Profile-Based Control for Central Domestic Hot Water Distribution

Félix Iglesias and Peter Palensky, *Senior Member, IEEE*

***Abstract*—A main goal of hot water distribution research is to improve the system's efficiency, i.e., to fulfill hot water requirements while minimizing energy and water losses. Central domestic hot water (CDHW) systems represent an important part of current installations worldwide, e.g., hotels, hospitals, sports centers, social facilities, and multifamily residential or apartment buildings. The optimization of such systems claims for forecasting capabilities and context-aware enhancements are based on patterns of use. Thus, the level of uncertainty is reduced, and systems are not forced to operate using blind/oversized/generic assumptions. This paper presents a novel control strategy based on habit profiles for the management of a CDHW system. A simulated environment is utilized to compare the introduced strategy with habitual performances. Simulations are supported by real databases concerning users' behavioral patterns. Results are promising and point to place profile-based strategies as a suitable approach for an optimized water and energy management in future buildings.**

***Index Terms*—Building simulation, DHW control, energy profiling, habit-based control.**

I. Introduction

THE progressive integration of renewable sources in current and future energy systems gives an increasing prominence to district heating installations, i.e., centralized space and water heating systems [1]. Within this field, as far as research is concerned, domestic hot water distribution received little attention compared with, for instance, air conditioning equipment and delivery [2].

To emphasize the importance of savings in domestic hot water (DHW) is nowadays a truism, note the diverse policies that governments around the world are applying in recent times to improve sustainability in buildings.[1] In the referred official text, DHW accounts for 14% of overall energy consumption in European residences. A previous survey carried out by the United States government in the late 1990s considers that it is around 32% of energy used for existing multifamily units [3].

The low efficiency of DHW systems is well known by field practitioners. Experts complain about the lack of research to quantify time, water, and energy waste of different DHW systems. In a thorough survey published in 2005, Hills even warns about detected counterproductive trends [4]: "Most disturbing of all, interviews with many new residential building owners revealed that hot water delivery times and water waste have been getting steadily worse with newer buildings."

The sources of inefficiency can be found in every one of the diverse phases entailed by DHW systems: from the design of the piping structure and the sizing of equipment to the selection of the applied control strategies. A better understanding of water deployment is desired in order to improve the whole system, both in the initial design phase and in the final control phase.

In the current work, the focus is placed on control aspects, proposing a novel approach based on habit profiles (or patterns) for central DHW (CDHW). Profiles are useful for individual, smaller DHW systems as well, but here central cases are specifically dealt with to check the suitability of profile-based strategies in complex scenarios that are submitted to simultaneities.

Beyond the isolated control DHW case, the introduced profile-based approach entails further benefits. First of all, it belongs to incipient design methodologies of smart homes and buildings that look for suitable methods to cope with the inherent complexities of the field and solve decision-making processes sensitive to psychological aspects [5]. By means of the shared deployment of behavioral patterns, smooth performances and synergies can be achieved [6]. In addition, the collection, generationm and storage of habit patterns can be very useful in the design-phase of future DHW systems. Nowadays, such designs usually trust in generic, vague constants and assumptions published in official directives and recommendations. The usual result is oversized, low-efficient installations. This is an obvious phenomenon if we take into account the current lack of available data of buildings' use. Here, it is worth citing [7], where both the study of use patterns and the use of code permitted minimums for DHW are strongly recommended. Indeed, profile-based methodologies empower the existence and management of summarized, meaningful building data. A common information and communications technology (ICT) infrastructure with repositories of building information would pave the way to obtain more accurate designs of DHW, but also for the rest of building services [8].

In short, in this paper, the advantages of habit profiles to improve CDHW control are checked, but also the benefits of profiling methodologies for the overall management of buildings are brought forward. It also covers the exploitation of buildings' energy information in order to achieve more realistic use rates and simultaneity coefficients for tailored, accurate future designs.

Manuscript received September 12, 2012; revised December 30, 2012; accepted May 06, 2013. Date of publication July 26, 2013; date of current version December 12, 2013. Paper no. TII-12-0671.

The authors are with the Energy Department, Austrian Institute of Technology (AIT), Vienna 1210, Austria (e-mail: fiv@gmx.at; peter.palensky@ait.ac.at).

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Digital Object Identifier 10.1109/TII.2013.2275032

[1] E.Commission, Energy Efficiency Plan 2011 – COM(2011) 109 final. [Online]. Available: http://ec.europa.eu/energy/efficiency/action_plan/action_plan_en.htm

II. Related Work

The study of the performance of piping structures and systems for hot water delivery are found in several works. Obviously, the approaches are different and commonly consist of simulations or sensitivity analysis that combine some of the next determining factors and assume the rest as constant (or they are simply obviated):

- climatic data, outdoor air temperatures, working and setpoint temperatures;
- behavioral data, levels of hot water demand, schedules, or user habits;
- insulating materials and equipment conductivities;
- geometry of pipes and pipelines, piping structures, sizes, and arrangements (e.g., parallel, tree);
- heat generation technologies and equipment sizing;
- system configuration or distribution system types (e.g., tank-based, tankless, or recirculation);
- control strategies.

