Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

Victor Sætre Aasvær
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Designing a Zonal Flexibility Market and Modelling Strategic Opportunities in Combination with the Intraday Market

Combining Optimization and Machine Learning Approaches

Master's thesis in Industrial Economics and Technology Management
Supervisor: Asgeir Tomasgard
Co-supervisor: Pedro Crespo del Granado
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Preface

This master's thesis was written during the course of the spring 2023 at the Norwegian University of Science and Technology by Victor Sætre Aasvær and Anders Strand Ryssdal. The thesis is submitted in the course TIØ4905 Managerial Economics and Operations Research, Master's Thesis, accounting for 30 credits. The work presented in this thesis thus concludes our Master of Science at the Department of Industrial Economics and Technology Management (IØT).

The thesis is based on work we conducted during the fall of 2022 in the course TIØ4500 Managerial Economics and Operations Research, Specialization Project, accounting for 15 credits. In the report, we investigated a novel flexibility market design, where the grid was dynamically partitioned into zones to represent congestion patterns. When offered the opportunity, we decided to base the master's thesis on two scientific papers, both of which are planned for academic publishing.

We would like to thank our supervisors Prof. Asgeir Tomasgard and Prof. Pedro Crespo del Granado for valuable contributions and discussions during our work with the thesis. We would also like to thank Dr. Naser Hashemipour for his help with pre-processing the data and guiding us during the development of the grid models. We have also received crucial advice from Prof. Ruud Egging-Bratseth, Dr. Anders Gullhav, Prof. Hossein Farahmand, Dr. Stian Backe, Paul Seifert, and Nicolo Barboni on modelling approaches and implementation.

Finally, we would like to express our appreciation for discussions on flexibility markets as a part of the PowerDig project.

Abstract

As the global community endeavors to transition towards sustainable economies in order to mitigate the impact of climate change, the power grid faces escalating challenges. The integration of electrification and intermittent renewable energy sources results in increased loads, leading to Congestion Management (CM) issues and necessitating flexibility within the power system. Well-functioning Flexibility Markets (FMs) play a vital role in enhancing flexibility and ensuring optimal utilization of flexibility assets by system operators. However, there is a lack of consensus among researchers regarding the optimal design of FMs. While the market design should convey accurate price signals and incentivize investment in flexibility assets where the demand is highest, the geographical scope of FMs may pose challenges related to liquidity and market power. Furthermore, the complexity of FM design is compounded when viewed within the broader power market structure, as it may give rise to arbitrage opportunities and be susceptible to gaming, affecting the economic efficiency of the market sequence. This thesis investigates a novel design of FMs, specifically FMs with a zonal grid representation. The research comprises two papers that examine the proposed FM design from different perspectives.

The first paper builds upon the work conducted during the specialization project in the fall of 2022. It introduces a zonal FM design that generates hourly zones based on congestion from the Day Ahead (DA) schedule. The market's theoretical performance is evaluated by modelling two additional cases: a business-as-usual case involving conventional redispatch without flexibility assets, and a nodal FM design that optimally utilizes flexible assets. The research findings indicate that the zonal FM design closely approximates the theoretical performance of its nodal counterpart. However, the effectiveness of the zonal FM design depends on congestion levels, available flexibility, and the configuration of the zones. This underscores the challenges associated with effectively partitioning a meshed power grid and emphasizes the need for a sophisticated zonal partitioning algorithm. Nevertheless, the market design significantly reduces CM costs compared to the business-as-usual case.

The second paper builds upon the framework of the first paper, expanding it to include the integration of an intraday market alongside the existing FM model. To capture strategic behavior among certain market participants, we present a reinforcement learning framework, based on the Q-learning algorithm. The study encompasses two additional scenarios: one where strategic bidding is limited to the intraday market only, and another scenario without any strategic bidding. Through our analysis, we identify various profit-enhancing strategies adopted by strategic participants and investigate their impact on market prices, social surplus, and CM.

The results highlight a substantial increase in profits for participants engaging in strategic bidding. Moreover, our findings show that strategic bidding in the FM improves rewards by 27% compared to solely bidding strategically in the intraday market.

Sammendrag

Mens samfunnet jobber mot en overgang til bærekraftige økonomier for å begrense virkningen av klimaendringer, står kraftnettet overfor økende utfordringer. Integreringen av elektrifisering og fornybare energikilder fører til økt last, noe som resulterer i utfordringer med håndtering av flaskehalser og nødvendiggjør fleksibilitet i kraftsystemet. Velfungerende fleksibilitetsmarkeder spiller en avgjørende rolle i å forbedre fleksibiliteten og sikre optimal utnyttelse av fleksibilitetsressurser av systemoperatører. Imidlertid er det ingen konsensus blant forskere om den optimale utformingen av slike markeder. Mens markedsdesignet bør formidle riktige prisignaler og motivere investeringer i fleksibilitetsressurser der etterspørselen er størst, kan det geografiske omfanget av fleksibilitetsmarkeder skape utfordringer knyttet til likviditet og markedsmakt. Videre øker kompleksiteten i markedsdesignet når det ses i sammenheng med det bredere kraftmarkedet, da det kan gi opphav til arbitrasjemuligheter og sårbarhet for spekulasjon, noe som påvirker den økonomiske effektiviteten til markedsstrukturen. Denne avhandlingen undersøker en nyutviklet utforming av fleksibilitetsmarkeder, spesifikt fleksibilitetsmarkeder med soneprising. Forskningen består av to artikler som undersøker det foreslåtte markedsdesignet fra ulike perspektiver.

Den første artikkelen bygger på arbeidet som ble gjennomført under fordypningsprosjektet høsten 2022. Den introduserer et soneinndelt fleksibilitetsmarked som genererer timesbaserte soner basert på flaskehalser fra spotmarkedsklareringen. Markedets teoretiske ytelse blir evaluert ved å modellere to tilleggstilfeller: en business-as-usual-situasjon som involverer konvensjonell omdirigering uten fleksibilitetsressurser, og et nodeinndelt fleksibilitetsmarked som optimalt utnytter fleksible ressurser. Forskningsresultatene indikerer at det soneinndelte markedet i stor grad samsvarer med den teoretiske ytelsen til sin nodeinndelte motpart. Imidlertid avhenger effektiviteten til det soneinndelte markedsdesignet av overbelastningsnivåer, tilgjengelig fleksibilitet og konfigurasjonen av sonene. Dette fremhever utfordringene knyttet til effektiv oppdeling av et sammenflettet kraftnett og understreker behovet for en sofistikert algoritme for soneinndeling. Likevel reduserer markedsdesignet kostnadene knyttet til håndtering av flaskehalser betydelig sammenlignet med business-as-usual-tilfellet.

Den andre artikkelen utvider rammeverket fra den første artikkelen ved å modellere et intradagmarked. For å fange opp strategisk adferd blant utvalgte markedsdeltakere, presenterer vi en forsterkende læringstilnærming basert på Q-læring-algoritmen. Studien omfatter to ekstra scenarier: ett der strategiske bud kun tillates i intradagmarkedet, og ett scenario uten strategiske bud. I analysen av resultatene identifiserer vi ulike strategier som øker profitten for strategiske deltakere, og undersøker deres påvirkning på markedspriser, samfunnsøkonomisk overskudd og håndtering av flaskehalser.

Resultatene i artikkel nummer to fremhever en betydelig økning i profitt for strategiske markedsdeltakere. Videre viser våre funn at strategisk deltakelse i både

fleksibilitetsmarkedet og intradagmarkedet gir en 27% økning i profitt sammenlignet med scenariet hvor strategiske deltakere kun byr i intradagmarkedet.

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Abbreviations

AC Alternating Current

BAU Business As Usual

BRPs Balancing Responsible Parties

CM Congestion Management

DA Day Ahead

DC Direct Current

DERs Distributed Energy Resources

DS Distribution System

DSO Distribution System Operator

EU European Union

GSK Generation Shift Key

FM Flexibility Market

FA Flexibility Area

LFZ Local Flexibility Zones

MC Marginal Cost

PTDF Power Transfer Distribution Factor

RES Renewable Energy Sources

TS Transmission System

TSO Transmission System Operator

ZPTDF Zonal Power Transfer Distribution Factor

Chapter 1

Introduction

1.1 Future challenges for power systems

The pressing issue of climate change has intensified the global urgency to transition towards more sustainable economies. The European Union (EU) member states and several other countries have committed to measures that aim to limit the global temperature increase to 2 degrees Celsius, while striving to keep it below 1.5 degrees Celsius, relative to pre-industrial levels. Further emphasizing its commitment to climate action, the EU has set ambitious goals of achieving climate neutrality by 2050 and reducing greenhouse gas emissions by 55% by 2030, using 1990 levels as a benchmark (Directorate-General for Climate Action).

Meeting these ambitious targets will impact the power sector significantly. Firstly, the power production sector must lower greenhouse gas emissions by integrating a high share of Renewable Energy Sources (RES). This shift towards RES will transform the power generation landscape from a centralized model, characterized by large units connected to the Transmission System (TS), to a more decentralized approach featuring Distributed Energy Resources (DERs) connected to the Distribution System (DS). Secondly, the decarbonization of sectors such as transport and industry hinges on increased electrification, resulting in a higher load on the power system. Consequently, future power grids will need to accommodate much higher loads than they were originally built for. Given the structure of European power markets, these changes pose substantial challenges for Congestion Management (CM).

1.2 Congestion management in the Nordic power system

In deregulated electricity markets, two primary principles for determining market outcomes have emerged, namely zonal and nodal pricing (Weibelzahl, 2017). Nodal pricing involves determining prices at a nodal level while accounting for the capacity limits of all transmission lines. This method accurately represents the electricity grid in the market clearing process, resulting in optimal dispatch. The resulting nodal prices provide a signal of the actual scarcity of power at each node. On the other hand, in zonal pricing, nodes are grouped into zones, each with a uniform price across all nodes. This implies that transmission line capacities within a zone are ignored during the market clearing process, which may lead to internal congestion. Although grouping nodes into zones significantly reduces the complexity of the market clearing process, neglecting internal line constraints may thus result in an efficiency loss.

The Nordic power markets are characterized by a timeline, as shown in Figure 1.1. In the DA market, participants submit their bids before 12.00 CET one day prior to delivery. Zonal pricing is employed in the Nordic and Western European DA markets. In this pricing mechanism, critical branches, i.e., power lines that are significantly affected by cross-border trading, are identified by the Transmission System Operators (TSOs). The TSOs publish these critical branches along with their remaining available margins. The market is cleared in a closed auction by maximizing social welfare, while considering transmission capacities between zones. Participants are remunerated at the zonal market clearing price. This price is determined such that the price in a zone is equal to that of a neighboring zone if there is remaining capacity on the lines connecting them after the market clearing. However, if the lines are fully utilized, a price difference arises between the zones.

The intraday market, which closes one hour before delivery, provides participants the opportunity to trade closer to real time and therefore allows them to trade themselves into balance. Similar to the DA market, the intraday is zonal. However, unlike the DA market, the intraday market operates continuously, and bids are matched while taking inter-zonal constraints into account, with participants being remunerated at bidding price.

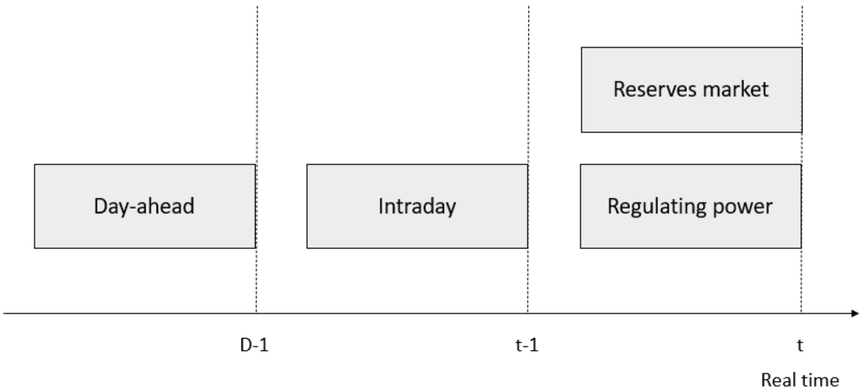


Figure 1.1: Timeline for Nordic power markets (inspired by Lund (2014)).

Given that the DA and intraday markets are zonal markets, the scheduled line flows at t-1 in 1.1 may prove to be physically infeasible, i.e. they exceed line capacities. The market zones are designed to intersect lines that commonly experience congestion. Nevertheless, the dynamic nature of the load and production profiles makes it practically impossible for a static zonal design to capture all congestion at all times. The resulting internal congestions need to be addressed by the system operators, often through a redispatch performed after t-1. The cost of the redispatch represents an economic inefficiency arising from the disregard of intrazonal constraints in the DA market. Moreover, the challenge of internal congestion is likely to intensify in the future due to more intermittent production profiles from a larger share of RES and the substantial load increase driven by electrification.

The conventional redispatch approach involves requesting a downstream generator to increase production while directing an upstream generator to decrease production. This approach is profit-neutral, which implies that generators increasing their production are reimbursed at their marginal cost, while those decreasing their production are reimbursed at their lost profit, i.e., the zonal price less their marginal cost. This method of redispatching is less economically efficient than using a market to adjust loads and generators, as it lacks price signals and only has limited resource options. Furthermore, since the CM scheme is profit neutral, the scheme provides no incentive to invest in resources that can provide flexibility for system operators (Cramton, 2019).

1.3 Power system flexibility

Figure 1.2 depicts the power flow within a European power grid. The TS serves as the central hub, is managed by the TSO and comprises a meshed network of high-voltage lines and cross-border interconnectors. Conventional power generators are typically connected to the TS, which then transmits power to the end-users via the DS, under the supervision of a Distribution System Operator (DSO). Unlike the TS, the DS in Norway operates on a radial configuration, employing medium and low-voltage infrastructure. Historically, the DS has been designed to facilitate unidirectional power flow, with only consumer loads being connected to it. However, with the rise of prosumers (consumers who also generate power) and the increasing deployment of DERs, the connection of generators to the DS has become more prevalent. This development has introduced complexities in the operation of this section of the power grid.

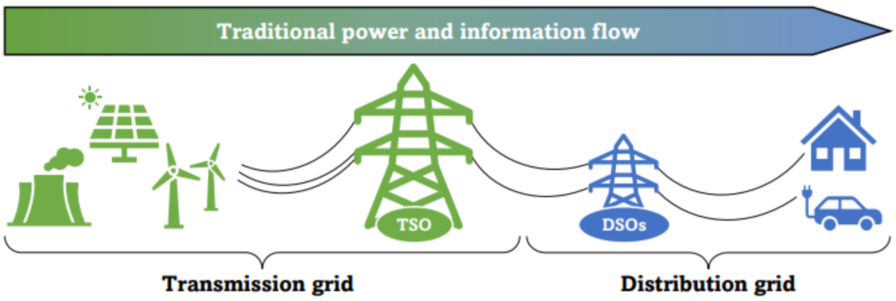


Figure 1.2: Power and information flow in traditional power systems (Wellnitz and Pearson, 2022).

The power system is set to experience increasing congestion problems in the future, as stated in Section 1.2. One solution addressing these long-term congestion issues is the expansion of the power grid. However, grid reinforcements are both expensive and time-consuming. Therefore, the utilization of flexibility has been proposed as a feasible complement to grid expansion. In this context, flexibility refers to the capability to modify the demand and supply of power to offer services to the power system. This flexibility can be derived from conventional dispatchable generators such as hydro and gas power plants. However, there is a growing recognition of the increasing significance of demand-side flexibility, encompassing battery storage and demand response, as a valuable source of flexibility in the future.

Flexibility resources are valuable for multiple parties, notably the TSOs and the DSOs, who bear the responsibility for CM. These resources also offer benefits to Balancing Responsible Parties (BRPs), market participants committed to either delivering or consuming power, who face penalties for non-compliance. The need for flexibility in both grid operations and for the balancing requirements of BRPs has stimulated extensive research projects proposing market designs for trading flexibility products. These proposed designs aim to create mechanisms for buying and selling flexibility resources, thereby establishing a marketplace where the true value of flexibility can be capitalized. However, determining the optimal design for these FMs remains a complex and unresolved issue.

1.4 Objective of the thesis

The principal aim of this thesis is to confront and seek solutions to a set of challenges identified in the preceding discussions. Specifically, the research focuses on two main challenges: firstly, the lack of price signals and investment incentives within CM, and secondly, the intricate task of designing an efficient FM capable of effectively integrating demand-side flexibility resources.

In the first paper we present a novel FM design featuring a zonal grid resolution. Our approach innovates by implementing dynamic zones within the FM to more accurately represent a grid with congestion patterns that vary over time. In order to promote CM, we model a system operator as an active market participant with a vested interest in limiting congestion. Additionally, we offer a comparative analysis of the performance of our proposed market design against a nodal FM and the conventional redispatch process.

While the first paper primarily focuses on the theoretical performance evaluation of the market design, the second paper delves into the practical implementation challenges of the proposed FM and FMs in general. Specifically, the study investigates potential effects and problems that may arise when implementing a FM in parallel with the intraday market. To examine this, a reinforcement learning algorithm is presented, where agents engage in trading activities in both the FM and the intraday market, aiming to maximize their own profit

1.5 Structure of the thesis

Chapter 2 of this thesis provides an overview of the central problem that the research endeavors to address. Following a paper-based format, Chapter 3 introduces the first paper titled "Dynamic Zonal Flexibility Markets for Congestion Management." This paper primarily focuses on the theoretical evaluation of the proposed FM design. Chapter 4 serves as a bridge between the two papers, offering an explanation of the interconnection and relevance between them. Subsequently, in Chapter 5, the second paper titled "Modelling Strategic Behavior in Flexibility and Intraday Markets: Combining Optimization and Machine Learning Approaches" is presented. This paper tackles practical challenges associated with the coexistence of an FM and the intraday market, specifically emphasizing the disparities in grid resolutions and the consequential variations in the accuracy of information derived from market outcomes. These differences may potentially create gaming opportunities for agents seeking to maximize their individual profits, ultimately leading to societal costs. Following the presentation of the second paper, Chapter 6 provides concluding remarks based on the results obtained from both papers. Additionally, this chapter outlines prospects for future research, identifying areas that merit further investigation.

Chapter 2

Problem description

In this chapter, we delineate the scope of the thesis, outlining the specific areas of investigation. We provide an overview of the primary research questions guiding the study and highlight the modelling approaches employed to address these inquiries.

The present thesis centers on the efficient trading of flexibility among diverse actors with varying demands, while also examining the challenges and opportunities that arise from the integration of a FM alongside traditional wholesale markets. As discussed in the preceding chapter, advancements in technology and the proliferation of flexibility assets have made the utilization of flexibility for both grid constraint management and balancing increasingly viable. Throughout this thesis, we operate under the assumption that multiple actors compete to procure flexibility. However, our primary focus lies in the utilization of flexibility for CM. This emphasis stems from the inherent limitations of cost-based redispatch, as discussed earlier. While BRPs can decrease imbalances through intraday market transactions, the absence of a Nordic market for redispatch impedes the provision of price signals and investment incentives for entities seeking to offer CM services.

This subject lends itself to investigation from multiple perspectives. The first paper adopts a theoretical approach, wherein we introduce a FM design and assess its performance in terms of societal costs associated with CM. We compare this design to an alternative market framework as well as traditional redispatch mechanisms. However, this analysis primarily examines the FM in isolation, disregarding potential effects that may arise from the concurrent implementation of multiple market structures. The second paper adopts a more practical stance, whereby we consider the strategic behavior of select actors participating in both the FM and the intraday market. By incorporating strategic decision-making into our examination, we aim to capture a more realistic depiction of market dynamics and outcomes.

2.1 Zonal flexibility markets

In Chapter 3, we introduce a novel and previously unexplored design of FMs, namely a zonal FM. While zonal wholesale markets have been extensively studied and implemented in Western Europe and the Nordics, the existing literature predominantly presents FM designs based on nodal market structures. Consequently, our investigation centers on assessing the potential benefits of zonal FMs in the context of CM. Our research endeavors to address the following research questions:

- How can zonal FMs contribute to facilitating more efficient CM?

- To what extent can dynamic zones limit the efficiency loss associated with zonal pricing in FMs?

To address these research questions, we employ a modelling framework that encompasses three distinct cases: Zonal FM, Nodal FM, and Business as usual (BAU). These cases diverge in terms of their utilization of flexibility resources and market structure. Through the application of this modelling approach, we aim to shed light on the comparative dynamics and outcomes within each case

2.1.1 Zonal FM

In the Zonal FM case, we introduce the zonal FM design, characterized by competition on both the supply and demand sides. With respect to the power flows resulting from the DA schedule, the geographical area under investigation is partitioned into hourly dynamic zones. This zone partitioning approach is designed to capture the temporal variations in congestion patterns. Subsequently, the FM undergoes a clearing process where system operators, flexibility providers and BRPs participate. Finally, the updated net positions are forwarded to a redispatch model where remaining congestions are alleviated.

Given the zonal nature of the FM, there exists a likelihood of incurring costs associated with the efficiency loss resulting from the approximation of the grid topology using zones. To mitigate this, we adopt a dynamic zoning approach aimed at minimizing the associated cost. However, it is improbable that the zonal FM will achieve the optimal nodal dispatch of flexibility resources.

2.1.2 Nodal FM

To evaluate the efficiency loss arising from the zonal market design, we introduce a Nodal FM case as a comparative framework. In the Nodal FM, we maintain consistency in terms of participant composition and bid submissions, mirroring the previous case. However, a key distinction lies in the grid representation used in the market clearing, as the nodal resolution ensures the optimal dispatch of the flexibility resources. By adopting this nodal approach, we aim to quantify the disparity in efficiency between the zonal and nodal FM designs, providing insights into the impact of grid representation on the optimal allocation and utilization of flexibility.

2.1.3 Business as usual

In the Business As Usual (BAU) case, we employ a modelling framework that encompasses traditional cost-based CM through a redispatch mechanism. As a result, none of the flexibility assets utilized in the previous cases are incorporated, and the redispatch process relies solely on conventional generators. This approach allows us to evaluate the potential of flexibility resources to enhance CM and mitigate associated costs.

2.2 Integrating FMs with wholesale markets

In Chapter 5, we present our second paper, which investigates the challenges of integrating the FM into the current wholesale market framework. It focuses on the dynamic between the FM and the intraday market, as they share several operational similarities. Most notably, both markets are performed within the same time window, following the DA clearing and leading up to real-time. Additionally, participants in today's intraday markets are also eligible to participate in the FM, providing an alternative market to meet their needs. The dynamics arising from these shared and overlapping traits present unresolved issues. To address this, we extend the model from our first paper by incorporating interactions with the intraday market, and investigate the implications.

The FM provides a more detailed representation of the grid compared to the intraday market. This may cause opportunities for gaming and arbitrage by actors participating in both markets, especially because both markets are intended to operate concurrently. The occurrence of gaming in power markets with this kind of asymmetric grid information has been extensively researched, particularly in the context of inc-dec gaming between DA and redispatch markets. Nevertheless, the shift of focus towards the intraday market and FMs represents a novel area of investigation. We therefore seek to answer the following research questions:

- How does the introduction of a reinforcement learning framework contribute to the understanding of strategic bidding behavior between power markets?
- How does the introduction of a FM operating in parallel with the intraday market create arbitrage or gaming opportunities for participants bidding in both markets?

In order to address these questions, we propose and implement a model representing an intraday market operating alongside the FM introduced in Chapter 3. The bid data utilized in the intraday market is derived from actual orders submitted to the continuous Nordic intraday market in the year 2021. In our investigation of strategic behavior among market actors, we apply machine learning to uncover the strategic opportunities.

Within this setup, a subset of intraday participants are also allowed to bid in the FM, and can deviate from their initial rebalancing requirements. We utilize Q-learning, a form of reinforcement learning, to assist each strategic actor in formulating the most effective bidding strategy.

