# The Design of a Hardware-software Platform for Long-term Energy Eco-feedback Research


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### ABSTRACT
Researchers often face engineering problems, such as optimizing prototype costs and ensuring easy access to the collected data, which are not directly related to the research problems being studied. This is especially true when dealing with long-term studies in real world scenarios. This paper describes the engineering perspective of the design, development and deployment of a long-term real word study on energy eco-feedback, where a non-intrusive home energy monitor was deployed in 30 houses for 18 months. Here we report on the efforts required to implement a cost-effective non-intrusive energy monitor and, in particular, the construction of a local network to allow remote access to multiple monitors and the creation of a RESTful web-service to enable the integration of these monitors with social media and mobile software applications. We conclude with initial results from a few eco-feedback studies that were performed using this platform.



### Author Keywords
Hardware-Software platform; Eco-feedback; Non-Intrusive Load Monitoring; Sustainability;

### ACM Classification Keywords
H.5.2 [Information Interfaces and Presentation]: User Interfaces – Prototyping;


### INTRODUCTION
The world is witnessing a change in residential energy consumption habits. For the past couple of decades, electricity emerged as the main source of residential energy consumption [1]. The factors leading to the growing consumption are well known, and are tightly coupled with economic indicators of development [2]. As more people in emerging countries have access to higher levels of comfort the impact of domestic electricity consumption will increase significantly world wide [3].



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The effects of residential electrical consumption on our energy balance and carbon emissions are hard to overestimate. This effect is so relevant that increasing the energy efficiency in residential buildings is considered one of the top seven actions that may lead to large savings in carbon emissions [4]. Nevertheless, any attempt to improve building efficiency generally involves changing the lifestyles of the residents. Thus, the transition to a more sustainable future involves behavior change, which can only take place in response to peoples' changing needs, drives and motivations.

The Human-Computer Interaction (HCI) community embodies knowledge and expertise that will be crucial to address the design, interaction, and usage issues surrounding sustainable technologies and practice. Eco-feedback technology plays a central role in reducing and motivating sustainable behavior [5]. This technology is defined as that which provides feedback on individual or group behaviors with the goal of influencing future energy saving strategies thus reducing the environmental impact of the actions.

This paper presents a hardware and software platform that was developed to enable the quick deployment of long and short-term studies of eco-feedback technology and at the same time serve as a research platform for developing non-intrusive load monitoring algorithms and techniques. Here we report on more than 2 years of experience developing and improving a research platform that combines low-cost non-intrusive monitoring of energy in households and quantitative measures of user behavior. We start by reviewing the state of the art eco-feedback technologies, and then provide an overview on the work that has been done to date on Non-Intrusive Load Monitoring (NILM). Following this, we introduce the research platform that we have been developing to support research in both of these fields. Lastly, we report on a few studies that were performed using this platform and offer recommendations for future improvements.

### Eco-feedback Technology
Many studies sustain that providing users with real-time energy eco-feedback is an effective way of changing consumption behaviors. Savings reported in the literature

range from 5% to 10% [6]. However other studies showed that this effect is not long lasting [7, 8] and hence might compromise the long-term effectiveness of eco-feedback technology.

There are many examples of eco-feedback systems that promote behavior change. For instance Kohlenberg and colleagues in the 1970s [9] found that a simple eco-feedback mechanism that turned *on* a light bulb when the household energy was reaching 90% of peak consumption, was effective in promoting behavior change. More recently Spagnolli et al. [10] reported on a disaggregation system that gave detailed feedback information to users using pervasive technologies to decrease the energy usage and preliminary results shown that households that used their prototypes saw an energy consumption reduction of 5% over the previous year's when the prototype was not available. Similarly, Peschiera and colleagues [7] investigated how residents of a dormitory building would respond to different information regarding their consumption. The results demonstrated that providing comparisons between building occupants results in more reliable improvements in energy utilization when compared with individual feedback.

Eco-feedback is of value in itself as a learning tool and must be considered in context. The outcomes vary according to circumstances, but they can also sometimes be improved when used in conjunction with advice and information.

Sometimes people need help in interpreting eco-feedback and deciding their courses of action. This help may come from energy conservation programs such as the one promoted by the company OPower[1], which mails home energy report letters comparing the energy usage of households in similar neighborhoods and provides energy conservation tips to the residents. This program began near the end of 2009 with nearly 600.000 US households in treatment and control groups, and results show that after two years it is still possible to find average savings if feedback is consistent. For example, reports show 2.89% average savings for high consuming households receiving monthly reports, and 1.70% for low consumption households receiving only quarterly reports [11].

