Smart Home Energy Management Including Renewable Sources: A QoE-driven Approach

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***Abstract*—Smart Home Energy Management (SHEM) systems can introduce adjustments in the working period and operations of home appliances to allow for energy cost savings, which can however affect the Quality of Experience (QoE) perceived by the user. This paper analyses this issue and proposes a QoE-aware SHEM system, which relies on the knowledge of the annoyance suffered by users when the operations of appliances are changed with respect to the ideal user's preferences. Accordingly, a number of profiles describing different usages are created in the design phase. At the deployment stage, users behavior and annoyance are registered to assign one of these profiles per appliance. The assigned profile is then exploited by the QoE-aware Cost Saving Appliance Scheduling and the QoE-aware Renewable Source Power Allocation algorithms. The former is aimed at scheduling controlled loads based on users profile preferences and electricity prices. The latter re-allocates appliances' operations whenever a surplus of energy is available by Renewable Energy Sources (RES). Experimental results demonstrate that the annoyance perceived by users is severely diminished with respect to a QoE-unaware strategy, at the expenses of only a limited reduction in energy saving.**

***Index Terms*—Quality of Experience, Customer Comfort, Smart Home Energy Management, Renewable Energy Sources**

I. Introduction

Internet of Things (IoT) [1] enables network objects of the most diverse types to dynamically cooperate and make their resources available in order to reach a common goal. Such a paradigm is currently revolutionizing a variety of fields. Among them 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, one of the major goals is to provide decision-support tools in order to aid users in making cost-effective decisions when utilizing electrical energy.

As a matter of fact, nowadays domestic electricity usage accounts for 30% of the global energy consumption and usage awareness and scheduling optimization alone have the potential to reduce consumption by 15% in private households [3]. However, also the quality (i.e. comfort) perceived by final users when policies are put in place 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, which is commonly evaluated by conducting a subjective quality assessment in which a group of people have to rate the quality of an application or a service. Currently, most of the literature considers the customer comfort as a set of hard constraints on appliance usage, a priori set without profiling among different kinds of customers, which are likely to have different subjective needs. Moreover, emphasis is often put on the cost or energy optimization, but no metrics for a posteriori evaluation of the perceived quality is given, which is instead a widely exploited concept in the QoE domain.

In this paper, a SHEM system based on profile characterization of the involved users' appliances and a posteriori evaluation of the customer comfort is proposed. The aim is to dynamically shift tasks of controlled appliances to lower the overall energy cost of a household while also exploiting Renewable Energy Sources (RES) [4], in a QoE-aware manner which considers annoyance as a multi-value scale rather than a hard constraint. To do so, a survey has been conducted on a population sample of 427 subjects, about the degree of annoyance perceived when the starting time or the set temperature of appliances is modified with respect to users' preferences. The results have been clustered in different profiles using the k-means algorithm [5]. Based on these results and on the created profiles for each appliance, a Smart Home environment has been created where smart appliances can be easily installed and the proper profile for each user is assigned. In the proposed system, the customers adopting the proposed SHEM system do not fill the form used for clustering. Instead, simple annoyance rating questions are made to the customer at the end of those usages which add significant information to user's profiling, so as to learn what the customer preferences are without annoying them with too many interactions.

Based on the assigned profiles, a SHEM system is run that relies on two algorithms:

- the *QoE-aware Cost Saving Appliance Scheduling (Q-CSAS) algorithm* that is aimed at scheduling controlled loads based on users' profile preferences and Time-of-Use (TOU) electricity prices;
- the *QoE-aware Renewable Source Power Allocation (Q-RSPA) algorithm* that modifies the working schedule of appliances whenever a surplus of energy has been made available by renewable sources.

The final objective is that of scheduling the appliances' operations, such as starting time and set temperature, so that a trade-off between energy expenses and annoyance perceived is achieved. Results show that the proposed system obtains a significantly lower annoyance perceived by users and similar energy savings, compared to QoE-unaware SHEM systems.

The remainder of the paper is organized as follows. Section II presents past works and highlights the novelties we introduce. In Section III an overview of the considered SHEM system is given. Section IV presents in details the work behind the creation of user's profiles, fundamental to take into consideration the QoE perceived by each user in the scheduling process. Section V describes the task scheduling model and used algorithms. Finally, in Section VI a performance analysis is provided in order to demonstrate the advantage of using a QoE-aware scheduling with respect to a QoE-unaware system. Section VII concludes the paper.

II. Related Works

SHEM has been treated in many different studies: [6] and [7] propose a middleware for energy awareness integration into Smart Homes; [8][9][10] study autonomous systems for cost-effective energy consumption; [11] introduces SHEM systems that take into account RES sources. 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 the final users is considered.

In [12][13][14][15], SHEM algorithms with user preset priorities on household loads are used to keep grid power consumption below a certain level. Appliances are classified based on the priority given by users to each load regardless of the day of the week and the time of the day in which are used. In [16], an algorithm for Distributed Energy Resources (DER) is proposed to reduce power consumption and minimize appliances execution shifts and turn off actions based on the priority class they belong to. Consequently, customer comfort is evaluated as the minimization of appliances turn-off operations, but no profiling is considered for different user types. A similar algorithm was also presented in [17] for the case study of a microgrid. In [18], end users assign values to energy services so that DERs (the only energy supply considered) are scheduled based on these preferences in order to coordinate their optimization and turn off appliances with lower priority at first. In [19] and [20], an algorithm that takes into account the tradeoff between customer comfort and cost of energy, by setting minimum and maximum boundaries for the thermal comfort is presented. These boundaries are taken as hard constraints for a priori setting but a background on customer comfort profiling lacks. In [21], a mathematical model to optimize the control of all major residential energy loads together with RES is proposed. Comfort levels are defined as the preferred hours for using appliances and as the maximum allowed shift from the preferred time. However, similarly to the above mentioned works, hard constraints are considered and no a posteriori evaluation as well as customer profiling are given. [22] proposes a multi-agent architecture for optimal energy management in smart homes considering grid power supply. Customer comfort is considered as a thermal comfort zone delimited by hard boundaries which must not be left, similarly to [19]. In [23], a distributed algorithm for appliance scheduling based on cost minimization of grid energy is presented. With respect to the previously cited works, [24] and [25] introduce a demand-response optimization algorithm in which energy usage and power cost are optimized over a neighbourhood rather than for a single household.

Differently from related works, in this paper customer comfort is taken into account using the QoE paradigm, which 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; the measured QoE is then used to improve the performance of the service/application. In the case of SHEM systems, the users have to select their preferences with regard to the utilization of appliances; these preferences are used to train the SHEM system in order to minimize the energy consumption of appliances while maximizing the QoE of the users. To the best of authors' knowledge, till now only few papers took QoE-awareness into consideration for resource allocation. In [26], QoE is used to drive resource allocation in the multimedia communications domain. Concerning the domain of this paper, in [27] a QoE-driven power scheduling strategy for SHEM is presented. However, the QoE model is based on objective measures (power price and power consumption) rather than subjective quality assessments, as required by the definition of QoE itself.

The main contributions of this work and its importance in comparison with related works are:

- a system that jointly optimizes DER and grid network power usage in a neighbourhood, taking into consideration uncertainties of the former and cost variations of the latter in a realtime manner;
- classification and inclusion in the presented results of appliances pertaining to different classes and having the most diverse usage patterns;
- usage of a comfort scale which takes into account the intensity of the annoyance perceived by final users rather than setting hard "on/off" limits;
- a subjective survey to differentiate and cluster users based on appliance usage preferences and needs;
- a quantitative evaluation of users' perceived quality considering appliance scheduling based on the proposed algorithm, and a comparison with the resulting cost saving;
- a system which classifies different subjective quality perceptions, which represent a compulsory step for wider user understanding and system adoption.

