Università degli Studi di Cassino
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Corso di Dottorato in
Metodi, Modelli e Tecnologie per l'Ingegneria
Dipartimento di Ingegneria Elettrica e dell'Informazione

Digitalisation in Energy: New Frontiers for Smart Monitoring

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Otto anni, due mesi e ventisette giorni...scelsi Ingegneria
un po' per passione e un po' per non avere rimorsi in futuro
e ciò si è rivelata la decisione migliore che potessi prendere.

Questa scelta mi ha permesso di seguire i miei interessi,
vivere esperienze uniche e conoscere persone straordinarie.

Sono davvero soddisfatto del mio percorso, in particolare riguardo
questi ultimi tre anni di dottorato. Se potessi tornare indietro,
rifarei tutto esattamente allo stesso modo.

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di Misure Elettriche e gli amici presenti in questi anni.

Un ringraziamento speciale alla mia Famiglia e a te, Chiara,
che mi hai sempre sostenuto in questo percorso.

A chi c'era, c'è e ci sarà sempre,
a chi mi ha insegnato ad essere...la mia Famiglia,
A tutti Voi e soprattutto a ME stesso!

Summary

The digitisation of the energy sector represents a strategic lever to respond to global challenges in terms of sustainability, efficiency, interoperability and resilience, orienting systems towards a full application of the Smart Energy concept.

This research investigates the central role played by measurements and Smart Meters in Smart Monitoring processes, a strategic concept in the reference context, irrespective of the type of energy vector under consideration. The analysis is centred on two pivotal parameters: this investigation elucidates the direct influence of Electrical Signature Quality and Monitoring Quality on the performance of advanced digital tools in the smart field, including Load Profiling, Digital Twin, Predictive Diagnosis and Non-Intrusive Load Monitoring. The investigation is conducted with a concrete and methodological approach, analysing the digital potential of smart meters currently on the market and proposing a new ad-hoc smart meter architecture for the implementation of the aforementioned digital tools. Furthermore, the research addresses the issue of cyber security, proposing non-invasive methodologies based on side-channel for the protection of critical infrastructures. It demonstrates how electromagnetic emissions can be used to detect potential threats without compromising business continuity.

The findings demonstrate that a comprehensive approach to measurement quality and digital security can facilitate and expedite the transition to safer, more efficient, and sustainable energy systems. The author posits that Smart Monitoring not only represents an advanced energy management tool but also a strategic enabler of new services and functionalities to address the challenges of the global energy transition.

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Introduction

Digitisation can break down the boundaries between the energy sectors, increasing their flexibility, interoperability, and resilience, offering efficient integration of new systems, technologies, and digital services. The electricity sector is at the heart of this transformation and has been the first to project and enable the full application of the Smart Energy concept, aiming at an increasingly efficient and sustainable use of energy.

As economies depend on reliable and affordable electricity, in addition to the urgent need to address climate change, this projected growth requires a radical transformation of the world's energy systems. Achieving this transformation requires policy actions, enabling regulatory frameworks, new business models, and large-scale investments. However, alongside global efforts to decarbonise energy systems, the world needs innovative approaches to the design and operation of electricity systems, as well as the development of new technologies and services aimed at smart and energy-conscious energy use. Without such innovation, increasing electrification could lead to greater energy insecurity, unnecessary transmission and distribution losses, and missed cost-saving opportunities for consumers and energy producers.

In this context, Smart Monitoring emerges as a central aspect of modern energy management; it represents a milestone in the digitisation of the energy sector, focusing on the real-time collection, analysis and management of energy flow data. This is also thanks to the implementation of technologies and new digital services that make electricity systems more dynamic, efficient, reliable, and sustainable. In particular, Smart Meters. In fact, the number of smart meters worldwide will exceed 1 billion by 2022, a 10-fold increase since 2010. Meanwhile, connected devices with automated controls and sensors are estimated to reach 13 billion in 2023, up from less than a billion a decade ago. This number could reach more than 25 billion in 2030. And there are similar trends in electricity grids, with around 320 million distribution sensors distributed globally. All these devices generate data: smart meters collect consumption details and transmit real-time data from networks. If well utilised, these data provide information on consumption patterns and patterns, predicts demands, and helps to better manage energy systems. But for this to happen, data must be collected, stored, analysed, and shared according to certain criteria, while ensuring privacy and cyber security. These requirements include multiple layers of interoperability that are in reality far from seamless. This creates enormous challenges for energy systems, but also brings enormous potential benefits. Effective management helps increase energy efficiency and can benefit energy systems in many ways. For example, it has been estimated that in the European Union, proper data sharing could potentially unlock over 580 GW of flexible energy resources by 2050, which would then cover over 90% of the flexibility needs of EU electricity grids.

However, globally, the use of smart meter data is still below its potential, with only 2-4% of available data currently being used. Despite the increasing amount of information generated by smart meters and distributed sensors, only a small fraction of this data is actually used to improve the efficiency of energy systems.

Smart monitoring and digitisation together offer the possibility of overcoming these barriers, enabling the efficient use of data with new services and advanced functionalities that enable a more dynamic and conscious energy management. In this context, the quality of energy measurements becomes a decisive factor. It is no longer enough to collect data: this data must be accurate, reliable and representative of the phenomena it is intended to monitor.

The quality of the data, therefore, is not just a technical issue but represents the fulcrum around which Smart Energy applications revolve. This parameter can take on several facets, but from a measurement point of view, it can be divided into two key parameters: Electrical Signature Quality, and Monitoring Quality. These directly influence the performance of algorithms used in the smart energy field, such as Load Profiling, Digital Twin, Predictive Diagnostics, Forecasting, Non-Intrusive Load Monitoring, etc.

This research is part of this framework of digital transformation of the energy sector, with the aim of exploring and deepening the potential of Smart Monitoring and related technologies. In the field of smart energy, the role that measurements are called upon to play today and the impact of their associated quality in smart analysis processes is analysed in detail. The details of the research are presented below.

The first chapter introduces the concept of Smart Energy and the crucial role of energy measurements in this context. It explores how smart meters, integrated with advanced digital technologies, can provide a detailed, real-time view of energy consumption, enabling more efficient and sustainable energy management. The importance of ensuring a high quality of measurements, both in terms of Monitoring Quality and Electrical Signature Quality, is emphasised as a prerequisite for successful Smart Monitoring applications.

The second chapter delves into the crucial role of smart meters in the collection of high-quality data, which is necessary for the development of advanced smart energy applications. It highlights the importance of the quality of energy measurements, in particular the Electric Signature Quality and the Monitoring Quality, in ensuring the reliability of monitoring and optimisation algorithms. An innovative dataset is introduced that offers an unprecedented level of detail in energy measurements, capable of supporting the development of advanced techniques.

The third chapter presents a methodological approach to Load Profiling intended for integration into digital and data-based monitoring. This approach is conceived above all as an enabler of digital services. Moreover, the presentation of an analysis protocol and illustrative examples demonstrates how the Electrical Signature Quality and the Monitoring Quality can markedly enhance the efficacy of algorithms in the context of Smart Energy. The findings of the methodological work offer indispensable guidance for the design of Load Profiling.

The fourth chapter explores the use of Load Profiling techniques for the diagnosis and detection of anomalies in electrical systems. The crucial role of energy measurement quality in Predictive Diagnosis is emphasised, highlighting experimentally how high-quality data can improve the accuracy and timeliness of maintenance interventions.

The fifth chapter examines Non-Intrusive Load Monitoring as a strategic technology for optimising energy monitoring processes and reducing operating costs. It discusses how adequate Electrical Signature Quality can improve load disaggregation, even in complex scenarios, and contribute to more efficient and sustainable energy management.

The sixth chapter addresses the crucial issue of data security in digital energy networks and Cyber Security. Using a “Side Channel” approach, it explores how electromagnetic emissions, generated by devices during their operation, can be hacked and/or used to identify and prevent potential security threats, without requiring direct access to the systems. This demonstrates how Smart Monitoring can go beyond energy management, also contributing to the protection of critical infrastructures from cyber attacks, thus ensuring greater security and reliability of the overall energy system.

The seventh chapter presents the design of an innovative smart meter with metrological and communication properties suitable for advanced, state-of-the-art smart energy applications. In summary, the aim is to give an insight into the life cycle of a smart meter, from initial design to practical implementation, characterisation and calibration; highlighting the technical challenges faced and the solutions adopted in line with the standards and requirements of the industrial application environment.

The knowledge advancement, the implementation of algorithms and hardware components, the deep analysis of each development and the validation in real-world or near-real-world conditions establish the contribution of this doctoral dissertation as solid new ground in monitoring of smart energy systems.

In summary, the research offers an in-depth and multidisciplinary analysis of the challenges and opportunities offered by digitisation in the energy sector, with a special focus on the quality of measurements in Smart Monitoring processes. Through a rigorous and innovative approach, it aims to provide useful tools and knowledge to improve the efficiency, safety and sustainability of the energy systems of the future.

Chapter 1

Smart Energy and Digitalisation

1.1 Highlights

- **Innovation in energy management**: This research explores the revolutionary impact of digitisation on the energy sector, with a focus on the "Smart Energy" concept and the importance of intelligent energy monitoring to optimise resource use and reduce waste.
- **Central role of Smart Monitoring**: It is highlighted how Smart Monitoring, supported by advanced digital technologies such as artificial intelligence and machine learning, enables detailed and real-time analysis of energy consumption data, improving the efficiency and resilience of systems.
- **Smart Meters as the core of digitisation**: The chapter emphasises the importance of smart meters, key devices that enable real-time and multi-physical monitoring, enabling a new era of energy management based on accurate and reliable data.
- **Electric Signature and Measurement Standards**: The concept of the electric signature is explored in depth, explaining how its advanced analysis can provide crucial information for the actual fulfilment of smart energy objectives, using recognised standards such as IEEE 1459 and IEC 61000-4-30.
- **Security challenges and data protection**: The research highlights the critical issue of cyber security, highlighting the risks associated with digiti-

sation in the energy sector and proposing innovative solutions to ensure the protection of infrastructure and sensitive data.

- **Practical applications of smart energy**: The chapter presents various areas of application of smart monitoring in the context of smart energy, showing how digital technologies are radically changing the way we approach the analysis of energy flows.

1.2 Introduction

The evolution of the energy sector is unstoppable, driven by the advancement of digital technologies and the growing urgency to address environmental challenges. In this context, the concept of "Smart Energy" has gained extraordinary relevance. This concept encompasses a wide range of digital solutions and strategies aimed at improving energy efficiency, reducing waste and promoting intelligent management of energy resources. At the heart of this transformation is the important issue of monitoring energy consumption, an essential pillar in promoting an efficient and sustainable energy culture.

In this scenario, the energy sector is undergoing a constant transformation in terms of digitisation and the development of new energy services based on the intelligent use of energy information. In Europe, for example, the development and use of smart metering systems and techniques has been encouraged by European Directives in recent years and supported by the "International Energy Agency" - IEA [1]. These directives set strict requirements for member states concerning both metering and charging, identifying the use of smart metering systems as one of the tools for improving energy efficiency. In addition, the IEA has launched a four-year inter-agency initiative, "Digital Demand-Driven Electricity Networks" - 3DEN [2], which works to accelerate progress in the modernisation of the electricity system and the efficient use of distributed energy resources through policy, regulation, technology and investment guidance.

It is therefore necessary to introduce a new paradigm for energy management, aimed at maximising energy efficiency, thus reducing waste due to sub-optimal management of energy installations, to lower the environmental and economic impact. It should be noted that efficient energy use also arouses considerable interest in commercial and industrial activities, especially if they are highly energy-intensive. The reason is simple: energy efficiency makes it possible to *do the same thing with less energy*, reducing costs and burdens. The energy sector was among the first to use digital technologies to facilitate the management and operation of networks, as well as to modernise plants. Today, digitalisation is an indispensable tool for achieving the objectives set by the European Union within the "Clean Energy for All Europeans" package [3], but more generally for meeting the goals of the energy transition. An energy transition that has led to a radical transformation of the traditional electricity system, which has gone from being a passive network - where the flow of energy passed from the place of production to the place of consumption - to becoming an active network, where energy flows follow a discontinuous and bidirectional path.

But above all, digitisation has supported the development of smart grids, the evolution of urban centres into smart cities, and of living spaces into smart buildings and smart homes. Digitalisation has also brought about a radical change in the world of industry, which first evolved towards a 4.0 system and is now oriented towards an Industry 5.0 model. In practice, it makes the concept of smart energy possible.

In this context, Smart Monitoring emerges as a central aspect of modern energy management; it represents a milestone in the digitisation of the energy sector, focusing on the collection, analysis and real-time management of energy consumption data. This technology makes it possible to monitor energy consumption in detail, detect inefficiencies and optimise the use of resources, offering a clear and precise view of energy consumption patterns thanks to innovative digital methods and tools. Today, Smart Monitoring is distinguished by its ability to integrate advanced instruments and tools, such as smart meters, and digital technologies such as artificial intelligence and machine learning, which enable automated and accurate analysis of energy data. Not only does it improve energy management and efficiency, but also the interoperability and resilience of electrical systems, in any application context. Smart Monitoring has long played a strategic role in Smart Grids, which use data to balance energy supply and demand in real-time, in smart cities and smart buildings, where energy monitoring helps to create more efficient and sustainable environments. In addition, the industry, increasingly oriented towards the Industry 5.0 paradigm, benefits greatly from Smart Monitoring, which enables improved predictive maintenance, reduced downtime and optimised operations.

As repeatedly stated in this research by the author, *it is clear that smart meters are the key link between the digital revolution and the energy sector, enabling a new era of real-time, efficient and multi-physics monitoring.*

This chapter explores these aspects in detail, with a particular interest oriented towards the role that the smart meter is called upon to play today concerning the smart energy context and the relative methodologies for implementing smart monitoring. The objective is to bring out a series of fundamental aspects and concepts, useful for understanding the subsequent chapters, regarding the real added value associated with the use of smart meters as well as the associated influence parameters, especially regarding the extraction and synthesis of the monitored "Electrical Signature".

The structure of the chapter is as follows: first, key concepts relating to the context of smart energy and energy digitisation are defined and the relative regulatory reference scenario is illustrated. Next, smart monitoring and the smart meter concept are presented, highlighting the concrete benefits of their adoption. Subsequently, of fundamental importance, the electric signature concept and the extraction and synthesis methodologies are discussed, as well as the associated parameters that influence the performance of a smart monitoring process. Finally, some typical smart energy applications are summarised; applications that will be studied in subsequent chapters.

1.3 Context and Definitions

In today's scenario of constant digital transformation and evolution, the concept of smart energy lends itself to various interpretations. Smart Energy can be understood as the set of techniques and devices that aim at a more efficient and sustainable use of energy. However, in addition to efficiency, two other factors must be considered: energy use and consumption. In detail [4]:

- *Energy Efficiency* is the ability of a physical system to achieve a particular result by using less energy while increasing its overall performance;
- *Energy Use* refers to how energy is used and exerted, regarding how it is managed in terms of time and the application area in which it is used;
- *Energy Consumption* refers to the amount of energy used by a system, machine, building or company during a given period; it reflects the use of natural resources and the level of exploitation of energy sources.

By managing these factors intelligently and sustainably, today's energy and environmental problems can be addressed. Together, as shown in Figure 1.1, these three factors define the concept of energy performance, i.e. the "Measurable Outcome related to Energy Efficiency, energy use and consumption".

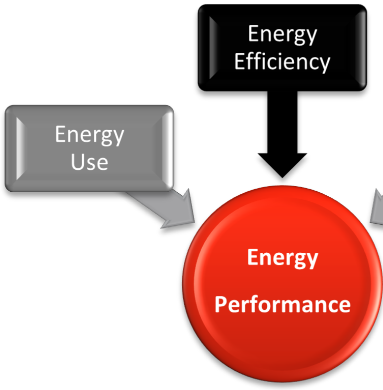


Figure 1.1: **The concept of Energy Performance.**

These concepts are fundamental to addressing today's energy and environmental problems, as energy is becoming localised: it is not only *how much* that counts, but also *when*, *where* and *how* it is produced and consumed. Therefore, it is crucial to use energy intelligently and consciously. A better understanding of where, how and why energy is used can help companies, or consumers in general, to unlock opportunities for immediate energy savings and long-term energy efficiency improvements [5]. Increasing the monitoring of management systems, integrating smart meters and controls and carrying out energy audits are some actions that can help to significantly reduce companies' energy use.

According to the current European Commissioner for Energy, *Kadri Simson*, and the Executive Director of the IEA, *Fatih Birol*, it can be stated that [6] [7]:

- smart meters and controls, when used to identify and manage energy consumption, can lead to a reduction in energy consumption of up to 40%;
- it has been shown that energy audits, supported by appropriate monitoring campaigns, can generate an average potential saving of 18% of total energy consumption;
- smart energy management systems can lead to an average reduction of 10-17% of annual energy consumption;
- training and awareness campaigns on the smart use of energy and digital tools provide annual energy savings of almost 6% in companies, and when combined with technological support and expertise, these can increase to 21%;

- the automatic identification by state-of-the-art tools of inefficient equipment and replacement with energy-saving options can lead to immediate energy savings, usually with short payback periods;
- the implementation of digital tools for predictive diagnosis to optimise maintenance and management processes can reduce energy costs by up to 30%, particularly in heating and cooling, refrigeration, lighting and insulation, among others.

It is therefore a transversal subject, which includes the use of advanced technologies to manage and optimise the production, distribution and consumption of energy. By combining innovative tools and techniques, Figure 1.2, this discipline aims to improve the analysis, monitoring, maintenance, safety, efficiency and sustainability of the energy system, regardless of the application context.

Figure 1.2: **What is digitalization?**

The fields of application where the use of digital tools and smart energy management is found are many and cover different areas of the energy and industrial sector. Some examples include [8–10]:

- Smart Grids - are an electricity grid that use digital and other advanced technologies to monitor and manage the transport of electricity from all generation sources to meet the different electricity demands of end users. Smart grids coordinate the needs and capabilities of all generators, grid operators, end users and electricity market stakeholders to manage all parts of the system as efficiently as possible, minimising costs and environmental impacts while maximising system reliability, resilience, flexibility and stability.
- Smart Buildings - are equipped with integrated automation systems that can control the building's lighting, temperature, ventilation, heating and air conditioning. Thanks to installed sensors and devices, smart buildings can reduce

energy consumption and improve system efficiency. They are also equipped with energy management systems that can monitor energy consumption in real-time and analyse the data to identify any waste or inefficiency.

- Smart Cities - are cities that use advanced technologies to improve the quality of life for citizens, increase the efficiency of urban systems and reduce environmental impact. In a smart city, data collected by sensors and monitoring systems are analysed to obtain useful information for urban planning and the management of public services. This leads to reduced costs and a more sustainable urban environment. In smart cities, citizen participation is often promoted through the use of online platforms and mobile applications, which allow citizens to report problems, suggest useful tips and participate in urban planning. This interaction promotes greater citizen empowerment and participation in city management. Thus, smart cities represent an innovative solution to urban challenges, creating more efficient and sustainable cities.

- Electric mobility - smart energy plays an important role in the promotion of electric mobility, through the creation of charging facilities in people and the management of energy demand. Thanks to these infrastructures, electric cars can be recharged efficiently, safely and sustainably.

- Smart Factory - as well as smart manufacturing, are manifestations of the technological transformation and digitisation of production processes, known as Industry 4.0 and 5.0. Thanks to interconnected networks of machines, communication mechanisms and computing power, the smart factory is a cyber-physical complex that harnesses advanced technologies such as artificial intelligence and machine learning to monitor analyse data, promote automated processes and learn from experience.

Overall, digital technologies and data have enormous potential to accelerate transitions to clean energy in the power sector. In power systems, digital technologies can help integrate increasing shares of variable renewable sources and improve grid reliability, while in end-use sectors they can improve energy efficiency and reduce emissions. Advances in digital technologies and services, cost reductions and ubiquitous connectivity have accelerated the digital transformation of energy in recent years, particularly in electricity grids. Grid-related investments in digital technologies have grown by more than 50% since 2015; by 2023 they have reached about 19% of total grid investments [11].

There is an increasing focus on the monitoring and distribution segment, which now accounts for more than 75% of total digital expenditure. The number of smart meters worldwide exceeded 1 billion in 2022, a tenfold increase since 2010. The

IEA estimated that connected devices with automated controls and sensors reached 13 billion in 2023, up from less than 1 billion a decade ago. This number could reach more than 25 billion in 2030. Similar trends are being observed in electricity grids, with around 320 million distribution sensors deployed globally. There has also been a substantial increase in investment in electric vehicle charging infrastructure, which doubled in 2022 compared to the previous year.

However, much of the progress to date is limited to developed countries and further efforts by policymakers and industry are needed to realise the full potential of digitisation to accelerate transitions to clean energy. This includes the implementation of enabling standards, policies and regulations that prioritise innovation and interoperability while addressing cyber-security and data privacy risks. In addition to accelerating the implementation of key digital technologies, there is a need to make better use of existing data and digital assets to deliver benefits to consumers and the energy system; in 2019, it was estimated that utilities exploited only about 2-4% of collected data [12]. For instance, Transmission System Operators (TSO) recognise their underutilisation of data opportunities. A survey of 10 TSOs shows that most agree that their control rooms do not make full use of data analysis applications, even when they have fully digitised networks equipped with sensors and remote control.

1.3.1 Reference regulatory standards

Countries have been preparing their infrastructures for digitisation for some time now, and increasingly so. In the context of the smart energy revolution, the European Union has promulgated the *Clean energy for all Europeans package* [3], a set of directives and regulations in the field of energy. Furthermore, in 2022, the European Union launched the action plan *Accelerating the Digital Transformation of the European Energy System* [13], for the digitisation of the energy system to promote connectivity and interoperability, foster coordinated investments in smart grid technologies, empower customers, improve cyber-security, promote greater efficiency and design effective governance through joint planning. But that is not all, over time a series of regulations and packages have followed to help define the "Europe strategy" [14], including: *Directive 2009/72/EC*, *Directive 2012/27/EU*, *Energy Efficiency First principle*, *National energy and climate plans*, *FIT FOR 55*, *REPowerEU plan*, etc. These legislative packages and regulations aim to promote energy efficiency, the use of new technologies, and renewable energies and the flexibility of the energy system on a European level.

The IEA's *Tracking Clean Energy Progress* (TCEP) [15], assesses recent developments for more than 50 components of the energy system that are critical to clean energy transitions, following what was also established at the last *COP28* in Dubai [16]. The assessed components include sectors, sub-sectors, technologies, infrastructure and cross-cutting strategies. Today, thanks to all these packages and regulations, the analysis and perspectives at the European level reported according to the TCEP are certainly more promising than a decade ago. Innovative digital infrastructures are gaining importance in electricity grids, both in distribution and transmission, with investment growth of around 7% in 2022 compared to 2021. The distribution sector accounts for about 75% of all investments in grid-related digital infrastructure, through the implementation of smart meters and the automation of substations, lines and transformers using sensors and monitoring devices [17].

In addition, as early as 2006, *Directive 2006/32/EC* [18] identified the use of smart metering systems as one of the tools for improving energy efficiency through appropriate algorithms and techniques. In 2009, the Electricity Directive *2009/72/EC* [19] declared the obligation for Member States to ensure the adoption of smart metering systems. Finally, in 2012, the European Energy Efficiency Directive *2012/27/EU* [20] reaffirmed the importance of the use of smart meters, with stringent requirements for Member States regarding both metering and billing. In addition, in recent years, the IEA has recommended policies and new services that improve the reliability, affordability and sustainability of energy, also promoting the *Clean Energy Transitions Programme* (CEPT) [21] with the goal of global net zero emissions through safe and people-centred clean energy transitions, with a focus on major emerging and developing economies.

Italy, in particular, is at the forefront in this regard, as in addition to being the first to have completed the complete installation of first-generation smart meters for electricity on distribution networks, to date, according to "ANIE Federazione" in the "Sistema Confindustria" and "Smart Metering Group - SMG" [22], it has approximately 36 million smart meters installed. In Italy, like other European countries, significant steps have been taken to address the challenges and exploit the opportunities offered by smart energy. The *Piano Nazionale Energia e Clima* (PNIEC) [23] represents the central pillar of Italian initiatives. This plan is aligned with European objectives and establishes a roadmap for the energy transition in Italy. It contains ambitious targets for energy efficiency, renewable energy sources and the reduction of greenhouse gas emissions. Digitisation, innovation and green transition also appear among the main axes of the *Piano Nazionale di Ripresa e Resilienza* (PNRR) [24], where there is a close connection between digitisation and green transition and, therefore, between energy and climate objectives on the one hand and innovation objectives on the other. Following the European strategy, in Italy, of particular relevance concerning this objective are *Directive 2018/2022/EU* [25] on energy efficiency and *Directive 2018/844/EU* [26] on the energy performance of buildings. In particular, the use of new technologies is encouraged to create smart buildings that, hand in hand with the development of smart grids, enable the goal of more efficient energy performance to be achieved. In this sense, Italian legislation also promotes the development of sustainable mobility, a crucial aspect of the smart energy ecosystem, including measures in favour of electric and sustainable vehicles.

Furthermore, in this context, *Legislative Decree 102/2014* [27], establishes a framework of measures for the promotion and improvement of energy efficiency, which contribute to the achievement of the national energy savings target and contribute to the implementation of the European principle of putting energy efficiency first. The aforementioned decree provides a comprehensive regulation of the entire energy production, transmission, distribution and marketing cycle, aimed at removing barriers in the energy market and overcoming market failures that hinder efficiency in the supply and end use of energy. In particular, it provides detailed guidance on how to plan, perform and document energy audits/diagnoses in various sectors (carried out by certified entities such as Energy Services Companies - ESCo), and provides a set of recommendations for the identification of energy efficiency improvement opportunities, following the technical standards *UNI CEI/TR 11428* and *UNI CEI EN 16247* [28, 29].

To this end, companies, especially energy-hungry ones, have in recent years implemented suitable metering and sub-metering networks within their plants, to assess the efficiency and effectiveness of the processes implemented and define energy improvement strategies. In 2019 alone, 3.2 million meters were installed in companies in Italy.

1.4 Smart Monitoring

In the context of smart energy, the Smart Monitoring concept represents a milestone in the transformation of the energy sector towards a more efficient, sustainable and intelligent management of energy resources. This advanced technology focuses on the real-time collection, analysis and management of energy consumption data, providing unprecedented insight into energy use patterns. A crucial feature of Smart Monitoring is its ability to monitor energy consumption in a detailed and constant manner. This not only makes it possible to track energy consumption patterns but also to detect any anomalies or inefficiencies in the loads associated with the energy structure in question.

For example, a key role of Smart Monitoring is played in the improvement and implementation of Smart Grids, which use data from *Advanced Metering Infrastructure* (AMI) devices to balance energy supply and demand in real-time. This approach is not only limited to the energy distribution sector but also to the residential sector, enabling users to make informed energy management decisions (such as adjusting devices to reduce consumption peaks or detecting energy losses at an early stage, actions to increase energy efficiency [30]). In addition, there are also practical advantages in today's increasingly digitised and smart Industry 5.0. For example, Smart Monitoring enables immediate operator-machine collaboration by visualising the electrical parameters of industrial machines in real-time, making it possible to perform maintenance operations remotely when necessary, avoiding the interruption of plant operations for the intervention of specialised personnel. This minimises operating expenses and has a significant impact on the environment.

Smart Monitoring is constantly evolving, with an increasing integration of advanced technologies such as artificial intelligence and machine learning [31]. These technologies enable automatic analysis of energy consumption data, detecting patterns and trends that might escape simple human observation, making monitoring even more sophisticated and responsive to changing energy market conditions. However, it is crucial to address privacy and data security concerns in this area. As this technology collects sensitive data on energy consumption, it is essential to ensure that the information is protected from unauthorised access and used only for legitimate purposes. Energy companies and regulators must therefore establish strict data security policies and ensure compliance with privacy regulations.

As illustrated in the Figure 1.3, the smart monitoring concept can be applied to different sectors [32]: residential, industrial and electricity distribution and transmission. In general, regardless of the application scenario, the process is always aimed at meeting objectives in terms of: monitoring, analysis (AI), management, efficiency, diagnostics, retrofit (extraction of quality or system performance indices) and cost savings, in accordance with smart energy objectives.

1.5 Smart Meter

It is well known that the first phase of a smart monitoring process, cannot be separated from a phase dedicated to the acquisition and collection of data and therefore the use of meters. Therefore, it is possible to state that: although digitalisation today represents the real revolution in Energy, Smart Meters represent the means that makes this epochal evolution possible, opening the door to real-time, efficient and multi-physical smart monitoring.

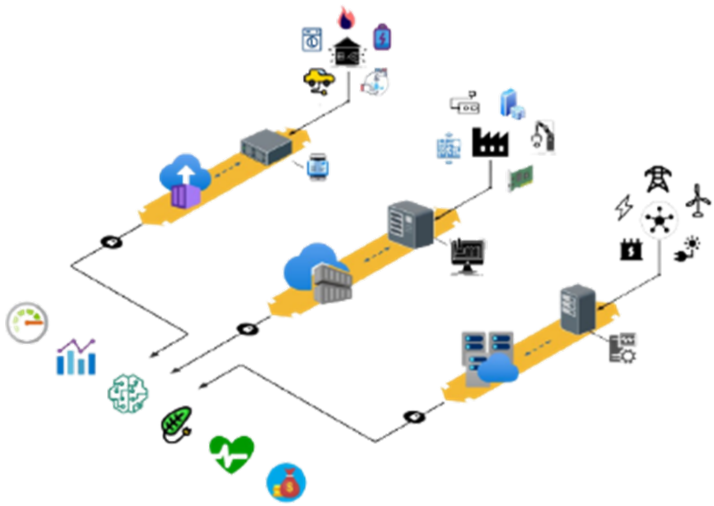


Figure 1.3: **Context and objectives of a smart monitoring process.**

Nevertheless, the process of digitisation has stimulated the development and adoption of increasingly advanced meters, which have in turn undergone a process of evolution over time. In fact, in recent decades, the metering sector applied to energy monitoring systems has developed considerably thanks to increased investments by states, authorities and companies. In particular, as mentioned above, the spread of smart metering systems is currently enjoying particular success in Europe, especially thanks to legislation in many countries that promotes, or even obliges, the replacement of old metering devices with modern smart meters. The process supported for years by the "European Smart Meter Industry Group" (ESMIG), focusing on achieving tangible benefits for consumers and society [33]. An example of this progress is represented by the considerable number of commercial metering solutions offered on the market today, or in the field of distribution by the Open Meter 2.0 produced by the company *e-distribuzione*, a state-of-the-art electronic meter that offers a series of remarkable technical specifications [34].

However, the success of smart meters is not only due to national and international policies triggered by the energy and climate crisis, but above all is linked to the multitude of advantages and opportunities that these devices now offer in every application. To date, there is no universal definition, but regarding the literature [35], it is possible to state that smart meters are electronic metering devices capable of providing energy services and information regarding the consumption, billing and operation of electrical, water, gas and heating systems.

Naturally, to be considered *smart*, smart meters must meet minimum requirements for measurement, processing, operation and control, according to European Recommendation 2012/148/EU [36]. Furthermore, ESMIG also highlights the minimum characteristics of a smart meter in terms of: remote reading; two-way communication protocols; support of tariff systems; and remote control over energy.

The great potential of smart meters, a fundamental characteristic that the following research seeks to highlight (Figure 1.4), is linked to the fact that: since energy consumption in all its forms pervades the operation of every single piece of equipment or complex system, the use of smart meters offers the consumer the possibility not only of monitoring, pricing and power quality analysis as is the case to date, but also of obtaining useful information to profile and disaggregate the monitored loads, assess their state of health, efficiency and how their behaviour evolves over time.

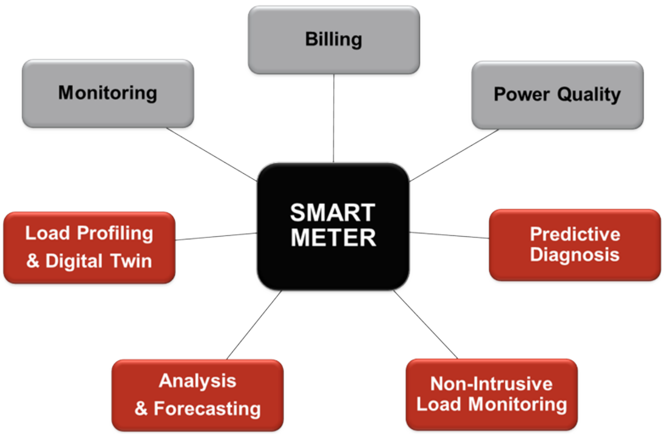


Figure 1.4: **Potential services and functionalities offered by smart meters.**

The real added value associated with the use of smart meters is evident due to the new functionalities and services offered associated with energy measurements, regardless of the application and physical context [37].

In this context, chapter 7 discusses some aspects on the design and implementation of innovative instruments, capable of operating in today's increasingly digitised energy scenario, in accordance with reference standards. Furthermore, an innovative smart meter prototype developed by the author is presented that is able to offer multi-physical (electrical and mechanical/thermal) monitoring with an integrated approach, while offering high flexibility and scalability.

1.6 Electrical Signature

Each device or electrical system, whether simple or complex, is characterised by its own unique "Electrical Signature" that distinguishes it from others. That is, any device, e.g. connected to the power supply network, when in operation, leaves an imprint of itself on the system that feeds it, the properties and characteristics of which depend on many factors, including: operating conditions, state of health, state of operation of the power supply system, etc.

An electrical signature therefore means everything the system or device leaves behind on the system to which it is connected, i.e. the entire harmonic spectrum of voltage and current absorbed by the load and/or electrical system being monitored. From a theoretical point of view, such information is complicated to obtain, as the absorption spectrum by definition is a concept that can be extended to infinity. It is no coincidence that the Fourier transform, the main tool for signal analysis, is applied to continuous signals in the $[-\infty \; +\infty]$ range (In 1994 Gilbert Strang, an American mathematician, described the FFT (Fast Fourier Transform) as t*he most important numerical algorithm of our lifetime*, and it was included in Top 10 Algorithms of 20th Century by the IEEE magazine Computing in Science and Engineering).

Of course, from a practical measurement point of view, to be able to analyse a signal, it must first be acquired, then sampled and discretized; this acquisition is characterised by a finite observation time. For these reasons, the entire world of signal processing is based on the DFT (Discrete Fourier Transform [38]) or most often on the FFT, which ensures shorter processing times thanks to certain algorithmic expedients that reduce the computational cost.

In this context, the concept of electrical signatures is frequently referred to throughout the following research, highlighting its peculiarities and associated metrological aspects, as well as the role it now plays in smart monitoring processes.

1.6.1 What and how it is necessary to extract the Electrical Signature

It is not always possible to use advanced analysis tools for detailed extraction of the electrical signature (time, cost, hardware and software limitations, etc.), or at other times a high degree of detail may not be required if the application under consideration does not need it. For example, if the monitoring activity performed on an electrical device is only aimed at recording the energy absorbed, such as billing operations, the meter will only need to be able to calculate the active power and integrate this value over time. At other times, for a slightly better view, in terms of the power of the monitored system, it may be useful to also display the "classic" parameters of apparent power, power factor and reactive power simultaneously, to also have an idea of the type of load connected to the system.

It is a different matter if the meter, in addition to performing pricing functions, is also called upon to perform Power Quality or predictive diagnostics functions (e.g. Motor Current Signature Analysis). In this case, the information that the meter has to extrapolate is much more and necessarily requires harmonic analysis of the signals.

Therefore, it is easily understood that it is the application that defines the degree of accuracy and detail of the extrapolated electrical signature. In particular, from a practical point of view, the latter will be represented by a finite and reduced number of parameters, which can be derived and calculated using appropriate metrics and standards.

1.6.2 IEEE1459 and IEC61000-4-30 Standard

In today's harmonically distorted electrical scenario, a set of power definitions is required that can maintain its veracity and reliably describe the properties of the system. The selection of appropriate power parameters has an impact on system efficiency. The criticality of the choice is reflected in the measurement algorithms and data acquisition systems, which are designed to validate the reliability of the expected results, cost savings and quality of service.

Power definitions in the electrical sector can be divided into two main categories [39, 40]: *energy-based definitions* and *shape-based definitions*. The former emphasises the transferred energy and power concerning the signal waveform, while the latter aims to ensure that the output of a signal is as close as possible to a pure sinusoidal waveform.

From a functional point of view, a power theory that can be considered valid should meet some basic requirements [41]. Firstly, it should apply to both single-phase and multi-phase systems, thus covering a broad spectrum of applications. Furthermore, this theory must be clear and easy to understand, as well as require minimal computational load, so that it can be implemented efficiently even in systems with limited resources (IoT and smart meters). Another crucial aspect is the reliability of the theory under non-sinusoidal conditions; in these cases, the metrics adopted must still provide accurate and useful results. It should also make it possible to assess power quality, identify possible sources of distortion and determining the burdens caused by harmonics on the power grid. Finally, there must be an accurate breakdown of the different power contributions, to optimise both the energy use and the economic costs of the grid.

However, despite the multiplicity of efforts and results proposed over the years by power theories [42] (*Bodeanu*, *Akagi-Kanazawa-Nabae*, *Emanuel*, *Czarnecki*, *Fryze*, *Sharon*, *Page-Filipski*, *Depenbrock*, etc.) it can be said that there is still no generalized theory that meets all the proposed criteria. For example, at present, under non-sinusoidal conditions and the presence of harmonics, var-meters give different results with errors of up to 200% because they present an operating principle based on definitions developed eighty years ago for balanced and symmetrical three-phase systems [43, 44]. In addition, the increasing presence of harmonics in the grid corresponds with increasing attention to their effects on the grid itself [45]. Although many current measurement specifications do not define accuracy requirements in the presence of harmonics, meters must be able to screen the energy transmitted at the fundamental frequency from the remaining harmonics. Due to the separation of fundamental and harmonic components, for each power term, the IEEE 1459 Standard proposes an optimal set of parameters, suitable for smart meters [46].

The publication of the IEEE 1459 Standard represents, without a shadow of a doubt, an important reference point for Power Theory. Furthermore, the scientific community strongly supports the mutual integration [47] of Standard IEEE 1459 and Standard IEC 61000-4-30 [48]; this would simultaneously include both the study of power flows and the evaluation of power quality parameters. This would lead to a deeper understanding of the phenomena related to energy utilisation. The IEC 61000-4-30 standard defines the measurement methods, time aggregation, accuracy and evaluation, for each energy quality parameter to obtain reliable, repeatable and comparable results. IEC 6100-4-30 standardises the measurements of: Power frequency; Supply voltage magnitude; Flicker; Voltage dips/sags and swells; Voltage interruptions; Supply voltage unbalance; Mains signalling voltage; Rapid voltage changes; Magnitude of current; Current unbalance; Voltage and Current harmonics, and interharmonics (IEC 61000-4-7 [49]).

The combination of these concepts and definitions is not just a pure mathematical formalisation but has as its goals the evaluation of the quality of electricity transmission and utilisation, the improvement of pricing, and the development of more accurate measurement methods. In this context, the use of smart meters certainly represents a key element, as they provide the necessary capabilities to continuously monitor and improve energy management.

Therefore, thanks to smart meters and the ability to extract all these parameters and indices (features), there is the possibility of implementing a multitude of new digital services and functionalities, aimed at fully meeting the Smart Energy objectives. Monitoring, billing and Power Quality, but above all the implementation of techniques and algorithms capable of extracting useful information to profile and disaggregate the monitored loads, assess their state of health, define feedback and efficiency retrofits are just some of the potentialities offered. A true energy intelligence is at the heart of the energy digitisation process.

1.7 Smart Meter Influence Parameters

As previously stated, to be considered "smart", smart meters must possess minimum measurement, processing, communication and management and control requirements. In general, it is fundamental to highlight that, although there is no complete standardisation in this regard, the effectiveness and efficiency of a network of metering and sub-metering systems are closely related to (Figure 1.5:

- *i)* the quality and quantity of measurement information collected from the field;
- *ii)* to the ability to convey the system's information quickly (concerning the dynamics of the application) and reliably.

The first property refers to the Quality and Quantity of the measurement information extracted from the system or more generally to the *Monitoring Quality* (MQ) and the *Electrical Signature Quality* (ESQ), which certainly also influence the cost of the smart meter; while the second property is related to the communication system employed by the smart meter.

