Tabu search for the optimization of household energy consumption

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***Abstract*— This paper focuses on Demand-Side load Management applied to residential sector. A home automation system controlling household energy is proposed. It is decomposed into three layers: anticipation, reactive and device layers. This paper deals with anticipation layer that allocates energy in taking into account predicted events. It consists in computing both the starting times of some services and to determine set points of others while satisfying the maximal power constraint. A Constraint Satisfaction Problem formulation has been proposed. Because the complexity is NP-Hard, a tabu search is used to solve the problem. It maximizes user comfort and minimizes energy cost. An application example is presented.**

I. Introduction

Demand-Side load Management(DSM) [1] is a set of methods that coordinate the activities of energy consumers and energy providers in order to best fit energy production capabilities to 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 [2], can be reduced. In residential sector, the development of Home Automation (HA) systems make it possible for energy consumers to be involved in DSM in adapting their consumption to production needs [3].

[2] presents basic kinds of DSM control:

- Direct control that shifts power requests by directly interrupting the high power consuming appliances.
- Local control that consists in setting up a policy that encourages consumption at off-peak periods in reducing energy costs.

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

A home automation system [4] basically consists of appliances linked via a communication network allowing appliances to communicate one each other. These home automation systems can carry out a new load management mechanism which is called *distributed control* [3]. This DSM control allows energy providers to charge user for the actual energy production cost in a very precise way. It also allows users to adjust their power consumption according to energy price variation. In the peak period, the domestic customer would be able to decide whether to wait and save money or to use appliances even so. This strategy is more reactive than the basic DSM control but more complex to control when comfort has to be 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 in scheduling all tasks as soon as possible in order to reduce the overall consumption while satisfying maximum energy resource constraint. These approaches do not manage the differences between predictions and effective values. [5] 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. In [6], an adaptation of the static Resource Constraint Project Scheduling Problems (RCPSP) is presented to improve the management of electric heating systems. This approach is able to coordinate the electric heaters while satisfying a maximum power resource constraint. Nevertheless, the problem requires precise predictive models and, moreover, it is NP-hard. [7] presents a new three-layer household energy control system capable both to satisfy the maximum available electrical power constraint and to maximize user satisfaction criteria. This approach carries out more reactivity for fitting the energy provider needs. Rooms equipped with electric heaters are used to illustrate the capability of the control mechanism for using natural thermal accumulation to adjust power consumption in real time.

This paper proposes a control algorithm, which consists in finding the global solution for the household energy management problem (HEMP). In order to fit the housing consumption to the available energy, the home automation system controls the equipment in housing in determining starting time of some services and also in controlling the temperature set point of HVAC systems. Because this problem is NP-hard, a metaheuristic Tabu Search is proposed in this paper to solve the HEMP.

II. Control mechanisms

In classic predictive scheduling like job shop or RCPSP, the data of scheduling procedure are: the resource and the duration of a task and, the earliest and the latest starting time. All these data have to be well known before the procedure of scheduling starts. However, the main issue in HA scheduling problems is the presence of uncertainties of predictions: solar radiation, outdoor temperature, starting times and durations of services requested by inhabitants. Uncertainties are so important in 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: an device layer, a reactive layer and an anticipative layer. This structure of control improves the adaptability of the system and reduces the solution research space of the energy allocation plan.

A. Device layer

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

- the *permanent services*, such as HVAC systems, which are linked with a one-to-one relation with device
- the *timed services*, such as cooking or washing, which are bounded in time. Contrary to permanent services, several timed services can occur on the same device but not at the same time.

The interest of this layer is to render devices more abstract for other layers: continuous phenomena and fast dynamics are hidden at this level.

B. Reactive layer

Objective of the *reactive layer* is to manage the real-time adjustements of energy allocation. This layer is responsible of decision making in case of violation of predefined constraints dealing either with energy or with comfort [8]. The control actions may be either to enable or disable controllers of the *device layer*.

C. Anticipative layer

The *anticipative layer* is responsible of managing predicted events dealing with electric sources and loads in order to avoid as much as possible the use of *reactive layer*. The prediction procedure forecasts several information about future user requests but also about the future available energetic ressources and about the price fluctuation of energy. This layer has slower dynamics and includes predictive models with learning mechanisms [1]. This layer also contains an anticipative control mechanism that schedules energy production and consumption several hours in advance. This layer adjusts set points of devices. The sampling period of the anticipation layer is denoted Δ.

