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Leveraging Consumers' Flexibility for the Provision of Ancillary Services

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Kongens Lyngby 2019

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Summary (English)

This thesis deals with the development and application of models and algorithms to leverage consumers' flexibility for the provision of ancillary services (AS).

The output of most renewable sources is intermittent and can only be predicted with a limited accuracy. Therefore, the increasing penetration of variable renewable sources leads to an unprecedented level of stochasticity and non-linearity in power system dynamics. Such complexities cause various operational challenges for power systems operators by requiring more AS resources. Larger integration of cost-effective renewable sources marginalises the operation of thermal power plants, due to the lower energy prices. As thermal power plants consist of the main source of AS, their retirement will intensify the lack of AS resources. Moreover, as renewable sources become widespread at the distribution level (e.g., with the installation of rooftop photovoltaic panels), AS requirements will extend to the distribution grids, which is unprecedented in existing power systems. For these reasons, it is necessary to look for alternative operational flexibility to serve as new AS for the sake of continuity and security of electricity delivery. In this regard, demand response is a valid solution that leverages demand flexibility to provide services to the grid.

To optimally exploit consumers' flexibility, it is important to account for consumers' different preferences and constraints. Specifically, studies must approach the heterogeneity of loads and understand what influences consumers' behaviour. Unfortunately, no study in the technical literature has discussed the aggregate potential of consumers' flexibility, and estimation studies have been carried out only for specific types of loads. The first part of this thesis intends to fill this gap by proposing methodologies to estimate the potential of consumers'

flexibility. To do so, we assume that consumers receive dynamic electricity prices and can autonomously schedule their consumption to minimise the electricity cost. Such studies consider several factors that influence consumers' price responsiveness (i.e., loads' rebound effect, outdoor temperature and electricity price) and accounts for a heterogeneous pool of consumers. Finally, these flexibility estimation models account for consumers' stochastic behaviour toward prices.

Consumers are effectively able to provide reliable services only if a proper framework is developed. Such a framework must satisfy different power systems' requirements, e.g., the provision of services to different levels of the grid, as well as account for consumers' preferences. The second part of this thesis discusses several alternatives to provide AS in smart grids. From the analysis, none of the existing solutions is capable to optimally leverage consumers' flexibility. Therefore, we proceed in this research by proposing an innovative framework that can exploit consumers' flexibility at different grid levels. This solution is based on a one-way communication structure and relies on dynamic electricity prices which are broadcast to consumers. In this thesis, the simulations of this proposed method are carried out to evaluate its potential in supporting frequency and voltage management.

Resumé (Danish)

Denne afhandling beskæftiger sig med udvikling og anvendelse af modeller og algoritmer til at udnytte forbrugernes fleksibilitet til systemydelser (SY).

Produktionen af de fleste vedvarende energikilder er intermitterende og kan kun forudsiges med begrænset nøjagtighed. Derfor fører den stigende indtrængning af variable vedvarende kilder til et hidtil uset niveau af stokasticitet og ikkelinearitet i dynamiske egenskaber hos strømsystemerne. Sådanne kompleksiteter medfører forskellige operationelle udfordringer for operatørerne af strømforsyninger ved at kræve flere SY-ressourcer. Større integration af omkostningseffektive vedvarende energikilder marginaliserer driften af termiske kraftværker på grund af lavere energipriser. Da termiske kraftværker består af SY's primære kilde, vil deres pensionering intensivere manglen på SY-ressourcer. Da fornyelige kilder bliver udbredt på distributionsniveau (fx ved installation af tagfotovoltaiske paneler), vil SY-kravene udvides til distributionssystemoperatørerne, hvilket er uden fortilfælde i de eksisterende elsystemer. Af disse grunde er det nødvendigt at søge alternative driftsfleksibilitet til at fungere som ny SY for at sikre kontinuitet og sikkerhed for elforsyning. I denne henseende er efterspørgselsrespons en gyldig løsning, der udnytter efterspørgselsfleksibilitet til at levere tjenester til nettet.

For at udnytte forbrugernes fleksibilitet optimalt er det vigtigt at redegøre for forbrugernes forskellige præferencer og begrænsninger. Specielt skal undersøgelser nærme sig heterogeniteten af belastninger og forstå, hvad der påvirker forbrugernes adfærd. Desværre har ingen litteraturstudier diskuteret det samlede potentiale for forbrugernes fleksibilitet, og estimeringsundersøgelser er kun udført for bestemte typer laster. I den første del af denne afhandling har vi

til hensigt at udfylde dette hul ved at foreslå metoder til at estimere potentialet for forbrugernes fleksibilitet. For at gøre det antager vi at vi beskæftiger os med forbrugere, der modtager dynamiske elpriser, og kan selvstændigt planlægge deres forbrug for at minimere elprisen. Sådanne undersøgelser overvejer flere faktorer, der påvirker forbrugernes prisresponsivitet (dvs. belastningernes genvindingseffekt, udetemperatur og elpris) og tegner sig for en heterogen forbrugerpool. Endelig tegner disse fleksibilitetsestimeringsmodeller forbrugernes stokastiske opførsel mod priser.

Forbrugerne kan kun levere pålidelige tjenester, hvis der udvikles en ordentlig ramme. En sådan ramme skal opfylde forskellige kraftsystemers krav, fx yde tjenester til forskellige niveauer af nettet, samt tage hensyn til forbrugernes præferencer. I den anden del af denne afhandling diskuterer vi flere alternativer til at levere SY i smart grids. Fra analysen er ingen af de eksisterende løsninger i stand til optimalt at udnytte forbrugernes fleksibilitet. Derfor fortsætter vi i vores forskning ved at foreslå en innovativ ramme, som kan udnytte forbrugernes fleksibilitet på forskellige netniveauer. Denne løsning er baseret på en envejs kommunikationsstruktur og bygger på dynamiske elpriser, der sendes til forbrugerne. I denne afhandling udføres simuleringerne af denne foreslåede metode for at evaluere dens potentiale til understøttelse af frekvens- og spændingsstyring.

Preface

This thesis was prepared at the Department of Applied Mathematics and Computer Science at the Technical University of Denmark (DTU) in partial fulfilment of the requirements for acquiring a Ph.D. degree.

The thesis deals with the development of methodologies to estimate the aggregate flexibility potential of consumers' electricity demand. Furthermore, it proposes an innovative framework to leverage consumers' flexibility for the provision of ancillary services in power systems.

This thesis consists of a summary report and five research papers, documenting the work carried out during the period between April 2016 and March 2019. Two of these papers are published in international peer-reviewed journals and another paper is currently submitted. Finally, the remaining two papers appear in conference proceedings.

Kgs. Lyngby, 31-March-2019

Giulia De Zotti

Acknowledgements

A tree without roots will fall over, whereas a tree with roots eventually becomes part of a forest.

Margrethe II of Denmark

The first acknowledgement goes to my supervisors, Prof. Niels Kjølstad Poulsen, Prof. Henrik Madsen, Prof. Juan Miguel Morales and Dr. Ali Pourmousavi Kani. I have learned so much from their supervision and I really appreciated their continuous support.

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List of Publications

Scientific Research Publications in this Thesis

A G. De Zotti, A. Pourmousavi, H. Madsen, and N.K. Poulsen (2018). "Utilizing Flexibility Resources in the Future Power System Operation: Alternative Approaches". *IEEE 2018 International Energy Conference ENERGYCON*. IEEE, 2018.

B G. De Zotti, A. Pourmousavi, H. Madsen, and N.K. Poulsen (2018). "Ancillary Services 4.0: A Top-To-Bottom Control-Based Approach for Solving Ancillary Services Problems in Smart Grids". In *IEEE Access*, vol: 6, pp. 11694-11706. IEEE, 2018.

C G. De Zotti, A. Pourmousavi, J.M. Morales, H. Madsen, and N.K. Poulsen (2018). "Consumers' Flexibility Estimation at the TSO Level for Balancing Services". *IEEE Transactions on Power Systems*, vol: PP, issue: 99. IEEE, 2018.

D G. De Zotti, D. Guericke, A. Pourmousavi, J.M. Morales, H. Madsen, and N.K. Poulsen (2019). "Analysis of the rebound effect modelling for flexible electrical consumers". *2019 IFAC Workshop on Control of Smart Grid and Renewable Energy Systems CSGRES*. IFAC, 2019.

E G. De Zotti, A. Pourmousavi, J.M. Morales, H. Madsen, and N.K. Poulsen (2019). "A Control-based Method to Meet TSO and DSO Ancillary Services Needs by Flexible End-Users". Submitted to *IEEE Transactions on Power Systems*. IEEE.

Other Work Not Included in This Thesis

F G. De Zotti, H. Binder, A. Bavnhøj Hansen, H. Madsen, A. Pourmousavi, R. Relan, J.M. Morales, and N.K. Poulsen (2019). "Prediction of the Price Signals for Demand Response Programs," Submitted to *2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids, SmartGridComm*. IEEE, 2019

Presented Conferences

1. COST Action Mathematical Optimization in the Decision Support Systems for Efficient and Robust Energy Networks, TD1207 2017, Modena. De Zotti Giulia, Pourmousavi Ali, Madsen Henrik, Poulsen Niels Kjølstad. A Control-Based Approach for Solving Ancillary Service Problems in Smart Grids. March 2017.

2. International Graduate School of Science and Engineering, IGSSE 2017, Munich. De Zotti Giulia, Madsen Henrik, Poulsen Niels Kjølstad. Researching at DTU: Market Mechanisms for the Integration of Distributed Energy Resources. May 2017.

3. Møde i Branchefælleskab for Intelligent Energi, SydEnergi. Madsen Henrik, De Zotti Giulia, Pourmousavi Ali, Poulsen Niels Kjølstad. A Control-based Approach for Solving Ancillary Service Problems in Smart Grids. May 2017.

4. POWERGEN 2017, Köln. De Zotti Giulia, Pourmousavi Ali, Madsen Henrik, Poulsen Niels Kjølstad. A Framework for Controlling Electricity Load in Integrated Energy Systems. June 2017.

5. WholeSEM 4th Annual Conference 2017, London. De Zotti Giulia, Pourmousavi Ali, Madsen Henrik, Poulsen Niels Kjølstad. A Framework for Controlling Electricity Load in Integrated Energy Systems. July 2017.

6. CITIES workshop: Integration of prosumer buildings in energy systems, 2018, Copenhagen. De Zotti Giulia, Pourmousavi Ali, Morales Juan Miguel, Madsen Henrik, Poulsen Niels Kjølstad. Ancillary Services 4.0: A Top-to-bottom Control-based Approach for Solving Ancillary Services Problems in Smart Grids. April 2018.

7. 5th IEEE International Energy Conference, ENERGYCON2018, Cyprus. De Zotti Giulia, Pourmousavi Ali, Madsen Henrik, Poulsen Niels Kjølstad. Utilizing Flexibility Resources in the Future Power System Operation: Alternative Approaches. June 2018.

8. 23rd International symposium on mathematical programming, ISMP 2018, Bordeaux. De Zotti Giulia, Pourmousavi Ali, Morales Juan Miguel, Madsen Henrik, Poulsen Niels Kjølstad. Consumers' Flexibility Estimation at the TSO Level for Balancing Services. July 2018.

9. 5th Edition of CITIES General Consortium Meeting, Fredericia. De Zotti Giulia, Pourmousavi Ali, Morales Juan Miguel, Madsen Henrik, Poulsen Niels Kjølstad. Control-based Ancillary Services Provision from the Flexibility of Electricity Consumers. September 2018.

10. IFAC Workshop on Control of Smart Grid and renewable energy systems, CSGRES 2019, Korea. De Zotti Giulia, Guericke Daniela, Pourmousavi Ali, Morales Juan Miguel, Madsen Henrik, Poulsen Niels Kjølstad. Analysis of the Rebound Effect Modelling for Flexible Electrical Consumers. June 2019.

Contents

Part I

Summary Report

Chapter 1

Introduction

Quite frankly, there is no answer to climate change without substantially, dramatically, increasing the amount of renewable energy in the global energy system.

Christiana Figueres

1.1 Context and Motivation

In the last decades, power systems have been experiencing significant changes in design and operation. Grid operators used to manage electricity generated by large centralised thermal plants and deal with predictable loads. Today, the introduction of renewable energy sources (RES) and flexible energy resources (e.g., storage devices and shiftable loads) is driving power systems toward a decentralised structure. In this new setting, generation and consumption follow a dynamic and less predictable behaviour [1]. These changes also impact the provision of ancillary services (AS), which grant the integrity of transmission and distribution systems as well as power quality [2].

The higher penetration of RES naturally demands more AS [3]. Indeed, by depending on meteorological variations [4], RES introduce an unprecedented level of stochasticity, non-linearity in power systems dynamics [5]. Such complexities bring severe operational challenges to power system operators (i.e., frequency deviations and voltage excursions) which need to be addressed by a higher amount of AS [6]. The increasing need for AS has already caused inflating AS prices [7] in Australia [8] and California, where in the latter the total AS market value raised from US$20M in 2015 to US$172M in 2017 [9]. The higher amount of RES also affects the need for AS at different levels of the grid. In a conventional power system, AS are mainly required by the transmission system operator (TSO) at high voltage level. However, when RES become more and more present at the distribution system (e.g., through the installation of photovoltaic panels), the associated risk of over-voltage and congestion leads distribution systems to inevitably require AS which were previously not necessary [10, 11].

Besides changes in AS demand, schemes for AS provision are evolving as well. In the past, thermal power plants used to be the main source of AS. Today, these plants have to compete with cost-efficient RES, whose operation is reducing electricity prices [12]. The higher competition marginalises the operation of conventional power plants and results in reduced profit and ultimately retirement [13, 14]. Furthermore, many countries in the world are investing to reduce their overall dependence on thermal plants for electricity generation [15, 16], in line with international environmental targets against climate change [17]. An example of this is Strategy 2050 in Denmark, whose intent is to fully rely on RES in the national energy mix by 2050 [18].

As AS need increases and conventional thermal plants are set to retire, it is crucial to seek for alternative ways to provide AS at a minimum cost for the future power grid [14, 19]. While electricity storage systems constitute a natural solution to the problem, they are an expensive approach that is sometimes not accessible to grid operators.

Alternatively, RES can be approached as a source of AS to adjust the generation according to grid needs. However, RES curtailment leads to green energy spillage and opportunity losses [20]. In order to optimally provide AS, it is necessary to investigate cheap and valid alternatives that can be readily available to the system at different voltage levels.

Demand response (DR) is a promising alternative to address the need for services in power systems. It promotes changes in electricity demand by relying on the flexibility of consumers. The strength of DR is that it exploits flexible resources that are already present in power systems. In this thesis, we consider DR for the provision of AS for both transmission and distribution levels. Although several programs have been proposed to exploit DR, their application is limited to demonstration projects that do not consider heterogeneous types of consumers. Therefore, their applicability is limited by loads capability. Furthermore, the literature lacks a comprehensive analysis of the effects of AS provision from consumers' flexibility on the entire power system. In fact, existing studies only focus on portions of grids (e.g., frequency management at transmission level in [21]). Due to the importance of AS provision for a reliable power system operation, our research investigate the potential of demand flexibility for AS provision. In particular, we aim to determine to which extent consumers are able to provide AS and under which conditions they can optimally provide services. To this purpose, we formulate a unified simulation model to assess consumers' flexibility potential and a DR-based AS framework for future power systems.

1.2 Thesis Objectives

The objective of this thesis is to analyse and quantify the role of electrical consumers for AS provision in the smart grid era. We formulate algorithms to estimate consumers' flexibility potential in AS provision. Furthermore, we introduce a new AS framework to leverage consumers' flexibility potential. This thesis is organised around two core research questions, which we present in the following.

1.2.1 How Can We Estimate the Potential of Consumers' Flexibility in Providing AS?

Quantifying demand flexibility is key in planning AS for future power systems. In this first question, we propose methodologies to estimate the flexibility potential of electrical consumers. The aggregate price response of consumers is analysed when providing AS through DR programs. In particular, we develop procedures to account for different dynamics and the stochastic nature of consumers' behaviour.

1.2.2 Which Framework Can Help to Optimally Exploit Consumers' Flexibility for AS Provision at Different Voltage Levels?

Unlocking the consumers' flexibility potential is necessary to fulfil AS needs in smart grids. As the success of using DR for AS provision highly depends on the framework under which demand flexibility is obtained, we formulate a procedure by means of dynamic electricity prices and individual local controllers.

In particular, we develop a framework that provides a systematic solution for system operators to fulfil their AS needs through one-way communication.

This thesis is motivated by a lack of existing research material addressing the need for AS in smart grids with high penetration of variable RES. Despite numerous existing research works on DR formulation and provision, the question of how to exploit consumers' flexibility both at transmission and distribution levels is less investigated. Moreover, addressing services through DR has always been approached from the demand perspective and not considering the users of the demand flexibility. Therefore, the aggregate flexibility potential of different types of consumers is overlooked in these studies. This thesis aims to fill this gap by taking the system's operator point of view and developing DR-based procedures for AS provision in the smart grid era.

1.3 Thesis Contributions

As a motivation to this thesis, in Paper A, we discuss alternative approaches for accommodating larger amount of RES at different levels of the grid in presence of high stochasticity, dynamics and non-linearity of the resources. In particular, we analyse pros and cons of mechanisms that leverage flexibility resources of electrical consumers to provide services to the power system. From the analysis, we conclude that none of the alternative methods satisfies all the requirements for a future optimal grid operation, which calls for real-time management of the entire electricity system. Therefore, there is a need for further analysis and research to optimally exploit flexibility resources.

We address this task in Paper B, where we introduce the ancillary services 4.0 (AS4.0) framework. AS4.0 consists of an alternative solution to the current market-operation structure for AS provision. It allows system operators to exploit consumers' price-responsiveness according to grid needs, by varying the electricity prices offered to consumers. Consumers can automatically and individually react to these prices and minimise their own cost. By offering a price-based control mechanism to exploit the entire fleet of flexibility resources, AS4.0 provides AS for the entire grid, and handles stochasticity, non-linearity and dynamics. Furthermore, a one-way communication system supports fast and simple operation and preserves consumers' privacy. This way, electricity demand is locally controlled by end-users without the requirement to exchange any information with system operators in real-time.

Since AS4.0 is based on the exploitation of consumers' flexibility, it is necessary to obtain a better understanding of consumers' behaviour and demand flexibility dynamics. Such a study would respond to our first research question and defines suitable procedures for the estimation of DR potential for the provision of AS. Therefore, we investigate and estimate the aggregate consumers' flexibility potential in Papers C and D. These studies are conducted at an aggregate level, considering different categories of consumers and a DR program based on time-varying electricity prices. The effect of stochasticity on consumers' response dynamics is handled in Paper C, where we leverage chance-constrained programming to model consumers' behaviour.

In Paper D, we investigate the effect of consumers' operational constraints on overall flexibility potential. Specifically, we develop an algorithm to assess different types of rebound effects that represent the behaviour of consumers. Furthermore, we consider the effect of outdoor temperature on the overall DR potential.

Finally, in Paper E, we demonstrate that AS4.0 can be a solution for the optimal AS provision in smart grids. By modelling and simulating the AS4.0 framework, we show that it performs up to 60% better in frequency management than conventional AS provision. At the same time, this new framework successfully deals with voltage deviations at the distribution system.

1.4 Thesis Structure

This thesis is structured as follows. Part I is a summary report outlining the main contributions of the thesis. Chapter 2 provides an overview of the approaches that guarantee a reliable operation of power systems, with a focus on DR. Chapter 3 describes the methodologies applied in this thesis, including the concepts of control, optimisation, machine learning and power system modelling. Chapter 4 deals with the potential of consumers' flexibility for DR and presents a solution for the provision of AS based on consumers' flexibility. Chapter 5 provides conclusions and perspectives. Appendix A presents the main objectives of the SmartNet project and discusses how they relate to our research.

Part II consists of the publications that contributed to this thesis. In such regards:

Paper A is a conference paper published in IEEE ENERGYCON 2018. It discusses alternative approaches for RES management and AS provision in the presence of significant uncertainties due to RES.

Paper B is a journal paper published in IEEE Access. It offers a conceptual design of a comprehensive AS provision mechanism that is based on dynamic prices and indirect control techniques.

Paper C is a journal paper published in IEEE Transactions on Power Systems. It deals with the formulation of a stochastic optimisation problem to estimate the aggregate flexibility of rational consumers with different elasticity and preferences at the TSO level in response to time-varying prices.

Paper D is a conference paper published in the IFAC Workshop CSGRES 2019. It investigates different approaches for modelling the dynamics and rebound effect of electrical consumers that respond to price-based DR programs.

Paper E is a paper under review in IEEE Transactions on Power Systems. This publication presents the modelling and simulations of AS4.0 for the provision of AS from consumers.

Chapter 2

Reliable Operation in Smart Power Systems

Please take responsibility for the energy you bring into this space.

Oprah Winfrey

2.1 Introduction to Ancillary Services

The main purpose of power systems is supplying electricity to the consumers that are located all over the grid. A reliable electricity supply service ensures service continuity and power quality, i.e., handling unexpected operational issues to deliver electricity without interruption [22]. Also, electricity supply must take place under the condition that the integrity and the stability of the power system are always respected: the system is meant to survive and recover from a credible disturbance [23]. Operational issues that affect power system continuity include voltage and frequency deviations; these depend on the imbalance between electricity demand and power supply from generation units. For this reason, it is fundamental that the balance between generation and demand is always guaranteed in real time.

To this end, AS consist of operations designed to support power system management and maintain a reliable electricity supply service [24]. Although in the technical literature there is no absolute definition of AS [25], they are supposed to provide dedicated amount of electricity reserve that is used to address imbalances between consumption and generation, ensure power system recovery and maintain proper flow and direction of electricity. AS provision delivers different services at different levels of the grid, whose management widely varies among countries [2]. These services include frequency control services (such as spinning reserve, remote automatic generation control and frequency regulation), voltage control services (such as voltage regulation) and emergency services (such as black-start capability and emergency control actions) [26, 27, 28]. In this thesis, we focus on the regulation of frequency and voltage.

Frequency regulation is related to the management of active power in a grid. Different levels of operation can be identified, i.e., primary, secondary and tertiary frequency controls [29]. Primary frequency control represents the local automatic response to frequency deviations which acts within seconds and up to minutes [30]. Secondary frequency control operates as a centralised automatic control to stabilise the frequency. It addresses imbalances at the interconnections, typically within minutes [30]. Tertiary frequency control is a manual reserve used in the event of outages or unexpected activations of secondary frequency control. Its activation time varies from minutes to hours.

On the other hand, voltage regulation depends on the management of reactive power, which is injected and absorbed through synchronous sources and static compensators. Voltage regulation mainly relies on automatic control of passive reactive components, e.g., capacitor banks or reactors. Nevertheless, suppliers that are capable of fast regulation can also modify their production/consumption of reactive power until acceptable levels are achieved [24]. These suppliers include spinning generators, synchronous compensators, reactors and capacitors. Voltage regulation is organised in a similar structure to frequency management, normally providing service within thirty seconds [30].

Countries provide services for frequency and voltage regulation in a variety of ways. Four main approaches can be identified [31]:

- **Compulsory provision**: Specific users, i.e., large generators with ramp-up and -down capabilities, are supposed to provide a certain amount of AS upon request of the TSO. This approach guarantees AS provision in a transparent manner, as the requirements for providing AS are available to the public. On the other hand, it might imply unnecessary costs for AS providers, since the requested AS volume can exceed the needed amount. Compulsory provision might also lead to an inefficient resource management, as AS providers are treated in an equal manner despite the fact that they operate with different costs [31].

- **Bilateral contracts**: System operators and providers can negotiate on the quantity and price for AS provision. Such an approach encourages a better use of resources, as the TSO acquires the cheapest and needed amount of services. However, the overall solution of bilateral contracts lacks transparency, as the terms of negotiation are not disclosed to third parties. Furthermore, such a negotiation can be time consuming, costly and difficult. Due to their high transaction cost, bilateral contracts settle fixed AS prices and volumes for a long time, which is not in line with the modern dynamic operation of power systems [31].

- **Tendering process**: When services are needed, the TSO can initiate a tender process and receive auction bids from AS providers. Such a solution supports competition and transparency in AS provision. Nevertheless, tendering processes deals mainly with AS that have long duration and therefore do not follow the real-time operation of the power system, which is affected by an increasing level of stochasticity, non-linearity and dynamics [19]. Also, it requires extensive data management when dealing with the auctions bids.

- **Spot market**: Similar to the tendering process, AS providers participate in the AS market by submitting their bids, i.e., prices and quantity values [32]. In spot markets, AS provision can take place daily, in a single session, or hourly [26] and deals with products that have short duration (i.e., one week or less [31]). In spite of its capability to better represent the condition of the grid compared to the other approaches, spot markets still rely on bids that are deterministic and linear. Furthermore, the market clearing process might require few minutes to provide a solution, due to the large-scale optimisation problems it must solve. Therefore, by dealing with thousands of variables and constraints along with power flow equations, it might be too slow to cope with the new level of uncertainty and dynamics [33, 34].

Besides these alternative approaches for AS procurement, the current AS provision still relies on conventional thermal plants with ramp-up and -down capabilities. Furthermore, with the integration of RES in power systems, additional AS are needed to manage the increased variability and uncertainty [35]. While most of the RES are not able to provide balancing services effectively [36, 37], thermal plants become less competitive and their capacity is reducing to meet environmental targets [13]. For these reasons, it is challenging to ensure reliability and stability of smart grids from alternative sources while reducing our dependence on AS from thermal plants.

2.2 Approaches to Stability in Smart Grids

Ensuring a reliable electricity supply can be pursued through alternative solutions, as shown in Fig. 2.1. It is important to understand the benefits and limitations of each alternative.

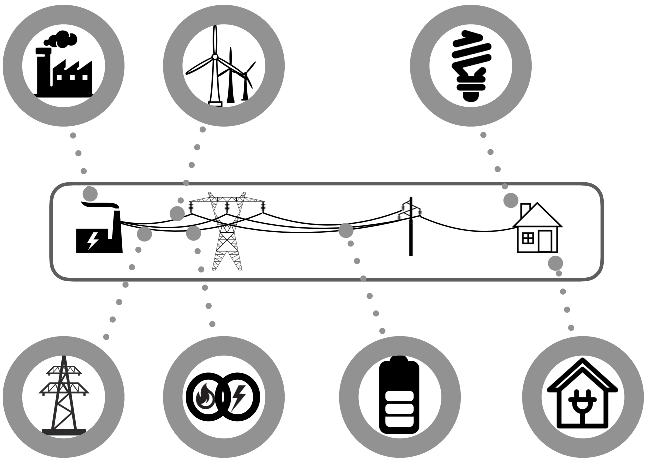

Figure 2.1: Various approaches for a reliable operation of power systems.

Investing in power system infrastructure can guarantee that electricity is transported to areas where consumers are located while minimising congestions. Nevertheless, such a solution can be very costly, especially for large countries where consumption and generation are geographically scattered.

Alternatively, electricity storage systems can be adopted to provide regulation services [38]. They include batteries, hydro-pumped storage and hydrogen. Besides the flexibility potential of such solutions, they have some limitations that must be considered. In particular, batteries raise concerns over their limited lifetime, decreasing performance and recycling costs. Furthermore, the high prices make them financially unattractive in many cases [38]. The main barriers to hydrogen are related to the cost and the overall low efficiency compared to other storage technologies [38]. Although hydro-pumped storage has high efficiency (around 80% [39]), its operation is only suitable for specific sites, characterised by geographical height and water availability.

A different approach considers the management of flexible generation units. This solution addresses flexibility from conventional thermal plants, such as ramping and minimum load operation [40], as well as from RES [28]. We already discussed the limitation of solely relying on conventional thermal plants in Section 1.1: their profitability is challenged by competitive RES which reduce electricity prices. RES might provide regulation by adjusting their output, e.g., for windmill turbines [41]. However, this solution is limited in up-regulation by the effective wind availability. Furthermore, the curtailment of RES leads to green energy spillage and opportunity loss which must be compensated.

Although we mainly focus on electricity management in this thesis, it is possible to consider other energy carriers, such as gas and heat. This concept is known as multi-carrier energy systems [42]. By adjusting the choice of energy carrier used according to grid condition, demand can be satisfied while providing services to the power system. Furthermore, integrating the use of different energy carriers in a single framework facilitates the optimal utilisation of resources thanks to sharing flexibility and increases the overall efficiency of the integrated energy system. However, it has limited application in countries that do not rely on combined-heat and power (CHP) systems or central heating systems (e.g., Australia).

Another way to support a reliable operation of power systems is demand-side management (DSM) [43]. Such a solution relies on changing the way consumers use electricity and can be implemented in two ways: *i*) by increasing loads' energy efficiency or *ii*) through demand response (DR). In DR, electricity demand acts as a source of flexibility, whose characteristics depend on the capabilities of electrical devices and consumers' preferences in altering their consumption. DR can take the form of load curtailment and load shifting (see Fig. 2.2). While load curtailment represents an overall reduction of electricity demand, load shifting implies that a certain over-consumption results in a subsequent decrease in consumption and vice versa.

Although a combination of these different approaches might be the optimal solution in practice, this thesis focuses on DR. In particular, we consider the application of load shifting, as it does not compromise the overall welfare of consumers and models demand flexibility in a more conservative manner. In order to provide services through DR, operators need to formulate dedicated programs that can obtain consumers' acceptance.

2.3 Services Provision through Demand Response

Over the last two decades, DR programs have been used to address operational needs of power systems in numerous research studies [44]. As an example, time of usage (ToU) rates programs feature prices that change by time periods, e.g., by peak and peak-off periods [45]. Such solutions are able to reduce electricity

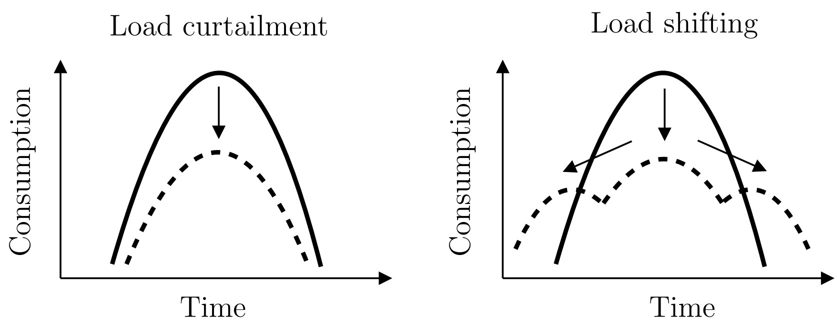

Figure 2.2: Concepts of load curtailment and load shifting.

consumption at peak hours, which is the main concern for a system relying on controllable and predictable conventional plants. However, in an electricity grid with significant amount of RES generation, new kind of DR programs is needed to account for an unprecedented dynamic and unpredictable operation in real time. Therefore, DR programs must be automatic and intelligent with high granularity in time to facilitate consumers participation in power system operation in real time and provide services in a fast manner [43]. For these reasons, new solutions have been proposed over the years, which can be divided into two main categories: explicit and implicit DR programs. Their main functioning is shown in Fig. 2.3.

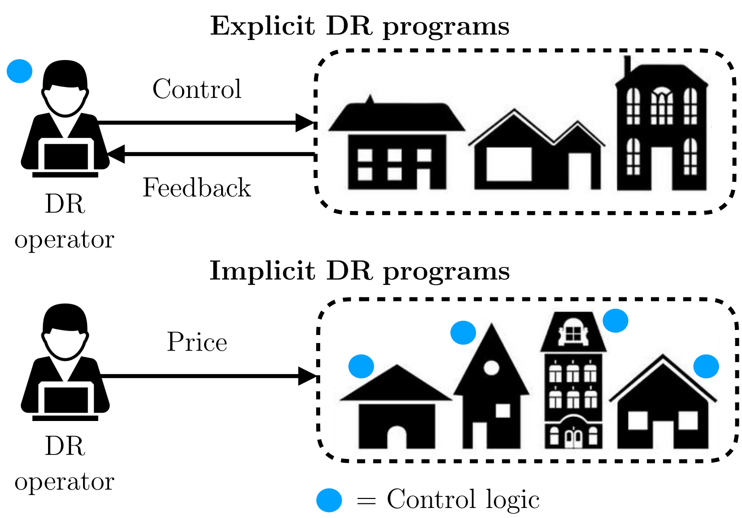

Figure 2.3: Concepts of implicit and explicit DR programs.

In explicit DR programs (also known as incentive-based mechanisms [46, 45]), flexibility is traded and committed by consumers through incentives [47, 48, 49]. These programs mainly rely on classical control mechanisms, i.e., direct load control (DLC) techniques, and market-based mechanisms. In DLC, an external entity is entitled to directly control consumers' load through a two-way communication link [50]. This approach minimises the uncertainty of consumers' response [51]. However, consumers' privacy and autonomy can be dramatically affected, by allowing an external entity to decide about the way they consume electricity [52]. Indeed, some consumers may have also other priorities than reducing electricity costs. For example, waste water treatment plants need to prioritise the treatment of incoming waste water to ensure effluent water quality and environmental reasons [53]. As a consequence, DLC requirement may result in limited participation of consumers in DR programs. This fact has been shown in [54] and [55], where consumers were willing to accept automation of consumption only if allowed to autonomously manage it. Furthermore, in the implementation of DLC, the need for feedback from consumers to aggregator (i.e., DR operator) requires the adoption of a two-way communication scheme, as shown in Fig. 2.3. Such programs highly depend on the communication channels (exposing them to significant cyber-security risks). Moreover, the infrastructure can become very costly when scaled to millions of devices. DLC program agreements can take place in the form of demand bidding or long-term contracts. In the former case, consumers trade their flexibility through an aggregator, who formulates a bid of the overall change in consumption [56]. However, scaling this solution to a high amount of players might be very costly and complex, due to the two-way communication required [57]. An alternative to demand bidding is offered by long-term contracts. Long-term contracts consist of a simpler solution that does not need aggregation or bidding and has long duration. However, they require consumers to plan their future consumption ahead of time - a non-trivial task [48]. Therefore, DLC methods allow to exploit only a part of the flexibility potential for power system services.

In implicit DR programs (or price-based mechanisms [46]), flexibility arises from consumers' reaction to price signals. These programs are referred to as indirect load control (ILC) [1, 58, 59] and dynamic pricing schemes [59]. In ILC mechanisms, control signals are broadcast from a centre to consumers, which can individually decide about their consumption [60, 59]. In order to be able to make decisions, consumers must be equipped with individual controllers, also known as home energy management systems (HEMS) [61, 62]. As shown in Fig. 2.3, implicit DR programs are based on one-way communication, avoiding any feedback from consumers to operator. Indeed, only aggregated consumers' response can be measured by the operator. This approach addresses privacy and comfort issues, as each individual controller can satisfy consumers' constraints and preferences locally [63]. Depending on the specific implementation of ILC, consumers receive different dynamic signals, which can be either control or price signals. Control signals are formulated by a central controller and depend on the model of specific types of loads. This condition implies that different specialised control signals must be issued for every type of load, which is a limit for heterogeneous pools of devices [64], [65]. Furthermore, control signals are generated based on simplified and linear models of the devices, which do not always represent the true dynamics of the underlying appliance and thus can be error-prone [66]. Price signals have interesting properties that avoid these issues. Indeed, the same price signal can be broadcast to a various pool of heterogeneous loads [67], which then schedule the electricity consumption to minimise the individual cost. Therefore, employing a single price signal simplifies the algorithm and computation on the central controller side and the required communication on the consumers' side.

In our research, we focus on the potential of implicit DR programs and dynamic prices to address operational challenges in power systems (i.e., frequency and voltage deviations). As the penetration of RES affects both transmission and distribution systems, AS challenges become ubiquitous in the grid. For this reason, AS provision demands holistic changes in the way it is provided at both levels of the grid. In this thesis, we firstly intend to understand the role of DR in AS provision. For this reason, we need to investigate how to estimate demand flexibility potential at an aggregate level. Secondly, we focus on the optimal exploitation of consumers' flexibility in AS provision. To do so, we study how to facilitate consumers' engagement in AS programs while solving the operational challenges of power systems at the distribution and transmission levels. We address these research questions with the support of mathematical models and simulations which are covered in greater detail in the relevant papers. In the next chapter, we present the applied methodologies that are key to developing this research.

Chapter 3

Applied Methodologies

Look to the past to help create the future. Look to science and to poetry. Combine innovation and interpretation.

Drew Gilpin Faust

In this chapter we provide the reader with a basic understanding of the concepts employed in Section II. The research questions addressed in this thesis translate to a set of optimisation problems that describes the price responsiveness of consumers. First, this chapter provides an introduction to the applied optimisation concepts, discussing mixed-integer linear programming and chance-constrained programming. In our studies, the aggregate responsiveness of consumers has been exploited to support power system operation. Therefore, we needed to model the behaviour of power systems following the reaction of consumers. This chapter discusses the control techniques used for this purpose, such as load frequency controllers. Power flow analysis is also briefly presented, as we have employed it to calculate nodal voltages in distribution systems. In conclusion, this thesis proposes a framework for AS provision which relies on the submission of dynamic electricity prices. Implementing this framework required a way to generate dynamic prices according to system needs. To do so, we used an artificial neural network whose concept is explained in the following. However, alternative methods to artificial neural network might also have been used, such as time series analyses [68, 69].

For additional details on these subjects, the reader can refer to [70] on mixed-integer linear programming, [71] on chance-constrained programming, [6] on load frequency controllers, [72] on linear quadratic regulators, [73] on PID controllers, [74] on power flow analysis and [75] on artificial neural network functions.

3.1 Mixed-integer Linear Programming

A mixed-integer linear program (MILP) consists of a mathematical optimisation problem where some of the variables are integers [1]. We provide the canonical form of a MILP in the following.

$$\min_{x,y} \quad c^T x + h^T y \tag{3.1a}$$

subject to:

$$Ax + Gy \leq b \tag{3.1b}$$

$$x, y \geq 0 \tag{3.1c}$$

$$x \in \mathbb{Z}^n \tag{3.1d}$$

In this formulation, x and y represent the decision vectors. In particular, x_j is constrained to be non-negative integer and y_j is non-negative real [70].

MILP is a popular way to formulate optimisation problems, as binary variables can describe categories or the status of the system. It is widely used in the energy sector, e.g., for unit commitment problems [76]. In this setting, binary variables describe whether generating units are on-line or off-line. MILP are also suitable to solve the scheduling problem for electricity consumption in DR programs. In this matter, binary variables allow the formulation of constraints related to the duration of flexibility provision as well as maximum amount of times that flexibility can be provided. In our studies, we have employed MILP to model the scheduling of electricity consumption in the presence of electricity prices, while also considering different dynamics of loads' rebound effect.

3.2 Chanced-constrained Programming

Chanced-constrained (CC) programming belongs to a set of techniques to deal with random parameters in optimisation problems. A major challenge posed by power system problems is that decisions must be taken prior to observing uncertain parameters and cannot be lately amended (due to safety or economic limitations). As prior decisions might result in future constraint violations, we have to ensure that only a low percentage of realisations of the parameters violates the constraints [77]. In CC, the objective function is maximised (or minimised) while ensuring that the probability of meeting a certain constraint is above a prescribed level. This condition is achieved by restricting the feasible region in a way that the confidence level of the solution meets the requirement [78]. We can start from the general formulation of a linear optimisation problem (LOP) stated as follows:

$$\min_{x} \quad c^T x \tag{3.2a}$$

subject to:

$$Ax \leq b \tag{3.2b}$$

$$x \geq 0 \tag{3.2c}$$

where x is the decision vector. In a deterministic formulation of the LOP, A is the known coefficients matrix and b is the known coefficients vector. However, when including stochasticity in the problem, we consider that the constraint $Ax \leq b$ is affected by a certain amount of uncertainty, which can either appear in A, b, or both. Therefore, A and/or b become stochastic. CC is applied by replacing Eq. (3.2b) with:

$$Pr\Big(Ax \leq b\Big) \geq \beta \tag{3.3}$$

In Eq. (3.3), β represents the prescribed level of probability, or security level, for which the constraints should not be violated. Its value can vary between 0 and 1. When dealing with CC, there is not a general solution method and its solution widely depends on which parameter is uncertain (e.g., matrix A and/or right-hand side vector b in Eq. (3.2b)), the convexity of the constraint function and the probability distribution of the stochastic variables. Depending on the specific case, CC can be solved through a variety of methods. In order to provide a graphical illustration of CC, let us consider a simple case where b is a null scalar and A is a vector contingent on a Gaussian random variable:

$$Pr\Big(Ax \leq 0\Big) \geq \beta \tag{3.4}$$

In Fig. 3.1, the dashed rectangle represents the constraint $Ax \leq 0$. The probability distribution (PD) of Ax is normal, and part of it lies outside the dashed rectangle. Therefore, a higher uncertainty leads to a bigger area outside the constraint.

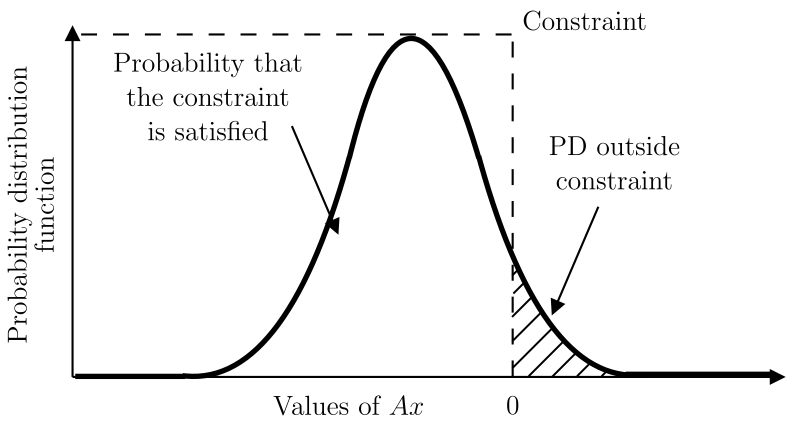

Figure 3.1: Normal distribution of the uncertainty and constraint. Case for which b has dimension 1 with value zero. [79].

Being introduced by Charnes and Cooper in 1959 (see [80]), CC has been used for a wide range of applications in engineering and finance. In power system engineering, it is a popular method to deal with the uncertainty in unit commitment problems [77] and reserve scheduling [81]. Furthermore, researchers have been using CC for optimal storage sizing [82] and generating prices in DR programs [83]. In our research, we have applied CC to estimate consumers' flexibility potential while considering the stochastic nature of consumers' behaviour.

3.3 Load Frequency Controller

Load frequency controller (LFC) is a small-signal model used to manage the frequency system-wide. A schematic representation of a single-area LFC model is provided in Fig. 3.2. It includes the power system (i.e., loads and rotating mass), an equivalent generating unit (composed of a speed governor and a turbine) and a controller. In power systems, rotating masses have the property of inertial response, i.e., act to overcome the immediate imbalance between electricity generation and demand. When a certain power disturbance ΔP_ω occurs in the system and the rotational frequency of rotating masses increases (i.e., for excessive generation) or decreases (i.e., due to excessive demand), the effect of the disturbance results in a relatively small variation of frequency Δf. This condition is described by the swing equation, as:

$$\Delta P_T(s) - \Delta P_\omega(s) = 2Hs\Delta f(s) + D\Delta f(s) \tag{3.5}$$

Where H represents the inertia constant of rotating masses and D is the load damping coefficient [6]. In order to handle the variation of frequency in the system, we consider two main frequency control loops for system stability, i.e., primary and secondary frequency regulation, which rely on generating units. In primary regulation, the speed governor is used to measure the frequency locally and change the steam valve position to stop frequency changes. It acts through the transfer function $\frac{1}{R}$, where $R = \frac{(f_0 - f)}{f}$ and f_0 is the reference frequency value. Secondary regulation is a central control that sends a signal to a controller (or automatic generation control, AGC) to specify the amount of power that the generator must produce, i.e., ΔP_G. This amount of power is applied by the steam valve of the turbine, i.e., ΔP_T. The response of the equivalent generating unit depends on the time constants of the generator and turbine, i.e., T_g and T_t [6].

