Architecture and operation of a Demand Side Management Evaluation Tool in the Residential Sector

Tommaso Mura

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Supervisor: Prof. Luís António Fialho Marcelino Ferreira

Examination Committee

Chairperson: Prof. Duarte de Mesquita e Sousa

Supervisor: Prof. Luís António Fialho Marcelino Ferreira

Member of the Committee: Prof. João José Esteves Santana

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Abstract

The electricity demand management of the residential sector proved to have a high potential for boosting the transition towards a cleaner and more decentralized energy sector. This practice is still underdeveloped in Europe, thus creating an obstacle to the penetration of renewable energy sources and a threat to a capital-intensive electric network upgrade. In this context, this thesis considers the combination of LV grid status assessment and Non-Intrusive Load Monitoring (NILM) techniques at the secondary substation level to overcome those limitations.

The scope of this dissertation is the ideation of a commercial service that can combine LV grid assessment and NILM to facilitate the management of the LV network flexible loads for the DSOs. The techno-economic analysis of this service, the Demand Side Management Evaluation Tool, is performed to establish the accuracy of NILM when applied at the secondary substation and the economic viability of the service.

The market feasibility study shows the regulatory maturity of the UK for the first application and the DSOs interest for this kind of service. The cost-benefit analysis proves that the generated benefits surpass the costs assessing with a good degree of certainty the financial viability of large-scale application. On the other hand, the outcomes of the testing phase reveal that the performance yielded by the reference algorithms when applied to multiple aggregated houses is not yet adapted for commercial application. The weak points are identified to adjust the most promising algorithms and untap the high environmental and economic benefits of the Demand Side Management Evaluation Tool

Key words

Non-intrusive Load Monitoring; Demand Side Management; LV Network; EV identification; Distribution System Operator

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List of abbreviations

EV: Electric Vehicle

LV: Low Voltage

MV: Medium Voltage

HV: High Voltage

DSM: Demand Side Management

DR: Demand Response

PV: Solar Photovoltaic

IoT: Internet of Things

DER: Distributed Energy Resource

BRP: Balance Responsible Party

PTU: Program Time Unit

DSO: Distribution System Operator

DNO: Distribution Network Operator

TSO: Transmission System Operator

EU: European Union

AMI: Advanced Metering Infrastructure

NILM: Non-Intrusive Load Monitoring

SM: Smart Meter

H2020: Horizon 2020

CVD Continuously Variable Devices

FFT: Fast Fourier Transform

SVM: Support Vector Machine

HMM: Hidden Markov Model

ANN: Artificial Neural Network

REDD: Reference Energy Disaggregation Dataset

WAN: Wide Area Network

HAN: Home Area Network

A/D: Analog/Digital

PLC: Power Line Communication

ML: Machine Learning

HP: Heat Pumps

GHI: Global Horizontal Irradiance

UKPN: UK Power Network

CBA: Cost-Benefit Analysis

NPV: Net Present Value

NILMTK: NILM Toolkit

FHMM: Factorial Hidden Markov Model

1. Introduction

1.1. Context

Global warming, energy security, and local pollution are just an example of the innumerous factors pushing towards a cleaner and more decentralized energy supply that presents itself as the antithesis of the current one. The necessary growing electricity consumption and the higher penetration of intermittent renewable power sources are generating a great challenge for the electricity grid and its operators. The aging power grid is approaching its capacity constraints and the fluctuating energy supply is increasing significantly the difficulty of balancing the demand. The possibility of a blind increase in capacity and storage of the power system is not an option because of the incredibly high investment that would be needed.

The energy sector is experiencing a radical transformation based on three major trends; Electrification, decentralization, and digitalization. The industry is expected to change at a pace that can be compared to the telecommunication one, wherein a few years an extremely costly and inefficient sector increased exponentially the quality of its service cutting its costs. Electrification is proceeding fast in sectors that traditionally have been based on fossil fuels like transportation and heating. This change is necessary to reach the long-term carbon reduction goals set by the European Union and maintain the atmospheric temperature increase below 2 °C in 2100 as stated by COP 21 in Paris. For instance, an exponential growth is expected in EV industry with Bloomberg New Energy Finance predicting the price parity with gasoline counterpart in 2022. In 2017, the electric vehicle market in the US grew by 26%, giving less than 5 years to the system operators to update the electrical grid [1]. The rapid decrease in cost of distributed energy resources, with the leadership of solar PV and storage, is stimulating the decentralization of energy production in the electricity grid that was originally built considering just one direction power flow from big centralized power plants to the loads. From 2008 to 2013, under incentives regime, distributed PV in Italy scaled up from 0.1% to 8.7% of total national electricity generation. The incentives needed to be suppressed in 2013 because the grid infrastructure could not tolerate that production increase [2]. Digitalization is another leading trend in the energy industry pushing the two others mentioned before through intelligent control and automation.

The traditional electricity network is evolving beyond delivering electricity to consumers and becoming a digital platform where they can actively engage and participate giving their own contribution, ultimately getting several benefits including economic ones [3]. The Internet of Things (IoT) technologies, including smart meters, controllable switches, and communication infrastructure together with Big Data management and analysis are making this transformation possible and the consumers more aware of their electricity consumption and possible benefits in this process.

1.1.1. Overview on Demand Response (DR)

Demand-Response (DR) appears in this transition environment as a possibility to match the electricity consumption with the supply with an upside-down approach, where the end users participate actively consuming electricity when it is abundant and receiving an incentive to do so. In a growing number of countries, the share of intermittent renewable energy sources is reaching a level where a larger degree of flexibility becomes necessary compared to the conventional grid, DR can play a key role in this phase as a relatively cheap source of additional flexibility [4]. The residential sector represents the 20% [5] of the total energy consumption worldwide and its potential as a DR energy source is largely undeveloped in Europe. Nonetheless, the digitalization of the energy system, the penetration of IoT devices in the quotidian and the positive push from European regulation framework are creating the perfect environment for its disruption and for business creation. Many programmes have targeted industrial and commercial customers so far since the residential sector can be more difficult to involve due to customer engagement issues, and the limited range of flexibility available per consumer. However, smart devices and the IoT make residential users capable of responding to automated price signals together with the potentiality of aggregation of consumers, are helping make DR programmes more available even for residential customers [6]. Demand-Response represents a clean, low cost and fast dispatch energy source that would boost renewable energy penetration and smart electricity consumption in our future society.

1.1.2. Useful definitions

Some definitions necessary for the comprehension of the work are listed in this paragraph.

Demand Response (DR)

The Department of Energy of the United States defines the term like this "Demand response provides an opportunity for consumers to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage during peak periods in response to time-based rates or other forms of financial incentives". The word can also have a broader meaning including every asset in the distribution network able to provide or consume energy reacting to a certain control signal. With the latter definition, any distributed energy resource (DER) can be considered as DR resource if able to vary its energy output from its static generation or demand pattern in response to a control signal.

Demand Side Management (DSM)

Demand Side Management represents a broader sense of Demand Response including also the reduction of end-user consumption and behavioral changes. It can be formally formulated as "The planning, implementation, and monitoring of activities designed to encourage consumers to modify patterns of energy usage, including the timing and level of electricity demand. Demand side management includes demand response and demand reduction." [4]

Aggregator

Smart Grids Task Force – Expert Group 3 defines the aggregator as: "A legal entity that aggregates the load or generation of various demand and/or generation/production units. Aggregation can be a function that can be met by existing market actors or can be carried out by a separate actor. EED: aggregator means a demand service provider that combines multiple short-duration consumer loads for sale or auction in organized energy markets." [4]

Balance Responsible Party (BRP)

The Balance Responsible Party is a legal entity that manages a portfolio of demand and supply of electricity and has a commitment to the system operator in an ENTSO-E control zone to balance supply and demand in the managed portfolio on a Program Time Unit (PTU) basis according to energy programs. Legally, all metered nodes in the power system have program responsibility; this responsibility currently ultimately is delegated to the BRP. [4]

Distribution System Operator (DSO)

The distribution System Operator (DSO) is the entity in charge of securely operating and developing an active distribution system comprising networks, demand, generation and other flexible distributed energy resources (DER). It must cover the position of a neutral facilitator of an open and accessible market and enable the competitive access to the electricity markets and the optimal use of DER in the distribution network to deliver security, sustainability, and affordability in the support of whole system optimization. A DSO promotes customers to be both energy consumers and producers, facilitating customer access to networks and markets [7].

Figure 1 explains how the different actors of the demand side management environment are connected to each other. For the scope of this thesis, the aggregator needs to deal with the DSO only, framed in red, even if it can create relationships with all the entities in the image.

Figure 1. Demand side management value chain

1.1.3. Institutional context – Policies and Regulation

European Union directives regarding energy policies do not establish a detailed legislation that can differ for every single state, but a series of requirements and guidelines that the member states should follow to achieve the European goals. The current EU directives regarding the electricity sector and the demand side management concern the internal electricity market (Directive 2009/72/EC [8], part of so-called 3rd energy package) and energy efficiency (Directive 2012/27/EU [9]). Grid codes of the European Network of Transmission System Operators for Electricity [10] states a series of rules that the member states have to follow regarding the transmission of electricity at high voltage. Directive 2009/72/EC supports the empowerment of final customers and gives suggestions about how data should be used, nonetheless, DSM or DR are not mentioned. Directive 2012/27/EU and grid codes recognize the importance of DR and set some guidelines for reducing the barriers of the regulatory framework.

The recent package of directives "Clean Energy for All Europeans" (known as "Winter Package") stresses on the need of integration of renewable sources and empowerment of end users by rewarding flexibility sources like generation, demand, and storage on the market. The European directive represents a milestone for DSM and specifically expresses "*Every consumer will also be entitled to a smart meter equipped with common minimum functionalities. The Member States not planning to roll-out smart meters are required to assess the cost-effectiveness of a large-scale smart metering deployment on a regular basis*" and "*Every consumer will be able to offer demand response and to receive remuneration, directly or through aggregators*" [11]. Despite the importance of this document for the acknowledgment of DR as a resource for the electrical system and for the acceptance of the role of the aggregator, the member states resulted to have a different vision about its actual adoption. The situation at European level appears indeed extremely scattered with states like France and the UK where a mature regulation framework is in place about demand-side energy resource and aggregation [12]. On the other hand, countries like Portugal and Italy are laying far behind with neither DR or load aggregation allowed. However, the DSM market is moving fast, and the regulatory barriers are expected to fall in a relatively short time.

Figure 1 shows the status of the European regulatory framework in a matter of DR and aggregation in the year 2017 [12].

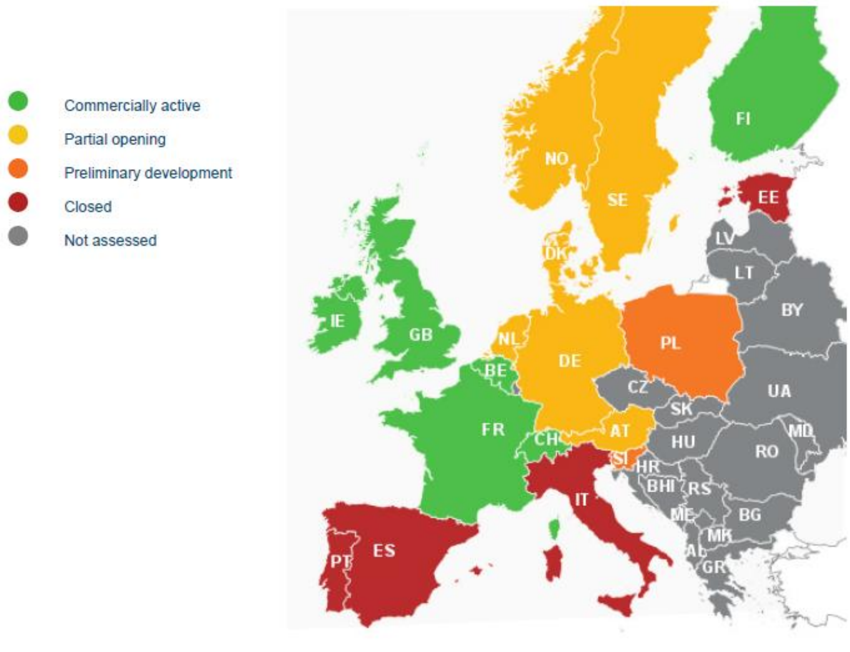

Figure 2. Map of explicit demand response development in Europe today [12].

1.1.4. Load disaggregation techniques

The changing energy system presents several challenges that are nowadays offering a unique opportunity for resolution or at least significant improvement. First, the residential sector roughly contributes to 20% of global energy demand and an enormous potential for low-cost energy reduction is estimated, yet not achieved. 8% of total energy use and emissions can be abated with efficiency improvements in these buildings [13]. In addition, experts believe that a major barrier for this missed achievement is represented by behavioral resistance. Second, the multi-billionaire smart meter infrastructure is far behind from reaching its full potential of financial benefits that are estimated to be up to 8% from energy shifting and conserving benefits [14].

An opportunity to leverage smart meter infrastructure and untap the energy savings and peak shifting potential of the residential and commercial sector is represented by load disaggregation techniques. It refers to a series of methods to extract single load features from an aggregated energy signal [15].

Load disaggregation, also known as nonintrusive load monitoring (NILM) or energy disaggregation, is a technique to deduce what appliances are used in a household and their individual electricity consumption analyzing changes in current and voltage at smart meter level. The name NILM is since this method present itself as an antithesis to the intrusive load monitoring techniques that require a measurement at a single appliance level. The measurement at the single point of the house allows indeed to reduce significantly the intrusiveness of the hardware for the householders and cut the installation and operation costs. Figure 3 illustrates the concept of Load Disaggregation that was previously explained.

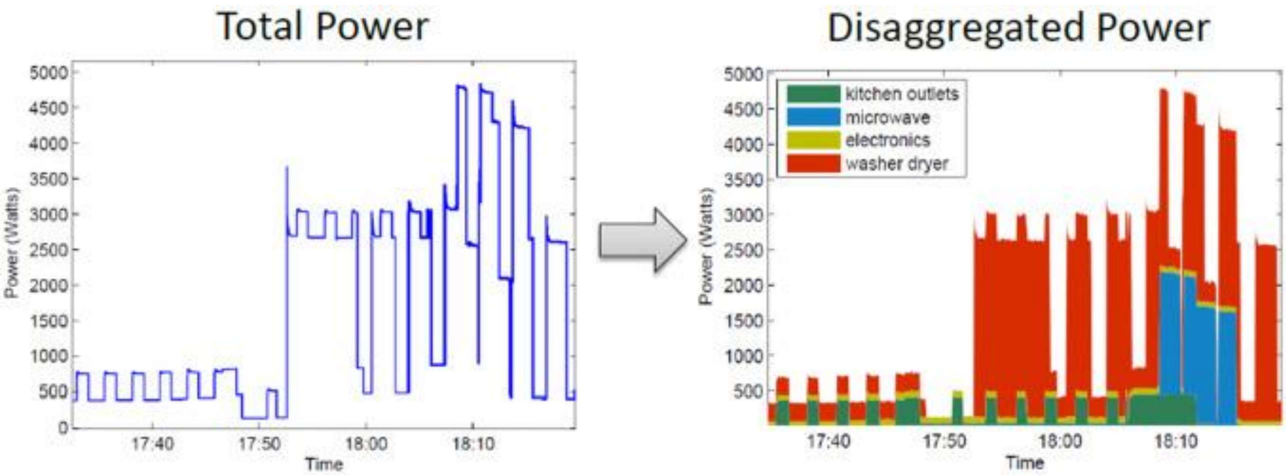

Figure 3. Load Disaggregation concept illustration [16]

Energy disaggregation has a wide range of applications that go far beyond the simple household appliance detection and represents a fast-growing industry in the last years. The most interesting applications of NILM are explained below [17].

- Detailed bill information: this is the most widespread application and tries to provide detailed information about the single appliance use to improve end users' awareness about their electricity consumption and achieve reductions in their bills.
- Industrial monitoring: it represents a highly promising, yet a less explored application that allows monitoring of the key industrial assets from a single point reading to prevent failures and reduce maintenance costs.
- Utility and Policy applications: Load disaggregation presents multiple applications for utilities such as improved load forecasting, theft detection, energy efficiency targets evaluation, grid planning, and demand response. The last two applications will represent the focus of this thesis.

Load disaggregation techniques for demand-response applications

The contribution of load disaggregation techniques in demand response consists of the identification of flexible loads or inactivity periods in the end users' electricity consumption pattern. This makes possible to target specific customer segments for demand response programs. In addition, utilities would be able to increase the accuracy of demand forecasting using improved models of usage at appliance level to better identify the peaks of energy consumption. Moreover, utilities could know at any time the amount of flexible or deferrable loads in the electricity grid and, if a direct control infrastructure is in place, could suggest or activate load sheds to conserve energy during peak load times or perform other grid services. Finally, a possible scenario for utilities is to differentiate their electricity provision offer with *type of usage* pricing models that would flank the already existing *time of usage* ones [18].

The demand response application to ease the balancing of the electricity grid, reduce energy consumption and postpone or avoid investments in grid infrastructure is part of a bigger picture of Utility and Policy benefits that space out from this type of use. Indeed, the disaggregation of electric loads creates a series of strategic advantages that involve the whole energy system. The main benefits can be grouped as follow [15].

- Offer evaluation: the improved quantification of savings and customers behavior knowledge results in the increased objectivity of program evaluation allowing a better program design and diversification of offer for customer retention and new sales.
- Segmentation of energy efficiency marketing: it allows a specific and strategic energy efficiency marketing with the aim to have tailored offers and incentives.
- Building contractor ratings and incentives: the disaggregation of loads leads to more accurate performance-based metrics which could impact real estate value and the evaluation of contractor performance.
- Economic modeling and policy recommendations: it permits to better identify the targets for funding allocations in energy efficiency and grid planning policies thanks to assets recognition and enhanced load forecasting.

1.2. Distribution network demand response services

In the past chapter, an overview of what is demand response and on the potential of non-intrusive load monitoring for grid management was completed. This part will deepen the topic and explain why the DSO can use DR and NILM as resources and which are the barriers slowing down this process.

The electricity distribution grid is planned to reliably and safely manage the power flows up to its rated capacity. The maximum electricity demand is forecasted at different parts of the distribution network one or more years in advance to plan system improvements and maintain a reliable supply. The system operators may also activate specific mechanisms to reduce loading on part of the distribution system due to forecasted or unexpected peak conditions during the operation. These activities traditionally consist in either a manually operated load transfer from one feeder to one other or in advanced systems that perform the same action automatically. An additional advantage of these procedures is to defer the investments on the distribution grid and increase assets lifetime [19].

As previously mentioned, the variability of DER is also creating new load patterns that may result in working conditions for which the distribution assets were not designed for. For instance, transformers that are currently taking advantage of the lower demand and ambient temperature to cool down overnight may not be able to do so if a large fleet of electric vehicles is connected after dark [20]. Indeed, the penetration of DER decoupled from grid planning is creating challenges to maintain the reliability and stability of the local distribution systems. To better understand the nature of these challenges, the most usual problems in the low voltage network are described in the following paragraph.

Figure 4 illustrates the physiognomy of the distribution network, the area of the distribution network that needs to be designed and operated by the DSO.

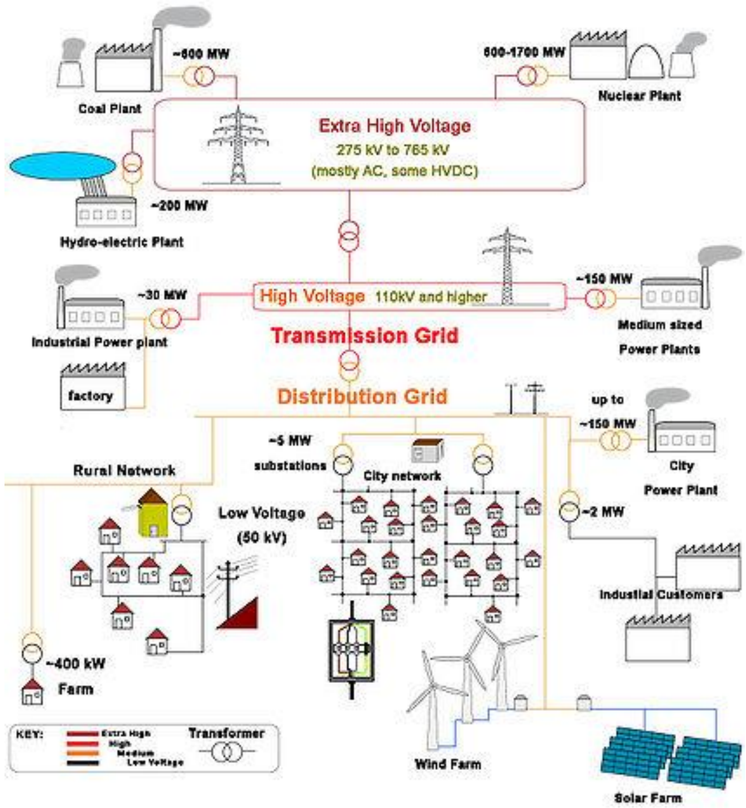

Figure 4. Distribution network schematics of the Ancillary services for the DSO [21]

Ancillary services are defined by EURELECTRIC as all the necessary activities performed by the transmission and distribution system operator to maintain the integrity and stability of the transmission or distribution systems as well as the power quality [22]. As previously stated, this thesis will keep the focus on the distribution system only and the most typical issues affecting the LV network are voltage unbalance, overvoltages, line congestion, and transformer overheating. To tackle these problems the DSOs can upgrade the grid infrastructure, limit the penetration of DER or purchase ancillary services from generators or demand-side resources. The two main ancillary services for the DSOs are [23]:

- **Voltage control:** reactive power can be used to compensate for voltage drops, but this is generally provided from or to the transmission network because of the lack of resources in the distribution one. Voltage control can also be operated with tap chargers at HV/MV substation level. Nonetheless, reactive power generated by DER connected at MV or LV nodes can be used for reactive power support of local voltage control.

