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Preference Elicitation and Reasoning While Smart Shifting Of Home Appliances

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Abstract

A crucial part of the total electricity demand is energy consumption in the residential sector. In parallel to optimizing energy consumption within houses, user comfort is still an essential success criterion for automated solutions used within the house. Choosing the most comfortable appliance schedule is often a challenging task for the members of the house. To bring focus on this challenge, residential customer involvement is enhanced by a trend towards automation of appliances. This trend is reflected by pilot projects such as Linear which uses automated smart appliances at the demand side to attain more flexibility in the electricity system. Moreover, industrial interest from the Telecom, energy and household appliance sector to promote smart schedules for appliances is growing. To meet this trend, this paper describes new ways to model and reason with the user preferences when scheduling appliances in a household under dynamic pricing schemes given different user preferences. These methods have been proven to be efficient in eliciting and computing the user preferences to increase the user comfort in the house.

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Keywords: preferences; smart houses

1. Introduction

A crucial part of the total electricity demand is energy consumption in the residential sector. In parallel to optimizing energy consumption within houses, user comfort is still an essential success criterion for automated solutions used within the house. Choosing the most comfortable appliance schedule is often a challenging task for the members of the house. In view of this paradigm shift, residential customer involvement is enhanced by a trend towards automation of appliances [10,14]. This trend is reflected by pilot projects such as Linear [13] which use automated smart appliances at the demand side to attain more flexibility in the electricity system. To meet this trend, this paper describes a way to model and reason with the user preferences when scheduling home appliances in a household under dynamic pricing schemes given different user preferences. The remainder of this paper is organized as follows. In Section 2 we

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present some shortcomings with current smart home proposals and we review research on energy management within smart homes. Section 3 describes our contribution which is a new way of eliciting and reasoning with preferences for smart scheduler for household appliances. Section 4 reports an experimental study and gives some analysis of the results. Finally, some conclusions and future works are derived in Section 5.

2. Related work

Smart homes are residential buildings equipped with automation systems which manage the home for the benefit of the end-users. Demand Side Management (DSM) tries to balance the load on the power grid by reducing end user demand at peak times. Visser et al. claimed that there can be no intelligent decision support system without knowing the preferences of the user [32]. This leads us to infer that the representation of preferences is a central topic in decision making. In parallel to optimizing energy consumption and performing automated adaptations, user comfort continues to be an essential success criterion for ICT-based solutions [26]. Individual preferences enable the system to achieve multi-objective optimization by balancing the satisfaction of both objectives: users comfort and energy saving.

Demand side management (DSM) includes a number of methods to control the exchange of energy between consumers and suppliers and adapt the power production to the user energy needs. It also focuses on the reduction of demand peaks which add a significant cost in energy production. According to Long Ha et al. [16] there are two basic forms of DSM: one form is aiming at a direct control of appliances' loads, by cutting off directly those requesting high power or by absorbing the sudden variations in demand which cannot be supplied efficiently. This type of DSM is called emergency DSM. The other form is the economical DSM, which includes the encouragement of consumers to shift the energy from peak hours to off-peak hours providing financial incentives. With these forms the peak periods are reduced or shifted during the day. When dynamic tariff is applied, energy saving can reach 14% of the consumption. This percentage is twice that of the saving which can be achieved when only meters are adopted [9].

Most current industry approaches, and most studies in the literature, focus only on load management and cost reduction, and neglect user comfort. Although this approach may be easier to implement, we believe it to be a mistake. Sustained behaviour change will only occur when the user is satisfied with experience [34].

Choosing the best appliance scheduling is often a demanding and challenging task for the user when there are many available alternatives. In fact, the user rarely knows which schedule will provide the highest value. To reduce the complexity of this process, automated schedulers will propose the most preferred and cost efficient schedule. This schedule would take into account the preferences collected from the user in an explicit (e.g., letting users express the preferred starting times) or implicit (e.g., learning some features from usage data) way.

Because of the complexity of the electrical system, the total management and control can be divided into different layers interacting with each other via information flows [16]. A low layer is the appliance layer which includes all the appliances and their embedded controls. This layer takes actions of control like enabling and disabling certain appliances. This style of home energy management is one a current focus in the industry, and maybe the most interesting and promising: customers want to reduce their energy bills, and there is a societal benefit from reducing fossil fuel use [11]. Home management systems enable households and utilities to monitor all the appliances, which are connected to each other and to the entire system, control them even remotely and conserve energy.

