A QoE-aware Approach for Smart Home Energy Management

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***Abstract*—In this paper, a Quality of Experience (QoE)-aware Smart Home Energy Management (SHEM) system is proposed. Firstly, a survey has been conducted on 64 people to investigate the degree of satisfaction perceived when the starting time of appliances was postponed or anticipated with respect to the preferred time. Secondly, the results were clustered in different profiles using the k-means algorithm to control appliances' working time according to the detected user profile. Thirdly, a SHEM system is run that relies on two algorithms: the QoE-aware Cost Saving Appliance Scheduling (Q-CSAS) and the QoE-aware Renewable Source Power Allocation (Q-RSPA). The former is aimed at scheduling controllable loads based on users' profile preferences and Time-of-Use (TOU) electricity prices, thus taking into account the level of annoyance perceived when a task is postponed or anticipated. The latter re-allocates the starting time of appliances whenever a surplus of energy has been made available by Renewable Energy Sources (RES). This re-allocation takes place using a distributed max-consensus negotiation algorithm. The objective is that of scheduling the appliances starting time so that a trade-off between cost saving and annoyance perceived is achieved. As demonstrated by simulation results, the two algorithms ensure a cost saving that goes from 19% to 84% depending on the presence of RES, with a resulting average annoyance factor value of 1.01 to 1.03.**

***Index Terms*—Quality of Experience, Smart Home Energy Management, k-means, Renewable Energy Sources**

I. Introduction

A number of domains are currently being revolutionized by the Internet of Things (IoT) [1], which enables network objects of the most diverse types to dynamically cooperate and make their resources available in order to reach a common goal. Within these domains are Smart Home Energy Management (SHEM) systems [2]. Smart Homes are characterized by the presence of smart devices, which give the opportunity to monitor and to remotely control key equipment within homes. In such an intelligent environment, the goal is to provide decision-support tools in order to aid users in making cost-effective decisions when utilizing energy services.

As a matter of fact, nowadays domestic electricity usage accounts for 30% of the global energy consumption [3] and usage awareness alone has the potential to reduce consumption by 15% in private households [4]. For this reason, SHEM has been treated in many different studies: [4] and [5] propose a middleware for energy awareness integration into Smart Homes; [6] studies an automatic cost-effective light adjustment system; [7] introduces SHEM systems that take into account Renewable Energy Sources (RES). However, all of the mentioned papers consider energy awareness from the pure cost saving perspective, rather than from a user centric perspective in which the tradeoff between optimal energy usage and quality perceived by appliances' final users is considered. This latest aspect is crucial for wide user acceptance and pertains to the domain of Quality of Experience (QoE). QoE is a subjective measure of user's satisfaction. Commonly, QoE is evaluated by conducting a subjective quality assessment in which a group of people have to rate the quality of an application or a service. In the literature of SHEM systems, the only paper that talks about QoE is [8]. However, the architecture presented in there considers QoE as an objective measure given by cost savings rather than a subjective quality assessment as it is required by the definition of QoE itself.

In this paper, a Smart Home Energy Management system based on profile characterization of the involved users is proposed. The aim is to dynamically shift tasks of controllable appliances in a QoE-aware manner. To do so, a survey has been conducted on a random population sample, about the degree of satisfaction perceived when the starting time of appliances was postponed or anticipated. The results were clustered in different profiles using the k-means algorithm. The aim is to create a Smart Home environment where smart appliances can be easily installed and the proper profile for each user can be easily chosen. After smart appliances are set, a SHEM system is run that relies on two algorithms:

- the *QoE-aware Cost Saving Appliance Scheduling (Q-CSAS) algorithm* is aimed at scheduling controllable loads based on users' profile preferences and Time-of-Use (TOU) electricity prices, thus taking into account the level of annoyance perceived when a task is postponed or anticipated of a certain amount of time with respect to the user' preferences;
- the *QoE-aware Renewable Source Power Allocation (Q-RSPA) algorithm* re-allocates the starting time of appliances whenever a surplus of energy has been made avail-

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able by renewable sources. This re-allocation takes place using a distributed max-consensus negotiation algorithm.