In fact, one concern of the effectiveness of eco-feedback is called the response-relapse behavioral pattern meaning that after a while consumption would relapse to values prior to the study, and this was also the subject of a study reported in [7] where it was possible to observe that users will gradually return to previous behaviors if feedback is no longer present or is less frequent.

Despite the need to properly assess its long-term effectiveness, the promising results of eco-feedback technology have lead researchers to propose the expansion of this technology to other areas of consumption, in particular water, personal transportation, product purchases and garbage disposal [12]. These new areas of eco-feedback have been the central subjects of several studies. For instance Strengers and colleagues [13] explored 26 households using water and electricity meters, and came up with a set of design implications to improve user experience with eco-feedback systems. Miller and Buys [14] conducted a study with 7 families that had an energy and water consumption meter installed, and obtained guidelines in how eco-feedback systems should be built and marketed as a product. Finally in [15], Froehlich et al. explored a mobile tool for tracking and supporting green transportations habits. After a 3-week field study the results show that such tools can easily engage the user into sustainable actions, and that there is a potential to enable behavior change regarding transportation habits.

With the advent of low costs sensing technology for both energy consumption and human behavior there is a new opportunity to assess the effectiveness of eco-feedback technology beyond the small-scale, short-term studies promoted in the past. Moreover, having access to better sensing technology, promotes the low-cost capability to disaggregate power consumption, hence offering the possibility of providing users with disaggregated information regarding the consumption of house divisions or even individual appliances. The basic assumption is that people will be able to change their behavior and thus their consumption if they understand which appliances are responsible for their overall energy consumption breakdown. This was especially noticeable in [6], were Parker and its colleagues performed a pilot evaluation of two low-cost monitoring systems and found that users quickly discovered that by looking at the differences in demand from turning on and off appliances they could easily approximate the energy use of each individual appliance and better understand the consequences of their actions.

**Non-Intrusive Load Monitoring**

Attempts to monitor and disaggregate electric energy from a single sensing point go back to the early 1980's. Schweppe and Hart first introduced Non-Intrusive Load Monitoring (NILM) [16]. Generally a NILM system is designed to identify and monitor the energy consumption of individual appliances that co-exist in a building's electrical circuit. The main assumption of the first NILM algorithms is that every change in the total power consumption of a building happens as a response to an electric device changing its state, e.g. a television turning *on* or a hair drier going from *low* to *high*. The approach consists of applying sophisticated signal processing and statistical learning techniques to current and/or voltage measurements taken at a limited number of locations in the electric distribution

[1] www.opower.com

system of the household [16]. In high-level terms a NILM process can be described in six consecutive steps:

1. **Data acquisition**: sensors measure the current and voltage signals flowing into the house from a single point.
2. **Data pre-processing**: previously acquired current and voltage signals are converted into traditional power metrics (e.g., real power, reactive power and power factor).
3. **Event detection**: changes in certain metrics (traditionally real power is used) are detected and flagged as events for further processing in the other modules.
4. **Feature extraction**: features are extracted from the samples surrounding the detected event. Together these features form an individual signature that presumably uniquely identifies each power event.
5. **Event classification**: previously trained machine learning algorithms are applied to unclassified event signatures to obtain a classification.
6. **Energy computation**: by keeping track of all the load events that occur and their associated power levels it is possible to estimate how much energy each appliance is using.

Much research was done is this field since the early days when Hart presented his approach that consisted of analyzing real and reactive power steady state changes at the fundamental frequency (60Hz in the US). With the improvement of sensing technology researchers saw an opportunity to explore frequency domain features of the electric signal and in particular power harmonics. For instance Laughman et al. [17] found that by using information in the 3$^{rd}$ and 5$^{th}$ spectral envelope coefficients it was possible to distinguish between loads that would otherwise overlap when using only the changes in real and reactive power. In [18] the research team used linear regression to extract features from the first seven odd power harmonics of the current signal. Different basis functions (polynomial, Gaussian, radial and Fourier) were used for the linear regression and traditional machine learning algorithms (e.g. nearest neighbor and decision tress) were used to classify the power load events based on these features. Results reported classification accuracy ranging from 67% to 100%.

Some authors achieved similar results with completely different approaches. Patel et al. [19] proposed to monitor electric noise in voltage measurements taken at electrical outlets in the home to detect and classify the behavior of most appliances. Three years later the same authors criticized their previous work mentioning problems such as the computational expense of analyzing transient noise, and presented ElectriSense [20] a system that focuses on sensing very high frequency (36-500 kHz) electromagnetic interference (EMI), which is constantly generated by switch mode power supplies (SMPS) that are present in most modern consumer electronics, as well as fluorescent lightning. A very good summary of the work being done in this field and future directions can be found in [21].

