Smart Building Energy and Comfort Management Based on Sensor Activity Recognition and Prediction

Francesca Marcello, Virginia Pilloni
Department of Electrical and Electronic Engineering - University of Cagliari - Italy
National Telecommunication Inter University Consortium - Research Unit of Cagliari - Italy
Email: {francesca.marcello,virginia.pilloni}@unica.it

***Abstract*—Thanks to Building Energy and Comfort Managements (BECM) systems, it is possible monitor and control buildings with the aim to ease appliance management and at the same time ensuring efficient use of them from the energetic point of view. To develop such kind of systems, it is necessary to monitor users' habits, learning their preferences and predicting their sequences of performed activities and appliance usage during the day. To this aim, in this paper a system capable of controlling home appliances according to user preferences and trying to reduce energy consumption is proposed. The main objective of the system is to learn users' daily behaviour and to be able to predict their future activities basing on statistical data about the activities they usually perform. The system can then execute a scheduling algorithm of the appliances based on the expected energy consumption and user annoyance related with shifting the appliance starting time from their preferred one.**

Experimental results demonstrate that thanks to the scheduling algorithm energy cost can be reduced of 50.43% and 49.2% depending on different tariffs, just by shifting the use of the appliance to time periods of non-peak hours. Scheduling based on probability evaluation of preferred time of usage of the appliances allows to still obtain evident energy savings even considering the errors on predicted activities.

***Index Terms*—Activity Recognition; Activity Prediction; Energy Management; Comfort Management; Smart Building**

I. Introduction

Smart buildings are characterised by the presence of sensors, actuators and smart devices that give the opportunity to monitor and control, either manually or automatically, key equipment within buildings [1]. This is the concept behind Smart Building Energy and Comfort Management (BECM) systems [2][3]. As a matter of fact, domestic electricity usage accounts for about 40% of the global energy consumption and contributes over 30% of total greenhouse gas emissions [4]. Nevertheless, user comfort is crucial when policies of Demand-Side Management (DSM) are put in place [5]. In such an intelligent scenario, one of the major goals is to provide users with tools that support cost-effective solutions to appliance management, which: i) demand the lowest effort in terms of training and management, dynamically adapting to user requirements, and ii) take into account user habits so that appliance management decisions do not conflict with them, causing a disaffection that may lead the user to turn off the system [6].

Currently, most of the literature considers user comfort as a set of hard constraints on appliance usage, which are a priori set considering general statistics [7][8]. This approach neglects the fact that users are likely not only to have different subjective requirements with respect to the others, but they also dynamically change over time.

In this paper, user preferences and habits about appliance usage are continuously monitored, recognised and predicted, by means of a BECM system based on sensors deployed inside the reference building. The system merges two previous studies about activity recognition [9] and appliance scheduling [6], by including the crucial activity prediction functionality. Indeed, activity prediction enables appliance scheduling by predicting which appliances are likely to be used in the following hours and scheduling them in advance, so that their starting time is shifted to off-peak times when electricity tariffs are lower.

The main contributions provided by this paper can be summarised as follows:

- an activity recognition algorithm used to model user profiles, which was first proposed in [9] and whose accuracy is here improved;
- an activity prediction algorithm is proposed, along with statistics about mutual correlation of activities. Accordingly, appliance usage is predicted for a specified time window (test were run for a time window of 6 hours);
- user profile and activity prediction are incorporated into the user-annoyance-aware energy-cost-saving appliance scheduling algorithm proposed in [6].

To the best of the authors' knowledge, this is the first comprehensive system to use sensor-based activity prediction and occupants' preference inference, and integrate them into a BECM. Accordingly, based on simulations of the system on a real dataset, this paper further analyses how the proposed system affects energy-related costs.

The remainder of the paper is organised as follows. Section II presents past works and the required background. In Section III an overview of the proposed system model is provided. Section IV describes the reference use case considered to test the performance of the system. Finally, in Section V a performance analysis is provided. Conclusions and final remarks are drawn in Section VI.

