PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE

ESCUELA DE INGENIERIA

NONINTRUSIVE LOAD IDENTIFICATION & MONITORING: TECHNIQUES AND APPLICATIONS FOR SMART METERS

NICOLÁS A. KIPREOS

Thesis submitted to the Office of Research and Graduate Studies in partial fulfillment of the requirements for the Degree of Master of Science in Engineering

Advisor:

DAVID E. WATTS

Santiago de Chile, June, 2011

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A mi papá y mi tía Tasa.

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ABSTRACT

During the last decade there has been an accelerated adoption of smart meters, some of them with the potential to become the backbone of the Smart Grid. Several meters have the potential to help utilities characterizing their clients, motivating the use of Non-Intrusive Load Monitoring (NILM) and Identification (NILI). These techniques have been the target of research for nearly 30 years, but few advances have been made over the last decades. They have been characterized by very low accuracies, without achieving real applications in the market. This paper offers a critical review of these techniques and the most relevant literature, proposing a 4-stage steady state algorithm capable of being implemented with numerous low frequency smart meters. The algorithm shows good results that can be further improved with higher frequency techniques. Some implementation and evaluation issues are also presented.

Keywords: Nonintrusive Load Identification, Load Signatures, Transient Signatures, Steady State Signatures, Load Monitoring .

RESUMEN

Durante la pasada década ha habido una acelerada adopción e instalación de diversos tipos de medidores inteligentes, algunos de ellos con el potencial de convertirse en la piedra angular de las futuras redes inteligentes. Muchos de los nuevos medidores tienen la capacidad de ayudar a las empresas de distribución a caracterizar a sus clientes, motivando así el uso de tecnicas de detección de carga no intrusiva (NILI) y monitoreo no intrusivo (NILM). Estas técnicas han sido objeto de investigación por ya cas 30 años, pero pocos avances se han realizado al pasar los años, los cuales se han caracterizado por muy baja presición y ninguna aplicación seria a nivel de mercado. Esta investigación ofrece revisión crítica de las técnicas propuestas en la literatura existente, además de proponer un algoritmo de 4 etapas facilmente implementable en medidore inteligentes de baja frecuencia. El algoritmo muestra buenos resultados que pueden ser mejorados con técnicas de mayor frecuencia de muestreo. Algunos problemas de implmentación y evaluación también son presentados.

Palabras Claves: Detección de carga no intrusiva, monitoreo de carga no intrusivo, Firmas de carga, Monitoreo de carga, Medición inteligente.

1 INTRODUCTION

The current energy supply system is undergoing fundamental challenges. Systems are facing strong pressure to increase energy efficiency, accommodate large amounts of renewables, reduce local and global emissions, minimize their footprint, and at the same time become more cost effective and reliable. Several smart grid technologies are expected to help meet these demands in the future, and those based on smart metering technologies are among those with the largest potential in the near term.

1.1 Smart metering, consumption feedback and more

Smart metering technologies promise to reduce residential energy consumption between 5 and 10% and to cut down CO_2 emissions by around 2.5 million tons per year in the U.S. Advanced meters have the ability to effectively show the consumption information to customers so they can manage their consumption patterns and save energy (Houseman, 2005). More advanced features on meters can push these figures up considerably. The advanced metering infrastructure (AMI) offers the possibility of services such as demand side management (DSM), the realization of virtual power plants VPPs (van Gerwen, Jaarsma, & Wilhite, 2006), and many others, having the potential to boost reliability, while smoothly integrating large amounts of distributed resources without compromising reliability, dealing economically with non-dispatchable natural resources such as wind and solar.

Smart metering plays an important role in future power distribution networks for the efficient and effective management of distributed power resources, and for the control of smart houses and offices (Houseman, 2005). From telemetry to active control of resources and demand, smart metering is the door to the future of the distribution networks. It allows the operator to manage the grid more efficiently, reduces costs and emissions, and offers an effective way of performing demand side management by only changing the architecture of the network to a more communicated an automated one, as shown in Figure 1-1.

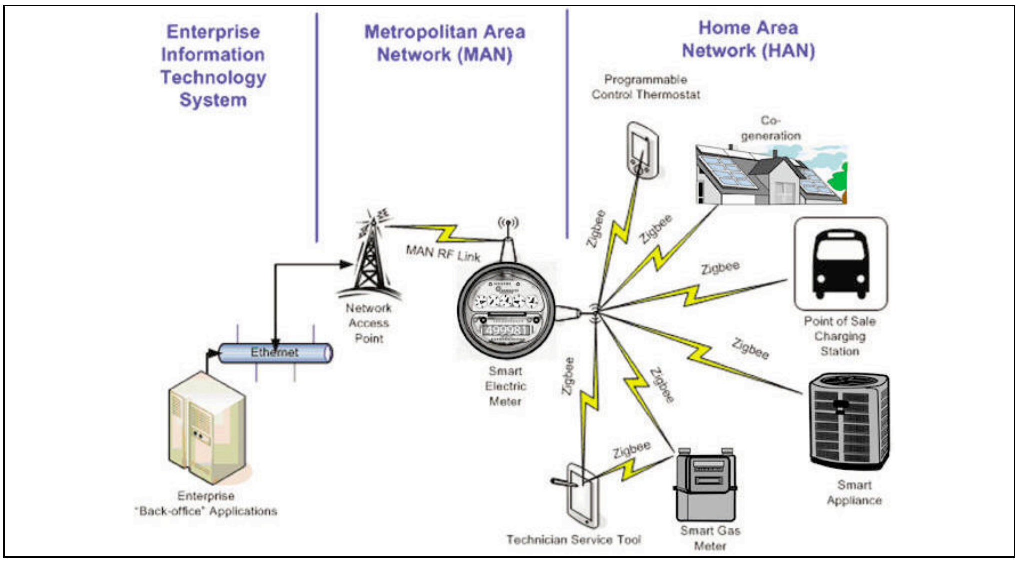

Figure 1-1: Advance Metering Architecture

1.2 Smart metering beyond consumption feedback

Smart metering technologies offer the potential ability for the utility company to characterize and know better its clients. For example, a utility could estimate (or even determine) which clients have a pool, and sell effective advertising on the monthly bill for pool products. Also, they could offer or recommend distributed generation solutions according to the consumption profile of the client to help him save money. Moreover, the utility could measure demand price elasticity of each client type (or even individual clients) in the long and short run and then assess the sources of those changes in consumption behavior. This could be pushed even harder and assess demand price elasticity associated with specific residential appliances and determine how certain policies or events could affect the energy consumption in a residential client or client type.

While the potential for these technologies goes well beyond improving load profiles, estimating elasticities, detecting appliance disconnection and scheduling, pushing energy efficiency and residential energy management (Sawyer, Anderson, Foulks, Troxler, & Cox, 2009), this article has a more limited but fundamental scope. It focuses on the load characterization through nonintrusive load monitoring and identification, as these techniques are needed to perform all others accurately, requiring urgent further development.

The structure of the rest of the thesis is the following: Section 2 provides some basic definitions; Section 3 shows the different families of load signatures and their classification. Section 4 presents our proposed methodology and its application to our field test, Section 5 contains the conclusion and Section 6 contains some recommendations for future work on the subject.

2 NILM, NALM, NILI

While smart meters have been widely deployed in several areas, getting good use of their data and deriving meaningful information from it is still a pending task. Techniques such as non-intrusive load monitoring (NILM), non-intrusive appliance load monitoring (NALM) or non-intrusive load identification (NILI) have great potential nowadays. They all are based on a principle called *disaggregation*, in which the constituent parts of the load are extracted from an aggregated or total load signal, as shown in Figure 2-1. This total contains the components from all the devices or appliances within a client's total load[1]. This disaggregation process is quite simple in theory, but the diversity of appliances, their different uses and consumption patterns, the limitations on the meters' capabilities and on their communication and data centers provides pending challenges such as how to perform accurate NILI and how to perform cost-effective and accurate NILI?

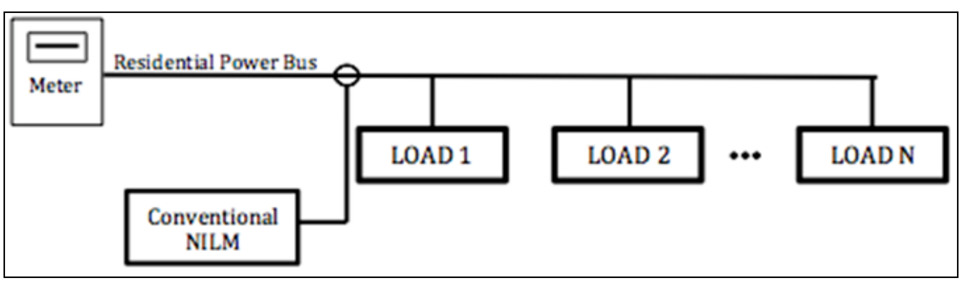

Figure 2-1: Non-Intrusive Load Monitoring Connection Architecture

Non-intrusive techniques yield detailed information about the load's energy consumption without measuring each end device directly, so that fewer sensors are

[1] While loads can be residential, commercial or industrial, residential ones are simpler to deal with, and provide a large set of smart meters to take advantage of, but they also are the ones with the least capable smart meters.

needed and monitoring, storage and transmission gets cheaper (Marceau & Zmeureanu, 2000). Another advantage of nonintrusive approaches is that consumers are not necessarily aware that they are being monitored, so psychological effects don't affect their consumption profiles.

The basic principle for data collection is measuring the waveforms or RMS values of both voltage and current, and computing other variables of interest from them (real/reactive power, power factor, etc.). Obtaining accurate and frequent measurements of these parameters is crucial for the identification of the load. The sampling frequency and the level of detail of the signal (waveform or rms value) will depend on the kind of algorithm to be implemented; the goal is often to do more with less resources.

2.1 Basic definitions

Some basic definitions are introduced next. They are necessary to allow for understanding and classifying the methodologies presented in the literature review.

2.1.1 Load identification and monitoring

While load identification (LI) and load monitoring (LM) may seem to be equivalent, they are not and it is worth understanding the difference:

- LI and State: The **identification** of a load, e.g. an electrical appliance in a house, is the ability of a system to successfully detect the **state** (that could be on/off or an intermediate state in the operation of the load) in which the appliance is operating.