- **Line congestion**: current congestion of the distribution feeders is mainly related to the electrification of the heating and transportation sectors that is adding a vast number of loads to the aging LV network. Hierarchical control applied to the DER in the distribution network could significantly extend the transport capacities of the existing distribution lines. The value of this service can be evaluated through the avoided or postponed investment in the grid infrastructure.

1.2.1. Problem identification

Despite the potential of flexible loads and DER to deliver low cost ancillary services for the DSO and the opportunity to identify these resources in the grid with NILM techniques, this does not represent the real-world scenario and two main technical barriers are identified and analyzed. The first is the lack of a geographical information in the demand response environment and the second is the violation of customer privacy when NILM techniques are applied at a single house level. These limitations are explained in the following paragraphs and later in the thesis, a solution will be studied.

1.2.1.1. Lack of a geographical information in the demand response environment

Although DR represents an opportunity to facilitate grid balancing and boost the penetration of renewable sources, the many incentive-based programs in the market are designed with little or no regard to more specific and localized geographic necessities of the distribution network. For example, load relief may be necessary for a specific part of utility's service territory to achieve system reliability, but program rules are often not conceived to target the end users of a specific geographical region. Other distribution system problematics such as power quality of phase balancing have a highly localized nature and suffer from the same regulations. Hence, because of the inability to set event dispatch at a granular geographical level, the incentive-based or time-based programs have little or no potential to address the distribution network problems [20]. This problem is strictly related to the regulatory framework that does not allow either to target only the end user from a specific region or to ask for a differentiated performance in case of events because of discriminatory reasons.

A program design change towards a more geographical specificity could instead generate value for the distributed system operator with a decisively positive impact on maximum capacity relief, emergency load transfer, voltage management, and outage recovery. Faster response and direct control from the utility side could also improve power quality and phase balancing [20]. Figure 5 gives an overview of what is a localized problem. If a line congestion event happens it will influence the area fed by that specific line only (area in red) and if some demand response resources want to be unleashed to solve it, this must be done within the red area. Nowadays, the DSO, that is in charge for solving the LV network problems, has nearly zero visibility on the flexible loads in the red area and the regulatory framework does not allow to involve the customers in the red area only in the delivery of a load relief. This results in an almost complete inefficiency of DR programs to solve the DSO grid management problems.

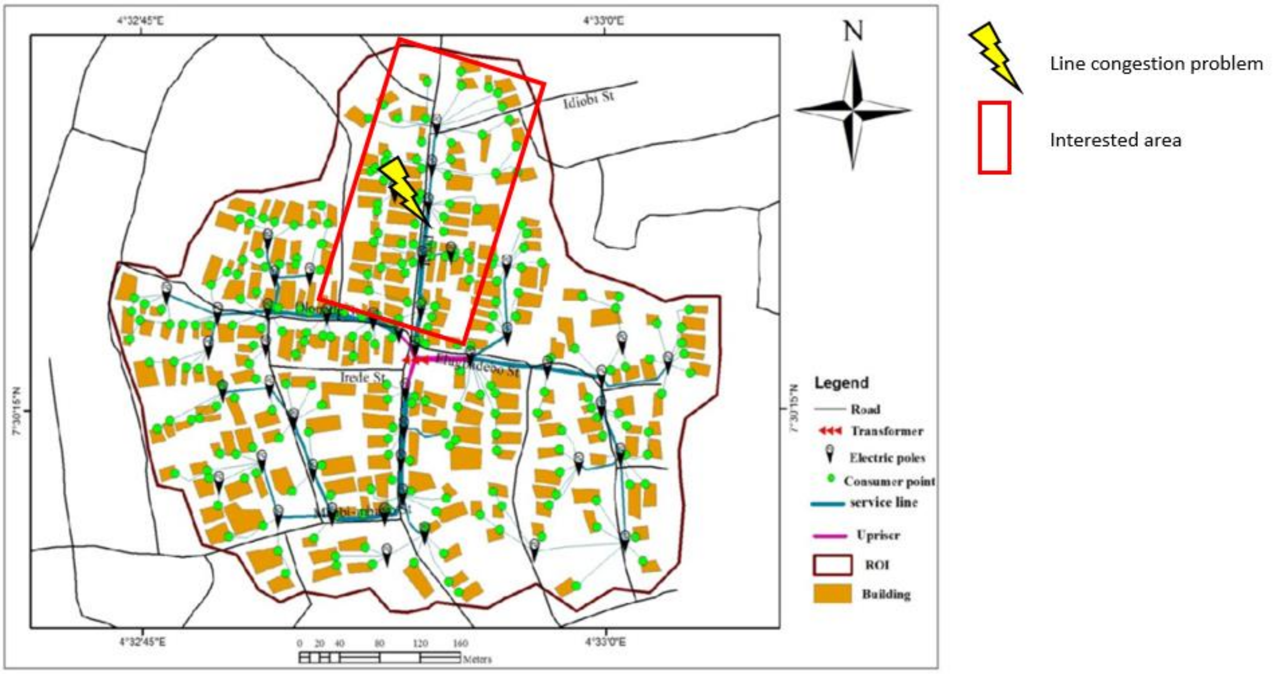

Figure 5. LV Line congestion event

The geographic approach for more efficient DR resources dispatches also pulls other opportunities to face the distribution system needs like advanced metering infrastructure (AMI) deployment and improved DER installation planning. The visibility of the operating state at certain parts of the distribution system is very limited for several utilities. The lack of advanced metering infrastructure makes the identification of some grid challenges extremely difficult and then the assessment of what resources would be needed to tackle them inefficient and expensive. A renovated interest towards local solutions would attract investments to position AMI in the territory and perform complex operational analytics in the field of advanced distribution management for efficient utilization of DR resources and grid planning. In addition, a higher resolution visibility on the territory would incentivize the location of DER in the right place of the distribution grid avoiding reaching the location maximum capacity and with the possibility to defer or replace conventional infrastructure build-out. Moreover, microgrid with controllable DER may ensure the electricity supply in some specific locations even if there is an outage elsewhere.

On the other hand, an increased geography-based DR design may complicate the work of aggregators that would need to look for flexibility sources only in specific areas. Furthermore, if the concentration of these resources is not high enough it may be difficult to develop a business model that could collect enough value to justify the investment in infrastructure and make the business viable. The modeling and evaluation of the DR resource at such a local level would make the aggregators' duties even more challenging.

1.2.1.2. Violation of customer privacy of NILM techniques

The monitoring of end users' consumption gives information about their Typical Load. The analysis of these data can yield to the disclosure of sensitive information about user behavior such as house occupancy and occupant activities causing severe privacy issues. The data to discern consumers' actions through electrical consumption disaggregation algorithms come from smart meters installed at single house level, hence the analyzed data can be easily connected to a specific person or family. A smart meter (SM) is an internet-capable device that measures the electricity consumption of a household. Whereas traditional meters are only able to evaluate the total consumption, smart meters record the electricity usage on a live basis and allow bi-directional communication with the electric utility. SM represents a €45 billion market only in the European Union, its installation is strongly recommended by the European directive (Clean Energy for All Europeans, 2016) and the forecasted penetration rate per country in 2020 is shown in Figure 6 [24].

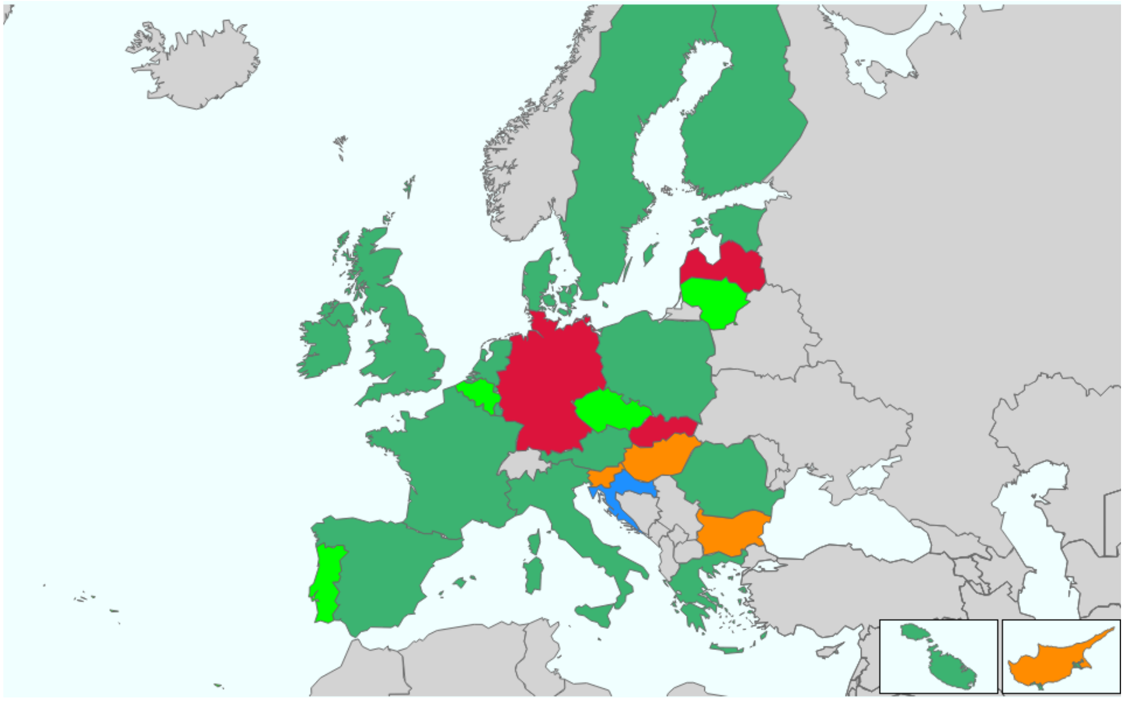

Figure 6. Regulation for the roll-out of SM by 2020, in green wide-scale deployment (>80%), in light green NO wide-scale deployment (<80%), in red Selective roll-out, in orange no data and blue no clear regulation (European Commission, 2014).

The large availability of granular data is generating information-rich societies and users can benefit out of it to increase the awareness over their electricity consumption and reduce their bills and impact on the Planet. Nonetheless, this process is paving the way for inappropriate use and it becomes crucial to address the end users' privacy concern of sensitive data while providing a service. Consumers' data are protected by EU directive on the processing of personal data that sets who can access personal data and under which circumstances. The European Commission also elaborated a guidance on data protection and privacy for data controllers and investors in the smart grids. However, the European Directives do not have direct validity in each country where the management of personal electricity consumption data requires national regulations and often the electricity utilities are the only owner of the data.

The energy ecosystem is populated by a wide range of active participants such as appliance manufacturers, retail industry, healthcare and many more. The availability of house consumption data is making possible a set of derivative application offered by third parties like theft detection, elderly monitoring and dynamic pricing [25]. Once smart meter data are shared with third parties intended or unintended leakage of private information is inevitable, creating primary privacy concerns. NILM can derive with high precision every single appliance usage, then the user activity profile can be easily identified [26]. For instance, health insurance providers could record user's sleeping, eating, exercise, even late partying activities to elaborate ad hoc risk premiums [27]. The high granularity of users' electricity consumption gives also information about the type and conditions of house appliances that could be used by home retail manufacturers to push more efficient products at house level. Indeed, the access to such granular data can make every information about users from gender to financial condition easily derivable [26].

1.3. Solution overview: DSM Evaluation Tool

In the previous chapters, the potentiality of non-intrusive load monitoring for demand response applications was presented highlighting the opportunity to decrease the cost of transition towards a renewable energy system together with the obstacles to its implementation. The main technical barriers for untapping the potential of demand-side management to provide the distribution system flexibility services can be sum up as:

- The inability to dispatch flexibility at a precise geographical location reducing significantly its efficacy to solve DSOs' issues in the LV grid
- The violation of people privacy when NILM techniques are implemented at a single house level

To overcome these barriers a new service is needed in the energy sector and this could be provided through the application of NILM techniques at the distribution substation level. Indeed, load disaggregation algorithms could extrapolate from the power readings the characteristic signatures of the flexible assets such as electric vehicles, heat pumps, and distributed energy resources and identify where and when they are consuming or producing electricity in the low voltage network. When the data from the MV/LV transformer derivation are used to perform energy disaggregation multiple value propositions can be generated:

1. Deliver real-time notification and recommendations on the state of the LV network such as feeders' capacity, transformer thermal rate, and grid voltage
2. Identify the demand response potential of the LV network due to flexible controllable loads in the area preserving the privacy of the end users
3. Boost the installation and limit the curtailment of the local distributed energy resources cross-checking the grid capacity and available flexibility

The described service, that will be called DSM Evaluation Tool, would benefit both DSOs and energy aggregators. The former with a platform for the dispatch of localized distribution system services and the latter with a market to deploy its demand response solutions as explained in Figure 7.

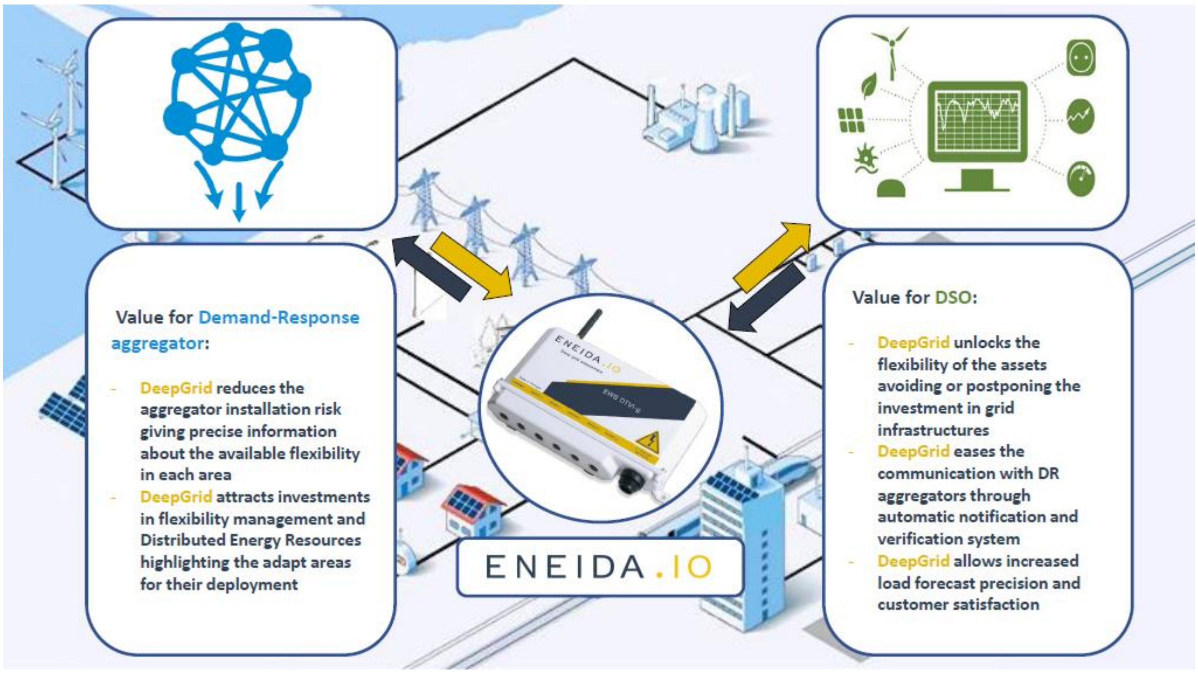

Figure 7. The value proposition of NILM for demand response at the secondary substation level

The detailed description of the service comprehensive of software and hardware requirements expected impact and preliminary operation will be presented in the next chapters of the work.

NILM at the secondary substation level

The evaluation of the flexibility potential of the LV grid requires the application of NILM-based signal processing techniques at the power measurements on the LV derivation of the MV/LV transformer. The characterization of data and the modality of the acquisition will be explained in the chapter relative to the hardware and software requirements. Nowadays NILM is mainly applied at a single house level where the analysis of the aggregated power consumption at smart meter level allows the recognition of the single appliances. It is possible to disaggregate the individual loads from the total power consumption thanks to the load signature which is the peculiar current pattern observed during the operation of an electric equipment.

For the purpose of this thesis, it is necessary to extend the application of these techniques at a higher level in the distribution network. Energy disaggregation at substation level allows the breakdown of the transformer load among each type of end user making possible to identify daily, seasonal and yearly electricity consumption trends. The qualitative and quantitative data about end users' consumption allows the evaluation of the substation expectancy to meet the demand and the eventual planning of corrective actions such as asset upgrade or replacement and smart grid solutions. The focus of this thesis is indeed the possibility to highlight the amount of flexible and manageable loads in the LV grid to evaluate the demand side management potential of a specific area. The disaggregation at substation level makes also possible to correlate load patterns with environmental variables such as temperature to forecast with higher accuracy the variation of the transformer load when the external conditions are changing.

The electrical loads served by one MV/LV transformer are a mix of industrial, commercial and residential consumers, but for sake of simplicity, this thesis with deal with a substation that is supplying electricity to residential customers only.

The problem of disaggregating individual electrical loads acquires additional difficulty when applied at the secondary substation level for two basic reasons [28]:

1. The number of involved loads increases significantly
2. Current harmonics, that are often used for signature recognition, are more difficult to reconduct to a specific appliance when a lot of non-linear loads are operating at the same time

However, for the scope of identifying the flexibility potential of an area served by a specific MV/LV transformer, is not necessary to identify every single load as the research and industry are doing at single house level, but only the most energy-hungry and flexible assets. This equipment is generally the easiest to recognize among the house loads for their magnitude of energy use and type of electrical consumption pattern. The considered flexible assets will be discussed in the chapter relative to the critical assets to disaggregate.

Figure 7 illustrates how NILM techniques applied at the secondary substation level would work to identify demand response resources and enable the delivery of flexibility services for the DSO. In Figure 8 it is shown that the detected flexibility resources could be used for relieving the congestion of an LV feeder.

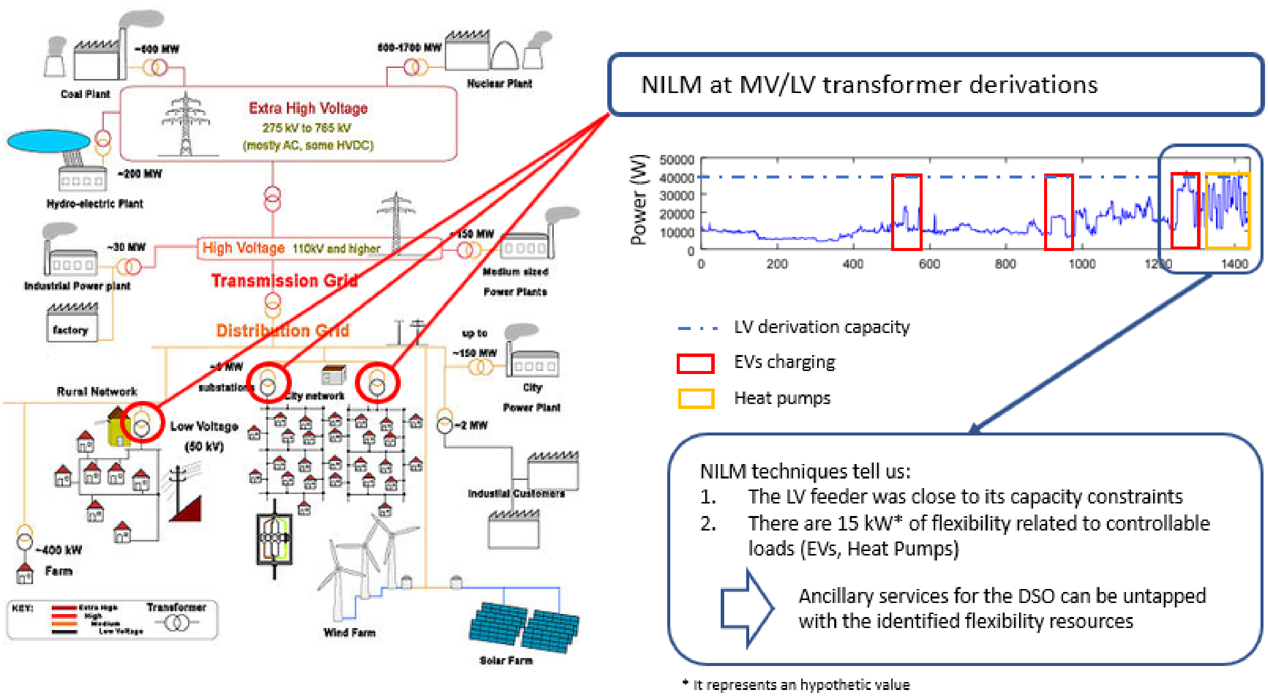

Figure 8. Example of NILM for demand response applied at the secondary substation

Some relevant works are available about the topic of energy disaggregation at a secondary substation or even higher aggregation. In the H2020 project FLEXMETER, partners from research and industry treat different topics relative to smart grid applications and among them NILM at the single house and substation level. Nonetheless, the details and results of the applications of NILM techniques at the MV/LV transformer derivations are not divulgated [29]. Gregory S. Ledva et Al. in [30] and Diptargha Chakravorty et Al. in [31] also investigated the NILM problem at distribution feeder level but using load models to perform the disaggregation at higher level than the conventional smart meter one.

