

Challenges and Opportunities in Large-Scale Deployment of Automated Energy Consumption Scheduling Systems in Smart Grids

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Abstract—Recent studies have shown that the lack of knowledge among users on how to respond to time-varying prices and the lack of effective home automation systems are two major barriers for fully utilizing the advantages of real-time pricing. Therefore, there has been a growing interest over the past few years towards developing automated energy consumption scheduling (ECS) devices to constantly monitor the hourly prices and schedule the operation of users' controllable load to minimize their energy expenditure. While the prior results in using ECS devices are promising, all prior work are limited to *small-scale* deployment of ECS devices. For example, in most cases, the users that are equipped with the ECS devices are assumed to be part of a microgrid or a feeder connected to a sub-station. In this paper, we rather investigate *large-scale* deployment of ECS devices in a power grid with several buses and generators. The price of electricity at each bus is set according to the locational marginal price (LMP) at that bus. We show that a key challenge in large-scale deployment of ECS devices is *load synchronization*. However, we propose to use a moving average smoothing mechanism for LMPs that can fix the load synchronization problem and stabilize the system. Furthermore, we show that the proposed large-scale ECS system has a close to optimal performance in terms of reducing peak-to-average-ratio in load demand, minimizing the total power generation cost, and lowering users' electricity bills.

Keywords: Energy consumption scheduling, large power grid, load synchronization, real-time pricing, locational marginal price.

I. INTRODUCTION

Real-time and time-of-use electricity pricing models can potentially lead to several economic and environmental advantages compared to the current commonly used flat rates. In particular, they can provide power consumers with the opportunity to reduce their electricity expenditure by responding to pricing that varies at different times of day and is higher at peak load hours [1]. Furthermore, they can help utilities and independent system operators to reduce the *peak-to-average-ratio* (PAR) in aggregate load demand which can lead to minimizing the need for building new power generation capacities [2].

Despite several advantages that real-time, time-of-use, and other non-flat pricing models can offer, recent studies have shown that the lack of knowledge among users about how to respond to time-varying prices and the lack of effective home automation systems are two major barriers for fully utilizing the benefits of non-flat electricity pricing tariffs [3], [4]. In fact, most of the current residential load control activities are

operated manually. This makes it difficult for users to optimally schedule the operation of their appliances in response to the hourly updated pricing information they may receive from the utilities in a non-flat pricing program. For example, the experience of the real-time pricing program in Chicago, IL has shown that although the price values were available via telephone and the Internet, only rarely did households actively check prices as it was difficult for the participants to constantly monitor the hourly price values to respond properly [5].

To tackle the problems with manual load control, there has been a growing interest recently towards using automated energy consumption scheduling (ECS) devices [6]–[12], similar to the one shown in Fig. 1. In this setup, each user is equipped with an ECS device, e.g., in its smart meter, which is assumed to be connected to a smart power distribution system with a two-way digital communication capability through computer networking [13]. Based on the updated pricing signals that the ECS device receives from the utility through the available communications infrastructure, and also given the users' personal energy needs, the ECS device optimally schedules the energy consumption for the users' controllable load such that it can minimize the users' daily or monthly electricity expenses. The use of ECS devices is recommended not only for residential consumers [6] but also for industrial consumers [14]. Furthermore, there have been companies that have already started offering commercial ECS devices for home automation products, e.g., see [15].

While the prior results in using automated ECS devices in smart grids have been very promising, all prior work along this line of research have been limited to small-scale deployment of the ECS devices. For example, in most cases, the users that are equipped with the ECS devices are assumed to be part of a microgrid or part of a small feeder in a distribution line that is connected to a single generator or a sub-station. Therefore, in this paper, we rather investigate large-scale deployment of ECS devices in power grid such as the one shows in Fig. 2. The price of electricity at each bus in this system is assumed to be set according to the locational marginal price (LMP) at that bus. Note that, most existing deregulated electricity markets in the United States currently use LMPs to settle various bulk sale and ancillary service transactions [16]. Although setting retail prices according to LMPs is still not a common practice in most regions, it is recently shown that by reflecting the prices

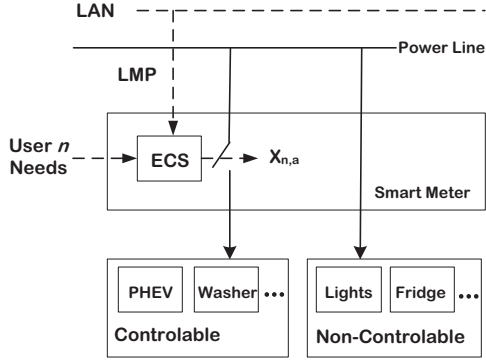


Fig. 1. An automated energy consumption scheduling device in a smart meter [6]–[12]. The prices are obtained through a communications infrastructure.

