Applied Energy 183 (2016) 1065–1074

Contents lists available at ScienceDirect

Applied Energy

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

Responsiveness of residential electricity demand to dynamic tariffs: Experiences from a large field test in the Netherlands

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HIGHLIGHTS

- The demand response potential in residential areas is studied based on real-life measurements.
- Flexible load and effects of peak-pricing variations are quantified.
- The use of white goods proves to be flexible enough to shift to moments of off-peak-pricing.
- Variations in moments of peak-pricing prove hardly effective for manual demand response.
- A simple and transparent design for dynamic tariffs stimulates manual demand response.

ARTICLE INFO

Article history:
Received 12 February 2016
Received in revised form 24 August 2016
Accepted 20 September 2016
Available online 28 September 2016

Keywords:
Data-driven analysis
Demand response
Dynamic tariffs
Field test
Price responsiveness
Smart appliances

ABSTRACT

To efficiently facilitate the energy transition it is essential to evaluate the potential of demand response in practice. Based on the results of a Dutch smart grid pilot, this paper assesses the potential of both manual and semi-automated demand response in residential areas. To stimulate demand response, a dynamic tariff and smart appliances were used. The participating households were informed about the tariff day-ahead through a home energy management system, connected to a display installed on the wall in their living room. The tariff was intuitively displayed: self-consumption of photovoltaic generation was stimulated by means of a low tariff, but also the generation itself played a central role on the display. Household flexibility is analyzed, focusing on: (i) the load shift of (smart) appliances, and (ii) the response of the (overall) peak load towards the dynamic tariff. To assess the latter, i.e. price responsiveness, the participants were split up in two comparable groups which were subject to a different moment of evening peak-pricing. Based on the results, it is concluded that mainly the flexibility of the white goods (i.e. the washing machine, tumble dryer and dishwasher) is used for demand response. The main part of the flexible load of these (smart) appliances is shifted from the evening to the midday, to match local generation. This load shift remained stable over a long period of time (>1 year) and is not responsive to the exact moment of peak-pricing. Therefore, it is concluded that a simple and transparent design for dynamic tariffs is sufficient and most effective to stimulate (manual) residential demand response. Such a tariff should emphasize the 'right' moments to use electricity, intuitively linked to renewable generation.

1. Introduction

As a consequence of the transition towards a more sustainable energy system, the traditional power system faces several challenges. Due to the increase in renewable generation, balancing supply and demand becomes increasingly difficult. Furthermore, due to the electrification of residential energy demand for heating and transportation peak loads are expected to increase, requiring both grid and generation capacity. This electrification is driven by an increase in overall energy efficiency; the use of heat pumps and electric vehicles reduces overall energy consumption, but increases electricity consumption. However, the electrification of residential energy consumption is both a challenge and an

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http://dx.doi.org/10.1016/j.apenergy.2016.09.051
0306-2619/© 2016 The Author(s). Published by Elsevier Ltd.

opportunity: flexibility at the demand side is expected to increase. Flexibility refers to the capacity to increase or decrease the load during a certain time frame. By applying Demand Response (DR) this flexibility can be used to shift the load to address certain objectives [1]. For example, DR can be used to reduce peak loads or to balance (renewable) generation with (flexible) demand. To exploit the potential of DR, the future power system is assumed to be equipped with ICT technologies. This so-called smart grid combines bi-directional flows of electrical power and information [2].

The benefits of the smart grid strongly depend on the flexibility available and hence on the successful implementation of DR programs [3]. Therefore, various smart grid pilots are being initiated to study the effects of DR. In [2] an overview is provided of 459 pilots launched across the EU. These pilots generally differ with respect to the involved stakeholders, DR objectives and technologies used, e.g. dynamic tariffs and/or automated control. In case of dynamic tariffs, tariff set-ups and the design features used for communication generally differ per pilot [4]. Thorough evaluation of the pilot results is considered essential for identifying the flexibility available at the demand side and understanding which design features can best be used to unlock this flexibility. However, notwithstanding the large number of pilots, the literature available on the quantification of the practical effects of DR over a long period of time is still relatively limited. This paper therefore focuses on the evaluation of the results of Your Energy Moment, a Dutch smart grid pilot, running from 2012 to 2015.

The objective of the pilot was to assess the available flexibility in residential areas. To be able to detect a structural change in behavior, flexibility was measured over a long period of time. Both manual and semi-automated DR were stimulated through the use of a dynamic tariff as well as so-called smart appliances. The participants were informed about the tariff day-ahead through a home energy management system, connected to a display mounted on the wall centrally in their living rooms. To respond to price fluctuations, consumers could manually shift their load in time and/or use the smart appliance, which automatically optimized its operation time based on the tariff. The majority of the total 188 participating households owned a smart washing machine. To assess the overall response of the peak load towards the dynamic tariff, referred to as price responsiveness, the participants were split up in two comparable groups which were subject to a distinct tariff, which sometimes differed in the moment of evening peak-pricing.

The paper is organized as follows. First, this research is put in perspective based on the literature currently available regarding household flexibility and the methods used for the evaluation of DR (Section 2). Thereafter, the method used to test and quantify the effects of manual and semi-automated DR in a real-life environment is discussed (Section 3), introducing also the Your Energy Moment pilot set-up and the design of the dynamic tariff and the smart washing machines. Section 4, covers the results, firstly the practical load shift of the washing machines is studied. Secondly, an outlook on the overall flexible household load is provided, based on the reported behavior measured throughout the course of the pilot. And, thirdly, price responsiveness of the flexible load is assessed, by analyzing the effect of a difference in the moment of peak-pricing between both groups on their respective peak loads. Finally, the conclusions and discussion in Section 5 are used to summarize and reflect on the work.

2. Related work

When considering the flexibility of households nowadays, it is mainly the white goods (i.e. the washing machine, tumble dryer and dishwasher) and thermal appliances (i.e. cooling and heating) that get most attention [5]. The use of white goods is generally considered as non-time-critical and in case of thermal appliances the available thermal buffers can be used. Potential flexibility is expected to increase in the future, due to an expected increase of heat pumps and electric vehicles [6]. To unlock flexibility the distinction between manual and (semi-)automated DR is often made [7]. In case of manual DR, consumers manually shift the operation of their appliances in time based on certain input, e.g. a dynamic tariff. With automated DR, smart appliances automatically respond to price fluctuations. As it requires little or no consumer interaction, automated DR is widely considered a promising strategy. In between manual and automated DR, we consider semi-automated DR. In this case, user interaction is required to optimize each appliance's cycle based on user preferences and input, e.g. by providing an ultimate finish time.