On the other hand, among the objectives of this thesis, there is the verification of the state of the art of NILM algorithms built for conventional disaggregation problems when applied with little or no modifications at secondary substation level.

1.4. Methodology

The electrification of the transportation and heating sectors together with the growing decentralized electricity production is creating new issues for the Distribution System Operator such as frequent line congestions and voltage drops. The management of the flexible loads of the residential sector is a great opportunity for reducing the impact of these issues through DSM schemes, however, this is hardly ever done. In addition, NILM techniques are a useful tool to improve the identification of flexibility resources and manage their operation within the context of a demand response program. Two important technical barriers are considered to slow down the deployment of DR schemes in the LV grid and these are the lack of geographical information in the demand response environment and the violation of customer privacy when NILM techniques are applied at single house level. The DSM Evaluation Tool is presented as a possible solution to these problems as the application of NILM techniques at secondary substation level combined to the conventional LV monitoring would allow to identify and manage the flexibility resources at local level preserving the privacy of the end users. At this stage, once a possible solution is elaborated, its techno-economic feasibility must be proved. This means that the research questions this dissertation is trying to find an answer to are, first, if a service such as the DSM Evaluation Tool can become a commercial product and second if NILM techniques can be applied at secondary substation level yielding good results.

A 3-step process was selected to verify the research questions and is composed by:

1. An extensive literature review of NILM and LV grid monitoring to assess the software and hardware requirements to deploy such a service in the LV grid and understand which flexible loads are considered a resource by the DSOs
2. Market feasibility analysis to evaluate the financial viability, the innovative connotation of the service and a first favorable application
3. Testing of NILM techniques at the secondary substation level to prove the technical feasibility of the service

This thesis is realized within a commercial context in collaboration with Eneida.io, a company delivering LV grid assessment services for DSOs, hence the final goal of this dissertation is to assess if the DSM Evaluation Tool could represent a commercial service to add to their portfolio of services. The adopted approach is considered effective for reaching this scope because it takes into consideration both technical and economic aspects giving a broad vision on the topic. The employed method in the NILM testing phase allows the complete reproducibility of the results, in fact, data and algorithms are all available to the public and this is considered a strong point for benchmarking and improving the work. In addition, the extensive literature review allows not to start from the ground zero, but on top of what the research did creating a significant advantage. The limitation of the used method is the difficulty to dig into the details of each section and perform a specific and exhaustive analysis when a very wide approach to the problem is selected. Indeed, both the technical and the economic analysis will need a further, more detailed investigation to actually develop a commercial service. Overall, the adopted line is chosen as a good tradeoff to estimate the potential and the restrictions of the DSM Evaluation Tool and understand if time and resources are worth to be invested on the topic.

2. Non-Intrusive Load Monitoring (NILM) for demand response and grid planning

In the previous chapters, Non-Intrusive Load Monitoring (NILM) was explained as a concept and its potential applications for demand response and grid planning were shown. Now, this chapter focuses its attention on the logic and algorithms that are behind the energy disaggregation techniques, on the infrastructure needed at the LV network level and on which flexible assets have value for the DSOs. The scope is to understand the requirements of the whole system architecture and define the features that the DSM Evaluation Tool should include.

2.1. Software requirements

2.1.1. Nonintrusive load monitoring approaches

Load disaggregation, also known as nonintrusive load monitoring (NILM), is a technique to deduce what appliances are used in a household and their individual electricity consumption analyzing changes in current and voltage at smart meter level. The name NILM is since this methodology present itself as an antithesis to the intrusive load monitoring techniques that require a measurement at a single appliance level. The measurement at the single point of the house allows indeed to reduce significantly the intrusiveness of the hardware for the householders and cut the installation and operation costs.

The decomposition of power consumption at house level into its components is possible because every electrical load presents a peculiar energy consumption pattern, often called appliance signature, that can be recognized by disaggregation algorithms. Diverse approaches have been adopted to recognize the appliances signatures, but they can be grouped in two main categories, event-based algorithms which try to identify the On/Off transitions in electricity consumption and non-event-based which identify if an appliance is On during the whole sampled record. The former method is shown in Figure 9, while the latter in Figure 10.

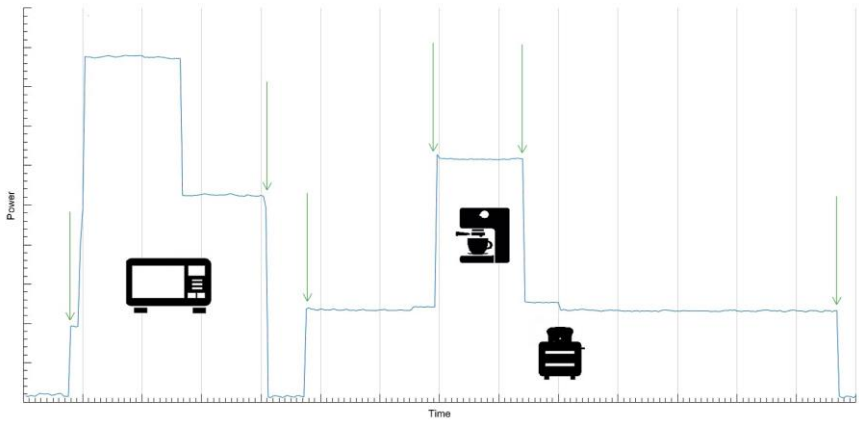

Figure 9. Event-based disaggregation algorithm [29]

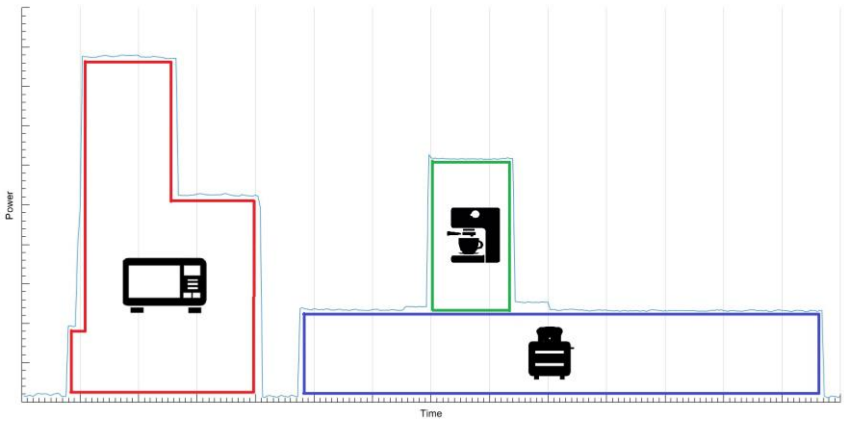

Figure 10. Non-event-based disaggregation algorithm [29]

The load disaggregation process is divided into three stages: data acquisition, features extraction and learning and classification [32] [33].

2.1.1.1. Data acquisition

The data acquisition consists in obtaining the aggregated load consumption with the appropriate data granularity that depends on the features of the appliance we want to extract and the type of NILM algorithm used for the identification. For instance, when transient features and noise generated by the appliance are used to isolate a load, a very high sampling rate will be necessary to capture these characteristics in the total electricity consumption. Table 1 shows which sampling rate corresponds to the desired feature to extract from the aggregated measurement.

Table 1. Data acquisition characterization

Feature extraction	Steady-state analysis	Harmonic Analysis	Transient/Noise Analysis
Sampling rate	1/60 Hz – 1 Hz	1 Hz – 40 kHz	40 kHz – 1 MHz

2.1.1.2. *Feature extraction*

The next step, the features extraction, include data optimization and processing [34] to identify the events in the total consumption that represent a change in state of one or more appliances. The most common methods to detect these events are either using steady-state signatures or transients ones. Steady-state means that changes in steady state real or reactive power are employed to recognize whether an appliance is On or Off. Transient methods instead capture transient signatures like shape, size, duration to define a load. Some different methods are avoiding the processing of data analyzing the raw voltage and current in the frequency spectrum.

Four different type of signature can be found in a normal household. The type of signature influences the finding accuracy of the different algorithms, then a method that performs really good with one type can be unappropriated to find an appliance belonging to another type. The four types can be divided as follow:

1. Appliances with only two states, On and Off, like toasters or incandescent light bulbs.
2. Multi-state appliances with a finite number of operating states. Washing machines, hairdryers, dishwashers and fans are part of this category.
3. Continuously variable devices (CVD) with a non-finite number of states that are particularly hard to find for the identification algorithms.
4. Appliances with a continuous power draw like smoke detectors or telephone sets.

Steady-state methods can be divided into three categories with different identification accuracy for different appliances typology. Table 2, highlights the main features, strengths, and drawbacks of each of them [35].

Table 2. Steady-state methods

Method	Features	Advantages	Drawbacks
Power change	Steady-state variation in active and reactive power	Power intensive appliances can be easily recognized, low data granularity needed	Simultaneous state transitions and power appliances overlap in P-Q plane significantly decrease the performance. Type II, III and IV appliances are difficult to recognize
V-I trajectory	V-I trajectory patterns: asymmetry, looping direction, area curvature of mean line, self-intersection, slope of middle segment, area of the left and right segments and peak of the middle segment	Appliances have a unique V-I curve that allows their categorization	Computationally intensive, no distinctive shape for low power loads, performance decreasing significantly with the number of appliances
Frequency domain	Higher order steady-state harmonics	The complex impedance allows very good appliances classification	High data granularity required, poor performance with type III appliances, unable to separate overlapping activation events

Transient-state methods analyze instead the pattern that the appliances leave in the total load consumption before they reach a steady state. Studies show that the transient behavior of each appliance is much more diverse and less overlapping than steady-state one giving a higher degree of precision for load identification. Nonetheless, they require a higher sampling rate, hence more expensive infrastructure. Table 3 shows the main characteristics of the used transient-state approaches.

Table 3. Transient-state methods

Transient Method	Features	Advantages	Drawbacks
Transient power	Transient response time and transient energy	Good performance with appliances with similar power consumption	The very high granularity of data required, not suitable for type IV appliances
Start-up current transients	Shape, duration and size of on/off transients, current spikes and response time	Good classification because of distinctive transient behavior or appliances	Unable to disaggregate type II and IV loads, sensitiveness to external noise, poor performance with simultaneous start-ups
High-frequency voltage noises	Noise FFT	Good performance with multi-state devices and consumer electronics	Computationally heavy, appliance-specific

In addition to steady-state and transient-state techniques, some non-traditional methods are used to recognize the appliances. These approaches take into account that the operational states of the appliances are not completely independent one from each other, then not only measured electric data are used as inputs. For example, when the induction cookers are on it is more likely that also the oven will be so or if it is a really hot day the AC consumption will be higher than normal.

2.1.1.3. Learning and classification

Eventually, load identification algorithms need to recognize the appliances state from aggregated measurements. The different techniques can be classified as supervised, semi-supervised and unsupervised learning.

Supervised learning is used in most of the cases to train the algorithms to identify the different loads, then a dataset of labeled data is necessary. In optimization-based methods, the aggregated power consumption is matched with a combination of appliances present in the database through an error minimization process. Integer programming and genetic algorithms have been employed for this type of approach [36].

Another adopted approach, the pattern recognition, consists in singularly matching the changes in state with a pool of features already available in the database. Pattern recognition techniques are the most used by researchers and include clustering methods, Bayesian approaches detecting the most likely of the potential appliances states, Support Vector Machine (SVM) classifying harmonics characteristics, Hidden Markov Models (HMM) and Artificial Neural Networks

(ANN) which demonstrated great potential for their ability to introduce temporal and state change information [17]. The combination of different methodologies showed a 10% increased performance compared to a single approach [35].

The need of training data represents one of the barriers to a broad diffusion of NILM and for this reason, semi-supervised and unsupervised training methods have been developed in the last years because they require minimal or no previous information. The most used approaches are based on classification or on probabilistic models using a variation of HMM. These methods generally have a lower accuracy than the supervised ones, but they are appealing for the companies working in the NILM ecosystem for their much easier deployment.

2.1.1.4. Algorithm hosting

One additional feature distinguishing NILM algorithms has a more practical nature and it is the place where they are hosted. They can reside in online cloud services with the main advantage that the raw data are available also for off-line processing allowing a dynamic change of the algorithm with updated or customized versions. On the other hand, it would require a huge transfer of data and dedicated computation for each customer on the cloud. A cheaper option would be to host the algorithm onboard the measuring device reducing the communicated data to the essential information. However, it would not be possible anymore to log permanently the raw data that would be periodically overwritten.

2.1.2. Energy datasets

In the previous sections, it was highlighted the importance of training data to perform an accurate disaggregation of the different appliances mostly if supervised learning methods are applied. Indeed, the majority of NILM algorithms must be trained on real data to recognize the appliances signature in the aggregated load consumption and even the completely unsupervised methods need a wide range of data for their verification and tuning.

Since 2011, many datasets from different institutions were made public in order to objectively compare the results and boost the advancement of the research on the subject. Before then, the researchers were working completely independently on their own libraries making extremely complicated to benchmark the different disaggregation approaches and resulting in slow progress.

The most used data set among the researchers is the Reference Energy Disaggregation Dataset (REDD) made by the MIT and publicly available. REDD includes the aggregated data of 6 households in the US with different granularity up to 15 kHz. Around 20 circuits per household are sub-metered in order to make possible the labeling of the different appliances. Apart from REDD, many datasets were made available in the last years measuring the aggregated data of multiple houses located mainly in the US and in Europe. These sets of data also contain a broad range of deferrable, energy-intensive loads and DER such as heat pumps, electric vehicles, and solar photovoltaics. This last feature makes them a valid instrument to test algorithms able to identify flexibility sources in the electric grid for demand response and grid planning application that represent the scope of this thesis.

Table 4 offers a detailed overview of the most valuable energy disaggregation datasets available in the market specifying their characteristics and provenience [37].

Table 4. List of open source energy disaggregation datasets

Dataset	Sampling rate	Duration	Number of houses	Classes	Ground truth	Origin
Dataport	1-minute	4+ years (still growing)	722	~70	Submeter channels	US
REDD	15 kHz/1 Hz	Several months	2/5	~20	Submeter channels	US
BLUED	12 kHz	1 week	1	~30	Labelled events	US
UK-DALE	16 kHz/1 Hz	2 years	3/6	~40	Submeter channels	UK
PLAID	30 kHz	5 seconds	55	12	Individual appliances	US
WHITED	44 kHz	5 seconds	9	46	Individual appliances	Multiple
Tracebase	1 Hz	1 day	158	43	Individual appliances	Germany
AMPds	1 minute	2 years	1	19	Submeter channels	Canada
RAE	1 Hz	72 days	1	24	Submeter channels	Canada
iAWE	1 Hz	73 days	1	33	Submeter channels	India
REFIT	8 seconds	2 years	20	9	Submeter channels	UK

For the specific purpose of this thesis public data sets with labeled data at secondary substation level were not found, hence the consumption at LV feeder level will be assembled aggregating the measurements from different households. The details of this process will be explained in a dedicated section in the chapter relative to the NILM testing.

2.1.3. Evaluation metrics

Nonintrusive load monitoring is generally considered as a classification problem, then its performance can be expressed as in Equation 1. [38].

$$Accuracy = \frac{Correctly\ assigned\ events\ or\ signatures}{Total\ events\ or\ signatures} \tag{1}$$

The fact that the performance of NILM algorithms is strictly correlated to the number of appliances considered, to the adopted hardware for data collection, and to the granularity of the used energy data set, created disagreement about the most suitable metric for method comparison [39].

Different methodologies are used to evaluate the accuracy of the disaggregation problem, some of them are explained here.

Equation 2 is the fraction of total energy assigned correctly that measures the fraction of the energy consumed by the appliances and the predicted one.

$$FTE = \sum_{n=1}^{N} min \left\{ \frac{\sum_{n=1}^{N} x_t^{(n)}}{\sum_{n=1,t=1}^{N,T} x_t^{(n)}}, \frac{\sum_{n=1}^{N} \bar{x}_t^{(n)}}{\sum_{n=1,t=1}^{N,T} \bar{x}_t^{(n)}} \right\} \tag{2}$$

Equation 3 is the total disaggregation error that is the difference between the predicted energy consumption and the actual one measured for each appliance and normalized by total energy consumed.

$$T_{error} = \frac{\sum_{n=1,t=1}^{N,T} |x_t^{(n)} - \bar{x}_t^{(n)}|}{\sum_{n=1,t=1}^{N,T} x_t^{(n)}} \tag{3}$$

Equation 4 is the proportion of error per appliance which evaluates the difference between the proportion of the energy assigned to each appliance and its measured actual consumption. Most often, its normalized version is used, Equation 5, the Normalized error by appliance.

$$P_{error} = \left| \sum_{t=1}^{T} x_t^{(n)} - \sum_{t=1}^{T} \bar{x}_t^{(n)} \right| \tag{4}$$

$$N_{error} = \frac{\sum_{t=1}^{T} \left| x_t^{(n)} - \bar{x}_t^{(n)} \right|}{\sum_{t=1}^{T} x_t^{(n)}} \tag{5}$$

The most used and reliable metric used by NILM researchers is the F1 score and it is based on Equation 1. First, some concepts must be introduced for its definition, the precision in Equation 6 and the Recall in Equation 7

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

And the

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

The terminology of these formulas is explained by the Contingency Matrix for binary classification in Table 5.

Table 5. 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 defines the ratio of True Positive in the universe of all the examples assigned as positive whereas the recall is the ratio of True Positive in the universe of all positive examples in the data set. Hence, the F1-score can be defined as in Equation 8.

$$F1 = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{8}$$

The F1-score evaluate the percentage of energy correctly allocated to each appliance and can be explained as a weighted average of the precision and the recall. Higher values of F1-score mean a better accuracy of the disaggregation method.

2.2. Hardware requirements

2.2.1. Low voltage grid characterization

The understanding of low voltage (LV) grid is fundamental to design the hardware necessary to implement accurate NILM techniques at the secondary substation level.

This thesis considers the LV network in European countries only that significantly differs from other type of systems such as the American one. The standard for LV networks in European countries is represented by the 3-phase 4-wires distribution voltage level of 230/400 V. Cities and medium-sized town are equipped with underground cable distribution systems, while rural areas are serviced by overhanging cables.

The LV network is clustered in areas corresponding to the MV/LV distribution substations, spaced at about 500-600 meters from each other. These are typically composed by:

- 3 or 4-way MV switchboard made of incoming and outgoing load-break switches for the transformer circuits
- One or two 1000 kVA MV/LV transformers
- One or two 6 or 8-way 3-phase 4-wire distribution fuse boards to control and protect 4-core distribution cables, called “distributors”

In areas with high load density, a standard size distributor is employed with 4-way link boxes located either in a manhole at a street corner or in weather-proof cabinets above the ground situated against the wall of a building. Link boxes are also in place to connect a distributor from one secondary substation with one from a neighboring substation. This arrangement makes the system flexible and a substation can be taken out of service without interrupting the electricity supply. This configuration for urban areas is shown in Figure 11. This principle is not adopted in less densely populated areas for economic reasons and conductors of reduced dimension develop radially [40].

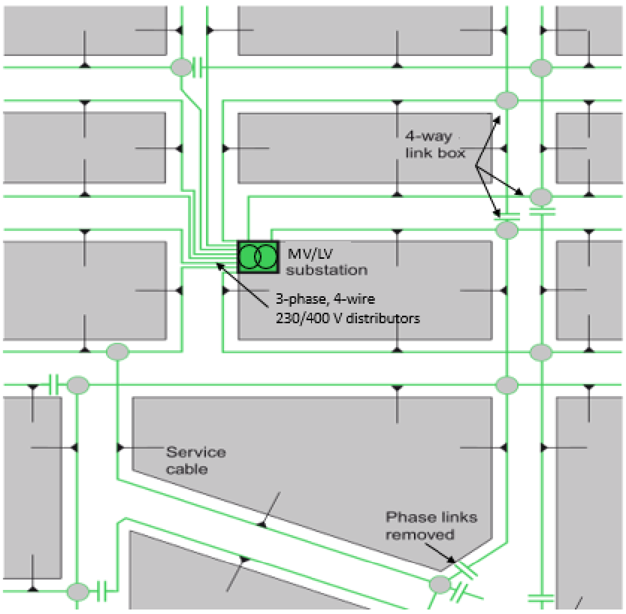

Figure 11. LV network configuration in densely populated areas

LV electricity consumers

When talking about NILM techniques it is important to define the amount and type of consumers connected to the distributors. The current-rating requirement for distributors and dictates indeed by the number of customers to be connected and the average consumption per consumer.

The two main parameters that limit the nature of the distributors are:

- The maximum current that the conductor can carry without overheating
- The maximum length of the cable that, when in maximum current conditions, will not surpass the voltage drop limit

These constraints limit the magnitude and the position of the loads that want to be connected to the LV network.

The LV network generally serves all type of residential users, little commercial and industrial activities. For the type of LV networks built in Europe, the maximum permitted loads connected to either 120 V single phase feeders or to 240/415 V 3-phase ones are shown in Figure 1 [40].

