Optimal Privacy-Preserving Load Scheduling in Smart Grid

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***Abstract*—With the wide deployment of smart meters in the power grid, it is becoming much easier to gather the detailed power consumption data of residential users, which enables the possibility of smarter and greener power grid. However, the fine-grained load profile of the individual user also introduces the severe concern of privacy leakage as the private information such as personal living habits may be inferred by the malicious third parties for unauthorized use and benefits. Different from most existing privacy-preserving energy management works which are solely based on the control of rechargeable batteries, we further introduce the proactive scheduling of widely used thermostatically controlled devices, including air conditioner, water heater, and laundry drier for effective load hiding. To minimize the weighed sum of financial cost, the deviation from the pre-defined load profile, and the user dissatisfaction, we formulate a novel load scheduling problem which is subject to both the device/battery physical dynamics and the practical user requirements. In order to solve the overall problem effectively under the uncertain price, we decompose the primal problem into a series of subproblems through dual composition, and design a stochastic gradient based two-level iterative distributed algorithm. Extensive simulations under various parameters are employed to demonstrate the effectiveness of our design.**

I. Introduction

With the recent advancement of information and communication technologies, the power grid is becoming more reliable, secure, and efficient with ubiquitous sensing, communication and control functionalities. Typically, the increasing number of deployed smart meters are able to provide fine grained energy consumption data of end users for various purposes, e.g., real-time pricing, demand response, and etc [1]. However, serious concerns have risen regarding to the possible privacy leakage which may lead to unauthorized usage of personal information or even malicious attacks [2]. For example, by non-intrusive load monitoring (NILM) of voltage and current into the house [3], it is possible to deduce the pattern of appliance usage and the resident behavior, which can be exploited by the retailers to promote sales or by the insurance companies to customize the insurance types.

The encryption mechanism [4] is a typical way to protect the smart meter data during the communication process, but the utility company is still able to collect the overall personal information which may be leaked to third parties. In order to mitigate the possible exposure of end user privacy, various passive data obfuscation methods have been proposed [5], where the basic idea is to add noise into the original raw data [6]. However, such perturbation of energy consumption may cause inaccurate billing and reduce the performance of power system controls [7].

At the other end of the research spectrum, some proactive scheduling methods have been proposed to mask the load signature [2, 8, 9], which mainly rely on the charging/discharging scheduling design of rechargeable batteries installed in each house. However, the performance in terms of both financial cost and guaranteed privacy is limited by the cost of additional installed rechargeable batteries. Motivated by this observation, this paper aims to minimize a weighted sum of financial cost, privacy leakage performance, and the deviation from the nominal user satisfactory by exploiting the scheduling capability of widely used thermostatically controlled loads (TCLs), including air conditioner, water heater, and laundry drier. By utilizing the underlying thermal storage of these TCLs, it is expected that the total load profile can be better modulated while the desired user requirements can still be satisfied [10].

The main contributions of this paper can be summarized as follows. First, we introduce the thermostatically controlled devices for load hiding, and formulate a unified load privacy-preserving scheduling problem with both batteries and shiftable loads under practical physical dynamics. Second, in order to solve the problem under uncertain market price, we propose a two-level distributed iterative algorithm to schedule the load, such that the problem can be directly tackled in each separate time slot. At last, we verify the performance of the proposed design under various practical settings.

II. System Model

In this section, we first introduce the detailed models considered in this paper, which include the TCLs, the energy storage devices and the market price. Then we present the formulated privacy-preserving scheduling problem which aims to track an arbitrary pre-specified energy consumption profile for privacy protection while reducing the electricity bill and providing certain user satisfaction.

A. Device Model

Let A denote the set of all devices to be scheduled. Since it is still infeasible to feed back the power to the distribution grid for residential users in some places like China, the following constraint is required:

$$\sum_{a \in A} x_a(t) + D(t) \geq 0 \tag{1}$$

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where $x_a(t)$ denotes the power consumption of device a and $D(t)$ is the overall base load in time slot t, i.e., the load that cannot be scheduled. For places adopting net metering policies, i.e., residential users can sell power to the distribution grid, this constraint can be simply removed.

