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Energy Disaggregation via Current Smart Metering Infrastructure - Study and Implementation Based on Present Constraints

Semester Thesis

EEH – Power Systems Laboratory
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Abstract

Nowadays energy efficiency is becoming a major concern. The improper use of electrical devices has been a significant problem and therefore solutions to improve the electricity monitoring must be demonstrated. On this basis, appliance specific consumption information motivates the consumers and lead them to change behaviours.

Non-intrusive load monitoring aims to estimate appliance energy consumption from aggregate energy signals of households. The direction today is the computational complexity of the considered problem in order to have accurate results. However this approach raises several issues regarding the scalability and privacy of consumer's data. In this thesis we address the state of current smart metering infrastructure in order to evaluate the methods that can be supported by them. The simplicity of the algorithm so that the Smart Meter can provide real-time feedback on appliance usage is crucial both for the consumer and the cost of the considered system.

Therefore the question we try to answer in this thesis is if we can design a non-intrusive load monitoring system with reduced computational complexity that can run on a local embedded system without sacrificing disaggregation accuracy.

Acknowledgements

My special thanks go to Prof. Dr. Gabriela Hug-Glanzmann who gave me the opportunity to work on the specific project concerning the smart metering. However, the completion of the thesis could not have been possible without the assistance of my supervisor Jack Chin whose contributions are sincerely appreciated and gratefully acknowledged. His commitment on my project and the excellent advise and constant support have been a great motivation for me throughout the project.

Contents

Nomenclature

$\bar{x}$=$[x_1, ..., x_T]$	Sequence of aggregate power readings
$z^{(n)} = \{z_1^{(n)}, ..., z_T^{(n)}\}$	Sequence of appliance instance power readings
$n \in \{1, ..., N\}$	An appliance
$t \in \{1, ..., T\}$	A time interval
$\theta = \{\pi, A, \phi\}$	Set of model parameters for a HMM
π	Vector of initial probabilities for a HMM
A	Matrix of transition probabilities for a HMM
ϕ	Vector of emission or output densities for a HMM
σ	Standard deviation
σ^2	Variance expressed as the square of standard deviation
$\tau = \frac{1}{\sigma^2}$	Precision parameter defining the width of the distribution
$\mathcal{N}(\mu, \tau)$	Gaussian distribution of mean μ and precision τ

Acronyms and Abbreviations

AMI	Advanced Metering Interface
AMPds	Almanac of Minutely Power Data Set
AMR	Advance Metering Reading
BLUED	Building-Level Fully-Labeled Dataset for Electricity Disaggregation
CBA	Cost Benefit Analysis
CEER	Council of European Energy Regulators
CERE	Centre on Regulation in Europe
CFHMM	Conditional Factorial Hidden Markov Model
CO	Combinatorial Optimization
DHMM	Difference Hidden Markov Model
DG	Distribution Grid
DSO	Distribution System Operator
EC	European Commission
ED	Energy Disaggregation
EM	Expectation Maximization
ETH	Eidgenössische Technische Hochschule
EU	European Union
FHMM	Factorial Hidden Markov Model
FHSMM	Factorial Hidden Semi-Markov Model
FN	False Negative
FP	False Positive
FTE	Fraction of Total Energy correctly
GPRS	General Packet Radio Service
GSM	Global System for Mobile Telecommunications
HAN	Home Area Network
HMM	Hidden Markov Model
HSMM	Hidden Semi-Markov Model
ICT	Information and Communication Technology
ILM	Intrusive Load Monitoring
IOHMM	Input-Output Hidden Markov Model
NIALM	Non-Intrusive Load Appliance Monitoring
NILM	Non-Intrusive Load Monitoring
PLC	Power Line Communication
REDD	The Reference Energy Disaggregation Data Set

RES	Renewable Energy Sources
R&D	Research and Development
SG	Smart Grid
SM	Smart Meter
TLP	Typical Load Profile
TN	True Negative
TP	True Positive
TSO	Transmission System Operator
UP	Utility Provider
WAN	Wide Area Network

Chapter 1

Introduction

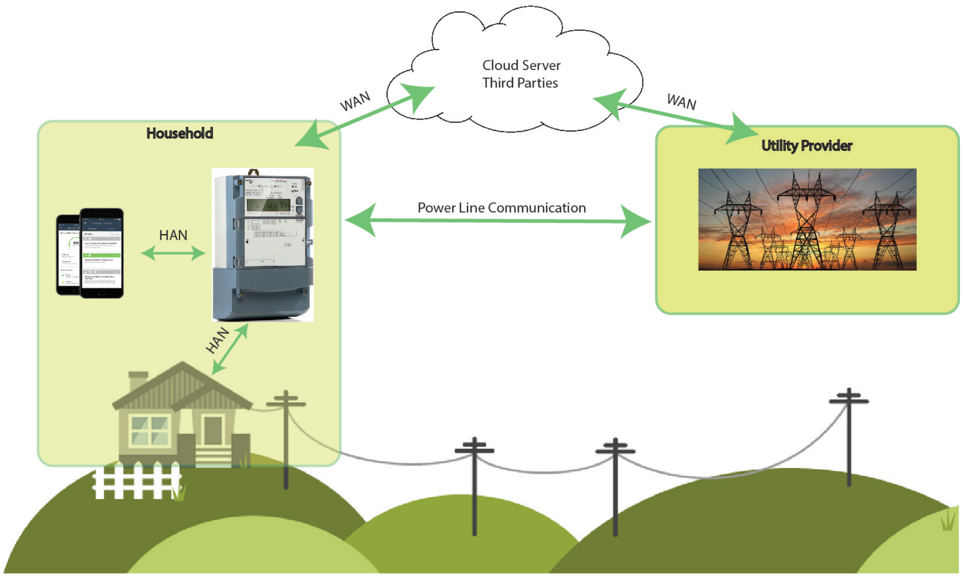

Figure 1.1: Current development of the Smart Grid by introducing Smart Metering Systems.

Nowadays, with the increasing integration of renewable energy in power systems in Europe, they are undergoing significant changes. Accommodating the relatively less controllable and predictable output of the new technologies is driving changes in the composition and operation of the entire power grid [1]. To move forward, we need a new kind of electric grid, one that is built from the bottom up to handle the great advances in digital and computerized equipment and technology; one that can automate and manage the increasing complexity and needs of electricity in the 21^{st} century. The Smart Grid (SG) represents an unprecedented opportunity to move the energy industry into a new era of reliability, availability, and efficiency. The

SG is not just about utilities and technologies; it is about providing the information and tools you need to make choices about your energy use [2]. A smarter grid will enable an unprecedented level of consumer participation. Combined with real-time pricing and the associated technologies, they may help households save money by managing and monitoring their electricity use and choosing suitable times to produce and consume electricity.

In an effort to secure a sustainable energy supply and minimize the effects of climate change, European Union governments have focused on the reduction of greenhouse-gas emissions. Since domestic use accounts for approximately 30% of worldwide electricity consumption, it is essential to optimize the efficiency of electricity use in homes by eliminating wastage and improving the behaviour of consumers.

In order to achieve these, there has been great discussion on the tools and the technological advances that may be used to make the grid smarter. One of these elements is the Smart Meter. It is a device measuring the energy consumption [3].

1.1 Overview of the Project

You cannot improve what you cannot measure and that is the problem where the increasing adoption of Smart Meters (SMs) in energy distribution networks are planning to address, so that the utility providers (UPs) will be able to monitor the grid more granularly. They allow more accurate predictions and faster detection in changes of the demand and adapt pricing and electricity generation more dynamically.

An important aspect of the use of SMs is the ability to foster positive behavioural change in consumers, which can be achieved by providing feedback to a household indicating individual appliance consumption [4], [5]. According to [6],[3] this may lead to more reasonable energy consumption and to better use of Distributed Generation (DG) capabilities. Thus, the customers may benefit by being able to monitor their consumption in real time, with possibilities to take advantage of time-of-use pricing, resulting in a smarter and more stable grid.

Therefore, significant low cost energy reductions can be made in the residential sectors, but these saving have not been achieved to date. Experts believe that they have not been achieved yet due to behavioral barriers [7]. Moreover, a great amount of money is invested to install SMs, however the energy savings and financial benefits of this infrastructure have yet to reach its full potential. Although most of the current SMs are equipped with the suitable hardware, they have not been enabled to deliver the above possibilities.

The research problem addressed in this Semester Thesis is about how the total energy consumed in a household can be disaggregated into individual appliances taking into consideration the present hardware constraints and the currently installed SMs. The aim is to measure how much energy goes into each major appliance which can be analyzed to identify and eliminate inefficiencies. This disaggregated result leads to two major impacts: increased utility customer engagement and reduced energy usage [8].

1.2 Research Objective

The problem addressed in this thesis concerns Energy Disaggregation, which is a set of statistical and machine learning approaches for extracting end-use and appliance-level data from an aggregate, usually a household energy signal. Under this context, the idea is to match an appliance profile with known appliance signatures with minimum error. From this perspective, Energy Disaggregation is related to the Knapsack or Subset Sum problem, which is NP-hard.

The literature on this subject dates back to 1992 with the first publication on this field by Hart [9]. On this point we should differentiate between Intrusive Load Monitoring which refers to appliance-level metering by installing one meter per appliance and Non-Intrusive Load Monitoring by using one meter for the aggregate household energy signal.

To compare the two approaches, the financial costs and practical issues should be considered. The first method would need enough meters for all the devices in a house, increasing the economic aspect of the project as well as being clearly inconvenient for the user. On the other hand, it reduces the complexity of the disaggregation problem at the expense of a more significant intrusion into the household. Therefore, until such appliance-level metering is available at a large scale with low cost, NILM should be considered the most reasonable implementation of Energy Disaggregation.

On the Fig. 1.2 all currently known hardware solutions (ILM approaches) are exhibited [7]. It is shown that in general these solutions require substantial investments from the hardware point of view. Thus, in an effort to avoid the use of such intrusive devices, research has instead focused on single point sensing. Electrical sub-metering requires an energy meter for each device while smart appliances come with inherent metering capabilities, reporting their energy to a central hub. Finally, it is also possible to tag each device with a reference ID through appliance tagging or you may also use existing sensors to infer appliance consumption with ambient sensors.

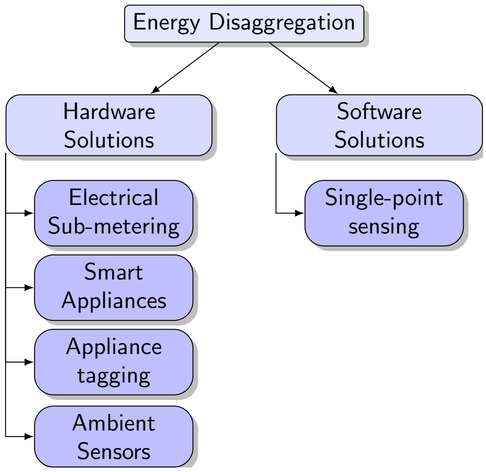

Figure 1.2: Intrusive methods for load disaggregation exploiting devices measuring energy consumption.

The fundamental difference of the two techniques is that ILM is mainly a hardware solution whereas the NILM focuses more on the software aspect. However, this does not mean that the latter does not require special equipment. For this reason, more and more European governments are adopting regulations for SMs' design. SMs are an example of premise-level meters already installed by the UPs primarily for automated energy reading and accurate billing. It should also be pointed out that many countries like the United Kingdom and Sweden have already announced the mandatory installation of SMs to all households. Thus, although up to now smart meters do not perform disaggregation themselves, they provide an ideal data collection platform and hardware characteristics capable of supporting Energy Disaggregation.

The complexity of the NILM task depends on the number of appliances and occupants of the target household. In [11] the typical number of appliances of a house is estimated to be around 30-50. These appliances exhibit a wide variation of power (0-5000 W) and are in operation for different durations of time over a period which is usually considered a day but it may also be per month (usage of air conditioners). As a result their energy profile may vary a lot from their rated power. For example, some typical appliances of an American household are presented in Fig.1.3, where devices of the same type are grouped together. The majority of the household's energy is consumed by relatively few appliances and especially from those which perform heating or cooling tasks. Therefore, it is most important for an NIALM algorithm to successfully disaggregate such high energy consuming appliances.

On this point, it should also be pointed out that the basic requirements of the method that will be explained in the rest of the thesis are as follows.

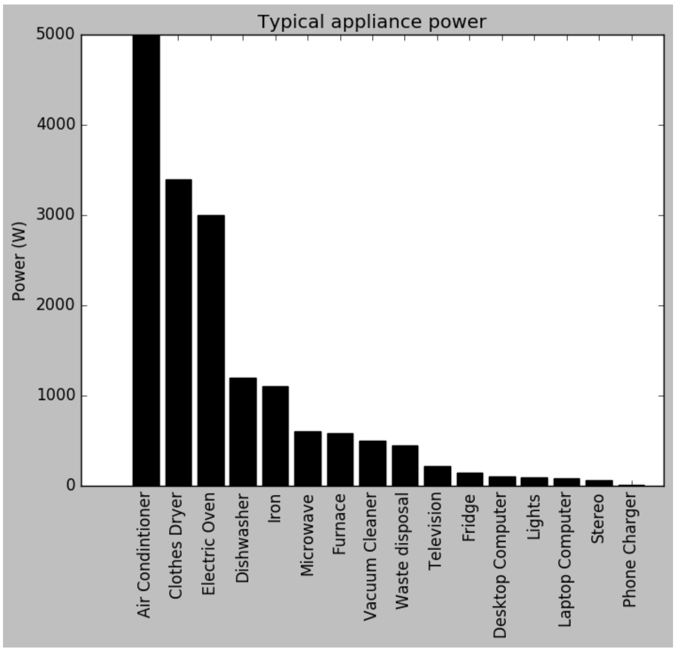

Figure 1.3: Typical appliances on an American household based on [10].

The first one is that the approach should not be intrusive which means that the energy consumption will be collected by a single point. Secondly, the hardware that will be used and tested should correspond to the present constraints and the current SM infrastructure so that no additional hardware will be required for the disaggregation at a household.

Having presented the problem and the approach followed for the solution, a typical scenario is described on the Fig.1.4 where the aggregate signal obtained by the SM is shown as well as the desired disaggregation signals. On this figure the expected output of the disaggregation procedure is exhibited.

1.3 Applications of Energy Disaggregation

In the previous section the concept of the Energy Disaggregation was introduced while here the reasons as well as the benefits that can be extracted from the output result are explained.

To begin with, the monitoring of the daily energy consumption yields information about the Typical Load Profile of the customer meaning the minimum, average, and maximum over specific periods of time [13]. Thus, information can be derived concerning the consumer behaviour such as the household occupancy and occupant activities. The key issue on this application is privacy. The data of each customer has to be processed with great

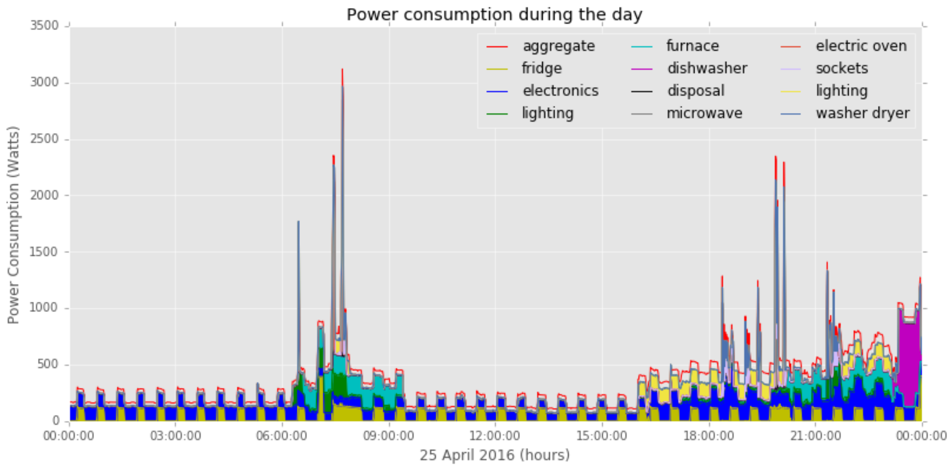

Figure 1.4: Power consumption for the aggregate and appliance level on a typical day in United States. Data was extracted based on the REDD data set[12].

attention and anonymously in order to maintain its privacy. One suggestion on this would be the individual dissagregation of each household of a community but without keeping any signature of the specific customer which could lead to his identification. So although the disaggregation occurs for each house, the collection and the processing of the data focuses more on the community behaviour which may be consisted of at least of hundred of households in order to make it difficult to reveal its identity. However, on the scope of this thesis we do not get involved on this issue but we are limited to do the disaggregation inside the SM so that no raw data will be sent back to the UP. By doing so, less sensitive data of the customer is transferred to the UP for processing.

Secondly SMs enable the possibility of pricing intelligence by setting up dynamic tariff structure. This may improve the efficiency in electricity markets by representing real-time the costs of generation and consumption. Thus, the costumers can benefit from these if they can be able to choose flexible pricing schemes. The advantages of dynamic pricing have also been identified in [14] as demand and cost reduction and economic efficiency gain.

Moreover, knowledge of consumption behaviors is very important as it is very useful for formulating tariffs and developing strategies, as well as allowing customized billing. Knowledge gathered from customers' load profiles could also be used to identify, detect and maybe predict behaviour irregularities that may be due to faulty metering or human intervention and fraud [15].

One of the most valuable analytics applications for the SG and the data availability is the possibility to perform load forecasting with high accuracy [16], [17]. Load predictions up to now ignore the consumer power profile which by collecting individual data can be integrated and adopt different categories of households for the prediction methods. Recently a spin-off from ETH called Adaptricity is involved on this domain and tries to solve the above problem [18].

Finally we should not neglect the positive aspects it will have for the customer. By providing disaggregated real-time feedback, it has been found to reduce electrical energy consumption [19],[8]. So individual customers may benefit financially and increase their awareness about energy saving. Additionally, disaggregated data can be used to provide personalised suggestions regarding the behaviour of the consumer or an appliance's use and state. The system may detect when an appliance needs to be replaced due to poor energy efficiency and quantify the savings to a more efficient mode.

1.4 Contributions of the Thesis

The purpose of this thesis was to investigate and develop a method to disaggregate the total power consumption of a household. The increasing complexity of the Non-Intrusive Load Monitoring (NILM) techniques come to compensate the simplicity on the hardware side since just one single-point is used to measure the total electric consumption by avoiding deployment of multiple sub-metering devices. The investigation of this work plans to identify the current hardware constraints of SMs in order to implement NILM methods which can run real-time in a low-resources environment.

During the work of the current thesis many obstacles needed to be overcome concerning mainly the software investigation and implementation. More specifically, the main contributions of this thesis focus on the following points,

- Insights and pitfalls when processing high frequency values of the REDD Data Set by providing a simple data set converter specifically for the current waveforms.
- Approaches concerning Semi-Supervised training of generalized models by using classification methods and by adding information regarding the time of usage of the appliances during the day.
- Extraction of harmonic components from aggregate data in order to be used for disaggregation purposes and improving current approaches.
- A modified version of the Combinatorial Optimization of the Energy Disaggregation method in order to be applied on a low-resources environment.
- Evaluation of the suggested algorithm on a low-cost microprocessor.

