Understanding the Limitations of Eco-feedback: A One-Year Long-Term Study

Lucas Pereira, Filipe Quintal, Mary Barreto, and Nuno J. Nunes

Madeira Interactive Technologies Institute, Funchal, Portugal
{lucas.pereira,filipe.quintal,mary.barreto}@m-iti.org, njn@uma.pt

Abstract. For the last couple of decades the world has been witnessing a change in habits of energy consumption in domestic environments, with electricity emerging as the main source of energy consumed. The effects of these changes in our eco-system are hard to assess, therefore encouraging researchers from different fields to conduct studies with the goal of understanding and improving perceptions and behaviors regarding household energy consumption. While several of these studies report success in increasing awareness, most of them are limited to short periods of time, thus resulting in a reduced knowledge of how householders will behave in the long-term. In this paper we attempt to reduce this gap presenting a long-term study on household electricity consumption. We deployed a real-time non-intrusive energy monitoring and eco-feedback system in 12 families during 52 weeks. Results show an increased awareness regarding electricity consumption despite a significant decrease in interactions with the eco-feedback system over time. We conclude that after one year of deployment of eco-feedback it was not possible to see any significant increase or decrease in the household consumption. Our results also confirm that consumption is tightly coupled with independent variables like the household size and the income-level of the families.

Keywords: Eco-feedback, Electric Energy Consumption, Sustainability.

1 Introduction

The notion of wellbeing based on personal ownership and mass consumption was largely identified as one of the factors leading to the growth of electricity consumption in the last years. As more people in developing countries have access to higher levels of comfort it is expected that the residential energy consumption will have a tremendous impact on the long-term effects in carbon emission and global warming.

Eco-feedback technology [1] is defined as the technology that provides feedback on individual or group behaviors with the goal of influencing future energy saving strategies. Eco-feedback has proven to be an effective way of promoting behavior change and considerable savings in electricity consumption [2]. However and despite the successful results reported, most research was conducted in short-term studies and therefore there is little evidence on the long-term effects of eco-feedback. Further research reported that after an initial period of exposure to eco-feedback the tendency

A. Holzinger and G. Pasi (Eds.): HCI-KDD 2013, LNCS 7947, pp. 237–255, 2013.

is towards a reduction in the attention provided to the feedback leading to behaviors relapse [3].

This paper contributes to the ongoing research efforts by presenting the results of the long-term deployment of a real time eco-feedback system in 12 households for the period of 52 weeks. We start by looking at the state of the art and defining our research goals for this study. In the next two sections we show how our eco-feedback system was designed and deployed, including an in-depth description of the sensing system and the process of selecting an adequate sample for the long-term study. We then present the most important results and discuss the key findings and implications of this work for forthcoming eco-feedback research. Finally we conclude and outline future work.

2 Related Work

In the last couple of decades considerable research was done in the field of eco-feedback technology. Fischer [2] reviewed approximately twenty studies and five compilations of publications between 1987 and 2008 exploring the effects of eco-feedback on electricity consumption and consumer reactions. The most notable findings reported that eco-feedback indeed resulted in energy savings between 5% and 12%, and that the greater changes in consumption would result from computerized eco-feedback like for instance in [4].

The literature is rich in interactive approaches to eco-feedback. For example in [5] the authors ran a three-month study in nine households where the eco-feedback was deployed in a clock-like ambient interface that would translate electricity consumption into graphical patterns. This study showed that people immediately became more aware of their energy consumption, and even developed the ability to associate the displayed patterns with the actual appliances used. In another example [6] the authors reported on a system that would give detailed eco-feedback information on individual appliances. Preliminary results on this experiment showed a reduction of 5% over the previous year when the eco-feedback was not available.

On the commercial side several models of eco-feedback systems reached the market in the last years. In an attempt to better understand the adoption and implications of commercial solutions, Miller and Buys [7] conducted a study with seven families that were using a commercial energy-and-water consumption meter and generated guidelines in how eco-feedback systems should be built and marketed. For instance, the cost of the system was a major issue for residents that were either engaged with the product or not. A second topic of discussion was the lack of product support advocated by the users, which immediately pointed out the problem of understanding the user experiences and perceptions around smart meters.

In an attempt to address this issue authors in [8] installed smart meters in 21 Belgian households between two and four weeks. They found out in accordance to other studies that despite an increased awareness there was no significant behavior change towards conservation of energy. Another important finding of this research reports that people had difficulties interpreting kilowatt-hour and that the corresponding conversion to monetary cost demonstrated irrelevant economic savings.

The emergence of smart handheld devices also presented new opportunities for researchers to test different eco-feedback systems. In [9] the members of 10 households were given access to a mobile power meter that would run either on a smartphone or a tablet. Findings suggested that the householders gained a deep understanding of their own consumption and that users found the feature of comparing their consumption with other community members useful. The mobility aspect was also important, as participants were able to access their consumption from virtually everywhere.

With the constant evolution of technology also came the possibility of providing disaggregated power consumption by individual appliance, division of the house or event daily activities like cooking dinner or doing the laundry. Recently in 10 Costanza and colleagues conducted a field study where they wanted to learn if users were able to easily leverage a connection between appliances and their day-to-day activities. This study lasted for two weeks and twelve participants were asked to use a system where they would be able to tag appliances to a time-series of their energy consumption. The results of the trial showed that the system was successful in engaging users and providing accurate consumption levels of some appliances that were consuming more than what they initially expected. Another important result was noticing that when tagging, users would refer to energy consumed by activity rather than just the tagged appliance.

Eco-feedback through persuasion was also attempted by some authors, for instance in [11] Gamberini and his pairs explored the possibility of encouraging electricity conservation practices through a mobile persuasive game. This eco-feedback game provided next-to-real-time, whole house and appliance based consumption information. Four families used the game during 4 months, and results showed that users kept playing it during the whole trial, despite the gradual reduction of accesses per day that was justified by the users as the result of getting more familiar with the application and what it had to offer.