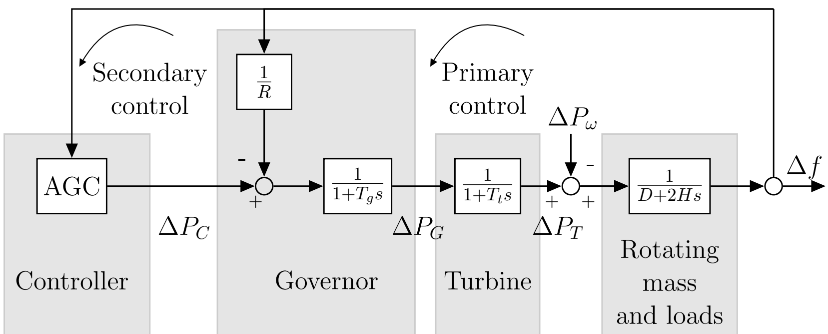

Figure 3.2: Conceptual scheme of the LFC.

As, in reality, power systems are often interconnected, we are interested to extend the LFC formulation to a two-area power system, as shown in Fig. 3.3, and add inter-tie power flows dynamics to the system. In the figure, we interconnect areas i and j and the interconnection introduces three main elements in the model: β_i and β_j representing the response coefficients of the two areas; $T_{i,j}$ describing the time constant of the tie-line flow; and $\alpha_{i,j}$, which guarantees correct power flow direction at the interconnection (i.e., areas i and j have opposite sign of power flow direction), where $\alpha_{i,j}$ =-1.

In the technical literature, LFC model has been widely used to analyse the

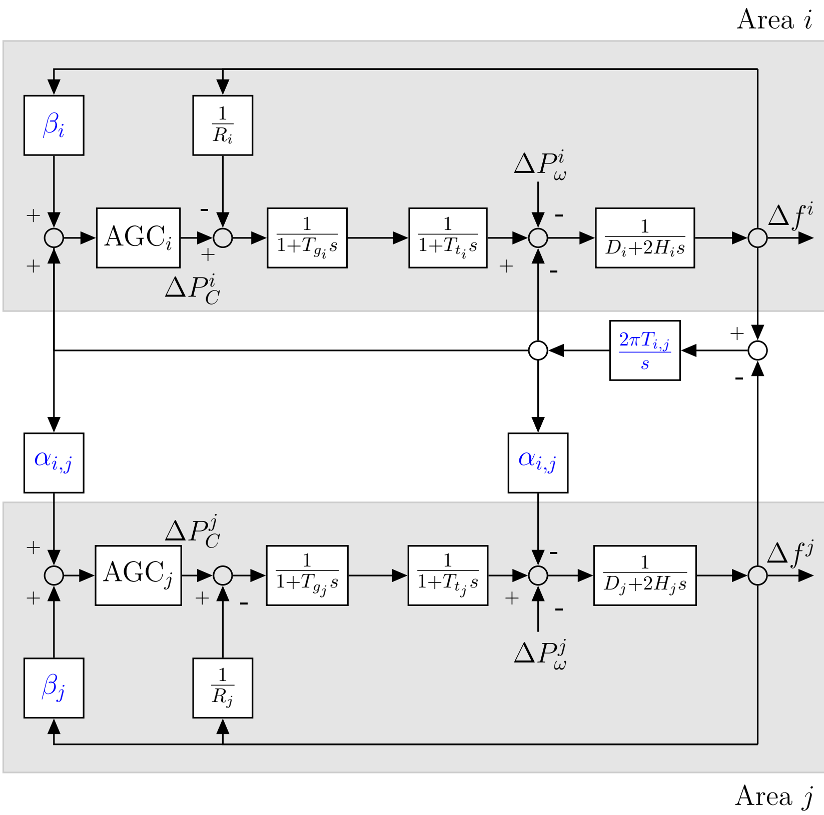

Figure 3.3: LFC for two interconnected power systems.

effect of new energy resources in power systems. In [84] and [85], LFC has been applied in a setting which combines conventional LFC with dynamic DR for a multi-area interconnected power system. Moreover, various control techniques can be considered when implementing AGC. In [86], authors discussed different types of AGC, such as proportional-integral-derivative controllers and model predictive control. In our research, we have used LFC to investigate the impact of power disturbances on the frequency trend at the transmission level, when relying on AS4.0 and CGU-based AS provision.

3.4 Linear Quadratic Regulator

As mentioned in Section 3.3, various types of controllers can be used in AGC. Among all, linear quadratic regulator (LQR) is a popular optimal control technique based on state-space representation. We consider the following system:

$$\dot{x} = Ax + Bu \tag{3.6a}$$

$$y = Cx + Du \tag{3.6b}$$

where x is the state vector and u is the control vector. The aim of LFC is to stabilise the system through a feedback loop.

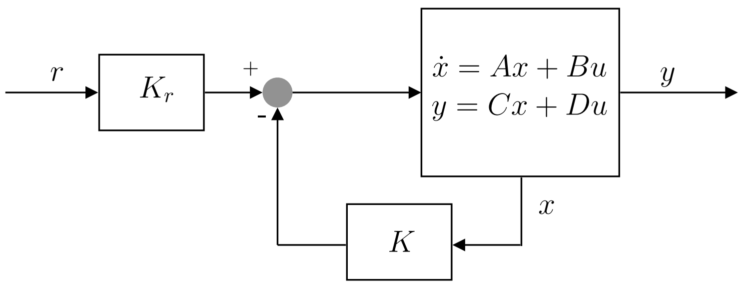

Figure 3.4: Conceptual scheme of a LQR.

We provide the conceptual scheme of LQR in Fig. 3.4. The state vector x is fed back and multiplied by a gain matrix K, as shown in Fig. 3.4. In order to avoid steady-state reference tracking error, Kx is also subtracted to a scaled reference, $K_r r$. For the design of K, we need to decide the close-loop characteristics of the system. In particular, we can select K as a trade-off between transient response (i.e., control performance) and control effort. This study can be approached by minimising a quadratic cost function $J(x, u)$ in which all the close-loop characteristics are associated to weights [72]. The cost function $J(x, u)$ can be designed in several ways. An example is provided as follows:

$$J(x,u) = \frac{1}{2}\int_0^{\infty} \left(x^T Q x + u^T R u\right) dt \tag{3.7}$$

In Eq. (3.7), Q is the weight of the control performance while R refers to the weight of the control effort. In this formulation, it is possible to penalise poor performance or high control effort by adjusting Q and R. In particular, Q must be a symmetric positive semi-definite matrix, in a way that its product with the state vector is positive and non zero. Similarly, R is considered as a symmetric positive definite matrix. In the formulation of $J(x, u)$, the integral calculates the cost over time, which is required to become zero in steady state; the squared values eliminate the problem of negative values. The feedback control law that minimises the cost function $J(x, u)$ [87] is:

$$u = -Kx \tag{3.8a}$$

$$K = R^{-1}B^{T}P \tag{3.8b}$$

where P is the solution of the Riccati equation [87, 88, 89].

LQR has many beneficial properties, e.g., generates static gain and achieves infinite gain margin [88]. For these reasons, LQR has been applied in different studies for the control of power systems [85, 90]. In our work, we have built an LQR for secondary frequency regulation in the LFC formulation.

3.5 Proportional–Integral-Derivative Controller

Proportional-integral-derivative (PID) controller consists of a control loop feedback mechanism where the control signal is the sum of three main components. They include P-term (which acts proportionally to the error), I-term (that deals with the integral of the error) and D-term (which considers the derivative of the error) [73]. The general PID formulation is:

$$u(s) = K_p\, e(s) + \frac{K_i\, e(s)}{s} + K_d\, e(s)\, s \tag{3.9}$$

where $u(s)$ is the control signal and $e(s)$ represents the control error. A block-diagram of this type of controller is provided in Fig. 3.5.

As shown in Eq. (3.9), PID controller parameters include proportional, integral and derivative gains, i.e., K_p, K_i and K_d. The choice of such gains can widely affect the performance of the controller, and the tuning of each parameter depends on the control element, control delays and the overall process. Depending

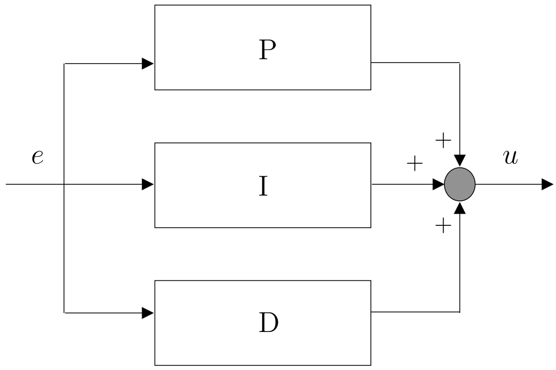

Figure 3.5: Conceptual scheme of a PID controller.

on the type of applications and the control requirements, variations of PID controllers can also be preferred. An example is the PI controller, which does not react to small error variations.

Due to their simplicity and effectiveness, PID controllers have been widely used in control engineering [91], by regulating flow, temperature and other industrial processes variables [73]. In frequency regulation, PID controllers have been employed as AGC in the secondary frequency control loop [92]. In our studies, we have used PI technology to control the price response of consumers, depending on the voltage deviation measured at the distribution system. In other words, we have used a PI controller to generate a control signal (i.e., price signal) that can address a certain change in consumption from consumers.

3.6 Power Flow Analysis

Power flow (PF) analysis is a numerical tool used to investigate the power system status in steady state. It studies node voltages and branch power flows in an interconnected system. PF analysis is based on Ohm's law and the definition of apparent power. The relationships between voltage, electrical current intensity and power are reported in the following.

$$I_i = \sum_{j=1}^{n} Y_{i,j}\, V_j \qquad i = 1, \dots, n \tag{3.10a}$$

$$S_i = P_i - jQ_i = I_i V_i^* \tag{3.10b}$$

In Eq. (3.10a), Y_i is the admittance matrix of the network, while V_i and I_i describe the polar form of the voltage and current magnitudes at node i. In Eq. (3.10b), S_i, P_i and Q_i represent the apparent, active and reactive power at node i, while V_i^* is the conjugate of the voltage. By combining Eq. (3.10a) and (3.10b), we obtain Eq. (3.11):

$$\frac{P_i - jQ_i}{V_i^*} = \sum_{j=1}^{n} Y_{i,j} V_i \qquad i = 1, \ldots, n \tag{3.11}$$

This equation must be solved for each node to calculate the values of P_i, Q_i, V. Therefore, we face a system of non-linear algebraic equations, which can be solved iteratively using Newton method [74]. Depending on the different information that we have at each node of a power system, we can classify the nodes in three main categories. In Fig. 3.6, we provide the diagram of a power system with four nodes, showing different types of nodes. These categories include:

- **PQ node**, for which we have knowledge of active and reactive power. These nodes mainly refer to load nodes, where electricity consumption is given. PQ nodes are shown in Fig. 3.6 at nodes 2 and 4;
- **PV node**, where active power and voltage magnitude are known. These nodes consider controllable reactive power resources and power plants. An example of PV node is shown in Fig. 3.6 at node 3;
- **Vθ node**, (also called slack node), for which we know the voltage magnitude and angle. In PF problems, only one node can be the slack node (usually the largest unit participating in the AGC). The generator at this node compensates for imbalance between generation and demand. Vθ node is shown in Fig. 3.6 at node 1.

PF analysis is used to support the operation and planning of transmission and distribution systems as well as smart grid management [93]. In particular, it is useful to simulate the power system state after the introduction of flexibility resources [94]. In our research, PF analysis has been used to quantify the effect of AS4.0 on nodal voltages at the distribution level.

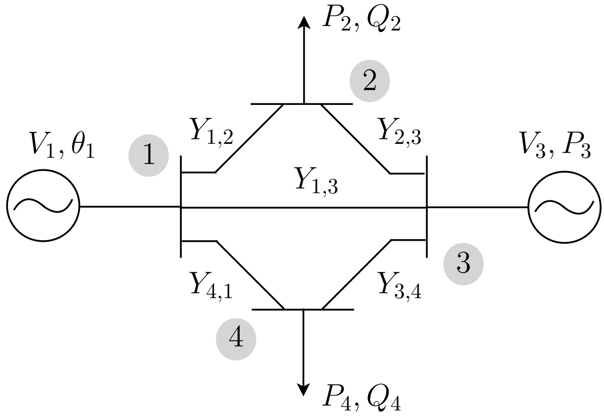

Figure 3.6: Example of the power system with four nodes. Node 1 is the slack node; node 2 and 4 are PQ nodes and node 3 is a PV node.

3.7 Artificial Neural Network

An artificial neural network (ANN) consists of a mathematical framework that is inspired by the way our brain operates. The formulation of an ANN is based on artificial neurons, i.e., functions that receive inputs, modify their internal state and produce outputs. The output of each neuron, $y(x)$, is formulated in the following.

$$y(x) = f\Big(\sum_{i=1}^{n} \big(w_i^T x_i\big) + \beta\Big), \qquad i = 1, \ldots, n \tag{3.12}$$

In Eq. (3.12), x is the set of training inputs, w is the set of the weights and β is the set of the biases. Weights consist of real numbers that show the importance of a particular input, while biases are constants used to adjust the output along with the weighted sum of the inputs to the neuron [95]. Neurons are organised in layers and can be linked to the inputs of other layers. Such graphs include input layers, multiple hidden layers and output layers, as shown in Fig. 3.7.

Depending on the complexity of the problem at hand, the most suitable number of neurons and hidden layers can widely vary. Neurons learn the relationships between inputs and outputs in a training process by tuning biases and weights through a chosen algorithm. This algorithm minimises a certain loss function

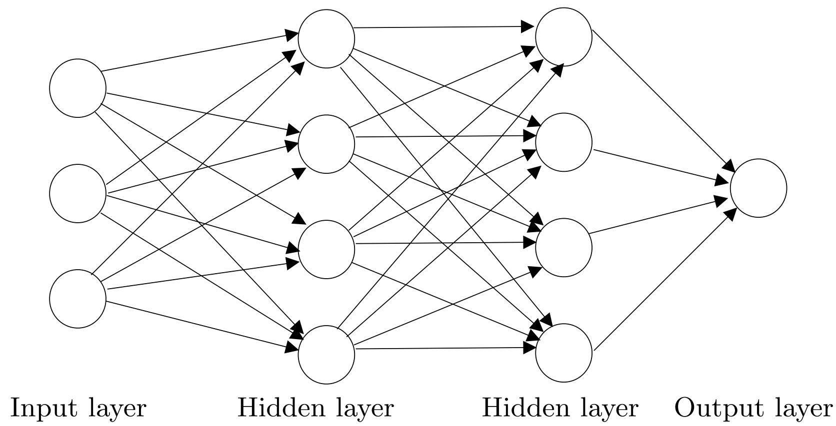

Figure 3.7: Conceptual ANN structure.

$C(w, b)$, which can be written as:

$$C(w,b) = \frac{1}{2n}\sum_x ||y(x) - \hat{y}(x)||^2 \tag{3.13}$$

where n is the number of training samples and $\hat{y}(x)$ is the actual output of the network for input x [95]. Several training algorithms have been developed to minimise such a function. In particular, the Levenberg-Marquardt algorithm gained popularity for its capability to achieve fast convergence [96].

ANN has been used in various applications, from medicine [97] to finance [98]. In electricity markets, it has been proposed as a way to forecast electricity prices [99]. In our research, we have formulated an ANN to understand the relationship between electricity prices and consumption. This information has been used to generate dynamic electricity prices that can address a certain change in consumption from consumers [59].

CHAPTER 4

Ancillary Services Provision from Consumers' Flexibility

> Denmark should be a green and sustainable society with a visionary climate and energy policy. (...) The answer to these challenges lies in the way we produce and consume energy and in our ability to adapt our society to climate change.
>
> *Connie Hedegaard*

In this chapter selected results from the research work conducted within the framework of this thesis are presented and discussed. Section 4.1 deals with methodologies to estimate consumers' flexibility potential for AS provision. Section 4.2 discusses AS4.0 as an innovative control-based approach that provides AS through consumers' flexibility at different grid levels.

4.1 Analysis of the Factors Influencing Consumers' Response

In order to fully exploit consumers' flexibility potential, operators need to understand how consumers respond to prices at an aggregate level. Such an understanding facilitates the formulation of dynamic prices that trigger a certain change in consumption from electrical consumers. Furthermore, it improves the power reserve allocation for system operation. For these reasons, the first research question that we address explores consumers' flexibility potential for AS from an aggregate perspective. To do so, we first need to analyse the factors that influence the aggregate consumers' behaviour. In this thesis, we assume that consumers' flexibility mainly depends on electricity price [100], rebound effect of consumers' devices [101] and outdoor temperature [102]. Other factors can also be considered, such as the type of day [103]. Indeed, our models could be extended to include varying requirements for different days (i.e., different reactions to prices and different electricity demand). However, a deeper understanding of this heterogeneity requires to collect specific data on the price response of consumers for different days. Further analyses relative to house-hold incomes [104], type of loads [105], on-site generation [106] and storage [107] are also possible. However, they too require a larger amount of information on the pool of consumers, which might be impractical to collect at scale. To avoid the need for additional data in estimating the aggregate potential of consumers' flexibility, these factors have been omitted in this work and and could be the subject of future studies.

4.1.1 Price-Responsiveness of Consumers

In implicit DR programs, consumers are responsive to dynamic prices and the overall flexibility provided derives from the aggregate reaction of consumers to prices. To formulate an accurate estimator, we first need to find a relationship between price and consumption for the aggregate pool of consumers. In this section, we define price-responsiveness as the consumers' willingness to change their consumption to provide regulation for different prices. While previous studies treated price-responsiveness as a constant (e.g., [108]) or a linear function (e.g., [109]), we describe it through a power function since it has been shown in [110] that power functions can better describe consumers' price-responsiveness than linear models. In order to achieve a certain reaction from consumers, we consider that consumers become responsive only beyond a certain price (see [108] and [111]). Furthermore, they have a bounded capability of adjusting their consumption according to a control signal, due to their finite and partially un-curtailable loads [67]. Therefore, consumers cannot provide additional flexibility beyond a certain price. In this matter, Paper C has proposed a power function to model consumer responsiveness to prices. Such a model accounts for an economic price threshold (i.e., dead-band price to which consumers start responding) and physical limitations of consumers in providing flexibility (i.e., saturation price at which no additional flexibility can be obtained).

The proposed model offers a deterministic formulation of consumer responsiveness to prices. However, when scaled to several heterogeneous consumers, this deterministic model might not represent the aggregate behaviour of the pool. In the decision-making process, system operators need to quantify and factor in the risk related to demand flexibility. Therefore, it is essential to consider the stochastic nature of consumers' behaviour in implicit DR programs and modify consumers' reaction accordingly in the model. In Paper C, the deterministic model is replaced by a stochastic one, as shown in Fig. 4.1. In this figure, the price-responsiveness of consumers is randomly drawn from a certain probability distribution. The reaction to prices follows a power law and price-responsiveness values are limited by the dead-band and saturation prices.

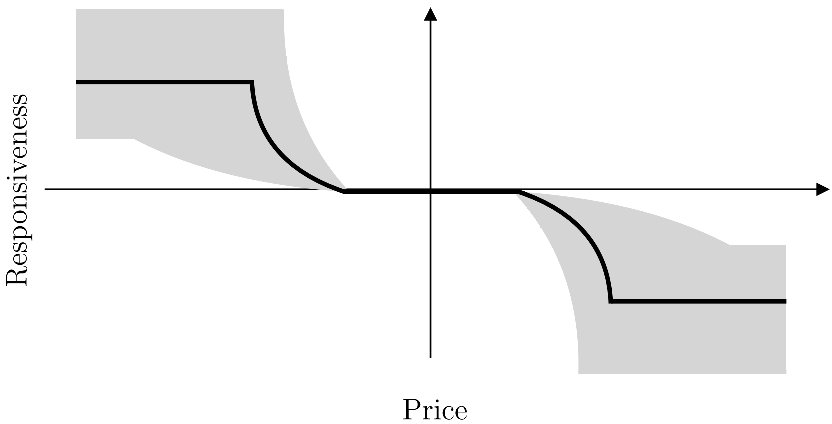

Figure 4.1: Range of consumers' price-responsiveness for different electricity prices. Modified image from Paper C.

4.1.2 The Rebound Effect

The rebound effect (RE) is of paramount importance in flexibility dynamics estimation. It arises from loads technical constraints and consumers' preferences and consists of the change in consumers' demand due to previous and future price reactions. While RE has been mainly investigated in relation to thermal loads or refrigerators, in our work we extend RE to general appliances by modelling different RE dynamics. Indeed, thermal loads and general shiftable loads (e.g., washing machine) have similar behaviour, in that they reduce (increase) their base-line consumption scheduled at a certain time and consume more (less) in the following time-steps. The main difference is the time span in which RE phenomenon occurs, e.g., refrigerators have faster dynamics than washing machines. In other words, thermal loads cause instantaneous RE, while other types of loads can be safely shifted forward by hours. In Paper D, we formulated a general mathematical model of the RE for both thermal and shiftable loads.

The different impact on dynamics is captured by the maximum RE duration parameter.

In order to model the RE, we assume that the increase and decrease in consumption perfectly match within a certain period of time, as shown in Fig. 4.2; we define this condition as perfect RE. Although this assumption might not be realistic for every type of load, it allows the estimation of the aggregate flexibility potential while overcoming the requirement of detail models and field data.

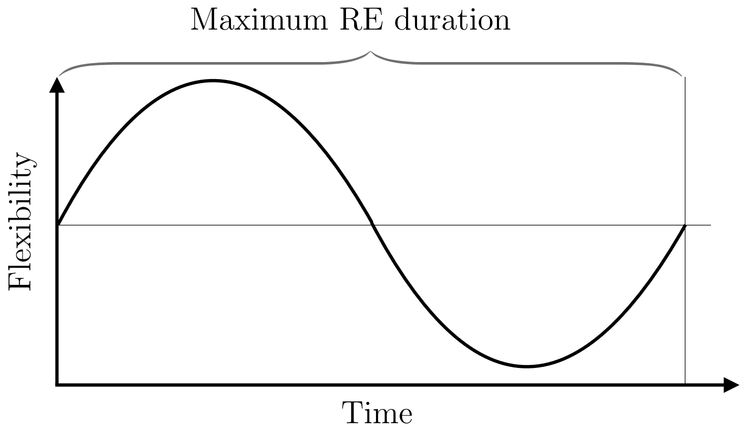

Figure 4.2: Basic concept of perfect RE. Modified image from Paper D.

Despite the importance of RE estimation, models of it have scarcely been proposed in the technical literature; the majority of studies evaluate RE in relation to the change in energy efficiency [112]. In [113], RE was modelled for a pool of residential heat-pumps, assuming that an operator has direct access to the consumption of the pool. In that study, RE included a delay period and a payback period. In delay period, heat-pumps followed their baseline consumption. In payback period, heat-pumps could deviate from their baseline consumption. As the study evaluates loads dynamics for a pool of residential heat-pumps, additional studies are needed to quantify the aggregate RE impact of different types of consumers.

In Paper D, we have addressed this research question by formulating two different models of consumers' behaviour. We model both a static RE, where we consider specific time periods, and a dynamic one, which allows more convenient scheduling of the consumers' flexibility. Static RE sets a time interval for which perfect RE occurs. This model of RE suits the operation of electric vehicles (EVs) that are put in charge mode at a specific hour and must be fully charged by a certain time in the future. A graphical representation of static RE is provided in Fig. 4.3. Dynamic RE imposes that perfect RE occurs at least once within the maximum RE duration. This type of RE covers the requirements of thermal loads, since they can always provide flexibility as long as some operational constraints are met. The concept of dynamic RE is shown in Fig. 4.4. In the figure, when perfect RE is fulfilled (as shown in the grey area), a new RE cycle can be started.

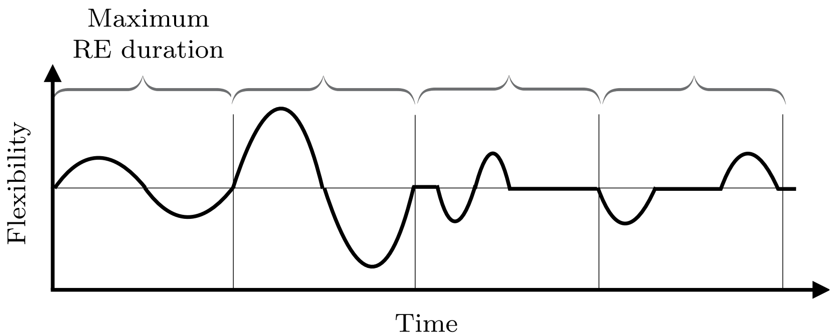

Figure 4.3: Static RE. Modified image from Paper D.

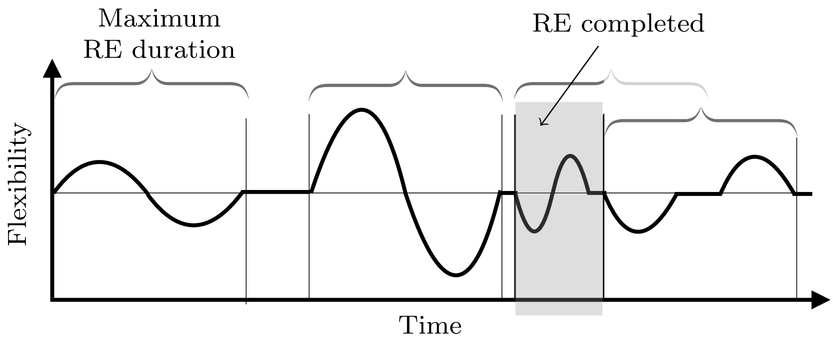

Figure 4.4: Dynamic RE. Modified image from Paper D.

4.1.3 Outdoor Temperature

Outdoor temperature can significantly influence consumers' flexibility, due to the close relationship between weather conditions and electricity consumption [114]. As an example, in [115], authors showed that the overall reaction of flexible consumers to prices was faster during cold weather. From the system operator perspective, higher electricity consumption presents higher chances that enough consumers are willing to provide services through DR, provided that their comfort is unaffected. In Paper D, we include the effect of outdoor temperature on the aggregate consumers' flexibility estimation.

4.1.4 Flexibility Modelling

After considering several factors that can influence consumers' flexibility provision, we moved on to analyse the aggregate flexibility. In Paper C and Paper D, we develop models that achieve cost minimisation for consumers, while respecting their preferences and the technical constraints of their devices. These models have been formulated as MILPs and encompass different types of electrical consumers (i.e., industrial, commercial and residential). In these studies, we estimated the consumers' flexibility potential taking into account the uncertainty of consumers' price response and the role of RE dynamics and outdoor temperature. In Paper C, the uncertainty of consumers' behaviour has been considered through the application of CC programming. In Paper D, we covered the modelling and benchmarking of static and dynamic RE formulation, as well as the effect of outdoor temperature.

4.1.5 Case Study

The studies have been carried out using data provided by the Elforbrugspanel project about Danish electricity consumption [116]. They represent the behaviour of 29 different types of consumers, e.g., paper industry, agriculture with heating and restaurants, in hourly resolution. From this data, we investigated the aggregate flexibility potential of electrical consumers in Denmark. Consumers' response has been simulated for various price-sets, in order to obtain a flexibility range in numerous operational scenarios. In Paper C, a MILP has been solved to schedule the daily electricity consumption, while understanding the effect of consumers' uncertainty in the overall flexibility provision. In Paper D, we have solved an updated MILP for two-days simulations. This study has covered the modelling of different RE types and has shown the performance of static and dynamic RE. Below, we report the main results from the analysis of consumers' behaviour, RE modelling and outdoor temperature.

4.1.5.1 Analysis of the Uncertain Consumers' Behaviour

In Paper C, we have estimated consumers' flexibility in the presence of uncertain consumers' behaviour. Through the application of CC, we have investigated the flexibility provision for a certain level of risk related to consumers' price-responsiveness. We have analysed two different values of security levels to estimate the flexibility for a conservative and a high-risk case (i.e., 95% and 50%). The results are shown in Fig. 4.5 and Fig. 4.6 for the two security levels.

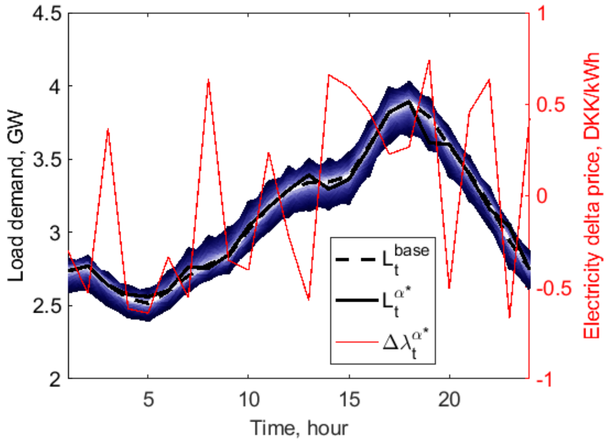

Figure 4.5: Flexibility achieved by CC optimisation for a 0.95 security level: baseline consumption, flexibility for the reference dynamic price component $\boldsymbol{\Delta\lambda}_t^{\alpha*}$, and the dynamic price component. Image from Paper C.

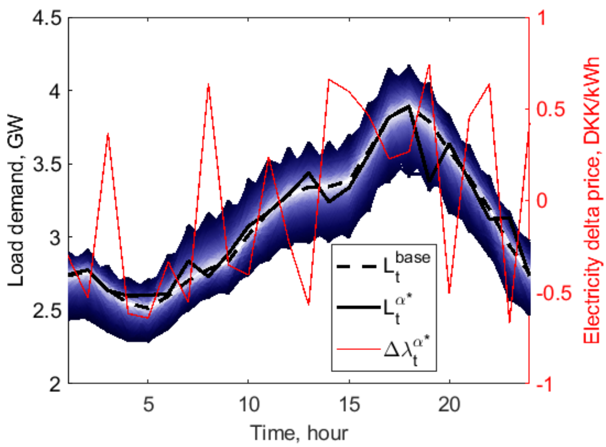

Figure 4.6: Flexibility achieved by CC optimisation for a 0.50 security level: baseline consumption, flexibility for the reference dynamic price component $\boldsymbol{\Delta\lambda}_t^{\alpha*}$, and the dynamic price component. Image from Paper C.

By comparing the figures, it can be noticed that the high-risk case has a flexibility range that is up to 76% higher than the low-risk case. Furthermore, Table 4.1

shows that the average values of flexibility achieved for the conservative case decreases by 66% compared to the high-risk case. This large difference depends on the different levels of risk: in high-risk case, the flexibility estimated is much higher. However, the probability of achieving this amount of flexibility is only 50%. By neglecting a low-risk analysis of the uncertainty, we might expect a much higher response from consumers than for the conservative case. Therefore, these studies have proven the importance of considering uncertainty and risk in the model.

Table 4.1: Average values of up- (down-) flexibility provided during one day, considering different security levels. Table from from Paper C.

Study case	Up- (down-) regulation [GWh]
50% security level	0.719
95% security level	0.243
Difference	-66%

4.1.5.2 Analysis of Different RE Dynamics

In Paper D, we have considered the estimation of consumers' flexibility through the formulation of different RE, i.e., static and dynamic. For these studies, 95% security level has been preferred, to keep a conservative viewpoint. The analysis of the RE provides a better understanding of loads dynamics and supports operators in estimating the achievable flexibility. The main outcome of this study has been estimating consumers' flexibility for different RE formulations. In Fig. 4.7 we show the amount of flexibility achieved for static RE, while Fig. 4.8 covers the case of dynamic RE. From the figures it can be seen that dynamic RE provides a higher amount of flexibility for the same price-sets. Finally, Table 4.2 reports the amount of flexibility achieved for different REs. As dynamic RE offers 45% more flexibility than the static case, it is fundamental for operators to understand which RE dynamics are most likely to happen on the consumers' side.

Table 4.2: Average values of up- (down-) flexibility provided during two days simulation, considering different RE formulations.

Study case	Up- (down-) regulation [GWh]
Static RE	0.600
Dynamic RE	0.874
Difference	+45%

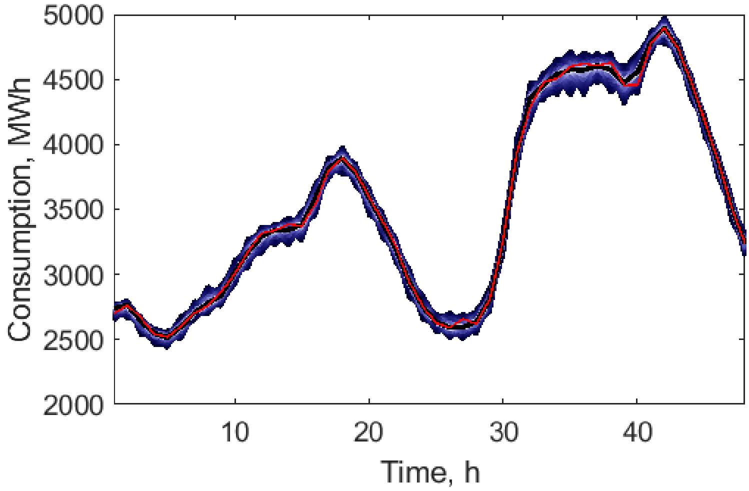

Figure 4.7: Range of consumption for static RE. Base-line consumption (in black); Sample daily price response (in red). Image from Paper D.

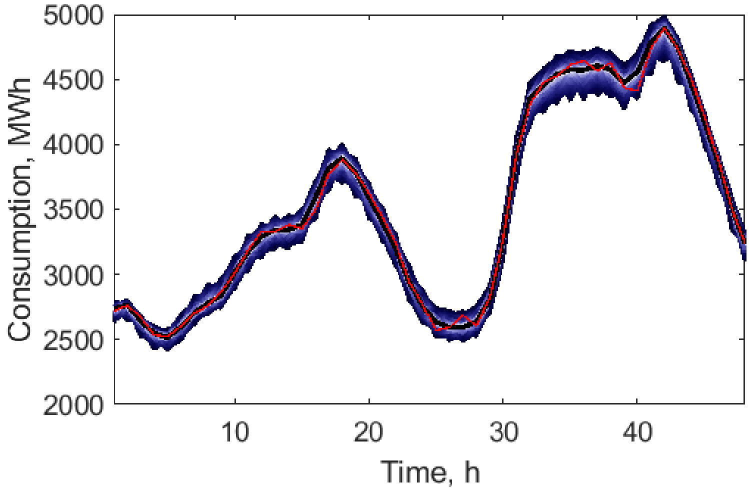

Figure 4.8: Range of consumption for dynamic RE. Base-line consumption (in black); Sample daily price response (in red). Image from Paper D.

4.1.5.3 Analysis of Different Outdoor Temperatures

In Paper D, we have extended the analysis of different REs to include the impact of weather conditions on the overall flexibility. Therefore, consumers responsiveness has been expressed as a function of the outdoor temperature. In Fig. 4.9, such a relationship is shown for the case of extreme temperatures during hot season. In the figure, Case I represents the base-line temperature (i.e., the case discussed in our previous studies where we did not consider the effect of temperature); Case II refers to higher outdoor temperatures and Case III models the responsiveness for lower outdoor temperature. The results of this study are reported for different cases in Table 4.3. The outdoor temperature and RE dynamics seem to significantly affect the overall flexibility, which varies between 0.482 and 1.032 GWh. Therefore, it is fundamental for the operator to account for weather condition in estimating the flexibility provision from electrical consumers.

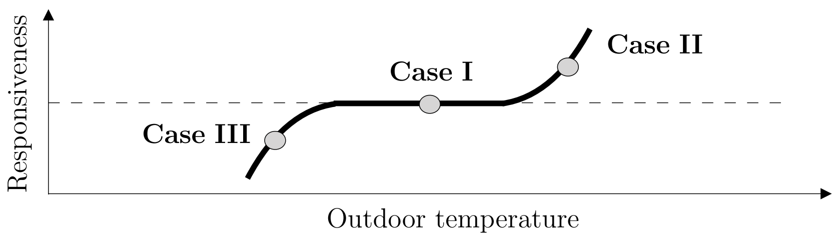

Figure 4.9: Relationship between temperature and price-responsiveness of consumers. Modified image from Paper D.

Table 4.3: Average values of the flexibility provided in two days for different temperatures.

RE model	Outdoor temperature case	Flexibility provided [GWh]
Static	I	0.600
	II	0.714
	III	0.482
Dynamic	I	0.874
	II	1.032
	III	0.714

In this section we introduced procedures for the estimation of consumers flexibility. In the rest of the chapter we address the second research question of this thesis and introduce AS4.0 as an alternative DR-based framework for AS provision.

4.2 A General Framework for Ancillary Services Provision

In future power systems, leveraging demand flexibility will be key to accommodating higher amounts of variable renewable generation. However, in the absence of a proper framework to account for system operators requirements and consumers' preferences, consumers will not be able to provide any reliable service. Indeed, power system operation requires real time provision of services that cope with the stochasticity, dynamics and non-linearity of RES generation. Such services must address needs at transmission and distribution systems in a reliable and fast way. At the same time, consumers are keen on maintaining the control over their demand and their stochastic behaviour can constraint the overall flexibility. By analysing the existing AS procurement methods, it emerges that none of them can successfully accommodate consumers' flexibility for AS in real time. Indeed, compulsory AS provision refers to generators only. It cannot rely on consumers for flexibility exploitation, as it requires two-way communication infrastructure in real time for a pool of heterogeneous loads and imposes external control over consumers' demand. Using demand flexibility through bilateral contracts turns out to be complicated, since consumers have to plan their consumption ahead of time - an unrealistic request. Tendering processes require costly, complex and long negotiations, which do not fit with the dynamic operation of the system. Although AS market mechanisms can deal with a shorter time-frame, e.g., by running every five minutes, they are not able to operate in real time. Furthermore, AS markets mainly rely on deterministic and linear bids formulated by aggregators. In order to accommodate consumers' flexibility in real time, alternative methods must, therefore, be investigated.

Research works have already proposed approaches to use consumers' flexibility in power systems. Such solutions are intended to provide AS beyond the transmission system, down to the distribution system. In Paper A and Paper B, we discussed transactive energy (TE), control-based approach (CBA) and peer-to-peer (P2P) as potential solutions to AS markets for power system management through consumers' flexibility. These approaches address only some of the requirements of power systems, where the benefits and drawbacks of each AS method are summarised in Fig. 4.10.

As none of these approaches can optimally provide AS to power systems, there is need for a new framework to take into account various requirements of power systems, i.e., ensuring services at different levels of the grid. For this purpose, in Paper B and Paper E, we formulated the AS4.0 framework. It consists of a unified, demand-flexibility based mechanism for the future power systems. The main novelty of AS4.0 is that distribution and transmission system operators

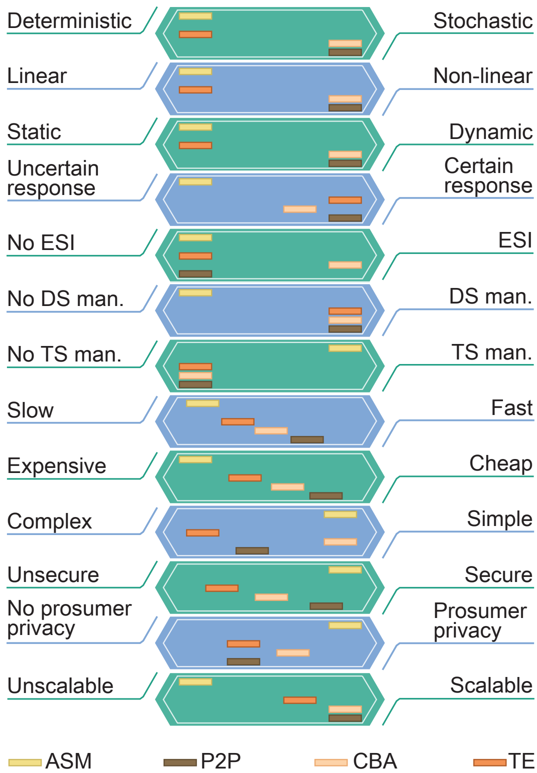

Figure 4.10: Benchmark of AS market (ASM), TE, P2P, CBA for AS provision. Modified image from Paper B.

can exploit the flexibility of consumers located in their territories independently and simultaneously. This is achieved by generating and submitting dynamic prices based on the real-time condition of their portion of the grid. AS4.0 is inspired by the concept of the smart-energy operating-system (SE-OS) described in [59], which promoted the adoption of hierarchical control techniques for balancing power systems. In AS4.0, prices are formulated at the operators' levels, considering the aggregate price response of consumers located in their part of the grid, as shown in Fig. 4.11.

The AS4.0 framework has been described in Paper B, while modelling and simulations have been presented in Paper E. In the following subsection, we will discuss the main requirements for the implementation of the AS4.0 framework.

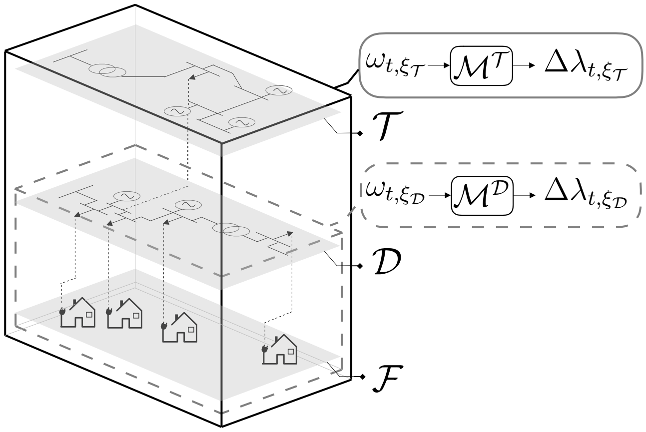

Figure 4.11: Basic concept of the AS4.0 mechanism. The three levels represent transmission system $\mathcal{T}$, distribution system $\mathcal{D}$ and flexibility resources $\mathcal{F}$, where consumers are located. Each time a certain power disturbance ω occurs in the system, operators formulate price signals $\Delta\lambda$ through models $\mathcal{M}$ that have knowledge of the overall price responsiveness of consumers. Modified image from Paper E.

4.2.1 Ancillary Services 4.0

The AS4.0 framework requires the introduction of power system models at different levels of the grid, as shown in Fig. 4.12. First, we need to design appropriate models of the grid at the transmission and distribution levels, which account for system operation and requirements in real time. Furthermore, each system operator needs to estimate consumers' reaction to price signals in order to generate dynamic electricity price signals that result in the needed change in consumption. Finally, we model the actual consumers' reaction to prices and quantify the aggregate flexibility that is achieved after the submission of prices. Although this last type of model is not going to be needed in a real implementation, we included it for simulation purposes. In Fig. 4.12, we formulate different models when handling transmission and distribution levels. Indeed, operational issues (e.g., voltage and frequency deviations) can always occur at transmission and distribution levels. However, some of these issues are more significant at specific levels of the grid. In particular, the transmission system mainly focuses on frequency management while the distribution system has to deal with voltage management. Indeed, size, type, and responsiveness of the consumers are widely different for TSO and DSO: this requires different models for the various operators. In Paper E, such models have been developed by using the methodologies discussed in Chapter 3.