In the literature the DR potential is often studied using simulations. These simulations are based on assumptions with respect to the households' willingness and ability to shift load in time. For example, in [8,9] the effects of dynamics tariffs are simulated and in [10–13] the effects of smart appliances are studied. Generally, the flexibility of white goods is (also) considered, e.g. in [10] the aggregated flexibility of these appliances is analyzed, while in [11,12] this flexibility is used to simulate the potential peak load reduction and increasing self-consumption of renewable generation. The attitude of consumers towards introducing smart appliances is studied in [14–17] using consumer surveys. However, due to attitude-behavior gaps [18], these studies only provide limited insight into the flexibility in real-life. This calls for detailed evaluations and sound quantifications of the practical effects of DR in residential areas.

The limited number of existing studies, which quantify the real-life effects of DR over a long period of time, mostly focus on the effect of variable pricing schemes. In [19–24] short- and long term price responsiveness is analyzed in respectively Canada, Australia, Spain, Sweden, England and Italy. The results differ significantly, including even a reported increase of the peak load and overall energy consumption due to the introduction of a Time-of-Use (ToU) tariffs [24]. These deviations are expected to be caused by various factors. Amongst others, the type of appliances available for DR influences price responsiveness, e.g. the presence of electric heating and/or cooling systems can increase price responsiveness [25]. This addresses the need to break flexibility down to appliances level. However, deviations in reported price responsiveness are expected to be influenced by other variables as well: in [22,26,27] the effects of weather, active occupancy, type of house and type of pricing (e.g. ToU or critical peak pricing) on price responsiveness are studied. The sensitivity of the results towards the method used for quantification and variables considered for the evaluation of the effect of variable pricing schemes is also addressed in [20,28], based on an extensive literature review of the reported price responsiveness in various different settings. Therefore, it is considered important to understand the incentives used to simulate DR and to have sufficient data available to assess the effects in a transparent way, supported by statistical analyses to account for uncertainties as much as possible.

In the studies in which consumer surveys were conducted in conjunction with the implementation of a variable pricing scheme, the use of white goods to shift load in time is mentioned by the participants [23]. However, the flexibility and load shift of these individual appliances often remains unquantified due to a lack of adequate measurements. Considering the long-term application of smart white goods in real-life, the results of Moma (a German pilot [29]) and Linear (a Belgian pilot [30,31]) seem to be exceptional. In Moma an overall peak reduction of 11% was measured, however the specific contribution of the smart white goods is not studied in detail. It is, however, mentioned that the usage of the automated 'smart' function of the appliances was limited. In Linear the use of smart white goods is quantified, reporting a more frequent use of the automated function. This is most likely due to the pilot design, in which solely the provision of flexible hours for the schedule horizon was rewarded (0.025 € per flexible hour, with a maximum of 24 hours). Hence, a manual load shift of appliances was not incentivized in this setting.

This paper adds to the existing literature by presenting the results of a real-life experiment in which both manual and semi-automated DR were studied over a long period of time (>1 year), using a dynamic tariff as well as smart appliances. The results of [32,33], in which the manual and semi-automated load shift of the smart appliances is quantified, are extended and used to study the overall household flexibility and the effect of variable peak-pricing on the peak load. This enables a mutual comparison of the effect of both manual and semi-automated DR and provides essential insight into the available flexibility of households and which design features can best be used to unlock this flexibility.

3. Method

3.1. Your Energy Moment pilot set-up

End of 2012, the pilot Your Energy Moment (YEM) was launched in Zwolle (The Netherlands), involving a group of 77 households in a newly built residential area. The houses in this area are equipped with photovoltaic (PV) panels and connected to a district heating system. When in the beginning of 2014 the second part of the residential area was finished, another group of 111 households joined the pilot. The relevant building and demographic characteristics of both participant groups are listed in Table 1, with respect to demographic characteristics these groups are comparable and are considered a good representation of the Dutch society in general [32].

To assess the long-term flexibility available at these households a dynamic tariff was introduced and consumers were informed about this tariff day-ahead through a Home Energy Management System (HEMS), connected to a wall-mounted display in their living room. The HEMS was designed to incorporate persuasive methods, providing feedback and feed-forward, enhanced with visuals, comparisons and rewards, enabling instant interpretation of the results and understanding of one's electricity consumption and production [32]. To this end, the display was connected to the smart meter and a separate PV generation meter, providing direct and historical feedback on in-home electricity consumption and PV generation (Appendix A, Fig. A1 (*left*)).

To present the dynamic tariff in an intuitive way, the two-hours-averaged price was translated into three different categories, displayed on the screen using symbols which correspond to: (i) a high tariff (>0.3 €/kWh), (ii) a medium tariff (0.2–0.3 €/kWh), and (iii) a low tariff (<0.2 €/kWh), as shown in Appendix A, Fig. A1 (*left*). The implemented dynamic tariff reflects the objectives of both the distribution system operator and the energy supplier. The objective of the algorithms used to determine the tariff is best summarized as reducing the load during the evening peak hours by shifting it to moments when electricity is locally generated by the PV panels, or to the night when electricity demand and energy market prices tend to be low. Hence, the tariff is generally high during the evening peak hours and low during the daytime and night. To assess price responsiveness, the two groups of participating households were subject to a distinct tariff, which sometimes differed in the moment of evening peak-pricing. Roughly half of the days the two groups had the same moment of peak-pricing (equal tariff), while the other half of the days they had a different moment of peak-pricing (unequal tariff). The average tariff for both groups is depicted in Fig. 1. The design of the tariff is described in more detail in [32,35]. As an extra stimulus for self-consumption of PV generation the screen also provides information regarding the day-ahead expected PV generation, stressing also the relation between tariff level and local generation.

Table 1
Characteristics of the two groups of participating households involved in YEM.

	Zwolle	
	Group 1	Group 2
Start pilot	Dec. 2012	Apr. 2014
House type	Terraced houses	Terraced houses
Number of households (N)	77	111
Average PV capacity (kWp)	1.15	1.15
Heating system	District heating[a]	District heating[a]
Average number of occupants[b]	2.1	1.8
Median household income	Modal	Modal

[a] Used for both space heating and domestic hot water demand.
[b] Dutch average: 2.2 [34].

