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Güray Kara

Stochastic programming in analyses of flexibility in power systems and markets

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of
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Management

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"For everything in the world, for civilization, for life, for success, the truest guide is knowledge and science. To search for a guide other than knowledge and science is somnolence, ignorance, error. ...It is necessary to be aware of and understand the evolution of the stages and to follow the progress of knowledge and science at every moment of our lives"

Mustafa Kemal Atatürk
(Samsun/Turkey, 1924)

Abstract

After a high level of integration of variable renewable energy resources and distributed energy resources to distribution level networks, a transformation from supplier-centric to consumer-centric power system and market architecture is initiated. It is important to ease this transformation for market and system participants in a cost-efficient setting.

In the research for this thesis, I used techniques of operations research applied in power markets and systems to investigate the usage of flexibility under conditions of uncertainty. I established economic dispatch models and optimal power flow models for designing and analyzing power markets and systems. In the economic dispatch models, I analyzed economic factors and their relations with power markets, while in optimal power flow models, I searched for answers to power grid operations for voltage and network congestion. All models and decisions were constructed and solved in a stochastic decision-making environment. During the research, the first research question addressed was how to determine the flexibility concept, products, and services with regard to various power and energy markets. This led to the development of a theoretical and empirical taxonomy for flexibility trading and related market structures. The second question addressed during the research considered how to use flexibility according to two separate systemic approaches, different tariff designs to exploit flexibility usage for reducing peak pricing, and a stochastic optimal scheduling methodology for end user's flexibility assets to solve grid problems. The third and final question addressed during the research concerned how it is possible to have a cost-efficient and productive local flexibility market design for grid operations under uncertainty.

Answers to the research questions are provided in the four papers that form the basis of this thesis. Paper I explains the taxonomy and provides an overview of flexibility and its products along four dimensions—time, spatiality, resource, and risk profile—according to the market design. Paper II shows how to activate and use flexibility with a dynamic tariff design for peak shaving. Paper III provides solutions to grid problems under uncertainty (i.e., voltage and congestion) by using flexibility from the demand side, storage side, and supply side. Lastly, Paper IV proposes a stochastic local flexibility market design, bidding, and dispatch methodology to contribute grid operations on a local scale.

I determined the flexibility along different dimensions, used it for grid operations, and designed a market that increases cost-efficiency and system productivity. Thus, the use of the flexibility concept increases the quality of power systems and markets. The flexibility is useful both via direct procurement from end users and via a local flexibility market design with an aggregator. In both approaches, I achieved cost-efficient grid operations and increases in welfare.

The results presented in this thesis indicate that the four dimensions of flexibility (i.e., time, spatiality, resource, and risk) are important for understanding modeling and trading in markets, in addition to modeling them. The flexibility needs to be valued in an optimal market design. In practice, flexibility allows for cost-efficient solutions to grid problems such as voltage drops and congestion under uncertainty. Furthermore, a local flexibility market design can provide flexibility-based services to the grid via optimal price signals.

Together, the four papers contribute to the literature on the usage of flexibility in power and energy markets. In a particular research area, from the understanding of flexibility to the design of a market for flexibility, this thesis provides and insights into the transformation of power systems and markets and answers to problems arising from the transformation.

Acknowledgments

This thesis is a result of my 4 years of work at the Norwegian University of Science and Technology (NTNU) at the Department of Industrial Economics and Technology Management. I always consider myself lucky to meet all the people I have met during my PhD process. The contributions of my supervisor, my co-supervisors, and co-authors made this research possible to complete. Because of my university, my department, and the CINELDI research center, I had opportunities to travel across the globe and to develop my intellectual and scientific knowledge.

First and foremost, I would like to express my gratitude to my supervisor, Professor Asgeir Tomasgard (INDØK). His support, ideas, and supervision really shaped this thesis. In his busy schedule, he always replied to my need for help. His patience for all my questions and his feedback for my thesis developed me and my research to a higher level.

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Third, I express my sincere thanks to my other co-supervisor, Dr. Paolo Pisciella (INDØK) for his help and guidance in mathematical programming and co-authorship. His contributions to our papers helped me to complete this thesis. His insights in modeling developed my modeling skills during my PhD process.

Further, I would like to thank my co-authors, Stian Backe (INDØK) and Dr. Pedro Crespo del Granado (INDØK). They are perfect collaborators, both of them contributed to my thesis beautifully. I am grateful to Stian for inviting me to our paper in the first place and I am grateful to Pedro for his insights about flexibility markets, operations research, and how to publish and align myself in the literature.

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Contents

Chapter 1

Introduction

The utilization of the end-user flexibility becomes more important when there is a high share of integration of variable renewable energy resources (VREs). Some VREs are adaptable in small sizes for households on a local scale, such as rooftop solar panels (i.e., as photovoltaic systems, PVs). Therefore, under uncertainty, power generation increases especially on the local scale. Furthermore, it is possible to use changes in the consumption or generation pattern of end users—*flexibility*—by providing them incentives to have more elasticity in their demand.

In this PhD thesis, I examine the flexibility of power systems and markets, its usage, and local flexibility market designs under uncertainty. The research for this thesis was primarily conducted in Norway. The work on this thesis has been funded by the Centre for Intelligent Electricity Distribution (CINELDI), as part of Work Package 3: Interaction DSO/TSO. The research center and work package aim to promote the usage of flexibility, especially end-user flexibility, for balancing grid operations and supply-demand in order to delay investments in grid infrastructure.

According to the main scope of the project, three main research questions for this thesis were identified:

1. What is the flexibility of end users and generators in power markets and systems along time, spatiality, resource, and risk dimensions?

2. How can flexibility be used in grid operations and problem-solving in power systems?

3. Do we need a (local) flexibility market to exploit the value and increase the efficiency of flexibility usage or is direct control over flexibility technologies sufficient?

The four co-authored research papers aim to answer these questions from engineering and economic perspectives in a stochastic environment under conditions of uncertainty.

- Paper I, "Characterization of flexible electricity in power and energy markets", explains the flexibility along time, spatial, resource, and risk dimensions.

- Paper II, "Comparing individual and coordinated demand response with dynamic and static power grid tariffs", investigates the usage and efficient provision of flexibility with a capacity-based and dynamic tariff scheme.

- Paper III, "The impact of uncertainty and time structure on optimal flexibility scheduling in active distribution networks", explains the usage of flexibility for grid operations under uncertainty.

- Paper IV, "Stochastic local flexibility market design, bidding, and dispatch for distribution grid operations", establishes a local flexibility market to increase the efficiency of flexibility usage for grid operations with stochastic demand.

In each paper, we describe its contribution to the literature, as well as the contribution of each author. Furthermore, for the purpose of this thesis, the four papers complement each other. The papers interrelations with each other and with the research questions are illustrated in Figure 1.1.

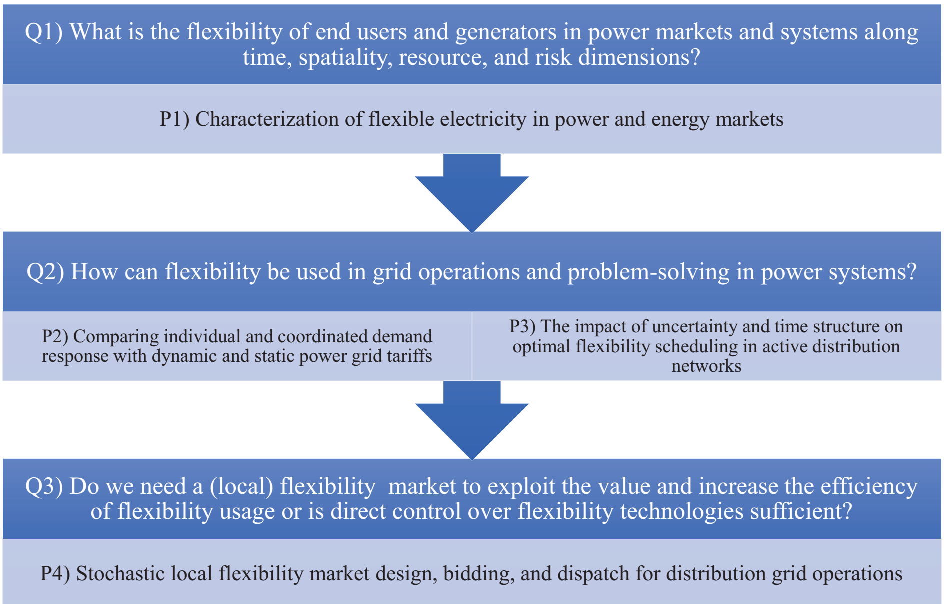

Figure 1.1: Interrelations and structure of research questions and papers in the thesis (Q: Question, P: Paper).

The structure of the thesis as follows. Chapter 1 is the introduction, and provides preliminary information about the research questions and papers. Chapter 2 shows the perspective taken in this thesis and papers with regard to the literature. It provides background information on research relating to the flexibility concept and transformation from supplier-centric to a consumer-centric power system. Furthermore, it explains existing power market designs and their sufficiency/insufficiency for flexibility usage. Thereafter, I discuss the research methodology of the thesis. Chapter 3 summarizes the four research papers and their scientific contribution by emphasizing the specific contributions of each author. In Chapter 4, I present my conclusions and suggest directions for further research. Thereafter, research papers that form the bases of this thesis are presented.

Chapter 2

Background and Literature

The purpose of this chapter is to provide a solid perspective on where the research presented in this thesis stands in the academic literature on operations research, industrial economics, and power markets/systems. First, I provide information about the flexibility concept and why we need research for flexibility usage. Second, I describe the demand for the flexibility in power markets and systems. Third, I provide information from the literature on the transformation from a supplier-centric market and system architecture to a consumer-centric architecture. Fourth, I give brief information about current energy-only and/or capacity-based markets by considering their sufficiency for flexibility usage. Fifth, and finally, I introduce the research method used for this thesis.

2.1 Flexibility in power systems and markets

The concept of *flexibility* has long existed in production economics. A supplier can shift or reduce its production according to changes in market demand, and this a fundamental type of flexibility type that can be observed in every free market. In the context of power markets and systems, the flexibility concept is a characteristic of energy resources that are valued on the basis of energy prices, resources, time, and geography [1]. Flexibility is not a service itself, but has been a concept since the first days of electricity generation. Earlier power markets and systems were solely based on the supplier technologies and flexibility in their generation patterns due both to low electrification (low demand) and controllable power plants. Thus, the term 'controllable' refers to a group of power generation technologies that provide a certain amount of power at a specific time to a specific place, regardless of the fuel technology used to generate it. After the introduction of intermittent (variable) renewable power generation technologies, a transformation started to make end users more flexible in coping with variability in power generation. Subsequently, power markets and systems were transformed from supplier-centric architecture to consumer-centric architecture for more intermittent renewable power. In this chapter, the supplier side, consumer side, and the transformation are explained.

2.1.1 Supplier-centric system and flexibility

In traditional power systems and markets before recent developments on communication and power generation technologies, the system architecture was supplier-centric. Hence, to make an improvement in the system, one had to work with suppliers with traditional technologies such as coal plants, nuclear plants or hydropower plants. It was not possible to communicate with consumers directly or efficiently to ensure supply-demand balance. Therefore, the system only had the ability to use the flexibility from traditional resources.

Supply-side, which is termed ‘operational flexibility’ by [2], is the oldest flexibility resource in power markets and systems. Suppliers can shift, curtail, or ramp up/down their power generation against changes, peaks, and drops in the demand profiles. Supply-side flexibility is a natural result of the electricity generation process.

The power balance should be sustained by the supply-side flexibility under normal conditions, for example by power plants. Three subcategories of providers of flexibility are baseload, peak load, and load-following power plants. Suppliers can be considered under two categories: controllable plants and uncontrollable plants. Hydropower plants and some of the fossil fuel power plants are controllable plants, whereas VREs (e.g., wind or solar plants), are uncontrollable plants in the sense of power generation. Thus, the curtailment of power generation from VREs is another type of supply-side flexibility. Combined-cycle gas turbines and combined heat and power (CHP) are attractive options for supply-side flexibility from a traditional power system perspective [3]. The existence of conventional power plants (load-following power plants) is helpful because, with their ramp-up and down availability at the right time, it is possible to keep supply-demand balance in the market.

In this PhD thesis, I do not focus on supplier-centric design particularly, but supply-side flexibility and associated market designs are examined in Paper I. Rather, I evaluate conventional and intermittent supply-side flexibility resources along time, resource, risk, and spatiality dimensions in different market designs.

2.1.2 The demand for flexibility

One of the primary objectives of power markets is to create a competitive market environment to prevent the abuse of market power. The transformation in power markets can increase competitiveness [4]. Currently, the power markets, as well as systems, are undergoing transformation. Deregulation and restructuring of power markets increase competition and create regulatory and technological challenges for market participants. By contrast, in monopolistic power markets, restructuring and deregulation of markets create a clear distinction between activities of market agents. The current transformation in power markets has led to increased research activity concerning flexibility, renewable energy, and local power generation [5].

In the case of the transformation of power systems to include more renewables and local production, we need to consider supply-demand balance in local grids, as well as power quality. Solutions to keep systems in balance include VRE production, pooling of resources, restructuring markets to remunerate flexibility, enhancing grid infrastructure, deploying advanced battery technologies, developing demand-side management, and enhancing the cycling capabilities of thermal generators. Many of these solutions are low-cost or investment-free solutions [6].

According to [7], the sharp increase in renewable energy resources, especially VREs, has had a strong impact on the volatility of the residual load in power systems and markets, in addition to the flexibility requirements. However, any market design that provides incentives for total investments on the power system, such as new power plants and grid upgrades with a cost-minimization perspective, will also increase incentives for investments in flexibility. [7] claim that the main reason for new flexibility resources is the achievable full load hours (time intervals with the high demand) with relevant backup capacity for peaks in demand.

To exploit the potential demand for flexibility, sufficient investment signals are needed in competitive market areas. In some cases, without sufficient flexibility supply, system operators may need to shed the load, even frequently. A high number of load shedding periods implemented by a central system operator would reduce the confidence of investors and end users in the market design and the usage of VREs, as well as distributed energy resources (DERs) [8].

When power systems and markets decide to include more VREs, additional flexibility is needed to keep the supply and demand in balance, reduce grid problems, and protect market efficiency. This need for additional flexibility in markets is named the *flexibility gap* by [9], and is illustrated in Figure 2.1. New flexibility options such as intermittent supply-side flexibility, storage flexibility, and demand-side flexibility could fill the gap in a cost-efficient way. In addition to the new flexible electricity technologies, new market design or improvement in existing markets could fill the flexibility gap. In existing markets, some of the improvements have included reducing the minimum bid sizes, having short scheduling periods or bidding periods, dynamic tariffs, and reduced time intervals between gate closure and physical delivery [9].

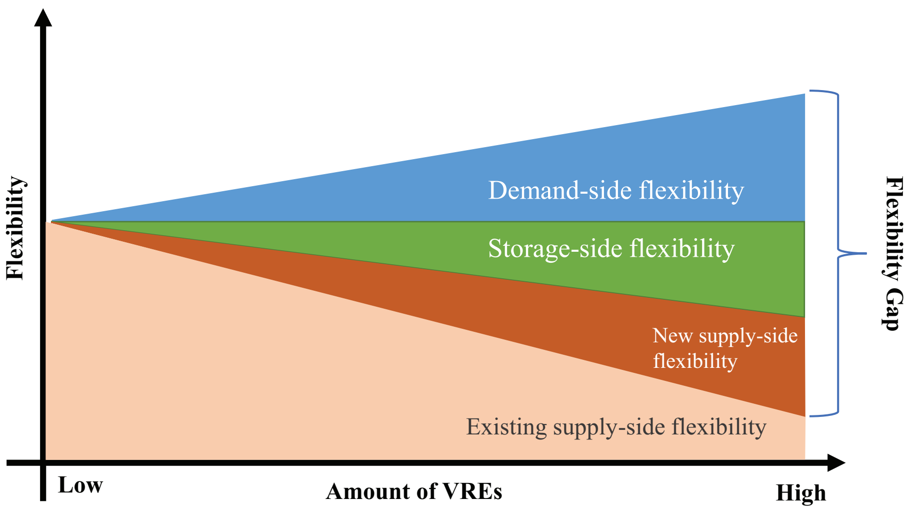

Figure 2.1: Flexibility gap after the introduction of VREs, adapted from [9].

2.1.3 Transformation to consumer-centric systems and flexibility

The transformation of power systems and markets to a comparatively more consumer-centric architecture is a result of several innovations. Smart home and automation technologies, in addition to information and communications technology (ICT) are being introduced to power systems [10, 11, 12]. Due to these technologies, consumers can adapt their consumption according to prices and power generation. Consequently, it is we can observe a system that is shifting its center of gravity from suppliers to consumers.

In addition, there is an increasing trend in (DERs) and VREs, such as storage, solar panels, windmills, and vehicle-to-grid (V2G). From a location-specific perspective, these new resources provide variable and uncertain power to the system [13]. The growth in VREs and DERs, in combination with reforms in power markets, is transforming consumers into prosumers. The term *prosumer* refers to a power market and system participant or agent that both consumes and produces energy. In this transformation, consumers are passive participants who only pay for the service to active prosumers who in turn buy and sell services in a power market and system [14]. It is possible that such consumers and prosumers can replace certain actors in traditional power markets.

Market price changes when uncertainty about supply either increases or decreases. Therefore, due to the high integration of VREs and DERs, when the share of an uncertain or stochastic production increases in an energy system, balancing costs for supply-demand or merit-order curves will increase. Without the support of flexibility, especially in balancing markets and ancillary services, the operation of power markets could show inefficiencies [15].

The cost of integrating new technologies can decrease if the power system adapts demand-side flexibility and supply-side flexibility from new resources. Flexibility resources from the demand side can shift the power usage from peak hours to off-peak hours or curtail the electricity usage to reduce uncertainty with respect to the power system or market [13]. Furthermore, the usage of the demand-side flexibility reduces the costs of enabling technology, inconvenience costs, rescheduling costs, on-site generation costs, metering costs, and other costs [16].

Thus, flexibility from consumers/prosumers (i.e., the demand side) can be defined as the change of consumption patterns in response to changes in the price of the electricity over time (i.e., price signals) [16]. Market participants from the demand side can decrease their electricity consumption during peak load periods when electricity prices are high. Another behavior of consumers/prosumers is load shifting, whereby consumers shift their electricity consumption from peak periods to off-peak periods, and prosumers use power from VREs and DERs from their locations (self-consumption).

Demand-side flexibility appears in different dimensions in the market. The first dimension of demand-side flexibility is technology. The demand-side flexibility technology can be flexible or inflexible. For flexible end users, demand-side flexibility can be procured from various end-user technologies by rescheduling or reshaping the consumer's electricity consumption pattern. The second dimension of demand-side flexibility is the time dimension, which concerns the availability of the flexibility resource for usage. Depending on the availability of time, the demand-side resource can be used for different purposes in the grid and markets. The third dimension of the demand-side flexibility is the spatiality dimension, which refers to the geographical location of the resource. If the resource is located at a distance from the problem on the grid, the provision of active and reactive power from demand-side resources might be challenging, due to network losses. Therefore, it is important to consider the geographical location of the demand-side flexibility resource. The fourth and final dimension is the risk dimension. An end user or a power plant might have different risk profiles than other market participants or the operator, and therefore the demand-side flexibility provider can choose not to participate in the trading. In such situations, it is possible to observe a scarcity of flexibility in the market.

Consequently, the usage of flexibility from demand-side resources requires careful consideration of these dimensions in order to ensure optimal product and service deployment. The dimensional understanding of the demand-side flexibility could be extended or adapted to include different flexibility types, such as supply-side, storage-side, or grid-side flexibility, as discussed in Paper I.

Individual contributions via demand-response programs or end-user storage facilities may not be sufficient and profitable for the power system and flexibility providers. At some level, to activate a significant amount of flexibility for the market, an *aggregator* might be needed. An aggregator provides an opportunity for small end users to exploit their flexibility potential and use it in a cost-efficient way [17]. Several vendors or providers of flexibility among market participants are interchangeable depending on direct and indirect control. Knowledge of the exact properties of industrial or household appliances requires huge amounts of data and a high level of resource management. Therefore, authorities, scholars, and market participants suggest using an aggregator to combine DERs and their flexibility resources [17]. An aggregator should be a separate entity from distribution system operators (DSOs), transmission system operators (TSOs), and retailers in the market in order to avoiding the system operator turning into monopolies [18].

There are two methods to activate flexibility from the demand side: incentive-based programs and price-based programs [16]. In incentive-based programs, flexibility can be obtained by an operator through direct control or by load curtailment without a market design. To incentivize market participants in a market environment, bidding based on price signals, capacity market design (in addition to an energy-only market), ancillary market design, and ad-hoc demand response programs become prominent.

By contrast, in the case of price-based programs, tariffs are important for flexibility activation. However, historically, households and most other end users have been charged fixed prices based on grid investments and the rest of the electricity supply chain [19]. When there are flat tariffs, price signals based on VREs are not sent to end users to motivate them to shift their consumption pattern (insufficient incentive) or to prosumers to sell locally generated power to the grid [20, 21]. Therefore, besides an efficient market design, to exploit flexibility from the demand side, there is a need for price-based demand response programs. Such programs or tariffs are the time-of-use (TOU) tariffs, critical peak pricing (CPP), extreme day CPP (ED-CPP), extreme day pricing (EDP), and real-time pricing (RTP) based on demand response programs literature [16, 19]. In addition, capacity-based subscription tariffs (dynamic) have become prominent in recent years [22]. The advantages and disadvantages of demand response programs have been compared by [23].

The benefits of demand response programs for demand-side flexibility vary according to the different actors in the market. [16] present the benefits of having demand response programs on the market. However, it is possible to extend the benefits of using demand-side flexibility as a way to consider overall transformation from a supplier-centric system to a consumer-centric system. The benefits of flexibility usage, especially end-user flexibility, seen from different perspectives, are listed in Table 2.1.

Besides the demand side for flexibility trading, storage resources are strong candidates for flexibility provision due to the precision they afford when used. Different types of storage technologies exist, including electrochemical batteries,

Table 2.1: Benefits of the flexibility from the transformation to consumer-centric system.

For Actors	For Market	For System	For Grid
Incentive payments	Price Reduction	Defer of investments	Stabilized voltage
Bill savings	Capacity increase	Customer participation	Congestion management
	Reduction of market power	Diversified resources	Islanding prevention
	Reduced price volatility	Reduced blackouts	
	Cost-efficient energy options	Increased local production	

capacitors, umped-hydro, and compressed air systems. The important feature of all storage flexibility assets is their controllability. It is possible to eject or inject an instant power into an electricity grid using storage flexibility assets. Therefore, the controllability of storage technologies allows means they can have many applications in electricity grids. By using storage-side flexibility, supply-demand balance can be achieved or contribute to solutions for grid problems such as voltage variations and network congestion. In addition, it is possible to store surplus electricity that is generated by VREs and DERs in end user's storage facilities. The value creation process of storage-side flexibility has become prominent due to their fast, accurate, active and reactive provision of power to the grid. Furthermore, storage flexibility assets can balance surplus power from excessive generation of DERs by prosumers by storing them. Storage technologies are beneficial for consumer-centric transformation, both an individual technology and for complementing other flexibility technologies, such as demand- and supply-side flexibility [24].

In Paper I, my co-authors and I explain supply-side, demand-side, and storage-side flexibility along four dimensions. In Paper II, we apply dynamic and static tariff schemes for peak shaving in the way described by both [16] and by [22], and we compare static tariffs with dynamic tariffs. In Paper III, we discuss the use of demand-side, storage-side, and supply-side flexibility for grid problems such as voltage variations and network congestion.

2.2 Market designs and flexibility

In this subchapter, I compare power markets and the links between them. In this thesis I discuss the following markets: day-ahead markets (DA), intraday markets (ID), ancillary services, and balancing markets. A timeline of energy-only and capacity-based power markets is illustrated in Figure 2.2, where the primary intention is to give a clear picture of trading markets for power and energy.

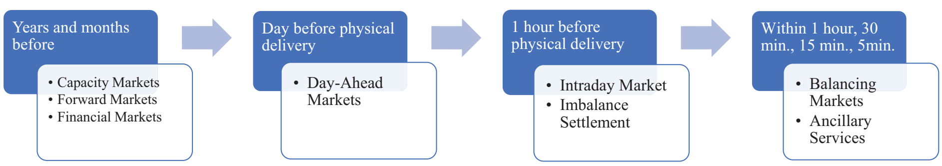

Figure 2.2: Timeline of energy-only and/or capacity-based power markets.

For this thesis, I conducted research on new and existing market designs mainly between DA market, ID market and balancing market time frames. Besides wholesale markets (DA, ID, and balancing), forward markets and capacity markets exist for risk management and the provision of enough capacity to the system during the blackouts, respectively. However, in this subchapter I do not consider either forward markets or capacity markets for flexibility pricing, since my focus is on short-term operational decisions.

2.2.1 Day-ahead markets

DA markets are financially binding and voluntary, with physical implications. The trading agreement occurs one day before the actual delivery time. Market participants submit their bids to buy or sell electricity. DA markets are identified as wholesale or spot markets. Trading in DA markets can be done either by bilateral contract as over the counter (OTC) trading or by power exchanges, such as done by the DA markets Nord Pool-ELSPOT and EPEX Spot.

In short, the bidding sequence starts in the morning and finishes around noon (24 hours before actual delivery). This process allows participants to schedule their generation plans. If a drift or a distortion occurs during power provision, it is possible to solve it in the ID market or with balancing markets, depending upon the situation.

There are different examples of trading flexibility among DERs and prosumers in DA markets. [25] propose that an aggregator should bid flexibility in a DA market as a price taker with a stochastic two-stage model. In a separate study, [26], present the value of flexibility in spot markets such as DA and ID markets under different market barriers.

Participants in the DA markets are often supply-side flexibility providers. Usually, controllable power generation technologies, such as hydropower plants or coal plants, bid on the DA market. In cases when there are deviations from their original power generation plans, they bid on ID markets or balancing markets.

In this PhD thesis, I examine DA market design and prices, which in Paper II are discussed together with dynamic tariff designs for flexibility trading. Due to the research design used for this thesis, I focus on shorter time resolutions for the usage of flexibility in the case of grid operations.

2.2.2 Intraday markets

The mismatch in supply-demand balance in power markets pushes participants to trade in ID markets in order to fix market imbalances close to real-time settings. In a DA market settlement, the likelihood of fault or disturbance occurring is significant in power generation or in transmission plans. ID markets are suitable places for correcting market imperfections.

Especially after the integration of a high number of VREs, the trading volume in ID markets is increased due to corrections and rescheduling. The transformation from supplier-centric design to consumer-centric design incentivizes the usage of the ID market. Due to demand-side flexibility, end users can respond faster to the deviations and corrections of power plants in ID markets. Furthermore, in a competitive environment, if there is an unfeasible generation plan due to non-convex production costs (e.g., start-up and no-load costs), it will allow for readjustment and remodeling of unit commitment [27]. ID market designs vary between countries. ID markets are continuous and auction-based trading markets, and they operate until one hour before actual delivery [28].

[29] emphasize the increase in intraday market volumes and their importance for end user's flexibility trading. Market proposals to exploit the value of flexibility for short-term purposes mainly depict ID market designs [30]. The difference between DA and ID markets are the market participants, the time horizon, and the gate closure time. These differences allow market participants to maximize profits from wholesale markets (mainly on DA markets) and minimize bidding deviations from original bids (mainly on ID markets) [31].

In the research for this PhD thesis, I focused on flexibility in an operational time frame. Therefore, ID market design was important for the local flexibility market design and valuation of the flexibility discussed in Paper IV. We used an ID market design as the main power purchase place for end users, due to the market gate closure time and short time horizon.

2.2.3 Balancing markets

Although ID markets stand between DA and real-time delivery, the balancing markets, or in other words real-time (RT) markets, are critical for either ad hoc or emergency needs in a power system. A balancing market continuously values and determines power resources during the operating time interval and dispatches them. The existence of a balancing market is mandatory due to changing merit-order balance. Balancing markets generally deal with supply-demand changes at either 5-minute or 15-minute intervals [32] (in Norway, the balancing market is based on hourly time frame). The usage of flexible products in shorter time intervals becomes more significant when they get closer to real-time delivery. The effect of flexibility usage for either 5-minute or 15-minute intervals in the DA market might be harmful to market efficiency because it might decrease the market liquidity [1].

Provision of the electricity includes a condition, such as quality, that must be sustained at all times. The electricity in a power system may originate from various heterogeneous resources. However, the electricity in a grid should fulfill the quality requirements, such as security of supply (SoS), frequency, and voltage. Ancillary services, such as transmission security and real-time balancing, and their providers are considered similar to public goods and should not be traded in regular market mechanisms. This puts the system operator in a monopsonist position. Market participants from all markets can participate in ancillary services provision by reserving a certain quantity of power. They can provide reactive and active power to the system operator while the system operator can take care of load shedding, production tripping, and economic dispatch [27, 33].

The ancillary services and their regulations differ between countries but there is a fundamental market design for these services [34]. Traditionally, ancillary services are provided by the system operator (DSO, TSO, or independent system operator, ISO) and its vendors. There is ongoing research on the allocation of ancillary services provision among DSOs and TSOs [35], but most power markets provide these services throughout a TSO. Decentralization of the ancillary services (i.e., provision of services from DERs and prosumers) is a novel idea, but there are counter arguments. It is not possible to track the power that is injected into or ejected from the grid. We can only understand who the provider/providers is/are prior to the injection if a system operator meters and compares the amount of power change on the grid, [27].

In this PhD thesis I propose a novel market design to address grid operations and power quality problems. The market design presented in Paper IV includes a pooled flexibility market approach with cost minimization to replicate balancing markets to some extent.

2.2.4 Sufficiency of existing power and energy markets for flexibility usage

As stated by [9], to reduce the flexibility gap we need to increase the efficiency of existing market designs or introduce a new market design for evaluating the flexibility from supply-, demand-, and storage-side resources. Hence, there is a need to discuss the sufficiency of the existing market designs to increase the contribution from flexibility resources to the grid and markets.

Power markets and systems have two edges: economics and engineering. A power system is a technological concept, but also has a strong connection with markets and the economy [3]. An optimal market design needs to consider economics and engineering, together with other factors. It follows that we cannot consider supply-, storage-, and demand-side flexibility resources in the same way of thinking, due to the bid in the same wholesale market. We should address them separately for rigorousness and technology differences. In addition, different providers who bid in the same market might compete for the same services from the system operator, although market participants' incentives are different from each other. An inefficient market design may limit access to technical flexibility and incentives [36]. Consequently, the process is not just about balancing the market or optimally bidding for profit. From the perspective of different market agents, a good market design should have security in terms of supply and provide optimal incentives for flexibility resources according to their properties.

From an economic perspective, an efficient market design has both short-term and long-term benefits. In their economic analysis, [37] list the benefits of design elements for efficient market design as including interconnection and market integration, electricity storage, the design of renewable energy support (RES) systems, distributed generation, efficient electricity pricing, and long-term contracts. However, in the same article, only the benefits of cross-border integration and interconnection are presented in the short term and long term. Based on findings reported in the existing literature, an efficient power market and system design should increase market efficiency in the short term by fixing congestion and incentivizing (or defer, depending on the policy) new investments [38, 39, 40]. Hence, new market designs for trading flexibility among participants must consider grid operations and incentives for the flexibility.

During the process of power generation and trading, VREs such as wind and solar power have zero marginal costs of production, which is a strong incentive for them to be dispatched in the short-term markets [3]. Production from VREs is supported by feed-in-tariff schemes, and sometimes the schemes cause negative prices in conventional power markets due to tariffs and uncertain power production [41, 42]. These short-term effects could increase the demand for power from VREs and DERs in the long term, especially for peak load capacity [43]. Due to the uncertainty in the generation of power from VREs in the short term, the demand for balancing markets and ID markets is increasing [29, 44]. In the long term, also investments, maintenance, and expansion decisions for the grid and conventional power resources could increase as a consequence of decreasing initial and investment costs of renewables such as those provided by wind and solar plants [45].

Given the short-term and long-term effects of VREs and DERs in markets and systems, it is important to exploit the real potential of the flexibility in existing markets or, if necessary, a new market design. The status of trading in existing market designs is changed by forecast errors for power generation by VREs, the uncertainty in generation scheduling, higher resolution time intervals from 1 hour to 15 minutes for resource scheduling, and grid operations (for frequency problems, it is even shorter) [3]. To exploit the flexibility and deal with grid problems (voltage and congestion) under these conditions, higher market time resolution and location-dependent pricing might be the answer [44, 46].

Insufficient demand-side flexibility in existing market designs can lead to the capacity and energy markets for cost recovery [47]. According to [48], using demand-side flexibility and investing in long-term flexibility resources could increase market efficiency. There are different ways to ensure demand-side flexibility. It is possible to design either a bilateral market or a pooled market mechanism for demand-side flexibility trading according to the market liquidity.

In a consumer-centric market design, to use flexibility for grid operations under spatiality and time constraints, end users, generators, and aggregators could improve the flexibility supply process. The flexibility could be purchased by a DSO and/or a TSO for supply-demand balancing or grid operations. Balancing in the transmission grid, balancing in the distribution grid, and flexibility for the distribution grid represent three forms of flexibility usage in markets [49, 50]. With regard to all forms of flexibility usage, one of the main discussion points is whether or not a local flexibility market is efficient for valuation.

Recent studies have reported the usage of flexibility in ID markets or even shorter time resolutions (e.g., [30]) for various purposes in the grid. To address the spatial, time and technology constraints of demand-side, supply-side, and storage-side flexibility resources, a local flexibility market could be aligned with day-ahead (DA) and real-time (RT) markets for coordination purposes to prevent imbalances between markets and players or to solve grid problems.