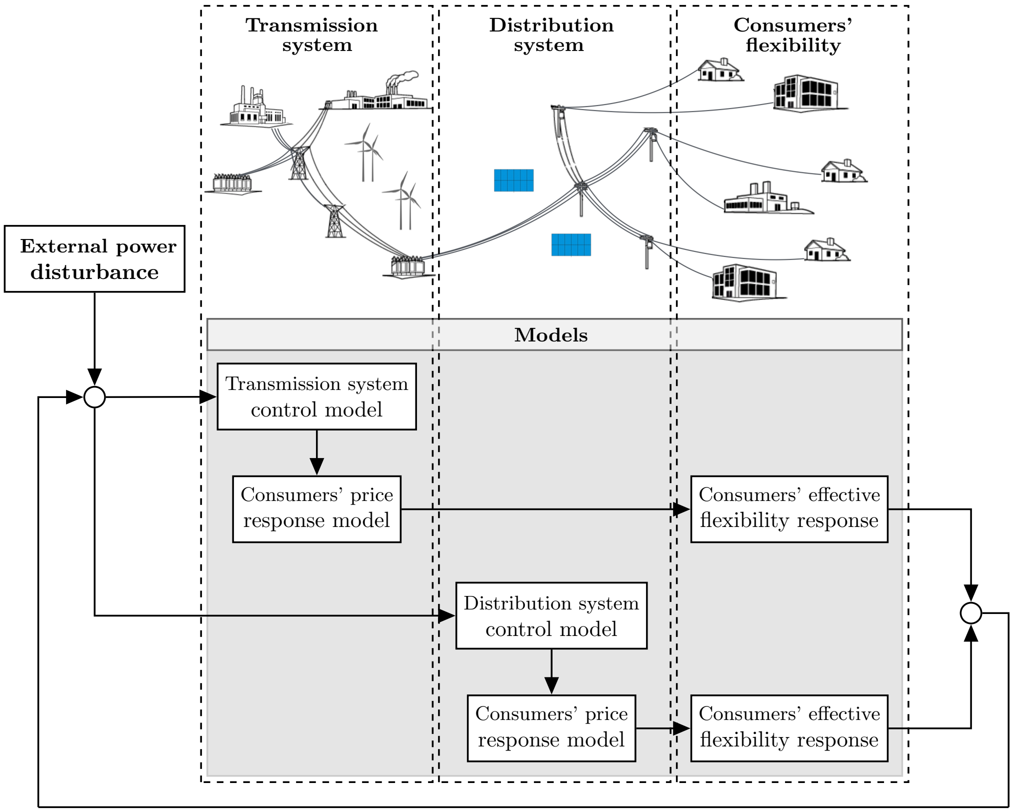

Figure 4.12: Models required for the implementation of the AS4.0 framework. They differ for each level of the grid.

4.2.2 Case Study

In Paper E, AS4.0 has been implemented for the case of Denmark, using data provided by the Elforbrugspanel project about Danish electricity consumption [116] and a two-control areas transmission system representing DK1 and DK2. In this study, we carried out simulations to verify the AS4.0 performance in providing services at transmission and distribution levels. Therefore, we needed to investigate the behaviour of frequency and voltage levels when power disturbances occur in a system built upon AS4.0. In this subsection, we present the main findings of Paper E.

4.2.2.1 Analysis of the Frequency Management

Frequency management has been analysed through an LFC model. In Paper E, we modified the traditional LFC model to evaluate the impact of load flexibility, as shown in Fig. 4.13. In the figure, the traditional LFC model (consisting of the model in red and black) represents frequency regulation through conventional generation units (CGU). The modified LFC model (in black and blue) shows frequency management through AS4.0.

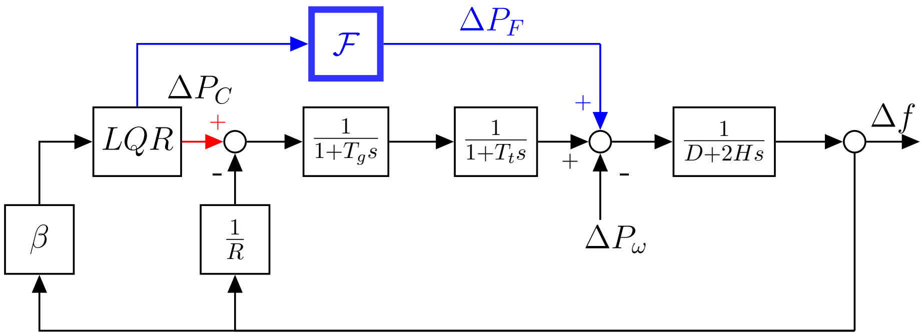

Figure 4.13: LFC model: conventional model in black and red and AS4.0 model in black and blue. Modified image from Paper E.

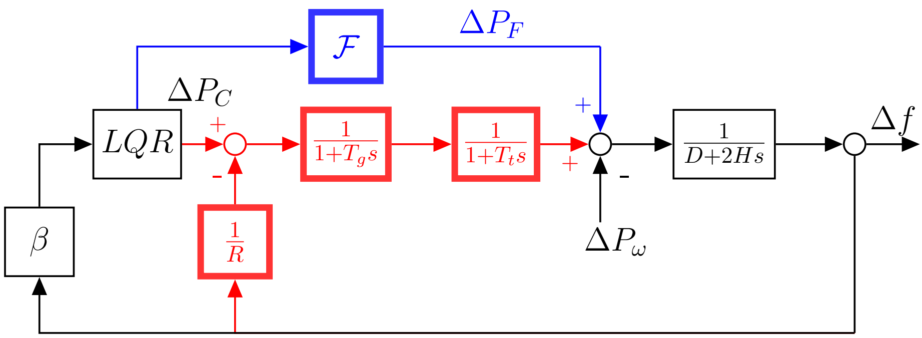

Figure 4.14: LFC model: conventional model in black and red and AS4.0 model in black and blue. In this setting, AS provision from consumers' flexibility is extended to primary frequency regulation.

In Paper E, simulations have been carried out for both LFC models; results are compared in Fig. 4.15. It can be seen from the figure that the frequency performance is significantly improved for the case of AS4.0 with respect to settling time and overshooting. In Fig. 4.15(b), the zoomed-in part shows that, by handling the same amount of power disturbance in the system, AS4.0 is able to reduce the frequency deviation by 52% compared to the CGU-based solution. Results are also reported in Table 4.4, showing that AS4.0 outperforms the CGU-based AS provision by reducing the frequency deviation within 30 seconds. Such an improvement in frequency regulation highly depends on the capability of consumers to provide faster response than CGUs. Therefore, it is possible to remove CGU from the LFC and rely only on consumers' flexibility, as shown in Fig. 4.14, without affecting frequency management.

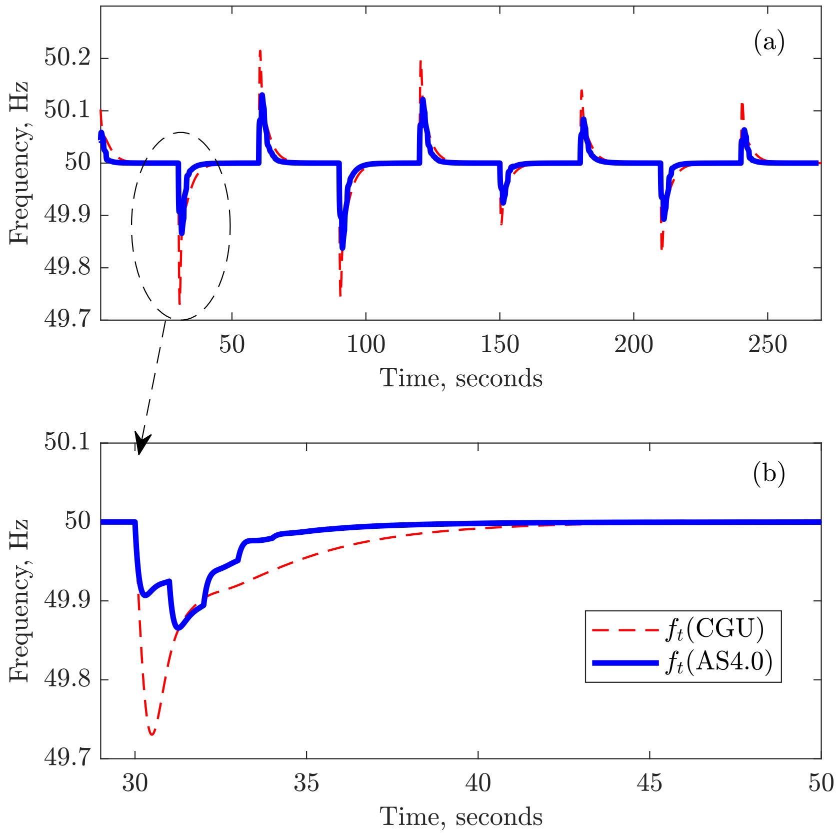

Figure 4.15: Frequency profile of the system. (a) Overall frequency. (b) Zoomed-in part to see dynamics. Modified image from Paper E.

In Fig. 4.16, consumers' price response is used to provide services to the transmission system. The TSO is able to achieve an aggregate change in demand that is up to 268 MW when broadcasting dynamic prices.

Table 4.4: Performance benchmark for AS4.0 and CGU-based AS.

Time and disturbance injected, [sec, MW]	Maximum frequency deviation, Hz		Deviation reduction, %
	CGUs-based AS	AS4.0	
[1, 1000]	+0.10	+0.06	40%
[30, 350]	-0.27	-0.13	52%
[60, 852]	+0.21	+0.13	38%
[90, 500]	-0.26	-0.16	38%
[120, 1148]	+0.20	+0.12	40%
[150, 1000]	-0.12	-0.08	33%
[180, 1300]	+0.14	+0.08	42%
[210, 1056]	-0.17	-0.11	35%
[240, 1500]	+0.12	+0.07	41%

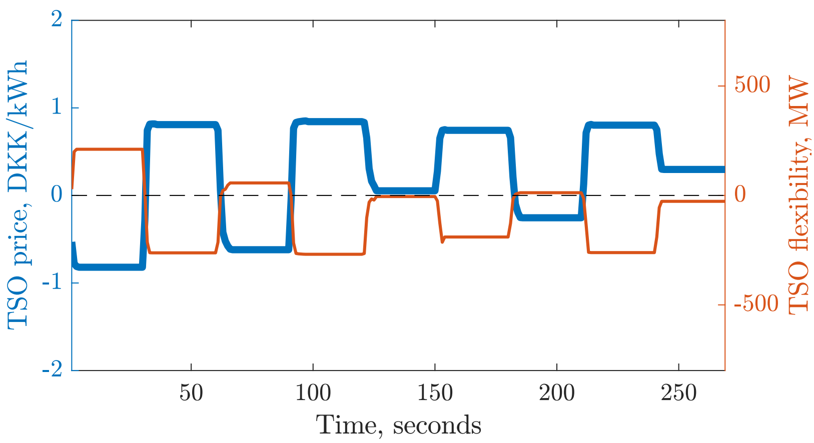

Figure 4.16: Delta prices and the corresponding response from consumers at the TSO level. Modified image from Paper E.

4.2.2.2 Analysis of the Voltage Management

Although AS4.0 offers overall improvements in frequency management, it is important that such a solution also guarantees proper voltage management at the distribution level. Therefore, we need to investigate how voltage evolves at different buses. Results from Paper E are presented in Fig. 4.17.

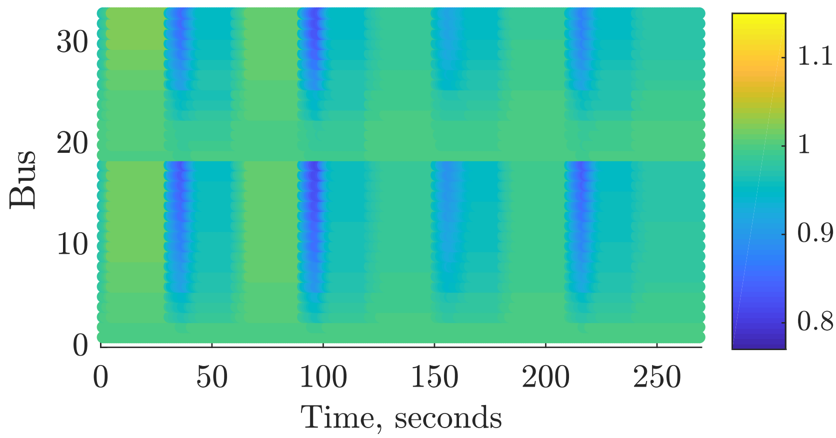

Figure 4.17: Voltage at different buses. Modified image from Paper E.

From the figure, it is apparent that the injection of power disturbances initially cause issues at different buses. However, the DSO is able to mitigate such issues in less than 10 seconds in most cases using the prices shown in Fig 4.18.

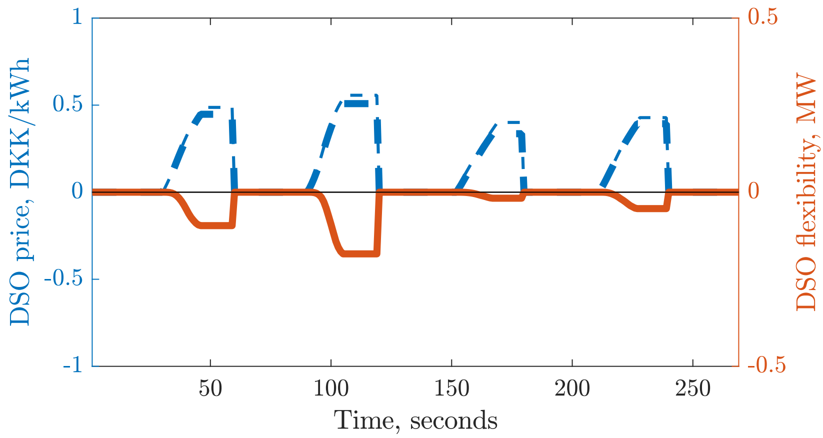

Figure 4.18: Delta prices and corresponding flexibility at the DSO level. Modified image from Paper E.

Furthermore, we evaluate voltage management by analysing the number of buses with voltage issues in the distribution system. Fig. 4.19 shows that the number of buses with voltage issues decreases over time, while TSO operation has not been compromised by the DSO operation of voltage regulation. It confirms that independent and simultaneous operation of TSO and DSO is plausible without jeopardising system stability.

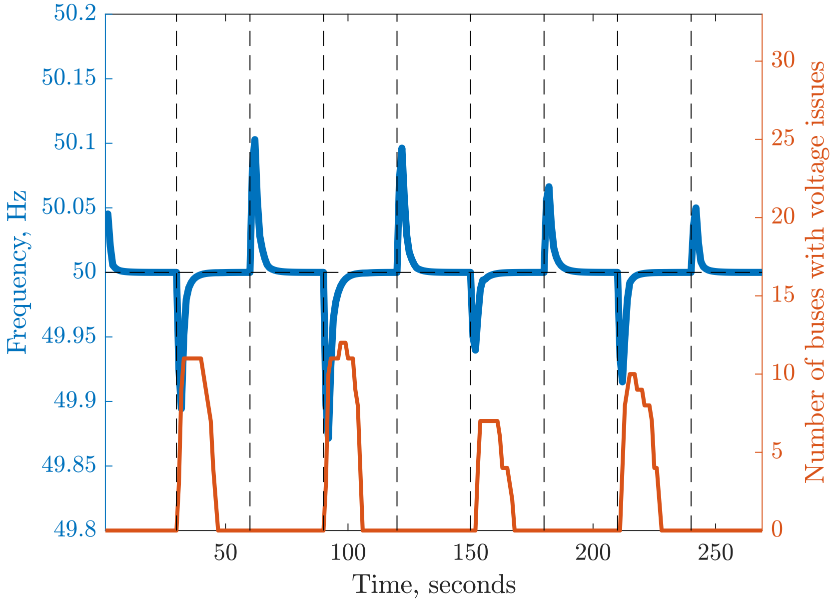

Figure 4.19: Number of buses with voltage violations along with the system's frequency.

CHAPTER 5

Conclusions

Nothing in life is to be feared, just understood.

Marie Curie

5.1 Contributions

In the course of the research described in this thesis, we provided a number of novel contributions to the state of the art. We developed a set of methodologies for the estimation of aggregate flexibility potential of electricity consumers. Furthermore, we proposed, modelled and simulated an alternative framework to optimally exploit consumers' flexibility for AS provision at different levels of the grid. Finally, we demonstrated that the adoption of control-based approaches for AS provision exploits consumers' flexibility for the operation of future power systems.

In the estimation of consumers' flexibility, we considered multiple factors that influence the overall responsiveness of consumers, such as uncertainty in consumers' behaviour, RE dynamics and outdoor temperature. These factors have been included in the models to better estimate the flexibility potential from consumers.

We investigated the application of CC programming to handle the risk in flexibility provision from consumers. Simulation results showed the importance of risk analysis for the system operator. In fact, high-risk scenarios can lead to three times the amount of flexibility estimated in the system. However, targeting such flexibility for AS can be a challenge for power system operation: this amount of flexibility has only 50% probability to be delivered by consumers.

In the analysis of aggregate flexibility potential, we proceeded by taking into account the impact of RE. We proposed appropriate models to simulate different RE dynamics. Moreover, we provided a benchmark of the overall flexibility provided for different RE formulations. These studies highlighted the importance of understanding the constraints and dynamics under which loads operate. For instance, a dynamic formulation of the RE resulted in 45% more flexibility than in the case of static RE. For this reason, operators shall carefully investigate the dynamics of consumers' load for a better estimation of the aggregate flexibility potential. Alternatively, for a more conservative approach to RE, static RE shall be preferred. This solution avoids to over-estimate the flexibility when the load dynamics are not known or are difficult to estimate from aggregate measurements.

Finally, we extended the study of consumers' flexibility to include the effect of outdoor temperature, as it influences the overall responsiveness of the consumers. This model is developed by formulating the overall responsiveness of consumers as a function of outdoor temperature. This study shows the importance of considering different weather conditions, as they affect the overall flexibility.

These proposed models for demand flexibility estimation enable operators to understand consumers' reaction toward prices at an aggregate level. Furthermore, they help to formulate proper dynamic prices that induce a certain change in consumption from electrical consumers.

In the second part of our research, we dealt with the AS4.0 framework to provide fast and reliable services from flexible consumers to power systems. In AS4.0, each operator generates and broadcasts prices in an independent and simultaneous manner. Such prices are able to reflect the real-time condition of power system at different network levels. By relying on control mechanisms, prices can be updated and submitted on a second-by-second basis. The criterion defining the optimal price-based control can be tailored to handle various aspects of the spectrum of AS needs for power systems operation. Therefore, prices can influence the aggregate consumers price-response and meet system needs that change very rapidly. In our study, we proved that consumers can be utilised as a significant source of flexibility for frequency and voltage management. In particular, the simulation studies showed the capability of TSO and DSO to simultaneously handle their operational issues by AS4.0. At the TSO level, frequency regulation has been significantly improved through AS4.0 compared to the conventional CGU-based AS provision. Overall, we can conclude that AS4.0 outperforms the existing approaches for AS management, as it provides services to transmission and distribution system while respecting consumers' autonomy.

5.2 Perspectives and Opportunities for Further Research

In this thesis, we set the ground for a better management of consumers' flexibility potential. Despite the novel contributions achieved, additional analyses are beneficial to better assess the role of consumers' flexibility in AS provision.

In order to extend and improve the existing models, the collection of high resolution data about consumers' price-responsiveness is a necessary step. Such an effort can provide a better understanding of the true potential of the proposed methods. In particular, in Paper C and D, we presented several methodologies to estimate the aggregate amount of consumers' flexibility. In this regard, our work could be extended by including additional factors that influence the price-responsiveness of consumers, such as type of day, household income, on-site generation, storage and type of loads.

Furthermore, in Paper E, we showed through a proof-of-concept study that AS4.0 is a promising solution for AS provision in smart grids. Nevertheless, additional studies are needed to investigate the power system operation in a more realistic manner. As an example, future studies shall consider a more detailed representation of the distribution system, i.e., extending the analysis to several large-scale distribution systems.

Appendix A

Research Affiliation: the SmartNet Project

Alone we can do so little; together we can do so much.

Helen Keller

The research carried out in this thesis has been developed as part of the SmartNet Project. SmartNet consists of a three-year project funded by the European Commission – Horizon 2020. This appendix briefly presents the main objectives of SmartNet and shows how they relate to this research. For additional details on this project, the reader can refer to [117] and the related publications.

A.1 About SmartNet

The SmartNet project proposes solutions to accommodate the integration of renewable energy sources in power systems [117]. The increasing amount of intermittent energy generation affects power system continuity and stability as well as the interaction between TSOs and DSOs. In this regard, SmartNet has developed tools to improve the coordination between grid operators at national and local levels and provide ancillary services.

Different TSO-DSO interaction schemes have been compared in national key cases (i.e., Italy, Denmark and Spain) and physical related pilots have been developed to provide ancillary services from distributed resources at the distribution level.

Specifically, the Italian pilot deals with the feasibility of communication processes to enable generators to provide grid services. The Danish pilot investigates the capability of flexible demand to provide services, by leveraging the thermal inertia of indoor swimming pools. Finally, the Spanish pilot focuses on the flexibility potential of base-stations distributed storage for telecommunication [118].

A.2 The Danish Pilot

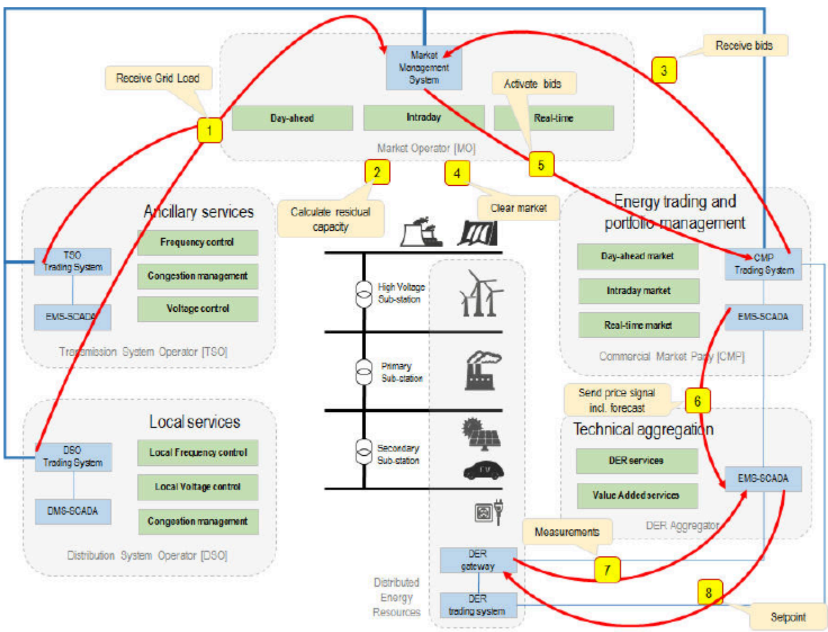

Figure A.1: Architecture of the Danish pilot [118].

Fig. A.1 shows the architecture of the Danish pilot. In the figure, the main entities (in dashed rectangles) are the market operator (MO), TSO, DSO, distributed energy resources (DERs), commercial market party (CMP) and DER aggregator. Such entities exchange information with each others (in red arrows). In particular, the MO communicates with TSO and DSO for grid status and interact with CMPs to obtain the needed flexibility. The CMP has knowledge of consumers' demand in function of electricity prices through a flexibility model [119]. Therefore, CMP submits prices and price forecasts to an aggregator, which finally calculates the optimal set-point for the summerhouses thermostats. Measurements from summerhouses are collected and used to update the flexibility model.

Although the solution proposed in this pilot still relies on market mechanisms at the transmission level, it leverages the lowest level of the SE-OS setup by using price-based control to obtain a certain change in consumption from distributed energy sources. Furthermore, it discusses the formulation of a flexibility model (i.e., flexibility function [119]) to support the generation of dynamic electricity prices broadcast to consumers. A parallel setup in the CITIES project adopts CO_2-based control. This setting demonstrates that considerable CO_2 savings can be achieved [120].

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Part II

Publications

Paper A

Utilizing Flexibility Resources in the Future Power System Operation: Alternative Approaches

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Utilizing Flexibility Resources in the Future Power System Operation: Alternative Approaches

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Abstract

Future power system will experience large amount of renewable generation with highly stochastic and partly unpredictable characteristics. To safely operate power system, new Flexibility Resources (FRs) are needed to participate in the operation. Some of the new FRs are linked to the electricity system, but they are managed outside of the electrical network by other energy sectors. To this end, an Integrated Energy System (IES) is needed to exploit such cross-sectoral opportunities. On the other hand, small FRs at the distribution level exist which can play an important role in the future. To exploit existing FRs, however, new operational strategies are needed. In this paper, Transactive Energy (TE) and Control-Based Approaches (CBA) are explained as the two mainstream frameworks in relation to the future energy system operation. The paper investigates benefits and drawbacks of each framework and finally defines a benchmark to better understand the potential of these solutions for the future energy management. The paper also concludes that more comprehensive operational approaches, beyond distribution system management, are required to fulfil the upcoming requirements.

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A.1 Introduction

In the last decades, electricity transmission and distribution systems went through significant changes by introducing large- and small-scale Renewable Energy Resources (RES). These assets are scattered all around the network at different voltage levels. Although RES provide unquestionable benefits to the power system operation, e.g., sustainable and clean energy production and reduction in energy losses and T&D costs [1], they imply some challenges. In fact, RES are characterized by unpredictable and highly stochastic generation, mainly affected by the weather condition. As a result, increasing penetration of RES implies higher risk of local congestion and unbalances that need to be properly handled in real-time. Since energy generated from RES changes instantaneously and it is almost impossible to predict their generation accurately in different time steps, new Flexibility Resources (FRs) are becoming more and more important and valuable. FRs include shiftable and curtailable loads, storage devices, and inherent inertia of other energy carriers. Although the size of provided flexibility could be significant when aggregated, it adds new stream of stochastic behaviour to the power system operation which has to be managed. For instance, different types of flexible load are constrained by end-users' preferences and their behavior. They might not be as reliable as their conventional counterparts, however, predictability of their behavior can become acceptable when aggregated.

In the EU's new legislative proposal, the so-called Clean Energy Packages (Winter Package) [2] released on November 30$^{\text{th}}$, 2016, a power system management that becomes more consumers-centred and, from a grid perspective, more centered around distribution network is encouraged. As a part of the Clean Energy Package, priority of dispatching RES disappears, and the main focus is going to be on Distribution System Operator (DSO) to utilize local FRs and handle grid issues.

Beside small FRs, Integrated Energy System (IES) is a concept that is attracting more and more attention [3, 4, 5]. The concept states that there are synergies between different energy carriers, such as electricity, gas, and heat, which can be exploited for the benefit of secure operation of the entire energy system with large amount of wind and solar power. This way, IES accounts for all the interactions among different energy carriers and large-scale infrastructure including waste-water treatment plants, transport and communication networks, and so on [5]. IES also increases efficiency of the system as a whole, where different assets are called to combine their strengths to work optimally together [6]. However, existing operational strategies in power system do not facilitate participation of new FRs accounting for their inherent stochasticity neither support IES. Therefore, it is crucial to create a smart transmission and distribution management structure that can support emerging FRs and IES potential.

In order to effectively deal with the magnitude of stochasticity and dynamics in the future power system operation by new FRs, dedicated operational strategies (particularly in shorter time intervals for Ancillary Services, AS) are required to be fast (to work as close as possible to real-time operation), cheap (to be a viable solution economically without increasing energy prices), simple (to guarantee feasibility and service continuity), efficient (to allow optimal service at the lowest cost), and to account for space and time differentiation, as shown in Fig. A.1 (to focus on the local constraints of the network at different level). In fact, multiple operational levels with unique objectives and constraints are expected to work autonomously, while cooperating with each other on a broader perspective to guarantee global optimality of the entire system operation.

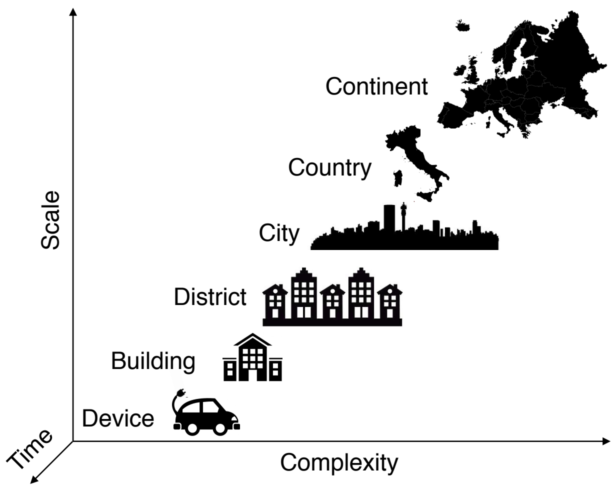

Figure A.1: Schematic of power system operation in different time and space

Nowadays, two mainstream solutions, namely Transactive Control/Energy (TC/TE) and Control-Based Approach (CBA), are preferred for the future energy management of distribution systems. This paper offers thorough analysis of the two energy management systems by addressing integration of FRs in the future smart grid framework. The authors intend to investigate pros and cons of these approaches and identify the caveats which urge more comprehensive solutions for the future power systems.

The paper is organized as follows: Section A.2 presents TE and CBA from a conceptual point of view together with some relevant applications. Direct (DC) and Indirect controls (IC) for CBA are described in detail in Section A.2. Section A.3 discusses limitations of the two approaches. Finally, the paper is concluded in Section A.4, by focusing on the main findings and detailing future possibilities for smart energy management in research.

A.2 Approaches for Distribution-Level Energy Management

Two different approaches have been proposed in literature to modernize distribution level energy management: Transactive Energy (TE) and Control-Based Approach (CBA). These approaches have been developed to handle new requirements of operation at the distribution level. Specifically, these methods are explained in the next two subsections.

A.2.1 Transactive Energy (TE)

According to the definition of the Gridwise Architecture Council (GWAC), TE consists of a set of economic and control mechanisms that allows dynamic balance of supply and demand across the entire electrical infrastructure using a value as key operational parameter. It proposes a scalable coordination approach to electricity distribution system operations [7] while being able to provide services to the upper grid. The approach becomes particularly interesting in presence of high penetration level of DERs, by encompassing the entire electric system to the end-use customer meters [8]. To better understand TE approach, a conceptual block-diagram is shown in Fig. A.2. In the top layer, existing wholesale market (both electricity and AS) is considered without any modification in its structure nor functionality. The wholesale market operator (e.g., TSO) communicates with energy suppliers and Balancing Responsible Parties (BRPs) to run power system effectively. In this framework, BRPs and energy suppliers are responsible for any deviation in their generation and/or demand from scheduled values. They have to purchase required balancing services from AS market (in the conventional power system operation) to compensate their variation. TE, however, provides mechanism to procure required services from small FRs at the distribution level through Virtual Power Plants (VPPs) or equivalently Aggregators. In fact, VPPs behave as effective power plants and indirectly represent end-users' flexibility located at the lowest level. VPP can include small- and medium-scale generation, aggregated load flexibility, and storage devices. Any request for up and down regulation services is submitted to the Global Flexibility Agents (GFAs), which are main aggregators to coordinate pools of Local Flexibility Agents (LFAs). This request is then broadcasted to LEAs, which are entities representing and communicating with a pool of end-users directly. By operating in the interest of the end-users, LFAs submit possible price signals to the pool to realize their reaction/responsiveness. Then, end-users receive potential price signal by their Home Energy Management Systems/Energy Management Systems (HEMSs/EMSs). By solving an

optimization problem to minimize overall cost of energy, they decide about the reaction to the price considering local preferences set by the user. Optimization results are then communicated back to LFAs in the form of price-quantity bids. Once all end-users feedback is received, LFAs submit the bids to GFAs where information is aggregated and broadcasted to higher level agent. By receiving all the bids from GFAs, VPP is able to aggregate the bids using forward market principles and clear the price. Ultimately, the cleared price will be communicated to the end-users through the channels to procure required amount of service.
In TE framework, Grid Agents (GAs) are also defined as entities whose responsibility is to look after the grid benefits. Utility company and DSO are two examples of the entities which can serve as GA in this setup.
As you can see, the market mechanism in TE uses feedback to determine price and reach balance between supply and demand or procure services. As a result, TE can be defined as "uberization of energy"- for its connotations of personalized on-demand service and elimination of intermediates [9].
Several applications of TE have been developed in the last two decades, a few of which are: Olympic Peninsula Demonstration [10] (USA, 1996-2007); AEP Ohio gridSMART Real-Time Pricing Demonstration [11] (USA, 2010-2014); Pacific North West Smart Grid Demonstration [10] (USA, 2010-2015); Couperus Smart Grid [12] (EU, 2011-2015). These demo projects were evaluated successful by the operators.

TE, beside providing mechanisms to activate small FR potential at the lowest level of the grid, has several advantages which are summarized below:

- **End-users' Reaction**: It requires a feedback from end-users to know their reaction to a potential price. This way, uncertainty in end-users' behavior is minimized. In other words, TE does not need to model end-users' reaction in an abstract/aggregated way to predict their behavior and preferences. Therefore, there is a better chance for operator to procure required services without any surprises.

- **Privacy**: In this framework, no sensitive information from end-user is needed to be shared with any agent because local operation and decision-making occur at the end-users' level. The exchanged information is only price and energy quantities which in turn reduces privacy and security issues and threats.

- **Scalability**: The TE framework operates based upon receiving bids from participants and clearing the market accordingly. Therefore, numerous bids can be aggregated and the approach can be used in high scale. Also, market operation can be distributed among multiple LFAs and GFAs to accommodate more FRs.

- **Accommodating IES**: Very recently, studies emerged to show applicability of TE approach in IES operation [13], which provides larger amount of flexibility for power system operation.

Although TE satisfies some of the main requirements of the future smart grid in terms of exploiting new FRs, it comes with its limitations, as explained in the following items:

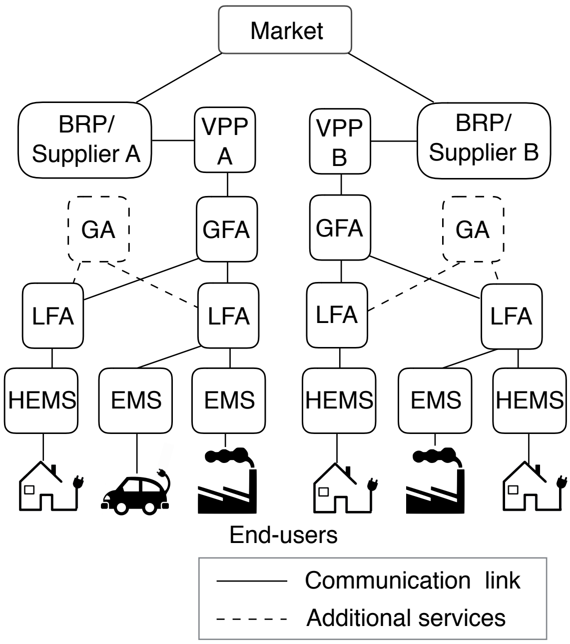

Figure A.2: Conceptual block-diagram of TE

- **Over-simplification**: The actual dynamics of the system is widely ignored in this approach. Every interaction among agents ends up with a price-quantity bid which is a linear representation of the underlying system. It is very difficult, if not impossible, to integrate stochasticity, true dynamics and non-linearity of FRs and power system operation through a set of linear supply and/or demand bids.
- **Computational effort**: As explained earlier, TE framework requires a cycle of bid-clearing mechanism whenever a new service request is received by VPPs. Basically, EMS/HEMS are invoked upon receiving a new price signal to generate new set of price-quantity bids. This requires to solve an optimization problem which is computationally expensive. Then, bids aggregation and

market clearing should take place which requires additional computational efforts. As one can realize, the entire process seems to be computationally intensive considering the fact that there could be millions of FRs participating in this structure.

- **Slowness**: Service request from wholesale market participants are generated according to the wholesale market operation, which is updated every 5 minutes or so. Compared to actual changes in power system operation, 5 minutes is a long time to deal with true system condition. Additionally, every iteration of TE operation, as explained earlier, requires intensive communication, computation, and market processes which makes it substantially slow. Communication delay also plays an important role in slowing down the whole process.

- **Security**: While TE framework respects end-user's privacy, many communications between end-users and system's agents makes the framework vulnerable to cyber-attacks. It further threatens the power system operation in real-time. Additionally, relying on too many instances of communication increases sensitivity of power system operation with respect to communication malfunction.

- **Sub-optimal Solutions**: If TE is going to be scaled up so much to accommodate millions of FRs while accounting for physical limitation of the network, more VPPs, LFAs and GFAs are required. These agents are operating autonomously which means that their solution for power system operation might not be globally optimal.

A.2.2 Control-Based Approach (CBA)

CBA primarily is developed based on the application of control theories for managing FRs at the distribution level [14]. The main idea is to replace slow and linear market principles in FRs procurement with control problems which can accommodate stochasticity, non-linearity, and true dynamics. To do so, CBA offers a real-time pricing mechanism for FRs operation at the lowest level of the grid. In this approach, every Sub-Aggregator (SA) defines a control problem to determine appropriate varying price signals. To do that, SA needs to model end-users' response to different prices which creates a certain change in consumption/generation of the rational end-users. To model end-user's behaviour, no real-time communication is needed in CBA. In fact, one-way communication channel from SA to the end-user's EMS/HEMS is the only required communication in real-time operation. At the consumers' level, a control/optimization problem (e.g., model-predictive control (MPC)) is solved to act upon receiving

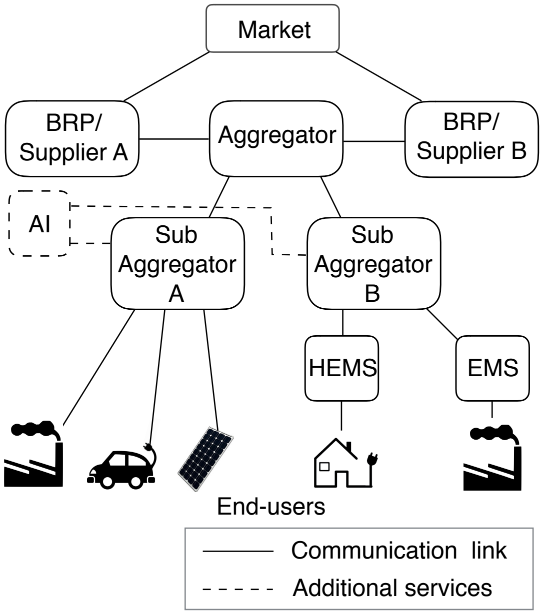

Figure A.3: Conceptual block-diagram of CBA

the price signal. Contrary to the TE approach, local end-users do not send feedback or share any information with other agents which makes the whole process very fast and secure.

For a comprehensive understanding, the CBA entities and operation is shown in a block-diagram for CBA in Fig. A.3. At the highest level, similar framework to the one for TE, existing wholesale market is maintained including wholesale market operator, energy suppliers and BRPs. When BRP or suppliers encounters deviation from their schedules, they submit a service request to the aggregators. The aggregator submits the request to numerous Sub-Aggregators (SAs) scattered all around the network. According to the end-users' price-responsive model, which is created offline using aggregated data, SAs are able to generate price-quantity blocks of bids to participate in the wholesale market through aggregators at the top level of the grid. The top aggregator is then responsible to receive all the bids, aggregate them, and participate in the wholesale market on behalf of SAs. When market is cleared and prices are determined, top aggregator dis-aggregates the market schedules and communicate prices and quantities to the SAs. Later, SAs submit new prices to their associated pool of FRs to achieve a certain amount of service, as awarded in the market. Additional Information (AI) are agents with information which can improve SAs operation. It could be an agent with information about weather which helps SAs to generate more appropriate price according to the ambient conditions.

It can be realized that TE and CBA have many operational characteristics in common. An example of up and down bid generation based on end-users' reaction to a certain price signal is presented in the flexibility curve of Fig. A.4 (for the case of supermarket refrigeration system [15, 16]). The figure shows the correlation between rebound effect and a modified consumption response. The adoption of these curves is based on the simplification of flexibility characteristics where stochasticity and non-linearity are not effectively represented. This is effective when load response of end-users can be controlled directly. If no direct control is assumed to the loads, an impulse response function is preferred, as presented in Fig. A.5. The figure shows reaction of a pool of responsive loads to varying price signal in a real-world demonstration in North West Project [10]. By increasing price at time 5:00, overall consumption decreased.
So far, CBA with Indirect Control (IC) to the FRs is presented. Alternatively, each SA can coordinate the pool of end-users through Direct Control [17]. The main difference between them is that DC directly alters power consumption of load, while IC activates flexibility response through time-varying price.

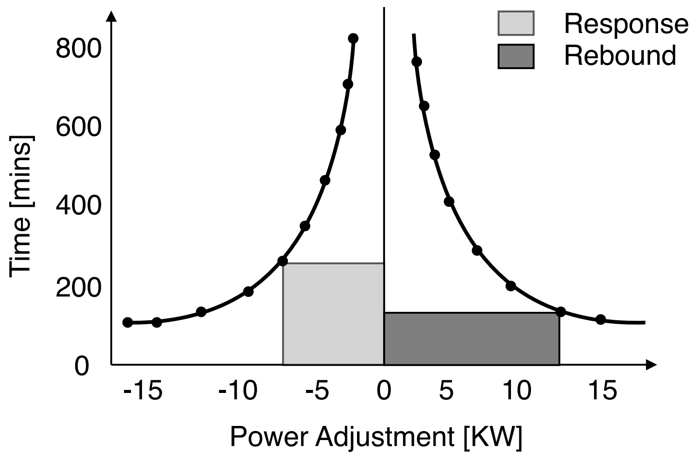

Figure A.4: Proposed bidding mechanism for CBA

In this study, we present both DC and IC methods for the sake of completeness. However, IC method is considered as the optimal solution since it requires very simple communication infrastructure while preserving end-users' privacy.

