Near Optimal Demand-Side Energy Management Under Real-time Demand-Response Pricing

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***Abstract*—In this paper, we present demand-side energy management under real-time demand-response pricing as a task scheduling problem which is NP-hard. Using minmax as the objective, we show that the schedule produced by our minMax scheduling algorithm has a number of salient advantages: significant peak-shaving, cost reduction, and risk-aversion for the consumers. We prove that our algorithm finds near-optimal solutions and our simulation study show that the actual performance is better than the worst-case bound. The algorithm is simple to implement and efficient at the scale of large enterprises.**

***Index Terms*—smart grid, demand-response, energy management**

I. Introduction

The growing awareness of global climate change has elicited a collective human response in drastic reduction of carbon-emission. One of the major field for change is in electricity production where many "dirty" power plants (e.g. coal and gas plants) are still operating around the globe due to demand. Furthermore, the rate of electricity demand increase in many countries far out-strides the growth of production capability. A consequence of this discrepancy is the noticeable increase in electricity price over the past decades and the increasingly frequent power curtailment and scheduled blackouts during peak demand such as hot days of summer. The ability to reduce electricity usage and wastage through better demand-side management and control is considered a key solution ingredient to the global energy crisis.

One effective measure that has been put into place in many countries around the globe is the Demand Response (DR) program. The DR programs have been active in the US since 1999 when abnormal hot weather combined with electricity generation shortage resulted in unheard of electricity whole-sale prices and defaults by some major power brokers. The DR program played a major role in mitigating electrical system emergencies in several regions of the US during summer 2001 [1]. Some key benefits of DR programs are:

- **Decrease peak demand**: peak demand induces unpredictability in power management and is a major contributor of electric grid faults. Although peak demand happens very infrequently, as much as 20% of the electric infrastructure is built to meet periods of peak demand. The majority of these power plants have large carbon-emission footprint. DR programs allow the suppliers to smooth out significant peaks by curtailing/reducing or shifting demand.
- **Cost saving**: as a consequence of peak shaving and overall energy demand reduction, DR programs help to reduce electricity price in the long run.
- **Efficiency**: DR programs facilitate high degree of transparency between the consumers and the electricity market such that the consumers are made aware of the consequence of demand shortage. This increased awareness motivates more demand-side energy reduction and better consumer management.

In recent years, smart grid has become a term synonym with the evolution of the power grid infrastructure. It encompasses four technological and economical evolution of today's power grid distribution and management infrastructure (Figure 1): technology upgrade of the electric grid system, all-digital management infrastructure, integration of new energy generator technologies, and an economical market for electric power generation. The regulation of the electric power demand via market-based regulatory measures is complimentary with market-based DR programs, and calls for the large scale adoption of real-time pricing DR programs.

With the current state of development in DR programs and in the smart grid innovation, there is a strong need for a comprehensive demand-side management solution at the consumer side. In this paper, we consider the demand-side energy management problem as the scheduling of a consumer's daily tasks according to user-specified deadlines and the real-time pricing of the market, while achieving cost saving, peak reduction and risk-aversion. We construct an efficient approximation algorithm to this NP-hard problem. Compared to optimization-based approaches, a schedule-based approach can better represent the consumer's energy usage preference and preserve task atomicity. Our algorithm serves as a viable