1) Type 1: Thermostatically Controlled Load: Thermostatically controlled loads are the appliances such as air conditioner, water heater or laundry drier, which control the temperature of certain environment. For each TCL $a_1 \in A_1$, let $T_{a_1}^{in}(t)$ and $T_{a_1}^{out}(t)$ denote the temperatures at time slot t inside and outside the space that the appliance is in charge of respectively ($T_{a_1}^{in}(-1)$ denotes the temperature in the latest time slot of last scheduling horizon). Then the following linear equation describes the dynamics of each TCL

$$\begin{aligned} T_{a_1}^{in}(t) =& T_{a_1}^{in}(t-1) + \alpha_{a_1}\left[T_{a_1}^{out}(t) - T_{a_1}^{in}(t-1)\right] + \beta_{a_1} x_{a_1}(t) \\ =& (1-\alpha_{a_1})^{t+1} T_{a_1}^{in}(-1) + \alpha_{a_1} \sum_{i=0}^{t} (1-\alpha_{a_1})^{t-i} T_{a_1}^{out}(i) \\ &+ \beta_{a_1} \sum_{i=0}^{t} (1-\alpha_{a_1})^{t-i} x_{a_1}(i) \end{aligned} \tag{2}$$

where α_{a_1} and β_{a_1} are tunable parameters. The second term in equation (2) models the heat transfer process, and the third term models the efficiency of thermostatical controlled devices. This equation holds for both heaters and coolers ($\beta_{a_1} > 0$ for heaters while $\beta_{a_1} < 0$ for coolers).

Taking air conditioners for example, it is common that the users may feel comfortable when the temperature is within a specified range. We transform it into the following user requirement constraint

$$T_{a_1}^{lower}(t) \leq T_{a_1}^{in}(t) \leq T_{a_1}^{upper}(t). \tag{3}$$

Meanwhile, the power of a thermostatically controlled device is limited as follows

$$0 \leq x_{a_1}(t) \leq x_{a_1}^{max}(t) \tag{4}$$

where $x_{a_1}^{max}(t)$ denotes the maximum device power at time slot t.

2) Type 2: Rechargeable Batteries: In the modern house, various rechargeable batteries are equipped into different appliances such as electric vehicle, tesla home battery, and etc. Let $B_{a_2}(t)$ denote the state of charge (SOC) of an arbitrary battery, the dynamic of $a_2 \in A_2$ can be characterized as

$$\begin{aligned} B_{a_2}(t+1) &= B_{a_2}(t) + x_{a_2}(t) \\ &= B_{a_2}(0) + \sum_{i=0}^{t} x_{a_2}(i) \end{aligned} \tag{5}$$

while satisfies the following constraints:

$$\begin{aligned} &-x_{a_2}^{max\_dis}(t) \leq x_{a_2}(t) \leq x_{a_2}^{max\_char}(t) \\ &-B_{a_2}(t) \leq x_{a_2}(t) \leq B_{a_2}^{max} - B_{a_2}(t) \end{aligned} \tag{6}$$

where $B_{a_2}^{max}$ denotes the battery capacity, $x_{a_2}^{max\_dis}(t)$ and $x_{a_2}^{max\_char}(t)$ denote the maximal discharging rate and maximal charging rate at time slot t respectively. It is noteworthy that some energy storage devices like tesla power wall can provide energy to the household appliances while the others may not due to the lack of AC-DC converter. In this paper, our model and later solution can handle the general setting, but in the evaluation part, we only consider the scenario where only power wall can act as a power supplier while other charging devices cannot for practical concern.

