A GLOBAL APPROACH OF HABIT PROFILES FOR SMART HOME CONTROL

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ABSTRACT

Smart homes and Ambient Intelligence Environments require embedded technologies able to work and *think* jointly. Indeed, home technologies are expected to form together an individual supportive system whose cooperation and context awareness capabilities make it more than the sum of the different parts (equipments, functionalities, services, appliances, etc.).

The present article introduce *habit profiles* as elements to build a common underlying basis for home services, stating the foundations to interpret the shared context and perform global reasoning. Some profile-based services covering the main domestic application fields are displayed, as well as simulations that check the cooperative performance of profile-based control.

INTRODUCTION

The slow uptake of smart homes has been referred throughout the last years (Hindus, 1999; Harper, 2003), usually claiming for a more serious attention to home technologies. Indeed, lacking always of certain personality in the technical and scientific frameworks, home automation has been inheriting solutions and concepts from different areas: building, architecture, electronics, energy, telecommunications, security, safety, entertainment, multimedia, etc. This fact also highlights the potential interdisciplinary and transversal nature of the field, open to the contribution of many, varied actors.

Diverse attempts have arisen aspiring to get unity in concepts and practices. For instance, in 2005 the Smart House European Project consolidates as a "Code of Practice" for all actors, systems, networks, applications and services involved in the Smart-House, specifying functionalities, methodologies, recommended standards and working practices that ensure interoperability and interactivity of multiple products, applications and services. Although useful, such recommendations do not guarantee either a satisfactory overall experience by users or an optimized relationship among home services. Usability is one of the missing issues in the evaluation (Davidoff et al., 2006), but also the coherence of global design perspectives is not properly considered.

The literature of HBA (Home and Building Automation) shows diverse projects where the improvement of the overall comfort and energy performances is due to designs that face the smart home as a whole, detecting conflicts, synergies, relationships and dependences under the same reasoning structure, e.g. (Mozer, 1998; Das et al., 2002). Some of these approaches use *behavioural profiles* and *patterns* as a way to optimize the interaction between the users and the automated house, or also as elements that identify contexts of which services must be aware, e. g. (Hoes et al., 2009).

The present work explores *habit profiles for smart home control*. Beyond the suitability for specific goals, habit profiles are presented as objects of global reasoning and common resources to be shared by the coexisting home applications. Hence, as a consequence of such proposal, holistic smart home designs can aspire to progressively achieve the homogeneity and coherence it lacks nowadays.

PROFILES IN HBA

Similarly to the concept of *smart home*, e. g. (Harper, 2003), behavioural profiles have been utilized by HBA without adapting to any canonical definition, being the features of each specific profile built over the requirements of the intended application.

In any case, in smart homes the deployment of profile techniques is mostly dedicated to reduce energy consumption and enhance comfort conditions. In the daily-life scenario of a house or a building, if the smart system is aware of inhabitants' habits, it is able to predict future events and act ahead (Barbato et al., 2009). Also in pre-design or study phases habit profiles are useful to carry out realistic building energy simulations. Generalizations and models of people' habits are important inputs to predict how the energy performance of a future building will be (Mahdavi and Pröglhöf, 2009), indeed users' behaviour has been detected as the main factor adding uncertainties in building energy calculations (Corrado and Mechri, 2007).

Focusing on control purposes, profiles or patterns have been utilized to directly abstract home activities – e. g. eating, sleeping, etc. – (Mori et al., 2004). By means of activity abstraction, being aware about unexpected changes in repeated habits, it seems to be possible to infer user feeling (Takada et al., 2006), predict future services in intelligent homes (Kim and Son, 2009), or detect possible accidents or situations that can require special attention (Mori et al., 2007).

Simpler patterns have been also deployed to monitor functional health status of elderly people (Kaushik and Celler, 2007); or discover actions that a smart agent should automate based on the repetition of device usage (Heierman and Cook, 2003). Combining occupancy and energy usage profiles, the house energy consumption can be reduced (Barbato et al., 2009).

Occupancy profiles are the most required type of profile *de facto* for HBA. For instance, together with hot water usage profiles and profiles that store the likelihood that a zone will be entered, they can control temperature, light, ventilation and water heating (Mozer, 1998). Moreover, occupancy patterns improve HVAC control and energy use (Tachwali et al., 2007), and together with lightning usage profiles can result in behavioral models for the automated adjustment of the lighting level (Bourgeois et al., 2006).