II. Related Works

Smart technologies can be used in all kinds of different buildings (i.e., residential, office, and retail sectors) to improve the comfort and the safety of people in their home, concerning various topics, from healthcare and providing living assistance, to environmental monitoring and ensuring energy saving. Accordingly, BECM systems have the objective of combining power consumption minimisation while preserving user comfort [10][11]. This issue has been addressed by researchers from many different perspectives. The authors in [10], present a review of control systems for energy management and comfort in buildings, where the quality of the comfort is considered mostly dependent on thermal comfort, indoor air quality and visual comfort, explaining current and conventional controller solutions and their disadvantages. Also in [12][13] two different solutions for building management considering user preference in terms of indoor environment comfort are presented. In [14], an algorithm for thermostatically controlled household loads based on price and consumption forecasts of grid energy is presented. The issue of scheduling appliances according to user preferences was also addressed by [6], where Quality of Experience (QoE) is measured as a function of the interval between the preferred and proposed appliance starting time for switching controlled loads (e.g., washing machines and clothes dryers), and as a function of the interval between the preferred and proposed temperature for thermostatically controlled loads (e.g., conditioning systems and water heaters).

It is evident that user preferences and habits severely affect results of BECM systems. For this reason, in recent years researchers have started to observe users' behaviour, in order to infer their habits and preferences. The monitoring of activities of people in their home can be done by analysing data that can be gathered with different technologies. Different studies proposed solutions based on using cameras and wearable sensors or gathering data provided by phone accelerometer and gyroscope [15][16]. These solutions are not very practical in home scenarios where people are often not inclined to accept those devices. To monitor what activities people are performing in their house, non-intrusive sensors are often preferred: typical devices that are installed in the environment are motion sensors, door sensors or temperature and pressure sensors [17]. The data collected from sensors inside resident houses are analysed using data mining and machine learning techniques to build activity models that are used as the basis of behavioural activity recognition.

With reference to modelling and classification methods, researchers have investigated the recognition of resident activities using a variety of mechanisms, such as Naïve Bayes classifiers, Markov models, and dynamic Bayes networks. In multiple cases, in spite of its simple design and simplified assumptions, Naïve Bayes classifiers often work much better than expected, especially when a specific group of sensors can easily be identified as characteristic of a certain activity [18].

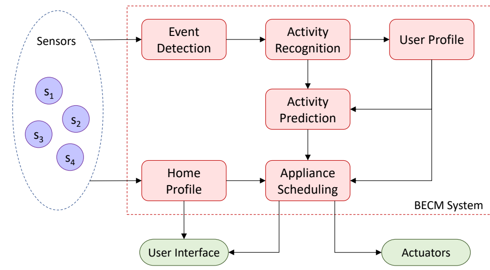

Fig. 1. Overview of the proposed BECM system

III. System Model

In this paper, the considered scenario is that of a BECM system, based on distributed smart home sensor networks. An overview of this system is represented in Figure 1. More specifically, sensors are used to make observations on users and their interactions with the surrounding environment; the combinations of these interactions, which are detected by the *Event Detection* module as events, provide meaningful information on users' activities. As described in more details in [9], after a training period the *Activity Recognition* module can correctly recognise activities with an accuracy of more than 80% on average. Accordingly, a correlation can be observed between detected events and activities, which can be used to infer users' habits. These habits, stored in the *User Profile* module, are used with information about previously recognised activities by the *Activity Prediction* module, with the aim to predict the following activities that are expected to be carried out by the users. The information related to activity prediction, user profile and home profile are then processed by the *Appliance Scheduling* module to find a scheduling for controllable appliances that corresponds to the best trade-off between energy cost reduction and user comfort. Note that the *Home Profile* module stores home-related information collected by sensors and/or through user interfaces, such as electricity tariffs, and which appliances are installed along with their energy consumption characteristics.

In the following, more details will be provided about the core modules of the proposed BECM system, i.e. the Activity Recognition module, the Activity Prediction Module and the Appliance Scheduling module.

