LOW COST FRAMEWORK FOR NON-INTRUSIVE HOME ENERGY MONITORING AND RESEARCH

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Abstract: This paper presents a low-cost framework for non-intrusive home energy monitoring and research built on top of Non-Intrusive Load Monitoring (NILM) concepts and techniques. NILM solutions are already considered low-cost alternatives to the big majority of existing commercial energy monitors but the goal of this work is to make its cost even lower by using a mini netbook as a packaged solution. The mini netbook is installed in the home's main circuit breaker panel and computes power consumption by reading current and voltage through the built-in sound card. At the same time, feedback to the users is provided using the 11'' LCD screen as well as other built-in I/O modules. The meter is also capable of detecting changes in power consumption and tries to find out which appliance lead to that change. It is believed that such a system will not only be important as a tool for energy monitoring and feedback, but also serve as an open system that can be easily changed to accommodate and test new or existing non-intrusive load monitoring techniques.

1 INTRODUCTION

Back in 1992 world leaders got together in Rio de Janeiro for the United Nations Conference on Environment and Development (UNCED). Two of the issues addressed were, the use of alternative sources of energy to replace fossil fuels and the growing scarcity of water.

Twenty years later many actions have been taken to face those issues, with a big focus on improving and creating alternative sources of energy.

The building industry has also been shifting gears towards more environmentally friendly practices. Energy and water efficiency are two key points of the so-called *green buildings* and many technological solutions have been implemented to improve these. Yet, although well intentioned, green buildings are still expensive to the average homeowner, and it did not take a lot of time to realize that representative savings come from a more efficient use of the building's utilities and not from the building itself. But are humans ready to assume this major role in contributing to a more sustainable use of natural resources? The short answer is NO. And even if human beings are at the center of concerns for sustainable development, they are not really aware of how their actions and behaviors can affect sustainability.

Electricity is a paradigmatic example of this lack of awareness and this is shown in a series of studies that present significant contradictions between consumer perceptions and their knowledge of energy efficiency. For example in (Attari, 2010) authors show that most humans have a wrong perception of the most effective thing to do when trying to be energy efficient. While there is strong evidence that generally efficiency-improving actions save more than reducing the usage of inefficient equipment, only 11.7% of participants refer to the former while 55.2% pointed out the later.

These wrong perceptions were also the subject of Chisiks' work (Chisik, 2011), which focus on understanding how people perceive electricity. The findings are quite informative about the lack of perception regarding how much electricity is consumed by a particular device, which users tend to associate with the frequency and duration as well as with the size of the device.

This working hypothesis, that most people lack awareness and understanding of how their everyday behaviors affect the environment, is the base for eco-feedback technology, which is defined as technology that provides feedback on individual or group behaviors with a goal of reducing environmental

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impact (Froehlich et al., 2010). Eco-feedback technology has been around for more than 40 years, and literature shows that providing feedback to the consumers, even at a low level of disaggregation, may result in savings between 10% and 15% (Parker et al., 2006). However there are other studies that show that this effect is not long lasting, and that consumers tend to return to previous consumptions values is a few weeks (Peschiera et al., 2010).

Today the advances in sensing technology that promote the ability to disaggregate power consumption at a low-cost, combined with the widespread use of internet based social networks and the dissemination of handheld devices, open the potential of eco-feedback to millions of households. It is therefore important to understand how people will react to the feedback, and to what extent they are willing to change their behaviors in favor of a more sustainable lifestyle.

This paper presents a low cost framework for non-intrusive home energy monitoring and research, which is capable of monitoring and disaggregating the electricity energy consumption from a single sensing point and at the same time provide eco-feedback to the consumers using different communication channels.

2 HOME ENERGY MONITORING

As seen above, humans deeply misunderstand energy consumption, and perhaps its invisible nature is one of the main reasons for this. After all the task of quantifying something that hides from the human senses is merely impossible. Lets face it, everybody knows electricity, but nobody has actually been in direct contact with it.

The role of quantifying electric energy consumption is delegated to smart meters, which are electric devices that record the electric energy consumption in pre-defined intervals and communicate the measured results back to the utility. It is possible to find all kinds of smart meters. **Single point (plug-level)** meters are probably the easiest to find and their mode of operation is very simple. Basically the appliance is connected to the meter that in turn is connected to the outlet. **Multi point (whole house)** meters provide measurements at the service entrance and have extra channels to track sub-panels or larger electrical loads. These are installed in the main entry feed, and the feedback to the user can be provided in several ways, e.g. portable displays and http via built-in webservers or online services. Finally, the **Circuit panels (Circuit-level)** offer the possibility of measuring each individual circuit in the house, with up to 12 or 16 circuits in each meter. These are considered, by far, the most expensive and difficult to install requiring the presence of a professional.

