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Department of Electrical Electronics and Computer Science Engineering (DIEEI)

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STUDY OF AN INNOVATIVE NON INTRUSIVE LOAD MONITORING SYSTEM FOR ENERGY EMANCIPATION OF DOMESTIC USERS: HARDWARE AND ICT OPTIMIZED SOLUTIONS

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Thesis for the degree of Doctor of Philosophy

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ABSTRACT

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Non-intrusive appliance load monitoring (NIALM) is the process of disaggregating a household's total electricity consumption into its contributing appliances. Smart meters are currently being deployed on national scales, providing a platform to collect aggregate household electricity consumption data. Existing approaches to NIALM require a manual training phase in which either sub-metered appliance data is collected or appliance usage is manually labelled. This training data is used to build models of the household appliances, which are subsequently used to disaggregate the household's electricity data. Due to the requirement of such a training phase, existing approaches do not scale automatically to the national scales of smart meter data currently being collected.

In this thesis an unsupervised disaggregation method is presented which, unlike existing approaches, does not require a manual training phase. A NIALM system reads real-time data from a smart meter, usually positioned at the point on the public electricity network at which the customers is connected, and uses algorithms not only to quantify how much energy is used in the home, but also to determine what main devices are being operated. NIALM algorithms need a complete load signature and complex optimization algorithms to find the right combination of single loads that fits the real electrical measurements. It is practically impossible to get the detailed signature of all appliances inside a house/building and sophisticated optimization algorithm are not suitable for on-line applications. To do so, we address the following topics.

First, a straightforward NIALM algorithm is proposed, it is based on both a simple load signature, rated active and reactive power and a heuristic disaggregation algorithm.

Second, on real applications, this approach cannot reach very high performances; this is the reason why an active involvement of users is considered. The users' feedback aims to: correct the load signatures, reduce the error of disaggregation algorithm and increase the active participation of users in saving energy politics.

Third, the NIALM algorithm has been accurately tested numerically using as input load curves generated randomly but under given constraints. In this way, the causes of inefficiency of the proposed approach are quantitatively analyzed both separately and in different combinations.

The above contributions provide a solution which satisfies the requirements of a NIALM method which is both unsupervised (no manual interaction required during training) and uses only smart meter data (no installation of additional hardware is required). When combined, the contributions presented in this thesis represent an advancement in the state of the art in the field of non-intrusive appliance load monitoring, and a step towards increasing the efficiency of energy consumption within households.

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Nomenclature

Acronyms

CDA	Conditional Demand Analysis
CS	Contemporary Switching
GLP	Global Load Profile
GLPd	Disaggregated Global Load Profile
GLPg	Generated Global Load Profile
LMS	Local Monitoring Subsystem
LS	Load Signature
PM	Power Meter
NIALM	Non Intrusive Appliance Load Monitoring
PQ-DA	P and Q Disaggregation Algorithm
SMC	Central Monitoring Subsystem
SS	Simultaneous Switching

Variables

C_e	cumulative error
D_{gP}, D_{gQ}	factor for load profile characterization
e_{lin}	linearization error
KG_P, KG_Q	factor for load profile characterization
n_a	number of the appliances
n_S	number of samples
Pgd	power of the disaggregated load profile at the j-th sample
Pgg	power of the generated load profile at the j-th sample
P_n	rated active power (W)
PF_n	rated power factor
Q_n	rated reactive power (VAr)
s_j	generically sample between [1 ….n_s]
ΔS_{min}	minimum number of samples
ΔP_{min}	minimum active power variation to detect a switching

ΔQ_{min} minimum reactive power variation to detect a switching

η_P disaggregation energy efficiency (%)

η_S disaggregation state efficiency (%)

Chapter 1

Introduction

Nowadays the need to both solve environmental problems and cope with the exhausting of traditional fossils has forced many countries and organizations (e.g. the European Community) to put in their political agenda the energy problem. In this context to find a sustainable solution it is needed to combine three different strategies: energy saving, efficiency and renewable energies. On the other hand the great development of ICT technologies has drawn the attention of many researchers on the development of smart grids as a hardware and software structure that can allow the actuation of the energetic strategies. Smart grids are so complex and varied that a unique definition is needed.

The Organization for Economic Cooperation and Development (OECD) beholds Smart Grid in two perspectives [1]. From a solution perspective, the smart grid is characterized by:

- More efficient energy routing and thus an optimized energy usage, a reduction of the need of excess capacity and increased power quality and security.
- Better monitoring and control of energy and grid components. Improved data capture and thus an improved outage management.
- Two-way flow of electricity and real-time information allowing for the incorporation of green energy sources, demand-side management and time market transactions.
- Highly automated, responsive and self-healing energy network with seamless interfaces between all parts of the grid;

From a technical components' perspective, the main components of a smart grid are:

- New and advanced grid components.
- Smart devices and smart metering.
- Integrated communication technologies.
- Decision support systems and human interfaces.
- Advanced control systems.

In this continuously evolving system the user becomes the protagonist through the use of electronic devices which makes transparent consumption, encourages his active participation in the energy market, promotes a rational use of energy.

Commercial solutions to improve the management of energy demand have centered on the deployment of smart meters and in-home energy displays that can provide whole-house real-time energy monitoring and dynamic pricing from suppliers in order to motivate users to shift or reduce their energy consumption [2].

A number of countries and regions are deploying new electricity metering, and its introduction is being accelerated by legislation: in the European Union the 80% of households will have a smart meter by 2020. Austria and Switzerland commissioned a bi-national study on the topic “Smart Metering Consumption” [3]. The study, completed in 2012, assessed the energy used by existing and planned metering, to better understand the impact of implementing large scale roll out of smart metering, and to estimate the own energy consumption required for the operation of this infrastructure. In 2012 study on Smart Metering Infrastructure (SMI) was completed and presented by Austria and Switzerland to the 4E ExCo as well. The study included two major topics namely, Smart Metering Consumption (SMC) and Non Intrusive Load Monitoring System (NIALM). The term NILM is sometimes also used for NIALM.

The domestic energy monitoring infrastructure planned today will be set for decades, millions of smart meters will be deployed, and the associated energy consumption will be fixed with the technology and architecture chosen for these systems. However, end-users at household level have often been excluded from this energy efficiency optimization process: they have traditionally held a passive role in issues related to energy savings although it rests on them to decide the amount of energy to consume and how to utilize it. As a result, it is quite evident that consumers also need to be active players in this process and research suggests that users are willing and capable to adapt their behaviour to energy saving practices if the necessary feedback, support and incentives are given [4].

The increasing concern about the impact of energy usage on the environment as well as the rise of energy costs are arguably the main factors that encourage customers to look for ways of decreasing consumes.

Nevertheless, the major difficulty is the lack of information about day-to-day activities; for instance, energy bills, which are usually received at the end of each month, cannot be used to distinguish the effects of individual actions or to obtain meaningful feedback about the effectiveness of users' change of habits [5][6]. Such problems need innovative feedback mechanisms with greater transparency about the consumption at any time and the associated cost that can potentially improve energy savings practices. Current trends in the development and convergence of ICT and energy networks are ushering a range of possibilities in areas such as residential energy monitoring (measuring, processing and providing feedback in near-real-time), context-aware application and activity detection [7].

1.1 Scenario Description

The complexity of the NIALM task depends largely upon the target household, which is affected by many factors. The two most important of which are the appliances and occupants of the household. This section discusses a typical scenario in which a NIALM would be expected to operate, and the monitoring techniques which would be used.

Zeifman and Roth [8] estimate that a typical household contains 30–50 appliances. These appliances draw a wide variation of power (0–3000 W) and are in operation for different durations of time (0–24 hours per day). As a result, domestic appliances can consume vastly different amounts of energy. Figure 1 displays approximate figures for the average energy consumption per day for the most common appliance types. The figure collects appliances of the same type (e.g. multiple light bulbs) as would be expected in households, and consequently shows fewer appliances than the estimate of Zeifman and Roth. The estimates are calculated using power demands of household appliances [9] and scaled up using approximate durations of use. A full breakdown of the figures used is given in Appendix A. The shape of the graph appears to roughly follow an exponential distribution, in which the majority of the household's energy is consumed by relatively few appliances, specifically those which perform heating or cooling tasks. Therefore, it is most important for a NIALM to successfully disaggregate such high energy consuming appliances. Having described the typical households in which a NIALM will be required to operate, we now describe the potential applications which are enabled by disaggregated energy consumption data.

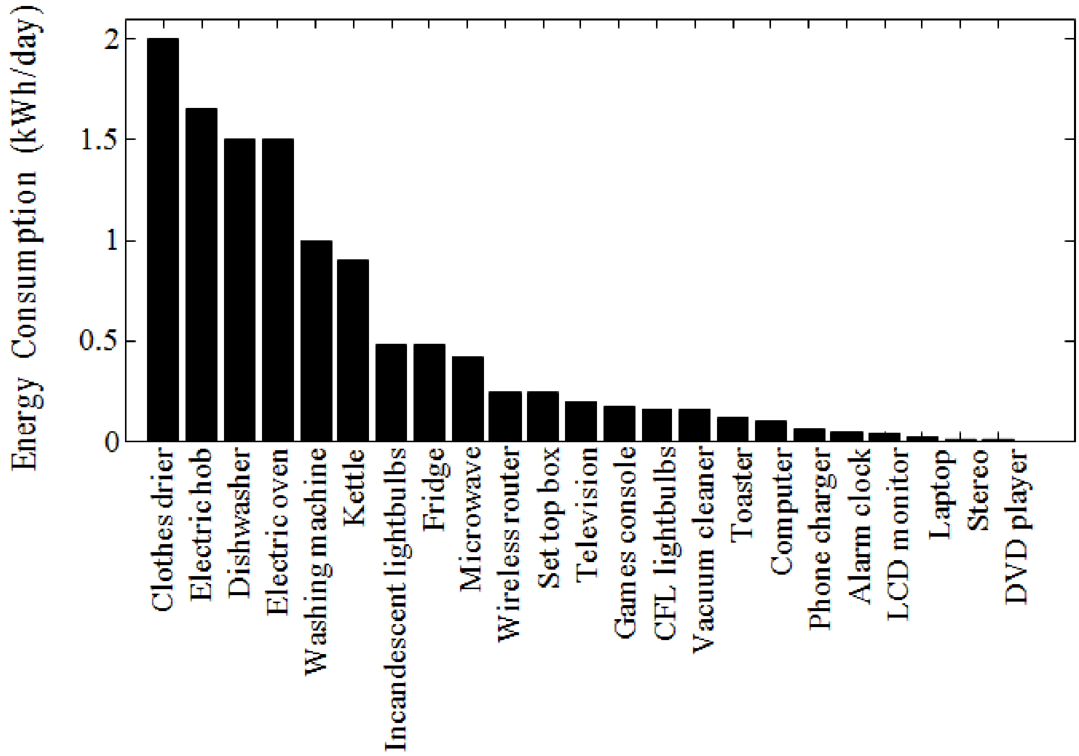


Figure 1: Average energy consumption of domestic appliances

1.2 Application Areas

Providing disaggregated real-time feedback has been found to reduce a household's electrical energy consumption by 9–18% [10]. Such a reduction in domestic energy consumption would clearly contribute to national goals of a reduction in carbon dioxide emissions. In addition, such an increase in the efficiency of domestic electricity consumption places a lower demand on electricity generation, and consequently a lower demand on the burning of fossil-fuels or international energy imports.

In addition to these national goals, individual consumers will also benefit financially from such reductions in electricity consumption. Furthermore, disaggregated energy feedback also has the potential to educate each household's occupants about the relative energy consumption of different appliances. This increase in awareness could also prompt energy savings in other domains, such as in commercial and industrial premises.

In order to realise such energy savings, disaggregated appliance data must be used to produce actionable suggestions which are then presented to a household's occupants. The remainder of this section discusses three types of such feedback.

First, disaggregated electricity consumption can be used to provide personalised suggestions regarding the mode of an appliance's use. The system would detect when an appliance is being used in a mode of poor energy efficiency and quantify the savings should the appliance be switched to a more energy efficient mode. Such suggestions do not prevent the household's occupants from carrying out their desired task, but instead allows them to make an informed decision regarding the mode of use of an appliance. Examples of such appliances are generally those with an economy or low power setting (e.g. an economy shower or a cool cycle of a washing machine).

Second, the disaggregated electricity consumption can also be used to provide automated load deferral suggestions. Since the mix of generators supplying electricity to the national grid varies with demand, so does the rate of carbon emissions. Load deferral is the act of delaying the use of electricity from a peak time to an off-peak time, therefore reducing the net carbon emissions despite the same amount of energy being used. An automated system could suggest the deferral of appropriate energy intensive appliances to off-peak times, and would therefore require information regarding the time of day when the appliance is used, the energy consumption of the appliance and the carbon intensity of the national grid throughout the day. Deferrable loads are generally appliances whose usage is not required to be performed immediately upon user interaction (e.g. running of a washing machine or dishwasher). Furthermore, with the introduction of time of use pricing or real-time pricing, load deferral can also decrease the overall cost of electricity for individual households.

Last, disaggregated electricity consumption could be used to detect faulty or deteriorating appliances [11]. Since the NIALM estimates the energy consumption of each appliance, a faulty appliance can be identified as either an appliance which draws significantly more power than the average for that appliance type or an appliance whose energy consumption increases over time. In such a situation, the automated system could suggest either a more energy efficient replacement for less expensive appliances or a repair for more expensive appliances. The system could even calculate how long it would take to break even after such a replacement or repair, compared to had the household occupants taken no action. Examples of such appliances are generally those which become less energy efficient throughout their lifetime (e.g. a refrigerator or oven with a deteriorating door seal). Having described the various applications which are enabled by disaggregated electricity data, we now consider existing solutions to the disaggregation problem.

1.3 Existing Solutions

A number of appliance monitoring methods exist which reduce the complexity of the disaggregation problem at the expense of a more substantial intrusion into the household.
The literature defines a clear distinction between intrusive and non-intrusive metering [12]. Intrusive metering refers to appliance-level metering; the deployment of one meter per appliance. Conversely, non-intrusive metering refers to premises-level metering; the deployment of one meter per premises. The term premises-level metering is used to describe the aggregate metering of appliances, whether contained within a household, a workplace or any other building.

Appliance energy disaggregation could be performed through intrusive metering. The deployment of one meter per appliance would allow each individual appliance's energy consumption to be communicated to a central hub. However, there are many practical disadvantages to this method that have prompted the study of non-intrusive metering. First, the financial cost of manufacturing and installing enough meters to match the number of domestic appliances would be considerable. Second, the installation of one meter per household appliance would clearly cause substantial inconvenience to the household's occupants. Third, the system would require additional meters to be deployed should the set of appliances change (e.g. appliance replacements or the introduction of new appliances). Therefore, until such appliance metering is available at scale at low cost, intrusive metering should not be considered as a practical or scalable solution to the appliance energy monitoring problem [13].

Alternatively, non-intrusive metering can be used to disaggregate appliance energy from a single point of measurement. Such a system is commonly referred to as a non-intrusive appliance load monitor (NIALM). One approach is to design a meter specifically for appliance energy disaggregation, which is able to sample the household's electricity demand thousands of times per second, therefore allowing multiple electrical features to be extracted. These features can be used to easily discriminate between appliance power demands, therefore simplifying the disaggregation task. However, the financial and convenience cost of installing a bespoke meter in each household is still substantial relative to the benefits of appliance energy disaggregation [13].

A summary of these methods is given below, and a full description is given in Chapter 2:

- *Electrical sub-metering:* Installing one electricity meter per appliance.
- *Smart appliances:* Appliances self-report energy consumption to a central hub.
- *Electrical probing:* Transmitting an electrical signal into the household mains circuit and analysing the return signal.
- *Appliance tagging:* Installing a low-cost appliance tag which detects usage through non-electrical methods.
- *Ambient sensors:* Using existing sensors such as occupancy, lighting and audio sensors to infer appliance usage.
- *Conditional demand analysis:* Using an appliance survey to estimate appliance energy consumption.

However, the intrinsically intrusive nature of these methods clearly violates the requiremnets of NIALM and as a result none of these methods constitute a solution for disaggregating smart meter data.

Having discussed the existing solutions, we now summerise the research contributions of this thesis.

1.4 Research Contributions

The following requirements contribute positively to define a good NIALM approach are described:

1. feature selection: the feature that characterize the appliances should be sample at 1 Hz;
2. accuracy: the minimum acceptable accuracy of the disaggregation algorithm is 80%-90%;
3. no training: no training algorithm should be necessary;
4. near real-time capabilities: the algorithm should perform in real time;
5. scalability: the algorithm should be scalable if the number of used appliances increase from 10 to 20;
6. various appliance types: the types of used appliances should be various (on-off appliances, multistate appliances, continuous consuming appliances, and permanent consuming devices).

Another important requirement to obtain a good NIALM approach is to involve the final user on the disaggregation algorithm, as in [13] has been demonstrate how using disaggregation method can lead to energy savings of up to 12% through a real time energy feedback at appliance level. This is consistent with the wealth of literature focusing on how provision of feedback to households on energy use data can facilitate energy savings [14] [15] [16] [17].

Our contributions towards this objective can be summarised as follows.

We have developed an “innovative” load disaggregation algorithm that respect the requirements above mentioned and exploits feedback algorithms. “Innovative”, because we use a simple algorithm but effeciently integrated with a feedback algorithms, in which the user plays an active role. Consumer systems for home energy management can provide significant potential energy saving. But most people have only an approximate idea of how much energy they are using and what impacts they could make by changing day-to-day behavior. On the other hand a detailed information about energy consumption is crucial especially when a PV system is also locally connected (e.g. load and PV generation curve overlapping). Hence it is important to develop systems, based on non - intrusive appliance load monitoring (NIALM), in which individual appliance power consumption information is disaggregated from single-point measurements, that provide a feedback in such a way to make energy more visible and more amenable to understanding and control. Digital electricity meters (e.g. power meters) measure total electricity consumption of a household at a fine temporal granularity. Using this data, the consumption of individual appliances can be retrieved and used to provide novel services, such as personalized energy consulting.

Our research focuses on the development of a software tool to direct, instantaneous non-intrusive load monitoring and energy disaggregation of individual home appliances.

Therefore, the final aim is to provide a service to the user that provides whole-house real-time energy monitoring and dynamic pricing from electrical energy retailers in an attempt to motivate users to shift or reduce their energy consumption. Particular attention is devoted to define the feedback functions and to evaluate their positive effects on the reduction of disaggregation errors.

These contributions are also detailed in the following five papers:

1. *V. Amenta*, G. Tina, “Load Demand Disaggregation based on Simple Load Signature and User’s Feedback”, SEB 2015, 7th International Conference on Sustainability in Energy and Buildings.
2. G.M.Tina, *V.Amenta*, G.Di Modica, O.Tomarchio, “Web interactive non-intrusive load disaggregation system for active demand in smart grids”, EAI Endorsed Transactions on Energy 2014,1(3): e4

3. G.M.Tina, *V.Amenta*, “Consumption awareness for energy savings: NIALM algorithm efficiency evaluation”, IREC, IEEE International Renewable Energy Congress, Hammamet, 25-27 March 2014.
4. *V.A.Amenta*, G.M.Tina, S.Gagliano, G. Di Modica,O.Tomarchio, “Web interactive non intrusive load disaggregation system for energy consumption awareness”, National Conference AEIT, Mondello , 3-5 October 2013, IEEE pages 1 - 6 , ISBN: 978-8-8872-3734-4
5. *V.A.Amenta*, G.M.Tina, “Non Intrusive Load Monitoring Techniques for Energy Emancipation of Domestic Users”. International Conference, CISBAT, Lausanne, 4-6 September 2013.

Having summarised our research contributions, we now describe the structure of this thesis.

1.5 Thesis Structure

The remaining chapters of this thesis are structured as follows:

Chapter 2 provides a background of theoretical and empirical research relevant to non- intrusive appliance load monitoring. First, intrusive monitoring methods are discussed. Second, approaches based on high frequency electricity monitors are considered. Last, low frequency methods are introduced.

Chapter 3, we present an overall ICT architecture for energy consumption awareness: data about energy consumption collected in users' homes are sent to a service provider site that, after disaggregating and processing them, allows a user friendly representation of energy consumption providing the user with a direct feedback about his habits and distribution of consumption among his appliances.

Chapter 4 describes the disaggregation algorithm and the function to generate a random and controlled load profiles.

Chapter 5 shows the experimental results. The robustness of the disaggregation algorithm has been tested both numerically and experimentally. Secondly, we defines the users’ feedback and the different feedback algorithms.

Finally, Chapter 6 gives a summary of the research presented in this thesis. We also discuss future extensions of the work presented in this thesis, with specific attention to apply NIALM system in a real scenario.

Chapter 2

Background

This chapter gives a background of various existing approaches which aim to disaggregate a household's total energy consumption into individual appliances. We begin by describing intrusive methods for appliance monitoring, and highlight their intrinsic dis- advantage of poor scalability. We then move on to non-intrusive monitoring methods and introduce high frequency based approaches. However, such methods require bespoke hardware to be installed within homes since smart meter data is of insufficient granularity. Next, we discuss low frequency event based methods, although such approaches inherently consider all appliance switch events to be independent, and as a result have poor sensitivity to errors.

2.1 Intrusive Monitoring

Intrusive monitoring refers to the deployment of multiple hardware sensors throughout a household. Such intrusive methods can be further divided into direct and indirect monitoring methods. Direct monitoring methods measure the electrical characteristics of each appliance's power demand. In contrast, indirect methods measure non-electrical characteristics, from which each appliance's power demand is inferred. We give a discussion of both direct and indirect methods in Section 2.1.1 and Section 2.1.2 respectively, and highlight the reasons why neither category of methods is an appropriate solution for the disaggregation of smart meter data.

