ELECTRICITY LOAD MANAGEMENT IN SMART HOME CONTROL

Félix Iglesias Vázquez[1], Wolfgang Kastner[1], Sergio Cantos Gaceo[2] and Christian Reinisch[1]
[1]Automation Systems Group, Vienna University of Technology, Vienna, Austria
[2]Electronics & Communication Department, La Salle (URL), Barcelona, Spain

ABSTRACT

The achievement of sustainable goals in the home environment demands an optimized management of electricity loads from the control side.

The present work proposes a control approach based on an appropriate load definition, context awareness regarding user behaviours and the persuasive capabilities of pervasive systems. Beyond further benefits, the main aim is focused on the improvement of the elasticity of the electricity market.

In order to check the proposal, some simulations comparing common users and "optimized" users are performed. The simulations deploy statistical information from Austria in 2008 and conclude with hypothetical savings for future homes with the proposed enhancements.

INTRODUCTION

A well-known characteristic of the current electricity market is the low elasticity of its short run prices (Yusta and Domínguez, 2002). This is mainly due to the fact that end consumers hardly react against peaks of demand, in spite of the fact that their consumption habits are largely causing imbalance. Most electricity markets do not consider consumers as active elements capable of adopting optimized strategies and decisions but simply as loads to be continuously supplied (Kirschen, 2003).

From the point of view of the load side control (or more exactly from a home control's scope), the objectives dealing with electricity loads remain: reducing energy demand and costs while minimizing CO_2 emissions (as a whole, and considering the entire chain from power generators to end consumers). So, home control systems are expected to work in three levels to reach and optimize the exposed aims:

- Reducing energy consumption.
- Displacing consumption from peak to valley hours, i.e., tending to flatten the consumption. This is reached by means of load shifting according to demand or price forecasting (Kirschen et al., 2000).
- Giving real-time information to users about energy prices and demand evolution (Zedan et al., 2010), advising and instructing them to acquire optimized energy usage habits.

Indeed, flattening the curve of demand and avoiding high peaks are two claimed solutions whose benefits have been calculated in huge amounts of energy and economic savings (Faruqui et al., 2007).

The present work explores these aspects and suggests application proposals and control strategies based on a suitable load definition, context awareness regarding users habits and load usage, and the exploitation of the persuasive capabilities of technology.

Moreover, a home load controller that fits the approach is proposed. It is designed as a flexible and independent agent that can run within a multi-agent framework or under the supervision of a comprehensive home control system. Thus the present work may be embraced under the coverage of a top-down and holistic smart home control approach (Reinisch et al., 2011).

A set of simulations performed with MATLAB and Simulink tools supports some of the exposed proposals, comparing the consumptions of common or representative homes with optimized ones. The simulations have been performed with real data about how electricity is consumed and distributed in devices and equipments in Austria (2008). Also, real data about electricity spot prices and demand curves for the same period in Austria/Germany have been deployed to develop representative home models. The selected models represent diverse sorts of homes based on the number of inhabitants (dwellings with 1, 2, 3, and 4 or more residents), the dwelling size (below $90m^2$, between $90m^2$ and $130m^2$ and over $130m^2$), and flat/house differentiation (one or two family house or flats).

For the evaluation, data about spot prices are also used as benchmarks to assess potential benefits obtained by means of the optimized control, as well as other performance indexes based on consumption, demand flattening and current electricity tariffs for end users. Thus, the results of the simulations show potential savings for representative homes where the described proposals are applied.

PROPOSED APPROACH

The proposed approach consists of a set of simple and non-expensive applications for the electrical load management whose real implementation results in important savings. The applications are:

- Definition of loads for control purposes.
- Control of standby loads based on occupancy and control of shiftable loads.

- Usage of an informative panel.

Load definition

The *load definition* is necessary to identify potential control solutions as, by means of a good recognition of energy loads, the system gets more context awareness. It is not mandatory that all the electrical loads are recognized by the smart control, but the more information the system has, the better it can react.