Paper 1

Dynamic Zonal Flexibility Markets for Congestion Management

Chapter 3

Dynamic Zonal Flexibility Markets for Congestion Management

Abstract

The integration of renewable energy sources into the electric grid and the corresponding rise in power demand due to electrification is creating challenges for CM. Flexible resources have the potential to reduce the costs associated with CM, which raises the demand for an efficient framework for trading flexibility. In this paper we present a preliminary examination of zonal flexibility markets by introducing a novel market design aimed at improving CM. The design utilizes zones that are dynamically allocated based on grid congestion after the day-ahead market. The proposed market design is compared to both the optimal utilization of flexible resources and to conventional redispatch in order to evaluate its economic efficiency. Our findings indicate that it performs close to a nodal flexibility market, but that a more refined partitioning algorithm is needed to stabilize performance across various scenarios.

3.1 Introduction

As the power system transitions to electrified economies and increases deployment of renewable energy technologies to mitigate climate change, it faces new challenges in managing congestion in the power grid. The power grid was designed for small increments on projected loads, and is now under strain due to rapidly accelerating electrification (e.g, transport and heat). In addition, the intermittent nature of RES introduces new challenges for CM, raising the risk of grid instability.

Managing congestion is critical to ensure reliable grid operations. One key approach to achieving this is through flexibility, which involves utilizing a range of strategies to adjust energy supply and demand in response to changing conditions. These strategies might include energy storage technologies, demand response programs, and adjustments to power supply. However, an effective use of flexibility requires a robust market framework for trading it (Ramos et al., 2016), which in turn will create a more resilient and responsive energy system that is better able to meet the challenges of the future.

In this paper we provide an initial investigation into zonal FMs, by proposing a novel FM design aimed at improving CM. A central idea behind the zonal market design is to guarantee liquidity and other advantages associated with the grouping of nodes into zones, while concurrently conveying accurate pricing signals, thus ensuring the optimal utilization of flexibility. The grid congestion is addressed by the system operators, which participate in the market as flexibility procurers. The research questions we aim at answering are:

- How can zonal FMs contribute to facilitating more efficient CM?
- To what extent can dynamic zones limit the efficiency loss associated with zonal pricing in FMs?

To answer these questions, the zonal FM is modelled and bench-marked against a nodal FM and a case where flexibility is unavailable.

The following section reviews the literature on flexibility in power systems and design of markets where they are traded. The market design proposed in this paper is presented in section 3.3.1. Then, we elaborate on the modelling framework used to model the three cases, before we explain the data. Afterwards, we present and discuss our result and several sensitivities, before we finally conclude in section 3.6.

3.2 Related literature

Puente et al. (2014) define flexibility as the adjustment of generation and/or consumption patterns in response to an external signal in order to provide a service within the power system. According to Eid et al. (2016), the range of flexibility services can be described by their direction (i.e. up or down), power capacity, starting time, duration and location. Other characteristics mentioned in the literature include delivering time, time availability, predictability, controllability and purpose (e.g. portfolio optimization, balancing, constraint management, and deferral of grid investments) (Villar et al., 2018; Eurelectric, 2014).

3.2.1 Flexibility products and markets

Effective use of flexibility in the power grid requires a framework where the flexibility can be bought and sold (Ramos et al., 2016). Ramos et al. (2016) define local markets as: "long-or short-term trading actions for flexibility in a specific geographical location, voltage level, and system operator (DSO and TSO), given by grid conditions or balancing needs, where participants in a relevant market can be aggregated to provide flexibility services". Villar et al. (2018) list the participants in FMs as: TSOs, DSOs, BRPs, aggregators and retailers. TSOs buy flexibility for balancing needs, while both TSOs and DSOs buy flexibility for CM and voltage control (Villar et al., 2018). BRPs buy flexibility to balance their own portfolio, while aggregators and retailers provide flexibility services.

Several types of flexibility products are described in the literature and both Villar et al. (2018) and Jin et al. (2020) categorize these into three types: Balancing flexibility at the transmission grid, balancing flexibility at the distribution grid and flexibility for the distribution grid. The first category considers flexibility products offered to the TSO, provided in the TS, for balancing in the TS, while the second category considers flexibility services offered to the TSO for balancing in the TS, but provided in the DS. The products provided in the first category are usually traded in already existing markets, but new products from the same suppliers, such as ramping capacity products are being considered (Villar et al., 2018). The flexibility products in the second category come from DERs, such as electric vehicles (Zhang and Kezunovic, 2016) and long term capacity contracts for distributed generation and demand response (RTE, 2014). Finally, the third category considers flexibility products provided to the DSOs in the DS. Similar to the second category, the flexibility products provided in the third category consist of DERs, but are used by DSOs to ensure reliable distribution grid operation (Torbaghan et al., 2016; Ding et al., 2013).

3.2.2 Market clearing and modelling

Several studies of FMs have been carried out, with differing modelling approaches and market clearing methods. Jin et al. (2020) review the literature within the type of flexibility that Villar et al. (2018) refer to as flexibility for the distribution grid, with special emphasis on modelling and market clearing methods. The authors divide the modelling approaches into four categories: centralized optimization models, game theory-based models, auction theory-based models and simulation models. In centralized optimization models, the market is modeled as an optimization problem and cleared by solving the problem. This category can be further subdivided into social welfare maximization and operational cost minimization (Jin et al., 2020). The game theory-based models consider situations where one participant's action depends on the actions of other participants (Tushar et al., 2018). Auction-theory based models consider allocation mechanisms aimed at balancing supply and demand through a competitive process (Fanzeres et al., 2019), while multiagent simulation models are suitable to model markets where each participant can be considered as an agent (Jin et al., 2020).

Numerous authors have presented FMs that are cleared by minimizing the operational costs of a particular participant (Spiliotis et al., 2016; Torbaghan et al., 2016; Zhang et al., 2013, 2014; Olivella-Rosell et al., 2018). Spiliotis et al. analyze the trade-off between grid expansion and flexibility dispatch by developing a long-term planning model which minimizes the DSO's total cost. In Torbaghan et al. (2016), a framework for trading prosumer flexibility used to minimize the DSO's cost of resolving network congestion is presented. Zhang et al. (2013) analyze a FM where a DSO procures flexibility from aggregators to relieve congestions in local grids. Three trading setups representing different contractual arrangements between DSOs and aggregators are presented. The work is extended in Zhang et al. (2014), where two of the trading setups are analyzed in more detail and a quantitative example is provided. In contrast, Olivella-Rosell et al. (2018) present a FM design where an aggregator operates the market and minimizes the cost of dispatching its flexibility units.

Centralized optimization models maximizing social welfare have also been discussed in the literature (Jiang et al., 2022; Torbaghan et al., 2018). Jiang et al. (2022) argue for the need for a joint energy and flexibility market clearing to capture the interaction between the TSO and DSOs. The authors propose a bi-level optimization problem, where the upper level problem maximizes social welfare and the lower level problem minimizes the cost of supplying flexibility to the TS. In Torbaghan et al. (2018), a framework for trading flexibility consisting of a DA and an intraday market cleared by an independent third party is presented. Both the DA and intraday markets are cleared with the objective of maximizing social welfare.

3.2.3 Contribution

Regarding the papers discussed above, two key observations are worth mentioning. Firstly, most papers focus on minimizing one of the market participant's costs. Secondly, all papers consider FMs with a nodal grid resolution.

The inclination to prioritize the minimization of one participant's costs in the aforementioned papers can be attributed to the geographical extent of the studies. Many of these papers solely concentrate on the low-voltage DS, where DSOs and aggregators are the primary participants in the FM. Despite some mention of the need for coordination between the TSO and DSOs for the interaction between the transmission and distribution systems, these studies largely overlook the impact of flexibility dispatch on the TS. Moreover, only a handful of studies analyze FMs wherein both the TSO and DSOs function as procurers of flexibility.

While there is an extensive body of literature on zonal versus nodal pricing in DA markets, zonal FMs have not received much attention in the research. Ramos et al. (2016) discuss the concept, pointing out that nodal pricing has been criticized for its difficulty in explaining certain nodal prices. However, as far as our knowledge goes, no design of a zonal FM has been presented and modeled yet. Additionally, the notion of dynamic zones has not yet been applied to FMs.

Based on the literature review above and the gaps identified, we aim to provide:

- A first investigation into zonal FMs.
- A novel market design for a multi seller, multi buyer FM connected to both the TS and the DS, designed to improve CM after the DA clearing.
- An investigation into the role of dynamic zones in FMs.

3.3 Modelling framework

3.3.1 Market design

The proposed FM aims to enhance the management of intra-zonal congestion after DA by providing system operators with more flexible resources. The market operates through discrete auctions held throughout the day, with a time resolution for bids that is similar to both the DA and intraday markets, in this paper hourly. The FM is administered by an independent third party, with system operators serving as flexibility procurers.

The core concept of the FM is to dynamically divide the grid into zones, based on the internal congestion arising from the DA clearing. This zoning strategy enables the system operators to mitigate congestion through inter-zonal trading. It is worth noting that the optimal zone sizes may be strongly influenced by the degree and location of congestion. The proposed FM zones are distinct from the DA zones and are hence referred to as Local Flexibility Zoness (LFZs).

Theoretically, zonal markets are less economically efficient than nodal markets as they do not account for all system information. Furthermore, these markets may experience internal congestion after clearing, necessitating a traditional redispatch at a nodal level by the system operators. The implementation of a zonal FM thus incurs an alternative cost that this paper aims to assess.

Zonal FMs offer several potential benefits that warrant further investigation. Firstly, zonal markets may be more accessible to various actors. For example, aggregators that represent flexibility across multiple nodes may find it easier to participate in a zonal market with zonal-based bidding. Additionally, zonal market prices may be politically more acceptable to market actors, as price differences can be readily attributed to significant grid congestions.

A zonal FM may also differ from a nodal FM in terms of liquidity, price signal effects, market power, and gaming vulnerability. It is important to note that these benefits are uncertain and require further investigation. Moreover, advanced modelling beyond the scope of this paper is necessary to analyze these potential advantages. Therefore, this paper only addresses the short-term economic efficiency of zonal FMs, leaving the exploration of benefits offered by zonal FMs for future research.

As previously mentioned, system operators are engaged in the FM as flexibility procurers. Apart from them, the participants considered in this study are consumer aggregators, energy storage, demand-side industry, and intermittent power producers. This list aims to capture the expected behaviors and characteristics of the FM's participants, except for non-intermittent generation, which is assumed to provide only redispatch options in this study. While CM is the primary focus of this paper, the market is also intended to be utilized by BRPs and prosumers seeking to rebalance their portfolios.

3.3.2 Modelling a zonal FM

The zonal FM investigated in this paper is modelled using a four-step approach, as illustrated in Figure 3.1. We first run a load flow analysis based on the disaggregated DA volumes to calculate the congestion on each line. This information is then used to determine the configuration of the LFZs. Steps 1 and 2 are performed independently for each hour, and the heuristic used to solve the problem of optimal zonal configuration is presented in Section 3.3.4.

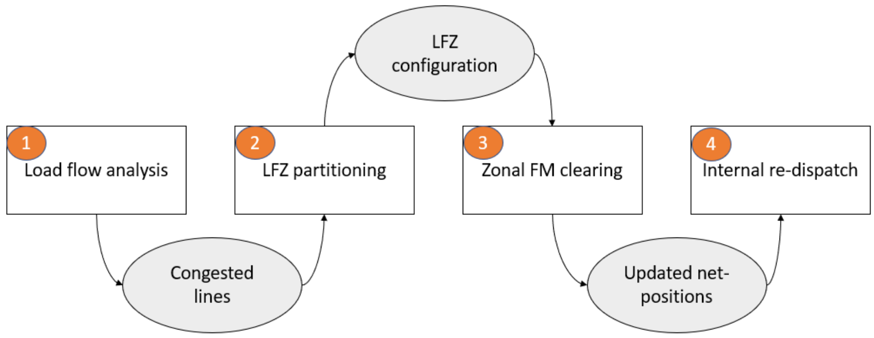


Figure 3.1: Modelling approach for the Zonal FM case.

The zonal market clearing problem is solved based on the LFZs from step 2. As the zonal FM clearing ignores intra-zonal constraints, congestions may still be present within the LFZs after the clearing. Step 4 addresses this issue by utilizing conventional redispatch. The model in step 4 uses a nodal grid, and the starting net positions are equal to the net production obtained in step 3. The formulations for the models used in step 3 and 4 can be found in Section 3.3.5, and are presented comprehensively in Appendix 1B.

3.3.3 Additional cases

To assess the efficacy of the zonal FM, two additional modelling cases are introduced: Nodal FM and BAU. The Nodal FM case utilizes a nodal grid approach to clear the flexibility market, providing a benchmark for the most efficient use of the flexibility resources. The BAU case also uses a nodal grid formulation, but it only considers the redispatch resources available outside the FM. This case corresponds to only running step 4 in the Zonal FM case, and it thus represents the threshold beyond which a zonal FM will lead to increased costs to society, a worst case benchmark.

The Nodal FM and the BAU case can each be modelled in a single step, and the formulations for these models are presented in section 3.3.5.

3.3.4 Zonal partitioning problem

The zonal partitioning problem has the ambivalent goal to both maximize the amount of congestion being considered in the market clearing, as well as to create zones that are practical for the market participants and secure liquid markets. Having multiple objectives complicates the problem, and we handle this by removing all considerations except congestion and converting them to constraints or solution-requirements. As a result, the zonal partitioning problem solved for this paper concerns maximizing the amount of congestion in inter-zonal lines, with requirements for a maximum number of zones and a minimum number of grid nodes per zone. This can be defined as a maximum k-cut problem, an NP-complete problem that involves partitioning a graph into k connected components (Goldschmidt and Hochbaum, 1994). As our graph-partitioning problem is NP-complete, it must be solved using a heuristic.

The zonal partitioning heuristic takes as input a set of nodes, lines, and associated congestion volumes. The algorithm follows an iterative approach where one zone is divided into two at each iteration. The selection of the zone to be split is based on finding the best cut, which maximizes the amount of congestion between the two resulting zones. The algorithm ends when there is no more internal congestion or the desired number of zones has been reached. A more detailed description of the algorithm is presented in Appendix 1A.

An important aspect of the algorithm is the choice to only split zones in two. This is an advantage with regard to simplicity, but it may come at the cost of losing potential optimal solutions. Additionally, the heuristic may not find the optimal way of splitting a certain zone in two. There are thus several ways of losing optimal solutions in this heuristic, but it has proven to be both fast and easy to implement.

It is also important to note that to maximize the inter-zonal congestion does not necessarily result in the most efficient zonal configuration. The performance of a zonal configuration is for example dependent on how the FM clearing will affect internal congestion, which is neither taken into account in the heuristic nor in the zonal model itself. Future research should therefore look into the zonal FM performance of more sophisticated partitioning algorithms. One example can be found in Hu et al. (2021), where a zone partitioning method using PTDFs and spectral clustering is presented.

3.3.5 Mathematical formulation

This subsection presents the mathematical formulations for the FM and redispatch models used in the three cases. We start by introducing the Nodal FM model as a foundation, since it shares most of its notation with the other models. We then present the differences and additions in the other models. The complete formulations as well as nomenclature and major assumptions behind the models can be found in Appendix 1B.

Nodal FM model

Objective function. The objective function of the Nodal FM model minimizes the total cost of flexibility and redispatch over a 24 hour period.

$$\min \sum_{t\in\mathcal{T}}\Big(\sum_{b\in\mathcal{B}^+} C_{tb}x^+_{tb} + \sum_{b\in\mathcal{B}^-} C_{tb}x^-_{tb}\Big) \tag{3.1}$$

where $\mathcal{B}^+$ and $\mathcal{B}^-$ are sets containing the up-regulatory and down-regulatory bids respectively. In the model context, bids can either represent available flexibility or available redispatch.

Power flow. The power flow in each line is calculated using Power Transfer Distribution Factors (PTDFs).

$$P^{DA}_{nt} + \sum_{b\in\mathcal{B}^+_n} x^+_{tb} - \sum_{b\in\mathcal{B}^-_n} x^-_{tb} = p_{nt} \qquad n\in\mathcal{N}, t\in\mathcal{T} \tag{3.2}$$

$$f_{lt} = \sum_{n\in\mathcal{N}} PTDF_{ln}\cdot p_{nt} \qquad l\in\mathcal{L}, t\in\mathcal{T} \tag{3.3}$$

$$-CAP_l \leq f_{lt} \leq CAP_l \qquad l \in \mathcal{L}, t \in \mathcal{T} \tag{3.4}$$

In Equation 3.2, net positions are calculated hourly at each node by adjusting the DA volumes with the bid volumes cleared up and down. Subsequently, the power flow is determined in accordance with Equation 3.3, while complying with the capacity constraints specified in Constraint 3.4.

Balancing constraints. The Nodal FM model only has one stage, which means it considers both flexibility bids and available redispatch volumes simultaneously. This is a valid simplification when assuming that the system operators have perfect information about the available redispatch, but it requires two distinct balancing constraints: one to accommodate adjustments made by flexible resources (Equation 3.5), and another to factor in conventional redispatch (Equation 3.6).

$$\sum_{b \in \mathcal{B}^+ \setminus \mathcal{B}^{RE}} x^+_{tb} - \sum_{b \in \mathcal{B}^- \setminus \mathcal{B}^{RE}} x^-_{tb} = 0 \qquad t \in \mathcal{T} \tag{3.5}$$

$$\sum_{b \in \mathcal{B}^+ \cap \mathcal{B}^{RE}} x^+_{tb} - \sum_{b \in \mathcal{B}^- \cap \mathcal{B}^{RE}} x^-_{tb} = 0 \qquad t \in \mathcal{T} \tag{3.6}$$

Battery constraints. We introduce constraints ensuring the authenticity of the battery participants' behavior.

$$\sigma_{it} = \sigma_{i(t-1)} + \sum_{b \in \mathcal{B}^-_i} x^-_{tb} \cdot \eta^- - \sum_{b \in \mathcal{B}^+_i} \frac{x^+_{tb}}{\eta^+} \qquad i \in \mathcal{I}^{Batt}, t \in \mathcal{T} \setminus \{1\} \tag{3.7}$$

$$\sigma_{i1} = S^{init}_i \qquad i \in \mathcal{I}^{Batt} \tag{3.8}$$

$$\sigma_{i|T|} = S^{init}_i \qquad i \in \mathcal{I}^{Batt} \tag{3.9}$$

$$0 \leq \sigma_{it} \leq S^{Cap}_i \qquad i \in \mathcal{I}^{Batt}, t \in \mathcal{T} \tag{3.10}$$

Constraint 3.7 calculates the state of charge for battery actors. By requiring the state of charge to be greater or equal to zero in Constraint 3.10, Equation 3.7 ensures that battery actors cannot sell more power than they have available. Constraint 3.8 and 3.9 fixes the initial and final state of charge of batteries. This results in a more restrictive operation than would be the case in a practical setting, especially as each day is modelled independently.

Aggregator constraints. We also subject aggregators to constraints governing their behavior. Constraint 3.11 stipulates that within a six-hour interval, an aggregator cannot curtail more than a fraction λ of the consumption scheduled in the DA clearing, $\mathcal{K}_i$. Similarly, constraint 3.12 limits the amount of extra power consumption during the day. Both constraints are meant to reflect that aggregators represent end-users and, despite being motivated by price signals, are unlikely to adjust their average consumption significantly.

$$\sum_{\tau=t}^{t+5}\Big(\sum_{b\in\mathcal{B}_i^+} x_{\tau b}^+ - \sum_{b\in\mathcal{B}_i^-} x_{\tau b}^-\Big) \leq \mathcal{K}_i \cdot 6\lambda \quad i\in\mathcal{I}^{Agg}, t\in\mathcal{T}\setminus\{|T|-5,...,|T|\} \tag{3.11}$$

$$\sum_{t\in\mathcal{T}}\Big(\sum_{b\in\mathcal{B}_i^-} x_{tb}^- - \sum_{b\in\mathcal{B}_i^+} x_{tb}^+\Big) \leq \mathcal{K}_i \cdot 24\zeta \qquad i\in\mathcal{I}^{Agg} \tag{3.12}$$

Bid constraints. Constraints 3.13 and 3.14 ensure that volumes cleared up and down are non-negative and are kept below the maximum volume of the bid.

$$0 \leq x_{tb}^+ \leq V_{tb}^+ \qquad t\in\mathcal{T}, b\in\mathcal{B}^+ \tag{3.13}$$

$$0 \leq x_{tb}^- \leq V_{tb}^- \qquad t\in\mathcal{T}, b\in\mathcal{B}^- \tag{3.14}$$

Zonal FM model

This subsection describes the model used in step 3 of the Zonal FM case. There, constraints 3.5-3.14 are identical to those in the Nodal FM model, with the exception that redispatch bids are not included. Thus, equation 3.6 is absent and constraint 3.13 and 3.14 only applies to flexibility bids, $b\in\mathcal{B}\setminus\mathcal{B}^{RE}$. Apart from this, the differences between the two case models lie in the objective function and the power flow constraints, which are expounded upon below.

Power flow. Since the zones are dynamic, we introduce a set $\mathcal{Z}_t$ representing the zones in time period t. The net positions are calculated in 3.15 similarly to Constraint 3.2 in the Nodal FM model, but the nodes are now aggregated into their respective zones. Hourly line flows on critical branches, $l\in\mathcal{L}_t$, are calculated using Zonal Power Transfer Distribution Factors (ZPTDFs) indexed by time period, line, and zone. ZPTDFs are derived from PTDFs, and a detailed description of this derivation is presented in Appendix 1C.

Unlike the Nodal FM model, the Zonal FM model does not constrain line flows below the line capacity. This is because conventional redispatch is not available in the model clearing, and inadequate flexibility combined with hard flow constraints may lead to an infeasible solution. Hence, Constraint 3.17 introduces a variable y_{lt} which represents congestion on a critical branch and is penalized in the objective function. These variables are forced to be non-negative in Constraint 3.18.

$$P_{zt}^{DA} + \sum_{n\in\mathcal{N}_{zt}}\Big(\sum_{b\in\mathcal{B}_n^+\setminus\mathcal{B}^{RE}} x_{tb}^+ - \sum_{b\in\mathcal{B}_n^-\setminus\mathcal{B}^{RE}} x_{tb}^-\Big) = p_{zt} \qquad t\in\mathcal{T}, z\in\mathcal{Z}_t \tag{3.15}$$

$$f_{lt} = \sum_{z\in\mathcal{Z}_t} ZPTDF_{lzt}\cdot p_{zt} \qquad ,t\in\mathcal{T}, l\in\mathcal{L}_t \tag{3.16}$$

$$-CAP_l - y_{lt} \leq f_{lt} \leq CAP_l + y_{lt} \qquad t\in\mathcal{T}, l\in\mathcal{L} \tag{3.17}$$

$$0 \leq y_{lt} \qquad t \in \mathcal{T}, l \in \mathcal{L} \tag{3.18}$$

Objective function. The objective function for the Zonal FM case is given by Equation 3.19. The two first terms correspond to the objective function of the Nodal FM case, while the last term penalizes congestions in critical branches, where γ represents the unit penalty of congestion.

$$\min \quad \sum_{t \in \mathcal{T}} \Big(\sum_{b \in \mathcal{B}^+ \setminus \mathcal{B}^{RE}} C_{tb} x_{tb}^+ + \sum_{b \in \mathcal{B}^- \setminus \mathcal{B}^{RE}} C_{tb} x_{tb}^- \Big) + \gamma \sum_{t \in \mathcal{T}} \sum_{l \in \mathcal{L}_t} y_{lt} \tag{3.19}$$

Business as usual case

In the BAU case, where only conventional redispatch volumes are included, the model formulation closely resembles the model for the Nodal FM case. The objective function remains the same, with the exception that we sum over $\mathcal{B}^+ \cap \mathcal{B}^{RE}$ and $\mathcal{B}^- \cap \mathcal{B}^{Re}$, as flexible resources are not available. Constraints 3.2-3.4, 3.6 and 3.13-3.14 are also present, while the rest are irrelevant.

