Stine Morberg Larsen and Amanda Njøten

Optimal Resource Allocation and Pricing for Distributed Demand-Side Flexibility Services

Master's thesis in Energy and Environmental Engineering
Supervisor: Jayaprakash Rajasekharan
June 2021

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Abstract

The increasing share of renewable energy will significantly challenge the stability and reliability of power systems as balancing generation and consumption becomes more difficult. As a result, there is a growing interest in exploiting the demand-side flexibility to mitigate imbalances in the grid, and in particular, the use of residential flexibility services procured through an aggregator. Since participating in a flexibility program can cause inconvenience for the end-users, the aggregator needs to provide financial incentives to encourage them to participate. It is therefore necessary to establish an allocation algorithm that ensures user preferences and technical constraints, as well as a pricing mechanism that is considered fair to both the aggregator and end-users for residential flexibility to be realized. This thesis investigates the allocation feasibility and economic viability of residential flexibility from the perspective of an aggregator, assuming that the buyer of flexibility is a Balance Responsible Party (BRP).

A method is proposed for the optimal allocation of residential flexibility sources from a portfolio of batteries, curtailable, regulatable, and shiftable loads in response to a flexibility request, which takes into account user preferences and technical constraints. Then, a novel pricing mechanism with three different pricing strategies is developed to find a price range within defined bounds that ensures a profit for both the aggregator and the end-users. The strategies are used to test and analyze the profitability for an aggregator and end-users. Strategy 1 assumes uniform prices bounded by existing power market prices in each quarter of the day. The same is assumed for Strategy 2, but with individual prices for each source. Strategy 3 assumes uniform prices for all sources bounded by heuristically determined fixed bounds of 0 NOK/kWh and 100 NOK/kWh in each quarter of the day.

An optimal schedule is determined for each day of the week, and the results show that shiftable sources and batteries provide the most flexibility but benefit the least. This suggests that it is fairer to differentiate flexibility prices for each source type. A feasible price range is found to exist only for three days of the simulated week with Strategies 1 and 2 but found to exist for all seven days with Strategy 3. The results show that the aggregator's profit increases when individual prices are allowed compared to uniform prices, and it increases further when prices are constrained by fixed values independent of existing power market prices. In conclusion, this thesis shows that bounding the flexibility prices based on the existing power market prices is profitable for both the aggregator and end-users. However, future research on the pricing of residential flexibility services should incorporate measures of fairness and explore how prices can be set based on additional parameters, taking into account social and behavioural aspects.

Sammendrag

Den økende andelen fornybar produksjon vil utfordre kraftsystemenes stabilitet og pålitelighet, ettersom balansering av produksjon og forbruk blir vanskeligere. Som et resultat er det en økende interesse for å utnytte etterspørselssiden for å redusere ubalanser i nettet, og særlig for bruk av fleksibilitetstjenester i boliger som tilbys gjennom en aggregator. Siden deltakelse i et fleksibilitetsprogram kan forårsake ulempe for sluttbrukerne, må aggregatoren gi økonomiske insentiver for å oppmuntre dem til å delta. Det er derfor nødvendig å etablere en allokeringsalgoritme som sikrer brukerpreferanser og tekniske begrensninger, samt en prismekanisme som anses som rettferdig for både aggregator og sluttbrukere for at forbrukerfleksibilitet skal bli realisert. Denne avhandlingen undersøker allokeringsgyldigheten og den økonomiske levedyktigheten til forbrukerfleksibilitet fra en aggregator's perspektiv, forutsatt at kjøperen av fleksibilitet er en balanseansvarlig part (BRP).

Det foreslås en metode for optimal tildeling av forbrukerfleksibilitetskilder fra en portefølje av batterier, reduserbare, regulerbare og skiftbare laster i respons på en fleksibilitetsforespørsel som tar hensyn til brukerpreferanser og tekniske begrensninger. Deretter utvikles en ny prismekanisme med tre forskjellige prisstrategier for å finne en prisrekkevidde innenfor definerte rammer som sikrer fortjeneste for både aggregatoren og sluttbrukerne. Strategiene er brukt for å teste lønnsomheten til aggregatoren og sluttbrukerne. Strategi 1 forutsetter uniforme priser for alle kilder begrenset av eksisterende kraftmarkedspriser i hvert kvarter av dagen. Det samme antas for strategi 2, men med individuelle priser for hver kilde. Strategi 3 forutsetter uniforme priser for alle kilder begrenset av heuristisk bestemte grenser på 0 NOK/kWh og 100 NOK/kWh i hvert kvarter av dagen.

En optimal tidsplan er bestemt for for hver ukedag og resultatene viser at skiftbare kilder og batterier levere mest fleksibilitet, men er de minst lønnsomme. Resultatene indikerer at det er mer rettferdig med forskjellige priser for hver kildetype. En gyldig prisklasse eksisterer for den optimale tidsplanen for tre av syv simulerte dager med strategier 1 og 2, og for alle dager med strategi 3. Resultatene viser at aggregatorens profitt øker når individuelle priser er tillatt sammenlignet med uniforme priser, og den øker ytterligere når prisene er begrenset av faste verdier uavhengig av eksisterende kraftmarkedspriser. Avslutningsvis viser denne oppgaven at avgrensning av fleksibilitetsprisene basert på eksisterende kraftmarkedspriser er lønnsomt for både aggregatoren og sluttbrukerne. Imidlertid bør fremtidig forskning om priser på forbrukerfleksibilitetstjenester omfatte tiltak for rettferdighet og utforske hvordan prisene kan settes basert på tilleggsparametere, med tanke på sosiale og atferdsmessige aspekter.

Preface

This master's thesis is written in the spring of 2021 for the Department of Electric Power Engineering at NTNU and in association with the FME NTRANS project. Several people need to be thanked in the completion of this master's thesis. First, we would like to thank our supervisor Jayaprakash Rajasekharan for his dedication, feedback and motivation. We would also like to thank the PhD student Kasper Emil Thorvaldsen for his valuable help in Python. A special thanks are also addressed to the PhD student Surya Venkatesh for helpful insights and suggestions for improvement during the completion of the thesis.

Although this year has been different due to the ongoing pandemic, we would like to thank our classmates and friends for their support and fun during the process. Finally, we would like to thank each other for a great cooperation throughout this year.

Thank you.
Stine and Amanda

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Abbreviations

aFRR	Frequency Restoration Reserve
BRP	Balance Response Party
CPP	Critical Peak Pricing
CPR	Critical Peak Rebates
DR	Demand Response
DSO	Distribution System Operator
EV	Electric Vehicle
FCR	Frequency Containment Reserve
HP	Heat Pump
HVAC	Heating, Ventilation and Air-Conditioning
LFM	Local Flexibility Market
mFRR	Tertiary Reserves
PV	Photovoltaic
RTP	Real Time Pricing
SESP	Smart Energy Service Provider
TE	Transactive Energy
ToU	Time of Use
TSO	Transmission System Operator
WH	Water Heater

1 Introduction

1.1 Background

The United Nations considers the mitigation of climate change as one of the main goals of sustainable development, along with the provision of sustainable, reliable and affordable energy for all citizens. Specifically, the European Commission has set a target for Europe to become carbon neutral by 2050 [1] and the Paris Agreement aims to limit global warming to 1.5°C [2]. Achieving these goals will require a major transformation of the global energy sector [2]. 60% of the energy-related CO_2 emission reductions required by 2050 can be met by renewable power generation combined with electrification of the transport and space heating sectors [2]. As a result, there is a growing interest in renewable energy sources [3].

Total global installed renewable energy capacity has more than doubled in the last decade [4], accounting for nearly one-third of the global installed capacity [5]. To meet the global climate goals, renewable energy sources must account for two-thirds of global energy supply [2]. However, the share of renewable generation is expected to continue to grow rapidly in the coming years. The question is therefore not whether there is a need or commitment for an energy transition, but rather how to successfully enable integration while maintaining security of supply [5, 6].

Electricity generation from renewable energy sources fluctuates according to prevailing weather conditions and is therefore intermittent, unpredictable and uncontrollable. A high proportion of electricity generation from renewable sources increases the system imbalance which leads to operational problems such as higher peaks and congestion in the power grid [7]. This increases the need for backup capacity, flexibility and ancillary services for distribution system operators (DSOs) and transmission system operators (TSOs) [2, 8]. Traditionally, imbalances have been resolved with grid reinforcements and generation side flexibility, often provided through dispatch of fossil fuels. To achieve the climate goals, fossil fuels must be phased out. Further, grid reinforcements are not considered a cost-effective solution on the way to a climate-neutral future, due to low utilization and high marginal costs [7].

With the recent development of information and communication technology, smart meters and computational advances, an alternative solution to enable the integration of renewable energy sources is the integration of demand-side flexibility [7]. Traditionally, flexibility has been offered through generation-side supply. However, uncontrollable supply from renewable energy sources makes it difficult to adjust supply in response to demand. By introducing demand-side flexibility services, demand can instead be adjusted to meet supply by consumers changing their power consumption. Under demand-side flexibility services, residential flexibility services can avoid an estimated $9 billion per year in capital costs to the U.S. grid [9]. Photovoltaic (PV) panels, batteries, Electric Vehicles (EV), Heating, Ventilation and Air-Condition (HVAC) units, and Water Heaters (WH) can be controlled to provide residential flexibility. The capacity of these sources is small compared to the flexibility needed to stabilize the grid. However, the aggregated sum represents a significant amount of flexibility.

Introducing residential flexibility will not only improve security of supply and help create efficient power markets, but will also empower consumers. One incentive to participate as a flexibility provider, besides contributing to the green shift, is the reduction of energy costs. The future energy system is fully decentralized and digitized, and digital market platforms enable all stakeholders to trade energy [6]. The importance of a fair energy transition that creates growth and secures benefits for all citizens is emphasized by the European Commission [10]. Active participation in local, regional and continental energy markets will allow energy prices to be set at an economic optimum [6]. This can further alleviate energy poverty, protect vulnerable citizens, and improve the quality of economy and life for consumers [10].

1.2 Motivation

Residential flexibility is a promising solution to mitigate imbalances caused by large-scale renewable energy integration and can improve market efficiency as well as provide both economic and social benefits to consumers [11, 12]. Previous research has demonstrated that flexibility trading can be successfully implemented in existing power markets or through new, separate markets for flexibility [13–16]. However, the current grid operation rules and regulatory frameworks need to be updated before flexibility can be fully implemented. In addition, there are several potential buyers of flexibility. Since the buyers operate in different markets and want to utilize flexibility for different purposes, there is no straightforward way to determine a common framework that realizes the integration of flexibility trading in existing power markets.

Although residential flexibility sources are highlighted as promising sources for providing demand-side flexibility services, they have very low power ratings compared to what is needed to stabilize the grid. Therefore, it is established in the literature that there is a need for aggregation of several sources [12, 17]. This motivates the creation of new actors, such as aggregators, which are suggested to possess a portfolio of residential flexibility sources to activate upon request from flexibility buyers. To meet the flexibility request, the aggregator must quantify the available flexibility and allocate sources in a cost-efficient manner. Quantifying the available flexibility is challenging, as user preferences and occupant behaviour play a major role [18–21]. Furthermore, resource allocation is challenging as the aggregator cannot allocate sources optimally without knowing the price of flexibility. To date, there are few studies that have investigated the relationship between optimal allocation and pricing of flexibility services.

Generally, prices are determined using classical market clearing, marginal cost analysis, or opportunistic cost analysis. Although some research has been conducted on how to price flexibility based on these approaches [22–24], there is still very little scientific understanding of how to take each sources' unique marginal costs into account in the computation. As a result, none of these methods can currently be used to determine a price for flexibility and there is no definitive framework from an operational perspective that ensures the economic viability of an aggregator.

The aggregator receives payments from flexibility buyers to provide the requested flexibility. To create an incentive for end-users to participate as flexibility providers, the aggregator has to pay for the flexibility services provided by the end-users. The price for flexibility is the price the aggregator pays the end-users. A common understanding is that flexibility the price must provide sufficiently high financial incentives to motivate the end-users to change their consumption [25]. Participating in flexibility programs can cause inconvenience in the form of reduced comfort for the end-users [21]. That is reduced comfort in terms of indoor temperature, freedom of driving range and increased wear and tear on flexibility devices [21, 26, 27]. Consequently, the pricing of flexibility is not only a matter of economics, but also a behavioural and technical issue. While some research has been conducted on the fairness of flexibility pricing, a mechanism by which the profit is equitably divided among contributing providers is yet to be established

[28–30]. Therefore, establishing a pricing scheme that satisfies all participants and is considered fair is highlighted as one of the major challenges with the implementation of flexibility services.

1.3 Scope of Work

The goal of this thesis is to facilitate the implementation of residential flexibility. This work examines both the allocation and pricing of residential flexibility services, as they are closely related. While previous studies have analyzed the opportunities and benefits of residential flexibility, this thesis examines the pricing and profitability of residential flexibility services.

To address the problem of quantifying flexibility, relevant operational parameters, and user preferences for quantifying flexibility in residential buildings are identified through a literature review. Based on the identified parameters, flexibility is allocated in response to a flexibility request from a BRP. The allocation is done through a scheduling model that optimally allocates flexibility sources from an aggregator's portfolio with the objective of minimizing the aggregator's cost. The lowest existing power market price in each hour is taken as input to the allocation model.

Traditional methods of price determination cannot yet be applied for flexibility services. However, one implementation-ready solution for determining a price for flexibility is to set the price at the level of existing power market prices. In the Nordic power market there are three levels of existing market prices: spot price, intraday price and balancing prices. This thesis, therefore, assumes that the buyer of flexibility is a Balance Responsible Party (BRP) responsible for imbalances in the grid. Further, this thesis creates a pricing mechanism that finds a price range within defined bounds that ensures a profit for both the aggregator and end-users. This pricing mechanism is used to investigate the profits for the aggregator and end-users through three different pricing strategies. In the first strategy, uniform prices are found, constrained by existing power market prices in each quarter. The same is assumed for Strategy 2 but with individual prices for each source. In the third strategy, uniform prices are found that are bounded by fixed values in each quarter.

To address the inevitable problem of fairly determining a price that satisfies both the aggregator and the end-users, this thesis uses an economic approach to determine a fair price for flexibility. From a simplified game theory perspective, it can be argued that the price for flexibility is fair as long as profit is guaranteed for all participants. Therefore, this thesis investigates whether a range of prices that guarantees a profit for both the aggregator and end-users can be found.

The main research questions for this thesis are formulated as follows:

> *How can an aggregator optimally allocate flexibility sources in response to a flexibility request subject to user preferences and technical constraints? How can an associated feasible price range be found that guarantees a profit for both the aggregator and the end-users when the buyer of flexibility is a BRP?*

1.4 Contributions

This thesis contributes to the transition to the future power system by improving the state of the art in pricing of residential flexibility. A model for allocating residential flexibility sources and a novel pricing mechanism are proposed. The models are verified through simulations. The results demonstrate the allocation feasibility and viability of residential flexibility services. The results imply that an individual pricing mechanism is better for the aggregator than a uniform pricing mechanism, as this increases the aggregator's profit. The results also imply that restricting flexibility prices to fixed prices independent of the existing power markets can further increase the aggregator's profit. The contributions of this thesis can be summarized as follows:

- An optimization model that minimizes the cost of an aggregator by optimally allocating flexibility sources from a portfolio of batteries, curtailable, regulatable, and shiftable sources in response to a request from a BRP, taking into account user preferences and technical constraints.
- A novel pricing mechanism that determines a price range for the computed optimal schedule that ensures profit for both the aggregator and end-users when the price range is constrained by a lower and upper bound.

1.5 Thesis Outline

The contents of this thesis are structured as follows. Chapter 2 provides an extensive literature review on possible setups for flexibility markets and pricing mechanisms for flexibility services. In addition, the necessary theory about the Nordic power market and pricing is presented. Chapter 3 describes the optimization method used to find an optimal schedule and the price mechanism used to find price ranges for flexibility. Chapter 4 presents the results obtained from the simulations. Chapter 5 discusses the results and their implications, and suggests improvements and perspectives for future work. Finally, conclusions are drawn in Chapter 6.

2 Background

To answer the research question of fairly determining a flexibility price that satisfies both the aggregator and the end-users, a comprehensive literature review is conducted. This chapter includes the theory and concepts on which this thesis is built upon. The concepts of flexibility provision are presented along with an explanation of existing market structures and allocation methods. In addition, this chapter includes a literature review of how the prices are set in different markets to provide a deeper understanding of what the work in this thesis builds upon.

2.1 Introducing Flexibility

The share of renewable generation is expected to increase rapidly in the coming years in response to the climate targets. This will significantly challenge the stability and reliability of power systems, as balancing generation and consumption becomes more difficult [31]. DSOs and TSOs strive for stable generation, making off-peak and on-peak periods undesirable. Intermittent generation from renewable energy sources causes large fluctuations in voltage, frequency and current. This is a challenge for grid operators, who are responsible for ensuring stability and reliability by balancing generation and demand to keep system voltage, frequency and current within safe operating limits [32].