The objective is that of scheduling the appliances starting time so that a trade-off between cost saving and annoyance perceived is achieved. The remainder of the paper is organized as follows. Section II presents in details the work behind user profiling that has the aim to consider the QoE perceived by each user. In Section III an overview of the considered system is presented. Section IV describes the task scheduling model and used algorithms. Finally, in Section V a performance analysis is provided in order to demonstrate the advantage of using a QoE-aware scheduling. Section VI concludes the paper.

II. QoE-DRIVEN PROFILE CLUSTERING

QoE is defined by ITU as "the overall acceptability of an application or service, as perceived subjectively by the end user" [9]. Typically, QoE is evaluated conducting a subjective quality assessment in which a group of people have to rate the quality of an application or a service. In this work, we investigated people preferences by asking them to complete a survey in which they had to indicate the degree of satisfaction perceived when the starting time of appliances was shifted. The aim is to collect people preferences with regard to the utilization of home appliances. From the survey results we expected to find similar preferences provided by different users in order to create specific saving profiles for each appliance.

The survey was conducted online with a first page in which instructions for compiling the survey were provided. In the second page, personal information about the user were asked: sex, age, profession, days off and working days in a whole week, number of people living in the home and parts of the day passed inside the home (morning, afternoon, evening, night). Once this information was provided, the remaining pages of the survey were dedicated to a specific appliance each, namely: washing machine (WO), dishwasher (DW), clothes dryer (CD), electric oven (EO), microwave oven (MO), air conditioner (AC) and water heater (WH). For each appliance, the users could select up to 5 preferred times in which they usually start using it. Furthermore, they were asked if they were willing to anticipate or postpone the selected preferred starting time for energy bill saving. These questions could be answered separately for days off (DO) and working days (WD), since users may have different habits in the two cases.

If the users selected they were willing to anticipate or postpone the starting time of the appliance, a pop up page appeared in which users were asked to rate the annoyance (in a scale ranging from 1 to 5, where 1 is minimum annoyance and 5 the maximum annoyance) provided by the postponement and anticipation of the starting time within a range of $\pm$ 3 hours with a step of half hour for a total of 12 choices to make. As a matter of fact, by default the preferred starting time has value 1 so that a QoE vector $\mathbf{Q}(t_i^{PT})$ of dimension $d = 13$ elements is formed as follows

$$\mathbf{Q}(t_i^{PT}) = [a(t_i^{PT}-3), \cdots, a(t_i^{PT}) = 1, \cdots, a(t_i^{PT}+3)] \quad (1)$$

where $a(t^{PT} \pm h)$ represent the level of annoyance when the execution time is postponed $(+)$ or anticipated $(-)$ by h hours. On the other hand, if the user did not will to shift appliance's starting time, the value 5 was automatically assumed for each of the 13 evaluation points, except the preferred time. In rating their annoyance level, the users were reminded about the possibility of saving money if the appliance's starting time was shifted. Therefore, inverting the scale, evaluations can also be seen as the user's inclination to save money with respect to a specific appliance in a given day.

The survey has been completed by 64 people, each of them providing two different evaluations for each appliance (DO's and WDs' user preferences) for a total of 14 different evaluation sets. Therefore, 14 categories of data, each one made of 64 different evaluation sets have been collected. In order to create user's profiles for each of these 14 categories, a clustering algorithm has been used: the k-means algorithm. The k-means algorithm is a process for partitioning an N-dimensional population into K sets on the basis of a sample [10]. The optimal number of clusters for each of the 14 categories has been defined according to the following steps:

1) start with $K = 2$;
2) run the k-means algorithm;
3) once the k-means algorithm has run, calculate the *d-dimensional* euclidean distance of each sample set from the centroid of the cluster it belongs to;
4) take the greater value obtained at step 3); if this value is lower than 6 then K is the value searched, if not then increase K by 1 and go back to step 2).

We assume that an euclidean distance in the 13-dimensional space lower than 6 is acceptable, since the minimum distance between two different evaluations is 1 and setting this constraint means that in the worst case, a sample will have an average error per sample point of less than 0.5.