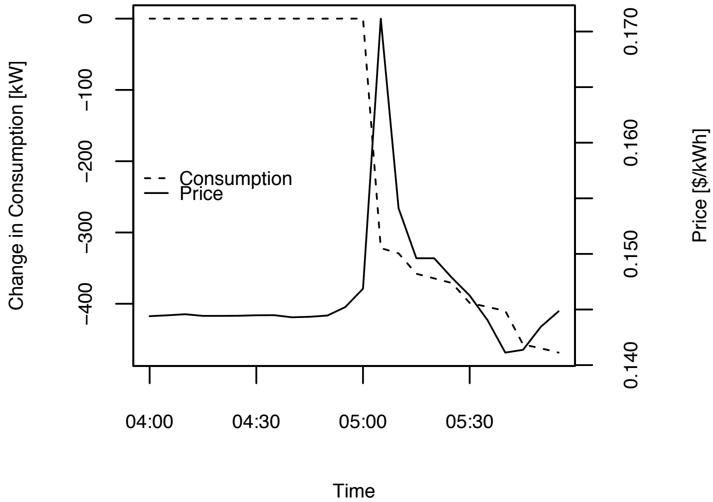

Figure A.5: Correlation between Price and Consumption from the North West Project Data [10] on March 23, 2013

A.2.2.1 Direct Control (DC)

DC is based on a two-way communication where FRs are directly controlled in a closed-loop feedback. In Fig. A.3, this type of control is adopted by sub-aggregator A, which centrally runs an optimization problem. MPC is a popular application of DC, optimizing a sequence of control moves over a finite prediction horizon [18]. Such moves are computed at each time step as a solution to the optimization problem [14]. The strength of MPC is that predicted behaviour and constraints are directly formulated into the design of the problem, exploiting the full flexibility of the resources. Also, adding predictions in the controller improve control performance. A mathematical formulation of MPC is provided in Eq. (A.1) [14]:

$$\begin{aligned} \min_{x,u} \quad & \mathrm{E}[\sum_{k=0}^{N}\sum_{j=1}^{J}\phi_j(x_{j,k},u_{j,k})] \\ \text{s.t.} \quad x_{k+1} &= Ax_k + Bu_k + Ed_k, \\ y_k &= Cx_k, \\ y_k^{min} \leq y_k &\leq y_k^{max}, \\ u_k^{min} \leq u_k &\leq u_k^{max} \end{aligned} \tag{A.1}$$

where $k = 0, 1, ...N$ is the prediction horizon; x is the state; d is the disturbance (e.g., outdoor temperature); y is the output of the system (e.g., indoor temperature); (A, B, C, E) represent the discrete time state-space model [14]; u is the control input (e.g., electrical power). ϕ represents the aggregator objective function to be minimized. It tracks a reference power consumption profile by manipulating total power consumption $z_k = \sum_J u_{j,k}$ via individual FRs [19]. The reference to track is formulated in Eq. (A.2), where λ represents penalization factor related to control moves.

$$\phi_{track} = \sum_{k=0}^{N} \sum_{j=1}^{J} ||z_k - z_{ref,k}||_2^2 + \lambda ||u_{j,k}||_2^2 \tag{A.2}$$

In MPC, it is also possible to consider individual costs related to FRs' consumption, formulated in Eq. (A.3).

$$\phi_{eco} = \sum_{k=0}^{N} \sum_{j=0}^{J} p_{j,k}^T u_{j,k} \tag{A.3}$$

This way, MPC should achieve a trade-off between tracking and economic objective, as expressed in Eq. (A.4).

$$\phi = \alpha \phi_{track} + (1-\alpha)\phi_{eco} \qquad \alpha \in [0, 1] \tag{A.4}$$

A.2.2.2 Indirect Control (IC)

IC consists of one-way communication in real-time where SA formulates and submits varying price signals to the pool of rational end-users to influence their generation/ consumption patterns. In Fig. A.3, this type of control is adopted by sub-aggregator B, as end-users of its pool are equipped with controller and the optimization is run in a distributed way. Operating in an open-loop scheme, IC does not need any feedback in real-time. However, SAs require end-users' behaviour model which has to be created based on aggregated offline data. Such a data is available today at the distribution system substations. Therefore, CBA-IC only requires one-way communication in real-time from SAs to the end-users' EMS/HEMS. Optimization problem of a SA can be formulated as follows:

$$\begin{aligned} \min_{p} \quad & \mathrm{E}[\sum_{k=0}^{N} w_{j,k} ||\hat{z}_k - z_{ref,k}|| + \mu ||p_k - p_{ref,k}||] \\ \text{s.t.} \quad & \hat{z}_{k+1} = f(p_k) \end{aligned} \tag{A.5}$$

where N is the length of the regulation horizon; μ is the penalization factor related to the deviation from the reference in price; $w_{j,k}$ is the penalization factor related to the deviation from the reference in load.

CBA has been implemented in several projects over the last decade. The most prominent ones are CITIES [20] (a Danish Research project, 2014-2020) and SmartNet [21] (an EU project, 2016- 2019), results of which are reported in [22, 14, 19, 23, 24]. Several advantages can be identified from CBA-IC approach, as listed below:

- **Suitable for Real-World Applications**: CBA turns power system operation into a set of control problems where the model of system, devices, and services can be non-linear, dynamic and stochastic. It requires one-way communication, which is faster and cheaper solution. CBA-IC can be updated fast, in the range of seconds if needed, to compensate for the sporadic changes in RES and consumers' behaviour.
- **Privacy**: CBA does not imply any privacy issue because there is no real-time feedback from end-users to the system operators. Only offline historical data are needed to develop consumers' price-responsiveness model which is created by using aggregated data.
- **Security**: In CBA-IC, a price signal is submitted to the end-users from SAs to address a certain behaviour. Therefore, communication is not intensive and system operation does not depend on the feedback signal from end-users. As a result, lack of real-time feedback diminishes risk of communication malfunctions and cyber attacks.
- **Cost**: Due to the one-way communication structure, CBA offers a cheaper solution in terms of implementation and regular maintenance costs. The limited need of measurements to control grid condition (e.g., over-voltage) further contributes to a lower management cost, where all expenses for distribution-side measurement equipment are avoided.
- **Interaction between Energy Carriers**: CBA simplifies interaction among energy carriers (e.g., shifting consumption from electricity to gas) by reducing the problem to creating several prices.

Although CBA looks promising in addressing several requirements in the future smart grid, it comes with limitations that are identified in the following items: [12]:

- **Uncertain End-Users' Reaction**: End-users do not provide real-time information to SAs in CBA-IC. This way, uncertainty related to the end-users' behavior implies a risk if not properly estimated. The changing behaviour of the end-users and the difficulty to include proper explanatory variables in a model can also lead to wrong estimation in consumer's behaviour. This could be dangerous for power system operation in real-time.

- **Market Inefficiency**: In [12], market inefficiency is mentioned as an issue of CBA. In economic terms, market inefficiency asserts that market prices are not always accurately calculated and tend to deviate from the true discounted value of their future cash flows.

- **Slowness**: Similar to TE approach, CBA operates according to the wholesale market requirements. Therefore, slowness and linearity in the wholesale energy and AS markets can also affect CBA operation.

A.3 Necessity of a Comprehensive Solution

TE and CBA offer substantial improvements over existing operational approach, which does not provide any solution to use FRs at the lower levels of the network. The two methods are able to accommodate FRs in the power system operation. However, these solutions have been formulated exclusively for distribution system management while maintaining the existing energy and AS market structures at the transmission level. As a result, CBA and TE inherit slowness from wholesale markets. Additionally, the wholesale market cannot deal with the magnitude of stochasticity and non-linearity introduced by large penetration of renewable generation. In the current structure of TE and CBA approaches, incapability of the wholesale market deteriorates the effectiveness of the FRs for power system operation. In other words, FRs cannot properly be managed in the proposed TE and CBA approaches.

Moreover, both approaches seem to be incapable of properly addressing stochasticity, dynamics and non-linearity. The reason is that FRs operation is represented by simple and linear price-quantity bids at the end. Although local EMS/HEMS might consider stochasticity and non-linearity to full extent, the true operational condition of FRs is ultimately reduced to several blocks of linear bids submitted to the LFA. This undermines the capability of TE and CBA methods to model stochastic, nonlinear, and dynamic behaviour of the end-users in the system operation.

The other drawback of the two approaches is the complexity in their structure where many agents and entities are considered to deliver services requested from FRs. Malfunction in any of these entities will result in the failure of the approach completely. For these reasons, we still need more comprehensive solutions for the future energy management. Such an approach ideally replaces existing electricity and AS markets with more suitable solutions, deals with complexity characterized by new RES and FRs, and allows system operators at different level of space and time to fulfill their requirements.

A.4 Conclusions

This paper explains two approaches, namely TE and CBA, for distribution energy management in presence of high stochasticity due to RES. From analyses, it emerges that CBA and TE offers new capabilities which are needed in the future smart grid, and mechanisms to deal with FRs by considering end-users' behaviour. However, they still do not satisfy all the requirements for a future optimal energy system operation, such as extension to the entire electricity system and real-time operation. More comprehensive solutions are therefore needed in the future to optimally exploit FRs.

Acknowledgment

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PAPER B

Ancillary Services 4.0: A Top-to-Bottom Control-Based Approach for Solving Ancillary Service Problems in Smart Grids

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Ancillary Services 4.0: A Top-to-Bottom Control-Based Approach for Solving Ancillary Service Problems in Smart Grids

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Abstract

Power systems are experiencing a large amount of renewable generation with highly stochastic and partly unpredictable characteristics. This change in energy production implies significant consequences related to the provision of ancillary services (AS). Current markets dedicated to the provision of AS are not able to benefit from the flexible energy resources. They also cannot cope with the new level of stochasticity, non-linearity and dynamics of generation and flexibility. To overcome such issues and exploit the potential of flexibility resources, a new strategy is required. In this paper, by capitalising on flexibility resources' potential, AS 4.0 approach is proposed, which offers a comprehensive solution for the AS provision in the smart grid era.

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B.1 Introduction

Power systems are experiencing high penetrations of renewable generation, with stochastic and mainly unpredictable characteristics. According to the Global Wind Energy Council, the global wind energy capacity reached 486.5 GW in 2016, meanwhile this is expected to double by 2021 [1]. Larger share of renewable energy sources (RES) in the generation mix introduces an unprecedented level of complex dynamics and non-linearity because of its dependency on meteorological variations [2]. To guarantee the service continuity, the complexity must be properly handled by the system operators (SOs) in real-time. Unfortunately, this is not always possible for the SOs, as their current practices have not being designed to handle high penetrations of RES. For this reason, an increase in complexity will dramatically affect the service, with consequences to the power system operation (e.g., increasing number of outages [3]) and to the ancillary services (AS) provision (e.g., inflating AS prices [4]).

AS consist of a variety of operations, beyond the generation and transmission, that guarantee service continuity and security from the distribution (e.g., voltage regulation) to the transmission level (e.g., frequency regulation and congestion management). The AS required capacity is procured through conventional market mechanism, i.e., bidding and clearing procedure. This mechanism has been originally implemented to deal with real-time operational issues in conventional power systems. In such a framework, time-varying bids are received every couple of minutes, and the market is cleared accordingly to obtain price and quantity values. The changing market prices reflect the true condition of the grid over time. This approach, which is implemented exclusively at the transmission level, works satisfactorily in case of conventional power systems with low RES penetration (below 30%) [5]. However, when the stochasticity and the dynamics of the generation resources become prominent, the existing AS mechanism becomes less effective, as it does not deal with the new complexity. Higher penetration of renewable energy causes an overall increase of under- and over-frequency events, which requires a higher amount of AS [6]. To avoid costly and environmentally unfriendly capacity reserves for AS provision [7], flexible resources (FRs) found to be a promising solution, by modifying their usual behaviour according to the need of the grid. While different studies have already shown the great potential of FRs [8], their application has been undermined because of the existing AS mechanisms, which do not allow a wider utilisation of FRs. Structurally, existing AS mechanisms prohibit FRs at the distribution level from participating in the market, as this is designed only for the resources at the transmission level. Moreover, expanding the existing AS platforms to millions of flexibility entities located at the distribution level would require extraordinary control and computational power. Such a condition is neither practical nor desirable.

Furthermore, an effective solution for the future AS provision should be able to accommodate energy system integration (ESI) concept [9, 10, 11], as yet another possibility to achieve higher levels of flexibility. ESI takes advantage of the synergies between different energy carriers, e.g., electricity, gas, and heat, to ensure safety and continuity of the service [12]. It provides flexibility and potentially increases the efficiency of the energy system as a whole. In this framework, different assets from various energy carriers are required to combine their strengths to optimally work together [13]. Unfortunately, the existing operational strategies in power system operation do not offer capabilities to integrate multi-energy carriers in a single framework.

To guarantee service continuity and security in spite of the increasing penetration of the intermittent resources, it will be necessary in the future to include every FR into the AS provision [14]. In order to exploit the flexibility potential to the maximum extent, and for the benefit of power system operation, new AS provision mechanisms should be developed. These solutions are a trade-off between computational complexity and simplification without compromising the efficacy. In this paper, we propose a new framework for the AS provision in the future smart grid. The proposed approach holistically changes current practices in the AS market. The structure is based on a hierarchy of nested control problems. It allows participation of every flexibility at various levels of the grid by developing time-varying electricity prices. To the best of our knowledge, no previous study has approached AS provision through the adoption of control problems.

The paper is organised as follows: Section B.2 introduces AS and their role in electricity supply service. Section B.3 focuses on the existing alternatives to the AS market . Section B.4 introduces the proposed approach of Ancillary Services 4.0 and the necessary tools and methods to implement the new mechanism. Ultimately, the paper is summarised in Section B.5, where we outline the main findings and suggest future focuses and practical applications.

B.2 Ancillary services (AS)

In presence of equipment outages and generation/consumption variations, it is fundamental for the power system operation to maintain the balance between generation and demand momentarily. This condition guarantees secure and efficient operation of the power system by adequately responding to the frequency and voltage deviations. At the distribution level, local varying generation and consumption units inject/absorb active and reactive power into/from the system, provoking deviations in the voltage level. At the transmission level, frequency is affected by any mismatch between generation and demand accounting for transmission losses. As a result, frequency and voltage vary with the amount of generation and demand in real-time. For inadmissible values, operation continuity and system stability are compromised. Also, frequency and voltage deviations threaten synchronous operations of the generator machines, which can cause widespread blackouts in the grid. In fact, the number of power interruptions as well as the duration of such events have increased at a rate of two percent in the USA over a period of ten years [15, 16].

In order to ensure the balance between consumption and generation, power system operator should manage the variability of production and demand in real-time. This condition cannot be handled by the energy markets, since they run every 5 minutes or so. Therefore, power mismatch within an interval must be compensated with other means. For the purpose, dedicated AS markets have been designed as parallel services to ensure generation and demand balance in real-time. In reality, AS markets need to procure capacity ramp-up and down in real-time operation, and balance electricity generation, demand and losses. Although literature suggests little harmonisation on the definition of AS [17], they consist of all the services required by the transmission system operator (TSO) and the distribution system operator (DSO), enabling them to maintain integrity and stability of the transmission and distribution systems operation as well as power quality [18]. These services may include spinning and non-spinning reserves and remote automatic generation control for frequency regulation, voltage control, black-start capability, grid loss compensation, and emergency control actions [18, 19, 20]. Nowadays, AS are provided through classical market operation, where market participants interact with AS market operator through a two-way communication. In this setting, market participants submit their bids, i.e., prices and quantity values [21] and the AS provision takes place in a single session every 5 minutes before the delivery [22]. Various types of commodities are traded in the AS market, depending on the characteristics of the power system disturbances [23]. The AS market design varies from one system operator to another. As an example, we explain here the AS market operation for the case of Denmark. The Danish grid is divided into two main control areas: DK1 and DK2 [24]. In DK1, frequency management is handled through primary (FCR), secondary (aFRR) and manual (mFRR) reserves. For frequency regulation, three levels of operation are defined as follows:

- **Primary reserve**: Named frequency-controlled reserve (FCR), it is the automatic response to frequency deviations. FCR is released increasingly with time over a period of seconds to restore balance between production and consumption. It stabilises the frequency at close to, but deviating from 50 Hz [24]. Characterised by instant response [25] and a full activation time of up to 30 seconds, FCR must be maintained by the production and consumption units for up to 15 minutes, before it is released. It can be activated automatically and locally.

- **Secondary reserve**: Known as automatic frequency restoration reserve (aFRR), it is applied to indirectly restore the frequency balance to 50 Hz following the stabilisation of the frequency. Its purpose is to release FCR and restore imbalances on the interconnections. Instead of FCR, aFRR is activated centrally, delivering energy within 15 minutes [25].

- **Manual reserve**: Named manual frequency restoration reserve (mFRR), it serves in the event of outrages, power restrictions affecting international connections and unexpected sustained activation of aFRR. Activated manually, mFRR has an activation time from 15 minutes to hours.

Additionally, voltage regulation in Denmark is automatically handled by the grid through passive reactive components. Reactive power is injected and absorbed through synchronous sources and static compensators. However, when automatic restoration of the voltage is not possible, suppliers capable of fast regulation are ordered to modify the reactive production/consumption until acceptable levels are achieved [24]. These entities may include spinning generators, synchronous compensators, reactors and capacitors. The request operates similar to the frequency management, normally providing service within thirty seconds [25].

Although this AS mechanism has successfully served power systems in the past, it lacks of certain features and requirements to cope with the emerging requirements. For example, the current AS market structures oversimplify assets' operation to linear price-quantity blocks of bids. The inherent dynamics and uncertainty of underlying systems and equipment are simply ignored. Moreover, the AS market procedures are understandably slow, due to the large-scale optimisation problems they solve. In fact, such problems include thousands of variables and constraints along with power flow equations and require a couple of minutes to provide the solution. The existing AS markets are designed to procure services exclusively from conventional power plants, neglecting any contribution of the end-users' FRs. This flexibility cannot be included in the current mechanism, as it would imply managing bids and activation of millions of FRs, which is not practical. Also, being the current market designed only for electricity resources, it is technically impossible to directly incorporate flexibility of other energy carriers in an ESI framework. Finally, the existing AS market structures are relatively expensive, as they require large power plants to operate below their full capacity to provide the needed flexibility.

B.3 Existing alternative solutions

To address the issues related to the existing AS markets, several solutions have been proposed in literature in the recent years. In particular, three major alternatives are transactive energy (TE), peer-to-peer (P2P), and control-based approach (CBA). While not all of these mechanisms are designed for AS provision, they offer features and capabilities, which can partially address the issues of the existing AS markets. In the rest of this section, we explain these solutions in detail and provide a list of their strengths and weaknesses.

B.3.1 Transactive energy (TE)

TE proposes a market-based solution for energy management of small DERs, storage devices, and other FRs at the distribution level [26]. It adopts classical market principles to trade energy and AS among local players as well as the upper grid, either individually or through aggregators [27]. In this framework, prosumers generate price-quantity pairs through economic optimisation problems that minimise their operation costs [28]. These are submitted from the prosumers to the local operator. Similar to the electricity market at the transmission level, local market operators run day-ahead/real-time energy and AS markets. The ultimate goal of the local markets is to maintain balance between local generation and demand, and to provide services to the upper grid through aggregators.

The core of TE is the definition of a feedback between prosumers and aggregator. The feedback refers to a certain price reaction of the consumers. The market structure uses this information to determine the price and reach the balance between supply and demand at the local level [29]. The feedback is allowed from a proper IT infrastructure to minimise the uncertainty of the customers' behaviour and formulate an electricity price accordingly.

In Fig. B.1, a conceptual scheme of the TE framework is provided. In the figure, market, energy suppliers and balance responsible parties (BRPs) mimic the existing mechanisms while preserving the structure of the electricity market schemes at the TSO level. In such a framework, BRPs consist of independent entities that guarantee the constant balance between generation and consumption in the grid. In case of deviation from their own schedule, BRPs can interact with the entities located at the lower levels of the grid to purchase adequate amount of flexibility. For this reason, BRPs are supposed to communicate with the TSO electricity market as well as downstream virtual power plants (VPPs). Every VPP represents a pool of FRs, which virtually behave as an effective

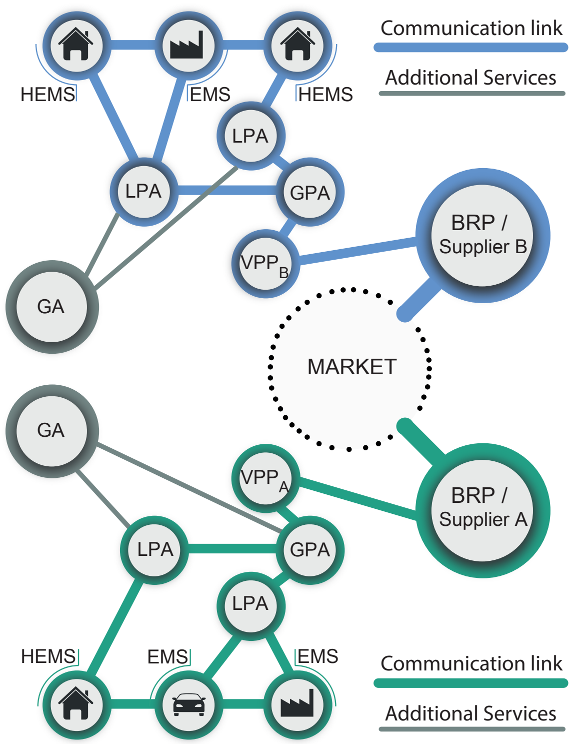

Figure B.1: Conceptual block-diagram of the TE approach.

power plant. These include any combination of traditional generating units, renewable generators, and pools of flexible prosumers.

To explain the TE operation, we assume a scenario where BRPs detect the deviations from their market schedule. In order to solve such issues, each BRP submits an up- or down-capacity request to the VPPs. At this level, VPPs formulate potential price signals and submit them to the corresponding pool of global prosumer agents (GPAs). GPAs handle a pool of aggregators of smaller prosumer agents, called local prosumer agents (LPAs). LPAs represent specific types of prosumers, which are located at the lowest level of the grid. Once an LPA receives the price signal from the associated GPA, it has to adjust the price signal according to the respective type of load, as each LPA responds to the price in a peculiar way.

In this framework, grid agents (GAs) are asked to provide additional information about the grid condition to the LPAs, so that they can make an informed decision accordingly. In the figure, GAs provide additional services for the greater benefit of the power grid operation. Once the prices are set, each LPA submits them to the pool of residential prosumers, equipped with home energy management systems (HEMS). For commercial and industrial businesses, prices are submitted to energy management systems (EMS). These devices allow prosumers to receive varying electricity prices and run individual optimisation problems to estimate their optimal response. Afterwards, their reaction is communicated back to the PAs through HEMSs/EMSs, as their willingness to alter their operation and provide flexibility. This potential response to price signals is interpreted as the feedback signal, which refers to the quantity of energy that the LPA is potentially willing to purchase/generate at that specific price.

Afterwards, the potential aggregated flexibility is communicated back to the VPPs. At this stage, VPPs can aggregate the price-quantity bids and formulate the ultimate electricity price signal that addresses a certain service at the BRP' s level.

Several benefits can be identified in the TE approach, as highlighted below:

- **Reducing uncertainty in prosumers' response**: Since TE acts upon receiving the reaction of the prosumers to a certain price in almost real-time, the negative impact of stochastic behaviour of the prosumers is minimised. Moreover, the definition of real-time feedback from the prosumers allows LPAs to receive required information about their participation directly. Thus, abstract modelling of prosumers' response to different prices is not needed in this approach.

- **Privacy**: As it was explained earlier, prosumers communicate their preferences in response to certain prices in price-quantity blocks of bids. Therefore, there is no direct access to the prosumers' appliances, generation, and/or storage resources. Exchanged information among agents consists of only price and quantity values, which does not compromise the privacy of the prosumers.

- **Scalability**: TE approach adopts simple bidding mechanism and distributes market operation among various LPAs. For this reason, it allows the inclusion of numerous prosumers into the system, while bid aggregation and price determination can be extended effectively to thousands of prosumers through multiple LPAs. However, scaling-up the approach requires the involvement of many operators.

While the TE approach offers a solution to exploit the FRs potential at the distribution level, it also introduces challenges and limitations, which are highlighted below:

- **Over-simplification**: Similar to the existing market structure at the TSO level, the TE method tends to over-simplify power system operational problems to simple linear bidding mechanism. In this approach, non-linear, dynamic and stochastic characteristics of the FRs are completely ignored.
- **Complexity**: The TE framework requires various entities (e.g., VPPs, GPAs, LPAs, GAs) for the operation. Their coordination is very complex in practice. Moreover, some entities might compete for the required services from the same group of FRs.
- **Optimal solution**: The TE operation involves potential price calculation, bidding aggregation and clearing price mechanism, which are computationally expensive. The computational burden can be lowered by increasing the number of LPAs. However, the involvement of numerous local operations leads to a solution that is not necessarily the global optimal one. This is due to the fact that operators do not interact with each other.
- **Computational time**: Although TE can accommodate thousands of prosumers and devices in a distributed manner, the aggregation and dis-aggregation process can become very slow. For this reason, market schedules are not updated fast enough to cope with the new level of uncertainty.
- **Security**: Because the TE approach demands an intensive exchange of information, it exposes critical operations of power systems to cyber-security threats.
- **No solution for ESI**: While the necessity of the ESI becomes more apparent among all stakeholders, the TE framework does not offer solutions to accommodate multi-energy carriers operation in the framework.
- **Cost**: Although FRs at the prosumers' level might be cheap, the TE method requires minimum latency in two-way communication channels, which further necessitates adequate IT infrastructure. Moreover, it needs the intervention of different agents (i.e., GA, GPA, LPA). This condition implies high costs for the overall TE operation, which increase when scaling up the approach.

Recently, several TE-based projects have been implemented. These include: Olympic Peninsula Demonstration in USA (2006), represents one of the first efforts to provide automatic load response to price signals every 5 minutes, and the first demo to include the costs of transmission and distribution within that price [30]; Pacific Northwest Smart Grid Demonstration (2010), as a large-scale project involving 60 000 metered customers in the USA [31]; AEP Ohio gridSMART Real-Time Pricing Demonstration (2010), adopting a two-way consumer communication and information sharing approach to integrate RES, energy storage systems and metering infrastructure in power system operation [32]; Couperus Smart Grid (2011) in The Netherlands [33], which manages a pool of heat pumps for 300 residential houses.

B.3.2 Peer-to-peer (P2P)

Peer-to-peer (P2P) is an emerging electricity trading model, inspired by the sharing economy concept that relies on numerous agents [34]. It consists of a coordinated multi-lateral trading framework [35], whose ultimate goal is to maximise social welfare for all agents [36]. The P2P approach avoids any interference of the market operator [37], as agents interact and trade directly among each other through the use of an online platform that can be based on the blockchain technology. Blockchain is becoming popular in power system as it is claimed to be an "incorruptible digital ledger of economic transactions, programmed to record virtually everything of value" (Dan Tapscott, co-founder and executive director at Blockchain Research Institute [38]). It consists of an open and transparent infrastructure that allows agents trading without any middle-man. In such a structure, a digital ledger of transactions is created and shared between distributed computers on a network [39]. The ledger is accessible to every agent and not owned by any authority.

In Fig. B.2, we present a general structure of P2P approach. In this setting, the current market structure is omitted. Instead, a community of agents is created to facilitate local energy trading. These agents can include independent prosumers (agents A and C), generators (agent D) and flexible consumers (agent B). Each agent is equipped with HEMS/EMS to collect information about its own consumption and generation in real-time.

Entities communicate with each other through HEMSs/EMSs in an online platform [40], where the price of trading energy are set by each agent. Typically, different surge-pricing algorithms are used for pricing and the generated price varies as supply and demand conditions change [41]. The definition of each price can take into account the preferences of the agents participating in the trade (either buying or selling) by submitting information to the platform. This way, agents' willingness for trading can depend on demand/price condition, on the specific trading agent (i.e., a more favourable price might be evaluated when dealing with relatives), the distance (i.e., preferring short-distance trades to minimise the losses) or on the type of energy resource. Once each agent pro-

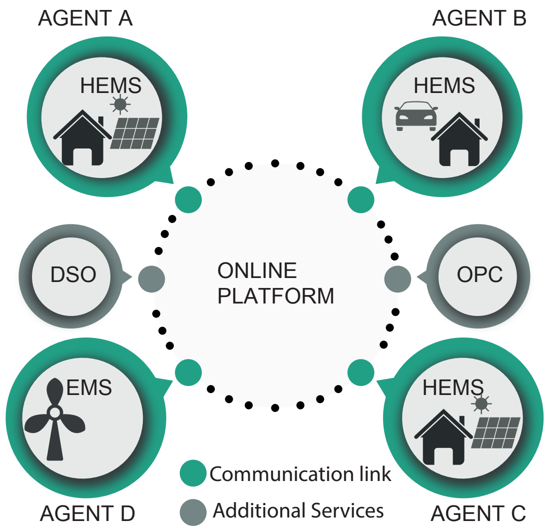

Figure B.2: Conceptual block-diagram of the P2P approach.

vides information to the peers, these can run an internal optimisation problem in HEMS/EMS to define their optimal trade. When an agent intends to add a transaction to the digital ledger in the online platform, the transaction information is encrypted and verified by the others HEMSs/EMSs in the network through cryptographic algorithms [39]. The transaction needs to receive the approval from the majority of the HEMSs/EMSs. Afterwards, it is added as a new block of price/quantity data and shared. At this stage, the transaction is paid in crypto-currency.

Besides the agents, P2P operation requires additional two regulating entities: the online-platform coordinator (OPC) (e.g., the utility [42]), which is responsible for the platform maintenance; the regularising grid entity (e.g., the DSO), which ensures the legitimate use of the distribution grid (e.g., limiting the trades below the grid capacity).

To understand the P2P operation, we assume a scenario where agents C and D in Fig. B.2 are encountering over-production (according to their HEMSs/EMSs). Therefore, they need to sell their excess energy to other agents. At the same time, agents A and B experience an over-consumption situation so that they need to buy electricity from other agents. If the only preference among agents is physical distance, it is more likely that agent A will trade with D, and that agent B will trade with C. The most notable strengths of the P2P method can be identified as follows:

- **Scalability**: Depending on the definition of the community (e.g., neighbourhood, cities), P2P can be scaled-up to different groups of agents. Therefore, there is no limit to the scale of the platform and number of agents to trade energy in theory.
- **Privacy**: Since only price and quantity information is shared over through the platform, the privacy of the prosumers is preserved, similar to the TE approach. In other words, there is no direct access to the agents devices to compromise privacy of the prosumers.
- **Cost**: Since intermediary entities are ignored in this framework, agents purchase energy and other services directly from providers at the local level. As a result, intermediary costs are avoided. Moreover, trading energy resources within the community minimises the transmission/distribution costs and the system-wide losses.
- **FR exploitation**: Since energy trading takes place in real-time, dynamics of the community generation and demand are reflected in the real-time prices computed by the P2P platform. As a result, it is possible to exploit the full potential of FRs at the distribution level by time-varying prices if the negotiation updates very fast. Moreover, by setting the preferences for trading green electricity, P2P facilitates trading in real-time, where stochasticity, dynamics and non-flexibility of the assets is accounted for to some extent.
- **Computational complexity**: As agents match their generation and demand through a set of interdependent bilateral negotiations, they are able to reach joint optimisation with reasonable computing power [36]. However, computational complexity can become higher for complicated pricing mechanisms.
- **Security**: The information shared in the P2P framework is based on the blockchain concept. This solution prevents information leakage, reduces transaction time, and risk of cyber-attacks. It further allows to observe the transaction in real-time and removes transaction intermediaries [39]. However, it might become more challenging in the future when the solution is extended to large-scale applications.

In spite of the innovative structure and the new opportunities offered by the P2P approach, several weaknesses and challenges can be realised in real-world applications, as highlighted below:

- **Multi-energy systems**: The P2P approach does not offer unified mechanism to integrate other energy carriers, which limits its application in the future.

Also, some energy carriers, e.g., gas, are generated centrally and distributed to consumers. Therefore, their operation cannot be easily accommodated in the P2P framework anyway.

- **Electricity availability shortage**: When the trading process among agents does not satisfy the total energy demand of the community, intervention of the existing electricity market is inevitable. This condition leads to purchasing energy from the upper grid. As a result, a new stream of uncertainty is reflected in the TE operation of the upper level of the grid.
- **Computational time**: In real-time, a series of negotiations has to take place among various agents, before settling the price and system operation. This process can be time-consuming, while power system by nature changes rapidly. Additionally, communication delay is always a concern in the P2P approach.

Several P2P energy trading models have already been implemented as pilot studies in different countries. In the Netherlands (2014), Vandebron developed an online P2P energy marketplace [43] for consumers to buy electricity directly from independent producers. In Germany (2015), Sonnen developed a software, SonnenCommunity [44], to support energy sharing generated from RES within a community of prosumers. In Spain (2015) and Finland (2015), EM-Power project and P2P-SmarTest investigated formulation of local electricity markets to promote the role of the prosumer and micro-generation [45, 46]. In the UK (2015), Open Utility launched an online P2P marketplace for RES, which is called Piclo [42]. In Australia, Power Ledger implemented P2P by adopting blockchain technology to undertake energy transactions [47].

B.3.3 Control-based approach (CBA)

CBA refers to the adoption of control theories for energy management in the distribution system [48, 49, 50]. It introduces an alternative approach to the market operation, offered by the TE and P2P frameworks. In Fig. B.3, we present the method and the main entities involved.

In the CBA setup, electricity market structure at the transmission level is preserved. It means that wholesale electricity market, energy suppliers and BRPs entities remain intact. At the lower level of the structure, BRP communicates with a new entity, named aggregator. This is an independent entity that operates as coordinator between FRs and the wholesale electricity market. When BRP encounters imbalance in generation or demand from its own schedule, it sends a request to the aggregator. Upon receiving the query, aggregators

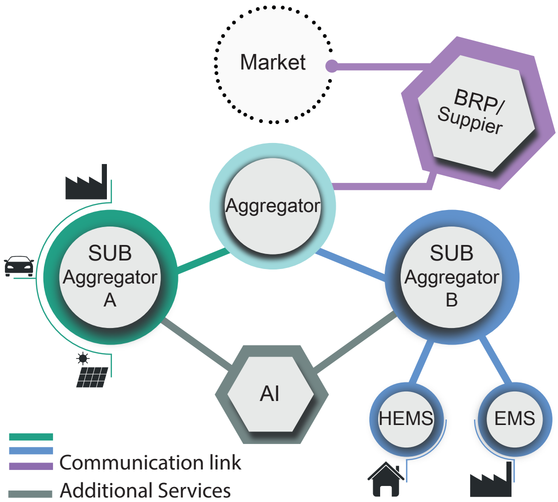

Figure B.3: Conceptual block-diagram of the CBA.

interact with different sub-aggregators, scattered all over the grid. Each sub-aggregator represents a pool of prosumers and act on behalf of them. They are expected to communicate with the pool of prosumers and collect offline data from prosumers' reaction to different prices. This way, sub-aggregators are able to estimate an aggregated model of the pool, which is used to formulate price-quantity bids for different price signals. In order to achieve a better accuracy of prosumers' behaviour modelling, specialised sub-aggregators can be sought to manage a specific type of FRs. Moreover, sub-aggregators can optionally receive additional information, e.g., weather parameters, in order to improve the accuracy of predicting consumers' behaviour. Such additional services therefore provide additional information (AI).

As shown in Fig. B.3, the interaction between sub-aggregators and prosumers can take place in two different manners: through direct (sub-aggregator A) or indirect control (sub-aggregator B) [51]. Direct control (DC) is based on a two-way communication between prosumers and sub-aggregator. Although it requires an adequate IT infrastructure, it enjoys the benefit of directly controlling the loads, minimising the uncertainty of the consumers' response. On the other hand, indirect control (IC) includes the utilisation of HEMSs/EMSs and one-way communication. It implies a simpler communication infrastructure, which significantly reduces the complexity and vulnerability of the system [52]. While DC enables the operator to directly alter prosumers' power consumption and local generation, IC only provides flexibility by using a price signal. However, the optimal utilisation of these solutions relies on the available information and infrastructure [51].

In this paper, we focus on the IC approach, which requires simpler infrastructure. This is formulated in two main steps: 1) a control problem at the sub-aggregator level to determine the price signal, 2) a model-predictive control (MPC) at the prosumers' level, embedded in HEMSs/EMSs to act upon receiving the price signal. Different optimisation problems can be formulated through control concepts at various levels to fulfil the requirements of different stakeholders.

The benefits of the CBA approach through IC method can be summarised as follows:

- **Scalability**: The structure guarantees a scalable solution for the future power system operation at the distribution level because the control problems can be extended to millions of devices without significant computational power requirements.

- **Dealing with mathematical complexity**: It is based on formulating and solving control problems at the sub-aggregator and prosumers' level. Therefore, it deals with non-linearity, real-world dynamics and stochasticity of the power systems with rather simple, fast and cheap communication infrastructure by adopting one-way communication. This is valid only for the distribution system, since the existing wholesale market structure is maintained at the transmission level.

- **Cheap**: The simple architecture in the CBA-IC approach guarantees low-cost implementation and maintenance costs. Moreover, the CBA-IC avoids the cost for distribution-side measurement equipment, as it requires a few measurements at the higher level of the grid for consumers' modelling. This condition facilitates troubleshooting of operational issues in real-time.

- **Privacy**: CBA-IC does not imply privacy issues, as only price signals are broadcasted from the aggregator to the end-users.

- **Security**: The lack of real-time feedback from consumers to the sub-aggregators diminishes risk of communication malfunctions and cyber-attacks.

- **Integrated Energy Systems**: Regarding the possibility of integrating the entire energy system, CBA offers a valid solution via adoption of specialised sub-aggregators for FRs of other energy carriers. These entities can develop a flexibility price-reaction model suitable for their own load, offer a unique price signal, and act in the market afterwards through main aggregator, in the same way as other sub-aggregators.

Despite all the benefits, CBA has its limitations, as highlighted below:

- **Dependency on the market**: Although it can partially exploit existing FRs at the distribution level, it operates as a part of the AS market at the transmission level. Consequently, CBA inherits slowness, linearity assumption, and deterministic approach from the existing wholesale AS market which does not fulfil many of the future power system needs.
- **Uncertainty**: Since prosumers' price-responsiveness is an uncertain phenomenon, the operation of CBA will inevitably have uncertainty with respect to the prosumers' reaction to the price signal [29]. It becomes a significant issue when the model over-estimates consumers' reaction to a set of price signal. This situation might in fact jeopardise the power system stability and safe operation.
- **Market Inefficiencies**: By avoiding any market process, CBA is potentially subject to market inefficiencies, where prices might deviate from the true discounted value of their future cash flows [29].

Several CBA projects have been implemented in the past. These include: FlexPower [53, 54] in Denmark (2010), which is the first project using price-based CBA to control individual power flow of intelligent controllable power units; price-based control of electrical power systems (E-Price) in The Netherlands (2010) [55], focusing on price-based control strategy to facilitate increasing amounts of RES; CITIES [56] in Denmark (2013), which employs the aggregated response of FRs in a control framework design; ECOGRID Eu project in Denmark (2013) [57], where residential consumers participate with flexible demand responses to real-time price signals; SmartNet [58] in Italy, Denmark and Spain (2015), applying economic-model predictive control (E-MPC) technology to swimming-pools.

B.4 Ancillary Services 4.0 (AS4.0)

From the analysis of the alternative solutions to the existing AS market, it emerges that these lack of certain features to comprehensively address the requirements of the future smart grid. In this section, we propose a comprehensive solution for AS provision, named AS4.0. In Fig. B.4, a schematic diagram of the proposed framework is shown. It refers to a control-based operation to procure required AS, extended to the entire grid management. We build AS4.0 on two main assumptions: firstly, every prosumer device is operated and controlled by an HEMS/EMS. Therefore, we deal with rational prosumers through automated systems (as implicitly assumed in the previous approaches) [49]. Secondly, power system operation problems at different spatial and temporal scales can be split into multiple independent problems in space and time. This assumption roots in the fact that major operation entities, e.g., TSO and DSOs, handle problems at different geographical scales and time-frames, as shown in Fig. B.5. It is worth mentioning that the system operator (SO), in the proposed framework, refers to any entity that regulates power system operation at different level. The major SOs consist of TSO and DSO entities. For instance, frequency regulation is the responsibility of TSO, which expands to the whole control area. Meanwhile, voltage management at the DSO level is limited to a certain area of a DSO' s territory. The proposed mechanism employs delta prices to move FRs in the right direction for the benefit of power system operation in real-time. Every SO formulates an independent control problem, based on the required resolution of space and time to generate adequate delta price signals. Afterwards, these delta prices are constantly summed up to the base-line costs (e.g., taxes, profit margin of SOs, O&M costs) and submitted to the rational prosumers, as flexible retail electricity prices. Such new prices intend to exploit the rational behaviour of the prosumers, promoting a certain behaviour from the pool to handle various AS requirements. Time-varying utility pricing is the core concept of the proposed method to effectively exploit FRs potential. Several studies have already been done to evaluate the effectiveness and required mechanisms for real time-time pricing [59, 60, 60, 61, 62], and associated benefits and impacts on the energy flexibility [48].

At the highest level of the structure, SOs constantly measure the parameters of their interest (e.g., frequency for TSO) in the grid. Due to the varying generation and consumption, these parameters might show deviation from their schedule. When this happens, SOs run independent control problems that evaluate the required FRs from the lower level of the grid to compensate the deviation according to their respective standards. In the definition of the control problems, SOs need to estimate the reaction of their pool of rational prosumers to a certain price. For this reason, each pool requires an accurate price-response model of the associated FRs. Proper models are formulated from the offline information, that is collected from real-time measurements. This is provided by the model operators (MOs), which are specialised entities in modelling price-response behaviour of the prosumers in different time and space resolution. They can sell their services (i.e., models) to SOs according to their needs. Once delta prices are formulated with geotag, they are submitted to the ancillary services operator (ASO), which is responsible to sum-up different delta prices and broadcast the final price to the prosumers located in the right area. ASO guarantees and

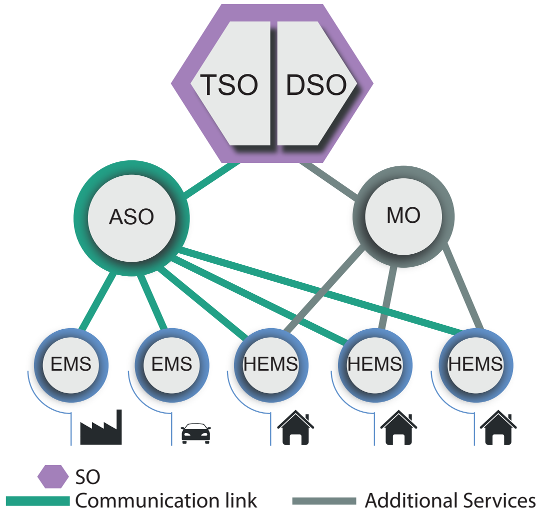

Figure B.4: Conceptual block-diagram of the AS4.0 approach.

secures an easier communication with prosumers through their HEMSs/EMSs. We can consider the case of a DSO that operates a low-voltage network of thousands of buses. When a couple of buses has voltage issues, the DSO needs to fix it by generating proper delta prices to submit to the prosumers located in those buses and in the surrounding areas. For this reason, not all the prosumers will receive the same delta prices. When these prices are submitted to the HEMS/EMS, they will change the consumption/generation accordingly.

Studies have shown that FRs can make a significant contribution to the frequency regulation [63, 64]. In the future, severe shortages of flexibility will be avoidable [65] and AS will not need services from conventional generators. A wider application of HEMS/EMS, as predicted for the next few years, will provide a higher amount of FRs at different levels of the grid. This way, the AS4.0 intends to provide all the AS requirements through FRs instead of conventional generators with reserve capacity.

B.4.1 Generating delta prices at the DSO and TSO level

At the distribution level, numerous DSOs own and operate medium- and low-voltage delivery network. Each SO attempts to satisfy its objective by generating appropriate delta prices based on the system condition. In Fig. B.5, we show a hypothetical power system, with a TSO at the highest level, and a DSO at the lower level. These are generally referred to as S_i, where $i = TSO, DSO$. Every SO might need different services S_i^j, where $j = 1...n$ and n is the number of services of SO_i. For example, the TSO might request services for frequency regulations or congestion management. Each service is defined independently with specific time and space tags.

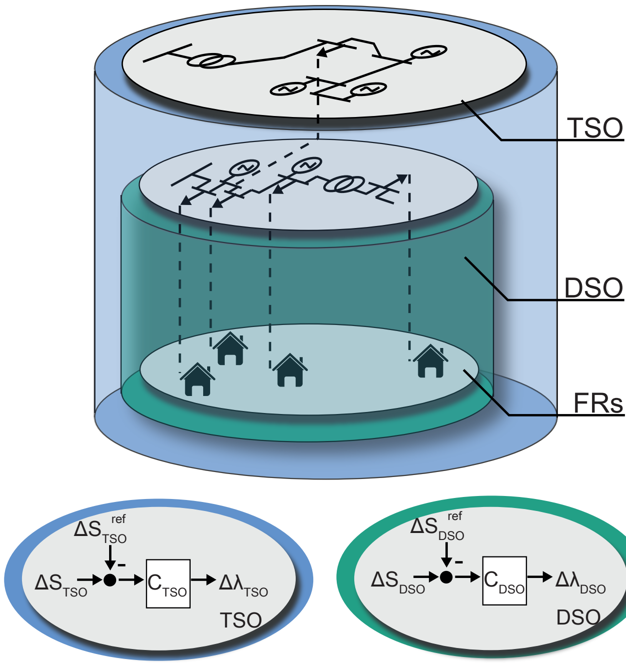

Figure B.5: The interaction between two operators located at different levels of the grid in the AS4.0 approach.

