Applied Energy 155 (2015) 79–90

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Demand response flexibility and flexibility potential of residential smart appliances: Experiences from large pilot test in Belgium

R. D'hulst [a,c,*], W. Labeeuw [b,c], B. Beusen [a,c], S. Claessens [a,c], G. Deconinck [b,c], K. Vanthournout [a,c]

[a] VITO, Boeretang 200, 2400 Mol, Belgium
[b] KULeuven, ESAT-ELECTA, Kasteelpark Arenberg, Leuven, Belgium
[c] Energyville, Dennestraat 7, 3600 Genk, Belgium

HIGHLIGHTS

- Experiences and findings regarding the flexibility of smart appliances are shown.
- The flexibility quantification is based on measurements.
- Measurements were executed in 186 households, during 3 years on 418 smart appliances.
- The flexibility potential calculated can be used to determine the impact of demand response.

ARTICLE INFO

Article history:
Received 13 February 2015
Received in revised form 28 May 2015
Accepted 29 May 2015
Available online 16 June 2015

Keywords:
Demand response
Flexibility
Residential households

ABSTRACT

This paper presents a well-founded quantified estimation of the demand response flexibility of residential smart appliances. The flexibility from five types of appliances available within residential premises (washing machines, tumble dryers, dishwashers, domestic hot water buffers and electric vehicles), is quantified based on measurements from the LINEAR pilot, a large-scale research and demonstration project focused on the introduction of demand response at residential premises in the Flanders region in Belgium. The flexibility potential of the smart appliances, or the maximal amount of time a certain increase or decrease of power can be realized within the comfort requirements of the user, is calculated. In general, the flexibility potential varies during the day, and the potential for increasing or decreasing the power consumption is in general not equal. Additionally, an extrapolation of the flexibility potential of wet appliances is presented for Belgium. The analysis shows that, using smart wet appliances, an average maximum increase of 430 W per household can be realized at midnight, and a maximum decrease of 65 W per household can be realized in the evening. The resulting flexibility potential can be used as an instrument to determine the impact or economic viability of demand response programs for residential premises.

1. Introduction

Four evolutions cause an increased need for flexibility in the electricity system. Firstly, the share of intermittent renewable energy is growing. Secondly, renewable electricity generation is increasingly injected in a decentralized manner. Thirdly, an increase of the electrical load is expected, caused by a shift from fossil fueled systems toward high efficient electrical equipment for transport and heating [1]. Fourthly, the number of traditional controllable power plants is stagnating or even decreasing [2]. Due to the combination of these four evolutions, maintaining the electricity power balance while respecting electricity grid constraints is becoming increasingly challenging [3]. Demand response, i.e. intentional modifications to consumption patterns of electricity of end-use customers that are intended to alter the timing, level of instantaneous demand, or the total electricity [4], is being deployed to cope with above mentioned evolutions [5].

For such consumption changes to be acceptable, they may not impact the correct functioning of the appliances, nor reduce the comfort level of the users. This is what defines 'the flexibility' of the appliances: the power increases and decreases that are possible within these functional and comfort limits, combined with how long the changes can be sustained.

LINEAR (large-scale implementation of smart grid technologies in distribution grids) was a large-scale research and demonstration

* Corresponding author at: VITO, Boeretang 200, 2400 Mol, Belgium.
E-mail address: reinhilde.dhulst@vito.be (R. D'hulst).

http://dx.doi.org/10.1016/j.apenergy.2015.05.101

project focused on the introduction of demand response technology at residential premises in the Flanders region in Belgium [6]. The project ran from 2009 until 2014. The LINEAR project included a large-scale pilot in which residential demand response technology was validated in real-life conditions. In this the pilot, smart appliances were installed in 239 households and tested during a period of 36 months. The appliances used were smart washing machines, dishwashers, tumble dryers, electric hot water buffers and electric vehicles. Dishwashers, washing machines and tumble dryers are further in the paper referred to as 'wet appliances'.

During the pilot, a wide selection of potential applications or business cases of residential flexibility were investigated. (1) Portfolio management achieved a better day-ahead production/consumption balance using the flexibility offered by the households [7] (2) Real-time intra-day balancing of wind production used residential demand response to cover the mismatch between predicted and actual wind production [8]. (3) Residential flexibility was used to decrease voltage deviations on the distribution grid, caused by local production as well as increased consumption [9]. (4) The lifetime of distribution transformer was increased by using demand response to lower transformer temperature and sustained current peaks [10].

The flexibility of all users taking part in the LINEAR pilot was used for all business cases. Experiments for the different business cases were executed consecutively at various user clusters. Participants were not aware which business cases ran at which instant in time, and rather were rewarded using a capacity fee which stimulated the participants to offer as much flexibility as possible.

This paper describes the experiences and findings from the LINEAR pilot regarding the flexibility of the smart appliances that can be achieved without reducing the user's comfort.

Well-founded and sound quantifications of flexibility of residential appliances are hard to find in literature. Most studies give flexibility potential quantifications based on rather rough assumptions and simulations, such as e.g. in [11–13]. In [11] the flexibility potential of residential appliances is estimated, and the availability of these flexible appliances is based on survey data. No information is given in the paper on how the user behavior is modeled. In [12], the flexibility potential of residential households is estimated as a fixed percentage of the household consumption. How this percentage is obtained is not mentioned. In [13], the flexibility potential estimation of residential appliances is executed more in depth. However, the user behavior is based on survey data obtained to study the usage of non-flexible appliances. In some studies the flexibility potential of residential appliances is based on the extrapolated consumption of residential smart appliances, such as in [14–16]. In [14], the future flexibility potential of GB is estimated as the extrapolated future electricity demand from some selected residential appliances (wet appliances, refrigerators, etc.). Also in [15], the flexibility potential of the residential sector in Denmark is estimated as the future consumption of certain residential appliances. In [16], the flexibility potential of residential A/C systems is extrapolated from hourly electricity consumption data. In [17–20] impacts and quantifications of residential flexibility are given. However, the flexibility measured in these works was specifically for users that participated to dynamic tariff schemes. Such tariff schemes have a strong impact on when and how smart appliances are used. As a capacity fee is time of day independent and stimulates the user at offering as much flexibility as possible, the work presented here is a better estimation of the flexibility potential, independent of a specific business case or energy tariff structure. In [21,22] quantification methods for flexibility potential in residential premises are discussed. In [21] the flexibility potential of households is quantified based on data from only one household with flexible appliances. In [22] is discussed how demand response opportunities of a building can be identified based on its energy measurements.

In [23], the results of a pilot test with smart washing machines combined with dynamic tariffs is discussed. In this work is stated that the smart appliances were only used with smart configurations for 14% of the time, and the question is raised whether this number could be increased by using a different reward for offering flexibility, i.e. different than the dynamic tariff incentive. In this work is shown that by using a capacity fee, an increased smart use can be obtained.

The analysis given in the work presented here is based on *measured* flexibility from appliances in the LINEAR pilot. As mentioned before, the flexibility each participant of the pilot offered, was independent from the demand response application making use of the flexibility and gives a better estimation of the total potential.

The paper is further structured as follows: in Section 2 the flexibility offered by the participants in the LINEAR pilot is discussed for every type of appliance. In Section 3, the flexibility potential is calculated. Section 4 concludes the work.

2. Flexibility offered by pilot participants

Comfort protection is an essential requirement for residential demand response. Therefore, LINEAR has selected and deployed two types of smart appliances that offer a large amount of flexibility and that can be automated to minimize comfort impact: postponable and buffered appliances. Buffered appliances are here defined as appliances that inherently have a buffer in which energy (in any form) is stored or buffered. The presence of an energy buffer allows for a flexible operation of the appliance. Postponable appliances have flexibility because their operating cycle can be postponed or shifted within a time window defined by a user defined deadline.