After clustering data, we managed to minimize the maximum euclidean distance within each category to a value lower than 4.5. This means that within each cluster the maximum distance of a sample from its centroid is not higher than 4.5 and on average it is lower than this value. Furthermore, it should be noticed that each centroid is the Mean Opinion Score (MOS) of the cluster it represents, since it is computed as the average of the evaluations received for this group.

The optimal numbers of profiles identified for each appliance are as follows:

- *WM*: 7 profiles for WD and 6 profiles for DO;
- *DW*: 4 profiles for WD and 5 profiles for DO;
- *CD*: 3 profiles for both WD and DO;
- *EO*: 5 profiles for WD and 4 profiles for DO;
- *MO*: 3 profiles for both WD and DO;
- *HP*: 4 profiles for both WD and DO;
- *WH*: 4 profiles for WD and 3 profiles for DO.

Figure 1 shows an example of clustering data computed for the dishwasher for WD. From the evaluations sets provided by the users, the running of the k-means algorithm indicated that 4 is the optimal number of clusters and therefore the optimal number of saving profiles for the dishwasher for WD. In fact, it can be noted that each profile has a well defined trend. Profile0 identifies the users which are not willing to shift dishwasher's starting time at any time. Profile1 identifies the users which are willing to postpone, but not to anticipate, dishwasher's starting time. Profile2 identifies the users which are willing to shift dishwasher's starting time only at the nearest hours to the preferred time: higher the shift higher the annoyance. Finally, Profile3 identifies the users which are willing to shift dishwasher's starting time at the whole time range. This profile identifies the users which aims at maximum saving.

For space reasons, we cannot provide the complete set of results achieved. However, the interested reader can get a more complete picture of these results at this link: http://mclab.diee.unica.it/afloris/QoESHEM/index.php.

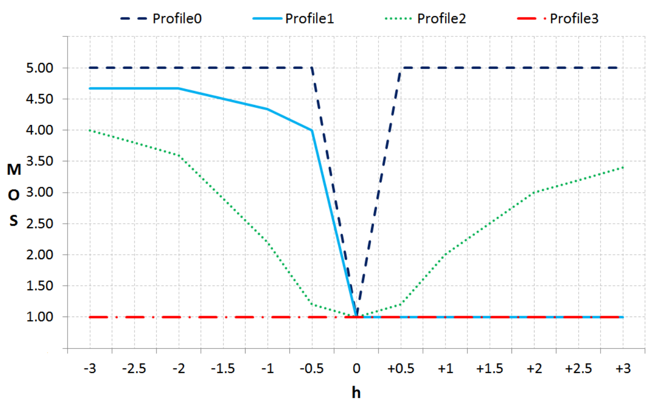


Fig. 1. Saving profiles for the dishwasher for WD.

III. System Overview

In this work, we consider a Smart Home scenario where the aim is to shift forward or backward the execution of tasks of controllable appliances so that the electricity costs are reduced and RES are exploited to their maximum extent. With controllable appliances, we refer to those whose start can be delayed provided that this action can generate cost savings but also user's annoyance depending on usage preferences. Our reference scenario is that of a group of houses such as a block or a condominium, which we define as Cooperative Neighbourhood.

Inside each house there are appliances that consume energy. On the other hand, power supplies such as electric grid, solar panels, and micro wind turbine provide energy that can be used to run appliances. Smart Meters and actuators are associated to these appliances to monitor their energy consumption/production and control their activation/deactivation.

The appliances are divided into 4 groups, based on their characteristics and requirements:

G1: small loads such as lights, battery chargers;
G2: not controllable high loads such as freezer, fridge;
G3: controllable loads, e.g. washing machines, clothes dryers;
G4: supplies such as solar panels, micro wind turbines.

At first, when a new appliance is plugged in a Home Area Network (HAN), information related to appliance's characteristics and tasks it is able to perform will be detected by Smart Meters and sent to a *Central Unit* that connects all neighbourhood's households. Users' habits and preferences on appliance usage are registered so that a user profile is associated (according to the clusters presented in Section II) and sent to the Central Unit as well. If, for example, the house is empty during working hours, it is unlikely that appliances such as TV or lights are turned on during this span of time.