A. The Activity Recognition Module

The activity recognition approach used in this paper was earlier proposed in [9]. It encompasses two phases: i) *training*, during which the system learns the association between activities and their instances, i.e. sequences of detected events; ii) *running*, which uses the probabilistic model created during the training phase to associate an activity to the detected events.

a) *Training phase:* for each k-th activity instance $\mathcal{I}_{jk}$ of activity $\mathcal{A}_j$ observed during an observation time window $\mathcal{O}^A$, a feature vector $\mathcal{F}_{jk}(\mathcal{I}_{jk}) = [f_{1jk}, f_{2jk}, \ldots, f_{ijk}, \ldots]$ is computed with the rates of detected event occurrences, that is the number of events related to one specific sensor with respect to the total number of events observed considering all the sensors within $\mathcal{O}^A$. Then, for each activity $\mathcal{A}_j$, a model vector $\boldsymbol{m_j} = \text{mean}_k(\boldsymbol{\mathcal{F}}_{jk}) = [\overline{f}_{1jk}, \overline{f}_{2jk}, \ldots, \overline{f}_{ijk}]$ is defined such that the rates of event occurrences of its sensors is the average rate for all the observed instances associated with the same activity.

b) *Running phase:* it relies on the use of a sensor-based windowing implementation [18], according to which sequences of detected events are divided into subsequences using an observation window $\mathcal{O}^{\mathcal{W}}(t)$ starting at time t, which contains a certain number of events equal to its size $\mathcal{W}$. Each subsequence $\boldsymbol{z}$ of events is then associated with a feature vector $\boldsymbol{\mathcal{F}}_{\boldsymbol{z}}^{\boldsymbol{W}}$, computed analogously to $\boldsymbol{m_j}$. Finally, the sequences of detected events are classified based on their probability to belong to a given activity.

For further details the reader is referred to [9].

B. The Activity Prediction Module

The main task of the the *Activity Prediction* module is to provide, for the next *Appliance Scheduling* module, a possible scenario in time t ahead in the future, that explains the probabilities of every activity that can begin in t, calculated thanks to information about all the activities happened and recognised before the current time t_0. Starting from the assumption that activities are linked between one another, so that when an activity $\mathcal{A}_i$ occurred at time t_i it is possible to evaluate the probability of another activity $\mathcal{A}_j$ to be performed by the user in a different time t_j, the module has to evaluate the probability in t for every single activity $\mathcal{A}_j$.

During the training phase, two different kind of probabilities have been evaluated for every activity under consideration:

- $p(\mathcal{A}_i(t_i))$ indicate the prior probability for activity $\mathcal{A}_i$ of starting at time t_i;
- $p((\mathcal{A}_j|\mathcal{A}_i)(k\Delta t))$ indicate the conditional probability of activity $\mathcal{A}_j$ of being carried out since activity $\mathcal{A}_i$ has started $(k\Delta t)$ before.

The period between the current time t_0 and the time t in which the prediction is needed, is split in different k time intervals of duration (Δt).

All the activities that have been recognised before the current time t_0 are stored with their respective starting time t_i, so that it is known how many time intervals outdistance every t_i up to t, and it is possible to calculate the conditional probability of activity $\mathcal{A}_j$ in t considering all the activities $\mathcal{A}_i$ that occurred in t_i. Then, for every $(k\Delta t)$ between t_0 and t, the probability of $\mathcal{A}_j$ to be happening in t is calculated with respect to the fact that $\mathcal{A}_i$ could be happening in $(k\Delta t)$. These two contributions are added together according to the equation below:

$$\begin{aligned} p(\mathcal{A}_j(t)) = \sum_i p((\mathcal{A}_j|\mathcal{A}_i)(\frac{t-t_i}{\Delta t}))+ \\ \sum_i \sum_k p((\mathcal{A}_j|\mathcal{A}_i)(k\Delta t)) \cdot p(\mathcal{A}_i(t_0+k\Delta t)) \end{aligned} \tag{1}$$

with $k \in \{0, (t-t_0)/\Delta t\}$.

Every activity coincides with one of the appliances in the house, so that the probability for each activity in t, calculated as explained, is then translated in the probability of one appliance to be used at time t. Therefore, the output from this module is going to enable the scheduling algorithm to make the validation necessary for the scheduling of controllable appliances and for evaluating energy consumption. The algorithm decides to schedule at time t only those appliances corresponding to activities that have their value of probability higher than a certain threshold.