This work is based on our previous work [28], which is significantly extended as described in the following. One major difference is in the appliance modeling where a new class made of thermostatically controlled high loads is considered. This introduces significant changes in the optimization algorithms and in the procedure for the creation of user profiles and makes the proposed algorithm more realistic. In the creation of the usage profile, the silhouette value has been introduced, which brings to more accurate clustering results. Bigger and more heterogeneous population samples for the profiling survey have been considered. Many details have also been added for the implementation of the system in real life scenarios. An extended formulation of the objective function

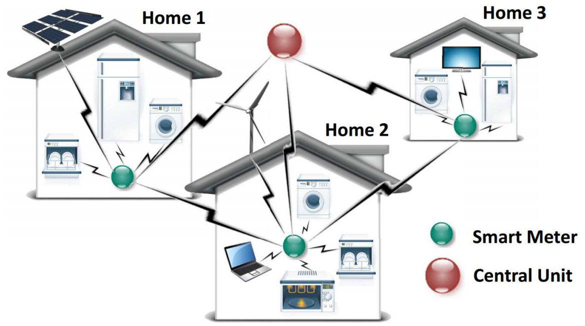


Fig. 1. Reference scenario

of the optimization algorithms has been introduced together with a better formalization of the involved variables.

III. System Overview and Model

In this work, we consider a Smart Home scenario where the aim is to modify the execution of tasks of controlled appliances, so that the electricity costs are reduced and RESs are exploited to their maximum extent while trying to minimize the annoyance perceived by users. With controlled appliances, we refer to those whose functioning behaviour can be modified provided that this action can generate cost savings and affects user's QoE within given limits. Our reference scenario is that of a group of houses such as a block or a condominium, which we define as Cooperative Neighbourhood. The rationale behind considering a Cooperative Neighbourhood is that in case the energy produced by RES in a Smart Home in a given moment cannot be partially or entirely used by loads in the same home, this energy is transferred to one of the neighbours according to a consensus algorithm.

Consider Fig. 1. Inside each house there are appliances that consume and produce energy. On the other hand, power supplies such as the electric grid, solar panels, and micro wind turbines 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: not controlled loads, i.e., small loads such as lights[1] and smartphone chargers, and not controlled high loads such as freezer and fridge[2];
G2: switching controlled high loads, e.g., washing machines and clothes dryers;
G3: thermostatically controlled high loads, i.e. appliances that are controlled by a thermostat such as Heating Ventilation and Air Conditioning (HVAC) and Water Heaters (WH);
G4: supplies such as solar panels and micro wind turbines.

A. *Energy Consumption Model for Controlled Appliances*

We define the energy E_i^{cons} consumed by appliance i to complete a given task as the product between its power consumption P_i^{cons} and the execution time it needs to complete the task t_i^{exec}

$$E_i^{cons} = P_i^{cons} \times t_i^{exec} \tag{1}$$

While for switching controlled appliances the execution time is a constant value, for the thermostatically controlled ones it depends on some variable parameters.

Considering the outside temperature $T_i^{out}(t)$ at time t (i.e., the temperature measured outside the house for HVAC, and the temperature of cold water for WH), and the inside temperature $T_i^{in}(t)$ at time t (i.e., the temperature measured inside the room for HVAC and the temperature of the water inside the boiler for WH), the inside temperature that is expected after a certain amount of time Δt can be defined as [30][31]

$$\begin{aligned} T_i^{in}(t+\Delta t) = &- (T_i^{out}(t) + R_i P_i^{heat} - T_i^{in}(t)) e^{-\Delta t / R_i C_i} + \\ &+ T_i^{out}(t) + R_i P_i^{heat} \end{aligned} \tag{2}$$

where P_i^{heat}, R_i and C_i are characteristic parameters for the appliance: 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, $P_i^{heat} = 0$.

After some simple computations, we can define the time $\Delta t = t_i^{exec}$ that is needed to take the inside temperature to an arbitrary amount T_i^{exp} as

$$t_i^{exec}(T_i^{exp}) = -R_i C_i \ln\left(\frac{T_i^{out}(t) - T_i^{exp} + R_i P_i^{heat}}{T_i^{out}(t) - T_i^{in}(t) + R_i P_i^{heat}}\right) \tag{3}$$

B. *System Functional Model*

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 also registered over a training period of few days or weeks (depending on the appliance), in which few simple questions about annoyance due to task shifting for G2 and G3 appliances are asked to the user at the end of usage or at the end of the week. Notice that, these questions are asked only on the first days in which new appliances are installed and will not be asked again if the same usage has already been registered. Based on these answers, a user appliances' usage profile is associated to the appliance, according to the clusters that will be presented in Section IV, and sent to the Central Unit as well. If customers do not answer any question over an extended period, they are profiled as customers which are not willing to save money using the proposed system. The survey in the next section takes into account also this kind of profile. As a consequence, users falling into this category will not benefit from cost savings differently from the customers who actively participate, thus indicating a certain flexibility on appliances' usage. This information is used as input to the algorithms composing the SHEM system, which will decide the best scheduling for each controlled appliance based on the metrics presented in Section V.

Consider the appliances (or energy sources) in the entire Cooperative Neighbourhood indexed with $i \in \{1, 2, \ldots, I\}$

[1]Although not controlled, presence sensors can be used for automatically switching lights on and off so as to save energy when nobody is in a room.

[2]Freezer and fridge account for approximately 10% of the total household consumption [29].

and the homes indexed with $h \in \{1, 2, \ldots, H\}$. Each house's smart meter, namely SM_h, stores the key parameters about appliance i, depending on which Group it belongs to, as illustrated in the following table

Type	**Par.**	**Description**
G1	G_h^1	set of appliances of G1 for home h
	$x_i(t)$	state (on/off) for appliance i at time t
	P_i^{cons}	power consumed by appliance i
	$Pr_i(t)$	probability that appliance i performs its task at time t
G2	G_h^2	set of appliances of G2 for home h
	$x_i(t)$	state (on/off) for appliance i at time t
	P_i^{cons}	power consumed by appliance i
	t_i^{exec}	time needed by appliance i to perform its task (fixed time)
	t_i^{PT}	user's preferred time for the task of appliance i
	$\hat{\mathbf{Q}}_i$	the QoE profile for appliance i, as explained in Section IV
	t_i^{ST}	time when i started its current task
G3	G_h^3	set of appliances of G3 for home h
	$x_i(t)$	state (on/off) for appliance i at time t
	P_i^{cons}	power consumed by appliance i
	t_i^{exec}	time needed by appliance i as defined in Eq. (3)
	T_i^{PT}	user's preferred temperature for the task of appliance i
	$\hat{\mathbf{Q}}_i$	the QoE profile for appliance i, as explained in Section IV
	$T_i^{in}(t)$	inside temperature of appliance i at time t (see Section III-A)
	$T_i^{out}(t)$	outside temperature of appliance i at time t (see Section III-A)
G4	G_h^4	set of RES of G4 for home h
	$x_i(t)$	state (on/off) for RES i at time t
	P_i^{prod}	power produced by RES i at time t
	$Pr_i(t)$	probability that RES i has power to deliver at time t

In the following two Sections, based on the described scenario and presented notation, we illustrate the devised QoE-based profiling and task scheduling model.