For example, within the residential scope, a rather complete work can be consulted in [7]. Alternative piping materials, trunk and branch configurations, piping insulations, and even recirculation strategies are compared using a model developed in NI LabVIEW (National Instruments, Laboratory Virtual Instrumentation Engineering Workbench). In addition, they offer a final, useful set of advice for home designers, contractors, and homeowners. Also, system configurations, different piping structures, and diverse levels of demand are compared in [9] using Transient System Simulation Tool (TRNSYS).

With regard to simulation groundings, there are currently few open models to simulate DHW distribution systems. The works introduced previously are based on equations proposed by researchers at Oak Ridge National Laboratory [10]. They carry out a very active research in DHW, but are extremely focused on the Californian scenario. In this context, the vast research conducted by Hiller and mainly published in American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) journals are well known among experts and researchers; the work in [11] is cited as an illustrative example.

There are some alternative models for DHW distribution. For example, HWSIM [12] is maybe the only simulation tool specific for hot water distribution that is publicly accessible. A recent proposal, developed with TRNSYS, that challenges HWSIM features and capabilities is introduced in [13]. On the other hand, considering district heating systems, a method for optimal design of piping structures is shown in [14]. Here, calculations of heat losses with 2-D modeling of pipes based on the finite-element method are utilized to check pipe configurations and insulations.

If we concentrate exclusively on control strategies, in [15], different recirculation systems are checked for diverse multi-family buildings. Here, and as a quite general rule, the recommended, most energy-efficient options are strategies based on temperature control, either managing the activation/deactivation of boilers according to temperature values of the recirculation circuit or directly adjusting the boiler setpoint based on the demand level. Beyond temperature control, assuming user active involvement, *demand recirculation* is commonly set as the most advisable solution [7].

Irrespective of the analyzed variables of the DHW system, a very relevant aspect for calculations and analysis has to do with the expected use given to the system, usually represented by hot water use draw profiles. The reader is addressed to [16], where several, commonly used sources of hot water profiles are commented and reviewed. In addition, an advanced spreadsheet tool capable to generate series of year-long hot water event schedules consistent with realistic probability distributions is presented in [17].

In general terms, the use of behavioral or habit patterns plays a fundamental role in home and building automation design and control. These aspects are widely explored in Section IV.

III. CDHW Design and Control

CDHW is usually integrated within the central heating system of the building, using the same furnace room to provide all thermal services. Thus water is heated by general boilers and later distributed to the consumption points by means of a dedicated network of pipes.

Depending on how DHW is produced, we distinguish between *on-demand* systems and *storage* systems. The design of on-demand (also instantaneous or tankless) systems is conditioned by the moment of maximum demand, requiring heaters capable to work at high power rates. To reduce such high power levels and obtain more homogeneous performances, storage systems use tanks to accumulate hot water and flatten the power demand. Both instantaneous and storage systems are common nowadays. Demand systems are usually more energy efficient as they eliminate standby heat losses from the tank, but the energy differences tend to be reduced in scenarios where the demand of DHW is high and frequent [9].

In any case, irrespective of the production option, centralized systems have to deal with the fact that distances covered by water from boilers to consumption points are usually long. In order to avoid unnecessary waste of water and user discomfort, CDHW systems normally have recirculation loops intended to keep hot water close enough to fixtures.

The introduced scenario entails severe sources of inefficiency, e.g., heater losses, recirculation loop losses, branch losses or wasted water. CDHW is therefore a research field that demands the application of operating control strategies in order to optimize the use of energy resources and improve users' comfort. Beyond the referred system with constant recirculation, habitual control options are as follows:

A. No Recirculation

Systems without hot water recirculation feel neither pipe heat losses nor extra pumping consumption due to recirculation, but account for important wastes of water, as it takes longer (time and distance) to get consumption points at an appropriate temperature (causing user discomfort). Nevertheless, such systems have the lowest degree of risk to incubate harmful bacteria (i.e., Legionella Pneumophila), a relevant aspect for care services buildings, for instance, hospitals and retirement homes.

B. Scheduled Recirculation

A basic control option to avoid recirculation losses is to shut off recirculation pumps during periods of minimal DHW consumption. As a representative example, in [15], shutdown during overnight periods has proved to entail considerable energy savings keeping an acceptable level of tenants' satisfaction (in comparison to shutdown during daytime periods).

C. Control Based on Temperature

By means of temperature sensors placed in the return circuit, recirculation pumps are switched on and off depending on upper and lower threshold values. The lower threshold must be sufficiently high to guarantee conditions of salubriousness along the whole pipe network (usually $T_{\mathrm{Lth}} = 50\,^{\circ}\mathrm{C}$ or higher).

On the other hand, systems provided with heater temperature modulation consist of constant recirculation but they reduce water temperature during low-demand periods. In addition, by means of closed control loops that consider setpoint temperatures at end fixtures, heater power can be adjusted to produce the desired levels and thus minimize the blend with cold water in consumption points.

D. Demand Recirculation

For this kind of control, users let the system know in advance the intention to consume hot water. As a response, the recirculation system is switched on, and hot water is available a short time later. The control action is triggered by special buttons, presence sensors, or flow sensors in the loop.

Demand recirculation systems point to be the ideal, optimal solution. They involve less cost, shorter waits for hot water, and reductions of energy and water waste. However, this option has some obvious drawbacks. To require the user collaboration (i.e., special buttons or commands) and the subsequent wait can be unfeasible with regard to usability or even unpleasant in some habitual scenarios. On the other hand, the activation by presence or movement sensors usually entails unnecessary recirculation and reduce the expected efficiency.

