Metaheuristics for the home load management system

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Abstract

This paper looks at Demand-Side load Management applied to the residential sector. A home automation system controlling household energy is proposed. It is broken down into three layers: an anticipative, a reactive and a device layer. The paper focuses mainly on an anticipative layer that allocates energy by taking into account predicted events. It consists in computing the starting times of specific services and the set points of others while satisfying the maximal available power requirement and taking into account user comfort criteria. A Constraint Satisfaction Problem formulation is proposed. Because the complexity of this problem is NP-Hard, two local search metaheuristics have been adapted to solve it. The objective is to maximize user comfort and minimize energy cost. An application example is presented.

Key words: Building, Energy Management System, Predictive Control Constraint Satisfaction Problem, home automation, Local Search, Tabu Search, Simulated Annealing

1 Introduction

In (G. Thomas, 2000), Demand-Side load Management (DSM) is defined as a set of methods to coordinate the activities of energy consumers and energy providers in order to best match energy production capabilities with consumer needs. Thanks to DSM, energy demand peaks, which, on the one hand, have negative environmental impacts and, on the other hand, increase energy production costs, can be adjusted. In the residential sector, Wacks (1993) shows that the development of Home Automation systems (HAS) makes it possible for energy consumers to be involved in DSM by adapting their consumption to production needs.

Wacks (1991) presents the basic kinds of DSM control:

- direct control that shifts power requests by directly interrupting high power-consuming appliances.
- local control that consists in setting a policy to encourage consumption during off-peak periods while reducing energy costs.

However, these kinds of control are not very reactive and do not take into account user comfort.

The home automation system proposed by (Palensky and Posta, 1997) basically consists of appliances linked via a communication network allowing them to communicate with each other. These home automation systems reflect a new load management paradigm called *distributed control* and presented by Wacks (1993). This DSM control system allows energy providers to charge users for the actual cost of the energy produced for them in a very precise way. It also allows users to adjust their power consumption according to energy price variation. During peak periods, the domestic customer can decide whether to wait and save money or to use appliances in spite of the higher price. This strategy is more reactive than the basic DSM control method but more complex when comfort has to be taken into account.

Salsbury (2005) have performed a survey of control technologies in building automation. The main energy management problems concern the control of the **H**eating, **V**entilation and **A**ir **C**onditioning (HVAC) system. The problem is formulated as a PID control design problem or as a supervision problem. The set point control of the HVAC system is considered. Unfortunately, the load shifting and load shedding possibilities are not studied. Building energy management can be improved when these flexible aspects are taken into account.

Energy management can be formulated as a scheduling problem where energy is considered as a resource shared by appliances, and periods of energy consumption are considered as tasks. Generally speaking, these approaches coordinate consumption activities by scheduling all tasks as soon as possible in order to reduce overall consumption while satisfying maximum energy resource constraints. These approaches do not manage the differences between predictions and effective values. Penya (2003) proposes a solution based on one-day user consumption predictions. A parallel and distributed genetic algorithm optimizes the consumption of buildings in order to adjust the consumption of appliances to energy provider needs. Ha et al. (2005) adapt the static Resource Constraint Project Scheduling Problem (RCPSP) to improve the management of electric heating systems. This approach is able to coordinate electric heaters while satisfying the maximum power resource constraint. Nevertheless, the problem requires precise predictive models and, furthermore, is NP-hard. (Ha et al., 2006) presents a new three-layer household energy control system capable both of satisfying the maximum available electrical power constraint and of maximizing user satisfaction criteria. This approach improves reactivity in terms of matching energy provider needs. Rooms equipped with electric heaters are used to illustrate the capability of the control mechanism. The control system uses natural thermal accumulation to adjust power consumption in real time.

This paper proposes a control algorithm that consists in finding a global solution to the **H**ome **L**oad **M**anagement **P**roblem (HLMP). In order to adapt housing consumption to available energy, the home automation system controls household appliances by determining the starting time of specific services and scheduling the temperature set point of the HVAC systems.

This HLMP actually combines two problems: the first involves adjusting the HVAC system set points and the second requires setting the optimal starting times for the scheduled services. The first could be formulated as a predictive control problem. The second problem requires cumulative resource scheduling (Schwindt, 2005). A specific type of formulation is therefore required to cover the combined problems. A scalable approach might be applied to the optimal control problem but it is not suitable for the scheduling problem. This is why discrete formulation has been chosen in order to group the two problems into one formulation. Furthermore, this formulation is also able to take into account discrete phenomena relating to the HVAC system set points.

In order to find the optimum solution to the Home Load Management problem, both problems must be solved at the same time because they are linked by resource constraints. These problems are very hard to solve. Indeed, a shift in a timed service can change the resource constraints of the optimal control problem while a change in HVAC system set points can lead to unfeasible timed service shifts. Furthermore, the problem is NP-hard and the computations are handled by micro-controllers with limited computation capacities. This means that an exact algorithm providing a global optimum, such as a branch and bound algorithm, cannot be considered. Instead, local search metaheuristics are preferable because they take into account the convexity of the HLMP.

2 Control mechanisms

In typical predictive scheduling, like job shop or RCPSPs, the scheduling procedure data considered are the resource and duration of a task and the earliest and latest starting time. All these data have to be known to set up a scheduling procedure. However, the main issue in HA scheduling problems is the presence of prediction uncertainties: solar radiation, outdoor temperature,

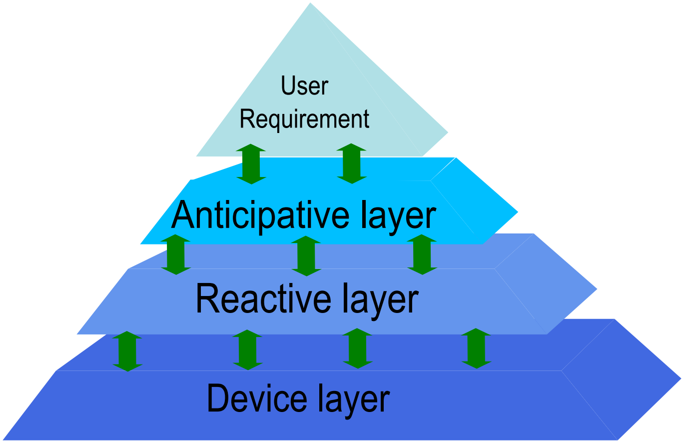

Fig. 1. Control mechanisms

starting times and durations of services requested by occupants. Uncertainties are such an important feature in these predictions that even robust scheduling approaches are not very efficient. Uncertain events are indeed often more important than events that can be predicted. In order to solve this issue, a three-layer architecture is proposed: a device layer, a reactive layer and an anticipative layer (see figure 1). This control structure improves the adaptability of the system and reduces the extent of the problem in terms of the energy allocation plan.