- LM and Consumption: The **monitoring** of the load is the following of all the loads or appliances inside an aggregated load and the estimation of the **energy consumed** by each one of them, and of all the loads together.

They are closely related, as load monitoring has to use load identification to estimate the energy consumed by each one of the appliances. Load monitoring can also be used for characterizing load types in different profiles (Gavrilas, Sfintes, & Filimon, 2001), which could be very useful for utility companies and load forecasters.

2.1.2 Load signature: Intrusive and Non-intrusive

A **load signature** is a characteristic that makes a load unique (e.g. real power consumption, in-rush current, admittance, etc.). Signatures can be classified according to their sources (or the level of disruption required for observing the signature) into two families, these are intrusive and nonintrusive.

Intrusive signatures require significant levels of intrusion or distortion at the client's facility, and they can be further classified according to the media used to assess the signature into two families: physically intrusive and electrically intrusive. **Physically intrusive signatures** can be generated by a sensor located on the electric cord of each of the appliances in a residence or by placing presence-activated sensors in the rooms of a house or also the generation of a unique signal that is emitted by a circuit present in each appliance at the moment it is turned on. An **electrically intrusive signature** is, for example, the injection of a signal at the energy meter to observe the system response signal. Evaluating the distortion of the signal could give useful information on the appliances that are operating at that time (Hart, 1992; Marceau & Zmeureanu, 2000).

Nonintrusive signatures are those signatures that don't require intrusion or disruption into clients' physical and electrical facilities. There are two main families of nonintrusive (electrical) signatures: **transient** and **steady state ones**. The former refers to short-run transitory changes in consumption patterns associated to an electrical appliance, while the latter refers to their steady state changes; this is when transient changes have died out. These signature families are described in more detail next.

3 FAMILIES OF LOAD SIGNATURES

Load signatures can be obtained by intrusive and nonintrusive methods. George W Hart (Hart, 1992) was the pioneer of nonintrusive load monitoring (NILM). He introduced the concept of load signature in the mid 80's and developed a nonintrusive appliance load monitor (NALM) aiming to determine the energy consumption of every appliance inside a house. His algorithm is based on the evaluation of the steady state change of real and reactive (admittance-corrected) power.

3.1 PQ Clustering

Every appliance has a positive and a negative real power variation, which corresponds to it being either turned on or turned off. This is shown in Figure 3-1 for some of the appliances we tested. Other appliances, such as a washing machine, have multiple state changes in their cycles, and because of that do not lie fixed in the PQ map, but cycle on it instead. This is why they are not shown in the PQ cluster map, where they would show a denser state trajectory or cycle. This simplified cluster map shows a group of 8 appliances, in which resistive loads, such as an iron or water heater are near the real axis (active power axis), while devices with some reactive nature (due to motor use for instance) move away from the real power axis, adding a significant reactive power dimension.

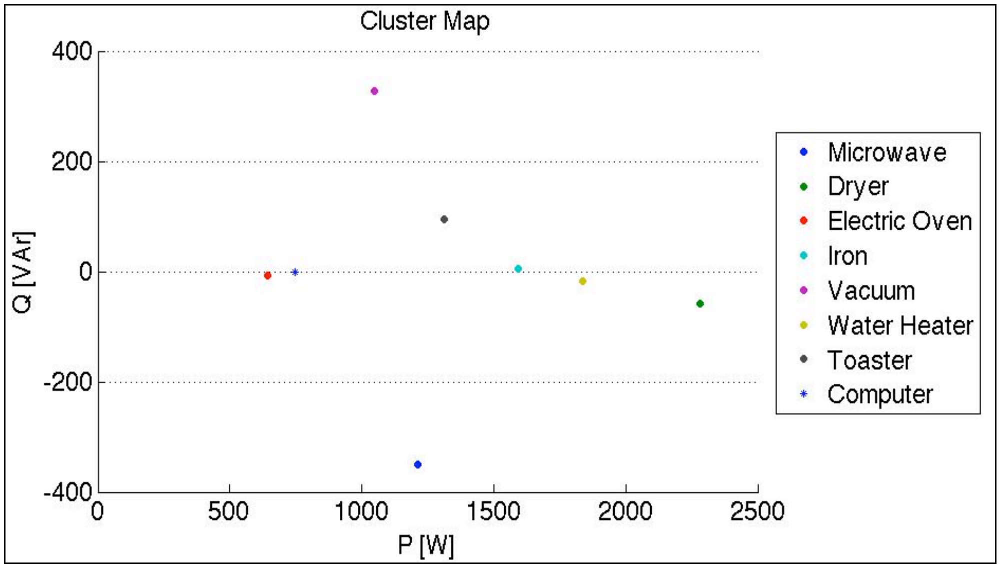

Figure 3-1: Cluster Map of Appliances Present in the Test Residence

3.1.1 Hart's algorithm

Hart's algorithm constructs on this idea. Steady state is defined (in his algorithm) as three or more data intervals where consumption does not vary more than 15W or 15VArs. The values within the steady state period are averaged for minimizing the effect of noise on the signal. A step change in this context is a change in the power consumption of the appliance with respect to two consecutive data samples. Hart proposes that step changes should be grouped into clusters, which contain the variations of the power consumption of each individual appliance.

Since the first applications of nonintrusive load monitoring and identification, different approaches have been proposed. The general basis for most of them follows a simple, but economic and meaningful steady state approach as proposed by Hart. A more formal and detailed classification is provided next.

3.2 Load signature classification

Hart (Hart, 1992) made an initial classification of load signatures in the year 1992. We extended/updated it to include two additional signatures, *steady state shape* and *distortion index* ones. The following figure shows this classification of energy signatures, where the main two families are steady state and transient ones, as we explain and compare next.

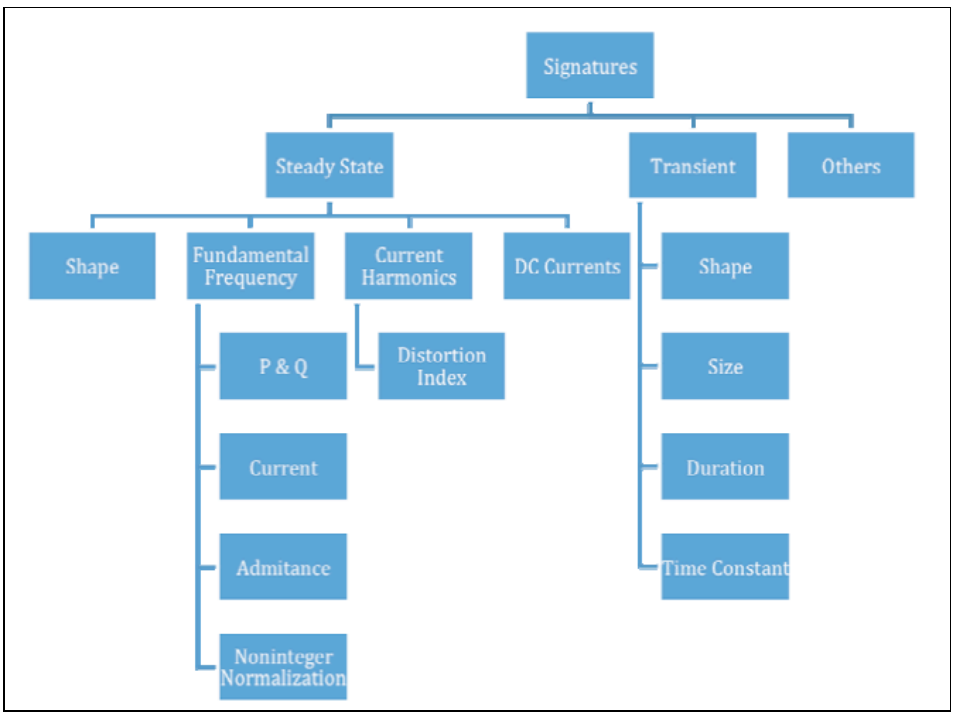

Figure 3-2: Classification of Energy Signatures

3.2.1 Steady state signatures

The steady state (SS) signatures are based on changes of the power consumption level (state) of a particular appliance in the steady state. These are mainly due to turning on or turning off the appliance, or due to energy changes in its cycle. Steady state changes are very informative of the nature of the load and they are easier to detect than a transient change. The sampling frequency of the SS meter needs to be far less than the one targeted to measure transient signatures. Another advantage of steady state signatures over transient state ones is that they are additive, that is, if two appliances of 2kW connect, then the total power consumption is 4kW. Transient state signatures are not additive.

3.2.1.1 Fundamental frequency signatures

The measurement of the power network's voltage and current at a fundamental frequency of 50Hz (or 60Hz) can lead to obtaining real, reactive and apparent power, as well as the load's admittance.

Due to local legislation, often the variation in a low voltage network cannot exceed ±10% of the nominal voltage, which is 220V (110V in other areas). Therefore, in linear loads a ±10% variation in the current and, consequently, a ±20% variation in the power, is possible. Hart proposes that instead of using a signature based on the power, which relies too much on the voltage, this signature should be corrected by the admittance, which is a voltage invariable feature of the load. Unfortunately, the load's admittance is an unfamiliar characteristic if one lacks engineering intuition, so Hart proposes the admittance-corrected power as a signature, as shown in (1):

$$P_{Norm}(t) = 220^2 Y(t) = \left(\frac{220}{V(t)}\right)^2 P(t) \tag{3.1}$$

This correction can be used for both active (P) and reactive power (Q). It can be seen that (1) is only the admittance correction by a constant scale factor, where the normalized watts and vars reflect the changes in impedance over time normalized to a constant ideal voltage supply (Cole & Albicki, 1998b). The quadratic expression is only true when assuming that the load is linear, which is unlikely because most of the loads in a residence are of a nonlinear nature. In the case of nonlinear loads, the formula is corrected by a β factor (2), which doesn't fit nonlinear loads perfectly but it makes a better approximation than a quadratic exponent. The problem with this is that β factors for P and Q must be calculated isolating every device preferably in a laboratory, which is not possible most of the time. Due to this difficulty in determining β factors, the admittance corrections are usually done using a quadratic exponent or extrapolating factors estimated for similar loads.

$$P_{Norm}(t) = \left(\frac{220}{V(t)}\right)^{\beta} P(t) \tag{3.2}$$

Although the effects of this normalization do not make a notable difference for the visualization of the signal, they help to clean the signal from noise effects, especially in moments where there is a large amount of step changes, as in the operation of the washing machine, which has many cycles due to the irregular operation of the motor.