Overall NILM represents a major change in the load-monitoring paradigm and it is definitely a low-cost alternative to traditional intrusive technology based on multiple individual sensors that are costly to install, maintain and monitor. The potential of non-intrusive sensing is growing rapidly from energy to other domains. For instance, Cohn et al. [22] developed GasSense, a single-point acoustic sensor for gas flow. A similar solution was implemented to control water usage. HydroSense [23] is a single-point pressure sensor and was presented by Froehlich and it colleagues. Their system allows the identification of any individual water feature activity, and is capable of estimating the amount of water each feature is using. The sensor is connected to a faucet in the houses' plumbing system and when a valve switches (for instance a bathroom faucet or a mechanical valve in a dishwasher), a pressure change will occur and a pressure wave is generated in the plumbing system that can be sensed anywhere in the house. The characteristics of this waveform will be different for every existing valve, what makes it possible to once again apply NILM techniques to classify events. For households sensor fusion will also enable a wider application range and accuracy of unsupervised or semi-supervised algorithms.

In the remaining sections of this paper we present and in-depth view of our low-cost implementation of a hardware and software platform for non-intrusive home energy eco-feedback research. We start by explaining how our load monitor works, and then we show how we are providing eco-feedback to the users including the management and collection of data. Finally we present our design decisions and experiences concerning the deployment of our system and finalize we some conclusions and results from eco-feedbacks studies that were done during the deployment of this research platform.

## SINAIS: A HARDWARE-SOFTWARE PLATFORM FOR NON-INTRUSIVE HOME ENERGY ECO-FEEDBACK RESEARCH

Although existing studies on eco-feedback show very promising results, there are still almost no studies that assess the long-term effects of this technology. We argue that this may be because conducting long-term studies is both costly and difficult with existing sensing technology. The research platform described here is part of the Sustainable Interaction with social Networks, context Awareness and Innovative Services (SINAIS) research project, which involves a team of multidisciplinary researchers looking at using NILM, social networking and context awareness to understand and motivate people to reduce their energy consumption in the residential and transportation domains.

We were required to develop a low-cost solution that could be easily deployed in dozens of houses with very little installation and monitoring costs. The system was required to acquire data from a single point in the household and preferably also provide users with feedback about their energy consumption. Additionally, we sought to acquire usage data from the sensor related to the capability of the system do detect human-activities.

Given this set of requirements we started looking at available commercial metering solutions and soon understood that none of the existing solutions offered enough flexibility at low cost of installation and monitoring. A good review of existing hardware can be found in [24]. While some commercial systems are relatively inexpensive, they do not offer all the data needed for a NILM implementation (some only sampled current and reported average values at 1Hz). Other systems did not offer a flexible method for providing feedback to the users. As for the most expensive solutions (e.g., circuit-level meters), some offered all the required data, from instantaneous current and voltage to power factor, but were considered too expensive and difficult to install. One final problem with these commercial solutions was the fact that none offered a built-in method for inferring human activity, which was an important requirement for our study.

The failure to find a viable commercial solution led us to build the custom end-to-end NILM home energy monitor described here. To lower the cost we decided to implement the hardware / software platform using a simple netbook. We used the netbook's built-in Analog to Digital Converter (ADC) of the audio input to sample current and voltage. The mini display and the speakers provide the feedback, while the Wi-Fi card enables communication over the Internet. Additionally the built-in camera and microphone can act as low- cost sensors for human activity. With this solution we were able to come up with a compact package that could be acquired for less than 300 euros and offered the possibility of being used in future research projects.

### Data acquisition and load monitoring

In our NILM solution the measurements are taken by combining current and voltage sensed at the main power feed. Selecting this sensing point enables the coverage of the whole house consumption. The measured values are then used for event detection, event classification and, ultimately, the breakdown of consumption into individual appliances. In the meantime 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. As described previously our power metering system is a combination of both hardware (sensors and netbook) and software (power calculation and load disaggregation algorithms).

#### *Hardware Components*

In many European countries residential buildings have single-phase electric circuits fed by 230V 50Hz AC. Therefore, only two sensors are required to measure power: one for current and the other for voltage. We use a standard split-core (clamp-on) current transformer (Figure 1, left) to measure current. The sensor costs up to 30 Euros, depending on the maximum current range. The input-end is placed around the current conductor and in the output-end there is a 3.5 mm Tip, Ring, Sleeve (TRS) connector. For the voltage sensor we opted for a custom solution that steps down 230V RMS input to 0.5V RMS that we can acquire using the line in. The sensor is a simple voltage transformer (Figure 1, center) that was tailor-made by a local company. The input-end is connected to a voltage source in the main fuse box, and we added a 3.5 mm TRS connector to the output-end that never reaches the peak 0.9 Volts, which is the maximum voltage that can be sampled by the sound card. Since both sensors have TRS connectors in the output ends it is possible to connect them to the netbook sound card using a 3.5 mm TRS splitter (Figure 1, right).