Keeping always the flexibility and autonomy of devices, dedicated hardware paves the way for an easy integration of old and new appliances (Kim et al., 2007). Here, the integration of wireless technologies into existing infrastructure (e.g., Zigbee) or usage of dynamic networking technologies for service discovery and usage (e.g., DPWS, UPnP) fits perfectly the proposed approach.

Indeed the load definition justifies the intelligent modeling as knowledge base or ontology, that allows the definition of sound top-down control approaches. The integration of an ontological description of energy loads as well as energy supply, as described in (Kofler et al., 2011), can be seen as profitable in order to model the dynamic environment in which a high amount of actuations can be expected. Such a formal categorization can be seen as basic form of intelligence, supporting semantic inference already on the level of information representation.

The load definition involves *classification* and *description*. A possible and basic load classification is given in Table 1, that can be more extensive depending on the control applications and requirements (e.g., if supporting control for distribution generation systems or smart grids is considered, new load types can be necessary). The description entails load types but it is also open to other parameters (if applicable) like status (on/off), nominal power, supply time, etc.

It is important to remark that load types in Table 1 are not exclusive labels, a load can be defined as “mandatory” and “standby” because it shows both behaviours depending on the time.

Control strategies

Control strategies can be designed based on the load definition. The next two examples are explored and simulated here.

–Control of standby loads based on occupancy.

Nowadays, the standby power consumption is responsible for 5-10% of total electricity use in most homes (International Energy Agency, 2007). A simple operation is to switch off loads in standby when there are no people at home or during night.

It is easily implemented with home occupancy detection – whether they be simple or use advanced methods (Dodier et al., 2006) – and allowing to bring the house to a “sleeping mode”. On the other hand, if users do not want some loads to be switched off when they are absent (or sleeping), these loads are not defined as standby and the system assumes their consumption as mandatory.

–Control of shiftable loads.

There are some electricity loads that users do not need to supply immediately and can be shifted to periods when electricity is cheaper and less demanding.

In those cases smart controllers find the best moments to supply shiftable loads according to context data (e.g., load definitions, predicted consumptions, the next day electricity prices, strategies and some additional constraints).

The schema of the proposed controller prototype, inputs, outputs and communication with the Home Automation System is shown in Figure 1.

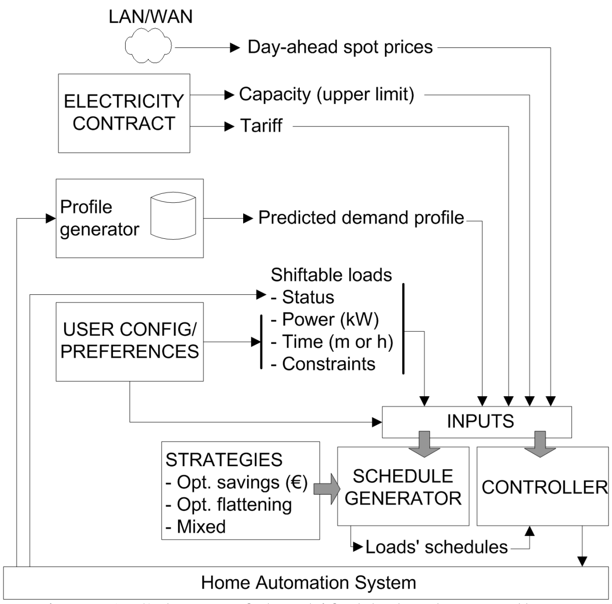

Figure 1: Schema of the shiftable load controller.

The next assumptions are considered:

- The electricity spot price values are available 24h in advance through remote servers. In case of linking failures or more day prediction needed, a module for price prognosis can be used.
- The *supply period* for each shiftable load is limited to 24 hours. It states the requirement of supplying shiftable loads within next day. Otherwise, for wider periods, a module for energy price prediction is necessary.
- The demand curve for the next day is provided by an electricity demand prediction module (Al-Alawi and Islam, 1996).