2.1.1 Direct Monitoring

This section describes three forms of direct intrusive monitoring: electrical sub-metering (Section 2.1.1.1), smart appliances (Section 2.1.1.2) and electrical probing (Section 2.1.1.3). We discuss the various costs involved with each method, and give reasons why each approach is not a suitable solution to the smart meter disaggregation problem.

2.1.1.1 Electrical Sub-metering

Electrical sub-metering refers to the installation of a system in which individual appliances are monitored directly using one meter per appliance. The appliance meters typically take the form of a plug-in meter or a clamp-on meter. Plug-in meters are installed by plugging the appliance into the meter, and plugging the meter into an electrical outlet. This allows the meter to both monitor the appliance and control the flow of electricity between the mains circuit and the appliance. Alternatively, clamp-on meters can be installed without breaking the electrical circuit, by attaching a clamp around a lightly insulated positive or neutral wire. The power drawn by theappliance can be calculated by measuring the electromagnetic field generated by the flow of current through the wire. The combination of plug-in and clamp-on meters allow appliances that are either plugged in to an electrical outlet or hard-wired in to the mains circuit to be monitored.

Although both plug-in and clamp-on meters allow accurate measurements to be made of the energy consumed by an appliance, they have many practical disadvantages. The significant cost and time required per installation are often cited as reasons why this approach is impractical to deploy for a large user base [11],[18],[19]. Therefore, the use of electrical sub-meters for appliance monitoring will not be considered further in this work. We now discuss smart appliances as an alternative form of direct monitoring.

2.1.1.2 Smart Appliances

Smart appliances can be used to self-report their energy consumption to a central hub, therefore circumventing the issue of installing additional monitoring appliances. Such smart appliances would therefore need to be fitted with a wireless enabled energy monitoring module. However, older appliances would need to be either replaced or retrofitted in order to self-report their energy consumption. Replacing every domestic appliance is clearly prohibitively expensive, while retrofitting appliances incurs the same disadvantages as appliance sub-metering. The turnover of domestic appliances is generally quite slow, as most appliances can only be expected to be replaced if the old appliance is faulty. Therefore, it would take many decades for most appliances to be replaced through this cycle. This is way beyond the 2020 target for the roll out of smart

meters in the UK (Department of Energy & Climate Change, 2009), and as a consequence smart appliances will not be considered as a complete solution to the non-intrusive monitoring problem.
It is worth noting that both smart appliances and NIALM systems could cooperate. In such a scenario, each smart appliance could report its energy consumption to the NIALM system. The NIALM could then subtract each smart appliance's power demand from the household aggregate power demand prior to performing disaggregation, therefore simplifying the disaggregation task for the remaining appliances. However, this would require the standardisation of energy consumption reporting that does not yet exist. Having ruled out a complete deployment of smart appliances, and shown that a partial roll out would only slightly simplify the disaggregation problem, we now discuss disaggregation via electrical probing.

2.1.1.3 Electrical Probing

Electrical probing is the process of transmitting a signal into a household's electrical circuit and using features extracted from the returned signal to classify the loads currently in use [12]. Electrical probing is not intrusive in the physical sense (as with sub-metering), but is instead intrusive upon the household's electrical circuit. However, electrical probing inherently adds interference to the electrical circuit, which can adversely affect the power quality delivered to each appliance. As a result, energy disaggregation by electrical probing has not been reported in the literature since it was first suggested by Hart [12]. For these reasons, electrical probing will no longer be considered as a solution to NIALM in this report. Having discussed three direct forms of monitoring, we now move on to indirect monitoring methods.

2.1.2 Indirect Monitoring

This section describes three forms of indirect intrusive monitoring: appliance tagging (Section 2.1.2.1), ambient sensors (Section 2.1.2.2) and conditional demand analysis (Section 2.1.2.3). We discuss the various costs involved with each method, and give reasons why each approach is not a suitable solution to the smart meter disaggregation problem.

2.1.2.1 Appliance Tagging

Appliance tagging refers to the modification of an appliance such that a tag emits a unique signal when the appliance turns on or off. These signals are detected by a central hub which estimates each appliance's energy consumption. McWilliam and Purvis [20] demonstrate the use of transmitting RFID signals through the live mains circuit to a central recorder in order to uniquely identify appliances. However, this approach requires the customisation of each individual appliance in addition to the installation of a central signature detector. The installation time and cost per household of this method is considerable and will therefore not be considered further in this work. Having dismissed appliance tagging as a reasonable solution, we now consider the use of ambient sensors.

2.1.2.2 Ambient Sensor

Multiple wireless sensors could be used to monitor feeds other than electricity in order to disaggregate premises-level power measurements into individual appliances [21], [22]. Examples of such sensors include audio, temperature and light sensors, which could be used to monitor both human behaviour and appliance operation. As with appliance tagging, this approach requires the intrusive installation of multiple sensors throughout each household, and therefore will not be considered further in this work. Since ambient sensors do not provide a suitable solution, we now discuss the use of conditional demand analysis.

2.1.2.3 Conditional Demand Analysis

Unlike other approaches requiring the installation of additional meters, conditional demand analysis (CDA) uses only a household's billed energy consumption. In addition, CDA also requires information about the consumer, household and weather. Such data from many households are analysed using a multivariate regression technique to learn the typical contribution of individual appliances [23]. CDA can then be used estimate the energy consumption of domestic appliances. Again, the lack of appliances installation makes this a non-intrusive approach in the traditional metering sense. However, CDA requires a large participant base, in which each participant must complete a detailed questionnaire; an example of a social intrusion. Furthermore, CDA does not capture unusual cases which are not accounted for by such questionnaires, e.g. a day when the washing machine has been run three times. Therefore, this method will not be considered further in this work.

Having ruled out intrusive monitoring methods as appropriate solutions to the problem of smart meter disaggregation, we now turn to non-intrusive methods.

2.2 Non Intrusive Monitoring

We consider non-intrusive appliance monitoring as the disaggregation of a household's appliances from the total load through a single point of measurement. In this section, we first give a brief history of the field, before describing non-intrusive methods based on high frequency data, which are capable of disaggregating household energy consumption to a high degree of accuracy. However, smart meters are not capable of reporting such high frequency data, and as a result such methods would require the installation of additional hardware to each household. This is followed by a description of non-intrusive methods which make use of low frequency data, in which we highlight a direction of research with the potential to solve the smart meter disaggregation problem.

2.2.1 History

Hart [12] first introduced the field in his seminal work, which outlined a set of principles NIALM algorithms should follow, a taxonomy of potential approaches, a set of features that such approaches could use to discriminate between appliances and the use of finite state machines to model appliances. Although Hart didn't pursue the problem of energy disaggregation much further, the concepts introduced in this work have since been consistently echoed by the literature.

Hart and Bouloutas later published an a theoretical method by which two appliances could be disaggregated via an approach based on the Viterbi algorithm [24], although it was never applied to energy disaggregation in practice. This work laid the foundations for what would become known as non-event based monitoring, which describes the application of probabilistic temporal graphical models to the area of energy disaggregation, as discussed later in Section 2.2.3.3.

The field of energy disaggregation drew limited attention over the subsequent 15 years, until it received renewed interest as a result of decreasing hardware costs, expanding connectivity infrastructure, and most recently, national roll outs of smart electricity meters. Such factors have contributed to the formation of a community of researchers to establish the field in its own right.

Since 2011, a number of public data sets designed specifically for energy disaggregation have been released, 4 international workshops have been held (EPRI EU NILM 2016, EU NILM 2015, NILM 2012, EPRI NILM 2013), and a toolkit has been released enabling the empirical comparison of various energy disaggregation algorithms [25]. We now go on to describe developments in the field which rely on high frequency sampling.

2.2.2 High Frequency Sampling

We consider high frequency sampling as the measurement of electrical characteristics at a rate greater than 1 Hz. By sampling the current and voltage thousands of times per second, various electrical features can be calculated. Most commonly, real and reactive power are calculated from current and voltage readings over one cycle of the alternating current waveform. Hart [12] first showed that such features could be used to discriminate between appliances of equal apparent power demand. Since, much research has applied various classification methods to such electrical features in order to disaggregate appliances [26], [27], [28], [29].

In addition, Hart [12] also demonstrated that certain appliances generate non-sinusoidal waveforms, and consequently create significant low-order odd harmonics. Such harmonic content of an aggregate load can also be used to accurately discriminate between appliances [30], [31], [32]. Furthermore, [33] have shown that appliances' switch mode power supplies create frequency peaks at non-harmonic frequencies, referred to as switching frequencies. Appliance disaggregation based on switching frequencies can achieve even greater accuracy than harmonic based disaggregation, since switching frequencies are often unique to each appliance while harmonic frequencies are always multiples of the power line's fundamental frequency.

Last, [34] have shown that the high frequency voltage noise generated by appliances as they switch on or off can be used to identify individual appliances. Since such transient voltage noise typically lasts only a few microseconds, these transients are unlikely to overlap, and as a result can discriminate between appliances with similar continuous power and frequency components. Furthermore, [35] have shown that a hierarchical Bayesian framework can be used to extract features which generalise over multiple transient signals from a single appliance class.

However, although smart meters typically sample a household's current and voltage internally at a high frequency, only low frequency power is reported externally by the household's smart meter. As a result, each of these high frequency based approaches would require the installation of additional hardware into each household. This would clearly violate one of the requirement of NIALM, and as a result will not be considered further in this work. We now move on to discuss approaches based on low frequency sampling.

2.2.3 Low Frequency Sampling

In contrast to high frequency sampling, we consider low frequency sampling as the reporting of household's electrical features at a rate less than 1 Hz. Smart meters belong to this category, since they will typically only report power at 10 second intervals. We now discuss low frequency methods in more detail, first covering event based methods in Section 2.2.3.1 and those based on blind source separation techniques, before giving an introduction to non-event based methods in Section 2.2.3.3.

2.2.3.1 Event Based Methods

Event based disaggregation methods aim to classify appliance switch events (e.g. a microwave turning on or off) using a set of features which can be immediately extracted from the power load. For low frequency methods, such features are generally the difference between the steady power demands before and after the switch event, and the duration of the switch event. However, since UK smart meters only report the power demand at 10 second intervals, the duration of each appliance's switch event will almost always be less than the sampling interval. As a result, the switch event duration cannot be used to discriminate between appliances, and therefore only the step change in power can be used.

Furthermore, event based approaches either consider each appliance switch event as independent, or make local classifications based on fixed previous classifications. In the first case of independent classification, the step change in power alone often does not provide enough information to produce an accurate classification. In the second case of local classifications, earlier incorrect classifications can 'lock' the algorithm into an incorrect event sequence [36].

As a result of these disadvantages, event based methods have focused only on the disaggregation of sequences of sampling rates of 1 Hz or greater [37], and have not been applied to power sequences of 0.1 Hz sampling rates as will be reported by UK smart meters. Therefore, we will not consider event based approaches further in this work, and move on to discuss methods based on blind source separation in the following section.

2.2.3.2 Blind Source Separation

Blind source separation aims to separate a set of mixtures of sources into a set of individual sources [38]. A classic example of blind source separation is that of speaker diarisation, in which multiple microphones are placed in a room containing multiple speakers, and the aim is to estimate when each speaker is speaking throughout the set of audio recordings. In the domain of energy disaggregation, the sources correspond to the appliances within a household and the mixtures correspond to electrical measurements taken at a single point of measurement. In the scenario in which smart meters are used as the measurement hardware, only a single mixture is observed (the household aggregate power demand), and as such the problem is severely underdetermined; there exist more unobserved sources than observed mixtures. This is in contrast to the typical scenarios in which blind source separation is applied, in which the number of mixtures is close to the number of sources, for example, the separation of two mixtures of three speech signatures [39]. Furthermore, blind source separation techniques are typically applied to scenarios in which little or no information is available regarding the structure of sources or the mixing process. Again, this is in contrast to energy disaggregation, in which rich prior information is available regarding the behaviour of appliances and the mixing process is known, although sub-metered data from individual appliances in each household is rarely available to directly learn the structure of such appliances.

Kolter et al. [40] proposed an approach for energy disaggregation via discriminative sparse coding, in which appliances are represented using a set of basis functions, and disaggregation is accomplished by finding a sparse set of activations which explain the household aggregate data. Crucially, the approach learns general appliance models from appliance data collected from households other than the test household in which disaggregation is performed. The authors then apply non-negative matrix factorisation to solve an optimisation problem in order to disaggregate appliances. This approach models sequential time slices independently, and as such this method is best applied to very low frequency data (e.g. data collected at 15 minute intervals). However, this approach is likely to ignore the strong dependency between sequential measurements taken at higher frequencies (e.g. 10 second intervals), and therefore will likely perform poorly when applied to the disaggregation of smart meter data in our scenario.

Dong et al. [41] applied a similar approach based on discriminative sparse coding to the disaggregation of domestic water consumption data. However, the approach suffers from the same core disadvantage; that the approach does not exploit the strong dependencies between sequential readings taken at 10 second intervals, and as such is not well suited to the disaggregation of electrical data collected by a smart meter. However, it should be noted that the authors proposed a recursive technique, in which appliances are iteratively separated from the household aggregate data. Such an approach is particularly interesting to electricity disaggregation, given the complexity of modelling a large number of potentially unknown household appliances, but the vast majority of household energy can typically be accounted for by less than 10 appliances.

The approaches drawn from the blind source separation field discussed in this section share a common disadvantage; that such approaches do not exploit the dependencies between sequential measurements, and as such will not be considered further by this work. However, it is exactly this disadvantage that motivates the study of non-event based methods in the following section.

2.2.3.3 Non-event Based Methods

In contrast to event based methods, non-event based methods do not require a separate event detection process. Instead, event detection is integrated directly into the disag- gregation model. All existing non-event based disaggregation methods use temporal graphical models to represent the event detection and disaggregation problems using a single probabilistic framework. Section 2.3 introduces the theory of relevant temporal graphical models, while Section 2.4 describes how related works have applied such models to energy disaggregation.

2.3 Temporal Graphical Models

This section introduces a class of probabilistic graphical models which address the short- comings of the event based approaches. Such probabilistic graphical models have previously been applied to a number of real world problems, the prototypical example being speech recognition [42]. Speech recognition shares a number of similarities with energy disaggregation, in that the aim is to identify the most likely sequence of discrete states (words) corresponding to a time series of continuous measurements (audio recordings).

However, with energy disaggregation, the aim is not to classify the operation of only a single appliance, but instead to classify the operation of a number of simultaneously operating household appliances given a time series of power measurements. The field of speech recognition has since expanded to address similar problems of simultaneous classifications, such as speech recognition with non-stationary noise or multiple speakers [43]. A key difference between such domains and appliance monitoring is that these domains generally consider the classification of a small number of simultaneous sources of noise or speech (e.g. 2 or 3), whereas energy disaggregation methods must be robust to large numbers of simultaneous sources (e.g. 20 or more). As a result, similar assumptions of model scalability cannot be made, and consequently solutions to speech recognition problems are rarely applicable to the problem of energy disaggregation.

2.4 Summary

This chapter has described various existing approaches to the energy disaggregation problem. We first introduced intrusive monitoring techniques, however they were dis- missed due to the requirement to install multiple sensors throughout each household. We then described a category of approaches based on the processing of high frequency data. However, such methods are not compatible with current smart meters, and would therefore require the installation of additional expensive metering hardware. We also discussed how existing event based methods could be applied to smart meter data. However, such methods assume all appliance switch events to be independent, and as a result are unlikely to provide realistic solutions when applied to 10 second power data

The following chapter describes a ICT architecture devoloped by us, where the measurements acquired by the power meters will be sent to low frequency (1 Hz) and the data are average values with respect to a sampling period set in advance in the above-mentioned appliances.

Chapter 3

System Architecture

In this chapter we present the overall architecture of the system. In the envisaged scenario, energy consumption data coming from users' homes are sent to a service provider where data are appropriately processed in order to give users detailed information about their energy consumption habits. The overall architecture, shown in Figure 2, is broken down into three main subsystems:

- *Local monitoring subsystem*: it is composed of a power meter installed at the user's home, where it measures the global energy consumption of the user (along with other energy parameters) and a network device able to communicate the measured data to the central monitoring subsystem by means of a common Internet link.
- *Central monitoring subsystem*: it is the core of the system, where all the processing takes place. It has all the software components required to process the data coming from the power meters, to execute the NIALM algorithms, to store processed data on an appropriate DBMS, and to generate a graphical data presentation for the end user.
- *User presentation*: being typically a web-based interaction, it does not require any special prerequisites on the user side allowing, among other things, to access the system wherever they may be (after a suitable authentication).

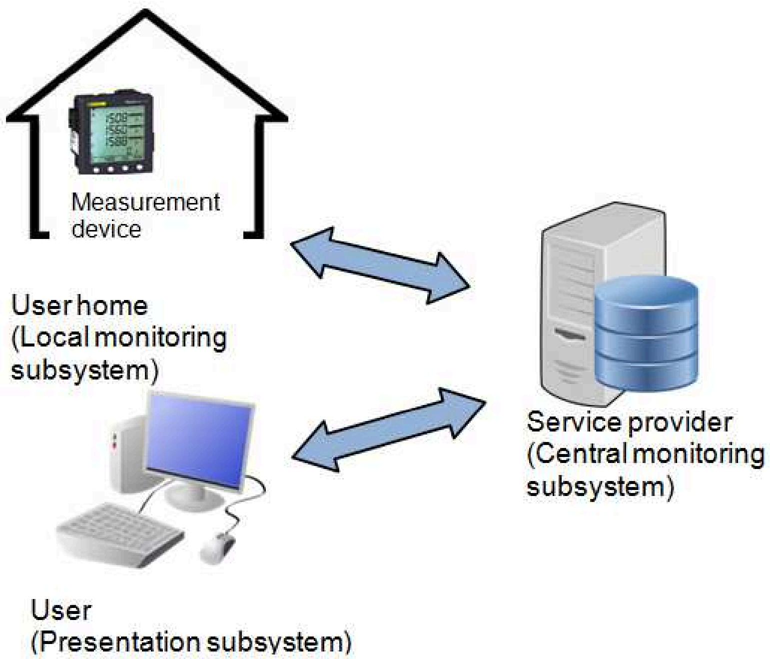


Figure 2 Overall system architecture

3.1 Local Monitoring Subsystem

In the Local Monitoring Subsystem (LMS), at the common coupling point with the public distribution system, a power meter (PM) is installed to monitor locally electrical loads. After a properly data processing, they are transmitted via the web to a central server (SMC) where an higher level processing is performed. Both data collected locally and those drawn from the central server will then be made available to the user through an appropriate platforms.
The SMC using this information, through an appropriate mathematical algorithms, named NIALM, by means of individual appliance power consumption information is disaggregated from single-point measurements, provides a feedback in such a way to make energy more visible and more amenable to understanding and control.

PM measures current and voltage and reports in real time the rms values for all three phases and neutral. In addition, PM calculates power factor, real power, reactive power, and others variables. It is also guaranteed a variation on the measurements of 0.5%. The updated frequency of the data is 1/second. The input current to the device is included in a range of values from 0 to 6 amperes, to

ensure the protection of the device is appropriate to use a TA (current transformer). The data are transferred via the RS485 port and, a Modbus RTU protocol can be used.
The device displays the following electrical parameters: voltage (V), current (I), active power (P), reactive power (Q), apparent power (S), power factor (PF), voltage and current THD.
The data captured by the PM can be classified in two types,: direct (V, I, PF) and indirect, that is processed internally by a micro-processor, (P, Q, S, THD).

The data provided by the power meter represent the inputs of the disaggregation algorithm. As in any measurement system, measurement errors have to be taken into account. These errors can impact greatly the efficiency of NIALM algorithm.

Another important aspect is data transmission. PM is built in isolated Half duplex RS-485 serial interface. The communication port setting is obtained through dedicated setup parameters. To connect to the web we use an intelligent Ethernet gateway. The gateway is used to allow a remote full control and configuration of the PM. PM allows us to be sampled at a frequency of 1 second.

3.2 Central Monitoring Subsystem

The logical architecture of the Central Monitoring Subsystem is represented in Figure 3.

It is composed of several modules providing the following features:

- *Data communication*: it is the module that manages the communication with the Local monitoring systems and deals with the store of measured data into the Raw DB. The protocol used to get the measured data is the Modbus/TCP, which allows to directly query the measurement device over an IP network.
- *NIALM module*: by means of a novel NIALM algorithm, it is able to perform a workload characterization that disaggregates the global energy consumption of the appliances. Details on the behavior and the algorithm executed by this module will be given in section III.
- *Data Management and Persistence*: it manages data persistence and controls data access for the purpose of historical data analysis and presentation to the end user. Three different databases are used:

- *Raw DB*: it stores the raw data coming from the local monitoring systems; these are the input data for the NIALM module;
- *Processed DB*: it stores the results produced by the NIALM module; it also contains intermediary information generated by the system's business logic;
- *User configuration management*: this module contains users related data, such as information about their appliances and their configurations, users' feedback, and so on.
- *Business logic*: it is the module containing the logic needed to process data and generate the useful information to be presented to the home user;
- *Presentation layer*: this layer is responsible for presenting the home user with the required information. It is equipped with a simple and effective web interface. Through the web interface users may also provide "feedbacks" regarding their consumption habit, thus proactively interacting with the system in order to improve the behavior of the NIALM algorithm.
- *Billing system interaction*: this module manages the interaction with the billing system of the energy provider. It retrieves information about the provider's cost of energy and transforms the users' data related to energy consumption (measured in Watt) into an actual cost.

  A simplified view of the information model used within the software architecture is represented in UML class diagram depicted in Figure 4.