2.3 Local Flexibility Markets: Stochastic and Deterministic Approaches

It is important to consider local flexibility markets along with time, spatiality, risk profile, and technology dimensions for distribution grid operations. There are two main approaches to the use of flexibility in grid operations: direct and indirect control [50]. In the direct control approach, a system operator can use and procure flexibility from providers by scheduling them. The direct approach in many ways underestimates the marginal utility of flexibility providers and alters the competition. However, it provides a cost-efficient solution. In an indirect control approach, a system operator can use and procure flexibility via price signals. If the price signal is strong enough, flexibility providers will participate in the solution process. The indirect approach promotes competition in a strategic bidding environment or minimizes the costs in a price-taker environment.

Various studies of local flexibility market design have been done but few of them have considered a stochastic market bid. [51] provide an indirect approach to flexible load management via local energy system by considering the uncertainty of local demand, PVs, and RES generation. Their main aim is to manage assets and DERs for cost minimization for market participants and to increase the efficiency of electricity usage. [52] use a clearinghouse concept to model a local energy market for bidding under uncertainty on wholesale and local markets simultaneously. However, they neglect the power flow and grid constraints. By optimally scheduling flexibility assets, they aim to replicate a short-term balancing market under uncertainty from renewables, local demand, and market prices.

Other studies, consider a local flexibility market for DSO needs instead of local energy markets (e.g., [53]). Olivella-Rosell, Lloret-Gallego, et al. 2018 developed a market design for an aggregator bidding process. In their design, the aggregator centralizes flexibility assets to bid on wholesale markets and local flexibility market (LFM) participation without considering power flow equations. By contrast, [54], treat end-user demands, DERs, and batteries as flexibility resources. Their pay-as-bid market design follows the traffic light concept (e.g., [55]) in a centralized manner (the aggregator). Additionally, their direct control method schedules flexibility assets to participate in DSO services. In cases when the local flexibility market is decentralized from wholesale markets, the network congestion problem could be solved by using flexibility resources [56]. Based on local market design, a DSO can use available flexibility bids to manage network congestion under demand uncertainty [56]. In addition to this flexibility or the use of energy-only trading designs, it is possible to observe a peer-to-peer local electricity market for storage-side flexibility [57].

In this PhD thesis, I consider direct and indirect approaches to bilateral trading system design and pooled local flexibility market design, respectively. The two approaches include network constraints for optimal power flow calculations, whereas market participants, aggregators, or customers bid stochastically. Paper IV investigates the efficiency of using flexibility for grid problems through a market design. The local flexibility market design in the paper considers the stochastic bidding of an aggregator, the DSO's approach to solving grid problems with flexibility, a local flexibility market design, and relations between them.

2.4 Research Method

The method used to address the research questions in this thesis was based on operations research and mathematical modeling. Both I and my co-authors approached the case studies presented in Papers I–IV from the perspectives of economic dispatch and optimal power flow modeling [58]. In this thesis I consider the operational timescale in the case studies reported in the four papers; therefore, mainly hourly or shorter time resolutions were used in the studies. Paper I presents an economic analysis and taxonomy. Paper II focuses on economic dispatch, whereas Paper III reports the use of optimal power flow modeling for analysis. In Paper IV both economic dispatch and optimal power flow modeling for market establishment, bidding, and clearing are discussed.

2.4.1 Stochastic and Deterministic Mathematical Modeling

In the case studies that formed part of the research process for this thesis, most of the cases involved uncertainty on prices and power demands. Therefore, my co-authors and I applied apply stochastic programming techniques. The problems we addressed in the research were modeled in linear programming (LP) and non-linear programming (NLP) forms.

In the academic literature, the main difference between stochastic and deterministic modeling is reported as the uncertainty in decision-making. If there is no decision-making under uncertainty, the model is deterministic (one stage). The *problem* is still stochastic (uncertain parameters), but the *model* is deterministic (one stage decision). In cases when there is a change in the information, for instance if new information is found between two subsequent periods, one can consider a stage-break and call the model a stochastic model. After the stage-break, different scenarios are realized for stochastic parameters [59]. Hence, as the main assumption, the probability distribution of the uncertain parameters is known. The application of the stochastic programming models in energy research is presented by [60].

The contributions of this PhD thesis to the literature on modeling power markets is the stochastic modeling of tariffs, local flexibility markets, and quality measure for reactive power provision under uncertainty. In Paper II, we propose a novel approach to stochastic modeling of dynamic tariffs. In Paper III, we propose a stochastic quality measure for optimal power models, in addition to two-stage alternating current optimal power flow (AC-OPF) modeling. In Paper IV, we model a stochastic market design, bidding, and dispatch with an optimal power model and a two-stage stochastic model.

2.4.2 Optimal Power Flow Models

Optimal power flow (OPF) models are used to answer different questions than those answered by using economic dispatch models. In OPF models, instead of focusing only on supply-demand balance and allocation of scarce economic resources in power markets, the decision-maker needs to focus on the engineering conditions of the power system.

An OPF model is an essential tool for operational and planning decisions concerning power systems. In grid operations, the OPF model considers power flow equations, whereas in planning it considers optimal scenarios for the future conditions of the power network [58]. OPF models are mainly non-linear programming (NLP) flow models, with an AC approach to consider the voltage. In cases when the model is a DC (direct current) approximation, the model becomes an LP model but loses the voltage limits. In recent years, convex relaxation algorithms for AC-OPF modeling have been proposed to find solutions to NLP modeling problems [61, 62]. However, my co-authors and I did not use these convex relaxation techniques during the research on which the four papers are based.

In this PhD thesis, the contribution to the OPF modeling literature includes the stochastic two-stage modeling of AC-OPF for flexible scheduling presented in Paper II. In addition, in the same paper, we propose AC power flow constraints for the first stage and DC power flow constraints in the second stage of the mathematical model, to show the impact of uncertainty on reactive power provision.

Chapter 3

Contributions

In this chapter I explain the contributions of this thesis as a whole to the literature. The four papers that form the basis of this thesis contribute to the existing literature by expanding discussions on the taxonomy of flexibility on power systems and markets, dynamic tariffs for end users, the usage of flexibility for grid problems, and the stochastic local flexibility market design.

3.1 Paper I: "Characterization of flexible electricity in power and energy markets"

Güray Kara, Asgeir Tomasgard, Hossein Farahmand

- Submitted to an international, peer-reviewed journal.

The paper presents the results of conceptual taxonomy research based on the literature, real-world applications, and theoretical industrial economics knowledge. In Paper I, we focus on the characterization of flexibility along four dimensions: time, resource, spatiality, and risk profiles. Numerous flexibility resources can appear from heterogeneous technologies in different time scales at various locations. Furthermore, in the case of flexibility usage, it is possible to observe systemic, technological, or financial risks. The paper investigates the four dimensions according to existing market designs and anticipated future local flexibility market design. To trade flexibility, there is a need for standardized flexibility products and services for grid operations and market efficiency. In the paper, products and services of flexibility are examined based on real-world examples and theoretical approaches from the literature. In addition, we present the distribution of products and services in a DSO-TSO coordination scheme based on the literature. To conclude the results of our research, we discuss the relation between market designs, flexibility dimensions, and products/services.

The main aim of Paper I is to answer the first research question: *What is the flexibility of end users and generators in power markets and systems along time, spatiality, resource, and risk dimensions.* We discuss the convenience of flexibility usage in different market designs along the four dimensions. The allocation of flexibility products and services in these markets is discussed and explained based on theoretical and empirical examples.

My contributions to the paper as the main author are conceptualization, performance of the analyses, writing, and editing. Asgeir Tomasgard and Hossein Farahmand contributed through supervision and reviews of draft versions of the paper.

3.2 Paper II: "Comparing individual and coordinated demand response with dynamic and static power grid tariffs"

Stian Backe, Güray Kara, Asgeir Tomasgard

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- This paper is also presented first in *Impacts of Neighbourhood Energy Systems on European Decarbonization Pathways, Stian Backe, PhD Thesis, Norwegian University of Science and Technology, 2021.*

It is possible to use flexibility for various purposes in power markets. As a concept, flexibility is a strong for discussing and modeling peak shaving in high-demand time intervals. For efficient usage, flexibility needs to be addressed in its spatiality and time dimensions.

In this paper, we examine a cost-optimal approach to reducing end-user demand in peak hours with capacity-based subscription tariffs. Our case study involves coordinated and individual demand response programs. Based on historical data, we establish a two-stage stochastic mathematical model to compare the impact of tariffs on two end users' demand responses, both coordinated and individually. The capacity-based, dynamic tariff design is applied in weekly and yearly frequencies and compared with a constant yearly fixed tariff scheme. Thus, we aim for a dynamic and successful tariff design to exploit efficient usage of end-user flexibility. Our case study is based on real-world data from eastern Norway.

The main contribution of the paper to the literature is the usage of a two-stage programming model for comparing yearly capacity-based tariff and fixed tariff on a yearly basis. We show that by activating a dynamic tariff scheme for end users, it is possible to exploit their flexibility potential for reducing peak hours and efficient electric power usage. Compared with a fixed tariff scheme, the use of a dynamic tariff provides cost-efficiency.

My contribution to this paper as the second author is conceptualization, writing, and both reviewing and editing of draft versions.

3.3 Paper III: "The impact of uncertainty and time structure on optimal flexibility scheduling in active distribution networks"

Güray Kara, Paolo Pisciella, Asgeir Tomasgard, Hossein Farahmand

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In cases of high power demand or low power generation, grid problems might occur at the distribution network level. In the traditional approach to solving grid problems such as voltage and congestion, a system operator uses ancillary services or balancing markets with power plants. However, according to the flexibility concept, it should be possible to solve grid problems by scheduling flexibility assets from end users.

In this paper, we report the use of flexibility from end users by optimal scheduling to solve voltage and congestion problems in an active distribution network. We use a two-stage stochastic programming to schedule flexibility assets such as load shifting, load curtailment, and batteries in addition to an AC-OPF model to capture the grid specifications. The research was conducted under demand and price uncertainty and therefore we calculated the impact of the uncertainty by using the well-known value of stochastic solution measure. In addition, we introduce a new solution for quality measure, deviated value of stochastic solution, which measures the impact of uncertainty on the reactive power provision during grid operations. Our case study is based on real-world data from southern Norway.

The main aim of the paper is to present the direct usage of flexibility for grid operations under uncertainty without a market design. We present the usage of the flexibility from demand-side, supply-side, and storage-side resources for grid problems, such as voltage variations and network congestion in a distribution grid with a centralized design. Under uncertainty, it is important to determine the activation and the duration time of a flexibility resource for a cost-efficient solution.

My contributions to this paper as the main author are conceptualization, modeling and formulating, data collection, performing formal analyses, programming, writing, and reviewing/editing of draft versions. Paolo Pisciella contributed through modeling and a new conceptualization of quality measure. Asgeir Tomasgard and Hossein Farahmand contributed through supervision and review of draft versions.

3.4 Paper IV: “Stochastic local flexibility market design, bidding, and dispatch for distribution grid operations”

Güray Kara, Paolo Pisciella, Asgeir Tomasgard, Hossein Farahmand, Pedro Crespo del Granado

- Submitted to an international, peer-reviewed journal.

The value and usage efficiency of flexibility in the context of grid operations could be improved through a successful market design. To provide sufficient price signals to end users and to procure a significant amount of flexibility, the usage of the flexibility could be done via a market design. However, to trade and use flexibility for grid operations, both voltage and grid congestion problems should be addressed when and wherever they occur. Accordingly, a local flexibility market needs to be designed as either pooled or bilateral.

In the paper, we propose a pooled local flexibility market with stochastic design, bidding, and dispatch for a distribution grid. Instead of using load shedding, a DSO could procure flexibility power from an aggregator with a portfolio of customers in a pooled market. For this purpose, we first identify grid problems by using power flow analysis and an AC-OPF model, and then we create a stochastic bidding mechanism for an aggregator to bid its flexibility portfolio in a pooled market design, respectively. In the pooled market design, the marginal cost of flexibility provision in a perfect competitive environment is the bidding price for a price-taker aggregator and the DSO. Our case study is based on real-world data from south Norway.

The main aim and novelty of the research presented in the paper is to show the efficiency of a stochastic local flexibility market design in solving grid problems, cost profiles of market participants, and the stochastic nature of the bidding process in a price-taker, risk-neutral, and perfectly competitive market for an aggregator. We propose a novel stochastic local flexibility market design for flexible usage as a pooled market. According to our results, the pooled market design provides an efficient solution to use by the aggregator with a stochastic cost-minimization bidding action. The pooled market design is up to 40% more cost-efficient than using only load shedding from value-of-loss load price by the DSO. Moreover, the aggregator that bids stochastically establishes a flexibility supply curve by bidding the same prices for different flexibility supply amounts for different scenarios in the pooled local flexibility market.

My contributions to this paper as the main author are conceptualization, modeling and formulating, data collection, performing formal analyses, programming, writing, and reviewing/editing draft versions. Paolo Pisciella contributed through modeling and conceptualization. Pedro Crespo del Granado contributed through conceptualization and review and draft versions. Asgeir Tomasgard and Hossein Farahmand contributed through supervision and reviews of draft versions.

Chapter 4

Concluding Remarks and Future Research

The main purpose and contribution of this thesis are the provision of a solid understanding of the flexibility of a power system, its usage, and related market structures for postponing investments in the power grid and increasing the productivity of the power system.

The four papers on which this thesis is based address several research questions. The first paper defines a taxonomy for the flexibility concept along four dimensions and provides a theoretical overview of flexibility products as well as related market designs. The second paper shows how to exploit the demand-side flexibility with a successful capacity-based tariff design from multiple end users for peak shaving. The third paper presents a solution concept for using flexibility in grid problems such as voltage and congestion, in addition to the impact of uncertainty on the flexibility usage process. The fourth and final paper proposes a local flexibility market design for solving grid problems cost efficiently in a stochastic design with bidding, and clearing.

The first finding includes the taxonomy and determination of the flexibility in power systems and markets along four dimensions, namely resource, time, spatiality, and risk. Under different market designs, according to these dimensions, flexibility could be evaluated and used differently. The second finding shows how a dynamic tariff scheme for end users, such as a capacity subscription-based tariff, could exploit the value and the usage of the flexibility better than a fixed tariff scheme. The improvement in the cost-efficiency resulting from the use of dynamic tariffs is 3–15%, depending on the annual, weekly, or combined subscription. The third finding concerns the impact of the uncertainty on the usage of flexibility and how a portfolio of flexibility assets could be used to solve grid problems. The impact of uncertainty and the availability of a flexibility resource could have an impact on the overall solution of up to 30%. The fourth and final finding is a stochastic local flexibility market design with bidding and dispatch in a pooled market design for grid operations. Usage of a pooled LFM design could improve the cost efficiency of the grid operations by up to 40% compared with a system architecture without an LFM under our assumptions.

For future research, it would be interesting to conduct the research presented in the four papers in a risk-averse environment with a strategic trading process. Also, DSO-TSO coordination is an important topic for locating the flexible resources during grid operations and peak shaving. Comparisons between dynamic tariff schemes with local flexibility markets could be a new perspective for research similar to that reported in Paper II. With regard to the research reported in Paper III, future research could include renewables, and more flexibility technologies might be a natural extension. In Paper IV, we consider deterministic ID prices, but it would be interesting to consider stochastic demand and ID prices for the design and clearing of a pooled local flexibility market with the spatial information of flexibility assets. Lastly, instead of having one local flexibility market in a monopolistic design, future research could focus on several DSOs that compete for the same flexibility assets.

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Papers

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Paper I

Characterization of flexible electricity in power and energy markets

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Characterization of flexible electricity in power and energy markets

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Abstract

The increasing share of variable renewable energy sources creates a need for flexible resources in the power system and management of these. This paper presents suggestion for characterization of flexibility, including dimensions of time, spatiality, resource type, and risk in power systems. We present interrelations between these flexibility dimensions, products, services, and suitable market designs. In light of this, we discuss TSO-DSO coordination and optimal resource allocation.

1 Introduction

The increasing share of variable renewable energy sources (VRES) introduces short-term uncertainty and variability in power systems. This creates a need for flexibility in order to maintain a continuous supply-demand balance [1]. There is not a unified definition of flexibility in the literature, but in this study we take as a starting point: "*Flexibility is the modification in the generation and/or consumption pattern of electricity according to an external signal in order to meet energy system needs*" ([2], p.5). The main reason for us to select this definition is to include uncertainty from changes in consumption and generation patterns in relation with market designs and systems.

[3] describe four dimensions mainly in relation to their technology. According to them, resources for flexibility are distributed energy resources (DERs), such as electric vehicles (EVs), combined heat and power (CHP) units, and electric water heaters. The four dimensions are the amount of power, the moment of provision, duration, and specific location of resources. Although the study by [3] is quite informative, only DERs are considered as flexible resources. They do not discuss the response time, flexibility resources other than DERs, and risk in flexibility provision. By contrast, [4] propose three dimensions of flexibility characterization: absolute power output capacity range (MW), speed of power output change (MW/min), and

the duration of energy levels (hours of MW). However, they do not discuss the spatiality dimension.

The authors in [5] investigate the flexibility characterization and indexing with high penetration of VRES. They propose response-time index using technical terms, and characterize it based on resource. [3] describes four dimensions mainly in relation to their technology. According to the authors, resources for flexibility are distributed energy resources (DERs), such as electric vehicles (EVs), combined heat and power (CHP) units, and electric water heaters. The four dimensions are the amount of power, the moment of provision, duration, and specific location of resources. Although the study by [3] is informative, only DERs are considered as flexible resources. The authors do not discuss the response time, flexibility resources other than DERs, and risk in flexibility provision. By contrast, [4] proposes three dimensions of flexibility characterization: absolute power output capacity range (MW), speed of power output change (MW/min), and the duration of flexibility provision. However, they do not discuss the spatiality dimension. [6] criticizes the main flexibility options in the literature by considering demand side, supply side, network side, and storage side flexibility options.

The primary aim of this paper is to provide an overview of dimensions for flexibility characterization in order to give insights into its usage in different market designs and systems for decision-makers and utilities. Hence, we discuss the concept of flexibility (e.g., [7]), by characterizing it in terms of four main dimensions: time, spatiality, resource type, and risk profile.

Our research contributes with a suggestion for how to characterize flexibility in power systems along four dimensions, and relate this to the existing literature. To exploit the flexibility, power markets should provide incentives for optimal valuation and allocation of flexibility for both short-term purposes (operations) and long-term purposes (investments). In addition TSO-DSO coordination affects the optimal allocation. We discuss this in relation to the flexibility dimensions mentioned above.

The main contributions of the paper are summarized as follows:

1. The characterization of flexibility in power and energy systems in terms of the spatiality, time, resource, and risk dimensions.

2. Discussion of the efficiency and suitability of existing and possible new power / energy markets for the exploitation of the flexibility, and adaptation to the proposed flexibility dimensions.

3. Introducing the risk dimension for flexibility characterization and related product, service, and market designs.

The paper is structured as follows. Section 2 discusses the dimensions of flexibility as time, spatiality, and technology. Section 3 describes the risk dimension of flexibility and related market designs. Section 4 explains the flexibility products. Section 5 discusses new market designs for flexibility trading and DSO-TSO coordination. Section 6 presents the conclusions.

2 The dimensions of flexibility

In this paper, inspired by the *Nordic market balancing concept* [8], we suggest four dimensions for flexibility characterization: resource, spatiality, time, and risk dimensions.

2.1 The spatiality dimension of flexibility

When looking at spatiality the location of any physical product is important for logistics. The price and provision of a product is related to where it is produced and consumed. Hence, in electricity transmission and distribution, especially for flexibility usage, the location of the flexibility resource connection to the electricity grid is important. Since the transmitting of reactive power over long distances is inefficient due to high grid losses, the geographical location of a resource is important for the reactive and active power type of flexibility product.

The location of the flexibility resource can affect flexibility trading and the effectiveness of the services provided by transmission system operators (TSOs) and distribution system operators (DSOs) [9, 10]. During times of grid congestion, the location of available flexibility will affect the decision-making process. In addition, for a location with a need for TSO-DSO interaction, some resources may be used both by the DSO in the distribution grid and by the TSO for the transmission grid. The possible geographies of flexibility provision are illustrated in Figure 1.

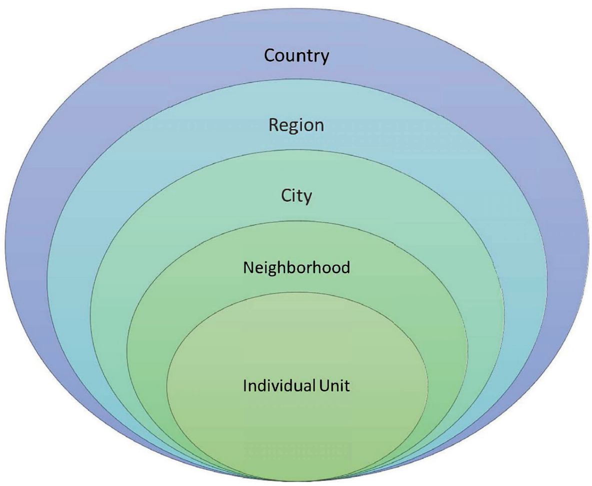

Figure 1: Spatiality dimension.

2.2 The time dimension of flexibility

Based on technological characteristics, market design, and system architecture, the time dimension can be divided into four subdimensions: activation time, ramping rate, duration time, and market time resolution. The activation time concerns how quickly the flexible resource becomes available for usage. The activated flexibility could be useful in a specific time interval (i.e., the duration). The ramping rate of the flexibility resource refers to how fast flexibility resource can ramp-up or ramp-down. Especially in the case of market designs with short time horizons, the ramping rate of a resource should be fast due to the immediate need for power. Based on [3] three subdimensions (activation time, ramping rate, duration time) are illustrated with some modifications in Figure 2.

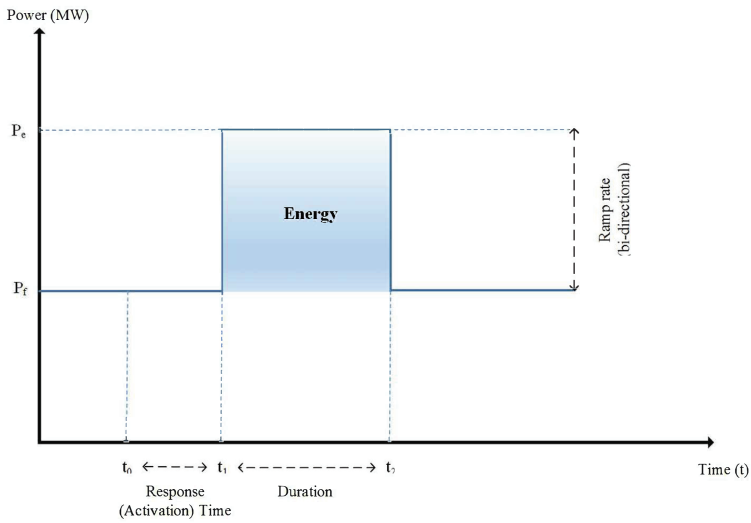

Figure 2: Characteristics of flexibility in system-wide scale [3].

In Figure 2 the difference between $P_e - P_f$ is the ramp rate—how fast power can be increased or decreased. The symbol t represents time, and t_0, t_1, and t_2 respectively symbolize the signaling, starting, and stopping time of flexibility. The difference between $t_1 - t_0$ is the response (activation) time of the flexibility, while $t_2 - t_1$ is the duration of the flexibility.

The fourth subdimension of time concerns the relevant market horizon. Different market designs are based upon various time intervals and customer needs [11]. Hence, the flexibility provision process should be considered with similar time-related decision-making. Different time properties of resources make it possible to participate in different markets for multiple purposes, such as ancillary services for restoring the quality of power in a grid. It is possible to observe different flexibility resources with relevance from milliseconds to years. The structure of the time dimension with respect to flexibility trading horizons and markets is shown in Figure 3.

The time dimension may be the most important dimension for flexibility and its usage. According to the results of a survey of industry players (managers and modelers) conducted by [12], with an accurate timing strategy, timing-based flexibility business models in the energy sector could increase their profits while reducing their downside risk. The timing of the market participant could differ for supply-side flexibility resources compared with demand-side flexibility resources. A system operator or a market participant could either use only a single flexibility resource

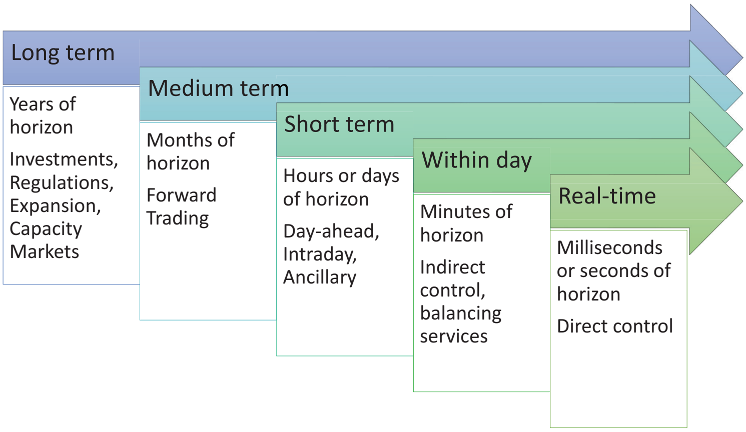

Figure 3: Flexibility trading horizons and markets.

with a single timing strategy or they could harvest multiple resources and have a time coupled portfolio of flexibility.

2.3 The resource dimension of flexibility

The resource type of a flexibility asset might vary with different time horizons and locations. In this context, we consider four major flexibility resources: supply side, demand side, grid side, and storage side. The four resources are represented in Figure 4.

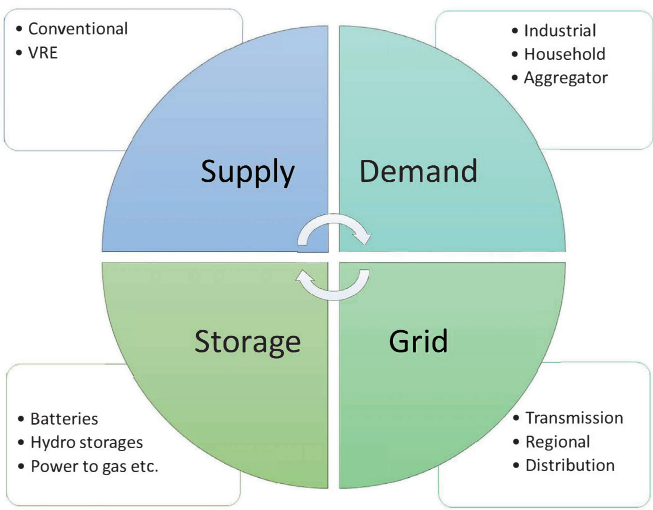

Figure 4: Resource dimension.

2.3.1 Supply-Side flexibility

The traditional flexibility in power systems originates from either ramp-up or ramp-down of conventional power plants. Variability in the load (demand) profile is the primary reason for conventional usage [1, 13]. In this respect, ramp-up and ramp-down rates, time of availability, and start-up and shut-down response times are all components of the power provision process from conventional resources. However, the integration of VRES and other new technologies into power systems and generation plans increases uncertainty and the need for flexibility [1].

The impact of VRES integration into power and energy systems creates a merit order effect due to lower marginal costs of production. Due to their low marginal costs of generation, the VRES plant bids enter the market merit order list before the conventional power plants bids [14]. Furthermore, due to the stochastic nature of VRES, their high provision of power can create supply-demand imbalance in the market. Supply-side flexibility resources, such as hydro power plants, may benefit from the imbalance by providing flexibility to restore the balance [14].

2.3.2 Demand-Side flexibility

Information and communication technologies (ICTs) have made it easier to monitor and control consumption profiles in power systems. Real-time pricing and hourly pricing are important practices that can help to maintain the supply-demand balance. Close coordination between producers and consumers about pricing and supply-demand balance is necessary until storage technologies become cost-efficient.

Demand-side flexibility is characterized along the direction (ramp-up or ramp-down), its electrical power composition (differentiation between power and energy), its temporal characteristics defined by its starting time, duration (time of availability), and its location (spatiality) [3]. Industry, households, and aggregators are flexibility resources for the demand side [1]. Although there is more ongoing collaboration with industrial users for demand side management, such as load curtailment, also participation by households has been motivated [2, 15]. In households, heating and cooling are important flexibility sources. Moreover, EVs are emerging as flexibility resources. They can shift their consumption in the short-term (grid-to-vehicle), while selling remaining electricity to the grid (vehicle-to-grid, V2G). Most often, demand-side technologies are applicable for local problems in short time intervals (e.g., voltage, network congestion). When congestion problem occurs, at distribution grid levels, demand-side resources are useful for congestion management. Thus, demand-side flexibility can improve the overall efficiency of the system [15].

The primary benefit of demand-side flexibility is its response to changes in market supply-demand balance and power quality problems with the support of end users. In this context, two control strategies, i.e., direct and indirect control [13] are existing. Direct control strategies manage demand-side flexibility resources by load curtailing or shifting according to system needs, and applied by TSO, DSO, or aggregator. The indirect control is applied by the economic incentives to encourage the consumers to change their consumption patterns according to optimal market price signals. It is possible to use demand-side flexibility resources with optimal price signals via an efficient market design. Thus, real-time pricing, real-time metering, and economic incentives are crucial for motivating demand-side flexibility.

In addition to market efficient and supply-demand balance benefits, the demand-side flexibility is beneficial for risk management and reliability, lower cost electric services, customer services, and environmental considerations [16].

2.3.3 Storage-side flexibility

Storage-side flexibility resources are important technologies for storing electricity and using it later [14]. Battery energy storage systems (BESS) can be categorized into centralized and decentralized storage units for flexibility provision [17]. Storage units provide power in time by collecting surplus power from VRES or other resources before the provision time [1]. Examples of different storage-side flexibility technologies are pumped hydroelectric storage technologies, compressed air energy storage, flywheels, power-to-gas plants, and batteries [18]. According to Divya and Østergaard (2009), BESS are the main storage flexibility resources. Some researchers regard EVs as battery storage technology due to their capacity for V2G, but in this paper, we consider EVs are demand-side flexibility resources. From a power system perspective, storage flexibility from BESS can provide solutions on short-, and medium-time horizons [18].

2.3.4 Grid-side flexibility

Grid infrastructure and reinforcements constitute grid-side flexibility. The definition of grid-side flexibility is the ability of a power grid to engage with demand variations, uncertainty in grid conditions, and changes in the power flow by using grid topology and system operators [19]. Transmission or distribution grid planning and operating may need grid-side flexibility to be efficient [20].

The grid-side flexibility is useful due to its physical capabilities to cope with changes in the power system. [19] classified grid-side flexibility resources in two items: discrete grid-flexibility and continuous grid-flexibility. Discrete flexibility resources include network topology, transmission expansion planning (TEP), and line switching (LS). Dynamic flexibility resources include reactive power compensation using power electronics, phase angle, optimal power flow, FACTS (flexible alternating current transmission systems), and HVDC (high-voltage direct current).

The limitations of grid-side flexibility are often technical and are challenged by VRES and DERs [17]. However, the technical capabilities of grid-side flexibility may lead to reductions in the following respects:

- Thermal ratings: A higher number of DER and VRES connections, and growing demand can lead to violation of installed capacity (thermal ratings) in the network.

- Voltage deviation: On-load tap changers (OLTCs) are controlled by automatic voltage control (AVC) schemes in the presence of high, low, and medium voltage situations for voltage preserve.

- Fault level: The short circuit capacity of networks is subject to the thermal and mechanical constraints of the network. Interconnection of DERs and VRES can push the network to exceed short circuit capacity.

- Reverse power flows: Having a reverse power flow makes balancing the low voltage side of the transformer harder and might cause congestion in both transmission and distribution systems.

- Rapid voltage change: Instant increase in power output (ramping-up) might create rapid voltage changes and impact the grid.

- Islanding: If a generator continues to the provision of power to an isolated grid part, consequently, the islanding occurs. Anti-islanding requirements are defined to sustain the distribution of electricity in the grid and prevent islanding.

- Protection: There are three protection challenges for the grid. First, faults on the distribution might cause voltage deviations in the grid. Second, the aggregate generation could exceed the load on the distribution bus and the flow of power might turn in the reverse direction to the transmission system. Third, a ground source from a generator could change the fault balance between the distribution feeder and the utility system.

- Power quality: Integration of DERs and VRES might decrease power quality and cause voltage fluctuations, flicker, harmonics, and signaling.

With regard to local problems in power grids, grid-side flexibility is related to TSO-DSO interaction. Local network constraint management, voltage optimization, network restoration, and power flow stabilization are major applications of grid operations with flexible resources [21].

3 The Risk Dimension

The risk dimension of flexibility provision is often neglected in characterization of flexible assets. Different risk profiles originate from the heterogeneity of technologies and end users. Also, due to the privacy concerns of participants (e.g., their data have commercial value), there is a lack of information in the market [22]. The theoretical relation between risk and uncertainty is outside the scope of this paper, but we use the term risk to address the effects of uncertainty and how it affects the ability of flexibility assets to provide flexibility. At one end of the scale, we have firm flexibility provision with low probability of disruption of the service or failure to provide as promised (e.g., a portfolio of hydropower plants with reservoirs), while at the other end of the scale, we find flexibility services provided by a single windmill with a high probability of disruption or failure to deliver as promised.

