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Demand Response Optimization for Smart Home Scheduling Under Real-Time Pricing

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Abstract—Demand response (DR) is very important in the future smart grid, aiming to encourage consumers to reduce their demand during peak load hours. However, if binary decision variables are needed to specify start-up time of a particular appliance, the resulting mixed integer combinatorial problem is in general difficult to solve. In this paper, we study a versatile convex programming (CP) DR optimization framework for the automatic load management of various household appliances in a smart home. In particular, an L_1 regularization technique is proposed to deal with schedule-based appliances (SAs), for which their on/off statuses are governed by binary decision variables. By relaxing these variables from integer to continuous values, the problem is reformulated as a new CP problem with an additional L_1 regularization term in the objective. This allows us to transform the original mixed integer problem into a standard CP problem. Its major advantage is that the overall DR optimization problem remains to be convex and therefore the solution can be found efficiently. Moreover, a wide variety of appliances with different characteristics can be flexibly incorporated. Simulation result shows that the energy scheduling of SAs and other appliances can be determined simultaneously using the proposed CP formulation.

Index Terms—Convex programming, demand response, energy consumption scheduling, energy management, L_1 regularization, smart home.

I. INTRODUCTION

WITH THE promise of smart grids, power can be more efficiently and reliably generated, transmitted, and consumed over conventional electricity systems. Through the two-way flow of information between suppliers and consumers, the grids can also adapt more readily to the increased penetration of renewable energy sources and encourage users' participation in energy savings and cooperation through demand response (DR) mechanism. An important issue in smart grids is therefore how to manage DR to reduce peak electricity load and hence future investment in thermal generations and transmission networks, and to better utilize renewable energies. Current DR schemes are usually implemented through either incentive-based or time-based rates schemes [1], [17]. In incentive-based DR, customers enroll voluntarily in certain rewarding programs and allow the operators to control directly some of their electric appliances such as air conditioners to shed loads during peak or emergency. On the other hand, time-based rates scheme relies on dynamic pricing of electricity to regulate electricity consumption and it can take many different forms,

ranging from simple schemes such as scheduled time-of-use pricing (TOUP), to peak-pricing (PP) which sets higher prices only during critical peak periods, to real-time pricing (RTP) specified at regular interval based on say the wholesale market rates. To achieve this goal, utilities gather the information such as the consumers' usage of electricity from the smart meters, and set the dynamic price level appropriately in order to reduce the peak electricity load through the cooperation of customers.

In response to the dynamic price signals, the customers can shift their demands automatically or manually, with the help of a home energy management system (EMS), to the off-peak hours so as to minimize their electricity payment. Therefore, the home EMS plays an important role of automatically coordinating the operating schedule of smart appliances with the consent of the customers, who have the option to monitor and directly control their own key appliances [2].

Developing efficient DR models of electrical appliances and efficient optimization algorithms for coordinating their operations are thus two key problems in a EMS in a smart home, which have received considerable attention recently [3]–[8]. In general, the main objective of DR optimization is to minimize the electricity bill or maximize their users' satisfaction/comfortability by continually monitoring the electricity price information, allocating available resources and actively managing the load of appliances. While the energy consumption of practical electric appliances can be modeled from physical consideration, the corresponding customer's satisfaction is usually encapsulated using the concept of utility function [5], [6], [11]. It may be a concave function of the energy consumed by the appliances and its values may be determined empirically by conducting survey from customers or from experienced designers. Given these functions, DR optimization seeks to find a reasonable operating point or tradeoff where the electricity cost can be reduced or being controlled to a given level without significantly discomforting the users.

As such, DR is intimately related to mathematical programming or optimization. Among the various algorithms proposed, linear programming (LP) [3], [4] and convex programming (CP) [5] based algorithms are very attractive because the problem can be solved efficiently in polynomial time complexity and the optimality of the solution is guaranteed [9]. The latter, in particular, is more general in the sense that most typical appliance models can be easily incorporated. Examples of these appliances include heating, ventilation, and air conditioning systems, whose physical models depend on environmental factors such as building structure, weather, thermal dynamics, etc. [5], [6], [8], [10]. In the CP approach, the appliances' models are usually chosen as convex or concave functions in order to obtain an overall convex problem. For more complicated problem formulation, heuristic algorithms may be required. For instance,

binary particle swarm optimization (PSO) algorithm was used in [6] to solve the mixed integer problem, where binary decision variables are required to determine on/off status of the appliances. Putting such appliance in the CP framework results in so called convex mixed integer nonlinear program (MINLP), which is in general difficult to solve [12]. Despite the generality of the heuristic algorithms, the optimality of the solution is not guaranteed due to premature convergence, and their complexities are relatively higher than the CP approach, especially for large scale problems.

In this paper, we consider a single household scenario given the price information, and propose a versatile CP framework for the load management of various household appliances for supporting DR through EMS in a smart home. Apart from some typical appliances that naturally fit into the CP framework, the proposed problem formulation is able to handle more general schedule-based appliances (SAs), for which their on and off statuses are the main concern. In the proposed approach, the binary decision variables associated with the on/off statuses are first relaxed from integer to continuous values so as to avoid the use of more complicated MINLP. An additional L_1 regularization term is then incorporated in the objective function so that the design problem can be reformulated as a new CP problem. The purpose of this regularization term is to enforce the relaxed continuous variables associated with the best starting schedules to be as large as possible, while keeping others as close to zero as possible. By so doing, the relaxed continuous variables can serve the role of the binary decision variables in picking the best schedules of the appliances in the original mixed integer problem. The major advantage of the proposed approach is that the overall DR optimization problem remains convex and its complexity is only polynomial time thanks to efficient large scale optimization algorithm using say interior point method. In addition, the proposed CP formulation with L_1 regularization is able to solve a subclass of convex MINLP problem, which has not been reported before to our best knowledge. Therefore, comparing with other existing works, our finding is very useful in the sense that a wider range of appliances as well as more flexible operating schedules, which involve binary decision variables, can be supported under the same CP framework. Simulation result shows that the energy scheduling of SAs as well as other appliances can be determined simultaneously and efficiently using the proposed CP formulation.

The paper is organized as follows: In Section II, the system model and the problem formulation of DR optimization under the CP framework are presented. The novel concept of L_1 regularization technique for schedule-based appliances is presented in Section III and models of other common appliances are introduced in Section IV. To illustrate the effectiveness of the proposed approach, simulation results are provided and discussed in Section V. Conclusions are drawn in Section VI.