The SO constantly formulates delta prices $\Delta\lambda_i$ that can alter the generation/consumption of prosumers. Such prices consist of the required efforts for the SO to fulfil services. As shown in Fig. B.5, delta prices are generated through a control model, C_i. It takes into account the price-response characteristics of FRs and it is formulated independently at every SO level. C_i needs to be continuously updated, ideally every few seconds, to follow the true conditions of the system. Existing standards (e.g., frequency regulations) can be accommodated in the control problem of C_i and updated by the associated SO, when needed.

B.4.2 Modelling prosumers' behaviour

Prosumers' price-response model is used to formulate appropriate delta prices. Therefore, each SO needs to have access to the aggregated information of the prosumers' behaviour at their respective scale for an accurate modelling. The aggregated data at the distribution substation is measured and collected so that proper models can be created offline. Therefore, no real-time or extra communication channels are needed in AS4.0 framework from HEMS/EMS to the SOs for prosumers' modelling. In fact, aggregated prosumers' models are different at each SO level because of the different amount and composition of FRs. In AS4.0 framework, models' accuracy can be improved by MOs, which develop aggregated models of the prosumers in different time and space scale. In fact, these have directly access to the prosumers' HEMS/EMS with their permission under bilateral contracts. They can also be specialised in a specific type of prosumers' load/generation (e.g., summer pools or roof-top PV) so that the model can estimate prosumers' behaviour more accurately. The models can be updated frequently to increase the accuracy. This process can be done through historical data time series modelling/analysis [48, 66] and machine learning approaches (e.g., neural network [67]). Moreover, prosumers could be represented by different models that are specialised based on several factors, e.g., season and day. This way, accuracy of the models will be improved, and the uncertainty of the consumers' response to a set of prices will diminish substantially.

B.4.3 Formulation of flexible AS-retail-price

Once delta prices are formulated by the SOs, these are submitted, together with geographical tags, to the ASO. The tags determine the area requesting the service. Afterwards, the ASO sums-up the delta price components, $\Delta\lambda_i$, with a baseline price, λ. The latter price is defined by the DSO to cover taxes and fixed costs. This can be assumed as flat, as it is today in many utility companies and retailers. Alternately, it can be based on the day-ahead market prices, to ensure legitimacy from the bidding and clearing process. The aggregated price, named flexible retail electricity price, is broadcasted to the HEMS/EMS at the prosumers' premises. In this setting, there will be different prices based on the geographical tags of the delta prices. It implies that different end-users might receive different prices according to the condition of the power system in their respective areas. Naturally, such a mechanism can provoke an unfair penalisation of the end-users which are located in specific areas that receive higher prices. In order to deal with this issue, the sum of the daily delta prices to every prosumer should always be zero. In other words, the sum of the negative prices should be equal to the accumulated positive prices within every day.

This solution prevents discrimination against prosumers that are located in different areas. In fact, consumers will be encouraged to modify their consumption throughout a day in order to minimise their operational cost without reducing their overall daily consumption. A similar concept has already been adopted by PJM for frequency regulation [68], forcing the load deviation within one hour to be zero.

B.4.4 Hierarchical operation model

SOs operate with different granularity in time and space. For this reason, it is unlikely that they compete over the flexibility provided by a particular group of end-users in a way that compromises the system operation. When such a conflict of interest occurs, it might promote chattering and oscillations in the prosumers' response, by cancelling the delta prices of the counterparts. In order to handle this situation, a hierarchical structure can be developed with pre-specified priority list for different conditions. Hierarchical operation is delegated to an independent entity (e.g., the federal energy regulatory commission for the case of USA [69] or ASO), which meddles in for the greater benefit of the power system security. This way, different SOs can fulfil their needs without interfering or competing with other SOs. The priority is given to the SO, which requires the most critical services for the benefit of power system operation as a whole. In a scenario where TSO asks for frequency regulation-up service (by generating a negative delta price to encourage more consumption), and a DSO encounters low voltage issues in a specific area, priority is given to the frequency regulation requested by the TSO, as it maintains the integrity of the power system operation.

B.4.5 AS4.0 infrastructure and regulatory requirements

In this subsection, we investigate the required infrastructure and regulations for successful implementation of AS4.0. At the prosumers' level, HEMSs/EMSs run optimisation problems to take advantage of the time-varying prices by minimising operational cost. Although a limited number of HEMSs/EMSs are installed at the prosumers' level, these already established a multi-billion dollar business with increasing market value to US$4 billion in 2017 [14, 70]. By many brands (e.g., Apple, Google and GE) being involved and invested tremendous amount of money in this business, it is expected to have many enclosed areas equipped with HEMSs/EMSs in the near future. Therefore, AS4.0 will be able to benefit from the existing potential of HEMSs/EMSs and their capabilities at that time to achieve their goals. Specifically, in AS4.0, HEMSs/EMSs are supposed to receive price signals from a communication channel. This channel might consist of encrypted exclusive radio signal or a regular encrypted internet packet of signal. Moreover, since an ASO is responsible for maintaining communication channels and broadcasting the signal to the prosumers, it needs an adequate IT security infrastructure. This can include several firewalls, where the access to the information is always restricted and limited to the entities in charge. In AS4.0, SOs formulate their own control problems, accounting for the technical constraints of the system. To achieve this and determine the delta price $\Delta\lambda_i$ in almost real-time operation, appropriate computational power is required. Also, SOs have to measure and store prosumers' response to different prices in order to update the aggregated prosumers' model. For this reason, big data warehouses are needed to store and maintain large amount of information.

Besides physical infrastructures, AS4.0 requires a set of new regulations at different levels of the electricity system to transform existing market-based AS into a control-based structure. Real-time utility pricing, anti-discriminatory pricing in different areas, subsidising HEMS/EMS business to develop faster, and changing existing business models of AS at the transmission level are among the most important regulatory revolutions, which have to be initiated by the policymakers.

B.4.6 AS4.0 for the AS provision: Summary

The advantages of AS4.0 over the existing alternative approaches for AS provision can be identified as follows:

- **Stochasticity, dynamics and non-linearity**: The AS4.0 framework manages stochasticity, non-linearity and dynamics of the prosumers by defining a suitable control problem. In fact, a SO price-response controller could be non-linear while accounting for the inherent stochasticity of the power system operation. Different tools at the higher (optimisation control problems, e.g., price-based control) and lower level of the grid (HEMS/EMS, e.g., E-MPC) can be employed to achieve this goal.
- **Simplicity**: It simplifies real-time energy management for AS provision for the entire grid within a set of control-based problems, where the electricity price is the only driver.
- **ESI**: The proposed methodology facilitates ESI because different energy carriers can be represented to the prosumers by a price signal. In this framework, each HEMS/EMS can select its preferred source of energy at any moment based on economic preferences.

- **Scalability**: Finally, this method can be extended to distribution and transmission systems, enhancing the provision of the AS to every flexibility [51]. In fact, there is no operational nor computational limit in the number of FRs and SOs involved in the AS4.0. approach.

In spite of its promising features for the future smart energy-system management, some challenges have to be properly addressed:

- **Lack of agreement on price**: In classic market structure, buyers and sellers submit their bids to determine a commodity price. This procedure implies an indirect agreement among the entities. In AS4.0, however, prices are obtained based on the expectations of the SO from the prosumers and their own needs. Therefore, additional mechanisms should take place (e.g., upper limit on the delta prices and daily price neutrality) to avoid price discrimination and pressure on the prosumers with unreasonable delta prices.
- **Models uncertainty**: SOs model the prosumers' behaviour considering available historical data. Nevertheless, the aggregated price response must be analysed considering a certain level of uncertainty. This is a challenge for the SO, and the MOs tries to minimise it by specialising in prosumers' behaviour modelling.
- **Conflict of interest**: When SOs look after fulfilling contradictory objectives, there is conflict of interests. Such a situation can be handled by hierarchical operational algorithms and prioritisation mechanisms.

B.5 Conclusions

In this paper, we present AS4.0 as a comprehensive and novel solution for AS procurement in the future energy system. It is developed as an alternative to the current market-operation structure for the AS provision. Nowadays, the AS market is deterministic, linear, static and does not include any mechanism to utilise FRs located at the distribution level. By offering price-based control mechanism to exploit the entire fleet of FRs, AS4.0 is able to manage AS provision for the entire grid while handling stochasticity, non-linearity and dynamics in a fast and simple way. This paper firstly explains the role of AS in presence of smart grid functionality and investigates existing alternatives to the market-based AS in literature. Analysing the alternative approaches (in terms of the core challenges regarding the AS procurement in the future) shows that none of them can provide a comprehensive solution accounting for spatial and temporal variability and potential of FRs.

In order to fill the gap, the concept of AS4.0 is here proposed. In the new framework, SOs can exploit the price-responsiveness of the prosumers according to their need by time-varying electricity prices. These are formulated through independent control problems for every SO. Time-varying prices are lately summed-up together with fixed price components (e.g., taxes) to generate flexible retail electricity prices. These are received from the prosumers through HEMS/EMS which can rationally react to minimise their own cost. The entire process is automatic and requires no manual interaction from the consumers.

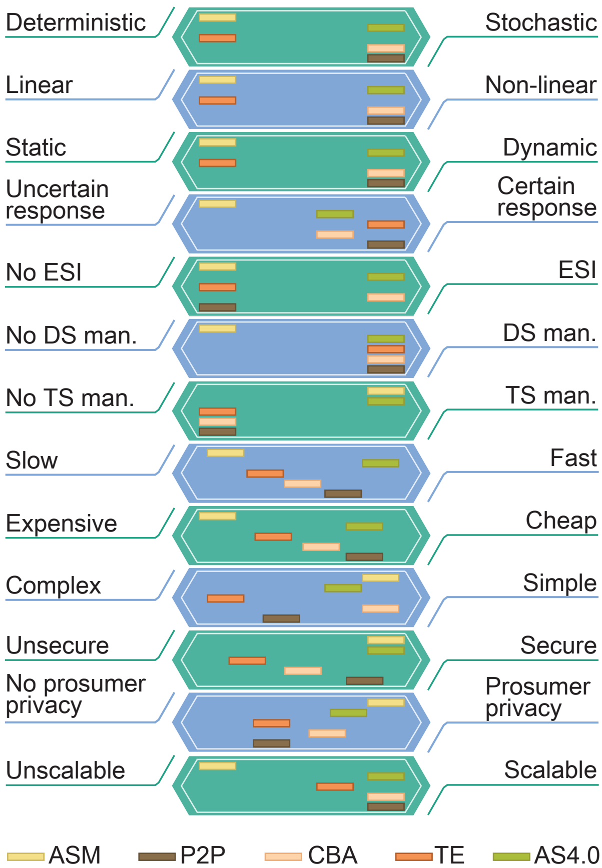

Figure B.6: Comparing the current AS market with the main features of TE, P2P, CBA, and AS4.0 frameworks, required by the future AS provision.

To summarise the advantages of the proposed framework, different alternative approaches are compared in Fig. B.6, in terms of core features required by the future power system and AS procurement. In this benchmark, AS4.0 looks very promising as it deals with all the requirements of the smart AS provision. In the future work, the AS4.0 mechanism will be implemented in several simulation studies to quantify the associated benefits and challenges.

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Paper C

Consumers' Flexibility Estimation at the TSO Level for Balancing Services

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Consumers' Flexibility Estimation at the TSO Level for Balancing Services

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Abstract

Demand flexibility will be an inevitable part of the future power system operation to compensate stochastic variations of ever-increasing renewable generation. One way to achieve demand flexibility is to provide time-varying prices to customers at the edge of the grid. However, appropriate models are needed to estimate the potential flexibility of different types of consumers for day-ahead and real-time ancillary services (AS) provision. The proposed method should account for rebound effect and variability of the customers' reaction to the price signals. In this study, an efficient algorithm is developed for consumers' flexibility estimation by the transmission system operator (TSO) based on offline data. No aggregator or real-time communication is involved in the process of flexibility estimation, although real-time communication channels are needed to broadcast price signals to the end-users. Also, the consumers' elasticity and technical differences between various types of loads are taken into account in the formulation. The problem is formulated as a mixed-integer linear programming (MILP) problem, which is then converted to a chance-constrained programming to account for the stochastic behaviour of the consumers. Simulation results show the applicability of the proposed method for the provision of AS from consumers at the TSO level.

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C.1 Introduction

In recent decades, a significant amount of renewable energy sources (RES) has been integrated into power systems, supported by the increasing global awareness towards climate change and the tremendous cost reduction in the new technologies [1]. While offering unquestionable environmental benefits and sustainability in energy production, large penetration of RES introduces new concerns and challenges in power systems planning and operation because of an unprecedented level of stochasticity, non-linearity, and dynamics [2]. Consequently, it causes higher risk of frequency deviation, voltage excursion, and network congestion in real-time operation. Furthermore, it requires larger amount of ancillary services (AS) to compensate demand and generation imbalances in real-time. AS consist of a variety of operations, beyond the electricity generation and transmission. These operations guarantee service quality, continuity and security from distribution (e.g., voltage regulation) to transmission level (e.g., frequency regulation and congestion management). Since RES are located at different levels of the grid, challenges are extended to all aspects of AS provision. This further demands a holistic change in AS provision in the future power system with high RES penetration.

An attempt of that nature is the so-called demand response (DR) programs. Different types of DR programs have been developed and tested in the last decade or so [3]. These include the application of time-of-use (ToU) rates, incentives, real-time prices (RTP) and direct load control (DLC). ToU schemes define different rates at different time of the day (i.e., usually two-tiered peak and off peak [4]) but that do not change based on the condition of power system. Incentives are designed to be added on top of a flat electricity retail price. The consumer is always rewarded to alter its consumption to support the DR scheme voluntarily. However, they are used in relation to two-way communication schemes [5, 6, 7]. Finally, RTP are generated to reflect the real-time condition of the grid [8]. RTP is different from incentives, as in RTP consumers only receive a time-varying price. On the other hand, in incentive-based schemes, consumers still receive a flat retail price and, on top of that, they can agree on an incentive to alter their consumption. This solution preserves consumers' autonomy as it is based on one-way communication structure. Prices are broadcast to consumers which autonomously decide how to respond to them through decentralised controllers. Also, no control signal is submitted to the consumers, and the same price signal can be broadcast to a various pool of consumers (i.e., at their HEMSs), as its formulation is not device-based.

Such price schemes have been used in the Olympic Peninsula Demonstration project, where the procurement of demand flexibility in response to 5-minute price signals was successfully tested [9]. Although RTP might potentially increase price volatility, it is possible to address such a concern by properly designing the price, e.g., imposing a fixed price cap [10]. The RTP can also be agreed in a market-based approach, such as in transactive energy (TE) [11]. TE allows the consumers to be actively involved in the formation of the price, which in turn reduces uncertainty in consumers' response. However, this type of methods requires regular feedback from the consumers for flexibility estimation, requiring costly and cyber security-prone two-way communication infrastructure.

Another type of DR programs is centralised and decentralised DLC schemes [12]. In centralised DLC mechanisms, an external entity directly controls consumers' load through a two-way communication link [13]. Although such solutions substantially reduce uncertainty in the consumers' response [14], they compromise consumers' privacy and autonomy [11]. In fact, consumers have to allow an external entity to decide about the way they consume electricity. In [15] and [16], it is shown that consumers might be reluctant in losing control of their consumption, and that automation of the consumption is accepted only if consumers can autonomously manage it. To gain higher acceptance from consumers towards DLC mechanisms, long-term contracts [17] have also been formulated. The main challenge of such approaches is that consumers need to plan their future consumption ahead of time, which most of the consumers are not accustomed to do so [6]. Therefore, only part of the available flexibility might be exploited in such programs. An alternative to centralised DLC schemes is decentralised DLC, which uses one-way communication [18]. It is implemented by simply broadcasting a control signal from a centre, where the ultimate decision is made by the local controller at the consumer's side. This arrangement addresses privacy and comfort issues in the DLC schemes (i.e., each distributed controller individually satisfies the consumer' constraints [19]). However, the control signal generated by the central controller is based on models for specific types of loads. Therefore, different specialised control signals should be issued for every type of loads in order to exploit the existing potential flexibility [20, 21]. In addition, the control signals are generated by assuming a linear model for the device, which might not represent the true dynamics of the underlying appliance, thus it might be error-prone. Nevertheless, it is true that the error might decrease as the number of aggregated devices grows.

While the authors acknowledge the benefits and disadvantages of various RTP and DLC methods, the RTP scheme is assumed in this study and the proposed flexibility estimation algorithm is developed based on the RTP concept. From the perspective of the transmission system operator (TSO), RTP must be properly formulated to address the desired aggregated change in consumption that solves the operational problems. Therefore, understanding how end-users respond to different price signals in an aggregated manner can help the TSO to estimate the potential of demand flexibility and design price signals accordingly [22]. In other words, by utilising appropriate models, the system operator can evaluate the impact of different prices on consumers' flexibility to determine the right price to obtain a certain amount of flexibility [23]. Unfortunately, literature scarcely reported load flexibility estimation from the system operator's point of view. In [24], a daily load response model for different end-users' categories is proposed based on the day-ahead spot market prices. However, the stochastic responsiveness of different end-users' categories and consumers' preferences have not been studied. Moreover, only few papers investigated the flexibility potential of various industrial loads [25], despite the fact that 80% of electricity usage is consumed in this sector in some countries [26]. Therefore, there is a gap in knowledge to properly estimate aggregated flexibility of the consumers while accounting for stochasticity in their elasticity and preferences without real-time communication links. In this paper, an optimisation problem is formulated to estimate the aggregate flexibility of rational end-users (REUs) with different elasticity and preferences at the TSO level in response to time-varying prices. The proposed tool can be used to quantify the amount of demand flexibility that is available for balancing. Estimating the amount of load flexibility in response to different prices can be useful for an aggregator to build blocks of load capacity bids for different time intervals (e.g., hourly, in CAISO). Although how to generate the time-varying prices is out of the scope of this study, the proposed method can also be used to evaluate the impact of different prices on demand flexibility. Moreover, balancing requirements might change due to the prediction errors in the load demand and renewable generation and unexpected outages. Therefore, having an estimate of the available load flexibility can be very useful during the real-time operation of the power system. Within this context, our method can be used to provide such an estimate both in advance or in real-time. Furthermore, having more flexible resources (from generation and demand) enhances competition in the balancing market, resulting in price reduction that ultimately reduces electricity prices for the end-users. In order to reduce the negative impact of the consumers' stochastic behaviour on the estimated flexibility, the original formulation is converted to a chance-constrained (CC) programming, where the risk level of the solutions can be guaranteed. The main contributions of the paper can be summarised as follows:

- Quantifying the aggregated up- and down- flexibility from various types of consumers' categories at the TSO level to address AS requirements;
- Formulating a chance-constrained optimisation to account for the stochasticity in the consumers' willingness in such an application;
- Developing a statistical model of aggregated consumers' willingness (i.e., elasticity and preferences) for different categories of consumers and incorporating it in the optimisation problem.

The rest of the paper is organised as follows: Section C.2 presents the theoretical foundation for the formulation in terms of time-varying prices and REUs. It is followed by a deterministic optimisation formulation of the aggregated load flexibility in Section C.3. Then, the formulation is converted to a CC programming problem to address stochasticity of the end-users' behaviour in Section C.4. In Section C.5, a case study is proposed and a series of simulations are carried out to show the effectiveness of the proposed model. Simulation results are discussed and the paper is finally concluded in Section C.6.

C.2 Modelling Concepts

Quantifying demand flexibility at the TSO level with limited aggregated historical data inevitably involves complex parameters and conditions, which must be simplified for appropriate modelling. To keep the proposed method practical and computationally tractable, two important assumptions are made based on the current trend in smart grid technologies, as explained below.

C.2.1 Time-varying prices

Time-varying prices are assumed to exist to activate consumers' flexibility in this study. In the smart grid era, the application of advanced metering infrastructure will further support the time-varying pricing mechanism in practice. Without loss of generality and similar to the Olympic Peninsula Demonstration, it is assumed that time-varying prices are superimposed on the existing retail electricity price. We refer to the existing flat retail price as the "baseline price", λ^{base}, while the time-varying price component is called "delta price" in the rest of the paper. The latter is denoted by $\boldsymbol{\Delta\lambda}_t^\alpha$, representing the time-varying price for flexibility type α at time t. Depending on the grid condition, upward regulation (i.e., $\alpha = u$) or downward regulation (i.e., $\alpha = d$) may be required. In the existing terminology, regulation is defined from the generators' perspective, e.g., in California ISO [27], where a load increase is equivalent to a decrease in generation (i.e., down-regulation) and vice versa. Therefore, down-regulation is achieved from negative delta prices, $\Delta\lambda_t^d$ or equivalently $\boldsymbol{\Delta\lambda}_t^\alpha : (\boldsymbol{\Delta\lambda}_t^\alpha < 0)$. On the other hand, load reduction is equivalent to an increase in generation (i.e., up-regulation), which is achieved by positive delta prices, $\Delta\lambda_t^u$ or equivalently $\boldsymbol{\Delta\lambda}_t^\alpha : (\boldsymbol{\Delta\lambda}_t^\alpha > 0)$. Since the source of real-time operation issues can be linked to many entities (e.g., load, generation plants, transmission and distribution networks, interconnected areas, and so on), it would be unfair to the consumers to pay more because of the issues that were probably initiated by other stakeholders [23]. To alleviate such a problem, zero accumulated delta prices should be enforced at the end of each day:

$$\sum_{t=1}^{\tau} \boldsymbol{\Delta\lambda}_t^u + \boldsymbol{\Delta\lambda}_t^d = 0 \tag{C.1}$$

Summing the delta prices to zero over a day of operation is preferred in this paper instead of the alternative approach, which is the sum of the demand-weighted prices. The main reason is that it is difficult to predict the aggregated response of each consumers' category in the hours ahead, which leads to higher uncertainty in the demand-weighted prices. By providing delta-prices whose sum is zero, some periods of low prices are ensured to exist from which the consumers can benefit (i.e., by responding to the time-varying price). In the simulation study, it is assumed that the delta prices are known in advance by the TSO. In the electricity markets where energy and AS are procured simultaneously in the day-ahead market, e.g., California ISO [28], such AS prices are available. Furthermore, the proposed tool could be readily used for real-time operation in a rolling horizon fashion to incorporate potential updates of the prices and load flexibility provided in previous hours.

C.2.2 Rational end-users (REUs)

Since manual consumers' reaction to the price signal is not practical nor effective, energy management systems (EMS) are required to successfully implement price-based DR programs in practice. Once the time-varying price is received by the EMS, they run an individual optimisation and/or control problem locally to minimise the incurred electricity cost accounting for the customers' preferences [29, 8, 30, 31]. As an important smart grid technology, the EMS market value reached US$4 billion in 2017 [32]. With the current market trend, it is likely that most of the future electricity consumers will have EMS at their premises. This, in turn, will enhance the elasticity of demand to time-varying prices, which is a key feature in successful DR implementation. In addition, application of EMSs improves the predictability of consumers' response to price signals while avoiding communication of any sensitive information over communication channels in real-time.

In this paper, we deal with EMS-equipped end-users, which are called REUs, to receive the time-varying electricity prices through one-way communication channels. The diversity of the REUs' behaviour towards the delta prices is modelled below.

C.2.2.1 REUs' responsiveness to the price signal

In order to appropriately model the diversity of consumers' flexibility, the willingness of each REU to deviate from its baseline demand, i.e., $\mathbf{L}_{t,j}^{\text{base}}$, is modelled as a stochastic phenomenon. Generally, the price-responsiveness of a consumer depends on various factors, e.g., weather conditions, electricity price, time and type of day, and season, etc. [33]. As an example, in [34], it is shown that the response of the load demand has been faster in the cold weather. In this paper, however, only electricity price, type of consumers and time of the day are considered in the REUs' responsiveness modelling, i.e., $\mathbf{a}_{t,j}^{\alpha}$, to keep the problem tractable. Other factors, such as the weather condition and type of day, could be included in the current model by adjusting the willingness parameter $\mathbf{a}_{t,j}^{\alpha}$, e.g., as a function of the ambient temperature and type of day. Weather conditions are neglected because various types of end-users react differently to the weather conditions. Therefore, proper data is needed to estimate the relationship, which is not available to the public at the moment. The value of $\mathbf{a}_{t,j}^{\alpha}$ varies within the range of $\left[-1, 1\right]$, where 0 indicates no intention to change consumption and 1 (-1) represents a 100%-increase (decrease) in consumption in response to the delta price. From literature, [24] approached the consumers' price-responsiveness in a similar manner to investigate the behaviour of a pool of end-users. Consumers' willingness, however, was considered constant over time and price in that study. Halvgaard et al. in [35] adopted a linear model of price and consumption to formulate the price response behaviour. In [36], Aalami et al. focused on nonlinear functions, which better describe the price response behaviour compared to the linear models. Following the work of Aalami, we adopted a power function to model the consumers' willingness, as shown in Fig. C.1. Similar to [24] and [37], where the authors assumed a price threshold for achieving DR, a dead-band is considered to address the fact that consumers become responsive beyond a certain price. Therefore, for a delta price smaller than the dead-band price, i.e., $\underline{\boldsymbol{\Delta\lambda}}_{j}^{\alpha}$ in the specific regulation direction, no response is expected from the pool and the flexibility is zero:

$$\mathbf{a}_{t,j}^{\alpha} = 0 \qquad\qquad |\boldsymbol{\Delta\lambda}_{t}^{\alpha}| < \underline{\boldsymbol{\Delta\lambda}}_{j}^{\alpha} \tag{C.2}$$

When the delta price increases beyond the dead-band, the pool of consumers starts reacting, which is modelled as follows:

$$\mathbf{a}_{t,j}^{\alpha} = \overline{\mathbf{a}}_{j}^{\alpha}\left(\frac{\boldsymbol{\Delta\lambda}_{t}^{\alpha} - \underline{\boldsymbol{\Delta\lambda}}_{j}^{\alpha}}{\overline{\boldsymbol{\Delta\lambda}}_{j}^{\alpha} - \underline{\boldsymbol{\Delta\lambda}}_{j}^{\alpha}}\right)^{\boldsymbol{\gamma}} \quad \underline{\boldsymbol{\Delta\lambda}}_{j}^{\alpha} \leq |\boldsymbol{\Delta\lambda}_{t}^{\alpha}| \leq \overline{\boldsymbol{\Delta\lambda}}_{j}^{\alpha} \tag{C.3}$$

Furthermore, we assume that, beyond a certain price, i.e., $\overline{\boldsymbol{\Delta\lambda}}_{j}^{\alpha}$, the pool cannot

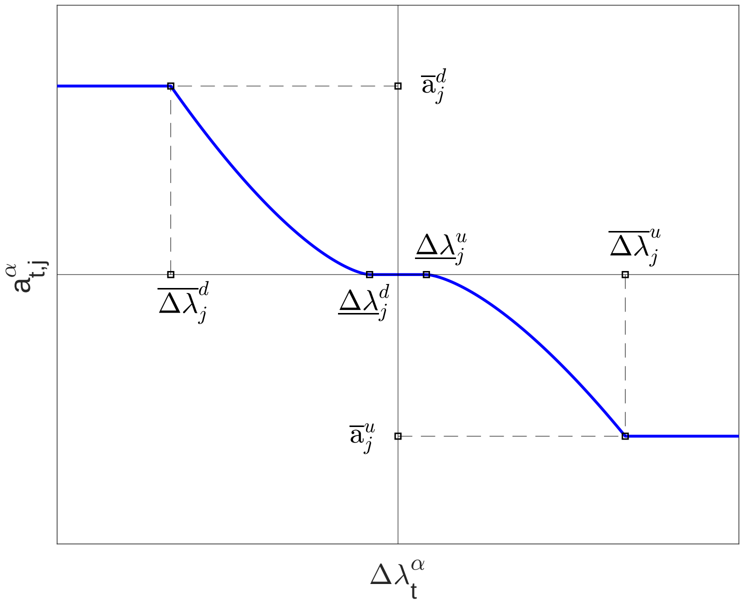

Figure C.1: Willingness parameter $\mathbf{a}_{t,j}^{\alpha}$ for time-varying electricity price $\boldsymbol{\Delta\lambda}_t^{\alpha}$. Positive prices lead to up-regulation (i.e., $\alpha \equiv u$), while negative prices induce down-regulation (i.e., $\alpha \equiv d$). The parameters $\underline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$ and $\overline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$ determine the dead-band and the saturation prices for each end-users' category j.

provide additional flexibility because of the rebound effect and the un-curtailable load, as discussed in [8]. Therefore, $\mathbf{a}_{t,j}^{\alpha}$ becomes constant:

$$\mathbf{a}_{t,j}^{\alpha} = \overline{\mathbf{a}}_j^{\alpha} \qquad\qquad |\boldsymbol{\Delta\lambda}_t^{\alpha}| \geq \overline{\boldsymbol{\Delta\lambda}}_j^{\alpha} \tag{C.4}$$

To account for the stochasticity and the diversity among consumers even from the same category of end-users, the six parameters defining the dead-band and saturation, shown in Fig. C.1, are treated as normally-distributed random variables. In subsection C.5.1, the statistical properties and a simulation framework will be introduced to generate a pool of consumers for each end-users' category.

C.3 Up- and down-flexibility: Deterministic case

The ultimate goal of this study is to estimate the amount of demand flexibility that can be provided by different categories of end-users, under a time-varying pricing scheme in the presence of stochasticity in consumers' willingness. By having the stochastic model of the consumers' reaction to the price signal and the assumptions made in the previous section, it is possible to formulate an optimisation problem for the REUs to estimate their flexibility. The formulation is developed based on the conservative assumption that a perfect rebound exists due to practical reasons and end-users' comfort. In fact, more than 90% of the flexibility resources at the residential premises is provided by appliances with shiftable load (e.g., heating, ventilation, and air conditioning systems, clothes dryers, and so on) [38]. Therefore, the rebound effect will be an inevitable aspect of demand flexibility modelling, although it adversely affects the overall flexibility. As consumers might not be willing to increase their overall daily consumption, which might result in higher electricity bills, a perfect load shifting is preferred in the model that must be completed within a certain time period. While this condition might further decrease the overall flexibility of the load demand, it provides a more realistic model of consumers' behaviour, which consequently improves the accuracy of the estimated flexibility. Since the TSO does not have direct access to the individual loads, and consumers only react to the delta prices submitted by the TSO, flexibility should be estimated from consumers' perspective. Therefore, the model is formulated as a minimisation of the daily cost of electricity consumption for each end-users' category, as shown below:

$$\min_{L^{\alpha}_{t,j}} \quad \sum_{t=1}^{\tau} \left(\boldsymbol{\lambda}^{\text{base}} + \boldsymbol{\Delta\lambda}^{u}_{t} + \boldsymbol{\Delta\lambda}^{d}_{t}\right) \sum_{j=1}^{J} \left(\boldsymbol{L}^{\text{base}}_{t,j} + L^{d}_{t,j} - L^{u}_{t,j}\right) \tag{C.5a}$$

subject to: (C.5b)

$$-\mathbf{r}^{\alpha}_{j} \leq L^{\alpha}_{t+1,j} - L^{\alpha}_{t,j} \leq \mathbf{r}^{\alpha}_{j} \qquad \forall\ t, j, \alpha \tag{C.5c}$$

$$0 \leq L^{d}_{t,j} \leq u^{d}_{t,j}\left(\mathbf{L}^{\max}_{t,j} - \mathbf{L}^{\text{base}}_{t,j}\right)\mathbf{a}^{d}_{t,j} \qquad \forall\ t, j \tag{C.5d}$$

$$0 \leq L^{u}_{t,j} \leq u^{u}_{t,j}\left(\mathbf{L}^{\text{base}}_{t,j} - \mathbf{L}^{\min}_{t,j}\right)\mathbf{a}^{u}_{t,j} \qquad \forall\ t, j \tag{C.5e}$$

$$\sum_{t'=(t-1)R_j+1}^{(t-1)R_j+R_j} \left(L^{d}_{t',j} - L^{u}_{t',j}\right) = 0 \tag{C.5f}$$

$$\forall\ t : [t \in T, (tR_j \leq \tau)], j$$

$$u^{d}_{t,j} + u^{u}_{t,j} \leq 1 \qquad \forall\ t, j \tag{C.5g}$$

$$y^{\alpha}_{t,j} - z^{\alpha}_{t,j} = u^{\alpha}_{t,j} - u^{\alpha}_{t-1,j} \qquad \forall\ t, j, \alpha \tag{C.5h}$$

$$y^{\alpha}_{t,j} + z^{\alpha}_{t,j} \leq 1 \qquad \forall\ t, j, \alpha \tag{C.5i}$$

$$\sum_{t=1}^{\tau} y^{\alpha}_{t,j} \leq \mathbf{n}^{\alpha}_{j} \qquad \forall\ j, \alpha \tag{C.5j}$$

$$\sum_{t'=t}^{t+\underline{\mathbf{d}}^{\alpha}_{j}} u^{\alpha}_{t',j} \geq \underline{\mathbf{d}}^{\alpha}_{j} y^{\alpha}_{t,j} \tag{C.5k}$$

$$\forall t : [t \in T, (t + \underline{\mathbf{d}}^{\alpha}_{j} < \tau)], j, \alpha$$

$$\sum_{t'=t}^{t+\overline{\mathbf{d}}^{\alpha}_{j}} z^{\alpha}_{t',j} \geq y^{\alpha}_{t,j} \tag{C.5l}$$

$$\forall\ t : [t \in T, (t + \overline{\mathbf{d}}^{\alpha}_{j} < \tau)], j, \alpha$$

The objective function in Eq. (C.5a) calculates the cost of each end-users' category for purchasing electricity within the time period τ (i.e, τ = 24 hours). The constraints are formulated as follows: Eq. (C.5c) is related to the up- and down-ramp limits of the flexible loads, which are represented for each end-users' category j by the ramp-rate parameter $\mathbf{r}^{\alpha}_{j}$; Eq. (C.5d) and (C.5e) impose lower and upper bounds on the amount of flexibility that can be provided by each end-users' category. Note that the minimum and maximum load for each category j at time t, i.e., $\mathbf{L}^{\min}_{t,j}$ and $\mathbf{L}^{\max}_{t,j}$, represent the lowest and highest possible consumption that each end-users' category can sustain at time t. In other words, they define the demand flexibility that can be achieved from each end-users' category in a specific time. Eq. (C.5f) implements the energy conservation rule for each end-users' category, as explained at the beginning of this section. In this constraint, the parameter R_j consists of the maximum rebound delay by which the load shifting must be completed for each end-users' category j. Eq. (C.5g) ensures that only one type of flexibility (i.e., up- or down-regulation) is provided by a specific end-users'category j at time t; Eq. (C.5h) and (C.5i) represent the flexibility activation and deactivation for each end-users'category j at time t; Eq. (C.5j) enforces a limit on the number of times that a certain end-users'category can be activated in a day. In Eq. (C.5j), it is assumed that only a certain number of processes can be shifted within the day; Eq. (C.5k) and Eq. (C.5l) refer to the minimum and maximum duration for which the load response can be sustained. Obviously, many of the parameters depend on the end-users'category, and hence the above optimisation will be solved for a certain number of consumers in each end-users'category, representing the characterisations and the statistical variability in that end-users'category.

C.4 Up- and down-flexibility: Chance-constrained programming

Due to the importance of AS in the power system operation and the stochastic nature of the REUs, it is valuable for the TSO to quantify the risk in demand flexibility and include it in the decision-making process. To do so, the deterministic optimisation formulation from the previous section is converted to a chance-constrained (CC) programming. This way, it is plausible to deal with the level of risk associated with the provision of a certain amount of demand flexibility. The CC formulation ensures that the probability of meeting a certain constraint is above a preferred confidence level [39] by restricting the feasible solution space. The CC programming has been used in the past to solve different power system problems. For instance, it has been applied to optimal storage sizing in [40], and to generate optimal price signals for DR programs from the householders in [41]. Also, in [42], such a method has been used in an optimal power flow model of a 30-bus system to schedule generation and reserve, where controllable loads have been considered as thermal energy storage units.

From our model formulation, it can be seen that each end-users' category acts independently to minimise its operation cost. In Eq. (C.3), $\mathbf{a}^{\alpha}_{t,j}$ is defined as a function of the electricity price, consumers' preferences, end-users' category, and time of the day. Even though this parameter does not explicitly depend on its previous values in time, the load price-response is made time-dependent by way of constraints (C.5f)-(C.5l), which directly limit the provision of flexibility from consumers over time. For instance, Eq. (C.5l) prevents the loads from providing flexibility beyond a certain period of time, in particular, $\overline{\mathbf{d}}^{\alpha}_{j}$ hours. This way, the provision of flexibility by loads at one hour depends of its previous values. Time dependency is also enforced by limiting the maximum number of load flexibility activations or by modelling the rebound effect, as explained in Section **??**. On the other hand, as $\mathbf{a}^{\alpha}_{t,j}$ does not depend on its previous values in time, it is possible to evaluate each constraint independently by using a disjoint CC method. From the formulation of the deterministic model, the flexibility was limited by:

$$\begin{array}{ll} L^{d}_{t,j} \leq u^{d}_{t,j}\big(\mathbf{L}^{\max}_{t,j} - \mathbf{L}^{\text{base}}_{t,j}\big)\mathbf{a}^{d}_{t,j} & \forall t,j \\ L^{u}_{t,j} \leq u^{u}_{t,j}\big(\mathbf{L}^{\text{base}}_{t,j} - \mathbf{L}^{\min}_{t,j}\big)\mathbf{a}^{u}_{t,j} & \forall t,j \end{array} \tag{C.6}$$

In order to apply CC programming, $\mathbf{a}^{\alpha}_{t,j}$ is treated as a random variable and denoted by $\tilde{\mathbf{a}}^{\alpha}_{t,j}$. It is a function of input parameters $\underline{\boldsymbol{\Delta\lambda}}^{\alpha}_{j}, \overline{\boldsymbol{\Delta\lambda}}^{\alpha}_{j}$, and $\overline{\mathbf{a}}^{\alpha}_{j}$, as given in Eq. (C.3). As argued in [43, 44], the input parameters are assumed to be normally distributed because of their dependence on a large number of individual human behaviour:

$$\begin{array}{ll} L_{t,j}^{d} \leq u_{t,j}^{d} \big(\mathbf{L}_{t,j}^{\max} - \mathbf{L}_{t,j}^{\text{base}}\big) \tilde{\mathbf{a}}_{t,j}^{d} & \forall t, j \\ L_{t,j}^{u} \leq u_{t,j}^{u} \big(\mathbf{L}_{t,j}^{\text{base}} - \mathbf{L}_{t,j}^{\min}\big) \tilde{\mathbf{a}}_{t,j}^{u} & \forall t, j \end{array} \tag{C.7}$$

The right-hand side of Eq. (C.7) can be re-written in a compact form, as follows:

$$\mathcal{A}_{t,j}^{d} \equiv u_{t,j}^{d} (\mathbf{L}_{t,j}^{\max} - \mathbf{L}_{t,j}^{\text{base}}) \tilde{\mathbf{a}}_{t,j}^{d} \tag{C.8a}$$

$$\mathcal{A}_{t,j}^{u} \equiv u_{t,j}^{u} (\mathbf{L}_{t,j}^{\text{base}} - \mathbf{L}_{t,j}^{\min}) \tilde{\mathbf{a}}_{t,j}^{u} \tag{C.8b}$$

$$L_{t,j}^{\alpha} \leq \mathcal{A}_{t,j}^{\alpha} \quad \forall t, j \tag{C.8c}$$

In CC programming, each constraint needs to be satisfied for a probability higher than a predefined theoretical confidence level $\boldsymbol{\beta}_{th}$, where th means that it is the theoretical value imposed in the formulation.

$$Pr\bigg(L_{t,j}^{\alpha} \leq \mathcal{A}_{t,j}^{\alpha}\bigg) \geq \boldsymbol{\beta}_{th} \tag{C.9}$$

Adding mean $\mu(.)$ and standard deviation $\sigma(.)$ of $\mathcal{A}_{t,j}^{\alpha}$ to the formulation, we will have:

$$Pr\left(\frac{L_{t,j}^{\alpha} - \mu_{\mathcal{A}_{t,j}^{\alpha}}}{\sigma_{\mathcal{A}_{t,j}^{\alpha}}} \leq \frac{\mathcal{A}_{t,j}^{\alpha} - \mu_{\mathcal{A}_{t,j}^{\alpha}}}{\sigma_{\mathcal{A}_{t,j}^{\alpha}}}\right) \geq \boldsymbol{\beta}_{th} \tag{C.10}$$

If $\mathbf{a}_{t,j}^{\alpha}$ follows a normal distribution, then it is possible to define the standard score as z_{α}:

$$Pr\left(\frac{L_{t,j}^{\alpha} - \mu_{\mathcal{A}_{t,j}^{\alpha}}}{\sigma_{\mathcal{A}_{t,j}^{\alpha}}} \leq z_{\alpha}\right) \geq \boldsymbol{\beta}_{th} \tag{C.11a}$$

$$1 - Pr\left(\frac{L_{t,j}^{\alpha} - \mu_{\mathcal{A}_{t,j}^{\alpha}}}{\sigma_{\mathcal{A}_{t,j}^{\alpha}}} \geq z_{\alpha}\right) \geq \boldsymbol{\beta}_{th} \tag{C.11b}$$

where the cumulative distribution function (CDF), called Φ, can be estimated as follows:

$$1 - \Phi\left(\frac{L^{\alpha}_{t,j} - \mu_{\mathcal{A}^{\alpha}_{t,j}}}{\sigma_{\mathcal{A}^{\alpha}_{t,j}}}\right) \geq \boldsymbol{\beta}_{th} \tag{C.12}$$

Eq. (C.12) can be further rearranged:

$$L^{\alpha}_{t,j} \leq \mu_{\mathcal{A}^{\alpha}_{t,j}} + \sigma_{\mathcal{A}^{\alpha}_{t,j}} \Phi^{-1}\big(1 - \boldsymbol{\beta}_{th}\big) \tag{C.13}$$

By defining $\Phi^{-1}\big(1 - \boldsymbol{\beta}_{th}\big)$ as $\Phi^{-1}_{\boldsymbol{\beta}_{th}}$, the constraints can be written as:

$$L^{d}_{t,j} \leq \mu^{d}_{a} u^{d}_{t,j} \big(\mathbf{L}^{\max}_{t,j} - \mathbf{L}^{\text{base}}_{t,j}\big) + \sigma^{d}_{a} u^{d}_{t,j} \big(\mathbf{L}^{\max}_{t,j} - \mathbf{L}^{\text{base}}_{t,j}\big) \Phi^{-1}_{\boldsymbol{\beta}_{th}} \tag{C.14a}$$

$$L^{u}_{t,j} \leq \mu^{u}_{a} u^{u}_{t,j} \big(\mathbf{L}^{\text{base}}_{t,j} - \mathbf{L}^{\min}_{t,j}\big) + \sigma^{u}_{a} u^{u}_{t,j} \big(\mathbf{L}^{\text{base}}_{t,j} - \mathbf{L}^{\min}_{t,j}\big) \Phi^{-1}_{\boldsymbol{\beta}_{th}} \tag{C.14b}$$

According to the value of the binary variable $u^{\alpha}_{t,j}$, two scenarios can be identified:

- **Scenario I**: $u^{\alpha}_{t,j} = 0$, where:

$$L^{\alpha}_{t,j} = 0 \tag{C.15}$$

In this scenario, the flexibility is zero.