C. The Appliance Scheduling Module

The appliance scheduling algorithm is based on the smart home energy management system proposed in [6]. This system dynamically shifts tasks of controlled appliances to times when it is more convenient (e.g. off-peak times), after finding a trade off between the overall energy cost and the annoyance experienced by users as a consequence of this shift. Accordingly, appliances are subdivided into three groups:

G1: not controlled loads, i.e., small loads such as lights, and not controlled high loads such as fridges;

G2: switching controlled high loads, such as washing machines and dishwashers;

G3: thermostatically controlled high loads, i.e. appliances that are controlled by a thermostat, such as water heaters.

The energy consumption for an appliance i is defined as $E_i^{cons} = P_i^{cons} \times t_i^{exec}$, where P_i^{cons} is its power consumption and t_i^{exec} is its execution time. While for switching controlled loads the execution time corresponds to a complete working cycle, for thermostatically controlled ones it depends on appliance characteristic parameters and temperature conditions. As described in more details in [6], the execution time of G3 appliances to reach a temperature T_i^{exp} is defined as

$$t_i^{exec}\left(T_i^{exp}\right) = -R_i C_i \ln\left(\frac{T_i^{out} - T_i^{exp} + R_i P_i^{heat}}{T_i^{out} - T_i^{in} + R_i P_i^{heat}}\right) \tag{2}$$

where $T_i^{out}(t)$ and $T_i^{in}(t)$ P_i^{heat} are the initial outside and inside temperature respectively, and P_i^{heat}, R_i and C_i are characteristic parameters for the appliance. More specifically, P_i^{heat} is the heat rate (in Watt), R_i is the equivalent thermal resistance (°C/Watt) and C_i is the equivalent heat capacity (Joule/°C). If the appliance is off, $P_i^{heat} = 0$.

The appliance scheduling algorithm then schedules appliances according to their related cost contribution value, which includes both the energy consumption- and user annoyance-related costs. User annoyance is computed according to the results of a survey, completed by 427 people, as reported in [6].

For G2 appliances, the cost to start at time t_i^{ST} and end at time $t_i^{END} = t_i^{ST} + t_i^{exec}$ is defined as

$$C_i^{G2}(t_i^{ST}) = \frac{P_i^{cons}}{\sigma\left(\Delta t_i^{ST}\right)} \cdot \sum_{t=t_i^{ST}}^{t_i^{END}} \Phi(t) \tag{3}$$

where $\Phi(t)$ is the electricity tariff at time t, and $\sigma\left(\Delta t_i^{ST}\right)$ is the relative satisfaction level for a time interval $\Delta t_i^{ST} = t_i^{ST} -$

t_i^{PT}, which is in inverse proportion with the user annoyance of shifting the appliance starting time. If $\sigma\left(\Delta t_i^{ST}\right)=0$, the cost value $C_i^{G2}(t_i^{ST}) \rightarrow \infty$.

For G3 appliances, the cost to start at time t_i^{ST} and end at time $t_i^{END}=t_i^{ST}+t_i^{exec}\left(T_i^{exp}\right)$ is defined as

$$C_i^{G3}(t_i^{ST},t_i^{END})=\frac{2\cdot P_i^{cons}}{\sigma\left(\Delta T_i^{ST}\right)+\sigma\left(\Delta T_i^{exp}\right)}\cdot\sum_{t=t_i^{ST}}^{t_i^{END}}\Phi(t) \tag{4}$$

where $\sigma\left(\Delta T_i^{ST}\right)$ and $\sigma\left(\Delta T_i^{exp}\right)$ are the relative satisfaction values for a difference in temperature respectively of $\Delta T_i^{ST}=T_i^{in}(t_i^{ST})-T_i^{PT}$ between the temperature at the starting time and the preferred temperature, and of $\Delta T_i^{exp}=T_i^{exp}-T_i^{PT}$ between the temperature expected at the ending time and the preferred temperature. Also in this case, if $\sigma\left(\Delta T_i^{exp}\right)=0$, the cost value is $C_i^{G3}(t_i^{ST},t_i^{END}) \rightarrow \infty$.