IV. Profile-Based Control

Profile-based control becomes a fair evolution with regard to the introduced strategies. It manages the operation of heating and recirculation systems by means of predictive algorithms. Therefore, controllers deploy DHW habit patterns to obtain context awareness and forecasting capabilities.

A. Overview

For the correct operation of profile-based approaches, each significant consumption area (e.g., apartment or floor) must be able to elaborate daily DHW use profiles and store them in local databases. This task is independently assumed by distributed units of the same building management system. Later on, every unit deploys a set of stored profiles to obtain a representative pattern, i.e., a profile that represents the set and contains the expected behavior of the specific area. This pattern is sent to a central controller and will be utilized in the decision making process for the next day (Fig. 1).

The pattern discovery process is a task that involves several complexities and uncertainties related to behavioral modeling,

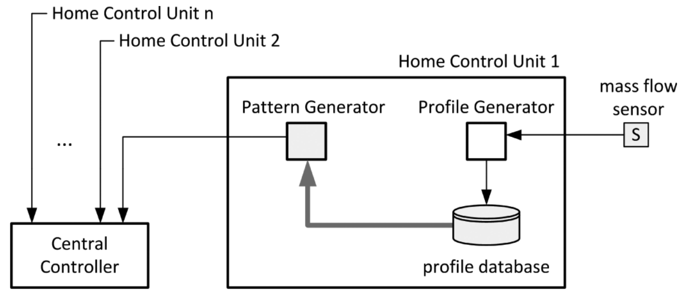

Fig. 1. Pattern generation and delivery process.

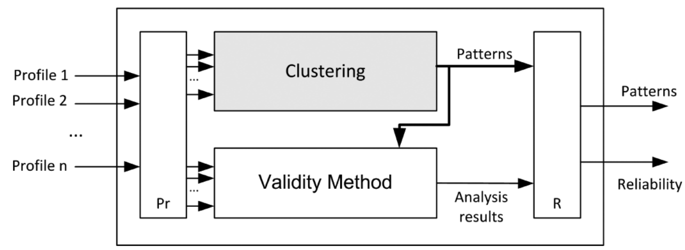

Fig. 2. Basic schema of a pattern generator. "Pr" stands for "preparation block," where profiles undergo a wrong-data/0-days filtering process; "R" is the "rules block," where *reliability* calculation and pattern rejection/fusion are carried out.

hence clustering tools supported by soft computing techniques have shown good, reliable outcomes in previous works [18]. In addition, pattern generation modules also provide information about the level of representativeness and reliability of the obtained patterns, a fact that allows the accurate and flexible implementation of control responses [19]. Indeed, the recognition of recurrent patterns in the behavior of persons, objects, and sensors in buildings is considered to be a key factor to improve the context awareness capabilities of smart systems [20].

B. Pattern Selection and Reliability

A pattern generator is formed by a clustering tool and a set of validation techniques that are in charge of inferring the context drawn by the cluster analysis. Fig. 2 displays a schema of a basic pattern generator.

Every day and for each distributed unit, given m collected daily profiles (past days), the clustering tool embedded in the pattern generator module obtains a (variable) n number of patterns. Such output patterns or representatives are established using the cluster centroids [21]. Therefore, the fitness of an output pattern j can be established based on *size* and *density*, where

$$\mathrm{size}_j = \frac{m_j}{m} \tag{1}$$

where m_j is the number of inputs embraced/represented by the cluster/pattern j and m is the total number of input profiles. *Size* is a discriminant factor, so clusters that are not sufficiently large are automatically discarded. With databases that deal with all of the days of the week together, tests in CDHW simulations (and

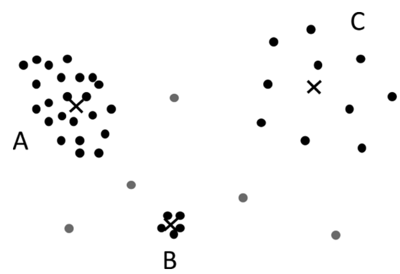

Fig. 3. 2-D map projecting the similarity relationships of a possible clustering solution.

also HVAC [6], [18]) establish 8% as a suitable criterion for the minimum cluster *size*. On the other hand, we have

$$\text{density}_j = \frac{1}{m_j}\sum_{i}^{m_j} \text{dist}(\text{pattern}_j, \text{profile}_{i,j}) \qquad (2)$$

i.e., the average distance between a cluster centroid and its clustered samples, usually named as *inter-cluster similarity* in the literature related to data-mining and pattern discovery [22]. $dist$ stands for the distance or similarity measure (e.g., Euclidean metric).

To clarify the introduced concepts, Fig. 3 shows a 2-D representation of the pattern generator solution space for a given hypothetical scenario (a single family or apartment). Dots represent past daily profiles, whereas Xs are patterns (centroids or representatives). In the illustrated case, the clustering tool finds three clusters: A, B and C, with sizes: A-53%, B-12% and C-23% (the tool considers gray dots as outliers), and densities: A–medium, B–high, and C–low.

The presented information is sufficient to have a first reading of the habit context. In addition, the preponderance of discovered habits over specific periods inside the database is also considered. Hence, in a control situation, for the current day of the week (e.g., Monday[2]), a *dominant* pattern is established based on the representativeness of each obtained pattern inside the subset formed by the same day of the week past days. For instance, if the past consecutive Mondays are represented by patterns A, A, C, A, A, B, A, A; it is obvious that A is the dominant pattern of the set. In case of a draw, the *bigger* pattern (higher *size*) is selected as the dominant. If there is no dominant pattern, the day is considered as *unpredictable*.