In order to adapt consumption to the available energy, the home automation system controls the appliances in dwelling by determining the starting time of services. This problem has been formulated as a multi-objective constraint satisfaction problem and has been solved by a dynamic Tabu Search. This approach can carry out the coordination of appliance consumptions of heating system and of services by achieving a compromise between the cost and the user comfort criteria. However, the user preferences were not represented in a way to emphasize the comfort of the user. A dynamic programming approach has also been proposed [28]. Other works used a multi-agent approach [27]. Energy management problems may need to be generated dynamically [31] as each dwelling is unique and evolving.

Starting from a basic dynamic pricing scheme, an appliance scheduler shifts consumption to the lowest price period. Several of these load control algorithms are discussed in literature, e.g., [30]. Most of these studies optimize the appliance schedule for one day, given a theoretical time window in which the predefined power consumption profile can be shifted [30]. Besides these works, other authors are interested in applying a scheduler to yearly measured consumption data of residential consumers (e.g., [12]).

Long Ha et al. [15] claim it is necessary to develop new tools [22] and algorithms for advanced optimized power management of the home appliances, able to adapt with additional situations and scenarios to get even closer to the occupant expectations. New approaches should help to keep the balance between consumption and electricity production on the home scale. Energy smart homes should be able to take into account external signals, like energy prices and attendees' preferences, and to modify the home appliance behavior to compromise between occupants' expectations and energy supplier wishes represented by energy costs. These issues involve sensing capabilities and intuitive human machine interfaces. Dynamic energy pricing schemes enable the user to decide how and when to use their appliances.

3. A smart schedule for smart houses

3.1. Our approach: a preference-focused scheduling

The idea developed in this paper is about an intelligent scheduler designed to effectively shift appliances based on total power consumption, pricing variations, user prioritized needs and overload management. In this work, we concentrate on the user experience, and thus we focus on how to represent the user preferences regarding the starting times of the tasks. In fact, we allow the user to specify preferences, then we compute the most possible optimal schedule with respect to the collected preferences.

Peak, shoulder and off-peak hours pricing are unknown when defining the problem. As a consequence of this, the preferred time(s), defined by the user, might coincide with peak hour(s). Thus, the system should be able to prevent this from happening by eventually shifting the starting time(s) to some off-peak hour(s). Therefore, the system might need to have several preferred time points available to cope with different off-peak hour(s) during the week, the month or even the year. For example, the system would be able to shift an appliance to one of the preferred times that does not coincide with peak hour(s). This will allow the scheduler to be more flexible and more autonomous. Thus, the user will not worry about examining the possible schedules and choosing the best as the system has her preferences and is able to do it automatically. Therefore, we are heading towards more autonomous scheduler.

How far the latest starting time is from the earliest starting time might shed a light on how a task or appliance is prioritized regarding starting time. The user might set a deal of time between the latest starting time and the earliest starting time, or propose several allowed time zones within the time horizon, to give closer idea about her preferences as she might not be aware of the peaks.

A simplistic way of entering the preferences would be to enter numerical values using a user interface. One key technique in achieving a considerable simplification of the task of preference elicitation is the use of easy-to-draw graphical forms. It would be useful to benefit from the mobile devices (e.g., tablet) which allow the user to draw curves and easily manipulate histograms. Then, the system can induce information about the user preferences from these shapes.

3.2. Satisfaction function

In home automation, the attendees' comfort is an increasingly critical aspect to take into consideration. The notion of comfort can be directly linked to the concept of satisfaction function. A satisfaction function characterizes a user's feelings with respect to a service (e.g., starting time for an appliance). Since the notion of comfort is not universal, we can even think of constructing different ways of representing the user satisfaction regarding different categories of users and services within the smart home. The comfort zone is defined by the comfort constraints. These constraints can be used to reveal the range of preferred starting times for example. An increase in the comfort zone will provide more flexibility to scheduling. This can induce higher savings and less energy consumption. The comfort zone can be time-varying. As the preferred bounds become more restrictive, there is less freedom for the optimal solution. This is why we intend to propose flexible ways of representing preferences.

Let $\mathcal{F}$ be the satisfaction function which measures how satisfied the user is. The larger the value of $\mathcal{F}$ is the more satisfied the user is. Let $P[t, i]$ be a preferred time slot regarding the starting time $S[t, i]$ of task t running on machine

i. Having a single preferred time slot would suggest $S[t,i]$ should come before, after or just coincides with $P[t,i]$. We consider two separate cost coefficients: $earlyPenal(P[t,i])$ and $latePenal(P[t,i])$ are the penalties imposed to satisfaction function $\mathcal{F}$ when task t starts earlier and later than $P[t,i]$ for every time slot respectively. In the following, the penalties (i.e., $earlyPenal(P[t,i])$ and $latePenal(P[t,i])$) allow the satisfaction function for reflecting to which extent the user is dissatisfied while $S[t,i]$ is getting farther from $P[t,i]$.

