Automatic Disaggregation of Residential Electrical Consumption with Non-Intrusive Methods

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To the only wise God.

To my loving parents: Emiro and Noris.

To "las chicas superpoderosas": my beautiful sisters, Yulibeth and Mayra, and my charming niece Abril.

My success is yours.

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Acronyms

ANN Artificial Neural Networks

CFL Compact Fluorescent Lamp

CWT Continuous Wavelet Transform

DAQ Data Acquisition systems

DC Direct current

DFT Discrete Fourier transform

EMI Electromagnetic Interference

EUT Equipment under Test

FFT Fast Fourier transform

FSM Finite-state Machine

GLR Generalized Likelihood Ratio

GOF Goodness of Fit

HMM Hidden Markov Models

LDA Linear Discriminant Analysis

NILM Nonintrusive Load Monitoring

NIALM Nonintrusive Appliance Load Monitoring

PC Personal computer

PCA Principal Component Analysis

ST Stockwell transform

STFT Short Time Fourier transform

RESUMEN

TÍTULO: DESAGREGACIÓN AUTOMÁTICA DE CONSUMO ELÉCTRICO RESIDENCIAL MEDIANTE MÉTODOS NO INTRUSIVOS[1].

AUTOR: YULIETH JIMÉNEZ MANJARRÉS[2]

PALABRAS CLAVE: CONSUMO ELÉCTRICO, RESIDENCIAL, DESAGREGACIÓN DE CARGA, NO INTRUSIVO, FIRMA DE CARGA, INTELIGENCIA ARTIFICIAL, IDENTIFICACIÓN DE ELECTRODOMÉSTICOS, TRANSFORMADA STOCKWELL, CLASIFICACIÓN DE UNA CLASE.

DESCRIPCIÓN:

La información detallada de los electrodomésticos individuales en el hogar, llamada desagregación de carga, puede motivar el ahorro energético y apoyar planes de gestión de demanda. Esta información se puede estimar mediante sistemas de Monitorización No intrusiva de Carga (NILM, por sus siglas en inglés), realizan procesamiento de señales y modelado matemático a partir de mediciones eléctricas en un solo punto. Bajo la premisa de que las señales de los electrodomésticos tienen características distintivas, denominadas firmas de carga, un enfoque es discriminar los electrodomésticos mediante técnicas de inteligencia artificial. Aunque la investigación en esta área está en crecimiento, aún se detectan algunas brechas en la literatura científica y esta tesis contribuye al conocimiento en varios aspectos. Primero, se presenta un marco para implementar sistemas NILM. Segundo, se propone un sistema basado en eventos que comprende las etapas de detección de eventos, extracción más efectiva de características transitorias basadas en el dominio del tiempo y de la transformada S, clasificación a través de un enfoque no tradicional y estimación de potencia mediante la dependencia de la tensión. Tercero, se evalúa la capacidad de discriminación de las firmas de carga para determinar el impacto del punto de los factores de impacto mencionados. Finalmente, se construyó una base de datos de medidas de aparatos residenciales bajo diferentes escenarios de tensión de alimentación, impedancia y operación de los aparatos. Así, estos sistemas NILM se vislumbran como aplicaciones de hogares inteligentes.

[1]Tesis de doctorado

[2]Facultad de Ingenierías Físico-Mecánicas. Escuela de Ingenierías Eléctrica, Electrónica y de Telecomunicaciones. Director: Gilberto Carrillo, Doctor Ingeniero Industrial.

ABSTRACT

TITLE: AUTOMATIC DISAGGREGATION OF RESIDENTIAL ELECTRICAL CONSUMPTION WITH NON-INTRUSIVE METHODS[1].

AUTHOR: YULIETH JIMÉNEZ MANJARRÉS[2]

KEYWORDS: ELECTRICAL POWER CONSUMPTION, RESIDENCIAL, LOAD DISAGGREGATION, NON-INTRUSSIVE, LOAD SIGNATURE, ARTIFICIAL INTELIGENCE, APPLIANCE IDENTIFICATION, STOCKWELL TRANSFORM.

DESCRIPTION:

One path to enhance energy efficiency and design demand side management plans is providing detailed information about the individual appliances in houses, namely, load disaggregation. Non-intrusive Load Monitoring (NILM) Systems aim to obtain the disaggregated information from measurements in a single point through signal processing and mathematical modeling. One approach assumes that appliances could be represented by characteristics computed from the electrical signals, i.e. load signatures. Although research in this area is increasing, several gaps are detected in the scientific literature: there is not a widely accepted set of load signatures, the complexity of the traditional systems increases exponentially with the number of appliances, fully labeled datasets of electrical signals are lacking, previous work has not been focused on the development of integral algorithms, and the question about the impact of factors (voltage distortion, network impedance, etc.) on NILM algorithms remains open. This thesis contributes to knowledge in several ways. First, a framework for implementing NILM systems is presented. Second, an event-based NILM system is proposed, which comprises the following stages: event detection, feature extraction based on waveforms and the S transform, classification through a nontraditional approach and power estimation by considering the voltage dependency. Third, the discrimination capacity of the load signatures is assessed to determine the impact of point-on-wave of switching, voltage distortion and network impedance. Finally, a fully dataset of residential appliances is provided under several scenarios of voltage, impedance and operation. These NILM algorithms are envisioned as smart home applications for appliance management.

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[1]Ph.D. Thesis

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Introduction

One path to enhance energy efficiency and design demand side management plans is providing detailed information not only about total load consumption but also about the individual appliances in houses, namely, load disaggregation. This is the time for Nonintrusive Load Monitoring (NILM) Systems. They aim to obtain the disaggregated information from measurements in a single point through signal processing and mathematical modeling. One approach assumes that appliances could be represented by characteristics computed from the electrical signals, i.e. load signatures. Although research in this area is increasing, several contributions to knowledge are made through this thesis. This chapter introduces the motivation, the problem statement, the scope and the contributions of this thesis.

Motivation and justification

Electricity demand forecast is higher than the generation forecast since it may reach 33 300 TWh by 2030 worldwide (Lee, Jung, Kim, Lee, & Kim, 2010). This is due to the increase in population and electrical device production. Thus, the supply of the required energy is becoming challenging; this is especially meaningful during peak hours. For example, Colombian generation capacity comes mainly from hydroelectric centrals. In 2016, the lack of rain due to *El Niño* phenomenon, the scarcity and hight cost of natural gas, the financial situation of thermoelectric companies and the system operational constraints created a risky situation where the electricity demand could not be satisfied. Moreover, some incidents, like the failure of key power generators (Guatape and Termoflores), cut off about 10 percent of electric resources.

Two alternatives are considered to face the rising electricity demand:

1. To **increase generation** by installing either conventional (carbon, fossil fuels, water, etc.) or alternative (sun, wind, biogas, etc.) plants.

(a) Electric power system generation from conventional sources involves important losses of 61.5% through generation and 3.5% through transmission and distribution as shown in Fig. 1, and it produces CO_2 emissions that worsen climate changes.

(b) Renewable sources could be seen as sustainable options because they are produced by nature faster than they are consumed, and they are suitable for distributed generation due to their extended availability, customer proximity and transmission loss reduction.

2. To **reduce the demand**. International Energy Agency (2015) stated: "Energy efficiency plays a critical role on limiting world energy demand growth to one-third by 2040, while the global economy grows by 150%. "According to Fig. 1, 13 units out of 35 units of energy supplied to the load are wasted, which means that 37.15% of the energy available for final use is dissipated through inefficient end use. This means that there is room to reduce the demand by improving the use stage. Indeed, one key aspect of the Smart grid concept is to involve the user to perform demand side management. Some measures that can be considered are:

   (a) During design: efficient building design and installation of efficient equipment.

   (b) During construction: activity programming for efficient use of the available energy resources.

   (c) During post-construction: behavior guidelines such as energy conservation practices and activity re-programming, energy wasting infrastructure repair, control systems (e.g., HVAC) in response to environment, occupancy or process requirements, or installation of efficient equipment with low investment.

Returning to the Colombian case, the government decided to reduce the demand, in the sense of cutting down the consumption to prevent a blackout. In March 7th, 2016, the President Juan Manuel Santos announced the "Turning off pays off"campaign that intended to save between 5%

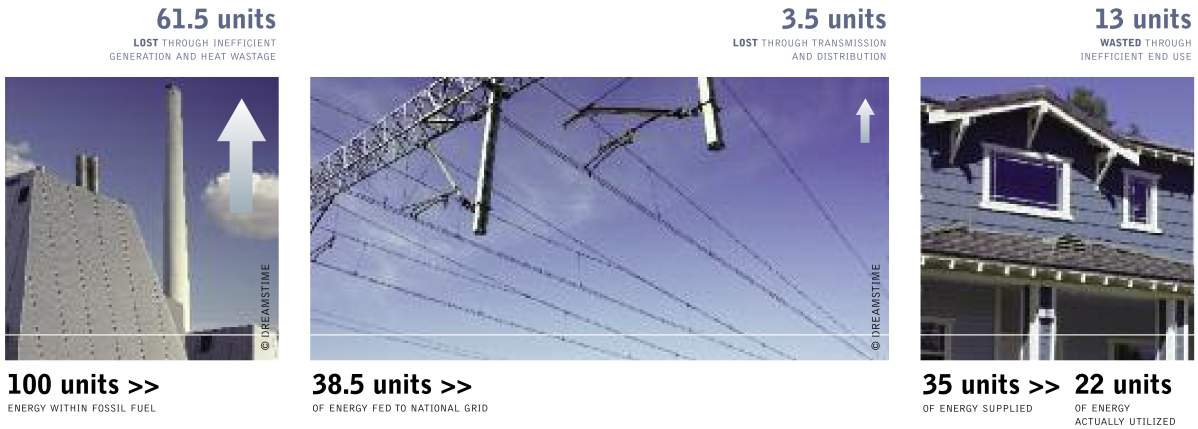


Figure 1. Energy efficiency along the electric power systems with centralized generation from fossil fuels according to (Greenpeace International and Global Wind Energy Council (GWEC), 2014). It is stated that 61.5% is lost through generation stage, 3.5% through transmission and distribution stages and 13% through inefficient end use.

and 10% of electricity by reducing consumption. A decree, CREG resolution 029 of 2016, was issued to temporarily change the way that electric bills were calculated: a consumption goal based on previous months consumption was established, and a monetary reward or penalty was provided depending on savings or increments of energy usage, respectively. A few days later, the President discarded a future rationing thanks to the rain return and the cutting down of 1 179 GWh by the Colombian people. This is an example of how the energy demand reduction avoided a worse situation.

Nevertheless, should savings be performed only during an energetic crisis or be rather a permanent policy? Should the users that already were prone to save energy be punished? What if Colombian citizens knew their actual energy consumption habits? Might load programming produce more savings than load cutting? Despite the best communication efforts of the government to promote useful tips about how to save electricity (e.g., to turn off lights in empty spaces and to use the washing machine with full load), these tips do not come from the specific consumption behavior of every customer. According to studies (S. Lin et al., 2016), (Faruqui, Sergici, & Sharif, 2010), (Altrabalsi, Stankovic, Liao, & Stankovic, 2015), an energy consumption reduction from

5% to 15% or more is expected when customers have more detailed information than the monthly bill, like feedback about the individual appliance consumption. In summary, if the load is known, more effective decisions regarding turning appliances on or off could be taken.

Load disaggregation

This analysis allows moving to the general framework of this thesis: the load disaggregation. This is defined as the knowledge of the individual appliance operation and consumption in a house or building, compared to the aggregated consumption knowledge. Load disaggregation might be obtained through surveys or by manual register of the user activity. However, automatized systems may be used to obtain more accurate information and less laboriousness during the execution stage [1]. In this sense, one might think about several types of systems. First, there are *intrusive systems* where the information of the appliances are captured separately. This would involve either buying smart appliances or installing dedicated sensors to regular appliances and then installing communication platforms to collect the data. Second, there are *non-intrusive systems* where the sensors are installed at a single point (e.g. at mains), to acquire the aggregated operation of the appliances and to decompose it through mathematical algorithms.

This thesis is focused on the non-intrusive systems for load disaggregation which are illustrated in Fig. 2. There, an aggregated power consumption is the input (left side of Fig. 2) and after the processing, it is obtained that appliances 2, 5 and 11 were operating over the time (right side of Fig. 2).

Fig. 3 depicts four approaches from the least (upper stair) to the most intrusive (bottom stair): the non-intrusive load monitoring (NILM) and three types of intrusive load monitoring (ILM).

What does *non-intrusive* mean? *Nonintrusive* means that the system is installed in the meter with no entry to the house to install sensors for appliances or branch circuits, or it can mean that

[1] The user intervention is usually required even for automatic methods in the initial setting stages.

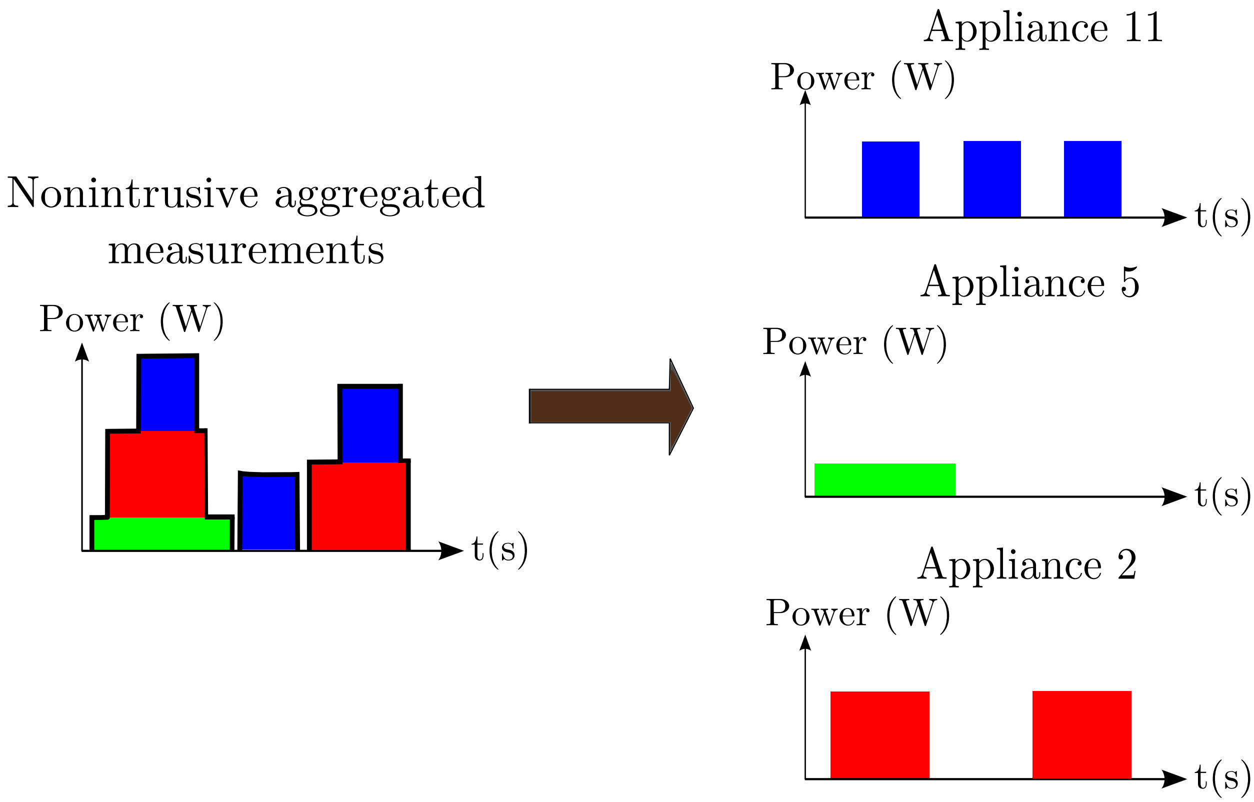


Figure 2. Illustration of an NILM (Nonintrusive load disaggregation) system.

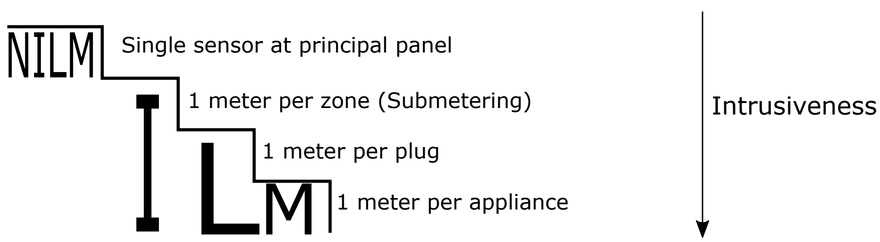


Figure 3. This diagram represents the intrusiveness level of load monitoring systems. Non-intrusive load monitoring (NILM) and three types of intrusive load monitoring (ILM) systems are distinguished.

the customer installs the system by himself. One can think that the sensors are cheap because of the mass production, but the installation cost of sensors is still high (Laughman et al., 2003). Some advantages of *non-intrusive* approach are:

- Low costs (hardware, installation)
- Hardware cost independent of the number of appliances
- Not many sensors

- Easy automation of lectures

What does *automatic* disaggregation mean? This means that during the running stage, no human intervention is needed by the system to provide the load disaggregation information.

Load disaggregation stakeholders are:

- Utilities: for designing and evaluating demand side management programs (Almeida & Vine, 1994) such as time-of-use, real-time pricing and other incentive rates applied to individual loads (Drenker & Kader, 1999), for demand response, e.g., load shedding notification (Bergman et al., 2011), for load forecasting to guarantee future energy capacity (Xu & Milanović, 2016) and for consumer education about energy consumption.

- Policy makers: for providing more accurate load models than those coming from surveys, which can be useful for better policy formulation, adequate regulation, load forecasting or energy consumption education.

- Manufacturers: for enhancing the knowledge about how their products are typically operated and for researching for new more efficient materials and technologies.

- Customer and energy service companies: bill disaggregation for detailed energy audit of the customer consumption behavior to lead to energy savings or load diagnostics (Shaw, Leeb, Norford, & Cox, 2008) to identify failure conditions in the appliances (Drenker & Kader, 1999), power quality offenders (Leeb, Shaw, & Kirtley, 1995), wasters (Paris, Donnal, Cox, & Leeb, 2014) or aging loads (Chang, Lee, Lee, Chien, & Chen, 2016). Moreover, human activity recognition and positioning could be visualized as applications (Yu, Li, Feng, & Duan, 2016).

- Neighbors: indirect benefits for power quality and voltage regulation enhancement.

These non-intrusive load monitoring systems (NILMS) present multiple challenges since the acquired signals are aggregated, and the aim is to provide the individual information per appliance as it will be described in the next section.

Problem statement

Load disaggregation problem could be stated as a combinatorial problem belonging to the *knapsack problem* family, that is similar to the problem of filling a knapsack with items to achieve a given amount of kilograms. In the case of load disaggregation, items are appliance powers, then the optimal subset of appliances operating at a given time has to be found. According to computational complexity theory, it is an $\mathcal{NP}$-complete (Non-deterministic polynomial time) problem, i.e. it cannot be solved in a polynomial time. In other words, knapsack problem is not quickly solved, especially when the number of items is high.

Combinatorial problems belong to the *discrete optimization* field. They could be solved either by exact methods such as enumeration of the solution space, dynamic programming or integer programming (Suzuki, Inagaki, Suzuki, Nakamura, & Ito, 2008) or by heuristic methods such as genetic algorithms. Exact methods are only recommended for problems with small number of items for the quantity of time and storage capacity required while heuristics might overcome this and provide faster results (Sabet, Farokhi, & Shokouhifar, 2012).

For load disaggregation, the sum of the optimal subset (individual powers) should correspond to the total measured power in the household, $\hat{P}(t)$. However, individual items have the following particular characteristics:

1. *Items within the solution space depend not only on the appliance itself but also on its operation state*. Some appliances have more than one on position since they have several speeds or possible states. Then, the power of the jth appliance is given by the state. If K_j is the total number of states of jth appliance, then $K_j = 1$ for ON/OFF or permanent consumer appliances, $2 < K_j < \infty$ for multiple state appliances, and $K_j \to \infty$ for variable consumer

devices. This implies that the actual number of items is not the number of appliances but $\sum_{j=1}^{N} K_j$.

2. *Items within the solution space are not constant along the time.* Appliance operation varies along the time according to the voltage variation due to several factors such as supply variation, voltage drop in the line impedance for connecting other loads and user activity. Then, a time dependence is needed in the relationship.

3. *Items might be different but have the same* weight. Several appliances could have the same power consumption.

4. *Size of the set can also vary.* The number of appliances, N, is not always the same since customers buy new appliances, hosts arrive home, etc. Then, N would also be time varying and even unknown.

Let $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_N(t)]$ indicate if the appliance is on or off (i.e. $x_j(t) = 0$ if the appliance is off, $x_j(t) = 1$ if it is on), $\mathbf{p}(t) = [p_1(t), p_2(t), \ldots, p_N(t)]$ be the estimated power of the appliances and $\hat{P}(t)$ be the measured aggregated power. The problem to address could be defined mathematically as follows:

$$\begin{aligned} \{\mathbf{p}^\star(t), \mathbf{x}^\star(t)\} \quad &= \underset{\mathbf{p}(t),\mathbf{x}(t)}{\text{argmin}} |\hat{P}(t) - \mathbf{x}^T(t)\mathbf{p}(t)| \\ \text{s.t.} \quad & x_j(t) \in \{0,1\}, j = 1, \ldots, N. \end{aligned} \tag{1}$$

In summary, Eq. (1) has a lot of unknown variables: $x_j(t), p_j(t)$, $j = 1, \ldots, N$, and yields infinite solutions.

Additionally, the problem is not additive because of the line impedance effect: if an appliance is connected at $t = \tau$, the total power right after, $\hat{P}(\tau^+)$, is not equal to $\hat{P}(\tau^-) + p_j(\tau^+)$, where $\hat{P}(\tau^-)$ is the consumption before the connection, and $p_j(\tau^+)$ is the consumption of the connected load.

Approaches other than knapsack problem are encouraged given these drawbacks. They will be presented in the state of the art in Chapter 1.

Scope

This thesis intends:

1. To use *one-sensor electrical metering*. Houses could have separated circuits for types of load. Neither measurements at circuit level, often called *submetering* (Marchiori, Hakkarinen, Han, & Earle, 2011), nor *virtual metering* (Kim, Schmid, Charbiwala, & Srivastava, 2009),(Marchiori et al., 2011), (Srivastava, 2012),(Kim et al., 2009) through side channel sensors, e.g., acoustic and vibration sensors to measure the emissions of appliances in operation, will be considered because this would be intrusive according to the explanation of intrusiveness in Section . Electrical sensors installed in a centralized location will be taken into account.

2. To work on single phase residential appliances. Studies at residential level are strategical because:

   - Residential consumption is representative of countries. For example, it reaches 40% of the total electric energy consumed in Colombia (Unidad de Planeación Minero Energética UPME, 2016). Thus, big saving opportunities exist, and the market for future commercial products for houses is promising.
   - In computerized grids, people will want to take advantage of all the available measurements and information.
   - Cheaper experiments might be implemented.
   - Solving the problem for house level would provide experience and bases for solving the problem in commercial and industrial locations. Laughman et al. (2003) indicated: “Medium to large size commercial and industrial facilities require a more sophisticated

approach, due in part to high rates of event generation, load balancing, and power factor correction."

Load monitoring at transmission or distribution levels would also provide valuable information for utilities, but it would have additional challenges. Some previous works for commercial sites can be found in (Shaw et al., 2008), (Drenker & Kader, 1999) and for industrial sites in (Leeb et al., 1995).

3. To use previous knowledge of the appliances in the specific house. This thesis does not intent to detect "all" the appliances in the market. Currently, efforts are made for some researchers to build a world repository of appliance measurements.

4. To assume that appliances change the state, e.g. switch on or off, at different times and not exactly in the same instant, as when multi-outlet adapters are used. Hart (1992) defined the switch continuity principle as follows: "In a small time interval, we expect only a small number of appliances to change state in a typical load ". He also said "It has a consequence that in any small enough time interval, we expect the number of appliances which change state to be usually zero, sometimes one, and very rarely more than one". This is widely accepted as NILM foundation and experiments say that it is valid for small houses (Makonin, 2016).

5. To analyze harmonics, not supraharmonics (2kHz-150kHz emissions). Metering equipment that allows measuring supraharmonics is not available in the laboratory. Load signatures are limited to what can be monitored at the meter.

Contributions

The contributions of this thesis are:

1. A new understanding of the disaggregation framework for continuous sensing NILM systems in Chapter 2.

2. Set of measurements from residential appliances whose labels of transients start/end, switching on, off, are provided in Chapter 3.

3. Proposal of a set of load signatures time - frequency, transient – steady state in Chapter 4.

4. "One-Class Classification" proposal in Chapter 4 to solve the scalability problem, i.e. the drawback of the need to re-train NILM systems and the exponential growth of the complexity when an appliance is added, and to identify new or unseen appliances identification.

5. Analysis of the discrimination capacity of event-based NILM systems under different scenarios to assess the following impact factors: voltage distortion, network impedance and dependency of switching transients on point-on-wave (angle of the starting point) in Chapter 5.

Document organization

The structure of the remainder of this thesis is as follows.

Chapter 1 examines the scientific literature review about Nonintrusive Load Monitoring system regarding the mathematical approaches to address load disaggregation problem and deeper detail about the pattern recognition approach. Methods and tools used by previous works for every stage of an NILM system based on pattern recognition are highlighted Finally, research gaps are revealed.

Chapter 2 explains a framework that comprises the input and output information for NILM systems and a general continuous sensing scheme.

Chapter 3 presents the measurement methodology for building a dataset to test NILM systems. Components of the measurement setup such as appliances and meters are described, and the scenarios and protocol definition are explained as well. The acquisition software is also shown.

Chapter 4 describes the proposed strategy in this thesis to cope with load disaggregation: the event detection method, the proposed load signatures and classification strategy. Also power estimation is indicated.

Chapter 5 presents the results of the proposed strategy and the analysis of impact factors on the discrimination capacity of characteristics or features computed from the electrical signals.

Finally, the conclusion and future work wrap up the document in Chapter 6.

1. Non-intrusive load monitoring systems

Research on NILM has gained interest in the last years. The seminal work is (Hart, 1992) with hundreds of citations, and every year, review papers have been published as shown in the timeline in Fig. 4. This chapter presents a review of the scientific literature focused on understanding the paths that authors have followed to handle the load disaggregation problem via non-intrusive methods, the contributions of those previous works and the research gaps.

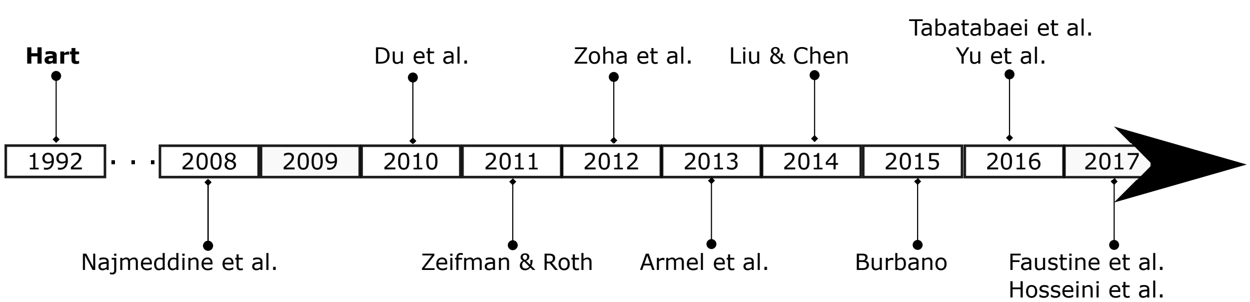


Figure 4. Timeline of review papers about non-intrusive load monitoring (NILM)

In this chapter, Section 1.1 discusses the mathematical approaches to solve the problem. Secondly, Section 1.2 explains the strategies observed in every stage of an event-based NILM system via pattern recognition. Finally, the identified research gaps are presented in the concluding remarks in Section 1.3.

1.1 Mathematical approaches to solve load disaggregation

Figure 5 presents a summary of the approaches found in the scientific literature to address load disaggregation problems. The first approach is using *combinatorial search* to directly solve the

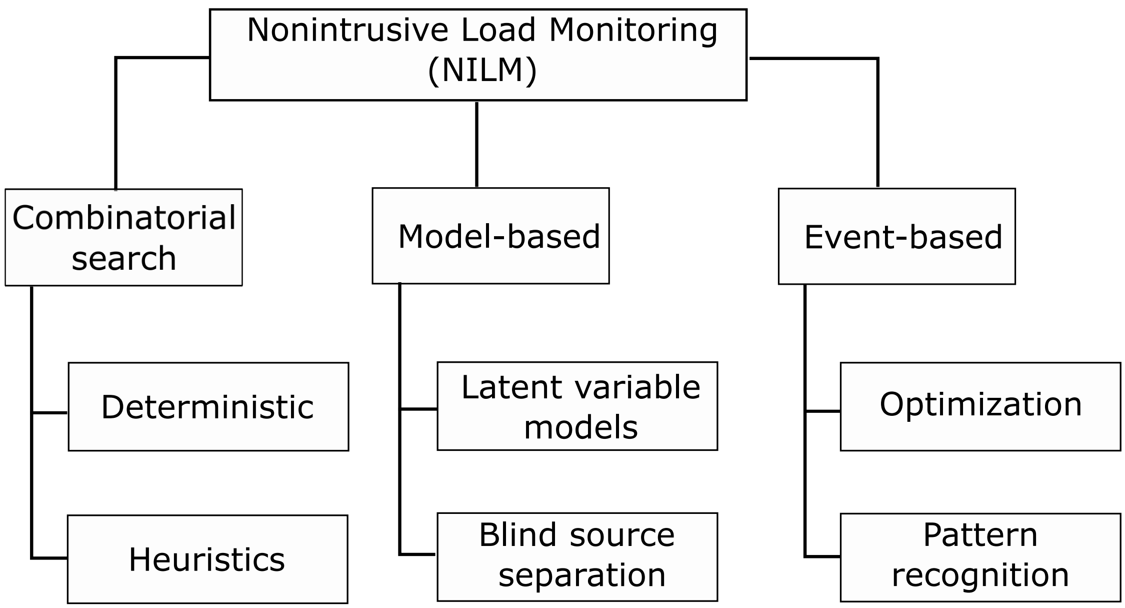


Figure 5. Mathematical approaches to solve load disaggregation problem according to the literature review

optimization problem stated in Eq. (1) through heuristic or deterministic methods. For example, Egarter, Sobe, and Elmenreich (2013) used evolutionary algorithms (heuristics) while Bhotto, Makonin, and Bajic (2017) used integer programming (deterministic).

The second is the *model-based* approach. Waveforms are converted to probabilistic or statistical models to make the appliance identification. In this category, latent variable models such as Hidden Markov Models (HMM) (W. Kong, Dong, Hill, Luo, & Xu, 2016), (Wong, Drummond, &

Sekercioglu, 2014), temporal motif mining (Shao, Tech, & Marwah, 2012) and blind source separation (Gonçalves, Ocneanu, Bergés, & Fan, 2011), (Figueiredo, Ribeiro, & de Almeida, 2014) have been formulated.

