Utilizing Renewable Energy Resources by Adopting DSM Techniques and Storage Facilities

Pedram Samadi*, Hamed Mohsenian-Rad†, Vincent W.S. Wong*, and Robert Schober*
*The University of British Columbia, Vancouver, Canada
†University of California, Riverside, CA, USA
E-mail: {psamadi, vincentw, rschober}@ece.ubc.ca, hamed@ee.ucr.edu

***Abstract*—A common assumption in the existing literature on energy consumption scheduling in smart grid is that users are aware in advance of their daily energy consumption needs. Therefore, most existing studies along this line of research have been inherently deterministic, e.g., see [1]–[3]. However, this assumption may not hold in practice. In particular, the energy consumption scheduling (ECS) devices may face load uncertainty. If a user is equipped with a behind-the-meter renewable generator, then the optimal operation of ECS devices becomes even more challenging due to *combined load and supply uncertainties*. Therefore, in this paper, we formulate a *stochastic optimization* problem to operate an ECS device in a residential unit that is equipped with a behind-the-meter renewable generator and a local battery bank. In our problem formulation, we consider different sets of *must-run* and *controllable* appliances. Our design only requires knowledge of some estimates of the users' future demand. To reduce computational complexity, we approximate the expected load in the upcoming time slots by adopting the *certainty equivalent* approximation technique. Simulation results show that the proposed energy consumption scheduling algorithm can tackle the uncertainties in load and supply and it can benefit both users and the utility companies.**

I. Introduction

Concerns about environmental issues and the need to reduce greenhouse gas emissions have attracted considerable attention to *renewable energy resources* (RERs) [4]–[6], *storage devices* [7]–[10], and various *demand side management* (DSM) programs. Among different techniques considered for DSM, *smart pricing* is known to be an effective means to encourage users to consume wisely and efficiently.

For a price-based DSM program to be effective, users must be equipped with automated control units to make price-based control decisions. Some difficulties due to an enhanced price responsiveness of the users have already been studied, e.g. in [11], [12]. For example, *load synchronization* is a common problem and refers to the concentration of a large portion of energy consumption in low-price hours. Load synchronization can be prevented by using pricing tariffs with *inclining block rates* (IBRs), where the marginal price increases with the total consumed power [13]. Considering the intermittent nature of RERs, the level of success of different DSM programs depends on the flexibility of the users' loads to match supply and demand. The mismatch between supply and demand can also be eliminated by using energy storage devices such as batteries, flywheels, compressed air, and water tanks [7], [8].

Considering the increasing penetration of intermittent RERs, to serve the user demand, which is also random, advanced methods are required to match supply and demand. Despite its importance, the *joint* effects of supply and load uncertainties on DSM programs have not been studied in the smart grid literature [14]–[19]. Therefore, in this paper, we focus on developing a novel automated optimization-based residential load scheduling algorithm with both load and supply uncertainties. We aim at minimizing each user's electricity payment by optimally scheduling the operation of its appliances and the charging and discharging rates of the storage facilities in real-time, subject to operational constraints defined by the user. As in [11], we adopt real-time pricing (RTP) *combined* with IBR to reflect the fluctuation of the wholesale electricity prices and to avoid *load synchronization*. Our contributions are as follows:

- We propose a novel energy consumption scheduling algorithm with *load* and *supply uncertainties* for DSM purposes. Our algorithm is designed to minimize the electricity payment of a residential user.
- To estimate the expected load in the future time slots, we take into account the effect of control decisions of the automated control unit. To reduce computational complexity, we adopt the *certainty equivalent* technique.
- Simulation results show that our design can incorporate both load and supply uncertainties, and leads to a reduction of the energy bills of users. Furthermore, the proposed approach improves the overall power system performance by reducing the peak-to-average ratio (PAR) of the aggregate load demand. It also facilitates a more efficient utilization of the RERs by encouraging the users to shift their load to time slots with high renewable power generation and thus, enables a reduction of the amount of energy that has to be imported from the power grid.