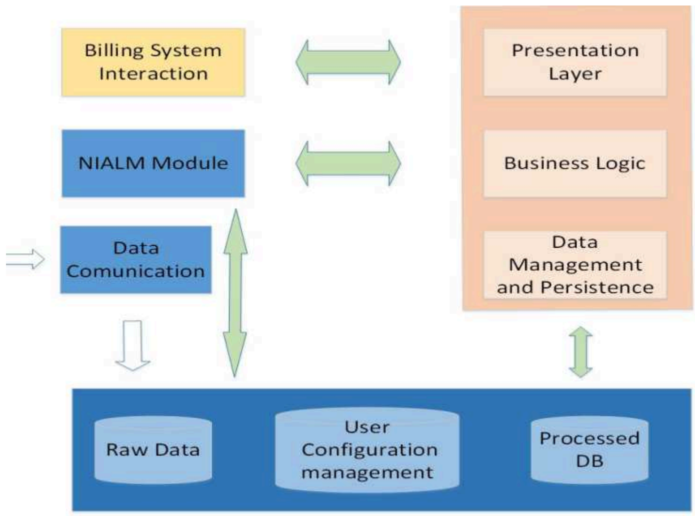


Figure 3 Software architecture

In the diagram entities, mutual relationships and relationships' cardinalities were modelled; entities-roles are briefly explained in the following:

- *User*: it models the information associated to the user (authentication information included).
- *Power Meter*: this entity models the measurement device installed at the user's home.
- *Device*: this entity models a generic device consuming energy (appliance). It is characterized by some energy parameters that constitute its *signature load*.
- *Category*: devices are grouped into categories, in order to allow for simple filtering and compact visualization by users.
- *Device energy consumption*: this entity stores all the consumption data associated to a device obtained from the NIALM algorithm.
- *State*: it represents the state of the device.
- *Global raw data*: this entity is needed to store the global consumption data and associated measurements produced by the Power Meter and locally stored into the RawDB.

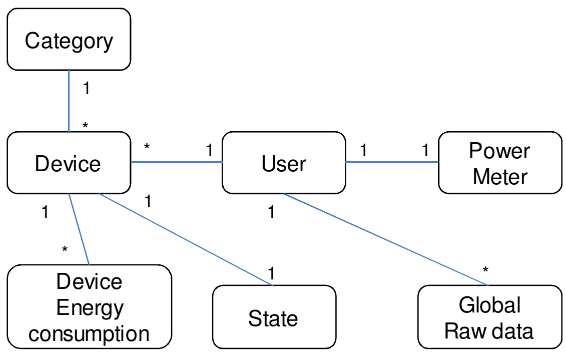


Figure 4 Information model

3.3 Presentation Subsystem

The intention of our research is to develop hardware and software solutions for providing advanced tools to electric utilities users (mainly residential) not only to optimize their energy consumptions but also to make them an active part of future Smart Grids.

In this way the users can have access to information and tools, in such a way to become aware of their energy consumptions habits. Further it will be possible to use information on the energy price and tariffs, and to reach many objectives such as: increasing the reshaping of load curves (i.e. redirect the electrical loads to the hours of low network usage), improving efficiency and reducing the electricity bill.

The main idea of the proposed architecture is to exploit as much as possible the commitment of the users by means of active interaction with a dedicated web site. The user plays an active roles in the whole process in many steps. Firstly, the user is required to communicate the list of appliances connected to the main power supply along with some information about their electrical characteristics.

The more complete the information provided by the user during this phase, the more accurate the results provided by the NIALM algorithm. However, since we are aware that not only the user may not be able to provide precise and complete data about his appliances, but also the results of NILM algorithm are affected by errors (see chapter 4), an interactive phase has been designed. So, during the normal operation of the system, the user can be engaged in two different kinds of interactions, i.e. feedback, named respectively “Check Status” and “Verify Signature” (see chapter 5).

Chapter 4

The NIALM Concept

Non-intrusive methods are intended to offer installation simplicity and the ability to distinguish important load changes measurements at a central monitoring point [44]. Researchers at MIT were the early users of this technology to monitor residential and commercial end-user loads [12].

4.1 Structure of the NIALM Algorithm

In the proposed method, the operating states of given appliance are determined by identifying moments where its active and/or reactive power consumption measurements change from one nearly constant or steady-state value to another one. These steady-state changes usually correspond to the appliance either turning on or turning off and they are characterized by a magnitude value and a sign (in active and/or reactive power ($\pm\Delta P$, $\pm\Delta Q$)).

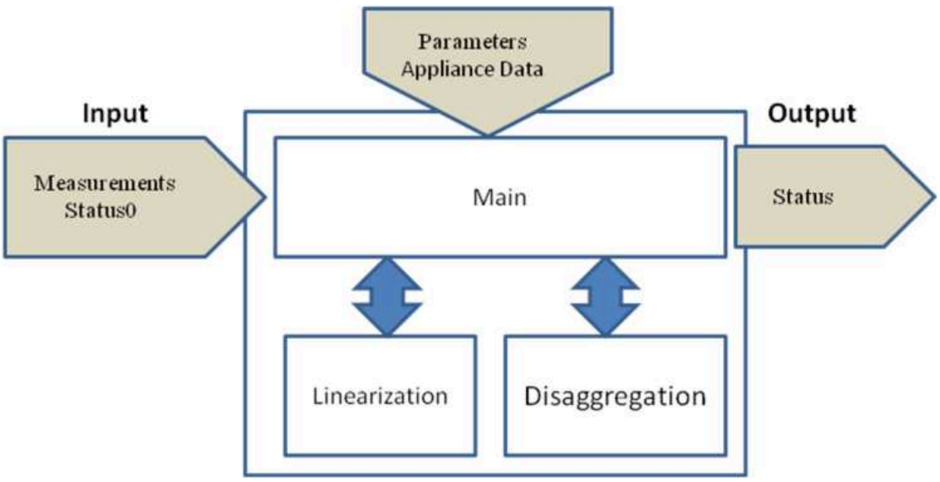


Figure 5 Overview diagram of the NILM algorithm

In Figure 5 the main structure of the NILM algorithm is presented. The output is the status of each appliance, whereas the input can be classified as follows:

- *Measurements*: it contains the information coming from the local monitoring subsystem (e.g. voltage, current, active and reactive power, total harmonic distortion and so on).
- *Status0*: it is the daily initial status of all appliances.
- *Appliance Data*: it contains information about type and signature of loads, mainly rated active (P) and reactive (Q) power. It is worth mentioning that the initial information about loads can be obtained only from data in nameplates or in technical documentation provided by the manufacturer.
- *Parameters*: the NILM algorithm needs some parameters that are somehow correlated with the set of appliances.

The NILM program is written in the Matlab programming language and its behavior is described by the flowchart depicted in tha paragraph 4.2. Measurements have to be preprocessed before entering the NILM algorithm: this data treatment aims to smooth out small or erratic variations in the total demand signal. This preprocessing consists mainly in P and Q linearization.

It performs also filtering of spikes and low frequency noise. Filtered signals consist of piecewise line where each positive or negative demand drop is more likely to represent a significant ON or OFF signal.

The algorithm compares each change in the global P signal to each rated power appliance. If the magnitude of the change is greater than the rated power of an appliance the change is attributed to that appliance. If there are more than one candidate that can generate the same power drop, a new comparison in change in the Q global signal is applied. So as matter of fact, the proposed algorithm uses only power analysis to characterize the signature of electric appliances.

Although this method achieves an estimated detection accuracy of about 70%, it is possible to improve these results by an effective interaction with customers.

4.2 Algorithm Description

In order to decompose the total load into its components, we need the model of each appliance and its main characteristics. The appliances can be modeled by a power constant load.

Some appliances contain more than one electrical load (for example, a front loader washing machine contains a heating element and a motor – each component drawing very different loads).

The system use a power meter for voltage (V), current (I) and active and reactive power (P, Q) measurement. The data for developing the algorithm were collected at 1s intervals in the laboratory IDRILAB (DIEEI-University of Catania).

The algorithm is able to detect the consumers based on changes of active and reactive power consumption (hereinafter, we name it as P and Q Disaggregation Algorithm –PQ-DA) of two states (on-off) and multi-state appliances.

This algorithm has been tested experimentally at the Power system Laboratory of University of Catania, where the load signature (LS) of certain appliances that might be found in a domestic environment have been performed.

Different appliances have been monitored, such as a light bulb, a laptop, a refrigerator, a radio a coffee machine and a microwave. The appliances are modeled as on/off appliance that consume constant power at a single steady state. In reality, coffee machine loads depend on the water volume, the refrigerator have a second power state corresponding to defrosting.

Due the pretty constancy of the voltage over the day, in the disaggregation algorithm have not been introduced a procedure to cope with it. Preliminary data analysis consisted of observing how the electric demand of each appliance varies over time and then comparing it to the total electric demand. For example, the refrigerator has a long low rectangular profile with a relatively large initial spike and a short period of decreasing demand at the end of the switching event. Each appliance event is characterized by an ON signal, an OFF signal and a duration.

The NILM program is written in the Matlab programming language and it is descript in Figure 6. The input are: an Excel data files (Appliance data.xls) which contain a series of information: the number of the appliance, the active nominal power (P), the reactive nominal power (Q) and a file with the information coming from the measurement system. This information can be preprocessing before enter in NILM algorithm.

These algorithms are called signal preprocessors (linearize P, linearize Q) because they filter the total demand signal before appliance load recognition is used. The preprocessor program aims to smooth out small or erratic variations in the total demand signal. The final filtered signal consists of distinct rectangular shapes where each increase or decrease in demand is more likely to represent a significant ON or OFF signal. To eliminate small or erratic variations it is necessary to set up: ΔP, ΔQ, and the related ΔT (time interval). If the variations ΔP, ΔQ is greater than a fixed value (Tolerance, that depends on the appliance) and this variation continues for a time interval greater than ΔT a steady-state value is detected. The filtered signal from the preprocessors are the input for the NILM algorithm. The algorithm compares each change in the P total signal to each appliance operating range (coming from Appliance data.xls). If the magnitude of the change is within the range of an appliance operating level, that is, the mean demand plus or minus two standard deviations, the change is attributed to that appliance.

Therefore, assuming that there are no coincident ON or OFF signals, at least 95% of the ON and OFF signals should be recognized. If an increase is within both two different appliances range, a new comparison in change in the Q total signal has been applied. In Figure 6 algorithm’s flowchart is presented.

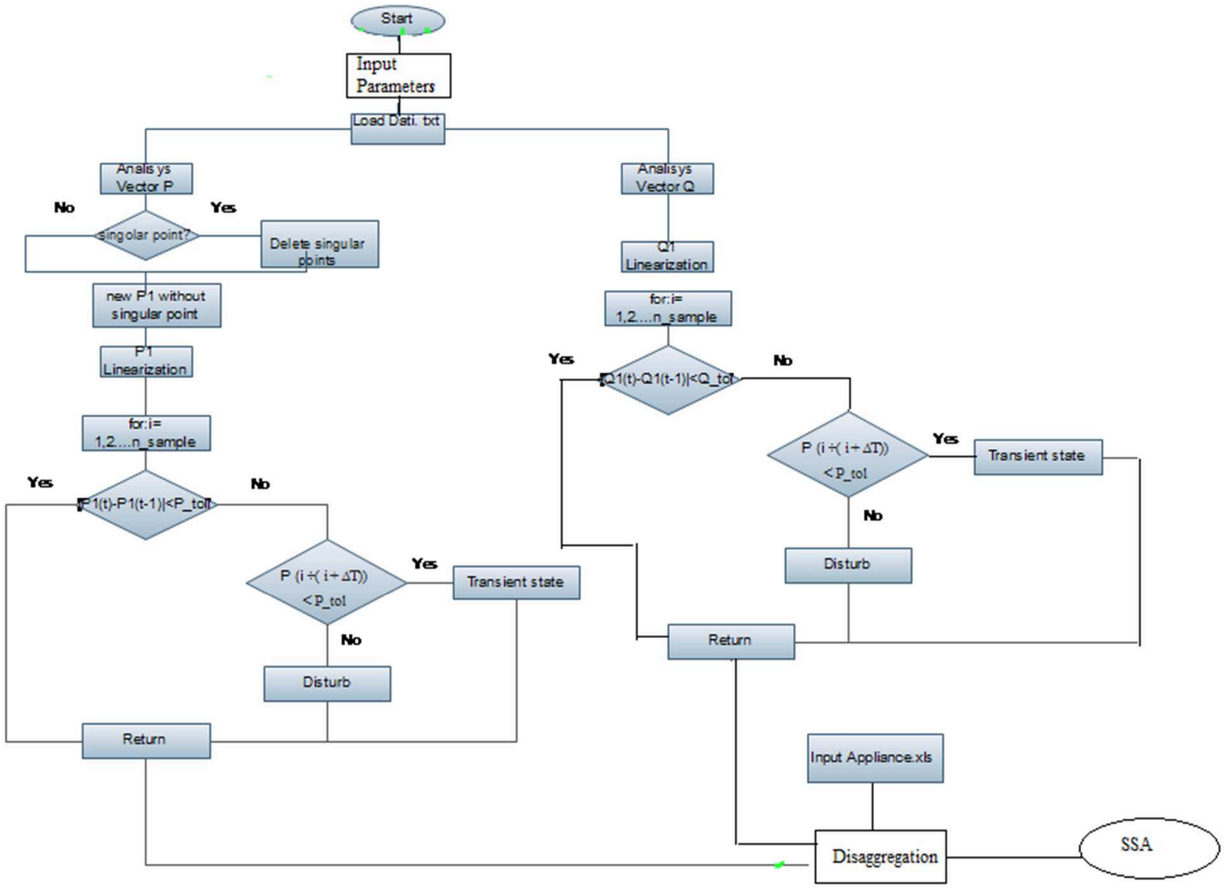


Figure 6 Flowchart of the proposed NILM algorithm

4.2.1 Experimental Results

The measurements of active and reactive power coming from the developed system have been linearized and the results have been reported in Figure 7 and Figure 8.

Of course the results of linearized process depend on the parameters values. Specifically, they are the minimum step of P and Q, named respectively P_tol and Q_tol, and the minimum duration of the variation of the considered variables (e.g. P and Q), named Delta_T, that can be considered as a switching on and off of an appliance. Of course, as far as the Delta_T tends to zero the precision of the linearization increases, but, on the other hand, it does not allow to distinguish adequately a transition from noise in the variables.

This condition affects greatly the process of disaggregation. The samples have been recorded every second. Figure 9 shows the results for four appliances: lamp, personal computer, refrigerator and radio.

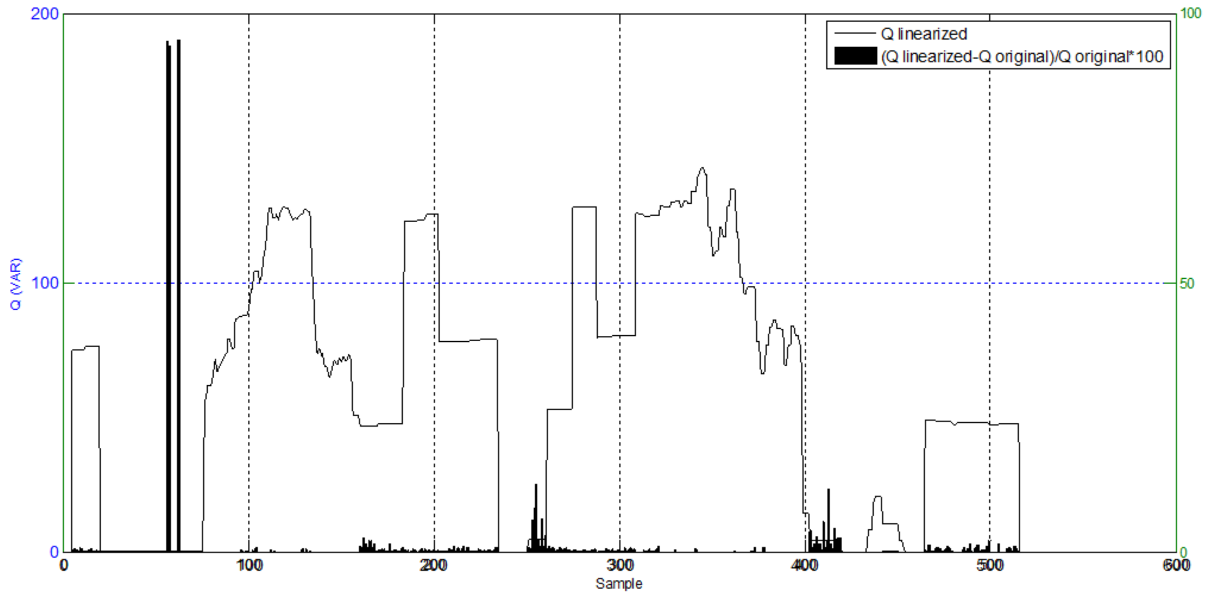


Figure 7 Reactive Power: measurements and percentage error

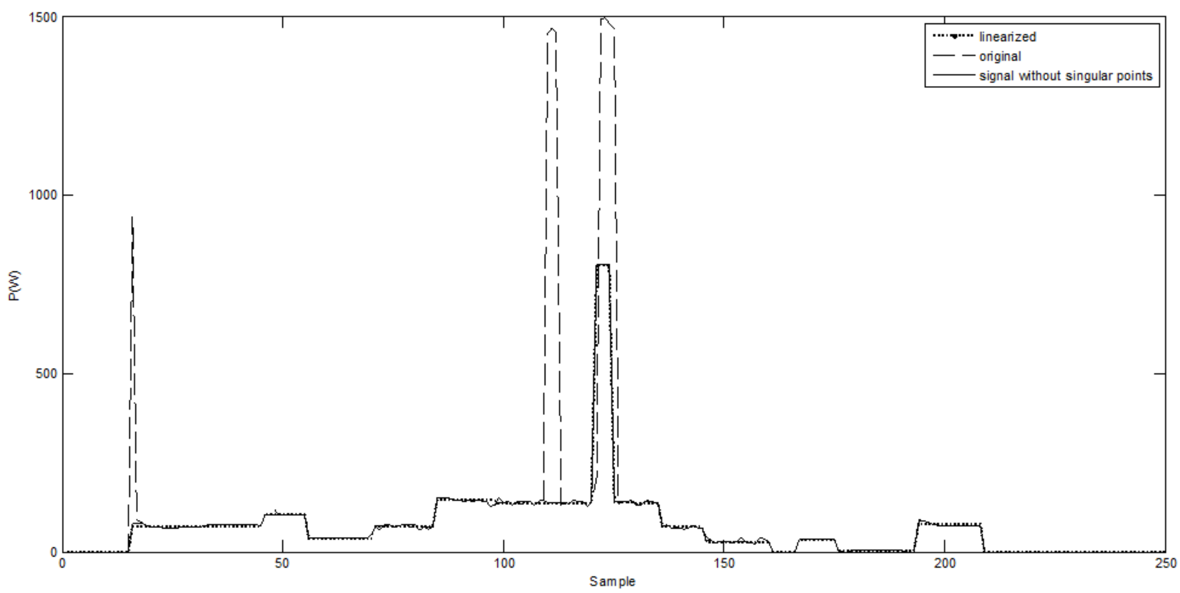


Figure 8 Active Power: measurements, corrected, linearized

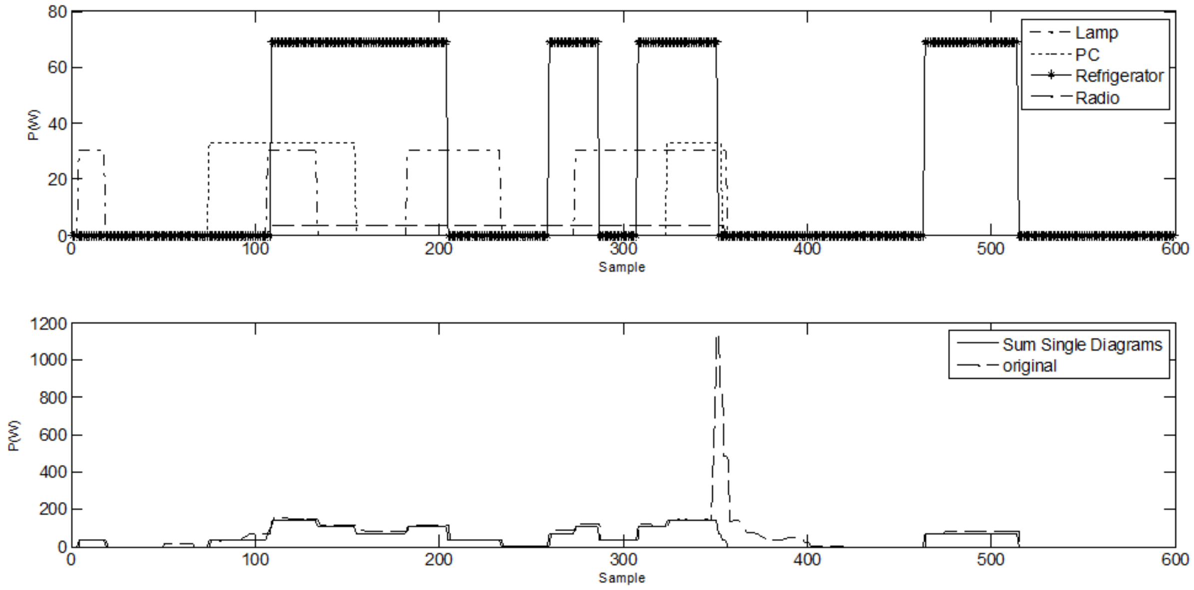


Figure 9 Load curve: single appliances (above), total load (below)

From the analysis of Figure 9, the disaggregation algorithm seems to perform adequately but some problems have arisen, it is worth mentioning the treatment of the switching on spikes of some appliances (e.g. refrigerator and coffee machine). In fact in the linearization process they are almost always eliminated but in this way important information for disaggregation process are lost.