Antipative layer is based on the most abstract models. Because of it follows slower dynamics, inferior layer is transparent for anticipation: reactive layer adjusts in real-time the set points coming from the anticipative layer. Because the dynamics of the reactive layer is higher, globally speaking, it does not modify much the energy allocation of the anticipative layer. The controllers of the device layer adjust the device controls in order to satisfy the set-points coming from highest layers. It is also transparent for higher layers.

[1]including models dealing with user habits

III. Problem modeling

This paper focuses on the anticipative layer in tackling the prediction mechanism and its combinational issue. The anticipation layer makes plans for energy allocations, which consist in determining both the starting dates of the timed services, and the set points of the permanent services mainly composed of HVAC systems of which the set points corresponds to temperatures. The following notations have been adopted:

- SRV_i denotes a service and $SRVS$ the set of all the services to be achieved. $SRVS$ can be partitioned into permanent services $SRVS_P$ and timed services $SRVS_T$.
- $DEV(SRV_i) = DEV_j$ denotes the device that achieves the service SRV_i with $\forall DEV_j, DEV_j \in DEVS$
- Δ_k denotes the k^{th} anticipative period following the current time

A. Timed services on loads

A timed service $SRV_i \in SRVS_T$ is modelled as an on/off service. After starting, it remains on until the service is ended. Its consumption during a period Δ_k is then modeled by: $E_{i,k} \in \{0, \Delta \times P_i\}$ where P_i characterizes the average power consumption of the service. The durations of timed services are modeled by number $d_i \in \mathbb{N}^*$ of anticipative periods. Let $EST(SRV_i)$ and $LST(SRV_i)$ be respectively the earliest and the latest starting times for the service coming from user comfort expectations. The starting time requested by user is denoted $RST(SRV_i)$. The variable s_i represents the computed starting time of timed service SRV_i.

B. Permanent services on loads

Permanent services are generally characterized by a controlled physical variable. In housing, the permanent services mainly deals with HVAC and water heating systems. Let's focus on HVAC systems. Anticipation requires a relevant thermal air environment model to predict the consumption of HVAC system. [9] and [10] have proposed precise models of a room. Nevertheless, given the importance of uncertainties in predictions, for example, outdoor temperature, thermal modeling parameter, which may cover several hours, the simple thermal dynamic models presented in [11], [12] has been preferred:

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

where i refers to a HVAC service SRV_i.

C_i is the heat capacity of SRV_i. $T_i(t)$ is the indoor temperature. Each service is linked to a room equipped with a controlled electric heater. $P_i(t)$ corresponds both to electric power consumed by the heater and to the heating power provided to the room. R_i represents the equivalent total thermal resistance between the room and outdoors. T^{out} stands for outdoor temperature. The thermal incidence of other environments and of solar radiations are considered as perturbations but, they could also be taken into account with a more precise model. The anticipation layer plans the consumption of heating systems according to the available electric power. For the sake

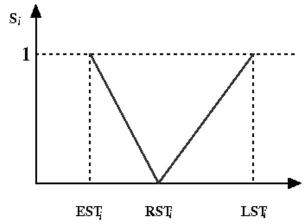

Fig. 1. Unsatisfactoriness service notion

of simplicity, the thermal modeling (1) is discretized according to the anticipative period Δ. Let T_i be the temperature set point for the heater linked to SRV_i, which will be computed several hours in advance. P_i stands for the average thermal power provided by the heater during the period Δ_k.

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

This model points out that to go from a temperature $T_{i,k}$ to $T_{i,k+1}$ when outside temperature is T_k^{out}, the average required power during period Δ_k is equal to $P_{i,k}$.

C. Permanent services on sources

Anticipation has to satisfy a maximum available power constraint: during each anticipative period, a maximum available power cannot be exceeded. Providing power is a permanent service in an one-to-one relation with the source device that provides power. This available power may depend on the sources and on contracts with energy providers. For the sake of simplicity, all the devices supporting the services on loads are assumed to be purely resistive. Therefore, the total power consumption corresponds to the summation of power consumptions:

$$\sum_{i=1}^{n} P_{i,k} \leq \hat{P}_k, \forall k \quad (3)$$

The supplied power has to be equivalent to the consumed power.