The algorithm proposed in this paper is different from other designs existing in the literature. For example, compared to [18] where the uncertainty in load is addressed, here, we tackle uncertainties in both load and supply. Furthermore, unlike [18], we consider the case where users are equipped with storage devices and also provide an estimate of the future load, taking into account the fact that the load in the future time slots does depend on the control decisions of the scheduler. Our work is also different from the load control algorithm in [17], as the proposed algorithm takes into account the impact of uncertainties for scheduling the appliances.

The remainder of this paper is organized as follows. The system model is introduced in Section II. The problem formulation and algorithm description are presented in Section III. Simulation results are provided in Section IV, and the paper is concluded in Section V.

II. System Model

In this section, we present a mathematical model for energy consumption scheduling with RERs. We consider a residential unit and a single *energy provider*. Each unit is also equipped with a *local*, *behind-the-meter* renewable generator. This can be a either rooftop solar panel or a small wind turbine. We assume that each user is equipped with a smart meter which has an energy consumption scheduling (ECS) unit capable of controlling the household energy consumption. Furthermore, we assume that the price values are informed by the retailer to the end user through a digital communication infrastructure.

A. Home Appliances

Let $\mathcal{A}$ denote the set of all appliances of a residential unit that participates in DSM. We assume that each appliance $a \in \mathcal{A}$ can work either as *must-run* or *controllable*. Must-run appliances such as TV and personal computer (PC) need to start operating immediately. The operation of must-run appliances cannot be interrupted by the ECS unit. In contrast, the operation of controllable appliances can be *delayed* or *interrupted* if necessary. Plug-in electric vehicle (PEV) and washing machine are examples of controllable appliances. We assume that based on the demand requirements of the user, each appliance can be set as must-run or controllable. This setting is decided by the user and can vary from time to time.

We divide the operation cycle into $T \triangleq |\mathcal{T}|$ time slots, where set $\mathcal{T} \triangleq \{1, \ldots, T\}$ contains the time slot indices. To start operation, each appliance sends an *operating request* to the ECS unit. The operating request determines whether the appliance is must-run or controllable and the specifications of its operational requirements. Once an operating request is submitted, the state of the appliance changes from *sleep* to *awake*. The appliance remains awake until its operation is *finished*. Different appliances may request to operate at *different* time slots, and the information about the operational requirements of the appliances is revealed gradually over time.

For controllable appliances, the deadline before which the operation of the appliance has to be finished is denoted by β_a. We define binary variable $x_t^a \in \{0, 1\}$ as the state of the power consumption of appliance $a \in \mathcal{A}$ at time slot $t \in \mathcal{T}$. We set $x_t^a = 1$ if appliance a is admitted to operate at nominal power P_a in time slot t (i.e., *active*), otherwise, we set $x_t^a = 0$ (i.e., *inactive*). Let E_t^a denote the amount of energy required to finish the operation of appliance a while the current time slot is t. Note that given E_t^a, for each future time slot $k > t > 0$, we have

$$E_k^a = \left[E_t^a - P_a \sum_{i=t}^{k-1} x_i^a \right]^+, \tag{1}$$

where $[\cdot]^+ \triangleq \max\{\cdot, 0\}$. For each controllable appliance a, its operation has to be finished before its deadline. That is, for the current time slot t, we must have

$$P_a \sum_{k=t}^{\beta_a} x_k^a = E_t^a. \tag{2}$$

B. Energy Storage Devices

To better utilize the RERs and match supply and demand, we assume the use of a storage device such as a battery. We define C_b as the storage capacity of the battery. We assume that the maximum charging and discharging rates of the battery are identical and denoted by g_b. For time slot t, we define $y_t^b \in [-g_b, g_b]$ as the charging and discharging rates of the battery. The battery can be charged from both the RER and the grid. We define S_t^b as the charging state of the battery at the beginning of time slot t.