Besides being the focus of the BAU case, a redispatch model must also be run in the Zonal FM case after the FM clearing to guarantee alleviation of all congestions. This corresponds to step 4 in Figure 3.1. We then run the same redispatch model described in the previous paragraph, except that net positions must account for adjustments cleared in the zonal FM. Equation 3.2 is therefore replaced by Equation 3.20:

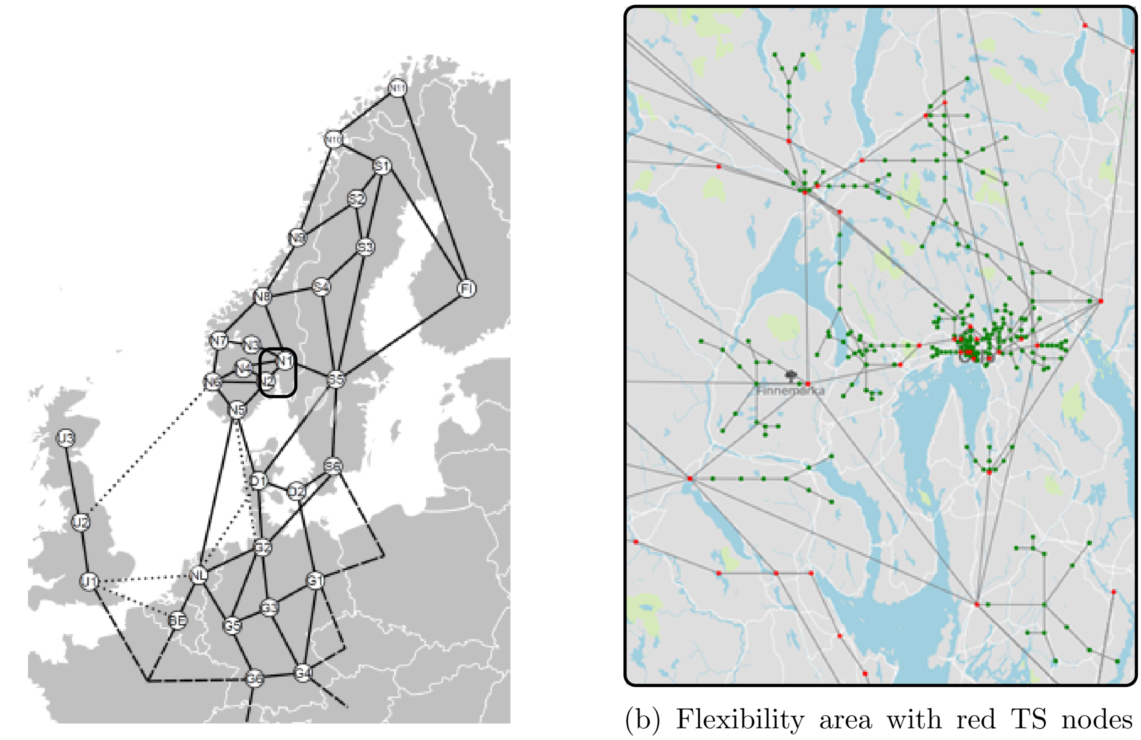
$$P_{nt}^{DA} + \Big(\sum_{b \in \mathcal{B}_n^+ \setminus \mathcal{B}^{RE}} X_{tb}^+ - \sum_{b \in \mathcal{B}_n^- \setminus \mathcal{B}^{RE}} X_{tb}^- \Big) + \Big(\sum_{b \in \mathcal{B}_n^+ \cap \mathcal{B}^{RE}} x_{tb}^+ - \sum_{b \in \mathcal{B}_n^- \cap \mathcal{B}^{RE}} x_{tb}^- \Big) = p_{nt}, \qquad n \in \mathcal{N}, t \in \mathcal{T} \tag{3.20}$$

where X_{tb}^+ and X_{tb}^- are the volumes cleared up and down in the zonal FM, respectively.

3.4 Data

3.4.1 Transmission system

The TS used in modelling is based on real-life data for the Nordic TS from 2012 (see Farahmand et al. (2013) for the full data set). Comprising a total of 446 nodes and 770 lines, the data set spans across Norway, Sweden, Denmark, and Finland, with voltage levels ranging between 110 kV and 420 kV. Each of these nodes is located within one of the 20 areas, displayed as N1-N11, S1-S6, D1-D2, and FI in Figure 3.2a. Additionally, the data set includes information about generator capacities and load volumes for the nodes, as well as capacities and reactances for the lines.



(a) Areas in the TS data set Farahmand et al. (2013).

(b) Flexibility area with red TS nodes from the reference dataset and artificially constructed green DS nodes.

Figure 3.2: Total system and flexibility area.

3.4.2 DA data

The DA volumes for production and load are gathered from historic Nord Pool data, using the interval from 17th of November to 30th November 2022 (Nord Pool, a). The Nord Pool data is aggregated for each DA zone, so it needs to be disaggregated onto the nodes in the TS. The following principles are used in the disaggregation process:

- Each of the 20 areas in the TS data set described above is assigned to a designated DA zone in accordance with their respective geographic locations. As a result, each individual node within the TS data set is also associated with a specific DA zone.
- Utilizing the load volumes and installed capacities belonging to the TS data set, nodal weights are computed for both production and consumption. These weights represent the proportion of the aggregate DA zonal volumes that are assigned to a particular node.
- As the load volumes and installed capacities from the TS data set are only indicative of a specific moment in time, their derived nodal disaggregation weights remain constant. To ensure more dynamic congestion patterns, stochastic perturbations are therefore introduced to the disaggregated nodal production and load volumes.

3.4.3 Distribution system

To investigate the effects of the proposed FM, we study a sub-part of the NO1 DA zone, encompassing the metropolitan Oslo area (hereafter referred to as the FA). When modelling, this area is represented both by a high voltage TS and a medium voltage DS (see Figure 3.2b). Additionally, we include the entire Nordic TS in the modelling to ensure realistic system flows, and to observe whether the FM has any adverse effects on the surrounding TS.

While information about the TS is often openly available, DSOs do not commonly publish detailed information about the DS. We therefore design a DS specifically for this paper. The following principles were used when designing the DS:

- Each TS node is assumed to be a net production node and each DS node is assumed to be a net consumption node.
- Three example DS radial grids are designed and one of these is attached to each TS node. Before attaching these radials, they are scaled and rotated to fit the terrain.
- The disaggregated DA load calculated as described above is allocated to the DS nodes.

For a detailed description of the DS design, see Appendix 1D.

3.4.4 Market participants

The flexibility market participants, like the grid system, are assumed to remain constant throughout the project. They are thus generated and allocated to nodes before running cases and sensitivities. Attempting to best represent a real system, we only allocate them to DS nodes, with each participant limited to one node for simplicity.

When a participant is created and allocated to a DS node, the participant is also defined with a size based on the expected node load, and a cost scaling factor that is randomly chosen on a uniform distribution between 0.5 and 1.5. These properties are later used when designing market bids of the participant and in model constraints.

For a detailed description of how market participants are allocated to nodes, see Appendix 1D.

3.4.5 Market bids

Available flexibility and redispatch volumes are represented by bids in the models. Each bid is characterized by their cost [€/MWh], a maximum volume [MWh], a node in the grid, an implementation hour and a direction. Flexibility bids are also associated with a market participant. The FM bids are important to represent the behavior of the four participant types presented in section 3.3.1. We therefore try to adapt the bid frequency, volumes and cost based on how the participants are expected to behave in practice.

The direction of a bid says whether the bid will increase or decrease the net production in the node. An "UP" bid will in this context mean a bid that increases the net production, while a "DOWN" bid is defined as decreasing the net production in the node. These definitions are fitting from a market clearing perspective, but are less intuitive when looking at the practical implications for various market participants. For example, an UP bid from an aggregator or industry actor represents an option to reduce their power consumption.

Bids are first generated deterministically based on a method described in Appendix 1D and cloned for each hour. Then, noise is introduced so that bids are differing in volumes and cost between hours, as well as removing bids from certain hours. This process is based on random variables and will give different results for each day and hour. The aim is to show how the FM clearing may vary between hours depending on available bids, and to show the solution's resilience to noise.

3.4.6 Available redispatch

Bids that represent conventional redispatch are not co-generated with flexibility bids. These participants can be regarded as supply-side actors, as they are the most common providers of redispatch volumes. In the Norwegian power system, which is largely dominated by hydropower, redispatch costs are heavily influenced by water values, which are complex to calculate and beyond the scope of this project. To approximate these costs, we use the average price premium obtained from the balancing markets for the same period as we collect DA data (Nord Pool, b). Given that balancing operations are closer to real-time and offer fewer options for planning than redispatch, we contend that the balancing market price premium can be considered an upper bound for the cost of conventional redispatch.

3.4.7 Implementation details

The models are solved on a computer running on Windows 10, with Intel Core i7-10700 CPU and 16 GB of RAM. They are implemented in Python using the Pyomo package (Hart et al., 2011) and Gurobi solver with default settings (Gurobi Optimization, LLC, 2023). Solving all three cases for a period of 14 days takes 4453 s.

Please see our repository on GitHub for more insight into the code implementation: LocalFlex_public.

3.5 Results and analysis

3.5.1 System cost

The system cost is minimized for all three cases, which under the assumptions of rigid demand equals a maximization of social welfare.

As depicted in Figure 3.3, which displays the daily FA costs for all cases, it can be observed that the cost of the Zonal FM case closely tracks the cost of the Nodal FM case throughout most of the simulated days. Focusing solely on the costs incurred in the FA, the Nodal FM approach incurs costs of 5.946 M€, the Zonal FM approach incurs costs of 6.071 M€, and the BAU strategy results in costs of 6.590 M€. This represents a relative cost reduction of 9.8% and 7.9% for the Nodal FM and Zonal FM approaches respectively.

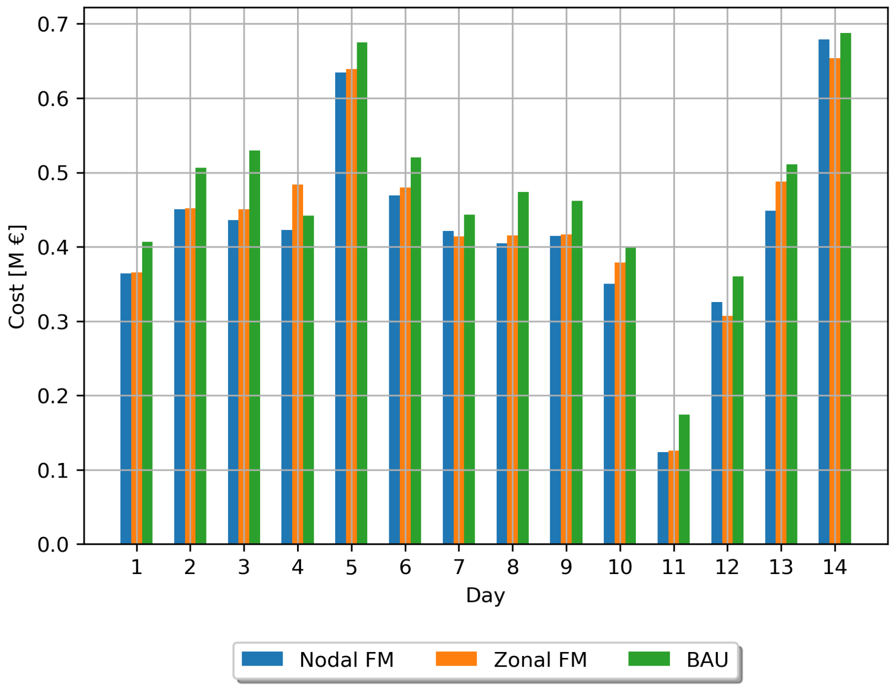


Figure 3.3: Daily FA costs for each case. Sum amounts to 5.946 M€, 6.071 M€, and 6.590 M€ for Nodal FM, zonal FM and BAU respectively.

As mentioned in section 3.4, we include a model of the TS for the whole Nordic region to ensure realistic line flows and study the effects of activating flexibility inside the FA. The implications are apparent in Figure 3.3, which reveal that the Zonal FM may in fact be cheaper than the Nodal FM, and more expensive than the BAU case for individual days. This is because the models may transfer costs into or out of the FA depending on the most optimal outcome for the overall system. Notably, when flexibility is accessible within the FA, the FA tends to bear a higher share of the total costs. This is evident when looking at the total system cost, which is found to be 124.843 M€, 124.897 M€, and 125.816 M€ for the Nodal FM, Zonal FM, and BAU cases respectively. Relative to the FA BAU cost, the Nodal and Zonal cases then exhibit a performance increase of 14.8% and 13.9%, respectively. This result is notably superior to isolating the FA area costs.

The findings in figure 3.3 align with the expectations outlined in Section 3.3.3. Specifically, the BAU case is identified as the costliest option, while the Nodal FM approach is consistently the most economical alternative. The superiority of the Nodal FM approach over the BAU case is unsurprising from a theoretical perspective. Additionally, it is well-established that zonal markets cannot theoretically outperform nodal markets in terms of cost efficiency. At best, the zonal method can emulate the nodal approach and clear the FM efficiently, but this is improbable due to less available grid information. Nevertheless, the results indicate that the zonal FM performance is significantly closer to the nodal than the BAU case across all simulated days.

3.5.2 Volumes

In Table 3.1, the total dispatch of flexibility units and redispatch for the whole system is presented for all three cases. The same numbers are presented for the FA in Table 3.2.

Total system volume adjustments [GWh]			
Type	**Nodal FM**	**Zonal FM**	**BAU**
Flexibility	27.312	27.161	0
Redispatch	2,495.678	2,496.858	2,516.318
Total	**2,522.99**	**2,524.02**	**2,516.318**

Table 3.1: Total system volume adjustments.

Flexibility area volume adjustments [GWh]			
Type	**Nodal FM**	**Zonal FM**	**BAU**
Flexibility	27.312	27.161	0
Redispatch	117.735	120.354	131.811
Total	**145.047**	**147.515**	**131.811**

Table 3.2: Total FA volume adjustments.

The total volume of flexibility adjustments in the Nodal FM case amounts to 27,312 MWh, while that of the Zonal FM case is 27,161 MWh. A slightly larger amount of flexible resources is therefore utilized in the Nodal FM case. For both the total system and the FA, the sum of flexibility and conventional redispatch is lowest for the BAU case. This result is unsurprising, as the uniform cost of conventional redispatch effectively makes the BAU case minimize activation volumes.

For the FA, the volume of conventional redispatch is 2,619 MWh higher in the Zonal FM than in the Nodal FM case, which is a major reason for the cost differences presented in section 3.5.1. The larger volume of activated flexibility in the Nodal FM case is one reason, but even more important is the effectiveness of the activated flexibility volumes. The ZPTDFs used in the Zonal FM case are similar for all nodes in a zone, which translates to an absence of nodal information. The activated volumes of flexibility in the Zonal FM case are therefore less effective at alleviating the congestion, necessitating a greater conventional redispatch volume in the next stage. The Zonal FM may also activate flexibility resources that must be countered by redispatch when all grid constraints are revealed.

Lastly, the LFZs fail to capture all congestion within the FA. This is demonstrated in Figure 3.4, which illustrates the total FA congestion following the DA clearing and the extent of congestion captured by the LFZs. The remaining congestion is entirely disregarded in the zonal clearing and must be addressed through conventional redispatch.

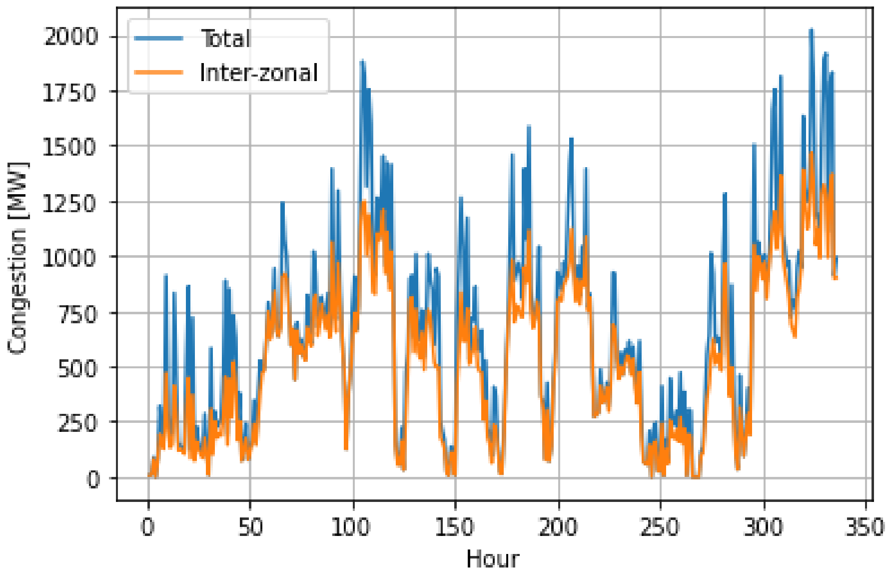


Figure 3.4: Total FA congestion and congestion on lines connecting LFZs.

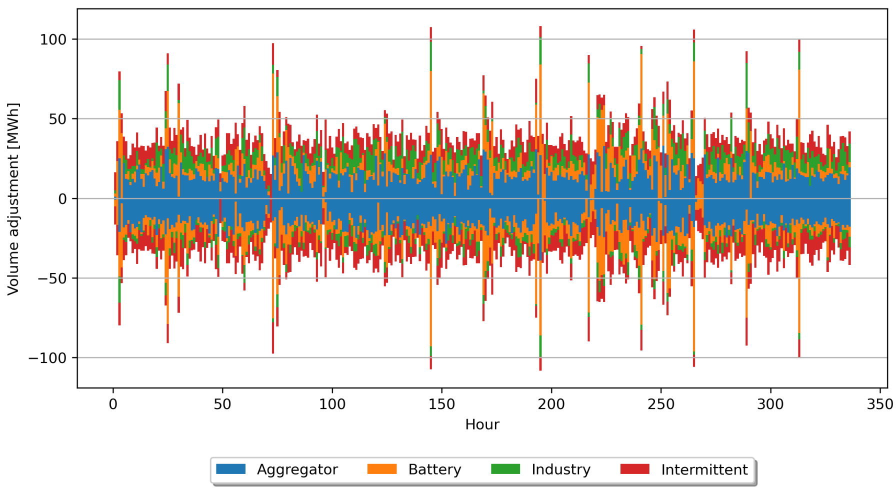


Figure 3.5: Volume adjustments by flexibility type for the Zonal FM case.

Figure 3.6: Volume adjustments by flexibility type for the Nodal FM case.

Figures 3.5 and 3.6 provide an overview of the hourly volumes of activated flexibility, categorized by flexibility type, for both the Zonal FM and Nodal FM cases. The graphs demonstrate significant deviations across individual hours, which may be attributed to noise introduced for bid availability, cost, and volume. Additionally, certain isolated hours demonstrate significant surges in volume when compared to the average volume. These spikes are caused by batteries satisfying their initial and final states of charge each day, and thus represent a weakness in the model that nevertheless is similar for both cases. Overall, the dispatch of flexibility volumes in the two cases exhibit notable similarities in total amount and market participant shares.

Despite the similarities discussed in the previous paragraph, Figure 3.7 shows that the exact bids activated differ between the two cases. More precisely, it shows that only about 2/3 of the activated flexibility is activated in both cases. In the Zonal FM model, using ZPTDFs means the cheapest bids within the zones are accepted first. In contrast, the clearing in the Nodal FM may prefer more expensive bids in nodes where high PTDFs reduce the required volume adjustments. Since nodal differences lead to divergent clearing preferences between the Nodal FM and Zonal FM cases, it suggests that using ZPTDFs results in an efficiency loss. This is also the case when all congestion is captured in inter-zonal lines.

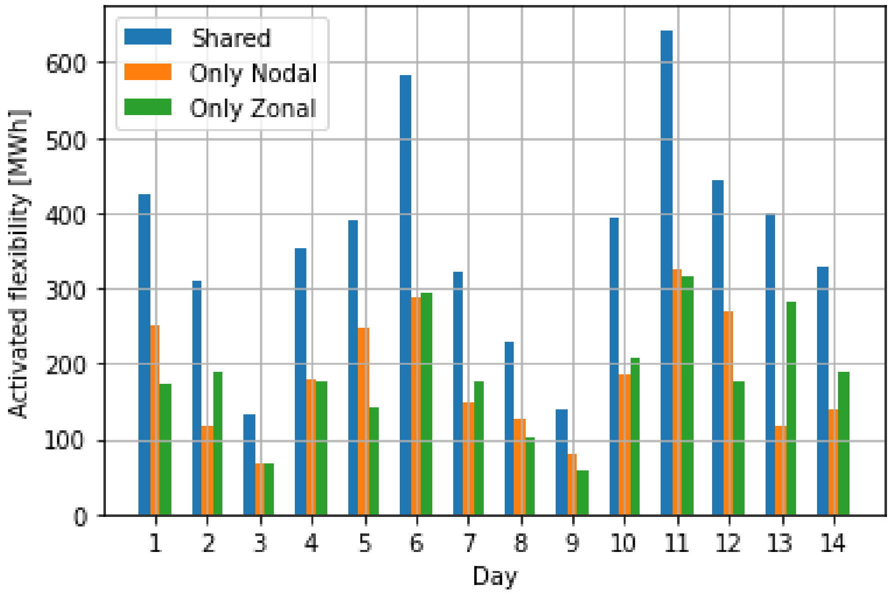


Figure 3.7: Activated flexibility that is shared or unique to either the Zonal FM or Nodal FM case, for each day.

3.5.3 Discussion and sensitivities

To account for uncertainties in the input data, we present sensitivities on several parameters. Furthermore, we discuss weaknesses in the modelling framework.

Number of LFZs. The determination of the optimal number of LFZs is a critical consideration in the implementation of the zonal FM. As outlined in Section 3.3.4, the heuristic utilized to identify LFZs is contingent a specified number of zones, and thus cannot effectively ascertain the optimal number of LFZs. The primary rationale for adopting a zonal FM is that aggregating nodes into zones may have various benefits. Most of these benefits are dependent on the number of participants and amount of flexibility volumes, so less aggregation may be needed when these numbers rise. However, the optimal LFZ configuration is also heavily influenced by congestion levels, congestion distribution and distribution of flexibility resources, complicating the optimal LFZ size further.

A sensitivity was run to test the impact of LFZ sizes, although the results are more or less trivial because the models focus on economic efficiency. For instance, specifying three LFZs instead of five resulted in a cost increase of 86,421 € over the first five days of the time horizon. This increase was primarily due to the zonal FM clearing neglecting a considerable amount of congestion, which lead to an unfavorable dispatch of flexibility. Similarly, more and smaller zones would mean that the zonal method approached the nodal method, increasing economic efficiency. A method to determine the zonal configuration should consider the impact on economic efficiency and weigh it against the benefits of aggregating to certain zone sizes, neither of which are considered by this paper's partitioning algorithm.

Flexibility volume. As the concept of FMs is fairly new and yet to be implemented in large scale, the volumes that will be available in such markets are difficult to estimate. In Table 3.3, the FA cost is presented for all three cases with a scaling of available flexibility volume by 0.5, 2, 4, 10, and 15.

As anticipated, the cost of both the Nodal FM and Zonal FM cases decreased as more flexibility was made available. The absolute cost difference between the zonal FM and the Nodal FM cases remained relatively stable up to a 10 times increase in flexibility volume. However, for the scaling of 15, the absolute cost differences increased significantly. This was because the zonal FM started creating internal congestion, which had to be addressed through redispatch after the zonal FM clearing.

Internal congestion initially occurred when flexibility volumes were scaled by more than 10. It has already been argued that higher volumes allow for smaller zone sizes, which would bring more grid information and limit the internal congestion problem. Nevertheless, different congestion patterns or capacities on internal grid lines could arguably make the Zonal FM clearing create internal congestion with much lower flexibility volumes as well. Further assessment is required to determine the prevalence of such conditions and to evaluate the effectiveness of improved grid partitioning algorithms in mitigating the problem.

Flexibility area cost [M€]			
Scaling	**Nodal FM**	**Zonal FM**	**BAU**
0.5	2.444	2.439	2.560
2	2.195	2.313	2.560
4	2.083	2.200	2.560
10	1.683	1.805	2.560
15	1.426	1.639	2.560

Table 3.3: FA cost for different scaling of available flexibility volume.

