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A Real-Time Dynamic Optimization Based Heuristic Algorithm for Home Energy Management System

Phương pháp tối ưu thời gian thực dựa trên thuật toán suy nghiệm sử dụng trong bài toán quản lý năng lượng trong tòa nhà

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Abstract

Modern buildings are being designed with increasingly sophisticated energy management and control systems that have the capabilities for monitoring and controlling the conditions in buildings. Reducing and scheduling energy usage is the key for any home energy management system. To better match demand and supply, many utilities offer residential demand response program to change the pattern of power consumption of a residential customer by curtailing or shifting their energy use during the peak time period. In the present study, real time optimal schedule controller for home energy management system is proposed using a heuristic algorithm to manage the energy consumption. The proposed method gives optimal schedule for home devices in order to limit the demand of total load and schedule the operation of home appliances at specific times during the day. A set of the most common home appliances, namely, air conditioner, water heater, refrigerator, and washing machine has been considered to be controlled.

Keywords: Energy Smart-Home, Residential demand response, Energy efficiency, Schedule controller.

Tóm tắt

Trong các tòa nhà dân dụng, tiêu thụ năng lượng ngày càng tăng của các thiết bị gia dụng đã trở thành một vấn đề đáng quan tâm. Do đó, việc giảm thiểu và lập kế hoạch sử dụng năng lượng hiệu quả là chìa khóa cho bất kỳ hệ thống quản lý năng lượng tại nhà. Để đáp ứng việc cung cấp và tiêu thụ năng lượng tốt hơn, nhiều giải pháp đã được đưa ra nhằm thay đổi thói quan tiêu thụ điện năng của người sử dụng trong các tòa nhà dân dụng bằng cách tiết kiệm hoặc cắt giảm sử dụng năng lượng trong thời gian cao điểm. Trong nghiên cứu này, phương pháp tối ưu thời gian thực cho hệ thống quản lý năng lượng trong tòa nhà được đề xuất sử dụng một thuật toán suy nghiệm để quản lý tiêu thụ năng lượng. Phương pháp đề xuất cho phép điều khiển tối ưu cho các thiết bị gia đình nhằm hạn chế đỉnh phụ tải và lập kế hoạch hoạt động của thiết bị gia dụng tại những thời điểm cụ thể trong ngày. Các thiết bị gia gia dụng, cụ thể là máy điều hòa không khí, máy nước nóng, tủ lạnh và máy giặt đã được mô hình hóa và tính toán hoạt động tối ưu.

Từ khóa: Quản lý năng lượng trong tòa nhà, Hiệu quả sử dụng năng lượng, điều khiển lịch trình.

1. Introduction

In recent years, many decision-support tools and optimization techniques have been applied to help domestic customers in reducing the energy consumption by creating an optimal home appliance scheduling of energy usage based on different pricing schemes and comfort settings. To achieve this goal, there is need to implement smart control in the domestic building. In [1], distributed control algorithms have been applied to schedule home appliances with Demand Response based on the communication network architecture. The genetic algorithm with artificial neural network (ANN) has been applied to schedule home devices and optimize energy consumption in the domestic sector by reducing the demand during peak periods [2]. Hybrid lightning search algorithm based ANN has been used to predict schedule controller in a HEMS [3]. In [4], autonomous demand-side management system based on game theory approach has been developed to optimize the appliances energy consumption and manage residential loads that help homeowners to select the priority of appliances considering either electricity cost reduction or customer comfort. In [5], electrical appliances have been scheduled to reduce electricity cost based on dynamic pricing using robust optimization and stochastic techniques. A real time optimal schedule controller for home appliances is proposed using a new binary backtracking search algorithm in [6].

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A major issue that is faced in scheduling and shifting user loads is the minimization of the electricity consumption during peak hours without affecting the comfort of occupants. However, most previous researchers focused on reducing electricity bills and saving energy without considering user comfort. Thus, to schedule and control home appliances there is need to take into account all possible challenges, such as comfort level, demand limit and tariff. This paper presents heuristic algorithm based real time optimum schedule controller for home energy management system to achieve energy savings and limit the household peak demand in the home on the basis of the scheduled operation of several appliances according to a specific time, resident comfort constraints.

2. Problem description

In this paper, energy is restricted to electricity consumption and production. Each service is depicted by an amount of consumed/produced electrical power; it is supported by one or several appliances [7].