- **Scenario II**: $u^{\alpha}_{t,j} = 1$, where:

$$L^{d}_{t,j} \leq \mu^{d}_{a} \big(\mathbf{L}^{\max}_{t,j} - \mathbf{L}^{\text{base}}_{t,j}\big) + \sigma^{d}_{a} \big(\mathbf{L}^{\max}_{t,j} - \mathbf{L}^{\text{base}}_{t,j}\big) \Phi^{-1}_{\boldsymbol{\beta}_{th}} \tag{C.16a}$$

$$L^{u}_{t,j} \leq \mu^{u}_{a} \big(\mathbf{L}^{\text{base}}_{t,j} - \mathbf{L}^{\min}_{t,j}\big) + \sigma^{u}_{a} \big(\mathbf{L}^{\text{base}}_{t,j} - \mathbf{L}^{\min}_{t,j}\big) \Phi^{-1}_{\boldsymbol{\beta}_{th}} \tag{C.16b}$$

According to Eq. (C.16a) and (C.16b), the amount of flexibility is bounded by a certain value that takes into account the mean and standard deviation of $\mathbf{a}^{\alpha}_{t,j}$ and the quantile of a standard normal variable. The latter will depend on the predefined theoretical confidence level, i.e., $\boldsymbol{\beta}_{th}$, and the estimated flexibility by this method will be guaranteed at that confidence level. Therefore, it will help TSO to make an informed decision considering its risk.

C.5 Simulation Study and Discussion

To show the effectiveness of the proposed model, a simulation study is carried out using actual data, which are provided by Elforbrugspanel in 2008. Data is collected by Energinet (the Danish transmission system operator) and Dansk Energi (the Danish advocacy group for energy companies) by monitoring hourly electricity demand for a selected pool of consumers in every Danish municipality [45]. The selected pool has been defined to represent the national demand. 2106 meters have been installed to study the residential, agricultural, industrial and commercial electricity demand in this project. The aggregated data of each end-users' category has been reported monthly to Elforbrugspanel. The main output of the project has been the calculation of the average of the hourly individual electricity demand for 29 end-users' category.

The proposed formulation can possibly work with different AS markets and time-frames in the order of minutes to hours, as long as the required data with the right time resolution is available. In our simulation studies, we consider balancing services that are procured one day in advance and use data for the hourly average consumption for 29 end-users' categories, a list of which is given in Table C.1. This way, the estimated delta prices are submitted to the REUs' EMS in a single shot 24 hours ahead, and the problem is solved once for all types of loads. In order to compound the aggregated behaviour of the consumers, the actual consumption of each category is weighted by the total number of consumers in that category, which is obtained from [46]. The data used in the simulations is also available in [47]. The simulation starts by generating a pool of consumers of diverse flexibility in subsection C.5.1. Then, the normality assumption of the consumers' willingness, $\mathbf{a}^{\alpha}_{t,j}$, is checked for the CC optimisation problem. In subsection C.5.4, the deterministic and CC optimisations are solved for different load categories with two different confidence levels. In subsection C.5.4, the impact of the confidence level on the results is analysed and the results of CC optimisation are validated in subsection C.5.5. Finally, in subsection C.5.6, the impact of different rebound effects on the results is investigated.

C.5.1 Generating a pool of consumers' willingness

In the first part of the simulation, a pool of consumers is created with different preferences, i.e., $\mathbf{a}^{\alpha}_{t,j}$, followed by checking the normality of their behaviour, as shown in the flowchart of Fig. C.2. Then, the CC optimisation problem is solved with the given theoretical confidence level, $\boldsymbol{\beta}_{th}$, to quantify the aggregated load flexibility.

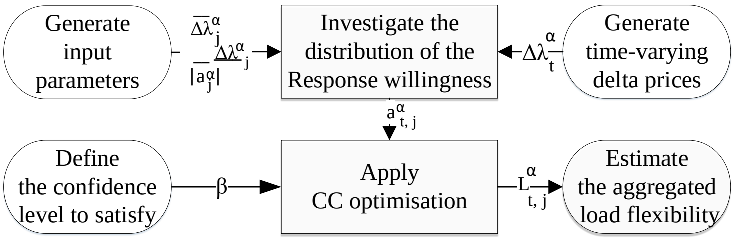

Figure C.2: Conceptual flowchart of the simulation study.

Prior to that, however, delta prices should be generated. As mentioned in Section C.2, a certain delta price set will be communicated from the system operator to the REUs to create a change in their consumption. In Eq. (C.5a), the baseline electricity price, $\boldsymbol{\lambda}^{\text{base}}$, is set to 225 DKK cent/kWh [48], the hourly delta price set is randomly generated by following a uniform distribution. The magnitude of delta prices (i.e., absolute value) is within the range of $[20, 75]$ cent DKK/kWh, following the rule defined in Eq. (C.1) and Eq. (C.3). As one can see, the delta price range is set to be well beyond the dead-band and below the flexibility saturation in consumers' willingness to avoid violating the upper and lower limits [8]. In fact, it is counterproductive for the TSO to submit an insignificant price (i.e., lower than the dead-band price) to the pool of consumers, as no reaction will be achieved. On the other hand, it is economically inconvenient for the TSO and consumers to submit an excessive price (i.e., higher than the saturation price), as the same price response can be achieved with a smaller price. Considering the limited accuracy of the estimated prices due to the unpredictable nature of AS requirements, the delta prices is unknown to a large extent. Therefore, it is reasonable to treat it like a normally-distributed random parameter. In this study, we simulate the aggregated flexibility response for 5000 different daily profiles of delta prices. This is to estimate the range of potential flexibility in each hour of the day, accounting for the stochasticity in delta prices and quantifying the risk for the system operator in exploiting load demand flexibility. In the future, these delta prices might be generated by another optimisation problem [23].

In the simulations, we will refer to the absolute value of the maximum willingness parameter $|\bar{\mathbf{a}}^{\alpha}_{t,j}|$. This is because we consider that the magnitude (i.e., absolute value) of the maximum willingness parameter will be the same to provide up- or down-regulation for each end-users' category j. For this reason, we just provide the absolute value of $\bar{\mathbf{a}}^{\alpha}_{t,j}$ to calculate $\mathbf{a}^{\alpha}_{t,j}$. However, $\mathbf{a}^{u}_{t,j}$ is supposed to be negative and $\mathbf{a}^{d}_{t,j}$ is positive, as shown in Fig. C.1. Therefore, we calculate $\mathbf{a}^{u}_{t,j}$ and $\mathbf{a}^{d}_{t,j}$ from Eq. (C.3), using the same magnitude of $|\bar{\mathbf{a}}^{\alpha}_{t,j}|$ but with opposite signs. The mean and standard deviation of the input parameters

Table C.1: Average values $\mu(.)$ and standard deviations $\sigma(.)$ of $\underline{\boldsymbol{\Delta\lambda}}_j, \overline{\boldsymbol{\Delta\lambda}}_j$ [DKK cent/kWh] and $|\overline{\mathbf{a}}_j^{\alpha}|$ [p.u.]; ramp [kW], flexibility activations [p.u.], flexibility duration [h] and rebound delay [h] parameters for different end-users' categories. H = with heating. NH = without heating.

End-users' category	$\lvert\overline{\mathbf{a}}_j^{\alpha}\rvert$ μ	σ	Reference	$\lvert\underline{\Delta\lambda}_{t,j}^{\alpha}\rvert$ μ	σ	$\lvert\overline{\Delta\lambda}_{t,j}^{\alpha}\rvert$ μ	σ	$\tilde{\mathbf{r}}_j^{\alpha}$	$\mathbf{n}_j^{\alpha}$	$\underline{\mathbf{d}}_j^{\alpha}$	$\overline{\mathbf{d}}_j^{\alpha}$	R_j	Reference
Apartment (NH)	0.4	0.10	[49, 45, 50]	5	1.1	105	11	3	7	1	6	8	[51]
House (NH)	0.5	0.11	[49, 45, 50]	6	1.2	100	12	3	8	1	6	8	[51]
House (H)	0.6	0.10	[49, 45, 50]	6	1.0	105	15	5	20	1	2	3	[51]
Cottage	0.5	0.13	–	6	1.1	100	13	4	13	1	4	6	–
Gardening	0.6	0.10	–	10	1.0	110	10	3	17	1	3	6	–
Agriculture (NH)	0.5	0.12	–	14	1.3	110	10	4	6	1	4	8	[52]
Agriculture (H)	0.7	0.08	–	14	1.3	110	11	5	20	1	2	3	[52]
Food	0.4	0.10	[49, 45, 53]	12	1.8	130	14	2	12	1	2	3	[51]
Basic metal	0.5	0.12	[49, 45, 53]	11	1.5	120	14	3	4	1	5	12	[51]
Wood	0.3	0.05	[49, 45, 53]	14	1.7	120	12	3	4	1	4	12	[51]
Textile	0.3	0.06	[49, 45, 53]	13	1.2	120	10	3	5	1	6	12	–
Paper	0.4	0.10	[49, 45, 53]	15	1.0	120	15	3	3	1	4	12	[54, 51]
Non-metallic	0.3	0.06	[49, 45]	12	1.1	120	10	3	5	1	8	12	–
Chemical	0.5	0.13	[49, 45, 53]	16	1.0	130	11	2	2	1	3	8	[55, 51]
Other industries	0.3	0.05	[49, 45, 53]	11	1.0	120	10	3	5	1	8	12	–
Construction	0.5	0.10	–	8	1.2	120	14	4	2	1	3	8	[51]
Retail	0.4	0.10	[49, 45]	8	1.2	120	14	6	4	1	3	4	[56]
Wholesale	0.4	0.10	[49, 45]	8	1.2	120	14	5	9	1	3	4	[56]
Bank	0.3	0.05	[49, 45]	17	2.0	150	10	6	8	1	2	3	–
Utility	0.3	0.06	–	14	1.4	110	10	3	3	1	2	3	[51]
Sewerage	0.3	0.05	–	17	2.0	150	12	3	3	1	2	3	[51]
Cultural	0.5	0.13	[49, 45]	10	1.2	140	10	6	11	1	3	4	–
Restaurant	0.6	0.10	[49, 45]	7	1.0	110	10	5	8	1	3	4	[51]
Health	0.3	0.06	–	17	2.0	150	11	3	4	1	4	6	–
Education	0.5	0.12	[49, 45]	10	1.2	140	16	5	20	1	2	3	–
Social	0.5	0.13	[49, 45]	10	1.2	140	15	4	12	1	3	4	–
Postal	0.6	0.10	[49, 45]	10	1.2	140	12	5	15	1	3	4	–
Public	0.6	0.11	[49, 45]	10	1.2	140	13	6	13	1	2	3	–
Public light	0.3	0.02	–	17	2.0	150	12	5	3	1	2	3	[57]

used in the simulation study, i.e., $\underline{\boldsymbol{\Delta\lambda}}_j^{\alpha}, \overline{\boldsymbol{\Delta\lambda}}_j^{\alpha}, |\overline{\mathbf{a}}_j^{\alpha}|$, are reported in Table C.1. The parameters are used to generate random numbers using a normal distribution. Due to data scarcity for different end-users' categories, input parameters are assumed to be the same for all time instances and up- and down-regulation. In order to determine the values of $|\overline{\mathbf{a}}_{t,j}^{\alpha}|$ for each end-users' category, reference [49] is used, where the amount of maximum flexibility is quantified for several consumers' sectors in Denmark. Such estimates are compared to the consumption that we previously calculated for each end-users' category from the data set. For instance, according to [49], cement manufacturing and iron foundries are able to provide 16 MW load reduction. From the consumption we previously calculated from the data set, the total electricity consumption of these consumers' categories is 30 MW. Therefore, a maximum willingness parameter of 0.5 (i.e., 50% of the total consumption) is estimated for these categories (i.e., basic metal and construction). In different studies, e.g., [58, 59], various sectors and countries have been investigated in price elasticity, whose concept is discussed in [60]. To include diversity in the willingness parameters for those sectors whose estimate in [49] is provided only for aggregated loads, this concept of price elasticity is used . Because of the lack of information, the willingness parameters of the remaining sectors are randomly chosen. Moreover, $\sigma_{\overline{\mathbf{a}}_j^{\alpha}}$ is defined in a way that the values of $|\overline{\mathbf{a}}_j^{\alpha}|$ are maintained between 0 and 1. When the value generated by the distribution function exceeds the higher or lower limits (1 for higher and 0 for lower limits), another random number is re-drawn from the normal distribution. The choice of $\underline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$ is approximately selected based on the nature of different end-users' categories [24]. For instance, we assumed that industries might behave such that they prevail the continuity of their service, unless very high delta prices are offered. Similarly, $\overline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$ values are intuitively determined. For the case of $\underline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$, the value of σ is chosen by considering a normal distribution of prices and that each price has to be bigger than zero. 5000 samples of $|\overline{\mathbf{a}}_j^{\alpha}|$ are generated for each category of end-users and time. The results of a sample end-users' category are shown in Fig. C.3. The number of samples is chosen in a way to statistically represent the variability of consumers' willingness in every end-users' category. These values are later used in the optimisation studies, both deterministic and CC problems, to estimate the aggregated load flexibility.

In the next step, we investigate the normality of $\mathbf{a}_{t,j}^{\alpha}$ in order to justify the application of CC programming. Eq. (C.3) is defined as the ratio of two normal components, namely $(\boldsymbol{\Delta\lambda}_t^{\alpha} - \underline{\boldsymbol{\Delta\lambda}}_j^{\alpha})$ and $(\overline{\boldsymbol{\Delta\lambda}}_j^{\alpha} - \underline{\boldsymbol{\Delta\lambda}}_j^{\alpha})$, which might lead to a non-normal distribution. In Fig. C.4, a statistical analysis using QQ plot and histograms of $\mathbf{a}_j^{\alpha}$ is carried out for a sample load category j and up- and down-flexibility at a specific time. In the QQ plots, the two vertical lines represent ± 2 standard deviations of the data, meaning that the values within those lines are 95% of the data. Fig. C.4 shows that the behaviour of up- and down-willingness

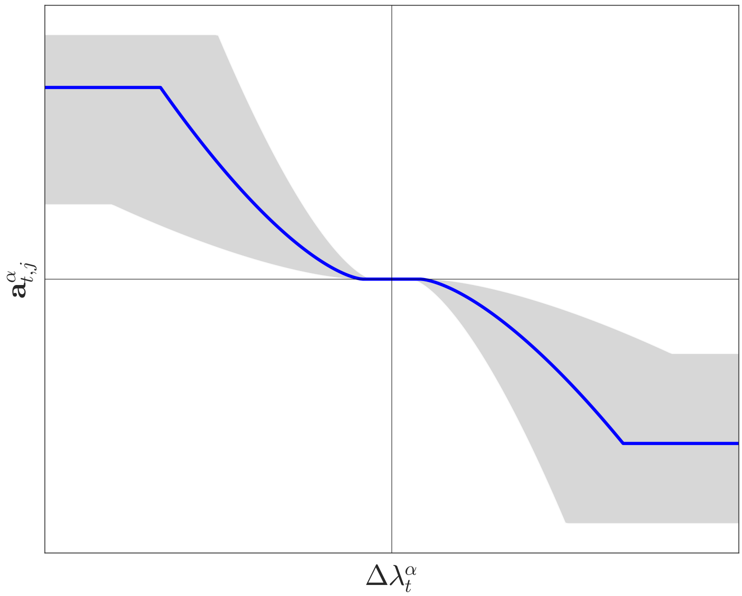

Figure C.3: Range of $\mathbf{a}^{\alpha}_{t,j}$ achieved for a sample end-users' category for different $\boldsymbol{\Delta\lambda}^{\alpha}_{t}$.

is approximately normal due to the dominating variance of $\bar{\mathbf{a}}^{\alpha}_{j}$ in Eq. (C.3).

C.5.2 Selection of γ

In [35], the price responsiveness of consumers is modelled as a linear function, which is equivalent to a value of γ equal to 1 in Eq. (C.3). In spite of that, it is reasonable to assume that consumers might be more inclined to alter their consumption profile when they receive big delta prices, as also suggested in [36]. The value of γ will be limited by the fact that consumers have different sensitivities to prices and some of them might always be responsive to achieve cost minimisation. In Fig. C.5, the distribution of $\mathbf{a}^{\alpha}_{t,j}$ is analysed for different values of γ (i.e., 1, 1.5 and 2). It is clear from the figure that a reasonable choice of γ does not compromise the normality assumption. In this paper, γ is equal to 1.5.

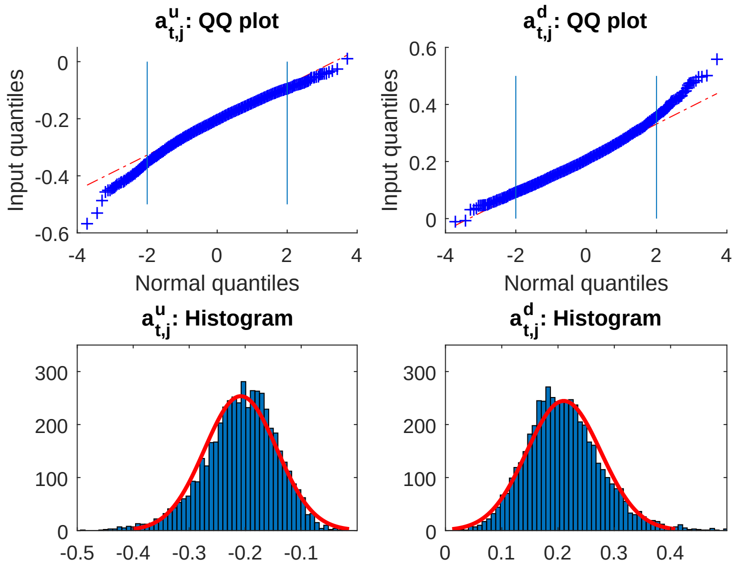

Figure C.4: QQ plots and histograms for $\mathbf{a}^{\mathrm{u}}_{t,j}$ and $\mathbf{a}^{\mathrm{d}}_{t,j}$ of a sample end-users' category j at a specific time t.

C.5.3 Explanation of the consumers' constraints parameters

In the simulations, $\mathbf{L}^{\min}_{t,j}$ and $\mathbf{L}^{\max}_{t,j}$ are calculated from the available data set [45], by identifying the minimum and maximum values of the historical electricity consumption for each time t and end-users' category j. This method is preferred in this study as it is the only information that was available at the time. Following a similar approach, $\mathbf{L}^{\mathrm{base}}_{t,j}$ is calculated from the data set by averaging the consumption of each end-users' category at time t. Parameters related to the consumers' constraints (e.g., ramp, flexibility provision duration and flexibility activation times) are estimated due to the current lack of more detailed information and provided in Table C.1. The ramp parameter $\mathbf{r}^{\alpha}_{j}$ is determined from the consumption data set, as $\mathbf{r}^{\alpha}_{j} = \tilde{\mathbf{r}}^{\alpha}_{j} \max\limits_{1\leq t\leq\tau}(\mathbf{L}^{\max}_{t,j})$, where $\tilde{\mathbf{r}}^{\alpha}_{j}$ is a parameter that depends on the type and characteristics of the loads of each end-users' category j. Considering hourly resolution of data and proposed formulation, it is reasonable to assume that $\tilde{\mathbf{r}}^{\alpha}_{j}$ will not be very restrictive since loads can change relatively fast. In fact, the majority of the loads have faster dynamics than an hour, i.e., they can go from 0 to 100% consumption in less than an hour. For the consumers' categories with mainly thermal loads (e.g., public [49]) and whose processes can be shifted in time (e.g., paper [54]), a

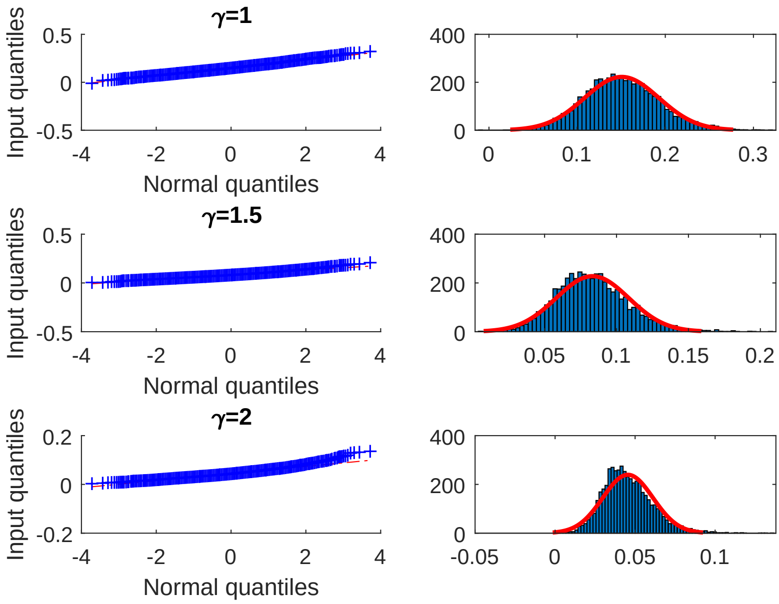

Figure C.5: QQ plot and histogram for generic $\mathbf{a}^{\alpha}_{t,j}$ of a sample end-users' category j at a specific time t for values of γ equal to 1, 1.5 and 2.

larger $\tilde{\mathbf{r}}^{\alpha}_{j}$ is assumed. For the industrial consumers, however,it will be more restrictive. In order to determine the amount of activation times for each end-users' category $\mathbf{n}^{\alpha}_{j}$, it is assumed that the industrial consumers have generally less shiftable processes compared to the residential and commercial consumers. Therefore, $\mathbf{n}^{\alpha}_{j}$ for industrial consumers is considered smaller than for residential consumers. By generally accounting on the flexibility from ventilation, heating and air conditioning (HVAC), it is feasible for the residential and commercial consumers to be activated and deactivated several times during the day without technical constraints. On the other hand, a waste water treatment facility from the industrial sector might be the only shiftable process, limiting the overall consumption flexibility. In determining $\underline{\mathbf{d}}^{\alpha}_{j}$, it is assumed that end-users' category can provide flexibility for a minimum duration of 1 hour, as HVAC is present in almost every end-users' category. Regarding the choice of the maximum flexibility duration values in Table C.1, the commercial consumers are assumed to be mainly affected by the thermal dynamics of HVAC [49]. For the industrial and residential consumers, longer dynamics are expected, as their loads are not only thermal and they might have different characteristics (e.g., electric vehicle charging, laundry machine and so on). In the simulation studies, the case of perfect daily rebound is solved for each end-users' category (i.e., R_j

= 23 for each j). Afterwards, a conservative case is considered by applying strict rebound effects, given in Table C.1, in order to evaluate the impact of the rebound on the overall flexibility. To determine the parameter R_j for the case of strict rebound, it is assumed that the end-users' flexibility is mainly constrained by the thermal dynamics of their loads. However, there are cases like the paper industry where production processes can be shifted to other times of the day [54]. For end-users' categories where processes can be shifted within the day, the rebound constraint is relaxed. Also, for the agricultural consumers, R_j is estimated by accounting for the processes involving animal waste treatment, irrigation and curing tobacco [52].

C.5.4 Up- and down-flexibility estimation

In this section, the CC optimisation problem is solved for different theoretical confidence levels using the $\mathbf{a}^{\alpha}_{t,j}$ values from subsection C.5.1.

- **Low-risk case**

For a conservative simulation study, $\boldsymbol{\beta}_{th} = 0.95$ is selected as theoretical confidence level. It implies that, globally, the constraints in Eq. (C.5d) and (C.5e) will be respected with a probability that is equal or higher than 95%. In other words, it guarantees that the estimated flexibility from the consumers, given their stochastic behaviour, will be achieved 95% of the time or higher.

In Fig. C.6, the achievable flexibility for different prices is shown in relation to the baseline consumption for $\boldsymbol{\beta}_{th} = 0.95$. It emerges that the maximum flexibility is about 7% of the hourly load demand. It is also noticeable that the flexibility in the early morning is mainly for up-regulation, while the down-regulation potential seems to be small, i.e., around 3% of the hourly load demand. Although such a result may appear counter-intuitive, it is due to the selected values of $\mathbf{L}^{\min}_{t,j}$ and $\mathbf{L}^{\max}_{t,j}$ that are used in the simulation studies. They are extracted from annual data by finding the minimum and maximum consumption values of each end-users' category at each hour of the day. Since the data set at hand does not include the impact of consumers' response to the prices, the maximum load in early hours is very close to the average consumption, which resulted in lower down-flexibility in the simulation results. In the future, advanced methods can be developed to calculate these parameters by collecting aggregated data from REUs in response to the delta prices. The correlation between delta prices and flexibility is −0.73, confirming a strong negative correlation between the two parameters. The correlation does not reach −1 because of the constraints applied to the minimisation problem and the different amount of flexibility available for up- and down-regulation. In order to

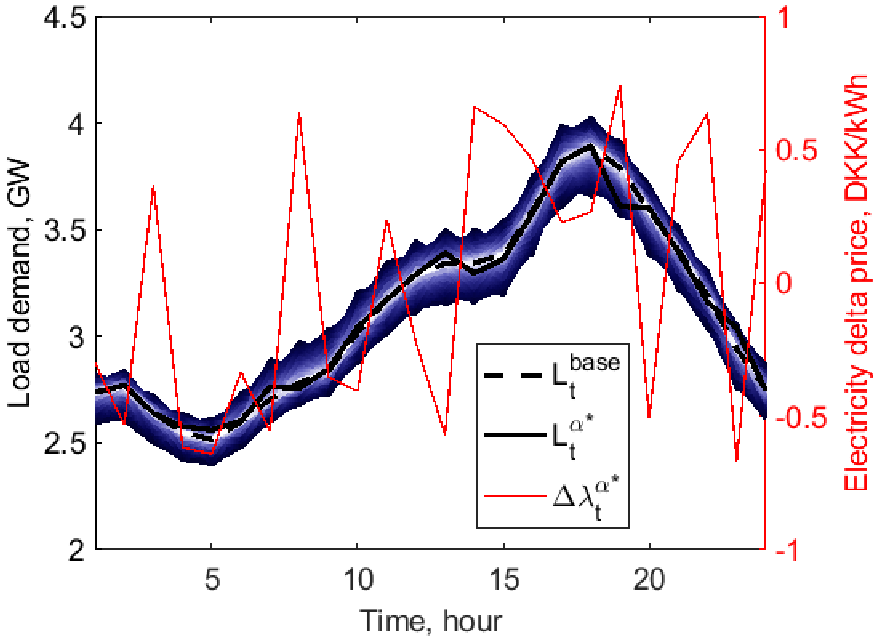

Figure C.6: Flexibility achieved for different delta prices by CC optimisation for $\boldsymbol{\beta}_{th}$ =0.95 considering daily rebound: baseline consumption, flexibility for the reference delta price $\boldsymbol{\Delta\lambda}_t^{\alpha*}$, and the delta price.

verify the correlation between flexibility and delta prices visually, the flexibility obtained in response to a randomly-selected daily delta prices, i.e., $\boldsymbol{\Delta\lambda}_t^{\alpha*}$, is shown in Fig C.6. It can be noticed that the highest amount of down-regulation (i.e., increased consumption) is achieved at hour 23:00, with 3.6% increase in demand, corresponding to the biggest negative delta price. The highest amount of up-regulation is achieved at hour 19:00 with 5.8% decrease in total demand, coinciding with a relatively large positive delta price.

- **High-risk case**

The CC optimisation for 5000 delta prices is repeated for $\boldsymbol{\beta}_{th}$ = 0.50. As expected, the up- and down-flexibility patterns are identical to the "low-risk case." However, their magnitude increases substantially for all hours, as shown in Fig. C.7. It can be seen that the flexibility range raises by 76% compared to the "low-risk case." At hour 23:00, the demand is expected to increase by about 7% in response to the given price, while 12.2% decrease in demand is observed at hour 19:00. The simulation results show that the TSO might over-estimate the flexibility potential if the associated risk is not considered in the formulation. It will, in turn, result in unsuccessful demand flexibility procurement in the real-time operation.

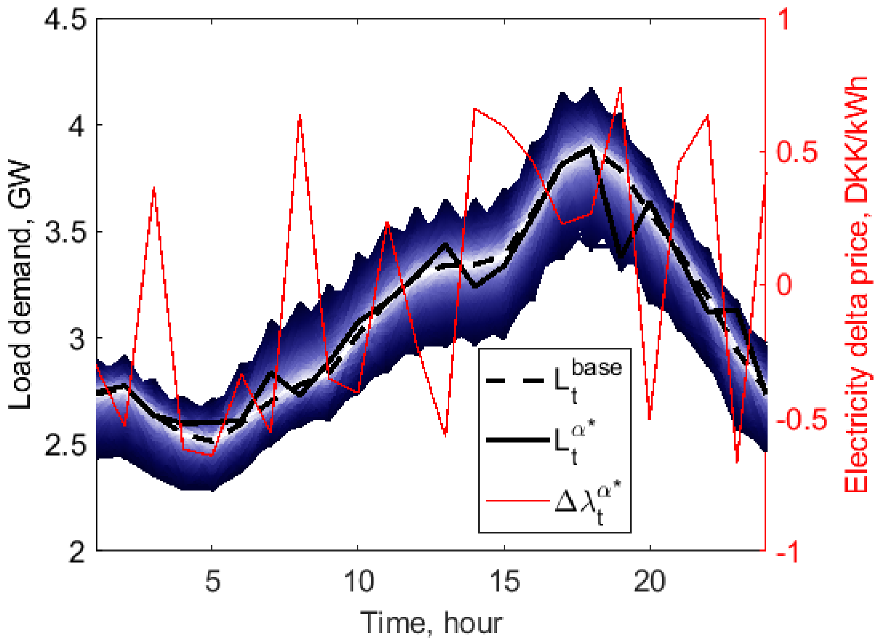

Figure C.7: Flexibility achieved for different delta prices by CC optimisation for $\boldsymbol{\beta}_{th}$ =0.50 considering daily rebound: baseline consumption, flexibility for the reference delta price $\boldsymbol{\Delta\lambda}_t^{\alpha*}$, and the delta price.

C.5.5 Validation of CC formulation

In this sub-section, we investigate the quality of the CC solutions for the case of daily rebound. As it was mentioned earlier, the CC solutions are valid only if the actual confidence level (i.e., $\boldsymbol{\beta}_{ac}$ achieved in the Monte Carlo simulation study) is bigger than or equal to the theoretical confidence level (i.e., $\boldsymbol{\beta}_{th}$ imposed on the formulation and associated simulation study) of the CC programming. To do so, we need to impose a theoretical confidence level and solve the CC formulation for a given price set. From the results, the flexibility $\mathbf{L}_{t,j}^{\alpha}$ is obtained. Afterwards, this value is used in Eq. (C.5d) and (C.5e) to investigate how many times the constraints are violated. In Eq. (C.5d) and (C.5e), $\mathbf{a}_{t,j}^{\alpha}$ is the generated pool of consumers' willingness discussed in subsection C.5.1. Since we are dealing with thousands of constraints in this simulation, while our intent is to provide a readable plot of the results, we calculate the mean value of the actual confidence level of the various constraints. This process is repeated for different values of theoretical confidence level, i.e., $\boldsymbol{\beta}_{th} \in [0.1, 0.98]$, and the mean values of $\boldsymbol{\beta}_{ac}$ are plotted in Fig. C.8(a) in comparison to the $\boldsymbol{\beta}_{th}$ imposed. From the figure, it can be seen that the actual confidence level is always higher than the theoretical counterpart. Therefore, it can be concluded that the constraints are always satisfied for the given confidence level, and that the normality assumption of $\mathbf{a}^{\alpha}_{t,j}$ was correct. Moreover, Fig. C.8(a) shows that the CC programming behaves more conservatively on the lower range of $\boldsymbol{\beta}_{th}$, where the actual confidence level is always greater than the theoretical one (e.g., for $\boldsymbol{\beta}_{th} = 0.50$, the actual confidence level is 0.54). This is because the constraints are loosely confined for small $\boldsymbol{\beta}_{th}$ values, which result in more availability of load demand to provide flexibility.

Also, in order to understand the value of using CC, we include a study where we compare the different performances of the deterministic and stochastic cases. Therefore, we solve the stochastic and deterministic formulations, where in the latter it is imposed a $\boldsymbol{\beta}_{th}$ of 0.95. Afterwards, we calculate for each formulation what is the percentage of the constraints that achieve a certain $\boldsymbol{\beta}_{ac}$. In Fig. C.8(b), the results are provided through probability density functions. For the actual $\boldsymbol{\beta}_{ac}$ show that, for the stochastic case (i.e., blue line), 92% of the constraints have a $\boldsymbol{\beta}_{ac}$ that is slightly above 0.95. In a few instances, $\boldsymbol{\beta}_{ac} = 1$ is obtained because of the condition imposed in Eq. (C.5f) and the rebound effect. For the deterministic case (i.e., black line), however, the actual confidence level lies below 92% for 95% of the constraints and is lower than the one obtained by the CC formulation. These results prove that quantifying the risk and trying to maintain a specific level of certainty is of paramount importance for the TSO in real-time operation, which is provided by the CC formulation in this study.

C.5.6 Effect of the rebound constraint

In the simulation studies so far, we investigated the CC validation for the case of daily rebound. However, in reality, different consumers' categories can defer their loads for a shorter range of time, leading to a strict rebound. In order to quantify the effect of the rebound on the flexibility estimation, Table C.2 reports the difference in flexibility obtained by the daily and strict rebound constraints. The values are calculated as the average amount of up-regulation flexibility (i.e., the amount of down-regulation will be the same, as we imposed perfect rebound in Eq.(C.5f)) provided during the day for the different price scenarios. It emerges that having a strict rebound reduced the flexibility provision by 35%.

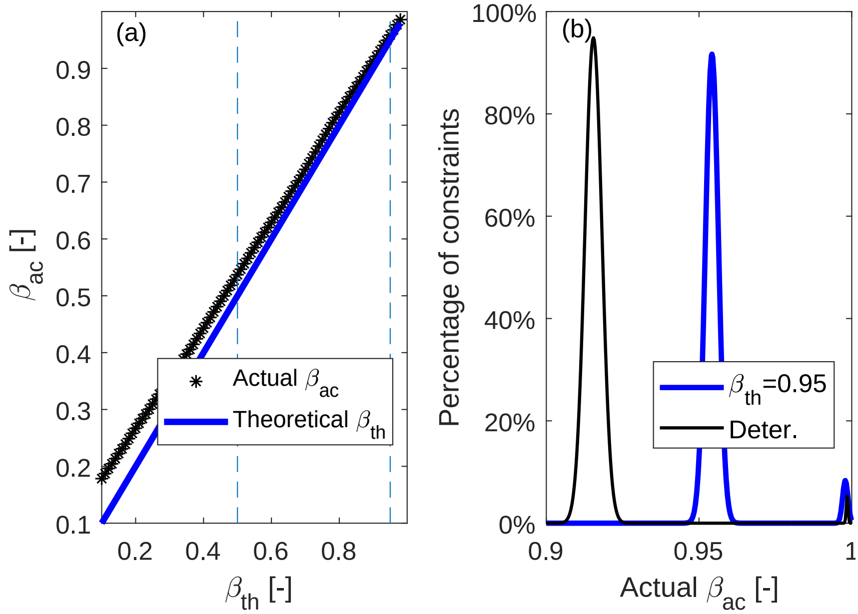

Figure C.8: CC validation for the case of daily rebound: (a) Imposed $\boldsymbol{\beta}_{th}$ and achieved $\boldsymbol{\beta}_{ac}$ in CC method for price set $\boldsymbol{\Delta\lambda}_t^*$; (b) Probability of $\boldsymbol{\beta}_{ac}$ for deterministic and stochastic case for price set $\boldsymbol{\Delta\lambda}_t^*$.

In Fig. C.9, the CC validation is repeated for the case of strict rebound.

From Fig. C.9(a), it can be seen that the actual confidence level is more conservative when dealing with a strict rebound by reaching $\boldsymbol{\beta}_{ac}$ of 0.96 for an imposed theoretical confidence level of 0.95. Also, Fig. C.9(b) confirms the relevance of adopting CC, where the deterministic approach leads to a confidence level that is lower than 0.92 for 73% of the constraints. Such a result violates the requirement of the TSO, which imposed a $\boldsymbol{\beta}_{th}$ of 0.95.

C.6 Conclusions

This paper offers a methodology to estimate the aggregated load flexibility of consumers given a certain price response function. It is formulated by considering the uncertainty in the consumers' willingness to react to the price signals. The proposed approach only requires aggregated historical consumption data to operate. In the proposed framework, the load flexibility at the TSO

Table C.2: Analysis of the flexibility provided during the day, considering different rebound effects and $\boldsymbol{\beta}_{th}$=0.95.

Study case	Up- (down-) regulation (GW)
Daily rebound	0.374
Strict rebound	0.243
Difference	-35%

level is quantified. Time-varying prices are submitted by the system operator to the end-users at the edge of the grid to alter their consumption while minimising their operation cost locally. A nonlinear and stochastic consumers' price-response function is considered in this study. In order to quantify the risk in the amount of estimated demand flexibility, a CC formulation of the problem is developed and its applicability is proven by the simulation studies. This approach allows to estimate the flexibility that can be achieved under a certain confidence level. Actual load data from Elforbrugspanel in Denmark is used for simulation studies. The simulation results show that the choice of confidence level significantly affects the flexibility estimation. For a conservative confidence level (i.e., 0.95), the method estimates a consumption change that is up to 7% of the total consumption. The quality of the CC solutions is also verified in two different ways. It is shown that the application of CC can provide a meaningful management of risk for the TSO, which is fundamental for AS provision. We finally evaluate the case of daily and strict rebound constraints, showing that a strict rebound effect limited the overall flexibility provision by 35%. The proposed approach can be used at the TSO level to quantify demand flexibility for day-ahead or real-time AS procurement. In our future work, we will investigate how to enhance our model to account for other uncertainties (such as uncertain delta prices) that the REU's EMS will most likely consider. Also, we will model $\mathbf{a}_{t,j}^{\alpha}$ as a function of weather and type of day.

C.7 Acknowledgement

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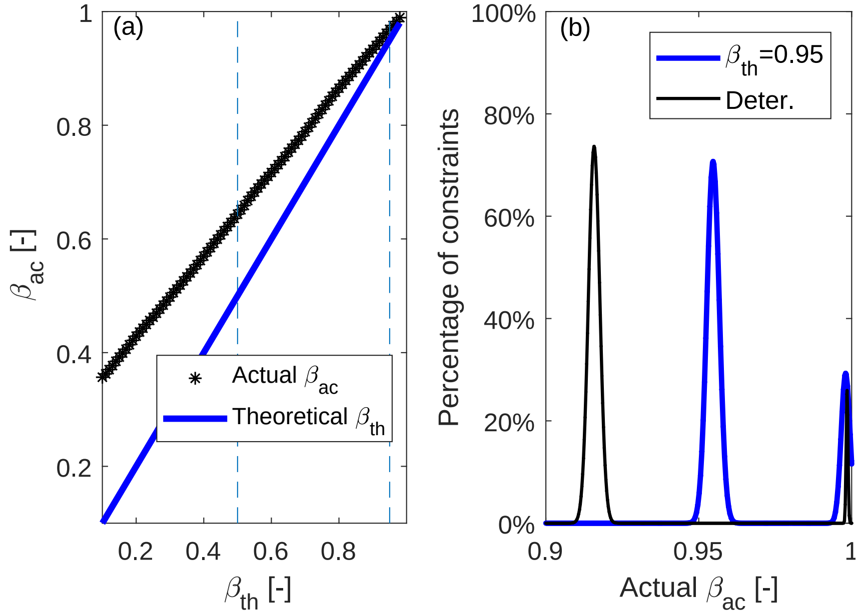

Figure C.9: CC validation for the case of strict rebound: (a) Imposed $\boldsymbol{\beta}_{th}$ and achieved $\boldsymbol{\beta}_{ac}$ in CC method for price set $\boldsymbol{\Delta\lambda}_t^*$; (b) Probability of $\boldsymbol{\beta}_{ac}$ for deterministic and stochastic case for price set $\boldsymbol{\Delta\lambda}_t^*$.

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Nomenclature

Sets:

T	Set of time, indexed by t, $t \in [1, \ldots, \tau]$.
J	Set of end-users' categories, indexed by j.
α	Type of regulation, i.e., up- or down-regulation.

Parameters:

$\boldsymbol{\lambda}^{\text{base}}$	Baseline electricity price [DKK cent/kWh].
$\boldsymbol{\Delta\lambda}_t^{\alpha}$	Time-varying electricity price (called delta price) for regulation type α at time t [DKK cent/kWh].
$\underline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$	Minimum delta prices for regulation type α of end-users' category j [DKK cent].
$\overline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$	Maximum delta prices for regulation type α of end-users' category j [DKK cent].
$\mathbf{L}_{t,j}^{\text{base}}$	Baseline end-users' demand of category j at time t [kW].
$\mathbf{L}_{t,j}^{\min}$	Minimum electricity consumption of end-users' category j at time t [kW].
$\mathbf{L}_{t,j}^{\max}$	Maximum electricity consumption of end-users' category j at time t [kW].
$\mathbf{a}_{t,j}^{\alpha}$	Actual willingness of end-users' category j to provide flexibility type α at time t [p.u.].
$\overline{\mathbf{a}}_j^{\alpha}$	Maximum willingness of end-users' category j to provide flexibility type α [p.u.].
$\mathbf{r}_j^{\alpha}$	Ramp-rate of end-users' category j for regulation type α [kW/h].
$\mathbf{n}_j^{\alpha}$	Maximum number of activation times for end-users' category j to provide flexibility type α.
$\underline{\mathbf{d}}_j^{\alpha}$	Minimum continuous flexibility duration of end-users' category j when activated to provide flexibility type α [h].
$\overline{\mathbf{d}}_j^{\alpha}$	Maximum continuous flexibility duration of end-users' category j when activated to provide flexibility type α [h].
$\boldsymbol{\beta}_{th}$	Theoretical confidence level imposed in the chance-constrained programming.
$\boldsymbol{\beta}_{ac}$	Actual confidence level achieved in the chance-constrained programming.
R_j	Maximum rebound delay for end-users' category j [h].

Variables:

$L_{t,j}^{\alpha}$	Flexibility of end-users' category j at time t for regulation type α [kW].

$u_{t,j}^{\alpha}$ Binary variables, indicating flexibility status of end-users' category j at time t for regulation type α.

$y_{t,j}^{\alpha}$ Starting binary variables of end-users' category j at time t indicating flexibility type α.

$z_{t,j}^{\alpha}$ Stopping binary variables of end-users' category j at time t indicating flexibility type α.

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Paper D

Analysis of Rebound Effect Modelling for Flexible Electrical Consumers

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Analysis of Rebound Effect Modelling for Flexible Electrical Consumers

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Abstract

Demand response (DR) will be an inevitable part of the future power system operation to compensate for stochastic variations of the ever-increasing renewable generation. A solution to achieve DR is to broadcast dynamic prices to customers at the edge of the grid. However, appropriate models are needed to estimate the potential flexibility of different types of consumers for day-ahead and real-time ancillary services provision, while accounting for the rebound effect (RE). In this study, two RE models are presented and compared to investigate the behaviour of flexible electrical consumers and quantify the aggregate flexibility provided. The stochastic nature of consumers' price response is also considered in this study using chance-constrained (CC) programming.

D.1 Introduction

Demand response (DR) programs are solutions that target changes in the power consumption of electrical consumers through economic incentives. With the higher penetration of renewable energy resources in the system, such programs are becoming a popular solution to better meet the stochastic electricity generation and support the power system operation. Several DR solutions have been proposed in literature, e.g., by offering long-term contracts, or by broadcasting dynamic prices.

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In the long term contracts, consumers allow an external operator to decide about their electricity consumption in exchange for an economic incentive (see e.g. [1]). In dynamic price schemes, however, consumers receive a time-varying price by their home-energy management system (HEMSs) and decide individually their electricity consumption schedule to minimise overall cost while preserving comfort and privacy (see e.g. [2]). As the latter does not restrict end-users' autonomy or independence, dynamic price schemes are most likely to be accepted by consumers. As a result, we focus on DR programs based on the dynamic prices as the control signal in this study.