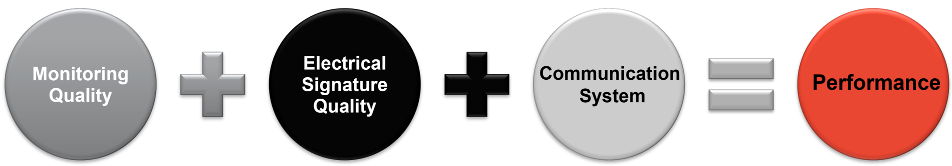


Figure 1.5: **Influencing parameters that have the greatest impact on the performance of a smart monitoring process.**

Thus, the MQ, the ESQ and the communication methodology implemented represent fundamental pillars in Smart Monitoring processes. The accuracy of the sensors and the measurement chain, the sampling frequency of the data, their resolution and the reliability of transmission play a crucial role in generating reliable information on energy consumption. The quality of the final result is closely linked to these properties of the smart meters.

1.7.1 Monitoring Quality - MQ

It refers to the metrological capabilities of the smart meter, i.e. it reflects the accuracy required by smart meters and defines the precision of energy consumption measurements. MQ is a crucial parameter for assessing the effectiveness of the metering system. Typically, meters are classified into different accuracy categories, such as classes A, B and C, according to IEC EN50470-1/2 [50, 51]. The choice of accuracy class greatly influences the quality of the collected data. For example, class A meters offer far less measurement uncertainty than class C meters, but at the same time, the cost is higher.

It should be emphasised that an incorrect acquisition of energy consumption (data collection) has repercussions on the entire analysis process. This is an aspect that is often considered less relevant, but which has greater consequences on the quality of the final results, as any measurement errors will propagate throughout the process regardless of the type of application. From the acquired quantities, typically voltage and current, other parameters, quality or system performance indices can be determined, and AI algorithms can be implemented for energy efficiency, diagnosis and energy retrofit, in accordance with smart energy objectives.

Therefore, as data acquisition is commonly related to the use of meters and smart meters installed in the vicinity of the electrical systems being monitored, the accurate definition of the MQ parameter becomes essential to ensure the reliability of measurements and the representative of the data acquired.

1.7.2 Electrical Signature Quality - ESQ

It refers to the computational capabilities of the smart meter, i.e. the number of electrical parameters extracted from the electrical signature of a monitored load or electrical system.

ESQ represents a highly technical parameter in smart monitoring processes; as mentioned earlier, the electrical signature represents everything a device leaves behind once it is powered, e.g. the entire harmonic spectrum of voltage and current absorbed. The ESQ allows one device to be accurately distinguished from others, as each device has a unique electrical signature that distinguishes it from other devices.

However, it is important to emphasise that an indiscriminate increase in the number of measured parameters (i.e. a high ESQ) does not always benefit the process in question, as many of the extracted features may have a low sensitivity to variations in the monitored system. When this happens, the increase in the number of measured features could lead the analysis algorithms to make wrong decisions, e.g. in a Load Profiling process to under- or over-estimate the actual number of energy states of the monitored system, as analysed in [52, 53]. No less important is the fact that the more parameters one decides to measure and/or calculate on board the measuring instrument, the higher the hardware and software costs to be borne; just think of the parameters relating to the IEC 61000-4-7 standard [12], which to be measured require the use of devices capable of performing a frequency analysis through FFT (Fast Fourier Transform), hence the use of high sampling frequencies.

Therefore, the high number of non-significant characteristics may in some cases produce worse results than the use of traditional power indices such as active power, non-active power and apparent power. In other situations, it may be necessary to push the quality of the monitored electrical signature to high levels, including harmonic information. Therefore, it is crucial to conduct a careful and balanced analysis of ESQ parameters, sometimes using feature selection algorithms, with the aim of monitoring and analysing only those parameters that are highly sensitive to changes in the operational state of the monitored devices. The careful choice of parameters is therefore essential to ensure efficient, effective and intelligent monitoring.

1.7.3 Communication system

Smart metering applications typically favour communication technologies that have particular aptitudes for operating in industrial environments, with good robustness to electromagnetic interference, and that are also characterised by ease of installation, integration with other industrial devices, and above all are inexpensive to implement [32]. For these reasons, despite the advantages of wireless solutions, in industrial environments, the choice typically falls on systems based on wired technologies. In addition, whenever possible, attempts are made to exploit existing communication infrastructures; the following is a brief description of some of those most frequently used in smart monitoring contexts.

For example, in energy distribution networks, when there is no ad-hoc network for communication and little data to exchange, smart meters implement PLC (Power Line Communication) technology. That is, a much higher frequency carrier signal is superimposed on the electrical current of the distribution system, which can then be easily separated using filters. In this way, the distribution system current and the data signal share the same transmission medium. A large number of devices can be connected even over long distances with data rates of up to 14 Mbps. Today, PLC systems in modern smart grids are being replaced by the

M-Bus (Meter-Bus - EN 13757). Developed by the University of Bremen and the University College of London, it is a simple and cost-effective European standard for networking and remote reading of smart meters. The system is fully compliant with the European standard EN 1434; it offers a high number of connectable devices, robustness, minimal cost and acceptable transmission speeds.

In industrial networks and the field of distributed automated systems, we find "Fieldbuses", a term set in the IEC to define the communication standard between different devices, which can be control or field devices (sensors). Serial standards for fieldbuses include RS-485 and CAN (Controller Area Network - ISO 11898-1). Initially applied in the automotive sector, CAN is now also used in many embedded industrial applications, where a high level of noise immunity is required. Another widely used standard is Modbus, a serial communication protocol consisting of a single master and slaves (max. 247). The master is the device that establishes communication and exchanges data with each of the slaves. The slaves are the smart meters installed in the system and the master is the central unit that manages, coordinates, interrogates and records the information received in special databases. The Modbus protocol was born and exalts its characteristics in industrial environments, guaranteeing stability and reliability even over long distances (max. 1200 metres) in the presence of disturbances.

Finally, among the most popular communication technologies that smart meters implement today, one cannot miss the Ethernet protocol. Currently, as a wired technology, it covers more than 70 per cent of the entire home networking market and is now a standard present and distributed in all companies, homes and buildings. It allows data of all kinds and types to be exchanged, guaranteeing low costs, high bandwidth, and reaching transmission speeds of over 1000 Mbps. The cabling is extremely simple, modular, and hierarchical, and thanks to appropriate measures, it is possible to make the system robust to electromagnetic noise.

Thus, there is no single communication technology for smart meters, but the choice depends on the application context. The "best" solution is the one that offers features and performance that are perfectly compatible with the application specifications with the industrial need to keep implementation and development costs sustainable and competitive.

1.8 Cyber security in the smart energy field

One of the main issues related to digitisation is data confidentiality, which becomes crucial in the context of energy consumption monitoring. The increasing integration of digital technologies and smart metering systems, such as smart meters, exposes energy infrastructures to an increasing number of cyber attacks [54]. Indeed, the collection of detailed data by devices such as smart meters increases concerns about data privacy and ownership [55]. These attacks can have serious consequences, such as the theft or manipulation of data, and, in extreme cases, compromise the stability of the electricity grid, with extensive economic and social repercussions. To get an idea, in the context of the Smart Grid, Advanced Metering Infrastructure can pave the way for hackers who might attempt to control smart meter switches to cause load fluctuations, or even manipulate and alter the load requirements of the grid. The result is that power flows are altered, compromising the stability of the electricity system, and creating the possibility of a domino effect that can lead to a blackout. A cyber attack can bring entire infrastructures to their knees and cause huge losses. According to an analysis conducted by Siemens [56], approximately EUR 223.5 billion in total losses incurred by small and medium-sized enterprises in Germany alone in 2021 were recorded. The value of unreported cases is probably higher.

It is evident that in this scenario, energy companies, which traditionally only dealt with system engineering processes (such as design, implementation, integration, procedures and maintenance), must now integrate cyber security services and technologies into these processes. This can lead to significant changes in the configurations, capabilities and constraints of new systems.

However, today there is a significant gap between the Information Technology level and the Operational Technology level. While continuous IT security measures in Information Technology are already taken for granted in many locations, the situation is unfortunately different in Operational Technology. This is why it is essential that the understanding of cyber security of energy systems also exists at the operational level. In practice, a comprehensive and systematic approach is needed to ensure security and multi-level protection against cyber attacks, as recommended by the international standard IEC 62443 [57] and the "Security of Industrial Automation and Control Systems" (IACS). This standard concerns all stakeholders: operators, system integrators or manufacturers. Everyone has their area of responsibility. This is the only way to guarantee cyber security holistically, with an end-to-end system approach.

Furthermore, according to an IEA report [54], in the operational environment of energy, there are five critical cyber security concepts to be understood as shown in Figure 1.6:

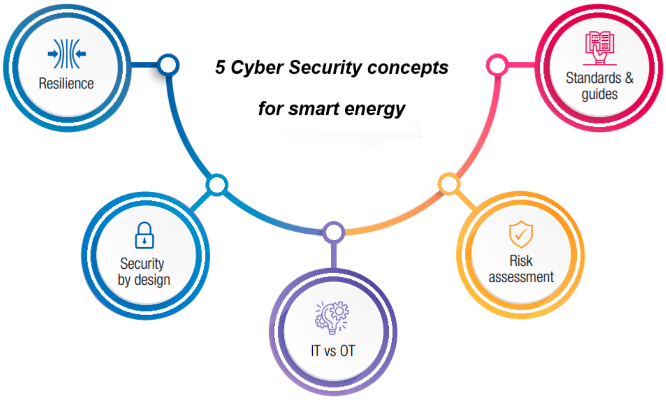


Figure 1.6: **Five cyber security concepts for smart energy.**

- *Resilience*: It must be the overall strategy to ensure business continuity. Resilience includes security measures that mitigate impacts before, during and after incidents. It is a process of continuous improvement that requires a comprehensive approach, combining cybersecurity techniques with systems engineering and operations to prepare for, adapt to and recover quickly from disruptions. Information sharing and interoperability are crucial elements of resilience. Resilience is defined as the "*ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents.*"

- *Security by design*: This is the most cost-effective approach to security. Security must be built into systems and operations from the outset, rather than added later. This principle also applies to existing systems, where safety must be integrated during upgrades and retrofitting. Security by design combines organisational policies with security procedures and supporting technologies, including physical and logical techniques such as access control and authorisation management.

- *IT and OT*: Although similar, they have significant differences. Operational technologies (OT) in the energy context have different security requirements than information technology (IT), mainly due to the physical consequences that security incidents can cause in energy systems. While IT focuses on data confidentiality, OT prioritises data availability, authentication and integrity. The increasing interconnection between IT, OT and IoT increases vulnerabilities, requiring appropriate security measures based on a risk assessment.

- *Risk assessment and mitigation*: Fundamental to improving security. It is necessary to assess the organisation's risk exposure and identify vulnerabilities, estimating the impact and likelihood of incident scenarios. The risk mitigation strategy must consider operational constraints and costs and must be continuously updated through periodic reviews or in response to security incidents.
- *Cyber security standards and guidelines*: They must support the risk management process and the establishment of security programmes and policies. Existing standards and guidelines must be used to improve resilience, security and interoperability in the OT environment, selecting the right ones for the right purposes at the right time.

In order to address the growing threats, it is therefore essential that all actors involved in the energy sector integrate cyber security into their corporate culture in order to first and foremost safeguard the consumer and the infrastructure involved. From designers to system integrators to operators, everyone should adopt and apply cyber security practices in their organisational processes and structures.

Therefore, in a context where cloud-based smart monitoring solutions and the Internet of Things (IoT) are becoming increasingly prevalent, especially among small and medium-sized enterprises and in the residential sector, ensuring the security and confidentiality of transmitted data is crucial to prevent serious economic and social consequences.

In detail, confidentiality can be seen from a double point of view: the security side and the attacker side. The first one regards the need to make the system secure from an authorized entity, user, or system. Together with integrity and availability, confidentiality is one of the three pillars of the CIA (Confidentiality, Integrity, and Availability) triad that must be guaranteed to implement an information system that is as secure and resilient as possible. They aim to ensure that information has not been modified and guarantee that only legitimate users have access to the information when they need it [58]. Data must be protected by encryption and decryption mechanisms, two-factor authentication, security tokens, and so on. The most common encryption systems implement symmetric and asymmetric algorithms: Advanced Encryption System (AES) and Triple-DES (3DES) belong to the first category. The second one includes, among the others, Rivest-Shamir-Adleman (RSA) and Elliptic Curve Cryptography (ECC) [59]. These algorithms aim to start from plaintext and obtain a ciphertext by applying mathematical functions that characterize the computational complexity to be resolved, determined by the length of the encryption key, which is a string of bytes. If no encryption method is applied, data are transferred as plaintext and subject to the risk of cyber attacks such as sniffing, profiling, eavesdropping and unauthorized interception by third parties [60], allowing reading and interpreting the information. For example, as demonstrated in the author's previous activities [61, 62], by leveraging the Side-Channel it is possible to go and profile activities performed by a user or more generally running on an IoT device, thus also on smart meters.

This requires a delicate balance between the protection of sensitive information and the need for utility innovation and operations. For example, security protocols, although essential, often do not offer sufficient protection against sophisticated attacks, leaving open vulnerabilities that can be exploited through unconventional methods, such as side-channel attacks.

The concept of "side channels" refers to information unintentionally emitted by a device during its operation, such as electromagnetic emissions, energy absorption or temperature variations. These emissions can be monitored to gather sensitive information, even without direct access to systems or data. For example, as demonstrated in [62, 63] and shown in Figure 1.7, by monitoring the electromagnetic field emitted by an IoT device, it is possible to identify what type of application is running on the device, what type of web-mail the user is using and thus generally spy sensitive information for fraudulent purposes. Furthermore, it is possible to identify whether a system uses robust security protocols by monitoring the electromagnetic field emitted during data transmission. This type of analysis makes it possible to assess whether data is transmitted unencrypted or encrypted, taking advantage of the fact that encryption requires a higher computational load.

In this context, chapter 6 analyses these aspects and proposes an innovative approach to detect the security of communications by monitoring and analysing the electromagnetic emissions of a device during data transmission, intending to identify possible vulnerabilities in security protocols, using Side Channel [64]. The proposed solution aims to be integrated into modern smart meters, improving cyber security and offering a more robust defence against cyber attacks.

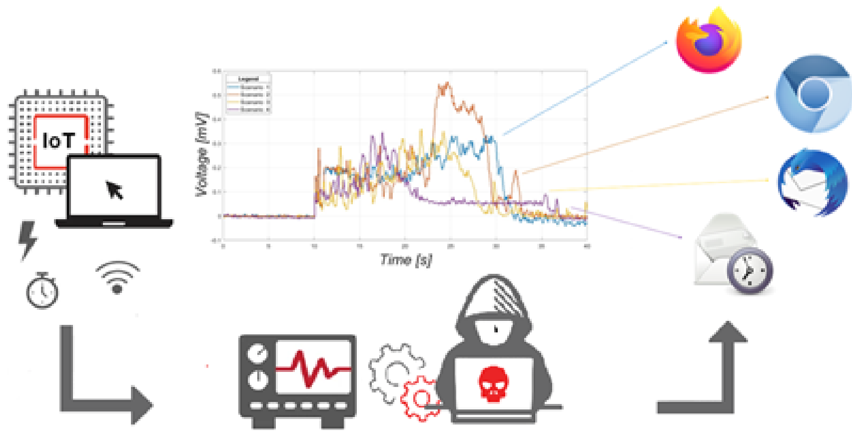


Figure 1.7: **The Side Channel concept: how a hacker can breach data security and privacy.**

1.9 Smart Energy applications

In the context of the digitisation and smart use of energy, the field of possible applications is much broader than one might imagine, encompassing a wide range of solutions aimed at improving efficiency, sustainability and intelligent management of energy resources. The following is a summary of some of the applications that will be explored and studied in the following chapters.

1.9.1 Digital Twin

In the context of the evolution of energy systems towards digitisation, the Digital Twin concept offers the opportunity to create virtual replicas of simple or complex physical systems, enabling the optimisation of the development and testing phases of algorithms and methods aimed at monitoring, analysis, management and optimisation of energy processes.

The use of the digital twin for optimising Smart Monitoring processes can have a significant impact on the management of electrical systems, both simple and complex. The digital twin makes it possible to monitor, control and optimise the real system through its virtual counterpart, as shown in Figure 1.8. This technology finds application in several sectors, including energy systems, enabling more efficient management, optimisation of smart energy management processes and predictive diagnosis and maintenance [65].

This is due to the possibility of simulating any operational scenario on which virtual policies and efficiency and optimisation techniques can be implemented and tested. In complex electrical systems, such as distribution networks or industrial plants, the use of the digital twin to optimise Smart Monitoring processes becomes even more relevant [66]. The complexity of systems requires advanced data management and detailed modelling to identify correlations and interactions between different components. This makes it possible to improve the accuracy of algorithms, e.g. for predictive diagnosis [67], by identifying potential failures even in complex scenarios.

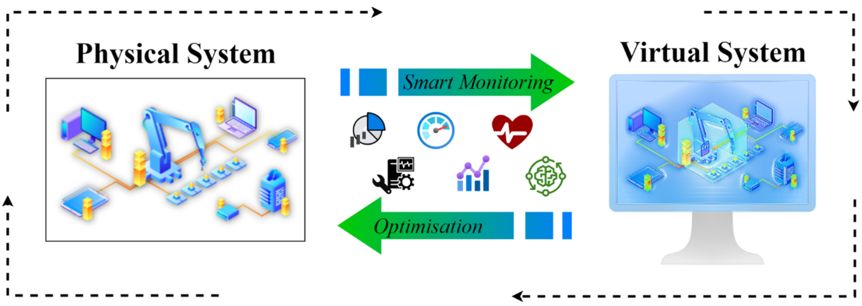


Figure 1.8: **Digital twin concept and how it can improve smart monitoring applications.**

In this scenario, Load Profiling is a useful tool for the creation of the digital twin model itself. In fact, by identifying and characterising, according to appropriate criteria, the operational states of the monitored physical system, it is possible to construct a virtual representation of it. In this way, it is possible to obtain a numerical, or analytical, model that serves as the digital counterpart of the physical system, indistinguishable for practical purposes. Practically, energy flow management can be improved and made more efficient, in line with smart energy objectives.

However, there are still some limitations (data integration and reliability, scalability, privacy and security, etc.) that can be addressed to further improve the effectiveness and applicability of this technology [68]. Among these, data reliability refers to the quality and goodness of the data used to feed and build the digital twin, which can affect the accuracy of simulations and analyses. If the input data collected in the field does not correctly describe the system to be modelled, the digital model will be far removed from the real one. This requirement is essential and is closely linked to the measurement chain involved in the initial Smart Monitoring process, from which the input characteristics for the digital twin are measured using smart meters, and then appropriately extrapolated. It therefore becomes of paramount importance to understand how data quality affects the analysis process. In detail, again following a measurement approach, the concept of quality is related to the MQ and ESQ parameters mentioned above.

In this context, chapter 2 presents an innovative energy dataset "eLAMI" [37] generated using an ad-hoc developed digital model of a residential system, which can overcome the current challenges related to data scarcity. eLAMI, based on real measurements, thanks to the implementation of combined stochastic models, highlights the need for a higher quality of the electrical signature in intelligent monitoring processes, expanding the "feature space" to be analysed by highlighting its importance in digital analysis processes based on Machine Learning and Artificial Intelligence.

1.9.2 Load Profiling

To reduce energy consumption, it becomes of paramount importance to become aware of how much one is consuming and, consequently, to adopt energy-saving behaviour. Recent studies show that the main barriers to improving energy consumption are caused by consumers' lack of knowledge about the energy market and inadequate awareness of their consumption [69]. Consumers must first of all have a good understanding and knowledge of their consumption habits and how these behaviours influence their energy consumption profile and trends. It is therefore essential to provide the end user with specific and customised guidelines on how to use electricity efficiently, to reduce the energy, economic and environmental impact, while not interfering with the user's consumption habits and comfort.

To this end, an appropriate Load Profiling process can be useful in identifying the end user's consumption pattern, making consumption forecasts, formulating strategies for optimal management and defining the operating conditions and nature of individual devices. This analysis provides detailed information on electrical load behaviour, such as peak and low consumption periods, seasonal variations, usage trends and specific load characteristics [70]. Load profiling is crucial for planning and optimising energy resources, identifying potential energy savings, assessing energy demand and managing the electricity grid and electrical systems [71]. In practice, through Load Profiling it is possible to identify and characterise the operational states of operation of a monitored electrical device or complex system (Figure 1.9). Where operating state refers to a particular combination of voltage and current quantities describing a nominal and non-nominal operating state of the monitored electrical system, whether simple or complex.

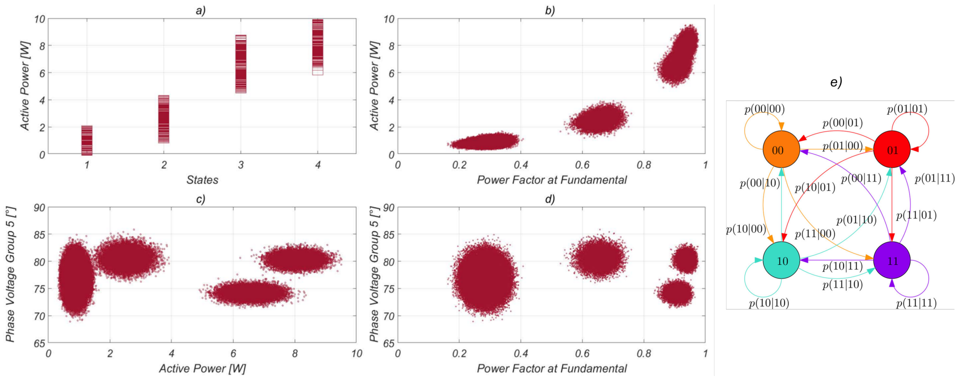


Figure 1.9: **Load Profiling: a-d) Identification and characterisation of the operational states of a device as the quality of the electrical signature changes; b) Concept of state machine representation of an electrical device.**

In this context, chapter 3 analyses the crucial role played by smart meters in load profiling applications [52], assessing the influence of monitoring quality and electrical signature quality in the process. The proposed methodological approach is not limited to electricity but can be extended to other physical quantities and multi-physical systems, offering a framework to define an MQ target and optimise the number of useful features for different application scenarios (*feature quality*).

1.9.3 Predictive Diagnosis

Diagnostics is a procedure aimed at identifying faults in equipment or systems through the analysis of collected data relating to relevant physical quantities. This activity requires the use of specific tools and techniques to examine the data and draw meaningful conclusions about the condition of the equipment or system (Figure 1.10). The main objective of diagnostics is to detect, locate and identify the fault to take the necessary corrective actions and ensure the reliability of the equipment in the short and long term.

Predictive Diagnosis is based on the use of advanced algorithms and analysis methods, such as machine learning and artificial intelligence, to predict and detect failures or anomalies in electrical systems in advance [72, 73]. By collecting real-time data from sensors and monitoring devices, predictive models can identify warning signals, performance anomalies, drifts or critical conditions that may indicate a potential impending failure. Predictive diagnosis allows preventive measures to be taken, maintenance to be planned proactively, maintenance costs to be reduced and the reliability of electrical systems to be improved [74].

Predictive maintenance, the next step in predictive diagnosis, is defined as maintenance "carried out following the identification and measurement of one or more parameters and the extrapolation according to appropriate models of the remaining time before failure". Predictive maintenance, in fact, through an upstream study of the device or process, aims to identify the critical, information-rich parameters to be studied. Once the quantities and parameters to be monitored have been identified, mathematical models and automatisms must be developed to signal an anomaly in operation or an impending failure.

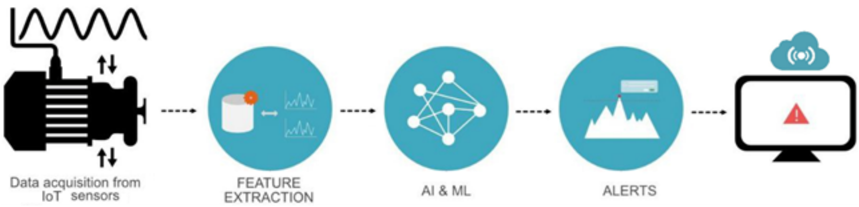


Figure 1.10: **Typical process aimed at diagnosing anomalies and faults of an electrical device under monitoring.**

It is evident that profiling a load and mapping it into a "state machine" can therefore offer various possibilities in terms of detection and predictive diagnosis since once a standard state profile of the load has been defined, diagnostic and efficiency evaluations can be made concerning standard operation according to certain criteria and thus understand whether the monitored load is moving away from a "state of normal operation". Of course, all these techniques and methods cannot be done without a data collection phase and thus a measurement process that inevitably influences all subsequent operations. The reason, as mentioned earlier, is related to the quality of the measured and collected data, in particular the MQ and ESQ parameters. These two factors play a crucial role. For this reason, it is necessary to combine traditional maintenance practices with new and more innovative strategies based on predictive actions, typical of smart energy.

In this context, chapter 4 presents a Load Profiling-based diagnostic methodology capable of determining the health status of the monitored device and anticipating the occurrence of a fault [75], to effectively direct maintenance resources where required. The proposed diagnostic method can be applied without prior knowledge of the monitored system and uses the ESQ as a key parameter, evaluating its sensitivity and impact on the diagnostic process.

1.9.4 Non-Intrusive Load Monitoring

Knowledge of the specific consumption of individual devices entails empowering consumers by making them aware of their energy consumption habits and how much this has contributed to total consumption. In general, There are two approaches to carrying out load monitoring: the first is the use of Intrusive Load Monitoring (ILM) methods and the second is the use of Non-Intrusive Load Monitoring (NILM) methods. In the ILM approach, the measuring device must necessarily be inside the plant and close to the monitored system, hence the term "intrusive". NILM consists of measuring electrical consumption using a meter, usually placed in the electrical panel upstream of the devices of interest [76, 77]. The qualification "non-intrusive" derives from the fact that no additional equipment is required at the ends of the devices to be monitored. As the electrical signatures of the devices overlap, with the NILM to understand the contribution of each device, these must be separated using appropriate algorithms, typically machine learning and AI. This operation is called aggregate consumption disaggregation (Figure 1.11).

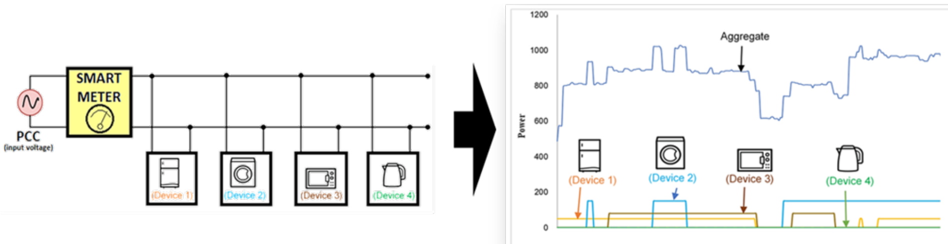


Figure 1.11: **Functional representation of a Non-Intrusive Load monitoring process.**

In this way, the combined consumption only needs to be monitored at a single point in the system, which has several advantages such as reducing the costs of installing the metering equipment, as there are fewer of them, and thus also of maintenance. On the other hand, there is a saying, known to all, which goes "*What is not there, will not break*" (Henry Ford).

Using NILM techniques, it is possible to determine the electricity consumption and operating conditions of individual appliances based on the analysis of the composite load measured by the main power meter [78]. The information can be used to formulate load planning strategies for optimal energy utilisation. Furthermore, especially in the residential context, it could be useful to illustrate within the energy billing following metering, not only the amount that has to be paid but also the consumption of each load and how much each appliance has contributed to this figure. Such an indication would not only help to detect any malfunctioning of the appliances but would also raise consumer awareness of environmental issues and make them more conscious of their impact.

In this context, in chapter 5 a new unsupervised approach for energy monitoring is presented, exploiting the advanced concept of Electric Signature Quality to overcome traditional limitations [79]. This offers new perspectives on intelligent energy management in the context of increasing digital evolution.

Chapter 2

Innovative Approaches to Advanced Smart Energy Applications: Overcoming Challenges with Simulated Datasets

2.1 Highlights

- **Challenges of Smart Energy applications**: Smart Energy applications are particularly challenging due to the scarcity of energy resources and high costs. Smart energy management is influenced both by user behaviour and by automated algorithms that aim to optimise and efficiently consumption and reduce waste.

- **Simulated datasets as an innovative solution**: Developing effective methodologies for monitoring consumption requires large amounts of data, which are detailed and often difficult to obtain due to the cost of monitoring campaigns. The "eLAMI" simulated dataset [37], based on real measurements, overcomes these limitations by offering over 400 discriminating electrical parameters on 36 household appliances in a residential context.

- **Improved electrical signature quality**: eLAMI highlights the need for improved electrical signature quality in intelligent monitoring processes, expanding the "feature space" to be analysed by highlighting its importance in digital analysis processes based on Machine Learning (ML) and Artificial Intelligence (AI).

- **Stochastic models for realistic scenarios**: To ensure fidelity with real scenarios, the proposed data simulation approach implements combined stochastic models that simulate energy consumption and manage state transitions for each load. The data produced, while only considering nominal operating conditions, are suitable for most Smart Monitoring applications.

- **Data validation and accessibility**: eLAMI dataset has been experimentally validated by comparing simulated data with real measurements. The data is publicly and freely accessible on the *IEEE Dataport*, providing scientists with a valuable resource for research and innovation in the field of Smart Monitoring and Energy Digitisation.

- **Applicability and future development**: The data produced by eLAMI is suitable for numerous Smart Monitoring applications, with possible future development in fault and anomaly simulation to optimise fault identification and localisation algorithms.

2.2 Introduction

In this new paradigm, in which energy efficiency and the development of new digital services based on the measurement of energy parameters have become strategic, smart meters assume a fundamental role. As highlighted in the previous chapter (chapter 1), on the one hand they perform the primary task of monitoring energy consumption; on the other hand they can provide new quantities useful for modern smart energy applications. These quantities include those related to the electrical signature of a device, power quality and the trend of energy use over time, to name a few, which could enable the implementation of new high value-added services for energy and facility management. In other words, the smart meter may be the key technology to implement modern algorithms and emerging techniques in the field of smart energy applications, such as load profiling, load disaggregation through Non-Intrusive Load Monitoring (NILM), digital twinning of equipment, and predictive fault detection and diagnosis on both plants and networks.

In more detail, the aforementioned techniques are generally based on machine learning algorithms or optimisation techniques that exploit electrical parameters related to the electrical signature of a load and/or power quality parameters.

Whichever approach is followed, all these techniques require the implementation of two fundamental steps to reliably train and tune the algorithms to the case study under consideration:

- *a)* the accurate measurement of energy consumption and parameters related to electrical signatures and other parameters that depend on the devices involved;
- *b)* monitoring over a sufficiently large time interval to acquire an adequate amount of data (monitoring campaigns).

The first step *a)* is crucial as it strictly influences the quality and quantity of the information collected. It is very important to have energy measurements characterised by low uncertainties and, at the same time, to provide various energy parameters, such as harmonic and inter-harmonic power, current and voltage values, total harmonic distortion, power factor, etc., that can characterise how a device, or a group of devices, is consuming electrical energy. In practice, it is crucial to ensure an adequate level of electrical signature quality - ESQ (subsection 1.7.2.

Concerning the second point *b)*, monitoring over large time intervals is very important not only to provide big data to the intelligent energy algorithms but also to enable the algorithms to work on operating conditions that provide reliable information about the monitored process or equipment. For example, to optimise the energy consumption of a household, it is important to monitor consumption patterns considering different days and the effects of seasonality. Similarly, in an industrial context, it is strategic to carry out monitoring campaigns such as to include variations in production and work cycles to define, for example, possible correlations with product production and sales volumes. Another example, such as the diagnosis or predictive maintenance of devices and networks, to predict equipment failures, it is important to have a reliable monitored energy footprint that is true to the energy status of the devices considering all possible operating conditions of the devices.

Since the above-mentioned requirements impose to perform very expensive and time-consuming measurement campaigns, in the last years some datasets have been proposed in the literature to facilitate the development of new algorithms addressing the cited emerging needs. Many are papers that propose the use of a dataset to train or tune smart energy algorithms. In particular, real datasets are composed of data, collected on the field, while simulated ones are obtained through suitable software simulators.

However, these datasets do not fulfil all the requirements for effective use of the data: the limited amount of electrical parameters monitored, the variability of the data, the seasonality, the proximity to real scenarios and the definition of current operating states are just some of the missing or incomplete information that make them unsuitable for modern Smart Energy applications.

To overcome these limitations, an innovative energy-electricity dataset is presented in this chapter. The main advantages of the proposal are: *i)* the variability of the data, in terms of the operating states of electrical loads and the adoption of appropriate consumption models; *ii)* the total number of electrical parameters available (433 in this case), which is enormously superior to the aforementioned datasets, such as the complete analysis of frequency behaviour and the calculation of harmonics; *iii)* the seasonality of the data. Furthermore, the presented dataset is a hybrid solution between simulated datasets and those based on real data. In fact, it is generated through simulation, starting from real measurements, and customised employing an effective calculated variability model. Finally, it was validated with an additional *a-posteriori* measurement campaign on real loads. From the output shown, the intention is to highlight how important it is today to ensure a higher Electrical Signature Quality in intelligent monitoring processes. in accordance with what is mentioned in subsection 1.7.2. The developed dataset, namely eLAMI [37], is made publicly available to the whole research community at [80] *(download here)* through a modular structure, allowing customized downloads and analyses.

The structure below is as follows: first, the state of the art regarding public energy datasets is briefly addressed; then the design of the synthetic data generator is described, highlighting its requirements and properties. Finally, some results of the proposed dataset are reported and appropriate observations and considerations are given.

2.3 Background

The growing demand for new monitoring devices with smart algorithms and techniques has led to the development of several datasets capable of tuning performance.

In Table 2.1, some examples of public datasets with data collected from the field are shown; they differ for the number of devices, number and type of provided electrical parameters and length. In the following, they are briefly described.

Table 2.1: **Main Characteristics of Some Public Dataset Based on Real Data**

Name	Number Appliances	Parameters	Period
AMPds[81]	20	P,Q,S,V,I	1 year
AMPds2[82]	20	P,Q,S,V,I	2 years
BLUED[83]	50	P,Q,V,I	1 week
Dataport[84]	8598	P,S	4 years
DRED[85]	12	P	6 months
ECO[86]	45	P,V,I	8 months
ENERTALK[87]	75	P,Q	1714 days
iAWE[88]	63	P,Q,S,V,I	73 days
REDD[89]	92	P,V,I	119 days
REFIT[90]	20	P	2 years
UK-DALE[91]	109	P,Q,S,V,I	2247 days

- **AMPds** [81] The Almanac of Minutely Power dataset is a public dataset, published in 2013, containing 1 year of collected data of residential appliances from a single household in Canada. This first version contains measurements of electricity, water and natural gas at one-minute intervals, for a total of 525600 readings per year per meter.

- **AMPds2** [82] This second version of the AMPds dataset differs from the previous one only in the number of total readings, 1051200, corresponding to 2 years of acquisition.

- **BLUED** [83] The Building-level fully labelled dataset for electricity disaggregation was released in 2012 with 1 week of electricity data from 1 building in the USA. This dataset contains not only the steady-state but also the state transition of each appliance.

- **Dataport** [84] The Dataport database was created by *Pecan Street Inc.* and published in 2015. It contains electricity data from 722 houses and commercial buildings across different cities in the USA. As it has a sampling period of 1 minute for aggregate and appliance signals, this is considered a low frequency dataset.

- **DRED** [85] The Dutch Residential Energy Dataset was released in 2015 and contains energy consumption data from a household in Netherlands, with a total duration of over six months. It includes electricity measurements for the aggregate and sub-metered signal of each device.

- **ECO** [86] Electricity Consumption and Occupancy dataset was collected in 6

Swiss households over 8 months. It contains data recordings of active power, voltage and current at low frequency sampling rate.

- **ENERTALK** [87] The ENERTALK dataset was created in Korea from 22 houses with a total period of 1714 days and it was published in 2019. It provides active and reactive power measurements (both aggregate and each device), with a sampling frequency of 15 Hz.
- **iAWE** [88] Indian Dataset for Ambient Water and Energy was released in 2013, from recordings of electricity, water and ambient data in a house in New Delhi, for a total duration of 73 days. The electrical data were recorded with a sampling period from 1 to 6 seconds over 63 electrical appliances.
- **REDD** [89] Reference Energy Disaggregation Dataset has been published in 2011. It contains 119 days of collected data from 6 households in the USA and includes both high and low frequency recordings.
- **REFIT** [90] The REFIT Electrical Load Measurements dataset includes cleaned electrical consumption data from 20 households in the UK from 2 years of recordings in 2016. It contains electrical data with a sampling period of 8 seconds and active power as the only parameter.
- **UK-DALE** [91] UK-Domestic Appliance Level Electricity was published in 2015 and it contains 2247 days of data by 5 residential buildings in the UK. Just like REDD, it reports high and low-frequency data and all appliances are sub-metered.

Collecting data to build a dataset is a fairly complex process. As long measurement campaigns have to be carried out, the process requires a considerable amount of time, effort, and instrumentation to measure and record data. One of the main limitations of the real datasets in the literature today is the small number of reported electrical parameters (almost 5 parameters - P, Q, S, V, I).

This could represent a limitation for algorithms in the field of Smart Energy. In particular, considering methods for load profiling, NILM and fault or predictive diagnosis, the optimal choice of needed parameters is still a research topic: therefore the availability of a large number of electrical quantities, able to define the complete "electrical signature of the load", could help in performing an accurate selection.

Furthermore, real datasets are often characterised by missing data due to several problems that may occur during the measurement campaigns, time mismatching between individual load data and aggregate data or possible errors due to malfunctioning and inaccuracy of the adopted instrumentation.

The absence of information about the current operating states of each device can also be a limitation for these datasets, e.g. in the case of supervised artificial intelligence algorithm training or in the definition of consumption quality as well as system efficiency indices. A solution to the aforementioned problems could be the simulation of data.

A simulated dataset does not require lengthy monitoring campaigns, saving time, costs, and instrumentation. All these advantages are provided as long as the simulation process is correctly implemented, which is not trivial in terms of suitable modelling and computational costs.

In literature, some simulated datasets are presented as reported in Table 2.2 and discussed below.

Table 2.2: **Main Characteristics of Some Public Dataset Based on Simulated Data**

Name	Number Appliances	Parameters	Period
AMBAL[92]	14	-	1 days
SHED[93]	66	P, S, V, I	14 days
SmartSim[94]	25	P	7 days
SynD[95]	21	P, S, V, I	180 days

- **AMBAL** [92] Automated model builder for appliance load dataset was published in 2017 and it comprises 14 domestic loads at a sampling rate of 1 Hz for a time duration of one day. The AMBAL dataset allows the user to build models using real energy consumption data, based on parameterised signature sequences. The main operational phase of the AMBAL dataset includes pre-processing, extraction of active segments, segmentation, and model fitting.

- **SHED** [93] Simulated high-frequency energy disaggregation dataset, released in 2018. It is a commercial dataset containing the power consumption of 66 buildings at a sampling frequency of 1/30 Hz. The data is generated synthetically and based on modelling the current flowing through an electrical device and is matched with the real model of electrical devices.

- **SynD** [95] SynD is a synthetic dataset that was published in 2020 and simulates readings of electricity consumption for a house for 180 days. The measurements campaign was based on the monitoring of 21 different residential devices from 2 households in Austria. In particular, the consumption patterns were observed, the absorption profiles of each device were then extracted and finally, the dataset was generated.

- **SmartSim** [94] A Device Accurate Smart Home Simulator for Energy Analytics was released in 2016 and is a simulated dataset of 1 week total duration. It uses the energy modelling of individual devices to build the final dataset to generate accurate domestic energy traces that are qualitatively and quantitatively similar to real energy data traces.

Despite the large number of simulated datasets in the literature, most of them still suffer some of the aforementioned problems, such as limited number of saved electrical parameters, absence of harmonic and power quality information of seasonality, monthly, and daily variability, as well as variability of operating states; furthermore, they often provide a low likelihood value with respect to real scenario profiles.

2.4 Design of Dataset generation

In this section, the design process of the eLAMI (electrical Loads Acquisition for Monitoring Instruments) dataset and its implementation is described. First, the main requirements that a modern energy data set must have to be able to offer smart services are discussed. Then, issues concerning the choice of simulator and possible solutions are addressed. Selected electrical loads, consumption models and a description of the simulator close the section.

2.4.1 Requirements

A modern energy dataset for monitoring and investigating consumers' energy behaviors must have specific characteristics. The main requirements, applicable to domestic or industrial scenarios, are:

a) High number of saved electrical parameters, both in time and frequency domain;

b) High likelihood to real scenario profiles;

c) Faithful representation of the devices;

d) Considering the metrological performance of commonly used energy smart meters;

e) Presence of Power Quality and harmonic data;

f) Appropriate observation times congruent with the objectives;

g) The current operating state of the monitored device.