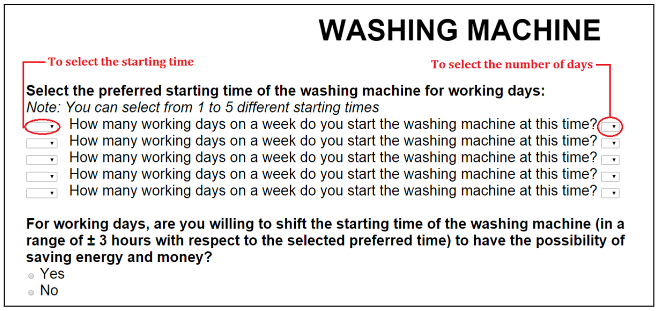
IV. QoE-driven appliance's usage profile

For any appliance we need to define a QoE-driven usage profile. To this we have conducted a survey, whose collected data has been processed to obtain different profiles. These are then used to select the best one for each used appliance when the proposed algorithm is in use. These aspects are described in the following subsections.

A. Conducted survey

QoE is defined by ITU as "*the overall acceptability of an application or service, as perceived subjectively by the end user*" [32]. Typically, the QoE is evaluated conducting a subjective quality assessment in which a group of subjects taking part to the tests have to rate the quality of an application or a service on the basis of their quality perception. Following this principle, in this work we investigated people preferences by asking the subjects to complete a survey in which they had to indicate their preferences with regard to the utilization of controlled home appliances. As introduced in Section III, controlled high loads are divided in switching controlled high loads (belonging to group G2) and thermostatically controlled high loads (belonging to group G3). Also, in the survey we distinguish between these two categories of appliances because their utilization is different. In fact, while for the former the user is interested in the starting time, for the latter the most important factor is the working temperature, independently from the starting time. Accordingly, in the survey we asked the subjects to indicate the degree of annoyance perceived when the preferred starting time (for G2) or set temperature (for G3) was changed. From the survey results we expected to find similar preferences provided by different users in order to create specific usage profiles for each appliance.

The survey was conducted online and it was spread to the greatest possible number of contacts of the authors and colleagues. In total, the survey was completed by 427 subjects. It consisted in some web pages in which the subjects were asked to answer some questions about their personal information and their appliances usage habits. Specifically, in the first page of the survey the 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 house and when the users were in the house (morning, afternoon, evening, night). This information is useful for understanding whether appliances usage habits could be related to some personal data of the subjects (age, profession, etc.). As a result, appliances usage habits were collected from a heterogeneous pool of subjects. Indeed, their age was ranging from 18 to 72 year old; their job fell mostly within the categories of student, employee, freelance and homemaker; they were living alone or with a number of people ranging from 1 to 7; there were subjects working in different time periods, included night jobs. At the end, the subjects that participated to the survey covered quite different customers behaviors. For the scenario of multimedia services, recommendations for performing the assessment of the user perceived quality indicate that the number of subjects should be at least 15 and should possibly reach 40 [33]. This is valid for tests conducted in laboratory as well as online [34]. Herein different services are considered, but we still believe that having exceeded these reference numbers is a positive feature. However, to collect a greater number of user' opinions assuring users heterogeneity



WASHING MACHINE

To select the starting time

To select the number of days

Select the preferred starting time of the washing machine for working days:

Note: You can select from 1 to 5 different starting times

How many working days on a week do you start the washing machine at this time?

How many working days on a week do you start the washing machine at this time?

How many working days on a week do you start the washing machine at this time?

How many working days on a week do you start the washing machine at this time?

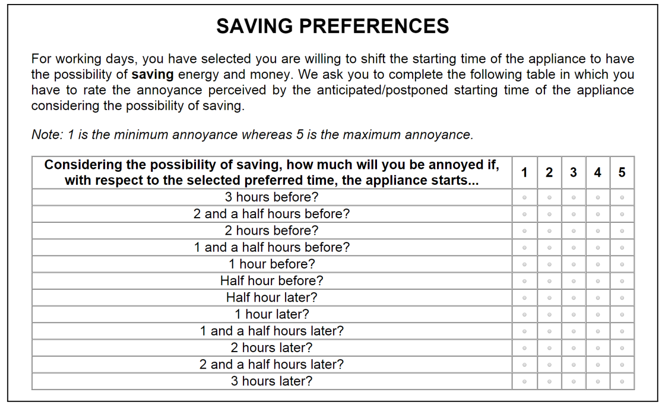
How many working days on a week do you start the washing machine at this time?

For working days, are you willing to shift the starting time of the washing machine (in a range of ± 3 hours with respect to the selected preferred time) to have the possibility of saving energy and money?

Yes

No

Fig. 2. Part of the survey page of the washing machine in which the users can select the preferred starting times for working days.



SAVING PREFERENCES

For working days, you have selected you are willing to shift the starting time of the appliance to have the possibility of **saving** energy and money. We ask you to complete the following table in which you have to rate the annoyance perceived by the anticipated/postponed starting time of the appliance considering the possibility of saving.

Note: 1 is the minimum annoyance whereas 5 is the maximum annoyance.

Considering the possibility of saving, how much will you be annoyed if, with respect to the selected preferred time, the appliance starts...	1	2	3	4	5
3 hours before?					
2 and a half hours before?					
2 hours before?					
1 and a half hours before?					
1 hour before?					
Half hour before?					
Half hour later?					
1 hour later?					
1 and a half hours later?					
2 hours later?					
2 and a half hours later?					
3 hours later?					

Fig. 3. Pop up page of the survey in which the users can select their saving preferences for switching controlled appliances.

and randomness, providers of online survey tools, such as Qualtrics, SurveyMonkey, SurveyGizmo, could be used. These allow to create an online survey and to spread the survey to a huge number of people. Moreover, a specific target audience can be selected, to get opinions from a certain set of people while assuring user heterogeneity and randomness. An additional online service which helps in spreading online surveys to many people is Prolific. Although Prolific does not provide a service for survey creation, it can be easily integrated with most of the aforementioned online survey platforms. In our case, the survey is already created and could be loaded into the Prolific platform to be spread to a huge number of people, whose characteristics can be precisely selected.

Once this information was provided, each of the remaining pages of the survey was dedicated to a specific appliance, namely: washing machine (WM), dishwasher (DW), clothes dryer (CD), and electric oven (EO) as switching controlled high loads (i.e., category G2); heating ventilation and air conditioning (HVAC) and water heater (WH) as thermostatically controlled high loads (i.e., category G3). For each switching controlled appliance, the users could select up to 5 preferred times in which they usually started using it. Furthermore, they were asked if they were willing to anticipate or postpone the selected preferred starting time for energy bill saving. For each thermostatically controlled appliance the users had to select their preferred set temperature and they were asked if they were willing to change this temperature value for energy bill saving. For both G2 and G3 appliances, these questions could be answered separately for days off (DO) and working days (WD), since users may have different habits in the two cases. For these reasons, the profiles had to be created for 12 types of combinations appliance/period of the week. Fig. 2 shows a part of the survey page of the washing machine in which the users could select the preferred starting times for WD. If the users selected they were willing to anticipate or postpone the preferred starting time (set temperature) of the switching (thermostatically) controlled 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 the minimum annoyance and 5 the maximum annoyance) caused by the modification of the preferred starting time or set temperature. The starting time could vary within a range of ± 3 hours with a step of half an hour, for a total of 13 choices. With regard to the set temperature, according to the different characteristics of these two types of appliances, we considered two dissimilar ranges for HVAC and WH. The set temperature for HVAC could vary within a range of $\pm$ 3 $°C$ with a step of 0.5 $°C$, for a total of 13 choices. The set temperature for WH could vary within a range of $\pm$ 18 $°C$ with a step of 3 $°C$, for a total of 13 choices. Fig. 3 shows the pop up page in which the users could select their saving preferences for switching controlled appliances. In rating their annoyance level, the users were reminded about the possibility of saving money if the appliance's starting time (set temperature) 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.