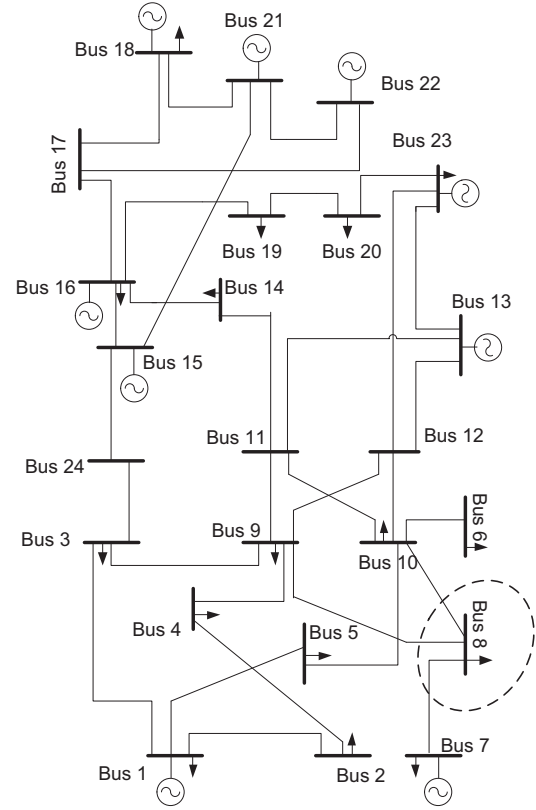
in the wholesale market to the consumer side, users will be better encouraged to consume electricity more efficiently [17].

We will show that a key challenge in large-scale deployment of ECS devices is *load synchronization*. This problem can be explained as follows. Every time the electricity prices, i.e., the LMPs, are set, the ECS devices move their load from high-price hours to low-price hours in an attempt to minimize their energy expenditure. However, this will in turn overload low-price hours, making them high-price hours in the next iteration, and underload high-price hours, making them low-price hours in the next iteration. This causes constant fluctuations in the electricity prices and makes the system unstable. To tackle this problem, we propose to use a moving average smoothing mechanism for LMPs. Our simulation results show that the proposed approach works well and can assure system stability. Furthermore, we show that the proposed large-scale deployment of ECS devices has a very close to optimal performance in terms of reducing PAR in the aggregate load demand, minimizing the total power generation cost in the system, and reducing each user’s individual electricity bill payments.

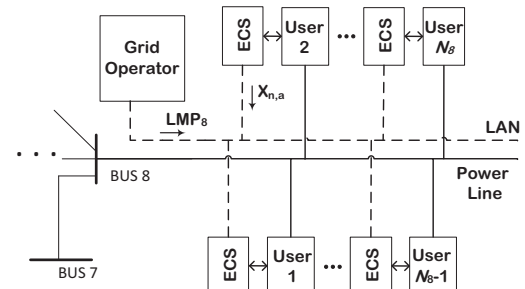
The rest of this paper is organized as follows. The system model is explained in section II. The interactions between the grid operator and the ECS devices is discussed in Section III. Simulation results are presented in Section IV. The conclusions and future work directions are discussed in Section V.

II. SYSTEM MODEL

Consider a power grid system, such as the IEEE 24-bus system in Fig. 2(a). Let \mathcal{B} , with cardinality B , denote the set of buses in the system. For each bus $i \in \mathcal{B}$, let \mathcal{N}_i , with cardinality N_i , denote the set of users connected to bus i . Clearly, if bus i is not a load bus, then we have $N_i = 0$. For each load bus, we assume that each user is equipped with an ECS device. An example for the case of bus 8 with N_8 users is shown in Fig. 2(b). The price of electricity at each load bus is set according to the locational marginal price at that bus. Let LMP_i^h denote the locational marginal price at load bus i at hour h . Consider an $H > 1$ hours ahead energy consumption scheduling problem for a user $n \in \mathcal{N}_i$ connected to bus i . Note that for day-ahead planning, we have $H = 24$.