II. Demand Response Optimization in Single Household Scenario

Consider the optimization in a smart home, where most electric appliances (smart appliances) are networked together and are controlled by a home EMS as shown in Fig. 1. The set of controllable appliances is collectively denoted by $\boldsymbol{A}$. We assume that the DR optimization problem is carried out in a finite time
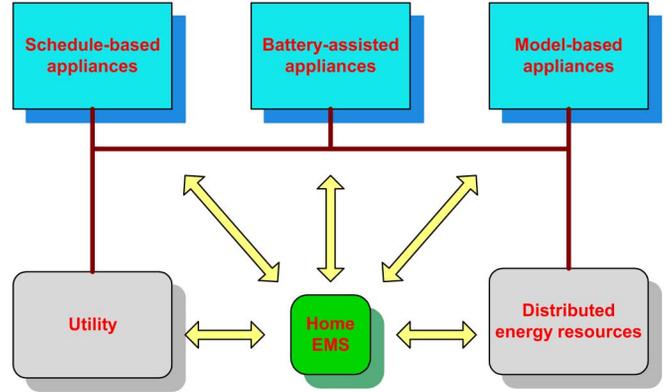
Fig. 1. Demand response optimization in a smart home through a home energy management system (EMS).

horizon for all $t \in \boldsymbol{T} = 1, 2, \ldots, T$, where T is arbitrary but finite. Further, we assume that each appliance $a \in \boldsymbol{A}$ consumes an energy of $e_{a,t}$ at time $t \in \boldsymbol{T}$.

Conceptually, we shall minimize an objective function which measures: 1) the total cost of using the appliances in T and 2) the users' dissatisfaction, subject to the operating constraints of the appliances and power supply. More precisely, if u_t and the total energy consumed at time t and $P_t(u)$ is the electricity price at time t for consumption of u_t, then the total cost is given by $\sum_{t \in \boldsymbol{T}} P_t(u_t)$. On the other hand, if the users' dissatisfaction of the appliance $a \in \boldsymbol{A}$ is modeled as $C_a(\widetilde{e}_a)$ where $\widetilde{e}_{a,t}$ denotes the quantity associated with the energy assumption $e_{a,t}$ for notational convenience, then the DR problem can be written as

$$\min \sum_{t \in \boldsymbol{T}} P_t(u_t) + \sum_{t \in \boldsymbol{T}} \sum_{a \in \boldsymbol{A}} C_a(\widetilde{e}_{a,t})$$

subject to operating constraints.

Since our main focus is on single household scenario, we simply assume that the price function is known either from the RTP information of the power utilities or from the forecasted values, if forward planning is required. It can also be seen that the detailed formulation of the constraints and users' dissatisfaction functions depend on the particular types of electric appliances. Therefore, for a systematic illustration, we assume in this paper that the smart home is equipped with the following types of appliances:

a) Schedule-based appliances with interruptible load (SA-IL): This refers to the class of appliances, which are allowed to run at any time within a user's defined time interval, and its load is interruptible in the sense that it can be shut down during operation. An example is the pool pump considered in [6].

b) Schedule-based appliances with uninterruptible load (SA-UL): Unlike SA-IL, this refers to the class of appliances, which are required to follow predefined steps of operation, and the operation has to be run to completion once it starts. An example is the laundry machine which cannot perform drying before washing

c) Battery-assisted appliances (BAs): This refers to the class of appliances where an internal battery is equipped. The advantages of which include their ability to 1) offer additional energy source during the peak hours and hence more efficient use of the overall energy, 2) harvest any

possible renewable energies, and 3) provide more stable power supply in case of emergencies.

d) Model-based appliances (MAs): This refers to the class of appliances whose energy consumption can be described by physical models. Such physical models facilitate the direct load control of the appliances and are usually characterized by a linear dynamical equation [5], [6], [8], [10].

Note that for the former two types of appliances, the EMS needs to decide when they should start or shut down, rather than how much energy they consumed. Usually, binary decision variables are required to indicate their on/off status, and therefore the resulting DR optimization problem becomes a combinatorial mixed integer problem, which is in general difficult to solve [12]. In this paper, we shall propose a L_1 regularization technique to transform the mixed integer problem to a standard CP, which can be solved more readily. More details will be discussed in Section III.

Under the proposed CP framework, the above four types of appliances are treated in a unified manner, and they can be mainly characterized by the following two aspects:

a) Characteristic function: As mentioned earlier, $C_a(\widetilde{e}_a)$ can be used to quantify the user's dissatisfaction on the energy assumption $e_{a,t}$ or the physical quantity associated with $e_{a,t}$ (e.g., temperature of air-conditioner), which are collectively denoted by $\widetilde{e}_{a,t}$ for notational convenience. A typical example includes the linear "energy equivalent" cost function with $C_a(\widetilde{e}_{a,t}) = \theta_{a,t}\widetilde{e}_{a,t}$, where $\theta_{a,t}$ is a monetary benefit derived by the users [6]. This monetary value is set to increase the cost of the objective function if the service offered by the appliance cannot be met. Another example is the utility function considered in [5], where $C_a(\widetilde{e}_{a,t})$ is generally described by a continuously differentiable convex (non-increasing) function of $\widetilde{e}_{a,t}$. Therefore, $C_a(\widetilde{e}_{a,t})$ is used to counter the further decrease in $\widetilde{e}_{a,t}$ (and hence electricity payment) if the user feels uncomfortable increasingly. We can see that the basic idea of both approaches is to establish a realistic measure that not only takes the actual users' need into account, but also prevents the EMS from solely minimizing the energy consumption/electricity payment and hence scarifying the users' comfortability.

In this paper, we shall also use the characteristic function $C_a(\widetilde{e}_a)$ to describe the property of the SAs. More precisely, it is called L_1 regularization term which allows us to relax the binary decision variables involved in the original mixed integer problem from integer to continuous values. Since the L_1 regularization term is convex, the overall DR optimization problem remains to be convex. Hence, the difficult mixed integer problem can be avoided.

b) Convex constraint: As mentioned before, such constraints are related to the operating constraints of the appliance $a \in \boldsymbol{A}$, and they are assumed to have the form of linear equality $L_{a,t}(\widetilde{e}_{a,t}) = 0$ and convex inequality $F_{a,t}(\widetilde{e}_{a,t}) \leq 0$, where $L_{a,t}(\widetilde{e}_{a,t})$ and $F_{a,t}(\widetilde{e}_{a,t})$ are respectively linear and convex functions of $e_{a,t}$ or the physical quantity associated with $e_{a,t}$. A simple example of linear equality is the total energy E_a^{tot} required for the operation of appliance $a \in \boldsymbol{A}$, that is $\sum_{t \in \boldsymbol{T}} e_{a,t} = E_a^{tot}$.

For the convex inequality, an example is the minimum or maximum bound of the energy required by the appliance, that is $E_a^{\min} \leq e_{a,t} \leq E_a^{\max}$. More details will be discussed in Sections III and IV.