Each household could opt-in for a smart washing machine. Additionally, as an exception, a limited number of smart tumble dryers was offered to those households in Group 1 that already owned as washing machine[1]. The smart appliances are equipped with an intelligent automated delay function. When using this smart function, the user defines the ultimate finish time and subsequently the load of the programmed cycle is scheduled with the objective to minimize energy costs. Hence, the optimal starting time is determined based on the schedule horizon and the dynamic tariff. The default schedule horizon of the smart washing machine was set to 24 hours plus the cycle duration. This default value of 24 hours is in-line with the day-ahead tariff setup, additionally this value is assumed to be appropriate as the average use frequency of the washing machine is less than once a day [5]. To adjust/shorten the schedule horizon both the interface of the washing machine and the HEMS in the living room (Appendix A, Fig. A1 (*right*)) could be used.

3.2. Relevant data and analyses

For the analysis the measured data of one year is used (from 01-May-2014 to 01-May-2015), of both the first and the second group of participating households ($N_{Gr.1} = 77$ and $N_{Gr.2} = 111$). This period excludes the first months of pilot data of Group 2, as according to [36] the period of getting used to the system may not representative. Since the data covers one year, seasonal fluctuations are included in the data. Furthermore, this is considered a large enough period to assess structural changes in behavior and/or response fatigue, especially considering that Group 1 already participated for over a year before the start of the measurement period.

To assess if load is shifted in time and to assess the effect of the tariff on this load shift, the data of the smart washing machine, smart meter and PV generation meter is used (all measured in Wh/15 min.). Of the first group of participating households in total 56 households were equipped with a smart washing machine. In case of the second group all households were equipped with a smart washing machine. However, due to a lack of data as a consequence of communication issues the washing machine sample size was limited to the machines that reported over 10 wash cycles, resulting in $N_{wm,Gr.1} = 50$ and $N_{wm,Gr.2} = 100$, for Group 1 and 2 respectively.

As a consequence of showing the dynamic tariff and the (expected) PV generation on the HEMS, the household's load is

[1] The results of the limited number of tumble dryers were used in [33] to assess load shift. Due to the small sample size, these appliances are left out for the analysis in this paper.

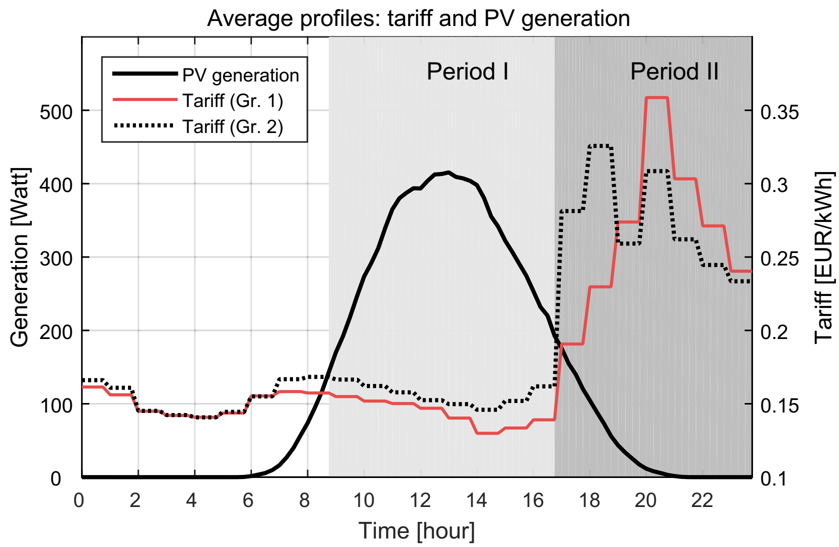

Fig. 1. Average PV generation and dynamic tariffs measured in YEM for the first (Gr. 1) and second (Gr. 2) group of participants.

expected to be higher during low-priced periods and/or periods of high PV generation and lower during high-priced periods. The latter is quantified by comparing the load of the smart washing machines of the participating households to that of a reference group. Consequently, the quantified load shift is used to reflect on the results of the surveys distributed throughout the course of the pilot. To study user behavior, four different questionnaires were distributed to Group 1. One upfront and three throughout the course of the pilot (with an interval of 6 months). Amongst others, survey data was used to study which appliances were used to shift load in time. By combining the survey results with the quantitative analyses concerning the washing machine load shift, insight into the total available flexibility is provided. Finally, to assess if this flexible load is responsive to the moment of peak-pricing, the difference in peak load of Group 1 and 2 is studied, as these groups were sometimes subject to a different moment of peak-pricing.

In conclusion, the smart appliance load shift, the reported behavior and the response towards the moment of peak-pricing provide an outlook on the available flexibility and the effect of the (tariff) design features applied in this study.

3.2.1. Smart washing machine

The washing machine load was measured separately by a metering cluster inside the machine (Wh/15 min.). Furthermore, whether or not a wash cycle was programmed using the automated function was registered for each cycle. If a cycle was programmed, the schedule horizon was also recorded. Similar to the approach in [32], the load shift of the washing machine is assessed by comparing the load of the participants to that of a reference group. The reference was obtained from smart plugs used by Dutch and Belgian households to measure the load of individual appliances. For the washing machine, the data of 274 plugs is used, for a period of one year (from 01-Jan-2013 to 01-Jan-2014). With respect to cultural and natural circumstances affecting electricity consumption Belgian and Dutch households are assumed to be similar. Also, seasonal fluctuations are taken into account as the reference data considers a period of one year.

As the washing machine load of each individual households is considered an independent random variable (i.e. independent of the washing machine load of other households) and the sample size is relatively large, the central limit theorem implies that the mean of the washing machine load is a normally distributed random variable centered on the true mean. Hence, the variance can be used to estimate the standard deviation. To assess the washing machine load shift, the average load of the participating households (Gr. 1 and Gr. 2) is compared to that of the reference group during two time periods: (i) Period I (09.00–17.00): time period with a relatively high amount of PV generation, and (ii) Period II (17.00–00.00): time period with a relatively high tariff. Both these time periods are highlighted in Fig. 1. To assess a significant difference between the washing machine load of the participants and the reference a two sample *t*-test is conducted, using the following input:

$$t = \frac{\overline{P}_{wm,P} - \overline{P}_{wm,R}}{\sqrt{\frac{(N_P-1)s^2_{wm,P}+(N_R-1)s^2_{wm,R}}{(N_P+N_R-2)}} \cdot \sqrt{\frac{1}{N_P}+\frac{1}{N_R}}} \tag{1}$$

s.t.