1.5 Structure of the Thesis

This thesis is organized as follows. First we introduce the current smart metering infrastructure by analyzing the current European Regulations in this field and developed Smart Meter Projects. Afterwards, in chapter 3 we provide detailed information about the design of commercial devices in order to evaluate their capabilities and limitations. The most prominent NILM approaches are explained and important issues concerning these strategies are addressed. Chapter 4 introduces the SM architecture under consideration and the low-cost micro-processor used for validation. Moreover it provides the results of the proposed method and a comparison with the state of the art techniques. In the final chapter the results are summarized while the industrial aspect of the issue is discussed.

Chapter 2

Smart Metering Infrastructure

Since the inception of opening the energy market and the emergence of renewable sources, there has been a great effort to match generation with consumption. In order to be achieved, according to [13] it is required to know the hourly power profile of customers. Traditional energy meters do not offer this possibility since they accumulate the energy signal over a long period without keeping any data of the time of the consumption. This gap is expected to be covered by the Smart Meters which are capable of recording the time of electric use and reporting back that information to the utility provider. According to the official definition based on [20] the smart metering system means a systematic process that can measure energy consumption, adding more information than a conventional meter, and can transmit and receive data using a electronic communication. Thus, SMs enable two-way communication which is the fundamental difference with the traditional metering infrastructure [21]. With Smart Meters, consumers can adapt their energy usage to different energy prices throughout the day, saving money on their energy bills by consuming more energy in lower price periods.

Intelligent buildings are difficult to imagine nowadays without smart metering devices. The European Union(EU) has forwarded regulations in order to modernize and update the old and bulky Distribution Grid. To succeed on this transition, it is needed to adopt and insert new elements and concepts in the system. Smart Meters offer the lowest cost and installation effort both for consumers and utilities and thus show the best potential for high market penetration [7].

It is clear that many of the functionalities and associated responsibilities for SMs will not be different from the existing analogue meters, but in comparison with the traditional meters, smart metering have a number of new concepts introduced in the Distribution Grid [22]. The new features are expected to yield benefits in retail service quality and cost, demand response to prices and distribution grid performance and cost.

2.1 European Regulations

The increasing installation of Smart Meters in EU countries raises many major technical, regulatory and organisational issues. The EU aims to replace at least 80% of electricity meters with Smart Meters by 2020 wherever it is cost-effective to do so [23]. This smart metering and smart grids rollout can reduce emissions in the EU by up to 9% and annual household energy consumption by similar amounts [22].

According to the EU energy market legislation in the Third Energy Package issued by the European Commission, Member States are required to proceed within a timescale of up to 10 years with the implementation and installation of intelligent metering systems where the Cost-Benefit Analysis is positive. The economic assessment was completed on September 2012 and later in this chapter the results will be presented. There is a roll-out target of 80% market integration by 2020. A 2014 Commission report, [23], on the electricity smart metering deployment in EU states that around 200 million Smart Meters for electricity will be installed in the EU by 2020. It is expected by then that almost 72% of European customers will possess a SM. On average, it is estimated that a SM costs between 200 € and 250 €. This represents a potential investment of 45 € billion in total [24].

Furthermore, in line with the provisions of the Third Package, the development of new energy services like demand response and dynamic prices must be based on data from Smart Meters. The new features should be implemented by respecting the customers' right to data protection and privacy as stipulated in regulations. Consumers' data is protected by the EU's Directive on the processing of personal data. The Directive sets rules on who can access personal data and under what circumstances. The Commission has also produced guidance on data protection and privacy for data controllers and investors in smart grids [25].

The hardware of SMs should be equipped with suitable characteristics so that it can support the common minimum requirements for new metering systems as described in [20] and are the following,

For the customer:

i Provision of readings to the customer and any third party designated by the customer. Thus, direct feedback may be given to the consumer which is essential to ensure energy saving.

ii Update the readings *frequently* enough in order to increase the reliability and the real-time response of the system. The general consensus is that at least a 15 minute refresh rate is needed.

For the Utility Providers:

iii Provide two-way communication between the SM and the UP for metering and billing purposes.

iv Support advanced and dynamic tariff systems. It is a key functionality to improve energy efficiency and save costs by reducing the peaks in energy demand.

v Allows remote control of the supply.

For grid security and data protection:

vi Guarantee reliable data paths through which secure and private communication between the operator and the consumer will be ensured.

vii Fraud prevention and detection.

viii Provide import/export power flow metering. This function is necessary to allow integration of RES and boost micro-generation.

From the above it is interesting to note that the case of pre-payment is not covered by the recommended functionalities as it is specific to certain energy markets and is not considered common.

One of the most challenging and most controversial issue concerning SMs is point (ii) which refers to data sampling of the energy consumption. An overview of the known refresh rates up to now is given on Table 2.1.

Table 2.1: Frequency of consumption data readings available to consumer for the countries which the data is available and specified,[24].

Country	**Data sampling**
Austria	15 min
Denmark	15 min
Estonia	60 min
Finland	60 min
France	10 min - 30 min
Germany	15 min
Ireland	seconds
Italy	10 min
Portugal	60 sec
Slovakia	15 min
Sweeden	60 min
United Kingdom	10 sec

This operation provides to customers the privilege to have direct feedback on their current devices. If consumers are to rely on the information provided by the system, they need to see the information responding to their actions [26]. This facilitates the replacement and development of more efficient products and services. However, the main concerns for high frequency data reading is the risk of user profiling and privacy and confidentiality policies.

It is worth to mention that this characteristic is compulsory for the SMs and therefore those who have not complied yet with the data sampling regulation should ensure that this possibility may be added later or met through other arrangements. Currently all the countries deploy SMs that are able to log data in the worst case every 15 min. The UK is the exception and exploits smart metering infrastructure with updates on the order of seconds ($\sim$10 sec). There are also countries like Portugal with resolution every second but for use only by the customer whereas the data is sent every 15 min to the UP. All Member-States have opted for regulated metering market with an exception of the UK, which explains why its SMs have better capabilities at the same price.

At present, few Member States have strictly set the guidelines on the functional requirements of smart metering systems and the others leave the analysis to the parties responsible for the roll-out, i.e. DSOs or third parties, without setting clearly the functionalities that the consumers may also benefit from, like dynamic billing according to cheaper prices.

Another important aspect is the Electricity meter ownership and data handling. In 15 out of the 16 Member States that have decided to proceed with a large-scale roll out, the distribution system operators (DSOs) are responsible for implementation and own the meters, so the operation is to be financed through network tariffs and bills. In four Member States (Denmark, Estonia, Poland and the UK) data will be handled by an independent central data hub. Finally, it is also noted that in the Czech Republic, Germany and Slovakia alternative options for data handling are being considered (customer responsibility) [22].

The cost of a Smart Meter varies a lot for the Member-States in EU. For example it ranges from under 100 € in Malta to 766 € in the Czech Republic. Smart metering systems are expected to deliver an overall benefit per customer of 309 € along with assumed energy savings of 3% [27]. The latter ranges from 0% in the Czech Republic to 5% in Greece. Of the countries that have completed roll-outs, Finland and Sweden have indicated energy savings of the order of 1-3% [23]. It is important to note that there is no direct link between the common minimum functionalities for the SMs and their overall cost but it is more influenced by local conditions.

On Fig 2.1 it can be seen that various questions have come up concerning the deployment arrangements of SMs. The different possibilities of the features that SMs introduce in energy markets are shown, however more details are beyond the scope of this project.

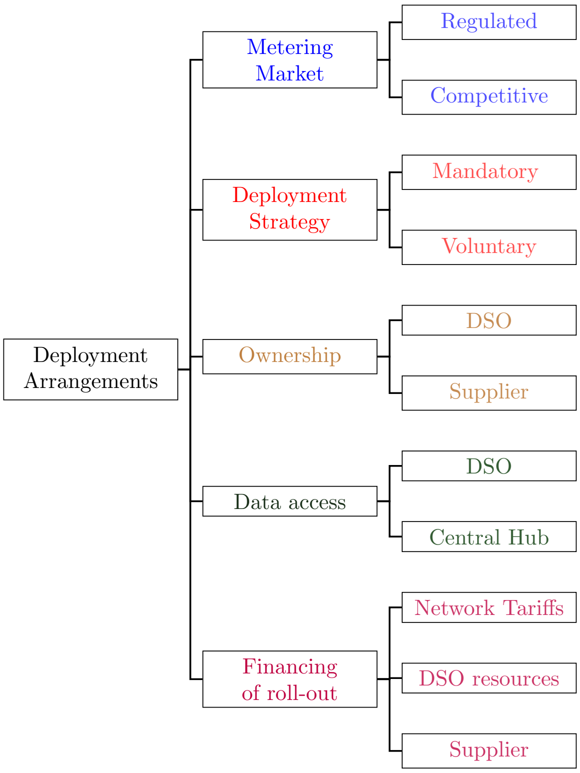

Figure 2.1: Deployment arrangements for electricity smart metering in EU Member States.

2.2 Cost-Benefit Analysis

In order to assess whether the smart metering Interface exceed costs and have benefits for the customer and the UP, Member States have conducted cost-benefit analyses, as prescribed by the EU law. Similar assessment was carried out on Smart Meter for gas but on this document the analysis is restricted just for electricity. The European survey is presented in this section where it is shown that smart metering deployment plans vary greatly as a result of different characteristics and cost-benefit results of each country.

It is important to carefully consider the functionalities that SMs need to have since different characteristics result in significant variations of the final outcome of the financial assessment and therefore in the decision of the deployment.

In most of the countries according to [24] the minimum requirements are met. However, there are some exceptions like Sweden, Italy and Finland which have already completed the procedure but do not have the expected results due to partial incompliance with the common minimum functionalities. Also, Malta has ignored a lot of these characteristics, which explains the extremely low price for the SMs currently installed there.

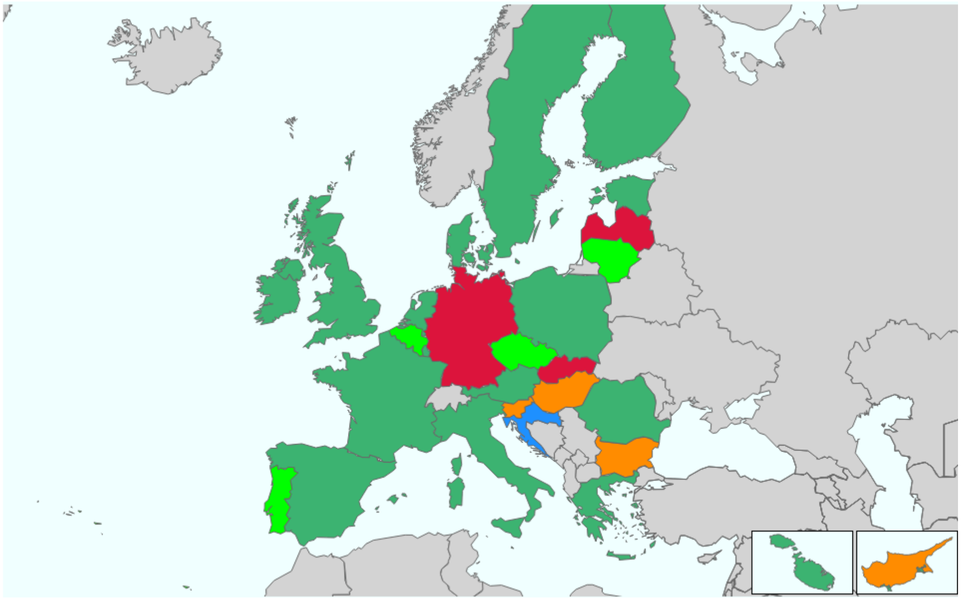

Figure 2.2: Regulation for roll-out of Smart Meters by 2020, ■ Wide-scale (>80%) roll-out by 2020 ■ NO Wide-scale (<80%) roll-out by 2020 ■ Selective roll-out by 2020 ■ No data ■ New, [28].

On Table 2.2 the different results for the CBA for each country in EU are shown as stated in the report of the European Commission in [24]. The range of values placed on costs and benefits may stem from different starting conditions in Member States, local realities and CBA scope and methodology.

Analysis shows that in over two thirds of cases, the evaluation is positive, therefore Member States are now committed to proceeding with the roll-out of smart metering. Major benefits during the analysis were the supplier-related saving and energy savings [29].

The results of Member States' cost-benefit analyses exhibit that 16 Member States (Austria, Denmark, Estonia, Finland, France, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Poland, Romania, Spain, Sweden and the UK) will proceed with large-scale roll-out of Smart Meters by 2020. In two of them, namely in Poland and Romania, the CBAs yielded positive results but official decisions on roll-out are still pending. Moreover, in seven Member States (Belgium, the Czech Republic, Germany, Latvia, Lithuania, Portugal, and Slovakia), the CBAs for large-scale roll-out by 2020 were negative or inconclusive, but in Germany, Latvia and Slovakia smart metering was found to be economically justified for particular groups of customers.

Table 2.2: Status of electricity smart metering large-scale roll-out in EU Member States [24].

Country	SM Wide-scale roll-out (80% of consumers by 2020)	Cost-Benefit Analysis	Outcome of the CBA for a wide-scale SMs roll-out
Austria	✓	✓	✓
Belgium	✗	✓	✗
Czech Republic	✗	✓	✗
Denmark	✓	✓	✓
Estonia	✓	✓	✓
Finland	✓	✓	✓
France	✓	✓	✓
Germany	Selective	✓	✗
Greece	✓	✓	✓
Ireland	✓	✓	✓
Italy	✓	-	-
Latvia	Selective	✓	✗
Lithuania	✗	✓	✗
Luxembourg	✓	✓	✓
Malta	✓	✗	-
Netherlands	✓	✓	✓
Poland	✓	✓	✓
Portugal	✗	✓	-
Romania	✓	✓	✓
Slovakia	Selective	✓	✗
Spain	✓	✗	-
Sweeden	✓	✗	-
United Kingdom	✓	✓	✓

Finally, legislation for electricity Smart Meters is in place in the majority of Member States, providing a legal framework for deployment and regulating specific matters such as time line of the roll-out and process of sensitive data of consumers, or setting technical specifications for the meters [23].

To sum up, about two thirds of Member States have concluded in favour of a large scale roll-out of smart metering by 2020 or earlier. Some, such as Italy and Spain, have decided to go ahead without conducting a detailed CBA. According to estimates, the planned roll-outs will involve the installation of 240 million Smart Meters by 2020 and a total investment of 45 € billion. On the basis of their CBAs, some countries (e.g. Germany, Latvia and Slovakia) are opting for a selective roll-out with an overall lower penetration rate by 2020. Nevertheless, these roll-outs add to the number of electricity Smart Meters scheduled for installation and associated investment levels, and bring the EU-27 average penetration rate, as forecasted for 2020, close to 72% of consumers [21].

2.3 Current Smart Meter Projects

After we have analyzed the European regulations and the decision that have been taken on national level based on the CBA outcome, on this section we proceed with an up to date description of the on going largest Smart Meter projects as well as the experience and the results that have been derived by these developments.

One of the largest SM project currently happening is the Linky project in France [30]. There are currently 35 million electricity meters in France which are aimed to modernize as a legal obligation imposed by EC. To comply with this requirement, ERDF is implementing the Linky project. For this purpose a new SM was designed in cooperation with many SM companies, among them Itron and Landis+Gyr. The new French electrical meter deployment is scheduled from 2016 to 2020.

Since the main focus is the SMs' deployment in Europe, another well-known initiative is one of the Italian operators ENEL and ACEA planning to replace 27 million meters. Moreover, Scandinavian operators also launched projects of SMs installation of around 3 million whereas ENDESA in Spain and EDP in Portugal have embarked on similar projects for 16 million SMs [31]. In Germany, the project Web2Energy which is a Research Project funded by the 7th Framework Programme and a collaboration with Landis+Gyr as the SM solution provider will install smart metering systems in selective areas mainly in Nothern and Central Germany [32].

Finally, in the United States, in Southern California there is a plan of 5 milion meters and in Canada, the Province of Ontario will also deploy 5 million SMs.

Based on experiences acquired from completed or the on-going pilot programmes, the following aspects may be derived for the roll-out of smart metering. Firstly, the minimum common set of requirements issued by EC should be respected. Otherwise the installed SMs will be replaced again in the future, increasing the total costs (like in some cases in Scandinavia). Secondly, data privacy and security are very sensitive matters and should be handled with great care and in cooperation with consumers in order to explain possible misunderstanding and correct any omittances and failures. Regarding consumer trust, there should be a communication strategy from the beginning to earn their confidence and use feedback services to stimulate their involvement and interest. Therefore, particularly important for residential consumers is a reading update rate of at least 15 min and a standardised interface to transfer and visualise individual consumption data in combination with information on market conditions and service or price options [33].

The benefits that have been reported from the customer perspective concern the energy savings because SMs help consumers reduce their consumption and sometimes even increase their energy efficiency. The information retrieved from SMs may offer innovative services to them and have an impact also on the competitive pressure within energy supply markets. To this end, the consumers will be able to choose from different offers and adapt their consumption patterns. Finally, since by introducing advanced monitoring infrastructure for real-time monitoring purposes may motivate households to decrease energy usage, the national goals for CO_2 emissions will be easier to be met.

2.4 Energy Disaggregation and Smart Meters

Since the main focus of this thesis is Energy Disaggregation based on the present hardware limitations which were presented previously in this chapter, it is needed to connect the smart metering systems currently developed with the commercial applications of Energy Disaggregation.

After the common minimum requirements have been analyzed and the SMs projects have been presented, the companies which are involved in the field of ED are investigated. Since the most mature markets as well as the regions with strong know-how on this domain come from UK, USA and Scandinavia, the most successful industries come from these countries.

These companies offer software and hardware solutions for real-time disaggregation. Most of the companies act in the UK and the USA where the smart metering market is competitive and therefore they usually provide their own custom Smart Meter design accompanied with a Home Display Interface where they visualize the energy breakdown of the consumption signal. They aim at reducing residential and business' costs as a result of personalized energy feedback and recommendations.

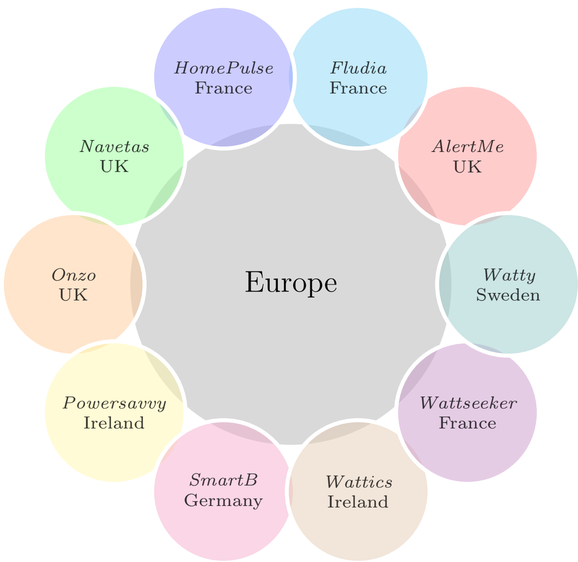

Figure 2.3: Available commercial companies offering Energy Disaggregation in Europe.