The third is the *event-based* approach, where electrical signals are monitored, and transitions between one stationary state to another, namely events, are detected. Events indicate that a switching on or off or a state change in the appliance took place. Thus, the signal is divided into shorter sequences to extract load signatures, i.e. particular characteristics computed to distinguish between appliances. Event based works deal with load disaggregation either as an optimization problem or as a pattern recognition problem:

- Optimization problem: a database of the appliance is created and used to make comparisons with the appliance under analysis to find the best match. The error between the cases in the database and the current case is minimized to find the most similar or closest appliance. Comparison can be performed either between raw waveforms through correlation analysis or between characteristics computed from the waveforms through distance metrics like Euclidean distance. Some works used deterministic techniques to solve the optimization problem as integer programming (Suzuki et al., 2008), while others used heuristics like Ant Colony Optimization (ACO) (Y. H. Lin & Tsai, 2014a).
- Pattern recognition problem: A learning technique is used to build models from the characteristics extracted from the appliance signals and to classify the appliance under analysis. A deeper review of pattern recognition methods for NILM is presented in Section 1.2.3.

1.2 Literature review of event-based approach via pattern recognition

Event based NILM systems through pattern recognition usually comprise four stages shown in Fig. 6: measurement, event detection, feature extraction and classification. Power estimation stage is not commonly defined by authors.

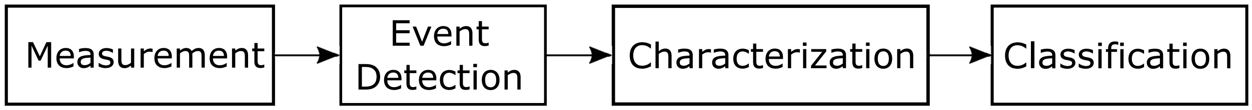


Figure 6. Stages of an event-based NILM system via pattern recognition.

The meaning of every stage and a review of the methods that authors have presented to develop them are introduced on the next subsections.

1.2.1 Event detection An event is defined as a change in electrical measurements from one stationary state to another, due to an appliance state change. For instance, Fig. 7 shows an example of two events in the operation of a CFL. The first event is a switching on at around 1 second, and the second event is a switching off at around 2.55 seconds. This is observed clearer in the current than in the voltage signal (unless the sampling frequency is high enough). Event detection aims to figure out that an event is taking place and to identify the time instant when it occurs (Jin, Tebekaemi, Berges, & Soibelman, 2011). In statistics, the abrupt change detection problem is better known as change detection.

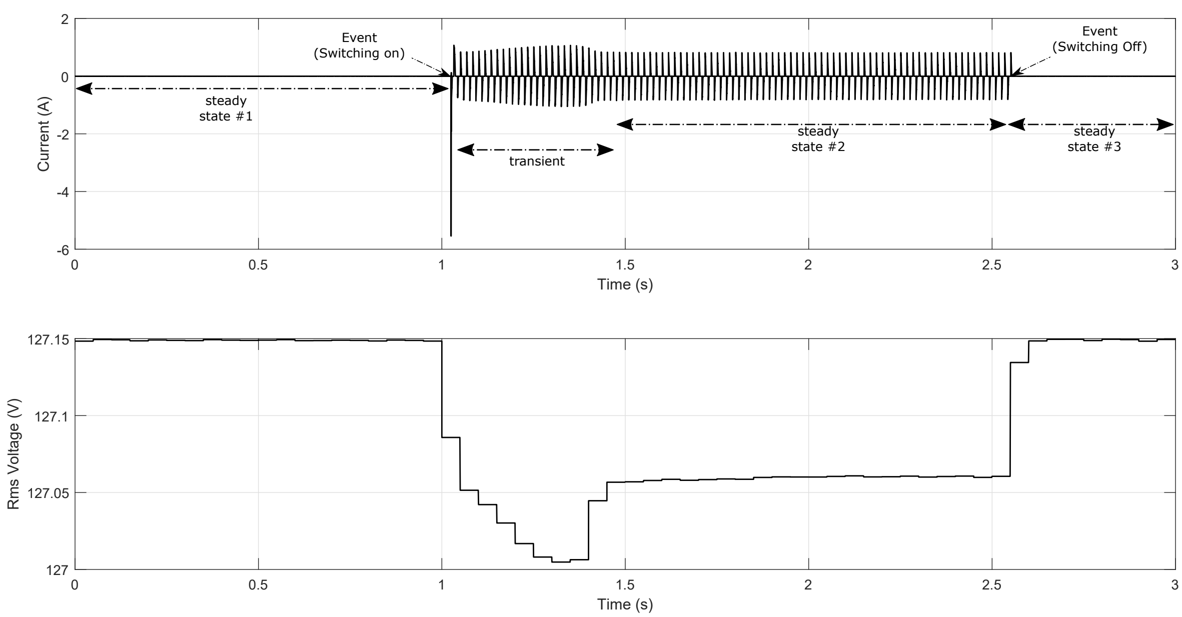


Figure 7. Example of the current and voltage of a CFL that is turned ON and then turned OFF.

Event detection algorithms for NILM could be grouped into four categories: comparative, statistical, frequency-based and machine learning based, as presented in Fig. 8.

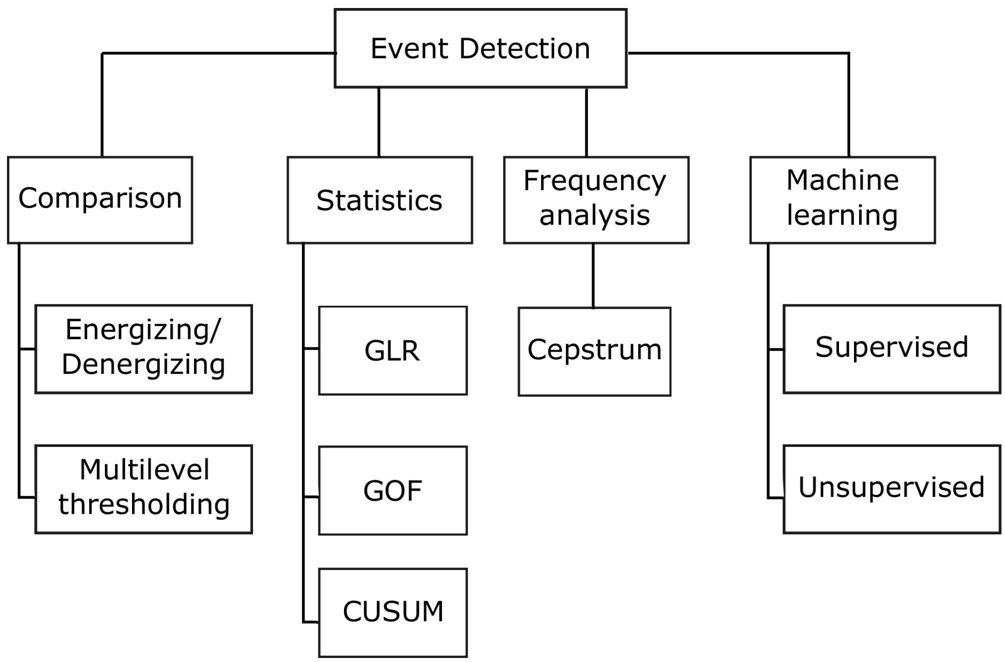


Figure 8. Event detection methods according to the literature review.

- **Comparative**: These methods compare the instantaneous values with a fixed or adaptive threshold or with the previous cycles.

  – *Energizing or de-energizing event detection*: Y. H. Lin and Tsai (2014a) proposed to detect the start of an event-based on the variation of a magnitude called "current intensity", i.e. the average of the difference of every point of the cycle to the mean value of the cycle. If current intensity in one cycle is greater than the one in the previous cycle according to a threshold, the change is recognized as an event. Similarly, the end of the transient is identified by the variation of the differential waveform of the current compared to a threshold. This method needs three parameters: for the starting event, for the ending of the transient and for the number of cycles to examine the transient.

  – *Multilevel threshold detection method*: A gradient waveform is computed from the filtered power signal. A lookup table is designed by assigning thresholds to on and off switchings of every appliance and their output values. This lookup table is applied to the gradient waveform, thus, matching responsible appliances (Quek, Woo, & Logenthiran, 2016).

The disadvantage of these methods is that dedicated thresholds for appliances are required as input parameters, which is not suitable because when NILM system is running, appliances are not known beforehand.

- **Statistical**: These methods divide the waveform into windows and perform statistical tests to search events.
  - *Generalized likelihood ratio (GLR) test* : a decision statistic is computed from the log likelihood ratio and a voting window in order to infer the presence of an event (Anderson, Bergés, Ocneanu, Benitez, & Moura, 2012).
  - *Chi squared goodness-of-fit (χ^2 GOF)*: this method assumes that the spectrograms of two consecutive windows of the instantaneous active power share a common distribution, and then, it develops a chi squared statistic test. An event is recognized if the null hypothesis is rejected, this is, if a meaningful change in the distribution takes place (Jin et al., 2011).
  - *CUmulative SUM (CUSUM)*: This method uses an adaptive threshold to control the state change and a drift parameter to control the duration (Trung, Dekneuvel, Nicolle, & Zammit, 2014.).
- **Frequency based**: These methods transform the signal to other domains to detect the transients, given that these exhibit changes in frequency too.

  Cepstrum: Baets, Ruyssinck, Deschriijver, and Dhaene (2016) proposes to find the Fourier spectrum of the power, to compute the Cepstrum coefficients of the spectrum and to apply a filter to smooth them and finally to transform back to frequency domain. Therefore, low and high frequency information is associated to steady and transient state, respectively. The author states that this is very useful for multiple appliance operation.

- **Machine Learning based**: These methods have high computational cost because a training step is required to optimally tune several parameters. Training could be based either on labelled data (supervised training) or on cost function (unsupervised learning) (Baets et al., 2016). Some pattern recognition techniques used in previous works are:
  - Kernel clustering (Volpi, Tuia, Camps-Valls, & Kanevski, 2012).
  - Hidden Markov Modeling (Luong, Perduca, & Nuel, 2012).
  - SVM (Grinblat, Uzal, & Granitto, 2013).
  - Bayesian Methods (Gu, Choi, Gu, Simon, & Wu, 2013).

1.2.2 Characterization The assumptions for NILM are that the appliance operation affects the current and voltage waveforms and that some distinctive characteristics or *fingerprints* from these signals can be computed to infer which appliances are operating, namely *load signatures*. Few authors have used raw signals instead of characteristics (Suzuki et al., 2008) and showed lower accuracies than using characteristics (Zeifman & Roth, 2011). Fig. 9 depicts the types of characteristics or load signatures used by authors in the literature. This stage is sometimes called *feature extraction* because it is a widely used term in the pattern recognition area.

Steady and transients states are alternated in current or power waveforms of appliances. Steady states are approximately periodical while transients exhibit non-stationary patterns that settle down after some time. For example, Fig. 7 portrays an appliance switching on and off, where three steady states and a transient state are visualized [1]. According to the type of signal used to compute the characteristics, they are classified into *transient* or *steady state characteristics*. The sampling

[1]Transients yielded by “off switchings”are usually less perceptible than “on switchings”

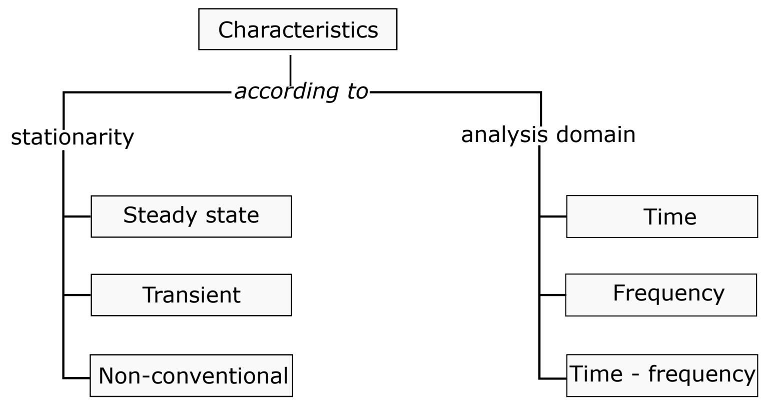


Figure 9. Types of characteristics used as load signatures in the scientific literature.

frequency of the sensor should be higher for the transient than for the steady state analysis.

Non-conventional characteristics are representations of the power signals in terms of rectangles and triangles and side data such as time of the day and appliance usage, that are not taken from the electrical signals but might enhance appliance identification. Combination of several types of characteristics are also encouraged to obtain better discriminative power, and this approach can be included in the non-conventional category as well.

In addition, information from time and/or frequency can be used to compute the characteristics. Time domain characteristics are extracted from the waveforms or intermediate representation such as P-Q plane or V-I trajectories, while frequency information characteristics are computed from the Fourier spectrum of the waveforms, like harmonic information. Signals, above all the transients, have been represented in a time-frequency space, such as short time Fourier transform (STFT) and wavelet transforms.

The most intuitive characteristics are active and reactive powers, but authors have explored others along the years (Laughman et al., 2003), (Liang, Ng, Kendall, & Cheng, 2010), (Yu et al., 2016) with the intention of identifying discriminative characteristics. In short:

From power:

Transient: spectral envelopes (Leeb et al., 1995),

Steady: power profiles and P-Q plane (Hart, 1992).

Non-Conventional: power signal graphic decomposed by rectangles and triangles (Wang & Zheng, 2012).

From current:

Transient: waveform parameters (Laughman et al., 2003), (Ruzzelli, Nicolas, Schoofs, & O'Hare, 2010), time-frequency information (Duarte, Delmar, Goossen, Barner, & Gomez-Luna, 2012), (Y. H. Lin & Tsai, 2014b), (Jimenez, Duarte, Petit, & Carrillo, 2014)

Steady: waveform parameters (Jimenez et al., 2014) and harmonics (Laughman et al., 2003)

From voltage:

Transient: noise (Patel, Robertson, Kientz, Reynolds, & Abowd, 2007) and RFI (Gulati, Singh, Agarwal, & Bohara, 2016)

Steady: waveform parameters (Liang et al., 2010), electromagnetic interference (EMI) noise (Patel et al., 2007), Cepstrum of EMI (Electromagnetic interference) noise of voltage signal (S. Kong, Kim, Ko, & Joo, 2015) and EMF (Kulkarni, Harnett, & Welch, 2015).

From voltage and current:

Steady: Geometrical properties of V-I trajectories such as looping direction, area enclosed, non-linearity of mean curve, number of self intersections, slope of middle segment and area of right and left segments (Lam, Fung, & Lee, 2007) (Liang et al., 2010), (Hassan, Javed, & Arshad, 2014)

A summary of the steady state and transient characteristics used in the literature is found in Fig. 10, where frequency and time-frequency characteristics are written in red italic format and the others correspond to time domain characteristics. Steady characteristics are presented in part

a) and transient ones, in part b). The diagonal of these matrices includes characteristics from one single variable: power, current or voltage, whereas off diagonal characteristics are computed by combining two of these three variables.

a) Steady state Characteristics

	Power	**Current**	**Voltage**
Power	Power profile P-Q plane		
Current		Parameters from waveform (rms, peak), *harmonics, time-freq. information*	Power factor
Voltage		V-I trajectory shape (slope, area, etc.)	Parameters from waveform (rms, peak), *Voltage Noise (EMI)*

b) Transient Characteristics

	Power	**Current**	**Voltage**
Power	Power edges Spectral envelopes		
Current		Parameters from waveform (duration, shape, spikes)	
Voltage			*Voltage Noise*

Figure 10. Summary of a) Steady state and b) Transient characteristics proposed in previous works. Frequency and time-frequency characteristics are displayed in red italic and time domain characteristics, in normal black.

1.2.3 Classification NILM can be modeled as a classification problem. In general, a classification problem is the task of building models to map the characteristic or feature vector of measured signals **x** (inputs) to predefined decision values or class label (outputs) y, thus:

$$\mathbf{x} \longrightarrow y = f(\mathbf{x}, \alpha) \tag{2}$$

where f is the target function or classification model, and α represents the set of parameters of the classification machine or technique (e.g. kernel parameters and penalty factors for a support vector machine). In supervised learning, there is a known set of instances or cases, usually called training set, that together with their label $(\mathbf{x}, y)$ provide knowledge to build the models and predict the labels for unknown cases $(\mathbf{x}, ?)$. Class labels are discrete; otherwise the task would be a regression problem.

1.2.3 Categories of NILM systems due to the classification stage Several categories of classification systems for NILM can be found as (see Fig. 11):

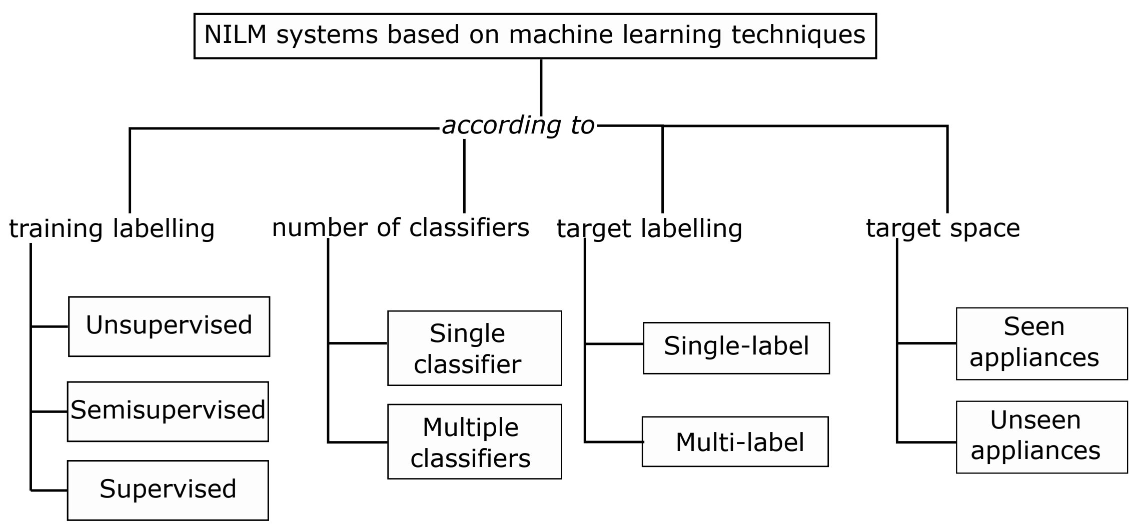


Figure 11. Summary of machine learning approaches for NILM found in the scientific literature

- **According to the number of classifiers**
  - Single classifier: Only one trained classifier is used for appliance identification (Jimenez et al., 2014).

  - Ensembles classifiers: several individually trained classifiers are combined to conform a classification strategy, usually through voting mechanisms (Liang et al., 2010), (Kramer, Klingenberg, Sonnenschein, & Wilken, 2014), (Y. H. Lin & Tsai, 2015).

- **According to the training data labeling**
  - Unsupervised: these algorithms do not require labeled training data (Y.-H. Lin, Tsai, & Chen, 2011).
  - Semi-supervised: these algorithms require only a small number of labeled training data in a larger set of unlabeled ones (Tabatabaei, Dick, & Xu, 2016).
  - Supervised: labeled instances of each appliance are acquired during a training or learning stage for these algorithms (Liang et al., 2010).

- **According to the target labeling**
  - Single-label: only one label is assigned to each instance. This is the classical approach where every class corresponds to a state of the appliances. This approach usually requires to train with combinations (Marchiori et al., 2011), (Srinivasan, Ng, & Liew, 2006). Disadvantages of this approach are explained in (Zeifman & Roth, 2011).
  - Multi-label: the input is not mapped to a single label output but to a vector of labels. This approach takes into account the interdependence among labels (in our case, the appliances) (Basu, Debusschere, Bacha, Maulik, & Bondyopadhyay, 2015). Works reported in (Li, Sawyer, & Dick, 2015), (Basu et al., 2015), (Tabatabaei et al., 2016) used multi-labeling classifiers.

- **According to the target space**
  - Limit the output to one of the classes in the training data. Thus, an instance belonging to an unseen appliance in the training is assigned to one of the classes of the training data.

  - Identify unseen appliances as *new*.

1.2.3 Techniques Some of the techniques used in previous works are:

- Naive based classifier (Marchiori et al., 2011).
- Neural networks (Chang, Chen, Tsai, & Lee, 2012), (Srinivasan et al., 2006), (Xu & Milanović, 2015), Neural Networks + particle swarm optimization (PSO) (Chang, Lin, Chen, & Lee, 2013), back-propagation artificial neural networks (BP-ANN) (Chang, Lian, Su, & Lee, 2014), Hellinger Distance + PSO + BP-ANN (Chang et al., 2016).
- Mean shift clustering instead k-means clustering (Wang & Zheng, 2012).
- Linear discriminant (Wang & Zheng, 2012).
- Supervised Self Organizing Maps (SSOM) (He, Lin, Liu, Harley, & Habetler, 2013), hybrid (SSOM + Bayesian) (Du, Restrepo, Yang, Harley, & Habetler, 2013), (Du, He, Harley, & Habetler, 2016).
- Support vector machine (SVM) (Figueiredo, de Almeida, & Ribeiro, 2012), (Jimenez et al., 2014).
- Fuzzy logic (Ducange, Marcelloni, & Antonelli, 2014).
- 3-nearest neighbors (Eibl & Engel, 2015), k-nearest neighbors (Koutitas & Tassiulas, 2016), (Gulati et al., 2016).
- Decision tree (Kulkarni et al., 2015).
- Hybrid classification technique that integrates Fuzzy C-Means (FCM) clustering-piloting PSO with Neuro-Fuzzy Classification (NFC) (Y. H. Lin & Tsai, 2014b).

1.3 Concluding remarks

Although the research on NILM has increased in last years, several questions arise, and some challenges remain. The following *research gaps* were identified:

- There is not a widely accepted set of load signatures. Authors coincide in the key role of the load signature choice in event-based NILM systems (Hassan et al., 2014). For example, Yu et al. (2016) stated: “Until now, a complete set of robust and widely accepted appliance features has not been established. The available features do not provide unambiguous appliance detection and classification.”
  Load signatures should be:
  1. Discriminative to yield a clear appliance identification.
  2. As simple as possible to be computed and stored.
  3. Able to provide information of a given appliance even when it is Operating at the same time than others because the information of all appliance is fused together.
- To the author best knowledge, research has been more focused on load signature exploration than on algorithm development. For example, Dong, Meira, Xu, and Freitas (2012) affirm that “traditional NILM algorithms only focus on single state/edge of appliance and thus, cannot identify appliances from entire process perspective.”
- Scalability problem: The complexity of the systems depends on the number of appliances in the inventory, sometimes with an exponential relationship. Adding more appliances to the house, which is common, implies:
  - Need of a re-training because the knowledge database should be updated.
  - More intensive training to build models and more complex algorithms.
  - Possibly less accurate systems.

Srivastava (2012) declares “It is hard to discriminate signatures when there is a large mix of devices and appliances ”.

- Need of more accurate systems: Authors express the performance of their algorithms in terms of different metrics as observed in (Armel, Gupta, Shrimali, & Albert, 2013). As a consequence, comparison between algorithms is not straightforward. In general, an NILM system should be accurate, this is, the percentage of correctly classified appliances should be high. Under this metric, accuracy of NILM systems still has room for improvement. Strategies for enhancing the accuracy might include the definition of more discriminative characteristics. Electrical signals might be mapped to other domains with transforms to make them more observable. So far, scientific literature shows representations with Fourier and Wavelet Transforms. Different transforms should be explored to obtain a better time location, time-frequency resolution, noise sensitivity and/or less computational complexity.

- Studies on the impact of factors such as voltage distortion and variation, network impedance and simultaneous appliance operation on load disaggregation algorithms are still lacking. It is important to have this knowledge because these factors are present in real household execution.

- Apart from the absence of standard metrics, the lack of availability of standard datasets to evaluate the systems must be improved in this research field. Table 1 presents a comparison of publicly available energy datasets (Faustine, Kaijage, Michael, & Mvungi, 2017). Public databases are not fully labeled or their sampling frequencies are not high enough; moreover, their circuits are not like the Colombian households. They might be helpful to use in the comparison among different proposals.

- Privacy issues: Some authors have pointed out that together with the benefits, a potential disadvantage appears with NILM systems related to the use of data for additional surveillance purposes (Hart, 1989), (Eibl & Engel, 2015), perhaps the violation of civil liberties. The information about appliances at home and their use is considered private by Ren, Song,

Table 1

Summary of publically available energy dataset. Aggregate (aggr), Sub-metering (sub).

Dataset	Location	Duration	No. Of houses	Sensors/house	Resolution
REDD	USA	3-19 days	6	24	15kHz (aggr), 0.5Hz and 1Hz (sub)
BERDS	USA	1 year	1	4	20
BLUED	USA	8 days	1	Aggregated	12kHz (agg only)
Smart	USA	3 months	3	21-26 circuits meters	1Hz
Tracebase	Germany	N/A	15	158 devices	1-10 sec (sub only)
AMPDS	Canada	1 year	1	19	1 min
AMPds2	Canada	2	1	21	1 min
UK-DALE	UK	499 days, 2.5 years (house 1)	5	5-54 devices	16 kHz (agg) and 1/6 Hz (sub)
IAWE	India	73 days	10	33 devices	1 sec (aggr) and 1 sec or 6 sec (sub)
REFIT	UK	2 years	20	11	8 sec
GREED	Australia/Italy	1 year	9	9	1 Hz
ECO	Switzerland	8 months	6		1 Hz
IHEPCDS	France	4 years	1	3	1 min
OCTES	Scotland, Iceland & Finland	413 months	33	Aggregated	7 sec
HES	UK	1 month (255 houses)	251	13-51	2 min
ACS-F1	Switzerland	2, 1 hour sessions	N/A	100, 10 types	10 sec

Note: adapted from (Faustine et al., 2017)

Yang, and Ren (2011) and Srivastava (2012). The question about how technology should be controlled remains valid not only for this type of technology but also for social media, the use of cameras, etc.

- Big data analytic problems: high volume of data storage, retrieval and processing for energy applications might be challenging depending on the type of NILM system (Paris, Donnal, & Leeb, 2014).

2. Framework for event based systems

This chapter contributes to a better understanding for the design of NILM systems through an explanation about several aspects to consider for solving load disaggregation problem, specially with the event-based approach. The aim is to provide to researchers a wide variety of design and implementation matters to bear complete NILM systems in a comprehensive way. This explanation or framework is presented from two perspectives. First, in Section 2.1 NILM systems are discussed like a box model, i.e. the types of input and output information are mentioned. Second, some guidelines for implementing NILM systems with a continuous sensing scheme are presented in Section 2.2.

2.1 On NILM information

If an NILM system is seen as a black box, several information sets could be used as inputs [1] to generate a given output, as shown in Fig. 12.

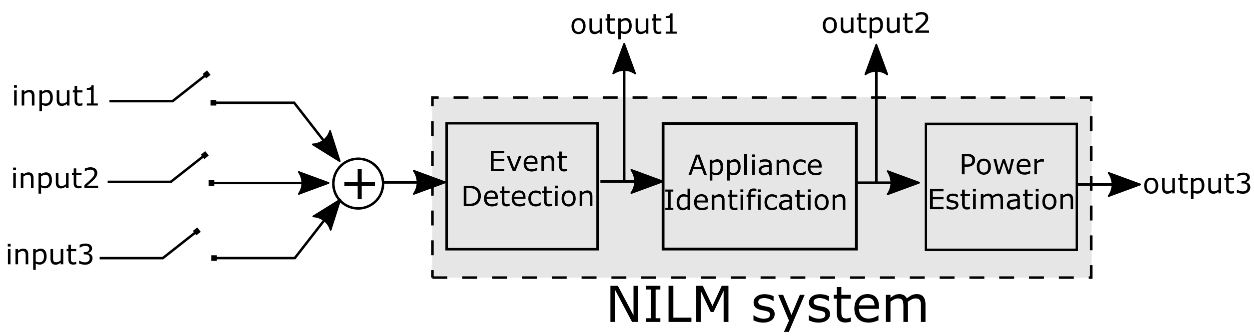


Figure 12. Possible NILM system inputs and outputs.

2.1.1 Input information The input information that can be used to derive the solutions can be categorized like this:

Input 1: A library built from measurements in different locations (houses, laboratories), for appliances of different powers, brands, ages, topologies, etc. The user selects from the library those appliances more similar to the ones in the house. Gathering this diverse information requires huge effort by researchers worldwide to release open-access datasets with detailed enough information (individual information, resolution, etc.) for the designed NILM algorithm . Moreover, there is always a risk that the appliances at home are not well represented in the database.

Input 2: Previous knowledge about appliances in the household, i.e. either only an inventory list or particular electrical signatures of the appliances. The system is designed or tuned for a

[1] Background sensor information might also help load disaggregation, but the definition of *non-intrusive* in Section discards the use of sensors other than electrical ones.

particular location and set of appliances. This specific information is obtained during a training stage.

- Individual information: electrical signatures when every appliance is connected individually.
- Simultaneous information: electrical signatures when several appliances are connected simultaneously which is is a common situation in houses. Building this knowledge database implies a big space of measurements. In this case, the question would be which combinations to consider.

If no previous information about the specific appliances was available, the system would have to "guess" the load by self-learning and to create the database during the operation, without a previous training stage. This is the least intrusive system but the hardest to design.

Input 3: A priori information. For example, this would include the customer habits, electric system behavior, weather conditions, etc.

The system would use one of these inputs or any combination of them (see addition mark in Fig. 12).

2.1.2 Output information The solution for load disaggregation can be thought as a table that is updated through time. For example, if the NILM system is sensing the aggregated current in Fig. 13 of a halogen lamp that connects at t_1 and disconnects at t_3 while a fan is operating simultaneously, several levels of information can be provided.

Output 1: Electric Activity. This is to address the question "*is there any appliance connection or disconnection?*". This is the most simple information that could come from an event detection stage that registers appliance state changes. This information could benefit inhabitant presence detection applications. The output would be as presented in Table 2.

Output 2: Appliance operation. This is to answer "*which appliances are connected/disconnected?*"This is the most common output information that authors in scientific literature about event-based sys-

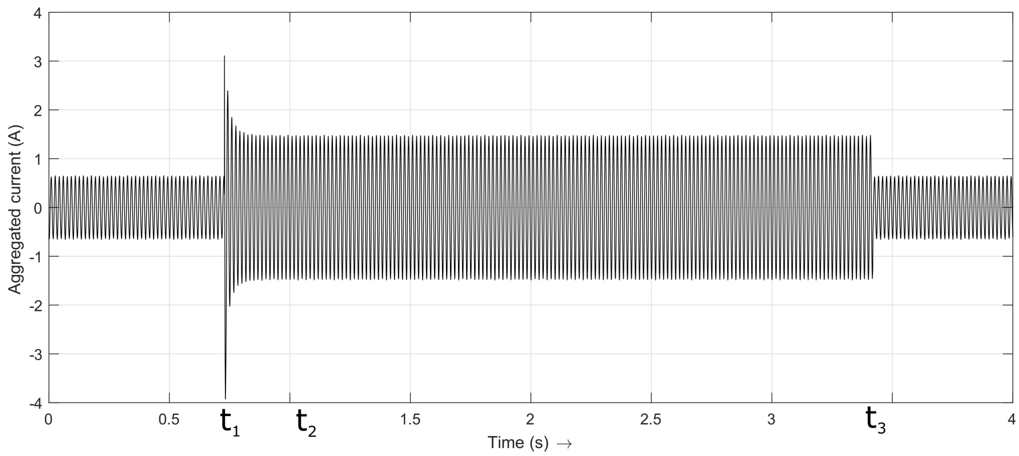


Figure 13. Aggregated current of a fan and a halogen lamp in simultaneous operation. The lamp connects at t_1, thus, causing a switching transient between t_1 and t_2, and disconnects at t_2.

