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Appliance Operation Scheduling for Electricity Consumption Optimization

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***Abstract*— This paper concerns the problem of optimally scheduling a set of appliances at the end-user premises. The user's energy fee varies over time, and moreover, in the context of smart grids, the user may receive a reward from an energy aggregator if he/she reduces consumption during certain time intervals. In a household, the problem is to decide when to schedule the operation of the appliances, in order to meet a number of goals, namely overall costs, climatic comfort level and timeliness. We devise a model accounting for a typical household user, and present computational results showing that it can be efficiently solved in real-life instances.**

I. INTRODUCTION

The advances of information technologies and the increased accessibility of renewable energy resources to end users have triggered new concepts in electricity power distribution and consumption. One such new concept is *Active Demand* (AD), which has been introduced in the context of the European project ADDRESS. The key idea is that the end users play an active role in the electricity distribution process, adjusting their consumption patterns depending on the dynamics of the energy markets.

Since individual consumers do not have direct access to the energy market, a new intermediary subject, the *aggregator*, is needed to coordinate the consumers' behavior with the market. Each aggregator has a pool of subscribers (end users), and is able to send them *price-volume signals* in order to affect their consumption pattern. These signals essentially consist in specifying a monetary reward (price) if power consumption, during certain hours of the day, is below specified thresholds (volume). Since consumers have a certain degree of flexibility, they might find it convenient to schedule certain tasks (e.g., running an appliance) so that they obtain the reward, actively contributing to the overall reduction of carbon dioxide production.

In this way, over specified time intervals the aggregator collects a certain amount of energy, i.e., the energy saved by a number of end users accepting the aggregator's offer. This energy can be used for several purposes. For instance, the DSO (Distribution System Operator) may ask an aggregator to enforce energy reduction in a given load area over a given time interval, if an overload is foreseen in that area, in order to counteract possible network unbalancing. Another reason for the aggregator to collect energy is that he has sold options for providing a certain amount of energy, and the option holder has now decided to exercise the option. Or, the aggregator can simply strive to gather energy during the time slots in which the market energy price is higher in order to sell the energy, possibly sharing part of the revenue with the users (the reward).

The aggregator interfaces with the end user through a device called *Energy Box* (EB). Devices of this type have started being installed in many houses, and their role is to manage and optimize electrical consumption. On one side, the EB receives information from the aggregator, and on the other side from the end user, specifying his/her own preferences. The EB also retains information on consumption characteristics of the appliances installed in the household, energy price paid to the retailer, and possibly other information related to forecasting energy consumption (see Section III).

Actually, the need for appropriately managing electrical loads exists even outside the framework of active demand. However, the savings opportunity offered by the aggregator and the variety of signals that, in principle, can be sent to the end users can result in a very complex scheduling problem, which has therefore to be tackled by an appropriate model and algorithm.

In this paper we focus on the problem faced by the end user, who will adjust his/her daily consumption schedule to account for the current calling plan as well as the signal(s) sent by the aggregator. Clearly, the profitability and the feasibility of an offer to an end user may depend on several issues, depending on the end user's own preferences and needs, the types of appliances installed at the user's premises and on the possibility of generating and/or storing energy in-house. Here we propose a mathematical programming approach which can be viewed as a support tool for the end user, integrating personal preferences and technical information and constraints. The very same approach can be used for a variety of end users, such as households or industrial users. However, for the sake of clarity and since this is the main focus of the ADDRESS project, from now on we refer to domestic users.

The problem of domestic energy management has gained increasing interest in the last years due to the evolution of the current energy grid into a 'smart grid', which accounts for a direct involvement of end-users in the energy management. This paradigm requires setting up a control scheme of residential loads, which typically consists of a local energy management unit, possibly coordinated with the smart meter ([1]). Some approaches proposed in the literature focus on load shedding only ([1], [2]) — thus neglecting possible load shifting; these authors formulate

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an optimization problem aiming at balancing electricity costs and end user's comfort through a stochastic dynamic programming approach; however, they limit their analysis to temperature control and battery management, including the option to sell back energy to the grid. Other research studies ([3], [4]) formulate an optimization problem to find a trade-off between cost reduction and minimization of the waiting time for starting the appliances. They also propose a distributed scheme based on game theory for coordination of a set of end-users; in this case, the minimization of the peak-to-average ratio is included for the overall area. [5] also propose a simulation study accounting for peak demand reduction for both single houses and a neighborhood; the dynamic programming approach proposed focuses on cost minimization of one appliance at a time, including penalties for delayed starting. With respect to most of these papers, one distinctive feature of our model is that we let the user specify (and possibly modify over time) the relative importance (to him/her) of the various objectives.