Compared with the control structure in (Palensky and Posta, 1997), a common point of view can be seen between the Long-term Power Management of (Palensky and Posta, 1997) and the anticipative layer: they both have the same objective when dealing with predictable event planning. However, the difference lies in the fact that Long-term Power Management deals only with the starting point of timed services. The anticipative layer, on the other hand, deals with the problem of computing the optimal starting point of timed services as well as the optimal set point of HVAC services. A second comparison can be drawn between short-term Power Management and the reactive layer.

2.1 Device layer

The *device layer* is composed of devices together with their existing local control systems generally embedded in appliances by manufacturers. This layer is responsible for adjusting device controls in order to reach given set points in spite of disturbance. It groups together two kinds of services:

- *permanent services*, such as HVAC systems, which are linked in a one-to-one relationship with each device
- *timed services*, such as cooking or washing, which are bounded in time. Unlike the permanent services, several timed services can be requested of

the same device but not at the same time.

The advantage of this layer is that it renders devices more abstract for the other layers: continuous phenomena and fast dynamics are hidden by the controllers at this level.

2.2 Reactive layer

The objective of the *reactive layer* is to manage real-time energy allocation adjustments. This layer is responsible for decision-making in case of violation of predefined constraints relating to energy and comfort (Abras et al., 2006). Control actions may involve either enabling or disabling the *device layer* controllers. Reactive layer actions have to remain transparent for the plan computed by the anticipative layer. This plan consists in a fast dynamic unbalancing system taking into account the actual state and including unpredicted disturbances in order to meet requirements in terms of energy, comfort and cost.

2.3 Anticipative layer

The *anticipative layer* is responsible for managing predicted events relating to electric sources and loads in order to prevent use of the *reactive layer* wherever possible. The prediction procedure forecasts various types of information about future user requests, but also about future available energy resources and energy price fluctuations. This layer has slower dynamics and includes predictive models with learning mechanisms[1] . It also contains an anticipative control mechanism that schedules energy production and consumption several hours in advance: it computes plans according to consumption predictions. The plans may of course be modified by the reactive layer to take into account the actual system state: the role of the anticipative layer is to reduce the number of arbitrations operated by the reactive layer. The sampling period of the anticipative layer is denoted by Δ: it is much greater than the dynamics of the reactive layer, whose action has to remain transparent for the plans. If the reactive layer detects too many arbitrations, it may request the anticipative layer to provide a new plan. This layer is based on the most abstract models. Because it follows slower dynamics, its lower layers are transparent: the set points coming from the anticipative layer are adjusted by the reactive layer in real-time. Because, globally speaking, the dynamics of the reactive layer are higher the energy allocation of the anticipative layer is not greatly modified. The controllers of the device layer adjust the device controls

[1] including models dealing with user habits

in order to satisfy the set points coming from the highest layers. This layer is also transparent for the higher layers.

3 Modelling of the HLMP

This paper focuses on the anticipative layer by tackling the prediction mechanism and its combinatorial issue. The anticipative layer computes energy allocation plans. This consists in determining in advance both the starting dates of the timed services and the set points of the permanent services, mainly composed of HVAC systems whose set points correspond to temperatures. The following notations have been adopted:

- $S_i, i \in \{1, ..., I\}$ denotes a service and S^S the set of all services to be performed. S^S can be divided into permanent services S^P and timed services S^T.
- $DEV(S_i) = DEV_j, j \in \{1, ..., J\}$ denotes the device that performs the service S_i with $\forall DEV_j, DEV_j \in DEVS$
- $\Delta_k, k \in \{1, ..., K\}$ denotes the k^{th} anticipative period following the current time

3.1 Timed services

Definition 1: *A timed service corresponds to an energy requirement limited in time which is supported by one appliance. It can be shifted by respecting the time window constraint defined by the user. The duration and the energy amount required by services are deterministic.*

Generally speaking, several timed services can be requested of the same appliance but they are mutually exclusive: only one service can be supported at any one time. A timed service $S_i \in S^T$ is modelled as an on/off service. In this paper, it is seen as a non pre-emptive activity. After starting, it cannot be interrupted and hence remains on until the service is complete. Its consumption during a period Δ_k is thus modelled by: $E_{i,k} \in \{0, \Delta_k \times P_i\}$ where P_i characterizes the average power consumption of the service. The durations of timed services are modelled by a number $D(S_i) \in \mathbb{N}^*$ of anticipative periods.

Let $EST(S_i)$ and $LST(S_i)$ be respectively the earliest and the latest starting times for the service arising from user comfort expectations. The starting time requested by the user is denoted as $RST(S_i)$. The variable $AS(S_i)$ represents the computed starting time of timed service S_i. If the service S_i is started such that $AS(S_i) = RST(S_i)$, the satisfaction or user comfort for service S_i is optimal.

As an illustration, consider the following timed service: a laundry washing service supported by a washing machine. This service can be programmed by the user, but the control mechanism will compute the optimal finishing time, the earliest starting time and the latest starting time.

3.2 Permanent services on loads

Definition 2: *Permanent services are services for which the energy consumption duration is equal to the energy consumption plan horizon P. These services are flexible owing to the possibility of varying energy allocation from time to time. User satisfaction with a permanent service depends indirectly on the allocated energy.*

A permanent service is generally characterized by a controlled physical variable. In housing, permanent services are mainly provided by HVAC systems and water heating systems. Let us focus on HVAC systems. Anticipation requires a relevant thermal air environment model to predict the HVAC system consumption. Fraisse et al. (2002) propose precise models of a room. However, given the extent of prediction uncertainty owing to outdoor temperature, for example, the simple thermal dynamic model presented in (Nathan, 2001) has been chosen:

$$C_i \frac{dT_i(t)}{dt} = P_i(t) - \frac{1}{R_i}(T_i(t) - T^{out}(t)) \tag{1}$$

where i refers to a HVAC service S_i.