For the winner pattern, *reliability* is stated as a function of *density* and the *level of dominance*. The level of dominance is the representativeness inside the respective subset of the current day (in the previous example, it would be $6/8 = 0.75$). Provided density and level of dominance are obtained as indices between 0 and 1, the reliability of pattern k can be established as follows:

$$\text{reliability}_k = \min(\text{density}_k, \text{dominance}_k). \qquad (3)$$

[2]Profiles are stored and classified in daily and seasonal databases so as to achieve an accurate management. If users facilitate information in advance about holidays, days off, and special dates, the performance is improved.

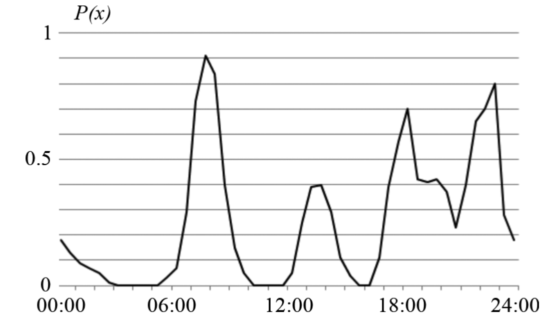

Fig. 4. Example of DHW pattern corresponding to a winter-season, working-day: Tuesday for an apartment occupied by one person. $P(x)$ stands for the probability of using hot water.

TABLE I
SIMPLE PROFILE-BASED CONTROLLER. k STANDS FOR PATTERNS OF THE SPECIFIC GROUP COVERED BY THE RECIRCULATION PUMP

max$\left(pattern_k[t + t_H]\right)$	Action
Low	Switch off boilers and recirculation pumps.
Moderate	Switch on recirculation pumps, boilers at low temp.
High	Switch on recirculation pumps, boilers at high temp.

Although closely related, reliability should not be mistook for likelihood; the former just shows stability and soundness of past behaviors.

Flats with unpredictable days or unreliable patterns indicate erratic behaviors or unstable, lax user habits. The isolated existence of such cases does not entail any critic situation or a severe degradation of the performance, they are simply submitted by the central controller to the habitual trend of the remaining flats that share the same recirculation circuit. In the worst (usually unlikely) case, the system is able to detect high and widespread levels of unpredictability or unreliability, and therefore switch to classic strategies (e.g., temperature control) as habit-based prediction would make no sense in such a situation.

C. Operation Within CDHW Systems

For the CDHW control, a profile (also a pattern by extension) is defined as a univariate time series with a 1-day length and fields that cover periods of 30 min. Fields take values that express the level of likelihood to have DHW during the respective time period (Fig. 4).

Therefore, depending of the area covered by every recirculation pump, the global controller manages from one to a set of DHW patterns, being able to predict whether hot water is going to be required in a specific branch/circuit with certain level of probability. In case the combination of probabilities reaches a predefined threshold, recirculation is activated and boiler temperatures are also adjusted. It is carried out a little time before the rise of probabilities, in a time defined as *preparation period* $(t_H).t_H$ is therefore the prediction horizon of the controller, i.e., the time in which the controller anticipates to users' habits. Table I shows a simple example for the controller table of decision rules.

Thus, the controller checks in advance (t_H) the probability of hot water consumption shown by the patterns belonging to the apartments of the same recirculation circuit. Obviously, only apartments with a predictable day are considered. Finally, the *reliability* measure adjusts the value of t_H (e.g., low reliability rates increase t_H) and triggers the application of smooth filters to patterns when reliability levels are low (i.e., users have erratic or lax behaviors, or do not follow stable habits). In case the reliability of a pattern is too low (e.g., under 0.4), it is considered as *unreliable*. When most of the apartments in the same recirculation circuit are *unpredictable* or *unreliable*, the system realizes that habits are not significant enough to perform control actions, and it automatically switches to the most suitable classic strategy by default (according to users/managers' preferences).

The values of the introduced thresholds concerning probabilities, boiler temperature adjustment and t_H cannot be generalized as they depend on the characteristics of the specific building or facility, e.g., piping distances, branches, type of boilers, number of floors, number of apartments per floor. Simulations of the building under design (or refurbishment), using real hot water use draw databases, are set to optimize the suitable values for the specific case. For guidance only, temperature adjustments can follow the usual recommendations utilized in temperature-based control; setting t_H between 10 and 30 minutes on account of reliability, and considering *high probability* when $\max(\text{pattern}_k[t + t_H]) > 60\%$ usually lead to good tradeoff results between energy cost and comfort performance.

Moreover, profile-based control can be smartly combined with demand recirculation to reach the best performance. The system can provide simple feedback to users in order to let them know the status of the recirculation according their own habits. For instance, using LEDs close to the hot water fixtures (e.g., red, yellow, and green lights to indicate water temperature in the recirculation circuit). In addition, the *demand* button fits the design and an additional command to stop the predicted DHW if it does not fit users' plans. Provided profile-based services, the system is always learning from users' habits, actions, and made decisions.

These last enhancements are additional, interesting options in keeping with proactive smart-home design approaches. They consider users as active elements, capable and willing to close the control loop of automation systems [23].