D. Criteria

1) Starting date of timed services: When the energy source is sufficient for all the timed services requesting for energy, the starting time s_i is equal to the requested starting time RST_i. Nevertheless, an issue appears when the available energy is not sufficient for all. Some services must be delayed or executed sooner, it means the actual starting time $s_i \neq RST_i$, this effect decreases the user comfort. To represent the level of user's uncomfort, a criterion of unsatisfactoriness $U_i \in [0, 1]$ is defined as follows:

$$\begin{array}{lll} U_i = 0 & if & s_i = RST(SRV_i) \\ U_i = \frac{(s_i - EST(SRV_i))}{RST(SRV_i) - EST(SRV_i)} & if & s_i < RST(SRV_i) \\ U_i = \frac{(LST(SRV_i) - s_i)}{LST(SRV_i) - RST(SRV_i)} & if & s_i > RST(SRV_i) \end{array} \quad (4)$$

2) Thermal sensation: Comfort is a subjective feeling, which is difficult to assess. [13] and [14] have proposed the ISO7730 thermal comfort standard. The function of PMV(Predict Mean Vote) is determine following this standard [14]. In this paper, only indoor temperature is taken into account. Other elements like outdoor temperature, humidity, user's clothes and mean air velocity are assumed to be constant. In this condition, the "ideal" temperature or the most comfortable thermal sensation is about 21°C. Objective of the control the system HVAC is to maintain the indoor temperature around this set point temperature. The range of acceptable indoor temperature is determined by $-1 \leq PMV \leq 1$, a predicted thermal sensation in anticipative period Δ_k is $PMV(T_{i,k})$. The criterion of unsatisfactoriness for HVAC service SRV_i is defined as follow:

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

3) Energy cost criterion: The DSM control in [15] allows energy providers to charge user for the actual energy production cost in real time. Thus this price variation is taken into account into a HA system. Assuming that during an anticipation period Δ_k, the energy cost is EC_k. An energy cost of a allocation energy plan EC is given by:

$$EC = \sum_{k=1}^{K} EC_k \sum_{i=1}^{n} P_{i,k} \quad (6)$$

4) Global criterion: The HEMP is a multi-objectives optimization, HA system try to minimize the total unsatisfactoriness services

$$Min(\sum_{j=1}^{J} U_j) \quad (7)$$

and the same time minimize the total energy cost

$$Min(EC) \quad (8)$$

Global criterion is a compromise between comfort and cost. An aggregation criteria is not suitable because weighting heterogeneous criteria is difficult for inhabitants. Modes can be defined. For instance, the energy cost 8 may be fixed and be considered as a constraint. For example, consider an economic mode where inhabitants accept to decrease the comfort level in order to reduce the energy bill. HA system can also be set to a comfortable mode, which amounts to search a solution based only on the comfort criteria. Secondly, HA system can search for several solutions and proposes a pareto of them to user. Then user can choose the solution that best fits his expectations. The comfort criterion 7 is defined by thresholds and treated as a constraint. HA system then select the best solutions based on the energy cost criteria 8.

E. Problem complexity

The HEMP aims at solving two problems. First problem is to minimize the total weighted delay of energy allocation E_i. Thus, the well-known problem of minimizing total weighted delay of job in a single machine is known to be a NP-hard problem [16]. The second problem in the HEMP deals with the management of permanent services such as HVAC. This problem is also NP-Hard in weak sense [7]. The complexity of the HEMP is NP-Hard or also NP-Complete. Therfore, an heuristic should be chosen to solved the problem.

IV. Constraint Satisfaction formulation

Many problems in operational research such as graph coloring, n queens, scheduling, car sequencing can be formulated as constraint satisfaction problems (CSP) [17]. A CSP formulation consists in a given set of variables V, a given set of domains $d_i \in D$ corresponding to variables of V and a given set of constraints C that must be satisfied. The objective of a CSP is to find values for all variables $v_i \in V$ such as $v_i \in d_i$ and that satisfy all the constraints in C.