Furthermore, these devices such as EVs may have additional requirement to satisfy the specific users' requirement. Let α_{a_2} and β_{a_2} denote the starting time and deadline for the battery charging, We use the following equation to model this usage demand:

$$R_{a_2}^{lower} \leq \sum_{t=\alpha_{a_2}}^{\beta_{a_2}} x_{a_2}(t) \leq R_{a_2}^{upper} \tag{7}$$

where R_{low} and R_{up} denote the lower bound and upper bound of the usage requirement.

By carefully setting $x_{a_2}^{max\_char}(t) = x_{a_2}^{max\_dis}(t) = 0$ for $t < \alpha_{a_2}$ and $t > \beta_{a_2}$, we can rewrite the constraint (7) as below:

$$R_{a_2}^{lower} \leq \sum_{t=0}^{N-1} x_{a_2}(t) \leq R_{a_2}^{upper}. \tag{8}$$

B. Market Model

In this paper, we consider a commonly used market model with the coexistence of LSE (load-serving entity) and RTP (real-time pricing) [11], where the consumer can either a) reserve day-ahead electricity (then use it the next day), or b) reserve day-ahead electricity (then use it the next day) and purchase power from the real-time market if the reserved capacity is insufficient. Specifically, the user can reserve certain amount of electricity denoted as $l(t)$ from the LSE with a cost of $C_1(l(t), t)$, which means that the user can use up to $l(t)$ amount of electricity in time slot t the next day with wholescale price. Let $x(t)$ denote the amount of electricity the user actually consumes. If $x(t)$ is smaller than $l(t)$, the electricity consumption will cost $C_2(x(t), t)$ in addition to the reservation fee. Otherwise, the user has to pay for the excess consumption at price $p(t)$ from the real-time market, where the real-time price is larger than that from the LSE in general. The total cost $C(t)$ paid by the user at time slot t is

$$C(t) = \begin{cases} C_1(l(t), t) + C_2(x(t), t) & \text{if } x(t) \leq l(t) \\ C_1(l(t), t) + C_2(l(t), t) & \\ \quad + p(t) \cdot (x(t) - l(t)) & \text{if } x(t) > l(t). \end{cases} \tag{9}$$

The real-time price $p(t)$ is released at the beginning of every time slot and maintains constant during that time slot. Here we assume the future price follows certain distribution which can be estimated from historical data.

C. Pre-specified Load Profile

The objective of privacy-preserving scheduling is to drive the final load profile to track a pre-specified curve so that the private information cannot be inferred from the data. One intuitive option is to make the load profile as flat as possible [2], which, nevertheless, may enable the attacker to notice the existence of protection method easily. Moreover, tracking such flat curves may also be costly.

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In this paper, we propose a data driven profile generation method. From the real energy consumption data, we can cluster the users into several groups based on their electricity usage patterns [12]. Then for privacy protection, the pre-specified load profile of a user in one group can be randomly selected from another group so that his electricity usage looks totally different from the original. Specifically, we adopt the correlation coefficient to depict the similarity of the load profile patterns, and utilize the hierarchical cluster method to cluster the energy consumption data. The clustering result can provide recommendatory target profiles to the users. The details of the clustering method and results are omitted in this paper due to the limited space. Note that our following scheduling design can be used for any pre-specified load profile although the tracking error will be affected by both the device capability and the shape of profile. It's also quite interesting to investigate the load profile optimization for further reducing the costs and improving the performance of power grid, which will be left as our future work.

D. Optimization Problem

Let $f(t)$ and N denote the aggregated target load in time slot t and the number of time slots, respectively. We formulate the problem as a multi-objective optimization problem, where the objective consists of three parts as shown below:

$$\min E\left\{\sum_{t=0}^{N-1}\left[C(t)+\gamma(x(t)-f(t))^2+\sum_{a\in A}\gamma_a(x_a(t)-y_a(t))^2\right]\right\}$$
$$\text{s.t.}\quad (1),\quad (3),\quad (4),\quad (6),\quad (8) \tag{10}$$

where $y_a(t)$ is defined as the nominal power consumptions of each device a for describing the user satisfaction [13] (more changes or shifts of the user's power usage leads to a higher dissatisfaction), and γ and γ_a are set to characterize the tradeoff among the electricity bill, the privacy preservation and the user welfare. The expectation notation E is introduced here out of the consideration of the uncertainty of $p(t)$. Notice that in the objective function, the first part describes the user's desire to minimize his financial cost while the second part describes the performance of privacy protection in terms of the profile tracking error, and the third term characterizes the deviation from the user nominal requirement of all devices.