C_i is the heat capacity of the thermal zone i of the permanent service S_i. $T_i(t)$ is the indoor temperature of the i^{th} thermal zone at time t. Each service is linked to a room equipped with a controlled electric heater. $P_i(t)$ corresponds both to the electric power consumed by the heater and to the heating power supplied to the room. R_i represents the equivalent total thermal resistance between the room and outdoors. T^{out} stands for equivalent outdoor temperature.

The thermal model (1) is then discretized according to the anticipative period Δ. Let $T_{i,k}$ be the temperature set point for the heater linked to service S_i, which is computed several hours in advance. $P_{i,k}$ stands for the average thermal power provided by the heater during the period Δ_k.

$$T_{i,k+1} = e^{(-\frac{\Delta}{R_i C_i})} T_{i,k} + R_i(1 - e^{(-\frac{\Delta}{R_i C_i})}) P_{i,k} + (1 - e^{(-\frac{\Delta}{R_i C_i})}) T_k^{out} \tag{2}$$

This model demonstrates that to move from a temperature $T_{i,k}$ to $T_{i,k+1}$ when the outdoor temperature is T_k^{out}, the average power required during period Δ_k

is equal to $P_{i,k}$.

Section 7 presents an HVAC service example.

3.3 Power resource

Anticipation has to meet a maximum available power requirement: during each anticipative period k, the maximum available power cannot be exceeded: it is defined as $\hat{P}_k$. Providing power is a support service in a one-to-one relation with a source device that provides power. The available power may depend on power availability and on contracts with energy providers. For the sake of simplicity, all the devices supporting the permanent or timed services are assumed to be purely resistive. Therefore, the total power consumption corresponds to the summation of power consumptions:

$$\sum_{i=1}^{I} P_{i,k} \leq \hat{P}_k, \forall k \tag{3}$$

where $\hat{P}_k$ stands for the maximum power production capacity of the power resource.

3.4 Criteria modelling

3.4.1 Satisfaction criteria for timed services

When the energy resource is sufficient for all the timed services requiring energy, the starting times $AS(S_i)$ can be set to the requested starting times $RST(S_i)$. Nevertheless, a problem occurs when the available energy is not sufficient. Some services must be delayed or advanced, which reduces the actual starting time $AS(S_i) \neq RST(S_i)$ and, consequently, user comfort. To represent the level of user discomfort, a dissatisfaction criterion $U_i \in [0, 1]$ is defined as follows:

$$U_i = \begin{cases} \frac{(RST(S_i)-AS(S_i))}{RST(S_i)-EST(S_i)} & \text{if } EST(S_i) \leq AS(S_i) \leq RST(S_i) \\ \frac{(AS(S_i)-RST(S_i))}{LST(S_i)-RST(S_i)} & \text{if } RST(S_i) < AS(S_i) \leq LST(S_i) \end{cases} \tag{4}$$

3.4.2 Satisfaction criteria for permanent services

Comfort is a subjective feeling and is hence difficult to evaluate. (Olesen and Parsons, 2002) and (CANDAS, 2000) propose the ISO7730 thermal comfort standard.
The PMV (Predict Mean Vote) function is determined according to standard

(CANDAS, 2000). In this paper, only the indoor temperature is taken into account. Other PMV parameters like the outdoor temperature, the humidity, the user's clothes and the mean air velocity are assumed to be constant. Under this condition, the "ideal" temperature corresponding to the most comfortable thermal sensation is about 21°C. The objective of an HVAC control system is to maintain the indoor temperature at around this set point. The acceptable indoor temperature range is determined by $-1 \leq PMV \leq 1$, and the predicted thermal sensation during an anticipative period Δ_k is denoted by $PMV(T_{i,k})$. The absolute value of the PMV is used as a criterion to be minimized. The dissatisfaction criterion for an HVAC service SRV_i is defined as:

$$U_i = \frac{\sum_{k=1}^{K} \mid PMV(T_{i,k}) \mid}{K} \tag{5}$$

3.4.3 Energy cost criterion

The DSM control proposed by (Boivin, 1995) allows energy providers to charge users with costs that vary according to time in order to take into account the actual energy production costs. These cost variations can be taken into account in the proposed HA system. Assuming that during an anticipative period Δ_k, the energy cost is EC_k, the energy cost of an allocation energy plan EC is given by:

$$EC = \sum_{k=1}^{K} EC_k \left(\sum_{i=1}^{I} P_{i,k} \right) \tag{6}$$

4 Constraint satisfaction problem

Many problems in operational research such as graph coloring, n queens, scheduling and car sequencing can be formulated as **C**onstraint **S**atisfaction **P**roblems (Brailsford et al., 1998). A CSP formulation consists in a given set of variables V, a given set of domains $dom(v_i) \in D_i; \forall v_i \in V$ and a given set of constraints C that must be satisfied. The objective of a CSP is to find a value assignment for each variable $v_i \in V$, such that $v_i \in dom(v_i)$. The assignment must satisfy all the constraints in C. In addition, a set of objective functions O may be optimized.

4.1 Variables and domains

The problem of household energy management can be formulated as a constraint satisfaction problem defined by a triplet (V, D, C).

4.1.1 Starting times

The starting times $AS(S_i)$ of the timed services belong to a set $dom(AS(S_i))$ defined by:

$$dom(AS(S_i)) = \left\{ EST(S_i) + m\frac{(LST(S_i) - EST(S_i))}{n_d}; m \in \{0 \ldots n_d\} \right\} \quad (7)$$

where n_d denotes the number of values within $dom(AS(S_i))$.

The energy consumption $E_{i,k}$ of a timed service is written as shown below (Esquirol and Lopez, 1999):

$$E_{i,k} = \bar{P}_i \times \mathrm{Max}\{\mathrm{Min}[AS(S_i) + \Delta D(S_i), (k+1)\Delta] - \mathrm{Max}[AS(S_i), k\Delta], 0\} \quad (8)$$

where $D(S_i)$ stands for the duration of the timed service S_i.

4.1.2 Temperature set points

The temperature set points for each anticipative period Δ_k also belong to discrete domains where values correspond to the possible set points of heaters (usually 3 to 5 values). Defining an acceptable thermal sensation range $-1 \leq PMV \leq 1$ leads to two thresholds characterizing acceptable indoor temperatures: $T^{min} \leq T_{i,k} \leq T^{max}$. The discretized domain $dom(T_{i,k})$ of indoor temperatures satisfies:

$$dom(T_{i,k}) = \{T^{min} + m\frac{T^{max} - T^{min}}{n_d}; m \in \{1 \ldots n_d\}\} \quad (9)$$

Other discretizations, such as temperature for the water heating service, are managed in the same way.