2.1. The concept of service

Housing with appliances aims at providing comfort to inhabitants thanks to services which can be decomposed into three kinds: the end-user services that produce directly comfort to inhabitants, the intermediate services that manage energy storage and the support services that produce electrical power to intermediate and end-user services. Support services deal with electric power supplying thanks to conversion from a primary energy to electricity. Fuel cells based generators, photovoltaic power suppliers, grid power suppliers such as EVN.

Intermediate services are generally achieved by electrochemical batteries. Among the end-user services, well-known services such as clothe washing, water heating, specific room heating, cooking in oven and lighting can be found.

A service with index i is denoted *SRV(i)*. Appliances are just involved in services: they are not central from an inhabitant point of view. Consequently, they are not explicitly modelled.

2.2. Characterization of services

Let us assume a given time range for anticipating the energy needs (typically 24 hours). A service is qualified as *permanent* if its energetic consumption /production/storage covers the whole time range of energy assignment plan, otherwise, the service is named *temporary service*. The following table gives some examples of services according to this classification.

The services can also be classified according to the way their behavior can be modified. Whatever the service is, an end-user, an intermediate or a support service can be modifiable or not. A service is qualified as *modifiable by a home automation system* if the home automation system is capable to modify its behavior (the starting time for example). There are different ways of modifying services. Sometimes, modifiable services can be considered as continuously modifiable such as the temperature set points in *room heating services* or the shift of a washing. Some other services may be modified discretely such as the interruption of a *washing service*. The different ways of modifying services can be combined: for instance, a washing service can be considered both as interruptible and as continuously shiftable. A service modeled as discretely modifiable contains discrete decision variables in its model whereas a continuously modifiable service contains continuous decision variables. Of course, a service may contain both discrete and continuous decision variables.

In addition, all the unpredictable services can be gathered into a global no-modifiable predictable service. A service can be managed by a home automation system if it is observable and modifiable.

2.3. Modeling services

Modeling services can be decomposed into two aspects: the modeling of the behaviors, which depends on the types of involved models, and the modeling of the quality of the execution of services, which depends on the types of service. Whatever the type of model it is, it has to be defined all over a time horizon $K\Delta$ for anticipative problem solving composed of K sampling periods lasting Δ each.

a. Modeling behavior of services

In order to model the behavior of the different kinds of services in housing, three different types of models have been used: discrete events are modeled by finite state machines, continuous behaviors are modeled by differential equations and mixed discrete and continuous evolutions are modeled by hybrid models that combine the two previous ones.

Using finite state machines (FSM). A finite state machine dedicated to a service SRV is composed of a finite number of states $\{\mathcal{L}_m; m \in \{1,...,M\}\}$ and a set of transitions between those states $\{\mathcal{T}_{p,q} \in \{0,1\}; (p,q) \in S \subset \{1,...,M\}^2\}$. Each state $\mathcal{L}_m$ of a service *SRV* is linked to a phase characterized by a maximal power production or consumption.

A transition triggers a state change. It is described by a condition that has to be satisfied to be enabled. The condition can be a change of a state variable measured by a sensor, a decision of the anticipative mechanism or an elapsed time for phase transition. If it exists a transition between the state $\mathcal{L}_m$ and $\mathcal{L}_{m'}$ then $\mathcal{T}_{m,m'} = 1$, otherwise $\mathcal{T}_{m,m'} = 0$. An action can be associated to each state: it may be a modification of a set-point or an on/off switching. As an example, let's consider a washing service. The service provided by a washing machine may be modeled by a FSM with 4 states: the first state is the stand-by state $\mathcal{L}_1$ with a maximal power of P_1=5W (it is negative because it deals with consumed power). The transition towards the next state is triggered by the anticipative mechanism. The second state is the *water heating* state $\mathcal{L}_2$ with P_2=2400W. The transition to the next state is triggered after τ_2 time units. The next state corresponds to the *washing* characterized by P_3=500W. And finally, after a given duration τ_3 depending on the type of washing (i.e. the type of requested service), the spin-drying state is reached with P_3=1000W. After a given duration τ_4, the *stand-by* state is finally recovered. Considering that the initial state is $\mathcal{L}_1$, this behavior can be formalized by:

$$\begin{cases} (state = \mathcal{L}_1) \wedge (t = t_{start}) & \rightarrow state = \mathcal{L}_2 \\ (state = \mathcal{L}_2) \wedge (t = t_{start+\tau_2}) & \rightarrow state = \mathcal{L}_3 \\ (state = \mathcal{L}_3) \wedge (t = t_{start+\tau_2+\tau_3}) & \rightarrow state = \mathcal{L}_4 \\ (state = \mathcal{L}_4) \wedge (t = t_{start+\tau_2+\tau_3+\tau_4}) & \rightarrow state = \mathcal{L}_1 \end{cases}$$