$$\overline{P}_{wm,P_i} = \frac{1}{(t_2-t_1)}\sum_{t_1}^{t_2} P_{wm,P_i,t} \quad \forall i \in \{1\ldots N_P\} \tag{2}$$

$$\overline{P}_{wm,P} = \frac{1}{N_P}\sum_{i=1}^{N_P}\overline{P}_{wm,P_i} \tag{3}$$

$$\overline{P}_{wm,R_i} = \frac{1}{(t_2-t_1)}\sum_{t_1}^{t_2} P_{wm,R_i,t} \quad \forall i \in \{1\ldots N_R\} \tag{4}$$

$$\overline{P}_{wm,R} = \frac{1}{N_R}\sum_{i=1}^{N_R}\overline{P}_{wm,R_i} \tag{5}$$

$$s^2_{wm,P} = \frac{1}{N_P-1}\sum_{i=1}^{N_P}\left(\overline{P}_{wm,P_i} - \overline{P}_{wm,P}\right)^2 \tag{6}$$

$$s^2_{wm,R} = \frac{1}{N_R-1}\sum_{i=1}^{N_R}\left(\overline{P}_{wm,R_i} - \overline{P}_{wm,R}\right)^2 \tag{7}$$

where $\overline{P}_{wm,P_i}$ and $\overline{P}_{wm,R_i}$ are the average washing machine load (Watt) of each individual participant and reference household during a certain time period, expressed by t_1 and t_2 (PTU). $\overline{P}_{wm,P}$ and $\overline{P}_{wm,R}$ are the average washing machine load of both the participant and reference group, of which the sample size is expressed by N_P

and N_R respectively. The unbiased sample variance of both groups is indicated by $s^2_{wm,P}$ and $s^2_{wm,R}$. To enable mutual comparisons of the time of use, the overall washing machine energy demand (kWh/year) of each household is aligned, based on average load of the participants. To determine the significance (*p*-value) of the results, the *t*-value is compared against the critical value defined by the *t*-distribution. If the *p*-value is less than 0.05, the difference between $\overline{P}_{wm,P}$ and $\overline{P}_{wm,R}$ is considered significant.

To assess flexibility due to the use of the automated function and potential response fatigue related to the use of this function, the average percentage of programmed cycles per households and the average schedule horizon of the programmed cycles of Group 1 and 2 is analyzed and used as input for the two sample *t*-test in a similar way as expressed in (1)–(7).

3.2.2. Overall electricity consumption

The tariff for both participant groups sometimes differed in the moment of peak pricing. The moment of peak-pricing is the time period with the maximum tariff during the day, as the tariff is presented in blocks of two hours, this period lasts two hours. As stated before, roughly half of the days the two groups had the same moment of peak-pricing (*equal tariff*), while the other half of the days they had a different moment of peak-pricing (*unequal tariff*). In case of an unequal tariff, the moment of peak-pricing for Group 2 generally occurred a couple of hours earlier during the evening (see Fig. 1 for the average tariffs of both groups). To gain more insight into the distribution of peak loads and the moment of peak-pricing over time, both are illustrated in the results section (Fig. 6). Fig. 6(e) also illustrates the distribution of days where both groups had the same (equal) tariff and a different (unequal) tariff. If the potential load shift is responsive to the moment of peak-pricing, the peak load is expected to be affected by the moment of peak-pricing. Therefore, price responsiveness is assessed by comparing the peak load of Group 1 and 2. To this end, the overall gross electricity consumption is determined using the smart meter data (Wh/15 min.) and PV generation data (Wh/15 min.) of the participating households.

Although Group 1 and Group 2 are similar with respect to the type of house and residents, deviations between both groups can exist caused by variables other than a difference in peak-pricing. As discussed in the literature review part (Section 2) it is of vital importance to exclude the effects of other variables to enable a transparent evaluation of the effects of price on the load. To isolate the problem, the difference in peak load between Group 1 and Group 2 is analyzed during days with an equal tariff and during days with an unequal tariff. The first, a difference in peak load during days with an equal tariff, indicates a potential bias in peak loads caused by factors other than the tariff. By comparing the difference in peak load during days with an unequal tariff to this bias, the response of the load towards the peak-price is isolated. In this case, the central limit theorem implies that the variance of the mean of the peak load, during days with an equal and unequal tariff, can be used to estimate the standard deviation. To assess the significance of this response, again a two sample *t*-test is conducted, using the following input:

$$t = \frac{\overline{\Delta P}_{eq} - \overline{\Delta P}_{uneq}}{\sqrt{\frac{(n_{eq}-1)s^2_{eq}+(n_{uneq}-1)s^2_{uneq}}{n_{eq}+n_{uneq}-2}} \cdot \sqrt{\frac{1}{n_{eq}}+\frac{1}{n_{uneq}}}} \tag{8}$$

s.t.

$$\Delta P_{eq,i} = \overline{P}_{Gr.1,i} - \overline{P}_{Gr.2,i} \quad \forall i \in \{1 \dots n_{eq}\} \tag{9}$$

$$\overline{\Delta P}_{eq} = \frac{1}{n_{eq}} \sum_{i=1}^{n_{eq}} \Delta P_{eq,i} \tag{10}$$

$$\Delta P_{uneq,i} = \overline{P}_{Gr.1,i} - \overline{P}_{Gr.2,i} \quad \forall i \in \{1 \dots n_{uneq}\} \tag{11}$$

$$\overline{\Delta P}_{uneq} = \frac{1}{n_{uneq}} \sum_{i=1}^{n_{uneq}} \Delta P_{uneq,i} \tag{12}$$

$$s^2_{eq} = \frac{1}{n_{eq}-1} \sum_{i=1}^{n_{eq}} \left(\Delta P_{eq,i} - \overline{\Delta P}_{eq}\right)^2 \tag{13}$$

$$s^2_{uneq} = \frac{1}{n_{uneq}-1} \sum_{i=1}^{n_{uneq}} \left(\Delta P_{uneq,i} - \overline{\Delta P}_{uneq}\right)^2 \tag{14}$$

where $\overline{P}_{Gr.1,i}$ and $\overline{P}_{Gr.2,i}$ are the average daily peak load (Watt) of the households in Group 1 and Group 2, respectively. $\Delta P_{eq,i}$ and $\Delta P_{uneq,i}$ indicate the difference in peak load between both groups during days with an equal tariff (n_{eq}) and days with a unequal tariff (n_{uneq}), respectively. The unbiased sample variance of this difference is expressed by s^2_{eq} and s^2_{uneq}.