Complex structures and patterns for the user behaviour analysis and future service optimization can be appreciated in (Ha et al., 2006), where users' behaviour and home context are related based on monitored tasks and activities. Also in (Das et al., 2002), complex patterns store movement history and actions, thus patterns participate in predictions for keeping inhabitant comfort with operation cost minimization.

The introduced works present several ways to *understand* home profiles, and the list is extensive. To sum up, habit profiles cover applications for the main pillars of HBA, i. e. comfort, energy consumption, HVAC, security, safety, informativeness, etc.

DEFINITIONS AND CLASSIFICATIONS

Within the scope of HBA technologies, we define a *profile* as the collection of time-related data (i. e. a *univariate time series*) that corresponds to a certain domestic phenomenon. Profiles can be understood as *models* which relates values with time in order to characterize the phenomenon (Figure 1).

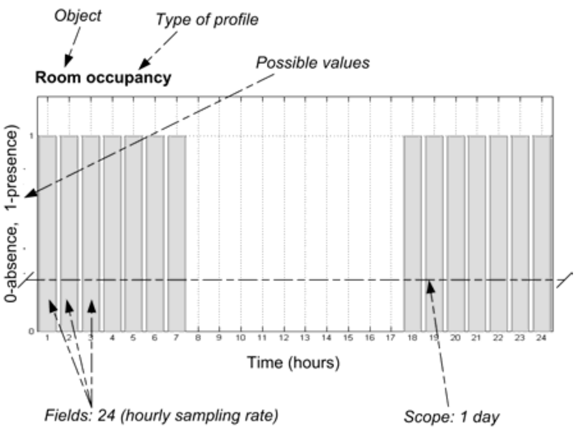

Figure 1: Example of the occupancy profile of a room.

The fact that profiles must be referred to time is coherent with the purpose of abstracting habits, as habits entail facts that are repeated throughout time. On the other hand, profiles can address different scale types (numeral, ordinal, interval, ratio), type of values (binary, integer, real), time scopes (daily, weekly, etc.) and sampling rates (minutes, hours, etc.).

Habits can also be seen as repeated events not necessarily related to times but to other events, e. g. (Ha et al., 2006; Das et al., 2002).

Another type of objects commonly mentioned as profiles are the so-called *preference profiles*, e. g. (Lee, 2010). They store static information concerning users' behaviours and device usage. We integrate them into our definitions and classifications, considered as *abstract* profiles with only one time field (constant).

Behaviours and Habits

Simple profiles are not *habit abstraction objects* but *behaviour abstraction objects*. A profile does not necessarily represent a habit, but always a behaviour. In other words, a behaviour can be singular (not representative), but can also become a repeated behaviour (so it involves a stable habit). Figure 2 illustrates the point. In the example, the system is aware of the number of daily showers divided in four 6-hour periods per day. Starting on the basis that we only have 5 profiles so far, we can see that three of them have the same shape, so they probably summarize a habit, whereas profiles 2 and 5 are considered as singular behaviours.

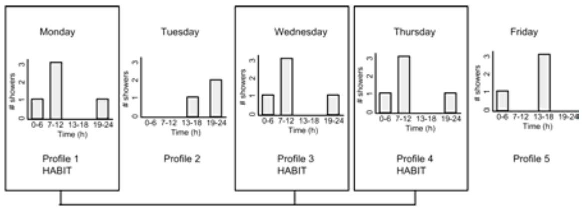

Figure 2: Profiles for behaviours or habits.

Design Recommendations

Habit profiles are designed for specific applications, or keeping in mind particular devices and even an underlaying system or hardware. This is one of the reasons they show such variable shapes in the related literature. We propose an open design of profiles to be used by different applications within the same framework. In order to facilitate a robust management by controllers, the following guidelines should be considered.

Profiles should be as *simple* as possible and *independent* each other, many simple types of profiles are preferable instead of few complex ones. Similarly, profiles should not deal with mixed information, keep any reasoning embedded or entail mixed scale types. In contrast, a considerable amount of data may be stored and processed without being strictly necessary. A correct design will state a commitment for the amount and size of profiles based on the system features and the global performance.

To facilitate the habit abstraction, profile fields should be *scale-invariant*, *equivalent* in size/length and their values equally weighted; i. e. all the fields have the same importance before any analysis.