To identify the risk, we first have to identify all uncertainty origins in the flexibility provision and their effect on the energy systems and markets. As long as we are able to measure or quantify the uncertainty of flexible resource, we can characterize its risk dimension. Since the beginning of flexibility research, most of the literature has highlighted the uncertainty in VRES generation plans. By contrast, risk management studies have emphasized either market price or trading risks. There are many sources of uncertainty and related risk profiles in energy systems and power markets. The following are examples of uncertainty types [23, 24, 25, 26, 27, 28]:

- VRES generation uncertainty
- Demand uncertainty
- Network availability capacity uncertainty and investments costs uncertainty
- Fuel availability and cost uncertainty
- Wholesale markets price uncertainty
- Policies and regulations uncertainty
- Participation uncertainty (in cases of a market-based approach)
- Duration of the resource uncertainty.

These uncertainties affect the flexibility assets and services from different angles. Furthermore, the risks profiles of flexibility assets in markets have impacts on the market design and process of the flexibility usage. During the flexibility procurement and activation process, flexibility is employed to cope with these uncertainties and at the same time can potentially be affected by the same uncertainties.

The time dimension is strongly connected to the risk dimension. According to the results of a survey conducted by [12], a power market participant's short-term planning contains a higher risk of inefficiency than their long-term planning. For example, many market participants conduct their trading agreements months ahead and sometimes one year ahead, and they trade the same resources to multiple markets. If they wait until the day-ahead market or intraday market, their risk could increase due to short-term uncertainties. Similarly, the shortage risk of flexibility products could originate from the contracts and obligations that the flexibility asset owner has on different time horizons. In our case, we are concerned with the uncertainty quantification of flexibility resources and the risk of shortage during provision and activation process. In a California ISO (CAISO) report, the shortage of ramping flexibility is described as procuring less than the requirement [29]. Flexible ramping product applies to both 15-minutes and real-time market designs, for upward and downward regulation. These products are designed for situations in which there is uncertainty due to demand or renewable forecast errors. The shortage of flexibility ramping products is discussed by [30, 31, 32]. Insufficient flexibility ramping capacity can increase power provision prices and create market imperfections such as supply-demand imbalance.

The risk of failing to deliver flexibility can be foreseen if a robust flexibility metric exists. [33] used a flexibility metric to calculate the time intervals of the flexibility shortage. They introduced a metric that they named insufficient ramping resource expectation (IRRE), based upon another generation adequacy metric, the loss of load expectation (LOLE). IRRE is the expected number of observations when there is a problem with the power system in the presence of forecasted or not forecasted changes in the load profile. The calculation of IRRE can represent the probability of the system coping with a shortage of flexibility. Moreover, IRRE measures individuals and the system flexibility probability. [34] state that there have not been any studies of the risks of the resource duration time (Figure 3). Consequently, the risk dimension needs to be addressed on an individual and resource basis according to time and spatiality dimensions.

Another type of risk associated with demand-side uncertainty is the *rebound effect* [35] which is also known as the payback effect [36]. We can observe the rebound effect in the demand profile of a power system when the demand-side participation exits. For example, during peak hours, a demand-side participant could decrease its consumption in the grid and remove the possibility of network congestion. During off-peak hours, the same participant might increase its consumption due to lower prices to charge an EV or a battery. This behavior shows an increase in the demand profile and is subject to the possibility of congestion in the distribution grid. In this regard, the main problem is not the amount of demanded power, but the time of the demand. The uncertainty of rebound effect occurrence creates a risk to the security of supply in later periods (short-term).

System operators (DSOs, TSOs/ISOs (independent system operators)) are subject to the risk. As shown in Table 1 and Table 2, the services that they provide are subject to grid congestion, shortage of flexibility, and market price risk, jointly.

An aggregator stands connected with DSOs to aggregate households' assets in order to reduce its risk in the system or market. In a similar way to the system operator's risk profile, the risk profile of an aggregator is a combination of all four dimensions under discussion (i.e., time, spatiality, resource, and risk). An aggregator has many flexibility providers with different resources, spatiality, timing, and risk profiles. Therefore, an optimal portfolio of assets is important for an aggregator because the risk profiles of individuals have an impact on overall risk. To ensure its flexibility supply process, an aggregator needs to find an optimal number of assets in its portfolio based upon risk, resource, and spatiality and time dimensions.

4 Flexibility products

Flexibility services and products are identified by [37] as the flexibility offered by a participant (e.g., an aggregator) to a market. The products offered to the TSO for system flexibility (ancillary services) usually are provided by a balance responsible party (BRP), such as CHP, hydropower plants (dispatchable), or zonal interconnections (energy products), which are defined as supply-side flexibility. The products offered to DSOs are mainly for local supply-demand balancing, voltage correction, or grid congestion management by the demand-side, storage-side, or grid-side flexibility resources (these products could also be offered by the supply-side flexibility). Furthermore, in existing market designs, power-based products such as demand-side, storage-side, and supply-side resources have shorter duration than capacity products such as grid-side flexibility.

4.1 Product examples

Real-life examples of ISO flexibility products are the ramping products in CAISO. In CAISO, flexibility products, which are named "flexiramp" products by [38], should be gathered from supply-side resources in the short-term (i.e., less than minutes). In the CAISO market such products are primarily used for correcting the difference between forecasted demand and realized demand without using major energy providers [39]. There is no bidding for flexiramp products, due to the zero variable cost assumption of the generators that provide the products. Other markets in the

USA have similar products based on ramping rate (e.g., [30, 40]), although their market settlement rules are different. Flexiramp products aim to achieve two goals: first improvement in the expected cost (market efficiency) of energy schedules; and second, the provision of incentives for generators to consider the value of ramping in both operating and investment decisions. Generators do not provide price bids for a ramping product, so prices are based just on the marginal opportunity cost of diverting capacity from energy or ancillary services to meet the ramp requirements.

Another example of a flexibility product is the DS3 plan from Ireland and its 14 products (flexible DS3) designed to meet system scarcities [41]. Ireland's TSO uses very short-term (2–10 seconds) products for frequency fixing, reactive power correction, ramping products, primary, secondary and tertiary reserves, and dynamic reactive response. Moreover, [41] point out that TSO-DSO interaction is important for planning and operating of the network. Furthermore, in France, the TSO proposes capacity contracts as a quantity-based market-wide mechanism to cope with increasing peak demand and to incentivize demand-side flexibility usage for all consumers with regard to their consumption [42].

In the case of DSOs, products show more variety since they include DERs. The reason for using these products is not just for market supply-demand balance but also for congestion management, voltage correction, and loss coverage [37]. Principally, the flexibility is presented in the distribution grid, but it is often used in the transmission grid. [43, 44, 45] propose approaches whereby an aggregator participates with multiple flexibility resources in the distribution grid in addition to bidding in the wholesale market.

Allocation of local and system-wide resources for flexibility is important for the distribution grid and cooperation between the TSO and the DSO [46]. According to [37], flexibility products are provided to local flexibility markets with DERs and other flexibility products to address grid operation issues. Many attempts to establish local flexibility markets in the industry have been reported in the literature [47]. For example, NODES marketplace[1] is a universal platform for local flexibility trading [48]. In distribution grids, with a pay-as-bid auction design, the NODES marketplace solves congestion problems by using continuous trading. [49] propose an aggregator-based local flexibility market with a flexibility clearing house (FLECH) market to promote DER for active participation in trading flexibility services. In a FLECH market, the DSO or sometimes the TSO acts as a flexibility buyer. In a FLECH design, there are three trading products: bilateral contracts, auctions, and the supermarket. In the market design, activation time, duration, and location are important for the product type. A FLECH design is aligned between the DSO and the aggregator interconnection. [50] investigated the usage of prosumers' flexibility in a decentralized perspective and found that the local market structure trades flexibility and solves problems by cost-minimizing objectives. The aim of their research is to solve distribution grid problems before using the wholesale markets.

Flexibility products can be designed as a combination of different flexibility technologies for a common purpose such as to fix voltage deviations or for congestion management. [51] combine flexibility from different providers for the purpose of congestion management in wholesale markets. Their product, *flexibility value stacking*

[1] `https://nodesmarket.com/about/`.

is based on multiple flexibility providers, who are combined either in a pool market design or a portfolio by an aggregator for trading in wholesale and balancing markets for congestion management. Flexibility value stacking products are designed as time-based, pooling/portfolio based, and double serving based.

4.2 Flexibility product design

The structure and purpose of flexibility products originates from the need for an efficient system and market design. In existing market designs, the time dimension determines the economic benefit of a flexibility product in relation to the resource dimension and technology dimension. Many existing flexibility product initiatives are system-wide products and therefore the spatiality dimension of the products is not considered [29, 39].

Flexibility service providers are heterogeneous along our four dimensions. Products may have different cost profiles for different time dimensions (activation time and duration). This leads to a need to consider the optimal alignment of markets where products can be traded. In the time dimension of flexibility (discussed in subsection 2.2), the properties of the time dimension such as ramping rate and duration are relevant. When designing a flexibility product, essential qualities are how quickly fast a flexibility asset will respond to the system operator and for how long it can provide power.

In an imaginary setting, two flexibility ramping products can be considered: the first has a 5-seconds activation time and the second a 20-seconds activation time as their sweet spot in terms of cost, but both can work in a 5-second or a 20-second activation time prior to physically delivery.

The resource with a 5-second activation time will always have lower marginal costs for the 5-second services than the 20-second resources. Similarly, the 20-second resource is better than 5-second resource for a 20-second flexibility service. If the operator dispatches 20-second technologies in 5-second markets, the operator will lose the efficiency of using flexibility. This economic viewpoint is illustrated in Figure 5 and Figure 6, where P5 and P20 represent 5-second and 20-second flexibility resources, respectively. Still, it is not practical or economically efficient to prepare a market design for each asset type or resource. Therefore, the optimal market design needs to address differences in product designs for market and trading efficiency.

Similarly, one could choose optimal spatial resolution when establishing marketplaces to procure power, energy, or capacity. TSO-DSO coordination would be needed, as there would be local and non-local optimal resource allocation.

In the CAISO market, the demand curves are calculated every hour independently according to the market design (5-minute or 15-minute market) and direction (ramping-up or ramping-down). Besides the system-demand curve, there are different demand curves for each region with market imperfection [39]. In the case of Ireland, there are markets for an inertial response (0 to 5 seconds), reserve (5 seconds to 20 minutes), and ramping (20 minutes to 12 hours).

An aggregator or a flexibility operator chooses the flexibility resource with regard to its abilities to be dispatched in the market. For example, in CAISO, flexibility resources and technologies are dispatched or disqualified from the provision of flexible ramping products according to regulations and their technology characteristics [39]. Consequently, resources for shorter time intervals and longer time intervals can be

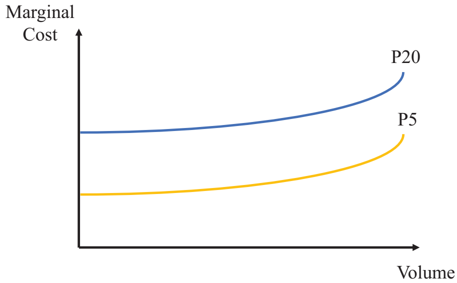

Figure 5: Cost of flexibility products in 5-second market (graphs are in same scale).

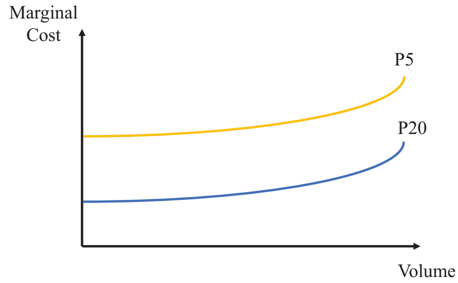

Figure 6: Cost of flexibility products in 20-second market (graphs are in same scale).

separated from each other according to their technologies, either by the system operator or by the aggregator.

In addition to the time and resource dimensions, the spatiality dimension needs to be considered in flexibility product design. For example, Irish and CAISO products have system-wide initiatives in their ISOs and TSOs [29, 39, 52]. With regard to CAISO products, the flexibility ramping products are designed as system-wide products (e.g., [29]). However, the ISO might apply some regional constraints according to the problem (e.g., congestion) in the power system. In the case of Ireland, flexibility providers are spatially clustered and they generate a cost-effective strategy for grid operations (e.g., [52]).

5 Markets for trading flexibility

To provide incentives for exploiting the value of flexibility from end users and generators, an efficient market design is essential. It is possible to provide price signals for flexibility assets in existing market designs, but they might not be sufficient. The efficiency of the existing power market designs, especially intraday (ID) and day-ahead (DA) markets for flexibility pricing could be analyzed along our four dimensions. Moreover, the spatiality dimension of flexibility refers to how to use local flexibility markets in distribution grid operations.

5.1 Pricing flexibility in power and energy markets

The ID market design is one of the major market designs to trade flexibility and incentivize flexibility resources [53]. In longer trading horizons (e.g., 1 week), ID market prices often are close to DA market prices. This convergence has led some researchers to disregard the importance of having separate flexibility markets [54]. However, in their studies of flexibility pricing they have not conducted analyzes along the dimensions as those we introduce at this paper. Especially, the time dimension of flexibility resources and their spatial differences are not addressed explicitly.

In some energy-only market designs, the flexibility is withheld for peak load hours by flexibility providers [55]. Many flexibility providers expect to recover their investment costs by trading their flexibility in peak hours. This strategy is in line with the findings of our research, such as the use of flexibility for deferring grid investments and recovering investment costs.

[56] describe the pricing and market mechanism for flexibility trading in the presence of price caps and cost recovery conditions. Price caps in energy markets lead to higher prices; hence, trading flexibility in peak hours increases the power prices (ramp-up in scarcity hours). Price capping might be an option for market mechanisms, but price cap revenues are related to revenues from flexibility trading. The major cost recovery for flexibility investments comes from earnings from trading pricing at peak pricing periods instead of off-peak or regular trading periods. Naturally, prices for flexibility are mainly affected by (marginal) costs of technologies and the applied price cap.

From the spatiality dimension perspective, aggregators can access different resources in various locations. Hence, integration of different market zones, both in time and spatiality, could increase the flexibility in the system if the products traded are relevant over a large geographical area (e.g., active power in non-congested grids). The combination of different areas and generators in the same market leads to better allocation of reserves and reduces the costs of marginal generation, especially for supply-side flexibility resources [57, 58, 59, 60].

Another problem with existing market pricing mechanisms is the lack of incentives for the flexibility providers of flexibility activation, in times of both power scarcity and power surplus. In situations when flexibility is provided from demand-side resources, we can observe that market power shifts from the generators to the end users of electricity [61]. [62] show that demand-side flexibility resources and their bids can outperform conventional price bids and reduce flexibility prices. Therefore, it is essential to incentivize the demand-side flexibility in a market design.

Flexibility pricing examples from CAISO, MISO (Midcontinent Independent System Operator), and SPP (Southwest Power Pool) markets indicate that the flexibility products are subject to DA market and real-time (RT) pricing. In these markets, flexibility is characterized by considering mainly the time dimension (i.e., ramping rate) [30, 38, 39, 40]. Another example is the Irish TSO, which proposes products by considering the spatiality, resource, and time dimensions, but mainly emphasizes the time dimension because of system needs. In EirGrid, the pricing of fourteen different products is ideally done under real-time pricing [41, 52]. In the French TSO case, capacity obligations and certificates construct the price mechanism, especially for peak-hours electricity provision [42].

5.2 Local flexibility markets

The introduction of the entity "prosumer" to the power and energy markets changes power market designs. The change in market designs from centralized to decentralized, and the integration of prosumers into existing markets is investigated by [63], with respect to four structural attributes: the peer-to-peer model, prosumer-to-islanded microgrids, prosumer-to-interconnected microgrids, and the organized prosumer group model. In the peer-to-peer model, prosumers are directly interconnected with each other for buying and selling power and energy from others. In prosumer-to-interconnected microgrids, prosumers provide their services to a microgrid that is a part of a larger grid. The prosumer-to-islanded microgrids comprise prosumers who provide services to independent, non-interconnected microgrids. In the fourth and final market structure, organized prosumers create a pool among themselves and trade with each other.

Each market design typology, whether pooled or bilateral, has different attributes along our four dimensions. A local and consumer-centric market design, such as a local flexibility market (LFM), might be an efficient market design for the flexibility pricing and trading.

In order to design a local flexibility market, a general list of market design principles needs to be followed before introducing the details of the flexibility trading. According to [64], six principles of a good market design are as follows:

1. Correct the market as quickly as possible in cases of failure. By reducing the reliability on subsidiarity, the market imperfection will be corrected as soon as possible.

2. Allow for appropriate cross-country variation in market design. Ensuring the security of supply is a local issue.

3. Use price signals and network tariffs to represent the value of electricity provision services. Include the provision of flexibility. This principle has long and short-term effects such as deferring the investments and sustaining the efficient dispatch.

4. Collect network fixed costs from the market. The difference between efficient prices and regulated prices allows for revenue from end users.

5. Provide incentives for low carbon investment. Provide efficient risk-averse financing for low-carbon and capital-intensive investments in electricity markets.

6. Retain the flexibility to respond to changing information in the market, such as information relating to lower costs and different technologies.

In addition to the six fundamental principles of a market design, [65] propose four local (flexibility) market design dimensions such as temporal, spatial, contractual, and price-clearing.

A local flexibility market requires incentives for the valuing flexibility. For stronger incentives to exploit flexibility from end users and to increase efficiency in the market and systems, LFMs are crucial on specific grid or market purposes. The need for an LFM is specific to each case. The majority of researchers consider the need for LFMs as decentralized and separate from wholesale markets. In some cases (e.g., [66]), they suggest that an LFM should complement the balancing markets. According to Jin, Wu, and Jia (2020), recent studies have provided good insights into an efficient market design for flexibility trading [67]. In addition, LFMs are useful for various services, such as market-oriented services, system-oriented services, and grid-oriented services [68]. Another detailed LFM modeling, challenges, and implementation review research for grid and market problems is investigated in [69] by considering blockchain applications for flexibility trading.

To design an LFM for pricing and trading flexibility, the market design needs to address our four dimensions. According to the flexibility service, for example the voltage deviation service or congestion management, the market considers the spatiality of the flexibility resource because the voltage needs to be fixed at certain locations in the grid topology (active and reactive power distribution) [70]. With regard to another flexibility service, namely congestion management, it is important to address the congestion with the correct timing (peak load time); this refers to the time dimension of the flexibility. In case of risk dimension, the LFM is requires to cope with the market liquidity risk in order to provide sufficient amount of power from flexible resources (scarcity of flexibility). Hence, the LFM design needs to be shaped with respect to the risk dimension discussed in this paper. However, the TSO-DSO coordination and the coexistence of different LFMs have to be considered for higher efficiency for flexibility usage.

5.3 The need for TSO-DSO services and coordination based on flexibility

A system-wide approach to coordination among multiple market participants and operators is needed for reliability and efficiency of the power system. DSOs can deal with local problems by flexibility trading, while TSOs manage TSO-DSO interaction [37, 71, 72, 73, 74]. Accordingly, [46], suggest five different coordination models: centralized ancillary services market, local ancillary service market, shared balancing responsibility, common DSO-TSO ancillary service market, and integrated flexibility market. According to the [46], in the centralized ancillary services model, a single market with only a TSO as buyer is designed without the participation of the DSO. In the local ancillary service market model, the DSO is the user of the local flexibility and establishes a local market. The shared balancing responsibility model indicates that the local markets have to provide lower entry barriers to DERs for TSO-DSO coordination. In a common TSO-DSO ancillary services market model, the TSO and the DSO collaborate to use flexible resources optimally. Lastly, the integrated flexibility model both increases the possibilities for BRPs to solve supply-demand imbalances, and increases the market liquidity.

The provision of flexibility services by the TSO and DSO are related to voltage, congestion, balancing, black-start, and interoperability for coordinated protection [74]. There are ongoing discussions about pricing these services based on flexibility assets, as we have mentioned in subsection 5.1. System services that are provided by the DSO and the TSO (or ISO) are listed in Table 1 and Table 2, according to [71] and [73].

Table 1: TSO and ISO services and pricing mechanisms [71, 73].

TSO/ISO services	ISO pricing	TSO pricing
Electrical energy	Local marginal prices (LMPs)	Zonal
Transmission energy losses	Local marginal prices (LMPs)	Zonal
Transmission congestion	Local marginal prices (LMPs)	Congestion management markets
Reserves	Co-optimized with LMPs	Balancing markets
Reactive power and voltage control	Regulated prices and bilateral contracts	Regulated prices and bilateral contracts
Black-start	Regulated prices and bilateral contracts	Regulated prices and bilateral contracts

Table 2: DSO services and pricing mechanisms [71, 73].

DSO services	Pricing
Electrical energy	Regulated or competitive retail supply tariffs
Distribution energy losses	
Distribution congestion	
Reactive power and local voltage control	
Peak shaving	
Network connection and reliability	Averaged network tariffs
Network deferral	

5.3.1 Interaction along flexibility resource

The distinction between DSO and TSO services in Table 1 and Table 2 originates from the voltage and frequency requirements of the system. The TSO considers frequency and grid congestion issues whereas the DSO focuses on voltage deviation, grid congestion, and losses issues. The requirements of frequency deviations for conventional resources (supply side) is much stricter than requirements for demand-side resources. The reason for this is that the voltage should be higher when electricity is injected into the grid from the supply side but should be lowered when it reaches end users for utilization (high-voltage to low-voltage grid). Therefore, local resources managed by the DSO have different voltage requirements compare with the non-local resources owned by the TSO. As a result, besides voltage and frequency challenges, the congestion management for an entire grid is diversified by the DSO and TSO concerning their local flexibility and grid resources. TSO and DSO services can differ because their products (e.g., flexibility resources) can differ.

According to [71], DSO and TSO services can compete with each other within the same level of the grid. Moreover, flexible power resources can compete in DA, ID or balancing markets as either energy or power, but not as capacity. Flexibility resources should be bid to markets that are most profitable for them. Furthermore, for flexibility trading, the bidding process should provide optimal incentives and price signals for market participants to continue [71]. In this regard, the reduction of market barriers would be helpful, as stated by [75].

5.3.2 Interaction along spatiality

To coordinate flexibility resources, system operators should communicate with each other according to their spatial responsibilities. The spatial differences among flexibility assets have impacts on their technology and their mitigation of grid problems [71]. Resources that are located in different geographies, as illustrated in Figure 1, have different incentives, technologies, contracts, and market power. In particular, we cannot expect flexibility resource from a transmission level (high-voltage) to act in a similar way to a small demand-side resource in a distribution grid.

The congestion management service is common in both types of system operators (i.e., TSOs and DSOs) and is increasing in importance due increases in local power generation. DSOs can use demand-side and storage-side flexibility resources for local congestion management, whereas TSOs can use supply-side and grid-side flexibility for transmission grid services. These facts stress the coordination of flexible resources. The geographical information tags for DSO and TSO market bids are presented by [72] for the coordination of flexible resources.

5.3.3 Interaction along time

Flexibility assets can provide long-term and short-term solutions for markets and services. Furthermore, a short-term resource can bid for a long-term perspective, and at any point in time there might be conflict (or overlap) among the contracts. A DSO could use its resources for local voltage balancing, while a TSO might want the same resources for congestion management in the grid. Such situations need a high level of coordination between the TSO and DSO. As shown in Table 1 and 2, the DSO and TSO provide different services, but both provide services for grid congestion management.

The coordination of the DSO and TSO should be evaluated in two time periods, such as short term and long term. Currently, there is an ongoing TSO-DSO coordination in long-term planning in the literature and in the industry. Smart grid initiatives, network expansion planning, and research programs are examples of long-term collaboration [71, 76]. However, the coordination between the DSO and TSO should include short-term solutions for congestion, voltage, and frequency problems in further consideration of new market designs.

5.4 Need for change in existing power markets

The integration of VRES and the transition of energy systems affect the management, technology, and economics of market designs and power systems from centralized to decentralized, and from a regulated structure to a deregulated structure [3]. From a centralized to decentralized perspective, the market scale is downsized from a national design to local market design. The resources available in national markets are still valid for use at the local scale, but it would be problematic to use certain flexibility technologies due to their market power, amount of power produced, and time of availability. Therefore, for flexibility trading, there is a need for change in market designs from national to local scale.

A comparison of existing market designs and their participant profiles is important in order to understand the need for change in market designs. Using DERs and VRES increases the risk for power markets and systems due to the uncertainty in generation and consumption profiles. Depending on the market design, the risk can be reduced. A change in power markets needs to include the risk profiles of intermittent resources in order to increase efficiency.

A structural comparison of flexibility provision in the current market situation and a basic understanding of the need for change in power systems and markets is presented in Table 3. Originally, [3] studied a similar version of this table with only DERs. For this reason, we propose an extension with all flexibility technologies, in a time-coupled context, considering our four dimensions, in addition to flexibility products and related market mechanisms. Our novel expansion is the introduction of uncertainty and risk in Table 3.

All dimensions discussed in this paper are incorporated in Table 3. In addition to the four dimensions, the Table 3 shows existing market mechanisms, flexibility products, and the connection type of the grid. Time interval presents the availability of flexibility resources according to the time dimension. Some of these resources exist in multiple markets. The type of product is mainly related to the flexibility resource. The technology of the resource is related to its location and connection to the grid. Distribution grid (DSO) technologies are used for local purposes, whereas transmission grid (TSO) technologies are used for non-local and local reasons.

For some flexibility technologies, it is possible to use the dimensions in multiple market designs and time scales as shown in Table 3. However, the risk profiles and spatiality of flexibility resources indicate a market design that is dimension-specific, especially for small-scale technologies such as demand-side and storage-side flexibility resources. In addition, throughout different market designs, the risk has different impacts on market participants and their choice of market for trading flexibility. Hence, there could be changes in existing market designs to include more flexibility resources, in addition to designing local (flexibility) markets by considering the discussed four dimensions.

Time interval	Market mechanism	Product	Flexibility provider	Spatiality	Connection to grid	Uncertainty
Real-time	Direct control	Power	Household appliances	Local	Distribution	Resource duration, Demand, Congestion
Within day	Indirect control		Household appliances, EVs	Local	Distribution	
	Balancing markets	Energy and power	EVs, Industrial DS, Aggregators	Local and non-local	Transmission, Distribution	Resource duration, Demand, Congestion, Fuel availability and cost, Wholesale market price, VRES generation
Short term	Ancillary services		Aggregators, Conventional, Renewable			
	Intraday	Energy	Aggregators, Conventional, Renewable			
	Day-ahead	Energy	Aggregators, Conventional, Renewable, Storage			
Medium term	Forward markets	Energy and power	Conventional, Renewable, Storage			Demand, Fuel availability and cost, Wholesale market price, VRES generation
	Capacity markets	Capacity	Conventional, Renewable			Demand, Fuel availability and cost, Wholesale market price
Long term	Network expansion and investments	Capacity	Network reconfiguration, Grid expansion, Capacity expansion			Network investments, Policy and regulation

Table 3: Structure of flexibility trading in current systems and market designs.

6 Conclusion and Outlook

In this paper, we argue that the flexibility services have to be procured and deployed in markets that recognize the four dimensions including time, space, resource type and risk. We have presented products and services from different countries with flexibility trading systems, that support the flexibility products and services that are needed to balance the power markets supply and demand side on different horizons. Typical problems to be solved by using flexibility are related to voltage, frequency and congestion.

For an efficient valuation of the flexibility and allocation of resources, a local flexibility market might be needed. Considering risk profiles and uncertainty of flexibility assets in flexibility provision could help to decrease inefficiencies in flexibility usage and local market design. At different levels in the networks, TSO-DSO coordination is essential to provide services based on flexibility with optimal resource allocation over time and space.

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Paper II

Comparing individual and coordinated demand response with dynamic and static power grid tariffs

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Comparing individual and coordinated demand response with dynamic and static power grid tariffs

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ABSTRACT

This paper investigates cost-optimal operation of flexible electricity assets with a capacity-based power grid tariff involving power subscription. The purpose of this research is to identify the characteristics of a subscribed capacity-based tariff that promotes efficient network development through demand response. Using historical load data, we compare two consumers with flexible assets being billed by their individual load versus their combined and coordinated loads in a two-stage stochastic program. The frequency of adjusting the subscribed capacity level (weekly versus annually) influences the effectiveness of the tariff in terms of reducing loads that dimension the grid. The results show that weekly subscription on average provides 5 – 6% cost savings, while annual subscription on average provides 3% cost savings. A combined annual peak load reduction of 15% occurs when the combined subscription level is adjusted weekly. We also find that when the subscription level is adjusted weekly, the load reduction is cost efficient even when capacity is not scarce, which ought to be avoided. Depending on where a bottleneck in the grid is located, the price signal should be based on the combined load of several consumers rather than individual loads if combined peak load shaving is to be cost-optimal.

1. Introduction

Successful mitigation of climate change will require decarbonization of the energy sector, increased production from variable renewable energy sources (RES), and electrification. Several of these measures are likely to be decentralized and require cross-sectoral thinking [1].

Flexibility in power systems relates to the ability to deal with variability in supply and demand. Demand-side flexibility through demand response has been proposed as being significant if assets can be coordinated and aggregated [2–6]. We will refer to consumers with demand-side flexibility as 'prosumers' because they both consume and produce energy services. Prosumers are seen as part of the solution to facilitate a large share of variable RES, making the demand-side more flexible through self-generation, market participation and active responses to price signals [7,8].

Several studies have been performed to analyze prosumer response to different grid tariffs [9–15]. However, to the authors' knowledge, no previous study compares dynamic intra-annual adjustment of tariff parameters with annually fixed parameters and simultaneously considers the difference between providing short-term price signals based on individual loads versus the combined load of several prosumers. To cover this gap, we propose a two-stage stochastic program where uncertainty is related to net load and spot prices with an hourly resolution for different prosumers. The novelty of this paper is using the two-stage stochastic programming framework to compare dynamically adjusting tariff parameters within a year versus statically fixing tariff parameters for a complete year. The paper also has the original contribution of comparing individual versus coordinated asset planning to analyze how effective different versions of a capacity-based grid tariff are in reducing load peaks in the grid. Based on our results, we address the implications for successful grid tariff design, i.e., a design that will trigger efficient utilization of the local flexible assets and reduce the highest loads.

The outline of the paper is as follows: Section 2 introduces the background regarding flexibility in energy systems and the purpose

Abbreviations: C1, Campus 1; C2, Campus 2; CA, Combined annual subscription scheme; CW, Combined weekly subscription scheme; DG, Distributed generation; DSO, Distribution system operator; IA, Individual annual subscription scheme; IW, Individual weekly subscription scheme; PV, Photovoltaic; RES, Renewable energy source.

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of grid tariffs. Section 3 presents the model developed to analyze subscribed capacity-based grid tariff schemes and the assumptions and input for our case study. Section 4 states our model results, while Section 5 discusses the implications of these results. Finally, Section 6 concludes our paper and suggests further research.

2. Background and literature

This section elaborates on the literature and previous studies related to our paper. The first part (Sections 2.1-2.3) explains the context of our study linking flexibility in power systems to grid tariff design, while the last part (Section 2.4) presents the reasoning behind the use of the two-stage stochastic program in this paper.

2.1. Flexibility services in power systems

Flexibility is a term used to characterize a service or property that is part of tangible assets [16]. Flexibility can be characterized along three dimensions based on the *Nordic Balancing Concept*: time, location, and resource type. Properties of the *time* dimension include activation (response) time, ramp-up or down rate, and the duration of the service. The *location* dimension describes how the service from an asset can be provided in geographical locations, e.g. individual unit (building), neighborhood, country, and cross-border. For example, services based on reactive and active power have different geographical relevance. The *type of resource* dimension describes the type of asset in the following classes: supply-side, demand-side, grid-side, and storage [17].

In our analysis, we focus on time horizons with hourly resolution, demand-side flexibility assets, the neighborhood level, and assume that all flexibility assets provide a firm service (there is no uncertainty related to delivery). We assume that the scheduling of flexible assets is driven by the prosumers' wish to minimize the total cost of energy consumption, including net trades in the spot market and the grid tariff paid. In addition, we investigate the effect of prosumer coordination by investigating what happens when an aggregator controls all the flexibility assets to minimize total costs. We do not discuss how to share the benefits of this, e.g. in a flexibility market [18], only the total effect.

2.2. Allocation of ancillary service costs and flexibility

In a power system, distribution of electricity by preserving power quality and maintaining adequate assets in the low voltage grid are the main tasks of a distribution system operator (DSO). The DSO is commonly regulated as a natural monopoly which is challenged by the development of a smart grid [19,20]. Full and timely recovery of network costs is important for the DSO's financial sustainability [21]. A successful tariff design should increase network efficiency in the short-term and signal efficient network capital development in the long-term [22,23].

The tariff design normally includes up to three elements: a fixed element, a volumetric (energy) element, and a capacity element. Volumetric elements generally do not incentivize demand-side flexibility services [24] as opposed to capacity elements that partly charge consumers based on the power use over a measuring period [23]. Due to an increase in distributed generation (DG), especially solar photovoltaics (PV), power systems with net-metering tariff designs are faced with the threat of a *utility death spiral* [25]. The threat appears when DG behind the meter triggers not just energy cost savings, but also tariff savings. Unless the DG reduces the DSO's costs, it creates a marginally higher cost for consumers without DG, which is demonstrated in Ref. [26] where a capacity element in the grid tariff increases the electricity costs up to 10% for consumers with high power outtake in Norway. A redesign of network tariffs is needed to avoid the allocation of grid payments away from DG owners [27].

Most current grid tariff designs in Europe are *static*, i.e., dependent on a single element (commonly energy) without any temporal rate variation [28]. In contrast, a *dynamic* tariff design will depend on several elements and/or be subject to temporal variation. Static tariff designs are practical, predictable, and good at achieving a single long-term objective, e.g. increasing energy efficiency. In theory, dynamic tariffs reflect the DSO's costs better and could create signals to trigger flexibility services by prosumers [29]. However, dynamic tariffs are harder to implement [21] and could cause political challenges related to an 'unfair' change in network costs for certain consumer groups [30].