At a later stage, information acquired and processed by the Central Unit is delivered to the appropriate smart meter that offers a unique interface for managing communication among appliances in a home and with the Central Unit.

The appliances are indexed with $i \in \{1, \dots, I\}$ while the homes are indexed with $h \in \{1, \dots, H\}$. Each house's smart meter, namely SM_h, stores the following information about appliance i, depending on which Group it belongs to:

G1: condition $i \in G_h^1$, where G_h^1 is the set of appliances of G1 inside home h; state (on/off) $x_i(t)$ for appliance i at time t; power P_i^{cons} consumed by appliance i; probability $Pr_i(t)$ that appliance i performs its task at time t, accordingly to the User Profile;

G2: condition $i \in G_h^2$, where G_h^2 is the set of appliances of G2 inside home h; state (on/off) $x_i(t)$ for appliance i at time t; power P_i^{cons} consumed by appliance i; probability $Pr_i(t)$ that appliance i performs its task at time t, according to the User Profile;

G3: condition $i \in G_h^3$, where G_h^3 is the set of appliances of G3 inside home h; state (on/off) $x_i(t)$ for appliance i at time t; power P_i^{cons} consumed by appliance i; time t_i^{exec} needed by appliance i to perform its task; preferred time t_i^{PT} in which the user would like appliance i to perform its task; a d-dimensional vector $\mathbf{Q}(t_i^{PT})$ taking track of the annoyance generated to the user by appliance i concerning execution at time t_i^{PT}, if the time is shifted backward or forward (see Section II to know what the elements inside the vector exactly represent); time t_i^{ST} when appliance i started to perform its task, if appliance i is running its task then $x_i(t) = ON$;

G4: condition $i \in G_h^4$, where G_h^4 is the set of renewable energy sources (G4) inside home h; state (on/off) $x_i(t)$ for renewable energy source i at time t; power $P_i^{prod}(t)$ produced by renewable energy source i at time t; probability $Pr_i(t)$ that renewable energy source i has power to deliver at time t.

IV. Task Scheduling Model

The proposed SHEM system is designed to perform three basic functions:

- It monitors and analyses users' habits with reference to appliance usage.
- It detects surplus power due to RES production and distributes this power to the houses of the same neighbourhood, with the aim of maximising its consumption.

- It sets the most suitable starting time of controllable appliances according to a trade-off between cost saving, which is affected by TOU tariffs and RES energy production, and annoyance generated on the user by anticipating or postponing the appliance starting time. In order to accomplish this function, two algorithms are developed both taking into account the QoE:
  - The Q-CSAS, which schedules tasks characterised by high power load in off-peak times;
  - The Q-RSPA, which dynamically shifts tasks in order to maximise the use of renewable energy.

As soon as appliance i placed in home h needs to start, it sends an activation request to SM_h. If appliance i is not controllable or it is not a supplier (i.e. it belongs to G_h^1 or G_h^2) it just needs to notify to SM_h that it is changing state ($x_i(t) = ON$) for the whole duration of the task. SM_h sets its probability to be on to 1 accordingly. When appliance i stops, it informs SM_h, which sets $Pr_i(t)$ to its probability to turn on again, according to the User Profile. Its power consumption and duration values are monitored and sent to the Central Unit, which analyses them and updates the User Profile accordingly.

If appliance i is a controllable consumer, i.e. it belongs to G_h^3, Q-CSAS is started. Q-CSAS is a centralized algorithm that is performed by the SM to assign the starting time t_i^{ST} of G_h^3 appliances, so that their tasks are executed during off-peak hours, when electricity charge is lower. According to the user profile, the preferred starting time t_i^{PT} is set and the vector $\mathbf{Q}(t_i^{PT})$ are set. Therefore, the starting time t_i^{ST} is computed by the Q-CSAS according to the user preferences, provided that the available power P^{max} is not exceeded by the simultaneous usage of the appliances that made an activation request.