In [6], a constraint satisfaction formulation is presented and a sub-optimal algorithm, based on tabu search, is proposed for a household energy management problem. The problem is similar to that addressed in this paper. However, our model, based on a mathematical programming formulation, allows to optimally and efficiently solve real-life instances of the problem.

II. THE EBOX SCHEDULING PROBLEM

In this section we describe the household energy consumption optimization problem. As already outlined in the previous section, our prototypical consumer acts in a smart grid framework, in which a new player of the energy market, the Aggregator, communicates AD requests via the EB.

Domestic power consumption is due to a number of electrical *loads*, which can be roughly divided into *manageable* and *non-manageable*.

Manageable loads can be characterized in terms of a certain consumption cycle, i.e., the specification of the energy consumption profile over time. For instance, the *delicate* program of a given washing machine is characterized by a duration and a certain power consumption profile throughout the program. It can therefore be viewed as a (nonpreemptive) *task* which should be scheduled within certain time limits, specified by the end user and more or less strict depending on user's preferences. Manageable loads can be further divided into *adjustable* loads, which can be altered by directly modifying their actual energy consumption (e.g. air conditioning), and *shiftable* loads, whose working cycle can be shifted in time (e.g. the washing machine). The devices corresponding to manageable loads are assumed to be "smart", i.e., they are able to exchange signals and information with the EB. Adjustable loads correspond to *Type 1 devices*, which can be driven by modifying their power absorption (e.g., air conditioning or devices controlled through "smart plugs"); whereas shiftable loads correspond to *Type 2 devices*, which can be programmed by the consumer and, when the delayed start command is set, send the EB complete information about their working cycle.

Other types of loads are inherently non-manageable, i.e., they are continuously run and little can be done to reduce or re-schedule them. Examples of these loads are the refrigerator or the lighting. The corresponding devices do not directly exchange information with the EB.

In addition, the user may have distributed generators, such as solar panel or micro-CHP, and storage devices, such as batteries used as energy buffers.

Our model addresses decisions concerning manageable loads, but it takes into account the availability of other resources as well as a forecast pattern for non-manageable loads. Coherently with the ADDRESS framework, the consumer does not have to explicitly respond to each AD requests, nor is the consumer asked to set up each appliance in order to satisfy the related consumption conditions. Rather, the EB is in charge of these functions, which controls the "smart appliances" taking into account the preferences specified by the user. The consumer will physically program the appliances via "delayed start" commands, which correspond to allowing the EB schedule their work cycle. Then, the EB solves the optimization problem and prompts the consumers to commit to the computed schedule.

Since in this framework non-manageable loads play the same role of disturbances, knowledge about their power absorption over time is needed, so that the EB can properly arrange smart appliances. We assume that an estimate of non-manageable load consumption (for each 15-minute time slot) is available. This type of information can either be provided by a direct link between EB and meter (if allowed by contractual and technical constraints), or by the aggregator. In any case, uncertainty about the actual household consumption due to non-manageable appliances still remains and it has to be treated as a disturbance.

The EB is called to schedule manageable loads in order to maximize the *utility function* of the user. In our model, such function encompasses three different criteria:

- *cost minimization* – this is pursued by exploiting the differences among retailer energy prices over time and the aggregator's proposals;
- *maximization of climatic comfort* – this is assumed to be directly related to the consumption of Type 1 devices, either it be air conditioning or electric heating;
- *scheduling convenience* – this is expressed by specifying preferred starting and ending times of working cycles for Type 2 devices.

The relative weight to be given to the three above objectives is specified by the user's preferences. A money-aware user will put more weight on objective 1, a comfort-seeking user will privilege objective 2 etc.

Summarizing, the *EB Scheduling Problem* (EBSP) can be stated as follows. Given:

- price/volume signals received from the aggregator
- the selected working cycles of Type 2 devices
- the forecast consumption pattern of non-manageable loads

- the user's settings, including desired home temperature and desired limits on starting and ending times of Type 2 appliances
- forecast external temperature (if air conditioning or heating is present)
- storage device (battery) charge level
- contractual issues (upper bound on power absorption from the network, hourly energy price paid to the retailer etc)
- other possible technical constraints (e.g. the impossibility to inject energy into the power grid)

compute an overall consumption schedule, i.e.