Cost of Redispatch and flexibility. Similar to the previous discussion regarding available flexibility volumes, the assignment of costs to both flexibility and redispatch resources is subject to a high degree of uncertainty. Modifying one or both of these costs would significantly influence the system costs associated with the three cases, presented in Section 3.5.1, but would not notably affect the relative performance of the Zonal FM when compared to both the Nodal FM case and the BAU case. For instance, decreasing cost of redispatch would narrow the differences between the Nodal FM case and the BAU case, but would also bring the Zonal FM case closer to the Nodal FM case in terms of performance.

3.6 Conclusion

In this paper, we investigated the economic efficiency of FMs with dynamic zones. Our findings suggest that the Zonal FM performs close to the Nodal FM in terms of cost. The cost differences were mostly due to the lack of nodal information in the Zonal FM case, resulting in less efficient use of flexibility and more need for redispatch after the market clearing. Subsequent sensitivity analyses revealed that the performance is contingent on the amount of congestion, available flexibility and the zonal configuration. However, a refined zonal partitioning algorithm that accounts for these factors should be able to stabilize performance and may even improve it compared to the results in this paper. Thus, this paper shows that a Zonal FM can have an economic efficiency close to the theoretical optimum.

The robustness of Zonal FMs economic performance to different system states is not proven, however, as a better zonal partitioning method would be required. Future research should therefore focus on developing a more sophisticated zonal partitioning algorithm for FMs, where the optimal number of zones is determined. Furthermore, determining the value of implementing a Zonal FM design and weighing the trade-offs associated with the losses of economic efficiency requires further investigation.

Appendix 1A: Zonal partitioning heuristic

To make the heuristic easier to understand, we have divided it into two parts: An outer and an inner algorithm, here called layers. The outer layer is shown in pseudo code below (Algorithm 1), and can be thought of as performing the more high-level loops of the heuristic.

Algorithm 1 Outer layer: Optimal partitioning of a network

```
repeat
    Index of best zone to split, i, := 0
    Value of best split, v, := 0
    The zones created by best split, s, := {}
    for all zones z_j in Z do
        if z has congestion and |N_z| ≥ k · 2 then    ▷ k is min. number of nodes per zone
            Split zone z_j in two parts, z_j1 and z_j2, and calculate value of cut v_j
            if v_j > v then
                i = j
                v = v_j
                s = [z_j1, z_j2]
            end if
        end if
    end for
    Remove z_i from Z
    Add s[0] and s[1] to Z
until |Z| = n    ▷ n is number of zones to be partitioned
```

The outer layer start with a set Z containing one zone, which represents the entire area to be partitioned. As can be seen in Algorithm 1, the heuristic tries to split each congested zone with a sufficient number of nodes into two smaller zones. Only the split option with the highest cut value is chosen for each iteration, and the heuristic ends when the set of zones contains the desired number of partitions. The way of splitting a zone is described by the inner layer, shown in Algorithm 2.

The inner layer contains slightly more complicated logic than the outer layer. The main idea is that the algorithm cuts a line in the middle of the shortest path between two nodes, $l[0]$ and $l[1]$. This is repeated until the two nodes are split into two disconnected areas. The complexity arises from protective measures trying to adapt infeasible solutions without throwing away the solution. When a zone is infeasible, it is here because it has too few nodes. In that case, the algorithm will redo its last cut and instead choose a line on the shortest path closer to the feasible zone. If the solution is still infeasible, the algorithm will throw away the current cut c_i completely and try to redo cut c_{i-1}. If the algorithm returns back to step $i = 1$ and still gets an infeasible solution, line j is discarded completely. The inner layer may in theory return no feasible solutions to the outer layer, and if this happens for all zones z_j, the heuristic will stop with $< n$ zones.

Algorithm 2 Inner layer: optimal splitting of a zone

```
Create list L, containing all congested lines in z

Value of best split, v, = 0
The zones created by best split, s, = {}
for all lines l_j in L do
    The cut lines for iteration j, C, := []
    Cut iteration, i, := 1
    loop
        Cut line in the middle of the shortest path between l_j[0] and l_j[1]
        Add the cut line c_i to set C
        if l_j[0] and l_j[1] are disconnected and zones are feasible then
            Break
        else if l_j[0] and l_j[1] are disconnected and resulting zones are infeasible then
            loop
                Remove c_i from C and reinstate it in graph
                Perform new cut c_i on the shortest path, this time on the line furthest from the infeasible zone
                if l_j[0] and l_j[1] are connected then
                    Break
                else if l_j[0] and l_j[1] are disconnected and resulting zones are feasible then
                    Break x2
                else if l_j[0] and l_j[1] are disconnected and resulting zones are infeasible then
                    Remove c_i from C and reinstate it in graph
                    i− = 1
                end if
            end loop
        end if
    end loop
    if Value of cuts in C are ≥ v then
        v = value of cuts in C
        The two zones created are put into s
    end if
end for
```

Appendix 1B: Modelling assumptions and complete model formulations

This appendix includes an overview of the most central assumptions made with regards to the market modelling of the three cases, as well as the nomenclature and complete mathematical formulations of the models.

Perfect competition. In a market with perfect competition, there is no market power and the market participants will bid their true marginal cost (This assumption is not valid for hydropower owners who will bid their water values. However, in this paper, hydropower units are included in the conventional redipspatch category and not as a part of the flexibility units). This assumption simplifies the modelling process and is common for centralized optimization models. However, it is questionable if this assumption is valid for FMs. The geographical scope of FMs could limit the number of potential market participants, which may be a problem in terms of market power. For the smaller lines in the DS, some actors may also get pricing power because they alone can cause or relieve congestion in the grid. Nevertheless, accounting for market power is not in this paper's scope.

Completely inelastic demand. Since the system operators are responsible for the grid operation, they have to make sure all line constraints are satisfied. We therefore assume the total amount of flexibility and conventional redispatch demanded by system operators is fixed and determined by adjustments needed to satisfy line constraints. Therefore, the problem of maximizing social welfare reduces to the problem of minimizing costs.

No changes to cross-border exchanges. The Nordic power system has interconnectors to other countries, such as Germany and the UK. Including the flow on these interconnectors complicates the data pre-processing, and changes to these flows are unlikely to alter the results of the FM performance. We therefore assume that the FMs and redispatch do not affect the transmission across interconnectors. However, interconnectors were taken into account when determining the DA volumes.

DC power flow. We assume Direct Current (DC) power flow. DC flow relies on the assumption that resistance is significantly smaller than reactance in the grid. This is a normal and valid assumption for the TS, but it is not always the case for medium voltage DS. For our DS specifically, these values are not satisfying the DC power flow assumptions, and Alternating Current (AC) power flow modelling would be needed to accurately model flows in the grid. However, including AC flow on these lines would require an extension to non-convex programming. Although there exist convex relaxation techniques to reduce this problem to a convex one (Low, 2014), the extension would likely increase the complexity and run time of the models significantly. Additionally, we will argue that the load flow modelling accuracy does not reduce the validity of this paper's results, as we aim to provide an initial investigation into zonal FMs and all cases are using the same load flow equations. Therefore, improving load flow by using AC power flow is beyond the scope of this project and we assume DC power flow for the whole system.

Each day is independent. The models solve for the 24 hours cleared in the DA market and consider interdependencies in this time interval, but do not take into account the state of the system from the previous day. The 24-hour scope corresponds with how the FM would be cleared in practice, as its purpose is to adjust volumes after DA. However, the FM participants' behavior would be dependent on their trading in previous days, and in some cases also their expectations for the future. These interdependencies are disregarded for the sake of simplicity and computational time.

System operators are not modelled explicitly. System operators are important FM participants in this paper, especially as they are responsible for procuring the flexibility that will alleviate congestion. When doing so, they must counter-trade in another zone or node to keep the market balance. This step can be skipped when modelling by only describing the volumes adjusted up and down. Assuming the system operators do not have any transaction costs connected to participating in the market, the models will then account for all the costs to society.

Congestion outside of the FA is also taken into account. We model the whole TS described in section 3.4.2, including the net positions after DA and the resulting congestions. All lines in the system are thus subject to capacity constraints. The reason is that the FA is not an isolated system, but is interdependent with the surrounding grid. Thus, solving solely for the FA will not provide an accurate description of how the FM will affect the grid in practice.

Nodal Formulation

Sets and indices

$\mathcal{N}$: Set of nodes, $n \in \mathcal{N}$

$\mathcal{B}^+$: Set of UP bids, $b \in \mathcal{B}^+$

$\mathcal{B}^-$: Set of DOWN bids, $b \in \mathcal{B}^-$

$\mathcal{B}^{RE}$: Set of bids representing redispatch

$\mathcal{L} \subset N \times N$: Set of lines, $l \in \mathcal{L}$

$\mathcal{I}^{Agg}$: Set of aggregator market participants, $i \in \mathcal{I}^{Agg}$

$\mathcal{I}^{Batt}$: Set of battery market participants, $i \in \mathcal{I}^{Batt}$

$\mathcal{T}$: Set of time periods, $t \in \mathcal{T}$

Parameters

P_{nt}^{DA} : Net production in node n and period t from DA clearing

V_{tb} : Available volume of bid b in period t

C_{tb} : Cost of bid b in period t

$PTDF_{ln}$: PTDF for line l, node n

CAP_l : Capacity of line l

S_i^{init} : Initial battery storage for participant i, $i \in \mathcal{I}^{\mathcal{B}}$

S_i^{Cap} : Battery storage capacity for participant i, $i \in \mathcal{I}^{\mathcal{B}}$

η^+: Efficiency of battery discharging

η^-: Efficiency of battery charging

Variables

x_{tb}^+ : Volume cleared up of bid b in period t

x_{tb}^- : Volume cleared down of bid b in period t

f_{lt} : Flow on line l in time period t

p_{nt} : Net production in node n in period t

σ_{it} : State of charge of participant i's battery in period t, $i \in \mathcal{I}^{\mathcal{B}}$

Model

$$\min \quad \sum_{t\in\mathcal{T}}\Big(\sum_{b\in\mathcal{B}^+} C_{tb}x_{tb}^+ + \sum_{b\in\mathcal{B}^-} C_{tb}x_{tb}^-\Big) \tag{1.1}$$

$$\sum_{b\in\mathcal{B}^+\setminus\mathcal{B}^{RE}} x_{tb}^+ - \sum_{b\in\mathcal{B}^-\setminus\mathcal{B}^{RE}} x_{tb}^- = 0 \qquad t\in\mathcal{T} \tag{1.2}$$

$$\sum_{b\in\mathcal{B}^+\cap\mathcal{B}^{RE}} x_{tb}^+ - \sum_{b\in\mathcal{B}^-\cap\mathcal{B}^{RE}} x_{tb}^- = 0 \qquad t\in\mathcal{T} \tag{1.3}$$

$$P_{nt}^{DA} + \sum_{b\in\mathcal{B}_n^+} x_{tb}^+ - \sum_{b\in\mathcal{B}_n^-} x_{tb}^- = p_{nt} \qquad n\in\mathcal{N}, t\in\mathcal{T} \tag{1.4}$$

$$f_{lt} = \sum_{n\in\mathcal{N}} PTDF_{ln}\cdot p_{nt} \qquad l\in\mathcal{L}, t\in\mathcal{T} \tag{1.5}$$

$$\sigma_{it} = \sigma_{i(t-1)} + \sum_{b\in\mathcal{B}_i^-} x_{tb}^-\cdot\eta^- - \sum_{b\in\mathcal{B}_i^+}\frac{x_{tb}^+}{\eta^+} \qquad i\in\mathcal{I}^{Batt}, t\in\mathcal{T}\setminus\{1\} \tag{1.6}$$

$$\sigma_{i1} = S_i^{init} \qquad i\in\mathcal{I}^{Batt} \tag{1.7}$$

$$\sigma_{i|T|} = S_i^{init} \qquad i\in\mathcal{I}^{Batt} \tag{1.8}$$

$$\sum_{\tau=t}^{t+5}\big(\sum_{b\in\mathcal{B}_i^+} x_{\tau b}^+ - \sum_{b\in\mathcal{B}_i^-} x_{\tau b}^-\big) \le \mathcal{K}_i\cdot\lambda \qquad i\in\mathcal{I}^{Agg}, t\in\mathcal{T}\setminus\{|T|-4:|T|\} \tag{1.9}$$

$$\sum_{t\in\mathcal{T}}\big(\sum_{b\in\mathcal{B}_i^-} x_{tb}^- - \sum_{b\in\mathcal{B}_i^+} x_{tb}^+\big) \le \mathcal{K}_i\cdot 24\zeta \qquad i\in\mathcal{I}^{Agg} \tag{1.10}$$

$$0 \le x_{tb}^+ \le V_{tb} \qquad t\in\mathcal{T}, b\in\mathcal{B}^+ \tag{1.11}$$

$$0 \leq x^-_{tb} \leq V^-_{tb} \qquad t \in \mathcal{T}, b \in \mathcal{B}^- \tag{1.12}$$

$$-CAP_l \leq f_{lt} \leq CAP_l \qquad t \in \mathcal{T}, l \in \mathcal{L} \tag{1.13}$$

$$0 \leq \sigma_{it} \leq S^{Cap}_i \qquad i \in \mathcal{I}^{Batt}, t \in \mathcal{T} \tag{1.14}$$

Zonal Formulation

The notation that differs or is added after the nodal model is presented below, while the zonal model is formulated in its entirety. Equations that deviate from the nodal model are denoted in bold, and numbering corresponds to the nodal formulation.

Sets and indices

$\mathcal{Z}_t$: Set of zones in period t, $z \in \mathcal{Z}_t$

$\mathcal{L}_t$: Set of lines between zones in time period t, $l \in \mathcal{L}_t$

Parameters

P^{DA}_{zt} : Net production in zone z, period t from DA clearing

$ZPTDF_{lzt}$: ZPTDF for line l and zone z in time period t

γ: Unit penalty of congestion

Variables

p_{zt} : Net production in zone z in period t

y_{lt} : Congestion on line $l \in \mathcal{L}_t$ in time period t.

Model

$$\min \quad \sum_{t \in \mathcal{T}} \Big(\sum_{b \in \mathcal{B}^+ \setminus \mathcal{B}^{RE}} C_{tb} x^+_{tb} + \sum_{b \in \mathcal{B}^- \setminus \mathcal{B}^{RE}} C_{tb} x^-_{tb} \Big) + \gamma \sum_{t \in \mathcal{T}} \sum_{l \in \mathcal{L}_t} y_{lt} \tag{\textbf{2.1}}$$

$$\sum_{b \in \mathcal{B}^+ \setminus \mathcal{B}^{RE}} x^+_{tb} - \sum_{b \in \mathcal{B}^- \setminus \mathcal{B}^{RE}} x^-_{tb} = 0 \qquad t \in \mathcal{T} \tag{2.2}$$

$$P^{DA}_{zt} + \sum_{n \in \mathcal{N}_{zt}} \Big(\sum_{b \in \mathcal{B}^+_n \setminus \mathcal{B}^{RE}} x^+_{tb} - \sum_{b \in \mathcal{B}^-_n \setminus \mathcal{B}^{RE}} x^-_{tb} \Big) = p_{zt} \qquad t \in \mathcal{T}, z \in \mathcal{Z}_t \tag{\textbf{2.4}}$$

$$f_{lt} = \sum_{z \in \mathcal{Z}_t} ZPTDF_{lzt} \cdot p_{zt} \qquad , t \in \mathcal{T}, l \in \mathcal{L}_t \tag{\textbf{2.5}}$$

$$\sigma_{it} = \sigma_{i(t-1)} + \sum_{b \in \mathcal{B}^-_i} x^-_{tb} \cdot \eta^- - \sum_{b \in \mathcal{B}^+_i} \frac{x^+_{tb}}{\eta^+} \qquad i \in \mathcal{I}^{Batt}, t \in \mathcal{T} \setminus \{1\} \tag{2.6}$$

$$\sigma_{i1} = S_i^{init} \qquad i \in \mathcal{I}^{Batt} \tag{2.7}$$

$$\sigma_{i|T|} = S_i^{init} \qquad i \in \mathcal{I}^{Batt} \tag{2.8}$$

$$\sum_{\tau=t}^{t+5} \Big(\sum_{b \in \mathcal{B}_i^+} x_{\tau b}^+ - \sum_{b \in \mathcal{B}_i^-} x_{\tau b}^- \Big) \leq \mathcal{K}_i \cdot \lambda \qquad i \in \mathcal{I}^{Agg}, t \in \mathcal{T} \setminus \{|T|-4 : |T|\} \tag{2.9}$$

$$0 \leq x_{tb}^+ \leq V_{tb} \qquad t \in \mathcal{T}, b \in \mathcal{B}^+ \setminus \mathcal{B}^{RE} \tag{2.10}$$

$$0 \leq x_{tb}^- \leq V_{tb}^- \qquad t \in \mathcal{T}, b \in \mathcal{B}^- \setminus \mathcal{B}^{RE} \tag{2.11}$$

$$-CAP_l - y_{lt} \leq f_{lt} \leq CAP_l + y_{lt} \qquad t \in \mathcal{T}, l \in \mathcal{L} \tag{\textbf{2.12}}$$

$$0 \leq \sigma_{it} \leq S_i^{Cap} \qquad i \in \mathcal{I}^{Batt}, t \in \mathcal{T} \tag{2.13}$$

$$0 \leq y_{lt} \qquad t \in \mathcal{T}, l \in \mathcal{L} \tag{\textbf{2.14}}$$

BAU

The BAU model can be seen as the nodal model without FM-specific constraints, as it only includes redispatch bids and does not take into account any constraints related to FM participants.

Model

$$\min \sum_{t \in \mathcal{T}} \Big(\sum_{b \in \mathcal{B}^+ \cap \mathcal{B}^{RE}} C_{tb} x_{tb}^+ + \sum_{b \in \mathcal{B}^- \cap \mathcal{B}^{RE}} C_{tb} x_{tb}^- \Big) \tag{3.1}$$

$$\sum_{b \in \mathcal{B}^+ \cap \mathcal{B}^{RE}} x_{tb}^+ - \sum_{b \in \mathcal{B}^- \cap \mathcal{B}^{RE}} x_{tb}^- = 0 \qquad t \in \mathcal{T} \tag{3.3}$$

$$P_{nt}^{DA} + \sum_{b \in \mathcal{B}_n^+ \cap \mathcal{B}^{RE}} x_{tb}^+ - \sum_{b \in \mathcal{B}_n^- \cap \mathcal{B}^{RE}} x_{tb}^- = p_{nt} \qquad n \in \mathcal{N}, t \in \mathcal{T} \tag{3.4}$$

$$f_{lt} = \sum_{n \in \mathcal{N}} PTDF_{ln} \cdot p_{nt} \qquad l \in \mathcal{L}, t \in \mathcal{T} \tag{3.5}$$

$$0 \leq x_{tb}^+ \leq V_{tb} \qquad t \in \mathcal{T}, b \in \mathcal{B}^+ \cap \mathcal{B}^{RE} \tag{3.10}$$

$$0 \leq x_{tb}^- \leq V_{tb}^- \qquad t \in \mathcal{T}, b \in \mathcal{B}^- \cap \mathcal{B}^{RE} \tag{3.11}$$

$$-CAP_l \leq f_{lt} \leq CAP_l \qquad t \in \mathcal{T}, l \in \mathcal{L} \tag{3.12}$$

$$0 \leq \sigma_{it} \leq S_i^{Cap} \qquad i \in \mathcal{I}^{Batt}, t \in \mathcal{T} \tag{3.13}$$

Appendix 1C: Zonal Power Transfer Distribution Factor

This appendix describes how PTDFs are transformed into ZPTDFs. The transformation requires Generation Shift Keys (GSKs), which describe how a change in net position in a zone is distributed among the generating units in the zone (Schönheit et al., 2020). As determining the GSKs exactly requires information about production and load, which is unavailable prior to the market clearing, several approaches to estimate GSKs exist. The choice of which generating units to include and how to assign the weight with which each unit contributes to the change in net position is called a GSK strategy. Schönheit et al. (2020) list four GSK strategies, where one of them uses the scheduled power output to determine the GSKs. Since the adjustments in the FM are made relative to DA volumes, we use the DA volumes to approximate the market output from the FM clearing and construct GSKs based on them.

Let P_{nt}^{DA} be the net DA position at node n in time period t, $\mathcal{N}$ the set of nodes, $\mathcal{N}_z$ the set of nodes in zone z, $\mathcal{T}$ the set of time periods and $\mathcal{Z}_t$ the set of zones in time period t. The GSK for node n, zone z in time period t is then given by equation C1.

$$GSK_{nzt} = \frac{P_{nt}^{DA}}{\sum_{n \in \mathcal{N}_z} P_{nt}^{DA}} \qquad n \in \mathcal{N}, t \in \mathcal{T}, z \in \mathcal{Z}_t \tag{C1}$$

Furthermore, let $PTDF_{ln}$ be the PTDF for line l and node n and $\mathcal{L}$ be the set of lines. The ZPTDF for line l, zone z in time period t is then given by:

$$ZPTDF_{lzt} = \sum_{n \in \mathcal{N}_z} GSK_{nzt} \cdot PTDF_{ln} \qquad l \in \mathcal{L}, t \in \mathcal{T}, z \in \mathcal{Z}_t \tag{C2}$$

Appendix 1D: Data

DS design

The FA is a subpart of the NO1 ELSPOT zone and it is the only part of the grid where a DS needs to be constructed. Since the Norwegian DS has a radial structure, we base this construction on three example radials designed after NVE Atlas data (NVE), seen in figure 3.8.

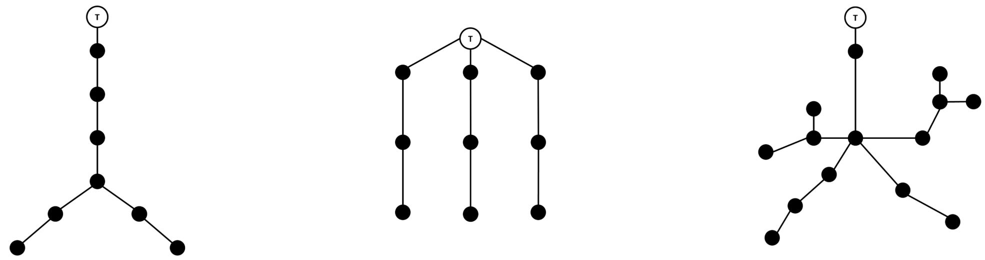


Figure 3.8: Example radials used to construct the DS grid.

For each TS node with a load, one of these radials is attached, scaled and rotated. Each radial grid is assigned a voltage, either 50 kV or 132 kV, based on the load in their respective TS node. Additionally, the example radials all have load distribution factors for their nodes, which are used to redistribute the load previously being allocated to the TS node.

The line properties are determined next. Based on data for a 72.5 kV overhead line from SINTEF Energi, the resistance and reactance values are set to 0.122 and 0.379 ohm/km respectively. The line capacities are based on Trohjell and Vognild (1994), who state that distribution lines in Norway with a voltage level of 66 kV typically have capacities between 50 MW and 125 MW, while lines with a voltage level of 132 kV typically have capacities in the range of 100 MW to 250 MW. To distribute capacities in the DS, we perform a load flow analysis on the DA volumes from 12.00-13.00 on 17th of November. We divide the set of DS lines into two sets: one with a voltage level of 50 kV and one with a voltage level of 132 kV. For each set of lines, we then partition the lines into ten quantiles based on their load flow. Additionally, the two capacity ranges are divided into 10 intervals each. The quantile to which a line belongs determines its capacity, where each line in a quantile is assigned the upper limit of the corresponding capacity interval. For instance, a 132 kV line that falls in the quantile with the highest flow will have a capacity of 250 MW, while a 50 kV line in the same quantile will have a capacity of 125 MW. This approach aims to evenly distribute the possible capacities while considering that some lines in the radial network may consistently experience higher load flows.

Market participants

The participants were allocated to nodes randomly based on the following probability:

$$p_{nt} = \begin{cases} 0 & L_n < d_t \\ b_t + a_t \cdot L_n & L_n \leq c_t \\ b_t + a_t \cdot c_t & L_n > c_t \end{cases} \tag{D1}$$

Where p_{nt} is the probability of adding a participant of type t to node n, and L_n is the expected load $[MW]$ in the node, using the reference dataset. a_t, b_t, c_t and d_t are parameters assigned to the various participant types to create an appropriate relationship between the probability and the expected load. Their values are found in Table 3.4 below along with the resulting number of participants.