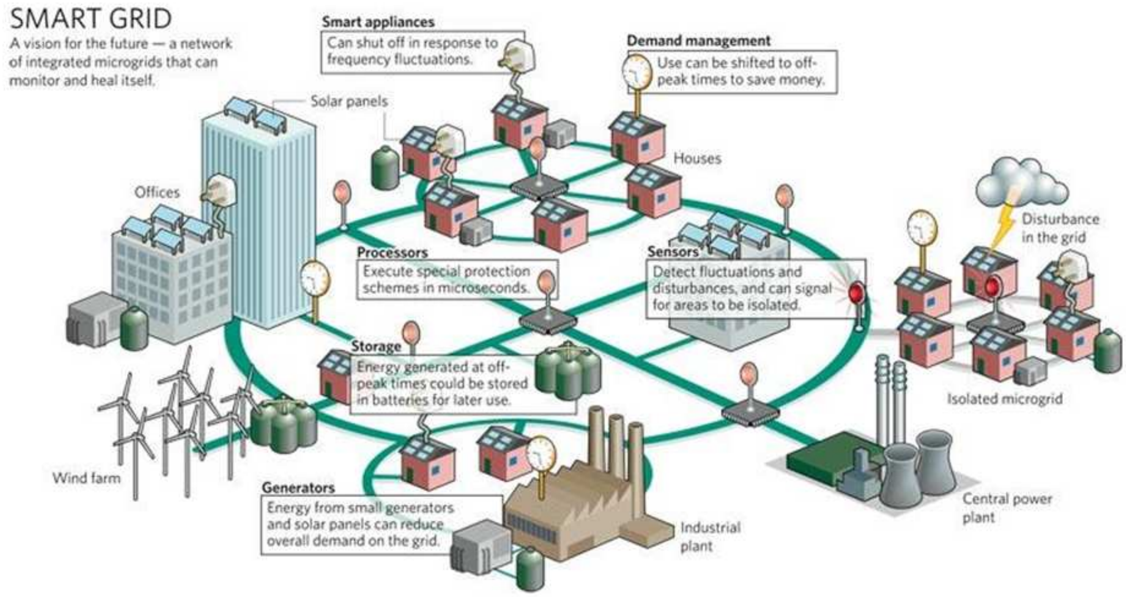

Fig. 1. Smart Grid Overview [2]

enabler of realizing real-time pricing DR programs.

The remainder of this paper is organized as follows. Section II presents related works on smart grid and demand-side energy management, and Section III presents the scheduling algorithm and its analysis. Section IV contains our simulation study on demand-side energy management for home and large enterprises. Section V concludes the paper.

II. Related work

The vision and development of a smart grid have been well documented in literature [3][4][5]. They aim at providing a high quality and well managed power grid service while reducing the energy wastage in production and transport. A number of characteristics are proposed as the principle features of a "Modern Grid" [3][4]:

- Enables and motivates active participation by consumers
- Accommodates all generation and energy storage options
- Enables new products, services and markets
- Provides the quality of power required for the digital, computer and communication based economy
- Operates efficiently and optimizes the utilization of existing and new assets
- Anticipates and responds to system disturbances in a self-healing manner
- Operates resiliently against attack and natural disaster

The management and control of a smart grid are underpinned by an Automatic Metering Infrastructure (AMI) that can accurately and efficiently monitor, process and aggregate varieties of information, such as market pricing signals, demand distributions, power quality, abnormal conditions, consumer energy consumption status, etc. At the demand-side, Automatic Meter Reading (AMR) [5] is proposed as an effective way of gathering detailed metering information about the consumer's energy consumption status and utilize this information for better power production planning and to make consumer aware of their power consumption levels. The activities in this area thus far have been producer-centric. The proposed solutions aim at gathering and processing aggregate consumer information for the purpose of global planning and market regulation, rather than to develop decision algorithms for the optimization of consumer's energy consumption activities. Our work compliments these efforts by focusing on the optimization of demand-side energy usage. Some works [6] have postulated the realization of demand response program in the smart grid setting. The proposed scheme is a combination of real-time pricing, advanced metering, and remote load control techniques. They suggest that in deed the customers should optimize and schedule their power consumption according to price and supply condition. However no concrete optimization problem and solution is developed thus far.

Some works apply optimization techniques to energy management. For instance, work on microgrids [7] focuses on the supplier aspect of power generation. They note that the use of renewable energy from microgrids (e.g. local wind and solar generators) can reduce the reliance on wholesale power suppliers, but the power quality is a variable that must be controlled. Work on optimizing domestic energy usage [8] focuses on the optimal on/off switching of thermal appliances such that energy consumption is minimized while a consistent level of comfort is maintained. The particular problem setting is amicable to the application of optimization techniques as the activation/deactivation of heaters can be regarded as a continuous tunable parameter over time. Some regards are given to the consumer's preferred heating times. Other works such as [9] proposes energy cost optimization based on the demand and supply market through agent-based bidding techniques. The work focuses on performing consumer-side energy optimization through time shifting, it accounts for the user's task preferences but no hard deadline guarantees.

We observe that consumer side task schedule is often accompanied by hard deadlines and requires task atomicity. For instance, a user with a business appointment must iron the shirt before some hard deadline; a scheduled TV football match cannot be time shifted; a computing server at the office must be available when it is required. Furthermore, once a task is committed it cannot be aborted in the middle. For instance, a consumer will not look kindly upon the turn on/off of the TV while in the middle of watching a program. The particularities of these requirement favors the optimization of demand-side energy consumption at the home/office level as a scheduling problem. A few work [10] focuses on this aspect of task scheduling as defined by classic scheduling problems such as Longest Process Time (LPT) and Just-In Time (JIT) are known to be NP-complete problem [11]. The work attempts to provide an approximation algorithm for this problem, but the proposed solution does not account for variability in task lengths or the variability in electricity prices.