As has been seen, there is a gap between the SM equipment currently

Figure 2.4: Available commercial companies offering Energy Disaggregation around the World.

installed on the largest projects in Europe and the Energy Disaggregation possibilities with these devices. Since most of the commercial companies offering disaggregation services need to install their own custom SM, the cost for the customer is increased while the SMs deployed by the UPs are not used to their full potential. Although many countries have not set specific regulations for the requirements of the SMs, the currently installed ones due to the EC obligations are capable of doing ED techniques and this is the problem that this thesis is focused on. The commercial sector on this field have started far before the EC regulations and therefore they ignore the capabilities of the new SMs and they insist on their own hardware solutions. However, in order to improve the customers' services and on the same time reduce the costs, ED methods should be done on the SMs that DSOs provide so that no extra operations and costs will be charged to the customers.

Figure 2.5: Most well-known commercial companies offering Energy Disaggregation around the World.

Chapter 3

Hardware and Software Considerations

The process of Energy Disaggregation aims to calculate and discriminate individually for each consumer the power signal for each appliance he has been using. A viable approach to this problem is a combined solution from hardware and software perspectives which can be supported both financially and practically by the UPs, DSOs and customers.

During the previous chapter, the main regulations - common minimum requirements - for the structure of a Smart Meter design were explained while the most well-known and largest current European smart metering deployment projects were presented. In the first section, the focus is on the specific commercial SM models that are installed today in Europe (in USA due to unique regulations and conditions on the energy system, the smart metering infrastructure differs) while the various possibilities for the elements like communication protocols, processing power and data sampling comprised a SM are described.

Additionally, the most active commercial companies implementing Energy Disaggregation methods were shown whereas on the second section the analysis of the used algorithms are explored and investigated. A viable solution without the use of intrusive and expensive sensor networks is the Non-Intrusive Load Monitoring (NILM) framework. Using only the aggregated electricity consumption data acquired by a single point measurement device, the energy signal is separated to appliance-level combined by an utility-customer interface. Thus, Energy Disaggregation can be considered as a single-channel source separation problem [34]. NILM employs machine learning and pattern recognition algorithms through which appliance signatures are acquired. This field has been increasing during the last years after the release of a number of public data sets [12], [35] designed specifically for these purposes as well as a Python toolkit enabling comparison of various algorithms [36]. However, yet, no set of distinctive characteristics has been found which can be able to accurately perform NILM and describe each appliance, mainly because of lack of a reliable training phase. Therefore existing approaches exploiting currently collected Smart Meter data are not used on a national scale.

3.1 Smart Meter Architecture

Similar to the evolution of embedded systems used in mobile phones, the energy meter has also evolved to a Smart Meter. SM will be a necessary part of the implementation of Smart Grid even with lower capabilities as described on previous chapters. Since the most important smart metering projects have already been presented, an interesting topic is that the SMs that are currently deployed have a life time of 15 years on average. The largest companies in the European and North American market are Landis+Gyr and Itron. The former is based in Switzerland while the latter in the United States. Typical examples of their products are shown on Fig. 3.1. In this figure, the model E650 from Landis+Gyr and the Itron Centron OpenWay are depicted. Also depicted is the Linky SM which is installed in France in Linky project. For the design of this SM, both companies co-operated to develop the product.

Figure 3.1: Various designs of currently deployed Smart Meters; Landis+Gyr E650 (left), Itron (centre), Linky (right).

Although every manufacture develops devices which may vary, it is possible to distinguish the critical elements involved on the hardware of the SM. These characteristics are described on Fig. 3.2 where the general block diagram of a SM as described on [7] is shown as well as the exhibition of a commercial SM by Landis+Gyr depicting its basic outline next to it for comparison reasons. On this point, it is reminded that the commercial companies introduced on section 2.4 are using different SMs where even the design differs a lot from the proposed models. As an example, we refer to the patent document of Navetas SM [37]. Since the disaggregation methods of this company are based on machine learning (and more specifically on Neural Networks), it was reasonable to enclose a fuzzy logic module inside the SM, increasing however substantially the cost of the unit, an idea which according to the knowledge of the author has been discarded today.

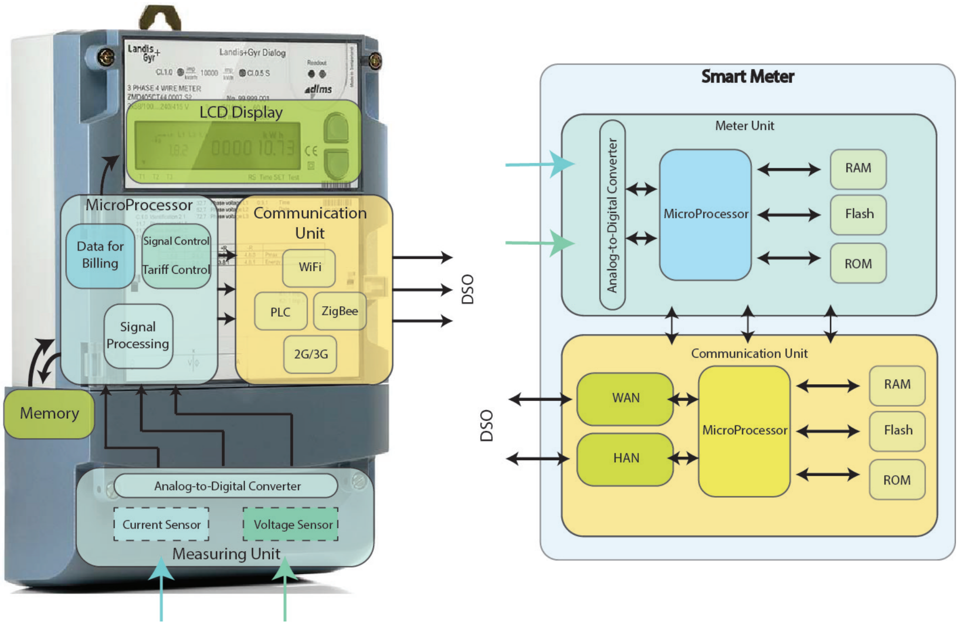

Figure 3.2: Internal hardware characteristics of modern Smart Meters. On the right a generalized block diagram for a SM as proposed in [7] while on the left the block diagram of the Landis+Gyr E650 according to its datasheet [38].

A critical result out of the Fig. 3.2 is the existence of two substantial components, the Meter (or Metrology Card) and the Communication Unit (or Network Interface Card). In most cases they are combined in a common housing so that one product will be supplied to the UPs and consumers.

The Meter samples the current and voltage waveforms according to the sampling rate of the A/D converter and extract the average complex and/or active and/or reactive power. It is comprised by the following elements,

- *Current and Voltage Sensor* responsible to record voltage and current in the individual phases (for the European 3-phase system).
- *Analog-Digital converters* digitize the previous values and feed them as instantaneous digital values via calibration stages to a (signal) processor. The power level resolution of this device must follow the billing

requirements by the DSO. For the purposes of this thesis, it is considered one of the most important components since it is responsible for the sampling rate of the SM. The meters available in the market and described above offer a sampling frequency of the A/D converter in the range of 1-2kHz. For example, Itron SMs have on average a refresh rate of 600Hz whereas the recent E650 from Landis+Gyr around 1.6kHz. According to the Nyquist-Shannon sampling theorem, it needs to be double of the harmonic frequency we need to extract. So with a fundamental frequency of 50Hz it is possible to read up to the 16^{th} harmonic for the E650. To date, research laboratories have been collecting data in high frequency (10kHz) since there is no difference in price. It also noted that the 1 Hz - 2 kHz range is of particular interest, given the potential benefit in appliance recognition [7].

- *Micro-processor*, responsible for various operations including billing, tariff control and security issues.Recent research proposes cryptographic solutions that enable sophisticated billing policies without leaking information. The goal is to provide Smart Meter designers with a general Metrology Card for selecting an appropriate balance between platform performance, power consumption, and monetary cost that accommodates privacy-preserving billing protocols [39].
- *Memory and Storage (RAM and Flash)* are a critical characteristic of the SM since RAM is used for intermediate storage operations. It is another constraint of our system since RAM is used for the disaggregation algorithms and its limitations restrict also the power of these techniques.

On the other hand, the Communication Unit is the interface between the consumer and the DSO. This card also consists of a microprocessor and memory to perform the necessary operations. However, the important features are the different types of communication functionalities it can support. The typical networks that can be used is the Wide Area Network (WAN) and the Home Network Area (HAN) which may offer higher frequency data. For these purposes, the following transceivers may be used,

- WiFi,
- ZigBee,
- Cellular network (2G, 3G),
- Power Line Communication (PLC).

Because of lack of regulations for a specific protocol which is to be used, most of the SMs offer multiple network transceivers which offer more possibilities to the operator but augments the costs with no apparent advantages. For example the E650 offers for remote reading and tariff control the communications interfaces and channels (RS232, RS485, CS, M-Bus, PSTN modem, GSM modem, GPRS modem and Ethernet).

3.2 Hardware Constraints

Based on the previous analysis, the present constraints regarding the hardware design are explained. It is clear that the bottlenecks of the Energy Disaggregation techniques come from the components below,

- Sampling frequency of the *A/D converter*,
- Processing power of the *Processor*,
- Storage capability of the *Memory*,
- Data transfer rate due to the used *Communication Interface*,
- Transfer rate of *Serial Interface* between the two type of cards.

Concerning the frequency of the data, since there is no significant difference on the price between the device of 1Hz and 2kHz, all the companies are currently offering high frequency sample rate on the A/D converter level. This rate is connected with the software aspect of the ED problem since if it is possible to use current harmonics the distinction procedure between the appliances is equipped with more resolution and device characteristics. However, since most of the NILM solutions are based on low-frequency they do not exploit the SM to its full potential.

Another restriction is the processing power of the microprocessor. On [39] and [40] an evaluation of the current possible implementations is done and the results are depicted on the Table 3.1. It is shown that the processing power is highly connected with the price and the power usage. So far the designs are using the first two microprocessors mainly because of the price. So it visible that a feasible operating frequency is between 25MHz and 80MHz which is a good start to offer a first approach on the ED problem. It is noted that such information is not publicly available for the specific models under consideration but their capabilities fulfill in the worst case the first two ones on the Table 3.1 as stated in [39].

Table 3.1: Characteristics of the most common microprocessor available for integration in the Smart Meters [39].

	MSP430F5438A	**LM3S9B92**	**Cortex-A8**	**Cortex-A9**
Operating Frequency	25 MHz	80 MHz	720 MHz	1 GHz
Operating Power	330 - 690 μW	333 - 524 mW	0.4 W	1.9 W
Family Price Range	0.25$ - 9$	1$ - 8$	41$ - 46$	>50$

The third bottleneck of the hardware design is the storage of the RAM memory. Since on the flash the ED software and the firmware of the SM are saved, it is considered that for not very complex codes it is more than sufficient. However, the described ED algorithm on this project which comes from the Optimization field need a great amount of RAM memory to perform disaggregation computations since a comparison matrix must be always on in order to extract the appliances' power. Therefore, the size of the matrix and the number of the appliances is limited.

Regarding the communication interface most of the operators are currently using the PLC interface which may be not sufficient for the full data transfer since if the harmonic content of the signal is to be included the volume of data increases a lot. However, there can be used other solutions like the HAN network through Ethernet or ZigBee interfaces.

The latter point refers to the issue on where it is more advisable to do the disaggregation. If a HAN network is available, then the data can easily be sent to a cloud storage where the ED can be done using a lot of processing resources. However, another option is the data to be stored and processed inside the meter. This is the most scalable option since it does note need any other hardware like a cloud storage to be installed either by the UP or the consumer. Thus, since raw sampled data is not sent outside the meter, this option can handle the high frequency sampling rate along with the cheap PLC communication.

Finally, a critical issue is also the data frequency of the Serial Interface between the two types of cards which must support the required needs according to the refresh rate of the A/D converter and the data transfer rate of the Communication Unit.

To sum up, as the frequency requirements increase, additional bottlenecks in getting the data out of the meter are shown due to the current hardware constraints of the Metrology and Communication Units which include the A/D converter, the Micro-processor, the memories, the used Communication channels and the Serial Interface. Regarding the Nyquist-Shannon sampling theorem and that no harmonic higher than the 11th is of interest, thus the ideal minimum value should be of about 1.2-2kHz. However this minimum may lead to transmission and storage limitations [11]. Since sending high frequency data over the HAN or the WAN is not possible, a number of different techniques have been proposed like the compression of the data and replacement of the ZigBee with WiFi. However, through the current work, we strongly believe that the current infrastructure without any additional elements (e.g. cloud services) can be used to offer reliable Energy Disaggregation methods comparable with up-to-date developments on the field.

3.3 Non-Intrusive Load Monitoring

More granular data and particularly appliance data offer a great opportunity to create strong links between algorithmic approaches and energy saving effects.

As was mentioned in the Introduction chapter, a separation between the intrusive and the non-intrusive monitoring must be done. The first option involves mainly hardware solutions, Fig. 1.1, while the latter refers to software approaches since the disaggregation is done based on software techniques. On this section, there is a review of the most well-known algorithms that are used worldwide for these purposes.

The NILM methods can be considered as signal processing and time series analysis strategies. Over the last years, many methods have been proposed and have succeeded substantial advances. Still, several challenges are pending to be answered so that NILM will be a viable energy signal disaggregation method. These methods refer to the extraction of appliance level data from a single measuring point. They use an appliance database of some known devices and are compared with the signal measured by the meters to conclude which signatures best match. The frequency and the resolution of the A/D converter has a significant role on the attempt to disaggregate appliances with low consumption or similar power with other devices. Therefore, low-frequency approaches are not capable of identifying small loads. Improved sampling rate improves both the number of recognized appliances and the accuracy of detection. A realistic example is given on the following figures where on Fig. 3.4 the appliance signature of three devices is given and is asked to extract information about their use on an aggregate energy singal, Fig. 3.3.

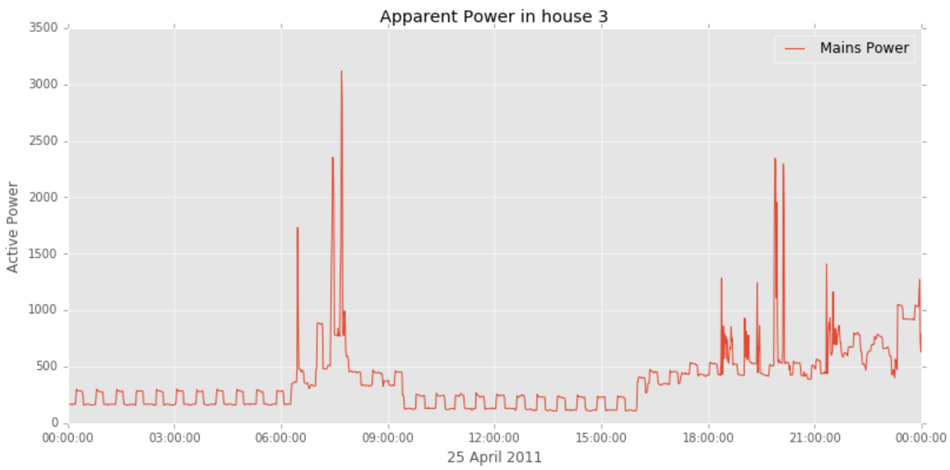

Figure 3.3: Aggregate Energy signal on a household.

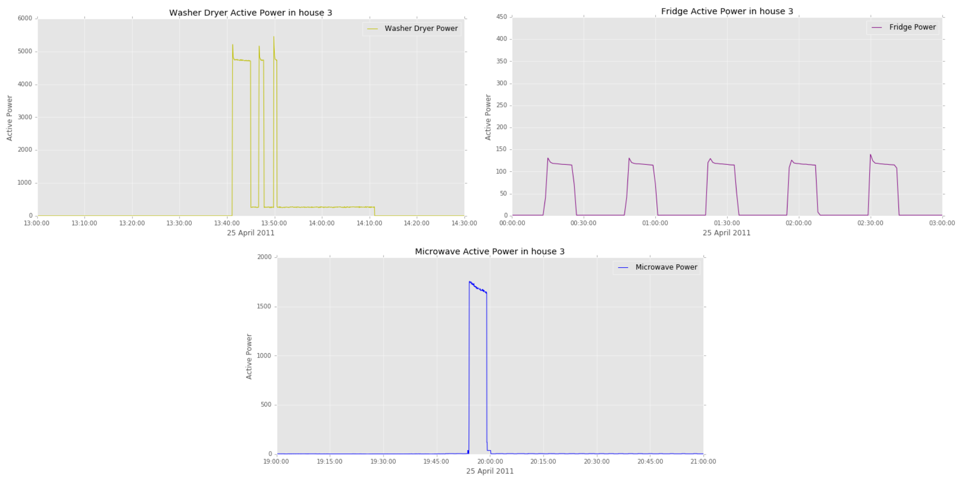

Figure 3.4: Sub-metering data for three appliances on a household; Washer dryer (left), Fridge (centre), Microwave (right).

The idea on this domain dates back on the publication of Hart in 1992 [9]. Nevertheless, after two decades of research and investigation, still a robust set of features able to describe the appliances regardless their manufacturer have not yet defined.

The formulation of the problem may be given as the identification from the aggregated signal the consumption of an appliance during a period of time T, where the total energy signal is represented as $\bar{x}$ and $\bar{x} \in \mathbb{R}^{\mathrm{T}}$ and it can break down in time according to,

$$\bar{x} = [\bar{x}(1), \bar{x}(2), ..., \bar{x}(T)] \tag{3.1}$$

while the signals associated with each device $x_i \in \mathbb{R}^{\mathrm{T}}$ where i denotes the number of appliances , $i = 1, ..., N$,

$$x_i = [x_i(1), x_i(2), ..., x_i(T)] \tag{3.2}$$

Under the assumption that $\bar{x}$ is obtained by a linear mixing process [41] corresponding to the sum of the signals x_i with $i = 1, ..., N$ and $t \in T$, then

$$\bar{x}(t) = \sum_{i=1}^{N} x_i(t) \tag{3.3}$$

This section gives a brief overview of the existing methods. They are distinguished mainly according to the sampling frequency they use as well as their specific features, Fig. 3.5. First we categorize the approaches according to the sample rate and discuss their characteristics and afterwards the algorithms which can be used to implement NILM are analyzed.

