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IMPACT OF DEMAND RESPONSE AND ELECTRICAL ENERGY STORAGE ON MULTI-ENERGY SYSTEMS MANAGEMENT

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TESE DE DOUTORAMENTO APRESENTADA
À FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO NO
PROGRAMA DOUTORAL EM SISTEMAS SUSTENTÁVEIS DE ENERGIA

Impact of Demand Response and Electrical Energy Storage on Multi-Energy Systems Management

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Programa Doutoral em Sistemas Sustentáveis de Energia

October 2023

This PhD thesis was supported by Fundação para a Ciência e a Tecnologia (FCT) (Portuguese Foundation for Science and Technology) through the grant 2020.08822.BD.

The grant was awarded to pursue the Doctoral Program in Sustainable Energy Systems at the Faculty of Engineering of the University of Porto (FEUP) as part of the MIT Portugal Program. The host institution for the research contained in this thesis was the Institute for Systems and Computer Engineering, Technology and Science - INESC TEC. In addition, the work involved a 6-month research visit to the Energy Analytical Group within the Laboratory for Information and Decision Systems (LIDS) at the Massachusetts Institute of Technology (United States of America). This visit was funded through a combination of the above-mentioned grant from FCT, the MIT Portugal Program, and LIDS.

In addition, the work in this thesis has contributed to two research projects. The research contributed to the FCT UNiTED Project (Unlocking demand response potential with Next-generation innovative optimization Tools Empowering prosumers and Distribution grid benefits), Ref. POCI-01-0145-FEDER-029803. The work also contributed to the Open Innovation – Research Translation and Applied Knowledge Exchange in Practice through University-Industry-Cooperation, OpenInnoTrain, GA ID: 823971, Marie Skłodowska-Curie Actions.

Abstract

Multi-energy systems that consist of two or more energy carriers enhance the system efficiency and increase the reliability and flexibility in energy supply and demand. Also, demand response (DR) and energy storage are important elements of such energy systems, which can have a positive impact on the performance of multi-energy systems. However, uncertainties and risks are also appearing in the system. Introducing the aggregators and choosing a proper risk measure presents a solution to this problem.

Under this scope, this thesis presents a set of optimization frameworks for aggregators to use in electrical energy systems and then extends it to multi-energy systems. Each computational tool considers a different risk management method.

In this research-based thesis, which is a collection of articles, several DR programs are implemented to provide more flexibility for the consumers and encourage them to participate in DR programs actively. Moreover, the integrated DR programs are also employed to include multiple load types such as electricity, heating, and cooling loads in the programs designed by the aggregator.

Moreover, the direct interactions of a DR aggregator with an ESS are neglected in many models. However, this consideration can lead to a significant improvement in the flexibility of the aggregator, thus increasing the profit of the entity by trading energy in the short-term markets to charge the ESS during the low-price periods. Hence, an analysis of the impact of the ESS unit on the DR aggregator's performance is applied to study the most appropriate size of the ESS that can maximize the profit of the aggregator.

In addition, the consideration of a suitable risk management method based on the nature and characteristics of the uncertain parameters is an important issue for the aggregators in the management and scheduling of energy systems. Thus, hybrid approaches are proposed for the management of the aggregators. Therefore, the most suitable risk measures for the decision-maker are chosen based on the characteristics of the uncertain parameters, which leads to a more precise decision.

Keywords: Optimization, Demand response, Uncertainty, Energy storage, Multi-energy systems.

Resumo

Os sistemas de multi-energia que consistem em dois ou mais portadores de energia aumentam a eficiência do sistema, aumentam a confiabilidade e a flexibilidade no fornecimento e na demanda de energia. Além disso, a resposta à demanda e o armazenamento de energia são elementos importantes desses sistemas energéticos, que podem ter um impacto positivo no desempenho dos sistemas de multi-energia. No entanto, incertezas e riscos também aparecem no sistema. A introdução de agregadores e a escolha de uma medida de risco adequada apresenta uma solução para esse problema.

Nesse contexto, esta tese apresenta um conjunto de metodologias de otimização para que os agregadores usem nos sistemas de energia elétrica e, em seguida, são alargadas aos sistemas de multi-energia. Cada ferramenta computacional considera um método diferente de gestão de risco.

Nesta tese, vários programas de resposta à demanda são implementados para fornecer mais flexibilidade aos consumidores e incentivá-los a participar ativamente nesses programas. Além disso, os programas integrados de resposta à demanda também são utilizados para incluir vários tipos de demanda, como eletricidade, aquecimento e arrefecimento, nos programas projetados pelo agregador.

Ainda, as interações diretas de um agregador de resposta à demanda com um sistema de armazenamento de energia são negligenciadas em muitos modelos. No entanto, essa consideração pode levar a uma melhoria significativa na flexibilidade do agregador, aumentando assim o lucro da entidade ao negociar a energia nos mercados de curto prazo para carregar o sistema de armazenamento de energia durante os períodos de preços da eletricidade mais baixos. Portanto, uma análise do impacto da unidade de armazenamento de energia no desempenho do agregador de resposta à demanda é aplicada para estudar a dimensão mais apropriada do sistema de armazenamento de energia que pode maximizar o lucro do agregador.

Além disso, a consideração de um método adequado de gestão de risco com base na natureza e nas características dos parâmetros incertos é uma questão importante para os agregadores na gestão e planeamento dos sistemas de energia. Portanto, são propostas abordagens híbridas para a gestão de agregadores. Assim, as medidas de risco mais adequadas para o agente de decisão são escolhidas com base nas características dos parâmetros incertos, o que leva a uma decisão mais precisa.

Palavras-Chave: Otimização, Resposta à Demanda, Incerteza, Armazenamento de Energia, Sistemas de Multi-Energia.

Acknowledgments

This PhD thesis was completed over several years, during which time I experienced many challenges and triumphs, met many people, and made many friends. All of these experiences contributed to this intellectual and emotional journey. I would like to express my appreciation to the family, friends, and colleagues who have supported me along the way.

First, I would like to thank my supervisor, Professor João P. S. Catalão, and co-supervisors, Professor Miadreza Shafie-khah and Dr. Mohammad Sadegh Javadi, and my advisor, Professor Sergio Santos for accepting to supervise my thesis. Their insights and guidance helped me to improve and enhance my work.

I would especially like to thank Professor Catalão for providing the initial ideas for this work and for serving as my primary mentor throughout this journey. He has always been a source of positive support, even during the most difficult times. He has trusted me and my work, and he has given me the flexibility to work independently and at my own pace.

I would also like to thank Dr. Javadi for working closely with me in recent years. His knowledge, vision, and dedication to hard work and detail have been essential to the success of this project. His passion for scientific research and excellence has inspired me. I have learned a great deal from him, including mathematical optimization topics, power system topics, how to write high-quality papers, and how to write well-organized mathematical formulations. All of this has contributed to much better work and made me a better scientific researcher overall.

I would also like to thank Professor Santos for being an excellent and compassionate advisor and a wonderful friend. I sincerely appreciate his advice and support from my early days at INESC TEC to today.

I would like to thank Dr. Audun Botterud for hosting me at the Energy Analytics Group at Massachusetts Institute of Technology (MIT), which was one of the greatest experiences of my life. During my stay, I was able to learn a lot from him, especially in the area of energy. He was also very helpful and supportive, and I will never forget how he facilitated my integration. I would also like to thank my other colleagues there, such as Mehdi Jafari, Vladimir Dvorkin, and Rahman Khorramfar, who provided me with a lot of help and made my stay much more enjoyable, interesting, and inspiring than I could have imagined.

I would also like to thank my colleagues at INESC TEC who helped me to improve the quality of this thesis by clarifying my doubts and providing helpful insights.

I am very grateful to all the professors and administrative staff with whom I have interacted over the past five years. Special thanks to Célia Couto, Paula Castro, Rachel Cohen, and Richard Lay for helping me navigate the often-obscure bureaucratic aspects of this PhD program.

I am grateful to the team members of the UNiTED project. I would especially like to thank Mohamed Lotfi, who was an excellent guide during the PhD program. I would also like to thank my colleagues within the Center for Power and Energy Systems at INESC TEC, especially those on the fourth floor. It was a pleasure to work with you and become your friend. A special thanks to Matthew Gough, who was with me at every step of the journey from the early days of the UNiTED project to our visit to Cambridge.

To the brilliant people I have collaborated with, a heartfelt thank you! Working with and learning from you has been a major highlight of my PhD. A special thanks to Gerardo Osório and Darwin Quijano. I have learned so much from all of you.

Family and friends are one of the most important things in life. Without their support, directly or indirectly, this work could never have been done. I would like to thank my Iranian friends in Portugal, Hamed, Parisa, Masoud, Sara, Hodjat, Leyla, Cyrus, and Hesam, for their friendship and support. I am also grateful to my friends at Cambridge, Farzad, Nasrin, Dongwei, Daniel, Robert and Miroslav.

I would like to thank my parents for their support and for the sacrifices they made to give me a proper education and a good living. I would also like to thank my sister for her support, especially during the years I am abroad. Without them, I would not be the person I am today and would not have been able to accomplish any of this work.

Finally, Sahar, my beloved wife, thank you for everything. I have been lucky enough to have you as my partner. Without your tremendous understanding and encouragement in the past few years, it would be impossible for me to complete my study.

I am truly indebted to all of these people for their support. Without them, this thesis would not have been possible.

Morteza

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Chapter 1

Introduction

1.1 - Motivation and Background

The widening chasm between the supply and demand of energy in our modern energy systems has prompted significant interest in demand-side management as a viable solution. Among the various strategies available, demand response (DR) stands out as a particularly practical approach for bridging the gap between electricity generation and consumption [1], [2]. This electricity consumption pattern recognizing its potential, the Federal Energy Regulatory Commission (FERC) has officially defined DR as a method aimed at motivating end-user consumers to alter their energy consumption behaviors in direct response to fluctuating electricity prices or enticing incentive payments.

The adoption of DR within the energy landscape offers a multitude of benefits. It acts as a pivotal tool for achieving equilibrium between electricity generation and demand, thereby mitigating issues stemming from energy imbalances. Additionally, it injects a newfound level of flexibility into the energy ecosystem, ensuring a more adaptable and resilient grid infrastructure. Furthermore, DR plays a significant role in enhancing the reliability of the electrical grid, thus reducing the occurrence of power outages and disturbances. Perhaps most notably, DR contributes to the ongoing global effort to combat climate change by curbing CO2 emissions associated with excessive energy consumption [3]. In essence, DR emerges as a multifaceted solution with the potential to address a myriad of pressing challenges in the energy sector.

Moreover, another essential feature in increasing the flexibility and resilience of modern energy systems resides in the integration of energy storage systems (ESS) [4]. ESSs represent a pivotal technological solution to address a host of challenges, particularly those engendered by the escalating integration of renewable energy sources within the power grid.

The growing adoption of renewable energy resources, such as solar and wind, has led to a new era of sustainability and environmental consciousness in the energy sector. However, the inherent intermittency and variability of these renewable sources pose a significant challenge to grid stability and reliability. The erratic nature of renewable energy generation can precipitate imbalances in the supply-demand equation, leading to voltage fluctuations, frequency deviations, and potential network instabilities. It is within this series of challenges that the necessary for ESSs becomes essential [5].

For instance, according to the data provided by the grid operators at the California Independent System Operator (CAISO), it can be observed that there is a sharp drop in net load (or the demand remaining after subtracting variable renewable generation) in the middle of the day when solar generation tends to be highest, i.e., Figure 1.1 [6]. This emphasizes the importance of the implementation of DR programs and ESS to balance the generation and demand in the presence of renewable energy resources.

ESSs serve as a dynamic buffer against the fluctuations of renewable energy production. By harnessing surplus energy during periods of high generation and releasing it during low generation, ESSs serve to smoothen the energy supply curve, obviating grid instability and ensuring a consistent, dependable power supply. This capability not only mitigates the challenges highlighted in the preceding discussion but also enhances grid resilience, effectively acting as a shock absorber in the face of unforeseen disruptions.

The confluence of DR and ESSs represents a synergistic approach to addressing the exigencies of modern energy management. Together, these complementary features synergize to form a more holistic and robust model for optimizing energy systems. By orchestrating demand-side adjustments through DR and concurrently deploying ESSs to store and release energy, the energy ecosystem attains a level of flexibility and reliability that is vital to its sustainable evolution.

This combination creates a resilient and efficient energy infrastructure controlled to meet the demands of the future while mitigating the environmental footprint through the integration of renewable resources.

On the other side, it should be noted that the concept of the microgrid has undergone a profound transformation. Initially, the microgrid concept primarily revolved around the domain of the electric power sector. However, with the advent of innovative models that facilitate the seamless integration of various independent single-energy systems into a cohesive Multi-Energy System (MES), the scope and functionality of microgrids have expanded significantly. Notably, these modern MES-enabled microgrids have transcended their conventional focus on electric energy and now encompass the realm of thermal energy as well [3].

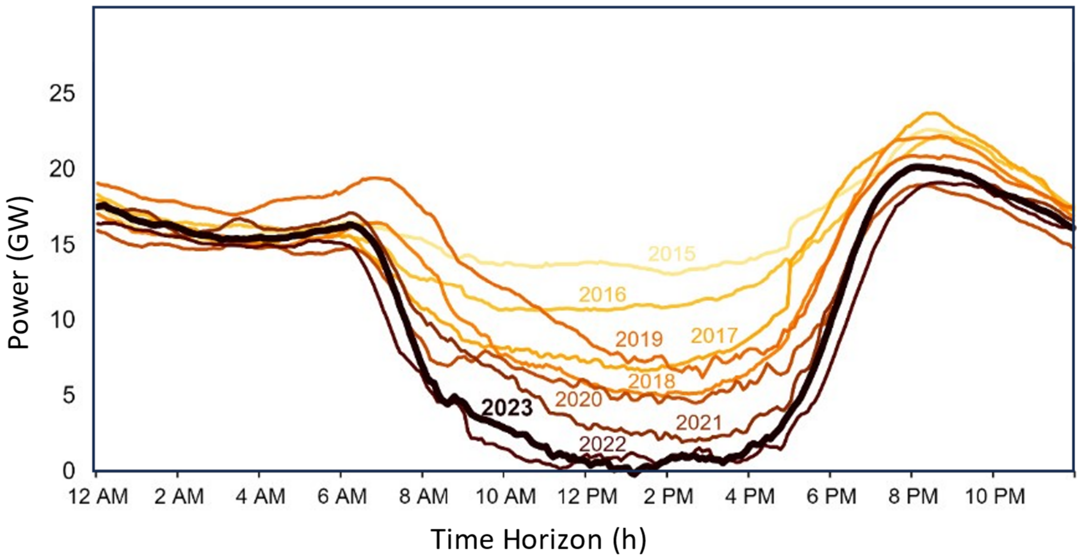

Figure 1.1 - CAISO net load pattern from 2015 until 2023 [6].

This paradigm shift represents a crucial milestone in the domain of energy management. MES-enabled microgrids are poised to play a key role in the contemporary energy landscape by offering an integrated approach to both electric and thermal energy management. This evolution has broadened the horizons of energy system applications, rendering them flexible tools for optimizing not only electrical power but also thermal energy distribution and utilization within a given ecosystem.

Crucially, the optimal management of distributed energy resources (DERs) and renewable-based generation within the framework of multi-energy systems is imperative. These components are widely anticipated to constitute the linchpin of future energy systems. DERs encompass a diverse array of small-scale power generation and storage resources, including solar panels, wind turbines, and energy storage systems, which are distributed throughout the grid. The integration of renewable-based generation, such as solar and wind power, further accentuates the significance of DERs in the broader context of MESs.

Given the anticipated prominence of DERs and renewable-based generation, the effective orchestration and management of these resources within MES has become paramount. Achieving optimal synergy between diverse energy sources, while ensuring efficient utilization and balancing of supply and demand, represents a formidable challenge. Yet, it is precisely in meeting this challenge that the future resilience and sustainability of energy systems will be forged.

1.2 - Research Questions, Objectives and Contributions of the Thesis

This thesis presents a comprehensive analysis of DR and ESS impact on the performance of energy systems and extends it to multi-energy systems. New analysis tools and methods are developed in this thesis that considers the operational variability and uncertainty associated with several resources such as consumption, generation, and energy prices. The overarching objective is to advance the state of the art in DR and energy storage utilization within multi-energy systems, contributing to the integration of different energy sources while maintaining the cost-effectiveness of the whole system.

In particular, the following **research questions** are addressed:

1. What are the recent developments and trends in DR programs and energy storage technologies within MESs, specifically focusing on the main challenges and optimization techniques in energy hub system models?
2. What is the behavior of a risk-seeking DR aggregator in the presence of several DR programs on the demand-side of the aggregator, and the day-ahead electricity market on the market side? How does the aggregator manage uncertainty on both sides?
3. How does it improve the scheduling and risk-based operation of the DR aggregator? How does the incorporation of DRPs and an energy storage unit enhance consumers' flexibility in engaging with the DR aggregator's operations?
4. What are the impacts of incorporating an ESS unit on the performance of a DR aggregator? How can the flexibility of end-users for their engagement in the DR programs be enhanced?

5. How can the integration of multiple DR programs for electrical, heating, and cooling loads provide increased flexibility to consumers while optimizing the operational efficiency of the distributed energy resources and the energy hub?
6. How can risk management be effectively utilized for an uncertainty posed by the DER aggregator in an MES?

The **main objectives** of this thesis are:

- To carry out a state-of-the-art review on the status of DR and energy storage utilization across the world (with a particular focus on multi-energy systems), their economic aspects, current integration challenges and prospects, and other related issues.
- To study the behavior of a risk-seeking DR aggregator considering two types of DR programs on the demand side of the aggregator, and the day-ahead electricity on the other side.
- To develop a comprehensive and efficient optimization framework for a DR aggregator that addresses various uncertainties from both the market and consumer sides through the integration of different risk measures.
- To enhance consumers' flexibility in participating in DR programs by accommodating two types of DR programs and incorporating an energy storage unit.
- To develop a comprehensive model that analyzes the impact of an ESS unit on the performance of a DR aggregator, considering various end-users (residential, commercial, and industrial loads) participating in short-term electricity markets, such as day-ahead and balancing markets.
- To demonstrate that the strategic integration of various DR programs targeted at different energy loads can not only offer consumers enhanced flexibility but also lead to improved operational efficiency of distributed energy resources and the energy hub.
- To advance the understanding of risk management strategies in the context of DER aggregators and to optimize decision-making processes within MESs.

The **contributions** of this thesis are summarized as follows:

- An overview of the concept of DR and energy storage and the various types of them in multi-energy systems. Recent projects using DR programs and energy storage systems are highlighted to show the diversity of applications of DR and energy storage systems. Then, the concept of multi-energy systems is discussed briefly, with a detailed focus on the application of DR and energy storage technologies to multi-energy systems. This contribution is published in the **Energies** [7] and the **Technologies for Integrated Energy Systems and Network** [8].
- The behavior of the risk-seeker DR aggregator is studied considering two DR programs, i.e., time-of-use (TOU) and reward-based DR on the demand side of the aggregator and the day-ahead electricity market on the other side of it. Further, the uncertainty of both sides of the aggregator is considered. This contribution was published in **2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)** [9].

- A hybrid optimization framework for a DR aggregator is developed that considers various uncertainties with different inherent characteristics of both the market and consumer sides through a combination of robust and stochastic methods, simultaneously. This model considers the stochastic and non-stochastic uncertain parameters to improve the scheduling of the DR aggregator and its risk-based operation. This contribution is published in the **IEEE Transactions on Industry Applications** [10].
- A model for analyzing the impact of the ESS unit on the performance of a DR aggregator is developed on behalf of various end-users such as residential, commercial, and industrial loads participating in the short-term electricity markets, i.e., day-ahead and balancing markets and increasing the flexibility for the end-users to participate in the DR programs through developing the participation roles of the end-users in DR programs through having renewable energy resources on the demand side of the aggregator. This contribution is published in the **Journal of Energy Storage - ELSEVIER** [11].
- An innovative, opportunistic risk-handling method for a hub is proposed comprising an μCHP, EHP, absorption chiller, boiler, and ESS. Three uncertain parameters of consumers are considered in this model- These are electrical, heating, and cooling loads. And multiple integrated DR programs are utilized to provide more flexibility to consumers. This contribution is submitted to the **Applied Energy – ELSEVIER.**
- A hybrid IGDT-stochastic approach for the self-scheduling of a DER aggregator in an MES is developed. Therefore, through the application of this hybrid method, solutions for two different types of DER aggregators (risk-averse and risk-seeker decision-makers) are provided which makes it easier for the decision-makers to choose the model based on their preferences. The most suitable risk measures for the decision-maker are chosen based on the characteristics of the uncertain parameters, which leads to a more precise decision. This contribution is published in the **Energy – ELSEVIER** [12].

1.3 - Methodology

The mathematical models developed in this thesis are based on well-established methods, namely, mixed-integer linear programming (MILP), mixed-integer non-linear programming (MINLP), robust optimization, information-gap decision theory (IGDT), and stochastic programming. To achieve the main research objective, beyond simulation models, this thesis develops methods and solution strategies to analyze the impact of DR and ESS in multi-energy systems under uncertainty with a special focus on the characteristics of the uncertain parameter.

The proposed optimization models and the solutions strategies are implemented in GAMS© and solved in most cases using the CPLEX™, SBB™, and DICOPT™ algorithms, mostly by invoking default parameters. The visualization of the results is done in MATLAB©, Microsoft Visio™ and Excel©.

1.4 - Notation

The present thesis uses the notation commonly used in scientific literature, harmonizing the common aspects in all sections, wherever possible. However, whenever necessary, in each section, a suitable notation may be used. The mathematical formulas will be identified concerning the subsection in which they appear and not in a sequential manner throughout the thesis, restarting them whenever a new section or subsection is created. Moreover, figures and tables will be identified with reference to the section in which they are inserted and not in a sequential manner throughout the thesis.

Mathematical formulas are identified by parentheses (x.x.x) and called "Equation (x.x.x)" and references are identified by square brackets [xx]. The acronyms used in this thesis are structured under a synthesis of names and technical information coming from the English language, as accepted in the technical and scientific community.

1.5 - Organization of the Thesis

The thesis comprises seven chapters which are organized as follows. Chapter 1 is the introductory chapter of the thesis. First, the background of the thesis is presented. Then, the research motivations and the problem definition are provided. Subsequently, the research questions and contributions of this thesis are presented. Then, the methodology used throughout the thesis is introduced, followed by the adopted notations. Finally, the chapter concludes by outlining the structure of the thesis.

In Chapter 2, a comprehensive overview of DR and ESS is presented. The most recent implementation of DR frameworks and energy storage technologies in multi-energy systems was comprehensively reviewed. The DR modeling approach in such energy systems was investigated and the main contribution of each of these works has been included. Moreover, the emerging topics within the area of MES are investigated using a bibliometric analysis to provide insight to other researchers in this area.

In Chapter 3, a non-probabilistic program is proposed as a trading framework for DR aggregators. Both sides of the aggregator, including the upper side and downside of this entity, have been considered. On the downside of the aggregator, two popular programs are considered such as reward-based program and time-of-use (TOU) program, where DR is obtained from these resources. The acquired DR is studied to be traded in the day-ahead electricity market. To the aim of increasing the desired target profit of the risk-seeker aggregator, the opportunity function of Information-Gap decision theory (IGDT) is employed to address the uncertainty.

Chapter 4 proposes a model to handle various uncertain parameters simultaneously to reduce their effect on the aggregator's operation through the development of a novel hybrid stochastic-robust optimization approach that incorporates the uncertainties around wholesale market prices and the participation rate of consumers. The behavior of the consumers engaging in DR programs is addressed through stochastic programming. Additionally, the volatility of the electricity market prices is modeled through a robust optimization method. Two DR programs are considered in this model to include both time-based and incentive-based DR programs, i.e., time-of-use (TOU) and incentive-based DR (ibDR) programs to study three sectors of consumers, namely industrial, commercial, and residential consumers. An ESS is also assumed to be operated by the aggregator to maximize its profit.

As it was considered a DR aggregator responsible for participating in the wholesale electricity market on behalf of the end-users who participated in the DR programs in the previous chapter, in Chapter 5, a model for analyzing the impact of the ESS unit on a DR aggregator's performance is developed to provide more flexibility for the consumers. The direct interactions of a DR aggregator with an ESS are neglected in many models. However, this consideration can lead to improvement in the flexibility of the aggregator and increase the profit of the entity by trading energy in the short-term markets to charge the ESS during the low-price periods and discharge it to the market while the electricity market prices are high. Hence, it is assumed that the DR aggregator owns an ESS unit and can cover a percentage of its traded power through the ESS. An analysis of the impact of the ESS unit on the DR aggregator's performance is applied to study the most appropriate size of the ESS that can maximize the profit of the aggregator. In addition, renewable energy production is employed for end-users through the installation of rooftop PV panels. This demand-side renewable generation can provide more flexibility for the participants in DR programs.

The electricity and natural gas systems are currently experiencing significant transformations, where an energy hub can be created by combining these two energy carriers. Therefore, energy hubs have the potential to be highly influential due to their ability to integrate and optimize multiple energy sources, improve energy efficiency, and provide flexibility in energy management. Hence, in Chapter 6, we extended our framework within the consideration of multi-energy systems to study and analyze them, particularly regarding their costs. This model introduces a novel energy hub risk-management method. Our risk management framework considers uncertainties arising from various load profiles, including electric and thermal loads, as the uncertainties originating from the end-user side are among the most important factors in optimizing the total cost of the energy hub. The proposed energy hub includes multiple distributed energy resources.

The optimal management of DERs and renewable-based generation in MESs is crucial. To optimally manage these numerous and diverse entities, an aggregator is required. Hence, Chapter 7 proposes the self-scheduling of a DER aggregator through a hybrid IGDT-stochastic approach in an MES. In this approach, there are several renewable energy resources. The approach also considers an EV parking lot and thermal energy storage systems (TESs). Moreover, two DR programs from both price-based and incentive-based categories are employed in the microgrid to provide flexibility for the participants. The uncertainty in the generation is addressed through stochastic programming. At the same time, the uncertainty posed by the energy market prices is managed through the application of the IGDT method. A major goal of this model is to choose the risk measure based on the nature and characteristics of the uncertain parameters in the MES.

Chapter 8 presents the main conclusions of this thesis. Guidelines for future works in these fields of research are provided. Moreover, this chapter reports the scientific contributions that resulted from this research work and that have been published in journals with high impact factor (first quartile), as book chapters, or in conference proceedings of high standard (IEEE).

Chapter 2

Demand Response Programs and Energy Storage Technologies in Multi-Energy Systems

In this chapter, the most recent implementation of DR frameworks and energy storage technologies in multi-energy systems was comprehensively reviewed. The DR modeling approach in such energy systems was investigated and the main contribution of each of these works has been included. Moreover, the emerging topics within the area of MES are investigated using a bibliometric analysis to provide insight to other researchers in this area.

2.1- Demand Response Programs in Multi-Energy Systems

There are numerous reasons behind the ongoing transition within the energy sector. These include major concerns about the emissions and other environmental impacts of fossil fuel combustion. DR has emerged as a key solution to help enable this energy transition [13]. DR can effectively increase the active participation of consumers within the energy sector.

The Department of Energy of the United States has reported that active participation of consumers, through load reduction or load shifting, could be a key solution to future decarbonized energy systems. This reduction or shifting of load can be done through DR programs but some inelastic electricity consumers cannot participate in DR programs for numerous reasons, for instance, they have critical or must-run loads. Therefore, relying on a single energy carrier is not appropriate for future energy systems. Multi-energy systems (MES) can solve this issue and can maintain the comfort of the end-user during the operation of the DR program.

As MES relies on numerous energy carriers such as electricity, gas, heating, and cooling there is an increased amount of flexibility within the system which can be harnessed by the utility to allow a diverse range of consumers to participate in DR programs. Consumers can utilize a multitude of energy carriers to help meet their needs for energy and comfort while participating in DR programs. The utilization of the energy hub (EH) for the MESs is essential.

Since the EH is usually employed to represent energy distribution systems within a well-developed combined gas and electricity transmission networks model [14]. Figure 2.1 presents a representation of the relationships between a power system, other energy carriers and DR features. The main contributions of this model are as follows:

- Review and synthesis of recent DR programs (DRPs) in MESs.
- Exploration of the main DR in Energy Hub Systems models and their optimization.
- Use of bibliometric techniques to examine emerging trends within the DRP in the MES research area to help display the relation of the topics that have been done in this area. This shows how certain topics have emerged over the years and highlights the direction in which the research is going.

2.1.1- Demand Response

DR can provide valuable solutions to several of the challenges that the current power system is facing. These challenges include managing load demand from consumers from the ongoing electrification of our society [15]. This increasing load demand could cause some major problems for system operators, especially in peak periods. To meet these challenges, numerous solutions other than DR have been proposed including the optimization of renewable energy generators, storage units, or capacitors. Another tool to tackle the issues relating to increased load demand is network reconfiguration [16]. This involves better management of the power flow within the network to reduce congestion.

DR programs offer great potential to help overcome the challenges faced by the modern power system. Before DR is discussed further, it is important to provide a robust definition of DR. Three definitions of DR have been identified for this purpose. One of these definitions is as follows: 'changes in the electricity usage pattern of the consumers if the prices of the electricity would change in several periods' [17]. DR can also be defined by the incentive payments provided to consumers to help modify both the magnitude and timing of their energy use. The other definition of the DR is the incentive payments that are created to encourage the consumers to use less electricity when the market prices are high, or the reliability of the power system is endangered. These definitions, although similar, focus on different aspects related to DR, making the definitions presented complementary.

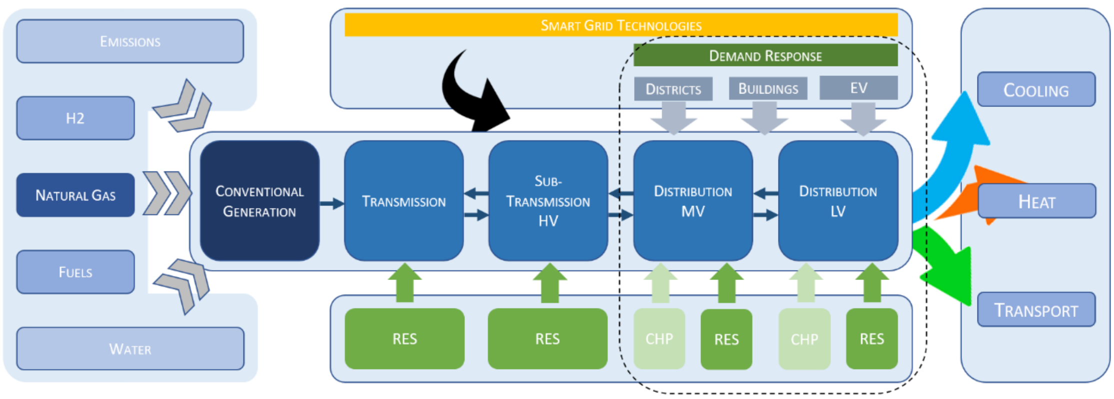

Figure 2.1 - Representation of the relationship between a power system and other energy systems.

These three definitions of DR show that there are different objectives for DR programs. These objectives can be reached through types of DR actions [18,19]. These include managing load profiles through elasticity peak shaving, and valley filling [17]. These results can be brought about by the use of time-dependent tariffs [20]. However, price is not always enough to convince a consumer to actively participate in DRPs [9]. Two main branches of DRP are prevalent and these are shown in Figure 2.2, and these two branches are price-based and incentive-based DRPs [21].

In price-based DRPs, electricity prices are the main tool used to modify consumer energy use [22]. Within this category, there are three main programs and these are Time of Use (TOU), Critical Peak Pricing (CPP), and Real-Time Pricing (RTP) [23]. In contrast to price-based DRPs, incentive-based DRPs aim to modify consumer energy demand through the use of rewards [24]. Within this category of DRPs, the most popular tools used include Direct Load Control (DLC), interruptible/curtailable services, emergency DR programs (EDRP), ancillary services markets, capacity markets, and demand bidding/buyback programs. The most important of these are discussed in the next section.

TOU pricing strategy contains different electricity pricing blocks corresponding to different periods of the day. In ToU programs, electricity prices can be increased during high-demand periods or decreased during low-demand periods to modify consumer behavior [25]. These programs generally do not change the amount of energy demanded but rather just shift the time of energy use to better suit the system status. CPP programs define the peak price period where the system's reliability may be at risk. Electricity prices are kept high during this period to reduce consumption and thus reduce the risk to the system. In RTP programs, prices are determined through real-time market interactions to match supply and demand.

Within incentive-based DRP programs, DLC programs give the utility the power to directly control various appliances owned by the consumer such as electric water heaters, air-conditioners (AC), and various pumps. During periods of high demand, the utility can effectively shut these appliances off while rewarding the consumers through incentives [26].

The consumers can be involved directly in the DRPs through interruptible/curtailable services. The main aim of these programs is to have an agreement with the consumers to decrease energy usage during peak periods. In return, they receive monetary incentives. Likewise, to compensate for the contingencies and enhance the reliability of the system, EDRP is being addressed. Transmission line failure or an outage in a generator could lead to insufficient generation during peak period and thus a system contingency can happen.

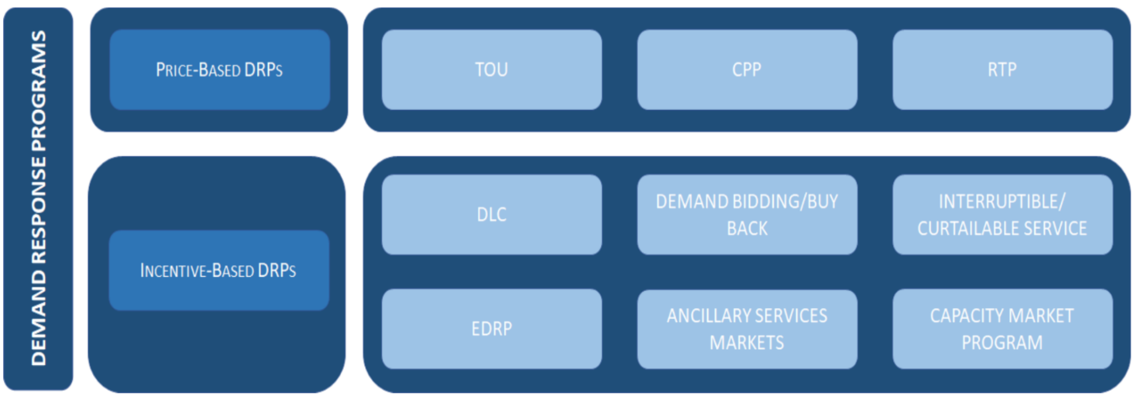

Figure 2.2 - Illustration of several DRPs.

In this condition, the best decision is to apply the EDRP to reduce the load supply by interrupting a major part of the large consumers' load for a small duration and the consumers usually run their backup power in this period. Besides this, there is another way to maintain the energy system's reliability and stability, which is implementing bulk load shedding. Consumers' load is being curtailed instead of offering them monetary incentives. The above-mentioned incentive-based programs are not the only available DRPs. Other incentive-based programs were created to meet various kinds of consumers in different conditions such as capacity markets, service markets, and demand bidding/buyback programs [18].

2.1.2- Energy Hubs for Multi-Energy Systems Management

An exact definition of an energy hub can be given as written: A unit that has the capability of conversion, storage, and management of multiple energy carriers [27]. Another definition of energy hub which is more precise is introduced in [28]. In this paper, an energy hub is defined as an interface that manages the inputs and outputs of the energy carriers as well as converting and storing them. Therefore, an energy hub is the main component of the MESs.

The energy hub concept was developed by a team at ETH Zurich through the VOFEN project. In this project, the future's energy market design for the next 20-30 years had been created through a greenfield design of the energy system, that is to assume no effects of legacy infrastructure [29]. The project's main highlights are written as follows [30]:

1. To gain more benefits from various energy carriers, a movement toward MES is required.
2. The energy system is required to implement non-hierarchical structures.
3. Energy systems are required to be more interconnected and more integrated.

M. Geidl et al presented the important outcomes of the VOFEN project in [27] which led to the above-mentioned goals. The first concept is an energy interconnector, and the second concept is an energy hub. According to the definition of an energy interconnector, several energy carriers are combined into just one transmission system for long-distance [31]. In the VOFEN project, the energy hub is defined and presented as follows: The energy hub is a direct or indirect interface that exists between the demand side and generation side as well as the storage and transmission devices in various models and it manages one or different energy carries.

In [32] the authors propose a nonlinear model for the combined power flow optimization in the presence of several energy carriers including electricity, gas, and heating systems that are based on the energy hub concept. They introduced a matrix as the model of an energy hub to simulate an optimization model for optimal power flow in the energy hubs. Thus, the main energy hub framework is provided in [33] with the aim of MESs management.

Several reasons encourage employing MES instead of single energy systems. For instance, in [34], the utilization of the MESs will lead to sufficient improvement in the operation of a microgrid. Moreover, employing the energy hub in the energy system in [35] would improve the balance between energy generation and demand as well as help to smooth the total load profile of the consumers through the implementation of the Stackelberg game approach.

The importance of energy hubs is described in [36], where the authors state that one of the solutions to increase the efficiency of the system, as well as a decrease in the operational investment costs, is to move toward MESs through energy hubs due to interdependency that both electricity and natural gas have with each other.

In addition, the MESs' characteristics are dependent on several parameters such as cost, emissions could provide availability of optimal dispatch of various energy sources, electricity, and gas. Thus, the utilization of the multi-generation systems can be more efficient by the EH employment instead of the conventional energy system. Since it can optimize energy usage, enhance efficiency as well, and decrease the amounts of the system costs and emissions. In some recent works, such systems are also defined as integrated EH [37]. Moreover, two other significant advantages of the MESs are listed as follows:

1. Increase in the system's reliability: The reliability of the MES is more than the single energy system as the system is not dependent on only one source of energy. On the other hand, the individual energy systems' reliability could be decreased since the availability of the loads is still high.

1. The EH supply will be optimized through the additional degree of freedom. Since it is possible to characterize the inputs of the EH based on their availability, costs, emissions, and other related factors. Hence, the dispatching of the EH's inputs will be more optimal based on these characteristics [27].

2.1.3- Demand Response in the Energy Hub Systems

In this section, a specific focus is placed on the operation of DR within Energy Hubs. Firstly, the methods used to model the DRP and the Energy Hubs are discussed, and then following this, the different optimization techniques most used are presented.

2.1.3.1- Modelling

Energy hubs could be modeled in two types in the power system. One of these methods is the energy flow method [38]. This type of energy-hub modeling is depicted in Figure 2.3. Accordingly, the equations could be obtained from the usual power system's energy flow. In these models, the inputs of the EH are the electricity and the natural gas and on the other side, the output ports can provide the electrical, heating, and cooling energies simultaneously. In this type of modeling, several types of energy carriers are coupled together. Thus all the energy balancing equations such as electrical, cooling, and heating have to be taken into account simultaneously [39].

The other approach for modeling energy hub equations utilizes concepts related to graph theory and is termed matrix-oriented energy hub modeling [41]. In this method, energy converters are being utilized to convert different types of energy. To model the EH based on the matrix-based framework, it is necessary to define some of the following components in advance. These components are energy flow resistance, node, graph, branch, branch-node incidence matrix, and branch energy flow impedance matrix.

The definition of these components is described in [42]. For instance, to model DR in this approach, [42] considered some assumptions that are required: $P_{l,j}^{DR}$ indicates the j-th load branch after DR. Therefore, the directed graph of the EH using this approach can be depicted in Figure 2.4.

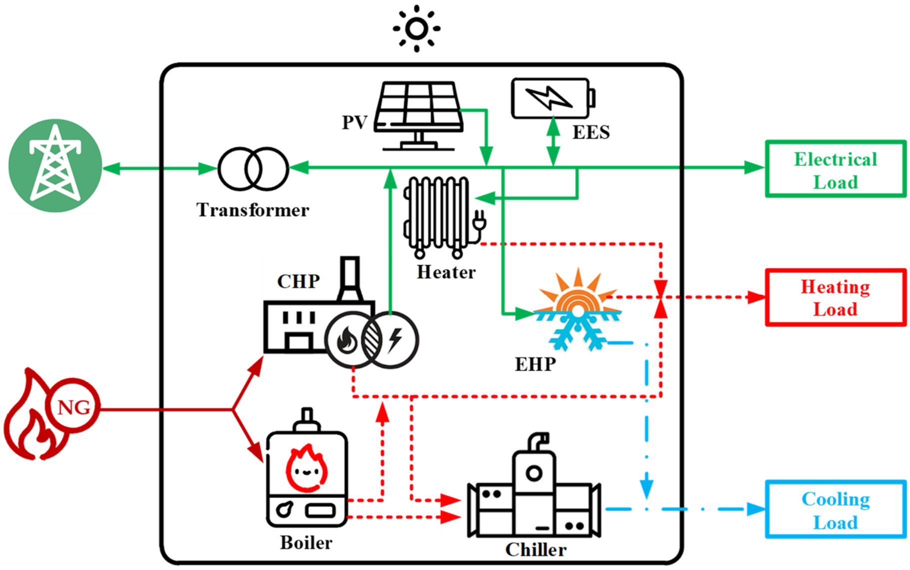

Figure 2.3 - Illustration of the EH modeled based on energy flow [40].

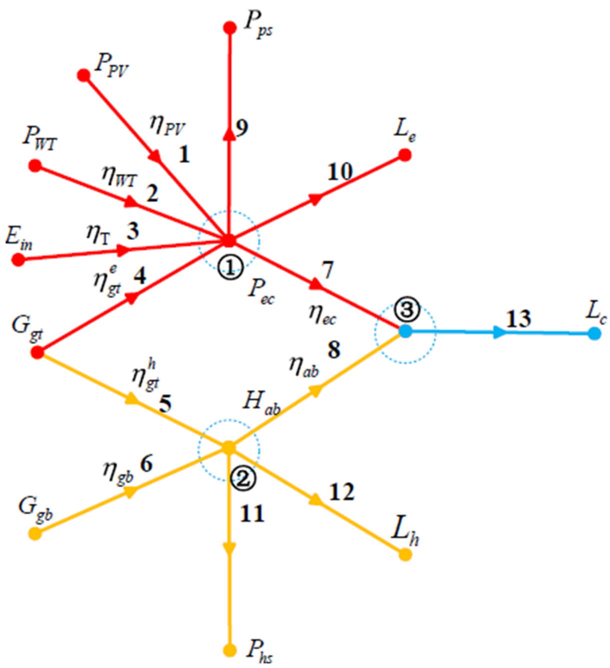

Figure 2.4 - Illustration of the EH modeled based on the matrix approach [42].

It must be noted most of the models dealing with DR in the EH are proposed by the first method, i.e., energy flow. For instance, in [43], the authors proposed an MES through energy flow method that consists of the heat recovery boiler, heat exchange device, micro gas turbine, gas boiler, electric boiler, absorption chiller, electric heat pump, electric energy storage and heat energy storage, wind turbine, photovoltaic unit. In this work, flexible DR for the electrical and heating loads is implemented. Similarly, the energy flow is used in [44] in the MES model and considering DR to provide more flexibility for the consumers. The DR program that is applied in this study uses TOU. Considering three periods during a day, i.e. peak, valley, and flat hours.

2.1.3.2- Optimization

There have been several methods and algorithms that could be employed in the models to find the solution for the problems defined. In [37], since the model was a bilevel optimization scheduling model, The proposed optimization operation model is a non-linear problem that is formulated in two levels. There are some main approaches to finding the solution such as the branch and bound method, Karush-Kuhn-Tucker (KKT), penalty function method, etc. In this work, it is possible to determine the decision variables within the bounds of the constraints after some simplification. Thus, the KKT conditions for the lower level of this model can be utilized as the upper level's constraints. Therefore, the bi-level model is being transformed into an equivalent single-level problem. Likewise, the solution that is considered in [45] leads to binary mixed-integer linear programming problems. To manage the coupling variables in the constraints, a binary variable is considered. In this work, linear interactive and general optimizer (Lingo) software is being used to find the optimal solution.

Some heuristic methods were applied as the solution method to find the optimization point. For instance, a Stackelberg Game Approach is taken in [35]. Another heuristic approach that can also be employed to find the best solution is a genetic algorithm. In [46], the authors search for the best price in the microgrid through a genetic algorithm.

In general, two separate objectives can be modeled. These are maximizing the benefit to the participants, mainly through maximizing their profit, or the other aim is to minimize their cost.

- Benefit Maximization

In some models, the optimization aims to maximize the profit For instance, the objective of [47] the electricity utility company is to maximize its profit. The proposed optimization model of [48] comprises two objectives one of which is maximizing the profit. The objective function is to maximize the expected aggregator's profit [49].

- Cost Minimization

There are some studies in this field in which their optimization goal is minimizing the cost. In [50], minimization of the incentive payment is introduced as the objective function of this optimization problem., while considering the load-shaving constraints. The main objective of the [51] in the upper level is minimizing the total operation cost of the EH while maximizing the exergy efficiency in the lower level. The cost minimization of the considered energy system in [52] is the main aim of this optimization problem considering the amounts of electricity and heat loads, energy carriers' tariffs, converters' efficiency, and the starting time of the costumers' preferred appliances. The MES is based on the minimum system costs.

2.1.4- The direction of the research

This section will examine the most recent studies that have a focus on DR in MES and present a synthesized overview of the current state of the art. Following this, a bibliometric study was carried out to investigate the emerging trends within the MES and DR research area.

2.1.4.1- The main contributions of the studied works

The area of DRP in multi-energy systems has been receiving increasing interest from the scientific community in recent years, as can be seen in Figure 2.5. This figure shows the number of studies published in which their main area is the application of DRP in multi-energy systems. Based on this figure, the number of publications is increasing in an exponential trend after 2016, which clearly shows the current relevance of the topic.

The type of publications dealing with DRP in multi-energy systems is illustrated in Figure 2.6. From the figure, it is possible to see that the largest number of works are published in scientific journals, i.e., more than 60 % of the reviewed works. However, there are other types of publications like presenting the proposed DR models in international conferences, books, and as well as PhD dissertations.

Each one of the existing publications focuses on different aspects, combinations of sources and technologies, from ME systems and DRP as well as approaches and models. A set of works in recent years are now discussed, having been classified according to the main area of the chapter, which ME sources are considered, and the presence of distributed energy resources (DER), plugin electric vehicles (PEVs), electrical storage systems (ESS) and Hydrogen storage.

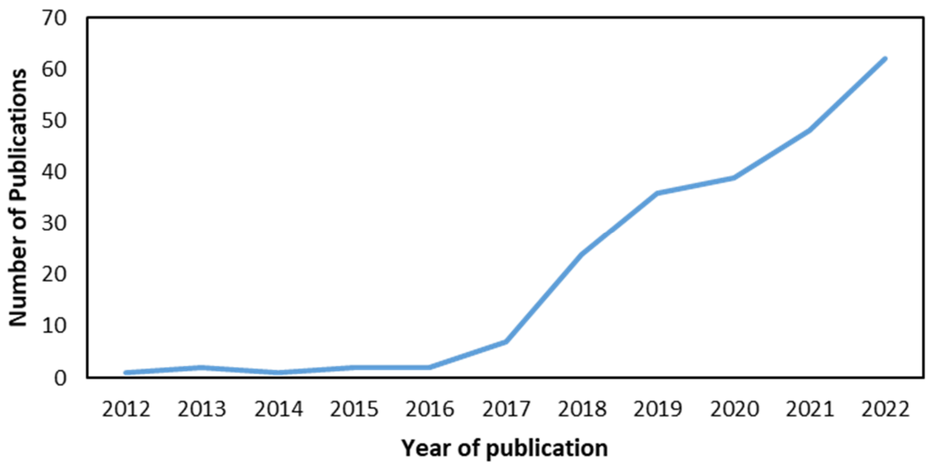

Figure 2.5 - Year of the studied publications.

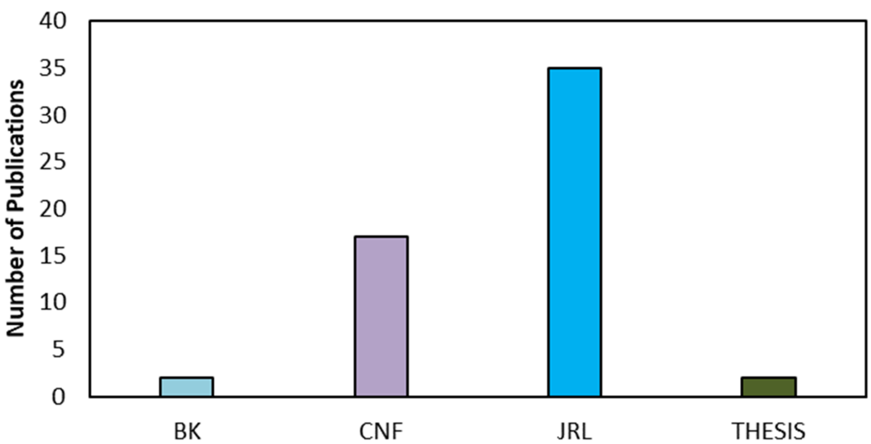

Figure 2.6 - Type of the studied publications.

For each work, the focus and the respective contributions area are highlighted. Also, the simulation environments of the optimization model of the models that utilize DR in the multi-energy carrier systems are described. The models can be carried out in several programs such as the General Algebraic Modelling System (GAMS), MATLAB, etc.