For further details about this appliance scheduling system, the reader is referred to [6].

IV. Reference Use Case

The algorithm for modelling the activities and then discovering what the resident is doing is implemented and tested using the Aruba real-word dataset from the CASAS smart environment project of the Washington State University [19]. The data were collected from one smart apartment provided with motion sensors, contact sensors in the doors or cabinets and temperature sensors. The events decoded by these sensors are significant for recording elementary actions that people are performing, while the aggregation of these elementary actions defines one activity of interest. To correctly evaluate the correlation between the sets of events and the observed user's activities, without interference from other people, a dataset with only one resident living in the home was considered.

To evaluate the proposed system, in addition to the activities of the Aruba real-word dataset, some other activities have been simulated as performed by the same user inside this home scenario, using the same kind of sensors already installed in the house. The simulated activities are the following three activities not reported in the real dataset: using the washing machine, using the dish washer, taking a shower, which, along with the activity of washing dishes by hand, causes the water heater to turn on. Taking a shower is supposed to be carried out by the user in the bathroom, therefore involving the motion sensors already installed close to this room and assuming that hot water is used, thus causing the water heater to switch on. The use of the dish washer is supposed to be performed in the kitchen, involving the sensors in that area and simulating the presence of a specific cabinet containing the appropriate detergent and with a magnet sensor to understand its opening or closing, so that the activity of loading the dish washer could be recognised concluded only when this cabinet had been closed. The same thing was done for the activity of using the washing machine, by setting up another specific cabinet with its magnetic sensor, and placing it in a room of the house where there are not other linked activities.

TABLE I
CORRESPONDENCE BETWEEN ACTIVITIES AND HOME APPLIANCES

	Activity	Appliance	Appliance type
1	Housekeeping (HK)	Vacuum Cleaner	G1
2	Meal Preparation (MP)	Microwave Oven	G1
3	Relax (Rel)	TV	G1
4	Wash Dishes (WD)	Water Heater	G3
5	Work	Laptop/Pc	G1
6	Taking Shower (TS)	Water Heater	G3
7	Laundry	Washing Machine	G2
8	Wash Dishes with Dish Washer	Dish Washer	G2
9	Always on	Fridge/Freezer	G1
10	Always on when user is at home/not sleeping	Lighting	G1

The system needs a correspondence between some of the activities and the use of certain household appliances, in order to predict energy consumption based on the probability of the activities to occur. Table I shows the considered activities along with their corresponding appliance owned by the user.

V. Experiments and Results

A. Activity Recognition and Prediction Algorithm

With respect to only the four activities corresponding to controllable appliances, i.e. appliances belonging either to G2 or G3, the recognition algorithm presented in [9] has an accuracy of 100% in recognising the activities of taking the shower and using the washing machine, while for the activity of using the dish washer it has an accuracy of 66.7% and for the activity of wash dishes by hand it gives an accuracy of 69.7%. This result is due to the fact that these two last activities are more difficult to recognize because they involve many of the kitchen sensors, which are also associated with other possible activities. The overall accuracy of the activity recognition algorithm is of 83.2%.

As for the prediction of future activities, the algorithm has an overall accuracy of 67%. The activities more accurately predicted are those with many samples and recurrent starting time, like the activity "Taking a Shower", because statistics about them are quite significant. For other less frequent activities, i.e "Wash Dishes", the prediction is instead less reliable.

B. Scheduling Algorithm

The algorithm has been compared with two different situations with respect to the case where no scheduling is involved. There are then three possible scenarios:

- the first one is the classic situation where appliances are normally used by the resident and the scheduling is never programmed (Without Scheduling Algorithm-WSA);
- the second one is based on a perfect knowledge of the time in which the user wants to use some of the

appliances in the house (Scheduling Based on Perfect Time-SBPT). This case coincides with the possible scenario in which the user instructs the system about the exact moment they want the appliance to start, but it has the disadvantage of requiring continuous interactions between users and system;
- the last one bases its scheduling evaluations on the probability of using any of the appliance at time t, calculated as explained in equation 1 (Scheduling Based on Probability-SBP). This solution allows to avoid interactions between users and the system, considering only the system's previous knowledge about user habits.