$$S_t^b = S_0^b + \sum_{k=1}^{t-1} y_k^b, \tag{3}$$

where S_0^b is the initial charging state of the battery. At any time slot t, the stored energy cannot exceed the storage capacity. Moreover, it is not possible to extract more energy from the storage unit than what is stored, i.e.,

$$0 \leq S_t^b \leq C_b. \tag{4}$$

C. Distributed Generation

For the RER, we require an estimate of the available amount of generated power. Different stochastic models have been proposed to predict the power generation from RERs [20]. Here, similar to [21], we approximate the distribution of the output power of the RERs at time slot t, Ψ_t, with a normal distribution with mean μ_t and standard deviation σ_t, i.e., $\Psi_t \sim \mathcal{N}(\mu_t, \sigma_t^2)$. The values of μ_t and σ_t can be derived from the examination of real data obtained from the system.

D. Real-time Pricing

Let $l_t \triangleq \sum_{a \in \mathcal{A}} P_a x_t^a$ denote the total household power consumption at time slot t. We consider a pricing function $\lambda_t(l_t)$ which represents the price of electricity in each time slot t as a function of the user's power consumption in that time slot. For combined RTP and IBR pricing tariffs, the price function $\lambda_t(l_t)$ is defined as [11]:

$$\lambda_t(l_t) = \begin{cases} m_t, & \text{if } \ 0 \leq l_t \leq b_t, \\ n_t, & \text{if } \ l_t > b_t, \end{cases} \tag{5}$$

where m_t, n_t, and b_t are known parameters, and $m_t \leq n_t$.

III. Problem Formulation and Algorithm Design

In this section, we consider the problem of *efficient power scheduling* such that the electricity payment of the user is minimized. The exact information about the list of appliances that are awake in each time slot, whether they are must-run or controllable, and the deadline by which the operation of each appliance should be finished is revealed *gradually* over time. For the current time slot t, we assume that the amount of generated power from RERs is either known or can be predicted precisely. Furthermore, based on the distribution of the generated power in each time slot, it is possible to estimate the generated power in upcoming time slots. In our system model, an update regarding the demand requirement of the user and the amount of generated power from RERs is received by the ECS unit at the beginning of each time slot, and the energy consumption schedule of each controllable appliance and the charging and discharging rates of the battery are adapted accordingly.

A. Problem Formulation

In each time slot t, as the demand information of the appliances and the available power from the RERs are updated, the operation schedule of each controllable appliance and the charging and discharging rates of the battery are adjusted, and the optimum power scheduling is identified in real-time as the solution of the following optimization problem for minimization of the expected cost from the current time slot t onwards:

$$\underset{\substack{\mathbf{y}_t^b, \mathbf{x}_t^a, \ \forall a \in \mathcal{C}_k, \\ k \in \mathcal{T}_t}}{\text{minimize}} \quad \mathbb{E}\left[\sum_{k=t}^{T} L_k \lambda_k \big(L_k\big) \right] \tag{6a}$$

$$\text{subject to} \quad x_k^a \in \{0,1\}, \quad \forall a \in \mathcal{C}_k, \ \forall k \in \mathcal{T}_t, \tag{6b}$$

$$P_a \sum_{i=k}^{\beta_a} x_i^a = E_k^a, \quad \forall a \in \mathcal{C}_k, \ \forall k \in \mathcal{T}_t, \tag{6c}$$

$$y_k^b \in [-g_b, g_b], \quad \forall k \in \mathcal{T}_t, \tag{6d}$$

$$0 \le S_k^b \le C_b, \quad \forall k \in \mathcal{T}_t, \tag{6e}$$

where $\mathbb{E}[\cdot]$ denotes mathematical expectation, $\mathbf{y}_t^b \triangleq (y_t^b, \ldots, y_T^b)$, $\mathbf{x}_t^a \triangleq (x_t^a, \ldots, x_T^a)$, $\mathcal{T}_t \triangleq \{t, \ldots, T\}$,

$$L_k = \left[\sum_{a \in \mathcal{M}_k} P_a + \sum_{a \in \mathcal{C}_k} P_a x_k^a + y_k^b - \Psi_k \right]^+, \tag{7}$$

E_k^a is as in (1), and S_k^b is defined as in (3). Here, $\mathcal{M}_k$ and $\mathcal{C}_k$ are the sets of all must-run and controllable appliances that are awake at time slot k, respectively, and Ψ_k is the amount of power generation from RERs at time slot k. Here, we assume that the user cannot sell energy to the grid. That is, the excess generated power from the RER is wasted. The objective function represents the expected payment of the user from the current time slot t up to time slot T.