In a realistic NIALM implementation, the users have to provide data input to the disaggregation algorithm, these pieces of information needed for load signature are reported normally on labels stuck on the appliances.

Specifically the user is required to communicate the list of appliances and for each appliance the following data: typology (on/off, multistate, so on), nominal electrical characteristics (P_n, Q_n) and some other information related to the time of use (e.g. daily or weekly switching frequency and duration of the operating time).

This input procedure can imply some problems related to the completeness and correctness of the information provided by the user.

As matter of fact, the efficiency of PQ - DA is impacted negatively by the following issues:

- Quality of the input: information about appliances are missing or incorrect.

- Difference between measured power and rating of the appliances (due to, for example, the effect of the variation of the voltage).
- Operational complexity: two or more appliances are switched at the same time (e.g. simultaneously one appliance turns on and another turns off).

Before implementing PQ-DA in a realistic context, it is crucial to test its performances numerically by means of the generation of random load profiles, named Global Load Profiles – GLPs, according to specific constraints in such a way to reproduce most of the situations that the disaggregation algorithm has to face in a real context.

4.3 Load Profile Generation

To evaluate quantitavely the performances of the proposed disaggregation algorithm, two different efficiencies have been defined. Further to understand deeply, the different causes of inefficiency of NIALM algorithm it has been decided to generate randomly load profiles (more details about this program are reported in the 4.4 paragraph). So in the following these profiles are cited specifically as generated (lowercase ‘g’), when the profiles come from random generation, whereas they are called disaggregated (lowercase ‘d’), if they come from NIALM algorithm.

The first efficiency is based on the different, sample by sample of the generated and disaggregated power. In (1) only the active power efficiency is shown, but the reactive power efficiency has a similar definition.

$$\eta_p = \frac{\sum_{i=1}^{n_s} \left| P_{gd}(i) - P_{gg}(i) \right|}{\sum_{i=1}^{n_s} P_{gg}(i)} \tag{1}$$

Where:

i is the ith sample;

n_s is the number of samples;

P_{gd} is global disaggregated load profile;

P_{gg} is global generated load profile.

Due to compensation phenomena it can be happen that η_p can be very high (e.g 80% ÷ 90 %), but the profiles of the single appliance can be wrong. This is the reason why another efficiency has been introduced, that is η_s. It is reported in (2).

$$\eta_s = \frac{\sum_{j=1}^{n_a} \left\{ \left\{ \frac{1}{n_s} \sum_{i=1}^{n_s} \left[xor\left(SSA_{g,j}(i), SSA_{d,j}(i) \right) \right] \right\} * P_j \right\}}{\sum_{j=1}^{n_a} P_j} \tag{2}$$

Where:

j is the j-th appliance;

n_a is the number of appliances;

P_j is the rated power of jth appliance

$SSA_{g,j}(i)$ and $SSA_{d,j}(i)$ are logical values, that indicate the states of the appliance j at time i.

The logical operation xor, allows to have a value equal to one when $SSA_{g,j}(i)$ and $SSA_{d,j}(i)$ assume the same value (that can be either 0 or 1).

There are many factors that significantly affect the efficiency of the disaggregation algorithm, such as: measurement accuracy of power meters (normally ± 1% f.s. and + - 0.25 f.s.), electrical characteristics of the customer's appliances, and, finally it is related to actions that can fulfill the users.

As far as measurement accuracy is concerned, the Italian technical standard UNI-CEI ENV 13005, recognizes that "the result of a measurement is only an approximation or estimate of the value of the measurand and is therefore complete only when it is accompanied by a statement of the uncertainty of that estimate".

Related to the appliances electrical characteristics there are two important aspects that impact greatly the effectiveness of disaggregation: the first one is connected with the nominal power of appliances. In fact when in a domestic dwelling, there are appliances whose rated powers are too small or close each other, considering a given power threshold (e.g. 4 W), the efficiency tends to decrease. The second one is linked with the simultaneous switching on and/or off of two or more appliances.

In this context two factors that characterize a given group of appliances have been defined, that is KG_P and Dg_P.

$$KG_P = \frac{P_{\min}}{Lim\_DeltaP} \qquad (3)$$

Where:

- P_{min} is the smallest value among the rated power of appliances belonging to a given group;
- Lim_ Delta P is a parameter, i.e. 4W, it is a threshold for the detection of the switching events.

$$Dg_P = \min\left\{\left|P_i - P_j\right|\right\} \quad where\, i, j \in \left[1, 2, ..., n_a\right] \qquad (4)$$

Dg_P is the smallest value among the values obtained from the differences between the rated power of i-th and j-th appliance.

Finally it has been introduced another parameter, named global number of simultaneous switching – GNSS. Given a certain periods of time, for example a day, it is equal to number of sample characterized by simultaneous switching, n_{ss}, by the number of the involved appliances n_{ca}.

$$GNSS = \sum_{i=1}^{n_{ss}} n_{ca}(i) \qquad (5)$$

4.4 Numerical analysis

The robustness of the disaggregation algorithm has been tested both numerically and experimentally. Specifically, in this section, the function, that randomly generates different and controlled load profiles is described. The main parameters that need to be set to generate a load demand profile are: the number of the appliances (n_a) and the number of samples (n_s), as well as deltaT, which is the minimum number of samples between a switch on and a switch off of an appliance. In this numerical analysis these parameters assume the following values: n_a = 10, n_s = 500 and deltaT = 2.

For sake of simplicity, in this numerical analysis, only ON-OFF appliances are chosen, whereas in the proposed NIALM algorithm also multi-state loads are considered.

Finally the load factors, defined in (3) and (4), are calculated considering the following parameters: Lim_ Delta P=4 W and Lim_Delta Q=20 VAr. It is worth to noting that in the group A there are two appliances (e.g. 2 and 9, written in bold in Table I) whose rated active and reactive power differ by less than the respective tolerance (Lim_ Delta P=4 W and Lim_Delta Q=20 VAr).

Table 1 RATING OF APPLIANCES AND GLOBAL INDICES

	A: 10 W < P < 100 W			**B: 10 W < P < 1000 W**		
App.	**P(W)**	**Q(VAr)**	**cos(ϕ)**	**P(W)**	**Q(VAr)**	**cos(ϕ)**
1	86	21.6	0.97	804	201.5	0.97
2	**64**	**99.8**	0.54	228	304	0.60
3	***17***	25.8	0.55	318	230.2	0.81
4	25	15.5	0.85	468	213.2	0.91
5	29	32.1	0.67	***104***	30.3	0.96
6	86	114.7	0.60	295	292.6	0.71
7	91	153.5	0.51	746	782.6	0.69
8	50	46.8	0.73	599	174.7	0.96
9	**62**	**87.08**	0.58	327	176.5	0.88
10	77	30.4	0.93	894	181.5	0.98
KG	4.25	0.77	**-**	26	1.52	**-**
Dg	0	1.70	**-**	9	1.78	**-**

Figure 10 shows an example of a generated global load profiles, active and reactive power, where: n_a is equal to 10, the number of samples, n_s, is 500. A numerical calculation of KG and Dg has been performed referring to the load profiles shown in Figure 10, and the results are reported in Table 1. The value reported in red is P_{min} in (5).

Considering the case (A) (seeTable 1 and Figure 10 A), the graphical results of the disaggregation algorithm, described in (see par. 4.2) are reported in Figure 11, where the global profile generated, named P_{gg}, is shown in red and the global profile coming from the application of the disaggregating algorithm, named P_{gd}, is shown in blue. The disaggregation efficiencies defined in (1) and (2) assume the following values: η_p = 75.08 % and η_s= 71.6 %. Such values are justified by the presence of two appliances (2 and 9).

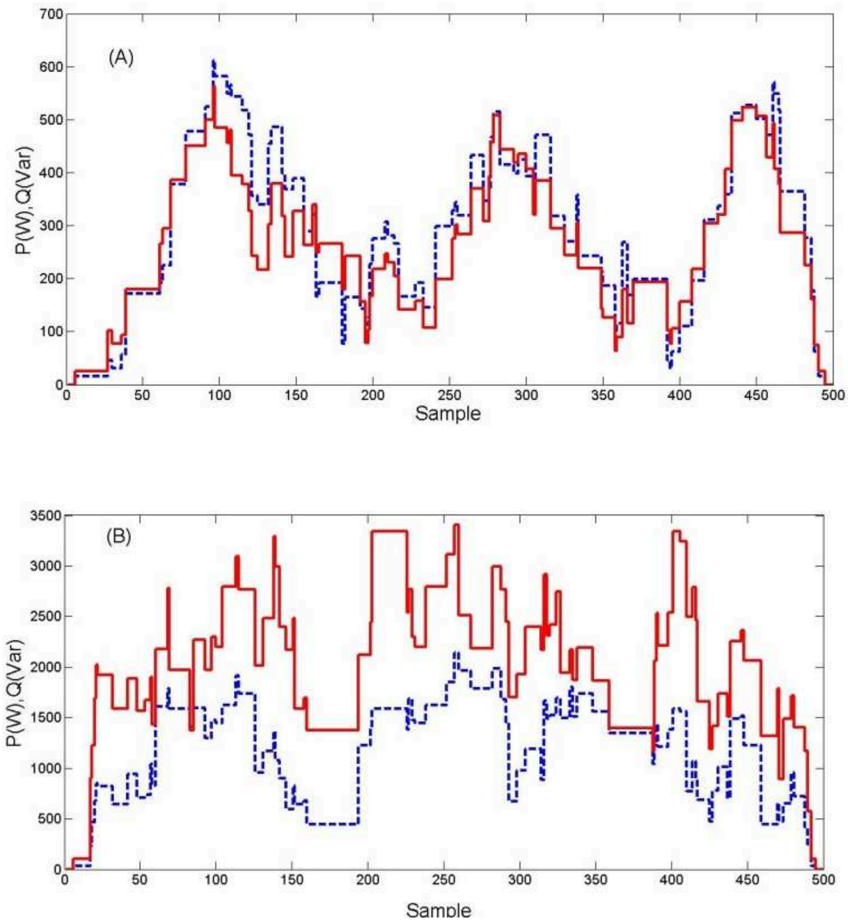


Figure 10 Global generated load profiles: active power (solid red line) reactive power (dashed blue line): A) P=10÷100 W, B) P=10÷1000 W.

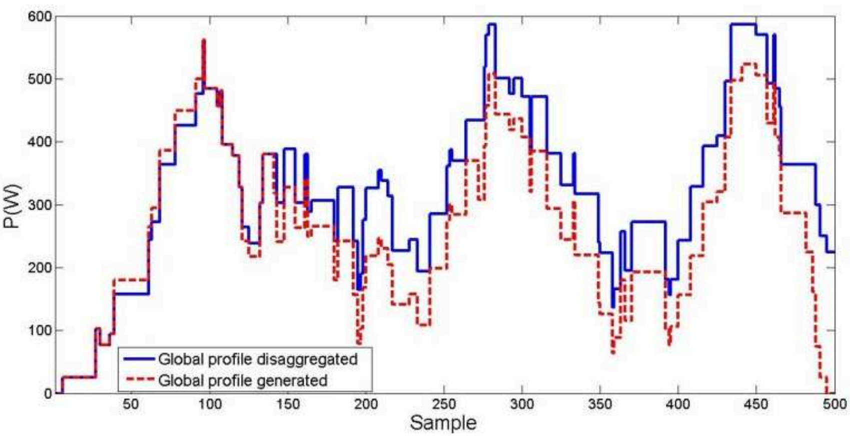


Figure 11 Global load profiles Pg: Pgg – generated (dashed red line) and Pgd (solid blue line).

Figure 12 depicts an example of comparison between the generated (SSA_g) and disaggregated (SSA_d) status profiles of two appliances (2 and 9); since the appliances are of ON/OFF type, the status can be 0 (OFF) or 1 (ON).

Considering the two cases A and B in Table 1, Figure 13 shows the cumulative relative error derived from the progressive difference of P_{gg} and P_{gd}. The curves highlight that an initial disaggregation error progresses very rapidly.

Often changes in the derivative of these curves happen, they can be explained by means of compensation phenomena due to the presence, for instance, of two appliances that have P and Q ratings very close.

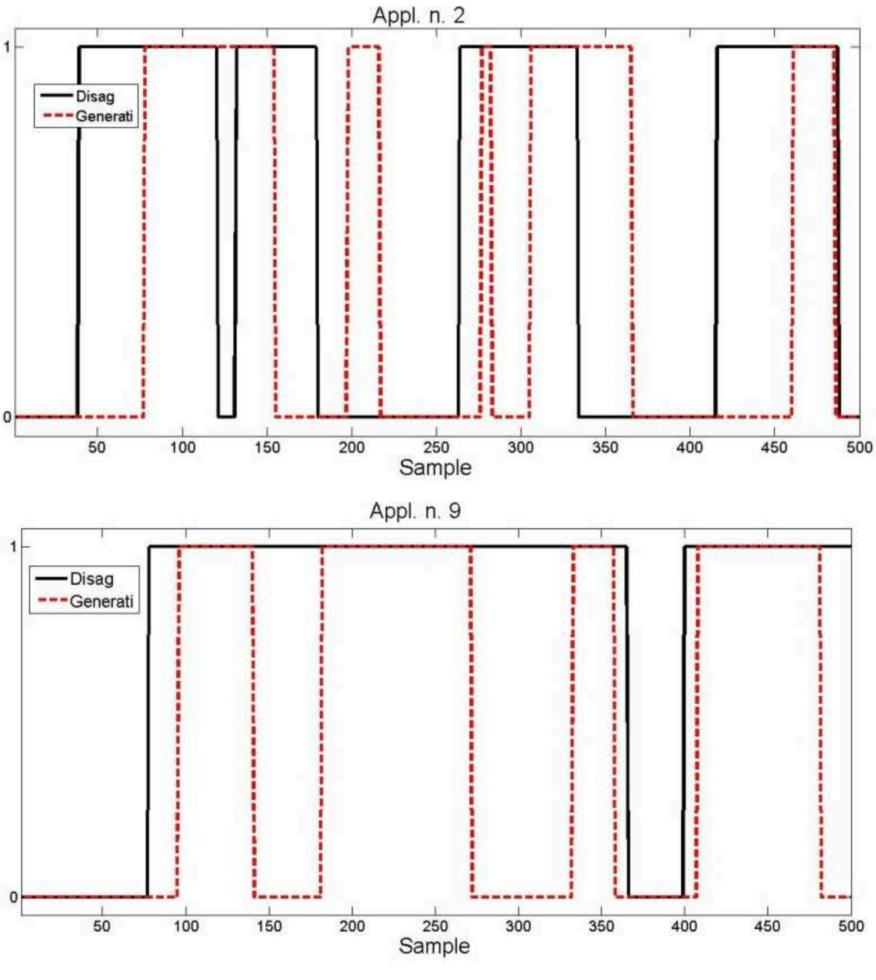
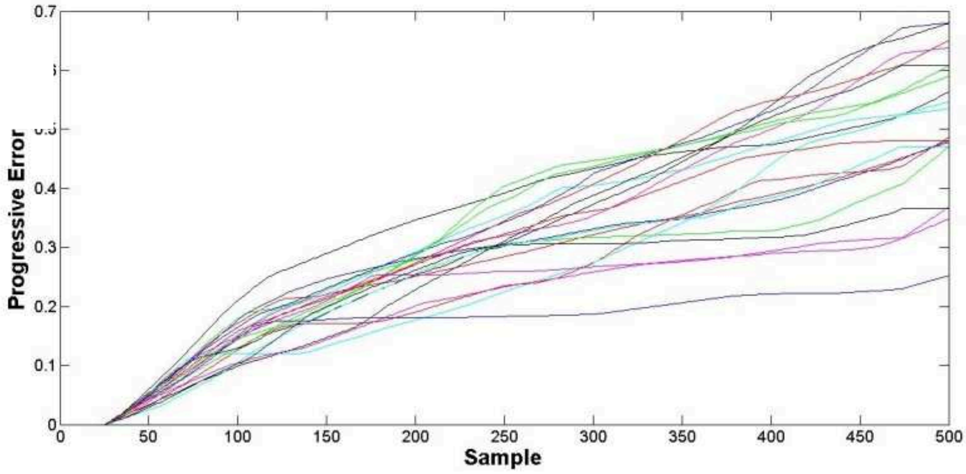


Figure 12 Graphs of the states of the appliances 2 and 9: SSAd - disaggregated (solid red line) and, SSAg - generated (dashed black line).

To evaluate how the disaggregation algorithm works with different set of appliances, represented by the two indices D_{gP} and KG_P, twenty sets of appliances have been generated and the global profiles disaggregated. Figure 14 a) and b) the η_P and η_S disaggregation efficiencies varying with respectively D_{gP} and KG_P considering 20 groups of appliances, randomly generated, that range among 10 W and 1000 W.

(A)



(B)

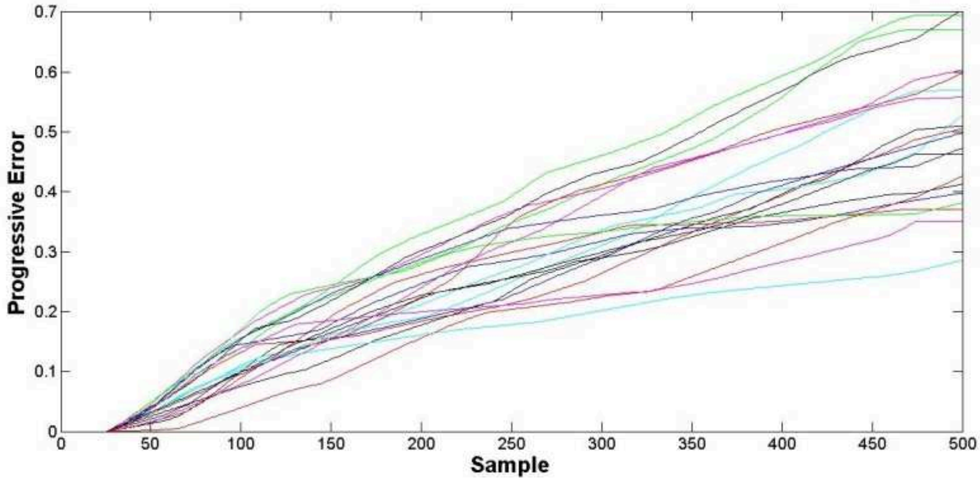
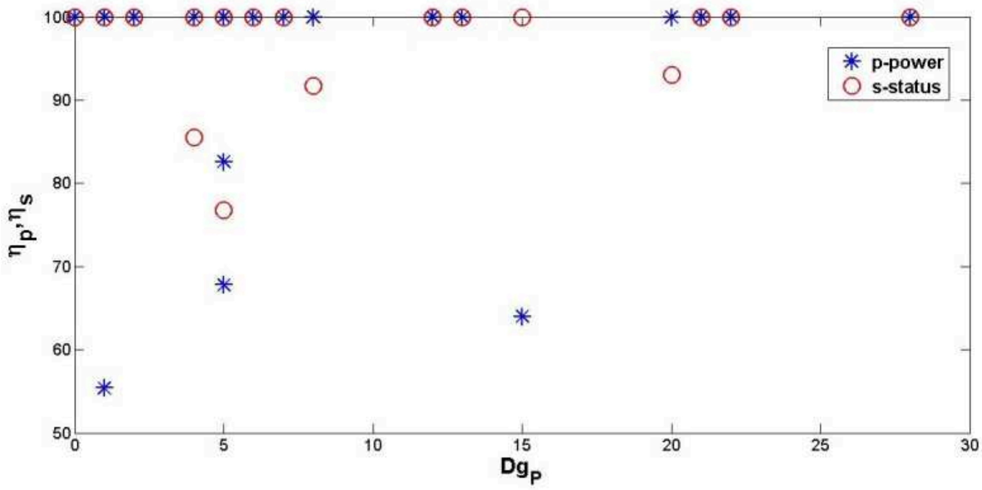


Figure 13 Cumulative relative progressive error: A) appliances into the range 10÷100 W and B) appliances into the range 10÷1000W.



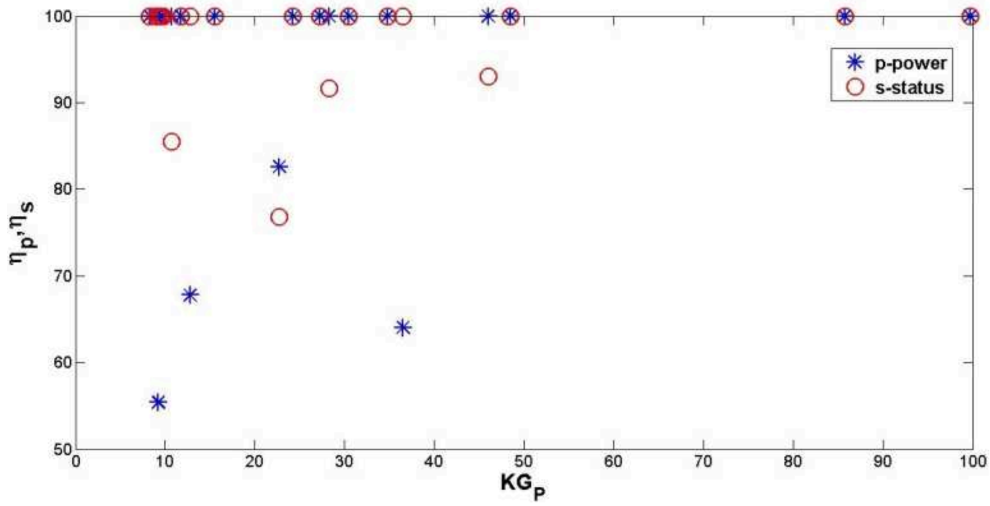


Figure 14 ήp ands ήs disaggregation efficiencies for appliances into the range 10÷1000 W: a) varying with DgP and b) varying with KGP.