III. Optimal Demand-Side Energy Management

A. Problem formulation

In the scope of this paper, we focus on the electricity usage of a consumer. The term energy and electricity are used interchangeably throughout this paper. A home consumer's daily activities can be characterized by a list of tasks to be scheduled at preferred time intervals. Some of these tasks are persistent, as they consume electricity throughout the day (e.g. A/C, refrigerator, etc.), while others are more flexible within a defined time interval (e.g. washer/dryer, oven, etc.). Furthermore, once a task has been started, such as washer or oven, it must be carried out to completion without interruption. Thus it is natural to model these tasks as atomic units with fixed scheduling intervals. Figure 2 illustrates our scheduling problem. a request d has a starting time s and a ending time f which we collectively refer to as the *deadline* in that the task must be scheduled to fit somewhere within the specified time frame. Since the price for electricity varies per time interval (here we consider a fixed price per unit of energy consumption each hour), the cost of scheduling the same task to different time slots also differs. Finally, a task must be scheduled in its entirety to preserve atomicity.

Accordingly, we define the demand-side scheduling problem as follows: Given a set of consumer demand $d_j = (s_j, f_j, r_j, l_j) \in D$ where $1 \leq j \leq m$, find an optimal assignment of tasks to timeslots such that:

$$\min\{\max_t\{\sum_{d_j \to t} P_t(r_j)\}\}$$

while obeying the constraint that, the schedule of a task $d_j \to t$ does not violate its deadline, i.e.

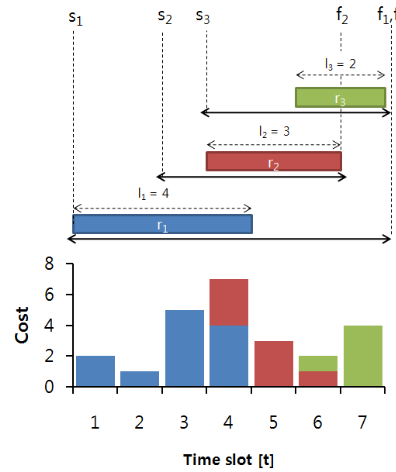

Fig. 2. The Demand-Side Energy Management Problem

$$s_j \leq t \textit{ and } f_j \geq t + l_j - 1$$

Specifically, we consider a task d_j to have a schedule interval $\{s_j, f_j\}$, an electricity requirement r_j and a length of use l_j. To schedule a task to a timeslot ($d_j \to t$) means to assign d_j to a set of contiguous time slots from timeslot t to timeslot $t+l-1$, such that it falls within the schedule interval $\{s_j, f_j\}$. The objective is one of minmaxing the cumulative energy cost in each timeslot ($P_t(r_j)$) rather than to minimize the total energy cost of all timeslots. This objective is motivated by a number of observations. Firstly, to achieve optimal demand planning and **peak shaving** at the aggregate national/regional level, it is desirable to have a "smooth" demand curve, this is exactly the objective of a minmax function. Such a characteristic also has a desired effect on stabilizing the spot market price for electricity as predictable aggregate demand results in more accurate production planning at the producer level, thus lessen the need for peak demand handling. Secondly, to guard against risks in sudden increase to spot price (e.g. due to unexpected production cost increase), it is optimal to have a smoothed demand curve such that the **degree of risk is minimized** over any given timeslot. This is the motivation on why cost is taken as the optimizing output rather than energy consumption levels. Finally, minmaxing the cost function allows us to achieve a high degree of total **energy cost reduction**.

If we do not care about the atomicity of a task and assumes a fixed uniform energy prices, then the demand-side energy management problem is similar to assigning multiple computing tasks with deadlines to a set of identical processors, which is known to be NP-hard. In the following subsection, we present an approximation algorithm to this problem.