**Figure 1: Hardware being used. From left to right: split-core current sensor, voltage sensor and TRS splitter connectors**

#### *Software Components*

In terms of software, we designed and implemented a real-time power meter using the Java programming language, taking advantage of its sound Application Programming Interface (API) to read the data from the sensors. The system represented in Figure 2, is based on the *pipe-and-filter* software architecture. This very simple but powerful, architecture consists of any number of components (filters) that transform or filter data, before passing it on via connectors (pipes) to other components. Because all the filters are working *in parallel* this architecture is very suitable for systems where data transformations need to be done as close to real time as possible, which was clearly our case. In the following section we describe the filters that comprise our load monitor.

#### *Data acquisition and Power Calculations*

Current and voltage are continuously sensed and sent to the *data acquisition filter* to be sampled. This module is able to extract current and voltage signals from the left and right audio channels, respectively. The resulting data is then added to a queue that is connected to the next filter where the power calculations will take place. As current and voltage are sampled they are sent to the *power calculations filter*. This filter is responsible for performing the power calculations and driving the resulting data to the splitter, which is an active filter and is responsible for sending the power samples to the filters that are connected to it.

The power values (current, voltage, real power, reactive power and power factor) are computed by applying a Fast

Fourier Transform (FFT) to each period of the current and voltage waveforms, which are represented by 160 samples each (considering a sampling frequency of 8000 Hz and a 50 Hz mains frequency).

*Splitter*

Because our system requires multiple filters to access the same data simultaneously (e.g., one filter is storing the power in a local database while another is running an event detector algorithm), we needed to find a way to share the same data among all the filters. This is a well know pattern in software engineering (*single producer and multiple consumers problem*), and our solution was to implement a publish-and-subscribe pool where the entire customer filters (consumers) have to subscribe in order to access the power samples. The producer is then responsible for driving the power samples to each of the subscribers.

*Graphical User Interface (GUI)*

The GUI is a sink, and is responsible for plotting the power as it is being calculated. Initially this technical GUI was important to calibrate our system and it is still being used to improve the implemented algorithms.

*Power storage*

The role of the power storage filters is to store instantaneous power measurements. However, given the high rate or power samples (50 measurements per second) we opted to store average power samples instead. The average power samples are calculated based on a predefined number of samples that by default was set to 1500 (roughly 30 seconds at 50Hz). This filter is also responsible for storing and updating the power events as they are detected and classified.

*Median filter*

The *median filter* is used to apply a median filter to the power samples, also based on a predefined window size. The filtered samples are sent to the *power event detector* filter. This process is used as a smoothing technique and it is particularly important to improve the event detection stage as currently the number of appliances that are running simultaneously inside a house is constantly increasing, hence resulting in noisy signals that can make the event detection harder.

*Event detections and load identification*

Once the power calculations are done, an event detector processes the power signal (normally the real power is used) to find the changes in the load that are generated by the working appliances. In the current system, the event detector is a modified version of the mean detector that uses a log likelihood ratio test [25]. When a change of interest is detected, this module triggers a programmable event that will be handled by the load identification filter.

The *disaggregation filter* is a composite filter that captures the events triggered by the *power event detector* It is composed of two filters that work together to disaggregate the load, the feature extractor and the event classifier.

The *feature extraction filter* extracts features from the samples that surround the power event and sends them to the classification filter to be analyzed and obtain a classification for the event. Two main features, extracted from both real and reactive power, are used in the current implementation: 1) the mean change in power when the event occurs and 2) the coefficients of a 3rd degree polynomial fitted to a fixed-window of samples around the event using a least squares curve fitting algorithm.

The *event classification filter* applies a machine learning algorithm to the event features and attempts to find the appliance whose features are a best match to any new set of features. Currently only the *k*-Nearest Neighbor (*k*-NN), a very simple instance-based learning algorithm, is implemented in the power meter. New instances are classified by observing the class label of their *k*-nearest neighbors and selecting the class that is found most frequently. The nearest neighbors are those instances on the training set that have the smallest distance (overall distance of the existing parameters) to the instance being classified.