All of the aforementioned studies clearly advocate for the short-term effectiveness of eco-feedback technology, in particular when considering disaggregated and interactive eco-feedback. However, we argue that these studies did not last enough to properly assess their long-term effectiveness. In fact, the gradual decrease of attention shown in the later study may indicate that once the novelty effect has passed users will go back (relapse) to their original behavior. This is defined in literature as response-relapse effect, where after a while the user behaviors (and hence consumption) will relapse to values prior to the intervention. This effect was reported by the authors' in [3] when investigating how the residents of a dormitory building would respond to different consumption information. The authors noticed that after a period when no feedback was provided the behaviors would approximate the ones before the study.

In this paper we argue that long-term studies of eco-feedback system are required in order to understand the lasting effects of this technology as a driver for behavior change. Here we explore some very important questions like: i) How is the eco-feedback system used after the novelty effect has passed? ii) How long does the novelty effect last? iii) How does the demographic data from the residents affect energy consumption?

This paper is a follow up to an initial short-term three-month study reported in [12]. In our first evaluation of this system we saw a reduction of 9% in consumption but also observed that users significantly decreased the interactions with the eco-feedback system after four weeks of deployment. Our initial results suggested that further research was needed in order to fully understand the potential and underlying issues with the long-term deployment of eco-feedback. In this second study we aimed to investigate further how the system was used after the novelty effect passed. We wanted to explore if there was a decrease in energy consumption as a result of eco-feedback intervention and also if further changes in the system could raise attention back to the eco-feedback. With a longer deployment we were also able to investigate other factors influencing behavior change, for instance demographic independent variables like family size and income.

3 System Design

In this section we briefly describe our eco-feedback research platform, which involves both the sensing infrastructure and the communication with the eco-feedback interface. For a throughout explanation of our framework please refer to [12] and [13].

3.1 Sensing Infrastructure

Our eco-feedback infrastructure is a low-cost, end-to-end custom made non-intrusive load monitoring system. Non-intrusive load monitoring (NILM) stands for a set of techniques for disaggregating electrical loads only by examining appliance specific power consumption signatures within the aggregated load data. NILM is an attractive method for energy disaggregation, as it can discern devices from the aggregated data acquired from a single point of measurement in the electric distribution system of the house [14].

Our NILM system consists of a netbook installed in the main power feed of each house (see Figure 1- left) covering the entire household consumption and thus removing the need to deploy multiple (intrusive) sensors. The netbook provides a low-cost end-to-end system: the audio input soundcard is used as the data acquisition module (two channels, one for current and another for voltage); the small display and the speakers provide the interactivity; the Wi-Fi card enables communication over the Internet; and the camera and built-in microphone serve as low-cost sensors for human activity sensing.

Fig. 1. System installed in the main power feed (left) and a householder interacting with the eco-feedback (right)

The current and voltage sample signals acquired with the soundcard are pre-processed and transformed into common power metrics (e.g. real and reactive power) that are representative of the energy consumption. These power values are used for event detection, event classification and, ultimately, the breakdown of consumption into individual appliances. In parallel, power consumption and power event data are stored in a local database to be used by any external application to provide eco-feedback to the householders.

3.2 Eco-feedback

The front-end eco-feedback component provides two different representations for the real time and historical consumption of the house. Our interactive visualization was implemented following the recommendations from previous studies in energy eco-feedback [15 - 17] that distinguish real-time and historical feedback. Real time feedback, which is said to be responsible for 5 to 15% of the changes in user behavior, displays the current energy consumption as well as major changes and trends in the current consumption. Conversely historical feedback refers to all the information collected (e.g. monthly values of energy consumption), and according to the literature can lead up to 10% of the users' behaviors towards future energy consumption by simply offering the possibility of reviewing and comparing data among different historical periods of time. To cope with these guidelines we have designed our eco-feedback user interface in a way that users could quickly switch between historic and real-time modes. Figure 2 shows how the information is organized in our user interface.

The center of the eco-feedback interface represents both real and historical consumption data using a wheel like graph. The left and right side of the interface present additional information, including weather, numerical consumption and comparison to previous periods. On the right hand side the interface provides notifications, suggestions and motivation hints. In the following we detail the interface for both the real-time and the historical views.

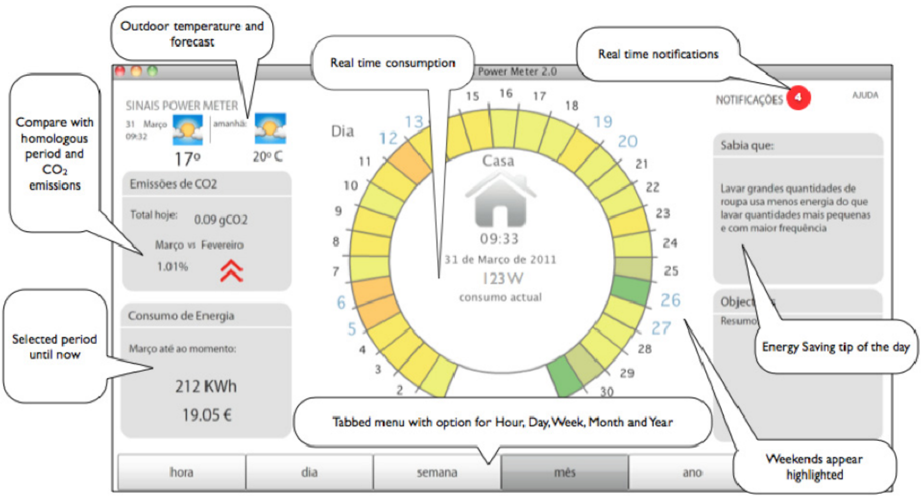

Fig. 2. Eco-feedback user interface showing the current month consumption

Real-Time Eco-feedback. The real time consumption as well as notifications and comparisons are always presented to the users regardless of the active view. The current consumption is presented in watts (in the center of the interface) and updated every second. The last hour view shows real time notifications, triggered every time the energy monitor detects a power change above a pre-defined threshold. The event notification is represented by a small dot that is added to the interface close to the time of occurrence, as shown in Figure 3. The size of the dot indicates the amount of power change, and clicking on it reveals the appliance that has the highest probability of triggering that event prompting the user to confirm, rectify or discard the guess.