Incorporation of Renewable Energy: Apart from the appliances, the possible utilization of distributed renewable energy sources such as rooftop solar electric systems and small wind turbines is also considered in the system model in this paper. Assuming that a renewable energy source can deliver a power of v_t up to a predicted maximum time-varying power of $V(t)$ at time t, the net energy request from the user is given by $u_t = \sum_{a \in \boldsymbol{A}} e_{a,t} - v_t$ at time t. Similar to most previous related works, we assume that the EMS receives from the utility company the price information and if necessary perform forecasting so that it is known for all $t \in \boldsymbol{T}$, and it is denoted by a known price function $P_t(u_t)$. Based on the price information, the EMS will attempt to optimize the load scheduling by minimizing the total cost $\sum_{t \in \boldsymbol{T}} P_t(u_t)$. For example in RTP model, we have $P_t(u_t) = p_t \cdot u_t$, where p_t is the unit price set by the utility company at time t.

Consequently, the DR optimization problem can be further refined as follows:

$$\min \quad \sum_{t \in \boldsymbol{T}} P_t(u_t) + \sum_{t \in \boldsymbol{T}} \sum_{a \in \boldsymbol{A}} C_a(\widetilde{e}_{a,t}) \tag{1a}$$

$$\text{s.t.} \quad u_t \geq \max\left\{0, \sum_{a \in \boldsymbol{A}} e_{a,t} - v_t\right\}, \quad t \in \boldsymbol{T}, \tag{1b}$$

$$0 \leq v_t \leq V(t), \quad t \in \boldsymbol{T}, \tag{1c}$$

$$L_{a,t}(\widetilde{e}_{a,t}) = 0, \quad a \in \boldsymbol{A}, \quad t \in \boldsymbol{T}, \tag{1d}$$

$$F_{a,t}(\widetilde{e}_{a,t}) \leq 0, \quad a \in \boldsymbol{A}, \quad t \in \boldsymbol{T}, \tag{1e}$$

where the constraint (1b) ensures that the electricity provided by the utility company at time t is always positive. Note that the above problem can alternatively be rewritten as a maximization problem, which optimizes the user's satisfaction $(-C_a(\widetilde{e}_{a,t}))$ minus the electricity cost $P_t(u_t)$, see [5] for example. For the sake of presentation, we will focus on the problem formulation in (1).

In the rest of the paper, we assume that the functions $P_t(\bullet)$, $C_a(\bullet)$ and $F_{a,t}(\bullet)$ are all convex so that the overall problem can be solved optimally using CP. In fact, the problem formulation is very general because the characteristics of most typical household appliances can be casted under this framework. Next, we will discuss the models of some typical appliances, with particular emphasis on SAs.

III. APPLICATION OF L1 REGULARIZATION TO SCHEDULE-BASED APPLIANCES

In conventional DR optimization problem, it is common to assume that the energy consumption $e_{a,t}$ of an appliance is a continuous variable which can be optimized to accommodate the user's need. This assumption fits nicely into the CP framework, such as the problem in (1). However, some appliances may not simply satisfy this assumption in the sense that $e_{a,t}$ only takes on discrete values. Taking the work in [6] as an example, the pool pump is required to run continuously at a fixed rating once it starts, but it has to shut down to save energy after its daily task is completed. Consequently, for such appliances, the

EMS needs to decide when it should start or shut down, rather than how much energy it consumes. As mentioned in Section II, we refer these types of appliances as SAs. In the presence of SAs, the problem in (1) would turn into a convex mixed integer nonlinear program (MINLP), which is known to be NP hard [12]. For general convex functions, solving a convex MINLP still poses a great challenge especially when the computational time is of great concern. Currently, state-of-the art commercial solvers such as CPLEX and MOSEK are capable of solving two important subclasses of convex MINLP, namely, mixed integer linear program (MILP) (i.e., when $P_t(\bullet)$, $C_a(\bullet)$ and $F_{a,t}(\bullet)$ are linear functions) and mixed integer second-order cone program (MISOCP) (i.e., when $P_t(\bullet)$, $C_a(\bullet)$ and $F_{a,t}(\bullet)$ are second-order cone functions). However, the restrictions of nonlinear functions involved and computational complexity may still limit appliances with general convex functions or constraints to be incorporated.

In what follows, we shall discuss the problem formulation involving SA-IL and SA-UL mentioned in Section II. For these two types of appliances, auxiliary binary decision variables are required for the EMS to determine their on/off statuses. To avoid the difficult convex MINLP, we will also discuss a L_1 regularization technique to get rid of the binary decision variables such that the original convex MINLP can be transformed into a standard CP problem. Therefore, the convexity of the problem in (1) can be maintained and its generality allows us to incorporate a wide variety of appliances that can be described by the convex characteristic functions and constraints.

A. Schedule-Based Appliance With Interruptible Load (SA-IL)

For the SA-IL, we assume that it only operates in either "on" or "off" statuses within a user's preferred time period $t \in [\underline{T}_a, \overline{T}_a] \subset \boldsymbol{T}$. In the former (latter) case, it consumes a fixed energy level of $E_a^{\max}$ ($E_a^{\min}$) at time $t \in [\underline{T}_a, \overline{T}_a]$. In other words, the EMS only needs to schedule when it is "on" or "off". Following the formulation considered in [3], the energy consumed by the SA-IL at time t can be expressed as

$$e_{a,t} = y_{a,t} E_a^{\max} + (1 - y_{a,t}) E_a^{\min}, \quad t \in [\underline{T}_a, \overline{T}_a]. \quad (2)$$

where $y_{a,t}$ is an auxiliary binary variable. From (2), we can see that $y_{a,t} = 1$ and $e_{a,t} = E_a^{\max}$ if the SA-IL is "on," and $y_{a,t} = 0$ and $e_{a,t} = E_a^{\min}$ if it is "off." Also, to fully complete its task, it has to be "on" for a certain period. Therefore, it is required that

$$\sum_{t=\underline{T}_a}^{\overline{T}_a} y_{a,t} = N_a, \quad (3)$$

where N_a denotes the total number of time slots for the SA-IL to complete its task and $N_a \leq \overline{T}_a - \underline{T}_a + 1$. Substituting (2) and (3) into the problem in (1) results in a convex MINLP with additional binary variables $y_{a,t}$.