The signal for flexibility need could be provided using market-based approaches, as proposed in e.g. Ref. [31–33]. An example of a market-based approach calling for flexibility can be found in Ref. [34] which proposes distribution locational marginal pricing. The idea of activating demand-side flexibility in both market-based solutions and through dynamic grid tariffs is to create price signals to trigger efficient flexibility responses. We analyze how market-based approaches could be similar to responding to a dynamic grid tariff. In Ref. [35], they analyzed different ways of creating incentives for prosumer flexibility, including tariff redesign and a direct payment to flexibility providers. They find that a redesign of network tariffs is up to 20% less costly than direct payment to flexibility providers. However [35], does not consider how the network tariffs should be redesigned.

2.3. Grid tariff design in Norway

Currently in Norway, grid tariffs for residential consumers have a fixed element and a volumetric element. The volumetric element is location dependent through a marginal loss factor, which reflects how far electricity generation is from a consumer [28]. The current Norwegian grid tariff design does not price high power outtakes for households [26], and it is shown that dynamic tariffs provide incentives for better utilization of the grid [36].

In this paper, we analyze the 'subscribed capacity' grid tariff scheme proposed by the Norwegian Regulator [37], where consumers subscribe to a capacity level. If their hourly load exceeds the subscribed level, a penalty is charged depending on the violation (see Fig. 1). As consumers pay both for the subscribed level and the penalty, they have incentives to subscribe to as low capacity as possible providing they can stay below it most of the time. We analyze four different versions of the subscribed capacity tariff scheme. In the first version, consumers have individual subscriptions that cannot be changed for a year (individual annual subscription). The second version is individual subscriptions where the consumers can adjust the subscription level on a weekly basis (individual weekly subscription). The third version is a combined capacity subscription on the total load of several consumers combined, and the subscription is fixed for one year (combined annual subscription). Finally, the fourth version is a combined subscription for several consumers that can be changed on a weekly basis (combined weekly subscription). By comparing these four versions of the subscribed capacity grid tariff, our contribution is to elaborate on the effect of providing inter-weekly rather than inter-annual tariff adjustment and coordinated rather than individual scheduling of flexibility assets. We study the effect on (1) the resulting cost savings and cost-optimized responses by prosumers minimizing their electricity bill and (2) the total peak load reduction for the grid. We assume the tariff rates are as presented in Ref. [37] (see Table 1). These rates are suggested by the Norwegian Regulator upon analyzing measured load data from 500 Norwegian consumers, and the rates are determined subject to the criteria that

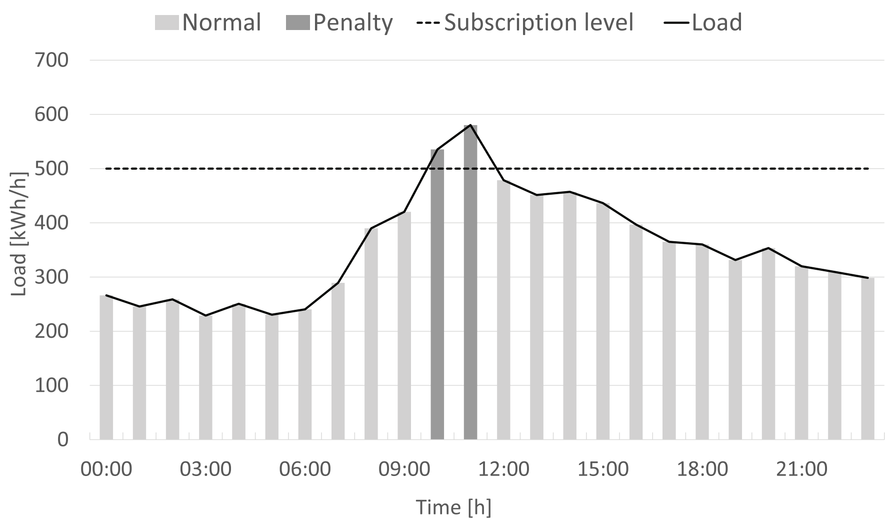


Fig. 1. Illustration of the 'subscribed capacity' grid tariff scheme. The illustration shows an example of measured hourly load over 24 h for the combined load of Campus 1 (C1) and Campus 2 (C2) and a combined subscription. The horizontal line represents the subscription level which causes a penalty charge for hours 11 and 12 (load exceeds subscribed level).

Table 1
Grid tariff rates provided as input in all our 52 instances. The rates are assumed to be as proposed by the Norwegian regulators [37] (see Section 2.3).

	c^{sub} [NOK/kW/year]	c^{norm} [NOK/kWh]	c^{pen}[NOK/kWh]
Rates	689	0.0500	1.00

the same annual income to the DSO is provided as with the current Norwegian gird tariff scheme.

2.4. Two-stage stochastic programming approach

Stochastic programming supports decision making under uncertainty [38]. In Ref. [39], a stochastic programming approach is used to analyze trading between prosumers under uncertainty; however, there are not multiple stages. Throughout different stages in stochastic programming, a decision maker ought to make decisions for short-term and long-term plans, where stages represent realization of uncertain outcomes. In our case, the short-term plans include operating flexible assets to minimize costs given a realization of prosumer load and day-ahead prices, and the long-term plan involves tuning the tariff parameters. We use two-stage stochastic programming to analyze the difference between long-term and short-term adjustment of the tariff parameters, where short-term adjustment of the tariff parameters is analyzed by solving deterministic versions of our two-stage stochastic program. Other examples of two-stage programming approaches for addressing uncertainty in energy management are [40–42].

3. The mathematical model

In this section, we present the model for the prosumer's cost-minimization problem. The model is a two-stage stochastic linear program [43] where the first-stage decisions include deciding the subscribed capacity level and the second-stage decisions include operating flexible assets. The complete nomenclature of the model can be found in Appendix A.

3.1. Time structure

The model considers one temporal scale with all operational time periods defined in the ordered set $\mathcal{T} = \{1, 2, \ldots, |\mathcal{T}|\}$. In every time step, decisions about how to operate a flexible asset is supported. Operational (second-stage) decisions can be different in all stochastic scenarios ω in the set of all scenarios Ω. Each stochastic scenario represents one realization of prosumer load and electricity spot prices for a time horizon. The flexible assets are located at different prosumers $p \in \mathcal{P}$, and the scenario independent first-stage decision is the subscribed capacity x^{I}_{p}.

The model includes flexible asset types $f \in \mathcal{F}$. If asset type f is located at prosumer p, it belongs to the set $\mathcal{F}_p \subseteq \mathcal{F}$. Any flexible asset type f is modelled as a conceptual storage. Depending on the asset type, it can be flexibly charged (prosumer demand can be increased, e.g. electric vehicle [44]); it can be flexibly discharged (prosumer demand can be decreased, e.g. curtailable loads [45]); or it can be both flexibly charged and discharged (e.g. battery [46]). Note that there is no resolving of uncertainty within a scenario as time passes, hence the storages are operated with perfect foresight within a scenario. For a static tariff where the subscribed capacity is decided for a year, each scenario may consist of all hours in a week with $\mathcal{T} = \{1, 2, \ldots, 168\}$. Scenarios can be sampled from historical data, and ideally, they represent seasonal variations over a year. If the scenarios represent all weeks of a year, we would have $\Omega = \{1, 2, \ldots, 52\}$. Note that each scenario is independent with no link or dependency between operations or storage levels in two subsequent scenarios.

3.2. Objective function

The objective function for an individual prosumer, z^{I}, minimizes the electricity bill by scheduling flexible assets subject to energy costs and a grid tariff:

$$\min z^{\mathrm{I}} = \sum_{p \in \mathscr{P}} \left(c^{\mathrm{sub}} x_p^{\mathrm{I}} + \sum_{\omega \in \Omega} \pi_\omega \sum_{t \in \mathscr{T}} \left(k_{p,t,\omega}^{\mathrm{I}} + c_{t,\omega}^{\mathrm{ret}} y_{p,t,\omega}^{\mathrm{load}} \right) \right), \tag{1}$$

where x_p^{I} are variables for the subscribed capacity level for prosumer p, the π_ω are scenario probabilities, and $k_{p,t,\omega}^{\mathrm{I}}$ are variables identifying the tariff cost depending on the prosumer's grid interaction in different scenarios. Resulting load profiles (import from the grid to the prosumer) are identified through the second-stage variables $y_{p,t,\omega}^{\mathrm{load}}$ and vary by scenario. The objective contains a time varying load dependent retail cost ($c_{t,\omega}^{\mathrm{ret}}$) and a fixed capacity dependent subscription cost (c^{sub}) for the capacity subscription.

For prosumer p, the tariff cost is identified through a two-step linear cost function depending on the subscribed capacity level x_p^{I} and the prosumer load $y_{p,t,\omega}^{\mathrm{load}}$:

$$c^{\mathrm{norm}} y_{p,t,\omega}^{\mathrm{load}} \le k_{p,t,\omega}^{\mathrm{I}}, p \in \mathscr{P}, t \in \mathscr{T}, \omega \in \Omega, \tag{2}$$

$$c^{\mathrm{pen}} \left(y_{p,t,\omega}^{\mathrm{load}} - x_p^{\mathrm{tariff}} \right) + c^{\mathrm{norm}} y_{p,t,\omega}^{\mathrm{load}} \le k_{p,t,\omega}^{\mathrm{I}}, p \in \mathscr{P}, t \in \mathscr{T}, \omega \in \Omega, \tag{3}$$

where c^{norm} and c^{pen} are load dependent prices for loads below and above the subscribed capacity, respectively. Constraints (2) make sure that the tariff has a lower bound of load multiplied by the cost below the subscribed capacity, whereas constraints (3) ensure that the tariff cost is increased when load exceeds the subscribed capacity to the penalty cost multiplied by the load.

3.3. Constraints

The original load before scheduling of the flexible assets (expected net demand) for electricity at prosumer p at time t in scenario ω is denoted $\xi_{p,t,\omega}^{\mathrm{load}}$. The total import from the grid to prosumers is identified in the following constraints:

$$y_{p,t,\omega}^{\mathrm{load}} = \xi_{p,t,\omega}^{\mathrm{load}} + \sum_{f \in \mathscr{F}_p} \left(w_{p,f,t,\omega}^{\mathrm{charge}} - \varepsilon_f^{\mathrm{discharge}} w_{p,f,t,\omega}^{\mathrm{discharge}} \right), \quad p \in \mathscr{P}, t \in \mathscr{T}, \omega \in \Omega, \tag{4}$$

where $w_{p,f,t,\omega}^{\mathrm{charge}}$ is charging of flexible asset type f at prosumer p while $w_{p,f,t,\omega}^{\mathrm{discharge}}$ is discharging. Constraints (4) ensure that prosumer p at time t will have a resulting load equal to the original load plus the charged and discharged energy from all the flexible assets at the prosumer. Note that losses $\varepsilon_f^{\mathrm{discharge}}$ are only considered for discharged energy in (4).

In time period t, $w_{p,f,t,\omega}^{\mathrm{storage}}$ is the available energy in flexible asset type f at prosumer p. The balance of storage must be maintained in between operational time steps:

$$\kappa_{p,f} \eta_{p,f,1}^{\mathrm{storage}} + \varepsilon_f^{\mathrm{charge}} w_{p,f,1,\omega}^{\mathrm{charge}} - w_{p,f,1,\omega}^{\mathrm{discharge}} = w_{p,f,1,\omega}^{\mathrm{storage}}, p \in \mathscr{P}, f \in \mathscr{F}_p, \omega \in \Omega. \tag{5}$$

$$\varepsilon_f^{\mathrm{diff}} w_{p,f,t-1,\omega}^{\mathrm{storage}} + \varepsilon_f^{\mathrm{charge}} w_{p,f,t,\omega}^{\mathrm{charge}} - w_{p,f,t,\omega}^{\mathrm{discharge}} = w_{p,f,t,\omega}^{\mathrm{storage}}, p \in \mathscr{P}, f \in \mathscr{F}_p, t \in \{2, \ldots, |\mathscr{T}|\}, \omega \in \Omega. \tag{6}$$

Constraints (5) make sure that a flexible asset type f at prosumer p start the operational horizon ($t = 1$) in scenario ω with an initial energy level equal to a percentage of installed capacity ($\kappa_{p,f}$) plus charging (subject to losses) minus discharging. Constraints (6) make sure that flexible asset type f at prosumer p has an energy level equal to the energy level from the previous period (subject to diffusion losses) plus charging in the current period (subject to losses) minus discharging for all operational time steps and scenarios. Losses are type dependent factors for flexible asset type f and they are considered for charging ($\varepsilon_f^{\mathrm{charge}}$), discharging ($\varepsilon_f^{\mathrm{discharge}}$) and diffusion of stored energy content ($\varepsilon_f^{\mathrm{diff}}$). Note that no losses are considered for discharging in (5) or (6) since it is accounted for in (4). The maximum energy content ($\eta_{p,f}^{\mathrm{storage}}$), charging ($\eta_{p,f}^{\mathrm{charge}}$) and discharging ($\eta_{p,f}^{\mathrm{discharge}}$) of flexible asset type f at prosumer p are defined as upper bounds for all time periods and scenarios.

Constraints (7) ensure that the energy level of flexible asset type f at prosumer p is at least the required level $\gamma_{p,f,t}^{\mathrm{req}}$ in period t for all scenarios:

$$\gamma_{p,f,t}^{\mathrm{req}} \le w_{p,f,t,\omega}^{\mathrm{storage}}, p \in \mathscr{P}, f \in \mathscr{F}_p, t \in \mathscr{T}, \omega \in \Omega. \tag{7}$$

The individual objective z^{I} in (1) is combined with constraints (2)–(7) to find the subscribed capacity level that minimize the combined energy and tariff cost.

3.4. Coordinated scheduling of flexible assets

The individual prosumer model can be extended to a model where an aggregator coordinates all flexible assets by changing the objective. The combined objective function minimizes the electricity bill for all consumers with flexible assets where the billing of the grid tariff is based on the combined load profile in the following way:

$$\min z^{\mathrm{C}} = c^{\mathrm{sub}} x^{\mathrm{C}} + \sum_{\omega \in \Omega} \pi_\omega \sum_{t \in \mathscr{T}} \left(k_{t,\omega}^{\mathrm{C}} + \left(\sum_{p \in \mathscr{P}} c_{t,\omega}^{\mathrm{ret}} y_{p,t,\omega}^{\mathrm{load}} \right) \right), \tag{8}$$

where x^{C} is a decision variable for the combined subscription level for all prosumers, and $k_{t,\omega}^{\mathrm{C}}$ are variables identifying the combined tariff cost depending on the sum of imports from the grid to all prosumers.

The total electricity load of all prosumers will determine the combined tariff cost through a two-step linear function:

$$c^{\mathrm{norm}} \sum_{p \in \mathscr{P}} y_{p,t,\omega}^{\mathrm{load}} \le k_{t,\omega}^{\mathrm{C}}, \ t \in \mathscr{T}, \omega \in \Omega, \tag{9}$$

$$c^{\mathrm{pen}} \left(\sum_{p \in \mathscr{P}} y_{p,t,\omega}^{\mathrm{load}} - x^{\mathrm{C}} \right) + c^{\mathrm{norm}} \sum_{p \in \mathscr{P}} y_{p,t,\omega}^{\mathrm{load}} \le k_{t,\omega}^{\mathrm{C}}, \ t \in \mathscr{T}, \omega \in \Omega. \tag{10}$$

Similar to constraints (2) and (3), constraints (9) make sure that the tariff has a lower bound of *the combined* load multiplied by the cost below the subscribed capacity, whereas constraints (10) ensure that the tariff cost is increased when *combined* load exceeds the subscribed capacity to the penalty cost multiplied by the load, respectively.

The combined objective z^{C} in (8) along with constraints (4)–(7) and (9)–(10) form a problem that cannot be decomposed per

Table 2
Assumed operational characteristics of the flexible asset types available for demand-side management at each of the two prosumers (Campus 1 (C1) and Campus 2 (C2)). The parameters identify available capacity for charging, discharging and storage.

Flexible asset	η^{charge}[kWh/h]	$\eta^{discharge}$[kWh/h]	$\eta^{storage}$ [kWh]
Electric battery	100	100	200
Vehicle charging	50.0	0.00	500
Curtailable loads	0.00	50.0	200

prosumer due to constraints (9)–(10) that make the tariff cost $k^{C}_{t,\omega}$ dependent on the load of all prosumers.

4. Case study for capacity-based grid tariff in Norway

In this section, the models presented in Section 3 are used to analyze the scheduling of flexible assets reacting to both an hourly retail price and a subscribed capacity-based grid tariff. We present the input data and assumptions (Section 4.1) before the results (Section 4.2). All input data, the implemented model, and output data is available in Refs. [47] for the reproduction of this case study.

4.1. Input data and problem instances

We build four classes of problem instances:

1. Individual Annual (IA): Subscribed capacity tariff based on the individual objective (1) under annual decisions on subscribed capacity level,
2. Individual Weekly (IW): Subscribed capacity tariff based on the individual objective (1) under weekly decisions on subscribed capacity level,
3. Combined Annual (CA): Subscribed capacity tariff based on the combined objective (8) under annual decisions on subscribed capacity level,
4. Combined Weekly (CW): Subscribed capacity tariff based on the combined objective (8) under weekly decisions on subscribed capacity level.

For IA and CA, we use stochastic models with sampled weeks representing the scenarios. Each week is a scenario with 168 h. For IW and CW, we optimize the subscribed capacity level weekly (only one scenario). This resembles a dynamic subscribed capacity tariff. As the model is solved under perfect foresight, it is overestimating the ability to estimate exactly the optimal subscribed capacity for the week.

The tariff rates used are as proposed by the Norwegian Regulator in Ref. [37] (see Table 1). We sample historical hourly load profiles from a rural Norwegian university campus, Campus Evenstad, from 50 weeks during 2016. We assume that two university campuses exist in the same part of the distribution grid, ‘Campus 1’ (C1) and ‘Campus 2’ (C2). Odd weeks are sampled from Campus Evenstad to create weekly load profiles with hourly resolution for C1 and even weeks for C2. Here, the samples are made so that two consecutive weeks from Campus Evenstad occur in parallel for C1 and C2 making up a total of 25 weeks for the study.

Three flexible asset types exist in the model at both prosumers: electric battery, electric vehicle charging and curtailable loads (e.g. fuel switching from electric to bio-based heating). Their assumed operational characteristics are presented in Table 2. Losses are assumed to be 1% for charging and discharging of all flexible assets. Diffusion losses are only defined for the electric battery at 0.1% per time step.

For vehicle charging, an annual demand of 14,000 km per vehicle is chosen based on the average use of battery electric vehicles in 2018 in the county of Campus Evenstad (Hedmark) [48]. Further, we assume one electric car needs 0.2 kWh per km,[1] so one car needs (on average) $\frac{14,000}{52}(0.2) = 54$ kWh/week. Then, a weekly demand of 500 kWh covers nine to ten vehicles (see Table 2). Some of the weekly demand must be met every 24 h, meaning daily demands sum up to the total weekly demand (see Fig. 2). The vehicle charging demand is essentially a lower bound for the energy level in the flexible asset f at prosumer p and time t implemented through the variables $\gamma^{req}_{p,f,t}$and constraints (7).

C1 and C2 face hourly retail prices that are dependent on the historical market data from price zone NO1 in Nord Pool in 2016. Retail prices follow the Nord Pool day ahead spot price plus Norwegian electricity charges and 25% VAT, and we sample hourly prices from odd weeks in 2016.

The two deterministic classes (IW and CW) for the two prosumers represent in total 50 instances for the 25 weeks, while the two stochastic classes (IA and CA) represent in total two instances for the 25 weeks. The model is implemented in the open-source optimization modeling language Pyomo [49] through Python version 2.7.8 and solved using Gurobi version 8.0.1. The optimization was run on a computer with an Intel(R) Core(TM) i7-7500U processor with CPU at 2.70 GHz and 16.0 GB installed memory (RAM). The total run time for all instances (50 deterministic + 2 stochastic) including reading, building, solving and printing results is around 60 s.

4.2. Results

This section describes the results from analyzing the four capacity subscriptions (IW, CW, IA, and CA) presented in Section 4. Recall that the modified load profile is a result of the model responding to the different schemes by (a) finding the cost minimizing subscribed capacity level and (b) operating the flexible assets to minimize the total electricity bill including variable energy costs and grid costs.

Table 3 presents the total electricity bill costs before and after the flexibility responses are optimized for the four different schemes. The cost ex-ante optimization is calculated by optimizing the subscription level without any flexibility available and includes constant charging to meet weekly vehicle charging demand of 500 kWh at each campus site. On average, the flexibility responses contribute to 5–6% savings for the weekly subscriptions (IW and CW), while 3% savings are achieved on average for the annual subscriptions (IA and CA).

The top part of Table 3 shows the results from the most expensive scenario (week 24), where costs avoided from responding to the grid tariff scheme (‘Grid’ in Table 3) are the dominant part of the savings as compared to the saved energy cost (‘Energy’ in Table 3). The results of all weeks for the weekly subscriptions (IW and CW) show that the grid savings are the dominant part of the savings for 23 weeks, i.e., there are more savings related to the grid tariff than hourly retail prices for the weekly subscriptions. For the annual subscriptions, the grid savings only dominate the savings for eight weeks for the IA scheme and six weeks for the CA scheme, indicating that responding to retail prices is more valuable than responding to the grid tariff for the annual subscriptions (the opposite to the weekly subscriptions). The bottom part of Table 3 lists the results from the scenario with the highest savings (week 2). Here, the energy costs avoided from responding to retail price variations are the dominant part of the

[1] https://pushevs.com/electric-car-range-efficiency-epa/accessed: April 15, 2020.

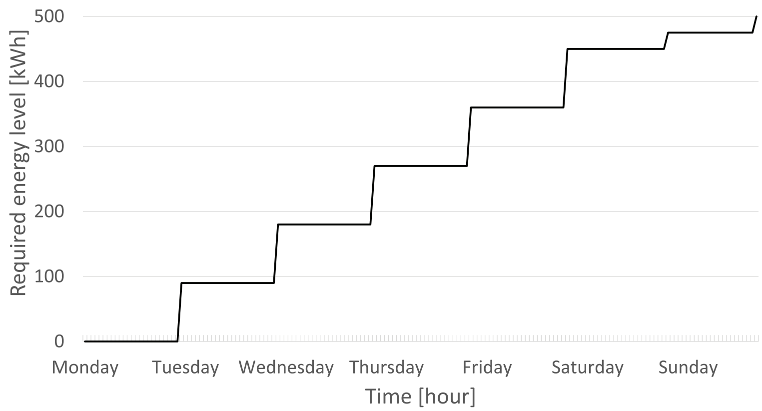


Fig. 2. The lower bound for energy that must be charged by time $t \in \mathscr{T}$ to battery electric vehicles. This offers flexible charging in every time-step with some constraints (daily demands).

Table 3
Cost results summed for both prosumers in NOK ex-ante (before flexibility responses) and ex-post (after flexibility responses) for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes. The table displays results for the most expensive scenario (week 24, top) and the scenario with highest cost savings from flexible operation (week 2, bottom). The two last columns show cost savings from responding to a variation in day-ahead spot price ('Energy') and responding to the subscribed capacity scheme ('Grid').

Scheme	Total cost,	Total cost,	Cost decrease	
	ex-ante	ex-post	Energy	Grid
Week 24				
IW	59,300 NOK	57,600 NOK (−3%)	468 NOK	1220 NOK
CW	58,900 NOK	57,100 NOK (−3%)	494 NOK	1230 NOK
IA	69,100 NOK	67,900 NOK (−2%)	475 NOK	716 NOK
CA	68,100 NOK	66,800 NOK (−2%)	448 NOK	825 NOK
Week 2				
IW	48,200 NOK	43,300 NOK (−10%)	4170 NOK	676 NOK
CW	46,900 NOK	42,300 NOK (−10%)	3990 NOK	615 NOK
IA	48,700 NOK	44,100 NOK (−9%)	4110 NOK	401 NOK
CA	46,900 NOK	42,400 NOK (−10%)	4000 NOK	526 NOK

savings for all schemes, which is linked to the average weekly spot price being highest for week 2 (0.72 NOK/kWh). This indicates that the load reduction in response to a grid tariff could be challenged by high and variable retail prices if the two price signals are not correlated.

Table 4 presents the weekly subscription level for C1 and C2. The last two columns in Table 4 are the sum of subscription levels for C1 and C2 from the individual metering schemes. Note that for the annual subscriptions (IA and CA), the subscription level is the same for all weeks. The average of the weekly subscription levels for all 25 weeks is consistently less than the annual subscription levels (see the bottom row in Table 4), which strengthens the need for the two-stage stochastic programming approach. The highest weekly combined subscription level is chosen in week 24 (591 kWh/h, see the CW column in Table 4). The sum of the weekly individual subscription levels for week 24 exceeds the combined subscription level (246 + 374 = 620 kWh/h, see the last two columns in Table 4), which is also the case for 92% of the weeks (all weeks except weeks 4 and 23, see Table 4). This is an indication that rationing several prosumers combined is less conservative than rationing them individually.

Table 4
Resulting cost-optimal subscription levels in kWh/h in all 25 weeks. The columns represent the subscription levels for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes for Campus 1 (C1), Campus 2 (C2), and combined. The last column shows the sum of individual subscription levels (C1+C2) for comparison with the combined subscription level.

	C1		C2		Combined		C1+C2	
Week	IW	IA	IW	IA	CW	CA	IW	IA
1	151	197	181	216	315	387	332	413
2	251	197	196	216	398	387	447	413
3	138	197	134	216	271	387	272	413
4	143	197	137	216	282	387	280	413
5	137	197	280	216	405	387	417	413
6	197	197	86	216	283	387	283	413
7	108	197	118	216	223	387	226	413
8	111	197	171	216	273	387	282	413
9	186	197	184	216	337	387	370	413
10	122	197	138	216	247	387	260	413
11	142	197	120	216	258	387	262	413
12	112	197	101	216	208	387	213	413
13	79	197	79	216	157	387	158	413
14	76	197	78	216	154	387	154	413
15	39	197	40	216	78	387	79	413
16	50	197	123	216	159	387	173	413
17	98	197	115	216	211	387	213	413
18	136	197	135	216	262	387	271	413
19	156	197	122	216	263	387	278	413
20	96	197	159	216	212	387	255	413
21	148	197	216	216	340	387	364	413
22	268	197	193	216	416	387	461	413
23	254	197	215	216	478	387	469	413
24	246	197	374	216	591	387	620	413
25	164	197	253	216	374	387	417	413
Average	144	197	158	216	288	387	302	413

Table 5
Annual original and resulting peak load in kWh/h for Campus 1 (C1), Campus 2 (C2) and combined for the individual weekly (IW), combined weekly (CW), individual annual (IA), and combined annual (CA) schemes. Note that the 'original' column represents the annual peak load ex-ante flexibility responses. The bold font marks the scheme triggering the lowest annual peak for C1, C2, and combined. The numbers in parentheses identify the week in which the annual peak load occurs.

Prosumer	Original	IW	CW	IA	CA
C1	413 (2)	**322** (2)	365 (2)	413 (2)	410 (2)
C2	479 (5)	**426** (24)	441 (24)	444 (24)	444 (24)
Combined	696 (24)	672 (24)	**591** (24)	696 (24)	696 (24)

Table 5 presents the results for the annual peak load at the individual prosumers (C1 and C2) and combined for both prosumers. Weekly individual (IW) subscription triggers the largest individual annual peak shaving, while weekly combined (CW) subscription best achieves combined annual peak shaving. The CW scheme reduces the original annual combined peak by 105 kWh/h (−15%), which is more than four times the annual combined peak shaving triggered by the IW scheme (24 kWh/h, −3%) (see Table 5). Annual subscriptions (IA and CA) trigger little or no annual peak load reduction of individual or combined load profiles (see Original, IA, and CA columns in Table 5).

Fig. 3 shows how the different schemes perform in reducing the weekly peak loads. For weekly subscriptions (IW and CW), some peak shaving is cost-optimal in all weeks, including weeks where the original weekly combined peak load is small (see e.g. the blue and orange bars in week 15 in Fig. 3). For annual subscriptions (IA and CA), the weekly combined peak load generally increases in low demand weeks and decreases in high demand weeks (see the yellow and gray bars in Fig. 3). However, the highest weekly combined peak load is unaffected for the annual subscriptions (see the yellow and gray bars in week 24 in Fig. 3).

Fig. 4 presents the hourly load profiles in week 24 with the highest annual combined load originally. The plot also shows the hourly retail price linked to the hourly day-ahead wholesale price. For all pricing schemes, flexible assets are operated to generally increase the load in low retail price hours, and decrease the load in high retail price hours: low loads occur in all pricing schemes when the retail price (green dotted line) is peaking in Fig. 4. For the weekly subscriptions (see Fig. 4a and b), load profile modifications are similar; however, combined peak shaving is significantly larger for the CW scheme compared to the IW scheme (see bottom row in Table 5).

Fig. 5 presents the relationship between grid costs (grid price multiplied by the load) and the combined load from C1 and C2 for the different pricing schemes. The CA scheme (yellow in Fig. 5) offers the highest cost (344 NOK/kWh) during the annual peak load in week 24 because it is the highest combined load and it exceeds the combined subscription level (387 kWh/h, see Table 4). Note that (a) paying this high penalty is cost-optimal in the CA scheme considering total cost over the whole year and (b) there is no combined peak load shaving in week 24 as a consequence of the high penalty (see the bottom row in Table 5 and the yellow bar in week 24 in Fig. 3). Fig. 5 also shows that the IA scheme has many penalty hours below the sum of the subscribed levels (413 kWh/h, see Table 4) because the individual loads exceed the individual subscription levels without causing a high combined load. This is a shortcoming of the individual subscribed capacity tariff in terms of signaling efficient grid utilization, as it often penalizes situations where the total flow into C1 and C2 is lower than the joint subscribed capacity (recall that the sum of the individual subscription levels is higher than the combined subscription level in 92% of the weeks, see Table 4). For the weekly subscriptions (IW and CW), there are significantly less penalty hours than for the annual subscriptions since the subscription can be adjusted for each week (see yellow and gray dots compared to orange and blue dots in Fig. 5). The CW scheme has the least amount of penalty hours after flexibility responses (see orange dots in Fig. 5), and it is the scheme that most successfully reduces the annual combined peak load (see Table 5).

5. Discussion

Our case study has been performed assuming perfect foresight on hourly load and retail prices for 25 weeks and no disutility (costs) of operating flexible assets except energy losses (see constraints (4)–(3.3) in Section 3.3). This means our results represent an upper bound to how much cost reduction prosumers can obtain for the different pricing schemes. Note that the stochastic structure of the problem in our case study is related to price and load variation between weeks, i.e., there is no uncertainty within a week. Note also that because we consider energy losses from flexibility responses, total energy consumption increases slightly after demand response even though total costs decrease.

The CW scheme is better at decreasing the weekly combined peak load than the IW scheme. This is a central feature as it is the combined load that dimension the grid connecting C1 and C2 to the rest of the system. However, three weeks show a higher combined peak load for the CW scheme compared to the IW scheme (see

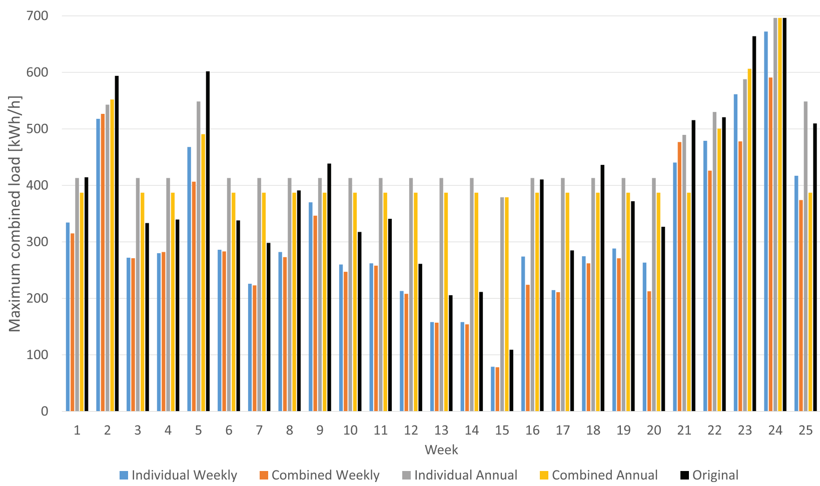
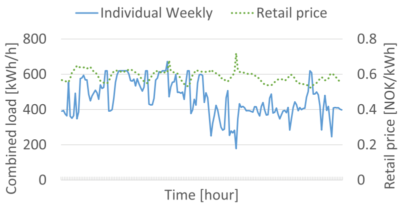
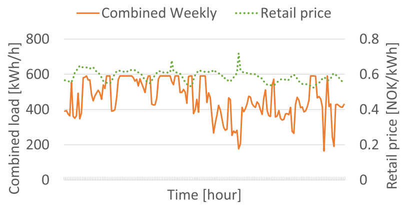


Fig. 3. Weekly combined maximum load after cost-optimal response to the individual weekly (IW) scheme (blue), combined weekly (CW) scheme (orange), individual annual (IA) scheme (gray), and combined annual (CA) scheme (yellow). The original maximum loads in the different weeks are displayed in black. The highest combined load occurs in week 24 where the combined weekly (CW) scheme triggers most peak load shaving. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

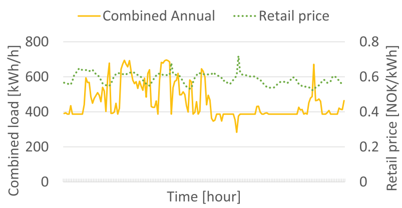


(a) Resulting cost-optimal load (blue) with the individual weekly (IW) scheme.