B. Approximate Solution

Problem (6) in its current form is difficult to solve as it requires the computation of the expected schedule of any currently sleeping appliance. There are different possibilities for the time at which sleeping appliance a may become awake and also for the time by which its operation has to be finished. Together, all different possibilities form the state space of outcomes. We refer to each possible outcome as a *scenario*. Considering the huge state space of outcomes, it is very difficult to calculate the expected schedule for every sleeping appliance. To tackle this problem, we *approximate* the expected load of sleeping appliances by confining the expectation to a limited number of scenarios. That is, to calculate the expected schedule, instead of taking all possible outcomes into account, we consider only a limited number of scenarios. We define Ω_t as the set of $W \triangleq |\Omega_t|$ randomly generated scenarios from current time slot t onwards, see Section III-C. Problem (6) can be approximated as

$$\underset{\substack{\mathbf{y}_t^b, \mathbf{x}_t^a, \ \forall a \in \mathcal{C}_t, \\ \mathbf{x}_t^{\omega,a}, \ \forall a \in \mathcal{S}_t, \\ \forall \omega \in \Omega_t}}{\text{minimize}} \quad \mathbb{E}_\omega \left[\sum_{k=t}^{T} L_k^\omega \lambda_k \big(L_k^\omega\big) \right] \tag{8a}$$

$$\text{subject to} \quad x_k^a \in \{0,1\}, \quad \forall a \in \mathcal{C}_t, \ \forall k \in \mathcal{T}_t, \tag{8b}$$

$$x_k^{\omega,a} \in \{0,1\}, \ \forall a \in \mathcal{S}_t, \ \forall k \in \mathcal{T}_t, \forall \omega \in \Omega_t \tag{8c}$$

$$P_a \sum_{i=t}^{\beta_a} x_i^a = E_t^a, \quad \forall a \in \mathcal{C}_t, \tag{8d}$$

$$P_a \sum_{i=\alpha_a^\omega}^{\beta_a^\omega} x_i^{\omega,a} = E_a, \quad \forall a \in \mathcal{S}_t, \forall \omega \in \Omega_t \tag{8e}$$

$$\text{(6d), (6e),} \tag{8f}$$

where $\mathbb{E}_\omega[\cdot]$ denotes the expectation based on the set of scenarios Ω_t, $\mathbf{x}_t^{\omega,a} \triangleq (x_t^{\omega,a}, \ldots, x_T^{\omega,a})$, and $x_k^{\omega,a}$ is the state of power consumption of appliance a under scenario ω. E_a is defined as the total energy required to finish the operation of appliance $a \in \mathcal{A}$. $\mathcal{S}_t$ is defined as the set of all sleeping appliances at time slot t. For scenario ω, α_a^ω denotes the earliest time at which the operation of appliance a can be scheduled, and β_a^ω denotes the time by which the operation of appliance a has to be finished. Furthermore, L_k^ω is defined as

$$L_k^\omega \triangleq \left[\sum_{a \in \mathcal{M}_t} P_a + \sum_{a \in \mathcal{C}_t} P_a x_k^a + \sum_{a \in \mathcal{S}_t} P_a x_k^{\omega,a} + y_k^b - \Psi_k^\omega \right]^+, \tag{9}$$

For the price function in (5), since $m_t \le n_t$, for a total load l_t at time slot t, the user's payment $l_t \lambda_t(l_t)$ is determined as the maximum of the two intersecting lines:

$$l_t \lambda_t(l_t) = \max\big\{ m_t l_t, \ n_t l_t + (m_t - n_t) b_t \big\}. \tag{10}$$