A linear load, such as a water heater, has a linear relationship between the voltage and the current, while a nonlinear load, such as a microwave, has a relation that describes a trajectory particular or specific to that device, and where the current doesn't follow the voltage linearly. In the case of the microwave, for instance, the relation between the voltage and the current describes something similar to an elliptical cycle around the origin. Our measurements comparing a linear and nonlinear load are shown in Figure 3-3.

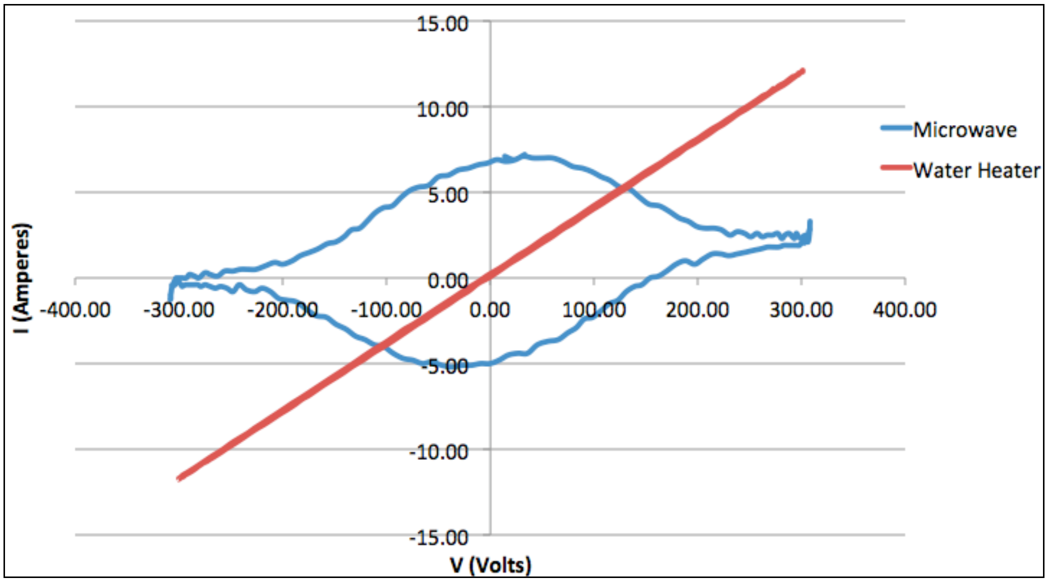

Figure 3-3: Difference between nonlinear and linear load

The most common fundamental frequency signature is the **PQ signature**, which corresponds to the variation of real and reactive power in the steady state operation of the specific appliance. They use a slow sampling frequency and they are relatively cheap in the use of computational resources. The sampling frequencies can go from 1 PQ sample per second to 1 PQ sample per minute, being 1 second and 16 seconds (used in (Farinaccio & Zmeureanu, 1999; Marceau & Zmeureanu, 2000)) the most common choices in the literature. On the other hand, transient signatures are very demanding regarding computational resources: they usually capture 256 (Chang, Lin, & Lee, 2010) or 128 (Shaw & Laughman, 2007) samples per cycle, which require sampling frequencies between 6kHz and 13kHz.

3.2.1.2 Harmonic current signatures

Harmonic signatures provide additional information when used together with fundamental frequency signatures and may be useful for increasing the algorithm's effectiveness. Most residential appliances have non-linear characteristics, which generate significant third, fifth and seventh harmonics. These harmonics can be easily identified by specialized sensors for particular frequencies and then treated as a steady state signature. This kind of signature can be very useful for detecting small appliances such as low power bulbs (Laughman, 2003).

In this area AL-Kandari (Al-Kandari & El-Naggar, 2006) proposes a recursive algorithm for the identification of harmonic admittance of the load. The advantage of this method is that it offers a fast estimation of the harmonic admittance even if the harmonic content varies with time. The disadvantage of this method is that it is based on complex signal analysis in which the parameters must be calibrated to a particular case. In Figure 6-1 we show the harmonic content of measurements we obtained from different appliances. It is clear that it can offer a very good tool to differentiate between them.

3.2.1.3 DC currents

DC consumption is another non-linear feature that makes an appliance unique. For example, some blenders have a diode for speed control (only half wave) and they generate a DC component that can be detected. However, Hart points out that they haven't encountered yet an appliance with a significant DC power flow that could be of interest to utilities.

3.2.1.4 Shape & Others

There are other types of signatures that can provide information for differentiating between appliances, but they are rather specific. One example could be a 1Hz ripple due to the cyclic reversal of the tub in washing machines. This would be a steady state shape signature.

3.2.2 Transient state signatures

In addition to steady state approaches, others (Leeb, 1993; Shaw & Laughman, 2007; Shaw, Leeb, Norford, & Cox, 2008), have used transient approaches to NILM. These algorithms are more complex and require more computational resources, but they have demonstrated to be very helpful by providing valuable extra information that can be used together with steady state signatures to improve the algorithm's effectiveness.

Transient signatures are more difficult to detect and require more complex and expensive data acquisition systems. The objective in using transient signatures is to help differentiate between two very similar loads to each other (Chang, et al., 2010; Leeb, 1993) or identifying low power consumption devices (Leeb, 1993). They may be useful for differentiating between two appliances that have similar power consumption in a steady state, but may look quite different during the transient period, for instance having different in-rush currents. However, a transient signature would not be useful to determine which of the two appliances turned off, because transients are usually present when appliances are turned on only. Hart classifies transients in three main categories:

a) Flat character with a sudden step power drop to the steady state operating level.

b) Large initial increase in the power, followed by an exponential drop lasting several seconds.

c) Transients lasting a few cycles, which are transients as defined in the linear circuit theory.

There are more parameters to characterize transients, like time constants, duration, size or parametric variables in models, which can be fitted to the observed waveform. Nowadays, a combination mainly composed of shape, size and duration of the transient is applied to recognize loads. As seen in (Chang, 2010; Leeb, 1993; Shaw, et al., 2008), where the measured wave transient is fitted to a stored transient wave, and the waveform that presents the minimum quadratic error with the measured one is assigned as the most likely one and is chosen.

Chang (Chang, 2010) states that the main problem with power signatures is that many devices have different consumption levels, like a refrigerator, which has only one load, a compressor, but it has different physical components for refrigerating and freezing. He states that the envelopes of transient behavior when appliances are turned on could offer a better tool for discriminating between similar loads (Chang, 2010; Chang, et al., 2010; Leeb, 1993; Shaw & Laughman, 2007; Shaw, et al., 2008), which is very typical in industrial loads. Current in-rush's when appliances are turned on offer a very unique and distinguishable parameter to accurately differentiate between two very similar steady state loads (Chang, 2010).

Some approaches to accommodate the power transient signal to a signal that is easier to process, obtain the envelope of the signal through signal processing, which is sometimes complex and requires additional information about the load, like parametric models of some appliances that are present in it (Shaw & Laughman, 2007; Shaw, et al., 2008). Shaw (Shaw & Laughman, 2007), proposed a Kalman-filter approach to compute spectral envelopes of current waveforms, but is complex and uses excessive computational resources.

4 ALGORITHM, LOAD CHARACTERIZATION AND FIELD TESTS

We developed and applied a steady state fundamental frequency algorithm, being the most traditional family of algorithms, well documented by Hart and others. The benefits of this are its low cost, low computational requirements and simplicity. These are ideal characteristics to combine it with low cost smart meter deployments in developing countries.

4.1 4 State algorithm

The proposed algorithm builds strongly on Hart and Farinaccio and is divided into four main stages; these are measurements, normalization, de-noising and appliance-specific algorithms and rules. After that, individual results are summed up and the total aggregated consumption is estimated and eventually compared with the original measurements. Figure 4-1 shows the flow chart of the implemented algorithm.

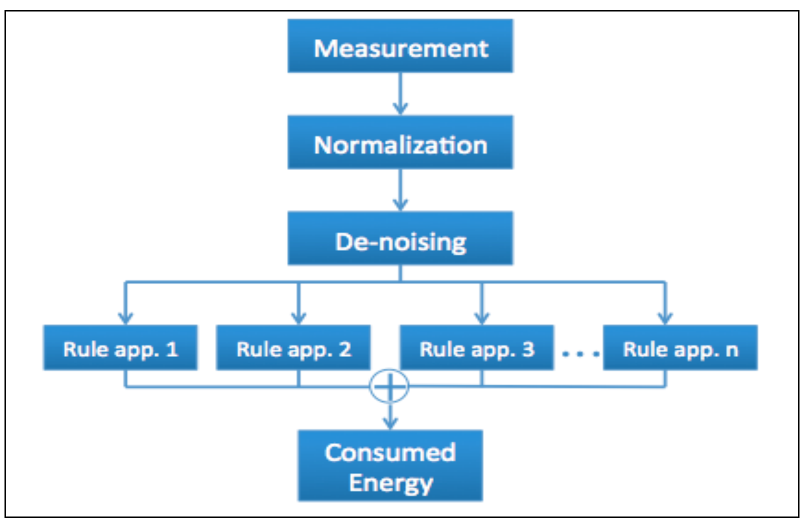

Figure 4-1: Algorithm's flow diagram

4.1.1 Measurement

The first step of the algorithm is the measurement, which is done at the utility meter, where the aggregated power demand of the residence is acquired.

4.1.2 Normalization

The following stage is the normalization, where the acquired data is admittance corrected by means of (3.1). This is well described in our literature review.

4.1.3 De-noising: Border detection

The third stage is a de-nosing stage that is performed in order to clean the data from its power transients, as they make the signal dirtier, complicating the identification process; this is done by applying (4.1). This softening of the signal must be performed before applying appliance-specific rulings onto the normalized aggregated measurement. This process is realized by an algorithm called “border detection”. A very useful border detection algorithm can be found in (Farinaccio & Zmeureanu, 1999). This reference proposed that instead of analyzing the variations of power (ΔP and ΔQ), the sum of the differences between adjacent data should be analyzed, as shown in (4.1):

$$\begin{aligned} x_i &= P_i - P_{i-1} \\ step &= x_i + x_{i+1} = P_{i+1} - P_{i-1} \end{aligned} \tag{4.1}$$

As seen in (3), the term P_i is eliminated which proves to be very useful for eliminating steady state in-rushes, which contaminate the signal. This is shown in Figure 4-2, which corresponds to the comparison between the actual power consumption signal on the test residence with and without the border detection algorithm applied.