3.2.1. A single preferred time-based satisfaction function

Let $C1$ be the cost function computed as follows:

$C1(S[t,i])= earlyPenal(P2[t,i])$ * $(P[t,i]$ - $S[t,i])$ if $S[t,i] < P[t,i]$

$C1(S[t,i])= latePenal(P2[t,i])$ * $(S[t,i]$ - $P[t,i])$ if $S[t,i] > P[t,i]$

Let Max($C1$) be the maximum value of $C1$ within the time interval $[P1[t,i], P2[t,i]]$. The satisfaction function is computed as follows: $\mathcal{S}1(S[t,i])$ = 100 - ($C1(S[t,i])$ / Max($C1$)) * 100

There will not be any cost inflicted to $\mathcal{F}$ when $S[t,i]$ coincides with the preferred time.

3.2.2. A multiple preferred time-based satisfaction function

To widen the user comfort zone, the system should be able to give freedom to the user to choose more than a single preferred time slot. Let $P1[t,i]$ and $P2[t,i]$ be two preferred starting time slots of task t running on machine i with $P1[t,i]$ coming before $P2[t,i]$ in the time horizon.

Equally preferred time slots-based satisfaction function. We propose a satisfaction function which computes the user comfort with regards to how far the starting time is from the preferred times that come before and after it. Let $C2$ be the cost function computed as follows: $C2(S[t,i]) = latePenal(P1[t,i])$ * | $S[t,i]$ - $P1[t,i]$ | * (Min(| $P2[t,i]$ - $S[t,i]$ |/(($P2[t,i]$ - $P1[t,i]$)/2),1)) +
$earlyPenal(P2[t,i])$ * | $P2[t,i]$ - $S[t,i]$ | * (Min(| $S[t,i]$ - $P1[t,i]$ |/(($P2[t,i]$ - $P1[t,i]$)/2),1))

Let Max($C2$) be the maximum value of $C2$ within the time interval $[P1[t,i], P2[t,i]]$. The satisfaction function is computed as follows: $\mathcal{S}2(S[t,i])$ = 100 - ($C2(S[t,i])$ / Max($C2$)) * 100

In the expression above we can see that for some task t starting to run on some machine i at some time slot j, the cost $C2(S[t,i])$ will be equal to zero if the starting time coincides with one of the preferred times. Consequently, the satisfaction is maximum. We can also see that the cost depends on how far the starting time is from a given preferred time but also depends on the penalty when being early or late regarding that preferred time. There will not be any cost inflicted to $\mathcal{F}$ when $S[t,i]$ coincides with the preferred time.

Example. Let us have a task $\mathcal{T}$ which is running on machine i for which the user has the following preferences. The user has two preferred starting times as follows. $P1[\mathcal{T},i])$ =7. $P2[\mathcal{T},i])$ =17. In this example we are interested in the time horizon between 7am and 17am. In other words the task might start anytime within this time horizon. Early and late penalties have integer values in the interval $[1,6]$; Figure 1 shows the curve of the satisfaction function (i.e., $\mathcal{S}2$) for different values of penalties. Figure 1 (a) shows $\mathcal{S}2$ for $latePenal(P1[\mathcal{T},i]) = earlyPenal(P2[\mathcal{T},i]) = 1$. Figure 1 (b) shows $\mathcal{S}2$ for $latePenal(P1[\mathcal{T},i]) = 1$ and $earlyPenal(P2[\mathcal{T},i]) = 6$. Figure 1 (c) shows $\mathcal{S}2$ for $latePenal(P1[\mathcal{T},i]) = 6$ and $earlyPenal(P2[\mathcal{T},i]) = 1$. Figure 1 (d) shows $\mathcal{S}2$ for $latePenal(P1[\mathcal{T},i]) = earlyPenal(P2[\mathcal{T},i]) = 6$.

The Figure shows that when the penalty regarding some preferred point gets high, the satisfaction function increases as the starting time gets closer to that preferred time. We can also see that the satisfaction reaches its maximum value when the starting time hits a preferred time.