Finally, *scalability* in profiles allows to condense information and create new profiles and pieces of information for wider scopes. It makes profiles flexible,

Table 1: Objects of Home Profiles.

Object	Comments	Examples
– Device or house element	not necessarily physical	lamp X lighting level, socket X state, window X state, etc.
– Group/line	logical or physical	lamp group X state, ring circuit consumption, etc.
– Room		occupancy of room X, comfort temperature of room X, etc.
– Zones/sub-zones	group of rooms or/and corridors	water consumption of baths, lighting usage of corridors, etc.
– Dwelling	the habitable space as a whole	number of people at home, flat electricity consumption, etc.
– Users[1]	individual or grouped	comfort temperature for user X, expected location for user X, etc.
– External	not strictly existing within the smart home	electricity spot prices, outdoor temperature, etc. etc.

compatible and shareable; indeed, quick parallel reasoning profits from profiles that are easily matchable.

Types and Objects of Home Profiles

Profiles refer to different objects or actors of the home environment. We propose the classification for *profile objects* given in Table 1. On the other hand, according to the nature of the captured phenomenon, we establish the following classification of *profile types*:

→ **Occupancy.** Users' occupancy is probably the most important object of habit abstraction as many application utilize it to automatically adjust the system configuration, manage the energy performance or advance comfort requirements.

→ **Consumption.** Consumption profiles are directly related to measurable consumed magnitudes or costs – usually energy, like electricity, water, DHW or gas –, but it is open to other applications that do not necessarily concern energy, e. g. money, time to fulfill tasks.

→ **Usage (or state).** Usage profiles address specifically whether one object is *switched on* or *being used*. It usually differentiates between two states: active/passive, on/off, open/close, etc.[2]

→ **Setpoint or level.** Setpoint or level profiles collect desired or detected input status. *Comfort temperatures, relative humidity levels* or *lighting levels* are some examples. If the measure belongs to a ratio scale, we will be prone to separate it into *usage* and *level profiles*, becoming the ratio scale into an interval scale for the profile management.

→ **Abstract aim.** Profiles that manage objects with some complexity or resulting from processing and reasoning phases are considered so. For instance, profiles that store users' activities (Mori et al., 2004), e. g. sleeping, having meal, working, spare time.

INTEGRATION IN HBA NETWORKS

Beyond solving concrete situations, an intelligent system must be able to undertake global reasoning based on the context abstraction. Furthermore, it must develop logics that glue, manage and operate upon all applications in parallel, being conscious of how they interact and construct the common environment.

User habits contain information about how users want things at home – how home is expected to work – and how the relationship among services must be. Facing complex situations where conflicts among services occur, the system makes decisions consulting how users managed such situations in the past, what they usually do, or latest adjustments after automated actuations. In short, habit profiles support the following functions:

→ Abstraction of expected performance.
→ To merge service operation in a common context.
→ Predictive control.
→ Supply of feedbacks based on past experiences.

These points are mandatory to implement flexibility, self-checking and adaptiveness skills, as well as to improve comfort and energy consumption rates.

Multiagent System Model

The integration of profile-based approaches specially fits control architectures based on multiagent systems (MAS). In (Reinisch et al., 2011), we introduced ThinkHome, a MAS for smart homes that uses habit profiles as shared resources in the agents' framework. In this respect, Figure 3 shows a model for the development of profile-based smart homes using a MAS.

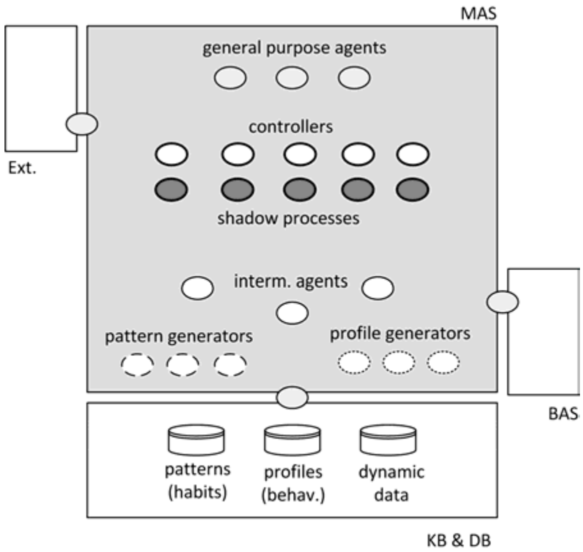

Figure 3: Schema of a profile-based multiagent system. BAS stands for the building automation system, KB & DB for knowledge base and databases, and Ext. represents remote sources of information.

