Application of Intelligent Techniques for Optimal Management of Weakly Connected Microgrids

by

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Doctoral thesis

Application of Intelligent Techniques for Optimal Management of Weakly Connected Microgrids

Aplicación de Técnicas Inteligentes para la Gestión Óptima de Microgrids Débilmente Conectadas

Applicazione di Tecniche Intelligenti per la Gestione Ottimale di Microgrid Debolmente Connesse

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Abstract

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The decarbonization and the climate change mitigation have become a priority for many countries and governments. One of the main tools for accomplishing these objectives is the growth of renewable generation sources in the power system, but their inclusion constitutes a great challenge for the network operation due to their high variability and their stochastic behavior.

In this context, the management of the power system and microgrids can be treated as optimization problems in which the resources are operated with the aim of minimizing the cost function. This cost function and the corresponding operative restrictions depend on each specific situation, for example, on which are the power consumption requirements, how weak is the connection with the power grid, and how critical are the loads to be fed in the zone. In this sense, despite the large variety of optimization approaches, these have in common the importance of counting on a high-quality forecasting system for predicting the uncertainties of the microgrid (or network) to operate. The main existing approaches for predicting the uncertainties are deterministic and stochastic (which in many cases is also called probabilistic) forecasting.

Considering the importance of forecasting systems for performing the optimization of microgrids and, in general, power networks, this doctoral thesis is focused on the design of a microgrid-oriented forecasting framework that includes a wide range of forecasting approaches, which makes possible its integration with other applications, for example, energy management optimization systems. This framework includes several deterministic and stochastic methods and is able to handle the training and selection of the models for performing the forecast according to the type of uncertainty representation that is required in each case.

Keywords: short-term forecasting; deterministic forecasting; stochastic forecasting; probabilistic forecasting; machine learning; distributed generation; renewable energy sources; microgrid; smart grid

Resumen

Aplicación de Técnicas Inteligentes para la Gestión Óptima de Microgrids Débilmente Conectadas

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La descarbonización y la reducción del cambio climático se han convertido en una prioridad para muchos países y gobiernos. Una de las principales herramientas para lograr estos objetivos es aumentar el número de fuentes de generación renovables en el sistema eléctrico, pero su inclusión constituye un gran reto debido a su alta variabilidad y su comportamiento estocástico.

En este contexto, la gestión del sistema eléctrico y de las microrredes puede tratarse como problemas de optimización en los que los recursos se operan con el objetivo de minimizar la función de coste. Esta función de coste y las correspondientes restricciones operativas dependen de cada situación concreta, por ejemplo, de cuáles sean las necesidades de consumo de energía, de lo débil que sea la conexión con la red eléctrica y de lo críticas que sean las cargas a alimentar en la zona. En este sentido, a pesar de la gran variedad de enfoques de optimización, éstos tienen en común la importancia de contar con un sistema de predicción de alta calidad para predecir las incertidumbres de la microrred (o red) a optimizar. Los principales enfoques existentes para predecir las incertidumbres son la predicción determinista y la estocástica (que en muchos casos también se denomina probabilística).

Teniendo en cuenta la importancia de los sistemas de predicción para realizar la optimización de las microrredes y, en general, de las redes eléctricas, esta tesis doctoral se centra en el diseño de un marco de trabajo para predicción orientado a las microrredes que incluye diversos enfoques para realizar la predicción, lo que hace posible su integración con otras aplicaciones como, por ejemplo, sistemas de optimización de gestión energética. Este marco de trabajo incluye varios métodos deterministas y estocásticos y es capaz de gestionar el entrenamiento y la selección de los modelos para realizar la predicción según el tipo de representación de la incertidumbre que se requiera en cada caso.

Palabras clave: predicción a corto plazo; predicción determinista; predicción estocástica; predicción probabilística; aprendizaje automático; generación distribuida; fuentes de energía renovables; microrredes; redes inteligentes

Sintesi

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La decarbonizzazione e la mitigazione del cambiamento climatico sono diventate una priorità per molti Paesi e governi. Uno dei principali strumenti per realizzare questi obiettivi è la crescita delle fonti di generazione rinnovabili nel sistema elettrico, ma la loro inclusione costituisce una grande sfida per il funzionamento della rete a causa della loro alta variabilità e il loro comportamento stocastico.

In questo contesto, la gestione del sistema elettrico e delle microgrid può essere trattata come un problema di ottimizzazione in cui le risorse vengono fatte funzionare con l'obiettivo di minimizzare la funzione di costo. Questa funzione di costo e le restrizioni operative corrispondenti dipendono da ogni situazione specifica, ad esempio, da quali sono i requisiti di consumo di energia, quanto è debole la connessione con la rete elettrica e quanto sono critici i carichi da alimentare nella zona. In questo senso, nonostante la grande varietà di approcci di ottimizzazione, questi hanno in comune l'importanza di contare su un sistema di previsione di alta qualità per prevedere le incertezze della microgrid (o rete) da far funzionare. I principali approcci esistenti per prevedere le incertezze sono la previsione deterministica e stocastica (che in molti casi è anche chiamata probabilistica).

Considerando l'importanza dei sistemi di previsione per eseguire l'ottimizzazione delle microgrid e, in generale, delle reti elettriche, questa tesi di dottorato si concentra sulla progettazione di un modello di lavoro di previsione orientato alla microgrid che include una vasta gamma di approcci di previsione, che rende possibile la sua integrazione con altre applicazioni, ad esempio, sistemi di ottimizzazione della gestione dell'energia. Questo modello di lavoro include diversi metodi deterministici e stocastici ed è in grado di gestire l'addestramento e la selezione dei modelli per eseguire la previsione secondo il tipo di rappresentazione dell'incertezza che è richiesto in ogni caso.

Parole chiave: previsione a breve termine; previsione deterministica; previsione stocastica; previsione probabilistica; apprendimento automatico; generazione distribuita; fonti di energia rinnovabili; microgrid; smart grid

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Chapter 1

Introduction and objectives

This chapter introduces the context, summarizes the objectives, and exposes the structure of this doctoral thesis.

This chapter aims to introduce the context of the thesis, which is focused on some of the new advances that are being integrated in the power system, especially the inclusion of renewable generation, flexibility services and microgrids (which increase the capacity of control over the power system). According to this context and the needs that have been identified, the objectives of the current thesis are summarized, and the chapter structure of the document is detailed. Details regarding the publications related to the thesis are also given and their references in the document will follow a special style for them to be easily identifiable.

Section §1.1 exposes the context. Section §1.2 details the objectives and goals. Finally, Section §1.3 explains how this document is structured.

1.1 Introduction

During the last years, ecological awareness is gaining relevance among the citizens of many countries, being these times especially marked by climate change, waste recycling, and pollution reduction [1]. It has favoured the emergence of popular movements and a strong environmentalism, which has changed the consumption habits of the society, showing a preference for products and services that cause a lesser environmental impact and looking for a more sustainable behavior [2, 3].

In this context, the use of clean and decarbonized energy is a priority for many governments and citizens, who seek an eco-friendlier and more sustainable behavior of the countries [4]. These principles can be applied in the ambit of energy and transport through the construction of more efficient buildings, the use of electric vehicles (EVs), and the gradual reduction of the use of fossil fuels, among other possible actions. In power systems, one of the main tools to accomplish these objectives is the gradual substitution of the traditional power generation sources by others that are based on renewable energy, achieving a reduction of the carbon footprint [5].

The deployment of renewable power generation is in many cases done through plants of a lesser size than traditional larger power plants, and are usually connected to distribution networks (sometimes also referred as medium-voltage and low-voltage networks in Europe) instead of being connected to the transmission network (sometimes also referred as high voltage network in Europe) [6]. One of the main advantages of this approach is that it makes possible to situate the generation units closer to consumption points, thus reducing the technical losses during transmission, and achieving a better integration of the renewable sources. Nowadays, thanks to this new way of approaching generation source planning, the global power system is experiencing radical changes, increasing the presence of renewable power resources and leading to what can be described as the renewable energy era [7]. In this sense, including renewable energy generation in this distributed way (with plants of a lesser size connected to the distribution network) supposes a change in the traditional paradigm from the previously established "centralized generation" to what is known as "distributed generation (DG)" [6].

With the DG paradigm, some difficulties arise. For example, the increase of the number of generation resources and the variability of their generated power (which, in the case of renewable sources, is usually dependent on weather conditions) increase the operation complexity of the power systems, which bring the need of having more accurate tools to perform such management in an optimal way. These conditions have favored an increasing research interest in the power system management and operation field. In particular, a number of proposals aim to mitigate the aforementioned problems by focusing on congestion management [8] or decision support for operators [9].

Among these solutions, energy systems as the *microgrids*[1], and tools as *power forecasting* (to predict, for example, the expected power generation and load consumption), *flexibility* and *demand response (DR)* have particularly attracted the attention of stakeholders (e.g., utilities) and researchers. Particularly, in the last years, they have provided ways to solve (or mitigate) those contingencies that could appear in the system, such as network congestion, voltage unbalances, sudden variations in generation (or consumption) or blackouts [10, 11].

These applications have been improved in the last years thanks to the advances in monitoring and data acquisition over electrical networks, which have greatly increased the availability of data (achieving better observability) and given place to more advanced models

[1] A microgrid consists of a group of devices that interconnects loads and a certain generation or storage capacity (or even both of them). Therefore, it can operate directly connected to the distribution network or even in islanding mode in case of grid failure or power unavailability. From outside, a microgrid can be seen as a single aggregated system.

of the behavior of the power system and better methods for its management and control (achieving better controllability). This high availability of data would not have been possible without the new automatic metering infrastructure (AMI) systems (which have recently experienced a great expansion in many countries), and in general the rest of the monitoring and operation devices that have been installed over the whole power system. Considering that the amount of data involved in the power system operation is growing exponentially (and becoming more complex), it can be said that artificial intelligence (AI) and machine learning (ML) techniques will be key for the data analysis and for the future improvement of power control and network management [12].

In a general sense, the technologies and applications that aim to improve the monitoring, controllability, analysis capacity, and active management of power networks are grouped under the *smart grid* paradigm. In this paradigm, the aforementioned microgrids play an important role, as they make easier the integration of the mentioned tools for the improvement of the power system [13].

The elements that can be included under the domain of a microgrid are consumption loads (which may have some degree of controllability in certain cases), generation units (which are frequently renewable), energy storage systems, and other elements for the monitoring, control, analysis and management of the microgrid (or even for communicating with other external agents in some cases). Thanks to these modifications, which increase the degree of *"smartness"* in the networks, the inclusion of distributed renewable generation can be done in a more secure and feasible way [14, 15].

To avoid continuously mentioning the different kinds of power elements that have some capacity of control (over their consumption, generation, or energy storage), these can be all grouped under the concept *distributed energy resources (DERs)*. DER is a common term not only in academic ambit, but it is also used by power system operators and utilities. Therefore, the elements that are part of a microgrid are frequently simply referred to as DERs [16].

The research on distributed power systems, which sometimes focuses on microgrids, is diversifying on different lines, such as the discussions on the coordination between different elements, their management, and the economic behavior of the market and stakeholders. These fields open many possibilities for the new power system [17].

The reason for this diversification is that distribution networks have a more complex topology than transmission networks, the former requiring a higher level of redundancy and control than the latter (from a topologic point of view), so the necessity of methods to improve their operation is a general concern for researchers and utilities. In this sense, microgrids bring a set of control possibilities that are of high interest as a tool for the effective upgrade of the power system. Additionally, as it was previously mentioned, the power system is currently evolving from the centralized (based on "large power plants") paradigm to a distributed one, where the DERs are proliferating increasingly. These DERs, because of their own conditions and characteristics, are directly coupled to the distribution grid. Consequently, distribution system operators (DSOs) are finding a problem that was not common before: the overflow of generation in their distribution networks, due to the impact of little generators [18]. For this reason, the research of methods for energy management and operation of microgrids (and, in general, of power networks) has become a task of great importance, encouraging system operators, electric companies, and academic researchers to develop new techniques to be applied in this field (e.g., the provision of flexibility services to be used by the operators [19]).

Despite the multiple applications and approaches, most of the proposed methods regarding microgrid management, network operation, market coordination, and unit commitment (UC) are based on the prediction (also called *forecasting*) of some variables, which are sometimes called *uncertainties* in the field of study of optimization methods. These variables can be, for example, load consumption, power generation, and energy prices. In this sense, it is suitable to highlight the importance that forecasting has in the described environment, being it an essential tool for many applications [13].

Considering the research context that has been exposed, the current thesis will be focused on the ambit of power distribution networks and microgrids. Its objectives will be detailed in the next section.

1.2 Objectives

The objectives of the current doctoral thesis include the study, analysis, and improvement of the tools for optimal microgrids and DERs management, not only considering the perspective of their management as standalone units, but also as active parts inside the power system where the needs of the other participant agents are also considered.[2] In this way, it is possible that the microgrids provide flexibility services to the operators when these are required.

As it will be appreciated in the bibliographical reviews made in Chapter §2 and Chapter §3, the optimization of resource operation in microgrids strongly depends on the forecasting of certain unknown variables, e.g., future expected generation and consumption. In this sense, two main aspects can be considered in this field, which are the optimization (according to the selected criteria) and the improvement of forecasting models (whose predictions are used as input information for the optimization problem).

To match these two aspects, the information provided by the forecasting model should be properly fitted to each optimization problem. For example, a forecast could be based on deterministic (points) or probabilistic (bands, quantiles, and probabilities) methods, and the set of microgrid management optimization techniques that can be applied considering these types of forecasts are different in each case. The same applies to the forecasting horizons,

[2]Some of these agents are the DSOs, which are entities that manage and operate their distribution networks, or the transmission system operators (TSOs), which manage their transmission networks.

the information availability, and the computation time limitations. For this reason, the forecasting and optimization methods should not be treated separately, but together instead.

This research is focused on the use of forecasting techniques for power generation and load consumption in distribution networks and microgrids. The relationship between the forecasting and the type of optimization problem is considered to ensure that the forecasting system can provide information in an adequate way to be used for such optimization according to the existing optimization methods that will be reviewed in Chapter §3.

Specifically, the objectives of this thesis are:

- O1: Identifying which are the problems associated with the optimal management of microgrids, in particular the energy management and flexibility services provision. In this regard, a literature review of the optimization methods will be made. Wherefore these optimization methods are heavily dependent on forecasting methods, these will also be reviewed (especially, the use of AI techniques).

- O2: Creating an architecture for flexibility applications provided by microgrids and customers, considering the technical requirements for their deployment. As part of this architecture, a special emphasis will be placed on the requisites for an energy management system (EMS) to include the possibility of applying flexibility actions while achieving an optimal management of consumption and generation.

- O3: Analyzing how the baseline consumption of customers could be calculated for the provision of flexibility services. This is an important task for performing the audit of provided flexibility services, i.e., checking if the provider of the requested service (e.g., a customer or an aggregator) accomplished the conditions that were agreed during the time of the flexibility event. In this regard, a new method for obtaining the baselines will be proposed.

- O4: Designing a forecasting framework focused on microgrids and distribution networks that includes deterministic and stochastic/probabilistic models. This framework would be used to forecast the different uncertainties that should be predicted to perform applications over microgrids and networks, e.g., energy management optimization, flexibility services provision, etc. In this sense, the framework should include the mechanisms and metric criteria to automatically choose the best model. Moreover, the existing metrics and indicators for the evaluation of models have to be considered to choose the most convenient one that should be applied, or even creating new metrics if required. The reason for this is the variety of uncertainty models that can be applied for forecasting the unknown variables, which therefore require an appropriate evaluation of each type of model.

Wherefore, the main goals of the thesis can be summarized as:

> ***Creating a microgrid-oriented forecasting framework that can apply deterministic and probabilistic methods and automatically select the best model among those that are available according to the type of uncertainty prediction that is required.***

Once explained which are the scope of the thesis and the research objectives, the next section will detail the structure and contents of this document.

1.3 Structure

The contents of this doctoral thesis are organized as follows:

- Chapter §1 introduces the scope of the document, the context, the justification of its relevance, and its main objectives.
- Chapter §2 analyzes the main characteristics of the power system and the difficulties of their operation. The importance of the advances and research in the smart grid paradigm (which includes microgrids, flexibility tools, and many other improvements) are herein presented, as these are useful for the mitigation of most of the problems in power resource management.
- Chapter §3 conducts a review of the state of the art on microgrid management techniques and tools. The different types of microgrid management methods and forecasting techniques are classified while specific examples of their application are also provided.
- Chapter §4 summarizes the problems that were identified during the literature review and exposes the main thesis proposals. These proposals include the definition of an architecture for flexibility dispatching, the design of a nanogrid EMS where flexibility events are included, a forecasting method called rule-based baseline, and finally, a forecasting framework focused on the prediction of generation and load consumption of microgrids and distribution networks.
- Chapter §5 shows the results and discussion of the experiments that were performed for each of the proposals in different case studies.
- Chapter §6 highlights the conclusions and future lines of this work. Additionally, the published results related to the exposed research are detailed.

Some parts of the literature analysis, problem identification, proposals, and results that will be mentioned along this text have already been published in scientific journals (***[[20]]***, ***[[21]]***, and ***[[22]]***). These references are remarked in bold italics and with double square brackets to indicate that they are directly related to the thesis.

Chapter 2

Power system and smart grid

This chapter provides an overview of the power system structure and the technical advances that are being applied under the smart grid paradigm, in particular the microgrids and their control systems.

Electricity has become an essential good for the prosperity of modern societies, being indispensable to have a secure supply to favor their development. For this reason, the power system is under a continuous evolution due to both the emerging technological advances and political decisions. This evolution is not equal in all countries, being possible to appreciate diverse differences in the structure and regulation of their respective power systems.

The objective of this chapter is to provide an overview of the power system structure and the technical advances that are being applied as part of the "smart grid" paradigm. Considering that many of these advances include new ways of coordination between the actors of the power system, making an initial review on their characteristics is of great interest. This review will be of help to understand how the new advances could be integrated according to the existing legislation and particular characteristics of the different countries. When reviewing these new advances, particular emphasis will be made on the microgrids and their capability for improving the controllability of the power system, being them also a valuable tool for the massive integration of renewable generation sources.

This chapter is structured as follows. First, in Section §2.1 the general aspects of power system structure are briefly explained. Section §2.2 is focused on the existing operation guides of the power system, using the case of the European Union (EU) as a representative example. Then, in Section §2.3 the emerging advances in the context of smart grids are exposed, in particular microgrids and their control systems. Section §2.4 presents some remarks on how the perspective and needs of the utilities have influenced in the evolution of the power system and in the integration of technological improvements. Finally, a summary and conclusions close this chapter in Section §2.5.

2.1 Power system structure

The structure and evolution of the power system in different countries and regions are the consequences of political decisions (which are strongly dependent on their economic, social, and geographical situation) together with the technical research and advances that keep emerging.

For this reason, the structure of the power system does not follow the same model in all countries and it is possible to find significant differences between them. Notwithstanding, it can be appreciated that most countries share a common interest on the improvement and research related to the power system. In this sense, some examples of the common new tendencies are the massive inclusion of renewable generation technologies and the fulfillment of decarbonization objectives, which are leading a radical change in the generation paradigm.

In this context, some countries have made efforts to reach a common (or, at least, a similar and compatible) organization structure of their power systems and energy markets, following their interest in the development and coordination of energy interchange, as it is the case of the EU, where common electricity markets are shared by some nearby countries. These markets are operated by the nominated electricity market operators (NEMOs), some of these operators being *Operador del Mercado Ibérico de Energía (OMIE)*, which operates in Spain and Portugal; *Gestore Mercati Energetici (GME)*, which operates in Italy; and Nord Pool, which operates in the Nordic and Baltic regions, in the United Kingdom and in Central Western Europe.

The existing structures of power systems and their particularities in different regions have been studied and compared in many reports and scientific papers by researchers, system operators, and legislative agents. For example, in [23] a comparison between various power markets (Chile, United States, and Germany) and their operating reserves is conducted.

These studies are very helpful to analyze which are the advantages and disadvantages of each type of structure and for comparing the behavior of different markets considering their characteristics. For this reason, they frequently serve as guides for developing new regulations. In this sense, the documents published by the EU that evaluate common politics and new actions that are considered convenient (e.g., [24], which is focused on capacity mechanisms) are examples of this. Their importance becomes even greater with the advances and technologies that are part of the smart grid paradigm, whose effective application depends in many cases on the current normative development. Therefore, before exposing such smart grid advances, a brief analysis about the power systems in diverse zones of the world will be performed, highlighting some of their main characteristics.

The set of common reforms that have been applied to the power system in many countries from the 1980s until today, include *unbundling*, *corporatization*, *market liberalization*, and some other aspects are called “standard model” or “textbook model,” as it is stated in [25, 26]. The term “corporatization” refers to “the formal commercialisation of unbundled entities or their incorporation as commercial businesses under Company Law.” Therefore, it can be said that corporatization “mandates economically rational operational decisions (as opposed to politically motivated decisions)” [26]. The meaning of the terms “unbundling” and “market liberalization” will be seen later in the text. These reforms have the objective of creating a power system based on competitive power markets, attracting private investment instead of depending on public entities.

In this sense, as it is exposed in [27], the restructuring process of the power industry in the United States started in 1996 with the *Order 888 from the Federal Regulatory Energy Commission (FERC)* [28]. It forced a transition from the previous structure, which was “vertically integrated” (the same utility could be at the same time in charge of the tasks of energy generation, transmission, distribution and comercialization) to another one based on a competitive market. In this new environment, the transmission and distribution companies operate the transmission and distribution networks, respectively. As a consequence, various wholesale electricity markets were created in the United States, being geographically distributed across the country [27].

However, there are some states where a type of vertically integrated structure is allowed. As said in [29], “most vertically integrated utilities only provide bundled service, or power supply plus distribution, while in restructured states most utilities provide only distribution service” (or may offer “an optional last-resort or default service for power delivery”). Therefore, both “bundled” and “unbundled” service models coexist in the United States.

Additionally to these changes, the power system of the United States has been modernized with the introduction of tools that aim to mitigate the difficulties that affect grid management (such as the growing presence of renewable generation), increasing the available flexibility in the system [27]. The natural disasters that have happened in the country [30] are also a reason for the impulse that has been given to these advances.

In a similar way than in the United States, various changes in the structure and management of the grid have been applied in other zones such as Canada or Europe (which will be analyzed in detail later), unbundling has also been introduced in these zones ***[[20]]***[1] to ensure the competition through electricity markets.

Additionally, in Canada, policies have been approved to encourage the investment in renewable generation, it being considered crucial for the plan against climate change. It was established in [31] (cited by [17]) that renewable energy generation would receive long-term contracts with predefined feed-in tariffs, so the investment risk is reduced. As a consequence of this policy, a reduction in the dependence of coal-fired generation (and progressively phase

[1]It is reminded that the publications that are part of the thesis are referenced using double square brackets, bold and emphasis (cf. Section §1.3).

out them) is expected in the province of Ontario.

The power sector reforms in Sub-Saharan Africa, South Asia, and Latin America are reviewed in [25]. It states that "some countries have completed the transition to market-based systems, but in the vast majority reform is a work in progress, often moving much slower or in a different direction than originally anticipated." For example, in many countries of Sub-Saharan Africa and South Asia, the single-buyer model is still dominant, and only some of them have privatized power utilities. "In Latin America, the implementation of reforms has been relatively successful by comparison" [25].

In Latin America, as it is exposed in ***[[20]]***, "changes in the electric legislation are under study by legislators and various federal and local authorities with the collaboration of industry stakeholders." The objective of these collaborations is constituting a more secure and reliable power grid applying appropriate policies and technologies. In this sense, "Chile is moving toward power grid improvements as part of the energy matrix modernization plan of the country, firmly advancing towards a greener, more sustainable and energy efficient state through the use of renewable energies and less dependence on fossil fuels" ***[[20]]***. With respect to the deregulation of the Chilean electrical sector, it started in 1982, when "unbundling was applied and generation competition and marginal costing were introduced" [32]. A more detailed explanation of the undertaken actions and initiatives in microgrid research in Latin America can be found in ***[[20]]***.

In Asia, according to [26], "although the logic of reform from public sector to market driven processes would imply that corporatisation follows unbundling, actual experiences with both have vastly differed in non-OECD Asia" (i.e., Asian countries that are not belonging to the Organisation for Economic Co-operation and Development (OECD)). According to some authors, "in smaller systems, the creation of an independent regulatory authority may be more important than the unbundling of the system, particularly in cases of politically unstable countries and especially for the case of countries where hydroelectric power is predominant" [26]. In this sense, as it is also expressed in [25], "there is now broad agreement that no 'one-size-fits-all' solution exists for power sector reform and that there is no ideal power sector model." Therefore, it can be appreciated how the particularities of each of the countries affect to the desired characteristics of their power systems, not being possible nor convenient to apply the same solution for all of them, but it is necessary to study each case in detail.

In the EU, unbundling has been one of the most important changes over the power system in the member countries. It was officially established by the European Directive 2003/54/EC [33]. Considering the four existing activities in electricity (which are generation, transmission, distribution, and supply), according to the Directive "it is necessary that the independence of the DSOs and the TSOs be guaranteed especially with regard to generation and supply interests. Independent management structures must therefore be put in place between the DSOs and the TSOs and any generation/supply companies." This independence of management structures is important to ensure that they do not have any direct market interest, as it could lead them to a conflict of interest between both areas, the system operation and market participation. That situation would not be compatible with the competitive markets that were desired for EU power systems.

A few years later, in 2009, the European Commission approved the Third Energy Package, which consisted of two Directives and three Regulations. One of them, the European Directive 2009/72/EC [34] (currently in force), substituted the Directive 2003/54/EC. It introduced new changes in the rules for the internal electricity market. Specifically, it establishes new aspects regarding the unbundling of electricity transmission and distribution activities from those regarding generation and supply. Additionally, new interesting concepts about additional services were also introduced, such as demand side management (DSM) and DR.

Due to the complexity of the practical fulfillment of this unbundling (as it has to be applied in all member countries of the EU), the European Commission published an interpretative note [35] to explain in a more detailed way how the European Directive 2009/72/EC should be applied. It exposes and clarifies three possible models that could be applied for the unbundling of the electricity transmission function. These are "the ownership unbundling model," "the independent system operator (ISO)," and "the independent transmission operator (ITO)." These three models are "subject to a certification procedure" [35]. In a similar way, it also established in more detail how the distribution function should be unbundled.

As stated in [35], each country had the liberty to establish the unbundling model that it desired among the various possibilities to choose. This fact could hinder the cooperation between energy agents of different countries. Due to this, in the same year, the Agency for the Cooperation of Energy Regulators (ACER) was created [36] with the objective of monitoring the "regional cooperation between TSOs in the electricity and gas sectors" and ensuring that the Directive was properly applied and therefore this cooperation "proceeds in an efficient and transparent way for the benefit of the internal markets in electricity and natural gas" [36]. In this regard, a summary of the characteristics of the European electricity markets can be found in [37] (a briefing of the European Parliament).

The integration of different countries and zones, and the possibility of energy interchange between them is one of the most important achievements that are advancing in the last years in Europe. The coordination between the countries of the EU, as can be observed in [35, 36] is the key for these operations. In this sense, the EU has been continuously working for improving this integration, providing guides of recommendations to perform the energy interchange between countries. As an example, [38] is focused on the explanation of EU electricity markets, with the objective of unifying intercountry energy interchange. In this way, it describes day-ahead markets, intra-day markets, and balancing operations. Some terms of great interest that are here mentioned are flexibility, congestion management, and capacity payments.

Another example of a European initiative which is focused on making the integration of markets easier is the Pan-European Hybrid Electricity Market Integration Algorithm (Euphemia), which was conceived to calculate day-ahead electricity prices for energy interchange between countries across Europe [39].

Finally, it is important to mention some of the last changes in European electricity normatives that have been made by the Regulation 2019/943 [40] and the Directive 2019/944 [19], which introduce and define more explicitly the participation of customers in the markets, the requirements that DSOs and TSOs must accomplish, and other advances as a massive inclusion of EVs. The content of these two documents will be analyzed at a deeper level in Section §2.3.

The EU has also published guides on how the power system must be operated, being these of interest to appreciate the complexity of the coordination tasks and the importance of the research in this area. Some of these operation guides will be reviewed in the next section.

2.2 Power system operation guides

The regulation of the power system is essential to keep its stability, which requires holding the frequency and voltage near to their nominal values, being 50Hz the nominal value for frequency in EU countries [41]. There are multiple technical methods for regulating these values; for example, the frequency can be controlled by means of the injection/consumption of active power to/from the network, while the voltage level can be controlled with the injection/consumption of reactive power (Volt/VAR control). Additionally, other actions required for the secure operation of the power system are, for example, capacity adjustments or participation in electricity markets.

Due to the size of the network, performing these regulation tasks requires a good coordination between the participant actors and between the interconnected countries. Therefore, the common normative for the European power system operation contemplates some types of actions that are necessary to keep the system stable, so some guides were developed for helping the involved actors to perform their tasks in a standardized way. The aim of the present section is to briefly describe their content.

Other countries and regions of the world have also made their own normative and legislation developments regarding the operation of the power system, which in some points and recommendations could differ from those of the EU. Notwithstanding, it has been preferred to show exclusively the example of EU in this section, as its case is closer to the scope of the present thesis document.

The Regulation [42] (published by the European Commission) is a guide for the balancing of the power system, being of application for TSOs and DSOs. It establishes "common principles for the procurement and settlement of frequency containment reserves, frequency restoration reserves and replacement reserves and a common methodology for the activation of frequency restoration reserves and replacement reserves." Moreover, it "establishes an EU-wide set of technical, operational, and market rules to govern the functioning of electricity balancing markets" [42].

This guide is closely related to [43], which is focused on the operation of the transmission system (which is precisely the power system level where the interconnections between countries are done), being of application for the TSOs/ISOs. This document exposes common operational security requirements and operational planning principles while taking into consideration load-frequency control processes and control structures. Thus, it also defines a common terminology with the objective of making their application easier in each of the countries of the EU.

In parallel, the Regulation on Capacity Allocation and Congestion Management (CACM) [44], which was published in 2015, according to its own description, constitutes a guide for "cross-zonal capacity allocation and congestion management in the day-ahead and intraday markets" [44]. About its scope of application, it is said that "this Regulation shall apply to all transmission systems and interconnections in the Union except the transmission systems on islands which are not connected with other transmission systems via interconnections" [44]. Again, it can be here appreciated the efforts made by the EU to achieve a common framework for the interchange of energy in a coordinated way.

The concept "capacity allocation" refers to the capability of modifying the planning when a transmission line is expected to be above of its operative capacity (for example, during a big energy exchange between two countries). Therefore, capacity allocation is such an important operation inside the power system, as it is crucial to avoid the overcharge of the transmission lines. In this regard, the Regulation on Forward Capacity Allocation (FCA) [45], which was published in 2016, contains "detailed rules on cross-zonal capacity allocation in forward markets, on the establishment of a common methodology to determine long-term cross-zonal capacity and on the establishment of a single allocation platform at European level offering long-term transmission rights," among other rules and procedures.

It is important to note that some of the proposals included in the normative required further development to be applied by the countries, as it was not totally defined how the recommendations would be applied in practice. For example, the capacity mechanisms are in many cases problematic, so it has been proposed the creation of market-based cross-border capacity mechanisms, which should only be used under certain conditions for not distorting the internal electricity market. A discussion on these aspects can be found in [24], which was published in the year 2017.

In the same way, the report [46] (published by ACER in the year 2019) intended to overview the implementation status of both FCA and CACM Regulations. In this way, it was possible to identify the challenges for their implementation, check if the objectives were accomplished, identify the potential problems, and suggest solutions.

It can be appreciated in these mentioned documents how the EU has made great efforts to create a common and conciliatory environment for the operation of the power system, aiming to integrate the networks of different countries for their coordination and energy interchange.

2.3 Smart grid: a new paradigm

The "smart grid" can be defined as "the next-generation electricity grid," which "is expected to address the major shortcomings of the existing grid" [47]. The smart grid is a complex system, so it can be described from various points of view, and therefore various definitions can be found in the bibliography [47, 48, 49].

According to [47], the smart grid needs "to provide the utility companies with full visibility and pervasive control over their assets and services." It "is required to be self-healing and resilient to system anomalies." Moreover, it "needs to empower its stakeholders to define and realize new ways of engaging with each other and performing energy transactions across the system" [47].

Alternatively, following an European point of view [49], a smart grid can be defined as "an electricity network that can intelligently integrate the actions of all users connected to it —generators, consumers and those that do both— in order to efficiently deliver sustainable, economic and secure electricity supplies. A smart grid employs innovative products and services together with intelligent monitoring, control, communication, and self-healing technologies" [49].

Therefore, according to these definitions, the smart grid paradigm integrates many kinds of improvements, covering all the levels of the power system, and aiming to reinforce their smartness, which can be done by including a wide variety of fields such as AMI, microgrids, and flexibility applications, as it will be seen later.

The implications of the advances in smart grids were already analyzed in ***[[20]]***, ***[[21]]***, and ***[[22]]***. Therefore, these papers will be sometimes cited in here, as they were made as part of the research of the present doctoral thesis.

The deployment of AMI systems over networks aims to increase their observability. This deployment is in an advanced state in the member countries of the EU, which has been implemented using smart meters. These smart meters are able to automatically register the electricity supply, i.e., the generation or consumption of electricity by each customer (and, in the same way, it is possible to use similar systems for gas and water consumption).

Regarding generation sources, if the evolution that power networks have recently undergone is observed, it is easy to identify that "during the last few years, the presence of renewable energy generation has increased significantly within power systems" ***[[22]]***, being able to minimize environmental impacts [50]. Precisely, in the definitions that have been previously given for the smart grid, some concepts are related with the new tendencies of penetration of renewable generation sources into the power system. This penetration is being done through the so-called DG paradigm [6], which makes it possible to "reduce the environmental impact" and reduce the consumption of customers. Moreover, these customers could actively participate in the power system as prosumers. Due to the variability in the renewable generation (as it depends on the weather behavior), integrating these generation sources is not an easy task as long as they make the operation of the power system more complex.

Some tools that are applicable to simplify the power system operation are *ancillary services* (which can be classified as frequency or non-frequency services) and *capacity mechanisms* [40, 19]. Additionally, the customers can also provide this kind of services thanks to the *DSM* and *DR* techniques ***[[21]]***. These techniques "can be a solution to the problem [51, 52], allowing customers to provide services of power adjustment when needed" ***[[21]]***.

In this context of renewable generation expansion, a new type of unit called microgrid can be highly useful to improve the integration of such heterogeneous groups of resources and control actions. Microgrids can bring many possibilities not only for the management of their resources under economical or efficiency criteria, but also for the provision of active tools and services to the power system operators through DSM and DR. Due to their characteristics, microgrids are expected to be convenient for the integration of such tools together with renewable generation sources. As it will be later explained, these objectives have some common technical requirements (e.g., monitorization of the microgrid elements, capacity of connection and disconnection of resources, communication between the involved agents, common rules for the operation in case of noncentralized approaches, etc.).

Therefore, it can be said that DG is one of the key points in the smart grid sector [53], together with microgrid control applications. In these fields, AI techniques have revealed to be powerful tools to improve their performance ***[[22]]***.

The smart grid is not a concept with a totally fixed meaning, but it has suffered deep changes during the recent years, as it is in continuous development. Some agencies and researchers have worked on the definition of reference architectures and recommendations for structuring the smart grid, its functionality, and the relationships between its components.

The National Institute of Standards and Technology (NIST) redacted the National Institute of Standards and Technology Interagency Report 7628 (NISTIR 7628) [54], which defines seven domains in the smart grid and analyzes their related characteristics, risks, and vulnerabilities. This document provides guidelines for cyber security in the smart grid [55].

In the European ambit, *Comité Européen de Normalisation Électrotechnique (CENELEC)* (in English: European Committee for Electrotechnical Standardization) has worked on the definition of the Smart Grids Architecture Model (SGAM) [56]. This model builds upon the NISTIR 7628 [57].

According to the mentioned parts that compose the smart grid paradigm, a general schema of the areas can be seen in Figure 2.1. These areas, which are closely related between them, are AMI, DG, microgrids, flexibility services, and AI. Other authors have also proposed other schemes, for example, the EV could be considered as an additional one. However, for the scope of the present thesis, it has been considered enough to define those areas of the figure.

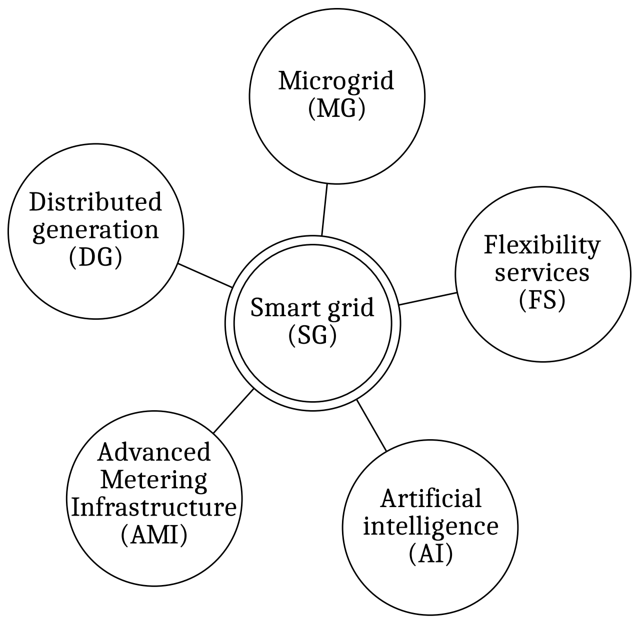


Figure 2.1: Smart grid areas that are studied in this section.

The objective of the DG is to increase the sustainability of the power system thanks to the use of renewable energy resources. For its integration, some of the existing tools are the usage of flexibility services and the deployment of microgrids, as both of them increase the capacity of control, and therefore make easier the integration of renewables. In parallel, the AMI increases the observability of the power system, also including their individual elements of consumption and generation. Finally, AI has revealed to be a tool of great value for being applied in all mentioned areas. A clear example is its use for the forecasting of power generation and consumption, which is required for the management of the power system.

Having exposed a general overview of the smart grid and its implications, the different areas that have been distinguished will be reviewed in detail in the next sections.

2.3.1 Advanced metering infrastructure

It is stated in *[[21]]* that "within the development that smart grids have experienced in the last years, it is worth highlighting the use of AMI [58, 59]." The deployment of AMIs in electricity networks aims to increase the observability of the system, providing measures in an automatic way that can be used to monitorize and study the state of the network and the energy flows across their lines. An AMI usually includes some measurement instruments (whose type depends on what section, element or physical magnitude of the network they are intended to monitorize) and some communication systems to send the information to a concentrator that collects them (whose characteristics will mainly depend on the location of the instruments).

One of the possible applications of the AMI is the monitoring of the electricity supplied to the customers by the corresponding DSOs (and another example could be the monitoring of feeders in a secondary substation by the DSO). In this particular case, the AMI can be implemented thanks to the deployment of customers' smart meters by the DSOs. As it is exposed in ***[[21]]***, the AMI applied to customer supplying "is composed by two main functions, which are automatic metering reading (AMR) and automatic metering management (AMM)" ***[[21]]***. It can be said that these two functions "are usually integrated in the smart metering architecture, which is used for the monitoring of customer consumption and other elements of the power system" ***[[21]]***.

Following the European directives, smart meters for monitoring the electricity supply are fully deployed in most of the European countries [60]. In this sense, "in Europe, the deployment of smart metering for gas and electricity started with the publication of the European Directive 2009/72/EC, by pointing out the advantages of such systems and recommending their deployment [34]" ***[[21]]***.

Regarding the data communication method for smart metering infrastructures, there are various ones that can be applied. As said in ***[[21]]***, "while non-wired solutions have many advantages, the power line communication (PLC) solutions are most extended for electricity metering, as they use the power lines as communication channels." A schema of an infrastructure of smart metering based on PLC is depicted in Figure 2.2.

2.3.2 Distributed generation

One of the latest advances that are taking place in the power system is the "progressive inclusion of renewable generation, which has significantly increased in the daily energy mix of many countries [61]" ***[[21]]***. These renewable generators are usually organized as small, mini, or micro power plants, but they are also commonly used as complementary generation devices for consumers ***[[22]]***, allowing them to produce their own energy. These customers, who are known as *prosumers* (as they are at the same time producers and consumers) "are adopting a more active role within the power system" ***[[21]]***, being expected that they can provide not only a certain energy production, but also flexibility services to the network operators.

The increasing presence of renewables marks a large change from a traditional centralized generation system to a distributed system ***[[22]]***, giving place to what is known as the DG paradigm [6]. Contrary to traditional generation approach, under the DG paradigm "active

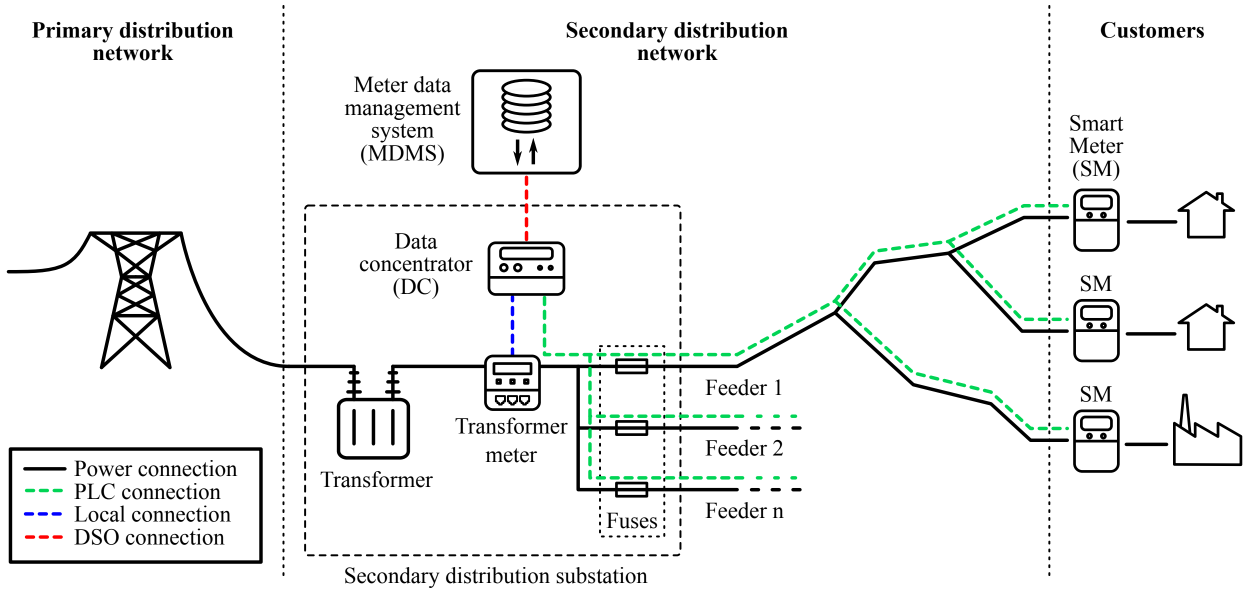


Figure 2.2: PLC-based smart metering infrastructure. Based on a figure published in *[[21]]*.

sources are connected directly to the distribution network, permitting them to be nearer to consumption points [19]" *[[22]]*. This brings some advantages, such as a reduction of the energy losses during the transmission.

In this context, the distributed elements that are connected to the network are usually known as DERs. In this sense, the concept of DER "is not only associated with generation systems [62] but also with the coverage of storage [63, 64] and even controllable loads [65, 66]. In this sense, EVs can also be considered DERs, adding to the difficulty of being a mobile load [67, 68, 69]. Traditionally, all these DERs have been coordinated by EMSs" *[[22]]*. With this penetration of these resources in the distribution networks, the DSOs "are responsible for maintaining the network stability, orchestrating these assets locally as DERs. This task is critical in sectors of the distribution network that are weakly connected, where congestion management tasks are delicate" *[[21]]*. As these DERs are being built deeply into the distribution networks, the boundary between transmission and distribution is blurring [27].

The DG paradigm "is one of the key points in the smart grid sector [47, 48, 49] and is characterized by better control of all connected resources (including consumers and producers) and other goals [70], coverage of the whole system, and the application of AI techniques [53]" *[[22]]*. It can be appreciated the important role that management and control systems have in this environment, as they are in charge of extracting the potential from the resources under their domain according to the established criteria.

In this context, with expansion of DG, microgrids are expected to mitigate the complexity of renewable generation, integration, and control thanks to their characteristics. Considering their importance, an overview of microgrids and their control systems will be given in the next section.

2.3.3 Microgrids

The microgrid is an element of high importance in the smart grid paradigm. In this sense, a microgrid "can be considered and exploited as a main building block of the Smart Grid" [17]. Therefore, this section aims to introduce the microgrids, their characteristics, and how these can be controlled to take advantage of their potential as part of the power system.

In the first place, the microgrid definition and some introductory generalities can be found in Section §2.3.3.1. The hierarchical structure for microgrid control that is commonly found in the literature is exposed in Section §2.3.3.2. The Section §2.3.3.3 shows which are the existing architectures for energy management (centralized, decentralized, and distributed). In some situations, the control systems affecting to a microgrid do not only include an EMS, but there can also be some others (e.g., distributed energy resources management system (DERMS)), so these additional microgrid-related control systems are to be explained in Section §2.3.3.4.

2.3.3.1 Microgrid definition

A microgrid can be defined as a small electric network that is designed for a reliable and massive integration of DG at the low (or medium) voltage level, especially with renewables (solar, wind, and other low carbon technologies) [10, 11].

In other words, according to the definition given in ***[[20]]***, a microgrid "is comprised of a group of heterogeneous power supply sources, both renewable and non-renewable, organized in a particular manner and located close to the loads to which it will supply electricity." They "usually include local generation, such as solar or wind or both, and at certain times they also resort to other means of power generation" ***[[20]]***, like microturbines. Additionally, other resources can be included as, for example, energy storage systems (such as batteries).

All these resources (generators or energy storage systems) are commonly referred as DERs, which correspond to any kind of energy resource that is connected to the distribution network or to a microgrid.

As reported in [13], "a microgrid system normally operates in two modes," so-called "grid-connected mode" and "island mode." Under the grid-connected mode, the microgrid system sells the surplus of electricity to the utility when the local generation overcomes the power consumption of the loads. Otherwise, the microgrid buys the needed electricity from the main grid. Under the island mode (e.g., in the case of a blackout), the microgrid is disconnected from the main grid and it operates autonomously (off-grid) during a certain time (or, in some cases, even permanently) ***[[20]]***. Beyond these situations, some microgrids could be equipped with power quality monitoring, being able to disconnect themselves from the main grid if the power quality is below a certain level and preventing in this way possible failures and technical problems due to unstabilities from the main grid [13].

The basic structure of a microgrid is sketched in Figure 2.3. As it can be seen, the point of connection between a microgrid and the main grid is called the point of common coupling. However, certain microgrids do not have any point of common coupling with the main grid. This decision can be motivated by the complexity of the connection, especially for those microgrids where the connection with the main grid would require an excessive economic investment. These microgrids, which are usually called "isolated microgrids" (or "not grid-tied microgrids" *[[20]]*), operate permanently in stand-alone mode [17] (i.e., island mode).

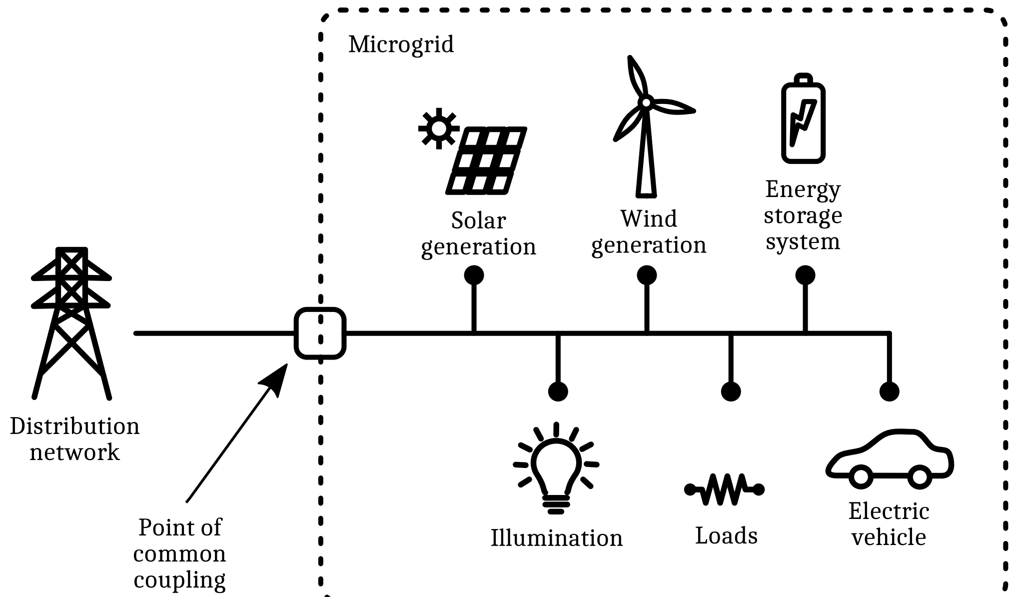


Figure 2.3: Basic structure of a microgrid.

For the design and sizing of the elements of the microgrid, the energy requisites of the involved customers, and the characteristics of the network where they are connected. As said in *[[20]]*, "the decision of whether to use or not to use batteries to store energy depends on the electricity consumption profiles and specific necessities of the community of users (e.g., electricity-dependent people who have medical equipment at home for specific treatments or health sustenance like kidney dialysis, which must always be connected to electric power supply), and on the particular plant capacity options versus peak load patterns, among other things" *[[20]]*. Therefore, the requisites that a microgrid should accomplish are not something universal and generalizable, but these depend on the specific use that the microgrid will have (e.g., what the expected energy generation, consumption and needed autonomy are). In this sense, the design of a microgrid can be optimized modelling their requirements in an optimization problem [71].

Therefore, the introduction and integration of microgrids in the power system brings multiple benefits, not only for the increasing of DER penetration, but also for improving the stability of weakly connected zones, as it is the case of rural areas [15].

These advantages explain the recent increasing of initiatives for the study, improvement and integration of microgrids by means of testbeds around the world. Some examples of these initiatives are CERTS testbed in the United States, project MICROGRIDS in various European countries [13] (such as Spain, Portugal, Italy, Germany, etc.), ESUSCON microgrid in Chile [72], LAMBDA Lab[73] and Smart Polygeneration Microgrid of Savona Campus (Università di Genova) [74] in Italy, REIDS microgrid in Singapore [75], Biomass technology demonstration centre BTDC in Namibia [76], solar-powered demonstration microgrid at Wilhelmina Farm in South Africa [76], and KEPCO Smart Energy Campus in South Korea. The location of these initiatives can be seen in Figure 2.4.

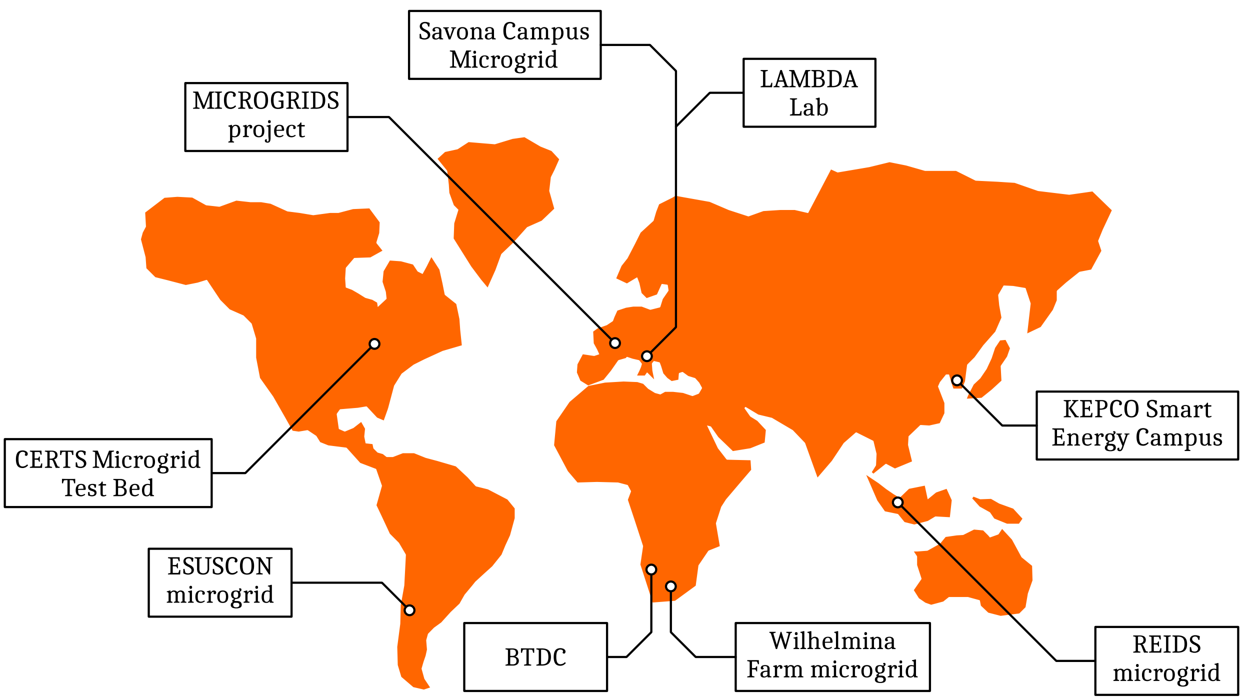


Figure 2.4: Diverse examples of microgrid initiatives around the world.

Taking into account that the word “microgrid” can refer to a wide variety of grids with different power sizes, some authors propose to use more specific terms according to their magnitude, as it is done in [73]. They distinguish between smart grids (unlimited capacity, considering small or large numbers of customers), microgrids (less than hundreds of kW), and nanogrids (less than tens of kW). The mentioned number criteria are not followed by all researchers of this field, many others considering installations of more than hundreds of kW also as microgrids. In the present doctoral thesis, the concept "smart grid" has already been used to refer to the paradigm of power system modernization (in the same way that most of the authors do in the reviewed literature). Henceforth, those microgrids of less than hundreds of kW will be called "nanogrids", while those bigger than that will be indistinctly referred to as "microgrids".

The microgrid configuration depends on the type of voltage it uses, which can be alternating current (AC), direct current (DC), or hybrid AC/DC (mixing both of them). According to [77], "AC microgrid is the most used configuration as it provides a direct way to integrate DG units in the current utility grid with minimum modifications." For those cases where AC and DC devices coexist, an "energy router" is proposed in [78] to make the interconnection of energy flow between different elements, mitigating the energy exchange problems ***[[20]]***.

It can be appreciated the large potential that microgrids have thanks to their control capacity, from the point of view of the microgrid as a unit, and in each of their individual DERs. However, extracting this potential depends on the control systems that are deployed, and on which control strategies are applied. Structuring control systems is not a trivial task, as various possible hierarchical layers, objectives, communications, and functionalities can be involved in them.

It is therefore considered necessary to expose which are the architectures that are usually applied for the control of microgrids and their coordination with other agents of the power system. These architectures are explained in the next section.

2.3.3.2 Hierarchical control for microgrids

The introduction of microgrids as part of the distribution network supposes the introduction of a new hierarchical level which must be considered for the coordination under their domain and above it for establishing communication or coordination with external agents and systems.

This hierarchy has been described by some authors [17] as a three-level structure in which different control systems find their place, including the coordination actions between them when required. While other more specific structures could be taken into account, this one has been considered descriptive enough for the study of microgrid energy management, so it will be the one taken as reference for the present doctoral thesis. These three levels, according to [17] and [79] (that refer to this structure as "hierarchical control") are as follows:

Primary control: The primary control level refers to the lowest control level of the different DERs and elements in a microgrid, such as the voltage and frequency controllers in the existing generation sources and smart inverters. This level takes care of islanding detection and power sharing between the elements, so the speed of communication (or even the absence of them) is a crucial aspect to assure the maintenance of the power stability (frequency and voltage levels).

The methods of primary control are usually classified in droop-based methods and non-droop-based methods [17]. In addition to these approaches, the modelling and analysis of disturbances affecting the microgrid must be considered to ensure its stability (this task has a particular importance while working off-grid), as the control method that the microgrid and its inverters (inside the microgrid domain) apply must be adapted to handle these disturbances. Some examples of this can be found in [80], whose authors propose performance metrics for power losses of synchronous generators due to the effect of variable voltages or [81], in which a method to enhance the stability of weak grids based on adaptative virtual resistors for the regulation of inverters is applied (obtaining an adaptative droop control). Other authors have studied how the characteristics of generators (such as wind) and converters affect the behavior of microgrids [82, 83].

Secondary control: The secondary control assumes the task of microgrid management under certain criteria (which are usually related to reliability, economical, and environmental aspects), while maintaining the UC in the microgrid. These actions are performed by an EMS, which is in charge of receiving the information and dispatching the orders to the different elements. According to [84] (cited by [17]), the three control strategies that an EMS can employ are "real-time optimization," "expert systems and fuzzy expert systems," and "decentralized hierarchical control." From the point of view of the control architecture, the two main types that are usually distinguished in the literature are "centralized architecture" and "decentralized architecture." As it will be seen later, some authors also define another type called "distributed architecture."

Tertiary control: The tertiary control involves an interchange of information with the outside of the microgrid domain, usually with some external agent, such as a transmission or distribution network operator, or the regulator of the market in which the microgrids participate. For example, the dispatching of requests of ancillary services, flexibility services, and DSM (or DR) actions that can be provided by microgrids and aggregators are included in this control level.

These three levels together with some of the existing strategies and methods to accomplish their requirements can be seen in Figure 2.5. In this figure, the strategies refer to the type of approaches that have already been mentioned for each of the hierarchical levels, while the methods are examples of solutions to handle the mentioned approaches.

This thesis is focused on the optimization and forecasting methods that can be applied for the energy management of microgrids. For this reason, special attention will be given here to the secondary level of the described hierarchy, i.e., the characteristics and requirements for the EMSs to perform the energy management according to the required criteria. In

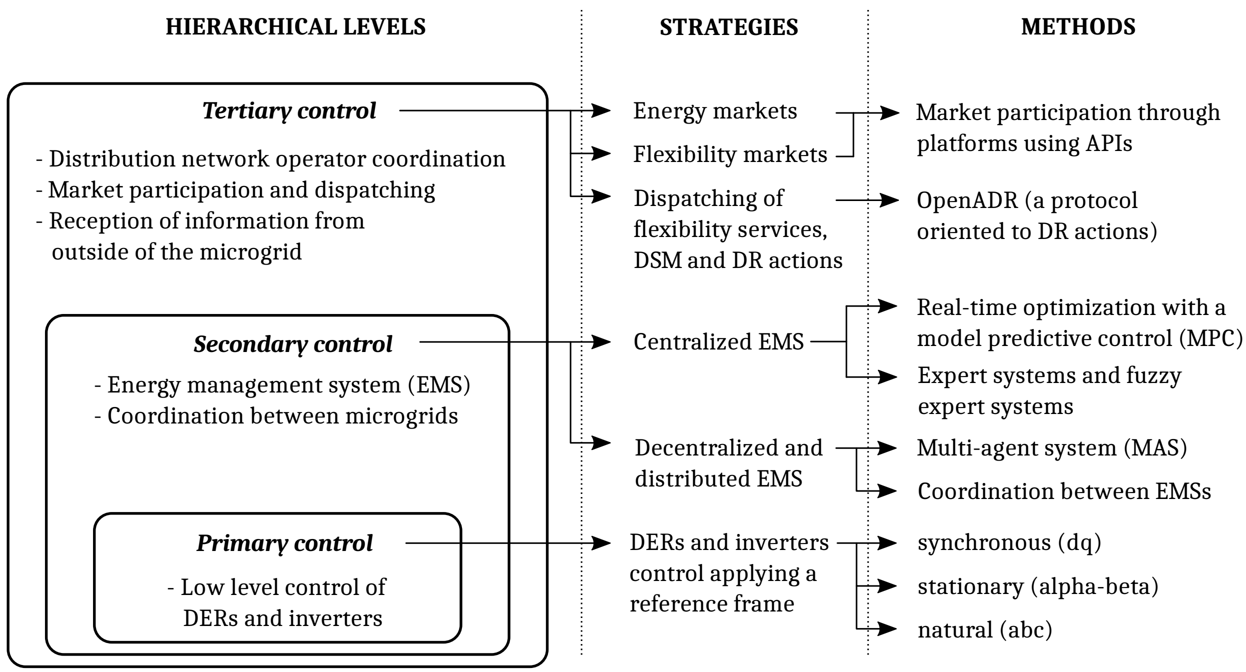


Figure 2.5: Hierarchical levels, strategies and methods for microgrid control.

this sense, the next section will review the existing energy management architectures for microgrids commonly found in the literature.

2.3.3.3 Energy management architectures for microgrids

This section intends to review the existing types of energy management architectures for microgrids, i.e., how the control system of each microgrid and DER can be structured to perform energy management, giving place to different approaches with their respective advantages and disadvantages.

As it was previously mentioned, a microgrid is usually under the control of an EMS, which "has the responsibility to manage the renewable energy generation and conventional one to keep the power balance between generation and consumption" [10] (i.e., the UC. In other words, as described in [13], the objective of an EMS "is to provide operational reference signals for microgrid units, state monitoring and device communication technology to construct a bi-directional interaction framework between the power production to be properly dispatched and the user consumption" [13].

There exist multiple ways of designing an EMS according to the expected behavior of the microgrid elements and the situations that this EMS must handle to keep the stability of the supply in the network. For example, in [85] it is said that the proposed "cooperative control system based on equal power sharing between storage devices" is more effective to avoid voltage failures, being able to maintain voltage regulation in situations for which the traditional droop control fails. This is an example of how the integration of DERs can overcome classical tools for distribution network operation, also favoring the integration of renewable generation sources over the power system.

Therefore, EMSs have the potential not only of improving the resource and energy management in microgrids, but also to permit service providing to the external distribution grid. In this sense, as it is exposed in ***[[20]]***, "the energy management in a power system can also be understood under the perspective of homeostatic control (HC) (based on homeostasis), in order to establish the relationship between the variables and actions that must be taken into account by the system. The concept of homeostasis, which was originally defined for the biological field, describes how living organisms regulate themselves to keep internal conditions stable (avoiding external disturbances) [86]. This biological principle can be adapted to create an EMS for a microgrid, whose objective is keeping all the conditions of the system (keep enough energy in batteries, load monitoring to avoid excessive consumption, etc.) stable [87]." The details on how the HC can be applied to power systems were already reviewed in ***[[20]]***. More details can be found also in [88, 89, 90, 91, 92, 93].

The importance of energy management tasks in the power system is so substantial that some authors state that "EMS is one of the pillars of next generation of power system called smart grid" [10]. For these reasons, the problem of managing a system composed by one or various microgrids (i.e., a cluster of microgrids) have been widely studied, existing some differences on the classification of the control strategies depending on the author [13, 10, 94, 17].

To successfully reach these objectives, an EMS requires a forecasting of power generation and consumption to optimize operative decisions while respecting the constraints of the microgrid. This is usually not an easy task, "as renewable power units are often coupled with a storage system and envisaged at a local scale (where the demand is more erratic than at a global scale), this makes the management of such electric microgrids delicate" [95]. In this regard, identifying the requirements on forecasting for each of these approaches will be key to achieve an appropriate use of forecasting techniques, including time horizon (hour-ahead, day-ahead, etc.), frequency of execution (rolling horizon, once a day, etc.), aggregation (hourly, quarterly, every minute, etc.) and even the source of the required information (local measurements, telemetry, aggregated values, etc.). These aspects will be reviewed in detail in Section §3.4.

Some authors classify the existing energy management approaches applied to microgrids in three main groups: centralized controllers, decentralized schemes, and distributed control strategies [13]. Similarly, in [10] the authors distinguish between centralized, decentralized, and distributed EMSs.

Those authors that make a strict distinction between decentralized and distributed control use the term "decentralized" exclusively to refer to the existence of coordination between different microgrid levels. This coordination could be considered as a multilevel structure inside the secondary control hierarchy level, or even as part of the third control level. The term "distributed" would then be used for those control schemes in which individual DERs (or individual groups of DERs) interact to collaborate between them, not existing any central controller for taking the management decisions.

Conversely, other authors simply distinguish between centralized and decentralized systems, this last one being a synonym of distributed [94]. This criterion is followed in [17], in which a review focused on state-of-the-art control strategies and control principles for microgrids is reported. In this sense, it is said that "while the centralized approach relies on the operation of a central controller, the decentralized approach allows the interaction of various units within the microgrid to facilitate a distributed decision making process" [17].

Therefore, to avoid confusion between these terms, it will be hereinafter preferred the term *centralized controller* for standalone central EMSs, *decentralized* to refer to those strategies that include various levels of decision or coordination between controllers in an hierarchical scheme (e.g., coordinated controllers that cover both the tertiary and secondary control), and the term *distributed* for those schemes in which a collaborative interaction between the individual elements is performed. This designation is similar to that found in [10]. According to this criteria, some examples of these control systems are depicted in Figure 2.6.

However, the categories in this classification are not always strictly and totally separated in practice. These methods can also be combined to adapt the functionalities of the different control levels to those existing applications that coexist in the microgrid. In this sense, "distributed, decentralized and hierarchical architectures can also be considered inside a single microgrid [96]" [97].

According to [10], "the centralized architecture is becoming outdated, the decentralized one is the most promising step before implementing a fully distributed system. In this context, the development of multi-agent systems (MASs) and their tested proprieties increase researchers' interest in applying them in microgrid context." Despite this affirmation, once revised the state of the art, it has been found that centralized architectures are still very present in microgrid research lines. While the distributed architecture will probably be extended with the gradual penetration of microgrids in the power system, the actions performed individually by each of them can still respond to their own EMS, guided by economic, environmental, and other objectives. Therefore, this affirmation about the outdating of centralized approaches will be interpreted as a recommendation on considering both approaches (centralized internal management, and the distributed coordination between the different parts of the power system) together as complementing parts, and not as a generalized sense in the area of research of microgrids. Nevertheless, it still reveals the implications that distributed methods will have in the power system of the future, especially when the number of microgrids and DERs increases (making it difficult to apply a totally centralized control strategy).

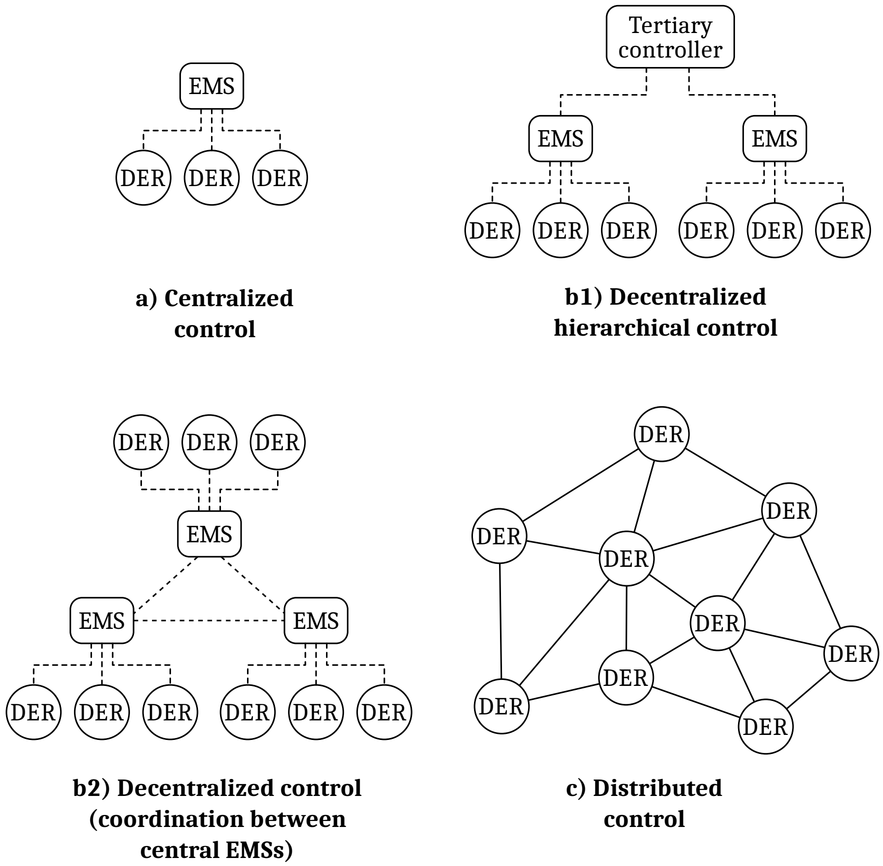


Figure 2.6: Control approaches for microgrids.

Having already established the existing architectures for EMSs, these will be analyzed in detail in the next sections reviewing some of the proposals that can be found in the existing bibliography.

2.3.3.3.1 Centralized EMSs

According to the definition given in [13], “a centralized EMS consists of a central controller with direct commands to each DER device, data acquisition of the characteristic and parameters about the microgrid's operation and information acquisition from the forecasting system in order to optimize an appropriate UC and dispatch of the resources with regard to the pre-set objectives.” In this sense, the referred paper provides a hierarchical microgrid structure consisting of three layers, which are the external layer (from which the information of human behaviour and weather conditions comes), the prediction layer and the operation layer (in which the centralized controller sends orders to the devices of the microgrid). These three layers should not be confused with the three hierarchical levels described in

Section §2.3.3.2, as they refer to a totally different ambit.

As stated in [98], the EMS obtains the schedule for the energy flows of the microgrid "by minimizing a properly defined objective function while fulfilling the given constraints to maintain a reliable, secure and safe operation of the microgrid" [98]. The objective function usually includes one or more penalty (reward) functions which are related with those DR programs agreed between the customer and the utility.

In the ambit of centralized control architectures, various trends can be found in the bibliography. To identify these main trends, according to [99] some EMS features can be used. These features are "objective functions (e.g., single-objective, multi-objective), resolution techniques (e.g., mathematical programming, computational intelligence), operating model (e.g., DC load flow, AC load flow), integration of uncertainties, optimization horizon, and modeling detail levels."

In general, many of the proposed controllers only consider the economic and availability aspects of their own supply. On the contrary, some authors also introduce frequency and voltage support (as services oriented to the external distribution grid) in the central controller of the microgrid. From the perspective of the power system level, these can be considered distributed control methods. For example, in this line, [88] introduces the HC over microgrids, which is precisely intended to provide frequency support to keep the stability of the network.

Computational intelligence is widely applied for EMS optimization. An example of this can be found in [98], where neural networks (NNs), fuzzy logic, and support vectors EMS based models are implemented. A graphical representation of the operational microgrid configurations is also proposed as a tool to perform such optimization. Other authors have applied reinforcement learning (RL) to microgrid management [100, 101].

One of the main differences between the different optimization methods for EMSs that have been observed in the bibliography is related to the uncertainties that those optimization methods require to be solved. These are closely related with the forecasting techniques, as "the application of optimization algorithms in energy scheduling must be supported by a suitable prediction system" [98]. Considering the forecasting method that is applied, the uncertainties can be divided between deterministic and stochastic (which in some cases are called probabilistic, when their probabilities are considered). The deterministic uncertainties are expressed as "point forecasts", while stochastic uncertainties are expressed by means of scenarios, uncertainty sets, or probabilistic constraints [102].

There is no unified criteria on how the optimization methods and forecasting techniques should be applied, as this depends on each specific situation. In [98], it is stated that "in smart grids and large scale microgrids, for example, the prediction accuracy can be fulfilled by exploiting aggregated historical data regarding both the local DG and the loads connected to the microgrid." According to the authors, "this allows the application of statistical methods for the optimal day ahead scheduling calculation applied in real time by means of a centralized EMS, accepting suboptimal solutions due to prediction errors" [98]. Specially, in the case of small-scale microgrids (e.g., residential use, smart homes or single buildings), "day-ahead scheduling can be risky [...] due to the higher stochastic behaviour of both the local generation and the loads" [98]. This makes sense, considering that the behaviors at a lower level of aggregation (individual customers) show a higher variability than in the case of higher levels of aggregation (as it could happens at a regional level). "To overcome this problem, mathematical programming based EMSs are usually equipped with suitable prediction systems, working with alternate optimization procedures, possibly in multistage schemes" [98]. Therefore, each situation can require a different approach for achieving an optimal management.

It can be appreciated that centralized controllers bring many possibilities for the control of devices under different criteria. However, some of their disadvantages are the dependence on the communications, and that these controllers usually require a deep knowledge about those devices that have to be controlled. For example, some authors introduce detailed models of devices to improve the performance of the centralized controller, as it is done in [103], where a cyber-physical energy sharing program to accomplish the requirements of a group of customers is proposed.

To minimize these disadvantages, other types of control were proposed. These alternatives, which are decentralized and distributed control, will be exposed in the next section.

2.3.3.3.2 Decentralized and distributed control

This section reviews the decentralized and distributed microgrid control architectures. According to [10], the decentralized architecture is "the most promising step before implementing a fully distributed system." Due to the closeness and similarities between both approaches, they will be reviewed in the same section.

The development of MASs and their tested proprieties are attracting the interest of researchers in the field of microgrids for implementing decentralized control methods [10]. Considering that a microgrid is composed by a certain number of elements and DERs, and a certain zone of the network can be composed by various DERs or microgrids, these can be modeled as a MAS. According to [13], "MAS, as a union of agents, has been applied for solving the problem which cannot be solved by a single agent, owing to its strong robustness and reliability by using proper communication, coordination and allocation within the agent group to solve the complex problems." Therefore, MAS can be used to create an effective cooperative control strategy for a distributed network. In fact, according to [13], MAS are applicable not only for distributed control schemes, but even for centralized control strategies. Under this perspective, "in a distributed energy network, the power flow information of the microgrid participants, such as loads, DGs and energy storage systems can be considered as the agent, respectively" [13].

When designing distributed control strategies, one of the most popular approaches for solving the cooperative problem is the consensus control. Its objective is "to design appropriate protocols so that all of the agents in the MAS can emerge to achieve a certain desired behaviour" [13]. Under this approach, for example, "coordination and cooperation of energy storage system is reflected in supporting frequency stability and dynamic supply-demand balance" [13]. Moreover, "an optimal schedule scheme of the battery energy storage system (BESS) allows renewable generators to operate in maximum peak power tracking model constantly based on the forecasting information of power generation and load demand" [13]. The use of microgrid controllers for frequency and grid stability support has been treated by several researchers [104, 105], some of them proposing solutions based on virtual power plants (VPPs) [106], hierarchical distributed control [107], or control schemes such as folded P-f droop [108]. In [109], a method for solving the power flow problem in droop-controlled islanded microgrids is proposed. These constitute some examples of applications under a cooperative approach.

Other approaches apply two levels of control for the management of microgrid clusters instead of a single one. In [10], a decentralized EMS based on a multiagent platform is proposed for a single microgrid and microgrid cluster. "Within a single microgrid, a dedicated multiagent EMS that performs power dispatch with the objective of minimizing power exchange with the grid is implemented. Within the microgrid cluster, another dedicated EMS is implemented to share power between different microgrids" [10]. The agent in charge of the management of the microgrid cluster is the DSO.

The importance of establishing which type of communication and coordination processes are required for a certain control strategy has already been mentioned in this thesis (see Section §2.3.3.2). In the case of a MAS, "the rule of communication among the multiple agents in the microgrid can be designed by the consensus protocol, which expresses the process of information exchange for each agent with its neighbourhoods" [13]. The specification of the information that should be shared among the agents and individual control systems in the consensus protocol must be carefully considered, as it could bring privacy issues. For example, it could not be acceptable to share individual consumption data from individual homes, despite being such information useful for an improved forecasting of load consumption. In the same way, the information on the expected generation of a resource could be owned exclusively by its owner, not having any obligation on sharing it with third parties.

In this sense, in order to overcome privacy problems "[110] presented an offline cooperative distributed energy scheduling algorithm" [13], which operates under limited information communication between the agents. Similarly, [111] (cited by [13]) presents "a dynamically updated energy management schedule" [13] that alters "the operation of storage devices and controllable loads to overcome the day-ahead forecasting error and system uncertainty" [13]. The same worry has been considered in [112], that proposed a decentralized algorithm for scheduling the energy consumption of residential nanogrids. The algorithm "preserves the privacy of clients by exchanging only the consumption, demand, and price of energy between the utility and each client." As it can be appreciated, privacy must be considered and kept when there exists an interchange of information.

Once exposed the existing types of energy management architectures for microgrids that are commonly found in the literature, it has been considered of interest to briefly overview some other systems that are related to the energy management process in microgrids (as some of them can be complementary to the EMSs). These systems will be reviewed in the next section.

2.3.3.4 Other microgrid-related systems

This section overviews some other systems that are closely involved in the control of microgrids in addition to the already exposed EMSs. In the first place, the general aspects of the smart building EMSs are exposed, which can be considered as special cases of microgrid due to their characteristics. Then, the DERMSs are covered, which are systems that control a set of DERs that can be part of a microgrid, or individual elements depending on the case.

2.3.3.4.1 Smart building EMSs

A "smart building" can be defined as a building that is more integrated in the power system, implementing the last advances in energy efficiency and controllability. Many of the principles and approaches that have been already described for energy management in microgrids are also applicable in buildings (in many cases, a building can have its own microgrid). As it is expressed in [97], "generally, microgrids are low voltage distribution networks installed in small areas (like University Campus sites or districts), but also buildings or industrial plants can themselves be seen as microgrids." The EMS that control a building (or various of them) is frequently called building management system (BMS) in the literature.

In the present document, it has been preferred to treat smart buildings in a different section due to some specific methods that are specifically oriented to building systems, not being applied to other types of microgrids. As it is stated in ***[[20]]***, taking into account "the importance and advantages of the microgrids into the power system, the next step should be selecting the method for the integration and control of a building (or an aggregation of customers) with the utility" ***[[20]]***. Therefore, the control systems (or EMSs) of smart buildings can be considered in a similar way than the previously explained microgrid EMSs.

It is said in [73] that "energy management is one of the main challenges in microgrids applied to smart buildings." The reason they are sometimes treated differently is the inclusion of some aspects such as comfort, indoor and outdoor lightning, occupation monitoring, and other applications that are very specific of edifices. In the same way, "in some cases, where a strong coupling between the operation of different energy carrier systems (heating, hot water, etc.) exists, microgrids can integrate and operate all these energy carriers in coordination" [17]. Those smart buildings that include generation resources (for example, photovoltaic (PV) panels) can be considered as prosumers in a similar way as it was previously exposed. In this sense, smart buildings can be understood as particular cases of microgrids where some additional systems are integrated and considered by their controller.

The building-related research are focused not only on the EMS, but on the analysis of the building from the point of view of energy analysis and energy efficiency. These analyses, while not being specific for microgrid applications, are still complementary to achieve their main purpose, which is precisely to facilitate the deployment of renewables while improving the reliability and stability of the whole system.

Regarding energy efficiency, which is one of the keystones for the decarbonization route, many proposals are based on the modeling of the buildings under study to find adequate improvements for each case, or even performing an energy analysis [113]. In this sense, "in [114] the authors show how the urban building energy modeling (UBEM) is a very useful tool when creating energy efficiency programs for buildings in a city" ***[[20]]***. In this sense, building simulation and consumption prediction has revealed to be of help not only to achieve a better EMS design, but also for improving building management policies [115], ***[[20]]***. Moreover, a continuous monitorization can help "to reduce the energy footprint, and also to determine the drivers that play a key role in curving down energy consumption" ***[[20]]***.

It has been previously exposed how an adequate coordination between the interests of the microgrid systems and those of the utilities is important. The same can be said in the case of smart buildings. The path to these interests can be followed applying different approaches that are included in what are called flexibility, DSM, and DR services.

One of these approaches would be the implicit DR, which merely provides information to the customers about the dynamic prices of energy, for them to adapt their consumption/generation according to the periods of more favorable prices. The second approach is the explicit (or dispatchable) DR, based on an explicit communication of the needs of the utilities for being executed thanks to the services provided by DER owners. This communication could be direct, or by means of some flexibility market (where the requested services can be scheduled).

In this way, the interests of both the customer and the power system operators can be taken into consideration for the building management. For example, [116] proposes a demand response management (DRM) program for commercial buildings that takes preemptive measures "to maintain the load demand within the contracted capacity or utility imposed demand limit (CC/DL)." This is done "by first employing dynamic EV charge scheduling when the current building load demand exceeds $x\%$ of CC/DL" [116] (i.e., when the demand exceeds a certain percentage of the CC/DL).

It can be appreciated that the importance of the communication between customers (or DER owners) and operators for the implementation of flexibility services (in which DSM and DR services can be included) is clear. There exists another kind of system that frequently serves as an intermediary for the dispatching of control orders to the DERs under their domain (with the purpose of providing flexibility services, or with some other management objective), which are the DERMSs. These systems, which are closely related with the EMSs, will be reviewed in the next section.

2.3.3.4.2 Distributed energy resources management systems

DERMSs, sometimes alternatively called "distribution energy resources management systems" [117], are optimization and control systems that take advantage of the characteristics of the DERs under their domain and manage their use to overcome the problems that could appear in networks or microgrids. In other words, these systems implement the power system applications and DER integration that was previously exposed in the present document, performing an optimal management of such resources and their functionality. The DERMS is a module that is connected to the advanced distribution management system (ADMS) in some utilities, but the DERMS module can also be part of the controller of a microgrid, as in [118].

According to the given definition, in many cases a DERMS can have some similarities with an EMS (especially when these systems are intended to control a single microgrid, instead of occupying some other higher control level), so the exact meanings of these two terms depend on the context, on what the authors intend to express, and on how the global control system is designed in each specific case.

Other systems that are closely related to DERMSs are the flexibility management systems (FMSs) [119]. The main difference between them is that the FMSs are specifically focused on choosing, managing, and/or providing flexibility services according to the established requirements. An example of FMS can be found in [119], which presents a system called Flex4Grid for achieving peak reduction from domestic users in distribution networks.

Despite their differences, in many cases both DERMS and FMS can have some similarities from the point of view of their architecture, operative aspects, and ambit of actuation, specially in those FMSs that perform an optimization based on the available flexibility resources. In this sense, many experts in the academic and industrial sectors consider DR actions (which conform a type of flexibility action) as DERs [120, 117]. The denomination of the FMSs and other similar systems depends on the author and context, and other alternative names can be found in the literature, such as demand response management system (DRMS) for those systems specifically focused on managing DR actions (and not any other type of flexibility service). In the present section, it has been preferred the term FMS to refer to a system that manages flexibility actions in general (therefore including DRMS and any other control systems that are similar in their functionality).

For example, [121] presents a flexibility-based operational planning paradigm for microgrid energy dispatch, in which the optimization process is based on decision trees. In

[122], a framework for the coordination of "energy hubs" is proposed for providing flexibility to the power system. The authors use the term "energy hub" to refer to a group of energy resources and consumptions (note here that other authors could use a different term for this, such as VPP, microgrid, or DER aggregation, depending on their characteristics and their control systems). In their proposal, the framework coordinates various of these energy hubs in an optimal way to explode their flexibility under DR programs.

These "energy hub coordination systems" could be considered FMSs according to their functions, as they intend to manage flexibility-related actions. It is important to note that the denomination of these kinds of systems in the literature is widely variable, so this fact should be taken into account when performing bibliographical database searches.

Similarly, the terms DER aggregator and DERMS could easily be confused, so their differences are clarified in [117]. DER aggregators offer services, but are usually unaware of the influence that their services can have on the system constraints and operation (like some FMSs, or like the energy hubs exposed in [122]). "On the other hand, utility DERMS is an intelligent platform for optimal management of DERs, DER aggregators, DR programs, and other available resources, with an objective to use all these resources to achieve system-wide benefits without violating any of the system constraints" [117]. For these reasons, "utility DERMSs should be understood as one hierarchy level above DER aggregators" (which are seen by the DERMSs as available resources). In this sense, a DER aggregator could use a FMS for managing the available resources to provide flexibility services inside the power system.

Regarding the functionalities that a DERMS should include, in [117] the authors stress out the importance of forecasting for the scheduling of the requirements and constraints of the network. Moreover, they expose the possibilities brought by smart inverters, as these are expected to allow the provision of services in a faster and more reliable way thanks to their connection with utility DERMS.

For these reasons, along with EMSs, DERMSs and FMSs are supposed to become a key element for the operation of the power system, as they can be used as the interfaces between the utilities (DSOs and TSOs) and the controllable elements in the system (microgrids, aggregators, and DERs).

It has been mentioned previously that flexibility services, which are closely related to control systems, microgrids, and DERs, constitute powerful tools for helping in the operation of the power system. These flexibility services will be analyzed in more detail in the next section, focusing on their main characteristics, the reasons why they are so important, and how they can be implemented.

2.3.4 Flexibility services

This section intends to define what flexibility services are, their role in the current power system evolution, and which are the possible mechanisms for their implementation from the point of view of the legislation and technical requirements.

2.3.4.1 Flexibility definition

As was previously mentioned in Section §2.3.2, the variability of renewable sources supposes an additional difficult when managing the power system. "The problem with these advances is that this type of system introduces an added difficulty in the power system management since they have a strong dependence on the meteorology [123, 124] and the mobility needs of the users [125, 8]. This uncertainty and variability, together with its increasing deployment of this kind of system, is creating problems due to the overage of the distribution line power capacity. Traditionally, the solutions to this problem consists of a reinforcement of the infrastructure (what is called a *wire solution*). However, the required investment would be too large to be assumed by the companies" ***[[21]]***, which has favored a rising interest in finding other alternative solutions to this problem (which are called *non-wires alternatives (NWAs)*) to permit a certain investment deferral when possible.

In this sense, if there exists an agreement (or consensus) between those customers that own generation resources (or that have some capacity for actively adjusting their consumption patterns), it would make it possible to mitigate the unexpected unbalances between the power generation and consumption levels. In other words, these customers (prosumers) could provide flexibility services to the DSO (or the TSO) integrating their resources at the network level following some common agreement. "Thus, they can help solve congestion problems as a non-wire solution, reducing their peak consumption, and avoiding oversizing in the distribution grid. Furthermore, they bring the possibility of investment deferral, as they can reduce the overcharge in the most congested power sectors" ***[[21]]***. These DSM and DR tools are usually included in the "flexibility services", which corresponds with those services that can be used by the operators of the system (TSOs and DSOs) for modifying the generation or consumption in some parts of the network when required.

"This philosophy is being more and more extended, as can be observed in the new changes in the EU power system regulations [19], where the use of distributed resources is being included under the concept *flexibility*. This concept means the ability to respond in a flexible manner to the changes and needs of the power system, using a set of available resources (generation or power reduction)" ***[[21]]***.

In practice, this is implemented under the name "flexibility program", i.e., "agreements between the operator and the prosumers (or even third parties as aggregators, when it is desirable or required by the regulations [19])" ***[[21]]***. Under these programs, the "prosumers receive incentives (which are processed separately from their contracted electricity tariff) when they successfully respond to the received request" ***[[21]]***, for example, reducing their consumption peaks during a certain period.

This integration between prosumers and system operators could be done by the TSO, by the DSO, or it could be done in a coordinated way [126, 127]. Moreover, it can be done with or without the intervention of aggregators.

The concept of flexibility includes ancillary services, congestion management, and of course DSM and DR actions, aiming the integration of customers for the provision of services. Precisely, one of the major benefits of the implementation of these DSM and DR services "is that customer-side resources can transact with the electric grid [128]" ***[[21]]***. A complete and extensive review about the flexibility of energy systems can be found in [129], including the definitions of flexibility and DSM, and their relation with ancillary services and with the markets. In [130] the benefits and challenges of DR are discussed. It poses an analysis about some modeling assumptions that are used by different authors when modeling DR actions. This paper studies the effects of the different analyzed proposals and identifies their lacks and shortcomings. Moreover, [131] shows the potential of diverse types of industrial customers for offering ancillary services by means of DR programs. It compares various classifications of ancillary services and DR programs that can be found in the literature and their characteristics.

The mentioned regulation establishes that "all customer groups (industrial, commercial, and households) should have access to the electricity markets to trade their flexibility and self-generated electricity" [19], "making it possible for aggregators to play a role as intermediaries between these customers and the market" ***[[21]]***. However, "how these flexibility programs and incentives are handled is still under discussion. As an example, [132] proposes that the registry and payment of such services could be done in a local market place at the DSO level using technologies such as Blockchain to manage the incentives" ***[[21]]***.