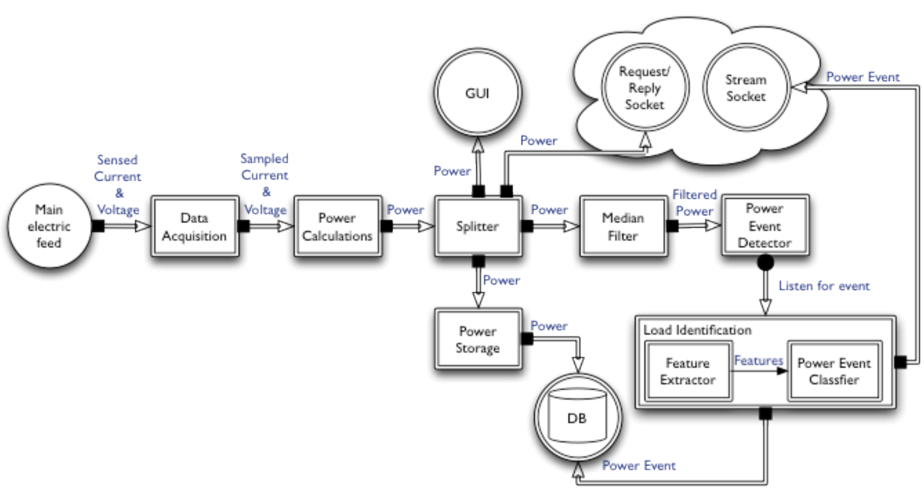


**Figure 2: SINAIS Non-Intrusive Load Monitor software architecture.**

Applying other machine learning algorithms is straightforward given that our system is compliant with the Java Machine Learning[2] and Weka[3] APIs that are already integrated in the system.

### *Communication*

In order no enable real time communication between the power meter and other applications we have also added a communication layer. This implements two socket servers that are opened to external connections.

One is a simple *request / reply socket* that will send data to its connected clients upon request. The requests and reply messages must follow a pre-defined structure that is understood by both server and clients. The other is a streaming socket that is used to stream the power event data as they occur. To facility the communication between both parts the exchanged data is in a predefined XML format.

## Eco-Feedback

Our system offers eco-feedback to the user using the netbook monitor. We have built two user interfaces that not only provide historic consumption data, but also connect to the energy monitor through the existing TCP sockets to get real time information for either energy consumption or power events. One of the unique features of our implementation is the possibility of inferring human activity and therefore having the chance to include quantitative measures of user attention.

Our research also aims at exploring other dimensions of eco-feedback, namely place and availability of information. The flexibility of our platform enabled the integration of a social networking and a mobile client that present consumption to the users in different ways.

### *Local Eco-feedback*

During the design of our research platform two different user interfaces providing consumption information to the users were deployed using local eco-feedback through the netbook screen. Both interfaces are capable of recording every user interaction with the local eco-feedback system. This is achieved in two ways: one by keeping track of mouse clicks an transitions between the different visualizations, and the second inferring human presence using the built-in webcam. For that effect we have implemented motion and face detection algorithms to sense when residents were passing by or looking at the netbook. We also used the sensing to trigger and initiate some user interaction with the system. For instance, if the system detected human presence the screen would become brighter in an attempt to call the user attention.

[2] www.java-ml.sourceforge.net

[3] www.cs.waikato.ac.nz/ml/weka

### *First deployment of the eco-feedback*

The first interface was design based on the feedback that we received after performing a pilot study with 5 families using commercial power meters. This interface uses mostly traditional column charts to display the consumption information. When the system detects motion nearby, it displays a “spectrum-like” graphic that represents the consumption over the last 8 hours (this representation is made through a color code: green, yellow or red depending on the consumption), it also presents the current consumption and the aggregate consumption over the day (represented in kWh and $gCO_2$). The users can also access detailed energy consumption. The system displays a column chart with the total energy consumption over the current day, and also the consumption of all the past days. It is also possible to compare the consumption of the current week against last week on a daily basis. In Figure 3 (top) we show an example of the daily consumption in a column chart, were each column represents one different hour of the day.

### *Second deployment of the eco-feedback*

The second version was designed based on feedback we received from the deployment of the first version. In this interface we used a gauge analogy to display consumption information to the user. The information was displayed in two forms: the more traditional displayed the quantities in numerical format 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 read when the consumption reached abnormal levels).

The interface displays information for the hour, week, month and year’s consumption and is organized in a tabbed menu. As described previously, the consumption is mapped through a color code ranging from green to dark red and if the mouse cursor hovers over the gauge it displays information about $CO_2$ emissions and cost associated with that time slot.