4.2 Constraints

4.2.1 Maximal energy constraint

The limited capacity of electrical sources is modelled by the maximal energy constraint. This constraint may vary over time. During an anticipation period Δ_k, the maximum available energy is $E_k^{max} = \hat{P}_k \times \Delta$. Obviously, the total power consumption of all the loads cannot exceed this value:

$$\sum_i^I E_{i,k} \leq E_k^{max} \quad (10)$$

4.2.2 Device capacity constraint

Some devices, such as a washing machine or an oven, cannot be shared by several timed services at the same time. These services must be executed sequentially. Let $x(i,k)$ be a binary variable standing for the occupation of the device $DEV(S_i)$ by the service S_i during the anticipative period Δ_k. The set of services sharing the same device DEV is defined as $\{S_i;\ DEV(S_i) \equiv DEV\}$. Variables $x(i,k)$ related to device DEV must satisfy:

$$\sum_{S_i \in \{S_i;\ DEV(S_i) \equiv DEV\}} \sum_{k=1}^{K} x(i,k) \leq 1 \tag{11}$$

4.2.3 Thermal capacity constraint

To reach the temperature $T_{i,k+1}$ from $T_{i,k}$, the average power required is $P_{i,k} = f(T_{i,k}, T_{i,k+1})$ where f is defined by (2). The thermal power must be positive and lower than or equal to the maximal power of the heater S_i denoted by $\bar{P}_i$. If this value is negative, it means that the temperature set point is $T_{i,k} \geq T_{i,k+1}$ and that the set point $T_{i,k+1}$ is too low to be reached. Conversely, if this amount is greater than P_i, the set point temperature $T_{i,k+1}$ is too high to reach $T_{i,k}$.

$$0 \leq P_{i,k} \leq \bar{P}_i \tag{12}$$

4.3 Global criteria

The HLMP is a multi-objective optimization problem, where the dissatisfaction criteria U_i and the energy cost EC have to be minimized. There are two typical approaches used in literature to deal with multiple objective optimization problems (Burke and Silva, 2006):

- Aggregating all objectives into a single objective
- Optimizing one objective at a time while imposing constraints on the other objectives

Both approaches transform the problem into a single objective optimization problem. Aggregation sets the weight for each elementary criterion for guiding the search procedure during the multi-objective optimization process. However, this approach applies to objectives of the same kind. In the HLMP, two kinds of criteria appear. The first kind is the set of criteria concerning user comfort. Because these criteria are of the same nature, they can be aggregated. Users can define their comfort profile for each service S_i, and the relative weight of services w_i can then be set. The aggregated comfort criterion

$CO \in [0, 1]$ is given by:

$$CO = 1 - \frac{1}{\sum_{i=1}^{I} w_i} (\sum_{i=1}^{I} w_i \times U_i) \tag{13}$$

The second kind of criteria deals with the total energy cost. Comfort and cost criteria should not be aggregated because they are heterogeneous. The second approach can be used here: the global comfort criterion is set to a given level and the energy cost criterion is then minimized. To be more user-friendly, different modes can be defined. For example, consider an economical mode where inhabitants agree to reduce the comfort level in order to lower the energy bill or a comfort mode where the comfort criteria take priority. The HLMP is thus subject to:

$$\begin{cases} CO \geq CO_{Lim} \\ \\ Minimize(EC) \end{cases} \tag{14}$$

4.4 Problem complexity

The HLMP involves two problems. The first problem is to minimize the total weighted delays of energy allocation E_i. This problem can be seen as the well-known problem of minimizing the total weighted delays of tasks in a single machine, which is known to be NP-hard (Bilge et al., 2006). The second problem in the HLMP concerns the management of permanent services such as an HVAC system. This problem can be solved by dynamic programming as outlined in (Ha et al., 2006). Hence, its complexity is also NP-Hard in a weaker sense. The complexity of the HLMP is then NP-Complete.

The optimal solution to this problem can be found using methods such as Branch and Bound and Dynamic Programming. However, these require many computations and a large memory space. Owing to the weak computing resources of embedded HLM systems, exact methods cannot be applied. In this paper, heuristics based on local searches have been chosen because they require a small amount of memory and rapidly locate near-optimal or optimal solutions with a limited computation time. Two metaheuristics, Tabu Search and Annealing Simulated, have been considered.

5 Tabu Search

Tabu Search (TS) is based on a metaheuristic method, which was originally developed by Glover (1989). It has been successfully applied to a variety of combinatorial optimization problems. The basic principle of TS is to pursue Local Searches until a local optimum is found and then to allow non-improving moves. A list, called Tabu list T, which records the recent history of the search, avoids going back over solutions that have already been considered. The TS procedure can be summarized as follows: from an initial solution Υ_0, which corresponds to the instantiation of variables V according to domains $dom(V)$, a neighborhood Υ of the solution Υ_0 is generated by performing elementary steps from the initial solution. The best solution for the neighborhood is then chosen as a candidate solution. This candidate is added to the tabu list T in order to prevent future reconsideration of this solution. The length of the tabu list T, denoted by $\mathcal{T}$, is called tabu tenure. In this paper, the tabu tenure $\mathcal{T}$ is controlled dynamically; when the threshold $\mathcal{T} := S\mathcal{T}$, i.e. the size of the tabu list is small, the number of neighborhoods that can be generated in each iteration is high. So the best neighborhood usually improves the best solution so far. It converges to a local optimum, and represents the intensification phase (or downhill phase). Otherwise, when the tabu tenure reaches the threshold $\mathcal{T} := M\mathcal{T}$ or $\mathcal{T} := L\mathcal{T}$, the tabu list is bigger, i.e. full, and many moves are therefore prohibited. The best neighborhood could be the worst solution rather than the best solution ever found. So, it is quite natural to move on to the uphill phase (diversification), which allows exploration of unexplored areas.