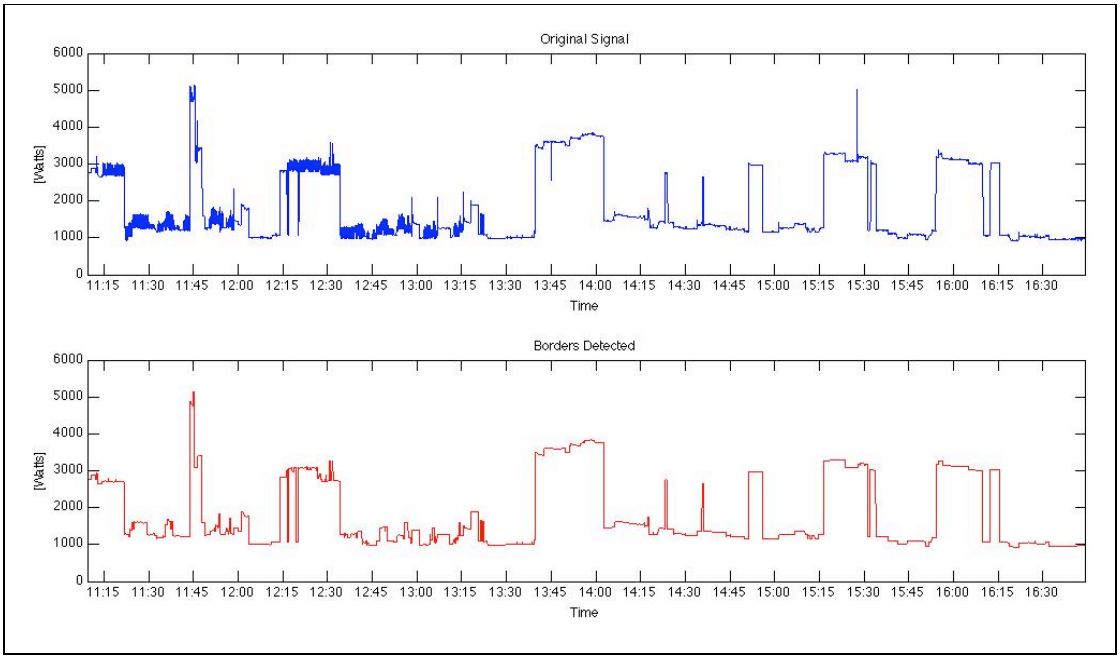

Figure 4-2: Signal without and with border detection

4.1.4 Rule-based appliance identification

Finally, individual algorithms are applied to each one of the appliances present in the residence. We developed and applied special or appliance-specific rules and thresholds that work in different ways for the different appliances. These rules are derived from careful observation of consumption patterns and appliance usage patterns and can be further improved on by simple automated learning techniques.

For all appliances there are thresholds for variations of active and reactive power consumption, ΔP and ΔQ. Some of them also have thresholds for the length of continuous use (e.g. a few minutes for a toaster, water heater, several minutes for a dish washer, etc) or the timing of its use (toaster typically used in the morning and afternoon).

The application presented here did not derive timing specific rules for pool motors, ironing, TV, dishwashers, etc., to avoid achieving a 100% identification based on studying a specific subject, rather than facing a more general subject. However, it is possible (and we are working on it) to develop web-based personal and shared databases on appliance use on order to achieve extremely high identification levels. For instance, the household of study has lunch at 13:30 hrs and runs the dishwasher at 15:00 hrs after lunch time. We didn't factor in this valuable information, because other families could wait until late at night to run the dishwasher.

Other appliances such as clothes washing machine pose larger challenges as they have multiple customizable complex cycles (wash, rinse, centrifuge, hard centrifuge, and cycles of different length, power and sequences). In this case, salient features of the cycle are detected and the signal is reconstructed.

4.2 Dealing with residuals

The consumption not recognized by this algorithm can further be allocated to specific appliances through a maximum likelihood stage. Others, like Farinaccio, do this by using a scoring system instead. Here we don't present this allocation stage because the proposed algorithm provides good results, thus, making this approximation unnecessary. We also need a measure of performance for the overall algorithm and the residual is the best available measure.

4.3 Results: Appliances consumption disaggregation

The application of the proposed algorithm provides good results. While we didn't have records, sensors and data registers for about a hundred connected devices to know the ground truth or actual individual consumption, we did have access to the total consumption measurement. We found an aggregate error, or unexplained consumption of approximately 2%.

We classified appliances into 17 different major appliance families which are: refrigerator, lighting, garage door, TV, dishwasher, sprinkler, Nintendo wii, pool motor, hair dryer, iron, clothes washer, microwave, toaster, water heater, computer, water and ice from the refrigerator and clothes dryer. Figure 4-3 shows power consumption from each family over a sample day.

After the disaggregation among appliance families is done, it is possible to compute the distribution of energy consumption between them at any point of time or based on overall energy usage, as shown in Figure 4-3. The two main appliances in power consumption are the refrigerator and the pool motor.

According to the observers, the algorithm performed very bad on TV detection, probably because of its low power consumption and irregular usage. For the iron and computer some observed events were not detected. Again, low power consumption, irregular usage, together with no additional or specific ruling in the detection algorithm provide the basis for the errors. However, larger devices are nicely detected as well as others where specific rules where designed, achieving great results in terms of energy error (2%).

Further calibration of the algorithm to the specific household would improve this error, but the algorithm was not conceived only for that specific house, but for a more general house. It is not meant to show 100% by over-calibrating the algorithm. A disadvantage with this algorithm is that it is very accurate for the cases for which it is calibrated, but in other cases it may achieve lower accuracies. For example, an algorithm calibrated to achieve a high degree of accuracy in one house would provide a worse result when applied to the neighbor's house. Keeping high accuracy requires using the house-specific equipment inventory and building a database to store load signatures of a variety of equipment from different homes. This means applying the algorithm to different houses, calibrating models to different appliances, saving the data into a database and using that data in other houses.

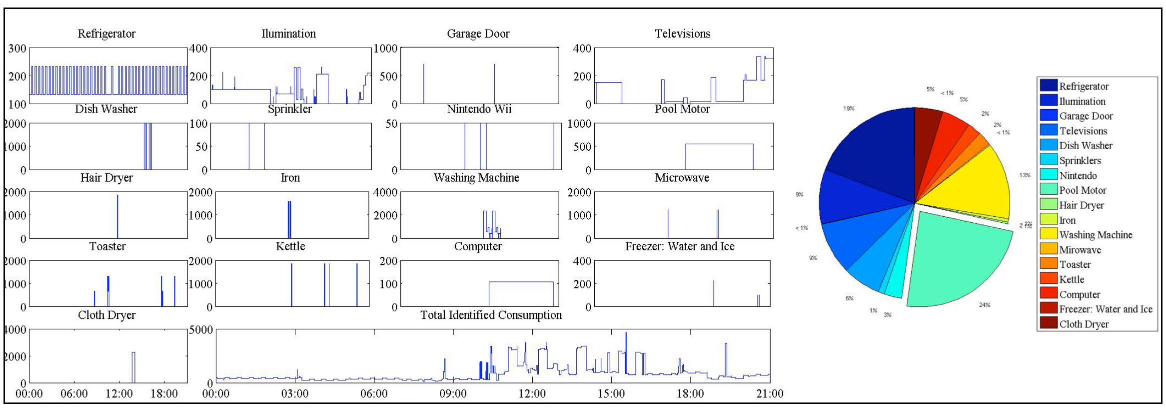

Figure 4-3: Energy disaggregation by appliance families and energy consumption by appliance family

5 CONCLUSIONS AND DISCUSSIONS

Residential smart meters, especially those used in developing countries, have limited computational power and communication capabilities. It is customary to obtain most of them, and techniques such as NILM and NILI have great potential to be implemented on them, to characterize clients, their appliances use and their performance. This paper presents a critical review of the different families of methods used for detecting, identifying and monitoring electric loads; starting from its pioneer and most cited work, Hart (Hart, 1989, 1992), to the newest approaches using steady state and transient analysis.

We find that the most common way to detect and identify loads is to use a steady state approach, but in the most contemporary literature, it is suggested to combine it with others, such as transient analysis, in order to improve the algorithm's performance.

We conclude that steady state algorithms must be the base for any NILM or NILI development, as they are low cost and require minimal computational power and metering frequency, being compatible with several smart meter deployments. However, there is still a long way to go to obtain accurate and reliable steady state algorithms. Transient algorithms are useful and have the potential to improve performance when used together with steady state techniques, but impose higher costs and measuring and computational burdens, not always attainable for basic smart meters.

From the literature review we conclude that most of the algorithms have been applied in very special and favorable environments, either in a bundle of a few loads, in simple test houses in which no information about the inside appliances is given to the reader, or in laboratories with too few appliances, which are very easy to differentiate and therefore to disaggregate. Literature is quite limited (nearly empty) on the application of algorithms to more challenging setups such as the one proposed here.

In non-ideal environments, like a total aggregated load inside a large house, it is very difficult to identify small appliances that are very alike between each other, like illumination devices, such as light bulbs or high efficiency light bulbs. Due to this, errors in the identification of low consumption appliances are very high, but surprisingly they aren't too high in monitoring. This is mainly because the identification of bulk energy consumption appliances, like the pool motor or the washing machine is more precise than that of appliances that don't have a high energy consumption, and also because the errors in monitoring of low power appliances tend to have a cancelling tendency, i.e., while some low power appliances are estimated to consume more than they do, others are estimated to consume less.

Even though it seems very easy to achieve accurate load disaggregation (after all it's just adding up and subtracting), parameters such as the nonlinearity of the loads, the simultaneous operation of appliances, loads with variable cycles, electric noise produced by the network or the same appliances (that alter the measurements and the process of disaggregation), and many other issues, complicate the analysis considerably. This explains why we found no reference on these techniques applied to industrial loads, where all these issues scale up considerably.