If the difference in the height of the peak load between Group 1 and Group 2 is significantly affected by the moment of peak-pricing is defined by the corresponding *p*-value of the *t*-value (based on the *t*-distribution). A difference in the timing of the peak load of Group 1 and Group 2 is analyzed in a similar manner as described in (8)–(14), using the time difference (minutes) between both peak loads during days with an equal and unequal tariff as input ($\Delta t_{eq,i}$ and $\Delta t_{uneq,i}$):

$$\Delta t_{eq,i} = \bar{t}_{Gr.1,i} - \bar{t}_{Gr.2,i} \quad \forall i \in \{1 \dots n_{eq}\} \tag{15}$$

$$\Delta t_{uneq,i} = \bar{t}_{Gr.1,i} - \bar{t}_{Gr.2,i} \quad \forall i \in \{1 \dots n_{uneq}\} \tag{16}$$

4. Results

The result section is subdivided into three different subsections, covering the load shift of the smart washing machine, the appliances used for load shifting (based on the reported behavior) and price responsiveness of the peak load.

4.1. Smart washing machine load shift and usage of the automated function

The results of two sample *t*-test demonstrate a significant 31% decrease in load during the evening (Period II, $\overline{P}_{wm,P} = 8.6$ W, $\overline{P}_{wm,R} = 12.3$ W, $t(416) = -6.43$, $p < 0.001$) and a significant 20% increase during the midday of (Period I, $\overline{P}_{wm,P} = 23.8$ W, $\overline{P}_{wm,R} = 19.8$ W, $t(416) = 6.57$, $p < 0.001$). The load shift from the evening hours (high tariff) to the midday (low tariff and high PV generation) is also illustrated in Fig. 2, where the average washing machine load of the participating households is plotted against that of the reference group. A great overlap between the participants' washing machine load and the PV generation can be observed (to increase visibility, the PV generation is scaled down by a factor 15). This analysis and the results are in-line with those reported in an earlier study considering solely the results of Group 1 [32]. In this earlier study, no effect of time on load shift was measured. The evolve of a structural change in behavior can also be observed by the minimum difference in the washing machine load pattern between Group 1 and Group 2. The participants of Group 1 were already participating in the pilot for over a year before Group 2 joined in.

With respect to the use of the automated function no significant difference is detected between Group 1 and 2. The average percentage of programmed cycles is 17% and 20% per household for Group 1 and Group 2 ($t(142) = -0.7$, p = ns) and the average

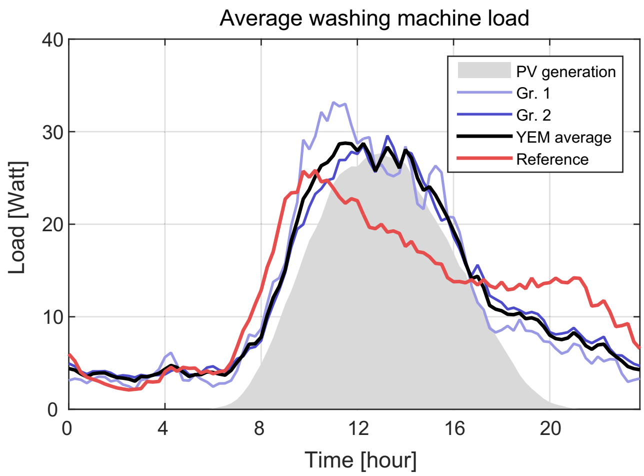

Fig. 2. Average PV generation (scaled down) and washing machine load of the participating households (*Gr. 1*, *Gr. 2* and *YEM average*) versus that of the reference group.

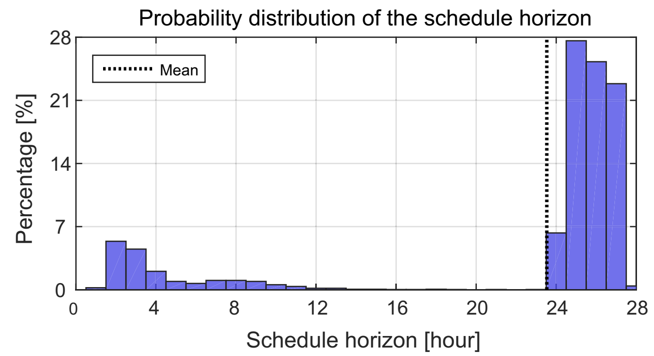

Fig. 3. Probability distribution of the number of hours provided for the schedule horizon of the programmed wash cycles.

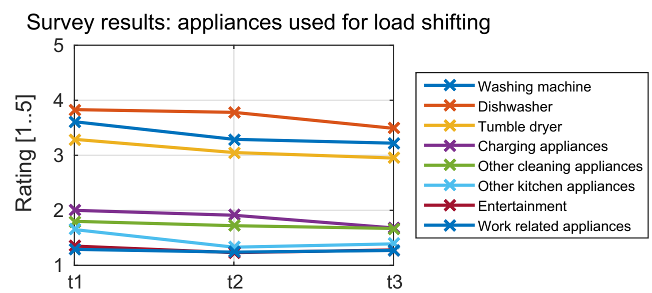

Fig. 4. Survey results indicating the appliances used for load shifting by the participating households. The surveys were conducted 6, 12 and 18 months after the start of the pilot of Group 1 (*t1*, *t2* and *t3*, respectively).

schedule horizon of the programmed cycles is 22.3 and 24 hours ($t(142) = -1.58$, p = ns). That there is no difference regarding the use of the automated function between both groups again confirms a structural change in behavior (also reported in [32]). In Fig. 3 the probability distribution of the schedule horizon of all programmed cycles is shown. It can be observed that the default schedule horizon (24 hours plus the cycle duration) is often preserved when using the automated function to schedule wash cycles. Only in 13% of the cases the default schedule horizon was shortened by using either the interface of the washing machine or the HEMS-display.

The effect of the use of the automated function on the washing machine load shift was investigated in [32]. With respect to the increase in self-consumption of PV generation, no significant effect of the use of the automated function was detected, indicating an effective manual shift of the washing machine load in time. The main conclusion was that the use of the automated function led to a washing machine load shift from the evening to the night, when people are asleep. Hence, the (semi-automated) load shift is not affected by the moment of peak-pricing during the evening. Based on the results in Fig. 3, this is explained by the respectively large schedule horizon available to schedule cycles, in general the schedule horizon is large enough to schedule each cycle during the cheapest time slot available. Hence, the load shift mainly depends on the moment of off-peak-instead of peak-pricing. This is also stressed by the similarity of the washing machine load of Group 1 and Group 2, the tariff of both groups is similar in terms of moments of off-peak-pricing (Fig. 1).

4.2. Appliances used for load shifting

In the surveys, which were distributed throughout the course of the pilot, amongst others, participants were asked to indicate if they used certain appliances to shift their load in time. To indicate this, a five-point Likert scale was used to respond to the question how often each appliance was shifted in time, ranging from 1: "*Almost never*" to 5: "*Almost always*". The results of the three surveys that were distributed after the start of the pilot (with an interval of 6 months) are shown in Fig. 4. The response rate of these surveys ranged from 78 to 90%, which is considered a high percentage, given a general drop-out of 40–60% in longitudinal studies [37].