Priority-based satisfaction function. Here we suppose all preferred times might not have the same priority for the user. As long as we have multiple preferred time slots, a partial order among these preferred slots can be elicited from the user. A partial order can be set through a priority list. Let $\mathcal{A}$ and $\mathcal{B}$ be two levels of priority. Let $\mathcal{A}$ be a user top priority followed by $\mathcal{B}$. Let $\mathcal{P}(P[t,i])$ be a function which returns the priority of some preferred time $P[t,i]$. $\mathcal{P}$ allows the user to give some preference ordering over the preferred time slots. For example, she might give top priority to some preferred time $P1[t,i]$ to express the fact that she will be fully satisfied if t starts at $P1[t,i]$. On the other hand, the user might not be fully satisfied if the starting time of a t hits some preferred time $P2[t,i]$. In that case, $P2[t,i]$ is given less than a top priority. Let $\mathcal{M}$ be the time slot in the middle between the two preferred times $P1[t,i]$ and $P2[t,i]$. The cost function is computed as follows:

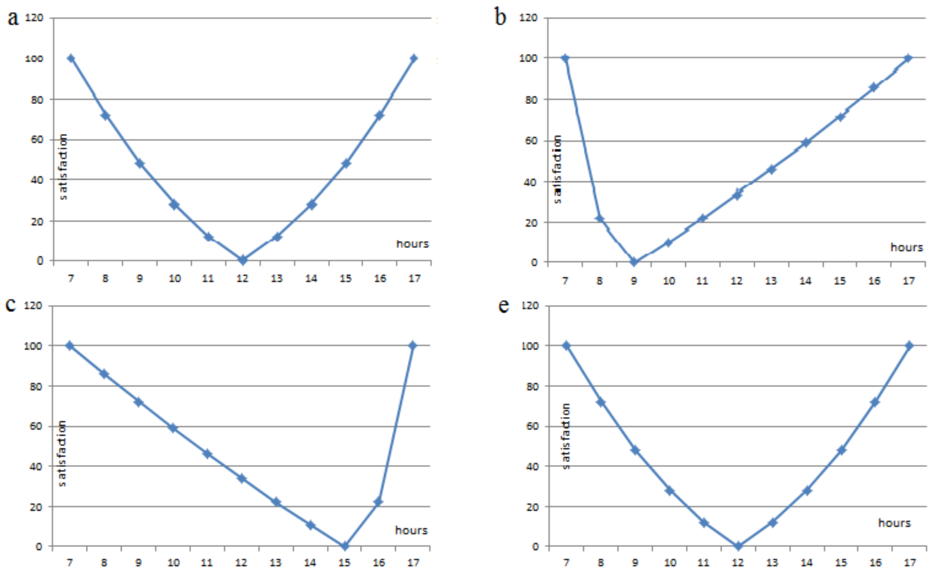

Fig. 1. Satisfaction function $\mathcal{S}2$ when there are different penalties for starting late after P1 and starting earlier than P2.

$C3(S[t,i])= earlyPenal(P1[t,i]) * (P1[t,i] - S[t,i]) + (\mathcal{A} - \mathcal{P}(P1[t,i]))$, if $S[t,i] < P1[t,i]$

$C3(S[t,i])= latePenal(P2[t,i]) * (S[t,i] - P2[t,i]) + (\mathcal{A} - \mathcal{P}(P2[t,i]))$, if $S[t,i] > P2[t,i]$

$C3(S[t,i])= latePenal(P1[t,i]) * (S[t,i] - P1[t,i]) + (\mathcal{A} - \mathcal{P}(P1[t,i]))$, if $P1[t,i] < S[t,i] < \mathcal{M}$

$C3(S[t,i])= earlyPenal(P2[t,i]) * (P2[t,i] - S[t,i]) + (\mathcal{A} - \mathcal{P}(P2[t,i]))$, if $\mathcal{M} < S[t,i] < P2[t,i]$

$C3(S[t,i])= [latePenal(P1[t,i]) * (S[t,i] - P1[t,i]) + (\mathcal{A} - \mathcal{P}(P1[t,i])) + earlyPenal(P2[t,i]) * (P2[t,i] - S[t,i]) + (\mathcal{A} - \mathcal{P}(P2[t,i]))] / 2$, if $S[t,i] = \mathcal{M}$

Let Max($C3$) be the maximum value of $C3$ within the time interval $[P1[t,i], P2[t,i]]$. The satisfaction function is computed as follows:

$\mathcal{S}3(S[t,i]) = 100 - (C3(S[t,i]) / \text{Max}(C3)) * 100$

Example (continued). Let $\mathcal{A}$ and $\mathcal{B}$ be two levels of priority. Let $\mathcal{A} = 10$ be a user top priority followed by $\mathcal{B} = 1$. Figure 2 shows the curve of the satisfaction function (i.e., $\mathcal{S}3$) for different values of penalties and priorities.