These shifts in time and temperature are coded into different vectors with a length of 13 elements, as follows

$$\mathbf{S}_t = [-3, -2.5, \cdots, 0, \cdots, +2.5, +3] \quad (4)$$

$$\mathbf{S}_T^{HVAC} = [-3, -2.5, \cdots, 0, \cdots, +2.5, +3] \quad (5)$$

$$\mathbf{S}_T^{WH} = [-18, -15, \cdots, 0, \cdots, +15, +18] \quad (6)$$

where $\mathbf{S}_t$ represents shift times for switching controlled appliances whereas $\mathbf{S}_T^{HVAC}$ and $\mathbf{S}_T^{WH}$ represent shift temperatures for HVAC and WH, respectively.

Annoyance vectors $\mathbf{Q}_{zw}$ of 13 elements are then used to code the survey results as follows

$$\mathbf{Q}_{zw} = [q_{zw}(1), q_{zw}(2), \cdots, q_{zw}(13)] \quad (7)$$

where $q_{zw}(y)$ represents the level of annoyance for subject w for the appliance of type z (as said before there are 12 possible combinations of appliance type and period of the week) when the relevant shift in time ($s(y) \in \mathbf{S}_t$) or temperature ($s(y) \in \mathbf{S}_T^{HVAC}$ or $s(y) \in \mathbf{S}_T^{WH}$) is introduced, depending on the category of the appliance. By default $q_{zw}(7) = 1$ (i.e., when no shifting is applied there is no annoyance). On the other hand, if the user is not willing to shift appliance's starting time or set temperature, the value 5 is automatically set for each of the 13 evaluation points, except the preferred time (i.e., $q_{zw}(7)$ is still set to 1).

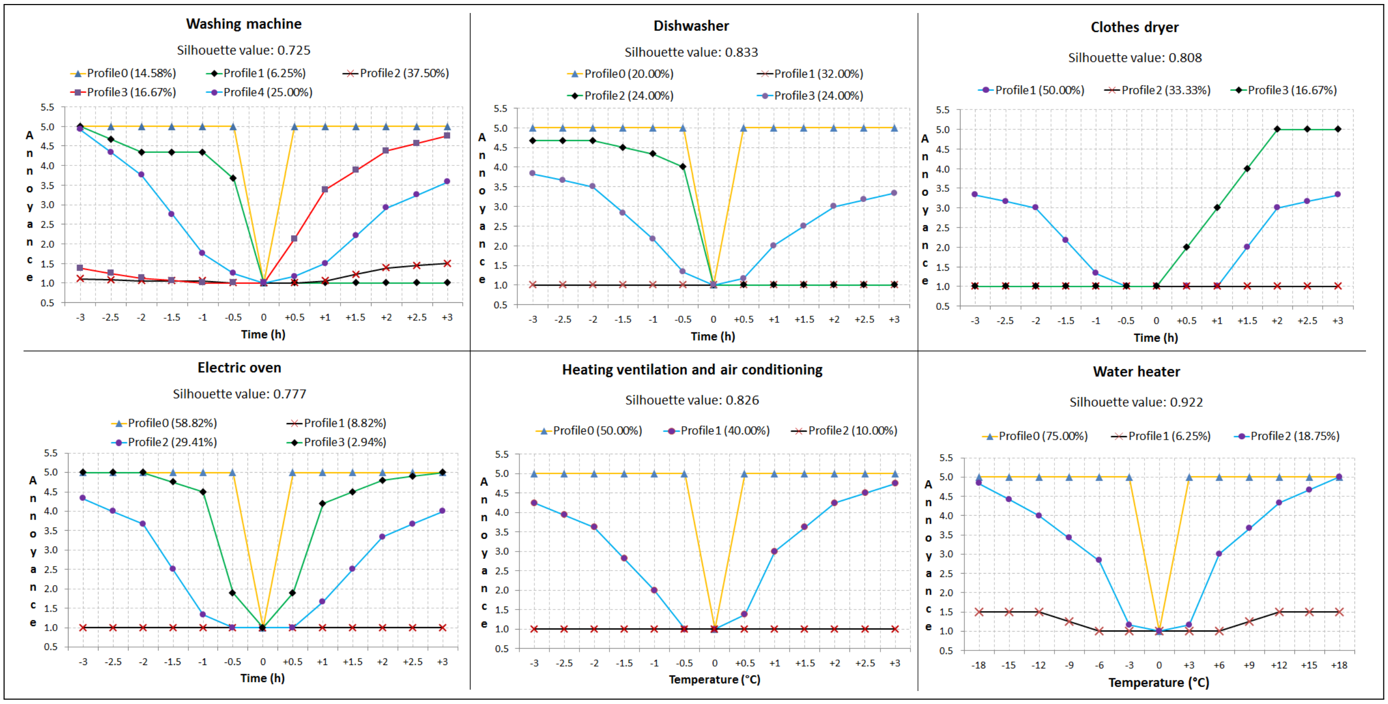


Fig. 4. Usage profiles computed for each appliance for working days. For each appliance, also the silhouette value obtained by selecting that number of usage profiles and the percentage of users belonging to each usage profile are indicated.

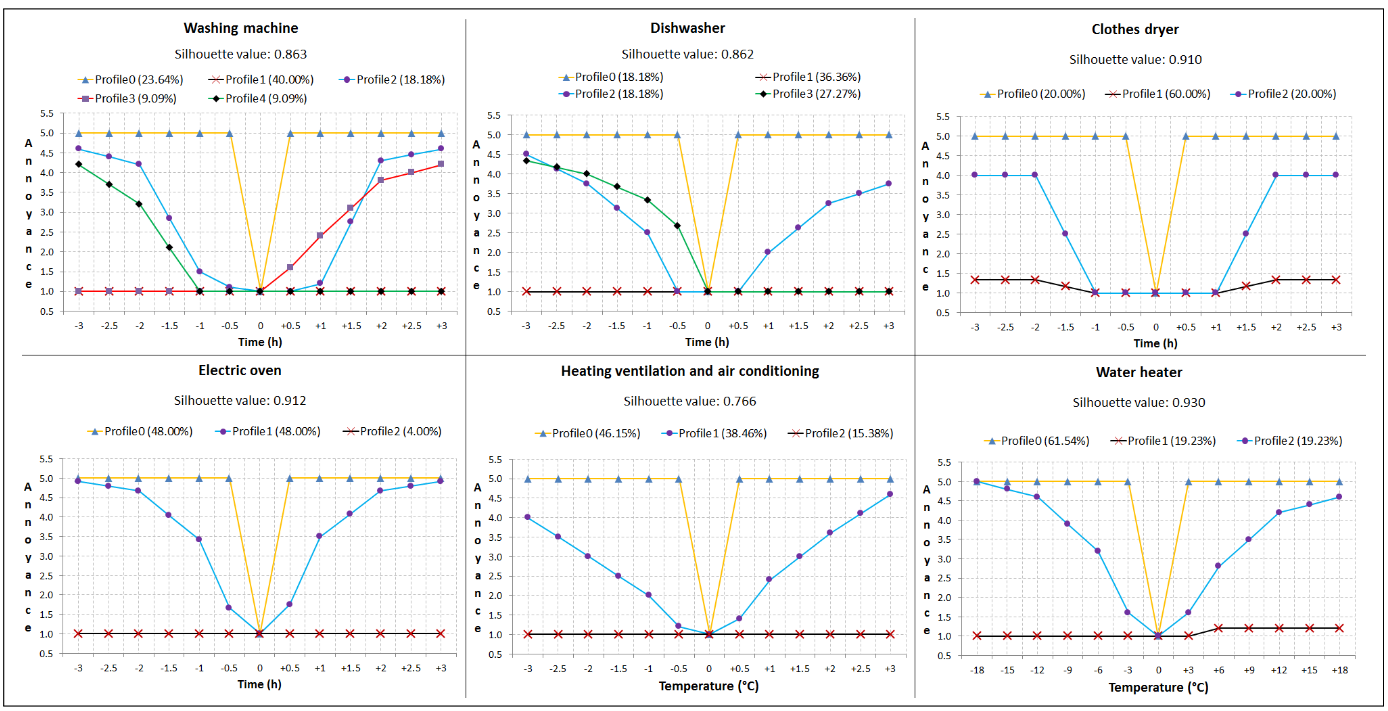


Fig. 5. Usage profiles computed for each appliance for days off. For each appliance, also the silhouette value obtained by selecting that number of usage profiles and the percentage of users belonging to each usage profile are indicated.