Following the figure, *profile generators* are set to

[1]Direct user profiles are appropriate to satisfy cases when a high-dedicated control is expected (*Ambient Assisted Living*) or when high-customized performance is desired.

[2]An *occupancy profile* is a special kind of 'usage profiles', which has been differentiated due to its remarkable role.

transform data collected by sensors into behavioural profiles. Analogously, *pattern generators* take sets of profiles from databases and generate newborn habit patterns. In this task, advanced data analysis tools are embedded in pattern generator for the behavioural context reading[3]. Later on, *intermediate agents* will interpret the context information offered by pattern generators, coordinating *control agents* and giving them the translated information required for the decision making. *Shadow processes* – introduced in (Iglesias and Kastner, 2012a) – are established to directly check the performance of control agents based on users' preferences and desires. Finally, global reasoning is undertaken by *general purpose agents* that act as referees as they establish priorities, switch control algorithms and adjust parameters.

PROFILE-BASED APPLICATIONS

The applications displayed as follows cover representative functions expected in HBA (the profiles mentioned in this section are listed together in Table 2). On the other hand, the integration of classic services not-based on profiles is assumed. A noteworthy feature of the presented services is that they do not demand either a high-sophisticated equipment or unaffordable technologies. They are feasible and deploy equipment and systems at our disposal in the current market.

Finally, the design of applications is representative but obviously not unique, being the number of profiles, the selected ones, their features, the control design and the control aims open to discussion and alternatives.

Zone Lighting Control

The integration of lighting by means of profiles improves the performance, becoming more adaptive to users. For instance, given a structure of groups for the home lighting where lights are physically or logically associated (i. e. living-room lights), a profile-based service – (1.1) *General Command for Lighting Groups* – can adjust automatically the state and levels of a group. A *general command* triggers the service and rules the group, whereas specific lamp commands are deployed by users to refine the desired customization whenever necessary. Thus, using profiles, the system progressively learns how the light combination of the group must be for every moment of the day.

Additionally, general and specific commands are monitored and related to usage profiles in order to perform evaluations of the system-user interaction. The application (1.2) *Self-checking, Lighting Management* measures the level of user dissatisfaction based on the rate of re-adjustments after the activation of a general command. A tendency to decrease is expected as the system gets adapted to users' habits and desires (if there are not manual re-adjustments, old habits are reinforced); otherwise, the system would ask for assistance (preferences, customization, disconnection of services) by means of *warning messages* in ambient indicators and graphical user interfaces (GUI).

Specially intended for Ambient Assisted Living scenarios, lighting activation and regulation can be directly triggered by occupancy and habitual scheduling. This is implemented by the (1.3) *Efficient Lighting* service, which is aware of occupancy and lighting habits and performs a smart, unsupervised lighting management (becoming aware of preferences, possible oversights, unexpected absences, etc.).

Automatic Shading Devices Control

In a common dwelling, shading devices (blinds, shutters, curtains, automated windows, etc.) have an influence on the visual and thermal comfort conditions, in a way that the control of heating, cooling, ventilation and lighting is partially affected. Using profile-based services, holistic management is set to optimize the overall running and avoid conflicts.

Services (2.1) *General Command for Blinds Groups* and (2.2) *Self-checking, Blinds Management* have a similar running to the equivalent services introduced for lighting. In addition, some users appreciate or make the most of an unsupervised management of blinds and shutters. If the (2.3) *Unsupervised Control for Blinds Groups* service is active, it operates shading devices according to profiles without supervision.

On the other hand, in unoccupied periods where the next user presence is approaching in time, advanced thermal comfort strategies can manage shading devices to balance indoor and outdoor climate conditions or improve indoor insulation; therefore, energy savings are achieved as cooling, heating or forced ventilation are not unnecessarily switched on.[4] This is implemented by the (2.4) *Thermal Comfort Support* service (Iglesias and Kastner, 2012b). The service is active in unoccupied periods. To avoid disturbing users or cause conflicts, in occupied periods it elaborates recommendations or advice by ambient indicators and GUI.