D. Integration in Home and Building Automation Networks

Additionally, the performance of profile-based control for DHW can be optimized as long as it is combined with other home automation services based on profiles. For example, profile-based control has been already deployed to ameliorate classic performances of heating and air-conditioning systems [6], [24] . In this line, NEST[3] is a commercial standalone habit-based application for heating control. Habits profiles are also useful to develop demand side management of electricity services [25], or to predict building electricity consumption in a daily fashion [26]. Finally, they are introduced as a basis for overall smart home control in [6], and widely explored in [27].

As long as more services are gradually integrated in a profile-based overall control structure, profiles become shared objects of global reasoning for the coexisting applications. For instance, in the intended CDHW scenario, occupancy habit profiles can be used to refine and validate DHW profiles, provided that loads that use DHW and do not require users' presence are correctly identified and scheduled (also might be linked to a profile-based service).

[3][Online]. Available: http://www.nest.com

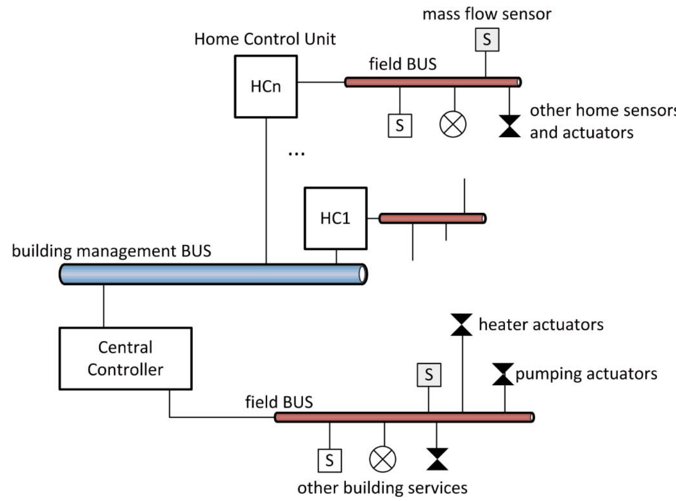

Fig. 5. Schema of the integration of profile-based CDHW control within home and building automation structures.

Fig. 5 shows a schema where smart homes are connected one another by a common building automation system. Some services and objects are transparent to the building control and others are exclusive to every specific home/flat. DHW profiles are an example of resource that can be deployed either in the home scope, in the building scope, or in both ones.

V. Simulation Environment

The current section depicts the simulation environment and the specific, representative simulated case deployed to compare the introduced DHW control strategies.

A. Building and CDHW System Model

Since the available hot water draw profiles belong to a set of Spanish residential dwellings, the design of the test-bed building and the CDHW system has been carried out according to Spanish rules and recommendations [28], [29] [30].

The model consists of a four-story building with four apartments per floor and three bedrooms per apartment. The system provides hot water on-demand by means of a heat exchanger and a set of pumps. It also has a pipe way for water recirculation, as shown in Fig. 6. Recirculation can be activated independently for each one of the different stories.

In order to size the piping system, instantaneous volume of mass flow and simultaneity coefficients are calculated according to Spanish—not compulsory—standards (UNE 149.201/07). They provide the following formula:

$$m_c = A \times {m_t}^B + C \tag{4}$$

where m_c stands for the *simultaneous mass flow* [l/s] and m_t is the *total mass flow* [l/s] considering all of the devices of the building. $A, B,$ and C are constants that depend on m_t and

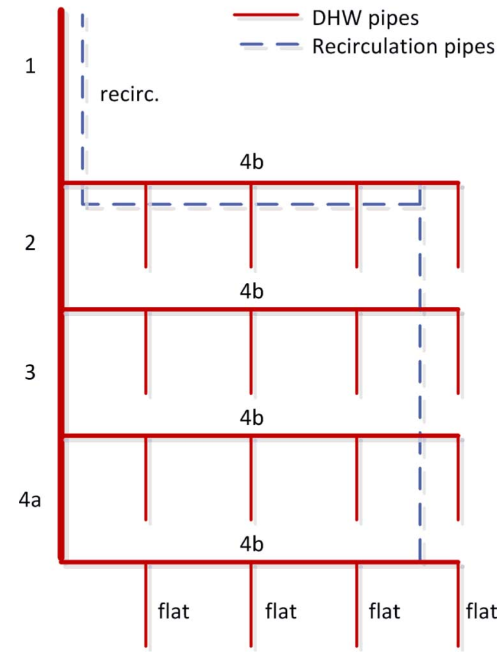

Fig. 6. Simulated DHW schema.

the maximum mass flow of an individual device (m_u [l/s]). Each apartment is modeled with a kitchen sink (0.1 l/s), a dishwasher (0.15 l/s), a washing-machine (0.1 l/s), a bathroom sink (0.065 l/s), a bath/shower (0.2 l/s) and a bidet (0.065 l/s)[4]. Therefore, $m_{t(\text{flat})} = 0.68$ l/s; for the whole building: $m_t = 4 \times 4 \times 0.680 = 10.880$ l/s. Finally, applying the corresponding constants, the simultaneous mass flow remains as follows:

$$m_c = 0.682 \times 10.880^{0.450} - 0.140 = 1.856\frac{l}{s}. \quad (5)$$

According to the standards and stating an average of 3.5 persons per flat, the expected daily energy consumption can be approximated as $Q =$ 78.602 kWh/day, considering 22 l of DHW at 60° per person and day [28]. The obtained m_c allows the calculation of the power rates for the heater exchanger to fulfill peak demands, giving $P =$ 426.286 kW. Both calculations require knowing the temperature of the cold water branch, which depends on the season and the location of the building. A restrictive value of 5 °C for the Spanish scenario have been taken.