5.1 *Principle of TS implementation*

5.1.1 *Penalty function modelling constraint violation*

Koji and Toshihide (1998) suggest using tabu search as a general solver for CSP. Each constraint $c_n \in C$ has a penalty function p_{c_n} and an appropriate weight w_{c_n} representing the extent of the constraint. The penalty function allows the TS to set up a balance between feasible search space and unfeasible space. Three kinds of constraints: (10), (11) and (12), can be formulated as linear constraints $g(v_m) \leq A_{c_n}$, where A_{c_n} is constant. Let Υ be a CSP solution corresponding to a feasible instantiation of the variables of V. Let $A_{c_n} + \epsilon$ be the tolerance of A_{c_n}. $p_{c_n}(\Upsilon)$ denotes the value of the penalty function for the constraint c_n corresponding to the solution Υ. $p_{c_n}(\Upsilon)$ is a non-negative number defined as:

$$p_{c_j}(\Upsilon) = Max\left(\frac{g(\Upsilon) - A_{c_j}}{\epsilon}, 0\right) \tag{15}$$

The penalty function modelling the violation level of a solution Υ is:

$$p(s) = \sum_{n=1}^{N} w_{c_n} p_{c_n}(\Upsilon) \tag{16}$$

5.1.2 Intensification phase

The intensification phase (IP) consists in recording a fixed length of consecutive solutions in a short-term memory. This search phase aims at a more thorough examination. Let $f_0(\Upsilon)$ be the objective criterion and $p_0(\Upsilon)$ be the value of the penalty function for solution Υ. If $p(\Upsilon) > 0$, this means that several constraints are violated. The first step in the intensification phase is to rapidly reach the feasible solution space. Only penalty function $p(\Upsilon)$ is considered as an objective:

$$\min_{\Upsilon \in dom(V)} p(\Upsilon) \tag{17}$$

When a feasible solution is found ($p(\Upsilon) = 0$), the second phase aims at improving this solution. The objective function of TS is $f(\Upsilon)$ alone and only steps satisfying $p(\Upsilon) = 0$ are allowed:

$$\begin{cases} \min\limits_{\Upsilon \in dom(V)} f(\Upsilon) \\ p(s) = 0 \end{cases} \tag{18}$$

5.1.3 Diversification phase

The diversification phase is an algorithmic mechanism that tries to avoid the problem of being trapped by the local optimum by forcing the search into previously unexplored areas of the search space. This phase may lead TS to an unfeasible solution space. However, moving to instantiation that violates a small number of constraints is permitted. The long-term memory is considered. The objective function is:

$$\min_{\Upsilon \in dom(V)} f(\Upsilon) + p(\Upsilon) \tag{19}$$

5.1.4 Initial solution

To start the TS approach, an initial solution $\Upsilon_0 \in dom(V)$ must be chosen. Then, the temperature set point of a thermal environment is set to its optimal value 21℃. The starting dates of timed services are set to their requested starting date $RSD(SRV_i)$.

5.1.5 *Neighborhood structure*

Υ is considered as an element of the neighborhood of Υ_0. In order to obtain Υ, Υ_0 is modified: it is modelled by a move denoted by $\Upsilon = move(\Upsilon_0, v, \mu)$ where v stands for a variable and μ for a value in $dom(v)$. The move $\Upsilon = move(\Upsilon_0, v, \mu)$ is determined by selecting a variable v and a given value μ from $dom(v)$: it corresponds to a new assignment for a variable v. Therefore, the size of a neighborhood $\sigma(\Upsilon)$ is given by:

$$\sigma(\Upsilon) = \sum_{i}^{I} (n_d(v_i) - 1) \tag{20}$$

The best element Υ_0^* of the neighborhood becomes the candidate solution Υ_1 for the next iteration of TS. $\Upsilon_1 = move^*(\Upsilon_0, v_0^*, \mu_0^*)$ is placed on the tabu list where "*" means "best". At the next iteration, only the moves that are not on the tabu list are allowed, except for the one that satisfies the aspiration criterion.

5.2 *Controlling tabu tenure*

The tabu tenure denoted by $\mathcal{T}$ (size of the tabu list) is very sensitive and must be tuned carefully because the performance of TS greatly depends on it.

5.2.1 *Fixed tabu tenure*

Recently Bilge et al. (2006) put forward a TS using different tabu tenure values including small ($S\mathcal{T}$), medium ($M\mathcal{T}$) and large ($L\mathcal{T}$) tabu tenure values. The setting of $\mathcal{T}$ depends on the number of elements in the neighborhoods that can be generated at each iteration. In this paper, $S\mathcal{T} \approx 10\%\sigma(\Upsilon_0)$. This means that the maximum number of prohibited elements in the current neighborhood represents 10% of the total number of elements generated in the neighborhood. In the same way: $M\mathcal{T} \approx 25\%N(\Upsilon_0)$, $L\mathcal{T} \approx 50\%\sigma(\Upsilon_0)$. Firstly, the TS with a fixed tabu tenure is stopped after 2000 non-improving iterations. Next, the best-known solution Υ^* is sent to the intensification phase with $\mathcal{T} = S\mathcal{T}$. The stop condition is 1000 non-improving iterations.

5.2.2 *Dynamic control tabu tenure*

By continuously varying the tabu tenure the intensification and diversification phases can be balanced. On the one hand, the setting $\mathcal{T} := S\mathcal{T}$ corresponds to the intensification phase. On the other hand, the settings $\mathcal{T} := M\mathcal{T}, \mathcal{T} := L\mathcal{T}$

correspond to the TS diversification phase. Consider that the tabu tenure varies according to a sequence $[S\mathcal{T}, M\mathcal{T}, S\mathcal{T}]$, i.e. the tabu tenure starts with $\mathcal{T} := S\mathcal{T}$. After $1.5 \times \mathcal{T}$ iterations of TS, the tabu list T is reset and the tabu tenure changes to $\mathcal{T} := M\mathcal{T}$. Two variation strategies for $\mathcal{T}$ are considered: $[S\mathcal{T}, M\mathcal{T}, S\mathcal{T}]$, $[M\mathcal{T}, L\mathcal{T}, S\mathcal{T}]$.

6 Simulated Annealing Optimization

Simulated Annealing (SA) is a metaheuristic search method that can generate a close approximation of the global optimum. This algorithm is based on a local search and on an analogy with annealing in metallurgy: the slow cooling gives the metal a better chance of adopting configurations with a lower internal energy. The principle of SA is: some random neighborhoods are generated based on the current solution Υ. The decision to move to a new state Υ' or stay in the current state Υ is made according to the probability $\mathcal{P}$. Let $\mathrm{T_{SA}}$ be the temperature of the simulated annealing. The probability $\mathcal{P}$ depends on $\mathrm{T_{SA}}$ and on the difference in energy between the solution Υ and Υ': $\triangle\mathcal{E} = \mathcal{E}(\Upsilon) - \mathcal{E}(\Upsilon')$, where $\mathcal{E}(\Upsilon)$ is the internal energy of solution Υ. The search procedure starts with a diversification phase when the annealing temperature $\mathrm{T_{SA}}$ is high. The solution is then randomly mutated before moving on to the intensification phase when $\mathrm{T_{SA}}$ decreases to zero.