Based on the results in Fig. 4, it is concluded that mainly the white goods (i.e. washing machine, tumble dryer and dishwasher) are reported to be shifted in time. The reported load shift of the washing machine is-line with the quantitative analyses of the measured load. Based on appliances use frequency ([5,30]), the time available for the delay of tumble dryer and dishwasher cycles is expected to be comparable to the delay times measured for the washing machine (Section 4.1). Moreover, these devices often have an autonomous delay function available, which could be used to manually program the load during the midday or night based on the dynamic tariff shown on the HEMS. Therefore, based on the quantitative and qualitative results, a similar load shift from the evening to the midday is expected for the dishwasher and tumble dryer. As no significant effect of time was found on the reported behavior related to shifting load in time [36], a structural change in behavior with respect to the use of the dishwasher and tumble dryer is expected, similar to that of the washing machine.

4.3. Overall response of the peak load towards the moment of peak-pricing

To assess price responsiveness of the flexible loads (mainly the white goods, Fig. 4), the overall load profiles of each participating household in Group 1 and Group 2 are used, of which the averages are shown in Fig. 5. When assessing price responsiveness the difference in peak load (maximum average 15 min. load during the day) between both groups during days with an equal tariff (n_{eq}=138 days) is compared to the difference in peak load during days with an unequal tariff (n_{uneq} = 227 days). As stated before, a difference in peak load during days with an equal tariff indicates a potential bias in peak loads caused by factors other than the tariff. By comparing the difference in peak load during days with an unequal tariff to this bias, the response of the load towards the peak-price is isolated. If the peak load is price responsive, the difference in peak load during days with an unequal tariff is expected to significantly differ from this bias.

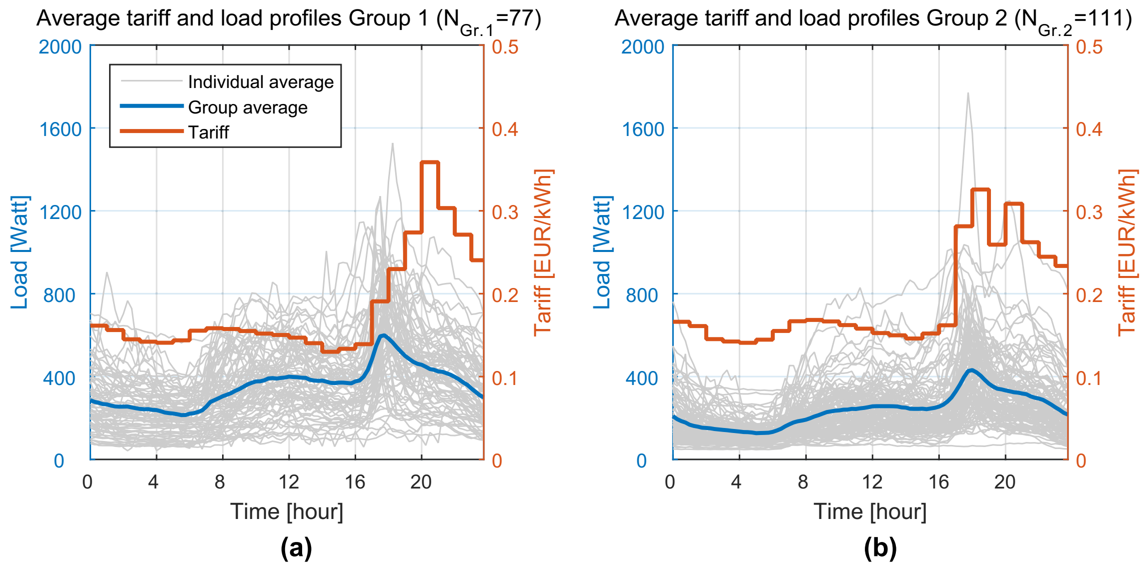

Fig. 5. Average daily load profile of each individual participating household and the average of Group 1 (*a*) and Group 2 (*b*) plotted against the average dynamic tariff for both groups.

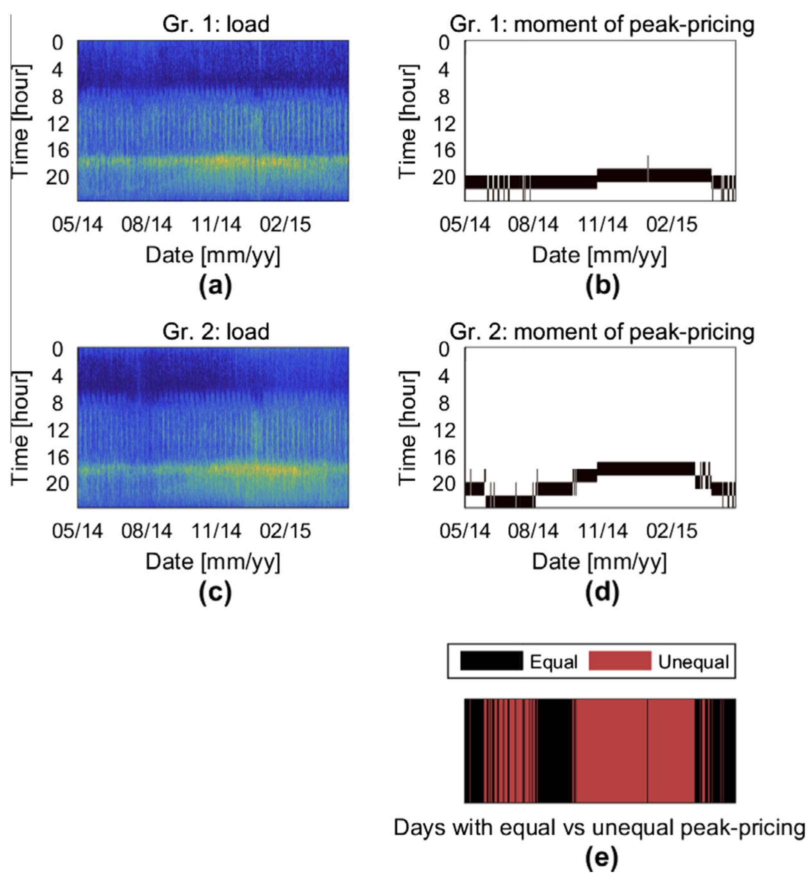

Fig. 6. Overall distribution of the load and moment of peak-pricing throughout the year for Group 1 (*a* and *b*) and Group 2 (*c* and *d*), and a distribution of the days with equal and unequal peak-pricing moments (*e*).