Supporting Security System

Alarm systems demand being operated by specific commands, keys or codes. A supporting profile-based security system can be developed for dwellings without contracted alarm systems or also to offer extra capabilities to the installation by default. For instance, the (3.1) *Unusual Presence Detection* service deploys occupancy profiles to warn users about unusual presence (through sms or email), even whether the alarm system is not active. Moreover, the (3.2) *Oversight Detection* application stores alarm status in profiles in order to warn users when there is any incongruence in alarm activation habits. In addition, the system can automatically activate the alarm system if a long absence is predicted. Note that holistic control does not bypass or replace the security system but develops a habit-aware, compatible pre-adjustment phase.

[3]Clustering tools for context inference in smart homes has been presented in previous publications, e. g. (Iglesias et al., 2011b)
[4]As an example, in (Galasiu et al., 2005), authors obtain 15%–20% of energy savings by an appropriate management of blinds.

Table 2: List of habit profiles for the defined services.

Profile name	Object	Type	Value	Scope	Samp.	Applications
– Light state	device/group	usage	on/off	daily	30’	1.1, 1.3, 6...
– Light level	device/group	level	%	daily	30’	1.1, 1.3, 6...
– Lighting user readj.	group	specific	$\mathbb{N}$	daily	1h	1.2, 6...
– General lighting command	device	usage	$\mathbb{N}$	daily	1h	1.2, 6...
– Occupancy	dwell./zone/room	occupancy	yes/no	daily	30’	1.3, 2.4, 3.1, 3.2, 4.1, 4.2, 6...
– Blinds level	device/group	level	%	daily	30’	2.1, 2.3, 6...
– Blinds user readj.	group	specific	$\mathbb{N}$	daily	1h	2.2, 6...
– General blinds command	device	usage	$\mathbb{N}$	daily	1h	2.2, 6...
– Alarm state	dwelling/zone	status	on/off	daily	1h	3.2, 6...
– Comfort relative humidity	dwell./zone/room	level	%	daily	30’	2.4, 4.2, 6...
– Comfort temperature	dwell./zone/room	level	$\mathbb{R}$	daily	30’	2.4, 4.1, 6...
– Rel. humidity user readj.	group	specific	$\mathbb{N}$	daily	1h	4.4, 6...
– Temperature user readj.	group	specific	$\mathbb{N}$	daily	1h	4.3, 6...
– Electricity consumption	dwell./line/device	consump.	$\mathbb{R}$	daily	30’	5.1, 6...
– Load state	line/device	usage	on/off	daily	30’	5.1, 5.2, 6...
– Electricity spot prices	external	consump.	$\mathbb{R}$	daily	1h	5.2, 6...

Thermal Comfort and Air Quality

The automated control of *air quality* and *thermal comfort* can be carried out by assessments of indoor temperature, humidity, wind, as well as diverse gases and pollutants. On the other hand, noteworthy is the fact that ANSI/ASHRAE Standards (specifically 62-2001 and 55-2004) define air quality and thermal comfort as dependents on users’ subjective evaluations.

Profiles are useful to improve the HVAC performance and reach better comfort and energy ratings. According to habits, a profile-based pre-control phase predicts setpoint values. Thus, the subjectiveness related to air quality and thermal comfort is overcome by the *particular feeling of comfort* stored by habit profiles.

The (4.1) *Setpoint Temperature Control* service has been previously tested in (Reinisch et al., 2011). The control system switches to comfort (comfort profiles), off, safety, setback values depending on instantaneous occupancy and occupancy profiles. Occupancy profiles are deployed to guess the next occupancy and reach anticipatively comfort before people arrive, as well as to know the duration of next absences and switch to the most suitable state. The (4.2) *Setpoint Relative Humidity Control* is similar to the previous application but considering humidity rates instead of temperatures. Finally, (4.3) *Self-checking, Temperature Management* and (4.4) *Self-checking, Relative Humidity Management* services are analogous to the self-checking services introduced before.