Table 2
Example of solution table for output level 1.

Time	State
t_1	An appliance was connected
t_3	An appliance was disconnected

tems intend to provide, which is still complex because appliances can have multiple operation modes. This operation information might be useful for some applications such as activity inference. The solution for the example in Fig. 13 between t_1 and t_3 is displayed in Table 3.

Table 3
Example of solution table for output level 2.

Appliance	State
TV	OFF
Halogen Lamp	ON
Fan	ON
Iron	OFF
⋮	⋮

Output 3: Appliance power consumption. This is to solve the question "*how much power is every appliance consuming?*"The individual power consumption is important for serving the stakeholders' interest described in Section and to motivate energy savings through user behavior changes. For this case, the solution table has not only the state of every appliance (0 if it is off,

1 if it is on) but also its power consumption, as it is shown in Table 4 for the example in Fig. 13 between t_1 and t_3.

Table 4
Example of solution table output level 3.

Appliance	State	Power (W)
TV	OFF	0
Halogen Lamp	ON	70
Fan	ON	3
Iron	OFF	0
⋮	⋮	⋮

2.2 Continuous sensing scheme

Several options of continuous sensing schemes can be adopted according to the way that the following inquiries are addressed. Aspects and possible ways to deal with them are the following.

- When shall sensing start to infer load disaggregation? The starting point for an NILM system could be at different instants.
  - To start when appliances are at a stationary operation from an undetermined time ago like at any time between 0 and t_1 or between t_2 and t_3 in Fig. 13. Probabilistic solutions should be approached for this case.
  - To start just when appliances switch from one state to another, e.g., in t_1 or t_3 in Fig. 13.
- When shall the solutions be computed or updated?
  - To compute the solutions every time an event is detected in the transient edge, e.g. between t_1 and t_2 in Fig. 13. The hypothesis for using momentary information is that whenever an appliance changes its state, this can be observed in the electrical signals.

  - To compute the solutions under a periodic base. In this sense, changes are not followed, and momentary steady state information is analyzed, e.g. between 0 and t_1 or between t_2 and t_3 in Fig. 13.

- Which load signatures shall be used? This aspect refers to the characteristics considered to compute the solution, which were explained in Subsection 1.2.2:
  - Transient characteristics
  - Steady state characteristics
  - Non-conventional characteristics
- Which type of data shall be used?
  - Present moment data: characteristics and weather conditions.
  - Past data: 1) previous solutions, e.g. to confirm the solution at t_2 in Fig. 13 through the solution between 0 to t_1, 2) *a priori* information like user preferences, e.g. to consider the probability of a given appliance operation according to the historical user preferences, or 3) generic appliance database.
- How long should the window be?
  - Typically 12 cycles are used in power quality analysis at 60 Hz.
  - Others

In this sense, there are multiple possibilities for the resulting scheme. If all the options were combined, the outcome would be as depicted in Fig. 14. This diagram is divided into the three stages indicated in Fig. 12: event detection, appliance identification and power estimation. The procedure in Fig. 14 begins with the initialization of a timer and the computing of a probabilistic solution based on steady state signals to identify appliances, followed by a power estimation. This step is repeated on a periodic basis (every T seconds). During the intervals between, an event detection process is running, and if an event is detected, transient features from the switching signals are computed, and a solution is inferred. The inputs for the inference process are not only the transient features but also previous solutions (appliance operation and power), a priori information (e.g. user habits) and a generic database from a variety of appliances. According to this scheme, the NILM system would be continuously sensing and updating the solutions which can be communicated to the customer, the utility or another stakeholder.

2.3 Concluding remarks

This chapter treated alternatives for NILM system input and output information. Also, a general scheme for continuous sensing in NILM system based on several aspects such as starting point, the way to compute and/or confirm the solutions, etc. was suggested as a guideline for researchers to design and implement them.

Particularly, the input of the proposed system in this thesis is previous knowledge about appliances in the household, and its output is power estimation information. Moreover, the continuous sensing scheme for the proposed system is as follows:

- When shall load disaggregation start? When appliances switch from one state to another.
- When shall the solution be computed or updated? Every time an event is detected, just in the transient edge.
- Which signatures shall be used? By using transient characteristics.
- Which type of data shall be used? Present moment data: characteristics.
- How long should the window be? Three cycles of the continuous signal may be used (one cycle of the discrete signal).

For testing the algorithms, measurements of residential appliances were taken as explained in next chapter.

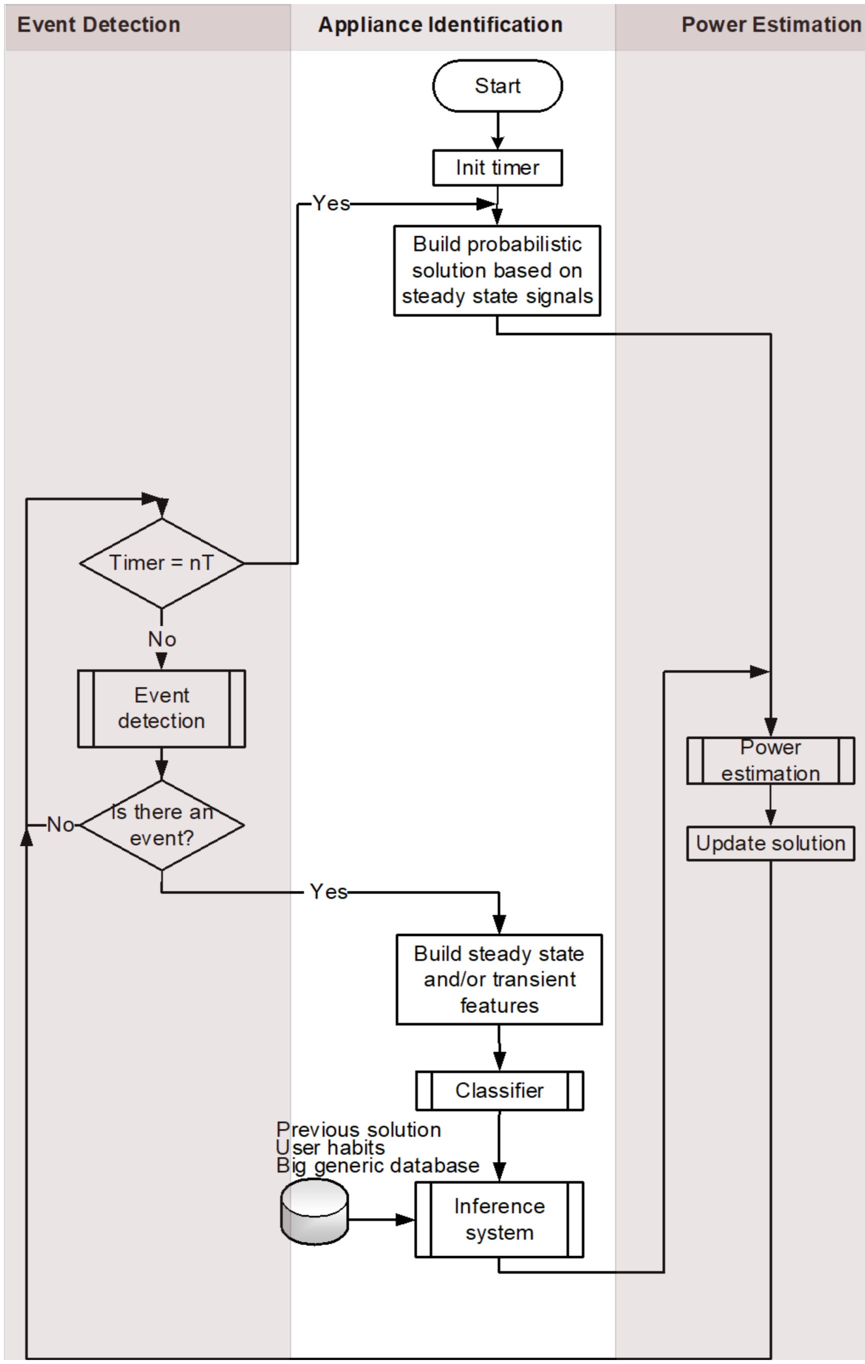


Figure 14. Continuous sensing scheme of an NILM system by considering all the options

3. Measurement Methodology

Non-intrusive load monitoring needs measurements to train and test the algorithms. Several experiments were designed for this thesis to build the database of electrical measurements of residential appliances. The procedure for the measurements is shown in Fig. 15. First at all, the appliances to be measured and the metering equipment should be selected and acquired. Then, the software interface to acquire the measurements should be designed and set up. Next, for every appliance, aspects such as operation states and characteristics should be figured out to define a measurement protocol. Afterwards, the measurements should be taken and verified. Finally, these experimental data are organized and processed offline.

```
1:  Select metering equipment and N appliances
2:  Define scenarios to measure (which variations to perform in voltage supply, line impedance
    and load)
3:  Program interface for data acquisition
4:  for n = 1 to N do
5:      Identify appliance operation states
6:      Define measurement protocol
7:      Take measurements
8:      if Measurements are not satisfactory then
9:          Go to step 7
10:     end if
11:     Process data offline
12: end for
```

Figure 15. Procedure for taking measurements in the laboratory.

More explanation of this procedure is provided on next sections. First, Section 3.1 discusses the selection of appliances considered in this study and the metering equipment to acquire the signals. Secondly, Section 3.2 presents the measurement setup to know the appliance operation, establishes scenarios and sequences for the measurements and exhibits software interfaces for data acquisition. The set of signals resulting from the measurement methodology is summarized in the concluding remarks of this chapter.

3.1 Appliance and metering equipment selection

A wide variety of appliances and meters are available in the market. Criteria and results of their selection are displayed in next subsections.

3.1.1 Categorization of appliances Circuit components of appliances influence the behavior of electrical signals due to appliance operation. Appliances can be sorted into two groups: non-electronic and electronic.

- Non-electronic: according to the predominant quantity of their circuits, these electric devices can be resistive (in phase), capacitive (leading phase) or inductive (lagging phase).
- Electronic: these appliances can be in turn classified according to the power factor correction (PFC), i.e., the mechanism to diminish the current distortion and enhance the power factor (Jimenez et al., 2015).
  - No PFC: appliances that include a rectifier and a DC link capacitor and none component to correct power factor. Examples: some CFL and chargers.
  - Passive PFC: appliances with passive elements (capacitors or inductors) before or after the rectification stage, as low frequency filters. Examples: some power supplies for desktop PC and LED lamps.
  - Active PFC: appliances with active components (DC-DC converters). Examples: some power supplies for desktop PC.

3.1.2 Appliance selection Experiments are carried out with residential appliances that are usually present in Colombian households, specially in stratum 1[1]. Table 5 presents the appliances selected according to the study of characterization of gas and electrical appliances, and Table 6

[1]Colombia classifies urban populations into different strata according to the social-economic characteristics (geographic location, public services, transportation, education level, household quality, appliance and comfort items) to set public service tariffs, taxes and subsidies. Then areas are classified on a scale from 1 to 6, where stratum 1 is supposed to correspond to the poorest urban areas and stratum 6 to the richest ones.

shows a more recent study about the percentage of Colombian households with electrical devices. Appliances with the highest percentage of ownership are included in this thesis. Some observations are:

- Electric and mixed stoves were disregarded because the gas stove has a higher ownership percentage (89.9 %).
- Cathodic ray TV was preferred to plasma - LED TV
- Video camera, video player and stereo were disregarded since the proportion is low and descending.
- Several technologies of lighting were included such as CFL, LED, halogen and incandescent[2].

Table 5
Percentages of electric and gas appliances ownership in Bogota for strata 1 to 6 (2006).

Appliance / Stratum	1	2	3	4	5	6
Lights	100%	100%	100%	100%	100%	100%
TV	96.9%	99.4%	99.5%	99.1%	98.1%	100%
Iron (Clothes)	84.3%	96.3%	94.1%	92.3%	94.2%	100%
Blender	79.9%	95.7%	94.6%	93.2%	94.2%	100%
Refrigerator	74.2%	89.6%	95.4%	96.4%	96.2%	100%
Washing machine	39.6%	65.6%	80.4%	85.9%	94.2%	93.3%
Water heater	32%	63%	75%	91%	92%	87%
Microwave oven	9.4%	22.1%	32.4%	60.9%	80.8%	86.7%
Electric stove	6.3%	4.9%	7.5%	13.6%	11.5%	20%
Gas Stove	89.9%	90.2%	78.6%	72.7%	63.5%	66.7%
Mixed Stove	3.8%	4.9%	13.9%	13.6%	25%	13.3%

Note: Adapted from (UPME, 2006).

As a consequence, the selected appliances are the ones in Table 7 with their rated powers. Only single phase appliances are considered in this study.

[2] Incandescent bulbs are end-of-life products, but they are still present in households

Table 6
Percentages of Colombian households with electrical devices.

Appliance	Power (W)	National	Bogota
Microwave oven	1080	20.3%	36.1%
Conventional TV	100	77.7%	76.5%
Plasma - LED TV	100	28.5%	44.9%
Video Player	19	44.7%	57.7%
Stereo	75	47.4%	58.8%
Video Camera	24	21.1%	36.4%
PC monitor	48	26.1%	39.7%
Desktop supply sources	475	26.1%	39.7%
Laptop chargers	93	23.3%	36.7%
Cellphone	15	94.7%	96.3%

*Note: adapted from (*Encuesta Nacional de Calidad de Vida 2013 (ECV)*, 2014).*

Table 7
Equipment under test

Appliance	Rated Power (W)
CFL	9
CFL	20
LED lamp	7
Incandescent bulb	75
Halogen Lamp	50
Halogen Lamp	70
Fan	48
Blender	600
Refrigerator	$1.15kWh/24h$
Sandwich Maker	750
Hair Dryer	1875
Iron	1200
Cellphone Charger	20
TV	90
Laptop	40
Desktop PC	250
Monitor	180

3.1.3 Metering equipment selection A National Instruments metering equipment was used to acquire the measurements. It comprises three data acquisition cards connected to a chassis **NI 9172** for simultaneous sampling, as depicted in Fig. 16 and detailed in Table 8. Voltages and currents are needed for NILM algorithms. Other quantities like power are derived from them.

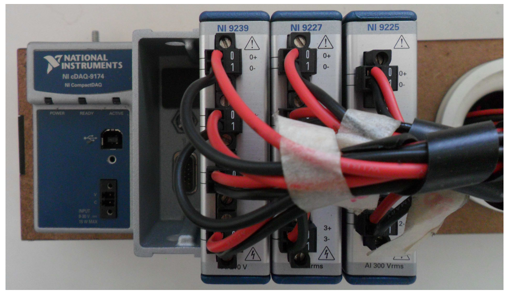


Figure 16. Picture of data acquisition system for electrical measurements. They are three cards inserted in a chassis with the advantage of simultaneous sampling.

Table 8
Metering equipment

Card	Variable	Range	Channels
NI 9227	Current	0-5A	4
NI 9239	Voltage	0-10V	4
NI 9225	Voltage	0-300V	3

Nota: Adapted from (National Instruments, 2016), (National Instruments, 2014a) and (National Instruments, 2014b).

Voltage Measurement: NI 9225 card was used to sense the overall voltage supply.

Current Measurement: The NI 9227 card can directly measure up to 5A currents. Another option was needed for higher currents. Then, the NI 9239 card was connected to a transducer to convert to the allowed variable, i.e., voltages up to 10V. Initially, four mechanisms were considered to be connected to this card:

- Current Transformers: these transducers have quite narrow frequency ranges and limitation for direct currents.
- Shunt resistor: it is a power resistance placed in series with the load. The current is proportional to the voltage drop across the resistor, according to the Ohm's Law. The quite small

resistance value is specified by the manufacturer with the voltage drop at the maximum current rating. However, the recommendation is to measure only 2/3 of the rated current.
Advantages: low cost and straightforward measurement because of the proportionality of Ohm's Law.
Disadvantages: power losses and lack of isolation because a resistor is added to the circuit.

- Hall effect sensor: it is an indirect transducer. The principle is the Faraday's Law. Example: ACS714
  Advantages: galvanic isolation and no losses.
  Disadvantages: DC offset, bandwith limitations (80kHz) and need of external power source.

- Current clamp Fluke: it is also based on Hall effect technology for use in measurement of both DC and AC.
  Advantages: non-intrusive and accurate measurements and easiness of use.
  Disadvantages: high cost, bandwidth limitations (100kHz) and need of external power source.

A current clamp was chosen as the transducer. The reference is Fluke i30s.

Appendix A presents the accuracies of the data acquisition equipment.

3.2 Measurement setup

Once the appliances and meters are selected, knowledge of the appliance operation is required to define the measurement protocols. Additionally, measurement scenarios have to be established according to the scope and further processing. These issues are described in this section, together with the design of the software interface.

3.2.1 Identification of appliance states According to the amount of states, the following categories of appliances can be numbered:

1. Permanent consumer Devices: their power consumption is approximately constant all day long.

2. On-off appliances (e.g. light bulbs and toasters).

3. Appliances with several speeds or functions (e.g. three-way lamp).

4. Finite state machine: a definite number of states may be observed for these appliances, similar to a finite state machine (e.g., washing machine).

5. Variable consumer devices: the power cannot be easily characterized because there is not a finite set of states. It depends on the burden of the equipment (e.g., dimmer lights, power tools and sewing machines).

A summary of the category description and the appliances in the equipment under test (EUT) that belong to them are presented in Table 9.

Table 9
Appliance categories according to the amount of states

Category of appliance	**Amount of states**	**Examples in this study**
Permanent consumer device	One single state	N/A
ON -OFF appliance	Two	Sandwich maker, lamps, iron, monitor
Several speed devices	Two or more finite number	Fan, hair dryer
Finite machine	3 or more	Refrigerator
Variable consumer devices	Undetermined	Desktop PC, laptop, TV

The identification of the possible states and transition between states is straightforward when the equipment is on/off. Conversely, for TV, laptop, desktop PC and refrigerator a more complex comprehension is required. For these elements, the possible factors that could yield a different energy consumption (for example, volume, screen brightness, mode, Internet connection, etc.) were determined, and the most influential ones on the power consumption were selected. Some appliances have a switch included (conventional home switches were installed in the modules as well).

3.2.2 Definition of scenarios for measurement setup A diagram of the measurement setup is displayed in Fig. 17, and a picture of how it looks in the laboratory is presented in Fig. 18. The load is supplied by a power source or the grid. There is a line impedance between the power source and the load.

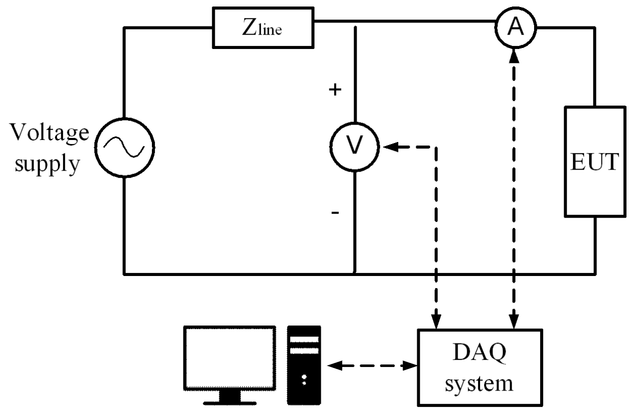


Figure 17. General diagram of the measurement setup: voltage supply, equipment under test (EUT) or load, data acquisition (DAQ) system, computer and wires. Dotted lines means data communication.

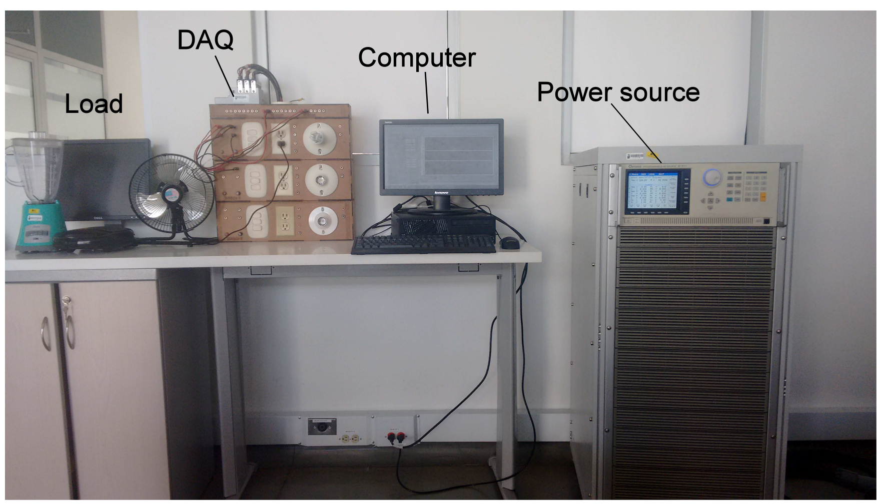


Figure 18. Picture of the measurement setup: power source, load, data acquisition (DAQ) system, computer and wires.

Several scenarios were considered to obtain the required data for knowing the problem and designing and training the algorithms, as shown in Fig. 19, by variations in:

- Voltage supply: Ideal, distorted voltage supply (flat-top signal) or grid. A power source

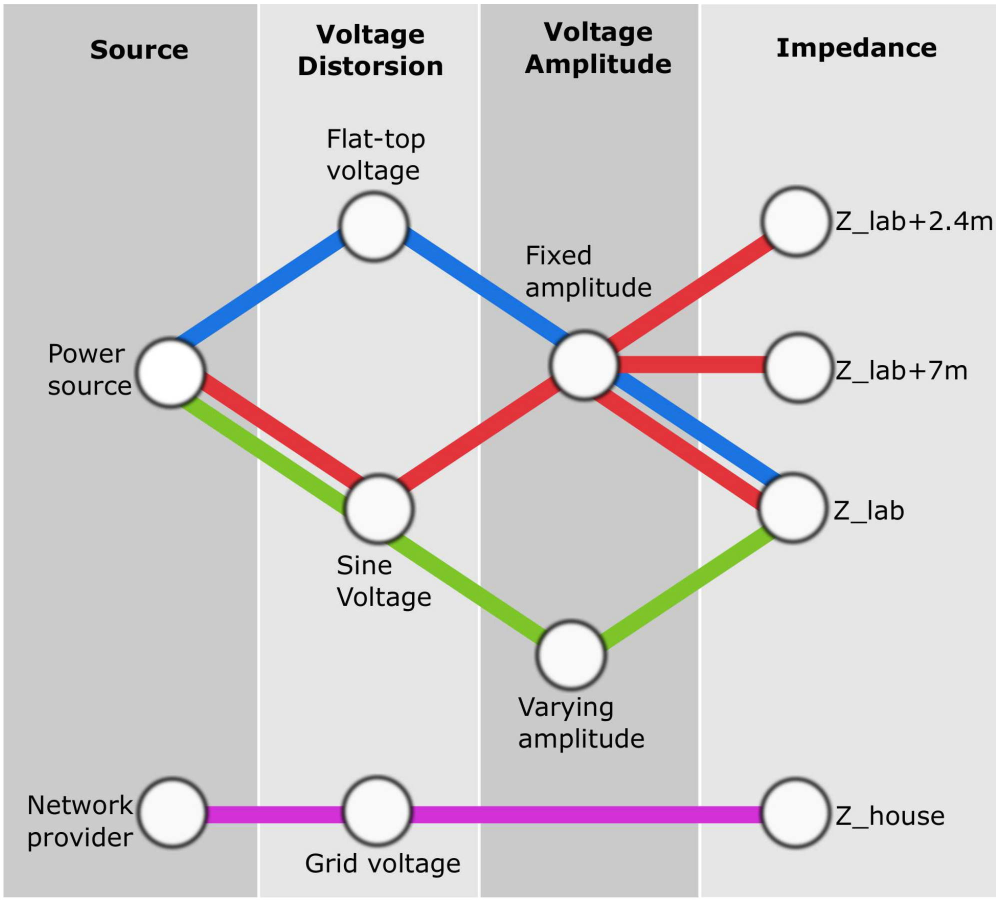


Figure 19. Route map of the measurements under different scenarios.

emulated the ideal (120V, 60Hz supply) and the flat-top signals. The flat-top signal was selected because in studies in Germany, the presence of this type of distortion has been found in residential low voltage grids due to the mass use of single-phase rectifiers (Blanco, Stiegler, & Meyer, 2013), (Blanco, Meyer, et al., 2015). The values for the flat-top signal for the experiments were adapted from the measured signal in the European grids because this characterization has not been done in 120V, 60 Hz grids.

- Line impedance: wires of 2.4 m and 7 m were connected to the power source. These lengths were taken from the Colombian Technical Standard NTC2050 (*Norma Técnica Colombiana 2050: Código eléctrico colombiano*, 1998): 2.4 m is the distance between power outlets, and 7 m is one of the shortest circuits in a house. These are copper wires, 12AWG. The impedances are depicted in Table 10.

Table 10
Impedances in the measurement setup

Element	R	X_L
Programmable AC source	0	0.002
Installation wiring	0.161348	0.0084654
$2.4m$ wire	$0,031488$	$0,0010704$
$7m$ wire	$0,09184$	$0,003122$

- Load: appliances operating individually or simultaneously with others.

3.2.2 Individual appliance operation The duration and amount of measurements had to be decided. One possibility is to consider the working cycle of the appliances and to take an integer number of cycles. For example, the refrigerator has on and off cycles that last several minutes; then, 3 to 5 refrigerator cycles should be taken to verify the reproducibility. However, this possibility would imply to take measurements for very long periods and, as a training set is needed, this would be very tedious. Another possibility is to figure out which states are involved in the equipment and capture the switching between several states (the probable ones) hundred times. This was the most outstanding option because details about the working operation can still be measured with less time since changes of states are forced.

There is no criterion to establish the minimum amount of measurements per equipment. Given that there are not specific conditions (impedance, sampling frequency, point-on-wave), one measurement cannot be considered as a representative sample. A widely accepted concept is the *peaking phenomenon* that says that "error of a designed classifier decreases and then increases as the number of features grows"(Sima & Dougherty, 2008). It is hard to establish an exact relationship, but a good practice in machine learning is to take $n = d > 10$, where n is the number of instances or cases, and d is the number of characteristics. Signal variability and reproducibility are discussed further in this thesis.

3.2.2 Simultaneous appliance operation This is the most realistic scenario in houses, especially when there are multiple occupants. Although in Colombia households could be designed to connect appliances to dedicated sub-circuits, in this thesis, sub-circuit information is not considered as explained in Section .

The number of measurements is an even more challenging issue than the individual scenario because of the number of combinations that appliances could yield. For a number of N appliances, the possible combinations are $\frac{N!}{k!(N-k)!}$, where k is the number of appliances taken at the same time. For example, for 10 appliances, the number of subsets of minimum two appliances that could appear are 1013 besides the individual operation. Other approaches should be considered, for example:

1. Measure the following subsets: high, medium, low and mixed groups.

2. Use latin hypercube.

3. Measure at least the most “probable ”combinations.

For the sake of finding the most probable combinations, the knowledge of every minute use of the appliances during the day should be available. Time-of-use is highly linked to the activities that people perform every day. Contrary to other countries, there are not available studies about how this time-of-use of appliances is in Colombia.

An informal survey was made to extract information about the perception about appliances that are likely to be connected at the same time, or at least during a period. The next steps were followed (adapted from (Collin, Tsagarakis, Member, & Kiprakis, 2014)):

1. List the activities per hours

2. Associate appliances to these activities

3. Ask to know the appliance use during weekdays, Saturdays and Sundays. Days were split in blocks of three hours.

4. Make Monte Carlo simulations.

Finally, the following datasets of measurements were built for simultaneous operation:

- Some combinations, steady state, under voltage variation.
- Combinations of two appliances (representative appliances of power or topology were selected), transient and steady state, fixed voltage supply.
- Appliance per activity, intuitive sequences, transient and steady state, fixed voltage supply.
- The most common combinations, steady state, fixed voltage supply.

3.2.3 Design of measurement protocol It is necessary to define a protocol that includes which states to measure and the duration and sequence of the measurement. For example, in the case of the laptop and desktop computers, a routine was proposed by considering the most common computer activities in Colombian households (to send and receive mails, to visit social networks, to use Internet browsers for general information, to watch videos and to download and to listen to music (Franco & MinTIC, n.d.)), and in the case of the TV, volume settings were made.
For individual scenarios, every signal is a window where the appliance takes a given state, and then, it goes back to the previous one. For example, for an on/off appliance, it is turned on and then, turned off.

3.2.4 Labview interface design and data storage Graphic language was preferred over written language for signal acquisition. The designed interface comprises two tabs as shown in Fig. 20 (left side):

1. User entries: information about the appliance (type, nameplate power, brand, etc.), number of consecutive measurements, duration of the measurement and sampling frequency.
2. Monitoring: some visual indicators of the progress of the measurements are displayed, e.g. percentage of the consecutive measurements made and elapsed seconds.

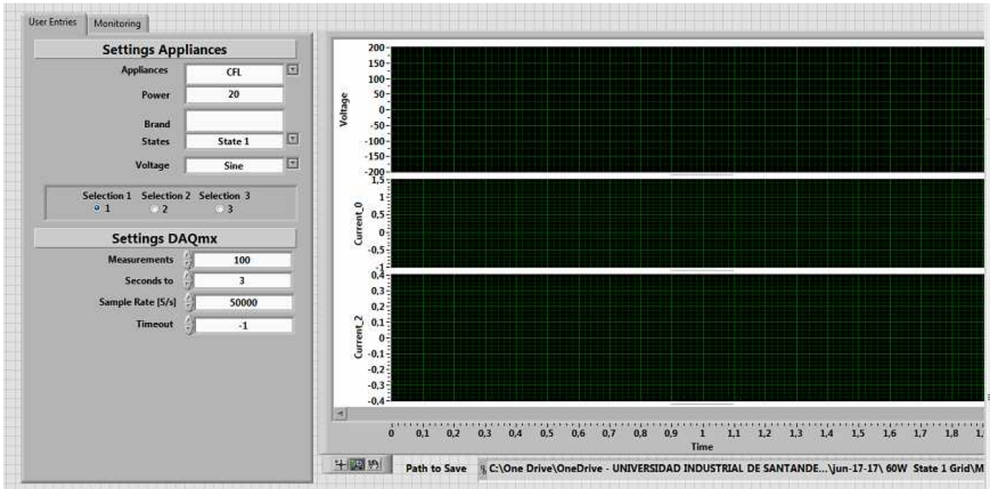


Figure 20. Tabs of Labview interface: a) User entries b) Monitoring

Also, the interface plots currents and/or voltage signals in the right side once the measurement is finished as it is shown in Fig. 21. This is to decide whether to keep or to discard the measurement as a validation step of the measurement process. When each measurement is accepted saying yes in a dialog box, it is recorded as a *.mat* file to be processed in Matlab.