A. Variables and Domain

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

1) Starting times: The starting times s_i of the timed services belong to the set V. The domain d_i of s_i is defined by:

$$d_i = EST(SRV_i) + n\frac{(LST(SRV_i) - EST(SRV_i))}{\Delta} \quad (9)$$

2) Temperature set points: The temperature set points for each anticipation period Δ_k has also to be included into V. In order to reduce the dimension of the search space, the domain of acceptable values for indoor temperature $T_{i,k}$ is discretized into n_d domains. In fixing the acceptable limit of the thermal sensation criterion $-1 \leq PMV \leq 1$, two thresholds characterizing acceptable indoor temperatures can be deduced: $T^{min} \leq T_{i,k} \leq T^{max}$. The discretized domain d_i of indoor temperatures satisfies:

$$d_i = \{T^{min} + j\frac{T^{max} - T^{min}}{n_d}; j \in \{0 \ldots n_d - 1\}\} \quad (10)$$

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

B. Constraints

1) Maximal energy constraint: Maximal energy constraint models the limited capacity of the electrical source. It may vary in time. During a anticipation period Δ_k, the maximum available energy $E_k^{max} = P_k^{max} \times \Delta$ where P_k^{max} stands for the maximum power capacity of the source. Obviously, the total power consumption of all the loads cannot exceed this value:

$$\sum_i E_{i,k} \leq E_k^{max} \quad (11)$$

2) Device capacity constraint: Some devices supporting timed services, such as washing machine or oven, are shared between several services. These services must be executed sequentially. Consider two services SRV_i and SRV_j that share the same device: $DEV(SRV_i) = DEV(SRV_j)$. If the requested starting times $RST(SRV_i) < RST(SRV_j)$, the following constraint arises:

$$s_j \geq s_i + d_i \quad (12)$$

3) Thermal capacities constraint: To reach the temperature $T_{i,k+1}$ from $T_{i,k}$, the average required power 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 less or equal than the maximal power of the heater SRV_i denoted $\bar{P}_i$. If this value is negative, it means that the set point temperature $T_{i,k} \geq T_{i,k+1}$ and that the set point $T_{i,k+1}$ is too low to reach $T_{i,k+1}$. Conversely, if this amount is greater than P_i, the set point temperature $T_{i,k+1}$ is too high to reach $T_{i,k}$.

$$0 \leq P_{i,k} \leq \bar{P}_i \quad (13)$$

V. Tabu Search

Tabu Search(TS) is based on a metaheuristic, which has been originally developed by Glover [18] and [19]. It has been successfully applied to a variety of combinatorial optimization problem. The basic principle of TS is to pursue Local Search until a local optimum is found and then, to allow non-improving moves. A list called Tabu list T, that records the recent history of the search, prevents from revisiting solutions that have already been considered. The procedure of TS can be summarized as follows: from an initial solution $s_0 \in S$ where S denotes the search space i.e. the instantiation of variables V according to domains of D, a neighborhood $N(s_0)$ of the solution s_0 is generated in performing elementary steps from the initial solution. The best solution of the neighborhood is then chosen as a candidate solution. This candidate is pushed into the tabu list T in order to prevent future reconsideration of this solution. The length of the tabu list T, denoted t, is called tabu tenure. To select a candidate solution from $N(s_l)$, an aspiration criterion is also considered. It consists in allowing a move, if this move steps to a solution which has a better objective criterion than the current best-known solution s^*. Even if it is in the tabu list.

A. Principle TS implementation

1) Penalty function of violation constraint: [20] has proposed to use tabu search as a general solver for CSP. Each constraint $c_j \in C$ has a penalty function p_{c_j} and an appropriate weight w_{c_j} representing the importance of the constraint. The penalty function is used to allow the TS to balance between feasible search space and infeasible space. Three kinds of constraint, (11), (12) and (13), can be formulated as linear constraints $g(x) \leq A_{c_j}$ where A_{c_j} is a constant. Let s_l be a solution of the CSP that corresponds to a feasible instantiation of the variables of V. Let $A_{c_j} + \epsilon$ be the tolerance of A_{c_j}. $p_{c_j}(s_l)$ denotes the value of the penalty function for the constraint c_j for the solution S. $p_{c_j}(s_l)$ is a nonnegative number defined as follows:

$$p_{c_j}(s_l) = Max(\frac{g(s_l) - A_{c_j}}{\epsilon}, 0) \tag{14}$$

The total amount of violation of a constraint $c_j \in C$ by a solution s_l is :