Traditionally, grid operators have relied on grid reinforcement and bulk power generation resources providing flexibility to keep the grid stable [11, 31]. Upgrading cables, transformers and capacitor banks alleviates overload problems and voltage fluctuations [11]. However, these components are capital-intensive and have low utilization, causing high marginal costs and time-consuming replacements [7, 31]. As a result, there is an increasing interest in exploiting the demand side to provide flexibility to the grid.

The introduction of demand side flexibility from residents is enabled by the development of communication and control technologies [7]. Residential flexibility is extracted by reshaping the consumers' demand profile. More specifically, CEN, CENELEC and ETSI define flexibility as the modification of generation injection and/or consumption patterns in response to an external price or activation signal [33]. The implementation of residential flexibility can help to balance supply and demand [12], reduce voltage fluctuations and defer grid reinforcements [11]. In addition, the implementation can help reduce CO_2 emissions and reduce the energy costs for end-users.

2.2 Provision of Flexibility

Promising sources for providing flexibility include water heaters, HVAC-units, electric vehicles, home batteries and PV panels. These sources are well suited because they can provide flexibility without significantly compromising the end-user's comfort. More specifically, water heaters and HVAC units can be interrupted or regulated for short periods [34] and charging of EVs and batteries can be shifted from one period to the next without causing discomfort for the end-users [15, 35]. As the capacity of these sources is small compared to the flexibility required to stabilize the grid, the aggregation of multiple sources is necessary [17, 36]. This has motivated the establishment of aggregators in the power markets. The role of an aggregator is to create a portfolio of multiple sources of flexibility while manage and operate the consumption of multiple end-users, to offer flexibility on behalf of the end-users [13, 25, 35, 37].

However, user preferences and occupant behaviour play a major role in how much flexibility the aggregator can retrieve at different times [18] and are therefore highlighted as important factors in quantifying flexibility [18–21]. Parameters that quantify the available flexibility are often referred to as activation parameters, which can be further divided into user preferences and technical constraints. Parameters ensuring that the end-user's comfort limits are not exceeded include a minimum run time and a minimum pause time. These should be implemented to account for the time it takes for the source to return to the initial state [18, 26, 38, 39]. Technical constraints that prevent damage due to rapid switching can be ensured by setting a maximum number of allowed activations allowed [40–43]. All of the above mentioned factors must be considered when the aggregator quantifies how much flexibility it can offer to the buyers.

Aggregators create value by providing flexibility services to buyers of flexibility [25]. Potential buyers of flexibility are BRPs, DSOs and TSOs [25]. The buyers request flexibility either as upward or downward regulation. From the aggregator's point of view, up-regulation can be provided by reducing the end-users' consumption, while down-regulation entails an increase of consumption [20, 27, 35]. The aggregator shares the profit made from providing upward and downward regulation with the end-users, as an incentive for them to provide flexibility [25, 36]. To determine the market or customer remuneration for providing flexibility, a baseline must be estimated and compared to the actual load. The baseline is the estimated amount of energy a unit consumes when no flexibility is activated [44]. To properly agree on the availability [44], price and volume [45], a suggested method is to sign bilateral contracts between aggregator and end-users [44].

With the most relevant parameters for quantifying flexibility established, the next step towards determining an optimal allocation program and a pricing mechanism for flexibility is to find an appropriate market architecture for trading of flexibility. Flexibility trading can be integrated into the existing power markets, or new, separate markets for flexibility trading can be created. Both options are presented in the following sections.

2.3 Integrating Flexibility into the Existing Nordic Power Markets

Several papers propose to integrate flexibility trading into the existing power markets [13, 14, 22, 35, 46]. The power markets facilitate trading of electricity and ensure that the most economical power dispatch is achieved. This section provides an introduction to the Nordic power markets and gives an overview of trading flexibility in these markets.

2.3.1 Introduction to Nordic Power Markets

The Nordic power markets consist of the day-ahead, intraday and balancing markets as shown in Figure1. To assess how flexibility trading can be integrated into these markets, an overview of the day-ahead, intraday and balancing markets is provided.

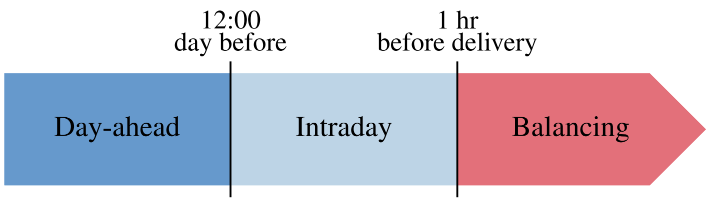


Figure 1: Time horizon of trading in the Nordic power market. The figure is based on a figure from [47].

Day-Ahead Market

The day-ahead market allows energy to be traded one day in advance of energy delivery, which provides the predictability needed by some large generating units [48]. In the day-ahead market, participants can buy or sell energy for the next 24-hour period through closed auctions. Bids can be submitted for the consecutive day until 12:00 noon [49]. The market is cleared to maximize social welfare and grid constraints are taken into account. The resulting clearing prices are published daily at 12:42 [49]. The physical volume traded in the day-ahead market constitutes the majority of energy traded in the power market [45]. On an annual basis, approximately 500 TWh is traded on the Norwegian day-ahead market [49].

Intraday Market

Trading in the intraday market allows the portfolio of generating units to be adjusted after the day-ahead market is cleared [48], allowing trading closer to operating hours [45]. The intraday market opens three hours after the day-ahead market closes [50]. Market participants can trade up to one hour before the production hour. 15-minute, 30-minute, hourly and block products are available for trading [50].

Balancing Market

Balancing markets provide the last opportunity to reduce imbalances and are used to balance generation and consumption as close as possible to operating hours [48]. Balancing markets are intended to provide security of supply at the lowest possible cost and reduce the need for back-up generation [51]. Ancillary services are traded on the balancing market and include a variety of functions necessary for the quality of electric supply [52].

Any power deficit or surplus immediately leads to a deviation from the nominal frequency of 50 Hz [53]. Balancing reserves are part of the ancillary services and are implemented to limit this deviation and restore the frequency to 50 Hz. Since the purpose of flexibility is to alleviate power imbalances, it is important to have an overview of the balancing reserves. Based on the response time, the balancing reserves are divided into primary (FCR), secondary (aFRR) and tertiary (mFRR) reserves. The primary reserve is responsible for immediate response to frequency imbalances and must be able to respond within seconds [52]. Secondary reserves are activated within minutes and tertiary reserves must be able to respond within 15 minutes [52]. Tertiary reserves are traded in the regulation capacity market [13]. Figure 2 shows the concept of balancing reserves.

In Norway, the balancing market is operated by the TSO. Balancing Service Providers offer balancing services to the TSO, which the TSO uses to balance the system frequency [54]. After the balancing market closing time, settlement is determined on the basis of marginal prices. Starting with the lowest price, bids are accepted until the required reserve is provided. The marginal price represents the price of the last bid activated to cover the required energy [54].

Two Price Model: BRPs are financially responsible for imbalances in their portfolios and any deviation from their production plan must be accounted for [54]. The two-price model is used to set the price for production imbalances, which implies that different prices are set for positive and negative production imbalances. A positive production imbalance implies that the BRP produces more than foreseen in the

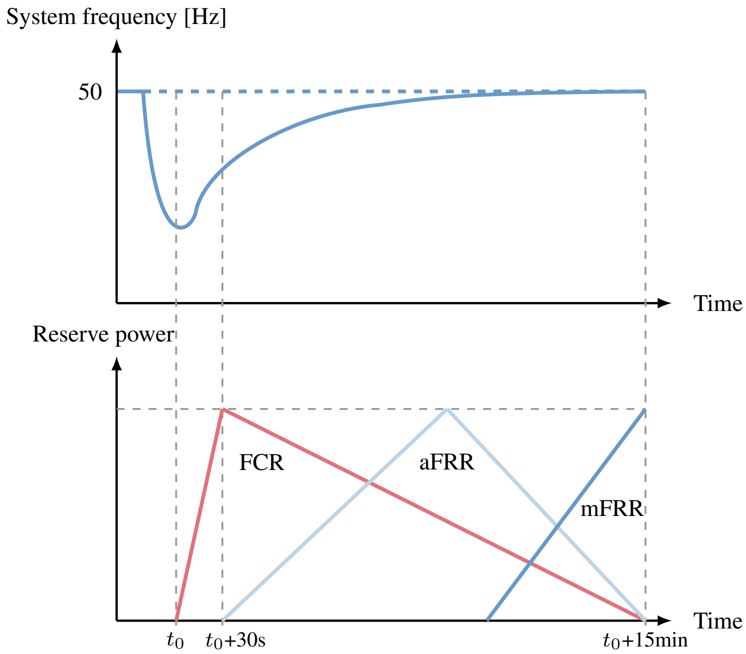


Figure 2: Required time response of the balancing reserves. The top figure shows a deviation from the nominal frequency of 50 Hz. The lower figure shows how the three balancing reserves react. The figure is based on a figure from [53].

original plan. In this case, the BRP must sell the surplus to the balancing market. A negative production imbalance occurs when the BRP produces less than planned. In this case, the BRP has to purchase the deficit from the balancing market. The price for a volume imbalance depends on the direction of the imbalance and the overall regulation direction of the delivery hour [55]. Table 1 summarizes the price setting of imbalances.

Table 1: Imbalance prices for different regulation directions, defined from the Two Price Model.

Regulation direction	Negative production imbalances	Positive production imbalances
Up regulation	Up regulation prices	Day-ahead spot price
Down regulation	Day-ahead spot price	Down regulation prices
No direction	Day-ahead spot price	Day-ahead spot price

Upward regulation prices are always greater than the spot price, and downward regulation prices are always lower than the spot prices [55]. The regulation direction is the direction in which the most energy was regulated in the respective hour (upward, downward, or no direction).

2.3.2 Trading Flexibility in the Existing Power Markets

It is necessary to adapt the regulatory framework to include new market participants such as aggregators, in order to efficiently integrate flexibility trading into the power market. An aggregator manages the flexibility and financial interactions between local energy systems and the market [46]. The objective of the aggregator is to maximize profit [35, 46] or to minimize the total cost of providing flexibility [13]. The aggregator's total cost depends on the daily price variations and the available flexibility in its portfolio [13]. When considering day-ahead trading, the objective is to allocate the most economic set of consumer flexibility sources over the next 24 hours [22]. During the time interval when the day-ahead market is open and accepting bids, the aggregator can estimate the available flexibility in its portfolio and place bids.

Price-dependent one-hour bids in the day-ahead market have been identified as best suited for bidding flexibility in the Nordic power market [13]. If the aggregator also participates in the regulation capacity market, the bid price reflects the activation costs of a reserve [13]. The study also demonstrated that the value of the aggregator largely depends on intra-day price variations and the available flexibility [13]. In most cases, a mix of load reductions on the spot market and the regulating reserve market has proven to be optimal, which illustrates the importance of considering both market types for an aggregator [13].

A study conducted in the Iberian power market in 2009 and 2010 demonstrated that participation and trading of flexibility in wholesale power markets is economically attractive for an aggregator [14]. In particular, participation in the secondary downward reserve market shows a negative cost that could increase the aggregator's competitiveness in the power market [14]. However, the need for advanced forecasting algorithms is highlighted to optimize the aggregators' participation in the day-ahead market [14]. Another paper also highlights bidding in the day-ahead market as a challenge due to uncertainties, including intermittent generation and the day-ahead market price [46].

2.4 New Markets for Trading of Flexibility

Another way to facilitate the integration of residential flexibility is to create new, separate markets for trading of flexibility services [56]. Different market structures can be characterized to meet different needs [17]. These markets are proposed as local markets, which makes them well suited to solve local problems where they occur. Elaborated, this means that distribution imbalance issues can be solved on a smaller, local scale. Local flexibility market (LFM) and distribution level flexibility markets are some of the proposed market architectures for flexibility trading.

2.4.1 Local Flexibility Markets

Several papers have considered the implementation of a local flexibility market [15–17, 44, 56]. The main purpose of implementing a LFM is to provide a trading platform to buy and sell flexibility from end-users in a regional scope [15, 17, 44]. Local flexibility markets are a complement to the traditional power market, not a substitute [16]. The implementation of LFMs is recognized as a promising tool to reduce costs, effectively manage demand response (DR) and support the development of smart grids [17]. Participation in LFMs strengthens the local economy [17], and reduce the operating costs for end-users due to the remuneration offered for the provision of flexibility services [56].

As LFMs are still under development, procedures, time-frames, market roles and flexibility products are described differently in the existing literature. One paper suggests that a local flexibility market should consist of DSOs, energy suppliers, aggregators and BRPs [15].The objective of the DSO is to ensure stable grid operation at the minimum cost [15]. The BRP aims to minimize the cost of imbalance and the objective of the aggregator is to maximize the profit [15]. Since this is only one paper's suggestion of how to define a framework for LFMs, a summary of the main findings and different frameworks for flexibility trading are discussed below.

A framework proposes an LFM activation mechanism based on the traditional energy market structure consisting of day-ahead and intraday trading, in addition to real-time dispatch [15]. The main purpose of the two ahead markets is to provide a platform for trading flexibility before it is submitted to the power market. Real-time dispatch consists of a set of control actions used to solve grid problems when the two ahead markets fail. The DSO will first attempt to negotiate with aggregators and pay for flexibility. If negotiations fail, the DSO takes control and make autonomous decisions to adjust loads and generating units [15]. The method proved to be an economically efficient framework for trading flexibility [15].

Another suggestion for using local flexibility markets to solve local grid problems is to connect them with the traffic light concept [16, 57]. The traffic light concept can be used to guide interactions between market participants, focusing on using flexibility to solve distribution problems [57]. Figure 3 explains the traffic light concept.

State	Description	Action
	No critical network or market restriction exists	Flexibility is used only for market benefit. No technical problems occur when flexibility is activated
	Potential for network shortage	Flexibility is used to restore stability and can only be partially activated
	System is in danger	The DSO may override contracts, perform emergency actions, and directly control the flexibility units

Figure 3: The traffic light concept for flexibility activation. The figure shows the different grid states and the following action. The illustration is based on the concept explained in [57].

The advantages of using the traffic light concept for flexibility activation are that the DSO can evaluate and classify flexibility sources in advance. One suggestion is that local flexibility markets operate on request from the DSO when the grid is in the yellow phase, attempting to solve a predicted problem in advance [16]. A one-year simulation of a local flexibility market in the distribution grid showed advantageous in avoiding critical grid conditions [16]. The study proved that a combination of different flexibility options is more cost-effective than curtailment of a single generator [16].

A third approach presented in the literature is to consider an aggregator's possibility to satisfy a flexibility request from a DSO. The role of an agent called Smart Energy Service Provider (SESP), who serves as a new type of aggregator, is highlighted [44]. Based on the flexibility requested by the DSO, the SESP schedules flexibility sources for the entire next day. The SESP determines which sources to activate based on parameters defined in contracts between the end-users and the SESP [44]. End-users with activated sources are compensated based on an agreed sum defined in the flexibility contract [44]. The framework for enabling the DSO's requests for flexibility to be met in a local flexibility market is validated through test case simulations [44].

A flexibility market based on aggregators, where trading happens through auctions or supermarkets, also proves efficient in meeting the requests of a DSO [58]. Auctions rely on aggregators submitting bids based on the flexibility requests of DSOs [58]. In supermarket trading, the aggregator estimates the predicted flexibility that the DSO wants to buy, and the aggregator bids the forecasted flexibility at a certain price [58]. The DSO can then choose among the offered flexibility from the different aggregators [58]. The proposed framework not only provides superior benefits to the owners of distributed energy resources, but also successfully satisfies the flexibility request of the DSO [58].

2.4.2 Distribution Level Flexibility Market

A similar alternative to a LFM is a flexibility market architecture that facilitates the provision of flexibility services in a distribution network [59]. The paper proposes a market architecture that ensures compatibility with existing energy markets, market efficiency, and avoidance of strategic behaviour by market participants [59]. A flexibility market operator operates the flexibility market on behalf of the DSO with the objective of procuring the required flexibility at the lowest possible cost. The flexibility market operator takes the dispatch from the power market, information about the distribution network from the DSO and bids from flexibility providers as input [59]. Based on this, the flexibility market operator runs an optimal power flow algorithm that successfully determines the optimal dispatch, while considering active and reactive power balance, mitigation of grid congestion and accommodating voltage regulation [59]. The remuneration for flexibility providers is determined by a payment algorithm that guarantees truthful participation of players by solving a social welfare maximization problem multiple times [59]. The mechanism successfully achieves optimal and efficient flexibility provision while guaranteeing truthful participation [59]. However, requirements such as fairness, accurate distribution modeling, and scalability require further work before new distribution level flexibility markets can be implemented [59].

So far, this thesis has focused on how flexibility can be integrated into the existing power market, as well as on the creation of new flexibility markets. Both options may prove viable for flexibility implementation, but it is problematic to adapt current grid operation rules to meet the needs of both DSOs and TSOs while guaranteeing sufficient returns for new market entrants [57]. It is therefore necessary to determine how to guarantee a sufficient rate of return before implementing flexibility services. This thesis has focused on a centralized approach to flexibility activation, where an aggregator facilitates the trading of flexibility in new or existing flexibility markets. However, flexibility can also be activated via demand response programs (DR) as well as transactive energy systems (TE). Since residential flexibility has been successfully implemented via DR programs already, the following two sections present the key success factors and limitations for flexibility activation in DR and TE programs.