In all business cases tested within LINEAR, user comfort had absolute priority over the technical objective of the business cases. The user comfort protection in case of postponable appliances means that any user is guaranteed that the appliance he has configured will have performed its cycle by the deadline he has given at configuration.

In the LINEAR pilot, a total of 418 postponable appliances, such as dishwashers, washing machines and tumble dryers, were deployed at 186 households. The appliances used were supplied by two manufacturers. The user interface of these smart wet appliances supports smart configurations: when users configure these appliances, they are requested to set a deadline for the end of the appliance's program as far as possible in the future, with a maximum of 24 h delay. This gives the LINEAR system a 'flexibility window' between configuration time and deadline. Within this window, the start of the selected program can be freely chosen at the time optimal for the technical target of the experiment in execution. Once started, the appliance's program cannot be interrupted.

Smart domestic hot water (DHW) buffers (15 deployed) and electric vehicles (7 deployed) were the buffered appliances used in the project. The DHW buffers all have a 200 l tank filled with water that is kept between a minimum and maximum temperature [24]. These settings ensure that the comfort of the user is protected. The DHW buffers have a nominal power of 2.4 kW when heating. Within the comfort settings, the demand response control system freely decides when the buffer is charging.

The electric vehicles are configured similarly to the postponable appliances, i.e., the user is requested to set a departure deadline as late as possible. However, contrary to the wet appliances, configuration of the smart charging required the user to log in on their Linear portal site and submitting the expected departure time

biz de
15 da
gelen
yukur
kaydi
olanin
taman
gerek
bir kis
belirle
bunun
sure
kaydi
ni bel
lazim

and the expected charging time, as indicated on the vehicle's dashboard. The demand response control system can interrupt the charging of the vehicles. The nominal charging power of the vehicles was 2.3 kW (i.e. 10 A at 230 V).

The capacity fee the users of the pilot received, amounted to 1€ per 40 h of flexibility window configured on the wet appliances or electric vehicles. As the operation of the domestic hot water (DHW) buffers was transparent to the users, no extra remuneration was foreseen there.

This section describes the flexibility characteristics of every appliance type. In the next section, the resulting flexibility potentials of every device type are discussed.

2.1. Postponable appliances: wet appliances

We noticed that the participants in the pilot did not always configure their wet appliances with a deadline in 'smart' mode. Still, the number of users that never configured their appliance as smart was very limited. Fig. 1 shows the measured percentage of smart configurations for all postponable wet appliances. During the pilot, several technical incidents were encountered (due to communication problems, etc.) [25], and these technical issues often resulted in a failed logging of smart configurations. Only the appliances that experienced limited technical issues, i.e. when communication was operating correctly for more than 40% of the time, are included in Fig. 1. Fig. 1 is based on measurements of 89 households, collected over approximately 1.5 year (April 2013 until September 2014) and is based on a total of 8390 dishwasher configurations (both smart and non-smart), 10445 washing machine configurations and 10488 tumble dryer configurations.

On average, dishwashers were configured more often with flexibility than washing machines and tumble dryers. On average 56% of all dishwasher configurations are smart, versus 29% and 31% for washing machines and tumble dryers respectively.

Fig. 2 shows the probability a wet appliance is configured in function of the time of day, together with the probability a wet appliance is configured with flexibility.

Note that on average not every appliance is used every day, this explains the lower probabilities. It can be seen that the majority of the smart configurations occurs during the evening, especially so for dishwashers. As a result, the bulk of the flexibility can be found during the night. Washing machines also show a peak of smart configurations in the morning. The same behavior was found in the pilot discussed in [23]. There is a slightly higher probability of smart configurations during the day at weekends. For dishwashers, the share of smart configurations compared to total number of configurations, remains more or less constant throughout the day. This is less so for the washing machines and tumble dryers. It seems to be more acceptable for users to configure the latter two with delay in the morning and evening.

The data in Fig. 2 is based on measurements on 65 dishwashers, 102 washing machines and 105 tumble dryers, i.e., all appliances that were configured at least once in smart mode during the overall course of the measurement period. It includes 4416 smart dishwasher configurations, 3464 smart washing machine configurations and 3087 smart tumble dryer configurations. For each appliance, only measurement periods with reliable communication were included in the analysis.

Fig. 3 shows the probability distribution of the length of the flexibility window set by the user, for each wet appliance. The figure shows a wide spread of the length of the flexibility window, ranging between 1 and 11 h. Note that the maximal flexibility users could offer was 24 h. The average time window is for all wet appliances close to 8 h. The data for Fig. 3 is based on the same data set that was used for Fig. 2.

Response fatigue occurs when the attention and motivation of participants drop during a test, mainly when they become tired of the task they are asked to do. Over the course of the pilot, virtually no response fatigue occurred for the wet appliances, as shown in Fig. 4: the group of users with fully functional smart appliances that did not offer flexibility did not grow substantially during the project. Moreover, the composition of this group changed from month to month, indicating it are users in the period between reparation of their devices and restart of the use of their smart

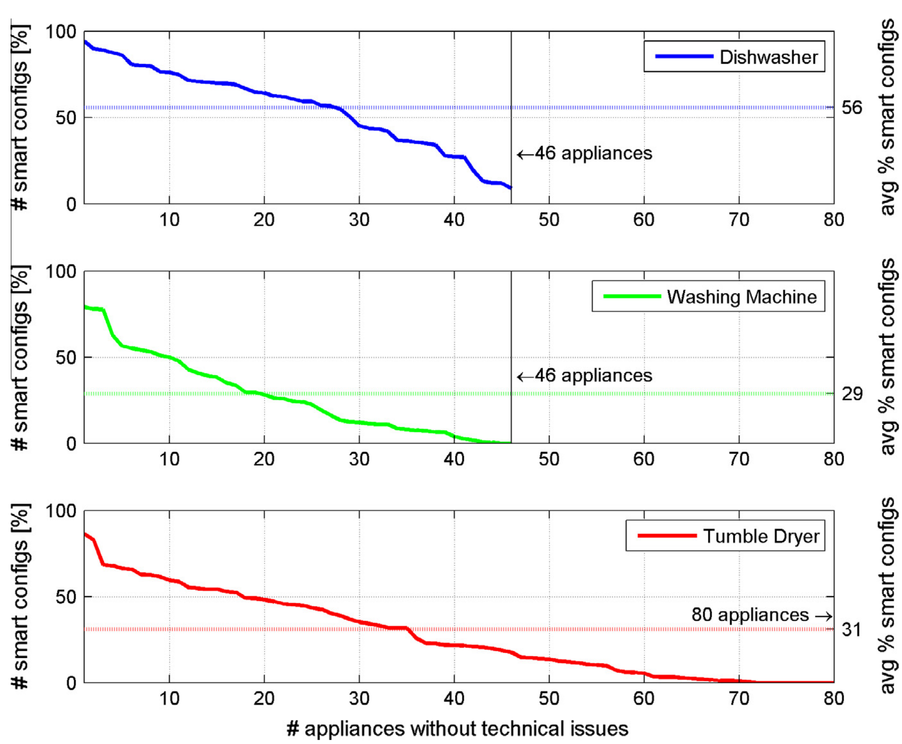

Fig. 1. Measured percentage of smart configurations of all wet appliance.