Table 6. The maximum permitted loads connected to a LV distributor

System		Assumed max. permitted current	KVA
120 V	1-phase 2-wire	60 A	7,2
120/240 V	1-phase 3-wire	60 A	14,4
120/208 V	3-phase 4-wire	60 A	22
220/380 V	3-phase 4-wire	120 A	80
230/400 V	3-phase 4-wire	120 A	83
240/415 V	3-phase 4-wire	120 A	86

Nonetheless, practices radically change from one distribution network operator to the other and no standardization exists in the sector. In addition, it is not possible to establish the number of customers per feeder just dividing its power capacity by the contracted power of the LV customers because this represents a condition that is never reached, and it is not used to design the network. The most influencing factors for connecting new loads to the LV network are:

- The extension of the existing distribution network which the new load is to be connected to
- The total load already provided by the distribution network
- The location of the new load in the distribution network with a focus on the nearness to the secondary substation

This lack of standardization makes the characterization of the LV network extremely difficult especially regarding the number and nature of loads that are connected to a distributor. For this reason, a load disaggregation service deployable at large scale in the low voltage network must work in absence of this information and be able to adapt to the single situation. The rule of thumb in the electricity network sector is there is a MV/LV transformer every 100-300 customers and this would mean between 5 and 15 customers per single phase obtained dividing by the number of distributors (6-8) and the number of phases (3). The selection process for the number of customers will be explained in the chapter relative to the implementation of NILM techniques.

2.2.2. Advanced metering infrastructure design

The concept of load disaggregation at secondary substation level aims to identify and track the electric loads in the LV network that represents a source of flexibility to perform demand response schemes and improve the network planning and operation. The ideal location to monitor the LV network is represented by the MV/LV substation and it is where the advanced metering infrastructure should be placed. This position represents multiple advantages for load disaggregation purposes because it is where the monitoring infrastructure is already placed for the management of the LV grid and because it limits the costs and preserves the customer's privacy if compared to the single-house smart meters.

The meter placed at the MV/LV transformer derivations is composed by three main parts:

- The measuring unit, where current and voltage are measured
- The meter unit, hosting the microprocessor processing the raw data
- The communication unit, that sends the data to the grid operator

Figure 12 gives an explanatory overview of the composition of the considered metering infrastructure.

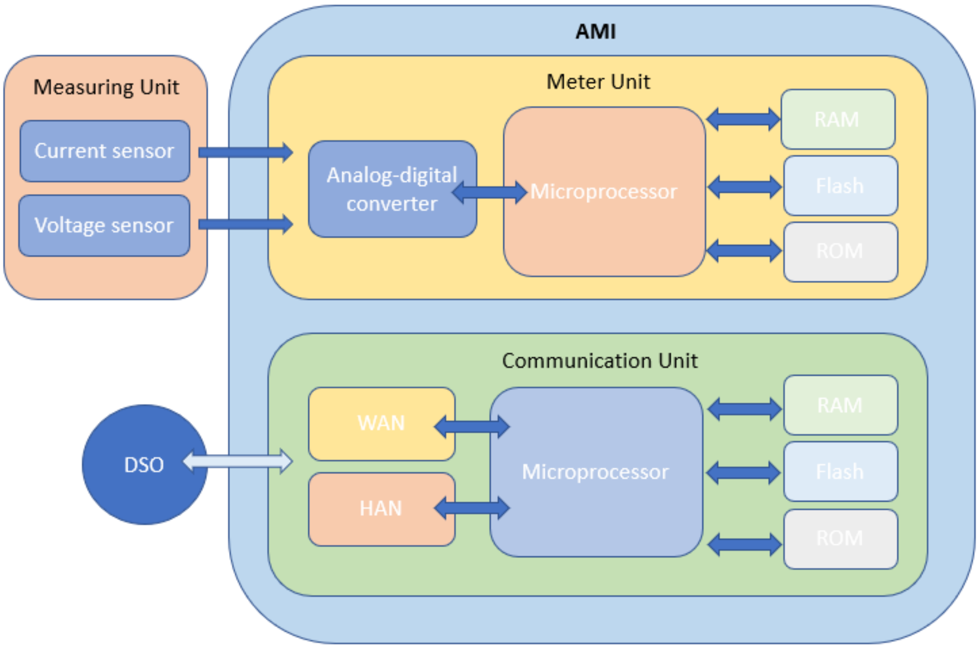

Figure 12. The composition of the metering infrastructure

The meter unit (or metrology card) and the communication unit are often hosted together in the same casing for sake of simplicity, while the measuring unit is placed outside to reach the different LV feeders.

The meter unit samples current and voltage waveforms according to the sampling rate of the A/D converter and extract the average complex, active and reactive power. The entire unit is composed by:

- Currents and voltage sensors that record the current and voltage of the individual phases. The sensors need to read the values for every single-phase derivation of the MV/LV transformer, hence 16 to 24 G-clamps, grouped by three for every 3-phase feeder are placed. Figure 13 shows how the G-clamps are attached to the LV feeders and connected to the metrology card and communication unit in the up-left corner.

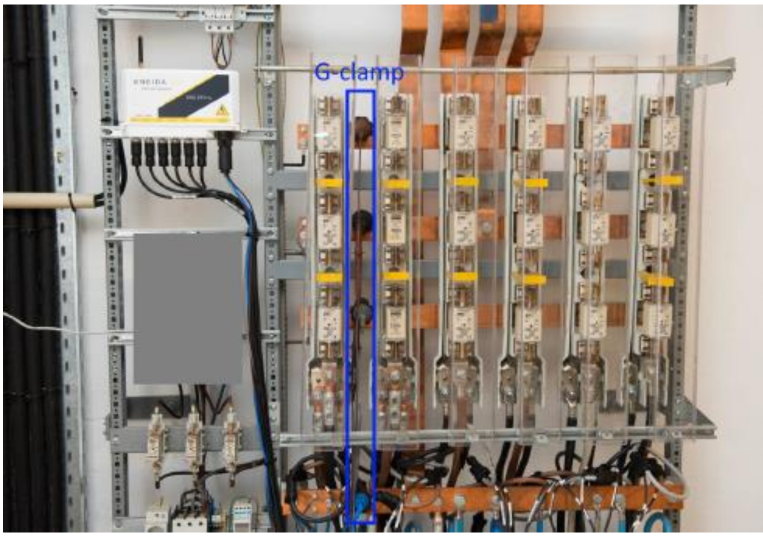

Figure 13. Meter unit connections

- Analog-digital converters transform the analog inputs into digital values and feed them instantaneously via calibration stages to a signal processor. This represents one of the most important components when talking about load disaggregation because it defines the sampling rate of the meter.
- The microprocessor, responsible for the signal processing and all the operations done in the meter. The microprocessor must be a tradeoff between performance, power consumption and monetary cost to be suitable for large-scale deployment.
- Storage and memory are important features of the meter because RAM is used for intermediate storage operations and it can be used for disaggregation becoming a limitation for the accuracy of NILM techniques.

The communication unit is used instead to communicate the measurements to the DSO. This part also includes a microprocessor for performing the needed operations, but it is rather necessary to focus on the communication functionalities of the device. The employed networks are generally the Wide Area Network (WAN) and the Home Area Network (HAN) which are characterized by a different frequency of data. The lack of standardization makes possible that different transceivers can be used for data communication and the devices can be equipped with more than one to be more flexible,

- WiFi,
- Cellular network (2G, 3G, 4G),
- ZigBee,
- Radio frequencies
- Power Line Communication (PLC).

The devices to be installed in the secondary substation are generally self-powered with batteries with several years of autonomy for the ease of installation.

Hardware limitations

The advanced metering infrastructure can represent a limitation for the energy disaggregation techniques if certain requirements are not fulfilled and these restrictions are due to the following features:

- The sampling frequency of the A/D converter, when really high granularity of data is needed such as in techniques analyzing the transient state of the appliances
- The processing power of the microprocessor is strictly correlated to the cost and power draw of the device. These two features are really important when the device is though for large-scale deployment and it is powered by a battery
- The storage capability of the memory since on the flash the NILM software is saved and a great amount of RAM is needed when algorithms from ML and Optimization fields are involved
- Data transfer rate and cost due to the used communication interface if the raw data are sent to a cloud storage for processing

The limitations described above do not represent a barrier for the deployment of the technology at the current status of development of the field but some important constraints that must be taken into consideration when designing to load disaggregation service for a certain device or vice versa.

2.3. Critical loads to disaggregate

The typical residential customer electricity consumption is composed of several energy-intensive appliances that can be targeted for demand response programs such as heat pumps, electric water heaters, electric furnaces, EVs, washing machines, etc. The ease of use of these appliances for demand-side management is a complicated combination between the intrinsic characteristics of the device (time of use, type of consumption, etc.) and behavioral aspects related to the people that are using them (user interaction, user perception, etc.). The scope of this work is not to study the best appliances to target but study the individuation of some of them for DR purposes.

Electric Vehicles, Heat Pumps and PV systems are selected for this study. The selection process was determined not by the literature review, but by the contingent situation of the partner company. Now, the UK represents the most interesting market for grid assessment services in Europe because of the aging electricity network combined with the fast electrification of the heating and transport sectors. In addition, the regulatory framework allows the DSOs to look for residential flexibility and launch public tenders [12]. These facts make the market ready for real-world implementation and drive the choice of appliances to target.

In the next paragraphs, the reason for addressing the targeted appliances will be explained in more detail.

2.3.1. Electric vehicles

The Electric vehicle (EV) is becoming an important load to be considered for smart grid analysis. The number of publicly accessible EV charging points is growing by 72% every year adding a significant stress on the distribution grid [41]. Home EV charging recently entered the market but its effects on the balancing and management of the LV network are to be considered non-marginal. In fact, whereas big charging stations, generally connected to the MV lines are constantly monitored and easily controllable, residential charging points are not, and their consumption is aggregated to the total house and difficult to forecast. The severity of the residential EV charging impact is highly dependent on the charging time and duration, the applied utility rate and the season of the year. A secondary advantage of isolating the EV consumption from the total household consumption is to provide an exact value for EV monthly energy consumption creating value for the end-users.

The single charging station direct monitoring would be highly unpractical and costly, hence NILM algorithms present again a good alternative to disaggregate the EV load from the rest of the house. Despite the availability of many algorithms in the field of load disaggregation, few of them specifically target EV and they often require extensive training and high computational load. The greatest challenge is represented by the fact that EV load signal is characterized as a square wave of high amplitude and long duration (from 30 to 200 minutes) that can be easily confused with the long cycles of heat pumps during really cold or hot days especially in presence of other smaller appliances power signals and fluctuating residential noise [42]. Other problems in using advanced NILM algorithms not designed for EV tracking are the low granularity of data at SM level that does not allow the usage of transient characteristics, and the absence of a large variety of ground-truth EV signal to train the algorithms that mirror the diversity of residential EV chargers in the market.

2.3.2. Heat pumps

The progressive electrification of the heating sector resulted in a consistent growth of the electric load in the form of heat pumps in the last 10 years. Heat pumps represent 15% of the primary energy consumption in mature markets like the US and grow at a quick pace all over Europe with France leading for the number of installations with 27% of annual increase [43]. Heat pumps currently outperform conventional fossil fuels-based systems in term of thermal efficiency and represent a great opportunity for decarbonization in energy system with high penetration of renewable sources [44].

The growth of heat pumps generates a challenge for the distribution network operator. The general 10 kW thermal output heat pumps are equipped with 2.5 kW electric compressors with high starting current and with the tendency of depressing the LV feeder voltage especially if many units are connected with the possible risk of collapse [45]. In addition, an increased number of heat pumps could generate local grid congestion and demand peaks mostly in case of switching from fossil fuel-based system in particular areas of the distribution network. However, because of the thermal inertia of the buildings, heat pumps become an optimum example of a flexible or deferrable load. In fact, if operated in a smart way, heat pumps would help to address the LV issues and also to integrate more distributed energy resources in the distribution network. To give some examples, a simulation study from Denmark (Danish task 3 report) showed that the optimization of the heat pumps portfolio could decrease by 18% the peak load at distribution feeder level resulting in a nearly flat load consumption along the day. A German study also proved that the pooling of heat pumps under direct load control and operating balancing services could generate up to 125 € of cost reduction for single heat pump operation costs [41]. In addition, an improved building insulation and buffer water tanks could significantly increase the flexibility of this resource.

The heat pumps load in the residential sector is highly fluctuating and strongly influenced by behavioral patterns and weather conditions. The precise forecast and control of air conditioning load at house or neighborhood level becomes then highly important to avoid grid events such as exceeded capacity or voltage problems. The independent monitoring of each heat pump would be unpractical for its complication and costs. The use of NILM algorithms at one house or much more aggregated level to disaggregate the heat pump load from the total consumption presents a good potential for heat pump load management.

2.3.3. Solar photovoltaic systems

Solar photovoltaic is the faster-growing energy market in 2017 with a global increase in capacity by 50% only in the last year [46]. The accurate forecast of PV power production is crucial for energy utilities to maintain the system balance and minimize the use of fossil fuels [47]. Utilities with scarce accuracy in solar energy prediction often experience large expenses due to excess fuel consumption or emergency purchases of electricity from other utilities [48].

Residential photovoltaic will represent 56% of the total solar capacity in 2020 with more than twice installed power than utility-scale projects [share of PV]. Currently, the majority of the utilities cannot measure the power output of residential photovoltaic because they can only access the net power reading of a household, that is the production from PV panels subtracted from the house consumption [49]. The inability to differentiate the house production from its consumption at smart meter level generates an increased uncertainty in energy forecasting leading to a more complicated balancing of the system and slowing down the deployment of new PV capacity. Indeed, a growing amount of distributed photovoltaic generation needs higher reserve requirements at the system level and violations of voltage and line capacity constraints during the peak production hours [50].

Some strategies to mitigate the distributed PV drawbacks are curtailment strategies, control of converters active/reactive power, PV self-consumption schemes and dispatch of local power flows to network-safe power consumption routes [51][52]. In order to implement these solutions, the real-time power production measurements from PV installations must be available. Nonetheless, as previously mentioned, the PV facilities are hardly ever under direct load measurement and a series of factors such as privacy issues, conflicts between different owners of the metering infrastructure and lack of standards for monitoring and aggregation measurements and communication are playing against its realization.

A possible alternative to direct PV monitoring is the disaggregation of PV generation from the aggregated power measurements of a group of prosumers. The problem of power consumption disaggregation has been highly investigated to perform Non-Intrusive Load Monitoring (NILM), but its application to solar disaggregation is relatively new. A significant difference between classical NILM and solar disaggregation is represented by the fact that the extraction of PV production from the net power signal cannot be achieved only detecting “signatures” in the data like transitions, steady-state features and harmonics [51]. In fact, as visible in Figure 14 shows the net power reading of the aggregated consumption, it is impossible to distinguish whether during the day the reduced export to the grid in the middle of the day is due to cloud cover or load usage.

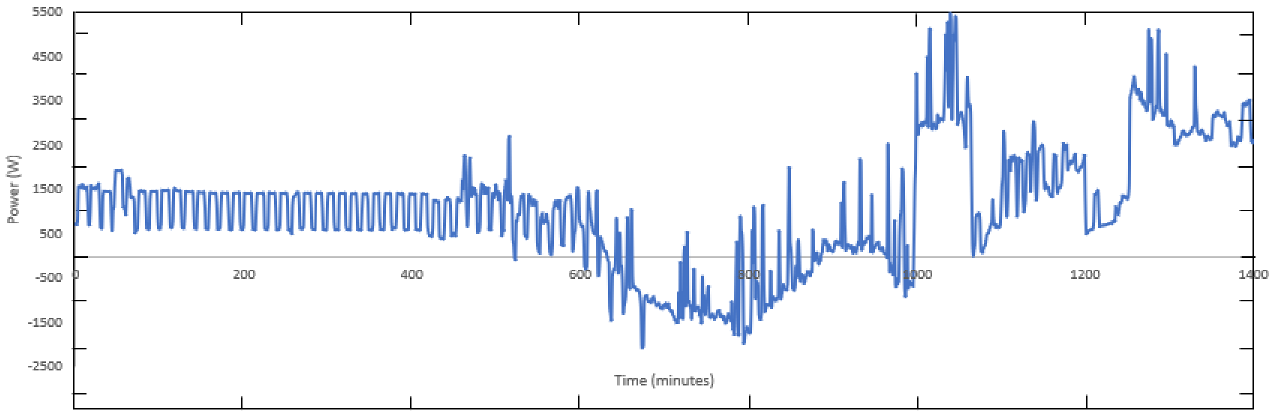

Figure 14. Net-metered consumption of a household with PV system

To overcome this problem, all the different available disaggregation algorithms rely on the modeling of PV generation as a function of the global horizontal irradiance (GHI) that is measured either in place or in the closest weather station. In addition, a transpose model is needed to project the GHI into a number of pre-defined differently oriented tilted planes to model the generation from installations with different configurations [51]. This represents a crucial factor in urban contexts where rooftop PV tilt and azimuth configurations are dictated mainly by the orientation and shape of the rooftop.

The statement of the problem of solar PV disaggregation highlights its importance even in a case where regular NILM wants to be carried out. In fact, if the disaggregation of house load is to be performed and the PV production is not separated from the household consumption, the majority of NILM algorithms would not be able to distinguish correctly the different appliances because of the PV interference.

In Figure 15, an example of disaggregated solar generation from the net measurement at house level is shown to remark the fact that oscillation in total metered consumption in the middle of the day can be either due to intermittency in solar generation or appliances usage making solar disaggregation crucial to solve this issue.

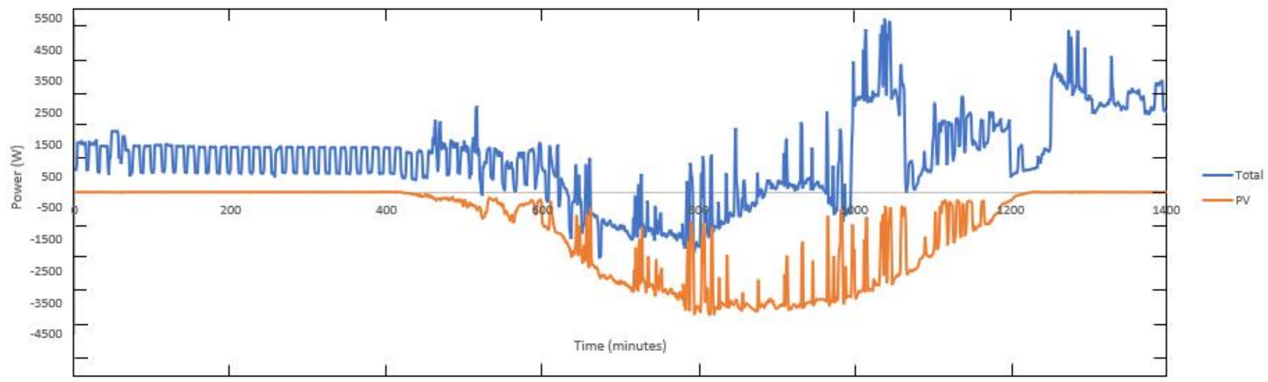

Figure 15. Solar disaggregation from the single house with PV panels

The literature review allowed to define what is the state of the art in term of NILM software, advanced metering infrastructure for LV grid monitoring and to identify which flexible assets represent a resource for the DSOs and why. This represents the foundations on which the next chapters are built on. Indeed, the economic analysis is based on the system constraints and on the potential of DR ancillary services and the testing phase employs the most advanced NILM algorithms and data analysis tools for load disaggregation research.

3. Market Feasibility

A short Market feasibility analysis was performed to assess the viability of the idea to become a commercial service. The target market is the UK because it is the only market in Europe currently opening the access to the ancillary services to the DSO [12] , hence the only one where a commercial service can be deployed.

The market feasibility analysis is composed of 3 parts:

1. Study of the UK regulatory framework and identification of a possible use case to assess the legal feasibility
2. Cost-Benefit Analysis of the DSM Evaluation Tool to evaluate the financial viability
3. Competition analysis to assess the innovative connotation of the DSM Evaluation Tool and identify possible threats

At the end of this process, it will be possible to evaluate if the DSM Evaluation Tool can become a commercial service.

3.1. Study of the UK regulation framework

The UK was the first country to allow the participation of demand-side resources to the electricity markets. The situation at the present day can be described as follow:

- Demand response contribution is accepted in almost all the balancing services as well as demand aggregation. Nonetheless, the product design is still immature for full end user participation.
- The capacity market is open to DR resources, but its impact is still irrelevant compared to the generation.
- The balancing mechanism and wholesale market access are still restricted for independent aggregators, that can participate only through a bilateral agreement with the retailer/BRP.
- Distribution network services like voltage control and congestion management are allowed for independent aggregators only through a bilateral agreement with the retailer/BRP.

Despite the early start among the European countries in term of demand response regulations, the difficult communication between providers, policymakers, Ofgem, and National grid did not create a mature market for its implementation. In fact, resource evaluation, baseline, bidding process, and other procedural and operational requirements are still inappropriate for demand-side response providers slowing down the deployment of the resource.

Ofgem is promoting demand-side flexibility as a useful tool to tackle congestion management and voltage control boosting innovation measures over capital investment and creating a Low Carbon Fund (£500m over 5 years). As a result, the majority of the DNOs are running demand-response trials.

The aging grid together with the growth of embedded generation, interconnection, large transmission-connected renewables and stress on the LV grid lamented by the DNOs are making the business opportunity for demand response higher than ever. However, because of the inadequate regulatory framework and design choices, the chance is still pending [12].

Possible use case

DSM programs are becoming more geographically localized and this can be noticed in some practical example such as the call for flexibility that UK Power Networks (UKPN) is carrying out. UK Power Networks is the distribution network operator for electricity covering South East England, the East of England and London. It manages three licensed distribution networks (Eastern Power Networks, South Eastern Power Networks and London Power Networks) which together cover an area of 30000 km^2 and approximately one quarter of UK population. The UK power system experienced a sharp growth in renewable energy installation peaking at 12 GW of solar generation and 16 GW of wind capacity at 2017, capable to surpass consumer demand at certain times during summer.