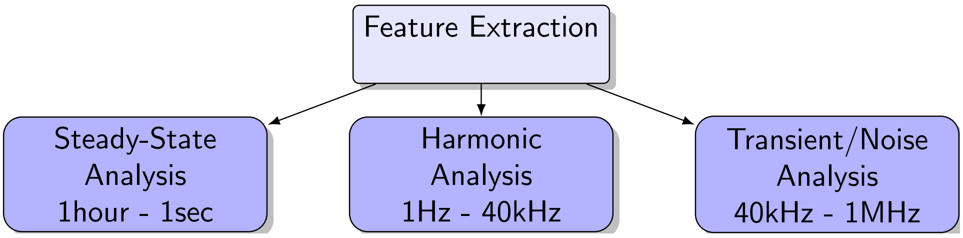

Figure 3.5: Aggregate data feature extraction possibilities based on the frequency rate.

3.3.1 Energy Disaggregation Approaches

Through the literature high frequency approaches are considered as those with a rate greater than 1Hz. By sampling the current, various electrical features can be extracted whereas the voltage waveform remains approximately sinusoidal and there is no clear reason to acquire it as accurately as the current.

To begin with, the Steady State Analysis exploits the transitions of the waveforms and extract information, most commonly, for the Active Power on low frequency implementations whereas for high frequency reactive power can also be available to discriminate the power demand of appliances, Fig. 3.6. For instance, a step change in the power (active and/or reactive) measurements may indicate that an appliance was turned on. When reactive power is available, it becomes easier to separate devices of equal apparent power demand [9] since we add another feature for a device on our algorithm. Hart's implementation in [9] successfully identified the two-state (on/off) appliances, but it had difficulties with the multi-state and continuous power devices with small consumption. Since then these characteristics have been used extensively in academic research to perform ED techniques mainly due to its simplicity [42], [43], [44], [45]. The steady-state changes in power are detected and may be clustered by fuzzy clustering. As a consequence, each cluster is composed by events with similar structures.

Furthermore, through Harmonic Analysis it is possible to extract low-order odd harmonics and discriminate appliances [46],[47]. Since switch mode power supplies and in general power electronic devices create strong harmonics in the current waveform in multiples of the power line's fundamental frequency [48]. Current harmonics should be captured with a sampling of about 1.2-2kHz considering that no harmonic higher than the 11^{th} is of interest, [11]. The harmonic analysis is usually performed by calculating the Fourier Transform using the FFT algorithm. The additional information provided by the harmonic currents is useful to distinguish loads that have the same real and reactive power, in particular, non-linear loads that present non-sinusoidal current waveforms during their operation (a linear load would have sinusoidal waveform), Fig. 3.7.

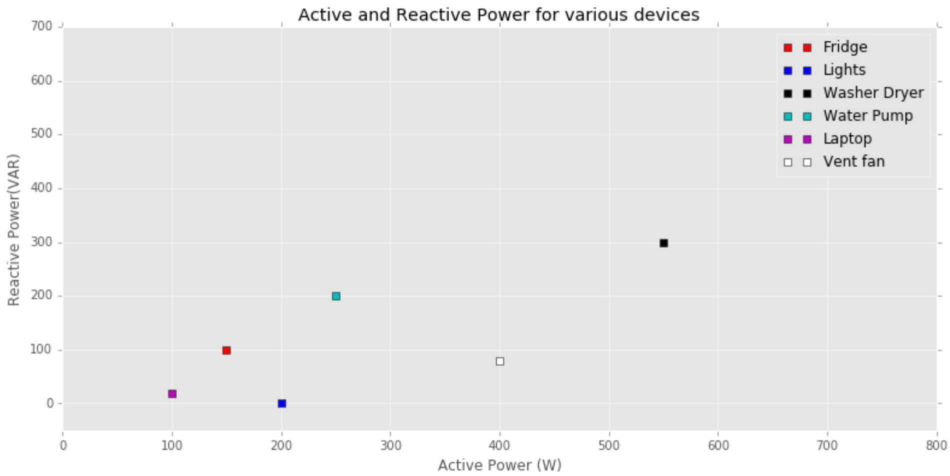

Figure 3.6: Active and Reactive Power for various devices to be used for Steady State Energy Disaggregation methods.

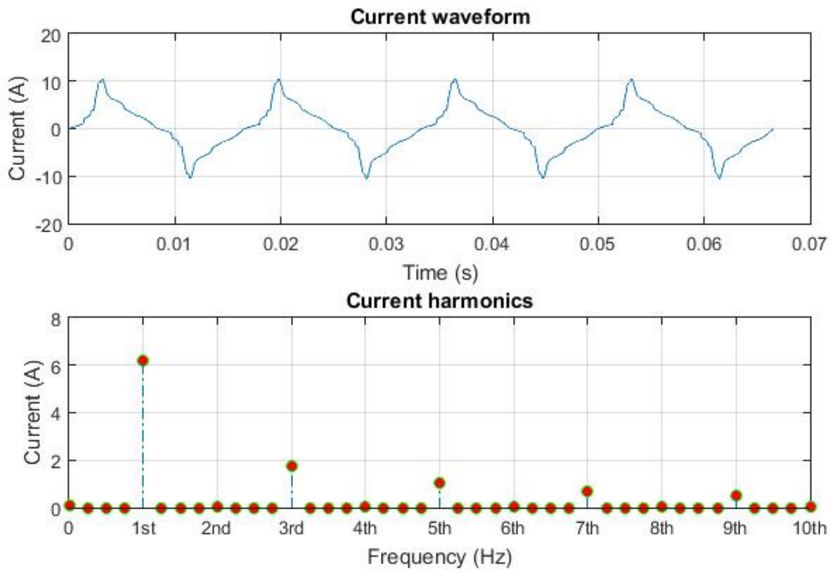

Figure 3.7: Current harmonics Characteristics of a device to be used for Energy Disaggregation purposes.

Finally, if instead of harmonic analysis the distinctive features of interest belong to the transient period between two steady-states then the sampling frequency should be in the order of hundreds of kHz or even of MHz. It has been shown in [49] that the high frequency voltage noise generated by the devices as they turn on and off can be used to identify the appliance signature, Fig. 3.8. Since such signal noise is unlikely to overlap, it can discriminate appliances with similar power consumption and harmonic components. However, there is a number of disadvantages for this approach considering that the computational process needed to capture the transient noise is expensive since an additional A/D converter is required to have a sampling frequency of MHz range. Also, the noise signatures are greatly dependent by the wiring of the house in study.

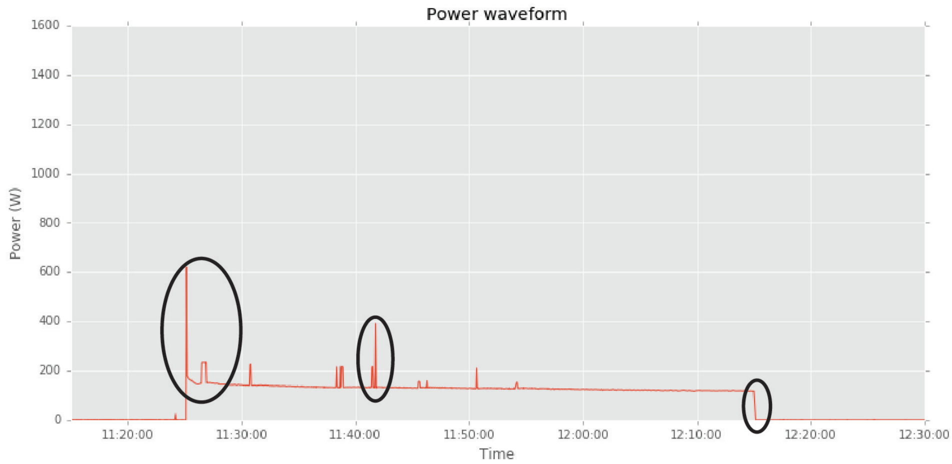

Figure 3.8: Illustration of transient/noise analysis during the turn on or off of a device.

An overview of the existed approaches was introduced in this section. Taking also into consideration the conclusions of the Section 3.2 it is obvious that Transient analysis needs extra hardware to perform ED which makes it impractical for widespread application and violates the purposes of our work. Therefore, the harmonics analysis seems to be particularly attractive since we can add more details on our algorithm without the use of extra hardware components since the current infrastructure already supports sampling rates of ∼2kHz. Next we outline the related work on this field and we try to choose the most appropriate ones to implement in a low-cost microprocessor.

3.3.2 Related Work on Algorithms for NILM

Recently, large scale deployments of SMs have attracted the interest of the academia and industries developing effective NILM solutions. First an overview of the existing approaches is given on Fig. 3.9 and afterwards we present the characteristics of the most used and prominent algorithms that used today.

Event-based models aim to cluster the appliances switch events using the difference between the steady power before and after a switch event takes place. However, as described in [50] they inherently consider all appliances switch events to be independent and therefore they exhibit poor sensitivity in errors [51]. With low frequency, the switch events can not be captured with great accuracy while even if the sampling rate is high the switch event itself does not include sufficient information for accurate disaggregation.

Blind source separation refers to a set of mixtures of sources into a set of individual components [51]. In the Energy Disaggregation problem, the set of mixture is considered the aggregate signal while the appliances are the individual sources. In [52] a discriminative sparse coding using a recursive technique to disaggregate the water consumption; such an approach is interesting for electricity problems. However, all the blind source separation solutions have a common disadvantage which is that they do not exploit the dependencies between the sequential measurements. This short-coming of this approach is solved by the non-event based methods which are using machine learning to represent the event detection and disaggregation problem and are discussed in the following of this section.

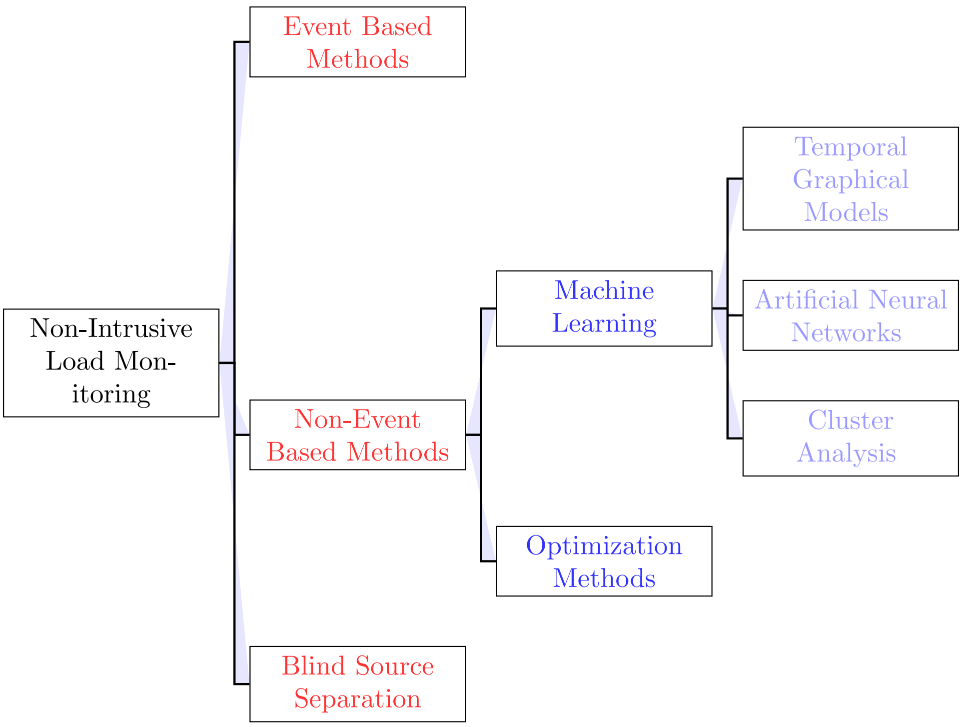

Figure 3.9: Methods to perform Non-Intrusive Load Monitoring.

In non-event based disaggregation methods event detection is integrated directly to the disaggregation model in contrast to the event-based implementations which seek for event detection. All the existing algorithms in this category belong to machine learning, pattern recognition and optimization field and next we are going to introduce the most prominent ones.

Optimization Methods

Optimization approaches require the existence of appliance signature libraries with all possible combinations of power demands of the appliances it is needed to disaggregate. If we include the combinations of all the installed appliances in a household, then this optimization approach is called brute-force. However, as was stated due to memory limitations brute-force methods are impossible to be applied in an embedded system. Thus the load identification requires the definition of an objective function and its minimization. Considering the aggregate data $\bar{x}$ and an appliance set $x = [x_1, ..., x_N]$, the problem is formulated as

$$\underset{1 \leq n \leq N}{min} ||\bar{x} - \sum_{n=1}^{N} x_n|| \tag{3.4}$$

The most important algorithm in this domain is the Combinatorial Optimization which minimizes the difference between the sum of predicted appliance power and the measure aggregate power. This method was also used by Hart in [9]. The computational complexity is $O(K^N T)$, where K is the number of appliance states, N the numer of appliances and T the number of times slices used in the implementation.

The problem complexity increases as the number of different loads in the aggregated signal increases, since the algorithm should take into account all possible combinations of appliances contained into the training set. The problems with this approach are

1. the presence of new loads in the aggregated signal
2. the sequential dependencies among the appliances are neglected
3. appliances with similar consumption are difficult to distinguish

Thus optimization methods address mainly disaggregation for the most power hungry devices and for a limited number.

In [53] it is discussed about the two commonly cited disadvantages of this approach is how its accuracy would decrease with the number of appliances and level of noise, Fig. 3.10. According to these the accuracy decreases with the number of appliances and level of noise. However, it is stated that its characteristics can be improved by variants of the original version and integration of multiple states for the appliances.

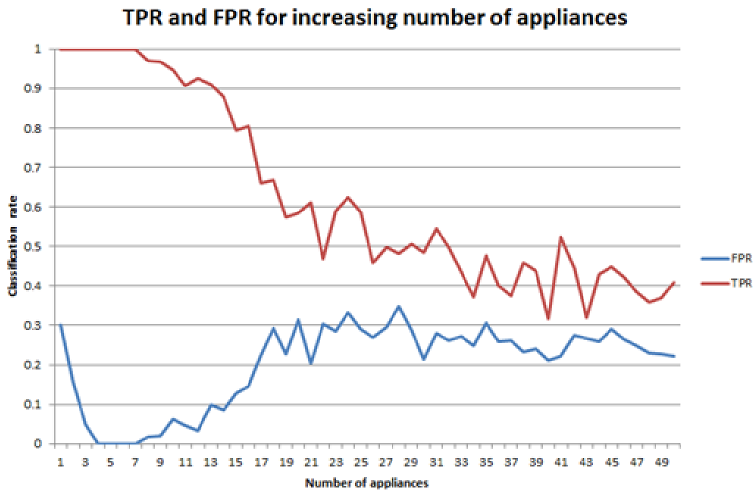

Figure 3.10: A graph of the true positive rate (TPR) and false positive rate (FPR) for increasing numbers of appliances[53].

A successful application of a modified version of the Combinatorial Optimization has been given by [54] where they introduced restrictions according to the position of the consumer on a household to restrict the set of the disaggregated appliances. However, this approach results to an intrusive method since it violates private data of the consumer like his position on an area.

Machine Learning

To overcome the mentioned issues, an alternative is the use of machine learning and pattern recognition solutions. Clustering analysis was used both by [9] and [55] where they broke down the aggregate data by clustering the appliances based on the power, the variation of electric current in time and on definition of rules for recognizing appliances.

Another successfully applied method for Energy Disaggregation is the Support Vector Machine (SVM) which is a kernel-based model [56]. The SVM is a decision machine, primarily developed to solve binary classification problems, which predicts labels of input examples based on projection of the examples into a decision hyperplane.

Artificial Neural Networks (ANNs) have also been used in the Energy Disaggregation context. ANNs are inspired by biological systems and how they process information. The most popular technique of learning for a ANN is back propagation which assigns weights to the neurons on the hidden layers. Such strategies have been adopted by [57] but it is noted that the processing power to run ANN and especially to train it is relatively demanding. The complexity of both ANNs and SVMs vary by the number of hidden layers and the number of appliances to be disaggregated, however it is expected to be $O(K^{3N}T)$ and this is the reason that it is preferred to use Temporal Graphical Models (TGM).

During the last years the research has focused mainly on TGM. A lot of research work has been done on this domain which is the reason they are analyzed separately in the following.

Temporal Graphical Models

Temporal Graphical Models refer to a class of probabilistic models which address the problem of blind source separation approaches. Such models have been applied previously to many real-world problems like speech recognition. The simplest representation of sequential data is through the use of a Markov chain which is a sequence of discrete variables. State transitions of devices are handled by the HMMs which is a statistical tool. Each variable is described by its real power consumption in addition to other useful information such as duration of the on and off periods and time of use during the day/week. Thereby, at an instant of time t of a period T, $t \in T$, the aggregate consumption is $\bar{x}(t)$ and needs to be broken down to a number of appliances z_t^n, where $t \in T$ and $n \in N$ with N the number of appliances. The value of each device z_t^n at any time corresponds to one of the K states of the trained model of the appliance.

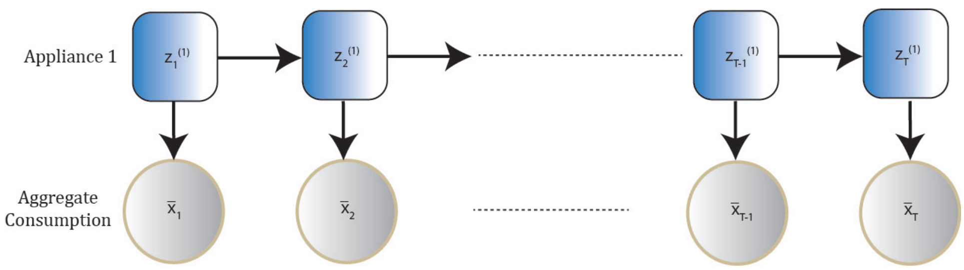

Figure 3.11: Illustration of a Hidden Markov Model.

The behaviour of a HMM can be completely defined and inferred by three parameters. First the probability of each state of the hidden variable at the time t can be represented by the vector π such that

$$\pi_k = p(z_t = k) \tag{3.5}$$

Second the transition probabilities from state i at t to state j at $t+1$ can be represented by the matrix $\mathbf{A}$ such that,

$$\mathbf{A}_{i,j} = p(z_{t+1} = j | z_t = i) \tag{3.6}$$

Third, the emission probabilites for $\mathbf{x}$ are described by a statistical function with parameter ϕ which is commonly assumed to be Gaussian distributed such that,

$$x_t|z_t, \phi \sim \mathcal{N}(\mu_{z_t}, \tau_{z_t}) \tag{3.7}$$

where $\phi = \{\mu, \tau\}$, and μ_{z_t}, τ_{z_t} are the mean and precision of a state's Gaussian distribution.