(b) Resulting cost-optimal load (orange) with the combined weekly (CW) scheme.

(c) Resulting cost-optimal load (gray) with the individual annual (IA) scheme.



(d) Resulting cost-optimal load (yellow) with the combined annual (CA) scheme.

Fig. 4. Resulting combined hourly load profile for 168 h for the individual weekly (IW) scheme (Fig. 4a), combined weekly (CW) scheme (Fig. 4b), individual annual (IA) scheme (Fig. 4c), and combined annual (CA) scheme (Figure d) in week 24 when the original maximum combined load is occurring. The left axis shows hourly load in kWh/h (solid lines) and the right axis shows hourly retail price in NOK/kWh (green dotted lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

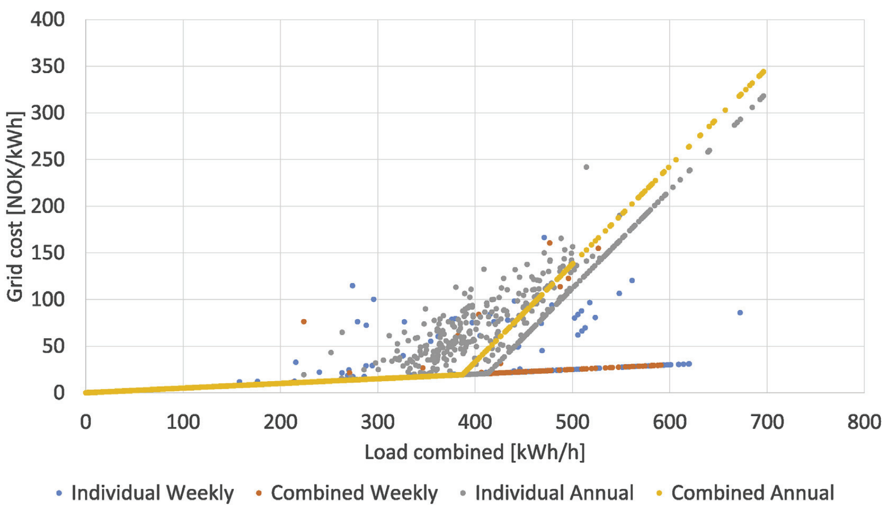


Fig. 5. Resulting hourly load dependent grid tariff costs, i.e., load dependent price multiplied by the load, in NOK/kWh plotted against the combined load of Campus 1 (C1) and Campus 2 (C2) for the individual weekly (IW) scheme (blue), combined weekly (CW) scheme (orange), individual annual (IA) scheme (gray), and combined annual (CA) scheme (yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

weeks 2, 4, and 21 in Fig. 3). This occurs due to three different (but related) reasons that are worth noticing:

- For week 2, the opportunity to respond to retail prices is more valuable than responding to the grid tariff scheme (see Table 3). The two opportunities for cost saving could be conflicting.
- For week 4, the sum of the individual subscription levels is slightly lower than the combined subscription level (see Table 4), so the individual subscriptions are more 'conservative' than the combined subscription.
- For week 21, low subscription cost and high penalty loads in the CW scheme are compensated by high subscription cost and low penalty loads in the IW scheme, so peak shaving is not always the cost-optimal response with the subscribed capacity scheme.

Two main factors should be considered depending on the goal of introducing a capacity-based grid tariff scheme: (1) The dynamics of the grid tariff, i.e., the adjustment frequency of tariff rates and subscription levels, and (2) the load signal that the grid tariff will depend on.

The first factor, the grid tariff dynamics, will impact the achievement of peak shaving through flexibility (see Fig. 3). For an annual decision on the grid subscription level, the cost-optimal strategy is to consider a full year of costs when finding the best subscription level. This consideration means the subscription level is too low for critical hours because costs are minimized for the whole year. Annual subscriptions also lead to more penalty hours than weekly subscriptions, i.e., annual subscriptions make it cost-optimal for prosumers to exceed their subscription level. However, weekly subscriptions trigger load reduction in weeks when grid capacity is not scarce, which results in a potential loss of consumer welfare by penalizing utilization of idle grid capacity. A lower bound on the subscription level combined with dynamic subscription rates can be introduced to avoid rationing of capacity during non-critical hours.

The second factor, the load signal, will impact at which connection point peak shaving is triggered (see Table 5). Under the condition that prosumers have significantly different hourly load profiles,[2] shaving peaks based on individual metering does not maximize the annual peak shaving of the combined load profile. There is more variety in load profiles of buildings for various purposes (e.g. households, shops, offices, etc.) [50], and the flexibility potential will likely vary for the different buildings [51]. The objective of reducing individual loads could be in competition with reducing the combined load, i.e., the individual load could increase and the combined load decrease within a measuring period (and vice versa). If the goal of a capacity-based grid tariff scheme is to trigger combined peak load shaving for a collection of prosumers, price signals based on individual metering are likely to be suboptimal (see Table 5) and could compromise consumer welfare when considering the disutility of offering flexibility. If the price signal is based on the combined load at a bottleneck connection of the grid, it is more likely to trigger combined peak load shaving.

In Norway, all grid-connected consumers are obliged to have individual metering, and this requirement is not challenged by introducing combined price signals. One could identify combined loads through: (a) summing individually metered data, or (b) combined metering at a potential bottleneck. This also points to other alternatives for local coordination in the grid, for example through flexibility markets. The efficiency of flexibility markets for resource allocation, either as an alternative or supplement to dynamic capacity-based grid tariffs, is an interesting area of future research.

[2] A quality check has been performed with our model confirming there is no difference between individual (IW and IA) and combined (CW and CA) metering schemes when two prosumers have identical load profiles.

6. Conclusion

This paper analyzes four different capacity-based grid tariff subscriptions by using a two-stage stochastic programming model in a case study of a Norwegian campus site with flexible assets. The novelty of our analysis includes: (1) comparing long-term annual tariff adjustment with short-term weekly tariff adjustment and (2) comparing the combined and coordinated demand response of several prosumers with the individual responses of single prosumers. The results show that cost-optimal operation of the flexible assets varies depending on the design of the grid tariff scheme. We find that a weekly adjustment of the subscribed grid tariff triggers a reduction in the maximum weekly load more efficiently than an annual subscription in 92% of the simulated weeks, while the combined subscription triggers combined load reduction more efficiently than individual subscriptions in 88% of the simulated weeks. According to our results, the capacity-based grid tariff subscription scheme is likely to be successful in promoting efficient grid development if: (1) the tariff parameters (subscription level) can be adjusted more frequently than annually and (2) the price signals for scarcity in the grid depend on the combined load of several consumers rather than the individual loads. The analysis also indicates that the tariff rates should be adjusted within a year to account for annual load variability and avoid rationing when grid capacity is not scarce. Depending on where a bottleneck in the grid is located, the price signal from a capacity-based tariff should be based on the combined load of several consumers behind this bottleneck (rather than individual load profiles) given different individual load profiles.

Further research should expand the stylized case study to see the impact in a larger collection of different prosumers and consumers. Also, the case study does not address remuneration to flexibility providers, for example in a flexibility market as a supplement or alternative to capacity-based grid tariffs. Combined metering schemes call for some remuneration from all who benefit from flexibility to those who provide flexibility. Further research should compare the difference and substitution between flexibility market designs and capacity-based grid tariff schemes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Stian Backe: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Visualization, Data curation, Writing - original draft. **Güray Kara:** Conceptualization, Writing - original draft. **Asgeir Tomasgard:** Conceptualization, Supervision, Writing - review & editing.

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Appendix A. Nomenclature

List of model components	
Sets	
$\mathscr{F}$	Set of flexible asset types
$\mathscr{F}_p$	Set of flexible asset types at $p \in \mathscr{P}$
$\mathscr{P}$	Set of prosumers
$\mathscr{T}$	Set of market clearing time steps
Ω	Set of stochastic scenarios
Input Data	
$\varepsilon_f^{\text{charge}}$	Charging losses of $f \in \mathscr{F}$
$\varepsilon_f^{\text{diff}}$	Diffusion losses (self-discharge) of $f \in \mathscr{F}$
$\varepsilon_f^{\text{discharge}}$	Discharging losses of $f \in \mathscr{F}$
$\eta_{p,f}^{\text{charge}}$	Charging capacity of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$
$\eta_{p,f}^{\text{discharge}}$	Discharging capacity of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$
$\eta_{p,f}^{\text{storage}}$	Energy storage capacity of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$
$\gamma_{p,f,t}^{\text{req}}$	Minimum required energy content of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$ at time $t \in \mathscr{T}$
$\kappa_{p,f}$	Share of energy storage capacity initially available in $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$
π_ω	Probability of scenario $\omega \in \Omega$
$\xi_{p,t,\omega}^{\text{load}}$	Net demand for electricity at $p \in \mathscr{P}$ in time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$
c^{norm}	Energy dependent grid cost below subscription level (per kWh)
c^{pen}	Energy dependent penalty cost for exceeding grid subscription level (per kWh)
$c_{t,\omega}^{\text{ret}}$	Retail cost of electricity import (incl. taxes) at time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$ (per kWh)
c^{sub}	Grid subscription cost per power level (per kWh/h)
Variables	
$k_{t,\omega}^{\text{C}}$	The (combined) tariff cost on import from the grid in time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$
$k_{p,t,\omega}^{\text{I}}$	The (individual) tariff cost on import from the grid to $p \in \mathscr{P}$ in time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{charge}}$	Charging of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$at time $t \in \mathscr{T}$and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{discharge}}$	Discharging of $f \in \mathscr{F}_p$ at $p \in \mathscr{P}$at time $t \in \mathscr{T}$and scenario $\omega \in \Omega$
$w_{p,f,t,\omega}^{\text{storage}}$	Available energy in flexible asset type $f \in \mathscr{F}_p$ at prosumer $p \in \mathscr{P}$ at time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$
x^{C}	The (combined) subscribed capacity level
x_p^{I}	The (individual) subscribed capacity level at prosumer $p \in \mathscr{P}$
$y_{p,t,\omega}^{\text{load}}$	Resulting grid import at $p \in \mathscr{P}$ in time $t \in \mathscr{T}$ and scenario $\omega \in \Omega$

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Paper III

The impact of uncertainty and time structure on optimal flexibility scheduling in active distribution networks

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III

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The Impact of Uncertainty and Time Structure on Optimal Flexibility Scheduling in Active Distribution Networks

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ABSTRACT The authors focus on a model for system operators that uses centralized scheduling of multiple flexibility assets and services to minimize the cost of managing problems with grid congestion, voltages, and losses. The model schedules flexibility assets using stochastic optimization for AC optimal power flow in an active distribution network. The novelty of the contribution lies in its focus on how the dynamic capabilities of the flexibility resources are defined with regard to how uncertainty is resolved in the model. The impact of uncertainty is studied by using well-known quality measures from stochastic programming, such as the value of the stochastic solution. Moreover, the authors introduce a new measure related to the impact of representing uncertainty and flexibility when considering reactive power. By changing the time attributes of flexibility assets, the authors show the impact of uncertainty and time structure on a scheduling problem. The uncertainties considered are price and load levels. The findings reveal that the quality of the scheduling of each flexibility resource depends on using a stochastic model with a rigorous consideration of time and uncertainty.

INDEX TERMS Flexibility, active distribution networks, optimal power flow, scheduling, stochastic programming, uncertainty.

NOMENCLATURE

Abbreviations:

ADN	Active Distribution Network
CB	Shunt capacitor banks
DER	Distributed Energy Resource
DSO	Distribution System Operator
DVSS	Deviated value of stochastic solution
EEV	Expected value of expected solution
FSP	Flexibility Service Provider
ICT	Information-communication technologies
LV	Low-voltage
MV	Medium-voltage
OLTC	On load tap changer
PV	Photo-voltaic module
RP	Recourse problem
SDP	Semi-definite programming
SO	System operator
SOP	Soft open point
SOS2	Special Ordered Sets of type 2
SVC	Static VAR compensators
TSO	Transmission System Operator
VoLL	Value of lost load
VSS	Value of stochastic solution

Parameters:

$\beta_{s,t}$	Power price from the grid parameter
η_c, η_d	Battery charge and discharge coefficients parameters

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σ_k	The percentage of load considered in correspondence of breakpoint k
$L^{p}_{s,i,t}$	Active load demand from node i, at time t, in scenario s
$L^{q}_{s,i,t}$	Reactive load demand from node i, at time t, in scenario s
P^{max}_{g},P^{min}_{g}	Upper and lower limits of active power purchase from the grid.
Q^{max}_{g},Q^{min}_{g}	Upper and lower limits of reactive power purchase from the grid.
R_s	Probability of the occurrence for a scenario
SoC_{max}	Parameter for maximum state of charge in batteries
VC_k	Variable cost of load shifting parameter
Z_i	Multiplying parameter for minimum battery capacity

Sets:

$g \in G$	Set of generators with index g
$i \in I$	Set of buses in network with index i
$j \in J$	Set of buses in network with index j
$k \in K$	Set of breakpoints with parameter index k
$s \in S$	Set of scenarios with index s
$t \in T$	Set of periods with hourly resolution with index t
$t_{shift} \in T$	Load shifting time index

Variables:

$\delta_{i,t}$, $\theta_{s,i,j,t}$	Voltage angles between buses i and j
ϵ_{t+1}	Prediction error
$\hat{L}_{t+1}$	Forecasted load level
$\lambda_{s,i,t,k}$	Continuous variable between 0 and 1
ϕ_m, α	AR(N)-process coefficients
$AF_{s,i,j,t}$	Active power flow between nodes i and j
$B_{i,j}$	Line reactance value in DC-OPF model
$C_{s,i,t}$,$C_{i,t}$	Costs of load shifting
$DP^{+}_{s,g,t}$, $DP^{-}_{s,g,t}$	Active power import or export from an external grid
$DQ^{+}_{s,g,t}$, $DQ^{-}_{s,g,t}$	Reactive power import or export from an external grid
L_{t+1}	Historical load data for forecasting
$P^{char}_{s,i,t}$, $P^{dis}_{s,i,t}$	Charging and discharging amount of a battery
$P^{shed}_{s,i,t}$	Amount of active power curtailment
$P^{shift}_{s,i,t_{shift}}$	Amount of active power shift
$P_{s,g,t}$, $Q_{s,g,t}$	Active and reactive of scheduled production from a generator
$Q^{shed}_{s,i,t}$	Amount of reactive power curtailment
$Q^{shift}_{s,i,t_{shift}}$	Amount of reactive power shift
$RF_{s,i,j,t}$	Reactive power flow between nodes i and j
$S_{i,j}$	Current flow between nodes i and j
$SoC_{i,t}$	State of charge for a battery
$V_{s,i,t}$	Voltage magnitude
$Y_{s,ij}$	Impedance value in AC-OPF model

I. INTRODUCTION

The penetration of Distributed Energy Resources (DER), located close to where electricity is consumed, e.g., households or commercial buildings is increasing considerably in the last years. However, due to the often-intermittent nature of DERs, as well as variations in demand, such developments can also cause several problems in low-voltage (LV) grid designs such as voltage variations (drops/rises), grid congestion, and network losses. Increases in electricity load are likely to continue in the future [1]. To solve these problems at grid level, distribution system operators (DSOs) have shifted from traditional passive and unidirectional distribution networks to bidirectional active distribution networks (ADNs).

An ADN can be described as a network system with control over its distributed generation resources. Some of the enabling technologies for ADNs are storage resources, demand-response programs, dynamic line ratings, and voltage/power control technologies [2].

In this regard, *flexibility* refers to the ability of a power system to respond to changes in demand and supply [3]. Based on recent developments in ICT, different levels of demand-side flexibility resources based on demand response programs and technologies could contribute to the efficiency of the ADNs by activating end users and their flexibility assets [4]–[6]. In this paper, we focus on the grid-relevant issues, including network congestion, voltage variation problems, and network losses, and investigate the impact of time and uncertainty on the activation of required flexibility services.

Several studies have reported on the traditional use of active management resources, such as on-load tap changers (OLTCs), static VAR compensators (SVCs), shunt capacitor banks (CBs), and standard operating procedures (SOPs), to deal with grid operational challenges(e.g., [7]). However, traditional solutions require significant investments in grid infrastructure and therefore flexible electricity resources can contribute to deferral of such investments. In this study, we focus on flexible electricity resources such as demand-response programs, change in supply, and batteries, which do not require additional investments in grid infrastructure and technology [8].

A. RESEARCH METHOD

In a traditional power market, grid congestion, voltage variations, network losses, and frequency deviations are handled by a system operator (SO) using ancillary services. Recent developments in DERs and demand-side flexibility (response) programs [9], [10] suggest that low-voltage grid issues resulting from high demand or high levels of local power generation could be dealt with at the distribution networks level [11]. In this context, traditional passive distribution networks are transformed into ADNs. Different flexibility assets, such as demand-side flexibility resources, batteries, and DERs are considered local flexibility assets in the ADN. Most of the aforementioned resources are stochastic in nature [12], but they can still play a crucial role in demand-side management and low-voltage grid operation. This is particularly the case when central operators have the possibility to shift or curtail loads over a particular period or to use energy storage or batteries when necessary. Therefore, the SO needs to assess possible future developments in terms of uncertainties and time.

In this paper, we study the impact of time and uncertainty on the decision processes of SOs in ANDs [13]. An SO uses centralized scheduling of multiple flexibility assets and services to minimize the cost of managing problems relating to network congestion, voltage variations, and network losses. A number of authors have studied uncertain parameters such as price, load, renewable generation, and fault situations in distributional grids in connection with optimal response to system or market conditions [14]. The novelty in this paper is our focus on how the dynamic capabilities of the flexibility resources (e.g.,) time are defined, how uncertainty is resolved in our optimal scheduling model, and the characteristics of the flexible assets. Two important parameters for optimal decision-making at the operational level are activation (response) time and duration of the flexibility provided by the assets. Fig. 1 shows the characteristics of a flexibility resource (asset), in which the SO procures a certain amount of flexibility from flexibility service providers (FSPs).

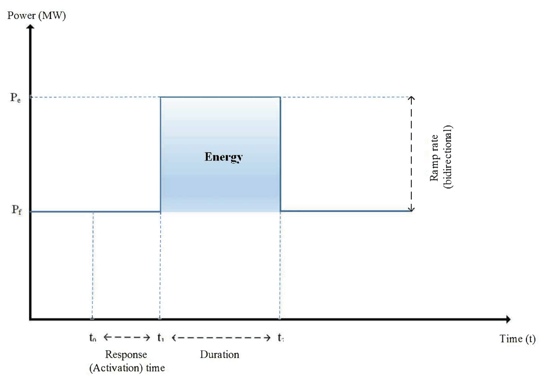

FIGURE 1. Characteristics of a flexibility resource base for time and power [15].

To study the impact of uncertainty representation when scheduling flexible assets in ADN management, we use well-known quality measures from stochastic programming, including the value of the stochastic solution. We also introduce a new measure related to uncertainty and flexibility when considering reactive power. By varying the characteristics relating to activation time and duration of flexibility provision from these assets, our analysis shows that the presentation of uncertain information regarding load and price in a model is very important when considering the value of flexibility.

A stochastic two-stage AC optimal power flow (AC-OPF) model is used in the analyses. The results can be generalized to a multistage setting. However, two stages are deemed sufficient to illustrate the importance of the information structure of the model, namely the time when uncertainty is resolved and how that affects decisions and the representation of flexibility in the available assets regarding activation time and duration of the flexibility supply. In peak load situations in which voltage drops and/or network congestion problems occur, the SO implements dynamic scheduling of a portfolio of flexible assets. The primary objective is to present the impact of uncertainty representation and timing on both active and reactive power. Accordingly, a moving interval approach is used, whereby both the first stage decisions and the recourse decisions in the second stage of the stochastic model are affected by the response and duration times of the assets. Fig. 2 shows the moving interval method, which uses load shifting for flexibility.

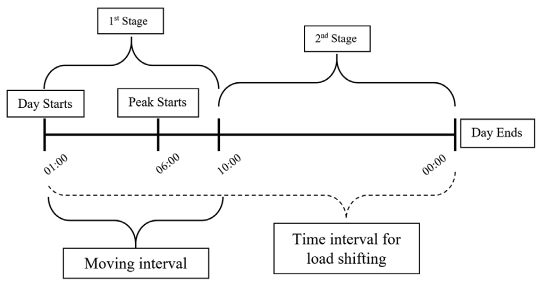

FIGURE 2. Timeline of the moving interval method.

B. LITERATURE REVIEW AND CONTRIBUTIONS

Authors in [16] investigated time aspects of flexibility provision through a qualitative survey-based study of different companies. They found that timing-based business models could perform in very short time intervals to complement traditional power generation capabilities when managing changes in generation or consumption plans.

An SO needs to choose between grid upgrades and using flexibility products by considering the time dimension of the network configuration and demand-side flexibility. Different factors such as response time, duration, and power amount of the demand-side flexibility, affect the ability to use flexibility assets to replace or delay network upgrades [8].

The time characteristics of some flexibility assets (technologies) could enable the assets to provide value in multiple time intervals. The authors in [15] conducted a survey to evaluate different flexibility technologies with respect to their time dimension and found that for optimal valuation and usage of flexibility resources, the decision-maker (in our case the SO) needs to know the time characteristics of the scheduled flexible asset before physical delivery of the flexibility services. The literature provides examples of stochastic models for scheduling flexible assets at the level of microgrids, DSOs, and transmission system operators (TSOs), based on central control [17], [18]. Often, such modeling approaches are based on optimal power flow models for scheduling and flexibility procurement [19], [20]. The importance of duration and activation times for flexibility assets (time characteristics) are discussed by [15], [21], but the authors do not present quantitative studies of flexibility in grid operations and the impact of uncertainty on flexibility services and assets. To our knowledge, no studies to date have used stochastic programming to examine both uncertainty and characteristics of flexibility (e.g., duration, activation time, and their relationships) in a dynamic schedule. This article makes a contribution in this respect.

In the case of ADNs, some studies present methods to deal with DERs and uncertain loads in cases of network congestion and voltage variation problems. Besides active management resources in ADNs, an SO or centralized management could use economic incentives and market-based approaches to mitigate such problems. As one approach, [22] present a congestion management strategy with a market-based mechanism and SOPs. Since original SOP-based congestion management is a non-convex problem, they applied convex relaxation, namely semidefinite programing (SDP). They specifically did not use demand-side flexibility such as load shifting and shedding. In another approach, authors in [23] used flexible demand and storage systems for an ADN with dynamic OPF modeling. Their results showed the efficiency of the use of flexible demand and storage systems for ADNs. In a recent study, [24] present a method for two-stage hierarchical congestion management in ADNs with SOPs, tie switches, DERs, and a microgrid. They used SOPs and switches as direct control mechanisms, while DERs contributed through a market. The above-discussed studies demonstrate the efficiency of flexibility in ADN management, but without emphasizing the impact of time and uncertainty in scheduling and decision making.

The authors in [25] and [26] discuss reactive power provision from DERs via market designs (optimal reactive power dispatch). Both sets of authors state the importance of uncertainty from the DER perspective. However, they do not discuss the provision of reactive power from demand-side flexibility assets for grid operations according to the time dimension. Our stochastic flexibility provision framework, which is the second contribution of this paper, includes the reactive power component.

Recent research on flexibility usage has focused on demand uncertainty [27], uncertainty in renewable resource generation [28], PV generation and ambient temperature uncertainties [17], and uncertain reserves from demand response [29]. In this paper, we mainly discuss uncertainties regarding resources and their availability in a binary manner (i.e., the power resource is either available at a certain level or not), rather than representing duration and time lags for activation (response).

The contributions of this paper are summarized as follows:

- We investigated the impact of uncertainty in decision-making and the importance of how to represent the time dimension (i.e., duration and activation (response) time) when scheduling flexibility assets and services as well as how uncertainty is resolved in optimal scheduling model.
- A new quality measure is introduced to evaluate the significance of representing uncertainty about availability of the usage in different assets, with a focus on reactive power.
- The impact of uncertainty and time when scheduling each flexibility asset is examined by applying two variants of our optimal scheduling model.

Our evaluations use both this new quality measure and traditional ones such as the Value of the Stochastic Solution [30].

The paper is structured as follows. Section II discusses the concept and the different flexible assets. Section III describes the mathematical model. Section IV explains the representation of stochasticity and scenario generation. Section V introduces a case study from Norway and the results of optimal scheduling. Section VI explains quality measures and the impact of how uncertainty is represented with regard to the activation time and the duration characteristics of the flexible assets.

II. FLEXIBILITY ASSETS AND SERVICES

Our study includes two primary demand-side flexibility resources: demand response in terms of load curtailment and load shifting; demand response in terms of storage.

A. DEMAND-SIDE FLEXIBILITY SERVICES-LOAD SHIFTING AND CURTAILMENT

Load curtailment is defined as a reduction in the maximum load (peak shaving) for a predefined duration and payment for a prosumer/consumer. As a flexibility asset, load curtailment is prepared for immediate use by the central system operator. The cost of using load curtailment could be too high in some circumstances and therefore the duration of this asset is less than other assets. However, the response time is shorter than that of other measures due to an immediate cut in consumption.

Load shifting differs from load curtailment in terms of cost, duration, and activation time. The main condition for shifting any flexible load is that it is possible to meet total demand after the shift. An SO or asset owner could shift the consumption within a time interval for specific **load volumes**. The load profile can be changed, but the total energy delivered over the planning horizon must be preserved. Alternatively, the whole **load profile** can be shifted. In this paper, we discuss the first approach with load preservation within a planning horizon. For a further discussion of the load shifting, see [31].

The duration and response time of load shifting, time dimensions illustrated in Fig. 1, are important attributes concerning its timing. The provision for flexibility through load shifting needs careful consideration, as it must include enough time to shift the volume as well as to meet the total power demand. Moreover, the load shifting should remain in the solution process for sufficient time for cost-efficient solution (duration).

Demand-side flexibility assets such as load shifting and load curtailment include uncertainty about their duration response time and load amount. Any changes in the time dimensions of these assets will also change the degree of uncertainty during the flexibility usage for grid problems.

B. STORAGE FLEXIBILITY- BATTERIES

The use of batteries allows for flexibility without incurring any operating costs. The reactive power compensation capability of PV inverters can be used to regulate the voltage magnitude [32]. In this paper, we discuss only active power sourced from batteries.

Batteries are flexible with respect to timing and managing uncertainty. An SO can plan exactly how long a battery should remain in flexibility usage process and batteries can be activated whenever the SO needs them to provide power.

C. SYSTEM ARCHITECTURE

Our proposed power system architecture has a central SO that can procure flexibility services from flexibility assets connected to an LV grid within limits defined by bilateral contracts with the asset owner. The contracts specify how the load can be shifted or curtailed within predefined limits and how batteries can be used to address grid operational issues. The central SO procures flexibility from the FSPs at a pre-agreed cost that reflects the batteries' disutility. The assets are located in residential areas, but the flexibility is controlled by the operator. The architecture of the suggested solution is shown in Fig. 3.

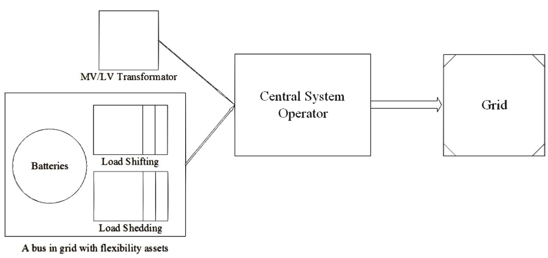

FIGURE 3. Proposed power system architecture.

1) COSTS OF FLEXIBILITY ASSETS

In the studied case from Norway, load curtailment is a voluntary action. Therefore, the cost is set at 1500 EUR/MWh, which is lower than the normal value of lost load (VoLL). The disutility cost [31] used for load shifting is shown as a piecewise-linear cost curve. The shifting is based on voluntary actions and therefore the cost is assumed to be lower than the VoLL, but it will increase with volume.

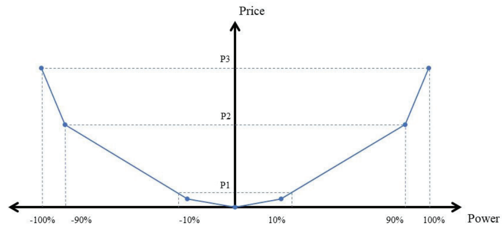

FIGURE 4. Piecewise-linear cost curve with four increments.

The disutility cost curve for load shifting includes four increments and five breakpoints on the cost curve, as presented in Fig. 4. Breakpoints in the cost function, as well as other details, are defined based on studies of variable costs of end-user appliances [33], [34].

III. MATHEMATICAL MODEL: STOCHASTIC TWO-STAGE AC OPTIMAL POWER FLOW

In this section, we present the stochastic two-stage AC-OPF model with demand-side and storage flexibility. The background information on load shifting was sourced from [31], whereas the AC-OPF model is based on the work of [35]. For comparison, both in terms of solution times and solution quality, we consider an AC formulation and an alternative DC relaxation formulation of power flow for the second-stage of the stochastic model.

We used a two-stage stochastic program to model the uncertainty in demand and prices [36]. The two stages, the uncertainties, and the decision-making process are all shown in Fig. 5. In the first 10 periods, all scheduling and load/supply balances are performed without knowing which of the scenarios will occur at $t = 11$ hence without knowing the realizations of load and prices from that point until the end of the problem's time horizon. Before $t = 11$, the parameters such as load and prices are deterministic. At $t = 11$ one of the scenarios will be realized and scheduling of flexible assets will be scenario-contingent from thereon. The main purpose

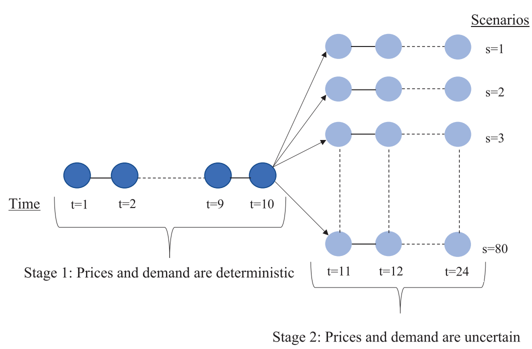

FIGURE 5. Two-stage decision-making structure with uncertainties.

of the stochastic program is to minimize the expected costs for all periods, considering the uncertainty process.