Despite the fact that owning a smart meter will not necessarily decrease the energy consumption it is strongly believed that the ability to reason on top of power consumption data would be of great interest for consumers and would be a huge help in the process of engaging the consumers into having a more energy efficient behavior. *"Does my new microwave spend more than my previous one?"*, *"Why do I spend so much electric energy at night if I am sleeping?"*, *"How much do I spend cooking dinner?"* are just a few examples of possible questions that consumers would like to see answered by their smart meters.

However this is not what smart-meters do because, although they can provide several different power metrics, their level of information disaggregation is not enough to answer such questions.

It is therefore safe to say that future power meters must provide their information with very high levels of disaggregation, that go beyond the overall consumption and the time of the day.

3 NON-INTRUSIVE LOAD MONITORING

The process of measuring and disaggregating, electricity consumption from a single sensing point, is called Non-Intrusive Load Monitoring (NILM).

NILM is not a new subject, its origins go back to the late 1980s, early 1990s (Hart, 1992), and it is built on top of the premise that every change in the power consumption is due to some appliance changing its state (either turning *on*, *off* or going to a different working mode), and that by analyzing these changes it is possible to determine the appliance that was responsible for them.

The NILM process can be explained as the combination of six consecutive steps. First sensors measure the current and voltage signals at the main circuit breaker. Second, the acquired current and voltage signals are converted into traditional power metrics like real and reactive powers. Next an event detection algorithm is applied to the computed metrics and load changes are flagged as power events for further processing by the feature extractor that will extract a set of generalized features that can mathematically characterize the event. The set of features that describe an event is called the event signature. In the next step previously trained machine-learning algorithms are applied to the unclassified signatures to obtain a classification. Finally in the last step it is possible to estimate how much energy each appliance is using by keeping track of all its events and associated power levels.

Much research has undergone in this field throughout the years after Harts first approach of analysing real and reactive power steady state changes at the fundamental frequency and the advances in sensing technology allowed researchers to greatly improve the classification accuracies by using “microscopic” features such as current harmonics. For example, in (Laughman et al., 2003) authors have used harmonics as complementary features, in addition to changes in real and reactive power, and found that this would help to distinguish loads otherwise indistinguishable. In (Berges et al., 2009) the authors have applied supervised machine learning algorithms, e.g. k-NN and decision trees, to classify the loads under different feature sets, which included harmonics powers. They have reported classification accuracies between 67% and 100% for different sets of appliances.

In a very different approach (Patel et al. 2007) proposed that by monitoring electric noise in a socket for transient signals they could detect most appliances that were connected to other sockets in the house. The same authors also presented ElectriSense (Gupta, Reynolds and Patel, 2010), 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) which are present in most modern consumer electronics, as well as fluorescent lightning.

4 NON-INTRUSIVE HOME ENERGY MONITORING

From a technical standpoint a non-intrusive energy monitor needs to commit to a set of requirements: 1) it has to sample both current and voltage from a single sensing location, 2) the data needs to be available for both offline and online analysis, and 3) it has to allow different representations of the measured energy trough different kinds of feedback.

Additionally, and for research purposes, it also needs to be able to sense when humans are exposed to the feedback, and possibly their interactions with the feedback interfaces. A final requirement, which is also due to the research purposes of this monitor, is that the final solution must be very cost effective. Otherwise it will become too expensive to conduct research with a fair amount of simultaneous installations.

To cope with these requirements, one opted to use a netbook as a whole-in-one solution. The laptop audio input Analog-to-Digital Converter (ADC) is used to sample current and voltage, the display and the speakers are used to provide the interactivity, while the Wi-Fi card enables communication over the internet and the built-in camera and microphone act as low-cost sensors for human activity.

4.1 Eco-feedback User Interfaces

The eco-feedback interfaces of this system were built on top of those studies, presenting consumption (in kW/h, € and CO_2 emissions) over hour / day / week / month / year, total consumption of the day / week / month / year and also showing comparisons between different months / weeks and days.

The interface also presents real time data to the user, namely power consumption in watts and power events. Figure 1 shows a snapshot of the eco-feedback user interface.

Figure 1: Eco-feedback user interface snapshots, from left to right: month view, year view, real time view (CO2/Month, kW/h and Euros/Month).

Another very important feature of the user interface is the fact that it stores the user navigation history (mouse clicks) as well as the instant when motion is detected (using the webcam as a motion detector).

4.2 System Architecture

The system architecture is based on the *“pipe-and-filter”* software architecture. Figure 2 shows the current system architecture.

