User-Friendly Demand Side Management for Smart Grid Networks

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Abstract— Demand side management (DSM) is an important technique for demand response (DR) system in smart grid networks. The DSM techniques traditionally have focused on minimizing electricity bill or peak load. More recent work reveals that users wish to reduce their electricity bills without sacrificing user convenience. Hence, waiting time has been introduced to reflect the user comfort for the DSM. Residents usually preferred that finish their work as soon as possible than less waiting time. These techniques have not taken previous usage pattern consideration, thus have been limited for use in home appliances. In this paper, we propose a system architecture and an algorithm for DSM referred to as user-friendly DSM (UDSM) using ICT. The UDSM is based on time-varying price information considering the following three-fold factors: electricity bill, usage pattern, and rebound peak load. Our proposed algorithm is divided into two steps. In the first step, we formulate the objective function based on electricity bill and usage pattern, and we minimize the electricity bill and maximize the usage similarity. Then, as the second step, we apply a load balancing algorithm to avoid black-out and to minimize rebound peak load. Our algorithm is tested in a real data from Jeju Island’s smart grid test site, and experimental results validate the proposed DSM scheme shifts the operation to off-peak times and consequently leads to significant electricity bill saving and user satisfaction ratio.

Keywords—smart grid algorithm, demand side management, demand response, time-varying pricing, modeling and simulation

I. INTRODUCTION

Smart grid technology is envisioned as future power systems with advanced metering infrastructure (AMI), energy storage systems (ESS), sensing technologies, demand response (DR) control methodologies, and communication technologies at transmission and distribution levels in order to optimize electricity resource usage in an intelligent fashion [16]. Demand response is one of the key technologies to enable smart grid, and can be defined as an incentive policy designed to induce lower electricity usage at times of high market prices or when system reliability is jeopardized [18]. Demand side management (DSM) is important technique of the DR. It focuses on utilizing power saving technologies, electricity bill and government policies to ease off the peak load demand instead of enlarging the generation capacity or reinforcing the transmission and distribution network [3]. For example, if appliance electricity usage can be shifted form peak periods to off-peak periods, peak demand can be reduced along with large amount of expensive power generation.

Therefore, DSM usually aims at more than one of the following design objectives: (1) reducing electricity bill (2) reducing peak load (3) controlling usage schedule according to consumption patterns.

Recently, a large variety of DSM techniques have been proposed in the literature. Commonly, DSM focused on only a single and/or multiple objective functions such as minimizing the energy cost, minimizing the peak-to-average ratio (PAR) and/or maximizing user convenience as well. In [4], minMax scheduling algorithm is aimed peak-reduction and cost reduction for the consumers. However this algorithm does not absolutely consider user consumption pattern to satisfy user convenience. In [9], there are two objective function minimize electric bill and minimize waiting time. But they not satisfy minimize peak load. A Water-Filling based scheduling algorithm [8] considers reducing the peak-to-average ratio of the overall demand. The most popular DSM analytical tools are game theory [1] [10] and evolutionary algorithm [5] [16].

In this paper, we suggest time-varying pricing based DSM system architecture and algorithm considering not only minimize consumption bill and peak load but also maximize user convenience using previous user pattern. Each objective depends on variables which are provided from user and supplier to ICT technologies. Users have previous electricity consumption information about each appliance. It is used to analyze user consumption pattern in database. The supplier provides time-varying pricing information to users. The price information directly affects to reduce consumption bill.

When scheduling is contented with two conditions, it is possible that electricity consumption is concentrate in specific time which has the lowest price and higher user convenience. In other words, if every home is given the same price information and is running such a DSM algorithm opportunistically utilizing the times with low prices of energy, some peak in energy use can happen at these times. We denote such peak as “rebound peak” [19]. In this result, the load balancing algorithm has to distribute electricity consumption to reduce rebound peak load.

If all objectives are satisfied with above condition then this scheduling is near optimal. However, it is hard to meet the requirements for optimal scheduling because each objective

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The parameter which needs to objective is different and the objectives do not depend on others. This is multiple objective problems. Therefore we firstly will propose DSM and resolve a multiple objective problems.