2.5 Demand Response

Demand response is a program established to provide incentives to end-users to change their electricity consumption at times when electricity prices are high or when the reliability of the electric grid is at risk [60, 61]. This includes altering the timing, level of instantaneous demand, or total electricity consumption [61]. To incentivize end-users to change their consumption, several reward strategies are proposed. Price-responsive DR programs reward end-users for reducing or shifting their energy consumption in response to a price signal [62]. Another option is offering incentives to end-users in exchange for participation in a top-down switching program where a system operator can manage end-users' consumption [62]. On this basis, DR programs can be divided into two main categories: incentive-based and price-based

DR [60, 61, 63]. Figure 4 shows the two main categories of demand response and their subcategories.

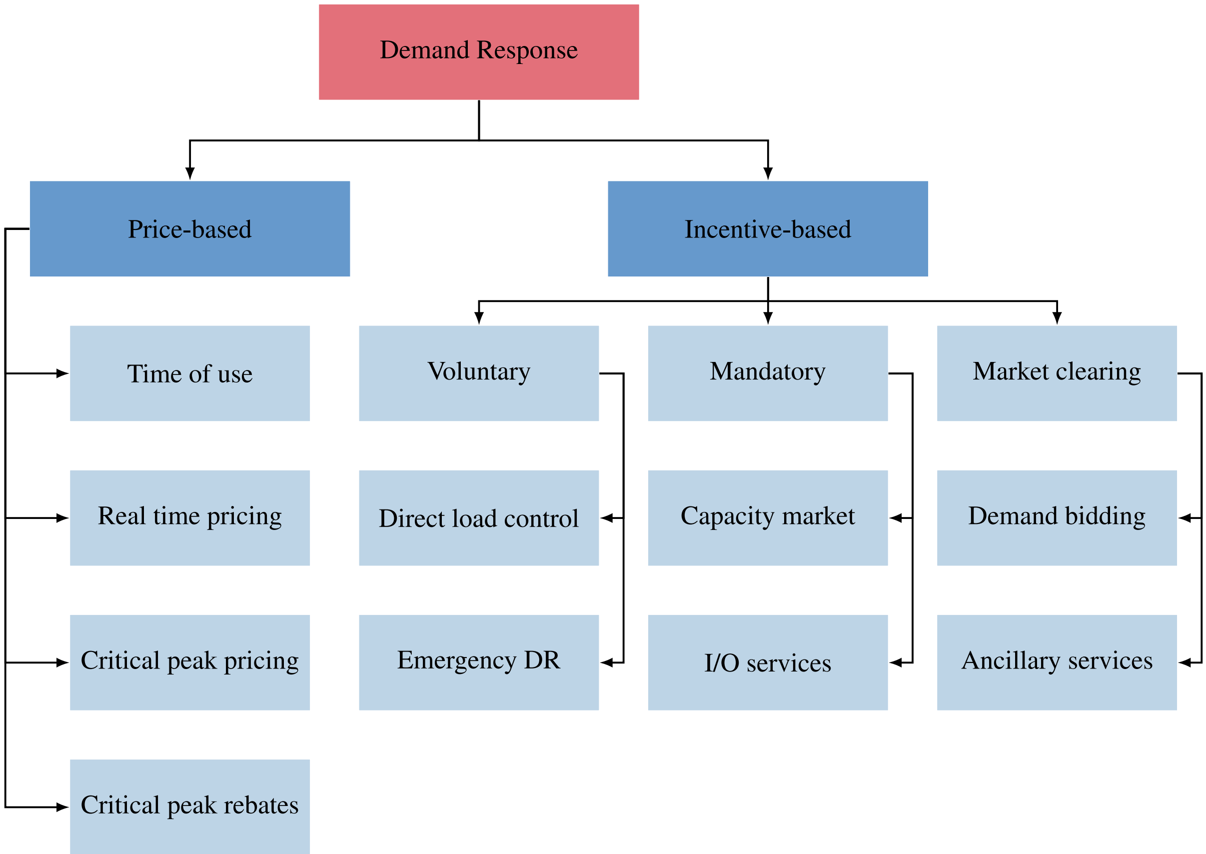


Figure 4: The two main categories of demand response: price-based DR and incentive-based DR with their following subcategories. The table is inspired from [64].

In incentive-based DR programs, end-users receive fixed or time-varying load reduction incentives [60, 65] that are separate from, or in addition to their retail electricity rate [60]. If the end-users do not respond, penalties may be imposed [60, 61]. End-users may receive participation payments in the form of a bill credit or rebate rate, upfront incentive payments, or payments for reducing their load during grid contingencies [60, 61]. Incentive-based DR programs can be voluntary, mandatory, or based on market clearing [60].

In price-based DR programs, price signals are used to induce end-users to shift their energy consumption in time [64]. The goal is to flatten the demand curve by offering high prices during peak periods and lower prices during off-peak periods [61]. The approach is based on one-way communication, where end-users respond to a price signal from the aggregator [66], which means that the modifications made by end-users are completely voluntary [60]. Various pricing schemes can be implemented, such as time of use (ToU), critical peak ricing (CPP), real time pricing (RTP), and critical peak rebates (CPR). Price-based DR programs are easy to implement in areas where the power prices are time-varying because these prices can be exploited as price signals [66]. Other advantages include low complexity and lack of privacy issues due to one-way communication. Consequently, price-based DR programs are considered more suitable for residential customers than incentive-based DR programs [65].

Several papers have investigated the efficiency of price-based DR programs to reduce system peaks and improve grid stability when price signals are broadcasted to the end-users day-ahead [67, 68]. A simulation conducted in Beijing achieved a near-perfect valley-filling of EV charging by using a decentralized valley-filling charging strategy [67]. The study created a day-ahead pricing scheme by solving a minimum cost optimization problem [67]. Similarly, a decentralized charging scheme for plug-in hybrid EVs with the objective of minimizing the overall generation costs, is found to reduce the generation costs and successfully shift most charging operations to off peak-hours [68].

An economic model is proposed that explains the response of end-users to changes in electricity prices in response to a ToU price signal [64]. The paper models the price-demand elasticity, which represents the willingness of end-users to shift consumption in response to changes in the relative price of peak and off-peak prices. The model successfully explains the willingness of end-users to shift their consumption and can therefore be implemented by utilities for setting peak and off-peak prices [64].

Concerns regarding the uncertainty of compensation may discourage customers from participating in DR programs [62]. The potential financial benefits to end-users of participating in DR programs are therefore investigated by implementing residential load scheduling algorithms in [65, 69]. A residential load scheduling framework based on cost efficiency is introduced, where cost efficiency is defined as the ratio between the electricity consumption benefit and the total cost [69]. An extension of this study proposes a residential load scheduling algorithm based on cost efficiency and end-users' preference for demand response in a smart grid [65]. The algorithm allows end-users to adjust their demand in response to price signals, taking into account their lifestyle and preferences [65]. Both studies successfully improve the the end-users' cost efficiency and demonstrate that DR programs can ensure the economic incentives necessary to encourage end-users to participate.

In most DR programs, a single price signal is applied to all end-users, regardless of the end-users' consumption or contribution to peak demand [70, 71]. This may result in low energy users getting penalized [70]. To avoid this unfairness, one proposal is to hedge the risk for end-users who do not contribute to the system peak load [71]. This is done by sending different price signals to customers who contribute to peak load and those who do not. A two-tier pricing mechanism that applies penalty price signals to consumers who contribute to the peak-demand increases their energy bills compared to the non-contributing users. Another proposed pricing mechanism to avoid unfairness for end-users is to calculate different electricity prices for each unit based on the end-user's share of total energy consumption [70]. The method is found to efficiently calculate prices based on the share of the energy consumption while keeping the net cost constant compared to the traditional uniform price signal. In summary, sending different price signals to the end-users results in a fairer distribution of compensation among end-users.

In summary, the development of DR programs can enable the implementation of residential flexibility [72]. The stability and reliability in the power grid is found to be improved, which is beneficial to both the market and the end-users [60–62]. In addition, demand response can reduce the energy costs for the end-users. However, if a uniform price signal is used, there is a risk of inequitable distribution of the compensation. Furthermore, imperfect information and competition are considered barriers to the implementation of DR [72]. DR programs ignore the consumer and do not consider user preferences [66]. However, the main drawback of demand response is the uncertainty of the aggregate response, as it depends entirely on the responsiveness of end-users [66].

2.6 Transactive Energy System

Since the introduction of DR, power systems have become much more complex [73]. Current DR models rely on many simplifications, making them less suitable for dealing with the increased complexity in the grid [64]. To cope with the rapid fluctuations in the power grid caused by the proliferation of DERs and to unleash the full potential of flexible loads, transactive energy systems are proposed as an extension of the DR framework [73, 74]. TE systems includes an energy market that enables real-time transactions of energy in a time scale of seconds [73]. Compared to the time scale of hours used in most DR programs, this results in a more stable grid, as consumers can respond immediately to changes in the grid rather than waiting for the power market prices to be updated [74].

Transactive energy is defined as the combined use of an economical control mechanism to manage the rate of consumption and generation, in order to improve grid reliability and efficiency [75, 76]. TE systems use a decentralized control where decisions are made locally and there is no direct control from outside [66, 73]. Similar to the price-based DR approach, devices are controlled based on price signals and participation is voluntary [73]. Compared to DR systems, TE is based on two-way communication, where end-users respond with anticipated consumption based on each price signal received from the aggregator [76]. Figure 5 illustrates the steps involved in DR programs and TE programs.

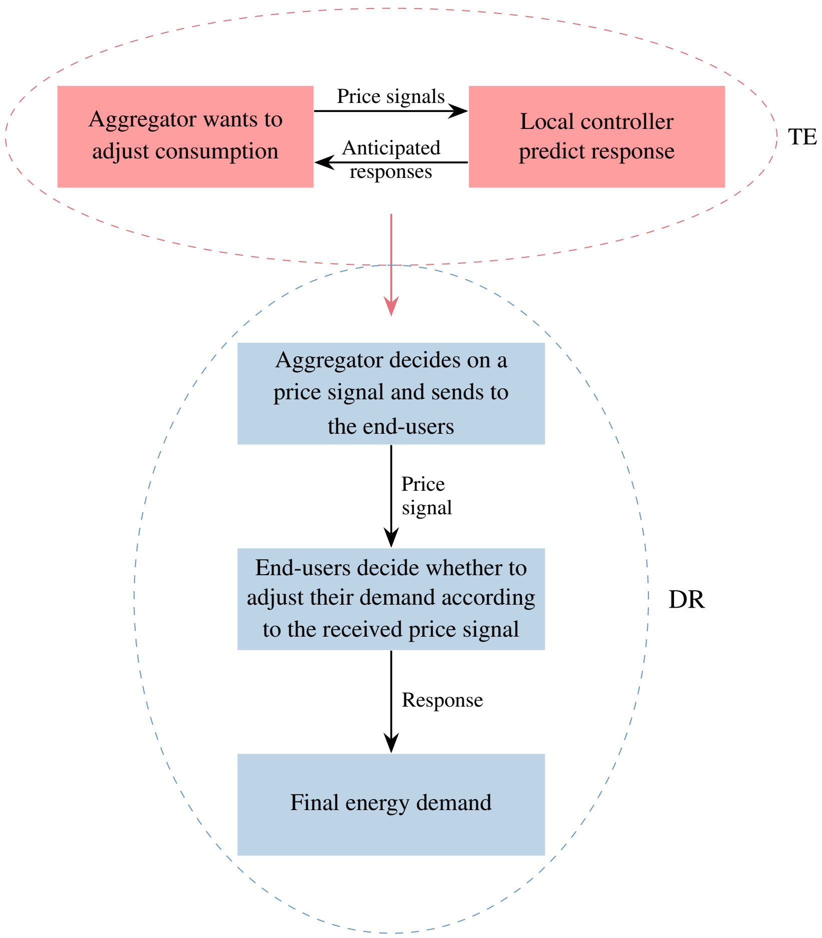


Figure 5: The differences between demand response and transactive energy systems where the upper, pink part applies only to TE systems and represents the two-way communication involved when the aggregator determines a price signal and sends it to the end-users. The lower, blue part applies to both DR and TE systems and represents the steps after the aggregator determines the price signal.

Figure 5 illustrates the principle of a local controller acting on behalf of the end-user to determine the optimal operation of the load based on the received price signals, the state of the device, and the user's preferences [66]. Based on the expected consumption of the end-user, a market mechanism determines the price such that supply and demand are properly balanced [66]. From a system perspective, transactive energy control transitions to a market-based control, where the collaboratively derived dynamic price is used as a control signal to trigger a predictable system response [66]. This differs from the uncertain response in price-based DR programs.

A study comparing the ability of the TE and DR frameworks to reduce electricity prices shows that the TE framework reduces electricity prices by 240% compared to the DR framework [74]. The real-time adjustment of flexible loads reduces the surges in power demand, thus reducing the power prices and resulting in a more stabilized price for electricity [74]. In general, TE offers opportunities for the power grid in terms of optimizing power flows, stabilizing the grid, and increasing energy efficiency [76]. However, there are several challenges associated with the implementation of TE, including privacy concerns, trading platforms and trust between network actors and devices [76]. Blockchain technology is proposed as a money exchange platform for TE, but it is uncertain whether it can overcome issues of congestion, power quality, and reliability [73]. Moreover, the TE approach does not include a central entity responsible for meeting the flexibility requirement, which might make it unattractive to DSOs and TSOs [44]. Therefore, determining a responsible party for monitoring and controlling the decentralized platform is an issue that needs to be addressed [73].

2.7 Flexibility Pricing

Developments in communications and metering technology are enabling the technological foundation to support the utilization of residential flexibility [57]. Various market structures have been proposed to enable flexibility trading. However, as participation in flexibility markets can cause inconvenience to end-users, incentive mechanisms are needed to facilitate participation in these markets [57, 77]. Determining how flexibility services should be priced is one of the main challenges associated with the implementation of flexibility services [59]. The following sections outline why traditional pricing approaches are not yet appropriate for flexibility pricing and identify two aspects that need to be considered when setting the price for flexibility: price discrimination and the degree of decision-making power of the end-user.

2.7.1 Traditional Approaches

Figure 6 shows how prices normally are cleared by supply and demand. For a flexibility market, this means that requests and offers are matched on a market platform, usually with aggregators handling the bidding and end-users handling the activations [23]. A study investigating a market-based approach to flexibility pricing in the Dutch and French markets revealed several challenges in terms of complexity [23]. The need for a minimum number of market participants to enable liquid transactions is highlighted as a milestone for market clearing of flexibility. Another challenge with a marked-based approach is the risk for market dominance and over-costs, as all providers would receive the clearing price, increasing the overall cost of flexibility [44].

Another way to price flexibility is through marginal cost analysis. The marginal cost represents the cost of producing one additional unit. Since flexibility can provide both upward and downward flexibility from both generating units and loads, the cost of one additional unit for flexibility services is not easy to

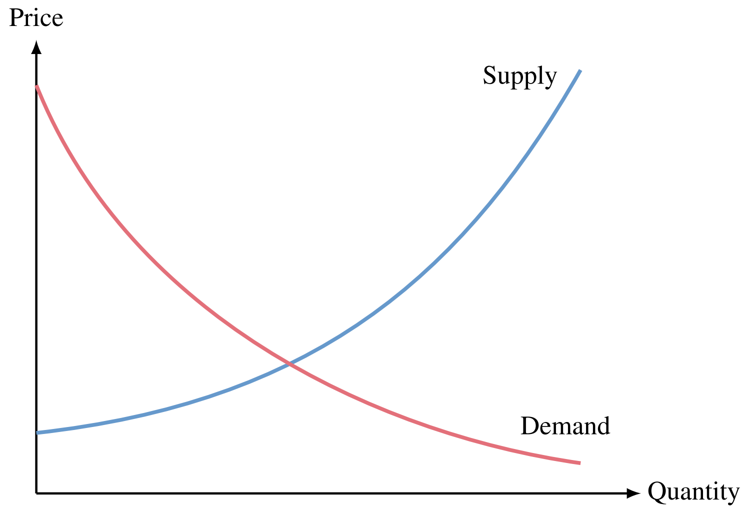


Figure 6: Classical market clearing where the price is set at the intersection between supply and demand.

determine. This is illustrated in a paper that found that the marginal price depends on the incremental cost rate of generation units, but also depends on the incremental cost rate of flexibility loads [22]. Another paper proposes a market clearing optimization model for the pricing of ancillary services and reactive power in a distribution-level electricity market based on the concept of distributional locational marginal prices [24]. However, a challenge in calculating the marginal cost of flexibility arises from the scale of a flexibility market. Since all sources will have separate soft costs, this means that each source may have unique marginal costs, complicating the calculation.