- Figure 2 (a) shows $\mathcal{S}2$ for $priority(P1[\mathrm{T},i]) = \mathcal{A}$, $priority(P2[\mathcal{T},i]) = \mathcal{A}$ and $latePenal(P1[\mathcal{T},i]) = earlyPenal(P2[\mathcal{T},i]) = 1$. This graph represents a classical case of multiple preferred time slots where the two levels of expressing preferences (i.e., penalties and priorities) over the preferred time slots are showing the user is indifferent between the two preferred time slots. Therefore, user is fully satisfied when the starting time hits one of her preferred time slots. Figure 2 (d) presents the same fashion for $latePenal(P1[\mathcal{T},i]) = earlyPenal(P2[\mathcal{T},i]) = 6$.
- Figure 2 (b) shows $\mathcal{S}2$ for $priority(P1[\mathrm{T},i]) = \mathcal{A}$, $priority(P2[\mathcal{T},i]) = \mathcal{B}$, $latePenal(P1[\mathcal{T},i]) = 1$ and $earlyPenal(P2[\mathcal{T},i]) = 1$. This graph shows the user is fully satisfied when the starting time hits the preferred time with top priority. The user satisfaction degree tends to decrease as the starting time gets farther from that preferred time. At some time slot (i.e., 13), the user is not satisfied at all as the starting time is far enough from the two preferred times. The user starts to be happy again while getting closer to the second preferred time slot which does not fully satisfy the user as a starting time because of its low priority. A similar fashion is shown in Figure 2 (c) when switching priorities.
- Figure 2 (e) shows $\mathcal{S}2$ for $priority(P1[\mathrm{T},i]) = \mathcal{A}$, $priority(P2[\mathcal{T},i]) = \mathcal{A}$, $latePenal(P1[\mathcal{T},i]) = 1$ and $earlyPenal(P2[\mathcal{T},i]) = 6$. This graph shows the user happiness is penalized when it gets far from the first preferred time till some time slot where the user's satisfaction reaches its peak. Beyond that time slot the user's

satisfaction increases fast as it diminishes the negative effect of the penalty of being early regarding the second preferred time slot. A similar fashion is shown in Figure 2 (f) when switching penalties.

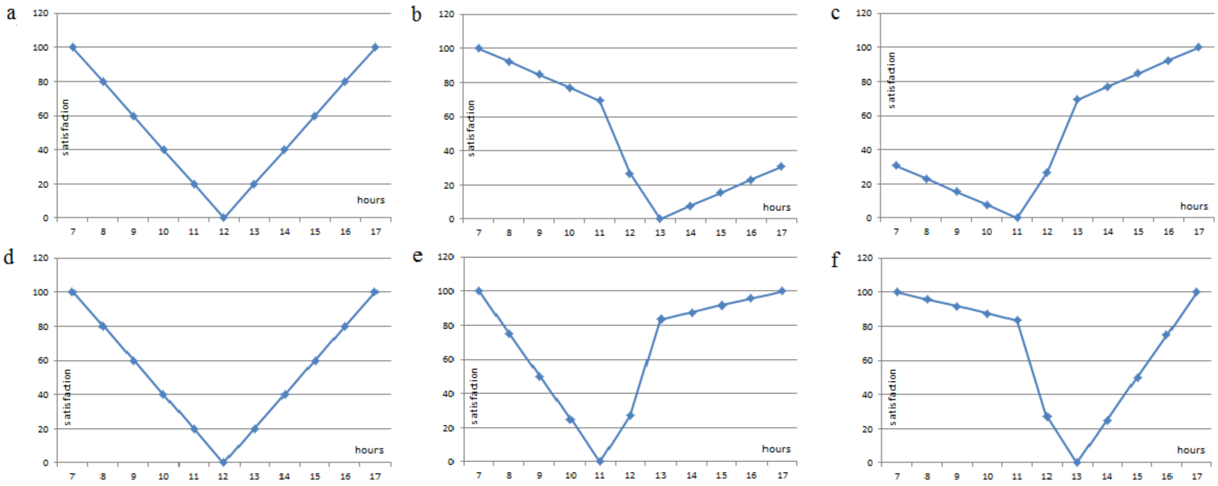

Fig. 2. Satisfaction function $S3$ when there are different penalties for starting late after P1 and starting earlier than P2 and two different levels of priorities.