As far as the predictive modules for demand (and for electricity prices) are concerned, research has obtained successful results deploying fuzzy and neural network clustering in similar scenarios. Clustering tools are remarkable to discover patterns based on behaviours and optimize the performance of predictive controllers (Iglesias Vázquez and Kastner, 2011).

The flowchart of the process followed for every

Table 1: Load definition.

Type	Definition	Included devices	Control action
Stand-by	Devices that have a consumption in standby mode and remain in standby when people are absent.	Cooker, oven, white goods, office equipment, entertainment (TV, DVD, etc.).	Open/close electrical supply depending on occupancy (or in sleeping periods).
Permanent	Devices that are continuously switched on with a quite stable energy consumption.	Fridge, freezer.	No control (green devices or specific solutions).
Shiftable (or movable, deferrable)	Loads that can be shifted in time.	Washing machine, dishwasher, storage heater and water heater, pumps, etc.	Move the load starting to a best moment for the energy system.
Priority (or arbitrary, mandatory)	Normal loads that must be supplied when it is required for their normal running.	Lighting, communication devices, cooker, oven, dryer, white goods, office equipment, entertainment electronics, battery chargers, ventilation, cooling devices, etc.	No control (green devices or specific solutions).

shiftable load is shown in Figure 2. The process is triggered every time users set a shiftable load in *waiting for scheduling*. It works as follows:

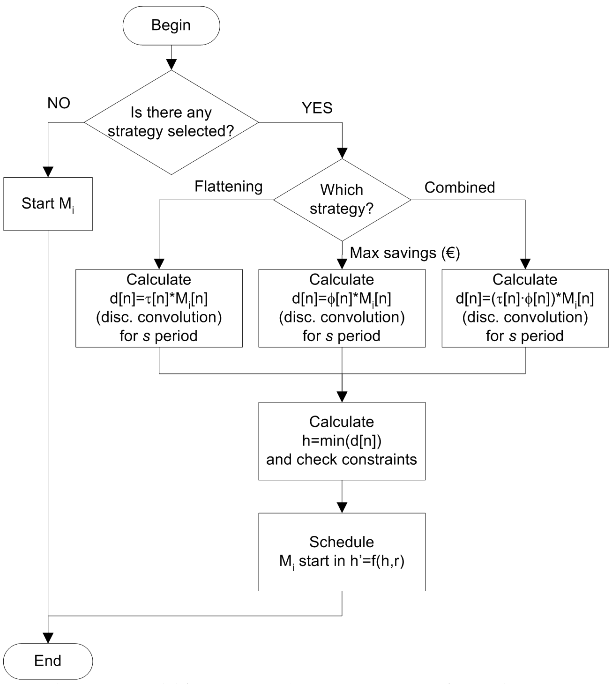

Figure 2: Shiftable load management flowchart.

1. The controller calculates an objective function $d[n]$ for the "shiftable load i" M_i (with p as the supply period and r as the running time).
2. The objective function states the best point for adding a new load (centered there).

The available objective functions are:

$$d[n] = \tau[n] * M_i[n] \tag{1}$$

$$d[n] = \phi[n] * M_i[n] \tag{2}$$

$$d[n] = (\tau[n]\phi[n]) * M_i[n] \tag{3}$$

where $*$ marks convolution, $\phi[n]$ refers to the next spot electricity prices curve, and $\tau[n]$ is the predicted demand. (1) pursues to maximize the flattening, (2) the cost savings, and (3) remains as a balanced combination of both.

The existence of two aims in the shifting control is due to the fact that, although the ideal situation tends to consider that all users should have a balanced demand curve, the possibility of counteracting bad widespread tendencies or profit from cheaper moments is obviously satisfactory. It draws a reality where energy retailers or suppliers can inform and automatically configure linked homes with the most suitable strategy (of course with the users' agreement or/and within an special contract/charging).

Informative Panel

The energy and comfort optimization in smart home control entail a high and complex casuistry with a high dependence on users' habits. A promising approach is to review the role of users and consider them as active actors integrated into control. On this basis, the design of the Informative Panel (IP) explores the idea of profiting the persuasive and pervasive capabilities of technology in order to empower people to improve their energy behaviour at home (Intille, 2002). Without being annoying, a well-designed system is able to show the right information at precisely the right time which makes users more aware about the current energy reality and their own energy behaviour.