2.7.2 Individual Pricing

The price for flexibility can be defined either uniformly or individually, whether the price for flexibility is set by market clearing, marginal pricing, or some other pricing mechanism. Uniform pricing means that the same price is set for each flexibility source. However, uniform pricing does not fully exploit the potential of residential flexibility for the aggregator, as different end-users value flexibility differently [78]. As discussed in Section 2.5, individual pricing can provide a more equitable distribution of compensation for the end-users. Therefore, another option to make better use of residential flexibility is to allow price discrimination through personalized pricing mechanisms. Individual pricing involves giving different prices to different consumers [79]. Individual pricing can allow buyers of flexibility to reduce their dependence on a single dominant user [30]. Moreover, individual pricing can lead to a significant reduction in energy costs without compromising consumer satisfaction [80]. Uniform pricing mechanisms may introduce the problem that end-users are unwilling to change their consumption because the changes have little impact on energy savings. Individual pricing mechanisms, however, can avoid this problem [80].

A paper proposes a price-discriminatory dynamic pricing scheme in which individual prices are set at the household level [78]. The paper concludes that social welfare can be higher when price discrimination is implemented. However, to enable the success of discriminatory pricing techniques, solutions that can maintain fairness among end-users are needed. The available surplus energy of end-users and their sensitivity to price changes need be taken into account [30]. If end-users are not satisfied with the price they receive, or if they envy each other's assumed discrimination, energy markets with discriminatory pricing schemes will eventually cease to exist [30]. Another paper proposes that a personalized real-time pricing mechanism is implemented such that users who consume a lower percentage of their desired consumption are assigned lower prices compared to users who consume a higher percentage of their desired consumption [80]. This implies that elastic users receive lower prices while inelastic users receive higher prices [80]. Simulations demonstrated that the suggested mechanism successfully reduces the end-users' energy costs without compromising their welfare.

2.7.3 Decision Power for End-users

Another aspect to be decided upon when it comes to pricing of flexibility is the degree of end-users' decision power. Several papers propose that end-users can determine their own prices, which are set in bilateral contracts between end-users and the aggregator [44, 56]. The flexibility provider is able to update the contract and thus adjust the price periodically [44]. However, the price cannot be set higher than the maximum price set by the aggregator [44]. Pricing through contracts avoids market dominance and excessive flexibility costs for the aggregator, but there is a risk that low-priced flexible assets are activated more frequently than high-priced assets [44].

While most research agrees that flexibility contracts implemented in a flexibility market give end-users strong decision power [44], there are also challenges related to these aspects. Since flexibility providers are responsible for updating their prices [44], this may increase the threshold for end-users to participate in the program. There is also a discussion about dynamic or static contracts between end-users and aggregators. Dynamic contracts typically have a higher compensation potential than static contracts [81]. In direct load control, the compensation depends on the size of the load that is part of the contract [81]. However, the loss of autonomy is absent in price-based contracts, limited in volume-based contracts, and high in direct load control contracts [81]. Depending on the preferences of the individual consumer, different contracts may be appropriate to increase a consumer's willingness to participate in flexibility programs.

2.7.4 Flexibility Pricing Methods

Different ways of determining flexibility prices are presented, as well as a discussion of price discrimination and the degree of decision power for end-users. Irrespective of the decisions on these aspects, one must also determine what to price. Since flexibility is valued differently by different parties, there are several options to consider when setting a price for flexibility. Pricing based on service, performance and time is outlined below.

Pay for Service

Prices can be set differently depending on the type of service for which flexibility is used [82, 83]. Since flexibility is used to relieve various grid issues, one suggestion is to set a separate price for each service that the aggregator can offer to the flexibility buyer [82]. The prices are differentiated by response time, activation time and capacity. Another proposal is to set a different price for services such as frequency response products, reserve products and reactive power products [83]. This means that the primary, secondary and tertiary reserves explained in Section 2.3 are priced differently when using a pay-for-service strategy.

Pay for Performance

A pay for performance strategy is discussed in [57] and consists of three components: the correlation between the control signal and the unit's response, the difference between the energy provided and the energy requested, and the time delay between the control signal and the point of highest correlation [57]. Another proposal is to split the flexibility price into three parts: a fixed price fee paid regardless of performance, a time-varying price per kWh provided, and a peak power fee depending on the maximum withdrawal [84]. In addition, prices can be differentiated according to the energy source, thus allowing a certain degree of individual pricing [84].

Time Based Pricing

Time-varying pricing is introduced to incentivize end-users to shift loads to off-peak hours while reducing their energy costs [85]. By introducing time-varying energy tariffs, utilities can incentivize consumers to shift their electricity consumption to periods of lower demand. This can reduce the need for peak capacity, thereby reducing the overall costs [85]. Figure 7 shows the different time-based pricing strategies.

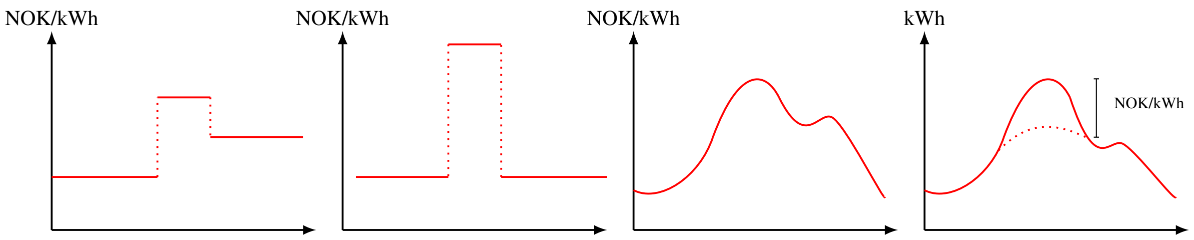


Figure 7: The four time-based pricing schemes. The illustration is based on a figure from [86].

Time of Use: Figure 7(a) shows the concept of time of use rates. In a ToU pricing scheme, price tariffs are divided into different time blocks to give end-users an incentive to shift their energy consumption from peak to off-peak periods [87]. The simplest ToU strategy has one price for peak hours and another for off-peak hours. The prices are determined by the power utility and communicated to the end-users one day in advance [88].

An important factor to consider when implementing a ToU tariff is that all consumers are encouraged to shift their loads to off-peak periods. As a result, additional peaks may occur during periods of low ToU tariffs. This phenomenon is called the rebound effect [88]. This is illustrated in an article describing off-peak charging of electric vehicles at night, which leads to a sudden increase in electricity demand as all charging starts at the same time [89]. The rebound effect can be mitigated by directly controlling the EV charging rate and time, or by modifying the ToU prices after incorporating the EV load model [87]. Another solution to avoid the rebound effect is to provide individual price signals to each end-user [86]. If individual prices are assigned to each end-user, a validated proposal to avert the rebound effect in ToU tariff determination is by a constraint-based electricity cost minimization function [90].

Critical Peak Pricing: Figure 7(b) shows the concept of critical peak pricing. Critical peak pricing strategies are similar to ToU pricing strategies, but the CPP has a predetermined high price during designated critical peak periods [65]. A project called Flex4Grid established that residential consumers can benefit economically from offering flexibility in the form of a reduced monthly energy bill, when critical peak pricing strategies are used [27]. Consumers must be notified in advance of the higher prices and in the Flex4Grid project, the DSO must notify participants at least 24 hours in advance. The project showed that a peak event (with a duration of 1h) per month could reduce the grid charge by about 10%, which in the project contributed to a 4% reduction in energy bills for the end-users [27]. One disadvantage of CPP, however, is the aforementioned rebound effect.

Real Time Pricing: While both ToU and CPP strategies have proven capable of reducing the end-users' energy costs and helping to stabilize the grid, there is a risk of a rebound effect. Moreover, neither approach facilitates for real-time adjustments. Therefore, a third option is real-time pricing schemes. Figure 7(c) shows the concept of RTP. RTP programs are considered the most direct and efficient DR program, suitable for competitive power markets [61]. In RTP programs, the price varies hourly and is typically based on the wholesale price of electricity [65, 86]. The electricity utility calculates the total forecasted demand and the associated electricity price and then announces it to the users [88]. The simulations performed by [88] show that the electrical input power curve is flatter for RTP strategies compared to ToU strategies. When real-time prices is used, demand response is able to balance the load variations better compared to a ToU tariff [91].

Critical Peak Rebates: A critical peak rebate is introduced as a pay-off incentive by giving money back to the end-users after reducing their energy consumption [90]. This means that the end-users are reducing their energy costs by reducing their consumption. Figure 7(d) shows the concept of CPR rates. The prices are set by aggregators or electricity providers [90]. However, when prices are set based on individual peak demand rather than system peak hours, they may not accurately reflect utility costs [9]. Figure 8 summarizes the various pricing strategies presented in this chapter.

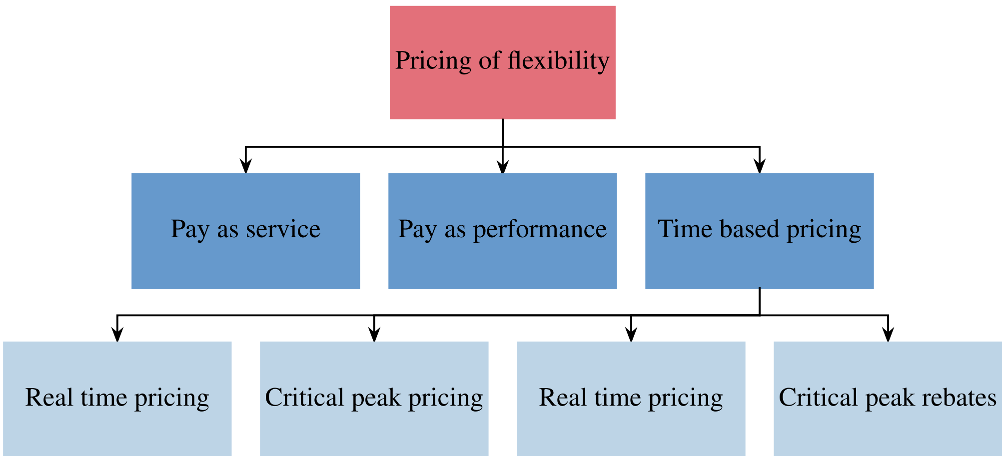


Figure 8: A summary of the presented pricing strategies.

2.8 Summary

To summarize this chapter, the existing literature identifies different market structures and possible pricing strategies for flexibility services. As presented, all approaches have both advantages and disadvantages. DR and TE provide opportunities for the power system in terms of optimizing power flows, stabilizing the grid, and increasing energy efficiency [76]. The supporting role of local energy systems is recognized by the European Commission as important for energy management [17]. However, the literature also highlights the need to determine a flexibility price before residential flexibility can be realized. This includes the issues of how to determine the price, how to define prices, and what to price. The main challenge identified for all methods of energy trading is to determine a reasonable and fair pricing scheme so that all participants can take financial benefits [76].

Any resource allocation must have some degree of fairness [28]. Fairness in resource allocation is often associated with the equal sharing of resources or the scaling of the utility function of one entity relative to others [28]. This should be seen in the light of the fact that end-users will only remain in the aggregator's portfolio if they are guaranteed a fair share of the financial benefits [80]. To address these questions, this thesis presents a model that optimally allocates various sources from an aggregator's portfolio and investigates whether there exists a price range within defined bounds that guarantees a profit for both aggregators and end-users for the obtained schedule. Since both market clearing and marginal pricing are currently difficult to implement, this work examines flexibility pricing based on existing electricity market prices. Analyzing whether using existing prices from the power markets as a basis for flexibility services is a first step in determining a fair price for flexibility.

3 System Model and Methods

The objective of this thesis is to determine a price range that ensures profit for both the aggregator and end-users when an aggregator provides flexibility to a BRP. To achieve this, a model for optimal allocation of different flexibility sources is needed. The model considers an aggregator operating a portfolio of N households, where each household own 1-4 flexibility sources. The flexibility sources represents one of the four flexibility source types: curtailable, regulatable, shiftable and battery. Each household has an individual contract with the aggregator that ensures the individual comfort settings and operating criteria. Based on the available sources in the aggregator's portfolio, the aggregator makes an optimal allocation of sources with the objective of minimizing its costs. When a feasible schedule exists, a new optimization is performed with a pricing mechanism to check if there is a price range that guarantees a profit for both the aggregator and each participating household.

3.1 Optimal Allocation

The optimization problem is an extension of the optimal allocation program presented in the specialization report [92]. The model is a mixed-integer nonlinear program with the objective of minimizing the total cost for the aggregator. All constraints are linear, except for a constraint on battery self-discharge. This constraint will be explained further when it appears in the model. Furthermore, some of the constraints are inspired by the work presented in [44, 84, 93], but are adapted to our model. The mathematical model is formulated with the objective of minimizing the total cost for the aggregator. The parameters and variables are described successively as they appear. A complete list of the sets, parameters and variables can be found in Appendix A. The objective function and the models for each of the flexibility sources are presented in the successive subsections, followed by a description of the flexibility request constraint. The allocation model to be presented can be summarized as follows:

$$
\begin{aligned}
\min\ & \textit{energy costs} \\
\text{s.t.}\ & \textit{curtailable load operation constraints} \\
& \textit{regulatable load operation constraints} \\
& \textit{shiftable load operation constraints} \\
& \textit{battery operation constraints} \\
& \textit{load balance constraint}
\end{aligned}
$$

3.1.1 Activation Parameters

The load operation constraints for each source type are implemented based on different activation parameters. The parameters presented account for the operational criteria and user preferences and are part of a flexibility contract. The parameters set the operational constraints for the optimal scheduling program and describe the user preferences and technical limitations of each source. The activation parameters described are an extension of the contract presented in the specialization report [92]. It is assumed that user comfort is taken into account in the contracts and therefore no inconvenience is caused to users by flexibility activation as long as there is a feasible schedule. Table 2 shows a summary of the main parameters for the operation of the different flexibility sources.

Table 2: The most important activation parameters for operational criteria and user preferences. The parameters must be agreed upon in a flexibility contract.

Source type	Parameter	Symbol	Description	Example
All sources	Reservation duration	T^{start}, T^{stop}	The hours the source is reserved, that is, the hours during which the aggregator can activate the source. Only one period can be selected.	06:00 - 09:00
Curtailable	Activation allowance	N_c	Maximum number of activations allowed in a day.	3 times
	Minimum rest duration	R_c^{min}	Minimum allowed duration between two activations.	2 hours
	Maximum activation duration	A_c^{max}	Maximum allowed duration of one activation.	3 hours
Regulatable	Activation allowance	N_r	Maximum number of activations allowed in a day.	3 times
	Minimum rest duration	R_r^{min}	Minimum allowed duration between two activations.	4 hours
	Maximum activation duration	A_r^{max}	Maximum allowed duration of one activation.	5 hours
Shiftable	Activation allowance	N_s	Maximum number of activations allowed in a day.	1 time
Battery	Minimum state of charge	SoC_b^{min}	The minimum SoC allowed within the reservation period.	15%
	Maximum state of charge	SoC_b^{max}	The maximum SoC allowed within the reservation period.	90%
	Final state of charge	SoC_b^{final}	The minimum allowed SoC at the end of the reservation period, at T_b^{stop}.	Same as start of period

All source types are constrained by the reservation duration, which represents the time period where the source is reserved. This is the time period in which the aggregator can activate the source in order to extract flexibility. The reservation duration is represented by the parameters T^{start} and T^{stop}. To ensure that the end-user's comfort preferences are upheld, a minimum rest duration R^{min}, a maximum activation duration A^{max} and an activation allowance N is implemented. A minimum state of charge SoC^{min} and a maximum state of charge SoC^{max} is implemented to ensure that the battery's state of charge stays within the allowed limits. To ensure that the battery is returned to the end-user's desired final value at the end of the reservation duration, a final state of charge SoC^{final} is implemented.