If appliance i is a supplier (i.e. it belongs to G_h^4), or a surplus power coming from neighbouring houses is detected by the SM_h, it computes the $P_h^{surplus}(t)$ value of the surplus power related to house h at time t. $P_h^{surplus}(t)$ takes into account all the surplus power contributions that are made available by the neighbour houses along with the power supplied by G_h^4 appliances, and it is decreased by the power consumed by the appliances inside home h if they are on

$$\begin{aligned} P_h^{surplus}(t) = \sum_{h^* \neq h} P_{h^*}^{surplus}(t) - \sum_{i \in \{G_h^1, G_h^2\}} P_i^{cons} \cdot Pr_i(t) \\ - \sum_{i \in G_h^3} P_i^{cons} \cdot x_i(t) + \sum_{i \in G_h^4} P_i^{prod}(t) \end{aligned} \tag{2}$$

Whenever $P_h^{surplus}(t) > 0$ is verified, SM_h broadcasts this information to the appliances it controls.

If there is any G_h^3 appliance that is waiting to turn on and its power consumption is lower than the available surplus power, Q-RSPA is started. Q-RSPA is a distributed consensus algorithm where appliances compete for the same resource, negotiating among each other. After the algorithm has converged, those appliances that have won the negotiation immediately turn on. If there is any surplus power still available, it is sent to the closest SM.

A. Cost Saving Appliance Scheduling algorithm

The Q-CSAS is a centralized algorithm based on the concept that tasks that can be postponed should they be performed during off-peak hours, when electricity charge is lower. When appliance $i \in G_h^3$ sends to SM_h an activation request, it sends its preferred starting time t_i^{PT} and its QoE profile identification number, to which a QoE vector $\mathbf{Q}(t_i^{PT})$ is associated. Consequently, SM_h starts Q-CSAS to assign/reassign to all G_h^3 appliances the most convenient starting time according to TOU tariffs and QoE annoyance values. Hence, a suitable starting time t_i^{ST} in the range $[t_i^{PT} \pm 3h]$ is computed, provided that the available power P^{max} is not exceeded by the simultaneous usage of several appliances. The optimization only takes into account consumer appliances and their probability to be turned on. It neglects suppliers, whose power is negotiated among appliances during Q-RSPA. Note that it is preferable that appliances wait for available RES power as long as it is possible, so that electrical costs are cut. For this reason, Q-CSAS assigns the farthest possible most convenient t_i^{ST}.

Finding an optimal scheduling assignment is an NP-hard problem [11], which complexity scales exponentially with the problem size. In order to reduce the complexity of the algorithm, and thus its convergence time and energy needed to be run, we propose a greedy approach, which is characterised by a linear complexity. The concepts on the basis of Q-CSAS are two:

- appliances that consume more energy, i.e. those that present higher values of energy consumption $E_i^{cons} = P_i^{cons} \cdot t_i^{exec}$, are those that generate more energy cost saving when they are shifted to off-peak hours;
- the annoyance of anticipating/postponing an appliance starting time needs to be proportional to its cost, so that the highest costs correspond to the highest values of annoyance, i.e. an appliance is never started when the corresponding annoyance is maximum.

Therefore, we define the cost contribution of an appliance starting at time t_i^{ST} as

$$C_i(t_i^{ST}) = \sum_{t \in [t_i^{ST}, t_i^{ST} + t_i^{exec}]} T(t) \cdot \frac{P_i^{cons}}{5 - a(t_i^{ST})} \tag{3}$$

where: $T(t)$ is the electricity tariff at time t. Recall that $a(t_i^{ST})$ is an element of the QoE vector as defined in Section II. The cost values that are lower than ∞ correspond, for the appliances, to the priority to be scheduled before, provided that P^{max} is not exceeded.

Let Λ_h be the array of appliances $i \in G_h^3$ that made an activation request. We define a tuple $\Gamma_h = (\Lambda_h, C_i(t))$ of all the appliances that made a request to SM_h and their related cost. We also define $P_h^{tot}(t)$ as the expected instant total power that is likely to be consumed at time t by all non-controllable appliances managed by SM_h as

$$P_h^{tot}(t) = \sum_{i \in \{G_h^1, G_h^2\}, k} P_{ik}^{cons}(t) \cdot Pr_{ik}(t) \quad (4)$$

$P^{tot}(t)$ is updated whenever the probability $Pr_{ik}(t)$ changes. The sequence of steps of Q-CSAS is described as follows.