On-demand heating requires high-power heaters compared with systems supported by storage tanks. In any case, the distribution system must be designed considering the maximum flow rates irrespective of the type of DHW production (tankless, tank-type or combinations), guaranteeing that outlets have the minimum flow and pressure rates. Thermoplastic pipes for the simulated model have been undertaken; provided m_c and m_t, the internal diameter of the required pipes can be established according to tables provided by pipe manufacturers (in our case, the concerned data is shown in Table II).

According to the Spanish norm, the DHW recirculation system must keep the next conditions: 1) the temperature of the furthest outlet is at most 3 °C under the temperature of the exchanger/tank; 2) the minimum recirculation flow is 250 l/h per column or 10% of the total m_c; and 3) the minimum ID (internal diameter) of the recirculation pipe is 16 mm.

[4]The provided flow rates account only for hot water demand.

TABLE II
FLOW RATES AND INTERNAL DIAMETER (ID) FOR PIPE BRANCH-TYPES IN THE SIMULATED MODEL

Branch-type	m_t [l/s]	m_c [l/s]	ID [mm]	length [m]
1	10.880	1.856	36.4	5
2	8.160	1.614	36.4	3
3	5.440	1.322	29.2	3
4a	2.720	0.930	29.2	3
4b	2.720	0.930	29.2	10
flat	0.680	0.433	18.2	10
recirc.	—	0.186	18.2	24

The whole piping system presents the same insulation characteristics, established according to the Spanish law of 2008 [31], i.e., insulation thickness of 25 mm with thermal conductivity ($\lambda_{10°C}$) equals 0.04 W/mK.

B. Calculation of Temperatures, Consumptions and Losses

The numerical model used for the simulation of pipe temperatures and losses is based on the equations proposed by Baskin *et al.* in [10], using a NI LabWindows/CVI simulation environment. The referred model presents a deep level of detail, it has been devised to evaluate energy performances of distinct DHW systems, comparing either structures or pipe materials and insulators.

As far as the current work is concerned, the nature of the intended comparisons allows us to assume some liberties. The most relevant assumptions are: 1) convection for boundary conditions of pipe surfaces are referred to a constant air temperature; 2) water temperature is constant in cross sections; 3) an overall heat transfer coefficient (including pipe insulation) is defined for the whole pipe structure; and 4) insulation has no thermal mass.

One of the most significant aspects of the simulation of DHW systems concerns the instantaneous temperatures taken by the fluid in the distinct points of the DHW installation. Within the pipe, temperatures change depending on time and the position along the pipe structure, i.e., $T = f(x,t)$; hence, axial temperature distribution can be stated considering the equation

$$\dot{m}c_p\frac{\partial T}{\partial x} + \rho c_p A\frac{\partial T}{\partial t} + UpT = UpT_a \quad (6)$$

where $\dot{m}$ [kg/s] stands for the mass flow rate, ρ [kg/m^3] is the density and c_p [J/kg · K] is the heat capacity of the fluid at constant pressure. A [m^2] stands for the cross sectional area of the pipe, and p [m] for the perimeter. T_a [K] marks the air temperature around the pipe, and U [W/m^2·K] is the overall heat transfer coefficient.

Note that the process that rules water temperatures distinguishes two different states: flowing and zero-flowing (whenever there is no pump working and the system remains in an idle state). With respect to (6), for zero-flowing states ($\dot{m} = 0$) the x-dependent term disappears, i.e., the temperature in a single point of the pipe structure evolves only considering its previous states.

Heat losses through pipes are calculated by means of the time integration of the heat transfer rate along the pipe circuit (PC [m])

$$Q_N = \int^{t} \int^{PC} Up\Big(T(x,t) - T_a\Big)\,dx\,dt \quad (7)$$

whereas the total heat demand in the exchanger (Q_H [kW]) and the power exerted by the pumping system (P [kW]) are established by simple models

$$dQ_H = \frac{\dot{m}c_p\big(T_{out} - T_{\rm in}\big)}{\eta_h(\dot{m})}\,dt + L_H(T_{\rm out})\,dt \quad (8)$$

$$dP = \frac{\sum_i \dot{m}_i \rho g h_i}{\eta_p}\,dt \quad (9)$$

where η_h and η_p are the respective dimensionless coefficients for the heater (boiler and exchanger) and pumping system efficiencies. η_h depends on the mass flow and the temperatures that take the fluid at the inlet and outlet valves of the exchanger ($T_{\rm in}$, $T_{\rm out}$), L_H stands for losses in the heater equipment due to convection and radiation, g is gravity (9.8 m/s^2), $\dot{m}_i$ is mass flow demanded by the fixture i (or the recirculation system), and h_i [m] is the maximum height that reaches the fluid for the corresponding fixture (or recirculation).

Note that the defined values for dQ_H and dP are valid when the heater and the pumps, respectively, are working; otherwise, when the system is in a zero-flow status, $dP = 0$, and, when boilers are off, $dQ_H = 0$.