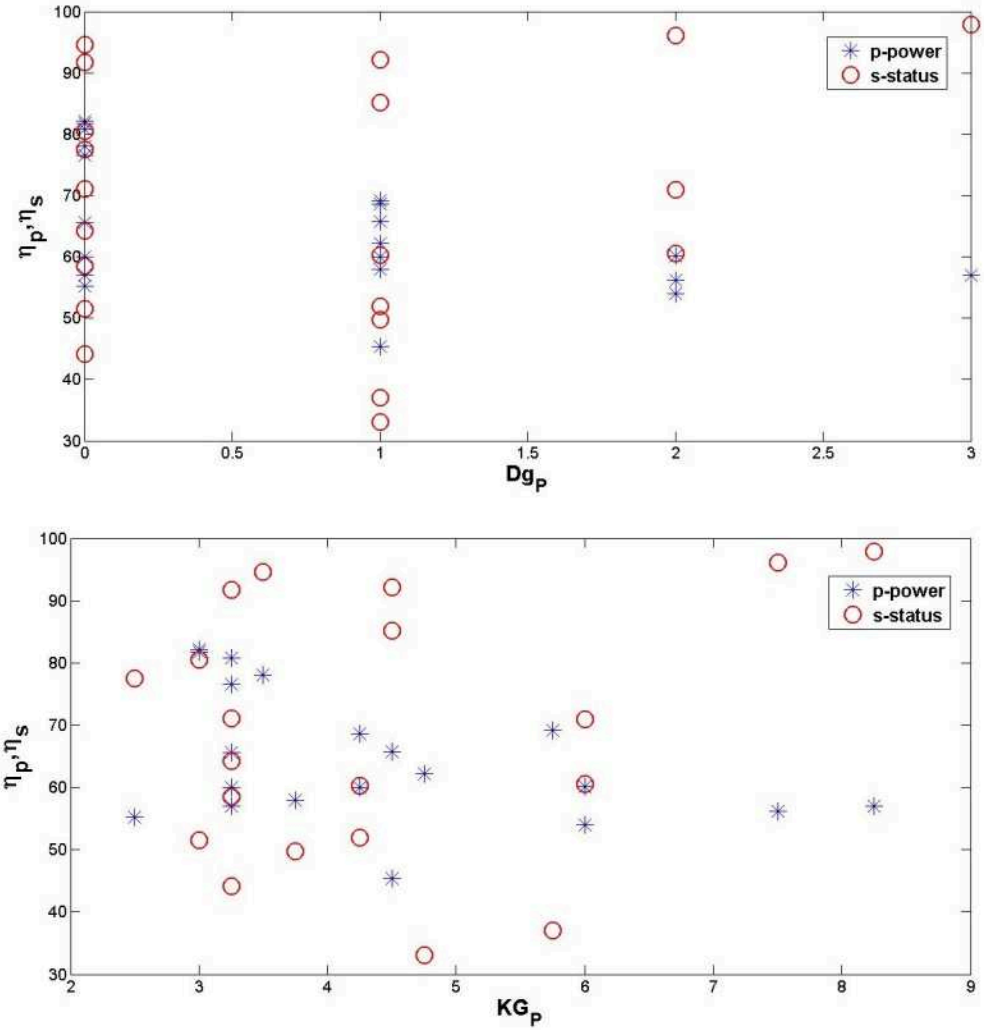


Figure 15 ήp and ήs disaggregation efficiencies for appliances into the range 10÷100 W: a) varying with DgP and b) varying KGP.

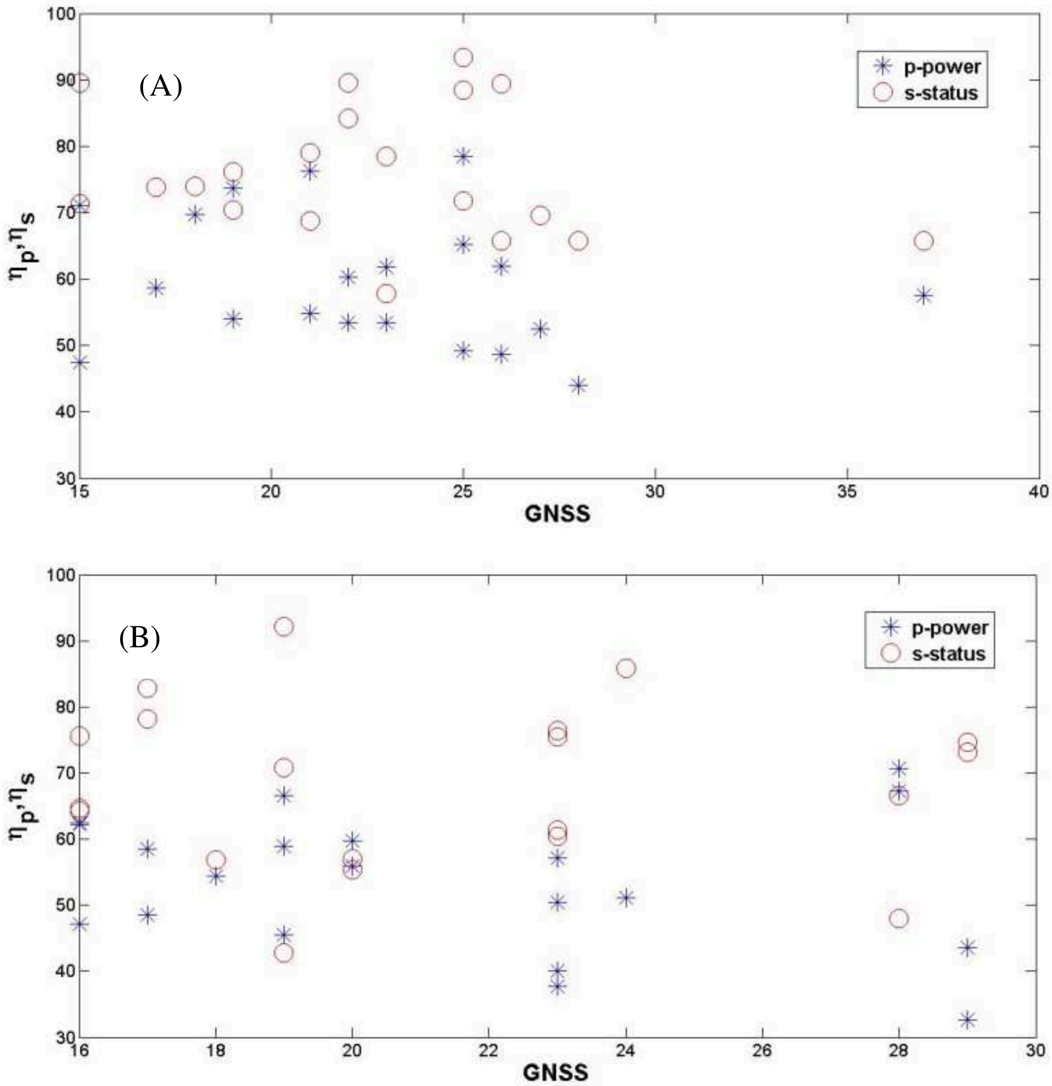


Figure 16 Disaggregation efficiencies varying with GNSS for appliances into A) the range 10÷100 W and into B) the range 10÷1000 W,.

We note that when the generated values of the rated power are below the threshold are varied, so it is clear that the values, obtained by disaggregation, are less than 90%. Then, we have increasing the range of nominal power, so the cases in which the differences between the powers are below the threshold decrease significantly, obtaining a percentage of disaggregation at 100%. Whereas Figure 15 a) and b) shows the results about 20 groups of appliances, randomly generated, that range among 10 W and 100 W. Considering the case A) and B) of the Table 1, Figure 16 shows how the simultaneous switching influences both status and power efficiencies.

In Figure 17 c, a GLPg of both active (solid line) and reactive (dashed line) power is shown. These curves have been built starting from the status profile of two appliances (App1 (Figure 17 a) and

App2 (Figure 17 b)). The rated powers of App1 and App2 are, respectively: $P_{n,1}$=28 W, $Q_{n,1}$=30 VAR and $P_{n,2}$=30 W, $Q_{n,2}$=60 VAR.

The two vertical lines, CS1 and CS2, show respectively the switch on and off, of both appliances, whereas the third line, SS1, shows a simultaneous switching; in fact, at the same time App1 switches on and App2 switches off. It is worth noticing that the variation of the active power ΔP is equal to – 2W, so it is smaller than ΔP_{min} (that has been set equal to 4W), so a disaggregation algorithm based only on active power measurements cannot detect this transaction. On the other hand, the variation of the reactive power ΔQ is equal to – 30 VAR, so it is greater than ΔQmin (that has been set equal to 20 VAR), so it can be detected by PQ-DA.

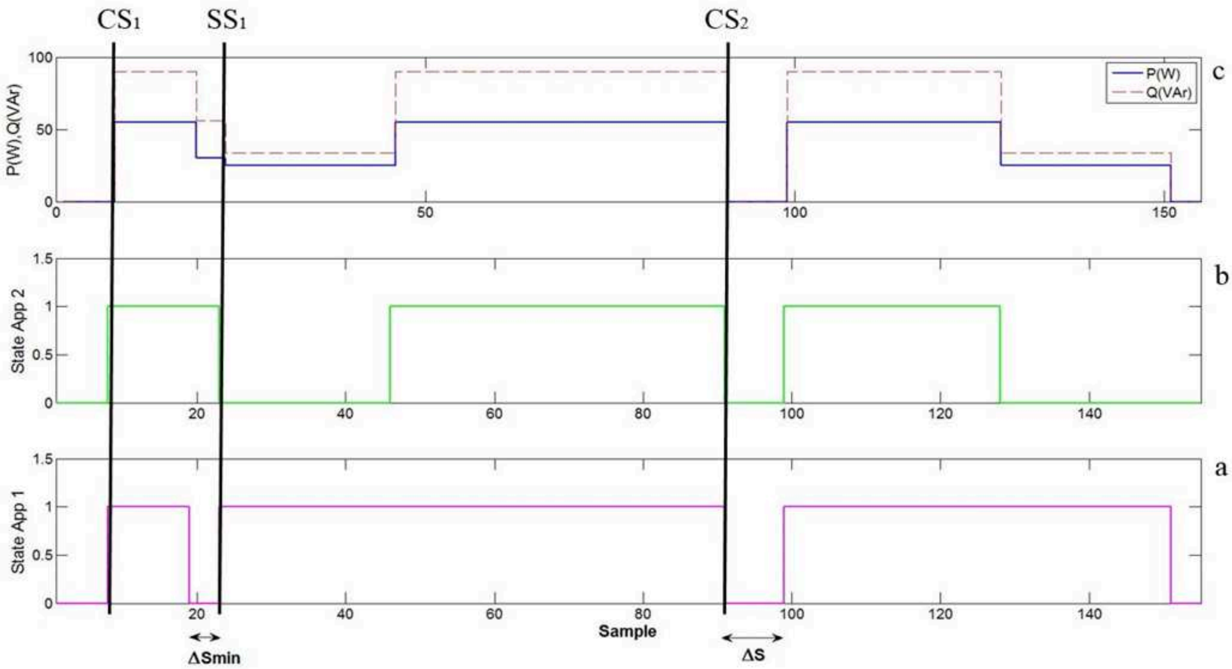


Figure 17 Example of construction of a GLPg (c) starting from the status profiles of two appliances: App1 (a) and App2 (b)

4.5 The effects of noise on disaggregation

The tests described above have used (automatically) generated profiles that were not measured in practice; in fact, the presence of noise affected the entire disaggregation process.

In order to create simulations that are closer to a real scenario, we decided to add a white noise with zero mean to the generated signals.

For the NIALM systems, the noise has a disruptive influence because it affects the algorithm's ability to recreate the profile and to discern the states of the individual appliances, thus finally changing their efficiencies.

4.5.1 Noise definition and analysis of the different causes

The noise can be defined as any abnormality that introduces artifacts in the input data.

In addition to purely electrical noise, its definition includes also:

- Uncertainty of the measurement device
- Loss of data synchronization between the readings and the disaggregation algorithm; (In this case the algorithm find some samples of which he does not know what is going on);
- Errors in the data transmission between the measurement device and the device processing data;
- Appliances that the algorithm cannot recognize because it has not been included in the database;
- Appliances whose power consumption is different from the nominal one, and is therefore not recognizable;
- Standby appliances, where the overall power consumption caused by individual contributions can reach power levels comparable with those of an on-line apparatus.

Based on this considerations, we can define the noise as the difference between the measured power value (aggregated) and the total power value given by the disaggregation [45].

In other words, it can be defined as the portion of aggregate energy for which it is difficult to find a suitable match with the values of the database.

$$noise = P_t - \sum_{m=1}^{na} P_t^{(m)} \tag{6}$$

Given the high number of factors that, in the end, will compose the overall noise, it is important to specify in advance, whether the results refer to conditions with or without noise.

In a situation where noise is present, we should determine its percentage:

$$\% - NM = \frac{\sum_{t=1}^{ns}\left|P_t - \sum_{m=1}^{na} P_t^{(m)}\right|}{\sum_{t=1}^{ns} P_t} \tag{7}$$

To perform the disaggregation in the presence of noise, we should establish a proper limit value that sets a threshold between the noise and the electric signal.

With a high threshold, we may restrict the noise impact, but we lose all the transitions characterized by a less variation in the power output on the value chosen as a threshold (Figure 19). On the other hand, a very low threshold involves the recognition of each event, but with the risk that the noise will be interpreted as a fictitious change (Figure 18).

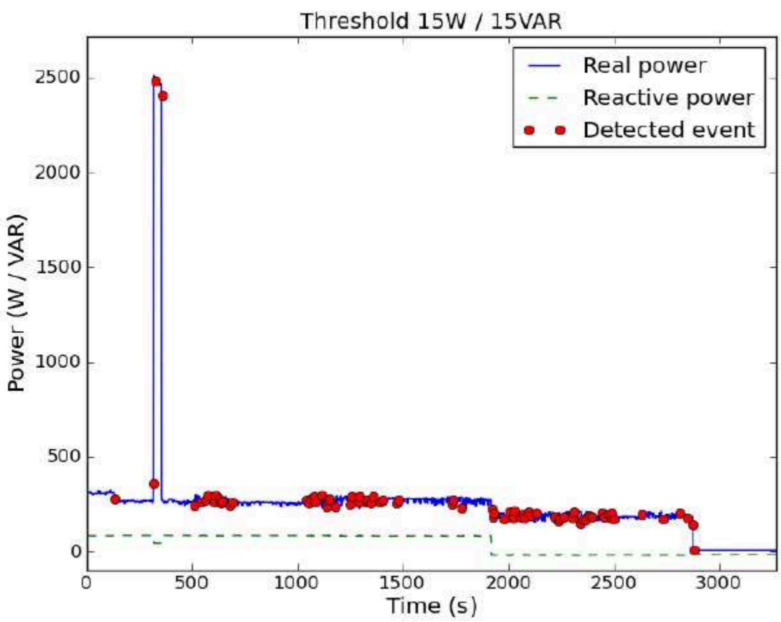


Figure 18 Load Curve: using a threshold 15W/ 15 VAR

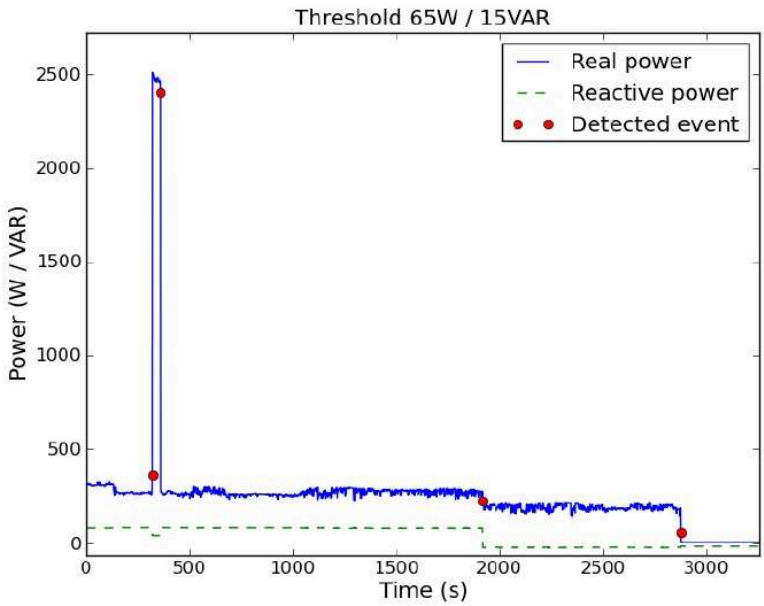


Figure 19 Load Curve: using a threshold 65W/ 65 VAR

With a limit sets to 65 W (see Figure 19) , events are uniquely identified, implying that everything happening under the threshold will not be recognized and then labeled as noise.

The establishment of the value to use as threshold should be made on a set of considerations that depends on the appliances' set, the quality of signals and the type of algorithm used.

It is worth noting that the algorithms based on the PQ mapping are only limited by the risk of losing the ignitions of appliances that have a power value lower than the threshold.

For the algorithms that use a recognition based on the profiles waveforms, a too high threshold value would result in the loss of information inherent to the shape, making impossible the identification of the status of a specific appliance.

In the literature, we can notice that the value used for the threshold are very different (ranging from 20W [46] to 100W [47]). In order to choose the threshold in the most appropriate way, it is better to refer to the working conditions rather than set a value a priori.

4.5.2 Efficiency and noise

The presence of noise leads to a reduction of the efficiency indexes η_s and η_p.

Due to an unpredictable nature, it is not possible to detect a unique correlation between the noise level (regarding power) and how it affects the efficiency. We can also note a deterioration in performance but, is not possible to have a quantitative estimate, due to the difficulties to analyze phenomena that affect the validity of the results.

To try to get an idea of how this influence occurs, we can refer to the average values that provide an estimate of the performance. To simulate the actual conditions, we generated a white noise of 10 dB amplitude that has been multiplied by a factor ([2, 5 or 10]) to obtain different power levels, while preserving the same shape (Figure 20) .

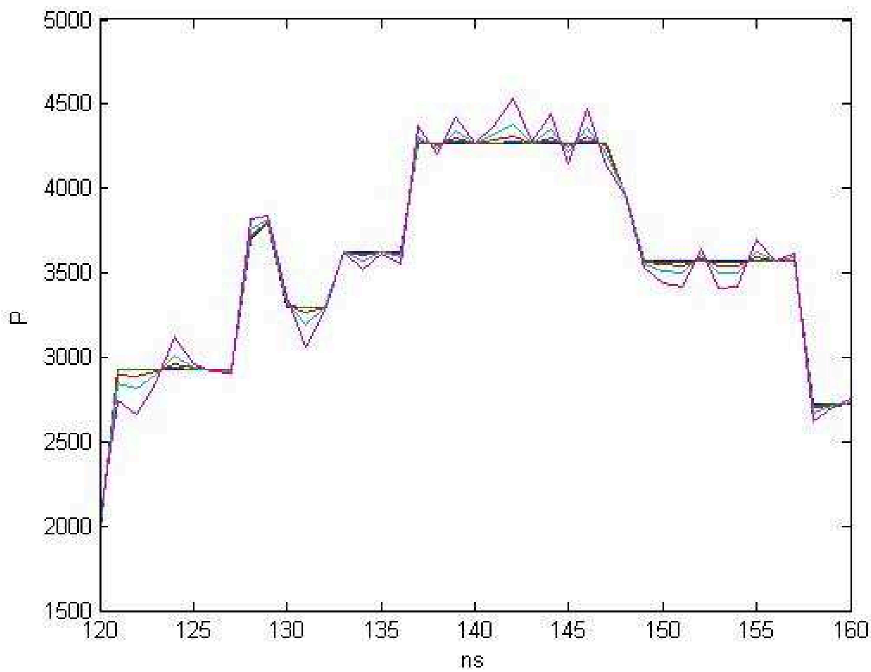


Figure 20 Global generated load profiles with different values of withe noise

To verify how the algorithm reacts to the presence of noise we generated a profile to which increasing values of noise are added. In cases where the signal with noise is disaggregated without any processing, we obtain a predictable decrease of the efficiencies η_s and η_p (Figure 21).

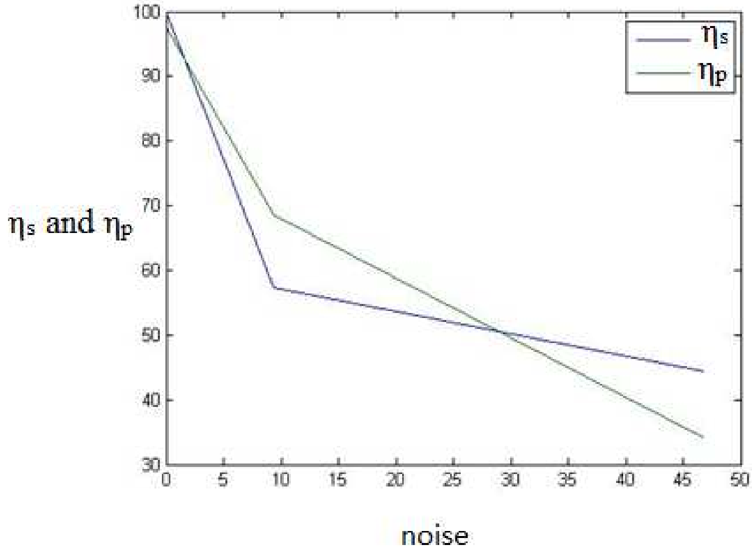


Figure 21 ηs and ηp disaggregations efficiences varying with noise

To improve the effectiveness of the algorithm we can proceed in two ways: raising the threshold for the events determination (Lim_ Delta P) or linearize.