Finally, Equations 3.4, 3.5, 3.6 can be used to compute the joint likelihood of a HMM:

$$p(\mathbf{x},\mathbf{z}|\theta) = p(z_t|\pi) \prod_{t=2}^{T} p(z_{t+1}|z_t, \mathbf{A}) \prod_{t=1}^{T} p(x_t|z_t, \phi) \tag{3.8}$$

where the set of all model parameters which must be found for each appliance during the training phase is represented by $\theta = \pi, \mathbf{A}, \phi$.

Therefore, when applying a HMM for Energy Disaggregation, it is needed to tune the θ parameters for each appliance during the training phase and afterwards, given a sequence of power signal $\bar{x}$ to find the optimal sequence of discrete states $\mathbf{z}$. Their ability to handle daily operation consumption and the information about state transition of devices makes them a suitable solution for the problem. The complexity of the disaggregation using HMMs is $O(K^2T)$, where K is the number of states of all the appliances and T is the number of the time slices, i.e. how many times the algorithm is required to be applied. As it is shown the complexity is exponential with regard to the number of appliances while re-training is needed when a new group of appliances is added [41]. In [58], the HMMs were used for appliance load recognition and it was also shown that they are useful in the field of NILM. Finally, Oliver Parson in [51] is using HMMs to disaggregate an energy signal using generalized appliance model and as a result it was possible to extract consumption of individual devices without any manual labeling. But he used low-frequency Smart Meter data because of lack of high frequency data and smart metering infrastructure supporting such high rates.

Although the HMM is a powerful technique, the methods for the inference of hidden states are often affected by local minima [56]. To overcome this limitation, variants of HMMs are used like the Factorial HMM (FHMM). The concept is that the output is an additive function of all the hidden states. In the model, each observation is dependent upon multiple hidden variables [59]. The graphical model is given oh Fig. 3.12. Similarly the joint likelihood of a FHMM as stated in [51] is computed by,

$$p(\mathbf{x}^{(1:N)}, z|\theta) = \prod_{n=1}^{N} p(z_t^{(n)}|\pi) \prod_{t=2}^{T} \prod_{n=1}^{N} p(z_{t+1}^{(n)}|z_t^{(n)}, \mathbf{A}) \prod_{t=1}^{T} p(x_t|z_t^{(1:N)}, \phi) \tag{3.9}$$

where 1:N represents a sequence of appliances 1,...,N. However, the computational complexity of both learning and disaggregating is greater for FHMMs compared to HMMs. This is due to the conditional dependence of the Markov chains.

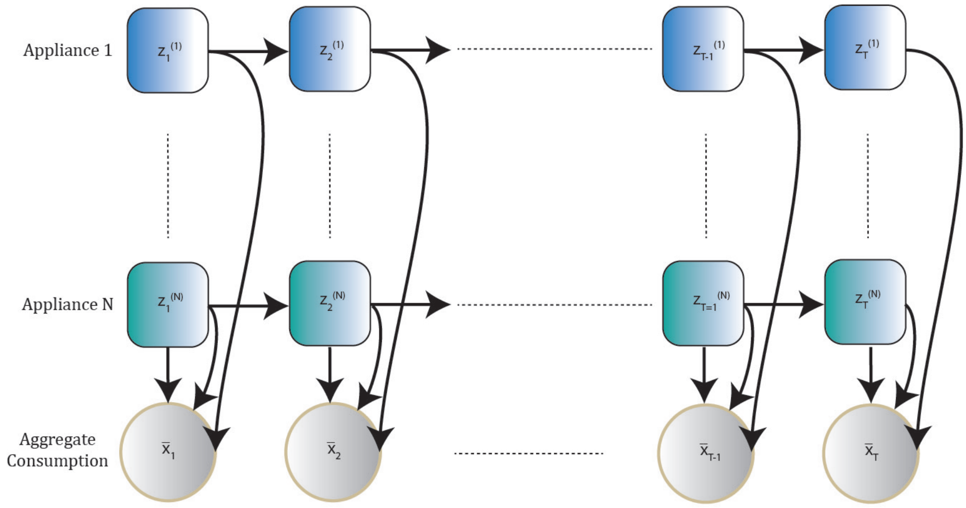

Figure 3.12: Illustration of a Factorial Hidden Markov Model.

The FHMM can be transformed into an equivalent HMM, which will allow standard HMM inference methods to be applied to the model. This can be achieved by using a single Markov chain with K^N states, one for each combination of states in the FHMM, resulting in a computational complexity of $O(K^{2N}T)$ [1] for exact inference. Since the computational cost is clearly exponential in the number of chains, N, the model will therefore become computationally intractable for large N [51]. This method was evaluated in [12] where the authors trained the model from sub-metered data appliance using an Expectation Maximization (EM) algorithm. The fact that they use sub-meter data makes the approach impractical, expensive and intrusive. They also showed that FHMM is not tolerant to non-stationary noise and requires training from all appliances in the household.

An interesting work on the FHMM and high frequency data has been done by [60] where they extended the model to include a generic mixture component enabling the model to discriminate a subset of all appliances. This ensures the model is robust to unseen observations. However, since the model does not consider prior knowledge about appliances, it requires manual labelling by the user.

There is also an extension of the FHMM which is called Conditional Factorial Hidden Markov Model (CFHMM) where the state of each hidden variable is additionally dependent on the state of each variable of all other Markov chains in the previous time slice [56].

Moreover, the Hidden Semi-Markov Model is another extension of HMM in which each discrete variable is additionally dependent on the number of

[1] O() refers to the Big O notation that is used to classify algorithms by how they scale to input size.

time slices since it changed state [61]. The benefits of modelling the state duration allow to the chained variable to take on distributions other than geometric distributions (e.g. Poisson distribution) and therefore the state transition is dependent by the current duration of the state. This comes with the cost of increased computation power as $O(K^2DT)$, where K is the number of states, T the number of time slices and D the maximum duration of each state.

If it is required to include also temporal dependencies external to the Markov chain, for example weather conditions or time of the day, the Input Output Hidden Markov Model (IOHMM) can be used [62]. In that case the joint likelihood function is

$$p(\mathbf{u},\mathbf{x},\mathbf{z}|\theta) = p(z_t|u_1, \pi, \mathbf{B}) \prod_{t=2}^{T} p(z_{t+1}|z_t, u_t, \mathbf{A},\mathbf{B}) \prod_{t=1}^{T} p(x_t|z_t, \phi) \tag{3.10}$$

where $\mathbf{B}$ is an input vector to the Markov chain while the computational complexity is still $O(K^2T)$.

The last variants of HMMs can be combined to perform NILM like in [63] where the CFHMM along with the HSMM and IOHMM were used. The CFHMM allows the dependencies between the appliances to be modelled while the HSMM includes the appliance durations and the IOHMM the time of usage during the day of individual appliances. However, these conclude to a very complex system which can disaggregate the consumption of a household of up to 10 appliances.

In summary, temporal graphical models provide a promising potential solution to the problem of Energy Disaggregation. However, the majority of existing methods require the consumption of each appliance within a household to be identified manually either before or after an unsupervised training phase.

Next on Table 3.2 we perform a comparison among the algorithms that have been considered through this section and have been used extensively for the NILM problem. In general, the pattern recognition and machine learning approaches are extremely demanding in terms of processing power and they must run on cloud services. For example, the FHMM approach of [51] requires 8GB of RAM which makes the FHMMs for Energy Disaggregation unsuitable for implementation in resource constrained environments like a micro processor. However, they present so far the most promising results. Consequently, the FHMM approach scales worse than Combinatorial Optimization. But the optimization methods as explained they present some drawbacks which must be overcome in order to be used with satisfying results which is done on the next chapter.

Table 3.2: Computational complexity and memory requirements for each algorithm under consideration.

Algorithm	**Computational Complexity**	**Memory requirements**
FHMM	$O(K^{2N}T)$	K^{2N}
CFHMM	$O(K^{2N}T)$	K^{2N}
HSMM	$O(K^{N}DT)$	$K^{N} \cdot D$
ANN & SVM	$O(K^{3N}T)$	K^{3N}
CO	$O(K^{N}T)$	K^{N}

3.4 Model Learning

After we have analyzed the appropriate models that can be used for Energy Disaggregation, we would like to discuss also the model learning of these approaches. The goal of the learning procedure is to extract the features of devices during their on time. They can be represented by finite state machines in Fig.3.13 where an appliance of two (on/off) and three (including an intermediate condition) states .These algorithms may perform

- Unsupervised NILM
- Supervised NILM
- Semi-Supervised NILM

In order to extract information for each appliance it is needed to train our models to specific signatures. Unsupervised NILM techniques use no prior knowledge of the appliances but often require appliances to be manually labeled afterwards. These techniques typically rely on accurate detection and modeling of the state change in the aggregate consumption data. In literature there have been approaches using the FHMMs, ANNs or genetic algorithms. As was mentioned, these strategies are computationally intensive and exact inference from models with large number of HMMs are intractable.

On the oter hand, Supervised NILM techniques assume that the power level of an appliance is available from a data set from which we train and develop the appliance models. To this approach, the fact that during the last year there have been a lot of publicly available data sets has helped a lot these techniques. These algorithms require extensive training on appliance level data to model the states accurately.

Finally, Semi-Supervised NILM is a combination of the two previous approaches. It avoids intrusively install sensors or manual labelling for deriving appliance signatures for each customer. Parson et al. [51] utilize prior models of general appliance types based on the publicly available data sets and afterwards these models are tuned to specific appliance instances using signatures extracted from the aggregate load for the specific consumer. But they demand high processing power and are not practical since it is required to keep appliance signatures available for each consumer inside the SM or in the cloud which makes the overall system complex and memory storage intensive.

Figure 3.13: Possible states of an appliance during the training phase: 2 states appliance(left), 3 states appliance(right)

3.5 Energy Data Sets

On the previous sections, the hardware of the Smart Meter and the algorithms used for the problem of the Energy Disaggregation were presented while next we would like to introduce the available household Data Sets to evaluate the explained techniques.

Since 2011, many public data sets became available for researchers of the described problem so that they can compare their results objectively. Before this release, most of the approaches were using their own libraries of signatures making the progress on this field very difficult since every one was working independently. On Table 3.3 the public data sets available up to the time of writing are described [64], [65], [66], [67], [68]. In the following the most important aspects of the useful Data sets for this work are summarized.

The Reference Energy Disaggregation Data set (REDD) is a publicly available Data Set from MIT in USA. It contains aggregate data from 6 households. Among them, two have also high frequency aggregate data of 15 kHz. Approximately 20 circuits on average are also getting sub-metered on each house at a frequency rate of 3 seconds. Many of these circuits include only one appliance which makes it useful for the purposes of this work.

The University of California, Berkley, have released electricity data collected from Cory Hall on the UC Berkeley campus. The data set contains data collected from 4 categories of sub-metered loads. Measurements of active, reactive and apparent power were collected at 20 second intervals. Household-level aggregate power data was collected from two current clamps

Table 3.3: Currently available Energy Data Sets, [51].

Data set	**Institution**	**Location**	**Duration**	**Number of houses**	**Number of Sub-meters**	**Appliance frequency Sampling**	**Aggregate data frequency**
REDD	MIT	MA, USA	3-19 days	6	9-24	3 sec	1 sec & 15 kHz
BLUED	CMU	PA, USA	8 days	1	✗	✗	12 kHz
Smart*	UMass	MA, USA	3 months	3	54	1 sec	1 sec
Tracebase	Darmstadt	Germany	✗	✗	✗	1-10 sec	10 sec
Sample data set	Pecan Street	TX, USA	7 days	10	12	1 min	1 min
IHEPCDS	EDF R&D	France	4 years	1	3	1 min	1 min
HES UK	DECC	UK	3 months	250	13-51	2 min	2 min
AMPds	Simon Fraser U.	BC, Canada	2 years	1	19	1 min	1 min
Colden Common	U.Southampton	UK	1 year	117	✗	✗	✗
BERDS	Berkley University	California	7 days	1	4	20 sec	20 sec
Dataport	Pecan Street	TX, USA	3 years	722	10-23	1 min	1 min
DRED	TU Delft	Netherlands	6 months	1	9	1 sec	1 sec
ECO	ETH Zurich	Switzerland	8 months	6	6-10	1 sec	1 sec
GREEND	**Alpen-Adria Universitat Klagenfurt**	Italy-Austria	1 year	9	9	1 sec	✗
iAWE	**Indraprastha Institute of Information Technology**	India	73 days	1	33	1-6 sec	1 sec
REFIT	U. of Strathclyde	UK	73 days	21 months	9	8 sec	30 min
UK-DALE	U. of Southampton	UK	2.5 years	5	54	6sec	1-6 sec & 16kHz

monitoring both phases of its split phase power, over a period of 8 days. High frequency (12 kHz) current and voltage data are available for both phases. We have chosen not to use BLUED in this report, since no sub-metered appliance power data was collected as part of the data set. In literature, it has not been used a lot by the researchers since it is suitable mainly for event-based methods.

UK-DALE is also a relatively new released Data Set (2015) [68] and it contains both low frequency sub-metering data and high frequency (16kHz) aggregate data. It exhibits the same characteristics with REDD but involves more houses and therefore more data.

However, due to the maturity of research on the REDD as well as the frequency of use of this Data Set, it has made it attractive for our work. The existence of many projects and approaches which are evaluated on this library makes it easy to compare it with other works which is the reason that this data set was chosen.

Finally, it is of interest to point out that REDD and UK-DALE, which are using high frequency sensors, measure in extremely high sampling rates (15kHz and 16kHz) although it is not necessary to reach such high levels. It is also noted in [7] that the cost of a 2kHz device compared to one with a frequency up to 16 kHz cost the same which further explains the preference of researchers of such projects in 16kHz devices and not lower. This further validates our results on the design considerations where we stated that a high frequency module in the range of 1kHz - 16kHz has the same price and therefore there is no reason not to use the maximum possible - if we know what to do and how to manipulate this raw data.

3.6 Evaluation Metrics

Several accuracy metrics both at house and appliance level are available and considered for the performance evaluation. However, no agreement about the most suitable metric exists [11]. The performance of load disaggregation approaches is intrinsically related to the type of appliances used in the experiment [41], the hardware used to collect the load data and even the time period of the Data Set that is selected for disaggregation.

In general, if we consider the NILM problem as a classification problem, the performance can be reported as, [56]:

$$Accuracy = \frac{Correctly\ assigned\ Events\ or\ Signatures}{Total\ Events\ or\ Signatures} \tag{3.11}$$

Fraction of total energy assigned correctly (FTE) measures the fraction of actual energy consumed by each appliance and the fraction of energy prediction of each appliance,

$$FTE = \sum_{n=1}^{N} min\left\{ \frac{\sum_{n=1}^{N} x_t^{(n)}}{\sum_{n=1,t=1}^{N,T} x_t^{(n)}}, \frac{\sum_{n=1}^{N} \bar{x}_t^{(n)}}{\sum_{n=1,t=1}^{N,T} \bar{x}_t^{(n)}} \right\} \tag{3.12}$$

Total disaggregation error (T_{error}) is the difference of the total assigned energy for all appliances and the actual consumption, normalized by the total energy consumed,

$$T_{error} = \frac{\sum_{n=1,t=1}^{N,T} |x_t^{(n)} - \bar{x}_t^{(n)}|}{\sum_{n=1,t=1}^{N,T} x_t^{(n)}} \tag{3.13}$$

Similarly we can measure the disaggregation error for each appliance with the **Proportion of error by appliance** (P_{error}). It measures the difference between the proportion of the energy assigned to an appliance and the actual energy consumed,

$$P_{error} = \left| \sum_{t=1}^{T} x_t^{(n)} - \sum_{t=1}^{T} \bar{x}_t^{(n)} \right| \tag{3.14}$$

However, most of the times **Normalized error by appliance** (N_{error}) is used,

$$N_{error} = \frac{\sum_{t=1}^{T} |x_t^{(n)} - \bar{x}_t^{(n)}|}{\sum_{t=1}^{T} x_t^{(n)}} \tag{3.15}$$

Finally we introduce the most used and reliable metric that most researchers follow to evaluate the NILM performance on appliance level. It is based on Eq. 3.11 but for application in Energy Disaggregation. First it is needed to introduce the following definitions,

$$Precision = \frac{TP}{TP + FP} \tag{3.16}$$

and the

$$Recall = \frac{TP}{TP + FN} \tag{3.17}$$

where the meaning are explained in Table 3.4

Table 3.4: Contingency Matrix for binary classification.

		True Label	
		Positive	Negative
Assigned label	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

The precision equation in Eq. 3.16 denotes the ratio of True Positive in the universe of all the examples assigned as positive while the recall in Eq. 3.17 is the ratio of TP in the universe of all positive examples in the data set. To overcome the shortcoming of both the individual recall and precision equations, the **F1-score** is introduced,

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision \ + \ Recall} \tag{3.18}$$

F_1 score is a measure of test's accuracy and is obtained by calculating the harmonic mean of precision and recall. F_1 score measures the percentage of energy correctly assigned to each appliance in the data set. It can be interpreted as the weighted average of the precision and recall. A higher F_1 score value indicates a better identification of an appliance.

3.7 Summary

In this chapter the hardware and software considerations of the NILM framework were presented. Firstly, we introduced the current capabilities and limitations of a SM design. It was shown that the deployed SMs have integrated a microprocessor with operating frequency of 25 MHz in the worst case as well as an A/D converter of 1.6kHz sampling rate. Another aspect which supports this direction is that nowadays energy consumption by non-linear devices like electronics, TV sets have surpassed every other category in the residential sector which makes it attractive to use the harmonics they emit during operation. Secondly, an overview of the appliance extraction from an aggregate data was given and it was stated that the suitable approach would be the steady state harmonic analysis since it can be supported by the today's infrastructure. Next there was a literature review of the known approaches to solve the NILM problem. The machine learning strategies were proved to be demanding from the resources perspective while the least intensive techniques belong to the optimization problems which however present some weaknesses. Additionally the variants of a model training phase were discussed and it was concluded that since the last years a lot of publicly available data sets have been released, they can be used to construct generalised models of the most important appliances. Finally, the evaluation metrics were introduced while it was mentioned that the F_1 score is suitable for the NILM problem. In general, although NILM reduces hardware requirements, it increases software complexity. The used algorithms can become complex enough not to be able to run them real-time nor in a local system within the house due to memory and processing constraints. Commercial products in the market offer Energy Disaggregation on the cloud to overcome these issues. In turn, this raises issues like privacy and cost that also need to be addressed. Therefore, to conclude, the question we try to answer in the next chapter is if we can design a non-intrusive load monitoring system with reduced computational complexity that can run on a local embedded system without sacrificing disaggregation accuracy.

Chapter 4

Implementation of the Energy Disaggregation

Over the last chapters a description of the current challenges that we are facing both on the Smart Meter design and the NILM algorithms was presented in order to evaluate the possibilities and options for a viable solution.