A. OBJECTIVE FUNCTION

The objective function in (1) aims to minimize the total system cost. There are four terms in the expression. The first two represent the deterministic first-stage decisions. The third and fourth terms represent exactly the same costs in the second stage and therefore variables are scenario-dependent, indexed by s, and the terms are multiplied by probability R_s. The first term includes the cost of electricity imported from the medium-voltage (MV) grid. $DP^+_{g,t}$, $DP^-_{g,t}$ are active power import and export from external grid and β_t is the electricity price. The second term consists of the active power load curtailment $P^{shed}_{i,t}$ as well as the cost of load shifting at time t in bus i, $C_{i,t_{shift}}$.

$$\begin{aligned}\text{minimize} \sum_{t\in T}\sum_{g\in G}\left[DP^+_{g,t}\beta_t + DP^-_{g,t}\beta_t\right]\\ + \sum_{i\in I}\sum_{t\in T}\left[\text{VoLL} * P^{shed}_{i,t} + C_{i,t_{shift}}\right]\\ + \sum_{s\in S} R_s\left[\sum_{t\in T}\sum_{g\in G}\left[DP^+_{s,g,t}\beta_{s,t} + DP^-_{s,g,t}\beta_{s,t}\right]\right.\\ \left. + \sum_{i\in I}\sum_{t\in T}\left[\text{VoLL} * P^{shed}_{s,i,t} + C_{s,i,t_{shift}}\right]\right] \end{aligned} \tag{1}$$

B. CONGESTION CONSTRAINTS

To prevent grid congestion, the equation 2 is added to the optimization problem with active power flow $AF^2_{s,t,i,j}$, reactive power flow $RF^2_{s,t,i,j}$ and upper limit of the line usage, S^2_{ij}, between buses i and j.

$$AF^2_{s,t,i,j} + RF^2_{s,t,i,j} \le S^2_{ij} \tag{2}$$

In the variant model with DC power flow, grid congestion is modeled in (3). The equation provides an upper limit for active power flow between buses i and j. The impacts of equations (2) and (3) are discussed in Section VI.

$$AF_{s,t,i,j} \le S_{ij} \tag{3}$$

C. IMPORT AND EXPORT CONSTRAINTS FROM AN EXTERNAL GRID

These import and export constraints in equations (4) and (5) represent the imported active power, $P_{s,g,t}$, and imported reactive power, $Q_{s,g,t}$, from the external grid. In our case study, the external grid is connected to the first bus in the LV grid and can be considered as a source of an external flexibility asset.

$$P_{s,g,t} = DP^+_{s,g,t} - DP^-_{s,g,t} \tag{4}$$
$$Q_{s,g,t} = DQ^+_{s,g,t} - DQ^-_{s,g,t} \tag{5}$$

D. POWER FLOW CONSTRAINTS

The AC power flow constraints enforces the active and reactive power balance at each bus in the LV grid for voltage regulations, $V_{s,i,j,t}$, at each bus.

$$\begin{aligned} AF_{s,i,j,t} &= V^2_{s,i,t} Y_{ij} cos\theta_{s,ji}\\ &\quad - V_{s,i,t}V_{s,j,t}Y_{ij}cos\left(\delta_{s,i,t} - \delta_{s,j,t} + \theta_{s,ij}\right) \end{aligned} \tag{6}$$
$$\begin{aligned} RF_{s,i,j,t} &= V^2_{s,i,t} Y_{ij} sin\theta_{s,ji}\\ &\quad - V_{s,i,t}V_{s,j,t}Y_{ij}sin\left(\delta_{s,i,t} - \delta_{s,j,t} + \theta_{s,ij}\right)\\ &\quad - \frac{bV^2_{i,t}}{2} \end{aligned} \tag{7}$$

In some the following formulations we use a DC optimal power flow equation in case we want to see the impact of uncertainty on just the active power balance (without considering voltage regulations):

$$AF_{s,i,j,t} = B_{i,j}\left(\theta_{s,i,t} - \theta_{s,j,t}\right) \tag{8}$$

E. LOAD BALANCE CONSTRAINTS

For each bus in our grid topology, equations (9) and (10) represent net demand, including flexibility for active and reactive power from all flexibility assets in the grid. In equation (9), we obtain active power from batteries, demand-side assets and services, and the main grid. In equation (10), we obtain reactive power from demand-side assets and the main grid only. The last two equations (11 and 12) show the upper and lower limits of purchases from the MV grid.

$$\begin{aligned} AF_{s,t,i,j} &= \sum_{g\in G_i} P_{s,i,g,t} + \left(P^{dis}_{s,i,t} - P^{chr}_{s,i,t}\right)\\ &\quad + P^{shift}_{s,i,t,t_{shift}} - L^p_{s,i,t} + P^{shed}_{s,i,t} \end{aligned} \tag{9}$$
$$\begin{aligned} RF_{s,t,i,j} &= \sum_{g\in G_i} Q_{s,i,g,t}\\ &\quad + Q^{shift}_{s,i,t,t_{shift}} + Q^{shed}_{s,i,t} - L^q_{s,i,t} \end{aligned} \tag{10}$$
$$P^{min}_g \le P_{s,t,g} \le P^{max}_g \tag{11}$$
$$Q^{min}_g \le Q_{s,t,g} \le Q^{max}_g \tag{12}$$

F. BATTERY CONSTRAINTS

Equations (13)–(16) represent the state of charge (SoC) in the batteries ($SoC_{s,i,t}$), the limits of the SoC, and the maximum and minimum charging capacities, respectively.

$$SoC_{s,i,t} = SoC_{s,i,(t-1)} + P^{char}_{s,i,t} * \eta_c - \frac{P^{dis}_{s,i,t}}{\eta_d} \tag{13}$$
$$SoC^{min} \le SoC \le SoC^{max} \tag{14}$$
$$0 \le P^{char}_i \le Z_i \cdot SoC^{max}_i \tag{15}$$
$$0 \le P^{dis}_i \le Z_i \cdot SoC^{max}_i \tag{16}$$

G. LOAD CURTAILMENT CONSTRAINTS

In equations (18) and (19) the amount of load curtailment is limited by $L^p_{s,i,t}$ for active power demand, and $L^q_{s,i,t}$ for reactive power demand in each bus (the power factor in (17) is assumed to be constant at each bus).

$$Q^{shed}_{s,i,t} = P^{shed}_{s,i,t} tan(\theta_{s,i}) \tag{17}$$

$$0 \leq P^{shed}_{s,i,t} \leq L^{p}_{s,i,t} \tag{18}$$

$$0 \leq Q^{shed}_{s,i,t} \leq L^{q}_{s,i,t} \tag{19}$$

H. LOAD SHIFTING CONSTRAINTS

The load shifting formulation is based on [31] and states that the total load volume could be reallocated in any period within the planning horizon: $t_{shift} \in \left[t^{down}_{shift}, t^{up}_{shift}\right] \subset T$. Within t_{shift}, our model is obliged to satisfy all demands at each bus.

Four equations represent the convex cost function of load shift, and in Fig. 4 they are depicted as the cost curve. The reference equation (20) gives the amount of load shifting ($P^{shift}_{s,i,t_{shift}}$), and equation (21) gives the cost of load shifting ($C_{s,i,t_{shift}}$) as the function equation. The convexity equation (22) creates a convex combination of auxiliary variables $\lambda_{s,i,t_{shift},k}$ with one of the variable's immediate neighbors. In a minimization problem with a convex and piecewise linear cost curve, such a formulation leads to an exact formulation without resorting to the formulation of Special Ordered Sets of type 2 (SOS2) variables. Equation (23) is used to calculate the load profile balance, which ensures that the shifted load is energy preserving at the end of the interval. Equation (24) calculates the shifted reactive power load.

$$P^{shift}_{s,i,t_{shift}} = \sum_{k\in K} \lambda_{s,i,t_{shift},k} L^{p}_{s,i,t}\sigma_k \tag{20}$$

$$C_{s,i,t_{shift}} = \sum_{k\in K} \lambda_{s,i,t_{shift},k} L^{p}_{s,i,t}\sigma_k VC_k \tag{21}$$

$$\sum_{k\in K} \lambda_{s,i,t_{shift},k} = 1, \quad 0 \leq \lambda_{s,i,t_{shift},k} \leq 1 \tag{22}$$

$$\begin{aligned} \sum_{t_{shift}} P^{shift}_{i,t_{shift}} + \sum_{t_{shift}} P^{shift}_{s,i,t_{shift}} &= 0, \\ t^{down}_{shift} \leq t_{shift} &\leq t^{up}_{shift} \end{aligned} \tag{23}$$

$$Q^{shift}_{s,i,t} = P^{shift}_{s,i,t} * tan(\theta_{s,i}) \tag{24}$$

where σ_k represents the percentage of load considered in correspondence of breakpoint k. After exceeding 10% and 90% respectively of the total load in each bus, different variable costs and increments in the cost function are activated. Concerning the $\lambda_{s,i,t_{shift},k}$ value, reference row increments will be activated and will give the cost of a load shift according to the related variable cost, γ_k. For the 10% shift and 90% shift, are EUR 10/MWh and EUR 50/MWh respectively based on [33].

I. VOLTAGE ANGLE AND MAGNITUDE LIMITS

The following equation (25) gives the magnitude limits for voltages:

$$0.9 \leq V_{s,i,j,t} \leq 1.1 \tag{25}$$

IV. STOCHASTICITY AND SCENARIO GENERATION

The main analysis is performed with a two-stage stochastic model in which load and electricity power prices are deterministic to describe scenarios representing the second-stage uncertainty, a scenario generation algorithm based on a combination of forecasting and *moment-matching* of residuals [37], [38] is used. This is similar to the approach used by [39]. Our method, which is based on articles by [37]–[39], collects the historical data, establishes (parameterizes) an autoregressive forecast model for load in the buses and prices, and combines estimated realizations for these into a scenario tree representing the realizations.

Probability distributions for the errors (residuals) in the load and price forecasts are used as a basis for modeling the uncertainty. For each error distribution, we estimate moments such as mean, variance, skewness, and kurtosis. Next, we use an algorithm for moment-matching scenario generation to estimate joint error distributions for prices and the 80 buses for all periods in the second stage. The approach captures both temporal correlations (through the forecasts) and inter-variable correlation (through the moment matching). The main feature of the scenario generation algorithm is to combine the time series information for the load in the 80 buses and price with the generated error distributions from the moment matching, thus enabling us to capture both the time correlation and inter-variable correlation. The scenario generation method is convenient to use in short-term scenario tree constructions [40], as described in the following six steps:

Step 1: Forecast the load in each bus. For each bus, use an $\mathbf{N}^{th}$ order, AR(N)-process to forecast load:

$$\hat{L}_{t+1} = \alpha + \sum_{m=1}^{N} \phi_m L_{t+1-m} + \epsilon_{t+1} \tag{26}$$

where L_{t+1} is the historical load data, $\hat{L}_{t+1}$ is forecasted load level, ϵ_{t+1} is the residual or prediction error and ϕ_m and α are AR(N)-process coefficients. This is parameterized based on historical data.

Step 2: Calculate the historical residuals of the forecasted parameters. This residual distribution will be the basis for all scenarios in all periods as the error processes are stationary.

Step 3: Calculate the statistical properties of the error distributions. Calculate the mean ($\bar{\epsilon}_{t+1} \sim$), variance ($Var(\epsilon_{t+1} \sim)$), skewness ($Skew(\epsilon_{t+1} \sim)$), and kurtosis ($Kurt(\epsilon_{t+1} \sim)$) and correlations between the residual series ($Corr(\epsilon_{t+1})$)

Step 4: Create a joint error distribution. It should be noted that this is valid in all periods because the errors are stationary. Use Høyland *et al.*'s moment-matching algorithm [37] to create a discrete joint scenario tree with error distribution for price and load in all the buses. The joint distribution approximates the four moments and correlations using s outcomes for the residuals (ϵ^{s}_{t+1}). In our case, the number of scenarios in the distribution is $s = 80$. The spatial (inter-variable) correlations of variables in scenarios are captured by the moment-matching algorithm. It should be noted that our algorithm captures the correlation of forecast model residuals, not the variables themselves.

Step 5: Create the first stage of the scenario tree. A scenario tree can be made by first using the forecasting methods directly for the first t_1 periods in a *rolling window* approach where in if t is the last observed period and $t+1$ is the first forecasted period, we will have

$$\hat{L}_{t+1} = \alpha + \sum_{m=1}^{N} \phi_m L_{t+1-m} \tag{27}$$

Then, proceed with

$$\hat{L}_{t+2} = \alpha + \phi_1 \hat{L}_{t+1} + \sum_{m=2}^{N} \phi_m L_{t+2-m} \tag{28}$$

until

$$\hat{L}_{t+t_1} = \alpha + \sum_{m=1}^{N} \phi_m \hat{L}_{t+t_1-m} \tag{29}$$

Step 6: Create the second stage of the scenario tree. For each second stage scenario s, we follow the same procedure, but, add the term ϵ_t^s, which is a sample of the error in period t used in scenario s. It is sampled from the s outcomes from Step 4 (without replacement), such that all S outcomes are used in a scenario within a period. This is then repeated for $t = t_1, \ldots, t_2$. The variables in each of the second stage scenarios can then be represented as

$$\hat{L}_{t+1}^s = \alpha + \sum_{m=1}^{N} \phi_m L_{t+1-m} + \epsilon_t^s \tag{30}$$

$$\hat{L}_{t+2}^s = \alpha + \hat{L}_{t+1}^s + \sum_{m=2}^{N} \phi_m L_{t+2-m} + \epsilon_t^s \tag{31}$$

until

$$\hat{L}_{t+t_2}^s = \alpha + \sum_{m=1}^{N} \phi_m \hat{L}_{t+t_2+1-m}^s + \epsilon_t^s \tag{32}$$

where $s = 1, \ldots, S$.

Without loss of generality, the above assumes that $m \leq t_1$ and $m \leq t_2$.

In our research, we parameterize 17 different (S)ARIMA load models, one for each bus in the grid. The same procedure is used to generate separate scenarios for the grid power price. Thereafter, the load and price scenarios are combined randomly, so that on expectation the expected correlation between the load and price is zero. We generate 80 joint scenarios for loads at every bus and the grid price. We capture the spatial correlation of model residuals because the load profiles of each variable are located in the same place, and they have similar time-series patterns. Furthermore, variables do not affect the national grid prices. Our model calculates in-sample accuracy simultaneously while generating scenarios at out-of-sample.

V. CASE STUDY FROM SOUTHERN NORWAY

In this section, we analyze the results of our case study of the islands that constitute Hvaler Municipality in southern Norway, in January 2016. The municipality has approximately a population of 4100, in 2016, whereas on warm summer days there can be ca. 40,000 people due to the number of second homes [41]. Consumers locate in the area are commercial buildings, two- to four-family houses, and Norwegian holiday homes. In addition to the second homes, there are two-family and to four-family residential buildings and commercial buildings.

The 22kV and 230V radial grid structure in this study is synthetically generated based on Hvaler Municipality, and it contains 26 buses, of which 17 buses have electricity demand and they represent households. The network is an LV grid and therefore we expect to see voltage problems and congestion. The radial topology of the grid is presented in Fig. 6. Red buses are end users with demand-side flexibility capacities. The first bus is the connection point to the MV grid with a transformer. Therefore, possible congestion might occur on the line between buses 1 and 26.

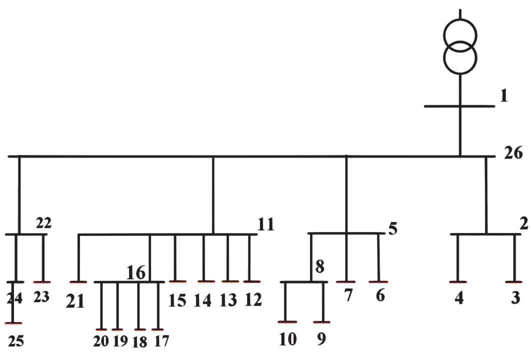

FIGURE 6. Radial grids structure based on Hvaler Municipality.

The anonymous data and demand-side flexibility parameters were provided by a distribution system operator (DSO). The data are observations of the grid participants and include the load profiles of 17 end users from January 1, 2014 to December 31, 2016. We used MATPOWER[1] to conducted power flow analysis in order to identify existing voltage and congestion problems on a predetermined day. Based on power flow analysis, the active and reactive power demands from each bus are represented in Fig. 7 and Fig. 8, respectively.

There are five batteries with 14 kW capacities connected to buses 6, 10, 13, 18, 23 (battery sites). In cases of immediate load curtailment, the system operator pays the VoLL to end users.

We use two main approaches in this research for optimal scheduling of flexibility assets. First, by using historical data, we solve a deterministic AC-OPF problem. Later,

[1] https://matpower.org/

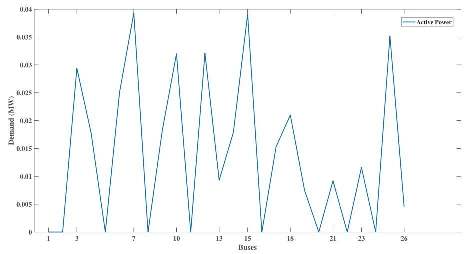

FIGURE 7. Fixed active power demand from each bus (MW).

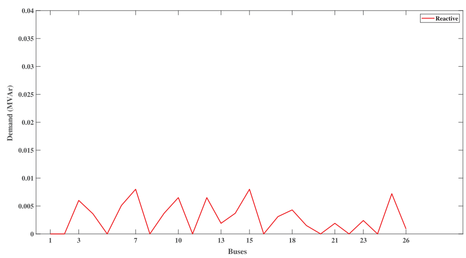

FIGURE 8. Fixed reactive power demand from each bus (MVAr).

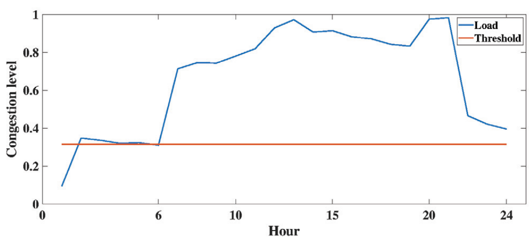

FIGURE 9. Congestion level on the predetermined sample day (hourly) in the case study.

to observe the impact of uncertainty in load and prices, we apply the two-stage stochastic AC-OPF model. The problems are solved using KNITRO and GAMS on a computer with Intel(R) Core(TM) i7-7500U processor at 2.70GHz and with 16GB RAM. The total run time for the deterministic case is 33 seconds, and for the stochastic case is 15 minutes.

A. GRID PROBLEMS

1) CONGESTION PROBLEM

Congestion in an LV grid results from pushing the physical limits of network lines, such as voltage limits, stability limits, and thermal limits [42]. The level of congestion in the case study on the predetermined sample day is presented in Fig. 9.

2) VOLTAGE VARIATIONS

If there is insufficient reactive power from system participants, a voltage variation problem will occur [42]. In our case study, the problem was a voltage drop due to high demand on the sample day (see Fig. 10).

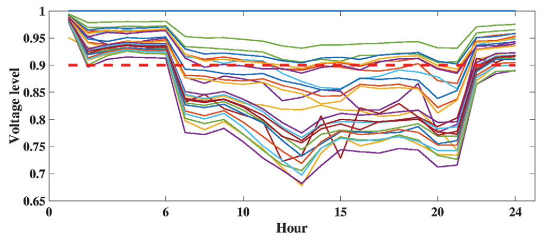

FIGURE 10. Voltage profiles on the sample day (hourly) in the case study.

B. DETERMINISTIC RESULTS

For the deterministic part of our study we used a single scenario AC-OPF model to schedule flexibility assets to keep the voltage within the required interval. In equations (6) and (7) buses are kept within the voltage interval, and grid congestion at the MV/LV transformer is prevented with Eq. (2). The results of the imported power from the MV grid, the state of charge (SoC) of the batteries, and the load shifting amount are respectively presented in Fig. 11, Fig. 12, Fig. 13.

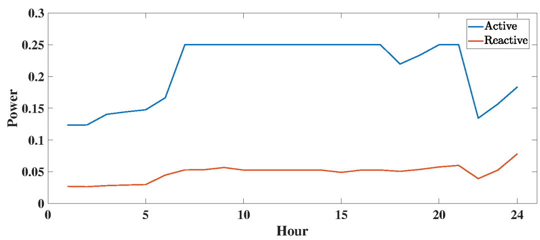

FIGURE 11. Power from the main grid (MWh).

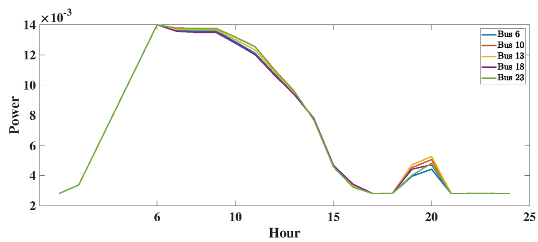

FIGURE 12. Battery SoC in the deterministic solution (MWh).

1) DISCUSSION OF DETERMINISTIC RESULTS

The deterministic case observes a significant impact of flexible assets when managing peak load hours. The main observation from Fig. 11 and Fig. 12 is that the feed from the main grid is used for charging batteries until 06:00 in the morning. Until peak hours start, the batteries are fully charged. As shown in Fig. 9, heavy congestion starts at 06:00. Between 06:00 and 21:00, load shifting is used to resolve voltage and congestion problems (see Fig. 13).

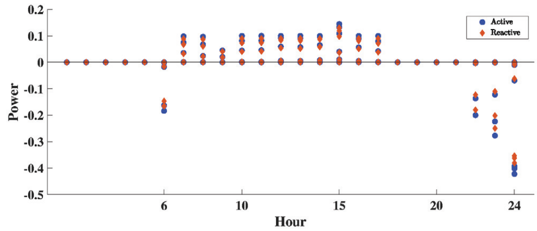

FIGURE 13. Load shifting in the deterministic solution (MWh).

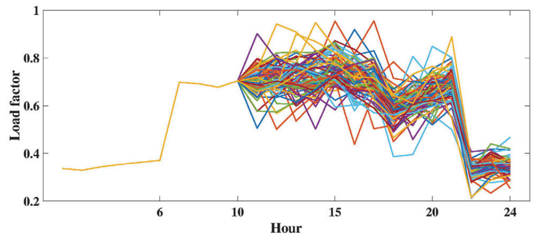

FIGURE 14. Load factor in the grid for 80 scenarios.

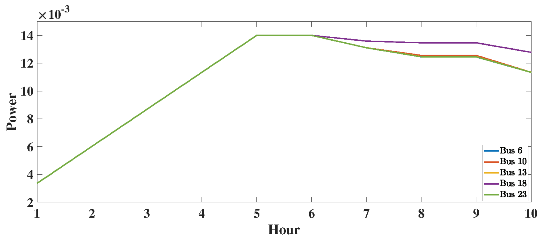

FIGURE 15. Battery state of charge at the first stage of AC-OPF (MWh).

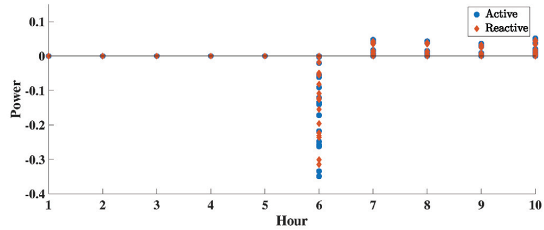

FIGURE 16. Load shifting at the first stage of AC-OPF (MWh).

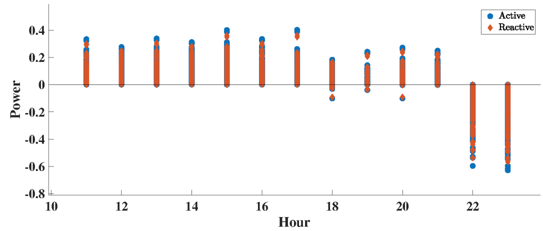

FIGURE 17. Load shifting at the second stage of AC-OPF (MWh).

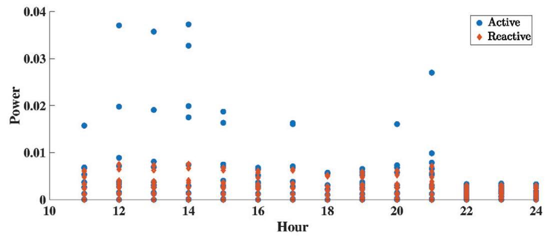

FIGURE 18. Load curtailment at the second stage of AC-OPF (MWh).

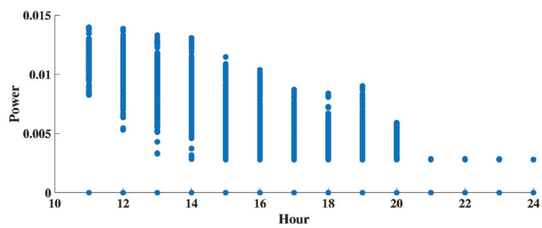

FIGURE 19. Battery state of charge at the second stage of AC-OPF (MWh).

C. STOCHASTIC RESULTS FOR WINTERTIME

The stochastic case includes 80 scenarios at the second stage for loads and prices. The results of the scenario generation are presented in Fig. 14 as *load factor* in the grid, i.e., $\left(\frac{\text{peak load}}{\text{max. poss. load}}\right)$, with an assumption of constant maximum load for every bus.

In the stochastic case, the AC-OPF model with all scenarios provides different results from the deterministic case. The peak period or increase in demand starts at 06:00. During the first stage of our AC-OPF model, the observations presented in Fig. 15 show that batteries are charging themselves from the main grid, and load shifting occurs at the same time (Fig. 16).

For the second stage, starting at 10.00, we observe load shifting (Fig. 17), load curtailment (Fig. 18), and battery power (Fig. 19). All these assets are contribute to grid operations.

1) DISCUSSION OF STOCHASTIC RESULTS

The 80 scenarios at the second stage of our AC-OPF model represent different paths in our LV grid. The results contain individual scenario responses to the uncertainty in load and price levels. Similar to the deterministic case, we observe that batteries are charging until 06:00 and discharging after that (see Fig. 19) In addition, we also see load shifting in the active and reactive power balance at the first stage Fig. 16.

In the second stage, the discharging process in the batteries to provide active power to the grid can be observed (Fig. 19), The load shifting shown in Fig. 17 shows different load patterns between peak hours (06:00–21:00) and off-peak hours (after 21:00). Moreover, load curtailment is observed (see Fig. 18). Although it is not substantial at each hour, it increases the cost of the solution compared with in the deterministic case.

The use of load curtailment is related to the interval used for load shifting. Load shifting is available between peak load hours, 06:00 to 21:00, and spans both stages. When the applied model cannot shift enough load to off-peak hours, the next option is to curtail the load. The difference between the deterministic and the stochastic cases will become more visible during the use of load curtailment. When uncertainty both occurs and is non-negligible, the system will require additional flexibility assets and services (i.e., additional to batteries) in order to fix voltage drops and congestion problems, such as load curtailment and shifting. In the next section, we discuss the relationship between uncertainty, time, peak loads, and reactive power.

VI. THE IMPACT OF UNCERTAINTY AND TIME

In this section we study the effect of time structures on our model's solution. We measure the effect of varying time characteristics of demand response assets. Moreover, we investigate how the timing of uncertainty is resolved and affects flexible scheduling.

The value of the stochastic solution (VSS) measures the expected difference between using the deterministic model (replacing uncertainty with expected values) and the stochastic model when the stochastic model is considered the true model. We calculate the expected value of the expected value solution (EEV). We start by replacing all stochastic variables with their mean and solve the deterministic model. The EEV will be the expected value of using this deterministic first stage solution in the true stochastic model, and the corresponding optimal second-stage responses are calculated. VSS is the difference between the optimal solution value for the stochastic model (recourse problem-RP) and the EEV [30].

Besides VSS, we define another measure in order to discuss the impact of uncertainty related to the relevance of modeling reactive power: *deviated value of stochastic solution* (DVSS). To calculate DVSS, we first need to model an AC/DC model that is a two-stage OPF model with AC-OPF first stage and DC-OPF second stage. For this purpose, we use equation (8) instead of equation (6). As is the case with VSS, we start to calculate DVSS first by solving the AC/DC model (model M1). Then, we solve the AC/AC model with fixed first-stage decision variables (model M2) corresponding to M1. Next, we solve the regular AC/AC model (model M3) and calculate DVSS as the difference between the objective function values of models M3 and M2. If DVSS is small enough, it will be possible to use the two-stage AC/DC model and obtain faster results, also allowing for decomposition methods, such as Benders' decomposition method (e.g., [43]), and utilizing the fact that the second stage is convex.

Furthermore, to see the relationship between the recourse actions, load shifting/curtailment, and uncertainty in load and prices, we apply a *moving interval* method to study load shifting. The availability interval of the load shifting changes in every instance of a problem in the moving interval. The beginning of the load shift interval changes between 01:00 and 10:00, but we keep the end of the interval at 24:00 as a fixed point, as shown in Fig. 2.

Furthermore, we investigate the VSS and DVSS values for two different instances in order to observe the impact on flexibility assets individually. In Variant 1, we use both types of flexibility assets (i.e., demand-side flexibility and storage) simultaneously in the solution process of the grid operations. Table 1 presents the changes in the values for VSS and DVSS as a result of a change in the uncertain parameters.

VSS increases in particular instances when load curtailment is a major part of the EEV, since the deterministic solution is not able to meet the load in some scenarios, mainly after 05:00. For both EEV and RP, the cost of load shifting and the cost of purchase from the main grid to charge batteries are almost the same. The main cost difference between RP and EEV is due to load curtailment. The SO activates the load curtailment if there is not enough time to shift the load in the available time interval for load shifting, thus demonstrating the importance of load shifting interval width. When the load shifting interval is too short, the applied model needs to shed load to deal with load uncertainty. The opposite case is also true: if the load shifting time interval is long enough, the central optimizer will not need to activate load curtailment and the cost of flexibility procurement will be lower than using the deterministic solution, hence the VSS will be lower. In that case, the value of using the stochastic model will be higher when solving a problem in which there is less flexibility.

DVSS measures the error of using the AC/DC model instead of AC/AC. When this value is small enough, it is possible to use AC/DC approximation instead of the AC/AC model. Table 1 shows that, as in VSS, DVSS is mainly impacted by load curtailment. In this case though, when the load shifting interval is longer, the value of using an AC/AC model will increase, and the AC/DC approximation will not represent the flexibility adequately. It is important to represent the AC power flow to utilize flexibility efficiently. The difference between the two approaches indicates the importance of reactive power and the impact of uncertainty. Similar to the VSS results, the DVSS results indicate that to fix voltage problem or insufficient reactive power problem at the grid, SO should consider the time of availability for reactive power flexibility resources. Otherwise, reactive power provision could cost more than usual for the SO due to lack of the activation time.

TABLE 1. The impact of uncertainty and time in Variant 1.

Load shift interval (hours)	VSS percentage	DVSS percentage
1-24	26	38
2-24	26	38
3-24	26	38
4-24	27	38
5-24	28	38
6-24	30	34
7-24	0	0
8-24	0	0
9-24	0	0
10-24	0	0

TABLE 2. The impact of uncertainty and time in Variant 2.

Load shift interval (hours)	VSS percentage	DVSS percentage
1-24	29	35
2-24	29	38
3-24	29	38
4-24	30	35
5-24	33	35
6-24	27	20
7-24	0	0
8-24	0	0
9-24	0	0
10-24	0	0

In Variant 2, we observe that the VSS and DVSS values change when demand-side flexibility, such as load shifting and load curtailment assets, is possible. We observe a similar result without the use of batteries. In the absence of batteries, that are controllable, demand-side assets such as load shifting and curtailment provide a solution to grid problems with regard to their availability time and uncertainty. These results are presented in Table 2.

In both variants of the case study from Norway, it is critical for the quality of the solution that the hour when uncertainty is resolved (the second stage starts) is within the load shifting interval, rather than at the beginning of the peak load hours. Then, load shifting will be the only flexibility asset with a recourse possibility. If the load shifting interval does not involve a stage break, both VSS and DVSS values will erroneously indicate that the impact of uncertainty will be insignificant. For an SO, this will require careful consideration of the time structure of the stochastic model, the related uncertainty structure, and, importantly, the representation of time characteristics of the flexibility assets.

VII. CONCLUSION AND OUTLOOK

In this paper we have studied the scheduling of a portfolio of flexibility assets to solve voltage variation and grid congestion problems in an ADN. The main results indicate the importance of considering the timing of decisions, the time characteristics of the flexibility assets, and the representation of uncertainty in the stochastic AC-OPF model in this research. Representation of flexibility assets, especially demand-side flexibility assets, must include information on duration and activation (response) times for those assets to have optimal impact on flexibility provision. In order for the assets to be effective for flexibility provision, the load shifting interval of an asset must be seen in relation to the time when uncertainty is resolved.

There are three main observations. First, if the available load shifting capacity is available in a wide enough time window to overlap with both the first and second stages of our model, the stochastic model will be better than the deterministic model. Second, the narrower the duration time interval, the more important the use of a stochastic model will become. Third, we observe that the greater the amount of flexibility available in the duration of the load shifting interval, the more important it will be to use an AC model, also for the second stage, to capture the value of this flexibility.

Future research topics for optimal flexibility scheduling under uncertainty might include risk-neutral or risk-averse actors in a power market setting to investigate the efficiency of the usage of the flexibility assets for grid operations. Another approach would be to include the use of active management technologies such as soft open point, on load tap changer, and static VAR compensators in an integrated way with flexibility assets. Furthermore, value could be added by including the customer's perspective in a market design in cases where more solar power and wind power are available.

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Paper IV

Stochastic Local Flexibility Market Design, Bidding, and Dispatch for Distribution Grid Operations

Güray Kara, Paolo Pisciella, Asgeir Tomasgard, Hossein Farahmand, Pedro Crespo del Granado

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IV

Stochastic Local Flexibility Market Design, Bidding, and Dispatch for Distribution Grid Operations

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Abstract

In order to unlock the flexibility potential of energy consumers and prosumers, the development of market mechanisms for flexibility planning and procurement is necessary. The authors propose a stochastic local flexibility market to solve grid issues such as voltage deviations and grid congestion in a distribution grid. Their proposed solution includes activation of flexibility assets at the consumers' premises, using a stochastic local flexibility market design. They consider a pooled local flexibility market design under demand uncertainty and stochastic bidding process. Mathematical modeling is used to determine flexibility demand and supply bids by the distribution system operator and the aggregator respectively. A stochastic AC-optimal power model for the distribution system operator and a two-stage stochastic model for the aggregator are implemented to simulate stochastic local flexibility market. Consequently, the authors obtain stochastic flexibility supply bid curves, and optimum flexibility supply dispatch. They prove that the cost of grid operations is reduced by up to 40% when the system uses the local flexibility market compared to not using it. The proposed methodology is applicable for intraday market or local flexibility market designs to use the potential end-user flexibility for grid operations.

1 Introduction

Electrification of sectors in the economy is not only beneficial for the power system, but also introduces the need for more demand-side flexibility at the distribution grid level in order to ensure grid security. The concept of *flexibility* in power systems relates to their ability to respond to sudden changes in power consumption and generation [1]. By using demand-side flexibility assets, such as load shifting or load curtailment, it is possible to address some grid problems in real-time [2]. In some cases of grid problems, this requires aggregating local flexibility resources [3] to ensure security of supply. An optimal utilization of flexible electricity resources in an efficient market design could address grid challenges and contribute to a deferral of costly grid investments [4]. One option would be to solve grid problems by using market pricing (indirect control). Another option would be to control flexible assets directly [5]. A centralized control of the flexibility assets might pose problems in terms of technical management of a large amount of resources by a single central planner. In this respect, we propose the utilization of a Local Flexibility Market (LFM) to solve grid problems using a market based mechanism between a group of agents, each one in charge of the management of different portions of the grid.

In general, three market players are considered in LFM research, according to [6]: consumers/the aggregators, the Distribution System Operator (DSO), and Balance Responsible Parties (BRPs). According to [7], the three main operational processes of an LFM are contracting and bidding, activation, and market settlement processes. In this paper, we first discuss how, via an aggregator, a number of consumers can provide flexibility from a portfolio of flexible assets in a market. Second, we discuss how the buyers of flexibility, in our case a single DSO, bid their flexibility need in the market. After the market is cleared, and the price and volumes are settled, the agreed-upon flexibility is provided by using load shifting, curtailment, and batteries. Thereafter, the optimal power flows, and load shedding if needed, are scheduled by the DSO in order to minimize system costs and to meet the demand for power in the local system.

[8] present the objectives and services of an LFM. According to them, the primary objective of an LFM is to support the trade of end-user flexibility for the benefit of the DSO's grid operations. According to [9], the congestion management, the voltage/reactive power, and the controlled islanding are solved via LFM. Furthermore, the cost of flexibility for congestion management is discussed by [10], based on the real-time activation of flexibility. According to [11], the DSO should make sure that the required flexibility is continuously available throughout the operational process. Such situations might be affected by short-term uncertainties [11]. In this paper we consider congestion management and voltage corrections under uncertainty with reference to our suggestion for a market design for LFM based on the paradigm of stochastic market clearing.