Using differential equations. In buildings, thermal phenomena are continuous phenomena. In particular, the thermal behavior of a HVAC system can be modeled by state space models. The structure of the model is obtained from space and time discretization of a continuous model expressed in state-space form [8]. The second order model based on an electric analogy has been preferred for our control purpose because it models the dynamic of indoor temperature. For a room heating service *SRV* (*i*), it yields:

$$\begin{bmatrix} T_{in}(i,k+1) \\ T_{env}(i,k+1) \end{bmatrix} = A_i \begin{bmatrix} T_{in}(i,k) \\ T_{env}(i,k) \end{bmatrix} + B_i \left[E(i,k)\right] + F_i \begin{bmatrix} T_{out}(i,k) \\ \phi_s(i,k) \end{bmatrix}$$
$$\forall k \in \{1,\dots,K\}$$

This model allows a rather precise description of the dynamic variations of indoor temperature with:

- T_{in}, T_{out}, T_{env} the indoor, outdoor and housing envelope temperatures, respectively
- P the power consumed by the thermal generator.
- φ_s the energy flow generated by the solar radiance

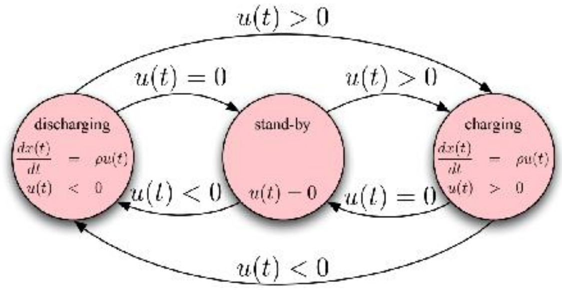

Fig.1. Hybrid model of a battery

Using hybrid models. Some services cannot be modeled by a finite state machine nor by differential equations. Both approaches have to be combined: the resulting model is then based on a finite state machine where each state *Lm* actually becomes a set of states which evolution is depicted by a differential equation. An electric-chemical storage service supported by a battery may be modeled by a hybrid model (partially depicted in Fig.1). $x(t)$ stands for the quantity of energy inside the battery and $u(t)$ the controlled electrical power exchanged with the grid network.

Using static models. Power sources are usually modelled by static constraints. Local intermittent power resources, such as photovoltaic power system or local electric windmill, and power suppliers are considered here. Using weather forecasts, it is possible to predict the power production $w(i,k)$ during each sampling period $[k\Delta;(k+1)\Delta]$ of a support service *SRV*(*i*). The available energy for each sampling period k is then given by:

$$E(i,k) = w(i,k)\Delta, \forall k \in \{1,...,K\}$$

According to the subscription between inhabitants and a power supplier, the maximum available power is given. It may depends on time. For a service of power supply *SRV*(*i*), it can be modelled by the following constraint :

$$E(i,k) \leq p_{max}(i,k)\Delta, \forall k \in \{1,...,K\}$$

where $p_{max}(i,k)$ stands for the maximum available power.

b. Modeling quality of the execution of services:

Depending on the type of service, the quality of the service achievement may be assessed in different ways. End-user services provide comfort to inhabitants, intermediate services provide autonomy and support services provide power that can be assessed by its cost and its impact on the environment. In order to evaluate these qualities different types of criteria have been introduced.