The European Directive [19] includes specific information about the implementation of DR. According to this document, "demand response" can be defined as "the change of electricity load by final customers from their normal or current consumption patterns in response to market signals, including in response to time-variable electricity prices or incentive payments, or in response to the acceptance of the final customer's bid to sell demand reduction or increase at a price in an organized market, whether alone or through aggregation" [19].

It has been previously mentioned the strong relationship between the penetration of renewable energy sources (RESs) and the increasing requirements of flexibility capacity in the power system. The main aspects regarding renewable generation impact will be exposed in the next section to understand its consequences.

2.3.4.2 Renewable generation impact and flexibility needs

Once justified the necessity of flexibility and DR from a technical (and legal, in the case of the EU countries) point of view, the next step will be the evaluation of their impact and the requirements for their viability. Specifically, these two points are essential to keep the deployment rate of renewable plants, as well as the growing implication of customers in energy markets (which can be done directly or through aggregators).

The deployment of renewable power plants is a priority for many countries. Due to this, many studies and reports have been done to analyze their impact on the power systems' capacity. This can be observed not only in Europe, but also in Asia and America.

Specifically, in [133] the authors make a study about the level of preparation of the Southwest Asian countries for the integration of renewable energy resources. Diverse types of data sources have been analyzed, such as the type of infrastructure, potential to incorporate renewable energy easily, investment, and the average daily load profile. The evaluation of flexibility is done through six indicators namely "grid reliability, electricity market access, load profile, ramp capacity, quality of forecasting tools, proportion of electricity generation from natural gas, and renewable energy diversity" [133]. The obtained results are used to classify the preparation level of each of the countries of this zone and analyze why they suffer this lack. According to the authors, most of the countries (except for Philippines) lack forecasting practices for wind and solar generation. In this sense, the importance of forecasting is pointed out.

The case of solar and wind generation in Philippines is extensively explained in [134]. This report points out the abundance of renewable resources in this zone, and which the impact of their massive penetration in the power system could be.

In North America, in the same way, the importance of solar forecasting is studied in [135] from the perspective of the Independent System Operator of New England (ISO-NE). This paper "investigates the value of solar power forecasting improvements, both in terms of variable electricity generation costs and its impact on bulk power system operations." These results show that forecasting is needed to allow a better use of renewable resources and its importance to reduce the use of fossil fuels. Additionally, as it is explained in its state-of-art, some of the techniques used in the ambit of solar forecasting are numerical weather prediction (NWP) models, statistical models, hybrid combinations of both, and ML [135].

For all these reasons, the need of using forecasting techniques is clear when talking about renewable generation, as this ability makes possible the correct use of energy and avoids unnecessary losses (for example, adapting the consumption) to keep the stability of the grid. The problem of managing the power system with a high presence of renewables is frequently treated in the literature by researchers. For example, the paper [136] raises a study of the flexibility needs, and the variables involved in power system operation. The main variables are the ramping limit, power capacity, and energy capacity. In [137], a planning model for power plant generation is proposed. It considers the generation units available, their constraints, and their demand to choose the optimal generator set for each moment. The renewable generation and their variability are also included in the model.

Having exposed the reasons why flexibility is required in the management and operation of the power system, the next section will be focused on the implementation of flexibility services.

2.3.4.3 Flexibility services implementation

This section is focused on the implementation of flexibility, DR and DSM services, which has previously been mentioned, but not fully developed. This implementation can include the organization of these services, and the systems for communication and control between the provider of flexibility services (resources/microgrid owner) and the agents that send the request (as, for example, the TSO, DSO or an aggregator) of a certain action. It has to be pointed out that this role would not be exclusive for TSOs, DSOs, and aggregators, but it could also be for other agents that participate in the power system and could require a flexibility service from the owner of DER resources. In this regard, the previous section exposed two types of systems that are involved in this process (DERMSs and FMSs), and which are their roles and relationships with the existing agents.

The provision of flexibility services is expected to be largely advantageous for all implied parts (the service provider and the utilities), being all of them favored by these agreements. For accomplishing the economic profitability of these interchanges, many authors have studied the effects of their inclusion in the power system. The importance of flexibility in power markets based on how it affects on the prices depending on the moment and the auction is established in [138] applying stochastic techniques (brownian movement). Some researchers have calculated which are the costs of electrical flexibility for DERs, as it is done in [139] specifically for the Netherlands. This kind of studies are of great help to achieve advances in DER integration, considering that the economic aspects are key to favor the investment in these resources.

"It is necessary to be prepared for these emergent paradigms, where the users and the rest of the power system need to be perfectly balanced, this being an advantage for both parts not only in Europe, but also in the rest of the world [140]" *[**[21]**]*. In this sense, some organizations and researchers are making efforts to define how flexibility can be handled and managed. As an example, the Universal Smart Energy Framework (USEF) Foundation has developed a framework that reflects their "vision and approach to the flexibility market design, with a description of the structure, market roles, tools and rules included" [141].

The inclusion of flexibility services in the power system could be done under various schemes, existing multiple proposals in this respect. Each of them has their own advantages and disadvantages from a technical point of view, but their selection for being applied in a specific country are also related with the existing power system legislation of that country, as it can be the case of the EU member countries.

Some authors state that these services should be included in the already existing markets, for example, [142] proposes a strategy for DER aggregators to participate in the day-ahead market (instead of participating in a local separate flexibility market) in an optimal way.

Other alternative approaches consider that new flexibility markets should be created for these services (in which TSOs, DSOs, prosumers, and aggregators could participate [143]). For example, in [144] a market of electric capacity for the use of VPPs as capacity market unit (CMU) is described. The article [145] proposes a framework for DR in smart buildings which considers thermal and electrical power. The type of market proposed contains three levels of the power system (ISO, DSOs, and aggregators), applying an optimization process in each of the levels. Similarly, [146] proposes a framework for congestion management applications using DR actions under a market-based mechanism in collaboration with retail electricity providers.

Another possibility is not to introduce these kinds of services through market mechanisms, but permitting their use by means of bilateral agreement between the utility and the customer (or aggregator), as it is mentioned in *[[21]]*. "There are, in fact, some examples of North American distribution companies that have already included DSM collaboration for their customers. This is the case of the companies San Diego Gas & Electric (SD-G&E) [147] or Pacific Gas & Electric (PG&E) [148], whose DR programs are focused on what is called a *Capacity Bidding Program (CBP)*, where a customer commits, under contract, to reduce their power a certain quantity when required. The maximum number of requests is also established in the agreement" *[[21]]*.

It has been observed in the literature that, among these options, the market mechanisms are receiving more attention by legislators and researchers than the bilateral contracts. Therefore, some of the existing market-based flexibility proposals will be exposed next in more detail.

2.3.4.3.1 Market-based mechanisms

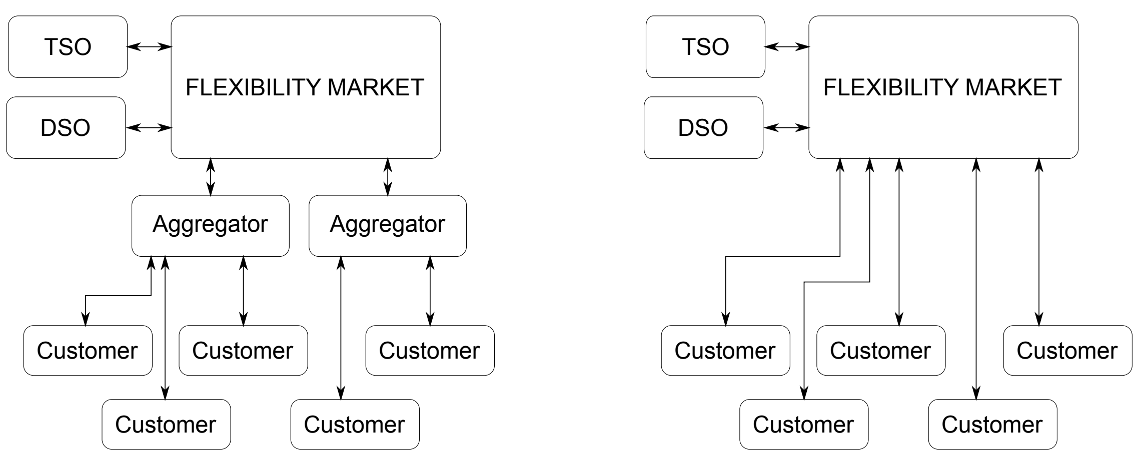
The management and interchange of flexibility services could be directly done between the system operators and the providers of these services, but it could result in an unbalanced and unfair access to the active inclusion of resources, as the operators would be entirely in charge of choosing or not the services offered by each provider. To guarantee a fair and equal participation of flexibility service providers (FSPs) under clear and open criteria, it can be currently observed a rising preference for the inclusion of such services in flexibility markets.

This idea goes in line with the active participation of the prosumers in the power system. As it was previously mentioned in this document, "driven by current regulations [40], there is expected to be a rising tendency toward the close participation of consumers in electricity and flexibility markets through tools such as DR services [66]. These markets could include aggregator participation to simplify the management of resources [149]" *[[22]]*. In the case of Europe, as it is stated in the Directive 2019/944 (June 2019) [19], there is a particular preference for the use of markets for providing flexibility. In this way, the customers could freely participate by offering their capacity and resources.

In this regard, it could be difficult to obtain significant flexibility services from a single small residential customer. Notwithstanding, these customers can still participate in the flexibility market thanks to the inclusion of third parties that are called “aggregators”. An aggregator makes an agreement with a group of customers and acts as an intermediary (communicating with the flexibility markets and/or with the implied actors) to achieve a valuable peak shaving, load shifting or capacity bidding thanks to the sum of customer resources. In these cases, it is not essential that the customer have a highly automated control system, but it could be enough if the customers change their consumption manually, attempting to reduce the load during some agreed hours (if the aggregator is asking for that to provide services of reduction to the DSO). In parallel, those medium-size or big-size customers that want to directly participate in the flexibility market can do it without the intermediary of an aggregator.

The role of the aggregator and their relationship with the customers are explicitly included in the European Directive 2019/944 [19]. The point (39) of the Directive states that: “Customers should be allowed to make full use of the advantages of aggregation of production and supply over larger regions and benefit from cross-border competition. Market participants engaged in aggregation are likely to play an important role as intermediaries between customer groups and the market” [19].

Following these principles, some basic participation structures in flexibility markets can be proposed for the customers. Figure 2.7a corresponds to the participation through aggregator and Figure 2.7b shows a direct participation.



(a) (b)

Figure 2.7: Participation in flexibility markets. a) Market participation through aggregator; b) Direct market participation.

The EU member countries are still deciding which is the best design and structure for the flexibility markets while following the established Directives and Regulations. Specifically, these aspects have been deeply studied, based on the most convenient, cheap, or technological viable solutions. In this sense, observing the experience of existing energy markets, some of them (as, for example, the Nord Pool [150]) implement access for the participants to the market platform by means of application programming interfaces (APIs). APIs can be commonly found in many industrial applications [151].

According to [152], "in all liberalized electricity markets, peak generation units face problems of economic viability." In this sense, many countries have taken action. "To face this problem called *the missing money issue in energy-only markets* [153, 154], several countries started integrating DR in their local markets, as well as some other capacity payment mechanisms, to secure the electric power system at peak times and improve its reliability." The authors point out that smart grid technologies have an important role in this ambit, as they make it possible "to apply several strategies to optimize DR in energy markets" [152].

Therefore, once exposed the requirements that involve renewable generation (which conforms the majority of the potential flexibility and DR elements) and their impact, the question of the structure of the market is still opened. In this line, many researchers have analyzed potential architectures for new flexibility markets, or for the integration of flexibility services in existing markets.

A market-based approach to introduce and integrate DR aggregators (industrial and residential) in the power system is suggested in [155], allowing their active participation in the electricity markets by means of biddings. This paper proposes a solution based on a MAS instead of a total centralization, and it is made up by three layers. In this structure, the markets, DR provider, aggregators, and customers are included, and the coordinated interactions between them are specified.

A market model where energy and reserves are dispatched is proposes in [156]. These reserves include demand-side reserves, so generators and consumers can participate submitting offers and bids. The products that compose this proposed market are energy, up spinning reserve, down spinning reserve, and two kinds of standby reserve. The market, which is managed by a market operator, has as an objective to achieve the minimization of the costs for the total energy and reserves, while maximizing the benefits obtained by the loads. This combined objective function, so-called social welfare, is calculated as benefits minus cost.

Other proposals are focused on specific types of facilities, analyzing how they fit into the flexibility services thanks to their characteristics. For example, [152] presents how the DR can be applied to the drinking water industry in France, employing optimization functions to maximize economic benefits. It explains how the DR programs are integrated in the spot markets of the French power system.

Not only Europe is interested in the flexibility market, but also in America they are deciding which is the best way for their architecture. For example, the paper [157] is focused on the ancillary services and market of the United States. It analyzes the capabilities of DR resources to provide ancillary services and which are the existing barriers for their implementation. In this sense, the proposed analyses “can be used to assess the economic value of the realizable potential of DR for ancillary services” [157]. Additionally, it distinguishes between DR for emergency loads and peak load management and its use for ancillary services.

Of course, the participation of a specific resource in the market requires a previous study of which products or services can be provided by such resources. In this sense, [158] describe the characteristics of flexibility units in the power system and their main parameters of interest, being they specially focused on big generation units.

Having reviewed some of the existing proposals for the inclusion of flexibility services by means of market-based mechanisms, it is still necessary to analyze how the required systems for controlling, communicating, dispatching, and auditing the flexibility actions. In this regard, the main aspects of flexibility services implementation from a technical point of view (which is closely related to microgrids, DERs, and DERMSs) are reviewed below.

2.3.4.3.2 Technical requirements

Regarding the process of performing a DR action, as it is analyzed in ***[[21]]***, “the participation of a customer in DR implies two steps: event dispatching, and the audit of the actuation during such an event. This means that the distribution company must check if the customer accomplished the requirements of consumption during the established time” ***[[21]]***. For doing so, “the conditions of the audit should be based on the expected or estimated consumption of the customer during the period of the event, which will be compared to the actual one to check if the power was effectively reduced or not. In the case of buildings, this estimation can be done using multiple techniques, based on statistical, or even artificial, intelligent methods [159, 160]” ***[[21]]***. The techniques than can be applied for forecasting will be analyzed with more detail in Section §3.4 and Section §3.5.

In addition to the different referred alternatives for the organization of these services, there are another aspects that are required for these services to be possible, which are the control and communication devices for the resources and controllable loads, and the systems for the scheduling and dispatching of flexibility actions (or other potential actions that could be applied) in an optimal way.

On the one hand, regarding communication and control systems, “in recent years, some technologies and protocols have emerged to solve these connections. Not only for DR, but also for managing the global smart grid environment, where DR is usually included” ***[[21]]***. On the other hand, some of the systems in charge of coordinating and managing different resources in an optimal way are EMSs, DERMSs and FMSs, as it was previously seen in the present document.

In this sense, “the implication of the prosumer for their participation in DSM and DR programs requires that their facilities become sensorized and connected. Fortunately, after some years, the sensorization of buildings and homes has become relatively easy. Lots of technology and protocols like Wi-Fi smart devices, Z-Wave, ZigBee, Modbus, and advances in computation [161] have facilitated the automation and monitoring at a wide range of levels [162]" ***[[21]]***. Moreover, these technologies are of help not only in the context of DR and DSM, but they can also "stimulate the extended use of DG, like home solar panels and batteries" ***[[21]]***.

The technical aspects for establishing and automating the communication between the DSO (or even TSO) and the user for flexibility services dispatching are currently under development and research, mainly since this user-DSO (or TSO) integration are not still fully extended ***[[21]]***. "This final connection between buildings and the distribution network is sometimes referred as *the last mile* of connection, as can be seen in [163]" ***[[21]]***.

When deploying DR and DSM systems, in addition to information and communication technologies (ICTs) [164], "standard communication protocols such as Open Automated Demand Response (OpenADR) are essential to allow interoperability, as it is stated in [165, 166]" ***[[21]]***. OpenADR is a protocol to allow remote automatic DR procedures, so it can be used "for running DSM and DR programs [167] in a variety of possible architectures" ***[[21]]***.

Another of the advantages of OpenADR is that "it includes functions for dynamic pricing, which are used for example in [168] as part of a more complex smart grid managing system" ***[[21]]***. Some examples of its use can be seen in [169, 170].

For the implementation of the audit in DR events, as it is said in ***[[21]]***, the existing smart meters that have been deployed in many countries (e.g., in EU member countries) for establishing the customer power bill can also be used for this purpose. "As [164] states, although automated demand response (ADR) can be conducted without them, smart meters can enhance the implementation of a DR program, as they enable a more elaborated means of compensating for DR participation by establishing baselines and comparing demand-side performance against those baselines. An example of the use of OpenADR and smart metering can be seen in [171]" ***[[21]]***.

In the case of various European countries, this approach can have some disadvantages which should be improved in the future. The reason is that, "currently, smart meter architectures are traditionally operating with aggregated measurements of one hour. Therefore, if DSOs want to use this system for auditing compliance with flexibility agreements, the offers and actions must match these time intervals. This limitation would be reduced if this granularity became a quarter of an hour, a possible period for this type of network, and more in line with flexibility services" ***[[21]]***. Therefore, if these smart meters were enhanced in the future to support a higher number of power measurements per hour, it could increase their adequacy to be used for auditing DR actions.

During the review of the advances included in the smart grid paradigm, it has been frequently mentioned that the use of AI can enhance the management of the power system.

Some of their possible applications will be analyzed in the next section.

2.3.5 Role of artificial intelligence in the smart grid

AI has been found to be of application in multiple fields of smart grid, such as network operation, planning actions, analysis of large amounts of data, or market-related decision support. Among the possible uses of AI, the capacity of forecasting is one of the main important ones, and it is useful in many of the smart grid fields.

Thus, it is worth to remark the importance of intelligent techniques for setting up flexibility unit availability and, in general, for helping to the market participants and to power system operators. In this regard, price forecast is such a typical application. Moreover, during the previous sections, the importance of flexibility and controllability in the multiple levels of the power system has been shown. These capacities are directly related to the capability of predicting some variables (uncertainties), such as power generation and load consumption [23].

In electric energy markets, the matching between generation and consumption requires a certain planning by the involved agents to accomplish the UC. The involved agents (generators, ISO, TSO, DSOs, aggregators, FSPs, and clients) participate in these markets according to the expected energy generation/consumption, the prices being very dependent on these estimations. Unexpected events such as abnormal consumption behaviors, extreme weather conditions, natural disasters, or severe blackouts could cause variations in prices resulting in great economic losses, or even damage to customers due to extended blackouts or supply curtailments. As it is states in [172], "1% increase in error can result in wastage of millions of dollars. Therefore, improving the forecasting accuracy can significantly reduce the power system operational cost." In the same line, according to [173], "a load forecast error of 1% in terms of mean absolute percentage error (MAPE) can translate into several hundred thousand dollars per gigawatt peak for a utility's financial bottom line."

Regarding the generation capacity of a certain power plant, their outcomes depend on the capacity of power generation (and its capacity to change this power in case it is required). This dependency scales when talking of renewable plants such as those based on wind or solar energy, where the weather forecast is the only way to make an estimation of their maximum production. An energy producer should therefore have a reliable forecasting system to maximize their participation in energy markets, as an erroneous estimation could reach to economical losses.

As an example, [174] applies diverse forecasting techniques to predict electric energy prices. The techniques used are time series analysis (including autoregressive integrated moving average (ARIMA), dynamic regression, and transfer function), NNs, and wavelets. Additionally, it also includes a brief overview of forecasting procedures and a literature review about this field.

Therefore, the importance of the forecast in market and generation levels is clear. It could be considered as a keystone in the power system management (taking into consideration their volume of power).

Furthermore, the role of forecasting should not be ignored even in lower hierarchical levels. One of the main pillars of the smart grid, the microgrid, can achieve great efficiency improvement, adaptability, and control capacity by optimizing their operation. Moreover, these microgrids have the capability of working in islanding mode (disconnected from the main grid) during a certain time, which reinforces the resilience of the power supply in the zone in question. These optimizations and operation modes, as it will be analyzed later, require forecasted information such as the expected consumption or generation during the period under scope (typically, some hours or one day).

Based on the described context, "it can be identified that good forecasting of power generation and consumption is essential at various network levels. For example, TSOs and DSOs use forecasting to perform power system operation tasks [136, 137]. Even the mentioned EMSs in customer installations usually require the forecasting of some power consumption or generation metrics to optimize the use of resources under different criteria. These can be related to energy efficiency in buildings *[[**20**]]* and microgrids [175], environmental and economic improvements [176], or even the control of active and reactive power [74]" *[[**22**]]*.

As conclusion, the current research on microgrid management includes not only the management optimization methods and control systems, but also the requirements on forecasting applications that are needed for those methods are essential to be applicable in real environments. This forecasting considers the existing constraints, information availability, and margins of error. Considering its importance, the topic of optimization and forecasting applied to microgrids will be deeply analyzed in Chapter §3.

Having exposed some of the elements that are part of the smart grid paradigm, it can be seen how they are closely interrelated, as each of them complements the others for globally improving the power system observability, controlability, security, and resilience (among other aspects). The next section will expose some of the actions that have been taken by the side of legislators and utilities regarding the inclusion of smart grid-related advances into the power system. These actions show how these aspects are considered of extreme importance for the future of the power system.

2.4 Remarks on legislation and utilities perspective

This section analyzes some of the efforts that are being made by the side of legislative agents and utilities to achieve the inclusion of smart grid principles over the power system. It does not intend to be a detailed report in this respect, but simply tries to depict the great interest that these advances are awakening.

Some of the legislative aspects that are referred in this section were previously mentioned in the present chapter, but in here these are considered together with the point of view of the utilities. This perspective is highly valuable to understand the importance of smart grid to improve the power system.

Due to their closeness to the research work of this thesis, the two regions that will be mentioned are exclusively Europe and Chile. Despite the other regions of the world have not been included here, they have appeared in the previous sections of this chapter when some reports and research papers were referenced. Thus, while this analysis could have been extended, it has been preferred to restrict its scope to these two regions.

Chile, as it was previously exposed, is immersed in "a radical change in the power environment, and this points to a great increasing complexity of electric power systems and the growing penetration of the smart grid concept by electric utilities like ENEL in Chile" *[[**20**]]*. In this evolution, the AMI and the microgrids have particularly attracted their attention. Specifically, microgrids are under consideration for favoring the integration of local generation, which is expected to bring important benefits according to many studies as for example [177]. Other actions performed in Chile with the efforts of both the government and the utilities can be found in *[[**20**]]*.

It is also worth mentioning the European case, as the EU has worked on the development of common guidelines for the integration of the power systems of different member countries. In this way, many concepts that are part of the smart grid paradigm have been included as common rules for the power system.

In the European ambit, according to the definition of Eurelectric report on Flexibility and Aggregation of the year 2014 [178], flexibility can be defined as "the modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system" [178]. Regarding the characterization of flexibility actions, "the parameters that are used to characterize flexibility in electricity include the amount of power modulation, the duration, the rate of change, the response time, the location, etc." [178].

Regarding the use that can be given to flexibility, this document also established that there are three possible market uses for flexibility, which are portfolio optimization, balancing, and constraints management [178]. Alternatively, many authors refer to the last as congestion management (instead of constraints management).

In the year 2015, the Expert Group 3 (EG3) of the European Commission published a document of recommendations for the integration of flexibility provided by customers (DR), where the role of consumers is pointed out, and an extra document to refine those recommendations [179, 180]. The authors claim that "consumers have an essential role to play in achieving the flexibility necessary to adapt the electricity system to variable and distributed renewable electricity generation. Technological progress in grid management and the generation of renewable electricity has unlocked many opportunities for consumers" [179].

The market-based mechanisms are signaled as the most convenient solution for the integration of these new flexibility services. It is said that "healthy competition in retail markets is essential to ensuring the market-driven deployment of innovative new services that address consumers' changing needs and abilities, while increasing system flexibility" [179]. However, this open participation of consumers in the markets brings some technical difficulties that must be solved. As the authors indicate, "the lack of real-time or near real-time information provided to consumers about their energy consumption has prevented them from being active participants in the energy market and the energy transition" [179].

Moreover, due to the need of better common methods to coordinate the use of this flexibility capacity, during the last years, consumers were not usually able to participate in those functions, excepting some special consumers (such as big industries, in the case of Spain).

In this regard, the organizations of TSOs and DSOs have expressed their worries regarding more specific regulations in this field, to share common rules that allow more common use of flexibility by all countries. One of these organizations was the Smart Energy Demand Coalition (SEDC). In the report [181], the authors stated that Europe would need to clarify the role of independent DR providers to motivate real, measurable change through market competition. A standardized process is described for allowing this competition around demand-side flexibility. According to the authors, it would allow aggregators to offer services to consumers independently from balance responsible parties (BRPs) and suppliers. The terms implicit and explicit demand side flexibility were used in the proposed process, being their basic characteristics described by the SEDC in [182].

Regarding the state of the European markets in relation to DR, the report [183] analyses every European country regarding their power system structure, functioning, and necessary changes for the inclusion of DR. As an example, in the case of Spain, this report exposes the interruptibility service (*"interrumpibilidad"*, in Spanish), a DR program that involves some big industrial customers. They have the capability of receiving DR orders for reducing their consumption when it is required, but this function has not been used in many years [183].

Beyond the efforts made by legislative entities, it cannot be forgotten the role played by the involved utilities in the collaborative discussion of power system improvements and their implementation, such as the TSOs and DSOs.

The point of view of the DSOs is reflected in the report [184], where the new EU Directives are summarized. The authors encourage policymakers and regulators to integrate new roles for DSOs in enabling flexibility in all future legislation. In their opinion, "DSOs will need to increasingly perform a more active role in developing, managing, and operating their networks." In this document, they make emphasis on the importance of TSOs and DSOs to collaborate on these discussions, which was put into practice some time after with the publication of new reports where both types of operators worked together.

One of the outcomes of this collaboration was the TSO-DSO report [185], where the authors highlight the need for TSO-DSO cooperation "to ensure efficient interaction with market parties." This document also defines the concept active system management (ASM) for putting together the previously described tools for the management of the power system. In this sense, "ASM is a key set of strategies and tools performed and used by DSOs and TSOs for the cost-efficient and secure management of electricity systems. It involves the use and enhancement of smart and digital grids, operational planning and forecasting processes, and the capacity to modulate, in different timeframes and distinct areas, generation and demand encompassing flexibility instruments (toolbox) to tackle challenges impacting system operation." It can be here appreciated the importance of digitalization, operation planning and forecasting for the implementation of these tools. According to this document, it can be said that ASM is useful for "ensuring the proper integration of RESs and a high share of DERs," and for their integration with energy markets.

With the rise of renewables, it is possible for more people to participate (not being restricted only to big customers), and new technological advances in smart grids and power system control allow to be "less restrictive" in the field of DG. In this sense, the Directive [19] states that "member States shall allow final customers, including those offering DR through aggregation, to participate alongside producers in a non-discriminatory manner in all electricity markets." Therefore, DR, flexibility and ancillary services interchange should be based on market mechanisms, being possible for customers to participate in them if they want. Participation through an aggregator is also permitted. It can be said that this legislative action has intended to accomplish with the ideas and recommendations expressed by the operators and the rest of the involved agents of the power system, as it was previously exposed.

Finally, some projects that have explored the mechanisms for the coordination and deployment of flexibility services will be briefly described. Some examples are CoordiNET, SmartNet, EASY-RES, and GridFlexibility&Resilience.

The objective of the CoordiNET Project was effectively establishing new pathways between flexibility providers such as DERs (both aggregated into VPPs and autonomously) and flexibility users, i.e., TSO and DSO [186]. Among their participants, the TSO Red Eléctrica de España and the DSO ENEL can be found.

The SmartNet Project, as it can be seen in [187], "proposes and evaluates five different coordination schemes between system operators using three benchmark scenarios from Denmark, Italy, and Spain." Additionally, other laboratory tests focused on "controller validation, analysis of communication impacts, and how well price-based controls can integrate with the SmartNet coordination schemes" [187] were made. Some of their participants are Endesa, *Ricerca sul Sistema Energetico (RSE S.p.A.)* and SIEMENS.

The EASY-RES Project has the objective of developing control algorithms and innovative ancillary services, which will allow the penetration of RESs in the European energy system. In [188], two methods for the "provision of primary frequency response as ancillary service from active distribution networks to the transmission system" are proposed. In this project some participants are the Greek TSO Admie, the Lancaster University, and FENECON.

The GridFlexibility&Resilience Project is focused on the provision of capacity bidding services by customers and aggregators to the DSO. As it can be seen in [132], the objective is to test OpenADR protocol for sending signals "from a basic DRMS to an infrastructure controlled by an aggregator" [132]. This project was promoted by ENEL with other participants such as the Universidad de Sevilla, the Università di Genova, MAPS Group, and mPrest.

Some other projects that have emerged in Europe focused on flexibility markets are Piclo Flex, Enera, GOPACS, and NODES [189].

The implication that legislative agents and electricity companies have in the advances and changes that are taking place is clear, with both parts making efforts to reach the desired network modernization and implementing new improved coordination mechanisms in the power system.

Having finished the review of some of the main characteristics of the power system, its operation, and the main advances that are taking place thanks to the smart grid paradigm, the next section will summarize the reviewed contents and extract some conclusions.

2.5 Summary and conclusions

The unbundling of the transmission and distribution tasks from those of generation and supply are one of the most common approaches for structuring the power system actors, and achieving a competitive market-based environment that encourages efficiency improvement and favors private investment.

Among the diverse world zones that have been reviewed in this chapter, a special emphasis has been done in the case of the EU countries. In this regard, several Directives and Regulations were reviewed, showing the efforts that were made to achieve a high level of coordination between the different countries while integrating new advances (e.g., renewable generation) and market-based mechanisms for energy interchange.

Despite the evident differences between the power systems of different countries and their particular circumstances, some aspects of the advances that are being integrated follow common lines of development. The main paradigm which includes the technological improvements of the power system is called "smart grid", including a wide variety of fields such as AMI, microgrids, and flexibility services. The agents that are implied in the regulation, operation, and participation of the power systems of the world are currently showing a high interest in it. The same increasing interest can be appreciated in both industry and academia.

Among the described smart grid proposals, microgrids have been identified as tools of special interest due to their versatility. The grouping of loads and energy sources as microgrids brings the possibility of a better monitorization and control of the available resources, which paves the way to other more complex smart grid applications (optimization of resource management, provision of flexibility services, reduction of blackouts, etc.). As it was stated, for implementing such applications, not only the internal information of the microgrid and its control system should be considered, but also other control systems and agents according to the existing hierarchical control levels. The power system environment involves various kinds of interactions and information exchange, so these should be considered in each of the control levels for achieving the optimization according to the sought objectives.

For these reasons, the present doctoral thesis is focused on the study of microgrid management optimization methods, their requisites, and how they could be improved to accelerate their implementation and integration into the power system. As it will be later appreciated, there is a key tool that is required for the successful deployment of microgrid-related applications, which is the capability of forecasting of power generation and consumption. The reason of its importance is that their prediction is used by the optimization systems and for the services that can be provided even to external agents. All these applications require to perform a good quality forecast of what it is expected to occur (e.g., generation and consumption power) in the microgrid domain in the next minutes, hours, or days.

Considering the previously exposed facts, the next chapter contains a review of the state of the art of microgrid optimization and forecasting methods.

Chapter 3

State of the art on microgrid-applied optimization and forecasting

This chapter reviews the state of the art of methods for the management and operation of microgrids. Specifically, two closely-related areas are covered, which are the energy management optimization methods and the forecasting techniques that can be used to predict the uncertainties, such as power generation and consumption.

The importance of microgrids in the power system was already exposed in the previous chapter. They are helpful for achieving a successful penetration of renewable DG and for providing new functions that improve the control capacity over the power system. To do so, these microgrids require the implementation of EMSs for operating their resources, among other systems such as communication devices (for their coordination with other external agents) if necessary. The management of microgrids (and networks) and the use of flexibility services usually implies an optimization process in order to extract the maximum potential from the available resources. This idea was previously exposed in Chapter §2.

Performing this optimization process usually requires some information about unknown variables, which are usually called the "uncertainties" or "uncertain parameters" [190] of the optimization problem, existing several ways of modelling them. Some uncertainties could be, for example, the expected power generation and consumption of the elements inside the microgrid. It will be appreciated how this optimization frequently relies on forecasting systems, as these are required to obtain estimations of those future values that are unknown. Therefore, it will be convenient to review the types of models that can be used to represent such uncertainties in order to introduce them in the optimization problems applied to microgrids.

Considering the importance and variety of approaches that can be followed in microgrid energy management for performing optimization and forecasting tasks, the present chapter reviews the techniques that can be applied in these fields.

This chapter is structured as follows. The ways of modelling uncertainties in optimization problems are reviewed in Section §3.1. According to these uncertainty models, different approaches can be followed to model the optimization problem including such uncertainties, which correspond to the optimization methods are exposed in Section §3.2. These methods determine how a problem with its different stages can be written and structured to represent the behavior of the system to be optimized. Once a certain optimization problem has been written with its cost functions and restrictions, various methods can be applied for solving it. In this sense, the existing optimization solving methods are reviewed in Section §3.3. Then, in Section §3.4, a literature review focused on the existing forecasting techniques applied to microgrids (and to the power system in general) will be performed. After that, some other aspects on how the forecasting procedures are implemented in microgrids are treated in Section §3.5. Finally, some conclusions extracted from the review will close this chapter in Section §3.6. These conclusions have guided the proposals that will be described in the next chapter.

3.1 Modelling of uncertainty in optimization problems

The present section will review the existing methods for modelling uncertainties, and how these can be introduced in optimization problems applied to microgrids. First, the preliminary concepts on optimization and types of uncertainty models (i.e., the ways of expressing the information of such uncertain variables) are reviewed in the present Section §3.1. Then, a study of the existing optimization methods (i.e., the form of expressing the problem and its stages in accordance to the uncertainties that will be included in such problem) will be done from Section §3.2 in advance.

It is stated in [191] that "problems requiring a sequence of decisions in reaction to uncertainty realizations are of crucial relevance in real-world applications, e.g., supply chain planning, scheduling, or finance." Moreover, the authors indicate that "insufficient attention has been paid to methods focusing on problems with multi-stage decision structures" [191]. The process of optimization of energy management in microgrids (by their EMSs) fits in this category of problems.

In the literature, it can be appreciated that many authors apply optimization techniques not only for the operation of microgrids, but also in the process of designing the microgrid itself. As an example, it is possible to decide the optimum number of PV panels that should be installed, the size of batteries, and other design parameters according to the expected requirements of generation and consumption for the network under study, or even consider the best design for the integration of electric mobility services in the microgrid area, as it is done in [71]. Some authors even consider both aspects (design and operation) under the same study, as it is done in [192], where this approach is called a bi-level planning for autonomous microgrids.

Tackling the review of these optimization methods is not a straightforward task because, “although these methods all intend to solve a similar underlying problem, they differ strongly with respect to the uncertainty representation, the prescriptive solution information they provide and the means of performance evaluation” [191]. The same authors point out another problem that can be found when reviewing the literature on optimization methods. According to their opinion, some reviews and case studies “fails to interconnect results from different disciplines or even comparing strengths and weaknesses of individual methods in particular applications” and “the choice of a concept is often based on personal preference or habit rather than suitability” [191]. As a consequence of these biases, in their opinion, these reviews constitutes “a fragmented picture of uncertain multi-stage problems both from a methodological and an application-oriented perspective” [191]. In the present thesis, while it is not the objective to have a complete view of optimization applications in other applications different from power system and microgrids, it has been considered convenient to review some papers of other areas to clarify some of the most common terms. In this sense, it has been intended to partially follow the advises given by the authors in [191] to avoid confusion and misuses of terms.

Regarding the methods that are chosen in each situation, problem, and discipline, “the approaches differ largely in terms of formalism, uncertainty model and solution concept” [191]. This warning has been considered in the present chapter for dividing the review process in various steps, which will be the uncertainty modelling approaches, optimization methods, and finally optimization solving methods. Moreover, several papers of different disciplines were reviewed with the objective of taking a general scope of how the different terms and definitions are applied. These definitions can be found in Section §3.1.1.

Several optimization methods that will be seen hereinafter discussed are designed to include some specific uncertainty models that are considered in the corresponding problem. When looking for an appropriate method, some questions arise, as, for example, whether the forecasted uncertainties deterministic or stochastic, if there are some quantile information available, or how many scenarios will be used to represent the uncertainties. Therefore, the application of a specific method will depend, in the first place, on the type of available information about such uncertainties, and on the computational requirements and complexity of the problem to be solved.

Moreover, in [191] the authors point out the convenience of separating both modelling and solution methods. They state that “decoupling uncertainty models from solution methods and developing standardized performance measures represent key steps for organizing multi-stage optimization under uncertainty and for eliciting further potentials of yet unexplored combinations of uncertainty models and solution methods."

During the literature review of optimization methods, it has been observed that various uncertainty modelling methods can be mixed inside the same problem. In a similar way, it has been found that the same type of uncertainty model can be applied as inputs in various optimization methods. To avoid confusion in this regard, it has been preferred to explain separately the uncertainty modelling (which only considers the information of the uncertainty) and the optimization methods (which fits the uncertainty information with the formal approach of the optimization problem). Considering the exposed reasons, the next sections will be organized as follows.

In Section §3.1.1 some common terms used throughout the literature will be defined. These definitions have been considered convenient to avoid misunderstandings because some differences on the use of certain common terms have been found, as it is pointed out in [191]. Then, the existing methods for uncertainty modelling will be studied in Section §3.1.2.

3.1.1 Preliminary concepts in optimization

Some preliminary concepts on optimization will be defined here according to their observed meanings in the literature. Due to the lack of consensus on the use of some of these terms, various alternative definitions will be given when it is considered of interest to avoid confusion.

Static models: According to [193], static models are those that "do not take explicit account of time. Decision variables do not depend on time. Calculations are carried out to obtain the optimal value of the objective function at a given moment. Time is not explicitly included in the model's structure" [193]. In other words, if the decision variables are not dependent on time, then each of the phases of the problem could be considered independently. As there are not interdependencies between them, there are not any dynamic behaviors to be modelled in the optimization problem (wherefore the problem is static).

Dynamic models: According to [193], dynamic models are those that "take time into account explicitly. Some of the decision variables are functions of time (usually separated into state variables and control variables). Model solution gives optimal decisions over time" [193]. An example of a dynamic model is the control of a microgrid that includes an energy storage system. The storage system can be charged or discharged by the control system, being its state of charge dependent on the operative decisions of the previous time. Therefore, this situation has to be modelled by a dynamic model (not being a static model applicable).

Deterministic dynamic models: "Deterministic dynamic models contain complete and perfect information on the future. All the model parameters, such as future prices, climate, yields, etc., are supposed *known* by the decision-maker" [193]. This means that the values of the uncertainties can be represented as point forecasts (i.e., as a single value for each of the uncertainties and time periods).

Stochastic dynamic models: In stochastic dynamic models, the uncertainty of some of the parameters is explicitly considered. Therefore, the information of these parameters is considered not totally known, but it is described in terms of probability distribution, scenarios, confidence, worst-cases, or other methods [173] (these methods can even coexist inside the same problem, using each of the uncertain parameters a different method to describe their expected behavior).

According to [193], there is two types of stochastic dynamic models, which are single decision stochastic models and sequential decision stochastic models.

- **Single decision stochastic models**: In single decision stochastic models, "the sequence of optimal decisions is determined at the beginning of the decision process and no modification is made afterwards" [193, 194]. In other words, the optimal decisions that were obtained at the start cannot be adjusted when the stages advance and the uncertainties are revealed, but they remain as they were firstly obtained.
- **Sequential decision stochastic models**: In sequential decision stochastic models, "decisions are taken sequentially and the decision-maker can adjust them when additional information is available" [193, 194]. Therefore, the optimal decisions can be adjusted according to the events that occur during the next stages.

Uncertainty: In the context of an optimization problem, the term "uncertainty" can refer to the existing phenomenon of incomplete (or missing) information in a certain value involved in the problem, or also to the defined parameters that model such lack of information. According to the definition found in [191], "uncertainty in an optimization problem means that some or all of the problem's parameters are not known at the time the problem has to be solved" [191]. The reason for introducing these parameters in some optimization problems is that "real world applications often suffer from incomplete information on relevant input data" [191]. Mathematically, one way of defining the information of uncertainties in the problem is modelling it by "a sequence $\xi_{[T]} = \xi_t : t = 1, \ldots, T$ of successively observable data vectors ξ_t over a planning horizon of T stages, with $T \in N$. The time between two successive observations ξ_t and ξ_{t+1} of elements from $\xi_{[T]}$ marks a (decision-) stage. At each stage, a new (partial) decision x_t has to be irrevocably fixed based on the information available at this point" [191]. Other authors can use other alternative names for the uncertainty array, but their models usually are similar in shape to that described in [191].

Exogenous and endogenous uncertainty: It can be said that an uncertainty is exogenous when it is not influenced by the decisions that are taken during the different stages of the process (e.g., solar irradiance). If the decisions have some influence over an uncertainty, that uncertainty is said to be endogenous (e.g., the state of charge of an energy storage system in a microgrid could be considered an endogenous uncertainty). These names were introduced in stochastic programming "in the research stream started by Goel and Grossmann [195]" [191].

Multi-stage optimization problem (according to [191]): This can be defined as a problem that requires "a sequence of decisions which react to outcomes that evolve over time, and information on these outcomes is disclosed gradually" [191]. The reason for introducing this requirement for formulating the problem is that "multi-stage models enable the decision maker to adapt decisions at later stages to the already observed realizations of the uncertain data. Thereby, multi-stage models yield the potential to lead to better solutions than their static counterparts which require that all decisions have to be fixed up front" [191]. In this context, the "static counterpart" would mean fixing the decisions for all the stages considered in the problem, applying the operative decisions that were obtained from this first solution, and not adjusting them in the future (nor resolving the equivalent problem again shifting the time one step nor making any adjustment according to the observed evolution of the uncertainties that have previously occurred). The most simple multi-stage problem would be composed by two stages, the first one for the initial decision, and a second one whose decision depends on the occurrence of the uncertainties during the previous stage. In that case, it is usually called a "two-stage optimization problem." The two-stage and multi-stage optimization problems will be analyzed in detail later as part of the stochastic programming methods.

Multistage (according to [95]): In this paper, the term "multistage" includes some additional models that are not considered in [191]. These techniques are deterministic model predictive control (MPC) and open loop feedback control (OLFC) [95]. In fact, these two techniques are not in conflict with the definition given by [191], but they accomplish their objective (adapting the decisions in each of the stages using the information observed until that moment) by a rolling-horizon strategy (solving the same problem for the next stage shifting the time by one step) instead of creating a set of solutions that can be used under all possible scenarios. It is remarkable that the authors in [95] take care of clearly explaining the use they give to the term "multistage" by clarifying what they want to express. In this sense, it is stated that a MPC is a "multistage deterministic optimization problem," the OLFC method uses a sequence of multistage open loop stochastic optimization, and stochastic dynamic programming (SDP) methods are considered closed-loop methods. While in [95] the authors reserve the term MPC for the rolling-horizon deterministic controller and OLFC for the rolling-horizon stochastic controller, other authors in the literature call these two controllers "deterministic MPC" and "stochastic MPC" respectively.

Dynamic programming: A family of mathematical programming methods oriented to solving multi-stage optimization problems (i.e., problems that are applied to optimize situations that can be described as a dynamic model). It is based on solving the Bellman's equation. The dynamic programming (DP) is reviewed in Section §3.2.8.

The terms "dynamic model" (which has also been previously defined) and "dynamic programming (DP)" should not be confused, as their meanings are totally different.

Recursive models: According to [193], in a recursive model "each optimisation depends on the results of the previous iteration." A method for solving this kind of optimization models is the recursive stochastic programming.

Recursive stochastic programming: According to [193], the recursive stochastic programming method "consists in solving the dynamic problem by making a series of sequential optimisations, thus it is a recursive method where each optimisation comprises a dynamic model." To sum up, the optimization problem is solved to obtain the operative decisions, and the same problem structure is repeated and solved for the next stage by shifting the time by one step. This method is very popular in the ambit of microgrids, but it is usually called a "rolling-horizon method" instead of a "recursive method". Considering that the term "recursive" is not usually applied in the research ambit of microgrids, its use will be hereinafter avoided. In other fields, the term "recursive" is commonly found, such as agriculture and natural resource economics [193] and livestock farming [196].

Offline and online optimization: It is said that an optimization method (or some of the steps that are followed during its solving process) is "online" if it includes some adjustment of the decision process in the middle of the time horizon. In other words, the "offline" process corresponds to the first set of operative decisions that is obtained in the first resolution of the problem. In advance, if these decisions are adjusted according to the evolution of the uncertainties, these adjustments can be said to be "online". It is possible to formulate optimization problems that are purely offline or purely online, or even include phases of both types in the same problem. The off-line control approaches for EMSs that are mentioned in [197] make the control decisions ahead of time and do not make any adjustment in real-time, therefore these methods are executed completely offline. The online MPC methods, that are mentioned in [197, 95] apply a rolling-horizon strategy, so these are online methods. Finally, some optimization methods include both offline and online phases, as it is the case of SDP methods [95].

Multi-objective optimization problems: In a multi-objective optimization problem, two or more objectives are considered instead of a single one. An example can be found in [198], where the operation of a microgrid is optimized considering cost and pollution at the same time. One of the methods for approaching more than one objective is the augmented Epsilon-constraint method, which is a modification of the Epsilon-constraint method [198]. In that paper, the method is applied in combination with stochastic programming.

Having defined the main concepts that will be applied for the study of optimization in microgrids, the next section will review the uncertainty modelling approaches.

3.1.2 Uncertainty modelling approaches

According to [102], uncertainty modeling in stochastic optimization problems "can be divided into three types: scenarios, uncertainty sets, and probabilistic constraints." These three ways of modeling are based on stochastic and probabilistic methods.

At this point, it is important to note that the designations "stochastic optimization" and "deterministic optimization" in some occasions refer to the mathematical problem itself (the way it is modelled) and in other cases refer to how uncertainties are handled (i.e., if only a point forecast has been applied, or if it includes some stochastic/probabilistic information). For this reason, some authors even talk about "deterministic counterpart of an stochastic problem" when an optimization problem is reformulated to change from its definition based on probability distributions (or any other source of stochasticity) to that formulation which include the actual information of uncertainties in a discrete form (scenarios) or simple constraints based on the probabilistic information of uncertain parameters.

Considering this usage of terms, probabilistic forecasting is not exclusively applicable on stochastic optimization problems, but also on deterministic ones. Not considering this fact would suppose an underestimation of the usefulness and applicability of probabilistic forecasting. As it is mentioned in the same paper [102], there are deterministic UC problems in which probabilistic forecasts are introduced as additional constraints in the problem. An example is the calculation of reserve requirements based on a probabilistic forecast. In this example, despite not being an optimization method stochastic by itself, it has been able to include information that comes from probabilistic models.

The importance of probabilistic forecasting methods in the field of optimization is clear. As it is pointed out in [102], "much research has been done in probabilistic forecasting," being some methods quantile regression [199], kernel density estimator-based forecast [200] and quantile-Copula estimator for kernel density forecasts [201]. The forecasting techniques which will be reviewed in Section §3.4, being the review especially focused on their application to microgrids and the power system in general.

Once the uncertainties of a problem have been modeled, the next step will be applying an approach for the problem definition that correctly fits the model of uncertainties. In this sense, "the coupling of the stochastic process with the optimization process is further considered in the multi-stage setting in [202] and [203]" [191]. The stochastic process, in many cases, is interconnected with the model that has been chosen for the uncertainties, as it will be later observed.

According to the existing literature of stochastic optimization for microgrids, the three main methods for uncertainty modelling are scenarios, uncertainty sets, and probabilistic constraints [102]. These will be reviewed next.

3.1.2.1 Scenarios

One of the most popular techniques for representing uncertainty in stochastic optimization is scenario representation. For doing so, a certain number of scenarios must be generated, being each of them a possible realization of the uncertainties being represented. This simulation intends to approximately reflect the true distribution of such uncertainties [102]. As said in [204], it is possible to use "a set of scenarios and corresponding probabilities to model the multivariate random data process," which can include for example electrical load, fuel prices, electricity prices or other data.

The structure of scenarios can be a number of parallel scenarios (which is suitable for two-stage stochastic optimization problems) or a scenario tree (suitable for multistage problems) according to [102]. While these two are the basic scenario structures, it will be seen that some other variations can be obtained, which are single-scenario (which simply corresponds to a deterministic forecasting), fan-of-scenarios (a way of converting a scenario tree into a bunch of independent scenarios) and stage-wise scenarios (scenario tress with independence between the different time stages).

The authors in [102] state that, for obtaining parallel scenarios, Monte Carlo simulation can be applied to create scenarios according to a predefined probability distribution function (PDF), which can be learned thanks to historical data. In the case of scenario tree, it can be generated using random paths "based on the underlying stochastic process(es)" [102].

The techniques for generating scenarios are closely related with forecasting. It is possible to model the forecasting error or directly model the required uncertainty (instead of modelling the error), applying normal or Weibull distribution, and even consider discrete probability distributions instead of continuous [102]. Moreover, these techniques can be combined with Monte Carlo for constructing the desired number of scenarios. A detailed literature review of these methods can be found in [102].

Probabilistic forecasting can also be applied in other uncertainty models that are not based on scenarios, as it could be robust optimization-based algorithms. In these algorithms, "a range/band needs to be defined to represent the upper and lower bounds of the uncertainty" [102].

According to [102], the most common output that can be obtained from probabilistic forecasts corresponds to a set of quantiles that represent the probabilistic levels of the forecasts for a certain look-ahead period. These "can be computed through probability density functions (PDensFs) or cumulative distribution functions (CDFs)."

An alternative approach to the mentioned techniques can be seen in [205], which makes each operation decision online and does not rely on a forecast model. Instead, "the optimal decision is obtained by conducting Monte-Carlo tree search (MCTS) with a learned model and solving an optimal power flow sub-problem" at each time step. According to the authors, "this article investigates the usage of RL" for avoiding the need of "a forecast model to predict the future PV/wind and load power sequences" in a residential microgrid [205].

The generation of the desired scenarios is performed in [95] by considering the point forecasting and the distribution of forecast error over historical datasets. The description on how the scenarios and their associated probabilities are obtained can be found in Sections A.1 and A.2 of [95].

In [198], for performing the stochastic programming, the authors create the scenarios following the next approach. Hereinafter, to avoid confusion between probability density function (PDensF) and probability distribution function (PDF), it has been preferred to reserve the acronym PDF for the probability distribution function, in the same way it is done in [198]. It should be remembered that other authors apply such acronym for the probability density function, so it is convenient to be cautious in this regard.

The method that is proposed in [198] is:

> "The uncertain parameters are assumed to have a continuous PDF with 30% standard deviation. Then, the continuous PDF is estimated by discrete PDF including N_n steps. If there are M_m uncertain parameters, and each parameter is estimated by N_n steps, therefore, there are $N_n^{A_a * M_m}$ scenarios. Where, A_a shows the time intervals of next 24-h (e.g., six time intervals and each one including 4 h). After producing all scenarios and the probability related to each scenario, the most probable scenarios with the highest possibility of occurrence are selected. This approach results in a trivial error at the outputs, but it significantly reduces the simulation time" [198].

It can be here appreciated the importance of keeping only those most probable scenarios due to computational cost reasons, as the cost increases with the number of scenarios. As it is said in [102], it can be expected to improve the quality of solutions using a larger number of scenarios (as it permits including more information about the behavior of the future uncertainties). "However, increasing the number of scenarios beyond a certain threshold may lead to only a marginal improvement in the quality of the solution and the objective function" [102]. The increment of the number of scenarios also has an impact on the computational cost, and therefore "a tradeoff usually needs to be made between the desired accuracy and the computational performance of the algorithm" [102]. For example, in the case study presented in [198], "only 50 scenarios which have the highest probability of occurrence are simulated" among all available scenarios.

The importance of scenario reduction as a tool for uncertainty modelling is expressed in [206], where the authors follow the next method to reduce the scenario tree. Firstly, "the probability of each scenario can be calculated by multiplying the probabilities from root node to leaf nodes corresponding to that scenario" [206] (as it will be seen later, this corresponds to the equivalent fan of scenarios). Then, "the scenarios with low probability —i.e. less than a specified value that can be determined by decision maker— will be ignored" [206]. This is a very simple method that allows to choose a number of scenarios by specifying a single parameter for limiting the minimum probability.

Other authors have proposed heuristics for generating scenario trees, which "are based on forward or backward algorithms for tree generation consisting of recursive scenario reduction and bundling steps" [207]. An example can be seen in [192], where the generated scenarios are reduced to 24 scenarios using the backward reduction algorithm.

It is said in [102] that, to decide an appropriate number of scenarios without unnecessarily increasing it (as it would get a "marginal improvement in the quality of the solution"), "sample average approximation (SAA) [208] and multiple replications procedure (MRP) [209] can be used to test the convergence of the solution and objective function, respectively" [102].

The application of "Monte Carlo sampling methods for solving large scale stochastic programming problems" together with SAA are discussed in [210]. An example of the application of these two methods can be found in [211], where these are used to model the uncertainty in DR applications.

Other scenario reduction techniques that have been proposed "bundle similar scenarios based on certain probabilistic metrics [212, 213, 204]" [102]. These methods are not used in microgrid management, but also in higher control levels, as it is power system planning and resource adequacy evaluation.

In this sense, when checking the similarity of scenarios, "the goal is to reduce the number of scenarios without sacrificing their accuracy to a large extent" [102]. This idea goes in line with that one expressed by other authors, who aims to keep only those more significant (or more probable) scenarios to limit the computational cost of the optimization.

According to [212], "different metrics can be used to define the distance between two scenarios i and j," which can be considered for selecting the scenarios of interest. In that paper, the maximum deviation is used for defining these distances, and clusterization is applied for reducing the number of scenarios.

In [213] the probabilistic metric that is applied is Fortet-Mourier metric. It is used in two algorithms (which are mathematically defined in detail in the referenced document) for reducing the number of scenarios, which are backward reduction and forward selection algorithms. A similar process with these two algorithms is performed in the proposal of [204], but the metric that is applied for calculating the distance between scenarios with multivariate probability distributions is the Kantorovich distance.

Other methods such as the contamination method are described in [214]. According to the authors, it is applicable "for the inclusion of catastrophic events in the scenario set," being useful in the field of risk management.

Additionally, in some optimization problems, there can be variables that depend on two or more uncertainties. Therefore, if the individual uncertainties are modelled using scenario sets, these should be combined for obtaining the corresponding scenario set of that other variable. The appropriate way to handle this process depends on the relationships between these variables and the characteristics of the optimization problem. An example can be found in [215], where there are two uncertainties (wind power and load) with their respective demand PDensF that are combined (their difference is calculated) to obtain the residual load. The two scenario sets are combined through their convolution, as the authors have created discrete scenario sets (sampling each of the PDensF) with a specific known step between their power values to be evenly distributed, making it possible to perform such convolution. A similar approach is described in [216], where some random variables are "convolved to create the surplus PDensF from which adequacy metrics can be calculated" [216]. In other cases where the convolution is not applicable, each occurrence of each of the variables can be simply combined to find all possible realizations (with their corresponding probabilities) of the new variable. This concept is closely related to the residual demand curve, which can be defined as the electricity demand minus supply from renewable sources [217].

Precisely in [216] these two methods, Monte Carlo simulation and analytical method (convolution) are considered as the two basic computational approaches for the evaluation of probabilistic reliability indices of a system. This document is a technical report focused on probabilistic adequacy and measures. It also exposes various metrics and indices that are applicable to the system, "such as loss of load probability (LOLP) and expected unserved energy (EUE)" [216].

Similarly, in [218] three adequacy metrics are defined and calculated applying Monte Carlo and the relationships between these metrics are studied. The scenario set approach that the authors follow in this study is structured in 12 scenarios, which result from the combination of "three load levels and four resource levels to reflect forecast uncertainties" [218]. In the case of [219], the authors also evaluate a very limited set of scenarios, which are conventional generation only, with wind, with PV and with the addition of both. As it can be seen, these approaches aim to keep a very limited number of situations for evaluating the adequacy. It is totally different to that other approach followed in some microgrid management studies, where a higher number of scenarios is applied to increase the quantity of information about the uncertainties. The reason for this difference is that in system planning it is more usual to keep reduced information and indicators that are sufficiently representative, instead of using a large amount of information that can make its interpretation more complex. It is common to find this same approach (i.e., using a very reduced number of scenarios) in the case of microgrid design optimization, as it is done in [71] for designing electric mobility services in a local energy community.

As it can be appreciated, while the documents [216, 218] are focused on system planning, many of their ideas of scenario generation and their uses are applicable (with some minor adjustments or modifications) to microgrids and other lower levels of the power system. Considering their importance, the main types of scenario sets that have been previously mentioned are next described in more detail.

3.1.2.1.1 Independent parallel scenarios

Each independent scenario establishes the values of the considered uncertainties for each of the time steps included in the optimization problem. Moreover, the probability of occurrence of each scenario must be known, being the sum of all of them equal to 1 (a hundred percent of probability). A set of ten scenarios can be seen in Figure 3.1.

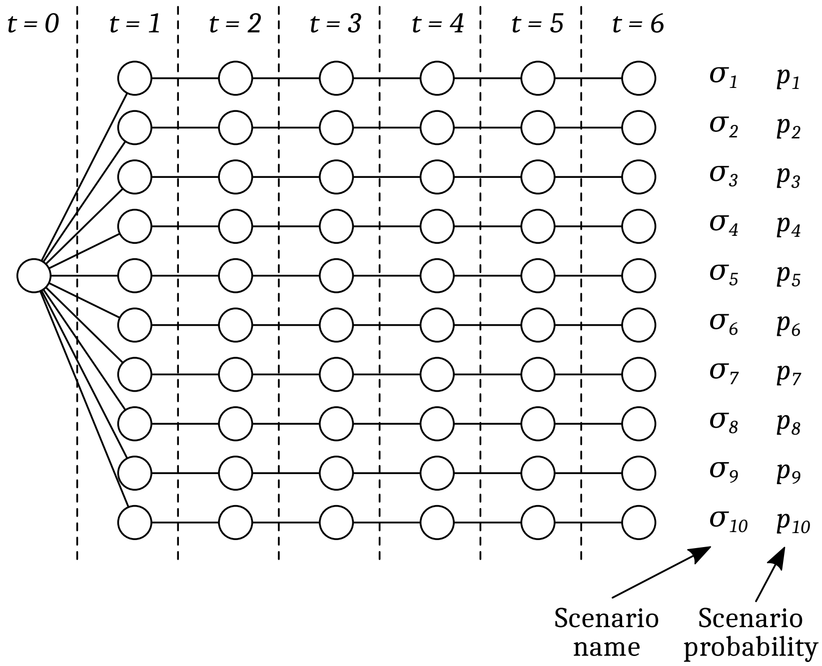


Figure 3.1: Independent parallel scenarios.

Some problems can even consider a single scenario, having this scenario a probability of 1 (see Figure 3.2). This approach corresponds to a deterministic optimization, but can be also used in "stochastic optimization problems as it provides noise-dependent strategies" [220]. The use of a single scenario can also be applied for reducing the computational cost of a problem.

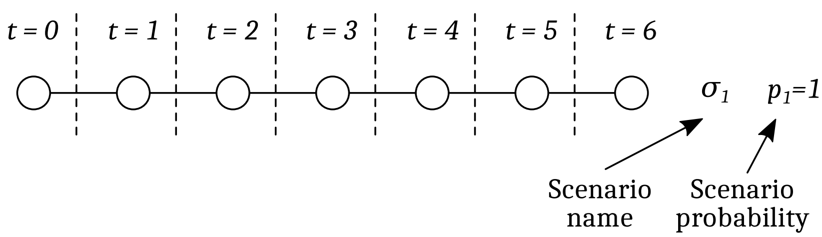


Figure 3.2: One single scenario.

In many papers, as in [191], it is common to see that the set of scenarios only shares the first node (also called the root node), as it is the node in which the optimization is started. In these cases, the nodes that come after the root node are situations where the values of uncertainties are not known (therefore, the considered scenarios are then divided as independent possible occurrences of the uncertainties). However, in some problems it can be considered that the variable scenarios of interest do not occur in the second time step, but in some other steps later, and various of the first nodes are common between all scenarios. Following this approach, the first nodes that are common will be directly considered in the function cost (without any stochastic information), while those time steps in which the scenarios are already divided will be modelled in a stochastic way. This approach, which is applied in [221], can be used in two-stage and MPC methods.

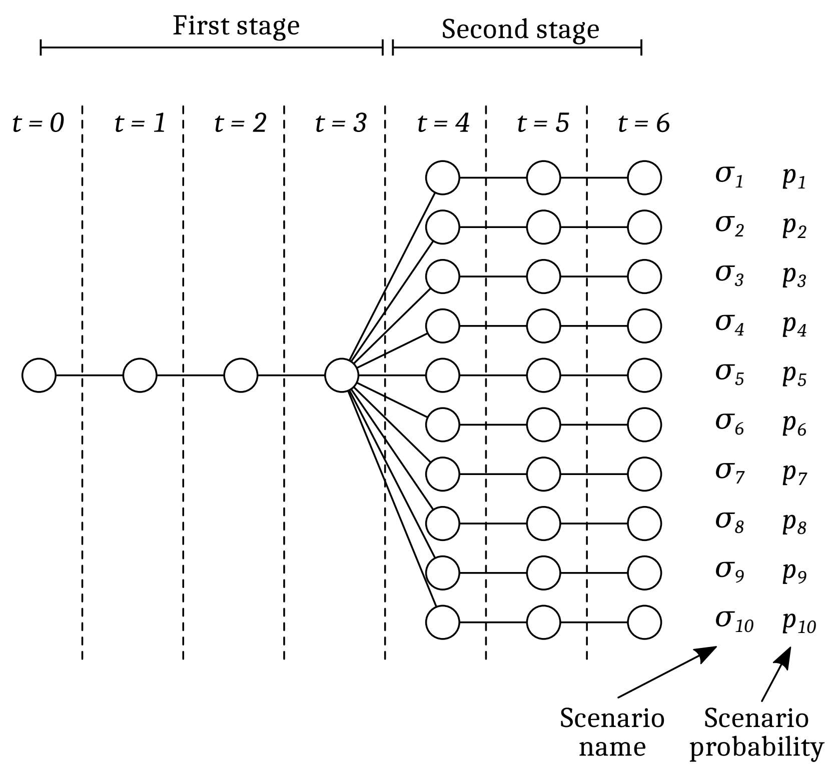


Figure 3.3: Independent parallel scenarios affecting only to some of the time steps. The terms "first stage" and "second stage" refers to the two parts of a two-stage optimization problem formulation, and not to the seven time stages that composes the time horizon of the problem.

An application of this idea is reducing the number of scenarios by trimming those node divisions where the scenarios are practically equal, or when they are not of high interest and can simply be substituted by a deterministic forecast of the uncertainties (instead of considering probabilities of occurrence).

3.1.2.1.2 Scenario tree

Unlike the independent parallel scenarios, the scenario tree includes some internal relationships between their nodes, being some of them common between the scenarios. The probabilities are expressed in each node division, being the sum of the probabilities of the branches of the node equal to 1. In the scenario tree, each possible path that can be followed from the initial node (the root node) to each of the final nodes (leaf nodes) is called an scenario [206]. An example of a scenario tree is depicted in Figure 3.4a. Some authors use tables of probabilities to define the probabilistic behavior of the decision tree in their papers [193, 194].

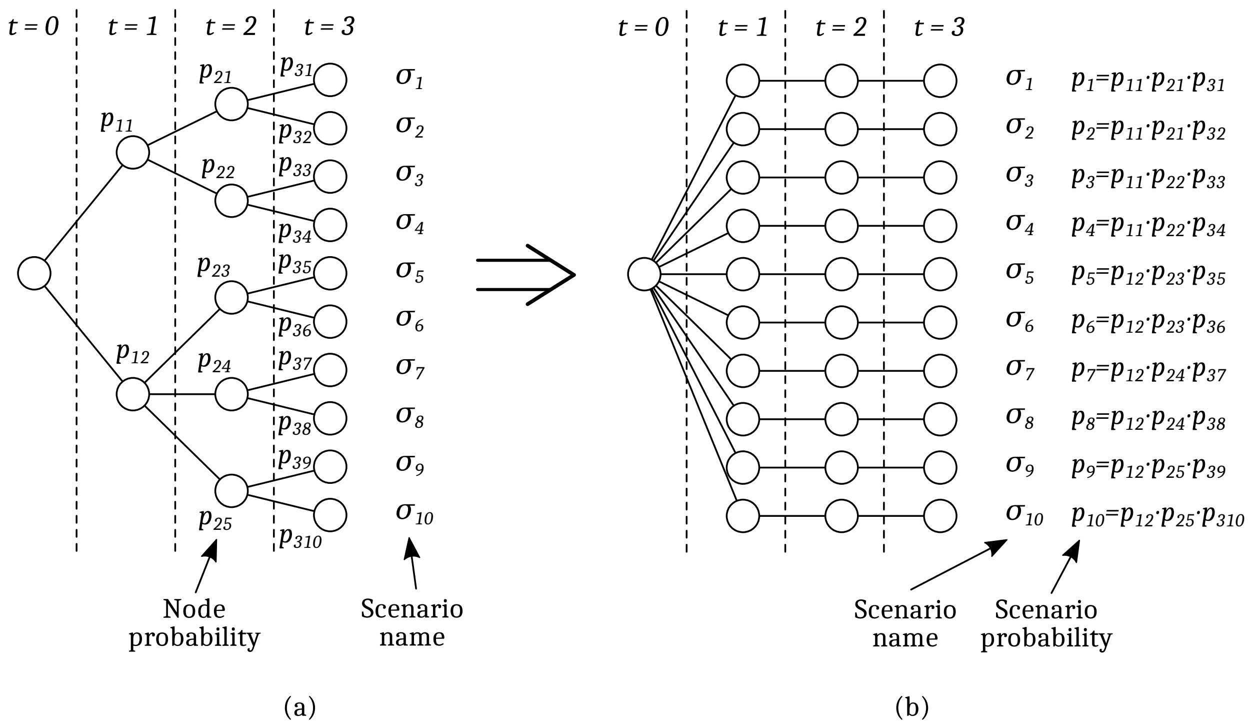


Figure 3.4: Scenario tree and fan of scenarios with their associated probabilities. (a) Scenario tree; (b) Equivalent fan of scenarios.

As it has previously been mentioned, "multistage stochastic programs with recourse are important modeling tools in real life applications such as the ones coming from the areas of energy, transportation and finance" [222]. Using a scenario tree is a typical approach for approximating the underlying random process to solve these problems [222].

Considering that multistage stochastic programs generally constitute mathematical programming problems of a large scale, they "can be handled using specialized algorithms that employ decomposition techniques (and very often sampling)" [222]. For doing so, "two very popular decomposition schemes for handling multistage stochastic programs are the nested decomposition (ND) proposed by [223] and the stochastic dual dynamic programming (SDDP) proposed by [224]" [222]. These two methods are variants of DP methods, so further details about them will be given in Section §3.2.8.

It is said in [191] that "the decomposition method of SDDP [225, 226] relies on the generation of scenarios to approximate the recourse cost function in multi-stage settings using cutting planes."

Solving stochastic integer programs (SIPs), which include some variables that are integer numbers, is generally difficult [227]. For dealing with these problems, "a new cutting plane method for two-stage stochastic mixed integer programming (SMIP) called Fenchel decomposition (FD)" is introduced in [228].

This FD is applied in [227], where it is made "a comparative study of stage- and scenario-wise FD for two-stage SIPs with special structure." According to the authors, "the standard FD approach is based on stage-wise or Benders' decomposition. This work derives a scenario FD method based on decomposing the SIP problem by scenario and performs a computational study of the two approaches. In particular, two algorithms are studied, stage-wise Fenchel decomposition (ST-FD) and scenario-wise Fenchel decomposition (SC-FD) algorithms" [227].

Instead of applying decomposition techniques, another way of making problem instances solvable when they include many scenarios is "by generating *significant* scenarios" [191]. "To this end, the technique of scenario generation through scenario trees gained importance [214, 229, 230, 207]. Likewise, general sampling outlines such as SAA became popular also for multi-stage stochastic programming [210]. Lately, researchers have combined sampling and scenario generation [231]" [191].

As it can be appreciated, there exist multiple ways of applying the information of an scenario tree in an optimization problem, and even of simplying the tree in case it is too complex to be directly handled. For those optimization problems where it is preferred to use independent scenarios instead of a tree, it is possible to redraw a scenario tree to obtain its equivalent set of independent scenarios, which is then called the "equivalent fan of scenarios," as it will be seen next.

3.1.2.1.3 Equivalent fan of scenarios

The aspect of the fan of scenarios is similar to that of the independent parallel scenarios, but the procedure for the generation of this one is different. The equivalent fan of scenarios is a way of converting the scenario tree (in which the scenarios are interconnected in some of the nodes) to a set of independent ones with their associated probabilities of occurrence. This reformulation is useful in some types of optimization problems because it makes it simpler to include the information of probabilities than if explicitly considering their relationships.

This procedure of converting the scenario tree to its equivalent fan of scenarios is exposed in [191] "it can be thought of as a graphic representation of a discrete (or reduced and discretized) stochastic process. Starting at the root node each level of the tree corresponds to the possible outcomes at a stage of the problem. Hence, the paths $\xi^s_{[T]}$, $s = 1, \ldots, S$, from root to leaves correspond to possible realizations of the (discretized) stochastic process, also referred to as the set of scenarios S. The probability π^s of an individual scenario $\xi^s_{[T]}$ can be determined by multiplying the probabilities of the individual out- comes at each stage along the path in the tree" [191]. This procedure permits to adapt scenario tree information to individual scenarios, which is sometimes convenient to apply certain types of optimization methods (such as many two-stage models, that precisely requires parallel scenarios).

An example of an equivalent fan of scenarios can be seen in Figure 3.4b.

3.1.2.1.4 Stage-wise independent uncertainty

For those uncertainties whose values do not have any relationship between stages, it can be said that these are stage-wise independent.

Therefore, the uncertainty can be modelled as it is done in Figure 3.5.

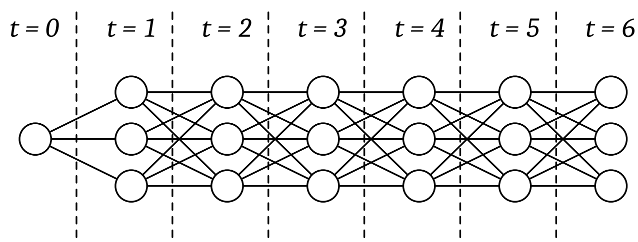


Figure 3.5: Stage-wise independent uncertainty.

The consideration of independence between stages may result in a very high number of different scenarios (due to the curse of dimensionality). Therefore, as the "dimensionality of the problem is large and DP is no longer an option," other methods are applied to tackle them, such as SDDP [232]. Precisely, in SDDP, the usual assumption is that the uncertainty is stage-wise independent. This method will be explained in Section §3.2.8.3.

The same idea is described in [233]. One of the methods that can be used for translating the uncertainty information into the optimization problem is nested Benders decomposition, which "requires solving a linear program at each time period and for each scenario, where a scenario represents a full history of events up to that point in time" [233]. It is pointed out that the number of independent scenarios exponentially grows with the number of stages, "making nested Benders decomposition impractical for even medium-sized problems" [233]. For this reason, the authors in [233] proposes a new "convergent cutting-plane and partial-sampling algorithm for multistage stochastic linear programs with recourse" that can be applied when random quantities in different stages are independent (i.e., stage-wise independent) and some other extra assumptions are accomplished.

ND can also be applied to multistage stochastic problems under the assumption that "the underlying stochastic process is stage-wise independent" [222]. In many cases, it is required combining decomposition and sampling for handling these problems [222].

The next section will briefly review how the scenario-based uncertainties are mathematically expressed in the microgrid-related literature. This is important to understand the connection between uncertainty representation and the optimization methods that will be later reviewed.

3.1.2.1.5 Mathematical expression of scenarios

The objective of this section is giving an overview of how the scenario-based uncertainties can be mathematically expressed for being included in optimization problems.

According to [191], one way of defining the information of uncertainties in a problem is modelling it by "a sequence $\xi_{[T]} = \xi_t : t = 1, \ldots, T$ of successively observable data vectors ξ_t over a planning horizon of T stages, with $T \in N$." According to this formulation, the time between two successive observations ξ_t and ξ_{t+1} of elements from $\xi_{[T]}$ is said to be a decision-stage (sometimes simply called a stage).

Something similar is proposed in [95] for the definition of the uncertainties in the model of a EMS controller for a microgrid. The uncertainties are defined as:

$$w_t = (g_t, d_t) \in \mathbb{R}^2, \forall t \in \{1, \ldots, T\}\,, \tag{3.1}$$

In which g_t represents the PV generation and d_t represents the energy demand. These uncertainties are exogenous, as they are not affected by the decisions that the EMS takes (otherwise, they would be considered endogenous). This is equivalent to a sequence:

$$(w_1, \ldots, w_T) \in \mathbb{R}^{2\times T}, \tag{3.2}$$

Notwithstanding, these uncertainties are not known previously to their occurrence, so they have to be forecasted. For the deterministic optimization problem, the forecasted uncertainties are represented in [95] as:

$$(\hat{w}_{t,t+1}, \ldots, \hat{w}_{t,t+H-1})\,, \tag{3.3}$$

where H is the time horizon considered in the optimization problem.

For the stochastic optimization, not a single sequence of forecasts will be defined, but various of them. Each of these possible sequences (that corresponds to a possible occurrence of uncertainties) is called an "scenario". A scenario will therefore be a sequence $\{w_t\}_{t\in\mathcal{T}}$ of uncertainties $w_t = (g_t, d_t)$ where $\mathcal{T} \subseteq \{1, \ldots, T\}$ [95].

For the open-loop feedback control optimization proposed in [95], the sequence of controls is not indexed by the scenario reference $\sigma \in \mathbb{S}$, as only the first value u_t^* of an optimal sequence is kept (see §5.1.2 [95] for more detail on the mathematical formulation). This problem is stochastic because of the scenarios $\left(w^\sigma_{t,t+1}, \ldots, w^\sigma_{t,t+H-1}\right)_{\sigma\in\mathbb{S}}$, together with their probabilities $(\pi^\sigma_t)_{\sigma\in\mathbb{S}}$. In their results, the authors apply a number of scenarios between 10, 50 or 100 scenarios to perform their tests of the EMS optimal controllers [95].

Similarly, in [220] a number S of scenarios $(\tilde{w}^s_{t'+1}, \ldots, \tilde{w}^s_T)_{s\in\{1,\ldots,S\}}$ with associated probabilities $(p_s)_{s\in\{1,\ldots,S\}}$.

For the SDP optimization in [95], two types of scenarios are prepared for the offline phase and the online phase of the algorithm. In this way, the scenarios $(w^{\text{off},\sigma}_{t+1})_{\sigma\in\mathbb{S}^{\text{off}}}$ are associated with their probabilities $(\pi^{\text{off},\sigma}_{t+1})_{\sigma\in\mathbb{S}^{\text{off}}}$ for the offline phase. Similarly, in the online phase the scenarios are $(w^{\text{on},\sigma}_{t+1})_{\sigma\in\mathbb{S}^{\text{on}}}$ and their probabilities are $(\pi^{\text{on},\sigma}_{t+1})_{\sigma\in\mathbb{S}^{\text{on}}}$ [95].

In [220], the difference between the two types of SDP optimization that they propose (which are the same used in [95]) is clarified. In stochastic dynamic programming online (SDPO), the random variables (the uncertainties) are considered stagewise independent, being μ^{of}_t the probability distribution. Therefore, for both offline and online phases, the distribution probabilities are the same ($\mu^{of}_t = \mu^{on}_t$) for each individual stage, not changing during the evolution of the time. In stochastic dynamic programming augmented (SDPA), the probabilities for uncertainties (and the possible states of the system) are not stage independent, but they depend on the value of the uncertainties during the previous stage. Therefore, as the authors state, "the limit of this state augmentation strategy is the well known *curse of dimensionality*" [220].

Having described the existing types of scenario-based uncertainty representations and their mathematical expression, the next section will be focused on another method of expressing information about uncertainties, which are the uncertainty sets.

3.1.2.2 Uncertainty sets

According to [102], "the most straightforward and basic uncertainty sets used in robust-optimization-based UC models are the box intervals." These intervals correspond to:

$$[\max\{0, \bar{d} + z_\alpha\sigma\}, \bar{d} + z_\beta\sigma], \tag{3.4}$$

where "$\bar{d}$ is the expected value and σ is the variance of a random variable, respectively; z_α and z_β are the α- and β-quantile of the probability distribution (with $\alpha < \beta$)" [102]. According to this expression, the variable cannot have negative values, and for that reason the lower limit corresponds to $\max\{0, \bar{d} + z_\alpha\sigma\}$. If the variable could have negative values, then the lower limit would simply be $\bar{d} + z_\alpha\sigma$.

This approach is frequently called "robust", as it can be used to consider the worst cases for the uncertainty values. This method can help to reduce the probability of apparition of undesired behaviors in the system, as the worst cases are being considered. Notwithstanding, it has some disadvantages. In the words of [102], the application of this method to UC "may yield overconservative solutions."

As alternatives to the robust approach, "polyhedral constraints on budget of uncertainty are also utilized to yield smaller (but not necessarily less confident) uncertainty sets" [102]. Moreover, "ellipsoidal uncertainty sets can also be considered by utilizing the expectations and covariance matrices" [102]. Other examples are nonconvex and discrete sets such as knapsack constraints [102].

The relationship between these approaches and probabilistic forecasting can be clearly seen. "Probabilistic forecasting can predict the level of a forecast output at a certain probability, and using two probabilistic forecasts can conveniently model the confidence intervals required in uncertainty set definitions" [102].

In the next section, the uncertainty representation by probabilistic constraints will be exposed. This method is also closely related to probabilistic forecasting.

3.1.2.3 Probabilistic constraints

Probabilistic constraints are related to risk consideration in stochastic models [102], constituting a variation of the previously described uncertainty sets. According to [102], "instead of directly using the box intervals, uncertainty sets can also be derived based on risk measures (such as Value-at-Risk) as in [234] and [235]." Stochastic and robust approaches (specifically, in UC models) are linked, as "constraints on coherent risk measures (such as Conditional-Value-at-Risk) can be translated to polyhedral uncertainty sets for some types of distributions [236]" [102].

In some documents of the literature, the probabilistic constraints receive other alternative names by some authors. For example, the probabilistic constraints restricting the LOLP are sometimes referred to as chance constraints [102].

It is said in [191] that "the use of risk-averse objective functions has gained prominence in multi-stage models [237]." The application of these objective functions to multi-stage problems brings some complications, as "concepts from the two-stage setting cannot be transferred ad hoc to multi-stage models as it is not evident how to evaluate recourse costs for the entire planning horizon. Opinions differ about whether to evaluate risk for the entire planning horizon, at every stage, or for individual scenarios. In this context the question of time-consistent risk measures, which give a persistent evaluation of risk across stages and scenarios, and a related definition of consistency arises [238, 239]" [191]. As it can be seen, including risk into the optimization problem is not a trivial task. The risk consideration in optimization methods will be later analyzed in Section §3.2.5.

Having exposed the three main methods for uncertainty representation, some final remarks on uncertainty modelling will be given in the next section.

3.1.3 Final remarks on uncertainty modelling

The need of further research regarding the introduction of uncertainties in stochastic optimization problems is expressed in [102]. In this sense, some important questions such as "the number of scenarios, scenario reduction, and the evaluation of the quality of scenarios" [102] require to be improved. Moreover, according to the authors, it is convenient to investigate how the integration of the advantages of stochastic techniques into system operation could be done [102].

The application of one optimization approach or another is highly dependent on the quality of the information of the uncertainties. As it is said in [102], "distributionally robust optimization assumes that the probability distribution of the uncertainty is not well known, and seeks to find a set of cost-effective solutions that for all possible probability distributions, are either always feasible or at least feasible in the worst case [240, 241]." This approach is different to that of the stochastic models with risk measures, as these "usually assume the complete knowledge of probability distributions of the underlying uncertainty" [102]. As it will be seen, these approaches can be even mixed in the same problem, choosing the most appropriate method for modelling each of the uncertainties. The nature of these uncertainties, and the quality of the forecast that can be achieved about them will affect on how they are handled in the optimization problem.

The next section classifies the existing optimization methods. In the classification, the previously defined terms will be frequently used to specify the characteristics of the models and their categories.

3.2 Optimization methods

This section is focused on the study of existing optimization methods, including those approaches that are inflicted by uncertainties. These methods are closely related to the uncertainty models that were reviewed in the previous section, being some methods appropriate to include certain uncertainty models but not others. Therefore, the selection of a certain model in a specific situation will be dependent on the available information about the uncertainties and their characteristics.

First, the existing classifications of optimization methods that can be found in the literature are reviewed in the next section. Next, the methods will be subsequently exposed in detail.

3.2.1 Classification of optimization methods

This section presents some of the classifications for optimization methods that have been proposed by other authors. In the microgrid ambit, the majority of energy management problems correspond to multi-stage optimization problems (whose definition can be found in Section §3.1.1). For this reason, this section will be specially focused on them (without excluding other approaches).

At the end of this section (§3.2.1), a general tree of optimization modeling methods for microgrids is proposed according to those trees that were found in the literature. The proposed tree has been made to clarify the naming criteria between the different papers on optimization. This problem has been repeatedly signaled by [191], stating that "concepts exist in parallel, deploy different terminology, and there is a lack of definitions on how they overlap and differ" which is frequently due to the bias that researchers have towards a certain concept [191]. This fact will be appreciated in the different alternative names that have been found to name the same concept, which can be confusing when comparing different papers found in the literature.

The general classification of methods and the main terms that are used to describe the characteristics of the problems to be solved are taken from [191]. This paper is not specifically focused on the field of microgrids, nor even on power systems, but it presents a general scope on decision and management problems. Precisely because of its generalist approach (as it aims to be common for multiple fields of study), and because of the definitions of the key concepts that it includes, its content has been selected as the main "basis" to structure the present section. Another paper which will be frequently cited is [193], which is focused on agriculture and natural resource economics, but performs a clear description of the existing kinds of optimization problems and their associated characteristics (including some that are not included in [191]). Other papers about power systems and microgrid control will additionally be cited in this section, taking care of clarifying those terms whose meaning could be in conflict with others of the cited papers. Some of these papers are [95] (focused on EMS design for microgrids) and [102] (focused on optimization methods for UC).

The content of [102], which is focused on UC, can be considered applicable by extension to the field of smart grid management. As the authors say, the UC can be defined as the "decision-making process of scheduling and dispatching electric power generation resources" [102]. The application of this process in a power system level has many similarities with its application over a smaller size domain, as in the case of a microgrid. For this reason, this paper is considered a useful and complete guide on the stochastic optimization methods and the ways of considering uncertainties in optimization problems for microgrids, so it will be frequently cited during the present review.

According to [191], the different methods for "multi-stage optimization under uncertainty have derived from three concepts," which are "stochastic programming, robust optimization, and online optimization," and three fields, which are mathematical programming, DP (which could be considered as a part inside the previous one) and computer science. Specifically, the authors state that “the algorithm-based concept of online optimization evolved from the field of computer science which deals with sequential decision making by definition” [191].

The classification of multistage methods under uncertainty that is made in [191] is as follows:

Multistage optimization methods under uncertainty [191]

- Stochastic programming
- Robust optimization
- Online optimization
- Combinations of stochastic programming, robust optimization, and online optimization
    - Online stochastic optimization
    - Online and robust optimization
    - Stochastic programming and robust optimization
- Dynamic programming
    - Stochastic dynamic programming
    - Robust dynamic programming

In [193], the authors explain separately the type of optimization problems and the optimization solving methods (resolution methods). The problem types are:

Optimization problems [193]

- Static models
- Dynamic models
    - Inter-temporal optimisation models
        - Deterministic dynamic models
        - Stochastic dynamic models
            - Single (or non-sequential) decision stochastic models
            - Sequential decision stochastic models
    - (Recursive model)

Additionally, there is another type of problem which is called “recursive model” (previously defined in Section §3.1.1). This term includes various types of problems, so it does not strictly fit into a single one of the previously listed categories. For this reason, in the previous tree this element has been written between parentheses.

The resolution methods for dynamic optimization problems, according to [193], are:

Resolution methods for dynamic optimisation problems [193]
- Non-sequential dynamic optimisation
  - Analytical solution
  - Method of dynamic programming
  - Mathematical programming method
- Sequential dynamic optimisation
  - Stochastic dynamic programming method
  - Discrete stochastic programming method
- (Recursive stochastic programming)

In [102], a review of stochastic optimization methods for UC is done. The types of methods according to the authors are:

Stochastic optimization unit commitment (UC) methods [102]
- Stochastic programming
  - Two-stage models
  - Multi-stage models
  - Risk consideration in stochastic models
- Robust optimization
  - Bi-level and tri-level models
- (Approx) Stochastic dynamic programming
  - Multi-stage, discrete time models

It is possible to classify the optimization approaches in deterministic and stochastic optimization. These differences are clearly established in [95] and [220], where EMS optimization approaches are explained: "MPC, OLFC (sometimes referred to as stochastic MPC) and SDP" [220] (cited by [95]). The second and third approaches, in a general sense, could be simply considered as stochastic scheduling (or stochastic MPC) methods due to their characteristics, so they will be considered in this way in the present text. The OLFC method, according to [220] can also be called *scenario based MPC*. The SDP methods include two variants, which are called SDPO and SDPA [220]. These approaches and their relationships can be seen in the next scheme.

Optimization approaches for EMS design [95] and [220]

- Deterministic optimisation
  - (Deterministic) model predictive control (MPC)

    *alternative name:

    - Certainty equivalent model predictive control (CEC)
- Stochastic (or probabilistic) optimisation
  - Open loop feedback control (OLFC)

    *alternative names:

    - Stochastic MPC
    - Scenario-based MPC
  - Stochastic dynamic programming (SDP)

    *classified as cost-to-go computation methods

    - Stochastic dynamic programming online (SDPO)
    - Stochastic dynamic programming augmented (SDPA)

The meaning of MPC in the ambit of microgrids can be appreciated in [197], where they point out what are the differences between off-line and online control approaches. As the authors state, “MPC method” is considered as a synonym of “rolling horizon control-based method.” The literature review that is conducted in [197] is exclusively focused on these methods whose “online phase” consists of reconsidering the problem after each time step, and solving it shifting in time. The methods that include both off-line and online phases in the same problem (as, for example, DP methods), are not included in their analysis. According to this paper, the existing methods are:

Optimal control methods for microgrids [197]

- Off-line control approaches
  - Deterministic optimization
  - Stochastic optimization
    - Robust optimization
    - Risk-based optimization
- Online model predictive control (online MPC)

  *alternative name:

  - Rolling horizon control-based methods
  - Deterministic optimization
  - Stochastic optimization
    - Robust optimization
    - Risk-based optimization

Considering the definitions given in [197], it can be said that they are coherent with those found in [95]. Both papers are focused on microgrid EMS optimization.

Moreover, it can be appreciated in [197] how the methods for handling uncertainties with stochastic (and probabilistic, when associated probabilities are considered) information can be mixed in the same problem formulation. In the referred paper, in the second proposed approach, the price uncertainty is treated by means of robust optimization, while the demand uncertainty is considered under a stochastic approach based on scenarios. Therefore, the methods of modelling uncertainties should not be considered as mutually exclusive categories, but as compatible tools that can be applied (and combined in the same problem) to handle those uncertainties that coexist in the system to be optimized. This same idea was appreciated in [191], where the authors dedicate sections specifically to discuss combinations of these methods.

It is said in [13] that some authors employ "an online approach called rolling horizon strategy to schedule energy storage devices and solve UC issues by using optimization methods based on two-day-ahead power forecasting results" [13]. This UC includes flexibility actions, as "a demand management mechanism was integrated to shift consumer's behaviour and maximize renewable energy utilization" [13]. According to [72], "the operation cost was minimized with the proposed UC-rolling horizon method compared with the conventional offline UC approach." Another example of its application can be found in [98], where a "rolling time horizon (RTH) EMS is used as benchmark solution."