Algorithm 1 Q-CSAS

$\widehat{P}^{tot}(t)$ is initialised with the value of $P^{tot}(t)$.
The tuple Γ_h is sorted in descending order with respect to cost values.
for all the appliances in Γ_h **do**
    take appliance i with the highest $C_i(t) \neq \infty$ and find the time t_i^{ST} for which the cost value $C_i(t_i^{ST})$ is minimum and $\widehat{P}^{tot}(t') + P_i^{cons} \leq P^{max} \quad \forall t' \in [t_i^{ST}, t_i^{ST} + t_i^{exec}]$
    if more than one t_i^{ST} corresponds to the minimum $C_i(t)$ **then** take the farthest possible
    end if
end for

The last condition is needed to ensure that, if some $P_h^{surplus}(t)$ is available, the appliance has more probability to be able to negotiate to start before the assigned t_i^{ST}. The total power consumption is then updated for the time when the task is expected to be in execution.

B. Renewable Source Power Allocation algorithm

Whenever SM_h detects some surplus power, whether it is caused by RES belonging to home h or it comes from neighbouring SMs, Q-RSPA is started to distribute this power to the appliances that SM_h manages. In particular, since G_h^1 and G_h^2 appliances are turned on independently from the SM decisions, Q-RSPA is run to control Γ_h appliances (recall from Section IV-A that Γ_h is the array of controllable appliances that made an activation request to the SM).

Since surplus power value continuously change, the algorithm needs to be as lightweight as possible to quickly adapt to changes. Furthermore, communication with appliances that are not visible from the SM need to be quick. For these reasons, Q-RSPA is chosen to be a distributed algorithm, where appliances negotiate in order to reach a consensus on which one of them should turn on first.

The assumptions on which Q-RSPA is based are analogous to those of Q-CSAS: the priority needs to be given to appliances that represent a higher benefit to start immediately, i.e. appliances with higher power consumption values and lower annoyance corresponding to the current time. We define the benefit for appliance i to start at time t as

$$b_i(t) = P_i^{cons} \cdot (5 - a(t)) \quad (5)$$

Summarising, if the available surplus power is sufficient, Q-RSPA assigns it to the appliances characterised by higher benefit values. In order for appliances to reach a consensus on the highest $b_i(t)$ value, a max consensus algorithm is used. Specifically, a Random-Broadcast-Max consensus algorithm has been chosen for its fast convergence to the solution in wireless channels [12]. The steps of Q-RSPA are described as follows.

Algorithm 2 Q-RSPA

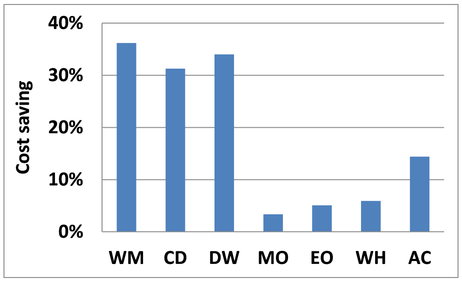
Let b^{max} be the consensus variable and b_i^{max} be the local consensus variable.
if some $P_h^{surplus}(t) > 0$ is detected by SM_h **then** $P_h^{surplus}(t)$ value is broadcast to controlled appliances.
end if
Consensus algorithm is started by SM_h sending the initial benefit value equal to 0.
while there is some surplus power and there are appliances that can use it **do**
    if appliance i receives a message with surplus and benefit values **then**
        if $P_i^{cons} \leq P_i^{surplus}$ and its local benefit value is lower than the received one **then** update local consensus value and forward surplus and updated consensus values to neighbours
        else do not update local consensus value and forward surplus and local consensus values to neighbours
        end if
    else Consensus is reached. The appliance with the highest benefit, i.e. the one which local consensus value corresponds to the consensus value achieved, turns on.
    end if
end while