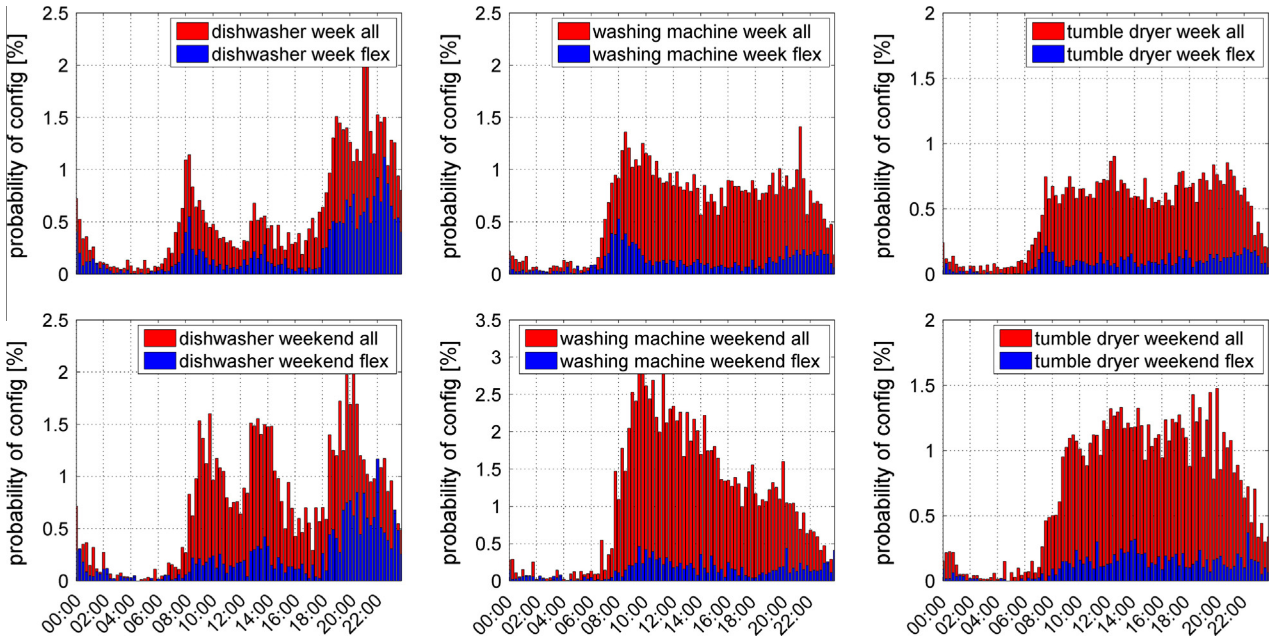

Fig. 2. Probability of configuration (both smart and non- smart, in red) and smart configuration (blue) according to starting time during an average weekday and weekend day, for every wet appliance. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

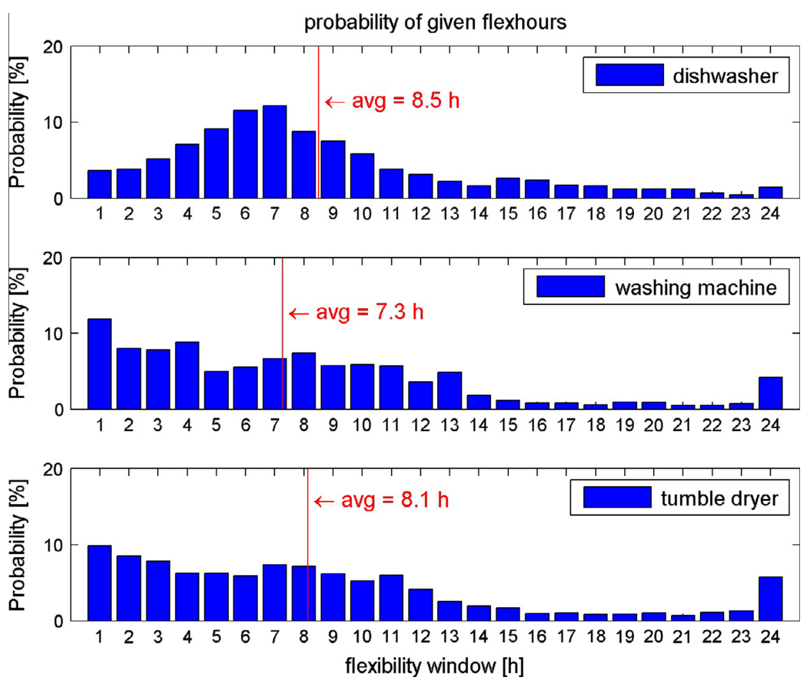

Fig. 3. Probability distribution for the length of the flexibility window, per wet appliance. The average number of flexibility hours is also indicated.

appliances. The large majority of people not giving flexibility were users that were temporary out due to technical issues. In-depth interviews with participants confirmed that technical issues were the main cause of the participants to (temporarily) give up configuring their appliances with flexibility [26]. A total of 82 dishwashers, 138 washing machines and 141 tumble dryers are accounted for in the data of Fig. 4.

2.2. Smart domestic hot water buffers

Domestic hot water buffers (DHW buffers) are electric domestic water heaters that can preheat and store heat in a water buffer. This buffer allows the decoupling of hot water production and consumption which offers opportunities to alter the electricity consumption profile and create flexibility. In the Linear project, a smart domestic hot water buffer was deployed that offers the flexibility to the control system, while protecting the comfort of the user. The technology and the interface of the smart domestic hot water buffers used in the pilot is explained in [24]. Two important comfort settings are applicable: the maximum temperature for water in the DHW buffer and the minimum (hot) temperature at which water is allowed to leave the DHW buffer. Below this minimal allowed temperature, the user experiences the water as too cold.

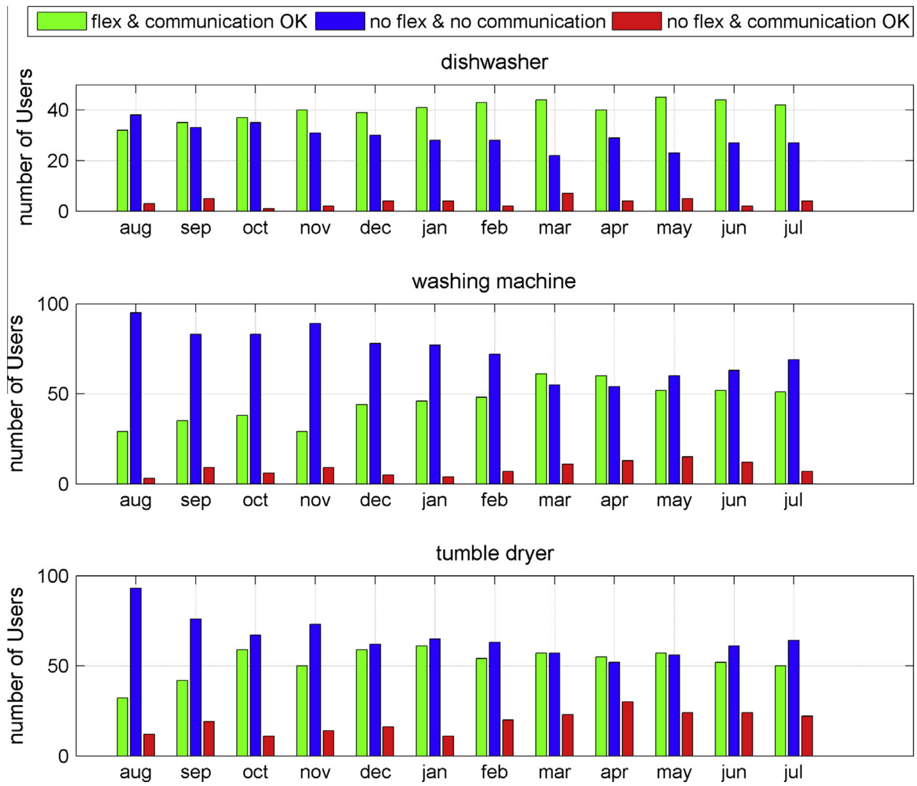

Fig. 4. The number of households giving flexibility (green), not giving flexibility but experiencing technical issues (blue), not giving flexibility and no technical issues (red) per month and per appliance, from mid-2013 until mid-2014. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The SoC (State of Charge, in%) of a DHW buffer is defined as the ratio of the energy content of the water in the buffer compliant to the minimal allowed temperature comfort setting, versus the reference energy content of a fully charged buffer. The SoC is an important parameter for the control system to schedule and dispatch the demand response actions. An additional comfort setting can be introduced based on the SoC, i.e., SoCmin, or the minimum SoC that must be maintained by the demand response control system to ensure that sufficient hot water is available to meet the users' immediate demands.