Day-ahead optimization techniques act as the "base" of the management planning, being the rolling horizon information used to make adjustments to the original planning. This is done in [242], where "an artificial neural network (ANN) ensemble was developed to predict 24-h-ahead PV generation and 1-h-ahead wind power generation and load demand." A similar idea is proposed in [96], in which "a two-level decision architecture based on a MPC scheme is presented. The upper decision level has the function of fixing the values of a certain set of parameters (reference values), by assuming a certain structure of the control strategies to be applied at the lower decision level. On the basis of such parameters, each decision maker at the lower level solves its own optimization problem" [96].

This double optimization structure is particularly useful in those cases where there exist events that cannot be scheduled in a day-ahead procedure, which can be the case of forecasting errors (which are common in weather-dependent renewable generation systems, for example) or in the case of externally coordinated actions such as DR services. Moreover, it is possible to apply various hierarchical control levels with their respective optimization processes in those cases where it helps to solve the coordination between different systems, agents, or optimization objectives affecting to the same resources.

This distinction between the existing types of optimization is needed for the study of forecasting methods that will be introduced later in the present document. The structure of methods that will be followed in the present thesis will be as follows:

Optimal control methods for microgrids (proposed classification)

- Off-line control approaches
- Model predictive control (MPC) and rolling horizon
  - Deterministic MPC
  - Stochastic MPC
- Stochastic programming
  - Two-stage models
  - Multi-stage models
- Risk-based optimization
- Robust optimization
- Online optimization
- Dynamic programming
  - Stochastic dynamic programming (SDP)
  - Robust dynamic programming
  - Stochastic dual dynamic programming (SDDP)
- Other combinations of methods

It is not the objective of this proposed classification to create totally separated categories, but simply overviewing different approaches with some of the most common names that are used to designate them. As it as been previously remarked, some of these approaches can be coincident in some (or all) of their characteristics. The degree of similarity will depend on which decisions are taken for modelling the uncertainties and the behavior of the system under study, so reflecting these facts in a classification would result pointless due to the wide variety of methods that have been proposed by the researchers. These optimization approaches will be reviewed in the next sections.

3.2.2 Off-line control approaches

According to the definition given in [197], off-line control methods are those in which "control decisions are made ahead of time." These decisions will be based on the model of the system and the predicted demand and prices, but they are not adjusted in an online way, so those initial decisions resulting from the optimization do not take into account any update on the behavior of the system nor the uncertainties. The consequence of this lack of feedback from the real system is that the performance of these methods is limited [197].

The off-line control methods can be deterministic or stochastic, depending on how they include the uncertainties (as it has previously been explained). An example of a deterministic method can be found in [243], where the forecasted quantities for each time are expressed as points (not including probabilistic information). Regarding off-line stochastic control applied to EMSs, some examples are [242, 244] (cited by [197]).

3.2.3 Model predictive control and rolling horizon

The rolling horizon strategy is sometimes mentioned in the literature as part of the MPC approach, being then frequently called online MPC (as in [197]). The MPC method is "one of the most famous lookahead techniques" according to [95].

According to [245], "receding horizon control (RHC) or MPC is a form of feedback control system that first became popular in the 1980s." In RHC, it is solved "an optimization problem at each time step to determine a plan of action over a fixed time horizon, and then apply the first input from this plan" [245]. This is repeated at the next time step "solving a new optimization problem, with the time horizon shifted one step forward" [245]. In this way, it is possible to include realtime measurements or other information as feedback to estimate future uncertainties [245]. RHC is also applied in [74] for a case study focused on the Savona Campus (Università di Genova).

In other words, in an MPC, each step of the operation is performed according to the forecast on a certain horizon. Depending on the time step size, it can be used for higher or smaller time steps. Regarding smaller time steps, among all applications that can be implemented over a microgrid structure, one of them is the provision of frequency support and Volt/VAR control techniques, which can be possible using smart inverters under a MPC approach [246]. A smart inverter is a power device able to regulate the injection or absorption of active and reactive power between an AC grid and a DER (or a microgrid domain). These applications are particularly useful over weakly connected grids [246].

Many authors apply a rolling horizon as part of the UC, being this approach usually known as a rolling-horizon unit commitment (RHUC) [247]. While this last example is nearer to the point of view of the ISO, this strategy is still applicable to flow management in microgrids, taking into consideration the internal power interchanges between its elements, and the interchange with the external distribution grid. A more advanced version of the UC has appeared with the rising interest of probabilistic forecasting methods, which is called stochastic UC. This method introduces the uncertainties of the forecast, which can be obtained thanks to the probabilistic forecasting methods. This approach is followed in [248].

In [98], is is stated that "RTH, demonstrated very effective when the supporting prediction system performs well. However, it is featured by high operational times" [98]. This is due to the requirement of reexecuting the optimization problem frequently to update the next operative decision.

As it can be seen, there are not unified name criteria for these approaches, some authors preferring to explicitly refer to their proposals as "rolling horizon," or "receding horizon" techniques (as in [97]), while others prefer using the term "online MPC" in their papers.

Two time magnitudes must be defined for the application of a MPC technique, which are "optimization horizon" and "simulation horizon." The optimization horizon indicates the length of the time period that is considered in the optimization problem. The simulation horizon depends on the number of times the problem is run (how many times the problem is reexecuted to obtain a new schedule for the management).

The receding horizon technique solves the optimization problem for the whole optimization horizon, obtaining the scheduled actions for each considered time step during that horizon. The first obtained action is then applied to operate the microgrid. When a time period equal to the simulation horizon has passed, the optimization problem is reexecuted for the current moment using the new forecast information of the uncertainties, obtaining a new schedule for the optimization horizon, and again applying the first of the actions that have been obtained.

Therefore, this method has as an advantage permitting to update the information about the expected behavior of the microgrid elements (which can correspond to the forecast of the power generation and consumption, and even some other important information) when available, in this way reducing the uncertainties of expected renewable generation availability and load consumption.

Another example of an optimization with lookahead in the ambit of power systems can be seen in [249], where the authors apply it for scheduling of generators. One of the interesting points of this paper is that the authors “model practical constraints of the generation sources, such as ramping constraints and multiple generation sources” [249]. The authors refer to their proposal as an online optimization for the smart microgrid.

In this category, two main variants can be distinguished, which are the deterministic MPC and the stochastic MPC. These will be exposed next.

3.2.3.1 Deterministic MPC

Deterministic scheduling methods are covered by [95], in which they are referred as “deterministic MPC methods.” This controller solves “a sequence of multistage deterministic optimization problems over a fixed horizon H” mainly exploiting the forecast data [95]. In other words, deterministic MPC applies point forecast for expressing the values of uncertainties.

In [220], deterministic MPC is called CEC, in which the future uncertainties are replaced by a single scenario, which is a forecast. Therefore, the number of scenarios will be $S = 1$ and its probability will be $p_1 = 1$.

Another example of a deterministic MPC can be found in [97], where the optimal solution is derived by applying “an MPC control scheme based on the receding horizon technique” (as it is similarly done in [245]).

The main disadvantage of deterministic MPC is that it can only use point forecast to express the uncertainties, which limits the quality of information that can be included. However, the main advantage is its lower computational cost.

The MPC that considers the stochastic behavior of uncertainties is called stochastic MPC. This method will be reviewed next.

3.2.3.2 Stochastic MPC

With the rising interest of probabilistic forecasting methods, a more advanced version of the UC has appeared, which is called stochastic UC. This method introduces the uncertainties of the forecast, leveraging the probabilistic forecasting methods.

Stochastic MPC is one of the methods in the family of stochastic scheduling methods that are covered by [95]. It is called OLFC (“sometimes referred to as stochastic MPC” [95]), which suppose a modification on the deterministic MPC to allow the introduction of stochastic uncertainties.

In [220], OLFC is also called scenario based MPC. From this perspective, it can be said that the deterministic MPC method (or CEC) is a case of OLFC where a single scenario is considered.

3.2.4 Stochastic programming

In this family of methods, as they are stochastic, "uncertainty is added to a problem by modelling some of the problem's parameters as a (multi-dimensional) random variable ξ following a probability distribution $\mathcal{F}$ which is assumed to be known to the decision maker" [191].

The stochastic MPC method proposed in [95] that was reviewed in the previous section could be considered under this same category. However, the ways of considering the scenarios in the mathematical definition of the problem are in some cases different, so it has been preferred to keep them in different sections.

In stochastic programming, the probabilistic information of the uncertain parameter can be comprised in a deterministic value, which is called expectation $\mathbb{E}_{\xi\sim\mathcal{F}}[\cdot]$, which transform the objective function f to a deterministic version [191]:

$$\min_{x} \mathbb{E}_{\xi\sim\mathcal{F}}\left[f(x,\xi)\right]. \tag{3.5}$$

This approach follows a risk-neutral attitude. Therefore, other ways of considering risk measures can be applied, such as the mean-variance criterion, the value at risk (VaR) or the conditional value at risk (CVaR) [191]. Some of these will be later reviewed in Section §3.2.5.

The stochastic programming introduces the concept "recourse", which refers to "a partial decision that is to be fixed after uncertainty has been disclosed so that feasibility is ensured" [191]. This concept aims to consider the temporal relations that decisions and uncertainty observations have between them [191].

However, it has been observed in the literature that not all authors apply that definition of [191] strictly, but with some variations. For example, in [198] they do not consider a disclosure of uncertainties explicitly in the stochastic programming problem, but they consider a bunch of independent scenarios with their associated probabilities. This approach is very similar to that of the stochastic MPC in [95].

Therefore, attending to these facts, it can be said that, in a general sense, most mathematical programming methods that include stochastic information can be said to be "stochastic programming methods," including the previously exposed stochastic MPC method. An exception to this rule is the DP methods (based on solving the Bellman's equation), which are usually considered in a different category due to the particular approach that they follow.

The advantages of stochastic programming over deterministic approaches have been frequently signaled by researchers. In [198], it is said that "stochastic programming is more robust and even can support the network under higher level of uncertainties," which according to the authors justifies the higher planning cost of the stochastic approach when optimizing energy management in microgrids.

According to [191] and other papers, there are two types of stochastic programming methods, which are two-stage models and multi-stage models. For both types of problems, when they have very large dimensions, decomposition can be applied to approximate their solutions and make them tractable [250]. The methods that are applicable in the case of convex stochastic programming problems are "cutting plane methods, ND methods, regularized decomposition methods, trust region methods, augmented Lagrangian methods, and splitting methods" [250]. Further details about these can be found in the referred paper.

The basic characteristics of two-stage models and multi-stage models will be next described.

3.2.4.1 Two-stage models

Two-stage models constitute a way of putting in practice stochastic programming by considering two decision stages. The first-stage decision x_1 has to be taken before observing the uncertainty ξ. The second stage decision x_2 is taken considering the expected value of the cost function according to the different x_1 that could be chosen [191].

According to [102], for the application of two-stage models in UC, decisions should be divided into two categories, which are day-ahead decisions and real-time decisions. The model would therefore be:

$$\min_{u \in \mathbb{U}} \mathrm{c}^{\mathrm{T}}\mathrm{u} + E_{\xi}\left[F\left(\mathrm{u}, \xi\right)\right]. \tag{3.6}$$

Where the first stage corresponds to those commitment decisions of traditional units that cannot be turned on or off quickly in real time. The second stage (the "expected" expression E subject to ξ) is the expected cost of real-time operations, which can include those actions that can be made in real time. ξ corresponds to the uncertain vector with a known joint probability distribution [102].

For each realization, s, of the random vector ξ, the second-stage problem can be formulated as:

$$F(\mathrm{u}, s) = \min_{\mathrm{p}_s, \mathrm{f}_s} f(\mathrm{p}_s), \tag{3.7}$$

subject to the corresponding cost function. p_s includes dispatches and reserves of multiple periods and f_s is the vector of other second-stage decisions. f represents the fuel cost [102].

For this problem, ξ could follow a continuous probability distribution, but discrete simulated scenarios are often used for computational purposes. These different scenarios are not linked between them, but each of them is treated independently [102]. This is the main difference with multi-stage models, where these scenarios are not independent, but they are interconnected forming the shape of a tree.

Some methods that can be applied to solve two-stage problems are Benders Decomposition or Lagrangian relaxation (LR) [102].

The other approach to apply stochastic programming, which is using a multi-stage model, will be next exposed.

3.2.4.2 Multi-stage models

As it is said in [191], the two-stage stochastic programming can be generalized to more decision stages, obtaining the multi-stage stochastic programming. The details of how the mathematical generalization is performed can be found in the cited paper and will not be exposed in here.

According to [102], "multistage models attempt to capture the dynamics of unfolding uncertainties over time and adjust decisions dynamically." This approach is totally different to that of two-stage models, in which the uncertainty is treated statically.

In these models, "the successive information disclosure is formally captured by extending the random variable to a stochastic process $\xi_{[T]} := \{\xi_t \mid t = 1, \ldots, T\}$ where each observed element $\xi_t \sim \mathcal{F}_t$ of the process determines the parameters of the t-stage subproblem" [191].

However, the modelling of multi-stage uncertainty by means of a stochastic process cannot always be followed in practice, as it can lead to practically unsolvable problems (particularly in the case of continuous distributions $\mathcal{F}_t$) [191]. For this reason, some other approaches, such as the scenario tree, can be applied to make the problem easier to solve. This scenario tree can include a division in branches when certain decisions (or realizations of the uncertain information) produce a change in the state of the system.

This structure of the scenario tree, which can be sometimes difficult to handle in the optimization problem, can be changed to a structure more similar to that used in two-stage models. This idea is exposed in [191], where it is said that "the multi-stage stochastic program in Eq. (4) can be transformed to what is called the deterministic counterpart" [191].

To do so, "the deterministic counterpart ignores the information based on uncertainty evolution inherent to the scenario tree. Instead, each scenario is represented as an independent path in the tree leading to a *fan of scenarios*. This does not only lead to increased complexity as the number of decision variables increases but also requires the additional constraints" [191]. Scenario trees and the equivalent set of independent scenarios were previously described in Section §3.1.2.1.

While this procedure can reduce the complexity of the problem, it has to be taken into account that the dimensions of the problem "grow quickly in the number of stages and scenarios," and "the practical solvability of multi-stage stochastic programs is strongly delimited due to large dimensions," as it is indicated in [191]. Therefore, the number of stages and scenarios should be limited to a number that result appropriate for the problem without oversizing its dimensions. This is not a trivial task, as it is very dependent on the application and the problem to be optimized. According to [191], using the scenario tree structure to effectively minimize complexity is a topic that, to the authors' knowledge, is relatively unexplored.

An example of the application of multi-stage methods to a microgrid can be found in [248], where "a *stochastic programming UC* model has been proposed for the scheduling problem of a hybrid generation microgrid in isolated mode of operation." In the case of UC problems, some of the most extended methods are LR, augmented LR, and column generation [102].

The information of uncertainties can be introduced in an optimization problem under a risk perspective, instead of applying scenarios. This perspective will be reviewed in the next section.

3.2.5 Risk consideration

The reason for introducing risk consideration is that "most of the stochastic models minimize the total expected cost while satisfying all technical operating constraints under any possible scenario" [102]. This approach usually includes extremely rare events, which can lead to overconservative solutions that are very costly. Therefore, risk-averse models aim to restrict the risk exposure according to the level of risk that is considered acceptable [102]. These risk-aversion models are also frequently used in economics, but this concept has been extended to other ambits, such as power system and microgrid management.

Some papers such as [102] consider risk consideration inside the group of stochastic programming methods, as it can be applied to the uncertainties (or to some of them) to simplify the optimization problem.

The way of considering risk in an optimization problem is made by means of risk measures. Some of these risk measures for UC problems are expected load not served (ELNS), variance of the total profit, LOLP, and CVaR [102].

According to the definitions given in [197], the risk measure VaR, which is applied with a confidence level β, and therefore being β-VaR the smallest cost α (see mathematical definitions in [197]) such that the probability of losses above that level is at most $1 - \beta$. The problem with VaR is that it is not a coherent risk measure (because of its lack of convexity and subadditivity). To overcome these problems, the risk measure CVaR can be instead applied [197].

In this line, two methods are applied in [197]. The first one employs scenario-based minimization of CVaR of the cost considering the joint uncertainty in the electricity demand and prices. The disadvantage of this approach is the exponential growing of the number of scenarios in proportion to the number of uncertain parameters. The two uncertain parameters (demand and price) are both independent from each other, so the developed scenarios should include situations in which both of them can be independently variant, which bring a higher number of scenarios. For the second method, to simplify these scenarios, these are created exclusively with the uncertainty of net demand (considering a Gaussian uncertainty). The prices are assumed to vary within known bounds and they are handled by worst-case robust approach [197]. It can be appreciated how the second method in [197] mixes two ways of handling uncertainties.

The worst-case robust approach [197], also called “worst-case regret” [102], is a special case of risk measure which, according to some authors, “is shown to be a coherent risk measure” ([237], as cited in [102]). It is applied in robust optimization, which will be seen in detail in the next section.

3.2.6 Robust optimization

According to [191], robust optimization is a way to extend a mathematical program by an uncertainty model, like stochastic programming. As it is defined by the authors, “robust optimization generally optimizes the worst case in the sense of a guaranteed outcome under any possible realization” [191] of the uncertainties. Therefore, it follows “a fat solution approach where only solutions are considered that are feasible for any outcome” [191] of the problem with its uncertainties. The detailed mathematical formulation for robust optimization can be found in [191].

The differences between stochastic programming (which explicitly incorporates the probabilistic information of the uncertainties) and robust optimization have also been signaled by other authors. According to the definition given in [102], “in contrast to stochastic programming models, robust UC models try to incorporate uncertainty without the information of underlying probability distributions, and instead with only the range of the uncertainty.” Therefore, “this type of models produce very conservative solutions, but computationally it can avoid incorporating a large number of scenarios” [102]. Other authors also agree with the conservative tendency of the solutions that this method provide: “Not only does this approach ignore the temporal context, it is also very conservative” [191].

As it is explained in [102], despite the higher expected cost that can be produced due to these conservative solutions, this approach has another advantage (in addition to the lower computational cost). It provides “security against worst-case scenarios” [102] in exchange for this conservativeness.

The mathematical modelling of robust optimization, which can be found in [102], include the definition of the deterministic uncertainty set (a range or region) $\mathbb{V}$. In this sense, “the conservativeness of an optimal solution depends on how the uncertainty set $\mathbb{V}$ is defined” [102].

In [251], a robust optimization-based is proposed for the operation of energy storage in microgrids employing box and polyhedral uncertainty sets. The maximum and minimum limits of the uncertain net demand p_d are defined using box uncertainties around the predicted nominal demand [197]. Therefore, in [251], it is assumed that:

$$\bar{\mathrm{p}}_d - \Delta\bar{\mathrm{p}}_d = \mathrm{p}_d^{\min} \leq \mathrm{p}_d \leq \mathrm{p}_d^{\max} = \bar{\mathrm{p}}_d + \Delta\bar{\mathrm{p}}_d, \tag{3.8}$$

where $\bar{\mathrm{p}}_d$ is the estimation of net demand and $\Delta\bar{\mathrm{p}}_d$ the bounded error vector [251] for obtaining the worst cases.

To minimize the disadvantages of this robust approach, other authors have proposed variants of robust optimization to reduce the over-conservatism [197]. An example can be found in [252], where they propose the adjustable robust counterpart (ARC) of the optimization problem, which is significantly less conservative than the usual robust counterpart (RC). Moreover, to overcome the problems associated with the computation of ARC, they propose what they call affinely adjustable robust counterpart (AARC). In these methods, two types of variables are distinguished, which are non-adjustable (or "here and now") variables and adjustable (or "wait and see") variables [252].

Robust optimization can be applied to various uncertain parameters at the same time, as it is done in [253] to cover the uncertainties of price, generation of RESs, and loads.

3.2.7 Online optimization (as defined by H. Bakker)

The term "online" applied to optimization methods has previously been introduced. It referred to any method (or some of its steps) that is (or are) applied in real-time, which brings the capacity of adjusting the operating decisions according to the occurrence of the uncertainties.

This is the definition that is commonly found in optimization applied to power systems and microgrids. However, in papers that have a general scope (not focused exclusively on power systems, but overviewing applications of optimization techniques in general), a different definition of the term "online" can be found. To cover (or, at least, consider) the alternative uses of the term, the definition of online optimization given by H. Bakker et al. in [191] will be briefly exposed.

It is stated in the referred paper that "online optimization addresses sequential decision making where elements (or requests) σ_t of an input sequence $\sigma_{[T]} = (\sigma_1, \sigma_2, \ldots, \sigma_T)$ are presented sequentially and each element has to be processed by an irrevocable decision before the next element is revealed [254, 255]" [191].

According to the authors, this online optimization gives two new perspectives that are missing in mathematical programming. It "has its roots in computer science and is fundamentally different from stochastic programming and robust optimization which emanated from mathematical programming" [191]. As "no information is required on subsequent requests to make a decision at a certain stage" ("neither of probabilistic nor of set-based nature"), the complexity of the decision at a certain stage is not affected by the overall problem size [191]. Moreover, "online optimization is generally associated with problems that require quick, short-term decision making under a constant inflow of information [256]" [191].

As it can be seen, this definition widely differs from the one given in the previous sections of the present document. Additionally, considering that the definition given by [191] is not commonly used in the ambit of microgrids, it will not be used hereinafter in the present document.

3.2.8 Dynamic programming

The problem definition and the procedure to find the solution under the DP approach are described in [191]. According to the authors, in DP, "multi-stage optimization problems are modelled over a state-action space in which I_t is the set of possible states of the system at stage t and X_t represents the set of feasible actions (or decisions) that the decision maker may choose from" [191]. This type of model has already been previously mentioned in the present chapter, being it related with scenario trees.

In this type of model, it can be said that "a decision $x_t \in \mathcal{X}_t$ results in the transition from state $i_t \in I_t$ in stage t to state $i_{t+1} \in I_{t+1}$ in stage $t+1$" [191].

Once this modelling is done, "in the deterministic set-up the goal is to find a sequence of actions, a so-called policy, which maximizes the reward function $f_t\left(i_t\right)$ associated with the final stage state $t = T$" [191].

The solution "is found by iteratively solving the Bellman equations which recursively determine the optimal reward obtained through the optimal policy $x_1, \ldots, x_T$ where $g_t(x_t, i_t)$ is the immediate reward in state i_t if decision x_t is implemented" [191]. In this way, the mathematical formulation is [191]:

$$f_t(i_t) = \min_{x_t \in \mathcal{X}_t} \left\{ g_t\left(x_t, i_t\right) + f_{t+1}(i_{t+1}) \right\}. \tag{3.9}$$

As stated in [102], "since the classic approach for solving DPs is the backward induction approach, based on Bellman's Principle of Optimality [257], all the earlier works of DP-based problems suffer the curse of dimensionality." As the authors say, this means that the time to find the solution will grow exponentially with the number of states or variables [102].

According to [191], DP could be considered a solution method rather than a modelling method. However, those problems that are desired to be solved through DP are often formulated according to the requirements of this method, i.e., they put emphasis "on a state space variable and transition probabilities between states" [191]. For this reason, DP has been included in the present section, and it will also be mentioned again in Section §3.3 as one of the methods for solving optimization problems.

To overcome the computational difficulties of DP, new methods have been developed, giving place to the algorithms referred to as approximate dynamic programming (ADP). These ADP methods "can be classified as value function approximation, policy function approximation, and state-space approximation" [102].

In [191], the authors distinguish two variants of DP methods, which are the SDP (which is a general approach for modeling stochasticity in the problem) and the robust DP (which aims to simplify the problem by means of worst-case consideration of some of the uncertainties).

Other ways of simplifying the solving process of DP problems are SDP and ND [222], which can be classified as decomposition methods. Some of these variants of DP are briefly described next.

3.2.8.1 Stochastic dynamic programming

According to [95], the *SDP*, which applies (as it is stated in its name) DP for solving the problem of optimization considering multiple scenarios with their inherent probabilities of occurrence. These methods are considered as part of the family of cost-to-go methods, as for every step $t \in \{0, \ldots, T-1\}$, a reference single-stage stochastic optimization problem is solved, which depends on cost-to-go functions that are computed offline.

As said in [191], "in stochastic DP, the transitions between stages occur based on probabilities $p\left(i_{t+1} \mid x_t, i_t\right)$ which may be simultaneously state- and action-dependent." In a similar way than in other stochastic programming approaches, the optimal policy is based on the the expected reward function.

The concept of Markov chains is applicable in this area, so "problems solved with stochastic DP are often formalized by Markov decision processes [258]" [191]. To do so, it is required that "transition probabilities fulfill the Markov property, i.e., the transition probability of one state to another must only depend on the current state and action and not on previous states" [191]. In this way, as the authors state, it must be accomplished that:

$$p\left(i_{t+1}=i \mid i_t, i_{t-1}, \ldots, i_0\right)=p\left(i_{t+1}=i \mid i_t\right), \tag{3.10}$$

Another variant which aims to simplify DP problems is the robust DP, which will be now reviewed.

3.2.8.2 Robust dynamic programming

Robust DP consists on the application of robust Markov decision processes for extending classical Markov decision processes [191]. This can be done by "imposing parameter uncertainty with respect to state transition probabilities $p\left(i_{t+1} \mid x_t, i_t\right)$" [191]. In this way, "another layer of uncertainty (also called ambiguity) is used to robustify classical Markov decision processes" [191].

Further details on this method can be found in [191, 259, 260]. As an example, this method is applied for scheduling charging operations of EVs in [261].

3.2.8.3 Stochastic dual dynamic programming and nested decomposition

Some variants that are applicable in SDP to deal with some highly complex problems are SDDP and ND. Both SDDP and ND methods "underestimate the cost-to-go functions (resulting from DP) using iteratively refined piecewise linear functions, defined by cutting planes computed by solving linear programs in the so-called backward step" [222].

SDDP and ND are directly related with the stage-wise independent uncertainty modelling, which was previously explained in Section §3.1.2.1. That type of modelling considers that the uncertainties of each of the time stages of the problem are independent. The consideration of independence between stages results in a very high number of different scenarios.

Therefore, as "the dimensionality of the problem is large and DP is no longer an option," other methods are applied to tackle them, such as SDDP [232]. In the words of the authors of this paper: "The usual assumption of SDDP is that uncertainty is stage-wise independent, which is highly restrictive from a practical viewpoint. When possible, the usual remedy is to increase the state-space to account for some degree of dependency" [232].

To make a simplification of the problem, according to [191], "the decomposition method of SDDP relies on the generation of scenarios to approximate the recourse cost function in multi-stage settings using cutting planes [225, 226]" [191]. "Due to curse of dimensionality, ND is usually applied to multistage stochastic problems of moderate size (e.g., up to hundreds of scenarios)" [222]. It can be appreciated the importance that decomposition methods have to deal with those multi-stage problems in which the model of uncertainties implies a great number of scenarios, or a complex scenario tree. In these cases, and particularly in problems where the underlying stochastic process is stagewise independent, combining decomposition and sampling can be useful to handle large scenario trees [222].

The complete mathematical formulation of SDDP problems applied to stage-wise uncertainties can be found in [262]. It has not been included in detail in here, as it is not the objective of this thesis to dig into the mathematical formulation of optimization problem solving.

3.2.9 Other combinations of methods

Some other combinations of the described methods are reviewed in [191], such as online stochastic optimization, online and robust optimization, stochastic programming and robust optimization, SDP, and robust DP. These aims to combine the characteristics of various methodologies to adapt to certain problems and their involved uncertainties.

An example of method combination can be found in [263], where a "two-stage risk-constrained stochastic framework is proposed, which can optimally schedule a dependent micro-grid in both normal and emergency situations" [263] (activating the islanding mode). In this case, "predominant uncertainties such as loads, prices, wind, and unplanned islanding events are managed based on risk constraints" [263]. The authors adduce that, "in stochastic scheduling formulations, the significant drawback of discounting risk constraints is that scenarios with high probability of occurrence can impact the optimum result substantially" [263]. This means that "high impact low probability scenarios are approximately neglected in decision-making procedure. In order to overcome such impotent scheduling, a risk criterion is included in the mathematical formulations" [263].

Having exposed some of the main optimization methods that can be found in the literature, the next section will be focused on the existing methods for solving optimization problems.

3.3 Optimization solving methods

This section compiles some of the most popular optimization problem solving methods. In many cases, some specific problems could be solved applying various of these solving methods, i.e., a problem could be solved using various methodologies when they have some similar characteristics. Which of these solving methodologies could be applied depends on the type of decision variables (integer, continuous, etc.), the type of constraints and cost function (linear, nonlinear, etc.) and other characteristics of the problem (such as its complexity). For example, a nonlinear problem could be solved by some nonlinear solver, but if the complexity is very high, maybe these methods are not feasible, being only possible to solve it using some heuristics to reduce the computational cost.

However, there are at least two exceptions in this free relationship between the optimization method of the multi-stage problem (how the problem has been written including its different stages, cost functions, modelling of uncertainties, and restrictions) and the optimization solving methodology. These exceptions are stochastic programming and DP (which were both studied in Section §3.2).

The stochastic programming, in a general sense, intends to consider the stochasticity of some of the uncertainties (or all of them) in the optimization problem. Depending on how this stochasticity is handled, the formulations of the problem can be very different. If this formulation has been done, for example, using the deterministic counterpart of a bunch of scenarios, this formulation includes integer and continuous variables and the problem is linear, then this problem could be solved applying mixed integer nonlinear programming (MILP). If the formulation is done in another way, maybe other methodologies should be applied. Due to the variety of situations that stochastic programming can provide, it has been preferred to include it in the list of optimization solving methods.

In the case of DP, this concept refers at the same time to the strategy of the definition of the problem, and to the method for finding the solution. The DP assumes some facts for finding the solution, which explains why this concept covers the whole process to be applicable. It is said in [191] that "despite DP being a solution method rather than a modelling method, problems are often formulated specifically tailored towards DP putting emphasis on a state space variable and transition probabilities between states" [191]. For this reason, DP is included in the present section as one of the optimization solving methods that is commonly found in microgrid control literature.

Once made the previous clarifications, the classification of optimization solving methods that some authors have proposed in the literature will be reviewed. The objective is to identify which are the main families of methods, and propose a tree of methods considering as far as possible the diverse opinions of the authors that are reviewed. There is not uniform criteria on how the optimization solving methods should be classified (it is possible to find different approaches in this regard), so the proposal will intend to consider the different classifications and unify them.

In this regard, some authors consider two types of big groups of optimization techniques in the field of grid optimization planning, as in [264]. The first one is called "numerical", which includes techniques based on graphical and/or heuristic methods. The second one is called "mathematical" and includes a wide group of techniques, not including those heuristic nor graphical ones. According to this classification:

- **Numerical approaches**:

  As it is explained in [264], "the numerical approaches include design space approach, power pinch analysis (PoPA) variants, and hybrid approach." Among these, there are some graphical optimization methods, which include various techniques used due to their simplicity and flexibility to be adapted to some problems. This simplicity resides precisely in the absence (or at least, reduction) of the formalism to declare the problem characteristics and restrictions. In [265], these techniques are also classified as graphical and/or numerical.

  "Design space approach is a graphical analogue of complete solution enumeration method" which, when applied in DG optimization, illustrates all feasible design configurations with respect to performance metric for visual optimization [264]. It can be "upgraded to three-dimensional form for simultaneously sizing two renewable power generators" [264].

  PoPA approaches are "more suitable for power supply/demand matching and minimum outsourced electricity targeting, wherein power generator capacities have to be initially specified" [264]. A variant that aims to reduce this design rigidity is "electric system cascading analysis (ESCA) and stand-alone hybrid system power pinch analysis (SAHPPA)" [264]. PoPA can also be applied for economical purposes, such as "generator sizing and energy storage technology selection for achieving the shortest payback period" [264]. Some other variants of PoPA are "extended power pinch analysis (E-PoPA) and modified extended power pinch analysis (ME-PoPA)" [264].

An example of the use of these numerical techniques can be seen in [265], where design space and PoPA are applied to size the energy storage in a microgrid. It can be therefore appreciated that these numerical techniques have many applications in the power system ambit, especially in the tasks of design and sizing of systems.

- **Mathematical approaches**:

  The "mathematical approaches" include two types, which are conventional approaches (also called in [264] "conventional mathematical modelling optimisation techniques") and new (or modern) approaches (also called "modern mathematical modelling optimisation techniques" in [264]). Conventional approaches include "iterative approach, trade-off approach, linear programming (LP) and MILP" [264]. In those mixed integer problems that are not linear, the mixed integer nonlinear programming (MINLP) can be applied [266, 267]. For those problems that are non differentiable, non-differential programming are suitable [266, 268]. On the other hand, modern approaches include genetic algorithm (GA), self-organising hierarchical binary particle swarm optimisation (SOHBPSO), and meta particle swarm optimisation (MPSO) [264]. Additionally, some other methods (including some nature-inspired ones) are mentioned in [264, 269]. These will be included in the proposed tree of solving methods. Some methods that have been classified as "iterative approaches" are gradient descent algorithm, back-propagation algorithm (commonly used for training NNs), and Newton method.

Other authors use a totally different denomination to classify optimization methods than that used in [264], as it is done in [270]. In the last, the term "heuristic methods" is used to refer to those methods used when other mathematical optimizations cannot (or should not) be used due to the difficult or impossibility of finding a solution. As it is stated in [270], "in the last decade, many heuristic methods have evolved for solving optimization problems that were previously difficult or impossible to solve. These methods include simulated annealing (SA), tabu search (TS), GA, differential evolution (DE), evolutionary programming (EP), evolutionary strategy, ant colony optimization (ACO), and particle swarm optimization (PSO)." Other authors call them "soft computing techniques," as in [271].

Attending to the characteristics that the numerical methods [264] have, these could also be considered inside the family of heuristic methods. In this sense, in [272], the extended pinch analysis and design (ExPAnD), which is a variant of pinch analysis, is said to provide heuristic rules. However, to keep a clear division of these families of methods, it will be preferred to maintain numerical methods [264] and heuristic methods [270] separated in the schema of optimization solving methods that will be proposed at the end of this section.

Parametric programming (which has previously been mentioned) consists of solving an optimization problem introducing uncertainties as parameters. This method is applied in

[273] for solving the energy management of a microgrid, where the uncertainties of wind and solar production are introduced as parameters. This procedure results in a parametric mixed integer nonlinear programming (p-MILP). In this sense, parametric programming could be considered not only as a solving method, but also as a way of writing the optimization problem (which would fit into the category of optimization methods). However, taking into account that it particularly affects on the way the problem is solved, it has been preferred to include parametric programming as an element in the tree of solving methods.

There are several software tools for solving the referred optimization problems. Some of these will be mentioned next, as they have been commonly found in the literature:

- **CPLEX Optimization Studio**: It is "a commercial solver designed to tackle (among others) large scale (mixed integer) linear problems" [243]. This software program was developed by IBM [274].

- **YALMIP**: MATLAB toolbox that "can be used to model and solve optimization problems" [275]. It can be applied to solve semidefinite programming, linear matrix inequalities (LMIs), supports "LP, quadratic programming (QP), second order cone programming (SOCP), determinant maximization, mixed integer programming, posynomial geometric programming, semidefinite programs with bilinear matrix inequalities (BMI), and multiparametric linear and QP. To solve these problems, around 20 solvers can be interfaced" [275]. Many of these types of programming have been seen in the context of microgrid control, as the semidefinite programming ([276]), QP ([277]), and SOCP ([278]). Due to the long list of programming types, only some of these were included in the tree of solving methods.

- **Pyomo**: Python-based, open-source optimization modeling language. It can be used for modelling and solving diverse types of optimization problems, supporting a wide range of problem types such as LP, QP, nonlinear programming (NLP), etc. [279]. An example of its use in microgrid planning can be found in [280].

- **MiniZinc**: A free and open-source constraint modeling language. It can be used to model constraint satisfaction and optimization problems in a high-level, solver-independent way [281]. An example of its application in the ambit of traffic management can be seen in [282].

Considering the reviewed points of view that were found in the literature, a general schema of optimization solving methods has been developed here, which is depicted in Figure 3.6. The detailed schema of conventional mathematical methods can be seen in Figure 3.7, while the nature-inspired algorithms (belonging to the category of heuristic optimization methods) can be found in Figure 3.8.

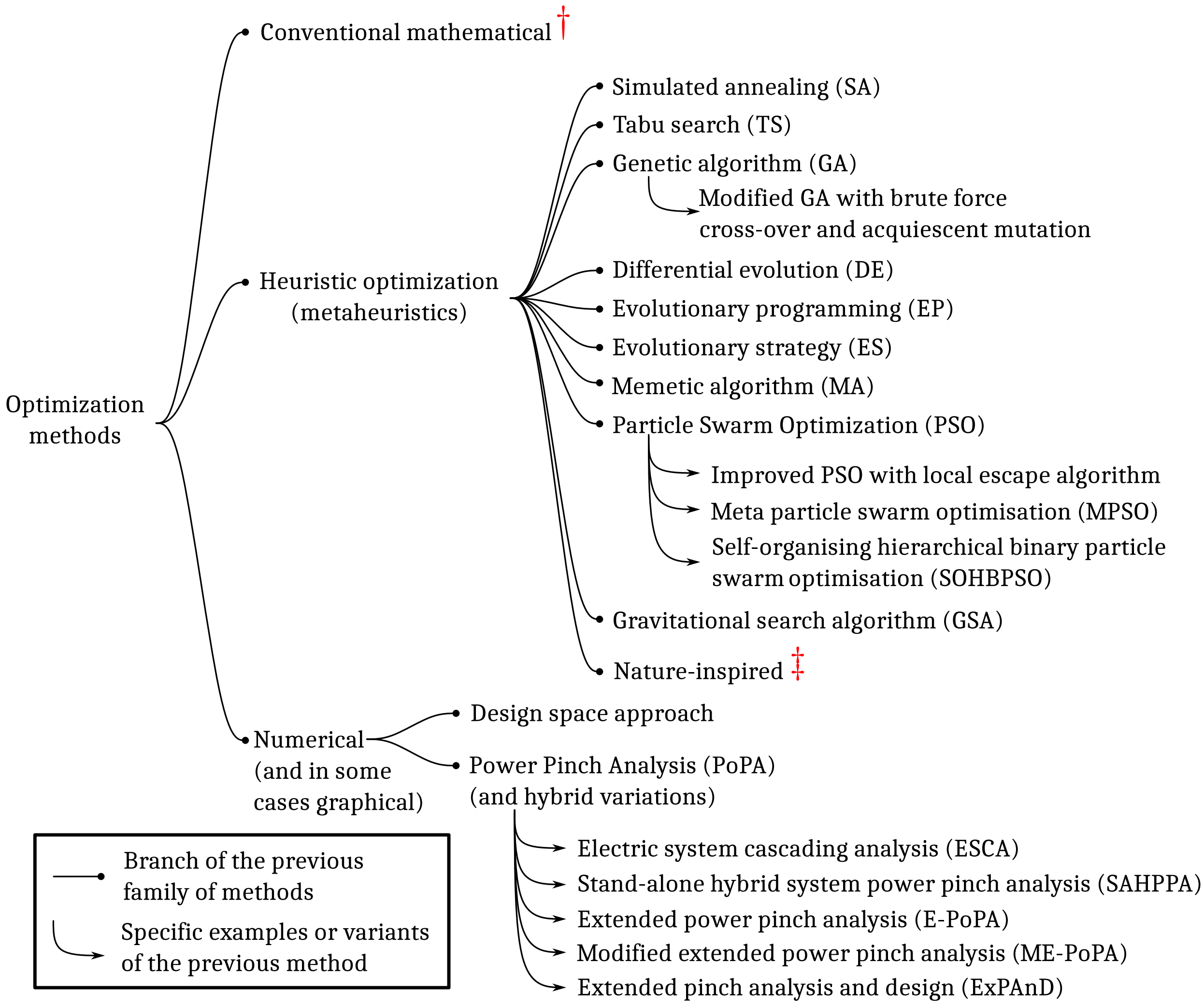


Figure 3.6: Optimization solving methods. † The family of conventional mathematic methods is broken down in Figure 3.7; ‡ The family of nature-inspired methods is broken down in Figure 3.8.

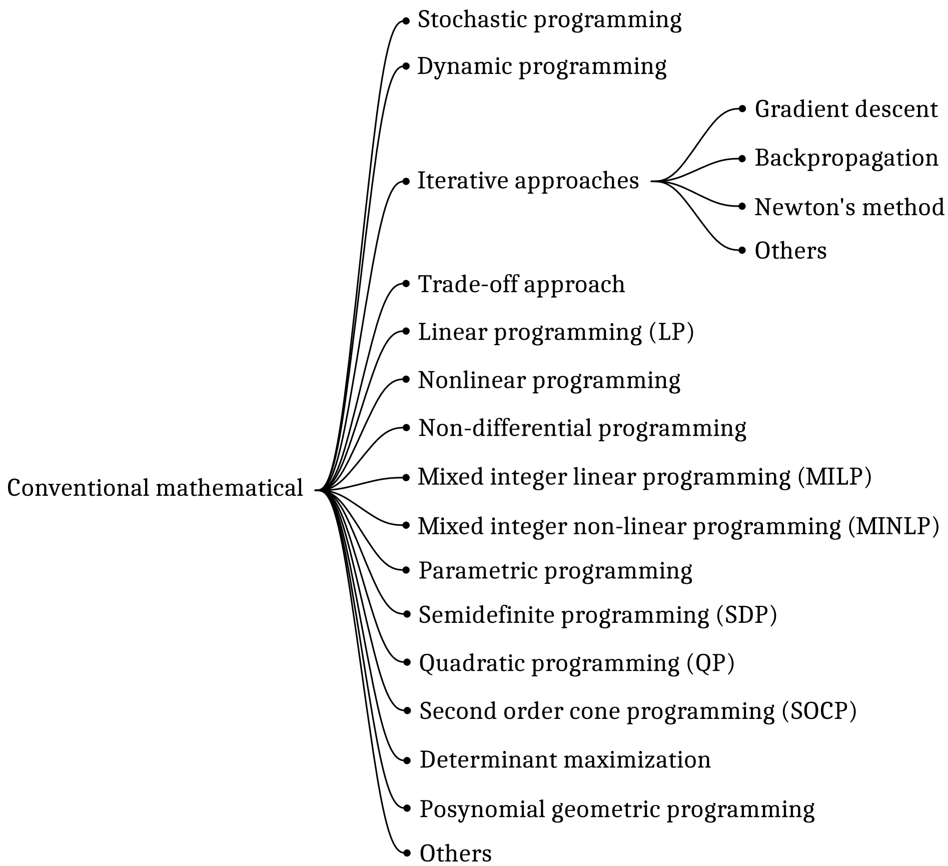


Figure 3.7: Conventional mathematical methods.

Up to this point, this chapter has been focused on the existing optimization methods for microgrid management and the methods to find their solution. Despite the wide variety of methods and variants, they have a common input information requisite, which is the estimation of uncertainties. These uncertainties usually are given in the form of points (deterministic forecast), scenarios, probabilities, and intervals (these last three can in many cases be based on probabilistic forecasts). Due to the importance of the forecasting procedures, the next section will be focused on the existing forecasting methodologies for obtaining the prediction of microgrid and power system uncertainties.

3.4 Forecasting applied to power systems

This section is focused on the study of forecasting techniques applied to microgrids and the power system. The role of forecasting in microgrid management was previously indicated in this document, and it was appreciated how the majority of optimization methods are precisely based on the prediction of one or various uncertainties in the microgrid. This

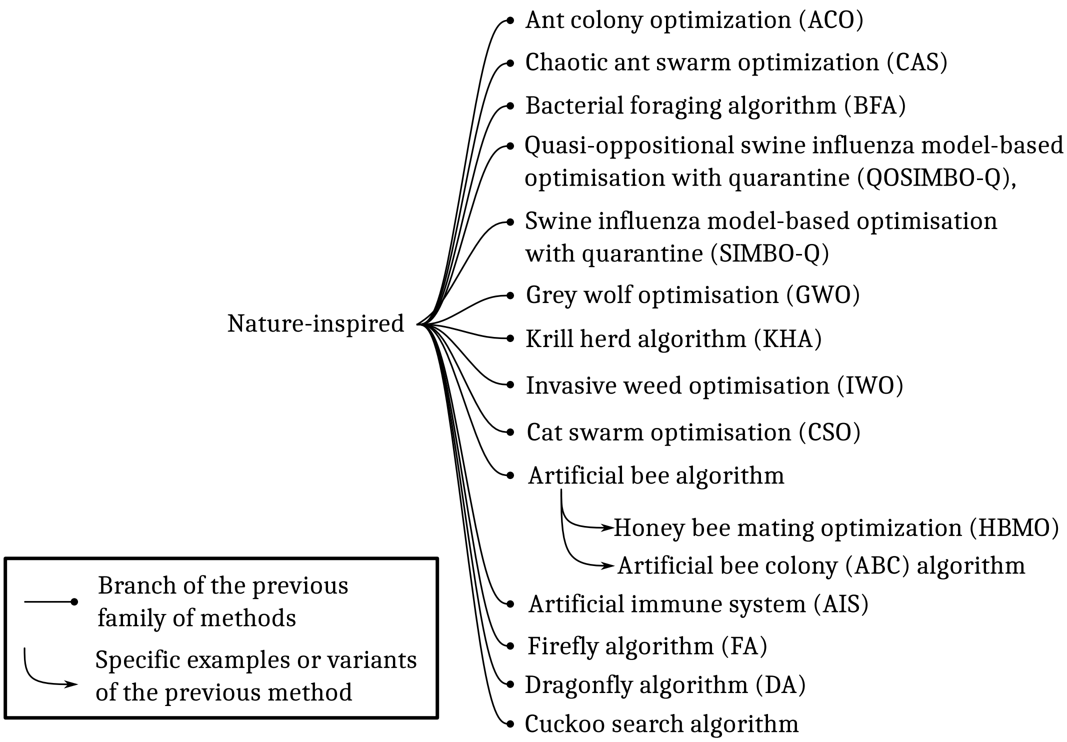


Figure 3.8: Nature-inspired optimization methods.

appreciation can be extended to the field of distribution network optimization (i.e., beyond the microgrid area), and to the rest of the power system levels. This does not mean that the same forecasting method works equally well in the whole range of network sizes and domains, as each method can show better results under specific situations and assumptions than in some others, and this is also dependent on the input information that each model uses. Therefore, the main purpose of this section is reviewing the state of the art of forecasting methods applied for microgrid-related optimal management.

The field of forecasting applied to microgrids (and, more generally, to the power system) is very extensive. The number of methods and techniques that are proposed grows day by day, and the researchers keep proposing numberless variants and combinations between them to reach adaptive solutions to the existing problems. For these reasons, some authors have worked on literature reviews with the aim of helping in their study, classifying numerous forecasting papers by technique, horizon of prediction, application, purpose, or some other criteria. Usually, these reviews do not only intend to show the general scope of the papers that are analyzed, but they also extract some recommendations or generalities on how the forecasting application should be oriented to improve their performance and how the data treatment should be done. Considering the usefulness of this information, one of the parts of the literature review that will be done in this thesis consists of a “meta-review”, i.e., a revision of papers that review forecasting methods.

Therefore, the literature review that is performed in the present section has a double purpose. The first one is obtaining a map of forecasting techniques that covers the typologies and variations that are commonly found in the literature. The second one is extracting recommendations and principles that should be considered in forecasting applications according to expert authors. This information will be then taken into consideration for studying the different proposals and case studies exposed in the next chapters of the present thesis.

To cover these contents, the present section will be structured as follows. The bibliographic analysis procedure is described in Section §3.4.1. Then, various metadata statistics extracted from the search are showed in Section §3.4.2. From these results, some selected documents are used to perform a bibliographic meta-review in Section §3.4.3. Finally, a tree of forecasting techniques is proposed in Section §3.4.4.

3.4.1 Bibliographic analysis procedure

This section describes the bibliographic analysis[1] procedure, being the main objective covering the forecasting application over microgrid. In this sense, performing an excessively specific search could result in biased results depending on the search terms that are used. This could be due to the relative novelty of the field of microgrids, in which the terminology suffers variations depending on the author's style and the year in which each paper was written. For this reason, the bibliographic search that will be exposed is not restricted to microgrid forecasting, but it covers the forecasting applied over the power system in general. From the global results obtained in that search, those papers focused on microgrids will be selected and reviewed in detail.

The preliminary considerations that were followed to design the procedure are next exposed in Section §3.4.1.1. The complete explanation of the procedure can be found in Section §3.4.1.2.

3.4.1.1 Preliminary considerations

Before establishing the procedure to be followed for the bibliographic search, it has been considered of interest to briefly analyze the papers of some authors that have performed similar massive searches focused in the same field of study, which are [283, 284, 285, 286]. The procedures that these authors followed in their respective papers for the bibliographic search in the selected databases are as follows:

- The first one to be mentioned is the paper [283] by C. Kuster et al., where they perform a critical systematic review about electrical load forecasting. This review follows a well-

[1] This analysis could also be called a systematic literature review (SLR), but it has been preferred to use the term bibliographic analysis in this document instead.

organized search process in the database Scopus, starting with some words to be found in the title, abstract, or keywords (referred in Scopus as a `TITLE-ABS-KEY` search). After that, the results are filtered by area (keeping only four of them), and another `TITLE-ABS-KEY` search is done using more specific words. Finally, the search is limited to those papers with the keywords "electric load forecasting" and "Energy demand". Despite the well-thought method that the authors propose, this last step could be considered quite restrictive, as it is limiting the results to specific exact keywords from the database. These keywords, which can be "author keywords (AKs)" or "indexed keywords (IKs)" (sometimes alternatively called "index keywords") in Scopus, despite being a common and easy way of describing the content of papers, have the problem of non-uniformity between different authors and editorials. There exist multiple variants of possible keywords to describe the same idea or concept, and therefore restricting a certain concept to only a possible writing form could result in the elimination of potentially enriching results from the search. For these reasons, in the search that will be performed in the present thesis, the filter of the search will not directly apply keyword filtering criteria, but regular expressions instead (as it will be exposed in detail later). Finally, it is remarkable that in [283] the authors do not apply any year-of-publication filter, which is commonly used in this kind of studies. Of course, its use is merely dependent on the objective that is sought and on the chosen approach, so its application is not considered indispensable.

- In [284], J. Runge et al. perform a review of the application of ANNs in energy use forecasting in buildings. It covers "papers published from January 2000 until January 2019, which were retrieved via Science Direct, Taylor and Francis, IEEE Xplore, ASHRAE Transactions, Journal of Building Performance Simulation Association, Proceedings of Building Simulation Conferences, and Google Scholar" [284]. The searches contain various terms, and papers are selected or not depending on their crossed appearance following some established criteria. As it can be observed in the description given by the authors, three phases are followed: data collection, data analysis, and discussion. Some graphs of the number of selected papers for each year of publication are also provided, which are considered helpful for the analysis of results. Despite the review covering multiple sources, many of these sources are already included in Scopus (which is one of the most extended bibliographic databases of scientific literature), so this single source could be considered sufficient for covering the fields under study. In this way, the search process would be simplified, as a single type of query would be used and mixing results from heterogeneous sources would not be required.

- S. Ahmad et al. [285] also use multiple sources to perform their compendium about various smart grid aspects, covering performance metrics, optimization, and DSM. Specifically, they use "major five search libraries including IEEE Xplore, ScienceDirect, Wiley Online Library, SpringerLink, and MDPI" [285]. In this regard, the same appreciation than in the previous paper can be done, i.e., that keeping Scopus as a common source to cover the majority (or at least the biggest part) of the material of these sources could be a way of simplifying the search.

- In [286], J. Nowotarski and R. Weron perform a bibliometric analysis on probabilistic forecasting applied to electricity prices, in which Web of Science (WoS) and Scopus are the chosen databases. The authors state that they keep more specialized queries for Scopus only, as "its search engine is more user-friendly and allows for more refined queries" [286]. They also explicitly comment that "since the collections of publications indexed by WoS and Scopus are not the same, the results do differ quantitatively, but the overall picture is similar" [286].

As it can be seen, various of these systematic reviews include more than one database source, which in some cases could be considered unnecessary having into account that the Scopus database already covers (or nearly covers) many of the other sources. Therefore, as it was previously said, it has been preferred to exclusively use Scopus in the literature review herein presented, in this way, achieving a regular format of queries and results and making easier their further analysis.

The Scopus searches exposed in [286], which are detailed in the explanatory footnotes of that paper, could be considered quite complex. These searches connect multiple concepts written in some different ways (e.g., "electricity market" and "electricity energy market"), covering most of the possible uses of each word or expression. In this way, they solve the problem that was previously signaled in the paper [283], where the search could be considered too restrictive because of keeping too short keyword searches (which can conduct to biased results). However, while the inclusion of multiple similar terms for the article search made in [286] is acceptable, it can be complex to perform modifications to these searches due to their intricate structure, which constitutes a disadvantage when the number of term variations increases.

Therefore, in the review method that is presented here, another approach is followed, aiming to overcome these disadvantages that were found in the previously analyzed literature reviews [283, 284, 285, 286]. This methodology includes a Scopus searching, downloading the metadata of the returned documents, and performing their analyses locally using tools such as regular expressions (also known as regexes, regex in singular). The reason to use regexes for the analysis is that they are much easier to use for the inclusion of similar terms and word variations in a unique text search than exclusively using Scopus searches [287].

Having analyzed the reviewing approaches of some authors and extracted various recommendations from them, the next section will describe the procedure that will be here followed for performing the bibliographic analysis.

3.4.1.2 Procedure description

The process of searching and filtering will be detailed here to ensure its repeatability, which could be of interest for performing updates or improvements on this bibliographic analysis in the future.

The whole reviewing process is depicted in the Figure 3.9. The description style of the searching process is partially based on those found in [283] and [284]. However, the analysis here presented includes additional steps that have not been found in the reviewed papers, such as a metadata analysis based on regular expressions and the proposal of a tree of forecasting techniques.

Despite the relative complexity of following a procedure like this for a literature review, it has been considered appropriate due to the nature of the field under study. As it is said in [173], "short-term load forecasting has been an active area of research for three decades," so "it would be difficult for researchers to follow even a fraction of the papers that are published each year" [173]. This fact can be extended to the whole forecasting on electric load and generation, especially with the popularity that microgrids are currently gaining in research ambits.

In the steps of the literature review, as they are detailed in Figure 3.9, two main parts can be distinguished, the database search (made in the online database platform) and the local analysis (executed in a personal computer). The database search comprised the search in Scopus and the downloading of the results in a *.csv* file[2] [288]. The local analysis comprised the steps to analyze the information retrieved from such *.csv* file. The steps of each of the parts are as follows:

- **Scopus search**: The review of the state of the art has been structured around online searches in the Scopus database platform, which is one of the most important and extensive bibliographic databases for scientific articles and conferences. These searches were performed on the day 5$^{\text{th}}$ November 2021. The process started with an extensive search under the terms "power", "load", "consumption", "forecasting", and "prediction". The search query, which returned 469031 results, is:

  *(*power* OR "*load consumption*" OR "*load forecast*" OR "*load predict*" OR *consumption*) AND (*predict* OR *forecast*) in TITLE-ABS-KEY*

  Then, an area filtering is applied. The search is restricted to "Engineering", "Energy", and "Computation" areas. The returned results are 245421 documents. This number is still too massive as to read and analyze each individual element, but it is still enriching from the point of view of their numbers and their most common keywords. Therefore, these results are downloaded in a *.csv* file [288], finishing the Scopus search phase. The

[2] This file is stored in the free repository Zenodo. It can be freely downloaded from: https://doi.org/10.5281/ZENODO.5825873

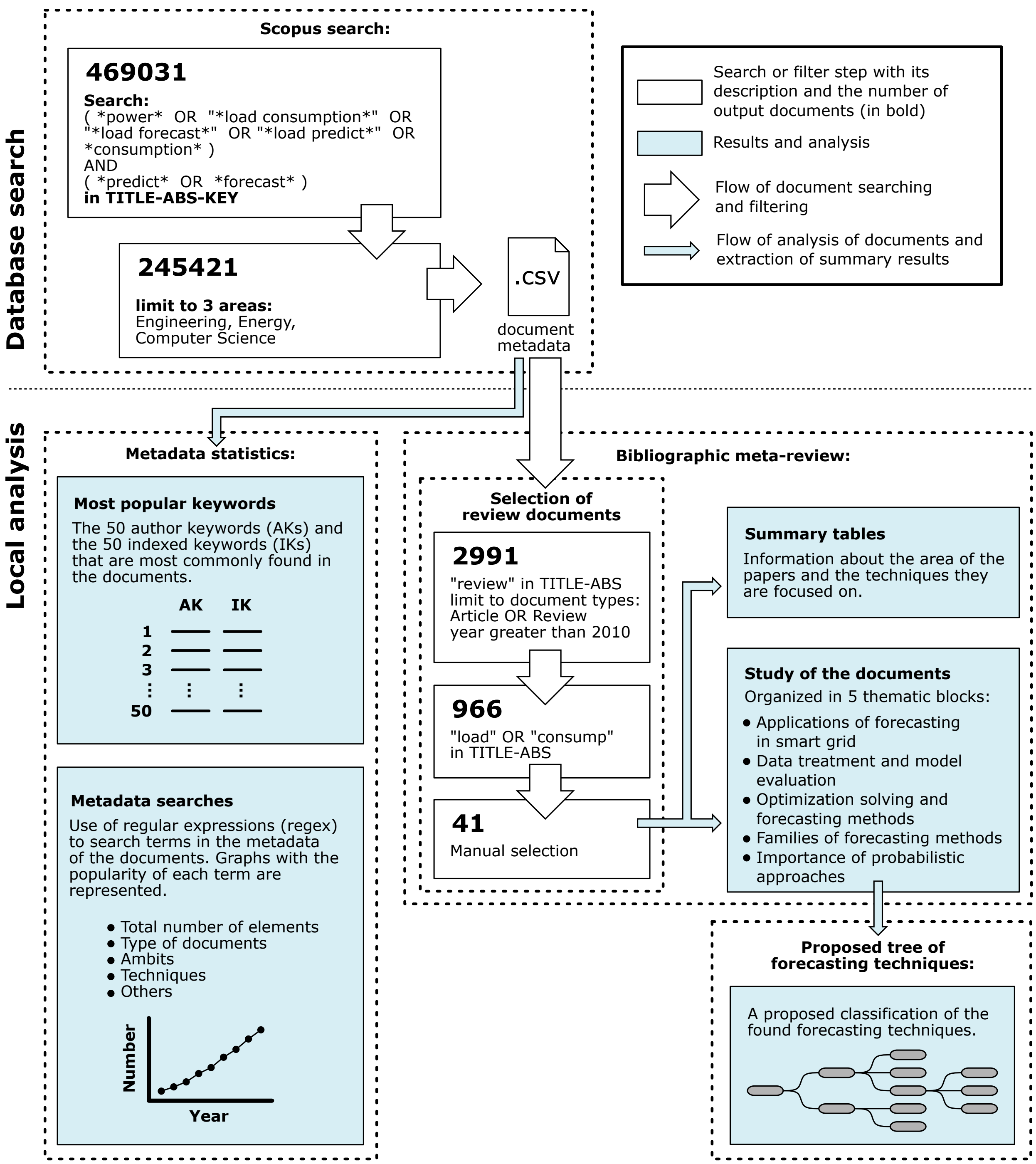


Figure 3.9: Methodology for the literature review on forecasting. The correspondence between blocks and sections is: Metadata statistics - Section §3.4.2; Most popular keywords - Section §3.4.2.1; Metadata searches - Section §3.4.2.2; Bibliographic meta-review - Section §3.4.3; Selection of review documents - Section §3.4.3.1; Summary tables - Section §3.4.3.2; Study of the documents - Section §3.4.3.3; Proposed tree of forecasting techniques - Section §3.4.4.

next steps, which are executed in a personal computer, belong to the phase of local analysis of the retrieved information.

- **Metadata statistics**: This step contains two different parts, the analysis of the most popular keywords and metadata searches. These are developed in Section §3.4.2.

  - **Keyword analysis**: Scopus keeps two types of keywords, those selected by the authors of the publication, called AKs, and those chosen by the content suppliers, called IKs (sometimes alternatively called index keywords). The IKs are standardized based on publicly available vocabularies and take into account synonyms, various spellings, and plurals, unlike AKs do [289]. This corresponds to Section §3.4.2.1.
  - **Metadata search**: The downloaded results contain various metadata fields about the papers, such as title, abstract, and keywords. Therefore, it is possible to apply regular expression (regex) searches to look for specific terms and filter these papers according to the desired content. This method will be used for checking the popularity of application areas, techniques, and other terms of interest, graphically representing the obtained results. This is made in Section §3.4.2.2.

- **Bibliographic meta-review**: The metadata search can be used to find papers focused on literature reviews with the objective of analyzing them to develop a meta-review. This procedure is developed in Section §3.4.3.

  - **Selection of review documents**: Some filters are applied to extract review-focused documents that will be analyzed. These are described in Section §3.4.3.1.
  - **Summary tables**: The review papers are analyzed to create summary tables giving an overview of their main characteristics and contents. These can be found in Section §3.4.3.2.
  - **Study of the documents**: The content and proposals of the review papers are briefly described grouping them by thematic blocks (including applications in smart grids, families of methods, and others). This corresponds to Section §3.4.3.3.

- **Proposed tree of forecasting techniques**: As it will be seen, in many papers, the authors propose their classification of forecasting methods in a very different way, being possible to appreciate even differences in the meaning of certain terms. To reach a certain unification on the use of these terms, a tree of forecasting techniques will be proposed according to the reviewed papers. This is done in Section §3.4.4.

Following the exposed procedure, the next section will expose the metadata statistics that were extracted from the retrieved search results.

3.4.2 Metadata statistics

The fields of the results (contained in a *.csv* file [288]) that was retrieved from Scopus can be easily analyzed for extracting some statistics. This information is of great help for understanding the main areas of the results, refine the search when needed (in case that some documents from an undesired area appeared in the results), and check which are the most popular terms that appears in the search.

The statistic extraction that is here proposed is divided into an analysis of the most popular keywords and metadata searches (made over titles and abstracts using regular expressions).

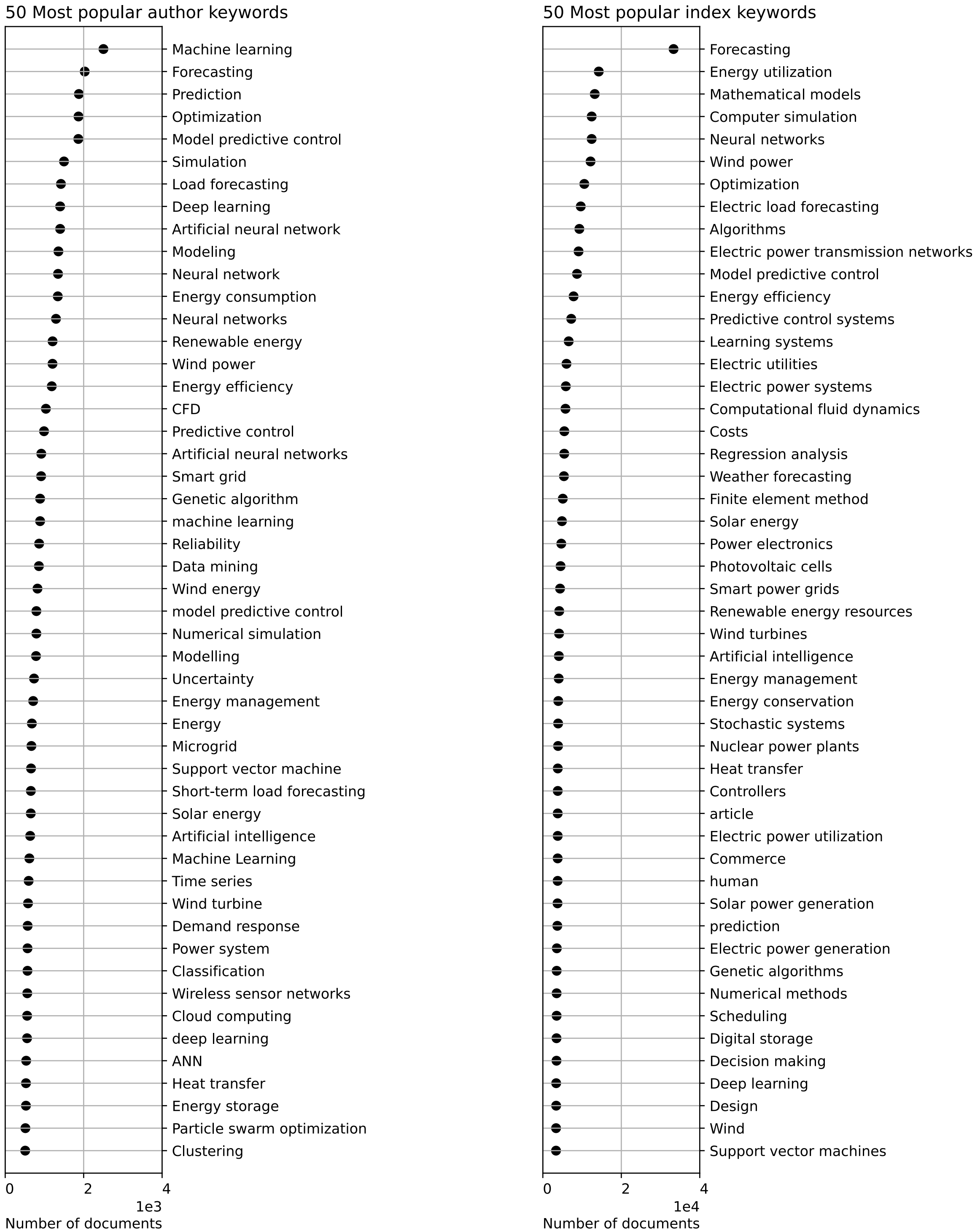
3.4.2.1 Most popular keywords

It is possible to extract statistics about the keywords from the metadata of the searched documents. The most popular 50 AKs and IKs can be seen in Figure 3.10.

The reason to treat the two types of keywords (AKs and IKs) separately during the analysis is the difference in their characteristics [289]. As can be seen, the AKs shows a preference on detailing the techniques applied, while most of the IKs describe the general ambit of the application of the documents in question. Nevertheless, even if the keywords can be very attractive due to their simplicity and descriptive capacity, they are still not considered as the most convenient ones for filtering. As it was previously mentioned, in [283], a keyword filter is introduced in the search process, which restricts the search to the keywords "electric load forecasting" and "Energy demand". The problem is that this type of search restriction could keep out some equivalent terms that other authors (or the indexation internally made by Scopus) could have written in another different way. This has been the reason for avoiding the use of keyword restrictions in the Scopus search that is proposed in this document.

This idea is supported by a simple overview of the most popular keywords of the search here described (not only the first 50, but even deeper in the two lists). In the two keyword lists, it is possible to find some equivalent terms, such as "Electric load forecasting", "Load forecasting" or "load forecasting". Therefore, strict keyword filtering (that only keep or discard by exact keyword coincidence) will be not used hereinafter recommended (unless it is unavoidable). Instead, the use of text search filters using regular expressions is preferred to include the consideration of slight variations in some words. These regular expressions can be used in the title, abstract, keywords, or some other available metadata fields.

These most popular keywords show some interesting results. Despite this search being focused on power and consumption forecasting, many optimization-related terms have appeared together with those forecasting-related terms. In particular, it is remarkable the frequent apparition of the term "model predictive control (MPC)" (and other similar terms such as predictive control systems). As it was previously observed, the MPC is one of the



(a) (b)

Figure 3.10: Most popular keywords. (a) Author keywords; (b) Index keywords.

most used optimization and control methods in microgrid management, and many forecasting models proposed by the authors are precisely oriented to be used in MPC. The keyword "uncertainty", whose importance was also previously studied, has also appeared in the list of most popular AKs. Finally, many other keywords related to forecasting methods (such as "artificial neural network (ANN)"), smart grid applications (such as "demand response (DR)"), and, less frequently, market-related concepts (such as "contract for difference (CFD)"). The strong relationship between forecasting and optimization can be here appreciated, in the same sense it was previously stressed in this document during the study of optimization methods.

The rest of the popular keywords (including more that those 50 for each category that have been included here), also contains more information about forecasting techniques, which will be of interest for developing the trees of the Section §3.4.4, so these have been considered during its construction. However, it has been preferred not to include more keywords in here to avoid the inclusion of lists that could result too long.

Having made a first analysis of the overall contents of the search results by means of the keywords, the next step will be to perform searches in the metadata of the results. This will be done next.

3.4.2.2 Metadata searches

The previous section analyzed the information of the keywords. However, the rest of metadata of the documents can also be analyzed. The main problem is that the use of various technical terms suffers in many cases from a lack of unification, in a similar way than it happens with the keywords. Many of the common words can be found written with slight variations due to singular/plural forms, hyphenation (or absence of hyphen) between words, or different word terminations. To overcome such problems, it has been preferred to use regular expressions (regex) for searching in the metadata, specifically in titles and abstracts.

Regular expressions constitute a powerful tool for describing text searches, specifying different cases, alternative forms, or even undefined structures that are not exactly known (as, for example, looking for a certain type or number of characters in a position of the text, without specifying which characters these are). The list of regex searches that have been applied for this analysis, which have been chosen according to the field under study, can be seen in Table 3.1.

For example, one of the searches of the list in which the advantages of using regex can be appreciated is:

$mpc|(model.?predictive.?control)$,

which searches for "model predictive control" including the apparition of the abbreviation "MPC", which are commonly used by the authors, and the complete name of the term, including the possible hyphenations that can be found between some of the words

Table 3.1: Regex searches and labels. Each list of searches constitute a group of searches that will be later represented in a same graph. The search labels serve as descriptors of the searches, and can include the term of the label and other related variations or acronyms, as seen in their corresponding regular expression. All the regular expressions has been applied without being case-sensitive.

List of searches	**Search label**	**Regular expression (regex)**
Types of documents	Review	*review*
	Survey	*survey*
	Comparison	*comparison*
	Case study	(*case.*?(*studies*|*study*)|*study.*?*case*)
Power system terms	Distribution	*distrib*
	Transmission	*transmis*
	Retail	*retail*
	Company	*compan*
	Utility	*utilit*
	Grid	*grid*
	Network	*network*
Services and management	Flexibility	*flexibility*
	Demand side management	*demand.?side.?management*
	Demand response	*demand.?response*
	Ancillary service	*ancillary.?service*
	Congestion management	*congestion.?management*
	Distributed energy resource	*distributed.?energy.?resource*
Control systems	Optimization	*optimiz*|*optimis*
	Control	*control*
	Energy management	*energymanagement*
	Model predictive control	*mpc*|(*model.?predictive.?control*)
	Unit commitment	*unit.?commit*
Techniques	Machine learning	*machine.?learning*
	Artificial intelligence	*artificial.?intelligence*
	Intelligent	*intelligent*
	Data mining	*data.?mining*
	Deep learning	*deep.?learning*
	Smart	*smart*
	Fuzzy	*fuzzy*
	Heuristic	*heuristic*
Time horizons	Long-term	*long.?term*
	Medium-term	(*medium*|*mid*).?*term*
	Short-term	*short.?term*(?!.?*memory*)
	Very-short-term	*very.?short.?term*(?!.?*memory*)
Approaches	Deterministic	*deterministic*
	Stochastic	*stochastic*
	Probabilistic	*probabili*
	Robust	*robust*
	Risk	*risk*

(some authors prefer to write "model predictive" while others write "model-predictive". The variation "model predictive controller" is also included in the search, as it would affect only to the end of the string. Moreover, this search (in the same way than all the others of Table 3.1) has been applied without activating the case-sensitive option, as some authors prefer capitalizing the first letter of each word while others do not. Making this same search without using regex could require a large number of parallel searches, each one including a specific way of writing the desired term, then making the procedure tedious and complex. For these reasons, regex searches were preferred instead of simple text searches.

The representation of the number of elements across the years (see Figure 3.11) shows a progressive increment in the number of publications related to the area under scope, passing from nearly 9000 documents published in the year 2010 to more than 20000 in the year 2020. The lesser number of elements in the year 2021 is due to the date when this search was performed, which was on the 5th November 2021, so the year had still not finished and therefore the total number of elements in this year is not available.

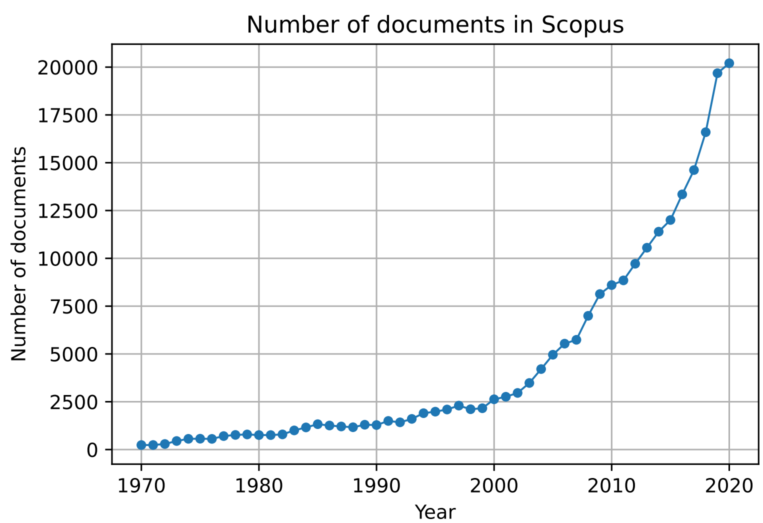


Figure 3.11: Number of documents based on the year of publication.

The regex searches in titles and abstracts give general information of the frequency of apparition of the chosen terms, so various groups of terms were searched (using regex) according to the Table 3.1 in order to obtain an overview of the results of the global search. Their results can be seen in Figure 3.12.

In Figure 3.12a it can be appreciated that the term "distribution" appears more frequently than "transmission" and some other terms relative to the utilities and companies. This goes in line with the rising interest that the management of distribution network and DG are receiving, which have exponentially increased the number of researches in this field.

The terms related to power system services can be seen in Figure 3.12b. The terms

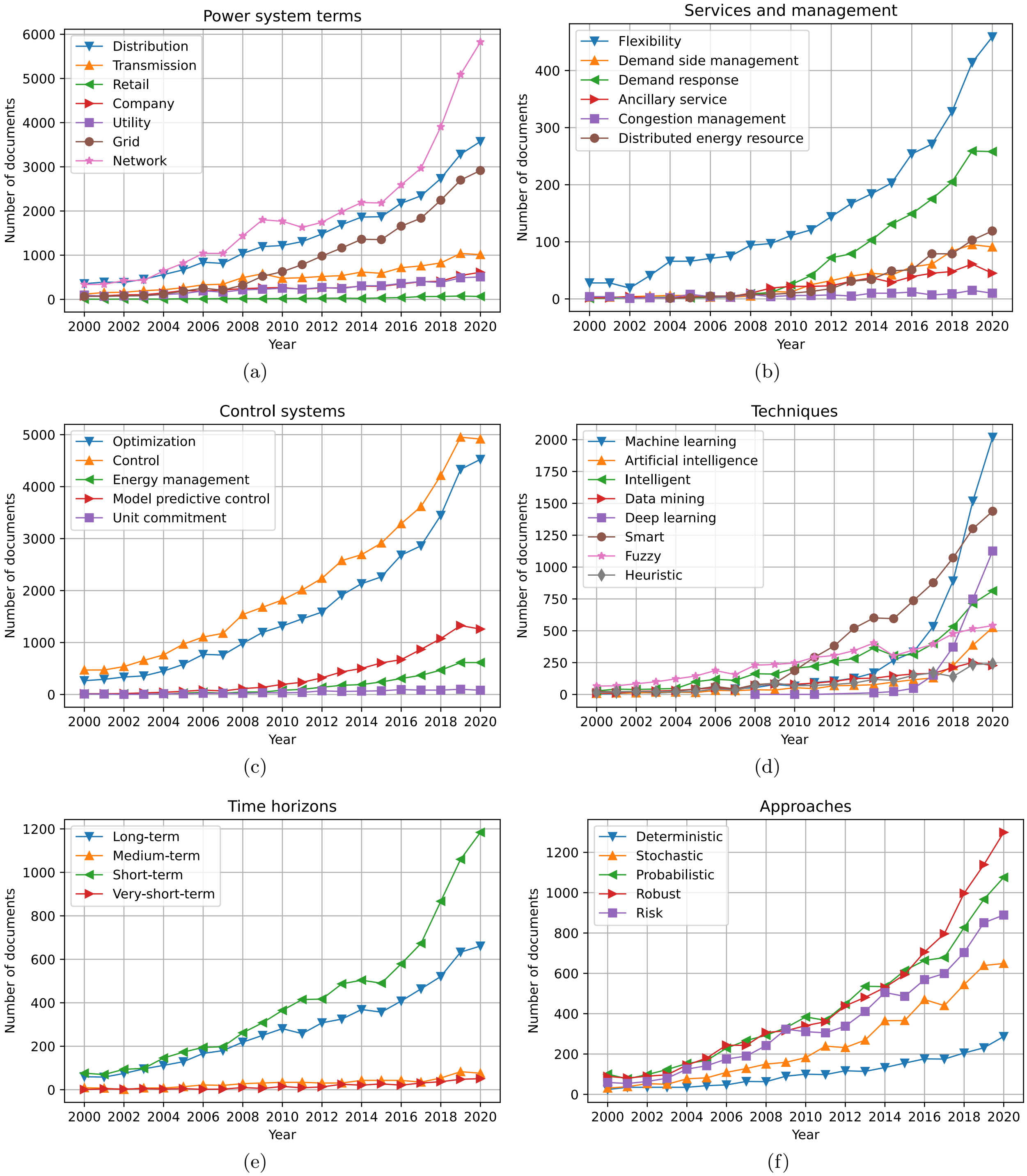


Figure 3.12: Number of documents containing specific terms in the title or abstract based on the year of publication. (a) Power system terms; (b) Services and management; (c) Control systems; (d) Techniques; (e) Time horizons; (f) Approaches.

"flexibility", "DR", and "DER" are more popular than "DSM", "ancillary service", and "congestion management". The reason for this is that, despite being DR a specific type of DSM action, the term "DR" is more widely used than "DSM". Moreover, the use of DERs and microgrids for providing flexibility actions (including the participation of customers) is currently attracting a lot of attention from companies, researchers, and legislators (as it was seen in Chapter §2), which explains the relatively high popularity of these terms. It can be observed that the terms "ancillary service" and "congestion management" show a much lesser frequency of apparitions in comparison to the others. One of the reasons of this could be that, in some papers of the literature, the authors describe proposals related with these two ambits that are included under the term "flexibility" (as it is done, for example, in [290, 291]), which increases even more the higher relative apparition of this term compared with the other two.

The list of the most popular keywords showed that many optimization-related and management-related terms have frequently appeared in the results, so various of these terms have been searched and their results represented in Figure 3.12c. The words "optimization" and "control" have appeared very frequently, showing the close relationship between forecasting and their application to perform optimization and control of systems.

It was previously mentioned that many of the keywords were about the techniques that are applied to perform forecasting (and in some cases, to perform optimization). Some of these terms can be seen in Figure 3.12d.

When using forecasting techniques, not only the technique itself is important, but also the time horizon in which the forecast is performed. In this regard, four types of time horizons have been searched, as seen in Figure 3.12e. It can be appreciated that "short-term" is the most frequently mentioned term, followed by "long-term", and by "medium-term" and "very-short-term" as the two lesser popular ones. The position of "short-term" was expected, as this is the typical horizon when managing microgrids, networks, and resources. The "long-term" is commonly applied in the field of power system planning [292], which is also related to the allocation of DERs considering their expected use and impact. The lower apparition of "very-short-term" (compared with "short-term") could be partially caused because some authors do not distinguish between "very-short-term" and "short-term", but they simply denominates these two under the name "short-term". An example of this can be seen in [293], where a one-hour-ahead forecast with five-minute intervals is performed. While this case could be considered "very-short-term", the authors simply describe it as "short-term" forecasting.

Finally, the last group of searches include various descriptors related to optimization methods, forecasting methods, and uncertainty modelling. These include "deterministic", "stochastic", "probabilistic", "robust", and "risk". In these results, it can be seen that "deterministic" was the lesser found term, which shows the importance of stochastic and probabilistic methods (in which robust and risk approaches are included).

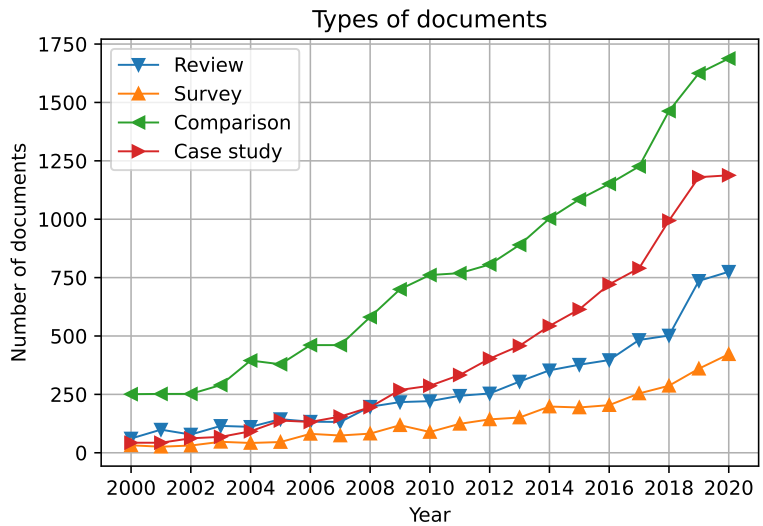


Figure 3.13: Number of documents of certain typologies.

It is also possible to search for a certain type of content and analyses of the documents, instead of searching for technical terms of the field (as it was previously done). The results of these document-type-related searches, which corresponds to the "types of documents", are represented in Figure 3.13. To illustrate the power of this type of search, the terms about document types that have been included in the graph are "review", "survey", "comparison", and "case study".

This search is related with the meta-review that will be performed, which is based on searching for those documents that make reviews on the field under study, so the search term "review" was applied to find this kind of documents (followed by some additional filtering, as it will be exposed). The objective is keeping some of the most interesting reviews in the ambit of load forecasting, being this the starting point for the analysis of the existing techniques and their organization in a tree. This meta-review shall be conducted in the next section.

3.4.3 Bibliographic meta-review

This section firstly describes how a number of documents containing reviews of forecasting (or forecasting-related) techniques and applications were selected (Section §3.4.3.1). These document will be later summarized in tables (Section §3.4.3.2), and their content will be analyzed in Section §3.4.3.3. These steps constitute a bibliographic meta-review that provides an overview on the use of forecasting in microgrids and power systems in general.

3.4.3.1 Selection of review documents

The selection of documents for the meta-review is done by searching for the word "review" in titles and abstracts using regex, and keeping only those from 2010 in advance. The number of documents is reduced to 2991. Then, the documents are filtered to those which contain the term load or consumption in their titles or abstract. In this way, the number of elements returned was 966. At this point, the number of remaining papers is low enough as to make possible a manual selection (by actually reading the abstract and content) among them. Specifically, among these 966, 41 papers are manually chosen for making a meta-review (a review of review papers).

The reason for performing this final selection of papers manually is that, in spite of the filters that have been applied, some of the 966 papers are not actually focused of reviews, but they simply make a brief review to complement the proposals of the authors (as a consequence of this, the word "review" may appear in their abstract), so these do not fit with the type of papers that are searched here. In other cases, the fields of the paper are not totally coincident with those of interest for the present meta-review, so these have been discarded. Due to the importance of this paper selection, and the complexity of doing so by using automatic filters, it was preferred to do it manually instead of automatically. While it would have been possible to add more documents by applying the described method, it has been considered that these 41 documents sufficiently cover the thematic under the scope of this meta-review, so it was preferred not to add more additional documents to these. Therefore, there are finally 41 of them.

The in-deep reading of these 41 elements reflects that they are all related to forecasting. Some of them are focused on the application of forecasting to complement some other tasks [270], as it could be the case of those papers that use forecasting for optimizing of grid management, market participation, or frequency adjustment. Some others are more focused on the forecasting itself [294], making the analysis of the existing techniques, their adequate use, or even the comparison of their prediction errors. Finally, a minority of papers are focused on very specific aspects, such as recommendations on the treatment of data, or the selection of adequate data sources [295].

The review papers that have been found in the proposed search provide a broad vision of the global problem and details about recommendations that should be taken into account when performing forecasting applications in the ambit of the power system. In the next section, a first review of these selected papers is done by means of summary tables.

3.4.3.2 Summary tables

The number of documents that will be analyzed in detail is 41. To get a first overview on their content and make easier their analysis, their domains and scope are listed in Table 3.2. This table also includes information such as the ambit of their approach, the year of publication, and the number of references that they include.

In this sense, the term "domain" has been used here to specify which level (of the power system) these papers are focused on. The categories are "*market*" (focused on price forecasting or optimal market participation), "*grid operation*" (upper levels of the power system), "*microgrids*", "*buildings*" (while these can be treated usually in the same way as microgrids, the buildings have some special characteristics, so they have been considered separately in here), and "*DSM or DR*" (for those about applications for DSM and DR and their implementation). The term "*scope*" has been used to differentiate between the two main types of papers that were found during this analysis, those about forecasting, and those that expose optimization methods for energy management and operation (which depend on the forecast for their execution). In this sense, it can be appreciated that most of them are focused on forecasting techniques (26), some of them analyze optimization methods (6), and a few of them treat both fields together (7).

Considering the the variety of forecasting approaches that the selected papers analyze, some of their main characteristics have been classified in the Table 3.3 according to the fields "*variable to predict*" (where it can be distinguished between load, generation, or others such as energy prices) and "*time horizon*" (short- and very-short-term, mid-term and long-term). In the statistical summary at the end of the table, it can be appreciated that short- and very-short-term approaches are more common than mid-term and long-term. A possible reason for this fact is the high popularity that optimal control of power systems has gained in recent years. As it has already been analyzed in this document, the application of optimal energy management methods in microgrids and power networks requires predicting the involved uncertainties in short- and very-short term. The mid-term and long-term predictions are more frequently applied in system planning, which is a field that is lesser represented in the search of this review than the field of management of microgrids and networks.

Table 3.2: Domain and scope of the review papers that have been analyzed.