Both versions are able to display the current consumption information, but only the second one is able to display power events. These are displayed in the hour view because displaying the events in the day or month view would result in a very confusing interface (the hour view is refreshed every hour, meaning that only events for the current hour are displayed). Every time a power event is detected a small dot is added to the interface as close as possible to the time of occurrence. The size of the dot is also used to help indicate the amount of power change, and a click on it reveals the appliance that has the highest probability of triggering that event. Additionally the user can confirm or correct the system’s estimate. In Figure 3 (bottom) we depict the hourly consumption with dots that represent the power events and the possibility of manually labeling them.

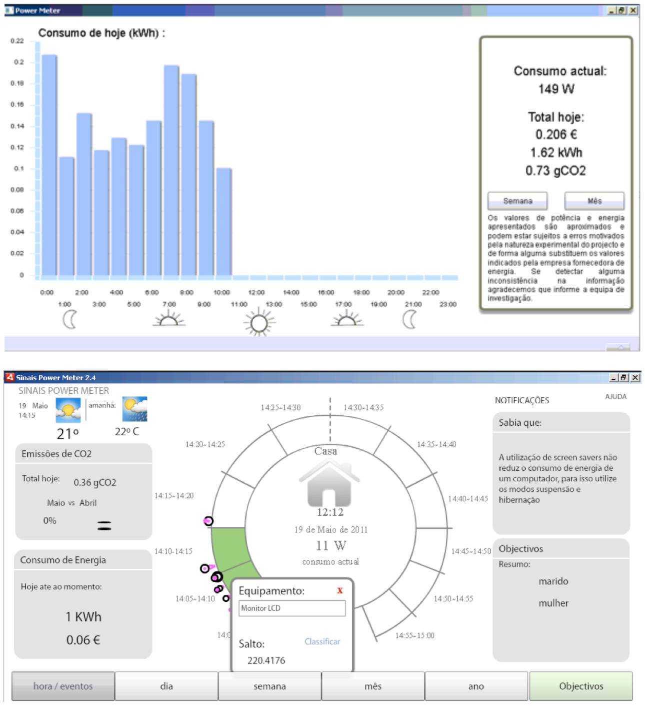


**Figure 3. Different eco-feedback interfaces: first deployment (top) and second deployment (bottom).**

Around the central gauge, additional information is presented, specifically: comparative information with analogous time periods, the total consumption in terms of monetary cost and $CO_2$ emissions and finally some generic advice regarding sustainable practices.

### *Social Networks Integration*

In order to provide eco-feedback to the users when they are not close to the power meter, we have integrated our system with the Stepgreen.org social networking platform. Stepgreen[4] is a free service provided by the HCI Institute at Carnegie Mellon University that tries to promote sustainable behavior and constructive discussion between its users by making them commit to a set of environmentally friendly goals.

Once the integration was done, the families with power meters installed in their homes were able to see a replicated version of their local system on the social network. To accomplish this we have created flash components similar to the gauges displayed in the local meter. The consumption data is loaded on these components using web-services that we have created for this purpose. These web-services will be further explained in the following sections. Figure 4 shows what was presented to the users after they have logged-in in to the social network system.

To integrate our system with Stepgreen all the website had to be translated to our users' native language and a user account had to be created for each family. To keep the original goal of Strepgreen, our platform is also able to retrieve the user-selected goals from the Stepgreen account and show them in the local eco-feedback interfaces.

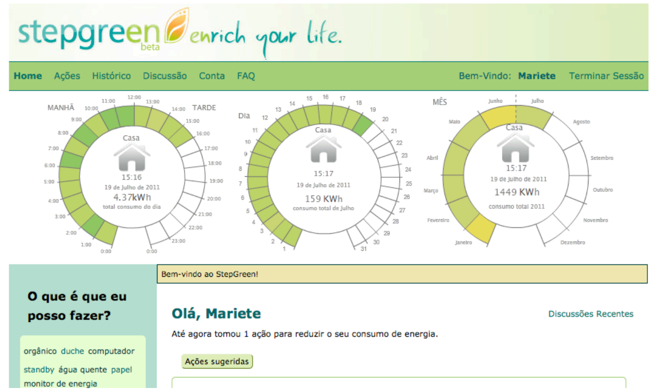


**Figure 4. Stepgreen welcome screen after user logs in.**

### *Smartphone prototype*

As a showcase of our framework capabilities and as exploratory exercise for future devices, a smartphone prototype was developed (see Figure 5). The prototype was implemented for the android platform. As with the social networking system, the mobile application also accesses our web-services to load consumption data. Another feature of the mobile application is the possibility of connecting to the TCP sockets provided by the power meter hence enabling the display of the current consumption and power events in real time. Additionally, there is a possibility of providing a classification for the detected events.