Our use of equation D1 and the weights in Table 3.4 to allocate participants is intended to increase the transparency of our assumptions and approach. The d_t values show that aggregators and industry are assumed to be present only in nodes with a certain amount of load. Similarly, c_t is used to define a threshold beyond which an increase in expected node load does not increase the probability of allocating a participant of type t. Lastly, a_t and b_t define the slope and intercept of the probability function, respectively.

Participant type	a	b	c	d	Max probability	Count total
Aggregator	2.5 %	5 %	30 MW	1 MW	80 %	41
Battery	0.3 %	5 %	50 MW	0 MW	20 %	19
Industry	2 %	0 %	40 MW	3 MW	80 %	34
Intermittent	2.5 %	5 %	10 MW	0 MW	30 %	41

Table 3.4: Participant types, their stochastic parameters and total number of market participants.

Market bids

There is a lack of reliable data on the subject of FM participants, especially the costs of providing flexibility, and the existing sources have inconsistent assumptions compared to this project. The bid costs are therefore determined based on assumptions made specifically for this project. Similar to when generating participants, the method used for generating bids is intended to be transparent. Instead of probabilities, however, it uses the participant type, size and cost scaling to construct bids for each participant. Given a set of participants, we deterministically construct a set with bids that are assigned to their respective participants as well as including a cost, volume, direction and hour. Table 3.5 below presents the input used for this method, where the cost is scaled with the ”cost scaling” attribute for each participant, and the bid size is given as a percentage of the participant’s size.

Participant type	Number of bids		Bid cost [€ / MWh]		Bid size[MWh]	
	UP	DOWN	UP	DOWN	UP	DOWN
Aggregator	3	2	2,8,15	5,15	5%,10%,25%	10%,25%
Battery	2	2	2,5	2,5	20%,80%	20%,80%
Industry	1	1	10	10	30%	10%
Intermittent	1	1	-10	-10	15%	15%

Table 3.5: Rules to determine the bids of a FM participant.

The Table 3.5 columns with the number of bids, indicate that aggregators and battery actors can place multiple UP or DOWN bids in a specific hour. This is reflected in the corresponding columns for bid cost and bid size, where each entry refers to a separate bid. Multiple bids are here used to show the actors' increasing cost of providing flexibility when the volumes increase. For example, the aggregators will demand more money when cutting load beyond 5% of their size, as the cost then jumps from 2 €/MWh to 8 €/MWh, and batteries will offer a smaller percentage of their capacity at a lower price. The table reveals several other assumptions; for example how it is easier for industry to decrease their power consumption than to increase it. Finally, the table indicates that intermittent power producers are not regarded as providers of flexibility, but rather as BRPs that need to procure flexibility due to incorrect forecasting in the DA market.

Further elaboration is needed regarding the costs presented in Table 3.5. It is first important to reiterate that the costs are not based on any external sources, as they were judged to be too uncertain to bring any value. However, there are also some assumptions behind these numbers that are more fitting to present here, and that relate to how costs are used in the FM models. When determining what an actor will charge for flexibility, we assume that the cost is closely related to the DA market. If an aggregator has expenses of 2 € per MWh power provided to the grid, we assume that it charges a DA price premium of 2 €, as we have perfect competition. Thus, the cost and the price charged in the FM are not the same, but are linked by the DA price, and it is the cost that is used when determining the bids. For modelling purposes, it is sufficient to only consider the costs as they appear to the participant and disregard the actual market price.

Chapter 4

Practical challenges for implementing flexibility markets

4.1 Reflections on the first paper

This section provides a critical analysis of the initial paper presented in Chapter 3, setting the stage for the introduction of the second paper. The previous paper introduced a zonal FM, incorporating dynamic zones to accommodate variations in congestion patterns, and evaluated its CM performance in comparison to a nodal FM and conventional redispatch. The modelling of the FMs was conducted within a subpart of NO1, while redispatch was performed for the entire Nordic region. The ensuing discussion will thus critically examine the modelling framework, assumptions, and data used in the study.

4.1.1 Modelling framework and assumptions

With policymakers contemplating the incorporation of FMs into the power system, assessing the economic efficiency of these markets becomes paramount. The first paper tackles this challenge, providing an evaluation of the proposed zonal FM design. However, the analysis must also consider the broader context of the market structure. If implemented, FMs would become part of a larger system that encompasses the DA market and the intraday market. The introduction of a new market into this structure necessitates a thorough economic efficiency assessment that acknowledges the interaction with the existing markets. As such, evaluating the FM in isolation falls short, given that its performance will be heavily influenced by the dynamics and interplay with other pre-existing markets. The modelling framework employed in the first paper does not account for this interplay, thus missing potential phenomena that may significantly impact the performance of the FM design.

Another limitation of paper 1 is the assumption it makes about perfect competition. As highlighted in Appendix 1B, the geographic resolution of FMs can potentially confer market power to select participants. This introduces a significant challenge to the validity of the perfect competition assumption, along with any results that are based on this premise. Even in the absence of explicit market power, there may exist opportunities for strategic bidding that can significantly alter market outcomes. A notable example of such strategic bidding is the inc-dec game, observed during the California electricity crisis, where it led to the abandonment of zonal pricing in favor of nodal pricing (Holmberg and Lazarczyk, 2015). This particular game arises from inconsistencies in the power grid representation across different power markets, thereby allowing market participants to exploit price differences by increasing their scheduled production in low-priced areas and decreasing it in high-priced ones. Given that FMs feature a more detailed grid representation than the DA and intraday markets, the risk of inc-dec gaming arises when integrating FMs within the existing market framework. Thus, strategic behavior becomes an important focus in its own right, as well as a crucial element to consider when modelling the interactions between FMs and the established power markets.

4.1.2 Data

In the first paper, the modelling of the three cases is conducted over a 14-day period. While these 14 days encompass hours characterized by variations in both DA prices and volumes, the relatively short time span might not adequately capture the full spectrum of market conditions encountered over a longer duration. Furthermore, the two-week modelling period is insufficient to account for seasonal fluctuations in power demand and production. Consequently, the performance evaluation of the market designs does not encompass the examination of their efficacy under these distinct conditions stemming from seasonal changes.

4.2 Introducing the second paper

The discussion in Section 4.1 represents the inspiration underpinning the second paper. Additionally, we got valuable input to the second paper when participating in a consortium meeting related to the Norwegian PowerDig project. At this meeting, we had the opportunity to present results from the first paper to a group of PowerDig stakeholders, including major energy companies like Statnett and Statkraft, as well as various academics. The ensuing discussions underscored a noticeable gap in the existing literature concerning the integration challenges between intraday markets and FMs. This recognition, along with the clear interest shown by both researchers and industry representatives, provided additional motivation for our investigation in the second paper.

In accordance with input from the PowerDig meeting, the second paper extends the first paper by incorporating an intraday market that operates alongside the zonal FM. This intraday market replicates the existing intraday market in terms of utilizing a zonal grid resolution. However, it differs in that it functions as a pooled hourly market rather than a continuous market. Consequently, there are inconsistencies in the grid representation between the FM and the intraday market, creating opportunities for the type of strategic gaming discussed in Section 4.1. Furthermore, the second paper dispenses with the perfect competition assumption to explore strategic bidding. A subset of market participants are modeled to participate in both the FM and intraday market, employing bidding strategies derived using Q-learning, a reinforcement learning technique. This method aims to uncover potential gaming opportunities, assess the potential for significant arbitrage between markets, and investigate the exploitation of market power.

In the second paper, the models are executed over the course of an entire year, employing historical data derived from the DA market and the continuous intraday market in the year 2021. By simulating a full year, we avoid solely evaluating the market design under overly specific conditions, and we can better account for seasonal effects that may influence market dynamics.

Paper 2

Modelling Strategic Behavior in Flexibility and Intraday Markets: Combining Optimization and Machine Learning Approaches

Chapter 5

Modelling Strategic Behavior in Flexibility and Intraday Markets: Combining Optimization and Machine Learning Approaches

Abstract

In the pursuit of sustainable development, the growing electrification of society and complexities in congestion management have prompted proposals for diverse FM designs. However, the integration with existing wholesale markets remains an open question. This paper focuses on modelling and analyzing a zonal FM operating alongside the intraday market without direct integration. We present a reinforcement learning framework designed to model strategic bidding in these two markets. By comparing the strategic bidding in this combined market structure to one scenario limiting strategic bidding to the intraday market and one scenario without strategic bidding, we aim to identify potential challenges related to the integration of the zonal FM with the intraday market. The results unveil various profit-enhancing strategies employed by strategic agents, along with their impact on market prices, social welfare, and congestion management.

5.1 Introduction

The transition towards low-carbon economies necessitates significant transformations within the power system. One of the key changes involves a higher proportion of power generation originating from RES, leading to a departure from the traditional dominance of dispatchable units. Additionally, the electrification of various sectors, including transportation and heating, imposes greater demands on the power grid, thereby complicating reliable grid operation. Consequently, the need for flexibility in the power system has gained increased attention, prompting numerous researchers to propose potential designs for FMs.

The concept of FMs is relatively new, with only a few pilot projects having been implemented thus far (Schittekatte and Meeus, 2020). Consequently, practical considerations concerning the design and implementation of FMs persist. Among the most fundamental questions is the integration of FMs with existing power markets. Since many grid services necessitate location-specific flexibility, FMs will require a more detailed grid resolution. This stands in contrast to the broader, zonal wholesale markets typically employed in the Nordics and Western Europe. This disparity in grid representation between the markets leads to more information about congestions being conveyed in the FM than in the intraday market, potentially introducing new gaming opportunities. Furthermore, price differentials between the markets may also give rise to arbitrage opportunities for strategic bidders.

In this study, we seek to address the aforementioned challenge posed by power markets characterized by inconsistent grid representation. Specifically, we implement the zonal FM framework introduced by Aasvær et al. (2023) in conjunction with an auction-based intraday market. To explore the behavior of market participants bidding in both markets and their pursuit of profit maximization, we propose the utilization of a reinforcement learning algorithm. Through this approach, we aim to shed light on the following research questions:

- How does the introduction of a reinforcement learning framework contribute to the understanding of strategic bidding behavior between power markets?
- To what extent does the introduction of a FM running parallel to the intraday market open for significant arbitrage or gaming opportunities for participants bidding in both markets?

The remainder of this paper is organized as follows: In Section 5.2, we conduct a review of the existing literature pertaining to the integration of FMs with wholesale markets, as well as the methodologies employed for modelling strategic bidding in power markets. Then, we present our modelling framework in Section 5.3 and give a brief explanation of the data in Section 5.4. In Section 5.5 we present our results and discuss them in Section 5.6, before we conclude and outline potential avenues for future research in Section 5.7.

5.2 Related literature

5.2.1 Intraday market design

As the proportion of power generated from renewable energy sources rises, the ability for market participants to modify their portfolio in close proximity to real-time becomes progressively significant, thereby increasing the importance of intraday markets. In accordance with the EU's guidelines on capacity allocation and congestion management, it is imperative to establish dependable pricing of transmission capacity and effective cross-border allocation (European Commission, 2015). However, reconciling these prerequisites with the present continuous intraday market is difficult (Schumacher et al., 2019).

An alternative market design to the current intraday market is the introduction of multiple intraday batch auctions throughout the day, as suggested by several authors (Schumacher et al., 2019; Neuhoff et al., 2016; Graf et al., 2022; Ocker and Jaenisch, 2020). Schumacher et al. (2019) examine various design options for a future intraday market and argue that a higher proportion of renewable energy generation and the need for products with greater time granularity necessitate intraday batch auctions. Neuhoff et al. (2016) investigate the impact of the introduction of a German intraday auction in 2014 and compare the market results with those of the continuous intraday market. Their findings indicate that batch auctions increase liquidity, trading volume, market depth, and reduce price volatility. Graf et al. (2022) propose a technique for transforming continuous intraday market outcomes into counterfactual outcomes from frequent auctions. In an empirical study of the German intraday market, the authors report that frequent auctions boost liquidity and produce less noisy price signals. However, contrary to the results presented by Neuhoff et al. (2016), they observe that trading volumes tend to be lower in discrete intraday markets than in continuous ones. Ocker and Jaenisch (2020) compare continuous and discrete market designs and identify liquidity, market power resilience, and effective utilization of cross-border capacity as the primary benefits of an auction-based intraday market.

5.2.2 Integration of FMs with wholesale markets

A central issue in the literature discussing the interaction between FMs and wholesale markets, is to what extent FMs should be integrated with already existing wholesale markets. Several authors have explored the trade-offs associated with trading flexibility in a separate market versus an integrated market (Ramos et al., 2016; Villar et al., 2018; Vicente-Pastor et al., 2019; Gerard et al., 2018). Notably, Gerard et al. (2018) have identified that a FM distinct from the wholesale market, where both regulated and non-regulated actors are buyers of flexibility, may have a detrimental impact on liquidity in the intraday market.

Schittekatte and Meeus (2020) interviewed FM project pioneers and highlighted six central FM controversies, emphasizing their differences regarding integration with the intraday market. The study revealed significant variation in the projects' integration, and the authors noted that "practice is moving faster than the conceptual debate around flexibility markets" (Schittekatte and Meeus, 2020).

The potential challenges and opportunities in the interaction between FMs and intraday markets are of paramount importance as FMs can operate in parallel with intraday markets (Jahns et al., 2023). In this context, Cramton (2019) presents a FM designed to enhance CM by introducing a continuous order book incorporating location-specific information alongside the intraday order book. The author also discusses measures to mitigate inc-dec gaming in market-based CM. Building on Cramton's conceptual work, Jahns et al. (2023) present a statistical model aimed at detecting biased baselines in FM bids. Additionally, Backstedde et al. (2021)

investigate gaming opportunities in FMs, modelling different sequences of wholesale markets, FMs, and redispatch markets using complementarity problems to identify gaming behavior by market participants. The authors observe that akin to inc-dec gaming in market-based redispatch, the introduction of FMs into the existing power market structure creates new gaming opportunities for flexibility providers.

5.2.3 Strategic bidding in power markets

One stream of literature investigating strategic bidding in power markets is the literature pertaining to inc-dec gaming. Beckstedde et al. (2022) have expounded upon two fundamental modelling methodologies employed in the analysis of inc-dec gaming. The first approach incorporates game theoretic models to ascertain the Nash equilibrium among strategic participants in the market, while the second approach employs bi-level optimization techniques to identify actors engaging in market gaming.

The analysis of inc-dec gaming in power markets has been examined through the utilization of game theoretical models by various researchers (Holmberg and Lazarczyk, 2015; Ehrhart et al., 2022; Hirth and Schlecht, 2019). Holmberg and Lazarczyk (2015) investigate the interaction between a DA market and real-time markets under diverse market designs and demonstrate the existence of inc-dec gaming in perfectly competitive markets. Ehrhart et al. (2022) extend this analysis by modelling a finite set of producers with incomplete information. The authors further investigate seven modifications to their fundamental model but discover that none of these alterations to market design completely eradicates inc-dec gaming. Hirth and Schlecht (2019) also report similar results as they examine the interaction between a DA market and a voluntary redispatch market, and analytically solve for the Nash equilibrium.

The strategic behavior of market participants and the consequential inefficiencies are examined by Sarfati et al. (2019) and Sarfati and Holmberg (2020) through bi-level equilibrium models. In this modelling framework, the initial stage corresponds to a zonal DA market, followed by the subsequent stage representing a re-dispatch market. Extending upon this approach, Beckstedde et al. (2022) enhance the market structure by integrating a FM. A shared characteristic among these methodologies is the underlying assumption of complete information about costs (Ehrhart et al., 2022).

The exploration of strategic bidding in power markets has attracted attention from researchers aiming to ascertain optimal supplier bidding strategies through the utilization of reinforcement learning techniques. Jia et al. (2022) propose a modified continuous action reinforcement learning algorithm to identify optimal bidding strategies, accounting for incomplete information, within a nodal power market. Similarly, Xiong et al. (2002) introduce a Q-learning algorithm to determine optimal bidding strategies within a nodal DA market. The authors observe that during peak load hours, market agents exert their market power, consequently driving up market prices. These findings align with the results reported by Tellidou and Bakirtzis (2006), who demonstrate how bidding strategies derived from a Q-learning algorithm foster cooperation among market participants.

5.2.4 Contribution

The existing literature raises the key question of how FMs should be integrated with the existing wholesale markets. As FMs are likely to be operated in parallel with the intraday market, allowing participants to bid in both, the interaction between the intraday market and FMs is especially susceptible to gaming and arbitrage. Despite this, the interplay between a FM and a separate intraday market remains a largely unexplored territory. There is currently a noticeable lack of comprehensive models and analyses in the literature to address this dynamic.

An additional observation arising from the literature review is that while game theoretic models and bi-level equilibrium models have been employed to investigate the dynamics among sequential power markets, reinforcement learning approaches have primarily been utilized for determining optimal bidding strategies within a single market. Nevertheless, the effectiveness of these methods in identifying optimal bidding strategies renders them appealing when analyzing intricate systems of sequential power markets with a high number of participants and nodes. Consequently, reinforcement learning approaches hold promise in addressing the complexity inherent in such multi-market scenarios.

Based on the observations above, we aim to provide:

- A multi-agent reinforcement learning algorithm for modelling strategic behavior of participants bidding in both a FM and the intraday market.
- An initial investigation into structural challenges when a FM and an intraday market with different grid resolutions are implemented in parallel.

The study will build upon the work of Aasvær et al. (2023), where a zonal FM facilitating CM was proposed and tested. This ensures a functioning FM framework that is well-suited for examining strategic behavior. Firstly, the FM is designed to improve CM by enabling system operators to participate as procurers of flexibility. This could potentially intensify price differentials on either side of a congestion, as the system operators are willing to pay flexibility providers for increasing their activation on both sides of the congestion. Consequently, these larger price disparities could foster conditions favorable for strategic bidding. Therefore, an FM aimed towards CM becomes a suitable setting for investigating such phenomena. Secondly, the zonal FM clearing has demonstrated significantly quicker computation times than its nodal counterpart – a vital characteristic considering the reinforcement learning algorithm requires numerous iterations to effectively train the agents.

5.3 Modelling framework

In our study, we investigate the behavior of 40 supply-side actors, hereinafter referred to as agents, which are allowed to participate in both the FM and the intraday market. While seeking to maximize profit, they are trained on data from 2021 using the Q-learning algorithm. Given that the agents are competing with each other, their rewards and Q-matrices are individually calculated.

We simulate each day by incorporating bids from both the agents and ordinary market participants into the FMs and intraday markets, determining the market clearings using optimization models. For modelling purposes, we assume that both the intraday market and the FM have two discrete market clearings each day. These market clearings are performed in a sequential manner, as illustrated in Figure 5.1. This allows market participants to receive the results from the preceding market clearing before they place their bids in the subsequent market.

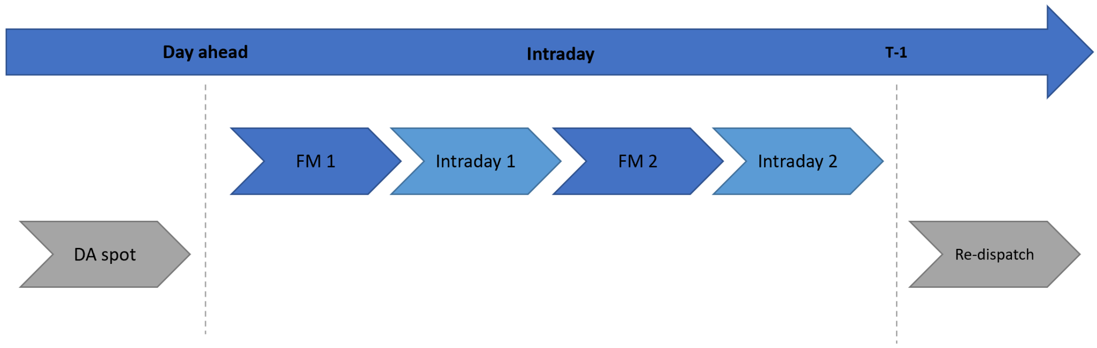


Figure 5.1: The sequence of the market clearings assumed to take place each day. The reinforcement learning algorithm is only applied to the four steps in the top row.

In order to establish a point of comparison, we also simulate two alternative scenarios. The first, termed the "no-learning" scenario, replicates the market sequence shown in Figure 5.1, with the exception that the agents only bid their rebalance needs. This scenario provides a baseline for understanding agent performance in the absence of strategic bidding. The second scenario, referred to as the "only-intraday" scenario, employs the Q-learning algorithm but restricts agent participation in the FM market. The aim of this scenario is to highlight the strategic opportunities afforded by the introduction of FMs in conjunction with the intraday market. The main scenario, simulating strategic bidding in both FMs and intraday, will later be referred to as the "learning" scenario.

5.3.1 Q-learning learning algorithm

As a form of reinforcement learning, Q-learning determines the optimal action-selection policy by interacting with the environment, obviating the need to model the environment explicitly. This renders Q-learning suitable for discovering advantageous bidding strategies, as stated in Xiong et al. (2002), particularly in simulations where outcomes are determined by optimization models.

The agents interact with the environment in four stages $T = 1, 2, 3, 4$ during the day, each corresponding to a market in which they participate. Each stage has a set of states $S_t = \{s_1, s_2, s_3, \ldots, s_n\}$ that the agents can find themselves in, as well as a set of actions $A_t = \{a_1, a_2, a_3, ..., a_m\}$ available. The agents choose an action a_t based on the current state s_t, consequently receiving a reward r_t and transitioning to a new state s_{t+1} based on the market outcome. Figure 5.2 represents the basic learning process of an agent, while Figure 5.3 illustrates the application of the Q-learning framework in our study.

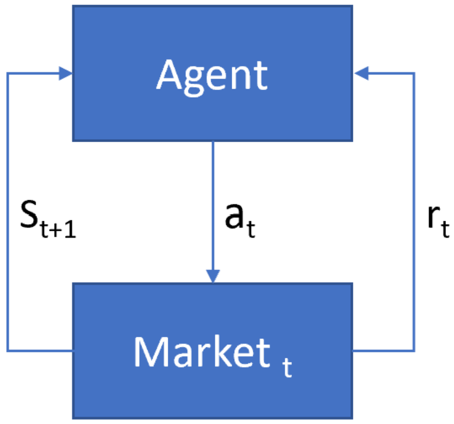


Figure 5.2: Q-learning agent interacting with the environment.

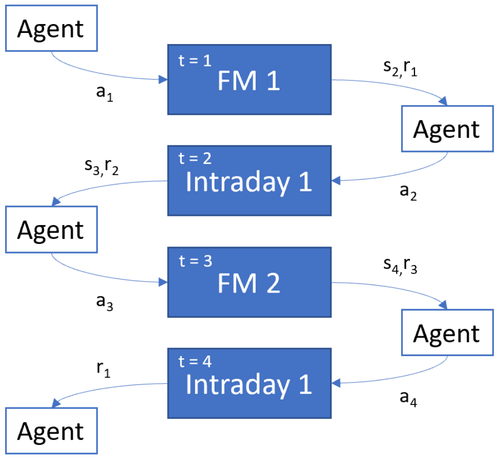


Figure 5.3: The Q-learning stages used in the study.

The initial state, s_1, is solely determined by the agent's rebalancing needs, which are derived from historical intraday bids as presented in Section 5.4. Consequently, the agent's actions from previous days do not influence the current day's initial state, enabling us to treat every day as independent. The situation is more complex for individual hours. The interaction process, illustrated in Figure 5.2, is performed on a per-hour basis, and the agents are not aware of the current hour. Market clearings for one hour also do not impact other hours through the Q-learning algorithm. Nevertheless, the optimization models are solved on a per-day basis, with the FM model incorporating interdependencies between individual hours. Hours within a day are therefore dependent on each other, but this dependency is not considered by the Q-learning nor recognized by the agents.