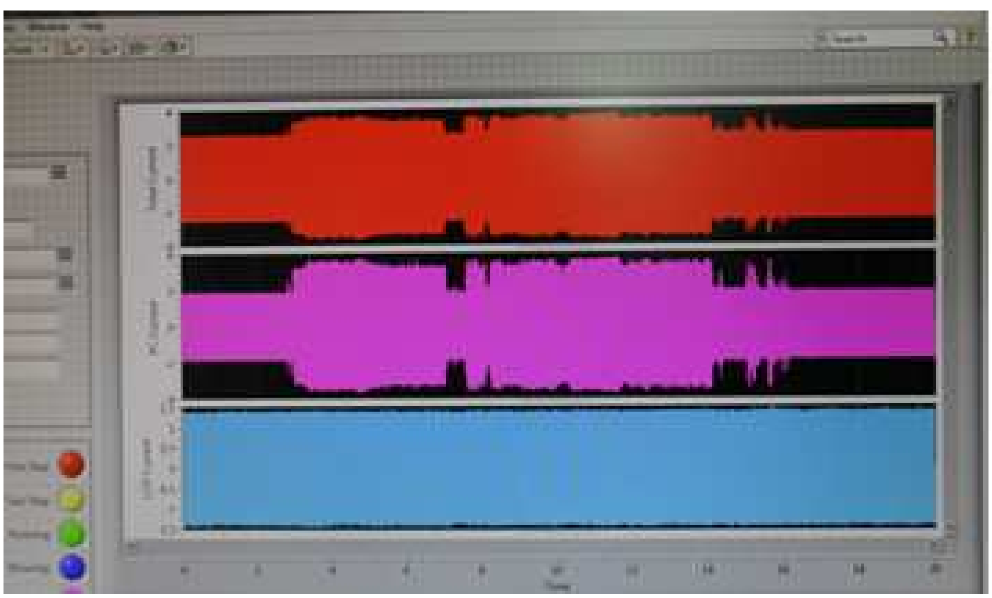


Figure 21. Plots of current and/or voltages that were measured.

3.3 Concluding remarks

In this chapter, a methodology for taking measurements has been presented. The result of this measurement stage is a set of signals under different scenarios. It is useful not only for this thesis but also for other research projects. Table 11 summarizes these measurements.

Table 11
Explanation of measurements made in both individual and simultaneous scenario

Scenario	Type	Description	Type of signal
Individual	Individual measurements	Long wires (ON/OFF): 10 repetitions for 2.4m and 10 repetitions for 7m. In total 20 per appliance.	Transient + Steady State
		Voltage variation: 5 repetitions for 108 V, 5 repetitions for 110V, ..., 5 repetitions for 126 V. In total 50 measurements, except for hair dryer state 2 that has 24 and for iron that has 49.	Steady State
		Others (ON/OFF) : 100 repetitions.	Transient + Steady State
Simultaneous	Group + Transients	One appliance switches when another one is operating in stationary state. 10 repetitions are taken for ”Appliance2” switching and ”Appliance1” fixed; 10 for ”Appliance1” switching and ”Appliance2” fixed. In total 20 repetition per group.	Steady State
	Group + Activities	ON/OFF: An established sequence per activity.	Transient + Steady State
	Knapsacks	ON: 5 repetitions per knapsack, during 5 seconds.	Steady State

4. Strategy for load disaggregation

According to the taxonomy of NILM systems explained in Section 1.1 and illustrated in Fig. 5, the proposed method is event-based. Fig. 22 presents the sequence of the method. The first step is to detect the switchings due to the change in the operation of the appliances, i.e. the *event detection*. Afterwards, two stages are considered in order to solve load disaggregation problem described in Eq. (1). First, *appliance identification* estimates $\mathbf{x}^{\star}(t)$ by considering the features that represent the appliances, namely *load signatures*. Secondly, *power estimation* infers $\mathbf{p}^{\star}(t)$.

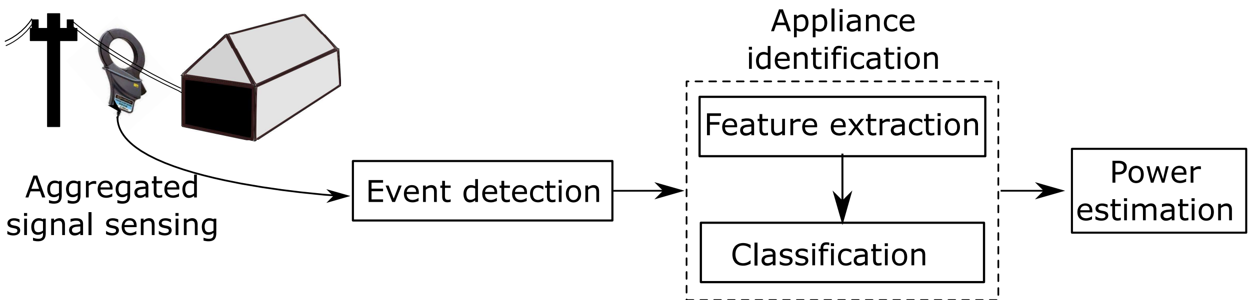


Figure 22. Stages of the proposed NILM system

At the same time, appliance identification comprises two stages: *feature extraction* and *classification*. Feature extraction computes load signatures from the electrical signals. These features can be compared with a feature database to be detected via Euclidean distance or correlation algorithms, or they can be learned and classified via machine learning techniques (see Section 1.1). The latter approach (classification) is used in this thesis.

The novelty of the proposed strategy is spread in the stages as follows:

- The proposal of sets of features from both the waveforms and the Stockwell transform of the current switching transients with higher discrimination capacity.
- The use of a classification approach that can detect unseen appliances in the database as outliers and requires a less demanding re-training when a new appliance is incorporated in the inventory list of the household.
- The proposal of power estimation models to be applied after the classification.

Details of event detection, feature extraction, classification and power estimation are presented in the next sections.

4.1 Event detection

The proposed method for event detection comprises the following steps:

1. *Flagging the windows as transients*: the procedure to deduce which windows of a stored measurement depict a transient behavior is based on the difference between the rms values of the current at consecutive windows. If this difference overcomes a given threshold β_1, the windows are labeled as 'transient', as shown in the algorithm in Fig. 23. Adjacent windows labeled as transients which are separated for less than a given number of cycles are supposed to be produced by the same switching transient.

2. *Identifying the time-instant of the event onset*: this process finds the start and the end points of switching on transients and the end of the switching off transient. First, the transients are classified into switching on or off as shown in the algorithm in Fig. 24. Then, the rms values are compared to a threshold β_2 to detect the exact point of the switchings as shown in the algorithm in Fig. 25.

```
Load current signal x and voltage signal y
windowLength = 1 cycle of the discrete signal
L = signallength
M = floor(L/windowLength)
Compute the rms value of every window rmsValue = [rms_1, rms_2, ..., rms_M]
Compute deltaRms = [rms_2 − rms_1, rms_3 − rms_2, ..., rms_M − rms_{M−1}]
Find transientWindows = windows such that abs(deltaRms) > β_1
counterTransient = 1
for i = 1 to M do
    if i ∉ transientWindows then
        windowLabel(i) = 0
    else
        if i > 1 then
            if i − previousTransient > 4 then
                counterTransient = counterTransient + 1
            else
                for j = previousTransient + 1 to i − 1 do windowLabel(j) = counterTransient
                end for
            end if
            windowLabel(i) = counterTransient
        end if
    end if
end for
```

Figure 23. Algorithm to identify the transients in a current signal

```
Compute the power of every window p = [p_1, p_2, ..., p_M]
Compute deltaP = [p_2 − p_1, p_3 − p_2, ..., p_M − p_{M−1}]
N = max(windowLabel)
for i = 1 to N do
    firstWindow = first window that belongs to ith transient
    if deltaP(firstWindow) ≥ 0 then
        onLabel(i)=1;                              ▷ Switching ON
    else
        onLabel(i)=0;                              ▷ Switching OFF
    end if
end for
```

Figure 24. Algorithm to identify if the transients correspond to switching on or off

for $i = 1$ to N **do**
  $\hat{L} =$ length of the samples that correspond to the ith transient
  $SubwindowLength = 2samples$
  $\hat{M} = floor(L/SubwindowLength)$
  Compute the rms value of every subwindow $rms\hat{V}alue = [rms_1, rms_2, \ldots, rms_{\hat{M}}]$
  Compute $delta\hat{R}ms = [rms_2 - rms_1, rms_3 - rms_2, \ldots, rms_M - rms_{M-1}]$
  $endingPoint(i) =$ last sample such that $abs(rms\hat{V}alue) >= \beta_2$
  if $onLabel(i) = 1$ **then** ▷ For switching ON
    $startingPoint(i) =$ first sample such that $abs(rms\hat{V}alue) >= \beta_2$
  end if
end for

Figure 25. Algorithm to identify the instant time when ith transient takes place in a current signal

4.2 Feature extraction

The assumption is that these features can be computed to distinguish one appliance from another. They are extracted from the electrical measurements (current and voltage) just after a switching or some time after. Usually, steady state or transient information is analyzed. Literature review in Chapter 1 showed the meaningful influence of the load signature selection over the results and suggested that combining both types of features provides benefits for appliance identification. The proposed features in this thesis are presented in this section.

4.2.1 Steady state features IEC (2017) defines *steady state* as "state of a physical system in which the relevant characteristics remain constant with time. A state under periodic conditions is often considered as a steady state." Steady state signals comprise those cycles where the state of the appliances remains constant unless a power quality disturbance takes place; thus, these signals are periodical, not time varying. Features in this thesis are extracted from stationary voltage and current signals, from time and frequency domains.

Time domain magnitudes defined in the IEEE Standard 1459 for the Measurement of Electric Power Quantities are employed as features to describe the steady state signals. These features are effective value of the current I_{rms}, active power P, fundamental reactive power Q_1, fundamental power factor PF_1 and apparent power S. Another set of steady features comprises some geometrical properties of steady state voltage-current plots such as enclosed areas and slopes, as it is shown in the example in Fig. 26.

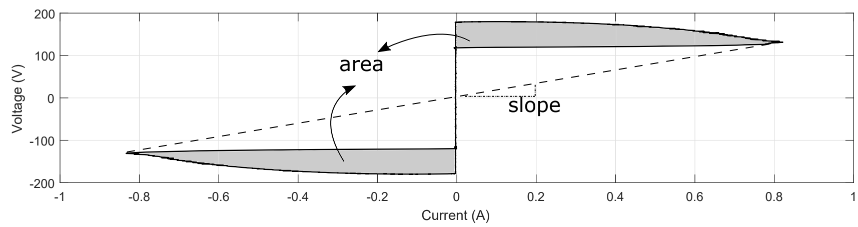


Figure 26. Example of VI trajectory features of a CFL: area and slope of the line betweeen maximum and minimum current.

In addition, it is expected that non-linear appliances have higher harmonic content than linear ones, and this might be a criterion to differentiate them. The steady state signals might be analyzed through the Fourier transform to obtain their harmonic information and to compute the following features: total harmonic distortion THD, current distortion power D_I, voltage distortion power D_V and some current harmonics. These are so-called frequency domain features.

4.2.2 Transient features IEC (2017) defines *transient* as “pertaining to or designating a phenomenon or a quantity which varies between two consecutive steady states during a time interval short compared with the timescale of interest.” A transient signal is the transition from one steady state to another. Other works studied voltage switching transients, but quite high sampling frequencies are needed to capture this information like electric noise when an appliance is connected (Patel et al., 2007). Transient features in this thesis are extracted from current switching transients.

The hypothesis is that current switching transients provide discriminative information to distinguish one appliance from others. It is supported by the fact that current switching transients can comprise information about:

- Construction and operation of the switch: ideal switches open or close such that the current changes instantaneously from one value to another. However, real switches have metallic contacts moved by other mechanisms; then, some phenomena such as bouncing, vibration, rocking, sliding and deformation can take place. Additionally, arcing can also be present because air between contacts becomes conductive (Duarte, 2013).
- Dynamic of the switched load: the impedance seen from the source changes when a load is connected or disconnected, so the current also changes.
- Interactions with other loads: when other appliances are connected either to the same branch circuit or to a different one, the poles of the system are influenced by these loads.
- Relative position of the load to the measuring point: the meter is supposed to be installed at mains in order to capture information from the branch where an appliance connects either individually (dedicated circuits) or together with others (multi-load circuits). The position of the load branch circuit introduces a change in the impedance, and this may be modeled by a small resistance.

Figure 27 shows a model where Z_s is the source impedance, A is the Ampere meter and $H(s)$ is the transfer function given by other loads and the wirings in both the same and other branch circuits.

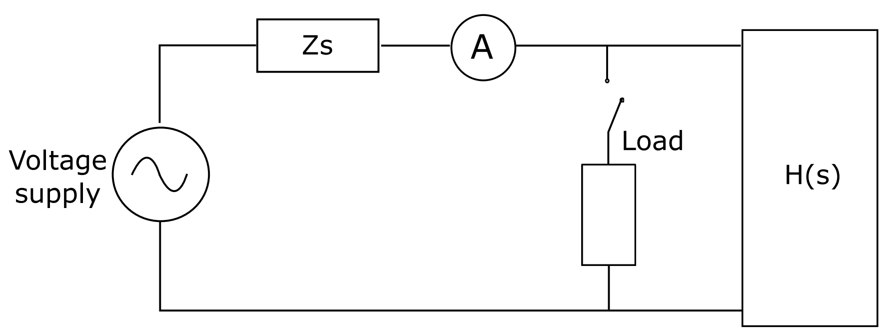


Figure 27. Model of the system, the switching load and the other loads and wirings. $H(s)$ is the transfer function given by other loads and the wirings (in the same and other branch circuits).

Connection switchings involve information from the connected load because the load poles determine the response, i.e., the imaginary part yields ringing frequencies, and the real part relates to the time constant. However, disconnection switchings do not have so much information about the disconnected load: disconnected load influences the initial conditions, but the shape is influenced by the source and the wiring. Disconnection switchings are due to the arcing phenomenon that randomly occurs between the switch contacts. The intensity of the arcing depends on the voltage source and the point-on-wave of switching.

Some features that describe the shape and magnitudes of the switching transients in time domain were computed, also illustrated in Fig. 28:

- **Mean** indicates how shifted is the signal from the zero reference.
- **Crest Factor** indicates how pointed is the signal with respect to the RMS value.
- **Standard deviation** accounts for the variability or dispersion including the mean, similarly to the RMS value.
- **Skewness** and **kurtosis** are measures of the shape.
- **Entropy** measures the randomness of the switching transient.
- **Duration** is the number of samples (or seconds) that the transient state lasts.
- **Point-on-wave** is the starting point of the current switching transient on the voltage waveform.

Additionally, time-frequency features were computed from these current switching transients. *Why using frequency or time-frequency analysis?*

- From the phenomenon point of view: Transient signals from appliance switchings are non-stationary, which means that there is a variation over time of the statistics of the signals

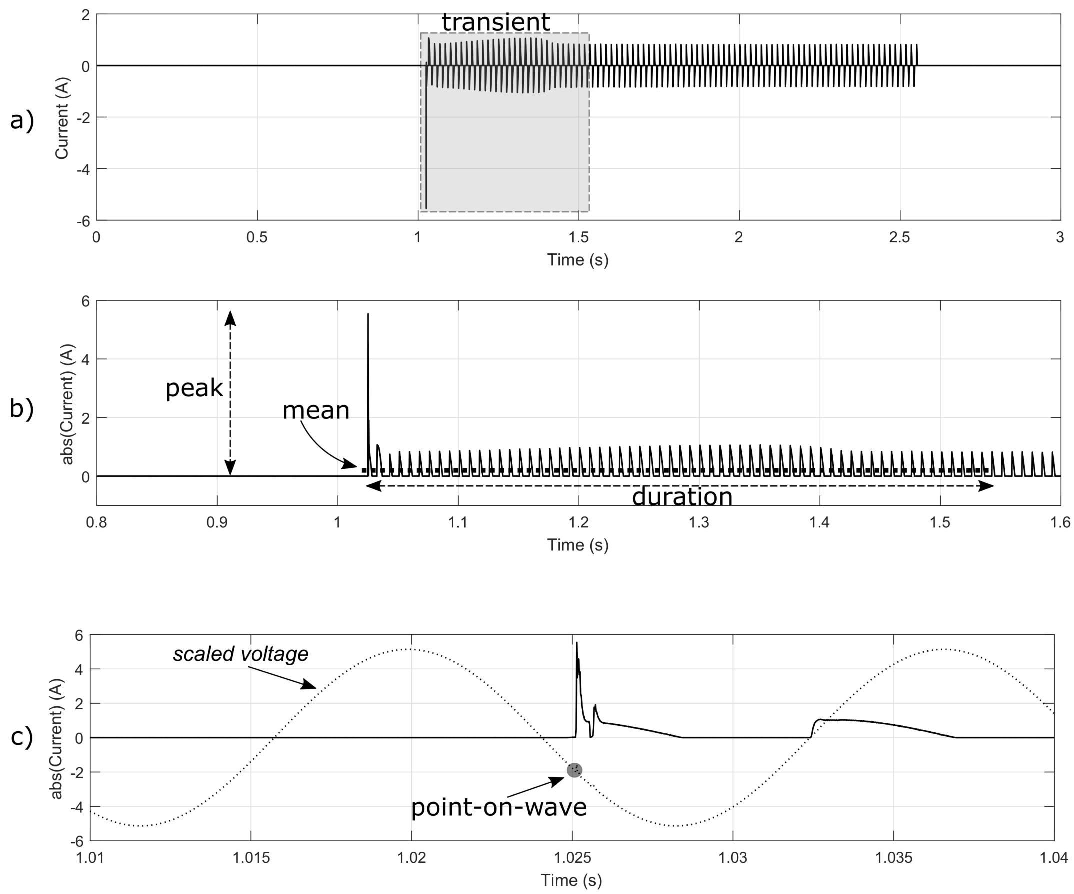


Figure 28. An example of transient features in time domain extracted from current waveform is depicted in this figure. a) Current waveform where the transient is highlighed in grey. b) Absolute value of the current switching transient. c) Point-on-wave of switching.

(Chaparro et al., 2013). Thus, varying frequency characteristics cannot be completely grasped in time domain because time domain only describes the change of the amplitude of the signal over time. (Qian & Chen, 1999) stated, “Different signal representations can be used for different applications. For example, signals obtained from most engineering applications are usually functions of time. But when studying or designing the system, we often like to study signals and systems in the frequency domain. This is because many important features of the signal or system are more easily characterized in the frequency domain than in the time domain.”

- From the pattern recognition point of view: A way for generating features from the measured signals is to compute linear transforms of the measurements (Theodoridis & Koutroumbas, 2003). There are several possibilities of linear transforms; for instance, Fourier is the most popular one.

Fourier transform is a powerful tool to represent stationary signals as a function of frequency. Conversely, non-stationary signals like current switchings need to be depicted as a function of time and frequency simultaneously to know not only the frequencies of the event but also the time location. Short time Fourier transform (STFT) would be a solution for this because it makes time windowing, but this window limits the accuracy. For example, a long window would yield high time resolution and low frequency resolution, which would not be desirable to analyze high frequency signals and the opposite for a short window. Due to the time-varying nature of transient appliance signals, another alternative to Fourier is explored in this thesis: Stockwell transform, also called S transform. It represents signals in time-frequency domain, where more details and discriminant information between the appliances can be explored.

This transform was proposed by R. Stockwell, Mansinha, and Lowe (1996) for seismic signal applications; lately, it has been used in related areas such as analysis of power quality disturbances and fault location (Dash, Panigrahi, & Panda, 2003), (Chilukuri & Dash, 2004), (Mishra, Bhende, & Panigrahi, 2008). S transform provides a complex function that represents the phase and magnitude of the signal over a time-frequency plane. It could be seen as an intermediate version of Short Time Fourier Transform (STFT) and wavelet transform. It might be related to these transforms, thus:

- STFT: The localizing window for STFT has a fixed size and shape. For S transform, that fixed window is replaced by a Gaussian window that is not only shifted but also stretched or compressed. This property is achieved because S transform window involves a dependency on the frequency. Moreover, it provides frequency-dependent resolution with a direct relationship to the Fourier spectrum (R. Stockwell et al., 1996).

- Wavelet: S transform is not strictly a CWT because the localizing window is not an admissible wavelet (its mean value is different from zero). "The differences between them lie in the use of the frequency notion instead of the scale one, a constant delay term, and the different normalization applied on the family of wavelets"(Ventosa, Simon, Schimmel, Danobeitia, & Manuel, 2008).

The continuous and discrete definitions of S transform and the mathematical framework of the relationship of S transform to Fourier and Wavelet transforms are explained in Appendix B.

Why to explore S transform? There are general and particular reasons. In general, Gaussian windows are desired because of the following properties (R. G. Stockwell, 2007):

- Symmetry in time and frequency because the spectrum of a Gaussian is also a Gaussian.
- It uniquely minimizes the quadratic time-frequency moment about a time- frequency point (Janssen, 1991). This means that it provides the best time-frequency resolution because of the high concentration in both time and frequency. Gaussians are the only minimizers for time-frequency uncertainty relation $\Delta t_x \Delta f_x \geqslant \frac{1}{4\pi}$, where t_x, f_x is the center of gravity of the signal $x(t)$ (Kumar, Sumathi, & Kumar, 2015).
- Absent of sidelobes in a Gaussian function: a local maximum in the absolute value of the S-transform is not an artifact.

For the particular application, current transient signals from appliances have sharp edges or abrupt changes. Since Gaussian functions have short time duration, they are suitable to characterize this type of signals (Qian & Chen, 1999),(Kumar et al., 2015).

S transform provides a complex $N \times L$ matrix $\mathbf{S}$ which rows and columns correspond to discrete frequencies and discrete times respectively. The discrete S transform implementation per frequency takes advantage of the Fast Fourier Transform (FFT) algorithm and the convolution theorem. This is represented in the block diagram in Fig. 30. Let $x[k]$ be the discrete sequence in time domain with length L and $X(m)$ be its FFT. Some indices are used: let n be the frequency domain in the S transform, m be the frequency domain in the Fourier transform, k be the time domain of the original signal and l be the time domain in the S transform. $X[m]$ is the FFT with L points of the original signal $x[k]$, $G_n(m)$ is the DFT of the Gaussian window, and $S_n(l)$ is the nth row of an output complex matrix. The symbol $\star$ denotes circular convolution operation and $\times$ product. The procedure in Fig. 29 is followed to compute the nth row of **S** denoted by $S_n(l)$ that describes a given frequency (Chilukuri & Dash, 2004).

function ST($x[k]$)
    Compute $X[m] = fft(x, L)$, the DFT of $x[k]$, with N points,
    for $n = 1$ to $fix((L-1)/2)$ **do**
        Compute $G_n(m) = fft(g_n[k])$, the DFT of the localizing Gaussian window $g_n[k]$.
        Shift the signal spectrum to obtain: $X_n(m) = X(m+n) = X(m) \circledast \delta_n(m)$, where $\delta_n(m) = \delta(m+n)$
        Compute the product $B_n(m) = X_n(m)G_n(m)$.
        Compute the inverse DFT of $B_n(m)$ to fulfill the nth row of **S**, $S_n(l) = ifft(B_n(m))$.
    end for
end function

Figure 29. Algorithm to compute the S transform matrix, **S**

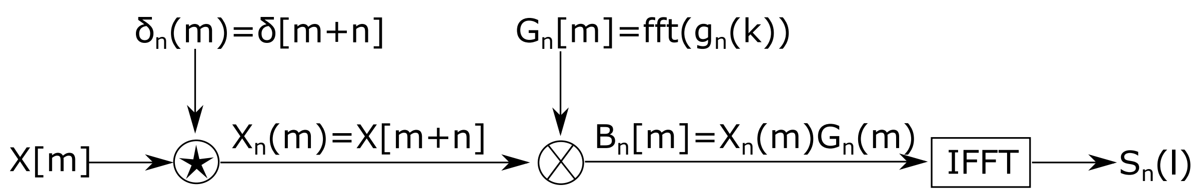


Figure 30. S transform implementation for the nth row, by taking advantage of FFT and convolution theorem.

(Martins, Lopes, Lima, & Vinnikov, 2012) and (Y. H. Lin & Tsai, 2014a) adopted S transform analysis for NILM. (Martins et al., 2012) compared the amplitude of the S transform to others in a database, and the class with the lowest error is assigned. This does not look promising because the error is computed as the squared of the element-wise difference of the matrices, and this error might be high even for matrices belonging to the same appliance class because of the dependence on the starting point of the transient. (Y. H. Lin & Tsai, 2014a) computed the standard deviation of the rows of the S transform corresponding to the signal harmonics to be involved in a combinatorial optimization algorithm, but the rest of the information in S transform matrix is not exploited. Conversely, this thesis aims to take advantage of the complete matrix and deals with a classification problem.

The challenge for this new domain lies in the dimensionality because signals are represented through a $N \times L$ complex matrix, $\mathbf{S}$, instead of a vector. Regarding the classification problem, every case or instance corresponds to a transient. Artificial intelligence techniques cope with a case or instance as a vector, usually called feature vector. An initial proposal could be to reshape $\mathbf{S}$ into a vector, thus, obtaining the suitable dimensions to be managed by the artificial intelligence techniques. However, this vector would be quite long with N times L elements. For example, the maximum frequency to be analyzed for a signal cycle (833 samples) is 416 points; then, an $\mathbf{S}_{833\times416}$ matrix would be computed. When this matrix is reshaped, it results in an $\mathbf{S}_{1\times346528}$ vector, which is quite long. What if more than a cycle is analyzed? So a feature extraction process is required to both reduce dimensionality and obtain a suitable separation.

Suppose that I dimension reduction methods are applied to the S transform matrices from the signal database to obtain datasets $1, 2, \ldots, I$. Let $f(x_j)$ be the prediction of the classifier for an instance x_j which label is y_i. The predictive accuracy of the classifier on the ith dataset would be $p_i \pm se_i$ where $p_i = \sum_{j=1}^{K_i} a_j(x)$, with $a_j(x) = 1$ if $f(x_j) = y_j$; otherwise, $a_j(x) = 0$; $se_i = \sqrt{p_i(1-p_i)}/K_i$ is the standard error, and N_i is the number of instances or cases of the ith classifier. If every S transform matrix is converted into a shorter vector, at the end, all the datasets will have the same number of instances K_i, so se_i would vary only as a function of p_i from one classifier to another. Thus, the dataset $i^\star$ where the classifier yields the highest predictive accuracy is searched as:

$$\begin{aligned} i^\star &= \underset{i}{\text{argmin}}(1 - p_i) \\ \text{s.t.} &\quad i \in \{1, 2, \ldots, I\} \end{aligned} \tag{3}$$

There does not exist a general methodology for dimensionality reduction. Two approaches were adapted for the application in this thesis: *aggregation* and *projection* methods. These methods will be explained on next.

Aggregation methods are derived based on the intuition that several statistics might describe the frequency variation along the time. This is the approach taken in previous works as shown in Table 12 for NILM, for power quality disturbance identification (a similar application to NILM due to the use of electrical signals) and other applications. These methods have also been used for feature extraction from wavelet packets in other pattern recognition applications.

Table 12
Aggregation methods for feature extraction in previous works.

Application	Time-frequency representation	Works
NILM	S transform	(Jimenez et al., 2014), (Y. H. Lin & Tsai, 2014a)
Power quality disturbance	S transform	(Dash et al., 2003), (Zhao & Yang, 2007), Biswal and Dash (2013)
NILM	CWT	(Duarte et al., 2012)
Power quality disturbance	Wavelet packet	(Panigrahi & Pandi, 2009)
Others	Wavelet packets	(Evagorou et al., 2010)

Projection methods are widely employed in pattern recognition area and are proposed to find transformed matrices that enhance the information representation or the separation between classes (Liwei Wang, Xiao Wang, & Jufu Feng, 2006), (Murali, 2015). Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are the techniques implemented for these methods.

Table 13 shows a comparison between both types of methods for feature extraction from the S transform considering if they are based on a optimality criterion, if the new matrix has a physical meaning, if all the instances belonging to all the classes and its computational cost.

Table 13
Aggregation against projection methods.

Issue	Aggregation Methods	Projection Methods
Optimality criterion	No	Yes. For example, PCA maximizes the variance, and LDA maximizes the class separability
Computational cost	Lower	Higher
Length of the new feature vector	Fixed	Variable
Physical meaning of new features	Known	Unknown. The original matrix is projected over new axes.
Information for all classes is required	No	Yes

- Approach 1: Aggregation methods

  This aggregation process consists in computing statistics to represent the S transform matrix of the signals into a vector, either per columns or per rows.

  Aggregation per columns: non-stationary signals have a time-varying frequency. If columns of S are aggregated, e.g. through max, mean, standard deviation or entropy computing, then, this frequency distribution along the time could be observed as a time series. In order to approximate the original time series and reduce dimensionality, properties can be assessed through statistical measures, such as: central tendency (mean, median, mode), variability (variance, std, interquartile range, range), shape (skewness, kurtosis, second moment), position (percentiles) and impurity (entropy) (Esmael, Arnaout, Fruhwirth, & Thonhauser, 2013). For this study, some of these statistical measures were computed for aggregated S transform columns.

  Aggregation per rows: every row of S represents a frequency component or voice, similar to the Wavelet subbands (R. Stockwell et al., 1996). Then, features for every S transform frequency voice can be computed to derive a frequency distribution. Therefore, this approach aims to extract representative features by aggregating either the complete or a part of the S matrix:

1. The complete S transform matrix:

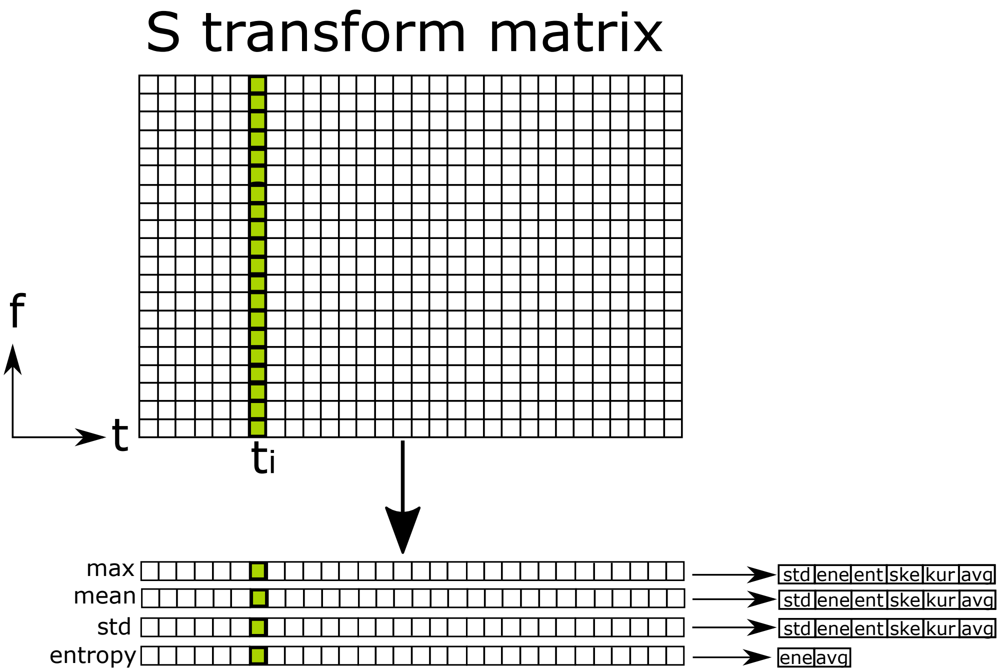
   Figure 31 presents a strategy to obtain a vector from an S transform matrix, **S**. First, to aggregate over the columns since every column of **S** describes the frequency profile for a time location. For example, in Fig. 31a green elements portray the frequency profile for a time t_i, and then, four representatives are computed for every frequency profile (column): max, mean, standard deviation (std) and entropy. They are concatenated in four vectors. At the bottom of Fig. 31a, the representatives of the profile for t_i are depicted in green as well. Afterwards, every representative vector is aggregated again with statistics (std, energy, entropy, skewness, kurtosis and mean), thus, resulting in four shorter vectors which are finally concatenated to build a 1×20 vector for the signal. Second, a similar process is used to aggregate over the rows as displayed in Fig. 31b.