(a)



(b)

Fig. 2. An example for large-scale deployment of automated ECS devices: (a) An IEEE 24-bus power system with 16 load buses. (b) The set of N_8 users, equipped with ECS devices, that are connected to bus 8. The retail price of electricity at each bus is set according to the LMP at that bus.

Given the following $H \times 1$ price vector

$$\mathbf{LMP}_i = [LMP_i^1, LMP_i^2, \dots, LMP_i^H], \quad (1)$$

the ECS device in user n ’s smart meter is responsible for scheduling the operation of all user n ’s controllable load such that user n ’s daily energy expenditure is minimized.

For each user n , let \mathcal{A}_n denote the set of all appliances that have controllable / shiftable load. Examples for such appliances may include washer, dryer, dishwasher, and plug-in hybrid electric vehicles. For each appliance $a \in \mathcal{A}_n$, we define an energy consumption scheduling vector as

$$\mathbf{x}_{n,a} = [x_{n,a}^1, x_{n,a}^2, \dots, x_{n,a}^H]. \quad (2)$$

Let $E_{n,a}$ denote the total energy needed to finish the operation of appliance a . For example, $E_{n,a} = 16$ kWh for a sedan electric car with 40 miles daily driving range [1]. Furthermore, for each appliance a , the operation needs to be scheduled within a time frame $[\alpha_{n,a}, \beta_{n,a}]$, where $1 \leq \alpha_{n,a} < \beta_{n,a} \leq H$. These parameters are set by user n based on his energy consumption needs for each appliance. For example, user n may set $\alpha_{n,a} = 1:00$ PM and $\beta_{n,a} = 5:00$ PM for the operation of a dishwasher after lunch table and before diner. Of course, the time duration $\beta_{n,a} - \alpha_{n,a}$ must be larger than or equal to the time needed to finish the normal operation of appliance a . To assure on time operation of appliances, it is required that user n 's ECS device fulfills the following constraints

$$\sum_{h=\alpha_{n,a}}^{\beta_{n,a}} x_{n,a}^h = E_{n,a}. \quad (3)$$

Furthermore, it is required that

$$x_{n,a}^h = 0, \quad \forall h \in \mathcal{H} \setminus \mathcal{H}_{n,a}, \quad (4)$$

where

$$\mathcal{H} = \{1, \dots, H\}, \quad \text{and} \quad \mathcal{H}_{n,a} = \{\alpha_{n,a}, \dots, \beta_{n,a}\}. \quad (5)$$

Finally, we note that some appliances may have some minimum standby power $\gamma_{n,a}^{\min}$ and/or some maximum supported power $\gamma_{n,a}^{\max}$. In that case, it is also required that

$$\gamma_{n,a}^{\min} \leq x_{n,a}^h \leq \gamma_{n,a}^{\max}, \quad \forall h \in \mathcal{H}_{n,a}. \quad (6)$$

For notational simplicity, for each user n , we introduce a new vector \mathbf{x}_n , which is formed by stacking up energy consumption scheduling vectors $\mathbf{x}_{n,a}$ for all appliances $a \in \mathcal{A}_n$. In this regard, we can define a *feasible* energy consumption scheduling set corresponding to user n as follows:

$$\begin{aligned} \mathcal{X}_n = \{ \mathbf{x}_n \mid & \sum_{h=\alpha_{n,a}}^{\beta_{n,a}} x_{n,a}^h = E_{n,a}, \\ & x_{n,a}^h = 0, \quad \forall h \in \mathcal{H} \setminus \mathcal{H}_{n,a}, \\ & \gamma_{n,a}^{\min} \leq x_{n,a}^h \leq \gamma_{n,a}^{\max}, \quad \forall h \in \mathcal{H}_{n,a} \}. \end{aligned} \quad (7)$$

An energy consumption schedule calculated by the ECS unit in user n 's smart meter is valid only if we have $\mathbf{x}_n \in \mathcal{X}_n$.