V. RESULTS

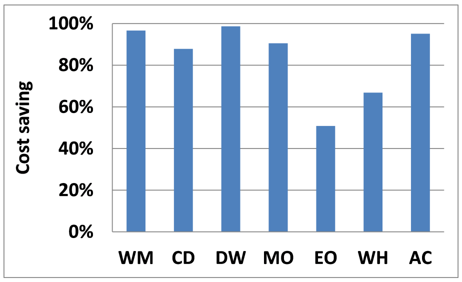
The SHEM system described in this paper has been tested supposing to have houses with user profiles chosen in accordance to a probability density function given by the percentage of the total sample population that fell into a given profile as defined in Section II. Power consumption values have been set according to [13]. With reference to TOU rates, it has been supposed to use the pricing set by the Italian electricity utility company, ENEL. Furthermore, we included two types of RES: a photovoltaic and a microwind turbine system. The produced power has been varied randomly, up to a highest value that is consistent with those of commercial home systems [14].

Results show the percentage of energy cost savings obtained when using the proposed SHEM system, with respect to the case where no SHEM system is used. In particular, Figure 2 shows the average electricity cost saving for different appliances, in the case that no RES are installed in the houses (i.e. only Q-CSAS is run, Figure 2(a)) and in the case of RES installed (Figure 2(b)). Cost savings amount on average to 19% for the case with no RES and to 84% for the case with RES. Note that cost savings are less significant for ovens and water heater. This behaviour is consistent with the results of the survey on the perceived QoE (Section II), and it is justified by the fact that these appliances correspond to a higher percentage of people that is less willing to shift their starting time.

In order to evaluate the performance of the algorithm with reference to the QoE perceived, we introduce the annoyance

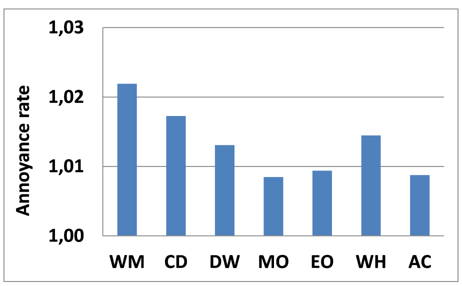


(a) No RES

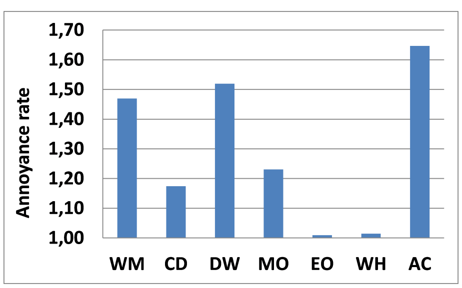


(b) With RES

Fig. 2. Energy cost savings for different appliances.



(a) No RES



(b) With RES

Fig. 3. Annoyance rate for different appliances.

rate estimated as the difference between the value of the QoE vector element corresponding to the starting time t_i^{ST} assigned by the algorithm, and the lowest possible QoE value, i.e. 1, which corresponds to the preferred time t_i^{PT}. In Figure 3, the average annoyance rate evaluated for each controlled appliance and in the absence (Figure 3(a)) or presence (Figure 3(b)) of RES is reported. Although cost saving values are considerable, the annoyance rate is still quite close to the lowest one, with an average of 1.01 with no RES, and 1.3 with RES.

VI. Conclusions

In this paper a SHEM system based on a scheduling model for controllable appliances that aims to reduce the electricity costs while preserving the QoE perceived by the users is described. Two algorithms are proposed: the former, the Q-CSAS, based on the presence of TOU tariffs, shifts the starting time of controllable appliances to off-peak times, taking into account the user habits. In particular, one of the strength points of the algorithm is the use of a QoE model that characterizes the user inclination to change the preferred starting time. The second algorithm, Q-RSPA, is started whenever a RES installed in the neighbourhood produces some power. In this case, appliances dynamically negotiate in order to share the available power, according to the corresponding annoyance of the user to turn on the appliance in that particular moment.

Simulation results carried out using different appliances prove that average energy cost saving using the proposed algorithms goes from 19% when there are not RES installed in the neighbourhood to 84% in the presence of RES. The perceived QoE is confirmed not to diverge much from the preferred one, with an average annoyance rate value between 1.01 and 1.03.

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