B. Creation of profiles

The survey has been completed by 427 people, each of them providing two different evaluations for each of the 6 appliances (DO's user preferences and WDs' user preferences) for a total of 12 different evaluation sets. Since we have not found any correlation between users' personal data (age, profession, etc.) and appliances usage habits, we decided to categorize users' profiles only on the basis of their preferences in modifying the starting time and set temperature of the appliances for DO and WD. Therefore, in order to create user's appliances usage profiles for each of these 12 categories, a clustering algorithm has been used: the k-means algorithm. The k-means algorithm is a widely used clustering technique for partitioning an N-dimensional population into K exclusive clusters [5]. The k-means algorithm treats each sample as a point having a location in space and seeks to minimize the average squared distance between points in the same cluster. Each cluster of data is represented by a centroid, which is the point to which the sum of distances from all points in that cluster is minimized. In this paper, for clustering the data we used the Matlab software, whose *kmeans* function uses the k-means++ algorithm (an improved version of the k-means algorithm [35]) for cluster center initialization and the squared Euclidean metric to determine distances. Furthermore, to select the optimal number of clusters for each data category, we used the silhouette value [36] that is a measure of how similar each point (annoyance vector of the subject's responses Q_{zw} in our test) is to the others in its cluster, when compared to points in other clusters. The silhouette value for a generic *j*-th point is defined as

$$silhouette(j) = \frac{b(j) - a(j)}{max\{a(j), b(j)\}} \tag{8}$$

where $a(j)$ is the average distance from the *j*-th point to the other points in the same cluster whereas $b(j)$ is the minimum average distance from the *j*-th point to points in a different cluster, minimized over clusters. The silhouette value ranges from -1 to +1. A silhouette value close to +1 indicates that j is well-matched to its own cluster and poorly-matched to neighboring clusters. Then, we selected the number of clusters K which provides the highest average silhouette value among all the points of the clusters.

The optimal number of clusters represents the number of different usage profiles for each data category. Note that at the end for any appliance we obtain a number of usage profiles $\widehat{\mathbf{Q}}_{zr}$ where z still indexes the appliance and r indexes the different usage profiles obtained for each of this. Figs. 4-5 show the usage profiles computed for each appliance for WD and DO. These figures also provide the silhouette value obtained by selecting that number of clusters (usage profiles) and the percentage of subjects belonging to each usage profile. It can be noticed that the obtained silhouette values range from 0.725 to 0.930, and are very close to 1. This means that each sample is well-matched with its own cluster.

As an example, here we analyze the graph of the dishwasher for WD (from Fig. 4). The same analysis can straightforwardly be extended to the other graphs of Figs. 4-5; we do not analyze here all the graphs for reasons of space. From the evaluation sets provided by the users, the execution of the k-means++ algorithm indicated that 4 is the optimal number of clusters and therefore the optimal number of usage profiles. In fact, it can be noted that each usage profile has a well defined trend with a physical meaning. *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 shift dishwasher's starting time at the whole time range. This profile identifies the users which aims at maximum saving. *Profile2* identifies the users which are willing to postpone, but not to anticipate, dishwasher's starting time. Finally, *Profile3* identifies the users which are willing to shift dishwasher's starting time only at the nearest hours to the preferred time: the largest the shift, the greater the annoyance.

C. Section of the appliance's usage profile

The identification of the usage profile to be used for appliance i is done through a training period for new appliances, during which the system registers preferred times of usage and proposes some potential time shifts whenever it is convenient. If time shifts are accepted, the user is asked to rate the perceived annoyance at the end of the task. If the user refuses, maximum annoyance is assumed. The user responses are then processed to select the best profile among the $\hat{\mathbf{Q}}_{zr}$ defined in the previous section. The user responses compose a new annoyance vector for that user and appliance. Then, the silhouette value of this vector is computed with respect to all the clusters (usage profiles) in order to reassign the vector to the best matching profile. This is determined by the highest value of silhouette obtained. If this vector belongs to another usage profile than the one initially assigned, the system changes the user's appliance usage profile accordingly. Once the user's appliance usage profile is assigned, the algorithm works without any further interaction with the user, unless unusual or unexpected usage is revealed with regard to the assigned usage profile (e.g., unusual hours of usage), or if the user proactively wishes to indicate a change on the perceived annoyance based on her experience. In this case, if changes result in a higher silhouette value for another usage profile, the assigned profile is updated accordingly.

When no information is collected to select the best usage profile, the proposed algorithm adopts the one with the highest number of subjects belonging to it for the reference appliance type. In the following, the usage profile selected for appliance i is referred to as $\hat{\mathbf{Q}}_i$.

V. Task Scheduling Model

The task scheduling relies on the following two algorithms:

- the Q-CSAS, which schedules tasks of G2 and G3 appliances in off-peak times;
- the Q-RSPA, which dynamically shifts tasks in order to maximise the use of RES.

Note that these make use of the usage profile $\hat{\mathbf{Q}}_i$ for each appliance i which is assigned as explained in the previous section. In Fig. 6 we provide a flow chart which describes the steps of the overall proposed SHEM algorithm. As soon as appliance i placed in home h needs to start, it sends an activation request to SM_h. If appliance i belongs to G_h^1, i.e., it is not controlled and it is not a supply, it just needs to notify to SM_h that it is changing state ($x_i(t) = 1$) 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. Its power consumption and duration values are monitored and sent to the Central Unit, which analyses them, updates $Pr_i(t)$ accordingly and changes future forecasting if needed.

If the requesting appliance i is a controlled consumer, i.e. it belongs to G_h^2 or G_h^3, Q-CSAS is started. G_h^2 appliances make an activation request as soon as they notice the need for them to start, either because the user requested it or because