Fig. 3. Real-time notifications offering users the chance to label power changes

Historic Eco-feedback. The historic data (current day, week, month and year) is presented in two different modalities: the more traditional displays the quantities in numerical format (when hovering the mouse over a specific time period), while the less traditional consisted of a color-code that would change according to the household consumption (the colors would vary from a light green when the consumption was low to a very dark red when the consumption reached high levels). For example, in Figure 2 it is possible to see the consumption for the whole month of March and that it was 1% higher than the previous month.

Inferring User Activity and Usage Patterns. One important feature of our eco-feedback research platform is the possibility to infer human-activity and therefore record quantitative measures of user attention and usage patterns.

We achieve this in two ways: 1) by keeping track of mouse clicks and transitions between the different visualizations, and 2) by inferring human presence using the built-in webcam to detect motion and detect faces when residents are passing by or looking at the netbook. We refer to these as user-generated events as the users trigger them when they are interacting with the system.

All of this quantitative data is stored on the local database and further exported to the data warehouse that collects all the data from the multiple houses participating in the experiment. Our goal was to complement the qualitative feedback with actual measures of user activities and usage patterns.

4 Deployment

In this section we describe the process of deploying our eco-feedback research infrastructure for the field-testing. We start by explaining the initial sample selection, installation procedures and the nature of the collected data. We finalize with a description of our participants and how we reached the final numbers of 12 families using the system during 52 weeks.

4.1 Sample Selection

The sample selection for the first study was based on an extensive analysis of the consumption patterns of 46 000 household consumers in Funchal, a medium sized city of southern Europe (about 150 000 inhabitants).

For that purpose the local electricity company gave us access to the energy consumption data of all the consumers in the city for a period of two years. From that baseline data we divided the consumers in four levels according to their annual consumption in Euros. These four levels were then used to select a nearby neighborhood where we could easily find a sample that would be representative of the city.

The recruitment was done with personal visits to the selected buildings explaining the project and collecting additional demographic data from those that would volunteer to participate. In the end we were able install the system in 17 apartments as well as in six individual homes that volunteered to participate and five additional houses recruited from professors and students involved in the project.

The first version of our system was installed in June 2010, and was remotely updated to the new version in the last week of November. Users were informed of the update via informal phone calls or in the previous two weeks during the first round of interviews.

4.2 Data Collection

The deployment lasted until the end of 2011. In figure 4 we present the major milestones of the deployment including three interventions with the users: i) interviews in the third week of February 2011; ii) informal visits in the last two weeks of July 2011 and iii) a last round of interviews during all of December 2011. The system was removed from the houses during January and February 2012.

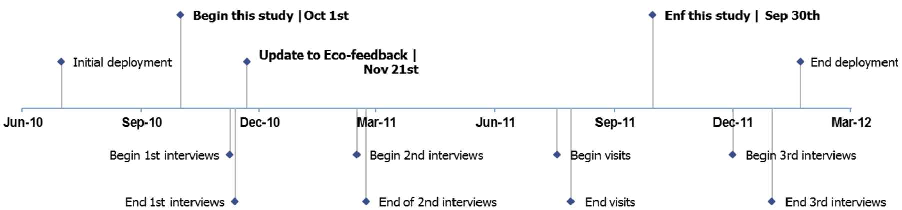

Fig. 4. Timeline chart showing the most relevant events of this eco-feedback deployment

During and prior to the study we collected both qualitative and quantitative data from the households. Quantitative data includes electric energy consumption samples (two per minute), power events (both on and off including the transient for active and reactive power) and user interactions with the eco-feedback system (including movement, face detection, mouse and menu selection). Qualitative data includes demographics (age, occupation, income, literacy, etc. for all family members), environmental concerns (from semi-structured interviews), and a detailed list of appliances in the house and reconstruction of family routines (from semi-structured interviews and diary studies).

4.3 Participants

From the 21 families that took part in the first study we ended with a final sample of 12 households. The main reasons for this high sample mortality (~ 43%) were mostly technical issues like stability of the Internet connection and long periods of absence of the families, including some moving out to a new house.

Our final analysis sample was the result of maximizing both the number of houses and the deployment time. Another requirement was that the final sample had to include data from both deployments in order to integrate the novelty effects introduced by the different versions of the eco-feedback system. This said we ended up choosing the period between the October 1st 2010 and September 30th 2011, as this represents exactly 52 consecutive weeks of data for 12 apartments all from the originally selected neighborhood. Table 1 summarizes the demographic data for our final sample participants.

Table 1. Demographics of the participating families

Family	Size (number of bedrooms)	People	Children (and ages)
1	3	4	2 (5, 10)
2	3	5	1 (10)
3	3	4	2 (8, 14)
4	3	3	1 (1)
5	3	4	2 (1, 7)
6	1	1	0
7	3	3	1 (5)
8	1	2	0
9	3	4	2 (2, 4)
10	2	2	0
11	2	3	1 (15)
12	3	2	0

4.4 Environmental Concerns

Since one important issue regarding the participants was their level of environment concerns we collected additional qualitative data from interviews with people from the households in the sample. When asked about environmental concerns nine out of the twelve families pointed global warming as a serious concern and six of these families considered that reducing their energy consumption would have a positive impact on the environment.