4.5.3 Lim_ Delta P variation in ideal conditions

To examine how the Lim_ Delta P variation has an effect on efficiencies η_s and η_p, we chose different configurations of the appliances, characterized by various $D_{gP,Q}$ and for each, we generated 50 random profiles. Each of these has been disaggregated, and the effectiveness determined.

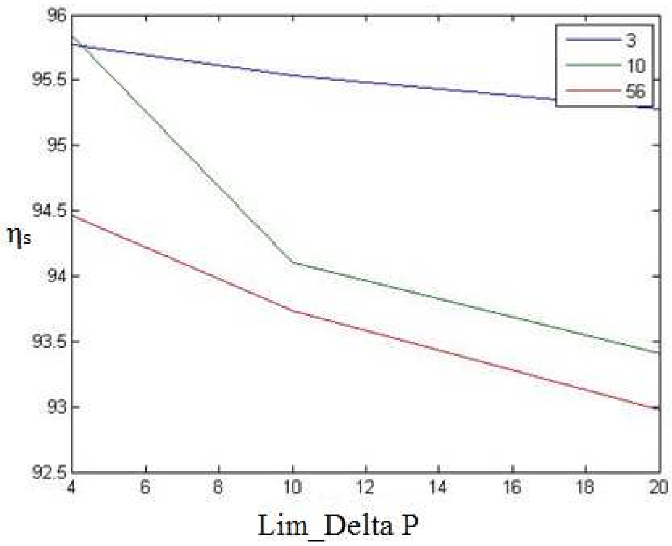


Figure 22 ηs disaggregation efficience varying with Lim_ Delta P and varying D_{gP}

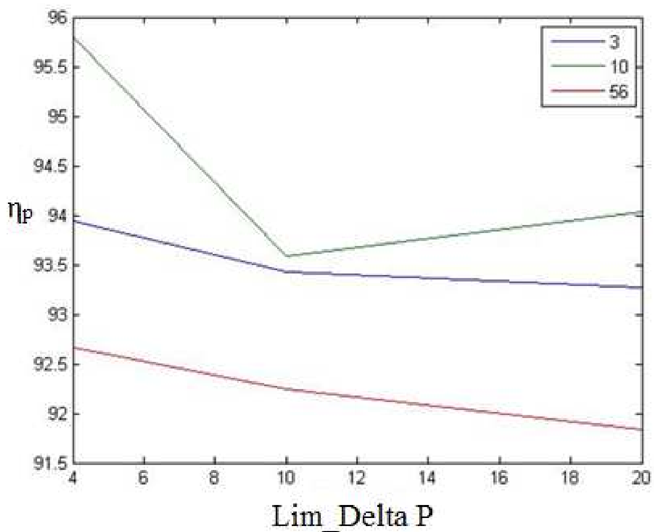


Figure 23 η_P disaggregation efficience varying with Lim_ Delta P and varying D_{gP}

The two figures (Figure 22 and Figure 23) have been obtained by referring to the average values. As expected we can see that the increase of Lim_ Delta P can result in a lowering of the efficiency.

The use of the average values gives only a qualitative idea of the trend of the two indices; in practice, we notice that the correlation between the efficiencies and the Lim_ Delta P is strictly connected with the profile type and with the power of the individual transitions, rather than with the set of appliances.

For example, if the profile does not contain transitions in which the power is less than the value of Lim_ Delta P, the values of the two indices will remain constant.

To investigate possible correlations between the efficiencies, the Lim_ Delta P and D_{gP} are used in 3D representations to look for any peaks (both positive and negative) of the efficiencies.

From the figures (Figure 24 and Figure 25) we notice as in ideal conditions (no noise), the variation of D_{gP} and Lim_ Delta P does not affect the efficiency significantly.

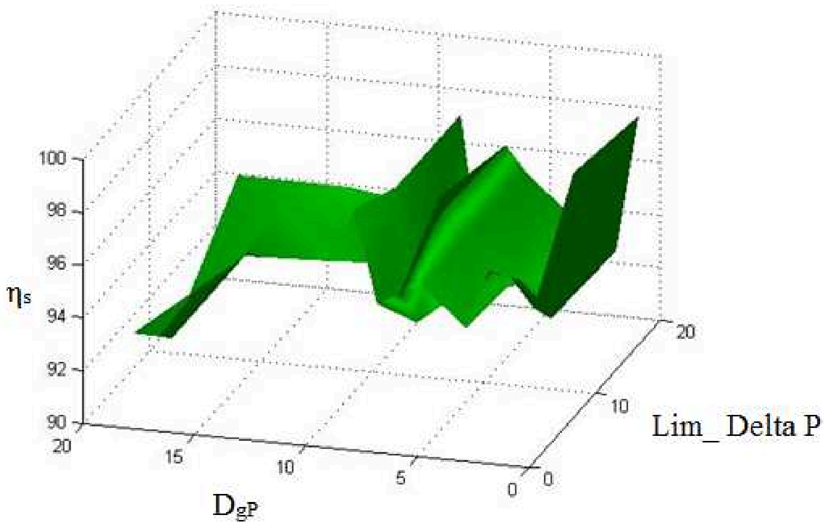


Figure 24 η_s varying with Lim_ Delta P and D_{gP}

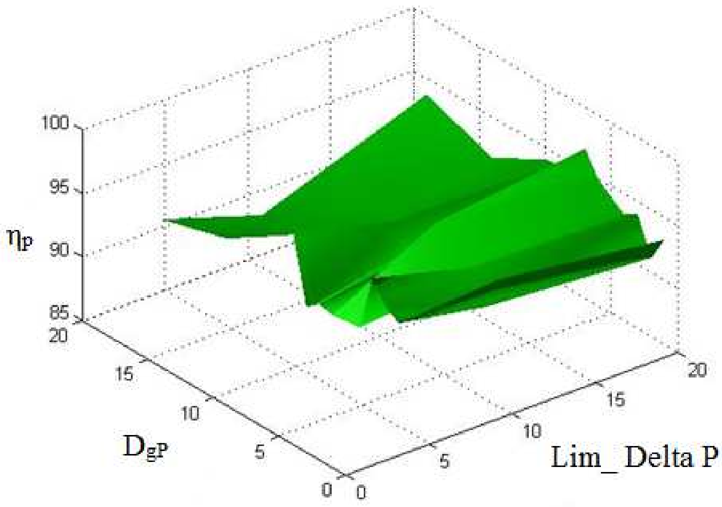


Figure 25 ηp varying with Lim_ Delta P and D_{gP}

On the other hand, if the profile is combined with the noise, from the tests we can notice that the increase of the threshold results in an improvement of the disaggregation process and therefore of the efficiencies.

The higher the noise level, the greater the benefit that it yields from the use of a higher threshold (Figure 26 and Figure 27).

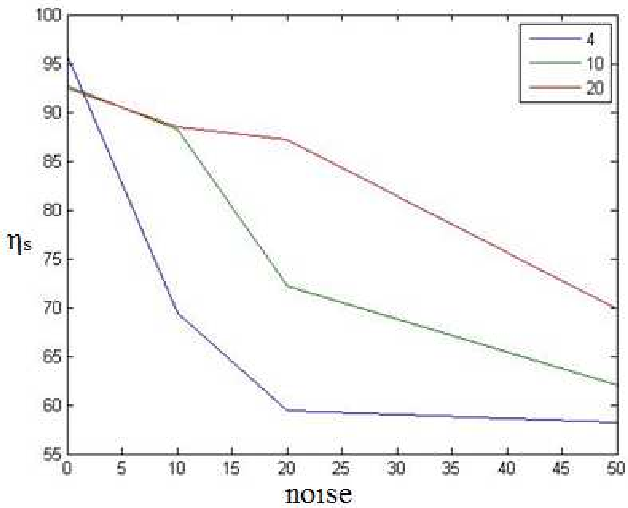


Figure 26 η_s with varying noise level, and with varying Lim_ Delta P

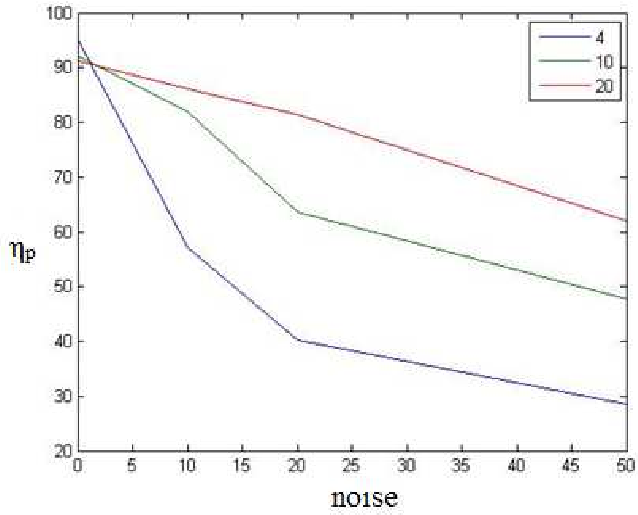


Figure 27 η_P with varying noise level, and with varying Lim_ Delta P

Analyzing of the figures (Figure 26 and Figure 27) it is observed that, even in the presence of noise, an increase of Lim_ Delta P, results in an increase of the efficiencies.

In fact, if the increase of the threshold value makes it impossible to identify the transitions whose powers are lower than this value, an increase commensurate with the requirements allows eliminating the effects of noise while preserving the significant transitions.

As we defined for the performance indices, in particular, η_S, we have that the transitions involving a higher power value have a greater weight. To verify that, we generated 100 profiles affected by a noise of 10 dB and then disaggregated with three different values of the Lim_ Delta P (4, 10 or 20 W]. The value of 20 W is not excessively high, in fact in the literature we can see higher values as well (up to 100 W).

In this scenario, a similar value is useful to see how the algorithm reacts to the noise and the threshold variation. From the analysis of the data in the Table 2 we can see that in the presence of a noisy profile, it is verified that the disaggregation undergoes the beneficial effect of a higher threshold.

Table 2 MEAN VALUES OF H_S AND H_P WITH VARYING LIM_ DELTA P

Lim_ Delta P	η_S mean	η_P mean
4	70.15	65.19
10	86.87	84.34
20	89.43	88.67

The use of a larger Lim_ Delta P may be useful in cases where the user is unable to provide accurate feedback. In these circumstances, we can use a higher threshold to try identifying the most significant transitions.

4.5.4 Signal linearization

The signal linearization is another possible solution to the electrical noise problem.

Since disorders (of any type) have an impact on the active and reactive power values, the measured values are first processed and then sent to the algorithm that implements the disaggregation of the input signal.

This first processing takes place via two algorithms (P linearization and Q linearization) that attenuate or eliminate the small variations in the signal.

In this way, the final signal will consist of an overlapping of square wave fronts that represent the changes of state on the devices.

In order to linearize, it is necessary to define ΔP, ΔQ, and a ΔT interval. If the ΔP and ΔQ variations are greater than a particular threshold (set in line with the set of appliances), and if these variations have a time duration greater than ΔT, the linearization algorithm will identify a steady-state condition and then will send the linearized data to the disaggregation algorithm [5].

In Figure 28 we can observe the result of the linearization applied to a signal affected by noise.

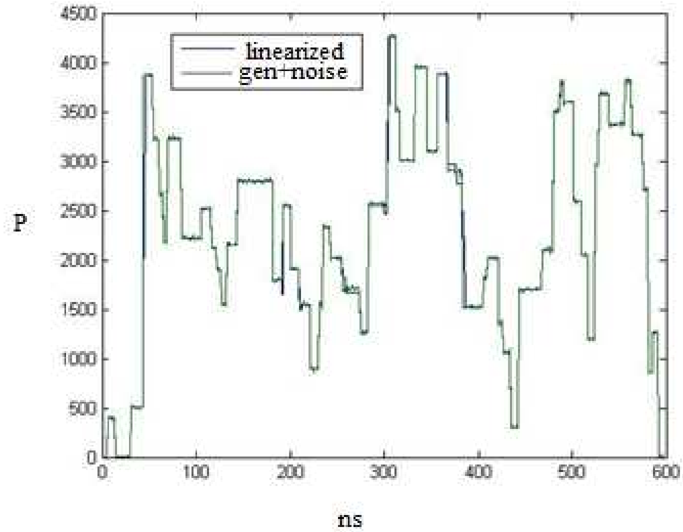


Figure 28 Load global Profile linearized, and Load global profile generated with noise

The linearization process changes the signal; therefore modifying the data that will be treated and on which depends the final result of the disaggregation.

We have to choose the tolerances and the threshold values very accurately so that they preserve the information, contained in the original signal, and that are useful for the disaggregation (we should then maintain the information related to transitions that represent the changes of real status of appliances). At the same time, we should eliminate those ailments that could be mistaken as changes in the status.

It is evident how the software implemented process depends upon an accurate analysis of the signal noise level. Figure 29 helps to understand these extreme conditions, where there is a constant power section of the signal in the presence of noise.

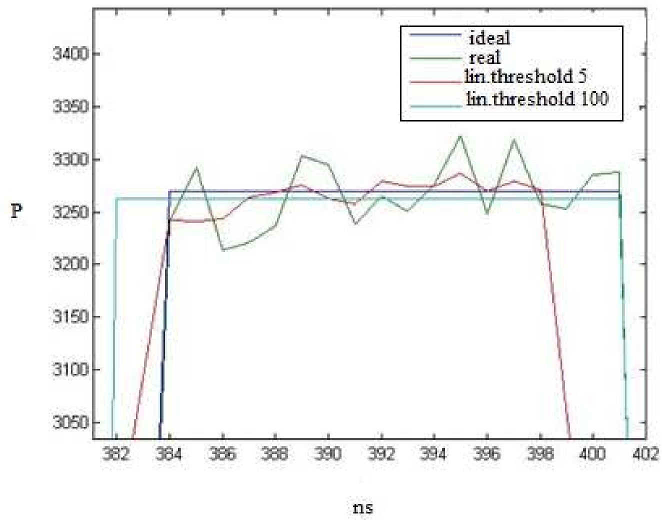


Figure 29 Signal effected by noise, and different threshold of linearization

In the presence of high noise, the use of a too small threshold implies that in the signal will still be present a ripple, but if we use a too high threshold, the linearization algorithm will tend to reconstruct the portions of the signal that are not really there (in Figure 29, samples ranging from ns= 382 to ns = 384 s).

During the tests, we performed a significant number of simulations inherent linearization and we tried different approaches, some based on a moving average operation and others on an energy approach.

Starting from the simple consideration, that the purpose of the linearization is to match the signal affected by noise with the ideal signal.

It can be defined an index e_{lin} (linearization error), that has the aim to evaluate the performance of linearization algorithm:

$$e_{lin} = \frac{\sum_{i=1}^{ns} |P_{gg}(i) - P_{lin}(i)|}{ns} \tag{8}$$

This index provides an estimate of the difference between the ideal and the linearized signal, for a perfectly linearized profile e_{lin} will be invalid and, it will increase with the growth of linearization errors.

It is perceived that e_{lin} is not related to the disaggregation efficiency, but provides only an idea of the result of linearization.

In other words, a small value of e_{lin} is not necessarily equivalent to a well-managed disaggregation. This consideration derives from the fact that during the test, we noticed many cases in which there has been a drastic drop of the efficiencies (in particular with η_p, with values in some cases even below 10%) without that the index e_{lin} highlighted this.

To evaluate the result of the linearization efficiencies, we generated 50 profiles affected by noise (with a peak-to-peak maximum of 10 W), and we obtained the efficiencies in this two cases:

1) when Lim_ Delta P =20 W;
2) when the same profile is linearized.

The values can be compared in the Table 3.

Table 3 PERFORMANCE OF LINEARIZATION ALGORITHM

	η_s mean	η_p mean	e_{lin} mean
Lim_ Delta P = 20	87.89	80.16	
Signal Linearized	57.3	11	117

The efficiency collapse appears to be caused by the transition from one condition to another. The linearization scheme carry out the change by intermediate values, which then force the algorithm to reconstruct the power levels that really are not present.

An interesting aspect of the simulations is the behavior of the two indices η_s and η_p.

At the operating conditions, the η_s index seems to suffer less the influence of external factors remaining at more stable values and high compared to η_p. Given the definition of η_s it is evident that this suffers any change of the operating state of the appliances according to the power of the same device.

Therefore, even in front of external disturbances, the disaggregation algorithm succeeds, in any case, to identify in the aggregate profile, the contribution given by appliances with higher power.

4.6 Summary

Before implementing PQ-DA in a realistic context, it is crucial to test its performances numerically by means of the generation of random load profiles, named Global Load Profiles – GLPs, according to specific constraints in such a way to reproduce most of the situations that the disaggregation algorithm has to face in a real context.

Two disaggregation efficiencies, η_P and η_S, have been defined (see par. 4.3). The first efficiency, η_P, is based on the difference, sample by sample, between the energy of the generated GLP, GLP_g, and the energy of the disaggregated GLP, GLP_d. The second efficiency, η_S, is based on the different, sample by sample, between the generated status of each appliance, and the disaggregated status of each appliance.

The input parameters that are needed to be set to generate a random GLP_g can be classified in two groups:

- Appliance data: number of the appliances (n_a), range of variation of both rated active power ($P_{n,min} \div P_{n,max}$) and reactive rating power of the appliances ($Q_{n,min} \div Q_{n,max}$).
- Algorithm parameters: number of samples (n_s), minimum number of samples between a switch on and a switch off of an appliance, ΔS_{min}.

Related to the electrical characteristics of the appliances, there are two important aspects that impact greatly the efficiency of the disaggregation algorithm:

- Measurement accuracy of power meters (normally ± 1% f.s. and + - 0.25 f.s.).
- Nominal power of appliances: when in a domestic dwelling, either there are appliances whose rated powers are too small or they differ less than a given power threshold, ΔP_{min}, the disaggregation efficiency tends to decrease. The use of reactive power allows to partially overcoming this problem, but from a realistic point of view, the measurement of the reactive power involves other problems especially under current and voltage deformed regime. In this context two factors that characterize a given group of appliances have been defined (see par. 4.3), that is: KG_P (ratio between the minimum power in the set of appliances and ΔP_{min}) and Dg_P (the smallest value among the values obtained from the differences between the rated power of i-th and j-th appliance). The similar factors can be defined for the reactive power (KG_Q, D_{gQ}).
- Multiple switching: in this context two cases can be considered:

- Contemporary Switching (CS): two or more appliances are switching on (or off), at the same time.
- Simultaneous Switching (SS): two or more appliances change the state simultaneously, some turn on and others turn off.

- The presence of noise causes a decrease of the performance of the algorithm. To improve the results were analyzed two possible solutions: an increase Lim_ Delta P and a preprocessing of the active and reactive power signals using a linearization algorithm.

However, for all these reasons, PQ-DA algorithm is unable to obtain exactly which is the real status of all appliances. To improve the results, a Feedback Algorithm has been developed.

Chapter 5

Feedback Algorithm

In [13] a review about electricity consumption feedback is analysed, two different feedback actions are identified and classified as: direct feedback action and indirect feedback action.

The direct, or real time, feedback is immediate and it comes from a meter or a display monitor, in the indirect feedback methods the information are processed in some ways, e.g. more detailed electricity bills or household- specific advices for reducing electricity usage.

The context in which we define our feedback algorithm is a mix of direct and indirect actions.
In real time, the results of the NIALM algorithm are shown, but for a series of reasons if, there are some differences respect with the real status of appliances, the user may interact with the system.

5.1 User Interaction

The main idea of the proposed architecture is to exploit as much as possible the commitment of the users by means of active interaction with a dedicated web site. The user plays an active roles in the whole process in many steps. Firstly, the user is required to communicate the list of appliances connected to the main power supply along with some information about their electrical characteristics.
The more complete the information provided by the user during this phase, the more accurate the results provided by the NIALM algorithm. However, since we are aware that not only the user may not be able to provide precise and complete data about his appliances, but also the results of NILM algorithm are affected by errors (see par. 4.4), an interactive phase has been designed. So, during the normal operation of the system, the user can be engaged in two different kinds of interactions, i.e. feedback, named respectively Check status and Verify signature, hereinafter described:

5.1.1 Check Status

The user is prompted to confirm some information about the status of one or more appliances. He has to provide information related to the state, (on/off) of the i-th appliance. By means of this information, the NIALM algorithm will improve, and correct, if necessary, its disaggregation results.

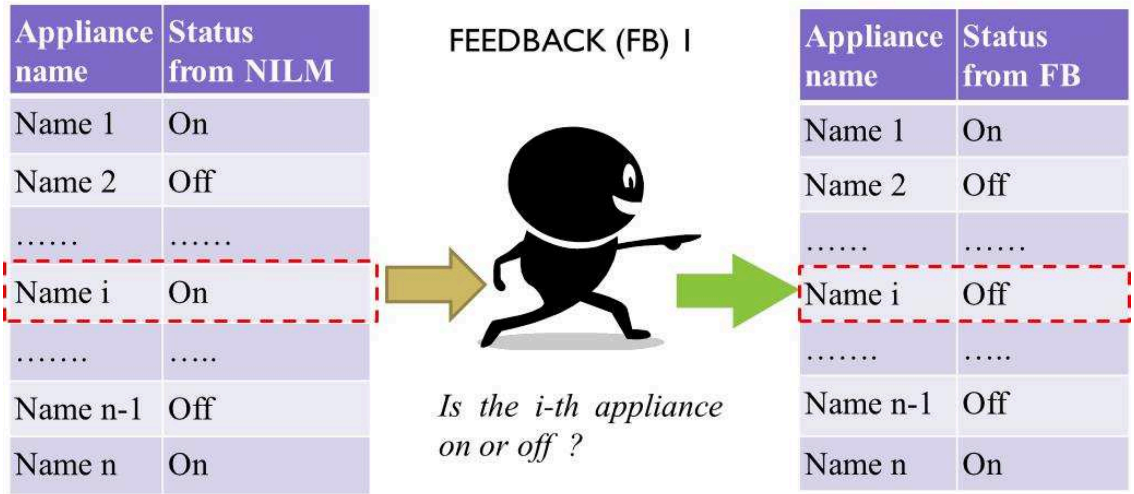


Figure 30 Logic scheme of check status feedback

5.1.2Verify signature

The user is asked to turn on and/or turn off a specific appliance, in order to revise the signature of the i-th load. This interaction is enforced if the user, during the preliminary step, has not been able to provide all the needed information related to nominal power of appliances. So the rated power of i-th appliance is corrected from P and Q to P' and Q'.