UKPN end customers driven by energy efficiency, new technologies, and government policies are changing their energy consumption pattern towards a more electricity intensive one reducing the country dependence on fossil fuels. The electrification trend, together with the expected rapid growth of electric vehicles penetration and more than 90% of solar capacity directly connected to the distribution system are creating issues to UKPN aging network. However, instead of slowing down the process leading towards a clean and secure energy supply, UKPN is renewing its role to face these challenges. Indeed, in the 2017 UKPN Flexibility design consultation is affirmed that “To continue to support the low carbon transition in a safe and cost-effective way our role will continue to evolve. Instead of acting as the passive manager of a network of cables and assets connecting centralized generators to homes and businesses, we need to become a more active manager of a system that enables local communities, renewable generation, small and medium sized businesses, prosumers and consumers to access the energy and flexibility markets, all whilst making sure the lights stay on” [53].

In UKPN flexibility program the elasticity of end users’ electricity demand will be crucial to manage the uncertainty and complexity of this new power network. Response from generators, demand side providers and electricity storage resources will support the efficient management of planning and operations. The flexibility resources will be used for various scopes from outages avoidance to manage the uncertainty related to demand growth for investment decision making.

UKPN specifies that the goals of the flexibility program at the distribution system level are to:

- Use flexibility to manage uncertainty as to when we invest in network infrastructure;
- Use flexibility where it is cheaper than the traditional network solution;
- Procure flexibility efficiently using competitive mechanisms where possible;
- Provide locational signals for new flexibility capacity;
- Support wider adoption of distribution flexibility by demonstrating that it is reliable, safe and secure;
- Facilitate the development of distribution flexibility markets to benefit the system as a whole, and

- Evidence and share learning to inform energy policy and regulation.

The localized nature of the described program is clear, and it is very different from the DR programs previously offered by the TSO National Grid where the position of the flexibility resources in the electricity network was irrelevant [54]. On the other hand, UKPN program is designed to address a specific distribution network location where system constraints, like maximum capacity exceedance, are likely to appear. When these events will occur, the service providers will be asked to deliver their contracted flexibility.

3.2. Cost-Benefit Analysis of the DSM Evaluation Tool

In the past chapters, it was explained the potential of NILM at the secondary substation to identify, manage and untap the flexibility resources of the LV grid and deploy ancillary services for the DSO. In addition, the UK presented to be a market ready for this kind of applications with a mature regulation framework and DSOs launching tenders for flexibility at low voltage level.

Before taking on this new project, a prudent management needs to conduct a cost-benefit analysis (CBA). The CBA is a process that businesses use to analyze decisions; all the potential costs and revenues generated by the completion of a project must be accounted and compared to define if it is financially feasible. The CBA is generally divided in three phases [55]:

1. Compilation of a list of all the costs and benefits associated with the selected project. The costs should include all direct and indirect costs, tangible and intangible ones such as opportunity cost or risk associated costs. Parallelly, all the tangible and intangible benefits must be accounted.
2. Application of a common unit of monetary measurement to all the listed costs and benefits. This passage is generally complicated when intangible cost/benefits must be converted. A conservative approach should be used not to overestimate the benefits and underestimate the costs.
3. Quantitatively comparison of benefits and costs to check if the former overweight the latter. If yes, the project is financially viable, otherwise, it should be review and adjusted to increase the benefits and/or reduce the costs. If in ultimate analysis this is not possible, the company should abandon the project.

In this chapter, a preliminary CBA for the DSM Evaluation Tool is executed. CBA requires a long and detailed study of every aspect of a complicated service such as the one analyzed, and it could be the topic of an entire thesis. The scope of this chapter is indeed to perform a preliminary analysis not to find the right proportion between cost and benefits, but to assess the financial feasibility of the project with a certain margin of security.

3.2.1. Phase 1: Cost-benefit compilation

The costs associated to this project are mainly related to the hardware manufacturing and installation, its operational costs and the software development. The marketing and sales costs are not considered because too variable on the specific case. The benefits are instead the identified value proposition for the DSOs and Energy Aggregators that were mentioned in the chapter relative to the description of the service. All benefits and costs are listed and shortly explained in Figure 16.

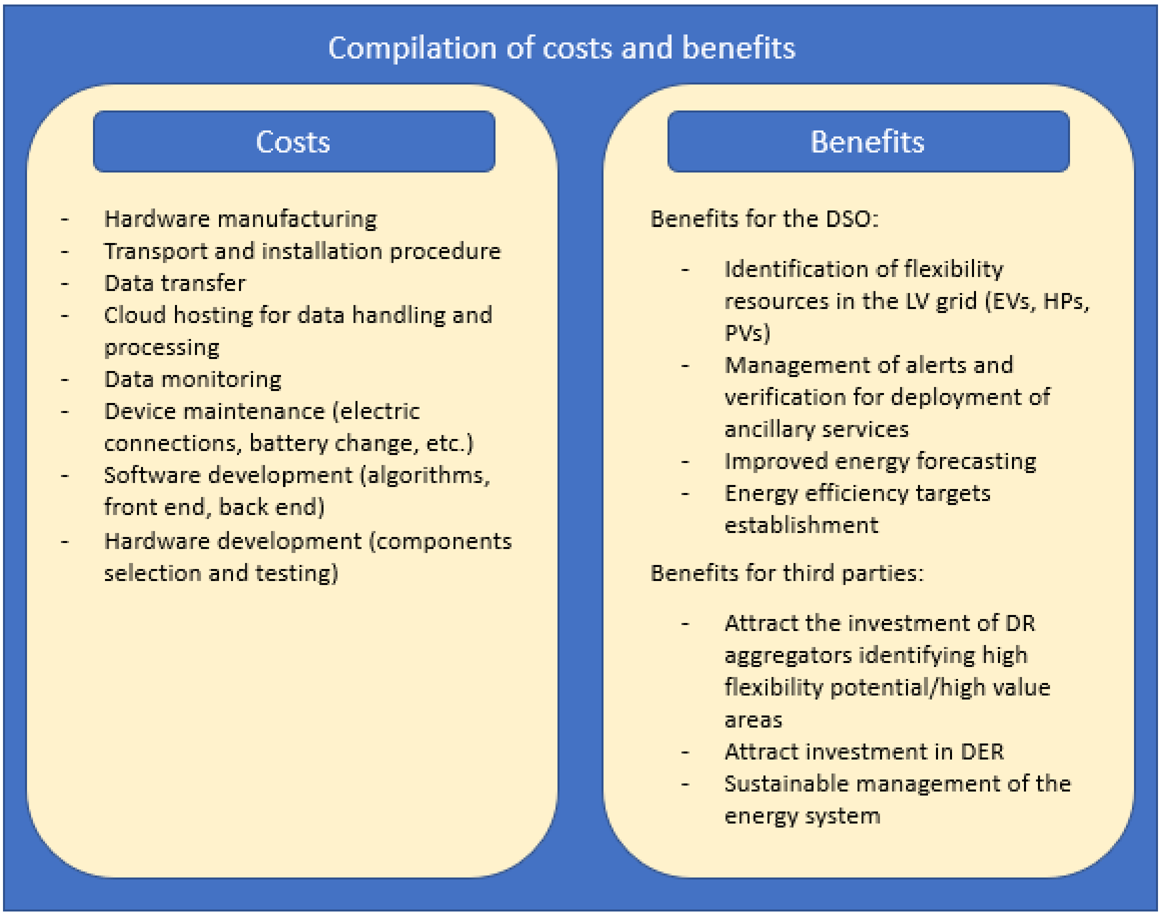

Figure 16. List of costs and benefits related to the service

3.2.2. Phase 2. Monetary quantification of costs and benefits

Benefits

The procedure for the calculation of the benefits is complicated because multiple parties are involved in the deployment of the ancillary services and because of the intangibility of some of them. To tackle this barrier a very conservative approach is chosen; only the benefits for the DSOs are considered being the DSO the target client for this service. This procedure significantly facilitates the quantification of the benefits because now they can be all reconducted to the avoidance or postponement of investment in the grid infrastructure. The rest of the benefits are not accounted, but they can be considered a strong selling point. The deployment of the ancillary services is not managed by the sole partner company, but a demand response aggregator would be needed to trigger the flexibility resources. Hence, the entire value of the ancillary services cannot be related to the DSM Evaluation Tool. A percentage of this value will be then assigned and discussed later in the chapter.

The monetary value of the ancillary services in the LV grid is considered to be equal to the cost of upgrading the grid because of the electrification of the transportation and heating sectors if any action for their coordination is taken.

UK Power Networks (UKPN) released a study where they developed a model to forecast the cost of grid upgrade because of the uptake of EVs in Great Britain. This is used as a reference to build an estimate of the benefits following a 3-steps process:

1. The benefits related to the flexibility of the EVs fleet are calculated with UKPN model
2. The benefits are enlarged to the contribution of heat pumps flexibility. No similar study was found for the UK market regarding heat pumps, then the same model is considered valid also for heat pumps.
3. A sensibility study and discussion are done over what percentage of the found value should be attributed to the service considered in the CBA

Step 1

The detailed description of the UKPN model goes beyond the scope of this thesis, that will focus instead on the outcomes. Even so, to better understand the process, the most important assumptions are listed in Table 7 [56]. The model is built on the LV network in the Merton EIZ substation, which is connected to a single 11 kV feeder from the closest primary substation.

Table 7. UKPN model assumptions

Assumption heading	Assumption value
Electric vehicle assumptions	
Number of EVs	The model considers the high EV uptake scenario developed by Smart Grid Forum in the UK and visible in Figure 17. Merton substation is supposed to follow the same trend.
Charging profile of EVs	Sample of 50 different real-world profiles randomly distributed in the LV network
Reinforcement investment decision	
Threshold for voltage violation	Voltage drops below 90% of the threshold value
Investment in response to voltage violations	It was assumed that a new secondary substation can tackle 150 nodal voltage violations. The associated cost to 150 violations is considered 66’000 €
Threshold for current violation	A violation is notified when the current exceeds 160% of the cable’s rating, that is considered the emergency rating.
Investment in response to current violations	The associated cost to the current violation is €220/meter per branch circuit length

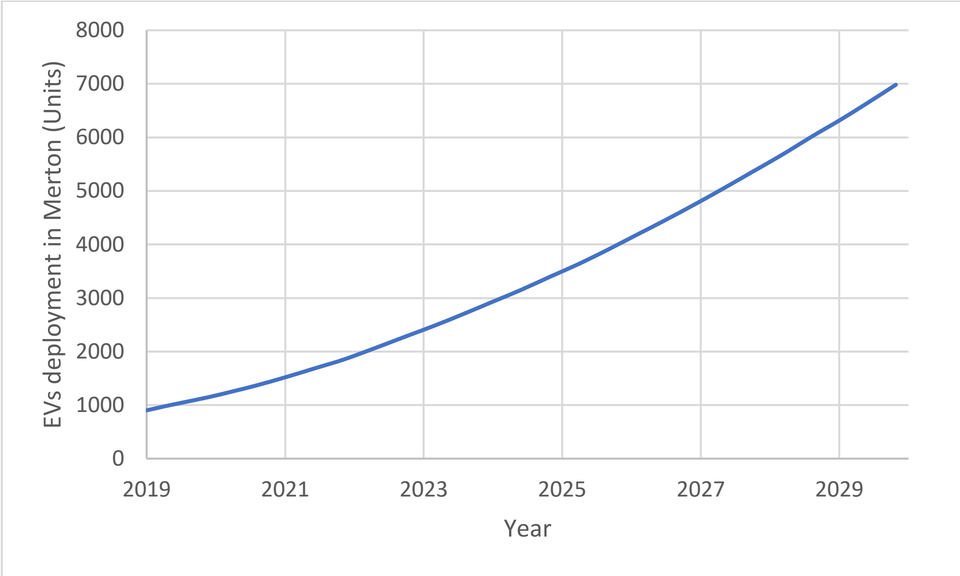

Figure 17. EV uptake scenarios in Merton

The model estimates a grid upgrade cost to tackle both voltage and current violations of £86,9k for Merton substation. This value can be extended to the whole UKPN grid with the assumption of proportionality between the upgrade cost and the number of EVs. The obtained value corresponds to £74,8m up to the end of 2031, that means an average of £5,72m per year over the period 2019-2031. The upgrade of the primary network is not considered in this analysis. These results need to be taken carefully because they are the outcome of a single bottom-up model.

Step 2

The penetration of heat pumps is considered to have a similar impact on the LV network because of the voltage drops inducted by the high start-up currents and the elevated power draw that could cause current violations, hence the same assumptions of Merton model are employed. In the same study, UKPN elaborated a series of scenarios on EVs and HPs growth within its grid and they will be compared to estimate the impact on the grid of Heat Pumps in Figure 18 [56].

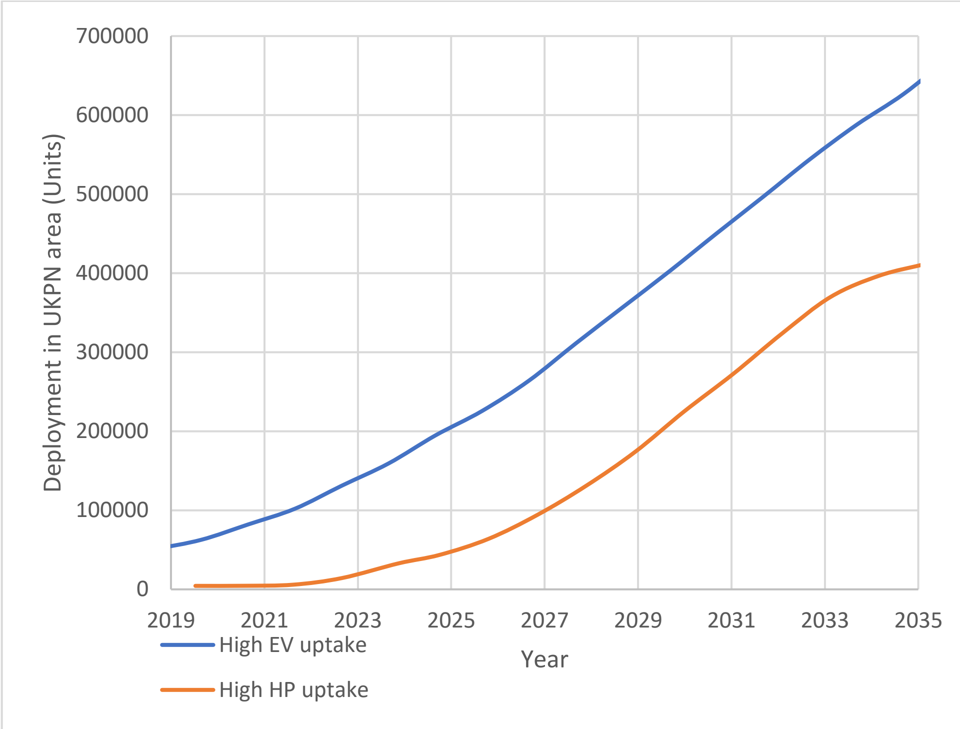

Figure 18. EVs and HPs growth scenarios

Looking at the high uptake scenarios in Figure 3 we can notice that up to 2031 the number of heat pumps is increasing significantly reaching nearly 300'000 units, that represents around the 55% of the forecasted number of EVs. In addition, the residential EV chargers considered in the study have very comparable power consumption to domestic heat pumps around 3 kW and both the appliances present a daily use even if with different load patterns. For these reasons EVs and HPs are assumed to have the same impact on the LV grid, then the total investment in infrastructure upgrade is increased by a factor of 1,55. The assumption of linearity is adopted in the UKPN study to extend the impact at the whole network level, it is considered valid also in this case. Table 8 summarized the total upgrade expenditure necessary to tackle the electrification of the transportation and heating sectors without any coordination such as the deployment of ancillary services for the DSO.

Table 8. Summary of the LV network upgrade costs

Asset Considered	Upgrade cost for one substation (k€)	Total upgrade cost for UKPN (m€)
Electric vehicles	86,9	74,8
Electric vehicles and heat pumps	134,7	115,9

Step 3

The previous step stated that for the whole UKPN grid the benefit of a coordinated utilization of EVs and HPs through the deployment of ancillary services is around 115,9 million €. The percentage of which is to attribute to the developed Flexibility service for the DSO is difficult to establish because any study regarding the topic was found in the literature to benchmark the estimation. Figure 19 shows the linear relationship between the assigned percentage and the service value.

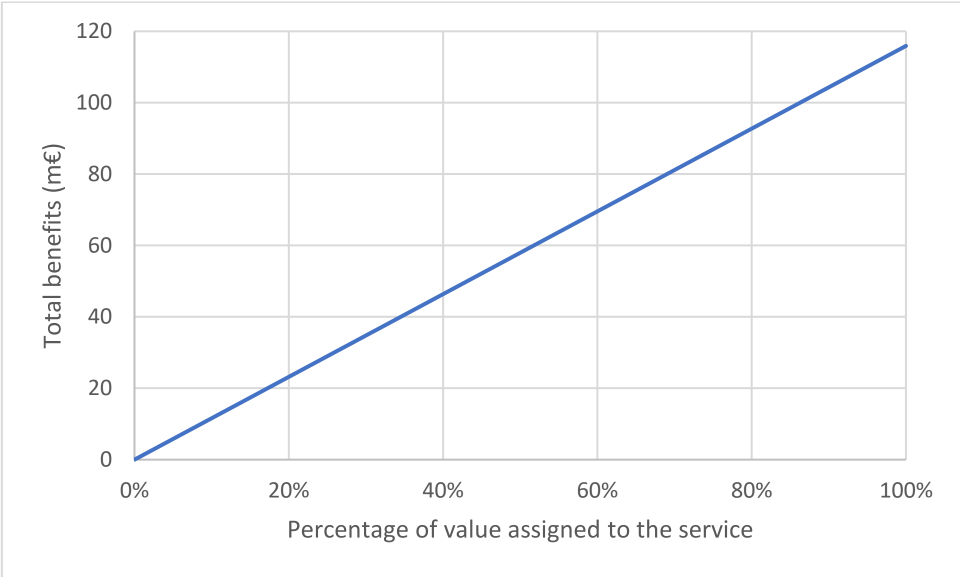

Figure 19. Sensitivity on the assigned value to the service

The developed flexibility service for the DSO potentially includes all the steps to deploy the ancillary services to the DSO, but the activation of the flexibility resource that could be done through an internet-connected switch connected to the flexible load unless the load is already connected itself. This step is managed by an energy aggregator that needs to cover its installation and operation costs and make a profitable business out of it. The aggregator remuneration generally comes from the system operator, the DSO in this case, so a part of the generated value must be assigned to it.

The value assigned to the service is then the result of an educated guess and it resides between 75% in case of need of an activation switch for every appliance and 100% in case of a future were EVs and HPs will be entirely internet connected and there will not be a need for an energy aggregator. The 35% left to the aggregator is enough to cover its costs and make a margin out of the sale. Smart plugs are sold indeed around 20-30 £/unit, that multiplied by 769’000 units in 2031, with a lifecycle of 10 years makes around the 25% of €115,9m value in the considered period.

The value of the service is indeed between 86,9 and 115,9 million € and it represents the total estimated benefits for the application in the whole UKPN grid.

Costs

The estimation of the costs is obtained by the partner company that is already performing a monitoring service at the secondary substation level. This means that the fixed costs related to the hardware will be kept the same. On the other hand, a multiplicator factor will be applied to the operating costs due to the additional data acquisition and transfer. In addition, the software development costs will be added on top of the current ones. Table 9 illustrates the cost breakdown for one device as indicated by the partner company.

Table 9. Cost breakdown for one device

Item	Associated cost (€/unit)
Hardware manufacturing	1500
Transport and installation procedure	200
Data transfer and cloud hosting	10/month
Data monitoring and system maintenance	150/year

On top of them it must be added the software development cost which includes algorithms, back end, front end, and apps. This cost was never calculated before, then it is impossible to benchmark it with previous studies. The chosen value is the result of personal experience and it is the equivalent of two years of full-time work for a team of three software development engineers. The average wage of this professional figure in Portugal is 25'000 €/year. The value is affected by high uncertainty, however, its contribution to the total costs is almost irrelevant due to the utility-scale deployment of the service. Moreover, the operational costs must be increased because of the additional data transferred and new monitoring requirements. The data traffic is strictly dependent on the type of algorithms employed and on their online or offline hosting. These features cannot be established at this stage because the exact software requirements are not known. For this analysis, an offline hosted algorithm is taken into account because this type of algorithm is yielding the best results during the testing phase. Hence, the data transfer is not considerably increased, and the associated cost is believed to grow between 50% and 100%. This wide and conservative range is chosen not to underestimate the increased volume of data and because the operating costs are relevant in the total cost estimation. The hardware does not need any change from its current situation, then its development is a sunk cost and it must not be considered in any economic analysis.

The calculation of the total costs for the period 2019-2031 requires to bring all the costs to the same year to be summed. To do so, Equation 1, the Net Present Value (NPV), is used where C_n represents the total costs at year n, N the total number of years and r the discount rate.

$$NPV\ (€) = \frac{C_0}{(1+r)^0} + \frac{C_1}{(1+r)^1} + \frac{C_2}{(1+r)^2} + \ldots + \frac{C_N}{(1+r)^N} \qquad (9)$$

The discounting process is correlated to the idea that future cash flows have less value than present ones since the former may not occur. Hence, higher risk investments will be correlated with higher discount rates.

The selected annual discount rate is 3,5% as it is the same used in UKPN study and this is required for comparison with the benefits. The variable costs should also be adapted following the inflation rate, but this is not done in UKPN study, so it would be advisable not to do it for the cost structure either.

The total costs for one single substation at present value is calculated and a value between €4889 and €5469 is found depending on the increase of data related to operating costs. The total cost for UKPN network is calculated with the same proportionality used for the benefits and the development cost is added on top. The total cost value is then between €4,37m and €4,86m.