6.1 Neighborhood structure

The neighborhood selection method is particularly critical in SA optimization. In order to compare two metaheuristics, the neighborhood structure of SA is defined in the same way as for the TS in section 5.1.5. One random move $\Upsilon' = move(\Upsilon, v, \mu)$ is generated in each step. This move jumps from the solution Υ to another random element of its neighborhood $\Upsilon' = move(\Upsilon, v, \mu)$. Several rules have to be set:

- The search phase attempts to converge towards a feasible region: only the amount of constraint violation is considered.
- When the search phase reaches a feasible region, a return to the unfeasible region is prohibited.
- The decision to restart the SA may be taken when the current solution is worse than the initial solution i.e. the constraint violation amount of the neighborhood exceeds is 300% higher than that of the initial solution Υ_0.

6.2 Transition probability

The transition probability is the probability of jumping from the current state to the next state. In SA a state worse than the current state can be accepted depending on the decrease in annealing temperature. This probability is reduced according to the decrease in annealing temperature $\mathrm{T_{SA}}$. If the random move $move(\Upsilon, v, \mu)$ is an improving move, the probability is reset to 100%. Otherwise, it is set to the Boltzmann annealing probability:

$$\mathcal{P} = \begin{cases} 1 & \text{if } \mathcal{E}(\mathrm{s}) > \mathcal{E}(\mathrm{s}') \\ exp(-\frac{\triangle\mathcal{E}}{\mathrm{T_{SA}}}) & \text{if } \mathcal{E}(\mathrm{s}) \leq \mathcal{E}(\mathrm{s}') \end{cases} \tag{21}$$

6.3 Annealing schedule

The initial annealing temperature $\mathrm{T_{SA}^1}$ is set to a high value. Another essential feature of SA is the annealing schedule. It is a rule that defines how the temperature decreases during the search procedure. A linear rule has been used where ${\mathrm{T_{SA}}}^n$ denotes the annealing temperature on the n^{th} iteration of AS:

$$\mathrm{T_{SA}}^n = \alpha \times \mathrm{T_{SA}}^{n-1}; \alpha < 1 \tag{22}$$

7 Application example

7.1 Problem statement

This example presents a short-term scheduling problem where the aim is to determine a $24h$ energy consumption plan. The energy price reflects the real energy production cost: it changes throughout the day. The energy price and the outdoor temperature are considered as known in advance thanks to the energy provider and the weather forecast. The energy consumption plan is generated by optimizing the user comfort criteria and the cost criterion. The anticipative period is chosen as $1h$. The energy price is a constraint for one hour. It varies from one hour to the next according to the sampling time chosen for the anticipative layer.

In this example, heating services S_1 and S_2 correspond to the permanent services. They are supported by two $2kW$ heaters $DEV(S_1)$ and $DEV(S_2)$. The thermal impact between the two rooms is neglected. The discretization of the temperature domains is given by: $nd = 23$. In practice, parameter estimation is applied to determine the model (Madsen, 1995). Thermal parameters are given by $C_1 = 1.2kWh/$°C, $R_1 = 21kW$°C for the first one and $C_2 = 1.4kWh/$°C, $R_2 = 23.2kW$°C for the second one. The average outdoor temperature is $T^{out} = 5$°C and the initial temperature is $T_{1,0} = T_{2,0} = 20$°C for the two rooms.

$$\begin{cases} 1.2\frac{dT_1(t)}{dt} = P_i(t) - \frac{1}{21}(T_1(t) - T^{out}(t)) \\ 1.4\frac{dT_2(t)}{dt} = P_i(t) - \frac{1}{23.2}(T_2(t) - T^{out}(t)) \end{cases} \tag{23}$$

The absolute PMV function can be modelled by a piecewise linear function:

$$|PMV| = \begin{cases} -\frac{1}{6}\,T_i + \frac{21}{6} & \text{if } 15\text{°C} \leq T_i \leq 21\text{°C} \\ \frac{1}{7}\,T_i - \frac{21}{7} & \text{if } 21\text{°C} \leq T_i \leq 28\text{°C} \end{cases} \tag{24}$$

Two timed services are considered. The first one S_3 is defined as $EST(S_3) = 6h$, $RST(S_3) = 7h$, $LST(S_3) = 12h$, $P(S_3) = 2kW$, and the second one by $S_4 : EST(S_4) = 16h$, $RST(S_4) = 19h$, $LST(S_4) = 22h$, $P(S_4) = 2kW$.

A specific solver has been developed to solve HLMPs. The aggregation of criteria relating to energy cost EC and user dissatisfaction $U(S_i)$ is not suitable. Three alternative strategies have been defined in order to deal with the different kinds of user expectations: Comfortable Mode, Compromise Mode and Economical Mode.

The **Comfortable Mode** leads to the most comfortable solution, i.e. only comfort criteria are taken into account. The different aspects of user dissatisfaction are aggregated into a single comfort criterion. Thus, the HLMPs amount to a single criterion optimization problem. The most comfortable admissible solution is then obtained. It corresponds to the upper bound of the comfort criteria CO_{comfort}: the energy cost criterion for this solution is termed EC_{comfort}.

In **Compromise Mode**, users agree to decrease the comfort criteria CO by decreasing the cost criterion EC. Thus, both criteria CO and EC are taken into account. EC is considered as a criterion and CO is set by $CO \geq 95\% \times CO_{\text{comfort}}$.

The **Economical Mode** is comparable to Compromise Mode but cost is set by $CO \geq 70\% \times CO_{\text{comfort}}$.

Table 1
Comparison between different modes (this result is obtained using TS with 3600 CPU seconds(CPUs) of the computing time limit)

Criteria	Comfortable Mode	Compromise Mode	Economical Mode
CO	99%	95%	70.2%
EC	2.74	2.24(saving 18%)	1.75(saving 36%)
$U(S_1)$	1.8%	12%	36.41%
$U(S_2)$	2%	8.12%	16.35%
$U(S_3)$	0%	0%	0%
$U(S_4)$	0%	0%	66.67%

7.2 A fixed maximum power resource

In this example, the maximum power resource is fixed at $4kW$. The problem has been solved according to three different strategies proposed in the above section. They are illustrated in table 1.