B. The Scheduling algorithm

The scheduling algorithm (Algorithm 1) is based on the LPT greedy search heuristic, with two differences. First, instead of scheduling the task with the longest processing time first, we schedule the task with the largest energy consumption first. Second, instead of tracking the cumulative energy consumption on each timeslot, we track the total cost on each timeslot. The algorithm first assigns tasks with the largest energy consumption, if there are multiple tasks with the same energy consumption, then assigns the one with the longest running time first. When assigning a task, the algorithm examines all of the possible timeslot assignments for the task within the specified deadline and assigns the task to the timeslots with the lowest cost among the candidate timeslots. As initialization, the algorithm first allocates tasks that are fixed (i.e. $f_j - s_j + 1 = l_j$) since they have no choice but to be assigned to the allocated timeslots.

Algorithm 1 minMax Scheduling

Input:
n number of time slots, m number of demands
Time slot $t \in T$ where $1 \leq t \leq n$
Consumer demand $d_j = (s_j, f_j, r_j, l_j) \in D$ where $1 \leq j \leq m$
$s \in T$ is start time, $f \in T$ is finish time, r is consuming rate, l is number of time slots of demand.
Cost for demand rate r at time slot t $P_t(r)$
Output:
$scheduleMatrix[n][m]$ such that $scheduleMatrix[i][j]$ is the energy cost of j-th demand at time slot t

Initialize $scheduleMatrix[n][m]$ to zeros
Initialize $c_{1..n}$ to zeros
Assign tasks in D with fixed schedules (i.e. $f - t + 1 = l$) to timeslots, and adjust c accordingly

Sort D based on r as the major key in descending order
Sort D based on l as the minor key in descending order

for $i = 1$ to m **do**
  $minMax \leftarrow \infty$
  $schedulingSlot \leftarrow 0$

  for $t = s_i$ to $f_i - l_i + 1$ **do**
    $minMaxAtT = maximum(c_t + P_t(r_i), c_{t+1} + P_{t+1}(r_i), \dots, c_{t+l-1} + P_{t+l-1}(r_i))$
    if $minMaxAtT < minMax$ **then**
      $minMax \leftarrow minMaxAtT$
      $schedulingSlot \leftarrow t$
    end if
  end for

  for $j = schedulingSlot$ to $l - 1$ **do**
    $scheduleMatrix[i][j] \leftarrow P_j(r_i)$
  end for
end for

We now show that the minMax scheduling is an approximation algorithm for the demand-side energy assignment problem.

THEOREM 1: *Given a demand-side energy management problem without deadlines, the minMax scheduling algorithm produces a solution at most $P_{max}(r_{min})$ more than the optimal solution.*

We now consider the problem without deadlines. With a optimal schedule, let Φ^* denote the highest cumulative cost among the timeslots of the optimal schedule. If there is no overlapping of tasks (i.e. there exists a schedule such that each timeslot contains at most one task), then the minMax schedule algorithm is guaranteed to find this solution. If overlap exists, then we have the following condition:

$$\Phi^* \geq 2P_{min}(r_k), \textit{where } r_k \textit{ is the last schedule} \tag{1}$$

Furthermore, we can consider the best averaging case where all the demands are evenly distributed across the timeslots regardless of their processing time, thus producing a better than optimal solution. It must be that the optimal schedule is lower bounded by this distribution below:

$$\Phi^* \geq \sum_t P_t\left(\frac{\sum_i r_i}{n}\right) \tag{2}$$

Now, consider the schedule produced by our minMax scheduling algorithm, let Φ denote the highest cumulative cost among the timeslots of the optimal schedule. Since the last task r_k which is the smallest task is scheduled onto the timeslot with the least cumulative cost, we have the following inequality:

$$\Phi - r_k \leq \sum_t P_t\left(\frac{\sum_i r_i}{n}\right) \tag{3}$$

Combining Equations 2 and 3 yield:

$$\Phi \leq \Phi^* + P_{max}(r_{min})$$

Therefore, the minMax scheduling algorithm produces a solution at most $P_{max}(r_{min})$ more than the optimal solution.

□

The minMax scheduling algorithm has the peculiar property that as the number of tasks increases, so does the absolution difference between Φ^* and $P_{max}(r_{min})$. Unfortunately, Theorem 1 only holds when there is no deadline imposed on the tasks, as otherwise the observation of the assignment to least cumulative timeslot does not hold.