Besides a complete comparative and critical review of the existing literature and their proposed algorithms, some improvements over these algorithms are proposed and the new algorithm is implemented in a challenging environment. The approach selected by us is a nonintrusive steady-state rule-based detection algorithm. In our work we applied a steady state algorithm enhanced with a system of specific rules to individual appliances, proving to be much more effective than applying a general algorithm for detecting all the appliances at once. We achieved a very high accuracy in a house chosen for its complexity and variety of loads.

5.1 Self-learning limited by lack of intrusive measurements and limitations

Another challenge with these techniques is that in the implementation of a self-learning network for NILM, obtaining validation data isn't as simple as it looks. If the washing machine is identified, there are no individual sensors that could help us determine if the washing machine really entered in operation. Although we could determine if it is really the washing machine by waiting for the turn off event, if we missed the turn on event, we wouldn't have a teacher for training the network. That seems to be one of the main challenges in automatic setup of NILM. Invasive approaches in some test houses could serve as teachers for self-learning networks.

6 FUTURE WORK

The next steps for this project are a) embedding this algorithm into the smart meters system developed by our group (HappyVolt.Com), b) developing more powerful algorithms that allow us to scale up into more numerous and complex loads in a single wire. The proposed algorithm is quite capable of facing complex industrial loads, but applying it to each individual feeder and adding up the results, instead of applying it to the connection to the utility. c) Developing a database and multiple houses and trying the algorithm with houses out of the sample. Our group is applying for funding for this.

A transient state envelope and harmonic distortion index (HDI) detection algorithms were also explored and evaluated, and although they are not fully described here due to space limitations. It can be seen from Fig 9 that harmonic content can offer a useful tool to discriminate between high efficiency and normal light bulbs and several other different appliances. We propose a simple HDI based on the RMS value of the normalized harmonic indexes (a_i) to take advantage of this.

$$HDI_{NILM} = \sqrt{\frac{\sum_{n=2}^{12} k_i \cdot a_i / a_1}{(n-1)}} \quad k_i \leq 1 \quad \forall i \in \{2,\ldots,12\} \tag{6.1}$$

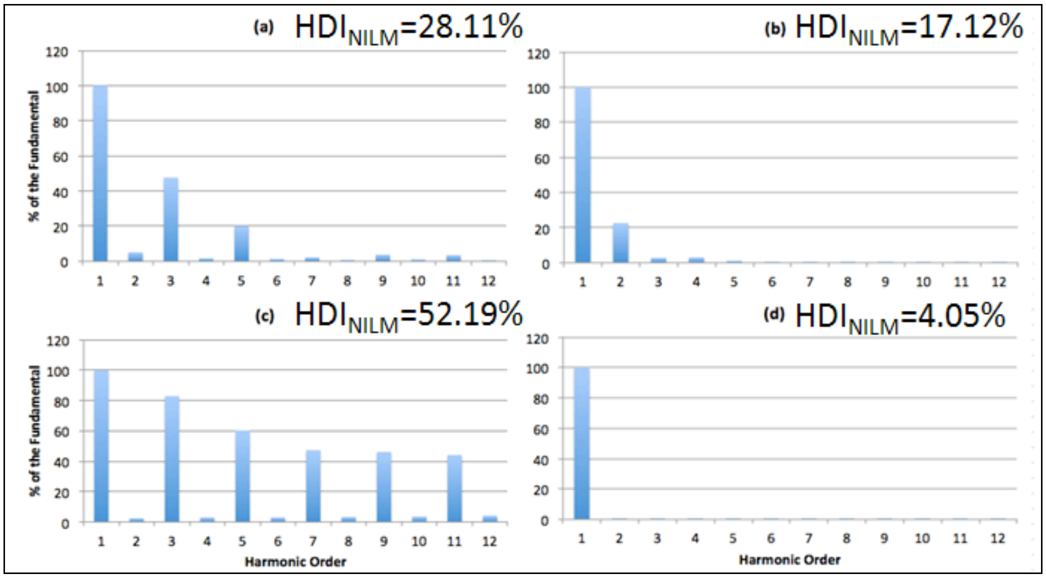

Figure 6-1: Current harmonics: (a) Microwave, (b) Vacuum Cleaner, (c) High Efficiency Light Bulb and (d) Normal Light Bulb

We find preliminarily that envelope and HDI could become a critical tool for future discrimination between similar loads in a more complex environment, such as the industrial one. However, in our test bed, results were already very good and assessing the potential of additional algorithms has limited use. Its serious assessment requires a more challenging test bed.

A proposed solution for increasing NILM accuracies, by cleaning the signal, is to measure from the electric panel, separated into the individual circuits instead of measuring at the main meter. Just isolating the illumination of the residence from the other appliances would greatly improve the algorithm's accuracy. With this the differentiation between different load families could be much more effective. Our recent meter ekeeper (Happyvolt.Com) is implementing this.

Finally, we see that the weakest link in NILM techniques is training, so future studies should focus on how to implement systems that require less training or on systems that are able to be learn by themselves, based on artificial neural networks (ANN) or on regression models. Having the training and self-learning issues resolved would help develop viable commercial products for NILM.

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APPENDICES

7 APPENDIX A: ALGORITHM RESULTS

We did have a couple of observers that manually registered the events (not the consumption) and found no error on the pool motor and cloth drier. When higher frequency and computational power is available, the accuracy for other appliances can be incremented.

The results of the algorithm were very varied. Fortunately, the identification and monitoring of appliances that translate in large amounts of energy consumption is far better and precise than appliances that signify a low power consumption. TABLE 7.1 shows some of our results. It is important to say, that, since the comparison in all the cases (except for the total) were realized between the algorithm estimated and the surveillance estimated, we don't have an actual precise number of the algorithm's accuracy by appliance, and in some cases the algorithm was even more precise that the people surveillance, allowing us to find data that was lost in our surveillance (e.g. Iron).

TABLE 7.1. NILM Algorithm Results

Appliance	Manual Error Estimate	Real Error*
Dish Washer	0.0943%	?
Refrigerator	0.5358%	?
Washing Machine	14.998%	?
Pool Motor	0%	?
Cloth Dryer	0%	?
Microwave	14.706%	?
Computer	14.636%	?
Iron	216.67%	?
Toaster	28.56%	?
Kettle	33.985%	?
TV	42.723%	?
Total	-	2.1%

*Real error is the relation between algorithm estimated and actual appliance measure, which requires invasive approach, which we didn't do, we only measured the total power consumption at the main meter, with an error of only 2.1%. People showed to be bad at performing estimations and surveillance of appliances usage

8 APPENDIX B: TYPES OF INTRUSIVENESS

We can classify the intrusiveness and the requirements of a load identification monitor in four main quadrants, which are delimited by two main limits, if the system is intrusive or not, which corresponds to the base differentiation, and if the kind of intrusion is physical or electrical. Physical intrusive signatures are the most intrusive type of signatures, the consumer notices them, and they can eventually produce discomfort. They are usually characterized by the presence of sensors, such as proximity sensors or by devices attached to the power cords of some appliances, called tags. These tags would allow identifying appliances such as a vacuum cleaner, regardless the part of the house in which where they are plugged. They could be very useful to differ between similar appliances or as a teacher for a self-learning algorithm. Lots of equipment is needed at the consumer premises and an intrusive stage is needed for the installation of sensors and tags. On the other hand, electrical intrusive monitors, is a less intrusive approach in which an electric signal is injected at the utility premises and the variation of that signal at the customers residence is an indicator of the number and type of appliances in operation at the moment. This electric signal could be a current harmonic or a transient, however they are a concern to utilities, because they could compromise the quality of service. In contrast with physically intrusive monitors, few hardware is needed, in fact, only a smart meter with the ability of generating and injecting a signal into the residence is needed. In the case of nonintrusive electrical monitors, there are many approaches, but they all have the same basic characteristics, which are that a load disaggregation algorithm is applied to the consumption and it separates it into it’s main appliances, without having much information about what is happening at the interior of the house. For this, an intelligent meter with advanced processing and communications capabilities is needed. Finally, there are some unusual practices that could be applied for making more accurate estimations of what is happening at the interior of a house. Physically nonintrusive practices could include the analysis of environmental data, such as ambient temperature for estimating the feasibility of occurrence of an event, like turning the AC on a snowy day. Also, satellite images, combined with image processing algorithms could be used for determinate if a house has a pool, which would explain the operation of a motor in the residence or thermal cameras could help determine which are the weakest links in a consumption and what makes it operate do inefficiently. The main disadvantage is that in many cases interpretation is needed, for example satellite images are some times damaged and a blind spot could be interpreted as a pool, also, they provide limited information, because we only realize once that a residence has a pool, and the ability of knowing doesn't tell us what is the operating time. Figure 8-1 shows a classification of the types of intrusiveness in the monitoring.