For each user $n \in \mathcal{N}_i$ at bus i , the total electricity bill within the scheduling horizon of interest is calculated as

$$\sum_{h=1}^H LMP_i^h \times \left(L_n^h + \sum_{a \in \mathcal{A}} x_{n,a}^h \right), \quad (8)$$

where L_n^h denotes the total load of user n at hour h due to his appliances that have non-controllable load. Examples for such appliances may include lights, refrigerator, television and other entertainment devices. Note that the operation of appliances with non-controllable load is *not* scheduled by ECS devices. To minimize user n 's energy expenditure, the ECS device in user n 's smart meter should solve the following optimization problem across appliances that have controllable load:

$$\underset{\mathbf{x}_n \in \mathcal{X}_n}{\text{minimize}} \sum_{h=1}^H LMP_i^h \times \left(L_n^h + \sum_{a \in \mathcal{A}} x_{n,a}^h \right). \quad (9)$$

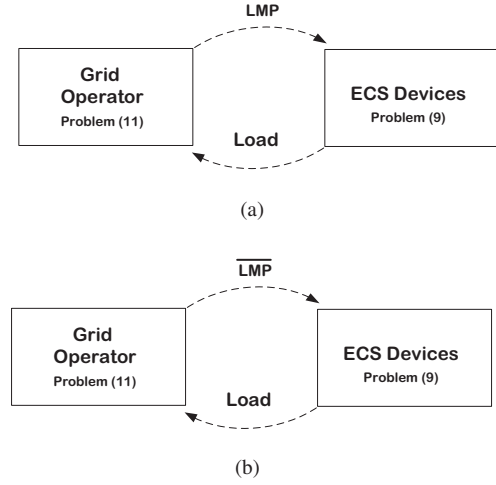


Fig. 3. Interactions between the grid operator and the ECS devices. (a) The electricity prices are set based on the original LMPs. (b) The electricity prices are set based on a smoothed version of LMPs in order to enforce stability.

Note that the above optimization problem can capture the behavior of each user's ECS device. Next, we investigate the interactions between the ECS devices and the grid operator when the ECS devices are deployed in a large scale.

III. OPERATOR-USER INTERACTIONS

If the ECS devices are deployed only in small scales, e.g., in a microgrid or in a single distribution feeder as in [6]–[12], the operation of ECS devices may not have any impact on the LMPs. However, if the ECS devices are deployed in a larger scale and at several buses, such as in the power system in Fig. 2, then the operation of the ECS devices may have a significant impact on the LMPs at different buses as we explain next.

Let X_i^h denote the total load at bus i at hour h . Once all ECS devices set the load by solving problem (9), we have

$$X_i^h = \sum_{n \in \mathcal{N}_i} \left(L_n^h + \sum_{a \in \mathcal{A}_n} x_{n,a}^h \right). \quad (10)$$

Using the standard power system dispatch control model in [18], at each hour h , the grid operator can solve the following optimization problem to calculate the LMPs at each bus:

$$\underset{G_i^h, \forall i}{\text{minimize}} \sum_{i=1}^B C_i(G_i^h) \quad (11a)$$

$$\text{subject to} \sum_{i=1}^B G_i^h - \sum_{i=1}^B X_i^h = 0 \quad (11b)$$

$$\sum_{i=1}^B f_{k,i} \times (G_i^h - X_i^h) \leq F_k^{\max}, \quad \forall k \in \mathcal{K} \quad (11c)$$

$$G_i^{\min} \leq G_i^h \leq G_i^{\max} \quad \forall i \in \mathcal{B}, \quad (11d)$$

where G_i^h denotes the amount of dispatched power generation at generator bus i at hour h , $C_i(\cdot)$ denotes the cost function for the generator at generator bus i , \mathcal{K} denotes the set of all transmission lines in the system, $f_{k,i}$ denotes the [19] injection shift factor to transmission line k from bus i , and

F_k^{\max} denotes the transmission limit of transmission line k . Finally, G_i^{\min} and G_i^{\max} denote the minimum and maximum generation range for the generator at bus i . Clearly, if bus i is not a generation bus, then we have $G_i^{\min} = G_i^{\max} = 0$. Assuming that power loss is negligible on transmission lines, the formulation of LMP at bus i can be written as [20], [21]:

$$LMP_i^h = \lambda + \sum_{k=1}^K f_{k,i} \times \mu_k, \quad (12)$$

where K denotes the number of transmission lines, i.e., the cardinality of set \mathcal{K} , λ denotes the Lagrange multiplier corresponding to the energy balance constraint in (11b), and μ_k denotes the Lagrange multiplier corresponding to the line capacity constraint in (11c) for transmission line $k \in \mathcal{K}$.