In this chapter the proposed solution for running Energy Disaggregation in a low-resources environment is described. Firstly, the hardware under consideration is explained and its limitations and the expectations from it are analyzed. After we have set the design constraints, we proceed with the implementation of a reliable ED algorithm. As was explained, because of the demanding requirements of machine learning and pattern recognition methods, their direct application is infeasible and as a result alternative and enhanced options in the optimization approach are explained and justified.

An important aspect of the implementation is the tuning of the model parameters. As a requirement, we set that the model for each SM installed at a household or at least for a significant number of them must be similar. The reason is that it is difficult to keep separate model characteristics for each consumer on a central hub or inside the SM due to memory limitations. Thus, the application of generalized appliance models at least at community level based on publicly available data sets is proposed. For this two approaches are presented. A significant contribution is that after the tuning of the parameters, the model is applied to the test data set in order to extract harmonic information on the main and most used appliances. The harmonic details of the devices are not available in the original data set and therefore it is needed to derive them from the aggregate signal so that we can exploit in full potential the SMs' capabilities.

Finally the results based on the metrics presented on the previous chapter are given while a comparison with the state-of-art and a traditional algorithm is done. For these reasons the NILM toolkit framework is used which was created to facilitate such purposes.

4.1 Considered Smart Meter Design

As was explained, the currently deployed SMs models in Europe are manufactured mainly by the companies Landis+Gyr and Itron. The former was supplying their model E350 [69], however there has been a trend lately for installation of their E650 model [38] which has better capabilities than the previous one. The new model is installed in projects in Germany and in Brazil [70] mainly for industrial customers since it costs 10 times more than the previous model, but there is going to be a preference for this one for new installations. Itron offer solutions in North America while for the Linky project there has been a co-operation between both companies and the result is closer to the new Landis+Gyr E650 model. It is also worth to mention that the average lifetime of each SM is estimated to be 20 years. Therefore our hardware considerations and limitations will be based on this new design.

Based on the analysis that has been done, we repeat here the main design constraints,

1. Sampling frequency of the *A/D converter*,
2. Processing power of the *Processor*,
3. Storage capability of the *Memory*,
4. Data transfer rate due to the *Communication Interface* used,
5. Transfer rate of the *Serial Interface* between the two types of cards.

Of these we may neglect point (4) since there is no information for this on SM data sheets [38] but it is implied that the communication unit can support the sampling rate of the A/D converter. Concerning the measuring system, the analogue values of the current and voltage are digitized in Sigma-Delta converters with a sample rate of 1.6kHz and then filtered. The storage capabilities of the Flash memory are around 2MB while there is no publicly disclosed data on the RAM and therefore we are going to make some reasonable assumptions during the application on the low-cost microprocessor. Finally the communication interface can support various channels (RS232, RS485, CS, M-Bus, PSTN modem, GSM modem, GPRS modem and Ethernet) either with on-board hardware or extension cards. The measured quantities are transformed into Active and Reactive Power values which may be also displayed on an LCD display.

After we have analyzed the capabilities and hardware characteristics of the preferred model, we proceed with the introduction of the micro-processor for the evaluation of the ED algorithm, shown in Fig. 4.1 whose capabilities are summarized in Table 4.1. We will use an Arduino mega 2560 for the evaluation of the suggested ED technique. It should be noted that only the algorithm itself will be tested on the Arduino while the measuring values will be given to it as inputs.

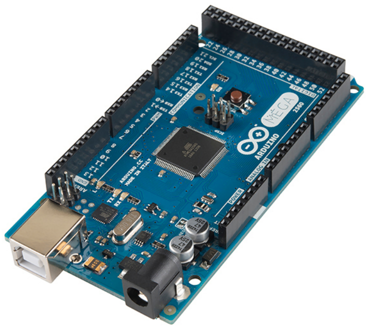

Figure 4.1: The used arduino model for the ED evaluation and considerations for the capabilities of the system.

Table 4.1: Characteristics of the considered design of the hardware system.

Sampling frequency of the A/D	1.6kHz
Processing Power	16MHz
Flash Memory	256kB
RAM	8kByte
Communication Interface	PLC

The considered system has a processing power of 16 MHz which is lower but close to the recommended processors for use in SMs in [39] which means that a real SM will be able to solve the ED problem much faster. The Flash memory on the real system is 2 MB but part of it is used for billing purposes and tariff control, so not all of it will be available. The Arduino mega 2560 has 256 KB of Flash memory which is enough for saving the code, the required operations and the temporal storage of the results of the disaggregation methods before they are sent to the UP. The RAM memory of the test system is 8KB which restricts the capability the number of the possible appliances that can be disaggregated. For the SM we do not know this value, however 8KB is a very reasonable and cheap value in the worst case.

Moreover, the sampling frequency is defined by the data sheet of the SM and is chosen to be 1.6kHz which according to the Nyquist-Shannon theorem means that it can support analysis up to the 16^{th} harmonic current order on the European Grid with fundamental frequency of 50Hz which is more than enough to perform Harmonic Analysis even for the non-linear loads. Finally, for the communication unit we are going to use the cheapest solution which is Power Line Communication since we do not need to send raw sampled data outside the meter because the ED algorithm which needs the high frequency harmonic content of the data is done inside the meter.

Consequently, it was concluded that the use of an Arduino mega 2560 may simulate the processing capabilities and investigate the limitations of the current SM infrastructure. In the rest of the chapter, we will focus on the software implementation of the considered system and on a practical procedure for the training phase.

4.2 Energy Data Set

A general description of the Energy data sets that can be used for our problem has been provided on section 3.5 and here we would like to discuss the characteristics and the limitations of the chosen set. The REDD (Reference Energy Disaggregation Data set) was developed by Kolter et al. in 2011 [12]. The measurements come from a region in USA and the American grid does not have the same features as the European one. For example the fundamental frequency is 60 Hz and all the current harmonics are odd multiples of this frequency. Another inherent difference between the two grids is that in the USA they use a 2-phase unbalanced system compared with the European symmetrical 3-phase. However, the Energy Disaggregation procedure is identical and the only difference is the characteristics of the trained model. This data set was chosen because it contains both household aggregate and individual appliance power measurements at 3 second intervals. Furthermore, at this time, it is the most widely used data set for benchmarking NILM methods.

More specifically, it contains sub-metered Active Power from 6 houses for 9-25 circuits with a sampling rate of 3 Hz and Apparent Power of the agreggate signal at 1 Hz. Among them, house 3 and 5 also have high frequency voltage and current aggregate waveforms at 15 kHz. It regards a time period between 16 of April 2011 and 30 of May 2011 which makes 45 days in total. However, because of problems they encountered with the equipment, it was not possible to operate the system full time and therefore there are some gaps on the final measurements. These facts are summarized on Table 4.2.

In Figures 4.2, 4.3 and 4.4 we illustrate the aggregate data of the available houses to visualize the results of Table 4.2. It is noted that for visualization purposes, the data sets for the households were re-sampled to 1 hour in order to emphasize the lack of measurements. Although the limited number of available days is a significant drawback for this data set it is enough to perform ED techniques.

REDD was chosen as the most suitable data set to evaluate our approach since apart from the low frequency data, we may also use the high frequency to test our harmonic analysis in houses 3 and 5. Unfortunately the health of the measurements of these two houses is not very good since we only have in total 17 days for house 3 and 4 for house 5. Ideally we would also like to have sub meter data for the harmonics of each device but since we do not, we extract the current harmonics of the most power hungry devices (because of the limitations of the CO) as explained in the next section.

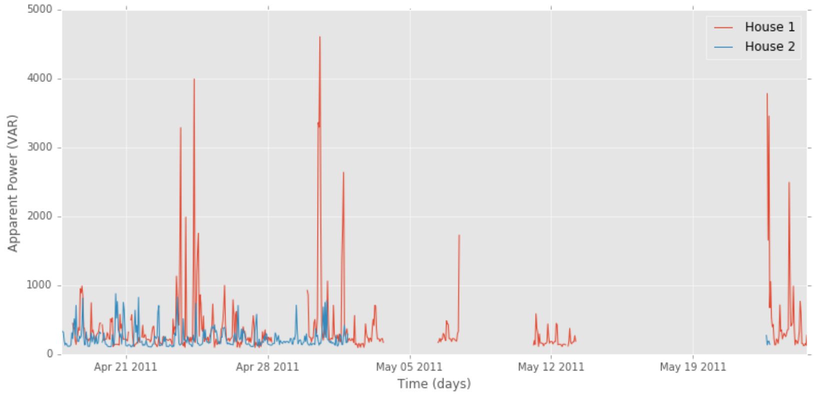

Figure 4.2: Aggregate data for houses 1 and 2.

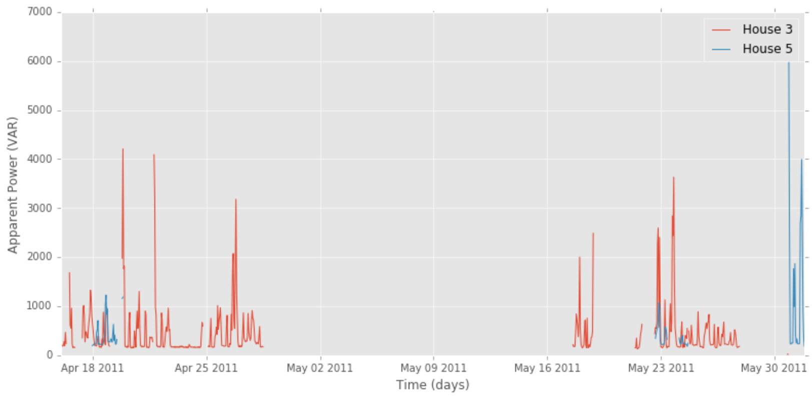

Figure 4.3: Aggregate data for houses 3 and 5.

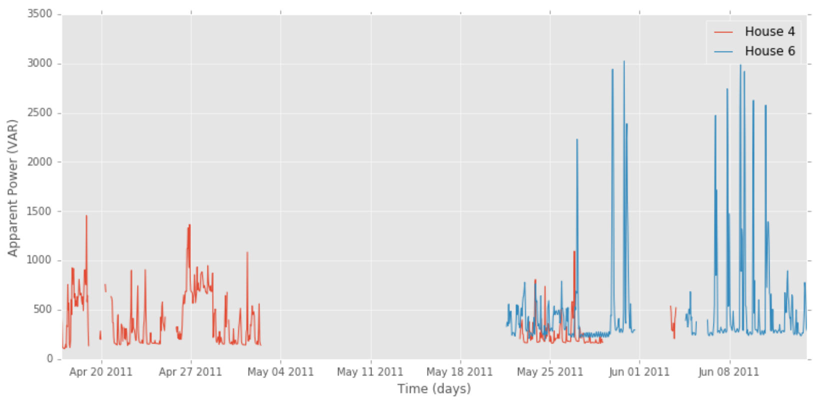

Figure 4.4: Aggregate data for houses 4 and 6.

Table 4.2: Amount of data for each house on REDD.

House	**Available days**	**High Frequency Aggregate Data**
1	18	✗
2	14	✗
3	17	✓
4	20	✗
5	4	✓
6	10	✗

Furthermore we also present the top used appliances for each household so that we can evaluate the specific characteristics of each house. It is shown that in all the houses the fridge is the most frequently used devices since it is always on. It is also the easiest tractable appliance since most of the times it is the only device which is on during the night. On this fact Parson [51] was based so that he can tune the previously generalized model for each household. Secondly the second most used device is a washer dryer which is usually the most power hungry appliance. Other common devices for all the houses are the microwave and the lighting which already consist an important number of appliances for the ED approach. Therefore we can see some difficulties for the load identification problem since in some households we can see unique devices like the Air Conditioner in house 6 probably for heating purposes which is not used in any other house. This could be solved by having extra high frequency information for this device. Additionally, the use of non-linear load like Electronics are only noticed in house 3 which means that we will be able to train our model based on observations of other households and afterwards extract high frequency harmonics from the aggregate data of house 3 since it is available at a high sampling rate.

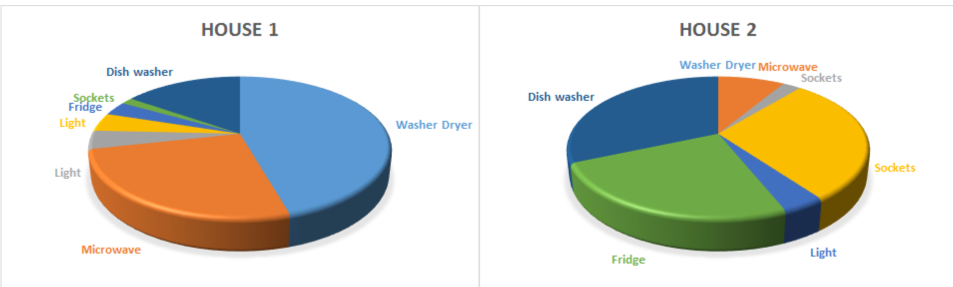

Figure 4.5: Usage of the top 7 appliances in houses 1 and 2.

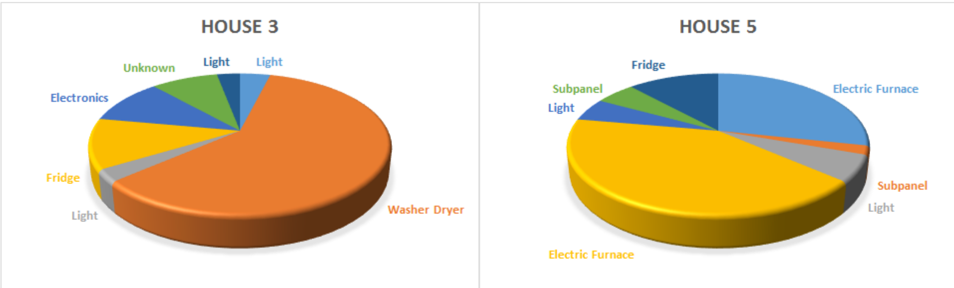

Figure 4.6: Usage of the top 7 appliances in houses 3 and 5.

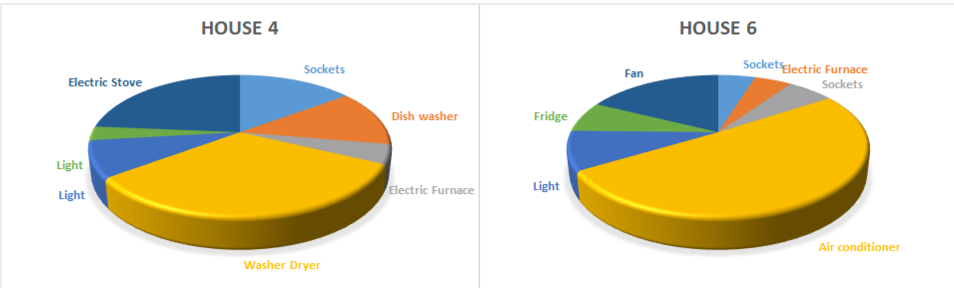

Figure 4.7: Usage of the top 7 appliances in houses 4 and 6.

Finally we provide some important aspects of the high frequency aggregate data of the REDD data. Since, there is no citations in literature and no one has used so far the high frequency data of the REDD, we state here some additional aspects of the data set which must be taken into consideration when processing. During the high frequency measuring, they have been using Current Transformer (CT) clamps which typically shift the angle of the current signal by some degrees and must be taken into account. Also, the CT clamps drifts the signal which creates a DC offset on the current readings. This offset was found to be of the order of tens of milliampers as is shown in Fig. 4.8 and must be removed. We also perform harmonic analysis to validate the existence of a DC component on the zero frequency. Lastly, CT clamps maintain their quoted accuracy when measuring currents above 10% of their nominal capacity. Consequently if someone is going to use the high frequency content of the REDD, they should consider the above points.

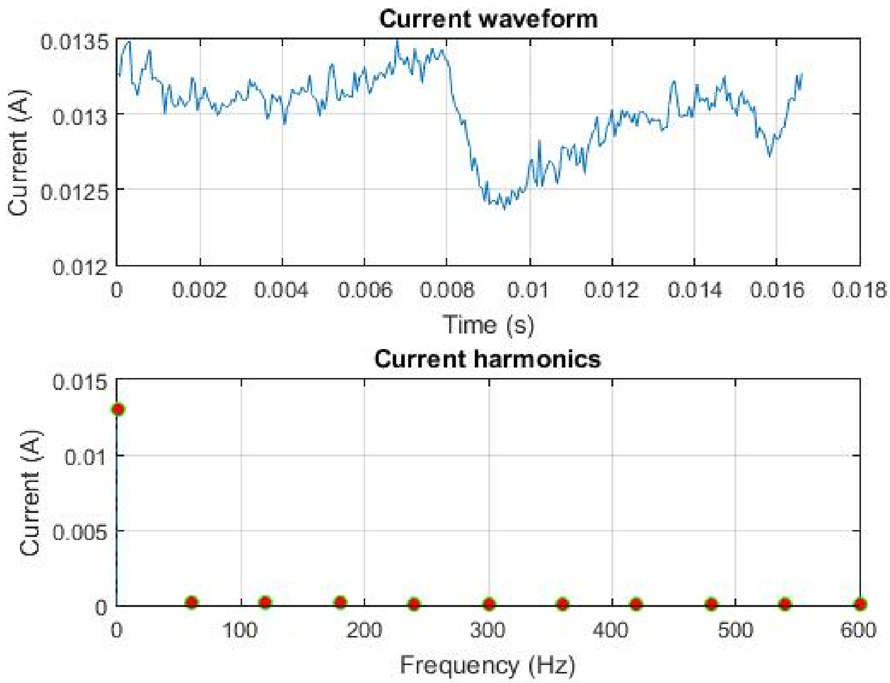

Figure 4.8: Noise existence in REDD which creates a constant DC offset.

To sum up, in this section we introduced the the REDD data set which is going to be used for our research problem. Although its disadvantages and limitations were presented it was shown that it has some characteristics which make it attractive for our purposes like the existence of a common subset of the top used appliances in all households and the high frequency data for non-linear loads.

4.3 Model Training

Ideally a data set of labelled signatures is required for further training of the classification/disaggregation methods. An optimal solution, yet impractical, would consider a data set composed of signatures of all possible appliances of every single manufacturer. Nevertheless, and as mentioned, if the signatures are network dependent, such training database must be built for each house [49]. Still, if the signatures are invariant from house to house, it would be possible to develop a community training data set. Another challenge is the signature data set update when a new load is added to the electrical network. An approach suggested in [49] would be an interactive system that in the presence of unknown loads, an unsupervised learning mode would label the new appliance, prompting the user for validation, and next update the data set.

Previous analysis has showed that there is an important number of strong algorithms addressing the problem of ED. However, as was seen all existing methods require each appliance within a household to be identified manually either before a supervised or after an unsupervised training phase. Therefore, there is an area of unexplored research into methods which would allow general prior knowledge about appliance types to be integrated into the models of the appliances, without any manual intervention on any point of the procedure.