Each state-action pair is represented by a Q-value $q(s, a)$, which indicates the expected value of choosing action a from state s. Aligned with our objective of uncovering strategic opportunities between the markets, we employ one distinct Q-matrix for each stage and agent. That means each a_t in Figure 5.3 is chosen from a dedicated Q-matrix. All states and actions utilized in the modelling can be found in Appendix 2A.

The Q-values are updated when the agent interacts with the environment, as seen in equation 5.1. In the equation, α represents the learning rate, which determines the extent to which the newly acquired information overrides the existing Q-value. On the other hand, γ is the discount factor determining the importance of expected rewards in the subsequent stages, here represented by $q(s', a')$.

$$q^{new}(s, a) = (1 - \alpha) \cdot q(s, a) + \alpha\big(r + \gamma \cdot \max_{a}\{q(s', a')\}\big) \tag{5.1}$$

Q-learning involves a crucial trade-off between exploration and exploitation. Initially, the agents should engage in exploration to learn from the environment, which is vital to avoid converging into local optima. However, keeping the exploration rate too high creates an unrealistic environment. Considering that the agents interact and compete with each other, it becomes necessary for them to train on other agents making realistic choices. To address this, we adopt an exploration probability that follows an exponential decay formula, as shown in equation 5.2.

$$p(\tau) = e^{-\lambda\tau} \tag{5.2}$$

The τ in equation 5.2 represents the learning step, which corresponds to the number of days the agents have been trained on. Since the study utilizes data from a single year (2021), but the agents require more than 365 days of training, we iterate over the year multiple times. In this approach, τ equals $(i-1)\cdot 365+d$, where i denotes the iteration number and d represents the day within the year.

Additionally, λ represents the decay constant, which determines the rate at which the decay formula decreases. Similarly to the learning rate and discount factor, there are no strict rules for selecting the decay constant. The objective is to guide the system toward convergence in the global optimum, but there is no definite way to determine which constant values will lead to that outcome. Therefore, we employ various cases with different combinations of the three constants and choose the case which converges towards the highest total reward for the agents.

5.3.2 Reward function

The agent rewards are a central part of the Q-learning algorithm, and their design is crucial for ensuring realistic behavior. In this study, the reward calculations are based on Marginal Cost (MC) curves, incorporating both the costs associated with power production and imbalance costs. When an agent engages in trading activities, whether selling or buying back power, the total cost is influenced by the net change in power production that is due. It is this net change in cost, as well as the revenue or expenditure from the market transaction, that constitutes the reward for an agent:

$$r = \triangle V \cdot P - \triangle C \tag{5.1}$$

In equation 5.1, $\triangle V$ is the net traded power, P is the market price and $\triangle C$ is the net change in cost. An implication of using relative changes in cost is that the reward equals 0 if no trade was made. Thus, agents failing to meet rebalance needs are not punished. Instead, we use rebalance needs to adjust the marginal cost curve in a way that incentivizes trading back into balance. The MC function is originally increasing with a fixed rate β, but a rebalancing need will transform it according to Figures 5.4 and 5.5.

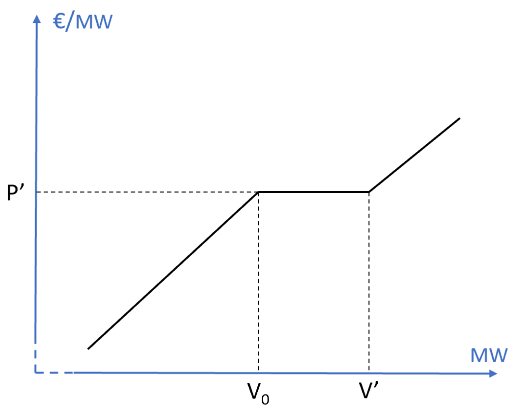


Figure 5.4: MC function where an agent wants to sell more power.

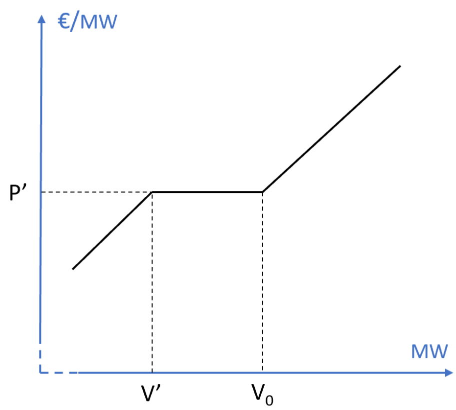


Figure 5.5: MC function where an agent wants to buy back power.

As detailed in 5.4.1, we use historical intraday bids to determine the rebalancing needs of the agents. Figure 5.4 illustrates how the MC function is adapted to a sell bid with volume $V'-V_0$ and desired price P'. This scenario is interpreted as the agent needing to increase production to V', and that all production between V_0 and V' incurs a marginal cost of P'. This same logic is applied to buy bids, as demonstrated in Figure 5.5.

The adapted MC functions incentivize the agent to trade in the direction of its rebalancing need. This is achieved by avoiding the relatively steep increases or decreases in cost that are inherent in the remainder of the curve. This is illustrated in Figures 5.6 and 5.7, which respectively depict the optimal trades for an agent with and without a need to increase output. In these Figures, P_m represents the market price, V_m denotes the new volume after trading and the coloured area illustrates the reward.

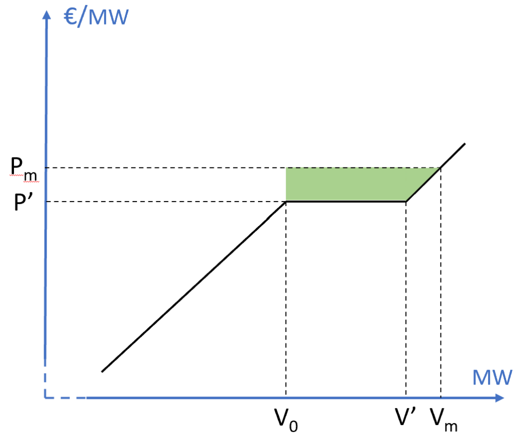


Figure 5.6: Optimal trade when an agent has a rebalancing need.

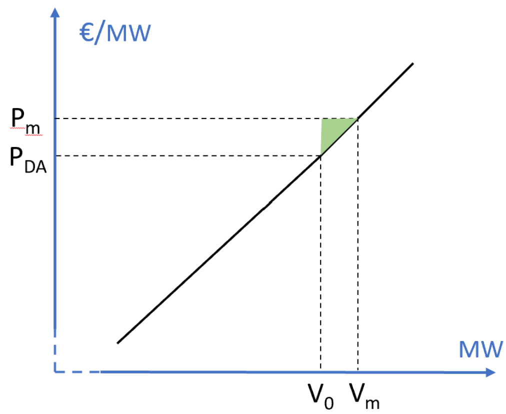


Figure 5.7: Optimal trade when an agent has no rebalancing need.

As seen in Figure 5.7, we assume that the current MC is equal to the day ahead price when there is no rebalancing need. Furthermore, it is important to highlight that neither the reward calculation nor the underlying MC function are influenced by the agent's net position after the DA market. Although this represents a major simplification compared to real-world scenarios, it aligns well with the scope of our study, which focuses on strategic behavior in the period between but excluding the DA and redispatch stages.

5.3.3 Power market optimization models

The power market modelling builds upon the work of Aasvær et al. (2023). The continuity includes the representation of the same zonal FM and redispatch, both operating under the same assumptions as in the previous paper. For comprehensive details regarding the FM and redispatch modelling, we therefore refer the reader to Aasvær et al. (2023).

The optimization model additions in this paper mostly concern the four Q-learning stages. New features include the two intraday clearings and a secondary clearing of the FM. The second FM constructs zones based on the power flow after the clearings of the first FM and intraday market, meaning there are two zonal partitioning processes throughout the day. Although the ordinary FM participants maintain consistent bids in both clearings, these bids are adjusted in the secondary FM to reflect the volumes cleared in the initial FM market.

The intraday market, a novel addition in this paper, is comprehensively formulated in the ensuing subsection. Participants in the intraday market differ from those in the FM, with only the agents assumed to take part in both market types. Just like the FM bids, the intraday bids in the second market are adjusted to account for the volumes cleared in the initial market.

Intraday market clearing

As indicated earlier in this section, we model discrete intraday auctions instead of the continuous market design currently implemented in Europe. This approach not only simplifies the modelling process, but also anticipates the future configuration of the intraday market, which is expected to be discrete.
Objective function. The objective function of the intraday market clearing problem maximizes social welfare.

$$\max \sum_{t\in\mathcal{T}}\Big(\sum_{o\in\mathcal{O}^B} C_{to}^{ID}x_{to}^{ID} - \sum_{o\in\mathcal{O}^S} C_{to}^{ID}x_{to}^{ID}\Big) \tag{5.1}$$

In the objective function, 5.1, $\mathcal{T}$ is the set of time periods, $\mathcal{O}^B$ the set of intraday buy orders, and $\mathcal{O}^S$ the set of intraday sell orders. Furthermore, C_{to}^{ID} and x_{to}^{ID} is the order price and cleared volume, respectively, for order $o \in \mathcal{O} = \mathcal{O}^B \cup \mathcal{O}^S$ in time period $t \in \mathcal{T}$. It is important to note that in the context of the intraday model, the time periods, t, represent hours, and not stages, as in the Q-learning model.
Power flow. The power flow is governed by constraints 5.2-5.4.

$$P_{zt} + \sum_{o\in\mathcal{O}_z^S} x_{to}^{ID} - \sum_{o\in\mathcal{O}_z^B} x_{ot}^{ID} = p_{zt} \qquad z \in \mathcal{Z}^{ID}, t \in \mathcal{T} \tag{5.2}$$

$$f_{lt} = \sum_{z\in\mathcal{Z}^{ID}} ZPTDF_{lz} \cdot p_{zt} \qquad l \in \mathcal{L}^{ID}, t \in \mathcal{T} \tag{5.3}$$

$$-CAP_l \leq f_{lt} \leq CAP_l \qquad l \in \mathcal{L}^{ID} \tag{5.4}$$

In constraint 5.2, hourly net positions in each intraday zone, $\mathcal{Z}^{ID}$, are updated from the net position before the intraday clearing, P_{zt} with the cleared volume of sell and buy orders for time period t. Constraint 5.3 calculates the flow on all critical branches, $\mathcal{L}^{ID}$, using ZPTDFs. Finally, the flow on all lines are subject to the capacity constraints given by constraint 5.4.

Balancing constraints. Constraint 5.5 states that the sum of accepted sell bids equals the sum of accepted buy bids, which under the assumptions of no changes to cross-border flows maintains the energy balance in the system.

$$\sum_{o\in\mathcal{O}^S} x_{to}^{ID} = \sum_{o\in\mathcal{O}^B} x_{to}^{ID} \qquad t \in \mathcal{T} \tag{5.5}$$

Bid constraints. Finally, the cleared volumes are forced to be non-negative and below the maximum volume of the bid in constraint 5.6.

$$0 \leq x_{to}^{ID} \leq V_{to} \qquad t \in \mathcal{T}, o \in \mathcal{O} \tag{5.6}$$

5.4 Data

The data and assumptions used in this study largely extend the work of Aasvær et al. (2023). The shared basis includes the use of the same power system and FM market participants, with bids generated and redispatch performed under identical assumptions. Additionally, the FM is located in the same sub-area of the NO1 Elspot zone, here called the FA. For a better understanding of these elements, readers are encouraged to consult Aasvær et al. (2023).

The power market data for this study, encompassing DA volumes and intraday bids, are drawn from the year 2021. While using more recent data might ordinarily be advantageous, the market disruptions caused by the conflict in Ukraine complicate this approach. Accordingly, we have chosen to use 2021 data, which aligns more closely with market outcomes from previous years and is more consistent with our future market expectations. Nevertheless, the latter months of 2021 were also affected by high prices and volatility due to Russia reducing its gas supply preceding its invasion. As such, our study will also provide insights into strategic opportunities in the context of more turbulent market conditions.

5.4.1 Intraday data

To ensure realistic power flows and produce reasonable market outcomes, the intraday market is modelled across all the Norwegian Elspot zones. The bids for our intraday auction stem from anonymous limit orders that were initially submitted to the current continuous intraday market. We restrict our analysis to these limit orders as our intraday model only accounts for buy and sell orders. Each order is attributed to a random market participant located at a specific node within the Elspot zone of the original bid. To streamline the analysis, we assume each participant submits a single buy or sell order per hour. Accordingly, the number of generated intraday market participants is adjusted to meet this assumption. For more information about the intraday market participants, see Appendix 2B.

The Q-learning agents are engaged in both the intraday market, which spans the entirety of Norway, and the FM, which is geographically confined to the FA. Consequently, the agents must be chosen from among the intraday participants situated within the FA. While the agents themselves determine their bids for the markets, the historical bids assigned to them primarily act as their rebalancing needs. As described in section 5.3.2, these rebalancing needs play a crucial role in the agent's reward function.

5.4.2 Implementation details

The simulation model operates on Solstorm, a data cluster managed by NTNU. The nodes utilized on this cluster are powered by a Linux operating system and are equipped with 12 cores, 12 threads, and 512 GB of RAM. Our implementation uses Python, employing the Gurobipy package and the Gurobi solver for optimization tasks (Gurobi Optimization, LLC, 2023). The training process for the agents requires substantial computing time; 25 iterations, each representing one year, cumulatively take 102,525 seconds, which is equivalent to approximately 28 hours, 28 minutes, and 45 seconds.

5.5 Results

We utilized the first intraday clearing in the no-learning scenario as a representation of the intraday market without any strategic bidding. The resulting NO1 intraday prices for 2021 are presented in Figure 5.8, which illustrates an increase in volatility and prices towards the end of the year, as discussed in Section 5.4.

In the following section, certain parts of the analysis will focus on specific weeks, allowing for a more focused investigation and reducing the impact of noise. Specifically, we concentrate on two distinct weeks: the first week is characterized by stable intraday prices, while the second week exhibits significant price volatility. This approach aims to highlight the variations in arbitrage and gaming opportunities available to strategic bidders under different market conditions. To examine the week with high price volatility, we selected week 51, encompassing hours 8400 to 8567. Conversely, for the week characterized by stable prices, we chose week 13, covering hours 2016 to 2183.

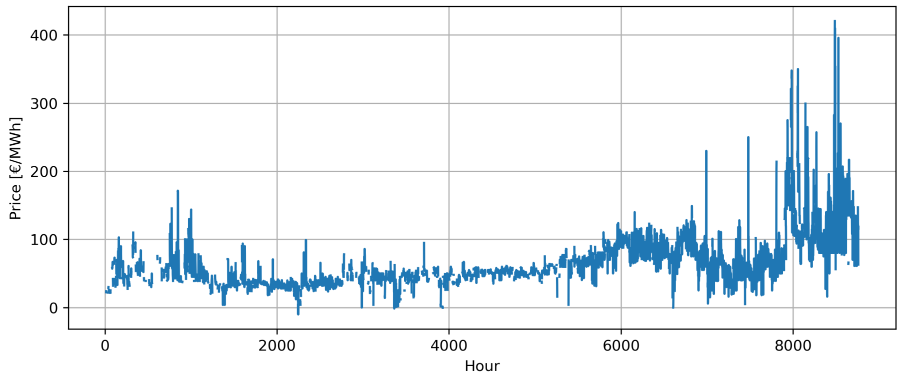


Figure 5.8: Hourly intraday prices in NO1.

5.5.1 Convergence of the Q-learning algorithm

As described in Section 5.3.1, we conducted simulations involving various cases with different Q-learning parameters. Each case involved training the agents for 25 iterations, after which the cases were compared and one case selected for further analysis. The parameter values used in each case are presented in Table 5.1, while the cumulative rewards earned by the agents in the last iteration are visualized in Figure 5.9.

Q-learning cases			
Case	**Learning rate α**	**Discount factor γ**	**Decay constant λ**
0	0.2	0.8	0.0006
1	0.4	0.8	0.0006
2	0.1	0.8	0.0006
3	0.2	0.8	0.001
4	0.2	0.8	0.0004
5	0.15	0.8	0.0004
6	0.25	0.8	0.0004
7	0.2	0.9	0.0006

Table 5.1: Parameter values for the Q-learning cases.

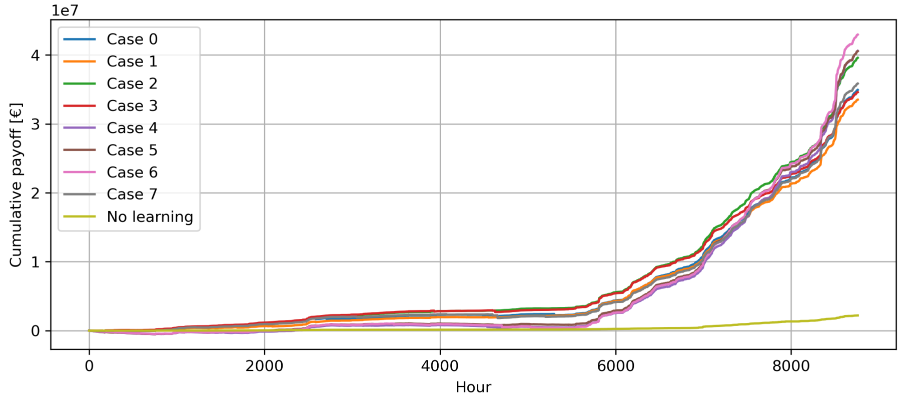


Figure 5.9: Cumulative payoff in the last iteration for all Q-learning cases. Also including the no-learning scenario.

The cumulative rewards displayed in Figure 5.9 are calculated based on the reward function described in Section 5.3.2. Since the agents aim to maximize their rewards, the total reward serves as a valuable measure of the cases' performance, indicating which cases are closest to achieving a global optimum.

During the initial months of the simulation, all learning cases exhibited a performance relatively close to the no-learning case. However, after reaching hour 6000, all learning cases experience a sharp increase in payoff. This performance enhancement coincides with an escalation in market volatility and price disparities between the DA and the intraday market, observed towards the end of the year. The upcoming sections will investigate how agents capitalize on these evolving market conditions.

Although case 6 ultimately achieves the highest cumulative payoff, its performance during the first half of the year is significantly worse than the other cases, only surpassing the no-learning case. This outcome was considered unfavorable for the analysis since we sought a case that could also extract a surplus in more stable market conditions. As a result, we made the decision to proceed with case 2. It attains the third highest cumulative payoffs while also demonstrating the potential to extract surplus payoff during the initial half of the year.

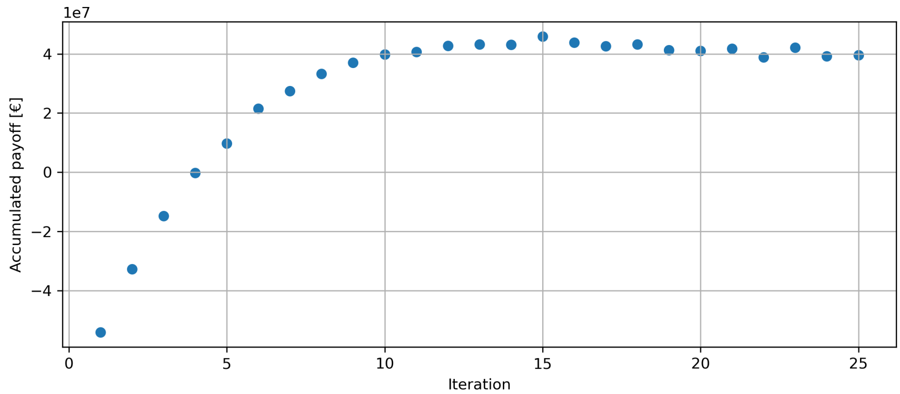


Figure 5.10: Accumulated payoff for all iterations of case 2.

Figure 5.10 provides a visual representation of the total reward received for each iteration of case 2, illustrating the convergence of the Q-learning algorithm toward a solution. As the iteration number increases, the discrepancy in payoff between iterations diminishes, leading to an increase and then stabilization of the payoff. This phenomenon can be attributed to two factors: the decreasing exploration probability and the agents refining their strategies over time. With a lower exploration probability, agents make smarter and more consistent actions, resulting respectively in the increasing and converging curve observed in Figure 5.10. While the improved strategies also contribute to the increase in payoff between iterations, it is challenging to isolate this effect from the increasing exploitation rate.

When performing a similar examination of the convergence for individual agents in case 2, the rewards appear to exhibit more fluctuations. This is illustrated in Figures 5.11 and 5.12, which depict two agents' total rewards per iteration, also compared with their reward in the no-learning scenario. The fluctuations persist even at high iteration numbers, where exploration rate and strategy turnover rates are low. One possible explanation is that an agent's payoff is contingent upon the market clearings and, subsequently, the choices of other agents. Consequently, the reward for a particular agent may be affected when other agents explore or change their strategies, which is more probable than the agent doing so itself.

An additional factor that could contribute to the observed phenomenon is the existence of multiple optimal solutions for the market clearing problems, particularly in the case of the intraday problem. As all agents are situated within the NO1 zone, their changes in net positions will impact line flows equally, owing to the utilization of ZPTDFs. Consequently, if two or more agents have identical intraday bids, the model will have multiple optimal solutions. However, the individual agent's reward is dependent on the specific solution chosen among these alternatives. The symmetry argument can also be extended to the FM clearings, although agents must be located within the same FM zones to possess equal ZPTDFs.

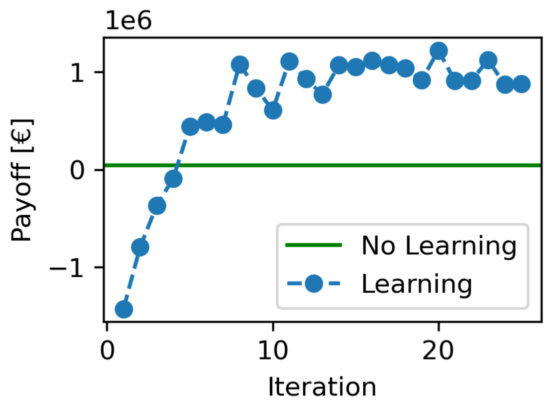


Figure 5.11: Total payoff for Agent 1 for each iteration.

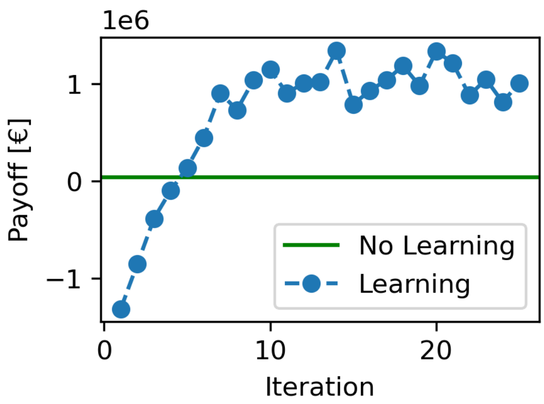


Figure 5.12: Total payoff for Agent 2 for each iteration.

5.5.2 Reward comparison across scenarios

After training the agents, we conducted simulations with a zero percent probability of exploration for three scenarios by assigning an infinite decay constant. The cumulative payoffs from these simulations are plotted in Figure 5.13. In the plot, the learning scenario represents the ordinary simulation of case 2. Remarkably, the only-intraday and learning scenarios demonstrate close alignment until approximately hour 7000, with the learning scenario ultimately yielding a 27% higher payoff compared to the only-intraday scenario. The payoff gap between these two scenarios are therefore significant, indicating that the agents profit from trading in the FMs. Furthermore, a substantial contrast arises when comparing the outcomes of these scenarios to the payoff accumulated in the no-learning scenario. This observation underscores the significant disparity that emerges from strategic behavior, as strategic agents successfully capitalize on surplus profit opportunities, with a majority of such opportunities evidently materializing in the intraday market.