## DATA MANAGEMENT

Storing data in a centralized repository is very important requirement for any research platform producing impressive amounts of data. After 1 year the data warehouse form this research project holds around 15 million power events and 25 million power samples corresponding to 5 gigabytes of storage data. In our deployment, every meter stores its own data in a local SQLite database. For integration purposes, we opted to use a web-based file hosting service as this allowed us to keep all the database files synchronized in one place as long as there was an Internet connection available. The local databases are then integrated into a single data warehouse using the SQL Server Integration Services.

### Web Server

In addition to the central SQL Server described previously, our framework also has an online web server. This server is running a MySQL database that is updated by our meters with consumption information every 20 min. (average consumption in W and power events information). The update process is accomplished by a simple application written in Java, executed by the task manager. A series of RESTful web-services were implemented in the server

[4] www.stepgreen.org

using an open source framework. With such services it is possible to easily access data aggregated in several ways. For instance the consumption average by day, the day with highest consumption or the top five houses with less consumed energy. The applications described in the section above (Stepgreen.org and the android prototype) obtain consumption information using these services.

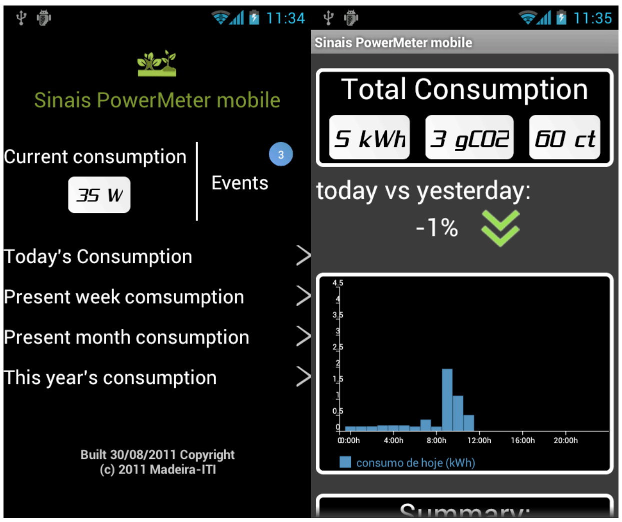


**Figure 5. Android prototype: main menu (left), daily consumption (right).**

## SYSTEM DEPLOYMENT

Our system was used in about 30 houses during a period that lasted from several weeks in some houses to more than 1 year in steady sample of 20 houses. During that period the system was constantly monitored and perfected and several eco-feedback studies, including qualitative interviews and surveys, were conducted. In this section we discuss the issues related to the deployment of the system and in particular positioning, installation and maintenance.

### Positioning

The main restriction to the positioning of our system is that the current and voltage sensors need to be connected to the main fuse box. Since both sensors were designed with very short cables we decided to attach our meter to the fuse box door with Velcro like shown in Figure 6. This solution allowed us to remove the system easily and it was proven to be secure. All of the houses in the study had the fuse box next to main door or in the kitchen, although we are aware that in some houses (mostly older ones) this box might be located in the basement or in the attic, and that in those cases the system would not work as a feedback mechanism unless the information was displayed through other means such as, for example, the smartphone prototype.

### Installation

In order to install the system, the netbook power cable had to be cut, stripped and connected to both edges of a circuit breaker and to the ground source**.** This procedure requires specialized labor and involved the support of an electrician from the local power company. The sensors and the netbook power cables are hidden in the box cover with only 2 audio cables passing to the front.

**Figure 6. Netbook installed near the main fuse box.**

### Wi-Fi Network

Our system required an Internet connection for synchronizing the data and for remote access and assistance. Given that 75% of the households were located near each other in 3 apartment buildings, we installed an extended-range Wi-Fi network. The local power company helped with the installation, and provided long ranged access points (AP) in power poles near the buildings. An ethernet cable was extended from our lab to the closer access point, and this device was responsible for both covering the closer households and repeating the signal to the remaining AP's.

Several constraints limited the use of our network. For instance, heavy rain in the winter of 2011 damaged one AP and left 4 houses offline for 2 weeks. Also, due to the architecture of one of the buildings, 3 houses on the back of that building were not covered or had a weak connection. Those problems were solved by the goodwill of the affected users who were willing to share their personal Internet connection. During the eighteen-month-long study we managed to keep 70% of the households always online

### Maintenance and Updates

When running such a long-term study it is very important that one have easy access to the deployed equipment for maintenance and update tasks. We use a proprietary software package for this purpose: Teamviewer[5]. With this software one can remotely control each deployed monitor. Additionally this software also allows file transfer, and this is very handy to upload small updates to the system.
Teamviewer was installed in every meter and also in the database server, and a partner list was created for easy access to each deployed meter.