A. Decentralized Model

The interactions between the grid operator and ECS devices can be analyzed under the real-time pricing framework in [22]. Given the price values, i.e., vector \mathbf{LMP}_i at each bus i , the ECS devices schedule the load based on the optimal solution of problem (9). In turn, if the updated load profiles are replaced in optimization problem (11), the resulted LMPs can become different from the original values. This is shown in Fig. 3(a). Note that, the message exchanges are supported through the two-way digital communications capability which is expected to be available in the future smart grid [1]. The key question is: *Do the back and forth iterations between the grid operator and the ECS devices converge to any fixed point?*

To answer this question, we perform a simulation based on the power grid topology in Fig. 2. The detailed simulation setup is explained in Section IV. As shown in Fig. 4, the objective value of the generation dispatch problem (11), i.e., the total cost power generation in the system, does not converge. The fluctuations in this figure can be explained as follows. Every time the prices are set, the ECS devices move their load from high-price hours to low-price hours. This will in turn overload low-price hours, making them high-price hours in the next iteration, and underload high-price hours, making them low-price hours in the next iteration. This problem is referred to as *load synchronization* [6]. While load synchronization does not have a major impact on electricity prices when the ECS devices are deployed only in a small scale, large-scale deployment of the ECS devices can cause significant instability in the price signals as well as the aggregate load profiles, as it is evident from the simulation results in Fig. 4.

Next, we propose a moving average smoothing mechanism for LMPs to resolve the load synchronization problem. Let $\mathbf{LMP}_i[t]$ denote the locational marginal price vector at bus i that is obtained by solving optimization problem (11) at iteration $t \geq 1$. We introduce a smoothed version of \mathbf{LMP}_i at iteration t , denoted by $\overline{\mathbf{LMP}}_i[t]$, to be calculated as follows:

$$\overline{\mathbf{LMP}}_i[t+1] = (1 - \eta_t)\overline{\mathbf{LMP}}_i[t] + \eta_t \mathbf{LMP}_i[t], \quad (13)$$

where $0 \leq \eta_t \leq 1$ is an iteration-dependent step-size. Choosing a diminishing step-size can particularly assure convergence to a fixed point. Therefore, we select η_t as

$$\eta_t = \frac{t_0}{t_0 + t - 1}, \quad (14)$$

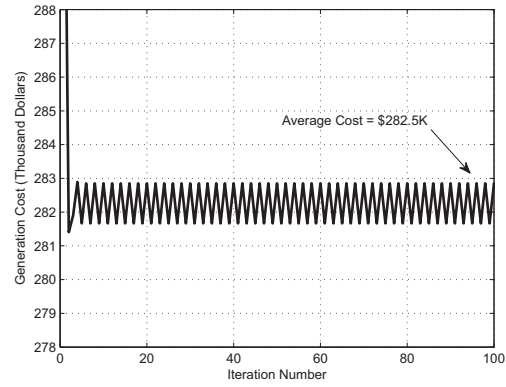


Fig. 4. The fluctuation in total power generation cost in the system when the electricity prices are set based on the original LMPs as in Fig. 3(a).

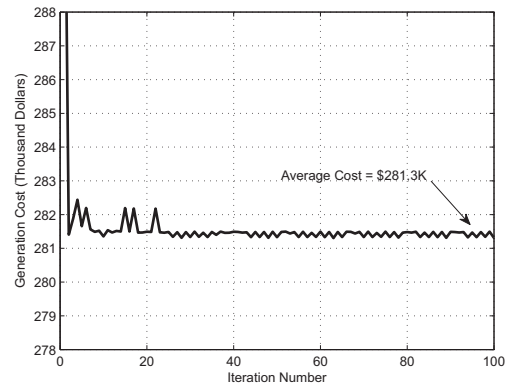


Fig. 5. The total power generation cost in the system when the electricity prices are set based on the smoothed version of LMPs as in Fig. 3(b).

where $t_0 \geq 1$ is a fix parameter. As iteration number $t \rightarrow \infty$, step-size $\eta_t \rightarrow 0$. In the new model, the interactions between the grid operator and the ECS device becomes as in Fig. 3(b). The simulation results in this case are also shown in Fig. 5. Note that, once the price signals sent to the ECS devices converge to a fixed point, the load profiles will also stop changing and the whole system reaches an equilibrium.