- the prescribed start time of Type 2 devices
- the amount of power to be used during each time slot to control Type 1 devices (e.g. air conditioning)
- the charging/discharging profile for storage devices

so that the user's utility function, as specified by the user's preferences, is maximized.

In the next section, the mathematical formulation of EBSP is presented in terms of a mixed-integer linear program.

III. The optimization model for EBSP

In this section, a Mixed Integer Linear Programming (MILP) formulation is presented for EBSP. To this aim, assumptions and notation useful to formally describe EBSP are first introduced.

We assume that the scheduling time horizon (typically, one day) is divided into a set of time slots $T = \{1, \dots, t_{tot}\}$, each of duration Θ (e.g. one day divided into $t_{tot} = 96$ slots, corresponding to time slots of $\Theta = 15$ minutes =0.25 hours). Let $N = \{a_1, \dots, a_n\}$ be the set of the Type 2 devices (also called appliances in the following), whose starting times can be directly controlled by the EB (e.g., dishwasher, washing machine, etc.). Each appliance $a_i \in N$ is characterized by a working cycle. Let D_i be the length, in terms of number of time slots, of the working cycle of appliance a_i. For each time slot $s = 1, \dots, D_i$, let $\Pi_{i,s}$ be the power consumption (in kW) of appliance a_i in the s-th time slot of the working cycle. Power consumption is supposed to be constant within one time slot (possibly, this is obtained as the average consumption during that time slot). The end-user may specify how desirable it is for him/her to run an appliance throughout the time horizon. Let $\sigma_{i,t} \in \{1, 2, 3, 4, 5\}$ be a conventional coefficient expressing how desirable is that appliance $i \in N$ starts in time slot t (1 and 5 indicating highest and lowest desirability respectively). Manageable loads include an air conditioning system (AC), characterized by a desired value of the house internal temperature (set by the user) in each time slot $t \in T$, denoted as T_t^{set}.

Regarding non-manageable loads, i.e., the devices which are not directly controlled by the EB, let P_t^{NM} be the power absorbed (kW) by the non-manageable appliances in time slot $t \in T$.

We also consider distributed generators, such as photovoltaic cells, and a storage system for the produced energy (e.g., a battery used as a buffer). In this context, let BI_t be the forecasted battery input (kW), coming from photovoltaic panels in time slot t.

The aggregator proposals are modeled as price-volume signals sent to the end-user. The user gets the reward (e.g., Euro) R_t^{red} (R_t^{inc}) from the aggregator if the power drawn from the network in time slot t is less (greater) than or equal to V_t^{red} (V_t^{inc}).

For each time slot $t \in T$, there is an upper limit on power consumption, according to the contract with the retailer. Let M_t and Ψ_t respectively be the maximum power (kW) that can be drawn from the net and the price of energy (e.g., Euro/kWh) in time slot t.

Our mathematical model makes use of a number of forecasts. One is the forecasted non-manageable load (that can be computed on the basis of historical data), another is the weather forecast. The latter allows the Ebox to have information on external temperature (during each time slot) as well as on the amount of energy coming from the distributed generators (e.g., photovoltaic cells) that is likely to be input (and stored in the battery) in the various time slots.

The following decision and auxiliary variables are employed in the optimization model.

- x_{it} an integer variable equal to 1 if the appliance i starts at slot t and 0 otherwise.
- y_t an integer variable equal to 1 if the reduction proposal of the aggregator is accepted in slot t and 0 otherwise.
- z_t an integer variable equal to 1 if the increase proposal of the aggregator is accepted in slot t and 0 otherwise.
- w_t the power (kW) drawn from the network in time slot t.
- p_t^{AC} the power absorbed (kW) by the AC system in time slot t.
- p_t^M the power absorbed (kW) by the other manageable appliances in time slot t (AC is excluded).
- bl_t the battery level (kWh) in time slot t.
- bo_t the battery output (kW) in time slot t.
- T_t^H the internal house temperature in time slot t.
- T_t^{gap} the absolute deviation between the desired and the actual house temperature in time slot t.
- T_{max}^{gap} the maximum value attained by variables T_t^{gap}, for $t \in T$.