The training phase to obtain all the information about user's behaviours and preferences, and that allowed the system to perform the calculations on the probabilities indicated in subsection III-B, took into consideration two months of data about performed activities. Due to the fact that the shortest duration for the activities in exam is around 15 minutes, while the longest activities can elapse for several hours, conditional probabilities between activities was valuated choosing duration of intervals (Δt) equal to 15 minutes. The scheduling algorithm was instead tested on one week of data. For every interval of time t_0 during the testing week, the algorithm schedules appliances that are going to be used every $k\Delta t$ time intervals after t_0, with $k \in \mathbb{N}$, trying to improve energy savings and user's comfort. Simulations were done considering time intervals of 30 minutes and predicting future activities in t up to 9 hours forward in the future, so that every half an hour the scheduling algorithm could re-evaluate its scheduling based on the new information about previously user performed activities and with new calculations of probabilities $p(\mathcal{A}_j(t))$. The obtained results were considered with respect to energy consumption in one week, comparing the case with scheduling in relation to the case of normal use of household appliances, and evaluating if the scheduling could generate some kind of annoyance for the user. The evaluation of the energy costs has been made using two different tariffs listed in Table II, based on some typical Italian tariffs. The annoyance rate is defined as in [6], in relation to a possible shifting of appliance starting time or, with reference to the water heater, to a variation in the water temperature with respect to the user preferred temperature of use. Value 1 of annoyance indicates that there is not any discomfort for the user in the change of time in which the appliance was turned on, while a value of 5 indicates the highest level of annoyance for the user. Annoyance levels are modelled as a normal distribution with 15% deviation.

Table III shows the results about energy saving comparing the two cases with scheduling against the case without scheduling. These results are obtained taking into account the fact that cost savings are coming from a scheduling of switching controlled high loads to hours where the energy has lower prices and considering that there is a reduction in energy consumption due to a better optimisation in the usage of the water heater, which is switched on only at times of interest for the user and not every time the temperature drops below

TABLE II
ENERGY PRICING

Weekends, holidays and everyday from 19:00 to 8:00	Everyday from 8:00 to 19:00
Tariff 1 0.0534 €/kWh	Tariff 1 0.07666 €/kWh
Tariff 2 0.067990 €/kWh	Tariff 2 0.07666 €/kWh

TABLE III
ENERGY CONSUMPTION FOR DIFFERENT SCENARIOS

	WSA	SBPT	SBP
Energy consumption in kWh/week	65.43	42.43	35.83
Cost Saving with Tariff 1	-	50.4%	64.7%
Cost Saving with Tariff 2	-	49.2%	63.18%

a certain value. Depending on the different tariff considered, energy consumption was calculated to be decreased of 50.4% with tariff 1 and of 49.2% with tariff 2, in contrast to the energy consumption with a classic use of appliances and energy over the week. As expected, greatest savings are obtained when there is a greater pricing difference between the higher cost range and the lower cost range. In particular, thanks to the scheduling, there is an evident better use of the water heater, since this appliance is scheduled and turned on only for the strictly necessary duration of time to obtain the water to be heated enough for when the resident needs to use it. This result can be verified in Fig.3, which represents the energy saving over the week differentiated by three of the appliances of the house: the water heater, the washing machine and the dish washer. Only those three appliances are considered because they are the only ones owned in the house that belong to groups G2 and G3 and that can be scheduled: the other appliances possessed by the user are part of G1 group. From Fig. 3 it is evident how most of the savings come from the scheduling of the water heater, while there is a lower incidence from washing machine and dish washer. This is explained by the fact that the preferred times of using those two appliances are already evaluated as the best compromise between energy consumption and user comfort, especially because in most cases they are very distant in time compared to the periods of non-peak hours. In fact, in Fig.2, where the average annoyance rate is presented, it is possible to observe how for every appliance the annoyance rate is always close to the lowest value of 1. The knowledge of user behaviours has therefore guaranteed the scheduling of the appliance with the best trade-off between energy costs and user preferences.