Tables 2.1 and 2.2 present a summarized list of all the publications analyzed for this review. The papers have been classified according to the type of energy carrier analyzed in the chapter. These were grouped into five separate groups. Group A [35,39,42,48,51–54,57–61,63,64,67,69,71,72,74,79,80,83–85,88]contains the paper which considers power, heat, and gas. Group B [34,38,44,45,65,66,68,70,72,75,77,78,82,86,87] includes those papers that considered heat, power, gas as well as cooling. In Group C [37,46,50], papers considered power heat and cooling were considered. Group D [55,62] considered power and heat and Group E [47,76] considered power and gas.

Most of the works which consider power, heat, and gas consider the presence of DERs and ESS as is the case of [54], [58], and [59]. In [54], a mathematical formulation for the optimal planning of a developed energy hub considering operation constraints is presented. The EH is constructed by a Transformer, Combined Heat and Power (CHP), Boiler, and Thermal Storage (TS). The EH is developed by Wind Turbine (WT), Energy Storage (ES), and DR programs. The hub input energy carriers are electricity, gas, and water. The authors in [58] focus on the optimal operation of a multi-carrier energy system in the presence of a wind farm, electrical and TS systems, electrical and thermal DR programs, the electricity market, and the thermal energy market. Stochastic programming is implemented for modeling the system uncertainties such as demands, market prices, and wind speed. In [59], a risk-constrained scenario-based two-stage stochastic method to solve the smart energy hub scheduling problem is presented. The smart energy hub scheduling model would determine the least-cost 24-hour operation of CHPs, boilers, and storage systems that would satisfy electrical and thermal demands.

The set of works with power, heat, gas, and cooling follows the same approach as the previous group, but in these, the MES model considers the presence of cooling systems, some examples are the works presented in [65], [66], [70]. In [65] a long-term configuration and sizing model with an integrated DR to determine the optimal size options of the components of an energy service company's energy hub is developed. In this paper, the concept of DR is applied to heating, and cooling loads, which are curtailable and shiftable is applied to enhance economic efficiency and system flexibility.

This modified version of the integrated DR program is denoted as integrated DR. The paper offers an approach for the energy service company to evaluate the probable cost including the investment and operation portion. The authors in [66] present a residential energy hub model that receives electricity, natural gas, and solar radiation at its input to supply the required electrical, heating, and cooling demands as the output. Augmenting the operational flexibility of the proposed hub in supplying the required demands, an inclusive DR program including load shifting, load curtailing, and flexible thermal load modeling is employed. In [70] the optimal scheduling of a smart residential energy hub (SREH) considering the uncertainties of electricity market prices, electrical demands, thermal demands, cooling demands, and solar radiation is presented.

In the group of power, heat, and cooling the works do not consider gas in the models as can be seen in [37], [50], and [46]. An example of this group is [50] where an interactive dispatching strategy based on demand-side bidding and multi-energy coordination for a virtual power plant (VPP) to provide system reserve is developed.

The VPP with flexible load and CCHP allow for the interactive dispatching strategy based on demand-side bidding and multi-energy coordination, which could achieve a certain load curtailment plan by taking advantage of CCHP and interruptible load. The remaining groups, power and heat ([55], [62]) and power and gas ([47], [76]) have these systems as a base, however, they address or integrate additional energy carriers as is the case with EVs in [55] and [62].

Table 2.1 — The most recently studied works - part one

Ref.	Main Area of research	Simulation Environment	Cool	Heat	Power	Water	Gas	DER	PEVs	ESS	Hydrogen Storage
[34]	EH	GAMS	×	×	×		×	×	×		
[35]	DR	MATLAB		×	×		×				
[42]	EH	MATLAB		×	×		×	×		×	
[53]	EH	GAMS		×	×	×	×	×		×	
[37]	EH	MATLAB	×	×	×	×		×		×	
[54]	EH	GAMS		×	×	×	×	×		×	
[55]	ME	MATLAB		×	×			×	×	×	
[56]	EH	NA			×			×			×
[57]	ME	NA		×	×		×	×			
[58]	EH	GAMS		×	×		×	×		×	
[59]	EH	GAMS		×	×		×	×		×	
[60]	DR	MATLAB		×	×		×	×		×	
[61]	ME	GAMS		×	×	×	×	×		×	
[62]	DR	GAMS		×	×	×			×		
[52]	DR	NA		×	×		×	×			
[63]	EH	GAMS		×	×		×	×		×	
[64]	EH	MATLAB		×	×		×			×	
[47]	DR	NA			×		×				
[65]	EH	MATLAB	×	×	×		×	×			
[66]	ME	MATLAB	×	×	×	×	×	×	×	×	
[67]	EH	GAMS		×	×		×	×		×	
[68]	EH	GAMS	×	×	×		×	×		×	
[69]	EH	GAMS		×	×		×	×			
[70]	EH	GAMS	×	×	×		×	×			
[71]	DR	MATLAB		×	×	×	×				
[72]	ME	MATLAB		×	×		×				

Table 2.2 — The most recently studied works - part two

Ref.	Main Area of research	Simulation Environment	Cool	Heat	Power	Water	Gas	DER	PEVs	ESS	Hydrogen Storage
[73]	EH	MATLAB	×	×	×		×				
[74]	ME	MATLAB		×	×		×	×	×	×	
[75]	DR	NA	×	×	×		×	×			
[50]	EH	NA	×	×	×						
[76]	DR	MATLAB			×		×	×			
[77]	ME	GAMS	×	×	×		×	×		×	
[78]	EH	GAMS	×	×	×		×	×		×	
[79]	DR	GAMS		×	×	×	×				
[51]	EH	GAMS		×	×		×	×		×	
[80]	ME	NA		×	×		×			×	
[81]	EH	MATLAB		×	×		×	×	×		
[82]	ME	NA	×	×	×		×	×		×	
[83]	EH	MATLAB		×	×		×	×			
[84]	EH	GAMS		×	×		×	×		×	
[85]	ME	GAMS		×	×		×	×			×
[45]	ME	LINGO	×	×	×		×	×		×	
[46]	HE	MATLAB	×	×	×			×		×	×
[48]	DR	GAMS		×	×		×	×			
[86]	ME	NA	×	×	×		×	×		×	
[44]	ME	NA	×	×	×		×				
[87]	DR	MATLAB	×	×	×		×				
[38]	ME	GAMS	×	×	×		×				
[88]	DR	GAMS		×	×		×	×		×	
[39]	EH	GAMS		×	×		×	×	×	×	

In [62] the paper proposes a method for short-term coordination of combined desalination, heating, and power systems, where the participation of aggregated PEVs in water-heat-power nexus is optimally scheduled. Real-time DR programs are implemented on water, heat, and electricity loads. The authors in [55] focus on optimizing a multi-energy hub that includes renewables, dispatchable energy sources, and energy storage with the vehicle-to-grid (V2G) interacting with the grid with a pricing scheme based on TOU. A stochastic model is used for modeling V2G-based DR. A new line of research can be seen in [56] and [85], where hydrogen storage systems are considered in the MES model. In [32] a self-regulating DR management mechanism is presented. Deferrable electrolyzers are used as a main controllable resource in a hydrogen-based clean energy hub, which includes a traditional generation plant, a low-carbon generation plant, and wind energy.

Based on the hysteresis control model for aggregated electrolyzers, a comfort-constrained optimal energy state regulation control strategy is implemented to model the deregulation feature of aggregated electrolyzers.

In [85] the optimal energy management of an energy hub designed to simultaneously minimize the operation costs and emissions (inside and outside the hub) in the presence of WT and DR is addressed. The hydrogen network is considered one of the main networks connected to the energy hub, and the hydrogen demand is included as one of the energy hub's outputs. Optimal management of the energy hub including hydrogen storage, thermal DR, power-to-hydrogen, hydrogen-to-power, and gas-to-power facilities, as well as the WT, is addressed to reach the lowest cost and the lowest emissions.

2.1.4.2- Trending Keywords in the Area

To better understand the underlying trends in the studied literature, a scientometric analysis was conducted. VOSviewer, a well-known scientometric analysis software, was used to better understand the relationships present within the studied literature. In this analysis, a total of 75 academic articles were studied using VOSviewer 1.6.15 [89]. A total of 173 keywords were identified and the most prevalent keywords are shown in Figure 2.7 below.

As is expected the DR and energy hubs are the main keywords. Integrated DR is also prevalent in several articles. This can indicate that utilization of the integrated DR in the MESs is also one of the most recent works that are being done in several studies [87,90]. From Figure 2.7, the different colors used in the figure represent the year of publication with the most recent publications shown in yellow while the older publications are shown in purple.

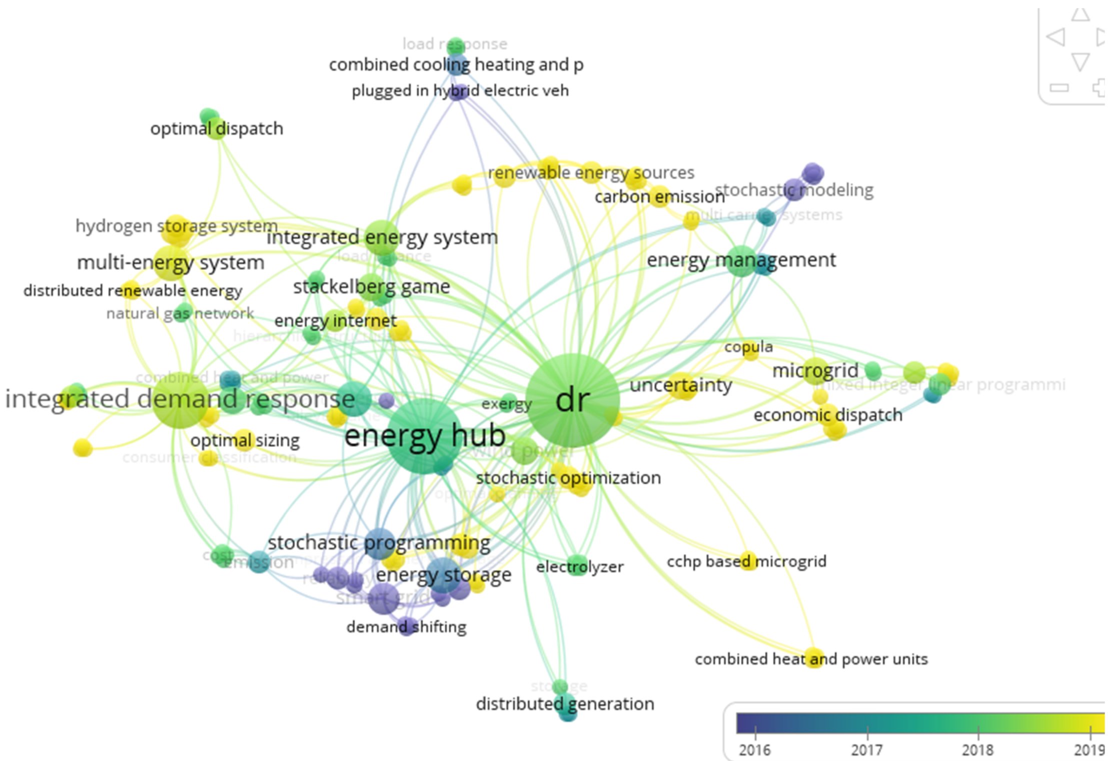

Figure 2.7 - Main keywords and the temporal relationship between them.

2.2- Energy Storage Technologies in Multi-Energy Systems

Now we are going to analyze the ESS technologies and their application in the energy system with a focus on MES as well. Energy storage is an important element of an energy system. In the power system, energy storage can be defined as components that can be employed to generate a form of energy or utilize previously stored energy at different locations or times when it is required. Energy storage can enhance the stability of the grid, increase the reliability and efficiency of integrated systems that include renewable energy resources, and can also reduce emissions. A diverse set of storage technologies are currently utilized for energy storage systems (ESSs) in a varied set of projects.

This chapter provides information about the current ESS projects around the world and emphasizes the leading countries that are developing the applications of ESSs. The main categories of ESSs are explained in this chapter as follows: electrochemical, electromechanical, electromagnetic, and thermal storage. Moreover, energy storage technologies are utilized in power grids for various reasons such as electricity supply capacity, electric energy time-shifting, on-site power, electric supply reserve capacity, frequency regulation, voltage support, and electricity bill management. Additionally, by integrating the various energy forms and developing the concept of multi-energy systems, ESS has become a fundamental component for the efficient operation of multi-energy systems. The main role of ESSs in multi-energy systems is to compensate for the fluctuations in power output from renewable energy resources. Moreover, the performance of the multi-energy system increases when it is integrated with an ESS. Thus, ESSs play an essential role in multi-energy systems. These storage systems not only allow for the balancing between fluctuations in energy supply and demand but can also offer important means to convert energy from one form to another. This ability of energy storage systems to store energy across time, location, and energy type greatly increases the flexibility of the integrated energy systems [91]. This chapter provides a comprehensive overview of energy storage technologies being applied to multi-energy systems and shows how these emerging technologies and systems play a critical role in any future energy system. Expectations are that the need for energy storage systems will triple by 2030 [91].

As the energy system evolves into one dominated by intermittent renewable energy sources, energy storage systems have experienced a massive increase in research and development from both academic and commercial developers [92]. This has led to immense reductions in cost and improvements in system efficiency and this is expected to continue in the near-term future. Despite these improvements, there still needs to be further development in this sector. This can be done through a combination of deployment-led innovation and active policies and regulations that shape research and development [93].

The breadth of energy storage applications is rapidly accelerating and is shown in the emerging sector of hybrid or multi-energy systems energy systems. These are systems that combine various renewable energy, traditional energy sources, and storage systems which complement each other to develop energy systems that take advantage of each of the component systems [92]. Within MES, energy storage technologies can be applied at nearly all scales and timeframes [94]. Each of the different energy storage technologies has its advantages and disadvantages and the exact combination of technologies for a given application should be carefully studied to ensure that the full potential of energy storage systems in multi-energy systems is harnessed [95].

This part of the chapter introduces the concept of energy storage and discusses the various types of energy storage systems. Recent projects using energy storage systems are highlighted to show the diversity of applications of energy storage systems. Then the concept of multi-energy systems is discussed briefly, with a detailed focus on the application of energy storage technologies to multi-energy systems.

2.2.1- Energy Storage Definition

In the energy system, an important component is energy storage. Within the power system, energy storage can be defined as a component that can be employed to generate a form of energy or store energy for use at a different time or location. Applications of renewable energy resources around the world have developed and increased exponentially due to their advantages over traditional energy resources such as power plants that use fossil fuels. Despite these advantages, the fast growth of renewable energy resources has brought some challenges to the power system as well.

One of the main issues of renewable energy resources is intermittent generation which is dependent on many factors such as solar irradiation, wind speed, and direction among others [96,97]. These factors lead to fluctuations in electricity generation from renewable energy resources. Utilization of ESSs can address this issue and play a complementary role for renewable energy resources to create a reliable and sustainable energy system.

The top countries in terms of installed ESS projects or those to be built are shown in Figure 2.8. The total capacity of ESS in these 20 countries is approximately 198 GW [98]. According to this figure, the US is the country with the highest capacity of ESS. The US has around 57.3 GW of ESS capacity [98],[99]. China and Japan are the second and third places with 31.7 GW and 28.1 GW of capacity, respectively. If we take a deeper look at Figure 2.8, there is a major difference in the capacities of these three countries relative to the remaining 17 countries. For instance, Germany's ESS capacity is 8.3 GW which is around four times lower than the ESS capacity of the US. This can indicate that ESSs are considered an important component of the energy system in the US, China, and Japan. The dimensions of Germany and Japan are almost the same; however, the ESS capacity of Japan is much greater than Germany. However, the observed data shows that the dimensions of the country have a positive relation on the ESS capacity on most of the cases.

Another important observation from Figure 2.9 is related to the share of ESSs on each continent. For instance, in Asia and Australia, considering China, Japan, India, South Korea, Taiwan, and Australia, the ESS share is equal to 72.5 GW. In European countries, this figure is 56.4 GW of ESS capacity which includes Spain, Germany, Italy, Switzerland, France, Austria, United Kingdom, Portugal, Ukraine, Russia, and Poland. North America has 62.1 GW of capacity which includes the US and Canada. Finally, South Africa is the only country from Africa that is listed in the top 20 countries with an ESS capacity of 2.8 GW. Therefore, Asia and Australia are the leading followed by North America and then Europe.

The ownership type of the current ESS projects is given in Figure 2.10. As shown in this figure, there are five main categories of ESS ownership. Most of the ESS projects are Investor-Owned projects which means that they belong to the investment companies that are developing the project.

A total of 640 projects are being implemented and managed by their investors. Public-owned ESS projects are in second place and then, Federally-Owned and State/Municipal-Owned are next. 188 projects are considered to be Publicly-Owned projects and there are 53 projects which are owned by Cooperatives. In Figure 2.10, two projects fall outside of the above-mentioned categories. In other words, their ownership does not belong to the public, state, investor, or other above-mentioned categories.

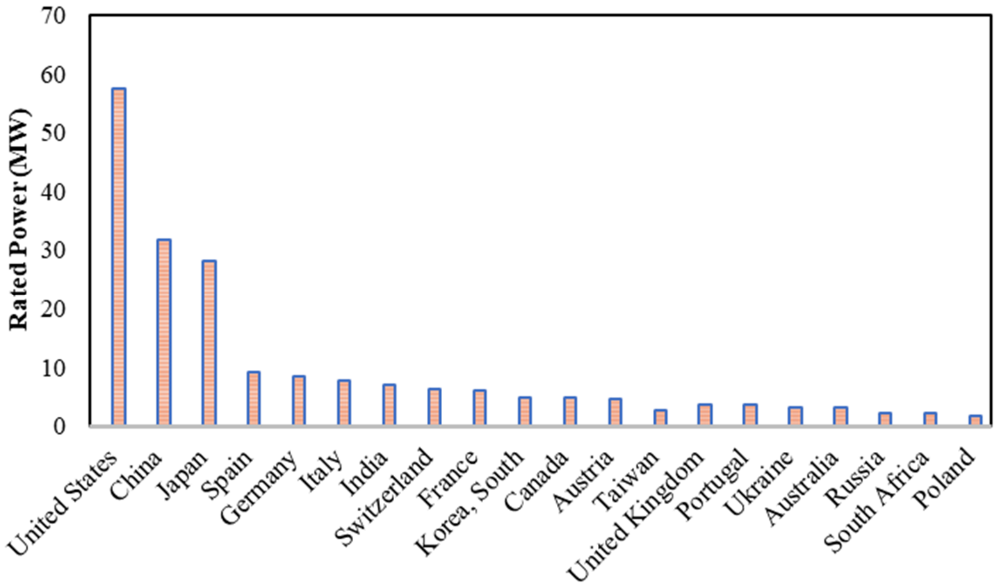

Figure 2.8 - Top countries in ESS capacities [98].

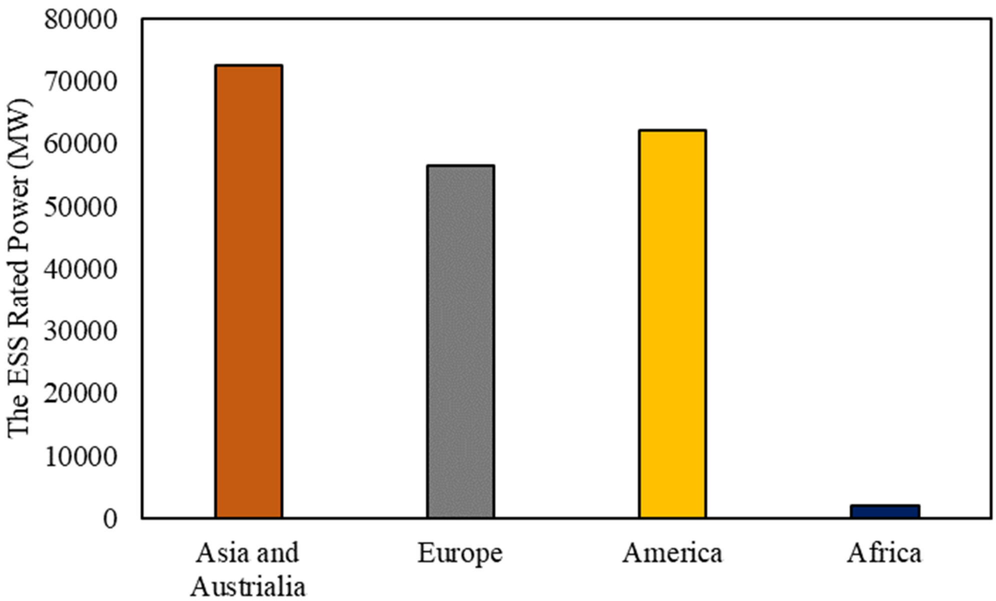

Figure 2.9 - The cumulative capacity of ESS of each continent [98].

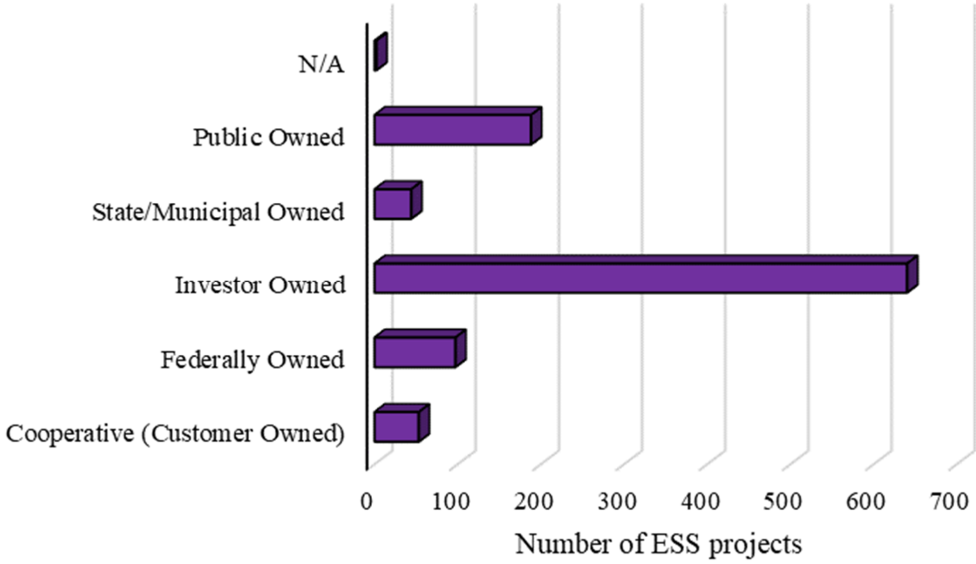

Figure 2.10 - Type of the ESS ownership [98].

2.2.2- Different types of energy storage systems

Many different technologies are being utilized for current ESS projects. The classification of these technologies is dependent on many factors such as the purpose of energy storage. For instance, they can be classified according to their operation duration, or type of function [100,101]. Electrical and thermal are the main types of energy that are being stored. The different energy storage technologies are listed in Figure 2.11.

In this list, the main storage systems are as follows: mechanical storage, pumped hydro storage, lithium-ion battery, liquid air energy storage, lead-carbon, hydrogen storage, electromechanical, electrochemical, and thermal storage systems [102–109]. According to the information provided in the literature, electrochemical energy storage systems are the most popular and common storage technology [100]. There are currently at least 998 projects around the world that are categorized as electrochemical energy storage systems [98]. Pumped hydro storage technology is another common type and there are more than 350 projects which employ pumped hydro storage technology. A total of 220 projects are using thermal storage technology according to the information shown in Figure 2.11. However, some technologies are less common and popular for companies that are designing and implementing energy storage technologies for the energy network. These less common technologies are liquid air energy storage and lead-carbon technologies [105,106].

Based on a report from the US Department of Energy, the global capacity of energy storage systems is equal to 191.2 GW in 2020 and this is a 12% increase compared to 2017 [110]. Table 2.3 shows the cumulative capacity of energy storage systems for each type of energy storage technology. According to this table, electrochemical systems have the greatest capacity of rated power among all currently available storage technologies at 118.2 GW. Lithium-ion batteries are also becoming an important source of energy storage due to their application in the electric vehicles section.

Then, the pumped hydro storage with 51.8 GW captures the second-greatest cumulative rated power capacity. The lithium-ion battery is also becoming an important source of energy storage due to its application in the electric vehicles sector [111]. Next in terms of installed capacity, there is pumped hydro storage with 51.8 GW of rated power capacity.

It should be noted that in this chapter, energy storage systems are classified into four main categories which are electrochemical energy storage, electromechanical energy storage, electromagnetic energy storage, and thermal energy storage as depicted in Figure 2.12. Each category will be introduced and explained in the next sections.

Table 2.3 — The rated power of each ESS technology

ESS Technology	Rated Power (GW)
Electrochemical storage	118.2
Compressed Air Energy Storage	1.6
Electromechanical	4.5
Hydrogen Storage	1.3
Lead-carbon	0.02
Liquid Air Energy Storage	0.33
Lithium-Ion Battery	1.7
Pumped Hydro Storage	51.8
Thermal Storage	12.5

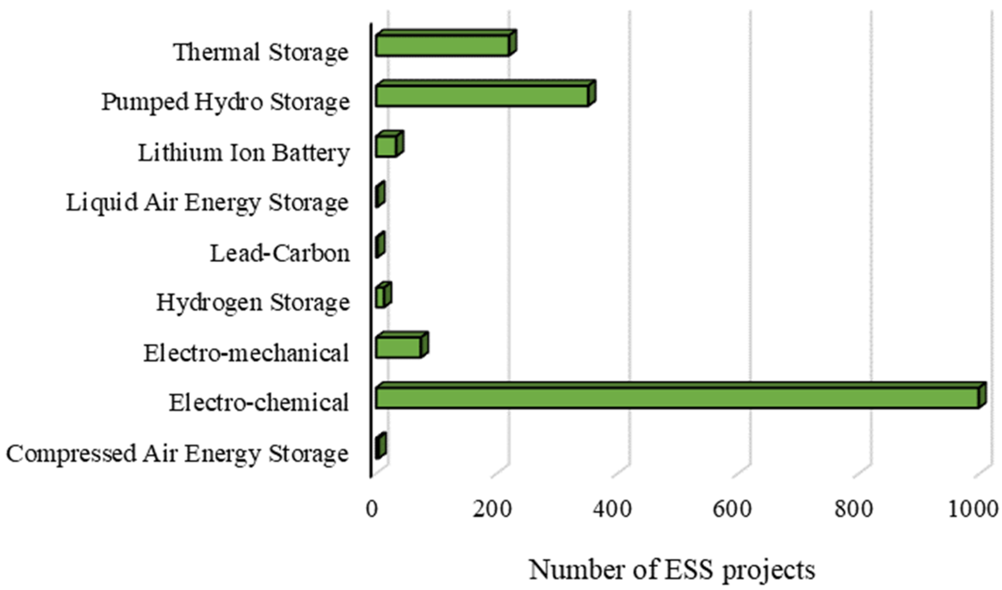

Figure 2.11 - The various ESS technologies [98].

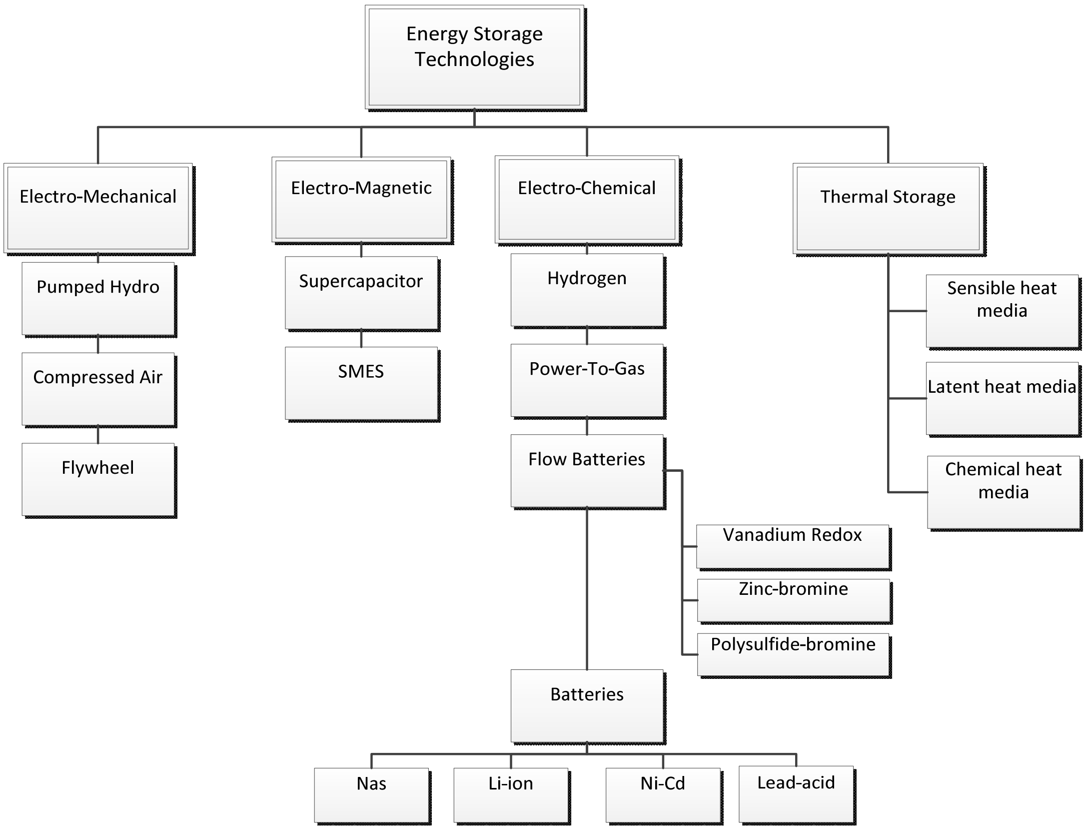

Figure 2.12 - The main classification of energy storage systems [112].

2.2.2.1- Electromechanical energy storage systems

The most established ESS in high-power applications is Pumped hydroelectric storage (PHS) which has been used since the 1890s. PHS is a sustainable energy source, with the flexibility and storage capacity to improve grid stability [113]. PHS is operated in low-demand periods, extra energy is used from the grid to pump water from a lower to an upper reservoir. Low-cost surplus off-peak electric power is normally used to run the pump. In high-demand periods, the opposite occurs with water flowing from the upper reservoir to the lower one and turning a turbine to generate electricity to export to the grid. The gravitational potential energy of the stored water determines the energy storage potential [112]. PHS allows energy from renewable sources like solar and wind, or excess electricity from sources like coal or nuclear, to be saved for periods of higher demand. PHS is a suitable technology for small autonomous island grids and large-scale energy storage. The energy efficiency of PHS is approximately 70 to 80% [113].

Another type of mechanical energy storage is compressed air energy storage (CAES). It also has a relatively simple operating principle. Air is compressed by an electrical compressor and this compressed air can be stored in suitable storage vessels. Electrical energy is changed to the potential energy of compressed air. An air turbine expands the air and it releases back the energy to the grid [114]. In comparison with other energy storage systems, CAES has a large storage capacity, low self-discharge, and a long lifetime [115]. These characteristics make CAES very suitable and cost-effective for bulk energy storage systems. In advanced CAES projects, the efficiency has been improved (around 70%-80% efficiency) [116]. A vast amount of compressed air can be stored underground so, CAES can provide a large amount of the world's future energy storage demands [115].

Another common type of electro-mechanical storage technology is flywheels [117]. Flywheels consist of a massive rotating cylinder, attached to a shaft, which is supported on a stator. The cylinder rotates and stores kinetic energy. The flywheel is connected to a motor generator that interacts with the grid through advanced power electronics. When the system is utilized as a motor and a generator, it is charged and discharged, respectively. Nowadays, some magnetic bearings are used to decrease friction and shear. To maintain efficiency, the flywheel system is operated in a vacuum to reduce drag. Low maintenance, long lifetimes, and low environmental impacts are some of the advantages of flywheel energy storage systems. Flywheels are more applicable to short-term storage systems as the self-discharge rate is nearly 20% of the hourly stored energy [112]. Flywheel energy storage systems are good choices for various applications in power systems such as power quality improvements, power smoothing, renewable energy integration support, and stability improvements [118].

2.2.2.2- Electromagnetic energy storage systems

One of the systems used to store the energy electromagnetically is supercapacitor. It is made from electrochemical cells containing two electrodes, an electrolyte, and a membrane. The porous membrane provides an area for the ions to transfer between the electrodes. No chemical reaction occurs in supercapacitors in contrast to what happens in batteries. Supercapacitors store the energy in the cells electrostatically. The anode contains negative charges, the cathode contains positive charges, and the electrolyte contains both. By applying a voltage to the electrodes, an electrical double layer forms in the vicinity of the anode and cathode. The electric field created by these double layers is where the energy is stored [112]. Because of the fast charge/discharge and high power density, supercapacitors are applicable as supplementary energy sources in electric vehicles, consumer electronics, and industrial fields. However, due to their fast self-discharge and low energy densities, supercapacitors are not suitable as primary power sources [119]. To overcome the issues, some improvements are needed in configuration, electrode material, and electrolyte.

Another system for storing energy in a magnetic field is superconducting magnetic energy storage (SMES). SMES system stores energy in a magnetic field. This magnetic field is generated by a DC current traveling through a superconducting coil [120]. The wire is made of a superconducting material that is cryogenically kept cold so the electric current passes through the coil with almost zero resistance. This allows the energy to be stored in the system for a longer period. Normally the superconducting material can be mercury, vanadium, and niobium-titanium. To discharge the stored energy in an SMES, the conductive coil is connected to an AC power convertor. SMES systems are very efficient storage systems (around 90 % efficiency), but they have very low energy densities and they are still far from being economically lasting [120,121].

2.2.2.3- Electrochemical energy storage systems

Hydrogen energy storage is a form of electrochemical energy storage in which electrical power is converted into hydrogen by an electrolyzer [122]. Later, this stored energy can be released by using the gas as fuel in a combustion engine or a fuel cell [123]. Electrolysis of water is a simple process to produce hydrogen.

The efficiency of water electrolysis depends on the technology, the hydrogen production rate, and the pressure level [112]. Most commonly, hydrogen is stored as a compressed gas in a container. Also, it can be stored at very low temperatures as a cryogenic liquid. Some other methods like metal hydride materials or chemical hydrides can be used to store hydrogen. In this method, the hydrogen is bonded to a material and it can be released as required. Hydrogen can be utilized as fuel in gas turbines, piston engines, and hydrogen fuel cells. Hydrogen energy storage systems can provide much longer duration storage compared to batteries [123].

Battery Energy Storage Systems (BESS) are a family of technologies developed for storing electric charge by using batteries. In most of the energy storage systems with batteries, electrical energy is converted into chemical energy and vice versa. Redox, reduction, and oxidation reactions occur in the battery cell. Each battery consists of two electrodes, an electrolyte, a separator, and a container. The electrolyte is a material in which the ions can be transferred between the anode and cathode, and the redox reaction can take place. This electrolyte is an electronic insulation material. The separator prevents internal short circuits of the battery from occurring and the container is needed to enclose and protect the battery cell [112].

Battery energy storage systems have the advantages of a small footprint and no restrictions on geographical locations where they could be located. Other storage technologies such as PHS and CAES are only suitable for a limited number of locations. For instance, topological conditions, long development time, and large land use are the main constraints in the development of PHS projects [124]. Batteries are of various types such as Lithium-ion, Lead-acid, Sodium Sulfur, Zinc bromine, and Flow.

2.2.2.4- Thermal energy storage systems

Another form of energy storage is thermal energy storage (TES). In thermal energy storage systems, thermal energy is stored by heating or cooling a storage medium [125,126]. The stored energy can be released later for power generation and other demands where it can generate steam for electricity production [93]. In this storage system, different materials with different thermal properties can be used and various results can be achieved. TES systems are commonly used in buildings and industrial processes. Solar thermal systems are the most common application in TES systems. There should be a heat-sensitive material in a solar power plant like molten salt. The solar field gathers the energy from the sun and heats the molten salt. A heat transfer fluid is heated up by the hot salt through a heat exchanger and then a turbine (connected to a generator) is spun using this fluid. Even if there is no sun, the turbine can be run with the heat stored in the molten salt [112].

2.2.3- Advantages of storage in the energy system

The energy storage technologies are employed in power grids for various reasons [127–129]. The most common advantages of the application of energy storage systems are given in Table 2.4. In this table, the various services that the storage technologies are being used for are listed in the first column. In the first row, the different storage technologies are given. Different storage services are electric supply capacity, electric energy time-shift, on-site power, electric supply reserve capacity, frequency regulation, voltage support, and electricity bill management.

Table 2.4 — The Energy Storage Systems Projects based on their storage type and services [98]

	Electrochemical	Electromechanical	Thermal Storage	Hydrogen Storage	Lead-Carbon	Liquid Air Energy Storage	Lithium-Ion Battery	Pumped Hydro Storage	Compressed Air Energy Storage
Electric Supply Capacity	100	4	0	1	0	0	0	302	2
Electric Energy Time Shift	267	16	84	1	2	1	1	325	3
On-Site Power	121	5	1	0	0	0	27	1	0
Electric Supply Reserve Capacity - Spinning	63	22	3	0	0	0	0	83	1
Frequency Regulation	225	34	6	3	0	1	1	66	0
Voltage Support	157	18	1	0	0	1	1	37	1
Load Following (Tertiary Balancing)	62	4	0	2	0	0	0	27	0
Black Start	51	2	0	0	0	0	0	15	0
Electric Bill Management with Renewables	105	3	2	1	0	0	3	1	0
Stationary Transmission/ Distribution Upgrade Deferral	44	0	4	1	0	0	0	0	0
Transmission Support	27	1	3	0	0	1	0	2	0
Renewables Capacity Firming	278	11	55	8	0	0	1	15	3
Renewables Energy Time Shift	202	17	62	6	0	0	28	18	3
Grid-connected commercial (reliability and quality)	81	4	3	0	0	0	2	2	0
Transportation services	51	1	0	2	0	0	0	0	0
Distribution upgrade due to solar	48	0	0	0	0	0	0	0	0
Ramping	54	4	1	1	0	0	0	5	0
Grid-connected residential (reliability)	47	0	3	0	0	0	1	0	0
Microgrid capability	170	9	1	0	0	0	26	0	0
Transmission congestion relief	20	1	3	1	0	1	0	3	0
Transmission support	27	1	3	0	0	1	0	2	0

According to this table, it is shown that electrochemical energy storage is broadly employed for electric energy time shift, frequency regulation, and renewable capacity firming. For example, 267 projects employ electrochemical energy storage systems for electric energy time-shift service. A total of 225 electrochemical energy storage systems are designed or operating for frequency regulation.

Furthermore, through the analysis of Table 2.4, it can be seen that the electric energy time-shift service is the only service that uses all types of energy storage technologies. Besides that, electrochemical storage is also being used for all of the power grid services. As there are no services that do not use an electrochemical type of energy storage. Electrochemical energy storage with 998 projects worldwide is the most popular storage technology that is used to supply one of the services to power grids.

According to data published by the US Department of Energy [98], 1698 projects are based on the development of the ESSs until 2020. Thus, the number of ESS projects in the top countries regarding the implementation of this technology is depicted in Figure 2.13. As illustrated in this figure, the US, by working on more than 740 projects is the world's lead country in this regard. China and Germany are in the next places by running 101 and 97 ESS projects, respectively. However, all of the projects are not in the operational phase. To present a better view regarding the applied ESS projects around the world, Figure 2.14. represents the current situation of the total ESS applications around the world. This figure indicates that there are 1363 projects out of 1698 whose design and construction are done and they are in the operational mode. This number is equal to almost 80 percent of all of the currently published ESS projects. 180 projects are also in the announcing phase and from this number there are 9 ESS that were announced but they were never built. More details about the current situation of the ESS programs can be found in Figure 2.14.

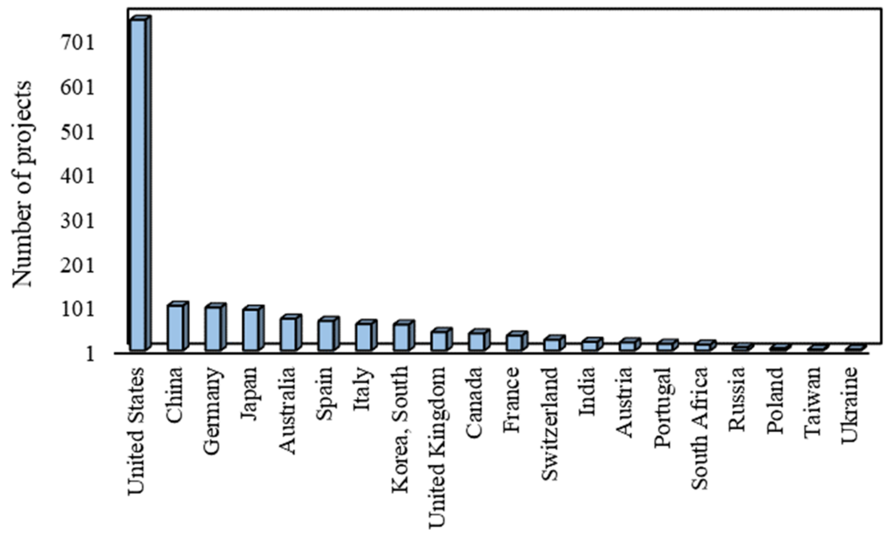

Figure 2.13 - Number of the ESS projects in the top countries [98].

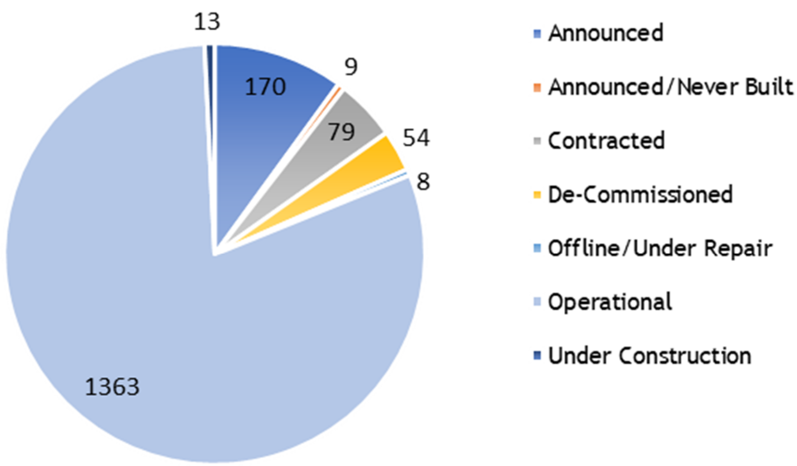

Figure 2.14 - The current situation of the total ESS applications around the world [98].

2.2.4- Energy storage technologies application in the multi-energy systems

The significance of energy storage systems in the power grid has been explained and discussed in the previous sections. ESS is expected to become more significant in future energy systems, especially in multi-energy systems [130].

The different forms of energy storage such as electrical and thermal are being combined in multi-energy systems. These multi-energy systems include several energy resources, including diesel engines, gas turbines, or renewable energy resources such as wind turbines, photovoltaics, etc. For optimal operation of multi-energy systems in the presence of various energy resources, the utilization of the energy storage system is one of the most important factors [131]. Energy storage can be installed at several points of the multi-energy system. It is common to install storage in the output sector of the energy hub.

An energy hub is defined as a place where the integration and management of several energy components such as production, conversion, storage, and consumption of different energy carriers in multi-energy systems occur [132]. While installment of the storage in the input side of it is also proposed in some cases. Thus, hydrogen and electrical storage can be installed on both sides of the hub, i.e., the input side or output side. However, thermal storage is usually employed on the output side of the hub. The usual structure of the multi-energy system in the presence of ESS is depicted in Figure 2.15. In Figure 2.15. (a)., a simple energy hub is drawn based on the definition which was provided in [30]. According to the concept of energy hub in this study, any structure that correlates the generation and the consumption sides through transmission, conversion, and ESS can be defined as an energy hub. In Figure 2.15. (b). more comprehensive structure of the multi-energy system is presented where demand can be supplied through electrical, cooling, and heating forms of energy.

The impact of storage size and forecasting period in the optimal operation of the multi-energy systems has been studied in [133]. This study proves that there is a reverse relation between the size of the energy storage system and the operational cost of the multi-energy system. In other words, larger energy storage will lead to a lower cost in the multi-energy system. However, the impact of the size of the energy storage is lower than the length of the forecasting horizon. A long forecasting horizon for energy storage can lead to a reduction in the costs of the energy hub. Moreover, Ivalin Petkov *et al.* proved that the application of ESS can reduce emissions by 90% in multi-energy systems which include renewable energy resources [69]. To better highlight the advantages of ESS in multi-energy systems, several applications of the energy storage systems are summarized in the following part of this section. To optimize the total operation cost of the energy hub and consider the uncertainty posed by the distribution system including electricity, heating, and cooling loads, power-to-gas storage with a tri-state compressed air energy storage system is proposed in [134]. Authors in [69] implemented a conditional value-at-risk approach for managing the uncertainties originating from wind power generation, electrical and thermal loads in a multi-energy system which utilizes a compressed air energy storage system to decrease the fluctuations caused by the renewable energy resources as well as increase the freedom of the multi-energy system's operator. An underground hydrogen storage system is proposed in [135] to minimize the CO_2 emissions in the context of an integrated energy system by developing a mixed-integer linear program optimization model which focuses on the dynamics of the stored energy during the hydrogen injection and withdraw processes.

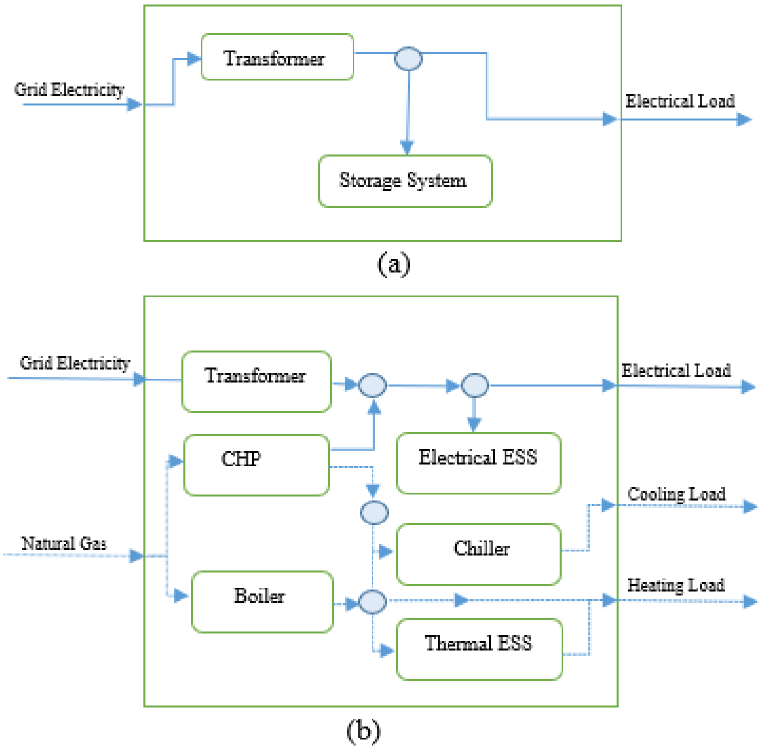

Figure 2.15 - Multi-energy structure in the presence of ESS [132].

The ESS is also a complementary component in the multi-energy systems for DR programs [136]. The goal of the operator from the employment of the DR programs is to meet the amount of the generation with the required load, especially during the peak period. The energy storage technology can also support this goal by providing a percentage of the demand to the consumers when there is a lack on the supply side and it is not possible for the consumers to participate in the DR programs. Therefore, the storage can be charged in multi-energy systems through the acquired DR during the off-peak period. This aggregated DR can be discharged in the multi-energy system during the peak period to meet the consumers' demand and reduce the pressure from the generation side. For instance, the authors in [137] presented an optimal model for the operation of an energy hub by utilization of renewable energy resources, DR programs, and energy storage systems. To provide more flexibility for the operation of the energy hub, several DR programs for the residential sector of the consumers such as shifting programs, and curtailing programs are proposed as complementary components of the energy storage system [66].

2.3- Conclusions

Due to the limited capabilities of the current power system, demand-side resources cannot be integrated very easily. DR helps to overcome these limitations and thus can help to integrate more demand-side resources. To capture the full potential of these resources, DRPs should consider various carriers of energy such as electricity and natural gas. This can be achieved through the use of Energy Hubs. This will help to maximize the benefits of DRPs and also minimize the side effects, such as consumer discomfort.

In this chapter, the main definitions of the DR, ESS, and multi-energy systems are reviewed. Then, the advantage of the energy hub over the conventional power system was addressed. Then, some recent modeling of the DR and ESS technologies in the energy-hub environment is studied. The comprehensive review that has been done in this work can be a reference for future research and improvements in applying the DR and ESS in the energy-hub systems. The emerging keywords that have been extracted from the studied works show that the “integrated DR” is getting more interest and is one of the main keywords that is linked to the energy-hub topic.

The work that has been done has identified some findings when it comes to implementing DRP in MES and these are as follows:

- The capability of converting between various forms of energy: Some limitations restrict the possibility of converting between the different energy carriers across time and for different consumers. For instance, there are some consumers with must-run loads that the only available form of energy is electricity. Therefore, it is not possible to participate in the DRPs through the reviewed works.
- For an optimization model, it is suggested to consider both consumer discomfort and profit at the same time. There have been some researches that only focused on decreasing the discomfort rate of the consumers participating in the DRPs in MESs. On the other hand, the main aim of some studies is to increase the profit of the consumers through their participation in the DRPs in the MES. However, there is a capability of developing models that consider minimizing the uncomforting rate of the consumers while increasing their profit from employing DRPs.

This work has gathered and summarized the most recent work concerning DR programs within MES. It has shown that there is a growing increase in the field and this is because of the several advantages that DR and MES can contribute to the future energy system. Both will be important as the energy transition takes hold and the combination of these two strategies can yield multiplicative advantages for both system operators and consumers. This work has provided a summarized foundation for future researchers to consult when working in this exciting and important field.