III. Solution

In this section we present the detailed algorithm for solving the original optimization problem (10). Due to the existence of temporally-coupled constraints of device dynamics, it can be observed that the primal problem (10) can't be solved over each time slot independently. Therefore, we first adapt dual decomposition approach [14] to decompose the primal problem into separable subproblems over the time horizon such that each subproblem concerning the objective of each time slot can be executed on different smart devices. Based on the offline decomposed subproblems, we propose a two-level iterative algorithm to solve the whole problem. In the outer level, the Lagrangian multipliers are updated on a coordinator node and sent to each smart device, while in the inner level, each smart device with the assigned subproblem calculates the scheduled loads of certain time slot by exploiting the stochastic gradient and update them to the coordinator. The detailed design is explained as follows.

A. Dual Decomposition

In this part, we explain how to decompose the original problem into separable subproblems so that each subproblem only needs to concern the objective over certain time slot and thus can be assigned to calculate on different smart devices.

For notation simplicity, we first define new variables as

$$T_{a_1}(t)=(1-\alpha_{a_1})^{t+1}T_{a_1}^{in}(-1)+\alpha_{a_1}\sum_{i=0}^{t}(1-\alpha_{a_1})^{t-i}T_{a_1}^{out}(i)$$
$$\phi_{a_1}=1-\alpha_{a_1}. \tag{11}$$

Then the Lagrangian is defined as

$$\begin{aligned}
&L(\boldsymbol{x},\boldsymbol{l},\boldsymbol{\lambda})=\\
&E\left\{\sum_{t=0}^{N-1}\left[C(t)+\gamma(x(t)-f(t))^2+\sum_{a\in A}\gamma_a(x_a(t)-y_a(t))^2\right]\right\}\\
&+\sum_{a_1\in A_1}\sum_{t=0}^{N-1}\lambda_{a_1}^1(t)(T_{a_1}^{lower}(t)-T_{a_1}(t)-\beta_{a_1}\sum_{i=0}^{t}\phi_{a_1}^{t-i}x_{a_1}(i))\\
&+\sum_{a_1\in A_1}\sum_{t=0}^{N-1}\lambda_{a_1}^2(t)(T_{a_1}(t)+\beta_{a_1}\sum_{i=0}^{t}\phi_{a_1}^{t-i}x_{a_1}(i)-T_{a_1}^{upper}(t))\\
&-\sum_{a_2\in A_2}\sum_{t=0}^{N-1}\lambda_{a_2}^1(t)(B_{a_2}(0)+\sum_{i=0}^{t}x_{a_2}(i))\\
&+\sum_{a_2\in A_2}\sum_{t=0}^{N-1}\lambda_{a_2}^2(t)(B_{a_2}(0)+\sum_{i=0}^{t}x_{a_2}(i)-B_{a_2}^{max})\\
&+\sum_{a_2\in A_2}\left[\lambda_{a_2}^4(\sum_{t=0}^{N-1}x_{a_2}(t)-R_{a_2}^{upper})-\lambda_{a_2}^3(\sum_{t=0}^{N-1}x_{a_2}(t)-R_{a_2}^{lower})\right]\\
&-\sum_{t=0}^{N-1}\lambda(t)(\sum_{a\in A}x_a(t)+D(t))
\end{aligned} \tag{12}$$

where $\lambda_{a_i}^j(t)$ denotes jth Lagrangian multiplier for device a_i corresponding to the physical constraint at time slot t.