The rest of this paper is organized as follows. We introduce the system model in Section II. The demand side management system is explained in Section III. Simulation results are given in Section IV. The paper is concluded in Section V.

### II. System Model

In this section, we provide smart grid residential system architecture. Smart appliances also are classified according to interruption.

Fig. 1 shows the proposed smart grid residential system architecture, as well as information iteration flow between different modules. The system consists of: Load Aggregator (LA), Database (DB), Demand Response Manager (DRM) and Load Controller (LC). Advanced metering infrastructure (AMI) is not only served with utility electric bill information but also sending the electric used to utility. It means that AMI is able to two way communication using LAN or PLC.

The LA is interacting with smart appliance for real-time load aggregation. Requested appliances are provide information that total energy need for operation of appliance \( E_a \), start and end of a time \( (t^s_a, t^f_a) \) and operating time duration \( t^{d_a} \) to LA. Where request information is defined as

\[
\begin{align*}
E_a & : \text{power consumption required by appliances} \\
(t^s_a, t^f_a) & : \text{start and end of a time} \\
t^{d_a} & : \text{operating time duration}
\end{align*}
\]

Also the LA is the entry point of the DRM system and operates as an interface to the smart grid. Various time-varying pricing strategies, such as day-ahead pricing (DAP), critical-peak pricing (CPP), time-of-use (TOU), and real-time pricing (RTP), can be handled by this module. The DB provides the DRM with information of previous user pattern to support taking advantage of the convenience form user.

The DRM, coordinate demand response management and admission control using optimization that spreads the load to minimize the operational bill and maximize user convenience while respecting capacity constraints defined by LA and based on previous user pattern by DB.

The LC address rebound peak using scheduled result in DRM and finally LC decides optimal start time and end time for appliances.

For efficient load management, appropriate classifications of power consumption modes are needed. Following similar ideas presented in the literature (see, e.g., [10], [11]), we divide power loads into three classes based on the intrinsic characteristics of appliances:

1) **Interruptible load** \( (C_1) \) is the power consumption required by appliances that are always in running state during a long time period, such as house HVAC (Heat Ventilation Air Conditioning), water heater, PHEVs, etc. However the related appliances can be interrupted intermittently and hence, their operation is manageable via admission control. With such characteristics, regular loads constitute a particular case of burst loads.

2) **Non-Interruptible load** \( (C_2) \) is related to appliances that have a fixed duration and are required to start and finish at given moments. Examples of these appliances include clothes dryer, dishwasher, washing machine. Indeed, the accumulation of Non-Interruptible load contributes to the increase of peak load. Therefore, a careful management of Non-interruptible load is a critical issue that has a significant impact on power consumption efficiency and energy bill on demand side.

3) **Baseline load** \( (C_3) \) is the power consumption of those appliances that must be served immediately at any time or for maintaining certain appliances on standby. These type of appliance include lighting, cooking stove, computing and Refrigerator. Baseline load should be taken into account while computing the available capacity for admission control and load balancing. Although baseline load is not managed by the system on run-time. The related appliances must provide their power consumption and operation state to the management system for other appliance scheduling.

When each appliance is scheduled, users should consider appliances types for efficiency. DRM also have to invoke classification of appliances because each class differ
scheduling system. In next section, we propose system formulation.

III. DEMAND SIDE MANAGEMENT SYSTEM

In this section, our focus is to briefly explain the energy consumption scheduling problem in each household as an optimization problem that aims to achieve a minimizing the electricity payment and maximize user convenience for the operation of each household appliance in response to the time-varying pricing announced by the retailer company. We will explain how to solve the optimization problem in this section.

For each appliances \( a \in \mathcal{A} \), we express its energy consumption over the scheduling time slot \( t \in \{1, ..., T\} \) by a scheduling vector \( x_a^t \). The total energy requirement of a device \( a \) is \( E_a \). For example, in the case of a PHEV, in total \( E_a = 16kWh \) is needed to charge the battery for a 40-mi driving range. As another example, for a typical front-loading clothes washing machine with warm wash/rinse setting, we have \( E_a = 3.6kWh \) per load.

