# A long-term study of energy eco-feedback using non-intrusive load monitoring

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**Abstract.** Electricity consumption in households is responsible for a significant portion of the total use, making this an important problem to tackle in the broader sustainability field. Researchers often report that raising users' awareness of their consumption results in real savings. Here we present the results of a long-term study of a low cost non- intrusive load monitoring (NILM) and eco-feedback system capable of providing real time and historical consumption information. The system was deployed in 13 single houses and apartments in an urban area in Portugal. 58 weeks after the deployment it was observed that, even though the users were more aware of their consumption, no significant steps were taken to decrease it

Keywords: Eco-feedback, NILM, Energy Consumption, Long-term study

## 1 Introduction

The world is witnessing a change in habits of energy consumption in households for the past couple of decades, with electricity emerging as the main source of energy consumed. Statistics show that electricity consumption in domestic environments increased by 6.4% in 2010[1]. And according to [2] increasing the energy efficiency in residential buildings is considered one of the top 11 actions that will lead to large savings regarding carbon emissions. Additionally, the largest efficiency improvements appear, as expected related to electricity consumption activities like water heating, lightning and electric appliances.

It is believed that eco-feedback technology will play a central role in motivating sustainable behavior. Eco-feedback is not a new subject, and early literature [3] shows that even with low-level feedback it is possible to change residents' behavior. In Norway researchers found that by improving the accuracy off electricity bills and providing extra information would encourage consumers to read them more often and with greater understanding, promoting a behavior change [4], [5]. Real time eco-feedback was the subject of research in [6]. Where the authors performed a pilot evaluation of two low-cost monitoring systems in case study homes, and found that users quickly discovered that by looking at the differences in demand from turning on and off respective appliances they could easily approximate the energy use of each individual appliance, which may indicate that power disaggregation by individual appliances may play an important role in future energy monitoring solutions.

Peer pressure was the subject of interest in [7] and one of the results was the observation of the response-relapse behavioral pattern, meaning that after a while the user behaviors would relapse to those prior to the study.

While in these studies the main feedback was given in amount of energy used, other studies looked at different ways of providing such feedback. For example, Broom et al. [8] ran a 3-month study in 9 households, where they deployed an ambient interface for energy feedback that translates electricity consumption into graphical patterns displayed in a clock-like device. In the end they observed that people became more aware of their energy consumption, and were able to associate the displayed patterns with actual appliances.

## 2 Method and Results

This paper presents the results of the long-term deployment of a low-cost real time eco-feedback solution in 13 households in an urban area in Europe (Portugal). The system, a custom- made non-intrusive load monitor is capable of measuring the energy consumption in Watts, as well as detecting power events (such events are an abrupt change in the consumption normally associated with an appliance changing its state). All the families were already familiar with this kind of device, since they used an older version of the system for 3 months. The study started once all the systems were remotely updated to the new version. In the next 2 days the users were informed about the update. During the 58 weeks of the study we kept an aggregated database with consumption data that reached more than 5 GB and 2 million data points. This paper presents the first approach to analyze this data set. The exploratory nature of this analysis means that no hypotheses were defined, and the data set was analyzed as an all. Comparisons between houses are postponed for future analysis.

### 2.1 Consumption through the study

To verify if there was any decrease in electricity consumption we ran a correlation between the energy consumption and the week of the study, $r$=0.026 ,$p < 0.0001$.

Note that even though this correlation was significant it has a small $r$ value. One possible cause for this is that when we conducted this study the subjects have already been in contact with the system for 3 months (in which we actually observed a decrease in consumption [9]) and already made small adjustments in their routines to reduce their overall consumption. To test this result further we ran a linear regression algorithm and got the following equation relating the consumption and the week of the study:

$$\text{EnergyConsumption} = 0.687 \times \text{WeekInStudy} + 423.2$$

By simply assigning the value 0 and 58 to the WeekInStudy variable, we get a difference of about 40Wh between the first week and the last week, which is really small (a

small lamp can spend that energy in about an hour). As result we can safely assume that there was no real change in the consumption during the course of the study.
To explore those results we individually asked families about any change in the consumption, most of them confirmed that there was no real saving in the electricity bill at the end of the month, but some of the families noticed a decrease.

### 2.2 Consumption vs Power Events

The relationship between energy consumption and power events seems obvious (since an appliance triggers events and consumes energy). However this relationship is not a simple as it might look, a high number of events could be related to low consumption (for example a high consuming appliance being turned on just when it is used), and the opposite is also true.

To determine the strength of this relationship we ran a Pearson's correlation, $r$ = 0.413, $p < 0.0001$. This confirms the strong relationship between consumption and events. We also noticed that users rapidly became aware of the strong relationship between the events and consumption. The relationship was also tested comparing different days of the week. There was no significant difference between the consumption throughout weekdays, but the difference was significant for power events this may indicate that even though the energy consumption is almost similar through the week, there is difference in how consumers use their appliances between weekdays.

### 2.3 Interaction with the system

Like it was explained in the Introduction the subjects were familiar with eco-feedback devices. They used one for 3 months, and it was noticeable a drop in interaction with it after 4 weeks [9]. To verify if this phenomenon would be present in the 2nd deployment we assumed that the number of interactions would negatively correlate with the week of study. The Pearson's correlation for this data returned a significant negative correlation, $r = -0.163$ , $p < 0.0001$. We also ran a linear regression algorithm and got the following equation:

$$\text{NumberOfInteractions} = -0.014 \times \text{WeekInStudy} + 0.871 \quad (2)$$

Also regarding the interaction with system, it was shown that the greatest decrease in interactions with the system occurred in the first four weeks like it was previously reported in [6]. For this the dataset was separated in 2 groups (first 4, and the remaining weeks) and we ran 2 regressions analyses, the results showed that the slope in the first 4 weeks (-0.054) is greater that in the rest of the study (-0.013), this indicates that the decrease in that period is greater that in the rest of the study.

When talking with the users we enquire them about this decrease of interest in the sys-tem. Some families justify it by the lack of time in their routines, others feel like after a few weeks they already had a good perception of their consumption.

# 3 Conclusions.

The scope of this study was limited to aggregate data and important results can surface when we compare different houses or different conditions within the same house. We found that events are related with energy consumption and this preliminary research might indicate that the increase in consumption is normally associated with more appliances. We did not found any significant difference between consumption on different days of the week but there was a difference in the power events, which might indicate different usage patterns during the week.

We also confirmed what other researchers found, users lost interest in the system after a while and even the small updates delivered over time were not enough to prevent this. From informal conversations with users it was noticeable that our system helped increase their perceptions on energy consumption that was perhaps the biggest contribution of our work. To better understand our speculations it would be important to use more qualitative data like investigate users routines during the period of the study. We also plan on extending the level of energy ci desegregation of our system to measure the added value of this feature in terms of energy savings.

# 4 References


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