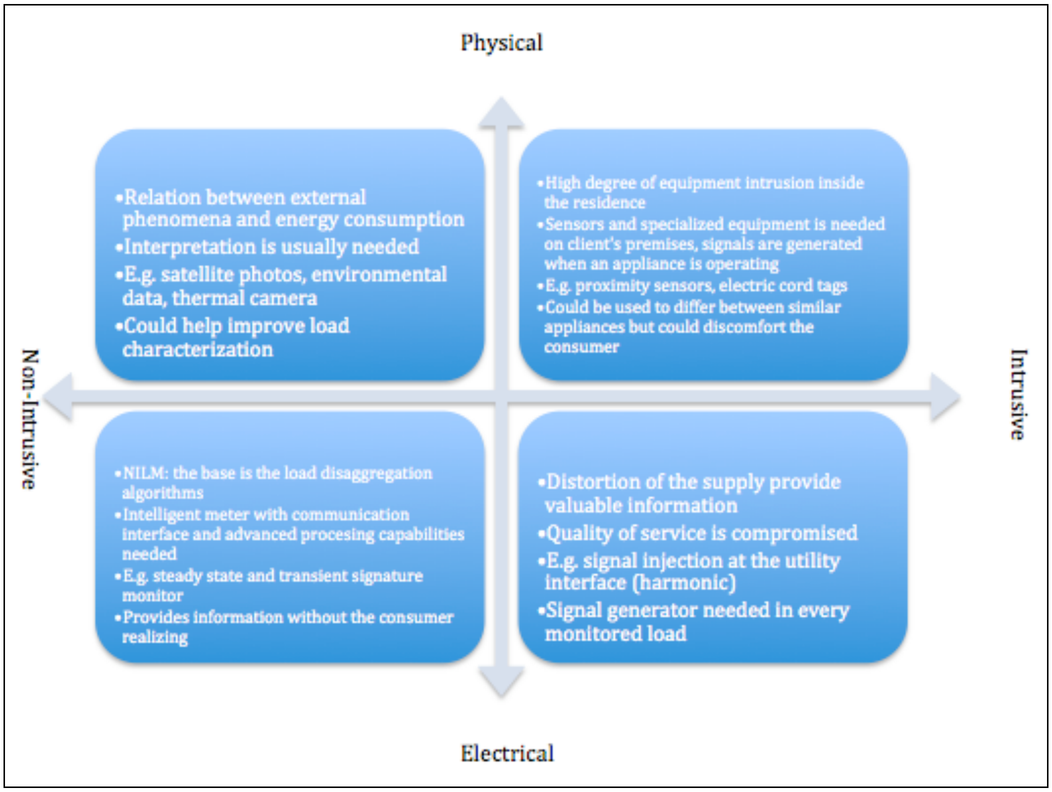

Figure 8-1: Types of Intrusiveness

9 APPENDIX C: LARGE SCALE APPLICATIONS

Our main concern in this investigation was how to apply this technique in large scale. Even though our application was a one case, test residence scenario, the further application to many houses could be achieved by well known and used today's practices. Clusterization of different residence types is done by utilities today in order to characterize and group different client types. This same clusterization could be applied to help the setup of a NILM system, or to train and teach a self-learning network. For example, a self-learning network could detect and learn that there are new appliances present in the residence due to replacement. Even more, the clusterization of clients could help respond not only to those specific changes in a house, like replacing old appliances, but also detect structural changes, like, learning from a new inhabitant in the house, with completely different consumption pattern, by simply comparing his profile to a general database, obtained from laboratory data of all the appliances (refrigerators, hair dryers, kettles, etc.) available in the market, or by comparing it to a database obtained from clustered type clients. In brief, we can characterize the profiles into three main databases, a general, which contains all the possibilities available in the market, a clustered, which is obtained from different client types in function of their socio-economical, geographical, educational characteristics and a local database that has to do specifically with the consumption of the client and his life habits.

Database information for large-scale implementation can be very useful at the time of setting rules for appliances algorithms based on the lifestyle and habits of a particular inhabitant. For example we can characterize habits such as toasting bread all mornings, so when the client stops toasting his bread we will know that something is happening, maybe the toaster was changed, the client went on vacation, or the house became abandoned.

Figure 9-1 shows the way in which the algorithm by being complemented by these databases could achieve to reduce the error and achieve 100% accuracy for load monitoring.

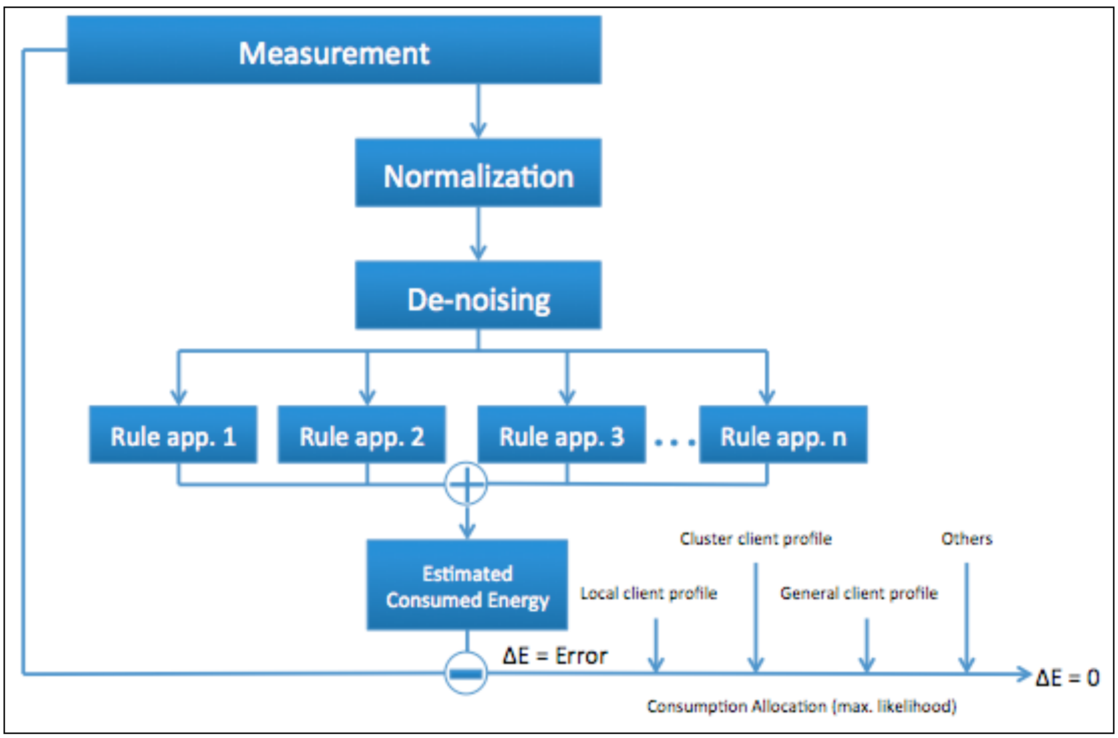

Figure 9-1: NILM algorithm with clustering integration

10 APPENDIX D: REFERENCES COMPARISSON

This section organize the references critically, first addressing the methodologies chosen by the authors, then the sampling period if mentioned and finally summarizing these two and presenting the scale of the field tests and its accuracy.

10.1 Signatures used

Even though there is a large number of families of load signatures, as defined by Hart, almost all methodologies followed by authors have been limited mainly to steady state fundamental frequency analysis, current harmonics, and transient event detection algorithms. Figure 10-1 shows a classification of the signatures used by the different references.

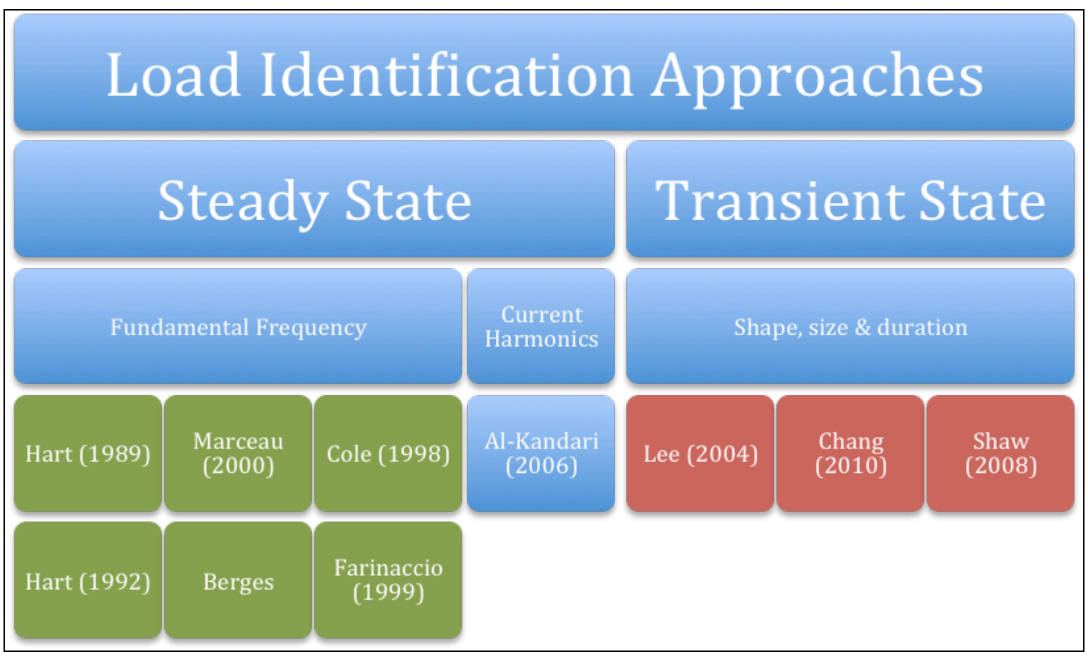

Figure 10-1: Classification of Signatures that are actually used for load identification

10.2 Sampling period and frequency

When it comes to sampling periods there doesn't seem to be a consensus, it depends mainly in the accuracy being looking for, with respect to the events inside the residence or load. A high sampling period, e.g. 1 minute, provide a very clean signal, with relatively low probability of sampling when multiple events occur simultaneously or when a transient occur, but may miss lots of important events (microwave is often on for less than 1 minute). On the other hand, a small sampling period (e.g. 1 second), would avoid missing events, but provides a noisy signal with many transients and simultaneous events. Figure 10-2 shows a classification of the sampling periods used in some of the references.

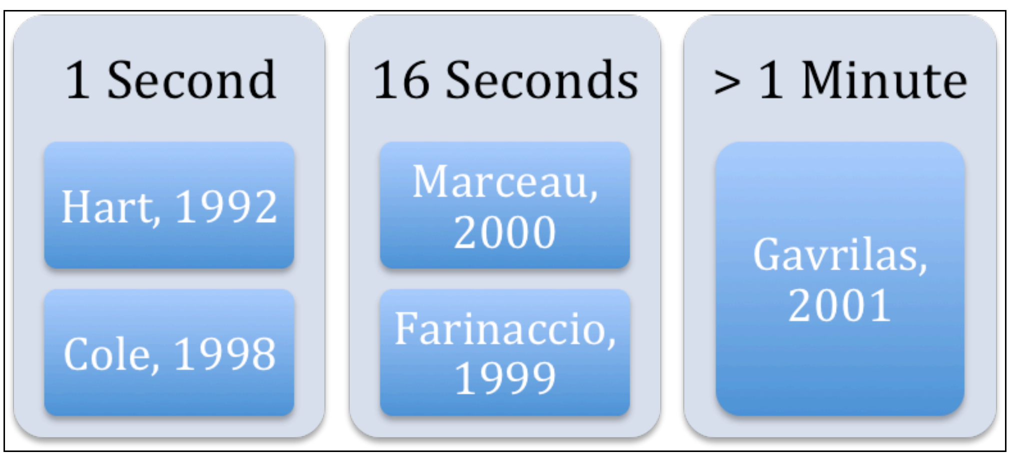

Figure 10-2: Sampling period classification

There is a tradeoff regarding the sampling frequency to use. When using 1 second or less, there is a huge data density were it could be possible to identify all the appliances in a house, even those who have a very short time of usage, like a garage door opener, but it would provide a very noisy signal, with many steady state transients due to in-rush currents at the turn-on of the appliances. If a long sampling period is used, e.g. 1 minute, there would be low data density, and a very clean signal, because the probability of sampling a turn-on event would be very low, but it would be missing lots of events that last less than a minute, like the microwave, a blender, or the vacuum cleaner in some cases. The frequency depends also on the algorithm type, i.e. for algorithms based on transient event detection a higher sampling frequency should be used, between 7 and 15 kHz, and for steady state algorithms frequencies of less than one Hz are very common.