Additionally, in the context of ESS in the MES, by integration of the various energy forms and developing the concept of the MESs, one of the key components of multi-energy systems is ESSs. The main role of the ESSs in multi-energy systems is to compensate for the fluctuations introduced by renewable energy resources. In this chapter, ESS technologies in the context of multi-energy systems are presented and explained. Moreover, in the context of the multi-energy system, the storage unit can be installed on both sides of the input or output of the system as hydrogen and electrical storage can be installed on both sides, while, thermal storage usually is employed on the output side of the system. Moreover, it is shown that the ESS can also be a complementary component for the DR actions to provide more flexibility for the operation of the energy hub, especially during high consumption periods.

Chapter 3

Application of Opportunistic Information-Gap Decision Theory on the Trading Framework of A Demand Response Aggregator

After reviewing the most recent trends and In this chapter, a non-probabilistic program is proposed as a trading framework for DR aggregators. Both sides of the aggregator, including the upper side and downside of this entity, have been taken into account. On the downside of the aggregator, two popular programs are considered such as reward-based program and time-of-use (TOU) program, where DR is obtained from these resources. The acquired DR is studied to be traded in the day-ahead electricity market. To the aim of increasing the desired target profit of the risk-seeker aggregator, the opportunity function of information-gap decision theory (IGDT) is employed to address the uncertainty.

3.1- Introduction

The traditional solution of the independent system operator to mitigate the power misbalancing matters due to the peak periods was to rely on the generators. However, many solutions have been introduced and even employed in the power system. DR is being used as one of the main key solutions of the general demand-side methods in the smart grids [138] and [139].

Several studies have been done in DR to enhance the participation of the end-user consumers in the electricity market environment. Aggregation of the obtained DR from the demand side is known as one of these solutions. However, the willingness of the end-user consumers in the DR programs plays an essential role to this end.

Therefore, considering their behavior as one of the uncertain parameters in the model is one of the main motivations of this work. Besides that, to increase the effectiveness of the model, the aggregator needs to consider the uncertainty of the electricity market prices too. The DR aggregator (DRA) has an intermediary role in trading the obtained DR into the electricity market [140,141].

Two uncertain parameters are taken into account in this study, the participation rate of the consumers in the DR program and the electricity market prices. One of these uncertainties belongs to the demand side and the other one belongs to the other side.

Several DR programs are implemented in the smart grids which could be classified into two main categories, i.e. incentive-based DR programs and price-based DR programs [142–145]. To employ a comprehensive model, in this study, one DR program from each category has been defined, i.e. time-of-use (TOU) and reward-based DR (RBDR). Further, DR programs can be modeled for different types of loads.

For instance, in Ref. [146], the residential consumers are considered the main participators in DR programs. The authors in [147] investigate the feedback of the commercial and industrial loads participating in DR programs. To observe the effects of the proposed model on the loads, all types of consumers are assumed simultaneously, i.e. industrial, commercial, and residential.

To address the uncertain parameters, information-gap decision theory (IGDT) is applied as a risk measure, and its advantages in comparison with other methods like scenario-based models have been studied comprehensively in [148]. The employment of the IGDT method in various areas of the power system and smart grid is discussed in [149]. There are two main IGDT functions, robust function and opportunity function. The robust one is used for risk-averse decision makers and the opportunity function is utilized for risk-seeking purposes. Therefore, the behavior of a risk-seeker DRA is modeled in this work through opportunity IGDT.

The contribution of this work is studying the behavior of the risk-seeker DRA considering two DRPs, i.e. TOU and RBDR on the demand side of the aggregator and the day-ahead electricity market on the other side of it. Further, the uncertainty of both sides of the aggregator is taken into account. For the risk management of the problem, the IGDT method is applied.

3.2- Problem Formulation

First, it is supposed that there is not any uncertain parameter. In other words, we assume that the day-ahead market price and participation factor of consumers in the RBDR program are determined. This section is considered as deterministic formulation. Then, in the second section of formulation, the uncertainties are considered, i.e. day-ahead market prices and participation rate of the consumers in the RBDR program. The opportunistic IGDT model is being used to address the uncertainties.

The full description of the parameters, variables, and terms used in the problem formulation is presented in Table 3.1.

Table 3.1 — Indices, parameters and variables used in this chapter.

Indices	
t	Time horizon index
j	RBDR steps index
p	Period index
c	Consumer index
Parameters	
$\tilde{\lambda}^{DA}(t)$	Expected day-ahead market price [$/MWh]
$\widetilde{PR}(t)$	Demand-side consumers' participation rate in the RBDR program
$D_0(c,t)$	Initial demand of consumer c in time interval t
$E(c,t,p)$	Consumer c elasticity in time interval t in period p
$\lambda_0(c,p)$	consumer c initial price in period p
$\lambda(c,p)$	consumer c TOU price in period p
$d(t)$	Duration of each period
B_0	Deterministic expected profit of the DRA [$]
B_w	Desired target profit of the DRA [$]
σ	profit deviation factor
$\bar{P}_j^{RBDR}(t)$	load reduction step in the reward-based DR [MWh]
$\bar{R}_j^{RBDR}(t)$	Given reward in the reward-based DR [$/MWh]
Variables	
β	horizon related to uncertain parameter
$\tilde{\beta}$	The function of optimal opportunity value
$PR(t)$	Consumers' participation rate in the RBDR program
TOU(t)	obtained TOU volume from consumers within time horizon t [MWh]
$\lambda^{DA}(t)$	Day-ahead market price [$/MWh]
$P^{DA}(t)$	Day-ahead power[MWh]
Binary Variable	
$v_j^{RBDR}(t)$	The reduced load level in RBDR

3.2.1- The Deterministic Formulation

In this section, the deterministic problem formulation is written as follows:

$$B_0 = Max \sum_{t=1}^{T} P_t^{DA}.\lambda_t^{DA} - \sum_{t=1}^{T}\sum_{j=1}^{N_J} PF_t.P_{t,j}^{RBDR}.R_{t,j}^{RBDR} \tag{3.1}$$

$s.t$:

$$P_t^{DA} = P_t^{RBDR} - TOU_t \qquad ,\forall t \tag{3.2}$$

$$\text{TOU}_t = \sum_{c=1}^{N} D_0(c,t) \sum_{p=1}^{P} E(c,t,p)\left(\frac{\lambda(c,p)-\lambda_0(c,p)}{\lambda_0(c,p)}\right) \quad ,\forall t \tag{3.3}$$

$$P_t^{RBDR} = \sum_{j=1}^{N_J} PR_t.\bar{P}_{t,j}^{RBDR}.\nu_{t,j}^{RBDR} \qquad ,\forall t,\forall j \tag{3.4}$$

$$R_t^{RBDR} = \sum_{j=1}^{N_J} R_{t,j}^{RBDR} \qquad ,\forall t,\forall j \tag{3.5}$$

$$\bar{R}_{t,(j-1)}^{RBDR}.\nu_{t,j}^{RBDR} \leq R_{t,j}^{RBDR} \leq \bar{R}_{t,j}^{RBDR}.\nu_{t,j}^{RBDR} \ ,\forall t,\forall j \tag{3.6}$$

$$\sum_{j=1}^{N_J} \nu_{t,j}^{RBDR} = 1,\forall t,\forall j \tag{3.7}$$

$$P^{Min} \leq P_t^{DA} \leq P^{Max} \qquad ,\forall t \tag{3.8}$$

$$\nu_{t,j}^{RBDR} \in \{0,1\} \tag{3.9}$$

DRA must know its schedule for trading in the day-ahead market. It has to be noted that in this part, the DRA can predict the uncertain parameters, i.e. participation rate of consumers in the RBDR program and day-ahead market prices.

The objective function is indicated in equation (3.1) which is a profit-maximization problem. The 1st term belongs to the revenue that is gained from trading the DR in the day-ahead market. The second term refers to the cost of participation in the RBDR program. The power balance equation is considered in (3.2). The amount of power that is traded in the day-ahead market must be equal to the amount of obtained DR from consumers for each type of consumer and each time step. In (3.3), the TOU program is being defined. In this program, consumers receive different price tariffs during a day, for instance, two tariffs for two time periods: low-peak and high-peak.

Thus, the consumers' power usage is being regulated according to this change in the tariffs. $E(c,t,p)$ shows the elasticity of the consumer type c in the time step t and period p. The RBDR program is indicated in (3.4). As stated in Figure 3.1, the volume of the load reduction will be increased as the aggregator offers higher rewards to the consumers in a stepwise manner.
The total value of the reduced load based on the RBDR program is specified by P_t^{RBDR}. PR_t shows the participation rate of the consumers in this program, which is used as the uncertain parameter in this model and varies from 0 to 1.

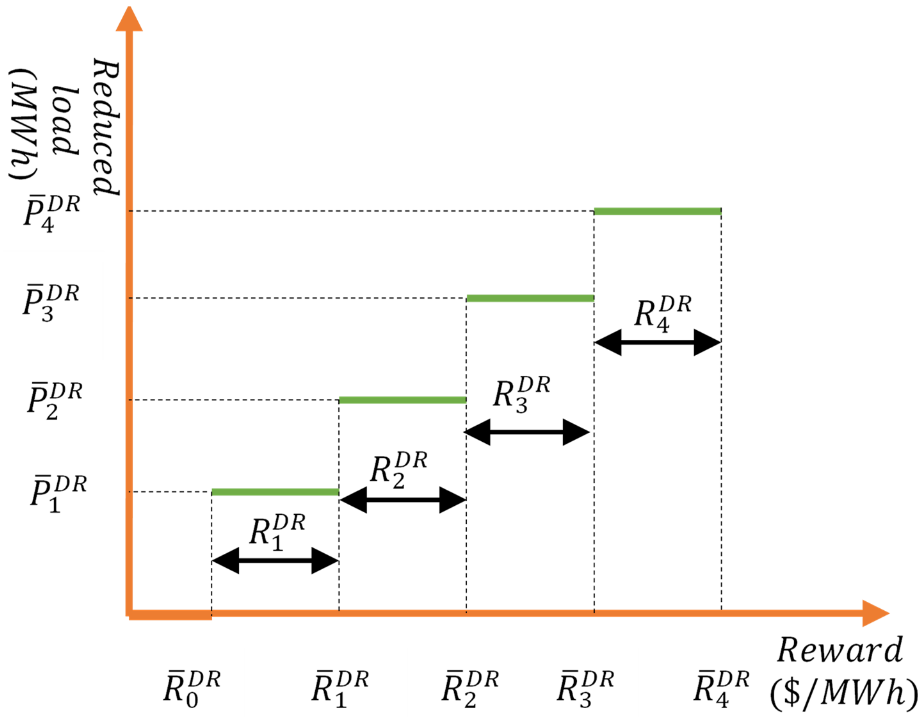

Figure 3.1 - The RBDR program curve.

High values in PR_t, show a high rate of participation of consumers in that time step. For instance, PR_t = 1 means that all the forecasted DR through the RBDR program is attainable. In (3.5), the total amount of reward in each time step based on the RBDR program is calculated. The level of the reward in each step j and each time t is shown in (3.6). Note that according to constraint (3.7), $v_{t,j}^{RBDR}$ is a binary variable and the aggregator can choose only one level j in each time step t.

As stated in (3.8), the aggregator can only trade an amount of λ_t^{DA}which is not less than its minimum or not more than its maximum capacity.

3.2.2- The Opportunistic IGDT Formulation

The opportunistic IGDT model is formulated in (3.10) - (3.16) as follows:

$$Obj\ Func: \quad \tilde{\beta} = \min \beta \tag{3.10}$$

s.t.

$$B^* \geq B_\omega = (1+\sigma).B_0 \tag{3.11}$$

$$P^{Min} \leq P_t^{DA} \leq P^{Max} \qquad ,\forall t \tag{3.12}$$

$$B^* = \{$$

$$Max \sum_{t=1}^{T} P_t^{DA}.\lambda_t^{DA} - \sum_{t=1}^{T}\sum_{j=1}^{N_J} PR_t.P_{t,j}^{RBDR}.R_{t,j}^{RBDR} \tag{3.13}$$

$$(3.2)\text{-}\ (3.9) \tag{3.14}$$

$$(1\text{-}\beta).\widetilde{PR}_t \leq PR_t \leq (1+\beta).\widetilde{PR}_t \qquad ,\forall t \tag{3.15}$$

$$(1\text{-}\beta).\tilde{\lambda}_t^{DA} \leq \lambda_t^{DA} \leq (1+\beta).\tilde{\lambda}_t^{DA} \qquad ,\forall t \quad \} \tag{3.16}$$

In this section, the uncertain parameters are taken into account. It is considered that the day-ahead market prices and the participation rate of consumers in the RBDR program the uncertain parameters. To address these uncertainties, the opportunistic IGDT approach is being implemented.

Note that the forecasted values of the uncertain parameters are available at the moment of modeling, i.e. $\widetilde{PR}_t$ and $\tilde{\lambda}_t^{DA}$. This program aims to minimize the horizon of the uncertainties (β) while the requirements are being fulfilled. In constraints (3.15) and (3.16) the uncertainties have been addressed.

The framework of this model is depicted in Figure 3.2. In the first stage, the model calculates the deterministic value of the objective function (the profit of the DRA). In this step, the forecasted values for the uncertain parameters ($\widetilde{PR}_t$and $\tilde{\lambda}_t^{DA}$) is employed to derive the deterministic results. In the next stage, by utilizing the deterministic profit of the aggregator and the profit deviation factor (σ), the uncertain parameters are addressed through the opportunistic IGDT method.

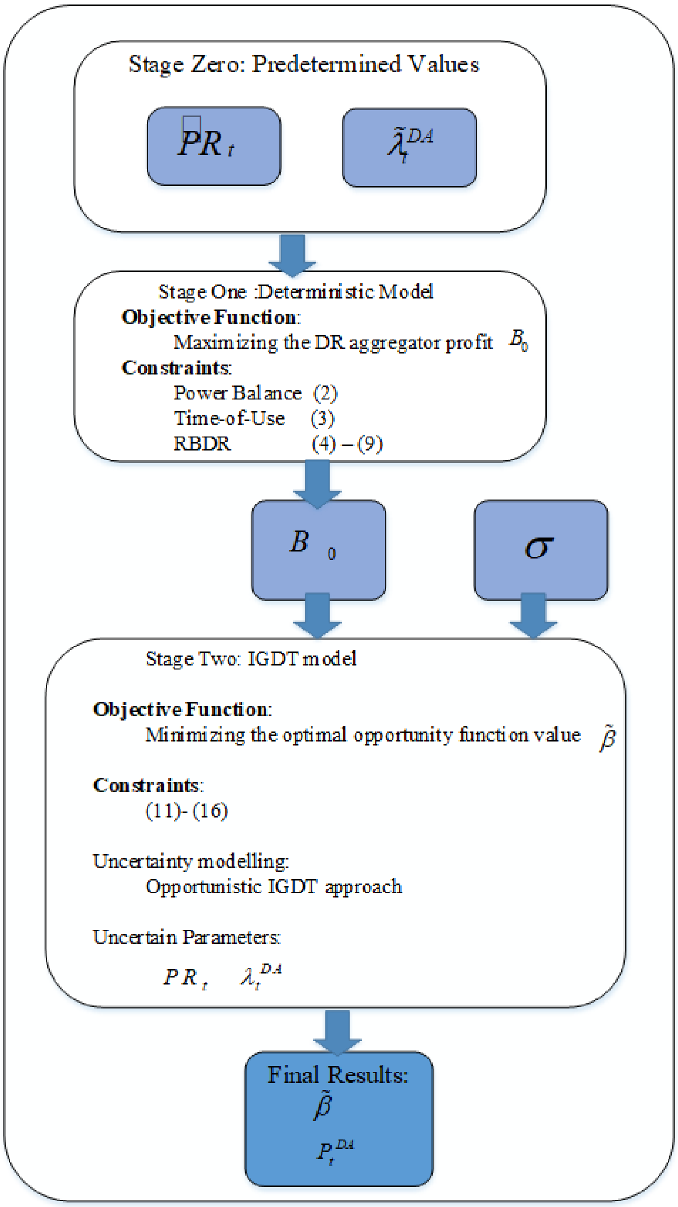

Figure 3.2 - The proposed model framework.

3.3- Case Study

This problem is a mixed-integer nonlinear programming (MINLP) model. As explained before, it aims to minimize the horizon of the opportunity function value while the constraints are satisfied or met. Various commercial solvers i.e. SBB could be used to solve this problem using General Algebraic Modeling System (GAMS) [150]. The model is simulated in a PC with 6 GB RAM and 2.43 GHz CPU speed. The model has 3745 variables and 3827 constraints and the simulation running time was less than a second, i.e. 0.9.

Reference [151] is used for implementing the load data. High-peak and low-peak periods are considered as periods for each day (p=2). The high-peak period is assumed from 08 to 22. Accordingly, from 23 to 07 is assumed as the low-peak period. Industrial, commercial, and residential are the types of consumers that are taken into account (c= 3).

The aggregator can offer the obtained DR from the end-user consumers during the high-peak period to the day-ahead market and vice versa during the low-peak. TOU and RBDR program is modeled on the lower side of the aggregator. The data regarding the elasticity matrix which is required for the TOU model is employed from [152]

As stated before, the profit deviation factor is utilized as the risk measure in the IGDT procedure. As the profit deviation factor increases, our model results become more risk-seeker. And σ = 0 gives the deterministic results of the programming. We change the σ from zero to 0.85. Each optimum value of the opportunity value is depicted in Figure 3.3. Higher profit deviation factors result in higher$\tilde{\beta}$.

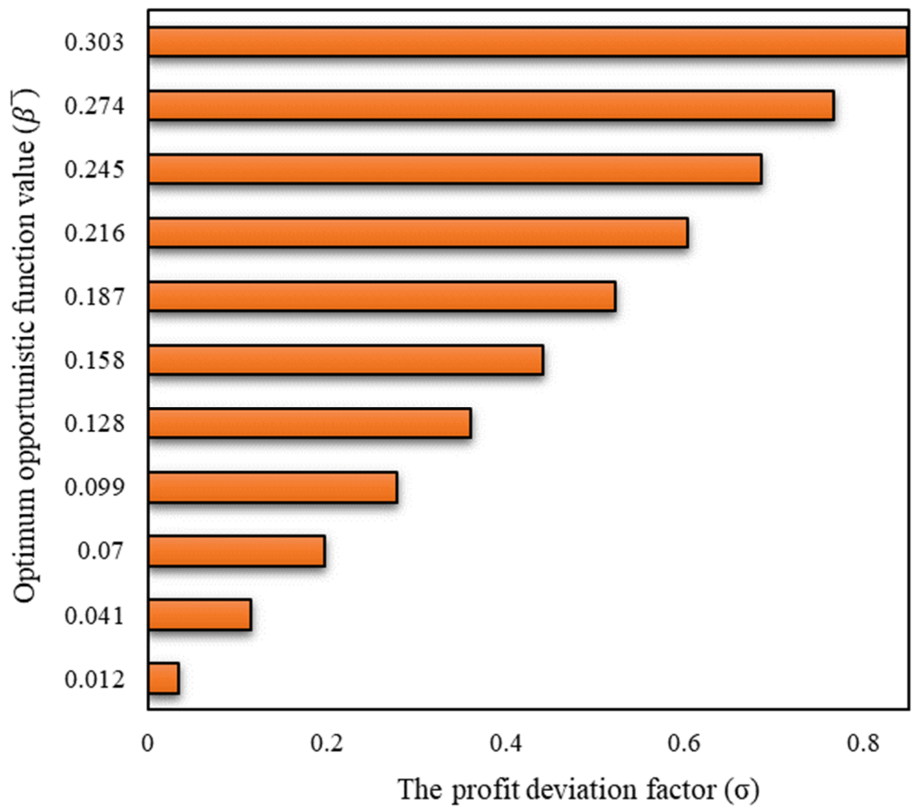

Figure 3.3 - Optimal opportunity function value for different profit deviation factors.

To investigate more in detail the results of the problem, an arbitrary value of σ= 0.15 is chosen. To gain the target profit $B_w = (1+\sigma).B_0 = (1+0.15).344{,}800 = 396500$, the$\tilde{\beta}$is 44% or 0.44, which means that if the observed uncertain parameters are 44% more than the forecasted values, the aggregator will gain $396,500.

The curve in Figure 3.4 indicates the results regarding the acquired DR through the RBDR program. During the high-peak period, the amount of DR which is obtained through this program is at its maximum when they are the usual work starting time (t=9 AM) and also the time that the night starts (t= 7 PM). Results from implementing the TOU program are demonstrated in Figure 3.5. As obvious in the figure, the amount of TOU in industrial consumers is much higher than the other consumers including residential and commercial. The industrial end-user plays the main role in the deployment of the TOU program.

The day-ahead traded power through the aggregator is also presented in Figure 3.6. During the high-peak period, the amount of power which is offered to the pool market is around 1000 kW in the early hours of the high-peak period. It is easily noticeable that the amount of the acquired DR from the consumers through RBDR and TOU programs is equal to the traded power in the day-ahead market, which proves the accuracy of the simulation.

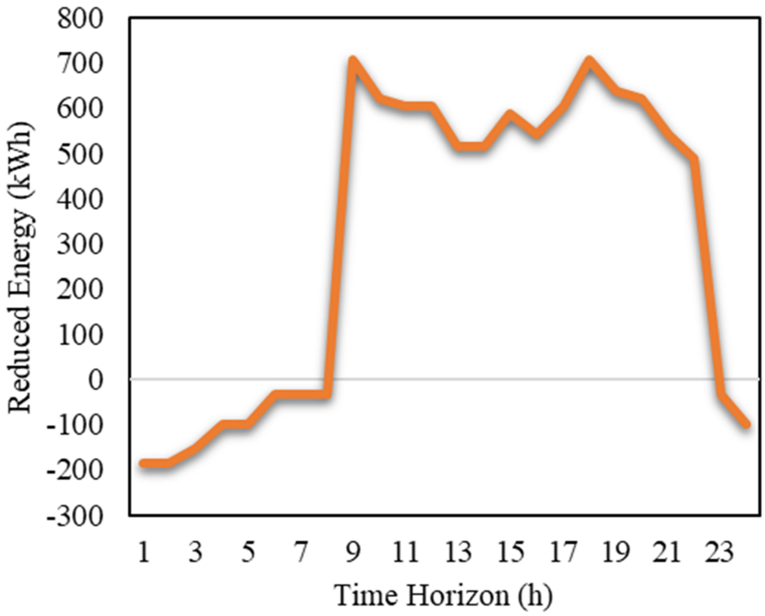

Figure 3.4 - Amount of reduced energy using the RBDR program.

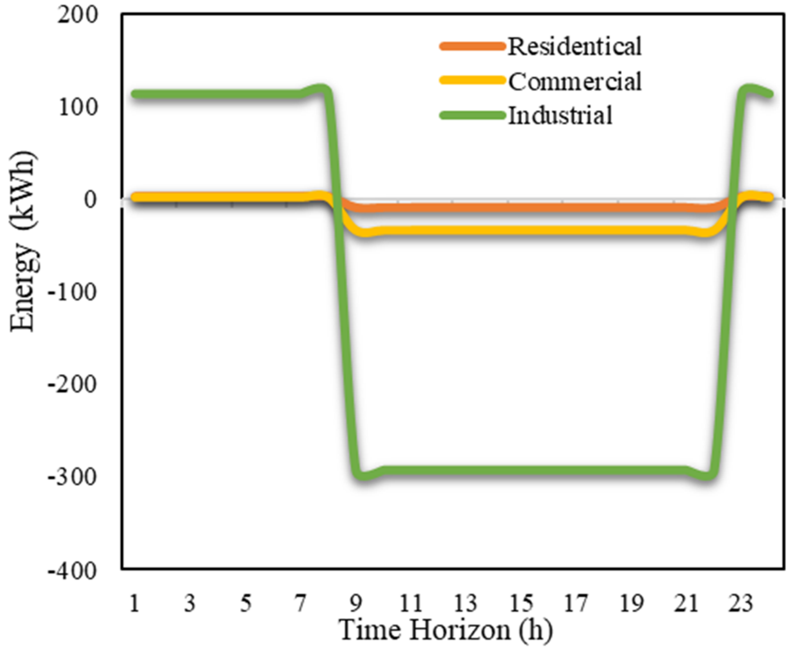

Figure 3.5 - The Impact of Implementation of Time-of-Use Program.

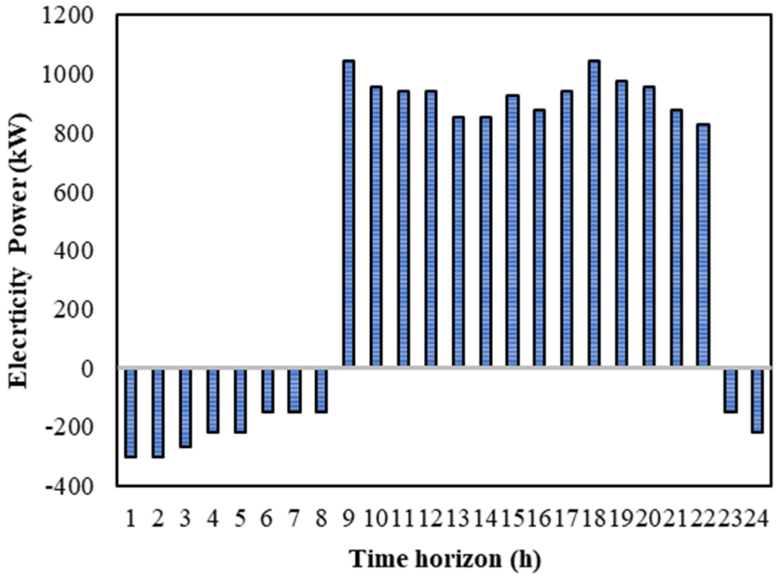

Figure 3.6 - The day-ahead traded power through the aggregator.

3.4- Conclusions

The behavior of a DRA is studied in the proposed model which tends to gain higher profits due to the favorable deviations of the uncertain parameters in the day-ahead electricity market. To this end, the opportunity IGDT method has been applied as a risk measure. Two uncertain parameters from each side of the aggregator (upper-side and down-side) are assumed simultaneously as follows: 1- the day-ahead market prices and 2- the participation rate of the consumers in the RBDR program. The model is simulated for various values of the profit deviation factors. The direct relation between the profit deviation factor and the optimum opportunity function value is shown in the results.

To analyze the model effects more in detail, one arbitrary value of the profit deviation factor is chosen and the correlated results are demonstrated comprehensively. The amount of the electricity power that is traded in a day-ahead market through the DRA is equal to the obtained DR from the consumers' side. Moreover, three types of consumers, i.e., industrial commercial and residential, industrial consumers play the main role in employing the TOU program.

Chapter 4

Novel Hybrid Stochastic-Robust Optimal Trading Strategy for a Demand Response Aggregator in the Wholesale Electricity Market

This chapter proposes a model to handle various uncertain parameters simultaneously to reduce their effect on the aggregator's operation through the development of a novel hybrid stochastic-robust optimization approach that incorporates the uncertainties around wholesale market prices and the participation rate of consumers. The behavior of the consumers engaging in DR programs is addressed through stochastic programming. Additionally, the volatility of the electricity market prices is modeled through a robust optimization method. Two DR programs are considered in this model to include both time-based and incentive-based DR programs, i.e., time-of-use (TOU) and incentive-based DR (ibDR) programs to study three sectors of consumers, namely industrial, commercial, and residential consumers. An ESS is also assumed to be operated by the aggregator to maximize its profit.

4.1- Introduction

4.1.1 - Background and Motivation

The power system has become increasingly dependent on the active participation of consumers as a result of the sharp increase in the use of distributed energy resources. Hence, managing this participation through the use of demand-side management techniques is essential to optimize the operation of the power system. The most effective solution for demand-side management is known as DR [153]. Various DR programs (DRPs) can be used to better balance the fluctuations in both the generation side and demand side. The two main categories of DRPs are price-based and incentive-based DRPs. Offering several DRPs encourages consumers to participate more actively and this leads to acquiring more DR potential for the aggregator to maximize the total profit through trading in the wholesale energy market.

Optimal DR scheduling by the aggregator should contain DRPs from both price-based and incentive-based programs to provide a degree of freedom for the consumers to choose the program that suits their individual needs and preferences, thus facilitating their engagement with the DRP. Price-based programs are designed to shift a percentage of the consumption by using variable energy usage tariffs to optimize the power system operation. An example is shifting the amount of demand from the peak period to the off-peak period or vice-versa. Incentive-based DRP aims to reduce or curtail consumption by offering an incentive (often financial) to the consumers who participate in such DRPs. The main goal of DRPs is to alter a consumer's energy usage profile and further incentivize them to engage in such programs. Implementation of DRPs reduces the energy consumption during peak periods while increasing the amount of energy usage during the off-peak periods [7].

Several challenges are posed to the DR aggregator as an intermediary entity in the power system. One of the main challenges is that the DR aggregator is that the aggregator has to manage various uncertainties posed by the market side and also the consumer side to reach its maximum profit. The aggregator should consider the uncertain behavior of the consumers during their participation in DRPs and also the uncertainty of the electricity market prices in order not to affect its profit negatively. To go more in detail, one of the significant challenges facing DRPs is how to incentivize the consumers to participate in the proposed DRPs and manage their correlating uncertainty. Individual consumers have a small amount of DR potential and this restricts their ability to directly trade their DR within the wholesale energy market. To resolve this issue, a DR aggregator is introduced into the energy system [154]. The DR aggregator's primary responsibility is to aggregate the obtained DR from individual consumers and trade the acquired DR into the wholesale market. Thus, two main sources of uncertainties exist, the behavior of the consumers in participation in DRPs and the electricity market prices. Another responsibility of the aggregator is proposing the DRPs to the end-users. The aggregator usually seeks to maximize its profit or minimize its costs from trading the obtained DR in the wholesale market [155]. Addressing these challenges seems to be essential.

4.1.2 - Literature Review

In recent years there have been various studies looking to optimize the operation of DR aggregators in wholesale markets considering the power system and consumers' constraints. Some of the most recent and closely related research on DR aggregators is included for context and to show how the current work extends the state-of-the-art. The DR optimization methods in the power system have been extensively reviewed in [18]. Examples of incentive-based DRPs include direct load control [156], load curtailment, demand bidding [145], and emergency demand reduction. On the other hand, the most common price-based DRPs are time-of-use (TOU), critical peak pricing, and real-time pricing [157].

According to the advantages of employment of various DRPs from both price-based and incentive-based categories, we have employed DRPs from both classifications, which provides more flexibility for the consumers. Additionally, studying the behavior of the DR aggregators in the wholesale market is also essential to improve the scheduling process of the aggregator [158]. For instance, the authors in [159] proposed a self-scheduling optimization program that considers a price-based DRP. Load uncertainty is addressed through a fuzzy method. The willingness of the consumers to participate in the DRPs is assumed to be uncertain. However, the uncertainty associated with the wholesale market is not taken into account.

In [160], a scheduling framework is proposed that uses stochastic programming and the alternating direction method of the multipliers algorithm. This model only considered the behavior of the residential consumers and neglected the other types of end-users. The uncertainties of the consumption side are managed. However, the uncertainties of electricity market prices are not assessed and these fluctuations are important for the scheduling.
Similar to the previous model, [161] only considered residential consumers and utilized stochastic programming methods for the uncertainty of load without considering market price fluctuations. Likewise, only industrial loads are studied in [162,163] without considering other types of consumers.

Several models only considered the uncertainty of the electricity market for DR frameworks [164], [165]. For instance, Abapour *et al.* proposed robust scheduling for a DR aggregator through game theory by the price uncertainty assumption [164]. Moreover, the authors of [165] formulated an optimal bidding strategy for an aggregator. The electricity price of the day-ahead market is managed as the risk factor. However, the uncertainties that are originating from the behavior of the consumers are not directly assessed. The behavior of the various uncertain parameters on each side of the aggregator could be modeled more realistic if the risk measure were selected based on the characteristics of the uncertain parameter. Moreover, a taxonomy table is presented in Table 4.1 to demonstrate the novelty of the work through a comparison of the proposed model with the recent similar works.

4.1.3 - Contributions and Chapter Organization

The above section shows that while exist several models that investigate the scheduling framework for DRPs, several research gaps have been identified. The major research gap is the inclusion of uncertainties associated with both the wholesale market and the uncertainties from the consumer side. Additionally, respecting the characteristics of the uncertain parameters is necessary for selecting the best risk management strategies.

Table 4.1 — The Comparison of The Proposed Method Vs. Similar Works

Ref	Study field	Uncertainty		Consumer Type*			Storage	Uncertainty model
		Market	Load	Res	Com	Ind		
[164]	DR Aggregator	×			Not classified			Robust
[166]	DR Aggregator		×		Not classified			Genetic Algorithm II
[167]	DER Aggregator		×	×			×	Robust
[49]	DER Aggregator	×			×		×	Stochastic
[168]	EV Aggregator	×			Not classified			Hybrid Stochastic-Robust
[169]	EV Aggregator	×	×		Not classified			Hybrid Stochastic-Robust
[170]	Retailers	×			Not classified			Stochastic
[171]	DR Aggregator	×	×		Not classified			Stochastic
[172]	DR Aggregator		×	×	×	×		Fuzzy
This work	DR Aggregator	×	×	×	×	×	×	Hybrid Stochastic-Robust

*Res: Residential, Com: Commercial, Ind: Industrial

For instance, in optimization models based on robust approaches, the robustness level of the uncertain parameter can be adjusted through the budget of uncertainty [173]. Based on the available characteristics of the load on the demand side, stochastic modeling is more effective as a risk measure [68].

In the proposed model the day-ahead market price can be forecasted by the DR aggregator based on the available price history. The main uncertainty of the market prices is due to the price fluctuations that could be addressed through an effective robust management method. On the other hand, stochastic programming can be employed to handle the uncertainty of the engagement ratio, as the participation ratio of consumers in the DRPs is known. Thus, a combination of both robust and stochastic approaches is proposed to model the aforementioned uncertain parameters. Another advantage of the proposed hybrid model is the mixed-integer linear problem which has a convex mathematical formulation.

Additionally, this model considers three types of consumers, industrial, commercial, and residential consumers, with different demand usage patterns, making the model more comprehensive.

Thus, the main contributions of the proposed model are summarized as follows:

- Proposing a hybrid mixed-integer linear programming (MILP) optimization framework for a DR aggregator that considers various uncertainties with different inherent characteristics of both the market and consumer sides through a combination of robust and stochastic methods, simultaneously.
- Proposing a hybrid robust-stochastic model that considers the stochastic and non-stochastic uncertain parameters to improve the scheduling of the DR aggregator and its risk-based operation.
- Providing more flexibility for the consumers regarding engagement in the DRPs by considering two types of DRPs and considering an energy storage unit for the DR aggregator.

The organization of the chapter is presented as follows. In the next section, the proposed hybrid stochastic-robust method is presented and explained. Section 4.3 presents the data used for the case study as well as the results of the simulation. Section 4.4 contains the conclusions drawn from the most important findings.

4.2 - The Proposed Hybrid Model

4.2.1 - The DR trading framework

In this section, the proposed DR framework is introduced and presented in detail. As mentioned before, this model uses a hybrid stochastic-robust optimization approach. Two uncertain parameters are addressed and managed through the combination of risk measures. The proposed DR framework is designed as follows.

On the demand side of the aggregator, there are three consumer sectors, namely residential, commercial, and industrial sectors. The aggregator manages the participation of consumers through two different DR programs, namely the TOU program and the incentive-based program. On the wholesale electricity market side of the aggregator, the day-ahead market is available. The aggregator can participate in the day-ahead market as a price-taker entity to trade its acquired DR. The proposed model is shown in the flowchart in Figure 4.1.

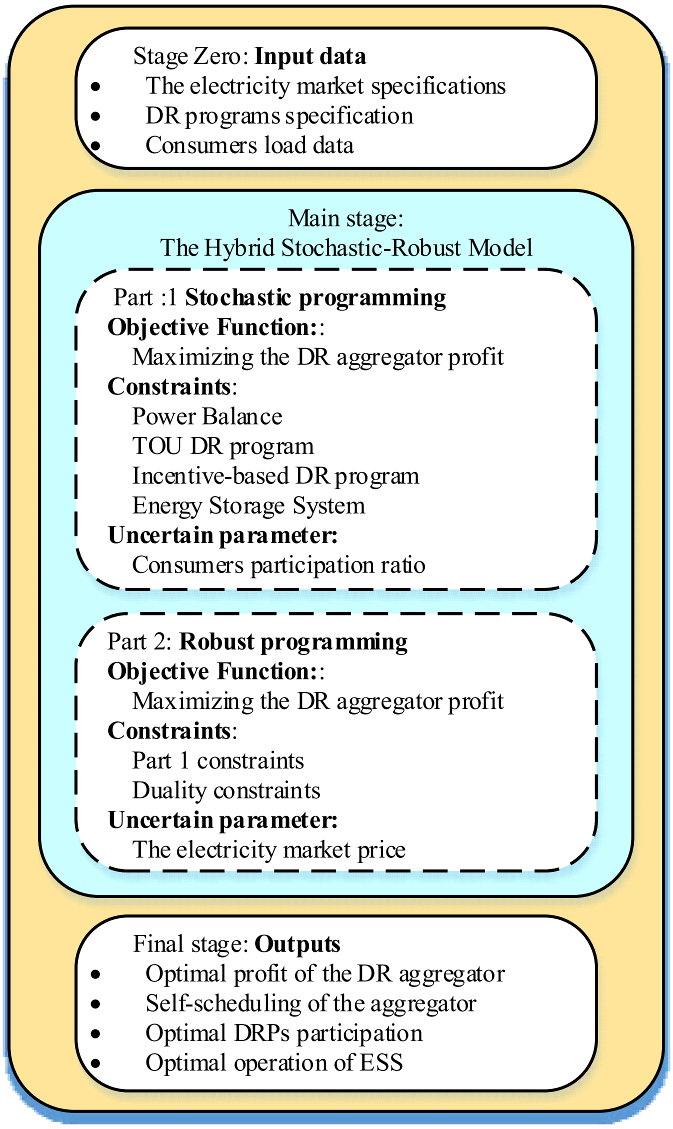

Figure 4.1 - The flowchart of the proposed DR trading procedure.

According to Figure 4.1, in stage zero, the input data are collected and employed, such as the electricity market specifications, DRPs specifications, and load data of the consumers who participate in this framework. The most significant sources of uncertainties that have the greatest impact on the profit of the aggregator are addressed and managed in this model which are the day-ahead market prices in the market side of the aggregator and the participation ratio of the end-users in the DR program in the consumption-side of the DR aggregator. Then, in the main stage, the combination of stochastic programming and robust optimization is considered. To do this, several scenarios for the participation ratio of consumers in the ibDR program are generated. In other words, the uncertainty of the consumers' participation ratio is managed and addressed through stochastic programming to maximize the DR aggregator's profit. In the stochastic phase, the uncertainty of market price is not considered. Then, the hybrid stochastic-robust model is introduced. The new uncertain parameter which is the electricity market price is considered to be accounted for through another risk measure that can indicate the effect of the electricity market on the profit of the aggregator, which is robust optimization.

Hence, both uncertain parameters are being managed through the hybrid stochastic-robust method. In the final step, the optimal result of the problem will be given and demonstrated. The full explanation of the hybrid model will be presented in the following sections.

4.2.2 - Mathematical problem formulation

The problem formulation of the hybrid stochastic-robust model is presented and described in this section. According to the first step of the flowchart depicted in Figure 4.1, the mathematical formulation of the stochastic programming is presented. This step is shown mathematically in (4.1) - (4.19). The problem is structured as a maximization model to achieve the highest possible amount of profit for the DR aggregator. In this section, the participation ratio is considered to be addressed through stochastic programming.

The full description of the parameters, variables, and terms used in the problem formulation is presented in Table 4.2.

The objective function is presented in (4.1).

$$
\begin{aligned}
Max: \sum_{\omega} \pi_{\omega} \Bigg[\sum_{t=1}^{T} (P_{t,\omega}^{DA,s} - P_{t,\omega}^{DA,b}) \lambda_t^{DA} \\
- \sum_{t=1}^{T} \sum_{j=1}^{N_J} PR_{t,\omega} P_{t,j}^{ibDR} R_{t,j}^{ibDR} - \sum_{t=1}^{T} \Bigg[\Bigg(P_{t,\omega}^{ESS,ch.} \eta_{ch.}^{ESS} \\
- \frac{P_{t,\omega}^{ESS,dis.}}{\eta_{dis.}^{ESS}} \Bigg) C_b^{deg.} \Bigg] \Bigg]
\end{aligned} \tag{4.1}
$$

The probability of each scenario is denoted by $\pi(\omega)$. There are four terms in the objective function. The first term, i.e., $(P_{t,\omega}^{DA,s} - P_{t,\omega}^{DA,b})\lambda_t^{DA}$, indicates the revenue and cost from selling and buying the acquired DR in the day-ahead market, respectively.

Afterwards, the next term that is denoted by $PR_{t,\omega} P_{t,j}^{ibDR} R_{t,j}^{DibDR}$, represents the amount of reward that has to be given to the consumers who participate in the ibDR program. This reward is paid to the consumers during the peak period and received from them during the off-peak period. Therefore, positive values for this term represent a reward for the demand reduction that is paid by the aggregator, being a potential revenue during off-peak periods due to the negative cost for the DR aggregator. Finally, the last term in this equation is related to the cost of the ESS that is operated by the aggregator to optimize its trading in the day-ahead market.

The ESS is being served if the amount of power that is going to be offered in the day-ahead market is greater than the available DR. This mismatch is being cleared through operating the ESS. Charging the ESS imposes costs on the aggregator, which decreases its total profit, while discharging the ESS entity will help and improve the aggregator's performance to gain more revenue. The energy balance constraint is presented in (4.2). The amount of demand that is traded in the day-ahead market is required to be equal to the amount that is obtained from the end-users through the ibDR and TOU programs and any shortfall would be compensated through the ESS. The negative value for $P_{t,\omega}^{TOU}$ is because of the nature of this program and is explained in more detail in the TOU constraint equations.

$$
P_{t,\omega}^{DA,s} - P_{t,\omega}^{DA,b} = P_{t,\omega}^{ibDR} + P_{t,\omega}^{ESS,ch} - P_{t,\omega}^{ESS,dis} - P_{t,\omega}^{TOU} \tag{4.2}
$$

Table 4.2 — Indices, parameters and variables used in this chapter.

Indices	
T	Time [h]
p	Period
c	End-users sector
ω	Scenario
j	ibid reduction steps
Parameters	
λ_t^{DA}	The day-ahead market price [€/MWh]
$\lambda_t^{DA,min}$	The minimum day-ahead price [€/MWh]
$\lambda_t^{DA,Max}$	The maximum day-ahead price [€/MWh]
$\lambda_0^{c,p}/\lambda^{c,p}$	The initial/TOU tariff of energy in consumption [€/MWh]
π_ω	The probability of scenario ω
$P_{t,j}^{ibDR}$	The steps of the reduced load in the ibDR program [kW]
$R_{t,j}^{ibDR}$	The steps of the incentive in the ibDR program [€/kW]
$\eta_{ch}^{ESS}/\eta_{dis}^{ESS}$	The charging/discharging efficiency of the ESS
C_b^{deg}	The degradation cost of the ESS [€/kWh]
$P^{DA,Max}$	The maximum capacity of the traded power of the DR aggregator [kW]
$D0_{t,\omega}(c,p)$	The initial demand of participants [kW]
$E_t(c,p)$	The elasticity matrix for the consumers
$E^{ESS,Max}$	The maximum capacity of the ESS [kWh]
$E^{ESS,min}$	The minimum capacity of the ESS [kWh]
α	The coefficient for the SOC of the ESS
Γ	The budget of the uncertainty
Variables	
$PR_{t,\omega}$	The ratio of participation of consumers in the ibDR program
$P_{t,\omega}^{ESS,ch}$	The charging power value of the ESS [kW]
$P_{t,\omega}^{ESS,dis}$	The discharging power value of the ESS [kW]
$P_{t,\omega}^{DA,s}$	The selling power value in the DA market [kW]
$P_{t,\omega}^{DA,b}$	The buying power value in the DA market [kW]
$P_{t,\omega}^{ibDR}$	The reduced load in the ibDR program [kW]
R_t^{ibDR}	The total amount of reward in the ibDR program [€]
$P_{t,\omega}^{TOU}$	The power value in the TOU program [kW]
$E_{t,\omega}^{ESS}$	The energy of ESS [kWh]
β, y, ξ	Dual variables for the robust model
Binary variables	
$I_{t,\omega}^{DA,s}/I_{t,\omega}^{DA,b}$	Binary variable indicating that the aggregator is selling/buying to/from the DA market
$I_{t,j}^{ibDR}$	Binary variable indicating the level of load reduction in the ibDR program
$I_{t,\omega}^{ESS,ch.}$	Binary variable indicating the charging mode of the ESS
$I_{t,\omega}^{ESS,dis.}$	Binary variable indicating the discharging mode of the ESS

The constraints for the amount of power that could be traded are shown in (4.3)-(4.5). In (4.3) and (4.4), the capacities of offering and buying the amount of power in the day-ahead market are addressed as, currently, the aggregator can only trade in the wholesale market. Equation (4.5) requires that in each time interval, the selling or buying of power cannot occur simultaneously through the use of the binary variables $I_{t,\omega}^{DA,s}$ and $I_{t,\omega}^{DA,b}$.

$$P_{t,\omega}^{DA,s} \leq I_{t,\omega}^{DA,s} P^{DA,Max} \tag{4.3}$$

$$P_{t,\omega}^{DA,b} \leq I_{t,\omega}^{DA,b} P^{DA,Max} \tag{4.4}$$

$$0 \leq I_{t,\omega}^{DA,s} + I_{t,\omega}^{DA,b} \leq 1 \tag{4.5}$$

The constraints related to the implemented ibDR program are described in (4.6)-(4.9). The amount of demand is reduced through (4.6). $PR_{t,\omega}$ indicates the participation ratio of the end-user in this DRP in time interval t and scenario ω multiplied with $P_{t,j}^{ibDR}$, which shows the amount of reduction chosen from the Demand Reduction Curve [15] through a binary variable denoted by $I_{t,j}^{ibDR}$. The demand reduction curve is a table which the aggregator proposes to the consumers, highlighting the relationship between demand reduction and the correlated amount of incentive (reward) considered for the end-user, as addressed in (4.7). This reward is greater than the previous step and smaller or equal to the current step. In other words, the amount of reward is within the range of $R_{t,(j-1)}^{ibDR}$ and $R_{t,j}^{ibDR}$, and $R_{t,j}^{ibDR}$ will be chosen as the reward amount (4.8). It should be noted that in each time interval, only one step of this reduction curve can be selected, which is ensured through (4.9) using a binary variable $I_{t,j}^{ibDR}$.

$$P_{t,\omega}^{ibDR} = \sum_{j=1}^{N_J} PR_{t,\omega} P_{t,j}^{ibDR} I_{t,j}^{ibDR} \tag{4.6}$$

$$R_t^{ibDR} = \sum_{j=1}^{N_J} R_{t,j}^{ibDR} \tag{4.7}$$

$$\overline{R}_{t,(j-1)}^{ibDR} I_{t,(j-1)}^{ibDR} \leq R_{t,j}^{ibDR} \leq \overline{R}_{t,j}^{ibDR} I_{t,j}^{ibDR} \tag{4.8}$$

$$\sum_{j=1}^{N_J} I_{t,j}^{ibDR} = 1 \tag{4.9}$$

As previously stated, there are two types of DRPs, the first type is introduced above and the second program is the TOU program. The TOU program is one of the most popular DR programs that can alter the usage pattern of consumers through different energy tariffs in different periods such as peak and off-peak periods.