B. Centralized Model

Before we conclude this section, it is worth emphasizing that the interaction between the grid operator and the ECS devices shown in Fig. 3 is due to the fact that the utility / grid operator does not usually have any centralized control over the operation of users' personal appliances. In fact, for each user, the ECS device in his smart meter does not follow the utilities commands. Rather it solely responds to the price signals sent by utilities and aims to minimize the energy expenditure specifically for its corresponding user. However, if the grid operator does have direct control over the operation of ECS devices, e.g., as in a direct load control (DLC) framework [23], then the interactions between the grid operator and the ECS devices would no longer be based on Fig. 3. Instead, the operator would solve the following global optimization problem and it would send the obtained optimal energy

schedules as a command signal to each corresponding ECS device to enforce optimal energy consumption scheduling:

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^B C_i(G_i^h) & (15a) \\ & G_i^h, \forall i, \\ & \mathbf{x}_n \in \mathcal{X}_n, \forall n \end{aligned}$$

$$\text{subject to} \quad \sum_{i=1}^B G_i^h - \sum_{i=1}^B X_i^h = 0 \quad (15b)$$

$$X_i^h = \sum_{n \in \mathcal{N}_i} \left(L_n^h + \sum_{a \in \mathcal{A}_n} x_{n,a}^h \right) \quad (15c)$$

$$\sum_{i=1}^B f_{k,i} \times (G_i^h - X_i^h) \leq F_k^{\max}, \quad \forall k \in \mathcal{K} \quad (15d)$$

$$G_i^{\min} \leq G_i^h \leq G_i^{\max} \quad \forall i \in \mathcal{B}, \quad (15e)$$

where X_i^h acts as an auxiliary variable. Recall that, in (11), X_i^h was a known constant. The centralized design in (15) is not the focus of this paper as it may not be practical as users could be reluctant to relinquish full control of their load to utilities. Nevertheless, the solution of optimization problem (15) can provide a benchmark to assess the performance of our proposed distributed design in Section III-A, when it comes to minimizing the total cost of power generation in the system.

IV. PERFORMANCE EVALUATION

To assess the performance of the distributed ECS system, we consider the IEEE 24-bus reliability test system [24]. It has a maximum of 2650 MW total load at any hour. To alleviate the computation burden and to better see the impact of energy consumption scheduling in the overall system performance, the scale of each user's load is assumed to be relatively high, such as the case for a major industrial unit. The total load is distributed among 100 users located across all load buses. Each user has both uncontrollable and controllable load.

A. Peak Shaving

To have a base for comparison, we examine the scenario where no ECS unit is installed and users start their consumption right after the start time $\alpha_{n,a}$ and continue until the operation of the appliance is done. This results in the load curve shown in Fig. 6 with a PAR of 1.58. On the other hand, when ECS systems are deployed, the PAR decreases as users shift part of their controllable load from peak hours to off-peak hours. This is shown in Fig. 6. For the results in this figure, it is assumed that for each user about 50% of the load is controllable. The PAR for the case of distributed ECS is 1.32. The PAR further decreases to only 1.23 for the case of centralized ECS. Recall from Section III-B that while centralized ECS deployment may not be practical it provides a benchmark to assess the performance of our proposed distributed design in Section III-A.

B. Reducing Total Power Generation Cost

The total power generation cost in the system when the portion of controllable load varies from 0 to 40% is shown

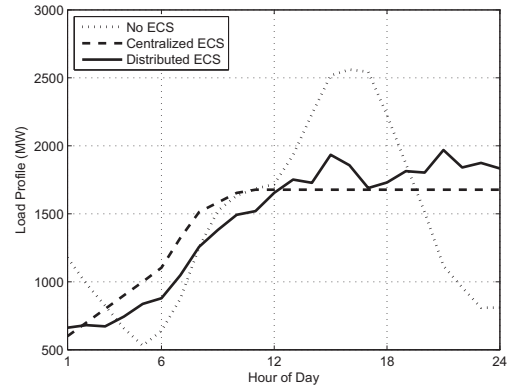


Fig. 6. The daily load profile for various ECS deployment scenarios.