$$p(s_l) = \sum_j w_{c_j} p_{c_j}(s_l) \tag{15}$$

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 performing a more thorough examination. Let $f_0(s); s \in S$ be the objective criterion and $p_0(s)$ be the value of the penalty function for solution s. If $p(s) > 0$, it means that several constraints are violated. First step of intensification phase is to reach rapidly the feasible solution space. Only $p(s)$ is considered as an objective:

$$\text{minimize } q(s) = p(s) \text{ subject to } s \in S \tag{16}$$

When a feasible solution is found($p(s) = 0$), the second phase try to improve this solution. The objective function of TS is only $f(s_l)$ and only steps satisfying $p(s) = 0$ are allowed:

$$\text{minimize } q(s) = f(s) \text{ subject to } s \in S : p(s) = 0 \tag{17}$$

3) Diversification phase: Diversification phase is an algorithmic mechanism that tries to alleviate this problem in forcing the search into previously unexplored areas of the search space. This phase may lead TS to infeasible solution space: moving to instantiation that violated some constraints is permitted. The long-term-memories is considered. The objective function is:

$$\text{minimize } q(s) = f(s) + p(s) \text{ subject to } s \in S \tag{18}$$

4) Initial solution: To start the TS approach, an initial solution s_0 must be prepared. Considering that s_0 is determined: the temperature set point of a thermal environment is set to its optimal value 21°C. The starting date of timed services are set to their requested starting date $RSD(SRV_i)$.

5) Neighborhood structure: A move, denoted $s_0 \overrightarrow{move(a,b)} s'_0$, is a step from an element s_0 of the search space to s'_0, which is considered as a element of the neighborhood of s_0. Let V and V' be the instantiated variables corresponding respectively to s_0 and s'_0. First, V' is initialized with V. Then, the $\overrightarrow{move(a,b)}$ is determined by two parameters a and b [20]. They represent the assignment: $v'_a \in V'$ $v'_a := (d_a)_b$ where $(d_a)_b$ stands for the b^{th} element of the domain d_a. Therefore, the size of the neighborhood $N(s_0)$ is calculated as follows:

$$\mid N(s_0) \mid = \sum_i (\mid D_i \mid -1) \tag{19}$$

The best element s'^*_0 of the neighborhood becomes the candidate solution for the next iteration of TS. The $s_0 \overrightarrow{move^*(a,b)} s'^*_0$ is pushed into the tabu list. At the next iteration, only the moves that are not in the tabu list, are allowed except for the one that satisfies the aspiration criterion.

B. Control tabu tenure

The tabu tenure t is very sensitive and must be tuned carefully because the performance of TS depended highly on it.

1) The fixed tabu tenure: Recently [16] has proposed a TS using different tabu tenure values including: small (St), medium (Mt) and large (Lt) tabu tenure values. The setting of t depends on the number of elements in the neighborhoods, which can be generated at each iteration. In this paper, $St \approx 10\% \mid N(s_0) \mid$. It means that the maximal number of prohibited elements of the current neighborhood represents 10% of the total number of generated elements of the neighborhood. In the same way: $Mt \approx 25\% \mid N(s_0) \mid$, $Lt \approx 50\% \mid N(s_0) \mid$. Firstly, the TS with fixed tabu tenure is stopped after 2000 not-improving iterations. Next, the best-known solution s^* is sent to the intensification phase with $t = St$. The stop condition is 1000 not-improving iterations.

2) Dynamic control tabu tenure: Varying continuously the tabu tenure results in a balance between intensification and diversification phases. On the one hand, a setting $t := St$ corresponds to the intensification phase. On the other hand, the settings $t := Mt, t := Lt$ corresponds to the diversification phase of TS. Consider that the tabu tenure varies according to a sequence $[St, Mt, St]$, i.e. tabu tenure starts with $t := St$. After $1.5t$ iterations of TS, the tabu list T is reset and tabu tenure changes to $t := Mt$. Three strategies of variation t are considered: $[St, Mt, Ht, Mt, St]$, $[Mt, Ht, Mt, St]$, $[Ht, Mt, St]$