When asked about the adoption of sustainable actions eight families indicated that reducing personal costs and guaranteeing the wellbeing of future generations was their main motivations to reduce energy consumption. Despite this, when questioned about a particular number of sustainable behaviors less than half reported they had adopted these on a daily basis. The more frequently mentioned behaviors were: switching off the lights on empty rooms, washing full loads of clothes and acquiring energy efficient lights.

The complete list of actions reported by the families was over 40 actions related to energy, water and food consumption or conservation. These actions included not only individual measures as for example use public transportation, but also, social oriented activities such as carpool. The interaction with the participants, facilitated by the interviews and the overall study, allowed us to observe their increased level of awareness. The participants already performed actions related to saving energy previously to having the system. These levels of awareness were enhanced when exposed to the eco-feedback system. However, this was not evaluated through a scale of environmental concerns.

5 Evaluation

In this section we report the evaluation of the data collected during the long-term deployment of eco-feedback. We start by analyzing only the aggregated data, handling the sample as one group and not selecting any particular house. Then we rank our sample into three categories and investigate if there were significant changes in the consumption when considering background variables, such as the weather conditions, the household size and income-level of the families.

For this analysis we use the week as our standard period because it provides the most stable variance as it was expected because it corresponds more directly to a recurring family routine. For some specific cases where other variables were more appropriate day and month were also used as the aggregation time period.

5.1 Overall Power Consumption

We first looked at the average consumption of all the houses aggregated by week. The weekly average of power consumption (n = 624) was 62.45 kWh (s = 27.49 kWh). The high variance is explained by the considerable differences between households, for example three households had a weekly average of less than 40 kWh, while four houses had an average consumption between 80 and 110 kWh.

As a consequence we decided to rank our sample in three categories (low, average and high consumption), based on the 1/3 percentiles of the weekly consumption expressed in kWh. The following categories were defined: A (<= 42.3kWh), B (42.3kWh – 76.92 kWh) and C (> 76.92kWh) with four houses each and the average consumption (n = 208) was 36.45 kWh (s = 7.76 kWh) for category A, 56.30 kWh (s = 11.59 kWh) for category B and finally category C with 94.6 kWh (s = 17.98 kWh) respectively.

Changes in Consumption. To check for significant changes in consumption during the deployment of the eco-feedback we used a Wilcoxon signed-rank test, to compare repeated measures between consecutive months. For this analysis we used months instead of weeks because the test used is known to perform better for less than 20 values in each sample. Results showed no significant differences (for $p < 0.05$) in any of the categories.

In an attempt to get a better understanding of these results we individually asked the families about any changes in their consumption with most of them confirming that there were no real savings in the overall electricity bill. This was either because families found it difficult to reduce or even control their consumption levels as stated *"We didn't notice major changes. We already did a couple of things we would already disconnect some devices, toaster or radios. (...) The electricity is the hardest thing to control for us, the water seems easier."* (Family 11, Mother). Or due to the fact of current tax increases the local company put in practice as stated by this family *"Our consumption wasn't reduced. We compared with the bills and there was a tax increase, the consumption seems to be always the same for us, before and after having this device here."* (Family 5, Mother). However others noticed some decrease in consumption after having taken some measures: *"We changed all the lamps in the house to more energy efficient ones. I started to turn off the lights more often because I could see the impact of it so I had to do it. (…) Our bill wasn't reduced to 50% but it was reduced.*" (Family 12)

Consumption and Weather Conditions. The deployment took place in Madeira Island known to have one of the mildest climates in the world with average temperatures ranging from 17°C in the Winter to 27° in the Summer. Still we wanted to understand how the climate might affect the electricity consumption. Therefore we compared the consumption between seasons as well as wintertime (WT) and daylight saving time (DST). For this analysis we used the daily consumption as the minimum unit of time.

The tests (for $p < 0.05$) have shown no significant differences in consumption between the seasons or between WT and DST for any of the categories suggesting that we should not expect a big variation of the energy consumption during the year. One possible explanation for this is, as previously mentioned, the low variation in the temperatures during the period of study - for the duration of the deployment ($n = 12$) the monthly average temperature was actually 19.8 ° C ($s = 2.89$ ºC).

Consumption and Household Size. According to literature the number of people living in the household is the single most significant explanation for electricity consumption. The more people living in the house the more energy is used [18]. If we look at our consumption categories this is a direct conclusion. In fact the number of people in each household increases with each consumption category: category A has 9 people (7 adults and 2 children); category B 12 people (8 + 4); and category C 16 people (9 + 7). Therefore we have further investigated this topic by dividing the sample in categories according to the number of people in the house and looking for significant differences among these groups. We found four categories: 1 person (1 house), 2 people (3 houses), 3 people (3 houses) and 4 people (5 houses).

We tested consumption by household size using a Mann-Whitney U test and found a significant difference between 2 or 3 people (mean ranks were 21.86 and 51.14 respectively; $U = 121$; $Z = -5.935$; $p < 0.05$; $r = 0.699$) and 2 or 4 people (mean ranks were 27.86 and 60.88 respectively; $U = 337$; $Z = -5.623$, $p < 0.05$, $r = 0.57$). However no significant differences were found between 3 or 4 people. We haven't considered the single-family house due to being an isolated case in our sample.

To further analyze the effects of the number of people in the energy consumption we then categorized our sample by the number of children. We found three categories: 0 children (4 houses), 1 child (4 houses) and 2 children (4 houses). The same test shows significant differences between having none or one child (mean ranks were 26.96 and 63.22 respectively; $U = 118$, $Z = -6.743$, $p < 0.05$, $r = 0.74$) and zero or two children (means were 31.69 and 72.75 respectively; $U = 345$, $Z = -6.770$, $p < 0.05$, $r = 0.65$). No significant differences were found for having one or two children.