Energy Consumption

Smart metering usually consists of recording electricity consumption for monitoring and billing. In addition, consumption profiles are useful to prepare reports (Fischer, 2008) and inform about device consumption, energy behaviour and failure detection. Such functionalities are provided by the (5.1) *Energy Behaviour Checking* service. On the other hand, by means of the (5.2) *Consumption Prediction* application, the system is able to control the connection of loads based on occupancy and forecast electricity prices, as well as to schedule deferrable loads (e. g. washing machine, dishwasher) in order to supply them in the most convenient moment (Iglesias et al., 2011a).

Moreover, profiles can be utilized to calculate *simultaneity factors* for power, water and gas, allowing the sizing of equipments, predictive configurations or to optimize the distribution provided a connexion to the grid and communal systems (Gwisdorf et al., 2010).

Reports and Self-checking

A smart home is expected to develop reports for users in order to provide evaluations, useful information and advice. In this respect, a varied selection of habit profiles can be managed. For instance, energy reports can simply show the consumption evolution of the house (only the *dwelling electricity consumption* profile is required), yet more accurate information is possible relating consumption with habits concerning occupancy, comfort temperatures, lighting levels, electricity spot prices, specific elements (devices, lines, energy sources), etc. Moreover, reports do not necessarily refer to energy, but also feedbacks related to comfort and health. In short, habit-based reports exploit the persuasive and pervasive capabilities of technology to motivate behaviour change in context and empower people with information that helps them make decisions (Intille, 2002).

Additionally, the (6.1) *Smart Home Customization* application allows users to fix their preferences in order to help the system reach a more accurate and customized performance. It manages the parametrization of the different controllers and tune them based on users’ general preferences, e. g. ‘switch to energy savings mode’, ‘increase the level of feedbacks’, etc. The system also evaluates itself by means of self-checking profile-services; therefore it discovers functions and conflictive aspects that require alternative actions or user assistance (Iglesias and Kastner, 2012a).

SIMULATION

As far as isolated applications are concerned, the suitability of control strategies based on the proposed habit profiles has been already shown in several works

(Iglesias et al., 2011b; Iglesias and Kastner, 2011; Reinisch et al., 2011). However, due to the high heterogeneity and casuistry of the intended field, there is a lack of simulation tools able to carry out complete calculations of the smart home as a whole, with the sufficient level of detail and able to join up advanced control strategies for the global management.

The aim of the simulations is *to qualitatively show the benefits and synergies obtained from the joint running of profile-based services*. To achieve this, we have developed a C++/MATLAB environment for multiagent simulation of simplified profile-based smart homes. The simulated services are: 1.1, 1.3 and 4.1.

Environment

The simulated facility consists of a 2-room up to 4-room house, where from 1 until 5 users live together. Rooms and users are modeled as independent agents. **[Room agents]** Rooms present 3 possible states concerning lighting (HIGH, LOW, OFF/DARKNESS) and heating (COMFORT, SETBACK, OFF/COLD). Outside is considered as an additional room, its temperature is fixed to COLD for the whole simulation, whereas the light level is DARKNESS or LOW according to the moment of the day.

[Simulation time] The day is split into 6 periods (early morning, morning, late morning, afternoon, evening and night). Whenever there is no user in a room or there is no control activated, this room inherits outdoor temperature and outdoor lighting conditions. With control active, heating and lighting are fixed by habit patterns or a schedule. In any case, if users are present, the room is *always* adjusted according to users' desires (see below).

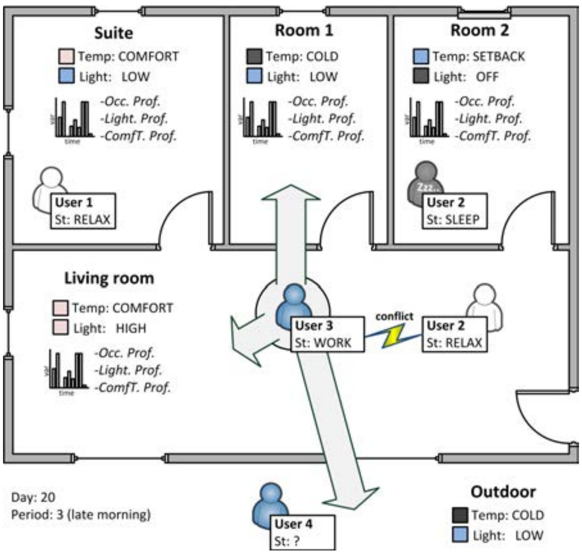

Figure 4: Representation of the simulation environment for the 5-user family case.