Supervised methods assume that sub-metered appliance training data is available from the household in which disaggregation is to be performed. However, this assumption dramatically decreases the scalability of such systems due to the inherent costs and time consuming nature of installing individual appliance meters. Unsupervised techniques use no prior knowledge and are able to learn appliance signatures by the aggregate data, however, they need manual labelling otherwise they are just a set of classes with parameters which is not useful for the NILM.

A realistic approach to this problem has been given in [71] who used the Tracebase data to build probabilistic appliance models which generalize to previously unseen households. Afterwards to improve the accuracy he tuned the appliance models using only aggregate data. These techniques were referred to the previous chapter as Semi-Supervised. However, to do so they used very intensive machine learning and probabilistic algorithms which are impossible to run on a micro-processor real-time. Additionally for the evaluation results, they used a small number of appliances (3-6) and for every household it was needed to keep an individual matrix characterised the specific household which is impractical in terms of storage requirements and privacy.

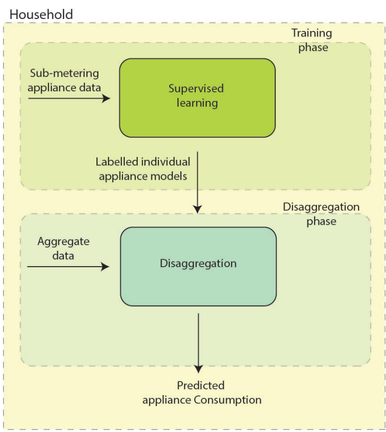

Figure 4.9: Existing Supervised models. The yellow dashed box indicates where the whole procedure takes place - in this case training and disaggregation inside the household.

4.3.1 Building Generalized Models

The increasing number of publicly available libraries of appliance signatures has given the opportunity to a lot of researchers to build general models based on these libraries instead of specific models applicable only to the considered data set.

On this section we describe a simple approach to build generalized models, yet with less accuracy since we do not use probabilistic methods for the sake of simplicity in order to be able to run on a low-resource environment. In principle we adopt the approach of [71] to create generalized models by a library of appliance signatures. However in the first approach we do not proceed with the tuning of the resulting models for the specific customer. But during the training phase we track a relaxation factor which is the average of the difference of the two extreme points (the smallest and the largest consumption) of each appliance. This strategy is able to overcome storage and privacy concerns since the models correspond to community level and not to individual consumers. The second approach is the same with [71] with the difference that we improve the generalized models by adding information about the daily use so that the tuning of the model may be easier.

Averaging Appliances Power Consumption

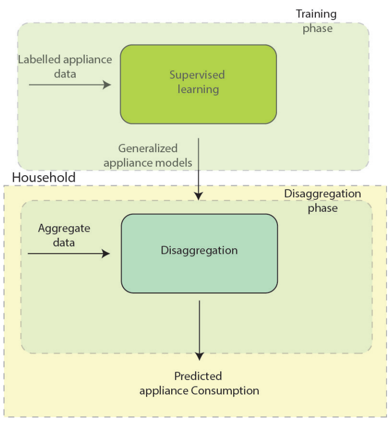

Figure 4.10: Proposed Semi-Supervised model with one out of the box training phase suitable for the Averaging Appliances Power Consumption approach. The yellow dashed box indicates where the whole procedure takes place - in this case only the disaggregation takes place inside the household while the training phase outside.

Averaging Appliances power consumption and keep a relaxation factor dependent on the training phase enables us to avoid probabilistic models as well as a second phase of training in the household. The suggested method performs cluster analysis in order to extract the parameters of the appliance model and after we have defined the most dominant values for each instance of an appliance (e.g. fridge) we average the values and identify a relaxation factor $\delta_i = \dfrac{z_{max} - z_{min}}{2}$ where $i \in \{1, ..., N\}$ denotes the number of the appliances and z the clustering values of each instance of an appliance. As a result it is equal to the average value of the maximum and minimum values of the cluster result of each instance. After we have defined the relaxation factor for every appliance based on its instances, we keep the maximum of this value which describes also the accuracy of our algorithm. It was noticed that the smaller this factor, the more accurate our disaggregation is but the more iterations and processing power is needed. It was proved in [71] that a small number of instances (2-6) is enough to evaluate a generalized model.

In Fig. 4.11 and Fig. 4.12 an example of the suggested training approach is illustrated where we use the sub-metering instances of the fridge from the houses 1, 2, 5 and 6 to train a generalized model. This procedure gives as a result a generalized power consumption for the fridge and the relaxation factor of an appliance.

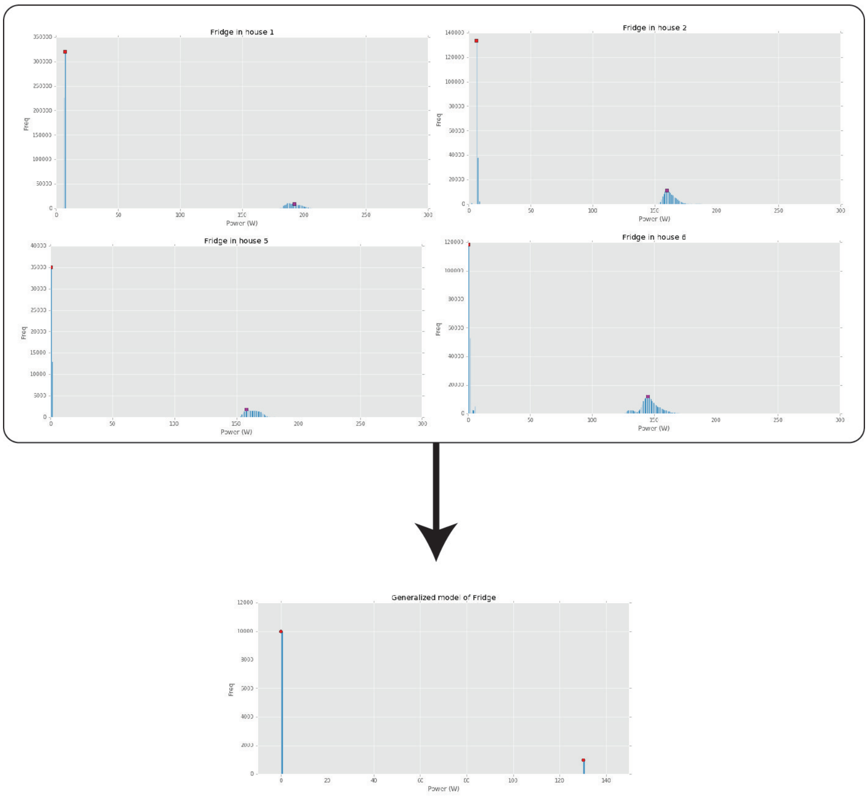

Figure 4.11: Visualization of the suggested procedure for the fridge in four houses.

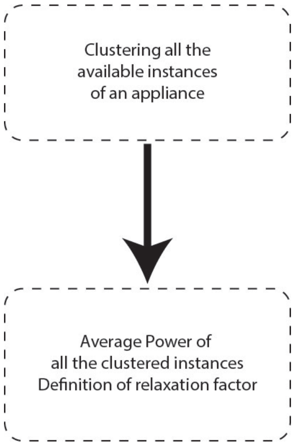

Figure 4.12: Overview of the suggested procedure.

Introducing Time dependency

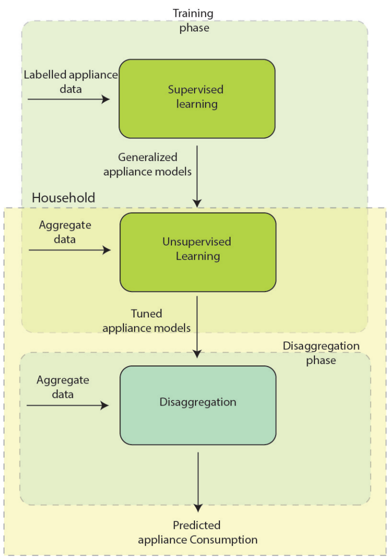

Figure 4.13: Proposed Semi-Supervised model. The yellow dashed box indicates where the whole procedure takes place. In this case the first training phase takes place outside the household by building general models. Afterwards a second round of training in order to tune the model and finally the disaggregation inside the household.

Afterwards an extension of the proposed method is given in order to tune the model to the specific household. It is based on the extraction of extra information for an appliance during the training phase of the generalized model. So, instead of keeping only the power consumption of each device as is suggested in [71] we also keep track of the time usage distribution of each appliance, in other words when it was used. By integrating this element on the appliance characterization it is becoming easier and more reliable to extract afterwards from the aggregate signal the use of the appliance.

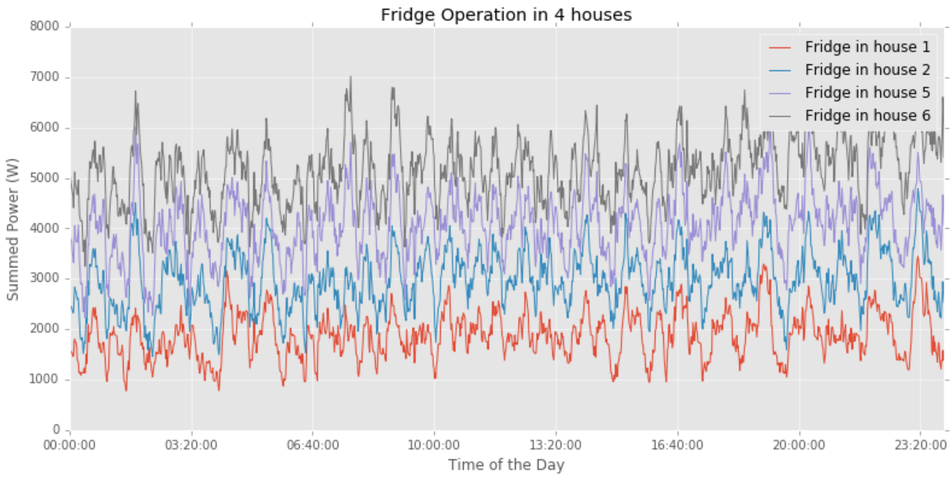

Figure 4.14: Time usage and operation of the fridge in 4 houses.

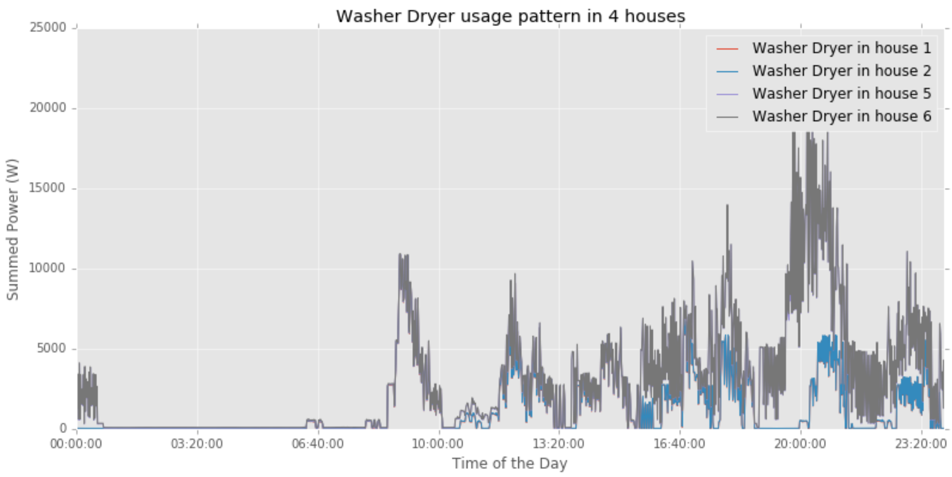

Figure 4.15: Time usage and operation of the washer dryer in 4 houses.

In Fig. 4.14 and Fig. 4.15 we can see the time usage of the fridge and the washing machine respectively. It is clear (more for the washing machine) that we can integrate in our model information regarding to when and how often during the day the consumer is using an appliance. Therefore this approach may outperform the suggestion of [71] where he was using just the power level like on the previous section. However, on the scope of this thesis this method was not further developed and consequently next we will consider the previous simplified technique to perform disaggregation. It is also noted that for this approach we should implement a training phase on the micro-processor which according to each limitations would not be possible. Thus it should be done on a cloud which violates the requirements of this project.

4.3.2 Extraction of Harmonic Content

The goal of this section is to introduce the benefits and the capabilities of the harmonics analysis. Ideally we would also like to have high frequency sub-meter data in order to extract the current harmonics of each appliance. However, since there is no data set offering such labelled information on high sampling rate we will extract them based on the previous trained model from the high frequency aggregate data.

To do so, we trained the model for the houses 1,2,4,5,6 and apply it into house 3. We are seeking for time slices where the aggregate power match with exactly one appliance of the described model and then we identify the harmonic signal as the harmonics of the predicted appliance. In order to adopt these values on our model we need to be very accurate and sure that the extracted current harmonics belong to the considered appliances otherwise it will introduce accumulated errors to the ED method.

It is easy to do so for the fridge since as we explained it is always on during the night. But then it is becoming extremely difficult for other appliances since always more than four devices are on for this data set. Therefore we were able to do so for the current waveforms of the fridge and the CE appliance used in house 3. The results are illustrated in Fig. 4.17 and Fig. 4.16.

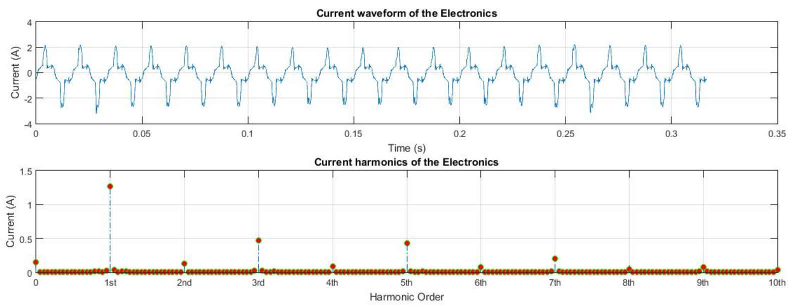

Figure 4.16: Harmonics content for the CE appliance.

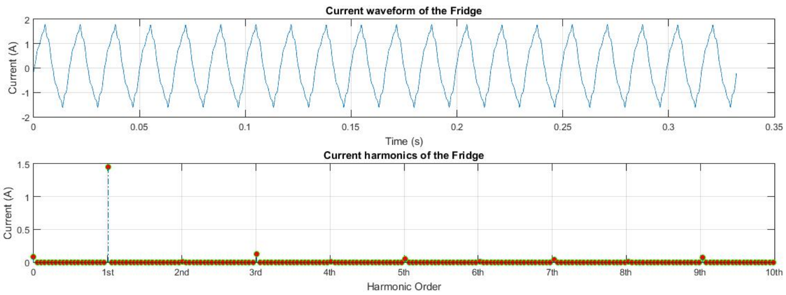

Figure 4.17: Harmonics content for the fridge.

Introducing harmonics details for the current waveforms will permit us to increase the accuracy and the discrimination capability of the signal under consideration. As we can see the fridge waveform is not so distorted and therefore after the third current harmonic it is almost zero. Even the measured value of the 3rd harmonic is on the borders of the error of the Current clamps used in REDD sub-metering devices as was stated on the section 4.2. Therefore the harmonic analysis of the fridge in house 3 is of no use since it does not help us to discriminate it based on this approach. On the other hand, the harmonics that are presented in the CE appliance (electronics) circuit of the house 3 are of great interest since we can clearly see the non-linearity of the load. It presents strong harmonics up to the 9th order and they are of great value for our purposes. Already from the third harmonic we can see that is significantly larger compared to the fridge although they have similar fundamental current. This important described feature for the electronics and in general for non-linear load must be exploited to the ED algorithms since the SM designs permit us to do so. Consequently for the two appliances due to storage limitations we keep the 3^{th} and 5^{th} order harmonics for our model.

4.4 Description of the Algorithm

Implementing disaggregation from a single measuring point using NILM techniques may become very complex as was shown in the previous chapter. The use of state of the art machine learning methods are not possible on running on a low-cost system not able to perform real time load disaggregation. Therefore in order to avoid such approaches, we focus more on the optimization methods.

In general the optimization methods are trying to eliminate the error between the measured singal $\bar{x}$ and the predicted power of the used appliances x_n as was presented in the previous chapter. However, to also integrate the suggested training model, we need to modify the objective function such that we introduce the maximum value of all the relaxation factors of the trained model,

$$\begin{aligned} \min_{1\leq n\leq N} \quad & ||\bar{x} - \sum_{n=1}^{N} x_n - \delta_{max}|| \\ \text{subject to:} \quad & \sum_{n=1}^{N} x_n(t-1) \rightarrow \sum_{n=1}^{N} x_n(t) \\ & I_{\bar{x}}^{(3),(5)} \geq \sum_{n=1}^{N} I_{x_n}^{(3),(5)} \end{aligned} \tag{4.1}$$

The drawbacks of the optimization methods as stated are mainly the fact that (i) they can not differentiate between appliances with similar power consumption and (ii) do not take into consideration any appliance sequential dependencies. For example, a laptop which consumes 100W has the same probability to be identified with an outdoor light bulb of the same power level. The main problem of Hart's approach [9] was the identification of multi-state devices since it did not take into account the transition between states of an appliance.

To answer these shortcomings we propose a Modified Combinatorial Optimization (MCO) algorithm to overcome the mentioned problems. To address the first disadvantage we add extra information to the system by introducing Harmonics Analysis into our system. Since our design allows us to have a sampling rate where we can read up to the 16^{th} harmonic current we should use this element to discriminate among appliances with similar power. Secondly, by taking into account appliance sequential dependencies based on multi-state models of the devices extracted during the training phase we may constrain the number of appliances considered for the disaggregation and thus make it more reliable and accurate. This approach has also been applied by [54] but they limit the number of appliances by gathering information for the room location of the consumer which violates private data and raises security issues. Usually, in the literature, in order to consider the different states of an appliance, Hidden Markov Models were used as they are more effective; but since we have hardware constraints we use CO to simulate the behaviour of a HMM.

Algorithm 1: Original Combinatorial Optimization

```
1: Define Model ← [x_1, ..., x_N]
2: A ← Sum of all possible State Combinations of the Model
3: for each time slice t ∈ T do
4:     x̄ ← aggregate measurement
5:     find min ||x̄ − A||
6:     identify [x_1, ..., x_N]
```

Algorithm 2: Modified Combinatorial Optimization

Define **Model**, $\delta_{max} \leftarrow [x_1, ..., x_N]$
Define **Harmonics Model**$\leftarrow [I_{x_1}, ..., I_{x_N}]$
A $\leftarrow$ Sum of all possible **State Combinations** of the **Model**
B $\leftarrow$ Sum of all possible **State Combinations** of the **Harmonics Model**
for each time slice $t \in T$ **do**
    $\bar{x} \leftarrow$ aggregate measurement
    Extract Aggregate Harmonics $I_{3,5} \leftarrow I_{\bar{x}}$
    modify A based on Harmonics where B $> I_{3,5}$
    find $min\ ||\bar{x} - A - \delta_{max}||$
    identify $[x_1, ..., x_N]$
    modify A based on current prediction

The original version of the Combinatorial Optimization in Algorithm 1 is presented while algorithm 2 represents the proposed approach. It can be seen on blue the modifications that were made. As is shown in optimization methods it is needed to compute all possible combinations of the appliances that the model has been trained. On the original version we just need the power consumption to disaggregate the signal but with low accuracy. To add more detail with the expense of more data storage we also store harmonics information for the trained model. Therefore, every time we acquire a signal, first we check the harmonics so that we only keep the combination of appliances which have smaller harmonics content in comparison with the total one. Afterwards we perform disaggregation on a reduced set compared to the Algorithm 1. Finally, by modifying on the last step the state combination matrix based on the updated predictions we add sequential dependencies based on the multi state diagram of each appliance. In order to extract the harmonics content we use a Fast Fourier Transform (FFT) which obviously makes our algorithm slower but we compensate by performing optimization on a reduced matrix and more accurately.