A MILP formulation for EBSP is the following.

$$\max \alpha_1 \sum_{t\in T}(R_t^{red} y_t + R_t^{inc} z_t - \Theta \Psi_t w_t) + \alpha_2 \sum_{t\in T}\sum_{a_i\in N} \sigma_{it} x_{it} - \alpha_3 \sum_{t\in T} T_t^{gap} - \alpha_3 T_{max}^{gap} \quad (1)$$

subject to

$$\sum_{t\in T} x_{it} = 1 \;\; \forall a_i \in N \quad (2)$$

$$\sum_{a_i\in N}\sum_{s=1}^{D_i} \Pi_{is} x_{it} = p_t^M \;\; \forall t \in T \quad (3)$$

$$w_t \leq V_t^{red} y_t + M_t(1-y_t) \;\; \forall t \in T \quad (4)$$

$$w_t \geq V_t^{inc} z_t \;\; \forall t \in T \quad (5)$$

$$bl_t \leq bl_{t-1} + \Theta(BI_t - bo_t) \;\; \forall t \in T \quad (6)$$

$$bl_t \leq BL^{max} \;\; \forall t \in T \quad (7)$$

$$T_t^H = T_{t-1}^H - \beta(T_t^H - T_t^E) - \gamma p_t^{AC} \;\; \forall t \in T \quad (8)$$

$$T_t^H - T_t^{set} \leq T_t^{gap} \;\; \forall t \in T \quad (9)$$

$$-T_t^H + T_t^{set} \leq T_t^{gap} \;\; \forall t \in T \quad (10)$$

$$T_t^{gap} \leq T_{max}^{gap} \;\; \forall t \in T \quad (11)$$

$$p_t^M + p_t^{AC} + P_t^{NM} = bo_t + w_t \;\; \forall t \in T \quad (12)$$

$$x_{it}, y_t, z_t \in \{0,1\} \;\; \forall t \in T \quad (13)$$

$$p_t^M, p_t^{AC}, bo_t, bl_t, w_t, T_t^H, T_t^{gap} \geq 0 \;\; \forall t \in T \quad (14)$$

The objective function (1) takes into account the three sensible terms introduced in the previous section, i.e.: overall energy costs (i.e., $\sum_{t\in T}(R_t^{red} y_t + R_t^{inc} z_t - \Theta \Psi_t w_t)$), the scheduling preferences (i.e., $\sum_{t\in T}\sum_{a_i\in N} \sigma_{it} x_{it}$) and climatic comfort (i.e., $T_{max}^{gap} + \sum_{t\in T} T_t^{gap}$). Observe that the latter term consists of two elements: the sum of the absolute deviations between desired and actual house temperature (through all the time slots), and the maximum absolute deviation (i.e., T_{max}^{gap}), the latter penalizing high values of T_t^{gap} in any slot t. The three terms are weighted with the three parameters α_1, α_2 and α_3. By changing the three parameters, different end-user behaviors can be modeled. For example, the "money saver" user can be modeled assigning a high value to the parameter related to the first objective and low values to the other two objectives.

Constraints (2) ensure that the working cycle of each appliance a_i is run. Constraints (3) state that, for each time slot t, the overall power required by manageable appliances is the total power required by all working cycles in execution at t. Constraints (4) and (5) refer to the price-volume signals received by the aggregator. If the power drawn from the network in time slot t is less (greater) than the value V_t^{red} (V_t^{inc}) then the reduction (increase) requirement is met and the corresponding variable y_t (z_t) can be set to 1, else it must be set to 0. The charge of the battery is modeled by the balance equations (6). They state that the charge in time slot t is equal to the charge in the previous slot minus the energy supplied to the electric loads (a variable), plus the energy supplied by photovoltaic panels (a forecasted data). Constraint (7) takes into account the maximum charge level of the battery, denoted as BL^{max}.

The AC system is modeled as a simple first-order heat-transmission process by constraints (8)–(10). Constraint (8) describes the dynamics of such process, driven by the power absorbed by the AC system. Here, β is an insulation parameter representing the temperature increase due to the difference of $1°C$ between internal and external temperature during one time slot, and γ is the temperature decrease yielded by 1 W of air conditioning during one time slot. Constraints (9) and (10) are used to set the value of the variable T_t^{gap} to the absolute deviation between desired and actual house temperature in time slot t. Inequalities (11) force the value of the variable T_{max}^{gap} to the maximum value achieved by variables T_t^{gap}, for $t \in T$. Constraints (12) are simple balances, for each time slot t, among the total power load from manageable appliances, the AC system, the non-manageable loads, and the power drawn from the network and supplied by the battery.