3.2.3. Phase 3: cost/benefit comparison

The performed calculations show that the benefits overcome the costs by one order of magnitude. The low value for the cost-benefit ratio, between 3,8% and 5,6%, can be explained by two factors, the low-cost infrastructure deployed at Utility scale and the extremely high cost of grid infrastructure upgrade. In addition, the deployment of ancillary services is considered to completely avoid the need of grid upgrade. The sensitivity on the benefits monetary value is shown again and compared with the total costs that are affected by less uncertainty in Figure 20.

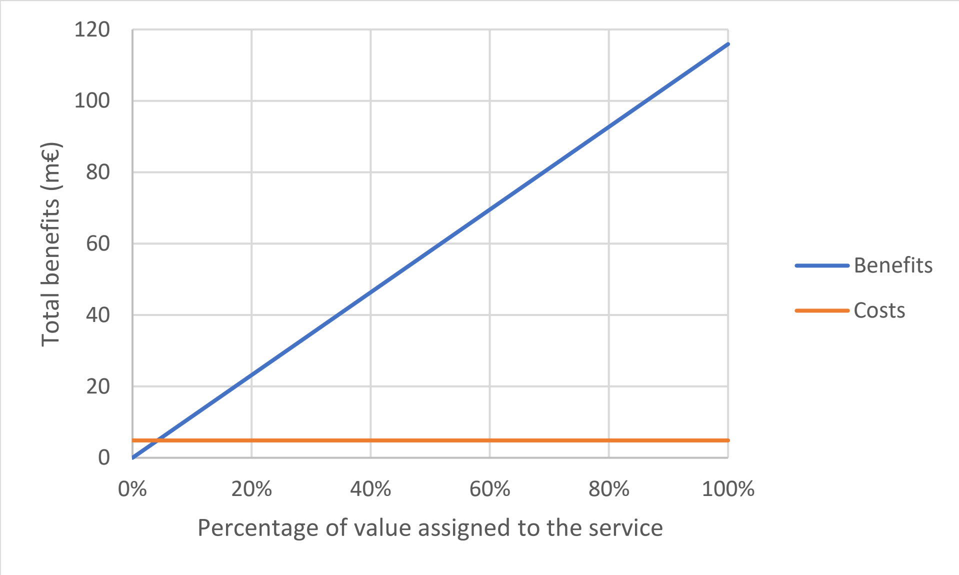

Figure 20. Sensitivity on the assigned value to the service compared with the fixed costs

Then, if the maximum value assigned to the energy aggregator is 25% of the total benefits and the cost of the DSM Evaluation Tool infrastructure is the 4,2% of the same value taking the most conservative assumption, it means that a minimum of 30% decrease in LV grid upgrade cost is necessary for the benefits to overcome the costs and make this service financially viable.

Once again, it is important to keep in mind that this is a preliminary CBA and its scope is not to assess the exact costs-benefits ratio, but only to establish if the benefits can actually surpass the costs with a good degree of certainty and this hypothesis is confirmed.

3.3. Competition overview

The study of the national policies and the cost-benefit analysis are the two first important steps in the process to evaluate the market viability of the Demand Side Management Evaluation Tool. The former established the maturity of the regulatory framework, while the latter the financial viability of the service. At this stage, the analysis of competitors in the Energy Disaggregation and LV Grid Assessment sectors is performed to see if the DSM Evaluation Tool represents an innovation and if some competitors could represent a threat.

A competition map is realized to have a better visualization of the considered market and highlight possible trends. The map considers all the companies using load disaggregation techniques and LV grid assessment in Europe and in the US.

The map is the result of an independent analysis where the considered companies are individually studied through the analysis of their websites and third parties' sources. The parameters used to characterize each company are:

- Headquarters
- Customer segment
- Target market in geographical terms
- Utilization of NILM techniques
- LV grid monitoring
- Involvement in DSM schemes
- Measure point
- Hardware sale

Table 10 shows the obtained competition map where 46 companies are analyzed.

Table 10. Competition map, C=commercial, I=industrial, SM=smart meter, SS=secondary substation

Name of the company	Headquarters	Customer segment	Target market (geography)	NILM	LV grid	DSM	Measure point	Device
AlertMe	UK	Household	UK	yes	no	yes	SM	no
Ecoisme	PL	Household	Europe	yes	no	no	SM	yes
Eliq	SE	DSO, Household	FR, SE, NO	yes	no	no	SM	no
Enetics	US	DSO, Household	US	yes	yes	no	SM/SS	yes
e-sylife	R	Household	FR	yes	no	no	SM	yes
Green Running	UK	DSO, Household	UK	yes	yes	no	SM/SS	yes
Informetis	JP	Household	JP	yes	no	no	SM	yes
Ipsum Energy	NL	Household	NL	yes	no	no	SM	yes
Luko	FR	Household	Europe	yes	no	no	SM	yes
Midori	IT	DSO, households	IT	yes	no	no	SM	yes
Mirubee	ES	Household	ES	yes	no	no	SM	yes
Navetas	UK	Household	UK	yes	no	no	SM	yes
Neurio	CA	DSO, households	US, CA	yes	no	no	SM	yes
Powersavvy	IE	Household	IE	yes	no	no	SM	yes
Sense	US	Household	USA	yes	no	no	SM	yes
Smappee	BE	Household	Europe	yes	no	no	SM	yes
Smart Impulse	FR	Commercial	Europe	yes	no	no	SM	yes
SmartB	DE	Commercial	DE	yes	no	no	SM	yes
Verdigris	US	C&I	US	yes	no	yes	SM	yes
Voltaware	UK	household, C&I	Europe	yes	no	yes	SM	yes
Wattsekker	FR	C&I	World	yes	no	no	SM	yes
Watty	SE	Household	Europe	yes	no	no	SM	yes
Bidgely	US	DSO, households	Europe, US	yes	no	yes	SM	no
Chai Energy	US	Household	USA	yes	no	no	SM	no
Econtagious	CA	DSO, households	US, CA	yes	no	no	SM	no

Eeme	US	DSO, households	US	yes	no	no	SM	no
Fludia	FR	Commercial	FR	yes	no	no	SM	yes
Grid4c	US	DSO	US	yes	yes	no	SM/SS	no
Home energy analytics	US	Household	US	yes	no	no	SM	no
HOMEpulse	FR	DSO, household, I	US, Europe	yes	no	yes	SM	no
Intelen	US	DSO, household	US	yes	no	yes	SM	no
Onzo	UK	DSO, households	World	yes	no	yes	SM	no
Opower	US	DSO, Household	World	yes	no	yes	SM	no
PlotWatt	US	DSO, household, C	US	yes	no	yes	SM	no
Powerly	US	DSO, household	US	yes	no	yes	SM	no
Qinergy	FR	Household	Europe, Fr	yes	no	no	SM	yes
Silver spring	US	DSO, Municipality	World	yes	yes	yes	SM/SS	no
Watt is	PT	DSO, household, C	Europe, Pt	yes	no	no	SM	yes
Gridkey by Lucy	UK	DSO	Europe, UK	no	yes	yes	SS	yes
Grideye by Depsys	CH	DSO	Europe, CH	no	yes	yes	SS	yes
Socomec	IT	DSO	Europe, IT	no	yes	no	SS	yes
Landys+gyr	CH	DSO	World	no	yes	yes	SM/SS	yes
smarter grid solutions	UK	DSO	World	no	yes	yes	SM/SS	no
Smart grid networks	SE	DSO	Europe	no	yes	no	SS	yes
Gridworks	US	DSO	US	no	yes	yes	SS	no
Gridhound	DE	DSO	Europe, DE	no	yes	no	SS	no

The chosen criteria to consider the DSM Evaluation Tool innovative is that any other company should present the same characteristics; a device installed at secondary substation level using NILM to assess and manage the demand response potential of the LV grid to deploy ancillary services to the DSO. Table 11 highlights Eneida.io characteristics following the same metrics.

Table 11. Eneida.io characterization

Name of the company	Headquarters	Customer segment	Target market (geography)	NILM	LV grid	DSM	Measure point	Device
Eneida.io	PT	DSO	Europe, UK	yes	yes	yes	SS	yes

Any other company in the map presents the same characteristics, then the service is considered innovative.

Analyzing the competition map primary and secondary threats are identified. A primary threat is a company that could develop a similar product in the short term. To do so, it must be a company selling a device to a DSO to measure data at secondary substation level and it must provide LV grid analytics with either a vision to manage DSM resources or to use NILM techniques. A secondary threat is instead a company that could develop a similar product in the medium-long term because it has some relevant barriers towards its realization such as the lack of a hardware or the lack of experience in LV grid analytics. A secondary threat can easily become a primary one in case of a partnership with a primary threat with complementary characteristics or a resource in case of a partnership with Eneida for the development of the service.

5 Primary threats and 9 secondary ones are identified in the market. A secondary threat to be considered complementary to Eneida.io and then a resource it must have expertise in NILM and DSM and must not have a developed hardware. Hence the number of possible resources goes down to 6 companies.

The market is considered a competitive environment, with a few major players and some big companies among them such as Landys+Gyr and Silver Spring by Itron that could represent a big threat. Nonetheless, the quick development of a service with innovative characteristics together with the right partnerships is considered a solid way for entering the market.

3.4. Interpretation of the market feasibility study

The three parts of the market feasibility study which are the analysis of the UK regulation framework, the CBA and the competition overview wanted to verify the three main necessary features to make the DSM Evaluation Tool a commercial service which are respectively,

- the maturity of the policies framework regarding the DSO flexibility services,
- the financial viability and,
- the differentiation in a competitive environment.

The study showed that the UK policies are incentivizing the DSOs to employ smart grid tools instead of normal grid upgrade to face the transformation of the electricity system creating a market pull for the DSM Evaluation Tool and similar services. Moreover, the CBA confirmed the financial viability of the service and the analysis of competitors highlighted its innovative nature and possibility to disrupt in the market. Indeed, the DSM Evaluation Tool is believed to have all the requirements to become a commercial service.

4. Test of NILM at the secondary substation level

The scope of this thesis includes the testing of the state of the art of load disaggregation techniques applied to the secondary substation measurements to assess their potential and limitations for this application. The goal of the implementation of NILM techniques at the LV derivations of the distribution transformers is to identify where and when flexible loads such as EVs, heat pumps and PV systems are exchanging energy with the grid to be able to manage the flexibility loads for the DSO.

In order to build and implement effective NILM techniques at the secondary substation, the used consumption data must fulfill some specific requirements that are listed below:

1. The granularity of the measurements must be high enough to support the chosen NILM techniques as specified in the chapter regarding the Load Disaggregation Approaches
2. Submetered data of the single appliances are necessary for the training of the algorithms if supervised learning techniques want to be used

3. Submetered data of the appliances to disaggregate are necessary to evaluate the accuracy of the employed algorithms and improve their performance

These requirements do not represent a problem when NILM techniques are applied to smart meter data because of the high availability of open source data from the research institutes, but it becomes a barrier when the problem is moved to the secondary substation. In fact, the secondary substation measurements are often taken at much lower granularity and hardly ever the submetered data of the entire area serviced by the MV/LV transformer are available.

At this stage, two possible roads are identified to test some NILM techniques at the secondary substation level:

1. Make a computer simulation of a secondary substation load curve and of the submetered flexible loads
2. Work with the open source datasets of single house data to build secondary substation energy consumption

The first option would generate a high volume of data at the desired granularity, but it is discarded because of time constraints and lack of skills to build a high-level simulation. On the other hand, the use of real-life open source data allows to shrink the time requirements and to benefit from the open source tools facilitating the analysis of data. The type of disaggregation technique and its accuracy will be constrained to the availability of data. In the next section, it will be explained how a test bed of NILM application at the secondary substation was assembled.

4.1. Test bed assembling procedure

The assembling of a test bed consists of the reproduction of the energy consumption measured at the secondary substation using single house data taken from the open source energy datasets that were shown in the relative chapter. As explained in the chapter on the Characterization of the LV grid, a 1000 kVA transformer, which is taken as a reference, has 6 to 8, 4-wires, 3-phase LV derivations, and the measurements are taken for each phase. Hence it is needed to reproduce the single-phase derivation and then the whole consumption of the transformer can be replicated with an additive process of all the 6-8 x 3 single phase derivations.

To use this assembling method two major assumptions are made:

- The secondary substation is supposed to serve only residential users
- All the residential users are connected to a single-phase connection

These two assumptions are made because of the lack of commercial activities and industry data in the employed datasets and for sake of simplicity. In fact, the simplest realistic case is intended to be analyzed at the beginning and then add some complication if this stage is giving satisfactory results.

At this point, the replication of a single-phase of the LV feeder is composed by three steps:

1. Choice of an energy dataset with enough data granularity and submetered measurement of the interesting flexible assets (EVs, heat pumps and PV)
2. Decision-making process over how many houses the single phase is feeding
3. Aggregation process of the chosen number of houses

4.1.1. Energy dataset

The choice of the energy datasets is mainly driven by the availability of data. For Demand Response application of NILM techniques, only a few energy-intensive appliances are interesting to identify, hence their presence determined the choice of the dataset. Dataport is chosen as the best database to work with for two main reasons:

- Submetered data of EVs, heat pumps and PV systems together are not available in any other energy database
- The compatibility with NILMTK, an open source data analysis tool for disaggregation purposes that will be explained in a later stage.

The Dataport database is the largest source of disaggregated customer energy data in the World with data collected from 722 houses in the US distributed between Texas, Colorado, and California. The monitored houses are 501 single-family homes, 183 apartments, 35 town homes, and 3 mobile homes. The houses are equipped with at least one eGauge, EG3000, EG2010 or EG2011 meter that allows the monitoring of 12 circuits via current transformer clamps [57]. Both individual appliance and main circuits were monitored in most houses. Figure 21 shows the building construction, the house size and the electricity consumption characterization of the whole datasets. The average active power of each circuit measured at one-minute interval is the only electric data available and it will constrain the type of NILM technique employed as it will be discussed in the chapter relative to the NILM algorithms.

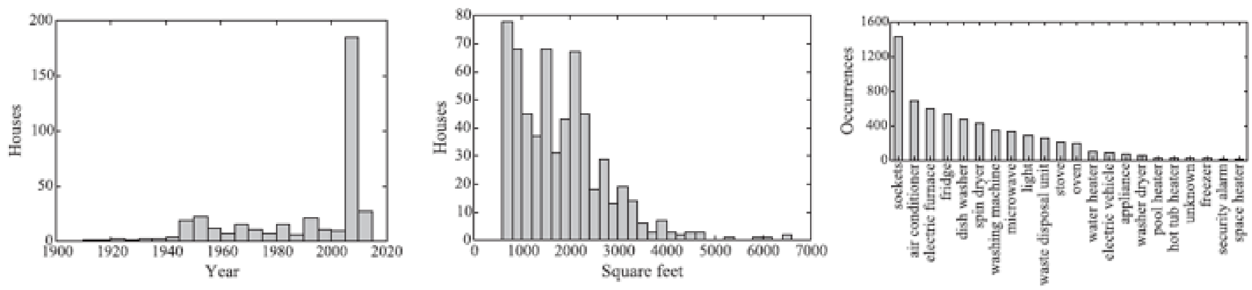

Figure 21. Dataport data characterization clamps [57]

The access to the portal containing the data is free for academic purposes while commercial access is limited to the members of Pecan Street's Industry Council that sponsored its creation.

Dataport portal also contains a subset of data in NILMTK format. The file is composed by one month of data from 669 houses which were selected for having at least 8 submetered circuits. For each house, the data has been converted from the Dataport names to the NILM Metadata controlled vocabulary. This makes possible to easily analyze the dataset using the tools of NILMTK. The non-intrusive load monitoring toolkit (NILMTK) was first released as an open-source software in 2014. It was specifically created to facilitate the access to data and improve the comparative analysis of energy disaggregation algorithms with different datasets to lower the entry barriers for researchers and boost the progress of NILM techniques. The software includes dataset parsers, dataset analysis statistics, preprocessors for reformatting the data, benchmark algorithms and accuracy metrics.

Figure 22 shows an example of data recorded for a single house both aggregated and disaggregated at appliance level over a period of 24 hours.

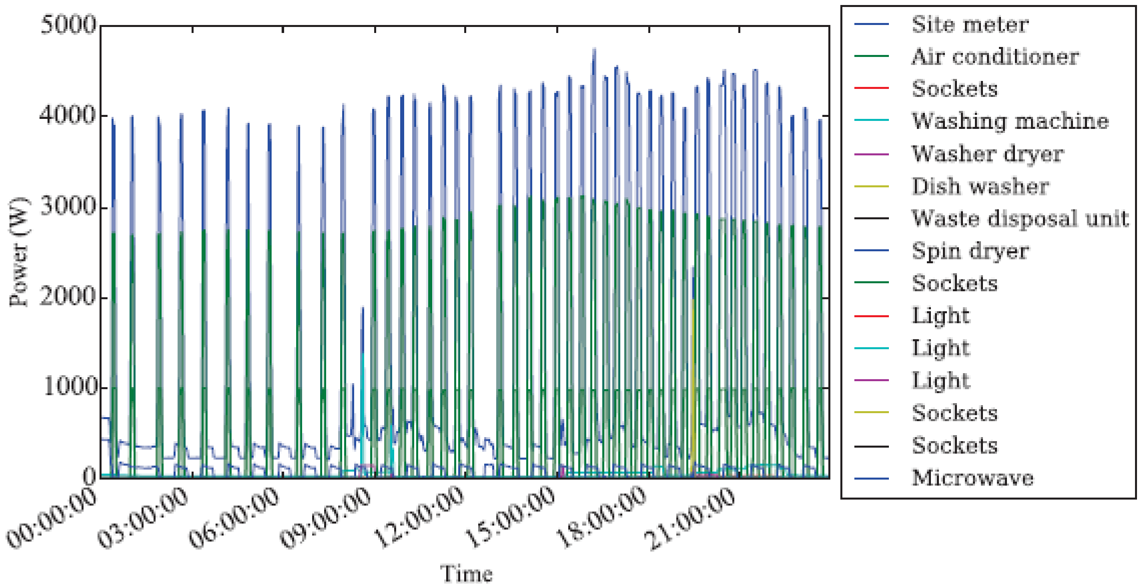

Figure 22. Disaggregated consumption of one house in Dataport clamps [57]

4.1.2. Number of houses

In the chapter relative to the low voltage grid characterization, it was highlighted how the lack of standardization in building the LV grid makes difficult to establish a priori the number of households connected to a single phase. The derivations of a MV/LV transformers are connected to a significantly different number of customers that goes from a few units in rural areas to a few hundreds in case of densely populated areas. The second condition was chosen for assembling the test bed because it represents the most common configuration and an independent analysis was performed to establish the number of houses fed by a single phase.

The independent analysis was performed on measurement at the secondary substation in the area of Aberdeen as real data from the partner company were available. 140 Secondary substations are monitored in the area and they are all situated in a densely populated zone. The histogram of the mean daily power consumption was obtained for the month of January 2018 for one single phase of the distributors and it can be visualized in Figure 23.

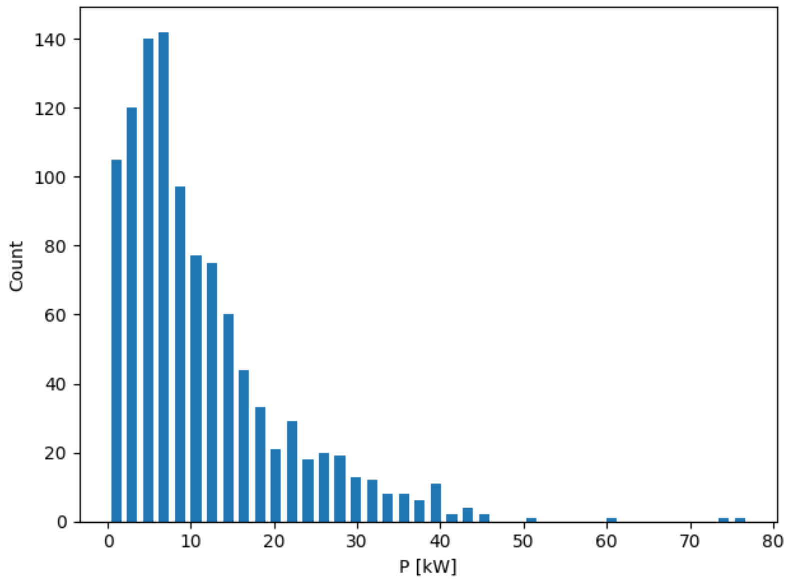

Figure 23. Histogram of the mean daily power consumption of a single phase of the distributor

The mean value of the distribution is 11,25 kW, which corresponds approximately to 9 houses from the Dataport dataset in the month of January that was used for the analysis. Hence, 9 was chosen as a credible number of electricity consumers connected to a single phase.

4.1.3. Aggregation process

Once the type of single house consumption and the number of electricity consumers are selected, the data need to be aggregated to reproduce the electricity consumption read at the single phase of the distributor.

The electricity consumption profiles to be aggregated are taken from a pool of 51 households that present both a residential EV charger and a heat pump that was available in Dataport database. Figure 24 shows a typical daily power consumption of a single-family house equipped with an electric vehicle charger.