This program is utilized in the proposed framework through (4.10). $D0_{t,\omega}(c,p)$ indicates the initial consumer's load in scenario ω before the use of the TOU program in sector *c* and period *p*. The elasticity of consumers is assumed through a matrix that is $E_t(c,p)$. This matrix indicates how the end-users are elastic to the change in their energy usage pattern. The last term in this constraint $\left(\frac{\lambda^{c,p}-\lambda_0^{c,p}}{\lambda_0^{c,p}}\right)$ denotes the new tariff after TOU employment in sector *c* and period *p*, i.e., $\lambda^{c,p}$ and the normal tariff, i.e., $\lambda_0^{c,p}$.

$$P_{t,\omega}^{TOU} = \sum_{c=1}^{C} \sum_{p=1}^{P} D0_{t,\omega}(c,p) E_t(c,p) \left(\frac{\lambda^{c,p} - \lambda_0^{c,p}}{\lambda_0^{c,p}}\right) \tag{4.10}$$

The specifications of the considered ESS are presented in (4.11) – (4.17). The amount of energy in time interval t and scenario ω is calculated in (4.11). The ESS energy is dependent on the previous time interval *(t-1)* and scenario ω plus the charging amount of power multiplied by the charging efficiency minus the discharging amount of power multiplied by the discharging efficiency [40]. As mentioned before, the ESS can be charged or discharged in each hour. In other words, at least one of the components of (4.11) that are $P_{t,\omega}^{ESS,ch.}$ or $P_{t,\omega}^{ESS,dis.}$ should be zero as the ESS cannot be charged and discharged at the same time. The energy level of the ESS cannot be less than $E^{ESS,min}$ or higher than $E^{ESS,Max}$.

$$E_{t,\omega}^{ESS} = E_{(t-1),\omega}^{ESS} + \left(P_{t,\omega}^{ESS,ch.}\eta_{ch.}^{ESS}\right) - \left(\frac{P_{t,\omega}^{ESS,dis.}}{\eta_{dis.}^{ESS}}\right) \tag{4.11}$$

$$E^{ESS,min} \leq E_{t,\omega}^{ESS} \leq E^{ESS,max} \tag{4.12}$$

The capacities related to the charging and discharging amount of power are limited through the inclusion of (4.13) and (4.14), respectively.

$$0 \leq P_{t,\omega}^{ESS,ch.} \leq P_{ch.}^{ESS,Max} I_{t,\omega}^{ESS,ch.} \tag{4.13}$$

$$0 \leq P_{t,\omega}^{ESS,dis.} \leq P_{dis.}^{ESS,Max} I_{t,\omega}^{ESS,dis.} \tag{4.14}$$

As stated before, charging and discharging of the ESS cannot occur simultaneously, as considered in (4.15). It is also assumed that the initial and final energy of the ESS is equal as stated in (4.16).

$$0 \leq I_{t,\omega}^{ESS,ch.} + I_{t,\omega}^{ESS,dis.} \leq 1 \tag{4.15}$$

$$E_{t=T,\omega}^{ESS} = E_{t=1,\omega}^{ESS} \tag{4.16}$$

Moreover, the initial amount of energy of the ESS is dependent on the ESS maximum capacity as indicated by (4.17).

$$E_{t=1,\omega}^{ESS} = \alpha E^{ESS,Max} \tag{4.17}$$

$$I_{t,\omega}^{ESS,ch.}, I_{t,\omega}^{ESS,dis.}, I_{t,j}^{ibDR}, I_{t,\omega}^{DA,s}, I_{t,\omega}^{DA,b} \in \{0,1\} \tag{4.18}$$

$$P_{t,\omega}^{DA,b}, P_{t,\omega}^{DA,s} \geq 0 \tag{4.19}$$

After introducing stochastic programming, the hybrid robust-stochastic optimization method is implemented. The uncertainty of the day-ahead market price is handled through robust programming due to the high importance of the wholesale electricity market. Meanwhile, the uncertainty of the participation ratio of the consumers in the DRPs is addressed by the scenario-based stochastic approach. It is noteworthy to mention that the general mathematical formulation of the robust optimization is given and demonstrated in [174], [175]. Thus, regarding the general form of robust optimization, the proposed hybrid robust-stochastic DR framework is formulated using (4.20) – (4.24).

$$min: -\sum_{\omega}\pi_{\omega}\left[\sum_{t=1}^{T}\left[(P_{t,\omega}^{DA,s}-P_{t,\omega}^{DA,b})\lambda_{t}^{DA,min_t}+\beta_{t,\omega}\right]\right.$$
$$-\sum_{t=1}^{T}\sum_{j=1}^{N_J}PR_{t,\omega}P_{t,j,\omega}^{ibDR}R_{t,j,\omega}^{ibDR}$$
$$\left.-\sum_{t=1}^{T}\left[\left(P_{t,\omega}^{ESS,ch.}\eta_{ch.}^{ESS}-\frac{P_{t,\omega}^{ESS,dis.}}{\eta_{dis.}^{ESS}}\right)C_{b}^{deg.}\right]+\Gamma\xi_{\omega}\right] \tag{4.20}$$

subject to:

$$(4.2)\text{ - }(4.19) \tag{4.21}$$

$$\xi_{\omega}+\beta_{t,\omega}\geq(\lambda_{t}^{DA,Max}-\lambda_{t}^{DA,min})y_{t,\omega} \tag{4.22}$$

$$(P_{t,\omega}^{DA,s}-P_{t,\omega}^{DA,b})\leq y_{t,\omega} \tag{4.23}$$

$$\xi_{\omega},\beta_{t,\omega},y_{t,\omega}\geq 0 \tag{4.24}$$

The hybrid robust-stochastic framework is solved through the reformulation of the maximization problem into a minimization problem, as shown in (4.20).

In the mathematical formulation of the DR model, $P_{t,\omega}^{DA,s}$, $P_{t,\omega}^{DA,b}$, $PR_{t,\omega}$, $P_{t,\omega}^{ESS,ch}$, $P_{t,\omega}^{ESS,dis}$, $P_{t,\omega}^{ibDR}$, $E_{t,\omega}^{ESS}$ are the decision variables. While the day-ahead market price (λ_t^{DA}) is assumed to be the uncertain parameter managed through the robust management method. The day-ahead market price can fluctuate from $\lambda_t^{DA,min}$ to $\lambda_t^{DA,Max}$.

As mentioned in [174], there is an important integer item in the robust optimization which is the budget of uncertainty, denoted by Γ. The budget of uncertainty is employed to enforce limitations of the electricity market price, which is considered as the uncertain parameter of the market size of the framework, and these limitations are given as $\lambda_t^{DA,min}$ to $\lambda_t^{DA,Max}$.

Moreover, Γ controls the level of conservativity of the DR framework during the scheduling time. Therefore, the value of the budget of uncertainty can be given as follows: $\Gamma \in \{0,1,2,\dots,T\}$. In the case Γ=0, the uncertainty of the day-ahead market price is ignored and the results are suitable for risk-neutral decision-makers. As the budget of uncertainty increases, the proposed DR framework results would be better suited for risk-averse decision-makers and the model would become more conservative. Hence, the most conservative condition (worst-case scenario) will occur when $\Gamma = \mathrm{T}$. In this condition, it is assumed that the day-ahead market price would fluctuate from its corresponding forecasted value in all the scheduling time horizons, [0- Γ]. Additionally, ξ, ß, and y are dual variables of the constraints considered due to the reformulation of the problem.

4.3 - Simulation and Results

4.3.1 - Data Preparation

In this section, the data and the test system assumptions are introduced and explained in detail. This problem is formulated as a mixed-integer linear programming (MILP) model and the CPLEX solver in the GAMS programming environment was used to obtain the optimal solution. The number of single equations in our simulation is equal to 4,057.

Moreover, 3,950 is the total number of single variables, and 1,898 of them are discrete variables. The execution time in our modeling was approximately 12.5 seconds on a personal computer with 6 GB RAM and 2.41 GHz of CPU speed.

4.3.2 - Data Assumptions

As explained in the previous section, the day-ahead market is chosen from the wholesale market for the upper side of the aggregator, allowing the DR aggregator to trade its acquired DR. The day-ahead market price is assumed to be an uncertain parameter managed through the robust management method. The day-ahead market price can fluctuate from $\lambda_t^{DA,min}$ to $\lambda_t^{DA,Max}$. The energy prices are taken from the Portuguese day-ahead market [176]. The prices are shown in Figure 4.2. According to this figure, the lowest market prices occur at 6:00 in the morning, while the highest prices are seen at 12:00, 14:00, and 22:00.

Additionally, Figure 4.3 illustrates the input data for the cumulative demand of each consumer's sector, which is based on real scenarios that are derived from Portugal. According to this figure, three consumer sectors are considered in this case study which illustrates the sum of the demands of the consumers that are classified into several sectors: residential, commercial, and industrial. The residential and commercial behavior are similar to each other. However, the load data of the industrial sector indicates a significant difference.

The residential and commercial peak period starts at 9:00 in the morning and ends at 22:00. The peak period for the industrial sector occurs at 9:00 and ends at 18:00. The hours that are not considered in the peak period are assumed to be off-peak periods.

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Regarding the parameters that are considered for the ESS, it should be noted that the maximum and minimum capacities of the ESS are 200 kWh and 100 kWh, respectively. The charging/discharging SOC of the ESS is assumed to be 20 kWh. It is worthwhile to mention that the initial SOC of ESS is considered to be set by the optimal solution. The efficiency of the battery for both charging and discharging mode operation is chosen as 90% from the nominal value. Finally, the degradation cost of the battery is supposed to be 0.07 €/kWh.

As stated in the problem formulation section, the ratio of participation by the consumers in the DRP is considered to be the uncertain parameter that is handled through stochastic programming. To this end, several scenarios are generated. After the scenario reduction process, 20 scenarios have been chosen as the final number of scenarios describing the ratio of participation of consumers in the incentive-based DR program.

In the incentive-based DR program, 20 steps of demand reduction are selected to correlate with a certain amount of reward [136]. Regarding the TOU program, the values used in the matrix of elasticity are taken from [15].

In the proposed hybrid stochastic-robust problem, the price of energy in the day-ahead market is chosen as the second uncertain factor that is being addressed through the robust approach. To this end, a price variation of 20% from the assumed values is considered and this is shown in Figure 4.2. It means that, in robust programming, it is supposed that the prices fluctuate 20% from the forecasted values.

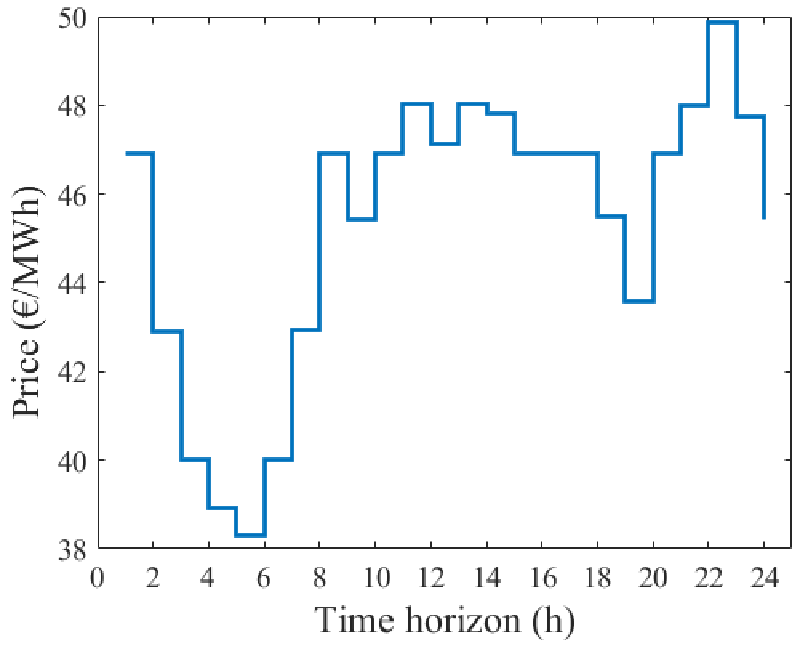


Figure 4.2 - The Electricity price in the studied period.

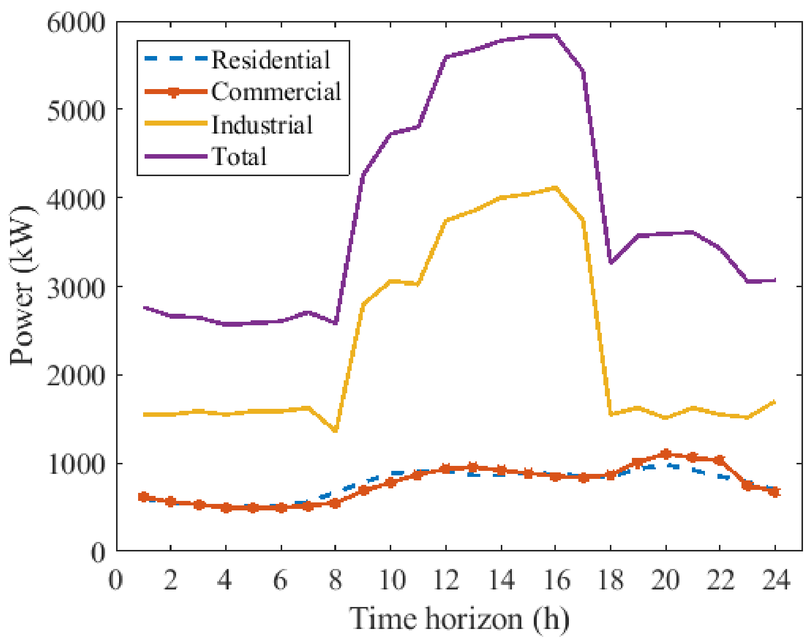


Figure 4.3 - The cumulative load profile of the consumers on the studied day.

4.3.3 - Simulation and Result Discussion

4.3.3.1 - The Performance of the TOU DR Program

In this section, the key results derived from the simulation of the proposed model are shown and discussed. The first result discussed is related to the impact of the TOU DR program, as shown in Figure 4.4. As indicated in this figure, the total reduction amount of the demand through the implementation of the TOU program is illustrated.

According to these results, it can be seen that during the off-peak period, there are positive values and during the peak period, there are negative values. The positive values mean that by implementing the TOU program, the consumers increase their consumption compared to their consumption without the TOU program. The negative values during the peak period indicate a decrease in consumption relative to the consumers' usage pattern without the TOU program.

As explained in the problem formulation, the TOU program has a direct relation to the amount of demand in each sector. Thus, the participation of consumers in this program in the residential and commercial sectors is lower than the corresponding values in the industrial sector. This is because the daily power use of the industrial consumers is greater than the daily usage in the other sectors. Therefore, the largest share of the total TOU program shown in Figure 4.4. is due to the industrial sector. Note that the peak and off-peak period is not the same for all the sectors.

Thus, from 18:00 to 22:00, the industrial sector is in the off-peak period and the other two sectors are still in the peak period, the total TOU is the summation of negative values in the residential and commercial section and positive values in the industrial one. This is the main reason that these hourly values are different relative to others in the studied time horizon.

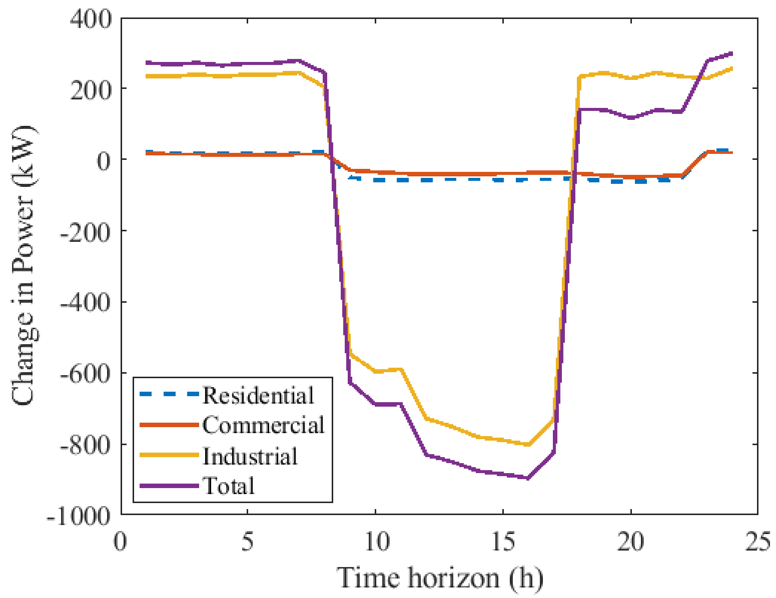


Figure 4.4 - The impact of the implemented TOU DRP.

It should also be noted that from 18:00 to 22:00, as the industrial sector is in its off-peak period and since it has the largest share of demand, the total amount of obtained demand is based on the behavior of the industrial sector.

4.3.3.2 - The Performance of the ibDR Program

As explained in the previous section, the ibDR program is also considered in this model. In this program, the participation ratio of consumers is assumed to be uncertain and modeled through stochastic programming. Moreover, the day-ahead market prices are modeled using robust programming. As explained before, the budget of uncertainty, i.e., Γ, plays the most crucial role in investigating the impact of the uncertain parameter.

Therefore, three values are chosen for the budget of uncertainty, which are $\Gamma = \{0, 2, 12\}$. When $\Gamma = 0$, it means that the robust impact is not considered and the results shown in this case are the same as when only stochastic programming is taken into account. In the second condition, it is assumed that the price can fluctuate in two hours from the observed hours, i.e., $\Gamma = 2$. It corresponds to a small share of robustness. Finally, in the last case, $\Gamma = 12$ is selected. It means that the optimal schedule is the most robust against fluctuations in market price, which is the uncertain parameter.

As illustrated in Figure 4.5, the participation of consumers in the ibDR program during the off-peak period for all the considered cases is the same. This means that the participation of consumers in this DR program is not dependent on the robustness of the market price. However, during the peak period, the impact of robustness varies.

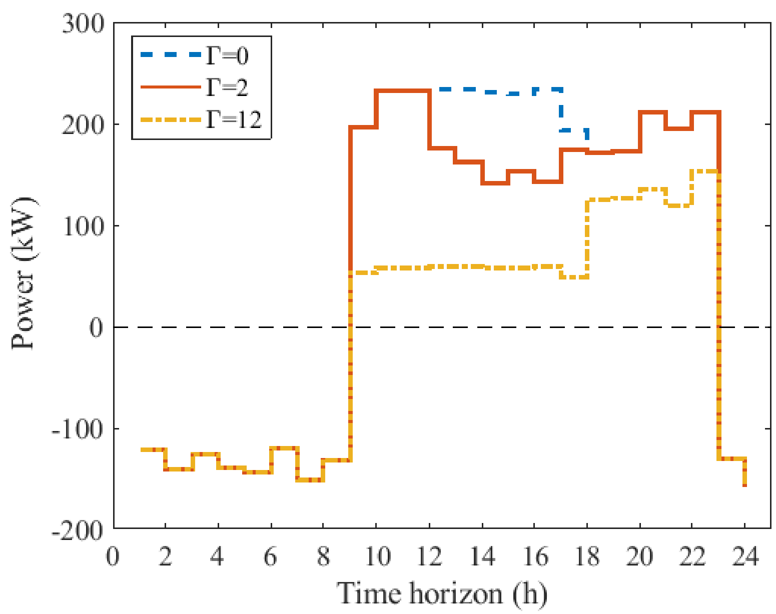


Figure 4.5 - The ibDR program engagement in the proposed framework.

According to this figure, when $\Gamma = 0$, consumer participation is at its maximum. For instance, the DR aggregator obtains more than 200 kW at 12:00 from the participants in this DR program. This is due to the high market price during these hours. Since the impact of robustness is neglected, consumers increase their participation to receive a high reward from the aggregator. However, by increasing the budget of uncertainty, the worst cases are simulated, and to make the programming robust against the price variations, the acquired demand from this type of DRP is decreased. Therefore, it is completely reasonable that the lowest demand is obtained from the consumers that are related to $\Gamma = 12$.

4.3.3.3 - The Performance of ESS

The hourly operation of the ESS is illustrated in Figure 4.6. According to this figure, when the level of energy in the ESS is increasing, it indicates that the ESS is in its charging mode. When the energy level in this entity decreases compared to the previous hour, the ESS is in a discharging condition.

Table 4.3 explains the behavior of the ESS in detail. In this table, the behavior of the ESS for various budgets of uncertainty is given. According to the problem constraints, it was expected that both charging and discharging of the ESS could not occur simultaneously. This is the reason why in every hour, one of the values in the charging or discharging related columns is zero.

Since the initial stored energy in the EES is supposed to be 100 kWh, at the end of the first hour, the stored energy has increased by 20 kWh, according to Table 4.3. The results given in Table 4.3 and Figure 4.6 show that the ESS charges until 03:00 regardless of the value of budget of uncertainty, while the behavior of storage changes from 04:00.

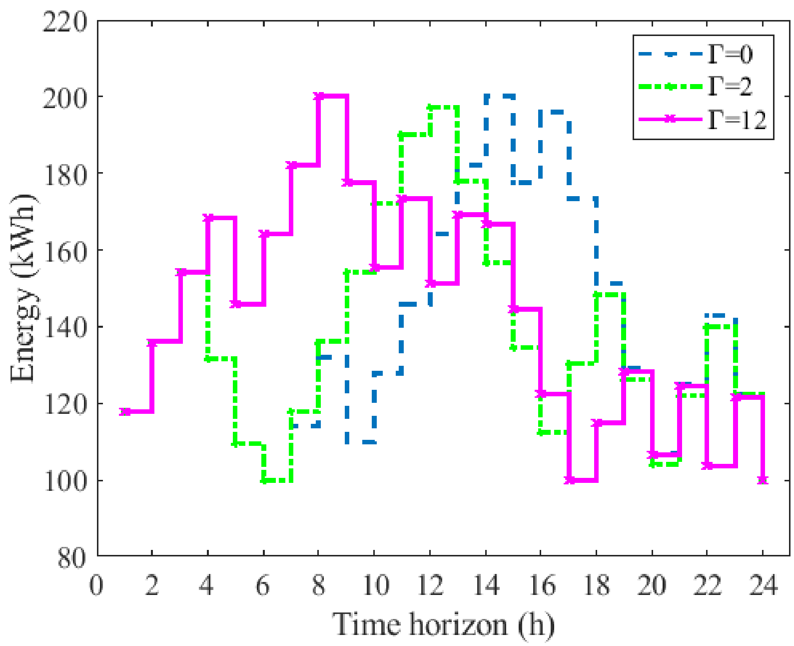


Figure 4.6 - The operation of the ESS over the scheduling period.

In the first two cases, i.e., $\Gamma = \{0, 2\}$, the ESS starts to discharge, while in the worst-case scenario that occurs when $\Gamma = 12$; the ESS is still charging, but not to the full capacity. It is worthwhile to mention that the number of charging cycles of ESS in each scenario is as follows: five when $\Gamma = 0$, four when $\Gamma = 2$, and seven when $\Gamma = 12$. The number of charging and discharging cycles in the first two scenarios is similar.

However, this is not the case in the worst-case scenario. In the worst-case scenario, it is considered that in 12 hours there is a price variation that affects the profit of the aggregator negatively. Thus, the aggregator operates the ESS to minimize the negative effect of price variations.

Table 4.3 — The Charging and Discharging behaviors of the ESS

T	Hybrid Γ=0		Hybrid Γ=2		Hybrid Γ=12	
	$P^{ESS,ch}$ (kW)	$P^{ESS,dis}$ (kW)	$P^{ESS,ch}$ (kW)	$P^{ESS,dis}$ (kW)	$P^{ESS,ch}$ (kW)	$P^{ESS,dis}$ (kW)
1	20	0	20	0	20	0
2	20	0	20	0	20	0
3	20	0	20	0	20	0
4	0	20	0	20	15.8	0
5	0	20	0	20	0	20
6	0	8.6	0	8.6	20	0
7	15.8	0	20	0	20	0
8	20	0	20	0	20	0
9	0	20	20	0	0	20
10	20	0	20	0	0	20
11	20	0	20	0	20	0
12	20	0	8.1	0	0	20
13	20	0	0	17.2	20	0
14	20	0	0	19.1	0	2.4
15	0	20	0	20	0	20
16	20	0	0	20	0	20
17	0	20	20	0	0	20
18	0	20	20	0	16.7	0
19	0	20	0	20	14.8	0
20	0	20	0	20	0	19.6
21	20	0	20	0	19.8	0
22	20	0	20	0	0	18.7
23	0	18.6	0	15.9	20	0
24	0	20	0	20	0	19.5

4.3.3.4 - The Scheduling of DR aggregator in the DA market

The daily schedule of the aggregator is depicted in Figure 4.7. In this figure, the amount of power that the aggregator trades with the day-ahead market is shown. According to the results, the flow of energy during the off-peak hours is from the day-ahead market to the consumers. While in the peak hours, from 9:00 to 22:00 for the residential and commercial sectors and from 9:00 to 18:00 for the industrial sector, the flow is reversed. In other words, during the peak period, the aggregator offers its acquired demand to the day-ahead market.

As there are some hours which are peak periods for the residential and commercial sectors and off-peak periods for the industrial sector, namely from 18:00 to 22:00, the aggregator is still offering its demand to the day-ahead market in these hours.

In contrast, this amount is much smaller than the previous hours. Since the majority of demand belongs to the industrial sector, it has a large impact on the results relative to the other two sectors. In the worst-case scenario ($\Gamma = 12$), the aggregator is not trading at all.

In other words, the amount of power reduction during the peak period of residential and commercial sectors is equal to the demand increase during the off-peak period of the industrial sector, which occurs between 18:00 and 22:00 during the worst-case.

4.3.3.5 - The Sensitivity Analysis of Proposed Method

Comparing the three cases, it can be seen that as the budget of uncertainty increases, the total amount of traded power in the day-ahead market decreases during the peak period and vice-versa in the off-peak period. Hence P_t^{DA} reaches zero during the worst-case at 18:00. The salient results obtained are depicted in Figure 4.8, which provides the sensitivity analysis of the proposed model. As it was stated in the previous sections, the profit is affected directly by budget uncertainty and market price variations.

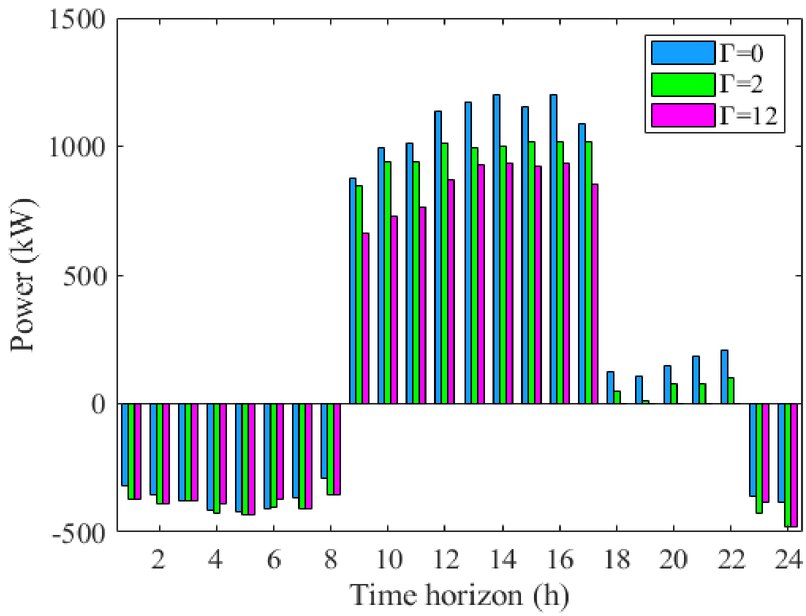


Figure 4.7 - The traded amount of energy in the DA market.

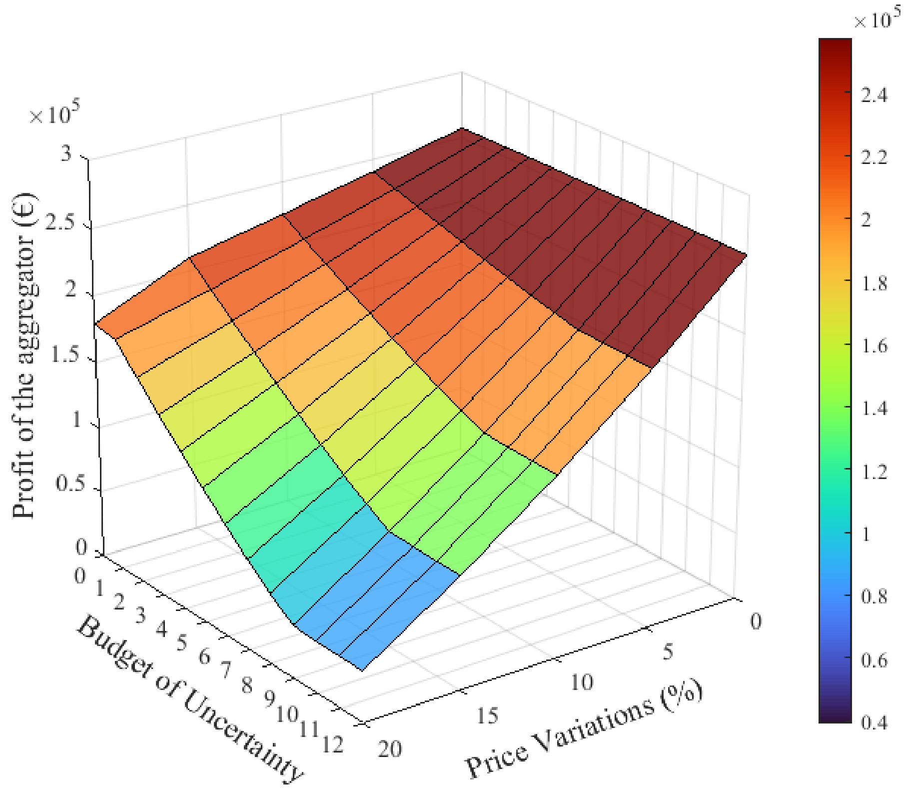


Figure 4.8 - The sensitivity analysis of the considered test system on the proposed hybrid model.

The variations for the day-ahead market price are chosen to be 0, 5%, 10%, 15%, and 20%, while the budget of uncertainty is selected from zero to 12 (worst-case). For a fixed value of Γ, as the price variation increases, the total profit of the aggregator decreases. The minimum value for the profit of the DR aggregator occurs during the worst-case scenario and maximum price variations from the forecasted values, that is, 39,070 € at $\Gamma = 12$ and $\alpha = 20\%$. On the other hand, the maximum profit of the aggregator is 257,300 € when there are no price variations and the budget of uncertainty is equal to zero.

4.3.3.6 - The *After-the-Fact* Analysis of the Proposed Method

In this section, the effectiveness and usefulness of the proposed model is demonstrated. To this end, three optimization techniques are applied to the employed case study which is named after the fact analysis [148]. In the robust optimization approach, it is considered that the uncertain parameter is addressed and handled through the robust method. On the other side, the uncertain parameters are only managed through the stochastic optimization approach.

The actual and forecasted day-ahead electricity market are considered in this stage for seven days which is illustrated in Figure 4.9. As seen in this figure, the forecasted market prices are slightly lower than the actual values during the first four days of the considered period. Then, in the remaining days of the assumed period, it is reversed where the forecasted prices are greater than the actual values of the day-ahead market.

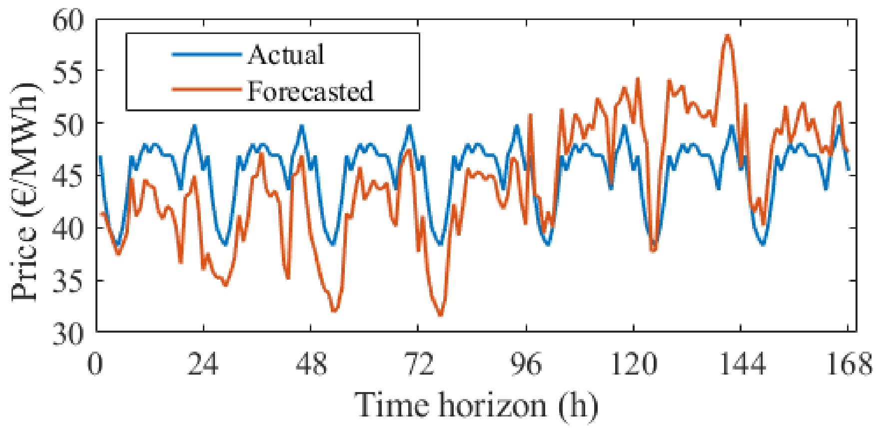


Figure 4.9 - The hourly day-ahead electricity market prices for a week.

Table 4.4 indicates the profit of the DR aggregator for the proposed hybrid, the stochastic and robust optimization methods using the actual day-ahead electricity market prices. According to the results, the total profit of the aggregator through the application of the hybrid robust-stochastic approach will be greater than the other two studied methods, i.e., the robust method and stochastic method in the typical week. Moreover, it can be seen that the total performance of the proposed approach is better than the other ones whenever the forecasted prices are greater than the actual prices or even when the forecasted prices are lower than the actual prices.

Table 4.4 — Comparison of the Profit of the Different Methods

Day	Hybrid profit (€)	Stochastic profit (€)	Robust profit (€)
1	133042	136131	130821
2	147101	147015	144876
3	153564	151217	151147
4	154140	151904	151830
5	167679	159383	165028
6	177394	165097	174096
7	168765	160681	165988
T	1101689	1071431	1083788

4.4 - Conclusions

A hybrid stochastic-robust model is proposed in this chapter to provide a better analysis of the DR aggregator in the evaluation of adverse scenarios during the scheduling of DR programs for the end-user. A stochastic method is applied to manage the engagement rate of the demand side in the DRPs, which includes three sectors of consumers, namely industrial, residential, and commercial end-users. A robust approach is implemented on the upper side of the aggregator that contains the wholesale electricity market. Fluctuations in the day-ahead market prices that can affect the profit of the aggregator are considered. The TOU and ibDR programs are utilized for the consumers and an ESS entity is operated by the aggregator. Unique peak and off-peak periods are considered for each sector of consumers to enhance the model's effectiveness in a real case study. The results indicate that the demand of the industrial consumers affects the profit of the aggregator more than the other sectors due to their high demand during the peak period. Regarding the ESS operation in the first hours of the off-peak period, the behavior of ESS is the same in all cases, that is, in the charging mode.

The ESS remains in the charging mode in the worst-case scenario, while it begins to discharge in the other scenarios to prevent any economic loss for the aggregator. Additionally, for a fixed value of the budget of uncertainty, as the price fluctuations increase, the total profit of the aggregator decreases in response. Moreover, the minimum profit of the DR aggregator occurs during the worst-case scenario and maximum price variations from the forecasted values. For future work, other electricity markets such as the balancing market, spinning market, and forward contracts could be considered to make this model more comprehensive. Another interesting development that can be done in this work is considering the prosumers as the clients of the aggregator instead of consumers. Meanwhile, multi-energy systems can be included alongside the electricity market to optimize the consumers' behavior in the gas and heating engagement, as well as the electricity demand.

Chapter 5

Energy Storage System Impact on the Operation of a Demand Response Aggregator

We considered a DR aggregator responsible for participating in the wholesale electricity market on behalf of the end-users who participated in the DR programs in the previous chapter. In this chapter, a model for analyzing the impact of the ESS unit on a DR aggregator's performance is developed to provide more flexibility for the consumers. The direct interactions of a DR aggregator with an ESS are neglected in many models. However, this consideration can lead to improvement in the flexibility of the aggregator and also increase the profit of the entity by trading energy in the short-term markets to charge the ESS during the low-price periods and discharge it to the market while the electricity market prices are high. Hence, it is assumed that the DR aggregator owns an ESS unit and can cover a percentage of its traded power through the ESS. An analysis of the impact of the ESS unit on the DR aggregator's performance is applied to study the most appropriate size of the ESS that can maximize the profit of the aggregator. In addition, renewable energy production is employed for end-users through the installation of rooftop PV panels. This demand-side renewable generation can provide more flexibility for the participants in DR programs.

5.1- Introduction

Due to the significant growth of the gap between the amount of electricity supply and demand in the energy system, demand-side management has received greater attention. DR is one of the most practical approaches to managing this gap between electricity generation and load [1,2]. The Federal Energy Regulatory Commission (FERC) has defined DR as a method to encourage end-user consumers to change their usage patterns in response to proposed electricity prices or incentive payments. The application of DR to the energy system has several advantages, such as balancing electricity generation and demand, increasing flexibility, enhancing the grid's reliability, and reducing CO_2 emissions [3].

Within the energy system, a DR aggregator has emerged whose primary responsibility is to design DR programs to encourage end-users to actively participate in demand-side management, as the volume of DR of each end-user is typically very small. Therefore, the DR aggregator can acquire DR from the end-users and trade it within the wholesale electricity markets [15]. Furthermore, another crucial solution for providing flexibility in the energy system is the ESS [4].

One of the main reasons for using ESSs is to overcome the challenges that can occur due to the high penetration of renewable energy resources in the power system. This significant volume of intermittent energy can lead to instability and low reliability in the network, which these challenges can make it essential to employ ESSs to prevent these issues [5]. The necessities for the application of DR and ESS have been mentioned above. Thus, using both features in a model is more beneficial to the overall system.

Hence, the primary motivation of this work is to apply an ESS to study its impact on the performance of the DR aggregator in the short-term markets. On the other side, the uncertainty posed by the electricity market prices should be managed and handled to help the aggregator increase its profit. The robust optimization method is also applied to address this uncertainty.

A number of the most recent similar works are reviewed and studied in this section. The DR models that handle uncertain parameters are stated and discussed in the first part. Then, models that utilized a DR aggregator are mentioned. Later, the studies considering both DR and ESS are given detailed attention. For instance, the authors in [177] developed a DR program to determine the solution for minimizing the costs for the third entity and maximizing the social welfare through a game theory approach. Similarly, a game theory approach is proposed in [178] for the optimal scheduling of a DR-enabled energy system.

The management of the uncertainty posed by the generation of renewables is addressed in this work. Moreover, the uncertainty of DR is taken into account in [179] to enhance the flexibility for scheduling an energy system integrated with an electric vehicle parking lot. The uncertainty of DR is handled in [180] to assess the congestion issues in the power systems. In these models, different aspects of the utilization of DR in the energy system are considered.

However, most of these works focused on the uncertainties on the demand side, and the uncertainties from the electricity market side are not given comprehensive attention. In addition, it seems crucial to take a closer look at models with an emphasis on applications of DR aggregators [171,181–184]. A stochastic approach is proposed between a DR aggregator and the end-users in [181] through an incentive-based DR program designation. Additionally, the uncertainty on the demand side is modeled through a Stackelberg Game. Meanwhile, the authors in [182] integrated the DR aggregator with the distributed network operators for residential loads to allocate power consumption from several electrical loads based on the TOU tariffs.

On the other hand, an optimal trading strategy for a DR aggregator is studied in [185], considering a bottom-up procedure for modeling end-users' responsiveness. Peer-to-peer transactions of a DR aggregator with a wind power producer are managed in [183] through a bi-level stochastic programming model combining the day-ahead and balancing markets. An Artificial intelligence (AI) based method is employed for the trading strategy of a DR aggregator in [184] with managing the uncertainty posed by the load and renewable energy resources.

In these studies, despite considering the uncertainties from several sources, the interactions of the aggregator with a direct ESS to improve the flexibility of the aggregator are missing. Nevertheless, a few research works considered the interactions between the DR aggregator and ESS components from the aggregator's viewpoint. For example, an aggregator with an ESS is considered in [186]. The aggregator purchases electricity from the independent system operator (ISO) to serve its customers with the primary objective of minimizing the aggregator's costs. However, the aggregator does not trade its energy within the wholesale electricity markets, and the uncertainty posed by the market side is neglected. While the authors in [187,188] considered the transactions between several components of the network, such as the DR aggregator and ESS in the wholesale markets, the impact of the ESS on the management of the trading strategy of the DR aggregator is not taken into account.

As stated above, several models applied both ESS and DR programs to their models for several purposes. However, the direct impact of the employment of an ESS unit owned by a DR aggregator has not been studied, to the best of our knowledge. Utilization of an ESS by a DR aggregator can lead this entity to increase its profit by trading energy in the short-term markets as well as increasing the flexibility for the aggregator to act as a retailer to charge the ESS during the lower price periods and discharge it to the market while the electricity market prices are high.

On the other side, using renewable energy resources on the demand side can increase the consumers' flexibility to participate in the DR programs. Since the surplus produced energy from the rooftop photovoltaic (PV) panels can be obtained through the DR aggregator. Thus, the decision-maker needs to optimize the characteristics of the ESS unit which directly affects the aggregator's performance to maximize its profit. In most of the works, the impact of the ESS on the DR framework is not analyzed.

Considering the above-mentioned research gap, a DR framework is modeled through robust optimization to study the impact of the ESS on the DR aggregator. The aggregator obtains DR from the end-users through two different DR programs, TOU, and reward-based DR programs. The TOU program is categorized as a price-based DR program, while a reward-based program is known as an incentive-based one. Therefore, the end-users can choose to participate in either DR programs or both based on availability. The end-users are assumed to be from various residential, commercial, or industrial sectors.

On the other side, the aggregator can trade DR in short-term electricity markets, i.e., day-ahead and balancing (real-time) markets. The market prices in both electricity markets are chosen as uncertain parameters. The robust optimization method is applied as a risk measure to handle these uncertainties. This risk-management method can protect the decision-maker against the worst-case market prices.

Hence, the novel contributions of the proposed model can be listed below:

- Development of a model for analyzing the impact of the ESS unit on the performance of a DR aggregator on behalf of various end-users such as residential, commercial, and industrial loads participating in the short-term electricity markets, i.e., day-ahead and balancing markets.
- Increasing the flexibility for the end-users to participate in the DR programs through developing the participation roles of the end-users in DR programs through having renewable energy resources on the demand side of the aggregator.

The rest of the chapter is organized as follows: Section 5.2 introduces the proposed optimization model, and then the mathematical formulation is explained. Then, to demonstrate the usefulness and effectiveness of the model, the results are discussed in Section 5.3. Finally, the chapter concludes by summarizing the most important findings of the studied model in Section 5.4.

5.2- Proposed Optimization Model

The proposed robust optimization approach for the DR aggregator is explained and presented in this section. The schematic of the DR trading model is illustrated in Figure 5.1.

A DR aggregator in the center of the model plays the role of a decision-maker in this framework. The aggregator has employed two DR programs, including TOU and incentive-based DR programs. These programs will be explained in detail in the problem formulation section. The aggregator is responsible for implementing these DR programs for the end users.

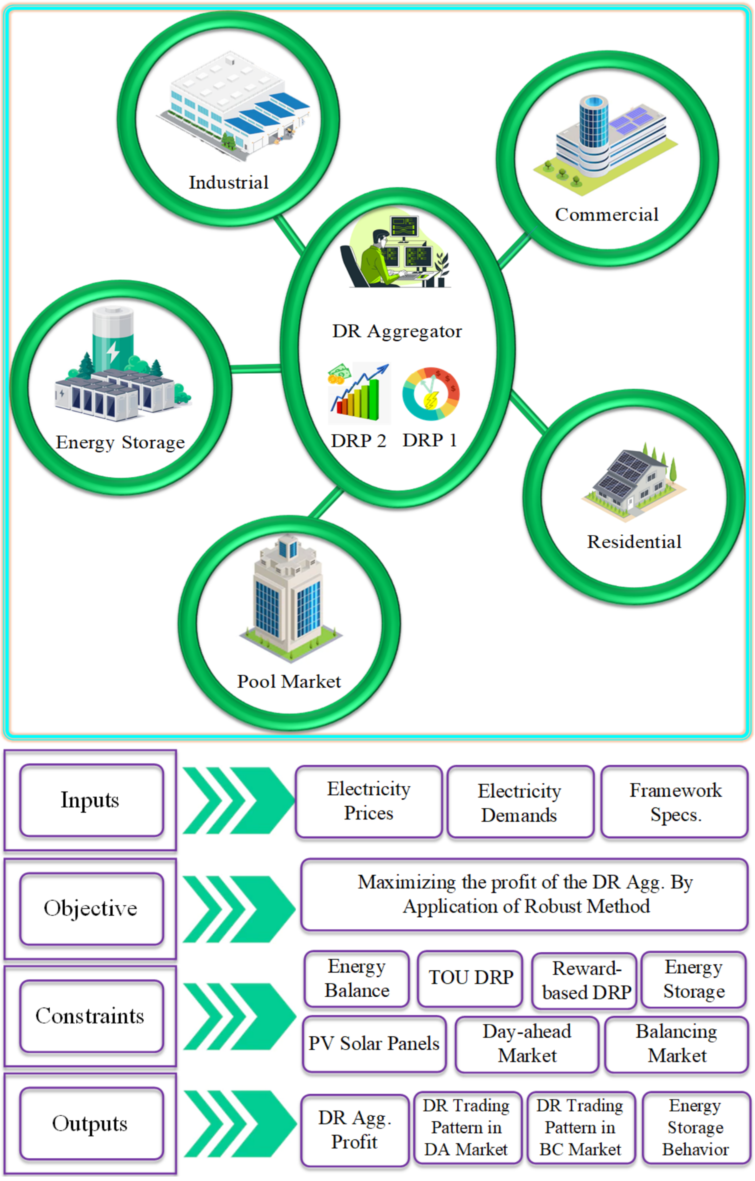


Figure 5.1 - The schematic of the DR trading model.

This study has three types of end-users, as displayed in Figure 5.1; they are the industrial, commercial, and residential sectors. These end-users are equipped with rooftop PV panels that cover a percentage of their usage and allow them to participate in the DR programs. On the other side, there is an electricity pool market that consists of two day-ahead and balancing (real-time) markets where the clearing procedure is based on the regulations indicated in [189].

There is also another component of the proposed framework, namely the ESS. The primary responsibility of this entity is to support the aggregator to avoid economic losses. Thus, the ESS will be controlled and operated by the DR aggregator. There is a bi-directional flow between the components of this framework. In other words, the energy can flow from the end-users to the market through the DR aggregator or vice-versa. Moreover, the ESS can be charged or discharged whenever the aggregator finds it beneficial for the decision-maker, the DR aggregator.

In the second part of Figure 5. 1, the model's objective and other elements are presented. This problem's objective is to maximize the profit of the DR aggregator. The electricity prices in the pool market, including day-ahead and real-time prices, are chosen as the uncertain parameters. It is worthwhile to mention that the uncertain nature of the wholesale electricity market prices has a significant and direct relation to the profit of the DR aggregator, where if the uncertainty of the electricity market prices isn't adequately addressed, it may lead to a sharp decline in its profit. A robust optimization model determines the optimal solution to study the case under severe uncertainty, whereas scenario-based methods find the optimal solution based on a limited number of possible price scenarios. Thus, it is crucial to study the uncertainty of market prices to result in the robust scheduling of the DR aggregator in an environment. Therefore, the robust optimization approach is selected to handle this uncertainty and manage the risk associated with electricity market prices. The robust optimization approach in the power system is explained in [174].

The full description of the parameters, variables, and terms used in the problem formulation is presented in Table 5.1.

The detailed mathematical formulation of the proposed model is expressed as follows:

$$
\begin{aligned}
Max \Bigg\{ & \sum_{t=1}^{T} \left[P_t^{DA} \lambda_t^{DA} + P_t^{B,+} \lambda_t^{B,+} - P_t^{B,-} \lambda_t^{B,-} \right] \\
& - \sum_{t=1}^{T} \sum_{j=1}^{N_J} P_{t,j}^{DR,rw} R_{t,j}^{DR,rw} \\
& - \sum_{t=1}^{T} \left(P_t^{ESS,Ch} \eta_{ch}^{ESS} - \frac{P_t^{ESS,dis}}{\eta_{dis}^{ESS}} \right) C^{Deg} \Bigg\}
\end{aligned} \tag{5.1}
$$

where this optimization model's objective is maximizing the DR aggregator's profit. The first term of the objective function is the revenue from trading the obtained DR in the day-ahead market which λ_t^{DA} is the day-ahead uncertain price. The following terms refer to the revenue/cost from trading in the balancing markets. Thus, if the aggregator has an excess amount of energy, it can be offered to the balancing market with a positive imbalance price. If the aggregator has a deficit, it can purchase from the balancing market with the negative imbalance prices. It should be noted that based on the balancing market regulations, the positive imbalance electricity prices are lower than the day-ahead prices, while the negative imbalance prices are greater than the correlated day-ahead prices. This is a reasonable rule to encourage market participants to avoid mismatches in scheduling in the day-ahead market as much as possible. This helps the ISO to have sufficient information about electricity transactions in advance.

Table 5.1 — Indices, parameters and variables used in this chapter.

Indices	
t	Time horizon index
p	Periods index
c	Consumer index
Parameters	
λ_t^{DA}	Day-ahead market price [€/kWh]
$\lambda_t^{B,+}, \lambda_t^{B,-}$	Imbalance prices in excess/deficit modes [€/kWh]
$\lambda_0(c,p)$	initial price related to consumer c in period p
$\lambda(c,p)$	TOU price related to consumer c in period p
M	A sufficiently large constant
$\bar{P}_{t,j}^{DR,rw}$	The steps of the reduced load in the reward-based DR program [kWh]
$\bar{R}_j^{DR,rw}(t)$	The steps of incentive in the reward-based DR [€/kWh]
$\eta_{ch}^{ESS}, \eta_{dis}^{ESS}$	The charging/discharging efficiency of the ESS
C_b^{deg}	The degradation cost of the ESS [€/kWh]
$P^{DA,Max}$/ $P^{DA,min}$	The maximum/minimum capacity of the traded power of the DR aggregator in the day-ahead market [kW]
$E^{ESS,Max}/E^{ESS,min}$	The maximum/minimum capacity of the ESS [kWh]
ρ	The coefficient for the SOC of the ESS
Variables	
P_t^{DA}	The traded power in the day-ahead market [kWh]
$P_t^{B,+}, P_t^{B,-}$	The traded power in the balancing market [kWh]
P_t^{TOU}	The changes in the electricity usage through the employment of the TOU program [kWh]
$P_t^{ESS,ch}$	The charging power value of the ESS [kW]
$P_t^{ESS,dis}$	The discharging power value of the ESS [kW]
E_t^{ESS}	The energy of ESS [kWh]
Binary Variables	
$I_j^{DR.rw}(t)$	The reduction level in the reward-based DR program
$I_t^{ESS,ch.}$/ $I_t^{ESS,dis.}$	Binary variable indicating the charging/ discharging mode of the ESS

It should be noted that the imbalance between positive and negative prices is also uncertain parameters. The next term in the objective function is the amount of reward that the aggregator pays to the end-users who participate in the reward-based DR program. This is categorized as an incentive-based DR program. There are several steps in each level, as there is a direct relationship between the reduced amount of energy and the reward offered. The last element of (5.1) relates to the cost of charging or discharging the ESS. The charging and discharging coefficients of the ESS are denoted by η_{ch}^{ESS} and η_{dis}^{ESS}. Finally, C^{Deg} is the degradation cost of the battery.