To solve this difficult problem, we first relax the binary decision variable $y_{a,t}$ to a real-valued variable as

$$0 \leq y_{a,t} \leq 1, \quad t \in [\underline{T}_a, \overline{T}_a]. \quad (4)$$

Then, we add a characteristic function of the SA-IL to the problem as follows:

$$C_a(\widetilde{e}_{a,t}) = \sum_{t=\underline{T}_a}^{\overline{T}_a} w_{a,t} |y_{a,t}|, \quad (5)$$

where $\widetilde{e}_{a,t}$ symbolizes $y_{a,t}$ with the fact that it is related to the energy consumption $e_{a,t}$ as mentioned in Section II, and $w_{a,t}$ is a positive weight that specifies the importance of a time slot for the SA-IL to work in. For example, it is reasonable to assume that the earlier time slots are more favorable so that the task of the SA-IL can be completed as earlier as possible. Therefore, a possible setting of $w_{a,t}$ is to relate it with the time t as follows:

$$w_{a,t} = 1 + \varepsilon_a t, \quad (6)$$

for a positive constant ε_a. On the other hand, a typical value of ε_a is zero and hence $w_{a,t} = 1$ so that the electricity payment is the main concern as usual. Minimizing (5) means that the value of $y_{a,t}$ associated with the best schedule is enforced to be as large as possible, while keeping others as close to zero as possible. Consequently, the relaxation of (4) and the additional regularization term in (5) allow us to transform the difficult mixed integer problem back into a convex real-valued one.

It should be noted that the characteristic function defined in (5) is called weighted L_1 regularization term commonly considered in automatic model selection and sparse signal processing [13], [14]. The underlying principle of the proposed algorithm is to employ an interesting property of L_1 regularization, which is particularly useful to search over a large set of pre-defined distinct models and find the least number of features that best fits the data model. This is similar to the current household optimization problem with binary decision variables especially when we are able to identify all possible schedules of a particular appliance within the period of interest. Moreover, since these possible schedules are known in the current setting of finite and discrete time horizon, the L_1 regularization is very effective in finding the best schedule with respect to the price information, and the proposed problem formulation (without binary decision variables) is a reasonable approximation of the original mixed integer CP.

In the Appendix, we briefly analyze the behavior of the solution of the relaxed problem according to some classical analytic results of general L_1 regularized problem previously reported in [18]–[20]. Although the solution of the new optimization problem cannot be an exact binary solution, it does help us to identify those cost-effective schedules to solve the overall scheduling problem as we shall illustrate in Section V. The basic idea is to simply round the first N_a largest continuous variables $y_{a,t}$ to one while setting the others to zero. Very often, the solution so obtained is identical to or very close to the optimal CPLEX solution if MILP and MISOCP are considered. However, we note that CPLEX could run into memory problems for large-scale problems, and is unable to handle more general convex MINLP problem and therefore the types of appliances that can be included in the problem are somewhat limited. In short, for general convex MINLP problem, the proposed approach can be treated as a good alternative to CPLEX for finding the nearly optimal solution with a reduced computational time.

B. Schedule-Based Appliance With Uninterruptible Load (SA-UL)

Different from the SA-IL mentioned previously, the SA-UL should run until completion once started. According to [3], the configuration of SA-IL can be extended to SA-UL by imposing additional constraints on the energy consumption. More precisely, let $z_{a,t}$ be an additional auxiliary variable indicating that the SA-UL starts operation at time $t \in [\underline{T}_a, \overline{T}_a]$ if $z_{a,t} = 1$ and otherwise if $z_{a,t} = 0$. Also, let τ_a be the number of time slots that the SA-UL needs to operate at an energy level of $E_a^{\max}$ consecutively. Then, the additional constraints needed by the SA-UL can be written as

$$\sum_{t=\underline{T}_a}^{\overline{T}_a - \tau_a + 1} z_{a,t} = 1, \quad \text{and} \tag{7}$$

$$y_{a,t} \geq z_{a,t}, \ldots, y_{a,t+\tau_a-1} \geq z_{a,t}, \quad t \in [\underline{T}_a, \overline{T}_a]. \tag{8}$$

The constraint in (7) ensures that only one start time is allowed, while the constraints in (8) ensure that the SA-UL operates consecutively once it starts. Therefore, it is clear that the DR optimization problem involving the SA-UL is still a mixed integer problem with two types of binary decision variables, $y_{a,t}$ and $z_{a,t}$.

To avoid solving the mixed integer problem, one may again employ the same technique mentioned in (4) and (5) to $z_{a,t}$. However, we shall consider a more general scenario that better describes the property of the SA-UL, which has to follow a set of predefined operation steps. For example, the laundry machine cannot perform drying before washing. Let $E_a^o(t)$ be such known load profile for $t \in [0, \tau_a - 1]$. Similar to previous definition, the user needs to specify a preferred time period $t \in [\underline{T}_a, \overline{T}_a]$ with $\tau_a \leq \overline{T}_a - \underline{T}_a + 1$. Hence, there are $M = \overline{T}_a - \underline{T}_a - \tau_a + 2$ possible load schedules, which can be written as

$$E_{a,m}(t) = \begin{cases} E_a^o(t - \underline{T}_{a,m}), & t \in [\underline{T}_{a,m}, \underline{T}_{a,m} + \tau_a - 1], \\ E_a^{\min}, & otherwise, \end{cases} \tag{9}$$

for $m = 0, \ldots, M - 1$, where $\underline{T}_{a,m} = \underline{T}_a + m$ is the start time of the m-th schedule. For example, when $m = 0$, the SA-UL starts working at $t = \underline{T}_a$, and then follows the known load profile $E_a^o(t)$ until $t = \underline{T}_a + \tau_a - 1$. For other time instants in $t \in [\underline{T}_a, \overline{T}_a]$, the SA-UL consumes the minimum energy of $E_a^{\min}$. Using the above definition, the scheduling problem is to select the best schedule in the set $\{E_{a,m}(t), m = 0, \ldots, M - 1\}$, which depends on the price information within the user's preferred time period. We can see that the definition of SA-UL described in the first paragraph is a special case of (9) if we set $E_a^o(t) = E_a^{\max}$ for $t \in [0, \tau_a - 1]$. By combining all possible load schedules, the energy consumed by the SA-UL at time t can be written as

$$e_{a,t} = \sum_{m=0}^{M-1} \lambda_{a,m} E_{a,m}(t), \tag{10}$$

where $\lambda_{a,m} = 0, 1$ is the binary decision variable indicating that the schedule is selected when it is equal to one. To ensure that only one schedule is selected at a time, we further impose

$$\sum_{m=0}^{M-1} \lambda_{a,m} = 1. \tag{11}$$

Therefore, the energy consumption model in (10) is more general and has fewer numbers of binary variables than the one previously reported in [3]. Similar to the discussion in Section III-A, the binary variable $\lambda_{a,m}$ can be relaxed by introducing the constraint

$$0 \leq \lambda_{a,m} \leq 1, \quad m = 0, 1, \ldots, M - 1, \tag{12}$$

and the characteristic function

$$C_a(\widetilde{e}_{a,t}) = \sum_{m=0}^{M-1} w_{a,m} |\lambda_{a,m}|, \quad \text{with} \quad w_{a,m} = 1 + \varepsilon_a \underline{T}_{a,m}, \tag{13}$$

in the problem. Again, with (12) and (13), the DR optimization remains to be convex. As mentioned earlier, under this convex framework, other appliances whose characteristics are described by a general convex function can be easily incorporated into the formulation. One of the examples is the BAs that will be discussed in next section.