2. A part of the S transform matrix:

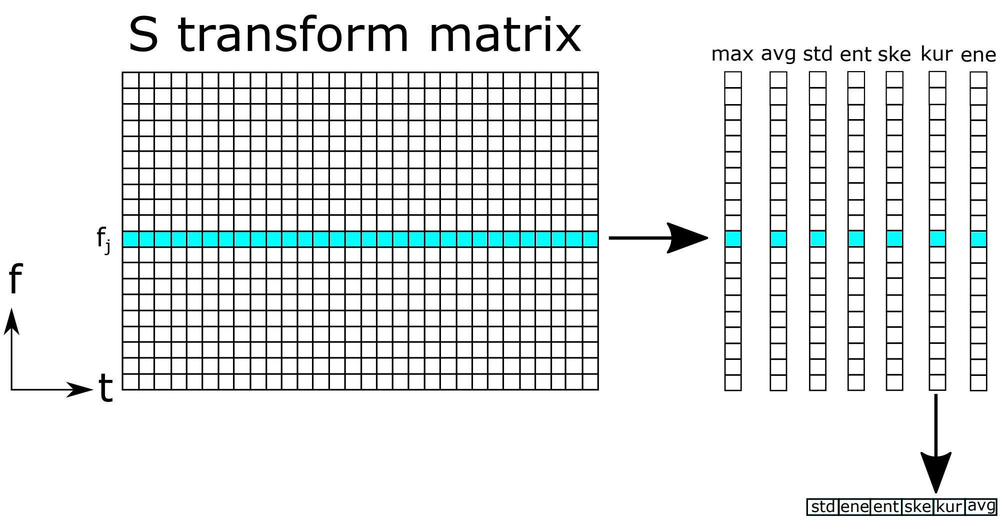
   Figure 32 depicts the process to extract features by considering only some of the frequencies, i.e. it is a particular case of the aggregation over the columns for the whole matrix because this time only a subset of frequency voices is considered. Three types of frequency selections are proposed:

   - Harmonics: $f = \{60n\}, n = 1, 2, ...$ (Y. H. Lin & Tsai, 2014a) This selection is intuitive since power system signals exhibit contents in these frequencies, above all due to non-linear loads.
   - Dyadical: $f = \{2^n\}, n = 1, 2, ...$ (Biswal & Dash, 2013)
   - Decimal: $f = \{10^n\}, n = 1, 2, ...$

   For every row representing a location in frequency $f_j \in f$, some statistics (std, mean, energy, entropy, skewness, kurtosis and maximum) are computed and stored in a 1×6 vector of features v_j. Afterwards, all the vectors $v_1, v_2, ..., v_N$ are concatenated into a single vector that represents the signal.



(a) Aggregation over the columns



(b) Aggregation over the rows

Figure 31. Feature Extraction based on aggregation of an S transform matrix for the complete frequency range, where the following abbreviations were used: standard deviation (std), energy (ene), entropy (ent), skewness (ske), kurtosis (kur) and average (avg).

The aggregation approach is simple to reduce dimensionality, but it does not take into account the final purpose: discrimination between classes. Also, different signals could

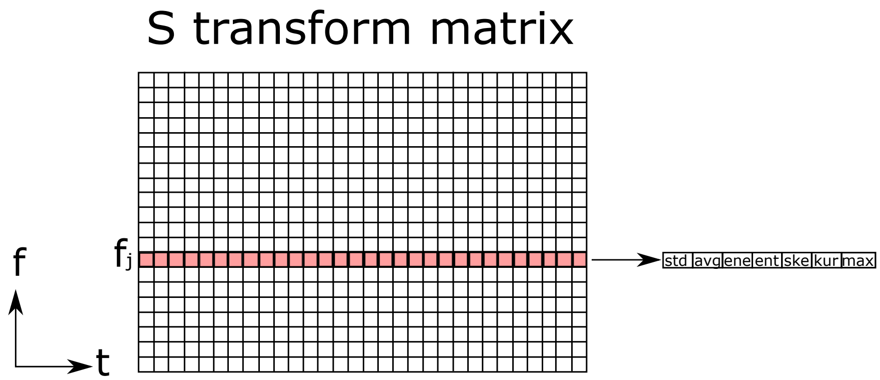


Figure 32. Feature extraction based on aggregation of a part of the S transform matrix for the complete frequency range, where the following abbreviations where used: standard deviation (std), energy (ene), entropy (ent), skewness (ske), kurtosis (kur), average (avg) and maximum (max).

yield similar representative feature vectors. So another approach is using the S transform matrices of the whole set of signals to make the feature extraction.

- Approach 2: Projection methods

Let $\mathbf{s}_i \in R^N$ be the S transform matrix. Find a mapping $y = f(s) : R^N \rightarrow R^M$ with $M < N$ such that the transformed feature vector $y_i \in R^M$ preserves most of the information or structure in R^N. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are widely known techniques to reduce dimensionality. They transform the known data into a new reference space by maximizing a given objective function. On the one hand, PCA maximizes the variance to achieve a signal representation with orthonormal axes in a lower dimension space. On the other hand, LDA maximizes the Fisher Discriminant criteria to improve the discrimination of the information in a lower dimension space.

Every S transform matrix is reshaped into a vector, and all those vectors are stacked into a single big matrix $\mathbf{X}$ as shown in Fig. 33. Subsequently, the PCA or LDA process is applied to $\mathbf{X}$, and a new matrix $\mathbf{Y}$ is obtained where every row corresponds to one of the signals.

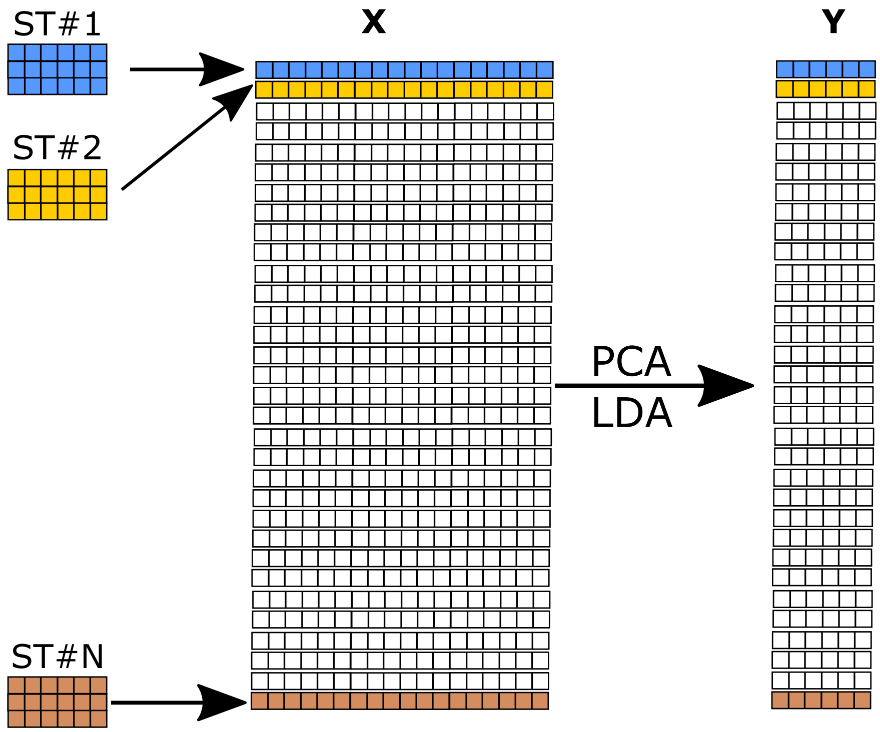


Figure 33. Feature extraction based on PCA or LDA from the S transform matrices of the whole set of signals.

4.3 Classification

This stage of the system assigns the instance or the example to a class in order to find $x^{\star}(t)$ in Eq. 1. The supervised classification strategies proposed in previous works (see Section 1.2.3) have the following problems:

- Excessive training, specially when more appliances are added to the inventory.
- Signals from combinations of appliances should be measured and processed to find example for classes correspondent to those combinations.
- Class labels should be defined; hence, unseeen appliances or states cannot be identified because prediction should be out of a predefined set.

Next, two strategies are presented in order to overtake these limitations: the transient extraction from aggregated signals and the one-class classification method.

4.3.1 Transient extraction This is the process to separate the transient event from the aggregated current. In this thesis, a strategy is proposed to avoid to train with all the combinations of appliances working at the same time.

In the previous chapter, a circuit was presented in Fig. 46 to illustrate the case of $Load2$ switching when $Load1$ was already connected.

How to extract the transients?

Figure 34 provides an example of the switching of a CFL while a fan is operating. Part a) and b) are the CFL and fan currents, respectively. Part c) is the aggregated signal, and it could be interpreted as the sum of the three signals in Fig. 35.

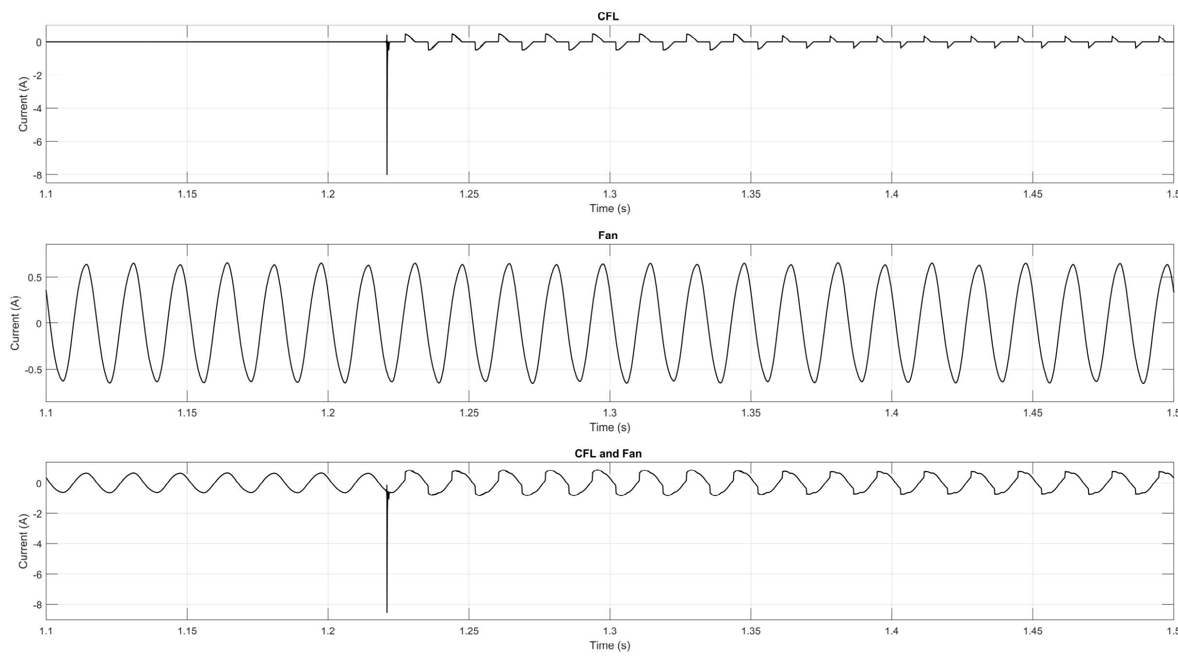


Figure 34. Example of a CFL lamp switching with a fan already working. a) CFL current. b) Fan Current. c) Aggregated current of CFL and fan.

In Fig. 35, $x_1(t)$ is a short duration signal that represents the transient while $x_2(t)$ and $x_3(t)$ are periodical signals in a specific range. The idea is to project $x_3(t)$ to the starting point of the transient t_1 by taking advantage of the periodicity. The transient, $x_t(t)$, would be as in Eq. 4:

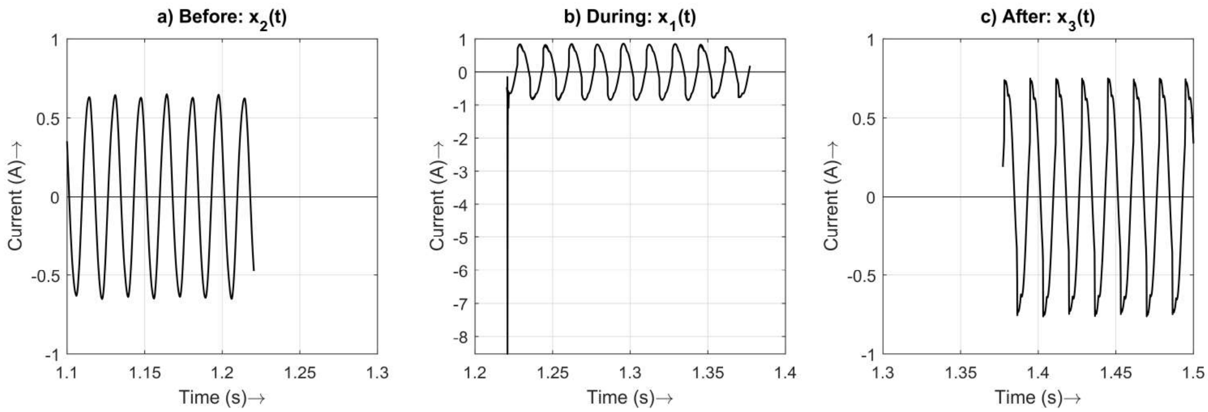


Figure 35. Sections of an aggregated signal before, during and after a switching transient

$$x_t(t) = x_m(t) - \hat{x_3}(t) \tag{4}$$

where $x_m(t)$ is the measured signal, and $\hat{x_3}(t)$ is the periodic version of $x_3(t)$.

4.3.2 One-class classification for NILM The system might be designed taking into account two prediction scenarios when appliances apart from the database, namely *unseen appliances*, are connected at the house. First, the system would assign the appliance to one of the known appliances. Second, the system would label this appliance as UNSEEN and it would assign it either to the category to which they belong (resistive, electronic, etc.) or to the most similar appliance.

One-class classification is a type of problem where one class is well- characterized while few information is available for the other class because it is challenging or expensive to take samples, like data from failures or sporadic situations. This makes the problem harder than the traditional two-class classification problem. The well-sampled class is usually called positive or target class, and the other one is called negative or outlier class. Then, a boundary is built around the positive class. The question is how tight and which shape this boundary should have in order to reduce the acceptance of outliers.

A complete review of the taxonomy and techniques for one class classification is found in (Khan

& Madden, 2014). Several categories of one-class classification are described as follows:

According to the availability of training data

- Learning with positive data only
- Learning with positive data and poor negative data or artificially generated outliers
- Learning with positive data and unlabeled data

According to the techniques used

- One class SVM
- Others: neural networks, decision trees, nearest neighbors, ensembles, etc.

One-class classification looks like a promising proposal to solve load disaggregation problem because unseen appliances during the training might be recognized, even when few or none data is available. Thus, unseen appliances might be interpreted as the failure or sporadic situation described before. Additionally, when the problem is modeled like a one-classification problem, it is possible to train independent classifiers for the appliances, hence, when new ones are included in the appliance inventory, a re-training stage that involves all the appliances would not be needed.

In the case of load disaggregation problem, it is usually a multi-class classification problem because the instances or cases should be classified into three or more classes, e.g. the number of appliances. Then, two paths can be followed to turn the problem into a set of binary classification problems. First, an one-against-all strategy decomposes the problem by creating N decoupled one-class classifiers as shown in Fig. 36, where the classifier kth is trained with instances in class k as the positive class and the instances in other classes as the negative class, instead of random outliers. Secondly, all-against-all strategy copes with the problem by building $N(N-1)$ binary classifiers, where classifier f_{ij} is trained with class i as positive and class j as negative.

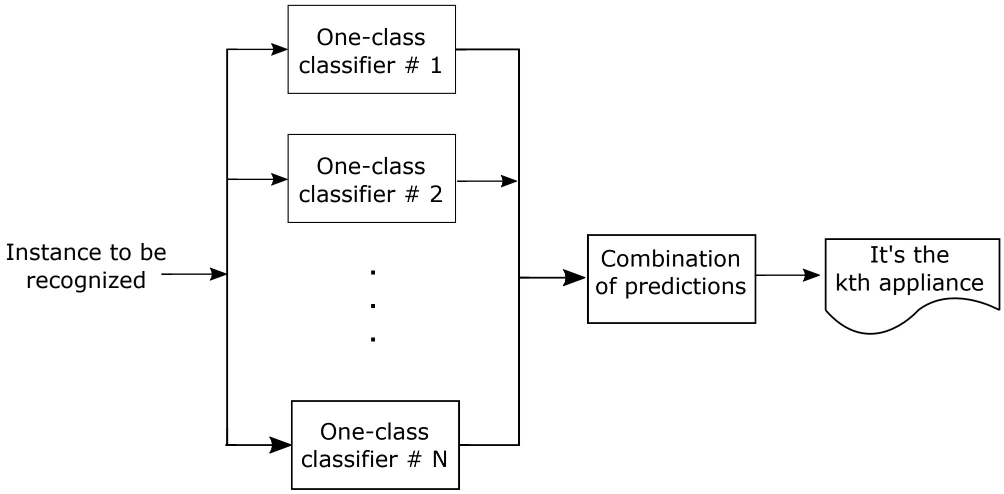


Figure 36. Approach No. 1 to solve the multi-class classification problem associated to load disaggregation: One-vs.-All.

Second, one-class classification allows to create a one-class classifier based on all the training set, i.e considering information from all the classes, as shown in Fig. 37. As a result, if the instance is classified in the negative class, it is an outlier, i.e. it belongs to an unseen appliance, and if the instance is classified into the positive class, then, the instance is transfered through a multi-class classifier as was explained before.

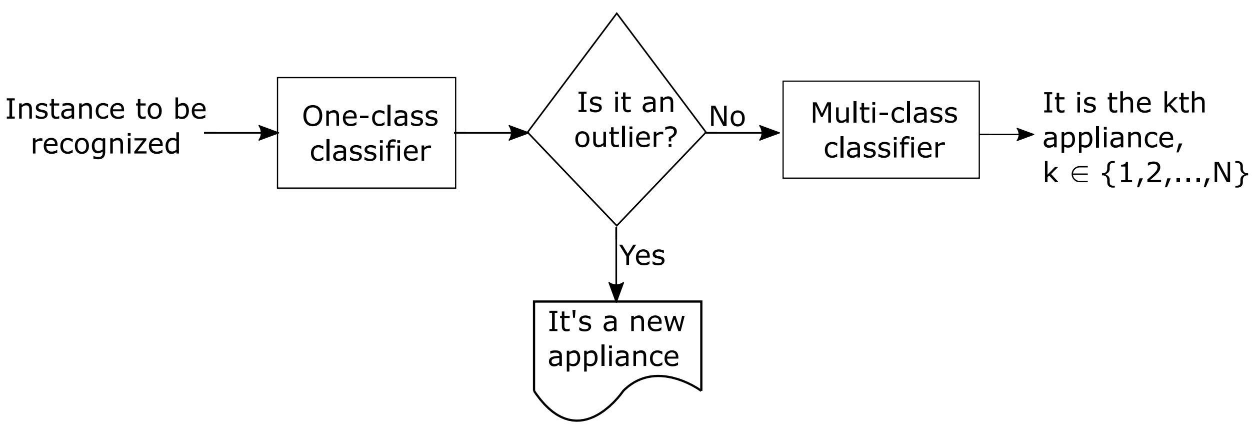


Figure 37. Approach No. 2 to solve the multi-class classification problem associated to load disaggregation: an one-class classifier in series with a multi-class classifier.

4.4 Power estimation

Power estimation stage aims to compute $P_j^{\star}(t)$ in Eq. 1. Several solutions could be computed. Then, if $x_j(t)$ is known, $P_j^{\star}(t)$ might be fit from rated powers or experiments. Appliance power consumption could depend on several factors:

- Operating state: speeds and heating levels.
- Load: motor consumption according to the load they take.
- Amplitude of the voltage supply: An increment (decrement) of the voltage yields an increment (decrement) on the power. The voltage supplied from the grid can vary around the nominal values. Some appliances are voltage dependent: the resistive loads (hair dryer, sandwich maker, iron, bulb, etc.) and some inductive ballast loads (some fluorescent lamps). Other appliances like computers have their own power supply unit to have a fixed output, so their power consumption is voltage independent (within a range).

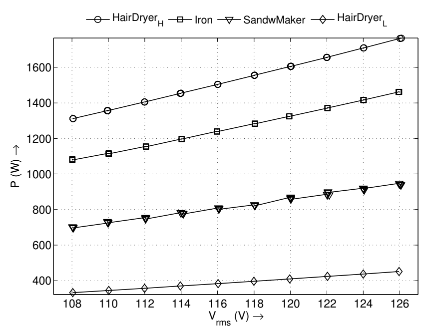
For that reason, the power estimation only based on the rated power can be inaccurate. For example, voltage supply fluctuation can cause overlapping in the P-Q plots which can lessen the load disaggregation performance (Hart, 1992), (Akbar & Khan, 2007). Hart (1992) proposed to deal with normalized powers based on exponential power-voltage relationships, but that proposal still yields inaccurate powers.

In this work, some models of power as a function of voltage are proposed to make a power estimation correction. The explanation of these models are based on (Jimenez et al., 2015) and reached from measurements by setting different voltage levels in the programmable source. According to the regulation of the local utility, the nominal voltage level should be maximum 5% and minimum 10% for low voltage ($< 1000V$). Voltage and currents were acquired when appliances operate individually, and these data were processed to compute the active powers as shown in Fig. 38, to further obtain some regression models. Besides, these models were assessed under simultaneous operation of appliances.

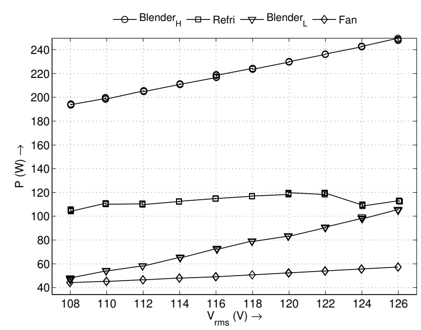
4.4.1 Trends in power under voltage variation The following trends are observed in the power when the voltage supply is changed as displayed in Fig. 38:

1. Directly proportional increase: This trend is observed for the heating based appliances in Fig. 38a, the motor based appliances in Fig. 38b and some of the lamps in Fig. 38c (incandescent bulb and halogen lamps). The frigde presents this trend until $122V$.

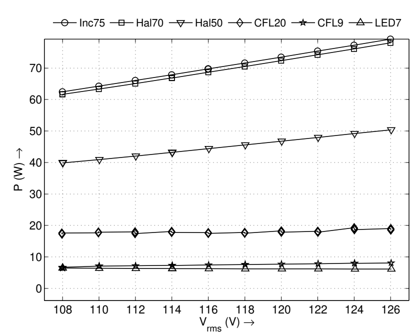
2. Approximately constant power behaviour: small power changes are observed (around 0.1 Watt per Volt) for some lamps in Fig. 38c (LED and CFL) and entertaining appliances in Fig. 38d.



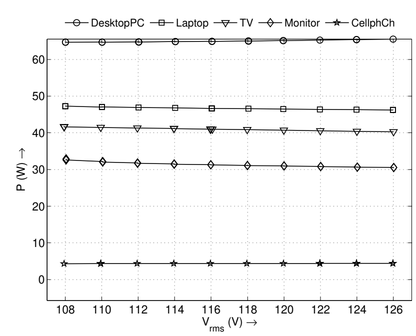
(a) Heating-based appliances.



(b) Motor-based appliances.



(c) Lighting appliances.



(d) Entertaining appliances.

Figure 38. Power vs. Voltage for appliances of every category. Each dot represents one measurement.

4.4.2 Regression models Three regression models of power data were computed for every appliance: linear, quadratic and exponential. The first two types of functions appear to be consistent with the shapes observed in Fig. 38 while the third one is recommended by Hart (1992), but here a constant term is summed. The functions, their parameters and the coefficients of determination, R^2, are presented in Tables 14, 15 and 16. R^2 indicates how the model predicts the dependent variable, and it can be negative as in the exponential model in Table 16 when the function is non-linear. The lowest values of R^2 appear in bold in these tables, thus, showing better fitting for linear and quadratic forms.

Table 14
Coefficients of the linear polynomial $a_1V(t) + a_0$ and R^2 of the appliance power model

Appliance	a_1	a_0	R^2
$Blender_L$	3.1925	-298.1604	0.9971
$Blender_H$	3.0798	-139.4219	0.9990
$Inc75$	0.9314	-38.2324	0.9998
$CFL20$	0.0656	10.3086	**0.5825**
$CFL9$	0.0753	-1.3299	0.9355
$CellphCh$	0.0043	3.8561	**0.8194**
Fan	0.7319	-35.3043	0.9947
$Refri$	0.3851	68.0197	**0.2590**
$HairDryer_L$	6.6381	-386.2303	0.9996
$HairDryer_H$	25.0655	-1400.7496	0.9997
$Hal50$	0.5859	-23.5190	0.9995
$Hal70$	0.9107	-36.8892	0.9997
$Iron$	21.3476	-1233.8088	0.9987
$LED7$	-0.0165	8.1982	0.9152
$Laptop$	-0.0543	53.0224	0.9791
$SandwMaker$	13.4995	-760.4014	0.9955
$DesktopPC$	0.0491	59.3013	0.9656
TV	-0.0763	49.8668	0.9997
$Monitor$	-0.1103	44.2525	0.9249

4.4.3 Proposed nominal powers The load could be modeled as a constant impedance or a constant current source in order to estimate the power, as follows:

- Constant Impedance: $Z = \frac{V_N}{I_N}$, where V_N and I_N are the nominal voltage and current, respectively. $V_N = 120V$ in Colombia.

$$P_{nn1} = \frac{V(t)^2 \cdot PF}{Z} = \left(\frac{V(t)}{120}\right)^2 P_N \tag{5}$$

Table 15

Coefficients of the quadratic function $a_2V^2(t)+a_1V(t)+a_0$ and R^2 of the appliance power model

Appliance	a_2	a_1	a_0	R^2
$Blender_L$	0,0198	-1,4423	-27,7068	0,9981
$Blender_H$	0,0057	1,7398	-61,2263	0,9991
$Inc75$	0,0023	0,3819	-6,1656	1,0000
$CFL20$	0,0059	-1,3074	90,4281	**0,7024**
$CFL9$	-0,0021	0,5580	-29,5050	0,9535
$CellphCh$	-0,0003	0,0720	-0,0924	0,9137
Fan	0,0101	-1,6269	102,3361	0,9995
$Refri$	-0,0998	23,7383	-1295,0370	**0,7059**
$HairDryer_L$	0,0271	0,2879	-15,6053	1,0000
$HairDryer_H$	0,0826	5,7294	-272,0233	1,0000
$Hal50$	0,0021	0,1015	4,7548	0,9999
$Hal70$	0,0032	0,1669	6,5158	1,0000
$Iron$	0,1411	-11,5771	683,0859	0,9998
$LED7$	0,0009	-0,2367	21,0549	0,9919
$Laptop$	0,0015	-0,3956	72,9374	0,9972
$SandwMaker$	0,0547	0,6890	-12,6480	0,9959
$DesktopPC$	0,0017	-0,3537	82,8075	0,9961
TV	0,0002	-0,1280	52,8854	1,0000
$Monitor$	0,0054	-1,3739	118,0121	0,9812

Table 16

Coefficients of the exponential function $a_2V^{a_1}(t) + a_0$ and R^2 of the appliance power model

Appliance	a_2	a_1	a_0	R^2
$Blender_L$	0.0012	2.4607	-77.0378	0.9981
$Blender_H$	0.2695	1.4356	-30.3193	0.9991
$Inc75$	0.0353	1.5897	2.0990	1.0000
$CFL20$	0.0017	1.7496	10.9642	**0.3892**
$CFL9$	19.2516	0.1017	-23.7696	**0.5558**
$CellphCh$	9.9410	0.0740	-9.7796	**-0.1016**
Fan	0.0000	4.0715	29.9664	0.9973
$Refri$	13.9472	0.5679	-95.5236	**-0.4136**
$HairDryer_L$	0.0356	1.9567	-7.3777	1.0000
$HairDryer_H$	0.3593	1.7713	-126.3208	1.0000
$Hal50$	0.0064	1.8233	7.3674	0.9999
$Hal70$	0.0103	1.8153	10.8531	1.0000
$Iron$	0.0058	2.5307	269.3154	0.9998
$LED7$	0.0000	4.2370	5.8197	**-2.4978**
$Laptop$	0.0000	5.0224	45.1085	**-3.5334**
$SandwMaker$	0.0768	1.9456	5.5454	0.9959
$DesktopPC$	0.0000	4.3427	62.1409	**-0.2712**
TV	0.0000	4.9494	40.6283	**-0.2998**
$Monitor$	0.0000	4.4176	28.7616	**-2.1547**

where PF is the power factor and

- Constant current source, I_N.

$$P_{nn2} = V \cdot I_N \cdot PF = \frac{V(t)}{120} P_N \tag{6}$$

4.5 Concluding remarks

In this chapter, an event detection method based on comparison and thresholding was pointed out. Afterwards, the characteristics or features proposed to identify appliances were explained. Table 17 summarizes these characteristics.

Table 17
Summary of characteristics for appliance identification

Analysis	Time Domain	Frequency domain
Quasi-stationary/ steady state	I_{rms}, P, Q_1, S, V vs. I geometry, maximum, crest factor, kurtosis, skewness and entropy.	Harmonics, THD, D_1 and D_v.
Transient	Crest factor, standard deviation, mean, kurtosis, skewness, entropy, duration and point-on-wave of switching.	Features ST all, Features ST Harmonics, Features ST Dyadically, Features ST decimal, Features ST PCA and Features ST LDA.

Thereafter the proposed classification approach by extracting transients from aggregated signals and redefining the problem as a one-class classification problem was presented. Finally, some functions based on experiments and constant models to correct the estimated power were described. The results of this proposed NILM methodology are discussed in next chapter.

5. Experimental performance

The previous chapter presented an explanation of the characteristics that are proposed to distinguish one appliance from others, usually called load signatures, that are computed from electrical signals. The feature sets extracted from the current switching transients are presented in Table 18.

Table 18
Feature sets extracted from current switching transients.

Feature set	Domain	Description
FvT	Time	Extraction of descriptors from the waveforms
FvST1	S transform	Aggregation over the columns of the complete S transform matrix
FvST2		Aggregation over the harmonic frequency profiles
FvST3		Aggregation over frequencies in a dyadical scale
FvST4		Aggregation over frequencies in a logarithmic scale
FvST5		Transformation of features through PCA
FvST6		Transformation of features through LDA
FvST7		Aggregation over the rows of the complete S transform matrix

The procedure of the proposed strategy for performing load disaggregation is shown in Fig. 39. It is the adaptation of the general scheme for continuous sensing in Fig. 14, and it follows the next particularities:

- Load disaggregation is inferred when appliances switch from one state to another.
- A solution comprises both the appliance identification and the power consumption similarly to Table 4.
- Solutions are computed every time an event is detected by using transient characteristics.
- Previous information of the specific house appliance is needed for load disaggregation for creating classifier and power models.