C. Studied Cases and Tests

Given the models for the building and the piping network depicted in Sections V-A and V-B, simulations need to be fed with realistic information with regard to the use of hot water. For the behavioral data models are not used, but real information collected in buildings that utilize a LEAKO centralized system.[5] The deployed database contains hourly information of DHW consumption of more than 700 dwellings, distributed in 8 multifamily buildings or housing developments, from 2002 to 2007 in the Basque Country (Spain). For the tests, 3/4-family/user flats have been selected at random from the same building or development.

In the modeled 16-family building, 70 days are selected from the database for every flat. The first 60 days are used for training (past days for the clustering tool), and the last 10 days are utilized for testing during the simulation. The initial date is selected at random, and the following days are consecutive, but considering only the same day of the week (e.g., Saturdays). This arrangement is carried out since habits usually follow weekly cadences. Therefore, a simulation run checks the performance of a DHW control strategy for 10 days. The control strategies under test are as follows:

- *On Demand (No Recirculation)*. The heating and pumping systems are switched on when a DHW demand happens.
- *Constant Recirculation.* A constant recirculation is established. Boilers work at fixed temperature, $T_{\rm boil} = 70\,^\circ$ C.
- *Scheduled Recirculation.* The recirculation system is stopped at night, from 23:00 h to 6:45 h, matching periods of low demand.
- *Recirculation with Temperature Control.* Boilers and pumps are adjusted depending on the temperature of the recirculation circuit, guaranteeing that temperatures never cool down under $T_{\rm boil} = 50\,^\circ$ C for the entire structure.
- *Demand Recirculation.* Floor recirculation is activated for the corresponding story three minutes before the next DHW demand takes place.
- *Profile-based Recirculation.* The simulated controller is a primitive version of the approach explained in Section IV. The central system checks habit profiles and switches on recirculation for the corresponding floor if at least one of the respective profiles predicts DHW demand with a likelihood over 50%. t_H is set to 15 min. Unlike in a real implementation, the controller does not react to unpredictable or unreliable patterns, it keeps deploying the pattern ranked as the best possible. This ensures that profile-based strategy given outcomes are not biased by the effect of alternative strategies.

With regard to boundary conditions, ambient temperature is fixed to 10 °C for the whole simulation. The peak power allowed to the heating equipment is 400 kW, which is a bit lower than that recommended by Spanish standards.

D. Performance Indexes

In order to evaluate and compare control strategies, we establish a set of indexes. They offer readings of the performance in terms of energy costs, waste of water and comfort appraisals. The indexes are defined as follows.

- *Time to Comfort TtC* [s]—the average time that users have to wait until hot water is available at the consumption point. For the flat i, we have

$$TtC_i = \int A_i\,dt \quad (10)$$

$$A_i = \begin{cases} 1, & \text{if}\,(d_i = 1) \wedge (T_i \leq T_c) \\ 0, & \text{others}\ldots \end{cases} \quad (11)$$

  where d_i becomes 1 when there is DHW demand in flat i, and T_i the temperature of the furthest fixture of the respective flat. T_c is a temperature value that determines the point over which water is considered to be sufficiently hot.
- *Delivered hot water m* [l]—the total heated water given by the system

$$m_i = \begin{cases} \int \dot{m}_i\,dt, & \text{if}\,(d_i = 1) \\ 0, & others\ldots \end{cases}. \quad (12)$$

- *Indirect profited hot water coefficient* η_w—(dimensionless), or the proportion of supplied heated water that are at the desired temperature T_c:

$$\eta_w = \frac{M}{m} \quad (13)$$

  where M stands for demanded liters at T_c.
- *Energy consumption per day E* [kWh/day]:

$$E = \frac{1}{D \times 60 \times 60}\Big(\int dQ_H + \int dP\Big) \quad (14)$$

[5][Online]. Available: http://www.leako.com

TABLE III
SIMULATION RESULTS WITH $T_{\text{boil}} = 70\,^{\circ}\text{C}$ AND $T_c = 40\,^{\circ}\text{C}$

Strategy	TtC [s]	m [l]	E [kWh/day]	E_L [kJ/l]	η_w	η_e
On Demand (No Recirculation)	46	21339	177.8	450.9	0.67	0.62
Constant Recirculation	3	14646	285.8	724.7	0.97	0.39
Scheduled Recirculation	6	15093	243.8	618.2	0.94	0.46
Recirculation with Temperature Control	5	14906	192.2	487.4	0.95	0.58
Demand Recirculation	7[6]	15312	140.4	355.9	0.93	0.79
Profile-based Recirculation	8	15453	153.1	388.2	0.92	0.72
Desired values	*low*	*low*	*low*	*low*	*high*	*high*

where D is the number of simulated days.

- *Energy cost per liter of hot water* E_L [kJ/l]—referred to M

$$E_L = \frac{1}{M}\left(\int dQ_H + \int dP\right). \tag{15}$$

- *Indirect energy efficiency coefficient* η_e—(dimensionless). It is a rough measure of the final fraction of a watt which transforms in end-use energy

$$\eta_e = \frac{mc_p\left(\overline{T_{\text{boil}}} - \overline{T_{\text{amb}}}\right)}{Q_H}. \tag{16}$$

VI. DISCUSSION AND RESULTS

CDHW[6] strategies pursue efficiency twofold: reducing waste of water and minimizing energy consumption. As examples of efficiency rates, in [32] the daily wasted hot water has been considered as about 20% of the total amount for residential single family building ($\eta_w = 0.8$). In [33], the usual energy efficiency of the whole CDHW for multifamily buildings is even under 30% ($\eta_e < 0.3$).