TABLE I

WORKING CYCLE DETAILS OF SELECTED APPLIANCES

Appliance	Working cycle duration (time slots)	Min power consumption (kW)	Max power consumption (kW)
Washing machine	6	0.10	2.00
Dishwasher	8	0.10	2.10
Dryer	6	0.30	2.00
Oven	3	0.60	2.00
Water heater	4	0.05	2.00

IV. SIMULATION RESULTS

Here we report on a set of computational experiments, analyzing the solution obtained in various scenarios, for different user preferences and varying offers from the aggregator. We also show how possible additional storage or generation devices can be adequately introduced in the model. Tests have been performed using the CPLEX 12.2 MILP solver on a 3 GHz Intel Core 2 Duo processor with 3.25 GB of RAM. In all cases, the computation time required to find an optimal solution was less than one minute.

We experimented with a set of appliances, chosen among those from Table I. In this table, we specify the duration of the working cycle of each appliance (number of time slots) and the minimum and maximum power consumption throughout the working cycle. Recall that we assume the power consumption as constant within a time slot. In what follows, we focus on $N = 5$ appliances, whose consumption profile has been generated based on the data from Table I, with random variations across instances (thus mimicking possible variations due to different manufacturers).

In our experiments, we accounted for an overall load profile of non-manageable appliances, without distinguishing among the specific appliances which contribute to that profile. We randomly generate 10 alternative profiles, characterized by minimum, maximum and average consumption as specified in Table II. Table II also shows the characteristics of the battery level profile associated to different degrees of solar insulation (identified as 'high', 'medium' and 'low'). To account for different weather conditions (which affect the power required by the air conditioning system), we consider two alternative scenarios for the outdoor temperature, namely *warm* (W) and *average* (A); see again Table II for details.

We used the electricity rates provided by the Italian Regulatory Authority for Electricity and Gas. We consider two tariffs, referred to as *peak* (typically applied to weekdays, from 8 to 19) and *off-peak* rate (for weekdays, from 19 to 8, and on weekends and national holidays). We consider four options:

- a *null* option (N), in which there are no flexibility requests from the aggregator; therefore, nominal electricity rates apply;
- a *reduction* option (R), in which the consumer gets a reward if he/she accepts to reduce his/her consumption in a specified time interval;
- an *increase* option (I), in which the consumer gets a reward if he/she accepts to increase his/her consumption in the specified time interval;
- an *increase/reduction* option (B), where the consumer gets a reward if his/her consumption remains within two given thresholds in the specified time interval.

Combining the three alternative configurations for the battery level profiles, the two scenarios for forecasted outdoor temperature and the four options for the aggregator's flexibility requests, we obtain 24 scenarios. For each scenario, we randomly generate 10 instances of EBSP with a 24-hour time horizon, which implies $t_{tot} = 96$ time slots and $\Theta = 15$ minutes.

We run the optimization algorithm according to each of the following operating modes, corresponding to different user profiles:

- *money saving* (MS) – the user is only interested in reducing the electrical bill, so we set $\alpha_1 = 1$, $\alpha_2 = 0$ and $\alpha_3 = 0$;
- *user preferences* (UP) – the user is only interested in scheduling the appliances according to its preferences, so we set $\alpha_1 = 0$, $\alpha_2 = 1$ and $\alpha_3 = 0$;
- *climatic comfort* (CC) – the user is only interested in keeping the house temperature as close as possible to the desired temperature he/she has set; so we set $\alpha_1 = 0$, $\alpha_2 = 0$ and $\alpha_3 = 1$;
- *balanced* (BL) – the user is equally interested in all the three aspects. Since the three objectives are expressed in different units, a preliminary computational campaign was needed to appropriately tune the alpha values, which turned out to be $\alpha_1 = 0.45$, $\alpha_2 = 0.15$ and $\alpha_3 = 0.40$.

Figures 1-3 summarize our simulation results, showing the values of the objective function at optimality, in terms of its three components (cost, scheduling preferences and climatic comfort respectively), for each of the four Ebox operating modes. On the x-axis, we report the 24 scenarios coded through the string 'X-Y-Z', where 'X' denotes the outdoor temperature profile, 'Y' the insulation level, and 'Z' the flexibility request coming from the aggregator.