The improvements in behaviours are expected as a consequence of having at users' disposal usable information about the next issues:

- Suitability for the energy consumption.
  Using real time information about spot prices, the system shows if the current hour and day are good or bad for energy consumption. Tendencies are shown as well and assessments for the next days can be fairly forecast.
- Self-consumption evolution.
  Users can get motivation comparing the latest consumption with consumptions in previous weeks, months, season and years. Indirectly, they evaluate their own habits and are able to find non sustainable routines and devices that are not working properly.
- Comparison with benchmarks.

Analogously, benchmarks facilitated and updated by linked repositories, services and servers allow users to check their energy habits and compare them with the normal rates in their neighbourhood, city or country (e.g., to know the expected consumption per inhabitant or square meter).

- Energy advices and recommendations.
  Customized advices or general recommendations and news about energy, health and lifestyle can be provided.

An informative panel perfectly fits the load definition and the proposed control strategies. E.g., the load displacement can be executed by the direct action of the automated controller or by the indirect action of the IP (through a well-informed user). Due to the psychological and subjective effect of the IP application, simulations can hardly consider it in their tests, but its addition in a real scenario would increase the potential benefits that are shown below (see "Results" Section).

On the other hand, a continuous interaction between users and the informative panel is not expected. As long as energy status has certain cadences in time, users early abstract the main tendencies and get a basic awareness about the best moments for the energy consumption and/or devices that use a big amount of energy. It is intended that users know and control the energy or electricity running at home. In fact, the "teaching" power of the smart system consists of an underlying supervision of the different energy status, a clear and easy-to-use interface, and an always quick and available source of outstanding information.

Together with other applications for the IP, energy savings and comfort are optimized as long as users get correct feedbacks to improve their own home experience. For example, using the example proposed by Intille, informing users about the convenience of opening or closing windows to balance indoor and outdoor thermal conditions (Intille, 2002) would lead us to better energy and thermal comfort performances. In short, IP applications are designed to allow a proactive user management that improves the overall users' acceptance and satisfaction concerning the automated environment at home.

The design of the IP must be carefully carried out, paying attention to usability and ergonomics and focusing on adaptive and self-checking capabilities. It must be refined progressively by usability studies. Figure 3 shows an example of IP design for the main screen or screen by default.

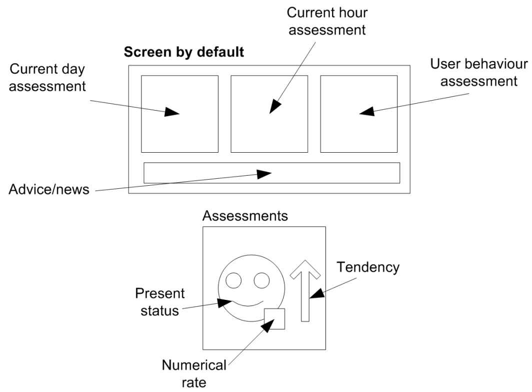

Figure 3: Informative Panel for the energy information. Example of the main screen.

SIMULATIONS

Objectives and methodology

The simulations utilize real data published by Statistik Austria (Wegscheider-Pichler, 2009). The documentation belongs to the year 2008 and informs about the average (mean and median) consumption distributed by devices in Austrian homes. Data are arranged according to seasons, size of dwellings, sort of dwellings and number of inhabitants. Considering these data, some representative Austrian home models have been abstracted. In the same way, real electricity spot prices from EXAA (Energy Exchange Austria) for the same year are deployed as control inputs.

Under this perspective, the simulations evaluate two modes for each model: a normal mode (typical and directly abstracted from the statistical data) and an optimized mode. The optimized mode adds control based on load definition. It takes the statistical data as a starting point as well, but saves or moves loads according to the possibilities of each model.