Therefore, problem (8) can be reformulated as

$$\underset{\substack{\mathbf{y}_t^b, \mathbf{x}_t^a, \ \forall a \in \mathcal{C}_t, \\ \mathbf{x}_t^{\omega,a}, \ \forall a \in \mathcal{S}_t \\ \forall \omega \in \Omega_t}}{\text{minimize}} \ \mathbb{E}_\omega \left[\sum_{k=t}^{T} \max\Big\{ m_k L_k^\omega, n_k L_k^\omega + (m_k - n_k) b_k \Big\} \right] \tag{11}$$

$$\text{subject to} \quad \text{(8b)-(8f).}$$

Finally, we introduce auxiliary variable ν_k, for each time slot k, and adopt *certainty equivalent* approximation technique [22], i.e., all uncertainties are fixed in their expected value. The certainty equivalent approximation technique is adopted to move the expectation, $\mathbb{E}_\omega[\cdot]$, inside the $\max\{\}$ operator.

Thus, we can re-write problem (11) as

$$\begin{aligned} \underset{\substack{\mathbf{y}_t^b,\, \mathbf{x}_t^a,\ \forall\, a \in \mathcal{C}_t, \\ \mathbf{x}_t^{\omega,a},\ \forall\, a \in \mathcal{S}_t, \\ \omega\ \in \Omega_t, \boldsymbol{\nu}_t}}{\text{minimize}} \quad & \sum_{k=t}^{T} \nu_k \\ \text{subject to} \quad & \text{(8b)-(8f)}, \\ & m_k\, \mathbb{E}_\omega[L_k^\omega] \le \nu_k, \quad \forall\, k \in \mathcal{T}_t, \\ & n_k\, \mathbb{E}_\omega[L_k^\omega] + (m_k - n_k) b_k \le \nu_k,\ \forall\, k \in \mathcal{T}_t, \end{aligned} \tag{12}$$

where $\boldsymbol{\nu}_t \triangleq (\nu_t, \ldots, \nu_T)$, $\mathbb{E}_\omega\{L_k^\omega\}$ is the expected load at time slot k based on the limited number of scenarios which can be calculated as

$$\mathbb{E}_\omega\{L_k^\omega\} = \frac{1}{W} \sum_{\omega \in \Omega_t} L_k^\omega, \tag{13}$$

Problem (12) is a mixed-binary linear program and can be solved efficiently by using MOSEK [23]. The solution of optimization problem (12) determines the appropriate scheduling of the controllable appliances as well as the charging and discharging rates of the battery. However, for controllable appliances and the battery, only the operation schedule of the current time slot t is executed, and the schedule of the future time slots $t+1, \ldots, T$ may change when the optimization problem is solved again in the next time slot as new information about the future load and power generation from RERs becomes available.

C. Scenario Selection

In our system model, we assume that the demand information of the appliances and the amount of power generation from RERs are not known ahead of time. However, we assume that some statistical information is available. That is, the probability with which each appliance becomes *awake* at each time slot t, p_t^a, is known at the beginning of the operation cycle [18]. Such information can be calculated, for example, based on the sleep and awake history of each appliance. In our model, each appliance can become awake only once. If an appliance becomes awake more often, we can simply introduce *virtual* appliances to deal with this issue. Therefore, we have

$$\sum_{t=1}^{T} p_t^a + p_0^a = 1, \tag{14}$$

where p_0^a denotes the probability that appliance a does *not* become awake at *any* time within the period $[1, T]$. We define $p_{\tau,t}^a$ as the probability that appliance a becomes awake in time slot $\tau > t$ given that it has *not* become awake until time slot t. Based on Bayes' rule, $p_{\tau,t}^a$ can be calculated as