A slightly different discussion has to be done with reference to the scenario in which the scheduling is evaluated based on the probabilities of activities and, accordingly, on the

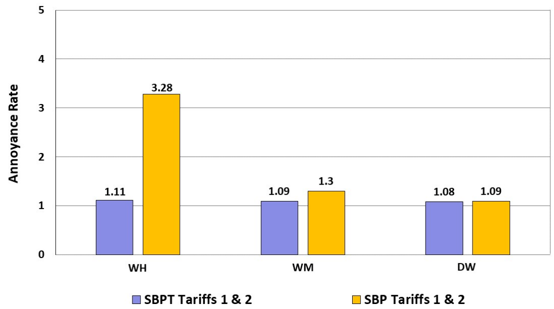

Fig. 2. Average annoyance rate with the proposed system

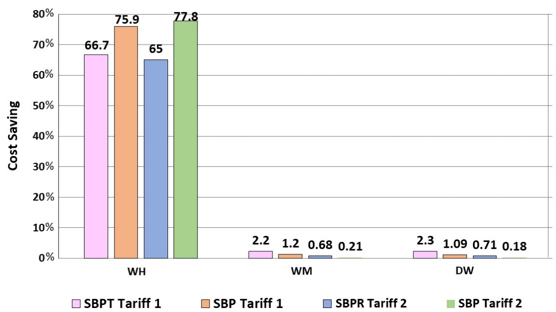

Fig. 3. Energy saving comparison differentiated by appliance

probabilities of using a certain appliance. Even in this case there is an evident reduction in energy consumption during the week, as shown in table III. Most of the saving come again from the wiser use of the water heater thanks to the scheduling only at appropriate time. Looking at Fig.2 it is possible to see, however, how the annoyance rate reaches a higher level. This is due to the fact that the use of the water heater is linked to two different activities, as shown in Table I. While activity 6 is always easily recognised and predicted, and therefore scheduled, activity 4 gives some problems because it is often confused with other activities [9]. Additionally, activity 4 is an activity that the user does not carry out often so there is not much statistical data on it. This last problem is common to the other two activities in exam, and this explains why even for this appliances there are higher level of annoyance rate due to the fact that the prediction module has made an error evaluating the probability of this activity to be performed. The algorithm has otherwise proved that the prevision about future activities can still ensure a good evaluation for the scheduling when the statistical data are reliable.

VI. Conclusion and Future Work

This paper focuses on a solution for energy and comfort management inside buildings, with the purpose of reducing energy waste thanks to a proper control over appliances, while on the same time ensure the well-being of users. To this aim, a BECM system is proposed that integrates a solution for two different problem: the first one concerns the needs for such a system to be able to know users behaviour and preferences and to predict usual activities; the second is about the necessity to manage appliances with respect of that behaviours and preferences and with respect of energy consumption.

The system has been tested in a real scenario, evaluating if the predictions were correct and proposing a coherent scheduling that could guarantee energy savings. The obtaining results show that, as expected, the scheduling of the appliances can guaranteed energy savings, reducing consumption over a week of at least 49.2% in comparison with classic use of energy and appliances. The prediction module permitted a quite accurate scheduling basing on probabilities, even if some of the activities has given some problem due to the fact that the statistic data about them were based of few instances. Furthermore, it was possible to guarantee that the annoyance rate was never too high, thus respecting user comfort.

Future works will investigate the adaptability of the proposed system to different real-case scenario, trying to improve the prediction module considering a larger training phase and more instances of the activities and corresponding use of appliances. Furthermore, it will be evaluated how the presence of Renewable Energy Sources could affect appliance scheduling and improve energy savings.

Acknowledgements

This work was partially funded by the INSIEME MiSE project, HORIZON 2020, PON 2014/2020 POS. 395, and by the LEAPH project, POR FESR Sardegna 2014-2020, Asse 1, Azione 1.1.3.