A bias in peak loads between both groups can be explained because the second building phase is made more efficient in terms of the operation of the pumps circulating the water in the floor heating system and the ventilation system. These energy saving measurements are expected to explain the overall difference in the energy demand and load shape (also visible in Fig. 5).

The distribution of the average load and moment of peak-pricing for both groups throughout the year is shown in Fig. 6. In Figs. 5 and 6, it can be observed that the peak load of Group 2 often coincides with the moment of peak-pricing. If the peak load of this group is price responsive, the difference in the peak load between group 1 and 2 is expected to be higher during days in which the

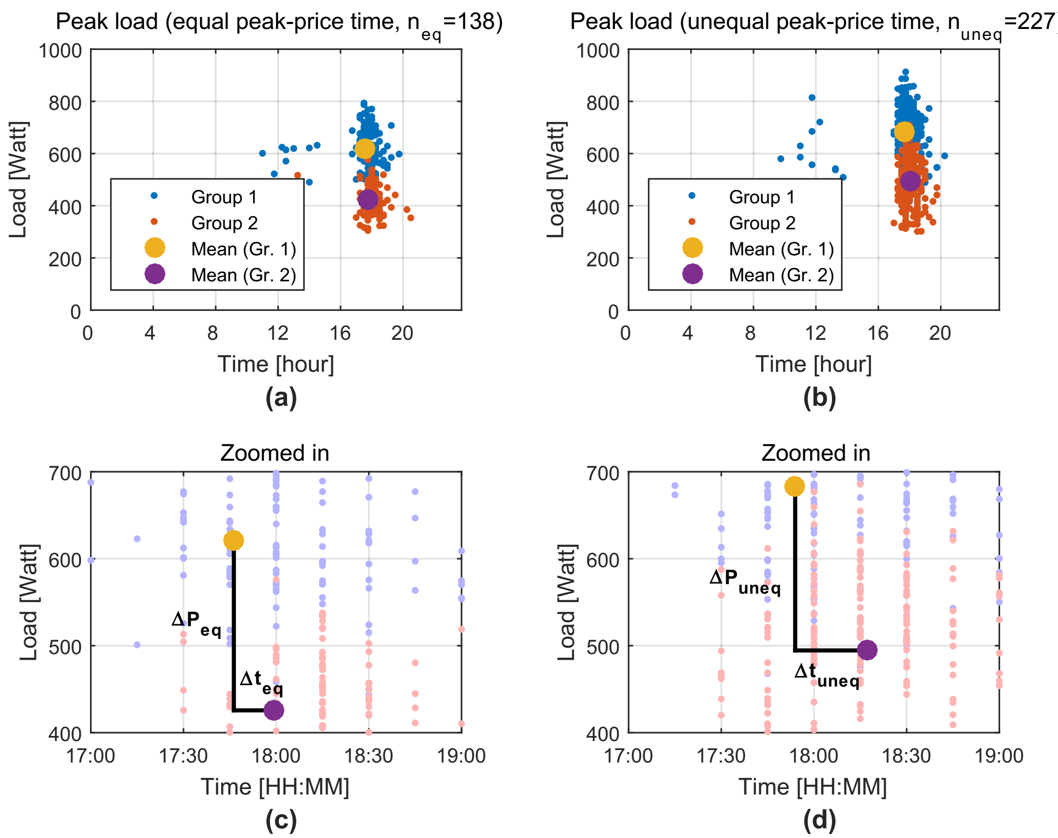

Fig. 7. Scatterplot of the peak loads (maximum average 15 min. load during the day) for Group 1 and Group 2, during days with an equal tariff (*a*) and during days with an unequal tariff (*b*). The difference between the average moment (Δt) and height (ΔP) of the peak loads is highlighted below (*c* and *d*).

peak load of Group 2 coincides with the moment of peak-pricing, while this is not the case for Group 1.

The results of the two sample *t*-test indicate that no significant change is detected regarding the difference in peak load height between Group 1 and 2 during days with an equal and unequal tariff ($\overline{\Delta P}_{eq} = 195$ W, $\overline{\Delta P}_{uneq} = 189$ W, $t(363) = 0.78$, $p =$ ns). Also, the timing of the peak load is not significantly affected by the tariff difference ($\overline{\Delta t}_{eq} = 13$ min, $\overline{\Delta t}_{uneq} = 23$ min, $t(363) = 0.88$, $p =$ ns). These results are illustrated in Fig. 7, where the scatterplot indicates the average peak loads of Group 1 and 2 during each day. The differences between both groups ($\overline{\Delta P}_{eq}$, $\overline{\Delta P}_{uneq}$, $\overline{\Delta t}_{eq}$ and $\overline{\Delta t}_{uneq}$) are also indicated in this figure.

As the difference in peak load between both groups is not affected by the tariff difference, it is concluded that the load shift that occurred as a consequence of the pilot, is not affected by a difference in the moment of peak-pricing. Moreover, it is concluded that the remaining evening peak load is mostly created by the use of appliances that are perceived strongly time-critical, such as cooking appliances (Fig. 4). That the flexible load is not responsive to the moment of peak-pricing, is in-line with the measured washing machine load shift, part of the washing machine load was shifted from the evening to the midday (cheapest time slots), irrespective of the *exact* moment of evening peak-pricing.

5. Conclusions and discussion

Interest in DR, as an opportunity to efficiently facilitate the energy transition, is high. However, the DR benefits heavily depend on the available flexibility, which in turn depends on successful implementation of DR. Therefore, the evaluation of DR implementations in real-life settings is considered essential for identifying the flexibility available and for understanding which design features can unlock this flexibility. This paper adds to the literature by presenting the results of a real-life experiment in which both manual and semi-automated DR were studied over a long period of time.

First, the real-life potential of shifting the use of the washing machine in time was quantified in this paper and it was shown that the load was shifted in time. Previous studies already concluded that white goods are suitable for manual and/or semi-automated DR [10–17]. However, these studies were based on expectations regarding the households' willingness and ability to shift these loads in time. In this study, participants were simulated to shift load from evening peak hours to the midday or night, when electricity is locally generated or when electricity demand and energy market prices are generally low. Participants received a HEMS, which was connected to a display in their living room, that showed the dynamic tariff and own PV generation. The results show, that the washing machine evening load was reduced by 31%, while the load during the midday was increased by 20%. No effect of time was found on these results, indicating a stable behavior change. To further investigate this load shift, the use of the automated 'smart' function was assessed. Although the use of this function was limited, the time horizon provided by the participants to schedule cycles was generally large (>23 hours). Within this schedule horizon, the washing machine load could easily be shifted from peak to off-peak moments, when prices are the lowest.