In order to fully exploit the potential of DR programs, it is important for the operators (i.e., DR aggregators and system operators) to understand how consumers respond to prices on an aggregated level. Such an understanding can facilitate the formulation of proper dynamic prices that achieve a certain change in consumption from consumers. Furthermore, it can support the operators in quantifying the potential flexibility that can be achieved from DR programs and better allocate the reserve requirements for the power system operation.

Of particular importance in this matter is the rebound effect (RE), which consists of the change in consumers' consumption due to previous and future price reactions and is related to the technical constraints of loads and consumers' preferences. RE represents the power consumption increase (decrease) that follows an event of up- (down-) regulation, for which the consumption is decreased (increased) ([3]). In the literature, RE is mainly investigated in relation to thermal loads or refrigerators ([3]) that will need to recover their consumption immediately after a decrease in their consumption by their own dynamics. In this paper, we extend this concept to shiftable loads (i.e., washing machines, as discussed in [4]) as they follow a similar behaviour. Both thermal and shiftable loads can be modelled by consumers that reduce (increase) their base-line consumption scheduled at a certain time and consume more (less) in the following time steps. The main difference between the types of loads is the time period for which the RE phenomenon must be completed (i.e., refrigerators have faster dynamics than washing machines). Therefore, we can formulate a general mathematical model of the RE for both thermal and shiftable loads, where the different dynamics impact appears in the maximum RE duration parameter. In this paper, the RE is formulated assuming that the increase and decrease in consumption perfectly compensate each other in a certain period of time, defined as perfect RE. Although such an assumption might not be realistic for all types of loads, a practical model of such requires detail models and field data. An alternative representation to perfect RE will be investigated in our future studies.

Despite the importance of quantifying consumers' price response, proper RE modelling has scarcely been investigated and the majority of studies evaluated RE in relation to the change in energy efficiency ([5]). In [6], RE was modelled for a pool of residential heat-pumps, assuming that an operator could decide the consumption of a pool of consumers. In that study, the RE was modelled by a delay period with no deviations from the baseline consumption, and a payback period during which deviations in consumption occurred to allow the heat-pumps to return to their baselines. Although the study evaluated the dynamics of loads for a pool of residential heat-pumps, additional studies are needed to quantify the aggregate RE impact of different types of consumers.

The main contributions of this paper can be summarised as follows. First, we present two different formulations to model RE on an aggregated level with different types of consumers using mixed-integer linear programming (MILP). Second, we compare both formulations and use them to quantify the overall flexibility provision that can be achieved from a heterogeneous pool of consumers. Furthermore, we benchmark the two formulations with each other in terms of computational time and model sizes.

The paper is organised as follows: in Section D.2, the two formulations of RE are explained; in Section D.3, results of the models are presented and discussed; in Section D.4, we summarise the conclusions.

D.2 Modelling

We start by briefly explaining the concept of perfect RE. In Fig. D.1, the condition of perfect RE is shown for a consumer of type j that provides regulation in α direction at time t. Load flexibility $L^{\alpha}_{t,j}$ can be provided either for up-regulation ($\alpha = u$) or down-regulation ($\alpha = d$).

In Fig. D.1, the increase in electricity consumption achieved from consumers responding to a DR program (i.e., $L^{d}_{t,j}$) is always compensated with a decrease (i.e., $L^{u}_{t,j}$) of the same magnitude in the following time steps. This concept is also valid vice versa, where an increase in electricity consumption follows a previous decrease. The duration period for which the RE must be completed depends on the characteristics of the loads and is here defined as maximum of R_j periods for each consumer type j. If we define $\Theta_{t,j} = L^{d}_{t,j} - L^{u}_{t,j}$, the general RE condition can be formulated as $\sum_{t}^{t+R_j} \Theta_{t,j} = 0$. Depending on the type and the dynamics of a load, it is possible to consider the RE duration as static (i.e., for specific time periods) or dynamic (i.e., allowing a more adaptable scheduling of the flexibility). These two different formulations are presented in the Sections D.2.1 and D.2.2, while the overall aggregation model of the consumers is given in Section D.2.3.

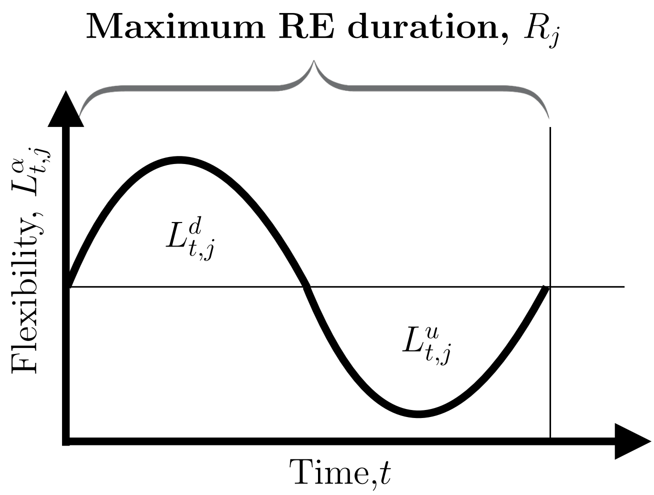

Figure D.1: Basic concept of perfect RE.

D.2.1 Modelling rebound for static RE duration

In this subsection, we model the RE for consumers that require a static RE duration. An example of this condition could be the charging of an electric vehicle (EV) that starts at 11:00 and needs to be completed by 16:00. In Fig. D.2, this RE model is graphically presented. With static time steps, the RE can be formulated as:

$$\sum_{t'=(t-1)R_j+1}^{(t-1)R_j+R_j} \Theta_{t,j} = 0 \tag{D.1a}$$

$$\forall t : [t \in T, (t \cdot R_j \leq \tau)], j$$

For this formulation, we divide the time set T by the RE duration of each type of consumers j. In this manner, we set the time intervals for which the total amount of flexibility provided by consumers type j up to time t must be nullified. Therefore, in Eq. D.1a, the overall flexibility provided by each type of consumers j must be nullified within each RE cycle.

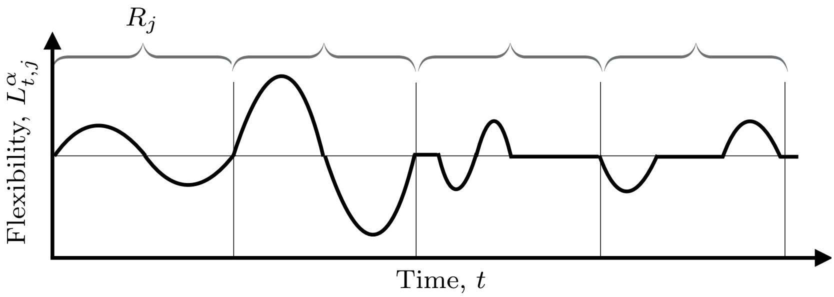

Figure D.2: Rebound effect for specific time steps.

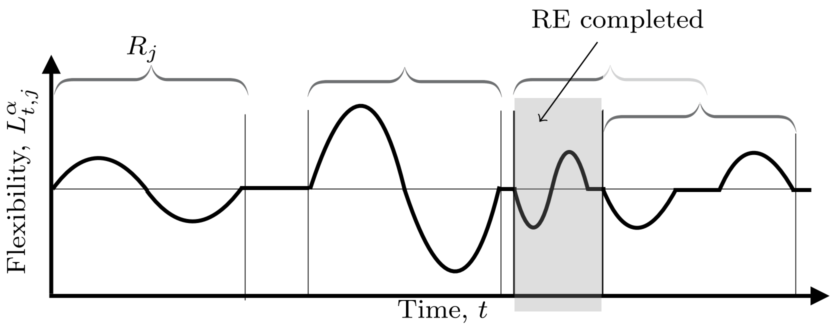

Figure D.3: Rebound effect for duration.

D.2.2 Modelling rebound for dynamic RE duration

Not all loads can be represented by a static RE model. An example is thermal loads, which can always provide flexibility as long as some operational constraints are respected. For this type of loads, the condition that the perfect RE is completed must be imposed only when flexibility is being provided. This concept is visualised in Fig. D.3.

In Fig. D.3, the RE duration is set dynamically whenever regulation is provided. However, the RE must be completed at least once within R_j (i.e., to guarantee a certain temperature in the room). When the perfect RE is achieved (highlighted as light grey area in Fig. D.3), a new RE cycle can be started. This RE model can be formulated as:

$$\epsilon x_{t,j} - M w_{t,j} - \epsilon v_{t,j} \leq \sum_{t'=1}^{t} \Theta_{t',j} \qquad \forall t, j \tag{D.2a}$$

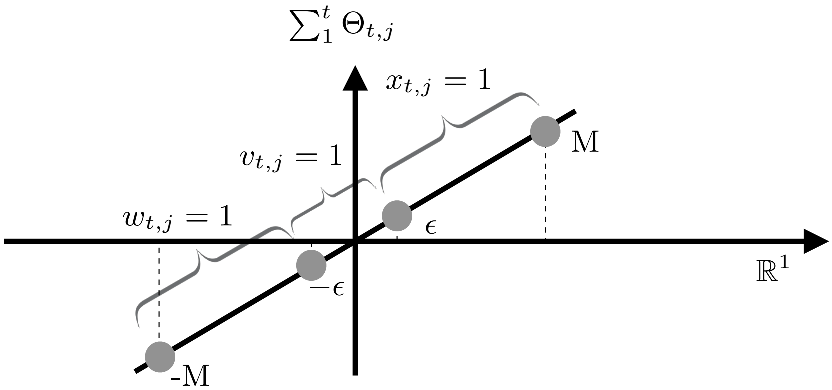

Figure D.4: Definitions of three possible regions of $\sum_1^t \Theta_{t,j}$.

$$\sum_{t'=1}^{t} \Theta_{t',j} \leq -\epsilon w_{t,j} + M x_{t,j} + \epsilon v_{t,j} \qquad \forall t, j \tag{D.2b}$$

$$x_{t,j} + w_{t,j} + v_{t,j} = 1 \qquad \forall t, j \tag{D.2c}$$

$$v_{t-1,j} - v_{t,j} \leq \sum_{t'=t}^{t+R_j} v_{t',j} \quad , \forall t : [t \in T, t \leq \tau - R_j], j \tag{D.2d}$$

The total amount of flexibility provided by consumer type j until time t, $\sum_1^t \Theta_{t,j}$, can either be zero (when the amounts of down- and up-regulation perfectly compensate each other), positive or negative. For this reason, we define three possible regions for the value of $\sum_1^t \Theta_{t,j}$ in Eqs. (D.2a)-(D.2b). These regions are modelled through three binary variables where only one of them can be non-zero at time t. $x_{t,j}$=1 represents the region where $\sum_1^t \Theta_{t,j}$ has positive values; $w_{t,j}$=1 describes the region where $\sum_1^t \Theta_{t,j}$ has negative values and $v_{t,j}$=1 models the region where $\sum_1^t \Theta_{t,j}$ is zero (see Fig. D.4). To define the three possible regions in the model, we use a big-M formulation, where M is a large constant and ϵ is small constant. Eq. (D.2c) guarantees that $\sum_1^t \Theta_{t,j}$ can only be in one of these regions at time t. Eq. (D.2d) ensures that when consumers start providing flexibility, the RE must be perfectly completed at least once within R_j periods.

D.2.3 Quantifying the flexibility provision

In this subsection, we provide the overall MILP that can schedule the flexibility provision to achieve cost minimisation for each customer type j (see [7]).

$$\min_{L^{\alpha}_{t,j}} \sum_{t=1}^{\tau} \left(\boldsymbol{\lambda}^{\text{base}} + \boldsymbol{\Delta\lambda}^{u}_{t} + \boldsymbol{\Delta\lambda}^{d}_{t}\right) \sum_{j=1}^{J} \left(\boldsymbol{L}^{\text{base}}_{t,j} + \Theta_{t,j}\right) \tag{D.3a}$$

subject to: (D.3b)

$$-\mathbf{r}^{\alpha}_{j} \leq L^{\alpha}_{t+1,j} - L^{\alpha}_{t,j} \leq \mathbf{r}^{\alpha}_{j} \qquad \forall\, t, j, \alpha \tag{D.3c}$$

$$\left(\mathbf{L}^{\max}_{t,j} - \mathbf{L}^{\text{base}}_{t,j}\right) = \Theta^{d} \tag{D.3d}$$

$$\left(\mathbf{L}^{\text{base}}_{t,j} - \mathbf{L}^{\min}_{t,j}\right) = \Theta^{u} \tag{D.3e}$$

$$0 \leq L^{\alpha}_{t,j} \leq u^{\alpha}_{t,j}\Theta^{\alpha}\mathbf{a}^{\alpha}_{t,j} \qquad \forall\, t, j, \alpha \tag{D.3f}$$

$$u^{d}_{t,j} + u^{u}_{t,j} \leq 1 \qquad \forall\, t, j \tag{D.3g}$$

$$y^{\alpha}_{t,j} - z^{\alpha}_{t,j} = u^{\alpha}_{t,j} - u^{\alpha}_{t-1,j} \qquad \forall\, t, j, \alpha \tag{D.3h}$$

$$y^{\alpha}_{t,j} + z^{\alpha}_{t,j} \leq 1 \qquad \forall\, t, j, \alpha \tag{D.3i}$$

$$\sum_{t'=(t_D-1)24+1}^{(t_D-1)24+24} y^{\alpha}_{t',j} \leq \mathbf{n}^{\alpha}_{j} \qquad \forall\, j, \alpha, t_D \tag{D.3j}$$

$$\sum_{t'=t}^{t+\underline{\mathbf{d}}^{\alpha}_{j}} u^{\alpha}_{t',j} \geq \underline{\mathbf{d}}^{\alpha}_{j} y^{\alpha}_{t,j} \tag{D.3k}$$

$$\forall\, t : [t \in T, (t + \overline{\mathbf{d}}^{\alpha}_{j} < \tau)], j, \alpha$$

$$\sum_{t'=t}^{t+\overline{\mathbf{d}}^{\alpha}_{j}} z^{\alpha}_{t',j} \geq y^{\alpha}_{t,j} \qquad (3k) \tag{D.3l}$$

$$\forall\, t : [t \in T, (t + \underline{\mathbf{d}}^{\alpha}_{j} < \tau)], j, \alpha$$

$$\sum_{t=1}^{\tau} \Theta_{t,j} = 0, \qquad \forall\, j \tag{D.3m}$$

The objective function (D.3a) minimises the cost of customer type j for purchasing electricity within the planning horizon of τ periods. In the objective function, the electricity price consists of a base-line component λ^{base} (that covers fixed costs and taxes) and a dynamic component, which might be positive ($\Delta\lambda^{\text{u}}_{t}$) or negative ($\Delta\lambda^{\text{d}}_{t}$) depending on the type of regulation needed. The dynamic price components are assumed to achieve a certain change in consumption

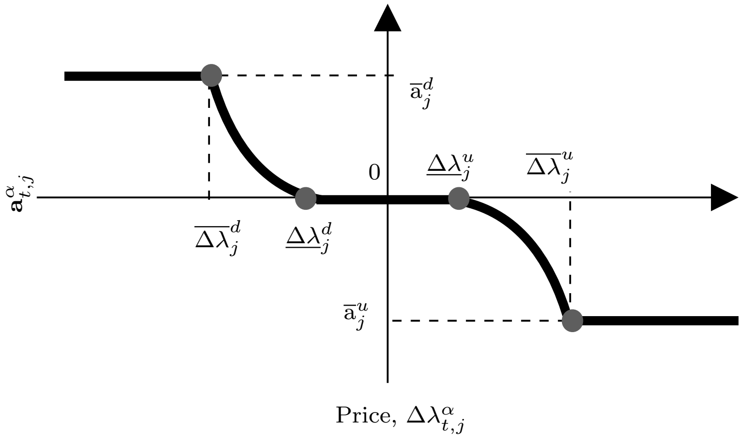

Figure D.5: Modelling consumers' willingness, $\mathbf{a}^{\alpha}_{t,j}$, as a function of delta price.

from the consumers. The constraints are formulated as follows: Eq. (D.3c) is related to the up- and down-ramp limits of the flexible loads, which are represented for each consumer type j by the ramp-rate parameter $\mathbf{r}^{\alpha}_{j}$; Eq. (D.3d)-(D.3f) enforce lower and upper bounds on the amount of flexibility that can be provided by each consumer type j. Note that the minimum and maximum load for each consumer type j at time t, i.e., $\mathbf{L}^{\min}_{t,j}$ and $\mathbf{L}^{\max}_{t,j}$, represent the lowest and highest possible consumption that each consumer type can sustain at time t. In other words, they define the demand flexibility that can be achieved from each consumer type in a specific time.

In Eq. (D.3f), $\mathbf{a}^{\alpha}_{t,j}$ represents the willingness of consumers to provide DR for regulation type α. It is a function of the price and can vary between -1.0 and 1.0. Beyond a certain price threshold, which we define as $\underline{\Delta\lambda}_{j}$, consumers have a willingness of:

$$\mathrm{a}^{\alpha}_{t,j} = \overline{\mathrm{a}}^{\alpha}_{j} \left(\frac{\Delta\lambda^{\alpha}_{t} - \underline{\Delta\lambda}^{\alpha}_{j}}{\overline{\Delta\lambda}^{\alpha}_{j} - \underline{\Delta\lambda}^{\alpha}_{j}} \right)^{\gamma} \tag{D.4}$$

However, beyond a certain cap price, denoted by $\overline{\Delta\lambda}_{j}$, price response saturates and no additional flexibility can be provided. The parameter $\mathbf{a}^{\alpha}_{t,j}$ is also illustrated in Fig. D.5.

In order to include the stochastic behaviour of consumers, we apply chance-constrained (CC) programming to Eq. (D.3f) for a confidence level of $\beta = 95\%$. In order to do that, we assume that $\mathrm{a}^{\alpha}_{t,j}$ follows a normal distribution, as it is related to human behaviour. Eq. (D.3f) is therefore reformulated to:

$$0 \leq L_{t,j}^{\alpha} \leq \mu_{\mathbf{a}}^{\alpha} u_{t,j}^{\alpha} \Theta^{\alpha} + \sigma_{\mathbf{a}}^{\alpha} u_{t,j}^{\alpha} \Theta^{\alpha} \Phi_{\boldsymbol{\beta}}^{-1} \tag{D.5}$$

In this formulation, $\mu_{\mathrm{a}}^{\alpha}$ and $\sigma_{\mathrm{a}}^{\alpha}$ represent the mean value and the standard deviation of $\mathrm{a}_{t,j}^{\alpha}$. For more information about the use of CC programming in this setting, the modelling of $\mathbf{a}_{t,j}^{\alpha}$ and the validity of the normality assumption, please refer to [7].

Eq. (D.3g) ensures that only one type of flexibility (i.e., up- or down-regulation) is provided by consumer type j at time t; Eq. (D.3h) represents the flexibility activation and deactivation for consumer type j at time t; Eq. (D.3i) implies that flexibility provision cannot be activated and deactivated at time t for consumer type j; Eq. (D.3j) enforces a limit on the number of times that a certain consumer type can be activated in a day. Eq. (D.3k)-(3k) refer to the minimum and maximum duration for which the load response can be sustained. Eq. (3m) guarantees that the overall flexibility provided is nullified over the time period.

For the numerical results, we combine the overall model with the two types of RE modelling. In the remainder of this paper, the model with static RE duration is referred to as model A and it consists of Eq. (D.1a) and Eq. (D.3a-D.3l). The model with dynamic RE duration is referred to as model B and involves Eq. (D.2a-D.2d) and Eq. (D.3a-D.3l).

D.3 Numerical results

In this section, we provide the numerical results to quantify the overall flexibility provision when considering different RE models and a computational study of the models. To solve the MILP problem, we use data related to the Danish electricity consumption for different consumers' categories (i.e., residential, commercial and industrial). The data have been collected by Energinet and Dansk Energi during the Elforbrugspanel project and are available at [8]. The values of the parameters which have been used in the simulation studies can be found in [7].

In this study, we investigate the two models A and B for 2 days (i.e., τ = 48 hours) for different delta price sets and temperature settings to identify the range of flexibility that can be provided at each hour. Therefore, we generate 1000 random delta price sets with uniform distribution, assuming that λ^{base}

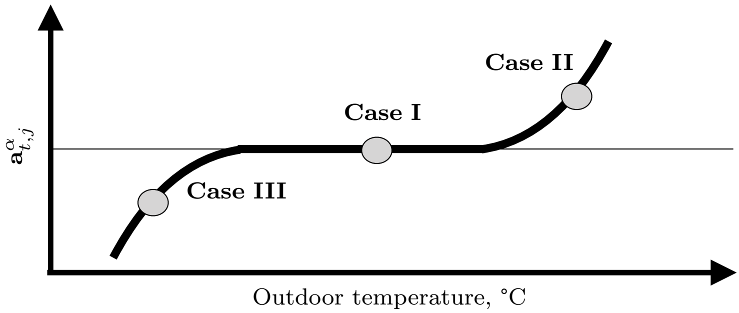

Figure D.6: Relationship between temperature and willingness parameter $\mathbf{a}^{\alpha}_{t,j}$.

is equal to 2.25 DKK/kWh and that the dynamic price set component varies within $\underline{\Delta\lambda}^{\alpha}_{j}$ = 0.2 DKK/kWh and $\overline{\Delta\lambda}^{\alpha}_{j}$ = 0.75 DKK/kWh.

Although $\mathrm{a}^{\alpha}_{t,j}$ is represented only as function of the price in Eq. (D.4), it is possible to extend its modelling and include the effect of the outdoor temperature. In fact, the temperature can have a close relationship to the electricity consumption (see [9]). For example, in summer, extreme temperatures require higher electricity consumption for cooling, as shown in Fig. D.6. Therefore, there might be higher chances for the operator that consumers are willing to provide DR under the condition that their comfort is guaranteed. To include the outdoor temperature in the $\mathrm{a}^{\alpha}_{t,j}$ formulation, we multiply $\bar{\mathrm{a}}^{\alpha}_{j}$ of Eq. (D.4) by a correcting parameter, ν. We consider three cases of outdoor temperatures: Case I deals with a base-line temperature and refers to the initial mean value of $\bar{\mathrm{a}}^{\alpha}_{j}$ (i.e., ν=1); Case II considers $\bar{\mathrm{a}}^{\alpha}_{j}$ for higher outdoor temperature (i.e., ν=1.1); Case III models $\bar{\mathrm{a}}^{\alpha}_{j}$ for lower outdoor temperature (i.e., ν=0.9).

We modelled both MILPs in GAMS 24.9.1 using Gurobi 8.1.0 as solver. The experiments where carried out on Intel(R) Core(TM) i7-2600 CPU 3.40GHz processor with 16 GB of RAM.

D.3.1 Socioeconomic analysis

In this subsection, we investigate the overall benefits achieved by the operator (by procuring flexibility) and the consumers (by minimising their electricity cost) through the proposed DR program with different RE models. The overall electricity cost for the consumers and the aggregate amount of flexibility achieved are given in Table D.1.

From the table, it can be seen that model A achieves a lower amount of flexibility

Table D.1: Average values of the flexibility provided and of the overall electricity cost.

RE model	Case	Flexibility provided [MWh]	Electricity cost [million DKK]
A	I	600.31	380.47
B	I	874.59	380.11
A	II	714.67	380.33
B	II	1032.10	379.92
A	III	482.89	380.60
B	III	714.50	380.30

than model B (about 31.3%). This is due to the fact that consumers in model A are more constrained by the RE formulation. Consequently, consumers in model A pay a higher cost for procuring electricity (i.e., 0.1%, 360,000 DKK). However, the difference in electricity cost depends on the price formulation (which in this case are capped and, therefore, limiting the cost reduction). From Table D.1, it can be further seen that the temperature affects the overall flexibility and cost, where Case II leads to an amount of flexibility that is around +45% more than Case III, and consequently, to an overall electricity cost that is around 320,000 DKK lower. In Figs. D.7 and D.8, the ranges of the overall flexibility that can be achieved for the two different types of RE are plotted. The results are obtained by running the simulations for 1000 different price sets considering Case I for the temperature setting.

From Figs. D.7 and D.8, we can see differences in the daily electricity consumption. This is due to the choice of the type of days represented, which are Sunday and Monday. The plots confirm the results given in Table D.1, because Fig. D.7 shows less flexibility in comparison with Fig. D.8. For example, model A achieves a range of flexibility between 4.5 and 4.7 MW for hour 37, while this range is between 4.4 and 4.7 MW for model B (i.e., +50% than model A). Furthermore, when referring to the sample daily price response plotted in red, we can see that the total amount of flexibility provided by model A for up-regulation (or down-regulation, as the amount of regulation flexibility is the same for each flexibility direction α) is only 436 MWh, while model B provides 700 MWh. It also confirms that model B is able to achieve a higher amount of flexibility throughout the day.

In summary, it can be concluded that, when approaching model A for the entire pool of heterogeneous consumers, the operator might behave rather conservative in setting the dynamic prices. In fact, such a model overlooks a significant amount of the flexibility potential, which could be delivered between different

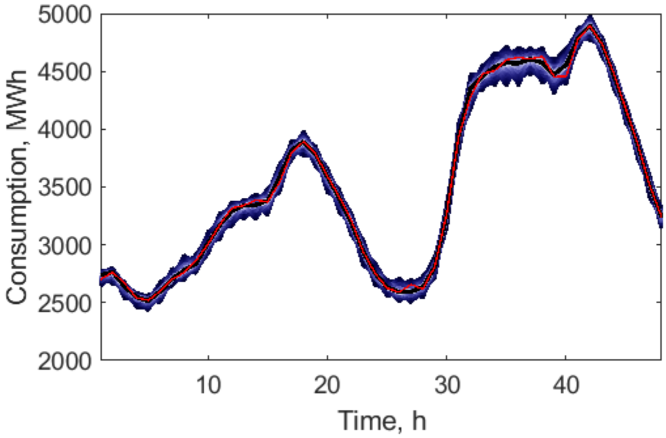

Figure D.7: Range of consumption achieved when considering static RE (i.e., model A). Base-line consumption (in black); Sample daily price response (in red).

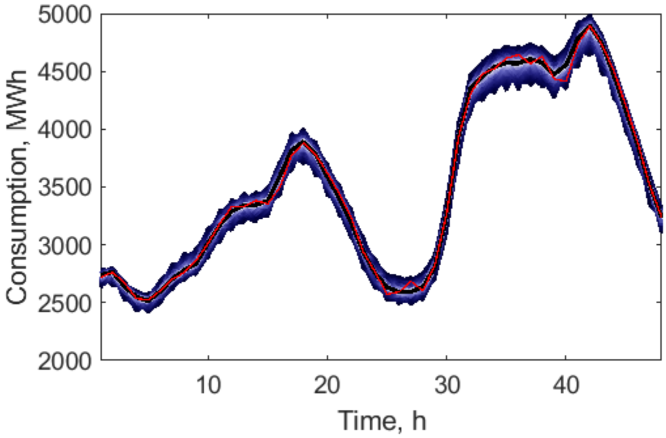

Figure D.8: Range of consumption achieved when considering dynamic RE (i.e., model B). Base-line consumption (in black); Sample daily price response (in red).

R_j periods. Therefore, it is crucial for the operator to understand the dynamics of the flexible loads and combine the two RE models to be able to quantify the aggregate flexibility potential. Moreover, the operator needs to take into account the effect of the temperature on the overall price response of consumers, as this factor influences the overall results. If the dynamic prices submitted to the consumers are capped, the overall cost reduction might not be that significant for the consumers.

D.3.2 Modelling benchmark

Beside the different results in electricity cost and amount of flexibility provided, it is also interesting to investigate the computational performance of the two modelling approaches. In Table D.2, we report the solution time, number of binary variables, MIP gap, number of equations and number of discrete variables for model A and B. From the table, we can conclude that model B takes longer to solve than model A. In our experimental setup, model A could be solved in less than 1 second on average, while model B required more then 82 seconds. The longer solution time can be explained by the larger amount of variables and equations in model B, in particular, the additional binary variables related to Eqs. (D.2a)-(D.2d). However, both models can be solved to optimality within a reasonable amount of time, which is indicated by the remaining MIP gap of 0.00 (i.e. less than the MIP gap tolerance of 10^{-5} set in the solver). We can conclude that the more flexible formulation of the RE requires some additional computational effort.

Table D.2: Computational results of the two RE models (solution time (t); MIP gap (Gap); number of variables (#Var), number of binary variables (#Bin.V), number of equations (#Eq)

RE	t[s]	Gap[%]	#Var.	#Bin.V.	#Eq.
A	0.61	0.00	15402	8352	28451
B	82.41	0.00	19578	12528	33573

D.4 Conclusions

This paper investigates different approaches for modelling the RE of electrical consumers that respond to price-based DR programs. Two RE models are formulated as MILPs and applied to quantify the aggregate amount of flexibility that can be achieved when time-varying electricity prices are submitted to flexible consumers. In this study, the stochastic nature of consumers' behaviour toward prices is considered by approaching CC programming. The effect of the temperature is also investigated on the overall consumers' price response. Moreover, a computational study is provided for both models' performance, where the overall electricity cost of consumers and the amount of flexibility achieved by the operator are highlighted and compared for different RE models.

From the numerical results, it can be concluded that different RE models lead to significant changes in the overall flexibility provision. Therefore, it is crucial for the operators to have a deep understanding of the types of loads they deal with so that they can estimate the amount of flexibility more accurately.

Due to the field data scarcity, we assume the condition of perfect RE in this study (i.e., where increase and decrease in consumption perfectly compensate each other). However, in future studies, an imperfect RE condition will be investigated for different consumers' categories.

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Nomenclature

Sets:

T Set of time periods, indexed by t, $t \in [1, \ldots, \tau]$.
J Set of consumers types, indexed by j.
α Types of regulation, i.e., up- or down-regulation.
D Set of days, indexed by t_D, $t_D \in [1, \ldots, \frac{\tau}{24}]$.

Parameters:

R_j Maximum rebound effect duration for consumer type j [h].
$\boldsymbol{\lambda}^{\text{base}}$ Base-line electricity price [DKK cent/Wh].
$\boldsymbol{\Delta\lambda}_t^{\text{u}}$ Dynamic electricity price for up-regulation at time t [DKK cent/Wh].
$\boldsymbol{\Delta\lambda}_t^{\text{d}}$ Dynamic electricity price for down- regulation at time t [DKK cent/Wh].
$\underline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$ Minimum delta prices for regulation type α of consumer type j [DKK cent].
$\overline{\boldsymbol{\Delta\lambda}}_j^{\alpha}$ Maximum delta prices for regulation type α of consumer type j [DKK cent].
$\mathbf{L}_{t,j}^{\text{base}}$ Base-line consumption of consumer type j at time t [W].
$\mathbf{L}_{t,j}^{\text{min}}$ Minimum electricity consumption of consumer type j at time t [W].
$\mathbf{L}_{t,j}^{\text{max}}$ Maximum electricity consumption of consumer type j at time t [W].
$\mathbf{a}_{t,j}^{\alpha}$ Willingness of consumer type j to provide flexibility type α at time t [p.u.].
$\overline{\mathbf{a}}_{t,j}^{\alpha}$ Maximum willingness of consumer type j to provide flexibility type α at time t [p.u.].
$\mathbf{r}_j^{\alpha}$ Ramp-rate of consumer type j for regulation type α [W/h].
$\mathbf{n}_j^{\alpha}$ Maximum number of activations for consumer type j to provide flexibility type α.
$\underline{\mathbf{d}}_j^{\alpha}$ Minimum continuous flexibility duration of consumer type j when activated to provide flexibility type α [h].
$\overline{\mathbf{d}}_j^{\alpha}$ Maximum continuous flexibility duration of consumer type j when activated to provide flexibility type α [h].

Variables:

$L_{t,j}^{\alpha}$ Flexibility of end-users' category j at time t for regulation type α [W].
$x_{t,j}$ Binary variable defining the region when the overall flexibility provided up to time t by end-users' category j is positive.

$w_{t,j}$ Binary variable defining the region when the overall flexibility provided up to time t by end-users' category j is negative.

$v_{t,j}$ Binary variable defining the region when the overall flexibility provided up to time t by end-users' category j is perfectly compensated.

$u_{t,j}^{\alpha}$ Binary variables, indicating flexibility status of end-users' category j at time t for regulation type α.

$y_{t,j}^{\alpha}$ Starting binary variable of end-users' category j at time t for flexibility type α.

$z_{t,j}^{\alpha}$ Stopping binary variable of end-users' category j at time t for flexibility type α.

$\Theta_{t,j}$ Overall flexibility provided at time t from consumer type j [W].

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Paper E

A Control-based Method to Meet TSO and DSO Ancillary Services Needs by Flexible End-Users

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A Control-based Method to Meet TSO and DSO Ancillary Services Needs by Flexible End-Users

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Abstract

This paper presents a new methodology to exploit consumers' flexibility for the provision of ancillary services (AS). The proposed framework offers a control-based approach that adopts price signals as the economic driver to modulate consumers' response. In this framework, various system operators broadcast price signals independently to fulfil their AS requirements. Appropriate flexibility estimators are developed from the transmission system operator (TSO) and distribution system operator (DSO) perspectives for price generation. An artificial neural network (ANN) controller is used for the TSO to infer the price-consumption reaction from pools of consumers in its territory. A PI controller is preferred to represent the consumers' price-response and generate time-varying electricity prices at the DSO level for voltage management. A multi-timescale simulation model is built in MATLAB to assess the proposed methodology in different operational conditions. Numerical analyses show the applicability of the proposed method for the provision of AS from consumers at different levels of the grid and the interaction between TSO and DSOs through the proposed framework.

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E.1 Introduction

Ancillary services (AS) are key elements to guarantee the stability and continuity of the electricity supply. They consist of up- and down-regulation services in different timescales to assist in grid frequency and voltage regulation, and congestion management. Traditionally, AS were provided by conventional generation units (CGUs) with fast ramp-up and down capabilities. However, in a power system with large penetration of renewable energy sources (RES), where most of the RES are not able to provide balancing services effectively [1], the AS provision cannot solely rely on the CGUs [2]. This issue is intensified by many CGUs retiring from the generation fleet due to low energy prices. In addition, higher penetration of RES leads to a higher demand of AS [3], which must be properly addressed to avoid extreme AS pricing events. This is happening already in the California Independent System Operator (CAISO), where the total AS market value raised from US$20M in 2015 to US$172M in 2017 [4]. Therefore, finding cheap flexibility resources (such as load demand flexibility) is necessary to provide short- and medium-term AS [5] that can cope with the sources of uncertainty involved in the future power system operation [6]. Although the potential of demand flexibility for AS has been proven in many research studies, only a marginal contribution from load flexibility has been realised for AS provision in practice. One reason is that involving millions of consumers in the AS provision requires tremendous computational power and increases the complexity of the existing AS markets due to non-linearity, stochasticity and dynamic characteristics of the demand. Therefore, the true potential of the demand flexibility has yet to be exploited in power systems.

In the last decade or so, the potential of different types of flexible consumers has been investigated for AS provision at different levels of the grid. For instance, a flexibility platform (called Flex operator) was proposed in the SmartNet project [7] to aggregate demand flexibility and offer AS to the system operators (SOs) in real time. However, as discussed in [8], such a framework might lead to operational conflicts (i.e., prioritisation of operators) and remuneration issues (i.e., double remuneration when an asset can satisfy the needs of both TSO and DSO). It also increases the complexity of the AS market for dealing with numerous aggregators with specific capabilities and drawbacks. In [9], the transactive energy (TE) approach was proposed as a market-based solution to unlock the flexibility from the end-users through the adoption of a two-way communication scheme. However, requiring feedback from the end-users complicates the grid infrastructure, compromises the scalability of the solution, and raises concerns regarding cyber-security and required computational efforts. The pros and cons of the TE framework are outlined by the authors in [10].

Quantifying demand flexibility is key to the AS planning of future power systems. In this direction, [11] characterises energy flexibility by a dynamic function. Such a tool enables the SO to determine which grid problem could be managed by the consumers' flexibility after the submission of a certain signal. In [12], aggregate flexibility of residential loads is estimated based on consumption availability, typical usage patterns, and technical constraints. However, such an approach is not data-driven, which makes the estimation less practical.

In this paper, we implement a new AS mechanism (called AS4.0) based on delta price signals. In the proposed method, each SO is allowed to optimally fulfil its requirements by quantifying the available demand flexibility in their area. Each SO generates a real-time price that is submitted to a pool of price-responsive consumers. Such prices are created by the demand flexibility estimator that each SO formulates based on its requirements and the pool of consumers. When consumers receive the time-varying prices, they alter their consumption to minimise their operation cost using local controllers, i.e., energy management systems (EMSs). In order to examine the performance of the proposed AS method, a multi-timescale simulation model is developed in this study including TSO and DSO operation. The load-frequency control (LFC) model is implemented at the TSO level for frequency regulation. At the DSO level, voltage is monitored at steady state by solving a power flow problem. The goal is to allow TSO and DSO to regulate frequency and voltage, respectively, by submitting a single delta price to their respective pool of consumers. The time-varying prices are generated at the TSO and DSO levels independently through an artificial neural network (ANN) and a PI controller, respectively. At the TSO level, the aggregated price-response of the consumers is modelled through a mixed-integer linear program (MILP) that minimises the operational cost of the end-users [13]. Multiple simulation studies are carried out to reveal the performance of AS4.0 for frequency and voltage regulation. The proposed approach can be thought as a supporting tool for AS provision, similar to the Flexible Ramping Product (FRP) in CAISO [14] and the Ramp Capability (RC) in Midcontinent ISO (MISO) [15]. The main contributions of the paper can be summarised as follows:

- Developing a comprehensive multi-timescale model of TSO and DSO interaction for AS4.0 evaluation.
- A novel demand flexibility formulation at the TSO level which considers a dynamic rebound effect.
- Offering an ANN-based price generator for the TSO operation.

The rest of the paper is organised as follows. In Section E.2, the AS4.0 setup is briefly explained, while Section E.3 provides the mathematical models for its implementation. In Section E.4, simulation results are discussed in detail. Finally, Section E.5 concludes the paper.

E.2 A Brief Description of the AS4.0 Mechanism

The AS4.0 mechanism uses control techniques to provide AS at different spatio-temporal scales of the grid using a delta price signal. Through the generation and submission of time-varying prices that depend on the actual conditions of the grid, each SO is able to exploit the flexibility of the consumers that are located in its territory. Upon receiving time-varying prices by the EMSs [16], consumers react to minimise their electricity cost.

A high-level discussion of the AS4.0 setup is provided in [10] and [13].

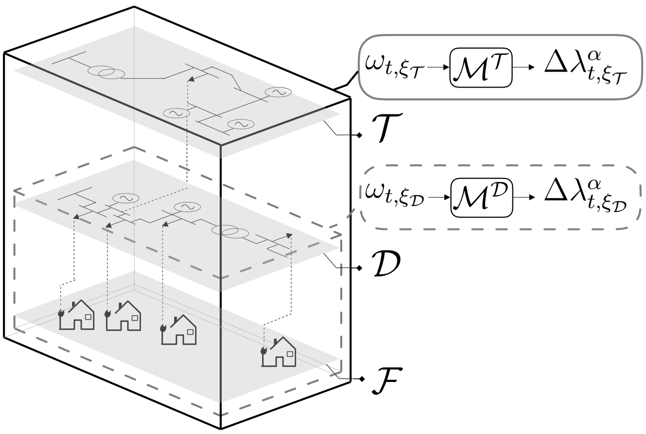

Figure E.1: Conceptual representation of the AS4.0 mechanism.

Structurally, the grid can be divided into three spatial levels, i.e., $\xi \in \Xi = \{\mathcal{T}_1, \cdots, \mathcal{T}_M, \mathcal{D}_1, \cdots, \mathcal{D}_N, \mathcal{F}\}$, for the operation of the AS4.0 in an interconnected power system with multiple control areas, as shown in Fig. E.1. These levels consist of G control areas, i.e., $\xi_\mathcal{T} = \{\mathcal{T}_1, \cdots, \mathcal{T}_G\}$, N distribution systems, i.e., $\xi_\mathcal{D} = \{\mathcal{D}_1, \cdots, \mathcal{D}_N\}$, and demand flexibility resources, $\mathcal{F}$. Based on the required AS, each spatial level can further be divided in different time scales. AS is required when a disturbance occurs in the power system (planned/unexpected outages, renewable generation variations, load changes, etc.). Regardless of the source of the disturbance, the TSO operation will observe a frequency deviation. Let the total power disturbance (which is the one that is seen by the TSO) be denoted by $\omega_{\xi_\mathcal{T}} = \{\omega_{t,\xi_\mathcal{T}} \in \mathbb{R}^+ : t \in \tau\}$ at time $t \in \tau = \{k\Delta t \mid 1 \leq k \leq B\}$. The disturbance at the DSO level is given by $\omega_{\xi_\mathcal{D}} = \{\omega_{t,\xi_\mathcal{D}} \in \mathbb{R}^+ : t \in \tau\}$, which is a fraction of $\omega_{\xi_\mathcal{T}}$, i.e., $\omega_{\xi_\mathcal{D}} = \chi\ \omega_{\xi_\mathcal{T}}$. It is worth mentioning that frequency regulation is performed continuously in a large power system. In this paper, we solve LFC model on a continuous basis, however control actions in the AS4.0 are discrete, i.e., every Δt seconds. Once the power disturbance hits, the TSO solves a control problem, denoted by $\mathcal{M}^{\mathcal{T}}$, to quantify the required AS based on the frequency deviation and formulate the price signal, denoted by $\Delta\lambda^{\alpha}_{\xi_{\mathcal{T}}} = \{\Delta\lambda^{\alpha}_{t,\xi_{\mathcal{T}}} \in \mathbb{R}^{+} : t \in \tau\}$. Superscript α specifies the type of regulation (i.e., $\alpha = u$ for up-regulation, and $\alpha = d$ for down-regulation). The price signal is submitted to the EMS of all flexible consumers located within the TSO's territory [17]. If the delta price is appropriate, the collective consumers' reaction will result in the desired change in consumption to compensate for the original disturbance and, therefore, stabilises system's frequency.

At the distribution level, a similar idea can be adopted for voltage regulation, congestion management, or load curtailment. In this case, only the flexible consumers connected to the distribution system in the DSO's territory will receive a time-varying price, denoted by $\Delta\lambda^{\alpha}_{\xi_{\mathcal{D}}} = \{\Delta\lambda^{\alpha}_{t,\xi_{\mathcal{D}}} \in \mathbb{R}^{+} : t \in \tau\}$. In principle, it is possible for the two SOs to broadcast delta prices asynchronously to their respective territories according to their requirements at different timescales.

The issues related to the DSO (e.g., voltage violation) are local and the DSO requires flexibility from a limited portion of consumers, as opposed to frequency issues, which are system-wide. Therefore, it is unlikely for the TSO and DSOs to compete for flexibility procurement. However, with the lack of coordination between different SOs, contradicting delta prices could be submitted to the same group of consumers with the aim of unlocking flexibility in opposite directions [8], leading to system instability. Therefore, a coordination scheme between different SOs is imperative to avoid such conditions. Since a TSO-territory involves a larger pool of consumers compared to that of a DSO, it is reasonable to assume that the TSO has a higher chance to gain a certain aggregate response. Hence, the priority is given to the DSO in times of conflict. This way, consumers in the conflicting zones will only receive the time-varying prices submitted by the DSO. The remaining pool of consumers will still receive the prices generated by the TSO.