It should be noted that $\lambda_t^{DA}, \lambda_t^{B,+}, \lambda_t^{B,-}$ are the uncertain parameters for which a robust optimization method is selected to handle these sources of uncertainties. When the robust optimization is implemented on the proposed model, the mathematical problem formulation is represented as follows:

$$\begin{aligned} Max \Bigg\{ & \sum_{t=1}^{T} [P_t^{DA} \hat{\lambda}_t^{DA,min} + P_t^{B,+} \hat{\lambda}_t^{B,+,min} - P_t^{B,-} \hat{\lambda}_t^{B,-,Max}] \\ & - \sum_{t=1}^{T} \sum_{j=1}^{N_J} P_{t,j}^{DR,rw} R_{t,j}^{DR,rw} - \sum_{t=1}^{T} \left(P_t^{ESS,Ch} \eta_{ch}^{ESS} - \frac{P_t^{ESS,dis}}{\eta_{dis}^{ESS}} \right) C^{Deg} \Bigg\} \\ & + \min_{\{t||t|\le \Gamma\}} \left\{ \left(P_t^{DA} \left[\widehat{\lambda}_t^{DA,Max} - \widehat{\lambda}_t^{DA,min} \right] + P_t^{B,+} \left[\widehat{\lambda}_t^{B,+,Max} - \widehat{\lambda}_t^{B,+,min} \right] \right. \right. \\ & \left. \left. - P_t^{B,-} \left[\widehat{\lambda}_t^{B,-,min} - \widehat{\lambda}_t^{B,-,Max} \right] \right) \right\} \end{aligned} \tag{5.2}$$

In the robust optimization, the uncertain parameters can deviate from their expected values, i.e., $\{\hat{\lambda}_t^{DA}, \hat{\lambda}_t^{B,+}, \hat{\lambda}_t^{B,-}\}$. This deviation range can be selected through α where α is a value between 0 and 1 that can adjust the uncertainty level. Hence, the day-ahead market prices, i.e., λ_t^{DA} can deviate between $\hat{\lambda}_t^{DA,min}$ and $\hat{\lambda}_t^{DA,Max}$ and $\lambda_t^{B,+} \in (\hat{\lambda}_t^{B,+,min}, \hat{\lambda}_t^{B,+,Max})$ for the positive imbalance price and $\lambda_t^{B,-} \in (\hat{\lambda}_t^{B,-,min}, \hat{\lambda}_t^{B,-,Max})$ for the negative imbalance, prices are also considered. In this objective function, the second part of the formula indicated through a min term is considered for wholesale electricity market prices as the uncertain parameters should not exceed Γ. The uncertainty interval of the day-ahead and balancing market prices are taken from a forecasting model [190]. Due to the complexity of this initial form of robust optimization, the objective function can be handled through the utilization of auxiliary variables χ and y_t. Hence, the objective function presented in (5.2) can be equivalently converted into the following mathematical function, i.e., (5.3) considering the auxiliary variables.

$$\begin{aligned} Max \Bigg\{ & \sum_{t=1}^{T} [P_t^{DA} \hat{\lambda}_t^{DA,min} + P_t^{B,+} \hat{\lambda}_t^{B,+,min} - P_t^{B,-} \hat{\lambda}_t^{B,-,Max}] \\ & - \sum_{t=1}^{T} \sum_{j=1}^{N_J} P_{t,j}^{DR,rw} R_{t,j}^{DR,rw} - \sum_{t=1}^{T} \left(P_t^{ESS,Ch} \eta_{ch}^{ESS} - \frac{P_t^{ESS,dis}}{\eta_{dis}^{ESS}} \right) C^{Deg} \Bigg\} \\ & + \min_{\{\sum_t \chi \le \Gamma,\ 0 \le \chi \le 1, (P_t^{DA} + P_t^{B,+} - P_t^{B,-}) \le y_t\}} \Bigg\{ \sum_j ([\hat{\lambda}_t^{DA,Max} - \hat{\lambda}_t^{DA,min}] \\ & + [\hat{\lambda}_t^{B,+,Max} - \hat{\lambda}_t^{B,+,min}] - [\hat{\lambda}_t^{B,-,min} - \hat{\lambda}_t^{B,-,Max}]) \cdot y_t \cdot \chi \Bigg\} \end{aligned} \tag{5.3}$$

In addition, by using the duality theory, this formula can be converted into the following objective function and constraints, in which, ξ and β_t are dual variables. A comprehensive explanation for obtaining the robust problem formulation from the initial form is provided in [191].

$$
\begin{aligned}
Max \Bigg\{ & \sum_{t=1}^{T} \left[P_t^{DA} \hat{\lambda}_t^{DA,min} + P_t^{B,+} \hat{\lambda}_t^{B,+,min} - P_t^{B,-} \hat{\lambda}_t^{B,-,Max} \right] \\
& - \sum_{t=1}^{T} \sum_{j=1}^{N_J} P_{t,j}^{DR,rw} R_{t,j}^{DR,rw} \\
& - \sum_{t=1}^{T} \left(P_t^{ESS,Ch} \eta_{ch}^{ESS} - \frac{P_t^{ESS,dis}}{\eta_{dis}^{ESS}} \right) C^{Deg} - \Gamma \xi - \sum_{t=1}^{T} \beta_t \Bigg\}
\end{aligned} \tag{5.4}
$$

$$
\xi + \beta_t \geq \left(\left[\hat{\lambda}_t^{DA,Max} - \hat{\lambda}_t^{DA,min} \right] + \left[\hat{\lambda}_t^{B,+,Max} - \hat{\lambda}_t^{B,+,min} \right] + \left[\hat{\lambda}_t^{B,-,min} - \hat{\lambda}_t^{B,-,Max} \right] \right) y_t \tag{5.5}
$$

$$
\left(P_t^{DA} + P_t^{B,+} - P_t^{B,-} \right) \leq y_t \tag{5.6}
$$

$$
\xi, \beta_t, y_t \geq 0 \tag{5.7}
$$

Variables ξ and β_t which are dual variables of the initial problem (5.3) used to take into account the known bounds of wholesale electricity market prices, i.e., day-ahead and real-time, while y_t is an auxiliary variable used to obtain equivalent linear expressions.

To protect the model from uncertainty, another parameter is essential to use in the robust approach, called budget of uncertainty, i.e., Γ. This is an integer parameter that controls the level of conservatism. It can range from 0 to *T* where *T* is the maximum number of uncertain parameters. If *Γ=0*, the uncertain parameter is precisely equal to its expected value, and the robust approach does not protect the model against uncertainty. However, *Γ=T* indicates that the model is fully protected against uncertainty. In other words, as the decision-maker becomes more risk-averse, higher values for the budget of uncertainty should be chosen.

The final form of objective function presents the worst case of uncertain parameters, and market prices can deviate unfavorably equal to the Γ.

The constraints of the proposed model can be expressed as follows:

$s.t$:

$$
P_t^{DA} + P_t^{B,+} - P_t^{B,-} = P_t^{DR.rw} - P_t^{TOU} + P_t^{ESS,Ch} - P_t^{ESS,dis} + P_t^{PV} \quad ,\forall t \tag{5.8}
$$

The power balancing constraint is presented in (5.8). Hence, the power traded on the market side of the aggregator should be equal to the amount of power on the consumption side in each time interval. The power traded in the day-ahead market is denoted by P_t^{DA} and power traded in the balancing market denoted by $P_t^{B,+}$ and $P_t^{B,-}$. On the other side, the first two variables indicate the amounts of DR acquired from the end-users. The next two variables are the amount of charging/ discharging power from the ESS and the last one is the amount of power generated from the PV panels.

The constraints related to the employed DR programs are given in (5.9) - (5.14).

$$
P_t^{TOU} = \sum_{c=1}^{N} D_0(c,t) \sum_{p=1}^{P} E(c,t,p) \left(\frac{\lambda(c,p) - \lambda_0(c,p)}{\lambda_0(c,p)} \right), \forall t \tag{5.9}
$$

$$
P_t^{DR.rw} = \sum_{j=1}^{N_J} \bar{P}_{t,j}^{DR,rw} \,.\, I_{t,j}^{DR.rw} \;, \forall t, \forall j \tag{5.10}
$$

$$
R_t^{DR.rw} = \sum_{j=1}^{N_J} R_{t,j}^{DR,rw} \,, \forall t, \forall j \tag{5.11}
$$

$$\overline{R}_{t,(j-1)}^{DR,rw}.\,I_{t,j}^{DR.rw} \leq R_{t,j}^{DR,rw} \leq \overline{R}_{t,j}^{DR,rw}.\,I_{t,j}^{DR.rw}, \forall t, \forall j \tag{5.12}$$

$$\sum_{j=1}^{N_J} I_{t,j}^{DR.rw} = 1, \forall t, \forall j \tag{5.13}$$

$$I_{t,j}^{DR.rw} \in \{0{,}1\} \tag{5.14}$$

The implemented TOU program is presented in (5.9). According to the definition of the TOU program, the participants are encouraged to reduce their consumption during the peak prices due to the high electricity tariffs, while they can consume more in the off-peak period with lower tariffs. The load profile is denoted by $D_0(c,t)$, where c indicates the type of end-user. The matrix of elasticity is also denoted by $E(c,t,p)$ where p shows the periods that peak and off-peak ones. The electricity usage tariffs before and after employment of the TOU program are $\lambda_0(c,p)$ and $\lambda(c,p)$, respectively.

The constraints regarding the reward-based DR program are stated in (5.10) – (5.14). The amount of demand reduced in each time interval is denoted by $P_t^{DR.rw}$. The correlated reward is given to the end-users based on the reduced amount of demand, i.e., $R_t^{DR.rw}$ is calculated through (5.11). The next equation indicates that the reward amount can change in a stepwise pattern. The last two constraints show that in each time interval, one step can be chosen, and this is indicated by a binary variable denoted by $I_{t,j}^{DR.rw}$.

$$P^{min} \leq P_t^{DA} \leq P^{Max} \quad ,\forall t \tag{5.15}$$

$$0 \leq P_t^{B,+} \leq P_t^{DR.rw} - P_t^{TOU} + P_t^{ESS,Ch} - P_t^{ESS,dis} + P_t^{PV} \quad ,\forall t \tag{5.16}$$

$$0 \leq P_t^{B,-} \leq P^{Max} \quad ,\forall t \tag{5.17}$$

The power that can be traded in the day-ahead market through the DR aggregator has a specific capacity presented in (5.15). Similarly, the positive imbalance power should be lower or equal to the amount of available power for the DR aggregator as the maximum amount of power that can be available for the aggregator in the excess mode happens if the aggregator does not trade its whole available DR in the day-ahead market as declared in (5.16). Whereas the imbalance negative power limits are shown in (5.17), where no DR is available, the aggregator schedules its maximum capacity to be offered in the market. The ESS constraints are written as follows:

$$E_t^{ESS} = E_{t-1}^{ESS} + \left(P_t^{ESS,Ch}\eta_{ch}^{ESS} - {P_t^{ESS,dis}}\Big/{\eta_{dis}^{ESS}}\right) \tag{5.18}$$

$$E^{ESS,min} \leq E_t^{ESS} \leq E^{ESS,Max} \tag{5.19}$$

$$E_{t=1}^{ESS} = E_{t=T}^{ESS} \tag{5.20}$$

$$E_{t=1}^{ESS} = \rho E^{ESS,Max} \tag{5.21}$$

$$0 \leq P_t^{ESS,Ch} \leq P_{Max}^{ESS,Ch} I_t^{ESS,Ch} \tag{5.22}$$

$$0 \leq P_t^{ESS,dis} \leq P_{Max}^{ESS,dis} I_t^{ESS,dis} \tag{5.23}$$

$$0 \leq I_t^{ESS,ch} + I_t^{ESS,dis} \leq 1 \tag{5.24}$$

$$I_t^{ESS,ch}, I_t^{ESS,dis} \in \{0,1\} \quad (5.25)$$

The amount of energy stored in the ESS unit is calculated in (5.18), where it is dependent on the previous level of energy plus the amount of power charged/discharged at time t with ESS charging/discharging coefficients, i.e., η_{ch}^{ESS} and η_{dis}^{ESS}.

It should be noted that the ESS has a minimum and maximum energy level declared in (5.19). Moreover, it is assumed that the ESS unit's initial and final level of the ESS unit in each time horizon should be equal. Also, (5.20) indicates that the stored energy level in the ESS directly relates to its maximum capacity. The initial amount of energy available at the beginning of the scheduling period is determined by (5.21). The amount of charging/discharging power in each time interval is limited, as stated in (5.22) and (5.23). In addition, $I_t^{ESS,ch}$ and $I_t^{ESS,dis}$ are the binary variables that are used to indicate that the ESS cannot charge or discharge simultaneously.

$$P_t^{PV} = \left({G_t^a}/{G_0^a} \right) \left[\bar{P}_0^M + \mu \left(T_t^a + G_t^a \frac{NOCT - 20}{800} - T_0^M \right) \right] \quad (5.26)$$

$$P_t^{PV} = P_t^{PV \to c} + P_t^{PV \to ESS} + P_t^{PV \to DRA} \quad (5.27)$$

Finally, the hourly PV generation constraints are presented in (5.26) and (5.27). Rooftop PV generation is wholly dependent on solar irradiance. Besides that, other factors can affect the generation value, such as the temperature and the characteristics of the panel (5.26) [192]. The PV panels' generated power can be exploited by either the end-users, ESS or the DR aggregator to be traded within the short-term electricity markets.

5.3- Case Study

5.3.1 Data preparation

In this section, the employed data from the case study is explained in detail. The proposed model is aimed at profit maximization, mathematically formulated as a mixed-integer linear programming (MILP). It is simulated and solved in GAMS optimization software through the CPLEX solver. The problem was solved in a personal computer with 6 GB RAM and 2.41 GHz CPU speed. It is considered that the peak period of residential and commercial consumers is from 9:00 to 22:00 during the day, while the peak period for industrial consumers is from 9:00 to 18:00. The rest of the time is an off-peak period. These load profiles are taken from a real case study in March 2016 from São Miguel, Portugal. It is noteworthy to mention that the peak and off-peak periods of the studied cases are chosen based on their daily initial load profiles which are presented in a figure that illustrates the influence of the application of the TOU program in the simulation result section. The expected day-ahead market prices are taken from the Portuguese wholesale electricity market [176]. The maximum value for the available power of the DR aggregator that can be exchanged in the day-ahead market is equal to 1000 kW.

The data for the TOU and reward-based DR programs are similar to the reward steps and tariffs. The values used for the steps of the reward-based DR program are presented in Figure 5.2. In our model, it is assumed that there are 25 unique steps for the reward-based DR program for each consumer type, such as residential, commercial, and industrial. The DR aggregator offers the obtained DR to the pool market during the peak period and purchases during the off-peak hours.

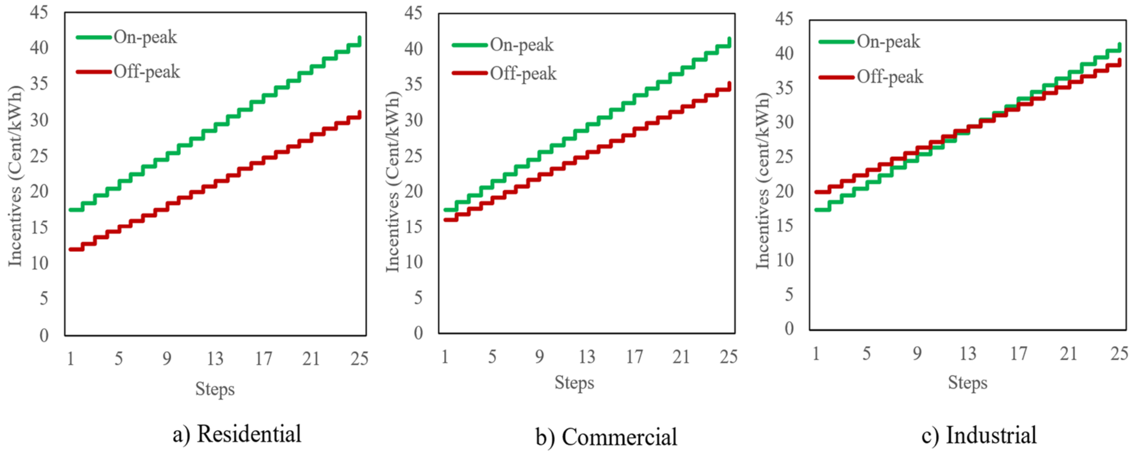


Figure 5.2 - The values for each step of the reward-based DR program.

As the pool market prices are assumed to be uncertain, robust optimization is selected as the risk management method, and 20% is chosen as the price variations from the expected day-ahead market prices. The expected electricity prices in the balancing market are assumed to be 10% higher or 10% lower than day-ahead prices for the negative or positive imbalance values, respectively [15].

Moreover, it is assumed that the end-users in all three sectors are equipped with rooftop PV panels, and their total generation for each section in the studied time horizon is illustrated in Figure 5.3. Regarding the ESS, it should be mentioned that three different cases are considered for the ESS to observe and study its impact on the profit of the DR aggregator. The degradation cost of the battery is assumed to be 0.07 €/kWh. The battery's efficiency for both charging and discharging modes is 88%. The remaining employed ESS data for each case is presented in Table 5.2 and Table 5.3.

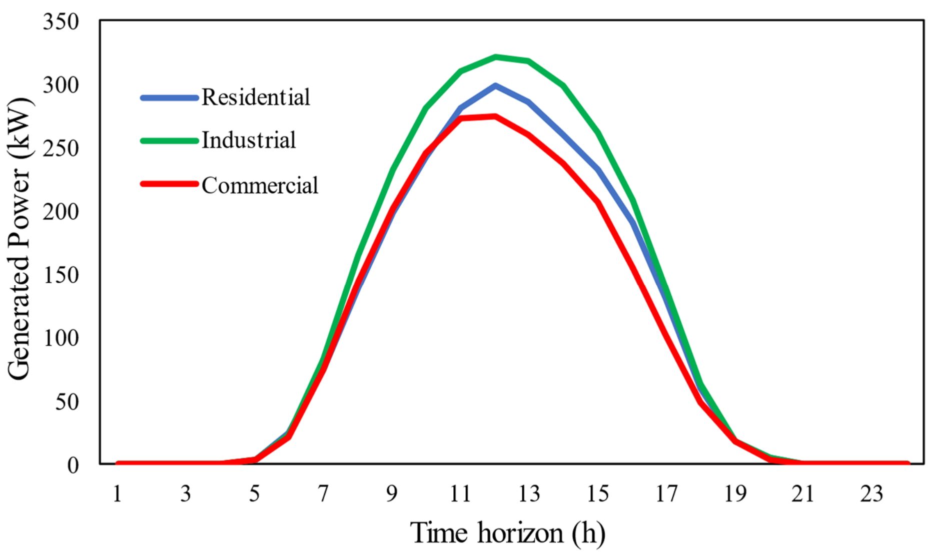


Figure 5.3 - The PV generation for each sector of the consumers.

Table 5.2 — The general input parameters of the ESS unit.

C^{Deg}	0.07 €/kWh
η_{ch}^{ESS}	88%
η_{dis}^{ESS}	88%
ρ	0.5

Table 5.3 — The characteristics of the ESS for three studied cases

ESS	$E^{ESS,Max}$ (kWh)	$E^{ESS,Min}$ (kWh)	$P_{Max}^{ESS,Ch}$ (kW)	$P_{Max}^{ESS,dis}$ (kW)
Case 1	100	40	20	20
Case 2	200	40	40	40
Case 3	400	40	80	80

5.3.2 Simulation results

The electricity pool prices are chosen as the uncertain parameters, and through the implementation of a robust optimization approach, the uncertainty budget, i.e., Γ, is an integer number that indicates the optimization level. As Γ increases, the robustness of the model against the worst-case scenarios increases as well. The sensitivity analysis of the proposed robust model for various ESS capacities is depicted in Figure 5.4.

Figure 5.4 illustrates the profit of the DR aggregator against several values for the budget of uncertainty. There are two significant findings from this result. First, when the level of robustness is low, there is small protection against the uncertain parameter that leads very sharp decrease in the profit of the aggregator. While it reaches a specific budget of uncertainty, i.e., Γ=9, the model becomes almost fully robust against the price uncertainty. Hence, this robustness protects the profit of the aggregator from unfavorable scenarios for the electricity market prices.

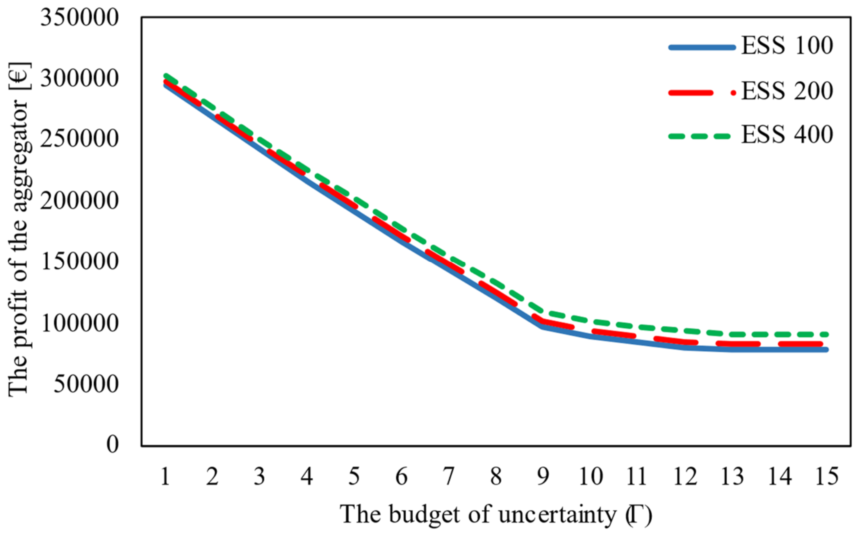


Figure 5.4 - The sensitivity analysis of the proposed robust model for various ESS capacities.

Meanwhile, it can be seen that when the budget of uncertainty is low, the impact of ESS on the DR aggregator's profit is insignificant. However, as the model becomes more robust against the electricity market prices, the impact of the ESS grows meaningfully.

Thus, to show the importance of the ESS in detail, a table provides data regarding the profit of the aggregator in two conditions, which is when our model is less protected against the price uncertainty, Γ=2. The following condition is when our proposed model is protected against the uncertain parameter and is fully robust, Γ=12, i.e., Table 5.4. According to the data shown in this table, when there is no ESS, the profit of the aggregator is €266,187 if the budget of uncertainty is equal to two.

By increasing the capacity of the ESS, it can be observed that the aggregator's profit is also increasing. Thus, when the ESS capacity is 400 kWh, the profit of the aggregator is €275,502 which is 3.5% higher than the case study without any ESS. On the other side, the profit of the aggregator increases by 20% when the budget of uncertainty is equal to 12. In other words, having a greater capacity for the ESS significantly impacts the DR aggregator's profit, even in the worst-case scenarios.

Therefore, according to the data shown in Figure 5.4 and Table 5.4, the necessity of having an ESS seems more reasonable when the decision-maker desires to protect its profit from the worst-case scenarios and reduce the uncertainty's negative effect. The influence of the implementation of the TOU DR program is expressed in Figure 5.5. In this figure, there are two columns for each hour. The first column indicates the initial amount of the total load. Meanwhile, the second column in each hour presents the new load values after the application of the TOU program. Each column shows the share of each sector, such as residential, commercial, and industrial in the total load amount. As presented in this figure, there is an increase in consumption compared to the typical energy usage without consideration of the TOU program during the off-peak period. On the other side, there is a reduction in the consumption of the end-users during the peak period.

Based on these results, the influence of industrial loads in implementing this DR program is almost ten times greater than the reasonable residential and commercial sectors due to the high consumption profile of the industrial loads. Based on this program, the end-users are encouraged to reduce their usage during the peak period and compensate for this reduction during the off-peak period with lower tariffs.

Table 5.4 — The profit of aggregator for different ESS cases

ESS Max Capacity (kW)	The profit of DR aggregator (€)	
	Γ=2	Γ=12
0	266,187	77,883
100	268,542	81,060
200	271,458	85,904
400	275,502	93,471

The robust results of the problem when the DR aggregator is trading the day-ahead and balancing markets are depicted in Figure 5.6 and Figure 5.7, respectively. To analyze the scheduling of the aggregator in the short-term markets in a robust condition, the chosen budget of uncertainty is equal to 12. Thus, the profit of the aggregator is protected against the worst-case scenarios that could happen in the day ahead and balance market prices.

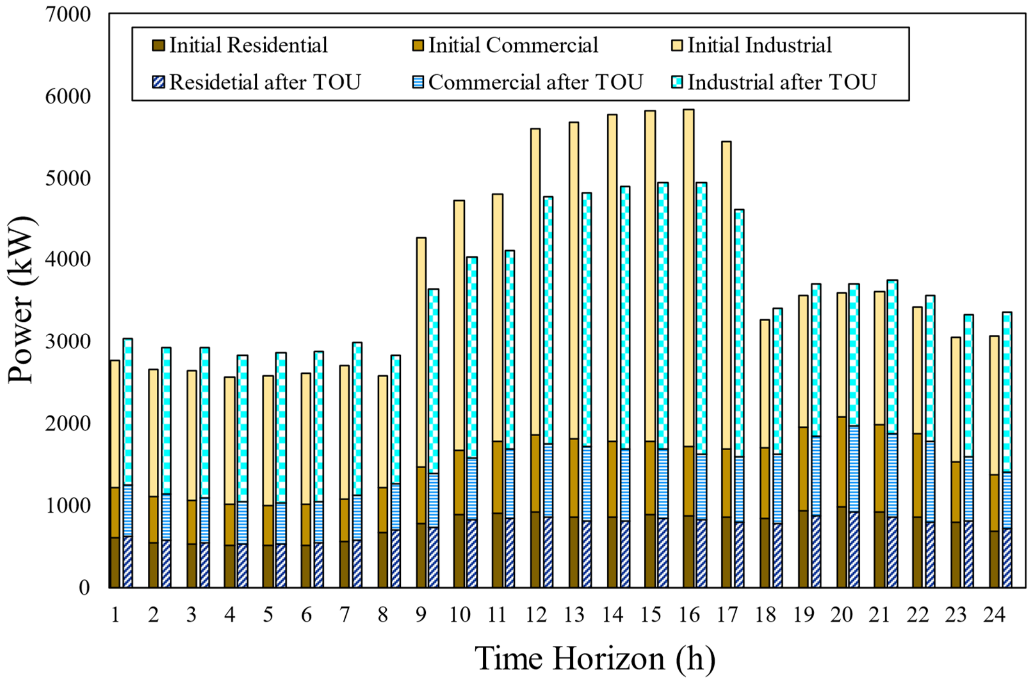


Figure 5.5 - The influence of the TOU program on the usage amounts of the end-users during the studied time horizon.

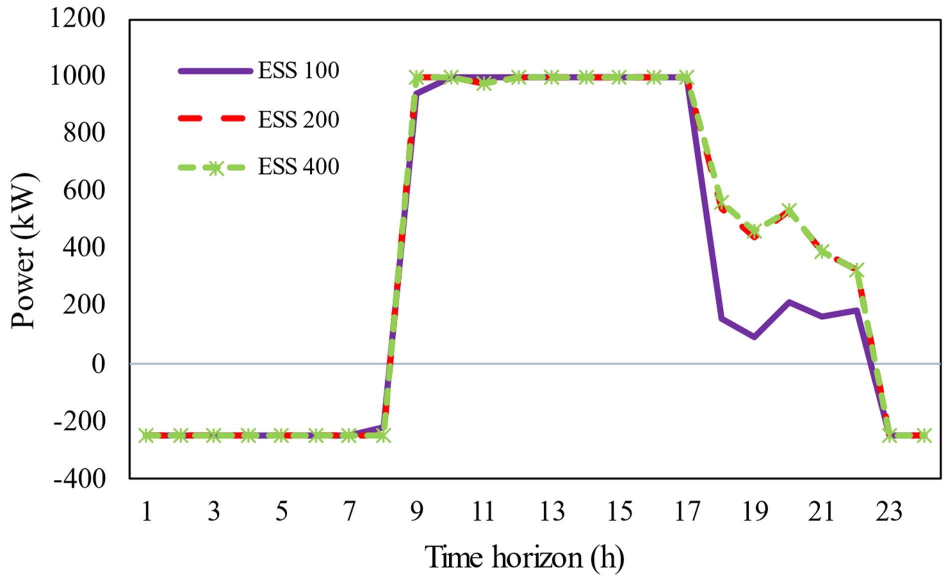


Figure 5.6 - The power traded in the day-ahead market for various ESS capacities.

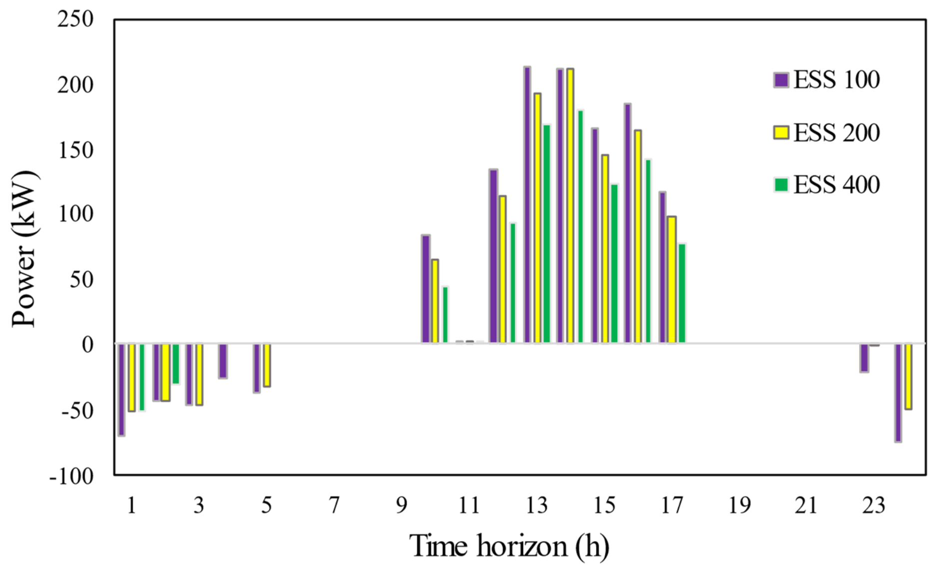


Figure 5.7 - The power traded in the balancing market for various ESS capacities.

According to Figure 5.6, the aggregator purchases energy from the day-ahead market at total capacity. On the other side, when the peak period starts, the aggregator offers the acquired DR to the day-ahead market, which is indicated in the figure as positive values. As presented, the performance of the aggregator in the day-ahead market when ESS maximum capacity is 100 kWh is entirely different from the other case studies. Thus, the trading behavior of the aggregator during the off-peak period of residential and commercial end-users is almost the same. At 18:00, the off-peak of the industrial section starts while the residential and commercial sectors are still in their peak period. Thus, the values shown in the figure from 18:00 to 22:00 are the total energy traded in the day-ahead market. During these hours, the residential and commercial sectors are reducing their demand by participating in the reward-based DR program while the industrial sector increases its usage as it is in the off-peak period.

Therefore, the participation of the industrial sector in the reward-based DR program is in the opposite direction of the other sectors from 18:00 to 22:00. After 22:00, the trading behavior becomes similar as all three sectors are again in the same period, i.e., the off-peak period.

The trading manner of the aggregator in the balancing market is illustrated in Figure 5.7. The aggregator trades the imbalance within the balancing market depending on whether it has a deficit or excess. The positive values in the figure indicate that the aggregator has an excess and is offering its surplus energy in the balancing market with positive imbalance prices that are 10% lower than the day-ahead market prices. On the other side, the negative values state that the aggregator has a deficit and is required to purchase energy from the balancing market with the negative imbalance prices that are 10% higher than the day-ahead market prices. Therefore, the DR aggregator trades its energy during the day-ahead market to avoid economic losses. The entity does not desire to purchase its required energy during higher-price periods and sell the excess during lower-priced periods.

Hence, based on the data shown in Figure 5.6, the aggregator gains more profit when its ESS maximum capacity is 400 kWh. The imbalance values during the peak and off-peak periods are lower than in the other cases. And the behavior of the aggregator with 100 kWh ESS is the worst as in many time slots; it is in the deficit or excess mode.

Finally, the behavior of ESS in the proposed model for three different cases is displayed in Figure 5.8. The green bars express the day-ahead market prices, while the lines show the current level of the ESS for different cases. Increasing the energy level means that the ESS is charging, and a decrease in the level of the ESS energy indicates the ESS is discharging. The first apparent outcome is the ESS's dependency on market prices. Thus, when the market prices increase, the ESS is discharged to cover a percentage of the required energy of the aggregator to avoid economic losses. If there was no ESS, the aggregator must purchase the whole amount of energy from the electricity markets at high prices. Therefore, owning an ESS allows the aggregator to charge it at low prices and discharge it at high prices, further supporting the aggregator to maximize its profit.

Another critical point is about the different capacities of the ESS employed by the aggregator. It can be seen that the initial level of energy of Case 3 is higher than the other cases. Hence, Case 3 starts discharging at 5:00 while Case 1 and Case 2 start discharging at 6:00. The main reason for beginning the earlier discharge for Case 3 is that the initial level of energy is high enough to cover the percentage of the aggregator's required energy. It can also charge up to its maximum capacity, which is 400 kWh. The ESS starts discharging for the second time at 18:00, which is when the peak period of the industrial sector ends. Therefore, because of high day-ahead market prices during the afternoon, it is more beneficial for the aggregator with 400 kWh ESS to cover a percentage of its demand.

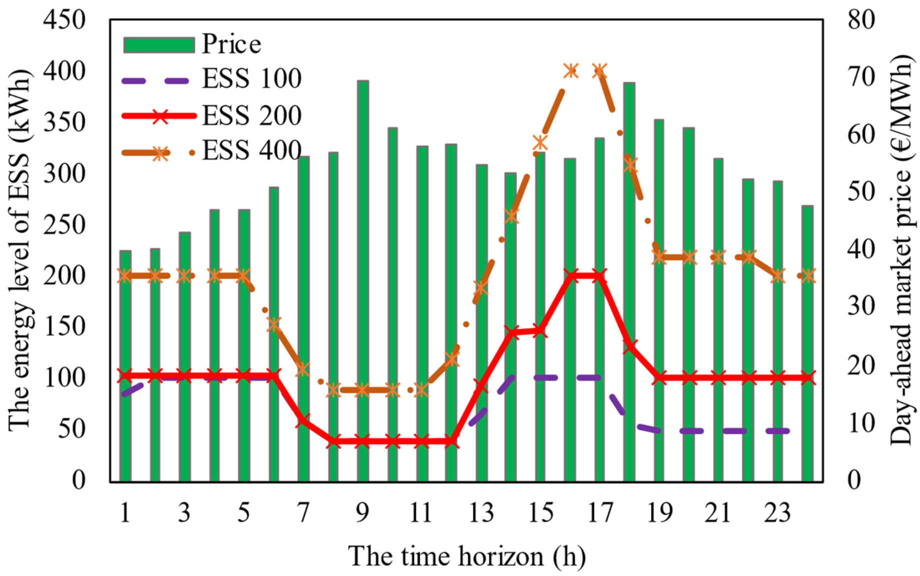


Figure 5.8 - The optimal performance of the ESS with different capacities based on the DA electricity market prices.

5.4- Conclusions

An optimal electricity trading model for a DR aggregator was developed in this work with a focus on the impact of the ESS unit that the aggregator owns. The DR aggregator was responsible for trading the available energy within the wholesale electricity markets, i.e., day-ahead and balancing (real-time) markets. The electricity market prices were assumed to be uncertain and a robust optimization approach was applied as the risk measure for these sources of uncertainty. On the demand side, three types of end-users were considered: residential, commercial, and industrial sectors. Two DR programs were implemented to allow end-users to participate in DR programs actively. Meanwhile, end-users were equipped with rooftop PV panels that could improve their participation in DR programs. In addition, three cases with different ESS characteristics were studied to evaluate better the impact of the ESS on the profit of the DR aggregator. Thus, it was demonstrated that an ESS with higher capacity was required as the decision-maker desires to be increasingly protected against unfavorable scenarios for uncertain parameters. By increasing the capacity of the ESS, it is shown that the aggregator's profit also increases. For instance, when the ESS capacity is 400 kWh, the profit of the aggregator is €275,502. This represents a 3.5% increase compared to the case study without any ESS, assuming a budget of uncertainty (Γ) equal to 2. On the other hand, if the Γ is equal to 12 in a case with an ESS capacity of 400 kWh, the profit of the aggregator increases by 20% from a case without an ESS unit. In other words, having a greater capacity for the ESS significantly impacts the DR aggregator's profit, even in the worst-case scenarios. Moreover, the results showed that the capacity of the ESS had a significant impact on the trading strategy of the aggregator in day-ahead and balancing markets. Hence, as the aggregator chooses an ESS with higher capacity, its transactions within the day-ahead market will increase. Therefore, the aggregator will require less power to be traded in the balancing market, which is desirable to prevent economic losses. The robust optimization method is suitable for risk-averse and conservative decision-makers who desire to investigate the worst-case scenarios that can occur. However, for better investigation of favorable changes in the uncertain parameter, it is suggested to implement other risk measures such as information-gap decision theory or stochastic programming that can generate several scenarios, including the favorable scenarios for the risk-seeking decision-makers. The role of the DR aggregator entity can be upgraded to a distributed energy resources aggregator that provides the control and management of several components of the energy system such as multiple renewables, on-site distributed generations, and DR programs to this entity. This upgrade can lead to more flexibility for the aggregator and make the model more comprehensive in optimizing its profit which can be worked as future work. Thus, the performance of the ESSs in such a system can be improved as the aggregator has several components under its control.

Chapter 6

Optimal Management of Electrical and Thermal Loads in Multi-Energy Systems Considering an Integrated Demand Response Program

It is crucial to study and analyze the optimization of energy hubs, particularly regarding their costs. This chapter introduces a novel energy hub risk-management method. Our risk management framework takes into account uncertainties arising from various load profiles, including electric and thermal loads, as the uncertainties originating from the end-user side are among the most important factors in optimizing the total cost of the energy hub. The proposed energy hub includes multiple distributed energy resources. Moreover, an ESS is also considered to cover a percentage of electrical energy. Multiple integrated DR programs, i.e., TOU and emergency DR, are also adopted to assist the energy hub operator in managing its components and adjusting the energy consumption volume when the energy prices are high, helping the operator attain lower costs in managing the energy hub.

6.1- Introduction

A significant challenge nowadays is the transition from fossil fuels to sustainable energy sources to match the global population's demand. Relying on fossil-fueled power plants as the primary energy source in future energy systems is not sustainable due to their drawbacks related to efficiency, costs, and, most importantly, pollution [193]. Energy systems that rely on a single energy vector to meet the final demand are typically more expensive to manage and operate than those that utilize multiple energy vectors, such as electricity, natural gas, and district heating. Multi-energy systems address the final demand using various energy carriers, including heating and cooling vectors [194].

Moreover, it has become simpler to transition from using single-energy systems to multi-energy related to several distributed energy resources, like electric heat pumps (EHPs) and combined heat and power (CHP) [3]. The operator of these systems must manage the different energy carriers to enhance efficiency and reduce the costs associated with the operation [196].

In addition, the replacement of several single-energy systems with a multi-energy system provides an efficient approach to integrating multiple energy sources and accommodating their input and output functions. The authors in [197] demonstrated that optimizing these systems with low-carbon concepts and technologies can increase the utilization of renewable energy resources and reduce carbon emissions. Additionally, incorporating DR programs into multi-energy systems can lead to the development of a low-carbon economic dispatch model while reducing the cost of the components running inside the energy hub.

Numerous studies have examined recent advancements in research related to energy hubs and multi-energy systems. For example, a thorough examination of different models and the energy hub concept was carried out in [132], which discussed the energy hub's various inputs, outputs, internal units, and entities. Similarly, the authors in [198] analyzed multi-energy systems focusing on their innovative performance and considering multiple sources of uncertainty in the generation, demand, and energy market sectors. Several papers have also focused on implementing and managing the energy hub.

In [199], the authors put forward an optimal bidding approach for the participation of an energy hub in energy markets. An ESS can be integrated into a hub and can supply some part of the electric loads through the energy hub.[200], [130]. As a result, including an ESS can lower the operational cost of the energy hub by enabling the charging of the ESS during off-peak (lower price) periods and discharging it to the energy hub during peak periods when prices are high.

DR programs can also be integrated into the multi-energy systems which is another crucial factor in such models [7]. Incorporating different energy types in the energy hub can enhance consumers' engagement in DR programs and improve the energy hub's performance [201]. For instance, an optimal self-scheduling of an energy hub is presented in [202] by considering the DR program. The authors demonstrated that using DR could reduce the total energy cost by adjusting the consumption based on the energy prices. The risk-averse attitude for the self-scheduling strategy is considered. In contrast, the possibility of reducing costs for the energy hub operator due to favorable deviations of the uncertainty resources is not studied. It should be noted that applying an integrated DR program for an energy hub is more beneficial than a traditional electric DR program.

Both electric and thermal loads can be optimized to provide more control and flexibility for the operator [13]. The authors in [203] proposed a two-level optimization model for an energy hub considering an integrated DR program for electric and natural gas demands. However, the impact of uncertainties on the demand side of the test system is not studied.

Research relating to managing and optimizing energy hubs is becoming increasingly important as this concept emerges. The uncertainty originated through electrical, heating, and cooling demands, renewables (wind turbine and PV) generation, and the price of energy carriers was addressed by a stochastic optimization approach in [68], in which the authors utilized the Monte Carlo method to generate the stochastic scenarios to maximize the profit of the energy hub.

To decrease the expected operational cost of the hub considering a risk-averse manner, a hybrid stochastic-IGDT technique was utilized for the assessment of the energy hub's management and scheduling [204]. The robust strategy of the IGDT method only manages the uncertainty posed by the electricity market prices and not those from the demand side. Moreover, an optimal energy hub management strategy is proposed in [205], where the uncertainty of the demand side is addressed using a Monte Carlo scenario-based approach.

As stated in [132], in much of the research around the concept of energy hubs, uncertainty modeling is addressed using robust or scenario-based approaches. However, such risk management methods usually neglect the behavior of a risk-seeking energy hub operator.

At the same time, the opportunity function of the IGDT method is extensively designed to examine the energy hub in a risk-seeking manner. Most methods for optimizing energy hub risk management approaches focus on handling uncertain parameters through robust or scenario-based frameworks. However, most of these methods cannot provide a clear scheduling strategy for a risk-seeker energy hub operator who desires to profit more by reducing its management costs.

Therefore, this work's main new contribution is the introduction of an innovative, opportunistic risk-handling method for a hub comprising an µCHP, EHP, absorption chiller (AC), boiler (BO), and ESS. The opportunistic strategy is more appropriate for risk-seeking decision-makers who leverage favorable deviations in uncertain parameters for more significant cost reductions. Three uncertain parameters of consumers are considered in this model- These are electrical, heating, and cooling loads.

Another new contribution of this model is that multiple integrated DR programs are utilized to provide more flexibility to consumers. Two DR programs are proposed for the electrical loads. To decrease the operating costs of the distributed energy resources and the energy hub, two DR programs for electrical loads are employed, i.e., the time-of-use (TOU) DR program and emergency DR program have been incorporated, which TOU DR program move a portion of the electric load from the peak period to the off-peak period. Also, an emergency DR program is defined to control the electric demand when there is difficulty in supplying the demand due to a significant increase in electric usage. Furthermore, one shifting DR program is considered for each heating and cooling load.

The organization of this chapter is as follows: Section 6.2 describes the proposed model. Section 6.3 presents simulation results and discussions. Finally, Section 6.4 summarizes the significant discoveries of the study as the conclusions.

6.2- The Proposed Hybrid Model

Figure 6.1 illustrates the energy hub proposed in this model, which is a multi-energy system that depends on two inputs from the upstream electricity and natural gas networks. The hub obtains its required natural gas supply from the upstream gas provider, while electricity can be purchased from or sold to the upstream power network with bidirectional electricity flow.

To clarify, the gas flow is unidirectional from the network to the hub, while the electricity power flow is bidirectional and can go from the upstream grid to the hub or vice versa. The energy hub has three outputs to satisfy the three consumer demands: heating, cooling, and electricity.

Several entities have been considered to optimize the energy hub's operation and minimize costs. These entities are depicted in Figure 6.1. The energy hub comprises the following units: EHP, µCHP, AC, BO, and ESS. Among these components of the hub, the µCHP, AC, and boiler rely on natural gas as the input, while EHP and ESS use electricity as their input

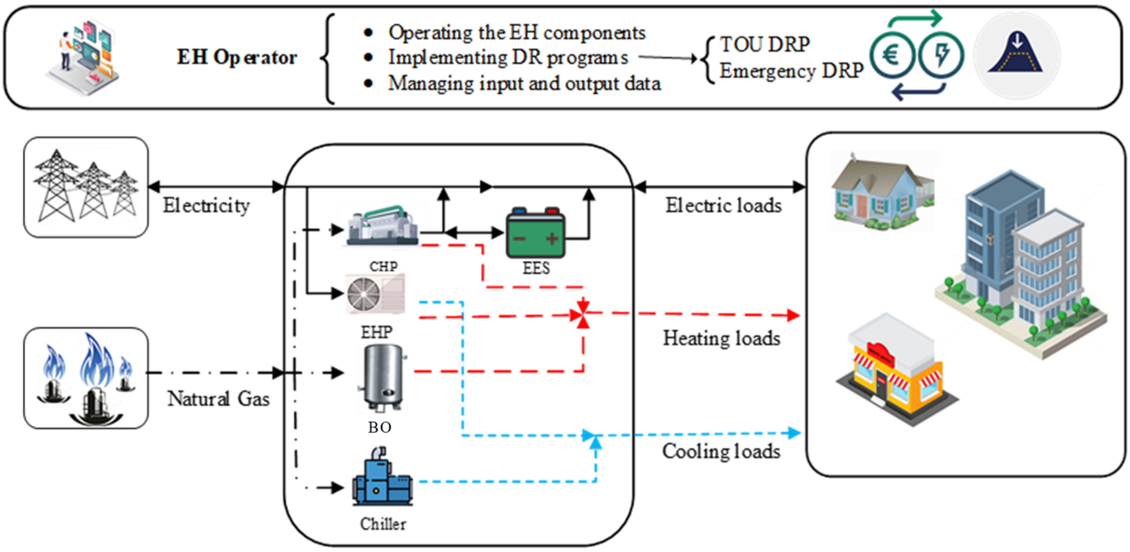


Figure 6.1 - The structure and components of the proposed energy hub.

The cooling demands of the consumers can be fulfilled by either the AC or EHP units within the energy hub, whereas the heating demand can be met by the BO and EHP units. In addition, the µCHP system is capable of delivering both electricity and heating to satisfy consumers' needs. Furthermore, the EHP unit can address both cooling and heating loads. Lastly, the energy hub utilizes an ESS to charge or discharge. The management of the designed multi-energy system consists of two stages: a deterministic stage that considers no uncertainty in the design and aims to reach the lowest possible (minimum) cost of the multi-energy system, and a second stage that takes uncertainty into account. The opportunistic IGDT risk-handling method is employed in the second part to assess the uncertainty.

6.2.1- The Mathematical Problem Formulation

The full description of the parameters, variables, and terms used in the problem formulation is presented in Table 6.1.

6.2.1.1- The Deterministic Stage

The problem formulation of the first part assumes no data uncertainty. It can be written as follows:

$$min\ OC_0 = \sum_{s=1}^{S}\sum_{t=0}^{T}\begin{pmatrix} OC_{s,t}^{EHP} + OC_{s,t}^{\mu CHP} + OC_{s,t}^{AC} + OC_{s,t}^{BO} \\ +\lambda^{NG} G_{s,t}^{NG} + \lambda_t^{PG} P_{s,t}^{PG} + OC_{s,t}^{DR} \end{pmatrix} \tag{6.1}$$

The objective function of the deterministic problem, shown in (6.1), is to minimize the operating cost of the energy hub by optimally scheduling the various assets. The cost function for the operation of each entity in the energy hub includes the EHP, µCHP, AC, and BO. The following two terms of (6.1) represent the cost of purchasing natural gas from the gas network and the electricity bought from the power grid.

Table 6.1 — Indices, parameters and variables used in this chapter.