$$\begin{aligned} p_{\tau,t}^a &\triangleq \mathbb{P}(\Delta_\tau^a = 1 \mid \Delta_1^a = 0, \ldots, \Delta_t^a = 0) \\ &= \frac{p_\tau^a}{\sum_{k=t+1}^{T} p_k^a + p_0^a}, \end{aligned} \tag{15}$$

where Δ_t^a is a random variable that is equal to one if appliance a becomes awake in time slot t, and equal to zero otherwise. Furthermore, we assume that given appliance a becomes awake at time slot τ, the probability with which its deadline is set as $k > \tau$, $q_{k,\tau}^a$, is known. That is,

$$q_{k,\tau}^a \triangleq \mathbb{P}(\theta_k^a = 1 \mid \Delta_\tau^a = 1), \tag{16}$$

where θ_k^a is a random variable that is equal to one if the operating deadline of appliance a is $k > \tau$, and equal to zero otherwise. We note that the feasible operational interval for each appliance, i.e., the difference between the time slot at which appliance a becomes awake and the time slot by which its operation has to be finished, determines whether the intended appliance is set as must-run or controllable. At the current time slot t, to calculate $\mathbb{E}_\omega[L_k^\omega]$, we need to determine different scenarios starting from time slot t. For this purpose, for each currently sleeping appliance $a \in \mathcal{S}_t$, the probabilities $p_{\tau,t}^a$ are calculated as in (15). Based on the calculated probabilities $p_{\tau,t}^a$, the time slot at which appliance $a \in \mathcal{S}_t$ will become awake for different scenarios $\omega \in \Omega_t$, α_a^ω, is determined. Next, for each scenario ω, by conditioning on the time slot at which appliance $a \in \mathcal{S}_t$ becomes awake, $\tau = \alpha_a^\omega$, the probability distribution $q_{k,\tau}$ is adopted to determine the deadline by which the operation of appliance $a \in \mathcal{S}_t$ has to be finished β_a^ω. Moreover, for each scenario ω, the amount of generated power from RERs, Ψ_k^ω, is derived based on normal distribution $\mathcal{N}(\mu_k, \sigma_k^2)$ for each time slot k.

Algorithm 1: Energy scheduling algorithm executed at the beginning of each time slot t.

1: Determine generated power of RERs.
2: Receive admission requests and update $\mathcal{M}_t$ and $\mathcal{C}_t$.
3: Update E_t^a according to (1).
4: Activate must-run appliances (start / continue operation).
5: Update $p_{\tau,t}^a$ according to (15).
6: For each $a \in \mathcal{S}_t$, and for each scenario ω, determine α_a^ω, β_a^ω, and Ψ_k^ω as discussed in Section III-C.
7: Solve problem (12) to activate / deactivate controllable appliances and charge / discharge battery.

D. Algorithm Description

In this section, we explain the different steps of the proposed energy consumption scheduling algorithm, i.e., Algorithm 1, executed by the ECS unit. At the beginning of each time slot t, the amount of power generation from RERs is determined, c.f. Line 1. In the operation control phase, all admission requests are received. Based on the specifications of the requests, each appliance is labeled as either must-run or controllable, and the sets $\mathcal{M}_t$ and $\mathcal{C}_t$ are updated accordingly, c.f. Line 2. Next, the remaining energy requirement of each awake appliance is determined according to (1), c.f. Line 3. The operation of must-run appliance $a \in \mathcal{M}_t$ is started immediately and will continue in the upcoming time slots until the end of its operation at the requested power P_a, c.f. Line 4. To calculate the schedule of controllable appliances and the battery, the expected load in the upcoming time slots has to be estimated. We approximate the expected load by adopting the *certainty equivalent* approximation technique and by confining the expectation to a limited number of scenarios, see Section III-B. For this purpose, the probability by which each currently sleeping appliance $a \in \mathcal{S}_t$ will become awake is updated according to (15), c.f. Line 5. For each scenario, the time at which each appliance $a \in \mathcal{S}_t$ will become awake is determined based on the probability distribution $p^a_{\tau,t}$. Considering the time slot at which each appliance becomes awake and the probability distribution $q^a_{k,\tau}$, the deadline for the operation of each appliance is determined as discussed in Section III-C. Next, the amount of power generation from RERs is estimated, c.f. Line 6. Finally, the schedule of power consumption of each controllable appliance and the state of charging and discharging of the battery are determined by solving optimization problem (12), c.f. Line 7.