As regards *a)* having a large number of electrical parameters allows for a better representation of the electrical signature of the load. In this way, for example, as also mentioned before, energy efficiency algorithms can drastically increase their performance. Therefore, in the eLAMI dataset, 433 electrical parameters are calculated at each measurement interval. In addition, an electricity scenario as close to reality as possible is represented in the above-simulated data set. In particular, the reported consumption refers to a family of 2 persons, one of whom works in smart working.

Having a good match between the simulated scenario and the real one, simply summarized as likelihood, is crucial as it offers the possibility, for instance, of training AI algorithms on consistent data, as mentioned in *b)*. This avoids possible mismatches between performance obtained in simulation and real scenarios.

As said in *c)* it is necessary to take into account both how the electrical energy is consumed, but also how the individual load behaves in terms of electrical operation in reality. In particular, equipment is represented here as “state machines”, simulating the corresponding nominal operating states. This choice turns out to be valid, having decided to simulate the assumed scenario in a permanent regime. Of course, in reality, between the different “operating states” there are transients that can lead to more or less marked variations in electrical quantities. However, these short variations, being of much shorter duration than typical measurement times, are negligible in the calculation of the parameters of interest.

As regards *d)*, furthermore, these variations can also be related to the natural duty cycle of the equipment or be due to the uncertainty of the monitoring system used [96]. eLAMI reports this variability thanks to the mathematical model for generating absorption profiles implemented.

As said in *e)* today, given the widespread use of electronic equipment, it can be said that the study of the harmonic behaviour of electrical loads is of great interest. For example, the analysis of the frequency spectra of voltage and current absorption of devices can provide useful information on the health of loads and in general of the entire system, also in terms of the quality of the power supply system (Power Quality). eLAMI in this case reports a considerable amount of harmonic and quality parameters.

About the observation time of the monitored system *f)*, it must be chosen in such a way as to meet the objectives of the applications for which it was hypothesized. Classification, clustering, NILM, Load Profiling, and energy retrofit algorithms in most cases aim at analyzing the system over sufficiently long time horizons. In this case, eLAMI refers to a time horizon of one year. As regards, *g)*, an operating state of the monitored device can be defined as a steady-state voltage and current joint profile, whose availability allows the dataset user to evaluate the proper load working cycle and extract electrical signature quality indices and detect possible incoming anomalies.

Indeed, referring to electrical signature as mentioned in section 1.7, it not only deals with the typical quantities (P, Q, I_{RMS}, etc.) but with the entire frequency spectrum of voltage and current profiles absorbed by the electrical load. Such informations are therefore also state-related, i.e. they can change for each operating state of the load.

Therefore, the proposed simulator must be designed to generate voltage and current profiles under all possible load states tested and for a predefined simulated time, to get the spectrum information. An issue raised at this stage is related to the way the frequency spectrum could be faithfully simulated. The approach here is to make measurements on real loads under different tested operating states and adopt acquired information as a basis to generate simulated profiles.

Based on the knowledge of these quantities and the known usage habits of the electrical loads, it is possible to create the dataset by using the acquired information. Any accidental failures or malfunctions that might occur in the real electrical system are neglected in the current status of the simulator. This is reasonable as these are very rare events in reality that, when compared with the simulation time frame, can be neglected. The simulator's modular structure would eventually permit to add such situations in a fairly easy fashion.

2.4.2 Electrical Loads Description

According to the aforementioned requirements of a new simulated energy consumption dataset for the residential appliances with innovative saved electrical parameters, namely eLAMI, has been developed. The choice of simulating a residential building consumption profile has the aim to provide a means with innovative characteristics compared to the datasets currently present in the literature for the evaluation of new techniques and algorithms in the field of Smart Energy, including NILM, Load profiling, Management Systems, and Energy Efficiency algorithms.

eLAMI refers to 360 days of simulation of a house having 36 connected appliances, as described in Table 2.3. But in the future other years will be added. The "ID" is the appliance identifier, N_S is the overall discrete number of tested

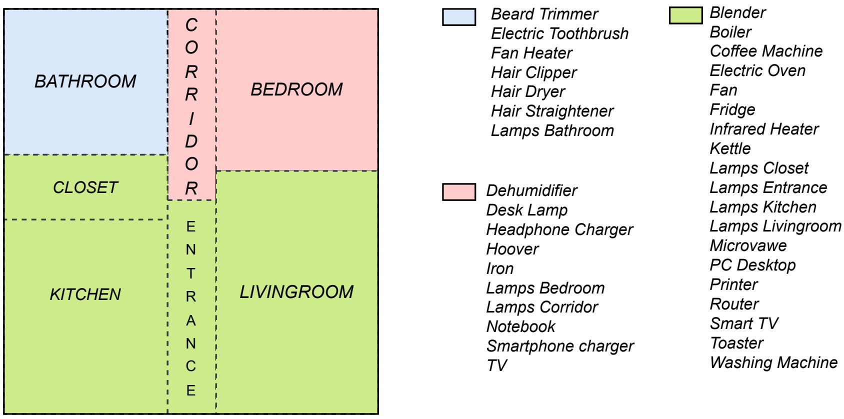


Figure 2.1: **House Scheme and Electrical Loads Distribution. The blue zone represents the *"Partial 1"* with 7 electric loads; the pink zone represents the *"Partial 2"* with 10 electric loads; the green zone represents the *"Partial 3"* with 19 electric loads**

operating states (including the OFF state) and the P_{Nom} is the upper bound each appliance can absorb, according to the manufacturer's indications. At each measurement interval, 433 electrical parameters are computed, whose details are reported in subsection 2.4.4. In addition to the information on the individual load, the same parameters are also calculated for the total aggregate and three partial sub-aggregates consisting of subsets of loads. In addition to the calculated quantities, current operating state is also provided.

The partial aggregates are provided for the three different identified zones of the virtual house. For each zone, a subset of loads was defined. The combination of loads for each sub-group was chosen to obtain aggregates with a progressive number of loads, as shown in Figure 2.1. This is an important feature for the structure of eLAMI as it offers researchers the possibility to test the algorithms on an increasing number of loads, therefore on an increasing complexity level.

Although all loads are connected in parallel, their supply is carried out by means of radial lines. Therefore, in eLAMI, the voltage at the terminals of each load is not the same but depends on the load conditions.

Moreover, the reported OFF state, for some devices, is an indication of a standby state. Therefore, the absorbed current is slightly different than zero.

Table 2.3: **Electrical Loads Specifications. Returns the appliance identifier (ID), the name of the loads (Appliance), the number of states tested (N_S) and and the maximum active power that each load can absorb (P_{Nom})**

ID	Appliance	N_S	P_{Nom} [W]
1	Beard Trimmer	2	4
2	Blender	2	60
3	Boiler	2	220
4	Coffee Machine	2	1200
5	Dehumidifier	2	190
6	Desk Lamp	4	10
7	Electrical Oven	3	2400
8	Electric Toothbrush	2	5
9	Fan	4	40
10	Fan Heater	4	1900
11	Fridge	2	140
12	Hair Clipper	2	6
13	Hair Dryer	3	420
14	Hair Straightener	2	65
15	Headphones Charger	2	5
16	Hoover	3	600
17	Infrared Heater	2	1350
18	Iron	2	1300
19	Kettle	2	2000
20	Lamps Bathroom	2	30
21	Lamps Bedroom	2	90
22	Lamps Closet	2	75
23	Lamps Corridor	2	55
24	Lamps Entrance	2	65
25	Lamps Kitchen	2	125
26	Lamps Livingroom	2	145
27	Microwave	2	1300
28	Notebook	2	60
29	PC-Desktop	2	300
30	Printer	2	750
31	Router	1	5
32	Smart TV	2	105
33	Smartphone Charger	2	25
34	Toaster	2	640
35	TV	2	85
36	Washing Machine	4	800

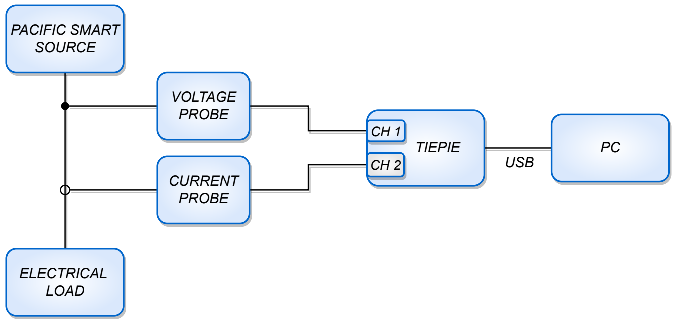


Figure 2.2: **Block Diagram of Data Acquisition Setup**

2.4.3 Simulation basis: data acquisition

In order to define the frequency spectrum of a load, as mentioned above, it is necessary to experimentally acquire its absorption profile. Through a measurement campaign in Industrial Measurement Laboratory (LAMI) in the University of Cassino and Southern Lazio, 36 residential typical electric loads (Table 2.3) have been acquired. Current and voltage waveforms for each devices has been recorded and get the corresponding reference profiles for use in data generation software.

The block diagram of the experimental setup for data acquisition is shown in Figure 2.2. The adopted power supply system is a Pacific Smart Source, an electrical network emulator which allows reproducing any mains profile both in terms of amplitude and harmonic content [97]. In particular, it has been used as arbitrary voltage generator to supply the electric loads.

In order to emulate real working conditions, the power grid voltage was first acquired and the corresponding harmonic characteristics were calculated up to the 50th harmonic order. The harmonic coefficients obtained, in terms of amplitude and phase, are used as an input for the Pacific Power Source. The emulated mains voltage profiles both with and without load, are shown in Figure 2.3, Figure 2.4 along with the harmonic contents. For clarity, the distribution of percentage harmonic coefficients from 2nd to 13th order is shown. The harmonic coefficients shown in Figure 2.4 were obtained by extrapolating the characteristics of the harmonics of the voltage signals and evaluating the amplitudes in percentage terms with respect to the corresponding fundamental tones.

Furthermore, it can be seen from the figures that there are differences between the voltages in different load conditions. In particular, the voltage under load is lower and has a slightly different distribution of harmonic coefficients. As expected, the voltage profiles of Figure 2.3 do not reproduce a perfect sinewave, since it contains the harmonics contributions.

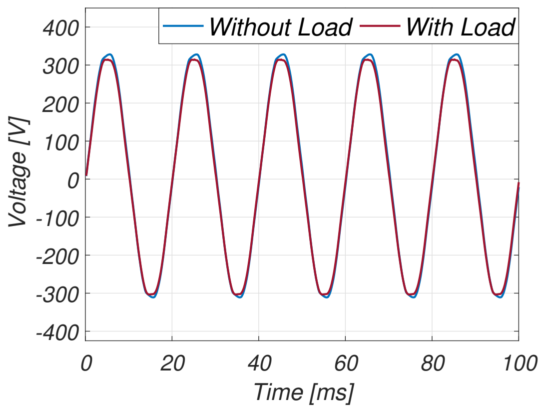


Figure 2.3: **Emulated Voltage profiles with load and without load**

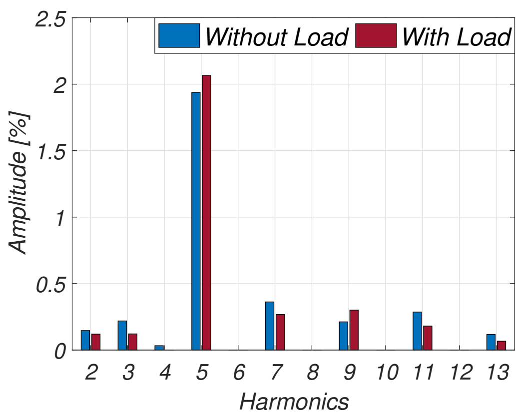


Figure 2.4: **Percentage harmonic coefficients normalized with respect to the fundamental frequency**

In Table 2.4, is reported a numerical comparison between the main acquired voltage and the emulated one, both with and without load. The compared values are: RMS value (V_{RMS}) of both the overall voltage and only the voltage first harmonic ($V_{RMS\text{-}F}$). In addition, the offset component (V_{DC}), the peak value (V_{PK}), and the total harmonic distortion (THD) voltage are also compared.

Table 2.4: **Comparison of some characteristics of the voltages: Acquired Main Voltage (V_{AM}), Emulated Voltage With Load ($V_{EM-Load}$) and Emulated Voltage Without Load ($V_{EM-NoLoad}$)**

	$\mathbf{V_{RMS}}$ [V]	$\mathbf{V_{RMS\text{-}F}}$ [V]	$\mathbf{V_{DC}}$ [V]	$\mathbf{V_{pk}}$ [V]	$\mathbf{THD_V}$ [%]
V_{AM}	231.35	230.82	12.79	326.27	3.94
$V_{EM-Load}$	232.27	231.99	10.06	327.31	4.85
$V_{EM-NoLoad}$	226.89	226.39	10.07	317.86	4.72

Through the use of a Tektronix P202A Hall effect probe [98], powered by a Tektronix 1103 power supply [99], with a transformation ratio of 100 mV/A, the electrical current flowing in the circuit was measured. Using a Tektronix P5200 differential probe [100], with a transformation ratio of 1:500, the voltage supplied by the Pacific to the electrical loads was measured. A TiePie HS5 [101] was used to acquire the measurements through a customized software developed in Matlab^{TM} environment. 30 repeated measurements (N_{ACQ}) were performed for each operating state tested. The iterated procedure allowed obtaining the corresponding average absorption profiles and the associated standard deviations for voltage and current waveforms. The sampling frequency (F_s) used for profile acquisition is 5 kHz. For each acquisition (of each load state) 25000 points (N_P) were acquired. The amplitude resolution of the acquisition system, through the TiePie Hs5, was set to 14 bits per channel, with a full scale of 0.8 for the voltage channel and 2 V for the current channel. Considering the conversion factors of the probes used, therefore (1:500 and 100 mV/A) this gives 400 V for the voltage channel and 20 A for the current channel. Values are chosen in relation to the electrical systems considered. All the sampling characteristics are summarized in Table 2.5.

Table 2.5: **Sampling characteristics used for the acquisition of electrical load profiles**

Specifications	**Descriptions**
F_s	5 kHz
N_P	25000
T_{OSS}	5 s
N_{ACQ}	30
A/D converter resolution	14 bit
Full scale of the voltage channel	0.8 V
Full scale of the Current channel	2 V
Voltage probe conversion factor	1:500
Current probe conversion factor	100 mV/A

2.4.4 Simulator Description

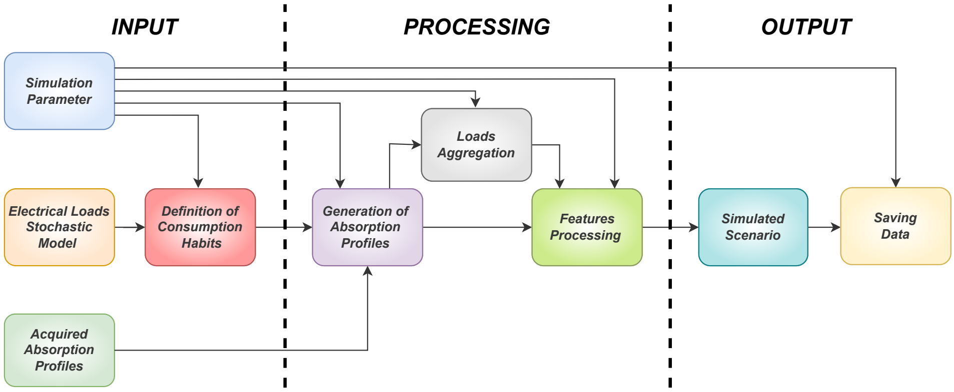


Figure 2.5: **Block diagram of the simulator composed of three steps: "INPUT", "PROCESSING" and "OUTPUT"**

The purpose of this section is to provide a general description of some of the fundamental parts that make up the innovative simulator created for the realisation of eLAMI, highlighting the procedures followed in the simulation. All processing operations were performed in Matlab^{TM} environment.

As shown in Figure 2.5, the simulator consists of three steps: (1) INPUT, (2) PROCESSING and (3) OUTPUT.

For each section, the chronological flow and the main operations are described.

1) The "INPUT" step consists of 4 macro blocks:

   1.1) In "Simulation Parameter" block, specifications for the simulation are defined, e.g. simulation interval (1 year), measurement time (5 s), and aggregation criteria, just to cite a few. The content in round brackets is the assignment of possible parameter values. They are sent to the following blocks, defining the characteristics of the electrical scenario to be simulated.

   1.2) In "Electrical Loads Stochastic Model", mathematical relations about operating state changes are defined according to output got by previous surveys performed by the authors in residential buildings.

   1.3) In "Definition of Consumption Habits", taking into account the many factors influencing the electric consumption and adopting the mathematical models defined in the previous block, along with the hypothesized simulation interval, typical consumption habits, or patterns, are defined and used as input to generate faithful absorption profiles. The behavioural consumption patterns, defined for each load, take into account daily variability and seasonality. This is made possible by the implementation of a stochastic process, studied ad-hoc for the assumed dynamic system. To explain the suitability of the implemented stochastic model to avoid a mismatch with real scenarios, in this simulation framework it is absolutely unlikely that the blender or hoover will switch on during the night as well as lighting or heating during winter periods for consecutive days is more likely than in summer times. In eLAMI, the defined stochastic model also considers all these factors. In this way, for each load, the days turn out to be dependent.

1.4) In "Acquired Absorption Profiles" contain the reference absorption profiles obtained as described in subsection 2.4.3.

2) The PROCESSING step is composed of:

2.1) "Generation of Absorption Profiles" is a block that, taking inputs as described before, generates the voltage and current waveforms related to the conditions to be simulated. Such signals are simultaneously sent to both "Loads Aggregation" and "Features Processing" to perform different operations, as described below. Such waveforms are referred to the i-th iteration for a specific instant of a simulated day and condition of each considered appliance. The compounded values define the "Current Operating State" of each load.

2.2) The "Loads Aggregation" block receives the output of "Generation of Absorption Profiles" and "Simulation Parameter" and aggregates individual loads in a macro-load condition, i.e. considers all appliances belonging to a specific category (e.g. bathroom) as they were one only aggregated load.

2.3) In "Features Processing", all electrical quantities assumed for individual loads and aggregates are calculated. For electrical parameters calculations, the simulator implements the definitions of Power in IEEE-1459, especially referring to single-phase non-sinusoidal case [46]. The calculated electrical parameters refer to: ${V_{RMS}}^{TOT}$ and ${I_{RMS}}^{TOT}$, V_{RMS} and I_{RMS} at the fundamental, of harmonics and DC components alone; active, apparent, non-active and distorted power; power factor and harmonics distorted parameters, for a total of 26 electrical parameters. Furthermore, for better identification of electrical loads signature, the simulator also implements the definitions of measurements in IEC61000-4-30 and IEC 61000-4-7 Standards [48, 49], regarding harmonics and interharmonics, including the RMS values of voltage and current groups up to the 50th harmonic order are calculated, including harmonic sub-groups ($\mathrm{SubG_rV}$, $\mathrm{G_rV_1}...\mathrm{G_rV_{50}}$; $\mathrm{SubG_rI}$, $\mathrm{G_rI_1}...\mathrm{G_rI_{50}}$) and the corresponding phase values of each group calculated for a total of 202 parameters. In addition, the harmonic index of the maximum amplitude tones of voltage/current in each group is also provided, the phase of each harmonic group and the current operating state, to achieve further 205 parameters. Considering the overall processing, the total number of electrical parameters reported in eLAMI is 433.

3) The "OUTPUT" step is composed of:

   3.1) In "Simulated scenario", the computed electrical parameters are packed considering the "simulation interval" (e.g. 1 day, 1 month, 1 year) parameter and their size also depends on the measurement time (e.g. 5 s), which is the time resolution over which the 433 parameters are computed. Future simulated years of eLAMI will be added to the main folder.

   3.2) In "Saving Data" block, a hierarchical structure is created for saving the dataset, as illustrated in Figure 2.6. The latter was created to make the data as much usable as possible for the end user. From a hierarchical point of view, eLAMI is divided into a first level "by months", then "by loads" and finally "by calculated electrical parameters". All information are stored in granular ".csv" files, one for each basic condition (day of the month).

2.5 Results

The aim of the work related to eLAMI, is to provide a dataset with innovative features compared to those currently found in the scientific literature, for the evaluation and development of new techniques and algorithms in the field of Smart Energy applications. Of course, it is of paramount importance that the dataset is physically consistent with real scenarios.

To this end, the dataset simulator is first validated, then some peculiarities of the dataset are highlighted, and finally, some examples of eLAMI applications in the field of Smart Energy are proposed, in particular Load Profiling, NILM and

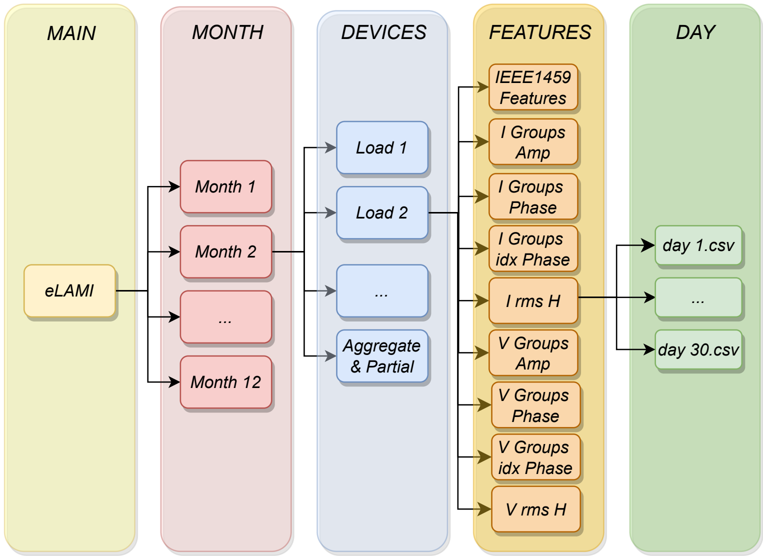


Figure 2.6: **Saving eLAMI Structure**

Energy Management systems. These examples highlight how important it is in the field of energy digitisation to increase the level of quality of the monitored electrical signature.

2.5.1 Validation of Dataset Simulator

For the technical validation of the simulator and the corresponding consistency of the generated data, a comparison between the measurements obtained from a real test and a simulated one has been carried out, by assessing their metrological compatibility. In particular, the electrical scenario assumed for the test, is composed of 3 real loads of eLAMI with different electrical characteristics, namely *"Fan"*, *"Fan Heater"* and *"Smart TV"*. They have been connected to the Pacific network emulator [97], then fed in parallel with the same voltage signal used for the creation of eLAMI reference profiles (subsection 2.4.3). At the same time, the absorption profiles, at the ends of every single load and the *"Aggregate"*, were monitored using a laboratory wattmeter, the Precision Power Analyzer WT3000 [102]. The same scenario, without WT3000 measurement instrument, has been replayed in the simulation environment, by starting from the reference profiles previously acquired. Test set-up settings are total test duration (1 hr), measurement time (5 s), and the total number of measurement points (720).

At the end of the test, a comparison was made between the results obtained in the two cases, with the aim of showing: *i)* a comparison between variability ranges in the case of real and simulated data; *ii)* the metrological compatibility of the simulated measurements, and thus of eLAMI, with real acquired values; the combination of *i)* and *ii)* leads to state the validity of the simulator implementation.

Starting from *(i)*, a comparison between the values obtained in the real and simulated cases is shown in Figure 2.7, in terms of variability ranges. In this figure, the behaviour of V_{RMS} (Figure 2.7.a), I_{RMS} (Figure 2.7.b), P (Figure 2.7.c) and S (Figure 2.7.d) are reported, for each individual considered load and its corresponding aggregate.

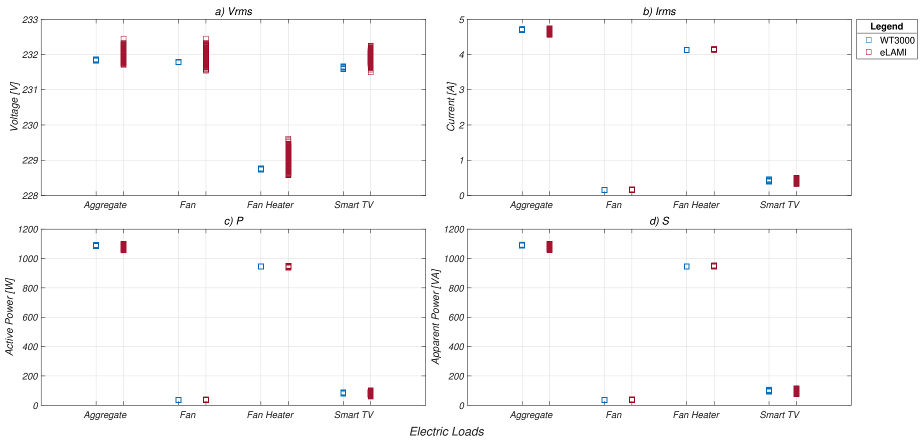


Figure 2.7: **Comparison between WT3000 and eLAMI for devices: *"Fan"*, *"Fan Heater"*, *"Smart TV"* and *"Aggregate"*. Comparison made in terms of features: a) Voltage RMS - b) Current RMS c) Active Power d) Apparent Power**

In this case, the variability ranges are overlapped, although WT3000's related range is almost always narrower than the simulated one. This is because the WT3000 has a higher accuracy level than what can be obtained by adopting the set-up used in the acquired reference profiles for simulation. In any case, since WT3000 has been chosen as a reference instrument, it is expected that it can exhibit a far better metrological performance. Furthermore, the reference profiles for the generation of eLAMI were constructed to take into account the variability of the data over a time horizon longer than 1 hour (total test duration).

Of course, increasing the acquisition time would tend to increase the variation intervals of the WT3000 distributions, due to measurand variability. An interesting aspect, that can be seen in this figure looking at the WT3000 measured values, is the behaviour of the V_{RMS} (Figure 2.7.a)). The 3 loads are simultaneously supplied by the same power source, each through its own power line: such a setting can cause a potential voltage drop. As reported in Figure 2.7.c), the *Fan Heater* is the load with the highest absorption: consequently, the V_{RMS} at its ends is the lowest (Figure 2.7.a)). Conversely, the WT3000 records the highest voltage at the ends of the *"Fan"*, which is the closest to the aggregate's one, i.e. the power source. Looking at the voltage behaviour of eLAMI, the same trend can be observed.

To demonstrate *(ii)*, only the mean value and standard deviation of a few monitored Features for the *"Fan"* load are reported, for sake of brevity, in Table 2.6. In particular, the considered features are: V_{rms}, I_{rms}, P and S. The standard deviation values of the measurements recorded by the WT3000, naturally, are much smaller than those related to eLAMI, due to the simulator design parameters, which had the purpose to replicate a typical commercial smart meter less accurate than the adopted reference (WT3000). Nevertheless, from a measurement point of view, the intervals (μ-σ, μ-σ) belonging to WT3000 and eLAMI are generally overlapped, demonstrating the validity of the generated dataset.

Table 2.6: **Comparison of mean and standard deviation values obtained from WT3000 and eLAMI for the electrical load *"Fan"*. Considered features: $\mathbf{V_{rms}}$, $\mathbf{I_{rms}}$, P and S**

Feature		WT3000	eLAMI
V_{rms} [V]	μ	231.68	231.94
	σ	0.13	0.59
I_{rms} [mA]	μ	159.90	161.30
	σ	0.58	1.40
P [W]	μ	36.38	37.12
	σ	0.22	0.37
S [VA]	μ	36.82	37.63
	σ	0.31	0.32

The validity of the algorithms implemented in the simulator for the generation of eLAMI is evident when analyzing the values and behaviors obtained from the features analyzed in Figure 2.7 and Table 2.6. Furthermore, the similarity between the behaviors of the *"Aggregate"* highlights the consistency of the process implemented in the simulator.

2.5.2 Descriptions of the general characteristics of eLAMI

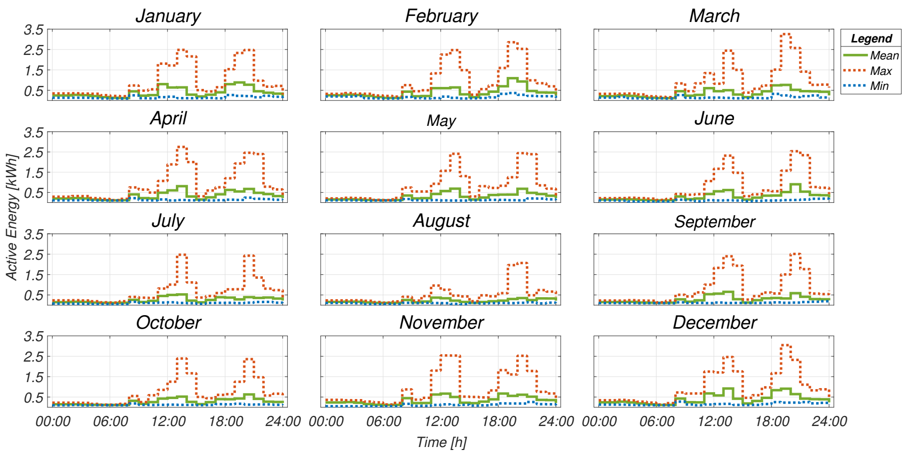


Figure 2.8: **Average Monthly Active Energy Consumption Profiles of the Aggregate Load**

As highlighted above, one of the peculiarities of eLAMI is the variability of the data, both in terms of operating states of the monitored devices and consumption habits. Figure 2.8 shows the average monthly active energy consumption profiles of the aggregate load, for the 24 hours of the day (x-*axis*), for each month. In particular, in terms of active energy consumption (y-axis), the curves show: in green, the average trend, in red the maximum reached for each hourly interval of the month considered, and similarly in blue the minimum. First of all, when analysing the individual month, one can see the variability of the absorption curve during the 24 hours of the day, consistent with what happens in the residential area. In particular, the curve shows an increase in the early morning hours followed by a rapid decrease until midday when the second absorption peak occurs. A further decrease follows this in consumption before arriving at the evening hours characterized by the highest energy absorption.

In addition to the variability during the day, by comparing the different months, it can value the seasonality of consumption and thus the variation in electrical-behavioral habits. In particular, consumption is higher during the winter months than in the summer months, which is particularly evident when comparing August and December (2.9). This is because in the winter months, according to defined habits, there is greater use of certain high-consumption devices, such as *Boiler*, *Electric Oven* and *Microwave*. Furthermore, it should be noted that during the winter months lamp utilization is higher than in the summer months, which has an impact on the consumption peaks mentioned above.

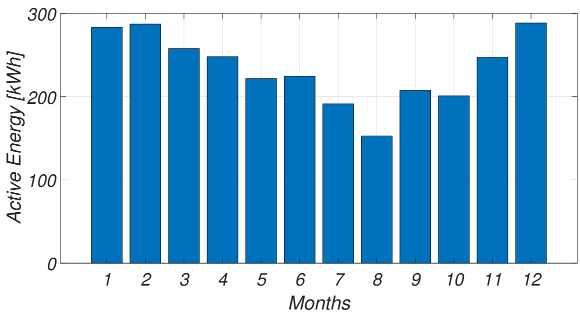


Figure 2.9: **Aggregate Active Energy Load Curve per Months**

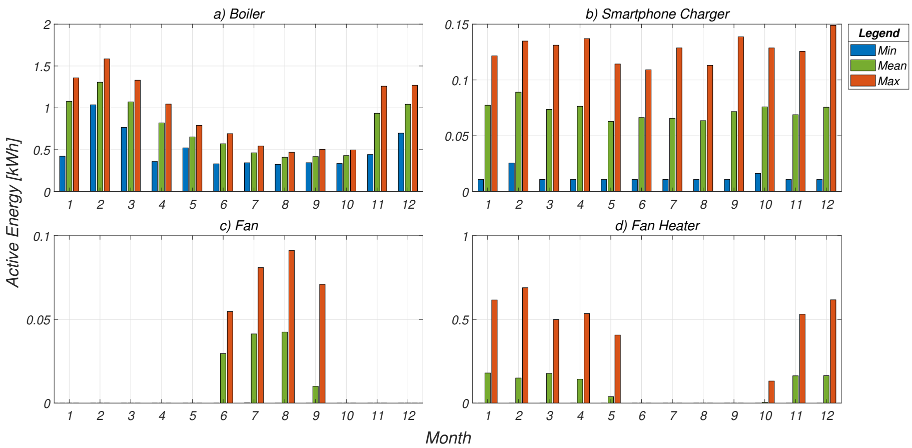


Figure 2.10: **Seasonality Example of Some Different Electrical Loads - a) Boiler - b) Smartphone Charger - c) Fan - d) Fan Heater**

A further interesting aspect is a non-zero consumption during nighttime hours present in all months, due to the presence of some devices in standby mode, characterized by minimal but not zero power consumption. This ceiling does not show much variability in terms of consumption, as the devices on stand-by during the night are almost always the same, so the 3 curves (average, minimum and maximum) almost overlap, with a consumption of less than 0.5 kWh.

In Figure 2.9 the total electricity consumption for each month of the simulated year is shown. In this case, the seasonality of consumption and thus the variation of the energy absorbed in the different months is particularly evident. Since there is no cooling system, total consumption is higher in autumn and winter than in spring and summer. In particular, starting the year in January, electricity consumption is high and remains more or less constant until March, and then begins to decrease in April with the arrival of spring. The lowest peak is reached in August and then starts to rise again from September forward. The highest electricity consumption is recorded in December, while the lowest is recorded in August in perfect analogy with what is shown in Figure 2.8.

In Figure 2.10 is shown the average daily consumption of 4 electrical loads for each month of eLAMI (in terms of average, maximum and minimum daily consumption), taken as an example, to show the variation in consumption patterns in eLAMI. Specifically, the devices are: *Boiler* (Figure 2.10.a), *Smartphone Charger* (Figure 2.10.b), *Fan* (Figure 2.10.c), *Fan Heater* (Figure 2.10.d). Analyzing *Boiler* consumption (Figure 2.10.a), it can be seen that the average consumption in winter is higher than in summer, where it is used only for hot water and not for heating. In contrast, the *Fan Heater* (Figure 2.10.d) is only used in winter, from October to April, peaking in February. The opposite behaviour is obtained by analyzing the *Fan* (Figure 2.10.c), which is only used in the summer months, from June to September, with a peak in August. Unlike the others, the *Smartphone Charger* (Figure 2.10.b) does not show substantial variations in consumption between months. This is because it is used on average every day of the year in the same way.

2.5.3 Smart Energy Application Examples

Load Profiling

Machine Learning and Artificial Intelligence techniques, in general, are based on the use of large amounts of input data. However, if these techniques have input data that do not correctly describe the phenomenon to be studied, the output may be far from the desired result. This is why feature selection algorithms are very often used to find the best set of features to build useful and robust models of the phenomena studied [103].

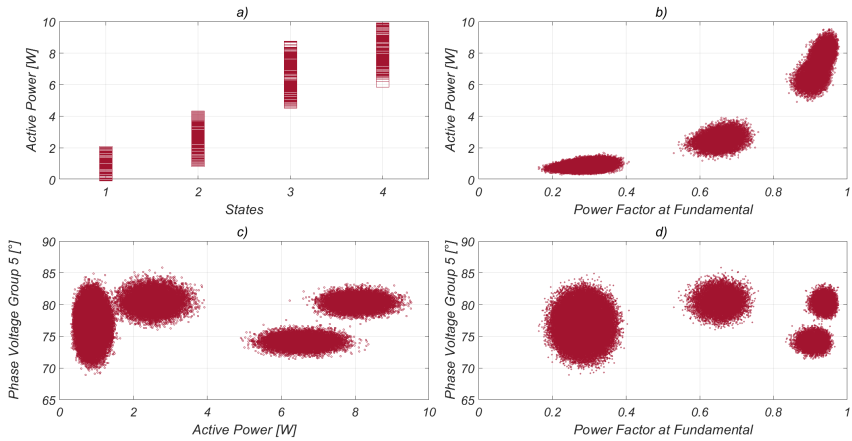


Figure 2.11: **Example of Load Profiling Application for Desk Lamp - a) Power consumption per state, b) Active Power as a Function of Power Factor at 50 Hz, c) Phase of 5th Voltage Harmonic Group as a Function of Active Power, d) Phase of 5th Voltage Harmonic Group as a Function of Power Factor at 50 Hz**

In Figure 2.11.a the active power absorbed by the *Desk Lamp* in January eLAMI is reported as a function of the corresponding assumed states. As previously verified, state variability is present. Consequently, the active power P alone is not able to discriminate the 4 different load operating state because states 1 and 2, and similarly 3 and 4, overlap in terms of P. Therefore, in terms of load profiling, other features must be found for the correct identification of operating states. For example, the active power P as a function of the power factor at fundamental is reported in Figure 2.11.b. This feature can discriminate states 1 and 2 better than P alone, while states 3 and 4 still remain indistinguishable. Conversely, in Figure 2.11.c it can be seen that the phase of the voltage group of the 6th harmonic identifies states 3 and 4 well but not the first two. Combining the two features identified, power factor at fundamental and phase of the 6th harmonic voltage group, Figure 2.11.d shows an optimal situation where 4 operating states of the load (cluster) considered are clearly visible. It is therefore very clear how the greater number of electrical parameters in eLAMI results in a better representation and distinction between the different electrical signatures of the individual load.

NILM

Below is reported an example of application in the NILM (Non-intrusive Load Monitoring) field. NILM presents as a time series identification and classification problem where the objective is to detect which appliances are active at a given instant and how much each of them contributes to the total percentage of consumption. Due to their advantages, techniques based on the analysis of steady-state features are the most widely used, typically referring to active power only [104]. This feature, however, is not always able to distinguish devices that absorb similar power or have similar operating principles.

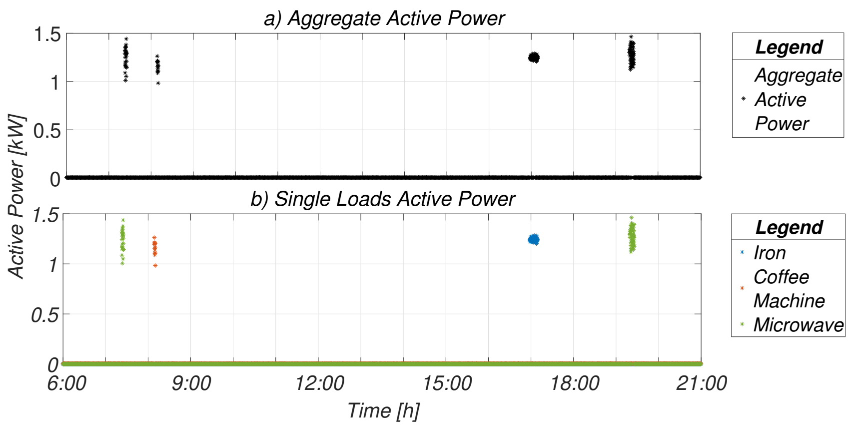


Figure 2.12: **Active Power in time: a) Aggregate - b) Single Loads**

In Figure 2.12.a shows the total active power obtained from an aggregation of 3 loads present in eLAMI and in Figure 2.12.b the individual active powers absorbed by the 3 considered loads, are reported. In particular, in Figure 2.12.a and Figure 2.12.b the active power in time, both for aggregate and some example of single load, are reported. Conversely, Figure 2.13.a and Figure 2.13.b show the RMS values of the 6th harmonic current group in time, both for the individual loads considered above and for the corresponding aggregate.

It is evident when analyzing the aggregate active power in Figure 2.12.a and the single active power in Figure 2.12.b, that the 3 loads are indistinguishable due to the problems mentioned above. This represents a critical case for NILM algorithms. Instead, analyzing the current harmonics of 6th group in Figure 2.13.a for the aggregate and in Figure 2.13.b for every single load, three different levels of absorption are present, allowing for correct identification of the active loads.