Our results confirm previous findings and general common sense that more people in the house result in more energy spent. Regardless one interesting finding worth investigating in the future is the fact that no significant differences appear when considering 3 or 4 persons or 1 or 2 children. One potential explanation is that after some point houses with more people will become more energy efficient, since the electricity usage per person tends to decrease.

Weekdays and Weekends Consumption. Finally we have also looked at average daily consumption and compared the weekdays and weekends. Table 2 summarizes the average consumption in each category for the given period.

Table 2. Weekday and weekend average consumption by consumptio category

	Weekdays (n=1044)	Weekend (n=416)
Category A	5.15 (s = 1.57)	5.39 (s = 1.72)
Category B	7.93 (s = 2.45)	8.40 (s = 2.67)
Category C	13.44 (s = 3.98)	13.78 (s = 3.82)

These results show that for all categories (and mostly B) there is a slightly higher consumption on weekends, which could be related to the fact that people tend to spend more time at home on weekends. Still (for $p < 0.05$) these differences are not significant in any of the categories.

5.2 Interaction with Eco-feedback

Similarly to the consumption analysis we will first look at the interaction events aggregated by week of study. The weekly average of mouse clicks ($n = 624$) was 8.93 ($s = 12.65$) and 23.92 ($s = 107.9$) for motion detection. After careful analysis of the data we found that the abnormal standard deviation for the motion events was related to the fact that one family also used the netbook to browse the web without closing the eco-feedback application. Hence our system detected a high number of non-intentional motion events (average motion for that house was 231.85 with a standard deviation of 304.64 for $n = 52$ weeks).

Therefore, after removing this house from the analysis, we ended up with a weekly motion detection average (n = 572) of 5.01 (s = 11.13) and 8.54 (s = 12.41) for mouse clicks. This difference between motion and clicks suggest that the notebook was only in the open position when users were in fact looking at the feedback and probably the main reason for that was its position behind the entrance door that would is some cases force the users to keep it closed. From this point forward we will be using only mouse clicks as the grouping variable for user interaction.

Long-Term Interactions. As mentioned in the introduction, one of the goals of this deployment was to achieve a better understanding on how the eco-feedback system was used after the novelty effect passed. Therefore we looked at the user-generated events (in this case the total number of mouse clicks) exactly when the novelty effect was introduced (deployment of the new user interface) until the last week of the study, as shown in Figure 5.

Our analysis shows an immediate increase of almost 25% in the user interaction right after installing the new interface (in weeks 8 and 9). These results confirm that as expected users react to new versions of the eco-feedback with an increased usage of the application. However our analysis also indicates that only three weeks after the new deployment the number of interactions dropped considerably until week 20 (a decrease of 45% when compared to the three weeks after the new deployment).

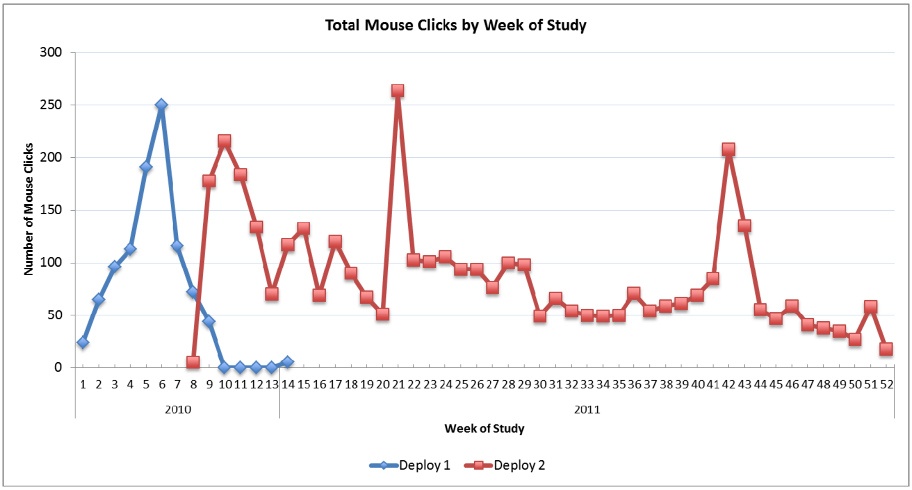

Fig. 5. Number of user interactions (mouse clicks) with the eco-feedback during 52 weeks

We clearly notice here the response relapse effect, which was significant if we consider that after 52 weeks the decrease in the number of interactions was almost 90% (at a drop rate of 2.2% per week). This decline was only interrupted by weeks 22 and the period between weeks 42 and 44 when we conducted interviews with the users, which also raised their awareness to the eco-feedback system.

Additionally, in the qualitative studies we asked users about this decrease of interest in the eco-feedback. Some families justified it with the lack of time in their routines, others felt like after a few weeks they already had a good perception of their consumption as shared by this family *"I wouldn't go there because most of the times I didn't have time to check it. I would just arrive home, get things done around here and go to sleep and start again the next day."* (Family 5, Mother). Their interaction with the system was reduced as a result of a more accurate picture of their consumption levels as stated by this family *"We would check our consumption more often initially until we got a rough idea or perception of what our consumption was but after that it would become less frequent."* (Family 12, Wife)

Another reason that was pointed for the lack of interest was the fact that the system became "yet just another electric device": *"And it became a habit to have it. I would check it whenever I would remember. I know already the power of each of device in the house, I already measured it (…) having this or that device working would not make me want to check the meter by itself."* (Family 7, father). Nevertheless other families kept using the system even if less frequently, as this father mentioned: *"We didn't ignore the device I would look at it everyday. What I noticed is that we achieve an average of consumption. And because we use the same devices all the time our attention to the system might decrease, we don't analyze it so carefully."* (Family 9, father)

5.3 Navigation in the Eco-feedback

We also wanted to understand which features of the system drew more attention to the users and the analysis showed that the most visited view was the current day consumption. This view had more accesses than all the other options together with an average (n = 11) of 179.27 (s = 63.84) mouse clicks. The second most used feature was the weekly consumption (average of 18 interactions, s = 13.15) while the least favorite was the year view (average of 6 interactions, s = 4.38). The total interactions with the different eco-feedback views are presented in figure 6.