In **Comfortable Mode**, the temperature set point for each room is based on the most comfortable temperature: 21℃. The starting time of the timed services is based on the requested starting times $RST(S_i)$. This solution leads to a comfort criterion of 99% and an energy cost of $EC_{\text{comfort}} = 2.74$.

The **Compromise Mode** is illustrated in figure 2. The upper panel plots the consumption curve of each device $DEV(S_i), i \in \{1, 2, 3, 4\}$. Curves $H0$ and $H1$ represent the consumption of the two heaters $DEV(S_1)$ and $DEV(S_2)$. $C1$ and $C2$ represent the consumption of timed services supported by devices $DEV(S_3)$, $DEV(S_4)$. The panel in the middle gives the indoor temperatures planned for the two permanent services. The lower panel shows the total power consumption, the energy cost and the maximal power resources.

Comparing comfort and compromise modes, the user can make a budget saving of 18% by reducing the comfort criteria by only 4%. The solution benefits from the lower energy price during the off-peak period, i.e. from 2:00am to 5:00am and from 1:00pm to 4:00pm, as thermal energy is accumulated. Indeed, at the end of off-peak periods, the indoor temperatures T_i reaches 23℃. Thus, the consumption of heating services can be reduced significantly during the peak-periods.

Figure 3 illustrates the **Economical Mode**. To decrease the energy cost even further, the solution also shifts the timed services: service SV_4 is shifted to $9:00PM$. The comfort criteria is equal to $70\% \times CO_{\text{comfort}}$ and the energy cost to $EC = 1.75 = 64\% \times EC_{\text{comfort}}$.

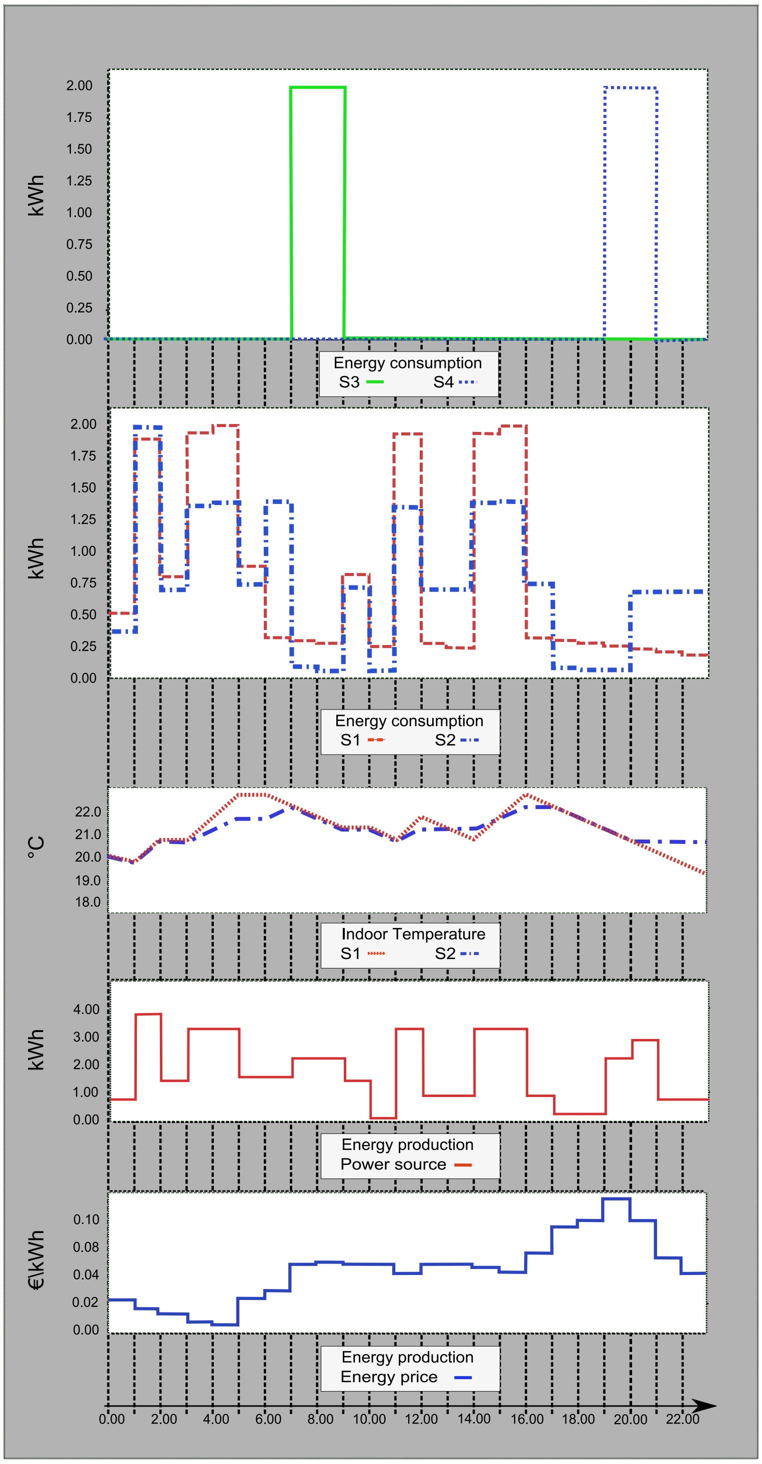

Fig. 2. Solution of compromising mode

The home load management system can control system consumption by taking into account energy price variations. This system offers greater flexibility for the user in terms of system configuration: he can set a constraint on the cost criterion and request the system to optimize the comfort criteria, for example. The solution is obtained by combining service shifts and HVAC service