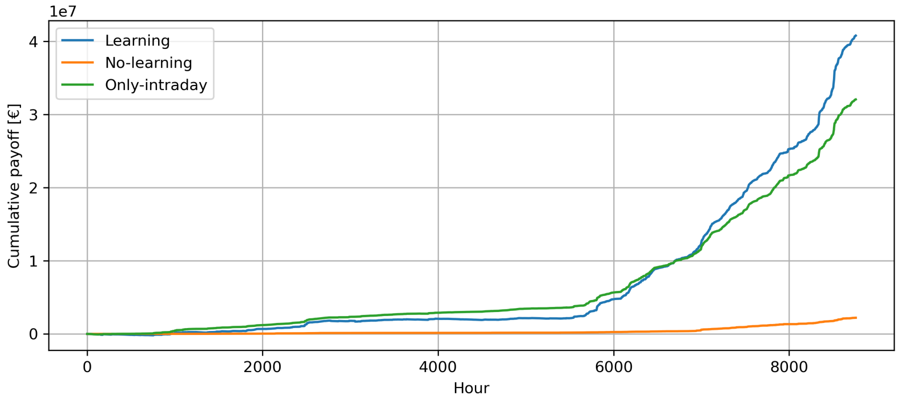


Figure 5.13: Cumulative payoff with no exploration for the three scenarios

Table 5.2 presents the distribution of total rewards between the FM and intraday markets among agents in the learning and only-intraday scenarios. Analyzing these rewards provides several valuable insights. Firstly, it is evident that the agents effectively utilize the FM to enhance their rewards. Secondly, participation in the FM also leads to higher payoffs in the intraday market. By balancing their positions in the FM, the agents are able to exploit strategic opportunities in the intraday market to a greater extent in the learning scenario than in the only-intraday scenario.

Total agent payoffs [M€]			
Scenario	**FM**	**Intraday**	**Total**
Learning	2.34	38.45	40.79
Only-intraday	0	32.06	32.06

Table 5.2: Total agent payoffs in the FM and intraday clearings for the learning and only-intraday scenarios.

5.5.3 Strategies

Figure 5.9 clearly illustrates a significant increase in agents' cumulative payoff when strategic bidding is employed, highlighting the effectiveness of strategic behavior in enhancing outcomes. Through our analysis, we have identified and examined multiple strategies employed by the agents to achieve this increase in profit. In the following section, we provide an overview of the observed strategies before delving into their association with the simulation results and discussing them in greater detail.

1. Exploit arbitrage between intraday and FM. During the year, there are consistent differences in prices between the intraday market and the FM. Generally, the FM prices tend to be higher than the intraday market prices. The agents strategically adapt to this price differential by selling power in the FM and purchasing power in the intraday market. However, it is important to consider that the presence of a greater number of strategic agents in the market would be expected to diminish this arbitrage opportunity, ultimately leading to price convergence between the two markets.

It is crucial to acknowledge that the price difference discussed above is contingent upon our assumptions regarding flexibility costs. While the intraday bids are based on historic data, the FM bids are designed based on various assumptions customized for the study by Aasvær et al. (2023). In a real case, however, the prices in the two markets may be expected to be more correlated. Therefore, the strategic opportunity for exploiting price differences between the FM and intraday may be exaggerated in this study.

2. Exploit arbitrage between DA and intraday and/or FM. For the majority of hours, individual agents have no rebalancing needs. In such cases, as described in Section 5.3.2, we assume that the agent possesses a MC equal to the DA price. They are then inclined to sell power if prices are higher than DA and buy back power if prices are lower than DA. As expected, this creates strategic opportunities within the FMs, where congestion-induced price signals can push prices in either direction from the DA price. However, there are also significant price differences between the DA and intraday markets, as seen in Figure 5.14.

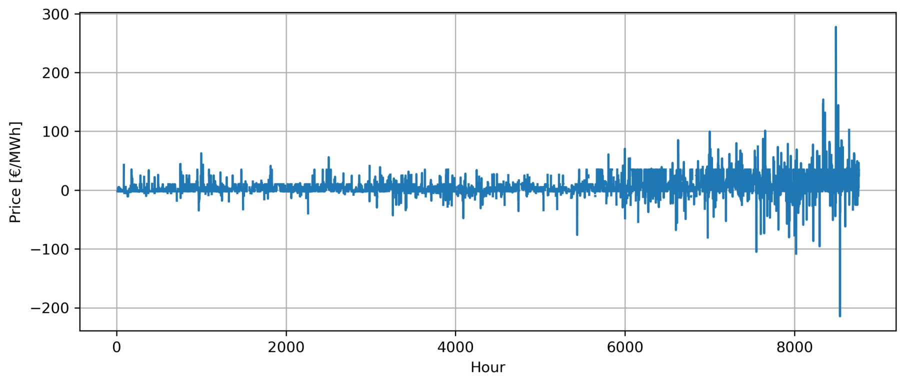


Figure 5.14: Hourly price difference between DA and intraday for the learning scenario.

3. Aggravating congestion through the intraday market to increase FM profit. This strategy is analogous to the inc-dec game observed for the DA and redispatch markets. Because the FM prices are affected by grid congestions, agents can potentially enhance their payoff by aggravating congestion issues through their bids in the intraday markets. This strategy is closely related to strategy 1, as both are characterized by agents bidding in opposite directions in the FMs and intraday markets.

While strategies 1 and 3 often lead to the same outcome, there are also circumstances where they are easily distinguished between. For example, an agent following strategy 1 may alleviate congestion in the intraday and exacerbate it in the flexibility market. Conversely, an agent following strategy 3 might sell power in the cheapest market and buy power in the most expensive market. Notably, the two strategies would more frequently coincide if the market price differences between the markets decreased, as the price signals resulting from congestions become more influential.

4. Exercising market power as a price setter. The agents consistently place sell bids above their MC and buy bids below their MC, suggesting market power. The market power opportunities are in theory more prevalent in the FMs, because of the more granular grid representation. Agents recognizing their influential position may effectively exert pressure on the market price within their respective zone, thereby increasing their reward.

Manifestation of strategic bidding in the simulations

Strategy 2 emerged as the most profitable strategy for the agents overall, as evidenced by the data presented in Table 5.2. The total rewards in the only-intraday scenario account for 79% of the total rewards in the learning scenario, demonstrating that the agents could earn a large portion of the rewards without using the FMs. The implications of agents utilizing strategy 2 is further detailed in Section 5.5.4, where intraday prices are observed to converge with DA prices.

Strategies 1 and 3 can be identified by looking at the agent bids, observing if the agent bid in the opposite direction in the intraday markets and FMs. This is done in Figure 5.15, which shows each agent's preferred bid volumes in the first intraday market clearing and the second FM clearing. The choice of these two markets is deliberate as agents will have congestion information obtained from the first FM clearing, facilitating the implementation of strategy 3. It should be noted that while agents employed various bid combinations throughout the simulation, the graph only represents their most frequently utilized combination.

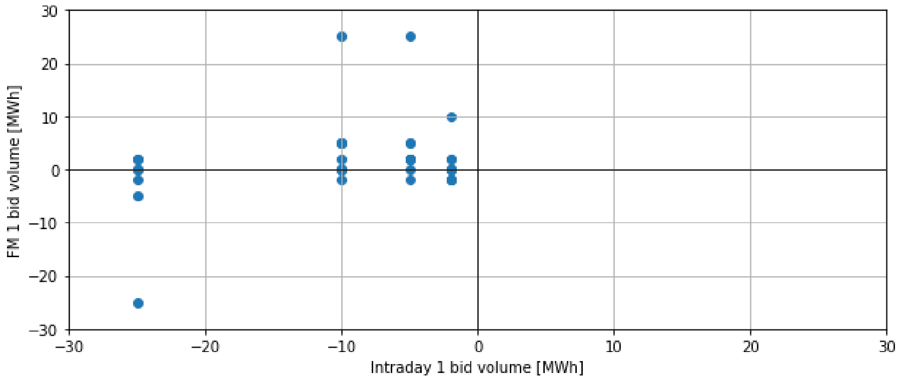


Figure 5.15: Scatter plot showing the bid volumes most frequently chosen by each agent in the first intraday market and second flexibility market.

Figure 5.15 reveals that agents are inclined to trade in opposite directions in the two markets, represented by the upper left quadrant. This observation suggests that strategies 1 and/or 3 are employed by certain agents, in which case they must have been profitable in the training period. Additionally, an important finding from Figure 5.15 is that all agents consistently engage in buying back power in the first intraday market. This behavior aligns with strategy 2 and can be attributed to the prevailing trend of intraday prices generally falling below DA prices, as illustrated in Figure 5.16.

Strategies 1 and 3 are more convincingly identified by examining the bids and cleared volumes of individual agents. Figures 5.16 and 5.17 serve as illustrative examples, showcasing distinct patterns of selling power in the FMs and buying power in the intraday market. It is worth noting that Appendix 2C presents additional examples of individual strategies, highlighting the substantial diversity and complexity that exists beyond the two showcased examples.

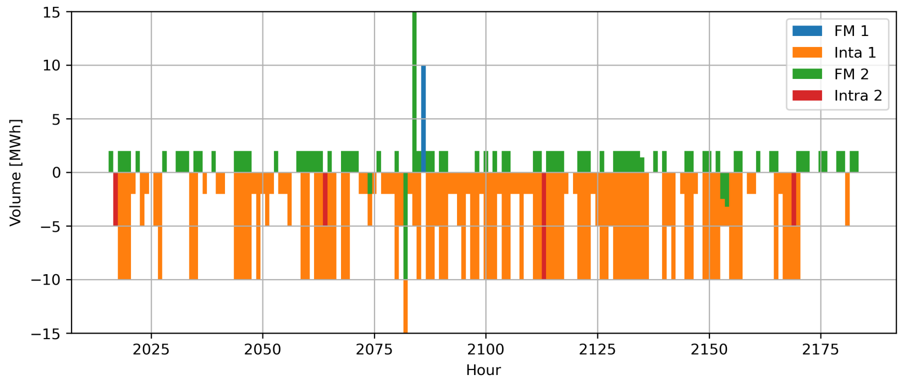


Figure 5.16: Cleared volumes in all four markets for an individual agent (1) during week 13.

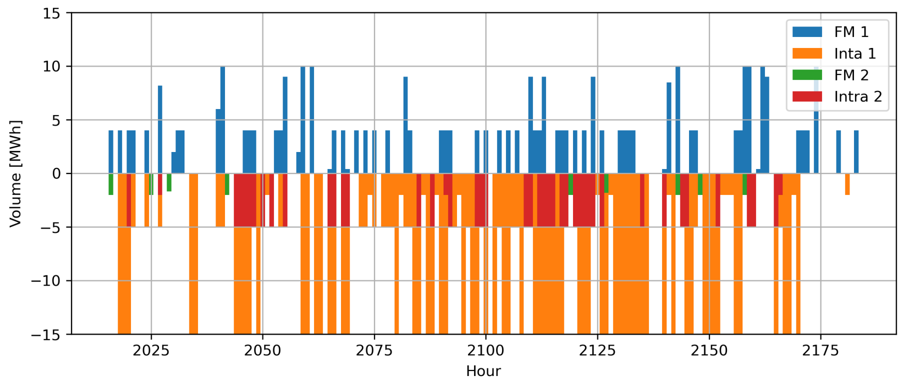


Figure 5.17: Cleared volumes in all four markets for an individual agent (2) during week 13.

Notably, the agent in Figure 5.17 prioritizes selling power in the first FM instead of the second. This is an important distinction, because the agent does not have the same information available as when participating in the second FM. Specifically, it rules out strategy 3, as the agent trades in the FM before it trades in the intraday market.

5.5.4 Market prices

In Figures 5.18-5.21, hourly intraday and DA prices for NO1 are plotted for weeks 13 and 51 for the learning and no-learning scenarios. The gaps in the intraday price data represent hours where no volumes were cleared. For the hours where market clearance was achieved, however, significant disparities emerge.

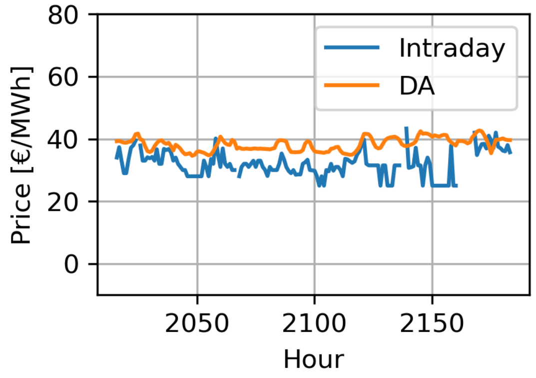


Figure 5.18: Intraday and DA prices for no-learning in week 13.

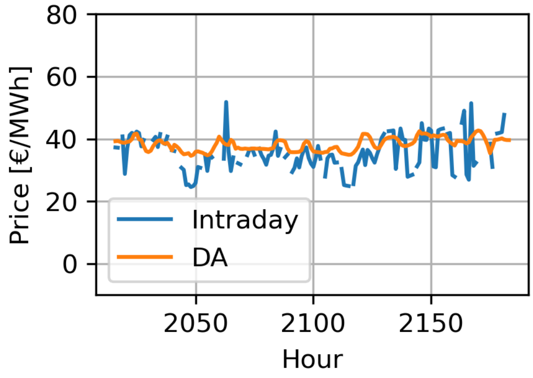


Figure 5.19: Intraday and DA prices for learning in 13.

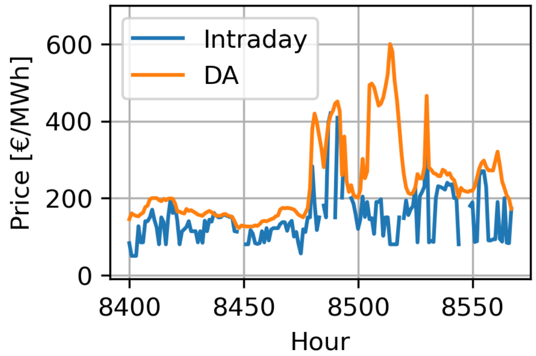


Figure 5.20: Intraday and DA prices for no-learning in week 51.

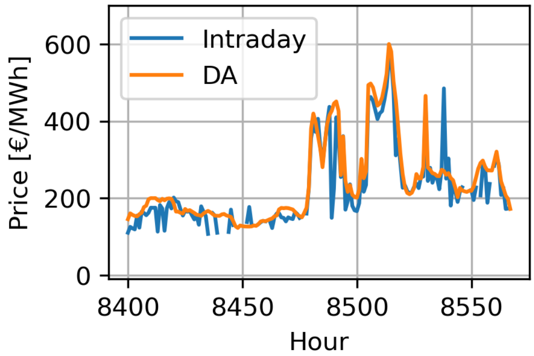


Figure 5.21: Intraday and DA prices for learning in week 51.

The figures reveal a notable disparity between the two scenarios. In week 51, the intraday price in the no-learning scenario consistently remains below the DA price. Most notably, there are significant price spreads of over 200 € /MWh between hours 8500 and 8530. However, the spread between intraday and DA prices is considerably lower during these hours for the learning scenario.

The price convergence observed in the learning scenario can be partially attributed to the utilization of strategy 2. As discussed in Section 5.5.3, this strategy relies on the assumption that the MC of agents aligns with the DA price when no rebalancing is needed. However, it is important to recognize that in reality, power producers do not possess a MC that precisely aligns with the DA price. Assuming that producers have submitted their true MC, or water values in the case of hydro producers, in the DA market, their MC must be lower than the clearing price in order for their bid to be accepted. As a result, they would stand to gain from repurchasing at an intraday price that is lower than their MC. This implies that a certain degree of price spread during these hours is likely to persist, and that strategy 2 observed in this study is representative of strategies employed in the real world today.

5.5.5 Social surplus

Figures 5.22-5.25 illustrate the distribution of the social surplus among agents and other market participants in the FA for weeks 13 and 51, in the no-learning and learning scenarios. Notably, the cost of CM is not included in the numbers. The data reveals that the agents' share of the social surplus was generally small or nonexistent for most hours when strategic bidding was not employed. This is in large part because agents rarely bid in the no-learning scenario, as detailed in Section 5.4.1. In contrast, when agents learned and adopted strategic behaviors, their portion of the social surplus experienced a significant increase.

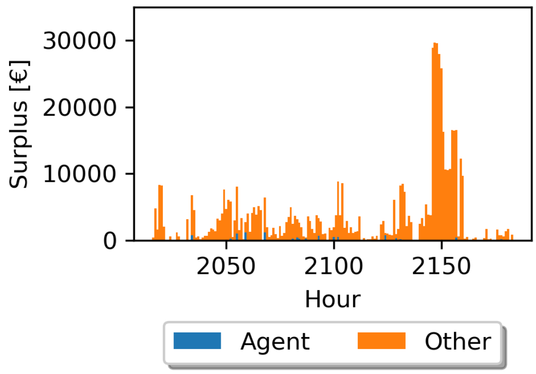


Figure 5.22: Social surplus split by agents and other actors without learning for week 13.

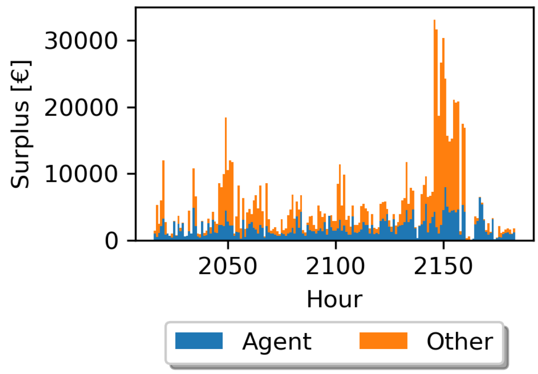


Figure 5.23: Social surplus split by agents and other actors with learning for week 13.

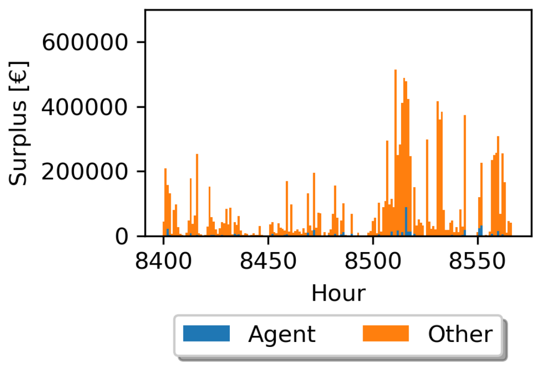


Figure 5.24: Social surplus split by agents and other actors without learning for week 51.

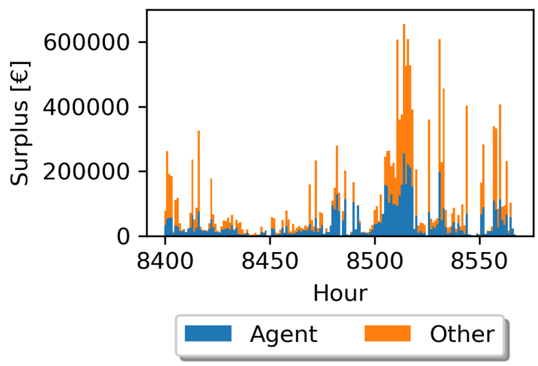


Figure 5.25: Social surplus split by agents and other actors with learning for week 51.

The figures demonstrate that strategic bidding impact the total surplus of the system. To provide more precise estimations of this effect, Table 5.3 presents the surplus results for the entire year, encompassing all three scenarios.

Total Surplus [M€]				
Scenario	**Agents**	**Intraday**	**Flexibility**	**Total**
Learning	40.79	69.54	1.94	112.27
Only-intraday	32.06	73.76	1.60	107.42
No-Learning	2.06	77.12	1.61	80.77

Table 5.3: Total surplus for different types of market participants and scenarios for the entire year.

Table 5.3 shows that the total system surplus increases when allowing for strategic bidding. The largest increase in surplus is observed when introducing strategic bidding to the intraday markets, as evidenced by the transition from the no-learning scenario to the only-intraday scenario. However, the inclusion of strategic bidding in the FMs also leads to a significant increase in the total surplus, as seen in the transition from the only-intraday scenario to the learning scenario. Furthermore, the FM participants increase their surplus in the learning scenario, indicating that the benefits of increased liquidity outweigh any competition from the agents. However, this is not the case for non-agent participants in the intraday markets, who experience a loss of surplus in the only-intraday scenario and an even larger loss in the learning scenario.

The comparison of non-agent intraday surplus between the scenarios reveals an interesting pattern: the agents not only generate surplus but also capture surplus at the expense of other intraday participants. Furthermore, the difference between the learning and only-intraday scenarios suggests that the agents enhance their capturing of intraday surplus when they also engage in trading in the FM. This can be attributed to the strategic behavior outlined in strategy 1, where the agents' intraday trades can become more aggressive with the support of FM trades in the opposite direction. Conversely, this observation could indicate that the agents in the learning scenario have converged on superior Q-values, also accounting for the impact of FM trades. Although both scenarios employed the same Q-learning parameters during the training period, such an outcome is plausible. This latter possibility introduces a significant limitation to the comparability of the scenario results.

5.5.6 Congestion Management

An important aspect of the strategic behavior is its impact on CM, especially as CM is a key objective of the FM. Additionally, CM represents a cost to society that was not covered by the discussion on market surplus. The impact on congestion can be measured in total congestion for the FA after the various markets, or by analyzing the cost of alleviating all congestion.

The cost of performing a redispatch can be determined by running a redispatch model after the second intraday market and calculating the cost of the activated redispatch. The cost of redispatch was computed for the months of March, April, and December. Interestingly, there was no significant divergence in the cost of redispatch between the learning scenario (82.8M€), the only-intraday scenario (83.3M€), and the no-learning scenario (83.2M€) for these three months. Furthermore, it is important to take into account the system operators' cost of activating flexibility through the FMs. However, neither this perspective illuminated any significant disparities in the cost of the no-learning and learning scenarios.

Analyzing congestion levels for the entire year, we find that the only-intraday scenario exhibited the highest overall congestion levels. Summing up all congestions in the FA over the entire year, the only-intraday scenario has 83,184 MW and 6,774 MW more in congestion compared to the learning scenario and the no-learning scenario respectively. Consequently, the no-learning and only-intraday scenarios display relatively similar congestion levels, whereas a decrease is observed in the learning scenario. However, it is important to note that the improvement in congestion levels for the learning case is small relative to total congestion levels. Specifically, the congestion reduction observed for the learning scenario amounts to a mere 1% decrease in congestion levels compared to the only-intraday scenario.

Instead of judging the congestion improvement for the learning scenario to be insignificant, it can be argued that there are exceedingly high congestion volumes inherent in the system. As detailed in Aasvær et al. (2023), which the grid models in the paper is based on, the congestion levels in the system are unrealistically high for most hours of the year. As a result, the volumes cleared in the FM become small compared to the congestion level, leading to a small relative change in congestion level before and after the FM clearing.

Several noteworthy observations can be drawn from the analysis of congestion levels. Firstly, the only-intraday scenario exhibits higher congestion levels compared to the learning scenario. This suggests that the agents, at least to some extent, respond to the price signals in the FM, resulting in lower congestion levels when allowed to participate in the FM. It also suggests that negative consequences from strategies 3 and 4 were limited. This may be because strategies 1 and 2 dominated the agents' behavior, and because the negative effects were outweighed by the increased liquidity in the FM.

5.6 Discussion

In this section, we discuss the key limitations and considerations associated with this study, stemming from underlying assumptions and modelling decisions. By acknowledging these limitations, we aim to provide a comprehensive understanding of the boundaries and potential implications of our conclusions.

Notably, it is important to reiterate the assumptions underlying the market costs, discussed in Section 5.5.3, as they have significant implications for the findings of this study. As previously mentioned, these cost assumptions create arbitrage opportunities between the intraday market and either the FM or DA, which favor strategies 1 and 2, respectively. While our study effectively demonstrates the feasibility of these strategies within the analyzed market structures, the precise nature and magnitude of their influence cannot be definitively determined. Furthermore, it should be acknowledged that the presence of unrealistically favorable conditions for certain strategies may restrict the exploration of alternative strategies. As a result, the limited negative impact observed for strategies 3 and 4 on system surplus and congestion may not be fully representative of other conditions and assumptions.

When conducting simulations where agents rely solely on their training to exploit opportunities, it is customary to be cautious of the issue of over-fitting when using the same dataset for training and evaluation. However, we argue that this concern is not a major factor in this study. Firstly, the agents' states and actions, as detailed in Appendix 2A, are not sufficiently advanced. The states and actions are discrete and lack fine-grained granularity, and the first stage only has three possible states. If the state space were larger or continuous, obtaining reliable information about specific hours would be a more significant concern, as individual states would occur less frequently. Notably, this would also significantly increase the necessary training time. Additionally, the agents exhibit a strong preference for only a few specific action patterns, as depicted in the bubble plots in Appendix 2C. This suggests that the agents consistently choose the same actions regardless of specific conditions, reducing the impact of over-fitting in our results.