References

[1] D. Minoli, K. Sohraby, and B. Occhiogrosso, “Iot considerations, requirements, and architectures for smart buildings—energy optimization and next-generation building management systems,” *IEEE Internet of Things Journal*, vol. 4, no. 1, pp. 269–283, 2017.

[2] A. I. Dounis and C. Caraiscos, “Advanced control systems engineering for energy and comfort management in a building environment—a review,” *Renewable and Sustainable Energy Reviews*, vol. 13, no. 6-7, pp. 1246–1261, 2009.

[3] M. Shafie-Khah and P. Siano, “A stochastic home energy management system considering satisfaction cost and response fatigue,” *IEEE Transactions on Industrial Informatics*, vol. 14, no. 2, pp. 629–638, 2017.

[4] L. Yang, H. Yan, and J. C. Lam, “Thermal comfort and building energy consumption implications–a review,” *Applied energy*, vol. 115, pp. 164–173, 2014.

[5] M. H. Shoreh, P. Siano *et al.*, “A survey of industrial applications of demand response,” *Electric Power Systems Research*, vol. 141, pp. 31–49, 2016.

[6] V. Pilloni, A. Floris *et al.*, “Smart home energy management including renewable sources: A qoe-driven approach,” *IEEE Transactions on Smart Grid*, vol. 9, no. 3, pp. 2006–2018, 2016.

[7] Z. Pooranian, J. Abawajy *et al.*, “Scheduling distributed energy resource operation and daily power consumption for a smart building to optimize economic and environmental parameters,” *Energies*, vol. 11, no. 6, p. 1348, 2018.

[8] M. Rasheed, N. Javaid, A. Ahmad, Z. Khan, U. Qasim, and N. Alrajeh, “An efficient power scheduling scheme for residential load management in smart homes,” *Applied Sciences*, vol. 5, no. 4, pp. 1134–1163, 2015.

[9] F. Marcello, V. Pilloni, and D. Giusto, “Sensor-based early activity recognition inside buildings to support energy and comfort management systems,” *Energies*, vol. 12, no. 13, p. 2631, 2019.

[10] S. Merabti, B. Draoui, and F. Bounaama, “A review of control systems for energy and comfort management in buildings,” in *2016 8th International Conference on Modelling, Identification and Control (ICMIC)*. IEEE, 2016, pp. 478–486.

[11] P. H. Shaikh, N. B. M. Nor *et al.*, “A review on optimized control systems for building energy and comfort management of smart sustainable buildings,” *Renewable and Sustainable Energy Reviews*, vol. 34, pp. 409–429, 2014.

[12] ——, "Intelligent multi-objective optimization for building energy and comfort management," *Journal of King Saud University-Engineering Sciences*, vol. 30, no. 2, pp. 195–204, 2018.
[13] M. Fayaz and D. Kim, "Energy consumption optimization and user comfort management in residential buildings using a bat algorithm and fuzzy logic," *Energies*, vol. 11, no. 1, p. 161, 2018.
[14] P. Du and N. Lu, "Appliance commitment for household load scheduling," in *PES T&D 2012*. IEEE, 2012, pp. 1–1.
[15] G. Bhat, R. Deb *et al.*, "Online human activity recognition using low-power wearable devices," in *2018 IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*. IEEE, 2018, pp. 1–8.
[16] M. M. Hassan, M. Z. Uddin *et al.*, "A robust human activity recognition system using smartphone sensors and deep learning," *Future Generation Computer Systems*, vol. 81, pp. 307–313, 2018.
[17] Y. Liu, L. Nie, L. Liu, and D. S. Rosenblum, "From action to activity: sensor-based activity recognition," *Neurocomputing*, vol. 181, pp. 108–115, 2016.
[18] N. C. Krishnan and D. J. Cook, "Activity recognition on streaming sensor data," *Pervasive and mobile computing*, vol. 10, pp. 138–154, 2014.
[19] D. J. Cook, "Learning setting-generalized activity models for smart spaces," *IEEE intelligent systems*, vol. 2010, no. 99, p. 1, 2010.