3.1.2 Objective

The objective is to minimize the total cost for the aggregator over the optimization horizon. The price for flexibility is divided into an activation price defined in NOK/kWh and a reservation price defined in NOK/hour, in conjunction with the conclusions drawn in the specialization project report [92]. End-users will not be willing to reserve sources for several hours if they are not compensated for it. Similarly, activating flexibility causes actual inconvenience that must be compensated. Therefore, both an activation price and a reservation price are included. The activation price is paid when a source is activated while the reservation price is paid when a source is reserved, but not activated. The total cost for the aggregator is the sum of activation cost and reservation cost, where the activation cost is the sum of switching off a curtailable source, reducing the power of a regulatable source, shifting load profiles in time and charging or discharging a battery. This is represented by Equation (1),

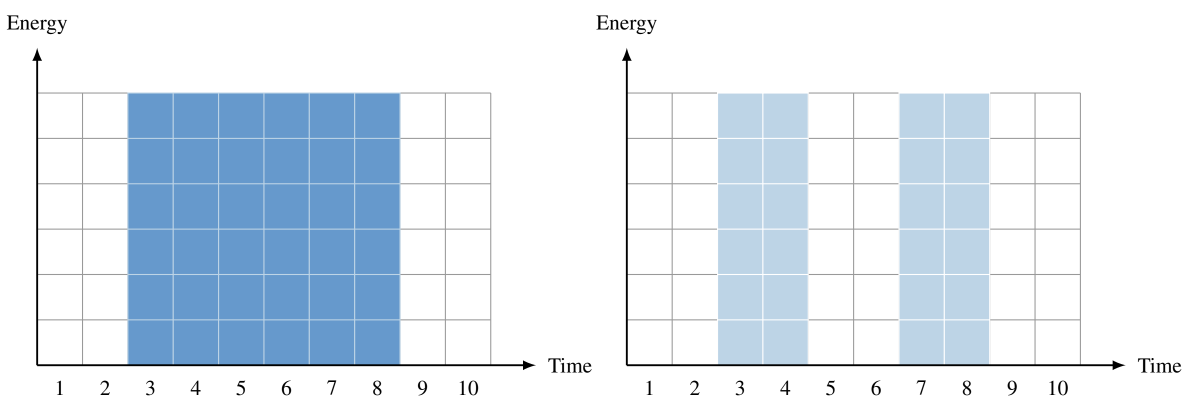
$$\min z = \sum_{t=1}^{T}[\sum_{c=1}^{C}(C_{c,t}^{act} \cdot F_{c,t} + C_{c,t}^{res} \cdot (\delta_{c,t}^{res} - \delta_{c,t}^{act})) + \sum_{r=1}^{R}(C_{r,t}^{act} \cdot F_{r,t} + C_{r,t}^{res} \cdot (\delta_{r,t}^{res} - \delta_{r,t}^{act}))+$$
$$\sum_{s=1}^{S}(\mathrm{C}_{s,t}^{act} \cdot F_{s,t} + C_{s,t}^{res} \cdot (\delta_{s,t}^{res} - \delta_{s,t}^{act})) + \sum_{b=1}^{B}((\mathrm{C}_{b,t}^{ch} \cdot F_{b,t}^{ch} + \mathrm{C}_{b,t}^{dis} \cdot F_{b,t}^{dis}) + C_{b,t}^{res} \cdot (\delta_{b,t}^{res} - \delta_{b,t}^{ch} - \delta_{b,t}^{dis}))] \tag{1}$$

where z is the total cost for the aggregator defined in NOK. *T* is the set of periods indexed by *t*, *C* is the set of curtailable loads, indexed by *c*, *R* is the set of regulatable loads, indexed by *r*, *S* is the set of shiftable loads, indexed by *s* and *B* is the set of batteries indexed by *b*. The parameters $C_{c,t}^{act}$, $C_{r,t}^{act}$, $C_{s,t}^{act}$ and $C_{b,t}^{act}$ are the cost of activating sources *c*, *r*, *s* and *b* in time *t*, defined in NOK/kWh. The parameters $C_{c,t}^{res}$, $C_{r,t}^{res}$, $C_{s,t}^{res}$ and $C_{b,t}^{res}$ are the cost of reserving sources *c*, *r*, *s* and *b* in time *t*, defined in NOK/hour. The binary parameters $\delta_{c,t}^{res}$, $\delta_{r,t}^{res}$, $\delta_{s,t}^{res}$ and $\delta_{b,t}^{res}$ have the value 1 if source *c*, *r*, *s* and *b* are reserved in time *t*.

The variables $F_{c,t}$, $F_{r,t}$, $F_{s,t}$, represent the activated flexibility from source *c*, *r* and *s* in time *t*, defined in kWh. The variables $F_{b,t}^{ch}$ and $F_{b,t}^{dis}$ represent the activated flexibility from charging and discharging battery *b* in time *t*, defined in kWh. The binary variables $\delta_{c,t}^{act}$, $\delta_{r,t}^{act}$ and $\delta_{s,t}^{act}$ get the value 1 if source *c*, *r* and *s* is activated in time *t*. The binary variables $\delta_{b,t}^{ch}$ and $\delta_{b,t}^{dis}$ get the value 1 if the battery *b* is charged or discharged at time *t*.

3.1.3 Curtailable Loads

Curtailable units are loads where consumption can be interrupted. The load is assumed non-recovered, meaning it does not consume the curtailed energy when reconnected. The curtailable loads are remunerated in kWh depending on the amount of flexibility provided. This model only considers upward regulation for curtailable loads. Upward regulation is provided when the load is turned off. An illustration of a curtailment is shown in Figure 9. Figure 9(a) shows the baseline profile, while Figure 9(b) shows a curtailment in time periods 5 and 6. The x-axis represents time periods and the y-axis represents the energy consumption.



(a) Base profile (b) Curtailed profile

Figure 9: Example of an curtailment. The illustration is based on a figure extracted from [84].

The baseline for a curtailable source c in time t, is denoted $W_{c,t}$ [kWh] and is calculated as in Equation (2). P_c is the rated power [kW] of source c and $\epsilon_{c,t}$ is a binary parameter with value 1 if source c consumes energy in time t. α [hours] is a parameter describing the duration of each time step t. A curtailable source that consumes energy from 3 pm to 9 pm has a baseline consumption as shown in Figure 9(a).

$$W_{c,t} = P_c \cdot \epsilon_{c,t} \cdot \alpha \tag{2}$$

Equation (3) ensures that the activated flexibility, $F_{c,t}$, is equal to the baseline consumption, $W_{c,t}$, of source c in time t when the source is activated. An activation is counted in periods where the load is curtailed.

$$F_{c,t} = W_{c,t} \cdot \delta_{c,t}^{act} \tag{3}$$

Equation (4) ensures that a source c cannot be activated in time t unless the source is reserved in the same time.

$$\delta_{c,t}^{act} \leq \delta_{c,t}^{res} \tag{4}$$

Equation (5) ensures that an activation is only counted if flexibility is provided. All curtailable loads must provide at least 0.01 kWh during the times when flexibility is activated.

$$\delta_{c,t}^{act} \leq F_{c,t} \tag{5}$$

Activation Allowances for Curtailable Loads
The start and stop of each activation must be counted to satisfy the activation allowance, minimum rest duration and maximum activation duration specified in the contract. $\delta_{c,t}^{start}$ is a binary variable that gets the value 1 in the period when an activation is started. $\delta_{c,t}^{stop}$ is a binary variable that gets the value 1 in the period after the activation is stopped. Table 3 illustrates the feasible values for the delta variables.

Table 3: Feasible values for the binary start and stop variables, used to satisfy the activation allowance, minimum rest duration and maximum activation duration.

Time	1	2	3	4	5	6	7
$\delta_{c,t}^{act}$	0	1	1	1	0	0	1
$\delta_{c,t}^{start}$	0	1	0	0	0	0	1
$\delta_{c,t}^{stop}$	0	0	0	0	1	0	1

By this definition, a start and a stop cannot occur in the same time. An additional assumption is that each activation must be stopped by the end of the optimization horizon T. Therefore, it is allowed to start and stop an activation in the last time of the horizon, as seen in table 3.

Equations (6a) and (6b) count each start of an activation. It is assumed that no sources are activated before the first time in the time horizon. Subsequently, Equation (6a) ensures that the start of an activation is counted in the first time period of the horizon if the source is activated in the first time period. Equation (6b) counts the starts of an activation in the remaining time periods of the optimization horizon.

$$\delta_{c,t}^{act} = \delta_{c,t}^{start}, t = 1 \tag{6a}$$

$$\delta_{c,t}^{act} - \delta_{c,t-1}^{act} \leq \delta_{c,t}^{start}, t \neq 1, t \in T \tag{6b}$$

Equation (7) ensures that the start of an activation is not counted in periods *t* when the curtailable source *c* is not activated.

$$\delta^{start}_{c,t} \leq \delta^{act}_{c,t} \tag{7}$$

Equations (8a) and (8b) count each stop of an activation. Equation (8a) counts the stop of an activation in all times except the first, consistent with the assumption that no sources are activated at the beginning of the time horizon. In conjunction with the assumption that no sources are activated after the end of the horizon, Equation (8b) ensures that the stop of an activation is counted in the last time of the horizon T.

$$\delta^{act}_{c,t-1} - \delta^{act}_{c,t} \leq \delta^{stop}_{c,t} \;, t \neq 1 \;, t \in T \tag{8a}$$

$$\delta^{act}_{c,T} \leq \delta^{stop}_{c,T} \;, t = \mathrm{T} \tag{8b}$$

Equation (9) ensures that a curtailment is not started and stopped in the same period.

$$\delta^{start}_{c,t} + \delta^{stop}_{c,t} \leq 1 \;, t \in T \;, t \neq \mathrm{T} \tag{9}$$

Equation (10) ensures that $\delta^{start}_{c,t}$ gets the value zero in periods where an activation is not started, and correspondingly that $\delta^{stop}_{c,t}$ gets the value zero in periods where an activation is not stopped.

$$\delta^{start}_{c,t} - \delta^{stop}_{c,t} = \delta^{act}_{c,t} - \delta^{act}_{c,t-1} \;, t \in T \;, t \neq 1 \;, t \neq \mathrm{T} \tag{10}$$

The allowed number of activations during the optimization horizon for each source *c*, is constrained in Equation (11), where N_c is the number of allowed activations for source c. The constraint is implemented to prevent damage from rapid on-off cycling.

$$\sum_{t=1}^{T} \delta^{start}_{c,t} \leq N_c \tag{11}$$

To ensure that the desired state of the source is restored after a curtailment, a minimum rest duration, R^{min}_c, is implemented as described in Equation (12).

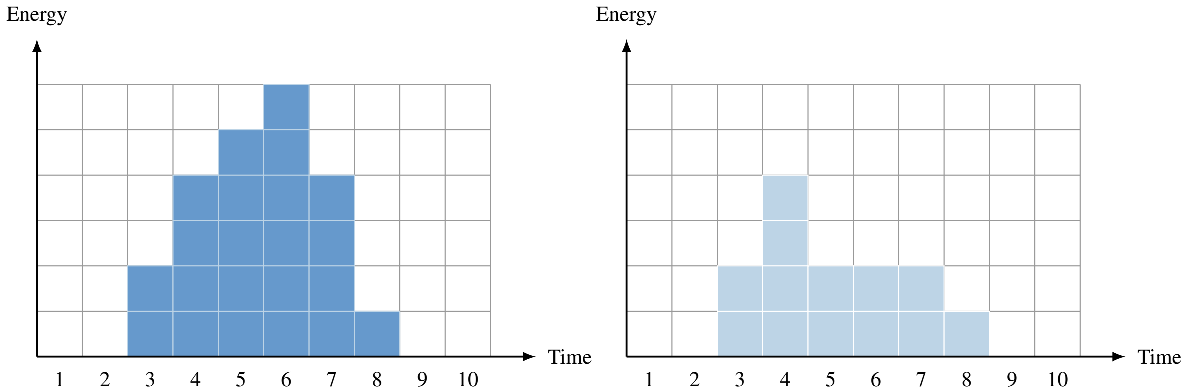
$$\sum_{i=t}^{t+R^{min}_c} \delta^{start}_{c,t} + \delta^{stop}_{c,t} \leq 1 \tag{12}$$

The activation duration is constrained by the maximum activation duration, A^{max}_c specified in the contract, as shown in Equation (13). The constraint is implemented to ensure that the user's comfort preferences are upheld by keeping the state of the source within the comfort range defined by the end-user.

$$\sum_{i=t}^{t+A^{max}_c} \delta^{stop}_{c,t} - \delta^{start}_{c,t} \geq 0 \tag{13}$$

3.1.4 Regulatable Loads

Regulatable loads are devices that can regulate their power consumption either up or down. The regulatable loads are remunerated in kWh depending on the amount of flexibility provided. The regulatable loads are assumed non-recovered and this model considers only upward regulation for regulatable loads. Upward regulation is provided when the loads reduce the consumption, as illustrated in Figure 10. The x-axis represents time periods and the y-axis represents the energy consumption. Figure 10(a) shows the baseline profile and Figure 10(b) shows an example of upward regulation of a regulatable source.



(a) Base profile (b) Regulated profile

Figure 10: Example of upward regulation from a regulatable load. The illustration is based on a figure extracted from [84].

The baseline for a regulatable source *r* in time *t*, is denoted $W_{r,t}$ [kWh] and is calculated as shown in Equation (14). P_r is the rated power [kW] of source *r*. $\epsilon_{r,t}$ is a parameter between 0 and 1, since the regulatable sources can operate between 0% and 100% of the rated power.

$$W_{r,t} = P_r \cdot \epsilon_{r,t} \cdot \alpha \tag{14}$$

Equation (15) ensures that the activated flexibility, $F_{r,t}$, does not exceed the baseline consumption $W_{r,t}$ from source *r* in time *t*. An activation is counted in periods when the load is reduced.

$$F_{r,t} \leq W_{r,t} \cdot \delta^{act}_{r,t} \tag{15}$$

The equivalent of Equations (4)-(13) for the curtailable sources is applied to regulatable sources by Equations (16)-(25).

$$\delta^{act}_{r,t} \leq \delta^{res}_{r,t} \tag{16}$$

$$\delta^{act}_{r,t} \leq F_{r,t} \tag{17}$$

$$\delta^{act}_{r,t} = \delta^{start}_{r,t}\, , t = 1 \tag{18a}$$

$$\delta^{act}_{r,t} - \delta^{act}_{r,t-1} \leq \delta^{start}_{r,t}\, , t \neq 1\, , t \in T \tag{18b}$$

$$\delta^{start}_{r,t} \leq \delta^{act}_{r,t} \tag{19}$$

$$\delta^{act}_{r,t-1} - \delta^{act}_{r,t} \leq \delta^{stop}_{r,t}\, , t \neq 1\, , t \in T \tag{20a}$$

$$\delta^{act}_{r,T} \leq \delta^{stop}_{r,T}\, , t = \mathrm{T} \tag{20b}$$

$$\delta^{start}_{r,t} + \delta^{stop}_{r,t} \leq 1\, , t \in T\, , t \neq \mathrm{T} \tag{21}$$

$$\delta^{start}_{r,t} - \delta^{stop}_{r,t} = \delta^{act}_{r,t} - \delta^{act}_{r,t-1}\, , t \in T\, , t \neq 1\, , t \neq \mathrm{T} \tag{22}$$

$$\sum_{t=1}^{T} \delta^{start}_{r,t} \leq N_r \tag{23}$$

$$\sum_{i=t}^{t+R_r^{min}} \delta_{r,t}^{start} + \delta_{r,t}^{stop} \leq 1 \tag{24}$$

$$\sum_{i=t}^{t+A_r^{max}} \delta_{r,t}^{stop} - \delta_{r,t}^{start} \geq 0 \tag{25}$$

3.1.5 Shiftable Loads

Shiftable loads are sources that can postpone consumption while maintaining the same profile, as Figure 11 illustrates. The x-axis represents time periods and the y-axis represents energy consumption. Shiftable loads provide upward regulation in the periods the load is shifted from and downward regulation in the periods the load is shifted to. All loads are assumed to consume as soon as possible and the profile cannot be split when shifted.

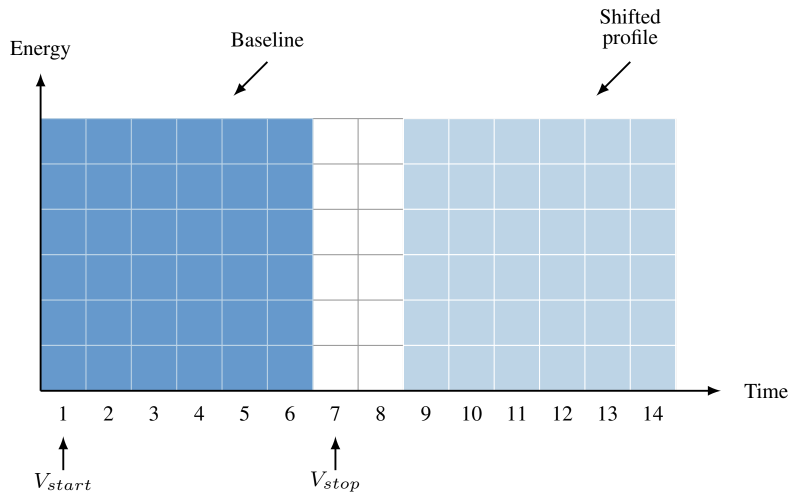
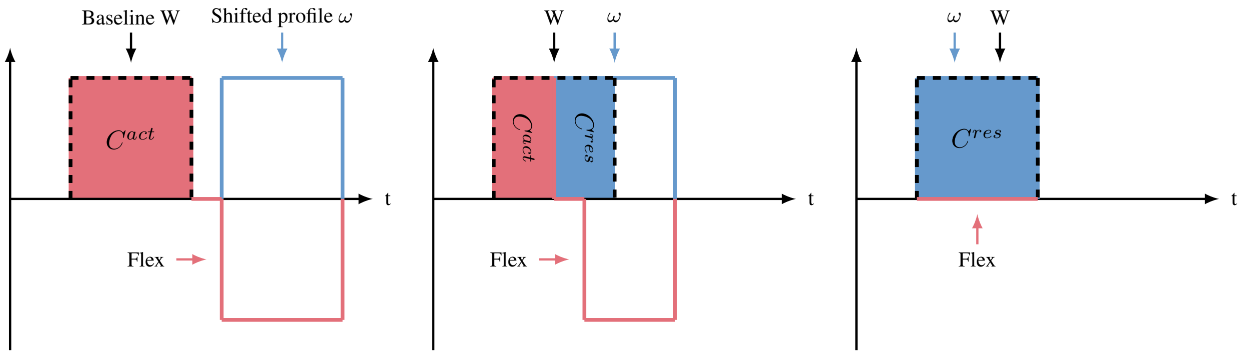


Figure 11: An illustration of a shifted load profile. The illustration is based on a figure extracted from [84].