E.3 AS4.0 Modelling

In this section, we provide models to simulate the power system's response at various spatio-temporal scales. Without loss of generality, the network issues at the TSO and DSO levels are limited to frequency and voltage regulation, respectively. As shown in Fig. E.2, the behaviour of the system frequency is simulated by the load-frequency control (LFC) model at the transmission level, $\xi_{\mathcal{T}}$. Layer $\mathcal{D}$ models the aggregate effect on the low- and medium-voltage distribution grids. The different parts of the simulation model in Fig. E.2 are explained in detail in the following.

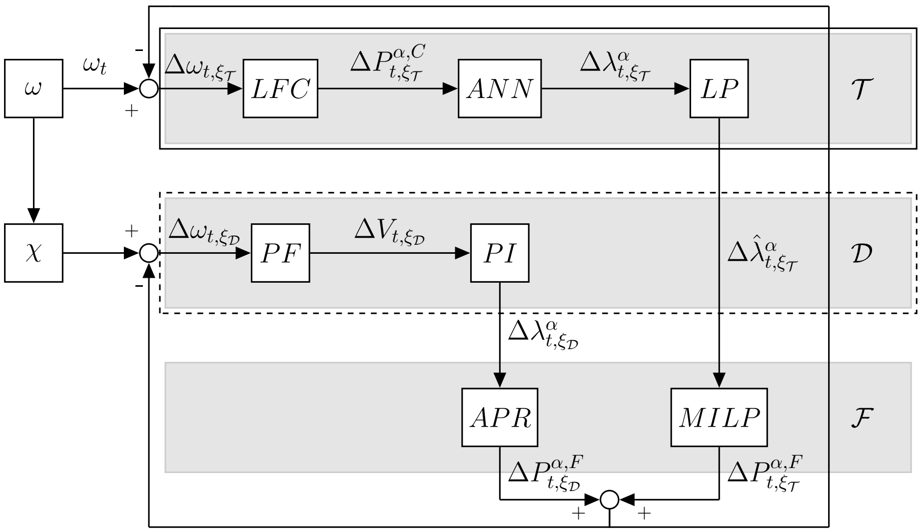

Figure E.2: The structure of AS4.0 simulation model.

E.3.1 TSO Model

To study the system's frequency response to disturbances, an LFC model is used [18]. The LFC model consists of a primary and secondary frequency control loop. The output of the controller is the amount of power, i.e., $\Delta P^{\alpha,C}_{\xi_\mathcal{T}} = \{\Delta P^{\alpha,C}_{t,\xi_\mathcal{T}} \in \mathbb{R}^+; t \in \tau\}$, that should be changed to stabilise frequency. The main role of the primary regulation is to arrest frequency excursions within a second or so. Therefore, it is a local control that is automatically provided by the CGUs and is generally modelled as a droop control [18]. Secondary regulation is a central automatic control carried out by the TSO to correct the steady-state frequency error within a couple of minutes by ramping up or down the eligible generators [18]. Various control methodologies, such as a linear-quadratic regulator (LQR) in [19] and a model-predictive control in [20], have been developed to this end. In Fig. E.3, a two-area LFC model (resembling the Danish transmission network with DK1 and DK2 areas [21]) is shown with an inter-tie connection, and primary and secondary control loops, in black and red blocks. For simplicity, the overall effect of the CGUs is modelled by a single non-reheat steam turbine unit [18]. The power disturbance and the resulting frequency deviation are denoted by $\omega_{t,\xi_{\mathcal{T}_1}}$ and $\Delta f_{t,\xi_{\mathcal{T}_1}}$, respectively, for area $\mathcal{T}_1$, and $\omega_{t,\xi_{\mathcal{T}_2}}$ and $\Delta f_{t,\xi_{\mathcal{T}_2}}$, respectively, for area $\mathcal{T}_2$ at time $t \in \tau$. An LQR is used in this study as the LFC controller, whose design is discussed in [19].

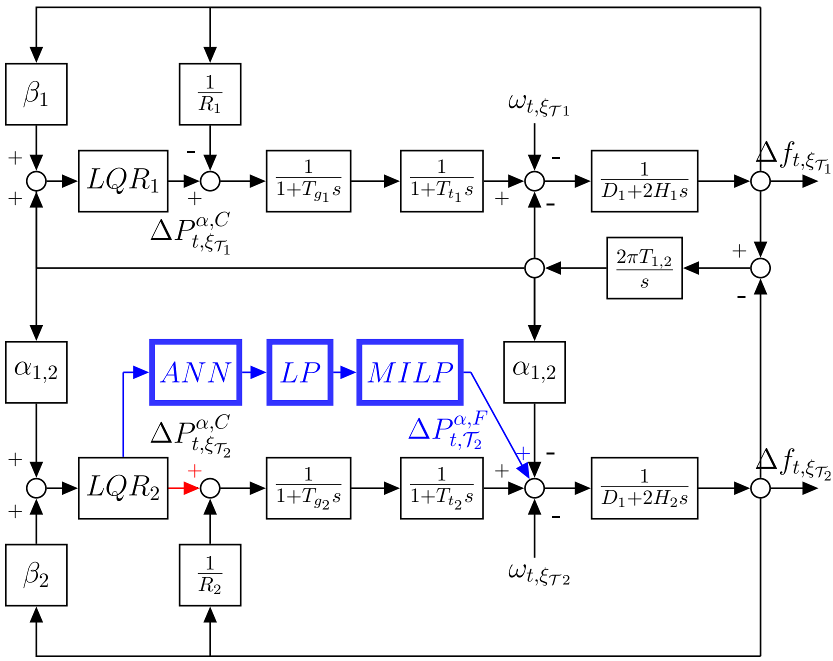

Figure E.3: LFC model of a two-area power system at the TSO level: Conventional model in black and red, AS4.0 model in black and blue.

The AS4.0-LFC model is shown in black and blue blocks in Fig. E.3. The conventional secondary loop is replaced by demand's contribution to frequency regulation in area $\mathcal{T}_2$, to evaluate AS4.0 performance. In the modified LFC model, $\Delta P^{\alpha,C}_{t,\xi_{\mathcal{T}_2}}$ is the required control effort for frequency regulation in area $\mathcal{T}_2$. The TSO generates delta prices based on $\Delta P^{\alpha,C}_{t,\xi_{\mathcal{T}_2}}$, and the realised flexibility affecting the balance between generation and demand is denoted by $\Delta P^{F}_{t,\xi_{\mathcal{T}_2}}$.

E.3.1.1 Artificial Neural Network (ANN)

A functional relationship between the amount of flexibility required by the TSO, i.e., $\Delta P^{\alpha,C}_{t,\xi_{\mathcal{T}_2}}$, and the price signal, i.e., $\Delta\lambda^{\alpha}_{t,\xi_{\mathcal{T}_2}}$, is needed for the TSO operation in the AS4.0 framework. ANN is found to be a suitable tool as it can map complex and non-linear inter-dependencies between electricity price, historical consumption and other factors (e.g., temperature and day of the week) [22]. In this study, we assume that consumers react to price signals by shifting their loads throughout the day. As a result, the input/output parameters to/from the ANN model should be daily profiles. Required data for ANN training are generated by simulation studies, where thousands of daily price profiles, $\Delta\Lambda^{\alpha}_{\xi_\mathcal{T}} = \{\Delta\Lambda^{\alpha}_{h,\xi_\mathcal{T}} \in \mathbb{R}^+ : h \in \mathbb{N}_{24}\}$, are generated using a normal distribution, as proposed in [13]. Then, the reaction of the consumers to the price signals is modelled through a MILP problem. This problem and the aforementioned ANN model are described in subsections E.3.3.1 and E.4.1.1, respectively.

E.3.1.2 Daily Price Neutrality

Due to the heterogeneous condition of the transmission and distribution system infrastructures in different areas, the consumers in under-developed areas will potentially face higher prices compared to others. In an attempt to avoid price discrimination, the sum of all delta prices is enforced to be as close as possible to zero over a day. To achieve that, the TSO solves a linear program (LP) that tries to marginally change a given delta price profile so that $\sum_{h=1}^{H} \Delta\Lambda^{\alpha}_{h,\xi_\mathcal{T}} \rightarrow 0$, $\forall\alpha \in \{u, d\}$. The new price signal is denoted by $\Delta\hat{\Lambda}^{\alpha}_{\xi_\mathcal{T}}$ and the LP is formulated as:

$$\min_{L,\Delta\hat{\lambda}^{\alpha}_{h,\xi_\mathcal{T}}} \quad L \tag{E.1a}$$

subject to:

$$\sum_{h=1}^{24} \Delta\hat{\lambda}^{\alpha}_{h,\xi_\mathcal{T}} + L = 0 \tag{E.1b}$$

$$\Delta\hat{\lambda}^{\alpha}_{h,\xi_\mathcal{T}} - \Delta\lambda^{\alpha}_{h,\xi_\mathcal{T}} \leq \psi \cdot \Delta\lambda^{\alpha}_{h,\xi_\mathcal{T}} \qquad \forall\ h, \alpha \tag{E.1c}$$

$$\Delta\hat{\lambda}^{\alpha}_{h,\xi_\mathcal{T}} - \Delta\lambda^{\alpha}_{h,\xi_\mathcal{T}} \geq -\psi \cdot \Delta\lambda^{\alpha}_{h,\xi_\mathcal{T}} \qquad \forall\ h, \alpha \tag{E.1d}$$

where Eq. (E.1b) defines the overall deviation from neutrality, denoted by L, over a day; and ψ is the maximum allowed relative difference between the new and old price at time h, which is enforced by Eq. (E.1c) and (E.1d).

E.3.2 DSO Model

Voltage issues may especially arise in populated areas with a large number of roof-top PV panels in the low-voltage networks. When voltage violation occurs due to disturbance $\omega_{t,\xi_{\mathcal{D}}}$, the issue may be resolved by load demand flexibility in that area. To exploit that flexibility, the DSO generates a delta price, denoted by $\Delta\lambda^{\alpha}_{t,\xi_{\mathcal{D}}}$, through a control problem. The dynamic prices are then submitted to the buses with voltage issues. The load flexibility service continues for a certain amount of time (30 seconds in this study) until the source of the voltage disturbance disappears.

Since the voltage at a bus depends on the load and generation in that bus and in neighbouring buses, and in order to increase the chances of getting enough load demand response, a price signal will be sent to a cluster of buses (and not only to the single bus with the voltage issue). Therefore, the DSO formulates a delta price for each cluster in accordance with an effective voltage metric (e.g., average voltage deviation of each cluster) in that cluster. In this study, the buses are clustered in two groups based on their location in the network. A PI controller is used to generate a dynamic price for each cluster from the voltage metric. In order to avoid extreme prices, a price cap, $\overline{\Delta\lambda}_{\xi_{\mathcal{D}}}$, is imposed, which also represents the upper limit of price reaction. It means that the pool of consumers cannot provide additional flexibility beyond this value due to load characteristics [23].

E.3.3 Flexibility resources

Next, we provide models to estimate the aggregate consumers' price-response from the TSO's and DSOs' standpoints. Since the TSO and DSO deal with two different pools of consumers (in size, type and response time), we use specific models for each of them. The load flexibility model at the DSO level is only used to quantify load changes due to delta prices. For the TSO, however, a MILP formulation is used to develop an ANN-based controller and to quantify the actual flexibility obtained from the consumers for simulation purposes. In practice, the actual load variations can be estimated by the aggregate measurements at the distribution and transmission substations.

E.3.3.1 Consumers' price response model at the TSO level

A MILP is formulated in this paper in which consumers' cost of electricity is minimised. Theoretical background, assumptions, and the parameters of the 29 load categories that are considered here are discussed in detail in [13]. The proposed MILP formulation accounts for the rebound effect that occurs when providing flexibility from consumption [24], and it constitutes a major improvement with respect to our previous model in [13]. The MILP problem is formulated as follows:

$$\min_{L^{\alpha}_{h,j,\xi_{\mathcal{T}}}} \left[\sum_{h=1}^{24} \left(\lambda^{\text{base}}_{\xi_{\mathcal{T}}} + \Delta\lambda^{u}_{h,\xi_{\mathcal{T}}} + \Delta\lambda^{d}_{h,\xi_{\mathcal{T}}} \right) \sum_{j=1}^{J} \left(P^{\text{base}}_{h,j} + \Delta P^{d,F}_{h,j,\xi_{\mathcal{T}}} - \Delta P^{u,F}_{h,j,\xi_{\mathcal{T}}} \right) \right] \tag{E.2a}$$

subject to: (E.2b)

$$-\,\mathrm{r}^{\alpha}_{j} \leq \Delta P^{\alpha,F}_{h+1,j,\xi_{\mathcal{T}}} - \Delta P^{\alpha,F}_{h,j,\xi_{\mathcal{T}}} \leq \mathrm{r}^{\alpha}_{j} \qquad \forall\ h, j, \alpha \tag{E.2c}$$

$$0 \leq \Delta P^{d,F}_{h,j,\xi_{\mathcal{T}}} \leq u^{d}_{h,j} \left(P^{\max}_{h,j} - P^{\text{base}}_{h,j} \right) \mathrm{a}^{d}_{h,j,\xi_{\mathcal{T}}} \qquad \forall\ h, j \tag{E.2d}$$

$$0 \leq \Delta P^{u,F}_{h,j,\xi_{\mathcal{T}}} \leq u^{u}_{h,j} (\mathrm{P}^{\text{base}}_{h,j} - \mathrm{P}^{\min}_{h,j}) \mathrm{a}^{u}_{h,j,\xi_{\mathcal{T}}} \qquad \forall\ h, j \tag{E.2e}$$

$$\epsilon x_{h,j} - M w_{h,j} - \epsilon v_{h,j} \leq \sum_{h'=1}^{h} \left(\Delta P^{d,F}_{h',j,\xi_{\mathcal{T}}} - \Delta P^{u,F}_{h',j,\xi_{\mathcal{T}}} \right) \qquad \forall\ h, j \tag{E.2f}$$

$$\sum_{h'=1}^{h} \left(\Delta P^{d,F}_{h',j,\xi_{\mathcal{T}}} - \Delta P^{u,F}_{h',j,\xi_{\mathcal{T}}} \right) \leq -\epsilon w_{h,j} + M x_{h,j} + \epsilon v_{h,j} \qquad \forall\ h, j \tag{E.2g}$$

$$x_{h,j} + w_{h,j} + v_{h,j} = 1 \qquad \forall\ h, j \tag{E.2h}$$

$$v_{h-1,j} - v_{h,j} \leq \sum_{h'=h}^{h+R_j} v_{h',j} \qquad \forall\ h : [h \in \mathbb{N}_{24}, h \leq \tau - R_j], j \tag{E.2i}$$

$$u^{d}_{h,j} + u^{u}_{h,j} \leq 1 \qquad \forall\ h, j \tag{E.2j}$$

$$y^{\alpha}_{h,j} - z^{\alpha}_{h,j} = u^{\alpha}_{h,j} - u^{\alpha}_{h-1,j} \qquad \forall\ h, j, \alpha \tag{E.2k}$$

$$y^{\alpha}_{h,j} + z^{\alpha}_{h,j} \leq 1 \qquad \forall\ h, j, \alpha \tag{E.2l}$$

$$\sum_{h=1}^{\tau} y^{\alpha}_{h,j} \leq \mathrm{n}^{\alpha}_{j} \qquad \forall\ j, \alpha \tag{E.2m}$$

$$\sum_{h'=h}^{h+\underline{\mathrm{d}}^{\alpha}_{j}} u^{\alpha}_{h',j} \geq \underline{\mathrm{d}}^{\alpha}_{j} y^{\alpha}_{h,j} \qquad \forall\ h : [h \in \mathbb{N}_{24}, (h + \underline{\mathrm{d}}^{\alpha}_{j} < \tau)], j, \alpha \tag{E.2n}$$

$$\sum_{h'=h}^{h+\overline{\mathrm{d}}^{\alpha}_{j}} z^{\alpha}_{h',j'} \geq y^{\alpha}_{h,j} \qquad \forall\ h : [h \in \mathbb{N}_{24}, (h + \overline{\mathrm{d}}^{\alpha}_{j} < \tau)], j, \alpha \tag{E.2o}$$

The objective function in Eq. (E.2a) calculates the cost of electricity for each end-users' category j within a day. The electricity price contains a flat price,

λ^{base} (covering fixed costs and taxes), and a time-varying price, $\Delta\lambda^{\alpha}_{h,\xi_{\mathcal{T}}}$, that is generated by the TSO. The electricity consumption is given by a baseline consumption, $P^{base}_{h,j}$, and the overall flexibility provided is $\Delta P^{\alpha,F}_{h,j,\xi_{\mathcal{T}}}$ from load category j at time h for regulation type α (i.e., $\alpha = u$ for a decrease in consumption, and $\alpha = d$ for an increase in consumption). Eq. (E.2c) enforces the up- and down-ramp-rate limits, r^{α}_{j}, for category j; Eq. (E.2d) and (E.2e) define minimum and maximum load flexibility that can be provided by category j. In this study, the minimum and maximum load for category j at time h, i.e., $\mathrm{P}^{\min}_{h,j}$ and $\mathrm{P}^{\max}_{h,j}$, are obtained from historical aggregate data for that category at time h. In this equation, $u^{\alpha}_{h,j}$ is the flexibility status variable for category j at time h for regulation type α. The parameter $\mathrm{a}^{\alpha}_{h,j,\xi_{\mathcal{T}}}$ represents the willingness of each consumer in category j to adjust load at time h for a certain flexibility type α. The consumers' willingness depends on the price they receive among other factors (e.g., temperature and day of the week). More details about the modelling of consumers' willingness is presented in [13]. We assume that $\mathrm{a}^{\alpha}_{h,j,\xi_{\mathcal{T}}}$ is computed by:

$$\mathrm{a}^{\alpha}_{h,j,\xi_{\mathcal{T}}} = \overline{\mathrm{a}}^{\alpha}_{j,\xi_{\mathcal{T}}} \frac{\Delta\lambda^{\alpha}_{h,\xi_{\mathcal{T}}}}{\max\left(\Delta\lambda^{\alpha}_{h,\xi_{\mathcal{T}}}\right)} \tag{E.3}$$

where $\overline{\mathrm{a}}^{\alpha}_{j,\xi_{\mathcal{T}}}$ is the maximum price responsiveness of category j for flexibility type α and $\max\left(\Delta\lambda^{\alpha}_{h,\xi_{\mathcal{T}}}\right)$ is the maximum value of the price set received. Eqs. (E.2f-E.2i) enforce the energy rebound effect (RE) for category j. In particular, we consider that the total amount of flexibility provided by consumer type j until time t can either be zero (when the amounts of up- and down-regulation perfectly counterbalance), positive or negative. These three cases are modelled by Eqs. (E.2f)-(E.2g) through binary variables $w_{h,j}, v_{h,j}$ and $x_{h,j}$, and the large and small constants M and ϵ, respectively. Eq. (E.2h) guarantees that only one of these binaries can be nonzero at time t. Eq. (E.2i) ensures that, when consumers start providing flexibility, the RE must be realised within R_j periods. Eq. (E.2j) ensures that only one type of flexibility (i.e., up- or down-regulation) is provided by category j at time h; Eqs. (E.2k) and (E.2l) represent the flexibility activation and deactivation for category j at time h, where $y^{\alpha}_{h,j}$ and $z^{\alpha}_{h,j}$ are the starting and stopping binary variables of category j at time h, respectively, for flexibility type α. Eq. (E.2m) enforces a limit on the number of times that category j can be activated in a day, where n^{α}_{j} is the number of times that a flexibility resource can be activated for load category j for flexibility type α. Eqs. (E.2n-E.2o) refer to the minimum ($\underline{\mathrm{d}}^{\alpha}_{j}$) and maximum ($\overline{\mathrm{d}}^{\alpha}_{j}$) duration for which the load response can be sustained. The values of the parameters used in the MILP are provided in [13].

E.3.3.2 Consumers' price-response model at the DSO level

The composition of the loads changes from one area to another from the DSO' s perspective. Therefore, using the MILP model at the DSO level will be overwhelming computationally as it will require specific model for each area. Moreover, it needs a profound knowledge of the load composition at each bus or area, which is not available. Therefore, an alternative solution is proposed for price response estimation at the DSO level, as the following aggregate price response (APR) function:

$$\Delta P_{F,t}^{\mathcal{D},\alpha} = 0 \qquad |\Delta\lambda_t^{\mathcal{D},\alpha}| \leq \underline{\Delta\lambda}_t^{\mathcal{D},\alpha} \tag{E.4a}$$

$$\Delta P_{F,t}^{\mathcal{D},\alpha} = \mathrm{a}_t^{\mathcal{D},\alpha} P_t^{base} \left(\frac{\Delta\lambda_t^{\mathcal{D},\alpha} - \underline{\Delta\lambda}_t^{\mathcal{D},\alpha}}{\overline{\Delta\lambda}_t^{\mathcal{D},\alpha} - \underline{\Delta\lambda}_t^{\mathcal{D},\alpha}} \right)^{\gamma} \qquad \underline{\Delta\lambda}_t^{\mathcal{D},\alpha} \leq |\Delta\lambda_t^{\mathcal{D},\alpha}| \leq \overline{\Delta\lambda}_t^{\mathcal{D},\alpha} \tag{E.4b}$$

$$\Delta P_{F,t}^{\mathcal{D},\alpha} = \mathrm{a}_t^{\mathcal{D},\alpha} P_t^{base} \qquad |\Delta\lambda_t^{\mathcal{D},\alpha}| \geq \overline{\Delta\lambda}_t^{\mathcal{D},\alpha} \tag{E.4c}$$

In Eq. (E.4b), $\Delta P_{t,\xi_{\mathcal{D}}}^{\alpha,F}$ is modelled as the product of three terms, consisting of the baseline consumption P_t^{base}, the willingness parameter, $\mathrm{a}_{t,\xi_{\mathcal{D}}}^{\alpha}$, and a price ratio. $\mathrm{a}_{t,\xi_{\mathcal{D}}}^{\alpha}$ represents the flexibility of consumers, which varies between 0 and 1. It can be a function of weather conditions, and load and day type, whose values are provided in [13]. A certain price response is achieved only when the price signal is bigger than a threshold price, i.e., $\underline{\Delta\lambda}_{\xi_{\mathcal{D}}}^{\alpha}$, [25]. Also, according to [26], the response saturates beyond a certain price signal, i.e., $\overline{\Delta\lambda}_{\xi_{\mathcal{D}}}^{\alpha}$.

The block-diagram shown in Fig. E.4 provides an overview of the simulation model of the entire system that was shown in Fig. E.2. As it can be seen from the figure, some assumptions are made:

- From the timescale point of view, two sets of simulations and models are designed in this paper: hourly ($h \in \mathbb{N}_{24}$) and second-by-second ($t \in \tau$). The former timescale is used in consumers' reaction modelling, as it is the only way to account for the consumers rebound effect. Therefore, the ANN model, the MILP model in Eq. (E.2a)-(E.2o) and the LP formulation in Eq. (E.1b)-(E.1d) are hourly for an entire day. In the hourly models, prices, i.e., $\Delta\Lambda_{\xi_{\mathcal{T}}}^{\alpha}$, are generated and submitted every hour and the disturbance is given by $\omega_{\xi_{\mathcal{T}}}$. The latter timescale, i.e., second-by-second, is used to run simulation for frequency (TSO model) and voltage regulations (DSO model). In this timescale,

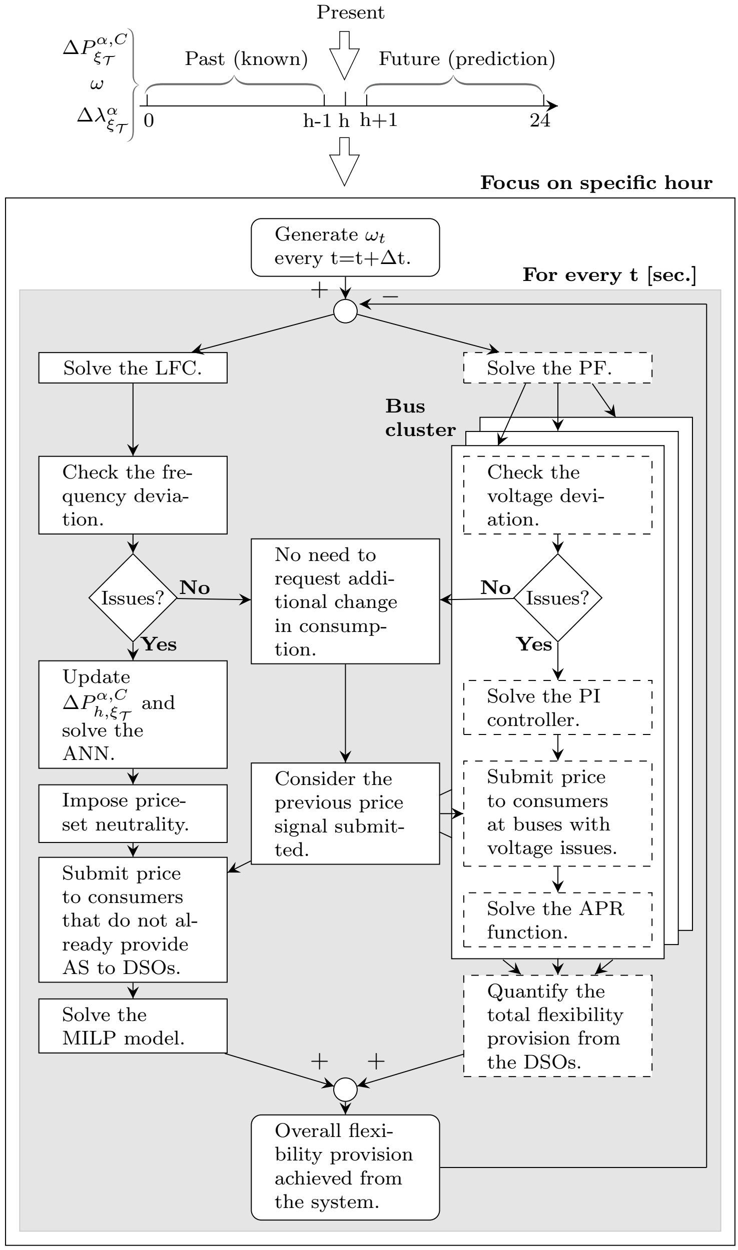

Figure E.4: Conceptual block-diagram of the simulation model.

prices ($\Delta\lambda^{\alpha}_{\xi_\mathcal{T}}$ and $\Delta\lambda^{\alpha}_{\xi_\mathcal{D}}$) are generated by TSO and DSO, respectively, and submitted every second (i.e., $\Delta t = 1$ second), and the system disturbances are $\omega_{\xi_\mathcal{T}}$ and $\omega_{\xi_\mathcal{D}}$. In order to solve hourly functions (e.g., MILP, price neutrality function and ANN) within the dynamic simulation model at hour h, as shown in Fig. E.4, the price/disturbance is placed in the hourly vector for hour h. While the hourly operation was inevitable because of limited data availability, all algorithms can be performed in higher resolution when high resolution data is available. As it is shown in Fig. E.4, values of the hourly vectors from hour 0 to hour $h-1$ are known, while the values of the future (i.e., from $h+1$ to 24) are estimated by prediction.

- Required flexibility from the consumers throughout the day at the TSO level is estimated with hourly resolution, denoted by $\Delta P^{\alpha,C}_{\xi_\mathcal{T}} = \{\Delta P^{\alpha,C}_{h,\xi_\mathcal{T}} : h \in \mathbb{N}_{24}\}$. This value is updated by the LFC model for hour h, and the new vector will be used as the input in the ANN model.

- It is assumed that delta prices are estimated for the entire day, which is defined in hourly basis and denoted by $\Delta\Lambda^{\alpha}_{\xi_\mathcal{T}} = \{\Delta\lambda^{\alpha}_{t,\xi_\mathcal{T}} \in \mathbb{R} : t \in \tau\}$. When running the simulations at hour h, only the present and future time steps are generated by the ANN, while the previous time steps are given by historical values.

- A certain external power disturbance is imposed on the system every $\Delta t = 30$ seconds during dynamic simulations, denoted by $\omega_{\xi_\mathcal{T}} = \{\omega_{t,\xi_\mathcal{T}} \in \mathbb{R} : t \in \tau\}$. Only a portion, i.e., χ, of the $\omega_{\xi_\mathcal{T}}$ reaches the DSO level, i.e., $\omega_{\xi_\mathcal{D}}$. Therefore, the DSO's load is modified according to the $\omega_{\xi_\mathcal{D}}$ disturbance at each iteration.

From the figure, it can be seen that the consumers' response to the delta prices issued by an SO affect the operation of other SOs. This has been modelled properly in the proposed framework. In this study, the DSO and TSO solve their control problems simultaneously.

E.4 Simulation Studies

In this section, simulation studies are carried out to assess the validity of the AS4.0 mechanism under different power disturbances. The LFC model is implemented for the Danish transmission system consisting of two areas of 3 GW peak demand each. Actual data from the Elforbrugspanel project [27] is used for the TSO level MILP model. A modified IEEE 33-bus standard distribution system is used to model the DSO network, where original loads are modified to avoid voltage violations at the beginning of the simulation. We consider to deal with 158 distribution grids, each based on the IEEE 33-bus system. Such a number is decided from the maximum power handled by a single DSO model and the size of the TSO area. Frequency and/or voltage regulation is initiated if the deviation exceeds a certain threshold. In order to show the impact of rebound effects on the performance of AS4.0, simulations are repeated for two hours, $h = \{5{:}00, 15{:}00\}$. The daily required flexibility ($\Delta P^{\alpha,C}_{\xi_\mathcal{T}}$) and prices ($\Delta\Lambda^{\alpha}_{\xi_\mathcal{T}}$) at the TSO level are generated randomly. Other general simulation parameters are given in Table E.1.

Table E.1: General simulation parameters.

ω_t injection every Δt [sec]	Time period simulated ,B [sec]	Max range of ω_t [MW]
30	270	1500

Simulation models are implemented in MATLAB and GAMS, which uses OS-IGUROBI solver. The power flow problem at the DSO level is solved using the MatPower 6.0 package in MATLAB.

E.4.1 AS4.0 Operation at the TSO Level

In this sub-section, the AS4.0 performance and the ANN training will be analysed for frequency regulation at the TSO level. In Table E.2, specific simulation parameters to TSO operation are given.

Table E.2: TSO parameters in the simulations study.

ψ $[-]$	$\underline{\Delta\lambda}^{\alpha}_{\xi_\mathcal{T}}$ $[\frac{\text{DKK}}{\text{kWh}}]$	$\overline{\Delta\lambda}^{\alpha}_{\xi_\mathcal{T}}$ $[\frac{\text{DKK}}{\text{kWh}}]$	ANN training price-sets	ϵ $[-]$	M $[-]$	f tol. $[pu]$
0.01	0.2	1	5000	0.1	20000	± 0.01

The ANN model is trained using 5000 sets of daily delta prices generated by random uniform distribution. Each delta price set is bounded by the dead-band and saturation price values, as discussed in subsection E.3.3.2, and has a null sum over the day. The ANN is trained using MATLAB Neural Net Fitting toolbox.

E.4.1.1 Artificial neural network performance

To define the optimal ANN structure (i.e., number of neurons in the hidden layer and training sample size), a sensitivity analysis is executed. The results are reported in Table E.3 along with mean squared error (MSE) and the correlation coefficient [28] for comparison. Typically, the number of neurons in the hidden layer is between the size of the input and the output [29], and it was changed between 10 to 24 for the sensitivity analysis. On the other hand, larger training samples, if providing better statistical representation of the underlying system, can improve ANN performance. The number of samples are varied from 1000 to 5000 in this study.

Table E.3: Sensitivity analysis for ANN model structure.

Observations sample size	Neurons in the hidden layer	Training perform. MSE	Training perform. R	Test perform. MSE	Test perform. R
1000	10	0.25	0.65	0.27	0.62
5000	10	0.25	0.64	0.26	0.64
1000	24	0.02	0.97	0.02	0.97
5000	24	0.01	0.98	0.01	0.98

It can be noticed that larger training samples and 24 neurons led to the best performance. However, despite the outstanding performance of the ANN, a small modelling error exists (i.e., R=0.98 and MSE=0.01), which indirectly represents the lack of perfect knowledge of the consumers' behaviour. In other words, if the MILP solutions are the actual realised flexibility from the consumers, then ANN model drifts away from true values by a small amount, as expected in practice. The existence of controller (i.e., LQR) at the TSO level, however, guarantees obtaining frequency regulation over time.

E.4.1.2 Frequency regulation

Table E.4 shows the system's frequency deviations at the end of each disturbance at steady state. The values are reported for the two areas: Area $\mathcal{T}_1$ in which CGUs provide secondary regulation services, and Area $\mathcal{T}_2$, where flexibility is provided through AS4.0.

Overall, the results show that the AS4.0 mechanism always outperforms CGU-based AS, reducing the frequency deviation up to 60% after 30 seconds. This is because of the faster response of load flexibility to price signals. From the table, it can be noticed that availability of the consumers' flexibility depends on the time of the day, which depends on the values of $\mathrm{P}_{h,j}^{\mathrm{min}}$, $\mathrm{P}_{h,j}^{\mathrm{max}}$ and $\mathrm{P}_{h,j}^{\mathrm{base}}$ as well as the rebound effect. The dynamic performance of frequency regulation is shown in Fig. E.5. It is clear from the figure that the frequency regulation is superior in AS4.0 mechanism in comparison with the CGU-based AS in terms of settling

Table E.4: Performance benchmark for AS4.0 and CGU-based AS.

Time and disturbance injected, [sec, MW]	Maximum frequency deviation, Hz			Deviation reduction, %	
	CGUs-based AS	AS4.0			
		Hour 5	Hour 15	Hour 5	Hour 15
[1, 1000]	+0.10	+0.04	+0.06	60%	40%
[30, 350]	-0.27	-0.14	-0.13	48%	52%
[60, 852]	+0.21	+0.13	+0.13	38%	38%
[90, 500]	-0.26	-0.15	-0.16	42%	38%
[120, 1148]	+0.20	+0.12	+0.12	40%	40%
[150, 1000]	-0.12	-0.07	-0.08	41%	33%
[180, 1300]	+0.14	+0.09	+0.08	35%	42%
[210, 1056]	-0.17	-0.10	-0.11	41%	35%
[240, 1500]	+0.12	+0.07	+0.07	41%	41%

time and overshooting.

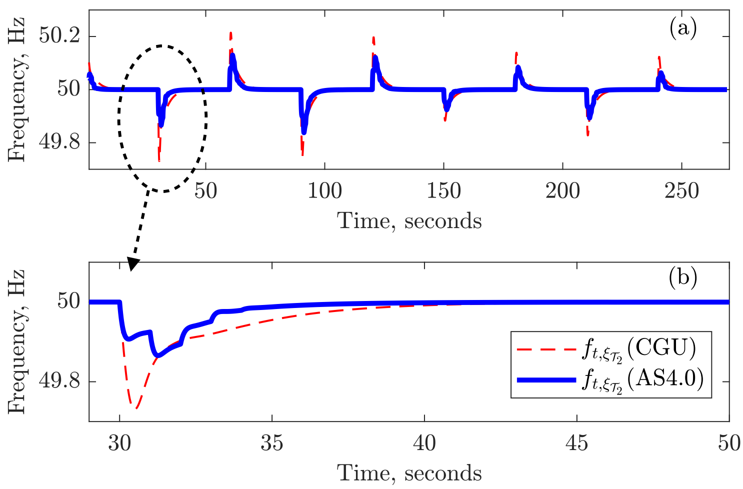

Figure E.5: Frequency profile of the system in $\mathcal{T}_2$ area at hour 15:00. (a) Overall frequency. (b) Zoomed-in part to see dynamics.

E.4.1.3 Price response

In Fig. E.6, the delta prices and consumers' reactions are shown for the same simulation study at the TSO level in hour 15:00. From the figure, it can be seen that the TSO obtained 268 MW flexibility from the load demand (in a system with 3 GW peak load) by submitting a positive delta price of 0.84 DKK/kWh. On the other hand, the TSO could manage to increase load consumption by 211 MW through a negative delta price of 0.82 DKK/kWh.

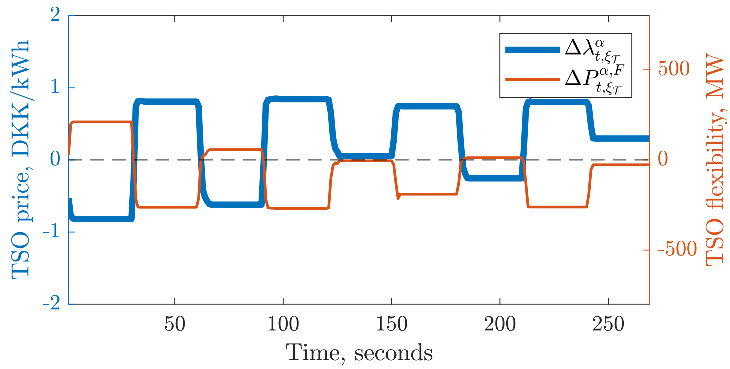

Figure E.6: Delta prices and the corresponding response from consumers at the TSO level at hour 15:00.

E.4.2 AS4.0 Operation at the DSO Level

In this sub-section, the performance of AS4.0 at the DSO level is examined for voltage regulation. Related parameters for the simulation model at the DSO level are presented in Table E.5. The PI controller coefficients, i.e., K_p and K_i, are selected in a way to achieve fastest response without oscillation and large overshoot by trial and error. In the APR function, $\gamma = 2$ models conservative consumers that only respond to large delta prices.

Table E.5: DSO parameters in the simulations study.

γ [$-$]	K_p [$-$]	K_i [$-$]	$\overline{\Delta\lambda}^{\alpha}_{\xi_\mathcal{D}}$ [$\frac{\text{DKK}}{\text{kWh}}$]	Buses clusters	V tol. [pu]	DSOs affected by $\Delta\omega_{t,\xi_\text{D}}$
2	-4	-0.5	1	2	$\pm$0.05	10%

E.4.2.1 Voltage regulation

In Fig. E.7, the voltage at different buses are shown over time. It can be seen that the voltage at several buses violate the lower limit (i.e., 0.95) at the beginning of the disturbances. However, the delta prices offered by the DSO manage to mitigate the issues in less than 10 seconds in most cases. Moreover, the figure shows that the voltage violations are not the same in the two different hours, i.e., $h = \{5{:}00, 15{:}00\}$, because of the different consumers preferences during the day, as discussed in subsection E.4.1.1.

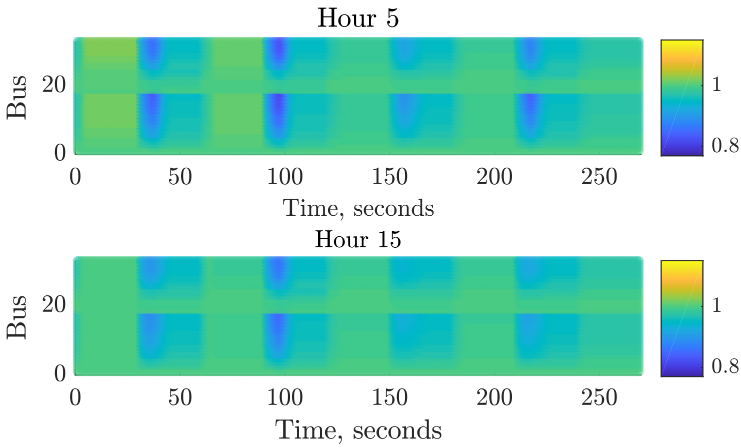

Figure E.7: Voltage at different buses in hour 5:00 and 15:00.

In Fig. E.8, the number of buses with voltage issues are plotted along with the frequency response of the system. It is observed that i) the number of buses with voltage issues decreases in time and ii) the frequency evolution in time shows that the DSO operation does not compromise the TSO operation for frequency regulation. Therefore, independent and simultaneous operation of TSO and DSO is indeed plausible without jeopardising the system stability.

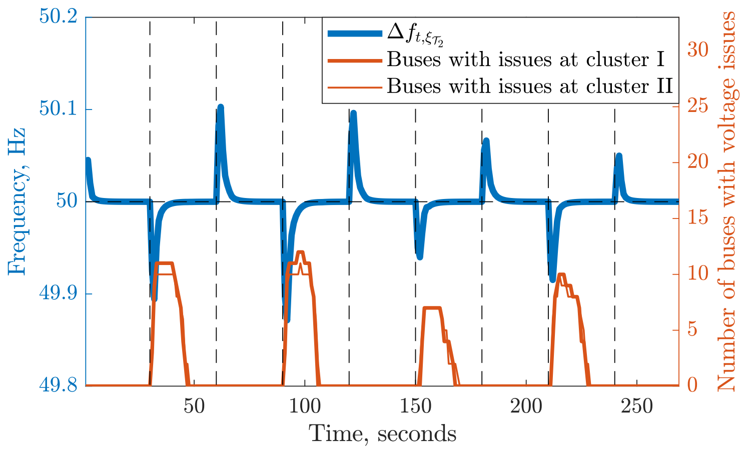

Figure E.8: Number of buses with voltage violations along with the system's frequency at hour 15:00.

E.4.2.2 Price response

In Fig. E.6, the delta prices and corresponding consumers' response are provided for the two clusters at the DSO level. When a voltage violation occurs, the PI controller starts generating a price signal that keeps increasing until the voltage issues are resolved within the cluster. The delta price will be maintained until the power disturbance disappears or another disturbance hits the network.

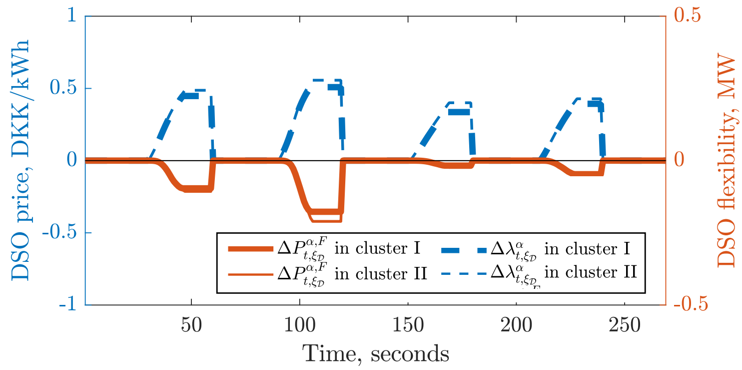

Figure E.9: Delta prices and corresponding flexibility at the DSO level at hour 15:00.

It can be seen from the figure that a significant power disturbance caused low voltage issues at many buses at 30 seconds. During this time, the PI controller generated a positive delta price that increased to 0.57 DKK/kWh to induce 202 kW of decrease in consumption to regulate voltage in those buses. This operation did not have any negative impact on the rest of the system.

E.5 Conclusions

This paper provides a control-based solution for the provision of AS from the consumers, which is called AS4.0. In this alternative approach, the SOs at different levels of the grid submit time-varying prices to the pool of consumers at their territory to address different operational issues. Consumers receive price signals in their energy management systems and react to minimise their electricity cost. The proposed AS mechanism is explained and appropriate simulation models and estimation algorithms are developed to implement the proposed mechanism. At the transmission level, we used a MILP to represent the price-response of the consumers accounting for the loads' rebound effect. Then, an ANN model is developed based on the MILP problem to generate appropriate prices to induce the required flexibility. At the distribution level, the aggregate price response of the consumers is modelled through an APR function and appropriate delta prices are generated by a PI controller.

Simulation results prove that both TSO and DSO are able to resolve operational issues through the AS4.0 approach simultaneously, and the performance of frequency regulation is better by way of AS4.0 compared to the conventional AS provision. In spite of the promising results in this paper, the AS4.0 approach needs to be further tested with high-resolution data, allowing a better representation of the price-response of the consumers at a higher scale. Moreover, the possibility of conflict and competition between TSO and DSO in obtaining flexibility from the load demand should be further investigated and appropriate coordination methods should be developed.

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