3.3. Mathematical model for household electricity consumption

We designed a model whose objective is to minimize the electricity bill and maximize the comfort level over the next 24 hours subject to constraints including energy capacity, energy storage, energy balances, starting time and finishing time.

Let M be the set of m appliances, N be the set of n time slots and T be the set of tasks to be scheduled. Let i be the index of the appliance, j be the index of the time slot and t be the index of some task. Let s_{ijt} be a boolean variable which is equal to 1 if the machine m_i starts some job t at time slot j. Let x_{ijt} be a boolean variable which is equal to 1 if the machine m_i is doing some job t at time slot j.

Let e_i be the energy consumption of the appliance i per time-slot. The duration of the task on appliance i, denoted by d_t, is assumed to be constant in these settings. A task is a job related to an appliance. A schedule is a collection of tasks planned throughout a period of time denoted by p. A period of time p is a fixed fraction of time (e.g., day, week, month, etc.). It is supposed that the period p is divided into a number of time slots. A time slot is a fixed fraction of time during the period (e.g., 30min). The user might have a single or multiple preferred starting time slots for each task t, it is denoted by pts_t.

An appliance i should not process any task outside the allowed time interval specified by the user (between the earliest time slot denoted by ets_i and the latest time slot denoted by lts_i) (1). At some time slot j, the appliance is processing one task only (2). Also a task has to be processed by one appliance only (3). Once the task t starts the appliance which processes that task will be busy for the duration d_t (4). Tasks should not be assigned to a busy machine (5). In fact, if there is any task already assigned to a machine, no other task can be assigned to that machine during the period of time that corresponds to the processing time of the assigned task. At time slot j the total energy usage $ECost_j$ has to be smaller than the maximum capacity of the electrical circuit denoted by EC (6).

In this model, we consider the energy price $Eprice_j$ for every time slot j. The total price of the consumed energy $EPrice$ depends on the energy rate e_i of the working machines and $Eprice_j$ (7). $EPrice$ should not exceed the budget $EBudget$ allowed by the user to be spent on the energy (8) during the given time horizon. The user also considers three objectives with three different importance degrees: $EnrgCoeff$, $PriceCoeff$ and $ComforCoeff$. $EnrgCoeff$ expresses how important are the environmental issues for the user. $PriceCoeff$ gives an indication on how important is the economical aspect for the user. $ComforCoeff$ emphasizes the importane of the fact that the functionning of the schedule suits the user desires.

The user may have different degrees of discomfort regarding whether the activity starts earlier or later than the preferred starting time regarding some task that involves some appliance. Two separate cost coefficients are considered. Let suppose now the user has more than one single preferred time slot in N for some task t in T. Then, let $P1[t,i]$ and $P2[t,i]$ be two preferred times regarding the starting times of task t running on machine i and which come before and after the effective starting time respectively. Let $earlyPenal(P1[t,i])$ and $earlyPenal(P2[t,i])$ be the penalties imposed to the cost function when task t starts earlier than $P1[t,i]$ and $P2[t,i]$ respectively. Let $latePenal(P1[t,i])$ and $latePenal(P2[t,i])$ be the penalties imposed to the cost function when task t starts later than $P1[t,i]$ and $P2[t,i]$ respectively (see constraint (9). Let $\mathcal{P}(P[t,i])$ be a function which returns the priority of a preferred time $P[t,i]$.

In the expression stated in (9) we can see that for some task t starting to run on some machine i at some time slot j, the cost $MCost_{it}$ will be equal to Zero if the starting time coincides with one of the preferred times. We can also see that the cost depends on how far the starting time is from a given preferred time but also depends on the penalty when being early or late regarding that preferred time.

According to the model stated below the user is asked to provide the following information: M, N, T, e_i, d_t, ets_t, lts_t, $P1[t,i]$, $P2[t,i]$, $earlyPenal(P1[t,i])$, $earlyPenal(P2[t,i])$, $latePenal(P1[t,i])$, $latePenal(P2[t,i])$, $\mathcal{P}$, $Eprice_j$, $EPrice$, $EBudget$, $EnrgCoeff$, $ComforCoeff$, $PriceCoeff$. The corresponding mathematical model of the problem is written as follows:

1. $\forall\ i \in M, \forall\ j \in N, \forall\ t \in T,\ s_{ijt} = 0$ if $(j < ets_t \parallel j > lts_t)$
2. $\forall\ i \in M, \sum_{j\in N, t\in T} s_{ijt} \leq 1;$
3. $\forall\ t \in T, \sum_{i\in M, j\in N} s_{ijt} = 1;$
4. $\forall\ i \in M, \forall\ j \in N,\ s_{ijt} = 1 \Longrightarrow \forall\ k,\ j \leq k \leq (j + d_t),\ x_{ikt} = 1$
5. $\forall\ i \in M, \forall\ j \in N$, if there exists $t \in T$ such that $s_{ijt} = 1$ then $s_{ij_1t_1} = 0\ \forall\ t_1 \in T - \{t\}$ and $j \leq j_1 \leq (j + d_t)$
6. $\forall\ j \in N,\ ECost_j \leq EC$, having $ECost_j = \sum_{i\in M, t\in T} x_{ijt} * e_i$
7. $EPrice = \sum_{j\in N} ECost_j * Eprice_j$
8. $EPrice \leq EBudget$
9. $\forall\ i \in M, \forall\ t \in T,\ MCost_{it} = \sum_{j\in N} s_{ijt}\ \mathcal{F}(j)$, $\mathcal{F}(j)$ is a cost function defined in Section 3.2.

Objective= Min $[(\sum_{j\in N} ECost_j)$ * EnrgCoeff] + [$EPrice$ * PriceCoeff] + [$\sum_{i\in M} MCost_i$ * ComforCoeff]

The model above states that the schedule has three objectives. First, it aims at minimizing the daily electricity cost by shifting the smart appliances to the lowest price periods. Secondly, it also intends to minimize the daily energy consumption by targetting the time slots where there is less energy consumption (e.g., for the same appliace). A third objective is to minimize dissatisfied requests (e.g., implied by appliances not starting at the preferred time) by shifting the smart appliances to the most preferred starting periods. Three separate coefficients are used to express the relative importance of the objectives regarding the user. In this work, we assume all tasks have constant power consumption [33]. In fact, we assume all the appliances consume the same amount of energy at any time slot. This allows us to focus on the energy cost and the user comfort.

4. Experimental study

4.1. Empirical evaluation

We have implemented the above model in Numberjack [19], a newly developed solver portfolio system which allows problems to be described in a common format, and then selects the appropriate solver. In these experiments, we use SCIP [23] as a solver, and we return optimal solutions in less than a second.

We considered 10 home appliances: dish washer (DW), washing machine (WM), ryer (D), cooker hob (CH), cooker oven (CO), microwave (M), laptop (L), desktop computer (DC), vacuum cleaner (VC), fridge (F) and electrical car (EC). Their descriptions and consumption rates (i.e., power loads) are shown in Table 1. All tasks have constant power consumption [33]. All appliances that will be managed by the control system are appliances that can only be switched on or off. No power modulating device behavior is possible.

Table 1. Electricity consumption for tasks.[33]

Task	DW	WM	D	CH	CO	M	L	DC	VC	F	EC
Power (KW)	0.75	1.2	2.5	3	5	1.7	0.1	0.3	1.2	0.3	3.5
Duration (h)	2	1.5	1	0.5	0.5	0.5	2	3	0.5	24	3

Real users might have different kinds of preferences including hard and soft ones. Hard preferences include earliest and latest starting time of the tasks. Soft preferences include single or multiple preferred starting time points of the task. Real users tend to spot one or more preferred starting times in the available time horizon. The ultimate evaluation and validation of the newly defined approaches for preference elicitation should be performed with real users. However, experiments with real users cannot be used to extensively test alternative newly-deployed approaches. Indeed, some researchers pointed out the limitations of simulated experiments and their evaluation mechanisms, whereas others argued that simulated experiments are attractive because they allow comparing a wide range of approaches at an affordable cost [29]. In this work, we run the model with 1000 randomized instances. In each instance, the user inputs, including the user preferences, are generated randomly.

We show below the results of empirical evaluation of the solver. In the first set of experiments the user has just one single preferred time slot per task, while the second set allows the user to have multiple preferred time slots. In each group of experiments, we have three ways of selecting the start time for each task: (1) the first category uses the scheduler, with the main objective of maximizing the user comfort (denoted by **MaxComf**), (2) the second one uses the scheduler to minimize the monetary cost (denoted by **MinCost**) and (3) the third simply selects a random time within each time window, where the random times are biased towards expected use patterns (denoted by **ETS**). **ETS** model assumes that consumers do not change their behavior under a dynamic pricing scheme. This implies that a consumer loads and initializes its smart appliance at the same time as in the non-automated case. In **MinCost** and **MaxComf** models, the appliance cycle is optimally scheduled based upon the dynamic pricing scheme and the user preferences.