According to the comfort standard 7730 [9], three qualitative categories of thermal comfort can be distinguished: A, B and C. In each category, [9] proposes typical value ranges for temperature, air speed and humidity of a thermal zone that depends on the type of environment: office, room,. . .These categories are based on an aggregated criterion named Predictive Mean Vote (PMV) modelling the deviation from a neutral ambience. The absolute value of this PMV is an interesting index to evaluate the quality of a HVAC service. In order to simplify the evaluation of the PMV, typical values for humidity and air speed are used. Therefore, only the ambient temperature corresponding to the neutral value of PMV (PMV=0) is dynamically concerned. Under this assumption, an ideal temperature T_{opt} is obtained. Depending on the environment, an acceptable temperature range coming from the standard leads to an interval $[T_{min}, T_{max}]$. For instance, in an individual office in category A, with typical air speed and humidity conditions, the neutral temperature is T_{opt}=22°C and the acceptable range is [21°C, 23°C]. Therefore, considering the HVAC service *SRV(i)*, the discomfort criterion *D(i,k)*, which is more usable than comfort criterion here, is modelled by the following:

$$D(i,k) = \begin{cases} \dfrac{(T_{opt} - T_{in}(i,k))}{T_{opt} - T_{Min}} & \text{if} \quad T_{in}(i,k) \le T_{opt} \\ \dfrac{(T_{in}(i,k) - T_{opt})}{T_{Max} - T_{opt}} & \text{if} \quad T_{in}(i,k) > T_{opt} \end{cases}$$

The global comfort criterion is defined as following:

$$D(i) = \sum_{k=1}^{K} D(i,k)$$

Generally speaking, modifiable temporary end-user services do not aim at controlling a physical variable. Temporary services such as washing are expected by inhabitants to finish at a given time. Therefore, the quality of achievement of a temporary service depends on the amount of time it is shifted. Therefore, in the same way as for permanent services, a user dissatisfaction criterion for a service *SRV*(*i*) is defined by:

$$D(i) = \begin{cases} \dfrac{f(i) - f_{opt}(i)}{f_{max}(i) - f_{opt}(i)} & \text{if} \quad f(i) > f_{opt}(i) \\ \dfrac{f_{opt}(i) - f(i)}{f_{opt}(i) - f_{min}(i)} & \text{if} \quad f(i) \le f_{opt}(i) \end{cases}$$

where f_{opt} stands for the requested end time and f_{min} and f_{max} stand respectively for the minimum and maximum acceptable end time.

3. Real-time dynamic optimization based heuristic algorithm

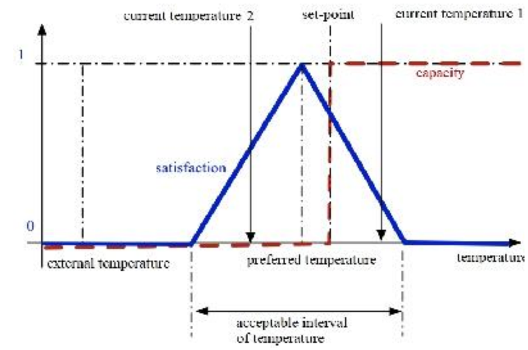

Fig. 2. Calculation of the capacity for a zone heating service

At each time period, the heuristic algorithm adapts the set-points values given by the schedule plan to the current context and re-initiates a forward calculation if the current context is too far from the predicted context. With this approach, the heuristic algorithm reacts in alert mode when the assessed levels of users' dissatisfaction are lower than the levels predicted by the scheduling plan. It is based on a list algorithm which relies on the concept of capacity defined as the capacity of a service to tend towards its operating set-points without consuming energy.

Let us take the example of a permanent service of heating type of an area represented by Fig. 2. If the current temperature is equal to temperature 1, it is useless to reserve energy for the heating service because the current temperature will tend towards the temperature set-points because the outside temperature is lower than the current temperature. Conversely, if the current temperature is equal to temperature 2, it is necessary to examine the possibility of an allocation of energy to the heating service so that the current temperature can reach the temperature set-points.

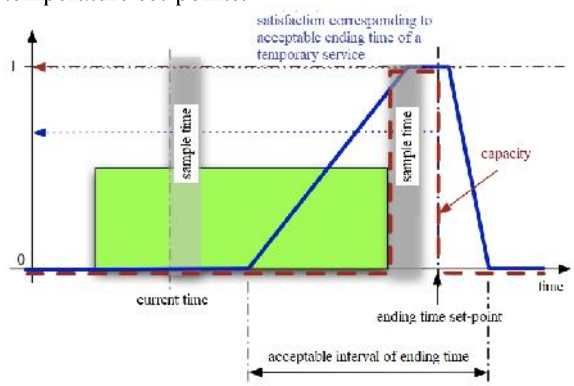

Fig. 3. Calculation of capacity for temporary service

Let us now take the example of a temporary service of washing service. Fig.3 shows how the capacity of a temporary service is calculated.