IV. Performance Evaluation

In this section, we present simulation results and assess the performance of our proposed energy consumption scheduling algorithm. We run each simulation 100 times with different patterns for the times at which the appliances become awake, and present the average results. Unless stated otherwise, the simulation setting is as follows. We assume that the RTP method combined with IBR is adopted as in (5). We assume $m_t = 4$ cents/kWh, and it increases to 6 cents/kWh and 8 cents/kWh during [12:00, 15:00] and [19:00, 24:00], respectively. n_t is selected as 8 cents/kWh, and it increases to 12 cents/kWh and 10 cents/kWh during [19:00, 24:00] and [24:00, 7:00], respectively. We consider a single household with various must-run and controllable appliances. Controllable appliances include: Electric stove ($E_a = 4.5$ kWh, $P_a = 1.5$ kW), clothes dryer ($E_a = 1$ kWh, $P_a = 0.5$ kW), dishwasher ($E_a = 2$ kWh, $P_a = 1$ kW), heater ($E_a = 4$ kWh, $P_a = 1$ kW), pool pump ($E_a = 4$ kWh, $P_a = 2$ kW), PEV ($E_a = 10$ kWh, $P_a = 2.5$ kW). Must-run appliances include: Lighting ($E_a = 3$ kWh, $P_a = 0.5$ kW), TV ($E_a = 1$ kWh, $P_a = 0.25$ kW), PC ($E_a = 1.5$ kWh, $P_a = 0.25$ kW), ironing appliance ($E_a = 2$ kWh, $P_a = 1$ kW), hair dryer ($E_a = 1$ kWh, $P_a = 1$ kW), and others ($E_a = 6$ kWh, $P_a = 1.5$ kW). The time slot at which each appliance becomes awake is selected randomly from a pre-determined time interval, e.g. [6:00, 14:00] for electric stove and [16:00, 24:00] for PEV. We assume that the user is equipped with a battery and a renewable generator. We assume the maximum charging and discharging rate of the battery is $g_b = 2$ kW and its capacity is $C_b = 5$ kWh. The output of the RER at different time slots is modeled as normal random variables with different means and standard deviations. For example, we assume that during [8:00, 12:00] the average generated power from the RER is $\mu_t = 2$ kW and its standard deviation is $\sigma_t = 1$ kW.

To have a baseline to compare with, we consider a system without ECS deployment, where each appliance a is assumed to start operation right after it becomes awake. The battery is charged whenever there is more generated power than demand and discharged otherwise. Similar to [18], we consider a system in which the effect of supply uncertainty is ignored and only the effect of load uncertainty is taken into account. As an upper bound, we also consider a system in which the complete information about the demand requirements of the user and the power generation at different time slots is available at the beginning of the operation period. In our simulation model, we set $b_t = 3.5$ kW in (5) for all time slots.

TABLE I
Average payment of the user and PAR for different systems.

	Average payment	PAR
Without ECS deployment	\$3.12	3.02
Algorithm in [18]	\$2.80	2.70
Proposed algorithm	\$2.47	2.41
With complete information	\$2.27	2.11

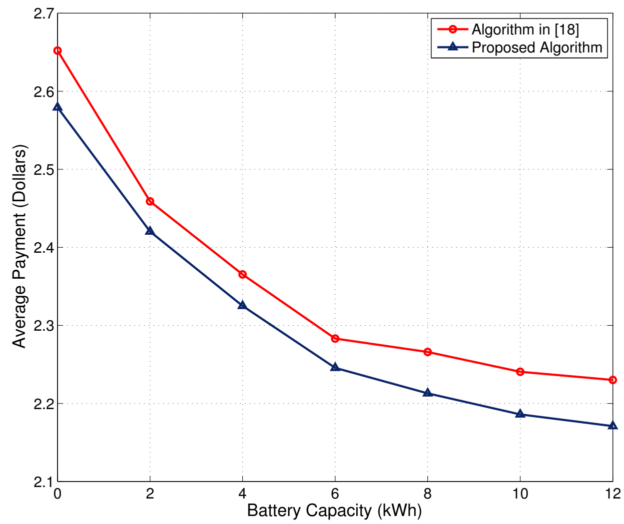

Fig. 1. Average payment of the users for different values of storage capacity.