The smart DHW buffers deployed in the LINEAR pilot expose their current operating status (switched On/Off) and internal State of Charge (SoC) on the interface they have with the control systems making use of the flexibility. No direct interaction with the buffer owner is required for offering flexibility once the system is installed and the comfort settings are configured.

From the logged SoC of each DHW buffer, and its measured power consumption, an estimate of the hot water demand is derived, as the hot water usage was not directly measured. The hot water demand together with the SoC boundaries of the buffer allows for the calculation of the flexibility of a DHW buffer, according to the model explained in [24]. Fig. 5 gives an illustration of the flexibility of one DHW buffer during three consecutive days of the pilot. The measured SoC of the buffer is indicated, as well as the electricity consumption of the buffer and the hot water demand calculated from the SoC. The flexibility of the buffer is shown as an upper and lower bound of the electricity consumption of the boiler. The distance between the upper and lower bound of the electricity consumption increases over time, because there are more heat losses to the environment when the water in the buffer is at a higher temperature. The flexibility indicates to what extent the electric energy consumption can be shifted within the user comfort settings: SoC limits must always be respected, and tapwater demand needs to be available when required.

In contrast with the other smart appliances discussed, there are no user-interaction measurements regarding the DHW buffer, since in this case the user does not have to perform any smart appliance specific task in order to make the smart DHW buffer offer flexibility. The flexibility of the DHW buffers is available 24/7, without specific user interaction needed.

2.3. Electric vehicles

A total of 7 electric vehicles were deployed in the LINEAR pilot, which were passed on between participants in the course of the pilot. The vehicles used in the pilot had a charging current of 10 A at a nominal voltage of 230 V, the battery capacity of the vehicles was 22 kWh.

In total 32 participants used an EV with smart charging, each time for 10 weeks. After plugging their vehicle in the electricity socket, participants had to enter the estimated charging time, as displayed on the vehicle's dashboard, and the required departure time via a dedicated web interface. The control system could freely stop and start the charging of the vehicles once this smart charging form was completed, but always made sure that the car was fully charged before the departure deadline. Fig. 6 shows the probability of a EV configuration throughout week and weekend days. Note that not every vehicle is plugged in every day, and that users could charge their vehicles without completing the web form and thus without offering flexibility. The majority of smart charging configurations were initiated during the evening, with flexibility windows stretching into the night. This behavior seems to coincide with the typical work-home commuting pattern. The peak of smart

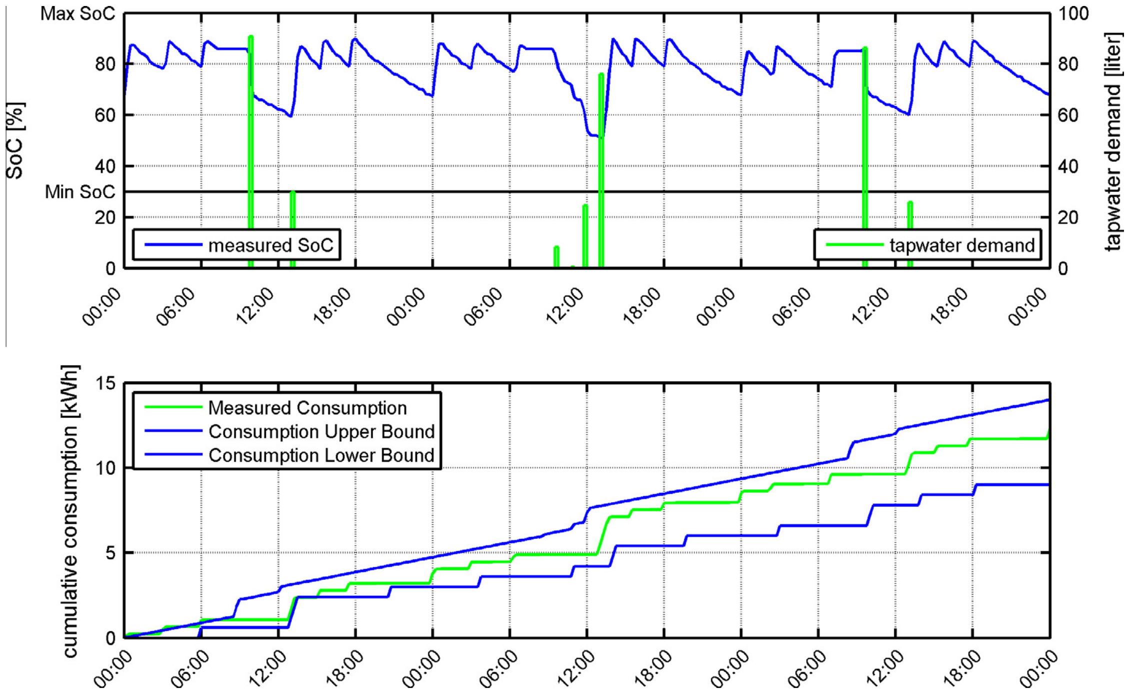

Fig. 5. Measured State of Charge and tapwater demand derived from the SoC for a DHW buffer during three consecutive days. The measured electricity consumption, and the upper and lower bounds of the electricity consumption are also shown.

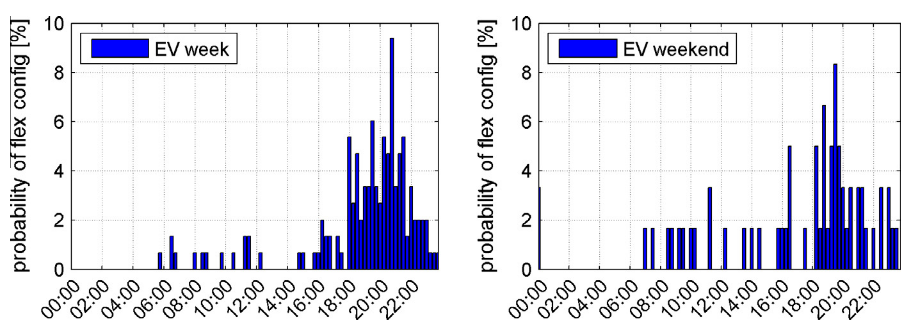

Fig. 6. Probability of smart configuration of an EV throughout an average weekday and weekend day.

configurations during weekends is situated earlier than during the week.

Fig. 7 shows the probability for the flexibility window, i.e., the time between configuration of the smart charging form and the charging deadline set by the user. As for the wet appliances, we see a large spread in the length of the flexibility window, ranging from 1 to 10 h. On average EVs are configured with a flexibility window of 5.6 h.

However, the procedure of logging into a web portal and filling a smart charging form provoked a lot of response fatigue. This is illustrated in Fig. 8, which compares the number of logged EV configurations, i.e. submitted through the web interface, to the theoretically possible number of EV configurations. The latter is derived from energy measurements of the EV charging plug, and track and trace data of the EVs. In-depth interviews with the participants confirmed that the interface for setting the smart configuration of the electric vehicles required too much and too complex operations.

It is assumed that an interface similar as the smart wet appliances, would significantly reduce the response fatigue. This implies an interface imbedded on the charging plug and the automatic registration of the car's estimated charging time, so the user interaction is limited to setting the departure time on the charging plug.