Satisfaction depends on the current time and on the end date chosen as the set-points (in the scheduling plan). In this example, interrupting the washing service for an period of time makes it possible to get closer to the ending time set-points. This service therefore has the capacity to tend towards its set-points without consuming energy. If the service had shifted behind the set-points, the capacity would have been zero.

Knowing that a service which is modifiable by the reactive mechanism is qualified as preemptive, the main procedure of the heuristic algorithm can then be described. It is triggered at each period Δ_r:

- for each service, the current state is evaluated using the available measurements
- taking into account the state of the services, the need of electrical energy for the next period is evaluated and compared with the production capacity of the energy supplier services
- if there is enough power for all services, energy is allocated to each service and the procedure stops there.
- for each service, the satisfaction of the inhabitants is evaluated from the current state
- for each service, the capacity to reach its operating set-points without consuming energy is evaluated starting from the current state
- the preemptive services that are candidates for an interruption are selected: only the services that current satisfaction is lower than the level determined by the anticipative mechanism are selected
- the maximum energy resource available for the next period is evaluated by taking into account the consumption of non-modifiable user services.
- pre-emptive services are classified in a list:
    - services with the capacity to tend towards their operating instructions without using energy are ranked first
    - services that do not have the capacity to tend towards their operating instructions without consuming energy are then ranked in the list in decreasing order of level of users' dissatisfaction
- by following this list, the energy resource is allocated to non-preemptive services and then to pre-emptive services in the order list until there is no longer an available energy resource.
- Activation and deactivation orders are then sent to the modifiable services for the next period.

4. Case study

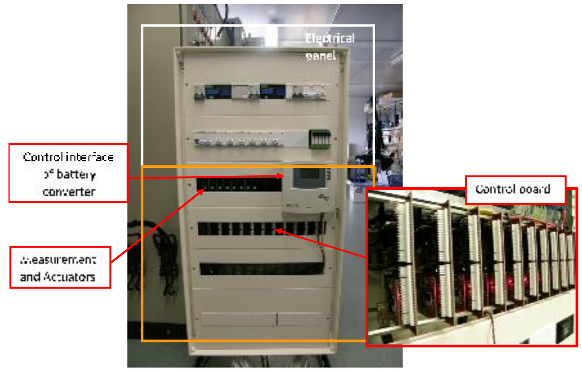

Fig. 4. Electric panel of platform

Fig. 4 shows the electric panel of the platform study. The equipment consists of a standard electrical housing panel, sensors for measurements, actuators and electronic boards for shaping measures. Fig.5 shows the prototype connected to its electro technical and software environment. On the one hand, it is connected to the monitoring software which is embedded on one PC and on the other hand it is connected to the sources and loads. This prototype allows control of the flow of power by the supervisor.

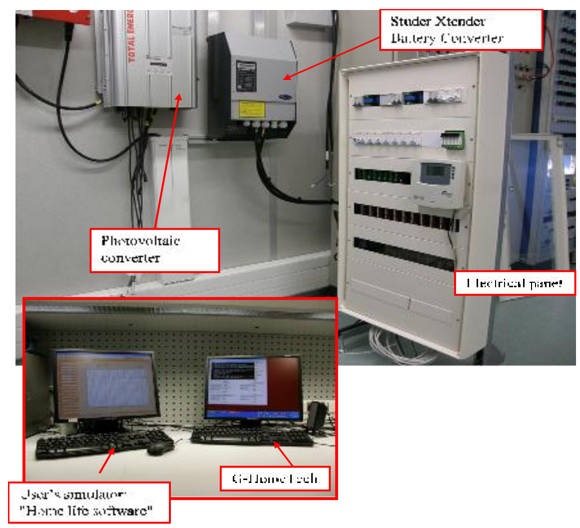

Fig. 5. Integration of G-HomeTech to the platform

4.1 Testbed

An energy smart home system (see Fig.6), namely G-HomeTech, has been developed based on the optimization process presented in this paper. It is composed of a supervisor which centralizes the characteristics of the house: the available appliances, the services required by the user, the weather forecasts, and the energetic constraints such as the subscription and the local production if it exists. The energy management problem to solve is generated dynamically because each living place is unique and evolving.