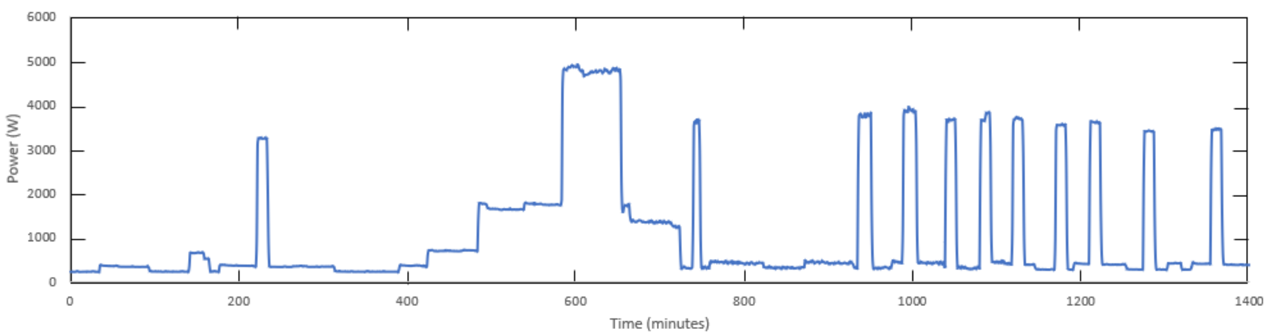

Figure 24. Single-family house daily power consumption

Then, 10 houses randomly chosen from the pool of 51 houses are aggregated with a simple addition of their respective active power consumption. The result is thought to approximate to a good extent the active power consumption measured at the single phase of the distributor. Figure 25 illustrates the aggregated power consumption of 10 houses with EV chargers and heat pumps.

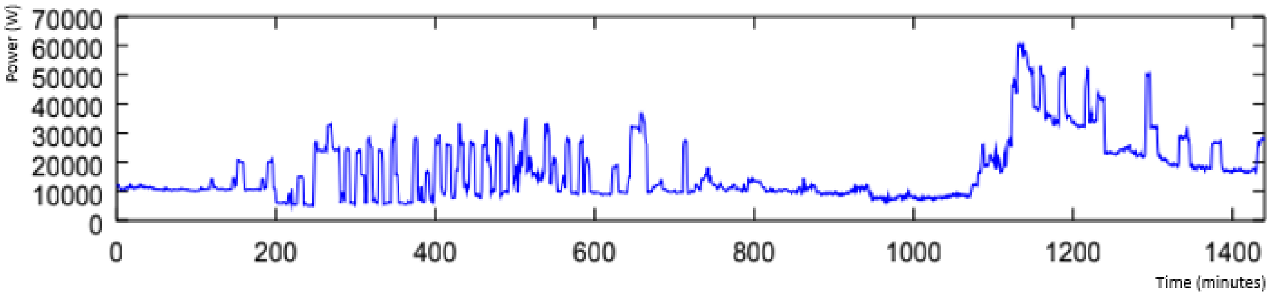

Figure 25. The aggregated power consumption of 10 houses

The power consumption profile shown in Figure 5 will be used to test the NILM algorithms when applied at the secondary substation level to disaggregate the single appliance consumption.

4.2. NILM Algorithms

The choice of Dataport database as a test bed for load disaggregation techniques introduces two main limitations in the choice of the algorithms:

1. The steady-state analysis only can be performed on the data because of the low acquisition rate of the selected dataset
2. Active power change is the only feature that can be extracted from the data because no other electrical parameters are available

In fact, the chosen granularity does not allow to realize any harmonic or transient/noise analysis because with 1-minute data these effects are not visible as explained in the chapter relative to Energy Disaggregation approaches. In addition, the NILM techniques using reactive power, V-I trajectory and frequency domain characteristics cannot be used for lack of data despite being steady-state methods.

Nonetheless, steady-state methods using active power resulted to be very effective in the identification of single state (on/off), energy-intensive appliances such as EVs and heat pumps and then considered acceptable for the purpose of this thesis [35]. On the other hand, if multiple state appliance, such as washing machines, were to identify the use of steady-state features would be ineffective. Moreover, these methods could lead to erroneous results in case of simultaneous state transition of several appliances, but this risk is accepted.

Figure 26 and 27 shows the active power consumption profile of a heat pump and an electric vehicle. As it is possible to notice, they present a quite simple pattern characterized by relatively big step changes in power and only two operational states (on/off).

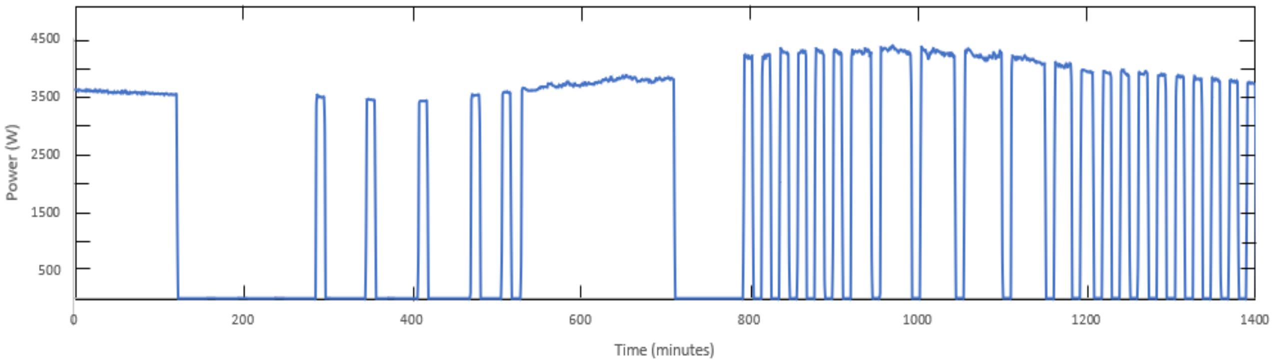

Figure 26. The daily power consumption of a residential heat pump

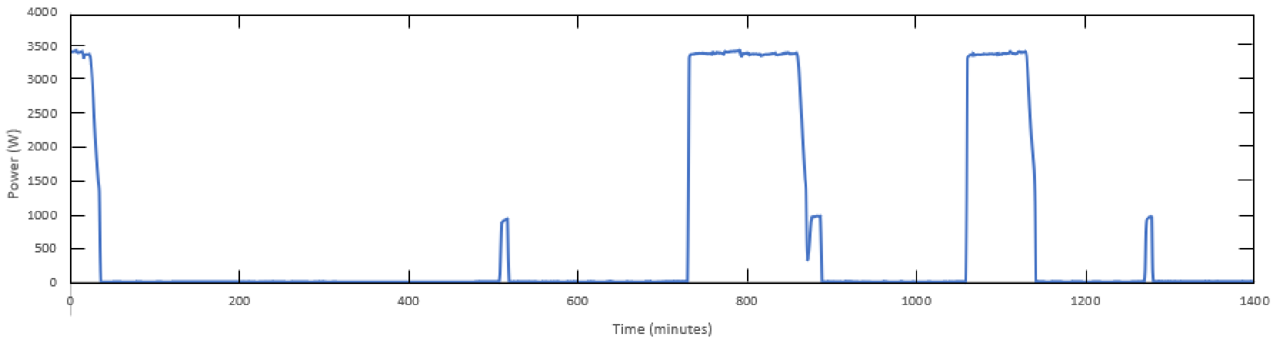

Figure 27. The daily power consumption of a residential EV charger

The detection of electric vehicles is identified as the simplest disaggregation problem as noticeable from Figure 7, hence the chosen load disaggregation techniques will be first tested for this case and, if delivering satisfactory results, then extended to heat pumps and PV systems.

For the problem of energy disaggregation, no new algorithms are realized but the state of the art, best-performing ones are employed to test their validity in a different condition, where several aggregated houses are considered instead of a single one. The benchmark algorithms chosen for the analysis adopt completely different approaches to the energy disaggregation problem and they were chosen for being among the best performers in term of accuracy. The significant difference between the chosen algorithms is considered as a strength point offering a broader analysis of the problem. Two benchmark algorithms are taken from literature and they are respectively:

1. Factorial Hidden Markov Model (FHMM), is a probabilistic tool using supervised learning to extrapolate the appliances signatures
2. EV Code by Zhilin Zhang, an unsupervised method based on sound physical knowledge of EV charging power draw.

In the next sections, the two algorithms will be shortly explained to better understand their working principle.

4.2.1. Factorial Hidden Markov Model (FHMM)

FHMM is one of the most used algorithms by NILM researchers and it was found as a reference algorithm available in the NILM Toolkit documentation. FHMM is particularly interesting for its ability to incorporate in its learning both temporal and appliance state information. It is a Temporal Graphical Model that is a class of probabilistic models that discourse the problem of blind source separation approaches. This type of algorithms is already applied in a series of real-life problems such as speech recognition where different voices talking at the same time need be separated from an aggregated record. In a similar way, different appliances working at the same time can be extrapolated from an aggregate power reading. Sequential data can be easily represented through a Markov Chain which is a stochastic model describing a sequence of possible events which the probability of each event depends only on the state attained in the previous event [58]. Each event is characterized by its real power consumption together with other useful information that can be the duration of the on/off periods and the time of use along the analyzed period of time. Hence, at each instant t of a period T, with t ϵ T, the aggregate consumption is $\bar{x}(t)$ and needs to be broken down to a series of appliances z_t^n, where n ϵ N with N the number of appliances. The value of each appliance at a certain time corresponds to one of the K states of the trained model of the appliance.

The working principle of an HMM can be described and inferred by three parameters:

1. The probability of each state of the hidden variable at the moment t, which can be defined as a vector
$$\pi_k = p(z_t = k) \tag{10}$$
2. The transition probabilities from state i at t to state j at t+1, which can be represented by the matrix
$$A_{ij} = p(z_{t+1} = j | z_t = i) \tag{11}$$
3. The emission probabilities for x, which are defined by a statistical function with parameter Φ that is commonly assumed to be Gaussian distributed such that
$$x_t | z_t, \Phi \sim N\ (\mu_{z_t}, \tau_{z_t}) \tag{12}$$
Where $\Phi = \{\mu, \tau\}$, and μ_{z_t}, τ_{z_t} are the mean and precision of a state's Gaussian distribution.
Eventually, the Equations 1, 2, 3 can be used to calculate the joint likelihood of the HMM:
$$p(x, z|\theta) = p(z_t|\ \pi) \prod_{t=2}^{T} p(\ z_{t+1}|z_t, A) \prod_{t=1}^{T} p(x_t|z_t,\ \Phi) \tag{13}$$

where the set of all the model parameters that must be found for each appliance during the training phase is represented by $\theta = \pi, A, \Phi$. Hence, when an HMM is used for energy disaggregation, θ parameters for each appliance must be tuned during the training phase and then, given a sequence of active power consumption signal $\bar{x}$ it is possible to find the optimal sequence of discrete states z.

A drawback of HMM when applied for energy disaggregation is that it is affected by local minima because of the interference of local minima. A variation of HMM is used to overcome this limitation, namely Factorial Hidden Markov Models (FHMM) where the output is an additive function of all the hidden states.

Figure 28 shows an illustration of a FHMM.

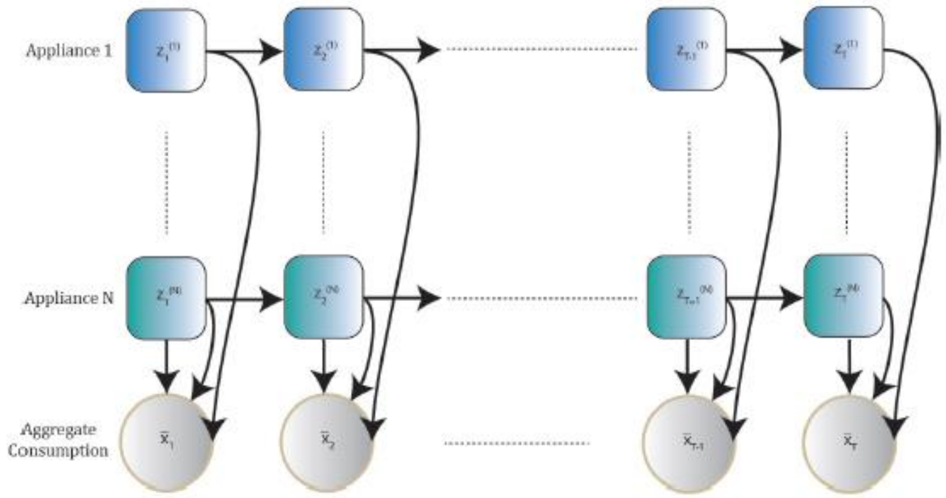

Figure 28. Illustration of a FHMM

Temporal Graphical Model and Machine Learning techniques for the energy disaggregation problem are generally computationally demanding in term of processing power and this means that they have to be run on cloud services instead that on locally installed microprocessors.

4.2.2. EV Code

EV Code is a training-free algorithm based on sound knowledge of the EV charging process. This represents an advantage over supervised learning methods for different reasons:

- It does not require an extensive training set for fine-tuning its parameters, so it can be applied to data where the submetered appliances consumption is not available
- It does not need to be retrained if new appliances are added to the system
- It is computationally light because of its structural simplicity

The code was publicly released in Matlab version in 2014 by Zhilin Zhang et Al. [42].

The algorithm can be described following a 4-step process:

1. Thresholding the aggregated signal. It allows to define the segments that could represent an EV charging and eliminate the background noise of low energy.
2. Filtering the spike train. After the thresholding process, the on/off heat pump cycles are all still in the signal and they need to be removed. The consumption pattern of residential heat pumps can have two different shapes, one resembles a spike train with very short duration, while the other shape resembles a rectangular waveform of high, slowly fluctuating amplitude and long duration. It is important to notice that the heat pump spikes gradually increase going towards the coldest/hottest hours of the day and gradually decrease later on depending on the season of the year. Therefore, it would not be possible to simply set a duration threshold to eliminate the heat pump spike train because of its changing duration. Then, the algorithm eliminates only the spikes that have a similar duration to the previous ones taking advantage of the gradual increase and decrease

of the spike train moving forward and back the signal. To avoid the algorithm to remove spikes of large duration an upper threshold is applied. If the spike train filter encounters a segment of significantly different duration from the previous and following segments does not mark it as a *segment to remove* even if lower than the upper threshold because it could potentially indicate a waveform of EV, oven or other resistive loads.

3. Classification of the type of each segment. The remaining segments can be classified in three types: Type 0, a resistive waveform or an EV waveform fully overlapping with a resistive waveform of nearly the same duration. In the latter case, the segment should have high altitude (>5 kW) and then possible to distinguish from the former. Type 1, The segment is an EV waveform, or a heat pump lamp, or an EV waveform overlapping with waveforms of non-heat pump appliances with relatively shorter duration, or an AC lump overlapping with waveforms of other appliances. Type 2, the segment belongs to an EV waveform overlapping with both an AC lamp and with other appliances.

   To distinguish the different types a cumulative counting function is calculated for every given segment and based on the number of prominent peaks of its gradient it is possible to choose which type the segment belongs to.

   Figure 29 shows an example of every type of segment illustrating the cumulative function and its gradient.

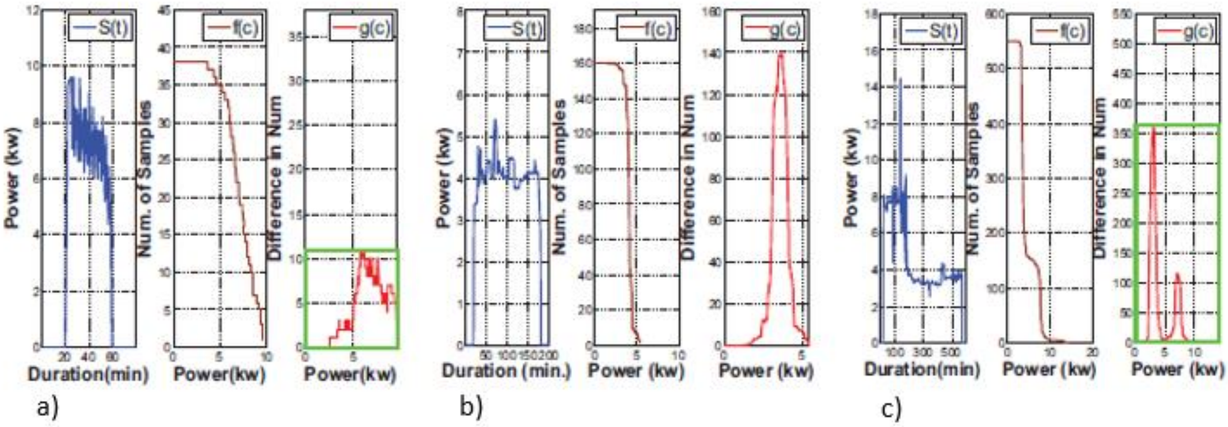

Figure 29. a) Type 0 (EV overlapped with a drier), b) Type 1 (EV with residual noise), Type 2 (EV overlapped with AC lamp and drier) [42]

4. Energy disaggregation. At this stage, the concepts of effective width and effective height are defined. The effective width is the actual width of the bottom of the segment while the effective height is the height at which the width of the segment becomes 80% of the effective width. Then, based on geometric considerations different for every type of segment and extrapolated from experimental measurements it is possible to separate the EV consumption from the heat pumps lamps and from the resistive loads.

Figure 30 shows the 4 steps of the algorithm as previously explained.

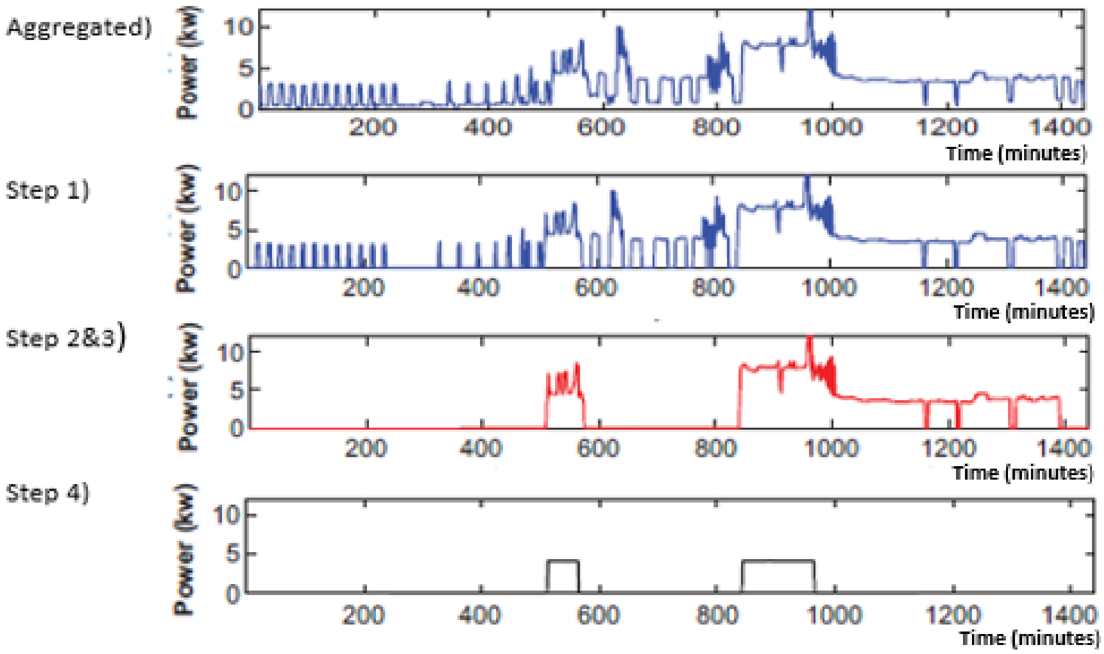

Figure 30. EV_code operational steps [42]

It is important to emphasize that the algorithm is based on default values from general knowledge of EV charging load characteristics, despite that, it is not restricted to a low number of cases which the algorithm is built for, but it maintains a robust performance across a large number of houses and different seasons.

4.3. Results

Once the test bed is assembled and the reference algorithms are chosen, the testing phase can start. To briefly summarize what it was discussed in the previous paragraphs, the test bed is constituted by a 10 single family house profiles randomly selected from a pool of 51 houses from Dataport database and all equipped with a residential EV charger and a heat pump. The algorithms that will be used to try to separate the EV charging waveform from the rest are Factorial Hidden Markov Models with supervised learning and the training-free EV Code from Zhilin Zhang. In the next paragraph, a separate showcase of the obtained results will be shown.

4.3.1. Factorial Hidden Markov Model (FHMM) with 10 houses

Using supervised learning means that the parameters describing the Markov chain must be fined tuned before their application training them with historical data. Indeed, out of the pool of 51 houses, 10 were used for energy disaggregation and the rest for training the parameters on the whole month of January.

Despite FHMM being one of the most promising tools for load disaggregation purposes, when it was applied to 10 houses aggregated the given results were unsatisfactory and it was not able to disaggregate the EV waveform from the aggregated measurements. Figure 31 shows the obtained results compared with the ground truth for two different days of the month.