Field experience in the existing literature on nonintrusive load identification is often invalid, because experiments are done in isolated environments (e.g. laboratories with few loads), seldom field tests are performed with an actual residential load, with many appliances on it and working at the same time. We organized the main references in TABLE 17.1 for better and easier visualization of the characteristics of each research. We emphasize the low accuracy achieved by these approaches.

11 APPENDIX E: HARMONIC DISTORTION INDEX

Although harmonic signatures fit in the definition of steady state signature, they provide additional information to fundamental frequency algorithms, increasing their detection accuracy as transient signatures. The main objective of harmonic signatures is to differentiate between devices with similar P and Q consumption in steady state. According to (Laughman, 2003), appliances that show a similar behavior in fundamental frequency power consumption can show differences in higher harmonics power consumption, which could be decisive for their differentiation. As seen in Figure 11-1 harmonic content in a signal may be a very good parameter for its differentiation, this figure shows the difference between the harmonic content of two appliances, a microwave, and a vacuum cleaner. The microwave has a harmonic content more present in the third and fifth harmonic, while the vacuum cleaner has a harmonic content more present in the second harmonic.

The differentiation in the harmonic content of a signal is mainly due to its non linearity, while linear loads have a simple relation between the voltage and the current in which those two parameters oscillate at the fundamental frequency, in nonlinear loads, there is a relation in which the current has other components than the fundamental one, that generates current harmonics, which make a huge difference between appliances.

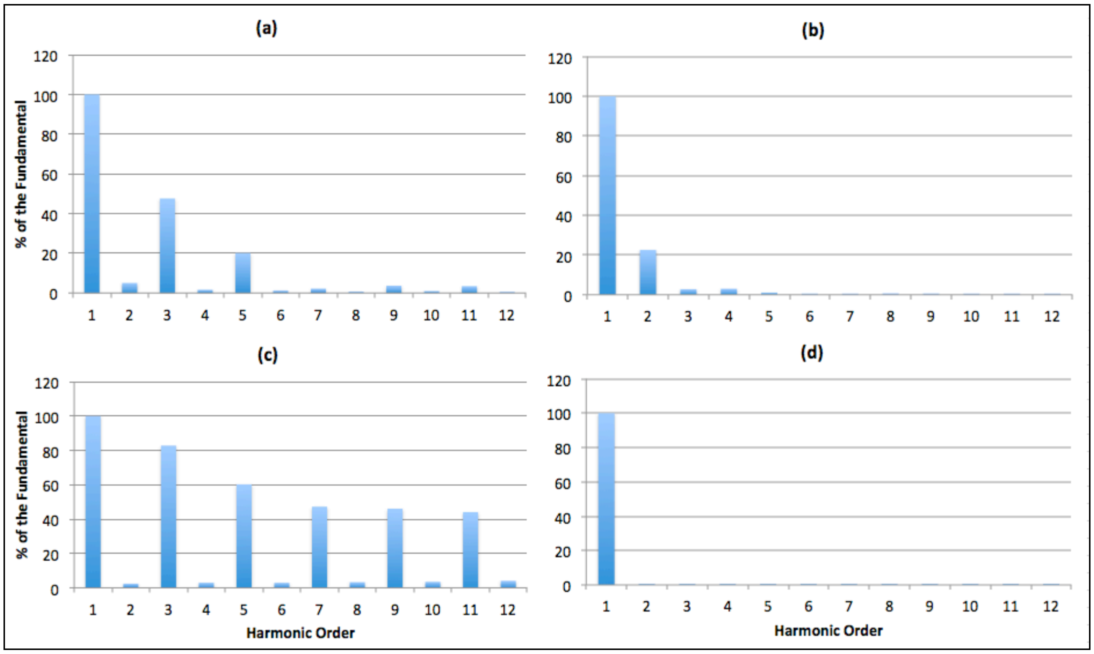

Figure 11-1: Current harmonics: (a) Microwave, (b) Vacuum Cleaner, (c) High Efficiency Light Bulb and (d) Normal Light Bulb

It can be seen in Figure 11-1, that harmonic content can offer a useful tool to discriminate between high efficiency and normal light bulbs. As part of our research, we propose a simple harmonic distortion index based on the RMS value of the normalized harmonic indexes as shown in (12.1).

$$HDI_{NK\&DW} = \sqrt{\frac{\sum_{n=2}^{12} k_i \cdot a_{i_{norm}}}{(n-1)}}$$

$$a_{i_{norm}} = \frac{a_i}{a_1} \quad \forall i \in \{2,...,12\} \tag{12.1}$$

$$k_i \leq 1 \quad \forall i \in \{2,...,12\}$$

k_i is a multiplier, which main purpose is to give more importance to the more significant harmonics, i.e. in the case of the microwave, harmonics indexes 1, 3 and 5, and in the case of the vacuum cleaner, indexes 1 and 2.

In a preliminary study on harmonic signatures using k_i=1 for every i, our distortion index proved to be very successful. The tests included a comparison between three different appliances, a refrigerator, a water heater and a microwave. Between these appliances the differences shown were of nearly a 70% between the heater and the refrigerator, of a 90% between the heater and the microwave, and the differences between the refrigerator and the microwave were of 65%. These differences could certainly be of great value to be used in addition with steady state fundamental frequency signatures.

12 APPENDIX F: DATA EXTRACTION AND EQUIPMENT

The data extraction for our field test was done on a single and fairly large residential load, and the instrument we used for our measurements was a Hioki 3197 power analyzer and ekeeper (by Happyvolt.com), a proprietary smart meter we developed that is capable of measuring mean, maximum and minimum of voltage (rms value), current (rms), frequency, among other parameters, every two seconds.

12.1 Limited memory

The internal memory of the network analyzer is filled every one and a half hour, so it required frequent oversight of instrument's memory and 24 hours almost fully devoted to this.

Our equipment database was obtained in the field, where we used the same instrument (Hioki 3197 and our Ekeeper - HappyVolt) to measure every appliance individually. The true load information was obtained performing a fast equipment inventory, while for the lighting of the house (mounted and with data not always available), the information was obtained through an estimate based on the number and type of bulbs that each illumination electrical circuit of the house.

13 APPENDIX G: GETTING THE GROUND TRUTH

As we didn't have the possibility of having individual sensors for every appliance to recover the ground truth, we used a record workbook which was posted in every circuit in the house (switch and appliance). Its purpose was to register every on and off event in the testing period. On Figure 13-1 we can see an example of the generic sheet used for this purposes, this sheet has 60 columns with corresponding to each minute in an hour, and 24 hours corresponding to a day. Every time an appliance or switch is turned on, the symbol "/" is placed in the coordinate correspondent to the actual time, and an "X" is placed when the appliance is turned off.

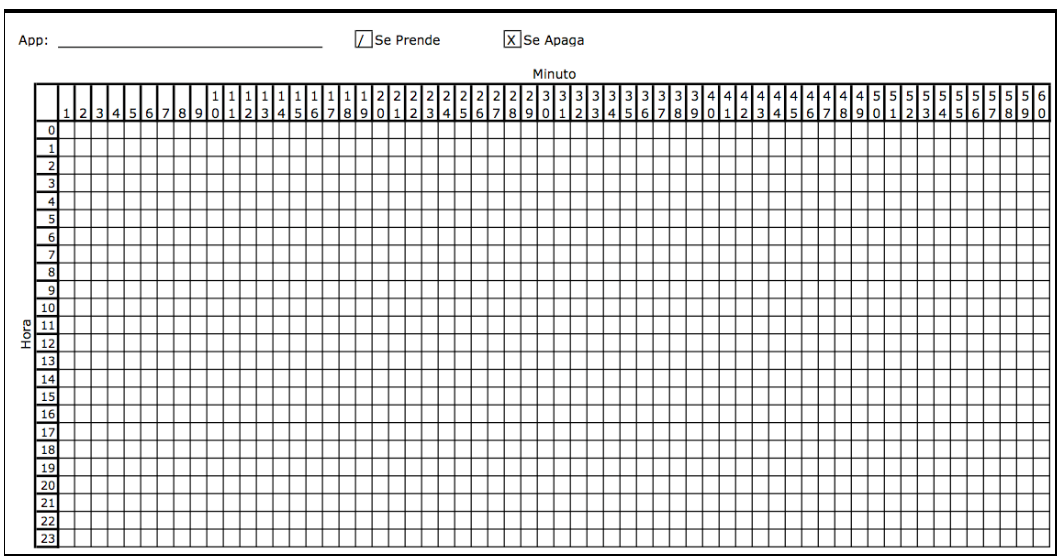

Figure 13-1: Sample worksheet for registration of events

While the operation of the appliances was determined through the worksheet shown in Figure 13-1, the real and reactive power database was determined measuring each appliance independently, except for the lighting, which was determined from the nominal value of each bulb.

Given our measured data, we wrote an algorithm in Matlab for the comparison between the measured data and the energy profile estimated from the record workbooks. Figure 13-2 shows this comparisson.