In the original problem, note that some constraints are originally separable over the time horizon while other constraints such as $\sum_{a_2\in A_2}\sum_{t=0}^{N-1}\lambda_{a_2}^2(t)(B(0)+\sum_{i=0}^{t}x_{a_2}(i))$ are not due to the existence of device dynamics. In the following, we show how to transform the constraints in order to decompose the original problem. Due to the limited space, we only show the transforming process of the fourth row of the Lagrangian which corresponds to the lower bound constraint of battery.

$$\begin{aligned}
&-\sum_{a_2\in A_2}\sum_{t=0}^{N-1}\lambda_{a_2}^3(t)(B_{a_2}(0)+\sum_{i=0}^{t}x_{a_2}(i))\\
=&-\sum_{a_2\in A_2}\sum_{t=0}^{N-1}\lambda_{a_2}^3(t)B_{a_2}(0)-\sum_{a_2\in A_2}\sum_{t=0}^{N-1}\left(\lambda_{a_2}^3(t)\sum_{i=0}^{t}x_{a_2}(i)\right)\\
=&-\sum_{a_2\in A_2}\sum_{t=0}^{N-1}\lambda_{a_2}^3(t)B_{a_2}(0)-\sum_{a_2\in A_2}\sum_{t=0}^{N-1}\left(x_{a_2}(t)\sum_{i=t}^{N-1}\lambda_{a_2}^3(i)\right).
\end{aligned}$$

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Thus the Lagrangian function (12) can be separated to several subproblems that can be solved at each time slot respectively. The subproblem can be represented as:

$$
\begin{aligned}
S(\boldsymbol{x}(t), l(t), t) = & E\Big[C(t) + \gamma(x(t) - f(t))^2 + \gamma_a(x(t) - f(t))^2\Big] \\
& - \sum_{a_1 \in A_1} \Big(\beta_{a_1} x_{a_1}(t) \sum_{i=t}^{N-1} \phi_{a_1}^{i-t} \lambda_{a_1}^1(i)\Big) \\
& + \sum_{a_1 \in A_1} \Big(\beta_{a_1} x_{a_1}(t) \sum_{i=t}^{N-1} \phi_{a_1}^{i-t} \lambda_{a_1}^2(i)\Big) \\
& - \sum_{a_2 \in A_2} \Big(x_{a_2}(t) \sum_{i=t}^{N-1} \lambda_{a_2}^1(i)\Big) + \sum_{a_2 \in A_2} \Big(x_{a_2}(t) \sum_{i=t}^{N-1} \lambda_{a_2}^2(i)\Big) \\
& - \sum_{a_2 \in A_2} \lambda_{a_2}^3 x_{a_2}(t) + \sum_{a_2 \in A_2} \lambda_{a_2}^4 x_{a_2}(t) \\
& - \lambda(t)(\sum_{a \in A} x_a(t) + D(t))
\end{aligned} \tag{13}
$$

where $\boldsymbol{x}(t)$ denotes a vector whose components containing all the $x_a(t)$ to be scheduled. It can be seen that the terms like $\sum_{a_2 \in A_2} \sum_{t=0}^{N-1} \lambda_{a_2}^3(t) B_{a_2}(0)$ are removed since they are independent from $\boldsymbol{x}$ and $\boldsymbol{l}$ for fixed Lagrangian multipliers.

B. Two-Level Iterative Algorithm Design

Based on the offline decomposition results, we are ready to present the two-level iterative algorithm. Given day-ahead reserve capacity $l(t)$ and a sample of the real-time price $p(t)$, the decision of $\boldsymbol{x}(t)$ in each subproblem becomes a deterministic optimization problem, which can be solved by commercial solver directly. After obtaining the optimal real-time load, we have $\tilde{S}(l(t), t) = S(\boldsymbol{x}^*(t), l, t)$. Due to the existence of uncertain $p(t)$, we adopt the method of stochastic gradient [13] to solve the subproblem iteratively by exploiting the distribution of $p(t)$. Note that $p(t)$ is independent on $l(t)$, then the following equation holds according to the theory of stochastic gradient,