Therefore, this second feedback allows to solve the problem linked to the quality of the information.

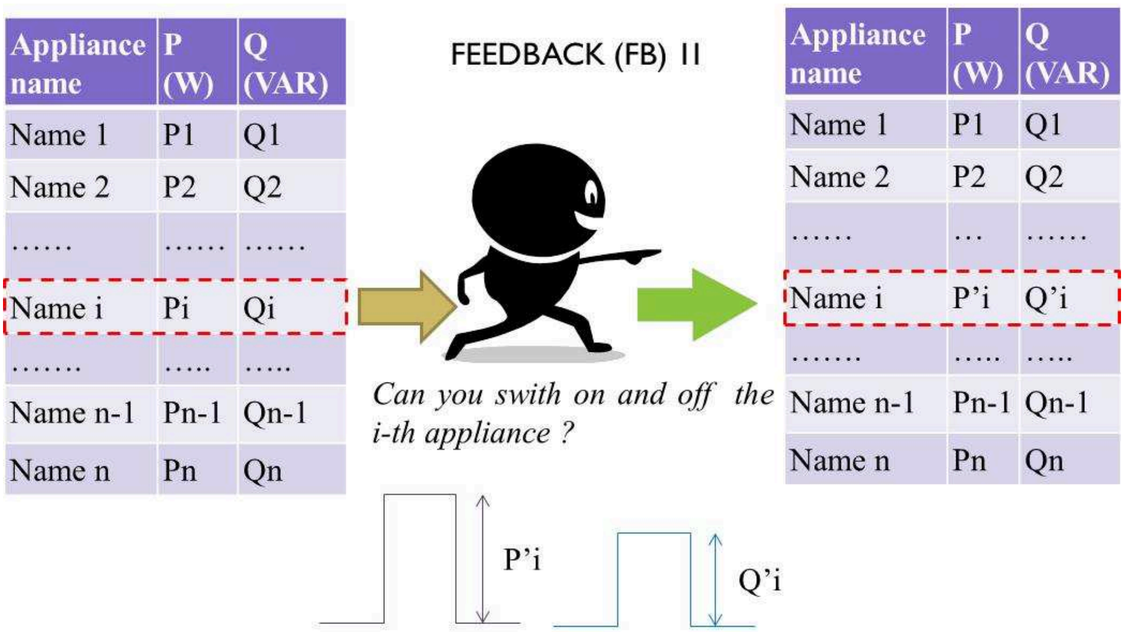


Figure 31 Logic scheme of verify status feedback

5.2 PQ-DA and User's Feedback

If a complete and precise information is provided, it is not necessary to implement the *"Verify signature"* feedback but the attention has to be focused on the "*Check status*".

To evaluate the NIALM algorithm an index C_e (Cumulative error), based on the difference, sample by sample, between the GLP_g and the one of GLP_d (coming from forward algorithm) has been introduced, as follows:

$$C_e(s_j) = \frac{\sum_{i=1}^{s_j} P_{gd}(i) - P_{gg}(i)}{\sum_{i=1}^{s_j} P_{gg}(i)} \text{ ; } s_j=[1 \ldots n_s] \qquad (9)$$

Where:

i is the i-th sample;

n_s is the number of samples;

P_{gd} is global disaggregated load profile;

P_{gg} is global generated load profile.

In (9) only the cumulative error of active power is shown, but it can be evaluate also for the reactive power.

The value of C_e (n_s) is used to ask for a user feedback. In fact, if it is greater than a given threshold, $C_{e,min}$, it means that the final status $S_a(n_s)$ vector, coming from the application of PQ- DA (Forward Algorithm) contains some wrong values. In this case, we ask the user to provide right information about the status of some appliances, by means of the "*Check status*" feedback. The output of this feedback is a correct status vector, named $S_a'(n_s)$. This information is used to perform disaggregation algorithm (Back Algorithm), starting from the final corrected status to the initial status $S_a(1)$.
The flowchart in Figure 32 shows the interaction between PQ-DA and the user's feedback.

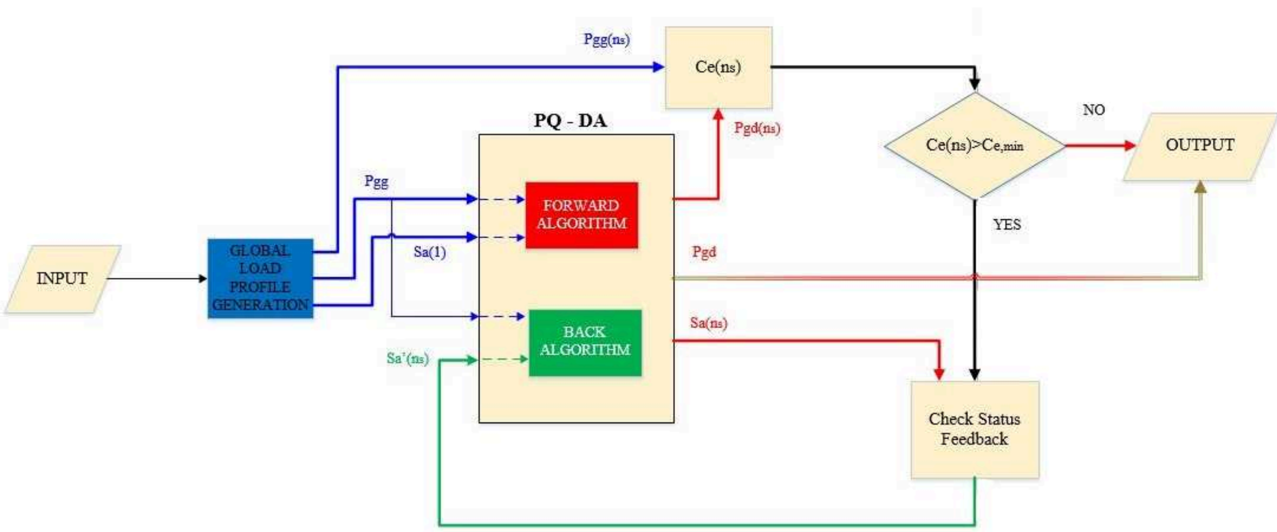


Figure 32 Flowchart of the PQ DA with the Feedback Algorithm

5.3 User Presentation

The Global load profile generation, the PQ – DA, and the Feedback Algorithm have been implemented in the Matlab programming environment. Specifically, MATLAB® /GUI based interface has been developed to handle to manager input and output of disaggregation system.
The numerical results relative to a given example will be shown by means of the GUI screen shots. The parameters of the example are: na = 10, ns = 500. In Table 4Table 4 there are the list of the characteristics of 10 appliances, they have been generated randomly with the following constraints: $10 < P (W) < 100$ and $0.5 < \cos(\phi) < 1$.

Table 4 RATING OF APPLIANCES

Appliance	P(W)	Q(VAr)	cos(ϕ)
1	43	10,77	0.97
2	44	68,58	0.54
3	37	56,18	0.55
4	36	22,31	0.85
5	33	36,56	0.67
6	52	69,33	0.60
7	99	166,9	0.51
8	45	42,13	0.73
9	95	133,4	0.58
10	25	9,88	0.93

For sake of simplicity, in this numerical analysis, only ON-OFF appliances are considered, whereas in the PQ – DA also multi-state loads are included.

The graphical interfaces of home page is illustrated inFigure 33, where the following sections can be detected: “Input”, “Random Load Profile”, “Disaggregation” and, “Quantitative Evaluation Nialm Algorithm”. In the same page, the graphs of generated and disaggregated load profiles are shown.

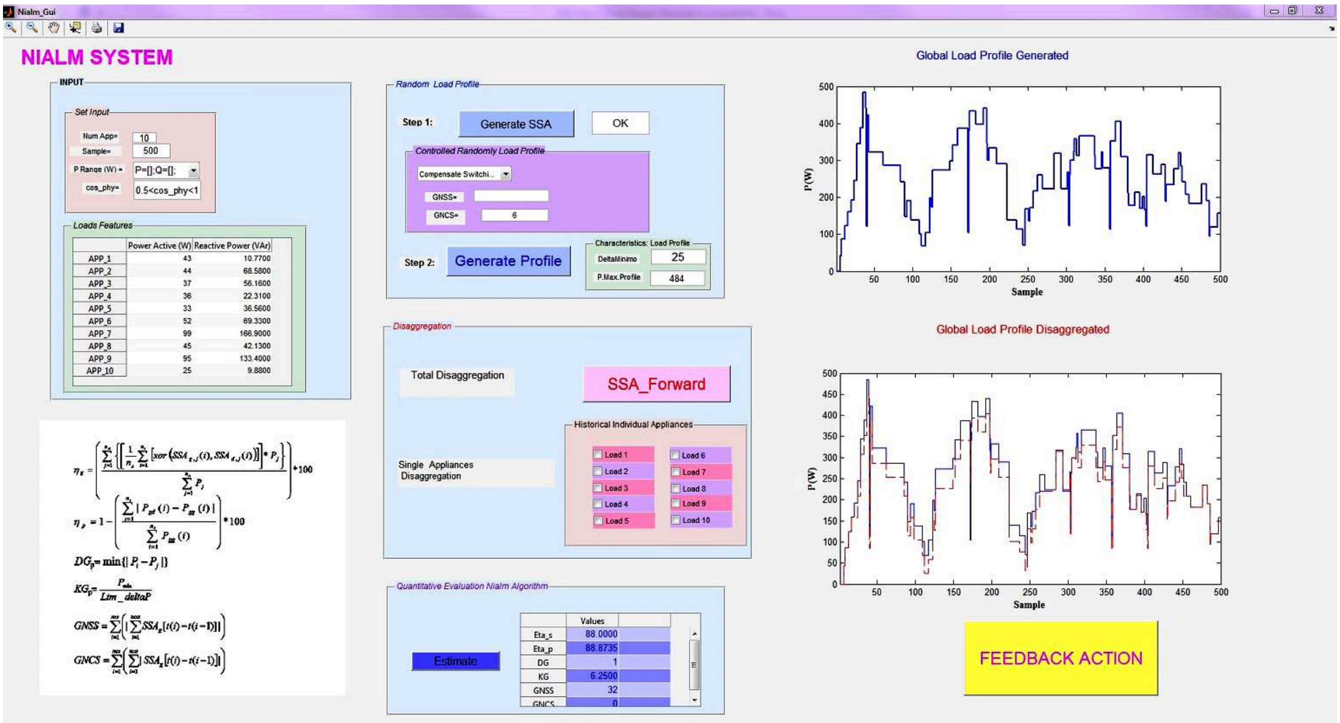


Figure 33 Screen shots of the Graphical Interface: NIALM GUI

By means of the FEEDBACK ACTION button, it is possible to move to the next page, shown in Figure 34. The graphical interface consists in the following sections: “Feedback Action”, and “Output results”.

In Feedback Action section, the type of Feedback action can be selected, that is: total feedback or partial feedback. In the first case, it is possible to change the status of all the appliances coming from the application of PQ- DA (Forward Algorithm), instead, in the second case only the status of several appliances is changed. The algorithm implements a criterion of choice, i.e. it provides a list of candidate appliances to change their status.

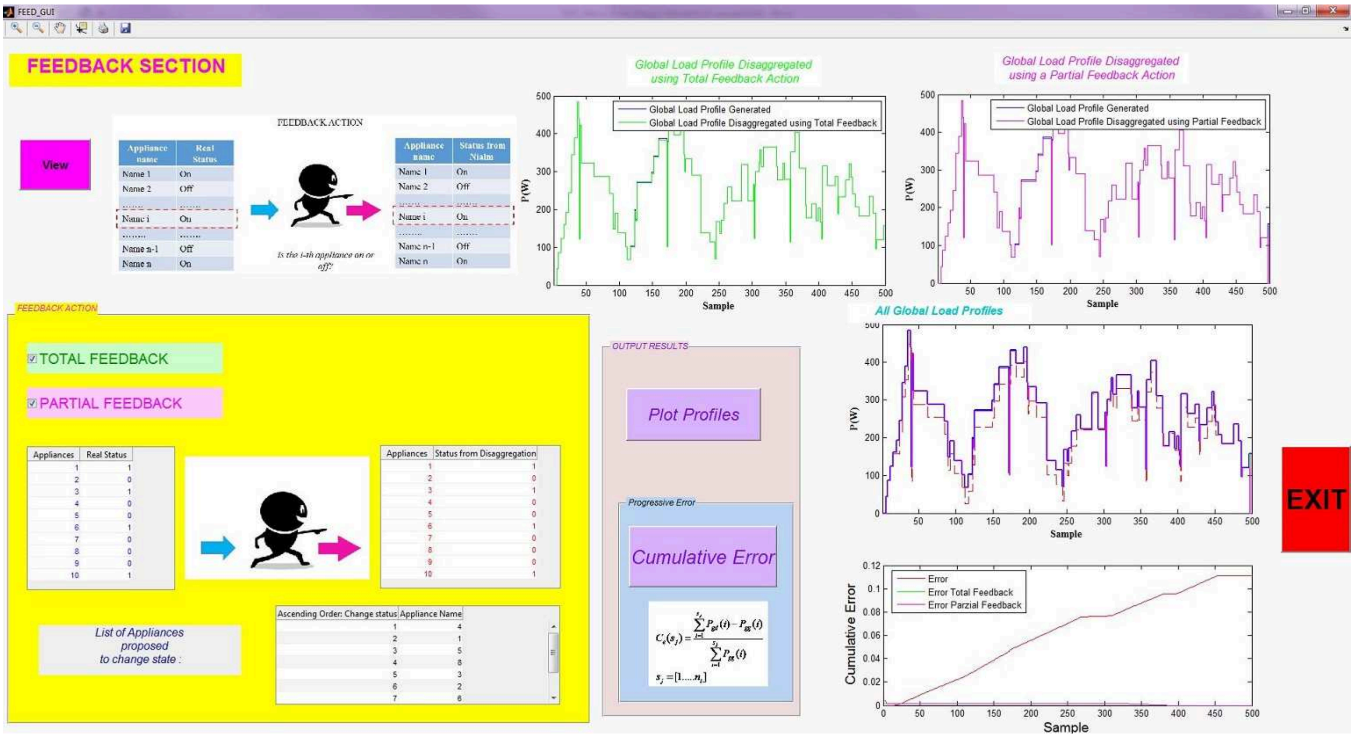


Figure 34 Screen shots of the Graphical Interface: Feedback GUI.

Results of PQ-DA, using a Feedback Algorithm, demonstrate that errors can be compensated. In Figure 35Figure 35 are shown: the cumulative error (Figure 35 (a)), defined in (9), and the GLPg and GLPd using Feedback Algorithm (Figure 35(b)). It is possible to note that the error coming from the application of PQ- DA (Forward Algorithm) is greatly reduced after the application of the Feedback Algorithm.

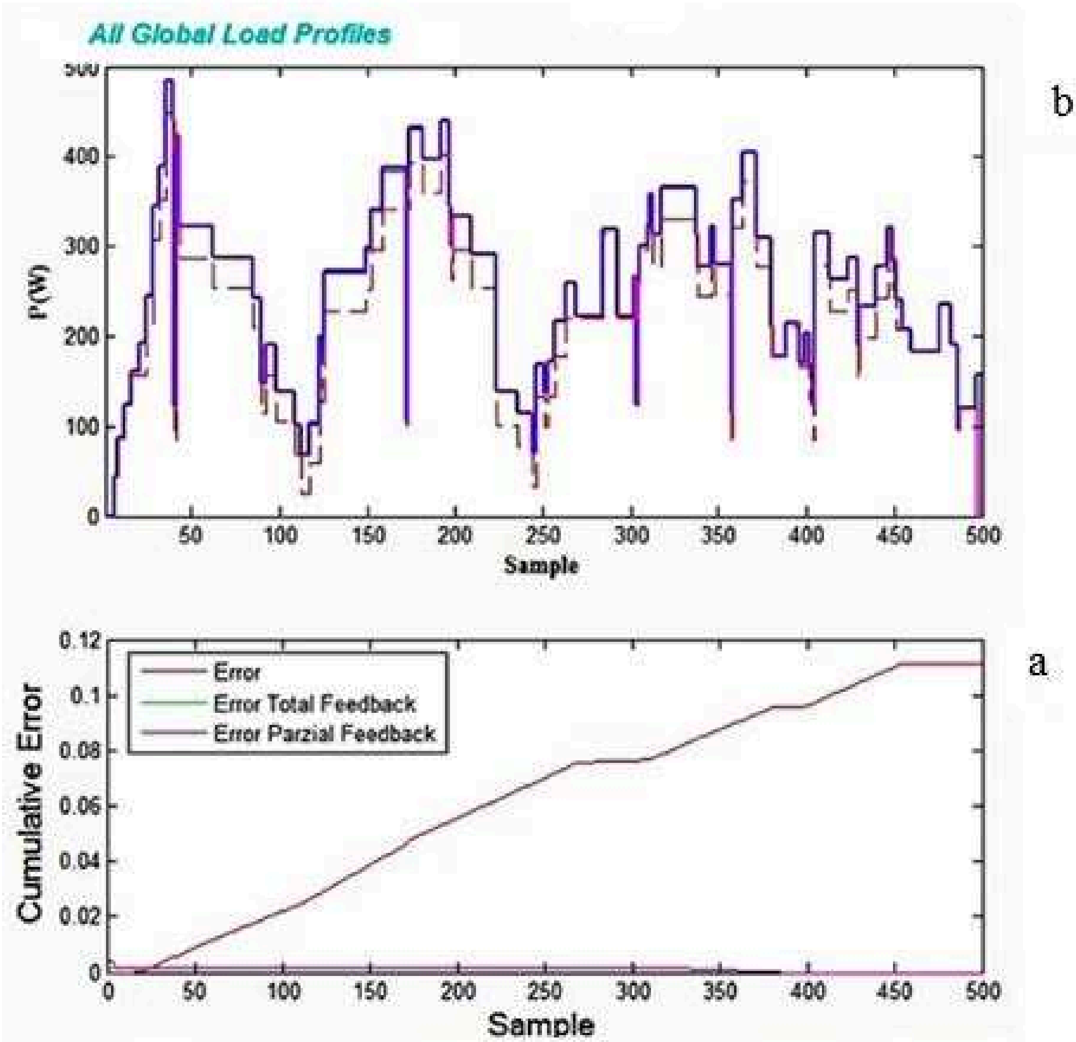


Figure 35 Output Results after Feedback Algorithm application

5.4 Validation Test

A project named SEEE (Systems Efficiency for Energy Emancipation), whose partners are the department DIEEI of University of Catania, Catania (Italy) and a Sicilian energy trader, is under development; it aims to study hardware and software solutions for providing advanced tools to electric utilities users (mainly residential) not only to optimize their energy consumptions but also to make them an active part of future Smart Grids.

The designed system has been developed in a real domestic scenario in order to better evaluate the overall behavior of the system.

The graphs, in Figure 36, Figure 37, and Figure 38, show the power consumption of a typical domestic user (*e.g.user A*). These pieces of information can help the user to understand his energetic behavior. Specifically Figure 36 shows the home page where the global measurements (P, Q, V, I, THD, Power factor) are shown in different time frames (one day, two days and one week), and updated every three minutes. Since data produced by the NIALM module are stored in the database (Processed DB), the user can decide what to analyze. Figure 37 shows the "Appliance Power" page, where the NIALM algorithm results are represented by a piecewise graph with the same time features as the previous graph.

Figure 36 Home page of SEEE web site.

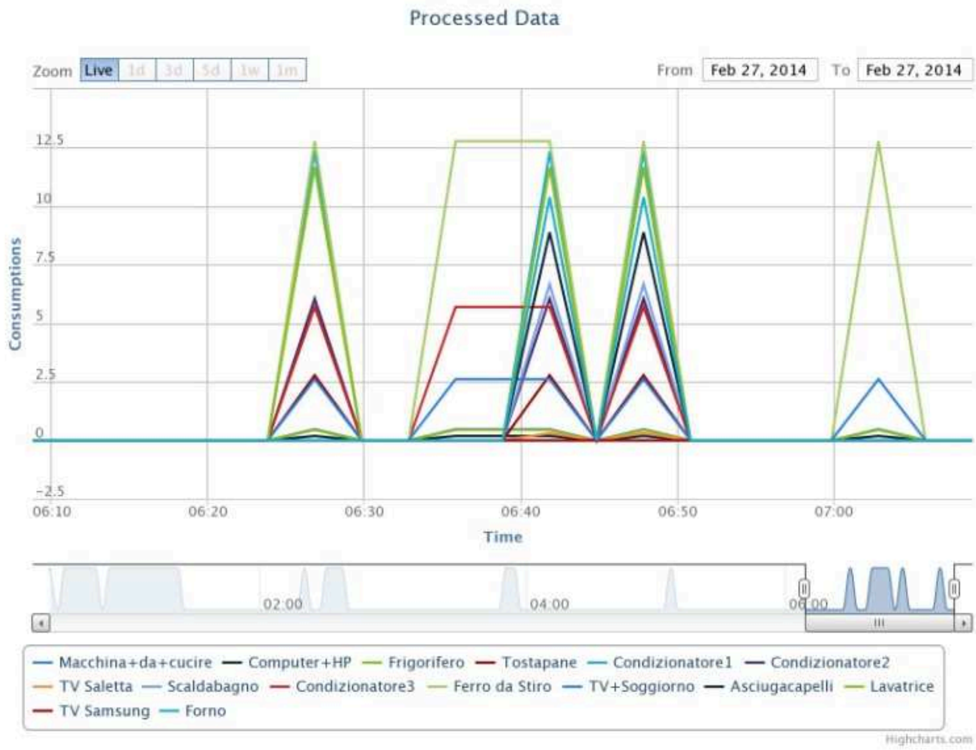


Figure 37 Power consumption grouped by appliance.