VI. RESULTS

An illustrative example based on two permanent services and two timed services is presented in this section. The two permanent services SV_1 and SV_2 are heating services in two rooms. Thermal parameters are $C = 0.025kWh/$°C, $R = 40kW$°C for both rooms. The average outdoor temperature is: $T^{out} = 5$°C and the initial temperature is $T_{0,0} = 20$°C for the first room and $T_{1,0} = 18$°C for the second one. The energy consumption plan covers a period of $2h$. The anticipation period Δ is fixed to $0.1h$. Domain of the temperature set-point belongs to $[15°C, 30°C]$. The discretization of temperature domains is given by: $n_d = 15$. The first timed service SV_3 is defined by: $EST(SV_3) = 0.2h$, $RST(SV_3) = 0.5h$, $LST(SV_3) = 0.8h$, $P(SV_3) = 1kW$. The second one is defined by: SV_4: $EST(SV_4) = 0.6h$, $RST(SV_4) = 0.8h$, $LST(SV_4) = 1.2h$, $P(SV_4) = 1kW$. The total power constraint is limited to $2kW$. The consumption of the best solution found by TS is illustrated in figure 1. Available power doesn't allow the simultaneous run of two timed services. SV_3 is on time but SV_4 has been delayed by $0.2h$. In figure 2, the temperature set points of SV_1 and SV_2 have been increased before the run of SV_3 in order to accumulate energy into the room. The user feels warm during several period but he doesn't feel too cold afterwards.

20 random cases of study have been used to test the performance of the different strategies of TS implementation. Two scores have been computed: the number of times that

	St	Mt	Ht	St,Mt,Ht,Mt,St	Mt,Ht,Mt,St	Ht,Mt,St
SC_1	12/20	10/20	8/20	15/20	17/20	14/20
SC_2	12.8s	32.3s	12.2s	343.7s	274.5s	213.8s

TABLE I
EXPERIMENTAL COMPUTATION

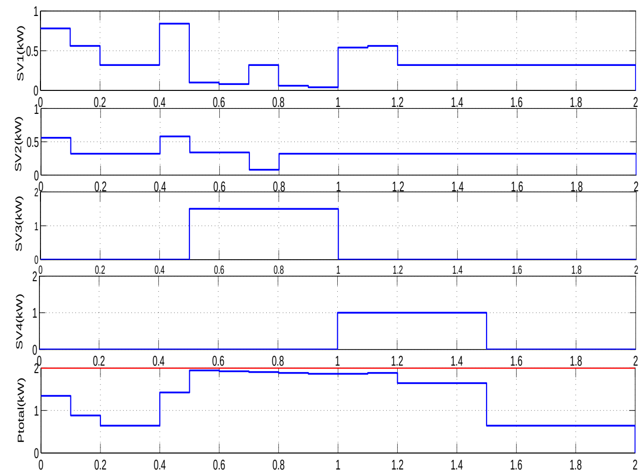

Fig. 2. Energy consumption plan

the best found solution has been retrieved by the different strategies (SC_1), and the CPU time required to find the solution (SC_2). All TS strategies have converged after almost 200 iterations. The dynamic variation of tabu tenure gives more chance to reach the global optimal solution but it takes more times to reach the solution. For a given case of study, there are no TS strategy, which guarantees to reach the optimal region in the search space, but all TS strategies have found a feasible solution.

VII. Conclusion

In this paper, an approach that manages power consumption in home automation is presented. Household energy management consists in setting both starting times of timed services and set points of permanent services. This problem has been formulated as a CSP with two objectives: cost and comfort criteria. An adaptation of tabu search has solved efficiently the household energy management problem. This mechanism synchronizes the energy consumption in satisfying the maximal power constraint and the user comfort remains at a good level. However, the results show that it is difficult to tune a TS strategy for all situations. Different strategies have to be performed at the same time.

The proposed solution makes it possible for the private households to automatically adjust their consumption in order to satisfy power constraints and consequently to participate into a DSM system.

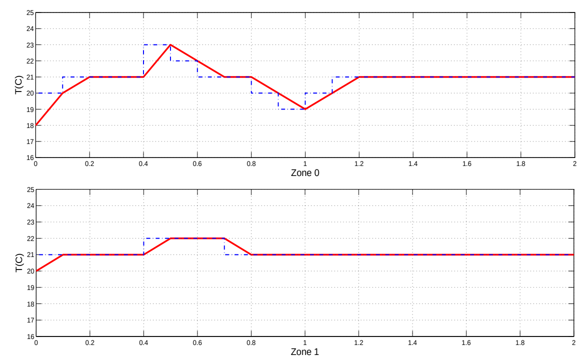

Fig. 3. Predicted temperature in rooms

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