We report the average results from 1000 randomized instances at each setting in Table 2. Table 2 illustrates the average monetary cost over random instances as well as the total amount of comfort the user can have. Moreover, it depicts the cost reduction if the flexible consumption is shifted towards the lowest price period, or the preferred time slots or set to particular starting times. In these experiments, the comfort loss is computed with regards to the best feasible comfort the user can achieve, and the cost loss is computed regarding the lowest feasible cost the user can achieve. For the first set of experiments, where we have a single preferred start time, i.e., case 1, we see that we can achieve optimal user comfort (100%) when we prioritize it over the monetary cost (exceeding the minimal cost by approximately 23%). Alternatively, the user would sacrifice 10% of her own comfort measure in order to optimize the cost (and thus some appliances will start at some time slots that are not preferred by the user). With *ETS* the results are poorer than the *MinCost* method on both measures, showing the advantage of the scheduler. In the second set of experiments where we can have multiple preferred start times, case 2, we notice that the increased flexibility allows us to save more of the cost when optimizing for comfort with similar improvements for *MinCost*.

Other figures within Table 2 show that multiple preferred time slots allow the user to have a schedule whose cost is minimum while losing less than 2% of her best comfort. In these settings, total profits are limited due to a limited variability in the electricity tariff [12]. Other tariff structures with higher variability can increase total profits.

Table 2. Monetary cost and user comfort achieved with different settings for 1000 instances[33]

		Cost (cent)	Comfort(%)	Comfort loss (%)	Cost loss (%)
case 1	MaxComf	189.93	100	0	23.07
	MinCost	154.32	89.19	10.81	0
	ETS	160.61	87.54	12.46	4.07
case 2	MaxComf	182.31	100	0	18.14
	MinCost	154.32	98.07	1.93	0
	ETS	160.61	98.13	1.87	4.07

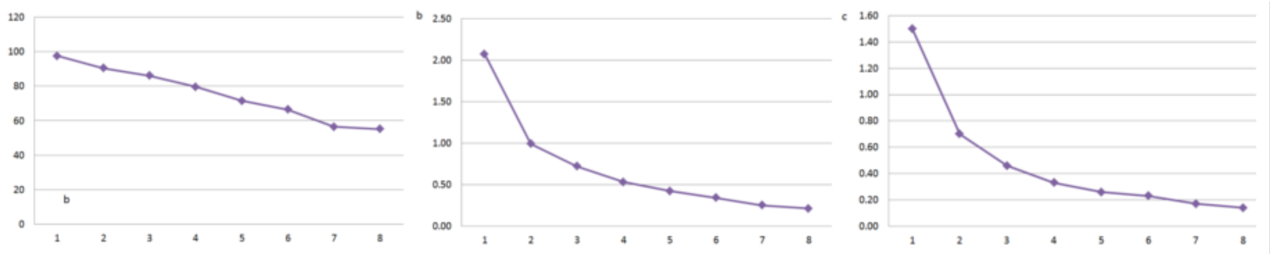

Fig. 3. (a) The average percentage of monetary cost loss when maximizing the user with different number of preferred time slots.; (b) The average percentage of user comfort loss when minimizing the monetary cost with different number of preferred time slots.;(c) The average percentage of user comfort loss in **ETS** settings with different number of preferred time slots.

Figure 3(a) shows the cost is decreasing when the number of preferred time slots increases in the **MaxComf** settings. In fact, when the user comfort reaches its maximum, the cost starts to fall as the scheduler has more room for optimizing the cost by visiting preferred time slots where the energy costs less. Figure 3(b) shows the user comfort loss is decreasing when the number of preferred time slots increases. Figure 3(c) shows the user comfort loss is decreasing when the number of preferred time slots increases.

4.2. Discussion

Priorities and penalties-based multiple preferred starting times offer a new perspective regarding the user comfort while scheduling smart home appliances. Eliciting these preferred times from the user can be a challenging task though. Besides, the method introduced in this paper does not handle multiple users. In fact, multiple users' preferences need reprocessing before being entered to this method.

5. Conclusion and future work

Energy consumption in the residential sector represents an important part of the total electricity demand. Clever management of the household appliances within the house will have a confirmed advantage in reducing the energy cost and increasing the user comfort when using these appliances. In this paper, we defined new ways of modeling preferences within the appliance scheduling and we proved these ways to be efficient in capturing and computing the user preferences and so increasing the user comfort within the house.

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