3. Flexibility potential of the smart appliances

3.1. Given all measurements done during the LINEAR pilot, an estimate of the flexibility potential has been made for each type of appliance

The flexibility potential of a group of appliances is defined as 'the power consumption increase (P_{inc}) and decrease (P_{dec}) that can be realized at a certain time of day, combined with how long this power increase or decrease can be sustained (Δt)'. This flexibility potential can be used as an instrument to determine the impact or economic viability of any demand response program based on the smart appliances discussed here: the flexibility potential shows how much flexibility is available at what time during the day and for how long.

Firstly, the procedure used to estimate the flexibility potential of a group of smart appliances is explained. Then, the results of the calculations for every type of appliance are shown.

3.2. Flexibility potential estimation procedure

Two cases are calculated. In a first scenario, the reference energy consumption of the group of appliances is when energy consumption is postponed as much as possible. For instance, for

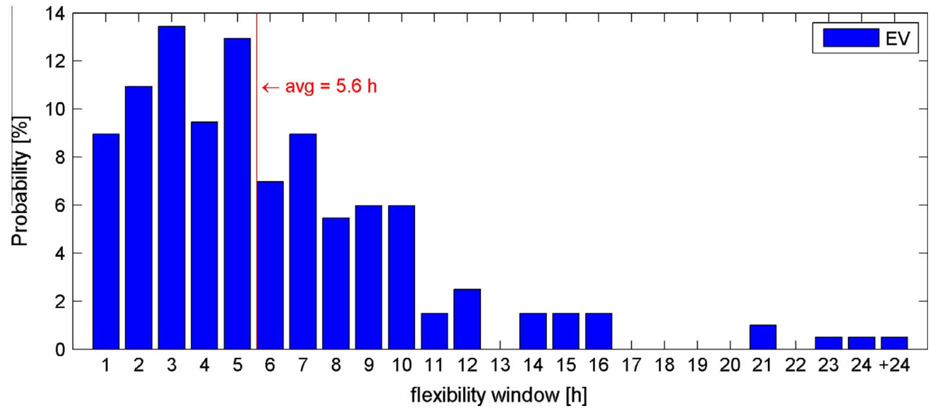

Fig. 7. Probability of the length of the flexibility window per smart charging configuration of an EV. The average flexibility window length is also indicated.

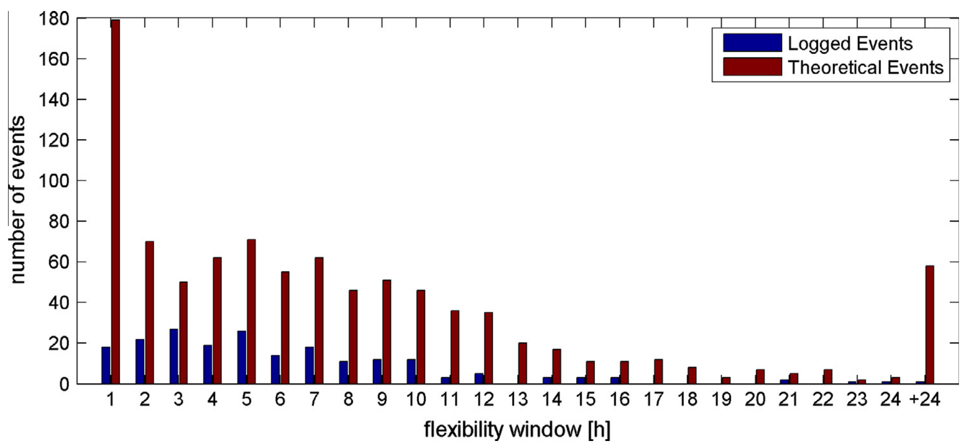

Fig. 8. Number of logged EV configuration events in function of the flexibility window length, versus the theoretically possible number of EV configurations.

wet appliances, this means executing the program at the deadline. Second is the scenario in which the reference consumption is so that all appliances consume energy as early as possible. The two scenarios are illustrated in Fig. 9. In Fig. 9(a) and (b), the flexibility of the group of appliances is depicted by two lines, i.e. E_{max} and E_{min}, representing the power consumption of the appliances when they consume energy as early as possible, and as late as possible respectively. E_{max} and E_{min} define the flexibility boundaries of the energy consumption of the group of flexible appliances. E_{min} represents the reference power consumption in the first scenario discussed, E_{max} is the reference power consumption in the second scenario. E_{max} and E_{min} are calculated based on the flexibility measurements for every appliance type, as discussed in the previous section.

In the first scenario, the flexibility potential for power consumption *increase* can be calculated, based on the principle that the potential for demanding extra power at any moment is maximized when the reference consumption is maximal postponement. At any moment, given the availability of all smart appliances at that particular moment, a power consumption increase of P_{inc} can be realized if the sum of the reference power consumption (P_{ref}) and P_{inc} does not exceed the maximal power of the available appliances. The power increase P_{inc} can be sustained during a time Δt, until the flexibility of all available appliances is used, this is until comfort settings force appliances to be switched off. This is illustrated in Fig. 9(a): P_{inc} can be sustained until the power consumption reaches E_{max}.

In the second scenario it is assumed that the reference consumption of the group of appliances is such that the consumption of every appliance within the cluster is as early as possible. The flexibility potential for power decrease can then be calculated based on the principle that the potential for decreasing power consumption at any moment is maximized when the reference consumption is consumption as early as possible. At any moment, given the availability of all smart appliances within the cluster at that particular moment, a power decrease can be realized as long as P_{dec} does not exceed the reference power consumption of the available appliances. The power decrease can be sustained during a time Δt until the flexibility of all available appliances is used, this is until comfort settings force appliances to be switched on. This is illustrated in Fig. 9(b): P_{dec} can be sustained until the power consumption reaches E_{min}.

The combination of both P_{inc} and Δt (or P_{dec} and Δt) give a measure for the flexibility potential of the group of appliances. The flexibility potential for power consumption increases and consumption decreases is in general not equal. Also, because of the varying availability of flexible appliances, the flexibility potential typically varies during the day.

Increasing or decreasing the power consumption at a certain time of day implies that energy consumption is shifted. This has an impact on the amount of flexibility available later, i.e., the so-called rebound effect. Note that our representation of the flexibility potential represents a 'snapshot' in time. It assumes that all flexibility is available and used at that specific point in time. It is hence an indication of the potential, rather than a tool that can be used for scheduling and/or calculating rebound effects.

In the results discussed below, the flexibility potential is given for an average day. For those appliances with a clear distinction

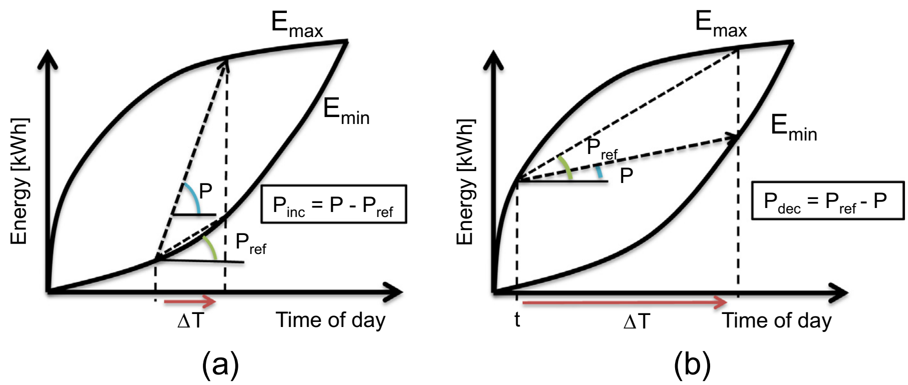

Fig. 9. Schematic illustration of the flexibility potential calculation for (a) increased power consumption and (b) decreased power consumption. E_{max} and E_{min} represent the power consumption when consumption is as early as possible, and as late as possible respectively. P_{ref} is the reference power consumption, P is the power consumption when a consumption increase or decrease would be realized.

in the flexibility potential between average week and weekend day, both are shown.