The user indicates \( t_a^b, t_a^e \in t \) as stating and end of a time interval in which the energy consumption for appliance \( a \) is valid to be scheduled, respectively. Clearly, we always have \( t_a^b < t_a^e \). For example, after loading a dishwasher with the dishes used at the lunch table, the user may select \( t_a^b = 2PM \) and \( t_a^e = 6PM \) for scheduling the energy consumption for the dishwasher as he expects the dishes to be ready to use by dinner time in the evening. As another example, the user may select \( t_a^b = 10PM \) and \( t_a^e = 7AM \) (the next day) for his PHEV after plugging it in at night such that the battery charging finishes by early morning time when he needs to use the vehicle to go to work. Given the predetermined parameters \( E_a \), \( t_a^b \), and \( t_a^e \), in order to provide the needed energy for each appliance \( a \in \mathcal{A} \) in times within the interval \( [t_a^b, t_a^e] \), it is required that

All appliances have certain maximum power levels denoted by \( P_{a,max} \), for each \( a \in \mathcal{A} \). For example, a PHEV may be charged only up to \( P_{a,max} = 3.3kW \) per hour. Some appliances may also have minimum stand-by power level \( P_{a,min} \), for \( a \in \mathcal{A} \).

For \( t \)-th interval, \( t = 1, ..., T \), the price of the energy that the utility company charges residential customer is assumed to be a given value of \( C^t \). The price \( C^t \) may be different or the same in each interval \( t \). Note that this paper, we assume \( C^t \) is pre-given price, such as the time-varying pricing that the utility company gives to each home.

Given the feasible energy scheduling and the time-varying pricing model, the key question is: What is the best choice when the applications are started? Before answering this question, we first argue that the user’s interest is twofold. First, each user wishes to minimize his payment. In fact, it is reasonable to assure that all users care about the amount on their electricity bills. Second, depending on the user experience, some users may also care about their comfort and getting the work as similar as possible. Clearly, these two objectives can be conflicting in many scenarios. For example, user wants to start washing dishes at 9:00 AM right after finishing the breakfast, he may choose to wait 5h and postpone the operation of the dishwasher (with \( E_a = 3.6kWh \) per load) to 2:00 PM in order to reduce the corresponding electricity payment. However, for some reason, the user may prefer to pay the extra 4.2 cents and finish the work by 10:00AM. As an alternative, the user might be willing to wait to 2h only and save 1.5 cents instead. We can see that there is a trade-off involved between the two design objectives.

In fact, our designed DSM aims not to change the amount of energy consumption, but instead to systematically manage and shift it, e.g., in order to reduce electric bill, user discomfort and rebound peak. In this regard, the user also need to select the beginning time interval \( t_a^b \), and the end of time interval \( t_a^e \) that the energy consumption for appliance \( a \) is valid to be scheduled.

For interruptible devices, the running cycle can be interrupted and the energy consumed in each interval can be variables. The running time for a in interval \( t \) is \( t_a^D \) and it should be not exceed the time interval \( t_a^b \) to \( t_a^e \). Assume for home, the main target is to minimize the energy bill and user discomfort, while having all required tasks done by all devices.

For non-interruptible device, once it starts to run, it would finish the running for the entire job. To model the running time for devices in Class 2, we assume there are \( N \) slots (indexed as 1,2, ..., \( N \)) in time interval with span (e.g. one hour).

To make a balance with load is processed after evaluate optimization problem. All slots scheduled to turn on appliance are checked to get value \( L_a^b \): load occupancy rate. Load occupancy rate are load share of each appliances at each slots. In other words, load occupancy rate means that an appliance affect how much to load at each slots. We select an appliance having the largest load occupancy rate at a slot having peak load. And we reschedule it to another slot from a slot having peak load. This process is repeated \( A \) times.