Current and voltage are continuously sensed and sent to the *data acquisition filter* to be sampled. As these are sampled they are sent to the *power calculations filter*. This filter is responsible for doing the power calculations and driving the resulting data to the *splitter*, which is an active filter that is responsible for sending the power samples to the

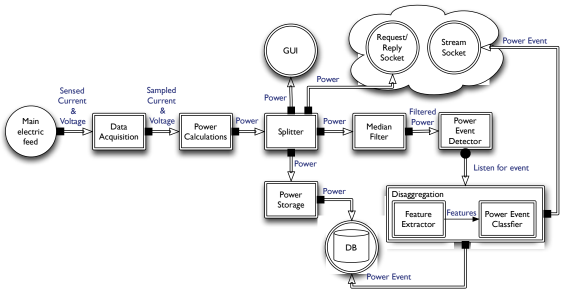

Figure 2: Framework architecture.

filters that are connected to it. The *GUI* is responsible for plotting the power as it is being calculated and the *Request / reply socket server* provides real time information about the system measurements to external applications. The *power storage filter* role is to average the power samples, based on a predefined number of samples value, and drive the resulting sample to the database. The *median filter* is used to apply a median filter to the power samples, also based on a predefined window size, and send the filtered samples to the *power event detector filter* that will apply a detection algorithm to the filtered power samples, and trigger a programmable event when a power event is detected. The *disaggregation filter* is a composite filter that captures the events triggered by the power event detector and is composed by two filters that work together to disaggregate the load. The *feature extractor* is used to extract the features that will be used by the *power event classifier* to classify the power event. The event is then sent to the database and streamed to the Internet using the *streaming socket filter*.

4.3 Data Acquisition

In order to measure the power being consumed by the house two sensors are installed at the main breaker circuit: one split-core current transformer to be placed around the cable that carries the current and one voltage transformer to be connected to one of the existing voltage sources. These two sensors are then connected to the netbook built-in sound card using an audio splitter jack. Custom made software is used to sample the acquired signal using the sound cards' ADC.

4.4 Power Calculations

The power metrics, real power, reactive power, voltage, amperage 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).

4.5 Event Detection

In the current system, the event detector is a modified change of mean detector that uses a log likelihood ratio test (Luo, Norford and Shaw, 2002).

In its essence the change of mean detector works with one sliding window, referred to as *detection window* that is used to calculate the likelihood of a change of mean in each sample, and a second sliding window, called *voting window*, that is used to select the edges with the highest likelihood.

The detection window [l, k] can been seen as having two windows, [l, j[and [j, k], pre-event and post-event respectively. The former is used to achieve a stable mean as the reference for coming events, while the later is intended to be very sensitive to events but yet robust to disturbances.

For each sample in the power signal the likelihood is calculated according to equation 1:

$$l_j = max_{l\le j\le k} \sum_{i=j}^{k} \left[\frac{\hat{V_j} \times (y_i - u_{pre})}{\sigma^2} - \frac{\hat{V_j}^2}{2 \times \sigma^2} \right] \quad (1)$$

Where $\hat{V_j}$ is the value of the mean change ($u_{after} - u_{pre}$) at which l_j reaches its maximum. Additionally a minimum change of interest V_m can be set, hence discarding changes in mean that are below this value. $\hat{V_j}$ is given by equation 2:

$$\hat{V_j} = \begin{cases} V_m & if\ step < V_m \\ \frac{1}{k-j+1} \times \sum_{i=j}^{k} |y_i - u_0| & if\ step \ge V_m \end{cases} \quad (2)$$

The magnitude of l_j will increase with the change in power and abruptness of the change, hence indicating the presence of a potential event of interest.

There are five tunable parameters: Minimum step change V_{min}; pre and post event windows lengths, w_{pre} and w_{post} respectively; voting window length w_{voting}; and the minimum votes an edge needs to be considered an event of interest $votes_{min}$.

4.6 Feature Extraction

The set of extracted characteristics is known as a power event signature and at the time of writing a very straightforward signature is being used, consisting of four features extracted from both real and reactive power: real and reactive power mean change; and 4) real and reactive power polynomial coefficients (3^{rd} degree polynomial).

The mean power change refers to the amount of change that just happened, and it is calculated by simply subtracting the average power before from the average power after the change. This value will be either positive or negative, hence indicating if there was an increase or decrease in consumption.

The polynomial coefficients are obtained by finding the best-fitting curve to the power samples using a least squares fitting procedure. It is believed that similar appliances will generate similar coefficients and that these will become very good features to add to the event signature.

4.7 Event Classification

Once the power event signature is extracted it is time to learn what appliance lead to such event. In this work a supervised learning method is being used. In the case, and due to good results reported in (Berges et al., 2009) the *k*-NN was chosen.