Shiftable loads are assumed to be recovered, and are therefore priced differently than curtailable and regulatable loads. Figure 12 illustrates the reservation and activation prices that the aggregator has to pay when shifting a load. There are three different pricing combinations. The first is the case where the load profile is completely shifted to another time interval. This is shown in Figure 12(a). In this case, the activation price is paid for the entire period from which the load is shifted. Figure 12(b) illustrates the second case where the load profile is partially shifted. In this case, part of the new consumption is shifted to a time interval where energy is already consumed. The activation price is paid in the periods in which there is no overlap between the shifted profile and the baseline profile and the reservation price is paid in the remaining periods. The third scenario is when the load is not shifted. This is shown in Figure 12(c). In this case, the reservation price is paid for the entire period.

The shiftable profile model is used to decide the new energy profile for each source s within its reservation period defined by the end-user. The contract defines the reservation period for each source s, represented by the parameters T_s^{start} and T_s^{stop}. Within this period, the duration of baseline consumption $W_{s,t}$ [kWh] is denoted by the parameters V_s^{start} and V_s^{stop}.



(a) Completely shifted load (b) Partially shifted load (c) Not shifted load

Figure 12: Pricing of flexibility from shiftable loads defined for three price cases: completely shifted, partially shifted, and not shifted. C^{act} is the activation price, paid in the pink boxes. C^{res} is the reservation price, paid in the blue boxes. The black dotted line represents the baseline profile W, the blue line represents the shifted profile ω and the pink line represents the flexibility extracted.

The baseline for a shiftable source *s* in time *t*, is denoted by $W_{s,t}$ [kWh] and is calculated as shown in Equation (26). P_s [kW] is the rated power of source *s*.

$$W_{s,t} = P_s \cdot \delta^{act}_{s,t} \cdot \alpha \tag{26}$$

Equation (27) ensures that the shiftable source *s* cannot be activated in time *t* unless the source is reserved in the same period.

$$\delta^{act}_{s,t} \leq \delta^{res}_{s,t} \tag{27}$$

Equation (28) ensures that an activation is counted only if flexibility is provided. It is assumed that all shiftable loads must provide at least 0.01 kWh when activated.

$$\delta^{act}_{s,t} \leq F_{s,t} \tag{28}$$

To ensure that activations are counted when flexibility is provided, Equation (29) is established.

$$\delta^{act}_{s,t} = \frac{F_{s,t}}{W_{s,t}} \; \forall \, \text{t} \in [V^{start}, V^{stop}] \tag{29}$$

The binary variable $\gamma_{s,t}$ gets the value 1 if the source starts consuming energy in time *t*. This corresponds to $\gamma_{s,t}$ = 1 for *t* = 9 in Figure 11. $\omega_{s,t}$ [kWh] is the shifted profile. The amount of shifted flexibility, $F_{s,t}$, is defined in Equation (30).

$$F_{s,t} = (1 - \gamma_{s,V_{start}}) \cdot W_{s,t} + \gamma_{s,V_{start}} \cdot W_{s,t} - \omega_{s,t}, \forall \, \text{t} \in [V^{start}, V^{stop}] \tag{30}$$

Equation (31) ensures that the shiftable load profile is scheduled within the reservation period T^{start}_s and T^{stop}_s and that the load profile is not split.

$$\sum_{t=T^{start}}^{T^{stop}-(V^{stop}-V^{start})} \gamma_t = 1, \forall \text{ t} \in [V^{start}, T^{stop} - (V^{stop} - V^{start})] \tag{31}$$

When flexibility is activated, the amount of flexibility must be equal to the baseline profile. Equation (32) ensures that the shifted load profile, $\omega_{s,t}$, consumes the same energy as the baseline load profile, $W_{s,t}$.

$$\omega_t = \sum_{i=0}^{\min\{T_s^{stop}-T_s^{start},\text{ t}\}} \gamma_{t-i} \cdot W_{s,T^{start}+i}, \forall \text{ t} \in [T^{start}, T^{stop}] \tag{32}$$

3.1.6 Batteries

Batteries can provide flexibility either by charging or discharging. Upward regulation is extracted by discharging the battery, and downward regulation is extracted by charging the battery. It is assumed that the aggregator can freely control the battery within the reservation period and the operational constraints. Battery owners receive the same price for charged and discharged flexibility.

Equations (33) and (34) limit the flexibility charged or discharged from the battery. $P_b^{ch,max}$ is a parameter representing the maximum charging power of battery *b* and $P_b^{dis,max}$ is a parameter for the maximum discharging power of battery *b*, both defined in kW.

$$0 \leq F_{b,t}^{ch} \leq P_b^{ch,max} \cdot \delta_{b,t}^{ch} \cdot \alpha \tag{33}$$

$$0 \leq F_{b,t}^{dis} \leq P_b^{dis,max} \cdot \delta_{b,t}^{dis} \cdot \alpha \tag{34}$$

Equation (35) ensures that a battery is not charged and discharged at the same time, and that charging and discharging is only provided when battery *b* is reserved in time *t*.

$$\delta_{b,t}^{ch} + \delta_{b,t}^{dis} \leq \delta_{b,t}^{res} \tag{35}$$

Equation (36) and (37) ensures that an activation is only counted when flexibility from either charging or discharging is activated. All batteries must provide at least 0.01 kWh of flexibility during times when flexibility is activated.

$$\delta_{b,t}^{ch} \leq F_{b,t}^{ch} \tag{36}$$

$$\delta_{b,t}^{dis} \leq F_{b,t}^{dis} \tag{37}$$

$SoC_{b,t}$ is a variable representing the state of charge [%] for battery *b* in time *t*. Equations (38a) and (38b) define the state of charge depending on the previous state of charge $SoC_{b,t-1}$, the self-discharge rate $SoC_{b,t}^{self-dis}$, the flexibility from charging $F_{b,t}^{ch}$ and the flexibility from discharging $F_{b,t}^{dis}$ battery *b*. The size of the battery is represented by the parameter E_b [kWh]. η_b^{ch} and η_b^{dis} are parameters representing the charging and discharging efficiencies [%] for battery *b*.

$$SoC_{b,t} = SoC_{b,1} - SoC_{b,t}^{self-dis} + \frac{F_b^{ch} \cdot \eta_b^{ch}}{E_b} - \frac{F_b^{dis}}{\eta_b^{dis} \cdot E_b}\ , t = 1 \tag{38a}$$

$$SoC_{b,t} = SoC_{b,t-1} - SoC_{b,t}^{self-dis} + \frac{F_b^{ch} \cdot \eta_b^{ch}}{E_b} - \frac{F_b^{dis}}{\eta_b^{dis} \cdot E_b}\ , t \neq 1\ , t \in T \tag{38b}$$

To account for the unavoidable chemical losses that occur when batteries are neither charging nor discharging, a self-discharge of the battery, represented by the variable $SoC_{b,t}^{self-dis}$ [%], is included in the model. $SoC_{b,t}^{self-dis}$ is defined as in Equations (39a) and (39b). These are the constraints making the problem nonlinear due to $SoC_{b,t}$, $\delta_{b,t}^{ch}$, and $\delta_{b,t}^{dis}$ being variables. $\eta_{b,t}^{self-dis}$ is a parameter representing the self-discharge rate and is defined as a percentage loss.

$$SoC_{b,t}^{self-dis} = SoC_{b,1} \cdot \eta_{b,t}^{self-dis} \cdot (\delta_{b,t-1}^{res} - \delta_{b,t-1}^{ch} - \delta_{b,t-1}^{dis})\ , t = T_b^{start} \tag{39a}$$

$$SoC_{b,t}^{self-dis} = SoC_{b,t-1} \cdot \eta_{b,t}^{self-dis} \cdot (\delta_{b,t-1}^{res} - \delta_{b,t-1}^{ch} - \delta_{b,t-1}^{dis})\ , t \neq T_b^{start}\ , t \in T \tag{39b}$$

Equation (40) ensures that the state of charge for source *b* is kept within the minimum and maximum values, defined by the end-users in the contract in time *t*. $SoC_{b,t}^{min}$ is a parameter representing the minimum allowed SoC and $SoC_{b,t}^{max}$ is a parameter representing the maximum allowed SoC.

$$SoC_b^{min} \leq SoC_{b,t} \leq SoC_b^{max} \tag{40}$$

The SoC of the battery at the end of the reservation period, T_b^{stop}, must be greater than or equal to the SoC at the beginning of the reservation period, T_s^{start}. It is assumed that the aggregator is not responsible for recharging the energy that is lost due to self-discharge. Therefore a tolerance ϵ_b [%] is accounted for as described in Equation (41).

$$SoC_{b,t=T_{stop}} \geq SoC_{b,t=T_{start}} \cdot \epsilon_b \tag{41}$$

Baseline Calculation

Since a home battery is used differently than the other flexibility sources presented, the baseline is calculated as the optimal use of the battery for one day. The optimal usage is found by minimizing the household's energy cost when it is not participating in a flexibility program. This means that the battery is used to minimize the cost of covering the energy consumption of the other flexibility sources while taking advantage of spot price fluctuations. This is a simplification made in the model due to lack of data. The baseline for the batteries is thus calculated by optimizing the charging and discharging of the battery, provided that the baseline consumption $D_{h,t}$ for the household's flexibility sources is met. *H* is the set of households, indexed by *h*.

Equation (42) formulates the consumption constraint by summing the parameters defining the baselines of the water heater $W_{h,t}^{curt}$, the heat pump $W_{h,t}^{reg}$ and the EV $W_{h,t}^{shift}$ for household *h* in time *t*.

$$D_{h,t} = W_{h,t}^{curt} + W_{h,t}^{reg} + W_{h,t}^{shift} \tag{42}$$

The baseline consumption, $D_{h,t}$, can be obtained either by purchasing energy from the grid or by discharging energy from the battery, as shown in Equation (43). The energy purchased from the grid to meet the household's consumption, is represented by the variable $E^{import}_{b,t}$ [kWh] and the energy discharged from battery *b* is represented by the variable $E^{dis}_{b,t}$ [kWh].

$$E^{import}_{b,t} + E^{dis}_{b,t} = D_{h,t} \tag{43}$$

For each household *h*, the objective is to minimize the energy costs, as presented in Equation (44). The energy cost is the sum of cost for the energy purchased to meet the consumption and the cost of the energy purchased to charge the battery. The energy bought to charge battery *b* is represented by the variable $E^{ch}_{b,t}$ [kWh] and the spot price by the parameter C^{spot}_t [NOK/kWh].

$$\text{min z} = \sum_{t=1}^{T} C^{spot}_t \cdot (E^{import}_{h,t} + E^{ch}_{b,t}) \tag{44}$$

The equivalent of Equations (33)-(41) is applied to the baseline calculations by Equations (45)-(53).

$$0 \leq E^{ch}_{b,t} \leq P^{ch,max}_b \cdot \delta^{ch}_{b,t} \cdot \alpha \tag{45}$$

$$0 \leq E^{dis}_{b,t} \leq P^{dis,max}_b \cdot \delta^{dis}_{b,t} \cdot \alpha \tag{46}$$

$$\delta^{ch}_{b,t} + \delta^{dis}_{b,t} \leq 1 \tag{47}$$

$$\delta^{ch}_{b,t} \leq E^{ch}_{b,t} \tag{48}$$

$$\delta^{dis}_{b,t} \leq E^{dis}_{b,t} \tag{49}$$

$$SoC_{b,t} = SoC_{b,1} - SoC^{self-dis}_{b,t} + \frac{E^{ch}_b \cdot \eta^{ch}_b}{E_b} - \frac{E^{dis}_b}{\eta^{dis}_b \cdot E_b}\ , t = t \tag{50a}$$

$$SoC_{b,t} = SoC_{b,t-1} - SoC^{self-dis}_{b,t} + \frac{E^{ch}_b \cdot \eta^{ch}_b}{E_b} - \frac{E^{dis}_b}{\eta^{dis}_b \cdot E_b}\ , t \neq 1\ , t \in T \tag{50b}$$

$$SoC^{self-dis}_{b,t} = SoC_{b,1} \cdot \eta^{self-dis}_{b,t} \cdot (\delta^{res}_{b,t-1} - \delta^{ch}_{b,t-1} - \delta^{dis}_{b,t-1})\ , t = 1 \tag{51a}$$

$$SoC^{self-dis}_{b,t} = SoC_{b,t-1} \cdot \eta^{self-dis}_{b,t} \cdot (\delta^{res}_{b,t-1} - \delta^{ch}_{b,t-1} - \delta^{dis}_{b,t-1})\ , t \neq 1\ , t \in T \tag{51b}$$

$$SoC^{min}_b \leq SoC_{b,t} \leq SoC^{max}_b \tag{52}$$

$$SoC_{b,t=\mathrm{T}} \geq SoC_{b,t=1} \cdot \epsilon_b \tag{53}$$

3.1.7 Flexibility Request

Flexibility buyers request flexibility in terms of reduced or increased energy consumption. The flexibility request is represented by the parameter, D_t [kWh]. A positive value of D_t represents a request for upward regulation, while a negative value for D_t represents a request for downward regulation. Figure 13 shows an illustration of a flexibility request curve for upward and downward regulation. The x-axis represents time units and the y-axis represents the requested energy.

Equation (54) ensures that the sum of all flexibility provided by the different sources equals the requested

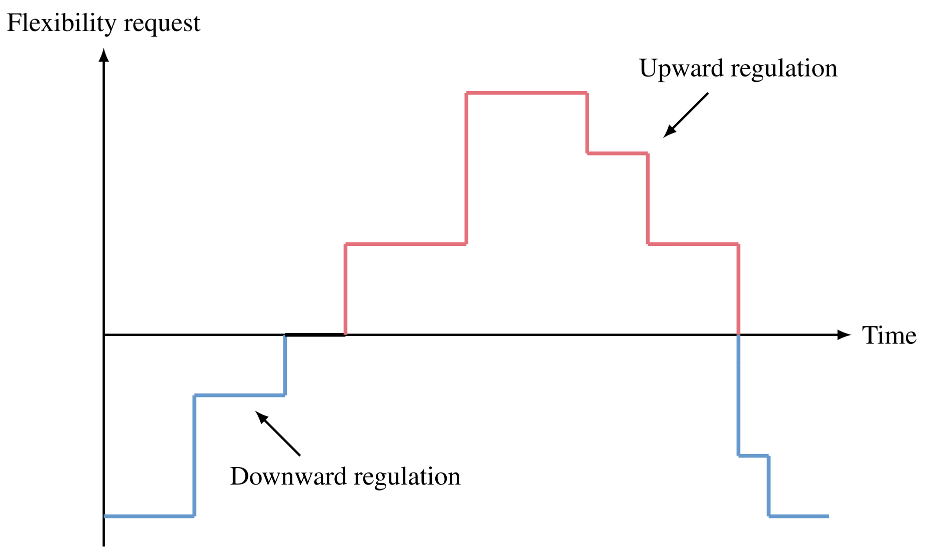


Figure 13: Flexibility request curve for upward and downward flexibility. The pink line represents a request for upward regulation and the blue line represents a request for downward regulation.

flexibility D_t [kW], in time t.

$$\sum_{c=1}^{C} F_{c,t} + \sum_{r=1}^{R} F_{r,t} + \sum_{s=1}^{S}(W_{s,t} - \omega_{s,t}) \sum_{b=1}^{B}(F_{b,t}^{dis} - F_{b,t}^{ch}) = D_t \ , t \in T \tag{54}$$

3.2 Pricing Mechanism

A program is created to allocate flexibility sources from a portfolio with the goal of minimizing the total cost to an aggregator. The program does not guarantee a profit for either the aggregator or the end-users, since the goal is to obtain an allocation feasible schedule that minimizes the cost to the aggregator. No constraint on profitability is included. The model is divided into two parts since the objective of this thesis is two-fold. Therefore, the next step is to determine whether the profit for the obtained schedule can be ensured by creating a pricing mechanism. If the profit can be ensured for both the aggregator and the end-users, a feasible price range can be found.

The aggregator receives a payment for providing the requested flexibility to buyers. The magnitude of this payment depends on the amount of flexibility requested, the type of flexibility buyer, and what the flexibility is utilized for. In this thesis, the flexibility buyer is assumed to be a BRP that normally trades imbalances in the balancing market. Consequently, the maximum price that the aggregator can receive from a BRP is the balancing price. However, the aggregator has to pay a part of the payment from the BRP to the end-users as an incentive for providing flexibility. This price is defined as the flexibility price and is divided into an activation price and a reservation price. Figure (14) illustrates this.