IV. SIMULATION RESULT

In this section, we conduct simulations to verify our design of optimization problem. Simulation is implemented in MATLAB 2013a and optimization interface is CVX version 2.0. Also we use optimization solver MOSEK version 7.0.0.75. We divide simulation into three parts: only bill, only usage pattern, and general optimization problem. Unit of time is 30 minutes. Our scenarios apply 35 appliances which have energy consumption, time duration, start time and end time.

A. For only bill aspect

Figure 2 shows a chart of total power consumption of all devices with considering bill only. We figure out that power consumption of devices is scheduled with avoiding high bill in the entire graph. For example 3660Wh is scheduled at time having the least expensive bill (23:00 ~ 24:00) while 92,064 Wh is scheduled at time having the most expensive bill (16:30 ~ 17:30) while 92,064 Wh is scheduled at time having the least expensive bill (23:00 ~ 24:00). And electricity bill is $76,405 which is lower than electricity bill of case B. As a result, users can have a lowest electricity bill, however considering only bill causes high peak load. All of appliances which have starting time such...
as 20:00~24:00 are allocated in specified time, because this time has the lowest electricity bill.

B. For only usage pattern aspect

Figure 3 shows a chart of total power consumption of all devices with considering pattern only. We can figure out total power consumption following total usage pattern in entire graph. It is scheduled load of 61,140 Wh at a slot 15:00 ~ 15:30. There are some differences between usage pattern and power consumption. The reason of it is that computing is done by one device. In this case, electricity bill is $85,456. Based on analysis of the result, we can expect that this scenario avoid peak load. However, if each appliance has a same starting time, usage pattern scheduling causes high peak load.

C. For general optimization problem

Figure 4 shows a chart of total power consumption of all devices with considering usage pattern and electricity bill. Different from case A and B, bars of this graph don’t follow any line. But you can find there are some rules. In range about 7:30~12:00, power consumption is relatively low to other ranges. Electricity bill is very high and usage pattern is low in the range. And in range about 20:00~21:30, electricity bill is low and usage pattern is high. Power consumption of the range is relatively high to other ranges. And electricity bill is $83,933 which value is between case A and case B.

By this fact we can infer our design of optimization problem satisfy our requirements; avoiding high electricity bill and following user pattern.

D. AfterAdapting Load Balancing Algorithm

Figure 5 shows a chart of total power consumption before and after load balancing to compare before and after load balancing. We figure out that peak near 15:00 is removed from 61,500Wh to 34,500Wh. Also peaks near 6:00 and 20:00~23:00 are too. It is seemed that load is distributed well. Actually, peak-average load rate is 2.7672 before load balancing. After load balancing, peak-average load rate is decreased to 1.7509. It’s 64.76% of before.
summarizes the result given above. Therefore, this algorithm works as we intended. We can see that our load balancing algorithm thoroughly attends shifting time to avoid the peak load and reduce electricity bill.

V. CONCLUSIONS

In this paper, we consider efficient automated demand-side management system of smart-grid. We design convex optimization problem to satisfy demand-side management. The first object is minimizing electricity bill. And the second object is following usage pattern. Using convex optimization, we can achieve our objects and certify that it schedule devices by demand-side management. Although electricity bill is not minimal, our proposal approaches near optimal solution. Continuously we will study to reduce peak load for optimization.

REFERENCES


Table 1 Scheduling result

<table>
<thead>
<tr>
<th>Case</th>
<th>Peak Load</th>
<th>Electricity Bill</th>
<th>Peak Load Time slot</th>
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</thead>
<tbody>
<tr>
<td>Only bill</td>
<td>92,064 Wh</td>
<td>$ 76,405</td>
<td>22:30 ~ 23:00</td>
</tr>
<tr>
<td>Only usage pattern</td>
<td>61,140 Wh</td>
<td>$ 85,456</td>
<td>15:00 ~ 15:30</td>
</tr>
<tr>
<td>UC Algorithm</td>
<td>61,500 Wh</td>
<td>$ 83,933</td>
<td>15:00 ~ 15:30</td>
</tr>
<tr>
<td>UCL Algorithm</td>
<td>38,913 Wh</td>
<td>$ 84,498</td>
<td>21:30 ~ 22:00</td>
</tr>
</tbody>
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