Stochastic dispatch and bidding strategies for reducing operational costs have been investigated in the literature. For example, [12] argue that demand and supply uncertainty can be addressed by using stochastic dispatch and clearing. Morales et al. [13] investigated a two-stage stochastic model for dispatch in a pooled design. Bjørndal et al. [14] consider an energy-only market with load uncertainty and flexibility costs for a stochastic dispatch mechanism and compared it with a myopic model (two-stage). In our research, we have designed a stochastic dispatch and bidding mechanism with deterministic cost parameters, influenced by [14], [15], and [16].

The main contributions of our research, presented in this paper, are as follows:

- We present a novel, stochastic LFM design in which flexibility is used for distribution grid operations, such as voltage correction and congestion management, to supplement an intraday market for power.

- We observed up to 40% cost reduction with a stochastic LFM design compared with only the use of load shedding by the DSO for grid operations.

- We explain the nature of stochastic flexibility bids with deterministic cost parameters in an LFM.

The remaining part of this paper is organized as follows. In Section 2 we present the stochastic LFM design, system architecture, and bidding process. Section 3 provides the mathematical models. In Section 4 we describe the case study, grid problems, and present the results of our research, which are then discussed in Section 5. The main conclusions are provided in Section 6.

2 Market design

The design of an LFM must address the grid topology, timing aspects, and the heterogeneity of flexibility technologies. In this paper, we present our design for a pooled market, including an aggregator that bids on behalf of flexibility providers, and a single buyer, the DSO. The approach can easily be widened to include more buyers and sellers in the market place.

2.1 Bidding process details

In the pooled LFM design, we assume perfect competition, where each market participant is a price-taker that does not act strategically. For the aggregator, this means that the objective is to provide stochastic bids with the aim of minimizing the expected cost of the flexibility supply by using the available demand-side assets. For the DSO, the aim is to minimize the system cost of meeting demand in the network (including the option to shed load at the cost of Value of Lost load VoLL).

The uncertainty structure of bidding is two-stage stochastic optimization, as illustrated in Figure 1 [17]. The bidding process is modeled as a two-stage stochastic problem due to the presence of flexibility assets that need to be considered over the entire time-span. Until time t_{10}, the parameters are deterministic and therefore both they and the bids have the same same values for each scenario (the reason for this particular choice is discussed by [18] for the same case study studied under direct control). After t_{10} up to t_{24}, the red filled-in circles in Figure 1 represent scenario realizations that are uncertain when seen from time periods until t_{10}. In the suggested pooled market design, the aggregator bids stochastically into the LFM to establish a flexibility supply curve for each scenario and each time period. At period t_{11}, the second stage—during which uncertainty is resolved—starts, and the scenario-dependent demand for each customer becomes known.

Although we have stochastic power demand, the model (AC-OPF) to be solved by the DSO at each time period and in each scenario is deterministic. This is because the DSO always balances the system in real time using the flexibility procured and the option to shed at VoLL, but otherwise does not have any flexibility or storage option. This leads to a one-period deterministic problem for each time period and scenario.

During the stochastic bidding process, the aggregator needs to know the individual costs of flexibility assets in order to determine bid prices (i.e., the marginal

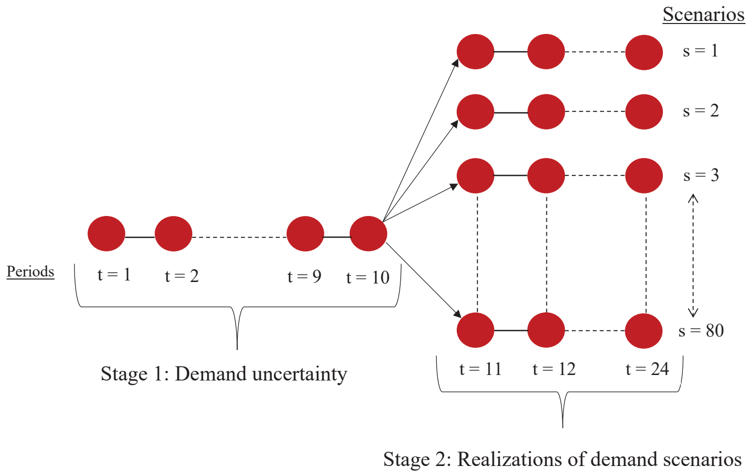


Figure 1: Uncertainty structure and stages of the aggregator model.

costs of providing flexibility after scheduling flexibility assets and consumption). This bidding process, based on marginal costs, establishes a *flexibility supply curve* in the LFM under conditions of perfect competition. These flexibility cost parameters are deterministic, but the load in the different scenarios is stochastic, as is the demand for flexibility in the LFM.

At this time, the DSO examines how much flexibility is needed in the LFM to solve voltage drops and grid congestion issues with minimum costs. The DSO has a perfect foresight of the grid status and load in the buses. In the bidding phase, the DSO does not know where flexibility will be provided in the grid, it just signals an aggregated demand to the market. After the LFM market is cleared, the different consumers' flexibility supply is dispatched by the aggregator and communicated to the DSO.

If the cost of flexibility supply (i.e., the LFM price) is higher than the VoLL, or if the flexibility supply is insufficient to solve the grid problem, the DSO will apply load shedding instead. This could also happen as a consequence of the dispatch, as the grid location of flexibility is not known when bids are made.

2.2 The stochastic LFM design and process

In our proposed design for LFM, the customers are the flexibility providers, but they are represented in the market by an aggregator. We assume perfect competition for our proposed pooled LFM design. In this LFM, the flexibility supply bids are priced at the marginal cost (similar to balancing markets [4]). The interaction between the power customers (the flexibility providers), the aggregator, and the DSO in the pooled market is summarized in Figure 2.

Every sixth period, the customers buy power from the grid at Intraday (ID) price. The delivery of the power is determined by the consumers' choice over the six periods until the next intraday trade possibility. It should be noted that when this is done, demand is known for the five periods, due to the uncertainty structure. In all periods, the aggregator can sell flexibility and the DSO can buy flexibility.

The DSO sees a set of stochastic scenarios of the active power demand for every customer and location in the grid. The bidding is done under uncertainty, so the DSO presents the flexibility demand bid for any time period in the form of a discrete probability distribution, with flexibility demand represented for each of the scenarios in every time period. The load used in these scenarios is before any demand-side actions are taken or battery scheduling is done.

The aggregator sees the same information as the DSO, without knowing the grid topology. However, as part of its bidding process the aggregator will perform optimal scheduling of batteries, load shifting, and curtailment in order to provide flexibility at an expected minimum cost over the whole horizon. The aggregator provides scenario-dependent flexibility supply bids that consist of the price needed to meet each scenario's flexibility demand. Only *active power* is traded in the LFM, but reactive power is considered by the DSO when solving the AC optimal power flow (AC-OPF) problems to calculate the demand for flexibility.

The purpose of the flexibility bids and the stochastic dispatch is to enable market clearing that equalizes the flexibility demand by the DSO to the flexibility supply by the aggregator in every scenario at every time period. The DSO's objective is to avoid load shedding due to congestion or voltage drops. As the LFM is pooled, the DSO cannot know or control which customer provides the dispatched flexibility; rather, the decision is up to the aggregator.

In short, the steps in the bidding, market clearing, and dispatch process for a specific time period are as follows.

Step 1. The DSO determines the amount of load shedding for active and reactive power before flexibility trade for each scenario and period, by using a deterministic AC-OPF model. After solving the AC-OPF problem, the DSO calculates flexibility demand according to the active power load shedding amount and bids this flexibility demand to the LFM for each scenario and time period.

Step 2. By considering the demand in each scenario and period, as well as the probabilities of the scenarios, the aggregator schedules flexibility assets, determines the new demand level of each customer, and bids a price-quantity pair as a scenario-dependent flexibility bid to the LFM for each period and scenario.

Step 3. For each scenario and period, the market is cleared so that the demand for flexibility is equal to supply. In each scenario, this results in a flexibility price. Prices in the LFM are the marginal costs of flexibility provision.

Step 4. For each scenario and period with a flexibility supply requirement and price, flexibility of customers are dispatched by the aggregator according to the schedule. The aggregator then communicates the dispatch to the DSO as the provided flexibility service at the cleared price, and provides information about the consumers' new demand level.

Step 5. By considering new demand levels after flexibility procurement, the DSO solves the new OPF. If new demand levels after the dispatch of flexibility do not resolve the congestion or voltage problems, load shedding may still be needed. This may also be because the flexibility has not been dispatched to the locations in the grid where it is needed. When load shedding is used, the DSO sells back purchased ID power to the main grid in order to compensate for reduced demand compared with the volume bought by the aggregator.

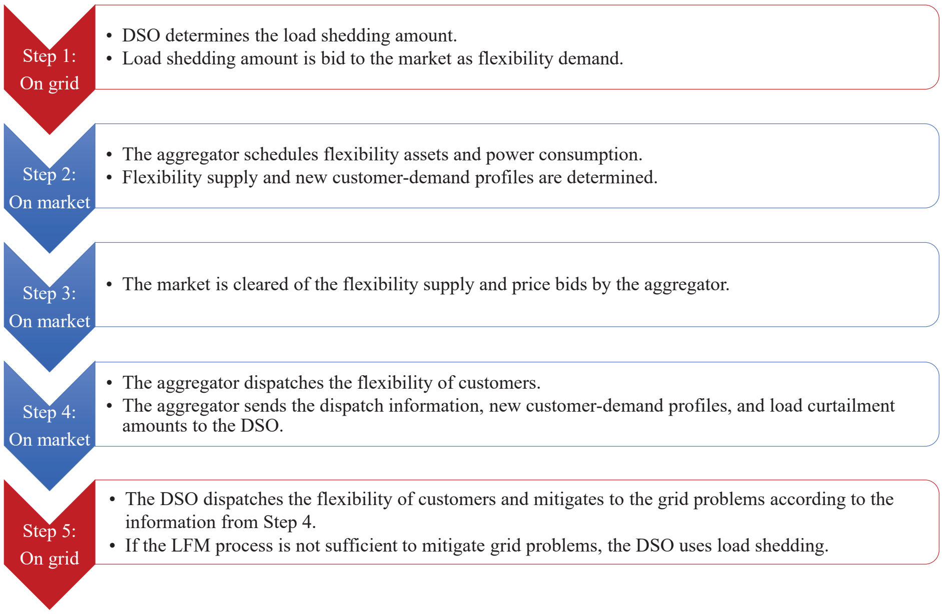


Figure 2: The stochastic LFM design and process.

3 Mathematical models and equations

In this section we describe three used models for flexibility demand determination by the DSO, for flexibility supply and LFM prices determination by the aggregator, and for final stochastic dispatch by the DSO. The first subsection 3.1 presents the AC-OPF formulations used by the DSO for determining how much flexibility is needed in the operation of the system. The second subsection 3.2 presents a two-stage stochastic aggregator model to schedule the flexibility supply from consumers and the corresponding bidding and market clearing in the LFM. The third and final subsection 3.3 presents the DSO's final power flow optimization in which dispatched flexibility is included and load shedding is used as the last resort. The nomenclature of mathematical models are provided in Table 2 at Appendix A.

3.1 Model 1: The DSO's calculation of the flexibility demand

To determine how much flexibility the DSO needs, we use a non-linear AC-OPF model with load shedding. While consumers buy power from the ID market, the DSO estimates how that will lead to congestion and voltage problems.

We assume perfect competition and let the DSO minimize the system cost. At this stage, the DSO does not consider the available consumer flexibility, but rather considers the different households' original demand, excluding the operation of batteries, load shifting, and curtailment. The DSO solves the model for each period and scenario in order to estimate flexibility demand based on the need for load shedding. The shed volumes are then used as bids for buying flexibility in the LFM. The aim is that the aggregator can provide flexibility at a lower cost than VoLL. The equations in the following subsections present the mathematical model used by the DSO for each of the scenarios and periods.

3.1.1 Load balance constraints

Equations 1 and 2 satisfy the active ($L^p_{i,t,s}$) and reactive power ($L^q_{i,t,s}$) demand at each bus by purchasing from the transmission grid, $P_{g,t,s}$ and $Q_{g,t,s}$, and by load shedding, $P^{shed}_{i,t,s}$ and $Q^{shed}_{i,t,s}$,

$$\sum_{j \in J} AF_{i,j,t,s} = \sum_{g \in G_i} P_{g,t,s} - L^p_{i,t,s} + P^{shed}_{i,t,s} \tag{1}$$

$$\sum_{j \in J} RF_{i,j,t,s} = \sum_{g \in G_i} Q_{g,t,s} - L^q_{i,t,s} + Q^{shed}_{i,t,s} \tag{2}$$

3.1.2 Allocation constraint

The allocation constraint in equation 3 outlines the purchases of active power / electricity from the ID market via the transmission grid according to consumer demands. The purchase is done at every *sixth* period, but it is allocated to be used in *every* period. The ID purchases take place in periods $(t_1, t_6, t_{11}, t_{16}, t_{21}) \in \mathcal{T}^1$ which we call operational periods while allocation to demand is done in all periods (from t_1 to t_{24}), which we call balancing periods.

The allocation process and interaction with the ID market and the LFM is illustrated in Figure 3. The aggregator purchases power from the transmission grid at ID prices (large circles in Figure 3). Purchased power is allocated to customers and the LFM is cleared (filled-in circles).

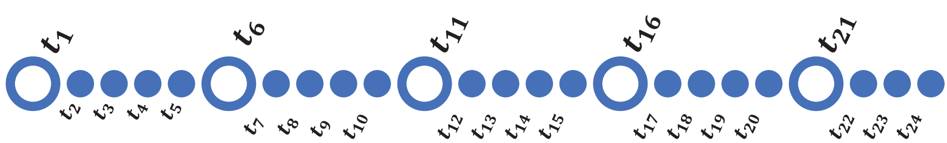


Figure 3: ID and LFM alignment.

It is possible to buy electricity, $\Omega^{DSO}_{g,t,s}$, from the ID market in every operational period $t \in \mathcal{T}^1$ and it can be consumed ($P_{g,t,s}$) in every period, $t \in \mathcal{T}^1 \cup \mathcal{T}^2$ (allocation). More specifically, the purchase/consumption relation is modeled as

$$\Omega^{DSO}_{g,t^1,s} = P_{g,t^1,s} + \sum_{t^2 \in \mathcal{T}^2_{t^1}} P_{g,t^2,s}, \qquad t^1 \in \mathcal{T}^1 \tag{3}$$

with $\mathcal{T}_{t_1}^2$ represents the balancing periods in which flexibility services can be bought, but only previously purchased ID power from the operational period t_1 is available, if not already consumed.

3.1.3 Grid congestion constraint

Equation 4 models the grid power flow limitation:

$$AF_{i,j,t,s}^2 + RF_{i,j,t,s}^2 \leq S_{i,j}^2 \tag{4}$$

where S represents the installed capacity of the line.

3.1.4 Power flow constraints

AC power flow constraints enforce the active power balance (equation 5) and reactive power balance (equation 6) at each bus in the distribution grid.

$$AF_{i,j,t,s} = V_{i,t,s}^2 Y_{i,j,s} cos\theta_{j,i,s} - V_{i,t,s} V_{j,t,s} Y_{i,j,s} cos\left(\delta_{i,t,s} - \delta_{j,t,s} + \theta_{j,i,s}\right) \tag{5}$$

$$RF_{i,j,t,s} = V_{i,t,s}^2 Y_{i,j,s} sin\theta_{j,i,s} - V_{i,t,s} V_{j,t,s} Y_{i,j,s} sin\left(\delta_{i,t,s} - \delta_{j,t,s} + \theta_{j,i,s}\right) - \frac{bV_{i,t,s}^2}{2} \tag{6}$$

3.1.5 Load shedding equations

Equation 7 is used to keep the power factor constant at the bus where the load shedding happens.

$$Q_{i,t,s}^{shed} = P_{i,t,s}^{shed} \cdot \tan(\theta_i) \tag{7}$$

3.1.6 Voltage magnitude limit

Equation 8 gives magnitude limits for voltage

$$\underline{V} \leq V_{i,t,s} \leq \overline{V} \tag{8}$$

3.1.7 The objective function of the DSO model

The objective function (equation 9) that is minimized under every scenario $s \in \mathcal{S}$ is defined by the total cost of the DSO's grid operations (OF1), considering both purchases of power (by the aggregator) and load shedding (by the DSO) in order to meet system demand. The cost of power purchases from the main grid is given by the ID market price, whereas the cost of load shedding is VoLL (EUR 3000/MWh). It should be noted that this does not consider the use of flexibility on the consumer side, as the purpose is to identify the flexibility demand from the system's perspective. Based on this assumption, there exists a joint multivariate distribution for all the consumer demands that the DSO, the aggregator, and the consumers see, which is the best available demand prediction. This is an approximation, as the consumers and the aggregator may have their own incentives to use demand-side flexibility, such as the ID price.

$$\text{minimize OF1}= \sum_{t^1\in\mathcal{T}^1}\sum_{g\in\mathcal{G}} B_{t^1}\cdot \Omega^{DSO}_{g,t^1,s} + \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}} P^{shed}_{i,t,s}\cdot \text{VoLL} \tag{9}$$

3.1.8 Flexibility demand bids to the LFM

After Model 1 is solved by the DSO and calculating the active and reactive power shedding amounts from equations 1, 2, and 9, the DSO bids the required flexibility amount, $D_{i,t,s}$, to the LFM as *active power* for each time period and scenario.

The index of consumers ($c \in \mathcal{C}$) in the aggregator model is mapped to the index of buses ($i \in \mathcal{I}$) in the DSO model. Each household represents a different bus in the distribution grid topology, as illustrated in Figure 4, but not all buses corresponds households ($\mathcal{I} \to \mathcal{C}$ and $\mathcal{C} \subset \mathcal{I}$). The demand for flexibility is transmitted to the LFM as pooled (i.e., $\sum_{i\in\mathcal{I}} D_{i,t,s}$ as post-calculation) without considering grid topology.

3.2 Model 2: The aggregator and flexibility supply bids

The aggregator formulates a two-stage stochastic program under uncertainty to schedule the use of flexible resources for all consumers, and provides aggregated (over the consumers) flexibility bid curves (active power) for each scenario and period. The scheduling process calculates the new demand level of each customer according to the flexibility supply bid. While the DSO can solve the grid problems as single-period single-scenario problems, the aggregator must solve the whole problem jointly as a stochastic program because the periods and scenarios are interlinked by using storage and load shifting.

3.2.1 Demand-side and storage-side flexibility balance

When considering the DSO flexibility demand and power prices, the main aim is to schedule the flexibility supply to minimize total system costs. Load balance equations are used to calculate the purchase from the ID market and scheduling of each customer's assets in order to define new demand levels after load shifting, curtailment, and battery scheduling.

Equation 10 expresses the purchases of active power from the ID market in every sixth period and allocation to consumer in every period, in the same way as in equation 3 and Figure 3, where it is estimated by the DSO:

$$\Omega^{agg}_{c,t^1,s} = \rho_{c,t^1,s} + \sum_{t^2\in\mathcal{T}^2_{t^1}} \rho_{c,t^2,s} \tag{10}$$

where $t^1 \in \mathcal{T}^1$.

The difference between Model 1 and 2 is that the DSO does not consider the available flexibility to the consumers, whereas the aggregator does, as will be shown in the following equations (equations 11, 12, 13, and 15). For every customer, the aggregator schedules flexibility assets in order to use demand-side flexibility in every scenario and period, and to determine new customer demand levels ($L^{new}_{c,t,s}$)

when supplying the flexibility, as modeled in equation 11. This action corresponds to Step 2 in subsection 2.2 and includes original load $L_{c,t,s}$, net battery discharge $(\rho^{dis}_{c,t,s} - \rho^{chr}_{c,t,s})$, curtailment $\varrho^{curt}_{c,t,s}$ and load shifting out of the time period t, $\rho^{\text{shift}}_{c,t,s}$.

$$L_{c,t,s} - \big((\rho^{dis}_{c,t,s} - \rho^{chr}_{c,t,s}) - \varrho^{curt}_{c,t,s} - \rho^{\text{shift}}_{c,t,s}\big) = L^{new}_{c,t,s} \tag{11}$$

where $t \in \mathcal{T}$ and

$$0 \leq \varrho^{curt}_{c,t,s} \leq L_{c,t,s} \tag{12}$$

In equation 13, $\rho^{A}_{c,t,s}$ represents the volume of power flexibility for accommodating the DSO's flexibility request after scheduling the assets of consumers and determining new demand levels. Equation 13 is used to ensure that the new demand level after the aggregator has scheduled the flexibility assets is either equal to or lower than the old demand level (i.e., the demand before shifting, curtailing, and battery usage) during congested hours, for each scenario. It should be noted that when flexibility supply is negative, it will correspond to the periods when batteries are charged or load is increased in the shifting process. These are periods and scenarios without flexibility demand from the DSO.

$$L^{new}_{c,t,s} + \rho^{A}_{c,t,s} = L_{c,t,s} \tag{13}$$

Equation 14 establishes the supply-demand balance in the ID market for the new demand levels.

$$L^{new}_{c,t,s} = \rho_{c,t,s} \tag{14}$$

3.2.2 Flexibility supply-demand balance in the LFM

The flexibility balance equation (equation 15) calculates the amount of flexibility supplied by the aggregator to meet the DSO's flexibility demand at each period and scenario where flexibility demand $D_{i,t,s}$ exists.

$$\sum_{c\in\mathcal{C}} \rho^{A}_{c,t,s} \geq \sum_{i\in\mathcal{I}} D_{i,t,s} : \quad \delta^{A}_{t,s} \quad \text{if} \quad \sum_{i\in\mathcal{I}} D_{i,t,s} > 0 \tag{15}$$

where $\sum_{i\in\mathcal{I}} D_{i,t,s}$ is the pooled demand of flexibility from the DSO, which is obtained as a result of solving the previous problem (Model 1).

The dual variable $(\delta^{A}_{t,s})$ of equation 15 measures *the marginal cost of flexibility provision* (Step 3 in Subsection 2.2). The aggregator's flexibility bid to the pooled market is for each scenario and time period in which the price $(\delta^{A}_{t,s})$ is combined with the volume $\sum_{c\in\mathcal{C}} \rho^{A}_{c,t,s}$.

3.2.3 Import power limit from the main grid

Equation 16 keeps the purchase from the main grid under the installed capacity of the transformer connecting the distribution grid to the main grid. The value $S_{i,j}$ shows the capacity of only one line, the line between LV and MV grid (between buses 1 and 26),

$$\sum_{c \in \mathcal{C}} \rho_{c,t,s} \leq S_{i,j} \tag{16}$$

3.2.4 Intertemporal constraints relating to batteries

Equation 17 calculates the state of charge for batteries, whereas equations 18, 19, and 20 calculate the capacity of batteries, and charging and discharging limits, respectively.

$$\Psi_{c,t,s} = \Psi_{c,t-1,s} + E^{chr} \rho^{chr}_{c,t,s} - \frac{\rho^{dis}_{c,t,s}}{E^{dis}}, \qquad s \in S \qquad c \in C \tag{17}$$

where $t \in T$.

$$\underline{\Psi} \leq \Psi_{c,t,s} \leq \overline{\Psi} \tag{18}$$

$$0 \leq \rho^{chr}_{c,t,s} \leq H \cdot \overline{\Psi} \tag{19}$$

$$0 \leq \rho^{dis}_{c,t,s} \leq H \cdot \overline{\Psi} \tag{20}$$

3.2.5 Load Shifting

Load shifting is modeled using four equations to make it convex and piecewise linear using breakpoints $k \in \mathcal{K}$. Equation 21, represents x-axis values (amount of power) in the load shifting cost function, whereas the function row, equation 22, represents the y-axis (non-linear cost function). The data for x-axis values, σ_k, and variable costs for the function's slope, VC_k, are taken from [18] as are other load shifting, battery, and load curtailment parameters. Equation 23 is used for the convex combination of breakpoints. As the cost function is convex, two neighboring breakpoints will be used by design, making the approximation as close as possible. Equation 24 restricts the usage of load shifting; that there cannot be any load shifting outside a pre-specified time interval. Equation 25 emphasizes that within a specified time interval the total load allocated in the different periods needs to be equal to the total load withdrawn from the other periods.

$$\rho^{\text{shift}}_{c,t,s} = \sum_{k \in \mathcal{K}} \lambda_{c,t,s,k} L_{c,t,s} \sigma_k \quad t^{down} \leq t \leq t^{up} \tag{21}$$

$$\pi^{\text{shift}}_{c,t,s} = \sum_{k \in \mathcal{K}} \lambda_{c,t,s,k} L_{c,t,s} \sigma_k VC_k \quad t^{down} \leq t \leq t^{up} \tag{22}$$

$$\sum_{k \in \mathcal{K}} \lambda_{c,t,s,k} = 1, \quad 0 \leq \lambda_{c,t,s,k} \leq 1 \quad t^{down} \leq t \leq t^{up} \tag{23}$$

$$\rho^{shift}_{c,t,s} = 0, \quad t \leq t^{down}, t \geq t^{up} \tag{24}$$

and

$$\sum_{t \in \mathcal{T} \cap [t^{down}, t^{up}]} \left(\rho^{shift}_{c,t_n} + \rho^{shift}_{c,t_m,s} \right) = 0 \tag{25}$$

3.2.6 The cost of discharging battery

To assign a cost to battery usage, we consider a cost coefficient associated with the battery discharge, while we assume that battery charge is done at no cost. In equation 26, we multiply the amount of discharge (MWh) by the fixed cost of battery discharge, EUR 0.140/MWh. The cost of the battery discharge is taken from [19],

$$\Gamma_{c,t,s} = \rho^{dis}_{c,t,s} \cdot \mathrm{IC} \tag{26}$$

3.2.7 Non-anticipativity constraints

The aggregator model is two-stages. Therefore, non-anticipativity constraints are needed to keep first-stage variables at the same values for all scenarios [20] in the first stage. The first-stage variables in the aggregator model are all variables up to and including period t_{10}.

3.2.8 The objective function of the aggregator

The aim of the aggregator is to minimize equation 27, which defines the cost of operations for the aggregator (OF2). The first term denotes the purchase from the main grid; the second element is the sum of battery usage cost, the load shifting cost, and the load curtailment cost. The third and fourth elements represent the same costs at the second stage.

$$\text{minimize OF2}=\sum_{t^1_m \in \mathcal{T}^1_m} \left(B_{t^1_m} \cdot \Omega^{agg}_{t^1_m}\right) + \sum_{c\in\mathcal{C}} \sum_{t_m \in \mathcal{T}_m} \left(\Gamma_{c,t_m} + \pi^{shift}_{c,t_m} + C^{curt} \varrho^{curt}_{c,t_m}\right)$$
$$+\sum_{s\in S} P_s \left(\sum_{c\in\mathcal{C}} \sum_{t^1_n \in \mathcal{T}^1_n} \left(B_{t^1_n} \cdot \Omega^{agg}_{c,t^1_n,s}\right) + \sum_{c\in\mathcal{C}} \sum_{t_n \in T_n} \left(\Gamma_{c,t_n,s} + \pi^{shift}_{c,t_n,s} + C^{curt} \varrho^{curt}_{c,t_n,s}\right)\right) \tag{27}$$

3.3 Model 3: The DSO's final dispatch of the flexibility

The formulation of the stochastic dispatch is mainly the same as in the AC-OPF model presented in subsection 3.1, except for the load balance equations. This corresponds to Step 4 in subsection 2.2. It should be noted that the new customer demand levels need to be represented as both active power and reactive power, hence $L^{new_p}_{c,t,s} = L^{new}_{c,t,s}$ and the reactive power is calculated in equation 28 as follows

$$L^{new_q}_{c,t,s} = L^{new_p}_{c,t,s} \cdot \tan(\theta_i) \quad c \in \mathcal{C} \tag{28}$$

The new demand level levels, $L^{new_p}_{c,t,s}$ and $L^{new_q}_{c,t,s}$, of each consumer of each consumer are mapped into different nodes $i \in \mathcal{I}$: $(\mathcal{C} \to \mathcal{I})$ and then into the respective active and reactive power as follows (see also Figure 4 in subsection 4.1). An important detail here is that although pricing of the flexibility supply is done in a pooled market, the information about the new demand levels from individual consumers are shared with the DSO by the aggregator (Step 4 in Subsection 2.2).

Equations 29 and 30 model the load balance constraints of the DSO, considering the flexibility services from the LFM and the new demand levels ($L_{i,t,s}^{new_p}$ and $L_{i,t,s}^{new_q}$) (Step 5 in Subsection 2.2).

$$\sum_{j\in J} AF_{i,j,t,s} = \sum_{g\in G_i} P_{i,g,t,s} - L_{i,t,s}^{new_p} + P_{i,t,s}^{shed} \tag{29}$$

$$\sum_{j\in J} RF_{i,j,t,s} = \sum_{g\in G_i} Q_{i,g,t,s} - L_{i,t,s}^{new_q} + Q_{i,t,s}^{shed} \tag{30}$$

3.3.1 The objective function for the DSO's dispatch

The objective function in equation 31 (OF3) aims to minimize the cost of electricity traded in the transmission grid by the DSO and the aggregator at the ID price, in addition to the cost of load shedding.

$$\text{minimize OF3}= \sum_{t^1\in T^1} \sum_{g\in G} \left(B_{t_1} \cdot \Omega_{g,t^1,s}\right) + \sum_{t\in T} \sum_{i\in I} \left(P_{i,t,s}^{shed} \cdot \text{VoLL}\right) \tag{31}$$

4 Case study and results

The case study includes real-life data with extensive analysis and solution proposals from a day with coercive conditions. First, we explain the grid structure and our consumer data. Second, we go through the steps of bidding, market clearing, and dispatch, as described above in subsections 3.1, 3.2, and 3.3.

4.1 Grid structure and consumer data

Our case study is a distribution system in the Norway-Hvaler municipality of Viken County in southern Norway, and the data were recorded in January 2016. The Hvaler area comprises small islands. The area has a population of 4000, but during holidays the population increases up to 40,000. The case study data were recorded in a single day, with coercive conditions for the grid. Most of the consumers in the grid are commercial buildings, family houses, and Norwegian second homes [21]. The mentioned ID market prices are ELSPOT prices from Nord Pool for the same period as for the demand data.

The case grid is a 22 kV and 230V radial structure, as shown in Figure 4. There are 26 buses in the grid, and 17 end users. We assume that the lines have sufficient capacity to feed end users, with the exception of the transformer between buses 1 and 26, they are connection to the transmission grid. The transformer has a capacity of 0.3085 MVA (for active power) and might be congested during peak load periods. End users and the aggregator have flexibility assets, such as load curtailment, load shifting, and batteries. Every grid member has a battery with 14kW capacity without inverters.

To include uncertainty, we generate 80 scenarios for the demand data by using a *forecast-based moment-matching* scenario generation algorithm [22, 23]. For details of this process, see [18].

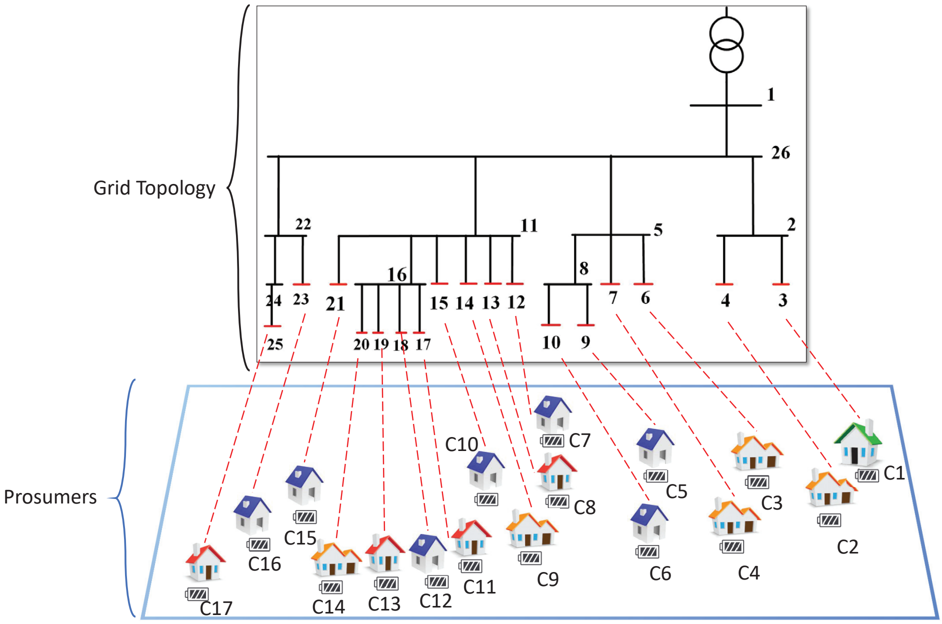


Figure 4: Grid topology and market participants presentations.

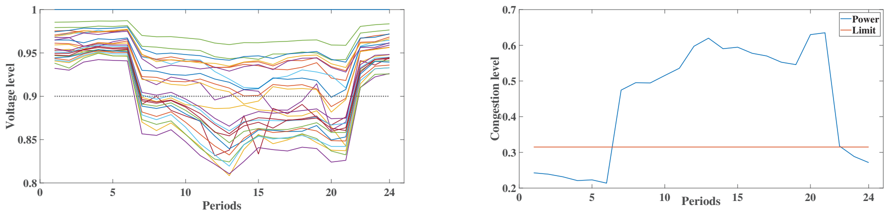
We use CONOPT for Non-linear programming (NLP) and CPLEX for Linear Programming (LP) problems as solvers, and our models are implemented in GAMS using a computer with an Intel(R) Core(TM) i7-7500U processor at 2.70GHz and 16GB RAM. The total run time for the NLP model is less than five minutes, whereas for the LP model it is 30 seconds.