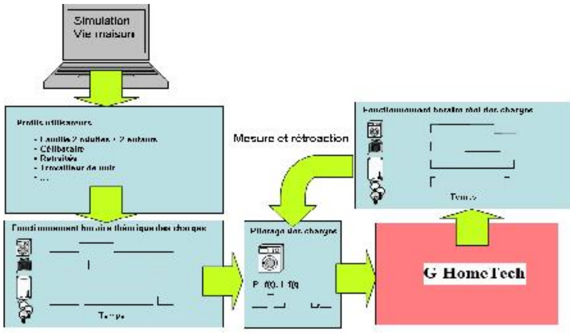

Fig. 6. Principle of the G-HomeTech testbed

4.2 Principle of testing

The tests are based on scenarios of one day of 24 hours. It is necessary to ensure that the different variants are comparable: constant energy balance, identical service rendered… The analysis parameters depend on the scenarios and are defined pour each scenario. In this test, the objective is to satisfy the maximum power constraints of a network subscription. The analysis parameter is the peak power of the subscription while the scenario evaluation criterion is the comfort cost for not having a disjunction. Fig.7 shows the daily operating schedule of these appliances (in orange the operating time range)

Table 1. Load descriptions and power ratings characteristics

Appliance	*Power rating (W)*	*Required Usage Frequency*	*Allowable margin*
Refrigerator	100	all day	(2;4)°C
Freezer	100	all day	(-20;-15)°C
Dishwasher	2000	once a day at 8h for 1,5 hours	shiftable
Heating and hot water	2000	all day 1 showers at 7am and 2 showers at 7pm	interruptible
Oven	2000	once a day between (7pm; 7:30pm)	no
Unsupervised appliances	500-2000		no

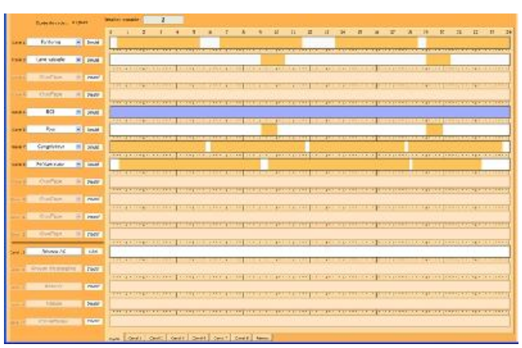

Fig. 7. Daily operating schedule of appliances

5. Experimental results

5.1 Reference scenario

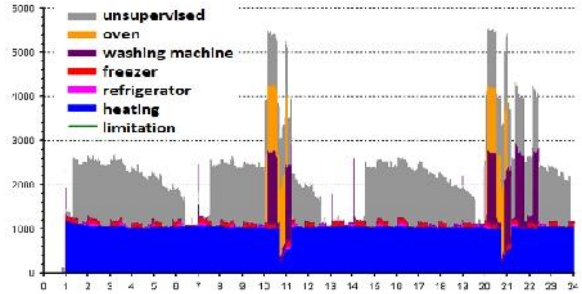

Fig. 8. Power consumption (W) on one day without G-HomeTech

The reference scenario corresponds to the operation of the equipment without G-HomeTech. Fig.8 shows the energy consumption throughout the day. Two peaks of consumption appeared between 10am and 11am and the evening between 8pm and 10pm which reaches 5.7kW. Fig.9 shows the power histogram during this scenario. The bar in red corresponds to the average power. One can note the simultaneous operation of the washing machine, the oven and the heater during peak consumption of noon and evening.