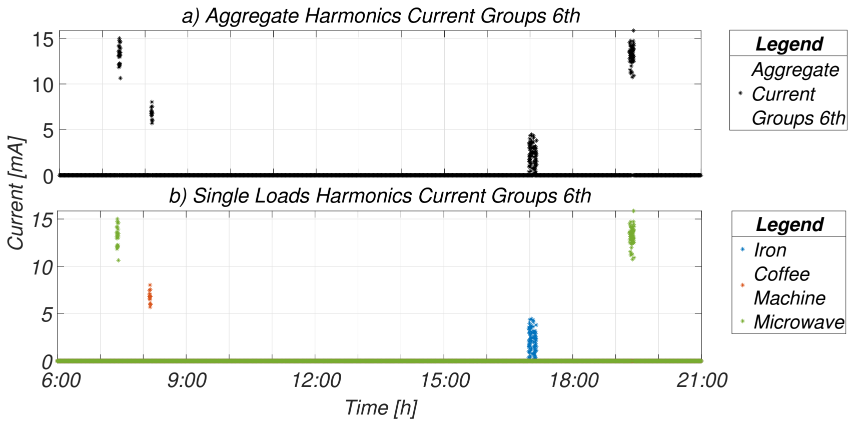


Figure 2.13: **Current Harmonics of 6th group in time: a) Aggregate - b) Single Loads**

Forecasting

In the world of Smart Energy, statistical and forecasting analyses based on time series are often carried out. In particular, one of the goals of an Energy Management System is to create mathematical models that can simulate trends in electricity consumption as a function of various factors. Furthermore, through statistical analysis, it is possible to define statistical and/or performance indices of the analyzed system. Some of the benefits of modeling analyzed electricity consumption are: *i)* construction of past seasonal trends and consequently of future ones, *ii)* definition of energy efficiency and optimization plans, *iii)* forecast balancing of electricity networks and performance verification.

To this end, eLAMI also offers the possibility of testing forecasting and modeling algorithms for electrical systems. For example, just to give a simple idea, in Figure 2.14 based on the knowledge of the first 10 months of the year (300 days) relating to the power consumption trend of the total aggregate, a consumption forecast was made for the last two months of the year. The mathematical model derived is based on a fitting of the input data. Using the mathematical model, a band ($2 * DevStd$ width) was derived within which the consumption for the 60 forecast days is estimated. As can be seen from this figure, the real data falls within the obtained forecast band with an error of approximately 6.6 %, i.e. 56 days out of 60 estimated correctly.

Furthermore, in diagnostic and predictive terms, thanks to the analysis of time series of data, it is possible to estimate the operating ranges of electrical loads to assess and/or predict any decay in their performance and any drift towards fault states.

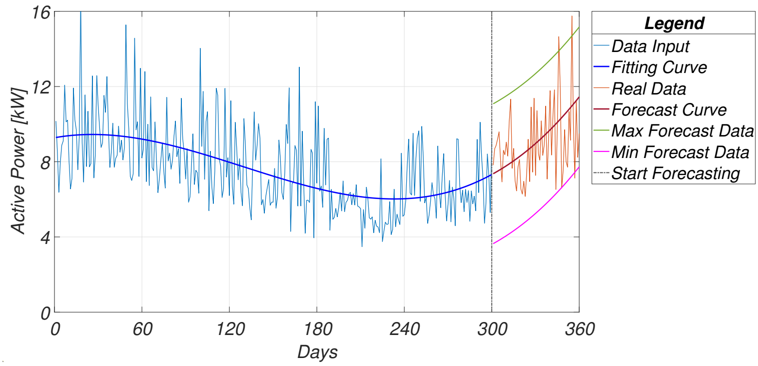


Figure 2.14: **Example of Forecasting for Electric Consumption with eLAMI**

2.6 Observations end Conclusions

In this chapter, an innovative approach to provide a simulated electricity dataset is presented, from the acquisition of the reference signal to the validation of the data. To explain the rationale behind its realisation and to demonstrate its suitability for Smart Energy applications, a final section on Smart energy profiling and management examples is also discussed. These examples highlight how, in the era of Energy Digitisation, Smart Monitoring processes are of paramount importance, especially when characterised by a high level of quality of the monitored electrical signature

The eLAMI-related output data, consisting of over 400 electrical parameters and the simulation of the energy profile of a residential building over a period of one year, are available for download in order to enhance research in the field of energy digitisation and smart monitoring with new, detailed, validated and widely applicable data.

The acquisition set-up was chosen based on the typical measurement capabilities of smart meters currently in use in homes. The voltage and current signals produced for 36 household appliances were processed in both time and frequency domains to provide a complete set of electrical parameters that make up the electrical signature of each appliance considered.

To get as close as possible to the real scenario, stochastic models were also implemented to obtain consumption patterns and manage state transitions for each load. At present, only nominal operating conditions were considered, i.e. no failures were assumed during the simulation interval. This is reasonable given the very low failure rate of the equipment considered during the period tested. The data produced are in any case suitable for most Smart Monitoring applications. One of the possible future developments of research in this field is the possibility of implementing faults and anomalies, in order to offer a tool for optimising fault identification and localisation algorithms.

Chapter 3

Load profiling as a tool to unlock advanced digital services: the role of measurement

3.1 Highlights

- **Load profiling in the digital context**: Load profiling emerges as a strategic tool for energy efficiency optimisation, characterisation, prediction and diagnosis of monitored systems, with applications that go beyond simple electrical monitoring [52].
- **Importance of smart meters**: The deployment of a new generation of smart meters is crucial to enable a reliable Load Profiling process [52]. The research conducted analyses the crucial role played by smart meters in load profiling applications, assessing the influence of Monitoring Quality and Electrical Signature Quality in this process.
- **Optimisation of measurement characteristics**: A larger number of measured energy characteristics does not always improve the reliability of load profiling. Research shows that the inclusion of parameters with low sensitivity to variations in the operating states of electrical loads can lead to incorrect decisions and less accurate results than the use of traditional power indices.
- **Advanced statistical methods**: The adoption of feature selection tech-

niques, such as the unsupervised "Kernel Density Estimation" (KDE) proposed in the research, can significantly improve the reliability of Load Profiling by eliminating parameters with low sensitivity and optimising the decision-making process.

- **Reduction of metering infrastructure costs**: Research shows that lower levels of metrological uncertainty than those required for billing can be sufficient for effective Load Profiling, enabling a reduction in metering installation costs without compromising performance.
- **Applicability to multi-physical systems**: The proposed methodological approach is not limited to electricity, but can be extended to other physical quantities and multi-physical systems, providing a framework for defining a "Monitoring Quality" (MQ) target and optimising the number of useful features for different application scenarios ("Feature Quality").

3.2 Introduction

The energy sector is undergoing a constant transformation in terms of digitisation and the development of new energy services based on the intelligent use of energy information. To this end, a proper process of *Smart Monitoring* and *Load Profiling* can help identify the end user's consumption pattern, making consumption forecasts, and defining the operating conditions of individual devices. In this way, electricity management can be improved and made more efficient. A Load Profiling process relies on the use of algorithms, typically classification and clustering, so it is crucial to consider a clear concept: if the input data collected do not correctly describe the phenomenon that one wants to analyze, the output of the process will be far from the desired result.

Therefore, in this process - following what was said in section 1.7 - two parameters play a strategic role: the *Monitoring Quality* (MQ) and the *Electrical Signature Quality* (ESQ) [37]. In summary, recalling some concepts mentioned in subsection 1.7.1, as regards "MQ", it refers to the minimum accuracy that smart meters have to warrant to accomplish for the given task. This parameter is very important since it influences both the energy consumption and energy signature measurements and the overall smart meter network cost [105–107]. About "ESQ" (subsection 1.7.2 it refers to the number of parameters extracted from the electrical signature of the device. This is essential because each electrical device has its unique electrical signature that distinguishes it from other devices. Following what was said in the previous chapter and in [37], an electrical signature does not mean the "classical" electrical quantities (P, Q, S, I_{rms}, etc.) but the entire harmonic spectrum of voltage and current absorbed by the electrical load, which for the sake of synthesis, can be summarised through the implementation of appropriate computational metrics [108] [109]. Using all or part of these extrapolated parameters makes it possible to bring out "spontaneously" the desired characteristics of the analysed system, i.e., the operating states in the case of Load Profiling. In particular - as seen in the previous chapter (section 2.5), with reference to the application examples of the eLAMI dataset - how in difficult Load Profiling scenarios, information from the electrical power parameters P, N and S is not sufficient to identify the operational state of an electrical load, whereas the addition of a few useful parameters selected from the electrical signature can significantly improve this process. Similar considerations are made in [110] and [111] about fault diagnosis on electric motors.

Concerning these two points, the purpose of the research discussed in this chapter is to highlight the importance of monitoring quality and electrical signature quality in a Load Profiling process and to analyse how the variation of these parameters impacts the Load Profiling performance. Specifically, the analyses reported in the following research were conducted for three levels of MQ and three levels of ESQ respectively derived from standards that regulate the commercialisation of smart meters and power definitions and measurements. Furthermore, since the performance of the Load Profiling process may also depend on the type and manner of implementation of the profiling algorithms, the analyses just mentioned were repeated three times using three different types of algorithms. This choice was made to have a broader and more general view of the problem and to return a result valid for different architectures and types of algorithms.

The analyses reported were first conducted on a *simulated scenario* considering the public energy dataset "eLAMI" discussed above; subsequently, to obtain more robust and reliable results, a *real scenario* with experimentally acquired electrical loads was considered. In addition, a novel unsupervised methodology is proposed in the research, based on the *Kernel Density Estimation* (KDE), to select useful features from those related to the electrical signature to improve the Load Profiling process allowing to consider only those features that show good sensitivity to the operative states of a load.

The structure of the chapter is as follows: first, some basic concepts of Load Profiling, the most commonly used applications and techniques are explained; then, the Load Profiling process implemented, the types of tests performed, the methods and the characteristics in terms of MQ and ESQ are presented. Next, the peculiarities and characteristics of the application scenarios considered in the research are briefly illustrated; and finally, the results of the analysis conducted are discussed, comparing the performance obtained for three levels of measurement uncertainty and for three different combinations of electrical parameters considered. At the end, some final remarks and considerations are briefly presented.

3.3 Background

This section briefly introduces Load Profiling, provides an overview of possible applications in various areas of intelligent energy, and describes its potential benefits. In addition, the structure of a Load Profiling process is presented and some of the most commonly used techniques are briefly described.

3.3.1 Some notes about Load Profile

The digitisation of the energy sector is part of the modernisation and evolution process aimed at tackling current energy and environmental problems, including: using energy smartly and consciously, reducing energy consumption, and developing advanced techniques to maximise energy efficiency. These concepts underpin the energy and ecological transition taking place worldwide [112].

To this aim, a Load Profiling process can be useful to identify consumption patterns, generate forecasts, develop optimal management strategies and identify each device's operating conditions and nature [113]. Knowledge of the specific consumption of individual devices implies empowering customers with respect to the issues highlighted, making them aware of their impact, their habits, and how much these have contributed to their total energy consumption [114], so that they can adopt energy-saving behaviours. Demand response, load forecasting, and non-technical loss detection, among other uses, are just some of the many applications of the Load Profiling process [115] [116]. Analyzing data streams collected by smart meters can provide detailed information on demand characteristics that can be used to improve grid operation and planning [117]. Demand-response, a very active area of research around the world, is an efficient strategy to encourage the use of renewable energy sources and minimise the gap between electrical load peaks and valleys [118] [119]. Time series-based statistical and forecasting studies are frequently used in smart energy.

By monitoring and profiling single loads using smart meters, energy savings can be achieved, as it allows action to be taken on the timing of individual loads and to eliminate unnecessary activities [120] [121]. For example, it is possible to define consumption trends, and performance indices or make evaluations on the operating cycle of the monitored machine (a very interesting application for industries, applicable to industrial production processes) as previously reported [122].

Moreover, downstream of the Load Profiling process, it is possible to construct past and future seasonal trends and define energy efficiency and optimisation plans for the monitored system. It should be emphasised that having the "history" of the electrical signature, or a summary thereof, of the monitored load and the corresponding identified operational state has a considerable advantage: the concept of predictive load diagnostics is realised [123]. In particular, by analysing the trends of the various calculated quantities, it is possible to identify the occurrence of any anomalous trends for each operating state which deviate from the behaviour of the same under normal operating conditions [124]. Based on this comparison, *alerts* can be activated if significant deviations occur.

3.3.2 How to implement a load profiling process to unlock new services

The author's aim in this section is to describe the structure of a Load Profiling process, highlighting its main aspects and the steps to be carried out to achieve the set objectives and unlock new functionalities such as those described in the previous chapter.

Of course, before starting the process, it is necessary to collect data from the system you wish to analyse or have a dataset already acquired. Then, depending on where the process is stopped, several application alternatives can be implemented: *a)* the collected data can be processed at regular intervals (dimensional, daily, hourly, etc.) for asynchronous Load Profiling with the monitored system; *b)* the data can be stored in a database to be used later for training Load Profiling real-time algorithms; *c)* if already trained algorithms are available, the data acquired from each device can be processed immediately for real-time Load Profiling.

The process, illustrated in Figure 3.1 and described in detail below, consists of three *steps*: 1) PRELIMINARY STEP, 2) OPERATING STEP, and 3) REAL-TIME STEP.

1) "PRELIMINARY STEP" - Consists of a preliminary analysis to understand the nature of the data and identify the methods best suited to the scenario analysed, in terms of Load Profiling and relation to the computational specifications. Thus, the first step consists of:

1.1) In "DATA OPERATION" data exploration and data cleaning operations are performed to assess and identify the characteristics of the monitored physical system, relationships and internal distributions, patterns and points of interest and anomalies or missing data.

1.2) In "IDENTIFICATION OF METHODS" different types of techniques for Load Profiling are identified and tested, e.g. clustering and classification, possibly combined with feature selection techniques (supervised and unsupervised), as reported in subsection 3.3.3.

1.3) In "EVALUATION OF METHODS" the identified methods and techniques are evaluated for robustness in relation to the analysed system. The evaluation can be done by resorting to appropriate metrics, operator experience, knowledge of the analysed problem, or if available, by resorting to ground truth.

Once the first step (iterating if necessary) is executed, the next *Step* is executed.

2) "<u>OPERATING STEP</u>" - In this section, starting from an unlabelled dataset faithful to the scenario studied in *Step 1*, it is possible to realise the two alternatives "*a*" and "*b*", described earlier or otherwise train the algorithm for alternative "*c*".

2.1) In "DATA ADJUSTMENT" the validity of the input data is checked, and, if necessary, corrections are made before proceeding with the subsequent analysis.

2.2) In "IDENTIFICATION OF CLASSES" a class search is carried out based on the methods chosen in *Step 1*, e.g. by clustering. In this way, the labelling of the considered dataset is obtained. Alternative "*a*" aimed at an asynchronous Load Profiling process with respect to monitoring ends at this point.

2.3) In "TRAINING ALGORITHM" the result of the implemented method for class identification is used to train the profiling algorithm, e.g. a classifier, which must subsequently work in real-time on the monitored system. This is followed by a verification phase of the training on a test data set. At this point, alternative "*b*"" ends, aimed solely at training the algorithm for real-time Load Profiling.

After completing *Step 2*, the Load Profiling tool is ready to be applied to a continuous data stream.

3) "REAL TIME STEP" - If a real-time process is desired, the last operation is the implementation of the algorithm on board the smart meter and the system is ready to run as follows:

   3.1) In "DATA ACQUISITION", during its operation, the absorption profile of the electrical device being monitored is acquired and processed in real-time. Then its electrical signature is extracted, with an accuracy given by the measurement system, and provided as input to the previously trained algorithm.

   3.2) In "Load Profiling", based on the considerations made in *1.3* and *2.3*, the operating state of the monitored system is discriminated and the information returned. In this way, the alternative "*c*" is concluded.

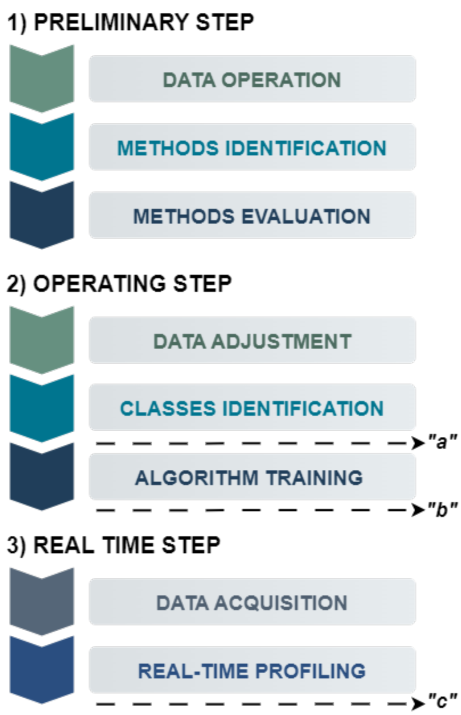


Figure 3.1: **Block Diagram of the Load Profiling Process composed of three steps: "PRELIMINARY STEP", "OPERATING STEP" and "REAL TIME STEP". The labels "*a*", "*b*" and "*c*" represent three possible instants of process interruption depending on the objective.**

The process is thus completed. It must be considered that such a process also applies to other systems of a different physical nature, not only electrical. Of course, the calculated electrical signature, in addition to being processed for Load Profiling purposes, can be used for further analysis, from which information and indices can be extrapolated to be associated with the identified operational state of the monitored load, as reported in subsection 3.3.1.

In particular, the "REAL TIME STEP" can be extremely useful in predictive diagnostics. Furthermore, for alternatives "*b*"" and "*c*", the electrical signature can be stored and reused occasionally to iterate the *Step 2* again to refine and/or update the capabilities of the profiling algorithm. Such an operation is very advantageous in that performance drops in the process are avoided by refining the training over time. Especially in the presence of a natural degradation of the monitored system, which would alter the absorbed electrical signature.

3.3.3 Some techniques for load profiling

Different types of processing techniques and methods can be implemented to realise the Load Profiling process described. Of course, the choice depends not only on the objective but also on the analysed scenario and desired output. The scientific literature is particularly active in this field, in fact, on Load Profiling, articles and several review studies have been published [125] [126]. In general, the most widely used techniques are: *i)* Clustering and *ii)* Classification algorithms. Clustering is an unsupervised learning technique, unlike classification, which requires a supervised approach. In both cases, both supervised and unsupervised feature selection techniques can be implemented to improve analysis performance.

As regards *i)* and *ii)*, the basic concepts of each of these techniques are summarised below to provide the reader with a better understanding of the considerations made later in this chapter.

Regarding *i)*, in [127] and [128], reviews on clustering methods and algorithms are proposed. In [129], three clustering techniques applied to data from meters at different frequencies are analysed, while in [130], two-stage clustering is proposed. In [131] a review is made of clustering (and classification) methods applied to residential and industrial electricity scenarios, while in [132] the authors report a comparison of clustering techniques for customer identification in the electricity sector. In general, the most widely used *clustering* algorithms are the *k-means*, the *Generalized Gaussian Model* (GMM) and the *Agglomerative clustering*. The k-means algorithm is a partition method that groups data by separating samples into n groups (partitions) of equal variance, minimizing a criterion known as *inertia* or sum of squares within the cluster. The method *GMM* looks for a set of multi-dimensional Gaussian probability distributions that can represent the data under consideration. This quantifies the probability with which a data item belongs to a given cluster. Moreover, each cluster is no longer associated with a sphere in space but with a Gaussian pattern; this represents a significant advantage over *k-means*. *Agglomerative clustering* is a hierarchical algorithm strategy that works "bottom-up". In practice, the algorithm starts by considering each sample as a single cluster and, at each subsequent iteration, recursively combines the two most similar clusters until all samples belong to one large cluster.

In general, regardless of the type of algorithm implemented, various evaluation criteria and metrics can be used after clustering [133] to define performance and the appropriate number of clusters. For example: *Silhouette Coefficient* takes into account both separation and cohesion, can vary in the range [-1, 1] where silhouette values close to 1 are preferred while negative values indicate that the cluster observations "fit" better with other clusters instead of their own, i.e., that the final clustering is not correct; *Rand index* is a statistical parameter defined as a measure of the similarity between two data clusters (it is assimilated to accuracy); *Inertia Index* can be recognised as a measure of the internal coherence of clusters; *Davies-Bouldin score* is defined as the average similarity measure of each cluster with its most similar cluster; *Elbow method*; *Index of separation of a pair of clusters*; etc.

With regard *ii)*, for example, through a previously trained classification algorithm, a system for real-time load identification can be realised. This is done by identifying the relationships between the different features of the system and the label associated with them using, for example, regression criteria (for continuous data) or classification models (for discrete data) [61]. Reviews on classification methods and algorithms are given in [134].

Along with clustering and classification techniques, feature selection algorithms are often implemented. In general, feature selection has three main objectives: Improve the model accuracy, Reduce computational cost, and produce a more interpretable model. In [135] and [136] the authors present general reviews on feature selection methods, while in [137] the authors review specialised feature selection techniques for clustering and classification. In [138] the features of greatest interest for identifying load profiles are selected. Often, feature selection techniques are of the supervised type, thus implying prior knowledge of the ground truth of the analysed system.

However, there are also non-supervised approaches that do not require knowledge of this parameter [139]. In this case, the selection is based on a critical data analysis in terms of variability, statistical distribution, trends, and internal correlations, aimed at identifying and selecting those features that potentially have higher information content. Of interest among these is the "*Kernel Density Estimation*" (KDE) method [140, 141], which is a non-parametric statistical method useful for identifying patterns through the estimation of metric spaces, i.e., the probability density function. In general, the KDE makes it possible to derive the continuous probability distribution function of a discrete quantitative variable.

3.4 The Methodological Approach

This section presents the tests, choices and methodologies followed during the analysis of the implemented Load Profiling process. The characteristics of the influence parameters considered, i.e. monitoring quality and electrical signature, are first illustrated. Subsequently, the tests conducted and the methods used are described.

3.4.1 Monitoring and Electric signature characteristics

Concerning MQ, in particular, for the definition of uncertainty levels analyzed in accordance with chapter 1, reference was made to several regulations and directives related to energy measuring instruments, including: "Directive 2014/32/EU" of the European parliament and of the council on the harmonisation of the laws of the Member States relating to the making available on the market of measuring instruments [142], and *EN50470-1* standard of the "European Committee for Electrotechnical Standardization" (CENELEC) on "Electricity metering equipment (a.c.)" [143]. The latter refers to newly manufactured energy meters intended for residential, commercial, and light industrial use and specifies general requirements, tests, and test conditions for the metering apparatus. Specifically, this standard, according to the metrological quality of the apparatus, discriminates meters into three different accuracy classes: A, B and C (A indicates the "worst" class).

In this study, for both *scenarios* analyzed, the metrological conditions of classes A, B and C were replicated, defining three different levels of monitoring quality, denoted by the acronym: MQ1, MQ2 and MQ3 respectively. For example, MQ1 indicates a monitoring quality condition of level 1, i.e., "worst" typical of lesser-performing commercial meters, while MQ3 represents the condition with lower uncertainty assimilated to meters with high-level performance. Please refer to section 3.5 for further details on data acquisition methods and techniques. In any case, the chosen MQ levels are intended to bring out through experimental tests, the importance of monitoring quality, thus the accuracy of the measurement chain, in today's scenario of energy digitization.

Regarding the electrical signature quality, i.e. the number of electrical parameters calculated by the meter, three levels of ESQ were considered, respectively denoted by the acronym: "ESQ1," "ESQ2," and ESQ3. The number of parameters considered for each level was chosen to replicate three types of commercial meters with different calculation capabilities. Table 3.1 summarises the electrical parameters considered for the three levels of ESQ described below.

- "**ESQ1"**" refers to meters with basic calculation capability - only the electrical parameters of the load relating to the measurements of active power (P), apparent power (S), and non-active power (N) are considered. These turn out to be the main electrical parameters extracted from "classical" metering systems. Their measurement does not necessarily require particularly complex and high-performance hardware, so they can be extracted with simplicity and reduced costs.
- "**ESQ2**" refers to meters with basic calculation capability but equipped with filters or evolved meters - in addition to the parameters P, S and N, the remaining parameters introduced by the standard *IEEE-1459* are also considered. These electrical quantities are of particular interest as they do not necessarily require a hardware enhancement of the meters compared to the ESQ1 case to be extracted during measurement. In fact, although they can be obtained more quickly via *FFT* (Fast Fourier Transform), they can also be obtained by applying filters.
- "**ESQ3**" refers to smart meters with high calculation capabilities - parameters related to *IEC 61000-4-7:2009* are considered in addition to the parameters of ESQ2. The latter is more complex to extract and necessarily requires a frequency analysis using *FFT*, consequently an upgrade at the hardware and firmware level of the meter is necessary, with an inevitable increase in costs.

The metrics and calculation methods implemented in the two case studies, *simulated* and *real*, are the same and allow a large number of electrical parameters to be extrapolated from the monitored system at each measurement interval. In addition, the ground truth of the operational state is also provided, which is very useful information for training algorithms underlying new digital services in the Smart Energy context.

All of these electrical parameters provide an electrical signature with a high degree of detail; Table 3.1 summarises these for the three "ESQ" levels considered.

Table 3.1: **Qualitative characteristics of the electrical signature considered in the three levels: ESQ1, ESQ2 and ESQ3. Report: the categories of electrical parameters considered (Type of parameters); the number of electrical parameters calculated (Number of parameters)**

ESQ	Type of parameters	Number of parameters
ESQ1	P-S-N	3
ESQ2	IEEE1459	21
ESQ3	IEEE1459 + IEC61000-4-7	123

These refer only to device-dependent electrical quantities, i.e. related to the absorbed current spectrum; voltage-dependent parameters alone are neglected as this is imposed in electrical systems. In practice, the power definitions of *IEEE-1459* are implemented, particularly in the single-phase non-sinusoidal case [46] [144].

The electrical parameters calculated according to IEEE1459, for voltage and current refer to: total RMS (*Root Mean Square*), RMS of fundamental component, RMS of the remaining harmonic content, and DC component. For the power components they refer to active, apparent, non-active and distorted power; power factor and total harmonic distortion parameters. Harmonic behaviour of the considered electrical loads has been assessed according to *IEC61000-4-30:2015 "Testing And Measurement Techniques - Power Quality Measurement Methods"* [48] and *IEC61000-4-7:2009 "Assessment of harmonic emissions"* [49]. In detail, in all the harmonic measurements, RMS and phase of harmonic groups of voltage and current up to the 50*th* harmonic order and RMS and phase of the harmonic subgroup have been considered, considering a time window of 200 ms (with a frequency resolution of 5 Hz).

3.4.2 Test set-up

Regarding the structure of the Load Profiling process illustrated in Figure 3.1, this research refers to the case "*a*" described in detail in subsection 3.3.2. In practice, an asynchronous Load Profiling process has been implemented concerning monitoring, i.e. the operational state of the considered device is identified at the end of the device acquisition process.

The tests for *simulated* and *real* cases, were conducted for three levels of MQ and ESQ. Furthermore, since the performance of the Load Profiling process may also depend on the type and complexity of the profiling algorithms implemented, the analyses just mentioned were repeated three times using three different types of Load Profiling algorithms: "*k-means*", "*Gaussian Mixture Modelling*" (GMM) and "*Agglomerative Clustering*". This provided a broader and more general view of the problem. The input data to the clustering algorithms were first appropriately normalised using the *z-score* method [145], i.e. mean 0 and standard deviation 1. The Figure 3.2 summarizes the tests conducted.

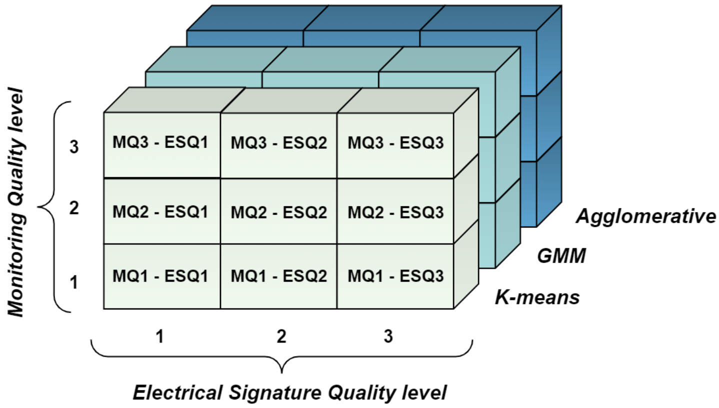


Figure 3.2: **Tests performed with: three different levels of Monitoring Quality (MQ), three levels of Electrical Signature Quality (ESQ), and three different Load Profiling algorithms (k-means, Gaussian Mixture Modelling, and Agglomerative clustering**

For example, considering the two extreme cases, the "worst" and the "best", there are: "MQ1-ESQ1" low quality of monitoring (high measurement uncertainty) and low quality of electrical signature (few parameters calculated by the meter); "MQ3-ESQ3" high quality (low measurement uncertainty) and high quality of electrical signature (many parameters calculated by the meter). While the opposite extreme cases refer to meters: with high metrological performance but low calculation capabilities ("MQ3-ESQ1"); with low metrological performance but high calculation capabilities ("MQ1-ESQ3"). In between are the remaining intermediate cases. In terms of the methods used, algorithms of different natures and operations were chosen, to highlight the potential and advantages obtained in a Load Profiling process by acting on the different impacting factors.

In addition, as a feature selection method, the *Kernel Density Estimation* (KDE) is described in subsection 3.3.3. Being an unsupervised technique, KDE does not require knowledge of the ground truth in the selection phase. The only consideration made is that only multi-state loads are considered in this work. Therefore, from the set of starting characteristics defined by the level of "ESQ" considered for each load, features with unimodal distribution were discarded through the KDE method. The Figure 3.3 shows an application of the KDE methods to the load "Desk lamp" considering two different features associated with two different probability distributions, *a)* unimodal and *b)* multi-modal. Using KDE applied to a subset of the starting samples, only features with several peaks in their probability distribution greater than one are selected. The peaks in the distribution represent potential areas of point densities attributable to operational states of operation. A characteristic with an unimodal distribution, therefore, represents a non-significant parameter for a multi-state load, being almost constant as the operating state changes. It should be considered that the number of peaks shown by a feature is not necessarily exactly the actual number of operating states. For example, the Figure 3.3, shows a case of unselected (*a)*) and selected (*b)*) features for a load used in this work ("Desk Lamp") which actually has 4 operational states.

The Silhouette Coefficient was considered to assess the goodness of clustering [133], which is extremely useful for simultaneously assessing the cohesion and separation of the clusters obtained. The number of identified operational states, hence classes of the system, according to this metric, is the one at the highest Silhouette Coefficient. The characteristics of the metrics and algorithms are described in subsection 3.3.3. All processing operations were performed in the Matlab™ and Python™ environments [146].

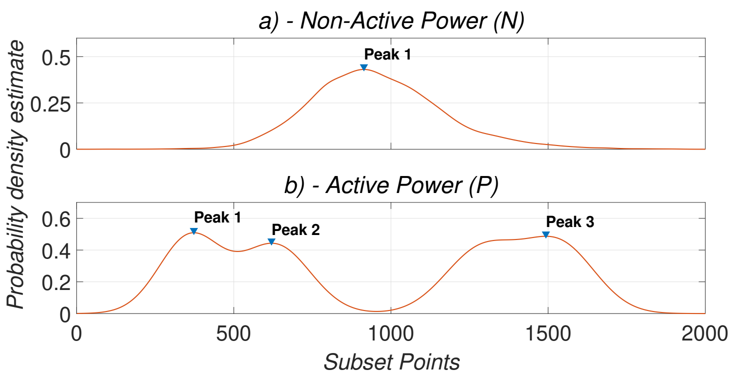


Figure 3.3: **Application of the Kernel Density Estimation (KDE) method to the "Desk Lamp" load (four operational states). In *a)*, an example of an unselected feature with an unimodal distribution is shown. In *b)* an example of a selected feature is given, the distribution being multi-modal and therefore potentially useful for identifying the states.**

3.5 Analyzed Scenarios

To validate the research conducted in this chapter, a two-pronged approach was applied by performing the analyses on simulated and real scenarios. As for the *simulated scenario*, the public energy dataset "eLAMI" described in the previous chapters was considered; in subsection 3.5.1, some characteristics of this dataset and how it was used are briefly described. As for the *real case*, in subsection 3.5.2, the characteristics of the chosen devices, the measurement setup and the confirmation process of the acquired data are described.

3.5.1 Simulated Scenario

As for the *simulated case*, the dataset used in this study is "eLAMI" whose characteristics are given in chapter 2. It represents a residential energy dataset with innovative characteristics. Briefly, the dataset features a large number of electrical parameters (433) provided for each operational state of each device, with a measurement time of 5 seconds. In addition to the calculated quantities, the operational state (ground truth) of each electrical load is also provided. The metrics and calculation methods implemented for the extraction of electrical parameters are based on the implementation of the *IEEE-1459* and *IEC61000-4-7:2009* standards, following the ESQ levels defined in subsection 3.4.1.

Analyses were conducted on the loads present in "eLAMI", for the sake of synthesis, section 3.6 shows the results for three electrical loads in the dataset that were considered most interesting. In particular, the devices shown are: "*D1: Fan Heater*", "*D2: Desk Lamp*" and "*D3: Smartphone charger*". This choice was made, in addition to synthesis, because these were the most interesting devices to be analysed in a Load Profiling process: D1 and D2 present the largest number of operational states among the loads available in "eLAMI", in D2 and D3 the "off" state corresponds to standby and therefore non-zero absorption that is confused with the state immediately following, and D1 is interesting from the point of view of load type, being comparable to an electrical machine. Table 3.2, summarises the information on the loads just mentioned, extracted from the previous chapter.

For the sake of clarity and to provide a better understanding of the problem, the example in Figure 3.4 shows the evolution of certain electrical parameters for different operating states of the "Desk Lamp" load at different levels of MQ and ESQ. In particular, the quality levels MQ1 and MQ3 and three sets of features belonging respectively to the levels: *a)* ESQ1, *b)* ESQ2 and *c)* ESQ3 are compared.

Table 3.2: **Simulated loads specifications. It shows: the identifier (Device), the type of the device (Type), the number of operating states ($\mathbf{N_S}$) and the nominal active power ($\mathbf{P_{Nom}}$)**

Device	**Type**	$\mathbf{N_S}$	$\mathbf{P_{Nom}}$ **[W]**
D1	Fan Heater	4	1900
D2	Desk Lamp	4	10
D3	Smartphone Charger	2	25

In detail, for the simulated device considered: *MQ1-a)* and *MQ3-a)* show the absorption profiles in terms of active power (P) with respect to the operational state; *MQ1-b)* and *MQ3-b)* show the voltage distortion power (D_V) as a function of the power factor at the fundamental (P_{50}); *MQ1-c)* and *MQ3-c)* show the phase trend of the $9th$ harmonic current group ($G_{phi}I_9$) as a function of the amplitude of the first harmonic current group (GI_1).

In Figure 3.4, it is possible to appreciate the behaviour of the device under the different test conditions considered and the criticalities in Load Profiling. It is evident how the quality of the monitoring system and the natural variability of the device, leads in some cases to an overlap between the operating states. At the same time, it is possible to appreciate the "separation" of operating states when more significant features are considered and the MQ is increased. The other loads considered show conceptually more or less similar behaviour, so for reasons of synthesis, the same representation is omitted.

Regarding the analysis interval, to deal with a sufficient number of data, tests were conducted for each load on several measurements per operational state equal to 5000 samples. In practice, a balanced sub-dataset was extracted from "eLAMI" with a small size and an equal number of points per operational state for the different loads. Regarding the MQ for the *simulated scenario*, as reported in the chapter 2, "eLAMI" in its basic version corresponds to an MQ2 level defined in this study. As for the other two MQ levels, using the "eLAMI" dataset and with the same methods and techniques implemented in [37], two more datasets were generated, with greater and lesser variability than the basic version, corresponding to MQ1 and MQ3.

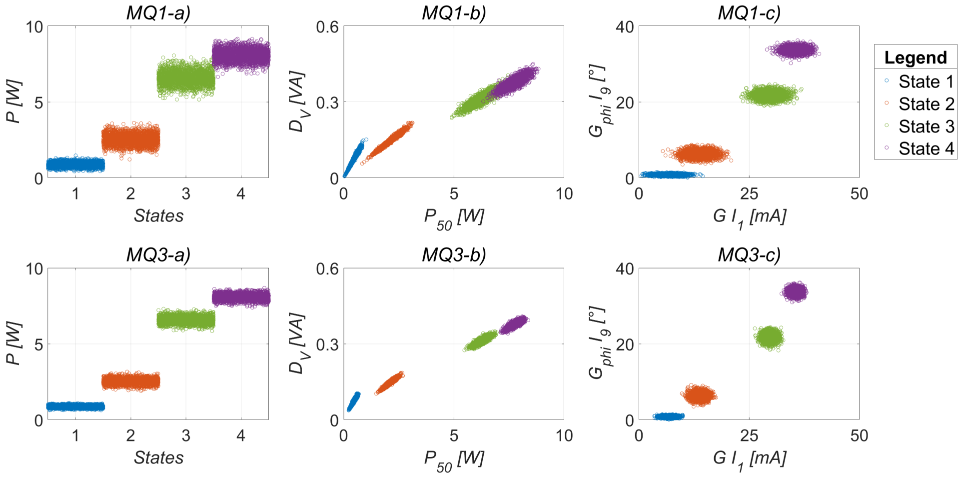


Figure 3.4: **Simulated electrical load "Desk Lamp". Shows a comparison of two MQ levels and three different sets of features belonging to the three ESQ levels considered. The labels in the Legend, from "*State-1*" to "*State-4*", refer to the operating states of the electrical load considered, to which the nominal active power (P) levels correspond respectively: 0.8W, 2.5W, 6.5W and 8 W.**

3.5.2 Real Scenario

With regard to the real electrical loads used for the analysis, a bank of dimmer lamps ("*Lamp*") controlled by a SCR (*Silicon Controlled Rectifier*) was considered as a sample of the residential case and a single-phase asynchronous motor powered by an inverter ("*Mot+Inv*") as a sample of the light industry case. Thanks to the control offered by the inverter and the dimmer, it was possible to realise an arbitrary number of operating states for both devices. In fact, 7 operational states were tested for the "Lamp" case, and 8 operational states for the "Mot+Inv" case. All the tests were carried out in the Laboratory of Industrial Measurements (LAMI) of the University of Cassino and Southern Lazio.

Concerning the three monitoring quality levels, MQ1, MQ2, and MQ3, according to the subsection 3.4.1, three different metrological acquisition conditions were implemented for both real loads treated. Considering a simple measurement chain model of a smart meter, the main hardware elements are represented by the voltage and current transducers and by the data acquisition systems. Their metrological performance defines the performance of the all measurement chain. Considering this model, to implement the three "MQ" uncertainty levels, three different voltage and current probes and three different resolutions of the acquisition system were considered.

Table 3.3 details all the sampling specifications used, while the block diagram of the experimental setup for data acquisition is shown in Figure 3.5.

Table 3.3: **Metrological specifications of the set-up used to acquire the actual loads for the three monitoring quality levels ("MQ"). Reports information in terms of: type of measured quantity (Type); probe scaling factor (K_{probe}); probe full scale (FS_{probe}); probe accuracy (Acc_{probe}); full-scale acquisition system (FS_{Acq})**

MQ	Type	FS_{probe}	Acc_{probe}	K_{probe}	FS_{ADC}
MQ1	V	1 kV	±2.5 %	1:200 V	±8 V
	I	50 A_{RMS}	±3 %	500 mV/A	±8 V
MQ2	V	1.3 kV	±2 %	1:500 V	±0.8 V
	I	15 A_{RMS}	±2 %	100 mV/A	±2 V
MQ3	V	1.5 kV	±1 %	1:500 V	±0.8 V
	I	30 A_{RMS}	±1 %	100 mV/A	±0.8 V

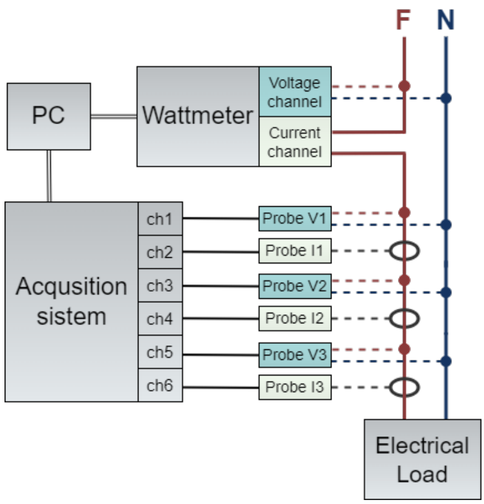


Figure 3.5: **Block diagram of the data acquisition setup and validation of the acquisition process**

In particular, as for the voltage transducer, a differential probe “Fluke DP120”, a differential probe “Tektronix P5200” and a differential probe “LeCroy HVD3106A-6M” (with a “LeCroy TPA10” probe adapters) were respectively adopted for MQ1, MQ2 and MQ3. As for the current transducer, a “Siglent CP4050” current probe, a “Tektronix TCP202A” current probe (powered by a “Tektronix-1103” power supply and a “Teledyne LeCroy CP030A” current probe (with a probe adapter) were respectively used for MQ1, MQ2 and MQ3. Acquisitions were carried out using a six-channel data acquisition system to make simultaneous acquisitions from all the aforementioned voltage and current probes. A synchronized data acquisition system based on a “TiePie HS6” and a “TiePie HS5”, and a suitable acquisition software developed in the Matlab^{TM} environment were adopted for all the experiments. To change the resolution of the data acquisition system, the number of bits (n_{bit}) used was chosen equal to 12, while the full scale of each acquisition channel was set to different values under the three “MQ” conditions. The sampling frequency was equal to 5 kS/s with a measurement observation time of 1 second. As the sampling rate is the same under the three measurement operating conditions, there are no changes in the phase resolution of the measured quantities between MQ1, MQ2 and MQ3. Concerning the acquisition interval, one hour of monitoring was carried out for each tested operating state of the loads considered, for a total of 3600 measurements per tested operating state. All the measurements in the frequency domain were carried out with a frequency resolution of 5Hz corresponding to a time window of 200ms to be compliant with the *IEC 61000-4-7:2009* standard.