Superscripts	
EHP	Electric heat pump
μCHP	Micro combined heat and power
AC	Absorption chiller
EH	Electric heater
BO	Boiler
ESS	Energy storage system
Ch./Dis.	Charging/discharging mode of ESS
NG	Natural gas from the grid
PG	Electricity power from the grid
Subscripts and indices	
s	Season
t	Time horizon
c/h	Cooling/heating
Parameters and variables	
OC_0	Deterministic minimum cost of energy hub
OC	The operation cost of each entity
$\lambda^{NG}/\lambda_t^{PG}$	Natural gas/ electricity price
$G_{s,t}^{NG}$	Purchased natural gas from the gas grid
$P_{s,t}^{PG}$	Amount of electricity bought or sold from or to the grid
$C_{s,t}^{EHP}/H_{s,t}^{EHP}$	Cooling/heating generation of the EHP
$P_{s,t}^{\mu CHP}/H_{s,t}^{\mu CHP}$	Electricity/heating generation of μCHP
$C_{s,t}^{AC}$	Cooling generation of AC
η^{AC}	The cooling conversion ratio of AC
$E_{s,t}^{ESS}$	The energy level of ESS
$P_{s,t}^{ESS,ch.}/P_{s,t}^{ESS,dis.}$	Charge/discharge amount of ESS
$\eta_{ch.}^{ESS}/\eta_{dis.}^{ESS}$	Charge/discharge ratio of ESS
$b_{s,t}^{ESS,ch.}/b_{s,t}^{ESS,dis.}$	Binary variables for charge/discharge mode of ESS
$P_{s,t}^{EDR}$	Load after the implementation of the DR program
$idr_{s,t}$	Shifted amount of demand
$TOU_{s,t}$	Movable amount of load in the TOU program
$P_{s,t}^{load}/H_{s,t}^{load}/C_{s,t}^{load}$	Initial electric, heating, and cooling loads

The variable $P_{s,t}^{PG}$ represents the electric power flow to or from the electric grid, and its sign depends on the direction of the power flow. If $P_{s,t}^{PG}$ is positive, it means the energy hub is buying power from the grid, and if it is negative, it means the energy hub is selling power to the grid. Therefore, if $P_{s,t}^{PG}$ is negative, it represents revenue for the energy hub. The final term in the objective function refers to the cost associated with the application of integrated DR programs. The constraints of this model are given as follows:

$$OC_{s,t}^{EHP} = x^{EHP}(H_{s,t}^{EHP} + C_{s,t}^{EHP})^2 + y^{EHP}(H_{s,t}^{EHP} + C_{s,t}^{EHP}) + z^{EHP} \tag{6.2}$$

$$C_{s,t}^{EHP} = \eta^{EHP,c} P_{s,t} \tag{6.3}$$

$$H_{s,t}^{EHP} = \eta^{EHP,h} P_{s,t} \tag{6.4}$$

$$C^{EHP,min} b_{s,t}^{EHP,c} \leq C_{s,t}^{EHP} \leq C^{EHP,max} b_{s,t}^{EHP,c} \tag{6.5}$$

$$H^{EHP,min} b_{s,t}^{EHP,h} \leq H_{s,t}^{EHP} \leq H^{EHP,max} b_{s,t}^{EHP,h} \tag{6.6}$$

$$b_{s,t}^{EHP,c} + b_{s,t}^{EHP,h} \leq 1 \tag{6.7}$$

Equations (6.2) to (6.7) present the constraints related to the EHP unit. The objective of equation (6.2) is to calculate the operating costs of the EHP based on its operation coefficients x, y, and z. The EHP's ability to provide heating and cooling is subject to conversion constraints, as expressed in equations (6.3) and (6.4). In addition, the limitations of the cooling-heating EHP generation are taken into account in equations (6.5) and (6.6), respectively. The EHP component is unable to produce both heating and cooling simultaneously, which is reflected in equation (6.7).

$$\begin{aligned} OC_{s,t}^{\mu CHP} = {} & u^{\mu CHP}(P_{s,t}^{\mu CHP})^2 + v^{\mu CHP}(P_{s,t}^{\mu CHP}) \\ & w^{\mu CHP}(H_{s,t}^{\mu CHP})^2 + x^{\mu CHP}(H_{s,t}^{\mu CHP}) \\ & y^{\mu CHP}(P_{s,t}^{\mu CHP})(H_{s,t}^{\mu CHP}) + z^{\mu CHP} \end{aligned} \tag{6.8}$$

$$P_{s,t}^{\mu CHP} - P_x^{\mu CHP} - \left(\frac{P_x^{\mu CHP} - P_y^{\mu CHP}}{H_x^{\mu CHP} - H_y^{\mu CHP}}\right)\left(H_{s,t}^{\mu CHP} - H_x^{\mu CHP}\right) \leq 0 \tag{6.9}$$

$$P_{s,t}^{\mu CHP} - P_y^{\mu CHP} - \left(\frac{P_y^{\mu CHP} - P_z^{\mu CHP}}{H_y^{\mu CHP} - H_z^{\mu CHP}}\right)\left(H_{s,t}^{\mu CHP} - H_y^{\mu CHP}\right) \geq -M(1 - b_{s,t}^{\mu CHP}) \tag{6.10}$$

$$P_{s,t}^{\mu CHP} - P_z^{\mu CHP} - \left(\frac{P_z^{\mu CHP} - P_u^{\mu CHP}}{H_z^{\mu CHP} - H_u^{\mu CHP}}\right)\left(H_{s,t}^{\mu CHP} - H_z^{\mu CHP}\right) \geq -M(1 - b_{s,t}^{\mu CHP}) \tag{6.11}$$

$$P_z^{\mu CHP} b_{s,t}^{\mu CHP} \leq P_{s,t}^{\mu CHP} \leq P_x^{\mu CHP} b_{s,t}^{\mu CHP} \tag{6.12}$$

$$0 \leq H_{s,t}^{\mu CHP} \leq H_y^{\mu CHP} b_{s,t}^{\mu CHP} \tag{6.13}$$

Equations (6.8) to (6.13) present the constraints related to the µCHP unit. Equation (6.8) calculates the operational cost of the µCHP [206]. The feasible operating region of the µCHP is defined by (6.9) to (6.11). Equation (6.12) restricts the maximum generated power of the µCHP. Moreover, (6.13) ensures that the generated heat falls within the capacity of the µCHP.

$$OC_{s,t}^{AC} = y^{AC}(C_{s,t}^{AC}) + z^{AC} \tag{6.14}$$

$$C^{AC,min} b_{s,t}^{AC} \leq C_{s,t}^{AC} \leq C^{AC,max} b_{s,t}^{AC} \tag{6.15}$$

$$C_{s,t}^{AC} = \eta^{AC} P_{s,t} \tag{6.16}$$

The cost function of the AC unit is expressed in (6.14), while constraint (6.15) indicates the minimum and maximum limitations of the AC unit. Moreover, the unit's cooling generation is shown in (6.16) which is dependent on the coefficient of the AC unit and its electricity.

$$OC_{s,t}^{BO} = y^{BO}(H_{s,t}^{BO}) + z^{BO} \tag{6.17}$$

$$H^{BO,min} b_{s,t}^{BO} \leq H_{s,t}^{BO} \leq H^{BO,max} b_{s,t}^{BO} \tag{6.18}$$

The cost of operating the BO to meet the demand for heating is expressed in (6.17). The BO unit's operating range is constrained by $H^{BO,min}$, min. capacity, and $H^{BO,Max}$, max. capacity.

$$E_{s,t}^{ESS} = E_{s,(t-1)}^{ESS} + \left(P_{s,t}^{ESS,ch.} \eta_{ch.}^{ESS}\right) - \left(\frac{P_{s,t}^{ESS,dis.}}{\eta_{dis.}^{ESS}}\right) \tag{6.19}$$

$$E^{ESS,min} \leq E_{s,t}^{ESS} \leq E^{ESS,max} \tag{6.20}$$

$$0 \leq P_{s,t}^{ESS,ch.} \leq P_{ch.}^{ESS,max} b_{s,t}^{ESS,ch.} \tag{6.21}$$

$$0 \leq P_{s,t}^{ESS,dis.} \leq P_{dis.}^{ESS,max} b_{s,t}^{ESS,dis.} \tag{6.22}$$

$$b_{s,t}^{ESS,ch.} + b_{s,t}^{ESS,dis.} \leq 1 \tag{6.23}$$

$$E_{s,t=T}^{ESS} = E_{s,t=1}^{ESS} \tag{6.24}$$

$$E_{s,t=1}^{ESS} = \alpha^{ESS} E^{ESS,max} \tag{6.25}$$

The constraints for the ESS are presented in (6.19)–(6.25) [40]. The volume of energy stored in the storage unit is determined as (6.19). The amount of energy in the ESS is bounded by its capacity limits, as shown in (6.20). The power used to charge the ESS is denoted by $P_{s,t}^{ESS,ch.}$, which is subject to the limit specified in (6.21).

Similarly, the maximum discharging power, denoted by $P_{s,t}^{ESS,dis.}$, of the ESS is limited by (6.22). Additionally, the ESS cannot charge and discharge simultaneously, as expressed in (6.23). Eq (6.24) ensures that the ESS's initial and final energy levels are the same. The ESS's initial energy level depends on its maximum capacity, as shown in (6.25).

$$OC_{s,t}^{DR} = OC_{s,t}^{EDR,TOU} + OC_{s,t}^{EDR,EM} + OC_{s,t}^{HDR} + OC_{s,t}^{CDR} \tag{6.26}$$

$$P_{s,t}^{TOU-DR} = P_{s,t}^{Load} + idr_{s,t} \tag{6.27}$$

$$idr_{s,t} = TOU_{s,t} P_{s,t}^{Load} \tag{6.28}$$

$$\sum_{t=0}^{T} idr_{s,t} = 0 \tag{6.29}$$

$$TOU^{min} \leq TOU_{s,t} \leq TOU^{max} \tag{6.30}$$

$$P_{s,t}^{EMDR,do} = \varphi_1 P_{s,t+1}^{EMDR,up} + \varphi_2 P_{s,t+2}^{EMDR,up} + \varphi_3 P_{s,t+3}^{EMDR,up} \tag{6.31}$$

$$0 \leq P_{s,t}^{EMDR,up} \leq LPF\ I_{s,t}^{EMDR,up} P_{s,t}^{Load} \tag{6.32}$$

$$0 \leq P_{s,t}^{EMDR,do} \leq LPF\ I_{s,t}^{EMDR,do} P_{s,t}^{Load} \tag{6.33}$$

$$b_{s,t}^{EMDR,do} + b_{s,t}^{EMDR,up} \leq 1 \tag{6.34}$$

$$P_{s,t}^{EDR} = P_{s,t}^{TOU-DR} + P_{s,t}^{EMDR,up} - P_{s,t}^{EMDR,do} \tag{6.35}$$

The cost of implementing DR programs is determined by (6.26), and the constraints for the TOU DR program are outlined in (6.27)-(6.30) [207]. The TOU DR program is implemented to shift the peak load to the off-peak period. Equation (6.27) defines $P_{s,t}^{TOU-DR}$ as the quantity of electricity demand following the implementation of the DR program, which is computed by adding the initial load and the load shifted together as a result of the time-of-use DR program. The shifted load value is determined by (6.28) as a percentage of the initial load's shiftable amount, $TOU_{s,t}$, multiplied by $P_{s,t}^{load}$. It is worth mentioning that the deterministic problem assumes that the cumulative shifted electrical load amount throughout the entire time horizon is zero, as indicated in (6.29). Additionally, (6.30) limits the amount of the initial load that can be shifted through the TOU program by setting the minimum and maximum amounts of shiftable load during the analysis period.

The constraints of the emergency DR program are given in (6.31)-(6.34) [208]. The mechanism for implementing the emergency DR program for electrical loads is given in (6.31). According to this equation, in case of a supply-demand imbalance for a given hour, the curtailed amount of electrical load must be recovered in the following three consecutive periods, where $\varphi_1, \varphi_2,$ and φ_3 are the recovery percentages. Additionally, (6.32) and (6.33) show the limitations of the upward and downward electrical demand, respectively. The binary variables in (6.34) indicate that the upward or downward electric demand cannot happen simultaneously. Finally, the total amount of the DR, including the TOU and emergency programs, is given by (6.35).

$$\sum_t H_{s,t}^{DR,up} = \sum_t H_{s,t}^{DR,do} \tag{6.36}$$

$$0 \leq H_{s,t}^{DR,up} \leq LPF^H\ I_{s,t}^{HDR,up} H_{s,t}^{Load} \tag{6.37}$$

$$0 \leq H_{s,t}^{DR,do} \leq LPF^H\ I_{s,t}^{HDR,do} H_{s,t}^{Load} \tag{6.38}$$

$$I_{s,t}^{HDR,do} + I_{s,t}^{HDR,up} \leq 1 \tag{6.39}$$

$$\sum_t C_{s,t}^{DR,up} = \sum_t C_{s,t}^{DR,do} \tag{6.40}$$

$$0 \leq C_{s,t}^{DR,up} \leq LPF^C\ I_{s,t}^{CDR,up} C_{s,t}^{Load} \tag{6.41}$$

$$0 \leq C_{s,t}^{DR,do} \leq LPF^C\ I_{s,t}^{CDR,do} C_{s,t}^{Load} \tag{6.42}$$

$$I_{s,t}^{CDR,do} + I_{s,t}^{CDR,up} \leq 1 \tag{6.43}$$

The implemented shifting DR programs for heating and cooling loads are presented in (6.36)-(6.43) [209]. To keep the heating load without any changes in the total amount of energy, (6.36) is considered. The upward and downward values are limited by (6.37) and (6.38).

Moreover, the EH operator can increase or decrease the heating loads in each period, as given in (6.39). The shifting DR programs for cooling loads are similar to the heating DR program, as stated in (6.40)-(6.43).

$$0 \leq P_{s,t}^{G2H} \leq P^{PG} b_{s,t}^{G2H} \tag{6.44}$$

$$0 \leq P_{s,t}^{H2G} \leq P^{PG} b_{s,t}^{H2G} \tag{6.45}$$

$$b_{s,t}^{G2H} + b_{s,t}^{H2G} \leq 1 \tag{6.46}$$

$$P_{s,t}^{EDR} = P_{s,t}^{G2H} + P_{s,t}^{\mu CHP} + P_{s,t}^{ESS,ch.} - P_{s,t}^{ESS,dis.} \tag{6.47}$$

$$H_{s,t}^{DR} = H_{s,t}^{EHP,h} + H_{s,t}^{\mu CHP} + H_{s,t}^{BO} \tag{6.48}$$

$$C_{s,t}^{DR} = C_{s,t}^{EHP,c} + C_{s,t}^{AC} \tag{6.49}$$

Equations (6.44)-(6.46) govern the energy exchange between the energy hub and the power grid. The variable $P_{s,t}^{G2H}$ represents the power purchased by the hub from the upstream network, while $P_{s,t}^{H2G}$ represents the energy sold by the energy hub to the grid. Notably, the model ensures that simultaneous import and export of energy is not possible for the energy hub, expressed in (6.46).

Constraints (6.47)-(6.49) represent the energy balance of the system, considering the DR programs. The grid, μCHP, and ESS units can provide the electrical load after the DR program implementation. Similarly, the EHP, μCHP, or the BO can supply the heating load. Moreover, the EHP and AC units must supply the cooling demand after the DR program.

6.2.1.2- IGDT-based Opportunity Stage

One of the significant challenges in energy hub operation is the uncertainty associated with the expected loads, which may differ from the actual loads. This discrepancy can significantly increase the operating costs of the energy hub. Utilizing the IGDT approach can address this challenge as it effectively manages the uncertainty associated with the expected loads [9].

Thus, below is the mathematical formulation for this stage.

$$\textit{min}\ \beta \tag{6.50}$$

s.t.

$$OC^{*} \leq OC_{\omega} = (1-\sigma) OC_{0} \tag{6.51}$$

$$OC^{*} = min \left\{ \sum_{s=1}^{S} \sum_{t=0}^{T} \begin{pmatrix} OC_{s,t}^{EHP} + OC_{s,t}^{\mu CHP} + \\ OC_{s,t}^{AC} + OC_{s,t}^{BO} + \\ \lambda^{NG} G_{s,t}^{NG} + \lambda_{t}^{PG} P_{s,t}^{PG} + OC_{s,t}^{DR} \end{pmatrix} \right\} \tag{6.52}$$

$$(1-\beta)\tilde{P}_{s,t}^{load} \le P_{s,t}^{load} \le (1+\beta)\tilde{P}_{s,t}^{load} \tag{6.53}$$

$$(1-\beta)\tilde{H}_{s,t}^{load} \le H_{s,t}^{load} \le (1+\beta)\tilde{H}_{s,t}^{load} \tag{6.54}$$

$$(1-\beta)\tilde{C}_{s,t}^{load} \le C_{s,t}^{load} \le (1+\beta)\tilde{C}_{s,t}^{load} \tag{6.55}$$

$$(6.2)-(6.49) \tag{6.56}$$

The energy hub's target cost under favorable deviations of the electrical, heating, and cooling loads is denoted by OC_{ω} in the equation. OC_{ω} is set to be less than the minimum cost obtained from the deterministic stage, which is represented by OC_0. As per the formulation of the proposed model outlined in (6.53)-(6.56), the minimum level of uncertainty (β) would be achieved when the values for $P_{s,t}^{load}$, $H_{s,t}^{load}$, and $C_{s,t}^{load}$ are equal to $(1-\beta)\tilde{P}_{s,t}^{load}$, $(1-\beta)\tilde{H}_{s,t}^{load}$, and $(1-\beta)\tilde{C}_{s,t}^{load}$, respectively. Therefore, the constraints (53)-(55) could be replaced with a new form as shown below:

$$min\ \beta \tag{6.57}$$

s.t.

$$OC^{*} = \sum_{s=1}^{S}\sum_{t=0}^{T}\begin{pmatrix} OC_{s,t}^{EHP} + OC_{s,t}^{\mu CHP} + \\ OC_{s,t}^{AC} + OC_{s,t}^{BO} + \\ \lambda^{NG} G_{s,t}^{NG} + \lambda_t^{PG} P_{s,t}^{PG} + OC_{s,t}^{DR} \end{pmatrix} \tag{6.58}$$

$$OC^{*} \le OC_{\omega} = (1-\sigma)OC_0 \tag{6.59}$$

$$P_{s,t}^{load} = (1-\beta)\tilde{P}_{s,t}^{load} \tag{6.60}$$

$$H_{s,t}^{load} = (1-\beta)\tilde{H}_{s,t}^{load} \tag{6.61}$$

$$C_{s,t}^{load} = (1-\beta)\tilde{C}_{s,t}^{load} \tag{6.62}$$

$$(6.2)-(6.49) \tag{6.63}$$

It is important to mention that the value of β represents the minimum amount of favorable deviation in uncertainty needed to achieve the target cost.

6.3- Case Study and Results

Details of the data used for each entity of the energy hub are provided in this part. The EHP unit's capacity ranges from a minimum of 10 kW to a maximum of 200 kW. This unit can supply both heating and cooling loads. During the winter season, the energy is priced in such a way that the price of natural gas is higher than electricity purchased from the grid. This allows the EHP unit to meet a considerable portion of the heating load by converting electricity into heat in winter.

The maximum capacity of the BO unit is 400 kW, whereas the AC unit can produce up to 75 kW. The absorption chiller can cover some percentages of the cooling load during hot weather. In other weather conditions, the EHP unit, which uses natural gas, will supply the cooling load.

Additionally, the AC unit relies solely on natural gas as its input. The test system includes a μCHP with a nominal capacity of 375 kW, which can generate a maximum of 125 kW of heat and 150 kW of electricity. The absorption chiller is unable to utilize the heat generated from the μCHP.

The performance parameters of μCHP could be defined accordingly: 2.869-e4 ($u^{\mu CHP}$), 2.0829 ($v^{\mu CHP}$), 1.658-e4 ($w^{\mu CHP}$), 0.1827 ($x^{\mu CHP}$), 0.001248 ($y^{\mu CHP}$), 13.747 ($z^{\mu CHP}$). The ESS can be charged up to 300 kWh, with maximum charging and discharging rates set at 10 kW and 20 kW, respectively. Charge and discharge of ESS cannot occur simultaneously. The ESS's lower energy limit is set at 50 kWh, and the ESS's initial and final states of charge are set to be 200 kWh.

Figure 6.2 displays the electrical demand profiles. Four different load profiles represent the four seasons, i.e., S1, S2, S3, and S4 for spring, summer, fall, and winter. Each season's behavior is examined by taking one day from that season and conducting hourly simulations. The high peak period for electricity demand is 9:00 to 22:00, as shown in Figure 6.2.

Figs. 6.3 and 6.4 present the expected sample heating and cooling load profiles for one day, respectively. The scheduling is simulated for one year. The deterministic (non-probabilistic) results indicate that to fulfill the yearly demand, the energy hub incurs a minimum cost of €56,100.

The IGDT opportunity function accounts for electric, heating, and cooling load uncertainties. To address the problem, various operational cost deviation factors are considered.

Figure 6.5 shows the minimum favorable deviation amounts of load uncertainties for the energy hub to achieve the desired cost. The increase in the cost deviation factor results in a corresponding increase in the value of the opportunity function. An example is given to highlight this relationship. Suppose σ is equal to 0.20. In that case, the target cost is $OC_\omega = (1-0.20)OC_0 = €44{,}880$. This means that to reach this cost, the observed electric, heating, and cooling loads must be reduced by at least 17.2% relative to the expected values.

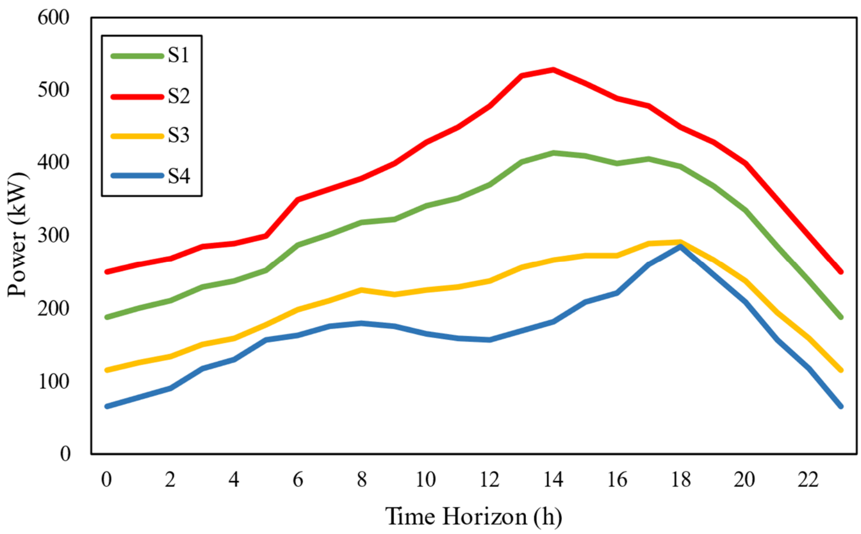


Figure 6.2 - The sample electricity load profiles for each season.

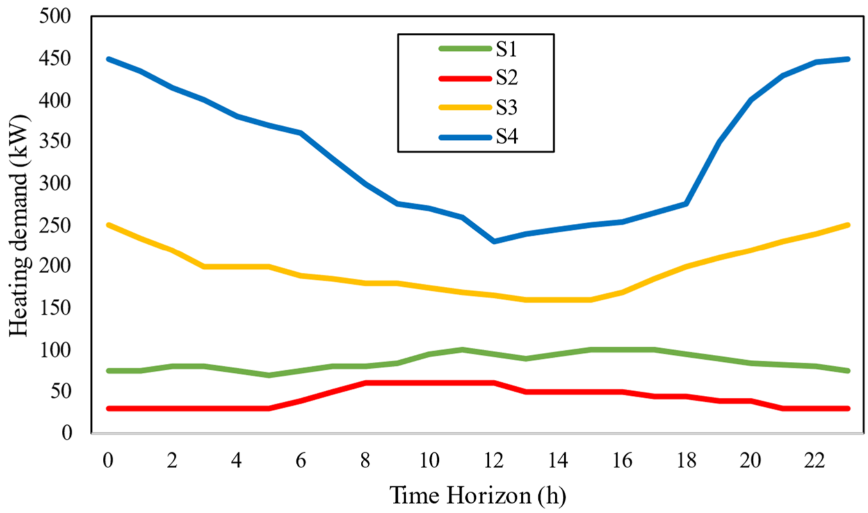


Figure 6.3 - The sample heating load profiles for each season.

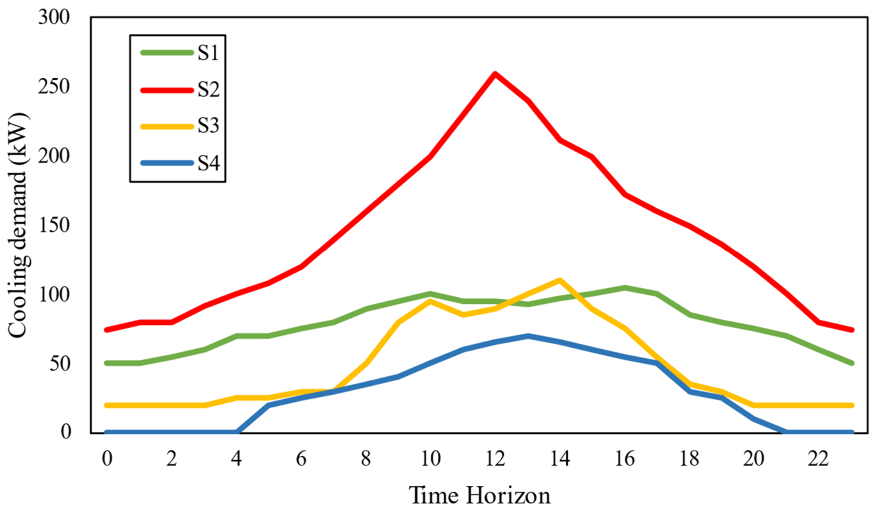


Figure 6.4 - The sample cooling load profiles for each season.

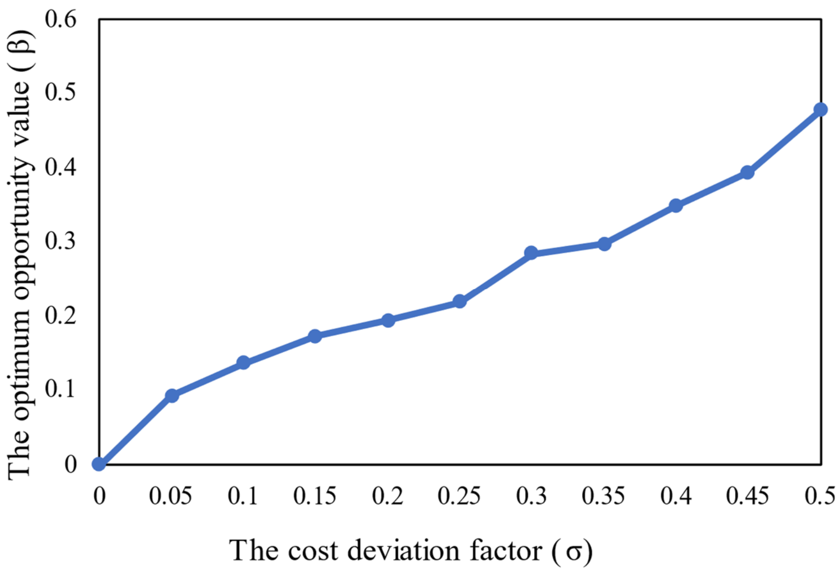


Figure 6.5 - The value of the opportunity function for various cost deviation factors.

In addition, the impact of the implementation of DR programs for electric loads is shown in Figure 6.6. To illustrate the effect of the DR program on the electric demand, each season is depicted in a single subplot. After the implementation of DR programs, the load profiles during the peak period have decreased and have been moved to the off-peak period, according to the results.

For example, the demand profile for S1 has experienced an increase during off-peak hours due to the price difference between low and high peak hours. Specifically, the daily load demand at 15:00 during spring is 400 kW, which decreases to 350 kW after implementing the DR program.

Similarly, the daily load profile in summer has changed from the peak period to the off-peak period, where there is a significant change in the morning and the evening, while it is reduced during midday. Electric consumption during autumn is increased from 7:00 to 14:00, thus reducing afternoon demands.

Finally, there is a significant peak shaving during winter at 18:00. To reduce the electricity usage at 18:00, the demand for the previous hours is increased to balance the reduced and recovered energy.

It should be noted that the emergency DR program is not used according to the current demand. The main reason for this issue is the high cost of exercising the emergency DR program, which the operator prefers not to exercise unless necessary because of the imbalance between supply and demand.

As mentioned in the problem formulation section, the shifting DR program is applied for both heating and cooling loads, where their associated results are shown in Figure 6.7 and Figure 6.8, respectively.

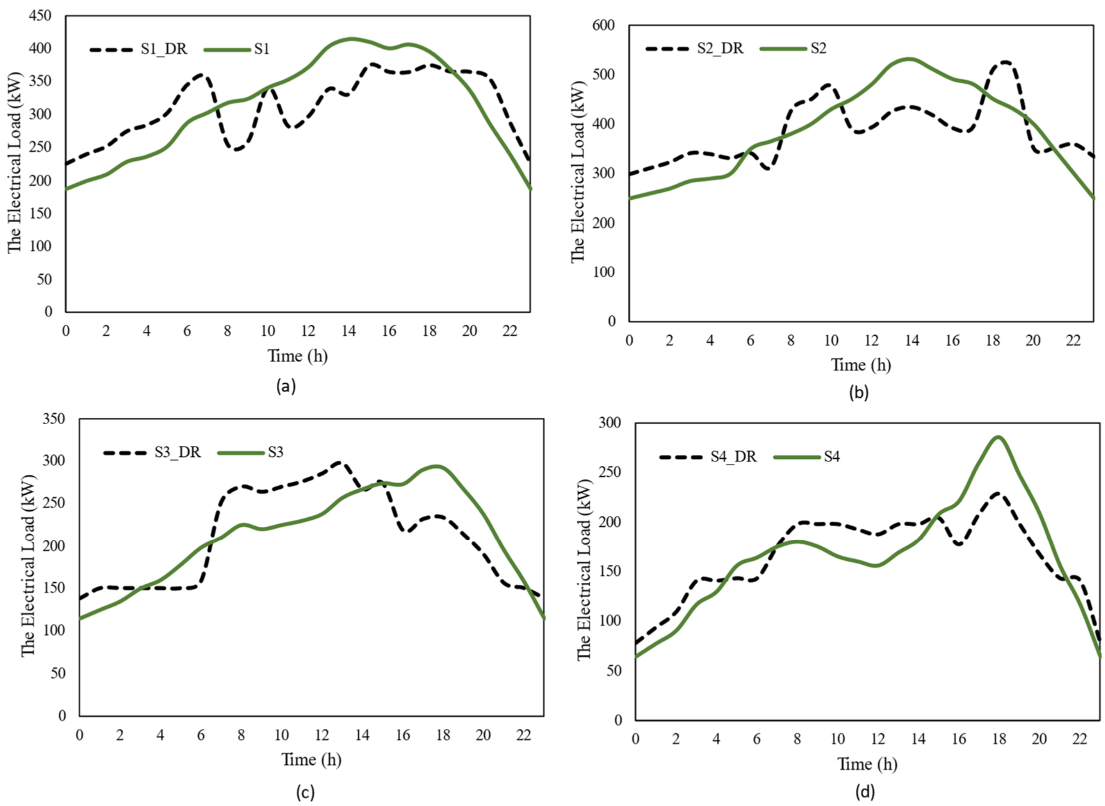


Figure 6.6 - The electricity profile after employment of DR programs for each season: (a) spring, (b) summer, (c) autumn, and (d) winter.

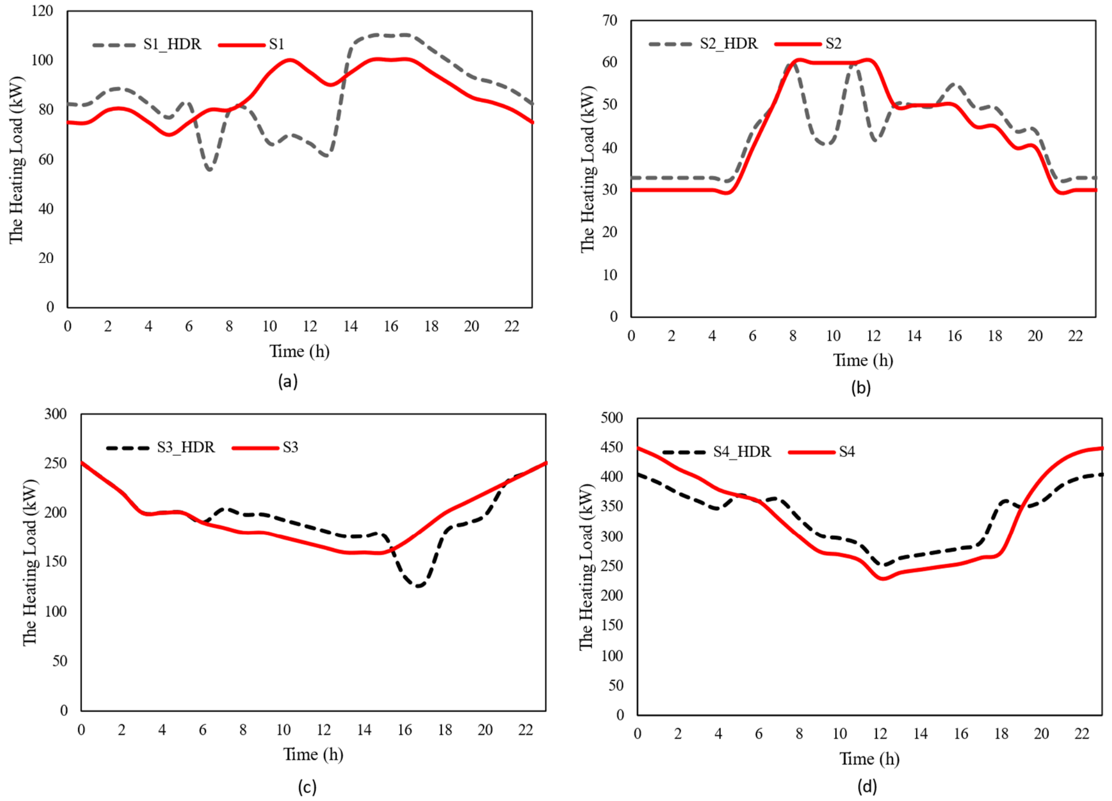


Figure 6.7 - The heating loads profile after employment of DR programs for each season: (a) spring, (b) summer, (c) autumn, and (d) winter.

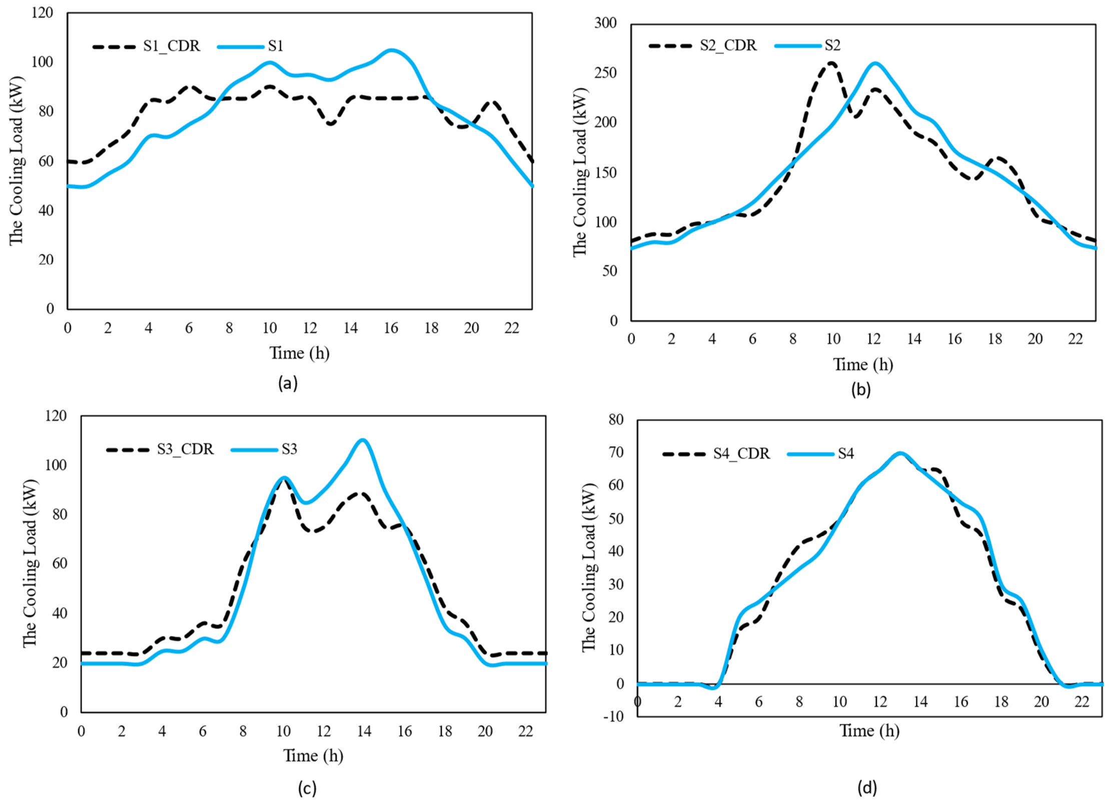


Figure 6.8 - The cooling loads profile after employment of DR programs for each season: (a) spring, (b) summer, (c) autumn, and (d) winter.

The impact of applying the shifting DR program for the heating loads is considerable on the total cost. The heating loads in the spring are reduced during the day, while they increase during the night and evening.

Therefore, the heating requirement for keeping the room temperature pleasant during the night is considered. Similarly, the heating loads in summer are reduced during the peak period and compensated during the off-peak period.

It should be noted that the shifting DR program for the heating loads in winter is more important than the other seasons as the heating demand is high during these periods. Thus, it can be seen that there are smooth changes in energy usage during the day based on the energy prices and the load participation ratio. It attempts to increase the heating demand during the day to decrease it at night.

As mentioned in the result discussion of Figure 6.6, the TOU DR program was only exercised in the studied case due to the high cost of applying an emergency DR program for the energy hub operator.

To analyze the performance of the emergency DR program, a sensitivity analysis is applied to the electric loads. Therefore, the electric load profiles are being studied using a range of $\{0.8, 1.0, 1.2, 1.5, 1.8\}$ times of the electricity demand given in Figure 6.2. When the load profile coefficient is $\{0.8, 1.0, 1.2\}$, the system can balance supply and demand. Hence, the emergency DR program is not being activated by the operator.

However, the multi-energy system cannot meet the power balance when the load profile increases to 1.5 or 1.8 times the regular pattern. Accordingly, the emergency DR program is activated to resolve this issue.

Figure 6.9 shows the performance of the system under the emergency DR program when $P_{s,t}^{load,new} = 1.5\, P_{s,t}^{load}$. It can be observed that this program is activated only in the spring and summer seasons. In other words, the dependency of the model on electric power in spring and summer is higher than the dependency of the model on thermal power.

However, when $P_{s,t}^{load,new} = 1.8\, P_{s,t}^{load}$, the energy hub operator is forced to enable the emergency DR program, which is costly for the system but necessary to meet the balance between the generation and consumption sides (as seen in Fig 6.10).

The utilization of a risk management approach leads to an expense for the entity making the decision, i.e., opportunity cost, an essential factor to consider.

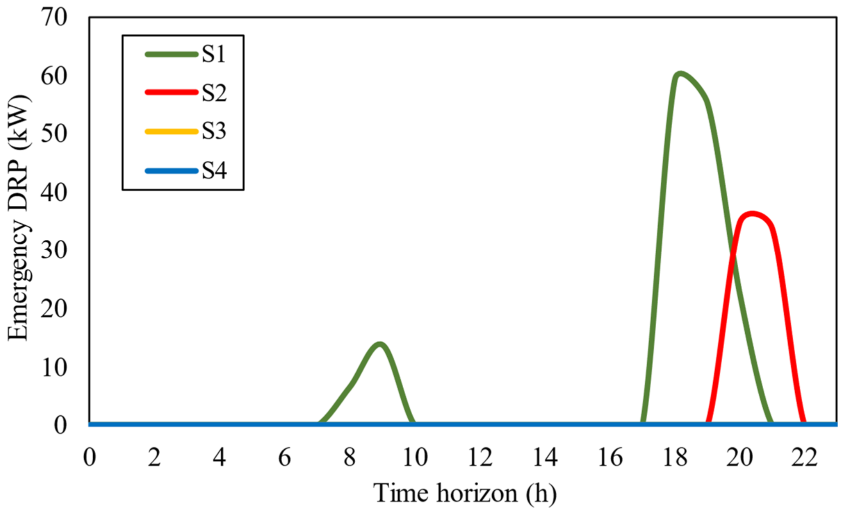


Figure 6.9 - The behavior of the emergency DR program when we consider $P_{s,t}^{load,new} = 1.5\ P_{s,t}^{load}$.

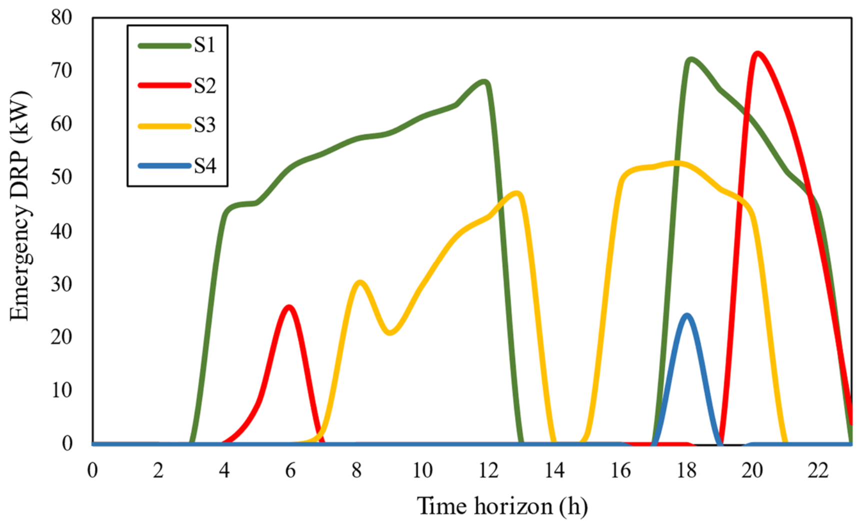


Figure 6.10 - The behavior of the emergency DR program when we consider $P_{s,t}^{load,new} = 1.8\, P_{s,t}^{load}$.

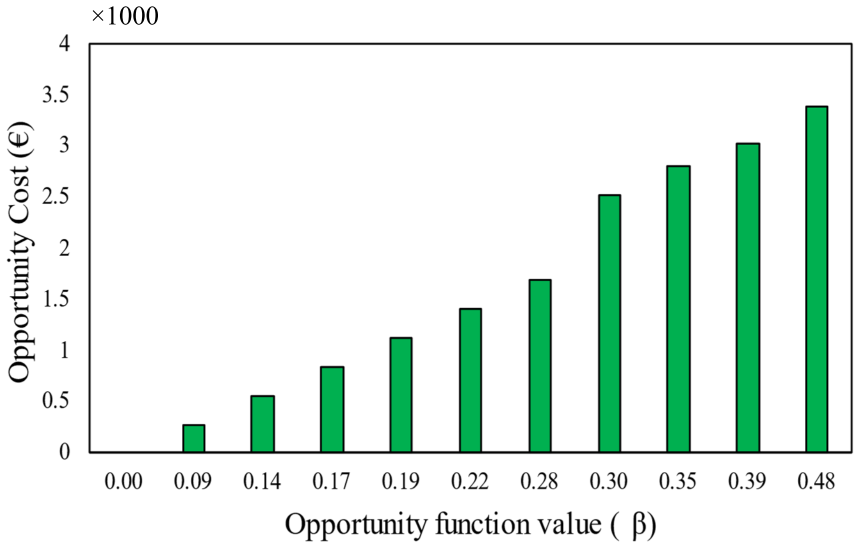


Figure 6.11 - Multi-energy hub opportunity cost considering several function values.

As shown in Figure 6.11, the opportunity cost of the system increases substantially with greater values of the IGDT opportunity function. It is possible that this cost could exceed the profit obtained by reducing operational costs through the use of the IGDT method. Therefore, decision-makers must weigh the potential benefits of the method against its associated costs before making a final decision.

6.4- Conclusions

This chapter developed a model for an energy hub consisting of various components/entities. The energy hub met the electric, heating, and cooling loads by using electricity and natural gas purchased from the external grid. Multiple integrated DR programs were also utilized to move a part of shiftable loads or change a portion of electric, heating, and cooling demand from the peak to the off-peak periods. This was done to reduce the cost of the energy hub operator. An ESS was employed in this energy hub to complement the different technologies. An approach based on the opportunity information-gap decision theory was implemented as the risk measure to ensure that the decision-maker achieved its target cost by electric, heating, and cooling load deviations from expected values. Three load sectors were considered as being uncertain parameters. Results demonstrated that using the proposed method imposed certain costs for the decision-maker.

The results revealed that the costs of the application of the risk measure sometimes were greater than the benefits gained by the decision-maker. Thus, the cost imposed through the application of the IGDT approach was a crucial factor to consider when the outcome of this method relied on it. Another significant result relates to employing integrated DR programs. The time-of-use DR program moved a portion of the shiftable loads from the periods with high demand to other periods, which could reduce the operational costs of the energy hub. Additionally, due to the high cost associated with the emergency DR program, the operator was willing to avoid activating this program unless there was an imbalance between supply and demand.

Chapter 7

Hybrid IGDT-Stochastic Self-Scheduling of a Distributed Energy Resources Aggregator in a Multi-Energy System

The optimal management of DERs and renewable-based generation in MESs is crucial. To optimally manage these numerous and diverse entities, an aggregator is required. Hence, this chapter proposes the self-scheduling of a DER aggregator through a hybrid IGDT-stochastic approach in an MES. In this approach, there are several renewable energy resources. The approach also considers an EV parking lot and thermal energy storage systems (TESs). Moreover, two DR programs from both price-based and incentive-based categories are employed in the microgrid to provide flexibility for the participants. The uncertainty in the generation is addressed through stochastic programming. At the same time, the uncertainty posed by the energy market prices is managed through the application of the IGDT method. A major goal of this model is to choose the risk measure based on the nature and characteristics of the uncertain parameters in the MES.

7.1- Introduction

7.1.1- Motivation and Background

The volume of energy generated from distributed energy resources (DERs) is significantly increasing in energy systems. Therefore, it is essential to manage the operation of these devices in the energy systems and a DER aggregator agent can provide this service. This can be done by aggregating the various offers from DERs, including the amount of DR and the amount of power through distributed generations, and trading it into the wholesale electricity market to maximize profit [49]. Moreover, it should be considered that the flexibility of a DER aggregator can be enhanced by operating within a multi-energy system (MES) [210]. Before the modernizing of the energy system, a microgrid was mainly focused on the electric power sector. However, after the introduction of new models that merge different independent single energy systems into an MES, the microgrid can also be utilized for the thermal energy sector [211].

Additionally, as a direct consequence of energy systems restructuring, on the one hand, and unprecedented renewable energy utilization on the other, the uncertainties of the energy systems are becoming more challenging. This fact intensifies the difficulty of decision-making in the energy system; therefore, the uncertainty analysis of the system performance is necessary. Moreover, one of the characteristic features of energy system operation and planning is that the decision-making problem is confronted with serious levels of uncertain information in the presence of renewable energy resources and wholesale electricity market prices. Therefore, the management of uncertainty through various risk measures such as stochastic programming, information-gap decision theory (IGDT), and robust optimization in the energy system models is crucial [212]. Meanwhile, each uncertain parameter can have its exclusive characteristics which means that employing a single risk-management method for all of these sources of uncertainty might result in misleading outcomes for a decision-maker. Therefore, to cope with this issue, a hybrid risk management method that manages several uncertain parameters in the MESs based on their characteristics can be proposed.

The DR programs are one of the main solutions to help the energy system cope with several challenges and issues it has [18]. Meanwhile, the end-user consumers are playing the main role in this area. Hence, it is sufficient to design and offer DR programs in a way to increases the participation rate of the consumers in the DR programs. There are two main classifications for DR programs, price-based DR (PBDR) and incentive-based DR (IBDR) programs [213,214]. Thus, consumers will find it more convenient to adjust their energy usage pattern based on the various available DR programs rather than a single DR program.

7.1.2- Literature Review

Several studies addressing the management of MESs have been proposed in the literature. For example, the planning and operation of MESs are investigated in [73] through a two-stage method that determines the optimal type and capacity of electrical and thermal equipment. In this study, electrical, heating, and cooling loads participate in DR programs through an energy pricing strategy. The DER uncertainties in the optimization model are not considered in this work. In [215], a cooperative framework is proposed to coordinate the operation of a network of MESs that contain electrical and heating loads participating in DR through price-based and incentive-based programs. The behavior of EVs is not simulated in the microgrid and there is no EV parking lot in the energy hub. The authors of [216] developed a modular energy management system for MESs that is generally applicable to various possible electrical, heating, and cooling components.

The management of MESs is subject to several sources of uncertainties such as demand, renewable generation, and electricity market prices. The uncertainty of wind power generation is taken into account in [217] through a two-stage stochastic formulation that seeks to minimize the operational cost of an MES. In [218], interval linear programming theory is used to model uncertainties of renewable generation (PV and wind) and demand in the optimal planning of MESs. Wang et al. [219] depict the uncertain behavior of electricity market prices as stochastic scenarios and use robust optimization to describe the uncertainties of renewable generation in a stochastic-robust optimization model for MESs operation. Yet, in [217–219], the implementation of DR programs is not studied. The study presented in [220] investigates the use of fuzzy logic to take into account the uncertainties of renewable generation and demand when optimizing the operation of MESs.

In [221], robust optimization for renewable generation uncertainty and a price-based DR program are considered in the day-ahead scheduling of MESs. In another work [222], robust optimization is used for renewable generation and demand uncertainties in an MES that implement DR based on an incentive program. The authors of [223] integrate an incentive-based DR program into a hybrid robust stochastic approach for scheduling MESs. Demand uncertainty is modeled through stochastic scenarios, and wind power uncertainty is taken into account using robust optimization.

The connection of electric vehicles (EVs) increases the complexity of the management of MESs due to the consumption characteristics of the load type. Ata et al. [224] present an optimization framework that schedules the MESs operation considering the impact of EVs, uncertainties of renewable generation through stochastic optimization, and a time-of-use pricing scheme. However, the uncertainty of wholesale market prices, which has a significant impact on the behavior of the decision-maker, is not analyzed. Uncertainties of EVs are considered in [225] by using a stochastic model predictive control framework that optimizes the MES schedule considering the TOU pricing for electricity. Stochastic optimization is also used in [21] to model uncertainties of renewable generation and EVs in the MES scheduling problem, considering price-based and incentive-based DR programs. All uncertain parameters in [21,225] are modeled through a risk-management method disregarding the characteristics and nature of the uncertainties.

A salient characteristic of IGDT is its property of handling the uncertainty problem without depending on the descriptions of the function or fluctuations in the range of uncertain variables. IGDT has been used to model uncertainties in issues related to power systems, such as the optimal bidding of DER aggregators and optimal bidding of smart microgrids [226], [227].