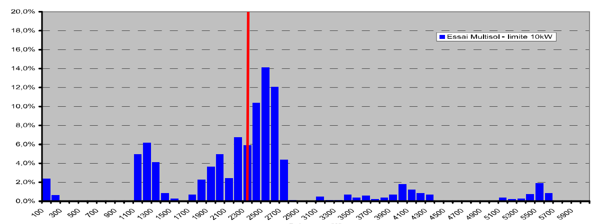

Fig. 9. Histogram of power consumption scenario without load shedding

5.2 Power limitation to 5 kW

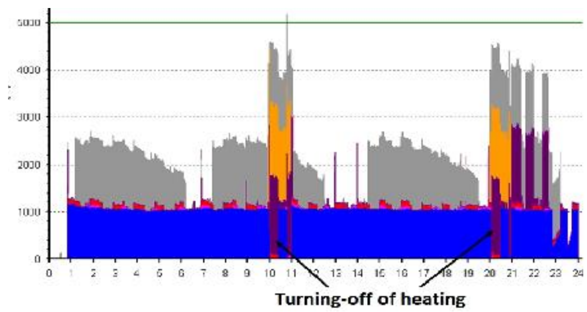

Fig. 10. Operation of the equipment in the scenario of 5kW load-shedding

As expected, the power demanded beyond 5kW has been greatly reduced 0.1 kWh in this scenario against 5.7 kWh in the reference scenario (illustrated in Table 2). Fig.10 shows the temporal operation of the equipment and the action of G-HomeTech. It relieved the heater during the high power demand phases to keep the oven, washing and unsupervised loads running simultaneously. The comfort of the user has been slightly decreased by reducing a little the quantity of heating energy.

5.3 Power limitation to 3 kW

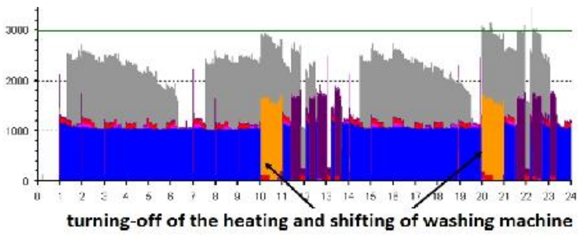

Fig. 11. Time graph of power consumption during the scenario of 3kW load shedding scenario

This limitation of power is much more severe than in the previous test. Fig. 11 shows the power consumed throughout the day. The morning and evening power peaks are greatly reduced. In order to respect the constraint, G-HomeTech has reduced the consumption of the heater and shifted the operation of the washing machine. The comfort of the user has thus been further reduced by a further reduction of the inside temperature and by a delay in the washing of the dishes. It should be noted that the dishwasher's shifting could have fallen to a period of high consumption in which case it would have been shifted again. The characteristics of obtained solution are given in the Table 2.

5.4 Power limitation to 1 kW:

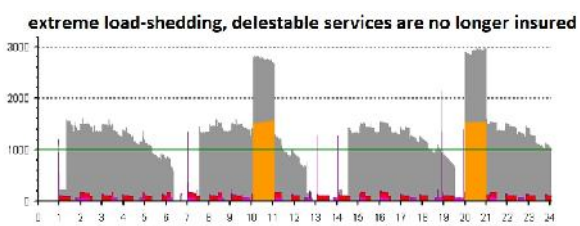

Fig. 12. Operation of the equipment in the scenario of 1kW load shedding

This test is extreme and serves to show the limits of power constraint. The power limitation of 1kW have been parameterized much lower than the average power of 2.2 kW. This power limitation should severely degrade the service. As expected, the load shedding is extreme with a very large drop in the overall energy consumed and the average power demanded. Fig.12 confirms that only the unsupervised charges, non-shiftable services (oven) and low power consumption services (refrigerator, and freezer) have been retained.

Table 2. The characteristics of obtained solutions

		Reference scenario	Power limitation		
			5kW	3kW	1kW
Average power [W]		2360	2313	2172	1216
Total energy consumption [kWh]		56,6	55,5	52,1	29,2
>1kW	*proportion [%]*	97	96,6	95	67
	energy [kW]	56,5	55,4	51,9	25,7
>3kW	*proportion [%]*	12,7	13,5	3,9	0
	energy [kW]	13,4	13,6	2,9	
>5kW	*proportion [%]*	1,4	0,1	0	0
	energy [kW]	5,7	0,1		

6. Conclusions

A real time optimal schedule controller for home energy management system has been proposed using a heuristic algorithm to minimize the electricity consumption during peak hours taking into account the comfort of occupants. These various tests show the capabilities and limitations of the approach:

• Respecting of limited power constraints without limited degradation the users' comfort: the limitation power of 5kW for a peak power of 5.7 kW (i.e. a reduction of 15%). In this case, it may be sufficient to reduce the consumption of heaters.

• On the other hand, for a more severe constraint: power limitation of 3kW for a peak power of 5.7kW (i.e. a reduction of approximately 50%), it must delay more sensitive services: washing machine, dishwasher. It is then necessary that the cycle of operation can be carried out completely without any further interruption, otherwise the consumed energy will increase greatly.

• It is necessary to compare these maximum powers constraints with the average consumption of the appliances in each the scenario. A limit of 5kW for an average power of 2.2 kW is not difficult. Otherwise, a limit of 3 kW for an average power of 2.2 kW is very severe.

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