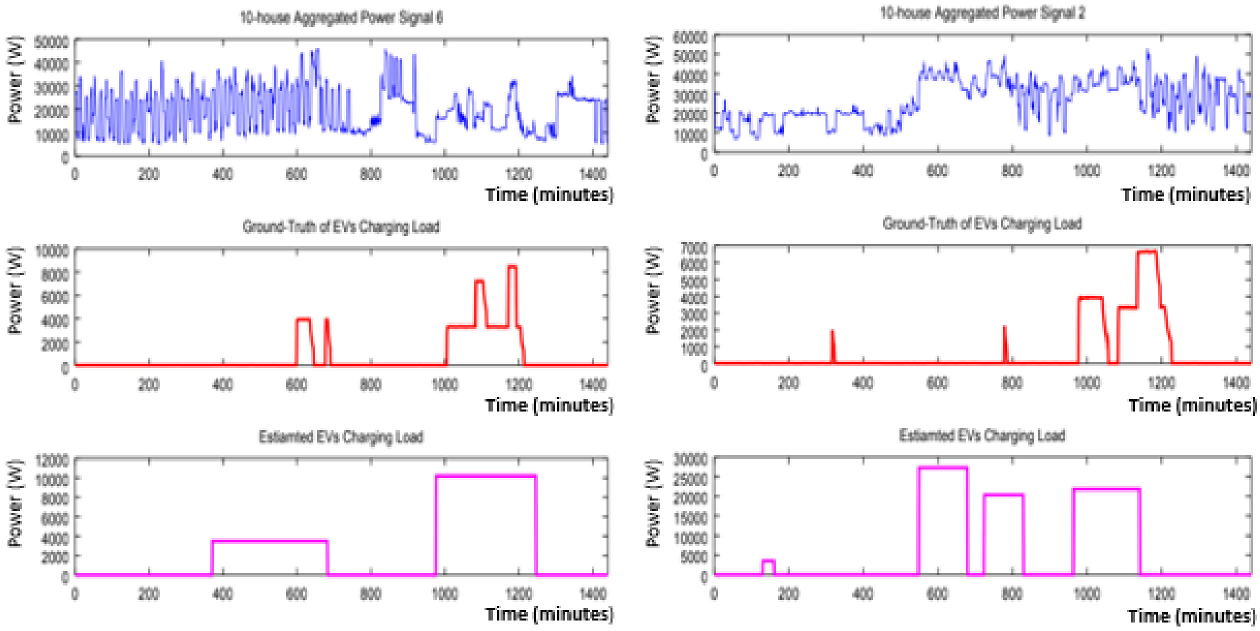

Figure 31. Two days EV energy disaggregation with FHMM

As it is possible to notice from Figure 10, the FHMM is not able to estimate accurately neither the timing nor the energy consumption of the EV charging profile whose submetered consumption is shown in red. In addition, in many cases, the FHMM are identifying an EV charging waveform where there is not. At this early stage is inadequate to talk about a quantitative analysis with evaluation metrics such as the F1 score that was previously explained in the section relative to the evaluation metrics for energy disaggregation problems. A qualitative analysis is enough to state that this combination of data and algorithm is not appropriate for energy disaggregation.

When dealing with probabilistic models such as FHMM is complicated to discover what went wrong in the disaggregation process and why this method was not adapt for energy disaggregation. Multiple reasons can be identified, and they can be related both to the algorithm, such as the inability to deal with a high number of appliances working at the same time and to the dataset whose granularity and amount of information about electrical parameters is not sufficient for the added complication of ten houses aggregated consumption.

4.3.2. EV Code with 10 houses

When dealing with unsupervised algorithms, the learning phase is not necessary, and the code was directly applied to the aggregated consumption profile of 10, randomly chosen, single-family house profiles.

The EV Code, when applied to a single house profile, is delivering very satisfactory results with an averaged estimation error of the monthly energy consumption of the EV of 7,5% only outperforming any alternative in the literature [42]. However, moving the same algorithm without applying any modifications to ten aggregated houses the situation radically changes. Figure 32 illustrates the disaggregation process with the EV Code in two randomly chosen days in the month of January.

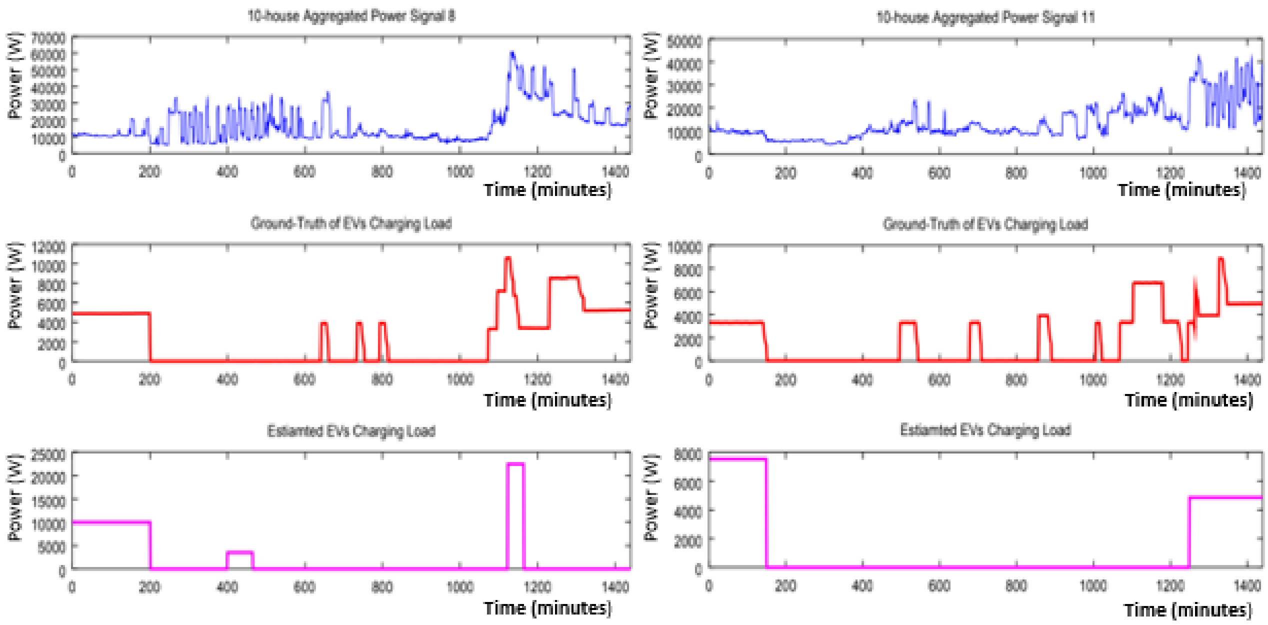

Figure 32. Two days EV disaggregation with EV_code

Figure 4 shows the estimated EV charging load in violet and it significantly differs from the ground-truth in red. The spike train filter performed well eliminating the heat pump fast cycling and the same partially happened for the Classification Tool of each type of segment since almost all the identified segments are actually EV charging profiles. Nonetheless, the Energy disaggregation tool is often not able to assign the right amplitude to the EV charging load. In addition, some EV charging profiles are lost during the day probably either for being removed by the Spike Train Filter or by the Energy Disaggregation Tool. It must be noticed that the removed EV profiles are unusually short for being residential chargers, in fact, their duration is only around 15-30 minutes instead of being in the normal range between 30 and 200 minutes and this could have confused the algorithm.

Overall, the results were considered unsatisfactory in term of accuracy for developing a commercial service to identify the EVs charging load at the secondary substation. No quantitative analysis is performed to assess the accuracy of the algorithm and only qualitative considerations are done.

The failure of the algorithm in the disaggregation purpose can be easily recalled to its design. In fact, it was specifically built to be applied at a single house level and its parameters were not suited for an aggregated consumption. Nonetheless, because its better performance compared to FHMM and its structure easier to understand, it was decided to continue its testing in a simpler scenario to improve its performance and see if it can be upgraded to a satisfactory level.

In the next paragraph, the same algorithm (EV Code) is tested with 5 aggregated house profiles instead than from 10. The energy consumption profiles are always randomly chosen from the pool of 51 single family households equipped with a residential EV charger and a heat pump.

4.3.3. EV Code with 5 houses

The aggregation of only 5 houses results in load profile much easier to understand and allows to see where and why the algorithm failed in its disaggregation purpose. In addition, 5 aggregated houses still represent a realistic scenario for real-world application. Therefore, the aggregation of 5 houses is considered an adapt playground for testing and improving the algorithm.

Figure 33 and 34 illustrate two days randomly chosen in the month of January where the EV Code was having a satisfactory performance in estimating the EVs charging load.

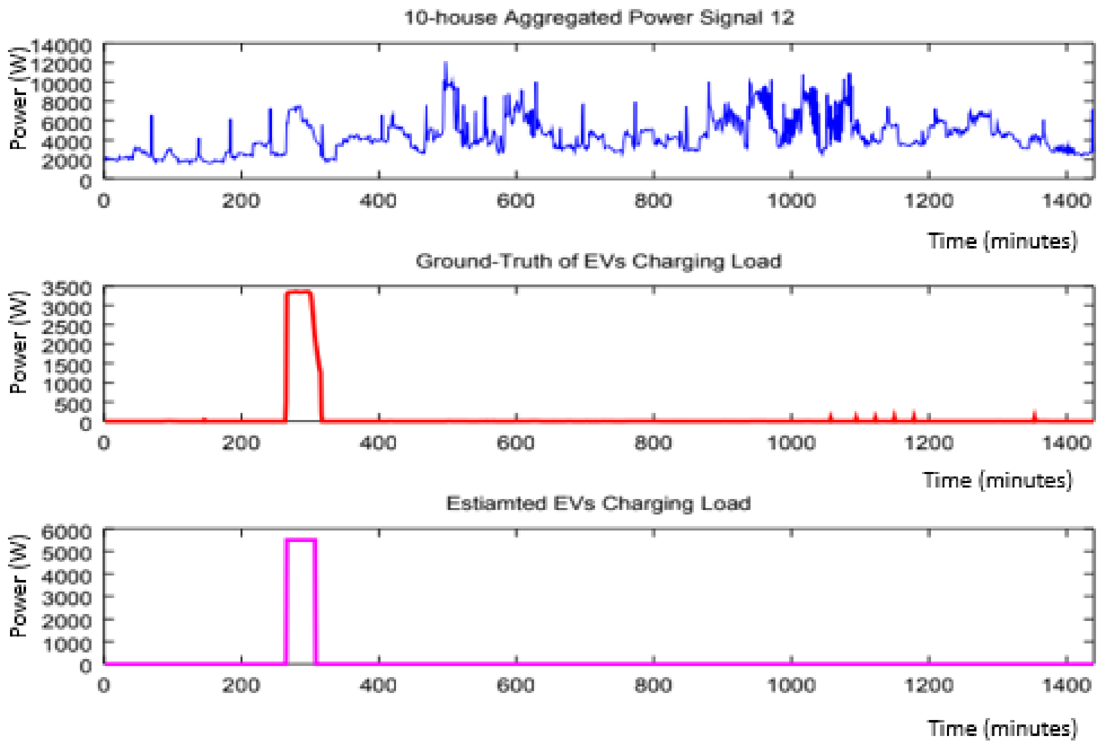

Figure 33. One day of EV consumption disaggregation

Figure 33 illustrates one day of total power consumption of 5 aggregated houses, the submetered consumption of the EV fleet of 5 vehicles and the estimated consumption by the EV Code. Along the day, a single electric vehicle is charged and the EV Code is able to identify it. On the second day in Figure 34, None of the 5 cars of the fleet is charged and the algorithm does not misguide any other appliance for an electric car. The EV Code demonstrates to have a quite good performance in days where there are any EV charging overlapping and the EV waveform presents the expected duration between 30 ans 200 minutes.

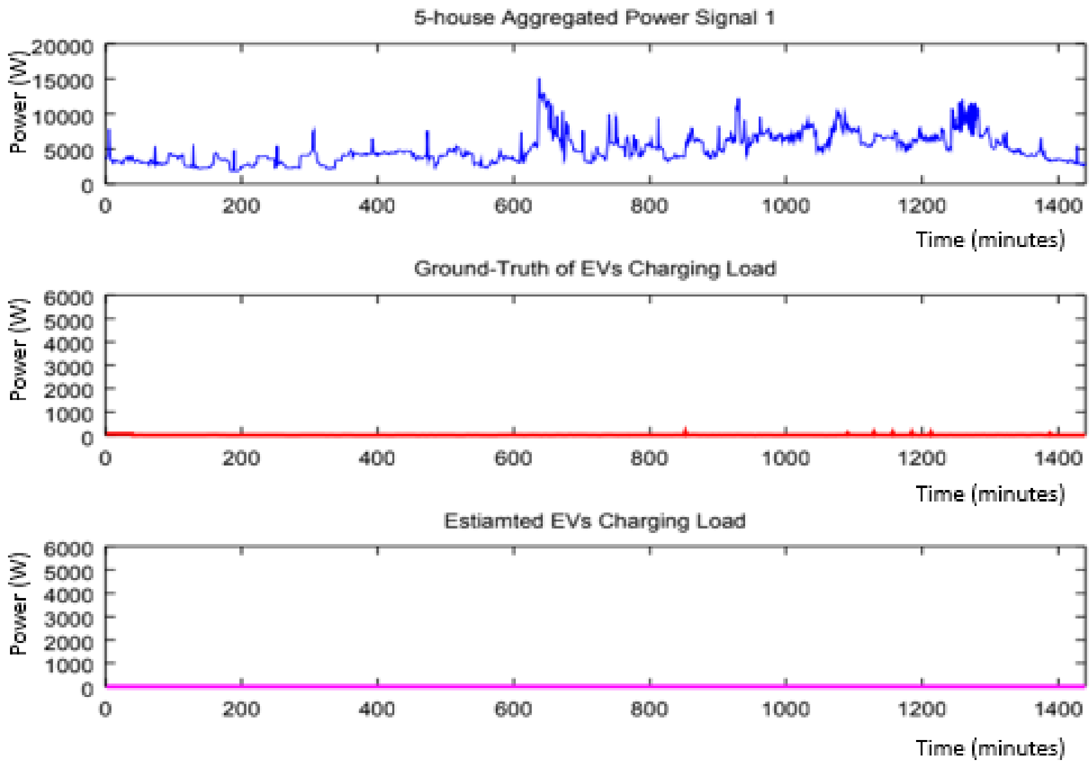

Figure 34. One day of EV consumption satisfactory disaggregation

As it possible to notice from Figure 33 and 34, during the two days the EV Code performed almost perfectly in its purpose to disaggregate the EV charging load. Indeed, the Spike Train Filter was able to remove the short duration cycles of the heat pump and the Classification and Energy disaggregation Tools were able to correctly assign the EV charging waveforms to their relative segments. The amplitude of the segments still represents an issue and it is probably due to a need for improvement of the noise removal section.

Unfortunately, despite the good performance registered in some days as the ones shown in Figure 33 and 34, the algorithm still has some issues in dealing with multiple aggregated houses consumption pattern as it can be visualized in Figure 35 where two underperforming days are shown.

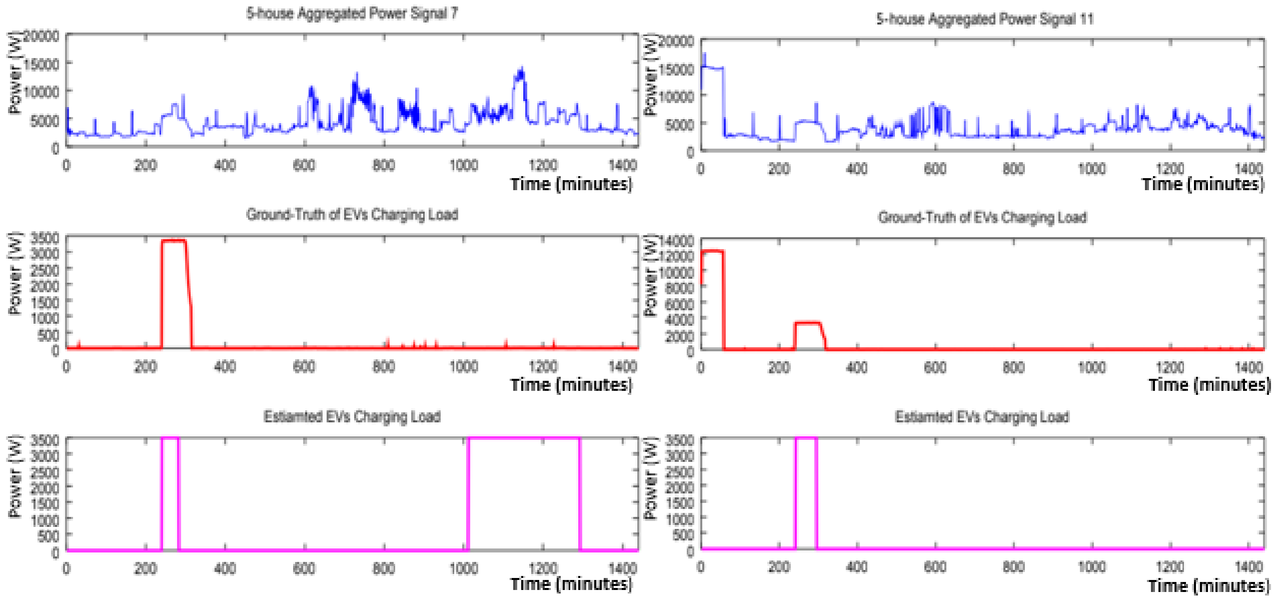

Figure 35. Two days of underperforming EV disaggregation with EV Code

Figure 35 shows that EV Code still underperforms in some cases and it is not ready for multiple houses application without any major modifications. In fact, it is affected by misidentification of EV waveforms where there are none and missed identification of others. The algorithm is still able to recognize the 3,5 kW charges correctly evaluating both the starting/ending points and the amplitude. However, when several appliances are overlapping or multiple EV are plugged in at the same time the algorithm misses the EV waveform or recognize other loads as EVs. These days make the monthly performance of the algorithm drop dramatically making inadequate any quantitative accuracy analysis.

The reason of the underperformance is that the Classification and the Energy Disaggregation Tools are mainly based on geometrical considerations, the gradient of the cumulative function and the effective width and height, that significantly change when multiple houses are aggregated. The improvement of these tools requires some major modifications that are listed below:

- The redefinition of the Classification Tool in order to include all the new combinations of overlapping appliances with the EV charging including the same type appliances overlapping in different houses. This is easy to notice in Figure 13 where during the second illustrated day there are two or more electric vehicles overlapping and the algorithm is not able to see them.
- The Effective Width and Height of the Energy Disaggregation Tool must be fine-tuned to the multiple-house condition either through a manual or supervised learning process.
- The Noise filter must be adjusted to get rid of the much higher background electricity consumption.
- Higher granularity of data should be used to avoid the excessive overlapping of different appliances that for 5 to 10 houses is consistent with 1-minute data.

The upgrade of the code would require an elevated amount of time for its realization and it goes beyond the scope of this thesis for time constraints. Furthermore, the difficulties encountered for disaggregating the EVs waveforms, which are the simplest to identify among the considered appliances, clearly state the impossibility to estimate the heat pumps and PV systems load profiles at this stage of advancement. Therefore, these tasks will be left as future work.

Overall, despite the relatively unsatisfactory results obtained, the EV Code presents a potential to disaggregate the consumption of multiple aggregated houses and this can be noticed in the days with a good performance in the process. In fact, it is designed with a specific focus on energy-intensive, 2-state loads and this represents an advantage on general-purpose methods such as FHMM when dealing with the complicated load compositions at secondary substation level. Moreover, the algorithm is designed to separate heat pumps and resistive loads waveforms from the EVs ones, then with few modifications they could be disaggregated as well from the total consumption. This procedure would upgrade the EV Code increasing the variety of flexible loads it can deal with, hence its value. For these reasons, the performed tests are considered a good starting point for a future work that could have important repercussions on the realization of a grid flexibility evaluation tool for the DSO.

5. Conclusion

The extensive work that has been carried out allows to have a broad view of what is the ideation, development, and verification of a commercial service for LV grid assessment and demand-side management. The literature review has shown the efforts done by the researchers in the energy disaggregation ecosystem and the creation of a big opensource movement that since 2011 released to the public several energy consumption datasets and analysis tools such as Dataport and NILMTK that are used for the purpose of this thesis. This phenomenon gave an incredible boost to the research in the field in the last years and allowed to use the state of the art of disaggregation algorithms for the technical verification of the DSM Evaluation Tool. In addition, the LV grid has been analyzed in an energy disaggregation perspective defining its challenges and highlighting the value of EVs and Heat Pumps as flexibility resources.

The market feasibility study has identified the UK as a mature market and a favorable first application within UK Power Networks (UKPN) flexibility services framework. In the cost-benefit analysis, the costs related to the installation and operation of the DSM Evaluation Tool infrastructure have been listed and quantified. Moreover, a reference study from UKPN on the impact of electrification of heating and transports sectors has been used to calculate the benefits of the service that result to be significantly higher than the costs for Utility-scale deployment. The overview of the competition has also defined the innovative character of the service and has recognized the possible threats and opportunities for partnerships.

Finally, the best performing benchmark algorithms for NILM have been tested. The secondary substation consumption has been recreated aggregating 5 and 10 single house data from Dataport dataset. Both FHMM and EV Code showed some limitations when trying to disaggregate the electric vehicle waveforms from the total consumption and they proved not to be ready for commercial deployment without major modifications. EV Code demonstrates to be able to correctly disaggregate the consumption of 5 houses for some of the trial days and it has the potential to radically improve its performance with some significant changes to the Classification and Energy Disaggregation Tools. The code also has the possibility to disaggregate heat pumps and resistive loads which are relevant for DR purposes with little additions.

The dissertation has shown the market feasibility and the highly beneficial impact of the DSM Evaluation Tool to decrease the costs of the LV grid upgrade and facilitate the transformation towards a cleaner and more decentralized energy system where the residential sector consumption is treated as a resource and not as an obstacle. Despite the unsatisfactory results of the tests, it is possible to see the light at the end of the tunnel and algorithms yielding satisfactory results will be seen in the near future. The wide scope of the thesis sometimes limited its accuracy of the single parts where deeper attention could be paid, and specific future studies are recommended. Even so, the selected approach is considered the best trade-off for the preliminary assessment phase where it is fundamental to understand if time and resources should be allocated for the development of a commercial product and the answer is yes.

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