Comparisons between normal and optimized performances state hypothetical savings for each case/model.

Models and data adjustments

The device consumption facilitated by the statistical data is classified according to the load definition (Table 2). *Median* assessments are selected for the model design considering the dispersion in the whole population and the fact that the data is not symmetrically distributed.

Table 3 represents how the electricity has been used in Austria in 2008 for dwellings where only one person lives, according to the load definition. The same table has been calculated for dwellings with 2, 3, and 4 or more residents; dwellings below 90m^2, between 90m^2 and 130m^2 and over 130m^2; and differentiating between one or two family houses and flats. The total number of polled dwellings is 3.548.532.

Occupancy schedules

Occupancy schedules have been designed for each model. The designed schedules do not try to be representative for the whole Austrian population, they are just suggesting possible users. In any case, they have been modeled following the feedbacks from polled inhabitants, trying to abstract common and extended occupancy habits.

The importance of schedules does not only remain in

Table 2: Electricity division from statistical data and load classification.

Device (consumption)	load type
Stand-by cooker, oven	standby
Stand-by office	standby
Stand by white goods	standby
Stand-by entertainment	standby
Fridge	permanent
Freezer	permanent
Water heater	shiftable
Washing machine	shiftable
Storage heater	shiftable
Dishwasher	shiftable
Communication devices	priority
Dryer	priority
Office equipment	priority
Battery chargers	priority
Lighting	priority
Cooker, oven	priority
White goods	priority
Entertainment electronics	priority
Elec. HVAC	priority
Circulator pumps	priority

Table 3: Representative daily electricity consumption: 1 inhabitant dwelling.

Load type	S (kWh)	W (kWh)
Stand-by	0.42	0.42
Permanent	1.50	1.50
Shiftable	0.52	0.49
Priority	2.61	4.57
TOTAL (per day)	5.05	6.98

Participants: 1.222.352 Austrian homes (2008)

the effect of the standby control. Note that dwellings owned by singles or few people are usually unoccupied a considerable part of the time. As far as the design of *model users* is concerned, it means that the estimated average daily consumption is not fairly shared in time but concentrated in few hours. Considering this fact is mandatory to obtain realistic simulations.

Curves of spot prices

The curves of electricity spot prices are useful for the simulations for three reasons:

1. Model design.
   To fix the shape of typical demand curves of normal users each season. Over this shape, the statistical rates and the schedules are superimposed.
2. Control input.
   Spot prices are known one day ahead, thus they are utilized to optimize the shifting load control.
3. Evaluation metric.
   Spot prices establish instantaneous real costs of electricity. Likewise, daily curves are deployed.

Figure 4 and Figure 5 show the variability of spot prices throughout the day (hour prices) in different seasons and throughout the year (average daily prices).

Thus, the electricity market draws a changeable scenario with good and bad times for the consumption.

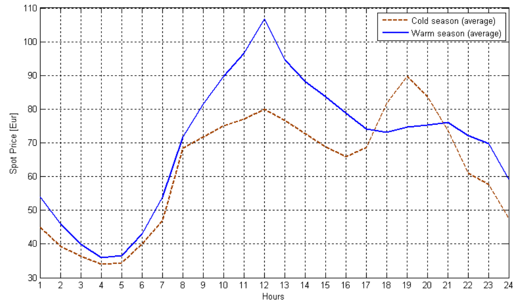

Figure 4: Electricity spot prices. Hourly averages for cold and warm seasons in Austria (2008).

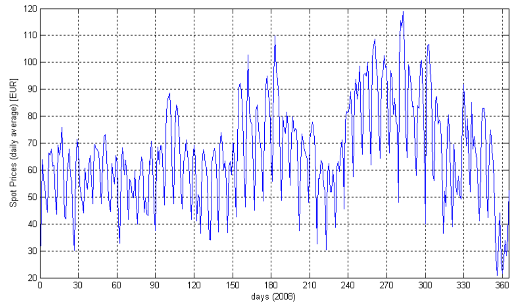

Figure 5: Seasonality. Electricity spot prices. Daily averages in Austria (2008).