Author and year	Ref.	Domain					Scope		Number of references
		Market	Grid operat.	Microgrids	Buildings	DSM or DR	Optim.	Forec. tech.	
Suganthi & Samuel (2012)	[296]	–	■	–	–	■	–	■	364
Huang et al. (2012)	[270]	■	■	–	–	■	■	■	81
Zhou et al. (2013)	[297]	–	■	■	–	–	–	■	73
Raza & Khosravi (2015)	[298]	–	–	■	■	–	–	■	128
Fagiani et al. (2015)	[299]	–	■	–	–	–	–	■	50
Ren et al. (2016)	[172]	■	■	–	–	–	–	■	37
Khan et al. (2016a)	[266]	–	–	■	–	■	■	–	186
Khuntia et al. (2016)	[294]	–	–	–	–	–	–	■	107
Khan et al. (2016b)	[300]	■	■	■	–	■	–	■	101
Shankar et al. (2017)	[271]	–	■	–	–	–	■	–	574
Theo et al. (2017)	[264]	–	■	–	–	–	■	■	360
Kuster et al. (2017)	[283]	–	■	■	■	–	–	■	74
Yildiz et al. (2017a)	[12]	–	■	–	■	■	■	■	156
Yildiz et al. (2017b)	[301]	–	–	–	■	–	–	■	68
Shao et al. (2017)	[302]	–	–	–	–	–	–	■	192
Deb et al. (2017)	[160]	–	–	–	■	–	–	■	216
Mat Daut et al. (2017)	[159]	–	–	–	■	–	–	■	100
Ren et al. (2017)	[23]	■	■	–	–	–	–	–	42
Agueera-Perez et al. (2018)	[295]	–	–	■	–	–	–	■	106
Carvallo et al. (2018)	[292]	–	■	–	–	–	–	■	40
Shepero et al. (2018)	[303]	–	■	–	–	–	■	–	214
Debnath & Mourshed (2018)	[304]	■	■	–	–	–	–	■	517
Ma & Ma (2018)	[13]	–	–	■	–	–	■	■	50
Ahmad et al. (2018a)	[51]	■	■	–	–	■	■	–	168
Chou & Tran (2018)	[305]	–	–	–	■	–	–	■	97
Ahmad et al. (2018b)	[285]	■	–	–	■	–	–	■	236
Fallah et al. (2018)	[306]	–	–	■	■	–	–	■	105
Nowotarski & Weron (2018)	[286]	■	–	–	–	–	–	■	124
Meer et al. (2018)	[307]	–	–	–	■	–	–	■	140
Bourdeau et al. (2019)	[308]	–	–	–	■	–	–	■	173
Liu et al. (2019)	[309]	–	–	–	■	–	–	■	151

Table 3.2: *(continued)*

Author and year	**Ref.**	**Domain**					**Scope**		**Number of references**
		Market	**Grid operat.**	**Microgrids**	**Buildings**	**DSM or DR**	**Optim.**	**Forec. tech.**	
Moharm (2019)	[310]	–	–	■	–	–	■	■	185
Glavic (2019)	[311]	–	■	–	–	–	■	–	117
Ellahi et al. (2019)	[312]	■	■	–	–	–	■	■	125
Runge & Zmeureanu (2019)	[284]	–	–	–	■	–	–	■	136
Croonenbroeck & Stadtmann (2019)	[313]	–	–	–	–	–	–	■	49
Wang et al. (2019)	[314]	–	■	–	■	–	–	■	216
Ozcanli et al. (2020)	[315]	–	■	–	–	–	■	■	134
Bukar et al. (2020)	[316]	–	–	■	–	–	■	–	58
Kalimoldayev et al. (2020)	[317]	■	■	–	–	–	–	■	45
Groppi et al. (2021)	[318]	–	■	■	–	■	–	–	109
Total number		10	21	11	14	7	13	33	
%		24%	51%	27%	34%	17%	32%	80%	

List of abbreviations:

Ref.: reference

Grid operat.: grid operation

Optim.: optimization

Forec. tech.: forecasting techniques

Table 3.3: Objectives and characteristics of the predicted variables in the review papers focused on forecasting.

Author and year	Ref.	Forec. tech.	Variable to predict			Time horizon			Number of references
			Load	Gen.	Others (prices)	Short and very short term	Mid term	Long term	
Suganthi & Samuel (2012)	[296]	■	■	–	■	–	–	–	364
Huang et al. (2012)	[270]	■	■	■	■	■	■	■	81
Zhou et al. (2013)	[297]	■	■	–	–	■	–	–	73
Raza & Khosravi (2015)	[298]	■	■	–	–	■	■	■	128
Fagiani et al. (2015)	[299]	■	■	–	–	–	–	–	50
Ren et al. (2016)	[172]	■	■	–	–	■	–	–	37
Khan et al. (2016a)	[266]	–	–	–	–	–	–	–	186
Khuntia et al. (2016)	[294]	■	■	–	–	–	■	■	107
Khan et al. (2016b)	[300]	■	■	–	■	■	■	■	101
Shankar et al. (2017)	[271]	–	–	–	–	–	–	–	574
Theo et al. (2017)	[264]	■	■	■	–	–	–	–	360
Kuster et al. (2017)	[283]	■	■	■	–	■	■	■	74
Yildiz et al. (2017a)	[12]	■	■	–	–	–	–	–	156
Yildiz et al. (2017b)	[301]	■	■	–	–	■	–	–	68
Shao et al. (2017)	[302]	■	■	–	–	■	■	■	192
Deb et al. (2017)	[160]	■	■	–	–	–	–	–	216
Mat Daut et al. (2017)	[159]	■	■	–	–	–	–	–	100
Ren et al. (2017)	[23]	–	–	–	–	–	–	–	42
Agueera-Perez et al. (2018)	[295]	■	■	■	–	■	■	■	106
Carvallo et al. (2018)	[292]	■	■	–	–	–	–	■	40
Shepero et al. (2018)	[303]	–	–	–	–	–	–	–	214
Debnath & Mourshed (2018)	[304]	■	■	■	■	■	■	■	517
Ma & Ma (2018)	[13]	■	■	■	–	–	–	–	50
Ahmad et al. (2018a)	[51]	–	–	–	–	–	–	–	168
Chou & Tran (2018)	[305]	■	■	–	–	■	–	–	97
Ahmad et al. (2018b)	[285]	■	■	–	–	■	■	■	236
Fallah et al. (2018)	[306]	■	■	–	–	■	■	■	105
Nowotarski & Weron (2018)	[286]	■	–	–	■	■	■	■	124
Meer et al. (2018)	[307]	■	■	■	–	■	–	–	140

(continued on next page)

Table 3.3: *(continued)*

Author and year	**Ref.**	**Forec. tech.**	**Variable to predict**			**Time horizon**			**Number of references**
			Load	**Gen.**	**Others (prices)**	**Short and very short term**	**Mid term**	**Long term**	
Bourdeau et al. (2019)	[308]	■	■	–	–	–	–	–	173
Liu et al. (2019)	[309]	■	■	–	–	■	–	■	151
Moharm (2019)	[310]	■	■	■	–	■	–	–	185
Glavic (2019)	[311]	–	–	–	–	–	–	–	117
Ellahi et al. (2019)	[312]	■	–	■	–	■	–	–	125
Runge & Zmeureanu (2019)	[284]	■	■	–	–	■	■	■	136
Croonenbroeck & Stadtmann (2019)	[313]	■	–	■	–	■	–	–	49
Wang et al. (2019)	[314]	■	■	–	–	■	–	–	216
Ozcanli et al. (2020)	[315]	■	■	■	–	■	–	–	134
Bukar et al. (2020)	[316]	–	–	–	–	–	–	–	58
Kalimoldayev et al. (2020)	[317]	■	■	–	–	–	–	–	45
Groppi et al. (2021)	[318]	–	–	–	–	–	–	–	109
Total number		33	30	11	5	22	12	14	
%		80%	73%	27%	12%	54%	29%	34%	

List of abbreviations:

Ref.: reference

Forec. tech.: forecasting techniques

Gen.: generation

Having obtained a first overview of the group of selected papers, the next section shall analyze them with more detail grouping them in thematic blocks.

3.4.3.3 Study of the documents

In this section, a review of the papers that were chosen for this meta-review is performed. Their contents have been grouped in thematic blocks to show the main areas of interest that have been identified, such as the applications of forecasting in smart grid, families of techniques including deterministic and stochastic/probabilistic approaches, etc.

3.4.3.3.1 Applications of forecasting in smart grid

Most of the reviewed papers, in addition to the study of forecasting and optimization techniques, treat some of the direct applications that these techniques have over the smart grid.

As it was previously pointed out, the capability of forecasting is frequently necessary for adequately performing multiple tasks in the power system, as it is the case of energy management in microgrids, network operation, or implementation of flexibility services. Among the types of modelling that can be done for prediction, it can be said that the historical data constitute a valuable material for the developing of high-quality models. With the new advances in computational analysis, the data has become more important than ever, so many improvements have been done with respect to collecting data from the smart grid, as, for example, the deployment of AMI that is currently taking place in many countries. The existing forecasting techniques are applicable not only in electricity ambits, but also in other types of supplying such as gas and water grids [299].

In the case of smart grids, the advantages of AMI deployment affect not only to the process of energy billing, but also to other related applications that can be done thanks to the data acquisition by smart meters, such as forecasting. Different applications are reviewed in [12], covering forecasting, clustering, and optimization in home energy management systems (HEMSs) (which corresponds to an EMS that covers the domain of a single home), load profiling, demand management and DR. It is also exposed that, despite all the advantages that household data availability brings, there are also security issues and privacy concerns that should be considered. The occupancy profile can give information about when the proprietaries are out of the house, and this information could be used by criminals. Therefore, a system that treats sensitive information should assure the security of the data, particularly in those procedures that imply communication of information about customers (as it could happen during coordination between different actors of the power system).

The applications based on smart meter data analytic are reviewed in [314], where they are classified in load analysis, load forecasting, load management, connection verification, outage management, data compression, and data privacy. Again, the importance of security and privacy of data is mentioned.

In [310], it is stated that the data gathered from microgrids are increasing in size and complexity. Considering that traditional data processing methods cannot handle amounts of data of high volume, the application of big data becomes necessary in many cases, especially in those microgrids that include a high number of elements.

With respect to the different objective functions that can be considered for microgrid optimization, a review is done in [266], showing the different ones that can be found in the literature. Moreover, the existing tools and approaches are exposed. While the majority of objective functions that are included are deterministic (they do not include probabilities), there are some of them that are probabilistic (include the probability of each considered scenario), specifically those that are included in [319] (cited by [266]). The importance of forecasting in the exposed optimization methods is frequently pointed out, as the good performance of the decisions made by the optimization method depends on the quality of the forecast.

Some reviews that are focused on the study of load forecasting methods in smart energy management grids are, for example [306], which mention various methods for classification and regression to perform "intelligent load forecasting (ILF)."

The importance of energy modelling for demand forecasting is stated in [296], including a review of the existing types of model. Considering the input information, the authors include the econometric models and input-output models as independent categories, despite being these two more related to the information they use than the model technique. They also provide various examples for bottom-up models, which are "the integrated MARKAL–EFOM system" (TIMES G5) and long-range energy alternatives planning system (LEAP).

The time horizon that is required for a certain application should always be considered, as the characteristics of the forecasting problems change a lot between horizons. In the review of methods for forecasting of building consumption made in [309] it is said that "long-term predictive results are easily affected by the uncertainties" [309], which make the prediction more difficult compared with short-term. It can be said that long-term forecasting supposes a very different problem than the short-term and mid-term forecast, and therefore many authors apply different input information and techniques for each of them.

Precisely, another task of great importance inside the power system is the load frequency control (LFC). As it is defined in [271], LFC mechanisms are used to modify generation or consumption levels with the objective of keeping the frequency of the system within desired limits. The details and problems of LFC, and the different control techniques and optimization methods that are applicable are reviewed in [271]. It is interesting to note how this article, even when is totally focused on LFC, still points out the relationship of LFC with the presence of microgrids and the convenience of forecasting techniques application. A group of techniques that are called "soft computing-based" are also reviewed in this paper, being some examples (with zoology and biology-based names) firefly algorithm, bacterial foraging optimization, artificial bee colony or bat-inspired algorithms.

The forecast is also a key element for the application of flexibility services. This can include the forecast of generation (for those customers that have any generation unit) and the load forecasting (LF). In this sense, in [300] the authors state that “future smart grids will utilize LF and dynamic pricing based techniques for effective DSM.”

It was previously mentioned that flexibility and DSM techniques have a special importance in those networks where there are weak connections or a high risk of power lack and congestion. These situations are frequent in zones such as islands, for example. Considering the importance of facing these problems, [318] presents a review of energy storage and DSM solutions that are applied in energy islands around the world. Its interest resides in the key role that storage plays in those microgrids that emphasize the capacity of working off-grid, as it is precisely the case of energy islands. Even in those microgrids that work connected to the grid most of the time, the storage units are still tools of high value, as they permit energy management procedures that would be impossible without such units.

In the survey [51], the authors “deduced that an efficient DSM scheme can optimize the consumer energy consumption through six different perspectives, i.e., electricity bill reduction, social welfare maximization, peak hour demand reduction, generation cost minimization, demand curve flattening, and maximization of consumer satisfaction” [51]. They also state that DSM schemes can be affected by the unpredictable and uncertain nature of renewable DERs [51].

It has been frequently mentioned here the importance of microgrid management, DSM, and DR as tools to provide flexibility to the power system. However, it shall not be ignored the importance of a correct planning by the power system operator regarding the expected generation. This task becomes particularly difficult with the inclusion of renewables such as PV and wind, due to their intermittency. The aspects of forecasting of these kinds of generation are reviewed in [312], including methods for their optimal dispatch.

Many papers propose the inclusion of renewable generation by means of coordination with EVs. The reason for these proposals is that it combines the battery charge of the EVs with the unpredictable character of renewable generation, permitting to surpass their respective disadvantages (the high peaks of consumption of vehicles and the difficult of prediction of the generation). In this line, [303] review the existing modeling techniques and the synergies between PV generation and EVs.

In the field of microgrid energy management, [316] contains a review on metaheuristic methods for the optimum planning of grid-independent microgrids, which has not been commonly seen in other papers. Unlike other papers that have been mentioned until now, this one is focused on long-term planning of microgrids. Its objective is not the short-term operation, but the design of sustainable energy systems (SESs) that are able to work independently from the main grid.

The role of forecasting is also key in the higher levels of operation of the power system, being used for performing the UC and for the calculation of reserves that are required.

In this regard, [23] makes a comparison between the types of operating reserves in some power markets of the world: Chile, United States of America, and Germany. It exposes how the kinds of reserve can be three or five according to the market criteria. North America distinguishes 5 main categories, while European markets uses only 3 types. The processes implied in the market adjustment and UC are also described in rich detail, including the importance of prediction. Most markets tend to use a deterministic forecast for the prevision of load, except in the case of Germany, that applies a probabilistic approach [23].

In many markets, the planning is usually done with 24 hours or 48 hours of margin, and the minimum time of response for tertiary (and sometimes secondary) reserves is of 15 minutes. In Germany, the power needs for the next 15 minutes are estimated based on the consumption during the previous hour [23].

In [294], the forecast of load in mid-term and long-term horizons is reviewed, emphasizing that these approaches constitute a very different problem than short-term forecasts.

The paper [292] discusses the long-term load forecasting accuracy in the context of electric utility integrated resource planning (IRP). The authors state that “most forecasts from early 2000s overestimated energy and peak demand growth” and that “utilities with higher share of industrial customers present less accurate forecasts” [292].

In the ambit of transmission networks, the paper [317] presents a review of statistical and AI methods, and a study case over real data from the United States wholesale transmission organization to test the described methods. As it is stated here, “the empirical analysis proves the extreme importance of clean high-frequency long statistics for high accuracy forecasts of energy consumption” [317].

3.4.3.3.2 Data treatment and model evaluation

In [313] various principles that should be considered in forecasting papers are recommended. Particularly, the authors make emphasis on the importance of performing a correct evaluation of the proposed models and compare their performance with some benchmark model (also called by other authors “reference model”). Various recommendations on how the results should be presented are given for both deterministic and stochastic/probabilistic forecasting. The examples that the author presents for their recommendations are extracted from wind generation forecasting, but the exposed principles can be extended also to load forecasting.

The paper [283] mentions the data preprocessing, proposing a certain procedure for its performance: “(1) smoothing and filling missing values, (2) measurement of variables dependency and significance, (3) data decomposition and classification and (4) check order of integration and stationarity” [283]. The most widely spread mathematical and statistical tools “are principal component analysis (PCA), which uses principles to transform a number of possibly correlated variables into a smaller number of variables called principal components, Pearson correlation coefficient (PCC) which show the interdependency of sets of variables, p-value that is used for testing a statistical hypothesis, analysis of variance (ANOVA), kernel density estimation (KDE) which is a non-parametric density estimator and canonical correspondence analysis (CCA)" [283]. This preprocessing procedure is one of the possibilities, being possible to find other different ones in other documents of the literature (as for example [320]).

The paper [295] contains recommendations for the use of weather data in microgrid-related forecast. One of them is precisely using real forecast data for modelling, not any other synthetic one, considering that "real forecasts provide the real context in which microgrid strategies and results should be validated" [295]. On the other hand, "synthetic forecasts generated by introducing some stochasticity in historical series lead to a simplified and more predictable problem" [295].

Similarly, the use of weather forecast is also mentioned in [264], which is a compendium of the existing branches of optimization techniques applicable for the planning of the power system, reviewing their use and pointing out their advantages and problems. Weather characterization and prediction are also discussed here for its application to DG sources such as solar, wind, or tidal. About the meteorological data, two main different approaches are employed for solar and wind energy availability assessment, namely "empirical meteorological data measurement and meteorological data forecast [321]" [264].

Finally, regarding the evaluation of models, the authors in [295] point out the importance of using well-defined indicators for the error metric. "One of the main problems in comparing forecast results from different microgrid studies is the absence of standardization of error metrics. This ambiguity is particularly noticeable in the normalized estimates – such as normalized mean average error (nMAE) or normalized root mean average error (nRMSE)" [295]. In this sense, a discussion on the existing indicators will be performed in the present thesis in Section §3.5.5.

3.4.3.3.3 Optimization solving and forecasting models

Along the present chapter, the optimization methods were mainly mentioned regarding their use in power system applications, especially in microgrid management. However, the optimization methods also find place in forecasting models.

This idea can be appreciated in [270]. This paper reviews a number of heuristic optimization methods for its application over the power system. Despite it is specifically focused on one of these methods (SA), it makes a review of some others and the different tasks where they are proposed to be applied. The hybrid use of annealing and other heuristic methods is also reviewed. As the authors states, "many kinds of combinational optimization problems arise in the planning and operation of power systems. The generation and transmission expansion planning, generator maintenance scheduling and UC, reactive power planning, load forecasting, and economic dispatch, and distribution systems planning and operation are typical problems” [270] (see Figure 3.14).

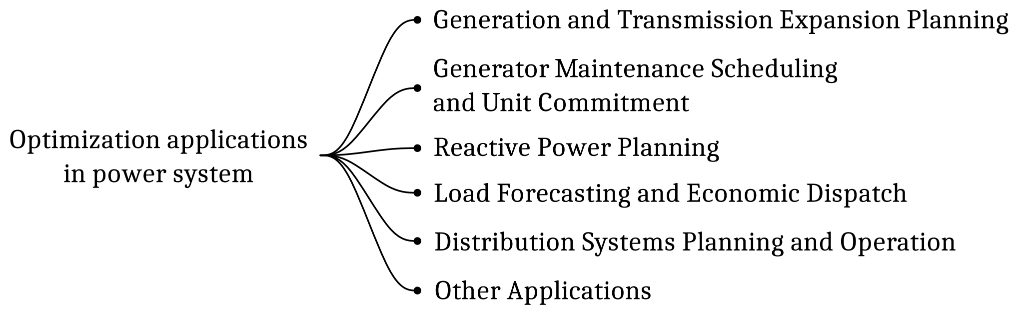


Figure 3.14: Optimization applications in power systems.

Therefore, in the context of optimization methods that are studied in [270], the forecasting is not treated only as a functionality required for performing other applications over the power system. It can be appreciated that forecasting is considered a field of the power system in which optimization methods (heuristics and others) can be applied to optimize forecast models. A conclusion that can be extracted from here is that the optimization solving methods that were mentioned in Section §3.3 are also applicable when developing forecasting models. This fact could be easily missed during the literature reviews, considering that many papers in this field usually apply the word “optimization” to refer to the final application for which the forecast models have been designed.

As they affirm, these heuristic methods are of great interest as “they may find a global optimum; they can produce a number of alternative solutions; no mathematical restrictions on the problem formulation exist, and they are relatively easy to program and numerically robust” [270]. This explains the popularity of these methods, which can be frequently mentioned across the reviewed literature.

It is remarkable that in [296] the authors have considered ACO and PSO as forecasting techniques, despite being these two heuristics for optimization (that can be applied to some forecasting models that require parameter adjustment). In the techniques classification that is developed in the present thesis, it has been preferred to consider heuristic optimization techniques as complementary methods for forecasting, instead of being forecasting techniques by themselves.

3.4.3.3.4 Families of forecasting methods

Regarding generation and load modelling, it can be said that there are two main types of techniques for creating models, regression (whose models are known as regressors) and classification (whose models are known as classifiers). On the one hand, regression techniques are those whose outcome is a continuous number. On the other hand, classification techniques are able to classify elements in categories (which can be previously established, or automatically created by the algorithm according to certain parameters).

For example, a regression is able to predict how much the power generation or load consumption will be during a certain future period. A classification can be of application for categorizing a bunch of customers according to their consumption profile, which can make easier the operation of the network according to these profiles.

In this sense, the importance of classification applied to electric loads is pointed out in [297], where the authors review the existing methods. According to this paper, the applications of load classification include “bad data identification and correction, load forecasting and tariff setting.” The methods for clustering will be not covered in the present thesis, as these are out of its scope. Instead, the focus will be on regression methods, which are those that can provide continuous numbers as results. However, it is pointed out the importance that classification methods have in the management and optimization of electrical networks, especially in those with a high number of customers where the application of clustering can enormously simplify their modelling and study.

A review of how different forecasting and/or optimization techniques can be combined to improve the global forecasting performance is performed in [305]. The authors distinguish between ensemble methods, in which various forecasting models are created and are after combined as voting (the results given by the individual models are considered together to vote the global result) or by means of bagging (training of each model with different training sets), and hybrid models, which are defined by the authors as the introduction of some optimization method for the improvement of a forecasting model (for example, using PSO to choose the hyperparameters of an ANN model, which is call a PSO-ANN model).

Inside the widely variated and colored different classifications that different researchers do to group prediction methods, in [159] two groups are considered, conventional methods and artificial intelligent methods. These authors point out the advantages of hybrid methods, which “have the potential to give better results in terms of accuracy when compared to the conventional methods,” as they combine the advantages of conventional and AI approaches (e.g., a regression model and PSO), or even two AI methods together (e.g., ANN model and PSO) [159].

The methodologies based on decomposition applied to forecast are reviewed in [302]. These are classified in component model-based decomposition and frequency domain analysis-based decomposition.

The category of hybrid methods, in a more general sense, can include any other model that mixes two methods together (even if none of them is a heuristic optimization method). In this way, according to [13], “the hybrid system is to integrate one or more algorithms to pursue a higher forecasting accuracy.” An example of an hybrid model is the adaptive neural fuzzy inference system (ANFIS) [13].

As it can be appreciated, both papers [305, 159] agree in what a hybrid method is. In this sense, one of the methods applied in this hybridation usually is a heuristic/AI optimisation algorithm that is applied to optimize the adjustment of a forecasting method. A compendium of heuristic optimization algorithms can be found in the present thesis in Section §3.3. Many of these heuristics can also be considered as AI-methods.

In [300], the methods are divided into statistical-based modeling (models that are represented by a mathematical equation) and AI-based modeling (which include expert systems, grey systems, ANNs, and fuzzy logic). Other authors refer to these statistical models as time-series models (as many of the equation models include information about the time evolution of the variable to be forecasted) or as traditional approaches (a term usually applied to those that are not based on AI).

A well-structured classification of the techniques is exposed in [304], showing multiple examples of each of the types, as well as a brief explanation of each of them. The techniques are divided in three big groups, statistical methods, computational intelligence methods, and mathematical programming. Some techniques included in the category "statistical" are regression analysis, univariate time series methods, multivariate time series methods, autoregressive conditional heteroscedasticity (ARCH) methods, autoregressive distributed lag (ARDL), log-linear analysis (LA), geometric progression (GP), transcendental logarithmic (Translog), polynomial curve model (PCM), partial adjustment model (PAM), and ANOVA. The category "computational intelligence" contains ML methods, knowledge-based methods, uncertainty methods (fuzzy logic and grey prediction methods), and metaheuristic methods. Mathematical programming includes methods such as NLP.

Regarding deterministic methods, an extensive summary of the different forecasting approaches can be found in [283], where the authors review different electrical load forecasting methods and analyze their convenience according to the time aggregation, the time required for forecasting and the most convenient type of data used as input. In particular, the analysis covers 113 different case studies reported across 41 academic papers. The different methods are categorized as "regression" methods, "bottom-up" approaches, "ANNs", "support vector machines", "time series analysis" methods, and other techniques used in mid-term fore-casting. Additionally, several tables and graphs are provided to show the situations in which these methods are most popular.

Regression and ML models for forecasting applied to buildings are reviewed in [301]. Moreover, a comparison of methods is done based on the consumption data of the Kensington Campus and Tyree Energy Technologies Building at the University of New South Wales. Their results indicate that ML models outperform regression models, but the authors estate that regression methods are more easy to understand by the users, so these permit a higher level of engagement than those "black-box models" that are usually obtained using ML methods. This observation goes in line with the requirements that could be convenient to accomplish for the inclusion of users in DR programs, so it will be taken into account in the next chapter of the present doctoral thesis during the proposals that are made about forecasting methods.

ANN are one of the most used techniques in the field of artificial intelligence applications. ANNs try to emulate the structure of the human brain [308]. They are composed by a set of elements called "neurons". Each of them is composed by an activation function (there are many different ones available) and the weights (a number multiplying the input value before entering in the activation function). These weights are tuned in order to minimize the error of the output during the training phase. There are multiple variants of ANNs that refers to the topology of the networks.

When an ANN has two or more hidden layers, it can be classified as a deep learning model, a family of methods that has recently increased its popularity in the last years. A review of deep learning methods applied to electrical power systems can be found in [315].

[298] is focused on the applications of ANNs for forecasting of load demand in smart grids, microgrids, and buildings. The process of preprocessing of data, selection of forecast model inputs, training, and test is exposed in detail. Regarding the preprocessing, various ways of performing the normalization of data are exposed.

The adjustment of parameters in ANNs has been widely studied by many authors. "In [284], J. Runge and R. Zmeureanu review the use of ANNs for forecasting energy use in buildings. A list of found methods that select hyperparameters is also detailed, including (i) heuristics (such as rules of thumb), (ii) cascade correlation, (iii) evolutionary algorithms and (iv) automated architectural search. The comparison of the reviewed papers includes information about the time steps, forecast horizons, and error metrics used by these methods. Other details about the limitations of ANN-based forecasting are explained" ***[[22]]***[3]. Some examples of thumb rules for selecting the number of hidden neurons can be found in [284].

A review of a few single hidden layer network configurations with random weights (RWSLFNs) is presented in [172], which constitutes a variant of the single hidden layer feedforward neural network (SLFN). "RWSLFNs with direct input–output connections is known as the random vector functional link network (RVFL network)" [172]. These techniques are applied in this paper for short-term electricity load demand forecasting.

The paper [299] mentions some special types of ANNs that were not found in others of the mentioned reviews, such as deep belief networks and echo state networks. It also mentions the extended Kalman filter (EKF) and its combination with genetic programming.

Another type of AI model that is of application to electric power system control is RL, and one of its variants which is called deep RL. In this regard, their multiple uses as, for example short-term load forecast and composite load modelling, are reviewed in [311].

The importance of smart buildings, which in some cases can have their own microgrid, was

[3]It is reminded that the publications that are part of the thesis are referenced using double square brackets, bold and emphasis (cf. Section §1.3).

pointed out in the Section §2.3.3.4. Many papers focused on the prediction of consumption of buildings can be found in the literature, as it will be seen next.

The paper [160] is focused on the forecasting of the consumption of buildings. Here, the term "time series forecasting" is referred to the use of techniques over time series data, and not specifically to time-series statistic techniques. The two main groups of techniques are called "data-driven" (those that require past data) and "deterministic", which is based on the science of building physics (as could be the thermal models mentioned in [301]). The use of the word "deterministic" could be confusing in this context, as this term is widely used to distinguish between "probabilistic forecast" and "deterministic forecast". Therefore, the term "physical modelling" will be preferred in advance in the present document to avoid confusion. This paper mentions a group of methods that have not been usually found in the rest of the literature, which are the case-based reasoning (CBR) methods. It also details the moving average and exponential smoothing (MA & ES) method. Finally, they explain that a usual approach in analyzing time series is to decompose the series into three components, which are trend, seasonality, and residual.

Another interesting characteristic of the case study made in [301] is that the authors forecast the consumption for each hour of the day and also the maximum expected peak consumption during the day, being these forecasts are made by independent models. The authors conclude that the task of peak consumption forecast is more difficult that the general day-ahead hourly forecast.

Other authors have analyzed study cases of building consumption forecasting classifying the ambit of such buildings, the type of load (not only electrical, but also heating and cooling). This is the case of [308], which perform the review under many of these perspectives. Some types of considered buildings are commercial, educational, residential, and mixed-use.

Finally, in [285] the approaches for forecasting of building energy demand are reviewed. In this regard, the authors distinguish between "data driven approaches" and "large scale based approaches."

The next section will be devoted to review the probabilistic approaches. This has been identified as a theme of increasing importance in the ambit of power system forecasting, so it has been preferred to treat this in an individual section instead of in the present one (despite it is also related to families of forecasting methods).

3.4.3.3.5 Importance of probabilistic approaches

In [286], J. Nowotarski and R. Weron expose their point of view on the importance and possibilities of probabilistic forecasting for price prediction. As the authors say, the importance of this approach was already stated by De Gooijer and Hyndman in [322], where they conclude that "the use of prediction intervals (PIs) and densities, or probabilistic forecasting, has become much more common over the years" because "practitioners have come to understand the limitations of point forecasts" ([322] as cited in [286]). It is stated in [286] that, despite the grow in the popularity of probabilistic methods in energy systems planning and operations [173] (cited by [286]), the use of probabilistic electric price forecasting (EPF) "is an underdeveloped topic, with both academics and practitioners not using the correct evaluation or testing procedures" [286]. These facts bring again the problem of the evaluation of forecast, not only in deterministic, but also in probabilistic methods. It is important to note that these techniques can be applied to other areas of power systems, not only for markets and prices. The review is done from multiple points of view, including the objective of the prediction, the techniques used, their parameter values, and the error indicators.

For the formulation of a probabilistic forecasting problem, four approaches are distinguished in [286]: "(i) historical simulation (or empirical/sample PIs), (ii) distribution-based probabilistic forecast, (iii) bootstrapped PIs and (iv) quantile regression averaging (QRA)" [286]. The paradigm of "maximizing sharpness subject to reliability" is also exposed to have the "numerical tools and statistical tests to assess reliability (i.e., the statistical consistency between the distributional forecasts and the observations; also called calibration or unbiasedness) and the techniques for measuring and analyzing the sharpness (i.e., the concentration of the predictive distribution)" [286].

Probabilistic forecast applied to PV generation and electricity consumption is reviewed in [307]. This paper remarks the importance of using appropriate metrics for each type of forecast, deterministic and probabilistic, as an inadequate use of these metrics could conduct to erroneous model evaluation. These aspects will be studied in detail in Section §3.5.5.

As a conclusion of this study of documents, the different ambits of the power system in which forecasting models are required where mentioned, such as power system planning and management optimization. It is important to note that forecasting and optimization methods are not totally separated, as their respective characteristics must be considered for their use in real systems. For each type of application, there are some technique families that are more frequently used than others in the reviewed literature.

To provide a complete view of the existing forecasting techniques families, the next section will propose a tree of forecasting techniques according to the analyzed documents from the literature.

3.4.4 Proposed tree of forecasting techniques

In many of the previously mentioned papers, the authors propose their own classification of forecasting techniques. There are some typologies and names that are commonly used without significant differences, but others vary from one author to another, which can result confusing in some cases. The objective of this section is proposing a unified tree of forecasting techniques that include those that were found in the reviewed papers. For those families in which more than one possible name exist, it has been preferred to use that one that was more frequently found in the reviewed literature.

Two main branches can be found in the forecasting literature: deterministic forecasting (sometimes called point forecasting) and probabilistic forecasting [173]. As exposed in *[[22]]*, "deterministic forecasting results in point outputs, with one value at each step, while probabilistic forecasting assigns probabilities to the various scenarios; these can be in the form of quantiles, intervals, or density functions [173]."

These two branches are interrelated, as it is possible to obtain a probabilistic forecasting by applying deterministic methods in certain ways (as, for example, combining various deterministic models to get a probabilistic distribution). In this sense, some of the methods that can be applied to obtain probabilistic forecasts from deterministic methods are "bootstrapped prediction intervals (BPIs) and QRA [286]" *[[22]]*.

The concept "time series forecasting", which frequently appears in the literature, can be used with different meanings according to the authors. Some of them use the term "time series" to refer to the typology of data, which are structured with their index being a time stamp (date and time). On the other hand, some authors use this denomination to express the group of techniques that have been traditionally associated and oriented to express events that evolve in time. These techniques are usually known as "statistical techniques" (as they are called in [323]) and are usually kept out of the group of ML and AI, constituting an independent group. To avoid confusion between these terms, it could be preferable to clarify in each context if the definition is applied to the technique (time series techniques or time series methods), meaning "statistical techniques", or if it refers to the type of data, meaning "time series data".

The set of statistical methods can include some of the techniques or not, according to the author in question. In case of reasonable doubt about if a technique should be merged inside a certain higher group or not, it will be usually kept apart in the proposed tree.

Other methodologies, even those which have a common trunk or principle, can be used in so many variants, as it is the case of ANNs. Inside this group, it will be covered as many variants as possible, using the names (and acronyms) that were more usually found in the literature. For example, there is a special type of ANN architecture which is oriented to reduce the dimension of the input data, which is called self-organizing map (SOM) [306]. SOM can be applied when the model training is too slow due to the number of dimensions of the input data. Therefore, a dimensional reduction can simplify the problem and reduce training and execution times [306].

Regarding decomposition methods, in addition to the previously mentioned wavelet decomposition, some other examples have been added to the tree, such as the Fourier transform, the empirical decomposition methods, and the Hilbert–Huang transform (which requires a previous empirical decomposition to be performed) [324].

In Section §3.1.2.1, where the techniques for the generation of scenarios were studied, Monte Carlo method appeared as one of the most frequently applied methods for modelling uncertainties in stochastic optimization. In the present forecasting method classification, this method will be considered in the category of probabilistic (or stochastic) forecasting methods. An example of an application of Monte Carlo can be found in [325], specifically a quasi Monte Carlo simulation (QMCS). Sometimes, Monte Carlo is used in combination with Markov chains, as in [326, 327].

According to these considerations, the proposed trees of techniques can be seen in Figures 3.15, 3.16, 3.17, 3.18, and 3.19.

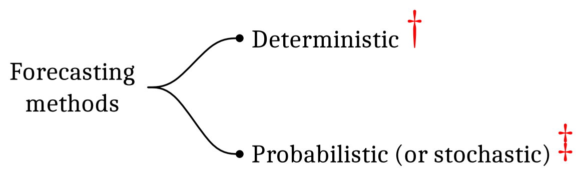


Figure 3.15: Main categories of forecasting methods. † The deterministic methods are broken down in Figure 3.16; ‡ The probabilistic (or stochastic) methods are broken down in Figure 3.19.

3.5 Use cases of microgrid-related forecasting

Once exposed the types of techniques, it is convenient to analyze some examples of diverse case studies from the literature which are applied in the field of power systems, which are usually focused on load consumption and generation. For these techniques and methods, "their ambit of application depends on the characteristics of the forecast, such as the time aggregation and horizon of prediction" *[[22]]*.

These are also dependent on the "ambit of application, such as the customer level, building level, renewable generation units, microgrids of diverse sizes, distribution networks, or even market level (e.g., price forecasting [286])" *[[22]]*.

The purpose of this section, in addition to showing some other case studies of interest from the literature, is to point out some identified problems and important aspects that arise in forecasting systems applied to microgrids. These problems and aspects will be exposed in more detail in here, including some aspects of case studies, applications, and techniques; a discussion on black-box models; a discussion on missing data; a review on how the different types of time horizons of prediction are called; and a discussion on forecast performance metrics.

3.5.1 Discussion on implementation and techniques

In the review of forecasting of power generation and consumption, it has already been mentioned the importance that weather data have. As seen in *[[22]]*, "the influence of weather conditions is of high importance due to the increasing use of renewable generation, such as solar and wind plants, which present power generation effects that change with atmospheric

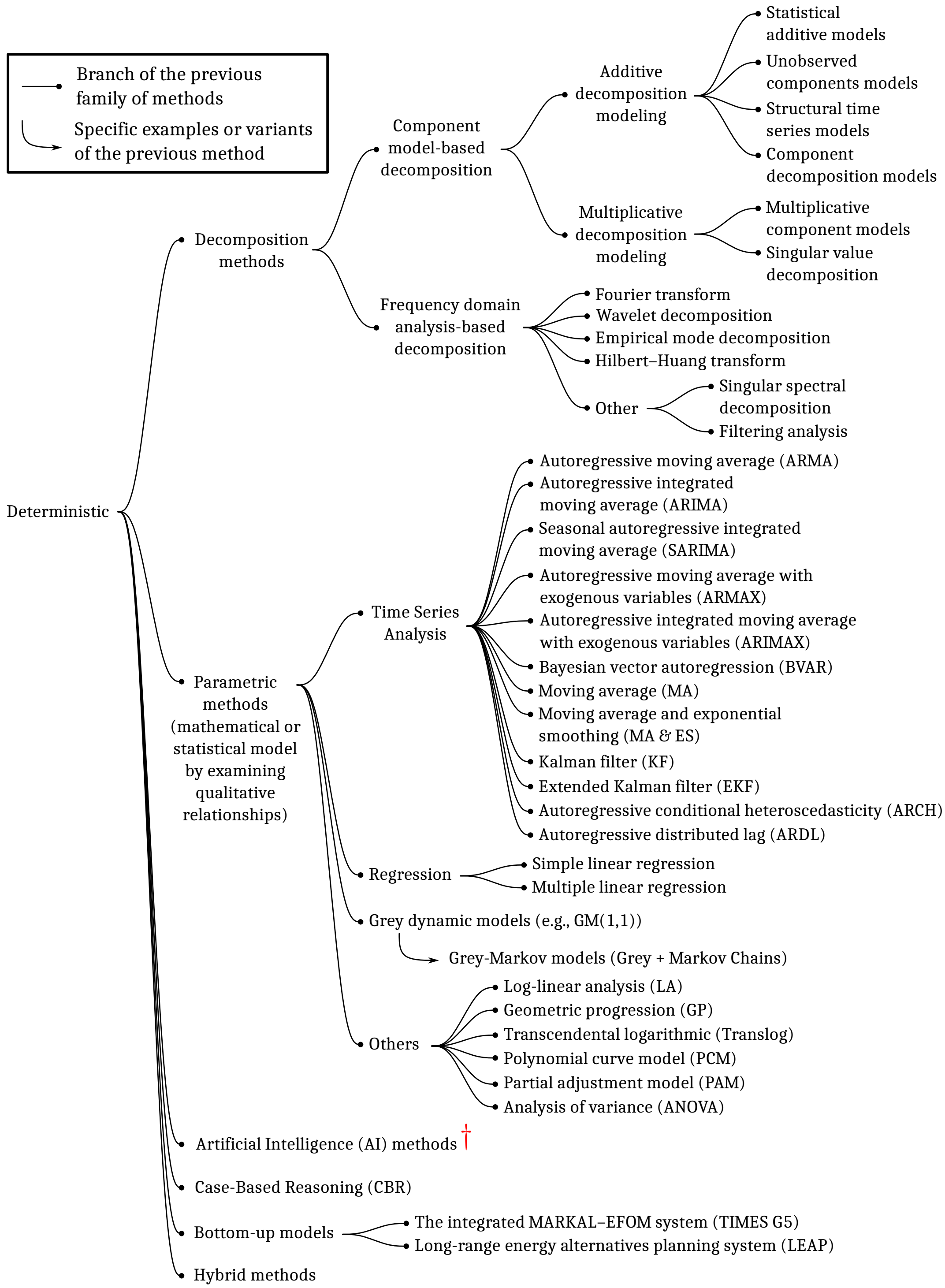


Figure 3.16: Deterministic forecasting methods. † The artificial intelligence (AI) methods are broken down in Figure 3.17.

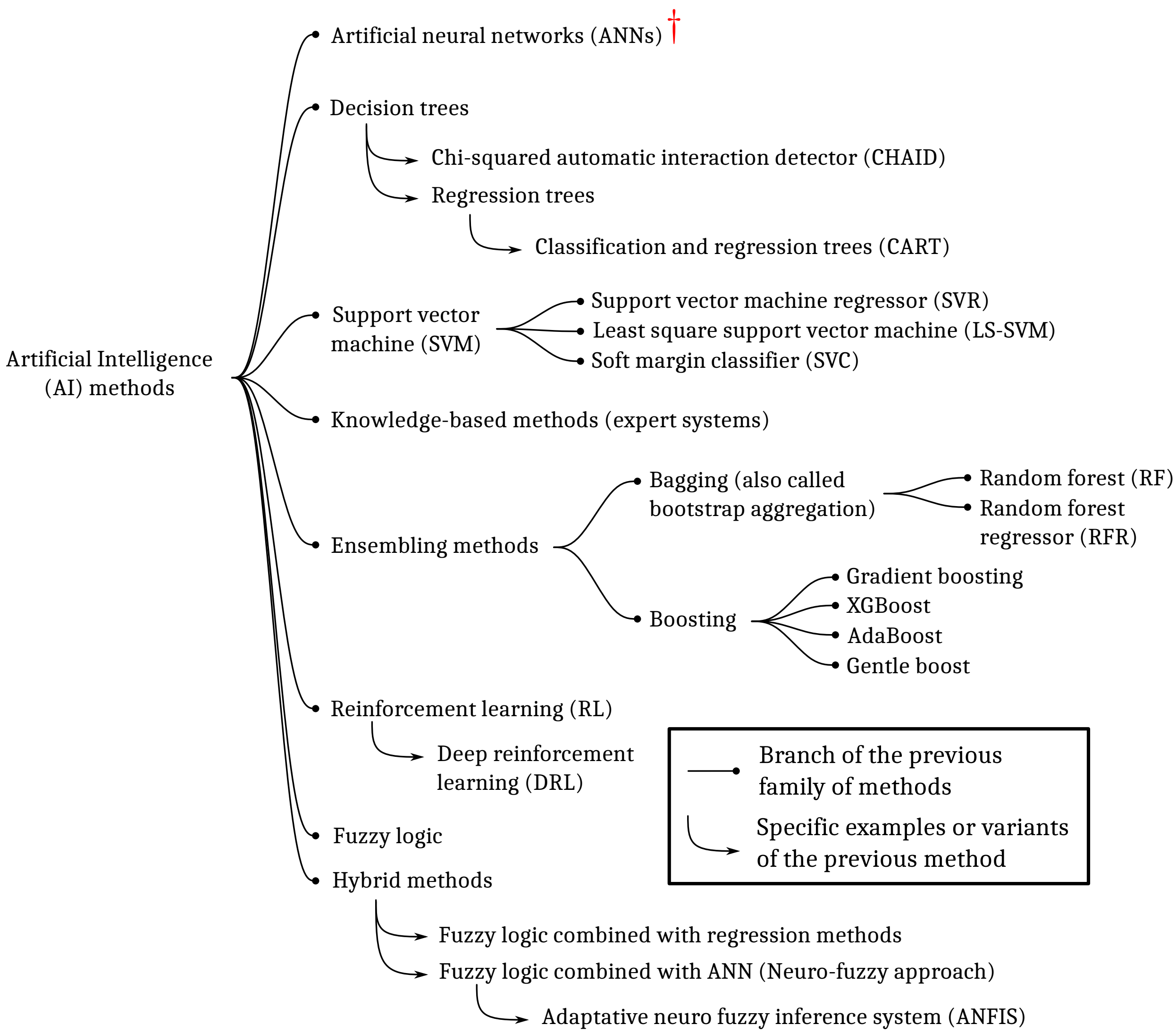


Figure 3.17: Artificial intelligence forecasting methods. † The artificial neural networks (ANNs) methods are broken down in Figure 3.18.

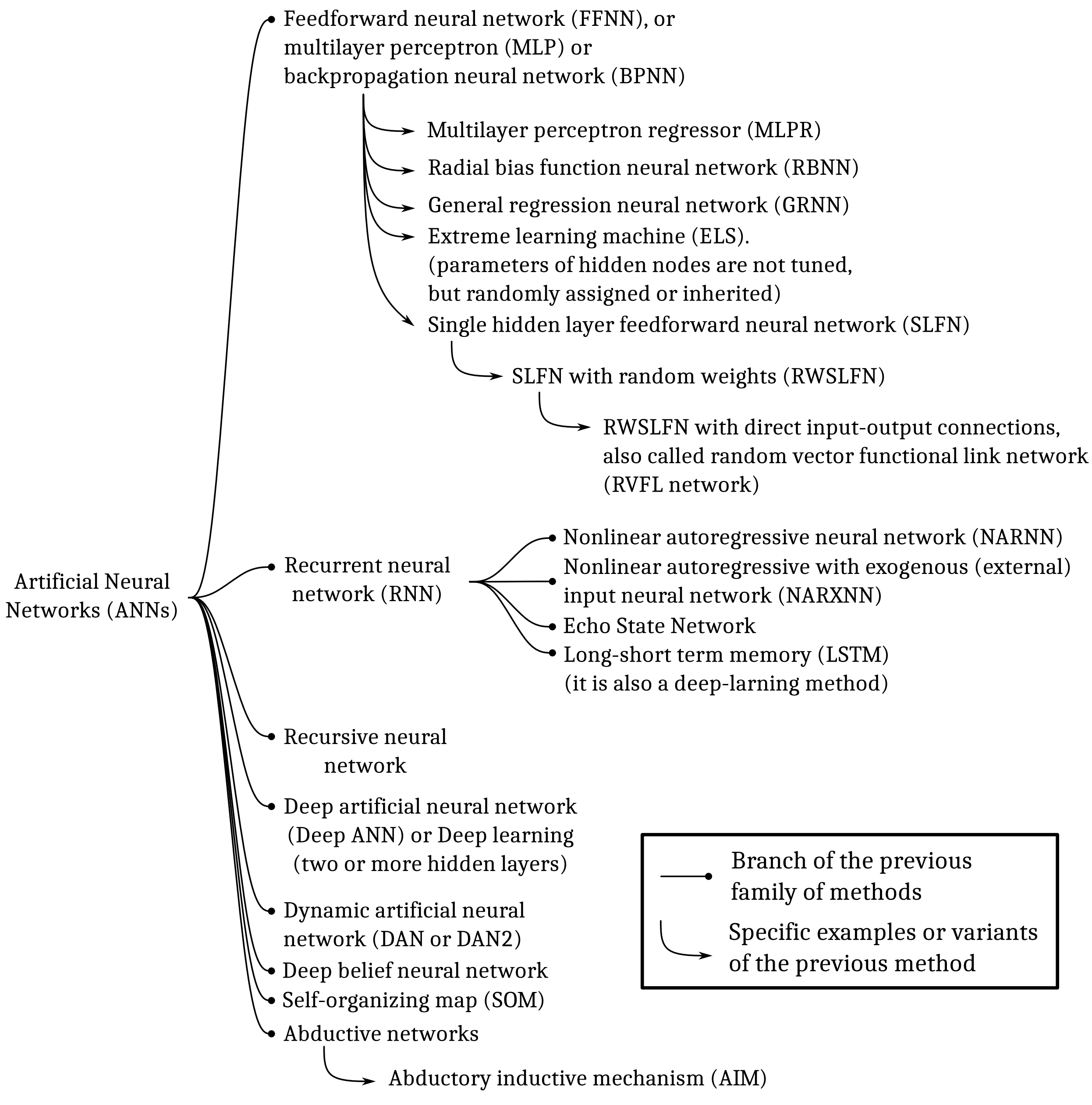


Figure 3.18: Artificial neural network methods.

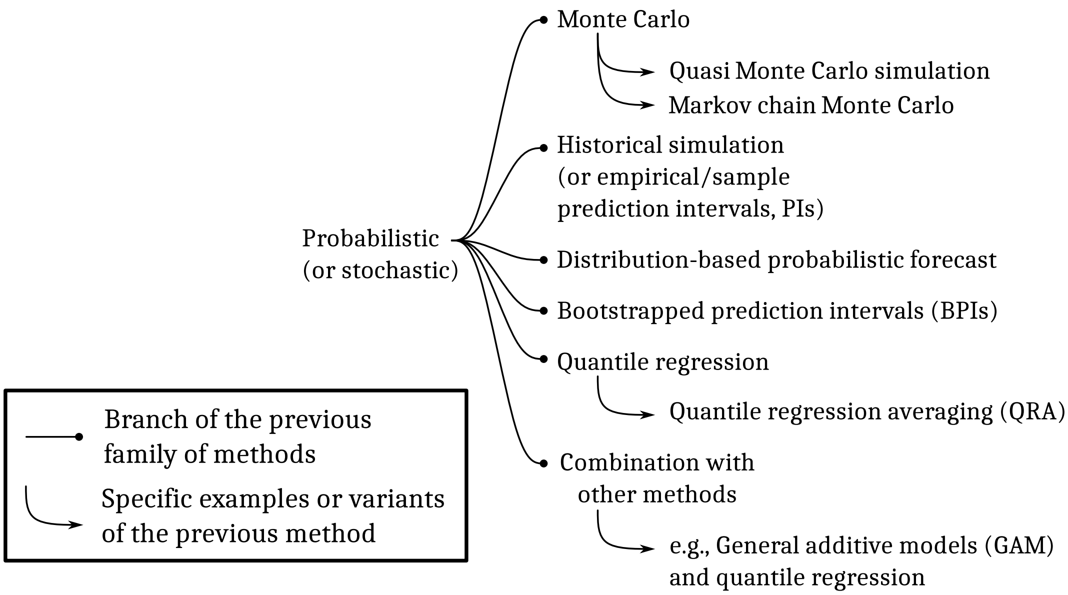


Figure 3.19: Probabilistic (or stochastic) forecasting methods.

conditions. For this reason, many authors have studied how to consider these conditions to improve forecasting methods. In this sense, reference [295] contains recommendations for the use of weather data in microgrid-related forecasts. The authors especially recommend using real forecast data (received from a public or commercial forecasting service) for modeling, not any other synthetic dataset (i.e., data specifically designed for the given experiment with different degrees of similarity relative to reality)" *[[22]]*. In [295], "the importance of clearly defining the error metrics to be applied is also pointed out" *[[22]]*.

These recommendation has been applied in the framework proposed in Chapter §4. The weather data is provided by some external meteorological service and, in the section of results, the model tests have been performed exclusively using real weather-data. Regarding the error metrics, a discussion can be seen later in Section §3.5.5, which have been considered to choose the metrics that are applied by the framework.

Among the deep learning methods that are applied in prediction, one of the most popular ones is the long short-term memory (LSTM), which belong to the family of recurrent neural networks (RNNs). "Regarding wind power generation, some approaches followed in existing studies for short-term and ultrashort-term forecasting include the use of autoencoders and back propagation [328], NWP [329], and LSTM [330, 331]. Thus, other approaches apply wavelet decomposition combined with ML techniques [332]" *[[22]]*. "In the field of PV generation, one study [333] presents a method for probabilistic forecasting based on LSTM and QRA. A 24-h-ahead forecasting method based on synthetic weather forecasting and LSTM is applied in [334]" *[[22]]*. The main characteristic of the RNNs is that, unlike feedforward neural networks (FNNs), they have feedback connections. For this reason, their training procedures are different from those usually applied in FNNs, and have higher computational costs in comparison.

It was previously seen that a microgrid can be of a diverse size, from those of a few kW (nanogrids) to those of hundreds of kW. Therefore, when performing the forecasting of generation and consumption, the difficult of prediction is related to the level of aggregation in the microgrid. In small customers the level of aggregation will be lower, while in bigger microgrids this aggregation will be higher.

About the lower aggregation levels, it was said in *[[22]]* that "in applications that are more focused on small customer forecasting, which mainly includes load consumption, customer segmentation by type is a very common approach. In [335], customers were divided into clusters to model and forecast the next 12 h of consumption. The existence of PV generation on the customer side and its effect on total consumption are also considered in [336]. In [337], a comparison of techniques was performed over a single household using one month of data, showing the superiority of ML techniques over linear regression. The inclusion of appliance (dishwashers, televisions, etc.) measurements have been shown to be useful for discovering resident behaviors and improving forecasting results, as described in [338]" *[[22]]*.

University buildings are examples of customers with a bigger consumption than houses. Some of them, when they integrate their comfort systems, their own generation, or other types of control systems, these can be considered smart buildings (see Section §2.3.3.4).

There are many proposals in the literature focused on this kind of cases, as it is mentioned in *[[22]]*. "Some examples of studies including buildings with greater consumption (such as universities) can also be found in the literature. A study of power consumption forecasting on a university campus is presented in [339] using conditional linear predictions. The authors compare the performance of a method using between 1 and 96 bins (the number of divisions in which a day is divided for forecasting), showing how an 8-bin division achieves more accurate performance than the use of 96 bins. In [340], Y. Ding et al. present a prediction model for campus buildings based on occupancy patterns. This is a good example of how knowledge of building use can be of great interest for consumption prediction" *[[22]]*.

In the case of microgrids that include wide areas, their management can be considered similar to that of distribution networks, as these have a similar level of aggregation of customer consumption. In some papers of the literature there are proposals of implementation of DR applications on these networks, as, for example [341].

"Regarding applications at the distribution network level, ANNs are applied in [341] to predict the maximum DR over a secondary distribution network in India. The aim is to avoid violations of the permitted contractual demand limit by utilities" *[[22]]*.

[342] contains a study case in which one-day-ahead electric power load is simultaneously predicted. According to the authors, this approach is opposed to the usual 1-24h forecast

in sequel (their approach is similar in this sense to which will be applied in the present doctoral thesis). The applied technique is time lagged RNN based on time delay NN model. However, it is focused on the prediction of highly aggregated consumption (at a state level, with thousands of megawatts), which differ from other proposals such as that presented in *[[22]]*, which is applied with powers of a few hundreds of kilowatts. Therefore, their respective computational needs and application are totally different, as it will be seen in the Chapter §4.

Finally, it is worth to mention that there are proposals in the literature in which the models and their evaluation differs from the typical approaches that have been seen. Typically, a forecasting model provides the predicted values for each of the time periods of the forecasting horizon, and these values are directly compared with the real measures. However, for specific prediction objectives, other authors have proposed alternative methods for the evaluation, which can include the shifting of the forecasted data in a certain range. This is the case of [343], in which a metric is proposed for peak prediction. "The study of consumption peaks is of particular interest for congestion management applications. Due to their importance and their difference from other more general forecasts, some authors have proposed specific methods and evaluation metrics for peak predictions, as in [343], where the proposed metric reduces penalization in cases of peak deviations between the real data and the forecasts" *[[22]]*.

3.5.2 Discussion on black-box models

As can be seen, many papers propose the use of AI techniques to perform forecasting *[[22]]*. "This type of method has been shown to obtain better results than other classical methods (such as statistical methods) in many situations. However, it is worth mentioning that in some cases, AI methods constitute black-box models, so their behaviors sometimes cannot be easily explained" *[[22]]*.

This characteristic, while does not suppose any problem in many applications, can be inconvenient in others. This is the case of customer consumption estimation in the context of bilateral contracts for DR, as it was already mentioned in Section §2.3.4.3.

According to *[[22]]*, "this fact becomes a drawback in some situations, such as in auditory processes or agreements (as, for example, in [147]), as poor interpretability could result in nontransparent contracts, where the expected consumption or generation could be biased due to the intrinsic nature of the AI model" *[[22]]*.

Wherefore it is useful to avoid black-box models in these cases, "some authors have proposed the use of rule-based methods that introduce expertise-based knowledge to permit the extrapolation of models in some cases [344] or that substitute black-box models by others that are more understandable [345]" *[[22]]*.

"Another type of forecasting model includes baselines, which are frequently obtained from the measurements taken on some previous similar days [173, 343] or from similar groups of customers [346]. In the context of new flexible service applications, baseline models could be considered good approaches for obtaining the expected consumption levels of customers, making it possible to evaluate their availability and audit their performance in flexible service scenarios. This interest is clearly stated by the European Commission in [347]: *Since flexibility (by definition) cannot be measured, a baseline is needed to quantify the delivered flexibility.* They also point out some recommendations regarding the design and implementation of baselines, such as the avoidance of inaccurate or biased baselines. Complex baseline methodologies could also impact the reproducibility, transparency, and implementation costs [347] of the processes. Despite the interest that these methods have generated, in many studies, they are usually reserved for conducting performance comparisons with more complex models (i.e., used as reference methods)" ***[[22]]***.

Therefore, taking into account this need that has been identified, in ***[[22]]*** "various rule-based baselines that are simple to understand and apply in the context of a transparent contract" are proposed. "Obviously, the methodology to be applied will depend on the characteristics of the time-horizon and aggregation of the forecasting." Specifically, the methodology and framework proposed in ***[[22]]*** are oriented to day-ahead multistep forecasting.

3.5.3 Discussion on missing data

In the literature review, it has been appreciated how some authors propose forecasting methods with some requirements of information (for example, previous measurements, as in the case of time series methods, weather forecast data, or any other exogenous information). They usually perform their study selection which models are the best, but they do not take under consideration how to solve the situation where some of the required data are not available in the moment of the prediction.

A paper where the problem of missing data is mentioned is [304]. The authors state that "in case of incomplete data sets, fuzzy logic is better. However, the accuracy level is not always satisfactory. Grey prediction is another useful method while working with uncertainty problems with the small sample; incomplete and discrete data" [304].

This problem, while can be considered relatively infrequent in applications focused on electricity markets (due to their size and level of aggregation, it is not usual that there are missing historical data). However, in a real ecosystem composed by microgrids of variable size, it can happen that local failures cause missing data in specific days, which makes necessary that the system has some type of model redundancy that permits a forecasting using the available information. For this reason, in the framework that is proposed in the next section, the models are created using different datasets, permitting to rank them and use the better possible with the available information.

The problem of missing data can happen not only in local microgrids, but also in smart metering-based applications. In this case, the main problem does not come from the loss of measurements, but from the delay between such measurements and their reception by the main database. This situation happens in those grids that are configured to send metering data once a day and contains a relatively high number of meters, causing a considerable delay (of some hours) between the starting of the data gathering and the reception of the last requested measure. Under this approach, the measurements of a specific day could not be available at the moment of performing the day-ahead forecasting. Therefore, only data from two days ago could be used in such forecasts, so it makes sense to develop models that can work under these conditions. Again, it can be seen that it imposes an extra difficult for the application of time series techniques, forcing a wider horizon of prediction which can reach to more erroneous predictions.

The found problem is common to both situations, microgrids and smart metering over distribution networks. In the proposals that will be exposed in Chapter §4, a common method for both is developed, bringing a way of obtaining models that covers the different availability of data, which permit the system to give a forecast even in conditions of data input failure.

3.5.4 Time horizon of prediction

The time horizon of a forecast expresses which is the gap between the moment of the prediction and the moment to be predicted. The criteria to express the horizon can be different according to the author, but a widely extended one is has follows, according to [294]:

- Short-term forecast: the time-period of short-term forecast lasts "for few minutes, hours to one-day ahead or a week." This band "aims at economic dispatch and optimal generator UC, while addressing real-time control and security assessment" [294].
- Mid-term forecast: the time-period of mid-term forecast "is a month to a year or two." It "aims at maintenance scheduling, coordination of load dispatch and price settlement so that demand and generation is balanced" [294].
- Long-term forecast: the time-period of long-term forecast is few years (more than one) to 10-20 years ahead. It "aims at system expansion planning, i.e., generation, transmission, and distribution. In some cases, it also affects the purchase of new generating units" [294].

Other authors also define one or two more terms to have a more detailed distinction. This is the case of [283, 12], where the band of very-short-term forecast is also considered. In that case, the four bands would be as follows:

- Very-short-term forecast: from 1 minute to 1 hour.

- Short-term forecast: from 1 hour to 1 week.
- Mid-term forecast: from 1 week to several seasons.
- Long-term forecast: 1 year and more.

As can be seen, even with slight variances, the intervals of time (and their functions inside the power system) are similar under both proposed classifications. Due to the nature of the present study, which is mainly focused on smaller horizons of time, the second classification will be preferred in the present document. Therefore, the concepts very-short-term (from 1 minute to 1 hour) and short-term (from 1 hour to 1 week) will be applied from here in advance, in the same way that in [283, 12].

Regarding the distribution of study cases regarding horizons, the ideas expressed by S.R. Khuntia et al. in [294] are remarkable. They indicate that most of the forecasting methods for load falls into the category of short-term load forecasting. "Mid-term and Long-term forecasting are much less popular as research topics as compared with short-term load forecast" [294]. They also make emphasis on the idea of "forecasting for the mid-term and especially for the long-term is a whole different problem from forecasting for the short term. It cannot be done by simply fitting a model (either statistical or computational) over a dataset, and then extrapolating from it" [294].

3.5.5 Forecasting performance metrics

There exist many different metrics for the evaluation of the performance of forecasting models [308]. Which of these metrics (or indicators) should be used for comparing the models in each case constitutes a common topic of discussion in the literature *[[22]]*.

Across many of the papers, the authors make emphasis on the importance of selecting a correct indicator to compare the quality of the forecast between different methods, as it is done in [295]. Moreover, they state that one of the main problems for the comparison of methods of different papers is precisely the difference (or in some cases, the absence of a detailed explanation) in the evaluation of the forecast.

"In classical approaches, the mean average error (MAE), root mean square error (RMSE) and coefficient of determination (R2) are considered useful for the evaluation of model performance. Furthermore, there are other widely used indicators, such as the MAPE [284]. However, the MAPE is not convenient for predicting certain variables that contain positive and negative values, which may exist in a distribution network that includes generation resources. In these situations, the MAPE tends to yield very large values due to the existence of zero or low values in the data to be predicted, and this could lead to misunderstanding in their interpretation. Finally, the main indicator used for the comparison of model performances is the coefficient of variation of the root mean square error (CV(RMSE)) [284, 308], also called the relative root mean square error (RRMSE) by some authors (i.e., [299]).

This indicator has the disadvantage of yielding higher forecasting error values than those of other indicators when the variable to be predicted has a low average value (as highlighted in [333]), but it avoids the appearance of very high (or even infinite) values in near-zero samples" *[[22]]*.

One of the biggest problems when comparing different methods for prediction, as it is pointed out in [295], is the lack of consensus in the definition of metrics for errors. While some indicators are relatively clear about their calculation (they are very well established and are calculated in the same way in all analyzed literature), others can suffer interpretation differences and misunderstandings in how they are calculated. This is the case of the indicators called "normalized" (e.g., normalized root-mean squared error). The normalization can be done in multiple ways. Precisely, according to [295], some studies perform the normalization "by dividing with the mean of the measurements, the installed capacity, or number of elements of the series" [295]. Therefore, it is essential that the expression of each indicator is detailed when used. To keep as many indicators as possible, those variants will be listed here, indicating their mathematical expression.

In *[[22]]*, the nRMSE is applied due to its simplicity. "While its definition can vary from one author to another [304], here, it is considered equal to the RMSE divided by the capacity of generation (in cases with generation resources) or by the capacity of consumption (in cases with loads)" *[[22]]*.

The expressions of the mentioned metrics are 3.11-3.16 *[[22]]*, [322].

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |y_t - \hat{y}_t| \tag{3.11}$$

$$MSE = \frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \tag{3.12}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \tag{3.13}$$

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \tag{3.14}$$

$$CV(RMSE)(\%) = \frac{\sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2}}{\bar{y}} \cdot 100 \tag{3.15}$$

$$nRMSE(\%) = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2}}{max(|y|)} \cdot 100, \tag{3.16}$$

where y_t is the actual value of the variable at time t, $\hat{y}_t$ is the prediction at time t, $\bar{y}$ express the mean value of the variable to predict, $max(|y|)$ is the maximum absolute value of the variable to predict, and n is the number of predicted points being evaluated.

"Furthermore, many other indicators can be found in the literature. The authors in [295] point out the importance of using well-defined indicators as error metrics. One of the main problems faced when comparing the forecasting results of different studies is precisely the absence of error metric standardization. This ambiguity is particularly noticeable in normalized indicators such as the nMAE or nRMSE" *[[22]]*.

"For other applications, some authors propose more specific metrics to emphasize certain aspects of the resulting forecast, such as consumption peaks. For example, the authors in [343] propose a *semi-metric* approach to avoid the double penalty effect when a forecasted peak deviates in time from the real peak. This approach is useful for applications specifically centered on peak reduction at the network level; as for these applications, it is more important that peaks be predicted at approximately the correct times rather than not at all. However, for general applications in energy management, it is preferable to follow some of the common indicators that were previously described, as most of the authors do in the reviewed bibliography (for example, [337, 338, 340])" *[[22]]*.

The list of commonly used forecast accuracy measures that can be found in [322] includes the percentage better (PB), a measure that does not consider the magnitude of the error but simply if the relative error is greater than 1 or not. In a similar way, two other metrics are defined to compare the models according to which of them is better for each of the predicted points. These measures are percentage better mean average error (PB(MAE)) and percentage better mean square error (PB(MSE)). Their definitions are as follows:

$$PB = 100 \cdot mean\left(I\left\{|r_t| < 1\right\}\right) \tag{3.17}$$

$$PB(MAE) = 100 \cdot mean\left(I\left\{MAE < MAE_b\right\}\right) \tag{3.18}$$

$$PB(MSE) = 100 \cdot mean\left(I\left\{MSE < MSE_b\right\}\right) \tag{3.19}$$

where $I\{u\} = 1$ if u is true and 0 otherwise, and r_t is the relative absolute error [322].

In [299], the normalized mean square error (NMSE) and the determination coefficient (R2) are defined as:

$$NMSE = \frac{\sum^{N} (\tilde{y}_t - y_n)^2}{\sigma_y^2 \cdot N} \tag{3.20}$$

$$R^2 = 1 - \frac{\frac{1}{N}\sum^{N} (y_n - \tilde{y}_n)^2}{\frac{1}{N}\sum^{N} (y_n - \bar{y})^2} \tag{3.21}$$

In [159], the mean absolute relative error (MARE) and relative mean error (RME) are applied, but their mathematical expressions are not defined. In [304], some other indicators are mentioned: mean absolute deviation (MAD), normalized root-mean-square error measure (NRMSE), standard error of prediction (SEP), and absolute relative error (ARE). The NRMSE is defined in [348] (cited in [304]) as:

$$NRMSE = \sqrt{\frac{\sum_{i=1}^{n} (d_i - y_i)^2}{\sum_{i=1}^{n} d_i^2}} \tag{3.22}$$

where n is the number of forecasting periods; d_i is the actual production value at period i; and y_i is the forecasting value at period i [348].

As it has been seen, multiple variants can be found for the normalized metrics. Some of them are those defined in 3.16, 3.20 and 3.22. The way these metrics are normalized varies from one author to another, so it is important that each applied metric is defined to avoid confusion.

For some models such as autoregressive moving average (ARMA) and ARIMA, the model selection among alternatives is sometimes based on the information criteria usage. In this regard, two of the most common criteria are Akaike information criterion (AIC) and Schwarz bayesian information criterion (BIC) [317].

In [349], the whiteness test is mentioned; whiteness test is used "to ensure that a selected model adequately describes a given set of data" [350]. According to [349], it has two steps, the "examination of the estimated residual graph (exploratory analysis)" and the "calculation of the residual autocorrelation function (RACF) at different time lags (confirmatory analysis)." The objective of the first step is to explore "whether or not the estimated residuals are white (uncorrelated)" and the objective of the second step is "to confirm whether or not the estimated residuals are white" [349].

The previously described indicators are suitable for deterministic forecasting, but not for probabilistic. The reason for this is that the evaluation of probabilistic forecasting models requires the consideration of quantiles or intervals, which requires some other specific metrics.

In this regard, "reference [173] contains a review of the applications of probabilistic methods in load forecasting. Despite these methods being of great interest, they present some additional problems from the point of view of their evaluation processes, as the typical metrics used for deterministic methods are not valid due to the existence of quantiles, PIs or confidence intervals. This is why some authors have proposed metrics such as the pinball score or the Winkler score [173, 333]" *[[22]]*.

The most common existing metrics for the evaluation of probabilistic forecasts are the pinball loss function and the Winkler score. Their expressions are defined in 3.23 and 3.24 [173] respectively:

$$Pinball(\hat{y}_{t,q}, y_t, q) = \begin{cases} (1-q)(\hat{y}_{t,q} - y_t), & y_t < \hat{y}_{t,q} \\ q(y_t - \hat{y}_{t,q}), & y_t \geq \hat{y}_{t,q}, \end{cases} \tag{3.23}$$

$$Winkler = \begin{cases} \delta, & L_t \leq y_t \leq U_t \\ \delta + 2(L_t - y_t)/\alpha, & y_t < L_t \\ \delta + 2(y_t - U_t)/\alpha, & y_t > U_t, \end{cases} \tag{3.24}$$

in which $\hat{y}_{t,q}$ corresponds to the forecasted value for a specific quantile, y_t is the real value to be forecasted, q is the quantile, L_t is the lower bound, U_t the upper bound, δ is the difference between the two bounds of the PI ($\delta = U_t - L_t$), and $(1-\alpha)$ is the nominal probability of the prediction interval.

The pinball score evaluates a forecast considering its associated quantiles. It is said in [173] that the pinball losses can be summed across all targeted quantiles (for example, summing the pinballs for q=0.01, 0.02, 0.03, ..., 0.99) to obtain the pinball loss of the probabilistic forecast.

The Winkler score evaluates an interval considering the upper and lower limit and its associated probability.

There are other metrics that are oriented to the evaluation of CDFs instead of evaluating specific quantiles or intervals. Some examples of these metrics are the continuous ranked probability score and the Dawid–Sebastiani score [351].

The main metrics for both types of forecastings are reviewed in [307]. Various metrics for probabilistic forecasting are here included, such as pinball loss function, Winkler score, and others.

In addition to the described metrics, in many studies a comparison between methods is performed to evaluate which one achieves a better forecasting. When conducting performance comparisons, a reference method is usually applied, i.e., the performances of the models under evaluation are compared with that of the reference. The reference method is also commonly called "base method" [322] or "benchmark method" [307] by other authors.

According to [322], one of the most common base methods that can be commonly found in the literature is the naïve method. It consists of using the last observation as the next prediction. This method is also called persistence method by some authors [336, 352, 353] (as seen in *[[22]]*). Alternatively, it is also sometimes called no-change (NC) forecast [351]. Other authors use other methods as a base case in their studies, such as the ARMA [336] or the ARIMA models [160].

Finally, another interesting recommendation is giving a proper notation to the results of error. "the formulae that define the error estimates should be provided to clearly define the calculation associated with each acronym" [295]. "Thus, the involved forecasting horizons can be indicated, providing a distinction between estimates associated with a specific forecasting horizon – MAE_{1h}, $MAPE_{24h}$, $RMSE_{10min}$ – and estimates associated with a range of forecasting horizons – MAE_{1h-24h}, $MAPE_{1h-6h}$, $RMSE_{10min-4h}$" [295]. This name criteria could be clarifying in those cases where various aggregations and horizons are applied.

This section has reviewed the main aspects of the forecasting performance evaluation, stressing out the importance of a correct metric choosing. The next section will present some conclusions that can be extracted from this chapter, especially regarding microgrid-applied forecasting, as these are of interest for the development of the systems that will be proposed in Chapter §4.

3.6 Summary and conclusions

Once reported the analysis of the state of the art on microgrid optimal management and their applicable forecasting techniques, some conclusions can be extracted.

Among the reviewed optimization methodologies for microgrid operation, it is possible to find single-objective methods (those that are able to consider a single objective) and multi-objective methods (that can consider various objectives at the same time). Moreover, it is possible to introduce in the optimization problem restraints of diverse nature, from those purely technical operative limits of the microgrid elements, to the coordinated actions that involve the microgrid and some external agents at the same time, as in the case of DR actions, energy shifting, or the consideration of the maximum time that a microgrid can hold in the islanded mode during a power cut-off.

The review of the state of the art regarding the functionality and applications of flexibility services, DSM, DR, and smart metering has shown that their use can highly improve the capacity, feasibility and resilience of the power system. However, these involve many difficulties regarding their technical deployment, management, and coordination.

The type of optimization method that can be applied to a specific situation firstly requires a study on how the involved uncertainties (unknown information) can be modeled and forecasted. In this regard, the two main types of models are deterministic and stochastic. Those stochastic methods that include information about the probabilities that are associated with the uncertainties can be also referred to as probabilistic methods. Considering the dependence of the optimization methods on forecasting information, it can be said that the keystone of management optimization in microgrids (and, in general, in power networks) is precisely the generation and load forecasting.

In the reviewed state of the art, one of the most important lines of development in microgrid operation at present is the rising importance of including probabilistic information, i.e., using probabilistic forecast instead of deterministic. It provides a more complete source of information that, according to many researchers, has shown to be very promising to operate a system with a high number of uncertainties, as it is the case of microgrids with a high presence of renewable generation, or with very changeable consumption profiles. However, the inclusion of stochastic information is computationally expensive compared to deterministic information, so their use should be done carefully according to the complexity of the optimization problem and the number of uncertainties.

The reviewed EMSs, despite their variations in the way they work (exclusively day-ahead, rolling horizon, etc.), use forecasting techniques according to their required horizons of prediction. In the same way, the papers focused on forecasting techniques have proposed multiple methods for different levels of the power system and microgrids. In the model comparison and selection of the best ones, it has been identified the importance of choosing an appropriate performance metric. The metric selection becomes especially complex in the case of probabilistic methods compared to deterministic methods. In this regard, some authors from the literature state that more research is required in this field for advancing in the inclusion of stochastic and probabilistic forecasting methods in power system applications.

In this regard, having identified the importance of the evaluation metrics, the proposals that will be exposed include a framework for the model test and selection of both types (deterministic and stochastic).

Beyond the evaluation of model performance, another type of problem was identified in the literature, which is the black-box characteristic of many of the applied models. These black-box models (as it can be the case of many AI-based models) do not have easy explainable parameters, as these are adjusted according to their optimization algorithm. There are a few applications in which performing the forecast by means of these black-box methods could incur into disagreements. An example of this could be the expected consumption of a customer in the context of a DR contract. In this case, to obtain the baseline of their consumption, it is usually required to use a model that can be easily understood by both parts (customer and utility), avoiding any type of black-box model.

In this sense, it was appreciated that some companies base their calculation of customer baselines on a fixed number of previous days (ten days in the observed cases). Considering the limited number of methods that have been observed, the proposals exposed in Chapter §4 include a method that has been called rule-based baseline, which provides a wider variety of non-black-box models for predicting power generation and consumption.

Chapter 4

Problem identification and proposed solutions

> ***This chapter summarizes the problems and lacks that were identified in Chapter §2 and Chapter §3, and exposes the proposed solutions that have been developed as part of the thesis research.***

In the previous chapters, during the study of optimization and forecasting methods that can be applied for managing microgrids, various problems and lacks were identified. In this sense, various solutions will be proposed in this chapter, which conform the main contributions of this doctoral thesis. Thus, the different projects and collaborations in which those proposed solutions have been designed will also be briefly described to provide the context where the research tasks have been developed.

This chapter is organized as follows. Section §4.1 exposes a summary of the research project, collaborations, and publications in which the author has participated. Section §4.2 summarizes the problems that were found in the previous chapters and the solutions that this thesis proposes. Section §4.3 shows an architecture for the participation in flexibility service provisions and their auditing. The relationship of this architecture with the customers' EMSs and their coordination requirements are studied in Section §4.4. Section §4.5 exposes a forecasting method which has been called rule-based baseline that can be used for setting up transparent flexibility and DR contracts, for being used as a reference when comparing the performance of other forecasting methods, and also for other general forecasting tasks. Section §4.6 proposes a forecasting framework for microgrids which compares deterministic and probabilistic methods for modelling uncertainties. Finally, Section §4.7 exposes the conclusions of this chapter.

4.1 Research development: context and publications

This section describes the context in which this thesis research was developed together with its related publications.

During the development of the thesis, the author participated in several projects in the smart grid research line and in international collaborations with researchers from Chile and Italy. These participations and collaborations are briefly described in Section §4.1.1.

Most of the outcomes of the research have been published in Journal Citation Reports (JCR)-indexed journals (as can be seen in Chapter §6). Considering that the developed research tasks are interrelated and they belong to a common research line, these outcomes will be described in Section §4.1.2 overviewing their scope, as these have influenced the research course of the thesis.

4.1.1 Summary of research tasks and collaborations

During the years of thesis development, the author was a member of the research group "Electronic Technology and Industrial Informatics" (*Tecnología Electrónica e Informática Industrial*, also called TIC-150, or eTIC). This group is part of the Department of Electronic Technology (*Departamento de Tecnología Electrónica*, DTE) belonging to the Universidad de Sevilla (Spain).

The research of the author on the field of smart grid started in 2015 with his collaboration in the project "*Sistema Inteligente Inalámbrico para Análisis y Monitorización de Líneas de Tensión Subterráneas en Smart Grids*" (SIIAM) granted by the *Ministerio de Economía y Competitividad* (Government of Spain). The aim of this project was to develop electronic devices for the fault location in primary distribution networks. The paper [354] shows some of the results of this project.

During the year 2018, the author did a research stay in the San Joaquín Campus (Santiago, Chile) of the Universidad Técnica Federico Santa María (UTFSM, Chile). It was possible thanks to the participation in the project "Grid Flexibility for Chile" (GridFlex4Chile) (promoted by ENEL company), whose objective was deploying systems to perform DR actions in distribution networks in Chile. From the works developed during this stay, the paper ***[[20]]***[1] was published thanks to the collaboration with researchers of the Department of Electrical Engineering (*Departamento de Ingeniería Eléctrica*, DIE) of the UTFSM, the Department of Mechanical Engineering (*Departamento de Ingeniería Mecánica*, DIM) of the UTFSM, and the Universidad Finis Terrae (UFT, Chile). This paper ***[[20]]*** proposes a simulation of a nanogrid under the control of an EMS, showing the importance of considering the DR functionalities on these kind of systems for the control of microgrids and nanogrids. Some aspects of the content of this paper are detailed in Section §4.4.

[1]It is reminded that the publications that are part of the thesis are referenced using double square brackets, bold and emphasis (cf. Section §1.3).

Some time later, the project "Grid Flexibility & Resilience" (GridFlex&Resil) (promoted by ENEL company) started. It was focused on developing DER control systems for their inclusion as flexibility resources. This project counted with the participation of researchers from the Department of Electrical, Electronic and Telecommunication Engineering and Naval Architecture (*Dipartimento di Ingegneria Navale, Elettrica, Elettronica e delle Telecomunicazioni*, DITEN) of the Università di Genova in the Savona Campus (Savona, Italia). As results of this project, the papers [143, 132] were published. These propose the use of OpenADR for the control of DR resources under a CBP. In the proofs of concept that were performed, the resources that were controlled are located in Savona Campus, while the system that dispatched the DR action was located in the Universidad de Sevilla.

In 2019, the author performed a research stay with members of the DITEN in the Savona Campus of the Università di Genova. The publication ***[[22]]***, which proposes a forecasting framework and some new forecasting methods for its application to the electric power elements of the Campus, is an outcome of the developed research. Some parts of this paper are exposed in Section §4.5 and Section §4.6.

Some other papers of the author are focused on specific DER management and operation. For example, in [67] an architecture for the management of EV fleets is presented. In the field of generation, [355] presents a simulator for the training of wind turbine operators. Solar generation aspects are treated in [140, 356], where it is discussed how the energy could be shared between various owners of the same generation resources. In the development of this thesis, these papers have enriched the vision on the operative aspects of DERs, which should be considered for the design of EMSs and their control strategies.

The last smart-grid-related project in which parts of this thesis have been developed is "*Bigdata Analitycs e Instrumentación Ciberfísica para Soporte de Operaciones de Distribución en la Smartgrid*" (BALANCE). This project, wich was granted by the *Ministerio de Ciencia, Innovación y Universidades* (Government of Spain), is focused on the development of cyber-physical systems and applications for improving electricity distribution networks using data from the customer smart meters. Some of the applications that this project explore are network topology analysis, consumption forecasting, and smart meter management. This project has the support of "Medina Garvey Electricidad S.L.U." (a Spanish DSO).

Thanks to this project, in ***[[21]]***, an architecture for flexibility services provision is proposed. The dispatching is based on OpenADR (in the same way that the proposals of [143, 132]) while the auditing part is based on the use of the smart meters that have been deployed in Europe. This proposal is exposed in Section §4.3.

The paper [357], which was done thanks to the previous project, shows a study of the impact of COVID-19 pandemic on the energy consumption of customers. For the comparison of the real consumption during the lockdown, some forecasting techniques were applied. This paper constitutes an example of the application of forecasting techniques in other ambits of the power system that are not related to microgrids or control of DERs.

Based on the analysis of the previously mentioned papers, it can be identified the importance of having a good forecasting for microgrid and power system management, and for a successful deployment of flexibility services. In this sense, this thesis proposes a framework for the forecasting of uncertainties that affect the process of energy management optimization in microgrids (e.g., load and generation power) and a forecasting method that has been called rule-based baseline. The proposed framework will also be called Probabilistic and Deterministic Forecasting (PRODEFOR) Framework and the proposed baseline method will also be called Rule-based Baseline Forecasting (Rulabi).

The study of the power system at higher levels, as it could be the internal management of markets and transmission networks, will not be treated in these proposals. Despite the high interest of the markets, and all possible developments regarding the UC problem, these will not be considered inside the current study as they fall out of its scope. Nevertheless, some market-related aspects are mentioned even if the study is not specifically focused on them. For example, the design of the specification of the time horizon and time steps of forecasting could not be understood and tackled if the needs of the electricity markets (including flexibility markets) were not considered.

In this thesis, two cases are raised regarding the forecasting applications using real datasets. The first one corresponds to a microgrid that includes loads and different types of generation together, i.e., a prosumer. This one will be in advance referred as the "microgrid case" (which is shown in *[[22]]*). The second one corresponds to a real distribution network. It is made up of various secondary distribution substations. In advance, it will be referred as the "distribution network case."

The next section will overview the previously mentioned publications according to the participant researchers and the smart grid areas in which these publications are focused on.

4.1.2 Publications in the research line

A brief summary of the publications in which the author has participated can be found in the Table 4.1. This table specifies the position that he occupies in the list of authors, and if the publications were made in an international collaboration. The same papers have been also classified in Table 4.2 according to the smart grid area on which each one is focused. These categories are: "utilities, markets" (for those that consider the point of view of the utilities, or participation in energy markets), "distribution networks" (which treat operative aspects of the distribution grid), "microgrid and DER management" (focused on management of microgrids and DERs, which can also consider their coordination with other external agents), "forecasting" (focused on the use of forecasting techniques applied to electricity networks, microgrids, and DERs) and "flexibility, DSM and DR" (these three types of services have been grouped in the same category because of the close relationship between them).

Table 4.1: Papers authored or coauthored by the author and their participants (in chronological order).

Authors and date of publication	Ref.[1]	Position of the author	DTE [2]	DTE-Chile [3]	DTE-Italy [4]
Parejo et al. (Jan 30, 2019)	[354]	1/6	■	–	–
Parejo et al. (May 12, 2019)	*[[20]]*	1/6	–	■	–
Guerrero et al. (Jun 22, 2019)	[67]	4/6	■	–	–
Yanine et al. (Jun, 2019)	[140]	5/7	–	■	–
Yanine et al. (Mar 5, 2020)	[356]	4/6	–	■	–
Larios et al. (Mar 13, 2020)	[355]	3/6	■	–	–
Guerrero et al. (Sep, 2020)	[143]	4/8	–	–	■
Guerrero et al. (Nov, 2020)	[132]	4/9	–	–	■
Garcia et al. (Jan 28, 2021)	[357]	2/6	■	–	–
Parejo et al. (Feb 9, 2021)	*[[21]]*	1/6	■	–	–
Parejo et al. (Jul 12, 2021)	*[[22]]*	1/6	–	–	■

[1] Reference.
[2] Participation of DTE members exclusively.
[3] Collaboration between DTE members and researchers from UTFSM and UFT (Chile).
[4] Collaboration between DTE members and researchers from Università di Genova (Italy).

Table 4.2: Papers authored or coauthored by the author and their fields of research (in chronological order).

Authors and date of publication	Ref.[1]	Utilities, markets	Distrib. networks[2]	Microgrid and DER management	Forec.[3]	Flexibility, DSM, and DR
Parejo et al. (Jan 30, 2019)	[354]	–	■	–	–	–
Parejo et al. (May 12, 2019)	*[[20]]*	–	–	■	–	■
Guerrero et al. (Jun 22, 2019)	[67]	■	■	■	–	–
Yanine et al. (Jun, 2019)	[140]	■	–	■	–	■
Yanine et al. (Mar 5, 2020)	[356]	■	–	■	–	■
Larios et al. (Mar 13, 2020)	[355]	–	–	■	–	–
Guerrero et al. (Sep, 2020)	[143]	■	■	■	–	■
Guerrero et al. (Nov, 2020)	[132]	■	■	■	–	■
Garcia et al. (Jan 28, 2021)	[357]	–	■	–	■	–
Parejo et al. (Feb 9, 2021)	*[[21]]*	■	–	■	–	■
Parejo et al. (Jul 12, 2021)	*[[22]]*	–	–	■	■	■

[1] Reference.
[2] Distribution networks.
[3] Forecasting.

Once finished the description of the published works in the smart grid research line, and their relationship with this thesis, the main contributions made by the author will be highlighted in more detail. First, the next section will review the problems that were identified in Chapter §3 and will summarize the proposed solutions. Then, these proposals will be later detailed in the forthcoming sections.

4.2 Identified problems and solution approach

The different aspects of the smart grid paradigm, in particular microgrid management and flexibility services deployment, were reviewed in Chapter §2. As it was seen, these processes are strongly dependent on optimization and forecasting procedures for achieving their objectives. In this sense, during the review of the state of the art made in Chapter §3, different problems and lacks regarding microgrid-related optimization and forecasting were identified, as it was analyzed in the conclusions of that chapter. The problems that have been identified during the reviews performed in both chapters are:

- The deployment of flexibility actions offered by customers (by means of DSM and DR actions) has been identified as a tool of large interest for the operation of the power system. However, the mechanisms for their implementation are still under discussion and they need more research.
- In the implementation of flexibility, specifically in DR actions, various stages can be identified, which are the evaluation of services and resources, dispatching, internal resource management, and audit.
  - The evaluation of the available services and resources (according to the flexibility markets, or to the existing bilateral contracts with FSPs) is performed by the TSOs and DSOs according to their requirements for managing their networks. This stage usually involves an optimization of the management operations to keep the stability of the system at the least possible cost.
  - The dispatching consists of sending the service request to the corresponding FSP. It requires systems to perform the communication between the operator (who dispatch the request) and the control system of the FSP, which can be the microgrid, aggregator, or EMS that manages the resources.
  - The internal management of the resources, which is usually done by an EMS that controls the microgrid, facilities, or building, usually performs an optimization to decide if the received request can be accomplished according to the expected energy requirements. Furthermore, in market-based flexibility provision, this optimization would also determine when and how a resource would participate in the pool of flexibility actions.
  - The audit is the last stage and it is done after the flexibility service provision (event) has finished. It consists of checking if the consumption (or generation) of the costumer during the dispatched request is accomplished with the conditions of the DR agreement. This check should be done with respect to the consumption profile that was expected for the customer, which should be forecasted according to transparent and clear rules. This restriction limits the types of models that could be applied, as many common modelling techniques create models whose

internal parameters are not easily explainable (due to their low interpretability) to be considered in a bilateral contract, which makes it difficult their inclusion in this type of agreement.

- The management of resources of a microgrid by an EMS includes not only the possibility of providing flexibility services (which has been previously mentioned), but also the optimal operation to minimize the cost while accomplishing the supply of the existing consumption from the available generation sources and the electrical network. Performing such optimization requires predicting the uncertainties that are considered in the optimization problem. These uncertainties can be modeled in various ways, such as deterministic forecasting, set of scenarios, worst-case restrictions, and risk management approaches.

- Forecasting the uncertainties at lower aggregation levels, as it could be the case of a single customer (or a microgrid), constitutes a totally different problem than forecasting at a higher level such as region or country levels. The stochasticity increases at lower levels of aggregation, which makes the prediction process more complex. The task of forecasting is critical especially in weakly connected microgrids which should be prepared for entering into islanding mode when a grid disconnection occurs.

- In addition to the complexity of the forecasting problem, it could occur that there were data lacks in the historical data of measurements due to delays in the data transmission. This is usually more frequent at lower aggregation levels as its measurement concentration system is slower (a high number of meters share the data communication channels, and these than in the case of a whole region or country (whose measurement systems are usually stronger and with higher redundancy). Therefore, it could happen that a certain data set is not available at the moment it is needed for performing a forecasting task, but in some time later.

- In the reviewed literature, when creating sets of scenarios, the most extended approach is to apply Monte Carlo and suppose a certain probability distribution (e.g., normal distribution) over historical data or a deterministic forecast, while probabilistic forecasting is usually reserved for risk constraints and worst-case considerations. It has been indicated by other authors in the literature that in many cases the probabilistic forecasting is not so widely applied as it could be convenient considering its potential. In this sense, it could be convenient to apply probabilistic forecasting models also in the creation of scenarios for the optimization of microgrids.