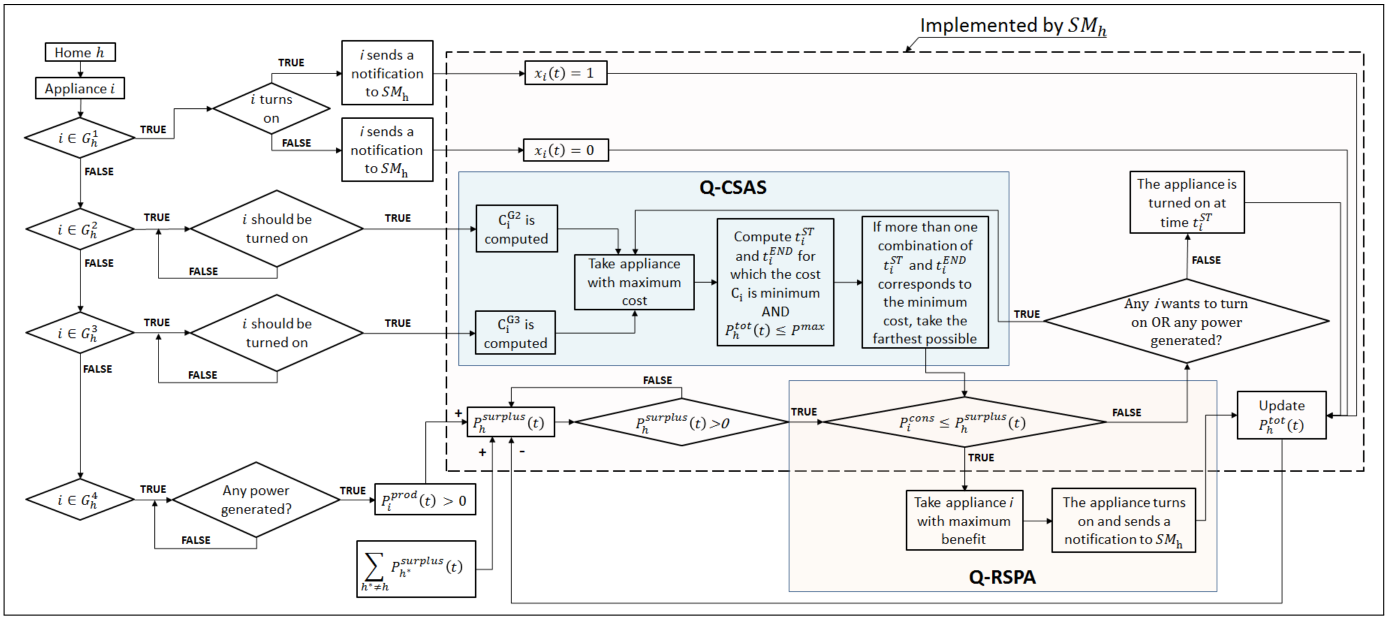


Fig. 6. Flow chart of the proposed SHEM system.

it has been set in the user profile. Differently, G_h^3 appliances make an activation request when the inside temperature $T^{in}(t)$ reaches a value that corresponds to an annoyance level higher than 1. Q-CSAS is a centralized algorithm that is performed by the SM to assign the starting time t_i^{ST} of controlled appliances, so that their tasks are executed during the most convenient hours, when electricity price is lower, according to the preferred starting time t_i^{PT} for G_h^2 appliances and preferred temperature T_i^{PT} for G_h^3 appliances. The annoyance vector for the profile the user belongs to is also considered. 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} (the maximum power the user can consume on the basis of the contract) is not exceeded by the simultaneous usage of the appliances that made an activation request.

If appliance i is a supply (i.e. it belongs to G_h^4), or a surplus power coming from neighboring houses is detected by the SM_h, SM_h 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 neighbor houses along with the power supplied by G_h^4 appliances, and it is decreased by the total power $P_h^{tot}(t)$ that is expected to be consumed at time t by the appliances inside home h if they are on $(x_i(t) = 1)$

$$P_h^{surplus}(t) = \sum_{h^* \neq h} P_{h^*}^{surplus}(t) + \sum_{i \in G_h^4} P_i^{prod}(t) - P_h^{tot}(t) \tag{9}$$

$$P_h^{tot}(t) = \sum_{i \in G_h^1} P_i^{cons} \cdot Pr_i(t) + \sum_{i \in \{G_h^2, G_h^3\}} P_i^{cons} \cdot x_i(t) \tag{10}$$

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

If there is any G_h^2 or 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. As opposed to Q-CSAS, which schedules the best starting time according to the expected user behavior, Q-RSPA adjusts the starting times that have already been scheduled by the Q-CSAS, in a real time fashion. More precisely, whenever there is a power surplus coming from RES, Q-RSPA evaluates if it is more convenient for appliances which starting time has already been set by Q-CSAS, to turn on immediately rather than waiting for their scheduled t_i^{ST}. If it is, their starting time is changed to the current time. 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 should be performed as much as possible during off-peak hours, when electricity cost is lower.

When appliance $i \in \{G_h^2, G_h^3\}$ sends to SM_h an activation request, the SM_h retrieves its preferred starting time t_i^{PT} or its preferred temperature T_i^{PT} and its appliance's usage profile $\hat{\mathbf{Q}}_i$. Consequently, SM_h starts Q-CSAS to assign to all G_h^2 appliances the most convenient starting time, and to all G_h^3 appliances the most convenient starting time and ending times, according to TOU tariffs and QoE annoyance values.

We now introduce the concept of *relative satisfaction level* defined as the user perceived quality when an appliance is activated with a difference with respect to preferred time or temperature $\Delta\theta$

$$\sigma(\Delta\theta) = \frac{q^{max} - \hat{q}_i(\Gamma(\Delta\theta))}{q^{max} - q^{min}} \tag{11}$$

where q^{max} and q^{min} are the highest and lowest possible values for the annoyance (i.e. respectively 5 and 1), $\hat{q}_i(.)$ is an element of $\hat{\mathbf{Q}}_i$ and $\Gamma(\Delta\theta)$ is a function that outputs the s_y

value included in $\mathbf{S}$ that is closest to $\Delta\theta$. Note that to simplify the notation we are considering this function for all types of appliances in G2 and G3.

We also define the *cost contribution* of appliance $i \in G_h^2$ starting at time t_i^{ST} and ending at time $t_i^{END} = t_i^{ST} + t_i^{exec}$

$$C_i^{G2}(t_i^{ST}) = \frac{P_i^{cons}}{\sigma\left(\Delta t_i^{ST}\right)} \cdot \int_{t_i^{ST}}^{t_i^{END}} \Phi(t)dt \qquad (12)$$

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 $\Delta t_i^{ST} = t_i^{ST} - t_i^{PT}$. If $\sigma\left(\Delta t_i^{ST}\right) = 0$, the cost value $C_i^{G2}(t_i^{ST}) \to \infty$.

For an appliance $i \in G_h^3$, we distinguish between 2 cases: if, at the current time t^{cur}, the inside temperature $T_i^{cur} = T_i^{in}(t^{cur})$ already corresponds to a relative satisfaction level $\sigma\left(\Delta T_i^{cur}\right) = 0$ (e.g. a sudden temperature change can be caused by a user opening a window, or using hot water), the appliance needs to start immediately, and thus its starting time is set to $t_i^{ST} = t^{cur}$, and the system is only left to decide the optimal ending time t_i^{END}. Otherwise, if the inside temperature corresponds to a relative satisfaction level $\sigma\left(\Delta T_i^{cur}\right) > 0$, the system decides both the starting and ending times. Analogously to Eq. (12), we now define the cost contribution of appliance $i \in G_h^3$ starting at time t_i^{ST} and ending at time $t_i^{END} = t_i^{ST} + t_i^{exec}\left(T_i^{exp}\right)$

if $\sigma\left(\Delta T_i^{cur}\right) > 0$

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

else if $\sigma\left(\Delta T^{cur}\right) = 0$

$$C_i^{G3}(t_i^{cur}, t_i^{END}) = \frac{P_i^{cons}}{\sigma\left(\Delta T_i^{exp}\right)} \cdot \int_{t_i^{cur}}^{t_i^{END}} \Phi(t)dt \qquad (13)$$

again with $\sigma\left(\Delta T_i^{exp}\right) > 0$, 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. Recall that $t_i^{exec}\left(T_i^{exp}\right)$ is computed as defined in Eq. (3). Also in this case, if $\sigma\left(\Delta T_i^{exp}\right) = 0$, the cost value is $C_i^{G3}(t_i^{ST}, t_i^{END}) \to \infty$.