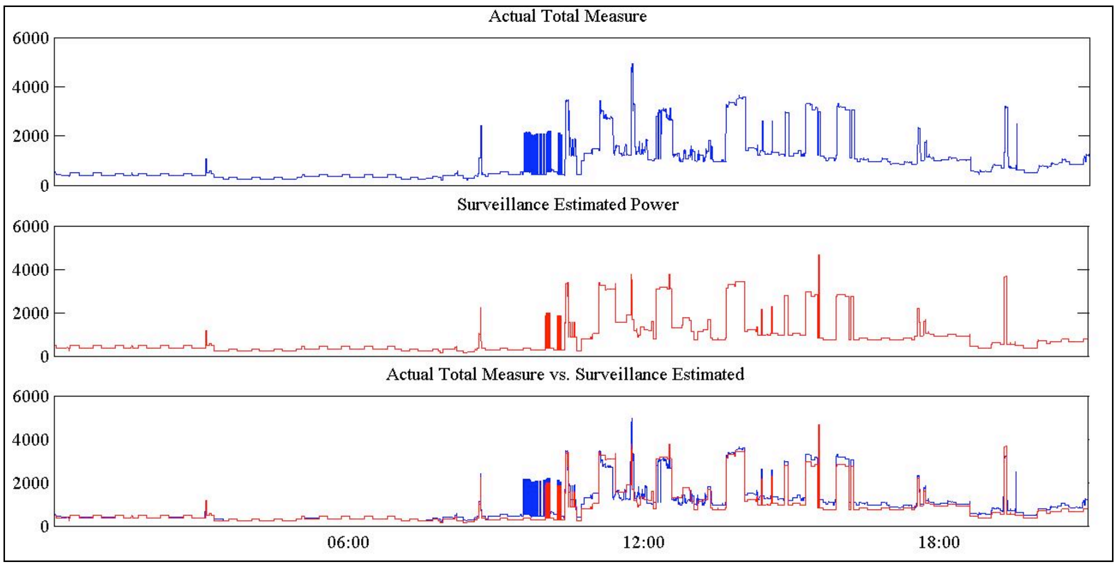

Figure 13-2: Comparison between estimated power profile (red) and measured power profile

Before the comparison is performed, a previous softening of the signal must be realized.

The differences between the estimated energy consumption, and the actual energy consumption using this practice was of approximately 5%, Which is a number much bigger than the one that we should obtain placing sensors in each individual appliance.

14 APPENDIX H: PILOT HOUSE STATISTICS

The pilothouse is subscribed to Chilean regulated tariff BT1. The main characteristics of the residence and the field test day are:

- Total installed capacity: 20.98 kW.
- Point of connection contracted power: 9.9 kW.
- Max. power demand on field test: 4.95 kW.
- Energy consumption on field test: 19.39 kWh.
- Load factor: 18.65%[1]
- Capacity factor: 4.4%[2]

[1] The load factor corresponds to the energy consumption on the field test divided by the maximum power demand on the field test multiplied by the number of test hours (21).

[2] The capacity factor corresponds to the energy consumption on the field test divided by the total installed capacity multiplied by the number of test hours (21).

15 APPENDIX I: ENERGY SHARE BY APPLIANCE

The following pie charts show the energy share and which are the appliances that signify higher energy consumption throughout the day.

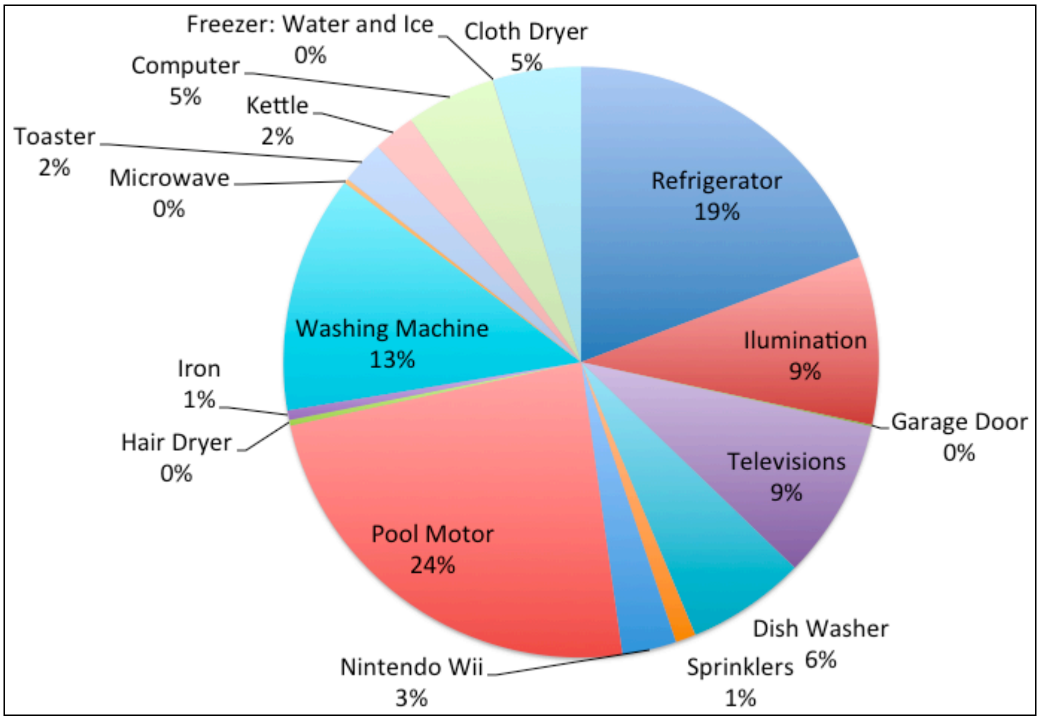

Figure 15-1: Energy cake

16 APPENDIX J: INVENTORY AND DATABASE

This is solved entering an equipment inventory to the meter or database system and/or with a database with consumption features of typical appliances. The pilothouse inventory consists of 97 devices, which are classified as follows:

16.1 Kitchen

TABLE 16.1. Kitchen Inventory

Quantity	Device	Aggregated Power (W)
2	Circular fluorescent tube	80
1	Light bulb	75
3	Fluorescent tube	120
1	Electric oven	650
1	Microwave (Daewo)	1,400
1	Kettle (Black & Decker)	2,000
1	Toaster (Black and Decker)	1,320
1	Television (RCA)	100
1	Refrigerator (GE)	150
1	Diswasher	2,000

16.2 Washing room

TABLE 16.2. Washing Room Inventory

Quantity	Device	Aggregated Power (W)
2	Circular fluorescent tube	80
1	Halogen Bulb	150
1	Washing Machine	2,200
1	Cloth Dryer	2,300
1	Iron	2,000

16.2.1 Others

TABLE 16.3. Rest of the House Inventory

Device	Quantity	Aggregated Power (W)
Normal Light Bulbs	15	1,125
Halogen Light Bulbs	2	300
Efficient Light Bulbs	7	140
Candle Light Bulbs	8	320
Dichroic Light Bulbs	27	1,350
Low Power Light Bulbs	5	100
Mini Halogen	2	40
Ventilator	3	150
Hair Dryer	1	2,000
Television	3	450
Nintendo Wii	1	50
Computer	2	300
Printer	1	30

16.3 Total

TABLE 16.4. Total Inventory

Device	Total Installed Power
Normal Light Bulbs	1,125
Halogen Light Bulbs	300
Efficient Light Bulbs	140
Candle Light Bulbs	320
Dichroic Light Bulbs	1,350
Low Power Light Bulbs	100
Mini Halogen	40
Ventilator	150
Hair Dryer	2,000
Television	450
Nintendo Wii	50
Computer	300
Printer	30
Circular fluorescent tube	80
Halogen Bulb	75
Washing Machine	120
Cloth Dryer	650
Iron	1,400
Circular fluorescent tube	2,000
Light bulb	1,320
Fluorescent tube	100
Electric oven	150
Microwave (Daewo)	2,000
Kettle (Black & Decker)	80
Toaster (Black and Decker)	150
Television (RCA)	2,200
Refrigerator (GE)	2,300
Diswasher	2,000
Total	**20,980**

17 APPENDIX K: REFERNCE CLASIFFICATION

TABLE 17.1. Reference Classification

Reference	Signature	Sampling Period or Frequency	Lab or Field Test	Accuracy	Number of Appliances	Observations
Hart 1989 (Hart, 1989)	Steady State Fundamental Frequency	1 second	Field: 3 Houses	75 to 90%	25	Pioneer on the subject
Marceau 2000 (Marceau & Zmeureanu, 2000)	Steady State Fundamental Frequency	16 seconds	Field: Single house	> 90%[1]	7[2]	
Berges 2010 (Berges, Matthews, & Soibelman, 2010)	Steady State Fundamental Frequency	-	Field: Refrigerator	85%	1	
Chang 2010a (Chang, et al., 2010)	Steady State and Turn on Transient	15 kHz	Lab: Between 3 loads	100%	3	
Cole 1998a (Cole & Albicki, 1998a)	Steady State Fundamental Frequency	1 second	Field: 8 Houses	> 99%	7	
Hart 1992 (Hart, 1992)	Steady State Fundamental Frequency	1 second	Field: 1 MS-NALM, 3 first generation AS-NALM and 10 second generation AS-NALM[3]	90%	Every household appliance	
Farinaccio 1999 (Farinaccio & Zmeureanu, 1999)	Steady State Fundamental Frequency	16 seconds	Field: 1 test house	85%	2[4]	Rule Based Algorithm
Cole 1998b (Cole & Albicki, 1998b)	Steady State Fundamental Frequency	1 seconds	Not specified	> 90%[5]	2, washer and hp compressor	
El-Ferik 2006 (El-Ferik, Hussain, & Al-Sunni, 2006)	Steady State Fundamental Frequency	-	Lab: Pilot house	99%	Air-conditioning system	AC[6] Physical model required
AL-Kandari 2006 (Al-Kandari & El-Naggar, 2006)	Harmonic	Varies between 10 and 400 samples per cycle	Lab	-	-	Estimates harmonics from distorted current and voltage waves
Leeb 1993 (Leeb, 1993)	Transient	-	Lab	-	3	
Shaw 2008 (Shaw, et al., 2008)	Transient	-	Lab	99%[7]	8	Parametric models are needed, and hand modification of data
Laughman 2003 (Laughman, 2003)	Transient and Harmonic	8 kHz	Field: Buildings and transportation systems	-	-	No results are shown
Chang 2010b (Chang, 2010)	Turn-on Transient	15kHz	Lab	100%	3	

[1] For most evaluation scenarios.
[2] 7 Major end use appliances with individual clamp-on current sensors.
[3] In the first two cases, there was no parallel instrumentation, so the detection of events was using criterion, and in the third case the field test were not fully analyzed.
[4] Rule based algorithms for two appliances, a domiciliary water heater (DWH) and a refrigerator.
[5] Comparison made between energy estimation and energy consumption in 15 minute intervals
[6] Air-conditioning system
[7] For induction motor