To sum up, in contrast to the original CO algorithm, we calculate the sum of all possible state combinations only from the appliances in the constrained set based on the harmonics data and the previous state of each appliance rather than from the whole set of appliances in the household. After that, we select the closest combination of appliances that match the aggregated energy consumption. The computational complexity of disaggregation for T time periods is then $O(K^{N_c}T)$, where K is the number of appliance states and N_c is the cardinality of the constrained set of appliances. It is worth noticing that $N_c \subseteq N$. The complexity for the FFT is $O(n \log n)$ where $n = length(T)$. As a result the total computational complexity is $O(K^{N_c}T + n \log n)$ which makes the algorithm time dependent with the length/time of the sampled measurements. We can reduce this dependency by considering that the sampling will happen every time there is an event identification and will last just for one period of 50Hz which is sufficient in order to extract the harmonics from the signal. The FFT processing time can be further reduced by the addition on the SM design a signal processor module which will be responsible to run the FFT and thus would not burden the central processor which is doing the ED with the CO approach. It is noted that the model E650 from Landis+Gyr is equipped with such module but not the Arduino. Therefore, by neglecting the FFT time it is shown that for any given signal in the worst case the complexity will be the same with the original CO, $O(K^N T)$, but with better accuracy due to the sequential dependency integration.

4.5 Results

In this section we present the results concerning the Energy Disaggregation problem. Taking into consideration all the hardware design limitation and our proposed algorithm, we show the results and we are doing comparison of our solution with the original CO as well as the state of the art Factorial Hidden Markov Model using the NILMTK in python (for the original CO and FHMM) and the arduino (for the Modified CO).

The goal of this thesis is the implementation of the Modified Combinatorial Optimization (MCO) algorithm on a low-resources environment. For the extraction of the training models the NILMTK [36] was used since it provides great tools for comparison between different algorithms on the same data sets while we also implemented the proposed approach on Python with the help of the NILMTK package. To further validate our results we implemented the code also in the arduino mega 2560. Because of the low memory of the device, we were only capable of doing disaggregation on a limited number of appliances. Since it has 8KB RAM memory available and each cell of a matrix is represented by a number of 2 bytes, we have,

$$2 \cdot (N+1) \cdot 2^M \cdot 3^L \leq 8KByte \tag{4.2}$$

where N is the number of appliances and M denotes the two state and L the three states appliances, while $M + L = N$. The factor $N + 1$ represents the number of the columns while it is noted that we need to add an extra column for the relaxation factor. The number of rows, which is all the possible combination states, is $2^M \cdot 3^L$. Therefore we may disaggregate 5-7 appliances depending on the number of the states.

On the following we perform Energy Disaggregation on 5 appliances, among them the fridge, the washer dryer, two different types of lights and one CE appliance device with three states. We train the model on houses 1, 2, 4, 5, 6 of the REDD data set and test the trained model on house 3.

Before we perform disaggregation, we apply the trained model to the half of the total period energy signal of house 3 in order to extract the harmonics of fridge and electronics as was explained in a previous section. In general, adopting the pre-processing considerations of [54] we resample the data set so that we eliminate the start up current which creates large spikes and are important only for a transient/noise approach. It was noticed that keeping these spikes make the training procedure more difficult to cluster on a steady value and tended to move the centroid to higher values of the appliance's histogram.

The whole training procedure is done on a desktop computer using python and the nilmtk module. This is done because it is considered that we already have a trained model for a specific area so that we program the SM before we install it on the consumer. During the disaggregation procedure it was noticed that due to lack of information on the harmonics of a significant amount of devices (only the fridge and electronics were available) it was proved redundant since the third and fifth harmonic always satisfy our limitation on the modified algorithm, $B \leq I_{3,5}$. This further validates the importance of the harmonic analysis because according to it, the electronics should be always on which is the case for the test data set. Therefore the FFT implementation at the arduino was omitted since it was proved that it offers no further improvement under the specific conditions. Finally, we point out that the behaviour of the arduino on the Modified CO was the same with the simulation tests on python which is reasonable since we only used 5 appliances of 3 states and no FFT algorithm. Thus we kept successfully the storage and processing power requirements as low as possible. Next we provide the simulation plots and results of our algorithm.

Firstly we study the behaviour of the fridge on Fig. 4.18. We illustrate the results for the Modified CO and the real signal. Because it is a device with high consumption, all the three considered algorithms have the same behaviour and as such we just visualize just our solution.

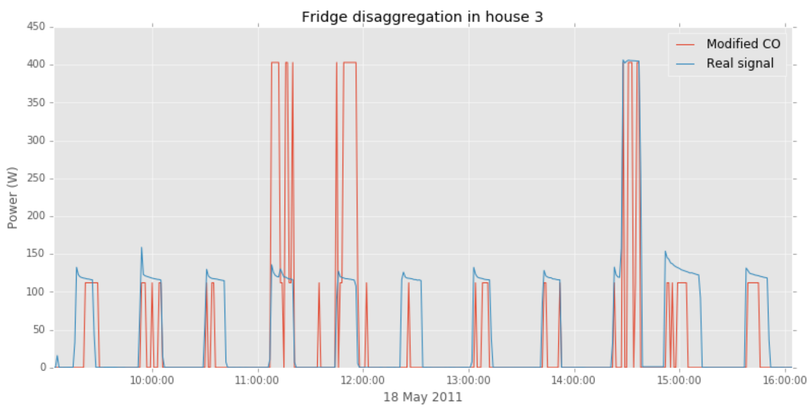

Figure 4.18: Energy Disaggregation of the fridge.

Secondly, we try to distinguish the washer dryer machine in house 3, Fig. 4.19. Our algorithm presents the same results with the FHMM and that's why we show only the original and Modified CO.

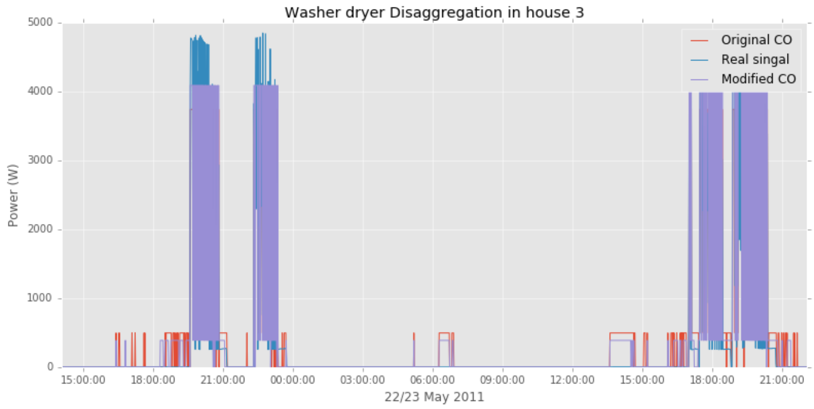

Figure 4.19: Energy Disaggregation of the washer dryer.

Thirdly the most interesting results are for the electronics devices and that's why we show all three implementations, Fig. 4.20. The FHMM manages to distinguish the device with excellent results since strangely enough the CE appliance is always on which denotes that it is not a laptop or a TV set but another non-linear device. Then our MCO extract satisfying results and still with significant improvement from the original one.

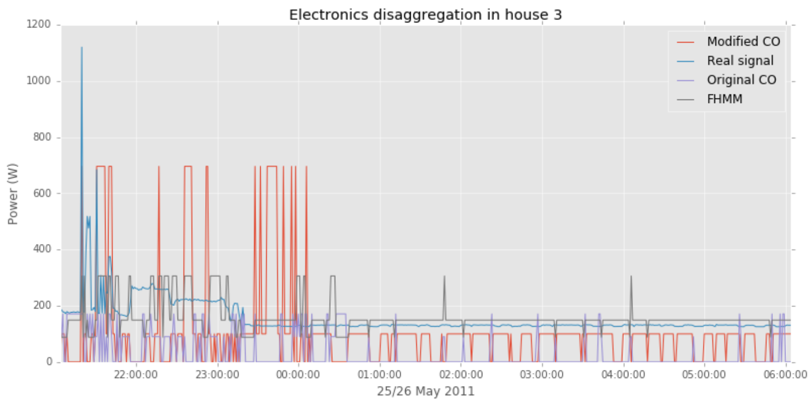

Figure 4.20: Energy Disaggregation of the electronics.

Finally, we show the lighting system disaggregation which is more or less the same for both the appliances on Fig. 4.21. When it is on, all the algorithms manage to discriminate it whereas when it is off, there are some errors which are mainly because lighting is a small consumption appliance and as that the CO has problems identifying it.

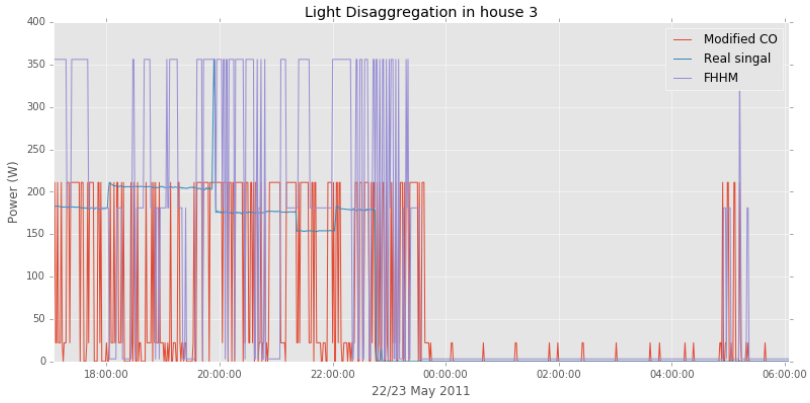

Figure 4.21: Energy Disaggregation of the lights.

To summarize the above results we present the F1 score for all the algorithms and the appliances. As was mentioned the significant improvement is done on the electronics appliance. We strongly believe that if we had harmonics information for all the appliances we would be able to distinguish clearly the specific device and have the same results with the FHMM. To emphasize more the outcome of the current chapter, it is noted that running a FHHM algorithm is needed a RAM memory of 8GB and processor power of 3GHz as stated in [54], whereas we used an Arduino mega 2560 with RAM 8Kb and processor 16MHz.

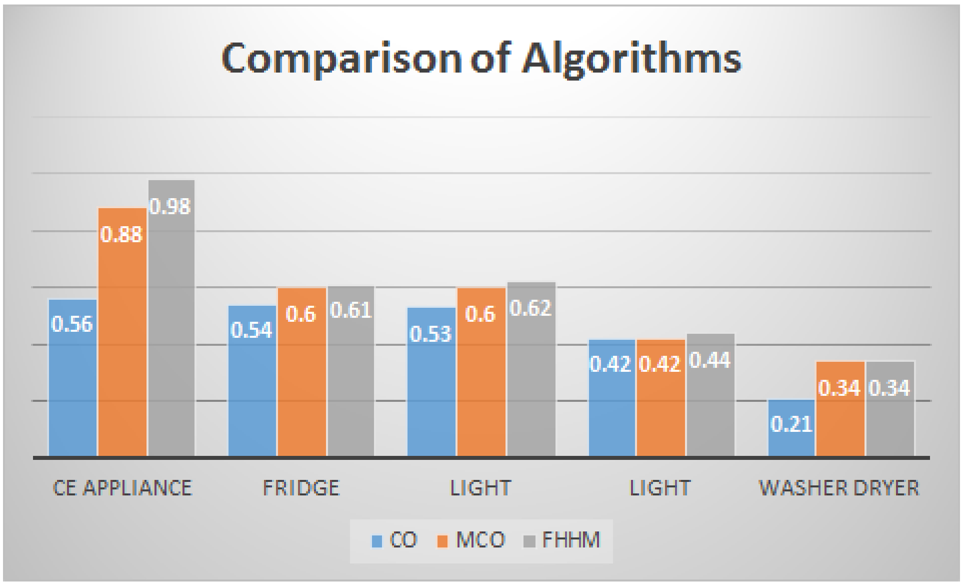

Figure 4.22: Comparison of the Energy Disaggregation algorithms.

Regarding the other results, we see that we performed an improvement of up to 30% compared with the traditional optimization approach without changing significantly the implementation and without increasing the complexity, since we neglected the harmonics data but introduced sequential dependencies on the system. Still FHMM has the best results but the Modified CO apart from the electronics has approximately the same F1 score which means that by adding extra info for each appliance we may reach the levels of accuracy of an algorithm with very powerful and demanding processing power requirements.

Chapter 5

Conclusions and Outlook

The purpose of our project is the implementation of Energy Disaggregation algorithms based on the current technology and infrastructure of Smart Meters and as such this work has described an approach to perform Energy Disaggregation on low-cost devices. In this chapter we discuss the results we have presented and evaluate the conclusions while we highlight limitations and give directions for future work. During the period of the work we also had some constructive conversations with people who already work in the Energy sector outside academia and have been involved either in Smart Metering or Smart Grid projects and here I would like to outline the most important aspects of their perspective.

5.1 Conclusions

The currently deployed Smart Meters in Europe due to the regulations issued by European Commission have created competition on the sector of manufacturing SM devices and as a result the hardware implementation are improving continuously and are running up to their limits. This constitutes a big difference in the approach of the Energy Disaggregation problem compared to the last years. Since the SM may offer more options then the NILM approaches may be moved on the SM and make redundant the cloud services that have been used mainly today. By building SMs capable of doing ED we may also reduce also the costs from the communication infrastructure between the UP and consumer since a Power Line communication will be sufficient.

After a thorough description of the restrictions, we moved to the part of algorithm implementation by proposing a training phase which may be dependent both from the power level and the time usage of each appliance. The drawbacks of the optimization methods were analyzed, yet they are an attractive solution for low-resources environments. The proposed Modified CO exhibited great results compared to the today's approaches and further improvements are possible. Consequently since we could run the algorithm on a low-cost microprocessor,then a SM is capable of performing disaggregation with satisfying results.

However, to address the main limitations of the NILM methods we need to consider realistic applications. Therefore further investigation is needed especially in the area of building generalized models since they are the main restriction in this field. If we manage to improve the accuracy of the labelled appliances then we would be able to present better results. There are loads that are very difficult to cluster and it would be very naive to model them just with two values. So future work should focus on the improvement of the training phase and of course in the application of the Modified CO to more data sets such that the application of the approach can be evaluated for more and different appliances.

5.2 Discussion

The current project would not have been so interesting if I did not have some private conversations concerning this subject with people working in industry.

The first person outside academia I discussed with on this topic was C. Graessner who is the head of Technology in BKW. His company has considered such options three years ago when they worked in collaboration with the University of Lucern for a similar project. However, soon enough they abandoned the development of this concept because they had mainly two objections. The first one is that ED is expensive since they needed special hardware and its price was not justified by the possible benefits. Secondly and most important is that such methods to identify appliances used and behaviours of consumers are still strictly forbidden in Switzerland. The head of Technology of EWZ also had similar perspective, however he was less reluctant to explore the possible advantages of such strategies.

To answer the first point I think it is sufficient to say that since Smart Meter deployment has already become European regulation, sooner or later it will also come to Switzerland. The price for the new systems will be paid in most cases by the customers. So it would be very interesting to further investigate the possibilities of disaggregation with such capabilities. Furthermore, concerning the second point BKW in cooperation with EWZ are currently involved in the Gridbox project which explores the benefits of installing powerful SMs on a district level rather than for individuals. Therefore they have already decided that it can be useful for state estimation of the grid in order to evaluate its condition and prevent possible faults faster.

Furthermore, after my communication with a Landis+Gyr representative responsible for the Linkys project I improved my insight regarding the hardware concerns. In France they are deploying a custom SM which presents better option than their previous E350 and E450 models and comparable with the newest E650. He found the topic extremely interesting, however they are not yet considering such an option but would like to do so in the future. His concerns were not about the processing power but mainly on the communication between the SM and the UP. He claimed that in order to send raw data you would need far better infrastructure than the current PLC. Thus, use of Ethernet or more local memory were his suggestions. On this thesis we addressed this problem and we assumed that if we are able to perform disaggregation locally there would be no need to send raw data to the UP making the PLC a viable solution for billing purposes and transfer of low frequency disaggregated data.

To conclude I would like to repeat the final discussion regarding the communication protocols and provide a modified version of the picture introduced in the first chapter in order to emphasize on the direction that research should focus on in the near future.

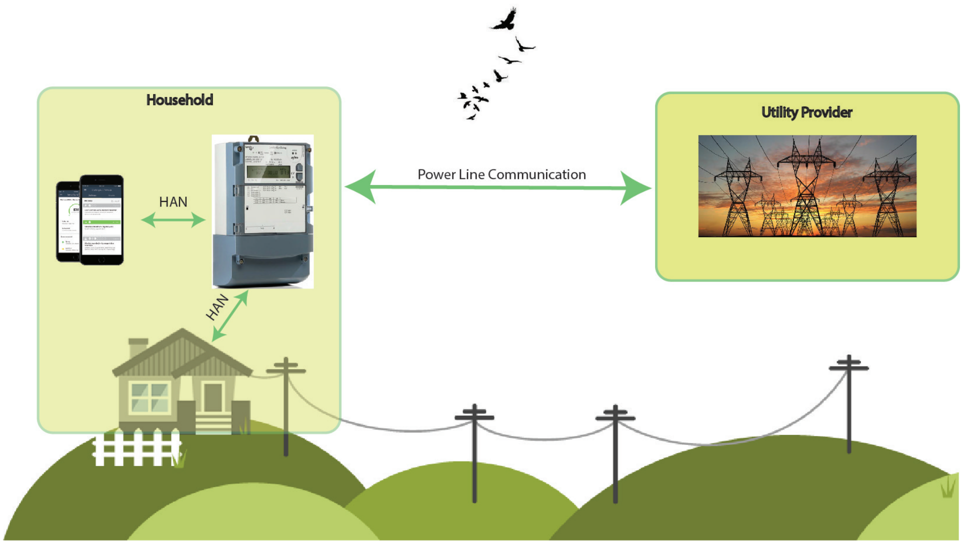

Figure 5.1: Future Energy systems concerning the deployment of Smart Metering Infrastructure.

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