For the sake of completeness, a summary and general analysis in terms of uncertainty propagation is given below, valid for the voltage and current quantities acquired under the different metrological conditions realised (i.e. different MQ levels). In terms of uncertainty assessment, the traditional GUM (*Guide to the Expression of Uncertainty in Measurement*) approaches or the Monte-Carlo method can be adopted.

In detail, from a theoretical point of view, in relation to Equation 3.1, the measured value and its uncertainty depend on all the elements of the measurement chain involved: the measurand (X_m), the probe (X_{probe}), the conditioning (X_{cond}), the analogue-to-digital converter (X_{ADC}), the environment (X_{env}) etc. [147]. Considering that the environmental conditions are controlled, since all experiments were performed in a reference and notified laboratory, and considering that there is no conditioning system, the uncertainty contributions are reduced to those arising from the probe and the data acquisition system. This reduces the complexity of Equation 3.1, to a simple case (i.e., a voltage or current probe and a DAQ system). This case has been analyzed by the papers referenced in [148] [149]. Both of these papers lead to the conclusion that even if the Monte Carlo approach is generally preferred, in this case, the two approaches lead to the same results. For this reason, for simplicity's sake, the traditional GUM approach has been used in the following research. Given Equation 3.1 in explicit form, applying the uncertainty propagation law given in Equation 3.2, the two contributions of uncertainty which characterise the measurement chain and which have the greatest impact on the measurement itself are then derived, namely those related to the probe used (u_{probe}) and the contribution introduced by the data acquisition system (u_{ADC}). The Equation 3.3 and Equation 3.4 give the definition of the latter. By substituting these expressions with the nameplate data given in Table 3.3, it is possible to obtain the uncertainty values for the voltage and current quantities, which define the metrological quality of the measurement system implemented in the three cases considered. The reported analysis, although trivial and well-known in the scientific literature, highlights the effect of the influence parameters considered to be preponderant in the "MQ" and consequently in the analysis process.

$$X_{meas} = f(X_m, X_{probe}, X_{cond}, X_{ADC}, X_{env}, ..) \tag{3.1}$$

$$u_{X_{meas}} = \sqrt{\sum_i (\frac{\delta f}{\delta x_{u_{x_i}}})^2 \cdot u_{x_i}^2} \tag{3.2}$$

$$u_{probe} = \frac{Acc_{probe}}{\sqrt{3}} \tag{3.3}$$

$$u_{ADC} = \frac{FS_{ADC}}{2^{n_{bit}} \cdot \sqrt{12}} \tag{3.4}$$

In order to validate and calibrate the considered measurement chain, namely the voltage and current probes, the data acquisition system and the implemented measurement algorithm, quantities measured on the two considered loads were compared with a reference power meter. In particular, a traceable "Yokogawa Precision Power Analyzer WT3000" reference wattmeter equipped with the harmonic analysis toolbox was adopted, as shown in Figure 3.5. The specifications adopted for the WT3000, in relation to the options made available by the manufacturer [102], are as follows: *Sampling Frequency* - Clock B 189.394 kS/s; *Data Update Rate* - 1 second for the P, S and N power measurements and 200ms for the harmonic measurements that correspond to a frequency resolution of 5Hz; *Wiring System* - 1P2W; *Measurement Functions* - Type2; *Measurement Range* - Auto. The different quantities calculated by the WT3000 were exported from the instrument via an IEEE-488 bus and a measurement software implemented in the Labview^{TM} environment.

To summarise, Table 3.4 shows the comparison in terms of mean value and standard deviation of the Active Power (P) extracted from the WT3000 and those processed by the implemented system for the three levels of MQ for each operating state of the monitored load "Lamp". The comparison shows both the compatibility with the reference and the increasing of the measurement uncertainty decreasing the "MQ" level.

Table 3.4: **Comparison between WT3000 and implemented acquisition system for electrical load "Lamp". Shows for the three monitoring quality levels (MQ) the comparison in terms of mean value and standard deviation of active power (P).**

Load - State	[W]	P_{WT3000}	P_{MQ1}	P_{MQ2}	P_{MQ3}
Lamp - 1	μ	0	0	0	0
	σ	0	0	0	0
Lamp - 2	μ	113.22	114.25	113.98	113.46
	σ	0.31	2.19	1.24	0.68
Lamp - 3	μ	115.45	116.44	115.82	115.51
	σ	0.25	2.98	1.79	0.71
Lamp - 4	μ	100.59	102.41	101.99	101.63
	σ	0.34	3.32	2.37	0.89
Lamp - 5	μ	140.42	142.86	141.93	141.69
	σ	0.29	3.58	2.51	0.93
Lamp - 6	μ	191.52	193.08	192.33	191.73
	σ	0.41	3.97	2.68	1.06
Lamp - 7	μ	59.51	61.39	60.88	60.36
	σ	0.28	3.03	1.95	0.88

Similar to the previous case, also for the *real scenario*, the metrics and calculation methods implemented for the extraction of the electrical parameters, considered in the Load Profiling process, are based on the implementation of the standards *IEEE-1459*, *IEC61000-4-30:2015* and *IEC61000-4-7:2009*, following the ESQ defined in subsection 3.4.1.

Furthermore, in analogy to the considerations made in the previous case, for the sake of completeness, Figure 3.6 shows the evolution of the absorption profiles of the *real* electrical loads considered "Lamp" and "Inv+Mot". In this case, given the large number of tested operating states of the two devices, only the trend in active power (P) relative to the intermediate monitoring quality level MQ2 is shown for each. In this way, it is still possible to observe the behaviour of the devices considered and the criticality offered in terms of Load Profiling. Given the overlap between the states, it is evident from the figure that it is of fundamental interest to search for further significant and representative parameters of the electrical signature for identification in each of the tested operating states.

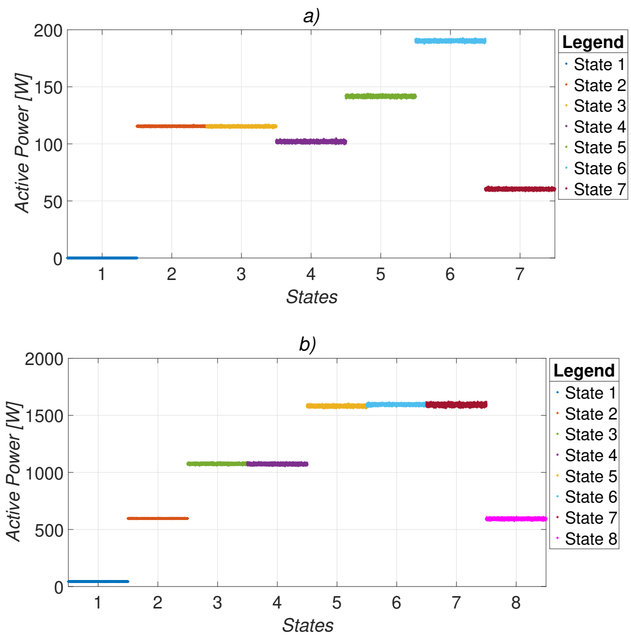


Figure 3.6: **Active power profile ($\boldsymbol{P}$) measured at monitoring quality level MQ2, for both *real* electrical loads considered. For *a)*, the labels in the Legend, from “*State-1*” to “*State-7*”, refer to the tested operating states to which the nominal active power levels correspond respectively: 0W, 115W, 115.5W, 102W, 140W, 190W and 60W. Similarly for *b)*, from *State-1*” to “*State-8*”, correspond to the nominal active power levels respectively: 43W, 595W, 1075W, 1070W, 1580W, 1595W, 1590W and 590W. Each operating state is highlighted in a different colour.**

3.6 Results

This section reports the results obtained from the tests conducted in terms of Load Profiling, varying the three influencing parameters: MQ, ESQ, and type of profiling algorithm. In summary, the loads considered refer to a simulated and a real scenario. As for the simulated scenario, the selected devices were a "Fan Heater", a "Desk Lamp" and a "Smartphone Charger". They have 4, 4, and 2 operating states respectively. In the real scenario, a bank of dimmer lamps ("Lamp") and a single-phase asynchronous motor powered by an inverter ("Mot+Inv"), with 7 and 8 operating states respectively were considered. The tests were conducted for three MQ levels (MQ1, MQ2 and MQ3), three ESQ levels (ESQ1, ESQ2 and ESQ3) and three types of Load Profiling algorithms (*k-means*, *Gaussian Mixture Modelling* and *Agglomerative Clustering*), as shown in Figure 3.2. All explanations and descriptions of the choices made are given in section 3.4 and section 3.5.

For the sake of clarity, the results are reported in tabular form. In analogy to what was done in the previous chapters, they are broken down by the type of *scenario* analysed. For each table reported, the "$Score_{sh}$" value (evaluation metrics used), i.e. the maximum silhouette coefficient obtained for that test, and the "$Err\ state_{sh}$" value, i.e. the percentage error committed in terms of the operational states identified through the silhouette coefficient with respect to ground truth, are reported within each cell. For the sake of completeness, Equation 3.5 gives the definition used for the calculation of "$Err\ state_{sh}$", where "$N_{sh\,state}$" represents the number of states identified by clustering at the maximum silhouette coefficient, and GT_{state} represents the number of ground-truth operational states of the analysed load. In this way, it is possible to tell immediately whether the algorithm overestimates, underestimates or correctly identifies the states of the system. The best condition is obtained when "$Score_{sh}$" is close to one and "$Err\ state_{sh}$" is equal to zero. In addition, the cells are coloured according to the error committed, so that the behaviour obtained from the analysis is immediately apparent.

$$Err\ state_{sh} = \frac{N_{sh\,states} - GT_{states}}{GT_{states}}\,x100 \tag{3.5}$$

3.6.1 Tests results: "*Simulated Scenario*"

Starting with the electrical load "Fan Heater", it can be seen from Figure 3.7, that at the quality level ESQ1, the process always tends to underestimate the number of operating states detecting three states instead of four with an error of −25%.

Looking a the nominal power of the considered four states [37], it can be highlighted that the power states have nominal values of 0W, 15W, 925W and 1900W respectively. In this case, as shown in the previous sections, the error is related to incorrect cluster separation of the first and second states even in the presence of low uncertainty levels (i.e. MQ1). As the "ESQ" level increases, adding new features to the clustering algorithms, a considerable improvement is highlighted. In addition to correctly identifying the number of states, the silhouette coefficient always assumes a fairly high value for both ESQ2 and ESQ3. It follows that for this load, it is more convenient to optimise the ESQ than the MQ. Therefore, a meter that is less performing from a metrological point of view but slightly advanced from a processing point of view, is sufficient to correctly identify the number of operating states for this analysed load. In any case, the progressive improvement of the analysis as the "MQ" parameter also increases is evident. Since the same behaviour was also obtained for the remaining simulated and real loads when varying the algorithm, only the results of the GMM algorithm, i.e. the intermediate case in Figure 3.2, are shown below.

Concerning the electrical load "Desk Lamp" (Figure 3.8) the following can be highlighted. *i)* for MQ1 value, whatever the "ESQ" levels, it is impossible to correctly profile the operating states. In detail, an error equal to −50% is obtained meaning that only two states are recognised. Looking at Figure 3.4 ("*MQ1-a)"*) this can be explained considering that state 1 and state 2 are very close and the same happens for state 3 and state 4. *ii)* For the MQ2 value a correct Load Profiling is obtained only for the ESQ3 signature level but a low silhouette score is performed. This means that a high number of features partially compensated for the variability due to the uncertainty measurement. *iii)* For MQ3 whatever the "ESQ" level a correct Load Profiling is achieved. When ESQ3 is experienced the silhouette score reaches a good value that highlights the good shape of the cluster and the reliability of the Load Profiling algorithm. Looking at Figure 3.4 ("*MQ3-c)*") it is possible to appreciate the good shape of the four power states clusters. That is, there is a tendency to obtain clusters characterised by increasingly better cohesion and separation. From these considerations, it follows that for this type of load, in a profiling process, it is not so important to optimise the processing, and thus the computational capabilities of the meter, but it is more advantageous first to improve the quality of the measurement system.

Finally, for the *simulated scenario*, Figure 3.9 shows the results obtained for the "Smartphone Charger" load. Given the "simplicity," in terms of the number of states of the analysed load, the profiling process always returns the correct number of operational states. Moreover, in this case, the effect of the improved quality parameters of monitoring and electrical signature is much more evident than in previous loads. In fact, the value of the silhouette coefficient goes from a minimum of 0.8 in the worst case to a value extremely close to 1 in the best case.

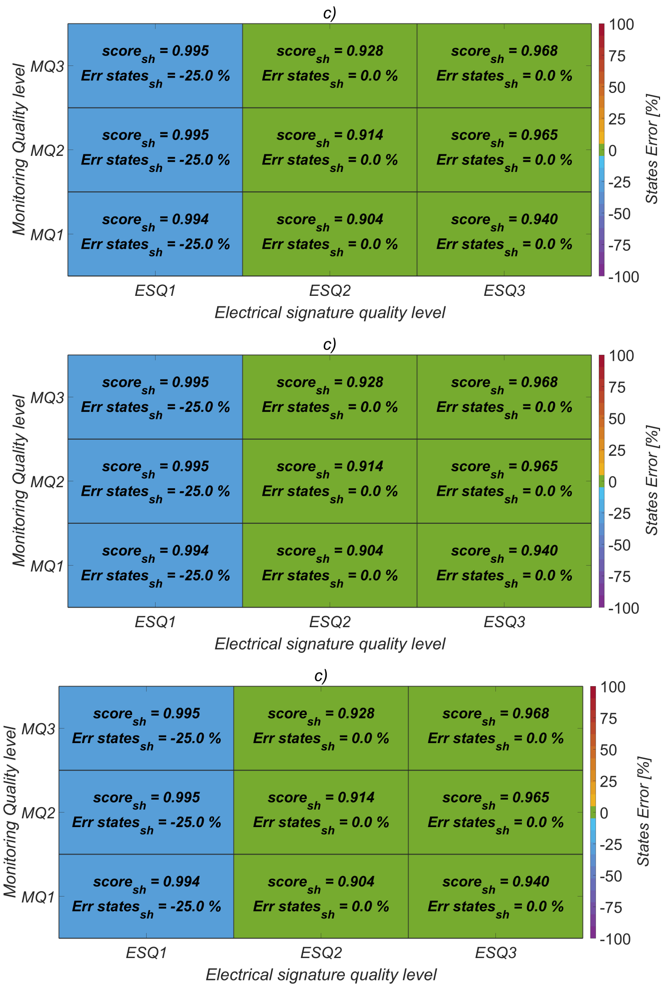


Figure 3.7: **Results obtained for the "Fan Heater" load with the clustering algorithms: *a)* k-means, *b)* Gaussian Mixture Model and *c)* Agglomerative.**

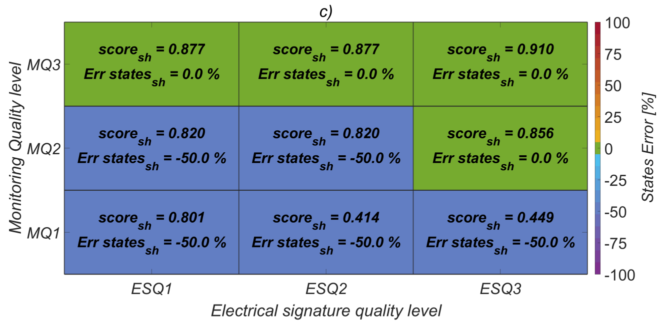


Figure 3.8: **Results obtained for load "Desk Lamp" by Gaussian Mixture Model clustering algorithm.**

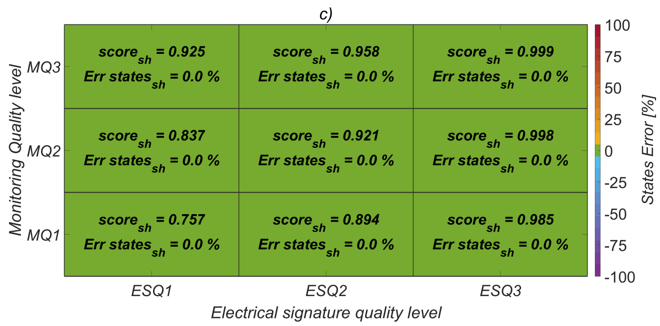


Figure 3.9: **Results obtained for load "Smartphone Charger" by Gaussian Mixture Model clustering algorithm.**

3.6.2 Tests results: "*Real Scenario*"

With regard to the "Lamp" load, i.e. the dimmer lamp bank, it is evident from Figure 3.10 that the load profile results on this electrical load are similar to those obtained on the "Fan Heater" analysed in the simulated scenario. In other words, in condition ESQ1, the process never identifies the correct number of operating states. At the ESQ2 and ESQ3 levels, on the other hand, it is evident that the algorithm always correctly identifies the number of clusters, and thus the operational load states. Furthermore, as explained in the previous subsection, the output obtained at levels ESQ2 and ESQ3 is characterised by a high value of the silhouette coefficient, which indicates a correct separation and cohesion of the clusters.

Lastly, the results obtained for the electrical load "Mot+Inv" are shown in Figure 3.11. This load is characterised by a high number of operating states (8), very close to each other in terms of power as shown in Figure 3.6 (b)) of subsection 3.5.2. It can be seen that at levels ESQ1 and ESQ2, as well as MQ1, it is never possible to correctly identify the operating states of the system considered. In fact, for a correct analysis in terms of Load Profiling, it is necessarily only necessary to work at the “MQ2-ESQ3” and “MQ3-ESQ3” levels. That is, it is necessary to have medium to high MQ and a representation of the electrical signature as complete as possible. Consider the use of high-performance smart meters. Under these conditions, the high number of parameters considered and the medium and high level of MQ lead to the optimal identification of operational states, characterised by a high silhouette coefficient value.

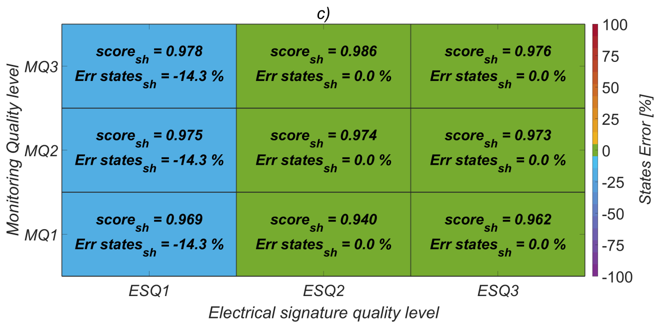


Figure 3.10: **Results obtained for load “Lamp” by Gaussian Mixture Model clustering algorithm.**

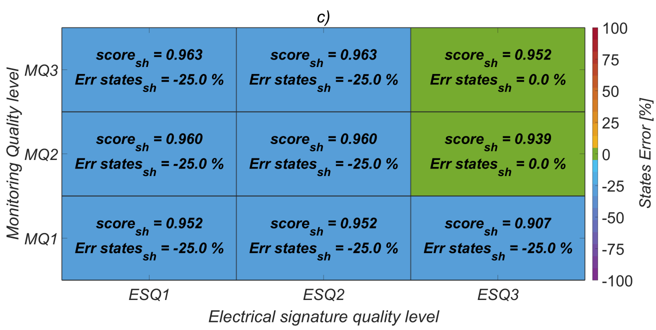


Figure 3.11: **Results obtained for load “Mot+Inv” by Gaussian Mixture Model clustering algorithm.**

3.7 Observations and Conclusion

This research analyses the crucial role played by smart meters in the Load Profiling task considering the influence of the monitoring quality, i.e. the measurement uncertainty, and the Electrical Signature Quality, i.e. the number of electrical parameters derived from the electrical signature. Some conclusions can be derived from the proposed study:

- Even if the increasing of the "MQ" improves the LP process, not always the increasing of the number of measured parameters (i.e. "ESQ") brings benefits in the Load Profiling process. This happens when many of the features taken into consideration do not have great sensitivity with respect to changes in the energy states. In these cases, even if a large number of features is calculated, the poor sensitivity could lead the Load Profiling algorithms to wrong decisions leading to an underestimation or an overestimation of the number of actual states of the system under test. In these cases, the high number of not-significant features return worse results with respect to the use of traditional P, N, S power indexes;
- to face this problem it could be useful to introduce statistical unsupervised methods, such as the proposed Kernel Density Estimation "KDE", which allow to eliminate the parameters with poor sensitivity;
- for the Load Profiling process, in many cases, uncertainties lower than those required by the energy billing (referred as MQ3 in this research) are sufficient to correctly assess the task allowing to reduce metering infrastructure costs. In this sense, this study could be useful to the developer since it suggests a method to define the target "MQ" level and the useful features required for the given Load Profiling task;
- "MQ" and "ESQ" values influence the Load Profiling process in the same way whatever the three clustering algorithms considered in the research;
- the methodological approach considered in this research by the author could be useful to analyse also Load Profiling problems related to other physical quantities (i.e thermal energy profiling) or *multi-physical* systems, allowing to user to define a target "MQ" and a minimum number of useful features to be adopted.

Chapter 4

Fault diagnosis based on Load Profiling: the role of Electrical Signature Quality for reliable fault detection

4.1 Highlights

- **Diagnosis in Smart Factories**: Optimisation of diagnosis and maintenance processes is essential to ensure continuity, safety and efficiency in Smart Factories and the electrical sector, taking advantage of advanced Smart Energy Monitoring technologies.
- **Load Profiling as a diagnosis tool**: The research explores Load Profiling as a low-cost diagnostic tool to identify faults and anomalies in an unsupervised manner, using the "Electrical Signature Quality" (ESQ) as a key parameter, evaluating its sensitivity in the diagnostic process [75].
- **A-priori knowledge-independent approach**: The proposed diagnostic method can be applied without prior knowledge of the monitored system, independently identifying healthy operating states and faults from the collected data.
- **Asynchronous motor case study**: In this research, an asynchronous motor is used as a case study, demonstrating how optimising the quality of

the monitored electrical signature can significantly improve diagnostic performance even in the presence of critical faults.

- **Guidelines for optimising diagnosis processes**: The analysis shows how the performance of a diagnostic process can be reduced depending on the type and degree of criticality of the fault, and how this loss can be recovered by optimising the quality of measurement data. This can provide guidelines for optimising the capabilities of diagnostic monitoring tools in electrical systems.

- **Future Perspectives**: Future developments could extend the approach to more complex electrical systems, analysing process performance by considering "Monitoring Quality" (MQ) as an additional optimisation parameter, and analysing "drift" faults by introducing cluster analysis tools to improve the timeliness of the diagnostic process.

4.2 Introduction

In the last years, artificial intelligence (AI) and Machine Learning (ML) based techniques are often used to improve diagnosis and anomaly detection in simple or complex systems [63, 150–152]. In detail, they help in collecting physical quantities, examining big data and making decisions on the monitored system. To obtain this big data necessary for the AI and ML-based techniques, smart monitoring technologies are therefore required. When the faults regard electrical system these technologies can be implemented by electrical smart meters that are capable to collect a huge number of electrical parameters on relatively short measurement intervals. In this scenario, the degree of detail of the information is closely related to the type and number of parameters collected namely the of "*Electrical Signature Quality*" - ESQ [52].

For example, concerning the identification of faults for electric motors, and typical industrial loads, various methods have been widely studied in the literature, both specific for mechanical faults and generic for electro-mechanical faults, based on the measurement and processing of electrical signals [153]. Among these, surely a reference technique is the Motor Current Signature Analysis - MCSA, which uses measurements of the current absorbed by the motor to diagnose faults [154], starting from the knowledge of the machine's characteristics.

Based on these considerations, the objective of this research reported in the following chapter is to present a low-cost diagnostic method based on Load Profiling. The peculiarity of the proposal is that the method is capable of extracting information on the operating conditions of monitored systems, regardless of the nature, type and previous knowledge of the system. Following a methodological approach, in this research the use of Load Profiling as a diagnostic tool through an unsupervised approach is experimentally tested on a real case study. In addition, considering different ESQ levels, the sensitivity of the system is evaluated with respect to the degree of detail of the electrical signature, and therefore the variation of the performance of the detection process in terms of accuracy and timeliness is assessed. It should be emphasised that the type of analysis conducted, allows us to extend the concepts and what has already been generally defined in the previous chapter regarding Load Profiling (chapter 3).

In particular, the case study taken into consideration is an asynchronous motor. Through a phase of experimental acquisition and analysis in terms of profiling, it was possible to characterise in the form of a state machine its operation in nominal and fault conditions, considering for the latter two types of fault, differing in criticality. About the fault conditions, experience and scientific literature were used to analyse a typical and realistic type of fault for the load considered.

The structure of the following chapter is as follows: first, the process and the analysis techniques implemented in the process are presented, as well as the chosen ESQ levels; then, the characteristics of the device chosen as a case study, the operating conditions tested and the experimental monitoring campaign carried out are illustrated; finally, the results obtained from the analysis process are reported and the appropriate final considerations are made.

4.3 Background: Protocol and analysis methods

In brief, as mentioned in the previous chapter (chapter 3), Load Profiling refers to the identification and characterisation of the operational states of a system. In the electrical case, an operating state is given by a particular combination of voltage and current quantities to which corresponds a specific operating state, nominal or otherwise, of the monitored system. In practice, through Load Profiling it is possible to map a load into a "state machine" [37, 52], and thus to define a pattern of standard operating states of the system and to perform diagnostic and efficiency evaluations against this to understand whether the monitored load is moving away from a "normal operating state".

Starting from the data set described in section 4.4, the implemented analysis procedure, according to the Figure 4.1, can be divided into the following *steps*:

1. *Data Adjustment* - The obtained dataset is trivially adjusted according to the specifications required by the implemented techniques.

2. *Feature Selection* - From the total number of electrical input parameters, only those most interesting and significant for profiling the system under consideration are selected.

3. *Load Profiling* - In the space of the same size as the number of selected parameters, a search is carried out for possible regions of point densification, i.e. possible clusters representative of the operating states of the system being analysed;

4. *Fault Detection* - It is checked whether the number and type of clusters obtained coincide with the number of operating states under normal operating conditions. The appearance of a new state may highlight the presence of a fault or an alteration in the operating cycle of the system considered.

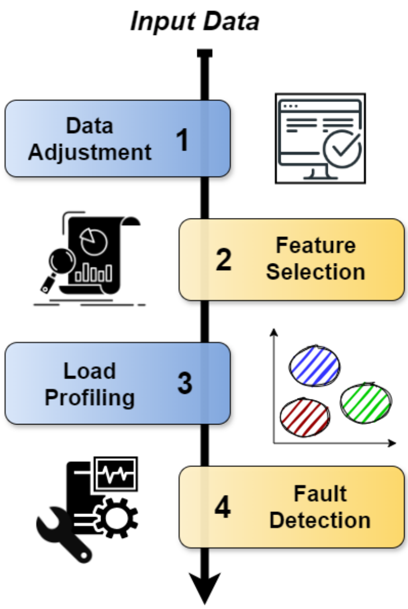


Figure 4.1: **Block diagram of the implemented analysis process.**

This procedure was carried out up to point *3*, for the analysis of the system under normal conditions (without failure), to define "the history of the system"; whereas the entirety of it when referring to the failure. In addition, this was repeated a number of times equal to the chosen ESQ levels described in the next section. The entire analysis was performed in the Matlab^{TM} environment.

With regard to the techniques adopted, the scientific literature is very active in this context. For example in [71] different techniques and processing methods are proposed, including neural networks, supervised or unsupervised methods and dimensionality reduction algorithms. In this research, according to the previous chapter, an unsupervised approach was used in order to gain a more realistic view of the problem without being constrained by the knowledge of a given ground truth (actual condition of the system). However, ground truth was used at the end of the process to highlight the degree of accuracy of the implemented analyses, offering the reader a comparison with the results obtained.

In detail, in the *Feature Selection* phase, the input features corresponding to each ESQ level were appropriately selected by implementing "*Kernel Density Estimation*" - KDE, as described in [52]. In general, KDE is a non-parametric and unsupervised statistical method. Clustering was used for *Load Profiling*, using the algorithm *k-means* [155]. The latter is a partition-type clustering algorithm that can identify similarities within the data based on certain characteristics of the data. To evaluate the quality of the clustering obtained in output, the "*silhouette coefficient*" was used, which can vary in the range [-1,1], where the value 1 is obtained in a condition where the clusters are well separated and cohesive [156]. Finally, in order to get an idea of the quality of the partitioning process (assignment of points to the identified states), the parameter "*Accuracy*" was considered, expressed in percentage terms, representing the precision of the implemented process concerning the true condition.

To assess the sensitivity of the system with respect to the quality of the electrical signature, three levels were considered, respectively for increasing quality: ESQ1, ESQ2 and ESQ3. In practice, three different sets of electrical parameters are representative of the electrical behaviour of the monitored system. The definition of these levels is similar and extensively described in subsection 3.4.1. The electrical signature is all that the system leaves behind once it is powered, i.e. the harmonic spectrum of voltage and current, unique and specific to the system itself. Quality' refers to how the measured electrical signature is summarised, i.e. the processing metrics implemented and the number of parameters extracted; these aspects are related to the computational capabilities of the meter implementing these metrics.

In detail:

- in ESQ1 reference is made to the 3 parameters of Active Power (P), Apparent (S) and Non-Active (N);
- in ESQ2 the IEEE1459 standard is implemented [46], specialised to the single-phase non-sinusoidal case for a total of 21 parameters excluding those related to voltage only;
- in ESQ3 the IEEE1459 standard and the IEC 61000-4-7/4-30 standard for harmonic analysis are implemented [49] [48], for a total of 123 parameters excluding those related to voltage only.

4.4 Experimental analysis

This section reports on the experimental monitoring activity carried out in the *Laboratory of Industrial Measurements* - LAMI, at the University of Cassino and Southern Lazio. In detail, the following are reported in order: the characteristics of the electrical load considered and the operating conditions tested; finally the measurement set-up and sampling specifications are described.

4.4.1 Considered Scenario

The Device Under Test - DUT, is a single-phase asynchronous motor. The latter is one of the most widely used types of rotating machine in any application context, especially industrial (similar to three-phase); as such, it is subject to various sources of failure that can affect efficiency and reliability. The nominal specifications of the DUT are shown in Table 4.1.

Table 4.1: **Electrical characteristics of the DUT. It shows the nominal values of: supply voltage (V_n), nominal frequency (f_s); speed (n_n), number of poles (p), number of rotor slots (R); active power (P_n) and power factor (PF_n).**

Specifications	Descriptions
Type	single-phase asynchronous motor
V_n - f_s	230 V - 50 Hz
n_n - p - R	1350 rpm - 4 poles - 24
P_n	0.55 kW
PF_n	0,96

Regarding to the operating conditions considered, two possible scenarios were assumed:

- "*System under Normal Operating Conditions*" - NOC
  A total of 8 operating states were tested under normal conditions (healthy system), obtained by running the motor at 8 different load levels, including the Off state (stationary rotor). This value was defined in order to have a "non-simple" scenario to deal with in terms of the number of states. The chosen operating cycle is based on an ordered succession of states. These two choices are consistent with the objective of this work, i.e. to investigate and preliminary consolidate the potential use of Load Profiling as a tool for fault detection and diagnosis, and is in line with the hypothesised analyses described in section 4.3.
- "*System in Abnormal Operating Condition*" - AOC
  In this case (i.e. subject to failure), the failure is added to the operational condition realised in NOC, which determines a new more or less critical state, for a total of 9 operational states. In detail, two failure cases were considered:
  - AOC-1 - Slight loss of performance. From a healthy state of NOC, the corresponding load is reduced by approximately 2%, resulting in a change in energy and monitored parameters compared to the healthy condition;
  - AOC-2 - Slight dynamic eccentricity. From a healthy state of NOC, an eccentricity of the motor axis was caused. This represents a "critical" case, interesting in diagnostic terms, as the energy variation between the healthy state and the corresponding fault state is not significant.

The DUT under consideration, being a rotating electrical machine, presents certain peculiarities in terms of the relationship between the machine characteristics and operating points [157, 158]. That is, knowing the structure of the rotating machine, it is possible to know in advance what the effect of the fault will be. Specifically, in AOC-2 there is a condition where the air gap between the rotor and stator is not uniform. As shown in Figure 4.2, there are two types of eccentricity: static (the position of the minimum radial air gap is fixed) and dynamic (the position of the minimum air gap follows the position of the rotor). Regardless of the type, air-gap eccentricity results in a variation of the air-gap flow waveform. Consequently, this induces stator current components given by [159]:

$$f_{ec} = f_s \left[(R \pm n_{ec}) \left(\frac{1-s}{p_p} \right) \pm n_{ws} \right] \tag{4.1}$$

where f_{ec} [Hz] is the frequency components in a current spectrum due to rotor slotting and air gap eccentricity; f_s [Hz] is the supply frequency; R is the number of rotor slots; n_{ec} is the eccentricity order number ($n_{ec} = 0$ for static eccentricity and $n_{ec} = 1, 2, ...$ for dynamic eccentricity; s is the slip ratio; p_p is the pole pairs; n_{ws} is the order number of stator current harmonic. The MCSA monitoring strategy is based on these concepts [154], where, with the machine characteristics known, the frequencies given by Equation 4.1 can be used to identify the failure pattern *a priori*. Unlike MCSA, which necessarily requires prior knowledge of the machine's structure and operating conditions (speed and load-dependent creep), the idea in this research is to present an approach that disregards these aspects. However, the considerations made are necessary to offer the reader a methodological approach and to justify the metrological choices that follow.

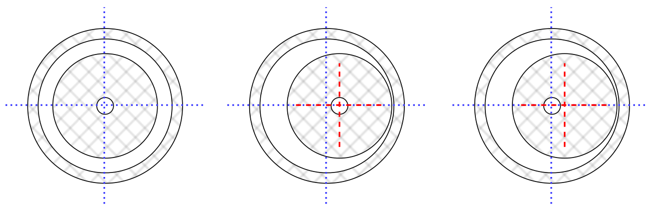


Figure 4.2: **Different operating conditions of a motor rotor: *a)* Normal state, *b)* static eccentricity, *c)* dynamic eccentricity**

4.4.2 Measurement Set-up

Figure 4.3 shows the block diagram of the set-up realised for the monitoring campaign of the chosen electrical device under the different operating conditions tested. The diagram can be subdivided into: *Measurement Section*; *Power Section*; *Validation Section*. The sections just highlighted are described below, with the exception of the power section, which does not require any particular detail as it consists of the DUT previously described and the power source.

About the measurement section, voltage and current waveforms were acquired using a "Tektronix P5200" differential voltage probe and a Hall effect probe "Tektronix P202A". A "TiePie HS5" programmable digital oscilloscope was used as the acquisition system, connected to a PC and managed by software specially developed in the Matlab$^{\text{TM}}$ environment.

All metrological characteristics of interest and sampling used for DUT acquisition are summarised below:

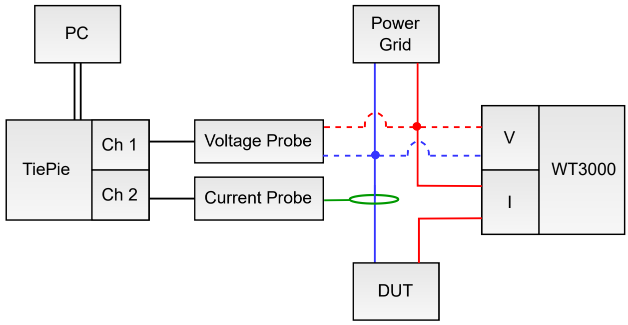


Figure 4.3: **Block diagram of the implemented measurement set-up**

- sampling frequency $\mathrm{F_s}$ of 5 kS/s with a frequency resolution $\mathrm{Res_F}$ of 1 Hz;
- 150 acquisitions per state $\mathrm{N_{ACQ}}$ with a measurement time $\mathrm{T_{Obs}}$ of 1 *second*;
- ADC TiePie resolution equal to 12 *bit* with full-scale voltage and current of 0.8 V and 2 V respectively;
- voltage and current probe scaling factors of 1 : 500 and 100 mV/A respectively.

Sampling parameters were chosen based on two aspects: ensuring consistency with metering systems, typically installed in the analyzed context, and attached regulations; ensuring consistency and comparison with scientific literature concerning what was said in the previous subsection. In particular, it was established: the frequency resolution Res_F (inverse of the measurement time T_{Obs} was such that the resolution-related error was contained within certain limits following IEEE 1459 standard; The frequency range analysed ($F_s/2$) was such that a band of at least up to the 50th harmonic of voltage and current was considered following IEC61000-4-30 standard. Moreover, the latter is consistent with Equation 4.1, even considering extreme variations in the n_{ecc} and n_{ws} factors (within common sense limits considering the decay of amplitudes as the band considered increases) and the DUT data shown in Table 4.1.

The monitoring and extraction of the electrical quantities of interest was carried out for each operational state of the DUT, under normal and fault conditions. Specifically, 150 measurements (N_{ACQ}) were taken per operational state (approximately 40 minutes); this value was unravelled to have a sufficient number of data to perform the analyses presented in section 4.3. About the calculation metrics implemented, in accordance with the ESQ levels described above, the application of the IEEE 1459 standard was used, specialised to the single-phase non-sinusoidal case, and the IEC 61000-4-7/4-30 standard for harmonic analysis. In this way, it was possible to monitor the DUT in varying degrees of detail, extrapolating different sets of electrical parameters from the electrical signature of voltage and current, allowing for a correct and comprehensive implementation of the assumed methodologies.

The validation section consists of the "Yokogawa WT3000 Precision Power Analyzer", which measures and records certain electrical quantities of the DUT, at the same time as the experimental measurement system, with a much higher resolution and accuracy, to verify the compatibility between the two systems. Table 4.2 shows, in terms of mean and standard deviation for each state in NOC, the values of active power extracted by the WT3000 and that processed by the realised system. To summarise, only the active power is reported, which is representative in terms of validation as it is the combination of several monitored electrical quantities. The result of the comparison is positive, with the measurement ranges for each tested operating state being metrologically compatible. In addition, a greater variability of the operating state 3 compared to the other states is evident in both cases. The DUT-load system probably exhibits greater torsional vibrations in this condition. These can sometimes result in fluctuations, more or less pronounced, in the rotor's rotational speed, similarly causing disturbances in the electromagnetic flux at the air gap, and thus in the currents in the motor windings [160].

Table 4.2: **Comparison between WT3000 and implemented experimental set-up. Shows, for each state, the comparison in terms of mean (μ) and standard deviation (σ) of active power (P).**

DUT-State	$\mathbf{P_{WT3000}}$ **[W]** $\mu \pm \sigma$	$\mathbf{P_{set\text{-}up}}$ **[W]** $\mu \pm \sigma$
DUT - 0 (off)	8.827 ± 0.072	8.94 ± 0.22
DUT - 1	22.363 ± 0.077	22.95 ± 0.81
DUT - 2	34.745 ± 0.064	34.64 ± 0.35
DUT - 3	67.5 ± 1.8	68.2 ± 2.6
DUT - 4	109.262 ± 0.097	108.95 ± 0.41
DUT - 5	152.34 ± 0.16	152.71 ± 0.52
DUT - 6	270.21 ± 0.25	271.1 ± 1.3
DUT - 7	367.34 ± 0.32	368.3 ± 1.3

4.5 Results

This section first summarises some of the outputs obtained from the monitoring campaign and then presents the results obtained from the analyses conducted under the different conditions tested.