- The evaluation of forecasting models can be done using performance metrics. However, each type of forecasting model (deterministic, scenarios, probability distribution, bands, etc.) and use case could require a different type of evaluation metric. As some authors indicate in the existing literature, this requires more research, especially considering that, in their opinion, the use of probabilistic forecasting is not as common as they consider it should be. This could be partially due to the described difficulties in the evaluation of probabilistic models.

These problems, as it can be seen, refer to different aspects of the energy management and coordination process, but they are closely interrelated. Therefore, these aspects should be treated together to improve their implementation.

In this sense, having analyzed the problems, the solutions that are proposed for these problems in this thesis will be described in the next sections of this chapter. For the sake of clarity, before exposing the proposals in detail, a brief summary of them is firstly given:

- A **flexibility participation architecture** for the inclusion of flexibility actions in the power system has been defined (see *[[21]]*). This requires a coordination between the operators and the FSPs for implementing flexibility (or, more specifically, DR) actions, and other systems for performing the optimization and control of the resources. In this sense, this architecture serves as a common frame in which the rest of the proposals are included.
- According to the previous architecture, **the steps that a microgrid EMS should execute will be analyzed**. During its operation, the EMS shall consider both the external flexibility request and also the energy requirements of the microgrid (see *[[20]]* and *[[21]]*). These two aspects are closely related, as both affect on the cost function of the optimization problem to be solved.
- A new **forecasting method called rule-based baselines** (Rulabi) has been proposed for the definition of consumption baselines according to clear and transparent rules (see *[[22]]*). These can be used to:
  - Establish DR contracts between utilities and customers.
  - Identify the behavior profile of a certain customer, microgrid, or group of DERs. In this sense, the type of baseline rule that achieves a lower error will correspond to their behavior profile.
  - Serve as inputs for other more complex forecasting models.
- Creation of a **forecasting framework focused on microgrids in which different types of uncertainty models can be handled** (see *[[22]]*), which is called PRODEFOR. In this framework:
  - It is possible to check multiple combinations of inputs from the available information fields to test different model variations. Moreover, these different models are stored together with their performance evaluation. When there are any missing input data, if a certain model cannot be executed, it is possible to use another

model whose inputs are available for its execution at that moment. This would avoid problems due to missing data in forecasting systems.

- The previously mentioned rule-based baseline information has been included as a possible input for the modelling. These baselines constitute a simplified representation of the data of various days, so the trained models will have a smaller dimension (a smaller number of inputs) when using these baselines instead of the raw data of those previous days. It will be seen in the analysis of the results that their inclusion can improve the quality of the trained ML models in some cases.
- The relationships between the probabilistic forecasting and each type of uncertainty modelling have been considered and integrated in the framework. A procedure for creating scenario sets using probabilistic forecasting is proposed.
- The error metrics that are applied will be discussed and specifically chosen for each type of uncertainty modelling (deterministic, quantile distribution, interval, or scenario set). A new metric has been defined for the evaluation of scenario sets that are created using the proposed method.

As it can be seen, the proposals have been structured around four main points. The first proposal that will be described next is the flexibility participation architecture.

4.3 Flexibility participation architecture

Considering the importance of flexibility services for the operation of the power system, the steps, communications, and control systems that are required for their implementation have been analyzed. According to these requisites and elements, an architecture for flexibility participation has been defined. This proposal has been published in the journal article *[[**21**]]*.

The most basic steps that a flexibility action (and, more specifically, a explicit DSM or DR action) involve are two, which are the dispatching and auditing. The dispatching consists of sending a request for performing a flexibility action, while auditing consists of checking if the action was correctly performed according to the agreement and performing the corresponding billing. The most basic interactions in flexibility actions between two agents are depicted in Figure 4.1.

As can be observed, according to this diagram, "three main parts can be distinguished from the customer side, the DSO-user communications (DRMS-BMS) through the OpenADR protocol, the BMS in the customer side, and the smart metering system to audit the DSM operations" *[[**21**]]*. By the side of the operator (in this case, the DSO), their systems include the DRMS, the audit system, and the remote management system of the smart meters.

These processes require an information interchange between the dispatcher and the service provider. For the implementation of these interchanges, it is proposed that "dispatching is

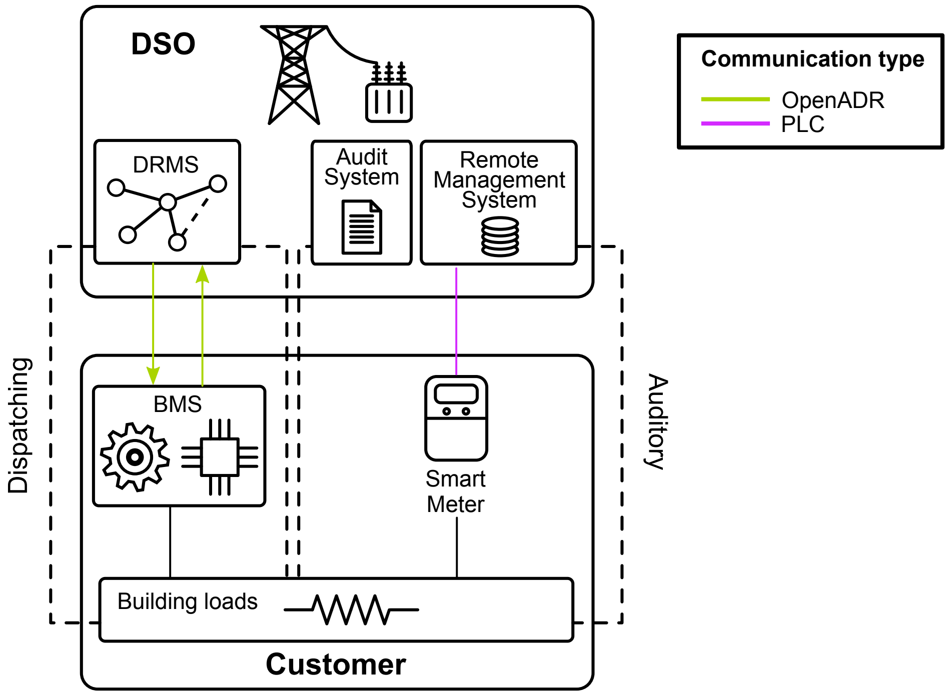


Figure 4.1: "Structure and communication of DSO and customer systems for DSM/DR and auditing" *[[21]]*.

done through the OpenADR protocol while the auditing is done through the AMI based on PRIME standard" *[[21]]*. The operator that acquires the flexibility services from the FSP is the DSO. It could be also extended to a TSO as a flexibility services purchaser. The reason why only the DSO was included in this proposal is that the scope of the paper was focused on the provision of services for DSOs.

In addition to the interchange of information between the two involved agents, the Figure 4.1 also includes diverse control systems which have been previously reviewed in Chapter §2. These are the control system of the building (BMS, which could alternatively be an EMS) and the control system of DR resources of the DSO (DRMS, which could alternatively be part of a FMS). In a building, the BMS (or EMS) should optimize the resources of the customer in order to manage them, and also deciding if the participation on flexibility services provision is convenient or not for each time interval. The DRMS should decide which of the available flexibility services are convenient to acquire and dispatch for the management of the network according to their existing restrictions and needs (expected consumption, congestions, etc.). The existence of these two control levels, each of them in their own domain, points out the importance of control and, consequently, the need of forecasting capabilities in the process.

This first definition of the architecture of Figure 4.1 has exclusively considered the flexibility action, but not the previous planning steps that are implied for choosing a certain service and provider. In this sense, these additional steps have been considered in the Figure 4.2. Figure 4.2 presents a summary of "the whole process of flexibility estimation, participation in the market, event receiving and execution, and audit" *[[21]]*. This diagram constitutes an extension of the previous one, so the flexibility services interchange platform has been included. The platform in which the flexibility services are offered and chosen can be a flexibility market platform (in case of market-based flexibility environments), or a system deployed by the operators (in case of direct contracts between operators and FSP. For this diagram, considering that it is intended to be applied in an European environment, it has been preferred to choose the market-based case, as it is the preferable option according to the EU legislation.

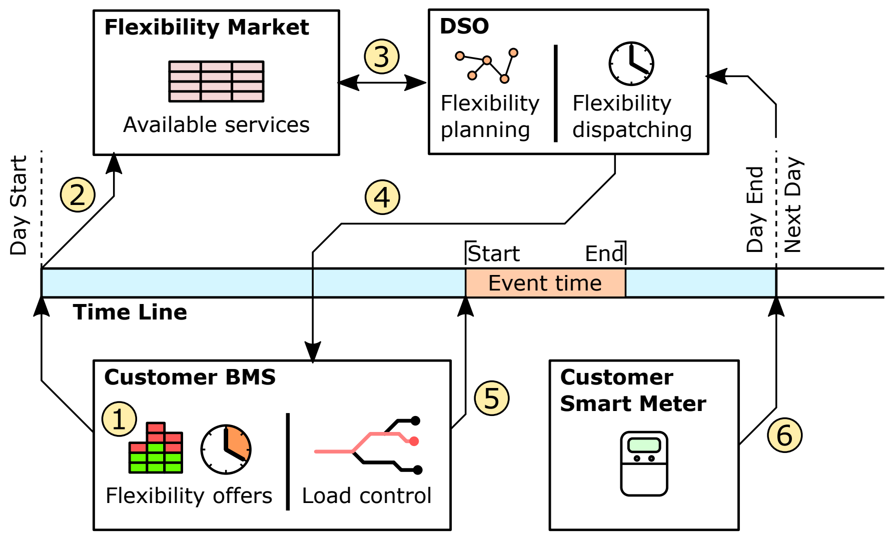


Figure 4.2: "Flexibility cycle. (1) Flexibility offers calculation [BMS]; (2) Send offers to market [BMS-Market]; (3) Services selection [DSO-Market]; (4) Service request [DSO-BMS]; (5) Load control for requested service [BMS-Loads]; (6) Auditory of the requested service [DSO]" *[[21]]*.

As said, the proposed architecture analyzes the different steps that are required for the participation of customers (or aggregators) in the provision of flexibility services such as DSM and DR. In this sense, "this architecture includes the complete cycle of DSM, including dispatching and auditing" *[[21]]* and the mechanism of service offering and selection, which is in this case done by a flexibility market.

The process described in Figure 4.1 is as follows. "At the start of the day (or before, depending on the flexibility program), the BMS performs an estimation of their own consumption (and generation, if any), and also considers which devices are curtailable (Stage 1 of the Figure 4.2). The flexibility offer is derived from these values, which is the description of the possible load reduction for each of the hours of the day (Stage 2). This offer is sent to the flexibility market, where all the offers of all the customers under the market are listed (Stage 3). The DSO selects those offers that are needed for the flexibility planning, and their selection is communicated to the affected customers using an OpenADR event (Stage 4). These events can be sent along the day but should be done some time before the moment when the requested event will start (e.g., at least one hour before). This restriction is usually described in the flexibility program. When the time of the event starts, the BMS will manage the loads to keep the requested power constraints according to the event characteristics, until the event finishes (Stage 5). At the end of the current day (or at the end of the settlement cycle), the DSO will have retrieved the data from the smart meters and make the audit for the billing adjustment, depending on whether the customer had correctly achieved the request of the event (Stage 6)" *[[21]]*.

The detailed explanation of these elements can be found in *[[21]]*. However, it is convenient to include here some details from the referred paper about the flexibility cycle process and the procedure followed by the EMS to check the available flexibility capacity.

One of the main advantages of the proposed architecture is that it "has been designed considering the same type of smart meters that are already deployed in most countries, which perform hourly consumption measurements. This restriction has been applied in order to avoid the need of deploying new metering systems for the present application, which would lead to higher costs" *[[21]]*. For these reasons, "the proposed architecture aims to take advantage of the already existing metering system for the audit process, not requiring any remarkable economic effort." In addition to these economical advantages, smart meters are the officially accepted method for billing in power system supply, which reinforces the reasons for using them in flexibility services instead of some other specific device for this purpose.

In the presented case, as the OpenADR protocol is being used, it could be possible to use the virtual end node (VEN) as a gateway to send power measurements to the operator. The VEN is the OpenADR device installed in the customer side for the communication with the virtual top node (VTN) that is in the operator side. This should be considered an auxiliary device, and not the main auditing metering device. As it is expressed in the paper, "it must be remarked that the smart meter system is considered here the most effective and adequate system to realize the auditory process. The VEN metering capacity constitutes just an additional auxiliary method which can be used for the measurement of specific parts of the consumption/generation, achieving a more complete understanding of the state of the customer systems, but should never be used for audits" *[[21]]*. In this sense, OpenADR is a protocol oriented to ADR, and not a metering protocol.

Regarding the control systems for the resources of the customer, their importance was analyzed in Chapter §2. As said in *[[21]]*, "the automation systems would require an update to fulfill the requirements, but there is currently a rising tendency to install BMSs in big and medium size customers and domestic automation systems, so it is expected that these systems will become relatively common and its integration with the proposed approach will be easy" *[[21]]*. These thoughts can be similarly applied to microgrid EMSs, as many of the characteristics are similar. The consideration of DSM together with the rest of resources in the optimization process of BMSs and EMSs was seems as a task of large importance during the literature review performed in Chapter §3. These aspects and the solutions that are proposed in this regard will be detailed in Section §4.4, where the DSM information is considered as an input information for the BMS. Later, a forecasting framework specifically oriented to microgrids will be proposed in Section §4.6.

The integration of the selection and dispatching of services in the DSO control systems will also imply a set of changes. However, this adaptation is of a high interest for the DSOs. "Proof of that is that various DSOs are already exploring the use of this kind of techniques, citing as examples the initiatives of SD-G&E Company [147] and PG&E Company [148]" *[[**21**]]*.

Finally, as it was said in the description of the architecture, the auditing implies to check if the flexibility request was accomplished or not. In this regard, it is crucial to use a known procedure for calculating the baseline of the customer, i.e., the expected consumption for the customer in case of not having any request. This baseline is the consumption profile with which their real consumption will be compared during the auditing. The importance of applying clear rules for this process were reviewed in Chapter §3, specifically in Section §3.5.2. The application of these aspects will be analyzed in Section §4.4.3, and a proposal of a new method for calculating such baselines will presented in Section §4.5.

Once explained the global aspects of flexibility services provision, and having proposed an architecture, the proposals that are proposed in this thesis affecting to some of their parts will be detailed. The first one will be studying how the flexibility actions should be considered and included by the BMS or EMS, which is exposed in the next section.

4.4 EMS with inclusion of DR

This section is focused on how the inclusion of flexibility services could be done in the EMS of a microgrid according to the required steps that were established in the previously exposed architecture.

A work focused on modelling and simulating a nanogrid with its EMS will be exposed, which has been designed to include DR signals as information inputs. The nanogrid that has been simulated (which is described in Section §4.4.1) corresponds to a real nanogrid in Chile. At the moment of this research, the nanogrid was being enhanced for including batteries with charging controllers, and this designed EMS (which is described in Section §4.4.2) was developed to serve as a proposed solution for the control system that could be implemented for managing the available devices while considering the possibility of participation in flexibility services provision (specifically, in DR actions). This proposal is published in *[[**20**]]*. As was said in Section §4.1, this work is done in collaboration with researchers from the UTFSM and UFT.

This paper served as the base for later research works, such as the previously presented flexibility participation architecture (published in *[[**21**]]*) and the forecasting framework (published in *[[22]]*) that will be presented later. These proposals are partially based on the conclusions that were extracted from *[[20]]* once the needs of an EMS were analyzed.

Regarding the audit process, the paper *[[20]]* took into consideration how the baseline for this audit should be done. The description of this step was later extended in *[[21]]* and included as part of the architecture of flexibility participation. These aspects from both papers are treated together in Section §4.4.3, as they are focused on how the estimation of flexibility capacity should be made. In this regard, a proposal of alternative models for calculating such baseline was made in *[[22]]*, which will be detailed in Section §4.5.

4.4.1 Nanogrid San Joaquin

The nanogrid which is modelled corresponds to the one existing in a laboratory building at the San Joaquin Campus of the UTFSM in Santiago (Chile). This nanogrid was deployed by researchers belonging to the DIE. This laboratory (see Figure 4.3) was "dedicated to a smart microgrid system to be tested prior to its installation in a building chosen by ENEL Distribution, which is the main and largest electric utility in the country" *[[20]]*. "The testbed is part of an ongoing research project to incorporate DG systems in the form of smart microgrids to a number of residential and commercial buildings currently being serviced by ENEL. The project's chief objective is the realization of probes about renewable energy generation and distribution by means of grid-tie microgrids installed and fully data-integrated with ENEL Smart Metering/Smart Grid division. Along with this, there are energy storage, AMI and heating, ventilation and air conditioning (HVAC) systems being operated and monitored by the electric utility" *[[20]]*.

(a) (b) (c)

Figure 4.3: Facilities. (a) Building; (b) Sensor connections; (c) Solar panels *[[20]]*.

For the proposed EMS, some design decisions were taken to introduce flexibility and DR capacity to the system:

- "The availability of batteries will give extra flexibility to the EMS, but it could also be possible to design other types of controls without them, as can be seen in [358]" *[[20]]*.

- "Additionally, in the case of an advanced building-utility integration, must be considered the exchange of information between the utility and the microgrid, focused on DR and energy price information, which allow a better adjustment of the consumption according to the needs of the power system, making its management by the distribution system operator easier. These functions seem to be an unavoidable part to get a more reliable electricity system" *[[20]]*.

- "The proposed EMS needs to manage the consumption and generation of the systems connected to the microgrid and also the implied temperatures" *[[20]]*. Therefore, it is the objective to achieve a complete integration of both types of energy flows: electric and thermal. In this sense, "the idea of considering thermal inertia and thermal storage has been previously used by other authors. An example would be [359], who study the impact of this inertia and how could affect demand response operations" *[[20]]*. This corresponds to a temperature model of the building that was developed by researchers of the DIM belonging to the UTFSM.

A schema of energy interchange in the building and the nanogrid is shown in Figure 4.4. "On one hand, the elements which exchange electric energy are wind/solar generation, energy storage, utility grid and load. On the other hand, the elements which exchange thermal energy are HVAC, the room and the thermal storage (the mass of the building). These two ambits are supervised by the EMS" *[[20]]*.

4.4.2 EMS design

According to the described elements and their relationships, an EMS for the nanogrid was designed. The flow diagram of the EMS strategy is depicted in Figure 4.5. As it can be seen, some of its parts are marked as "predictive" and others as "reactive."

In this sense, "the predictive branch, which is divided into two separated parts, are mainly centered in the use of the thermal model of the room to keep the temperatures at adequate intervals. It must be noted that this function would take on more and more importance when the building has more mass (which implies more thermal energy storage) and also when the thermal isolation with the outside is better (which implies less losses), having then more thermal inertia and having his management more impact in the total consumption of the building" *[[20]]*.

"The reactive branch, which conforms the core of the control system, must keep the batteries with enough charge to maintain the microgrid running, even if a blackout occurs. Additionally, the storage capacity can be used to actuate when the utility advice a high

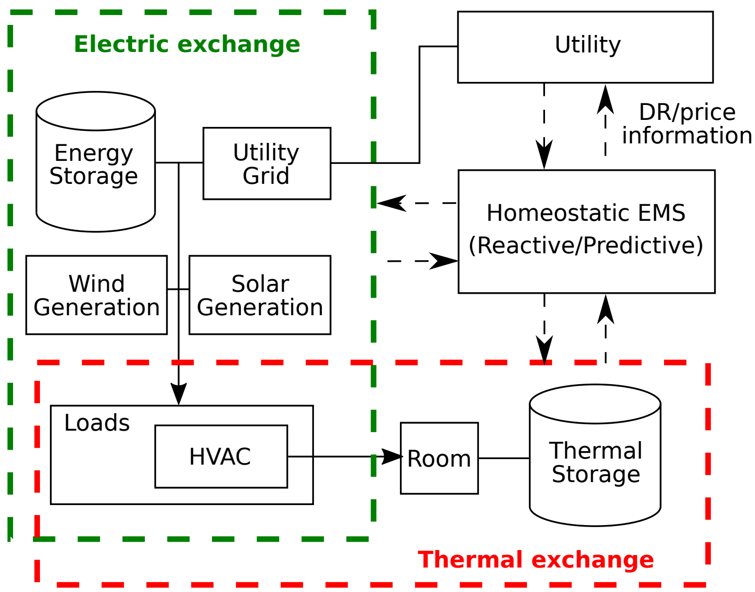


Figure 4.4: "Energy fluxes and control" *[[20]]*.

energy price (usually applied when a certain power or energy consumption value is reached), or even a DR event which requires a high reduction in the consumption of the microgrid. This fact is reflected with the parameter P_{lim} (power limit), which depends on the received information from the utility (or the distribution system operator)" *[[20]]*.

It is not the purpose of this section explaining in detail how the EMS works and how the temperature model of the building is considered. This content is out of the scope of this thesis. Its purpose is to show those details and conclusions referring to the application of DR, flexibility, and management of the microgrid, as these have been considered in the later research work and have influenced in their development.

As the conclusions of the paper *[[20]]* states, regarding the microgrids and buildings, "if these systems can be equipped with communication and advanced data processing interconnected systems that can operate together," it can make "the power generation and distribution elements work in a collaborative way" *[[20]]*. These ideas were precisely extended in the previous section, which presents a flexibility participation architecture for the inclusion of microgrids in flexibility markets as providers of DR services. Regarding the system for the communication with the operator, the articles [143, 132] are precisely focused on the application of OpenADR for this task (applied to a microgrid in Italy).

In particular, the most important aspect that was detailed in this paper regarding the research line of this thesis is the estimation of flexibility capacity. In the particular case of the exposed EMS, this will determine the value for the parameter P_{lim} in Figure 4.5. This will be exposed in the next section.

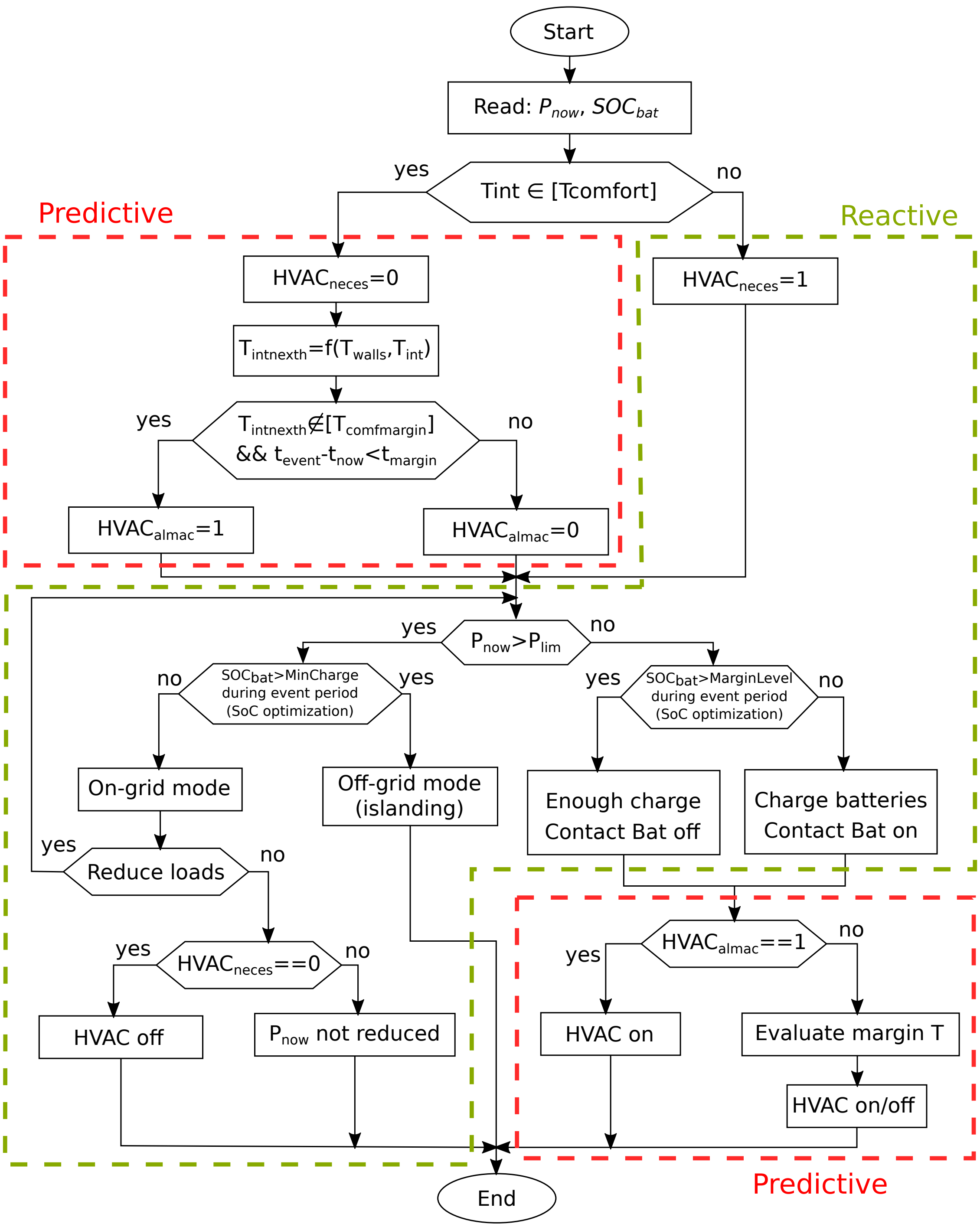


Figure 4.5: Flow diagram of the EMS *[[20]]*.

4.4.3 Estimation of flexibility capacity

The procedure that the EMS or BMS should follow to estimate the flexibility capacity (for performing DR actions) that is available during each time interval of the day. These aspects were treated in *[[20]]* (as part of the implementation of an EMS), and in *[[21]]* (as part of the flexibility participation architecture). A procedure that could be applied for the calculation of requirements during DR actions (which is explained in *[[20]]*) is as follows.

"The calculation of the limit power in the context of a typical DR event (of the type used by some utilities in North America [147]), is usually dependent on two variables, the client baseline for the event time and the minimum power reduction needed to avoid penalties" *[[20]]*. For the calculation of the baseline (the estimation of the expected consumption that is used as reference during DR events) in each hour (or other period needed), the mean of the ten previous days which are similar to the day of the event could be used. This approach is followed in the CBP of the utility company SD-G&E. It is said in [360] that the operational days for DR events of this program are Monday through Friday during the operational season, excluding utility holidays. Specifically, for the calculation of the baseline the similar days "exclude weekends, holidays, and days when load reductions were requested or when outages were called" [360]. Under these considerations, the baseline for a certain hour h would be calculated following 4.1.

$$P_{baseline(h)} = \frac{\sum_{i=1}^{10} P_{daysimilar\_i(h)}}{10}. \tag{4.1}$$

Indeed, the strategy depends on the type of DR program and the contract established between utility and customer (or aggregator). Following this idea, "the power limit will be calculated applying the minimum power reduction needed to the baseline power" *[[20]]*, as expressed in 4.2.

$$P_{lim(DR\ event)} = P_{baseline(h)} - P_{reductionrequired}, \tag{4.2}$$

"If the power reduction required is zero (penalties to the customer would only be applied if they consume more than their baseline)" *[[20]]*, then the limit would be established according to 4.3.

$$P_{lim(DR\ event)} = P_{baseline(h)}. \tag{4.3}$$

"Last, if during a specific period there is not any event active, then the power limit will not be necessary (no power restriction specified)" *[[20]]*.

When a DR event has been scheduled, the customer (or aggregator) must reduce their consumption during the established period. In this sense, "the required power reduction can be reached by disconnecting the microgrid from the power system, or also managing internal controllable loads (if available). In both cases, the control system must assure that the required reduction is achieved, when possible" *[[20]]*.

A generalized procedure for doing this is exposed in *[[21]]*. "The whole process of DR planning is analyzed from the point of view of the customer, including the use of their own sensing and control systems to check the flexibility services availability" *[[21]]*. A possible schema of the tasks that the BMS have to execute (as it can be seen in *[[21]]*) could be:

1. Start of the day:
    - Estimate power (using occupational model)
    - Include controllable loads (if any)
    - This result in the maximum and minimum values for each of the hours of the day
    - Calculate baseline (mean of consumptions of previous days for each hour according to the DSO rules)
    - Calculate flexibility margin (baseline minus maximum expected consumption)
    - Send participation offer to the flexibility market
    - The DSO evaluates if they are interested in sending any event and informs the customer
    - The BMS receives the event information
2. Event start (if any):
    - The BMS control the loads (if necessary) to accomplish with the event
3. End of the day and in advance:
    - Audit of the service requested by the DSO. If the audit power minus the actual power is greater or equal to the event reduction power, the customer would have successfully performed the requisites.

The proposed procedure highlights the importance of making a precise consumption (or generation, if any) forecasting for an appropriate participation in flexibility services and, in general, for the management of resources under the domain of the BMS. While in *[[21]]* it is only mentioned a BMS, its application would be analogous in the case of a microgrid EMS, or even in the case of a DERMS of an aggregator.

It should be noted that day-ahead planning is not absolute nor definitive, being subjected to adjustments due to variations in the expected behavior of the elements in the microgrid. In this sense, as it is expressed in [98], "a priori knowledge of local loads and energy production from RESs permits to optimally manage the loads" and the rest of existing elements "to accomplish the agreed DR program." However, "this is just an ideal condition, useful only for computing a benchmarking performance" [98]. This means that, in real systems, the original day-ahead schedule can suffer variations when any new event or unexpected change occur. Precisely, this is the reason why it is considered essential using an appropriate protocol (as OpenADR, or some other of the existing ones) for the management of the DR events (or other flexibility services), as they include functions for the coordination between the dispatchers of events (e.g., DSO, TSO) and the customers (or aggregators).

In any case, the use of appropriate forecasting models would reduce these variations thanks to the higher quality of their predictions. Therefore, forecasting constitutes a key tool not only for the appropriate scheduling of flexibility events, but also for the internal management of DERs and other elements belonging to microgrids and power networks. While in the previously proposed schema of steps it was mentioned an occupational model (which are frequently used in building-related research), the use of this kind of model or another one depends on the nature of the facilities and variables to predict.

It was previously seen that, for establishing flexibility (or DR) contracts, it is necessary to have a method of baseline calculation for evaluating if an event has been correctly handled by the customer (or aggregator) or not. In this regard, the next Section §4.5 will propose a method for the calculation of baselines according to a variety of rules. Additionally, this method could also be used to serve as references for the comparison of performance of other forecasting methods, or they could simply be used to obtain regular forecasts (in the same way that any other existing forecasting method). Moreover, this method is integrated inside the proposed forecasting framework oriented to microgrids that will be later presented in Section §4.6.

4.5 Rule-based baseline forecasting method

It was previously said that for the auditing process of flexibility service provision, the baseline of a customer must be calculated to compare this with their real consumption. "A baseline consists of a forecast of a power variable based on previous measurements of that variable" *[[22]]*. From this comparison, it will be possible to check if the customer accomplished with the flexibility agreement or not (i.e., if they modified their consumption as much as it was determined in the dispatched events).

For this reason, as part of this thesis, a new type of method called rule-based baseline (Rulabi) has been designed and published in *[[22]]*. This proposed method permit the creation of baselines selecting the type and number of days to average according to a variety of different rules, and choosing the option that fits better to the consumption of each customer. Additionally, these baselines can also be used as a simple forecasting method for consumption and generation, as input information for more complex models (such as ML-based models), or even as reference for the comparison of other forecasting methods.

This proposal constitutes an extension of the baseline methods. Baseline methods are "typical and classical prediction methods (some examples can be found in [361, 362, 363])" *[[22]]* that have been found also in industrial ambit. In this sense, the method that the electric companies SD-G&E [360] and PG&E [148] apply for the calculation of the consumption baseline of the customers subscribed to their DR programs consist on averaging the consumption of the ten previous days that are similar to the day in question. This method, which was already detailed in the previous section, is only applied considering days between Monday and Friday that are not holidays [360] (therefore, it cannot be applied for forecasting holidays nor weekend days). This method accomplishes the requisites of being clear and transparent in its calculation, but its application is restricted to Monday-to-Friday (business) days.

Considering the aforementioned limitations, the rule-based baseline method (Rulabi) that is proposed in this thesis is adapted to forecast a wider range of days, as it permits to choose how the days for the calculation of the baseline are selected among several existing options (i.e., the rules). As said in *[[22]]*, this proposal extend the baseline calculation "by the definition and specification of different rules that can be chosen depending on the type of variable to forecast" *[[22]]*.

"Specifically, these proposed models perform multistep day-ahead predictions for a whole day using only the historical data obtained on some previous days. The number of days to be used is defined by the integer n, which is the parameter that establishes the model configuration (therefore, it will hereinafter be referred to as a hyperparameter) depending on the rule to be applied. Once the days to be used are selected, the mean power value is calculated for each of the time intervals of those days, with these values being the forecasts for these days. This process is depicted in Figure 4.6" *[[22]]*.

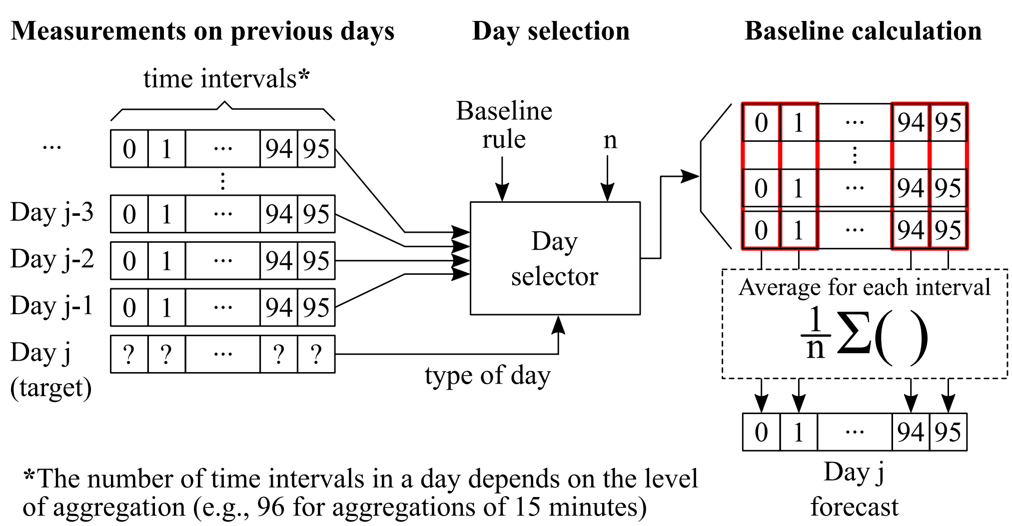


Figure 4.6: Method of rule-based baseline forecasting *[[22]]*.

The four types of baseline rules that are proposed in *[[22]]* are as follows:

1. Baseline "simple n" (abbreviated as *baseline_sn*): This rule takes the n days prior to the target day and calculates the mean for each time interval. There are no day-type distinctions with this rule. The proposed values for n are 1, 2, 3, 4, 5, 6, 7, 14, 21, 28, and 35.
2. Baseline "basic_weekend n" (abbreviated as *baseline_bwn*): In this rule, n days before the objective day are considered, but not all of them are used in the baseline calculation. If the objective day is a weekend day, the weekend days within the previous n days are averaged for each interval of each day. The same situation occurs if the objective is a nonweekend day, where all nonweekend days within n days are taken. The proposed values for n are 7, 14, 21, 28, and 35.
3. Baseline "const_num_back n" (abbreviated as *baseline_cnbn*): This rule takes n days before the objective day, which are of the same type; i.e., if the objective is a weekend day, n previous weekend days are taken. The proposed values for n are 1, 2, 3, and 4.
4. Baseline "same_weekday n" (abbreviated as *baseline_swn*): In this rule, from n days before the objective day, only those that are the same day of the week are used in the baseline calculation. For example, if the objective day is a Tuesday, the Tuesdays included in the set of n days are averaged for each time interval. The proposed values for n are 7, 14, 21, 28, and 35.

"Thus, the proposed values for the hyperparameter n are not the same for all rules. The selection of those values is due to the nature of each rule and the set of days that can be obtained. In the case of the 'basic_weekend' and 'same_weekday' rules, only multiples of seven are taken to ensure the availability of days of the needed type inside the set of n days (seven days contain two weekend days and five nonweekend days). Taking another value for n would result in an irregular distribution of days, so this is avoided by taking only multiples of seven" *[[22]]*.

"In the case of the rule 'const_num_back', the maximum value of n is four to avoid mixing data from different numbers of days back with respect to weekends (two weeks ago for $n = 4$) and non-weekends (one week ago for $n = 4$). If n is higher than four, a minimum of three weeks will be needed to calculate the baseline of a weekend day, which would be undesirable" *[[22]]*. The reason is that, in that case, the prediction of a weekday would be done only with data from the previous week, while the weekend days would be calculated using data from the three previous weeks. Therefore, there would be a high disbalance in the use of data between both types of days.

For all these rules, another option that should be determined is how the missing days (or missing time intervals inside days) are handled. This is specified in *[[22]]*:

"Once the rules are defined, their application can be classified into 'strict' and 'non-strict' types. The 'strict application of a rule' implies that a baseline for a certain day is considered valid only if the available number of days in the set n is the maximum number defined by the rule. If there are any missing data in the needed days according to the rule, this baseline is discarded and not considered valid. In contrast, the 'non-strict application of a rule', does not necessarily require a specified number of days. The baseline is considered valid if there is at least one day available for the calculation" *[[22]]*.

One of these rules, which is the "simple 1" (abbreviated as $baseline\_s1$), can be considered equivalent to the so-called naïve method, as it is indicated in *[[22]]*. "The $baseline\_s1$ method (the 'simple n' rule, where $n = 1$) could be considered the simplest rule, so can be used as the reference method for comparison with the other rules. This idea is, for example, exposed in [322], where it is mentioned that one of the most commonly used base methods is the naïve method [322]. This method consists of using the last observation as the next prediction. Therefore, the $baseline\_s1$ method can be considered equivalent to the naïve method in this methodology, with day-ahead forecasting being the objective. This method is applied in [336, 352, 353], where forecasting performed simply by using the measurements of the previous day was called the 'persistence method'. Other authors propose the use of other methods, such as the ARMA [336] or the ARIMA models [160], as references in their case studies" *[[22]]*.

Therefore, the $baseline\_s1$ method is proposed as a reference method "because of its simplicity, as it avoids a more complex parameter adjustment process which would be required for other models such as ARMA or ARIMA (which would be computationally expensive due to the high orders of the models with data aggregations of 1 h or 15 min)" *[[22]]*. Moreover, the rest of baseline models could also be applied as reference methods. In those cases in which a distinction of type of days (e.g., weekdays and weekends) is preferred, it would be possible to use a rule that applies such a distinction, for example, "basic_weekend 7".

In other ambits different to flexibility services and DR contracts, the main interest is obtaining a precise prediction (and not the clarity and explainability of the applied models). An example of this would be the forecasting of uncertainties for the optimal operation of a microgrid. While the rule-based baselines are models that result clear in their calculation and only require historical data of the variable to predict, these models may have a worse performance than other more complex models as, for example, AI models.

Therefore, it becomes necessary to develop systems that can handle the training, testing, and selection of diverse types of forecasting models, including AI and ML techniques. In this sense, a forecasting framework has been developed, which is exposed in the next section. The rule-based baselines, in addition to their use as forecasting models, can be used as inputs for other types of models inside such framework, as it will be seen later.

4.6 Forecasting framework for load and generation

As has been mentioned above, power system operation and energy management are highly dependent on the forecasting capability. In this sense, "power forecasting is needed in multiple applications, such as obtaining the available flexible capacity for a customer, performing grid management tasks based on expected customer behavior, or improving the daily optimization of resources with an EMS" *[[22]]*. Moreover, the introduction of forecasting data on optimization problems can be done in many ways, depending on if the information is deterministic, probabilistic, based on intervals, etc.

Based on the described forecasting needs, the author proposed in *[[22]]* "a complete framework for the multistep short-term forecasting of electric power consumption and generation." While the framework is mainly oriented to microgrids, it is also compatible with its use in distribution networks, because in both cases the types of variables to predict (consumption and/or generation) are similar in their characteristics (aggregation and prediction horizon).

The version of the framework presented in *[[22]]* exclusively include deterministic forecasting methods. It was designed in this way due to the difficulties related to the evaluation of probabilistic models (which requires different metrics than deterministic models), "and considering that many energy management applications are based on deterministic forecasts (for example, the above-mentioned approaches [175, 176, 74])" *[[22]]*. Therefore, that version was "focused on deterministic methods, with the inclusion of probabilistic techniques being a future research topic" *[[22]]*. The integration of probabilistic techniques has already been addressed in the present thesis.

Specifically, a new version of the framework (called PRODEFOR) has been designed to permit the use of probabilistic methods, and therefore the use of additional types of uncertainty modelling. To do this, some modifications have been introduced, specially in the ML techniques and performance metrics that are applied.

The next section will describe the design decisions that have determined the approach of the framework considering the reviewed literature and the needs that were identified in it. Later, the preliminary version of the framework, the procedure for the inclusion of probabilistic models, and the new version of the framework will be described in detail.

4.6.1 Main design decisions

In the literature review, it has been appreciated that the most common approach for performing energy management optimization in microgrids is the use of a day-ahead horizon, i.e., considering a period of one day in the optimization problem. For this reason, the proposed framework has the objective of modeling the power values of a system for all time intervals in a given day *[[22]]*.

In addition to the previous characteristics, the applied datasets (combinations of input information fields) that are used for training forecasting models should be defined. In the definition of these datasets, for those fields that have to be periodically gathered (such as measurements, or weather information) it has been avoided to include them in all the defined datasets. For example, some of these datasets include recent measurements from the system (i.e., previous values of those variables to predict), and others do not include such information. The reason for this is that, if all models required these measurements, the framework would not be able to provide a prediction when the measurement process fails. To increase the robustness of the system, there will be models that work with different combinations of information, and the framework will execute the best possible model considering the available information (that is required for their execution) at the moment of performing the prediction.

It is interesting to highlight that, among the input fields that have been tested for training prediction models, some of them correspond to the rule-based baselines (a method originally published in *[[22]]*) that was exposed in Section §4.5. "These proposed baseline models have been found to be useful not only as non-black-box methods but also as possible inputs for ML techniques" *[[22]]*. Specifically, the techniques multi-layer perceptron regressor (MLPR) and random forest regressor (RFR) are applied in the paper. These two ML techniques "have been evaluated under different combinations of inputs, identifying which input sets achieve better results. Among the evaluated input variables, the cross relationship between the power variables under study has also been considered and exploited to improve the forecasting results. The inclusion of this information is performed using what is called an external baseline (EXBL), i.e., adding a baseline of some other variable of the microgrid (e.g., load consumption) as an input of a ML method" *[[22]]*. This idea is one of the proposals of the referred paper.

A prediction model can be one-output (also called single-output) or multioutput. Specifically, "this forecasting could be achieved by developing a one-output model that gives a prediction for the selected time interval (or time step) with every execution or a multiple output model that gives predictions for all the intervals in a day with one execution of the model" *[[22]]*.

"Referring to time and performance criteria, the best approach would be to use multioutput models, which utilize a lesser amount of data for the training and testing processes (each dataset contains all the outputs for one day). In contrast, a one-output model is fed with every independent value for each interval of the available days, requiring more time for training and testing" *[[22]]*.

Once described the design decisions, the next section will first describe the preliminary version of the proposed forecasting framework. This version, which was published in *[[22]]*, only included deterministic methods. It has served as the base for the new version that will be proposed in this thesis in Section §4.6.4. Therefore, before exposing the new improvements that have been introduced, the preliminary version will be briefly exposed.

4.6.2 Preliminary version of the framework

The original version of the forecasting framework was published in *[[22]]*. This version was exclusively focused on deterministic forecasting models, so it has been enhanced to a new version in this thesis, as will be seen later in the next sections.

The structure of the preliminary version of the framework is depicted in Figure 4.7. Firstly, the available input information is received and combined to create datasets (which are different groups of information fields that can be used to train forecasting models). Then, three types of models are created, which are rule-based baselines, MLPR models, and RFR models. The rule-based baselines are also connected back to the block of dataset preparation, so their information can be used in some of the datasets. The models are created, evaluated using the CV(RMSE), and their evaluation score is stored together with them. When the daily forecasting must be performed, the best model (the model with the best evaluation metric, i.e., the one with the lesser CV(RMSE)) that can be executed in that moment (i.e., the required information inputs have to be available in the system) will be executed to obtain the forecast. Finally, this forecast would be sent to the final application that needs it.

The main lack of this version of the framework is that it does not enable the use of stochastic and probabilistic methods, but only deterministic ones. In the next section of this thesis, an enhancement is proposed to include these methods and diverse types of uncertainty models together with their corresponding evaluation metrics.

The procedures that have been followed for including probabilistic forecasting methods are next described in Section §4.6.3. After that, the new architecture that was designed, which includes stochastic and probabilistic models, will be exposed in Section §4.6.4. Considering that many of the internal blocks that integrate the framework are similar in both versions, their functionalities will be detailed only in Section §4.6.4 to avoid repeating such information in the current section.

4.6.3 Probabilistic forecasting inclusion

The procedures that have been designed for the inclusion of probabilistic forecasting in the framework are depicted in Figure 4.8. The steps are:

- Step A: Choose the uncertain parameters that will be characterized by probabilistic forecasting.
- Step B: Perform the probabilistic forecasting of the parameters to be predicted. This can be done by stochastic/probabilistic models that directly provide the quantiles, or by applying a known distribution (e.g., normal distribution) with a certain standard deviation over the predictions of a deterministic forecasting (see Section §4.6.3.1). The deterministic and probabilistic techniques that are implemented in the framework will be described later in Section §4.6.4.2.

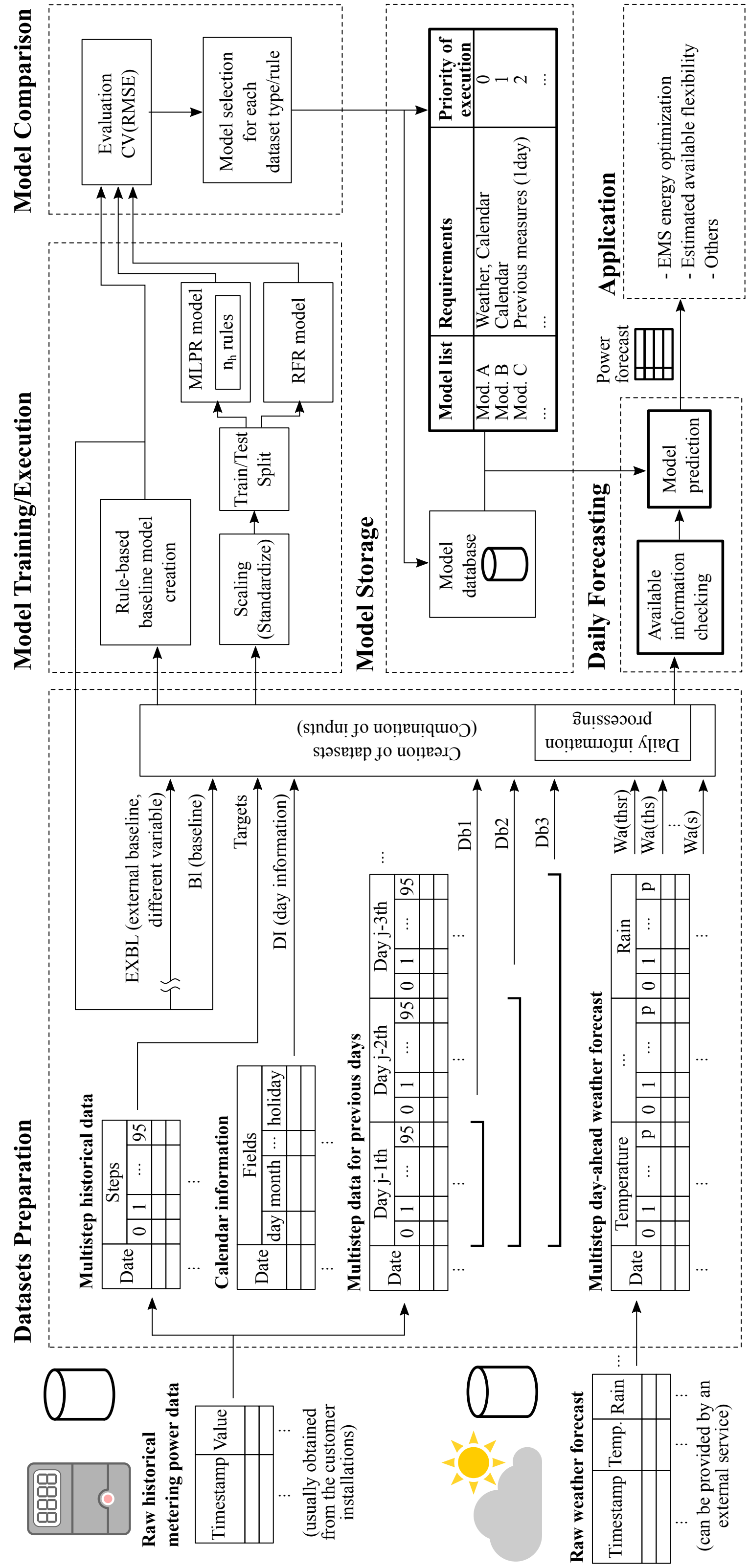


Figure 4.7: Preliminary power forecasting framework [[22]].

- Step C: Select the group of quantiles that will be used for creating intervals or scenario sets. This selection of quantiles can be done independently (i.e., a certain group of quantiles could be used for the intervals, and another different one for the scenarios).
- Step D: Create prediction intervals. This is done by picking pairs of quantiles and calculating their probability (which is equal to the difference between both quantiles that compose that interval).
- Step E: Generate scenario sets from the selected quantiles. The procedure that is proposed for doing this operation is detailed in Section §4.6.3.2.
- Step F: Evaluate the uncertainty models. As can be seen, instead of using the same metric for all models according to the distribution of quantiles that was originally used, it is proposed the use of a specific metric for each of the three types of uncertainty modelling: The pinball loss function is used for quantile distribution, the Winkler score is used for intervals (see Section §4.6.3.3), and the weighted pinball score (a metric that is proposed in this thesis, which is exposed in Section §4.6.3.4) is used for scenario sets generated by the method proposed in Section §4.6.3.2.

These steps are executed inside the framework when using probabilistic models. However, it has been preferred to introduce this procedure in the current section for clarity, instead of doing it during the explanation of the blocks that integrate the overall framework.

Some of the steps of the diagram describe complex procedures that should be better clarified, so these will be exposed in more detail in the next sections.

4.6.3.1 Probabilistic forecasting assuming a normal distribution

This method is based on the description found in [198], in which the authors create scenarios introducing a standard deviation of 30% over a deterministic forecasting to obtain new scenarios. In the words of the authors: "The uncertain parameters are assumed to have a continuous PDF with 30% standard deviation. Then, the continuous PDF is estimated by discrete PDF including N_n steps" [198]. Therefore, following this method, the generated scenarios will have an associated probability assuming a normal distribution. The standard deviation does not necessarily have to be 30%, but can take other values.

Firstly, the required deterministic forecasting will be obtained (by using some deterministic model). Then, it will be assumed that the searched probabilistic forecasting follows a normal distribution with a standard deviation σ centered on the deterministic forecast value μ for the instant t, so the desired quantiles will be proportional to that specific value. The value of the mean and standard deviation will be:

$$\mu = \hat{y}_t, \tag{4.4}$$

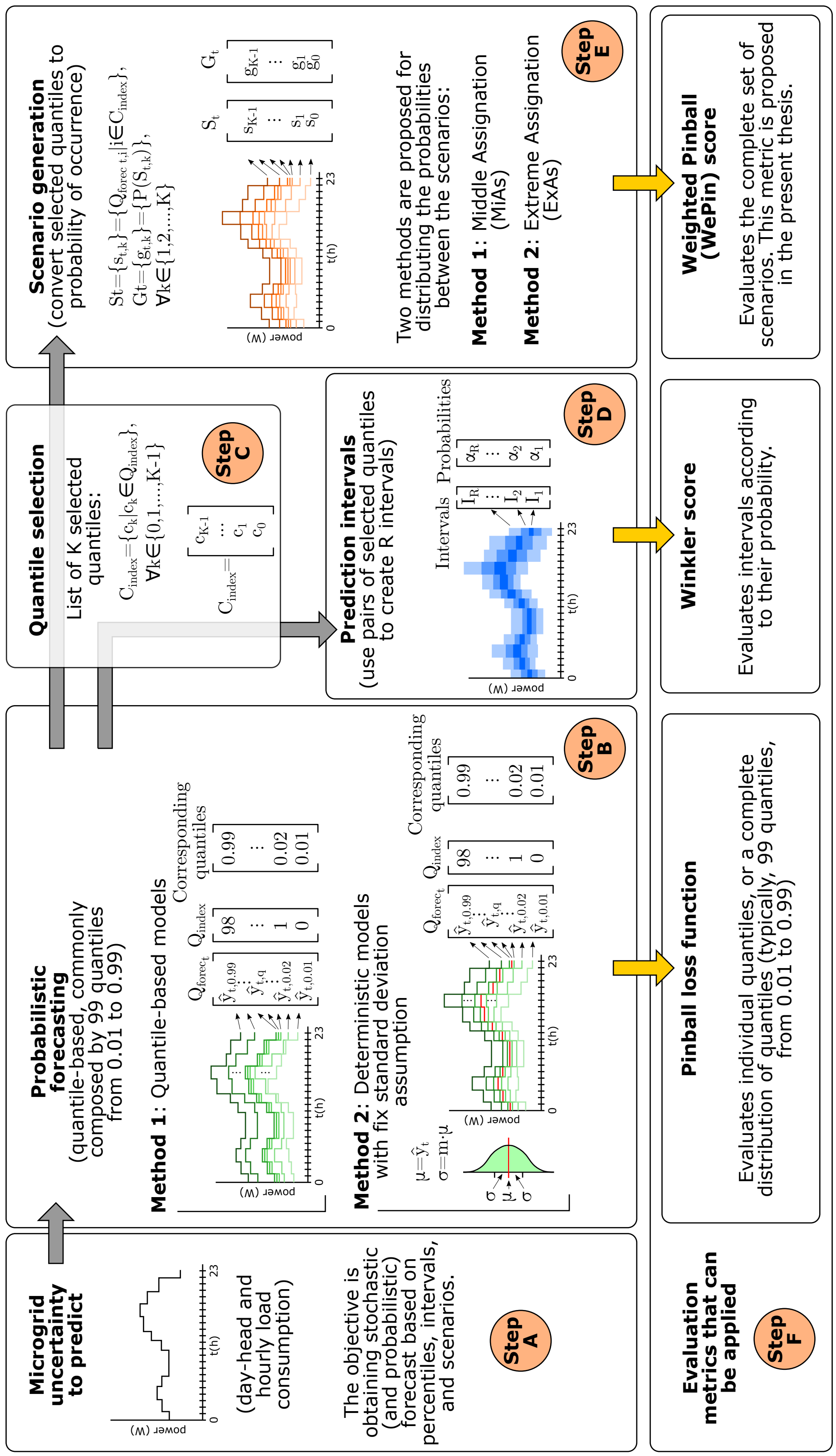


Figure 4.8: Proposed procedure for generation of scenario sets and intervals from quantiles.

$$\sigma = m \cdot \mu, \tag{4.5}$$

where m is a real number whose value would be chosen according to the desired deviation of the distribution. For example, m could be equal to 0.1 (sigma 10%), 0.2 (sigma 20%) and 0.3 (sigma 30%), in the same way that it was done in [198] (where they applied a 30%).

Once established such distribution for the forecasted variable, the values of the forecast for the desired quantiles are as follows.

For a certain quantile q, obtain the z-score z_q that accomplishes the condition:

$$q = Pr(Z < z_q), \tag{4.6}$$

and then, the value $\hat{y}_{t,q}$ for that quantile q is equal to:

$$\hat{y}_{t,q} = \mu + z_q \cdot \sigma, \tag{4.7}$$

4.6.3.2 Generation of scenario sets from quantiles

Theoretically, it is possible to generate as many forecasted scenarios as it is desired for a certain variable. However, it is important to note that the stochastic optimization methods usually have high computational requirements, so the inclusion of a high number of scenarios would drastically increase the computational cost, as it has been pointed out by other authors [102]. Therefore, it is a common solution to perform a limited selection of some scenarios for each uncertainty (for example, [198] uses 50 scenarios which have the highest probability of occurrence, including wind speed, solar radiation, thermal, and electrical loads as uncertain parameters).

For generating scenarios, it is said in [198] that "after producing all scenarios and the probability related to each scenario, the most probable scenarios with the highest possibility of occurrence are selected. This approach results in a trivial error at the outputs, but it significantly reduces the simulation time" [198].

In the present thesis, an alternative way to perform this process is proposed. Instead of producing all possible scenarios and keeping the most probable ones, a selection of the quantiles to be used will be done, and their corresponding probabilities will be assigned. The method exposed in [198], and other Monte-Carlo-based methods from the literature, despite being able to generate a massive number of different scenarios, it is not always easy to decide which forecasting model produces the better quality scenarios. With the method that is proposed in this thesis, the generated scenarios will be directly linked to their corresponding quantiles, which makes more clear their distribution, and what is the behavior of the forecasted variables.

It is not the purpose of this thesis to provide the results of the optimization problem using the generated scenarios, as the obtention and analysis of the results of such optimization would constitute a totally independent study. The goal of the proposed procedure is to provide a methodology to evaluate and choose the probabilistic forecasting model among all those that have been trained, and generate the desired number of scenarios and their associated probabilities. The use of this information to solve a microgrid stochastic optimization problem can be done following the methods that can be found in the bibliography.

For starting the proposed scenario generation, it is necessary to obtain a bunch of quantiles of the variable to be predicted. Two possible methods are described. The first one, that has been described in [198], obtain the scenarios from a single deterministic forecast by supposing a fixed standard deviation. The second one is to use some probabilistic forecasting technique that provides quantile information.

Under the proposed method, the uncertainty values for an scenario S at the time t for a certain quantile q will be equal to the probabilistic forecast during a period of time for a certain quantile q. Therefore, it can be said that:

$$S_t(q) = \hat{y}_{t,q} \tag{4.8}$$

However, the probability of the scenario is not equal to that of the quantile. This decision is made taking into account that the sum of the probabilities of all considered scenarios for an uncertainty have to be equal to 1 (to reach the 100% of probability). This will depend on the number of scenarios, and which are the quantiles that are chosen.

For distributing the probability to the scenarios, the proposed method is as follows.

Being $Q_{forec_t} = \{\hat{y}_{t,q}\}, \forall q \in \{0.01, 0.02, \ldots, 0.99\}$ the array of 99 forecasted quantiles (from quantile 0.01 to 0.99) of variable at a certain instant t.

Being $Q_{index} = \{0, 1, \ldots 98\}$ the array that contains the position indexes of the elements of the array Q_{forec_t}.

Being $C_{index} = \{c_0, c_1, ..., c_{K-1}\}$ the ordered array of K quantile indexes that will compose the scenario set (i.e., chosen quantiles), in which the position $k = 0$ is the lowest quantile of them and $k = K - 1$ is the highest quantile. Note that in this array, a value $q_k = 0$ means "the quantile 0.01 is used as one of the scenarios of the set," a value $q_k = 1$ means "the quantile 0.02 is used as one of the scenarios of the set," etc. The reason for this behavior is that the elements q_k express the indexes inside the array of 99 quantiles.

Being $S_t = \{s_{t,0}, s_{t,1}, ..., s_{t,K-1}\} = \{Q_{forec_t} | i \in C_{index}\}$ the ordered array of K scenarios corresponding to the K quantile values chosen, in which the position $k = 0$ is the scenario with the lowest quantile of them and $k = K - 1$ is the scenario with the highest associated quantile.

Being $G_t = \{g_0, g_1, \ldots, g_{K-1}\} = \{P(s_{t,0}), P(S_{t,1}), \ldots, P(s_{t,K-1})\}$ the array of probabilities of each scenario belonging to the scenario set S_t, given that $\sum_{k=0}^{K-1} P(s_{t,k}) = 1$.

If it is considered that the probability between two scenarios is equally divided between them, then the probabilities of the array G should be distributed between the scenarios according to the next expression:

$$g_k = \begin{cases} q_k + \dfrac{q_{k+1} - q_k}{2}, & \text{if } k = 0 \\ \dfrac{q_{k+1} - q_k}{2} + \dfrac{q_k - q_{k-1}}{2} = \dfrac{q_{k+1} - q_{k-1}}{2}, & \text{if } 0 < k < K-1 \\ 1 - q_k + \dfrac{q_k - q_{k-1}}{2}, & \text{if } k = K-1, \end{cases} \tag{4.9}$$

Therefore, Expression 4.9 establishes how the probabilities should be distributed to the scenarios once the set of quantiles has been chosen. However, firstly it is necessary to choose these quantiles.

Despite this selection could be done freely, it has been preferred to design a procedure in which the scenarios and their probabilities are as equally distributed as possible. In this sense, a conflicting aspect was found. If the two extremes of the quantile array (the lowest one and the highest one) are selected to create scenarios, in some cases it would not be possible to distribute the same probability to each of the scenarios, as these would not be equally distributed. Otherwise, if the scenarios are selected equally spaced in the distribution, it would be possible to distribute (exactly, or at least approximately) the same probability to them.

The procedure that is proposed for the automatic selection of quantiles for creating scenarios, and the assignation of probabilities for such scenarios is expressed in Algorithm 1. To execute the algorithm, it is only required to choose the number of scenarios to create, and choose if the extreme quantiles should be included in the pool (Extreme Assignation (ExAs) method) or not (Middle Assignation (MiAs) method). For simplifying the proposed algorithm, it has been considered that the vector Q has 99 elements, the value for quantile 0.01 (i.e., percentile 1%) is stored in position 0, and the value for quantile 0.99 (i.e., percentile 99%) is stored in position 98. However, the same idea could be adapted to other cases adapting the values and indexes in the given algorithm.

The Table 4.3 contains some examples of scenario indexes and probabilities that have been selected according to the proposed algorithm.

4.6.3.3 Existing metrics for probabilistic forecasting

As seen in Section §3.5.5, the most common existing metrics for the evaluation of probabilistic forecasts are the pinball loss function and the Winkler score. Their expressions are defined in 4.10 and 4.11 [173]:

$$Pinball(\hat{y}_{t,q}, y_t, q) = \begin{cases} (1-q)(\hat{y}_{t,q} - y_t), & y_t < \hat{y}_{t,q} \\ q(y_t - \hat{y}_{t,q}), & y_t \geq \hat{y}_{t,q}, \end{cases} \tag{4.10}$$

$$Winkler = \begin{cases} \delta, & L_t \leq y_t \leq U_t \\ \delta + 2(L_t - y_t)/\alpha, & y_t < L_t \\ \delta + 2(y_t - U_t)/\alpha, & y_t > U_t, \end{cases} \tag{4.11}$$

In which $\hat{y}_{t,q}$ corresponds to the forecasted value for a specific quantile, y_t is the real value to be forecasted, q is the quantile, L_t is the lower bound, U_t the upper bound, δ is the difference between the two bounds of the prediction interval ($\delta = U_t - L_t$), and $(1-\alpha)$ is the nominal probability of the prediction interval.

The pinball score evaluates a forecast considering its associated quantile. The Winkler score evaluates an interval considering the upper and lower limit and its associated probability.

It is said in [173] that the pinball losses can be summed across all targeted quantiles to obtain the pinball loss of the probabilistic forecast. However, from our point of view, this approach would be appropriate for evaluating regular intervals across the whole set of percentiles (for example, summing the pinballs for $q = 0.01, 0.02, 0.03, ..., 0.99$). In the case of evaluating a set of scenarios with a nonregular distribution, this metric could cause an excessive weight over certain quantiles if they are not equally distributed across the range from 0 to 1.

For these reasons, it is here identified the need of a new metric that is able to evaluate any set of scenarios with their associated probabilities, which would be desirable for the evaluation of probabilistic models focused on probabilistic optimization of microgrids, as it was previously raised. In this sense, a new metric for evaluating sets of scenarios will be proposed next.

4.6.3.4 Proposed metric for scenario sets: weighted pinball

The new metric that is proposed, which will in advance be called weighted pinball (WePin) score, whose objective is expanding the evaluation of the whole set of selected quantiles under a single score value. This metric is based on the pinball loss function, but assigns weights to each scenario according to its occurrence probability.

Algorithm 1 Create a set of scenarios applying the chosen method.
The algorithm gives the percentile indexes that correspond to a set of scenarios and the probability that should be assigned to each of these scenarios.
The total number of scenarios is equal to the input N_{scen}. The two available methods are MiAs and ExAs. This is selected according to the input $method_{scen}$.
The output C_{index} contains the indexes of the quantile array that are chosen to serve as scenarios (therefore, it has a length of N_{scen} elements).
The output G contains the probabilities of each scenario.

Input N_{scen}, $method_{scen}$
Output C_{index}, G
Ensure: N_{scen} is an integer number
Ensure: $N_{scen} \geq 1$
Ensure: $N_{scen} \leq 99$
Ensure: $(method_{scen} = \texttt{"MiAs"})\texttt{or}(method_{scen} = \texttt{"ExAs"})$

```
Declare C_index array of N_scen integers
Declare G array of N_scen floats
if method_scen is "MiAs" then
    n ← 1
    position ← 0
    while n < 2 · N_scen do
        index_n ← (100·n)/(2·N_scen)
        index_n ← round(index_n)
        index_n ← index_n − 1          ▷ Position 0 is percentile 1% in the array of quantiles
        C_index[position] ← index_n
        n ← n + 2
        position ← position + 1
    end while
    n ← 0
    while n < N_scen do
                ▷ The probabilities are considered equal for all the scenarios in the MiAs set
        probab_n ← 1/N_scen
        G[n] ← probab_n
        n ← n + 1
    end while
```

Algorithm 1 (continued)

else if $method_{scen}$ is `"ExAs"` **then**
  $n \leftarrow 0$
  if $N_{scen} = 1$ **then**
    $C_{index}[n] \leftarrow 49$ ▷ Save the percentile 50% in array.
    $G[n] \leftarrow 1.0$ ▷ Assign a probability of 1 (i.e., 100%) to the scenario.
  else
    $C_{index}[n] \leftarrow 0$ ▷ Save the lowest percentile (1%) in array.
    $n \leftarrow 1$
    while $n < N_{scen} - 1$ **do**
      $index_n \leftarrow \frac{100 \cdot n}{N_{scen}-1}$
      $index_n \leftarrow round(index_n)$
      $index_n \leftarrow index_n - 1$
      $C_{index}[n] \leftarrow index_n$
      $n \leftarrow n + 1$
    end while
    $C_{index}[n] \leftarrow 98$ ▷ Save the highest percentile (99%) in array.
    $n \leftarrow 0$
    while $n < N_{scen}$ **do**
      if $n = 0$ **then** ▷ Store probability for lower extreme scenario.
        $probab_n \leftarrow \frac{C_{index}[n]+1}{100} + \frac{C_{index}[n+1]-C_{index}[n]}{2 \cdot 100}$
      else if $n = N_{scen} - 1$ **then** ▷ Store probability for upper extreme scenario.
        $probab_n \leftarrow \frac{100-1-C_{index}[n]}{100} + \frac{C_{index}[n]-C_{index}[n-1]}{2 \cdot 100}$
      else ▷ Store probability for an scenario that is not an extreme.
        $probab_n \leftarrow \frac{C_{index}[n]-C_{index}[n-1]}{2 \cdot 100} + \frac{C_{index}[n+1]-C_{index}[n]}{2 \cdot 100}$
      end if
      $G[n] \leftarrow probab_n$
      $n \leftarrow n + 1$
    end while
  end if
end if

Note 1: This algorithm considers that the forecasting for each point is composed by a sorted array of 99 float numbers, where the number in position 0 corresponds to the prediction for percentile 1% and the position 98 corresponds to the prediction for percentile 99%. Otherwise, the algorithm should be adapted appropriately.

Note 2: For the calculation of scenarios under the method ExAs, the lower extreme correspond with the percentile 1% (whose index is 0) and the upper extreme corresponds with the percentile 99% (whose index is 98). Under the method MiAs, the extremes are automatically chosen depending on the number of scenarios.

Table 4.3: Examples of scenario set indexes and probabilities obtained by the proposed algorithm.

Scenario set configuration	Scenario number	Chosen indexes from quantile array	Corresponding quantile (and percentile)	Probability of scenario
2 MiAs scenarios	1	24	0.25 (25%)	0.5
	2	74	0.75 (75%)	0.5
3 MiAs scenarios	1	16	0.17 (17%)	0.333
	2	49	0.5 (50%)	0.333
	3	82	0.83 (83%)	0.333
5 MiAs scenarios	1	9	0.1 (10%)	0.2
	2	29	0.3 (30%)	0.2
	3	49	0.5 (50%)	0.2
	4	69	0.7 (70%)	0.2
	5	89	0.9 (90%)	0.2
2 ExAs scenarios	1	0	0.01 (1%)	0.5
	2	98	0.99 (99%)	0.5
3 ExAs scenarios	1	0	0.01 (1%)	0.255
	2	49	0.5 (50%)	0.49
	3	98	0.99 (99%)	0.255
5 ExAs scenarios	1	0	0.01 (1%)	0.13
	2	24	0.25 (25%)	0.245
	3	49	0.5 (50%)	0.25
	4	74	0.75 (75%)	0.245
	5	98	0.99 (99%)	0.13

Consider a probabilistic forecast of a time series variable y_t that provides a group of K scenarios from $s_{t,0}$ to $s_{t,K-1}$, each of them corresponding to a certain quantile q (that goes from q_0 to q_{K-1}). Moreover, each scenario has a probability of occurrence g from g_0 to g_{K-1}. The WePin score for a certain day d that goes from $t=0$ to $t=T-1$ (being T the number of time intervals in one day) is defined as:

$$WePin_{daily_d} = \sum_{k=1}^{K} \left[g_k \cdot \sum_{t=0}^{T-1} \left[\frac{Pinball(s_{t,k}, y_t, q_k)}{T} \right] \right], \tag{4.12}$$

where T is the number of steps considered within a day (in the case of hourly data, T is equal to 24). q_k will be the quantile value associated to the scenario $s_{t,k}$. Therefore:

$$q_k = \frac{Q_{index} \cdot (C_{index}(k)) + 1}{100}, \tag{4.13}$$

Similarly, the mean daily WePin score for a group of D days will be equal to:

$$WePin_{D\ days} = \sum_{d=1}^{D} \frac{WePin_{daily_d}}{D}, \tag{4.14}$$

Once exposed the procedures for handling probabilistic methods, the architecture of the new forecasting framework will be exposed next.

4.6.4 Framework architecture

This section describes the blocks that integrate the architecture of the proposed PRODEFOR framework. These blocks perform the dataset preparation, training and testing of models, evaluation, storing, and also provide daily forecasting to the final applications.

The architecture of the new version of the forecasting framework is depicted in Figure 4.9. It includes stochastic and probabilistic models and the mechanisms for their evaluation and execution. Several of the main blocks are common to those of the old version of the framework, and therefore some of their descriptions are similar to those given in *[[22]]*. Thus, the main blocks that make up the framework will be explained in detail in the next sections.

4.6.4.1 Dataset preparation

This block is responsible for preparing the datasets that contain information about the variables to be predicted. These are used to feed the block of training and testing of models. As said in *[[22]]*, "the dataset preparation block receives information regarding the selected measures and weather data. These fields of information are formatted and combined to create the previously described datasets" *[[22]]*.

The total number of inputs and outputs for a dataset depends on the aggregation level. "Specifically, 15-min aggregations have 96 outputs for a whole day, while 60-min aggregations possess 24 outputs. The same applies for the other input fields that include measurements of previous days or baselines, where each input day implies the same number of inputs (96, 24, etc. according to the aggregation)" *[[22]]*.

"Based on the reviewed state-of-the-art methods and considering the typical needs of the mentioned applications, the aggregation levels are typically 15 min, 1 h and (in some cases) 2 h. This means that the number of time intervals (also called bins, time periods, or timeslots, depending on the author) is equal to 96, 24 or 12 for a whole day, respectively. The architecture is designed to perform multistep predictions at 00:00 of each day, obtaining a prediction for each variable for the next 24 h (day-ahead) under the desired aggregation level" *[[22]]*.

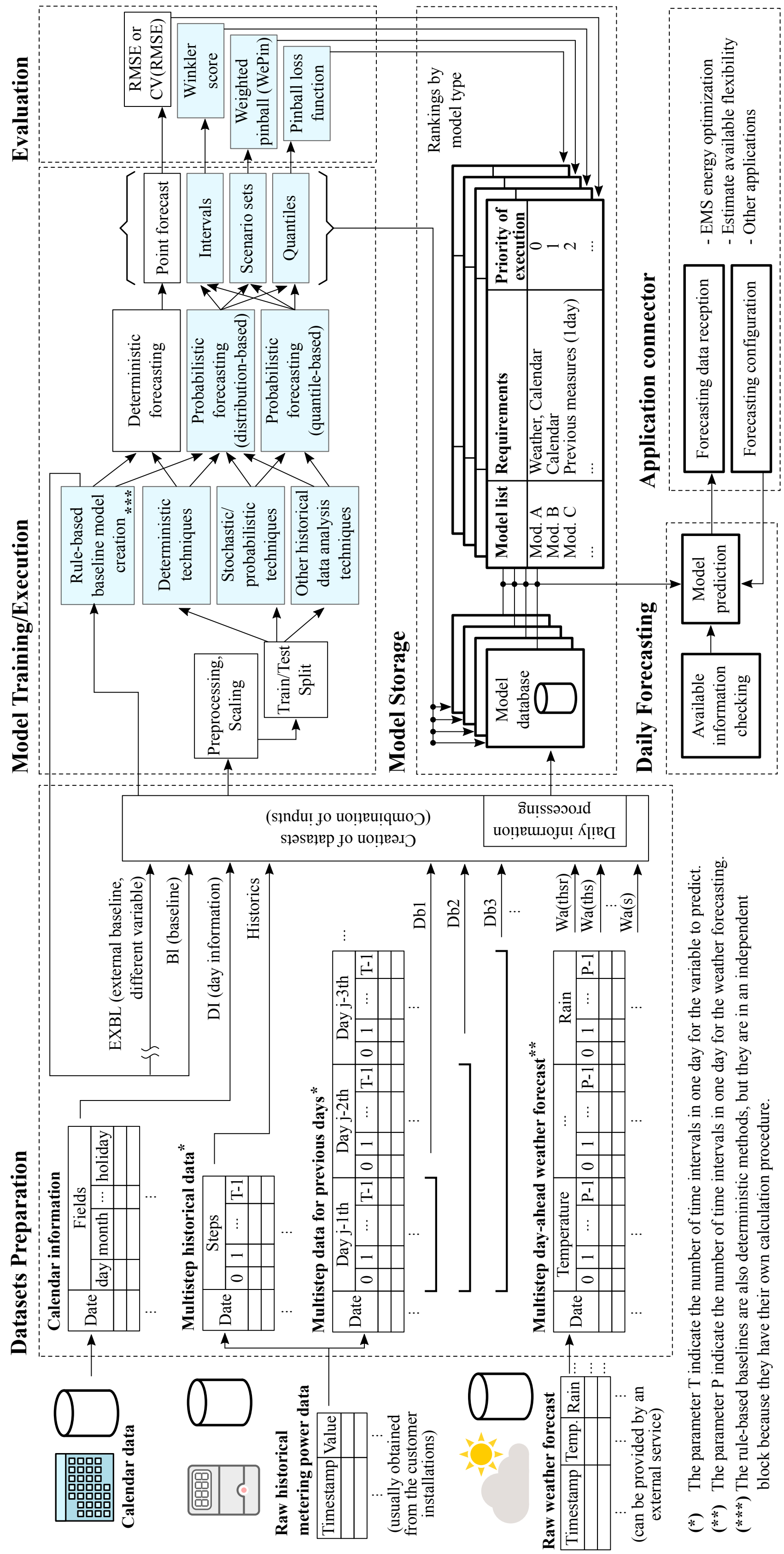


Figure 4.9: New proposed forecasting framework PRODEFOR. In blue, the blocks that participate in the inclusion of probabilistic methods according to the procedures exposed in Section §4.6.3.

The information fields that have been declared for creating datasets (by combining them) can be seen in Table 4.4. "In the field of power forecasting, it is common to use datasets that, apart from power values (with their corresponding timestamps), also include weather information such as temperature and humidity data" *[[22]]*. Weather data is labeled as Wa, followed by some letters that indicate what weather variables are included (t for temperature, h for humidity, etc.). "Moreover, this information can (and should) be enriched with the inclusion of extra information. This additional information could be date-related information (e.g., days of the week, workdays) or the inclusion of previous measurements (e.g., the raw measurements taken on some previous days)." In this sense, the fields under the group DI (which stands for "day information" include representative data about the date, for example, the month, the day of the week, and holidays *[[22]]*. Measurements of previous days (a maximum of 3, to limit the total number of input fields) are also included, which are those groups with the label Db (which stands for "days back").

Furthermore, as part of the proposals of the present paper, it is possible to include not only the raw data of previous days (which is usually done by other authors) but also their corresponding baseline forecasts obtained with the previously described rule-based baseline method" *[[22]]*. As indicated in Figure 4.9, "the baseline models are used as feedback for the dataset creator and included as input groups (the baseline and external baseline) in some of the datasets" *[[22]]*.

The datasets that include information from the rule-based baselines contains the tags Bl (a baseline of the variable to be predicted) and/or EXBL (a baseline of a different variable than the one to be predicted, e.g., another variable of the microgrid that could affect to the variable to predict). In the words of *[[22]]*, "the EXBL consists of a variable baseline that is different from the objective to be predicted (i.e., not the target variable but another variable of the microgrid, such as the load consumption). The reason for this inclusion is to take ad-vantage of the correlations between the different variables (i.e., load consumption and the variable to be predicted) of the microgrid to improve the forecasting results. The datasets that include an EXBL are identified on their tags at the end of their names" *[[22]]*.

Globally, "up to five groups of possible inputs (described in Table 4.4) are proposed for this framework. The exact number of inputs in some of these groups depends directly on the aggregation of the forecasted variables (the number of time intervals considered in a whole day) and the aggregation of weather forecasts (which could be different from the aggregation of the forecasted variable)" *[[22]]*. In Table 4.4, the new types of inputs that have been added in the framework later to the publication of *[[22]]* are marked in green.

"From the combinations of all these fields, multiple datasets can be generated to train models. In this sense, Table 4.5 summarizes the different datasets proposed for this forecasting framework. To simplify the identification of the datasets, a tag (*dataset type*) is assigned to those similar datasets. Each tag summarizes the information included in the datasets (calendar information, weather, previous measurements, etc.) using a simple, short name" *[[22]]*. In Table 4.5, the new types of datasets that have been added in the framework later

Table 4.4: Types of inputs. The newly added inputs that were not included in *[[22]]* are marked in green.

Input Group Names	Input Fields	Description
DI (stands for day information)	year	Year
	month	Month
	dayM	Day of the month
	dayW	Day of the week
	weekend	Whether the day is a weekend day (Saturday or Sunday)
	holiday	Whether the day is a holiday
	sw	Daylight saving time (summer or winter).
Wa(thsr)	Temperature (t), humidity (h), irradiance (s), and rain (r).	Day-ahead weather forecast for the whole day. The number of time intervals could be different from the number of intervals of the variable.
Wa(thr)	Temperature (t), humidity (h) and rain (r).	
Wa(ths)	Temperature (t), humidity (h), and irradiance (s)	
Wa(th)	Temperature (t) and humidity (h)	
Wa(t)	Temperature (t)	
Wa(s)	irradiance (s)	
Historics	Historical data of measurements	Historical data of the variable to predict adapted according to the number of time intervals that is considered for forecasting each day. These are used in those techniques that requires more flexibility in the use of fields form historical data, such as rule-based baselines and time series models (e.g., ARIMA).
Db1	Measurements of day -1	Power values for all time intervals of the previous day.
Db2	Measurements of days -1 and -2	Power values for all time intervals of the two previous days.
Db{-2}	Measurements of day -2	Power values for all time intervals of the day two positions before the day to predict.
Db3	Measurements of days -1, -2 and -3	Power values for all time intervals of the three previous days.
Db{-2,-3}	Measurements of days -2 and -3	Power values for all time intervals of days in positions two and three before the day to predict.
Bl(sn) Bl(bwn) Bl(swn) Bl(cnbn)	Day-ahead forecast using rule-based baseline models	The baseline[1] forecast of the variable to be predicted using a certain rule, with n as the chosen hyperparameter.

(continued on next page)

Table 4.4: *(continued)*

Input Group Names	Input Fields	Description
EXBL(sn) EXBL(bwn) EXBL(swn) EXBL(cnbn)	Time intervals of an external baseline	Baseline[1] forecasts of a variable that are different from the variable to be predicted, with n as the chosen hyperparameter. As this baseline is from a different variable, it is called an "external baseline" (EXBL).
Bl(t)	Day-ahead forecast of the temperature using rule-based baseline models	Baseline[1] forecast of the temperature. The baseline rule that is applied will be the same that is used for the variable to predict in each dataset; e.g., if the information Bl(t) goes together with the information Bl(s1), then the baseline rule for temperature is s1.

[1] The referred baselines are calculated as explained in Section §4.5.

Table 4.5: Types of datasets (combination of input groups). The newly added datasets that were not included in *[[22]]* are marked in green.

Dataset type	Dataset	Composition (input groups that are included) [1]
CaIn	CaIn	DI
Wa	Wa(... [2]) + DI	Wa (weather variables) and DI
Db	Db1 + DI	Db1 and DI
	Db2 + DI	Db2 and DI
	Db-2 + DI	Db-2 and DI
	Db3 + DI	Db3 and DI
	Db-2,-3 + DI	Db-2,-3 and DI
DbWa	Db1Wa(... [2]) + DI	Db1, Wa (weather variables) and DI
	Db2Wa(... [2]) + DI	Db2, Wa (weather variables) and DI
	Db{-2}Wa(... [2]) + DI	Db-2, Wa (weather variables) and DI
	Db3Wa(... [2]) + DI	Db3, Wa (weather variables) and DI
	Db{-2,-3}Wa(... [2]) + DI	Db-2,-3, Wa (weather variables) and DI
Bl	Bl(... [3]) + DI	Bl (baseline rule and number of days) and DI
BlWa	Bl(... [3])Wa(... [2]) + DI	Bl (baseline rule and number of days), Wa (indicating the weather variables) and DI
CaIn + EXBL	CaIn + EXBL(... [3])	DI and EXBL (baseline rule and number of days)

(continued on next page)

Table 4.5: *(continued)*

Dataset type	Dataset	Composition (input groups that are included) [1]
Wa + EXBL	Wa(... [2]) + DI + EXBL(... [3])	Wa (indicating the weather variables), DI and EXBL (baseline rule and number of days)
Db + EXBL	Db1 + DI + EXBL(... [3])	Db1, DI and EXBL (baseline rule and number of days)
	Db2 + DI + EXBL(... [3])	Db2, DI and EXBL (baseline rule and number of days)
	Db3 + DI + EXBL(... [3])	Db3 and DI and EXBL (baseline rule and number of days)
DbWa + EXBL	Db1Wa(... [2]) + DI + EXBL(... [3])	Db1, Wa (weather variables), DI and EXBL (baseline rule and number of days)
	Db2Wa(... [2]) + DI + EXBL(... [3])	Db2, Wa (weather variables), DI and EXBL (baseline rule and number of days)
	Db3Wa(... [2]) + DI + EXBL(... [3])	Db3, Wa (weather variables), DI and EXBL (baseline rule and number of days)
Bl + EXBL	Bl(... [3]) + DI + EXBL(... [3])	Bl (baseline rule and number of days), DI and EXBL (baseline rule and number of days)
BlWa + EXBL	Bl(... [3])Wa(... [2]) + DI + EXBL(... [3])	Bl (baseline rule and number of days), Wa (indicating the weather variables), DI and EXBL (baseline rule and number of days)
BlWa + Bl(t)	Bl(... [3])Wa(... [2]) + DI + Bl(t)	Bl (baseline rule and number of days), Wa (indicating the weather variables), DI and Bl(t). The rule for the baseline of the temperature is the same that is specified between the parentheses of Bl(... [3]).
RawHist	Historics + DI	Historics and DI. This dataset is used for creating rule-based baselines and some time series models such as ARIMA.

[1] The abbreviations used for the inputs are specified in Table 4.4.

[2] The weather variables that are included as inputs are specified here. These variables can be temperature (t), humidity (h), solar irradiance (s) and rain (r).

[3] The type of rule and the number of days for the calculation of the baseline (Bl) or the external baseline (EXBL) are specified here.

to the publication of *[[22]]* are marked in green. When the proposed framework is applied to a specific case, it is not necessary to apply the whole set of datasets that are proposed, but only some of them could be activated according to the desired configuration of the system. Additionally, other new datasets could be defined when required.

Having exposed how the datasets are created, the next section will describe the block where the forecasting techniques are applied for creating models.

4.6.4.2 Model training/execution

In the framework presented in *[[22]]*, the techniques that were included were "rule-based baselines and artificial intelligence regression methods (which also consider the inclusion of baseline forecasts as additional inputs)" *[[22]]*. These AI techniques (which are also ML techniques) are MLPR and RFR.

The main enhancement of the new version of the framework has been the inclusion of probabilistic methods. For that, the RFR technique now permits the use of bootstrapping (by using decision tree estimators from RFR models) for obtaining a distribution of points which can be converted to quantile prediction. This technique is referred to as probabilistic random forest regressor (RFR_prob).

It has been frequently observed through the literature review that many authors perform probabilistic forecasting by applying a known distribution (e.g., normal distribution) with a certain standard deviation over a deterministic forecasting. Therefore, this method has been implemented, permitting the use of normal distribution over the deterministic models that were mentioned in Section §4.6.3.1. This process has permitted the inclusion of the technique probabilistic random forest regressor with fixed sigma (RFR_probSIGMAFIX) with three different configurations, which are RFR_probSIGMAFIX10, RFR_probSIGMAFIX20, and RFR_probSIGMAFIX30.

The ARIMA method has also been included for obtaining deterministic predictions.

Further details of the previously mentioned techniques can be found in appendix A.

This framework enables the inclusion of additional modelling techniques while the required characteristics are accomplished (obtaining predictions for all time intervals of a day, and being able to work with some of the described datasets). As a future work, it could be considered the possibility of including LSTM models, which is one of the most extended approaches that is gaining importance nowadays.

4.6.4.3 Evaluation metrics

The existing metrics for the evaluation of forecasting models were already reviewed in Section §3.5.5 of the current thesis. Among these metrics, it was necessary to choose which ones should be used in the proposed framework. As it is exposed in *[[22]]*, despite there exist many indicators to study the forecast for specific applications (such as peak prediction), "for general applications in energy management, it is preferable to follow some of the common indicators that were previously described, as most of the authors do in the reviewed bibliography (for example, [337, 338, 340]). Therefore, this is the approach adopted in the present study" *[[22]]*.

It is said in *[[22]]* that the CV(RMSE) (see 4.15) "is appropriate for the evaluation of a series with both positive and negative values" *[[22]]*, so it was used for the case study presented in such paper. The RMSE (see 4.16) is also considered appropriate in such situations, so this indicator will also be included in the framework for evaluating deterministic models and have been applied in other case studies in Chapter §5.

$$CV(RMSE)(\%) = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2}}{\bar{y}} \cdot 100 \tag{4.15}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2} \tag{4.16}$$

For each situation in which the forecasting framework is applied, only one of these two metrics is used for the evaluation of deterministic models. In most of the situations, it would be appropriate to use any of the two metrics indistinctly. An exception to this would be those cases in which some variables to predict have an average value near to zero, or a sparse behaviour, which could cause very high values or abrupt changes in the values of CV(RMSE). In these situations (as it occurs in one of the case studies of Chapter §5), it will be preferred to apply the RMSE for evaluating deterministic models.

In the case of probabilistic forecasting methods, despite being all applied techniques based on quantile forecasting, it has been found that using the same evaluation metric for all of them could not be the most convenient solution.