Let Λ_h be the array of appliances $i \in \left\{G_h^2, G_h^3\right\}$ that made an activation request, either because a new task of a G2 appliance has to start, or because the current temperature T_i^{cur} of a G3 appliance corresponds to a relative satisfaction level $\sigma\left(\Delta T^{cur}\right) < 1$. Given Eqs. (12) and (13), we can now define the problem to be solved by the Q-CSAS algorithm as:

$$\min \sum_{i \in \Lambda_h} \sum_{t,t'=t^{cur}}^{t^{cur}+24\text{h}} C_i^{G2}(t) y_i(t) + C_i^{G3}(t,t') y_i(t) y_i(t') \qquad (14a)$$

$$s.t. x_i(t) = 1 \;\; \forall t \in \left[t_i^{ST}, t_i^{END}\right], \forall i \in \Lambda_h \qquad (14b)$$

$$x_i(t) = 0 \;\; \forall t \notin \left[t_i^{ST}, t_i^{END}\right], \forall i \in \Lambda_h \qquad (14c)$$

$$y_i(t) = 0 \;\; \forall t \neq t_i^{ST}, \qquad y_i(t_i^{ST}) = 1 \qquad (14d)$$

$$y_i(t') = 0 \;\; \forall t' \neq t_i^{END}, \quad y_i(t_i^{END}) = 1 \qquad (14e)$$

$$P_h^{tot}(t) \leq P^{max} \quad \forall t, \forall i \in \Lambda_h \qquad (14f)$$

Algorithm 1 Q-CSAS

$\widehat{P}^{tot}(t)$ is initialized with the value of $P^{tot}(t)$.
for all the appliances in Λ_h **do**
  take appliance i with the highest possible value of function C_i^{G2} or C_i^{G3} (except the case its value is infinite) and find the times t_i^{ST} and t_i^{END} for which this cost value is minimum and the constraints of problem (14) are fulfilled
  if more than one combination of t_i^{ST} and t_i^{END} corresponds to the minimum $C_i^{G2}(t_i^{ST})$ or $C_i^{G3}(t_i^{ST}, t_i^{END})$ **then**
    take the farthest possible
  end if
end for

where the limit to the considered time span has been set to the 24 hours following the current time, constraints (14b) and (14c) refer to the nodes' status, constraints (14d) and (14e) guarantee that the cost is only considered if t is the starting time and t' is the ending time for node i, and constraint (14f) ensures that the available power P^{max} is not exceeded by the simultaneous usage of considered active 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} with same annoyance level.

The problem given by Eq. (14) is NP-hard [37], and therefore its complexity scales exponentially with the problem size. 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 characterized 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} (as defined in Section III-A), are those that generate more energy cost saving when they are shifted to off-peak hours, and thus they should be minimized first;
- each cost needs to be proportional to the annoyance of anticipating/postponing an appliance starting time, 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.

The steps of Q-CSAS are described in Algorithm 1. We first take the appliance with the maximum cost and then we find the best solution for it. Notice that the condition to take the farthest starting time possible is needed to ensure that, if some $P_h^{surplus}(t)$ becomes available, the appliance has more probability to be able to negotiate its 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 neighboring SMs, Q-RSPA is started to distribute this power to the appliances that SM_h manages. In particular, since G_h^1 appliances are turned on independently from the SM decisions, Q-RSPA is run to control Λ_h appliances (recall that Λ_h is the array of controlled appliances that made an activation request to the SM).

Since the surplus power value continuously changes, 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. In the literature there is a large amount of distributed solutions where nodes negotiate to share the available power, mostly based on game theory [38] and consensus [39]. 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 present a higher benefit to use the power produced by RES. For appliances belonging to G2, higher benefits correspond to higher energy consumption values (recall that E_i^{cons} is defined by Eq. (1)), and higher relative satisfaction levels of starting immediately $\sigma\left(\Delta t_i^{cur}\right)$. We define the benefit for appliance $i \in G_h^2$ to start at time t^{cur} as

$$b_i^{G2}(t^{cur}) = E_i^{cons} \cdot \sigma\left(\Delta t_i^{cur}\right) \tag{15}$$

On the other hand, G3 appliances make an activation request as soon as their inside temperature has reached a value for which the relative satisfaction level has lowered to $\sigma\left(\Delta T^{cur}\right) < 1$, so their benefit of starting immediately will always be equal or higher than that of starting later. Therefore, their benefit to use RES power only depends on their energy consumption value, which in turn depends on the expected temperature value (see Eq. (3)). For this reason, the benefit for appliance $i \in G_h^3$ only depends on the ending time and its related relative satisfaction level

$$b_i^{G3}(t_i^{END}) = E_i^{cons}\left(t_i^{END}\right) \cdot \sigma\left(\Delta t_i^{END}\right) \tag{16}$$

The problem to be solved by the Q-RSPA algorithm can now be defined as

$$\max \sum_{i\in\Lambda_h} \sum_{t'=t^{cur}}^{t^{cur}+24\text{h}} b_i^{G2}(t^{cur}) y_i(t^{cur}) + b_i^{G3}(t') y_i(t^{cur}) y_i(t') \tag{17a}$$

$$s.t. x_i(t) = 1 \ \ \forall t \in \left[t_i^{ST}, t_i^{END}\right], \forall i \in \Lambda_h \tag{17b}$$

$$x_i(t) = 0 \ \ \forall t \notin \left[t_i^{ST}, t_i^{END}\right], \forall i \in \Lambda_h \tag{17c}$$

$$\text{if } b_i^{G2}(t^{cur}) = 0 \text{ OR } b_i^{G3}(t') = 0 \Rightarrow y_i(t^{cur}) = 0 \tag{17d}$$

$$\text{if } y_i(t^{cur}) = 1 \Rightarrow t_i^{ST} = t^{cur} \ \ \forall i \in G_h^2 \tag{17e}$$

$$\text{if } y_i(t') = 1 \Rightarrow t_i^{END} = t' \ \ \forall i \in G_h^3 \tag{17f}$$

$$P_h^{surplus}(t) \geq P_i^{cons} \ \ \forall t \in \left[t^{cur}, t_i^{END}\right], \forall i \in \Lambda_h \tag{17g}$$

with $P_h^{surplus}$ computed as defined by Eq. (9). Again, the limit to the considered time span has been fixed to the 24 hours following the current time. Constraints (17b) and (17c) again refer to the status of nodes, constraint (17d) ensures that, if the benefit is equal to 0, the appliance does not start, and constraints (17e) and (17f) set the starting and ending time, if appliances are started immediately.

Algorithm 2 **Q-RSPA**

Let b^{max} be the consensus variable and b_i^{max} be the local consensus variable.
if $i \in G_h^2$ **then** set $b_i^{max} = b_i^{G2}(t^{cur})$.
else if $i \in G_h^3$ **then** set $b_i^{max} = \max_{t_i^{END}} b_i^{G3}(t_i^{END})$
end if
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

Analogously to the Q-CSAS algorithm, in order to reduce complexity we use a greedy approach to solve this problem. Summarizing, if the available surplus power is sufficient, Q-RSPA assigns it to the appliances characterized 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 [40].

The steps of Q-RSPA are described in Algorithm 2. In this algorithm, each SM only needs to evaluate its highest benefit possible, i.e. b_i^{G2} for G2 appliances and $\max_{t_i^{END}} b_i^{G3}(t_i^{END})$ for G3 appliances, and to determine some inequalities. Since the complexity of this process is negligible, it can be executed even by the most simple device. Nodes converge to the maximum benefit value in a few steps, therefore almost instantly. As soon as convergence is reached, the node with the highest benefit value sends a notification to the SM_h and immediately turns on. The SM_h updates the new power surplus value according to the power consumption of the node that has just turned on and, if it is still higher than 0, initiates the consensus algorithm again.