The survey results indicate that the dishwasher and tumble dryer are roughly as often used for DR as the washing machine. Supporting the washing machine load shift by the reported behavior of the participating households, confirms findings from previous research that households are able and willing to shift the use of white goods in time. As the use frequency of these appliances is comparable, a similar load shift is expected for the dishwasher and tumble dryer. Similar to the measured washing machine load shift, the reported load shift of the tumble dryer and dishwasher did not change over time (>1 year), again indicating a structural change in behavior.

Second, price responsiveness was assessed based on the difference in peak load between group 1 and 2, as these groups were subject to a distinct evening peak-pricing tariff. Based on the results, it is concluded that the remaining peak load is not influenced by the moment of peak-pricing. The load that was shifted in time (mainly white goods), was shifted to the midday or night (to profit from the lowest prices and/or increase in self-consumption of PV generation). Hence, the load was shifted irrespective of the moment of evening peak-pricing. Moreover, it is concluded that the remaining evening peak load is mostly created by the use of appliances that are perceived time-critical, such as cooking appliances.

In this study, the dynamic tariff was presented in an intuitive way, in blocks of two hours and linked to local generation, which proved to be effective to stimulate a structural change in behavior to use flexible appliances when prices are the lowest. However, as the load shift was not affected by a different moment of peak-pricing, this suggest that advanced tariff schemes are unnecessary and according to [38] can even distract and confuse the consumer. Therefore, we suggest that a simple and transparent tariff design is most effective to stimulate (manual) residential demand response. Such a tariff should consists of limited blocks and should mostly emphasize on the 'right' moments to use electricity, intuitively linked to renewable generation.

The analysis concerning price responsiveness in this paper was conducted in a transparent way, by isolating the problem as much as possible. This way the effect of other variables, which are often found to influence price responsiveness and hence causing deviations in reported results in the literature [19–24,26–28], are eliminated in an appropriate manner. However, by isolating the problem, the conclusions drawn solely cover the effect of evening peak-pricing on the peak load. Thereby, amongst others, the effects of demand reduction due to the introduction of dynamic tariffs are not covered and hence remain outside the study scope.

This study gained many valuable insights into the flexibility available at residential households and which design features can best be used to unlock this flexibility. The results show that households are willing to be involved in DR programs which incentivize shifting load in time. Therefore, it is likely that they will also embrace other forms of (semi-)automated DR programs. However, it is important to increase insight in the effects of real-life DR implementations. In this study the use and effect of the automated function for the washing machine was studied, and based on survey results, similar results are expected for the tumble dryer and dishwasher. Still, it would be worthwhile to study the use and effect of an automated function for these appliances in practice as well. Additionally, the effect of different design features should be studied, such as the use of different or adaptable default values for the automated function.

However, most of all, future research should move to the acceptance and the effects of shifting the load of new energy efficient technologies, such as electric vehicles and heat pumps. In terms of absolute load, the flexibility potential nowadays is limited. With the increasing penetration of electric vehicles and heat pumps, the flexibility potential is expected to increase significantly. As utilizing the flexibility of electric vehicles and heat pumps requires limited to no consumer interaction, it might also be suitable to use different designs and incentives to exploit the total potential of manual and (semi-)automated DR in (future) residential areas. However, effects of DR implementation on the use of these new energy technologies remain uncertain, until real-life insights from different pilot set-ups are gathered.

Acknowledgments

Your Energy Moment Zwolle is a partnership between Enexis (Dutch DSO), Eneco (energy supplier), SWZ (housing cooperation), Flexicontrol (developer of smart in-home devices), CGI (developer of Central Energy Management System) and Eindhoven University of Technology. The research was partially performed within the framework of the research program Innovatie Programma Intelligente Netten (Innovation Program Smart Grids) that is supported financially by RvO, the Netherlands Enterprise Agency. The authors gratefully acknowledge the contributions of all partners and participants involved, who made it possible to test concepts and ideas in a living lab environment.

Appendix A

This appendix provides an overview of the homepage of the HEMS and the screen that can be used to adjust the start and finish time of the schedule horizon of programmed wash cycles. The dynamic tariff on the homepage is presented in an intuitive way using different symbols, e.g. a low tariff (<0.2 €/kWh) corresponds to a wallet with two coins, a medium tariff (0.2–0.3 €/kWh) to a wallet with one coin, while in case of a high tariff (>0.3 €/kWh) no wallet is displayed (see Fig. A1).

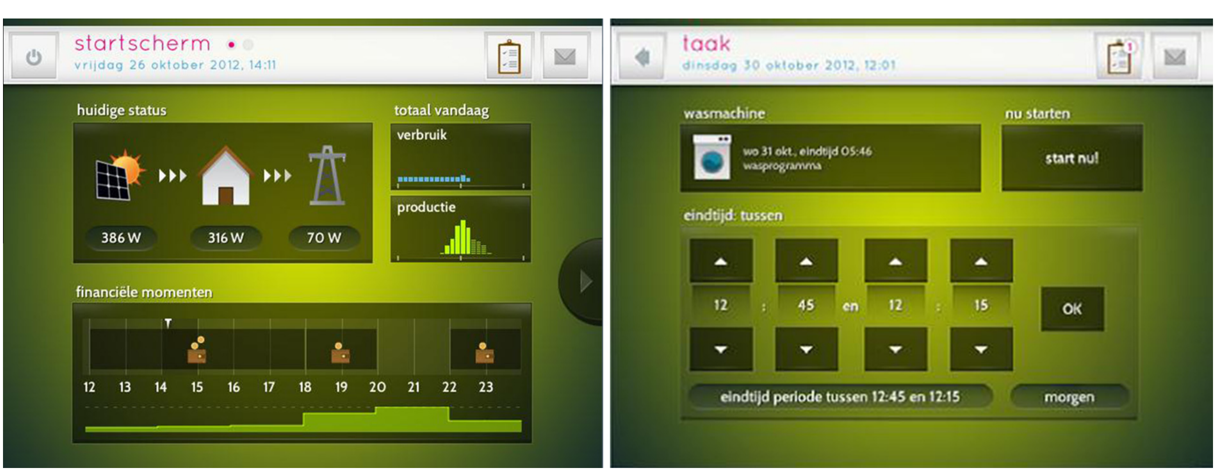

Fig. A1. *Left:* HEMS homepage, which provides direct and historical feedback on electricity in-home flows, indicates the expected PV generation and the relative tariff height. *Right:* screen to adjust the start and finish time of the schedule horizon of programmed wash cycles.

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