The reason for using different metrics is that, as seen in Section §4.6.3, the uncertainty modelling can be expressed in different ways by including stochastic (or probabilistic) information. The main ones are intervals (frequently used in robust optimization), that aims to reflect the worst cases in the optimization problem; risk management, that consider the whole distribution of quantiles to find which is the level of risk that should be taken; and scenarios, that express some of the possible occurrences of the known variables.

In the present framework, all these kinds of representations for the uncertainties are obtained from the same type of information, which is a set of predicted quantiles (99 quantiles that go from 0.01 to 0.99) of the variable. In this sense, a possible approach for the selection of the best model (that should be executed for performing future predictions) would be directly evaluating the set of 99 quantiles using the pinball loss function, and using the best selected model (under the pinball criterion) for creating other types of uncertainty models (intervals and sets of scenarios, which could only require to use some of these quantiles). However, considering that the creation of intervals and scenario sets are made from a selection from the original set of 99 quantiles, each type of uncertainty model that is obtained from these quantiles should be evaluated with an appropriate metric. For example, if a probabilistic model will be used for obtaining the worst cases, only those quantiles that are used to construct the considered intervals should be evaluated to select the best model for this task. The same applies when a set of scenarios is required (for example, in stochastic MPC optimization).

Therefore, the three metrics that will be applied in the framework are the pinball loss function (for models that provide the whole set of quantiles or percentiles of the distribution), Winkler score (for intervals with a certain probability) and a new variant that have been proposed called WePin (for scenario sets created following the method proposed in Section §4.6.3.2). The expression of these metrics can be found in 4.10 (pinball loss function), 4.11 (Winkler score), and 4.12 (WePin).

It should be noted that, for all the described metrics that are used for evaluating models, a lesser value expresses that the forecasting has a better quality.

4.6.4.4 Model storage

As said in *[[22]]*, "one of the steps inside the proposed framework is to select which of the provided datasets is most convenient to perform forecasting" *[[22]]*. However, the life cycle of the compared models does not end if they are not the best of their category, and therefore these are all stored for their future use. The reason for this is that the data required for their execution (inputs) are different from one model to other. Therefore, it could happen that the best model of the list could not be executed at a certain moment due to a lack of data.

Therefore, "the trained models are then evaluated and ordered according to their performance metrics. The best models and their characteristics are stored in a database and are used by the daily forecasting block, which executes the best available model once a day (obtaining the day-ahead forecast). Notably, in this process, the type of information needed to execute each of the models must be specified, as the system must check the availability of the information before deciding which model to use. For example, if the temperature information is missing for a specific day (because of a failure in data reception from the provider), the forecasting models that require temperature are discarded for that day, and another model (whose required input information is available) is applied" *[[22]]*.

Those models that can be used to generate various types of uncertainty models (e.g., deterministic forecast, intervals, scenarios, etc.) must indicate their respective performance metrics for each of these types independently. In this way, the metric that will be checked at the moment of selecting a model will depend on the type of uncertainty that is required.

These models that were inferred can be used until it is decided to retrain them (or create new model instances from zero). "The framework does not necessarily require online training. Therefore, the model updating (the execution of the model training/execution block in the procedure can be done every few days or even every few weeks, when the inclusion of newly available historical data is desired to retrain the models. This characteristic may maintain the bounded daily computational cost of the proposed framework, as it does not need continuous updates" *[[22]]*.

These stored models and the ranking of their performances are used in the daily forecasting according to the requests of the application connector. These two blocks will be exposed together in the next section, as they are closely interrelated.

4.6.4.5 Daily forecasting and application connector

The daily forecasting block is able to execute the solicited type of uncertainty modelling (deterministic, interval, scenario set, etc.) according to the given requirements and the available information. In this way, the best model that can be executed for each of the requests will be employed. These requirements come from the application connector block, which inform about which are the needs of the final application that will use the forecast data.

The selection of the best model is done according to the rankings (list sorted by their performance metric from best to worst) of available models. There will be multiple rankings, one for deterministic models (using RMSE or CV(RMSE), one for quantile distributions (using pinball loss function), one for each type of interval with a certain probability (using Winkler score), and one for each type of scenario set that is configured (using WePin).

As said in *[[22]]*, "the obtained forecast (for all the power variables that are included in the system) is taken by the application block, whose characteristics depend on the locations of the resources; the type of power information utilized; and the objective of the operator, aggregator or customer who owns the system" *[[22]]*. In particular, this framework is addressed to its use on microgrids and on the operation of distribution networks, as both cases are closely related. The framework can be used, for example, for feeding the optimization system of an EMS.

Once finished the description of the main blocks of the proposed framework, the next section exposes the conclusions of this chapter.

4.7 Conclusions

This chapter has exposed the research trajectory of the author, summarized the problems that were identified during this research, and presented the main contributions of this doctoral thesis.

The first proposal consists of a flexibility participation architecture for including flexibility services provision in the power system. According to this architecture, a customer (or aggregator) can participate as a FSP and have their audit performed by means of the smart meters that are currently being deployed by the DSOs of many countries (like in Europe). Moreover, the process that the EMS (or BMS) should execute for their participation and control of resources is depicted. This architecture serves as a common frame in which the rest of the proposals take part. The proposal of this architecture has been published in *[[21]]*.

Considering the role of EMSs and BMSs in flexibility participation and in DER operation, an EMS was proposed for a real nanogrid in Chile during the development of an international collaboration with researchers from this country. The development of this EMS revealed the importance of considering flexibility (and, in the same way, DSM and DR) participation in order to achieve a total integration of the customers in the power system management and the advance of the DG paradigm. Moreover, it showed the complexity of estimating the flexibility margin that a microgrid can provide, not only due to the difficult of consumption/generation forecasting, but also for the establishment of a baseline that reflects the expected consumption of a customer when establishing flexibility contracts with power system operators. This proposal has been published in *[[20]]*.

For this reason, a forecasting method called rule-based baseline (Rulabi) has been proposed. These consist of a set of rules that can be applied to obtain a baseline by means of the measurements of previous days. The number and type of days that are selected to calculate the baseline depend on the rule that is applied. This proposal has been published in *[[22]]*.

Regarding the difficult of forecasting of power consumption and generation, which is even greater in the case of lower levels of aggregation (as it happens in individual customers or microgrids of small and medium size), a forecasting framework (PRODEFOR) has been proposed. Their main advantages are being able to handle multiple types of uncertainty modelling. In this way, it serves as a tool that can provide forecasting information to the final applications in the way that would be requested. It tests a wide set of different models to find which is the best input dataset and technique for the forecasting of each variable in order to be robust to the lack of data (thanks to saving various types of models that have different input requirements). The first version of this proposal (which only includes deterministic methods) has been published in *[[22]]*. It has been later improved with the inclusion of probabilistic forecasting methods.

Chapter 5

Case studies and results

This chapter exposes the performed experiments and results of the proposals on microgrid-related research that were explained in Chapter §4

This chapter exposes a number of experiments and case studies that are focused on the forecasting applied to microgrids and distribution networks according to those proposals that were exposed in Chapter §4.

The rule-based baseline models (Rulabi) and the forecasting framework (PRODEFOR) have been applied in two different situations in Chapter §5, the Smart Polygeneration Microgrid (SPM) of the Savona Campus (Università di Genova, Italy) and a distribution network in the town of Manzanilla (Huelva, España). Some of these experiments were already published in ***[[22]]***[1], where "the methodology of the proposed framework is applied in a study case to forecast five different power variables (load, generation metrics of various types, and others) for the Savona Campus of the Università di Genova in Italy" ***[[22]]***. Additionally, new experiments will be included in this thesis. Moreover, the framework will be applied to predict the consumption of a set of secondary distribution substations of a real distribution network.

It will be seen how these two situations show different characteristics, the microgrid having both consumption and generation, and the distribution network having only consumption (of a number of secondary substations). Despite their differences in characteristics and power magnitude, the proposed framework can be applied over both of them with very little adaptation, achieving satisfactory forecasting results according to the error indicators.

[1] It is reminded that the publications that are part of the thesis are referenced using double square brackets, bold and emphasis (cf. Section §1.3).

First, Section §5.1 presents some conclusions that can be extracted from two of the publications that are directly related with the thesis regarding the forecasting requirements, as these have influenced the subsequent case studies focused on forecasting. Section §5.2 contains a case study in which the proposed forecasting framework is applied to the microgrid of Savona Campus (Italia). Then, this case study is expanded with the inclusion of new types of models in Section §5.3. Section §5.4 exposes the case study of the framework over the distribution network of the town of Manzanilla (Spain).

5.1 Preliminaries: Identified forecasting requirements for flexibility and energy management

Previously to the development of the proposed forecasting framework PRODEFOR, some of the made publications (*[[20]]* and *[[21]]*) had already identified and analyzed the great importance of forecasting when performing power system management tasks, such as the provision of flexibility services and energy management in microgrids.

The architecture for participating in flexibility services (DSM dispatching and audit) that was proposed in the previous chapter (see Section §4.3) has been actually tested in a proof of concept in a laboratory, as can be seen in *[[21]]*.

The deployment and experiments were done over the Living-Lab of the Escuela Politécnica Superior (Universidad de Sevilla). In these tests, the market was not considered, but the flexibility requests were directly requested by a computer (that simulated the role of the DSO) to perform the experiments. The calculation of flexibility margin is performed under different situations for each of the experiments. These experiments showed the importance of performing a high-quality forecast of the energy needs (in this case, consumption, as there is not any source of generation) to achieve a good estimation of these margins before market participation can be done.

As said in *[[21]]*, "the inclusion of DSM over the power system undoubtedly constitutes a powerful tool to improve the management capacity and flexibility of distribution networks. However, the use of these kinds of services implies an agreement between the two parts, i.e., the customers and the DSO, which could be performed under multiple existing terms, principles and methods" *[[21]]*.

"A possible architecture for DSM dispatching and audit is proposed and tested. In this architecture, all the controllable devices are connected to a BMS. As it was exposed, the BMS established communication to the DSO systems using the standard OpenADR, providing a channel to inform about availability, scheduling, prices or any needed data" *[[21]]*.

"The audit function depends on the DSO smart meter infrastructure that provides remote information about the hourly consumption, this data being used to check the behavior of the loads in question during the period of the dispatched DSM events. The accomplishing or not of such events will therefore be evaluated using information from the smart meters to perform the audit process. Likewise, this hourly information is enough for this purpose, although its extension to a quarter hour is considered interesting for the future to increase network flexibility" *[[21]]*.

"The proposed architecture clearly shows the possibilities of use of controllable loads under the established DSM contract conditions. The principal difficulty from the customer side would be the requirement of the OpenADR VEN device, which would not be such a big problem in the case of buildings that count with a BMS. Thus, thanks to taking advantage of the available power meter infrastructure that is used for the electricity billing, the audit process can be done by the DSO in a secure and appropriate manner, showing the adequacy of the AMI for this task, as this system makes easier the integration of flexibility services" *[[21]]*.

"It can also be concluded that the described laboratory constitutes a complete platform where some of the most important smart grid related technologies can be evaluated, integrated and taught" *[[21]]*.

Regarding the paper *[[20]]*, it presents a study focused on the EMS of a nanogrid in the San Joaquín Campus (Universidad Técnica Federico Santa María, Chile), where the requirements of forecasting generation and consumption can be identified. Additionally, it can be appreciated in *[[20]]* that the inclusion of DR signals in the EMS is a crucial task for achieving a complete integration of distributed resources in the power system, serving as supporting tools for its operation.

Finally, the simulation presented in *[[20]]* shows the importance of performing a correct internal management of both the energy consumption needs and also the generation sources to accomplish the DR request. This preliminary idea was developed in more detail for the proposal of the flexibility participation architecture that was previously exposed in Section §4.3.

5.2 Forecasting framework over a real microgrid

In this section, the preliminary version of the proposed forecasting framework (see Section §4.6.2) is applied to the SPM, which is a real microgrid that is installed in the Savona Campus (Università di Genova). Several parts of the current section are published in the paper *[[22]]*. Due to the characteristics of the preliminary version of the framework (which is also included in the publication *[[22]]*), this case study only includes deterministic models.

This case study will be later extended in Section §5.3, where the new version of the framework (which includes deterministic and probabilistic forecasting methods, as seen in Section §4.6.4) will be applied. This extension is out of the scope of *[[22]]*, and for that reason it has been preferred to present it in a different section.

First, Section §5.2.1 presents the microgrid under study, its main characteristics, and which are the power variables that will be forecasted. The presentation and discussion of the results are made in Section §5.2.3. Finally, Section §5.2.4 contains the conclusions of the study together with a discussion of the research tasks that could be made to improve the quality of the forecasting.

5.2.1 Microgrid description

As it is said in *[[22]]*, this case study is focused on the Savona Campus of the Università di Genova (Italy). In this campus, there is the SPM, which is "an innovative facility used to provide electricity and heat to the campus" [74]. "The SPM constitutes a good example of the penetration of DERs [143] and a complete living lab for smart grid technology" *[[22]]*.

"The campus network has various generation systems (two microturbines and PV panels); an electrical storage system; and buildings used for living, research, and teaching, which are mainly consumption loads" *[[22]]*. The existing elements of the campus can be seen in Figure 5.1.

"The optimal daily operation of the SPM was determined by an EMS. Among other actions, the EMS decides when and how to charge and discharge the storage system, modulate the energy generation of the microturbines, and even decides when to sell electricity to the national grid (if there is a surplus of energy). There are other elements of the campus that could also be used as controllable loads, thereby increasing the capacity that can be provided in flexibility services [364]" *[[22]]*.

"The objective of the present study is to use historical and weather data from the Savona Campus to forecast some considered power variables under a day-ahead approach. The available data refer to three years of SPM operations (2016, 2017 and 2018). All electrical variables were measured with a sampling time of 1 min. The day-ahead weather predictions, which were provided by a meteorological service, are given in 30-min intervals for the whole day" *[[22]]*.

"The five power variables of interest for the present study are the following" *[[22]]*:

- $ge1$: The power absorbed by the SPM.
- $ge2$: The power withdrawn from the external distribution network.
- ut: The production of the two cogeneration microturbines.
- lc: The electrical demand of the buildings.
- pv: PV generation.

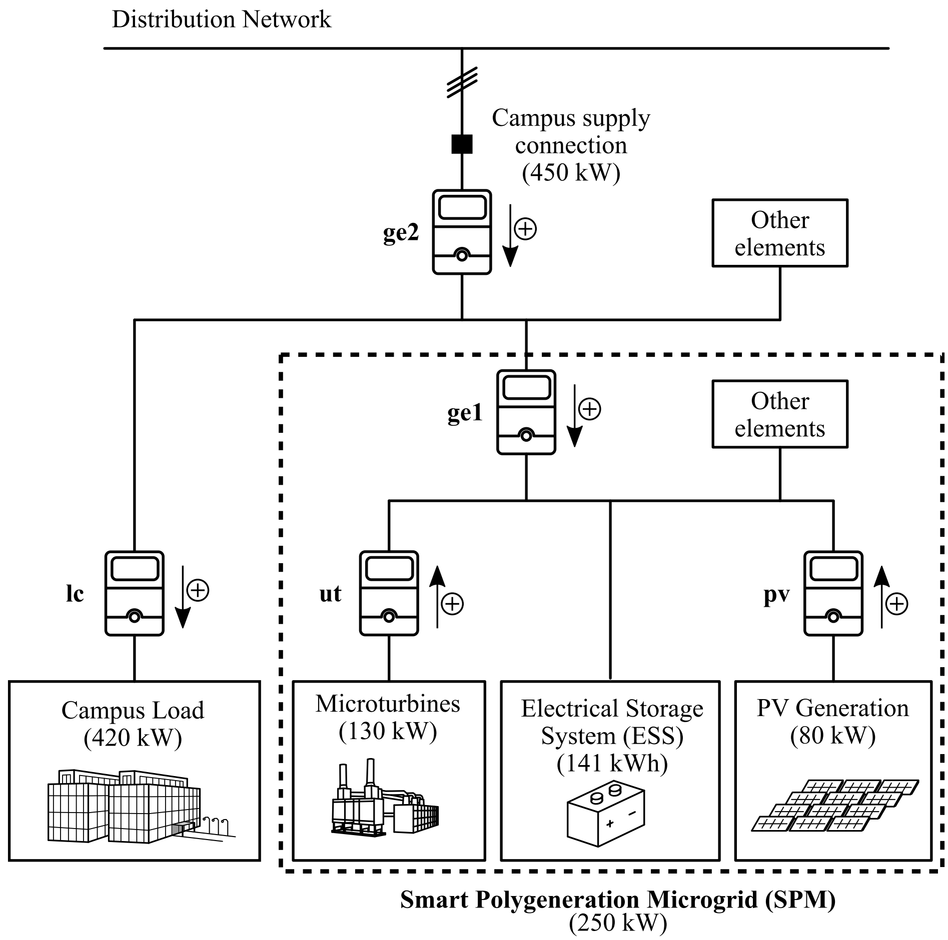


Figure 5.1: Electrical schema of the campus and its main systems *[[22]]*.

"A representation of a summary of these variables can be seen in Table 5.1. For each of the five variables, some statistical values are provided: the average value (mean); standard deviation (std), minimum value (min); first, second and third quartiles (25%, 50% and 75%, respectively); and maximum value (max). All these values are expressed in kW" *[[22]]*.

The historical data concerning the day-ahead weather forecasts for Savona contain the temperature, humidity, pressure, irradiance, and rainfall variables. "A summary of the data can be seen in Table 5.2, with the interpretations of the given values being similar to those in Table 5.1. The units are indicated in the head of the table" *[[22]]*.

Considering the existing historical data, and the five variables that were considered, the preliminary version of the framework will be applied for obtaining day-ahead deterministic forecasts of such variables.

Table 5.1: Summary of historical power data (2016–2018) *[[22]]*.

Value	*ge*1	*ge*2	*ut*	*lc*	*pv*
mean	−28.1	99.7	26.1	133.2	11.0
std	46.8	55.4	40.1	63.2	18.0
min	−263.0	−94.3	−29.1	−15.1	0.0
25%	−65.4	71.7	−0.3	88.1	0.0
50%	−3.4	93.7	−0.2	107.8	0.0
75%	9.7	125.1	57.6	163.5	16.0
max	59.3	437.8	136.2	475.3	80.4

All the magnitudes are expressed in kW.

Table 5.2: Summary of historical weather prediction data *[[22]]*.

Value	Temperature (°C)	Humidity (%)	Irradiance (W/m2)	Rainfall in 30 minutes (mm)
mean	15.8	68.5	174.3	0.36
std	7.6	16.6	251.7	1.92
min	−3.9	18.8	0.0	0.00
25%	9.7	54.7	0.0	0.00
50%	15.3	70.9	1.8	0.00
75%	21.3	82.6	303.0	0.00
max	34.7	100.0	932.6	42.96

5.2.2 Description of the case study

This section describes the case study based on applying the preliminary framework described in Section §4.6.2 to the Savona Campus, which includes five power variables to be predicted. "The two aggregation levels considered are 15 min and 1 h, and the three described forecasting techniques were tested for both configurations" *[[22]]*. These techniques are Rulabi (simply called "rule-based baselines" in *[[22]]*), RFR, and MLPR. These techniques will be used to obtain deterministic forecasts.

"The data of consumption (or generation) of each of the variables was monitored with a resolution of 1 min. For adapting these variables to 15-min and 1-h intervals, the power measurements of the interval are averaged" *[[22]]*.

"The weather forecast (which have a resolution of 30 min) was not modified for use in the 15-min and 1-h aggregation models. For both types of aggregations, the weather data were directly used as inputs for the models in a row of 48 points for each weather variable" *[[22]]* (which are temperature, humidity, irradiance, and rain).

"In the description of dataset types, one of the fields is the EXBL. It consists of the use of the baseline of a different variable as input information. Therefore, which variables are supposed to be correlated must be established to implement this type of model" *[[22]]*. Taking into account that the EMS of the campus considers the expected load consumption (i.e., an estimation of the consumption of the buildings of the campus) to control the available power resources (the microturbines and battery), it could be useful to use lc as an external baseline for the rest of the variables. In this regard, "this method is discarded for pv, as its behavior depends on the solar source, not on the EMS. Therefore, the three variables for which the EXBL datasets (made from lc) that were tested were $ge1$, $ge2$ and ut" *[[22]]*.

"The results of the experiments are presented in independent subsections for each type of technique (baseline rules and machine learning techniques, including the RFR and MLPR). Finally, a comparison of all the results is performed to check which of the models are best among all the presented techniques" *[[22]]*.

In the case study of this section (published in *[[22]]*), the error metric that is used to evaluate the model performance is the CV(RMSE) (and not the RMSE). In this sense, "it will be appreciated in these results that the obtained CV(RMSE) for the variables $ge1$ and ut are considerably larger than in the variables $ge2$, lc and pv. The reason for this fact resides in how the CV(RMSE) indicator is calculated" *[[22]]*. "As this indicator is normalized by its average value, the models of variables with a lower average value tend to have greater CV(RMSE) values. However, like only the models of a same variable are compared between them to select the best, the relative magnitudes of the indicators between different variables are not important" *[[22]]*.

As the metric CV(RMSE) is proportional to the error of the forecasting, a lower value of this metric means a better quality of the forecast under evaluation. This should be considered for the interpretation of the obtained results that will be presented next.

5.2.3 Analysis of models

This section presents the results of the case study. It includes the rule-based baseline models, machine learning models, and their comparison and discussion.

5.2.3.1 Baseline rule results

As it is said in *[[22]]*:

"The following graphs contain the results of the application of the proposed baseline rules over the five power variables (see Figure 5.2). On the x-axis, the number of days back expresses the value of the hyperparameter (n), while the y-axis shows the absolute value of the CV(RMSE). The colored circular points (connected by continuous lines) correspond to the strict application of the rules, while the triangles (connected by dotted lines) are obtained from the non-strict application" *[[22]]*. The details of how rule-based baseline method

(Rulabi method) is applied, and how the strict and non-strict application is performed can be found in Section §4.5.

"In the cases of *ge*1, due to its negative average value, the values of CV(RMSE) are negative. For this reason, the axes of the graphs show the absolute value of this indicator. It must be remembered that the best forecast corresponds to the lowest absolute values (the nearer to zero, the better)" *[[22]]*.

"It can be noted that the *ge*2 and *lc* variables show behaviors that are strongly dependent on the type of day (weekday and weekend), with the rules of type *baseline_cnb* ('const_num_back') and *baseline_bw* ('basic_weekend') being the best" *[[22]]*.

"For *ge*1 and *ut*, the best rule is *baseline_s* ('simple'), as they show behaviors that are less related to the type of day. This is probably because the need for hot water (partially produced by microturbines) does not change substantially from weekdays to weekends (as many students live on campus)" *[[22]]*.

"Finally, *pv* is best forecasted using the *baseline_s* rule," which was expected because solar irradiance is independent of the type of day *[[22]]*.

"These results show how testing multiple types of baselines provides information about the behaviors of the variables, while addressing which type of days are the best indicators of each of these variables. Particularly, in the case of the variable *ge*1, whose behavior could at first be difficult to guess without a previous analysis, it was found that this variable is strongly dependent on the most recent previous days" *[[22]]*.

5.2.3.2 Machine learning results

As it is said in *[[22]]*:

"The results of the RFR and MLPR models for all the different datasets that are described in Table 4.5 are presented in Figure 5.3. To simplify the representation of such a number of different datasets, the x-axis groups them by the tag 'dataset type', as shown in the same table" *[[22]]*. Each point represented in the graphs (called "model" in the legend) represent the error of the model obtained using a certain ML technique (RFR or MLPR, as it is indicated in the title of each graph) with a certain dataset (the applied datasets are defined as it was exposed in Section §4.6.4.1). The reason for not identifying the exact dataset of each individual model in the graphs (and grouping them by types of datasets instead) is to simplify the representation of the results. These graphs provide information of what type of information was applied in the different families of datasets (as these correspond to the 'dataset types' of the x-axis).

"To avoid the presence of negative metric values, the y-axis represents the absolute value of the CV(RMSE). Therefore, the best model is the one with the minimum value" *[[22]]*.

"Each of the points in the graph represents the error for a given dataset, while the red

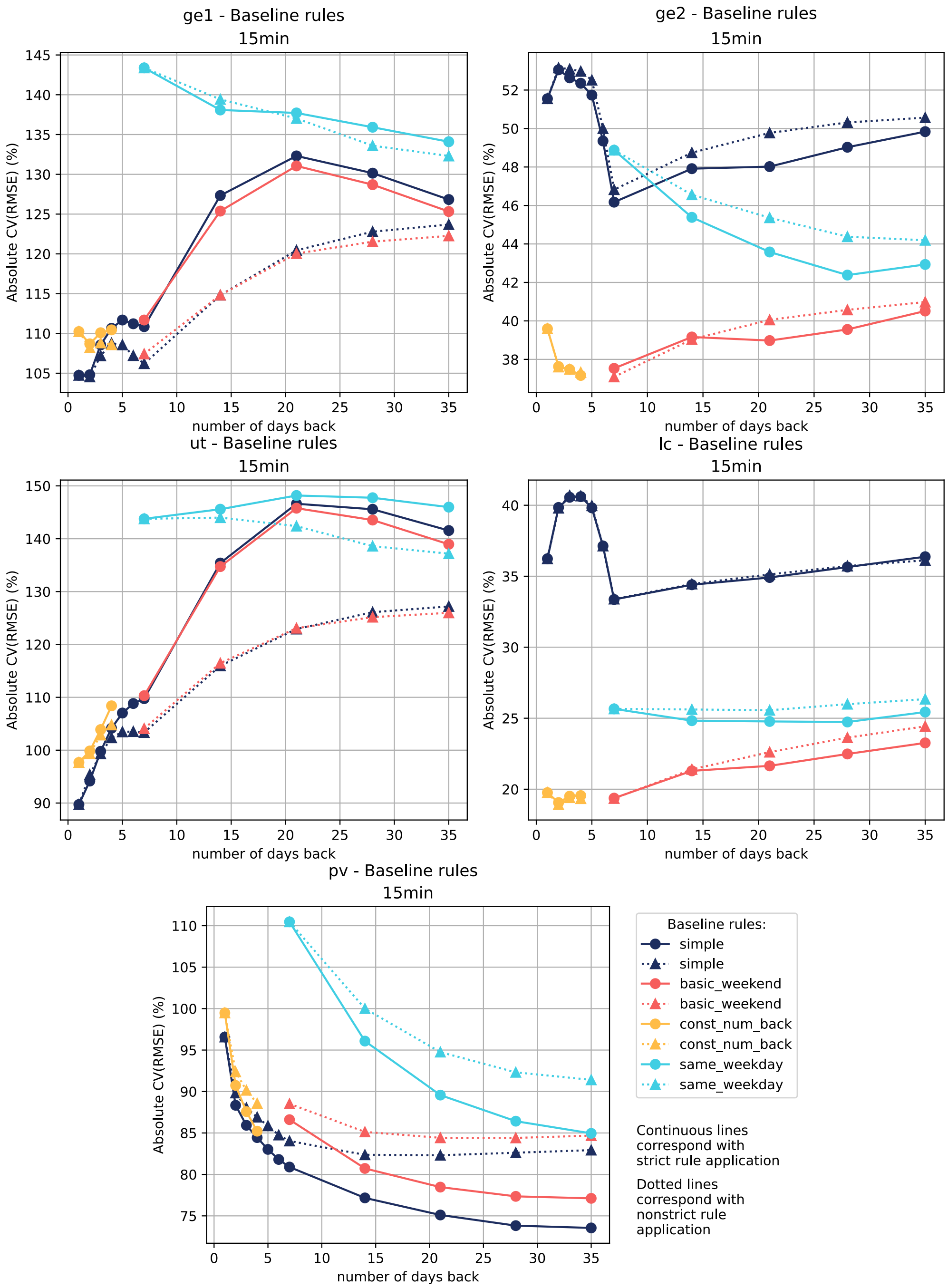


Figure 5.2: Baseline results for each variable ($ge1$, $ge2$, ut, lc and pv) with an aggregation of 15 min by rule and number of days *[[22]]*.

hyphens indicate the model with the minimum error value (i.e., the best model for each of the dataset types). As defined at the start of the present section, the variables $ge1$, $ge2$ and ut also include datasets with external baseline information (the expected load of the campus, i.e., lc). The variables lc and pv do not include any 'EXBL' dataset, as this is not considered to be of interest" *[[22]]*.

"For the RFR models, these results indicate that the dataset types 'Db', 'Db + EXBL', 'DbWa' and 'DbWa + EXBL' are usually the best for all variables. The two exceptions are pv, which is better forecasted by the dataset types 'DbWa' and 'BlWa', and lc, whose best model for 15-min aggregations is obtained with the dataset 'CaIn'" *[[22]]*.

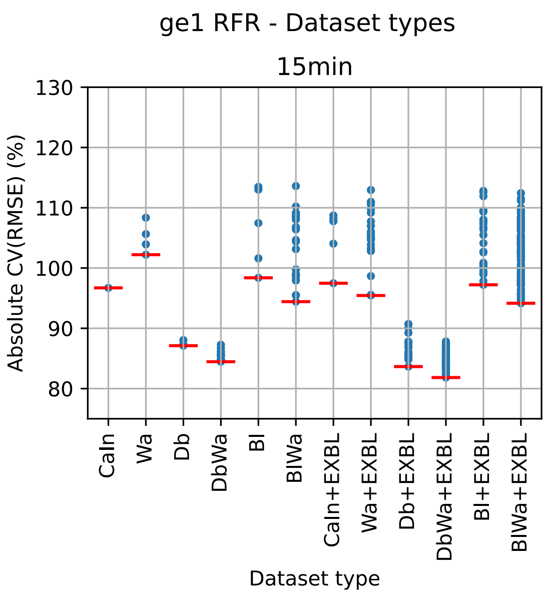
"For the MLPR models, the dataset types 'Bl' and 'BlWa' also obtain good performances for the variables $ge2$ and lc" *[[22]]*.

"The comparison between the RFR and MLPR techniques for the five forecasted variables shows that the errors of the MLPR models are less than those of the RFR models for almost all variables ($ge1$, $ge2$, ut and lc), except for pv, which is better forecasted using the RFR models" *[[22]]*.

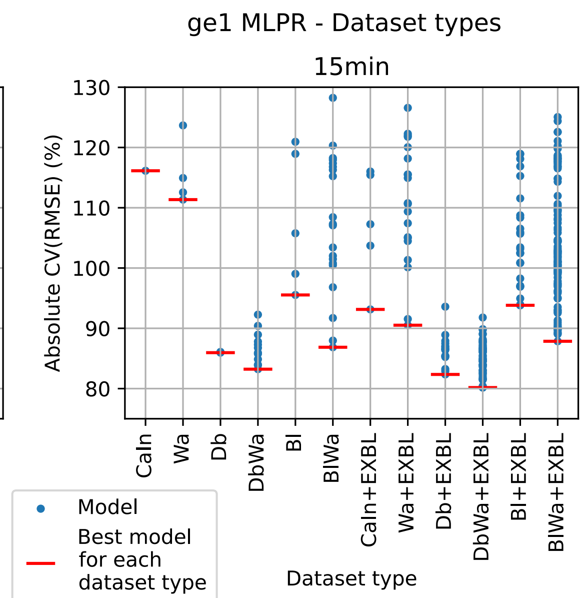
5.2.3.3 Comparison and discussion

As it is said in *[[22]]*:

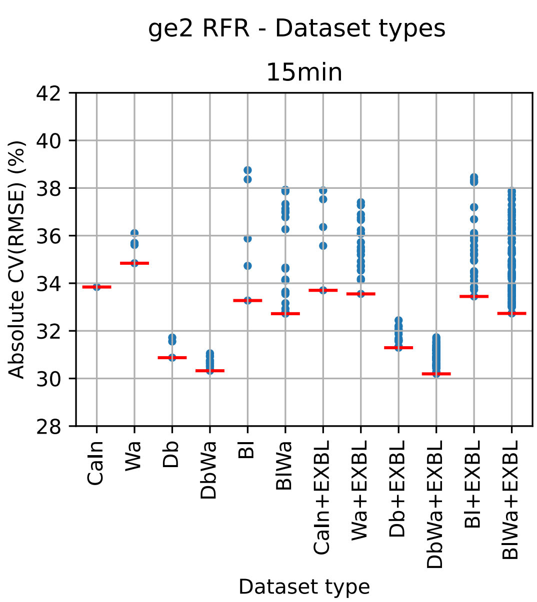
"Once the results are obtained, the different models for each objective variable can be compared. This comparison is reported in Table 5.3 and Table 5.4, which gives the CV(RMSE) value for the best model according to each variable, aggregation, and dataset type. To simplify the visualization of the results, the category 'XX+EXBL' (the datasets that include external baseline information, as shown in Table 5.3 and Table 5.4) is not detailed for each type of baseline rule, and only the model with the best indicator value is kept. Some reference models are also included, such as $baseline\_s1$ (previous day) and $baseline\_s7$ (mean of the seven previous days). The $baseline\_s1$ method is finally the one chosen as a reference method, as here it is considered analogous to the naïve method" *[[22]]*.



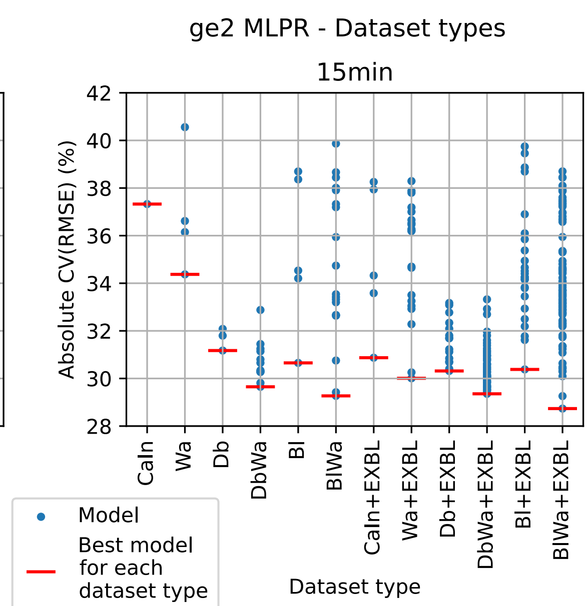
(a)



(b)



(c)



(d)

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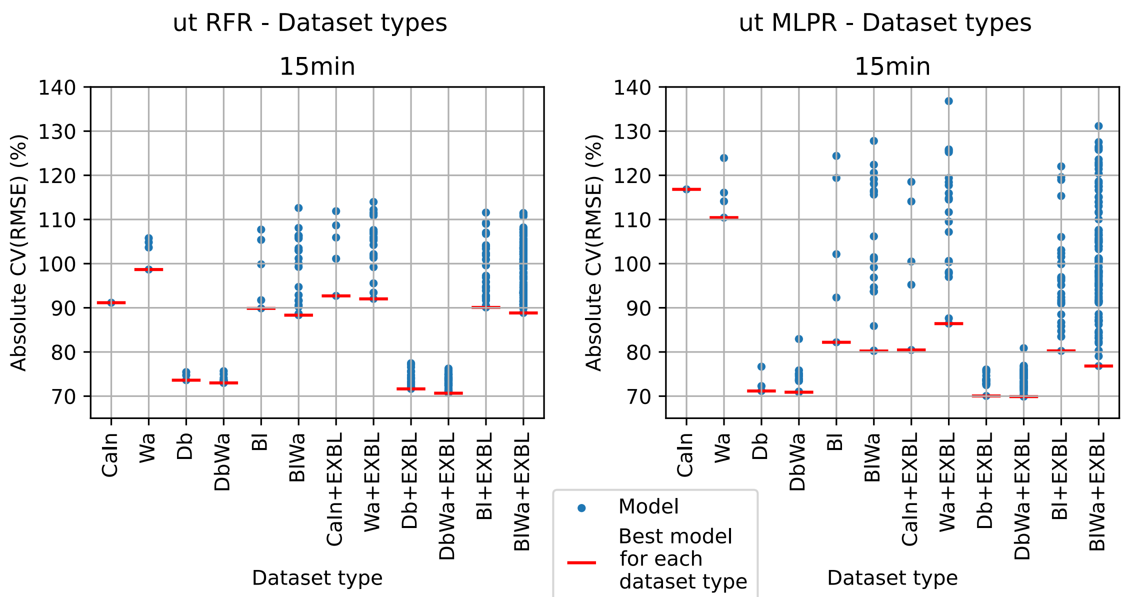
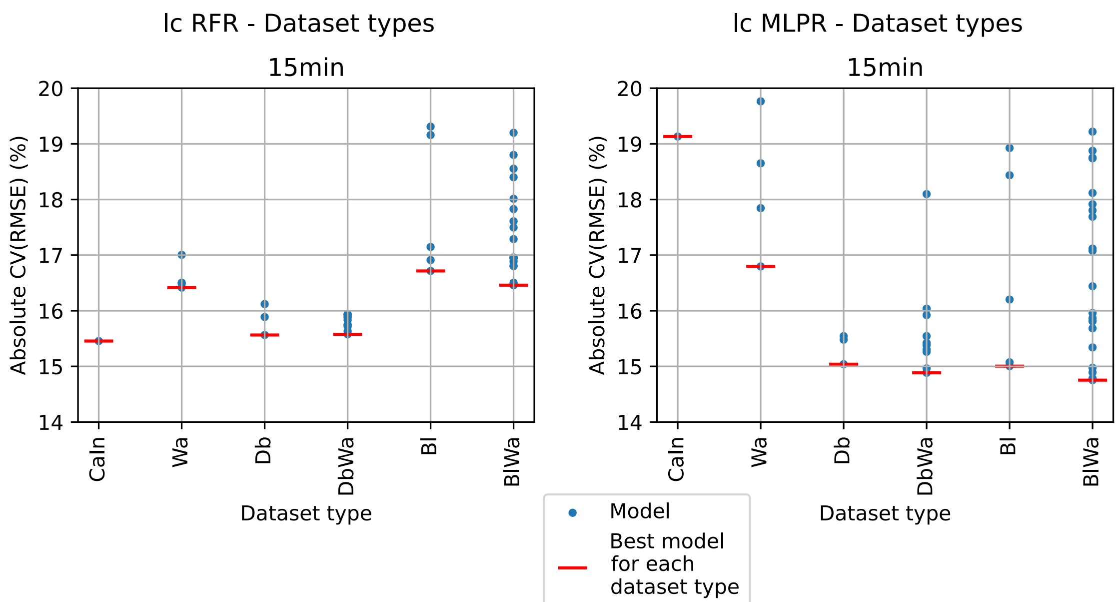


(e) (f)



(g) (h)

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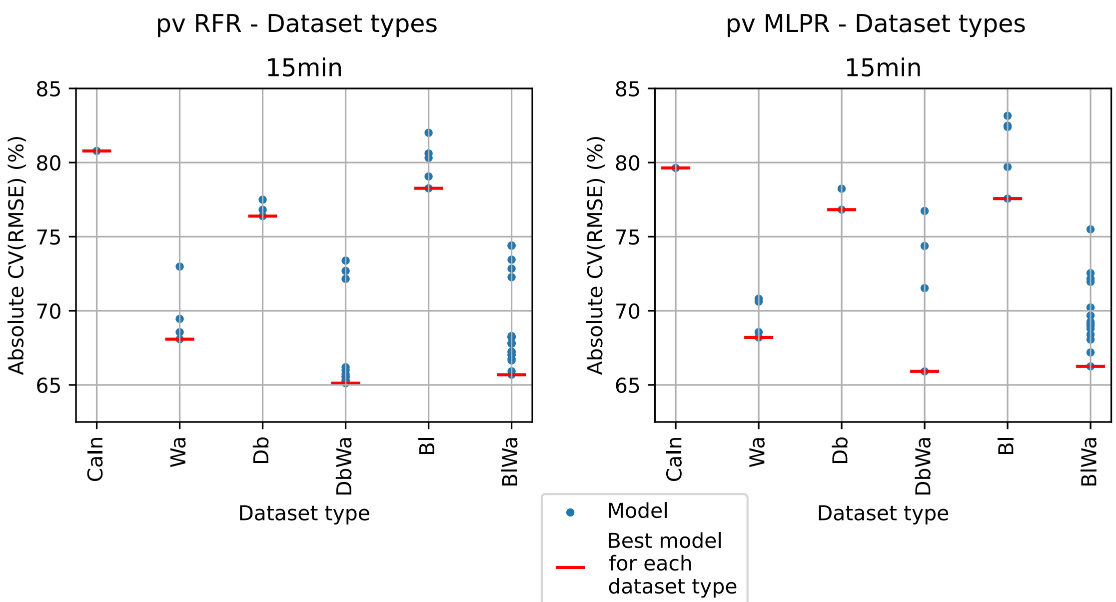


(i) (j)

Figure 5.3: Metrics for the RFR and MLPR models for each forecasted variable ($ge1$, $ge2$, ut, lc and pv) with an aggregation of 15 min. The x-axis is grouped by dataset type. The left column corresponds to the RFR models, while the right column corresponds to the MLPR models. (a) $ge1$ using RFR; (b) $ge1$ using MLPR; (c) $ge2$ using RFR; (d) $ge2$ using MLPR; (e) ut using RFR; (f) ut using MLPR; (g) lc using RFR; (h) lc using MLPR; (i) pv using RFR; (j) pv using MLPR *[[22]]*.

Table 5.3: Summary of forecasting results. Baselines and RFR models [[22]].

Indicator: Absolute CV(RMSE) (%)												
Variable	**Aggregation**	**Reference methods**		**Best Bl**		**Best RFR**						
		baseline_s1	*baseline_s7*	**Baseline Rule**		**CaIn**	**Wa**	**Db**	**DbWa**	**Bl**	**BlWa**	**XX+EXBL** [1]
ge1	15min	104.7	110.9	s1	104.7	96.7	102.2	87.1	84.5	98.4	94.4	81.8
	1h	101.3	107.0	s1	101.3	92.0	101.5	84.3	80.5	92.3	92.3	78.3
ge2	15min	51.5	46.2	cnb4	37.2	33.8	34.8	30.9	30.3	33.3	32.7	30.2
	1h	50.4	45.5	cnb4	36.0	32.9	34.0	29.6	29.0	32.7	31.9	28.9
ut	15min	89.7	109.7	s1	89.7	91.2	98.7	73.6	73.0	89.9	88.3	70.7
	1h	89.0	106.4	s1	89.0	87.4	97.7	74.0	72.2	86.3	87.5	69.0
lc	15min	36.2	33.4	cnb2	19.1	15.5	16.4	15.6	15.6	16.7	16.5	-
	1h	35.7	33.0	cnb2	18.4	14.8	16.1	14.6	14.7	15.3	15.5	-
pv	15min	96.6	80.9	s35	73.5	80.8	68.1	76.4	65.1	78.3	65.7	-
	1h	91.5	77.5	s35	71.0	78.2	63.9	73.0	60.4	76.2	61.5	-

[1] XX + EXBL represents the best obtained model from those that include the EXBL as input (therefore, XX denotes CaIn, Wa, Db, DbWa, Bl or BlWa).
Green color: best model for each variable and aggregation.

Table 5.4: Summary of forecasting results. MLPR models [[22]].

Indicator: Absolute CV(RMSE) (%)								
Variable	**Aggregation**	**Best MLPR**						
		CaIn	**Wa**	**Db**	**DbWa**	**Bl**	**BlWa**	**XX+EXBL** [1]
ge1	15min	116.1	111.4	86.0	83.2	95.5	86.9	80.2
	1h	110.6	106.4	81.7	78.1	90.5	88.8	77.4
ge2	15min	37.3	34.4	31.2	29.7	30.7	29.3	28.7
	1h	35.8	33.2	28.9	27.8	30.7	29.9	27.1
ut	15min	116.8	110.4	71.2	70.9	82.2	80.2	69.9
	1h	112.1	107.2	70.2	68.7	81.9	83.3	67.3
lc	15min	19.1	16.8	15.0	14.9	15.0	14.8	-
	1h	18.3	17.2	14.0	13.7	14.2	14.1	-
pv	15min	79.6	68.2	76.8	65.9	77.6	66.2	-
	1h	76.0	64.4	74.1	65.6	75.9	62.9	-

[1] XX + EXBL represents the best obtained model from those that include the EXBL as input (therefore, XX denotes CaIn, Wa, Db, DbWa, Bl or BlWa).
Green color: best model for each variable and aggregation.

"Moreover, the percentage of improvement (5.1) is calculated in a way similar to that reported in [328] (with $baseline\_s1$ as the reference method), and the CV(RMSE) for the reference model and the proposed model are shown" *[[22]]*.

$$I_{imp} = I_{improvement} = \frac{e_{reference\ model} - e_{proposed\ model}}{e_{reference\ model}} \cdot 100\% \tag{5.1}$$

"These results can be seen in Table 5.5. The CV(RMSE), RMSE and nRMSE indicators for the best models are given. Specifically, the nRMSE values are calculated considering the magnitudes that are included in Figure 5.1" *[[22]]*.

"As previously indicated, the table of improvement (Table 5.5) uses $baseline\_s1$ as reference. However, it can be appreciated that this table is directly obtained from the numbers in Table 5.3 and Table 5.4 of the results, so it is possible to calculate the relative improvements considering any other model from those included in the table applying expression (5.1)" *[[22]]*.

Table 5.5: Achieved forecasting improvement *[[22]]*.

Variable	**Aggregation**	**Ref. Model** $baseline\_s1$	**Best Model**			I_{imp} **(%)**
		CV(RMSE) (%)	**CV(RMSE) (%)**	**RMSE (kW)**	**nRMSE (%)**	
ge1	15min	104.7	80.2	22.5	9.4	23
	1h	101.3	77.4	21.7	8.8	24
ge2	15min	51.5	28.7	28.6	6.5	44
	1h	50.4	27.1	27.0	6.2	46
ut	15min	89.7	69.9	18.2	14.2	22
	1h	89.0	67.3	17.6	13.8	24
lc	15min	36.2	14.8	19.6	4.7	59
	1h	35.7	13.7	18.2	4.3	62
pv	15min	96.6	65.1	7.2	9.0	33
	1h	91.5	60.4	6.6	8.3	34

"Table 5.3 and Table 5.4 show some interesting data about the behaviors of the evaluated models and input dataset types" *[[22]]*.

"First, it can be observed that the models obtained using the RFR and MLPR are better than the best baseline models. This is expected, as according to the reviewed literature, these machine learning models usually achieve good results in the current field of study. However, it should not be forgotten that baseline models are still useful in some scenarios. They are very easy to calculate, give information about tendencies and are very clear in their behavior. Moreover, they are suitable for application in the auditory process in flexibility agreements, as a customer could be more disposed to accept one of these baseline rules than trained models, as they are RFRs and MLPRs" *[[22]]*.

"Second, it is interesting to note that the use of sets that include EXBLs yield the best results for $ge1$, $ge2$ and ut. This fact can be explained considering that in the campus ($ge2$), the zone under the direct control of the EMS is precisely the microgrid ($ge1$) where the microturbines (ut) are installed. It is therefore logical that $ge1$, $ge2$ and ut achieve good performance when they are modeled considering the load of the campus (lc), as the EMS estimates it to manage the microgrid" *[[22]]*.

"Regarding the forecasting of the load of the campus (lc variable), the datasets that include information from previous days and weather predictions for these days (dataset types 'DbWa' and 'BlWa') yield the best results under the MLPR" *[[22]]*.

"In the case of photovoltaic generation (pv variable), the results show that the inclusion of previous day measurements together with weather information (dataset types 'DbWa' and 'BlWa') improves the modeling results. The RFR outperforms the MLPR for this variable" *[[22]]*.

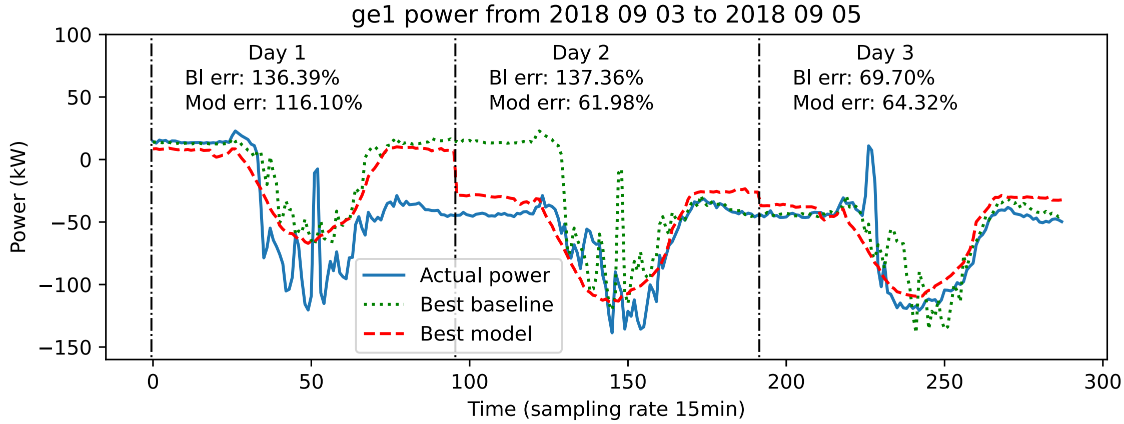
"The proposed models achieve accuracy improvements of up to 62% and a mean of 37% (average improvement value across the five variables and the two aggregations evaluated) over that of the reference model, which is $baseline\_s1$ (see Table 5.5)" *[[22]]*.

"Finally, as an example, some illustrative comparisons between the actual data, the best baseline and the best model are shown in Figure 5.4 for each of the five variables. The CV(RMSE) for each of the individual days is calculated for both the baseline and the best model" *[[22]]*.

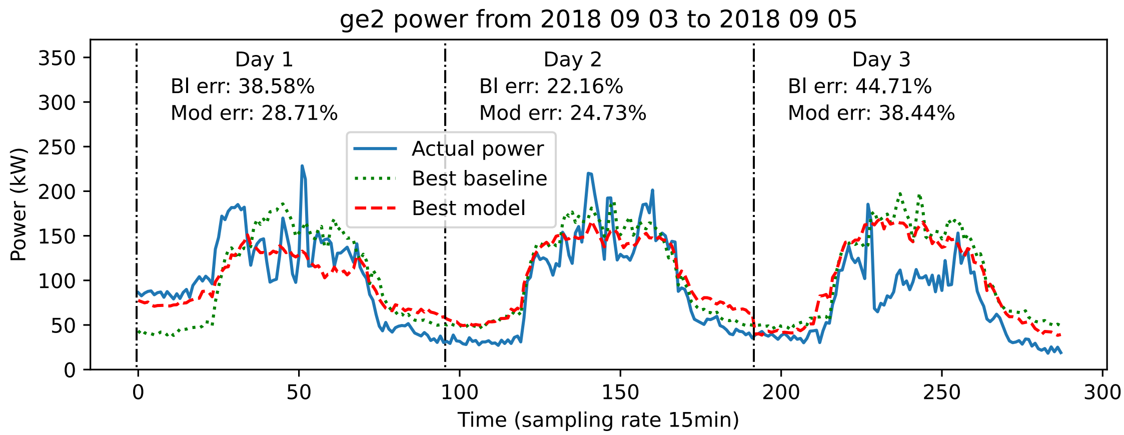
It can be seen that "the error of the baseline is usually greater than the error of the best model" *[[22]]*. There are some exceptions to this, as can be appreciated in the second day of Figure 5.4b, for example. "On this day, it can be appreciated how the best baseline model occasionally achieved a better result than the best model. However, these kinds of occurrences are expectable in the environment under study. The consumption and generation of the campus have low levels of aggregation, which produce behaviors that are difficult to predict. For this reason, on some specific days it may happen that the best selected model is outperformed by another one, which occurred on the indicated day" *[[22]]*. In spite of the existence of these events, the CV(RMSE) (that has been used as a criterion for model evaluation) shows from a global point of view the goodness of each model, as can be seen in Table 5.3, Table 5.4 and Table 5.5.

5.2.4 Conclusions and possible improvements

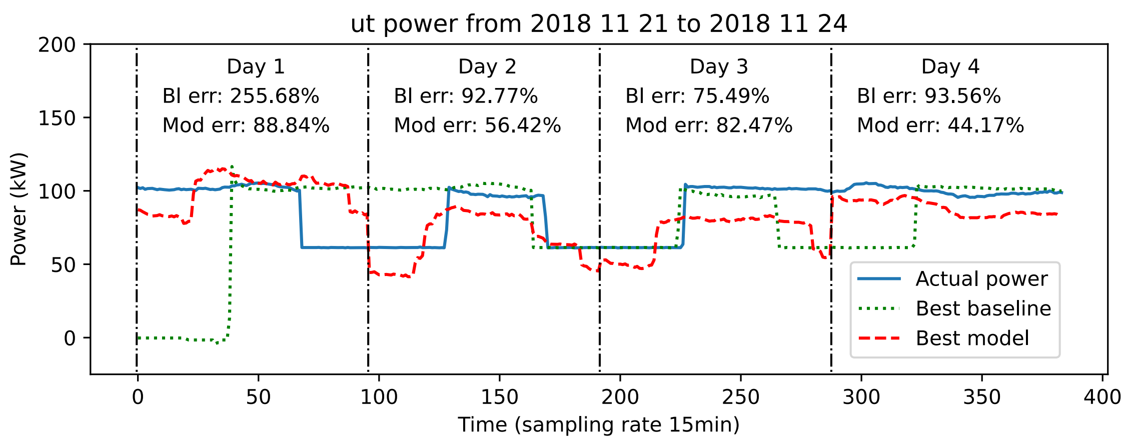
As previously mentioned in Chapter §3 (and in *[[22]]*), forecasting is an essential tool for energy management. For this reason a methodology (the preliminary version of the framework) has been proposed for performing the forecasting of power variables. "This methodology can be used by all the actors involved in flexibility services and/or the energy


ge1 power from 2018 09 03 to 2018 09 05
Day 1
Bl err: 136.39%
Mod err: 116.10%
Day 2
Bl err: 137.36%
Mod err: 61.98%
Day 3
Bl err: 69.70%
Mod err: 64.32%
Actual power
Best baseline
Best model
Power (kW)
Time (sampling rate 15min)

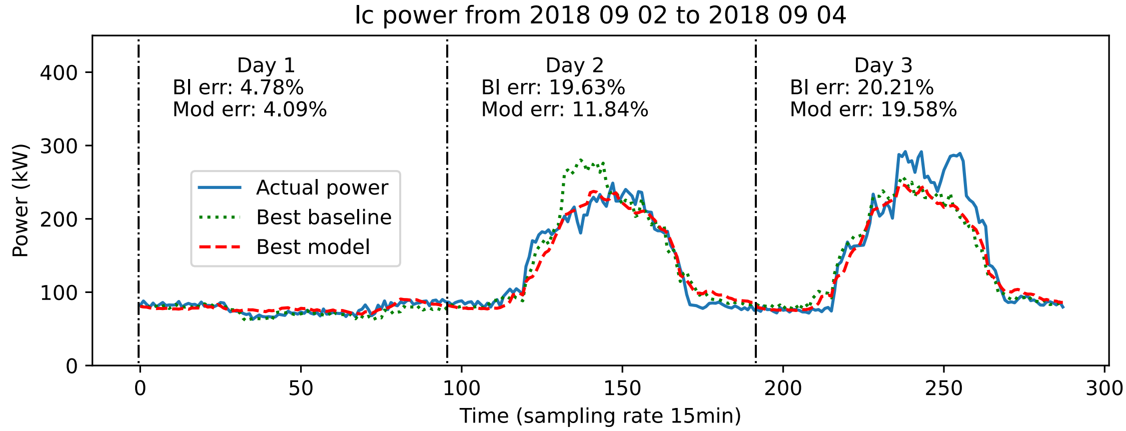
(a)


ge2 power from 2018 09 03 to 2018 09 05
Day 1
Bl err: 38.58%
Mod err: 28.71%
Day 2
Bl err: 22.16%
Mod err: 24.73%
Day 3
Bl err: 44.71%
Mod err: 38.44%
Actual power
Best baseline
Best model
Power (kW)
Time (sampling rate 15min)

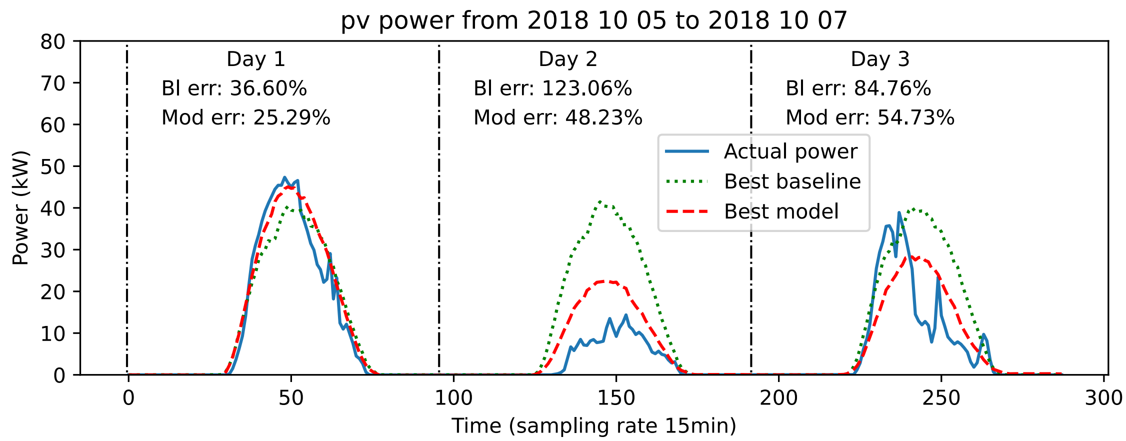
(b)


ut power from 2018 11 21 to 2018 11 24
Day 1
Bl err: 255.68%
Mod err: 88.84%
Day 2
Bl err: 92.77%
Mod err: 56.42%
Day 3
Bl err: 75.49%
Mod err: 82.47%
Day 4
Bl err: 93.56%
Mod err: 44.17%
Actual power
Best baseline
Best model
Power (kW)
Time (sampling rate 15min)

(c)



(d)



(e)

Figure 5.4: Actual power vs. forecasting (baseline and models) with an aggregation of 15 min. "Bl err" (baseline error) indicates the CV(RMSE) for the best baseline model. "Mod err" (model error) indicates the CV(RMSE) for the best model. (a) *ge*1; (b) *ge*2; (c) *ut*; (d) *lc*; (e) *pv* *[[22]]*.

management of microgrids, i.e., DSOs, aggregators, and customers" *[[22]]*.

In the literature, several types of approaches can be found regarding the procedure of model training and updating. "Many approaches apply online training, which can increase the daily computational cost (as the system must perform tasks related to updating the model daily) and does not usually involve tests with many different dataset types. Therefore, this paper presents a methodology for power variable forecasting that provides multiple combinations of information inputs and techniques without necessarily requiring online training. Therefore, model updating can be performed every few days or even every few weeks, when the inclusion of newly available historical data is desired to retrain the models. This characteristic permits a reduction of the daily computational cost incurred by the proposed framework according to current needs" *[[22]]*.

A problem that may occur in forecasting systems that require the reception of external data is that there is some failure in the process of measurement or reception, which would cause a lack of some of the input data. In this sense, the proposed framework aims to minimize the effects of this type of problem. Therefore,"in the proposed methodology, it is important not only to identify the best obtained model, but also to retain the information of the best model for each type of input information required. This approach makes it possible to use another model for which the system has the required inputs if for a certain day a portion of the information is missing (e.g., the weather forecast is not received). In this way, the feasibility and robustness of the system is increased, lowering the probability of failure during the forecasting process" *[[22]]*. The implementation of this mechanism correspond to the rankings inside the framework, as seen in Section §4.6.4.4.

The types of datasets that could be created depend on the available information, such as the mentioned baselines, weather data, calendar information, and other data of interest (see Section §4.6.4.1). "Moreover, the forecasting horizon can also change depending on the application. In the present case study, the prediction horizon is one day, but the same models could be trained and tested using other horizons. The only requirement is to adapt the input datasets with the information that is available in the considered horizons" *[[22]]*.

In addition to the definition of the preliminary version of the forecasting framework, "the applied methods include the definition of rule-based baselines, which perform forecasts using the measurements of the previous days obtained under different criteria" *[[22]]*. These methods have been included in the framework together with some well-known machine learning techniques (RFR and MLPR). "Moreover, the proposed baselines are included as inputs of machine learning methods, which has been shown to improve the quality of the forecasting" *[[22]]*.

In this case study, the proposed methodology "was applied to a university campus in Italy and used for the prediction of five different power variables" *[[22]]*. "The presented case study shows that an MLPR outperforms an RFR for the majority of the variables (except for the forecasting of the PV generation, pv). Moreover, the inclusion of EXBL information from the campus load (lc) yields a forecast improvement over those of the models in which EXBLs are not included" *[[22]]*. "From a global point of view, the presented experiments show that the proposed models achieve an accuracy improvement of up to 62% over that of the reference model" *[[22]]*.

Regarding the future continuation of the proposals made in *[[22]]*, various possible improvements could be done in the applied methods and in the performed analysis. First, the version of the framework that was applied only included deterministic models. While most operation and optimization applications in the literature work exclusively using deterministic forecasts, the inclusion of probabilistic information has been signaled by many authors as a powerful tool for improving the performance of EMSs and the operation of the power system in general. This inclusion would require a definition of which metrics should be applied for model selection, as those used in deterministic models are not applicable to evaluate probabilistic models.

It was said that, according to the framework, models with different types of inputs are stored to increase the robustness of the system in situations where there are missing input data. However, the potential of this characteristic was not strongly emphasized in the proposed case study, as it was more focused on the comparison of the individual performance of the proposed datasets and techniques. The process of model retraining was not either considered in the case study, which is an aspect of great importance for the framework to be applied in a real system. Therefore, it would be desired to expand the case study including more details about the process of model ranking, selection, and execution.

These ideas were considered as issues to be tackled in the performed research. As a consequence, the new version of the framework that was presented in Section §4.6 was developed. This framework has been applied in an expanded case study focused in Savona Campus (as the previously seen one), and in a new case study focused in the distribution network of the town of Manzanilla (province of Huelva, Spain). These two studies, which have followed a similar procedure, show in more detail the processes of retraining, ranking, selection, and execution of the corresponding models, as it will be exposed next.

5.3 Forecasting framework over a real microgrid (extended)

This section will expose a case study of application of the proposed framework to forecast several variables in a microgrid. This constitutes an extension to the previously presented case study (see Section §5.2). In this new one, the new version of the proposed framework (see Section §4.6.4), which includes deterministic and probabilistic forecasting techniques, has been applied. In this way, it will be possible to obtain different types of uncertainty models, deterministic, probabilistic distribution, intervals, and scenario sets. The description of the campus where the microgrid is installed, the datasets and some other general aspects were already exposed in Section §5.2.1.

The procedure for the training and evaluation of models for each of the performed experiments will be explained in Section §5.3.1. The experiments and results for deterministic models are exposed in Section §5.3.2, while those of probabilistic models can be found in Section §5.3.3. Finally, Section §5.3.4 shows the computation times of the exposed experiments.

5.3.1 Description of the case study

In this study, three variables of the microgrid will be forecasted. These correspond to the demand of the campus (variable *ge*2), consumption (variable *lc*), and PV generation (variable *pv*). These variables have been chosen because they are directly related to the energy management of the campus. In this sense, these variables could be considered for optimizing the management of the existing controllable elements, which are the microturbines and the batteries. Moreover, the demand of the campus would also be of interest in the management of the distribution network where it is connected.

For studying how the framework works, the available historical data has been divided into smaller periods in which the models are successively retrained and executed during a number of days, after which the models are retrained. This will be hereinafter called a "ranking cycle", as it is a cycle in which a certain model ranking (ordered according to their performance) is applied to predict a consecutive number of days.

A period of a few months has been taken as the initial data for training the first models, and after that each ranking has been operative during one month. Therefore, once a month, new models are trained and a new ranking is created for them to be executed during the month to perform the forecasting tasks.

The cycles that will be applied in the experiments are listed in the Table 5.6. As it can be seen, the models that are trained and validated in a cycle will be used to predict during one month. After that time, a new cycle starts and all models are retrained.

The selection of the training and validation sets for training the models and constructing the ranking for the selection of models to make predictions is as follows. The validation set corresponds to the last 15 days of data of the historical dataset that is available in the system when the modeling process is performed. All data except these 15 days are used for training the models, while the 15 last days are used for validating, i.e., choosing hyperparameters and creating the ranking of models (see the proposed framework). The main advantage of this approach is that the models are selected based on their performance on the moments near to the present, which can increase the quality of the prediction in the nearby days. However, the models would be less generalistic when applied to periods of time that are far away from the period used for validation, so a more frequent model retraining could be required to keep up-to-date models.

For the ML models, the list of datasets that have been applied in this case study can be seen in Table 5.7 (which lists the datasets that are used for *ge*2, *lc*, and *pv*) and Table 5.8 (which lists other additional datasets that are exclusively used for *ge*2, as they include EXBLs in their fields). The reasons for using the EXBL datasets only for predicting *ge*2 were previously described in Section §5.2.2. These datasets are in accordance with those defined for the framework in Section §4.6.4.1 (see Table 4.5).

Considering the above-mentioned procedure, in the case of deterministic models, the

Table 5.6: Dates of model training, validation and prediction for each of the cycles.

Cycle number	**Model train and validation**		**Days to predict (testing)**	
	Initial date	**End date**	**Initial date**	**End date**
0	01-01-2016	31-12-2016	01-01-2017	31-01-2017
1	01-01-2016	31-01-2017	01-02-2017	28-02-2017
2	01-01-2016	28-02-2017	01-03-2017	31-03-2017
3	01-01-2016	31-03-2017	01-04-2017	30-04-2017
4	01-01-2016	30-04-2017	01-05-2017	31-05-2017
5	01-01-2016	31-05-2017	01-06-2017	30-06-2017
6	01-01-2016	30-06-2017	01-07-2017	31-07-2017
7	01-01-2016	31-07-2017	01-08-2017	31-08-2017
8	01-01-2016	31-08-2017	01-09-2017	30-09-2017
9	01-01-2016	30-09-2017	01-10-2017	31-10-2017
10	01-01-2016	31-10-2017	01-11-2017	30-11-2017
11	01-01-2016	30-11-2017	01-12-2017	31-12-2017
12	01-01-2016	31-12-2017	01-01-2018	31-01-2018
13	01-01-2016	31-01-2018	01-02-2018	28-02-2018
14	01-01-2016	28-02-2018	01-03-2018	31-03-2018
15	01-01-2016	31-03-2018	01-04-2018	30-04-2018
16	01-01-2016	30-04-2018	01-05-2018	31-05-2018
17	01-01-2016	31-05-2018	01-06-2018	30-06-2018
18	01-01-2016	30-06-2018	01-07-2018	31-07-2018
19	01-01-2016	31-07-2018	01-08-2018	31-08-2018
20	01-01-2016	31-08-2018	01-09-2018	30-09-2018
21	01-01-2016	30-09-2018	01-10-2018	31-10-2018
22	01-01-2016	31-10-2018	01-11-2018	30-11-2018
23	01-01-2016	30-11-2018	01-12-2018	31-12-2018

Table 5.7: List of datasets applied in the case study of Savona Campus for training models of variables $ge2$, lc, and pv. There are 45 datasets for each variable to be predicted.

Datasets	**Datasets**
CaIn	Bl(s7)+DI
Wa(thsr)+DI	Bl(bw7)+DI
Wa(ths)+DI	Bl(sw7)+DI
Wa(t)+DI	Bl(sw14)+DI
Wa(s)+DI	Bl(cnb2)+DI
Db1+DI	Bl(s7)Wa(thsr)+DI
Db2+DI	Bl(s7)Wa(ths)+DI
Db3+DI	Bl(s7)Wa(t)+DI
Db1Wa(thsr)+DI	Bl(s7)Wa(s)+DI
Db1Wa(ths)+DI	Bl(bw7)Wa(thsr)+DI
Db1Wa(t)+DI	Bl(bw7)Wa(ths)+DI
Db1Wa(s)+DI	Bl(bw7)Wa(t)+DI
Db2Wa(thsr)+DI	Bl(bw7)Wa(s)+DI
Db2Wa(ths)+DI	Bl(sw7)Wa(thsr)+DI
Db2Wa(t)+DI	Bl(sw7)Wa(ths)+DI
Db2Wa(s)+DI	Bl(sw7)Wa(t)+DI
Db3Wa(thsr)+DI	Bl(sw7)Wa(s)+DI
Db3Wa(ths)+DI	Bl(sw14)Wa(thsr)+DI
Db3Wa(t)+DI	Bl(sw14)Wa(ths)+DI
Db3Wa(s)+DI	Bl(sw14)Wa(t)+DI
	Bl(sw14)Wa(s)+DI
	Bl(cnb2)Wa(thsr)+DI
	Bl(cnb2)Wa(ths)+DI
	Bl(cnb2)Wa(t)+DI
	Bl(cnb2)Wa(s)+DI

Table 5.8: List of datasets applied in the case study of Savona Campus for training models of variable $ge2$. The EXBLs corresponds to rule-based baselines of the variable lc. The different rules that have been applied for such EXBLs are "bw7", "cnb2", "s7", "sw7", and "sw14", which makes a total of 225 different datasets that include an EXBL.

Datasets
CaIn+EXBL
Wa(thsr)+DI+EXBL
Wa(ths)+DI+EXBL
Wa(t)+DI+EXBL
Wa(s)+DI+EXBL
Db1+DI+EXBL
Db2+DI+EXBL
Db3+DI+EXBL
Db1Wa(thsr)+DI+EXBL
Db1Wa(ths)+DI+EXBL
Db1Wa(t)+DI+EXBL
Db1Wa(s)+DI+EXBL
Db2Wa(thsr)+DI+EXBL
Db2Wa(ths)+DI+EXBL
Db2Wa(t)+DI+EXBL
Db2Wa(s)+DI+EXBL
Db3Wa(thsr)+DI+EXBL
Db3Wa(ths)+DI+EXBL
Db3Wa(t)+DI+EXBL
Db3Wa(s)+DI+EXBL

Datasets
Bl(s7)+DI+EXBL
Bl(bw7)+DI+EXBL
Bl(sw7)+DI+EXBL
Bl(sw14)+DI+EXBL
Bl(cnb2)+DI+EXBL
Bl(s7)Wa(thsr)+DI+EXBL
Bl(s7)Wa(ths)+DI+EXBL
Bl(s7)Wa(t)+DI+EXBL
Bl(s7)Wa(s)+DI+EXBL
Bl(bw7)Wa(thsr)+DI+EXBL
Bl(bw7)Wa(ths)+DI+EXBL
Bl(bw7)Wa(t)+DI+EXBL
Bl(bw7)Wa(s)+DI+EXBL
Bl(sw7)Wa(thsr)+DI+EXBL
Bl(sw7)Wa(ths)+DI+EXBL
Bl(sw7)Wa(t)+DI+EXBL
Bl(sw7)Wa(s)+DI+EXBL
Bl(sw14)Wa(thsr)+DI+EXBL
Bl(sw14)Wa(ths)+DI+EXBL
Bl(sw14)Wa(t)+DI+EXBL
Bl(sw14)Wa(s)+DI+EXBL
Bl(cnb2)Wa(thsr)+DI+EXBL
Bl(cnb2)Wa(ths)+DI+EXBL
Bl(cnb2)Wa(t)+DI+EXBL
Bl(cnb2)Wa(s)+DI+EXBL

structure of the analysis in Section §5.3.2 is:

- The framework will be applied to predict the previously defined period. For each day, the model that is ranked as the best in the corresponding cycle will be executed. If the best model cannot be executed that day (due to the lack of some of the input information that it requires), the next model of the ranking will be used, and so on until one model is executed effectively and the forecast for the day is obtained. The global performance of the predictions of the framework will be compared with the naïve modes and ARIMA models (these two will serve as reference methods).

- The relevance of the tested models for the studied period in the framework will be analyzed. In this sense, a list of models and datasets that were successfully used more frequently will be given. It will be indicated the number of days in which a certain model was chosen by the framework for predicting certain days and was successfully executed (success). Similarly, it will be indicated which of the models was requested by the system for making a prediction and was not available (failed) for that day. This failure may occur when certain information that the models require is not available (due to a problem in the reception of data), such as weather information, measurements of previous days, or some other externally received data.

- Prediction examples. Representation of predictions performed by the system using deterministic methods. These will merely serve as illustrative examples of the forecasting process.

In the case of probabilistic models, the structure of the analysis will have some similarities with that of deterministic models, but some new comparisons are added to evaluate the use of different metrics. This is done like that due to the multiple types of uncertainty models that can be obtained from the framework. Considering this, the structure of the analysis in Section §5.3.3 is:

- Comparison of the global performance of the applied framework (using the best available model) according to the ranking criteria that were chosen. In this sense, as the framework is able to provide different uncertainty models (distributions, intervals, and sets of scenarios), it will be analyzed what is the effect of using rankings only with the pinball loss function, or using the specific metric for each type of model (pinball, Winkler score, or WePin). This comparison will have various cases resulting from the combination of the indicators used for the ranking, and the indicator corresponding to the type of uncertainty modelling that is actually made. This will show the consequence of taking into consideration the type of uncertainty that is going to be created during the ranking step, or if it is ignored.

- Prediction examples. Representation of predictions performed by the system using probabilistic methods for each type of uncertainty modelling from those included in the system. These will merely serve as illustrative examples of the forecasting process for each type of uncertainty.

Once exposed the structure of the analyses, the results are presented next.

5.3.2 Analysis of deterministic models

For the evaluation of the results of deterministic models, the metric will be the RMSE for each day. For evaluating some of the global results that include various different days under a same number, it has been chosen to use the mean value of the RMSE of each individual day. Note that this number is not equal to the RMSE of all the hourly predictions of the group of days, as the corresponding expressions are not similar. It has been preferred to do this in this way to simplify the aggregation of results and achieve a easier comparison and evaluation in this case study.

5.3.2.1 Framework performance results

As previously said, it is firstly necessary choosing the training/validation sets for training the models and constructing the ranking for the selection of models to make predictions. The validation set corresponds to the last 15 days of data of the historical dataset that is available in the system when the modeling process is performed. It is reminded that the rankings are ordered according to the RMSE value that the models obtain during the validation process.

The global metrics that have been obtained are the mean value of the daily RMSE for each of the variables. The forecasting performance of the framework (using the best model that is available for each day according to the ranking) is compared with those of naïve models and ARIMA models. The results can be seen in Table 5.9.

As it can be seen, the proposed framework yields the best global results, considering that it achieves the smaller mean value of daily RMSE.

5.3.2.2 Relevance and applicability of models and datasets

A more detailed analysis of how the forecasting system has operated can be done by observing which are the models that have been used. Moreover, it is also convenient to observe which models have been required by the system, but have not been able to be executed at a certain moment due to a lack of input data. This event, which was previously referred, is precisely the reason for keeping multiple types of models (each one with their own input requirements) inside the system and ordering them in rankings. In this way, it is possible to apply some other alternative model in case the chosen one is not able to be executed in a certain day.

Table 5.9: Comparison of performance of naïve model, ARIMA, and the proposed framework for deterministic forecasting. The mean value of RMSE of the method that yields the best results is remarked in bold and green for each of the variables. Additionally, the standard deviation of each metric is also given.

Variable	**Daily RMSE (kW)**					
	Naïve method		**ARIMA**		**Proposed framework**	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
*ge*2	41.10	29.86	38.13	26.06	**26.89**	16.36
lc	34.33	31.85	22.54	16.18	**18.79**	11.38
pv	8.30	6.06	8.65	5.27	**6.80**	5.88

The five most used models among all the predicted days can be seen in Table 5.10 (for variable *ge*2), Table 5.11 (for variable *lc*), and Table 5.12 (for variable *pv*).

Table 5.10: Models that have been used more frequently by the forecasting system. Variable *ge*2.

Technique : Dataset	**Success counter**
MLPR : Db1Wa(s)+DI	33
MLPR : Db2Wa(t)+DI+EXBL_lc(sw7)	32
MLPR : Db1Wa(s)+DI+EXBL_lc(cnb2)	32
MLPR : Bl(bw7)Wa(s)+DI+EXBL_lc(cnb2)	31
MLPR : Bl(cnb2)Wa(s)+DI	31

Table 5.11: Models that have been used more frequently by the forecasting system. Variable *lc*.

Technique : Dataset	**Success counter**
MLPR : Db1Wa(ths)+DI	90
MLPR : Db1Wa(s)+DI	58
MLPR : Db3+DI	58
MLPR : Bl(bw7)+DI	49
MLPR : Bl(sw7)Wa(t)+DI	49

The five models that have been unavailable when their use was required can be seen in Table 5.13 (for variable *ge*2), Table 5.14 (for variable *lc*), and Table 5.15 (for variable *pv*).

Table 5.12: Models that have been used more frequently by the forecasting system. Variable *pv*.

Technique : Dataset	**Success counter**
RFR : Db1Wa(thsr)+DI	79
MLPR : Db1Wa(s)+DI	56
MLPR : Bl(cnb2)Wa(ths)+DI	55
MLPR : Db2Wa(ths)+DI	51
MLPR : Db1Wa(ths)+DI	32

Table 5.13: Models that have failed more frequently due to the lack of input data when requested by the forecasting system. Variable *ge*2.

Technique : Dataset	**Fail counter**
MLPR : Db2Wa(t)+DI+EXBL_lc(sw14)	35
MLPR : Db2Wa(s)+DI+EXBL_lc(bw7)	28
MLPR : Db2Wa(s)+DI+EXBL_lc(sw14)	27
MLPR : Db3Wa(s)+DI+EXBL_lc(bw7)	25
MLPR : Db3Wa(ths)+DI+EXBL_lc(sw14)	25

Table 5.14: Models that have failed more frequently due to the lack of input data when requested by the forecasting system. Variable *lc*.

Technique : Dataset	**Fail counter**
MLPR : Db3+DI	22
MLPR : Db3Wa(t)+DI	20
MLPR : Bl(bw7)+DI	18
MLPR : Bl(s7)Wa(ths)+DI	17
MLPR : Bl(s7)Wa(t)+DI	17

Table 5.15: Models that have failed more frequently due to the lack of input data when requested by the forecasting system. Variable *pv*.

Technique : Dataset	**Fail counter**
MLPR : Bl(bw7)Wa(t)+DI	19
RFR : Bl(cnb2)Wa(ths)+DI	17
RFR : Db1Wa(thsr)+DI	14
MLPR : Bl(cnb2)Wa(s)+DI	13
RFR : Bl(cnb2)Wa(thsr)+DI	13

As the list of failures shows, the use of a ranking and many different models reinforces the forecasting system to guarantee the availability of predictions for the days. In an extreme case in which there is a total lack of input data, it would be possible to apply the models trained using the dataset ‘CaIn’, which exclusively contains calendar information, and not any weather nor measurement information. This ensures that the forecasting system will be able to provide a forecast.

5.3.2.3 Examples of deterministic predictions

This section depicts some examples of days forecasted by the framework under the proposed approach. The forecast is represented together with the actual consumption. The daily RMSE is also indicated for each represented day. The representations corresponds to the variable *ge*2 (see Figure 5.5), *lc* (see Figure 5.6), and *pv* (see Figure 5.7).

Once finished the study focused on deterministic forecasting methods, the next section will focus on probabilistic methods. This new analysis is more complex than the previously one due to the higher number of uncertainty representations that are included in the framework (quantile distributions, intervals, and scenario sets), and consequently this analysis will involve three different evaluation metrics (pinball, Winkler score, and WePin) instead of a single one.

5.3.3 Analysis of probabilistic models

It was said in the proposed framework that each type of uncertainty model that can be created from probabilistic methods will have its own metric for being evaluated. These are the set of quantiles (evaluated using the pinball loss function), the intervals (evaluated by Winkler score), and the scenario sets (evaluated by the proposed WePin).

The application of some of these metrics requires an additional step, which is deciding which specific modelling is done inside each category (configuration of intervals, configuration of scenarios, etc.).

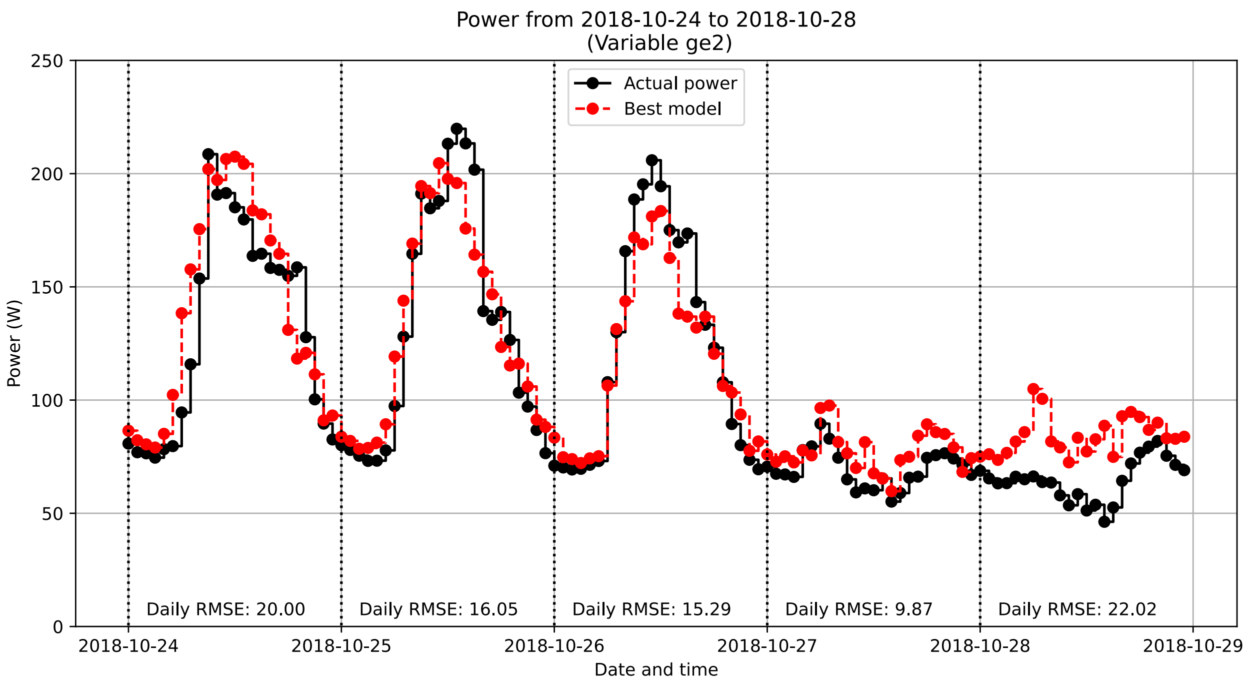


Figure 5.5: Example of deterministic forecasting for the variable $ge2$.

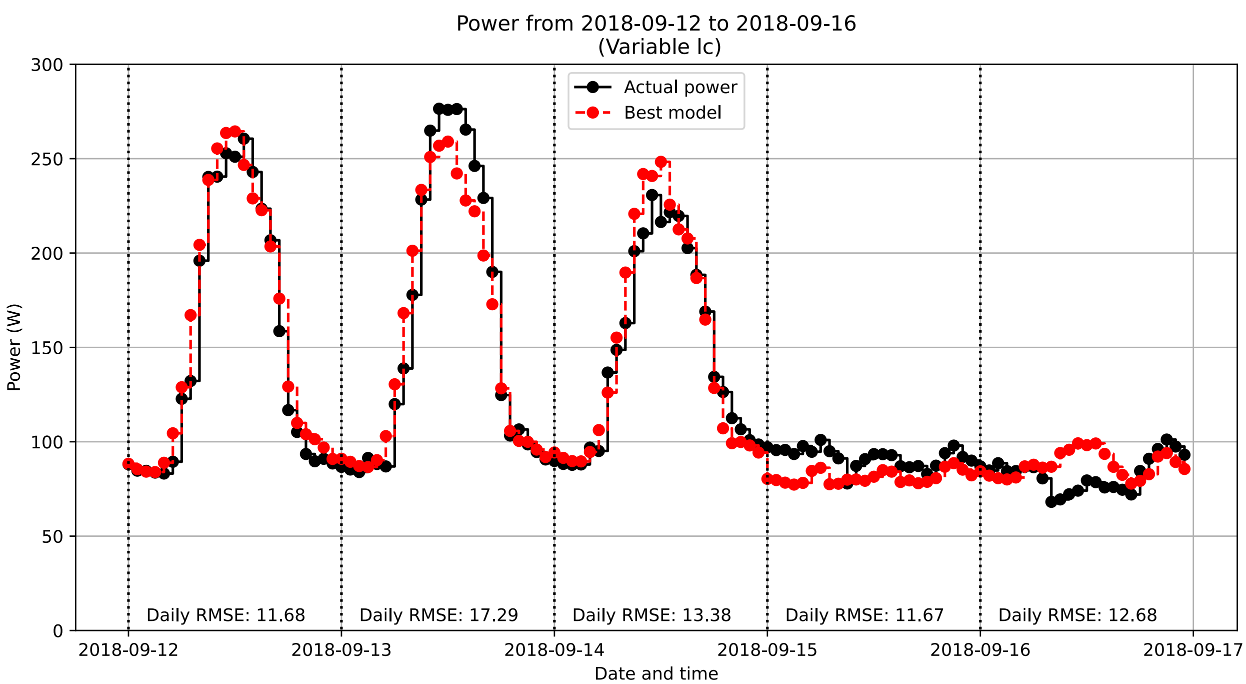


Figure 5.6: Example of deterministic forecasting for the variable lc.

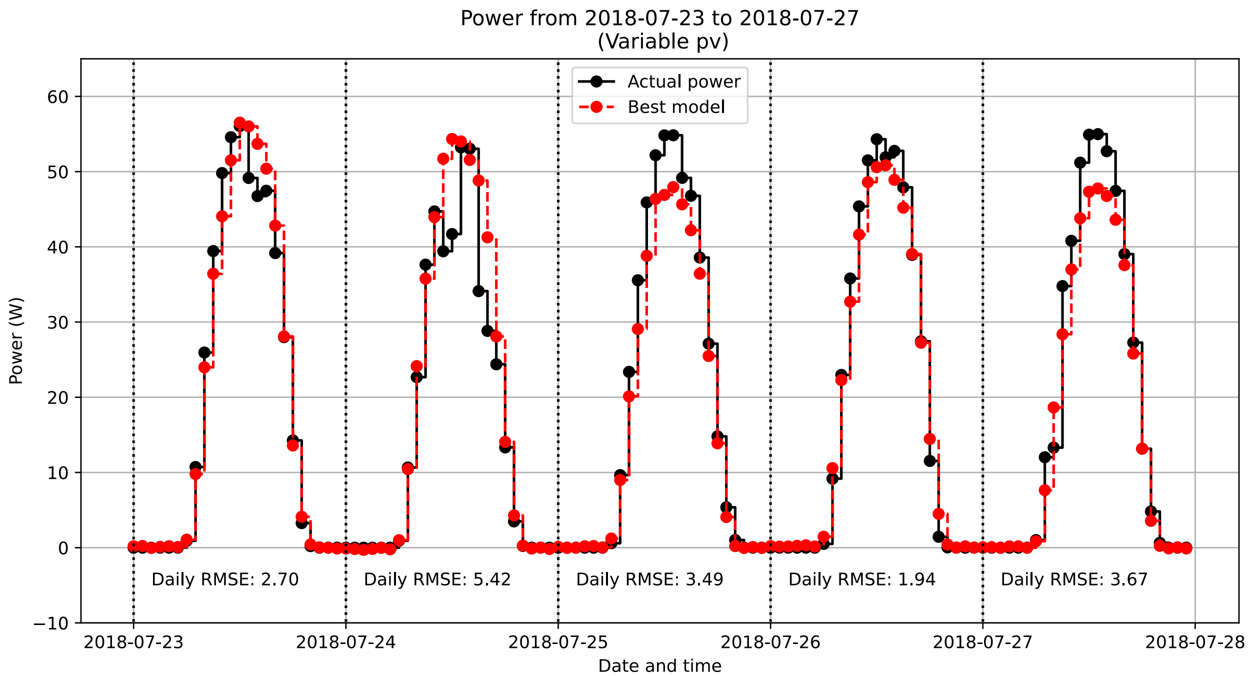


Figure 5.7: Example of deterministic forecasting for the variable *pv*.