Steps for obtaining the dwelling/user model

The design of models for the simulations follows the next steps:

1. Schedule function (for each model).
   -$H[m, n] = H_{m,n}$ with $H_{m,n} \in \mathbb{N}\{0, 1\}$, where m is the present day and n is the current hour. 0 means absence and 1 presence.
2. Normalized typical consumption.
   -$C[n] = C_n$, where $C_n \in \mathbb{R}[0, 1]$. This function is the same for all the models which is obtained from the normalized average of the demand curves in 2008. There are two functions: winter and summer.
3. Model consumption functions (for each model).

$$C'[m, n] = H_{m,n} C_n \tag{4}$$

In (4) the consumption curve is customized for the selected model schedule.

$$C''[m, n] = C'[m, n] \frac{\hat{C} M N}{\sum_n C[n]} \tag{5}$$

where $\hat{C}$ is the average total daily consumption obtained from statistics for the selected model (in kWh). N is the total simulated hours, M is the total simulated days. In (5) the level of the consumption curve is adjusted to the statistical information of the selected model.

-$S[m, n] = stby, \forall(m, n)$ is the function for standby loads, where $stby$ is a constant for the average standby hourly consumption (in kWh).

-$P[m, n] = permt, \forall(m, n)$ is the function for permanent loads, where $permt$ is a constant that represents the permanent consumption (in kWh).

-$M_j[m, n]$ are the functions for shiftable loads. There is one for each different shiftable load in each model. They are defined considering the load power (pow_j), the running time ($runt_j$), the supply period ($supp_j$), certain time constraints and the peaks of demand in $C[n]$.

$$M_j[m, n] = \begin{cases} pow_j, \forall(m, n) \in \{(a, b)_j, ..., (p, q)_j\} \\ 0, \forall(m, n) \notin \{(a, b)_j, ..., (p, q)_j\} \end{cases}$$

$\hat{M}_j$ is a constant that represents the daily consumption of the shiftable load j (in kWh).

$$\hat{M}_j = \frac{(pow_j * runt_j)}{supp_j} \tag{6}$$

$$G[m, n] = C''_{m,n} + S_{m,n} + P_{m,n} \tag{7}$$

$$\hat{H} = \frac{\sum_{m,n} H[m, n]}{MN} \tag{8}$$

-$K[m, n]$ distributes the consumption for standby and permanent loads considering the schedule and keeping the average level in the statistics.

$$K[m, n] = \begin{cases} G[m, n], & \forall H_{m,n} = 0 \\ G[m, n] - (S_{m,n} + \\ \quad P_{m,n} + \sum_j \hat{M}_j)\hat{H}, & \forall H_{m,n} = 1 \end{cases} \tag{9}$$

-$A[m, n]$ is the function for priority loads.

$$A[m, n] = K[m, n] - (S[m, n] + P[m, n]) \tag{10}$$

Finally, the function for total consumptions results in:

$$T[m, n] = A[m, n] + S[m, n] + P[m, n] + \sum_j M_j[m, n] \tag{11}$$

where

- $T[m, n]$, total consumption function.
- $A[m, n]$, priority loads function.
- $S[m, n]$, stand-by loads function.
- $P[m, n]$, permanent loads function.
- $M_j[m, n]$, shiftable j-load function.

4. Shiftable loads for normal users: $M_j[m, n]$ are fixed according to the schedule $H[m, n]$ fitting with the typical consumption curve $C[n]$, it is within the hours where the consumption is maximum based on statistical data.
5. Shiftable loads for "optimized" users: The controller places shiftable loads based on the selected strategy. In the simulations, the predicted demand is calculated as follows:

$$\tau_d[n] = \frac{1}{d-1} \sum_{i=1}^{d-1} K[i, n] + \sum_{k=1}^{l} M_k[d, n] \tag{12}$$

where d marks the day to be predicted and l the total of shiftable loads that have been already programmed for the next day. $M_j[d, n] = 0, \forall n$ before the first shiftable load have been programmed. In short, it means that the prediction takes into account the average of the previous days consumption without considering shiftable loads. The already programmed shiftable loads for tomorrow are added afterwards.