THEOREM 2: *Given a demand-side energy management problem with deadlines, the minMax scheduling algorithm produces a solution that is upper-bounded by $\gamma(\Phi^* + P_{max}(r_{min}))$ where $\gamma = \frac{\max_t Overlap_t}{\min_d \lfloor (f_i - s_i)/l \rfloor}$.*

For a given timeslot t, we denote the number of tasks that may be scheduled to this timeslot by $Overlap_t$. It is sufficient to examine the behavior of $Overlap_\Phi$ which is the timeslot containing the maximum cumulative cost produced by minMax scheduling algorithm.
As each task in the set of $Overlap_\Phi$ is scheduled from the largest energy consumption block to the least. it is always

scheduled to the least cumulative cost timeslot constrained by the specific deadline time frame. This produces a constrained sub-problem spanning from timeslot s_t to f_t, under which we can bound the marginal loss of optimality by applying Theorem 1. Therefore, each time Φ is raised, a marginal loss occurs on the sub-problem, resulting in the total optimality loss of $\gamma(\Phi^* + P_{max}(r_{min}))$.

γ is upperbounded by $\max_t Overlap_t$, the highest number of tasks that can be scheduled into a single timeslot. However, not every task will be scheduled into the timeslot, by the greedy property of minMax scheduling, once a task is scheduled into a timeslot, it is guaranteed that the following number of tasks will not be scheduled into the same timeslot unless other non-overlapping timeslots have been scheduled a task.

The minimum number non-overlapping timeslots is dependent on the tightness of the deadline and the length of the tasks. Therefore, the number of tasks that will be scheduled into the timeslot of Φ is upperbounded by:

$$\gamma = \frac{\max_t Overlap_t}{\min_d \lfloor \frac{f_i - s_i}{l} \rfloor}$$

□

We observe that the quality of the approximation is dependent on the degree of overlapping of the task preferences. Generally the more overlapping the tasks are, the higher potential for optimality loss. Similarly, the tighter the deadline is with respect to the task length, the higher potential for optimality loss. Our simulation study (Section IV) show that the general performance of minMax is much better than this upper bound.

IV. Simulation Study

In this section, we report the simulation studies we have performed to determine the runtime performance of the minMax scheduling algorithm and the effect of battery use. We study the performance of the minMax scheduling algorithm under both small home consumer case scenario and under large enterprise case scenario. For the home scenario, the test set is small enough for us to obtain the exact optimal solution using depth-first branch-and-bound. For the enterprise scenario, we use the average demand distribution as the better-than-optimal lower bound.

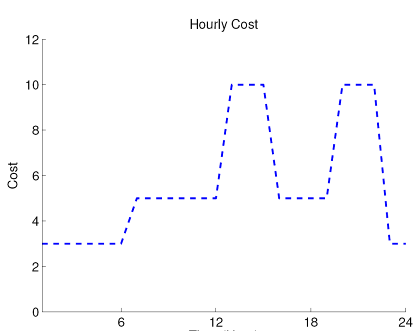

Fig. 3. Daily energy price from utility

To model the user's task preference, we use four parameters: $EnergyDemand$ denotes the amount of energy that is required by each task. $TaskLength$ denotes the contiguous running length (in timeslots) of each task, and $ShiftTime$ denotes the maximum margin that each task is able to be shifted (i.e. $TaskLength + ShiftTime = f - s + 1$). Table I lists the parameters and their value range. For each variable uniform random sampling is applied on the given value range. This setup quite generic as we would like to test the performance of our algorithm under general setting as not to be biased towards a specific data set.

TABLE I
Simulation Parameter Settings

Variable	Value	Description
$EnergyDemand$	1 ˜ 5	The amount of enery that required by each task per hour.
$TaskLength$	1 ˜ 5	The contiguous running time of each task.
$ShiftTime$	1 ˜ 5	Shift time range of each task.
$DailyEnergyPrice$	3 ˜ 10	Energy price per 1 power unit in each hour.

To simulate the real time pricing scheme, we used a normalized energy usage graph. The energy price is varied at 1 hour intervals starts from 1:00 and ends at 24:00. The energy price pattern follows an off-time, normal-time, peak-time price setting (Figure 3). We take the 1:00 to 6:00 as the off-peak time and introduces two peak-time intervals correspond to summer day A/C usage peak and night time residential peak.