Figure 39 describes that once an event is detected, the transient state features are computed from the current switching, and the appliance responsible of the switching is identified through the classifier built previously. When the transient is extinguished, the power is estimated through the proposed power models, thus updating the solution due to the state change of such appliance.

Section 5.1 displays the performance of the classification approaches for the proposed feature sets. Section 5.2 presents the experimental performance of the proposed models in comparison with nominal powers in the scientific literature. Section 5.3 shows the overall performance of

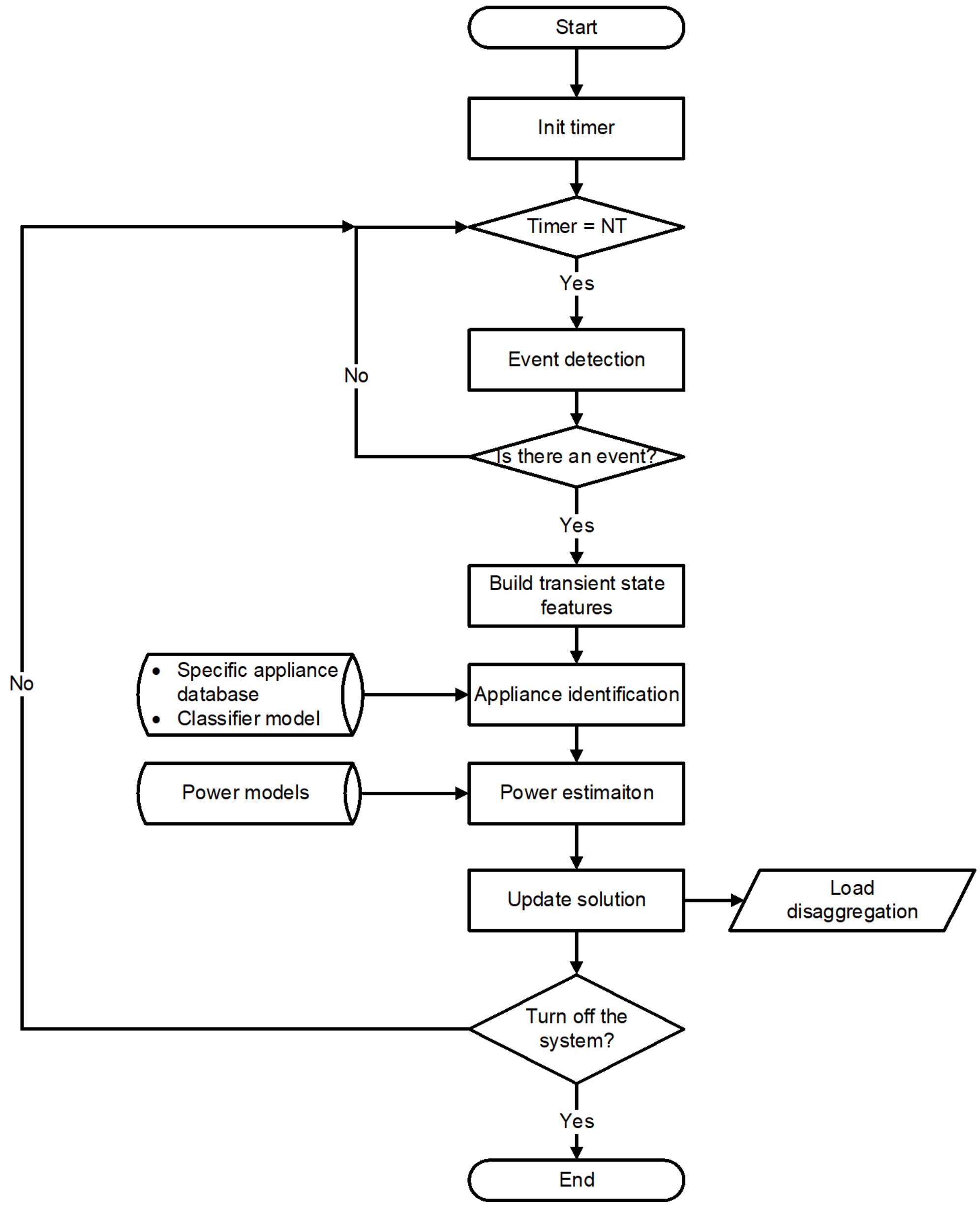


Figure 39. Procedure for performing load disaggregation.

the NILM system and discusses its limitations, advantages and applications. Finally, Section 5.4 addresses the question about how the discrimination capacity of the characteristics is affected by several factors.

5.1 Classification results

Two approaches are compared experimentally for achieving the load identification problem as a classification task: the traditional multi-class classification approach which assigns an instance to one of the established classes and the one-class classification approach. Here, a class corresponds to an appliance state. The results of these approaches are presented below.

5.1.1 Traditional multi-class classification Three classifiers were implemented to tackle the multi-class classification problem: linear discriminant, diaglinear (naive Bayes) and support vector machines (SVM). These three classifiers differ in the mathematical formulation and the complexity. A cross-validation process is introduced to train and test the models.
A first experiment was conducted to classify by considering every feature set separately. Several runs of the classifiers were performed, and the *accuracy*, i.e the percentage of correctly classified cases (see Eq. (7)), is the metric chosen for assessing the performance of the classifiers [1]. Here, every class corresponds to data extracted from current switching transients of an appliance at a given state. Results of the average accuracies are shown in Table 19, where the ones around 70% or higher appear in bold format.

$$\texttt{Accuracy} = \frac{\texttt{Correct predictions}}{\texttt{Total number of predictions}} * 100\% \tag{7}$$

An ANOVA-Tukey statistical test was executed to check the significant differences between the classifiers as presented in Appendix C. The conclusion of the tests is that significant differences were found between all the classifiers, except for:

- Diaglinear classifiers for Feature sets FvST5 and FvST6: they do not have significant differences between them.
- SVM classifiers for Feature sets FvST5 and FvST6: they do not have significant differences

[1] The *accuracy* is suitable as a metric for this case because proportion of instances for each class is similar, i.e., data are balanced, and to the equal relevancy of all the classes

Table 19

Average percentage accuracies for the reference case (sine scenario)

Feature set	Linear	DiagLinear	SVM
FvT	43,59	35,39	**87,89**
FvST1	64,94	49,56	**80,65**
FvST2	**71,55**	46,89	**71,44**
FvST3	N/A	5,24	5,18
FvST4	N/A	5,24	5,18
FvST5	**84,81**	**72,37**	**96,14**
FvST6	**74,01**	54,32	**90,06**
FvST7	62,12	50,41	**80,80**

between them.

- Linear and SVM classifiers for Feature set FvST2: in this sense, SVM has an outstanding performance for all the feature sets, except for FvST2 where the performance is similar for the SVM and the linear classifier.

5.1.2 One-class classification A system that complies with the philosophy *one vs. all* was implemented as demonstrated in Fig. 36 for reference case data. A one-class classifier is created per class. Then, the output of every classifier is a probability, and the highest probability is selected to say that the appliance corresponds to that class. Several types of classifiers were tried for every feature set, and it was selected a “minimum spanning tree”classifier where the similarity metric is computed as the distance to the edges (Tax, 2013). The resulting confusion matrices for the feature sets are depicted in Fig. 40 in color scales. Dark red cells indicate big values and dark blue cells, small values. A high concentration in the diagonal of the confusion matrix is expected for accurate classification models. This behavior is observed above all for FvST5 and FvST6 whereas a poorer classification is made with feature vectors coming from the rest of the feature sets.

Another classifier that provides outstanding performance is the “minimax probability machine”as shown in Fig. 41. In this case, the feature vectors from FvT, FvST1 and FvST3 allowed a better discrimination than the others.

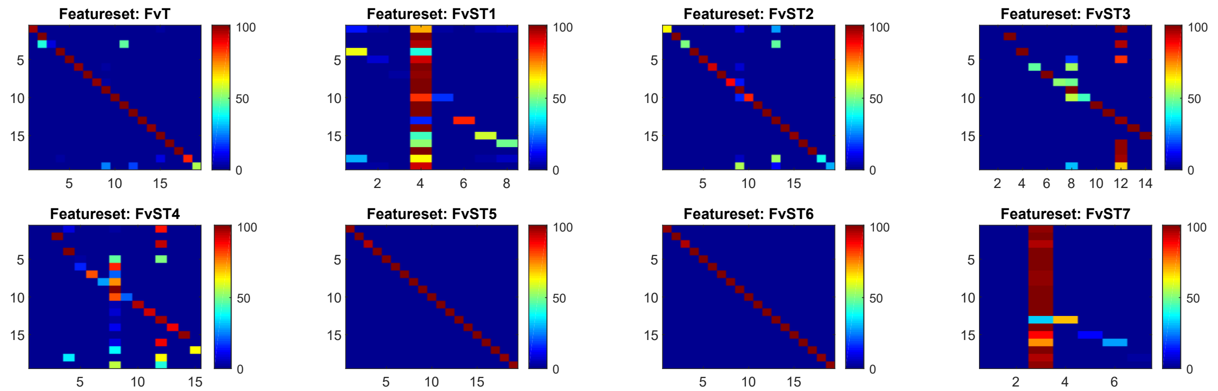


Figure 40. Confusion matrix from the novel multi-class classification approach based on one-class classifiers by using minimum spanning trees.

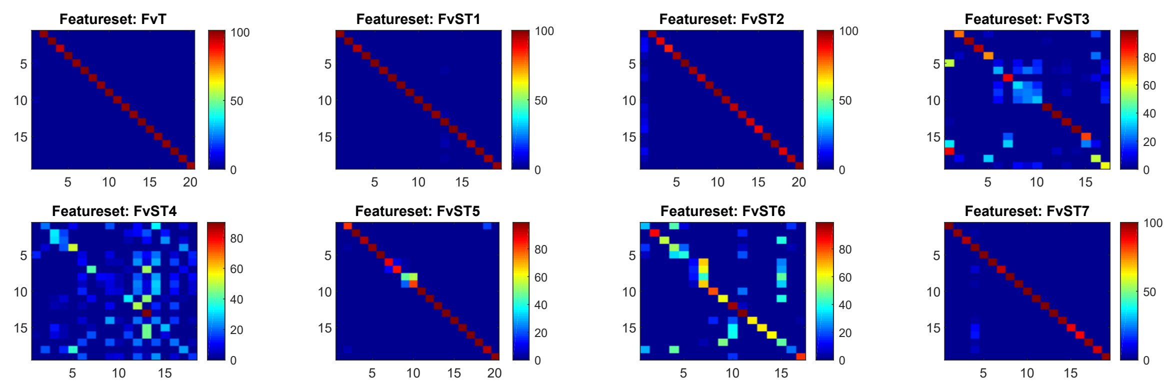


Figure 41. Confusion matrix from the novel multi-class classification approach based on one-class classifiers by using minimax probability machine.

5.2 Power estimation results

In this section, the proposed power estimation models described in Section 4.4 are compared with the nameplate (rated) power and the models in the literature. All these models are:

1. Nameplate power (P_{np}): these values are provided by the manufacturers (see Table 7).

2. Nominal powers in the scientific literature (P_{nh1},P_{nh2}): Hart (1992) proposed a normalized power, P_{nh1}, that corresponds to the power if utility provided steady 120 V and load behaved as a linear model. The expressions are presented in Eq. 8 and **??**.

$$P_{nh1} = \left(\frac{120}{V(t)}\right)^{a_1} P_N, \tag{8}$$

where a_1 is the coefficient shown in Table 16, and P_N is the measured power at 120 V. Hart also proposed to use a generic value of $a_1 = 2$:

$$P_{nh2} = \left(\frac{120}{V(t)}\right)^2 P_N. \tag{9}$$

3. Regression powers (P_{rg}): power models that obey the quadratic function $a_2V^2(t)+a_1V(t)+a_0$ (see Table 15).

4. Proposed nominal powers (P_{nn1},P_{nn2}): when the load is modeled as a constant impedance, $Z = \frac{V_N}{I_N}$, or as a constant current source, I_N, the nominal power can be computed as in Eq. (10) and (11), respectively.

$$P_{nn1} = \frac{V(t)^2 \cdot PF}{Z} = \left(\frac{V(t)}{120}\right)^2 P_N \tag{10}$$

$$P_{nn2} = V \cdot I_N \cdot PF = \frac{V(t)}{120} P_N \tag{11}$$

Notice that the factor of P_N for P_{nn1} in Eq. (11) is the reciprocal of the factor of P_N for P_{nh2} in (9).

The error, ϵ, between these estimations and the actual measurements is quantified for all the appliances; thus, $\epsilon = \dfrac{|P_{actual} - P_{estimated}|}{P_{actual}} \times 100\%$. The box plots in Fig. 42 display these errors to make a graphical comparison. For every box plot, the central mark shows the median, the top of the box displays the upper quartile and the bottom of the box indicates the lower quartile. The whiskers extend to the highest and lowest observations (not outliers). For example, the plot for the sandwich maker shows that by using simply the name plate power value, errors up to 20% can be reached, and that the lower and upper quartile correspond to 4 and 16%, respectively while the median is 8%. On the other hand, power models found in literature ($Hart_1$ and $Hart_2$ that correspond to P_{nh1} and P_{nh2}, respectively) produce errors that can reach or exceed 50%, and the most of the errors are between 8 and 31 %, with medians close to 15%. Conversely, the proposed models yield better performance because their errors are below 10%. Actually, $Regression$ and $Constant_Z$ models produce quite low error values; the boxes even look like lines.

In general, the power estimated from the regression models, P_{rg}, and the proposed nominal powers, P_{nn1} and P_{nn2}, have the lowest errors. The values of these powers for the refrigerator are the least close to the actual values. On the contrary, the nominal powers computed from the nameplate, P_{np}, and the literature proposals, P_{nh1} and P_{nh2}, have the highest errors. Strong differences are observed between the nameplate powers, P_{np}, and the measured ones.

5.3 Validation of complete method

Validation stage aims to evaluate the overall performance of the NILM system, i.e. how well the designed models generalize an independent data set. The idea is to obtain the performance of the load disaggregation which comprises appliance identification and power estimation. A perfect event detection was considered in this stage because the strong contributions of this thesis are in further stages (feature extraction, classification and power estimation).

5.3.1 Validation strategy Appliance identification performance is evaluated as the result of the classification of independent data sets.

- Traditional multi-class classification

  The available database conformed by instances or cases from all the appliance is partitioned into 5 folds, and 5 experiments are performed as shown in Fig. 43. This partition is stratified, i.e. all the classes have examples in all the folds with equal or similar proportion. In every experiment, one fold (the darkest one) is kept for future validation, and the other folds are used to train and test through cross-validation to get the best model for every experiment. At the end, all instances are used for validation, and the highest advantage is taken from

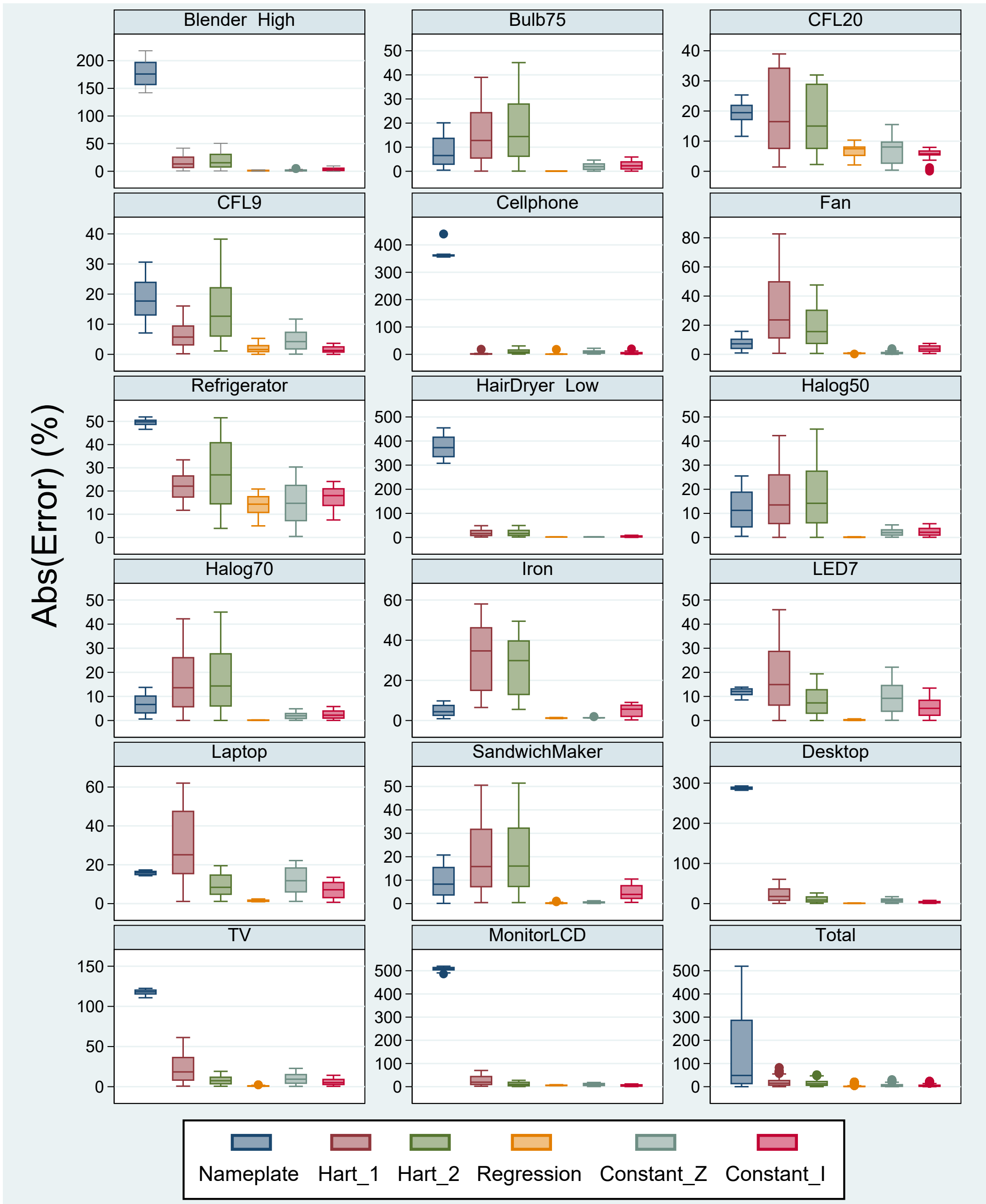


Figure 42. Errors of the power estimation based on several models compared to the actual measured power.

the database. A validation accuracy is computed as the average of the accuracies of all the experiments.

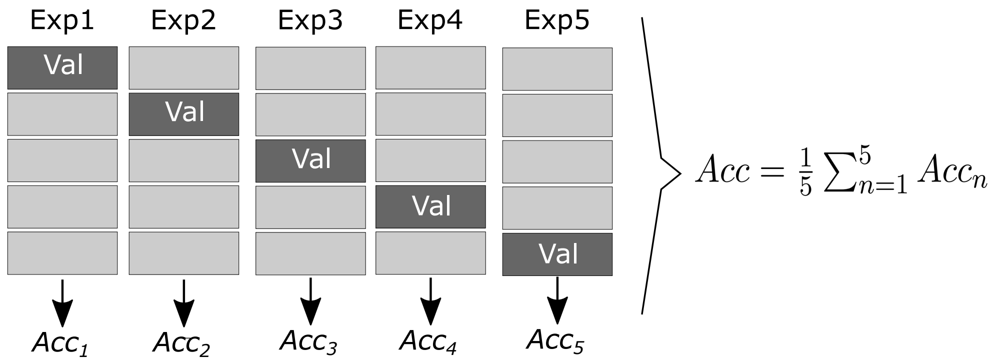


Figure 43. Validation methodology for traditional multi-class classification

Here, SVM is used as classifier, and the dataset $Feature_{ST5}$ is used to represent the signals. Results are displayed in Table 20 and 21 for the individual and simultaneous operation case, respectively. Testing accuracy is the one yielded by the cross-validation process while the validation accuracy comes from predicting instances that were not used previously neither to select nor to build the model. Generally, validation accuracy was lower than testing accuracy, as was expected, except for the 4th and the 5th fold of the individual operation case where the model generalizes accurately the instances.

Table 20
Validation of appliance identification with SVM under individual operation

Fold	Testing Accuracy (%)	Validation Accuracy (%)
1	$95,84$	$87,04$
2	$95,70$	$89,45$
3	$95,64$	$93,92$
4	$95,84$	$96,56$
5	$95,70$	$96,30$
	Total	**92,65**

- One-class classification

  Figure 44 displays the results when the classification is performed based on one-class classifiers, where confusion matrices are presented.

Table 21

Validation of appliance identification with SVM under simultaneous operation

Fold	Testing Accuracy (%)	Validation Accuracy(%)
1	91, 23	66, 91
2	89, 25	55, 00
3	90, 14	77, 14
4	89, 43	70, 00
5	90, 16	79, 14
	Total	**69,64**

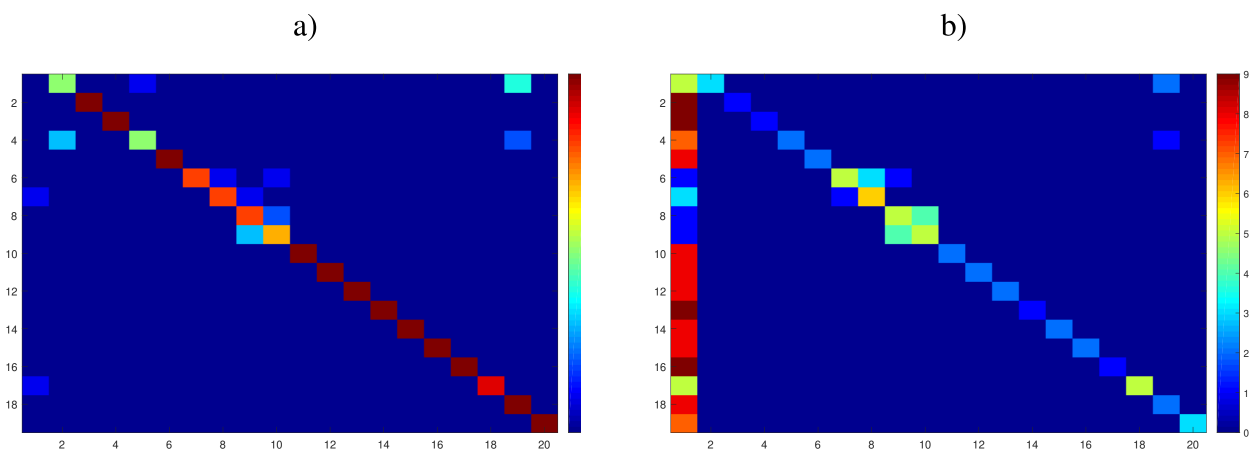


Figure 44. Validation of appliance identification with one-class classifiers: a) Minimum spanning trees and b)Minimax probability machine

Regarding the assessment of the power estimation performances, the *percentage of explained power of each appliance* was used as metric by considering what authors and previous works has contemplated (Zoha, Gluhak, Imran, & Rajasegarar, 2012), (Armel et al., 2013). This result is presented for every appliance in Table 22.

5.3.2 General discussion on the advantages and limitations of the proposed system

Load disaggregation is a challenging task because of several factors such as the diversity and amount of appliances present in a house that can operate not only individually but also simultaneously, which increases the complexity of the problem, thus, requiring high efforts in signal processing. Under the event-based approach, the electrical signals of appliances are analyzed in order to extract characteristics to represent the appliances, called *load signatures*. Then, the selec-

Table 22

Percentage of explained power of each appliance when using the power models: regression, constant impedance based and constant current based.

	Model		
Folder	powerRegression	powerConstantZ	powerConstantI
1	101.9%	101.9%	102.0%
2	103.2%	102.3%	102.5%
3	100.7%	100.4%	101.2%
4	99.8%	99.7%	99.9%
5	**477.1%**	**488.1%**	**487.9%**
6	99.7%	99.7%	101.3%
7	101.4%	100.9%	107.3%
8	99.4%	99.2%	104.4%
9	98.8%	99.2%	102.7%
13	99.5%	99.5%	99.5%
17	98.8%	98.7%	98.7%
18	97.0%	97.0%	97.0%
19	105.3%	104.9%	104.8%
20	99.9%	99.9%	100.0%
21	99.3%	99.2%	99.4%
22	96.9%	97.1%	97.1%

tion of the most discriminant feature sets is another hard task. In the proposed system, a training database of the individual appliances in the specific house is needed. Thus, the transients produced by the connections of the appliances are examined to make appliance identification and then, to assign the power consumption. It is assumed that only one appliance is switching at the same time, i.e. two or more switchings should not overlap, and high frequency meters (order of kHz) are preferred for this proposed strategy to characterize rapid changes with enough details. The following limitations and advantages are identified for the proposed system:

- *Limitations*:
  - The proposed methodology is sequential, i.e. an incorrect inference in an early stage affects the total inference. For example, the power estimation accuracy depends on the prediction from the classification.

- Power estimation is less accurate for variable impedance appliances, like the refrigerator.

- *Advantages:*

  - Contrary to other systems in the scientific literature, both high and low consumption appliances can be identified.
  - A connection to the cloud or big databases is not required, saving storage and transmission costs. Training and inferences can be made autonomously because information apart from the specific home appliance information is not employed; thus, privacy issues are less concerning.
  - Not all the scenarios of appliance operation (combinations) need to be trained in advance. Commonly previous works propose NILM systems where the training stage is fed, not only with the individual appliance information but also with the appliance combinations, where every combination is considered as a class. For the proposed system, the knowledge base is built with the individual appliance operation.
  - Appliances that are not included in the database could be identified as UNSEEN appliances, which is a novel functionality in NILM systems. This would provide the user an alert about a new appliance in the inventory that should be named and characterized to re-train the system.
  - Contrary to the traditional systems, when a new appliance is added to the training database, the training stage complexity of the proposed system does not grow exponentially which is typical for the combinatorial problems.
  - Suitable accuracies are obtained with the generated classification models: up to 92.65% for individual operation and up to 69.64% for simultaneous operation (see validation results in Section 6.3.).

5.4 Effect of impact factors on characteristics

The effect of the following impact factors is here discussed: point-on-wave of switching, voltage distortion, network impedance and connection of other appliances. Subsection 5.4.1 presents a description of the impact factors, and Section 5.4.2 shows the methodology for the analysis.

5.4.1 Impact factor description Now the impact factors and their relationship with the switching phenomena are explained.

- **Point-on-wave of switching**

  Appliance switches can open or close at different points on the voltage cycle, e.g. close to 0 degrees or to 90 degrees. Hart called this *transient variability*, and it was one of the reasons why they did not pursue transient load signatures (Hart, 1992). Zeifman and Roth (2011) stated, "In (Norford & Leeb, 1996) the detection is then based on a distance metric, even though the authors have mentioned the problem of poor repeatability of transient events. "(Yang, Chang, & Lin, 2007), a more recent work than (Norford & Leeb, 1996), analyzed the reproducibility of turn-on switching transients of industrial equipment. Here, this reproducibility is analyzed for residential appliances instead, thus, figuring out how current switching transients are affected by the instantaneous point-on-wave. The dependence on the point-on-wave on the proposed sets of characteristics is also quantified, and it will be examined if the knowledge of the point-on-wave helps load disaggregation. Each appliance was randomly switched in the laboratory hundreds of times in order to ensure a good coverage of the half wave by the switching moment between $0°$ and $180°$. Fig. 45 presents examples of the variability of one of the characteristics: the maximum of the switching transient current for two appliances. It was observed that a given characteristic can be variable for some appliances and uniform for other appliances.

- **Voltage distortion**

  Generally, residential low voltage grids are prone to exhibit a flat-top supply voltage due

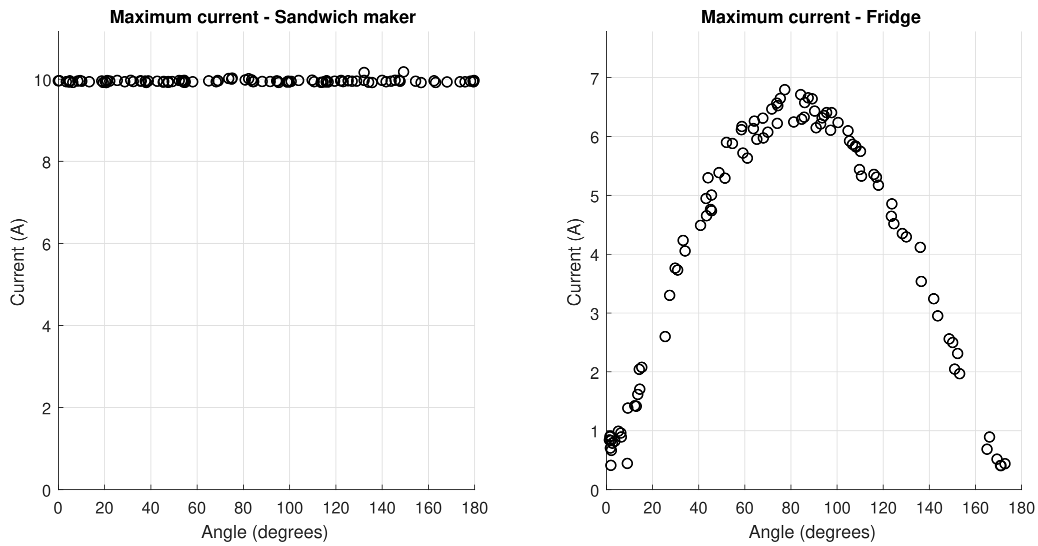


Figure 45. Maximum of the switching transient currents as a function of the angle of the point-on-wave of switching. Every circle represents a measurement. a) A sandwich maker b) A fridge.

to the mass use of single-phase rectifiers which inject harmonic currents (Blanco et al., 2013), (Blanco, Meyer, et al., 2015). This voltage distortion affects the harmonic emission of the appliances. For linear appliances, the voltage harmonics are mirrored in the currents while for non-linear loads there can be cross-interferences which means a non-linear relation where one voltage harmonic influences multiple current harmonics, and even harmonic cancellations can take place (Blanco, Yanchenko, Meyer, & Schegner, 2015). Therefore, the extracted characteristics from the appliance switching currents are expected to vary from the sine supply case.

- **Network impedance**

  A finite network impedance and multiple wirings are present in real houses that can be modeled as a source impedance located in series with an ideal voltage source. This impedance is the sum of the impedances in the following stages: utility, service, feeder, transformer and branch circuit (Russell, 2000), (Pavas, Blanco, & Parra, 2011). Subsequently, this impedance causes a voltage drop that can generate some additional problems:

  – Voltage line fluctuation because the load changes, and this voltage is proportional to the current.

– Voltage transients can be generated due to fast changes in current due to inrush or start-up that will subtract to the voltage supply.

– Voltage distortion when non-linear appliances connect and inject current harmonics that are reflected toward the supply due to this impedance.

Wires of $2.4m$ and $7m$ were connected between the loads and the voltage source to make the measurements by emulating separations of residential outlets.

- **Other appliances connected**

  When an appliance, represented in Fig. 46 as $Load2$, switches in the presence of other appliances, represented as $Load1$, that were already operating, the transient behavior is due to the dynamics of the whole load ($Load1//Load2$).