The behaviour of the different operating states, normal and fault (blue and red respectively), is shown: in Figure 4.4 in terms of Active Power (P); and in Figure 4.5 in terms of Current Distortion Power (D_I) as a function of Active Power (P). Only a few of the electrical parameters monitored are shown at a glance. It can be seen from the figures that, as to be expected, as the motor load changes, the motor's absorption mode changes. On the other hand, it can be observed that in AOC-1 (Figure 4.4.a), the loss of performance in terms of load of the healthy state *3*, results in an absorption pattern equal in form, but smaller in amplitude. This is confirmed by the Figure 4.5.a, which shows the appearance of a new thickening region of a similar shape. Furthermore, in Figure 4.5.a, 9 zones of point densification, representative of operational states, 8 healthy and 1 fault, are easily visible. Regarding the AOC-2, dynamic eccentricity at the axis is caused at healthy state *4*, which responds in terms of active power with a behaviour very similar to the healthy condition as shown in Figure 4.4.b. In fact, extremely interesting is the behaviour obtained by observing Figure 4.5.b which shows the overlap between the healthy state *4* and the same subject to eccentricity. It is evident that this condition is extremely critical in diagnostic terms and difficult to detect.

4.5.1 Test results

In relation to the observations made, the results obtained from the detection process in the two AOC tested are shown. For completeness, the output of Load Profiling under NOC is also shown before and after the application of feature selection as a starting reference.

In NOC, starting from the features extracted from the realised system, through the application of the KDE algorithm, the most significant features were selected in terms of profiling for the monitored system. Of course, in the feature selection phase, the three ESQ levels mentioned in section 4.3 were considered and consequently discarded, for each ESQ subset, the features that were not significant for the process. Table 4.3 shows the effect of correct parameter selection, i.e. the results obtained in terms of Load Profiling, before and after feature selection ("NOC pre FS" and "NOC" respectively). In the "NOC pre FS - ESQ1 and ESQ2", the

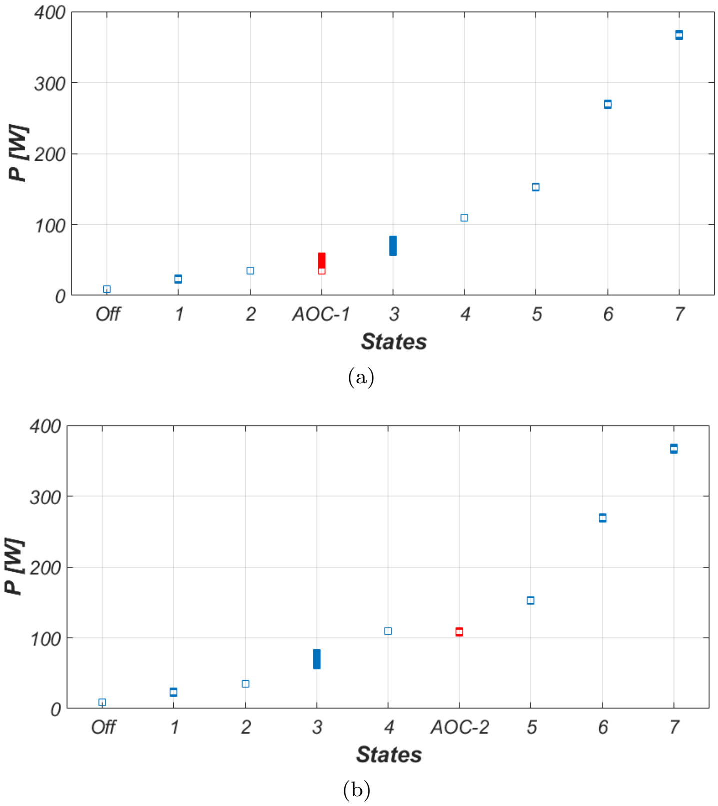
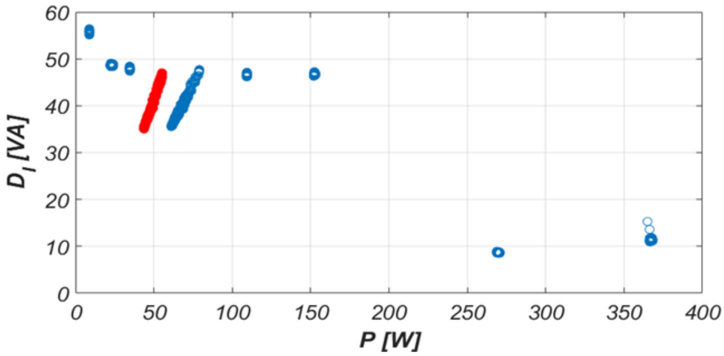
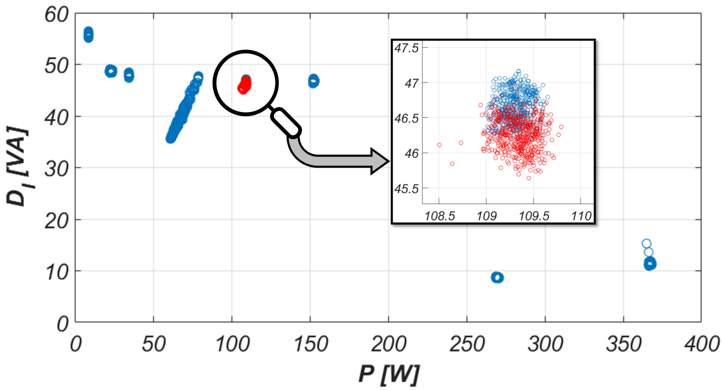


Figure 4.4: **Comparison between "system under Normal Operating Conditions" (blue) and "system in Abnormal Operating Condition" (red), in terms of active power (P) as a function of operating states. *a)* shows the AOC-1; *b)* shows the AOC-2.**

k-means algorithm returns a corrected number of clusters (k) of 8. For these values of k, the average Silhouette coefficient (Sh) obtained is given. In "NOC pre FS - ESQ3", the algorithm gives an incorrect result in terms of identified states ($k = 18$), with a relatively small Sh coefficient. This highlights the presence of many non-significant parameters that bias the result towards an incorrect solution, especially in ESQ3. Observing the results in NOC conditions with the application of KDE, it is evident that there is also a significant overall improvement in performance in terms of Accuracy (Acc). The condition of $Acc = 100\%$ indicates that all the clusters identified coincide perfectly with the tested operational states.



(a)



(b)

Figure 4.5: **Comparison of "system under Normal Operating Conditions" (blue) and "system under abnormal operating conditions" (red) in terms of Current Distortion Power (D_I) as a function of active power (P).** ***a)*** **shows the AOC-1;** ***b)*** **shows the AOC-2 with a zoom on the critical fault.**

In AOC, the presence of the fault causes a new operational state to appear; therefore, the number of expected operational states is 9. For summary in Table 4.3 for the fault conditions, the results obtained with the application of KDE are directly reported.

- In AOC-1, the motor performance loss is correctly detected in ESQ2 and ESQ3 as evidenced by *Acc* parameter. Furthermore, the values assumed by the *Sh* coefficient show good cohesion and separation of the clusters representing the identified states. In the case of ESQ1, the quantities *P, N, S,* are not sufficient to identify the anomaly probably due to the reduced variation of the energy content of the system.

- Regarding AOC-2, similarly to the previous case, only at ESQ2 and ESQ3 is there a correct k value. However, in this condition, the offset to which the motor is subjected results in lower Sh coefficient values than at AOC-1. Furthermore, and very interestingly, even if the detection algorithm converges to the exact number of clusters, the Acc value varies significantly between ESQ2 and ESQ3, from 42% to 97.2% respectively.

Table 4.3: **Results obtained in the different operating conditions (OC) tested for each ESQ *level*. Shows: the number of operational states detected (k); the goodness associated with the result obtained in terms of the silhouette coefficient (Sh); the accuracy associated with the result obtained (Acc).**

OC	level	k	Sh	Acc
NOC pre FS	*ESQ1*	8	0.9618	97.2%
	ESQ2	8	0.9864	100%
	ESQ3	18	0.6141	0%
NOC	*ESQ1*	8	0.9618	97.2%
	ESQ2	8	0.9913	100%
	ESQ3	8	0.9923	100%
AOC-1	*ESQ1*	11	0.9613	0%
	ESQ2	9	0.9630	98.9%
	ESQ3	9	0.9720	100%
AOC-2	*ESQ1*	10	0.9696	0%
	ESQ2	9	0.9560	42.4%
	ESQ3	9	0.9654	97.2%

4.6 Observations and Conclusions

In this work, a low-cost diagnostic method based on Load Profiling that can be easily implemented in monitoring systems was presented. The main feature of the proposed diagnostic method is the capability to be applied without none *a-priori* knowledge about the monitored system since it is able to retrieve the operating states of the system learning from monitored data. In addition, the research carried out a sensitivity analysis about the influence of the Electrical Signature Quality on the performance of the proposed method. This analysis can provide guidelines to help developers on the required capabilities of the instruments to be installed for the diagnostic monitoring of electrical systems. To validate the proposal and to test the effect of the Electrical Signature Quality, a simple experimental case study based on an asynchronous motor has been considered. The asynchronous motor was chosen as a case study as it is a typical electrical load in the industrial sector considered. Through a methodological process of experimental acquisition and analysis, aimed at ensuring consistency with the usual metering systems, standards and scientific literature, the study highlights the usefulness of Load Profiling in diagnostic processes. The analyses conducted show how the performance of the diagnosis process can be significantly reduced depending on the type and degree of criticality of the fault, and above all how this loss can be recovered by optimising the quality of the measurement data. Hence the real importance of the intelligent monitoring concept in fault detection and predictive diagnosis processes.

Regarding potential future developments, in addition to generalising and replicating the approach on complex electrical systems, there are: the possibility of analysing process performance by considering the *"Monitoring Quality"* (MQ) as a further optimisation parameter; the analysis of further fault types, also of the "drift" type, to also assess the timeliness of the method, introducing a cluster analysis process downstream of Load Profiling.

Chapter 5

A new unsupervised approach for energy disaggregation in NILM applications based on Load Profiling

5.1 Highlights

- **Innovation in Non-Intrusive Load Monitoring (NILM)**: The research introduces a new unsupervised approach for energy monitoring, exploiting the advanced concept of Electric Signature Quality to overcome traditional limitations. This offers new perspectives in intelligent energy management in the context of increasing energy digitisation [79].
- **Simple and Effective Disaggregation Methodology**: An energy consumption disaggregation technique based on Load Profiling is proposed, using clustering methods and statistical analysis. The proposed approach allows the operational states of the monitored system to be represented through state-load combinations, improving the accuracy in distinguishing between different electrical appliances.
- **Validation on Realistic Scenarios**: The study was experimentally validated in an office environment, simulating a real context with three multi-

state electrical appliances. This practical approach lends robustness to the results obtained, demonstrating the method's effectiveness under realistic conditions.

- **Reduced Dependence on Prior Knowledge**: The approach only requires knowledge of the nominal nameplate characteristics of the equipment, eliminating the need for historical data or trained models, thus simplifying implementation and reducing costs.
- **Promotion of Intelligent NILM Techniques**: Research highlights how advanced NILM techniques can be implemented that do not require training phases, but exploit an enriched electrical signature over traditional energy parameters, paving the way for new applications in energy management.
- **Future Development Perspectives**: The results obtained suggest the possibility of applying the proposed methodology to more complex scenarios and further optimising the clustering process through the use of advanced algorithms. Furthermore, integration with artificial intelligence methods could improve the accuracy and efficiency of monitoring, representing a potential quantum leap in NILM technology.

5.2 Introduction

In the context of optimising energy monitoring processes, Non-Intrusive Load Monitoring- NILM lends itself as one of the most useful and advantageous technologies for minimising the costs of Metering network management [37] [161]. In brief, the principle on which it is based on the analysis of the monitored powers, mainly active and rarely also apparent and reactive, to identify the power rate of the individual device. Thus, from a single "aggregated" measurement of the monitored system, it is possible to know which devices are active or not. Using more accurate methods, it is also possible to know which operational state the individual devices that make up the aggregate are in. An operational state is defined as a combination of the consumption spectra of the electrical quantities of a monitored device such that a specific working condition of the device is determined [52].

However, some factors can influence the performance of a NILM process. They can be summarized in the following items:

- *a) Type of scenario* - In the presence of two or more devices with very similar operating states in terms of energy consumption, it may be very difficult to "distinguish" subjects and thus to correctly disaggregate an aggregate consumption; this is because the analysis is mainly based on “basic” power quantities [162].

- *b) Size of the scenario* - The number of devices constituting the aggregate and the relative number of operational states of each, determine the number of possible state-state combinations (N_{SL}) constituting the aggregate considered [163]. In artificial intelligence (AI) and machine learning (ML), this translates into the number of “classes” of the problem. The greater the number of classes, the greater the complexity of the model. To get an idea, in the presence of multi-state loads (and/or single and double state), defined as n_L the number of loads and n_{si} the number of operational states of the *i-th* load, the number of possible combinations is: $N_{SL} = \prod_{i=1}^{n_L} n_{S_i}$;

- *c) Implemented disaggregation methodology* - The type of technique implemented defines how the disaggregation is carried out, as well as how much additional information of the monitored system is required [161]. For example, in the case of NILM processes based on supervised algorithms, it will be necessary to provide information on the actual state of individual loads (*ground truth*) in addition to the aggregate in the training phase.

As mentioned, a NILM process is based on the disaggregation of the monitored power. However, this parameter is only one of many that characterise the operational state of a device. To this end, to limit the *a)* and *b)* points and optimise performance, other additional parameters could be considered. This would increase the Electric Signature Quality (ESQ); a highly technical, as well as strategic, parameter in Smart Monitoring processes [52]. This refers to the degree of detail against which the system is analysed; i.e. the methodology and number of synthetic parameters extracted from the harmonic spectrum of voltage and current consumed by the electrical device being monitored. As pointed out in [37], a higher ESQ would solve the problems mentioned in *a)*; moreover, this helps to address the issues mentioned in *b)* more consistently, as an increase in the ESQ leads to a useful increase in the size of the “feature space”. Regarding point *c)*, a multitude of algorithmic solutions for disaggregation processes have been proposed over time. In this sense, it can be said that the best condition is when the amount of information input to the implemented method is minimised, i.e. only aggregate consumption is provided.

This research aims to propose a non-intrusive solution for load disaggregation based on an unsupervised approach. The role of ESQ in the context of disaggregation is analysed by proposing a non-intrusive solution based on an unsupervised ML approach while guaranteeing simplicity and low computational cost. Following this approach, it is researched what should be the minimum level of parameters, in the case under consideration three ESQ levels, such as to guarantee good disaggregation performance even with electrical signature values close to each other. The only prior knowledge required is that of the nominal nameplate characteristics of the monitored devices, which, through a verisimilitude approach, allows each state-load combination of the monitored system to be associated with its respective physical label. The study is conducted with reference to a realistic scenario representative of an "office" location consisting of three *multi-state* electrical loads, monitored with an appropriate experimental setup implemented.

The structure of the chapter is as follows: first, the main aspects of a NILM process are briefly discussed; this is followed by a presentation of the scenario analysed, the characteristics of the measurement setup and the disaggregation methodology implemented. Finally, the preliminary results obtained are shown and appropriate considerations and conclusions are drawn.

5.3 Background

NILM - Non-Intrusive Load Monitoring is characterised by a high level of software implementation and almost no hardware implementation as it does not require the installation of meters directly on the monitored devices; in practice the opposite of ILM - Intrusive Load Monitoring. In NILM, since the signals (electrical signatures) of the devices are superimposed, to understand the contribution of each device, they must be processed using appropriate algorithms, typically ML and AI [161] [164]. This operation is called aggregate consumption disaggregation. In this process, electrical loads can be divided into four categories according to the type of operating states [165]: *type-1)* two-state (on/off); *type-2)* multi-state, called Finite-State Machines (FSM); *type-3)* time-varying consumption, called Continuously Variable Devices (CVD); *type-4)* permanent "constant" consumption. Operationally, NILM can be articulated in different ways, in terms of structure, as well as approach: Supervised or Unsupervised, each with its own methodologies, advantages and disadvantages.

The supervised approach to disaggregation typically has a better disaggregation capability because the algorithms (classification, regression, neural networks, etc.) learn in advance from the labelled training data of the system in question [166]. This is at the expense of the higher computational cost required and, above all, prior knowledge of the system in terms of the consumption of the individual loads to be disaggregated. On the contrary, in unsupervised approaches, algorithms, typically clustering, are used to discover hidden patterns, relationships or structures in the data without the need for pre-defined labels. In general, once the disaggregation process has been completed, the final step consists in assessing the quality and reliability of the output by means of appropriate figures of merit, which can always be divided between supervised and unsupervised [167].

As mentioned above, NILM is based on the analysis of power flows, typically active, reactive and apparent. Imagining a process based on these three parameters (features), in AI and ML terms, means analysing a system in a "feature space" of dimension three [163]. When the number of classes increases, and thus of state-load combinations, these features may no longer be sufficient to distinguish the consumption patterns of individual devices. In such cases, increasing the size of the feature space may highlight new relationships and features useful for disaggregation. This means increasing the quality level of the ESQ signature. As reported in [52], the ESQ level depends on the metrics and standards used to synthesise the harmonic spectra of voltage and current; these aspects are related to the computational capabilities of the meter implementing these metrics. However, it is important to emphasise that an indiscriminate increase in the number of measured parameters does not always directly benefit the process in question. Therefore, it is crucial to conduct a careful and balanced analysis of the ESQ parameters, sometimes using Features Selection algorithms (supervised and unsupervised), with the aim of monitoring and analysing only those parameters with a high sensitivity to the phenomena of interest.

5.4 Experimental analysis

The characteristics of the experimental monitoring activity carried out in the *Laboratory of Industrial Measurements* - LAMI, at the University of Cassino and Southern Lazio are reported below. Finally, the implemented NILM process is explained.

5.4.1 Case Study

The preliminary study conducted in this research refers to an experimental scenario, comparable to an office condition, consisting of three electrical loads: *Fan*, *Lamp* and *PC* (Personal Computer). Respectively with a number of states equal to: *4*, *3* e *2*. Considering the devices as *multi-state* and *dual-state*, in relation to the formula given in point *b)* in section 5.2, the number of state-load combinations, hence classes, is *24*. The available nameplate values of the devices used, which will later be used in the implemented NILM process, are given in Table 5.1. These by definition refer to higher power load states.

Table 5.1: **Rated electrical specifications of the devices considered.**

Nominal Parameter	**Fan-4**	**Lamp-3**	**PC-2**
Voltage - frequency	230 V - 50 Hz		
Active power P_n	30 W	80 W	200 W
Apparente power S_n	//	//	230 VA
Power factor PF_n	//	0.65	0.9

The *Fan* device is assimilated to an electrical machine, while *Lamp* is generally present in every type of utility. The operating states (*Fan-1* to *Fan-4* and *Lamp-1* to *Lamp-3*) correspond respectively to different ordered speed levels and different progressive brightness levels, starting from the off condition. Basically, both are ordered in terms of increasing power. The *PC*, a widely used electronic device, has two peculiarities: the off state (*PC-1*) is characterised by a very low but non-zero absorption related to the internal electronics; the on state (*PC-2*) is characterised by a variable absorption (however low, which is why it has not been considered as a *type-3* CVD device) related to the internal processes performed.

Regarding monitoring methods, it was decided to proceed by considering all classes of the system and for each of them using a specially developed acquisition system, described below *120* measurements were collected, thus ensuring sufficient data for the disaggregation process. The Figure 5.3 show the state-load combinations monitored.

5.4.2 Measurement Set-up

According to the Figure 5.1, the setup consists of: a power section and a measurement section. The first consists of the grid and the electrical loads considered. Using a multi-socket power strip, the three devices are supplied in parallel by the grid voltage, while the aggregate current is a function of the operating state of the individual loads.

The measurement section consists of a programmable data acquisition system (TiePie HS5) with extremely high-performance metrological characteristics, and the voltage (Tektronix P5200) and current (Tektronix TCP-202A) measurement probes used to take the signals of interest from the field. In addition, using a computer in a MATLAB^{TM} environment, the acquisition process is managed and the analysis and processing of the signals for feature extraction is performed. The sampling specifications adopted are as follows:

- sampling frequency F_s of 5 kS/s with a frequency resolution Res_F of 1 Hz;
- 120 acquisitions for each class in the system N_{ACQ} with a measurement time T_{Obs} of 1 *second*;
- ADC TiePie resolution equal to 14 *bit* with full-scale voltage and current of 0.8 V and 2 V respectively;
- voltage and current probe scaling factors of 1 : 500 and 100 mV/A respectively.

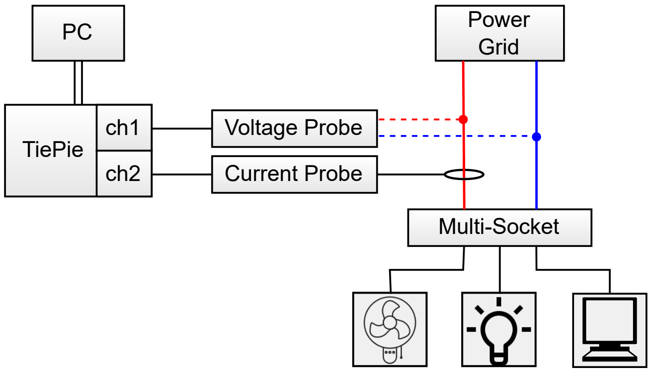


Figure 5.1: **Block diagram of the implemented measurement set-up**

These choices were made in order to: guarantee a sufficient number of measurements for post-processing; analyse a band up to the *50th* harmonic of voltage and current as indicated in the *IEC61000-4-30* standard [48]; guarantee good measurement accuracy comparable to commercial meters. Furthermore, during the tests using a reference instrument (Yogogawa WT3000), the implemented processing was validated, i.e. the extraction of the features of interest, verifying the compatibility between those provided by the experimental setup and those of the WT3000 in the same way as described in [52].

Regarding the processing for feature extraction, reference was made to the *IEEE1459* Standard specialised to the "single-phase non-sinusoidal case" [46] and to *IEC61000-4-7/30* for harmonic analysis. At the end of the monitoring and processing process, to assess the sensitivity of the process with respect to the ESQ parameter, in accordance with [52] three different sets of electrical parameters representative of the electrical behaviour of the monitored system were defined, respectively for increasing quality:

- *ESQ1* with only 3 parameters of Active Power (P), Apparent (S) and Non-Active (N);
- *ESQ2* with 21 parameters, excluding voltage-only parameters, related to *IEEE1459*;
- *ESQ3* with 123 parameters, excluding voltage-only parameters, related to *IEEE1459* and *IEC61000-4-7/30*.

5.4.3 Proposed Method

The approach proposed in this research can be generalised to any actual electrical system with loads of *types-1*, *2* and *4* (section 5.3). The only assumption that is made is the following: *monitoring such an electrical system by waiting a sufficient amount of time will result in a recorded aggregate consumption with all state-load combinations of the devices involved.* However, this is a realistic assumption which, under normal operating conditions after this waiting time, makes the number of classes in the system known. While the following remains unknown: *i)* the distribution of the measurements into the different classes (*Disaggregation Process*); *ii)* the physical correspondence between each class and the actual state-load combination (*Assignment Process*).

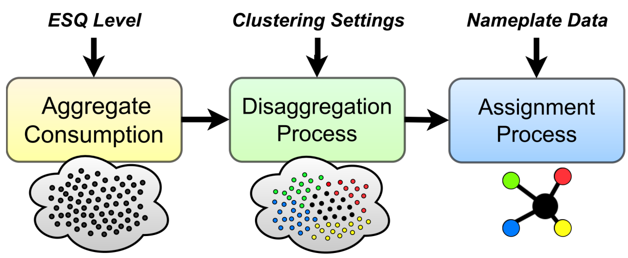


Figure 5.2: **Flow chart of the implemented process.**

About the Figure 5.2, concerning *i)*, the *Disaggregation Process* is realised by clustering in a feature space that is large in terms of dimensionality according to the ESQ level considered. The algorithm used is *k-means* with the following specifications: Euclidean distance type, the maximum number of iterations equal to 1000, and repetitions for finding the optimal solution equal to 20. According to the assumption made, from the equation given in point *b)* in section 5.2 the number of "k" partitions to be searched for the case under consideration is 24. Preliminarily for clustering, in each ESQ level mentioned before, the most significant features are selected in a non-supervised way using *Kernel Density Estimation* in the same manner as in [52]. In summary, the model receives as input the aggregated data monitored with reference to a selected ESQ level and proceeds to partition it into the chosen number of partitions, i.e. clusters. The output is given by a vector of "indices", which for each measure (row) in the input dataset associates a corresponding cluster among those found.

Concerning point *ii)*, in the *Assignment Process* starting from the nameplate data of the monitored loads and the electrical analytical relations of the system, the correspondence between the identified clusters and the state-load combinations of the system is defined. This step is described in this research in relation to the case study considered. However, it is crucial to emphasise that all the reasoning and choices implemented in the assignment process, since they are based on physical relationships, are generalisable and implementable in an AI model, e.g. in fuzzy logic.

The *Assignment Process* in this research is divided into 7 steps; in each, specific state-load combinations are sought in an order known a priori for *Step 1* and *2*, and subsequently dependent on the process itself. At each subsequent step, combinations already found are excluded from the search. The first part of Figure 5.3 shows all possible state-load combinations of the system in the order in which they were searched. Preliminarily, each cluster obtained is characterised in terms of the central tendency (average) parameters calculated for each available feature related to the treated ESQ level. In detail:

- *Step 1* - The total On and Off conditions of the loads (combinations 321 and 000) are immediately identified by the cluster at P_{max} and P_{min} (then I_{max} and I_{min}). Once P_{max} is known, the ratio of the P-rates of the individual loads is updated if necessary (similarly for any plate features).
- *Step 2* - Known the central tendency parameters of each cluster at the nameplate features, 1/3 of the total off is subtracted from each (because it is not known a priori whether the off absorption is zero). In this way, the combinations 300 - 020 - 001 are assigned to the clusters most similar to the input plate values.
- *Step 3* - Adding the combinations identified in *Step 2* in pairs and subtracting 2/3 of the total Off, the combinations 320 - 301 - 021 are obtained. These are assigned to the most similar clusters.
- *Step 4* - Based on the energy levels of the combinations found, the next combinations to be searched for are identified by delineating the corresponding existence range. Preference is given to those whose range of existence

comprises fewer clusters. To determine the most appropriate allocation, the most significant physical parameters are examined, and conditions of maximum similarity are sought. In this case, the parameter used is the powers absorbed by the individual loads, the 100 and 200 combinations being between 000 and 300. In general, this assignment approach can be generalised by selecting other physical similarities, such as the harmonic arrangement in ESQ3.

- *Step 5* - From the two combinations just found: adding 020 gives 120 and 220; adding 001 gives 101 and 201; adding 021 gives 121 and 221. The assignment of these pairs of combinations is iterated by searching for the common optimum solution in terms of similarity to the clusters.

- *Step 6* - Among the remaining unknown combinations, there is a new maximum and minimum in terms of power in analogy to *Step 1.* As the state-load characteristics are now known here, these are assigned to 010 and 311 respectively.

- *Step 7* - Looking at the state-load characteristics of the devices, the remaining combinations are sortable by energy level and thus immediately assignable to the corresponding clusters. If they are not all sortable, one can still proceed algebraically.

The concept of similarity used refers to the search for the shortest distance expressed as the average of the relative distances for each feature. All algebraic operations of sum and difference between state-load combinations described are performed between only those features of the considered ESQ level for which it is physically allowed (I, P, S, harmonic groups). Following this, the other features can be estimated indirectly (N, Power Factor, etc.). In general, assignment performance will depend on: the quality of the input data nameplate, the quality of the clustering performed and the features used in the physical relations - the latter two depending on the ESQ level considered.

5.5 Results

5.5.1 Disaggregation Process

Figure 5.3 shows, for each ESQ level, the relative error committed, in terms of assigned measures, by the clustering algorithm for each state load combination, i.e. in each of the 24 clusters. The order of the combinations shown refers to the protocol described in subsection 5.4.3 in the different steps. Please note that the nominal number of measurements per partition is 120. From the results it is possible to observe, thanks also to a colour map used, how the output improves as the ESQ level increases. In particular, especially at ESQ1, it is possible to observe confusion on the part of the algorithm to correctly search for classes in the system. This is due not only to the high number of classes but also to the presence of many state-load combinations characterised by similar values of the relevant ESQ1 parameters. In ESQ3, this aspect is clearly improved, with few contained errors probably related to the presence of outliers. This is due to the high level of ESQ used (*Harmonic Current Groups*) in the clustering process, as shown in Figure 5.3, and during algebraic operations between clusters during the *Assignment* process.

Step	State-Load $_{comb}$			Partition Error [%]		
	Fan	*Lamp*	*PC*	*ESQ1*	*ESQ2*	*ESQ3*
1	0	0	0	0	0	0
	3	2	1	0	0	0
2	3	0	0	0	0	0
	0	2	0	0	0	0
	0	0	1	35,83	5,83	1,67
3	3	2	0	62,50	4,17	1,67
	3	0	1	-14,17	-11,67	-2,50
	0	2	1	0	0	0
4	1	0	0	-4,17	3,33	3,33
	2	0	0	0	0	0
5	1	0	1	-39,17	-11,67	-3,33
	2	0	1	-45,00	-13,33	0
	1	2	0	0	0	0
	2	2	0	20,83	5,83	0
	1	2	1	0	0	0
	2	2	1	1,67	4,17	0
6	3	1	1	-18,33	-2,50	-2,50
	2	1	1	-5,00	2,50	0
7	1	1	1	5,00	3,33	0
	0	1	1	0	0	0
	3	1	0	17,50	22,50	3,33
	2	1	0	0	0	0
	1	1	0	0	0	0
	0	1	0	-17,50	-12,50	-1,67

Figure 5.3: **Normalised error of the output of the *Disaggregation process* by clustering at varying ESQ level. Shows the error for each state-load combination associated with each analysis step of the proposed method.**

5.5.2 Assignment Process

For each ESQ level tested, the *Disaggregation process* outputs the index vector identifying the clustering performed. The *Assignment process* receives this information as input and the first operation it performs is the definition of the centroid (midpoint) of each cluster in the feature space relative to the ESQ considered. At this point, following the protocol described in subsection 5.4.3, the process verifies the adherence or otherwise of each state-load combination to the different clusters by assigning according to a criterion of maximum similarity. In the end, to give the reader an idea of the performance of the proposed method, the compatibility between the solution sought and the real one is verified. For this purpose, the standard deviation is used and a coverage factor of 3 (99.7% associated probability) is considered [63]. It is easy to see how the different curves behave differently when a different ESQ level is considered. The latter naturally influences not only the *Assignment process*, but also the clustering process as described above. It can be seen how the different combinations in some conditions present similar values of active power. Indeed, especially for low ESQ levels, under these conditions, the process fails to assign the clusters found to the corresponding state-load combinations. This is evidenced by Figure 5.4.b, which shows the outcome of the compatibility check between the actual and the obtained condition.

Figure 5.4 shows the output obtained for all tested system combinations, in terms of active power (Figure 5.4.a) and compatibility check (Figure 5.4.b).

In general, it can be observed from the figures that ESQ1 shows a correct assignment for the combinations of *Step 1* and *2* and then is confused in subsequent phases. Initial errors in the *Assignment Process* lead to a chain reaction that affects subsequent assignments. This is evident for example for combinations involving the *Fan* device from 320 onwards. Moving on to ESQ2, the goodness of the assignment improves, reducing inconsistency situations from 8 to 5 but still retaining some assignment problems, especially in the *step* 5 and 7. Similar to ESQ1, a possible cause could be incorrect partitions in the clustering phase and confusion introduced between algebraic operations between clusters in the *Assignment process* due to the reduced level of ESQ. In ESQ3, this aspect is clearly improved for each analysed state-load combination. This is due to the use, in both the *Disaggregation* and *Assignment* process, of harmonic as well as energetic information characterising the monitored system.

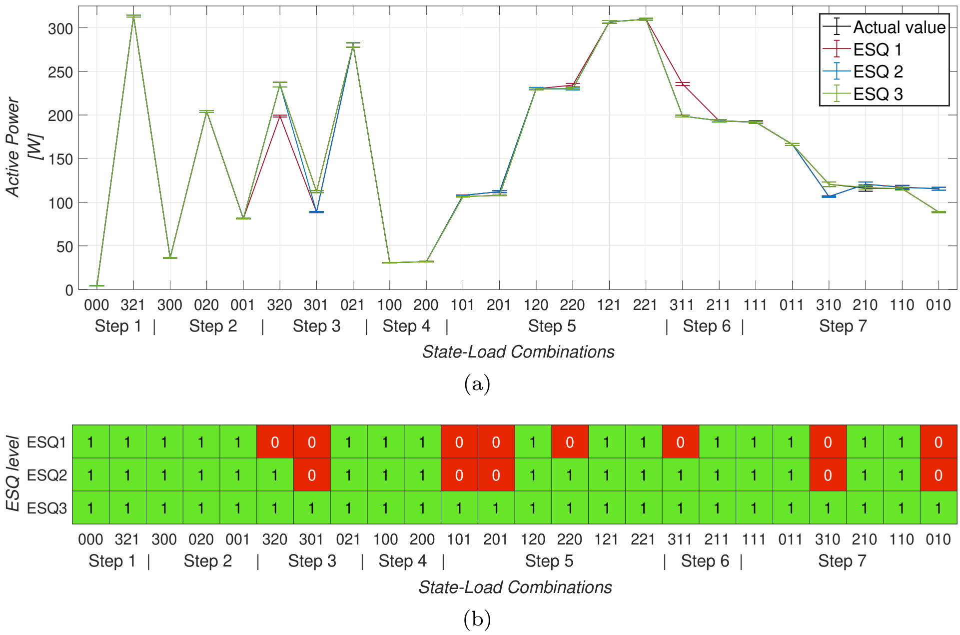


Figure 5.4: **Output of the *Assignment Process* related of the proposed method for each analysis step described. It shows for each actual and method-assigned state-load combination: (a) the active power trend in terms of mean and standard deviation with a coverage factor of 3; (b) the metrological compatibility check between the actual condition and the one identified by the proposed method.**

5.6 Observations and Conclusions

Despite the advantages offered by NILM processes, even today the type of scenario considered, the size of the scenario itself and the disaggregation methodology implemented may represent significant limitations in this field.

Through an innovative unsupervised approach based on clustering, the present study has preliminarily demonstrated how to effectively overcome these limitations by intelligently exploiting the concept of *Electrical Signature Quality*. The proposed method, with reference to a real case study, experimentally demonstrated its effectiveness, allowing a detailed disaggregation of energy consumption from a single aggregate measure of the monitored system using an unsupervised approach. It is clear that this research has the potential to be useful in promoting and identifying innovative *smart* NILM techniques, capable of offering interesting results without the need for training, by exploiting an Electrical Signature that is richer in information than traditional energy parameters. This could represent an important step forward in smart energy management.

Future developments could focus on the analysis of more complex real-world case studies involving a larger number of devices and a wider variety of load-state combinations. In addition, optimisation of the clustering process could be achieved through the use of better-performing algorithms, e.g. density-based. Furthermore, the generalisation and formulation of the allocation process using AI methods could further improve the accuracy and efficiency of the monitoring system. Finally, it may be interesting to compare the proposed method with classical supervised methods, considering different levels of electrical signature quality.

Chapter 6

Cyber security in the context of the digitisation of energy

6.1 Highlights

- **Risks of digitisation in the energy sector**: Digitisation can make energy systems more vulnerable, introducing cross-cutting risks such as cybersecurity, privacy and economic disruption, which require targeted assessment and management to mitigate potential negative impacts.
- **Digital resilience as a priority**: It is impossible to completely prevent cyber attacks, but it is crucial to limit their impact by integrating digital resilience into technology research and development activities, as well as regulatory and market frameworks.
- **Privacy and data security**: With the increase in the collection of detailed data, especially from smart meters, there is growing concern about privacy and data ownership, requiring a balance between these concerns and the promotion of innovation and operational needs of utilities.
- **Innovations in energy data security**: Research proposes an innovative approach to detect communication security through electromagnetic emission analysis based on the Side Channel [64].
- **Practical application**: Development of a client-server system on an IoT device to test data security, to integrate this technology into modern smart meters to improve cybersecurity in energy contexts.

- **Contribution to the community**: The research provides a framework for improving the privacy protection of energy data, raising awareness of the need for robust security protocols.

6.2 Introduction

Digitisation enables new functions in power distribution, such as energy monitoring, condition monitoring and remote diagnostics. But it can also provide a gateway for cyber attacks when systems are directly networked: a single weak point can be enough to hack into a system and block operations. If the electrical infrastructure fails, this has an impact on downstream processes, regardless of the application context (industrial, residential and tertiary). A cyberattack can bring entire infrastructures to their knees and cause huge losses: around 223.5 billion euros in total losses incurred by small and medium-sized enterprises in Germany alone in 2021. The value of unreported cases is probably higher. Low-voltage power distributions also constitute a potential risk and require appropriate measures for protection [168].

Therefore, one of the most critical aspects of the information system in the energy digitisation process is data confidentiality. Confidentiality and change prevention mechanisms are extremely important in different contexts: from economic transactions to public administration documentation, as well as in a very sensitive field, the exchange of energy data for both metering and remote management and control systems. The deployment of systems that allow users to know their impact on the grid moment by moment by offering greater energy awareness through Cloud platforms is one of the main objectives of the energy digitisation process.

Attacks against the confidentiality of an information system can be carried out by analyzing the network traffic (e.g. packet sniffing, port scanning) to perform brute force attacks or discover other vulnerabilities that hide private information [169]. This part opens the second vision, the attacker side, where a malicious user may exploit the vulnerability of a system that does not guarantee proper confidentiality. In this framework, this research aimed to show how it is possible to identify vulnerabilities in a system, breaking confidentiality, leveraging on quantity unrelated to network traffic or similar. In detail, it is possible to determine the security level of a communication by leveraging on the monitoring and measuring of the side-channel information in a non-intrusive way. The expression "side channel" usually refers to all information leaked by a device, involuntarily, during its execution. Although the information released can be of various kinds (e.g. light, vibrations, thermal, power) [170], in this study, it was chosen to exploit the emissions in terms of the magnetic field that a device generates during its working cycle [171]. The idea is to demonstrate that the electromagnetic side channel is a very sensitive part and that various information can be retrieved from it (without the need for complicated profile or device access mechanisms).

An example of this methodology was reported in [172] where it was demonstrated, how leveraging the use of data-driven techniques, it is possible to detect some common cryptographic algorithms, such as AES-128, AES-256 and 3DES, running on a device, by exploiting the electromagnetic field emitted by the monitored device. In [173], it was proved the capability of a convolutional neural network, feeding with power signals, to perform recovery key bytes in a system that adopts AES cryptographic mechanism, highlighting the limitation to use traces belonging to the same device for training and validation tests. A further study of side-channel attacks, leveraging on the kernel execution time of GPU, is reported in [174]. Since this time is directly related to the number of unique cache line requests generated during a kernel execution, an AES 16 key bytes recovery on a commercial GPU architecture was performed.

Starting from the state of the art in the field of side-channel and the past experience of the author, on the achievement of the physical setup [64, 175–177], and implementation of an optimal measurement method to monitor and analyse the physical quantities and on data analysis in time and frequency domain [61, 62, 178–181], the purpose of this research is twofold. The first one is to apply a methodology to determine whether data transfer in a remote client-server system is secure or not, which means sending the data in plaintext or encrypted, starting from the assumption that cryptographic algorithms require a greater computational burden due to the resolution of the mathematical functions they implement. The second one is to highlight that the amount of data analysed by the measurement method may influence the capability of the system to identify accurately the involved protocol, i.e. one wants to study how to obtain accurate information and, at the same time, to reduce the acquired data amount and observation time.

To prove these results, a physical client-server configuration was implemented to emulate a typical Advanced metering infrastructure of a smart grid, or distributed intelligent monitoring, architecture, where one typically has a sub-meter network connected to a concentrator geteway. In this case, only one client was considered, the approach being scalable to multiple actors. The system allows the server and client to exchange a bulk of data bytes. A magnetic probe was adopted to acquire the magnetic field emitted by the monitored device and, a PC desktop was used to elaborate the time series and extrapolate the information.

The final aim of this activity is to move computation on the edge and adopt a low-cost device to perform both acquisition, processing and protocol detection jointly and in a nearly real-time fashion. The idea associated with this objective is to ensure that the aforementioned low-cost device, considering further developments in this regard, can become an additional add-on to a modern smart meter, such that it can also meet the cybersecurity challenges affecting the digitisation process of energy.