3.3. Postponable appliances: wet appliances

For the wet appliances, an extrapolation of the flexibility potential for the overall Belgian population is calculated. The extrapolation is done by clustering the participants according to their characteristics, and by modeling the flexibility behavior of customers within each cluster through a statistical description.

In [27,28] it is shown that every household can be attributed to a certain 'household cluster'. 10 clusters were defined, and each cluster is characterized by its electricity consumption and consumption pattern. In Table 1 the characteristics of all clusters are given.

Each participant is attributed to one or more clusters based on the electricity demand at the point of common coupling of the participant's household. Based on the measured flexibility behavior of the participants of the pilot, statistical flexibility information was procured per cluster: probability density of a smart start configuration of every appliance at a certain time of day and the probability density of the length of the flexibility window. Table 2 shows for each cluster, and for each appliance type, the number of (measured) appliances that were taken into account to define the probability density of smart configurations and probability density of flexibility window lengths. As can be seen in Table 2, the spread of the participants, i.e. the spread in customer type, was relatively well achieved in the pilot. The larger clusters (in terms of household share) have sufficient appliances attributed to them, only the number of participants on the 'Day Small' cluster might be too small. Also no information could be procured for the 'Night Average' cluster, but in terms of household share, this cluster is relatively small, the effect on the extrapolation is thus rather small.

Based on the obtained flexibility profile per cluster, and given the distribution of Belgian households over all clusters, an estimation was made of the flexibility of all postponable wet appliances in Belgium (see Fig. 10). As explained before, the flexibility potential of a cluster of appliances is measured by a combination of P_{inc} (or P_{dec}) and Δt. Fig. 10 shows the variation of P_{inc} and P_{dec} during the day, the colors indicate the duration Δt the power decrease or increase can be sustained.

The extrapolation shown in Fig. 10, assumes a total of 4.6 million households in Belgium [29]. It defines the maximal potential, as it is assumed that every household participates in a demand response program. However, this estimated maximal potential is an underestimate, since the figures shown are based on the measurement results of a pilot, during which some users where temporary prevented of offering flexibility due to technical issues. To calculate the flexibility potential shown, we included all LINEAR pilot participants that configured their smart appliance in smart mode at least once in the measurement period (April 2013 until September 2014).

The flexibility potential of wet appliances varies considerably during the day, and from weekend to weekdays. The potential is found to be higher during a weekend day than during a weekday. The highest potential is found during evening and nighttime hours, especially for weekend days. The consumption of all wet appliances in Belgium can be increased maximally at midnight in the weekend with 2 GW. This 2 GW increase can be sustained for 30 min. The maximum power decrease possible is 300 MW at 10 p.m. in the weekend. This decrease can be sustained only for 15 min. This translates to an average maximal increase of 430 W per household, and a maximum decrease of 65 W per household. Fig. 10 also shows for example that the maximal power decrease that can be realized with wet appliances during the Belgian winter peak time, i.e. starting from 6 p.m., and for at least 4 h, is 60 MW

Table 1
Cluster information (appliance ownership, consumption, percentage of households, . . .).

Cluster name	Annual consumption (kW h)	Household share (%)	Ownership rate washing machine (%)	Ownership rate tumble dryer (%)	Ownership rate dishwasher (%)
Day small	800	14.1	85.4	46.7	26.3
Day relatively small	2500	25.9	98.1	69.8	57.4
Day average	4250	27.8	98.0	83.9	76.7
Day relatively Large	6650	15.4	97.3	86.9	79.5
Day large	11,600	7.7	71.9	60.3	54.1
Night average	6200	3.2	100	48.3	7.8
Night large	8750	2.9	100	87.5	62.8
Business average	28,350	2.3	8.83	8.83	34.2
Business relatively large	70,000	0.5	54.9	19.3	100
Business large	189,600	0.1	NA	NA	NA

Table 2
Appliance membership per cluster: the number of measured appliances that are attributed to each cluster.

Cluster name	Washing machine membership per cluster	Tumble dryer membership per cluster	Dishwasher membership per cluster
Day small	1.03	1.17	0.50
Day relatively small	9.67	11.08	5.88
Day average	23.71	24.74	15.02
Day relatively large	27.34	28.45	17.68
Day large	20.93	21.35	13.59
Night average	0.00	0.00	0.00
Night large	8.87	8.45	5.19
Business average	9.26	8.65	6.15
Business relatively large	1.18	1.08	0.97
Business large	0.02	0.02	0.01

during weekdays. The overall installed generation capacity in Belgium is about 16.6 GW [30].

The flexibility potential has been found to be highly asymmetrical: at any given moment during the day, more devices can potentially be switched on extra than delayed. This can be understood intuitively as follows: the flexibility window of a wet appliance is generally much longer than the actual running time of the appliance's program. There are hence many more points in time where the appliance's consumption can be shifted to, than those where the consumption can be shifted away from.

3.4. Smart domestic hot water buffers

In total, 15 200 l 2.4 kW domestic electric hot water buffers were installed in the LINEAR pilot. 10 of these were measured reliably enough to be considered for further analysis.

Fig. 11 shows a plot of the potential consumption power increases and decreases of an average DHW buffer. The flexibility potential was calculated based on the average flexibility of the 10 buffers measured from November 2013 until August 2014. No significant difference in flexibility potential between weekdays and weekends was observed.

The flexibility potential of a 200 l hot water buffer for an average day shows that a maximum increase of 2.4 kW per buffer can be realized, and that this extra power can be initiated at any time during the day. It can be sustained for 15 min at nighttime or for a few hours at daytime. The flexibility potential for increasing the power demand during daytime is larger than during nighttime. Reason is that on average, more hot water demand occurs during evening hours, and that on average the DHW buffers are at a lower SoC during the evening, leaving less flexibility for increasing the power for a longer period of time, i.e. more than what is needed to cover the minimal comfort settings.

On the other hand, the maximal power decrease is limited to 0.3 kW per buffer. This power decrease can be sustained for more than 10 h during the day.

Similar as for the postponable appliances, the flexibility potential is highly asymmetrical. This can be understood as follows. The

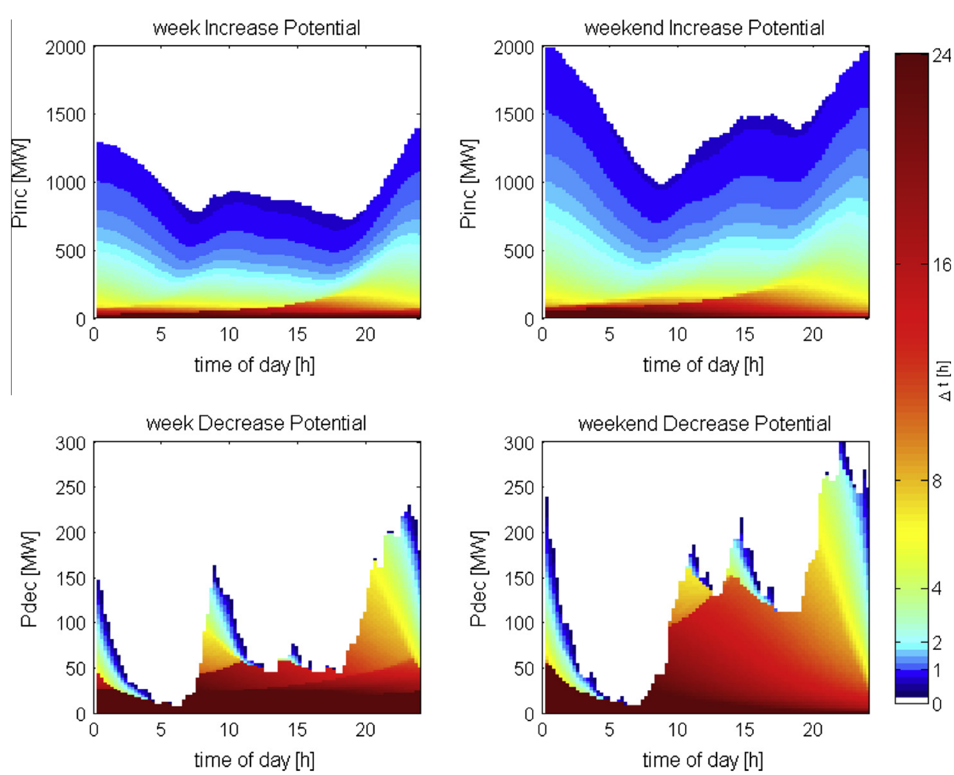

Fig. 10. Flexibility potential of all postponable wet appliances combined (dishwasher, tumble dryer, washing machine) for the Belgian population. The top figures indicate what power consumption increase is possible in function of the time of day (P_{inc}), while the bottom figures show the potential in terms of power consumption decreases (P_{dec}). The color indicates how long a certain increase or decrease can be sustained (Δt). The results for both the average week and weekend day are shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