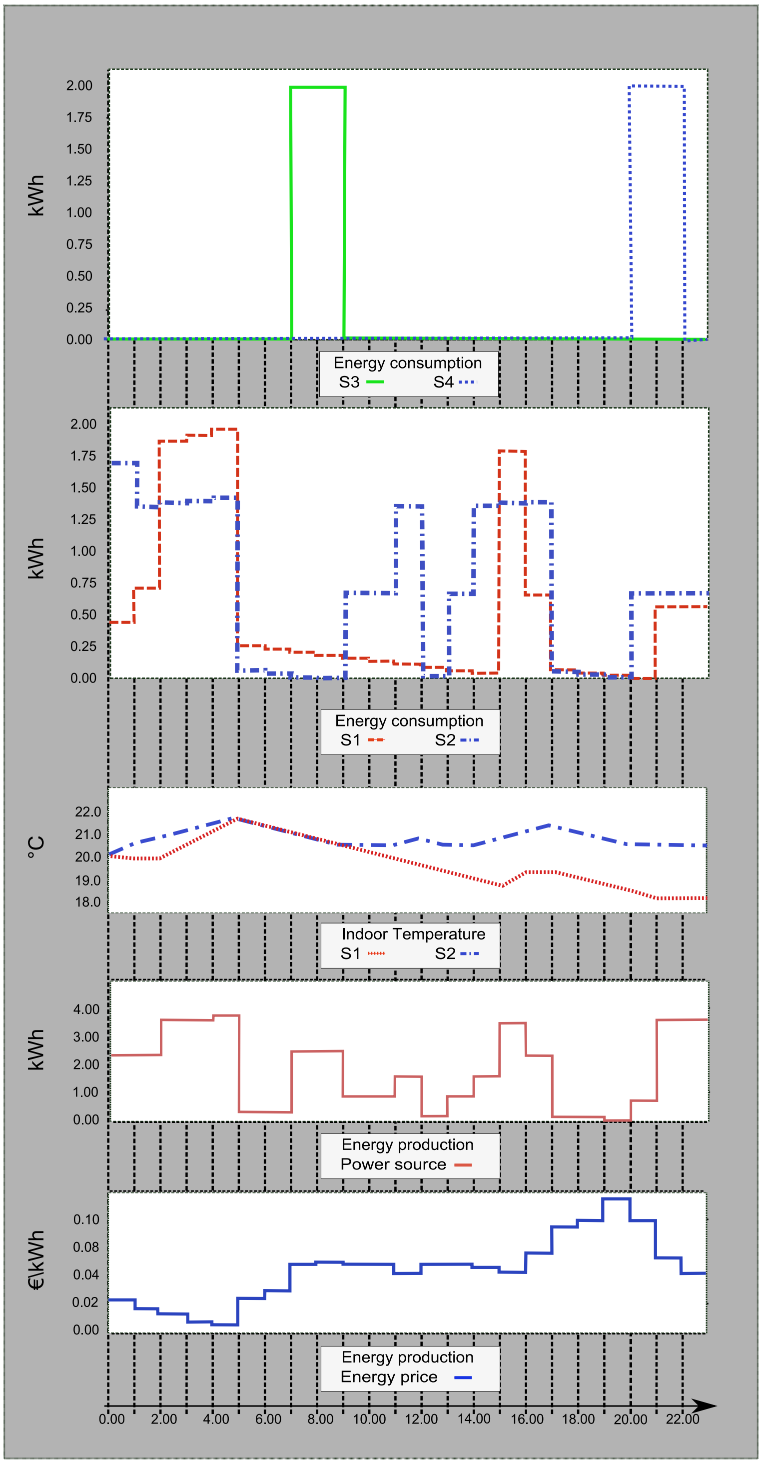

Fig. 3. Solution of economical mode

modulation. Currently, a simple feedback controller with different set points is used for HVAC programming. It is up to the user to configure the different temperature set points for different periods during the day. This solution is not optimal regarding comfort and cost criteria because it does not take into account variations in outdoor temperature and variations in energy price.

Table 2
Comparison between different metaheuristics

Algorithms	**N Optimum found**	**Worst deviation**	**Average deviation**
TS, $T = ST$, $T_{lim} = 180$	20%	7.4%	4.73%
TS, $T = MT$, $T_{lim} = 180$	15%	7.9%	5.26%
TS, $T = LT$, $T_{lim} = 180$	15%	8.12%	5.61%
SA $T^0_{SA} = 20$, $T_{lim} = 180$	20%	Infeasible	12.3%
TS:$T = ST, MT, ST$, $T_{lim} = 300$	45%	5.5%	3.42%
TS: $T = ST, LT, ST$, $T_{lim} = 300$	50%	5.3%	3.38%
SA $T^0_{SA} = 25$, $T_{lim} = 300$	35%	7.8%	5.57%

It is not flexible because it does not use all the degrees of freedom such as the possibility of shifting timed services. The configuration of the proposed control system is very simple for the user because it automatically adapts to variations in energy price and weather forecasts.

8 Comparison between different metaheuristics

In order to compare the performance of the two different local search heuristics TS and AS, 20 random problems have been tested. Two kinds of tests have been performed. For the first kind, the computation time is limited to 180CPUs and, for the second one, the time limit is set to 300CPUs (CPUs is the computation time in seconds). Table 2 gives the results obtained for different settings of fixed TS, dynamic TS and AS.

Different evaluation criteria have been chosen:

- the number of optimal solutions found by metaheuristics for the 20 random problems using a personal computer CPU=1.6GHz
- the worst deviation between the optimal energy cost and the one given by metaheuristics (sometimes, the metaheuristics do not lead to the global optimum. Sometimes, the search procedure does not reach a feasible region)
- the average deviation between the optimal energy cost and the one given by metaheuristics for the 20 random problems

The example has 48 $T(i, k)$ variables for temperatures in the thermal zone with domain $n_d = 23$ values and two variables for the starting time of timed service $AS(S_i)$ with the domain $n_d = 24$. The complexity of the exact algorithm leading to the optimal solution is theoretically $23^4 \times 2^{24} \times 2^{24}$. The solution obtained by metaheuristics is compared to the best solution found by the exact method (Mix Linear Programming method) with a limited computation time T_{lim} equal to 3600CPUs.

When the computation time is limited to 180s, a TS with a small fixed tabu tenure leads to the best performance. When the computation time is limited to 300s, a dynamic tabu search should be used to achieve the best performance. SA requires more computation time to reach a feasible region and to converge towards an advantageous solution.

9 Conclusion

In this paper, a new approach for managing power consumption in home automation is presented. Household energy management consists in setting both the starting times of timed services and the set points of permanent services. This problem has been formulated as a CSP with two objectives: cost and comfort criteria. An adaptation of TS and AS has been developed in order to efficiently solve the household energy management problem. This mechanism adjusts the energy consumption to satisfy the maximal power constraint while maintaining user comfort at a high level. These results point to new possibilities for energy management, which traditionally involves adjusting power resources to meet consumers needs and using an unbalancing mechanism when adjustments are no longer possible.

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