TABLE I
CHARACTERISTIC PARAMETERS OF APPLIANCES [41][42][43]

Name	Group	Power [Wh]	Mean t_i^{exec} [min]	Probability to have it
Fridge/freezer	G1	70	Always on	100%
Lighting	G1	40	Always on when someone is at home	100%
PC/laptop	G1	50	150	95%
TV	G1	30	210	100%
Game console	G1	90	120	5%
Hair dryer	G1	1500	15	100%
Iron	G1	1100	20	100%
Microwave oven	G1	1000	90	52%
Washing machine	G2	600	130	86%
Dishwasher	G2	400	160	34%
Clothes dryer	G2	1300	90	8%
Electric oven	G2	2000	15	53%
HVAC	G3	1000	Always on when someone is at home. Set according to (3)	31%
Water heater	G3	2000	Always on. Set according to (3)	50%
PV system	G4	1250[3]	NA	10%
Wind turbine	G4	500[3]	NA	10%

TABLE II
ENEL PRICING

Weekends, holidays, and everyday from 19:00 to 08:00	Everyday from 8:00 to 19:00
0.12 €/kWh up to 150 kWh/month 0.2 €/kWh over 150 kWh/month	0.53 €/kWh

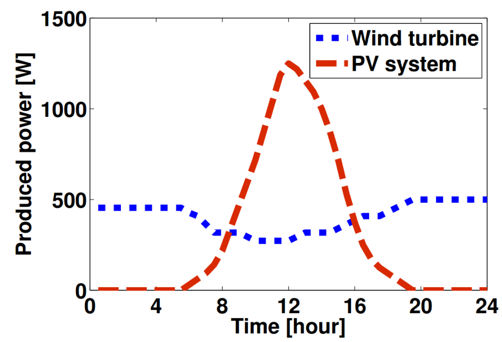


Fig. 7. Daily power production for PV and wind turbine systems [43]

VI. RESULTS

The SHEM system described in this paper has been tested in real time supposing to have 1000 houses with user profiles chosen pseudo-randomly according to the probability density function generated by the percentages given in Figs. 4-5 about the overall population that fell into a given profile. Power consumption values, mean execution times and probability to have a given appliance at home have been set according to the conducted survey results and to [41][42], and are listed in Table I. The power consumption and execution time values have been set according to a normal distribution with 20% deviation. Also the characteristic parameters that describe the dynamics of G3 appliances have been set with a normal distribution (with 20% deviation) around typical mean values, that are [31]: $P_i^{heat} = 18$ kW, $R_i = 2$ °C/kW and $C_i = 2$ kWh/°C for HVAC; $P_i^{heat} = 5$ kW, $R_i = 120$ °C/kW and $C_i = 0.2$ kWh/°C for water heater. Furthermore, we included two types of RES: a photovoltaic (PV) and a microwind turbine system. The produced power has been varied according to a normal distribution (20% deviation) around the values in Fig. 7, up to a highest value that is consistent with those of commercial home systems [43]. With reference to TOU rates, it has been supposed to use the pricing set by the Italian electricity utility company, ENEL (listed in Table II).

Results in Fig. 8 show the average electricity cost savings obtained when using the proposed QoE-aware SHEM system, with respect to the case where no SHEM system is used. In order to compare it with a similar one that does not take into account QoE, we ran the scenario using the algorithm in [44], which only optimizes the starting time with reference to cost saving (QoE-unaware in Fig. 8). Results are shown both in the case that no RES are installed in the houses (wo RES, i.e. only Q-CSAS is run) and in the case that there are RES installed (w RES). Furthermore, the 95% confidence interval is reported to take into account the variance of results and the number of trials that have been made. For the QoE-aware SHEM system, cost savings amount on average to 22% for the case without RES, and 30% for the case with RES. Note that the highest difference between QoE-aware and QoE-unaware results is experienced for electric oven and HVAC. This behavior is consistent with the results of the survey on the perceived QoE (Section IV), 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 the QoE-unaware case, cost saving values are higher, with an average that goes from 33% without RES to 46% with RES.

In order to evaluate the performance of the algorithm with reference to the QoE perceived, we introduce the annoyance rate computed as the value of the QoE vector element in $\hat{\mathbf{Q}}_i$, for the resulting starting time or temperature. In Fig. 9, the average annoyance rate evaluated for each controlled appliance and in the absence (wo RES) or presence (w RES) of RES is reported, along with the corresponding 95% confidence interval. Again, the QoE-aware system proposed in this paper has been compared with the QoE-unaware system proposed in [44]. With reference to the QoE-aware SHEM system, although cost saving values are considerable, the annoyance rate is still quite close to the lowest one, with an average of 1.65 without RES, and 1.70 with RES. It is straightforward to note that, even if cost savings are higher using the QoE-unaware algorithm, also the annoyance rate is higher, with an average of 3.36 when there are no RES and 3.43 when RES are installed.

Note that the annoyance rate for the QoE-aware system

[3]This is the maximum produced power. The power produced by RES varies during the day according to a normal distribution around the values in Fig. 7

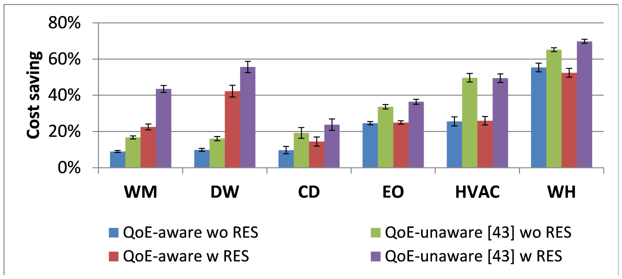


Fig. 8. Energy cost savings using the proposed QoE-aware SHEM system and the QoE-unaware SHEM system in [44], in the case where RES are not installed (wo RES) and in the case where RES are installed (w RES).

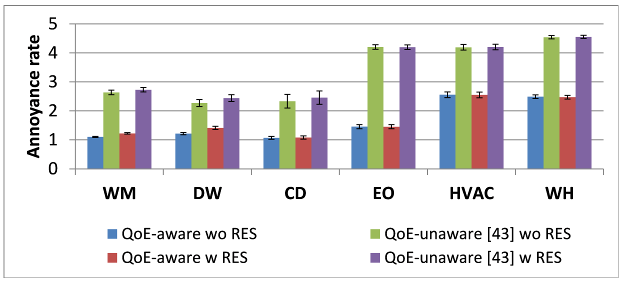


Fig. 9. Annoyance rate with the proposed QoE-aware SHEM system, compared with the QoE-unaware SHEM system in [44].

is sometimes higher when RES are installed in the house. The reason is that, when a RES produces some power, the appliances of the house compete for that power according to the benefit of starting their task immediately, that is in inverse proportion to the relevant level of annoyance of the user (see Eq. (17)). Therefore, it may happen that appliances with high power consumption and annoyance level correspond to higher benefit values than appliances with low power consumption but even lower annoyance level. Since RES power is available for a limited amount of time and associated savings are considerable, the SHEM system tries to exploit it all immediately. For this reason, the annoyance level is sometimes higher, particularly for those appliances, such as WM and DW, for which, according to Figs. 4-5, users are usually more willing to shift their starting time, in spite of annoyance levels slightly higher. On the other hand, when no RES power is considered, the starting time is only assigned according to electricity tariffs, and thus it is more likely that there is a time, when electricity is cheaper, that is closer to the user preferred time.

VII. 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 first (Q-CSAS) based on the presence of TOU tariffs, shifts the starting time of controlled appliances to off-peak times, taking into account the user habits. The second algorithm (Q-RSPA) is started whenever a RES installed in the neighbourhood produces some power. Simulation results carried out using different appliances prove that average energy cost saving using the proposed algorithms goes from 22% when there are not RES installed in the neighbourhood to 30% 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 1.65 and 1.70. As a future activity, we aim at extending the survey using available online survey tools, such as Qualtrics, SurveyMonkey, SurveyGizmo, which would allow us to have better usage clustering results.

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