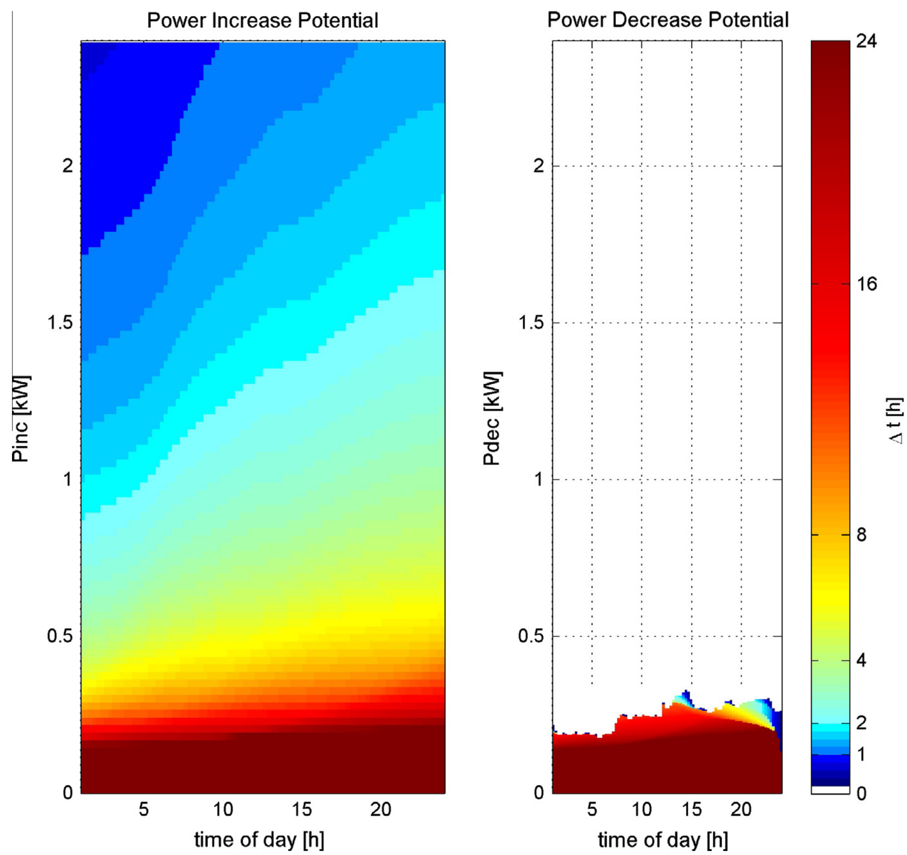

Fig. 11. Flexibility potential of an average DHW buffer as used in the LINEAR pilot. Both consumption increase and decrease potential are shown.

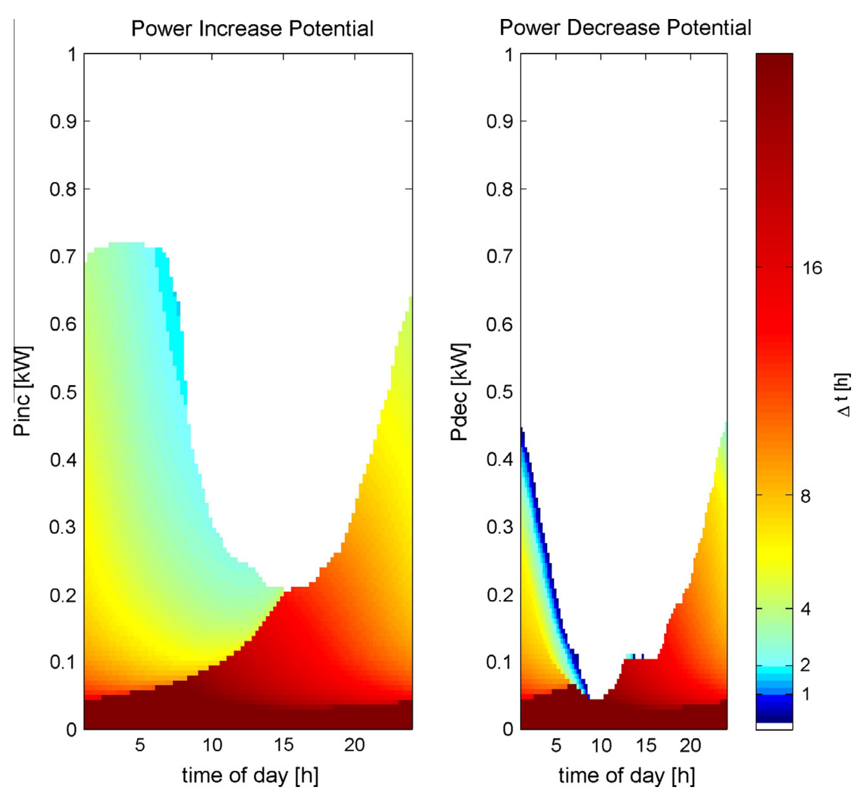

Fig. 12. Theoretic maximal flexibility potential of the average electric vehicle as used in the LINEAR pilot. Both potential power increases and decreases are shown.

maximal power decrease would be reached if the buffer is kept at its maximal SoC until the time of the decrease starts, and then left to discharge to its minimal SoC. In this case, we delay the power that would have been required to keep the buffer at maximal SoC, which is limited to the tap water demand and the thermal losses. On the other hand, the maximal power increase is achieved when the buffer is kept at minimal SoC until the time of the power increase start, and is then charged to its maximal SoC. The total energy that can be stored in the buffer far surpasses that of the losses and water demand during the time it takes to fully charge the buffer. Result is a larger potential to increase the power demand.

In contrast with the flexibility potential pattern of wet appliances, the variability of the potential of DHW buffers during the day is relatively limited. The DHW buffer is an always on device, offering flexibility continuously as opposed to the wet appliance, where the availability of flexibility is linked to the user's infrequent configurations.

Furthermore, the flexibility potential of the DHW buffers is much larger than the potential of wet good appliances: the potential of one buffer equals the potential of the wet appliances of about 6 households. Thermal buffered appliances have a much larger potential to reach a cost-effective application in demand response programs.

3.5. Electric vehicles

The flexibility potential of the 7 electric vehicles used in the LINEAR pilot is calculated, using the same procedure as for the smart domestic hot water buffers. The resulting flexibility potential is shown in Fig. 12. Fig. 12 shows the flexibility potential of the average electric vehicle as it is used during the pilot, from June 2013 until June 2014.

The flexibility potential shown in Fig. 12 is not based on the flexibility data that was entered via the web interface but is instead based on when the vehicle was plugged in/out and energy measurements. It is thus the maximum theoretical potential for flexibility.