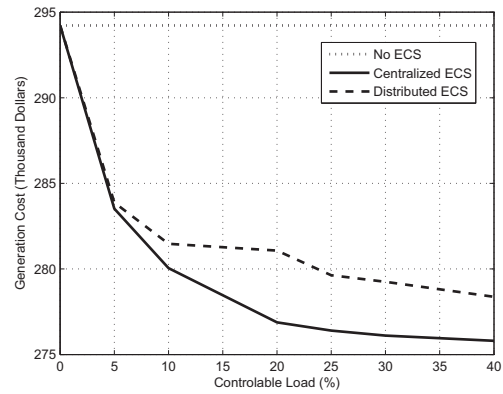


Fig. 7. The total power generation cost in the system versus the portion of controllable load for various ECS deployment scenarios.

in Fig.7. We can see that although the proposed large-scale distributed ECS deployment system cannot achieve the same benchmark performance as in a centralized energy consumption scheduling scenario, its performance is close to optimal and much better than the case with no ECS deployment.

C. Benefit to Users

In addition to shaving the peak load and reducing the total power generation cost in the system, large-scale deployment of ECS devices can help each user reduce his electric bill. This is shown in Fig.8, where 50% of the load is controllable. We can see that all users on all buses can reduce their bill compared to the case with no ECS deployment.

D. Collected Revenue by Utility

Fig.9 shows the collected versus intended revenue from the users at different controllable load percentages. The collected revenue is what users actually pay based on the smoothed LMPs. The intended revenues are rather calculated based on what users should have paid if we use the original LMPs. Interestingly, although the smoothed LMPs that are used to stabilize the price do not exactly match the original LMPs, the total collected revenue is very close to (and even sometimes slightly higher than) the total intended revenue in all

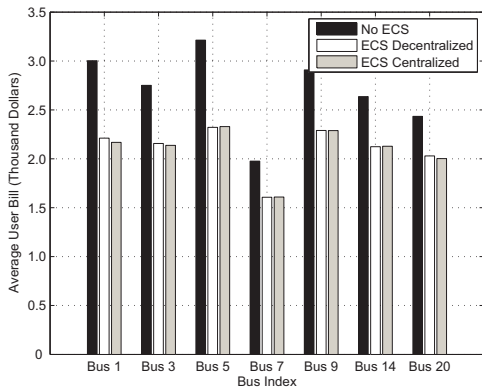


Fig. 8. The average user bills for various ECS deployment scenarios.

scenarios. Therefore, the proposed large-scale distributed ECS deployment system can be of interest to utilities.

V. CONCLUSION AND FUTURE WORK

This paper represents the first step towards understanding the challenges and opportunities in large-scale deployment of automated energy consumption scheduling devices in smart grids. To gain insights, we considered an IEEE 24-bus reliability test system with nine generator and 16 load buses. We assumed that all users on each load bus are equipped with an ECS device to obtain the updated price information from the smart grid and accordingly schedule the operation of the user's controllable load to minimize the user's electricity bill. We showed that unlike the case when only a few users are equipped with ECS devices, the large-scale deployment of ECS devices can directly impact the electricity prices. In particular, load synchronization can cause fluctuations in locational marginal prices at different buses. We proposed to fix this problem using a moving average smoothing mechanism for LMPs. We showed that once this mechanism is applied, the interactions between the grid operator and the ECS devices can be coordinated such that a very close to optimal performance is achieved in terms of reducing peak-to-average-ratio in load demand, minimizing the total power generation cost in the system, and lowering all users' electricity bill payments.

The results in this paper can be extended in several directions. First, in addition to using a smoothing mechanism, new pricing models can be examined to enforce stability. Second, larger grid topologies with renewable power generators can be considered. Finally, while we assume that users are price taker and ignore the impact of their load on LMPs, the scenario where users are price anticipator can be considered. The interactions in this case can be studied, e.g., using game theory.

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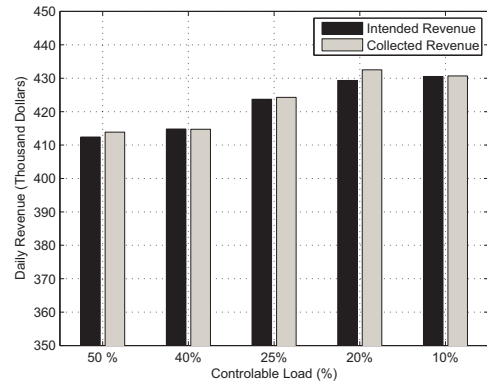


Fig. 9. The intended revenue based on original LMPs versus the collected revenue based on smoothed LMPs in distributed ECS deployment scenario.

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