Furthermore, the study aims to provide suggestions and a basic framework for all applications where data privacy is crucial, to establish how common data transfer methods can be vulnerable and how to protect their communication, which is particularly critical in cases such as the energy field. In practice, the research also aims to make the community aware that weak transfer mechanisms should always be avoided, as they become susceptible to cyber-attacks, as the attacker could assess the lack of security protocols in such a non-intrusive way. This could have high-impact consequences, such as the theft or manipulation of data and, in high-priority situations, such as the control of smart grids or the management of energy flows in companies, potentially leading to serious economic and social problems.

The structure of the chapter is as follows: first, the problem of computer and data security in the field of energy is examined in general terms; then the methodology adopted, the proposed scenarios and the physical set-up capable of realising them are described. Finally, the results obtained, the performance and the analysis of influencing factors are reported, and final considerations are made.

6.3 Background: Cyber threats to energy security

Smart meters are being progressively adopted globally for a variety of implementations, including electricity, gas and water. Their two-way communication feature allows real-time monitoring of utility usage by both the utility provider and the consumer. Like any other smart device, as the number of smart meters increases, so does their exposure to cybercrime [54, 182].

It is clear, therefore, that digitisation brings many benefits, but it also opens the door to increasing energy security risks [183], in particular from unintentional cyber incidents and intentional cyber-attacks. In general, cyber attacks - whether aimed at sabotage, taking control of energy systems, industrial espionage or ransomware - are becoming easier and cheaper for hostile actors to organise. They range from amateurs to professional hackers for hire, to the use of proxies by other states [184].

Below are some examples of cyber attacks that the energy and related IoT sector has suffered in recent years [1].

- In 2012 in Saudi Arabia, the computer virus “Shamoon 1” carried out computer sabotage and destroyed over 30,000 computers of the company “Saudi Aramco’. There was no direct impact on oil production, but the company was forced to return to traditional paper and telephone trading for several weeks. Later in 2016, the Qatari natural gas company RasGas was also affected. The virus, “Shamoon 2’, was set to run after working hours to minimise detection. The virus targeted similar vulnerabilities and was used to overwrite parts of computer hard disks.
- In December 2015, hackers illegally breached the computer and control systems of a Ukrainian regional electricity distribution company and managed to disconnect substations, causing 225,000 customers to lose electricity. It was the first confirmed cyber-attack specifically against an electricity grid. This was followed by a second attack in December 2016 [185], which appears to have used malware specifically designed to take control of power grid circuit breakers (ESET, 2017).
- In 2016, the “Mirai” malware exploited the poor security of connected smart devices, such as cameras, to use a botnet (a network of devices simultaneously commanded by the attacker to overload the victim with continuous data delivery) to launch the largest DoS attack to date. This attack did not target or impact the energy infrastructure but illustrates the vulnerability of the Internet of Things (IoT).
- Generic cyber attacks, such as the global ransomware incidents “WannaCry” and “NotPetya” in May and June 2017 respectively, have also impacted the energy sector by damaging corporate information technology (IT) systems.

Some cyber-attacks target operational technology (OT): the computers, software and networks used to control, monitor, manage and protect energy delivery systems. Other attacks might target only the IT business systems of energy companies that do not control the physical process of energy delivery, but result in administrative interruptions (as in the case of Shamoon). Unintentional cyber incidents linked to the increasing complexity of “systems of systems” that combine many layers of ICT and OT are also becoming more frequent, for example when an update in one type of equipment causes malfunctions in other equipment.

The growth of the IoT and changes in digital technologies are increasing the potential “cyber-attack surface” in energy systems. The expansion of the IoT, combined with the diversification and decentralisation of energy technologies, will link millions of new small-scale prosumers and billions of devices into the electricity system. Indeed, as reported in [186, 187], the number of IoT devices installed worldwide in 2015 was estimated to be 15 billion; to become over 75 billion devices by 2025. If there is one suspect device at the edge of a network, this can be a weak point for the whole system. A recent study by the European Parliament concluded: "*The development of smart energy has also led to exponential growth of networked intelligence throughout the energy grids and also consumer premises. The result is that a massively expanding "attack surface' now forms the operational foundation of the energy ecosystem. As the energy system is also fundamentally interconnected with every other critical infrastructure network, the cybersecurity threat to the energy sector impacts every aspect of modern society*" [188].

Digital technologies used in centralised energy systems are also changing [189]. Early digitalization often relied on IT and OT that were proprietary or vendor-specific. Electricity substations typically might use several generations of equipment, assembled piecemeal over time. This older infrastructure often pre-dates embedded security standards but can benefit from an element of "security by obscurity", so that hacking it requires specialised knowledge. Today, with more connectivity between system components, more automation, a shift to cloud computing, and the replacement of energy-specific IT by sophisticated open-protocol industry standards, newer systems have higher security, but lose the protection of obscurity and the level of specialised energy system knowledge needed for attack diminishes. Cyber-attack techniques can target personnel, products (both data and physical infrastructure) and processes (system data flow). This means that there is greater need to protect the integrity and confidentiality of information, and to identify trustable sources and authorised recipients, also in supply chains and procurement [190]. Meanwhile, the global scope of the internet and the geographical reach of multinational energy companies mean that an attack at one location can instantly spread worldwide. Risk analysis, therefore, needs to span products, people and processes.

Taking all of this into account, some experts in strategic risk assessment see credible scenarios for "low-probability, high-risk" attacks that could shut down the electricity grids of a major economic region for a period of days or – on a rolling basis – weeks [191–193]. Energy professionals and oversight authorities also foresee a future of many small-scale nuisance attacks from bots (numbering thousands per day). While cyber-attacks can affect a variety of parts of the global economy, attacks on energy systems are likely to be particularly disruptive. Unlike most IT systems, electricity OT systems must operate in real-time and cannot simply install patches or updates, or shut down and reboot as in the typical response to digital failures or breaches. Special security considerations and precautions are therefore needed.

However, full prevention of cyber-attacks is impossible, but their impact can be limited if countries and companies are well prepared and have built-in resilience. This is particularly important for critical infrastructure: the physical and institutional assets that are essential for an economy to function, such as large-scale energy systems. In this context, it is clear that research and technological innovation play a key role.

6.4 Device and scenario

This section explains the device used for the experimental tests from which the magnetic field information was profiled, and then the scenarios considered are described.

6.4.1 Device Under Test - DUT

As for the DUT, faced with the challenge of performing a side-channel electromagnetic attack, one of the most popular devices in the IoT field was chosen, namely Raspberry Pi 4 Model B 2018 (Figure 6.1). This is involved in a client-server architecture, implemented in Python code, and it is able to exchange data implementing the four cited protocols. In detail, on the hardware side, it is equipped with a Broadcom BCM2711, SoC quad-core Cortex-A72 (ARM v8) running at 1.5 GHz, 4 Gigabyte LPDDR4 RAM. Furthermore, as software-side regards, it runs a Linux-based operating system, namely Ubuntu 22.04 LTS (Jammy Jellyfish).

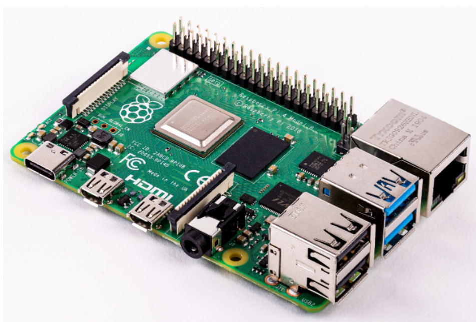


Figure 6.1: **Raspberry Pi 4 Model B 2018.**

This device was chosen in the following study because in addition to being widely deployed and used in the IoT field, it also turns out to be very similar to a modern smart meter. This is because, as reiterated several times in previous chapters, a modern smart meter is a device called upon to perform a multiplicity of functions and services that go beyond simple measurement, sometimes even interacting with neighboring devices.

6.4.2 Test scenarios

In the case of a distributed measurement system consisting of meters and sub-meters, or more generally IoT devices, different protocols may be used when data transfer is based on the use of the Internet. However, these differ in the type of data to be transferred and the mode. Focusing only on application-layer protocol, FTP, FTPS, HTTP, and HTTPS are the most used until now, as Figure 6.2 depicts.
In particular:

- File Transfer Protocol (FTP): it is a standard communication protocol developed to share data between computers, in a particular way for the remote control, working using 21 port. FTP is a client-server-based architecture and may be implemented in active and passive mode. The first one establishes the command channel and the server establishes the data channel. In the passive mode, the client establishes both the data channel as well as the command channel. Generally, the data are transferred in ASCII default format, on the contrary, the images are in binary;
- File Transfer Protocol Secure (FTPS): it is also known as FTP over SSL (Security Socket Layer), and represents the security extension of the FTP standard implementing secure algorithms such as AES and Triple DES. The authentication phase is guaranteed via x.509 certificates to guarantee the authenticity of an entity (e.g. users), trusted by the Certification Authority (CA);
- HyperText Transfer Protocol (HTTP): differently from the FTP standard, the HTTP is commonly used to transmit hypertext over the Internet, and load pages or other resources that are linked through a web browser, establishing communication between a web browser and web server, though the use of methods such as GET and POST. The standard reserves port 80 for an HTTP connection;
- HyperText Transfer Protocol Secure (HTTPS): like between FTP and FTPS, HTTPS represents the security combination between the HTTP protocol and

SSL/TLS. As well as HTTP, HTTPS is used for transmitting hypertext over the Internet but in an encrypted manner. It uses port 443 for secure communication. Also, in this case, the authenticity of the entity is trusted by the CA and it uses digital certification.

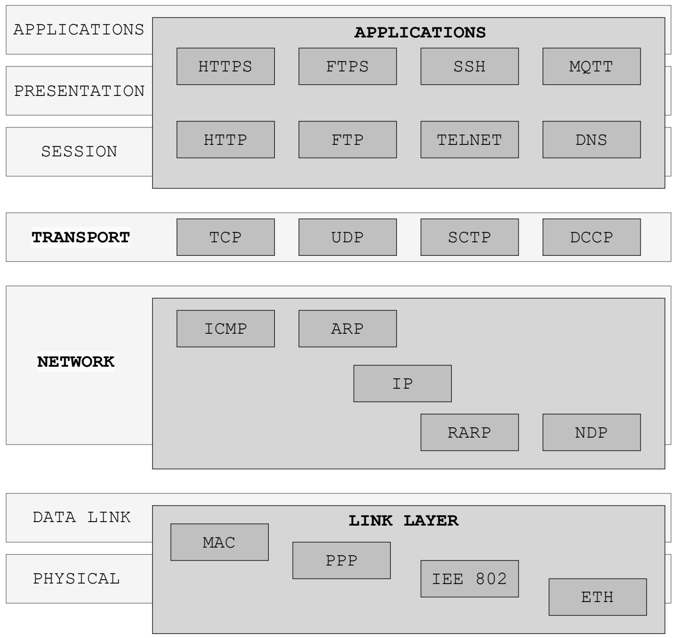


Figure 6.2: **TCP/IP suite protocol: overview.**

In this study, for the sake of convenience, each protocol involved has been referred to by the term scenario ($S\#$), as follows:

- S_1: FTP;
- S_2: FTPS;
- S_3: HTTP;
- S_4: HTTPS,

where the first and third ones represent the ones not over SSL standard. On the contrary, the remaining two, S_2 and S_4 are implemented over the security protocol. Each scenario is characterized by an execution time equal to 35 s and a repetition trial equal to 30.

6.5 Measurement and methods

This section proposes the experimental setup implemented and the analysis method adopted. The measurements were carried out in the Laboratory for Industrial Measurements (LAMI) of the University of Cassino and Southern Lazio.

6.5.1 Experimental set-up

The creation of the experimental setup is divided into a measurement system and a monitored device. Through a detailed characterization campaign conducted by the author in [61, 64, 176], a final measurement setup, as shown in Figure 6.3, is composed by:

- TiePie HS6 oscilloscope guarantees a range of resolution between 8 and 16 bit, up to 1 GSa/s sampling, up to 250 MHz bandwidth and up to 256 Mpoints memory per channel [194]- 1 MSa/s adopted in the current acquisition process;
- S-Lindgren 7405-901 magnetic field probe, with a six centimetres loop, has a bandwidth of [100 kHz – 3 GHz] [195];
- PC Desktop to control the TiePie, export and elaborate the data.

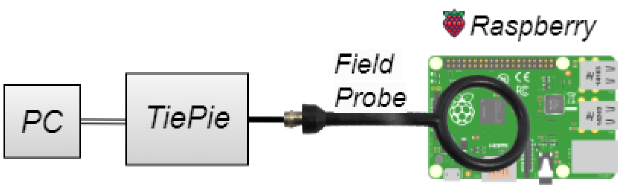


Figure 6.3: **Block diagram of the final acquisition system. It consists of: Raspberry, an electromagnetic field probe, and a programmable acquisition system.**

Figure 6.4 reports the overview of the actual physical setup. The chosen analysis range is [0 Hz - 500 kHz], the sampling rate (F_s) used is 1 MS/s so the sampling step (T_s) is 1μs, the acquisition time 35 seconds (Acq_{time}, so 35 MS points ($N_{P_{tot}}$) were acquired for each acquisition, according to the execution time of each scenarios reported in subsection 6.4.2. The resolution of the TiePie's analog-to-digital conversion system (Res_{ADC}) was set to 14 bits, with a full scale of 0.2 V for the field probe channel. All sampling characteristics used by the TiePie acquisition system are summarized in Table 6.1.

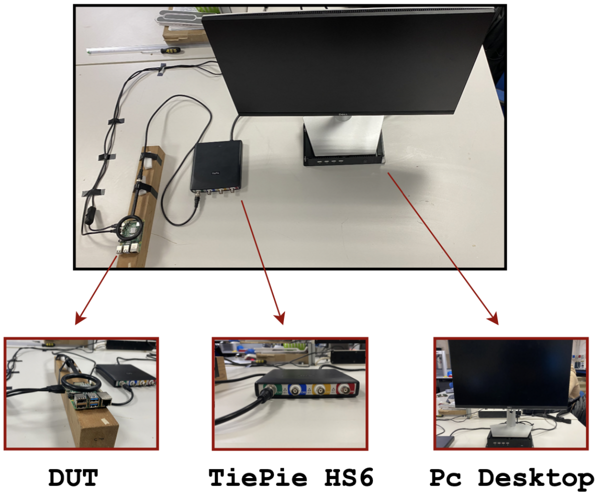


Figure 6.4: **An overview on three components of physical setup: DUT, acquisition device and Pc Desktop.**

Table 6.1: **Sampling characteristics used to acquire the profiles of the tested scenarios.**

Specifications	Descriptions
F_s	1 MS/s
T_s	$1\mu s$
$N_{P_{tot}}$	40 MS
Acq_{time}	40 s
N_{ACQ}	30
Res_{ADC}	14 bit
Full scale channel	0.2 V

It should be noted that to identify the frequency range of interest on which to focus the analysis, laboratory instruments with extremely high-performance characteristics were preliminarily used. In particular, an "ETS-Lindgren 7405-901" magnetic field probe and a "LeCroy WavePro Zi760" oscilloscope were used [196]. The latter was used in "FFT analyzer" mode. In practice, referring to the set-up previously shown in Figure 6.3, the oscilloscope performed the functions of the

PC and TiePie. With the above set-up and preliminary analysis, starting from an observed range equal to the maximum bandwidth of the instrument (6 GHz), the analysis range was progressively narrowed down to the most significant frequency range of the emitted electromagnetic field, which was identified in terms of correlation with the scenarios chosen for this study. Of course, the oscilloscope sampling and frequency resolution specifications were adjusted from time to time to work under optimal conditions in the average. This procedure was crucial because it allowed us to optimize the range of analysis by focusing on a specific band of interest, ultimately chosen in $[0Hz - 500kHz]$

6.5.2 Analysis method

To reach the goal of identifying the presence of secure communication in an information system, to emulate a typical situation in which data is exchanged within a meter network, the methodology implemented in [62] was adopted. In particular, the frequency analysis methodology was chosen. Figure 6.5 depicts the three blocks that led to the evaluation of the measurement system's capability to perform the vulnerability assessment. The first one, the Preliminary Analysis phase, involved the acquisition of the magnetic field (Step 1) emitted by the Device Under Test (DUT), during the transmission of the data. After that, the acquired time series were processed to compact and synthesise the information through the application of the Root Mean Square (RMS) using a 100 ms time-slot observation window (Step 2), allowing a smaller amount of data to be handled, while still guaranteeing good observation dynamics of the monitored phenomenon. In the end, a selection of the signal of interest was chosen to eliminate the part of the signal that did not contain a quantity of information relevant to the purpose (Step 3).

To get relevant data, a Fast Fourier Transform operator is applied to the reduced dataset (RMS-reduced) (Step 4). To the obtained frequency spectrum, a grouping operation is applied (Step 5). Particularly, the frequency spectrum is uniformly divided into several groups and the energy of each group is computed. In practice, a similar grouping methodology to that proposed by the IEC61000-4-7 power Quality standard was applied [49], but considering different operating specifications following the case study. Repeating the process 30 times per scenario, the mean energy $\overline{e}$ and its standard deviation σ_e is computed per group. The interval $[\overline{e} - \sigma_e, \overline{e} + \sigma_e]$ is called Adherence Zone (AZ) and it represents a sort of electromagnetic fingerprint for the considered scenario (Step 6). Drawing a fingerprint for each scenario made it possible to verify which test trace fitted best with the fingerprint evaluated in the previous step (Step 7). The Measurement Performance phase concluded the measurement method in which the results were represented in confusion matrix form. Because the scenarios involved in the profiling (Step 1) were four, the output was characterized by a multi-label classification (Step 8). Moreover, another novelty introduced in this study regarded the mapping of the problem in binary output, adding a new point of view: the feasibility of identifying the presence or absence of a cryptographic communication without considering which protocol was implemented. A detailed explanation is left to section 6.5.

6.6 Results

The last phase of the measurement method corresponds to the evaluation of the confusion matrix in two different conditions. The first step involved measuring the performance by varying the number of acquisition points in the time domain used to evaluate the capability of the system to distinguish the scenarios. Starting from the acquired data, and having already performed the selection step of the signal of interest (Step 3 in Figure 6.5), the number of points was equally divided to consider different increasing time slots. In detail:

- Time_1: 10 s;
- Time_2: 15 s;
- Time_3: 20 s;
- Time_4: 25 s;
- Time_5: 30 s;
- Time_6: 35 s (the whole test duration);

In terms of number of processed samples, its value ranges from 10 MSa (in case of Time_1) to 35 MSa (in case of Time_6).
For each time slot selected, a grouping method was applied in the following way:

- Gr_1: 5 group uniformly segmented spectrum;
- Gr_2: 10 group uniformly segmented spectrum;
- Gr_3: 15 group uniformly segmented spectrum;
- Gr_4: 20 group uniformly segmented spectrum;
- Gr_5: 25 group uniformly segmented spectrum;
- Gr_6: 30 group uniformly segmented spectrum;

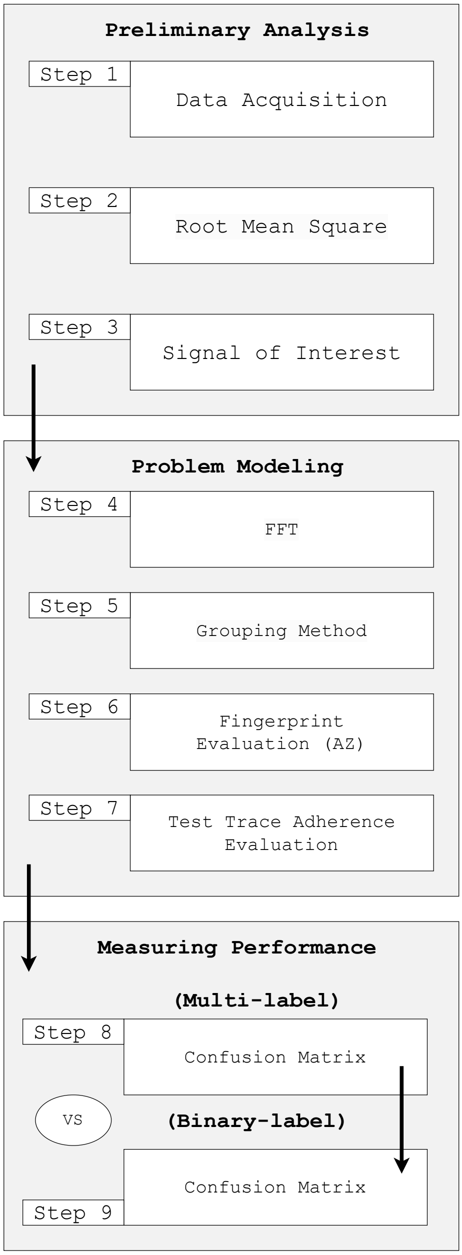


Figure 6.5: **Flow chart of measurement method adopted.**

Thus, the average accuracy associated with all scenarios was evaluated to summarize all the matrices in a unique value. Figure 6.6 reports on the y-axis the average accuracy, expressed in percentage, associated with a time slot and grouping. In detail, once the first slot time was fixed, which was the smallest, six average accuracy values were evaluated. The next group of bins indicates the average accuracy value fixed in the second slot time, varying the grouping of the tones.

As can be seen, as the time slot increases, the average accuracy improves. In particular, from Time_3, the average accuracy approaches 100% and weakly depends on the grouping method selected.

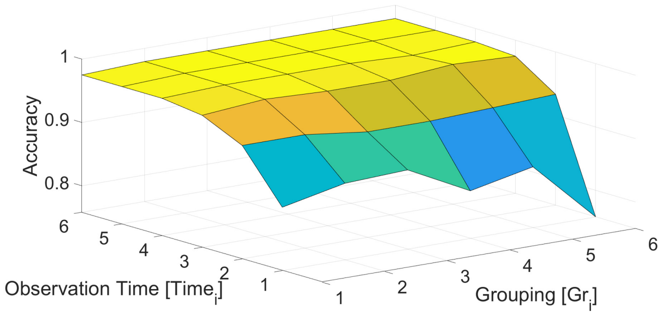


Figure 6.6: **Trend of the average of accuracy evaluated on confusion matrix, varying time slot and grouping (4-by-4 pair of True Label Predicted Label).**

Figure 6.7 represents the confusion matrix obtained by considering a time series of ten seconds (i.e. Time_1), where the grouping value was fifteen (i.e. Gr_3). This matrix reports the best overall accuracy achieved when processing the first time slot. On the contrary, Figure 6.8 shows the best confusion matrix associated with the sixth slot time (i.e (i.e. Time_6)), which involves thirty seconds of data. In this case, the maximum accuracy matrix is obtained by dividing the frequency tones into ten groups.

The next condition regards the application of a mapping procedure from a four-by-four to a two-by-two problem, which means turning a multi-class problem into a binary classification. In detail, this process was performed after evaluating the confusion matrix on the multi-label classification. At the end of this procedure, new scenarios are obtained as follows:

- $S_{1_\mathrm{m}} \leftarrow (S_1 \cup S_3)$;
- $S_{2_\mathrm{m}} \leftarrow (S_2 \cup S_4)$,

where the S_{1_m} is the result of aggregation of not encryption scenarios; on the contrary, the S_{2_m} represents the mapping of encryption scenarios, that are FTP and HTTP over SSL.

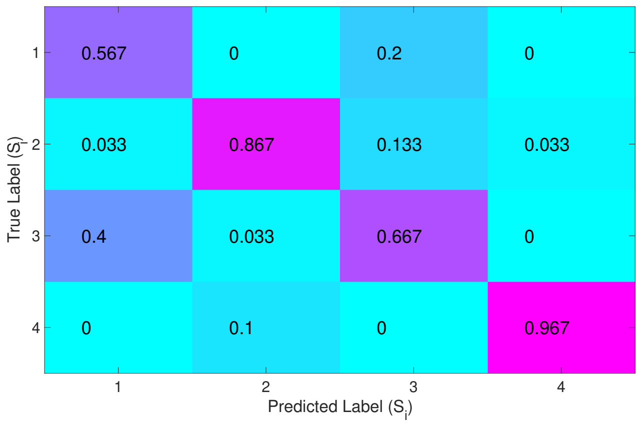


Figure 6.7: **Confusion matrix evaluated processing 10 seconds slot-time ($Time_1$) and grouping 3 (Gr_3 = 15).**

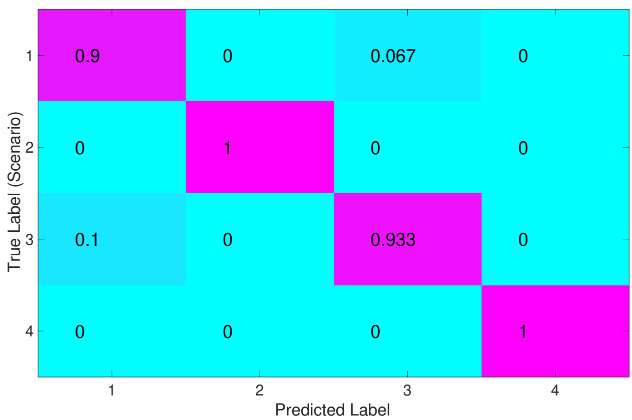


Figure 6.8: **Confusion matrix evaluated processing 30 seconds slot-time ($Time_6$) and grouping 3 (Gr_2 = 10).**

The methodology involves the following mapping: the cell of the new mapped confusion matrix was obtained aggregating the cells $\{(1,1),(1,3),(3,1),(3,3)\}$ of the four-by-four confusion matrix. Following the same reasoning, the cell (1,2) in the aggregation of false negative values mapped from cells $\{(2,1),(2,3),(4,1),(4,3)\}$ of the starting matrix, and so on for all the others.

Figure 6.9 shows, in a similar way to Figure 6.6, the mean accuracy trend over the time slot and grouping variation.

Also in this case, the first group of bins indicates the average accuracy evaluated by processing ten seconds of the data frequency and varying the grouping among the six, reported in Figure 6.10. Since the best metric is the same for all the six grouping values, only the first one was represented. The same is true for the sixth slot time as well as shown in Figure 6.11. Looking at the results, it is clear how the amount of analyzed information, directly proportional to the signal acquisition time, was relevant for obtaining valuable accuracy in the discrimination of the scenarios.

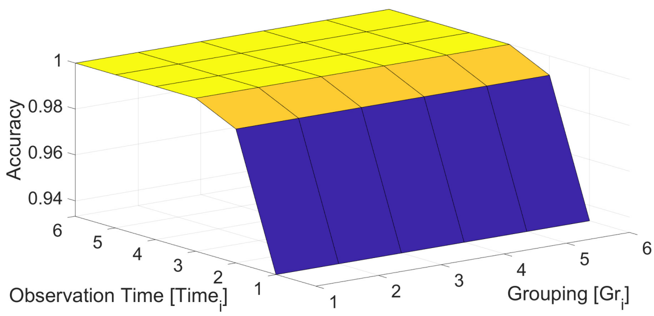


Figure 6.9: **Trend of the average of accuracy evaluated on confusion matrix, varying time slot and grouping (2-by-2 pair of True Label Predicted Label).**

As Figure 6.6 - Figure 6.8 show, to obtain high accuracy and therefore to guarantee the ability to classify the four scenarios correctly, it is best to process as much information as possible, i.e. sixth time slot (thirty seconds) and applying 10 groups.

Alternatively, if the goal is to identify whether an information system uses a cryptography protocol, it is possible to process less information, choosing a time slot equal to one and performing a mapping operation scaling the problem to a binary classification.

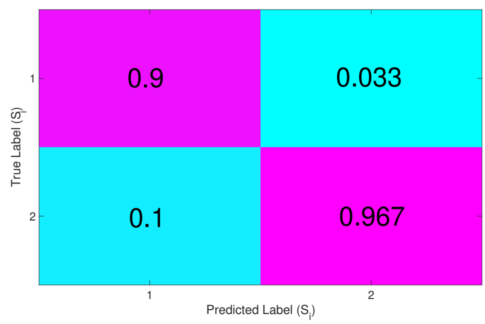


Figure 6.10: **Confusion matrix evaluated processing 10 seconds slot-time ($\mathbf{Time_1}$) and grouping 1 ($\mathbf{Gr_1 = 5}$).**

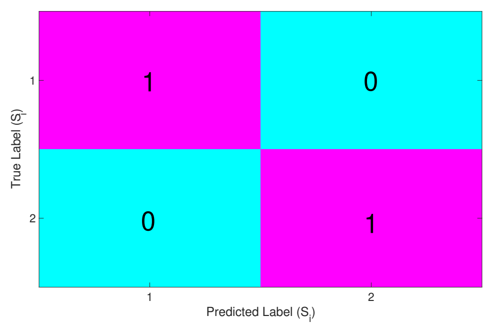


Figure 6.11: **Confusion matrix evaluated processing 30 seconds slot-time ($\mathbf{Time_6}$) and grouping 1 ($\mathbf{Gr_1 = 5}$).**

6.7 Observations and Conclusions

Thanks to digitisation, the entire energy system will undergo profound mutations in the coming years, reaching unprecedented levels of efficiency and sustainability. As highlighted several times, this mutation is based on the spread and implementation of innovative measurement and IoT systems, such as smart meters. However, the success of such devices in the coming years will depend on their security properties. Another crucial feature of the energy system is user privacy and security, regardless of the application context; i.e. how to aggregate consumer data without disclosing their personal and sensitive information.

In this context, with a view to investigating possible vulnerabilities of a distributed metering system based on smart meters, the following research investigated the ability to detect the security level of remotely transferred content in an IoT network. This was done using a side-channel measurement approach in the frequency domain. The results were evaluated on four different transmission protocols: FTP, FTPS, HTTP, and HTTPS.

In detail, results are evaluated by varying two computational-demanding parameters: the observation time and the number of spectral groups. The main result is that by observing the phenomenon for at least 15 s, highly accurate performance is achieved, while a slight worsening can be observed in the case of fast observation (10 s). In terms of spectral group, the main outcome is a pretty constant behaviour whenever the observation time is at least 15 s, while a slight predominance of low group cases when the observation time is 10 s. Aggregating scenarios in secure (S_2 and S_4) and not-secure (S_1 and S_3), performance results are highly accurate also in case of fast time observations ($Time_1$).

The results obtained open the way for several crucial considerations on the feasibility of detecting security protocols based on the emitted electromagnetic field alone. This is particularly critical for possible intrusion attempts and cyber attacks in energy management systems, and robust solutions should be considered to reduce their impact on a data-sensitive society. This also suggests considering different levels of security based on the different priorities of data and provides critical information in one specific area, namely the mechanisms for communicating energy consumption data. In particular, in a world where cloud solutions are spreading widely in the context of the digitisation of energy, especially among SMEs and the residential sector, the security of transmitted data and the limitation of their possible modification is crucial.

Clearly, the need for an integrated strategic communication framework with robust security and privacy features should be designed from the very beginning of the implementation of smart grid technology. Therefore, security and privacy in the power grid is considered an emerging research topic, which is worth analysing.

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Chapter 7

An innovative smart meter for the digitisation energy era

7.1 Highlights

- **Role and Innovation of Smart Meters**: The importance of smart meters as advanced intermediaries between energy consumers and smart electricity grids is highlighted, presenting a new prototype for advanced applications offering multi-physical monitoring with a high level of configurability and integration.
- **European Norms and Standards**: The European regulatory framework for smart meters is explored, ensuring measurement accuracy, safety, interoperability, compliance and electromagnetic compatibility of devices.
- **Smart Meter Functional Architecture**: The architecture of a modern smart meter is outlined, highlighting the main functional components, which are crucial for ensuring accurate and reliable measurements.
- **Prototype Design and Development**: The process of designing and developing a prototype smart meter, specifically designed to monitor complex industrial machinery, ensuring high performance in harsh operating environments, is detailed.
- **Prototype Characterisation and Calibration**: The steps followed in the process of metrological characterisation and calibration of the prototype for

compensation of measurement errors are illustrated.

- **Integration, Scalability and Flexibility**: The prototype is designed to be integrable with existing infrastructure and scalable over time. The ability to monitor various physical, electrical and mechanical quantities makes it a flexible and versatile tool suitable for future challenges in the energy sector.

7.2 Introduction

Technological developments in recent decades have led to a significant transformation of energy management systems, laying the foundations for the development of smart electricity grids, or smart grids. In this context, smart meters play a crucial role, acting as intermediaries between energy consumers and distribution infrastructures. These advanced devices, as mentioned several times above, not only enable the precise measurement of electricity consumption, but also offer additional functionalities such as energy quality monitoring, detection of operational anomalies, and two-way communication with central systems.

The following chapter is dedicated to a brief presentation of the design and development process of an innovative smart meter designed for advanced industrial applications. An example of a prototype developed with cutting-edge features for the context of reference is proposed, such as to offer high flexibility in configuration and management, as well as interfacing with devices already installed and, above all, capable of multi-physical monitoring. All with an integrated approach.

Naturally, the design of such a device requires an in-depth understanding of the specific requirements of the application context, as well as the careful selection of hardware and software components to ensure high performance, reliability and compliance with regulatory standards.

The chapter is structured as follows: in the first part, the reference regulatory context related to smart meters is briefly presented; this is followed by a brief illustration of the general functional architecture of a smart meter. Next, the design and development process of a smart meter prototype is briefly presented, highlighting the design objectives, the technical choices related to the system architecture, and the development phases of the prototype. Finally, a summary of the characterisation and calibration process of the implemented instrument is given.

The aim is to provide an overview into the life cycle of a smart meter, from initial design to practical implementation, highlighting the technical challenges faced and the solutions adopted.

7.3 Regulations and Reference Standards

Smart meters are key devices for managing and monitoring energy, water, gas and other services in an efficient and automated way. In Europe, the installation and use of smart meters is regulated by a series of standards and regulations covering various aspects such as metering, metering, IT security, compatibility and compliance.

Compliance with these regulations and standards ensures that smart meters are not only accurate and safe but also that they are marketed and manufactured according to certain criteria, guaranteeing their reliability and operational integrity.

Below is a list of the main European regulations and standards relevant to smart meters:

Measuring and Metering Standards

- *MID (Measuring Instruments Directive) - Directive 2014/32/EU*: This directive sets out the essential requirements for measuring instruments used for commercial transactions, including smart meters for electricity, gas, water and heat. It ensures that devices are accurate and reliable [197].
- *EN 50470-1/3*: Specific standards for electricity meters, defining metrological and technical requirements, including accuracy and reliability [198].

Cyber Security

- *GDPR (General Data Protection Regulation) - Regulation (EU) 2016/679*: Although not specific to smart meters, the GDPR regulates the protection of personal data collected, processed and stored by devices, imposing stringent cyber security measures [199].
- *ETSI EN 303 645*: European standard for cybersecurity in IoT devices, including smart meters, providing guidelines to minimise vulnerabilities and protect data [200].
- *ISO/IEC 27001*: International standard (also recognised at European level) for information security management systems, which can also be applied to smart metering systems [201].

Interoperability

- *DLMS/COSEM (Device Language Message Specification/Companion Specification for Energy Metering)*: International standard for communication between smart meters and central systems, ensuring interoperability between devices from different manufacturers [202].

- *M/441 Mandate*: Mandate of the European Commission to CEN, CENELEC and ETSI to develop standards to ensure the interoperability of smart metering systems in Europe [203].

Standards of Conformity and Installation

- *CE Marking (European Conformity)*: Smart meters must comply with CE regulations, which certify that products meet the essential requirements of applicable European directives, including those relating to safety, electromagnetic compatibility and performance.
- *Energy Efficiency Directive 2012/27/EU*: This directive promotes the installation of smart meters as part of Member States' energy efficiency strategies.

Industry Specific Standards

- *EN 62056*: Set of standards for the communication protocol for smart meters, specific to the electricity and gas industries [204].
- *EN 13757*: Standard covering communication protocols for heat and water meters, ensuring compatibility and integration into wider smart metering systems [205].

Environmental and Safety Standards

- *RoHS (Restriction of Hazardous Substances) Directive - 2011/65/EU*: Regulates the use of hazardous substances in electronic equipment, including smart meters [206].
- *WEEE (Waste Electrical and Electronic Equipment) Directive - 2012/19/EU*: Manages the collection and recycling of electronic waste, including the disposal of obsolete smart meters [207].
- *CEER (Council of European Energy Regulators)*: Provides recommendations and guidelines on the implementation of smart meters, focusing on aspects such as consumer protection, data security and accessibility [208].

Electromagnetic Compatibility (EMC)

- *EMC Directive 2014/30/EU*: This European directive sets out the essential requirements to ensure that smart meters do not generate electromagnetic interference that may affect the operation of other devices and that they are protected against external interference. The directive applies to all electrical and electronic devices sold in the European Union [209].

- *EN 55022/EN 55032*: Standard for limits and methods of measurement of electromagnetic emissions for information technology equipment, which also apply to smart meters to ensure that electromagnetic emissions are within acceptable limits [210].

- *EN 61000-6-1/2/3/4*: Set of standards for electromagnetic compatibility, which specify requirements for immunity to electromagnetic interference and allowable emissions. Smart meters must comply with these standards to ensure that they operate correctly in different environments without interfering with other devices [211].

- *EN 50412*: Specific standard for the electromagnetic compatibility of measuring equipment, including smart meters, which defines requirements to ensure interference-free operation with other electronic devices in the vicinity [212].

7.4 Functional Architecture

The architecture of a smart meter is designed to provide accurate measurement of energy consumption, efficient data management and the ability to communicate with external infrastructures to transmit this data. In recent years, smart meters have evolved to integrate advanced sensors, signal processing, communication and security technologies, making them key elements of smart electricity grids, smart factories and households. In summary, the main functional components of a modern smart meter for electrical applications are outlined below.

7.4.1 Sensors

Energy measurement in smart meters is based on sensor technologies that can detect not only the quantity of energy consumed but also its quality (e.g. the presence of harmonics, disturbances and phase imbalances). The main technologies used for voltage and current measurement include:

- *Voltage dividers*: Used to reduce the voltage to a safe level suitable for subsequent steps; voltage dividers must be carefully designed to maintain measurement accuracy. Thermal stability and linearity are crucial to ensure accurate measurements over a wide voltage range.

- *Voltage Transformers*: are used to measure high voltages by reducing them to manageable values for subsequent circuits. Such measuring transformers are designed to minimise losses and maintain signal integrity, particularly in industrial environments where voltage variations can be significant. In addition, they have the advantage of being able to guarantee galvanic isolation if properly designed.

- *Current shunts*: shunt resistors offer a simple and inexpensive method of measuring current through the voltage drop that occurs when current flows through them. While providing good linearity in terms of response, these sensors can introduce power losses and are less suitable for high currents.

- *Current transformers and current clamps*: similar to voltage transformers, these devices are essential for current measurement in high-power applications. Current transformers reduce the primary current to a lower, more manageable value while maintaining galvanic isolation between the measuring circuit and the main circuit. With appropriate measures, the phase error can be reduced by extending the operating range.

- *Rogowski coils*: offer a flexible, nucleus-free alternative for current measurement, particularly suitable for measurements in harsh environments or for high currents.

- *Hall Effect Sensors*: widely used for non-contact current measurement, using the Hall effect to detect the presence and strength of a magnetic field generated by the current itself. They are particularly useful for measuring direct and alternating currents, offering high accuracy without introducing significant losses into the circuit. They also provide galvanic isolation, making them suitable for a wide range of applications, including high-power applications.

7.4.2 Signal Conditioning

Signal conditioning is essential to ensure that analogue signals from sensors are prepared for subsequent digital conversion without loss of information or introduction of distortions. In the state of the art, signal conditioning in smart meters involves different technologies and methodologies:

- *Amplifiers*: typically operational amplifiers, are precision devices that are used to amplify signals from voltage and current sensors. The selection of low-noise, high-linearity amplifiers is crucial for maintaining measurement accuracy. More advanced models also offer built-in filtering capabilities.

- *Anti-Aliasing Filters*: To prevent high-frequency signals from causing aliasing during analogue-to-digital conversion, low-pass filters, designed to attenuate frequencies above the band of interest, are used. Digital filters, such as FIR (Finite Impulse Response) filters, can be used to further improve signal quality after conversion.

- *Over-voltage Protection Circuits*: These circuits protect the sensitive components of the meter from surges and spikes, using devices such as varistors, Zener diodes, and arresters. These elements ensure that external disturbances do not affect the accuracy of measurements or damage the circuits.