This way to predict consumption is quite defective for real applications but easy to implement and suitable enough for simulations. As we have referred above (see "Control strategies" Section), real applications require accurate options for the demand prediction based on user behaviours.

Applied strategies and control cases

Simulations have been carried out combining the next control options and comparing the results (with a total of 8 performances: 1, 2, 3, 4, 5, 2&3, 2&4, 2&5).

1. No control.
2. Stand-by control[1].
3. Shiftable load control based on flattening.
4. Shiftable load control based on spot prices.
5. Shiftable load control based on flattening and spot prices.

Figure 6 shows an example of different demand curves for an arbitrary day of the same model depending on the applied control strategy: no control (1), flattening (3) and spot prices/minimize EUR (4).

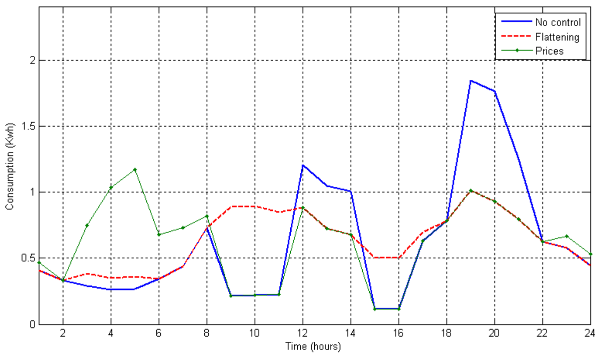

Figure 6: Example of daily consumption curves depending on the control strategy.

It is obvious that standby control savings (based only on occupancy) are very easy to calculate and it does not require any simulation. Furthermore, it depends directly on the schedule and habits of the respective user/family. In any case, it has been simulated in order to show the improvements when strategies based on occupancy and load shifting are applied together.

[1]The *sleeping mode* option is obviated in simulations due to the uncertainties that its modeling involves.

Comparison indexes and percentages of savings

In order to compare strategies and evaluate the proposed approaches, the next performance indexes have been utilized for the simulations:

- T_d. Average daily consumption in kWh.

$$T_d = \frac{\sum_{i=1}^{MN} T_i}{M} \tag{13}$$

T_i is the consumption in kWh in the hour i.

- ES. Average daily Energy Savings in kWh.

$$ES = T_d - T_d' \tag{14}$$

The prime mark denotes that standby control is being applied.

- SP. Average daily electricity cost (EUR) based on Spot Prices.

$$SP = \frac{\sum_{i=1}^{MN} T_i\phi_i}{M} \tag{15}$$

ϕ_i is the spot price for the hour i in EUR/kWh.

- NT. Average daily electricity cost (EUR) based on real Austrian electricity Tariff with Night-time mode contracted (*Wien Energie*).

$$NT = \frac{\sum_{i=1}^{MN} T_i\rho_i}{M} \tag{16}$$

ρ_i is the tariff price for the hour i in EUR/kWh.[2]

- UT. Average daily electricity cost (EUR) based on Usual normal Austrian electricity Tariffs (*Wien Energie*).

$$UT = \alpha T_d \tag{17}$$

α is the constant price per hour in EUR/kWh.[3]

- FI. Index of Flattening. Calculated simply with the standard deviation of the consumption.

$$FI = \sqrt{\frac{B}{MN}\sum_{i=1}^{MN}(T_i - \mu)^2} \tag{18}$$

μ is the mean value of T. B is a constant for the result customization.

Test features

Tests consist of a 30 simulated days in winter and further 30 days in summer. For winter season the selected month is January (and some days of February) and July-August for the summer (both in 2008).

For each of the nine models, eight control performances are applied. Therefore, a total of 144 executions have been fulfilled, analyzing 72 hypothetical users for two months (cold/warm) periods.