$$\frac{\partial E[\tilde{S}(l(t), t)]}{\partial l(t)} = E[\frac{\partial \tilde{S}(l(t), t)}{\partial l(t)}] \tag{14}$$

which means that the gradient of the expected objective can be estimated by $\partial \tilde{S}(l(t), t)/\partial l(t)$. In summary, we obtain **Algorithm 1**, which can solve the subproblems distributedly among the smart devices while satisfying all the physical constraints. Here we index $l(t)$ and $p(t)$ by inner level iteration number m while $\boldsymbol{\lambda}$ by outer level iteration number k, and introduce a new operator $\max(a, b)$ to find the larger value between a and b.

The **Algorithm 1** has two levels of iterations. The outer level updates Lagrangian multipliers to satisfy all the physical constraints, while the inner level solves subproblems given corresponding Lagrangian multipliers. A coordinator allocates the subproblems to each smart device and updates $\boldsymbol{\lambda}$ based on the feedbacks of subproblem solutions. The algorithm returns the optimal load scheduling when the Lagrangian multipliers converge to their optimal values, which is guaranteed by the convexity of the primal problem. The proof of the convergence and optimality is dismissed due to space limitation.

Algorithm 1 Two-level iterative method

Input: the user preferences and environmental parameters
Output: $\boldsymbol{x}^*$,$\boldsymbol{l}^*$,$\boldsymbol{\lambda}^*$

Initialization: the user selects a random value for each Lagrangian multiplier;
repeat
  Inner Level: the coordinator node allocates the subproblems to different smart devices with a random day-ahead load $\boldsymbol{l}^0$. For each subproblem,
  repeat
    With $l^m(t)$ and sampled $p^m(t)$, obtain the corresponding optimal real-time load $\boldsymbol{x}^{*m}(t)$;
    Update the day-ahead load l^{m+1} using stochastic gradient:

$$l^{m+1}(t) = \max\Big[l^m(t) + \epsilon \cdot \frac{\partial \tilde{S}(l^m(t), t)}{\partial l^m(t)}, 0\Big]$$

    where $\epsilon < 0$ denotes the step size;
  until The variation between $l^{m+1}(t)$ and $l^m(t)$ is smaller than a threshold.
  Outer Level: Update the Lagrangian multipliers based on the result from inner loop according to:

$$\boldsymbol{\lambda}^{k+1} = \max\Big[\boldsymbol{\lambda}^k + \varepsilon \cdot \frac{\partial L(\boldsymbol{x}^*, \boldsymbol{l}^*, \boldsymbol{\lambda}^k)}{\partial \boldsymbol{\lambda}^k}, 0\Big]$$

  where $\varepsilon > 0$ denotes the step size;
until The variation between $\boldsymbol{\lambda}^{k+1}$ and $\boldsymbol{\lambda}^k$ is smaller than a threshold.

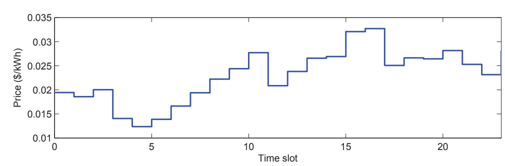

Fig. 1: Real-time price

IV. Evaluation

To illustrate the effectiveness of our design, we consider a family with three major shiftable appliances: an air conditioner, a Tesla Model S and a Tesla Powerwall. The daily scheduling horizon is divided into 24 time slots. For the air conditioner, the thermal parameters are set as $\alpha = 0.9$ and $\beta = -10$, and the region of tolerable temperature is set as [70F,79F] [15]. The extraventricular temperature is derived from the climate data of Hangzhou, China in July. For electric vehicle and home battery, the parameters are chosen directly from the official data of Tesla. Besides, the electric vehicle has a minimum charging amount 60kWh from the initial SOC of 10kWh to meet the basic usage demand. The real-time price information is derived from [11] as Figure 1 shows, and we assume the real-time price follows gauss distribution with standard deviation 0.002. For space limitation, only the flatten load profile is verified in this paper although our algorithm can also applied to any arbitrary pre-specified load profile.

