduling is also clearly seen.

6. CONCLUSION

In this work, we proposed a real-time joint energy storage management and load scheduling algorithm aiming at minimizing the system cost within a finite time period. We considered unknown arbitrary system dynamics and included both battery operational cost and delays cost. Our proposed real-time algorithm decouples the storage management and load scheduling which are solved sequentially. We showed that our proposed algorithm resulted in a guaranteed bounded performance from an optimal T-slot look-ahead scheme.

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