In this sense, the configuration that has been chosen for the present case study is:

- Quantile distribution composed by 99 quantiles, from 0.01 to 0.99. The complete quantile distribution will be globally evaluated using the pinball loss function, by averaging the pinball values of the 99 quantiles. Alternatively, these could be summed instead of averaged, but the result would be equivalent when compared between different models (simply, the numbers would be multiplied by 99).

- Intervals of 98%, 94%, 90%, 80%, 70%, 60%. In worst-case analyses from the literature, it is usual to consider intervals that have a high probability of determining the interval in which the variable will be. In this sense, probabilities of 90% and higher are more commonly found in these types of studies than intervals with probabilities below that. However, in order to study the behavior of the system, it has been preferred to include some smaller ones in the present case study.

- 49 sets of scenarios of type 'MiAs' and 49 of type 'ExAs'. These corresponds to sets of 2, 3, 4, ..., 50 scenarios MiAs and sets of 2, 3, 4, ..., 50 scenarios ExAs. The metric of handling the evaluation of scenario sets under the WePin score depends on the quantiles and probabilities of scenario sets, so the WePin will be calculated specifically for each set of scenarios depending on the number of scenarios it contains, and the method applied for obtaining it ('MiAs' or 'ExAs').

To evaluate if it is convenient or not to include these specific metrics during the phase of ranking creation, two cases will be compared, one exclusively using the pinball loss for creating the ranking, and another case using each specific metric for each type of uncertainty model (each of these with its own ranking made according to its corresponding metric). In the case of the quantile distribution (the first type of uncertainty model), there will not be a difference between both cases, as its corresponding metric is precisely the pinball loss. For the other metrics, it will be seen what the change on the model performance is.

It is reminded that, as said in Section §4.6.4.3, these metric will have a lesser value when the forecasting quality is better.

5.3.3.1 Framework performance results according to pinball

In this section, the forecasting system will perform probabilistic predictions using the best available model according to the value of the pinball loss function (averaged for the quantiles from 0.01 to 0.99) that these obtained during the respective validation phases. In those cases in which the required model is not available for being used (due to a lack of needed data), the next better model of the ranking will be executed. This procedure will be repeated until a model that is able to provide a forecasting is found.

The results that were obtained can be seen in Table 5.16.

Table 5.16: Results for probabilistic models. Only the pinball loss function (averaged for quantiles from 0.01 to 0.99) is considered.

Variable	**Mean pinball**
$ge2$	9.99
lc	5.54
pv	1.31

In the described situation, the forecasting system is providing a probabilistic forecast made of 99 quantiles. However, as it was described in Section §4.6.4, the proposed framework is also able to provide other types of probabilistic models. According to the proposal, these other types of models would require the use of their respective evaluation metrics (instead of the pinball loss function).

The next section will analyze the effect of using the specific metrics in rankings for those types of uncertainties that cannot be directly evaluated by the pinball.

5.3.3.2 Impact of using specific metrics in rankings

It was said in Section §4.6.4 that the probabilistic models are not handled by a single ranking, but by three of them. One of them is based on the pinball loss function of the distribution (99 quantiles) that is forecasted, some others based on the Winkler score for each of the intervals, and some others based on WePin for each type of scenario set. The objective of the present section is to compare the quality of the predictions considering these multiple rankings with the performance of the system based exclusively on the pinball. It should be noted that the use of pinball would be possible by selecting the model according to this metric, and later creating the desired uncertainty model (interval, or scenario set) from the obtained quantiles that the model gave. However, the proposal that was made in Section §4.6.4.3 establishes that it could be better to evaluate each type of model using their respective metric for creating their own separate rankings. These two approaches will be now compared to check what is the effect of using one or another in this case study.

Therefore, the two situations that will be compared are the "value with pinball ranking" (i.e., obtaining all the uncertainty models with the model that has the better pinball) and the "value with specific ranking" (i.e., obtaining the forecasting with the best model of the ranking specifically made for each type of uncertainty: interval or scenario set). It will be seen which of the approaches permit the system to obtain better global results.

The numerical results of the comparison for the intervals (which are evaluated using Winkler score) are given next. The intervals evaluated are 98% (Table 5.17), 94% (Table 5.18), 90% (Table 5.19), 80% (Table 5.20), 70% (Table 5.21), and 60% (Table 5.22).

Table 5.17: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 98%.

Variable	**Winkler score for interval 98%**		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
*ge*2	121.28	68.90	43.19
lc	73.55	63.76	13.31
pv	17.40	9.27	46.75

To simplify the analysis of these results, they have been summarized in the chart of Figure 5.8. Each square corresponds to one of the variables under an interval. Their colors indicate if the performance improves (in yellow), remains equal (in white), or gets worse (in red) with the use of specific rankings instead of pinball ranking.

As it can be seen, in most of the cases, the use of rankings based on the specific metrics (Winkler score for each interval) produces an improvement on the quality of the forecasting. Especially, the improvement is notable for the intervals with higher probability (90% and more), which are precisely the type of intervals that are more commonly found in applications of robust optimization.

Table 5.18: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 94%.

Variable	**Winkler score for interval 94%**		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
*ge*2	105.60	64.88	38.56
lc	62.26	56.00	10.06
pv	15.32	9.04	40.98

Table 5.19: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 90%.

Variable	**Winkler score for interval 90%**		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
*ge*2	96.84	63.49	34.44
lc	56.34	51.08	9.34
pv	14.06	9.05	35.66

Table 5.20: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 80%.

Variable	**Winkler score for interval 80%**		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
*ge*2	84.65	65.42	22.72
lc	48.30	46.17	4.41
pv	12.14	9.40	22.60

Table 5.21: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 70%.

Variable	**Winkler score for interval 70%**		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
*ge*2	79.75	70.51	11.58
lc	45.07	44.77	0.66
pv	11.25	10.18	9.54

Table 5.22: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 60%.

Variable	**Winkler score for interval 60%**		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
*ge*2	80.42	79.55	1.08
lc	45.24	44.54	1.55
pv	11.01	10.98	0.20

Regarding the WePin metric applied to the evaluation of scenario sets, the results can be seen in Figure 5.9 and Figure 5.10.

The global results shown in the previous charts have been summarized in Table 5.23, where the cases are counted according to the change in the performance of the system (better, equal, or worse) for each variable and criterion. It can be seen that in most of the cases, the system improves the quality of forecasting when the rankings apply each specific metric instead of using only the ranking based on pinball.

Considering the previous results, it can be concluded that the consideration of specific indicators for ordering the model ranking results in better quality models for each type of desired uncertainty. Therefore, it is convenient to consider such different indicators in the ranking and model selection processes, instead of using a single ranking (based on the pinball loss function) for all the probabilistic uncertainty models.

5.3.3.3 Examples of probabilistic predictions

This section depicts some examples of days forecasted by the framework under the previously described approach. The daily values of indicators corresponding to each type of uncertainty model are included for each of the represented days.

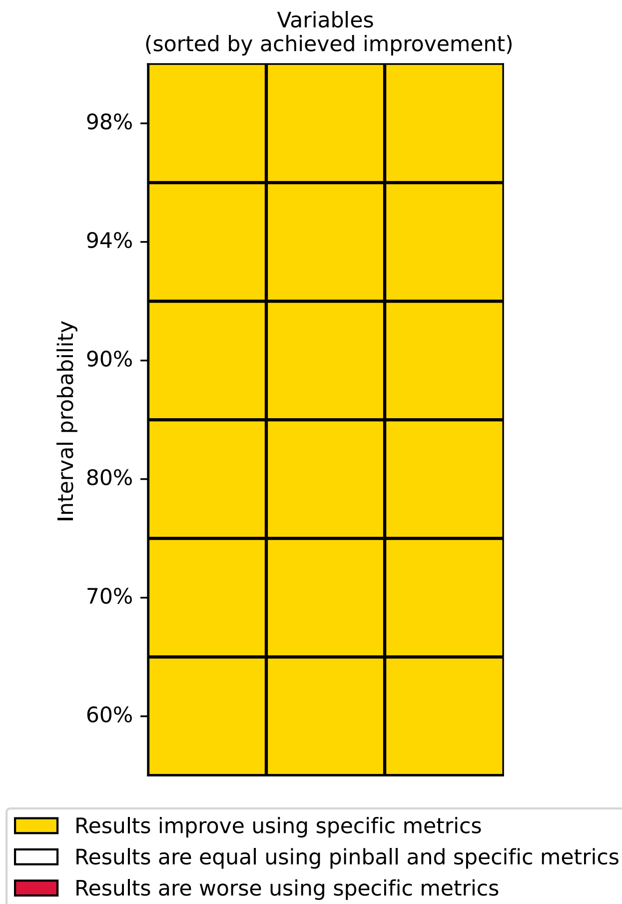


Figure 5.8: Winkler improvement when the rankings are created considering Winker score instead of pinball.

Table 5.23: Summary of performance change on the forecasting system when specific metrics are used to construct the rankings.

Type of uncertainty	Number of tested cases	**Effect of using specific metrics in rankings over the quality of the forecasting (counted by number of cases)**		
		Gets better	Remains equal	Gets worse
Interval	18	18	0	0
Scenarios MiAs	147	55	44	48
Scenarios ExAs	147	71	48	28

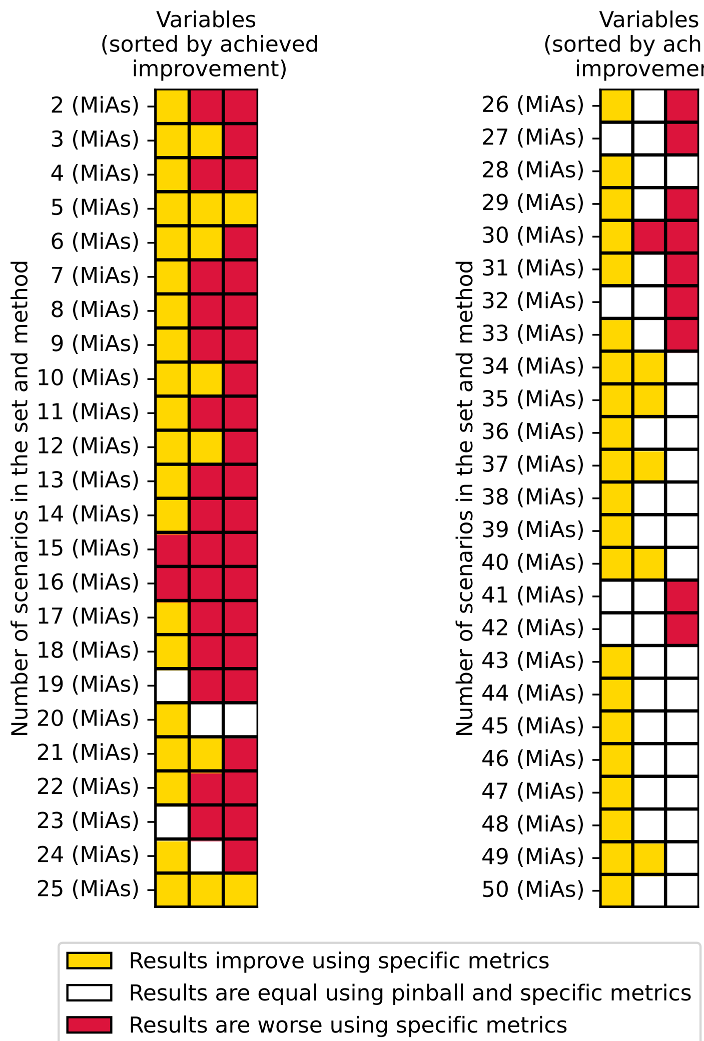


Figure 5.9: WePin improvement for MiAs scenarios when the rankings are created considering WePin score instead of pinball. In the y-axis the number of scenarios and the method that has been used (MiAs) is indicated. In the x-axis, the three variables are simply ordered by their achieved improvement.

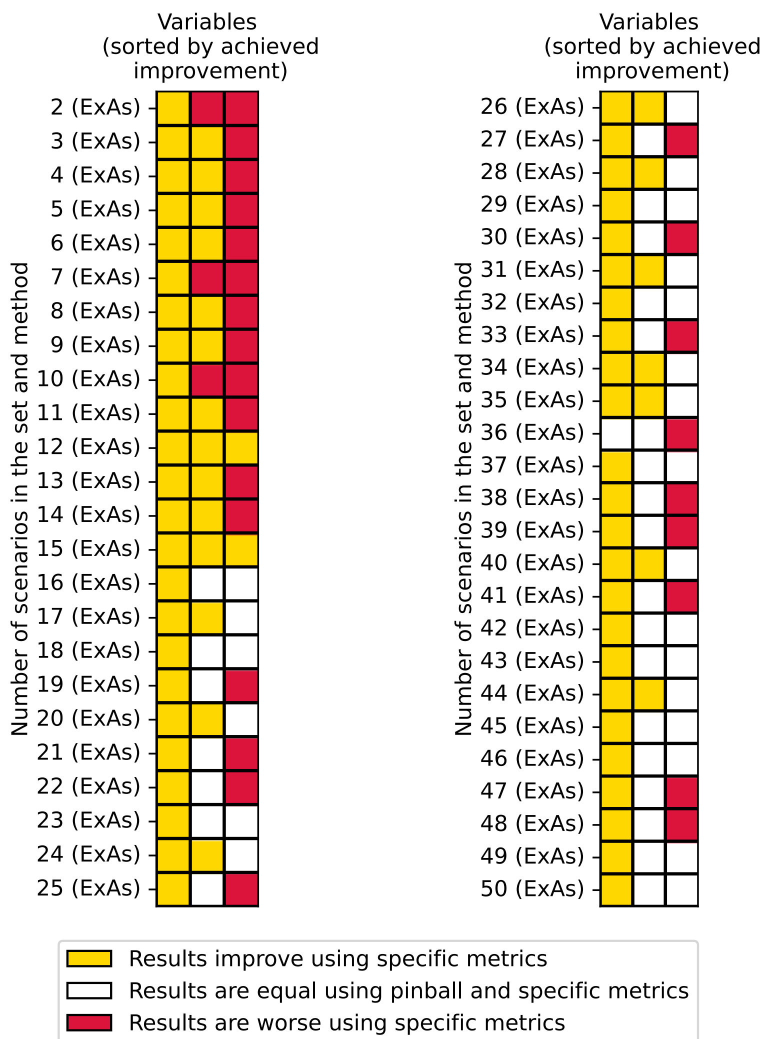


Figure 5.10: WePin improvement for ExAs scenarios when the rankings are created considering WePin score instead of pinball. In the y-axis the number of scenarios and the method that has been used (ExAs) is indicated. In the x-axis, the three variables are simply ordered by their achieved improvement.

For the forecasting based on 99 quantiles (from 0.01 to 0.99), the representations correspond to the variable lc (see Figure 5.11).

For the forecasting based on intervals, the representations correspond to the intervals 98% (see Figure 5.12), 90% (see Figure 5.13), and 80% (see Figure 5.14) for the variable lc.

For the forecasting based on sets of scenarios, the representations correspond to the set MiAs of 3 scenarios (see Figure 5.15), the set ExAs of 3 scenarios (see Figure 5.16), the set MiAs of 10 scenarios (see Figure 5.17), and the set ExAs of 10 scenarios (see Figure 5.18) for the variable lc.

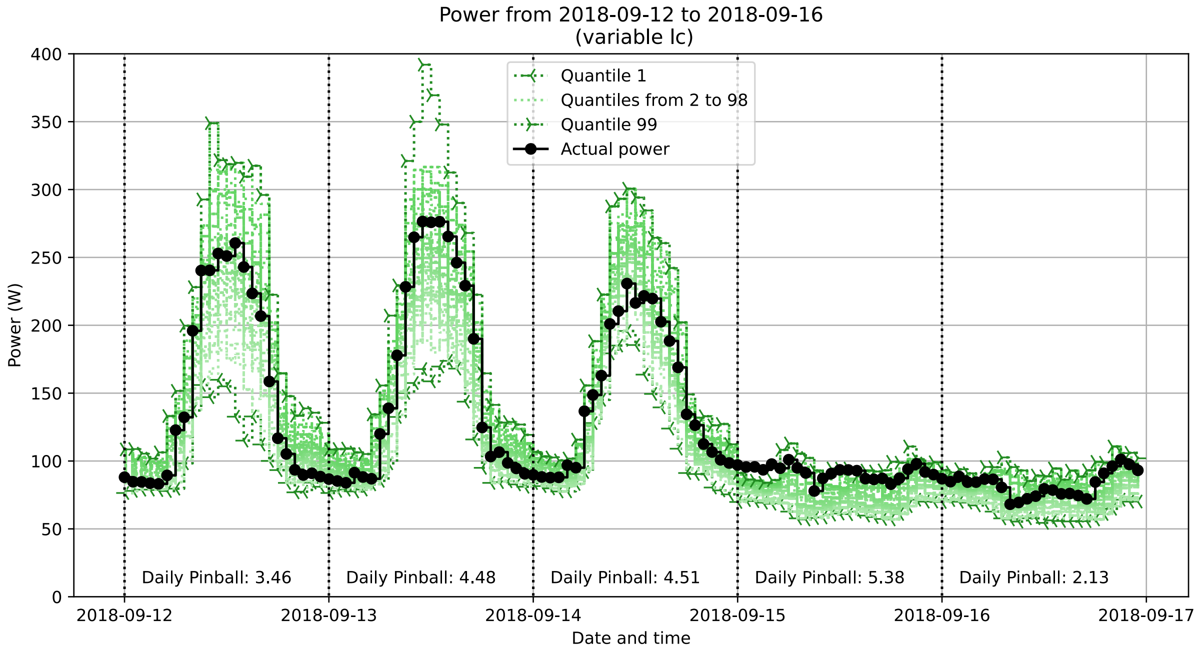


Figure 5.11: Example of probabilistic forecasting based on the 99 quantiles for the variable *lc*.

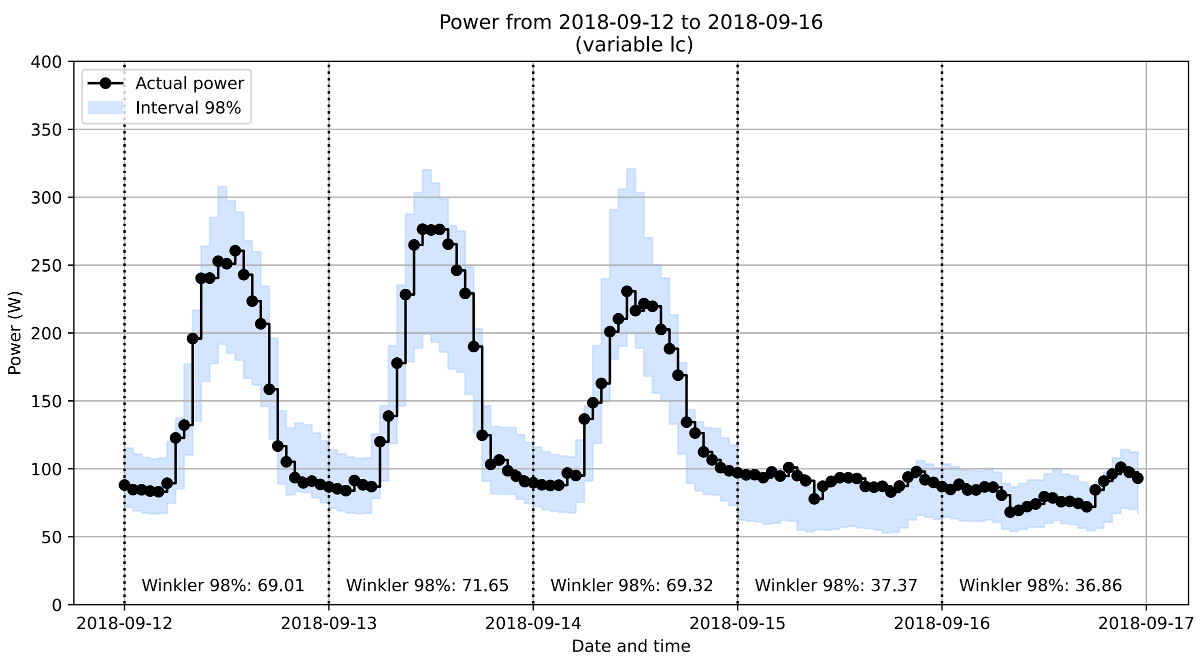


Figure 5.12: Example of probabilistic forecasting based on interval with 98% of probability for the variable *lc*.

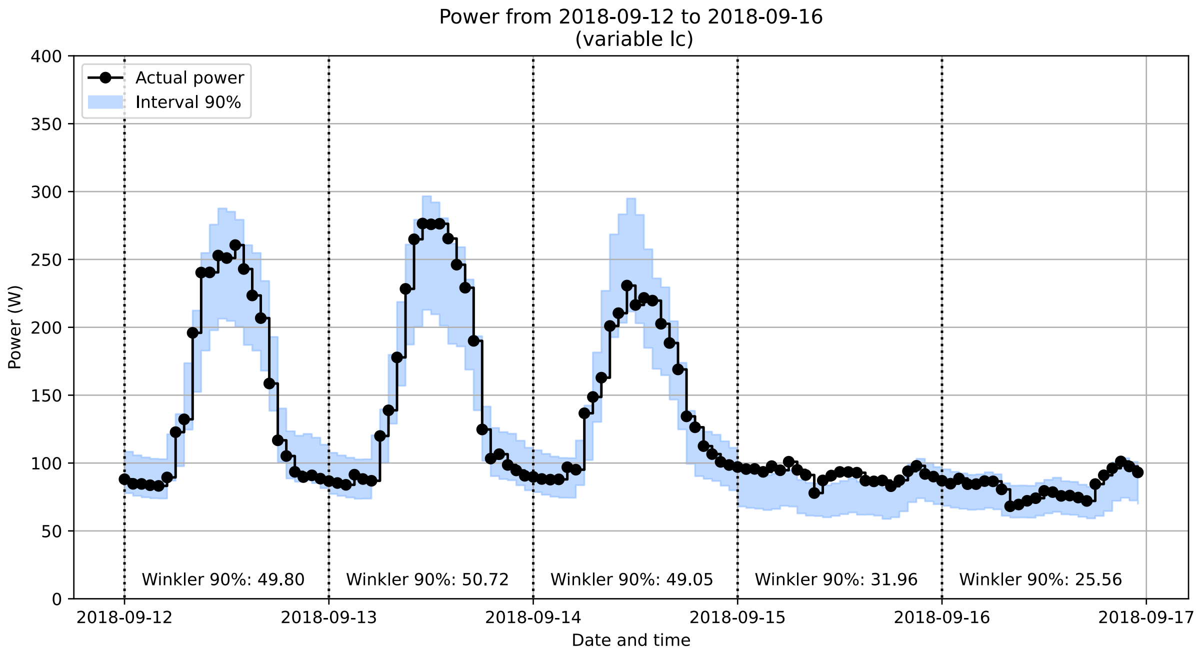


Figure 5.13: Example of probabilistic forecasting based on interval with 90% of probability for the variable lc.

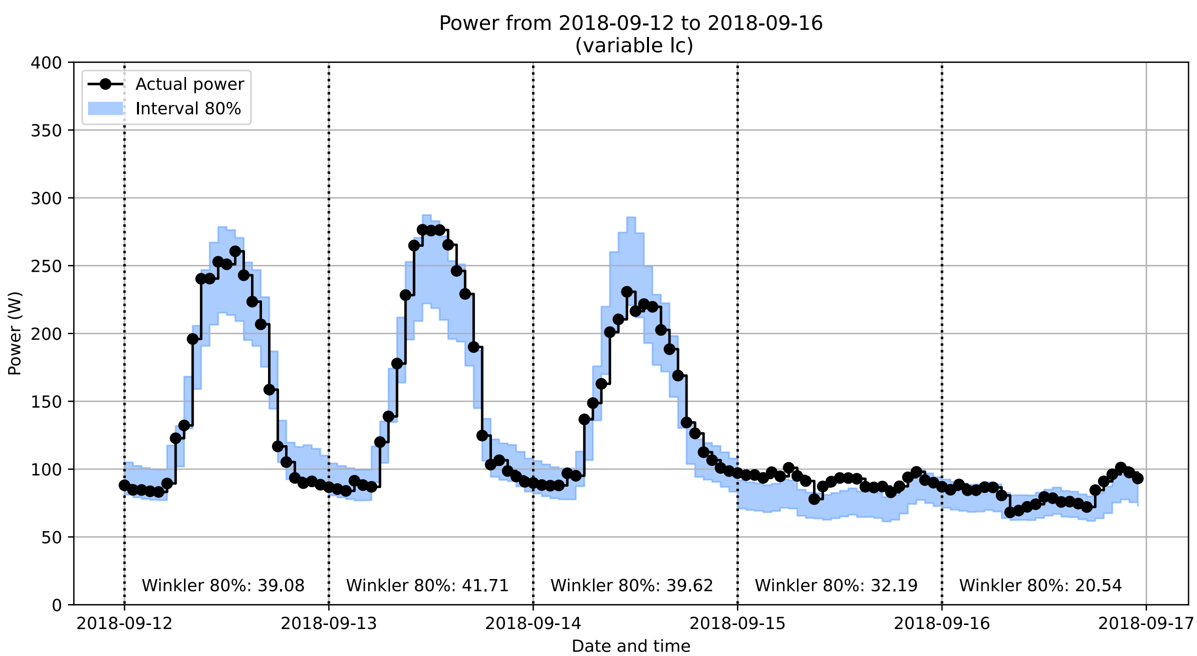


Figure 5.14: Example of probabilistic forecasting based on interval with 80% of probability for the variable lc.

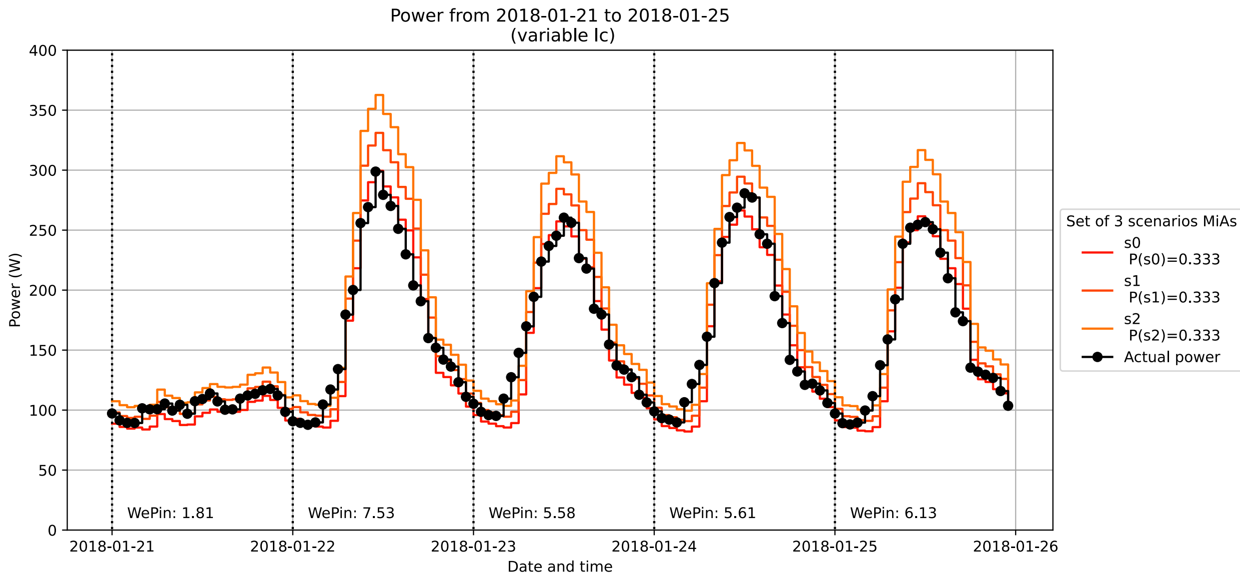


Figure 5.15: Example of probabilistic forecasting based on a set of 3 scenarios MiAs for the variable lc.

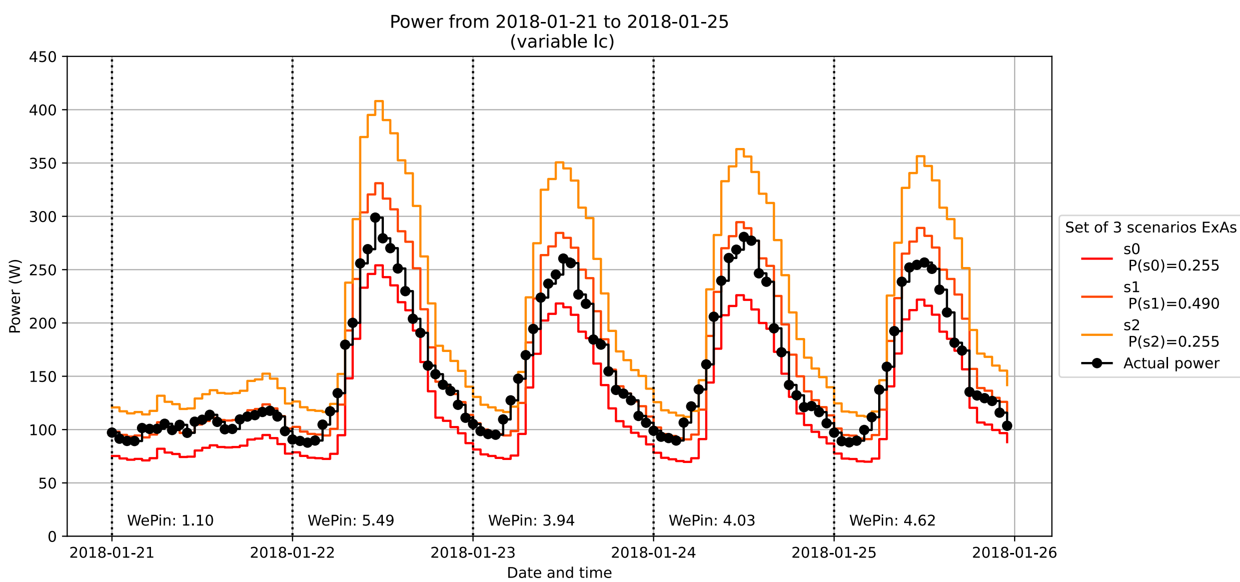


Figure 5.16: Example of probabilistic forecasting based on a set of 3 scenarios ExAs for the variable lc.

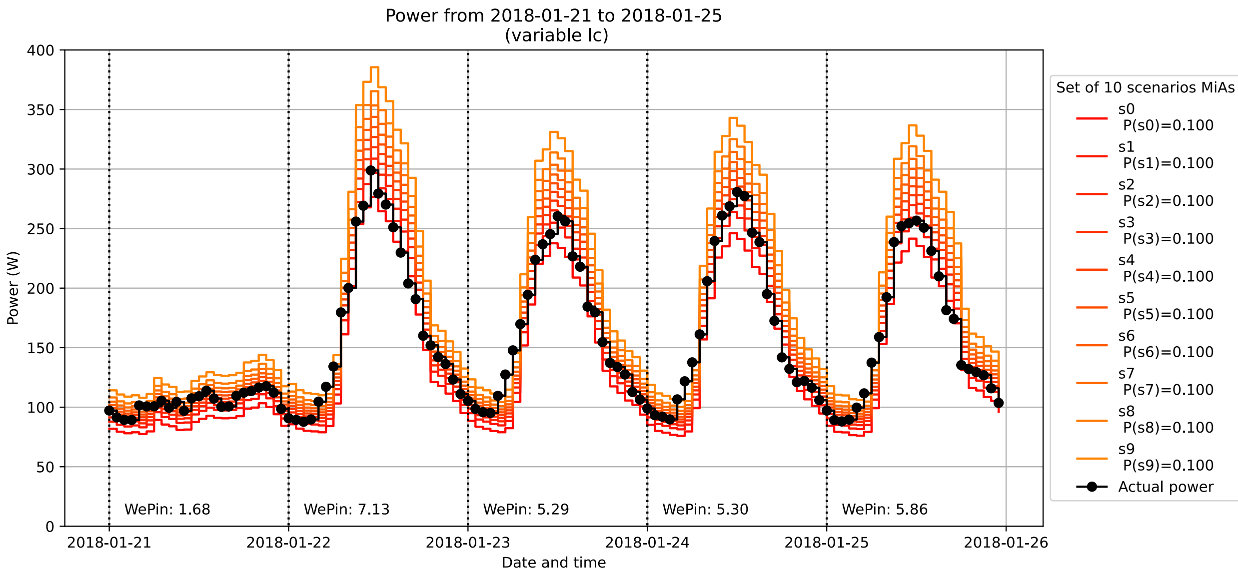


Figure 5.17: Example of probabilistic forecasting based on a set of 10 scenarios MiAs for the variable lc.

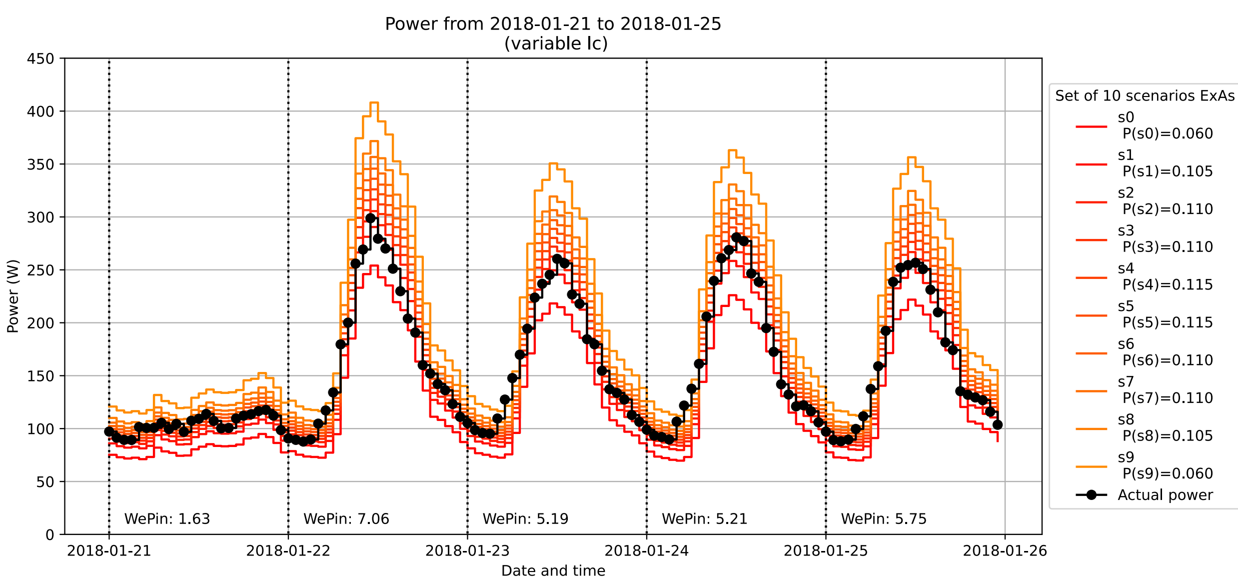


Figure 5.18: Example of probabilistic forecasting based on a set of 10 scenarios ExAs for the variable lc.

5.3.4 Computation times

This section presents the computation times that the forecasting system has required for the period under study. The times for deterministic and probabilistic techniques that require a training process are included here. In this sense, the predictions that have been directly obtained using Rulabi are not included, as these models do not imply a training, but simply an averaging based on the data of certain previous days. Therefore, as their computation time is mainly dependent on the speed of the forecasting system to get and manipulate the data, it has not been considered of interest the inclusion of their times here.

The two types of times that are exposed are the time of training/validation (which includes the total time for training the models and constructing the rankings of the forecasting system) and the daily time of execution (which represents the time that a model needs to forecast one single day).

The times that have been needed for training the models with the available datasets, performing their evaluation, and constructing the rankings for each technique and cycle (for a single variable to predict) are represented in Figure 5.19 and Figure 5.20.

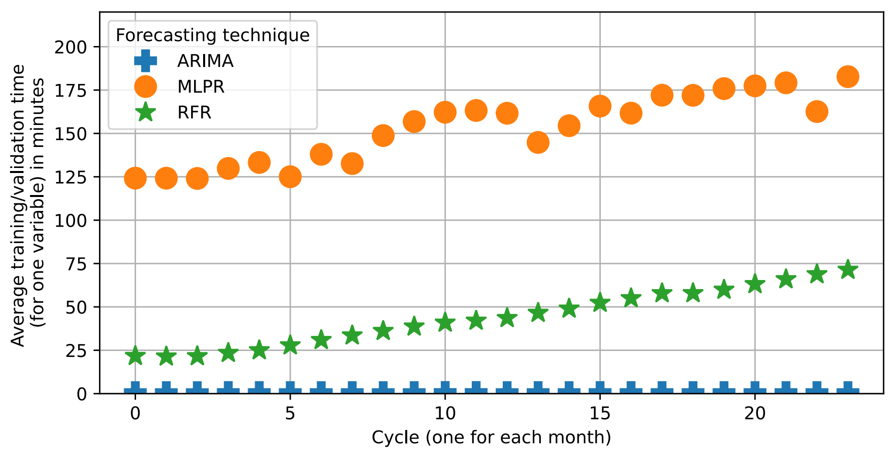


Figure 5.19: Time of training/validation for a single variable to forecast. Deterministic techniques.

The times of training/validation of each technique (average for a single cycle of a single variable) are included in Table 5.24 and Table 5.25.

Finally, the total computation time that was needed for forecasting one single day with each technique can be seen in Table 5.26 and Table 5.27.

These results show that the ARIMA models, despite requiring a lesser time to be evaluated and included in the rankings (it is reminded that the validation period to construct the rankings is the last 15 days of the historical data), their time to be executed is much higher than MLPR and RFR models, as the ARIMA is retrained for each day that has to be predicted.

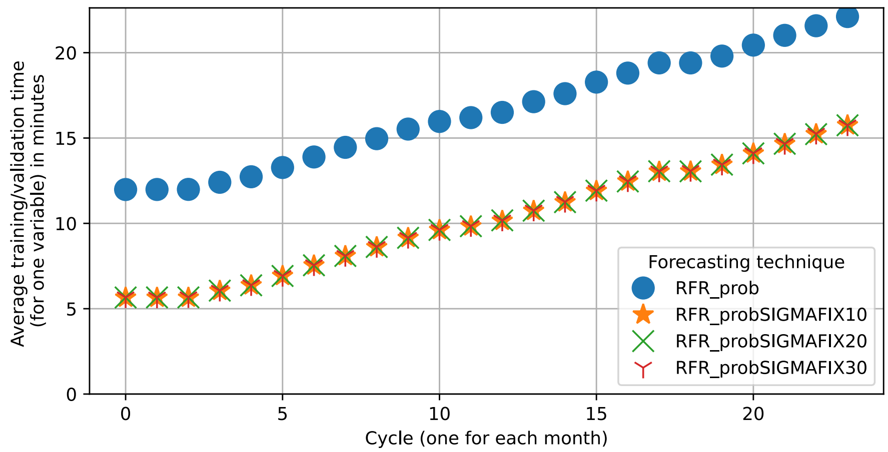


Figure 5.20: Time of training/validation for a single variable to forecast. Probabilistic techniques.

Table 5.24: Times of training/validation of each technique (average for a single cycle of a single variable to predict). Deterministic techniques.

Technique	**Average training/validation time (for one cycle and one variable) in minutes**
ARIMA	0.60
MLPR	153.02
RFR	43.93

Table 5.25: Times of training/validation of each technique (average for a single cycle of a single variable to predict). Probabilistic techniques.

Technique	**Average training/validation time (for one cycle and one variable) in minutes**
RFR_prob	16.56
RFR_probSIGMAFIX10	10.20
RFR_probSIGMAFIX20	10.21
RFR_probSIGMAFIX30	10.21

Table 5.26: Times for forecasting one day for each technique (in ms). Deterministic techniques.

Technique	**Average prediction time (for one day) in ms**
ARIMA	2396.67
MLPR	0.78
RFR	1.14

Table 5.27: Times for forecasting one day for each technique (in ms). Probabilistic techniques.

Technique	**Average prediction time (for one day) in ms**
RFR_prob	256.24
RFR_probSIGMAFIX10	47.68
RFR_probSIGMAFIX20	47.70
RFR_probSIGMAFIX30	47.65

Therefore, the total computation cost of the forecasting system to apply the ARIMA models, and the ML models would depend on how frequently the models are retrained and ranked (which have been called a "cycle" in the presented case study) and how many different variables should be forecasted.

The use of the mentioned ML models, while having higher times of training and evaluation, permit to keep the majority of the computational cost in the moment of training, while their execution time will be much lower than ARIMA models. Therefore, the computational cost during the normal operation would be reduced. Additionally, the ML models have shown a better performance than ARIMA for the studied variables.

5.3.5 Conclusions and possible improvements

The main innovation of this case study with respect to the previous one (see Section §5.2) is that the new version of the forecasting framework that was applied includes probabilistic (and stochastic) models. Moreover, these models include various types of uncertainty representation that can be obtained according to the requirements of the application that is fed by the forecasting system.

To evaluate the performance of the framework in this case study, the system has been retrained once a month. The last 15 days available were used to validate the models and create the rankings, while the rest of the historical data were firstly used for training the models. The results showed that for most of the forecasted variables (the consumption of several secondary substations), the proposed framework achieved better forecasting results than the naïve method and ARIMA method, which were used as references.

Regarding the evaluation of different kinds of probabilistic models, it has been appreciated that the decision of including independent model rankings with their respective evaluation metrics can produce a global increasing of the quality of forecasting. Specially, this improvement has been appreciated during the prediction of intervals and ExAs scenario sets. Therefore, this approach (which was exposed in the description of the framework in Section §4.6.4.3) is more convenient than simply evaluating the global quantile distribution (using pinball) of all types of models and using the best of these to obtain the rest of the probabilistic models (which would be computationally simpler, but would achieve a worse quality of forecasting).

5.4 Forecasting framework over a real distribution network

This section will expose a case study of application of the proposed framework to forecast the consumption in a distribution network. Specifically, to forecast the hourly consumption of 13 secondary substations in a town in Spain in a day-ahead basis. It will be possible to obtain different types of uncertainty models, deterministic, probabilistic distribution, intervals, and scenario sets.

First, a brief description of the distribution network under study will be given in Section §5.4.1. Then, the procedure for the training and evaluation of models for each of the performed experiments will be explained in Section §5.4.2. The experiments and results for deterministic models are exposed in Section §5.4.3, while those of probabilistic models can be found in Section §5.4.4. Section §5.4.5 shows the computation times of the exposed experiments. Finally, Section §5.4.6 contains the conclusions of this case study.

5.4.1 Distribution network description

The proposed forecasting framework has been applied in a distribution network in the town of Manzanilla (Huelva, España), whose location can be seen in Figure 5.21. The available dataset corresponds to the hourly consumption data of 13 secondary substations from the year 2017 (or, for some of the substations, from the year 2018) to the end of the year 2020. Their location in the map can be seen in Figure 5.22.

The objective of this case study will be the day-ahead hourly prediction of the consumption of each of these secondary distribution substations by means of diverse deterministic and probabilistic models. Therefore, there will be 13 variables in this case study that correspond to each individual substation.

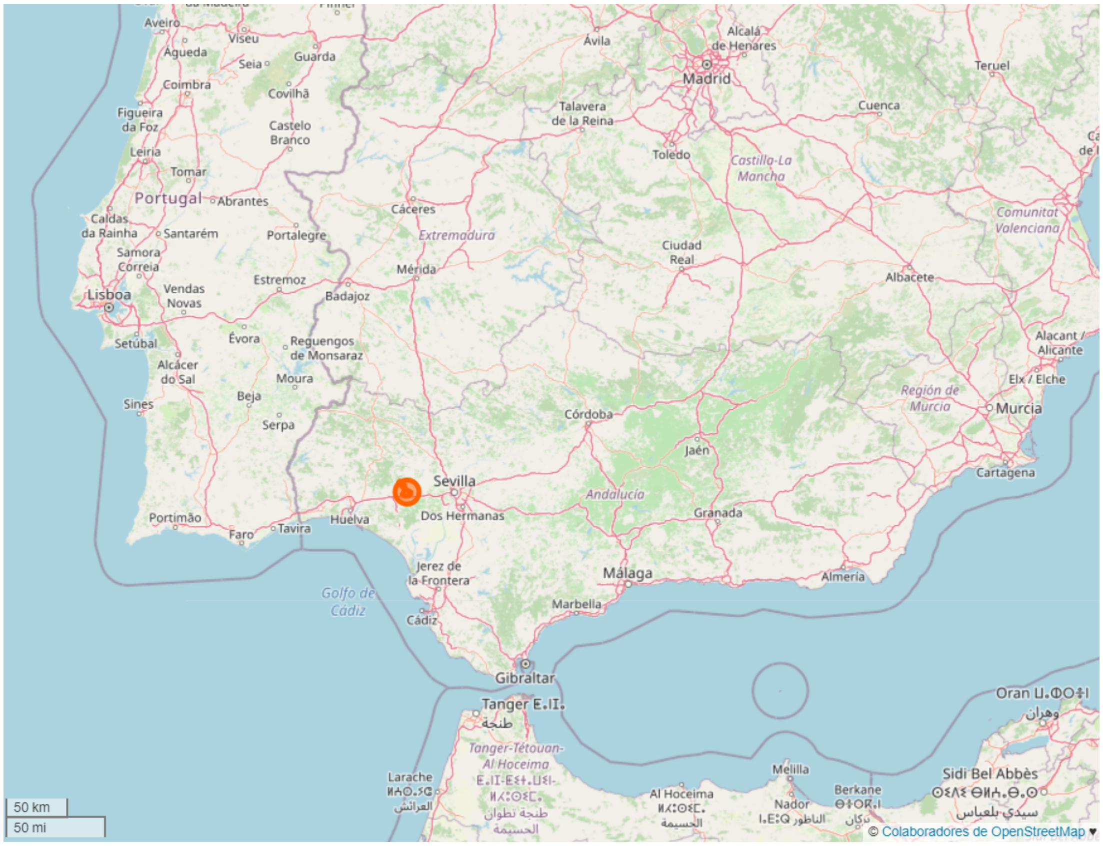


Figure 5.21: Location of the town of Manzanilla (province of Huelva) in Spain (marked in orange). The background map have been obtained from the website *OpenStreetMap* (https://www.openstreetmap.org/copyright/en).

Before starting with the experiments, an overview of these data will be given. To provide a vision of the magnitude of each secondary substation, their global mean power values are represented in Figure 5.23. These same numerical values can be found in Table 5.28. Additionally, the mean hourly powers of the substations are summarized in Figure 5.24. To refer to each specific substation, only their assigned numbers will be used (from 0 to 12).

When observing the power magnitudes of the substations, it can be appreciated that there are high differences between them. In particular, the substations 11 and 12 have the lowest powers among them, their mean power being lesser than 4kW. These two substations therefore are less significant than those of the others, as their impact over the distribution network will not be as high as in other substations. All others have a mean power of 10kW or more. The biggest one presents a mean power of more than 130kW and a mean peak hourly value near to 200kW (see Figure 5.24).

Those substations with lesser power tend to have consumptions that are more difficult to

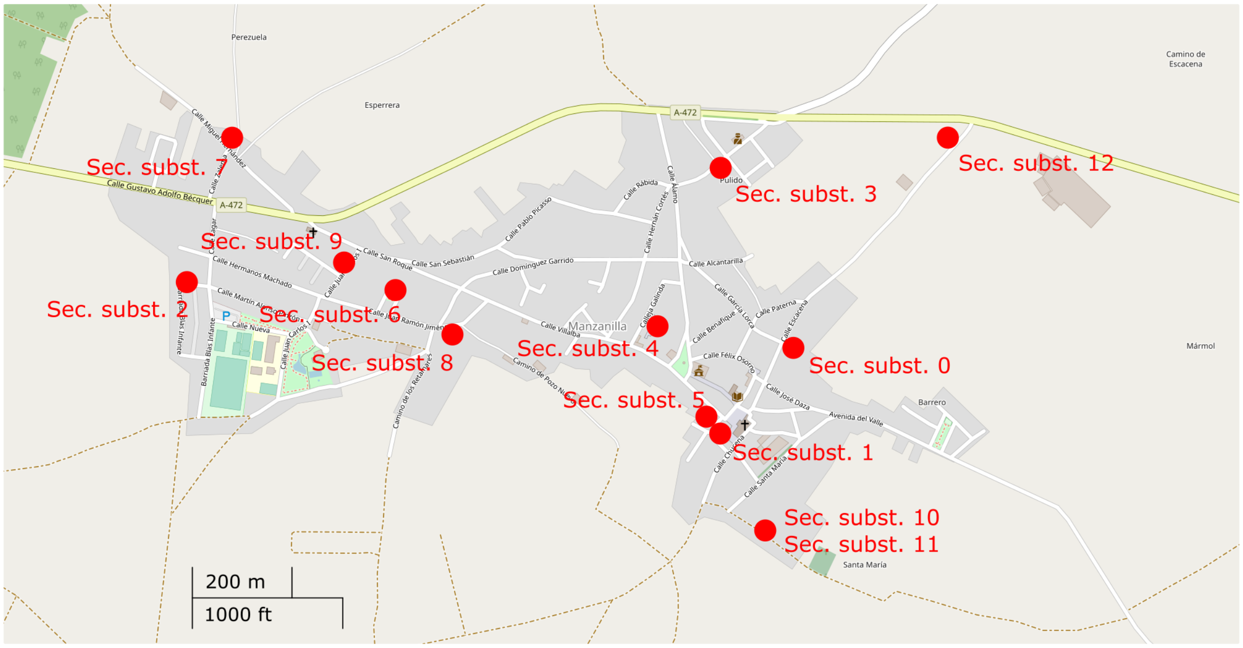


Figure 5.22: Location of the 13 secondary substations (abbreviated as *sec. subst.*) of the town of Manzanilla (province of Huelva, Spain) whose data are included in the present case study. The background map have been obtained from the website *OpenStreetMap* (https://www.openstreetmap.org/copyright/en).

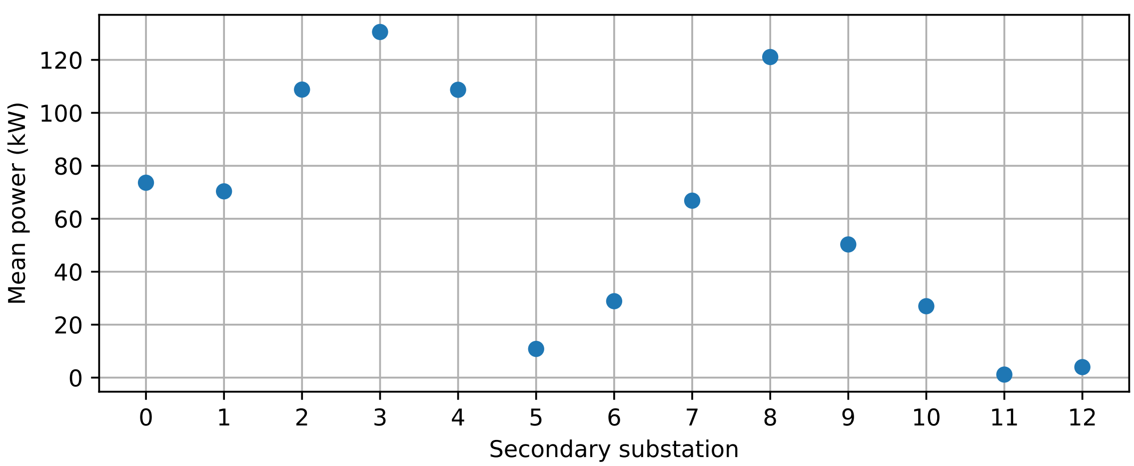


Figure 5.23: Mean power (in kW) of each of the 13 secondary substations.

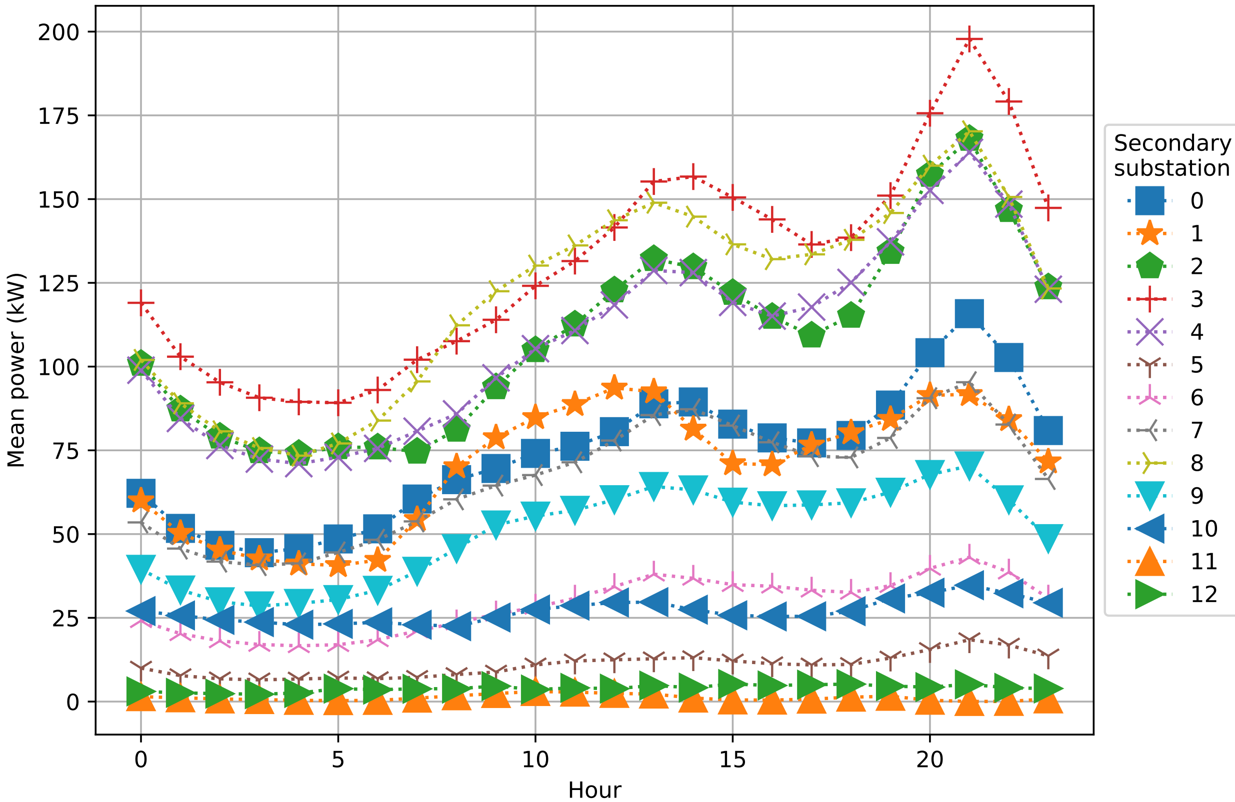


Figure 5.24: Mean power (in kW) of each of the 13 secondary substations for each hour of the day.

predict due to their high variability. This fact should be considered during the interpretation of results of the case study.

Additionally, weather data will be used together with the power historical data for being used in the prediction process. The variables that are included are the hourly temperature, humidity, and rainfall. The summary of these weather data can be seen in Table 5.29.

Considering the data that is available, these fields will be combined to create several datasets to serve as inputs for the forecasting models, as it will be described later.

Having explained the variables to be predicted and the characteristics of the available data, the next section will explain how the experiments will be performed.

5.4.2 Description of the case study

For studying how the framework works, the available historical data has been divided into smaller periods in which the models are successively retrained and executed during a number of days, after which the models are retrained. This will be hereinafter called a "ranking cycle", as it is a cycle in which a certain model ranking (ordered according to their perform-

Table 5.28: Mean power value for each secondary substation (in kW).

Mean power summary	
Secondary substation	**Mean power value (kW)**
0	73.6
1	70.4
2	108.8
3	130.5
4	108.7
5	10.8
6	28.9
7	66.8
8	121.1
9	50.3
10	27.0
11	1.1
12	4.0

Table 5.29: Summary of historical weather data of Manzanilla for the period under study. "mean" express the mean value; "std" express the standard deviation; "min" is the minimum value; "P_{25}", "P_{50}", and "P_{75}" express the percentiles 25, 50 and 75 respectively; "max" is the maximum value.

Weather data summary			
Statistical value	**Temperature (ºC)**	**Humidity (%)**	**Rainfall in one hour (mm)**
mean	19.5	66.6	0.046
std	8.1	22.8	0.487
min	0.0	0.0	0.000
P_{75}	13.6	49.0	0.000
P_{50}	18.6	69.0	0.000
P_{75}	24.8	87.0	0.000
max	44.0	100.0	19.000

ance) is applied to predict a consecutive number of days.

A period of a few months has been taken as the initial data for training the first models, and after that each ranking has been operative during one month. Therefore, once a month, new models are trained and a new ranking is created for them to be executed during the month to perform the forecasting tasks.

The cycles that will be applied in the experiments are listed in the Table 5.30. As it can be seen, the models that are trained and validated in a cycle will be used to predict during one month. After that time, a new cycle starts and all models are retrained.

Table 5.30: Dates of model training, validation and prediction for each of the cycles.

Cycle number	**Model train and validation**		**Days to predict (testing)**	
	Initial date	**End date**	**Initial date**	**End date**
0	01-01-2017	31-08-2019	01-09-2019	30-09-2019
1	01-01-2017	30-09-2019	01-10-2019	31-10-2019
2	01-01-2017	31-10-2019	01-11-2019	30-11-2019
3	01-01-2017	30-11-2019	01-12-2019	31-12-2019
4	01-01-2017	31-12-2019	01-01-2020	31-01-2020
5	01-01-2017	31-01-2020	01-02-2020	29-02-2020
6	01-01-2017	29-02-2020	01-03-2020	31-03-2020
7	01-01-2017	31-03-2020	01-04-2020	30-04-2020
8	01-01-2017	30-04-2020	01-05-2020	31-05-2020
9	01-01-2017	31-05-2020	01-06-2020	30-06-2020
10	01-01-2017	30-06-2020	01-07-2020	31-07-2020
11	01-01-2017	31-07-2020	01-08-2020	31-08-2020
12	01-01-2017	31-08-2020	01-09-2020	30-09-2020
13	01-01-2017	30-09-2020	01-10-2020	31-10-2020
14	01-01-2017	31-10-2020	01-11-2020	30-11-2020
15	01-01-2017	30-11-2020	01-12-2020	31-12-2020

The selection of the training and validation sets for training the models and constructing the ranking for the selection of models to make predictions is as follows. The validation set corresponds to the last 15 days of data of the historical dataset that is available in the system when the modeling process is performed. All data except these 15 days are used for training the models, while the 15 last days are used for validating, i.e., choosing hyperparameters and creating the ranking of models (see the proposed framework). The main advantage of this approach is that the models are selected based on their performance on the moments near to the present, which can increase the quality of the prediction in the nearby days. However,

Table 5.31: List of datasets applied in the case study of Manzanilla for training models of each variable (the secondary substations). There are 48 datasets for each variable to be predicted.

Datasets
CaIn
Wa(thr)+DI
Wa(th)+DI
Wa(t)+DI
Db1+DI
Db2+DI
Db{-2}+DI
Db3+DI
Db{-2,-3}+DI
Db1Wa(thr)+DI
Db1Wa(th)+DI
Db1Wa(t)+DI
Db2Wa(thr)+DI
Db{-2}Wa(thr)+DI
Db2Wa(th)+DI
Db{-2}Wa(th)+DI
Db2Wa(t)+DI
Db{-2}Wa(t)+DI
Db3Wa(thr)+DI
Db{-2,-3}Wa(thr)+DI
Db3Wa(th)+DI
Db{-2,-3}Wa(th)+DI
Db3Wa(t)+DI
Db{-2,-3}Wa(t)+DI

Datasets
Bl(s7)+DI
Bl(bw7)+DI
Bl(sw7)+DI
Bl(sw14)+DI
Bl(cnb1)+DI
Bl(cnb2)+DI
Bl(cnb3)+DI
Bl(cnb4)+DI
Bl(s7)Wa(t)+DI
Bl(bw7)Wa(t)+DI
Bl(sw7)Wa(t)+DI
Bl(sw14)Wa(t)+DI
Bl(cnb1)Wa(t)+DI
Bl(cnb2)Wa(t)+DI
Bl(cnb3)Wa(t)+DI
Bl(cnb4)Wa(t)+DI
Bl(s7)Wa(t)+DI+Bl(t)
Bl(bw7)Wa(t)+DI+Bl(t)
Bl(sw7)Wa(t)+DI+Bl(t)
Bl(sw14)Wa(t)+DI+Bl(t)
Bl(cnb1)Wa(t)+DI+Bl(t)
Bl(cnb2)Wa(t)+DI+Bl(t)
Bl(cnb3)Wa(t)+DI+Bl(t)
Bl(cnb4)Wa(t)+DI+Bl(t)

the models would be less generalistic when applied to periods of time that are far away from the period used for validation, so a more frequent model retraining could be required to keep up-to-date models.

For the ML models, the list of datasets that have been applied in this case study can be seen in Table 5.31. These datasets are in accordance with those defined for the framework in Section §4.6.4.1 (see Table 4.5).

Considering the above-mentioned procedures, in the case of deterministic models, the structure of the analysis in Section §5.4.3 is:

- The framework will be applied to predict the previously defined period. For each day, the model that is ranked as the best in the corresponding cycle will be executed. If the best model cannot be executed that day (due to the lack of some of the input information that it requires), the next model of the ranking will be used, and so on until one model is successfully executed and the forecast for the day is obtained. The global performance of the predictions of the framework will be compared with the naïve modes and ARIMA models (these two will serve as reference methods).

- The relevance of the tested models for the studied period in the framework will be analyzed. In this sense, a list of models and datasets that were successfully used more frequently will be given. It will be indicated the number of days in which a certain model was chosen by the framework for predicting certain days and was successfully executed (success). Similarly, it will be indicated which of the models was requested by the system for making a prediction and was not available (failed) for that day. This failure may occur when certain information that the models require is not available (due to a problem in the reception of data), such as weather information, measurements of previous days, or some other externally received data.

- Study of the impact of the lack of previous day measurements over the performance of the forecasting system. It will be presented a comparison of performances between the models that include the measurements the day previous to the objective day, and those that do not include such measurements. The reason for this comparison is that, if the forecasting system is fed with data from the smart meters, it can happen that the frequency of data extraction is not as quickly as it should be for having the data at the very start of a day. Therefore, in that case, the forecasting system could not use those models that required such measurements, needing some extra time to receive those measurements and executing the models.

- Prediction examples. Representation of predictions performed by the system using deterministic methods. These will merely serve as illustrative examples of the forecasting process.

In the case of probabilistic models, the structure of the analysis will have some similarities with that of deterministic models, but some new comparisons are added to evaluate the use of different metrics. This is done like that due to the multiple types of uncertainty models that can be obtained from the framework. Considering this, the structure of the analysis in Section §5.4.4 is:

- Comparison of the global performance of the applied framework (using the best available model) according to the ranking criteria that were chosen. In this sense, as the framework is able to provide different uncertainty models (distributions, intervals, and sets of scenarios), it will be analyzed what is the effect of using rankings only with the pinball loss function, or using the specific metric for each type of model (pinball, Winkler score, or WePin). This comparison will have various cases resulting from the combination of the indicators used for the ranking, and the indicator corresponding to the type of uncertainty modelling that is actually made. This will show the consequence of taking into consideration the type of uncertainty that is going to be created during the ranking step, or if it is ignored.

- Study of the impact of the lack of previous day measurements over the performance of the forecasting system. For simplifying the results, only the effect over the pinball loss function will be analyzed.

- Prediction examples. Representation of predictions performed by the system using probabilistic methods for each type of uncertainty modelling from those included in the system. These will merely serve as illustrative examples of the forecasting process for each type of uncertainty.

Once exposed the structure of the analyses, the results are presented next.

5.4.3 Analysis of deterministic models

For the evaluation of the results of deterministic models, the metric will be the RMSE for each day. For evaluating some of the global results that include various different days under a same number, it has been chosen to use the mean value of the RMSE of each individual day. Note that this number is not equal to the RMSE of all the hourly predictions of the group of days, as the corresponding expressions are not similar. It has been preferred to do this in this way to simplify the aggregation of results and achieve an easier comparison and evaluation in this case study.

5.4.3.1 Framework performance results

As previously said, it is firstly necessary choosing the training/validation sets for training the models and constructing the ranking for the selection of models to make predictions. The validation set corresponds to the last 15 days of data of the historical dataset that is available in the system when the modeling process is performed. It is reminded that the rankings are ordered according to the RMSE value that the models obtain during the validation process.

The global metrics that have been obtained are the mean value of the daily RMSE for each of the variables. The forecasting performance of the framework (using the best model that is available for each day according to the ranking) is compared with those of naïve models and ARIMA models. The results can be seen in Table 5.32.

As it can be seen, the proposed framework yields the best global results in 11 of the 13 secondary substations, considering that it achieves the smaller mean value of daily RMSE.

Table 5.32: Comparison of performance of naïve model, ARIMA, and the proposed framework for deterministic forecasting. The mean value of RMSE of the method that yields the best results is remarked in bold and green for each of the secondary substations. Additionally, the standard deviation of each metric is also given.

Secondary substation	Daily RMSE (W)					
	Naïve method		**ARIMA**		**Proposed framework**	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
0	10237	5430	11860	6319	**9597**	5237
1	12769	6718	12965	6071	**9545**	3599
2	16052	9000	19244	11460	**15557**	9212
3	24457	20108	29036	22163	**21631**	12494
4	14198	11257	17957	19620	**13333**	7241
5	3528	1274	4088	1536	**3007**	1220
6	5259	1681	6056	2036	**4546**	1478
7	9933	5912	12076	7582	**9483**	4829
8	16750	14895	21079	17160	**15869**	11078
9	10008	6637	11789	7178	**8333**	5079
10	**6362**	9293	9499	19048	6643	12429
11	**1478**	3505	2434	5499	2699	6798
12	2446	903	2895	1214	**2212**	794

5.4.3.2 Relevance and applicability of models and datasets

A more detailed analysis of how the forecasting system has operated can be done by observing which are the models that have been used. Moreover, it is also convenient to observe which models have been required by the system, but have not been able to be executed at a certain moment due to a lack of input data. This event, which was previously described, is precisely the reason for keeping multiple types of models (each one with their own input requirements) inside the system and ordering them in rankings. In this way, it is possible to apply some other alternative model in case the chosen one is not able to be executed in a certain day.

The ten most used models among all predicted days can be seen in Table 5.33. There are no distinctions between the secondary substations, but all them have been considered together for simplifying the presentation of these results.

The ten models that have been unavailable when their use was required can be seen in Table 5.34. Like in the previous table, the given numbers correspond to the aggregated results of all secondary substations being predicted.

Table 5.33: Models that have been used more frequently by the forecasting system.

Technique : Dataset	Success counter
MLPR : Db3+DI	786
MLPR : Db2+DI	503
MLPR : Db1Wa(t)+DI	406
MLPR : Db1+DI	333
MLPR : Db2Wa(t)+DI	307
MLPR : Db3Wa(t)+DI	261
MLPR : Db1Wa(th)+DI	215
MLPR : Bl(cnb4)Wa(t)+DI	157
MLPR : Bl(sw14)Wa(t)+DI	134
MLPR : Db2Wa(th)+DI	125

Table 5.34: Models that have failed more frequently due to the lack of input data when requested by the forecasting system.

Technique : Dataset	Fail counter
MLPR : Bl(s7)Wa(t)+DI	126
MLPR : Db3Wa(t)+DI	124
MLPR : Bl(bw7)Wa(t)+DI	118
MLPR : Db1Wa(t)+DI	118
MLPR : Bl(cnb4)Wa(t)+DI	114
MLPR : Wa(t)+DI	112
RFR : Bl(s7)Wa(t)+DI	111
MLPR : Db2Wa(t)+DI	111
MLPR : Bl(s7)Wa(t)+DI+Bl(t)	107
MLPR : Db1Wa(th)+DI	99

As it can be seen, many of the most used models are MLPRs. As the list of failures shows, the use of a ranking and many different models reinforces the forecasting system to guarantee the availability of predictions. In an extreme case in which there is a total lack of input data, it would be possible to apply the models trained using the dataset ‘CaIn’, which exclusively contains calendar information, and not any weather nor measurement information.

5.4.3.3 Impact of the lack of previous day measurements

The present case study, which is focused on a distribution network, uses historical power data that comes from smart meters and data concentrators installed in secondary distribution networks. The availability of the data of the previous day depends on the moment of the day in which the data collection process start, and also depends on the state of the smart meter network and the response times.

Therefore, considering that many of the datasets that are applied by the framework include data of the measurements of the day prior (i.e., the day before) to the objective day that will be predicted, it will be analyzed the effect that this lack of data has over the forecasting system.

In this sense, the performance of models that include the day before the objective day and those that do not include such information will be compared next. In this comparison, among the baseline models, the types sw7 (baseline “same_weekday 7”) and sw14 (baseline “same_weekday 14”) have been included, as these do not require the previous day for being obtained. The baselines made by means of the rule bw (“basic_weekend”) and rule s (“simple”) have been suppressed, as these require the prior day. In other types of baselines, the previous day would be included for its calculation or not depending on the day of the week. For example, in a baseline bw7, for a Monday the previous Sunday is not applied, but for a Tuesday the previous day (Monday) would be used for calculating the values. Therefore, the day of the week has been considered to establish the availability of these datasets according to the objective day.

Therefore, the datasets that have not been included when suppressing the availability of the data of the previous day are those that contain the fields of information ‘Db1’, ‘Db2’, ‘Db3’, ‘Bl(s7)’. Conditionally, the days that contain the information have been included or not depending on the day of the week: ‘Bl(bw7)’, ‘Bl(cnb1)’, ‘Bl(cnb2)’, ‘Bl(cnb3)’, ‘Bl(cnb4)’.

Some of the datasets that are tested were included precisely due to this possible lack of data, such as ‘Db{-2}’ and ‘Db{-2,-3}’. These are equivalent to ‘Db2’ and ‘Db3’, but excluding the previous day from them.

The comparison between the operation of the system without and with previous day information can be seen in Table 5.35. The results have been shown for each secondary substation.

Table 5.35: Results of comparison of performance with or without the inclusion of data from the previous day for making the predictions.

Secondary substation	**Mean daily RMSE (W)**		Improvement with the inclusion of previous day data (%)
	Including previous day	Without previous day	
0	9597	10777	10.95
1	9545	10876	12.24
2	15557	18436	15.62
3	21631	24517	11.77
4	13333	16012	16.73
5	3007	3298	8.82
6	4546	4977	8.65
7	9483	10581	10.37
8	15869	18296	13.27
9	8333	11104	24.96
10	6643	7756	14.35
11	2699	2903	7.04
12	2212	2241	1.30

It can be observed that in all the presented cases, the inclusion of information of the previous day increased the quality of the predictions (the error was reduced). This reinforces the reasons for including datasets that are able to work in both cases, to be prepared for this type of contingency, as the proposed framework does.

5.4.3.4 Examples of deterministic predictions

This section depicts some examples of days forecasted by the framework under the proposed approach. The forecast is represented together with the actual consumption. The daily RMSE is also indicated for each represented day. The representations correspond to the substation 0 (see Figure 5.25), 7 (see Figure 5.26), and 8 (see Figure 5.27).

Once finished the study focused on deterministic forecasting methods, the next section will focus on probabilitic methods. This new analysis is more complex than the previously one due to the higher number of uncertainty representations that are included in the framework (quantile distributions, intervals, and scenario sets), and consequently this analysis will involve three different evaluation metrics (pinball, Winkler score, and WePin) instead of a single one.

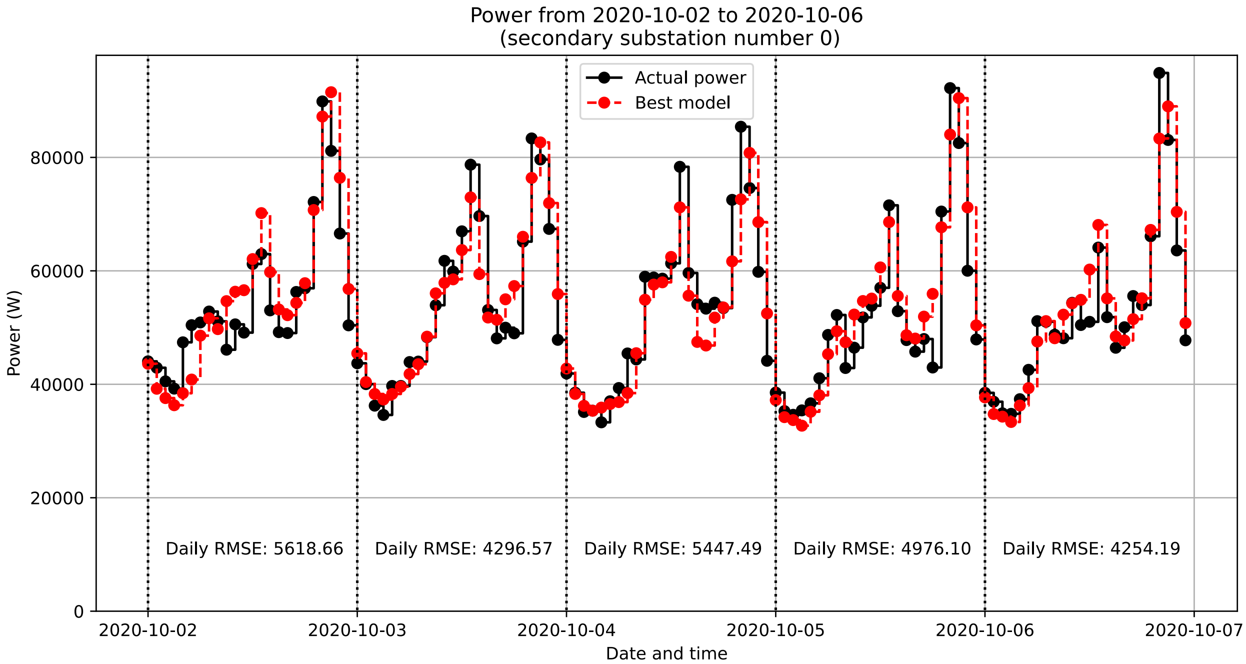


Figure 5.25: Example of deterministic forecasting for the secondary substation 0.

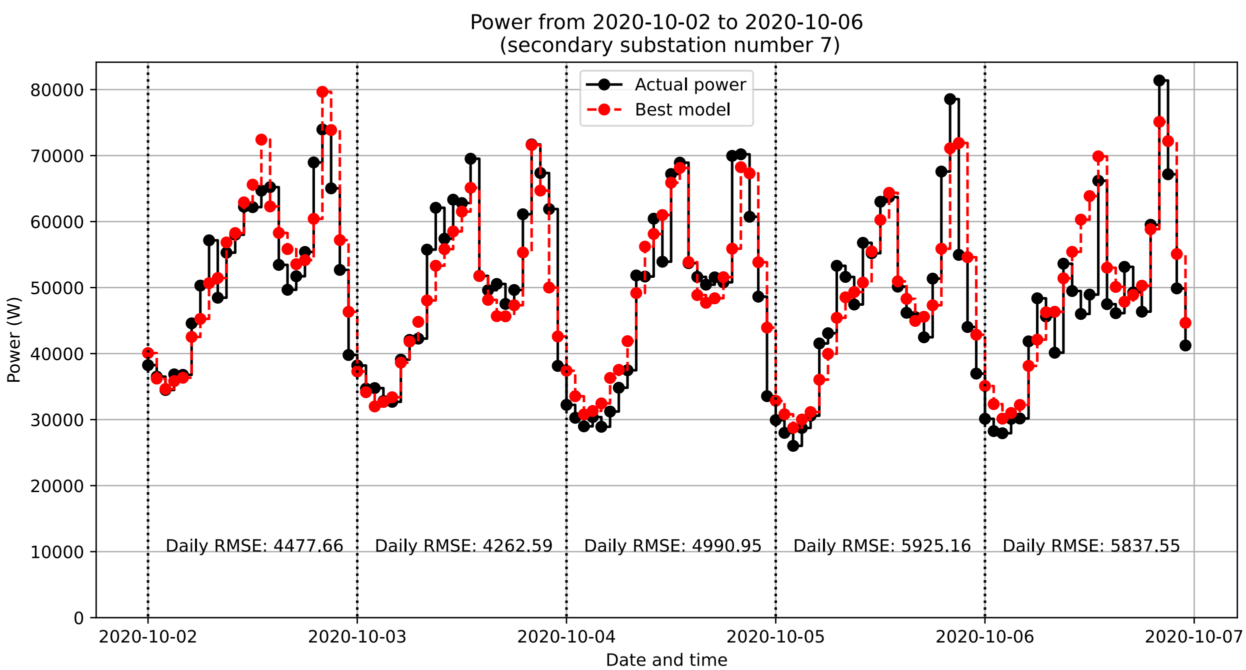


Figure 5.26: Example of deterministic forecasting for the secondary substation 7.

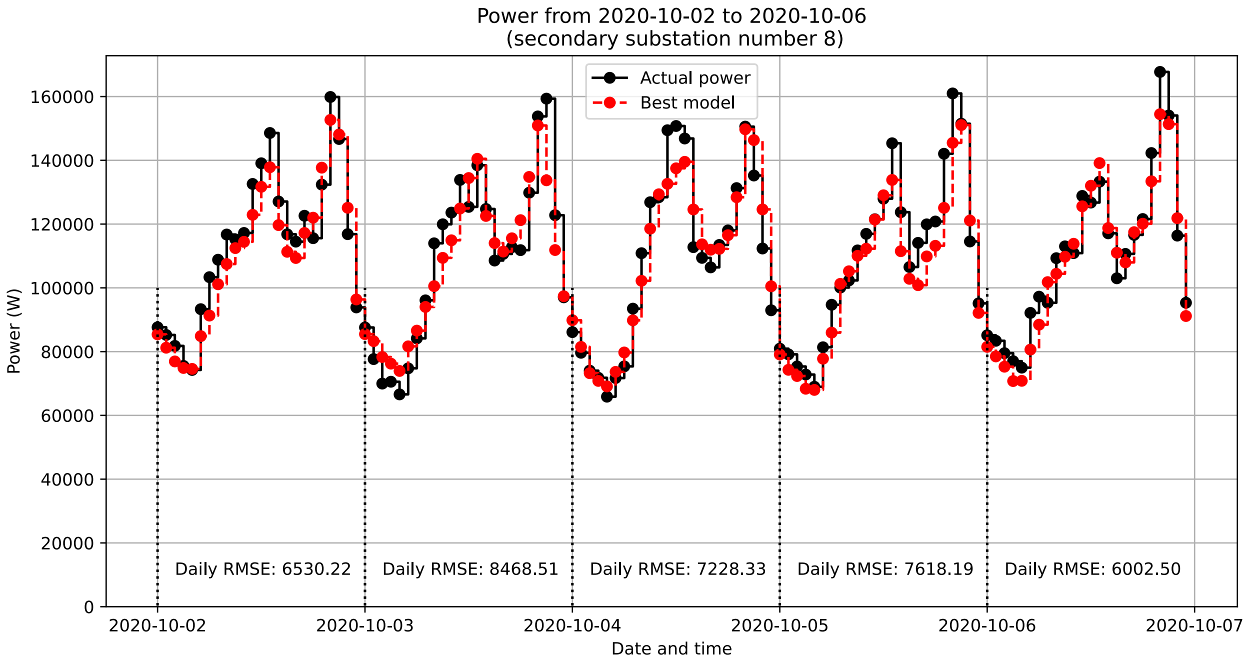


Figure 5.27: Example of deterministic forecasting for the secondary substation 8.

5.4.4 Analysis of probabilistic models

It was said in the proposed framework that each type of uncertainty model that can be created from probabilistic methods will have its own metric for being evaluated. These are the set of quantiles (evaluated by the pinball loss function), the intervals (evaluated by Winkler score), and the scenario sets (evaluated by the proposed WePin).

The application of some of these metrics requires an additional step, which is deciding which specific modelling is done inside each category (configuration of intervals, configuration of scenarios, etc.).

In this sense, the configuration that has been chosen for the present case study is:

- Quantile distribution composed by 99 quantiles, from 0.01 to 0.99. The complete quantile distribution will be globally evaluated using the pinball loss function, by averaging the pinball values of the 99 quantiles. Alternatively, these could be summed instead of averaged, but the result would be equivalent when compared between different models (simply, the numbers would be multiplied by 99).
- Intervals of 98%, 94%, 90%, 80%, 70%, 60%. In worst-case analyses from the literature, it is usual to consider intervals that have a high probability of determining the interval in which the variable will be. In this sense, probabilities of 90% and higher are more commonly found in these types of studies than intervals with probabilities below that.

However, in order to study the behavior of the system, it has been preferred to include some smaller ones in the present case study.

- 49 sets of scenarios of type 'MiAs' and 49 of type 'ExAs'. These corresponds to sets of 2, 3, 4, ..., 50 scenarios MiAs and sets of 2, 3, 4, ..., 50 scenarios ExAs. The metric of handling the evaluation of scenario sets under the WePin score depends on the quantiles and probabilities of scenario sets, so the WePin will be calculated specifically for each set of scenarios depending on the number of scenarios it contains, and the method applied for obtaining it ('MiAs' or 'ExAs').

To evaluate if it is convenient or not to include these specific metrics during the phase of ranking creation, two cases will be compared, one exclusively using the pinball loss for creating the ranking, and another case using each specific metric for each type of uncertainty model (each of these with its own ranking made according to its corresponding metric). In the case of the quantile distribution (the first type of uncertainty model), there will not be a difference between both cases, as its corresponding metric is precisely the pinball loss. For the other metrics, it will be seen what the change on the model performance is.

It is reminded that, as said in Section §4.6.4.3, these metric will have a lesser value when the forecasting quality is better.

5.4.4.1 Framework performance results according to pinball

In this section, the forecasting system will perform probabilistic predictions using the best available model according to the value of the pinball loss function (averaged for the quantiles from 0.01 to 0.99) that these obtained during the respective validation phases. In those cases in which the required model is not available for being used (due to a lack of needed data), the next better model of the ranking will be executed. This procedure will be repeated until a model that is able to provide a forecasting is found.

The results that were obtained can be seen in Table 5.36.

In the described situation, the forecasting system is providing a probabilistic forecast made of 99 quantiles. However, as it was described in Section §4.6.4, the proposed framework is also able to provide other types of probabilistic models. According to the proposal, these other types of models would require the use of their respective evaluation metrics (instead of the pinball loss function).

The next section will analyze the effect of using the specific metrics in rankings for those types of uncertainties that cannot be directly evaluated by the pinball.

5.4.4.2 Impact of using specific metrics in rankings

It was said in Section §4.6.4 that the probabilistic models are not handled by a single ranking, but by three of them. One of them is based on the pinball loss function of the distribution (99

Table 5.36: Results for probabilistic models. Only the pinball loss function (averaged for quantiles from 0.01 to 0.99) is considered.

Secondary substation	**Mean pinball**
0	2912
1	2899
2	4618
3	7194
4	4170
5	863
6	1492
7	2898
8	4729
9	2613
10	2524
11	452
12	635

quantiles) that is forecasted, some others based on the Winkler score for each of the intervals, and some others based on WePin for each type of scenario set. The objective of the present section is to compare the quality of the predictions considering these multiple rankings with the performance of the system based exclusively on the pinball. It should be noted that the use of pinball would be possible by selecting the model according to this metric, and later creating the desired uncertainty model (interval, or scenario set) from the obtained quantiles that the model gave. However, the proposal that was made in Section §4.6.4.3 establishes that it could be better to evaluate each type of model using their respective metric for creating their own separate rankings. These two approaches will be now compared to check what is the effect of using one or another in this case study.

Therefore, the two situations that will be compared are the "value with pinball ranking" (i.e., obtaining all the uncertainty models with the model that has the better pinball) and the "value with specific ranking" (i.e., obtaining the forecasting with the best model of the ranking specifically made for each type of uncertainty: interval or scenario set). It will be seen which of the approaches permit the system to obtain better global results.

The numerical results of the comparison for the intervals (which are evaluated using Winkler score) are given next. The intervals evaluated are 98% (Table 5.37), 94% (Table 5.38), 90% (Table 5.39), 80% (Table 5.40), 70% (Table 5.41), and 60% (Table 5.42).

To simplify the analysis of these results, they have been summarized in the chart of

Table 5.37: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 98%.

Secondary substation	Winkler score for interval 98%		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
0	40177	37016	7.87
1	41556	36535	12.08
2	60822	56400	7.27
3	78045	62024	20.53
4	59671	54125	9.30
5	12412	6924	44.21
6	18999	14313	24.66
7	37020	32608	11.92
8	68100	59903	12.04
9	33178	24979	24.71
10	28070	17066	39.20
11	7724	3578	53.68
12	8886	3818	57.03

Table 5.38: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 94%.

Secondary substation	Winkler score for interval 94%		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
0	33326	31315	6.03
1	34590	30754	11.09
2	51126	50142	1.92
3	67076	58167	13.28
4	49230	49968	-1.50
5	10426	6218	40.36
6	16145	12436	22.97
7	31357	28973	7.60
8	57514	50942	11.43
9	28155	22098	21.51
10	24032	15215	36.69
11	5784	3693	36.15
12	7544	3802	49.61

Table 5.39: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 90%.

Secondary substation	Winkler score for interval 90%		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
0	29832	29220	2.05
1	31028	27876	10.16
2	46366	45374	2.14
3	61863	55384	10.47
4	43490	44407	-2.11
5	9354	5997	35.89
6	14628	11548	21.06
7	28519	27352	4.09
8	51148	48840	4.51
9	25612	20563	19.71
10	21715	14715	32.24
11	5075	3828	24.58
12	6771	3864	42.93

Table 5.40: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 80%.

Secondary substation	Winkler score for interval 80%		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
0	25541	27623	-8.15
1	26318	25321	3.79
2	39847	41166	-3.31
3	55293	51287	7.24
4	36838	36584	0.69
5	7924	6042	23.75
6	12718	10840	14.76
7	24714	23108	6.50
8	43231	45384	-4.98
9	22281	19175	13.94
10	19289	14826	23.14
11	4269	4340	-1.67
12	5676	4197	26.05

Table 5.41: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 70%.

Secondary substation	**Winkler score for interval 70%**		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
0	23777	24029	-1.06
1	24264	22925	5.52
2	37462	37934	-1.26
3	53726	51141	4.81
4	34185	34707	-1.53
5	7286	6378	12.46
6	11993	11055	7.82
7	23150	22687	2.00
8	39753	37658	5.27
9	21031	19356	7.97
10	18764	17471	6.89
11	3905	4610	-18.07
12	5216	4601	11.79

Table 5.42: Comparison of performance using pinball ranking and a Winkler score ranking for intervals of probability of 60%.

Secondary substation	**Winkler score for interval 60%**		Improvement (%)
	Value with pinball ranking	Value with specific ranking	
0	23785	23869	-0.35
1	24033	23269	3.18
2	37524	37150	1.00
3	55951	56255	-0.54
4	34192	33724	1.37
5	7178	7054	1.72
6	12122	11905	1.79
7	23468	23822	-1.51
8	39230	38127	2.81
9	21241	20390	4.00
10	19544	19806	-1.34
11	3822	3972	-3.93
12	5202	5037	3.18

Figure 5.28. Each square corresponds to one of the secondary substations under an interval. Their colors indicate if the performance improves (in yellow), remains equal (in white), or gets worse (in crimson) with the use of specific rankings instead of pinball ranking.

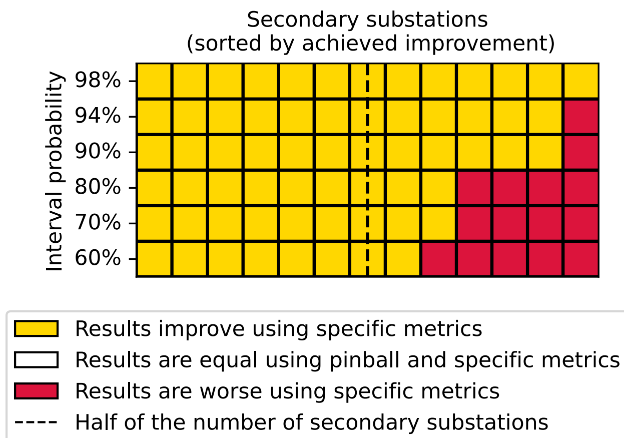


Figure 5.28: Winkler improvement when the rankings are created considering Winker score instead of pinball.