This raises the question of how the aggregator should share the payment from the BRP with the end-users. More specifically, how can the price for flexibility be set in such a way that both the aggregator and the end-users are satisfied. Since the aggregator's profit decreases when the price paid to the end-users increases, the aggregator would like to set the price as low as possible. On the other hand, end-users desire a high price for flexibility. In summary, it is a zero-sum game, since one person's loss is directly

Figure 14: Payments between each party. The BRP must pay the aggregator for the requested flexibility. This price is the balancing price, defined in NOK/kWh. Further, the aggregator must pay the end-users for the reserved and activated flexibility. These prices constitute the flexibility price. The activation price is defined in NOK/kWh and the reservation price is defined in NOK/h.

the other person's gain. In this case, it means that a high flexibility price reduces the aggregator's share of the payment from the BRP and increases the share for the end-users. The aim of this thesis is therefore to find a price range for flexibility that satisfies both the aggregator and the end-users, as an economic perspective is considered and an accurate price for flexibility cannot be found without considering social, behavioural and fairness aspects.

A simplified way to assess aggregator and end-user satisfaction is profitability. In this thesis, it is assumed that as long as all participants profit from participation, all parties are satisfied. As previously stated, the aggregator desires a low price for flexibility, while the end-users desire a high price for flexibility. For this reason, the flexibility price range is defined by the lowest and the highest price that guarantees a profit for both the aggregator and the end-user. All prices within this price range guarantee a profit for all participants. The lowest price that ensures profit for all participants is found when the aggregator is the price setter and is found by maximizing the aggregator's profit while ensuring a non-zero, positive profit for all households. Similarly, the highest price that ensures profit for both parties is found when the end-users are the price setters and is found by maximizing the profit of the households while ensuring a non-zero, positive profit for the aggregator.

3.2.1 Setting the Price Bounds

The flexibility price range is constrained by some lower and upper boundaries, represented by the parameters C^{lower} and C^{upper}. These can be based on the time-varying existing power market prices or extracted as fixed values. Irrespective of how these price bounds are set, there is no guarantee that the bounds will be sufficient to deliver a price range that guarantees a profit for both the aggregator and the end-users. Figure 15 explains this concept by showing a sketch of the bounds along with a feasible price range that guarantees a profit.

Bounds from Existing Markets

In the case where the bounds are formed from existing power markets, C_t^{upper} is determined as shown in Equation (55). This is motivated by the payment that the aggregator receives from the BRP, which is determined based on the existing power market prices and the flexibility request. When the flexibility request is zero, both the activation and reservation prices are set to zero. This is motivated by the fact that there is no incentive for the aggregator to neither activate nor reserve sources.

$$C_t^{upper} = C_t^{up} \cdot \delta_t^{up} + C_t^{down} \cdot \delta_t^{down} + 0 \cdot \delta_t^{zero} \tag{55}$$

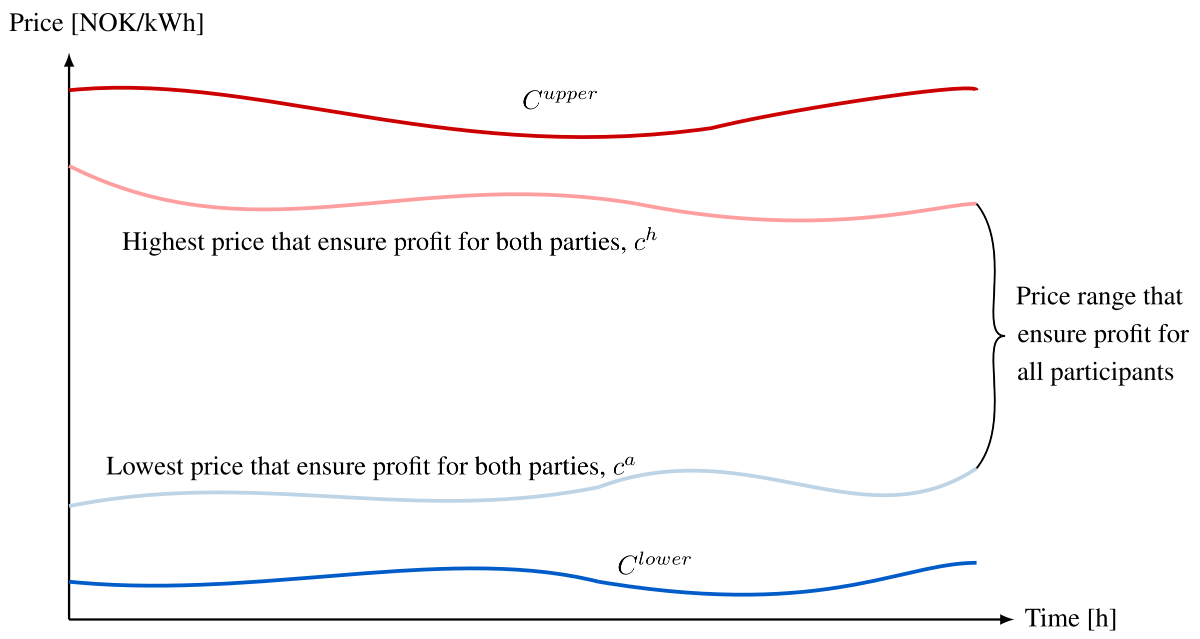


Figure 15: Price bounds and feasible price range within the bounds. The red line represents the desired price for the end-users and the blue line represents the desired price for the aggregator. The light blue line represents the lowest price that ensures profit for all participants, and the pink line represents the highest price that ensures profit for all participants.

where C_t^{up} is the upward regulation price in the balancing market in period t and C_t^{down} is the downward regulation price in period t. δ_t^{up} is a binary parameter with value 1 if the flexibility request is for up-regulation, δ_t^{down} is a binary parameter with value 1 if the flexibility request is for down-regulation, and δ_t^{zero} is a binary parameter with value 1 if there is no flexibility request for period t.

In this case, C_t^{lower} represents the lowest price from the existing power markets. It is defined as the lowest price of the spot price, C_t^{spot}, the intraday price, C_t^{intra}, and the balancing prices, C_t^{up} and C_t^{down}, in each time step t of the day, as shown in Equation (56).

$$C_t^{lower} = min\left(C_t^{spot}, C_t^{intra}, C_t^{up} \cdot \delta_t^{up} + C_t^{down} \cdot \delta_t^{down} + 0 \cdot \delta_t^{zero}\right) \tag{56}$$

Fixed Bounds

The payment from the BRP to the aggregator is still assumed to be the same, but the question arises whether this must mean that the flexibility price that the aggregator has to pay to the end-users must be limited by the existing power market prices. As there are no other market prices on which to base this assumption, a heuristic price range is used to test this. This means that when fixed prices are used as flexibility price bounds for each period, a fixed value is set for the lower bound, C^{lower}, and another fixed value is set for the upper bound, C^{upper}.

A price range that guarantees a profit for all participants can be found under the assumption of both uniform prices and individual prices. A uniform price mean that all flexibility sources receive the same flexibility price, while individual prices mean that each source in the portfolio receives an individual flexibility price. The following mechanism can be used to test both uniform prices and individual prices, since the only difference in the models is the index s (lacking for uniform pricing). Therefore, only the model for individual prices is presented.

3.2.2 Obtaining the Lowest Price that Ensure Profit for All Participants

It is clear that the aggregator wants to pay end-users a low price for flexibility in order to increase its own profit. Therefore, the lowest price that ensures profit for all participants is found by maximizing the profit for the aggregator, conditional on all households having positive profits. The objective is to maximize the profit for the aggregator, with the obtained schedule as input and the activation and reservation prices as variables, as shown in Equation (57),

$$\max \pi_a = \sum_{t=1}^{T} C_t^{payment} \cdot |D_t| - \sum_{t=1}^{T}\sum_{s=1}^{S} \left(c_{s,t}^{act,a} \cdot |F_{s,t}| + c_{s,t}^{res,a} \cdot (\delta_{s,t}^{res,a} - \delta_{s,t}^{act,a}) \right) \tag{57}$$

where π_a is the profit of the aggregator [NOK]. The product of $C_t^{payment}$ and D_t represents the revenue received by the aggregator from the BRP, where $C_t^{payment}$ is the parameter describing the payment the aggregator receives from the BRP and D_t [kWh] is the parameter representing the requested flexibility in period *t*. $\delta_{s,t}^{res,a}$ is a parameter with value 1 in periods when source *s* is reserved and $\delta_{s,t}^{act,a}$ is a parameter with value 1 in periods when source *s* is activated. $F_{s,t}$ [kWh] is a parameter representing the activated flexibility of source *s* in period *t*, obtained from the schedule. $c_{s,t}^{act,a}$ [NOK/kWh] is a variable representing the lowest activation price that ensures a profit for source *s* in period *t* for both the aggregator and the end-users. $c_{s,t}^{res,a}$ [NOK/h] is a variable representing the corresponding reservation price.

If the reservation price is of the same order of magnitude as the activation price, it will be cheaper to activate a source than to reserve it. This will cause unnecessary wear and tear on the source and possibly inconvenience to the end-users. For this reason, the reservation price is defined as a percentage of the activation price, as described in Equation (58). ϵ^{res} is a parameter that specifies the percentage. The reservation price $c_{s,t}^{res,a}$ is defined in NOK/hour, as in the optimal allocation program.

$$c_{s,t}^{res,a} = \epsilon^{res} \cdot c_{s,t}^{act,a} \tag{58}$$

The activation price for flexibility must be greater than or equal to the lower bound in each time period *t* of the day. This is described in Equation (59).

$$c_{s,t}^{act,a} \geq C_{s,t}^{lower} \tag{59}$$

The activation price must be less than or equal to the upper bound in each time period *t* of the day. This is described in Equation (60).

$$c_{s,t}^{act,a} \leq C_{s,t}^{upper} \tag{60}$$

End-users have the option to decide whether or not to participate in flexibility programs. If participation results in losses for end-users, they will choose not to participate. As explained earlier, it is assumed that the end-users are satisfied with the flexibility price as long as they make a profit at the end of the day. Since the objective is to maximize the aggregator's profit, the household's profit must be secured.

Equation (61) ensures that all participating households receive a profit of at least 0.001 NOK/day.

$$\pi_h \geq 0.001 \tag{61}$$

The profit of each flexibility source, π_s [NOK], is the sum of the activation and reservation remuneration received from the aggregator, in addition to the energy savings. The energy savings [NOK] is represented by the variable $S_{s,t}$ for source *s* in time *t*. This is described in Equation (62),

$$\pi_s = \sum_{t=1}^{T} \left(c_{s,t}^{act,a} \cdot |F_{s,t}| + c_{s,t}^{res,a} \cdot (\delta_{s,t}^{res,a} - \delta_{s,t}^{act,a}) + S_{s,t} \right) \tag{62}$$

The energy savings result from the spot price variations and the differences between the baseline consumption and the actual consumption. Actual consumption refers to the source's energy consumption after the aggregator adjusts consumption to provide the requested flexibility. $W_{s,t}$ [kWh] is the parameter representing the baseline consumption and $\omega_{s,t}$ [kWh] is the parameter representing the actual consumption of source *s* in time t. The energy savings are defined in equation (63).

$$S_{s,t} = (W_{s,t} - \omega_{s,t}) \cdot SpotPrice \tag{63}$$

Moreover, the profit for a household *h*, π_h, is the sum of the profit from all flexibility sources of the household, as described in Equation (64). N_h is the number of flexibility sources that household *h* owns.

$$\pi_h = \sum_{s=1}^{N_h} \pi_s \tag{64}$$

3.2.3 Obtaining the Highest Price that Ensure Profit for All Participants

End-users want a high price for flexibility to increase their own profit. Therefore, the highest price that ensures profit for all participants is found by maximizing the total profit for end-users, provided the aggregator has a positive profit. The objective is to maximize the profit for the end-users, with the obtained schedule as input and the activation and reservation prices as variables, as shown in Equation (65),

$$\max\ \pi_h = \sum_{t=1}^{T} \sum_{s=1}^{S} \left(S_{s,t} + c_{s,t}^{act,h} \cdot |F_{s,t}| + c_{s,t}^{res,h} \cdot (\delta_{s,t}^{res} - \delta_{s,t}^{act}) \right) \tag{65}$$

where π_h is the profit of household *h*. $c_{s,t}^{act,h}$ is a variable representing the highest activation price that ensures a profit for both the aggregator and end-users, for source *s* in time period *t*. $c_{s,t}^{res,h}$ is the variable representing the corresponding reservation price.

The activation price for flexibility must be greater than or equal to the lowest price that ensures a profit for all participants in each time period *t* of the day. Similarly, the activation price in each time period *t* of the day must be less than or equal to the upper bound. This is represented in Equations (66) and (67). The reservation price, $c_{s,t}^{res,h}$, is defined as a percentage of the activation price, as described in Equation (68).

$$c_{s,t}^{act,h} \geq c_{s,t}^{act,a} \tag{66}$$

$$c_{s,t}^{act,h} \leq C_{s,t}^{upper} \tag{67}$$

$$c_{s,t}^{res,h} = \epsilon_{s,t}^{res} \cdot c_{s,t}^{act,h} \tag{68}$$

Since the objective is to determine the highest price that ensures profit for all participants, the aggregator's profit must be secured. Equation (70), ensures that the aggregator receives a profit of at least 0.001 NOK/day.

$$\pi_a \geq 0.001 \tag{69}$$

The profit of the aggregator, π_a, is calculated as described in equation (70).

$$\pi_a = \sum_{t=1}^{T} C_t^{max} \cdot |D_t| - \sum_{t=1}^{T}\sum_{s=1}^{S} \left(c_{s,t}^{act,h} \cdot |F_{s,t}| + c_{s,t}^{res,h} \cdot (\delta_{s,t}^{res} - \delta_{s,t}^{act}) \right) \tag{70}$$

3.3 Summary of Method

The flowchart in Figure 16 explains the steps involved from when the aggregator accepts a request for flexibility from the buyer, until the feasible prices for the schedule are determined.

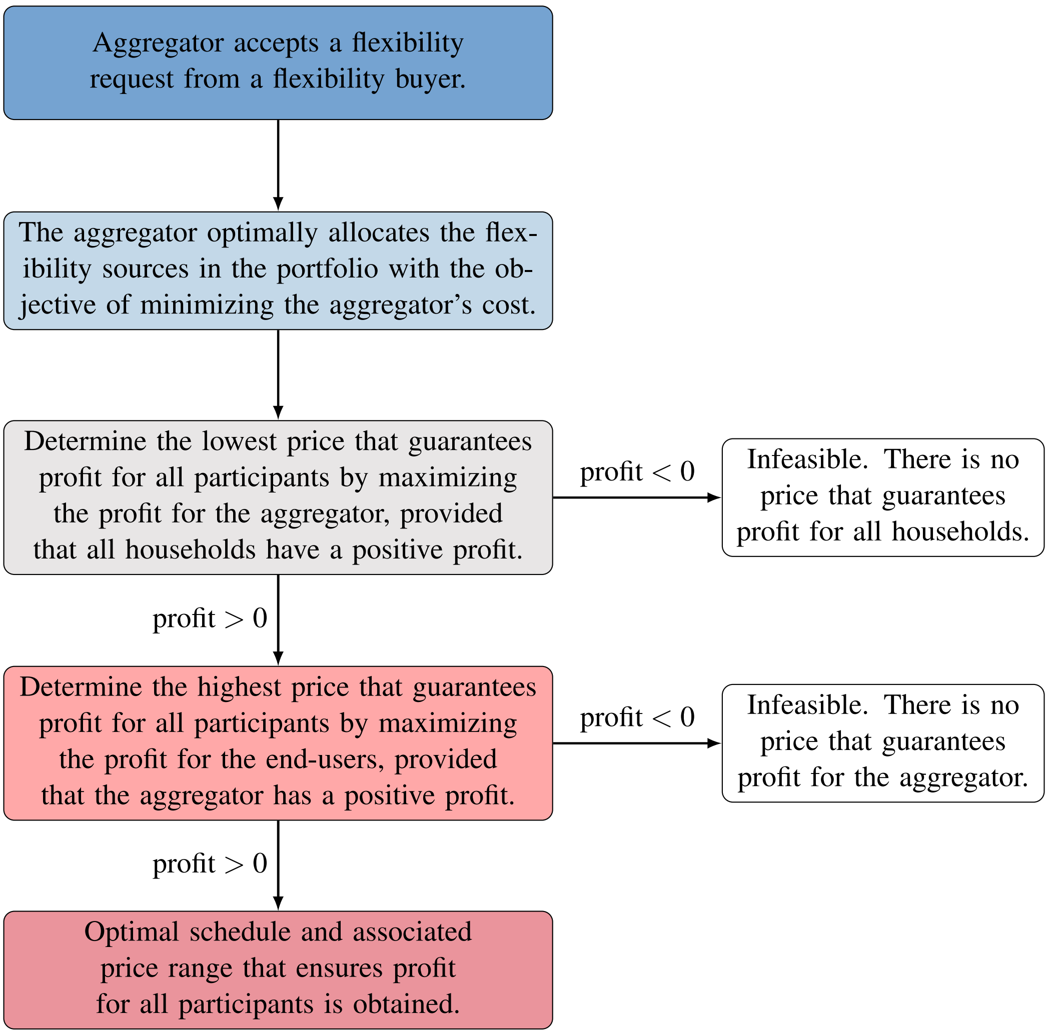


Figure 16: Flowchart of the presented method to achieve an optimal schedule that minimizes the costs for the aggregator and an associated feasible price range that ensures profit for all participants for the schedule. The process is repeated every day.