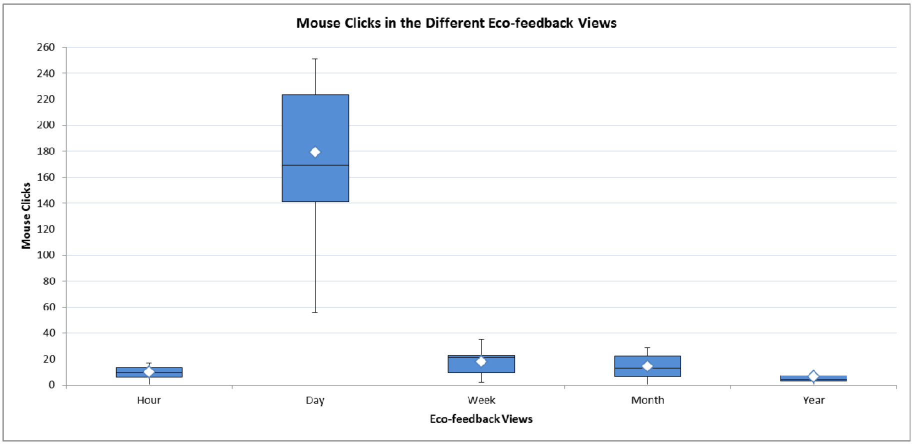

Fig. 6. Average interactions (mouse clicks) with the different eco-feedback screens

Another characteristic of the data that drew our attention was the fact that most interactions happened after 9PM peaking at 11PM with an average (n = 11) of 91.18 mouse clicks (s = 34.04). We believe this is a strong indicator that checking the consumption was something that users did at the end of the day. Most likely due to availability as referred by this family *"I would use it more at night when I was at home. I would see the consumption levels and if I saw something more than usual, I would assume that she had done something different or had used a device."* (Family 1, Husband) The average number of mouse clicks per hour of the day is shown in figure 7.

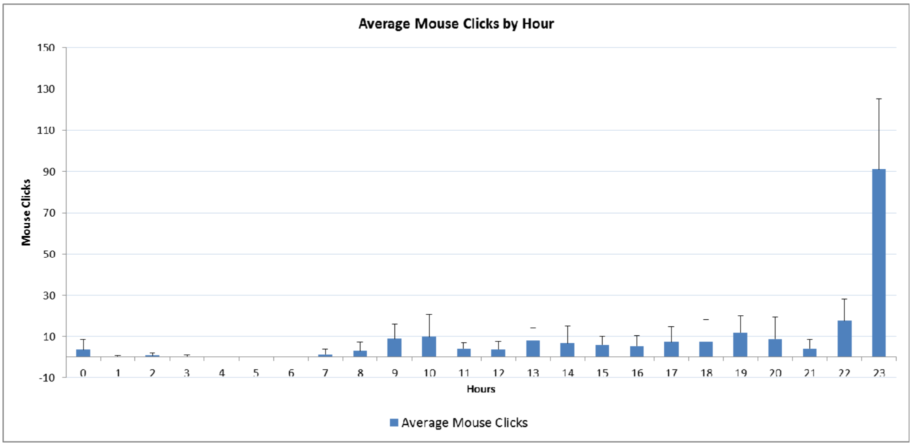

Fig. 7. Average interactions (mouse clicks) by hour of the day

When asked about the new user interface the tendency was to prefer the last one better, as shared by this family *"The other previous graph [column chart] was harder to interpret. This one is much better, its way more usable."* (Family 7, Father) - Especially the color-coded display of the consumption as stated by the following family *"The color tells me immediately if I increased or decreased my consumption."* (Family 9, Husband)

5.4 Load Disaggregation

Our NIML system also provided the possibility of load disaggregation, i.e., the identification of different appliances from the analysis of the total load parameters (active and reactive power). This is possible by using supervised learning and classification techniques from machine learning algorithms we use in our sensing platform on the high frequency signals acquired by the non-intrusive sensors. Our objective with the addition of the load disaggregation feature was twofold. Firstly we wanted to learn how users would react to having the possibility of labeling their own power consumption though power events. Secondly we wanted to see how adding a single new feature during the deployment would affect the interaction with the eco-feedback. The selection criterion for having this feature was being part of the top-5 most active families in terms of user-generated events, and it was installed during weeks 40 and 43 when we visited the families and helped them labeling some of the existing appliances.

Our expectations were that adding this new feature would work as another trigger to increase the interaction between the users and the eco-feedback system. However the results show that adding this feature did not result in a significant increase in the number of interactions during that period (the houses with the new feature had a 14.3 (s = 9.29) mouse clicks average while those without had a 10.5 (s = 16.4) mouse clicks average during the same period).

Also, and despite we have chosen to deploy the feature in the more active users, none of the members of the selected house managed to label power events on their own. We believe that one of the main reasons behind this was the high number of events that would show in the user interface making it hard to select and label the right appliance as described by this family member *"I think the most complicated thing to do is the consumption per device (…) it's complicated to manage such a large number of devices."* (Family 7, Husband)

Nevertheless, one important lesson learned for future designs was that not all the appliances seem to be of equal importance to the residents. This was especially seen when helping the users labeling their events as they kept asking questions about what they considered to high consumer appliances (e.g. oven and clothes washer / dryer).