Simulation results for the average payment of the user and the average PAR for the proposed residential load control algorithm, the system without ECS deployment, the system in which the effects of supply uncertainty is ignored, and the system in which complete demand and generation information is available ahead of time are summarized in Table I. The results in Table I show that, to reduce electricity payment, the ECS unit shifts the load to time slots with lower prices and the time slots with high expected power generation from RER. The high price penalty for exceeding the b_t threshold prevents *load synchronization* as discussed in Section I. Exploiting the use of the ECS unit reduces the average daily payment of the user from \$3.12 to \$2.47 compared to the system without ECS deployment. By estimating the generation from RER and shifting the load to time slot with high expected power generation, our proposed algorithm reduces the electricity payment of the user compared to the algorithm in [18]. Our proposed algorithm helps to reduce the average PAR of the system from 3.02 to 2.41 (20.2% reduction) compared to the system without ECS deployment.

We also examine how changes of the battery's capacity affect the performance of the system. Simulation results for the average daily payment of the user and the average PAR of the

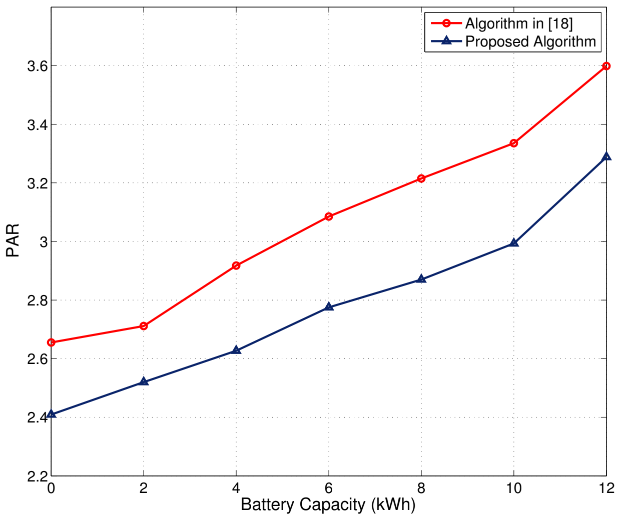

Fig. 2. Average PAR of the system for different values of storage capacity.

system for different values of parameter C_b are illustrated in Figs. 1 and 2, respectively. The results show that our proposed algorithm improves the performance of the system compared to the algorithm proposed in [18] for all values of C_b, since the effect of supply uncertainty is taken into account. Increasing the capacity of the battery reduces the energy expenses of the user by better utilization of the RER and shifting the load to time slots with high RER power output. However, by increasing the battery's capacity and increasing the flexibility of the load, the PAR of the system will increase as a large amount of energy is consumed during low price time slots to charge the battery. This energy will be released during high price time slots to cover the demand requirements of the user.

V. Conclusions

In this paper, we proposed an energy consumption scheduling algorithm for DSM in the presence of both load and supply uncertainty. We formulated the problem as an optimization problem to minimize the electricity payment of the user. In our system model, the user is equipped with a storage device. We employed RTP combined with IBRs to balance residential load to achieve a low PAR. Simulation results showed that our proposed algorithm reduces the energy cost of users, encouraging them to participate in DSM. The proposed algorithm helps to better utilize the RERs by encouraging the users to shift their load to time slots with high renewable power generation, and reducing the PAR of the system. The latter provides an incentive for utilities to support implementing the proposed DSM algorithm.

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