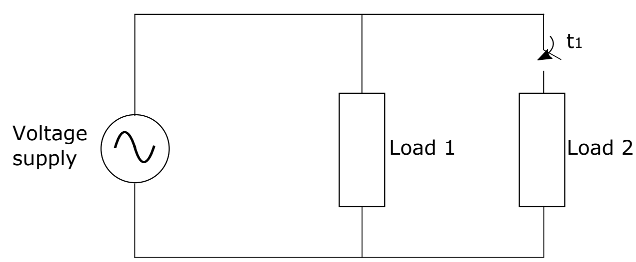


Figure 46. Circuit when another appliance is switching

The change of the transient caused by switching $Load_2$ in the presence of distinct load is investigated.

The next subsections present the methodology to assess the impact factor effects through statistical metrics and classification performance evaluation by using the features from the scenarios different than the baseline.

5.4.2 Methodology for impact analysis Two approaches might be followed for this analysis in order to determine how the factors impact the appliance features: *one at a time* or *all* *together*. In this study, a *one at time variation* is performed to individually attribute the change to the corresponding impact factor. The baseline and variation specifications are presented in Table 23 for the factors to be examined.

Table 23
Baseline and variation specifications to perform impact factor analysis.

Factor	**Baseline**	**Variation**
Point-on-wave of switching	Switching starting at [0 180] degrees	
Voltage distortion	No distortion	Flat-top distortion
Network impedance	Lab impedance	Lab impedance in series with wires
Appliance connection	Individual	Simultaneous

The reference case in this study comprises measurements under an ideal sine voltage supply with no distortion and with the nominal 120V, 60 Hz value. In the laboratory, switching transients for appliances were acquired to conform the sample for the study in this thesis. According to the Central Limit Theorem in probability, when there is a random sample of size n from a population which probability distribution has a mean μ and a standard deviation σ, and n is large enough, the distribution of the sample approximates to a normal distribution regardless of the actual distribution of the data. The general rule is that this is valid for $n \geq 30$. Then, the sample mean, $\bar{x} = \sum_{i=1}^{n} x_i$, is a reasonable estimate of μ, and the sample standard deviation, $s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2}$, is a suitable estimate of σ (Montgomery & Runger, 2003). For the case of this thesis, around $n = 100$ measurements were taken from every appliance state, thus, applying the statements of the Central Limit Theorem.

Two type of metrics namely coefficient of variation (CoV) and Fisher discriminant ratio (FDR) are computed to quantify data variability and separability respectively according to the impact factor. They are explained in the Sub-subsections 5.4.2.1 and 5.4.2.2. Further, the features under the scenarios of the impact factors are used to build classifier models, whose performance is presented in Sub-subsection 5.4.2.3.

5.4.2 Coefficient of variation *Coefficient of variation* (CoV) is calculated to quantify the data variability due the changes in point-on-wave of switching, i.e. the starting point of the transient on the voltage wave. It represents the repeatability of measurements under the same conditions with the same metering instruments (Nizami, Cohen-McFarlane, Green, & Goubran, 2017). In addition, this statistic has been used in previous works for the NILM area, e.g. in (Yang et al., 2007) “an experiment is used to explain that the statistical validity of the turn-on transient energy has repeatability with the coefficient of variation” for industrial electrical loads, and small variability was attributed to the variables which coefficient of variation was found less than 1%. On the contrary, in this thesis that repeatability analysis is made for residential appliances. Coefficient of variation of a given feature for the jth appliance is computed as the ratio of standard deviation to the average of the data as shown in Eq. (12). An illustration of the computing of CoV is depicted in Fig. 47 for the feature presented as example in Fig. 45 for two appliances, and this manifests that CoV is not a per unit metric because the base is the mean of every feature per appliance. In addition, CoV allows to compare the variability of several features expressed in different units since it is unit-less.

$$CoV_j = \frac{s_j}{\bar{x}_j} \tag{12}$$

CoV is computed for the characteristics extracted from the signals acquired under reference case conditions. Fig. 48 to 55 present the CoV values as images where each CoV value is shown as a pixel with a specific color. The color scale is on the side bar. Every image displays the results for a set of features from the transient signals, and appliances were analyzed separately. Low values of CoV indicate a low variability of the characteristic. In general, that is the case for the most of the features because a prevalence of blue colors is observed, which are defined for the lowest values of CoV.

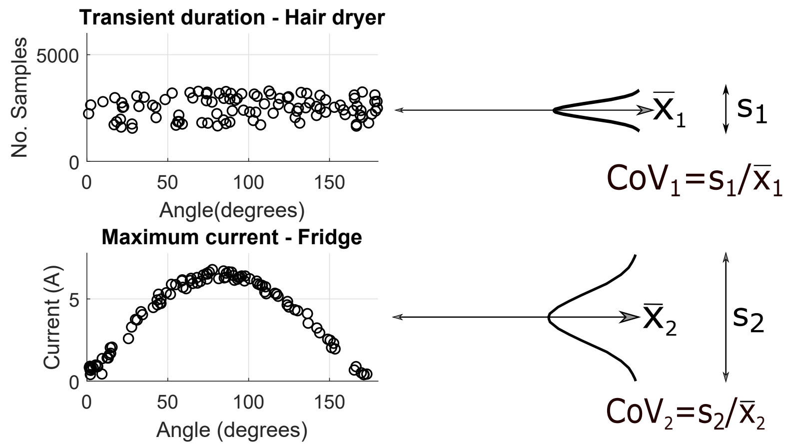


Figure 47. Computing of CoV of the feature "maximum current of the switching transients" for two appliances.

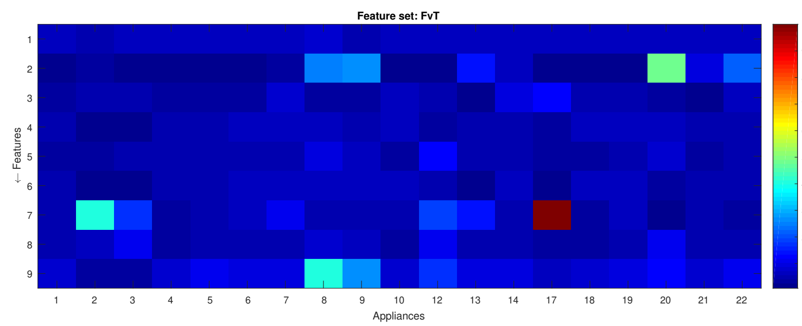


Figure 48. Coefficient of variation for feature set FvT

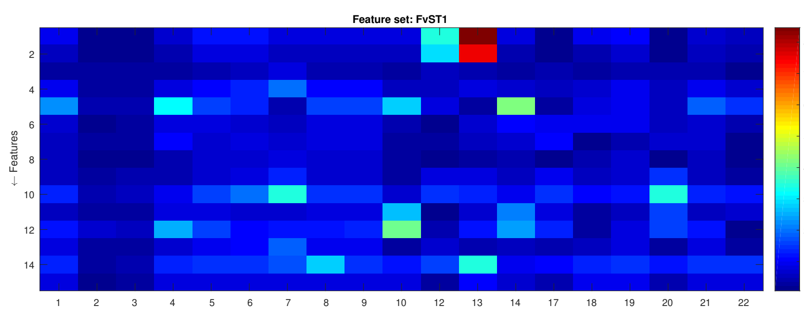


Figure 49. Coefficient of variation for feature set FvST1

CoV reports values of relative dispersion of a given feature for every appliance. Finally, to examine statistical differences between coefficients of variations, a Levene's test is performed (Schultz, 1985). The null hypothesis for this test is that the features have the same relative variability. If p-values are less than 0.05, the hypothesis is rejected. When comparing every feature for

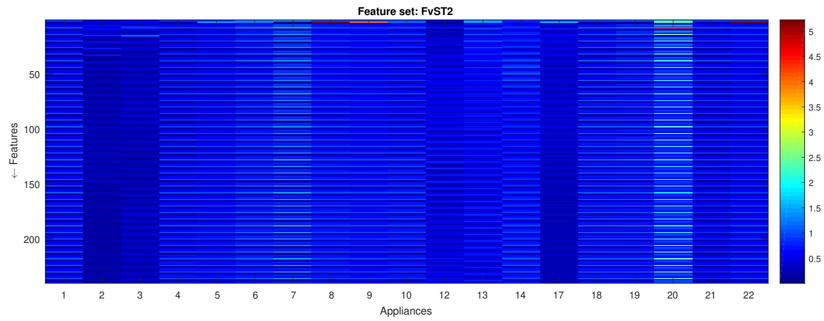


Figure 50. Coefficient of variation for feature set FvST2

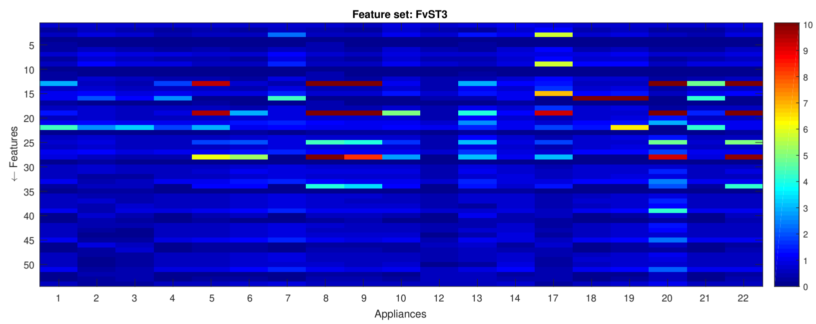


Figure 51. Coefficient of variation for feature set FvST3

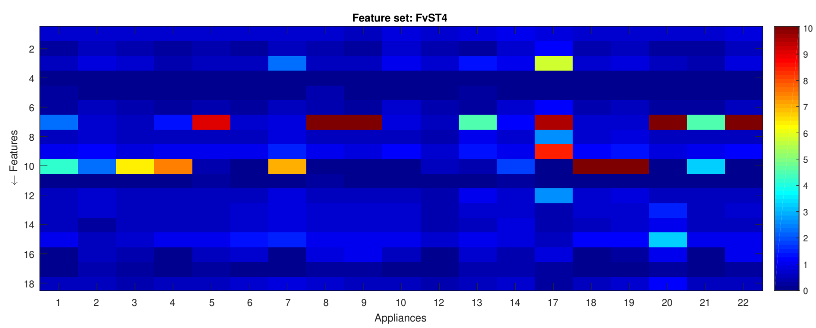


Figure 52. Coefficient of variation for feature set FvST4

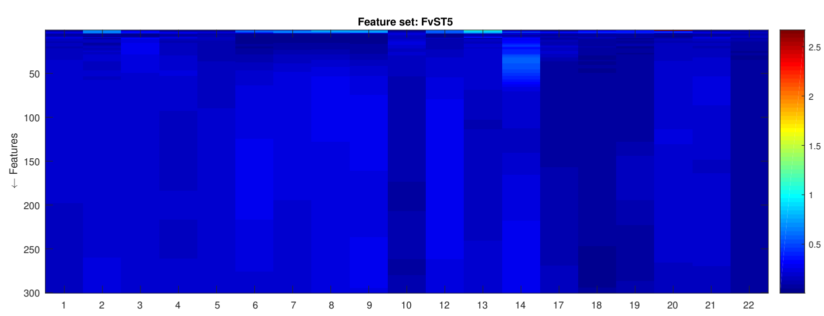


Figure 53. Coefficient of variation for feature set FvST5

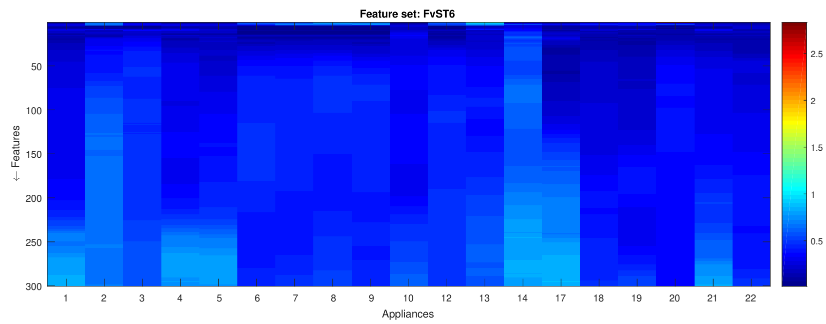


Figure 54. Coefficient of variation for feature set FvST6

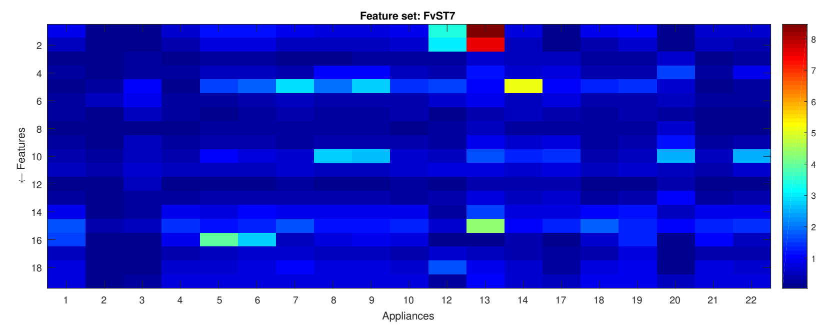


Figure 55. Coefficient of variation for feature set FvST7

the appliances, p-values respect to 0.05 are in Fig. 56, where white cells corresponds to $p < 0.05$. Given that the white cells are prevalent, there are significant differences between the coefficients of variation, except for the feature No. 1 from time domain in 56a), ie. point on-wave, and the feature No. 6 from the ST feature set in 56b).

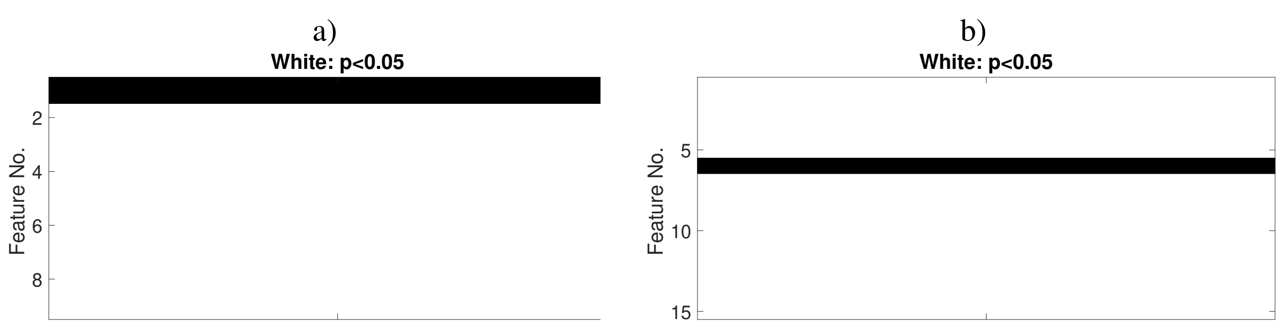


Figure 56. Matrices with p-values from the Levene's test to examine association. White cells:$p < 0.05$, black cells: $p > 0.05$. a) Time domain features. b) S transform domain features FvST1.

5.4.2 Fisher Discriminant Ratio (FDR) Another analysis is still missing: the impact of voltage distortion, network impedance and appliance simultaneous operation on feature discrimination capacity. This capacity refers to how useful a given characteristic is to distinguish one appliance from others.

For this purpose, the *Fisher Discriminant Ratio* (FDR) is employed. FDR is the quotient of the between class scatters, S_B, and the within-class scatters, S_W, as expressed in Eq. 13. The advantage of this metric is that it can be evaluated before a classification as a *filtering* method to rank the features (Guyon & Elisseeff, 2003), contrarily to methods which need to evaluate the performance of the classifier, namely *wrapper* method. In addition, since artificial techniques such as support vector machines and neural networks are not based on probability distributions (Kotsiantis, 2007), FDR is a suitable alternative over other metrics which look for a difference between probability distribution.

$$FDR = \frac{S_B}{S_W} \tag{13}$$

Let x_i be the value of a specific characteristic for the ith instance or case, C be the number of classes, C_k be the kth class, n be the total amount of instances, $\bar{x}_k$ be the center of C_k and n_k be the number of instances that belong to C_k. The global center for the specific characteristic would be $\bar{x} = \frac{1}{n}\sum_{k=1}^{C} n_k \bar{x}_k$, which is a weighted sum of the centers. Then, the scatters are:

$$S_B = \sum_{i=1}^{n} (x_i - \bar{x})(x_i - \bar{x})^T \tag{14}$$

and

$$S_W = \sum_{k=1}^{C} \frac{n_k S_k}{n}, \tag{15}$$

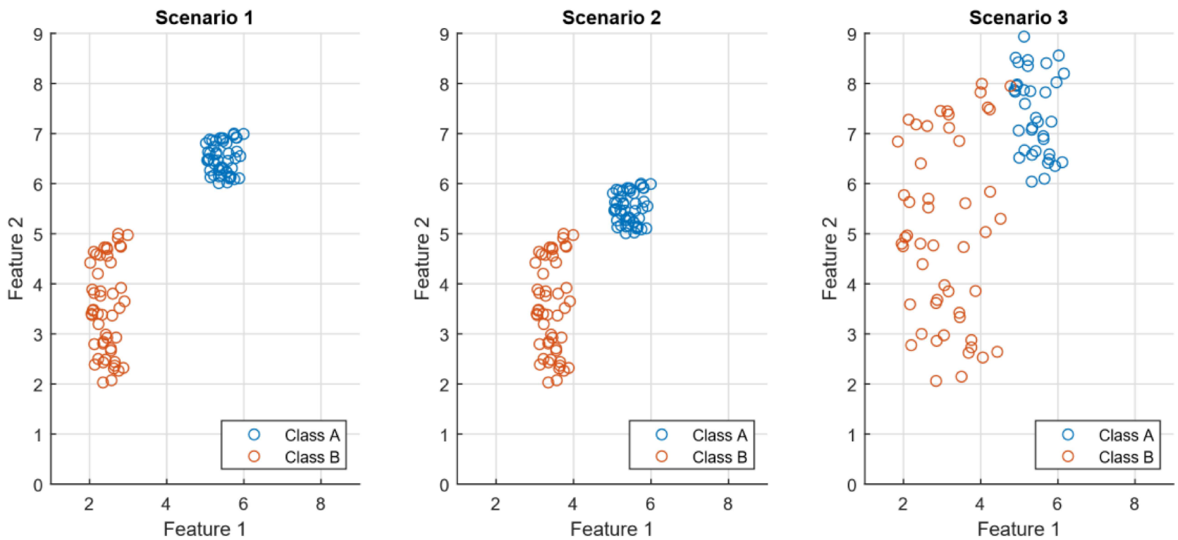
where

$$S_k = \sum_{i=1|i \in C_k}^{n_k} (x_i - \bar{x}_k)(x_i - \bar{x}_k)^T \tag{16}$$

is the within scatter of the class C_k. So, it is expected that a characteristic with a high discrimination capacity is one which values are quite confined within a region if they correspond to a specific appliance (low S_W) and far away from the values corresponding to other appliances (high S_B). Actually, for some classification techniques, e.g. SVM, a characteristic can be projected to another dimension, and the discrimination capacity might improve.

FDR is a geometrical property and can be understood through the following example. Let the circles in Fig. 57 be hypothetical instances that belong to two classes, and the axes represent two features. The idea is to examine how the FDR for every feature varies in Scenarios 2 and 3, in regards to Scenario 1. For Scenario 2, the dispersion inside each class is the same along both axes as in Scenario 1, but the distance between the centers of both classes is lower; then, S_B would diminish, so the FDR of both features diminishes as well. For Scenario 3, the distances between the centers of two classes are similar to the ones in Scenario 1. Nevertheless, instances are more spread along both axes, causing S_W and the FDR of both axes to decrease. In this sense, Scenario 1 is the most desirable for the sake of classification because it has the highest FDR which means a higher class separability.

FDR is computed not only for the reference case but also for other scenarios to evaluate the effect of the impact factors. Similarly to CoV, Fig. 58 to 65 present images which pixels represent the FDR values. Every image displays the results for a set of features from the transient signals. This time, the appliances were not analyzed separately because the FDR assesses the characteristics for all the appliances (every class is an appliance). Independent color scales were introduced for the scenarios to describe better the FDR but keeping the same convention: blue cells indicate low values and red cells, high values. This time, there is less value uniformity than in the case of CoV. The bigger the FDR, the more separated the classes and/or the more clustered the same class data is.



F	S_B	S_W	FDR
1	232.2	7.2	32.2
2	279.8	49.7	5.6

F	S_B	S_W	FDR
1	107.2	7.2	14.9
2	48.3	48.3	1.0

F	S_B	S_W	FDR
1	243.1	87.6	2.8
2	294.3	211.3	1.4

Figure 57. Example of hypothetical instances that belong to two classes. The axes represent two features, and every circle illustrates an instance.

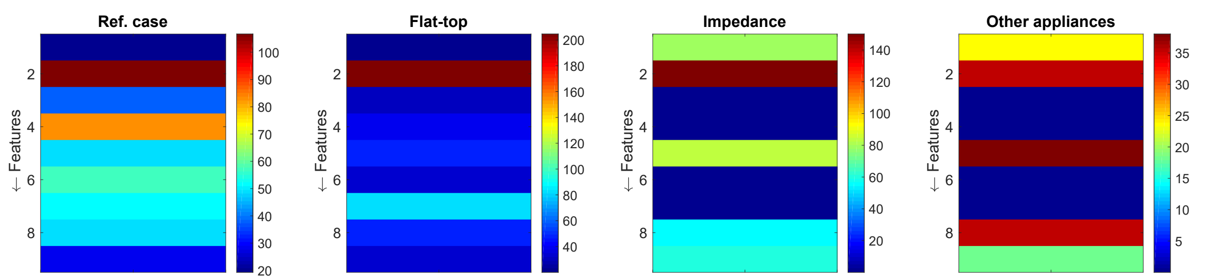


Figure 58. Fisher discriminant Ratio for feature set FvT

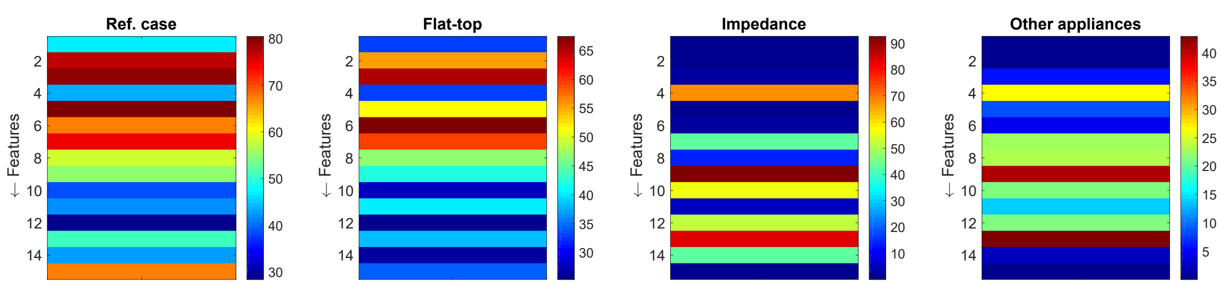


Figure 59. Fisher discriminant ratio for feature set FvST1

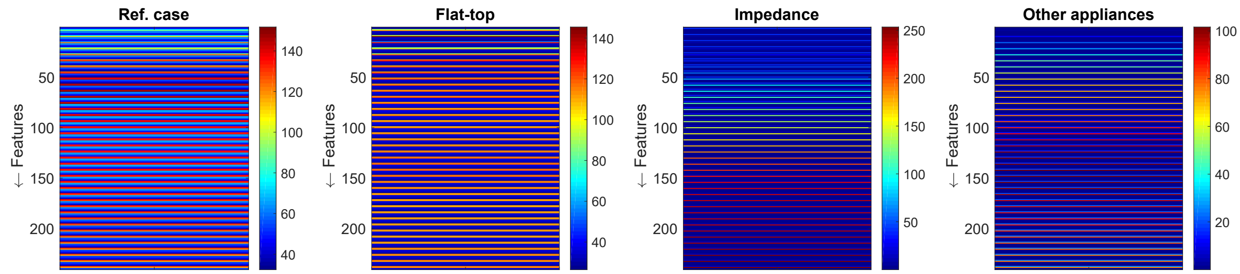


Figure 60. Fisher discriminant ratio for feature set FvST2

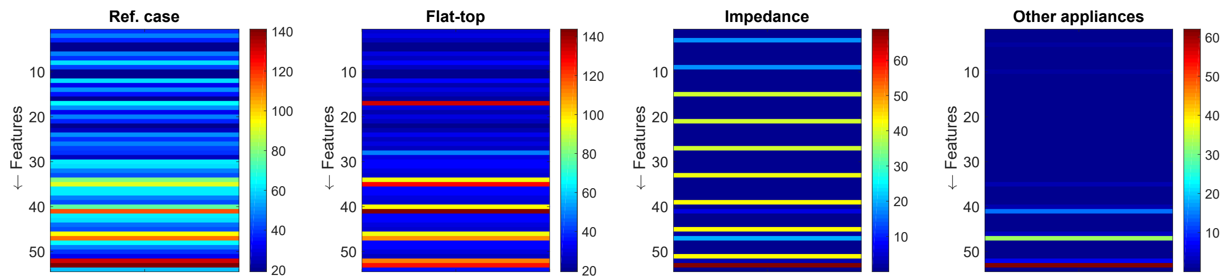


Figure 61. Fisher discriminant ratio for feature set FvST3

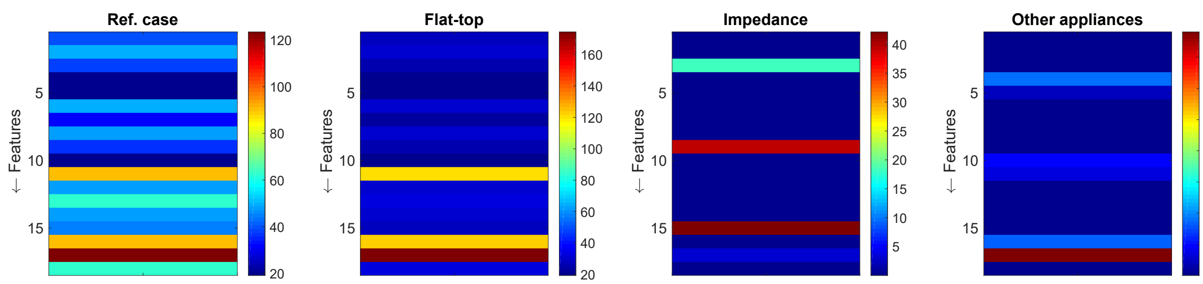


Figure 62. Fisher discriminant ratio for feature set FvST4

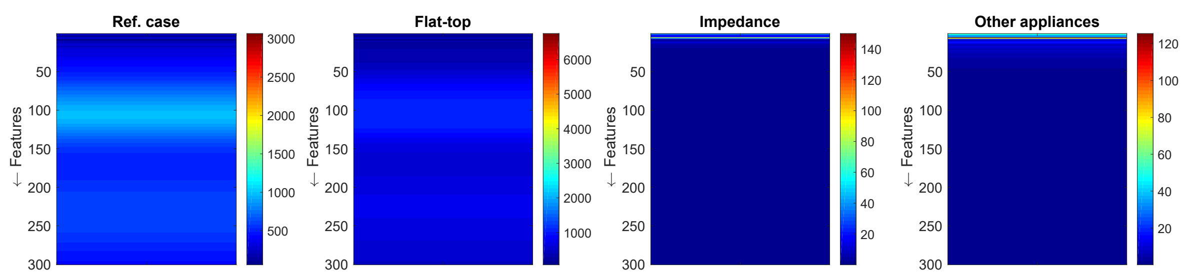


Figure 63. Fisher discriminant ratio for feature set FvST5

FDR is a feature selection strategy to rank the features according to the class separability (Guyon & Elisseeff, 2003). Table 24 shows the selection of the features with more and less dis-

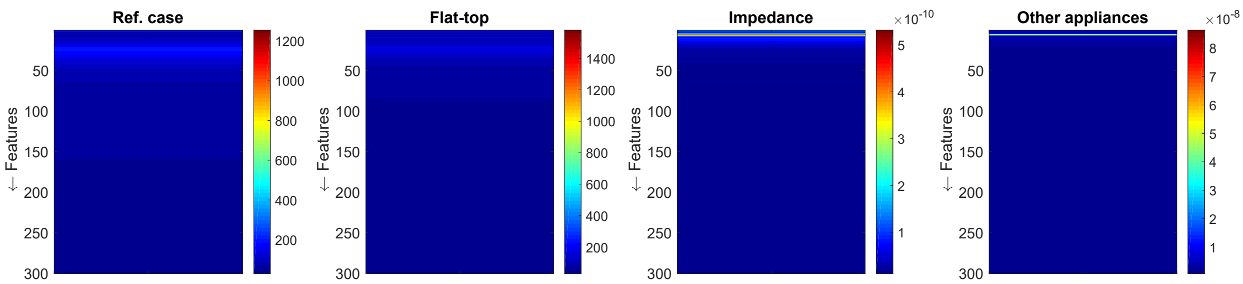


Figure 64. Fisher discriminant ratio for feature set FvST6

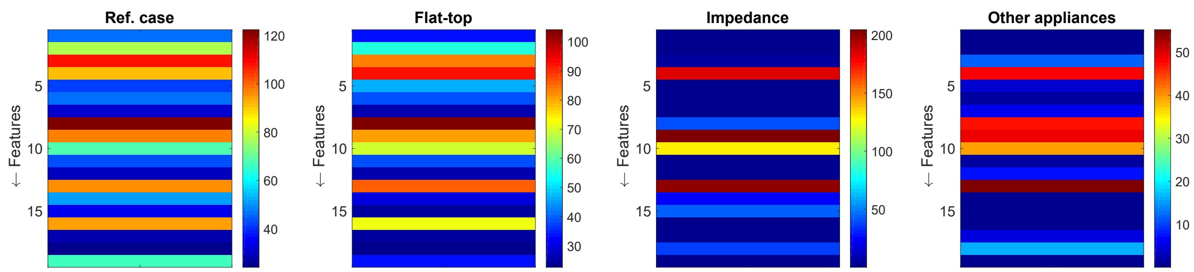


Figure 65. Fisher discriminant ratio for feature set FvST7

crimination capacity from every feature set. This corresponds to the extreme points of a feature benchmark as if each feature was used alone for the classification. Some of the features are in bold because they resulted to have either outstanding or unfavorable performance for more than one scenario.

Table 24
Features with the highest or lowest FDR, per feature set.

Feature set	Best Features				Worst Features			
	Ref. Case	Flat	Imped.	Other appl.	Ref. Case	Flat	Imped.	Other appl.
FVT	**2**	**2**	**2**	3	**1**	**1**	3	**1**
FvST1	5	6	9	7	**12**	**12**	1	14
FvST2	65	**11**	167	**11**	**51**	**51**	236	3
FvST3	**53**	**41**	**53**	**41**	10	11	1	4
FvST4	**17**	**17**	15	**17**	**4**	5	1	**4**
FvST5	**1**	**1**	**1**	12	9	**6**	300	**6**
FvST6	**1**	**1**	**1**	160	300	6	133	5
FvST7	**8**	**8**	9	**8**	**18**	**18**	1	12

In addition, Table 25 summarizes Fig. 58 to 65 by presenting the average values of CoV per feature set. The highest values per scenario appear in bold. Here, the last row includes the average of all the feature sets for every scenario. According to these average values of FDR, it is derived that:

- The impedance change and the presence of other appliances do change the discrimination capacity of the characteristics extracted from the appliances switching transients.
- FvST5 is the feature set with the highest discrimination capacity for the reference, the flat-top and the presence of other appliances scenarios, just as FVT is for the network impedance scenario.