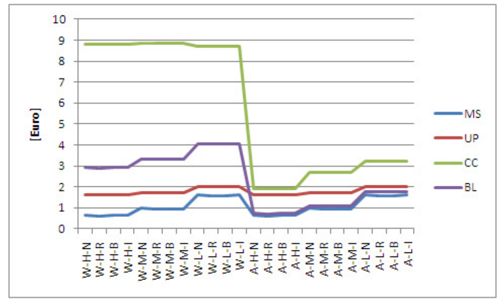

Fig. 1. Energy cost component of the objective function for the different Ebox operating modes

Fig. 1 illustrates the values of the energy cost component. Obviously, the lowest values are obtained in the MS operating mode. Note that the external temperature does not affect costs, which remain constant w.r.t. variations of this factor (passing from W to A). This is because in this operating mode climatic comfort is not taken into account. On the other hand, the CC operating mode (which only considers climatic comfort) requires the highest costs across all scenarios: in order to reduce the gap between desired and actual internal temperature as much as possible, significant use of air conditioning is needed, which increases power consumption and costs as well. From Fig. 1, we also note that costs are higher when solar radiation is lower. This behavior holds for all operating modes. Finally, observe that flexibility requests only affect the energy cost component in the MS operating mode: in fact, in this case the appliances are scheduled in a way that allows getting the rewards from the aggregator.

The BL operating mode, instead, partially pursues the aggregator's rewards. However, the energy cost of the BL solution is worse than in the MS operating mode, showing that the optimal schedule does not always allow to get the reward.

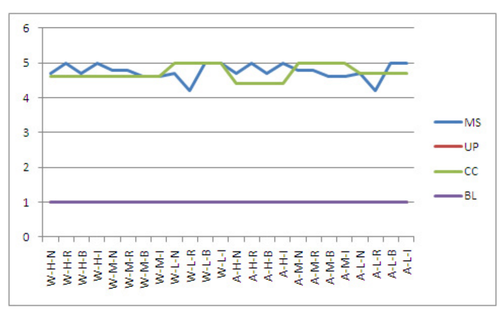

Fig. 2. Scheduling preferences component of the objective function for the different Ebox operating modes

Fig. 2 highlights that both UP and BL operating modes follow the user's preferences in scheduling the appliances during the day across all the scenarios, whereas the other

TABLE II

DETAILS ON THE INPUT DATA SETTING

	Configuration	Min value	Max value	Avg. value
Non-manageable load (kW)		0.2	0.9	0.6
Battery input level (kWh)	high insulation (H)	0	0.7	0.4
	medium insulation (M)	0	0.5	0.3
	low insulation (L)	0	0.3	0.1
Outdoor temperature (°C)	warm (W)	23	32	27
	average (A)	16	26	20

two operating modes typically schedule the appliances irrespective of user's preferences.

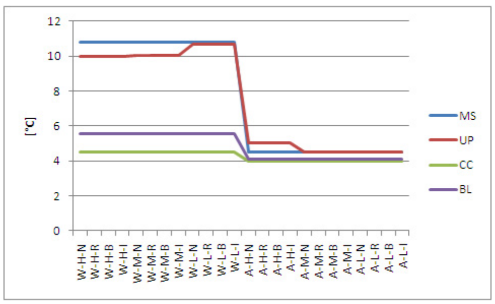

Fig. 3. Climatic comfort component of the objective function for the different Ebox operating modes

Concerning climatic comfort, Fig. 3 shows that obviously CC yields the best values across all the scenarios. Comfort appears acceptable also in the BL operating mode, whereas, as expected, both the MS and the UP operating modes provide the lowest comfort, since it conflicts with cost minimization and user preferences. We also note that all operating modes provide higher values of this component when the outdoor temperature is high (i.e., for all the scenarios associated to W) and they all decrease when the outdoor temperature is average (i.e., for all the scenarios associated to A). This derives from the fact that lower outdoor temperatures would reduce the temperature gap, possibly without even requiring the activation of air conditioning. As a consequence, even for the MS operating mode the average temperature gap between desired and actual temperature is smaller.

V. CONCLUSIONS

We presented an approach to the problem of planning appliance tasks in a household, taking into account the variability over time of the energy price paid by the consumer to the retailer. Various user's objectives are traded off against each other to pursue a satisfactory schedule on the basis of cost, climatic comfort and scheduling convenience considerations. A mixed-integer linear programming formulation of the problem allows to accommodate several issues, including the availability of power generators (e.g. photovoltaic panels), and/or storage devices. Preliminary experiments indicate that the model achieves good schedules, in very limited computation time, and without the need of sophisticated computational hardware. In any case, the solutions obtained using CPLEX can be used as a benchmark to possible heuristic approaches, if EB hardware/software requirements prevent the use of general-purpose MILP solvers. The development of specific heuristics for problem (1)–(14) will be the object of future research.

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VI. ACKNOWLEDGMENTS

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