The authors of [228] present a comprehensive approach that models the optimal scheduling of MESs considering uncertainties due to wind energy, demand, EV consumption patterns, and electricity market prices through robust optimization. Further, responsive loads participate in an incentive-based DR program. However, the impact of the favorable variations of the uncertain parameters for a risk-seeking decision-maker is not demonstrated. The authors in [229] proposed a stochastic-IGDT approach for the management of integrated energy systems. This energy hub consists of a PV unit, a CHP unit, a heat pump (HP) unit, an absorption chiller (AC) unit, a thermal energy storage (TES) system, electric energy storage (EES) system, and an energy demand for heat, cooling, and electricity. The uncertainty of the wholesale market prices is not included in this model. It should be noted that addressing the risk posed by the electricity market prices is crucial for the decision-maker to better inform the self-scheduling strategy. Moreover, the effects of demand-side management methods on the operation of the energy hub and its correlated benefits are neglected.

Wang et. al. considered the IGDT method to handle the uncertainty in their proposed MES model [230]. To this end, the uncertainties on renewable energy and load are addressed through a single IGDT method. However, the characteristics of the uncertain parameters are ignored in this paper. Moreover, consideration of a single shifting DR program might reduce the tendency of the end-user consumers to participate in the demand-side management process.

The authors in [231] utilized a hybrid IGDT-robust approach for the self-scheduling of multi-carrier energy systems. The uncertainty posed by wind power generation is handled through the implementation of an IGDT method and the uncertainty of the electricity market price is modeled by the robust optimization approach. The applied IGDT-robust method aims to maximize the horizon of the uncertainty of wind power generation in the worst-case scenarios.

Therefore, the IGDT applied to the wind power generation and robust method is managing the day-ahead market prices. The differences between our work relative to this work are mentioned as follows: The generation from various power sources including wind turbines and PV panels and EV charging/discharging patterns is managed through stochastic programming through the generation of various scenarios. The uncertainty of wind power generation in [231] is handled through robust optimization where only it is managing the worst-case scenarios. Two DR programs from each of the DRP categories are considered in our work to encourage the consumers and end-users to participate more actively in the proposed DR programs. In other words, this provides more flexibility for the consumers to choose the DRP which is more suitable for them. The behavior of both risk-averse and risk-seeking decision-makers is analyzed in our model. While the authors in [231] only consider the risk-averse behavior of the decision-maker. The study of the risk-seeking behavior of the DER aggregator is beneficial as there is the possibility of large spikes in the observed electricity market prices which is favorable for the decision-maker and the risk-seeking decision-maker would be interested in having this information beforehand. Thus, risk-seeking decision-makers prefer to pursue the additional benefits of uncertainty can pursue an improved goal, and minimize the negative disturbance of uncertain parameters. Furthermore, the authors in [232] have implemented a hybrid decentralized stochastic-robust model for the optimal coordination of an EV aggregator and energy hub entities. Stochastic programming is used to model the uncertainties of the EV patterns, while the uncertainties of the locational marginal prices are modeled via robust optimization to capture the worst-case realization. In this work, the authors considered the EV aggregator and the energy-hub operator as two independent entities while in our model, the DER aggregator is responsible for managing the EVs as well as controlling the generation from the renewable energy resources, designing the DR programs and offering them to the end-users. While the DR programs are not taken into account in [232]. Besides that, merging the role of the EV aggregator, DR aggregator, and the energy-hub operator could lead to making the transaction procedure simpler. Having three different independent entities which in some situations have conflicts of interest might make the optimization procedure more complex.

7.1.3- Contributions and Chapter Organizations

As shown in the literature review, the consideration of a suitable risk management method based on the nature and characteristics of the uncertain parameters is found to be an important issue for the DER aggregators in the management and scheduling of MESs. For instance, according to the features of the generation of renewables and DERs, applying the stochastic approach can more accurately address their corresponding uncertainty since the generation of these entities controls the DER aggregator. An aggregator has enough information about the amount of generation from their devices in the MES. However, the DER aggregator does not control the wholesale energy market prices as the aggregator is a price-taker, not a price-maker.

Therefore, with uncertain parameters, the application of the IGDT method is deemed practical. Moreover, the consideration of various DR programs from price-based and incentive-based categories provides flexibility for consumers and encourages them to participate more actively in the DR programs, which is included in this model. The novel contributions are presented as follows:

- Proposing a hybrid IGDT-stochastic approach for the self-scheduling of a DER aggregator in an MES. Therefore, through the application of this hybrid method, solutions for two different types of DER aggregators (risk-averse and risk-seeker decision-makers) are provided which makes it easier for the decision-makers to choose the model based on their preferences.
- Considering multiple uncertainties posed from both sides of the entity, which are the market side of the aggregator and the consumption side of it, simultaneously. Besides that, the most suitable risk measures for the decision-maker are chosen based on the characteristics of the uncertain parameters, which leads to a more precise decision.

The organization of the chapter is presented as follows. The proposed hybrid IGDT-stochastic model is explained in detail in Section 7.2. In Section 7.3, the numerical results are discussed to demonstrate the model's effectiveness. Finally, the conclusion includes the most critical findings, as presented in Section 7.4.

7.2. The Proposed Optimization Model

The main objective of the proposed model in the first step, i.e., the sole stochastic programming step, is the maximization of the profit of the DER aggregator through handling the risks associated with the generation of RES and EV charging/discharging patterns. In the second step, based on the risk strategy, the maximum or minimum deviation of the uncertain parameter from the predetermined values is obtained, while the critical or target profits of the risk-averse or risk-seeker DER aggregator are met and guaranteed. Hence, the proposed MES framework for the DER aggregator includes several sources of DERs such as CHP, boiler units, RESs such as PV and wind units, and thermal energy storage (TES). An EV parking lot is also considered in our model. The inclusion of EVs in the MES could significantly reduce the amount of excess renewable energy produced and also provide more flexibility for the DER aggregator to reduce its management and operational costs, making our model more comprehensive. The schematic of the proposed model is depicted in Figure 7.1. As shown in this figure, this model has two inputs (gas and electricity) and two outputs (electrical and thermal loads). As illustrated in Figure 7.1, the electricity from the MES is being supplied in two different directions, electrical loads of buildings and the EVs. It should be noted that the DR programs are only implemented on the electrical load of the buildings. The MES under consideration studies several DERs, including CHP units, ABs, and TES systems. Additionally, wind and PV units are included as renewable energy producers. EVs are also included.

As mentioned in the previous section, the two main classifications are price-based DR (PBDR) and incentive-based DR (IBDR) programs. In this model, DR programs from both categories are considered to provide more flexibility to consumers and encourage them to actively participate in the DR programs. In this case, the flexibility of consumers willing to participate in the DR programs will be increased. A TOU program is from the PBDR group and the emergency DR programs are from the IBDR group.

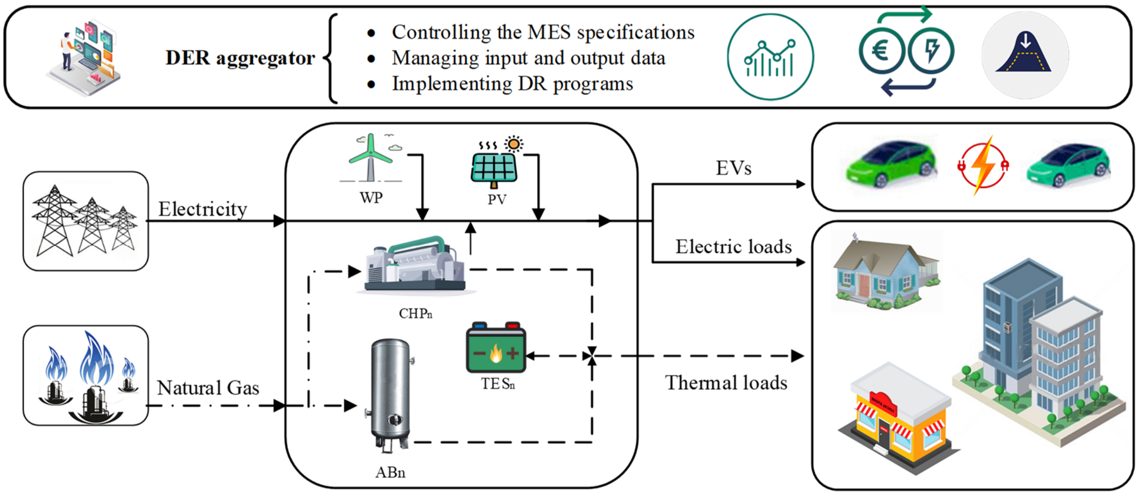


Figure 7.1 - The schematic of the proposed model.

To describe the model characterization more in detail, a flowchart of the proposed approach is depicted in Figure 7.2. Several sources of uncertainty are managed through a hybrid approach. The behavior of EV owners and the amount of power generated through renewable units, including PV and wind turbines, are modeled with stochastic programming.

The uncertainty relating to the wholesale market prices is managed using IGDT. This combination of stochastic and IGDT risk management methods leads to a hybrid IGDT-Stochastic model. In the MES, the DER aggregator has several costs and revenues and this model aims to optimize the self-scheduling model for the aggregator. The proposed model finds the most suitable solution for risk-averse decision-makers. The hybrid IGDT-Stochastic function is modeled in such a way as to protect the aggregator against unfavorable deviations of the uncertain parameter [15], as shown in Figure 7.2.

Moreover, it can be seen that two sub-stages are considered which form the main hybrid stage. In the first stage, it is assumed that the stochastic risk management method is applied to the associated uncertain parameters such as PV and wind units' generation and the charging pattern of the EVs. Therefore, the uncertainty posed by the electricity market prices is disregarded. In other words, in the first step, it is assumed that there is no uncertainty in the electricity market prices and that the aggregator has perfect foresight about the market prices. Thus, the objective function in this step will become a typical stochastic approach to maximize the profit of the DER aggregator in the MES. Then, in the second sub-section, the IGDT programming is taken into account. The uncertainty of the market prices is measured and addressed in this step. Therefore, the output from the stochastic risk-management method is being used as the input for the IGDT model. These two steps together form the main stage, i.e., the hybrid stochastic-IGDT approach.

The mathematical model is formulated from two different perspectives to analyze the risk-averse and risk-seeking behaviors of the DER aggregator. Therefore, the optimization strategy is determined at the beginning of the second sub-section. It should be stated that the associated constraints of each step are listed in the flowchart. These constraints will be described in detail in the mathematical formulation subsection.

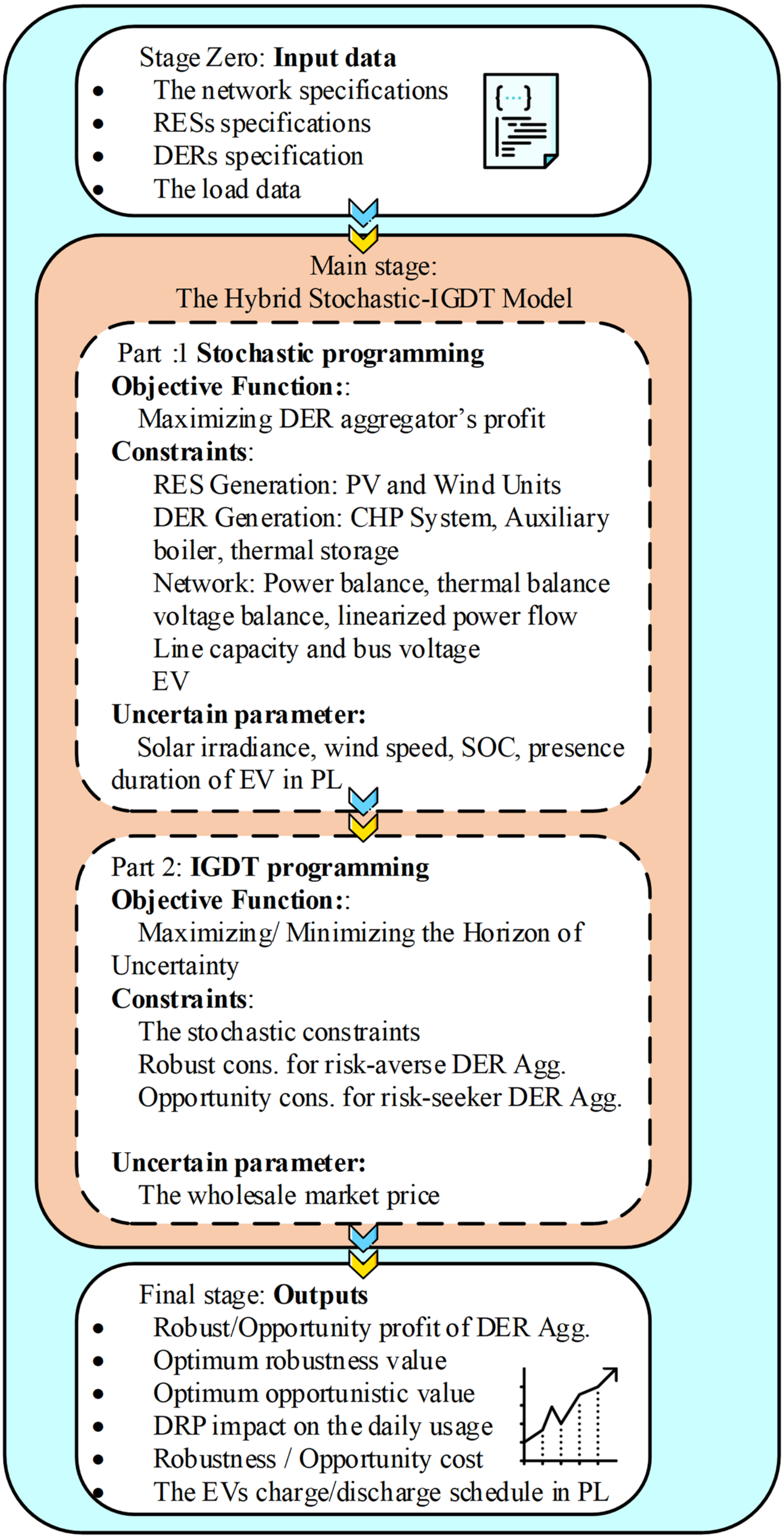


Figure 7.2 - The Flowchart of the proposed hybrid model.

7.2.1- Sole stochastic problem formulation

In this step, the stochastic approach is applied to the MES. Hence, to address the uncertainty of the PV, wind units, and EVs, stochastic modeling is well-suited and has been used extensively [21]. Historical data are used to produce the probability distribution functions for each hour to generate the scenarios. The scenario tree method is utilized to generate the scenarios, and the Kantorovich distance method is utilized to reduce the number of scenarios to ease the computation burden. This is done by measuring the distance between several generated scenarios. Then, the scenarios with the minimum Kantorovich distance are found. These scenarios will be omitted and their correlated probability will be added to the reference scenario. Finally, this procedure is repeated until the last batch of scenarios is found [233].

The full description of the parameters, variables, and terms used in the problem formulation is presented in Table 7.1.

In this step, the objective is to maximize the profit of the DER aggregator considering the uncertainty posed by the PV, wind units, and EVs. It should be noted that the aggregator model contains several terms, which are the primary terms indicating the profit sources and other terms showing the costs of the entity. The energy purchased to satisfy the loads is the main source of income, as well as the DR, sold to the customers in peak demand. Finally, the energy sold to the EV owners is the last income term for the aggregator. On the other hand, the main sources that impose costs on the aggregator are the gas and electricity bought from the grid; the DR purchased from the participants in DR programs, the battery degradation cost, and the electricity purchased from the EVs.

Table 7.1 — Indices, parameters and variables used in this chapter (Part 1).

Indexes	
s	Scenarios
n	EVs in the microgrid
b, b'	Buses in the network
Parameters	
σ	Profit deviation value
ρ_s	Probability of scenarios
$SOC_{n,t,s}^{max}, SOC_{n,t,s}^{min}$	Max/min SOC of EV at time t scenario s
P^{CHPmax}, P^{CHPmin}	Max/min generation of CHP
$\eta_{el}^{CHP}, \eta_{th}^{CHP}$	Electric and thermal efficiency of CHP
$P_{t,s}^{W,max}, P_{t,s}^{PV,max}$	Maximum generation of wind and PV units
$H^{Boilmin}$	Minimum heat of boiler
η_{th}^{Boil}	Thermal efficiency of boiler
$V_{max}, V_{min}, V^{Nom}$	Max/min and nominal voltage
$R_{nn'}, X_{nn'}$	Resistance and reactance of the lines
$\Delta S_{tnn'}$	The upper limit in the discretization of quadratic flow

Table 7.2 — Indices, parameters and variables used in this chapter (Part 2).

Variables	
$\alpha^{opportunity}$	Optimum opportunity value
α^{robust}	Optimum robustness value
$\mathrm{PR}^{sole\ \mathrm{stochastic}}$	Sole stochastic profit of the DER aggregator
$PR_{critical}$	Critical profit of the DER aggregator
$PR_{t\,arg\,et}$	Target profit of the DER aggregator
$P_{t,s}^{W}$, $P_{t,s}^{PV}$	Power generation of wind and PV units
COP^{HP}	Coefficient of the heat pump
$P_t^{req,HP}$	Power required by the heat pump
P_t^{CHP}	Generation of CHP
H_t^{Boil}	Heat rate of the boiler
H_t^{CHP}	Heat rate recovered by the CHP
RU^{CHP}, RD^{CHP}	Ramp-up/ramp-down generation of CHP
$P_{b,t,s}^{L}$	Demand of customers
Pen_t	Penalty in DR programs
A_t	Incentive of DR programs
$P_{b,t,s}^{L,DR}$	Demand by implementing DR
$P_{b,t,s}^{Con}$	Contracted power in DR programs
$P^{Boilmax}$	Maximum generation of boiler
$P_{n,t,s}^{Ch,EV}, P_{n,t,s}^{dis,EV}$	Charging and discharging power of EVs
λ_t^{L}	Electricity price after DR
λ^{g}	Price of natural gas
λ_t^{dis}	Discharging tariff of EVs
λ_t^{EV}	Price of electricity bought by EVs
λ_t^{DA}	Price of electricity from the DA market
$P_{t,s}^{Loss}$	Power loss of the system
V, V2	Voltage, squared voltage
I, I2	Current flow, Squared current flow
P+, P-	Active power flows in down/upstream sides
Q+, Q-	Reactive power flows in down/upstream sides
bi_t^{Boil}	Binary variable of boiler
bi_t^{CHP}	Binary variable of CHP

Thus, the objective function for this stage is written as follows:

$$Max\ PR^{sole\ \text{stochastic}} = \sum_{s=1}^{S} \rho_s \left(F_{1,\text{s}} + F_{2,s} - F_{3,s} - F_{4,s}\right) \tag{7.1}$$

where $PR^{sole\ \text{stochastic}}$ is the sole stochastic objective function. The first parameter is the probability of each scenario. $F_{1,s}$ is the aggregator's income from selling electricity to the consumers in the MES. $F_{2,s}$ is the amount of profit obtained through trading with the EVs. $F_{3,s}$ is the cost of purchasing energy from the upstream network. Finally, $F_{4,s}$ is the cost of implementing the DR programs on the proposed MES. The detailed problem formulation for the first source of income, i.e., $F_{1,s}$ is given as follows:

$$F_{1,\text{s}} = \sum_{b=1}^{B} \sum_{t=1}^{T} P_{b,t,s}^{L}\ \lambda_t^L\ d_t \tag{7.2}$$

Thus, in Eq. (7.2), $P_{b,t,s}^{L}$ indicates the load demand on bus *b*, time *t*, and scenario *s* that is being sold at the electricity price of λ_t^L and d_t is the time interval. The second income source of the DER aggregator is the amount of revenue obtained from selling energy to the EVs minus the cost of buying energy from the EV owners as given in Eq. (3). In this equation, $P_{n,t,s}^{Ch,EV}$ and $P_{n,t,s}^{dis,EV}$ are the charging and discharging values of the EVs where *n* is the index for the EV, *t* is the correlated charging time, and *s* indicates the scenario. The charging and discharging prices of EVs are denoted by λ_t^{Ch} and λ_t^{dis}, respectively. Then, in the last term of this constraint, the degradation cost of the EV battery is calculated, which usually occurs during the discharge. As stated in [234], the life cycle of EV batteries is usually affected by the depth of discharge. Therefore, to motivate the EV owners to participate in the scheduling plan of the DER aggregator, this cost is reasonable to be covered by the aggregator. Otherwise, the EV owners will not be encouraged to follow the charging and discharging patterns managed by the aggregator. Hence, the aggregator pays the degradation cost on each discharging period based on a specific price denoted by C^d.

$$F_{2,s} = \sum_{n=1}^{N} \sum_{t=1}^{T} \begin{pmatrix} P_{n,t,s}^{Ch,EV} \lambda_t^{Ch} d_t \\ -P_{n,t,s}^{dis,EV} \lambda_t^{dis} d_t - P_{n,t,s}^{dis,EV} C^d d_t \end{pmatrix} \tag{7.3}$$

Eq. (7.4) shows the costs of trading energy with the upstream electricity and gas markets. $P_{Sb,t,s}^{DA} \lambda_t^{DA} d_t$ shows the cost of buying electricity, i.e., $P_{Sb,t,s}^{DA}$ from the day-ahead market with a λ_t^{DA} electricity day-ahead market price. The second and third terms are the costs of purchasing gas to feed the CHP units. Thus, P_t^{CHP}/H_t^{CHP} is the amount of power/heat generated through CHP, η_{el}^{CHP} and η_{th}^{CHP} are the electric and thermal efficiency of CHP and LHV_g showing the lower heat value of natural gas. The last term in this constraint is the cost of the auxiliary boiler, where H_t^{Boil} is the heat that is generated by the unit considering the thermal efficiency of the boiler and LHV_g. The upstream gas price is denoted by λ_t^g.

$$F_{3,s} = \sum_{Sb=1}^{Sb} \sum_{t=1}^{T} \left(P_{Sb,t,s}^{DA} \lambda_t^{DA} d_t + \left[\frac{P_t^{CHP}}{(\eta_{el}^{CHP} LHV_g)} + \frac{H_t^{Boil}}{(\eta_{th}^{Boil} LHV_g)} \right] \lambda_t^g d_t \right) \tag{7.4}$$

The cost of implementing the DR programs in the proposed framework is considered in Eq. (7.5). Two DR programs are assumed for this model, the TOU and the emergency DR programs. These programs are applied to make the proposed framework more comprehensive by providing more flexibility to the consumers to choose the DR method based on their preferences and encouraging the consumers to participate more actively.

The TOU program belongs to the price-based DR category, and the emergency DR is categorized as an incentive-based DR program. In the following constraint, A_t is the value of the incentives of the DR program; $P^{L}_{b,t,s}$ indicating the initial demand of the end-user consumer at bus b, time t, and scenario s. Then, $P^{L,DR}_{b,t,s}$ is the amount of demand after the implementation of the DR program from the consumer. The difference between these two values is the amount of DR available for the DER aggregator. However, there is a possibility that the consumers do not participate in the DR program which is deducted from the cost that is imposed on the aggregator which is calculated through the second part of the constraint that is indicated by a negative sign, where $P^{Con}_{b,t,s}$ is showing the contracted power in DR programs.

$$F_{4,s} = \sum_{b=2}^{Nb} \sum_{t=1}^{T} \begin{pmatrix} A_t\left(P^{L}_{b,t,s} - P^{L,DR}_{b,t,s}\right) - \\ Pen_t\left(P^{Con}_{b,t,s} - P^{L}_{b,t,s} + P^{L,DR}_{b,t,s}\right) \end{pmatrix} \tag{7.5}$$

The related constraints regarding the DR program are given as follows:

$$E = \frac{\lambda_0}{P_0} \cdot \frac{\partial P}{\partial \lambda} \tag{7.6}$$

$$E_{t,t} = \frac{\lambda_{0,t}}{P_{0,t}} \cdot \frac{P_t - P_{0,t}}{\lambda(t) - \lambda_{0,t}} \leq 0 \tag{7.7}$$

$$E_{t,t'} = \frac{\lambda_{0,t'}}{P_{0,t}} \cdot \frac{P_t - P_{0,t}}{\lambda_{t'} - \lambda_{0,t'}} \geq 0 \tag{7.8}$$

$$P^{L,DR}_{b,t,s} = P^{L}_{b,t,s} \left\{ 1 + \sum_{t' \in \mathrm{T}} \frac{\lambda_{t'} - \lambda_{0,t'} + A_{t'} + Pen_{t'}}{\lambda_{0,t'}} \right. \tag{7.9}$$

The price elasticity is introduced in Eq. (7.6), which is the reaction of the load change to a change in the price. The self-elasticity and cross-elasticity values are calculated through Eq. (7.7) and Eq. (7.8), respectively. The load value after implementing the DR programs is calculated by Eq. (7.9). $P^{L}_{b,t,s}$ is the initial load without activating the DR programs. The new and initial prices are denoted by λ_t and $\lambda_{0,t}$, respectively. A_t is the incentive amount of the emergency DR program, Pen_t is the amount of penalty that must be paid if the DR is not exercised and $E_{t,t}$ is the elasticity value based on the time of the DR application. This elasticity calculation method is extracted from [235].

The related constraints of the renewables, DERs, EV, and the network and line limitations for the proposed model are presented as follows:

$$P^{W,min}_{t} \leq P^{W}_{t,s} \leq P^{W,max}_{t} \tag{7.10}$$

$$P^{PV,min}_{t} \leq P^{PV}_{t,s} \leq P^{PV,max}_{t} \tag{7.11}$$

The constraints (7.10) and (7.11) ensure that the renewables in the MES have a minimum and maximum capacity of generation for each time interval and that their generation cannot exceed these values. Then, the following section presents the constraints for each DER. In these constraints, the binary variables are denoted by $bi^{DER\,X}_{t}$ representing whether the devices are active or not.

7.2.1.1- CHP

The constraints related to the CHP unit are written as follows:

$$bi_t^{CHP} P^{CHP,min} \leq P_t^{CHP} \leq bi_t^{CHP} P^{CHP,max}, \forall t \tag{7.12}$$

$$RD^{CHP} \leq P_t^{CHP} - P_{t-1}^{CHP} \leq RU^{CHP}, \forall t \tag{7.13}$$

$$H_t^{CHP} = P_t^{CHP} \frac{\eta_{th}^{CHP}}{\eta_e^{CHP}}, \forall t \tag{7.14}$$

where P_t^{CHP} is the total amount of the generated power by the CHP unit in Eq. (7.12). This value should be within the allowed range as it cannot be lower or higher than the minimum and maximum capacities, respectively. The ramping constraints are presented in Eq. (7.13). This constraint shows that the amount of increase or decrease in electric power generation of CHP is dependent on various parameters such as its amount of generation in the previous time interval (P_{t-1}^{CHP}), ramp-down value (RD^{CHP}) and ramp-up value (RU^{CHP}). In Eq (7.14), the heat generated by the CHP unit is calculated, which is dependent on the generated power through the CHP unit, and the thermal and electrical coefficients.

7.2.1.2- Boiler

The constraint related to the boiler is presented as follows:

$$bi_t^{Boil} H^{Boil,min} \leq H_t^{Boil} \leq bi_t^{Boil} P^{Boil,max}, \forall t \tag{7.15}$$

The heating generation through the boiler is limited through this constraint, where H_t^{Boil} is the heating generation value limited by its min/max capacities where they are denoted by $H^{Boil,min}/P^{Boil,max}$, respectively. The binary variable (bi_t^{Boil}) indicates whether the boiler is being exercised in time interval *t* or not.

7.2.1.3- Thermal Energy Storage

In the proposed MES, TES stores the extra heat that is not required by the consumers. This energy will be supplied to the consumers when there is a demand for heat and the heat generation in that period is not enough.

$$H_t^{TES} = H_{t-1}^{TES}\left(1 - \varphi_{\square}^{TES}\right) + \left(H_t^{Ch,TES} - H_t^{Dis,TES}\right), \forall t \tag{7.16}$$

$$H_t^{TES} \leq H_{max}^{TES} \tag{7.17}$$

$$H_t^{TES} \geq 0 \tag{7.18}$$

$$H_t^{Ch,TES} \geq 0 \tag{7.19}$$

$$H_t^{Dis,TES} \geq 0 \tag{7.20}$$

$$H_t^{Ch,TES} \leq H_t^{CHP} \tag{7.21}$$

The heat stored in time interval *t* is dependent on its previous value and the amount of energy added or removed as stated in Eq. (7.16). In this equation, the losses are denoted by φ^{TES}, which indicates the thermal energy loss for each time interval. The charge and discharge rates of the TES are denoted by $H_t^{Ch,TES}$ and $H_t^{Dis,TES}$, respectively. The remaining constraints (7.17) -(7.21) clarify the capacity limitations of the TES. The TES has a maximum capacity which is given in (7.17). Moreover, the variables associated with the stored amount of heat, charge, and discharge rates of the TES cannot be negative, as stated in (7.18) -(7.20).

Finally, the last constraint regarding the TES ensures that the charging rate of the TES must be lower or equal to the heat stored at time interval t.

7.2.1.4- Other Constraints

In this step, the constraints related to the active, reactive, and heating power balancing equations are presented.

$$P^{DA}_{Sb,t,s} + P^{PV}_{b,t,s} + P^{W}_{b,t,s} + P^{CHP}_{b,t,s} + \sum_{n=1} P^{Dis,EV}_{n,t,s} - \sum_{n=1} P^{Ch,EV}_{n,t,s} + \sum_{b' \in B} (P^{+}_{t,b,b'} - P^{-}_{t,b,b'}) - \sum_{b' \in B} [(P^{+}_{t,b,b'} - P^{-}_{t,b,b'}) + R_{b,b'} I2_{t,b,b'}] = P^{L,DR}_{b,t,s} \qquad \forall t, \forall b \tag{7.22}$$

$$Q^{DA}_{Sb,t,s} + Q^{PV}_{b,t,s} + Q^{W}_{b,t,s} + Q^{CHP}_{b,t,s} + \sum_{n=1} Q^{Dis,EV}_{n,t,s} - \sum_{n=1} Q^{Ch,EV}_{n,t,s} + \sum_{b' \in B} (Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'}) - \sum_{b' \in B} [(Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'}) + X_{b,b'} I2_{t,b,b'}] = Q^{L}_{b,t,s} \qquad \forall t, \forall b \tag{7.23}$$

$$H^{CHP}_{t} + H^{Boil}_{t} + H^{Dis,TES}_{t} = H^{L}_{t} + H^{Ch,TES}_{t}, \forall t \tag{7.24}$$

$$V2_{t,b} - 2R_{b,b'}(P^{+}_{t,b,b'} - P^{-}_{t,b,b'}) - 2X_{b,b'}(Q^{+}_{t,b,b'} - Q^{-}_{t,b,b'}) - (R^{2}_{b,b'} + X^{2}_{b,b'}) I2_{t,b,b'} - V2_{t,b'} = 0 \quad \forall t, \forall b \tag{7.25}$$

The active power balance is presented in Eq. (7.22) where the input of the power to the MES should be equal to its output. Thus, the amount of power traded with the wholesale electricity market and generated power from the PV, wind, and CHP units and the charging/discharging values of EVs in the parking lot and active power flows in downstream directions ($P^{+}_{t,b,b'}$) and active power flows in upstream directions ($P^{-}_{t,b,b'}$) should be equal to the demand from the consumers after the implementation of the DR programs. Similarly, the reactive power balance is also considered in constraint (7.23). Then, Eq. (7.24) shows the heating power balance. According to the constraint, the heat generated through CHP, boiler, and the discharged rate of TES must be equal to the head demand of the consumers and the charging rate of the TES. Finally, the voltage balance is calculated through Eq. (7.25). To calculate the active and reactive power balance, two auxiliary constraints should be calculated as shown by Eq. (7.26) and Eq. (7.27). The nominal voltage is denoted by V^{Nom} and maximum current flow from bus b to bus b' is denoted by $I^{Max}_{b,b'}$. The linearized power flow calculations for the radial network are considered in equations (7.28)-(7.35), where the linearization technique is taken from [236]. The authors in [236] validated the accuracy of this linearization technique for optimal power flow through an illustrative example. The correlated constraint for calculating the power factor is given in Eq. (7.36).

$$P^{+}_{t,b,b'} + P^{-}_{t,b,b'} \le V^{Nom} I^{Max}_{b,b'} \qquad \forall t, \forall b \tag{7.26}$$

$$Q^{+}_{t,b,b'} + Q^{-}_{t,b,b'} \le V^{Nom} I^{Max}_{b,b'} \qquad \forall t, \forall b \tag{7.27}$$

$$V2^{Nom}_{t,b} I2_{t,b,b'} = \sum (2\tau - 1) \Delta S_{t,b,b'} \, \Delta P_{t,b,b'} \tag{7.28}$$

$$+\sum_{\tau}(2\tau-1)\Delta S_{t,b,b'}\,\Delta Q_{t,b,b'} \qquad \forall t,\forall b$$

$$P^{+}_{t,b,b'}+P^{-}_{t,b,b'}=\sum_{\tau}\Delta P_{t,b,b'}(\tau) \qquad \forall t,\forall b \tag{7.29}$$

$$Q^{+}_{t,b,b'}+Q^{-}_{t,b,b'}=\sum_{\tau}\Delta Q_{t,b,b'}(\tau) \qquad \forall t,\forall b \tag{7.30}$$

$$\Delta P_{t,b,b'}(\tau)\le \Delta S_{t,b,b'},\,\Delta Q_{t,b,b'}(\tau)\le \Delta S_{t,b,b'} \qquad \forall t,\forall b \tag{7.31}$$

$$I2_{t,b,b'}\le (I^{Max}_{b,b'})^2 \qquad \forall t,\forall b \tag{7.32}$$

$$V^2_{Min}\le V2\le V^2_{Max} \quad \forall t,\forall b \tag{7.33}$$

$$V2^{Nom}_{t,b}=(V^{Nom})^2 \quad \forall t,\forall b \tag{7.34}$$

$$\Delta S_{t,b,b'}=\frac{V^{Nom}I^{Max}_{b,b'}}{\tau} \qquad \forall t,\forall b \tag{7.35}$$

$$P^{\bar{U}}_{t,b}\,tan(\,cos^{-1}(\,-\,\theta))\le Q^{\bar{U}}_{t,b}\le P^{\bar{U}}_{t,b}\,tan(\,cos^{-1}(\,\theta)) \qquad \forall t,\forall b \tag{7.36}$$

In addition, it should be noted that each line in the considered MES has limits regarding its thermal energy capacity. Thus, the apparent power in each bus in each scenario is denoted by $S_{b,t,s}$ should be lower or equal to its maximum value denoted by $S^{Max}_{b,t}$ at time interval t, as in Eq. (7.37). Similar limitations also exist for the voltage in each bus voltage, as stated in Eq. (7.38). In other words, the voltage level of bus b in scenario s and time t ($V_{b,t,s}$) should be higher or equal to 0.95 and lower or equal to 1.05.

$$S_{b,t,s}\le S^{Max}_{b,t} \tag{7.37}$$

$$0.95\le V_{b,t,s}\le 1.05 \tag{7.38}$$

As stated before, in the proposed framework, it is considered that the microgrid has several EVs and their corresponding effects on the problem formulation should be taken into account. Therefore, the constraints related to the EVs are written as follows:

$$0\le P^{Ch,EV}_{n,t,s}\le bi^{Ch,EV}_{n,t,s}P^{max}_{n} \qquad \forall n,\forall t,\forall s \tag{7.39}$$

$$0\le P^{Dis,EV}_{n,t,s}\le bi^{Dis,EV}_{n,t,s}P^{max}_{n} \qquad \forall n,\forall t,\forall s \tag{7.40}$$

$$0\le bi^{Ch,EV}_{n,t,s}+bi^{Dis,EV}_{n,t,s}\le 1 \qquad \forall\text{ n},\ \forall\text{t},\ \forall s \tag{7.41}$$

$$SOC^{EV}_{n,t,s}=SOC^{EV}_{n,t-1,s}+\left(\frac{P^{Ch,EV}_{n,t,s}\eta_{ch}d_t}{E^{CH,Max}}\right)-\left(\frac{P^{Dis,EV}_{n,t,s}d_t}{E^{CH,Max}\eta_{dis}}\right)+\mathrm{SOC}^{\mathrm{EV,\ Arv}}_{\mathrm{n,t,s}} \tag{7.42}$$

$$SOC^{min}_{n,t}\le SOC^{EV}_{n,t,s}\le\ SOC^{max}_{n,t} \qquad \forall\text{n},\forall\text{t},\forall s \tag{7.43}$$

$$SOC^{EV}_{n,t,s}=\mathrm{SOC}^{\mathrm{EV,\ dep}}_{\mathrm{n,t,s}} \qquad \forall\text{n},\forall\text{t},\forall s \tag{7.44}$$

In our proposed model, the charging and discharging power of each EV is denoted by $P^{Ch,EV}_{n,t,s}$ and $P^{Dis,EV}_{n,t,s}$ in the time interval t and scenario s cannot be more than their maximum capacities, as stated in (7.39) and (7.40), respectively. Moreover, the binary variables ($bi^{Ch,EV}_{n,t,s}$ and $bi^{Dis,EV}_{n,t,s}$) indicate that EVs cannot be charged or discharged simultaneously, which this limitation is employed through Eq. (7.41). The state of charge (SOC) for each EV is determined by its SOC in the previous time interval ($SOC^{EV}_{n,t-1,s}$) plus the amount of charging or discharging in the current time interval considering the charging and discharging coefficients, which are denoted by η_{Ch} and η_{Dis}, see Eq. (7.42). Moreover, $E^{CH,Max}$ is the maximum energy level of the EV battery which is required in the calculation of SOC. It should be noted that the SOC cannot exceed its maximum and minimum values, as seen in Eq. (7.43). The last equation related to the EV, Eq. (7.44), shows that when the EV departs from the charging point, the SOC of the EV should reach the value desired by the consumer, denoted by $SOC^{EV,dep}_{n,t,s}$.

7.2.2- Hybrid IGDT-Stochastic Optimization Framework

In this stage, the uncertainty of the wholesale energy market price is considered by implementing the IGDT approach. In other words, the output of the stochastic programming is now utilized as a baseline to employ the IGDT approach. Therefore, this requires converting the solely stochastic problem formulation into a hybrid IGDT-stochastic problem formulation based on the characteristics of the uncertain parameters and considering the most suitable risk measure. The robust structure of the IGDT approach is applied to manage the proposed model for a risk-averse decision-maker. In contrast, the opportunity structure of the IGDT approach is applied to a risk-seeker decision-maker. Risk seekers prefer to pursue the additional benefits of uncertainty, have the opportunity to pursue an improved result, and minimize the negative disturbance of the uncertain parameters. As we considered the electricity-market prices as the uncertain parameter, which is being addressed by IGDT, it should be mentioned that unexpected high price spikes occur in electricity markets, and are favorable price variations for the DER aggregator. A risk-seeker decision-maker desires to benefit from these favorable variations using an opportunity function.

The problem formulation is presented in two different designs, that is, robust and opportunity forms. In the formulation for the risk-averse DER aggregator, the objective is to maximize the horizon of the uncertainty (denoted by α^{robust}) of the energy market prices, while the critical profit of the entity is guaranteed, which is denoted by $PR_{critical}$. The critical profit is defined as the minimum possible amount of profit considering the horizon of uncertainty. Thus, the hybrid IGDT-stochastic model for the risk-averse aggregator is formulated mathematically through Eq. (7.45) to Eq. (7.49). The defined robust function requires fulfillment of a set of constraints that can happen in the worst-case scenarios. In other words, the DER aggregator wants to immune its self-scheduling from the scenarios that can prevent the aggregator from achieving lower profits than the critical value.

As stated in (7.46), the robust profit of the DER aggregator should be higher or equal to the predetermined critical profit denoted ($\mathrm{PR}_{critical}$). The critical profit is calculated by a percentage of the result obtained from the stochastic programming ($PR^{sole\ \mathrm{stochastic}}$). Therefore, σ is the profit deviation factor. As the profit deviation factor increases, the decision-maker would become more conservative against the unfavorable variations of the wholesale electricity market prices. Hence, σ controls the level of uncertainty which is a value between 0 and 1. $\sigma = 0$ means that the DER aggregator is risk-neutral against the electricity market prices while the uncertainties managed through stochastic programming are applied. In constraint (7.47), the fractional info-gap uncertainty model is presented [151]. The model is also still governed by Eq. (7.10) through Eq. (7.44).

$$\widehat{\alpha}\left(P, PR_{critical}\right) = Max\ \alpha^{robust} \tag{7.45}$$

Subject to:

$$\mathrm{PR}_{robust} \geq \mathrm{PR}_{critical} = (1-\sigma)PR^{sole\ \mathrm{stochastic}} \tag{7.46}$$

$$(1-\alpha^{robust})PR^{sole\ \mathrm{stochastic}} \leq \mathrm{PR}_{robust} \leq (1+\alpha^{robust})PR^{sole\ \mathrm{stochastic}} \tag{7.47}$$

$$\text{Eq. (7.10)} - (7.44) \tag{7.48}$$

To formulate the problem in a way that the worst-case scenario occurs, the low range of the uncertain parameter, which is the day-ahead electricity market prices, should be chosen. Thus, if $\mathrm{PR}_{robust} = (1-\alpha^{robust})PR^{sole\ \mathrm{stochastic}}$, the lowest amount of the profit will be obtained. Therefore, in the above problem formulation, Eq. (7.47) is replaced by Eq. (7.49).

$$\mathrm{PR}_{robust} = (1-\alpha^{robust})PR^{sole\ \mathrm{stochastic}} \tag{7.49}$$

On the other hand, the objective of the risk-seeker DER aggregator is to determine the minimum value for the uncertainty horizon denoted by $\alpha^{opportunity}$ of the energy market prices, which can lead to the achievement of target profit for the entity, denoted by PR_{target}. Therefore, the full hybrid IGDT-stochastic model for the risk-seeker aggregator is formulated mathematically by Eqs. (7.50) – (7.53).

The objective function is formulated in Eq. (7.50). The risk-seeker decision-maker desires to analyze the amount of uncertainty horizon if the uncertain parameter deviates favorably using the opportunity form of the IGDT method. It is common to observe high spikes in the electricity market prices. The opportunity profit, denoted by $\mathrm{PR}_{opportunity}$ is profit the DER aggregator will gain if the uncertain parameter deviates favorably. This value should be greater or equal to the target profit denoted by PR_{target}. Target profit is calculated based on the percentage of the result obtained from the stochastic programming. Similar to the robust form, the degree of risk-seeking is chosen by σ as the profit deviation factor. As σ increases, the decision-maker becomes more risk-seeking relative to the wholesale market prices. The constraint (7.52) indicates that the opportunity profit can be within a range that is dependent on the horizon of the uncertainty ($\alpha^{opportunity}$) and profit of the aggregator gained from the stochastic programming. The model is also still governed by Eq. (7.10) through Eq. (7.44).

$$\widehat{\beta}(P, PR_{target}) = min \ \ \alpha^{opportunity} \tag{7.50}$$

Subject to:

$$\mathrm{PR}_{opportunity} \geq \mathrm{PR}_{target} = (1+\sigma)PR^{sole\ \mathrm{stochastic}} \tag{7.51}$$

$$\begin{aligned}(1-\alpha^{opportunity})PR^{sole\ \mathrm{stochastic}} &\leq \mathrm{PR}_{opportunity} \\ &\leq (1+\alpha^{opportunity})PR^{sole\ \mathrm{stochastic}}\end{aligned} \tag{7.52}$$

$$Eq.\ (7.10) - (7.44) \tag{7.53}$$

To formulate the model in the opportunity form, the best-case scenarios should ensure that the profit of the DER aggregator reaches the target profit. This situation happens only if favorable deviations for the uncertain parameter from the baseline values occur. Thus, the highest amount of value for opportunity profit will be obtained if $\mathrm{PR}_{opportunity} = (1 + \alpha^{opportunity})PR^{sole\ \mathrm{stochastic}}$. Therefore, the constraint (7.52) in the above form of problem formulation is replaced by Eq. (7.54).

$$\mathrm{PR}_{opportunity} = (1+\alpha^{opportunity})PR^{sole\ \mathrm{stochastic}} \tag{7.54}$$

7.3- Discussion of Results

7.3.1- Data Preparation and Assumptions

The proposed hybrid IGDT-stochastic model is formulated as a mixed-integer non-linear programming (MINLP) problem. The problem is modeled in GAMS and two different solvers are utilized: SBB and DICOPT. The model is simulated using a PC with 6GB RAM and 2.43GHz CPU speed and The Network-Enabled Optimization System (NEOS) Server [237].

Load data is taken from [21], where the model is employed on the modified IEEE 15-bus system which is illustrated in Figure 7.3. The expected wholesale day-ahead market prices are taken from [10]. However, MESs were not considered in [10], while this paper considers a multi-energy framework for the DER aggregator with CHP, boiler units, RESs (namely wind and PV units, installed on bus 12 with nominal power of 200 kW), and TES.

The EV parking lot is allocated to bus 11 in the test system with a capacity of 50 EVs. For the implementation of the DR programs, the time horizon is divided into three-time slots, namely peak periods (11:00-15:00 and 19:00 - 21:59), mid-peak periods (7:00-10:59 and 15:00-18:59), and an off-peak period (22:00-6:59). The elasticity matrix for the DR programs is presented in Table 7.3. The charge and discharge efficiencies of the EVs are 95% and 90%, respectively. The nominal capacity of the EV battery is equal to 50 kWh with a 10kW/h SOC. It is assumed that the EV batteries can be charged to a maximum of 85% of the nominal value.

7.3.2- The sole stochastic optimization stage

In the first stage, it is assumed that there is no uncertainty in the electricity market prices, which are the same as the expected values. Hence, the only uncertainty on the demand side is the generation of the DERs and this is modeled through stochastic programming. Hence, several scenarios are being generated based on historical data. In this case, the value of the objective function, which is the profit of the DER aggregator, is equal to €112,900.

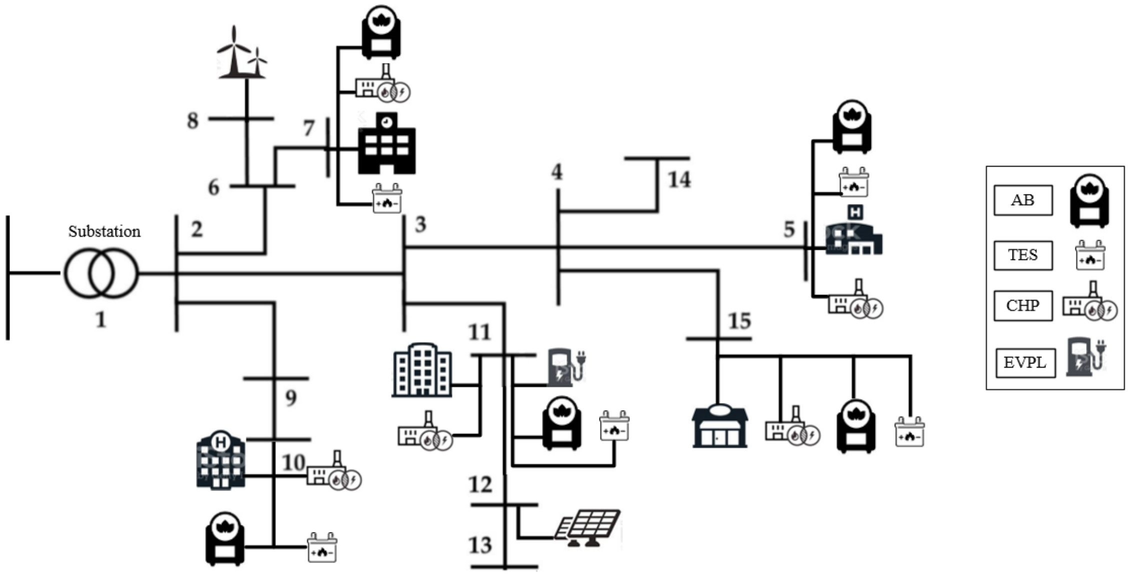


Figure 7.3 - The structure of the studied modified IEEE 15-bus test system.

Table 7.3 — Matrix of elasticity

	Peak	Mid-peak	Off-peak
Peak	-0.3	0.15	0.1
Mid-peak	0.15	-0.3	0.01
Off-peak	0.1	0.01	-0.3

In the MES, there is a set of CHP units used to produce a percentage of power supplied to the consumers. Based on the details of the problem formulation, Figure 7.4 illustrates the cumulative value of the power generated from each CHP unit. Due to its characteristics and size, CHP 5 is responsible for the highest generation among the CHP units. The generation of the units is managed by the aggregator. According to this figure and the generation of wind units and PV arrays presented in Figure 7.5 and Figure 7.6, the CHP units are being used at their maximum capacities when there is low generation from the other DERs. For instance, at 13:00, there is insufficient generation from both PV and wind units. Therefore, the CHPs generate a significant amount of energy to meet the demand and control the fluctuations due to renewables. The generation of renewable energy resources is highly dependent on weather conditions such as wind speed and solar radiation.

There are hours with low solar irradiation, for example at 14:00 in Figure 7.5. Similarly, the wind speed also fluctuates rapidly causing high output in some periods and low output in others, such as at 13:00 in Figure 7.6. These fluctuations are controlled and managed by the DER aggregator through other generation units and the implementation of the DR program. A DR program is applied to the proposed model to shift a percentage of the demand from the peak period to the off-peak or mid-peak hours. Figure 7.5. shows the load demand profile in the studied time horizon.

According to Figure 7.7, when there is no DR program, there is a significant difference in consumption. There is low demand during the off-peak period and high demand during the high-peak period. By implementing the DR program, some of the demand is shifted from the peak hours to the off-peak or mid-peak periods. In the early hours of the morning, with a low demand before the DR program, this load is now increased. The DR program increases electricity usage during the off-peak period and decreases consumption during the peak period.