7.4.3 Analogue-Digital Conversion

The conversion of analogue signals to digital format is a crucial point in the measurement chain. The ADCs used in smart meters must meet stringent requirements in terms of accuracy, speed and stability. In particular, the two main parameters (which mainly influence the cost of the ADC) are:

- *Resolution*: this parameter determines the granularity with which an ADC can measure (appreciate) a signal. In smart meters, resolutions of 12 or 24 bits are common, with newer models aiming for even higher resolutions to improve measurement accuracy over very wide ranges.
- *Sampling Frequency*: must be such that it captures all relevant variations of interest in the signal, including harmonics and transients. Modern smart meters can sample at frequencies ranging from a few kHz up to tens of kHz, depending on the specific application.
- *Observation time*: in practical terms, this represents how often the meter provides a measurement. This parameter must be chosen according to the dynamics to be observed. It is also of extreme importance for frequency analysis when the meter implements an FFT analysis, for example, as the observation time immediately determines the frequency resolution.

To guarantee certain requirements, different types of analogue-to-digital converters can be used depending on the application and requirements. Among these, the main ones are:

- *Integration ADCs*: these are commonly used for measurements of signals in a sufficiently limited frequency range, guaranteeing high measurement accuracy.
- *Sigma-Delta ADCs*: represent a reference for the precise and low-noise measurement of voltage and current signals. These ADCs use oversampling and noise modulation techniques to improve resolution and reduce interference.
- *Subsequent Approximation ADCs*: offer a good compromise between speed and accuracy, making them suitable for applications requiring both fast data acquisition and high accuracy.

7.4.4 Processor and Data Pre-processing

The processor is responsible for processing the measurement data and implementing advanced features such as communication management and data pre-processing. The processing module receives the acquired information and processes the data to calculate parameters and all derived electrical quantities of interest, correlating these with time information.

For example, machine learning algorithms and statistical analysis can be implemented to detect anomalies in consumption patterns, such as sudden peaks or interruptions, enabling a timely and targeted response. In addition, smart meter processors can calculate advanced parameters related to power quality and harmonic content, such as total harmonic distortion (THD), phase imbalance and the presence of interharmonics. These parameters are crucial for managing the electricity grid and ensuring a stable power supply to end users.

For these reasons, the choice of processor is strategic for the performance offered. In general, there are:

- 32-bit microcontrollers: Modern smart meters tend to use 32-bit microcontrollers, which offer sufficient computational capabilities to handle both the calculation of energy measurements and real-time data analysis. These microcontrollers can integrate DSP (Digital Signal Processor) modules to accelerate the processing of complex signals.

- Multi-Core Architectures: Some advanced smart meters use multi-core processors to separate measurement tasks from communication and system management operations. This approach improves operational efficiency and allows more complex algorithms to be implemented.

7.4.5 Data Storage, Management and Security

Data management is a crucial aspect of smart meters, which have to store and process large amounts of data related to monitored energy consumption. For example, a feature typically found in commercial meters for domestic and industrial applications is that of storing measurements obtained at short observation times and averaging them over longer time intervals. In other cases, the meters are required to record alarms or events occurring on the monitored system (power quality).

Therefore, the memory installed on board the instrument must be able to store the data acquired and processed for specified periods, typically not exceeding ten months. This makes it possible not to lose information should the communication system be interrupted and to guarantee a certain backup of information. In general, the types of memory on board are:

- Dynamic RAM: used for temporary computation and buffering of data, the RAM must be large enough to support the needs of the processor, especially during the execution of real-time measurement algorithms.
- Flash memory: this non-volatile memory is used to store the device's historical data and firmware. It must be resistant to a high number of write/read cycles and guarantee secure data storage even in the event of a power failure.
- EEPROM: Specifically designed to store critical information such as system configuration and system event logs, EEPROM ensures the persistence of essential data between reboots.

Furthermore, it is important to emphasise that smart meters are equipped with advanced security features to ensure the protection of energy consumption data and prevent cyber attacks. These features may include advanced encryption, data authentication and protection mechanisms against cyber attacks. These include *Data Encryption*, where modern smart meters use advanced algorithms such as AES (Advanced Encryption Standard) to ensure that energy consumption information cannot be accessed or manipulated by unauthorised parties. In addition, the meters can implement *backup and redundancy systems* to safeguard data and ensure business continuity even under fault conditions.

7.4.6 Communication System

Data communication is one of the distinguishing aspects of smart meters, enabling continuous interaction with distribution networks and/or neighbouring devices.

Communication ports allow connection to external devices. In this, depending on the type of device to which it is connected, the smart meter can play the role of "master" or "slave" in communication. For example, in a distributed network of smart meters, one of these may act as an aggregator (master) that collects information from the remaining devices (slaves) and establishes a connection with a server for data storage. Without going into detail, in general, smart meters can implement different communication technologies, wired and/or wireless, as well as communication protocols, depending on the desired application context and characteristics. Of course, regardless of the chosen technology, one aspect that must not be lacking is communication security. In particular:

- *Authentication and Encryption*: Smart meters must secure communications using robust authentication protocols and end-to-end encryption to prevent unauthorised access and tampering with transmitted data.

- *Interference Resilience*: Communication protocols must be designed to operate in environments with high electromagnetic interference, typical of power grids, using data modulation and encoding techniques that improve signal resilience.

7.4.7 Mechanical and Electromagnetic Considerations

Finally, the mechanical and electromagnetic design of a smart meter must ensure robustness and compatibility with the installation environments. Specifically, the aspects that must never be missing in a smart meter design are:

- Structural Robustness: Smart meters must be designed to withstand adverse environmental conditions, such as high temperatures, humidity and vibrations. The use of durable materials and a compact design reduce the risk of failure and extend the life of the device.
- Miniaturisation: Reducing the footprint is a key objective in the design of modern smart meters, enabling installation in tight spaces without compromising performance.
- Electromagnetic compatibility: Smart meters must comply with international regulations regarding electromagnetic compatibility and electrical safety, ensuring that the device does not interfere with other electronic equipment and is safe for use in domestic and industrial environments. In addition, to minimise electromagnetic emissions and protect the device from interference, smart meters are equipped with EMC shielding and filters. This ensures that the meter operates correctly even in electromagnetically noisy environments, such as transformer rooms or industrial plants.

7.5 Design and Development of a Smart Meter Prototype

The design and development of a smart meter requires a careful analysis of the functional requirements, operating conditions and applicable regulatory specifications.

In the following, the architecture of the smart meter developed, the measurement methods used, the communication system implemented and the protocol adopted will be examined in brief, initially going through the chosen project objectives. Subsequently, a number of explanatory images of the smart meter prototype realised will be concisely presented, as well as illustrations of the boards and functional diagrams created during the prototype design and development process. Finally, a summary of the characterisation process carried out and then the calibration operations of the developed meter is presented

7.5.1 Requirements Analysis

The first step in design is a detailed analysis of the specific requirements of the application. In this case, the smart meter in question is designed for industrial applications. The objective is to present a device capable of implementing a wide range of smart functionalities, as demonstrated in this research, ensuring an integrated, multi-physics approach. In the selected reference context, precise measurements are required not only of electrical energy, but also thermal energy, as well as parameters related to the diagnostic monitoring of equipment.

Therefore, the design requirements are as follows:

- **Metrological requirements**: the meter must be able to monitor energy flows of an electrical and thermal nature. In particular, the metrological specifications require the ability to measure in real-time electrical quantities on a three-phase system with neutral, such as voltage, current, active, reactive and apparent power, and power quality parameters such as total harmonic distortion (THD). It is essential that the meter is capable of safe operation on a low-voltage electrical system (230 V RMS phase voltage). Furthermore, it must be able to function on single-phase and three-phase systems with and without neutral (and sub-configurations), with a nominal chained voltage of 400 V and a nominal frequency of 50 Hz. In order to facilitate current measurements, the device must be capable of offering a high degree of flexibility in terms of its operating range, thereby ensuring the possibility of both direct and indirect insertion measurements. In addition, the meter must be able to measure real-time quantities from analogue and digital sensors, such as temperature, flow rate and volumes for thermal energy monitoring. Finally, the meter must be able to measure certain diagnostic parameters of the operation of the monitored equipment that are typical of the reference context, such as vibration, acoustic noise and temperature. These requirements influence the choice of sensors, ADC converters, and signal conditioning circuits.
- **Mechanical requirements**: The device must operate in an industrial environment; therefore, it must be resistant to harsh operating conditions, such as temperature variations, vibrations, and electromagnetic interference. This implies selecting robust components and adopting design solutions that minimise the risk of failure. In addition, the meter must guarantee fast installation and DIN-rail mounting.

- **Communication and Scalability Requirements**: The system must be compatible with existing communication networks (LAN, Modbus, M-BUS) and easily integrated with other devices and systems in the industrial environment. Scalability is another key factor, requiring the ability to easily add modules or expand the capabilities of the device.

- **Processing requirements**: the meter must offer high processing capabilities for real-time data analysis, enabling future processing also related to the implementation of new techniques and algorithms directly on board the device.

7.5.2 Architecture of the prototype

The architecture of the smart meter, in accordance with Figure 7.1, was conceived as the integration of three main functional blocks:

- **Main Board**: The heart of the system is the main board, which houses an iMX6 processor with 2GB of DDR3 RAM (1066 SDRAM) and 8GB of eMMC flash memory. In detail, a Quad ARM Cortex-A9 cores running at 1 GHz. This processor is particularly suitable for applications requiring high real-time data processing capabilities, such as measurement signal processing and communication management (basically, it was created for integrated multimedia applications such as video streaming). It also has many interfaces for connecting to peripheral devices, such as WiFi 802.11a/b/g/n, Bluetooth 5.0 (BR/EDR/LE), GPS, hard drives and displays, ensuring a high degree of flexibility when connecting to other peripheral devices. These also include a 10/100/1000 Mbps Ethernet and 2 USB Type-A ports for future expansion. In terms of connection options, an RS485 serial bus has also been provided. Overall meter management is via a *Linux* embedded system.

- **Expansion Board**: The crucial element of the system is the expansion board, which contains the 8 channels for voltage (4 channels) and current (4 channels) measurements, 2 BT wireless and WiFi short-range connection interfaces, 2 LEDs for checking active and reactive energy counting, 4 digital inputs for synchronising the meter with trigger systems or specific system conditions, 4 digital outputs for controlling relays and interface systems, and two piezoresistive sensors for acoustic measurements.

- **External Modules**: The external device section allows the modular integration of additional sensors and instruments, such as thermal energy measurement systems and vibration sensors. This modularity allows the system to be adapted to a wide range of industrial applications.

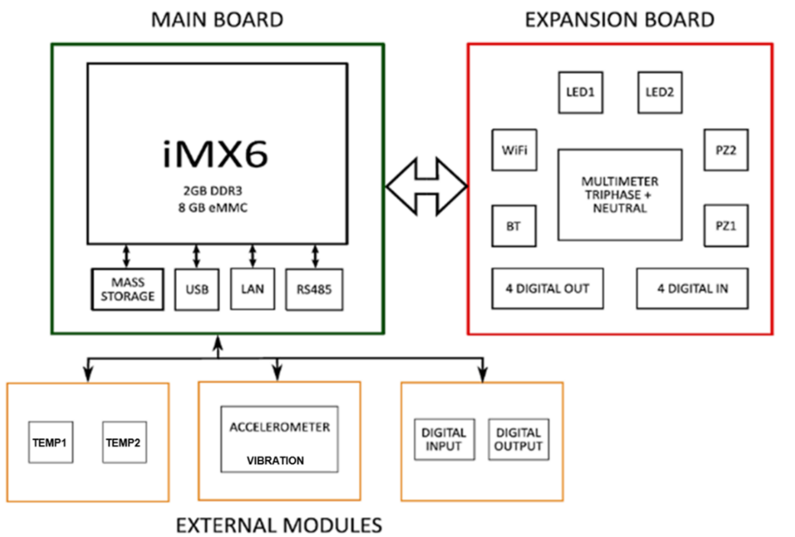

Figure 7.1: **Architecture of the prototype Smart Meter realized.**

7.5.3 Design of Measurement Circuits

To ensure measurement accuracy, sensors and conditioning circuits were selected to meet specific metrological requirements.

Voltage measurement is carried out by means of a voltage partitioning system combined with a voltage measurement transformer to ensure an adequate degree of isolation and attenuation. It should be noted that for voltage measurements, the insertion of the meter does not require a circuit break, as it is done by parallel connection of the meter to the measurand. Differently, current measurement can take place in two ways: in the direct mode, inserting the meter implies interrupting the circuit to be measured, as it requires a series connection. Of course, direct measurement is only possible when the quantity to be measured has a value within the meter's range. If this is not the case, or if there is an application whose continuity of service does not allow the power supply to be interrupted, the Indirect insertion mode is used.

In the case under consideration, the realised meter supports both insertions, isolated from the voltage channels. In detail, the current measurement can take place either in direct insertion (max. 5 A RMS nominal - max. 15 Ampere peak-to-peak) or indirect, using Amperometric Transformers (max. 5 A RMS nominal at secondary) and Rogowski probes. In particular, in the case of indirect insertion, the meter is equipped with an additional terminal block that is specifically designed for the separate connection of Rogowski coils (which have a voltage output) or current transformers with a voltage output. The probes generally offer the possibility of varying their full scale, thus extending the measuring range. At the output of the probe, the quantity will be scaled concerning the actual, so the meter will have to adapt the full scale of its acquisition system according to the scale factor of the probe to exploit the full dynamics of the converter and guarantee adequate measurement performance. In this case, voltage inputs are available for the connection of current probes with voltage output, which can be set by means of jumpers, equal to ±10 V, ±5 V and ±2.5 V.

The possibility of managing voltage inputs with independent amperometric channels allows the meter to interface with industrial systems of any type (3 phases with or without neutral and all sub-configurations). An example of direct and indirect insertion via rogowski, on a three-phase system with neutral is shown in Figure 7.2.

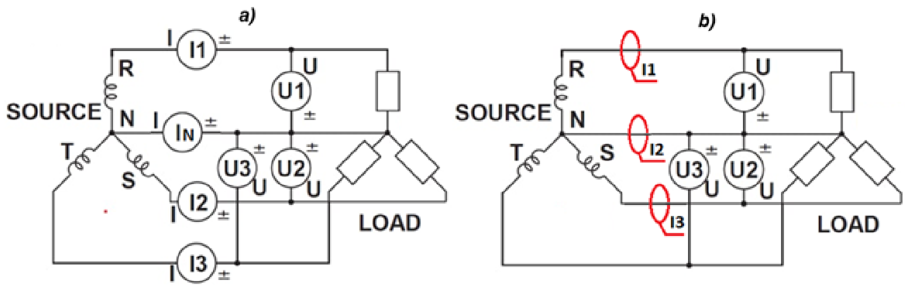

Figure 7.2: **Insertion mode of the prototype of Smart Meter realized: a) direct, b) indirect via Rogowski coil.**

About the ADC for the electrical section, the choice of analogue-to-digital converter was based on a compromise between accuracy and sampling rate. Simultaneous-sampling SAR-type ADCs were used, with a resolution of 16 bits and a sampling rate of 8kS/s per channel, guaranteeing high measurement quality even in the presence of harmonics and noise.

The raw data acquired from the sensors, downstream of the analogue-to-digital conversion, are processed locally using the integrated processor. This allows the real-time calculation of synthetic parameters, based on the chosen metrics, useful for system monitoring and diagnosis, reducing the amount of data to be transmitted and improving the effectiveness of on-board diagnostics.

About the processing required for the electrical quantities of interest, the meter implements the definitions given in the IEEE1459 and IEC61000-4-7 standards, following the considerations made in the previous chapters, particularly in section 1.7.

Concerning the measurement of the previously mentioned thermal energy and diagnostic parameters, it is possible to consider the parameters of vibration, temperature, flow rate, etc. as generic analogue quantities. To this end, the meter, thanks to the external modules, has been equipped with 5 additional analogue inputs (referenced to ground) in voltage with variable full scale via jumpers, equal to ±10 V, ±5 V and ±2.5 V. These analogue inputs report to a separate ADC converter with a sampling frequency of 1 kHz (as the dynamics are lower) and having 12 bits.

After the necessary parameters have been measured, the thermal energy can be evaluated by considering the temperature difference (between the input and output of the monitored thermal/mechanical system), the flow rate of heat transfer fluid flowing in the time interval, and a thermal coefficient, all following the UNI EN 1434-1 standard.

7.5.4 Design of the Communication System

Another interesting aspect addressed in the design of the Meter was the data transmission and communication system. The effectiveness and efficiency of a metering system network is closely related to both the quality of the measurement information collected from the field and the ability to transmit the system's information quickly (with respect to the dynamics of the application) and reliably. On the other hand, cost containment requirements, typical of industrial and tertiary applications, do not always allow the use of ad hoc networks and redundant systems. To optimise the requirements presented, the aim was to analyse and identify the hardware and software communication technologies most suitable for connecting the various systems in the field with the meter.

In this case, various types of communication buses were identified to identify those most appropriate for the typical operating environments of the industrial and tertiary sectors, and at the same time the most widespread to allow rapid and simple integration with devices already present in the field. These analyses involved the comparison of several figures of merit, including: supported physical media, reliability, immunity to electromagnetic interference, data transmission speed, robustness, extension and integrability with existing network infrastructures.

In summary, the communication system is designed to guarantee the reliability and speed required in an industrial environment, while maintaining a low cost. Communication is via wired buses (RS485, Modbus) and wireless networks (Wi-Fi, Bluetooth), with a focus on robustness against electromagnetic interference and ease of integration with existing infrastructures.

After a careful analysis of the application requirements, the Modbus protocol was selected, which offers high compatibility with existing industrial systems and robustness adapted to operating conditions. The system also includes an Ethernet module for external communication via the MQTT protocol, providing flexibility in the management and remote monitoring of the device.

MQTT

MQTT (Message Queuing Telemetry Transport) is a simple, lightweight protocol designed to exchange messages efficiently, reducing network traffic and requiring few device resources. It is ideal for bandwidth-constrained environments and devices with low computing capacity due to its scalability and reliability. The protocol operates according to the “publish and subscribe” paradigm, in which messages sent by a node (publisher) are only received by nodes that have subscribed to receive them (subscriber), thanks to the mediation of an MQTT broker (Figure 7.3). The broker manages messages and filters communications according to topics, which can be structured in several levels for greater precision. An interesting feature is the ability of the broker to hold messages until they are read, allowing the status of the devices to be consulted. There are several implementations of the MQTT broker, both local and based on virtual servers or commercial services.

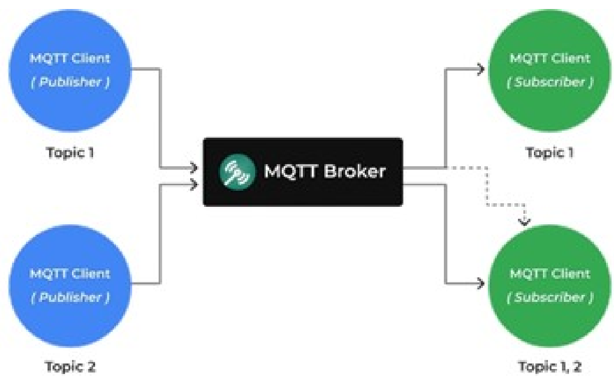

Figure 7.3: **Typical Broker MQTT.**

Security in MQTT systems is a trade-off between protection and usability, which is particularly complex for devices with limited resources. MQTT’s security architecture is articulated in three layers: the *Network Level*, which uses VPNs to create secure channels between brokers and devices; the *Transport Level*, which employs

TLS/SSL to encrypt communications, but can be burdensome for devices with low computing power, necessitating alternatives such as payload encryption; and the *Application Level*, which uses username/password authentication and can be reinforced with X.509 certificates. MQTT's multilevel approach balances protection and usability, adapting to device limitations and specific needs.

7.5.5 Realised Prototype

The following section presents a summary of illustrative images of the smart meter prototype. Some boards and functional diagrams of the boards realised during the development process are also shown. The prototype is encased in a 12-module modular housing that can be mounted on a DIN rail (EN 60715) and requires a 24 Vdc power supply. It should be noted that the device in question is at a TRL6 (Technology Readiness Level) design level.

Figure 7.4: **Realised Prototype (front).**

Figure 7.5: **Realised Prototype (back).**

Figure 7.6: **Realised Prototype (side).**

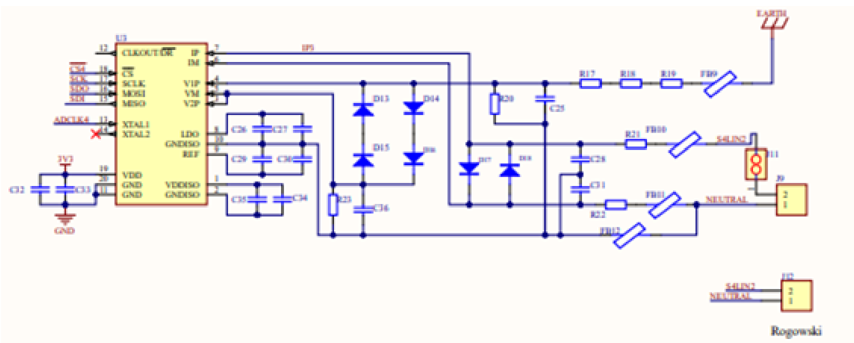

Figure 7.7: **Realised Prototype: example of functional diagram measurement module.**

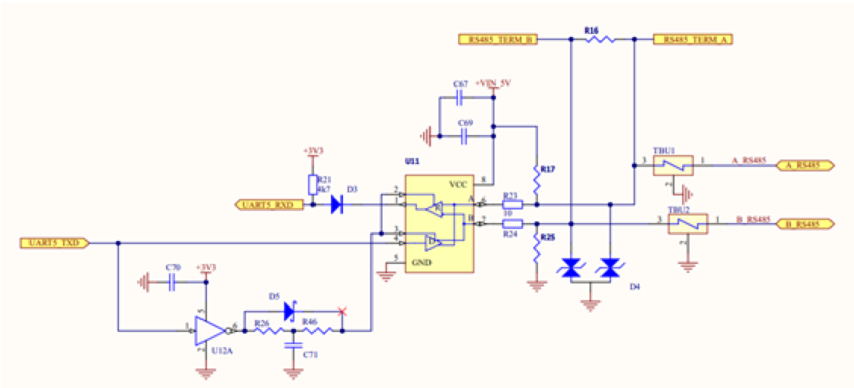

Figure 7.8: **Realised Prototype: example of functional diagram RS485 module.**

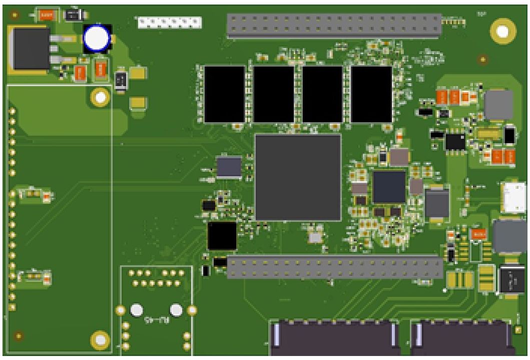

Figure 7.9: **Realised Prototype: Main board.**

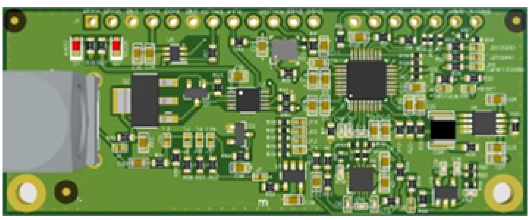

Figure 7.10: **Realised Prototype: Communications board.**

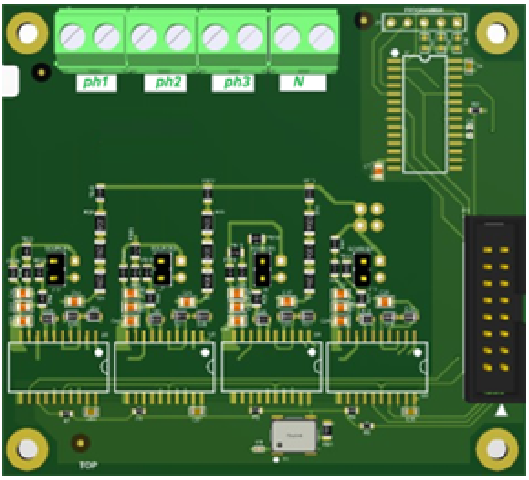

Figure 7.11: **Realised Prototype: Voltage and current measurement board.**

7.5.6 Characterisation and calibration of the realised prototype

It is not uncommon for unforeseen issues or unexpected behaviour to arise during the design and implementation of a measurement system. Hardware and software errors can compound, rendering it impossible to identify the source of the error and thus to resolve the problem. In such cases, the appropriate methodological solution from a measurement perspective is to conduct a characterisation process with the aim of understanding and defining the performance of the device under test. The characterisation process must be comprehensive, investigating all potential influences on the device's behaviour. This should be conducted using certified instrumentation with documented measurement accuracy. This was conducted during the construction of the smart meter prototype, with the objective of characterising the various measurement sections described above that comprise it. The calibration plan was fundamental to this process and ensured compatibility with the meter's measuring range, the nominal ranges of interest and a reasonable time for characterisation.

The measurement setup necessary for the experimental tests conducted on the prototype was established at the Laboratory of Industrial Measurements (LAMI) of the University of Cassino. In order to generate the requisite reference signals for the characterisation of the prototype, a FLUKE5500A calibrator was employed, capable of generating DC and AC voltages and currents separately with high precision. The instrument was operated via a PC using a GPIB-488 communication, which enabled the user to define the characteristics of the signal to be generated at the output. In order to ascertain the repeatability of the device, repeated measurements were carried out simultaneously with the prototype meter for each generated signal, whether voltage or current. Subsequently, the calibration methods for the smart meter were established with the objective of aligning the output responses from the measurement system, thereby compensating for potential measurement errors.

Once the characterisation and calibration process had been completed, an overall characterisation of the smart meter prototype realised was carried out, in order to assess its performance in terms of the quality of the measurements taken, comparing the latter with those produced by a certified instrument. In particular, a WT3000 Power Meter Analyzer was employed for the purpose of measuring the values of the electrical quantities provided as input to the smart meter at the same time as it did so, with a significantly higher resolution and accuracy than the prototype. In consideration of disparate test conditions, the reference values obtained by the WT3000 were compared with those yielded by the smart meter, with the aim of defining performance factors.

To summarise, the characterisation and calibration process is briefly explained in the following section with reference to the electrical section only.

It is evident that a comprehensive and accurate definition of the performance and capabilities of the smart meter in question necessitates a robust and comprehensive laboratory metrological characterisation of the aforementioned smart meter. Likewise, with regard to the operation and management of the smart meter, as well as the implementation of smart functions within it. However, in this paragraph, the level of detail is intentionally limited to avoid diverting attention from the primary focus of the research and to provide the reader with a general understanding of the design and implementation of innovative instruments capable of operating in today's increasingly digitised energy landscape.

Characterisation and calibration of voltage inputs

With regard to the electrical section used for voltage measurements, based on the requirements presented, since the meter has to operate on a low voltage system, characterisation was performed by investigating a very wide range of voltage amplitudes.

In detail, the RMS voltage values tested were as follows: *[0 20 40 60 80 100 120 140 160 180 200 220 230 240 260 280 300]* V - at 50 Hz. For each point, 30 measurements were taken to estimate repeatability. In addition, in order to assess the hysteresis of the system, the meter measurements were repeated for increasing and decreasing measurand. Characterisation was performed individually for each voltage channel of the meter. However, for the sake of brevity, the results are only reported in relation to one channel, the others being almost equal.

The average output of the prototype voltage amplitude characterisation is shown below in Figure 7.12.a and Figure 7.13.a. The responses for each phase are shown in terms of the RMS value and Offset of the quantisation levels of the meter's internal ADC.

Based on the reported output, an initial linear calibration was performed in order to identify for each channel the conversion factors "ADC levels-Voltage" and the offset compensation coefficients present. In particular, for the definition of these two factors, reference was made to the 230 V RMS response, this being the one of greatest interest for the context hypothesised. The values obtained were entered into the meter and then the amplitude characterisation was iterated again. Figure 7.12.b and Figure 7.13.b shows the result obtained.

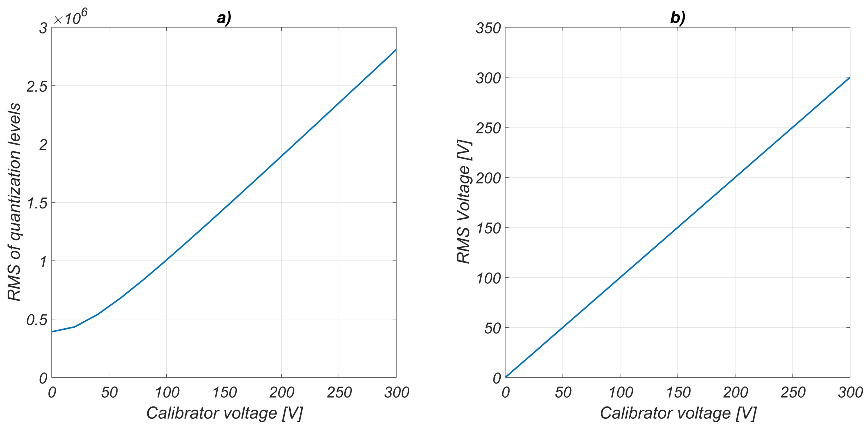

Figure 7.12: **Amplitude response of the voltage characterisation of the smart meter prototype. It shows, the RMS value of a voltage channel before (a), in terms of quantisation levels, and after (b) an initial amplitude calibration according to the voltage values provided by the calibrator.**

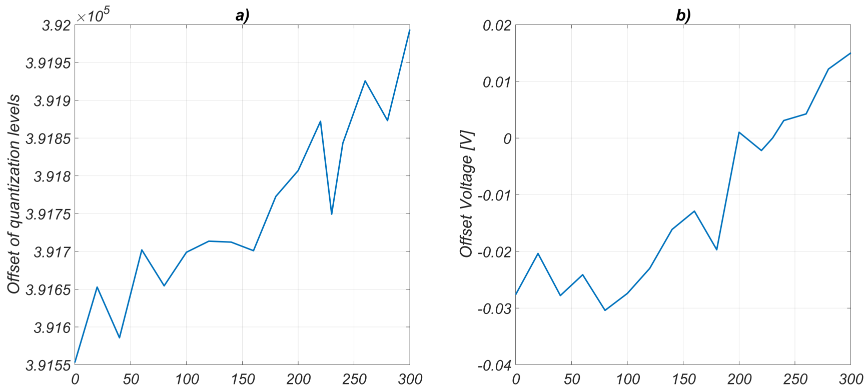

Figure 7.13: **Amplitude response of the voltage characterisation of the smart meter prototype. It shows, the Offset value of a voltage channel before (a), in terms of quantisation levels, and after (b) an initial amplitude calibration according to the voltage values provided by the calibrator.**

Subsequently, a frequency characterisation of the prototype was carried out to verify its stability. In particular, setting an RMS amplitude value of 230 V, the frequency response was evaluated for values: *[45 49 50 51 55 100 200 300 400 500 1000 1500 2000 2500 3000]* Hz. Figure 7.14.a shows the result of the frequency characterisation.

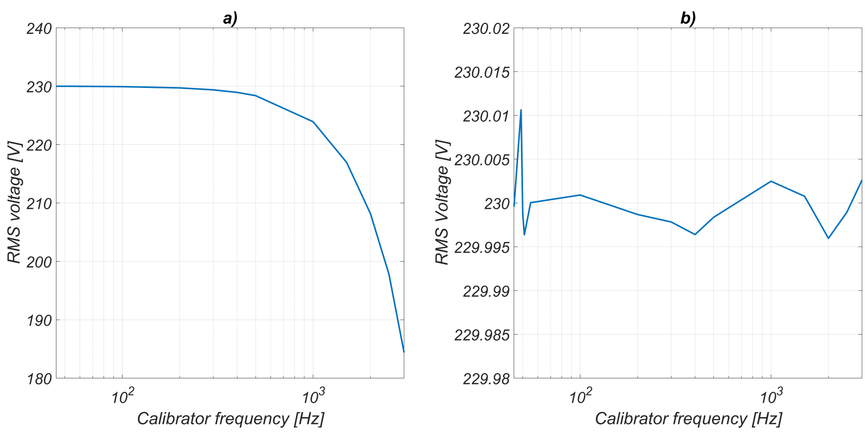

Figure 7.14: **Frequency response of the voltage characterisation of the smart meter prototype. Shows the RMS frequency response of a voltage channel before (a) and after (b) harmonic spectrum equalisation.**

The frequency response of the prototype suggested a software calibration of the spectrum in order to obtain a flat frequency response. This calibration was performed by defining the frequency response equalisation curve downstream of the FFT of the voltage signals. In detail, this was performed by defining an interpolating curve in the meter, such that each voltage harmonic is multiplied by a different gain. Figure 7.14.b shows the frequency response of the meter after calibration of the amplitude spectrum.

Characterisation and calibration of current inputs

The characterisation of the current channels was performed following the same steps described for the voltage channels. In detail, the current values tested for RMS amplitude characterisation were as follows: *[0 1 2 3 4 5]* A - at 50 Hz. A frequency characterisation was also carried out in this case. By setting an RMS amplitude value of 5 A, the frequency response was evaluated for the values *[45 49 50 51 55 100 200 300 400 500 600 700 800 900 1000]* Hz.

Below, in Figure 7.15, Figure 7.16 and Figure 7.17, are the outputs of the amplitude and frequency characterisation, before and after calibration, of the prototype for a current channel. As previously mentioned, only the characterisation related to direct insertion is shown for summary.

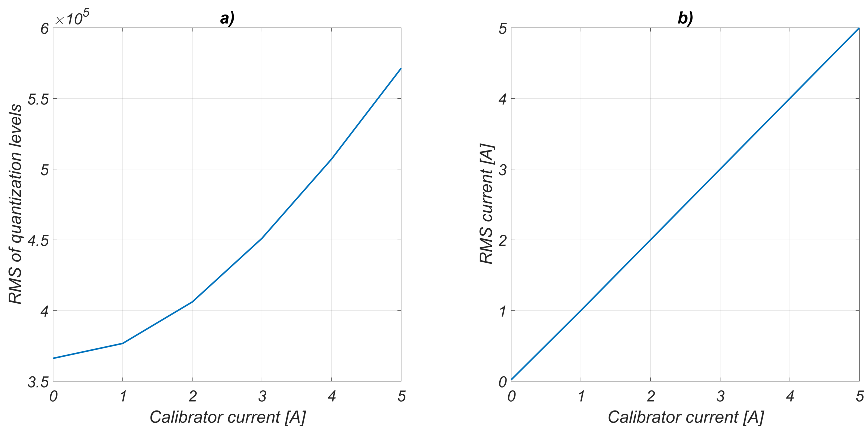

Figure 7.15: **Amplitude response of the current characterisation of the smart meter prototype. It shows, the RMS value of a current channel before (a), in terms of quantisation levels, and after (b) an initial amplitude calibration according to the current values provided by the calibrator.**

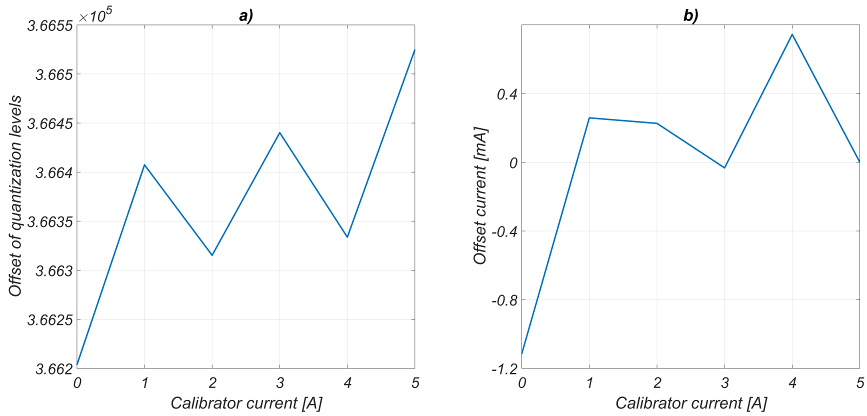

Figure 7.16: **Amplitude response of the current characterisation of the smart meter prototype. It shows, the Offset value of a current channel before (a), in terms of quantisation levels, and after (b) an initial amplitude calibration according to the current values provided by the calibrator.**

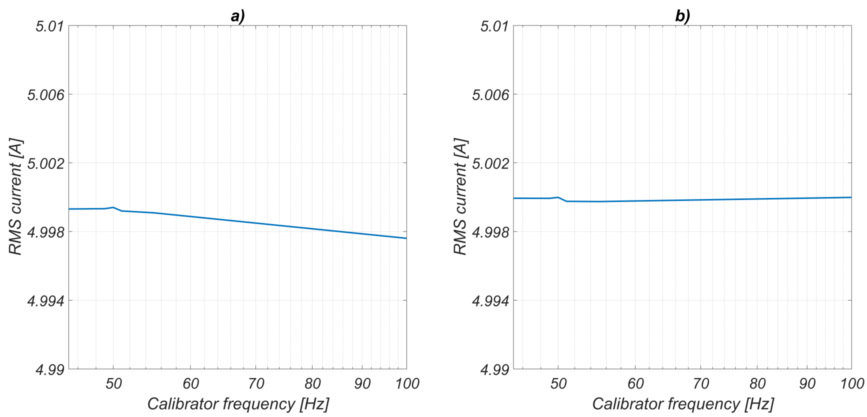

Figure 7.17: **Frequency response of the current characterisation of the smart meter prototype. Shows the RMS frequency response of a current channel before (a) and after (b) harmonic spectrum equalisation.**

Characterisation of the voltage-current inter-channel delay

As mentioned above, the smart meter prototype realised is equipped with an ADC of the SAR type with simultaneous sampling. This solution avoids problems related to inter-channel delay, i.e. possible acquisition delays that may exist between the measurement channels. However, since we had to calculate power, we still wanted to verify this aspect, since the phase shift present between voltage and current comes into play in the power calculation. Specifically, a voltage and current signal were applied simultaneously in phase with each other at the input to each phase of the meter via the calibrator. This was repeated at different frequencies.

The analysis showed that there was no inter-channel delay, so no correction had to be applied. In the event of a negative outcome, the solution would have been to define a table with the delay values introduced at the different frequency values and then perform a software compensation on the phase spectra of the signals downstream of the FFT.

7.6 Observations and Conclusions

The smart meter described in this document represents an innovative device with cutting-edge features compared to competitors on the market. It offers high flexibility in configuration and management, as well as interfacing with already installed devices. Furthermore, the proposed prototype offers the possibility of multi-physical monitoring, all with an integrated approach.

Its development is seen as a significant step towards the realisation of increasingly sophisticated devices, capable of playing a central role in the smart energy context, today and in the future. The combination of advanced measurement, data processing and communication technologies makes it possible to create systems that are not only highly efficient but also capable of supporting new smart applications and functionalities, such as those discussed in the previous chapters.

However, the evolution of smart meters does not stop there. Future iterations will face increasingly complex challenges, highlighted in part in this research, such as integrating with renewable energy networks, adapting to new security and cyber security regulations, and managing increasing amounts of data. Furthermore, the emergence of technologies such as 5G will open up new opportunities for improved communication capabilities and interoperability between different devices.

In conclusion, the implementation of effective and versatile smart meters requires an integrated, multi-physics approach that considers the entire energy ecosystem, from hardware design to data management and integration into existing infrastructures. Only through a continuous process of innovation and adaptation will it be possible to meet the growing needs of the energy sector and help build an increasingly digitised, efficient, sustainable and resilient smart electricity system.

Conclusions

The results achieved by the author in this research highlight how the digitisation of the energy sector, through the implementation of Smart Monitoring, represents a key breakthrough in addressing current and future energy management challenges. The widespread adoption of smart meters and the collection of increasingly detailed and accurate data pave the way for new advanced applications capable of improving energy efficiency, reducing operating costs and increasing sustainability.

One of the crucial aspects that emerged, and was repeatedly emphasised by the author, is the importance of measurement quality, both in terms of Monitoring Quality and Electrical Signature Quality. These elements proved to be crucial for the success of advanced applications such as Load Profiling, Digital Twin, Predictive Diagnosis and Non-Intrusive Load Monitoring. The focus on high-quality data collection and analysis not only allows for optimising energy consumption but also anticipating and preventing possible failures and inefficiencies, optimising their management.

Furthermore, the research emphasised how data security has become an indispensable component in the management of digital energy networks. The methods proposed by the author demonstrate that it is possible to improve the protection of critical infrastructures through innovative monitoring techniques that exploit electromagnetic emissions to detect potential threats without compromising business continuity.

In summary, Smart Monitoring, supported by a rigorous focus on measurement quality and Cyber Security, is a key enabler for a more efficient, secure and sustainable energy future. The solutions presented in this research not only improve energy management capabilities but also offer new tools to address the complex challenges posed by the ongoing energy transition.

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