[User agents] Users are modeled with patterns concerning *occupancy* (YES, NO), *occupied room* (LIVING, SUITE, ROOM 1, ROOM 2) and *activity* (WORK, RELAX, SLEEP), as well as a level of reliability, which states how devoted are users to their original, supposed habits. **[Modeled desires]** User activities imply users' performance desires, i. e. WORK (housework, professional activities, etc.) is defined demanding 'HIGH lighting' and 'COMFORT temperatures', RELAX (watching TV, reading a book, etc.) requires 'LOW lighting' and 'COMFORT temperatures', and SLEEP entails 'OFF lighting' and 'SETBACK temperatures'. Figure 4 shows a representation of the simulation environment.

[Conflict agreements] When diverse users coincide in the same room executing different actions, a conflict occurs. Users are programmed to solve such conflicts as follows: if they are in the living room the priorities are WORK>RELAX>SLEEP, whereas for the rest of the rooms it remains as RELAX>SLEEP>WORK.

[Room profiles] Each room collects its own information concerning *light level*, *occupancy* and *comfort temperature*, setting habit patterns for control by means of embedded clustering tools.

Evaluation

100-day simulation tests are run for different houses and families as shown in Table 3. **[Performance indices]** The deployed performance indices are *energy consumption* (EC) and *discomfort* (DC), both **'per person'**. Both indices utilize the same abstract values, i. e. lighting: **2** (HIGH), **1** (LOW), **0** (OFF); heating: **2** (COMFORT), **1** (SETBACK), **0** (OFF). Therefore:

$$EC = \frac{1}{\text{users}} \sum_{i}^{\text{rooms}} EC_i \quad (1)$$

$$EC_i = f_n(\text{lighting}_i - \text{lighting}_{out}) + \text{heating}_i \quad (2)$$

where $f_n(x) = x, \forall x > 0$, otherwise $f_n(x) = 0$.
The discomfort rate (DC) is set as follows:

$$DC = \frac{1}{\text{users}} \sum_{j}^{\text{users}} DC_j \quad (3)$$

$$DC_j = \Delta\text{lighting}_j + \Delta\text{temperature}_j \quad (4)$$

where $\Delta x = | \; x_{\text{desired}} - x_{\text{real}} \; |$, i. e. the difference between the state that users find when they enter the room and the state that they would desire (according to the defined in [Modeled desires]).

[Control options] Simulated test are repeated in three scenarios, with manual control (users directly adjust the system every time), with profile-based control (services 1.1, 1.3 and 4.1), and scheduled control. The scheduled control is not aware about real, ongoing habits, instead it fixes lighting and heating according the common, pre-defined use of the rooms.

DISCUSSION AND RESULT ANALYSIS

Table 3 shows significant, habitual performance values obtained from the conducted simulations. Note that different family models have been selected (from a single inhabitant to a five people family, through couples as well as flatmates), and test are repeated changing the levels of habit reliability (second column).

Table 3: Simulation results: arithmetic means of EC and DC after 100-day simulations.

Users /rooms	Hab. rel.	**Manual** $\overline{EC}$	$\overline{DC}$	**Sch.** $\overline{EC}$	$\overline{DC}$	**Prof.** $\overline{EC}$	$\overline{DC}$	Patt rel. (min)
1/Lv+1	high	4.1	5.9	15.2	3.8	4.5	1.0	9
	med	4.3	6.7	15.9	3.9	5.3	3.2	5
	low	3.7	6.2	15.2	3.8	4.3	5.7	0
2/Lv+1 (couple)	high	3.6	6.5	9.0	3.9	3.9	1.0	9
	med	3.8	6.6	9.1	3.8	4.5	2.6	5
	low	3.2	6.2	8.6	3.6	4.5	4.9	3
2/Lv+2 (mates)	high	4.8	6.1	13.5	3.7	5.2	1.7	9
	med	5.0	6.5	13.8	3.9	6.1	3.1	5
	low	4.4	6.1	13.4	3.7	5.4	5.0	3
3/Lv+2	high	4.0	6.4	9.7	3.8	4.2	2.0	9
	med	4.3	6.3	9.7	3.7	5.0	2.9	5
	low	4.0	6.1	9.5	3.7	5.2	4.3	2
4/Lv+3	high	3.2	6.3	9.2	3.9	3.4	2.2	8
	med	4.0	6.4	9.6	3.7	4.5	3.2	5
	low	4.2	6.1	9.6	3.9	4.9	4.1	2
5/Lv+3	high	3.0	6.2	7.4	3.6	3.2	2.5	8
	med	3.8	6.4	7.9	3.7	4.2	3.6	4
	low	4.0	6.3	7.8	3.6	4.7	4.3	1