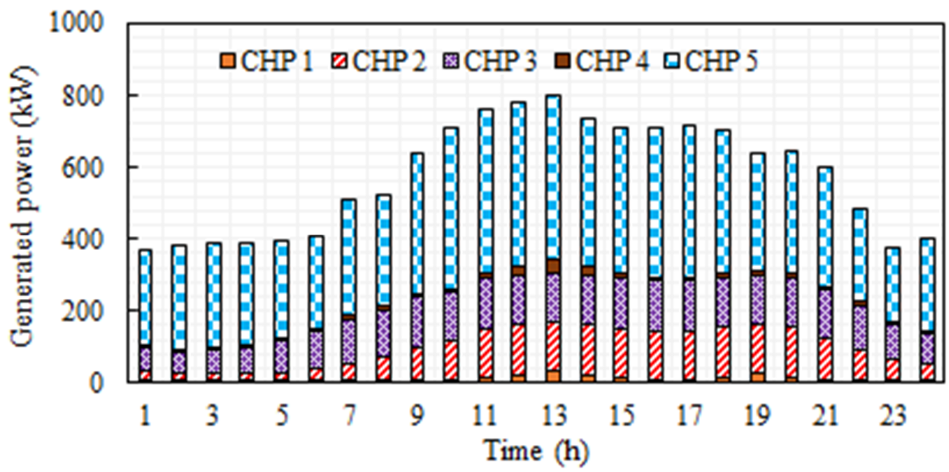


Figure 7.4 - Power generation of CHP units.

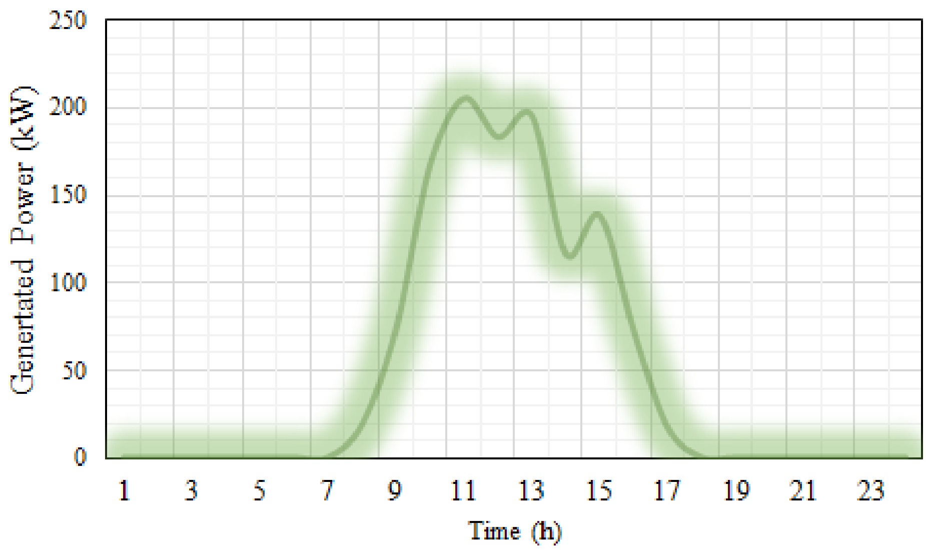


Figure 7.5 - Power generation of the PV unit.

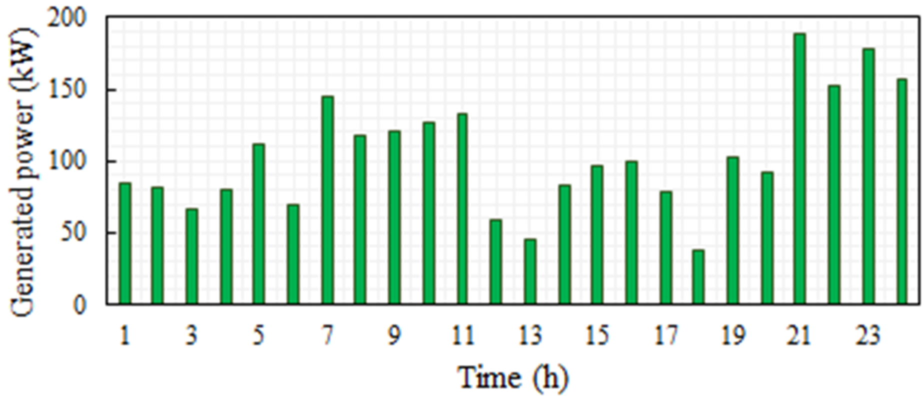


Figure 7.6 - Power generation of wind turbines.

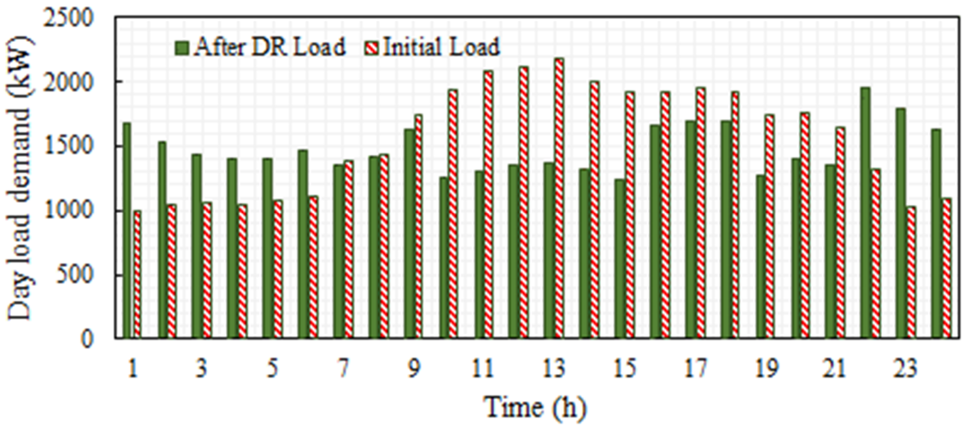


Figure 7.7 - Daily profile of the consumers before and after DR implementation.

7.3.3- Hybrid IGDT-Stochastic Optimization Stage

In the next stage, the uncertainty of the electricity market price is considered through IGDT. In this case, the uncertain parameters from both sides are considered. The uncertainty around the wholesale market side is managed through the IGDT method, and the uncertainty of renewable energy resources and EV charging/discharging patterns are assessed through stochastic programming. Therefore, the hybrid IGDT-stochastic optimization is implemented in this stage which is mentioned as one of the contributions of our work as considering the different risk measures for multiple sources of uncertainty based on their characteristics. The DER aggregator is assumed to have the forecasted wholesale market prices, i.e., $\{\bar{\lambda}_1, \bar{\lambda}_2, \ldots, \bar{\lambda}_{24}\}$. Then, the hybrid IGDT-Stochastic model is solved for several variations of σ. Therefore, several $PR_{critical}$ values are obtained. As stated in the problem formulation section, the proposed model for both types of decision-makers, risk-averse and risk-taker DER aggregators, is studied. The risk-averse decision-maker aims to guarantee the critical profit even if the worst-case scenario occurs. This type of uncertainty can be studied by implementing the robust function of the IGDT approach. On the other hand, the risk-seeking aggregator accepts the risks when targeting higher profits if a favorable scenario happens. Thus, the behavior of risk-seeking decision-makers is addressed through the opportunistic function of the IGDT approach. Therefore, the effect of considering the uncertain parameters in several risk strategies is depicted in Figs. 7.8 to 7.10.

In Figure 7.8, the optimum robustness value for different σ variations is presented. As expected, increasing σ leads to higher amounts of $\hat{\alpha}$. To explain the behavior of the optimum robustness function value for different variations of σ, an arbitrary value is chosen. Let us assume that, for σ = 0.2, the risk-averse decision-maker wants to be sure that in the worst-case scenario, its critical profit won't be lower than $PR_{Critical} = (1-\sigma)PR^{sole\ stochastic} = (1-0.2)\ 112{,}900 = €90300$. In this case, the optimum robustness value will be equal to 0.08. This means that if the observed market prices deviate by a maximum $\hat{\alpha} = 0.08$ or 8%, unfavorably, this amount of critical profit is still guaranteed for the aggregator.

In Figure 7.9, the optimum opportunity function values for different σ variations are shown. By increasing the electricity market prices, higher values for $\hat{\beta}$ can be found. Similar to the explanation given for the robustness function, an arbitrary σ amount is selected. If σ = 0.2, the target profit of the risk-seeking DER aggregator will be equal to $PR_{Target} = (1+\sigma)PR^{sole\ stochastic} = (1+0.2)112{,}900 = €135{,}500$. To reach the €135,500 aggregator profit, the wholesale market prices should be at least $\hat{\beta} = 0.08$ or 8% lower than the forecasted values.

In Figure 7.10, the optimum robustness function values ($\hat{\alpha}$) for various profit amounts of the DER aggregator are depicted. On the other side of the graph, the optimum opportunity function value ($\hat{\beta}$) for different variations of profits is shown. For the risk-averse aggregator, the robust performance of the model is desirable. For instance, as the critical profit decreases, the optimum robustness function increases. This indicates that higher unfavorable deviations of the uncertain parameter are possible for lower guaranteed critical profits, $\hat{\alpha}$, when the decision-maker chooses the risk-averse strategy. On the other hand, $\hat{\beta}$ is the minimum amount of favorable deviation of the observed values from the forecasted values of the wholesale market prices that ensure the target profit. Another interesting result is that the optimum robustness values and opportunity value for the same variation from the deterministic profit are almost the same and this is illustrated in Figure 7.10. Therefore, the optimal values for the two completely different objective functions (risk strategies) result in very similar outcomes.

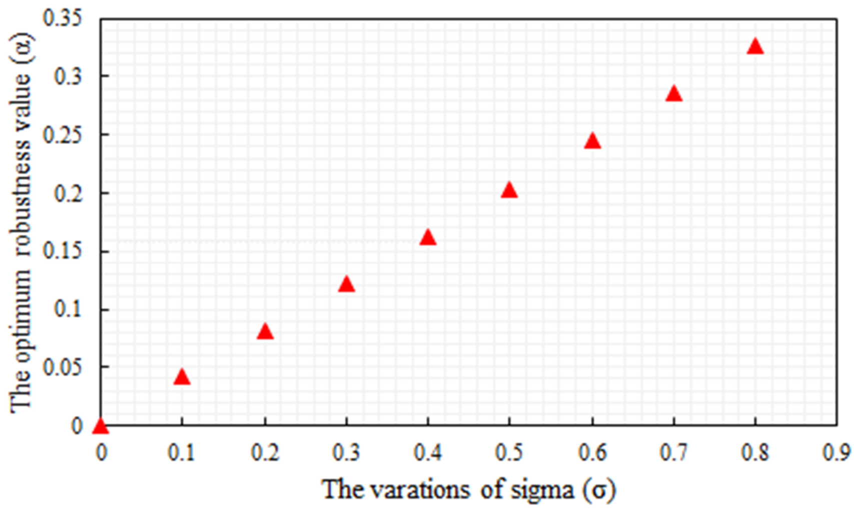


Figure 7.8 - Optimum robustness values of $\hat{\alpha}$ for different variations of σ in a risk-averse strategy.

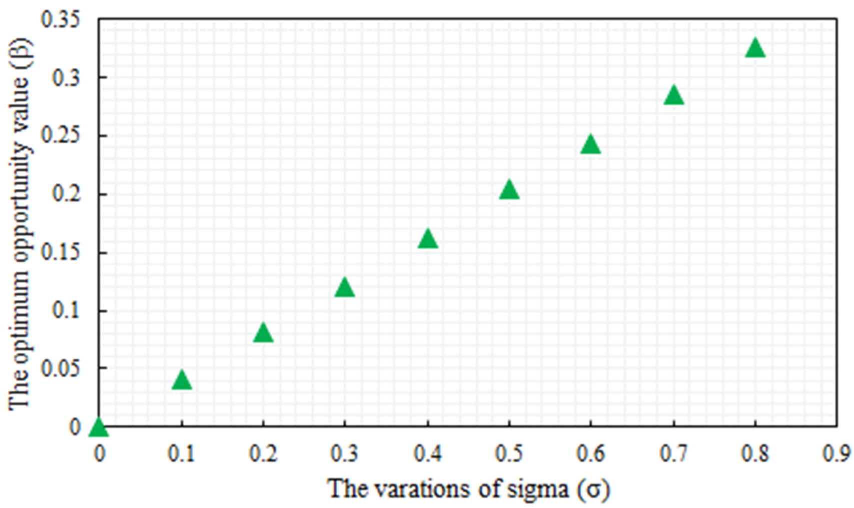


Figure 7.9 - The optimum robustness value $\hat{\beta}$ for different variations of σ in a risk-seeking strategy.

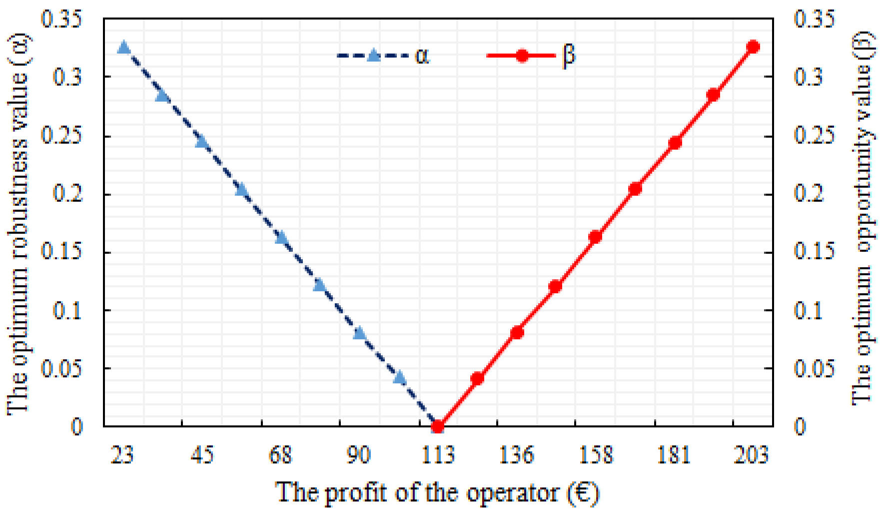


Figure 7.10 - Optimal $\hat{\alpha}$ and $\hat{\beta}$ for different profits of DER aggregators in both risk-averse and risk-seeking strategies.

The optimal values for the stored heat level of the installed TESs are illustrated under various risk strategies in Figure 7.11. It can be seen that TES 5 stores a significant level of heat. It should be noted that TES 5 is located on the same bus as the hospital. Therefore, it is essential to ensure that there is enough heat reserve to supply this important consumer. Moreover, it is shown that as the decision-maker chooses to be risk-averse, the level of energy in the TES increases. It is due to the characteristics of the risk strategy. The risk-averse DER aggregator prefers to have the highest possible level of energy stored in the TES to make sure it will satisfy the demand of the consumers. In contrast, the risk-seeking aggregator is looking for higher profits which results in lower costs associated with the TES. Therefore, the total energy level of the TES in the risk-seeking strategy would be lower than the other strategies, i.e., risk-neutral and risk-averse.

The behavior of the EVs in the PL in different conditions is shown in Figure 7.12. Figure 7.12 (a) and (b) present the charging of EVs in robust and opportunity conditions, respectively. Similarly, sub-figures Figure 7.12 (c) and (d) show the discharging of the EVs in robust and opportunity conditions, respectively. Three scenarios are chosen for each of the robust and opportunity conditions to analyze the impact of the risk attitude of the proposed approach for various scenarios. It can be seen that the number of EVs based on the several scenarios considered robust and opportunity strategies do not affect the behavior of the EVs in the parking lot significantly. While considering risk management strategies for the decision-maker, being robust or opportunistic does not affect the optimal result of the proposed model. Therefore, in either strategy, there are periods that the parking lot is occupied at its maximum capacity, 50 EVs, regardless of the aggregator's risk attitude.

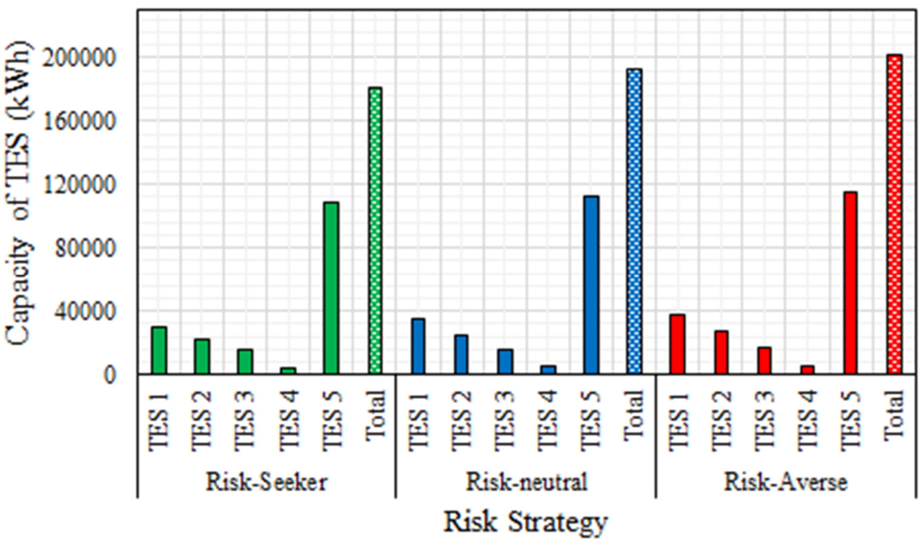
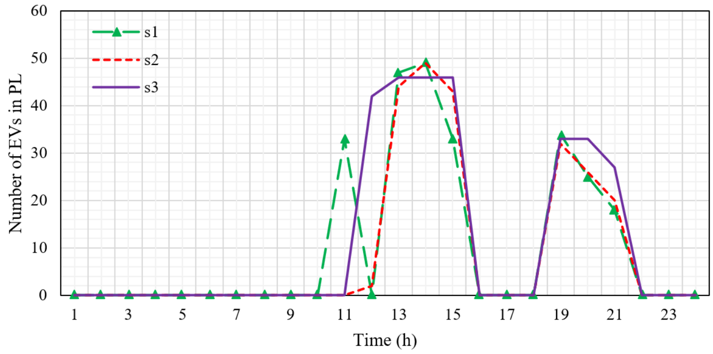
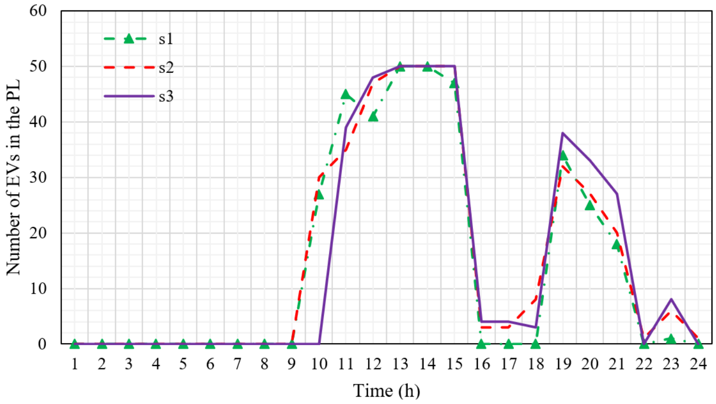


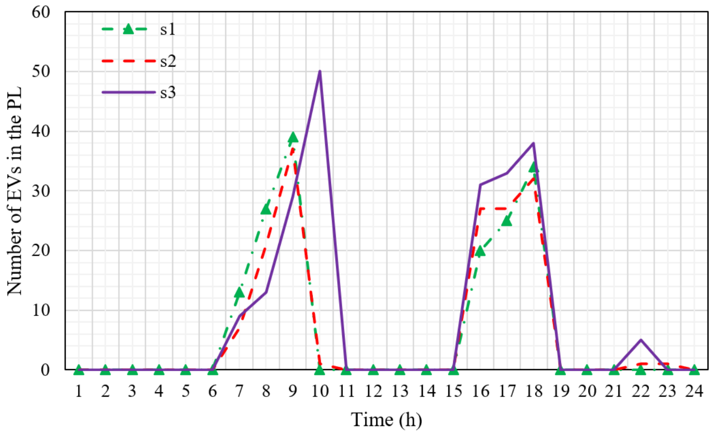
Figure 7.11 - The optimum stored heat of TESs under various risk strategies.



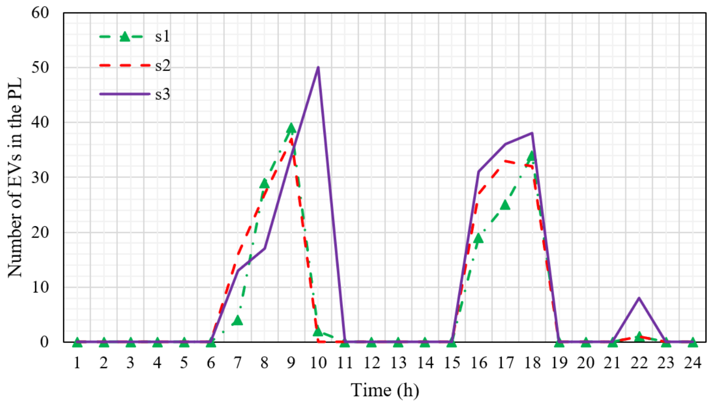
(a)



(b)



(c)



(d)

Figure 7.12 - The behavior of the owners of the EVs in the PL in (a) charging mode in the robust approach; (b) charging mode in the opportunity approach; (c) discharging mode in the robust approach; (d) discharging mode in the opportunity approach.

To go more in detail, the total amount of power that is exchanged between the microgrid and the vehicles is also depicted in Figure 7.13. This figure indicates that the total amount of power in whether grid to vehicle (G2V) or vehicle to grid (V2G) is not affected significantly in both risk-seeking and risk-averse strategies. Therefore, this figure validates the results achieved in Figure 7.12. where different risk strategies do not have a serious impact on the operation and scheduling of EVs, and the total amount of power exchanged between the EVs and the microgrid is not so sensitive against the risk strategy.

Furthermore, the implementation of any risk management model for addressing the uncertainties will impose some costs on the decision-maker. It will be essential to identify and quantify these costs to determine what level of risk management the decision-makers should enact based on their level of risk-seeking or risk-aversion. Table 7.4 and Table 7.5 display the robustness and opportunity costs of the hybrid stochastic-IGDT method for different optimum robustness index values against variations in σ. According to these results, increasing the level of the risk aversion of the aggregator leads to higher robustness or opportunity cost, which is entirely reasonable. The decision-maker is responsible for evaluating the MES and deciding the degree to which the aggregator is risk-averse in the robustness approach and risk-seeking in the opportunity approach.

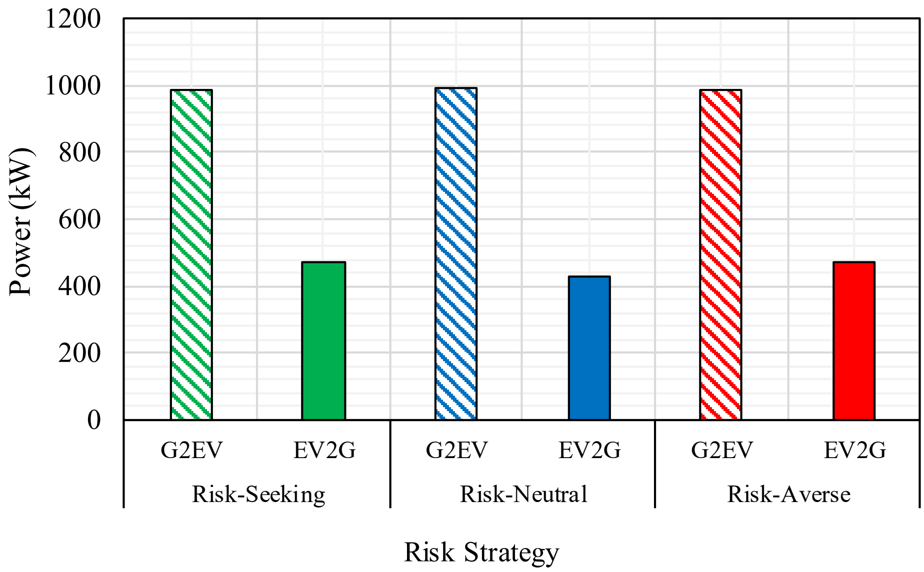


Figure 7.13 - The optimum values for the grid to vehicle (G2V) and vehicle to grid (V2G) under different risk strategies.

Table 7.4 — The robustness cost for various robustness function values

σ	$\hat{\alpha}$	Robustness cost (€)
0	0	0
0.1	0.043	4327.8
0.2	0.0812	6874.4
0.3	0.122	9003.5
0.4	0.163	11476.3
0.5	0.204	13994.2
0.6	0.245	15602.1
0.7	0.286	18109.5
0.8	0.327	20478.1

Table 7.5 — The opportunity cost for various opportunistic function values

σ	$\hat{\beta}$	Opportunity cost (€)
0	0	0
0.1	0.041	4571.4
0.2	0.082	7226.9
0.3	0.12	9103.5
0.4	0.163	12051.3
0.5	0.204	15190.3
0.6	0.244	15889.8
0.7	0.285	18933.4
0.8	0.326	22468.1

7.4- Conclusions

A hybrid IGDT-stochastic approach is proposed for a DER aggregator in an MES microgrid. The uncertainty posed by the generation of renewable resources and DERs is addressed through stochastic programming. As the DER aggregator is the operator of these entities, the level of generation is under the control of the aggregator. However, the energy market prices are not under the control of the aggregator, and additionally, there is a lack of information about the prices. Therefore, the uncertainty posed by market prices is managed through the IGDT method. There are two different structures for IGDT approaches, the robust structure, and the opportunity structure. The robust IGDT function can find the maximum value of the uncertain horizon, which can guarantee the critical profit of the aggregator in the worst case, even if unfavorable cases occur, which is the main aim of risk-averse decision-makers. However, the opportunity function of the IGDT approach can find the minimum value of the uncertain horizon that can lead to higher possible profits if favorable deviations of the uncertain parameter occur, which is the main goal of risk-seeking decision-makers. The results indicate that the aggregator manages the generation of DERs when there is a lack of generation from the installed renewable resources. For instance, in periods with low PV or wind generation, the CHP unit increases its generation to compensate for the shortage. Moreover, the optimum robustness and opportunistic function values for various amounts of profits of the DER aggregator are calculated to provide several risk levels for risk-averse and risk-seeking decision-makers. By increasing the deviation of the risk factor, σ, the obtained values for $\hat{\alpha}$ and $\hat{\beta}$ also, increase. Therefore, as $\hat{\beta}$ arises, the aggregator becomes more risk-seeking. Similarly, as $\hat{\alpha}$ arises, the aggregator becomes more risk-averse. Moreover, the imposed cost to the aggregator due to choosing the risk measure and its corresponding level is a crucial factor that should not be neglected. In terms of future work, different energy market structures could be explored to determine the optimal behavior of the DER aggregator.

Chapter 8

Conclusions, Directions for Future Work and Contributions

In this chapter, the main conclusions of the thesis are highlighted based on answering the research questions that constituted the main motivation of this research, and some directions for future work are also discussed. Finally, the contributions of this work are highlighted by presenting the set of publications, in journals with high impact factor (first quartile), as book chapters, or in conference proceedings of high standard (IEEE), leading to this thesis work.

8.1- Main Conclusions

The main conclusions drawn from the thesis work, about the research questions presented in Section 1.6, are summarized as follows. For the sake of clarity, the research questions are reproduced here.

- What are the recent developments and trends in DR programs and energy storage technologies within MESs, specifically focusing on the main challenges and optimization techniques in Energy Hub System models?

Due to the limited capabilities of the current power system, demand-side resources cannot be integrated very easily. DR helps to overcome these limitations and thus can help to integrate more demand-side resources. To capture the full potential of these resources, DRPs should consider various carriers of energy such as electricity and natural gas. This can be achieved through the use of Energy Hubs. This will help to maximize the benefits of DRPs and also minimize the side effects, such as consumer discomfort. This is a major advantage of using MES. Additionally, in the context of ESS in the MES, by integration of the various energy forms and developing the concept of the MESs, one of the key components of multi-energy systems is ESSs. The main role of the ESSs in multi-energy systems is to compensate for the fluctuations introduced by renewable energy resources. Therefore, it is crucial to review the main definitions of the DR, ESS, and multi-energy systems. Thus, a comprehensive literature review was done to achieve a clear definition of these terms. Then, the advantage of the energy hub over the conventional power system was addressed.

Then, some recent modeling of the DR and ESS technologies in the energy-hub environment is studied. The comprehensive review that has been done in this work can be a reference for future research and improvements in applying the DR and ESS in the energy-hub systems. The emerging keywords that have been extracted from the studied works show that the “integrated DR” is getting more interest and is one of the main keywords that is linked to the energy-hub topic. The work that has been done has identified some findings when it comes to implementing DRP in MES and these are as follows:

- The capability of converting between various forms of energy: Some limitations restrict the possibility of converting between the different energy carriers across time and for different consumers. For instance, there are some consumers with must-run loads that the only available form of energy is electricity. Therefore, it is not possible to participate in the DRPs through the reviewed works.
- For an optimization model, it is suggested to consider both consumer discomfort and profit at the same time. Since there have been some researches that only focused on decreasing the discomfort rate of the consumers that participating in the DRPs in MESs. On the other hand, the main aim of some studies is to increase the profit of the consumers through their participation in the DRPs in the MES. However, there is a capability of developing models that consider minimizing the uncomforting rate of the consumers while increasing their profit from employing DRPs.

This work has gathered and summarized the most recent work concerning DR programs within MES. It has shown that there is a growing increase in the field and this is because of the several advantages that DR and MES can contribute to the future energy system. Both will be important as the energy transition takes hold and the combination of these two strategies can yield multiplicative advantages for both system operators and consumers. This work has provided a summarized foundation for future researchers to consult when working in this exciting and important field. Additionally, in this chapter, ESS technologies in the context of multi-energy systems are presented and explained. Moreover, in the context of the multi-energy system, the storage unit can be installed on both sides of the input or output of the system as hydrogen and electrical storage can be installed on both sides, while, thermal storage usually is employed on the output side of the system. Moreover, it is shown that the ESS can also be a complementary component for the DR actions to provide more flexibility for the operation of the energy hub, especially during high consumption periods.

- What is the behavior of a risk-seeking DR aggregator in the presence of several DR programs on the demand-side of the aggregator, and the day-ahead electricity market on the market side? How does the aggregator manage uncertainty on both sides?

To answer this question, we investigate the behavior of a risk-seeking DR aggregator within the context of a complex energy landscape characterized by multiple DR programs on the demand side and the dynamics of the day-ahead electricity market on the market side. The primary objective was to ascertain how such an aggregator navigates and capitalizes on the inherent uncertainty that permeates both sides of its operations. Our model, designed to shed light on this intricate interplay, showcased the DR aggregator's propensity to pursue higher profits, leveraging favorable deviations in uncertain parameters observed in the day-ahead electricity market. To assess the DRA's risk tolerance and strategy, we employed the opportunity-based IGDT method as a risk measure.

In this thesis, we simultaneously considered two pivotal uncertain parameters from each side of the aggregator's operations—the upper side and the downside. On the demand side, we scrutinized the unpredictability of day-ahead market prices and the participation rate of consumers in the RBDR program. This approach allowed us to comprehensively gauge the aggregator's response to variations in these critical factors. Through rigorous simulations encompassing a spectrum of profit deviation factors, our research revealed a direct correlation between these factors and the optimal opportunity function value. This relationship not only elucidated the aggregator's risk-seeking behavior but also offered insights into its ability to harness uncertainty for profit optimization. To provide a deeper understanding of our model's implications, we selected a representative profit deviation factor and presented a detailed analysis of the correlated results. Notably, our findings underscored the integral role played by industrial consumers among the three consumer categories—industrial, commercial, and residential—in the adoption of TOU programs. This observation highlighted the significance of industrial consumers in shaping the DRA's operational strategies within the broader DR landscape. Therefore, Chapter 3 provides a perspective on the behavior of a risk-seeking DR aggregator operating within multiple DR programs and a volatile day-ahead electricity market. By shedding light on the aggregator's approach to managing uncertainty on both sides of its operations, we contribute valuable insights into the evolving dynamics of the modern energy ecosystem and the strategies employed by aggregators to thrive within it.

- How does it improve the scheduling and risk-based operation of the DR aggregator? How does the incorporation of DRPs and an energy storage unit enhance consumers' flexibility in engaging with the DR aggregator's operations?

To address this question, Chapter 4 has produced valuable insights into the enhancement of scheduling and risk-based operation of a DR aggregator through the incorporation of DRPs and an ESS, ultimately providing consumers with greater flexibility in engaging with the aggregator's operations. The contributions of our proposed model can be succinctly summarized as follows:

1- Hybrid MILP Optimization Framework: We introduced a hybrid mixed-integer linear programming (MILP) optimization framework tailored for DR aggregators. This framework deftly addresses the multifaceted uncertainties inherent in both the market and consumer sides by seamlessly integrating robust and stochastic methodologies. This novel approach allows the aggregator to make informed decisions considering a diverse range of uncertain parameters.
2- Robust-Stochastic Model: A key innovation in our research is the development of a hybrid robust-stochastic model. This model adeptly manages stochastic and non-stochastic uncertain parameters, significantly improving the scheduling and risk-based operation of the DR aggregator. It equips the aggregator to navigate adverse scenarios while optimizing DR program scheduling for end-users.
3- Enhanced Consumer Flexibility: By considering two types of DRPs and integrating an ESS, our model substantially enhances consumer flexibility. Consumers can now engage with DR aggregators in a more tailored manner, aligning their participation with their preferences and priorities.

Our hybrid stochastic-robust model provides a nuanced analysis of the DR aggregator's operations, particularly in evaluating adverse scenarios. On the demand side, we employed a stochastic method to manage consumer engagement rates across three sectors: industrial, residential, and commercial end-users. Simultaneously, we implemented a robust approach on the market side, specifically within the wholesale electricity market, to account for fluctuations in day-ahead market prices that may impact the aggregator's profitability. Within this framework, we harnessed TOU and ibDR programs for consumers and strategically operated an ESS under unique peak and off-peak periods for each consumer sector. Our findings revealed that industrial consumers' demand during peak periods had a substantial impact on the aggregator's profitability, underscoring the significance of considering different consumer categories. The behavior of the ESS was found to be consistent in all scenarios, primarily in charging mode during the initial hours of off-peak periods. In adverse scenarios, the ESS transitioned to discharge mode to prevent economic losses for the aggregator. Moreover, we observed that as price fluctuations in the market increased, the aggregator's total profit decreased, emphasizing the importance of effectively managing market uncertainties. In conclusion, our research not only enhances the scheduling and risk-based operation of DR aggregators but also empowers consumers with greater flexibility, paving the way for more dynamic and responsive energy systems in the future.

- What are the impacts of incorporating an ESS unit on the performance of a DR aggregator? How can the flexibility of end-users for their engagement in the DR programs be enhanced?

This thesis has presented insights into the impacts of integrating an ESS on the performance of a DR aggregator, while also enhancing the flexibility of end-users in their participation in DR programs. The contributions of our study in this regard can be summarized as follows:

1- Comprehensive Analysis of ESS Impact: We developed a comprehensive model for analyzing how the presence of an ESS unit influences the performance of a DR aggregator. This analysis was conducted considering various end-user categories, including residential, commercial, and industrial loads, actively participating in short-term electricity markets, such as day-ahead and balancing markets.

2- Enhanced End-User Flexibility: A significant aspect of our research involved increasing the flexibility of end-users to participate in DR programs. We achieved this by developing distinct participation roles for end-users and introducing renewable energy resources on the demand side of the aggregator's operations. This innovation empowers end-users with greater control and options for their engagement in DR initiatives.

The proposed optimal electricity trading model for the DR aggregator in Chapter 5 focused on the role of the ESS unit owned by the aggregator. The aggregator's responsibilities encompassed trading available energy within wholesale electricity markets, notably the day-ahead and real-time balancing markets. Given the inherent uncertainty in electricity market prices, we employed a robust optimization approach as the chosen risk measure to account for these uncertainties. On the demand side, we considered three categories of end-users: residential, commercial, and industrial sectors. To facilitate their active participation in DR programs, we implemented two DR programs and equipped end-users with rooftop PV panels, enhancing their ability to engage in DR initiatives.

The model’s analysis revealed that the capacity of the ESS played a pivotal role in the aggregator's profitability. In particular, a larger ESS capacity provided greater protection against unfavorable scenarios for uncertain parameters, translating into increased profits for the aggregator. For instance, when the ESS capacity reached 400 kWh, the aggregator's profit saw a notable 3.5% increase compared to a scenario without an ESS unit, assuming a specific budget of uncertainty. Furthermore, in a situation with higher uncertainty, a 400 kWh ESS capacity resulted in a substantial 20% profit increase. The capacity of the ESS also significantly influenced the aggregator's trading strategy in the day-ahead and balancing markets. With a larger ESS capacity, the aggregator had more flexibility to adjust its transactions in the day-ahead market, reducing the need for significant trading in the balancing market to avoid economic losses. While robust optimization is well-suited for risk-averse decision-makers, we acknowledge that alternative risk measures, such as information-gap decision theory or stochastic programming, may be more appropriate for risk-seeking decision-makers looking to explore favorable changes in uncertain parameters. Looking ahead, our research suggests exciting possibilities for upgrading the role of the DR aggregator entity to that of a Distributed Energy Resources (DER) aggregator. This transition would entail the control and management of multiple components within the energy system, including various renewables, distributed generation assets, and DR programs. Such an evolution could significantly enhance the aggregator's flexibility and expand the model's scope for optimizing profitability. In summary, in Chapter 5, the proposed model underscores the pivotal role of ESS units in DR aggregator operations, highlighting their impact on profitability and trading strategies. Simultaneously, we've demonstrated how end-user flexibility can be enriched through well-defined participation roles and the integration of renewable energy resources, paving the way for more dynamic and responsive engagement in DR programs. These findings have far-reaching implications for the future of DR and distributed energy management.

- How can the integration of multiple DR programs for electrical, heating, and cooling loads provide increased flexibility to consumers while optimizing the operational efficiency of the distributed energy resources and the energy hub?

To address this question, Chapter 6 has made steps in addressing the question of how the integration of multiple DR programs for electrical, heating, and cooling loads can not only provide enhanced flexibility to consumers but also optimize the operational efficiency of distributed energy resources within an energy hub. The primary contributions of our study are as follows:

1- Opportunistic Risk Management: One of the key innovations in our research is the introduction of an innovative opportunistic risk management procedure applied to an energy hub comprising various components, including micro-combined heat and power (μCHP), electric heat pumps (EHP), boilers (BO), absorption chillers (AC), and an ESS. This opportunistic approach is particularly well-suited for risk-seeking decision-makers who seek to explore the benefits of favorable deviations in uncertain parameters to further reduce costs. We specifically considered three uncertain parameters related to consumers: electrical, heating, and cooling loads.

2- Integration of Multiple DR Programs: Another significant contribution of our research is the integration of multiple DR programs to offer consumers increased flexibility. Specifically, we proposed two DR programs for electrical loads, each serving a distinct purpose. The TOU DR program was designed to shift a percentage of electrical load from peak to off-peak periods, effectively minimizing the operational costs of both assets and the energy hub. Additionally, an emergency DR program was defined to control electric demand during periods of supply-demand imbalance. Furthermore, we introduced a shifting DR program for both heating and cooling loads.

In the proposed model, we considered an energy hub comprising various entities responsible for supplying electric, heating, and cooling loads, while sourcing electricity and natural gas from the upstream network. The deployment of multiple integrated DR programs allowed us to strategically shift or alter a percentage of electric, heating, and cooling demand from peak to off-peak periods, thereby reducing the overall cost incurred by the energy hub operator. To manage uncertainties effectively, we adopted the information-gap decision theory opportunity approach as the risk measure. This approach empowered the decision-maker to align with a target cost while accommodating deviations in electric, heating, and cooling load values from their expected levels. Notably, our numerical results indicated that the application of this approach was contingent on the cost imposed on the system, underlining the importance of cost considerations. One significant outcome of our research pertained to the demonstrating positive impact of the time-of-use DR program. This program succeeded in shifting a percentage of demand to off-peak periods, which, in turn, positively influenced the minimization of the operational costs of the energy hub. Conversely, it also showed that the high cost associated with the emergency DR program made it less desirable for activation unless there was a clear imbalance between supply and demand. In conclusion, our research underscores the potential of integrated DR programs and opportunistic risk management to enhance consumer flexibility while optimizing the operational efficiency of distributed energy resources within an energy hub. These findings have practical implications for the effective and resilient management of energy systems in a dynamic and uncertain environment.

- How can risk management be effectively utilized for uncertainties posed by the DER aggregator in an MES?

To address this question, Chapter 7 has explored the effective utilization of risk management for uncertainties arising from a DER aggregator operating within a MES microgrid. The key contributions of this proposed model can be summarized as follows:

1- Hybrid IGDT-Stochastic Approach: A central innovation in our research involves the proposal of a hybrid IGDT-stochastic approach for the self-scheduling of a DER aggregator within an MES. This approach caters to the diverse risk preferences of decision-makers, providing solutions for both risk-averse and risk-seeking individuals. By offering a range of models, our approach empowers decision-makers to choose the most suitable framework in alignment with their preferences.

2- Management of Multiple Uncertainties: Our research simultaneously addresses uncertainties originating from both sides of the DER aggregator, encompassing uncertainties from the market side and consumption side. This holistic approach acknowledges the intricate interplay of uncertainties in an MES microgrid. Additionally, we strategically select the most appropriate risk measures for decision-makers based on the characteristics of the uncertain parameters, enhancing the precision of decision-making processes.

In our proposed hybrid IGDT-stochastic approach, we navigate the uncertainties arising from the generation of renewable resources and DERs through the application of stochastic programming. While the DER aggregator exercises control over the generation of these entities, market energy prices remain beyond its control and often lack complete information. Consequently, we manage the uncertainties associated with market prices through the IGDT method. Within the IGDT framework, we consider two distinct structures: the robust structure and the opportunity structure. The robust IGDT function focuses on securing the maximum value of the uncertain horizon, thereby guaranteeing critical profits for the aggregator even in the worst-case scenarios—a primary concern for risk-averse decision-makers. Conversely, the opportunity function of the IGDT approach seeks to identify the minimum value of the uncertain horizon that can lead to higher potential profits when favorable deviations in uncertain parameters occur—a primary goal for risk-seeking decision-makers. Our findings indicate that the DER aggregator effectively manages the generation of DERs when facing a shortfall in generation from installed renewable resources. For example, during periods of low PV or wind generation, the Combined Heat and Power (CHP) unit increases its generation to compensate for the deficit. Furthermore, we calculate the optimum robustness and opportunistic function values across various levels of profits for the DER aggregator, thereby offering several risk levels for both risk-averse and risk-seeking decision-makers. We observe that as the deviation of the risk factor, σ, increases, so do the values of $\hat{\alpha}$ and $\hat{\beta}$, signifying a shift towards increased risk-seeking behavior for the aggregator as $\hat{\beta}$ rises and heightened risk-averse behavior as $\hat{\alpha}$ increases. It is essential to note that the cost incurred by the aggregator due to the selection of a specific risk measure and its corresponding risk level is a critical consideration that cannot be overlooked.

Finally, it can be observed that the main contribution of this thesis is developing hybrid optimization frameworks that consider various uncertainties with different inherent characteristics on both the supply and consumer sides through a combination of risk management methods. This approach is crucial for appropriately handling uncertain parameters. These research endeavors contribute to economically viable and environmentally friendly energy systems and make a significant impact on a sustainable future.

8.2- Directions for Future Works

The following points may be further studied to broaden the understanding of the topics treated in this thesis:

1- Explore different energy market structures to further optimize the behavior of the DER aggregator. These efforts could offer additional insights into the adaptable and dynamic nature of risk management strategies within MES microgrids, ensuring the continued evolution and robustness of such systems.

2- The implementation of multi-objective optimization problems to gain deeper insights into the independent impacts of uncertain factors. This approach could provide a more comprehensive understanding of the trade-offs and interactions within the energy hub's operations.

8.3- Contributions of the Thesis – Primary Publications

8.3.1- Book Chapter

1. **Vahid-Ghavidel M**, Javadi S, Gough M, Javadi MS, Santos SF, Shafie-khah M, Catalao JPS. Review the energy storage technologies with the focus on multi-energy systems. in: Technologies for Integrated Energy Systems and Networks, G. Graditi and M. Di Somma (Editors), WILEY-VCH, Germany, ISBN: 978-3-527-34899-2, 2022;105-122. https://doi.org/10.1002/9783527833634.ch5.

8.3.2- Publications in Peer-Reviewed Journals

1. **Vahid-Ghavidel M**, Javadi MS, Gough M, Santos SFF, Shafie-khah M, Catalão JPS. Demand response programs in multi-energy systems: a review. Energies 2020;13:4332. https://doi.org/10.3390/en13174332.

2. **Vahid-Ghavidel M**, Javadi MS, Santos SF, Gough M, Mohammadi-Ivatloo B, Shafie-khah M, Catalão JPS. Novel hybrid stochastic-robust optimal trading strategy for a demand response aggregator in the wholesale electricity market. IEEE Trans Ind Appl 2021;57:5488–98. https://doi.org/10.1109/TIA.2021.3098500.

3. **Vahid-Ghavidel M**, Shafie-khah M, Javadi MS, Santos SF, Gough M, Quijano DA, Catalão JPS. Hybrid IGDT-stochastic self-scheduling of a distributed energy resources aggregator in a multi-energy system. Energy 2023; 265:126289. https://doi.org/10.1016/j.energy.2022.126289.

4. **Vahid-Ghavidel M**, Javadi MS, Santos SF, Gough M, Shafie-khah M, Catalão JPS. Energy storage system impact on the operation of a demand response aggregator. J Energy Storage 2023; 64:107222. https://doi.org/10.1016/j.est.2023.107222.

8.3.3- Under Review Works in Peer-Reviewed Journals

1. **Vahid-Ghavidel M**, Javadi MS, Santos SF, Gough M, Shafie-khah M, Catalão JPS. Optimal management of electrical and thermal loads in multi-energy systems in the presence of an integrated demand response program. Under Review in Applied Energy 2023.

8.3.4- Publications in International Conference Proceedings

1. **Vahid-Ghavidel M**, Catalão JPS, Shafie-Khah M, Barhagh SS, Mohammadi-Ivatloo B. IGDT opportunity method in the trading framework of risk-seeker demand response aggregators. 2019 IEEE Milan PowerTech. https://doi.org/10.1109/PTC.2019.8810601.

2. **Vahid-Ghavidel M**, Catalão JPS, Shafie-Khah M, Mohammadi-Ivatloo B, Mahmoudi N. Application of opportunistic information-gap decision theory on demand response aggregator in the day-ahead electricity market. 2019 IEEE PES Innov. Smart Grid Technol. Eur. ISGT-Europe. https://doi.org/10.1109/ISGTEurope.2019.8905744.

3. **Vahid-Ghavidel M**, Sadegh Javadi M, Santos SF, Gough M, Shafie-Khah M, Catalao JPS. Demand response based trading framework in the presence of fuel cells using information-gap decision theory. 3rd Int Conf Smart Energy Syst Technol (SEST) 2020. https://doi.org/10.1109/SEST48500.2020.9203313.

4. **Vahid-Ghavidel M**, Javadi MS, Santos SF, Gough M, Shafie-khah M, Catalao JPS. Optimal stochastic conditional value at risk-based management of a demand response aggregator considering load uncertainty. 2021 IEEE Int Conf Environ Electr Eng and 2021 IEEE Ind Commer Power Syst Eur (EEEIC / I&CPS). https://doi.org/10.1109/EEEIC/ICPSEUROPE51590.2021.9584827.

5. **Vahid-Ghavidel M**, Javadi MS, Santos SF, Gough M, Shafie-Khah M, Catalão JPS. Opportunistic info-gap approach for optimization of electrical and heating loads in multi-energy systems in the presence of a demand response program. 2021 IEEE Int Conf Environ Electr Eng and 2021 IEEE Ind Commer Power Syst Eur (EEEIC / I&CPS). https://doi.org/10.1109/EEEIC/ICPSEurope51590.2021.9584597.

8.4- Other Contributions – Secondary Publications

8.4.1- Publications in Peer-Reviewed Journals

1. Shafie-khah M, **Vahid-Ghavidel M**, Di Somma M, Graditi G, Siano P, Catalão JPS. Management of renewable-based multi-energy microgrids in the presence of electric vehicles. IET Renewable Power Generation 2020; 14:417-426. https://doi.org/10.1049/iet-rpg.2019.0124

2. Quijano DA, **Vahid-Ghavidel M**, Javadi MS, Padilha-Feltrin A, Catalão JPS. A price-based strategy to coordinate electric springs for demand side management in microgrids. IEEE Trans Smart Grid 2023; 14:400-412. https://doi.org/10.1109/TSG.2022.3188847

8.4.2- Publications in International Conference Proceedings

1. Ramos BP, **Vahid-Ghavidel M**, Osorio GJ, Shafie-Khah M, Erdinc O, Catalao JPS. Influence of Demand Response Programs in Microgrids Facing Photovoltaic and Battery Integration. 2021 10th Int. Conf. Power Sci. Eng. (ICPSE). https://doi.org/10.1109/ICPSE53473.2021.9656829.

2. Quijano DA, **Vahid-Ghavidel M**, Javadi MS, Padilha-Feltrin A, Catalão JPS. A price-based strategy to coordinate electric springs for demand side management in microgrids", 2023 IEEE NA Innovative Smart Grid Technologies Conference (ISGT NA). https://doi.org/10.1109/ISGT51731.2023.10066461

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