IV. MODELS OF OTHER COMMON APPLIANCES

The main purpose of this section is to illustrate the flexibility and versatility of the proposed approach in handling other common appliances found in the literature. As an illustration, we shall consider BAs and MAs as mentioned in Section II, whose characteristics are respectively described by a general convex function and a linear dynamical model. For simplicity, we shall only summarize their major properties and constraints based on the considerations reported in [5].

A. Battery-Assisted Appliances (BAs)

In addition to the above two types of household appliances, we now consider a type of appliances called BAs which are equipped with internal batteries. An important advantage of BAs is its ability to store or dispatch energy to better utilize the intermittent renewable energy sources, and improve the demand response to RTP information. Without loss of generality, we assume that each BA contains one internal battery. At any time t, the energy that flows into and out of a BA can be separated into two parts: the first part is the required energy consumption $E_a(t)$ to support the desired service, while the second part is the battery charging/discharging energy $b_a(t)$. Note in the latter that the battery can be considered as charging (discharging) when $b_a(t) > 0$ ($b_a(t) < 0$). Hence, the total energy consumed by the BA is

$$e_{a,t} = E_a(t) + b_a(t). \tag{14}$$

For the energy consumption part, we further assume that the BA is equipped with direct control demand response up to $E_a(t) =$

$(1 - d_{a,t})E_a^{\max}$ at time t, where $d_{a,t}$ is a continuous variable that specifies the energy reduction in response to the price information with the following the bound constraints

$$0 \le d_{a,t} \le D^{\max}, \quad t \in \boldsymbol{T}. \tag{15}$$

However, it is clear that the user will feel uncomfortable if the energy used by the BA (and hence performance) is reduced too much. Therefore, we also include in the objective function the following convex welfare or characteristic function to measure the users' dissatisfaction at a level of $d_{a,t}$:

$$C_a^{(d)}(d_{a,t}) = \lambda_1(D^{\max} - d_{a,t} + \lambda_2)^{-\lambda_3}, \tag{16}$$

where λ_1, λ_2, and λ_3 are positive constants. It can be seen that λ_1 specifies its relative importance with respect to the price level, and λ_2 and λ_3 specify the degree of tolerance on the energy saving.

For the battery model, we adopt the model recently proposed in [5]. First, the battery charging/discharging energy is bounded by

$$\underline{R}_{a,t} \le b_{a,t} \le \overline{R}_{a,t}, \quad t \in \boldsymbol{T}, \tag{17}$$

where $\underline{R}_{B\_i} < 0$ $(\overline{R}_{B\_i} > 0)$ denotes the maximum charging (discharging) rate. Second, the total charge stored in the battery is bounded by

$$0 \le B_a^{ini} + \sum_{k=1}^{t} b_{a,k} \le B_a^{\max}, \quad t \in \boldsymbol{T}, \tag{18}$$

where B_a^{ini} is the initial charge remained and $B_a^{\max}$ is the maximum capacity of the battery. Third, the following operating cost function is used to model the possible damage against the battery's lifetime:

$$C_a^{(b)}(b_{a,t}) = \eta_{a,1}b_{a,t}^2 - \eta_{a,2}b_{a,t}b_{a,t+1}$$
$$+\eta_{a,3} \min\left(b_{a,t} - \eta_{a,4}B_a^{\max}, 0\right)^2, \tag{19}$$

where $\eta_{a,k}$, $k = 1, 2, 3, 4$, are positive constants. These three terms penalize the fast charging/discharging, the charging/discharging cycles and the deep discharging, respectively [5]. Note $C_a^{(b)}(b_{a,t})$ is a positive convex function if $\eta_{a,1} > \eta_{a,2}$. Using the above results, the resultant characteristic function of the BA is given by

$$C_a(\tilde{e}_{a,t}) = C_a^{(d)}(d_{a,t}) + C_a^{(b)}(b_{a,t}), \tag{20}$$

while the set of the convex constraints consists of (15), (17) and (18). We can see from (20) that the characteristic function $C_a(\tilde{e}_{a,t})$ is a general convex function so that existing commercial MILP or MISOCP solvers may not be directly applicable. Alternatively, one may use heuristic algorithms (e.g., PSO algorithm used in [6]) to solve the problem, but it is known that they may easily suffer from premature convergence, which may affect the reliability and quality of the solution. Finally, we note that the BAs have not been discussed in the literature to our best knowledge despite the fact that it can be easily found in the household nowadays.

B. Model-Based Appliances (MAs)

The MA considered in this section summarizes the appliances previously reported in the literature, such as [5], [6], [8], [10]. Typical examples of this type of appliances include air-conditioners, heaters and refrigerators, in which the temperature can be adjusted by the amount of electrical energy consumed. In general, the service offered by the MA can usually be described by a physical model or more precisely a linear dynamic model that expresses the relation between energy consumption, desired qualities to be controlled and other physical quantities which can be measured or estimated. Without loss of generality, we shall take the air-conditioner previously reported in [5] as an example to demonstrate the flexibility of the proposed CP framework. To start with, let $W^{in}(t)$ be the indoor temperature adjusted by the air-conditioner. The relation between the indoor temperature and the energy consumption $e_{a,t}$ can be expressed as the following linear dynamical model:

$$W^{in}(t) = W^{in}(t-1) + \alpha\left[W^{out}(t) - W^{in}(t-1)\right] + \beta e_{a,t} \tag{21}$$

where α and β denote the thermal condition surrounding the air-conditioner, $W^{out}(t)$ is the outdoor temperature, and $W^{in}(0)$ is a known initial room temperature. Moreover, additional constraints can be imposed on $e_{a,t}$ to specify its possible operating range and associated temperature range as

$$E_a^{\min} \le e_{a,t} \le E_a^{\max} \quad \text{and} \quad \underline{W}^{des} \le W^{in}(t) \le \overline{W}^{des}, \tag{22}$$

where $\underline{W}^{des}$ and $\overline{W}^{des}$ denote the minimum and maximum desired temperature, respectively. In addition to the energy consumption, it is natural to measure the user's dissatisfaction in term of the indoor temperature $W^{in}(t)$ that is directly perceived by the user. More precisely, the following convex characteristic function may be used:

$$C_a(\tilde{e}_{a,t}) = c_1\left(W^{in}(t) - W^{comf}\right)^2 - c_2, \tag{23}$$

where c_1 and c_2 are some positive constants and W^{comf} denote the most comfortable temperature decided by the user. We can see that deviation from W^{comf} will incur penalty to the objective function.