4.2 Grid problems and analysis

In order to use the potential demand-side flexibility, we use the system data where the electricity demand increases significantly in a sample day, with coercive conditions for the grid. In our case study with consumer data, we observe voltage profiles (Figure 5a) that are under the feasibility threshold (≈ 0.80 p.u. at the lowest), with grid congestion (Figure 5b) that blocks the transfer from the transmission grid. We use MATPOWER developed by [24] to perform power flow calculations.

To estimate the need for flexibility under the voltage drop and grid congestion problems shown in Figure 5, the DSO initiates its AC-OPF model to determine how much flexibility is needed to keep the system within the normal range of operation (voltage within the range 0.9 p.u. and 1.1 p.u. and no grid congestion). The load shedding amount, according to the equations from subsection 3.1, represents the flexibility requested by the DSO that is bid to the LFM as demand.

In Figure 6 we observe the flexibility demand profile, where occurs mainly between t_6 and t_{21}.



(a) Voltage levels of each bus (MVA). **(b)** Congestion level (MWh).

Figure 5: Voltage and congestion problems.

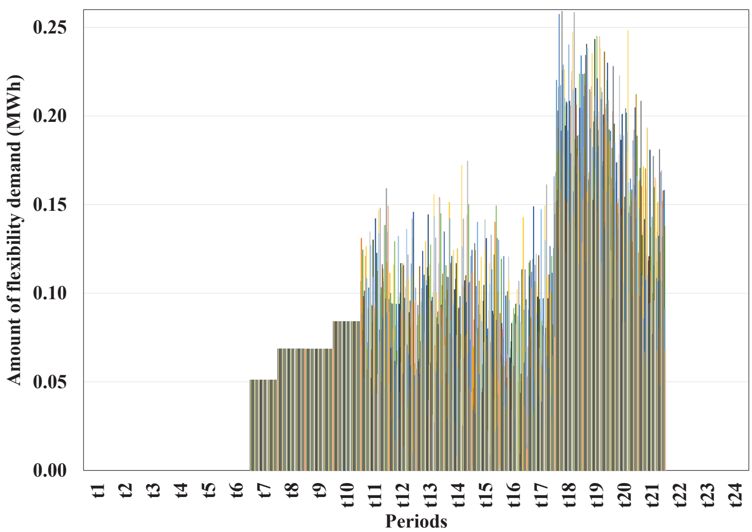


Figure 6: Flexibility demand by the DSO as active power (MWh), aggregated per customer (MWh). Each color represents a scenario.

4.3 The aggregator's perspective

The aggregator schedules flexibility assets such as load shifting, load curtailment, and batteries in order to meet load and flexibility demand. The scheduling results for these flexibility assets for the case study are presented in Appendix B.

The LFM prices are varied in order to clear flexibility supply and demand ranges between 4 EUR/MWh to 1500 EUR/MWh. Although it is possible to see lower prices than 1500 EUR/MWh for some scenarios (Figure 7), the results show that the aggregator often uses load curtailment as the marginal asset to supply flexibility, as illustrated in Figure 14 in Appendix B.

Figure 8, shows the flexibility provision from the aggregator in all scenarios and periods. It should be noted that this represents a stochastic market clearing, as in each period the dispatched supply depends on the scenario-dependent demand.

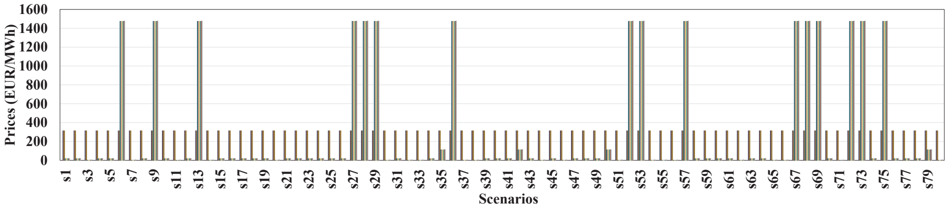


Figure 7: LFM prices in the pooled market (EUR/MWh). Each color represents a period.

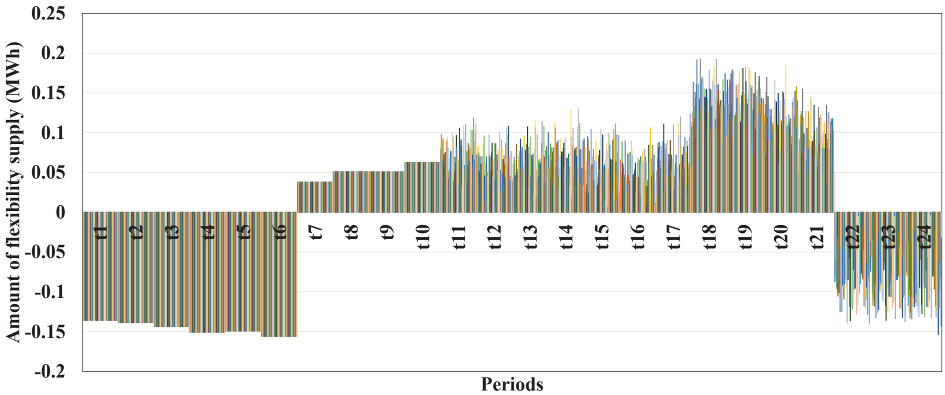


Figure 8: Flexibility supply from the aggregator in the pooled market as active power, aggregated for all consumers (MWh). Each color represents a scenario.

4.4 The DSO final dispatch

The DSO uses the new load from the aggregator's dispatch schedule for each period and scenario. The exception is the curtailed volumes, for which the DSO is free to decide whether or not they will be curtailed. The DSO knows the price of flexibility in each scenario and time period, as well as the new load for each consumer (bus).

It should be borne in mind that the main aim of the LFM is to reduce the usage of the load shedding by the DSO and to obtain cost-efficient solutions to grid problems. The flexibility supply by the aggregator's customer portfolio is equal to the flexibility demand by the DSO, but it is the aggregator, not the DSO, that decides on the location of the flexibility supply. As a consequence, the DSO still may need to use load shedding if the flexibility provided in the buses does not resolve all issues (see Figure 9).

The load shedding decision by the DSO is followed by reselling the same amount to the ID market to cancel out that part of the aggregator's ID buying. The income from this trade is paid by the DSO to the aggregator.

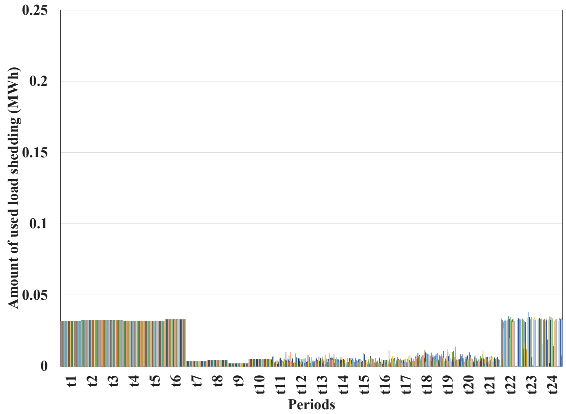


Figure 9: Used load shedding by the DSO as active power (MWh).

5 Discussions

In this section we discuss the nature of the stochastic bids, the cost-efficiency of using LFM, and the location of flexibility.

5.1 The stochastic bids

The cost parameters of our flexibility assets are deterministic. However, the aggregated flexibility cost varies depending on which assets are available within the flexibility portfolio of the aggregator in the different time periods and scenarios. Hence, we observe same LFM prices for different flexibility supply amounts at each scenario in Table 1.

In general, the curtailment or shifting of small amounts with a high number of prosumers is more cost-efficient than dispatching all the flexibility from one prosumer. This can be explained by the disutility curve used to calculate the cost of load shifting [18] with increasing marginal cost. When the number of customers providing flexibility increases, the cost of flexibility (bid price) will decrease. If the same amount of flexibility is provided by a single consumer, the marginal cost will increase. In our case study, we observe that the LFM prices increase for some scenarios when we get closer to the end of the operational period (t_{24}), due to the limited number of flexibility providers.

5.2 The cost-efficiency of the LFM

The cost-efficiency of our stochastic LFM is measured by considering the cost of the aggregator, the DSO, and the system. These costs are compared with the case without LFM, where only load shedding is available at the cost of VoLL. We separate this into the DSO cost, the aggregator cost, and the system cost.

The DSO cost includes the load shedding cost from OF3 and the revenue payment for flexibility supply to the aggregator by the DSO (flexibility supply multiplied by LFM price). *The aggregator cost* includes the aggregator's ID market purchase

Table 1: Price-quantity pairs (EUR/kWh-kW) for bid curves at each scenario per period.

	s1	**s2**	**s3**	**s4**	**s5**	**s6**	**s7**	**s8**	**s9**	**s10**
t7	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)
t8	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)
t9	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)
t10	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)
t11	(16.64, 79.4)	(16.64, 97.3)	(0.7026, 52.3)	(16.64, 89.4)	(16.64, 65.8)	(1473.51, 92.5)	(0.7026, 58.6)	(16.64, 72.9)	(1473.51, 38.6)	(16.64, 67.8)
t12	(16.64, 71.8)	(16.64, 66.4)	(0.7026, 36.7)	(16.64, 82.7)	(16.64, 70.4)	(1473.51, 74.2)	(0.7026, 51.2)	(16.64, 32.8)	(1473.51, 69.9)	(16.64, 46.7)
t13	(16.64, 37.2)	(16.64, 42.4)	(0.7026, 60.7)	(16.64, 38.1)	(16.64, 69.3)	(1473.51, 65.1)	(0.7026, 45.6)	(16.64, 39.5)	(1473.51, 46.7)	(16.64, 85.5)
t14	(16.64, 100)	(16.64, 55.7)	(0.7026, 52.4)	(16.64, 39.2)	(16.64, 71.6)	(1473.51, 85.9)	(0.7026, 40.8)	(16.64, 64.3)	(1473.51, 81)	(16.64, 75.8)
t15	(16.64, 92.4)	(16.64, 82.6)	(0.7026, 1.8)	(16.64, 51.9)	(16.64, 25.3)	(1473.51, 27.4)	(0.7026, 34.5)	(16.64, 63.2)	(1473.51, 95.2)	(16.64, 92.2)
t16	(17, 24.3)	(17, 65.8)	(1.0626, 1.6)	(17, 45.4)	(17, 48.5)	(1473.87, 88.6)	(1.0626, 61.6)	(17, 59.2)	(1473.87, 55.5)	(17, 43.8)
t17	(17, 11.1)	(17, 39.2)	(1.0626, 51.8)	(17, 22.7)	(17, 67.3)	(1473.87, 87)	(1.0626, 81.4)	(17, 56.3)	(1473.87, 87.9)	(17, 64)
t18	(17, 107.3)	(17, 112.5)	(1.0626, 125)	(17, 121.2)	(17, 163.6)	(1473.87, 133.1)	(1.0626, 113)	(17, 117.8)	(1473.87, 150.7)	(17, 143.5)
t19	(17, 166.1)	(17, 113.6)	(1.0626, 135.5)	(17, 113.3)	(17, 156.8)	(1473.87, 166.4)	(1.0626, 123.2)	(17, 161.6)	(1473.87, 174.1)	(17, 134.3)
t20	(17, 142.3)	(17, 75)	(1.0626, 92.1)	(17, 122.4)	(17, 111.7)	(1473.87, 135.2)	(1.0626, 71.8)	(17, 150.6)	(1473.87, 169.4)	(17, 118.2)
t21	(20, 50.9)	(20, 91.2)	(4.0626, 76.8)	(20, 121.4)	(20, 109.7)	(1476.87, 126.8)	(4.0626, 72.9)	(20, 122)	(1476.87, 154.8)	(20, 119.1)
	s11	**s12**	**s13**	**s14**	**s15**	**s16**	**s17**	**s18**	**s19**	**s20**
t7	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)	(312.74, 37.9)
t8	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)	(312.74, 50.9)
t9	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)	(312.74, 50.8)
t10	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)	(312.74, 62.4)
t11	(0, 75.2)	(16.64, 58.9)	(1473.51, 67.3)	(0.7026, 89.8)	(16.64, 74.5)	(16.64, 93.8)	(16.64, 80.4)	(16.64, 51.4)	(16.64, 42.3)	(0.7026, 50.5)
t12	(0, 60.7)	(16.64, 51.7)	(1473.51, 69.8)	(0.7026, 59.2)	(16.64, 53.5)	(16.64, 86.1)	(16.64, 53.8)	(16.64, 95.9)	(16.64, 45.8)	(0.7026, 12.6)
t13	(0, 50.3)	(16.64, 35.6)	(1473.51, 54.1)	(0.7026, 42.5)	(16.64, 70.7)	(16.64, 67)	(16.64, 76.3)	(16.64, 65.7)	(16.64, 91.9)	(0.7026, 52.4)
t14	(0, 34.4)	(16.64, 74.9)	(1473.51, 80.9)	(0.7026, 36.1)	(16.64, 69.2)	(16.64, 112.4)	(16.64, 105.6)	(16.64, 64.2)	(16.64, 57.4)	(0.7026, 86.7)
t15	(0, 23.8)	(16.64, 21.9)	(1473.51, 77.2)	(0.7026, 44.7)	(16.64, 57.9)	(16.64, 38.1)	(16.64, 104.1)	(16.64, 59.6)	(16.64, 59.7)	(0.7026, 56.1)
t16	(0.36, 28.1)	(17, 47)	(1473.87, 89.7)	(1.0626, 27.2)	(17, 43.6)	(17, 26.5)	(17, 36.8)	(17, 45.8)	(17, 73.2)	(1.0626, 46.8)
t17	(0.36, 42.4)	(17, 55.4)	(1473.87, 83.2)	(1.0626, 76.5)	(17, 71.1)	(17, 61.4)	(17, 88.6)	(17, 26.5)	(17, 110.6)	(1.0626, 23.8)
t18	(0.36, 93.4)	(17, 160.7)	(1473.87, 191.3)	(1.0626, 110.1)	(17, 156.2)	(17, 134)	(17, 161.4)	(17, 126.3)	(17, 142.4)	(1.0626, 117.7)
t19	(0.36, 87)	(17, 178.7)	(1473.87, 177.1)	(1.0626, 116.8)	(17, 176.7)	(17, 118.6)	(17, 112.5)	(17, 121.9)	(17, 121.5)	(1.0626, 124.8)
t20	(0.36, 89.1)	(17, 145.3)	(1473.87, 137.3)	(1.0626, 90)	(17, 129.2)	(17, 98.2)	(17, 121)	(17, 90.4)	(17, 129.1)	(1.0626, 112.1)
t21	(3.36, 82.7)	(20, 98.5)	(1476.87, 81.9)	(4.0626, 77.1)	(20, 100.2)	(20, 127.3)	(20, 63.7)	(20, 47.8)	(20, 105.3)	(4.0626, 49.4)

(the net trading with ID market from OF3), battery, load shifting, and load curtailment costs from OF2. *The system cost* includes the net trading with ID market from OF3 and load shedding cost from OF3, in addition to the flexibility cost from OF2 (load curtailment, shifting, and battery costs). All these costs are illustrated in Figure 10.

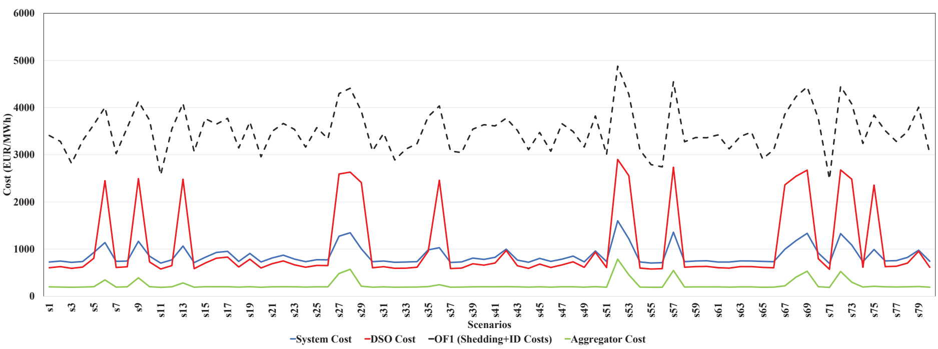
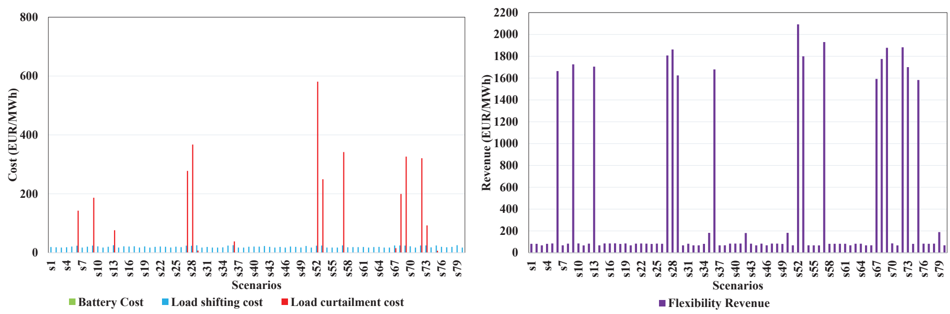


Figure 10: Cost profiles of the system and LFM participants -lines are valid only in the scenario points.

The cost efficiency of the LFM usage becomes prominent, as shown by the comparison between the system cost and load shedding cost in Figure 10. All cost profiles, especially the system cost (blue line), are lower than the only load shedding usage cost (dashed black line). For the majority of the scenarios, the DSO cost (red line) is lower than the system cost, except for scenarios when there is load curtailment usage. Accordingly, the social benefit of using LFM is illustrated in

Figure 10 as the area between load shedding cost and the system cost.

Figure 11 shows the flexibility revenue (blue line) and cost of using each flexibility asset in the aggregator's portfolio (red, green, and orange areas) for the aggregator's cost/revenue profiles. The *flexibility revenue* is defined as the revenue payment for flexibility supply by the DSO and the revenue from the repayment of ID market trades due to load shedding in OF3 (load shedding amount multiplied with ID price). In every scenario, the flexibility revenue exceeds the overall flexibility cost (summation of load shifting, load curtailment, and battery discharge costs). Especially in scenarios with load curtailment usage, such as scenario 6, most of the flexibility is provided by the load shifting. Even the load curtailment is a more expensive choice, as the load shifting and batteries are insufficient to supply all flexibility. However, for the aggregator, the load curtailment is the marginal choice for flexibility supply and it decides the price. Hence, the flexibility revenue of the aggregator (flexibility supply multiplied by the marginal cost) exceeds the flexibility cost because all flexibility supply is priced according to the marginal cost. When the aggregator has no other flexibility options available, it activates the expensive resource and that resource sets the LFM price.



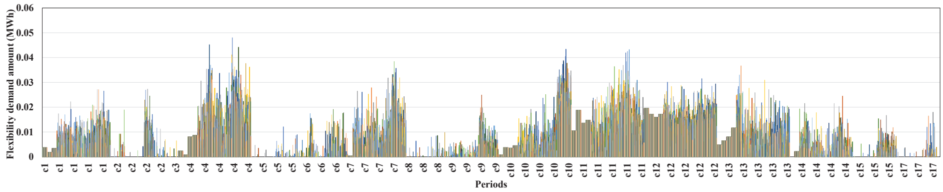
(a) Costs of flexibility assets (EUR/MWh). **(b)** Revenues from flexibility (EUR/MWh).

Figure 11: Cost and revenue profiles of the aggregator's portfolio -aggregated for all periods.

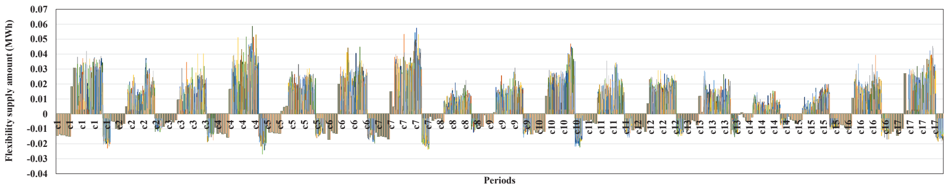
Thus, the usage of the LFM to mitigate the grid problems decreases the system cost up by to 40% in scenarios without load curtailment. In scenarios with load curtailment, the cost-efficiency is up to 30%. The usage of a local flexibility market is efficient for solutions to grid problems too, as it is cost-efficient for all participants in the LFM.

5.3 The location of flexibility

In the case study, the aggregator supplies flexibility for grid operations in real time but still we observe the usage of the load shedding by the DSO at the VoLL. In this regard, the location of a flexibility asset is important. As shown in Figures 12a and 12b, the flexibility demand of the DSO is compared with the flexibility supply of the aggregator from each customer for each scenario. We observe that the overall flexibility supply from the aggregator meets the overall flexibility demand of the



(a) Flexibility demand from the DSO per customer as active power (MWh).



(b) Flexibility supply from the aggregator per customer as active power (MWh).

Figure 12: Comparison of flexibility in supply-demand locations in the case study. Each color represents a scenario.

DSO in volume for each scenario. However, the location of the flexibility supply (i.e., the customer who supplies the flexibility in the aggregator's portfolio) does not meet with the DSO's location (bus) requirement. Hence, we observe the load shedding in Figure 9 (Figure 4 can show how to convert consumer index c to bus index i at the x-axis of Figure 12).

Thus, a pooled LFM could mitigate grid problems and supply all the needed flexibility demand in the right periods for each scenario, but to provide more effective and cost-efficient solutions, the spatiality of flexibility suppliers needs to be considered. The location-specific problems, such as voltage drop, ideally need to be addressed where they occur on the grid. An approach with direct control of the flexibility (e.g., [18]), could provide more cost-efficient solution based on bilateral contracts. However, this would have the drawback that there would not be an established market, and price formation would not be clear.

6 Conclusion and Recommendation

In this paper we have presented the results of our research on an optimal LFM design for grid operations under demand uncertainty. We have modeled a DSO and a radial distribution grid with a deterministic AC-OPF model to determine the flexibility demand for efficient grid operations. As the flexibility supplier for the pooled LFM, an aggregator is modeled with a two-stage stochastic model for bidding and scheduling with stochastic dispatch to clear the LFM.

The usage of a stochastic LFM provides efficient mitigation of grid problems. With a stochastic LFM design, we achieved up to 40% more cost-efficient solutions than a system with only load shedding (without LFM) for grid operations such as congestion and voltage management. The improvement was achieved by scheduling flexibility products such as load curtailment, load shifting, and batteries.

Our results suggest that it is possible to mitigate grid congestion problems by using a pooled LFM, but for the voltage problem, the DSO or the LFM needs to address the locations of the flexibility assets.

In this LFM design, the aggregator supplied flexibility with correct timing according to the stochastic demand distribution of the DSO. However, the spatiality of the flexibility resource is important because voltage problems are location-specific on the grid. For this reason, the DSO could not avoid load shedding. A direct control approach with bilateral contracts could avoid the problem, but it would have the disadvantage that a market-based price formation would not exist. An area for future research would be how to include spatiality in a pooled LFM market design.

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Appendix A Nomenclature

Table 2: Nomenclature

Sets	
$c \in \mathcal{C}$	Set of consumers indexed with c and $\mathcal{C} \subset \mathcal{I}$
$t \in \mathcal{T}$	Set of periods with index t
$t_m \in \mathcal{T}_m$	Set of periods for first-stage, $m = \{1, ..., 10\}$
$t_n \in \mathcal{T}_n$	Set of periods for second-stage, $n = \{11, ..., 24\}$
$\mathcal{T}_m \cup \mathcal{T}_n = \mathcal{T}$	
$t^1 \in \mathcal{T}^1$	Set of ID periods with index t^1
$t^2 \in \mathcal{T}^2$	Set of LFM market periods with index t^2
$\mathcal{T}^1 \cup \mathcal{T}^2 = \mathcal{T}$ and $\mathcal{T}^1 \cap \mathcal{T}^2 = \emptyset$	
$k \in \mathcal{K}$	Index for break points in load shifting cost function (decision maker defined)
$s \in \mathcal{S}$	Set of scenarios, index s
$i \in \mathcal{I}$	Set of buses in network with index i
$j \in \mathcal{J}$	Set of buses in network with index j
$g \in \mathcal{G}$	Set of generators with index g

Parameters	
$B_{t_m^1}$, $B_{t_n^1}$	Deterministic price at ID market
H	Multiplying parameter for minimum battery capacity
$\overline{\Psi}$ and $\underline{\Psi}$	Maximum and minimum capacities of batteries
VC_k	Variable cost for load shifting
IC	Battery investment cost
$L_{c,s,t}$	Stochastic power demand
$L_{c,t}$	Deterministic power demand
E^{chr} and E^{dis}	Charging and discharging efficiency coefficients of a battery
P_s	Probability of a scenario (%)
$L_{c,t,s}^{shed}$	Amount of load shedding demanded by DSO per customer
σ_k	The percentage of demand in correspondence of breakpoint k
$S_{i,j}$	Line capacity limit of the distribution grid as active power (0.3085 MVA)
C^{curt}	Cost of load curtailment (1500 EUR/MWh)
VoLL	Value of lost load (3000 EUR/MWh)
$L_{i,t}^{new_p}$, $L_{i,t}^{new_q}$	Active and reactive new demand
$\varrho_{c,t,s}^{curt_p}$	The amount of active load curtailment
Variables	
Ω_{g,t^1}^{agg}	The amount of total active power purchase by the aggregator from ID market
Ω_{g,t^1}^{DSO}	The estimated amount of total power purchase need by the DSO from ID market
Ω_{g,t^1}	The amount of net power purchase by the system from ID market
$\rho_{c,t,s}$	The purchase from the ID market
$\rho_{t,s}^{shift}$	The amount of shifted load
$\rho_{c,t,s}^{chr}$, $\rho_{c,t,s}^{dis}$	Charging and discharging amount of battery
$D_{i,t,s}$	Flexibility demand by the DSO
$\varrho_{c,t}^{curt}$	The amount of load curtailment by the aggregator
$\Psi_{c,t,s}$	State of charge for batteries at period t
$\Gamma_{c,t,s}$	Battery discharge cost
$\lambda_{c,t,s,k}$	Continuous variable between 0 and 1
$\pi_{c,t,s}^{\text{shift}}$	Cost of load shifting
$\rho_{c,t,s}^{A}$	Amount of flexibility supply for DSO's request
$\delta_{t,s}^{A}$	Dual value, the marginal cost of flexibility provision for pooled market
$AF_{i,j,t}$, $RF_{i,j,t}$	Active and reactive power flow between nodes i and j
$L_{i,t}^{p}$, $L_{i,t}^{q}$	Active and reactive demand from bus i
$V_{i,j,t}$	Voltage magnitude
$P_{i,t}^{shed}$, $Q_{i,t}^{shed}$	Amount of active and reactive power shedding
$P_{i,g,t}$, $Q_{i,g,t}$	Active and reactive of scheduled production from a generator

$Y_{s,ij}$	Impedance value in AC-OPF model
$\delta_{i,t}$, $\theta_{s,i,j,t}$	Voltage angles between buses i and j
$L^{new}_{c,t,s}$	The new demand profile for a customer after scheduling
OF1	Objective function result of Model 1
OF2	Objective function result of Model 2
OF3	Objective function result of Model 3

Appendix B Scheduling results of the aggregator model

The load shifting assets are scheduled to supply in LFM and minimize costs. The results are presented in Figure 13. Load curtailment is an expensive asset. According to the results presented in Figure 14, the load curtailment is needed especially when there is high flexibility demand. We assume batteries are already charged at the initial period and they return to their initial stage of charge at the end of operational period (t_{24}). The results are illustrated in Figures 15 and 16. The results of power purchase from the main grid are illustrated in Figure 17 and limited according to equation 16.

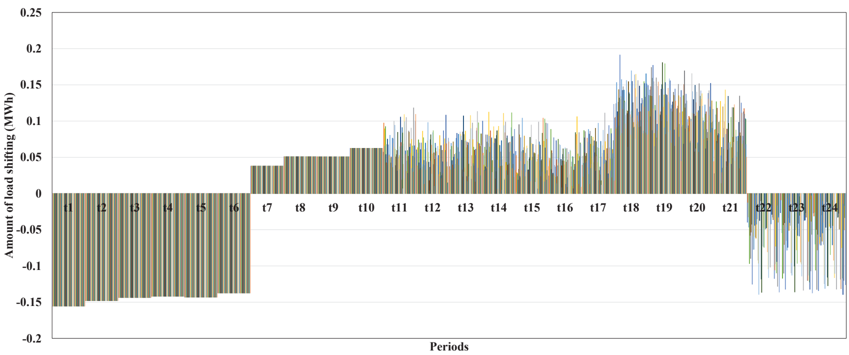

Figure 13: Load shifting by the aggregator as active power. Results are aggregated for customers. Each color represents a scenario.

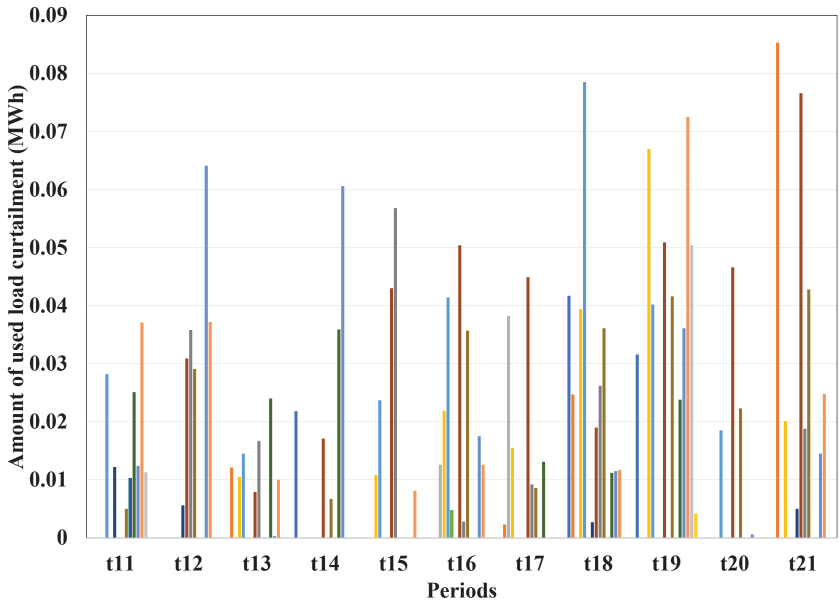

Figure 14: Load curtailment by the aggregator as active power. Results are aggregated for customers. Each color represents a scenario.

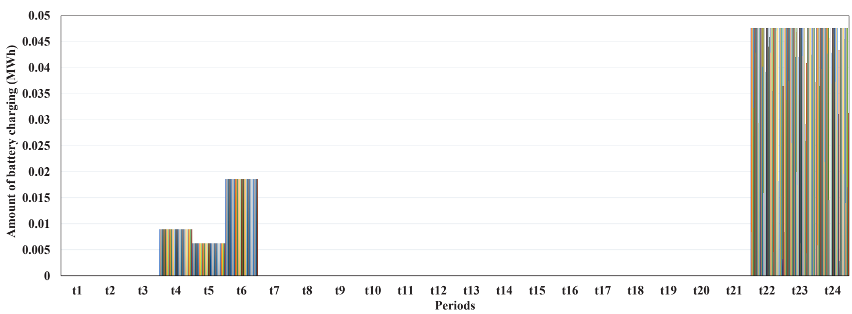

Figure 15: Battery charging pattern of the aggregator as active power. Each color represents a scenario.

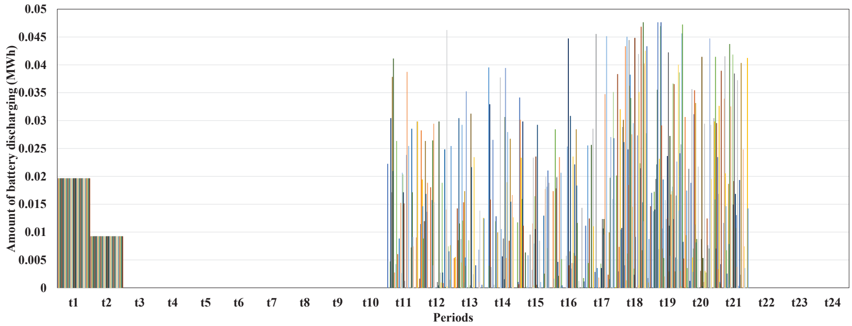

Figure 16: Battery discharging pattern of the aggregator as active power. Each color represents a scenario.

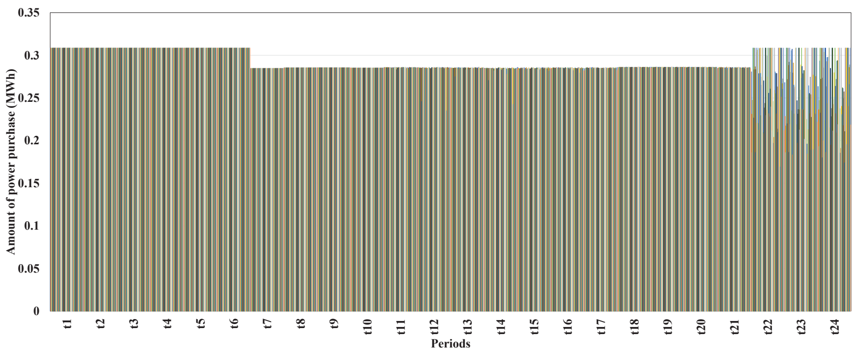

Figure 17: Power purchasing pattern of the aggregator as active power. Each color represents a scenario.

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