Table 25
Average values of the FDR, per feature set.

Feature set	FDR Avg values			
	Ref. Case	Flat	Imped.	Other appl.
FVT	53,15	59,67	**47,63**	**16,95**
FvST1	56,63	42,97	30,78	15,48
FvST2	77,73	59,29	30,18	15,51
FvST3	52,30	43,31	7,87	2,46
FvST4	50,84	46,09	5,77	0,74
FvST5	**583,96**	**678,20**	1,62	2,53
FvST6	64,77	64,60	0,00	3.36e-7
FvST7	62.85	51,92	46,01	15,81
Avg	125,28	**130,76**	21,23	50,83

5.4.2 Analysis of impact factors through overall classification performance

Similarly to the experiment described for reference scenario (Section 5.1), the performance of the classification was assessed for feature sets from the scenarios of the impact factors, thus, resulting in the average accuracies in Table 26. Again, the average accuracies around 70% or higher are displayed in bold.

5.5 Concluding remarks

In this chapter, some classifiers were presented to identify appliances by solving a traditional multi-class classification problem, where the SVM outperformed the linear classifiers. Later, the

Table 26

Average accuracies for the scenarios of impact factors: distorted voltage supply, network impedance and simultaneous operation.

	Distorted			Network Impedance			Simultaneous operation		
FeatureSet	Linear	DiaLinear	SVM	Linear	DiaLinear	SVM	Linear	DiaLinear	SVM
FvT	44,12	35,93	**87,46**	39,93	35,42	69,90	67,17	59,86	**85,75**
FvST1	62,95	47,70	**82,78**	61,54	49,75	**73,24**	60,18	46,8	**78,00**
FvST2	**73,23**	43,26	**74,87**	45,15	47,32	64,21	**75,25**	64,51	**79,55**
FvST3	N/A	5,20	1,09	N/A	43,95	61,20	N/A	11,28	12,69
FvST4	N/A	5,20	1,09	N/A	26,59	59,53	N/A	11,28	12,69
FvST5	**91,07**	69,15	**98,65**	N/A	**70,90**	**94,65**	**78,56**	57,25	**97,46**
FvST6	**78,05**	49,60	**90,84**	N/A	23,07	50,50	62,76	45,68	**84,49**
FvST7	64,13	49,17	**83,98**	66,29	48,09	**72,91**	65,92	47,36	**79,13**

load identification was designed through a one-class classification approach to overcome the need of dealing with new unseen appliances and the scalability of NILM systems to avoid retraining and increasing the complexity when those appliances are present to be predicted. Furthermore, the evaluation of power estimation models and a comparison with the approaches in the literature are also discussed.

Few studies had addressed the impact of factors such as point-on-wave of switching, voltage distortion, network impedance and the simultaneous operation of appliances on NILM algorithms. In this chapter, the variability and discrimination power of each feature extracted from current switching transient in time and time-frequency domain under several scenarios were explored through two metrics: coefficient of variation and Fisher discriminant ratio. Moreover, the effectiveness for classification in the scenarios of the impact factors was tested through the construction of multi-class classification models. Accuracies of more than 90% were reached for all the scenarios with one or more feature sets.

6. Conclusions and future work

This chapter summarizes the conclusions derived from this research. Contributions and research outcomes are also discussed. In addition, several ideas for future work are proposed.

6.1 Conclusions

This thesis considered Non-intrusive Load Monitoring (NILM) systems since they do not need neither dedicated sensors for appliances nor high efforts in communication platforms that may increase the cost and time of installation and maintenance. Besides, the lower the number of sensors is, the larger the reliability of the monitoring. Although research in this area is increasing, several gaps are detected in the scientific literature about event-based NILM systems such as: there is not a widely accepted set of load signatures, the inclusion of new appliances into the knowledge database demands a strong re-training step, fully labeled datasets of electrical signals for NILM are lacking, previous work has not been focused on the development of complete algorithms, and the question about the impact of factors (voltage distortion, network impedance, etc.) on NILM algorithms remains open. This thesis contributes to knowledge in several ways:

1. A new understanding of the disaggregation framework for continuous sensing NILM systems.
2. Proposal of a set of load signatures time - frequency, transient – steady state.
3. Analysis of the discrimination capacity of event-based NILM systems under different scenarios to assess the following impact factors: voltage distortion, network impedance and dependency of switching transients on point-on-wave (angle of the starting point).
4. “One-Class Classification” proposal to solve the scalability problem, i.e. the drawback of the need to re-train NILM systems and the exponential growth of the complexity when an appliance is added and to identify new or unseen appliances identification.

5. Dataset of electrical measurements from residential appliances which labels of transients start/end, switching on/off, are provided.

The proposed NILM system exploits a training database of the individual appliances in the specific house. Thus, the transients produced by the connections of the appliances are examined to make appliance identification and then, to assign the power consumption. It is assumed that only one appliance is switching at the same time, i.e. two or more switchings should not overlap, and high frequency meters (order of kHz) are preferred. This system comprises the following stages: event detection, feature extraction, classification and power estimation.

The proposed sets of features were computed from the waveforms and the S transform of the current switching transients. The question about the reproducibility of the transients and the features is verified through an analysis of the dependency of the current switching transients on the point-on-wave, which is the starting point at the voltage wave. The proposed S transform based features exhibit higher discrimination capacity than the proposed in the literature review, e.g. the one by (Y. H. Lin & Tsai, 2014a) which included only the mean and standard deviation of harmonic frequency profiles.

The load disaggregation is carried out as a classification task. The use of one-class classifiers is introduced in this work. Its potential lies in the fact that appliances unseen in the database could be detected as outliers. Moreover, a simpler re-training is needed when the user requires to include new appliances to the database of appliances in that specific household. In the traditional multi-class classification approach, the feature set that allows the best classification performance for all the scenarios (reference case, distorted, network impedance and simultaneous appliance operation) is the projected S transform matrix of current switching transients through PCA. The results discourage the use of the feature sets coming from only a part of the S transform matrix. Moreover, the selection of the classifier plays a key role in the accuracy yielded by the classifier model for both the traditional multi-class approach and the novel one-class approach.

Contrary to the traditional systems in the literature, the power estimation was addressed, and some models were proposed: one from nominal values and other based on experiments, with satisfactory results when compared to the actual measured power.

The discrimination capacity of the features was evaluated under different scenarios to know the effect of several impact factors: voltage distortion, network impedance and simultaneous appliance operation, by computing Fisher Discriminant Ratio (FDR). Although similar discrimination capacity was observed for the reference case and the voltage distortion scenarios, and this capacity gets detrimental under the other scenarios (network impedance and simultaneous operation), those features are still useful for identifying the appliances in all the scenarios. FDR quantifies the relevancy of every feature individually, with no dependency on a given classifier. Also, the discrimination power of feature sets (several features combined) was assessed through several classifiers. The feature sets computed from the projected S transform through PCA were the outstanding sets for appliance identification.

In conclusion, this thesis allows an understanding about the NILM system design from an integral perspective. The results supported the hypothesis about the possibility of appliance identification from the appliance transient electrical signals. Several advantages are observed in the proposed system. Contrary to other systems in the scientific literature, both high and low consumption appliances can be identified. The system works autonomously, saving storage and transmission costs, and connection to the cloud or big databases can be set in future approaches to perform or improve training and inference. Moreover, not all the combinations of appliances must be stored, but information about individual appliance operation. Also, a novel functionality is incorporated to identify if the signal corresponds to an appliance that does not belong to the training database. Furthermore, the training complexity is designed to grow linearly with the number of appliances, instead of exponentially. Finally, the validation stage yielded suitable accuracies for both appliance operations: individual and simultaneous

Climate change and the future of energy are motivating changes in power grids from the traditional top-down structure to a distributed one, namely *smart grids*, with the incorporation of information and communication technologies. The dynamics of the load has gained attention: preferences of the users, balance between the supply and the demand control are crucial topics to enable the grid of the future (*Utility of the future: An MIT Energy initiative response to an industry in transition.*, 2016). The pertinence of NILM systems lies in the importance of advanced load monitoring functions in the smart grid paradigm. In this sense, information provided by NILM systems allows the following applications:

- Comprehension of the house electricity consumption by users because more details than monthly bills are provided to, for example, identify the appliances responsible of the highest energy consumption. In addition, real time information about the appliance switching can be offered. According to studies, this detailed knowledge stimulates changes in the electricity consumption decisions to produce savings.

- Formulation and evaluation of demand side management programs. It requires to understand how the demand changes to, for example, identify deferrable loads and inactive energy consumption periods, thus, enabling to detect potential consumers to take advantage of the incentives and even to calculate the elasticity (customer reaction to economic offers) per appliance or assessing the energy savings by measuring before and after the program implementation. Therefore, the load information can come from NILM systems instead of from surveys.

- Remote or manual load control by inferring appliance operation or power consumption without installing additional sensors like in response to interruptibility incentives.

- Load prediction in long or short term by knowing the load composition over time. Then, power systems can be designed for more realistic load scenarios.

- Diagnosis to identify malfunction conditions can be performed by detecting meaningful deviations from the normal load signatures.

- Activity recognition and location of household inhabitants without deploying multiple sensors along the house or attached to the people since the use of some appliances can be associated to inhabitant activities. For example, this application is relevant for ambient assisted living and home care or elderly monitoring.

As a consequence of savings in the demand, higher savings are obtained in primary resources and electricity production cost, which causes reduction in CO2 gases, conservation of primary resources and deferment in investments. Thus, NILM is envisioned as an application for smart homes and together with the penetration of the Internet of Things they can bring significant interaction possibilities between the inhabitants and other power grid stakeholders.

6.2 Research outcomes

- Appliance identification algorithms

- Datasets of electrical signals from residential appliances

- Publications

Journals

1. Jimenez, Y.; Duarte, C.; Petit, J.; Meyer, J.; Schegner, P.; Carrillo, G., “Characterization of current switching transients for appliance identification”Renewable Energies and Power Quality No. 13, March 2015 La Coruña (Spain), ISSN: 2172-038X, March 2015

   `http://www.icrepq.com/icrepq’15/276-15-jimenez.pdf`

2. Jimenez, Y.; Duarte, C.; Petit, J; Carrillo, G.; Meyer, J; Schegner, P. “Steady state signatures in the time domain for nonintrusive appliance Identification”, Ingenieria e

Investigacion ISSN: 0120-5609 ed: Universidad Nacional de Colombia v.35 fasc.2 p.58 - 64, 2015.

http://www.revistas.unal.edu.co/index.php/ingeinv/article/view/53619

Conferences

3. Jimenez, Y.; Duarte, C.; Petit, J.; Carrillo, G., ”Feature extraction for nonintrusive load monitoring based on S-Transform” Power Systems Conference (PSC), 2014 Clemson University, pp.1,5, 11-14 March 2014

   http://ieeexplore.ieee.org/document/6758024/

4. Jimenez, Y.; Duarte, C.; Petit, J.; Meyer, J.; Schegner, P.; Carrillo, G., ”Characterization of current switching transients for appliance identification” International Conference on Renewable Energies and Power Quality (ICREPQ'14), 2015 La Coruña (Spain), 25-27 March 2015

5. Jimenez, Y.; Duarte, C.; Petit, J.; Meyer, J.; Schegner, P.; Carrillo, G., Steady State Signatures in the Time Domain for Nonintrusive Load Monitoring. SICEL Conference 2015, Valparaiso (Chile), November 17th -20th 2015.

6. Jimenez, Y.; Cortes, J.D.; Duarte, C.; Petit, J.; Carrillo, G., Nonintrusive load monitoring for awareness of residential electricity consumption. RIGMEI 2016 Cuartas Jornadas Iberoamericanas de Generación Distribuida y Microrredes Inteligentes. Bucaramanga (Colombia), June 14th-16th 2016.

7. Jimenez, Y.; Cortes, J.D.; Duarte, C.; Petit, J.; Carrillo, G., ”Nonintrusive Power Estimation of Residential Appliances under Voltage Variation”. International Conference on Harmonics and Quality of Power ICHQP 2016. Belo Horizonte (Brazil), October 16-19, 2016,

   http://ieeexplore.ieee.org/document/7783402/

Side publications

8. Cortes, J.D.; Jimenez, Y.; , Duarte, C.; ”Reasoner Design based on HYPO for Classification of Lighting Loads”, IEEE STSIVA 2016 - XXI Symposium on Signal Processing, Images and Artificial Vision 2016. Bucaramanga (Colombia), August 31 - September 2 2016,
   `http://ieeexplore.ieee.org/document/7743336/`

9. Cala, H. ; Jimenez, Y.; Torres, R.; Duarte, C., ”Efecto de una distorsión de onda achatada sobre un sistema de identificación de cargas basado en características extraídas a través de la transformada de Fourier fraccionaria.”, SICEL Conference 2017, Bucaramanga (Colombia), November 1-3, 2017

- Support Programs Name: Support for infrastructure for the doctoral formation for the thesis proposal *Automatic Disaggregation of Residential Electrical Consumption with Non-Intrusive Methods*
  Organization: Universidad Industrial de Santander. Research Vice-rectory.
  Year: 2014
  Description: This program provided founding for the current and voltage metering equipment.

- Undergrad and master thesis, and human resource training
  - Undergrad
    * *Monitorización No Intrusiva de Carga: recolección de datos y clasificación en el tiempo*. Jeisson David Bello Peña, Carlos Erixón Bello Peña, Yulieth Jimenez, Gabriel Ordoñez. 2014
    * *Monitorizacion no intrusiva de cargas eléctricas mediante la transformada S*. Henry Mauricio Cala, Yulieth Jiménez, César Duarte. 2014
    * *Análisis de firmas de cargas estacionarias para monitorización no intrusiva de*

cargas eléctricas. Nelson Daniel Castro Ospino, Edwin Darío Pinzón Díaz, Yulieth Jiménez, César Duarte. 2015.

* *Prototipo de monitor no intrusivo de energía residencial.* Sergio Ávila, Andrés, Carlos Angulo, Yulieth Jimenez, Cesar Duarte (*in progress*).
* *Automatización de mediciones eléctricas en el laboratorio del grupo GISEL en Guatiguará*. Edwin Páez, Johan Nicolás Riaño, Henry Cala, Yulieth Jiménez (*in progress*).

– Master

* *Clasificación de eventos para monitorización no intrusiva de cargas eléctricas utilizando razonamiento basado en casos.* José David Cortés, César Duarte (*in progress*).
* *Identificación de cargas eléctricas residenciales utilizando características basadas en la transformada fraccionaria de Fourier*. Henry Mauricio Cala, Rafael Torres, César Duarte (*in progress*).

- Research stays

1. Summer Research Program (2012). University of Delaware. Newark DE, United States.
2. Research Internship (2014-2015). Technische Universitaet Dresden. Dresden, Germany.

6.3 Future work

- Further work is required to: to combine feature sets and make a reasonable feature selection for attempting to enhance the accuracy of the classification task, to assess voltage variation and sampling frequency as impact factors on the discrimination capacity of the proposed features and to build a probabilistic approach to derive NILM solutions from steady state features.

- Electrical measurements in a real household were acquired. These data will be processed as future work, where the effect of a non-controllable environment, e.g. grid voltage supply, can be observed. In addition, the computing of the impedances in this scenario is a more challenging task.

- The flat-top signal employed in this thesis is an adaptation of the German flat-top signal. Small experiments in the GISEL research group have shown this flat-top trend in houses. Measurement campaigns are encouraged in real Colombian houses in order to determine the model of the flat-top signal for Latin America.

- It is extremely recommended to widen the dataset of measurements by including more scenarios and appliances to have a deeper understanding of appliances, e.g. Led lamps.

- Other feature extraction methods (Wavelet, Fractional Fourier Transform) and classification techniques (neural networks, case based reasoning) have been tested in the GISEL research group for load disaggregation problem. A future task is to compare them with the proposals in this thesis.

- Deep learning and big data tools can be explored in a future. Their advantages have been evidenced in other fields that also address classification and pattern recognition problems.

- A next stage of the research is to develop a portable prototype to be tested in real environments with costs and functionalities as much competitive as possible.

- A future research could combine the NILM algorithms with power quality disturbances in order to guarantee the accuracy even when these disturbances take place in the power system.

- A recommended future work is to associate NILM information with applications on load forecasting, demand side management and high impedance fault detection, among others.

- Research in alternative scenarios:
  - Commercial and industrial premises is scarce. In general, complexity of loads, difficulty to build the database and electrical noise are some factors to consider in those sites. Naturally, each type of industry or commercial site has proper restrictions. The findings already obtained for residential premises could also be useful as a starting point for this.
  - Penetration of renewable resources such as wind, solar, biomass and geothermal is encouraged worldwide. This distributed generation might lead to operational problems. Little work about NILM has been done in environments where these generation resources are connected.
  - NILM application in DC grids would be of interest because of the absence of zero crossings.

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APPENDIX A

Data acquisition equipment accuracies

The accuracies of the data acquisition cards are registered in Tables 27, 28 and 29 while the current clamp accuracy is $\pm 1\%$ of reading $\pm$ 2 mA. Uncalibrated accuracy refers to the accuracy achieved when acquiring in raw or unscaled modes where the calibration constants stored in the module are not applied to the data.

Table 27
*Accuracies of NI 9225. *Range equals 425 V.*

Measurement Conditions	Percent of reading (Gain Error)	Percent of range* (Offset Error)
Calibrated max (-40 to 70°C)	$\pm 0.23\%$	$\pm 0.05\%$
Calibrated typ (25°C, ±5°C)	$\pm 0.05\%$	$\pm 0.008\%$
Cailbrated max (25°C, ±15°C)	$\pm 0.084\%$	$\pm 0.016\%$
Uncalibrated max (-40 to 70°C)	$\pm 1.6\%$	$\pm 0.66\%$
Uncalibrated typ (25°C, ±5°C)	$\pm 0.4\%$	$\pm 0.09\%$

Note: adapted from (National Instruments, 2014a).

Table 28
Accuracies of NI 9227 at safe operating range of $5A_{rms}$.

Measurement Conditions	Percent of reading (Gain Error)	Percent of range (Offset Error)
Calibrated max (-40 to 70°C)	$\pm 0.37\%$	$\pm 0.18\%$
Calibrated typ (23°C, ±5°C)	$\pm 0.1\%$	$\pm 0.05\%$
Uncalibrated max (-40 to 70°C)	$\pm 5\%$	$\pm 2.4\%$
Uncalibrated typ (23°C, ±5°C)	$\pm 2.5\%$	$\pm 1.0\%$

Note: adapted from (National Instruments, 2014b).

On the other hand, the three cards have a flatness (fs=50kS/s) ± 100 mdB maximum.

Table 29

*Accuracies of NI 9239. *Range equals 10.52 V.*

Measurement Conditions	Percent of reading (Gain Error)	Percent of range* (Offset Error)
Calibrated max (-40 *to* 70°C)	$\pm 0.13\%$	$\pm 0.06\%$
Calibrated typ (25°C, ±5°C)	$\pm 0.03\%$	$\pm 0.008\%$
Uncalibrated max (-40 *to* 70°C)	$\pm 1.4\%$	$\pm 0.70\%$
Uncalibrated typ (23°C, ±5°C)	$\pm 0.3\%$	$\pm 0.11\%$

Note: adapted from (National Instruments, 2016).

APPENDIX B

S transform definitions

B.1 Continuous S transform

The S transform, $S(\tau, f)$, of a signal $x(t)$ is defined as (R. Stockwell et al., 1996):

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t) g_f(t-\tau) e^{-j2\pi f t} dt, \tag{17}$$

where $g_f(t) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}}$ is a Gaussian window function.

The expression in Eq. (17) might be written as a convolution:

$$S(\tau, f) = p(\tau, f) \star g_f(\tau), \tag{18}$$

where $p(\tau, f) = x(\tau) e^{-j2\pi f \tau}$ and $\star$ denotes the convolution operation.

The S transform can also be written as a Continuous Wavelet Transform (CWT) multiplied by a phase factor:

$$S(\tau, f) = e^{j2\pi f\tau} W(\tau, f) = e^{j2\pi f\tau} \int_{-\infty}^{\infty} x(t) w(t-\tau, f) dt, \tag{19}$$

with the mother wavelet described by:

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{-j2\pi f t}, \tag{20}$$

where f is a scaling factor that controls the width of $\omega(t, f)$ and consequently, the frequency resolution.

S transform provides a complex function that represents the phase and magnitude of the signal over a time-frequency plane. It provides frequency- dependent resolution with a direct relationship to the Fourier spectrum (R. Stockwell et al., 1996):

$$X(f) = \int_{-\infty}^{\infty} S(\tau, f) d\tau \tag{21}$$

In this vein, the S transform is a special case of Short-Time Fourier Transform (STFT) (see (17)), whereas it is not strictly a CWT because $w(t, f)$ is not an admissible wavelet (its mean value is different from zero). In fact, S transform sometimes has better performance than STFT and/or wavelet transform. For example, the modulating sinusoids of STFT are fixed with respect to the time axis while ST is based on a localizing Gaussian window that dilates and translates. This is quite advantageous for the NILM systems where the signals are non-stationary, and a fixed window width is not suitable to decompose them.

B.2 Discrete S transform

The discrete S transform of $x(kT)$, $k = 0, 1, \ldots, N-1$, a sampled signal at a time sampling interval T is given by (R. Stockwell et al., 1996)

$$X\left[\frac{n}{NT}\right] = \frac{1}{N}\sum_{k=0}^{N-1} x[kT]e^{\frac{-j2\pi nk}{N}} \tag{22}$$

where $n = 0, 1, \ldots, N-1$.

The discrete S Transform, $S\left[lT, \dfrac{n}{NT}\right]$, of $x(kT)$ is:

$$S\left[lT, \frac{n}{NT}\right] = \begin{cases} \sum\limits_{m=0}^{N-1} X[\frac{m+n}{NT}]e^{\frac{-2\pi^2 m^2}{n^2}} e^{j2\pi lm} & \text{if } n \neq 0 \\ \\ \frac{1}{N}\sum\limits_{m=0}^{N-1} x(\frac{m}{NT}) & \text{if } n = 0 \end{cases} \tag{23}$$

The discrete inverse of the S transform is

$$x(kT) = \sum_{n=0}^{N-1}\left\{\frac{1}{N}\sum_{j=0}^{N-1} S\left[lT, \frac{n}{NT}\right]\right\} e^{\frac{j2\pi nk}{N}}. \tag{24}$$

APPENDIX C

ANOVA-Tukey test

An ANOVA test is performed followed by a Tukey test for every classifier to verify the significant difference between the feature sets. Fig. 66, 67 and 66 show the results of these tests.

RESULTS FOR LINEAR CLASSIFIER

```
> summary(res1)
          Df  Sum Sq  Mean Sq  F value   Pr(>F)
group      5  9634     1926.7   16845   <2e-16 ***
Residuals 54   6        0.1
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> TukeyHSD(res1)
  Tukey multiple comparisons of means
    95% family-wise confidence level
Fit: aov(formula = fit)
$group              diff            lwr        upr        p adj
c2_fs2-c2_fs15 -18.535167 -18.982021 -18.088312    0
c2_fs3-c2_fs15   2.818614   2.371760   3.265469    0
c2_fs4-c2_fs15   9.434162   8.987307   9.881016    0
c2_fs7-c2_fs15  22.691698  22.244843  23.138552    0
c2_fs9-c2_fs15  11.893178  11.446324  12.340033    0
c2_fs3-c2_fs2   21.353781  20.906927  21.800636    0
c2_fs4-c2_fs2   27.969328  27.522474  28.416183    0
c2_fs7-c2_fs2   41.226864  40   .780010  41.673719    0
c2_fs9-c2_fs2   30.428345  29.981490  30.875199    0
c2_fs4-c2_fs3    6.615547   6.168693   7.062402    0
c2_fs7-c2_fs3   19.873083  19.426229  20.319938    0
c2_fs9-c2_fs3    9.074564   8.627709   9.521418    0
c2_fs7-c2_fs4   13.257536  12.810681  13.704390    0
c2_fs9-c2_fs4    2.459016   2.012162   2.905871    0
c2_fs9-c2_fs7  -10.798519 -11.245374 -10.351665    0
```

Conclusion: The classifiers based on all the feature sets have significant differences between them with p-value=0.

Figure 66. Results of Anova-Tukey tests for linear classifier

RESULTS FOR DIAGLINEAR CLASSIFIER

```
> summary(res1)
            Df    Sum Sq   Mean Sq   F value   Pr(>F)
group        7    39383     5626      53722    <2e-16 ***
Residuals   72        8        0
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> TukeyHSD(res1)
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = fit)

$group              diff           lwr           upr    p adj
c4_fs2-c4_fs15 -15.0185087 -15.4703102 -14.5667073 0.0e+00
c4_fs3-c4_fs15  -0.8461132  -1.2979146  -0.3943117 3.7e-06
c4_fs4-c4_fs15  -3.5166579  -3.9684593  -3.0648564 0.0e+00
c4_fs5-c4_fs15 -45.1718667 -45.6236682 -44.7200653 0.0e+00
c4_fs6-c4_fs15 -45.1718667 -45.6236682 -44.7200653 0.0e+00
c4_fs7-c4_fs15  21.9619249  21.5101235  22.4137263 0.0e+00
c4_fs9-c4_fs15   3.9079852   3.4561838   4.3597866 0.0e+00
c4_fs3-c4_fs2   14.1723956  13.7205941  14.6241970 0.0e+00
c4_fs4-c4_fs2   11.5018509  11.0500494  11.9536523 0.0e+00
c4_fs5-c4_fs2  -30.1533580 -30.6051595 -29.7015566 0.0e+00
c4_fs6-c4_fs2  -30.1533580 -30.6051595 -29.7015566 0.0e+00
c4_fs7-c4_fs2   36.9804336  36.5286322  37.4322351 0.0e+00
c4_fs9-c4_fs2   18.9264939  18.4746925  19.3782954 0.0e+00
c4_fs4-c4_fs3   -2.6705447  -3.1223461  -2.2187432 0.0e+00
c4_fs5-c4_fs3  -44.3257536 -44.7775550 -43.8739521 0.0e+00
c4_fs6-c4_fs3  -44.3257536 -44.7775550 -43.8739521 0.0e+00
c4_fs7-c4_fs3   22.8080381  22.3562366  23.2598395 0.0e+00
c4_fs9-c4_fs3    4.7540984   4.3022969   5.2058998 0.0e+00
c4_fs5-c4_fs4  -41.6552089 -42.1070103 -41.2034074 0.0e+00
c4_fs6-c4_fs4  -41.6552089 -42.1070103 -41.2034074 0.0e+00
c4_fs7-c4_fs4   25.4785828  25.0267813  25.9303842 0.0e+00
c4_fs9-c4_fs4    7.4246430   6.9728416   7.8764445 0.0e+00
c4_fs6-c4_fs5    0.0000000  -0.4518014   0.4518014 1.0e+00
c4_fs7-c4_fs5   67.1337916  66.6819902  67.5855931 0.0e+00
c4_fs9-c4_fs5   49.0798519  48.6280505  49.5316534 0.0e+00
c4_fs7-c4_fs6   67.1337916  66.6819902  67.5855931 0.0e+00
c4_fs9-c4_fs6   49.0798519  48.6280505  49.5316534 0.0e+00
c4_fs9-c4_fs7  -18.0539397 -18.5057412 -17.6021383 0.0e+00
```

Conclusion: There are significant differences between the classifiers based on all the feature sets, except between FvST5 and FvST6 (p-value = 1) which do not have significant differences between them.

Figure 67. Results of Anova-Tukey tests for diaglinear classifier

RESULTS FOR SVM CLASSIFIER

```
> summary(res1)
            Df   Sum Sq   Mean Sq    F value      Pr(>F)
group        7    98130     14019    7.256e+31   <2e-16 ***
Residuals   72    0             0
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> TukeyHSD(res1)
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = fit)

$group                    diff          lwr          upr     p adj
c1_fs2-c1_fs15  7.086198e+00  7.086198e+00  7.086198e+00 0.0000000
c1_fs3-c1_fs15 -1.586462e-01 -1.586462e-01 -1.586462e-01 0.0000000
c1_fs4-c1_fs15 -9.360127e+00 -9.360127e+00 -9.360127e+00 0.0000000
c1_fs5-c1_fs15 -7.562136e+01 -7.562136e+01 -7.562136e+01 0.0000000
c1_fs6-c1_fs15 -7.562136e+01 -7.562136e+01 -7.562136e+01 0.0000000
c1_fs7-c1_fs15  1.533580e+01  1.533580e+01  1.533580e+01 0.0000000
c1_fs9-c1_fs15  9.254363e+00  9.254363e+00  9.254363e+00 0.0000000
c1_fs3-c1_fs2  -7.244844e+00 -7.244844e+00 -7.244844e+00 0.0000000
c1_fs4-c1_fs2  -1.644632e+01 -1.644632e+01 -1.644632e+01 0.0000000
c1_fs5-c1_fs2  -8.270756e+01 -8.270756e+01 -8.270756e+01 0.0000000
c1_fs6-c1_fs2  -8.270756e+01 -8.270756e+01 -8.270756e+01 0.0000000
c1_fs7-c1_fs2   8.249603e+00  8.249603e+00  8.249603e+00 0.0000000
c1_fs9-c1_fs2   2.168165e+00  2.168165e+00  2.168165e+00 0.0000000
c1_fs4-c1_fs3  -9.201481e+00 -9.201481e+00 -9.201481e+00 0.0000000
c1_fs5-c1_fs3  -7.546272e+01 -7.546272e+01 -7.546272e+01 0.0000000
c1_fs6-c1_fs3  -7.546272e+01 -7.546272e+01 -7.546272e+01 0.0000000
c1_fs7-c1_fs3   1.549445e+01  1.549445e+01  1.549445e+01 0.0000000
c1_fs9-c1_fs3   9.413009e+00  9.413009e+00  9.413009e+00 0.0000000
c1_fs5-c1_fs4  -6.626124e+01 -6.626124e+01 -6.626124e+01 0.0000000
c1_fs6-c1_fs4  -6.626124e+01 -6.626124e+01 -6.626124e+01 0.0000000
c1_fs7-c1_fs4   2.469593e+01  2.469593e+01  2.469593e+01 0.0000000
c1_fs9-c1_fs4   1.861449e+01  1.861449e+01  1.861449e+01 0.0000000
c1_fs6-c1_fs5   7.105427e-15 -1.230033e-14  2.651118e-14 0.9447915
c1_fs7-c1_fs5   9.095717e+01  9.095717e+01  9.095717e+01 0.0000000
c1_fs9-c1_fs5   8.487573e+01  8.487573e+01  8.487573e+01 0.0000000
c1_fs7-c1_fs6   9.095717e+01  9.095717e+01  9.095717e+01 0.0000000
c1_fs9-c1_fs6   8.487573e+01  8.487573e+01  8.487573e+01 0.0000000
c1_fs9-c1_fs7  -6.081438e+00 -6.081438e+00 -6.081438e+00 0.0000000
```

Conclusion: There are significant differences between the classifiers based on all the feature sets, except between FvST5 and FvST6 (p-value = 0. 9447915) which do not have significant differences between them.

Figure 68. Results of Anova-Tukey tests for SVM classifier