Finally, in the Overview page shown in Figure 38, two pie charts are presented: pie chart A where the monthly percentage of energy composition of each appliance is depicted, and pie chart B which shows the cost rate of the electricity bill for each appliance.

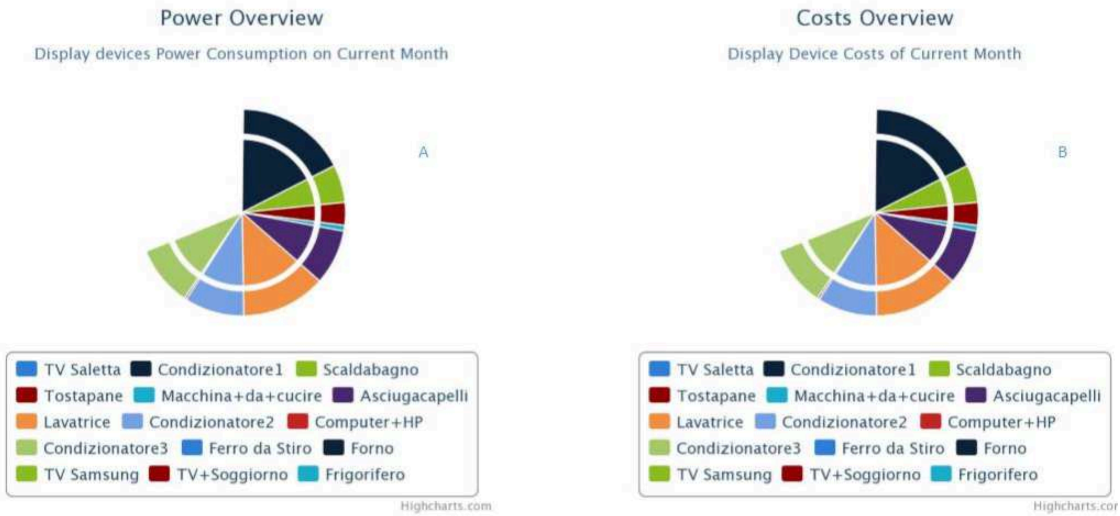


Figure 38 Pie Chart A about Power Consumption Overview, Pie Chart B about Costs Overview.

Before starting the monitoring of a given user, it is very important to characterize it by the historical data taken by the electricity bills. Hereinafter, we will report the results concerning the user that is now under monitoring (*user A*).

User A has a supply contract with power committed to 3 kW. During the first step of user's characterization, *user A* communicates the list of appliances connected to the main power supply. In Table 5, the various appliances, grouped by category, of *user A*' house are placed.

Table 5 USER APPLIANCES CHARACTERIZATION

	Category		
	Light	Appliances	Computer / entertainment
Total number	7	10	7
Global Power (W)	271	14073	666

The user has entered with an energy trader a contract that provides different tariff schemes, in this case a time-of-use tariff has been agreed.

Actually the Italian Authority for Electricity and Gas (AEEG) approved the entry into force of a mandatory Time-of-Use (ToU) tariff among residential customers subject to the universal supply regime in Italy from July 1st 2010. It provides for variable electricity prices during the day: the price is higher during "peak hours" (the hours between 8 am and 7 pm on working days, also called F1 time slots) and lower during "off-peak hours" (all the remaining hours, also called F2 and F3 time slots, which basically comprise nights and weekends). The AEEG established a 18-months transition period (until December 31st 2011): during such a period the price difference between peak and off-peak hours was limited (transitional ToU tariff) while, starting from January 1st 2012, it has become larger (final ToU tariff), based on the actual electricity market prices. ToU tariff is more convenient than the flat tariff only if more than 2/3 (i.e. 66.67%) of the total consumption occurs during off-peak hours: such value represents an "indifference threshold".

It is worth specifying that average consumption shift is only 1%, the main two factors that may have prevented a larger consumption shift are: a) rather limited price difference between peak and off-peak hours; b) other components of the final price are not time-dependent the variation on the final price between peak and off-peak hours was even lower. In our case there are three time slots (F1-F2-F3), and the electricity bill depends on the electricity usage habits, i.e. during which hours of the day, and in which day of the week, the appliances are used. Figure 39 shows the F1, F2, F3 daily and weekly time slots (F1 takes about 38 % of hours in a week, whereas F2 takes about the 21 %)

and relative price. On this regard, it is worth noticing that the price of electricity in F1 is about 30% greater than the one in F3.

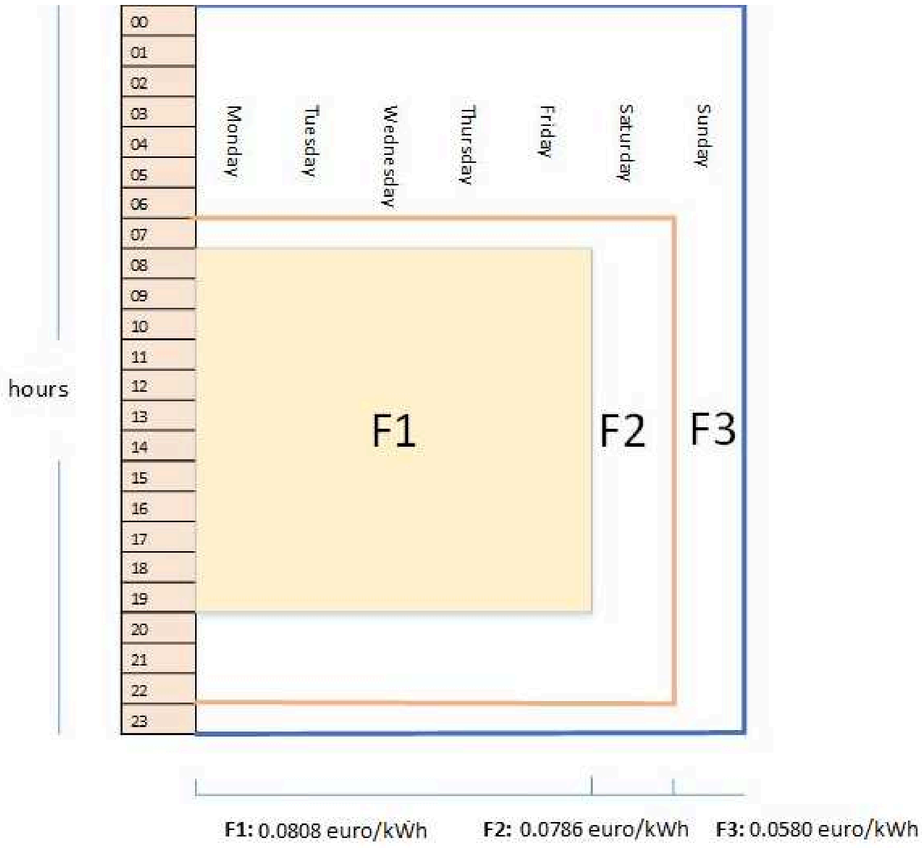


Figure 39 Time of use tariffs, F1, F2, F3: weekly time slots and relative prices.

Starting from the data reported in the electricity bills of an year, some information about energy behavior of the customer under study can be drawn. For example both cooling and heating of the house are based on electrical appliances (e.g. heat pumps), so the electricity demand increases during winter and summer and decreases in the other seasons. Figure 40 shows a bar graph with the monthly average daily demands, and the electricity usage habits over the year is very evident.

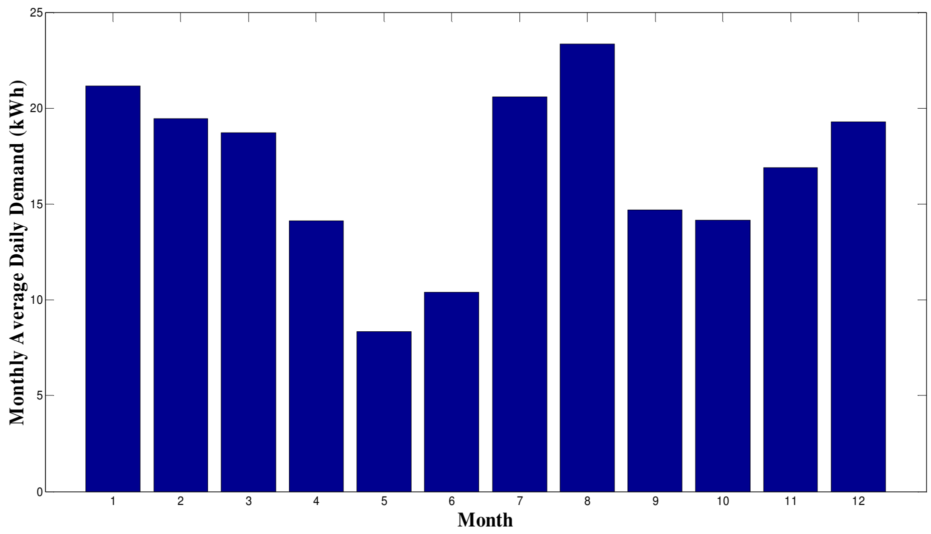


Figure 40 Monthly Average Daily Demand.

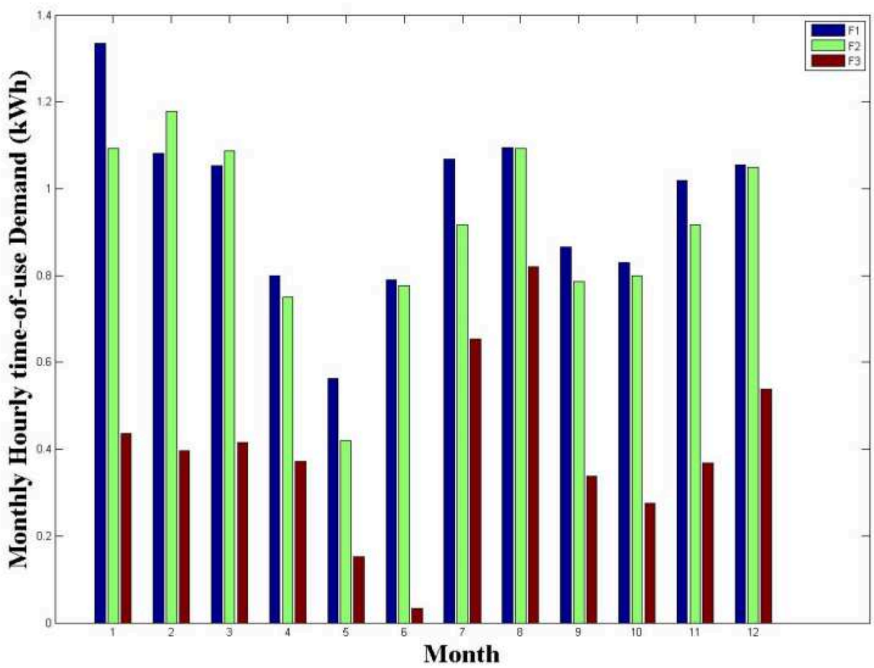


Figure 41 Monthly Hourly time of use Demand

Information reported in Figure 40 is not sufficient to understand how the user behaves respect with his electricity demand during a day and a week, so in Figure 41 the monthly hourly time-of-use demand divided by time slots is reported. It is clear that the demand is greatly concentrated in F1 and F2 slots whereas the nocturnal hours are much less used.

5.5 Summary

Since the disaggregation occurs in real-time, at all times, we can discover the status of all appliances parts of the domestic load (unless there has been a mistake on the disaggregation).

If these data are made available to the user, he has the possibility to monitor the consumption of every single appliance, thus obtaining a feedback regarding either the energetic or the economic perspective.

The above statement results more efficient compared to the reading of the total instantaneous power consumption for the following reasons:

- The knowledge of the operational status of every household appliance allows to examine and correct a behavior that can lead to wastage.

- With that detailed information, the user is in the conditions to adopt strategies to reallocate the consumption based on the time slot that results more convenient, contrary to an aggregated information that do not distinguish from the appliance but is limited to the evaluation of the overall consumption.

- [10] compare the financial saving based on the different type of feedbacks available for the user. Their results show that the application of the method proposed in this thesis leads to an economic saving of 12% per year.

Figure 42, compares the different methods with their own savings:

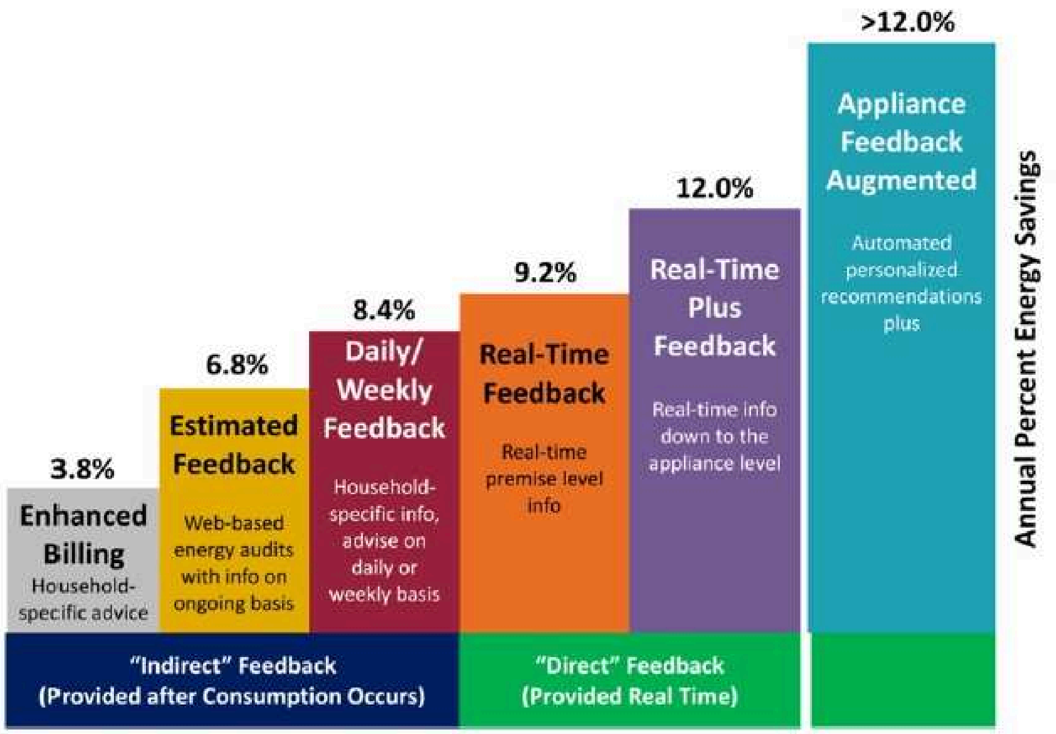


Figure 42 Energy Consumption Feedback

As said previously, the knowledge of the state of each single appliance would increase the financial saving because a careful user would recognize the combination of appliances with a greater impact on the total power consumption and therefore on the power bill.

A higher level of efficiency and saving can be achieved with the implementation of a system able to process the information in the form of guidance for the users, encouraging them to optimize their behavior.

A possible indication concerns the right time for the use of a specific appliance based on the energy cost, e.g. when to use the electric oven (usually on the evening or during the weekend), the change of a particular appliance setting (e.g. the washing machine temperature), a suggestion concerning the maintenance of the appliances (e.g. replacement of AC system filters) or information about the health status of each household appliance, with related "alert" notifying the user in the presence of an abnormal usage.

The NIALM system can provide even another type of suggestions, namely a comparison between the consumption patterns with the fares applied by the various energy providers, suggesting to the user the most suitable company for his needs. Such a system, composed of notifications, information, and suggestions would enable a saving of more than 12% per year on the cost for the power supply.

Chapter 6

Conclusions and Future Work

This thesis has described an approach to train non-intrusive load monitoring systems for use with household smart meter data.

The large-scale adoption of Non-Intrusive Appliance Load Monitoring (NIALM) systems would provide various benefits for both the end-user and the global system.

The disaggregation capacity, together with a front-end which is able to show the data and the average consumptions from individual appliances, could increase the user awareness in knowing his real-time utilization. Therefore the user will plan his behaviour moving the use of household appliances in times when the energy cost is less.

From the global system's view, this process will have a dampening impact on the peak periods of the load diagram, contributing to a uniform distribution of the demand for the different time slots, hence providing an adequate balance between the energy supply and demand.

The research in the field of energy efficiency would benefit from the use of this technology. Indeed, a more conscious consumer will be encouraged to buy energy-efficient household appliances, with a valuable impact on the manufacturers which, to avoid the loss of market share, should make adjustments designing more energy efficient appliances.

Also, the companies could use the information resulting from an analysis of the disaggregated consumption to plan new investments and marketing strategies. New promotional campaigns targeted to highlight the economic advantages emerging from the purchase of a new generation of household appliances able to break down the electricity consumption will attract the user to buy these products.

The traditional market segmentation, based on geographical, demographical and behavioral statistics, could be incorporated with the information coming from the NIALM systems. These systems, thanks to specific consumption patterns, would provide useful information for the design of appliances intended for a particular target of users with the same requirements.

Moreover, these data could be utilized to implement targeted advertising campaigns by combining specific machines to a particular group of users.

Finally, an additional scope is represented by the "social alarm" and "remote control". Given that the majority of consumption patterns mirror the "human" activity in the dwelling, subdividing the expenditures caused by the users' actions from those originated by appliances with an "automatic" functioning (e.g. refrigerators, boilers), we can monitor the activities of a particular class of people (e.g. people with health problems or limited mobility, etc...).

We now summarise the contributions of this work, and give directions for future work.

6.1 Conclusions

We first defined the problem of non-intrusive load monitoring in Chapter 1. We identified four key requirements that must be fulfilled in order to realise a realistic solution to this problem. The requirements stated that the solution must be able to disaggregate low granularity smart meter data into individual appliances. However, most importantly the solution must not require training data to be collected from each household in which disaggregation will be performed. This requirement is crucial since it allows the approach to scale with the recent national deployments of smart meters.

We then provided a background of existing work in the field of non-intrusive load monitoring in Chapter 2. We showed that solutions which involve the installation of hardware in addition to existing smart meters are too expensive for large scale deployments.

Chapter 3, represents the first major contribution of this thesis, in which we propose an overall ICT architecture for energy consumption awareness.

Chapter 4 describes the disaggregation algorithm and the function to generate a random and controlled load profiles. The proposed disaggregation algorithm is simple as it is based on a basic and straightforward signature (i.e. rated active power and power factor), as a consequence the results of this algorithm has to be corrected by means of the user interaction (i.e. feedback)

Chapter 5 shows the experimental results. The robustness of the disaggregation algorithm has been tested both numerically and experimentally. Secondly, we defines the users' feedback and the different feedback algorithms. User information are presented through a user-friendly Web interface; this interface also gathers the user feedback which is needed to improve the efficiency of the disaggregation algorithm.

Finally, Chapter 6 gives a summary of the research presented in this thesis. We also discuss future extensions of the work presented in this thesis, with specific attention to apply NIALM system in a real scenario.

6.2 Future Work

However, it is worth investigating ad hoc algorithms (e.g. Hidden Markov Model - HHM) that are able to characterize the appliances' profile before the load disaggregation, in this way, the information requested to the users can be less crucial.

The next step in the on field test is to enlarge the number of monitored users in such a way to perform a comparisons with users with similar characteristics. The results of this comparison, shown to the web users, could induce a 'positive competition' in electric demand reduction.

Finally, in the context of Smart Grids, it would be interesting to analyze a domestic user with a photovoltaic (PV) power plant; on this regard forecast methods for both PV production and electric demand could be used to predict them in the next 24 hours, with the aim of improving the predictability of energy exchanges with the network. Forecast algorithms can be also used to predict the preferences of the users in using the home appliances, in order to identify which appliances are going to be used by the user and at what time of the day.

Appendix A

Appliance Study

Table 6 shows approximate values for common appliances' power demands, usage per day and energy consumption per day. The approximate power demands were taken from [48]. Estimates of daily usage were then used to calculate the expected energy consumption of each appliance per day. The appliances were ordered for consistency with Figure 1.

Table 6 HOUSEOLD APPLIANCE POWER DEMAND, USAGE DURATION AND ENERGY CONSUMPTION.

Appliance Name	Power demand (W)	Time per day (hours)	Energy per day (kWh)
CLOTHES DRIER	2500	0.8	2
ELECTRIC HOB	3300	0.5	1.65
DISHWASHER	2500	0.6	1.5
ELECTRIC OVEN	3000	0.5	1.5
WASHING MACHINE	2500	0.4	1
KETTLE	3000	0.3	0.9
INCANDESCENT LIGHT BULBS	60	8	0.48
FRIDGE	20	24	0.48
MICROWAVE	1400	0.3	0.42
WIRELESS ROUTER	10	24	0.24
SET TOP BOX	10	24	0.24
TELEVISION	100	2	0.2
GAMES CONSOLE	170	1	0.17
CFL LIGHT BULBS	20	8	0.16
VACUUM CLEANER	1600	0.1	0.16
TOASTER	1200	0.1	0.12
COMPUTER	100	1	0.1
PHONE CHARGER	5	12	0.06
ALARM CLOCK	2	24	0.048
LCD MONITOR	40	1	0.04
LAPTOP	25	1	0.025
STEREO	10	1	0.01
DVD PLAYER	10	1	0.01

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