6 Discussion and Implications

In this section with discuss the most relevant outcomes of the one-year (52 weeks) long-term study of eco-feedback. We start by summarizing the overall results of the study and then we discuss some of the weaknesses and possible implications of this work regarding future deployments of eco-feedback systems.

6.1 Results

Here we presented the results of the long-term deployment of a real-time eco-feedback solution during 52 consecutive weeks in a stable sample of 12 households. During this period families had access to their energy consumption with two versions of an eco-feedback interface that also gathered usage and interaction data.

Our findings show that after 52 weeks there was no significant reduction in energy consumption but also no increase. Our results contradict the literature that suggests a positive impact of eco-feedback on energy consumption. We argue that such conclusions could be based on typical short-term (2 or 3 week) studies, which are not long enough to capture the relapse behavior pattern after the novelty effect of the eco-feedback. We recognize that further research is needed to isolate the relationship between consumption and eco-feedback but when huge investments in smart grids and eco-feedback technologies are under way it would be important to deploy more long-term studies that investigate these results further. This is particularly relevant if we consider the latest results from the European Environment Agency (EEA) that show a 12.4% increase in the final energy consumption of households, with electricity emerging as the fastest growing source of energy between 1990 and 2010 [19].

We have also confirmed that energy consumption in households is tightly coupled with the number of residents and that large families tend to become more energy efficient when considering average consumption by household member. Another interesting finding was learning that the income-level of the family is another powerful explanatory variable of energy consumption, with low-income families being able to spend less energy than high-income with the same household size. This suggests that there is a minimum acceptable point of consumption that once reached it may become impossible to implement other consumption-reduction initiatives without negatively affecting the family needs and routines. This is what was noticed by one of the low-income families with 2 children: *"I think the changes were mostly on making us more aware of devices we used and habits we had. We had some bills that were a little expensive and we started to reduce some consumption (…) now I feel we have reached a constant value, we pay around the same amount each month and it won't cost more than this."* (Family 1, Wife) And also one of the average-income families, with a teenage daughter *"We try to reduce here and there but this is an apartment we can't walk here in the darkness, we need to turn on some lights."* (Family 11, Wife)

Our study also shows other results that are in line with most of the reviewed literature especially when considering increased awareness and better understanding on what appliances really consume as shared by the this family "*This helped us to know more about our consumption, and we did some changes around here (…) this device brought us a new kind of awareness but it didn't disturb our routine. We don't feel it disturbed us in any way. It was beneficial for us to have it."* (Family 1) Or even, by helping deconstruct some devices initial consumption levels' associated perceptions as stated by this family *"It helped us to see some devices were consuming more than we initially thought and it changed the way or time we used those devices, for example the iron or the kitchen hood."* (Family 9, Husband) And in some, rare cases, this better understanding lead to some routine changes: *"We have a very conscious way of consuming energy, we were careful before having it here. It helped us to see some devices were consuming more than we initially thought and it changed the way or time we used those devices (…) one of those was doing laundry and use the dishwasher only at night [to take advantage of the night tariff] and this changed our routine completely."* (Family 9, Husband)

On the long run users feel that there's nothing new to learn from the provided eco-feedback and therefore the number of interactions are reduced to marginal values which is a strong indicator that the eco-feedback provided needs to encourage users to learn more about their consumption as well as provide more tailored and personalized feedback especially after relevant changes happen (e.g. buying a new equipment or someone leaving the house for long periods).

6.2 Implications and Lesson Learned

One limitation of our study was the lack of a proper control group in order to better access the effectiveness of the eco-feedback as a way to promote energy reduction. This is particularly relevant because our results are contradicting many of the findings in the literature that rely on two or three week deployments of eco-feedback, which might be too optimistic about the potential of this technology. Furthermore, considering the long-term nature of this study it would be important to keep an updated profile of our participant families (e.g. holiday absences, some family member visiting for a long period, and a list of actual appliances in the house at every moment) as this would have allowed us to perform other kinds of comparative analysis like the consumption of similar houses or correlating user concerns with their actual consumption patterns. All of these possibilities involve significant costs in deploying and running the studies but are rightly justified in particular given the environmental and economic impacts of household energy consumption and the expectations with large-scale deployments of smart grids that could make eco-feedback widely available.

Physical Location and Security. Our eco-feedback system also presented some limitations that could have an impact in the results. The fact that our eco-feedback system was implemented using a netbook that acted both as the sensor and the visualization platform placed at the entrance of the household presented some limitations. The system was not easily accessible to all family members in particular children, as one of the mothers shared with us*: She didn't reach it (youngest daughter 7 years old)",* (Family1, Mother). In addition the location of the netbook near the main power feed made it harder for family members to interact with the eco-feedback since it made them afraid of either dropping it in the floor or damaging the equipment since they considered it to be very fragile (the computer was stuck to the wall by only two adhesive velcro tapes). Finally some families also expressed concerns regarding the intrusiveness and safety of the system, even though it was properly and securely installed by a qualified electrician from the electrical company. For instance, some families did not allow their kids to come nearby or interact with fearing the risk of electric shock. In current deployments of our technology we are collecting data in the meters outside the houses and providing the eco-feedback using tablets and other mobile devices. Nevertheless our preliminary results are still consistent with the results presented here.

Appropriation of the Eco-feedback Technology. Finally, we have learned from the extensive interviews that family members tend to have naturally defined roles where some of them took over the task of checking and controlling the energy consumption and therefore, reducing the number of family members that would interact with the system. This made other family members feel they didn't need to worry or use the system, since someone (usually the husband or the person more comfortable around computers) was taking care of it as shared by two spouses: *"There are certain things I leave for him to do and other things I take care of myself. I was curious to use it and I would use it but not as often as him"* (Family 12, Wife) and *"He would check more because he would be more curious (husband) and me I would let him give me the report of it. He would summarize the information"* (Family 1, Wife)

7 Conclusion

This paper presents the results of a long-term deployment of eco-feedback technology in 12 apartment houses for 52 weeks in a southern European urban city. We collected both qualitative and quantitative data in order to assess the effectiveness of eco-feedback technology as a driver to promote energy conservation behaviors. Our results conflict the more promising expectations of eco-feedback based on short-term (two or three weeks) deployments reported in many HCI venues.