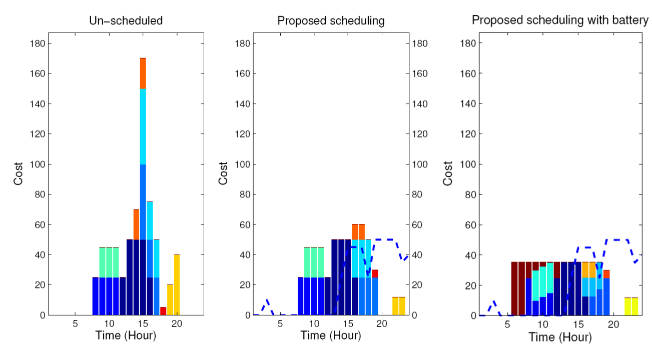

Fig. 4. Comparison of scheduling result with 10 tasks

For the home consumer case, we take a small task set (10 tasks) whose parameters are generated according to Table I. In domestic environment, there are not many tasks to be scheduled however the deadline for these activities tend to center around the peak times. Furthermore, given a small input set, it is feasible to obtain the optimal scheduling to which we can compare our scheduling result. Figure 4 shows the results of the initial schedule, our minMax schedule (bar graph) and the optimal schedule (dashed line graph). We see the effect of the smart scheduling. The original task set has a typical peak-demand pattern we see today, with smart scheduling the peak load can be reduced to close to 1/3rd of its size. This is mainly

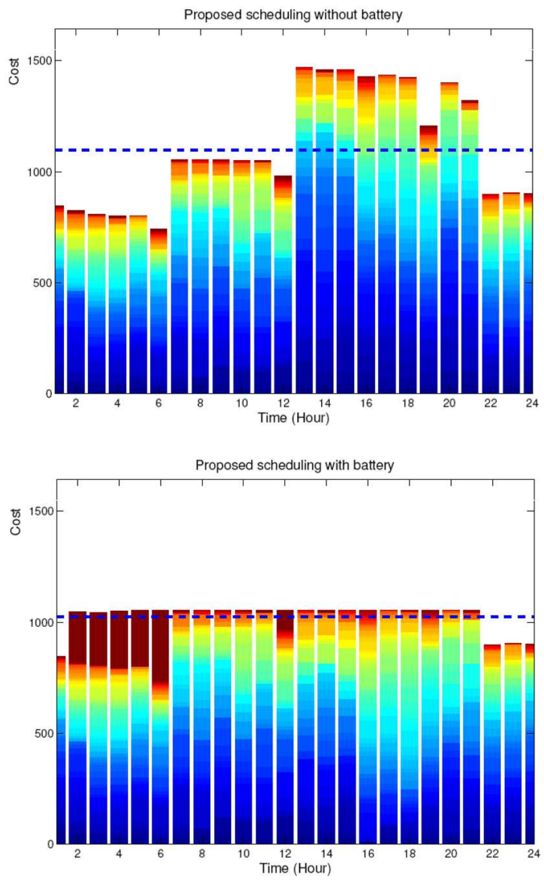

Fig. 5. Comparison of scheduling result with 1000 tasks

because the energy price during 20:00 to 22:00 is quite high, and appropriate time shifting to avoid the peak-time as much as possible has significant advantages in terms of cost saving and peak shaving. Compared with the optimal schedule, our minMax schedule shows higher peak time cost as expected. When battery solution is applied, the advantage is clear. The demand curve is smoothed significantly, as the battery is charged during off-peak time and is used to supplement energy output during peak time. The capacity of the battery determines how much peak load it can handle (around 70 energy units in this study) and the user can set preference to restrain the battery from charging during non-preferred times (e.g. early morning or late night).

To simulate the case of large enterprise, we apply our algorithm to a much larger task set (1000 tasks). The task deadline distribution is more even throughout. Figure 5 shows the result of our minMax schedule. Because of the test set size, it is impossible to compute the optimal schedule, hence we use the average load (i.e. total demand / time, without regard for task integrity or deadline). The bars on the graph represents the schedule our minMax algorithm produces while the dashed line graph represents average load which is better than optimal. We see that our minMax schedule is quite effective. We also show the results when battery storage is considered. As can be observed, the effect is significant, as it smoothed out the demand curve to the absolute average. We not that a battery with adequate storage capacity is needed to obtain this effect.

V. Conclusion

In this paper, we model the demand-side energy management problem as a NP-hard task scheduling problem. Using minmax as the objective, we show that the schedule produced by our minMax algorithm has a number of salient advantages: significant peak-shaving, cost reduction, and risk-aversion for the consumers. We show that our algorithm can find near-optimal solutions and our simulation study suggests that the general runtime performance is much better than worst-case. The algorithm is simple and efficient to implement for home and large enterprises. We further show the effect of battery on demand smoothing.

As the next-step we are implementing the minMax algorithm in a home energy-management system and will conduct field-test experiment in home and enterprise settings.

Acknowledgement

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