In summary, the proposed convex programming framework is very general, and it is easy to extend to other typical household appliances. Due to page limitation, the details are omitted here. The overall convex optimization problem is summarized in Table I, where we highlight key equations related to the characteristic function and the set of convex constraints for all types of appliances considered in this paper, namely SA-UL, SA-IL, BAs, and MAs.

TABLE I
KEY EQUATIONS FOR THE DR OPTIMIZATION PROBLEM IN (1) INVOLVING
DIFFERENT TYPES OF APPLIANCES. N/A: NOT APPLICABLE

Appliance	Energy consumption	Characteristic function	Convex inequality	Linear equality
SA-IL	(2)	(5)	(4)	(3)
SA-UL	(10)	(13)	(12)	(11)
BA	(14)	(20)	(15), (17), (18)	N/A
MA	(21)	(23)	(22)	N/A

V. DESIGN EXAMPLE

A. Linear Price Model

As an illustration, we consider a smart home shown in Fig. 1, where the EMS system is used to schedule the operation of four types of appliances in one-day time horizon with $T = [1, 2, \ldots, 24]$ after receiving the RTP information from utility company. If the RTP changes in day time, the scheduling can be updated at regular interval, say 1 hour or more. Fig. 2 shows the RTP information which will be used in this example. The parameters of different appliances used in the simulation are summarized as follows:

a) SA-IL: It is allowed to run at anytime between $\underline{T}_a = 9$ and $\overline{T} = 23$. Its task is considered to be completed if it operates at maximum power for $N_a = 3$ hours. The minimum and maximum working rate are $E_a^{\min} = 0.2$ kwh and $E_a^{\max} = 1.5$ kwh respectively.

b) $SA - UL_1$: It has a constant load profile of $E_a^o(t) = [1 \text{ kwh}, 1 \text{ kwh}, 1 \text{ kwh}, 1 \text{ kwh}]$ with a duration of $\tau_a = 4$, and the minimum working rate is $E_a^{\min} = 0.2$ kwh when it is "off." It has to run in a user-defined time interval of $[\underline{T}_a, \overline{T}_a] = [12, 22]$.

c) $SA - UL_2$: Different from $SA - IL_1$, it has to satisfy a variable load profile of $E_a^o(t) = [0.8 \text{ kwh}, 1.6 \text{ kwh}, 1.1 \text{ kwh}]$ with a duration of $\tau_a = 3$ in a user-defined time interval of $[\underline{T}_a, \overline{T}_a] = [1, 18]$, while the minimum working rate is $E_a^{\min} = 0$ kwh.

d) BA: It has to run for whole day. For the energy consumption part, the maximum working rate is $E_a^{\max} = 2.3$ kwh and the maximum direct control demand response is $D^{\max} = 0.2$. For the battery part, the maximum charging and discharging rates are 0.25 kwh, the storage capacity is $B_a^{\max} = 0.8$ kwh, and the parameters in (19) are given by $\eta_{a,1} = 5e^{-7}$, $\eta_{a,2} = 4e^{-7}$, $\eta_{a,3} = 1$ and $\eta_{a,4} = 0.2$.

e) MA: An air-conditioner is considered. According to the reference settings given in [5], we set $W^{comf} = 75$ F, $\underline{W}^{des} = 70$ F, $\overline{W}^{des} = 79$ F, $\alpha = 0.9$, $\beta = -0.0095$, $E_a^{\min} = 0$ kwh, $E_a^{\max} = 4$ kwh, $c_1 = 0.1$ and $c_2 = 0.1$. An example outdoor temperature $W^{out}(t)$ used in the simulation is shown in Fig. 2. The operation interval is $[\underline{T}_a, \overline{T}_a] = [8, 23]$.

We also assume that the smart home is equipped with a solar energy panel, which can deliver a maximum power of $V(t) = 0.2$ kwh at the time interval of [7,18].

All the convex problems considered below are solved using CVX, a package for specifying and solving convex programs [16]. It takes less than few seconds to obtain the solutions in a Pentium 4 3.2 GHz personal computer.
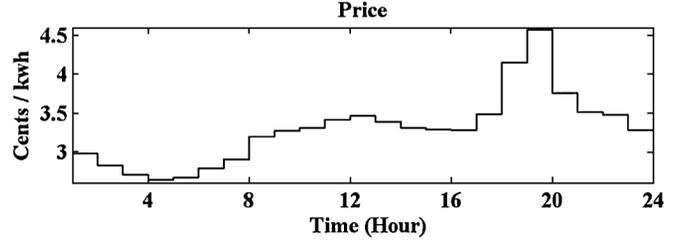
Fig. 2.   Real-time pricing information received from the utility.
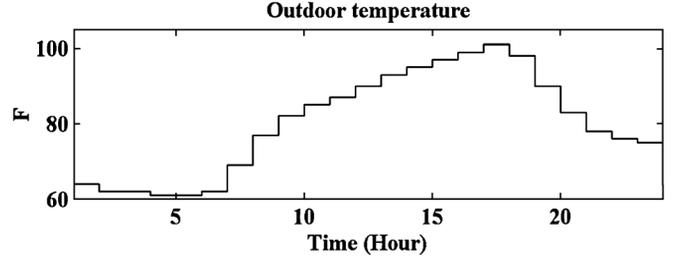
Fig. 3.   Outdoor temperature over a day.

First of all, we consider a scenario that the smart home only consists of SA-IL and SA-UL. The resulting DR optimization problem is a MILP, which can be solved by CPLEX if one takes the binary decision variables in (2), (3), (7), (8), (10), and (11) into account. On the other hand, we also consider the proposed CP formulation by relaxing the MILP as described in Sections III-A and III-B. The key equations of the proposed CP formulation for the SA-IL and SA-UL can also be found in Table I. With the parameters of SA-IL and SA-UL mentioned earlier, the continuous solution of the proposed CP is very close to the binary solution of the MILP. Even without rounding it to the closest binary number, one can easily identify the same schedule as the binary MILP solution indicates. As discussed in Section III-A, this is possibly due to the fact that all the possible schedules of the SAs can be pre-determined exactly and hence the problem becomes a model selection problem which can be handled well by the L_1 regularization. This suggests the usefulness of the proposed approach.

However, we note that if BA and MA are also incorporated into the DR optimization problem, the resulting MINLP cannot be solved by CPLEX. Fig. 4 shows electricity allocation of all appliances in the smart home in response to real-time price obtained by the proposed CP framework. In particular, we can see that: a) the operation times of the SA-UL is always chosen at the lowest price levels, and the corresponding continuous decision variables in (4) are all close to one thanks to the L_1 regularization term, b) similar arguments of the SA-UL hold for both SA-ILs, in which the decision variables corresponding to the best schedules can be easily singled out, c) the BA tends to consume more power and its internal battery is charged up in the case of lower price or vice versa, and d) the operations of all appliances are well coordinated to reduce the total energy consumption and avoid the peak prices at $t = 18$ and $t = 19$.