Despite the physical and methodological limitations of this study we have confirmed these results with a different deployment where the infrastructure is no longer placed inside the households removing the physical and security concerns with the eco-feedback device. We observed the same relapsing effects even when the eco-feedback is provided through a mobile device connected over the Internet to the non-intrusive sensor placed outside the house. After four weeks we observed the same decrease in attention and energy conservation behaviors.

We argue that in order to make eco-feedback technology effective further research is needed to understand what could lead users to retain attention over time in a way that promotes significant changes in their behavior capable of generating energy savings. We are also exploring other approaches like art-inspired eco-feedback [20] and social features like sharing energy consumption with in a community public display or social networks. In future work we also wish to further explore how the households perceive their consumption and how we can use family dynamic and routines to increase the effectiveness of eco-feedback technology.

In summary, our research highlights the importance of conducting long-term deployments of eco-feedback systems in order to understand the real potential and implications of this technology. Energy and resource consumption in general, are important application domains for persuasive technologies. However in order for this technology to have long-term impacts in domains like sustainability we need to overcome the novelty effect leading to response-relapse behaviors. Here we reported on such a study and presented some lessons learned that could lead to further research exploring new dimensions of eco-feedback.

Acknowledgements. This research was partially funded by the CMU | Portugal SINAIS project CMU-PT/HuMach/0004/2008 and the Portuguese Foundation for Science and Technology (FCT) doctoral grant SFRH/DB/77856/2011. Finally, we would also like to acknowledge all the participating families.

References

1. Froehlich, J., Findlater, L., Landay, J.: The design of eco-feedback technology. In: 28th International Conference on Human Factors in Computing Systems (2010)
2. Fischer, C.: Feedback on household electricity consumption: A tool for saving energy? Energy Efficiency 1, 79–104 (2008)
3. Peschiera, G., Taylor, J.E., Siegel, J.A.: Response-relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data. Energy and Buildings 42, 1329–1336 (2010)
4. Ueno, T., Sano, F., Saeki, O., Tsuji, K.: Effectiveness of an energy-consumption information system on energy savings in residential houses based on monitored data. Applied Energy, 166–183 (2006)

5. Broms, L., et al.: Coffee maker patterns and the design of energy feedback artefacts. In: 9th ACM Conference on Designing Interactive Systems, pp. 93–102 (2010)
6. Spagnolli, A., et al.: Eco-Feedback on the Go: Motivating Energy Awareness. Computer 44(5) (2011)
7. Miller, W., Buys, L.: Householder experiences with resource monitoring technology in sustainable homes. In: 22nd Conference of the Computer-Human Interaction Special Interest Group of Australia ozCHI (2010)
8. Wallenborn, G., Orsini, M., Vanhaverbeke, J.: Household appropriation of electricity monitors. International Journal of Consumer Studies 35, 146–152 (2011)
9. Kjeldskov, J., Skov, M., Paay, J., Pathmanathan, R.: Using mobile phones to support sustainability: a field study of residential electricity consumption. In: 28th International Conference on Human Factors in Computing Systems, pp. 2347–2356 (2012)
10. Costanza, E., Ramchurn, S., Jennings, N.: Understanding domestic energy consumption through interactive visualizations: a field study. In: 14th ACM International Conference on Ubiquitous Computing (2012)
11. Gamberini, L., Spagnolli, A., Corradi, N., Jacucci, G., Tusa, G., Mikkola, T., Zamboni, L., Hoggan, E.: Tailoring feedback to users' actions in a persuasive game for household electricity conservation. In: Bang, M., Ragnemalm, E.L. (eds.) PERSUASIVE 2012. LNCS, vol. 7284, pp. 100–111. Springer, Heidelberg (2012)
12. Nunes, N.J., Pereira, L., Quintal, F., Berges, M.: Deploying and evaluating the effectiveness of energy eco-feedback through a low-cost NILM solution. In: 6th International Conference on Persuasive Technology (2011)
13. Pereira, L., Quintal, F., Nunes, N.J., Berges, M.: The design of a hardware-software platform for long-term energy eco-feedback research. In: 4th ACM SIGCHI Symposium on Engineering Interactive Computing Systems, vol. 1, pp. 221–230 (2012)
14. Hart, G.W.: Nonintrusive appliance load monitoring. IEEE 80, 1870–1891 (1992)
15. Mills, E.: Review and comparison of web- and disk-based tools for residential energy analysis. LBNL Paper 50950 (2002)
16. Motegi, N., Piette, M.A., Kinney, S., Herter, K.: Web-based energy information systems for energy management and demand response in commercial buildings. LBNL Paper 52510 (2003)
17. Darby, S.: The effectiveness of feedback on energy consumption. A review for DEFRA of the literature on metering, billing and direct displays. Environmental Change Institute, University of Oxford (2006)
18. Gram-Hanssen, K., Patersen, K.: Different everyday lives: Different patterns of electricity use. In: 2004 American Council for an Energy Efficient Economy Summer Study in Buildings (2004)
19. European Environment Agency. Final Energy Consumption by Source (February 2013), `http://www.eea.europa.eu/data-and-maps/indicators/final-energy-consumption-by-sector-5`
20. Nisi, V., Nicoletti, D., Nisi, R., Nunes, N.J.: Beyond Eco-feedback: using art and emotional attachment to express energy consumption. In: 8th ACM Conference on Creativity and Cognition (2011)