Given the common CDHW structures, note that both goals seem to oppose each other. Therefore, the extremes of the chain are represented by the *on-demand* strategy, where water is heated only when necessary, so it tends to be more energy efficient; and, on the other side, the *constant recirculation* strategy, which assures that there is always hot water close to fixtures, so the waste of water is reduced.

The poor exploitation of water (waiting times) reduces the energy efficiency of the *on-demand* strategy, whereas good pipe and equipment insulation improve considerably the efficiency of systems with recirculation. In any case, provided a good insulation, heat losses in pipes are not as determinant as the inefficiency shown by boilers. Heaters are sized to fulfill infrequent peaks of demand but most of the time they work at very low power rates (e.g., 5% or 10% its capacity). Since active boilers must keep the working temperature, they present a fixed energy consumption due to convective and radiative losses regardless of the delivered power. Contrary to that, exchangers are more efficient when work with low flow rates as heat transfer between fluids is not so demanding. Finally, the consumption due to water pumps is negligible compared to the energy required by heaters.

The commented phenomena can be observed in simulations. They determine the performance results shown in Table III. As referred above and supported by the figures, *on-demand* and *constant recirculation* strategies can be stated as undesirable extremes. The *scheduled* strategy becomes a rough commitment solution beyond the previous strategies, stating a time period of application for each one based on a very superficial evaluation of the system dynamics. Beyond these basic strategies, the best balances among comfort, water waste and energy consumption are reached by *temperature control*, *demand recirculation* and *profile-based* strategies. Using different methods, these three approaches try to minimize the active time of heaters, but guaranteeing service quality.

Temperature control results in a general, satisfactory solution, but ignores the unbalanced behavior of the demand within the network. On the other hand,*demand recirculation* reaches the best figures, but provided the fact that users inform previously of consumption intentions and are forced to wait a prefixed time. The *profile-based* strategy avoids such drawback and still achieves an excellent performance, very close to the *demand recirculation* rates. The predictive capabilities combined to the awareness concerning behavioral simultaneities of the network gives the controller the ability to perform a customized management.

Please note that the deployed DHW profiles have not been modeled, but randomly taken from real databases. In the case of more chaotic, unstable scenarios, the *profile-based* performance would partially tend to the classical strategy adopted instead by the controller. Finally, in an advanced configuration where *profile-based* and *demand recirculation* options are combined, we would reach an optimum state in terms of resource exploitation and user satisfaction.

VII. CONCLUSION

The conducted research has mainly shown the suitability of profile-based techniques for the control of CDHW systems. Future steps include enhancements of the control design, for example by means of fuzzy decision making algorithms. Soft computing methods present good features to deal with the uncertainties and partial truth that are inherent to the prediction of human behaviors. It is expected that fuzzy controllers better manage profile data to optimally activate the recirculation and adjust setpoint temperatures.

Beyond the exploitation for control, some other noteworthy aspects and conclusions arise from the calculations. For instance, the review of the DHW use database discloses that, as a general rule, hot water demand of single flats is mostly located during daytime and distributed in very short periods. Limiting us to the location of the available data, official simultaneity coefficients seem to be oversized and require better calculations,

[6]In addition to this average waiting time, note that users have to wait a fixed time of three minutes after the system is informed of the intention of consuming hot water.

more realistic and tailored to the specific region. Note that the performance detriment of oversized systems is actually strong.

Hence, as we commented before, profiling techniques are useful for control but also for design phases. The spread collection of building profiles would allow to optimize the design of pipe structures and equipment, but also other smart home and building services. Indeed, profile-based designs sensitive to user cooperation are promising approaches for high-aware, global home and building control systems.

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Félix Iglesias received the Dipl.-Ing. degree in electronic engineering and Dipl.-Adv. degree in information technology from the La Salle URL, Barcelona, Spain, and the Ph.D. degree from the Vienna University of Technology, Vienna, Austria, in 2012.

He has worked on research for different firms, including the Institute of Automation, Vienna University of Technology, the AIT Austrian Institute of Technology, and the Department of Electronics and Telecommunications at La Salle URL. Beyond researching and project development, he has imparted professional and university lectures in the fields of electronics, physics, and home and building automation. In addition, he has worked as a freelance for projects of house and building control and management systems as well as R&D for the renewable energy industry. His further research interests include machine learning, artificial intelligence, and data processing.

Peter Palensky (M'03–SM'05) received the Ph.D. degree from the Vienna University of Technology, Vienna, Austria.

He is a Principal Scientist with the Energy Department, Austrian Institute of Technology (AIT), Vienna, Austria. Before that, he was head of the Business Unit for Sustainable Building Technologies at the AIT, CTO of Envidatec Corporation, Hamburg, Germany, Associate Professor with the University of Pretoria, South Africa, Department of Electrical, Electronic and Computer Engineering, University Assistant with the Vienna University of Technology, Austria, and Researcher with the Lawrence Berkeley National Laboratory, Berkeley, CA, USA. His main research fields are complex energy systems and smart buildings.

Dr. Palensky is an elected AdCom Member of the Industrial Electronics Society of the IEEE. He is active in international committees like ISO, IEEE and CEN.