As it can be seen, in most of the cases, the use of rankings based on the specific metrics (Winkler score for each interval) produces a improvement on the quality of the forecasting. Especially, the improvement is notable for the intervals with higher probability (90% and more), which are precisely the type of intervals that are more commonly found in applications of robust optimization.

Regarding the WePin metric applied to the evaluation of scenario sets, the results can be seen in Figure 5.29 and Figure 5.30.

The global results shown in the previous charts have been summarized in Table 5.43, where the cases are counted according to the change in the performance of the system (better, equal, or worse) for each substation and criterion. It can be seen that, in most of the cases, the system improves the quality of forecasting when the rankings apply each specific metric instead of using only the ranking based on pinball.

Considering the previous results, it can be concluded that the consideration of specific indicators for ordering the model ranking results in better quality models for each type of desired uncertainty. Therefore, it is convenient to consider such different indicators in the ranking and model selection processes, instead of using a single ranking (based on the pinball loss function) for all the probabilistic uncertainty models.

5.4.4.3 Impact of the lack of previous day measurements

The effect of the absence of measurements of the previous day has been analyzed (in a similar way that it was previously done with deterministic methods). For this comparison, only the

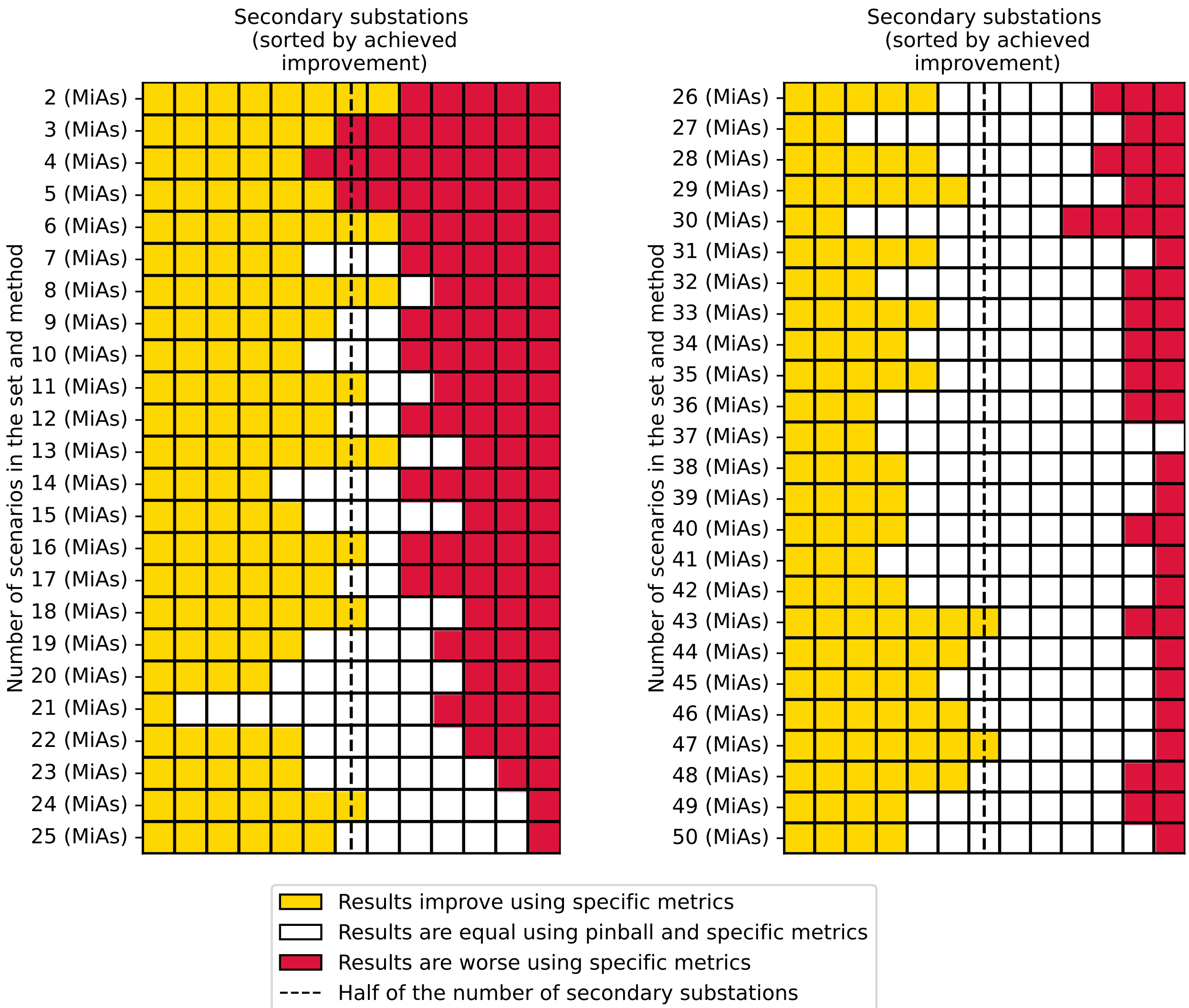


Figure 5.29: WePin improvement for MiAs scenarios when the rankings are created considering WePin score instead of pinball. In the y-axis the number of scenarios and the method that has been used (ExAs) is indicated. In the x-axis, the three variables are simply ordered by their achieved improvement.

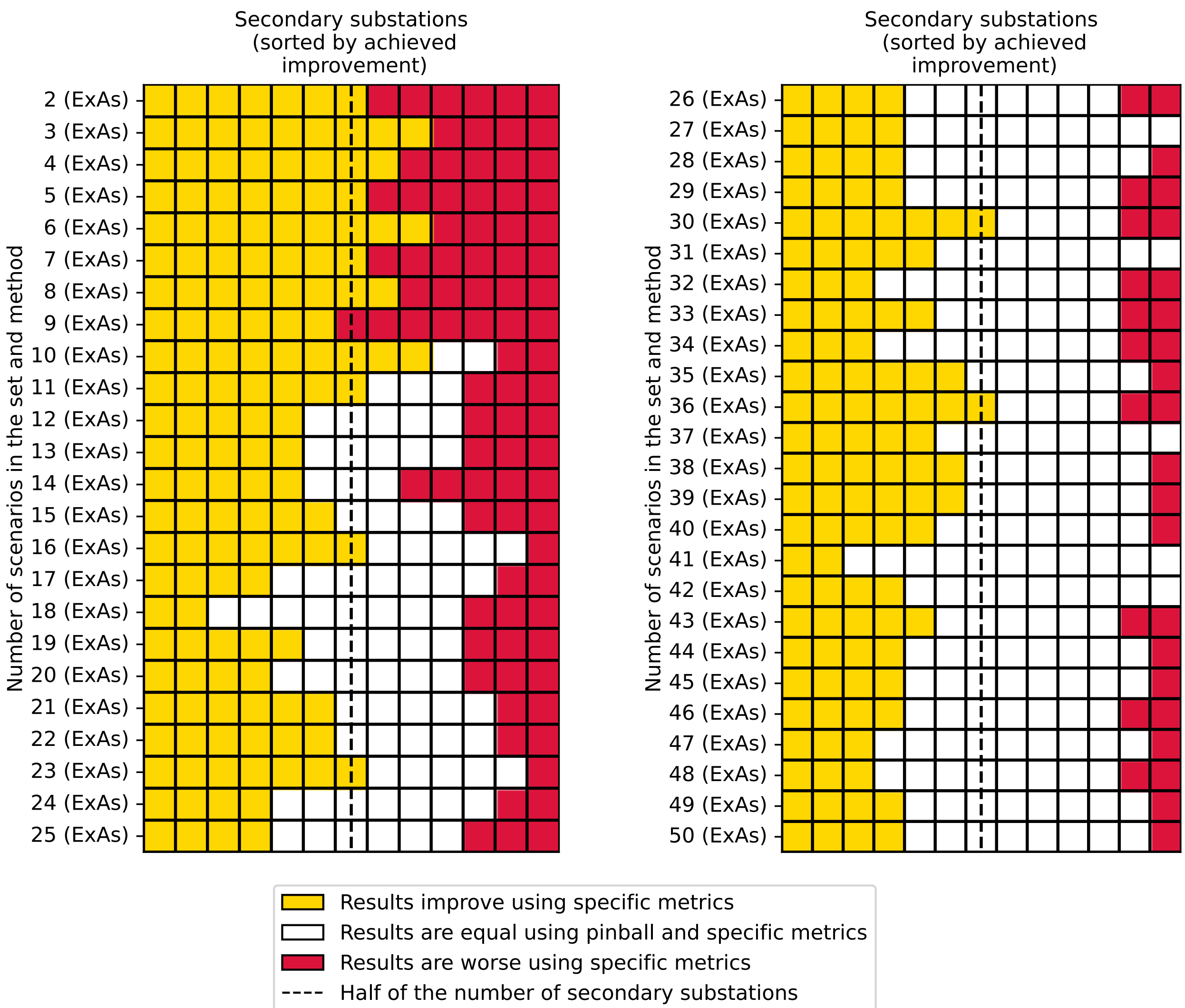


Figure 5.30: WePin improvement for ExAs scenarios when the rankings are created considering WePin score instead of pinball. In the y-axis the number of scenarios and the method that has been used (ExAs) is indicated. In the x-axis, the three variables are simply ordered by their achieved improvement.

Table 5.43: Summary of performance change on the forecasting system when specific metrics are used to construct the rankings.

Type of uncertainty	Number of tested cases	**Effect of using specific metrics in rankings over the quality of the forecasting (counted by number of cases)**		
		Gets better	Remains equal	Gets worse
Intervals	78	63	0	15
Scenarios MiAs	637	252	241	144
Scenarios ExAs	637	258	265	114

pinballs of the predicted distributions (mean value of pinball for quantiles from 0.01 to 0.99) have been considered. The comparison of performance with and without the data of the previous day is done in Table 5.44.

Table 5.44: Results of comparison of performance with or without the inclusion of data from the previous day for making the predictions.

Secondary substation	**Mean pinball**		Improvement with the inclusion of previous day data (%)
	Including previous day	Without previous day	
0	2912	3269	10.92
1	2899	3281	11.64
2	4618	5484	15.80
3	7194	8248	12.79
4	4170	5134	18.79
5	863	903	4.45
6	1492	1585	5.87
7	2898	3421	15.29
8	4729	5927	20.21
9	2613	2996	12.80
10	2524	2560	1.41
11	452	422	-6.99
12	635	651	2.34

In 8 of the 13 substations, the inclusion of data of the previous day results in an improvement of a 10% or higher over the quality of prediction considering the complete set of 99 quantiles (which are evaluated using pinball). Only in one of the substations the inclusion of data from the previous day has resulted in a worse prediction quality. This has happened in the substation number 11, which is one of the substations with a lesser power magnitude (as it was observed in Section §5.4.1).

According to these results, it can be concluded that the consumption of the previous day is closely related with the consumption of the present day. Considering this, it is important to have these data when performing day-ahead predictions. In those cases where the data gathering is based on smart meters (as in the present case study), if the smart meter network presents some delay in the process of sending the data to the data concentrators, it can happen that these data are unavailable at the time of performing the prediction. Therefore, the forecasting system should include models that do not require such type of information, or the data gathering system should be designed for obtaining the data at the time they are needed. This could be achieved by installing alternative metering systems in the substations, or configuring the smart meter network to give priority to the substation measures during their send to the data collectors.

5.4.4.4 Examples of probabilistic predictions

This section depicts some examples of days forecasted by the framework under the previously described approach. The daily values of indicators corresponding to each type of uncertainty model are included for each of the represented days.

For the forecasting based on 99 quantiles (from 0.01 to 0.99), the representations correspond to the substations 0 (see Figure 5.31), 4 (see Figure 5.32), and 7 (see Figure 5.33).

For the forecasting based on intervals, the representations correspond to the intervals 98% (see Figure 5.34), 90% (see Figure 5.35), and 80% (see Figure 5.36) for the substation number 0.

For the forecasting based on sets of scenarios, the representations correspond to the set MiAs of 3 scenarios (see Figure 5.37), the set ExAs of 3 scenarios (see Figure 5.38), the set MiAs of 10 scenarios (see Figure 5.39), and the set ExAs of 10 scenarios (see Figure 5.40) for the substation number 0.

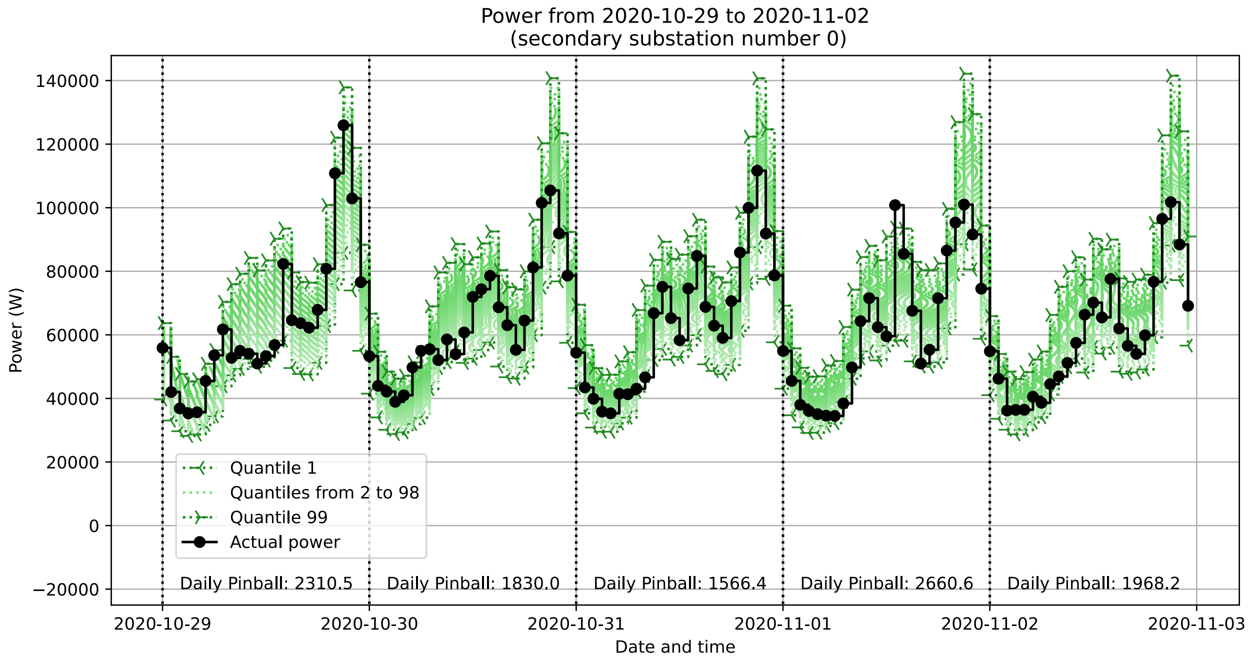


Figure 5.31: Example of probabilistic forecasting based on the 99 quantiles for the secondary substation 0.

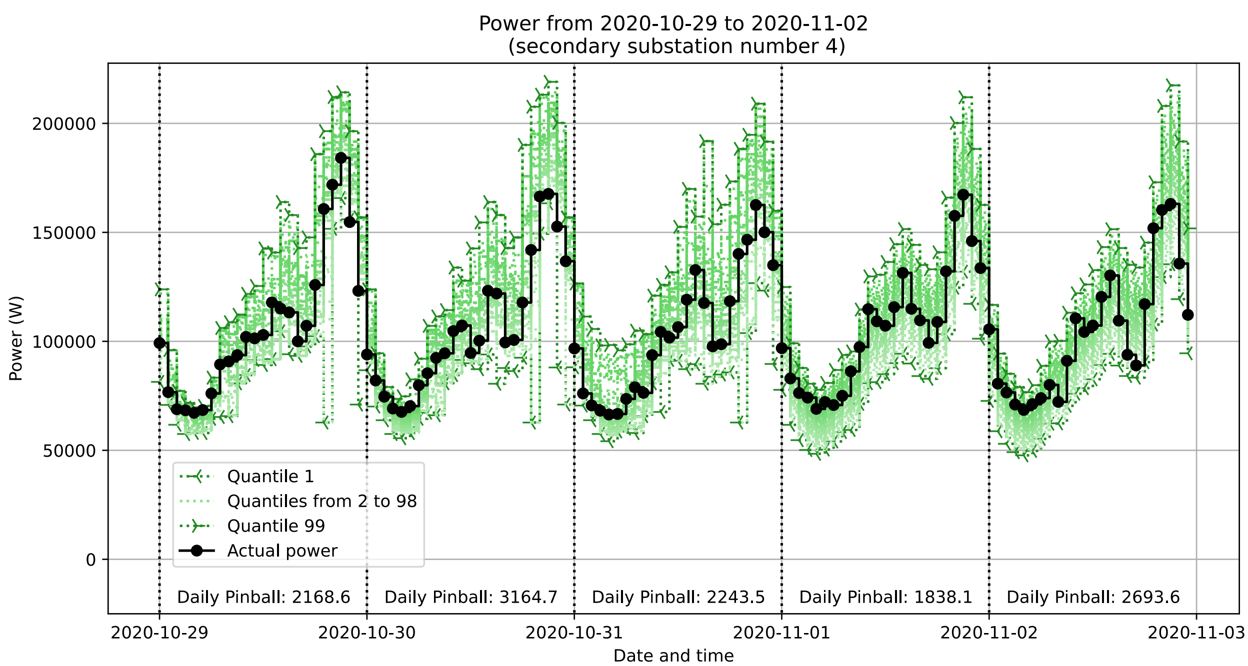


Figure 5.32: Example of probabilistic forecasting based on the 99 quantiles for the secondary substation 4.

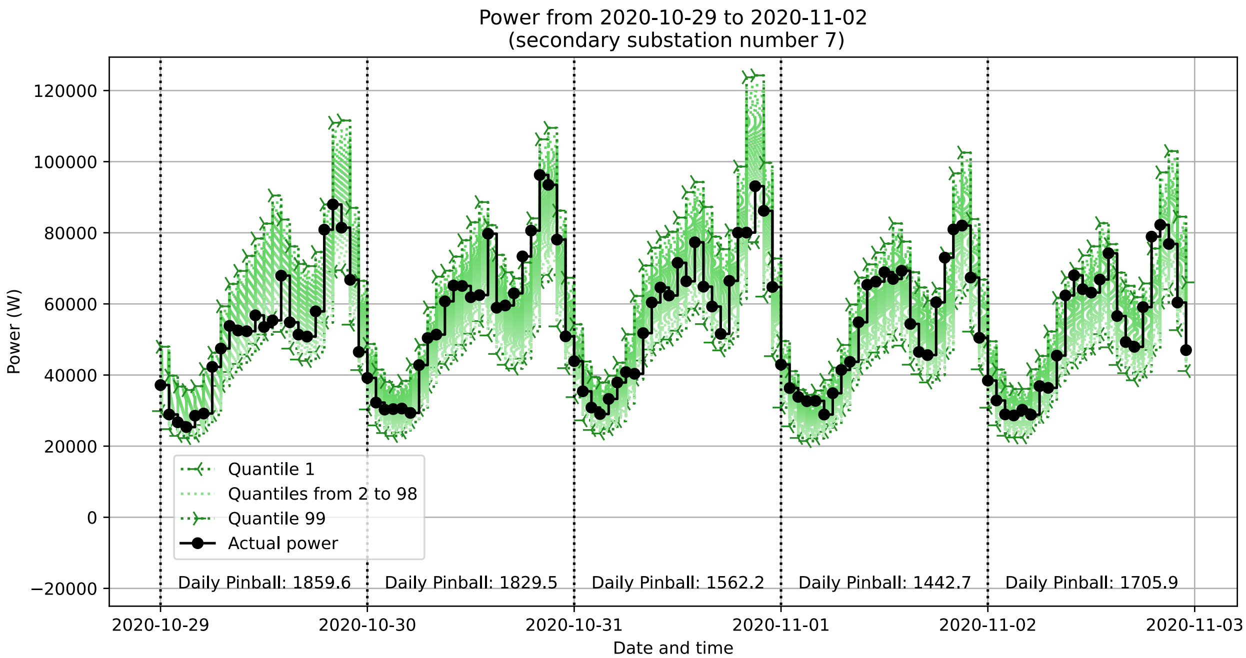


Figure 5.33: Example of probabilistic forecasting based on the 99 quantiles for the secondary substation 7.

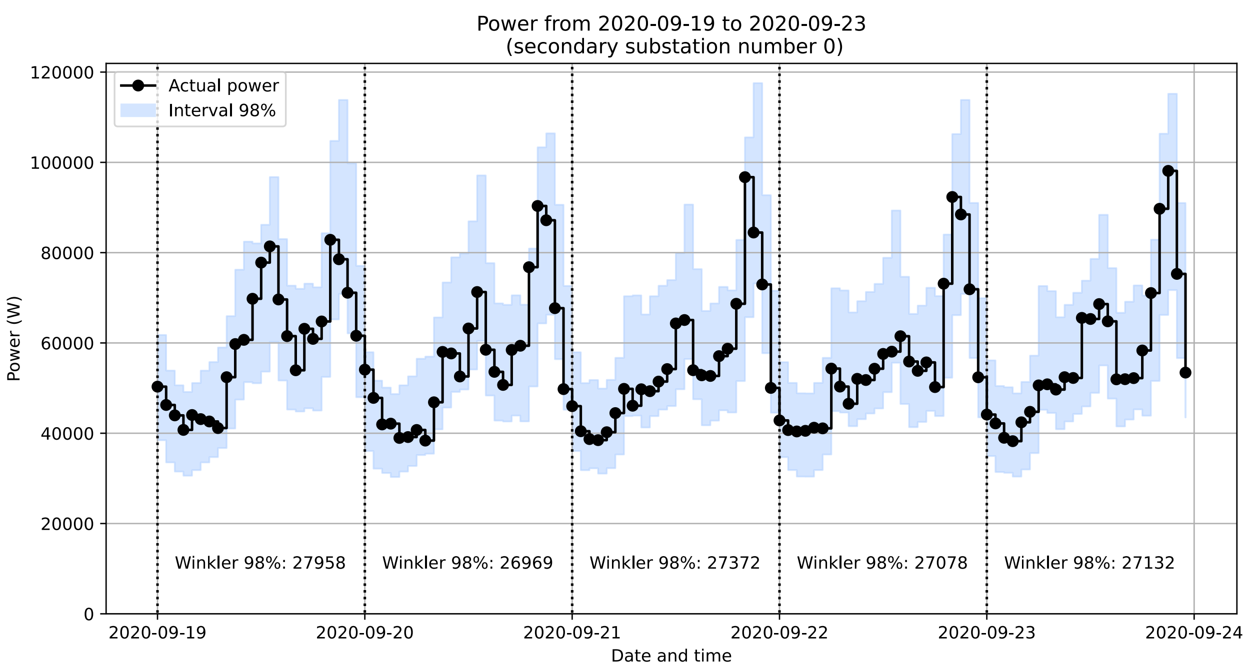


Figure 5.34: Example of probabilistic forecasting based on interval with 98% of probability for the secondary substation 0.

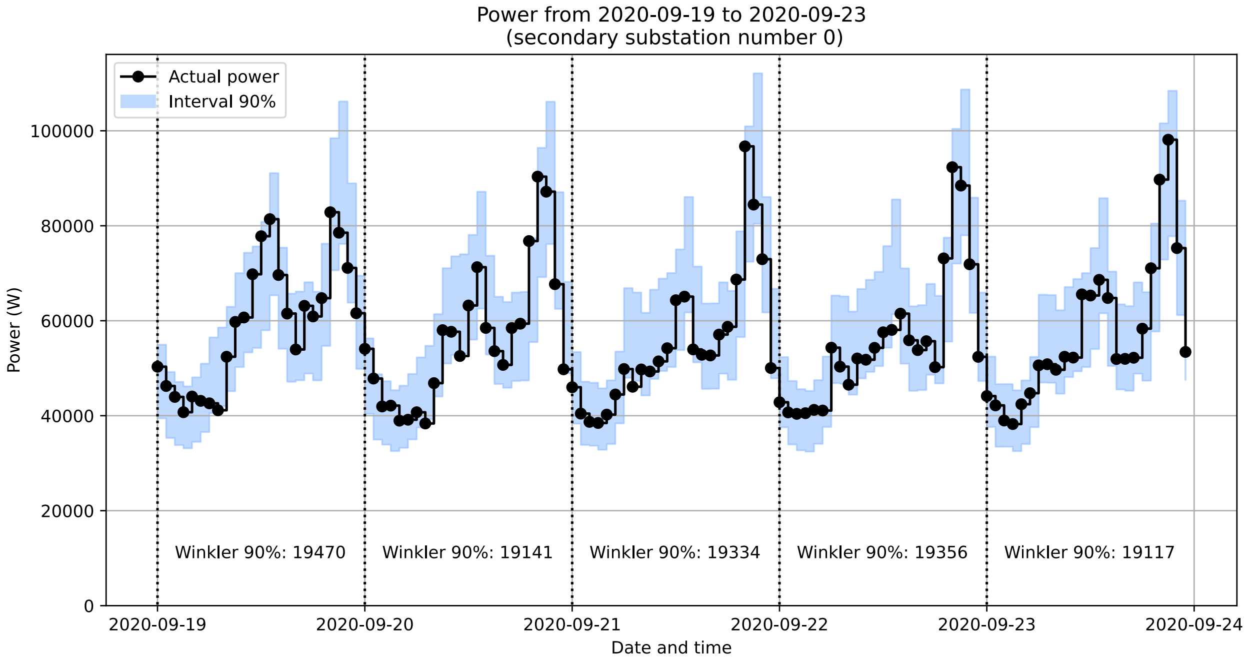


Figure 5.35: Example of probabilistic forecasting based on interval with 90% of probability for the secondary substation 0.

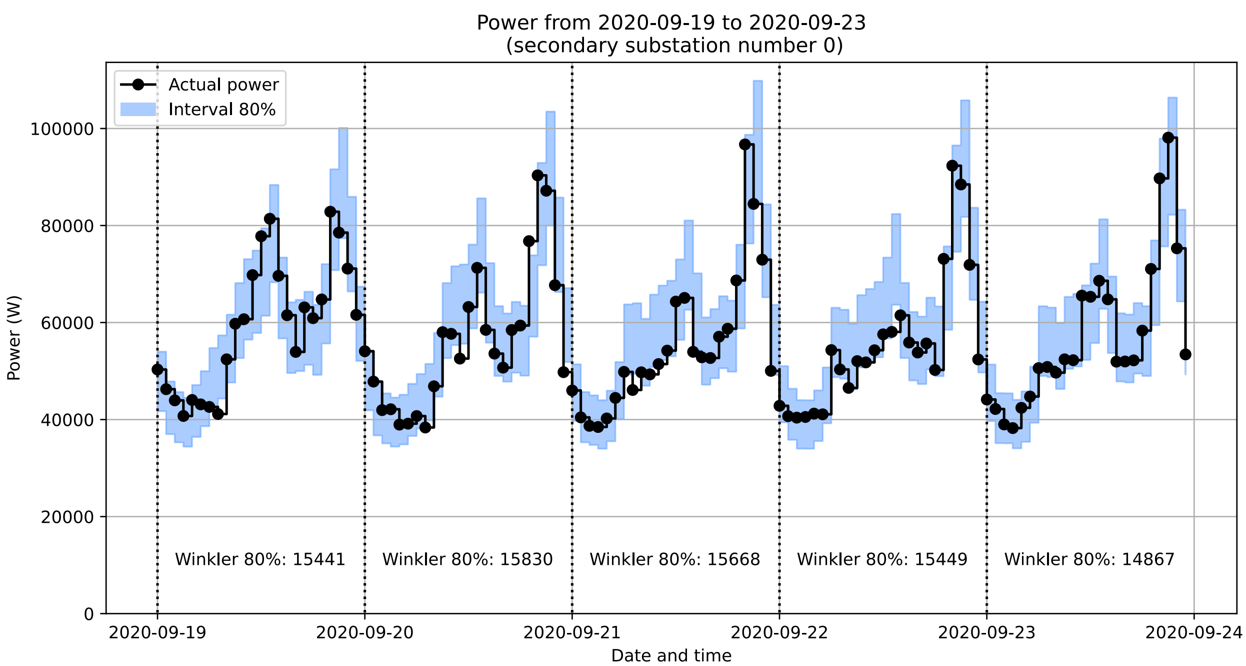


Figure 5.36: Example of probabilistic forecasting based on interval with 80% of probability for the secondary substation 0.

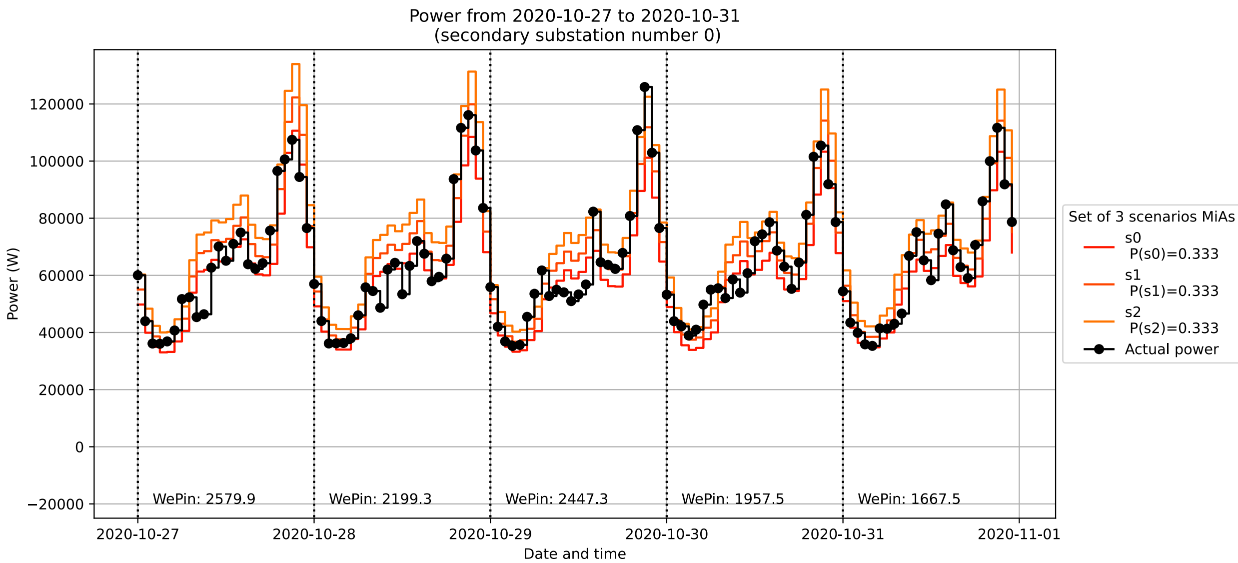


Figure 5.37: Example of probabilistic forecasting based on a set of 3 scenarios MiAs for the secondary substation 0.

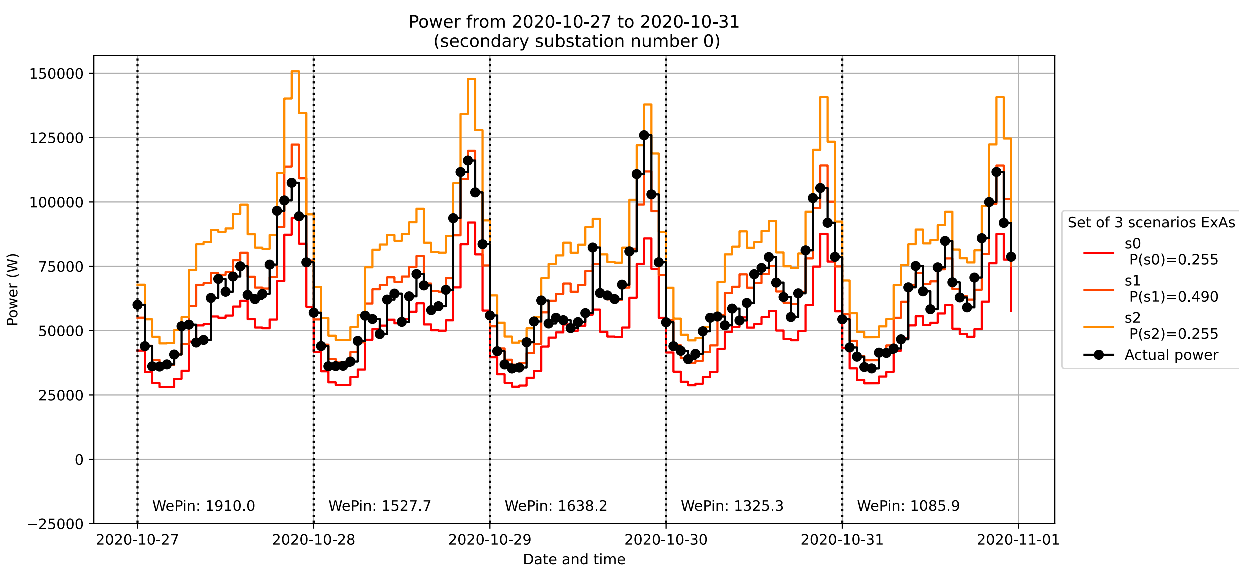


Figure 5.38: Example of probabilistic forecasting based on a set of 3 scenarios ExAs for the secondary substation 0.

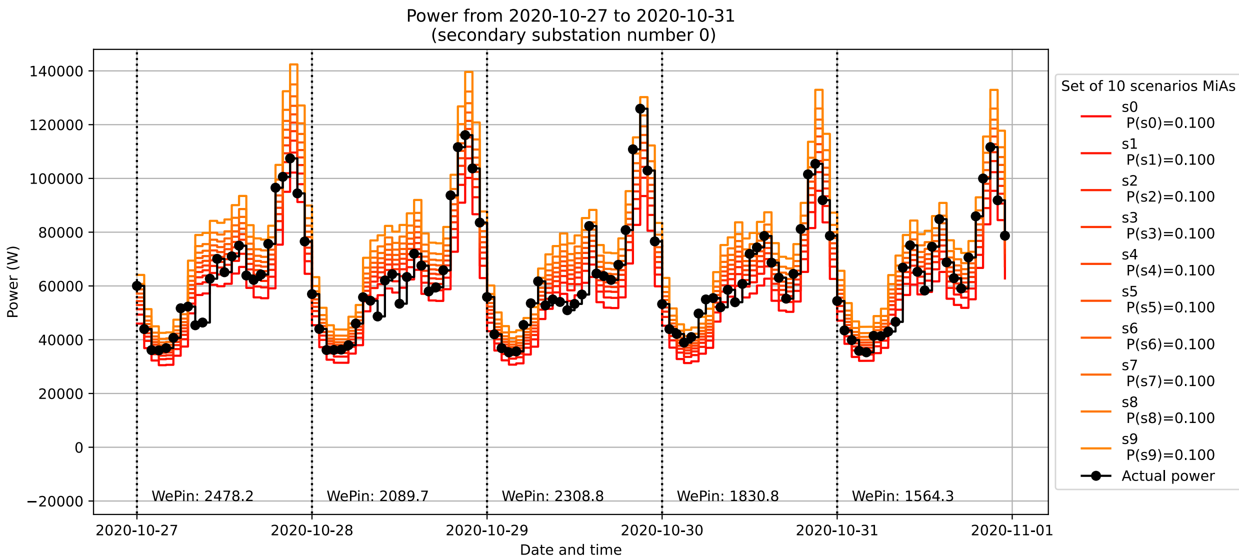


Figure 5.39: Example of probabilistic forecasting based on a set of 10 scenarios MiAs for the secondary substation 0.

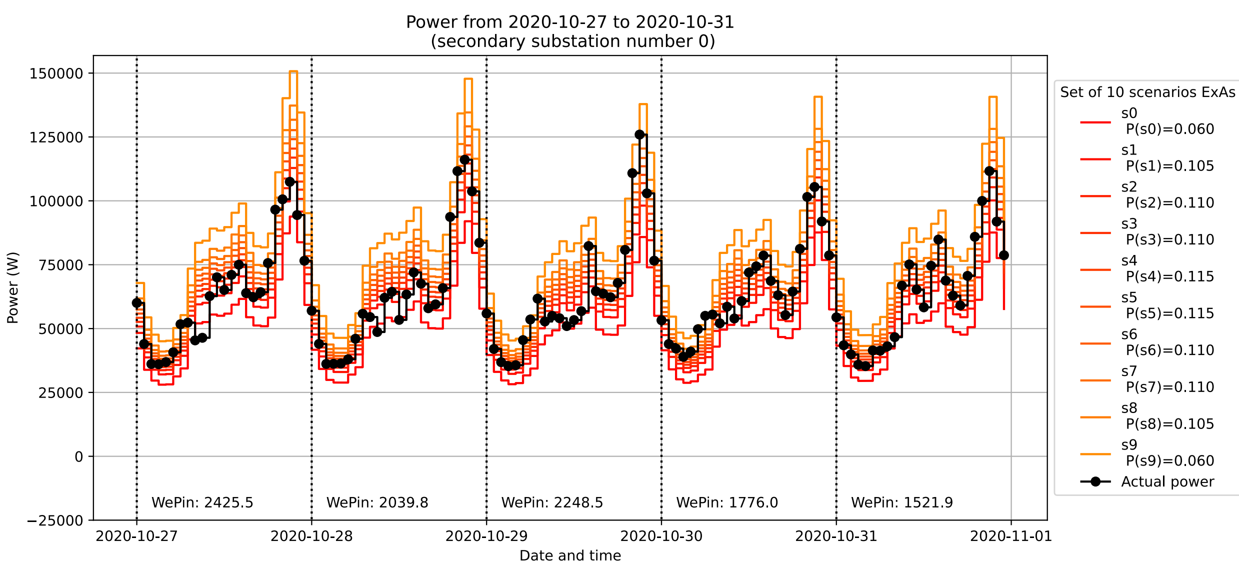


Figure 5.40: Example of probabilistic forecasting based on a set of 10 scenarios ExAs for the secondary substation 0.

5.4.5 Computation times

This section presents the computation times that the forecasting system has required for the period under study. The times for deterministic and probabilistic techniques that require a training process are included here. In this sense, the predictions that have been directly obtained using Rulabi are not included, as these models do not imply a training, but simply an averaging based on the data of certain previous days. Therefore, as their computation time is mainly dependent on the speed of the forecasting system to get and manipulate the data, it has not been considered of interest the inclusion of their times here.

The two types of times that are exposed are the time of training/validation (which includes the total time for training the models and constructing the rankings of the forecasting system) and the daily time of execution (which represents the time that a model needs to forecast one single day).

The times that have been needed for training the models with the available datasets, performing their evaluation, and constructing the rankings for each technique and cycle (for a single secondary substation to predict) are represented in Figure 5.41 and Figure 5.42.

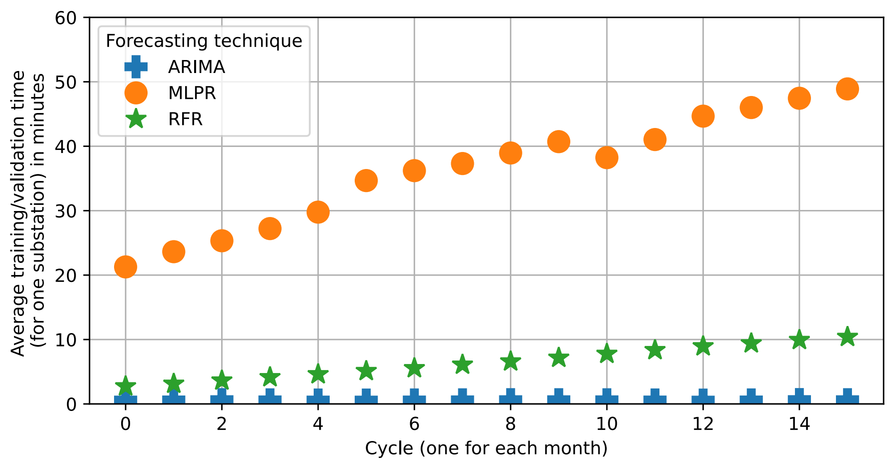


Figure 5.41: Time of training/validation for a single substation (i.e., for a single variable to forecast). Deterministic techniques.

The times of training/validation of each technique (average for a single cycle of a single secondary substation) are included in Table 5.45 and Table 5.46.

Finally, the total computation time that was needed for forecasting one single day with each technique can be seen in Table 5.47 and Table 5.48.

These computation times are very similar in their characteristics to those obtained in the case study of Savona. In this sense, it could be said that the use of the mentioned ML models, while having higher times of training and evaluation, would permit to keep the majority of the computational cost in the moment of training, while their execution time will

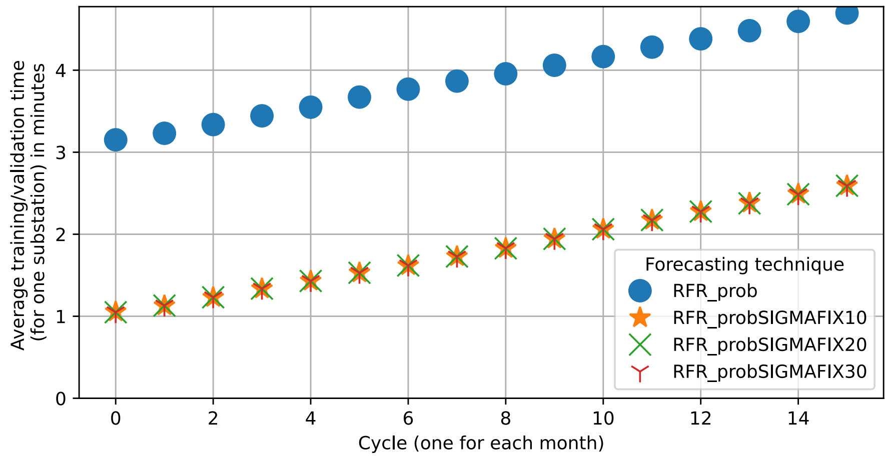


Figure 5.42: Time of training/validation for a single substation (i.e., for a single variable to forecast). Probabilistic techniques.

Table 5.45: Times of training/validation of each technique (average for a single cycle of a single secondary substation). Deterministic techniques.

Technique	**Average training/validation time (for one cycle and one substation) in minutes**
ARIMA	0.63
MLPR	36.34
RFR	6.47

Table 5.46: Times of training/validation of each technique (average for a single cycle of a single secondary substation). Probabilistic techniques.

Technique	**Average training/validation time (for one cycle and one substation) in minutes**
RFR_prob	3.91
RFR_probSIGMAFIX10	1.80
RFR_probSIGMAFIX20	1.80
RFR_probSIGMAFIX30	1.80

Table 5.47: Times for forecasting one day for each technique (in ms). Deterministic techniques.

Technique	**Average prediction time (for one day) in ms**
ARIMA	2513.23
MLPR	0.69
RFR	0.95

Table 5.48: Times for forecasting one day for each technique (in ms). Probabilistic techniques.

Technique	**Average prediction time (for one day) in ms**
RFR_prob	219.70
RFR_probSIGMAFIX10	44.01
RFR_probSIGMAFIX20	44.00
RFR_probSIGMAFIX30	43.91

be much lower than ARIMA models. Therefore, the computational cost during the normal operation would be reduced. Additionally, the ML models have shown a better performance than ARIMA for predicting the consumption of the studied secondary substations.

5.4.6 Conclusions and possible improvements

The present case study has followed a similar approach than the one made in Section §5.3. As it was previously said, the main innovation of this case study focused on a distribution network with respect to the case of Section §5.2 is that the new version of the forecasting framework includes probabilistic (and stochastic) models. These models include various types of uncertainty representation that can be obtained according to the requirements of the application that is fed by the forecasting system. Considering that this study was focused in a distribution network (and not in a microgrid, as the other two previous case studies were), it introduces a totally different use case of the proposed framework, which enriches the evaluation of its performance.

In the same way than in the previous study, to evaluate the performance of the framework in this case study, the system has been retrained once a month. The last 15 days available were used to validate the models and create the rankings, while the rest of the historical data were firstly used for training the models. The results showed that for most of the forecasted variables (the consumption of several secondary substations), the proposed framework achieved better forecasting results than the naïve method and ARIMA method, which were used as references.

The comparison between the models made from datasets that include the day previous to the objective and those similar ones that do not include the previous day shows that this lack reduces the goodness of the models. This behavior was appreciated for the deterministic and probabilistic model in their two independent analyses. It has been indicated that the availability of the previous day (specially when AMI is the source of data) depends on the frequency of data acquisition, the size of the network, and the specific data infrastructure that the network operator has deployed. Therefore, in the case of distribution networks, it is highly convenient to have different available models with different types of inputs. In this way, there will be alternatives in case a data is missing, as it could happen with the measurements of the previous day.

Regarding the evaluation of different kinds of probabilistic models, it has been appreciated that the decision of including independent model rankings with their respective evaluation metrics can produce a global increasing of the quality of forecasting. Therefore, this approach (which was exposed in the description of the framework in Section §4.6.4.3) is more convenient than simply evaluating the global quantile distribution (using pinball) of all types of models and using the best of these to obtain the rest of the probabilistic models (which would be computationally simpler, but would achieve a worse quality of forecasting).

Up to this point, the main pieces of the structure of the framework and the procedures for choosing the best forecasting model for each type of uncertainty representation are solved. The future tasks for further development will include the introduction of additional forecasting techniques, such as LSTM, support vector regressor (SVR), and others.

Moreover, the analyses included in this document were done under a day-ahead forecasting basis. In the future, it would also be desirable to analyze the performance for periods of more than one day ahead. These improvements would provide more flexibility to the forecasting system for being applied in a wider set of applications.

Finally, considering that the framework was designed specially to be used in optimization and system operation applications, it would be convenient using the obtained forecast in optimization problems for microgrid and distribution network management. Thanks to this, the performance of the optimization could be compared by using the proposed forecasting framework with the achieved performance using some other simpler forecasting models. This would serve to evaluate the impact of the increasing of forecasting quality in some final smart grid applications (management of renewable generation, battery charging, DR actions, etc.).

Chapter 6

Conclusions and future research lines

This chapter presents the main conclusions, future research lines, and related publications of this doctoral thesis.

This chapter summarizes the main conclusions that can be drawn from the literature review, summarizes the contributions of the current doctoral thesis, describes the future lines that are opened for the continuation of the research, enumerates the list of related publications in which the author of the current thesis has directly participated, and shows its relationship with research projects.

Section §6.1 highlights the conclusions. The main contributions of the thesis are summarizes in Section §6.2. Section §6.3 defines the future research lines. Section §6.4 contains the list of related scientific publications and the participation in projects of the author.

6.1 Conclusions extracted from the literature review

Some conclusions that can be extracted from those facts exposed and analyzed during the literature review have been:

- The power system is in constant evolution, especially with the deployment of DERs and more efficient renewable generation technologies in the distribution networks. As a consequence, the requirements of flexibility capacity to overcome the intermittent generation of renewable sources have increased.
- These changes require a continuous improvement on the optimization and allocation of resources, so as the technical capacity to estimate the behavior of the involved elements over the system.

- The inclusion of flexibility services becomes key for keeping the power system stability due to the increasing penetration of DERs. For this reason, the provision of such services by the side of customers and aggregators is currently under study by many researchers.

- In addition to the use of flexibility services, the improvement and optimization of internal energy management of buildings and microgrids is a way of achieving a more efficient use of energy. This can produce not only a reduction of the economical cost of the energy, but also a reduction of the network management complexity by the side of utilities due to the consequent reduction of energy consumption of the customers.

- For performing these tasks (energy management and flexibility services provision), it is essential to have a forecasting system that estimates the unknown variables of interest (the uncertainties). Depending on the optimization approach that is followed, the required forecasting can be deterministic, probabilistic, or both.

6.2 Contributions of the thesis

With regard to the mentioned problems and lacks that were found during the literature review, some proposals have been made as part of this thesis:

- A flexibility participation architecture for the inclusion of flexibility actions in the power system has been defined. This requires a coordination between the operators and the FSPs for implementing flexibility and DR actions, and other systems for performing the optimization and control of the resources.

- The steps that a microgrid EMS should execute (specifically, regarding the external flexibility requests and the energy requirements of the microgrid) for it to be part of the previous architecture have been analyzed.

- A new forecasting method called rule-based baseline (Rulabi method) has been proposed for the definition of consumption baselines according to clear and transparent rules.

- Once exposed the found problems with the day-ahead forecasting techniques in microgrid energy management and distribution network application based on telemetry, the PRODEFOR forecasting framework has been proposed. It can apply deterministic methods (for point forecast) and probabilistic methods, which can be used for stochastic optimization.

    – This framework, that integrates heterogeneous information sources and different techniques, has been tested over data from a real microgrid and a real distribution network, showing how the proposals improve the forecasting compared to the reference models.

- In the case of the microgrid (which is under the control of an EMS for its optimal operation), it has been found that those models which use the historical information of different power variables together as inputs are able to improve the quality of the forecasting. In the case of the distribution network, as it does not include resources under the control of any EMS, the different power variables were independently modeled.
- The framework can apply probabilistic forecasting for the generation of scenarios and apply evaluation metrics for choosing the best model to be applied. In any case, the framework is enough flexible as to be adapted to the optimization requirements according to the type of uncertainty modeling that is needed.

The main contributions of the thesis can be summarized in:

A microgrid forecasting framework called PRODEFOR that can apply deterministic and probabilistic methods has been proposed. The best forecasting models are automatically selected and executed according to the type of predictions that are required.

6.3 Future lines of research

The literature review on optimization and forecasting methods revealed the large variety that can be found in these research fields. Therefore, the proposals and studies made in the current thesis could be further extended in the future. Some future advances that are opened over the exposed research could be:

- Include additional options for setting the prediction horizon in the framework. In this way, it would be possible to perform not only day-ahead forecasting, but also choosing other time horizons according to the final application.
- Include additional forecasting techniques as part of the proposed framework, such as LSTM, SVR, or autoencoders.
- Integration of the framework as part of a real system connected to the data sources for automatically performing the required predictions.
- Implementation of some of the studied optimization methods for performing energy management while including the provision of flexibility services. The optimization

system could be directly fed by the forecasting system to obtain the type of uncertainty that is needed (deterministic forecasts, intervals, scenario sets, etc.).

6.4 Related scientific contributions

This section includes scientific publications focused on smart grids and microgrids in which the author of the current document has collaborated as the main author or as a coauthor.

6.4.1 Main publications that are directly related to the doctoral thesis

- **A. Parejo**, A. Sanchez-Squella, R. Barraza, F. Yanine, A. Barrueto-Guzman, and C. León, 'Design and Simulation of an Energy Homeostaticity System for Electric and Thermal Power Management in a Building with Smart Microgrid,' Energies, vol. 12, no. 9, p. 1806, May 2019, doi: 10.3390/en12091806. JCR: Q3 (2019); SJR: Q2 (2019). Cited as ***[[20]]***[1]

- **A. Parejo**, S. García, E. Personal, J. I. Guerrero, A. García, and C. León, 'OpenADR and Agreement Audit Architecture for a Complete Cycle of a Flexibility Solution,' Sensors, vol. 21, no. 4, p. 1204, Feb. 2021, doi: 10.3390/s21041204. JCR: Q1 (2020); SJR: Q2 (2020). Cited as ***[[21]]***

- **A. Parejo**, S. Bracco, E. Personal, D. F. Larios, F. Delfino, and C. León, 'Short-Term Power Forecasting Framework for Microgrids Using Combined Baseline and Regression Models,' Applied Sciences, vol. 11, no. 14, p. 6420, Jul. 2021, doi: 10.3390/app11146420. JCR: Q2 (2020); SJR: Q2 (2020); Paper selected as *Feature Paper* by the journal. Cited as ***[[22]]***

6.4.2 Other related publications

- **A. Parejo**, E. Personal, D. Larios, J. Guerrero, A. García, and C. León, 'Monitoring and Fault Location Sensor Network for Underground Distribution Lines,' Sensors, vol. 19, no. 3, p. 576, Jan. 2019, doi: 10.3390/s19030576. Cited as [354]

- J. I. Guerrero, E. Personal, A. García, **A. Parejo**, F. Pérez, and C. León, 'Distributed Charging Prioritization Methodology Based on Evolutionary Computation and Virtual Power Plants to Integrate Electric Vehicle Fleets on Smart Grids,' Energies, vol. 12, no. 12, p. 2402, Jun. 2019, doi: 10.3390/en12122402. Cited as [67]

[1] It is reminded that the publications that are part of the thesis are referenced using double square brackets, bold and emphasis (cf. Section §1.3).

- F. Yanine, A. Sanchez-Squella, A. Barrueto, S. K. Sahoo, **A. Parejo**, D. Shah, and F. M. Cordova, 'Homeostaticity of energy systems: How to engineer grid flexibility and why should electric utilities care,' PEN, vol. 7, no. 1, p. 474, May 2019, doi: 10.21533/pen.v7i1.424. Cited as [140]

- F. Yanine, A. Sánchez-Squella, A. Barrueto, **A. Parejo**, F. Cordova, and H. Rother, 'Grid-Tied Distributed Generation Systems to Sustain the Smart Grid Transformation: Tariff Analysis and Generation Sharing,' Energies, vol. 13, no. 5, p. 1187, Mar. 2020, doi: 10.3390/en13051187. Cited as [356]

- D. F. Larios, E. Personal, **A. Parejo**, S. García, A. García, and C. León, 'Operational Simulation Environment for SCADA Integration of Renewable Resources,' Energies, vol. 13, no. 6, p. 1333, Mar. 2020, doi: 10.3390/en13061333. Cited as [355].
  This paper was also published as a book chapter in the printed edition 'Optimal Control of Hybrid Systems and Renewable Energies'. 2020. MDPI. ISBN 978-3-03928-897-7 (Hbk); ISBN 978-3-03928-898-4 (PDF). doi: 10.3390/books978-3-03928-898-4. Cited as [365]

- J. I. Guerrero, E. Personal, S. García, **A. Parejo**, M. Rossi, A. García, R. Perez, and C. León, 'Evaluating Distribution System Operators: Automated Demand Response and Distributed Energy Resources in the Flexibility4Chile Project,' IEEE Power and Energy Mag., vol. 18, no. 5, pp. 64–75, Sep. 2020, doi: 10.1109/mpe.2020.3000688. Cited as [143]

- J. I. Guerrero, E. Personal, S. García, **A. Parejo**, M. Rossi, A. García, F. Delfino, R. Pérez, and C. León, 'Flexibility Services Based on OpenADR Protocol for DSO Level,' Sensors, vol. 20, no. 21, p. 6266, Nov. 2020, doi: 10.3390/s20216266. Cited as [132]

- S. García, **A. Parejo**, E. Personal, J. I. Guerrero, F. Biscarri, and C. León, 'A retrospective analysis of the impact of the COVID-19 restrictions on energy consumption at a disaggregated level,' Applied Energy, vol. 287, p. 116547, Apr. 2021, doi: 10.1016/j.apenergy.2021.116547. Cited as [357]

6.4.3 Conferences

- R. Pérez, H. C. Rother, J. Refoyo, A. Amarnath, M. Khattar, **A. Parejo**, and C. León, 'Grid Flexibility 4 Chile,' in *Proc. 25th International Conference and Exhibition on Electricity Distribution (CIRED 2019)*, Madrid. Jun. 03, 2019. AIM (Association des Ingénieurs de Montefiore). doi: 10.34890/711. Cited as [366]

- F. Yanine, A. Sanchez-Squella, **A. Parejo**, A. Barrueto, H. Rother, and S. K. Sahoo, 'Grid-tied distributed generation with energy storage to advance renewables in the residential sector: tariff analysis with energy sharing innovations; Part I.,' in *Proc.*

7th International Conference on Information Technology and Quantitative Management (ITQM 2019): Information technology and quantitative management based on Artificial Intelligence. Procedia Computer Science, vol. 162, pp. 111–118, 2019, doi: 10.1016/j.procs.2019.11.265. Cited as [367]

- A. Sanchez-Squella, F. Yanine, A. Barrueto, and **A. Parejo**, 'Green Energy Generation in Buildings: Grid-Tied Distributed Generation Systems (DGS) With Energy Storage Applications to Sustain the Smart Grid Transformation,' in *Proc. 6th International Conference on Communication Management and Information Technology (ICCMIT'20)*. Journal of Information Technology Management, vol. 12, issue 2, pp. 153-162, Apr. 2020, doi: 10.22059/jitm.2020.75798. Cited as [368]

- **A. Parejo**, S. Garcia, E. Personal, A. Garcia, J. I. Guerrero, and C. León, 'Living-Lab for Smart Grid technologies teaching,' in *Proc. XIV Technologies Applied to Electronics Teaching Conference (TAEE2020)*, Jul. 2020. doi: 10.1109/taee46915.2020.9163745. Cited as [369]

- S. Garcia, **A. Parejo**, A. A. Gomez, F. J. Molina, D. F. Larios, and C. León, 'Training Equipment for Automatic Control Systems and Industrial Automation subjects in Engineering Degrees,' in *Proc. XIV Technologies Applied to Electronics Teaching Conference (TAEE2020)*, Jul. 2020. doi: 10.1109/taee46915.2020.9163682. Cited as [370]

- J. I. Guerrero, **A. Parejo**, E. Personal, S. Garcia, J. A. Guerra, and C. León, 'Recharging prioritization method for the integration of electric vehicle fleets with the Smart Grid: an evolutionary computation approach,' in *Proc. Fifteenth International Conference on Ecological Vehicles and Renewable Energies (EVER2020)*, Sep. 2020. doi: 10.1109/ever48776.2020.9242963. Cited as [371]

- S. García, **A. Parejo**, E. Personal, J. Guerrero, F. Biscarri, and C. León, 'Effect of the COVID-19 pandemic at secondary power distribution,' in *Proc. International Conference on Applied Energy 2020*. Applied Energy Innovation Institute (AEii), Feb. 19, 2021. doi: 10.46855/2021.02.19.14.13.463074. Cited as [372]

6.4.4 Book chapters

- J. I. Guerrero, A. García, E. Personal, **A. Parejo**, F. Pérez, and C. León, 'A rule-based expert system for heterogeneous data source integration in smart grid systems,' (Book Chapter). Expert Systems: Design, Applications and Technology. 1 January 2017, Pages 59-104. Nova Science Publishers, Inc. ISBN: 978-153612520-7;978-153612503-0. Cited as [373]
  This book chapter is also published as an article: J. I. Guerrero, A. García, E. Personal, **A. Parejo**, F. Pérez, and C. León, 'A rule-based expert system for heterogeneous

data source integration in smart grid systems *,' International Journal of Computer Research. 2017. Huttington, 24(4), 347-374.
https://www.proquest.com/docview/2190325206, Last accessed 11 November 2021. Cited as [374]

- J. I. Guerrero, E. Personal, **A. Parejo**, I. Monedero, F. Biscarri, J. Biscarri, and C. León, 'High performance data analysis for non-technical losses reduction,' (Book chapter). Smart Grids: Emerging Technologies, Challenges and Future Directions. 1 October 2017, Pages 1-45, Nova Science Publishers, Inc. ISBN: 978-153612804-8;978-153612803-1. Cited as [375]

- J. I. Guerrero, **A. Parejo**, E. Personal, A. García, and C. León, 'The integration of systems in a smart grid infrastructure based on web service mining,' (Book chapter). Smart Grids: Emerging Technologies, Challenges and Future Directions. 1 October 2017, Pages 47-75, Nova Science Publishers, Inc. ISBN: 978-153612804-8;978-153612803-1. Cited as [376]

- J. I. Guerrero, E. Personal, **A. Parejo**, S. García, A. García, and C. León, 'Forecasting Recharging Demand to Integrate Electric Vehicle Fleets in Smart Grids,' (Book chapter) in Advanced Communication and Control Methods for Future Smartgrids, IntechOpen, 2019. doi: 10.5772/intechopen.88488. Cited as [377]

- J. I. Guerrero, E. Personal, **A. Parejo**, S. García, A. Martín, and C. León, 'Increasing the Efficiency of Rule-Based Expert Systems Applied on Heterogeneous Data Sources,' (Book chapter) in Application of Expert Systems - Theoretical and Practical Aspects, IntechOpen, 2020. doi: 10.5772/intechopen.90743. Cited as [378]

- F. Yanine, A. Sanchez-Squella, A. Barrueto, S. K. Sahoo, D. Shah, **A. Parejo**, F. Cordova, and H. Rother, 'Grid-tied distributed generation with energy storage to advance renewables in the residential sector: tariffs analysis with energy sharing innovations,' (Book chapter) in Low Carbon Energy Technologies in Sustainable Energy Systems, Elsevier, 2021, pp. 231–252. doi: 10.1016/b978-0-12-822897-5.00008-0. Cited as [379]

- F. Yanine, A. Sanchez-Squella, A. Barrueto, S. K. Sahoo, **A. Parejo**, D. Shah, and F. Cordova, 'Integrating green energy into the grid: how to engineer energy homeostaticity, flexibility and resiliency in electric power distribution systems and why should electric utilities care,' (Book chapter) in Low Carbon Energy Technologies in Sustainable Energy Systems, Elsevier, 2021, pp. 253–266. doi: 10.1016/b978-0-12-822897-5.00009-2. Cited as [380]

6.4.5 Participation in projects

- Project "*Sistema Inteligente Inalámbrico para Análisis y Monitorización de Líneas de Tensión Subterráneas en Smart Grids*" (SIIAM). Granted by the *Ministerio de*

Economía y Competitividad (Government of Spain). *Plan Estatal 2013-2016 Retos - Proyectos I+D+i*. Reference number: TEC2013-40767-R. Start date: 01-01-2014; Finish date: 31-12-2017.

- Project "Grid Flexibility for Chile" (GridFlex4Chile). Promoted by the company "Enel Iberia, S.R.L." Reference number: P060-17/E24. Start date: 20-10-2017; Finish date: 31-12-2018.
- Project "Grid Flexibility & Resilience" (GridFlex&Resil). Promoted by the company "ENEL Global Infrastructure and Networks S.R.L." Reference number: P020-19/E24. Start date: 15-05-2019; Finish date: 15-05-2021.
- Project "*Bigdata Analitycs e Instrumentación Ciberfísica para Soporte de Operaciones de Distribución en la Smartgrid*" (BALANCE). Granted by the *Ministerio de Ciencia, Innovación y Universidades* (Government of Spain). *Plan Estatal 2017-2020 Retos - Proyectos I+D+i*. Reference number: RTI2018-094917-B-I00. Start date: 01-01-2019; Finish date: 31-12-2022.

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Appendix A

Applied forecasting techniques

A.1 Autoregressive integrated moving average (ARIMA)

The autoregressive integrated moving average (ARIMA) models are belonging to the family of time series techniques. An ARIMA equation consists of a linear equation in which the inputs are the lags of the dependent variable and the lags of the forecast error [160]. The equation can be represented as the Expression A.1 establishes.

$$\begin{aligned} Output\ `y' = constant + weighted\ sum\ of\ one\ or\ more\ past\ values\ of\ `y' + \\ weighted\ sum\ of\ one\ or\ more\ past\ values\ of\ error\ `e' \end{aligned} \tag{A.1}$$

More specifically, the equation showing the coefficients that must be adjusted is:

As stated in [160]: "The lags terms of the stationary time series are referred to as *autoregressive*, whereas the lags of the forecasted error terms are referred to as *moving average*. A time series which requires to be differenced for the purpose of making it stationary is said to be an *integrated* version of a stationary series. These models are denoted as ARIMA (p,d,q), where p represents the order of the autoregressive part, d denotes the degree of first differencing involved and q denotes the order of the moving average part" [160]. The autoregressive part of the model with order p is represented as in Expression A.2 [160].

$$Y_t = c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + ... + \Phi_p Y_{t-p} + e_t \tag{A.2}$$

The moving average model of order 'q' is represented as in Expression A.3.

$$Y_t = c + \theta_1 e_{t-1} + \theta_2 e_{t-2} + ... + \theta_p e_{t-p} + e_t \tag{A.3}$$

"Where Y is the output of a time series like electricity consumption data and e_t is the error series. These models follow a common methodology which can be found in details in the work of Box and Jenkins" [381].

In [304] it is stated that the general form of ARIMA models "is ARIMA (p,d,q) where p is the order of the auto-regressive part, d is the order of the differencing, and q is the order of the moving average process" [304]. Those ARIMA that have seasonal and non-seasonal part are denoted as ARIMA (p,d,q) $(P,D,Q)S$ where S is the number of periods per season [304].

A.2 Artificial Intelligent methods

In the proposed framework, the input datasets for all the applied AI (and more specifically ML regression methods (MLPR, RFR, and some variants of the last) will be the same. These are all configured to be multioutput.

A.2.1 Multi-layer perceptron regressor (MLPR)

As it is exposed in *[[22]]*, "among the numerous types of existing ANNs [382], one of the most commonly used approaches for regression purposes is the MLPR [383]. It is a powerful tool for predicting continuous variables, thereby supporting multioutput regression" *[[22]]*. This type of ANN has been selected for the proposed forecasting framework due to its relative simplicity, and also because it is less computational costly than other ANN types, such as RNNs *[[22]]*.

The basic structure of a MLPR with a single hidden layer can be seen in the Figure A.1. A similar structure would be adopted if more than one single hidden layer is added *[[22]]*.

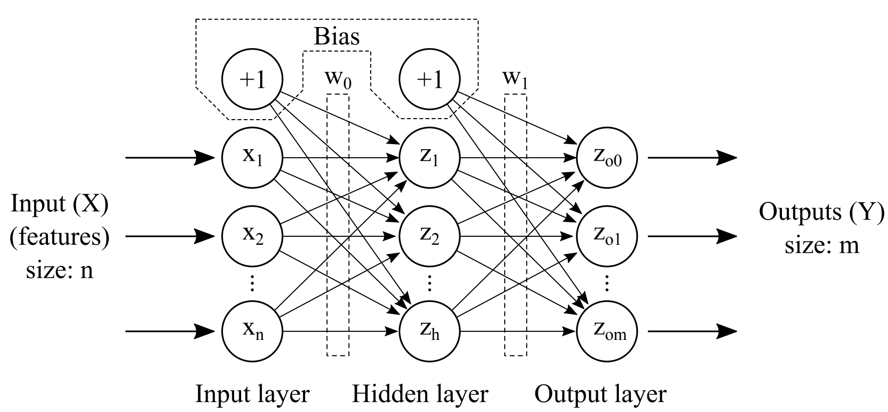

Figure A.1: Multilayer perceptron regressor with a single layer and multiple outputs *[[22]]*.

In *[[22]]*, a multi-layer perceptron (MLP) that conducts training using backpropagation [384] is used. "The activation function in the hidden layers is the rectified linear unit (ReLu) function (A.4), which has a lower computational cost than other activation functions, such as logistic or hyperbolic tangent functions. In contrast to the MLP used for classification, the activation function in the output layer is the identity function, achieving continuous values for the outputs (a regression behavior). Furthermore, the squared error is used as the loss function during training" *[[22]]*.

$$f(x) = max(0, x) \tag{A.4}$$

"Thus, as is usually recommended, parameter regularization techniques are applied to obtain better generalized models [385] (reducing the probability of overfitting during the training process). This means that weights with large magnitudes are penalized during training, so large values are not retained (they are regularized). Two well-known techniques for this purpose are lasso Regression ($\ell 1$) and ridge Regression ($\ell 2$) [385]; the penalty term is squared in $\ell 2$ (which brings higher sensitivity to high weight values). For this reason, the $\ell 2$ technique is preferred. The regularization effect is adjusted by a hyperparameter called *alpha*" *[[22]]*.

"The use of an MLPR for modeling requires deciding the number of hidden layer neurons (hyperparameter n_h) to be used. In this sense, some authors have proposed heuristics (rules of thumb) to select the number of hidden neurons [284]. Their expressions are shown in (A.5)-(A.10)" *[[22]]*.

$$n_h = (2 \cdot n_i) + 1 \tag{A.5}$$

$$n_h = 2 \cdot (2 \cdot n_i) + 1 \tag{A.6}$$

$$n_h = \sqrt{n_o + n_i} + l \tag{A.7}$$

$$n_h = \sqrt{\frac{N}{n_i \cdot log(N)}} \tag{A.8}$$

$$n_h = \frac{n_i + n_o}{2} + \sqrt{N} \tag{A.9}$$

$$n_h = \frac{n_i + n_o}{2} \tag{A.10}$$

where "n_h indicates the number of hidden layer neurons; n_i is the number of input neurons; n_o is the number of output neurons; l is an integer between 1 and 10; and N is the number of training samples" *[[22]]*.

"Considering the characteristics of each input and output dataset (their sizes), it is possible to directly calculate the recommended number of hidden neurons according to these rules. These recommendations are used to obtain initial estimations of the range of n_h values that will be tested during the experiments" *[[22]]*.

A.2.2 Random forest regressor (RFR)

"A random forest [386] is based on splitting the input dataset into multiple groups and training a decision tree for each of these groups. Finally, the results of each tree are passed to a voting block (in this case a random forest for classification) or an averaging block (for regression), obtaining a RFR in the second case. One of the main hyperparameters of a RFR is the number of trees to use. A higher number can improve the performance of the model, but the computational cost grows linearly with the increase in the number of trees" *[[22]]*. An example of a decision tree can be seen in Figure A.2 [308].

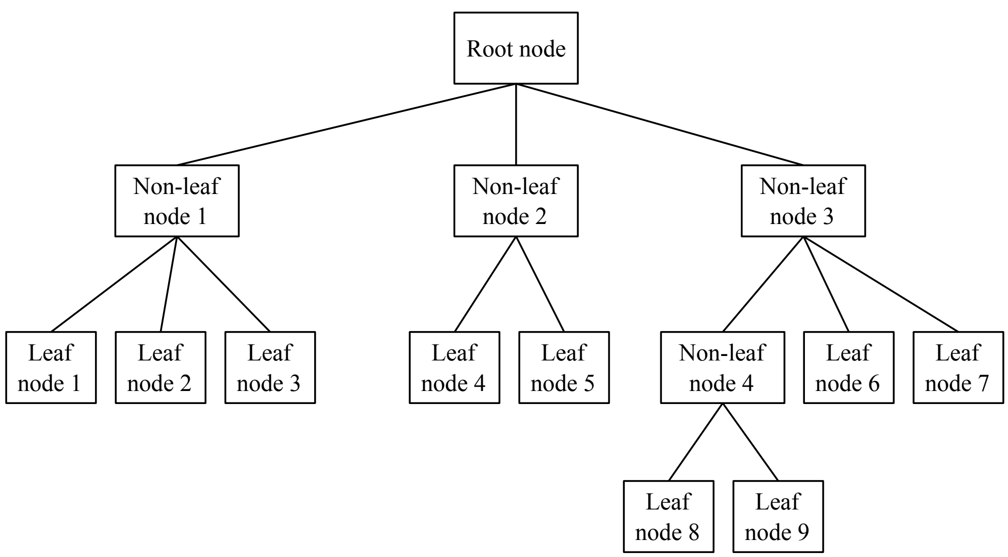

Figure A.2: Decision tree. Based in the figure found in [308].

"The structure of a RFR is shown in Figure A.3. It can be used for single-output or multioutput prediction simply by adding new tree structures for each of the desired outputs" *[[22]]*.

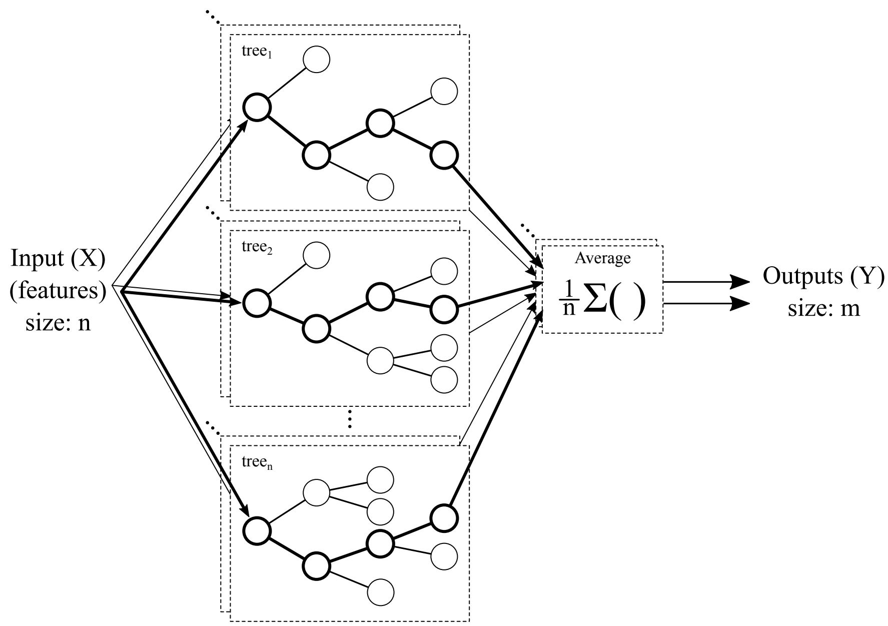

Figure A.3: Random forest regressor with multiple outputs *[[22]]*.

A.2.3 Probabilistic version of random forest regressor (RFR_prob)

For the inclusion of probabilistic forecasting techniques in the proposed framework, a modification was made to the previously seen RFR. This new variation, which has been labeled by the name RFR_prob, consist of obtaining each independent predicted point of each of the estimators that compose a trained RFR model (i.e., each of the individual trees).

This cloud of points is further processed to obtain the values of the 99 quantiles of the prediction (quantiles from 0.01 to 0.99). In this sense, a specific quantile will be the numerical value for which the corresponding fraction of the points is below it. For example, for the quantile 0.4, the 40% of the points have a value lower than that.

A.2.4 Random forest regressor with fixed sigma (RFR_probSIGMAFIX)

Another variant that has been created from the RFR assumes a normal distribution with a certain standard deviation sigma (σ) over the deterministic predictions given by a RFR model. This technique is referred in this thesis as RFR_probSIGMAFIX.

This procedure, which is already detailed in Section §4.6.3.1, has been used to configure the techniques RFR_probSIGMAFIX10 (with a sigma of a 10% of the value of each deterministic point), RFR_probSIGMAFIX20 (with a sigma of a 20% of the value of each deterministic point), and RFR_probSIGMAFIX30 (with a sigma of a 30% of the value of each deterministic point).

Abbreviations

AARC affinely adjustable robust counterpart. 88

AC alternating current. 24, 30, 81

ACER Agency for the Cooperation of Energy Regulators. 13, 15

ACO ant colony optimization. 94, 124

ADMS advanced distribution management system. 35

ADP approximate dynamic programming. 90

ADR automated demand response. 45, 160

AI artificial intelligence. 3, 5, 17, 18, 20, 45, 46, 122, 125–127, 130, 137, 146, 171, 191, 320

AIC Akaike information criterion. 143

AK author keyword. 100, 104, 105, 107

AMI automatic metering infrastructure. 3, 16, 18, 19, 48, 51, 119, 158, 162, 199, 276

AMM automatic metering management. 19

AMR automatic metering reading. 19

ANFIS adaptive neural fuzzy inference system. 125

ANN artificial neural network. 79, 100, 107, 125–127, 130, 136, 320

ANOVA analysis of variance. 123, 126

API application programming interface. 43

ARC adjustable robust counterpart. 88

ARCH autoregressive conditional heteroscedasticity. 126

ARDL autoregressive distributed lag. 126

ARE absolute relative error. 143

ARIMA autoregressive integrated moving average. 46, 143, 145, 171, 188, 190, 191, 221, 222, 240, 242, 243, 250, 251, 275, 319, 320

ARMA autoregressive moving average. 143, 145, 171

ASM active system management. 50

BALANCE Project "*Bigdata Analitycs e Instrumentación Ciberfísica para Soporte de Operaciones de Distribución en la Smartgrid*". 151, 284

BESS battery energy storage system. 32

BIC bayesian information criterion. 143

BMI bilinear matrix inequalities. 95

BMS building management system. 33, 157–161, 166, 167, 195, 198, 199

BPI bootstrapped prediction interval. 130

BRP balance responsible party. 49

CACM Capacity Allocation and Congestion Management. 15

CBP Capacity Bidding Program. 41, 151, 166

CBR case-based reasoning. 128

CC/DL contracted capacity or utility imposed demand limit. 34

CCA canonical correspondence analysis. 123

CDF cumulative distribution function. 61, 144

CEC certainty equivalent model predictive control. 77, 82

CENELEC Comité Européen de Normalisation Électrotechnique. 17

CFD contract for difference. 107

CMU capacity market unit. 41

CV(RMSE) coefficient of variation of the root mean square error. 140, 174, 192, 194, 203, 204, 206, 211, 212, 214

CVaR conditional value at risk. 83, 86

DC direct current. 24, 30

DE differential evolution. 94

DER distributed energy resource. 3, 4, 20, 21, 23, 24, 26–29, 31, 33–36, 40, 44, 50, 81, 111, 121, 151, 152, 156, 168, 195, 200, 277, 278

DERMS distributed energy resources management system. 21, 33, 35, 36, 40, 44, 167

DG distributed generation. 2, 17–21, 24, 30, 31, 45, 50, 53, 93, 109, 123, 162, 195

DIE Department of Electrical Engineering (*Departamento de Ingeniería Eléctrica*) of the Universidad Técnica Federico Santa María. 150, 162

DIM Department of Mechanical Engineering (*Departamento de Ingeniería Mecánica*) of the Universidad Técnica Federico Santa María. 150, 163

DITEN Department of Electrical, Electronic and Telecommunication Engineering and Naval Architecture (*Dipartimento di Ingegneria Navale, Elettrica, Elettronica e delle Telecomunicazioni*) of the Università di Genova. 151

DP dynamic programming. 58, 67, 69, 74, 77, 83, 89–93

DR demand response. 2, 13, 17, 25, 30, 34–38, 40, 41, 43–45, 48–50, 63, 79, 107, 111, 114, 119, 121, 126, 136, 137, 145, 146, 149–152, 154, 156–159, 161–164, 166–169, 171, 195, 199, 276, 278

DRM demand response management. 34

DRMS demand response management system. 35, 51, 157, 158

DSM demand side management. 13, 17, 25, 34, 37, 38, 40, 41, 44, 45, 100, 111, 114, 121, 145, 152, 154, 157, 159–161, 195, 198, 199

DSO distribution system operator. 4, 12, 14, 19, 20, 32, 36–38, 40–42, 45–47, 49–51, 151, 154, 157–161, 167, 168, 195, 198, 199, 214

DTE Department of Electronic Technology (*Departamento de Tecnología Electrónica*), belonging to the Universidad de Sevilla. 150, 153

E-PoPA extended power pinch analysis. 94

EG3 Expert Group 3. 48

EKF extended Kalman filter. 127

ELNS expected load not served. 86

EMS energy management system. 5, 6, 20, 21, 25–36, 44, 47, 53, 54, 59, 70, 71, 74, 76–78, 80, 119, 146, 149–151, 154–156, 158, 160–164, 166, 167, 172, 194, 195, 199, 200, 203, 212, 215, 278, 279

EP evolutionary programming. 94

EPF electric price forecasting. 129

ESCA electric system cascading analysis. 93

EU European Union. 9, 10, 12–16, 37, 38, 40, 42, 45, 48, 49, 51, 159

EUE expected unserved energy. 64

Euphemia Pan-European Hybrid Electricity Market Integration Algorithm. 14

EV electric vehicle. 2, 14, 18, 20, 34, 91, 121, 151

ExAs Extreme Assignation. 180, 182–184, 227, 232, 235, 243, 258, 266, 267

ExPAnD extended pinch analysis and design. 94

FCA Forward Capacity Allocation. 15

FD Fenchel decomposition. 68

FERC Federal Regulatory Energy Commission. 11

FMS flexibility management system. 35, 36, 40, 44, 158

FNN feedforward neural network. 135, 136

FSP flexibility service provider. 41, 46, 154, 156, 158, 159, 195, 278

GA genetic algorithm. 94

GME Gestore Mercati Energetici. 10

GP geometric progression. 126

GridFlex4Chile Project "Grid Flexibility for Chile". 150, 284

GridFlex&Resil Project "Grid Flexibility & Resilience". 151, 284

HC homeostatic control. 27, 30

HEMS home energy management system. 119

HVAC heating, ventilation and air conditioning. 162, 163

ICT information and communication technology. 45

IK indexed keyword. 100, 104, 105

ILF intelligent load forecasting. 120

IRP integrated resource planning. 122

ISO independent system operator. 13, 15, 41, 46, 81

ISO-NE Independent System Operator of New England. 39

ITO independent transmission operator. 13

JCR Journal Citation Reports. 150

KDE kernel density estimation. 123

LA log-linear analysis. 126

LEAP long-range energy alternatives planning system. 120

LF load forecasting. 121

LFC load frequency control. 120

LMI linear matrix inequality. 95

LOLP loss of load probability. 64, 72, 86

LP linear programming. 94, 95

LR Lagrangian relaxation. 85, 86

LSTM long short-term memory. 135, 191, 276, 279

MA & ES moving average and exponential smoothing. 128

MAD mean absolute deviation. 143

MAE mean average error. 140

MAPE mean absolute percentage error. 46, 140

MARE mean absolute relative error. 143

MAS multi-agent system. 28, 31, 32, 43

MCTS Monte-Carlo tree search. 61

ME-PoPA modified extended power pinch analysis. 94

MiAs Middle Assignation. 180, 182–184, 227, 232, 235, 258, 266, 267

MILP mixed integer nonlinear programming. 92, 94

MINLP mixed integer nonlinear programming. 94

ML machine learning. 3, 39, 126, 130, 135, 136, 157, 168, 171–173, 191, 204, 217, 242, 249, 273, 275, 320

MLP multi-layer perceptron. 321

MLPR multi-layer perceptron regressor. 173, 174, 191, 202–204, 206, 209, 211, 212, 215, 240, 254, 320, 321

MPC model predictive control. 58, 59, 66, 76–83, 105, 107, 193

MPSO meta particle swarm optimisation. 94

MRP multiple replications procedure. 63

NC no-change. 145

ND nested decomposition. 67, 69, 84, 90, 91

NEMO nominated electricity market operator. 10

NIST National Institute of Standards and Technology. 17

NISTIR 7628 National Institute of Standards and Technology Interagency Report 7628. 17

NLP nonlinear programming. 95, 126

nMAE normalized mean average error. 123, 142

NN neural network. 30, 46, 94, 137

NRMSE normalized root-mean-square error measure. 143

nRMSE normalized root mean average error. 123, 141, 142, 211

NWA non-wires alternative. 37

NWP numerical weather prediction. 39, 135

OECD Organisation for Economic Co-operation and Development. 12

OLFC open loop feedback control. 58, 76, 77, 82

OMIE Operador del Mercado Ibérico de Energía. 10

OpenADR Open Automated Demand Response. 45, 51, 151, 157, 158, 160, 164, 168, 198, 199

p-MILP parametric mixed integer nonlinear programming. 95

PAM partial adjustment model. 126

PB percentage better. 142

PB(MAE) percentage better mean average error. 142

PB(MSE) percentage better mean square error. 142

PCA principal component analysis. 122

PCC Pearson correlation coefficient. 122

PCM polynomial curve model. 126

PDensF probability density function. 61–64

PDF probability distribution function. 61, 62, 176

PG&E Pacific Gas & Electric. 41, 161, 169

PI prediction interval. 128, 129, 144

PLC power line communication. 19

PoPA power pinch analysis. 93, 94

PRODEFOR Probabilistic and Deterministic Forecasting Framework. 152, 156, 172, 185, 186, 195, 197, 198, 278, 279

PSO particle swarm optimization. 94, 124, 125

PV photovoltaic. 34, 54, 61, 64, 70, 79, 121, 129, 135, 136, 200, 215, 217

QMCS quasi Monte Carlo simulation. 131

QP quadratic programming. 95

QRA quantile regression averaging. 129, 130, 135

R2 coefficient of determination. 140

RACF residual autocorrelation function. 143

RC robust counterpart. 88

ReLu rectified linear unit. 321

RES renewable energy source. 38, 50, 88, 168

RFR random forest regressor. 173, 174, 191, 202–204, 206, 209, 211, 212, 215, 240, 320, 322, 323

RFR_prob probabilistic random forest regressor. 191, 323

RFR_probSIGMAFIX probabilistic random forest regressor with fixed sigma. 191, 323

RHC receding horizon control. 80

RHUC rolling-horizon unit commitment. 81

RL reinforcement learning. 30, 61, 127

RME relative mean error. 143

RMSE root mean square error. 140, 141, 192, 194, 203, 211, 222, 225, 251, 255

RNN recurrent neural network. 135, 137, 320

RRMSE relative root mean square error. 140

RSE S.p.A. Ricerca sul Sistema Energetico. 50

RTH rolling time horizon. 78, 81

Rulabi Rule-based Baseline Forecasting. 152, 156, 168, 169, 195, 197, 202, 204, 240, 273, 278

RVFL network random vector functional link network. 127

RWSLFN single hidden layer network configuration with random weights. 127

SA simulated annealing. 94, 123

SAA sample average approximation. 63, 68

SAHPPA stand-alone hybrid system power pinch analysis. 93

SC-FD scenario-wise Fenchel decomposition. 68

SD-G&E San Diego Gas & Electric. 41, 161, 166, 169

SDDP stochastic dual dynamic programming. 67–69, 79, 91

SDP stochastic dynamic programming. 58, 59, 71, 76, 77, 79, 90, 91

SDPA stochastic dynamic programming augmented. 71, 77

SDPO stochastic dynamic programming online. 71, 77

SEDC Smart Energy Demand Coalition. 49

SEP standard error of prediction. 143

SES sustainable energy system. 121

SGAM Smart Grids Architecture Model. 17

SIIAM Project "*Sistema Inteligente Inalámbrico para Análisis y Monitorización de Líneas de Tensión Subterráneas en Smart Grids*". 150, 283

SIP stochastic integer program. 68

SLFN single hidden layer feedforward neural network. 127

SLR systematic literature review. 99

SMIP stochastic mixed integer programming. 68

SOCP second order cone programming. 95

SOHBPSO self-organising hierarchical binary particle swarm optimisation. 94

SOM self-organizing map. 130

SPM Smart Polygeneration Microgrid. 197, 199, 200

ST-FD stage-wise Fenchel decomposition. 68

SVR support vector regressor. 276, 279

TIC-150 Research group "Electronic Technology and Industrial Informatics" (*Tecnología Electrónica e Informática Industrial*, also called TIC-150, or eTIC), belonging to the Universidad de Sevilla. 150

TIMES G5 "the integrated MARKAL–EFOM system". 120

Translog transcendental logarithmic. 126

TS tabu search. 94

TSO transmission system operator. 4, 12–15, 36–38, 40, 41, 45–47, 49–51, 154, 158, 168

UBEM urban building energy modeling. 34

UC unit commitment. 4, 25, 26, 29, 46, 60, 71, 72, 74, 76, 78, 81, 82, 84, 86, 87, 121–123, 139, 152

UFT Universidad Finis Terrae (Chile). 150, 153, 161

USEF Universal Smart Energy Framework. 40

UTFSM Universidad Técnica Federico Santa María (Chile). 150, 153, 161–163

VaR value at risk. 83, 86

VEN virtual end node. 160, 199

VPP virtual power plant. 32, 36, 41, 50

VTN virtual top node. 160

WePin weighted pinball. 181, 184, 185, 193, 194, 221, 225, 227, 229, 231, 251, 255, 257–259, 263

WoS Web of Science. 101

Nomenclature

$ge1$ power absorbed by the smart polygeneration microgrid in Savona Campus (kW). 200, 202–206, 209–212, 214

$ge2$ power withdrawn from the external distribution network in Savona Campus (kW). 200, 202–206, 209–212, 214, 217, 225

lc electrical demand of the buildings in Savona Campus (kW). 200, 202–206, 209–212, 214, 215, 217, 225, 235

pv photovoltaic generation in Savona Campus (kW). 200, 202–206, 209–212, 214, 215, 217, 225

ut production of the two cogeneration microturbines in Savona Campus (kW). 200, 202–206, 209–212, 214

Bl baseline. 187

Db day back. 187

DI day information. 187

EXBL external baseline. 173, 187, 202, 203, 212, 215, 217

Wa weather forecast. 187