Manual control obviously results in the lowest consumption rates ($\overline{EC}$), yet the highest discomfort levels ($\overline{DC}$). The *scheduled* strategy obtains better comfort ratings, but the energy cost is considerably higher. Both options are common in homes and buildings, where the chosen one depends on if users opt for comfort before energy savings or the other way round, as well as the available level of automation. As expected, note that EC and DC values in both options are not sensitive to habit stability (Hab. rel.) shown by users (performance indices do not significantly change).

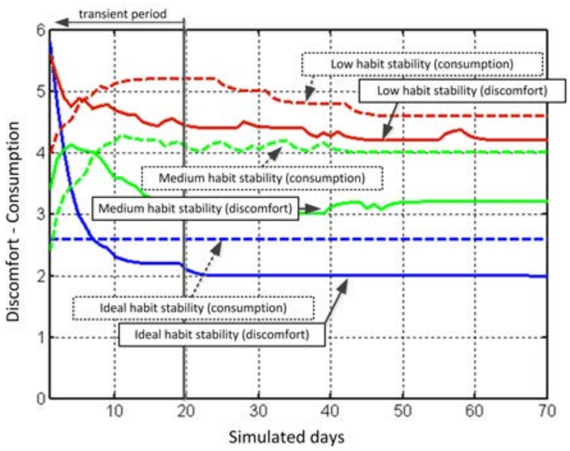

Figure 5: Evolution of EC and DC for ideal, medium and low habit stability cases (5 people).

Unlike the precedents, the *profile-based* strategy is sensitive to habit stability changes. Whenever habit reliability keeps in an acceptable range (high or medium), controllers obtain a considerable improvement in comfort rates with few energy cost (Figure 5). In such cases, the energy-comfort commitment reached using profile-based control clearly outperform classic control strategies (Table 3).

For a better understanding of the table, let us comment on one of the cases, for instance the two-room flat with two mates (2/Lv+2) showing medium habit reliability. In this case, the best average energy performance is obtained when the manual strategy is used ($\overline{EC} = 5.0$), but closely followed by profile-based ($\overline{EC} = 6.1$), and far from the scheduled one ($\overline{EC} = 13.8$). On the other hand, the best comfort rates are for the profile-based strategy ($\overline{DC} = 3.1$), before the scheduled one ($\overline{DC} = 3.9$), and finally followed by the manual option ($\overline{DC} = 6.5$). Hence, as a general rule, *whenever habits show an acceptable stability, the best performance commitment between comfort and consumption is reached by the profile-based strategy.*

One of the most attractive advantages of the profile-based approach is the implementation of self-checking capabilities. The last column of Table 3 shows the calculated *pattern reliability* of the less-reliable pattern used by controllers at the 100th day (*min*). Therefore, whenever the system detects patterns dropping under a pre-defined threshold (e. g. 5 in simulations), it knows that users' behaviours are not stable enough to profit habit-based control. Then, according to users' preferences, it switches to *manual* or *scheduled* control.

In profile-based control, transitory periods for the controller adaption must be defined, as the system requires a sufficient amount of collected profiles in order to properly tackle habit abstraction processes. Hence, in simulations, the system requires about 20 days to have reliable evaluations of user habit stability (Figure 5).

CONCLUSION

We have presented an overview of profile-based applications for smart home control. Dealing with the lack of unity and statutory definitions of the issue, we state some descriptions and classifications as a basis for the design of later consistent control. The global approach is necessary as habit profiles are seen as objects shared by applications, called to merge the system running in a fluent, common performance, and aiming to obtain further benefits beyond the isolated optimization of home services.

Services covering the main functionalities of the smart home are summarized and introduced together. Although simulations are built over simple models, outcomes are suitable to qualitatively display how satisfactory energy-comfort commitments can be achieved by the cooperative deployment of habit profiles for diverse home services. In addition, the system is tested to gain awareness about how reliable habits are, gaining flexibility and self-checking capabilities.

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