We first demonstrate the convergence of proposed two-level iterative algorithm, which is shown in Figure 2 and Figure 3. In Figure 2, it can be observed that the corresponding Lagrangian multipliers converge to their optimal values as the increase of iteration times. Note that some Lagrangian multipliers remain zero as the corresponding constraints keep

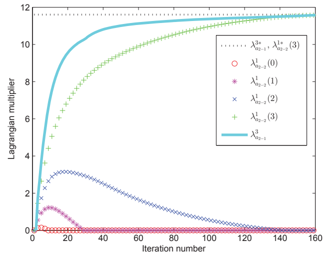

Fig. 2: Convergence of $\boldsymbol{\lambda}$

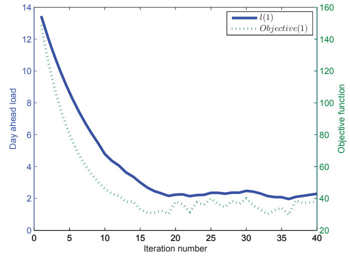

Fig. 3: Convergence of l and objective in the first time slot

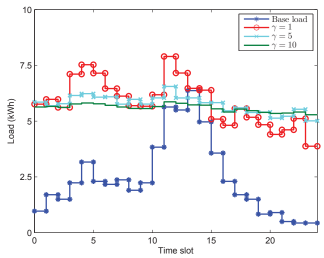

Fig. 4: Load scheduling under different γ

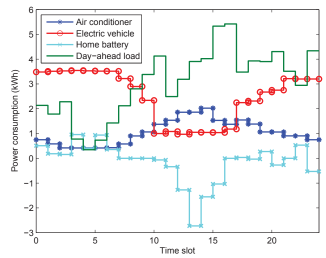

Fig. 5: Power consumption of different devices

valid, and thus are not depicted in this figure. In Figure 3, we show the convergence of inner level part for the first time slot, i.e., the day-ahead load calculation under price uncertainty. It can be seen that both the day-ahead load and the corresponding objective for the first time slot converges simultaneously with the iteration. It is interesting to notice that there exist some fluctuation around the optimal value caused by the price uncertainty. Such fluctuation may be reduced by setting a smaller step size at the cost of convergence speed.

In Figure 4, we evaluate the influence of the weight of privacy leakage γ in the objective function. It can be observed that the real load profile becomes closer to the pre-specified profile with the increase of γ. Specifically, we also depict the base load of the residential user (the blue line) to show the effectiveness of privacy protection in Figure 4. Correspondingly, Figure 5 shows the complete time-varying load schedule for each device under $\gamma = 1$.

For default $\gamma = 1$, we further investigate the privacy protection performance by comparing our design with the one only considering rechargeable batteries. Specifically, we calculate the corresponding total bills and the profile variance for two approaches. With even smaller financial cost (our approach 3.017$ v.s. battery-based approach 3.055$), the proposed design achieve 19% less variance (1.071 v.s. 1.337) compared with the battery-based approach, which demonstrates the effectiveness of our design.

V. Conclusions

In this paper, we investigate the feasibility of utilizing load scheduling to protect the residential user's behavior privacy. Unlike most of the existing works which only home battery to flatten the power usage profile, we adopt two kinds of flexible load to make the consumption profile tracking a pre-designed curve. We formulate the scheduling process as an optimization problem, and propose a two-level iterative algorithm to solve the problem efficiently. To cope with the price uncertainty, stochastic gradient method is utilized to calculate the optimal day-ahead load under expectation meaning. Simulation result reveals the convergence and optimality of the proposed algorithm and shows that our method can protect the residential user's behavior privacy efficiently. It is worth noting that our algorithm can be extended to design an online algorithm by adopting the receding horizon optimization method, which will be considered as our future work.

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