Per vehicle, a power increase of 0.7 KW during 2.5 h is possible during the night. During daytime, this drops to 0.2 kW. The average power decrease is 0.45 kW in the evening. At daytime, also the potential power decreases drop: a decrease of 0.04 kW can be sustained per vehicle for several hours. Again, the flexibility potential of the electric vehicles is asymmetric. However, this asymmetry is much less pronounced than for wet appliances and DHW buffers. Cause is that in most cases the ratio of EV charging time versus overall flexibility window is much larger than the ratio of the running cycle versus the flexibility window for wet appliances.

On average, the flexibility potential of one EV is about twice the flexibility potential of all wet appliances of one household.

4. Conclusions

The experiences and findings regarding the flexibility of smart appliances from the LINEAR pilot are described. The flexibility of 5 different appliances, i.e., washing machines, tumble dryers, dishwashers, domestic hot water (DHW) buffers and electric vehicles (EVs), is quantified based on the pilot measurements.

In addition to this, the maximal flexibility potential of every device type is calculated. Flexibility potential is defined here as the potential to increase and decrease the power consumption, in function of the time of day, combined with how long this power increase or decrease can be sustained. The presented flexibility potentials can be used as an instrument to determine the impact or economic viability of demand response programs for residential premises that builds on the flexibility of the 5 appliances analyzed.

It is shown that for every device type analyzed, except electric vehicles, the flexibility potential is highly asymmetric: at any moment in the day the maximal power increase surpasses the maximal power decrease strongly. For all wet appliances (i.e. washing machines, dishwashers and tumble dryers) and the electric vehicles, the flexibility varies significantly during the day. The flexibility of domestic hot water heater buffers remains more stable over time. The flexibility potential of DHW buffers and EVs is significantly higher than the flexibility potential of wet appliances.

An extrapolation of the flexibility potential of wet appliances is presented for Belgium. The fact that different groups of households have different grades of flexibility is taken into account. The consumption of all wet appliances in Belgium can be increased maximally at midnight in the weekend with 2 GW. This 2 GW increase can be sustained for 30 min. The maximum power decrease possible is 300 MW at 10 p.m. in the weekend. This decrease can be sustained only for 15 min). This translates to an average maximal increase of 430 W per household, and a maximum decrease of 65 W per household.

Acknowledgements

This work is supported by the Flemish Ministry of Science via the project Linear organized by the Institute for Science and Technology (IWT).

References

[1] International Energy Agency. World Energy Outlook 2014. Paris; 2014.
[2] International Energy Agency. World Energy Investment Outlook 2014. Paris; 2014.
[3] Cossent R, Gómez T, Frías P. Towards a future with large penetration of distributed generation: is the current regulation of electricity distribution ready? Regulatory recommendations under a European perspective. Energy Policy 2009;37:1145–55.
[4] Albadi MH, El Sadaany EF. Demand response in electricity markets: an overview. In: IEEE power engineering society general meeting. FL: Tampa; 2007. p. 1–5.
[5] Strbac G. Demand side management: benefits and challenges. Energy Policy 2008;36(12):4419–26.
[6] Dupont B, Vingerhoets P, Tant P, Vanthournout K, Cardinaels W, De Rybel T, et al. LINEAR breakthrough project: large-scale implementation of smart grid technologies in distribution grids. In: 2012 3rd IEEE PES international conference and exhibition on Innovative smart grid technologies (ISGT Europe); 2012; Berlin: 3rd IEEE PES international conference and exhibition on innovative smart grid technologies (ISGT Europe 2012). p. 1–8.
[7] Dupont B, De Jonghe C, Kessels K, Belmans R. Short-term consumer benefits of dynamic pricing. In: 2011 Zagreb 8th international conference on the european energy market (EEM 2011).
[8] Vanthournout K, Foubert W, Stuckens C, Robben B, Premereur G. A Norm behavior based deterministic methodology for demand response base lines. In: 2014 Wroclaw 18th power systems computations conference (PSCC 2014).
[9] D'hulst R, Hoornaert F, Vanthournout K. LV distribution network voltage control mechanism: experimental tests and validation. In: Industrial electronics society, IECON 2014–40th annual conference of the IEEE; 2014; Dallas: 40th annual conference of the IEEE industrial electronics society (IECON 2014).
[10] Jargstorf J, Vanthournout K, De Rybel T, Van Hertem D. Effect of demand response on transformer lifetime expectation. In: 2012; Berlin: 3rd IEEE PES international conference and exhibition on innovative smart grid technologies (ISGT Europe 2012).
[11] MacDougall P, Kok K, Warmer C, Roossien B. Flexibility dynamics in clusters of residential demand response and distributed generation. In: 2013 Stockholm 22nd international conference and exhibition on electricity distribution (CIRED 2013).
[12] Prüggler N. Economic potential of demand response at household level – are central-European market conditions sufficient? Energy Policy 2013;60:487–98.
[13] Nistor S, Wu J, Sooriyabandara, Ekanayake. Capability of smart appliances to provide reserve services. Appl Energy 2015;138:590–7.
[14] Drysdale B, Wu J, Jenkins N. Flexible demand in the GB domestic electricity sector in 2030. Appl Energy 2015;139:281–90.
[15] Kwon PS, Østergaard P. Assessment and evaluation of flexible demand in a Danish future energy scenario. Appl Energy 2014;134:309–20.

[16] Dyson MEH, Borgeson SD, Tabone MD, Callaway DS. Using smart meter data to estimate demand response potential, with application to solar energy integration. Energy Policy 2014;73:607–19.
[17] Hammerstrom DJ. Pacific Northwest GridWise Testbed Demonstration Projects. Richland, Washington: Pacific Northwest National Laboratory; 2007.
[18] Stamminger R, Anstett V. The effect of variable electricity tariffs in the household on usage of household appliances. Smart Grid Renew Energy 2013;4(4).
[19] Bartuscha C, Alvehagb K. Further exploring the potential of residential demand response programs in electricity distribution. Appl Energy 2014; 125:39–59.
[20] Saele H, Grande OS. Demand response from household customers: experiences from a pilot study in Norway. IEEE Trans Smart Grid 2011;2(1):102–9.
[21] Kouzelis K, Diaz de Cerio Mendaza I, Bak-Jensen B. Probabilistic quantification of potentially flexible residential demand. In: 2014 IEEE power & energy society general meeting (PES GM 2014). National Harbor, MD, USA.
[22] Mathieu JL, Price PN, Kiliccote S, Piette MA. Quantifying changes in building electricity use, with application to demand response. IEEE Trans Smart Grid 2011;2(3):507–18.
[23] Kobus C, Klaassen E, Mugge R, Schoormans J. A real-life assessment on the effect of smart appliances for shifting households' electricity demand. Appl Energy 2015;147(June):335–43.
[24] Vanthournout K, D'hulst R, Geysen D, Jacobs G. A smart domestic hot water buffer. IEEE Trans Smart Grid 2012;3(4):2121–7.
[25] Strobbe M, Vanthournout K, Verschueren T, Cardinaels W, Develder C. Large-scale demand response pilot ICT architecture. In; 2014; Istanbul: 5th IEEE PES international conference and exhibition on innovative smart grid technologies (ISGT Europe 2014).
[26] LINEAR. LINEAR demand response for families: the report; 2014 [accessed February 15] www.linear-smartgrid.be.
[27] Labeeuw W, Deconinck G. Residential electrical load model based on mixture model clustering and Markov models. IEEE Trans Industr Inf 2013;9(3):1561–9.
[28] Labeeuw W, Stragier J, Deconinck G. Potential of active demand reduction with residential wet appliances: a case study for Belgium. IEEE Trans Smart Grid 2015;6(1):315–23.
[29] Statistics Belgium. FOD Economy Belgium. [accessed May 15]. http://statbel.fgov.be/nl/statistieken/cijfers/.
[30] ELIA. www.elia.be. 2015 [accessed February 2015].