5.7 Conclusion

In this paper, we have introduced a reinforcement learning framework to investigate strategic bidding behavior in both FMs and intraday markets. Specifically, we have applied this framework to analyze the interaction between a zonal FM and a discrete intraday market, where a subset of market participants engage in strategic bidding in both markets. Our findings reveal that the agents have successfully learned various strategies that effectively enhance their profits by exploiting gaming and arbitrage opportunities. Notably, a substantial portion of the profit increase can be achieved through strategic bidding in the intraday market alone, but the ability to participate in both markets yields a significant 27% boost in agents' payoff. Furthermore, our study demonstrates how the price discrepancy between the DA and intraday markets diminishes as a result of agents strategically buying back portions of the cleared DA volume in the intraday market. Additionally, we illustrate how the strategic bidding of agents contributes to an overall increase in their total surplus.

The framework introduced in this paper provides opportunities for various extensions and future research. Firstly, as elaborated in Section 5.6, several of the assumptions made in this study have significant implications for the obtained results. Therefore, further investigations could focus on refining these assumptions by incorporating more realistic flexibility costs and developing more sophisticated reward functions for the agents. Such improvements may yield a more accurate assessment of the efficacy of the agents' strategies.

Secondly, the framework is amenable to exploring different designs of FMs. Thus, a promising avenue for future research involves implementing a nodal FM and examining the potential gaming and arbitrage opportunities that arise within this context. This would allow for a comprehensive investigation into the dynamics and strategic behaviors that emerge in such a market design and expand the understanding of how FM design affects strategic opportunities.

Appendix 2A: States- actions design applied to the Q-learning

In designing states and actions for Q-learning, it's crucial to balance two competing considerations. On one hand, the agents require sufficient information embedded in these states and actions to facilitate optimal decision-making. On the other hand, overly granular definitions can lead to inefficient and time-consuming training of the agents. With these challenges in mind, we made specific design choices to strike a balance between informational adequacy and training efficiency.

The available actions for the agents represent their potential bids in the various market stages, thus consisting of two factors: price and volume. To address the challenges outlined previously, both of these factors are expressed in relative terms. The prices are relative to the agent's desired price, which, as described in section 5.3.2, corresponds to the price of the Intraday bid used to determine an agent's rebalancing need. The volumes, on the other hand, are relative to either the desired volume or the current position. This design seeks to enable agents to choose optimal bids while keeping the number of potential bids manageable. The two factors consist of the following alternatives:

- Prices: $[-35, -25, -10, -5, -2, 0, 2 ..., 30]$ €/MWh
- Volumes: $[-50, -25, -10, -5, -2, 0, 2 ...,50]$ MWh

All four stages have the same set of actions available, which is defined by the cartesian product of these two factors. Because the volumes are relative to both desired volume and current position, the number of actions totals to $11 \cdot 11 \cdot 2 = 242$.

Similarly to the actions, the states also use relative quantities. The set of potential states remains the same for stages two, three, and four, and include information about the agent's zone's price in the first FM, as well as the volume remaining for the agent to achieve balance. The final factor included is the original re-balancing need, which is classified as "buy", "sell" or "no need". This last factor is the only determinant of a state for stage one, meaning that stage one only has three possible states. The three components forming the states are given below:

- Rebalancing need: [Sell, Buy, No need] €/MWh
- Remaining volume: $[-150, -75, -25, -10, -2, 0, 2 ...,150]$ MWh
- Zone price: $[-35, -25, -10, -5, -2, 0, 2 ..., 30, \text{None}]$ €/MWh

The "None" under zone price represents cases where there were no trades in the FM. As can be deducted from the factor lists, the latter three stages possess a total of $3 \cdot 11 \cdot 11 = 363$ states. It is also worth noting that the states are treated as intervals, rather than discrete points. This is because the remaining volume and zone prices have a continuous opportunity space. For example, the state (Sell,-75,10) is applicable to an agent who wants to sell, has a remaining volume between -150 and -75 MWh, and experienced a zone price in the FM between 10 and 25 €/MWh.

Appendix 2B: Intraday participants

Intraday participants are all assumed to be power producers, and are constructed for this study using historical intraday bids. As the bids have no information about the bidder, this process is based on a few simple assumptions:

- Intraday participants can only submit one bid per hour
- The total count of intraday participants in a given zone is determined by the peak hourly number of bids submitted throughout the year
- Intraday participants are located in transmission system nodes
- Intraday participants are more likely to be located in nodes with larger net production

The first and second assumptions were used to decide the number of intraday participants in each of the five Norwegian Elspot zones. Subsequently, these participants were assigned to nodes within their respective zones. To reflect the fourth assumption, the probability of a participant being assigned to a particular node was proportional to that node's share of the total zonal installed generation capacity. Once the participants were assigned to their respective nodes, the historical intraday orders were randomly assigned to the participants within their respective Elspot zone, using a uniform probability distribution.

Appendix 2C: Visualization of strategies for individual agents

The main text provides a glimpse into the diverse bidding strategies employed by the agents through a few selected figures. However, in order to offer a more comprehensive understanding of the implemented strategies, this appendix presents additional visualizations of bidding patterns for interested readers. By examining a broader range of agent strategies, a more complete picture of the strategic behavior can be obtained.

The agents represented in the visualizations are denoted by a number, and the discussion may also refer to the two agents in Figures 5.16 and 5.17, agents 1 and 2 respectively.

Cleared volumes in week 13

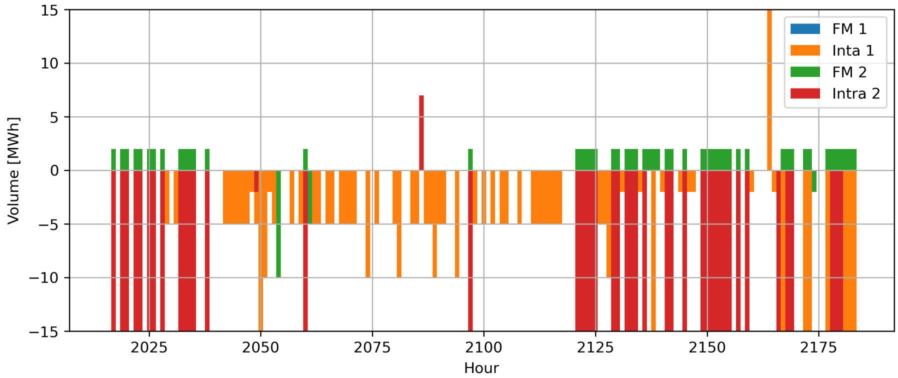


Figure 5.26: Cleared volumes in all four markets for agent 3 during week 13. The agent employs strategies 1 and/or 3, but differs from agent 1 by clearing much larger quantities in the second intraday market.

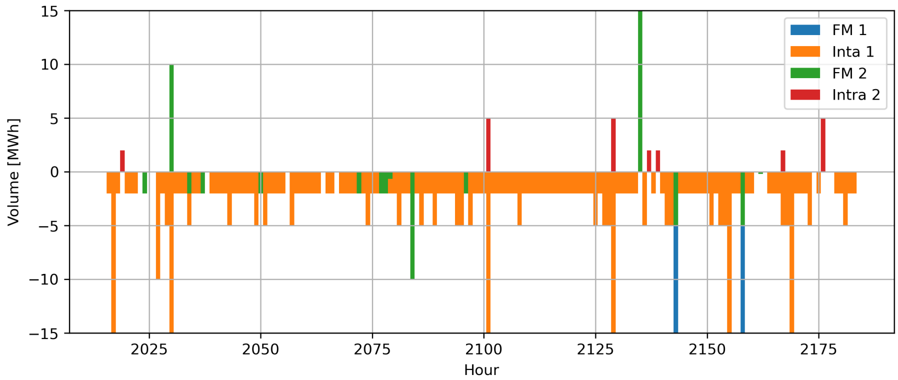


Figure 5.27: Cleared volumes in all four markets for agent 4 during week 13. The agent shows no sign of consistently utilizing either strategy 1 or 3.

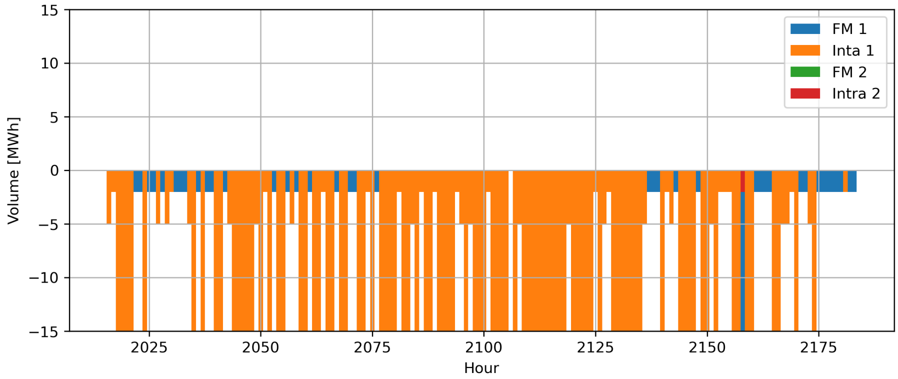


Figure 5.28: Cleared volumes in all four markets for agent 5 during week 13. The agent buys back power in all markets.

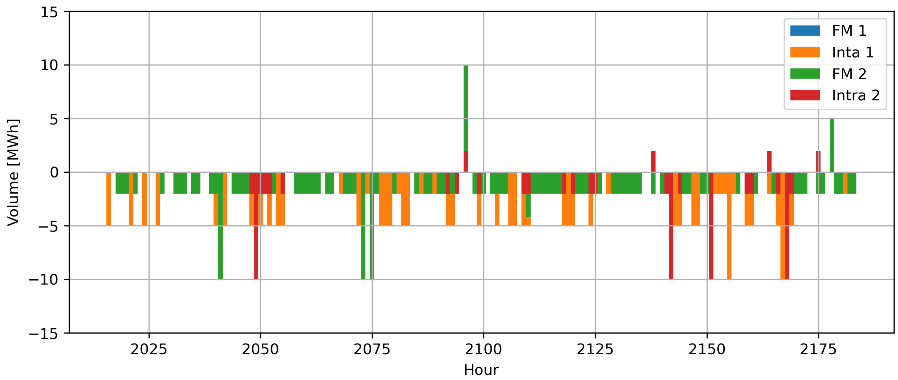


Figure 5.29: Cleared volumes in all four markets for agent 6 during week 13. Like agent 5, this agent almost exclusively buys back power. Nevertheless, other markets are prioritized instead of the first intraday market.

Bids submitted to intraday 1 and FM 2

We have also visualized the bidding strategies of the six agents in the first intraday market and the second flexibility market using bubble charts. In these charts, the size of each bubble corresponds to the frequency with which the agent chose the volume combination represented by the bubble.

The charts presented depict two out of the four markets, resulting in a partial representation of the bidding strategies and the loss of some information. However, these charts provide a comprehensive overview of the agents' bidding strategies throughout the year, without being restricted to specific weeks like the previous graphs. It is important to note that these charts display the bids submitted to the market, rather than the cleared volumes showcased in the previous graphs.

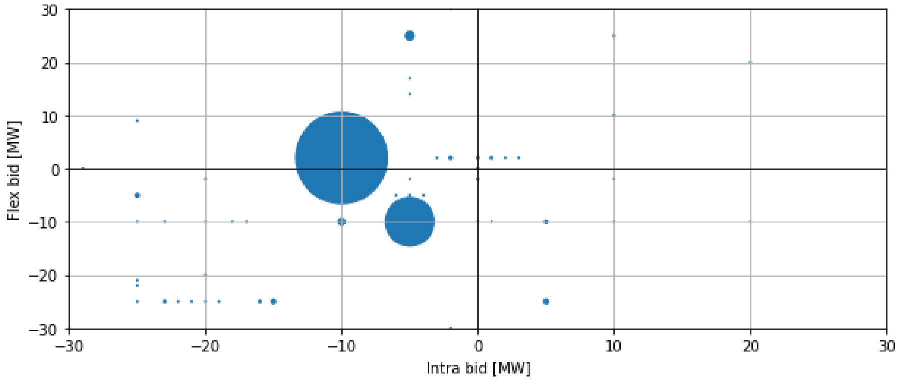


Figure 5.30: The bidding patterns of agent 1 in intraday 1 and FM 2. The main strategy corresponds well with the pattern in Figure 5.16.

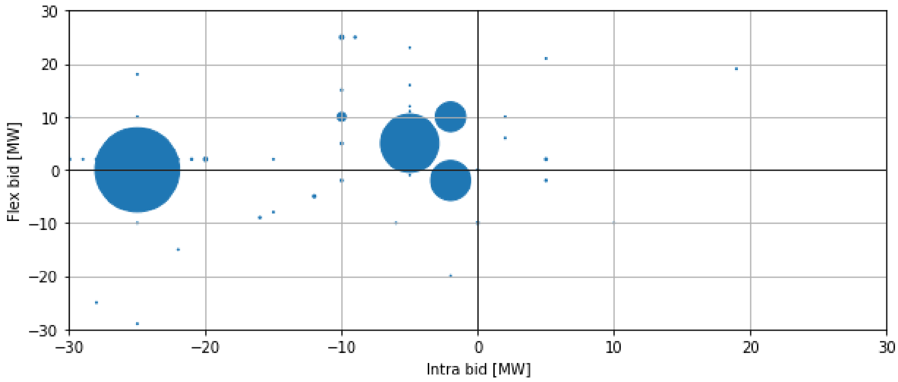


Figure 5.31: The bidding patterns of agent 2 in intraday 1 and FM 2. Figure 5.17 illustrated that agent 2 relies more on FM 1 than FM 2. Consequently, it is important to consider that the strategy depicted in this chart may present a less representative picture of the overall strategy. Nevertheless, it shows that the agent may choose strategies that correspond to strategy 1 or 3 as well.

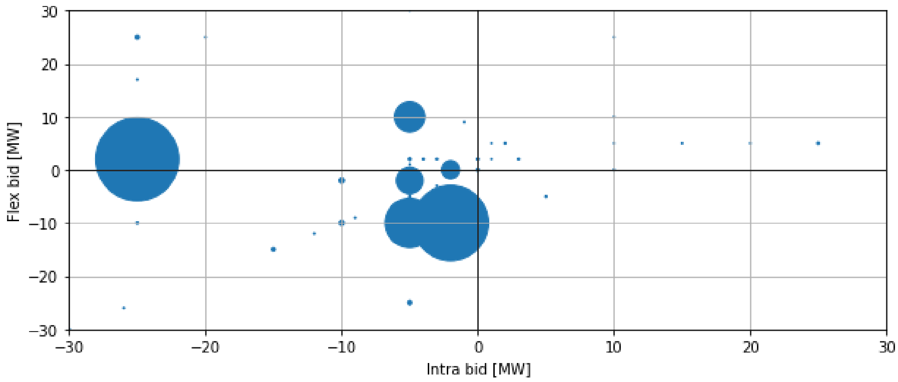


Figure 5.32: The bidding patterns of agent 3 in intraday 1 and FM 2. It shows how the agent often chooses strategy 1 and/or 3, but that it may also choose to sell in the FM.

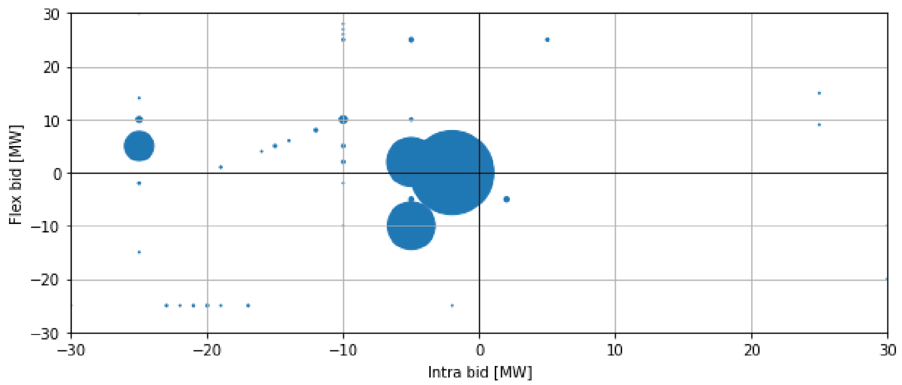


Figure 5.33: The bidding patterns of agent 4 in intraday 1 and FM 2. The main bidding pattern corresponding well with Figure 5.27.

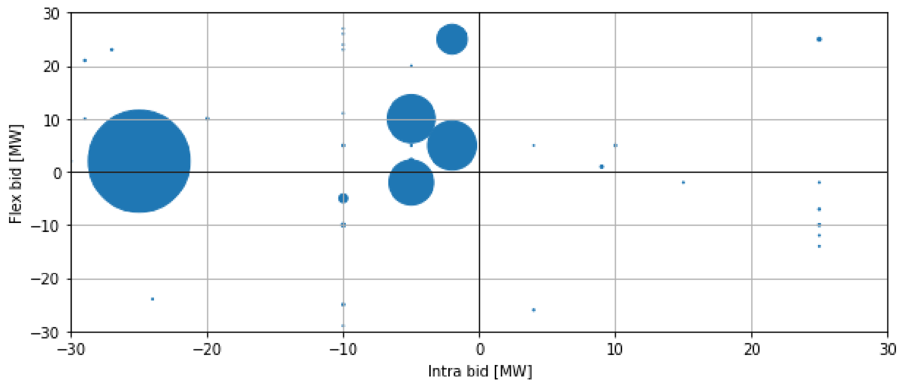


Figure 5.34: The bidding patterns of agent 5 in intraday 1 and FM 2. Interestingly, it clearly utilize strategy 1 and/or 3, but that fact is not displayed in Figure 5.28. That is most likely because the sell bids in FM 1 are not cleared for that week, as the other bid patterns also involve participating in FM 1.

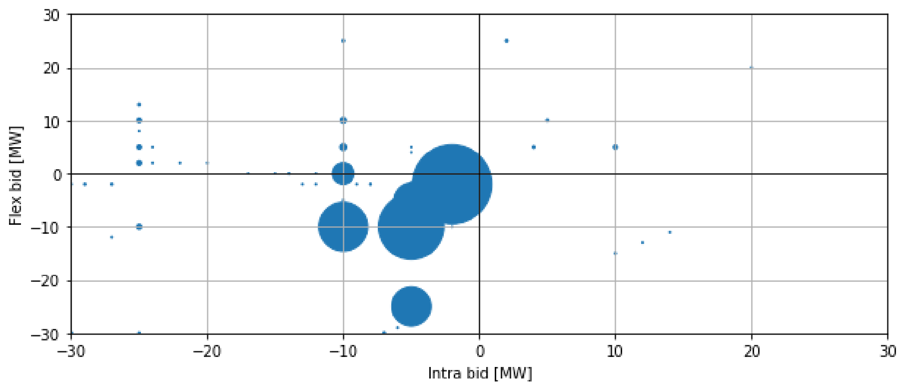


Figure 5.35: The bidding patterns of agent 6 in intraday 1 and FM 2. Unlike other agents, agent 6 does not demonstrate clear indications of employing strategy 1 or 3.

Chapter 6

Concluding remarks

In this thesis, we have conducted an investigation into zonal FMs, both comparing it to other market designs and analyzing its integration into the current power market framework. This investigation was developed in the form of two research papers.

The first paper presented the design of the zonal FM and modelled its performance in comparison to two additional cases. The primary objective of this market design is to ensure liquidity and other advantages by aggregating nodes into zones, while also representing the grid more accurately through dynamic zonal partitioning, as opposed to a static zonal allocation. Our findings indicated that the zonal FM performs closely to its nodal counterpart and achieves a 7.9% reduction in CM costs compared to conventional redispatch. Through a sensitivity analysis, we demonstrated that the performance of the market design is influenced by congestion levels, zonal allocation, and the availability of flexibility assets.

However, despite the zonal FM's close performance to the nodal market design, we observed a loss in economic efficiency associated with the zonal approach. This outcome is theoretically expected since zonal pricing overlooks intra-zonal line constraints, making it practically impossible to achieve optimal dispatch. Nonetheless, other considerations, such as market liquidity, vulnerability to gaming, and arbitrage opportunities, may outweigh this disadvantage. However, these considerations were beyond the scope of the first paper and require a more comprehensive modelling framework to assess.

In the second paper, we addressed practical challenges that arises when implementing a FM within the existing power market structure, specifically focusing on strategic bidding. While extensive research has been conducted on strategic bidding in DA markets and redispatch markets, the investigation of strategic bidding in intraday markets and FMs represents a novel and unexplored research direction within the literature. To tackle this research gap, we constructed a pooled intraday market where bids were derived from historical data obtained from the continuous intraday market. Furthermore, we simulated the dynamic interactions between this market and a zonal FM by implementing a multi-agent reinforcement learning algorithm. Specifically, our algorithm, based on the well-established Q-learning framework, enabled a subset of market participants to deviate from their marginal cost bids and underwent training to optimize their bidding strategies.

By employing the reinforcement learning algorithm in our study, we have effectively demonstrated the existence of significant strategic opportunities for the agents, encompassing both gaming and arbitrage strategies. These findings underscore the effectiveness of the framework presented in the second paper in identifying strategic opportunities within power markets. Although a considerable portion of these opportunities can be realized through strategic bidding in the intraday market alone, our results reveal a noteworthy 27% increase in agents' payoffs when they also engage in strategic bidding in the FM. Moreover, our analysis reveals how the presence of arbitrage opportunities between the DA and intraday markets contributes to a higher degree of price convergence between the two markets as the agents adopt strategic behaviors.

The modelling frameworks and assumptions employed in this thesis possess certain limitations that must be acknowledged. In the first paper, the costs utilized for generating flexibility bids were purposefully designed for the study and do not directly align with actual MCs associated with the underlying technologies. This limitation arises due to the lack of easily accessible data regarding these costs. Additionally, we made the simplifying assumption of a uniform cost for conventional redispatch, which was set equal to the average observed balancing price premium during the studied weeks. However, it is important to recognize that this approach oversimplifies the variability of redispatch costs over time. Furthermore, it is likely that the cost of redispatch is lower than the balancing premium, as there is more time for planning in redispatch operations compared to balancing operations.

In the second paper, the assumptions concerning flexibility costs exerted an influence on the results, as a price difference between the FM and intraday markets was frequently observed, thereby encouraging strategies that capitalize on this arbitrage opportunity. Additionally, the reward functions utilized to calculate agent payoffs mostly rely on the DA price, thereby fostering strategies that exploit price differentials between these markets. Consequently, it is crucial to acknowledge that our findings do not establish the absolute effectiveness of these strategies. Rather, they indicate the feasibility of these strategies and their potential to enhance profits for strategic agents under specific conditions.

Despite the inherent challenges and complexities, our research indicates that a zonal FM can achieve performance levels comparable to those of a nodal FM, given specific market conditions. This finding underscores the viability and effectiveness of the zonal FM design proposed in the first paper. Moreover, our study has contributed a novel framework for investigating the intricate dynamics between different FM designs and the intraday market in the presence of strategic participant behavior. Applying this framework to the zonal FM design presented in the first paper, we have conducted an in-depth examination of the market's behavior by analyzing one year of historical data. This analysis has revealed noteworthy findings pertaining to arbitrage opportunities and gaming, shedding light on the complexities and vulnerabilities associated with the interaction between FMs and the intraday market.

The findings from our study open up several avenues for further investigation in this field. Future work could focus on:

- Constructing a more sophisticated zonal partitioning algorithm specifically tailored to FMs, where the optimal number of zones is determined based on congestion levels and availability of flexibility.

- Implementing a nodal FM in the reinforcement learning framework to assess how arbitrage and gaming opportunities compare to a zonal FM.

- Refining the assumptions underlying flexibility costs and the reward function within the reinforcement learning framework to obtain a more accurate assessment of the effectiveness of various bidding strategies.

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