B. Quadratic Price Model

In this subsection, we consider a quadratic price model which is of the form $P_t(u_t) = g_t u_t^2 + p_t u_t$. For the sake of comparison with CPLEX, we only consider SA-ILs so that the overall
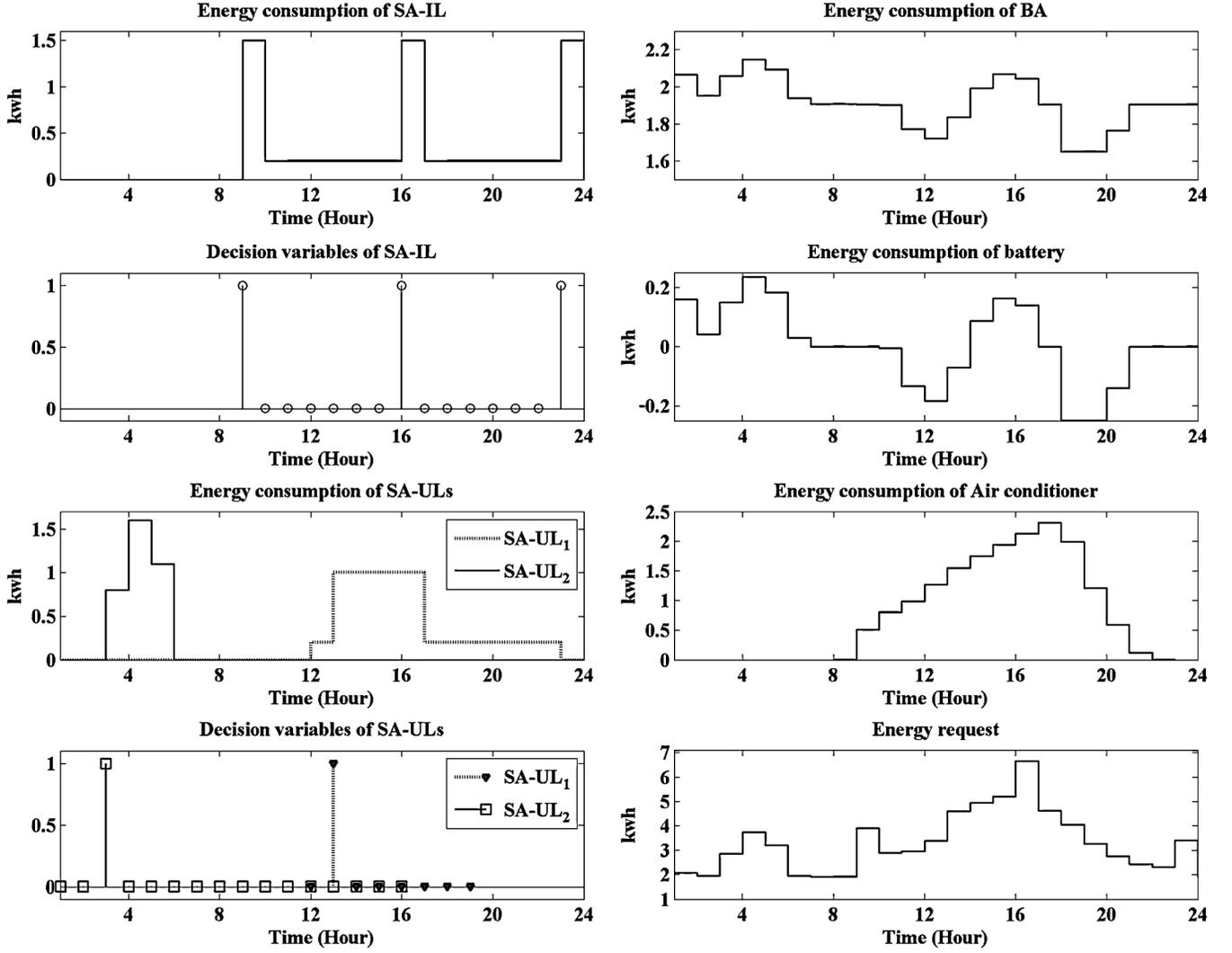
Fig. 4. Electricity allocation of various appliances in the smart home under real-time pricing.

problem belongs to MISOCP, which can be solved optimally by CPLEX. The solution obtained from CPLEX will therefore be used as benchmark to quantitatively assess the performance of the proposed and other approaches. To apply the proposed approach to solve the above problem, the binary decision variables are first relaxed as suggested in Section III. Three different approaches will be considered: 1) weighted L_1 norm as proposed, 2) weighted L_2 norm, and 3) no norm constraint. Then, the actual binary solution is obtained by rounding the first N_a most significant variables to one, while setting the others to zero. The general settings are summarized as follows:

a) The number of SA-ILs is 5, 10, or 15. For each configuration, the simulation is repeated 200 times.

b) The possible operation time interval $[\underline{T}_a, \overline{T}_a]$ is randomly generated such that $1 \leq \underline{T}_a < \overline{T}_a \leq 24$, and the number of time slots N_a is randomly generated such that $N_a \in [1, \overline{T}_a - \underline{T}_a]$.

c) The minimum and maximum working rates are randomly chosen from [0.1 kwh, 3 kwh] such that $0.1\,\text{kwh} \leq E_a^{\min} < E_a^{\max} \leq 3\,\text{kwh}$.

d) The quadratic price function $P_t(u_t) = g_t u_t^2 + p_t u_t$ is considered, where p_t is identical to Fig. 2, while g_t is

randomly generated according to the magnitude of p_t so that g_t follows a similar curvature of p_t.

e) The weight parameters for both weighted L_1 and L_2 algorithms are given by $w_{a,t} = 1 + 10^{-4}t$ as in (6).