The supervised learning algorithm analyzes the training data and produces a classifier that will then be used to assign class labels to future instances where the values of the predictor features are known but not the value of the class label.

5 METER VALIDATION

In order to test the event detection and load disaggregation algorithms an experimental setup consisting of 8 appliances was put together. The used appliances where: 1) Compact Fluorescent Lamp (CFL) - 10W; 2) Fan - 50W; 3) Hand blender - 250W; 4) Hand mixer - 250W; 5) Kettle 2kW; 6) LCD Monitor - 130W; 7) Microwave oven - 1,2kW; 8) Toaster - 900W. For these appliances only two state transitions were considered, OFF to ON and ON to OFF.

5.1 Event Detector

The event detector was applied, to two consumption scenarios. In the first scenario three appliances where used: CFL, LCD monitor and FAN. In the second scenario five were used: CFL, Fan, Kettle, LCD Monitor and Microwave oven. Because very low consumption appliances are present, the minimum power change of interest was set to 15 watts. The windows sizes are integer values referring to the amount of power samples. For example, at 50 Hz 150 samples represents 3 seconds. From these 150, 100 are used in the pre-event window and 50 in the after event.

In the first simulation the algorithm was able to detect 5 of the 6 transitions, only the CFL being turned off was not detected (1 false positive) because the step is of about 10 Watts. Still, it is interesting to notice that the CFL turning ON was detected even though the minimum step change was of 15W, and this is because although the average consumption of the CFL is 10W, when turning ON the step change reaches more than 15 Watts that then go back to 10W. As for the second simulation data the results were as expected. The algorithm is still able to detect all the appliances (except the CFL being turned OFF), however, the number of false positives greatly increases. 22 false positives were found, from which 13 happened when the microwave oven was working.

5.2 Event Classifier

To test the classification algorithm the first step was to collect and classify 10 ON and 10 OFF power events from the appliances under test, except for the CFL that was excluded due the difficulties in detecting its ON and OFF events. Apart from these 20 signatures, 4 others where extracted from them: 1) averaging all the points, 2) selection the median among all the points, which are referred to as “Jokers”. In total there are 168 classified signatures, 24 for every appliance (12 ON and 12 OFF), and all these are used as learners to *k*-NN classifiers. In total 6 classifiers were created, 3 for each set of features, for 1, 5 and 9 nearest neighbors.

The learners were tested using the *leave-one-out* cross validation. The results of the classification process are shown in table 1:

Table 1: Results from classification using leave-one-out cross validation.

Features	Accuracy (%)		
	1-NN	**5-NN**	**9-NN**
Step change P	90.48	91.67	92.26
Step change Q	64.29	67.26	70.24
P&Q	100	100	100
Poly P	98.02	98.40	99.78
Poly Q	98.94	99.40	99.40
Poly P&Q	99.51	99.51	99.51

Results show, in the first place, that there is not much variation when changing the number of neighbors. The second thing to notice is the low classification accuracy that is obtained when using only reactive power as a feature. The results for just the real power step change are better, with an overall classification rate that is above 90%. And the explanation for these results lie in the fact that using just one metric does not work properly for appliances with similar power consumption. Nevertheless, the combination of real and reactive power yields very good results, 100% for this set of appliances, which is in accordance to results in previous research.

As for the polynomial coefficients the classification accuracy is very high using any of the features, and the first thing that this shows is that this solution can overcome the difficulty of separating appliances with close consumption levels.

6 CONCLUSIONS

In this paper a low cost framework for non-intrusive home energy monitoring and research was presented. The final system is a very cost-effective, (less than 300 Euros), energy monitor with some load disaggregating capabilities and at the same time, provides a very flexible research platform for non-intrusive load monitoring.

Despite the promising results of the implemented algorithms there is still a lot of room for improvement and the flexibility of this framework will allow the testing of different algorithms with bigger sets of appliances, and, if possible, in different houses.

NILM offers a big field of research, for example, its concepts and techniques can be used in a lower scale to create a smart power strip that would be able to detect and turn-off appliances that are found to be in stand-by mode. Also, it cannot be forgotten that NILM can be easily exported to other domains, opening the possibility of creating lower-cost sensor networks. The ability to sense a whole house together with the possibility of inferring human activity will open various windows of research opportunities. For example home automation ambient intelligence and smart-grids are just three fields that can greatly benefit from NILM.

Finally, it is also believed that there is still a lack of services that use this technology making it appealing not only for the consumers but also for the electric companies and appliance manufacturers. Which also opens a window of opportunity in the area of service design, where researchers can aim at creating innovative services on top of low-cost technologies.

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