## STUDIES

During the deployment, several quantitative and qualitative studies were conducted. The first large-scale study with this

[5] www.teamviewer.com

research platform was made shortly after the system was first deployed and the results were presented in [8]. This study analyzed data gathered from 21 houses in the first 9 weeks of the deployment, and showed that 4 weeks after the initial deployment of the system the users started to pay less attention to the eco-feedback device. This is a very relevant result as much of the literature on HCI aspects of eco-feedback is based on deployments that last 2 or 3 weeks and will likely ignore this novelty effect. Another important result from the same study was finding that users with higher consumption had a greater interaction with the system and that during the period of the study they had an average of 6.4% decrease in consumption (as opposed to the 2.3% decrease of the users that had less interactions with the system). Again the relative long-term nature of our deployments enabled conclusions that are seldom found in the HCI literature on eco-feedback. Moreover after conducting some interviews with these users we learned that low consumers tend to interact less with the eco-feedback because they felt that they could not save any more energy than what they actually accomplished. The graph in Figure 7 represents the count of interactions with the system over the period of the first study. The bars display the sum of all interactions. And the line represents only the intended interactions (with the mouse).

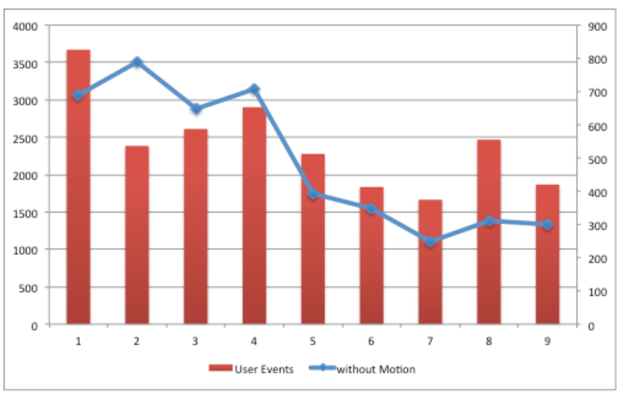


**Figure 7. User interactions with the meter over the first 9 weeks.**

A second study was conducted with 13 houses, one year after the first deployment and it involved the 2nd version of the eco-feedback interface. The results of this study can be found in [26], and they showed that in some houses the users stopped using the meter (some of them even closed the netbook), while others kept using it, although with less frequency (once or twice a day). This study also disclosed that even though we could find a decrease in consumption during the first 2 months of deployment, the average consumption remained virtually unchanged throughout the rest of the study.

From a qualitative perspective these studies also revealed that the system fostered discussion in the family about sustainable behaviors. For example, the father in one of the households complained that the kids always forget to close the fridge properly [27].

> *"I saw high consumption and went around to see that the fridge's door was open ... they always forget to close it properly!"* (Family 7 Father, ref 1).

Currently we are still exploring the big dataset collected during the 2 deployments. Comparisons between houses with different consumption profiles, analysis of the influence of the season in the consumption, exploring any change during the usage of appliances are all examples of future analysis.

## CONCLUSIONS

In this paper we report on the efforts to build a cost-effective NILM energy consumption research platform. The HCI research literature is abundant in research results coming out of short-term research deployments of eco-feedback technology. Here we report on the requirements of the long-term research efforts comprising in the domain of sustainability. The complex hardware/software platform the research team was required to build posed many engineering challenges that are seldom reported in the literature. This paper describes in detail the problems and solutions found by the research team to develop and deploy a low-cost non-intrusive energy-monitoring research platform that combines energy and human sensing with the potential do deploy different eco-feedback visualizations.

Our system was deployed for a period of 18 months in more than 30 different houses, running 24/7 and acquiring valuable data that was used by an interdisciplinary team of researchers to monitor and understand how people react to eco-feedback technology. During this time several quantitative and qualitative studies took place. In one of the studies it was possible to see that 4 weeks after the initial deployment of the system the users started to pay significantly less attention to the eco-feedback device. The architecture of our framework allows the implementation of different eco-feedback solutions, without worrying about the complex sensing and consumption calculations.

As future work, the team is already implementing new prototypes that use avatars, or images of the local endemic forest in an attempt to create an emotional connection with the user, and to reduce the decrease of attention that was noticeable during our studies. We also plan to deploy the system in other cities and countries in an effort to better understand the cultural and international aspects of energy consumption.

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