DISCUSSION AND RESULT ANALYSIS

Due to the lack of space, simulation results must be summarized in order to abstract some important conclusions. Tables 4, 5, 6 summarize the different performances focusing in four aspects or *comparisons*:

1. **Savings with market prices instead of normal rates and both control strategies.**
   The percentage of savings (EUR) if we compare the current price of energy that normal users pay in a flat rate with the price that optimized users would pay if they take part directly in the electricity market and apply both control strategies.
2. **Savings with both control strategies.**
   The percentage of savings (EUR) if normal users and users with both control options (standby and shifting) are compared using the metric established by the spot prices curve.
3. **Savings with shifting control (spot prices).**
   The percentage of savings (EUR) if normal users and users with shifting control (spot prices) are compared using the spot prices metric.
4. **Improvement with flattening control.**
   The percentage of improvement (in the flattening index) if normal users and users with load shifting control (flattening) are compared using the metric established by the flattening index.

Table 6: Final average results

	winter	summer
1. Normal rates vs spot prices	45.11%	33.67%
2. Both control strategies	12.35%	14.24%
3. Spot prices strategy	11.07%	12.34%
4. Flattening	28.91%	21.01%

The four assessments inform about potential improvements when some of the proposed solutions are applied. If we consider all the enhancements together (results, case 1), the benefits keep quite stable regardless of the dwelling type, but higher in winter than in summer. On the other side, shifting control seems to increase its benefits with bigger and more crowded dwellings, whereas standby control gets importance with smaller and single dwellings.

We take spot prices as a metric of the *real* cost of electricity in essence. It means that economic savings are virtual as soon as users keep paying flat rates whether they adopt smart energy behaviours or not.

In any case, the results are encouraging and entail benefits for all the involved actors, from end users to energy suppliers, who have claimed repeatedly the high expenses derived from the demand curve imbalance (Red Eléctrica de España, 2010).

In part, inflated flat rates are due to the fact that energy retailers have to balance and cover peaks and uncertainties. Even if end users could not profit from the spot price curve for billing, with an active and spread load shifting control, electricity costs would have tendency to go down (or lower increases).

CONCLUSION

It is very difficult to measure what would be the real effect of the proposed approach. The simulations re-

[2] We only consider the energy price (without additional charges or base prices).

[3] Idem footnote 1.

Table 4: Summarized results for winter

	1person	2persons	3persons	4persons	small	medium	large	house	flat
1	44.16%	44.91%	46.32%	46.63%	43.59%	45.79%	44.17%	43.88%	46.56%
2	7.98%	13.01%	13.95%	15.27%	8.87%	12.49%	13.38%	12.75%	13.45%
3	5.18%	12.21%	12.08%	14.13%	6.84%	11.44%	13.15%	12.53%	12.04%
4	15.17%	22.05%	34.47%	36.68%	3.98%	33.67%	41.00%	42.24%	30.92%

Table 5: Summarized results for summer

	1person	2persons	3persons	4persons	small	medium	large	house	flat
1	33.70%	34.32%	34.37%	34.95%	34.58%	33.14%	30.90%	29.99%	37.06%
2	10.02%	14.64%	14.69%	15.97%	15.55%	13.97%	12.80%	11.40%	19.17%
3	5.84%	13.33%	11.87%	14.24%	12.51%	12.39%	12.42%	11.06%	17.35%
4	12.66%	15.58%	27.22%	26.52%	2.75%	23.11%	26.28%	28.30%	26.63%

sults draw hypothetical benefits under a static scenario (Austria, 2008) that would change if the proposals become reality in a wide spread.

In spite of this fact, the benefits are obvious and the energy environment must boost the home-side load control support in order to improve the sustainability and elasticity of the electricity management and its market.

The ideal scenario introduced in this work introduces a smart control system that fulfills the next three aspects: (a) an automated management of energy loads based on a load definition (ontology) and awareness of other home applications and user habits; (b) a useful connection with other actors (retailers, suppliers, other smart homes, repositories, etc.) that allows a fair and cooperative energy management; and (c) informative capabilities that bring energy feedbacks within users' reach and increase user awareness.

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