The performances of various approaches are assessed using the relative difference with respect to the optimal CPLEX solution:

$$R^{(i)} = \frac{C^{(i)} - C}{C} \times 100\%,$$

where C denotes the total cost obtained by CPLEX and $C^{(i)}$, $i = 1, 2, 3$, denote the total cost obtained by approaches 1, 2, and 3. This measures the deviation of the solution away from the optimal one. Fig. 5 shows the simulation results for 5, 10 and 15 SA-ILs. We can see that the solutions of approaches 2 and 3 are more or less the same and they result in larger deviation as compared with the proposed approach. Unlike L_1 regularization, these solutions indicate a more even spread across all variables, and hence it is more difficult to identify the most effective solution. On the other hand, the proposed approach always offers a good solution that is close to the optimal one. The deviation is usually within 1% and at times the optimal schedule
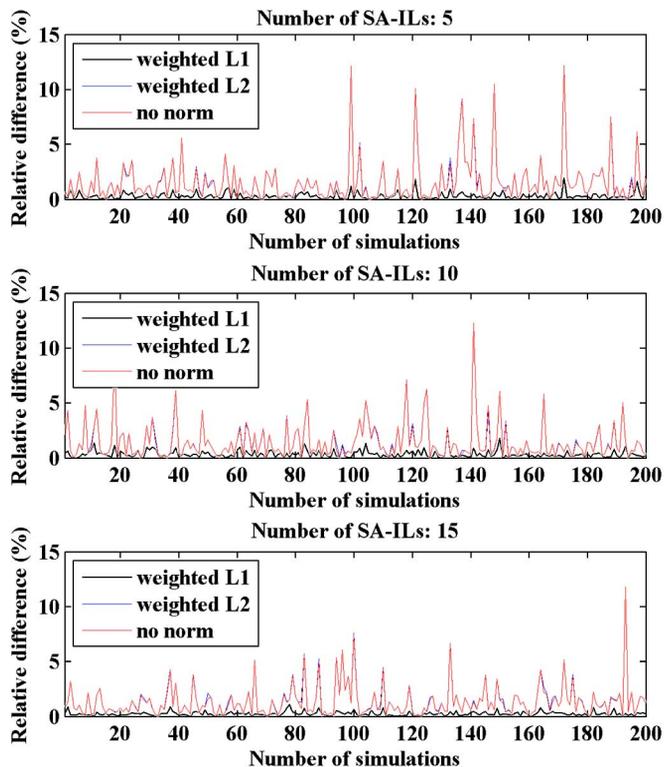
Fig. 5. Demand response optimization in a smart home through a home energy management system (EMS).

(i.e., 0% deviation) can be found. Also, we note that CPLEX occasionally ran into memory problems as the number of SA-ILs exceeds 20. This suggests that CPLEX may not be very efficient to handle large number of binary variables as in the proposed approach. Moreover, CPLEX is unable to handle general convex MINLP problem, which restricts the types of appliances incorporated in the problem. To verify the capability of the proposed approach, we repeat the above simulation, but consider a more general convex MINLP problem in which other types of appliances mentioned in Section V-A are additionally included. Simulation results again suggest the superiority of the proposed approach in finding better schedules than other norm regularizations. However, the results are omitted due to page limitation. In summary, the proposed approach can be considered as a good alternative to CPLEX and is very efficient in handling large-scale appliance scheduling problem in home EMS.

VI. CONCLUSION

We have proposed a versatile CP DR optimization framework for the automatic load management of various household appliances in a smart home. Also, we have shown that the start-up decisions of SAs, which unavoidably lead to mixed integer problem formulation conventionally, can be handled efficiently under the CP framework using the concept of L_1 regularization. Considering the characteristics of most typical appliances can be described by convex functions, our finding is very useful in the sense that traditional CP DR optimization framework can be readily extended to support a wider variety of appliances. Simulation result shows that the energy scheduling of SAs, as well as other appliances, such as BAs and

MAs, can be determined simultaneously using the proposed CP formulation.

Finally, we note that the current framework can be extended to handle multiple household scenarios say using a similar idea proposed in [5], which is concerned with a distributed algorithm based on CP. In particular, it showed that the utility and customers can cooperate to jointly compute the price level and demand schedule by iteratively updating the solution of their individual problems. Since each household needs to carry out a similar convex optimization problem in each iteration, we expect that the proposed framework can still be applied to additionally handle the energy scheduling of SAs. Due to page limitation, the comprehensive analysis of the resulting optimization problem is left in future work.

APPENDIX
CHARACTERISTICS OF THE SOLUTION OF THE RELAXED PROBLEM

As mentioned in Section III, the problem under consideration is more like a feature selection problem, where the usefulness of the L_1 regularization has been thoroughly justified in the literature [18]–[20]. Conventionally, the basic regularized problem is given by

$$\min_x \quad L(x) + \lambda J(x), \qquad (24)$$

where $L(x)$ is the loss function, $J(x)$ is the regularization term and λ is the regularization parameter. In [18], Osborne *et al.* made a detailed analysis on the L_1-regularized least squares problem, also known as Lasso, where $L(x)$ represents a squared error loss and $J(x) = \|x\|_1$. Later in [19], Rosset extended to the case where $L(x)$ can be any convex function. In what follows, we only summarize the major results that are related to our problem involving L_1 regularization, i.e., our main focus is on schedule-based appliance. First of all, the Karush-Kuhn-Tucker (KKT) condition of the L_1 regularized problem suggests that [19]:

$$\begin{cases} |\nabla L(x)_n| < \lambda \Rightarrow x_n = 0, \\ x_n \neq 0 \Rightarrow |\nabla L(x)_n| = \lambda. \end{cases}$$

This also implies that the properties of the problem include: a) $|\nabla L(x)_n| = \max_k |\nabla L(x)_k|$ and b) $sign(x_n) = -sign(\nabla L(x)_n)$ when $x_n \neq 0$ [20]. In other words, the solution of the problem tends to contain a set of nonzero coefficients, which corresponds to the variables whose "generalized correlation" (or sub-gradient magnitude) $|\nabla L(x)_n|$ is maximal. The remaining variables with smaller generalized correlation can be set to zero without violating the optimality condition. Thus, the solution enhances sparsity and in our case, the L1 regularization helps to focus on possible schedules that lead to largest cost reduction. To see this, if only SA is considered, the general form of our problem

$$\min_y \quad P(y) + \sum_t w_t |y_{a,t}|$$
$$s.t. \quad 0 \leq y_{a,t} \leq 1 \text{ and } \sum_t y_{a,t} = N_a$$

is similar to (24) except for the additional constraints. Here, we collectively express the total cost function as $P(y)$ with

$y = \{y_{a,t} | a \in \boldsymbol{A}, t \in \boldsymbol{T}\}$ for simplicity. From the analytic results above, we can deduce that the variable y_{a,t^*} associated with the largest cost reduction at time $t = t^*$ will always be selected. With the constraints $0 \leq y_{a,t} \leq 1$ and $\sum_t y_{a,t} = N_a$, the variable y_{a,t^*} will approach one and the other variable associated with the second largest cost reduction will be selected next. Similar argument can be repeated until the constraint $\sum_t y_{a,t} = N_a$ is satisfied. However, it may happen that the constraint $0 \leq y_{a,t} \leq 1$ is not active especially when $P(y)$ is a general convex function. Nevertheless, according to the analysis above, the larger magnitude of the resultant $y_{a,t}$ will indicate the importance of the direction towards the larger cost reduction. Therefore, the solution of the proposed relaxed problem can still be used to find the significant variables.

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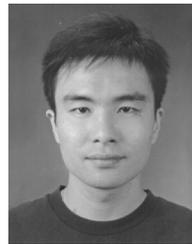
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