It is assumed that the aggregator has sufficient capacity in the portfolio to fulfil the flexibility request. As shown in Figure 16, there are two possible scenarios in which no feasible price that ensures a profit for all participants can be determined for the schedule. The first case is when there is no price within the defined price bounds C^{lower} and C^{upper} that ensures profit for all households. The second is when there is no price within the defined price bounds that ensures a profit for the aggregator.

3.4 Simulation Description

Simulations are performed to validate the proposed method. In this regard, the results chapter is divided into five parts. In step one, a portfolio is created. The source specifications for each source in the portfolio are found by collecting data, as presented in section 4.1. In step two, the goal is to determine an optimal schedule by allocating sources from the portfolio created in step one, with the objective of minimizing the costs for the aggregator. The activation price for flexibility is a parameter set to the minimum price of the existing power market pricesobtained from the Nordic power market. Section 4.2 presents an optimal schedule for each day of the simulated week, and analyzes how the optimal allocation program responds to variations in prices from the power market. Further, the aggregator's costs, the source distribution and the distribution of profits between the end-users are analyzed.

The schedule obtained in step two provides the absolute minimum cost of obtaining a feasible schedule. However, it does not guarantee a profit for either the aggregator or the end-users. The end-users have the power to decide whether or not to participate in the flexibility program. If they are not satisfied with the price offered, they will choose not to participate. The next step is therefore to investigate if there exists a feasible price range for the obtained schedule, that guarantees profit for all participants. The price mechanism presented in Section 3.2 is tested for three different pricing strategies. All strategies tested under the assumption of a BRP being the flexibility buyer. This means that the aggregator's profit is constrained by the balancing price received from the BRP in all three strategies. Further, it is assumed that the profit must be ensured within a 24 hour period (on daily basis) for all strategies. A summary of the price strategies is presented in Table 4.

Table 4: The three pricing strategies tested in the simulations. The price bounds are defined in NOK/kWh.

	C^{lower}	C^{upper}	Mechanism
Strategy 1	Lower bound formed from the existing power market price combinations	Upper bound formed from existing power market price combinations	Uniform for all sources
Strategy 2	Lower bound formed from existing power market price combinations	Upper bound formed from existing power market price combinations	Individual for each source
Strategy 3	0	100	Uniform for all sources

The time-varying bounds for Strategies 1 and 2 are found by the equations presented in Section 3.2.1. In each time period of the day, the prices are constrained by the existing power market price in the respective time period. For price Strategy 3, the price is constrained by the fixed values of 0 and 100 NOK/kWh in each period of the day, allowing the aggregator to freely distribute prices within the 24-hour period. The goal in setting up these three pricing strategies is to analyze the differences in aggregator and end-user profitability for first, uniform versus individual pricing, and second, fixed bounds versus bounds formed from the existing power markets.

Figure 17 illustrates the five steps. The colored boxes at the top represent the goal of each step. The boxes below represent the main things that will be investigated with respect to the main goal off the step.

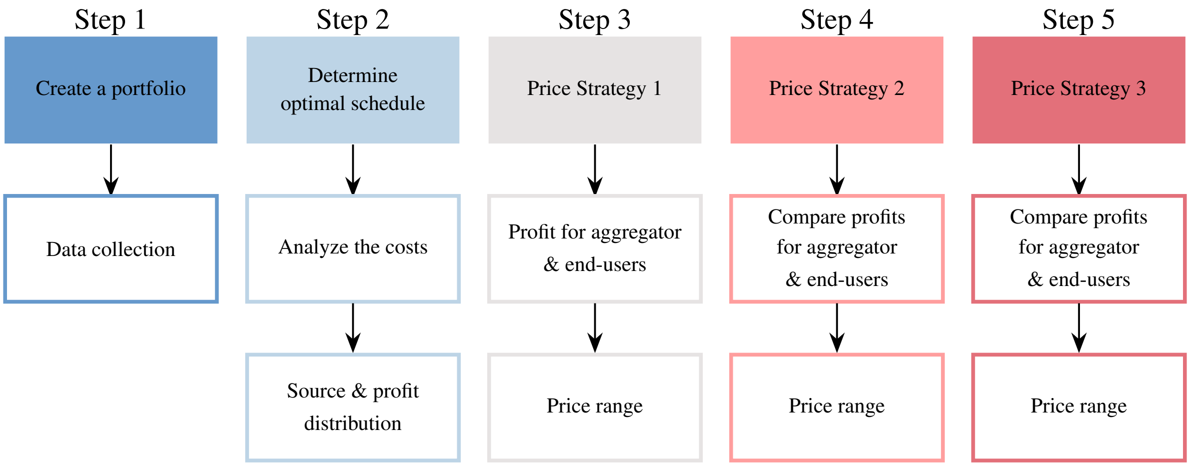


Figure 17: The five steps involved in the simulations and corresponding goals that the results are divided into.

4 Results

To validate the proposed optimal allocation model and to investigate the pricing of residential flexibility, simulations are conducted. The simulations are performed for one week, where the model is solved once for each day. A resolution of 15-minute intervals is used for the simulations. The model is deterministic and does not account for unpredictable changes in consumer power consumption. The optimization problem is solved using the Gurobi solver in Pyomo, Python. The simulations are run on a MacBook Pro from 2015 with the High Sierra operating system (10.13.6), a 2.7 GHz Intel Core i5 processor and an 8 GB 1867 MHz DDR3 memory. In the next section, an aggregator's portfolio of flexibility sources is created for the simulations.

4.1 Data Collection

The creation of a portfolio is necessary to allocate and price flexibility services. In order to create a portfolio, data must be collected. In addition, existing power market prices need to be extracted in order to allocate sources optimally and to test price Strategies 1 and 2. This section presents the data collected and the assumptions made for the simulations.

Portfolio

In this thesis, all curtailable sources are assumed to be water heaters, all regulatable sources are assumed to be heat pumps and all shiftable loads are assumed to be EVs. The simulations are run with a portfolio of 50 households. It is assumed that all households own a water heater, 80% own a heat pump, 50% own an EV, and 20% own a battery, as this roughly reflects a modern Norwegian neighbourhood. For the portfolio of 50 households, this equates to 50 water heaters, 40 heat pumps, 25 EVs and 10 batteries. Data for curtailable, regulatable and shiftable loads are extracted from real-life measurements by Pecan Street in New York, 2019 [94]. The data contains active power profiles at 15-minute resolution, from water heaters, heat pumps, and EVs. It is assumed that the activation allowance of curtailable and regulatable sources is between 1 and 3 times per day, and that the activation allowances of shiftable sources is 1 time per day. The minimum rest duration is between 1 to 2 hours for curtailable sources and between 1 and 4 hours for the regulatable sources. The maximum activation duration is between 1 and 3 hours for the curtailable sources and between 2 and 5 hours for regulatable sources. These numbers are chosen in conjunction with the literature review conducted for the specialization report [92].

Households that own batteries are assigned either a Tesla Powerwall or an xStorage Home battery as presented in Appendix B. The baseline profiles for batteries are calculated as explained in Section 3.1.6. All batteries are assumed to have a self-discharge rate of 0.1 % per hour and a charge/discharge efficiency of 0.9 %. To account for the self-discharge rate of the batteries, the tolerance ϵ_b is set to 95% of the desired final SoC value. The minimum SoC value is set to 15% and the maximum SoC value is set to 90%. Further, it is assumed that the minimum allowed SoC at the end of the reservation period is the same SoC that the battery had at the beginning of the reservation period. End-users can reserve their sources in one of the time slots presented in the contract shown in Appendix C. The entire portfolio of flexibility sources and associated specifications are shown in Appendix D.

Nordic Power Market Prices for Week 1, 2021

Data for Strategies 1 and 2 are collected from the existing power market, Nord Pool, for Monday 4th of January to Sunday 10th of January in 2021 for Trondheim [95–97]. Figure 18 shows the day-ahead, intraday, and balancing market prices for the analyzed week.

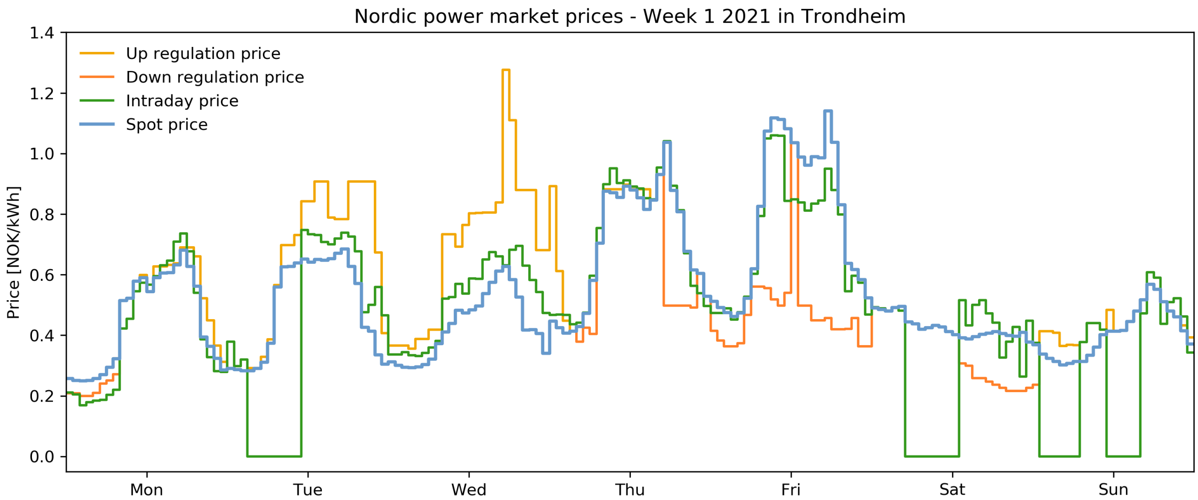


Figure 18: Norwegian power market prices for week 1 2021, in Trondheim.

The blue line in Figure 18 represents the spot price from the day-ahead market, the green line represents the intraday price, the yellow line represents the upward regulation price in the balancing market, and the orange line represents the downward regulation price in the balancing market. The figure shows that the prices are almost identical in some periods, while they differ more in other periods. A large difference in market prices indicates a larger imbalance in the system and thus a greater need for flexibility, while more consistent prices may represent less demand for flexibility in the market due to a smaller imbalance. This week was chosen as it represents some days with minor imbalances and some days with major imbalances. Power market prices vary throughout the year and from region to region. In Norway, the prices are relatively stable due to the production and regulation of hydro power. However, in countries dominated by renewable energy sources such as wind power, market prices are more volatile. Had a different week or region been chosen for the simulations, the prices could have been significantly different.

Figure 19 shows the lower and upper bounds formed from the existing power market prices presented in Figure 18, obtained from Equations (55) and (56). Consistent with the observations in Figure 18, there are large differences in the ranges between the upper and lower bounds for each day. For Tuesday, Wednesday and Saturday, the range seems to be larger than for the other days, where the range is really narrow or non-existent. Again, if another week had been simulated, the upper and lower bounds could have been different.

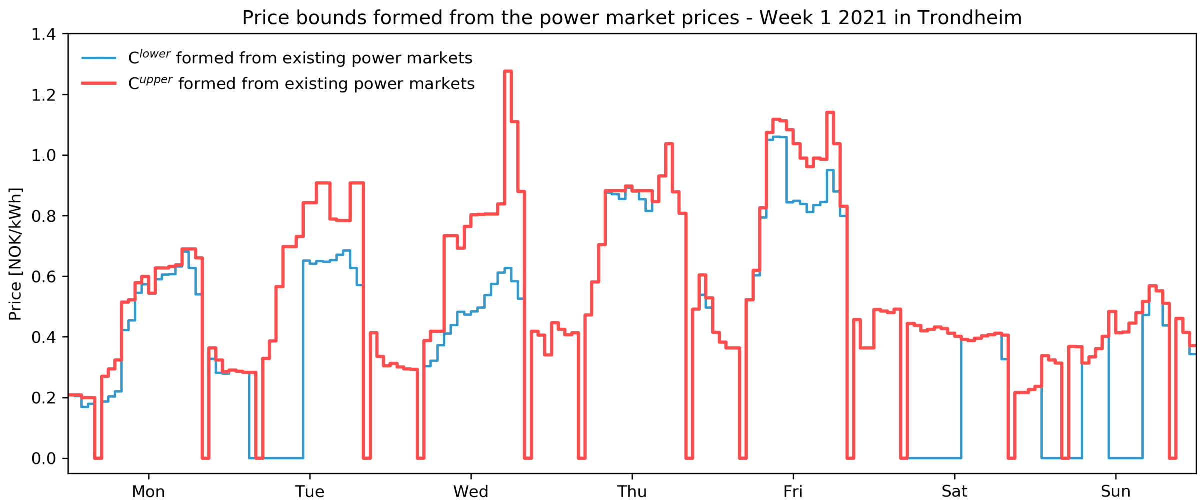


Figure 19: Minimum and maximum prices from the Norwegian power markets for week 1 2021, in Trondheim.

Flexibility Request

The program is run with the same flexibility request every day of the week to make it easier to analyze the impact of the prices. The daily request from the BRP consists of 91 kWh upward regulation and 37 kWh of downward regulation. In total, this adds up to 128 kWh/day. Figure 20 shows the BRP's daily request for flexibility.

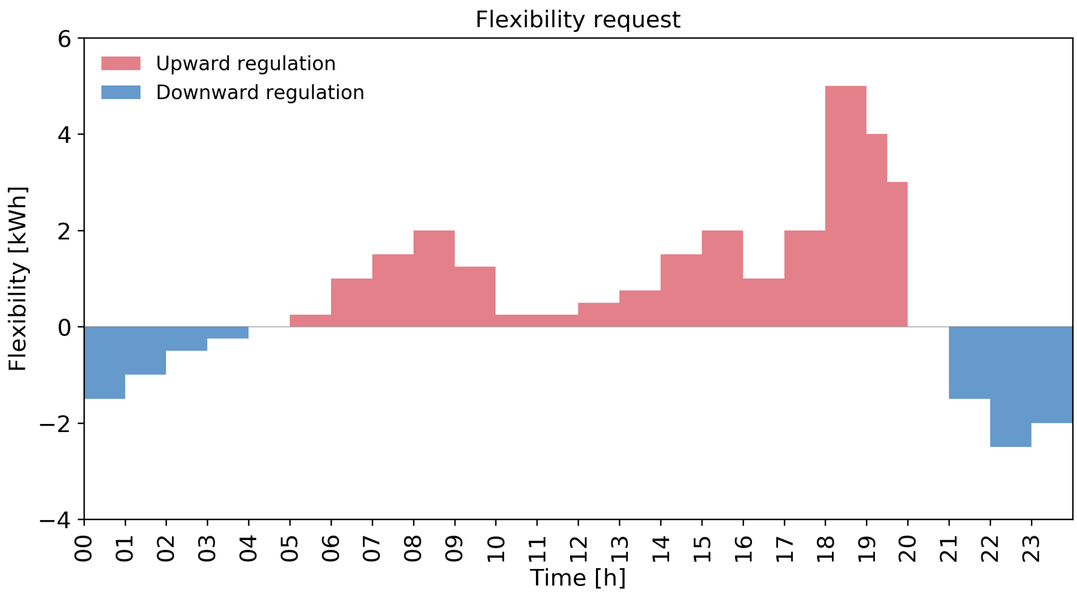


Figure 20: The daily flexibility requirement from the BRP used in the simulations. The blue area represents the request for downward regulation, while the red area represents the request for upward regulation.

Table 5 shows the payment the aggregator receives from the BRP for providing the requested flexibility, corresponding to the balancing market prices shown in Figure 18. The payment is calculated as in Equation 55.

Table 5: The payment the aggregator receives from the BRP for providing the requested flexibility, obtained from the Two-price model.

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Payment from BRP [NOK]	64.55	84.34	92.18	96.44	102.85	48.96	56.07

4.2 Optimal Schedule

Once the portfolio and a flexibility request is obtained, the next step is to determine an optimal schedule. This is determined by the optimal allocation model presented in Chapter 3. The maximum flexibility available in the aggregator's portfolio is 1124 kWh/day. However, the constraints from the contract will limit this value significantly. As previously stated, it is assumed that the requested flexibility is always available in the portfolio. The program is run with the minimum price from the existing power markets as the activation price for flexibility. This price represents the the lowest possible price the aggregator can pay the end-users to obtain a feasible schedule, when the prices are based on the existing power market prices. The reservation price is set to 1% of the activation price. An optimal schedule is obtained for each day of the week. Figure 21 shows how the aggregator optimally allocate the sources in its portfolio for each day of the week.

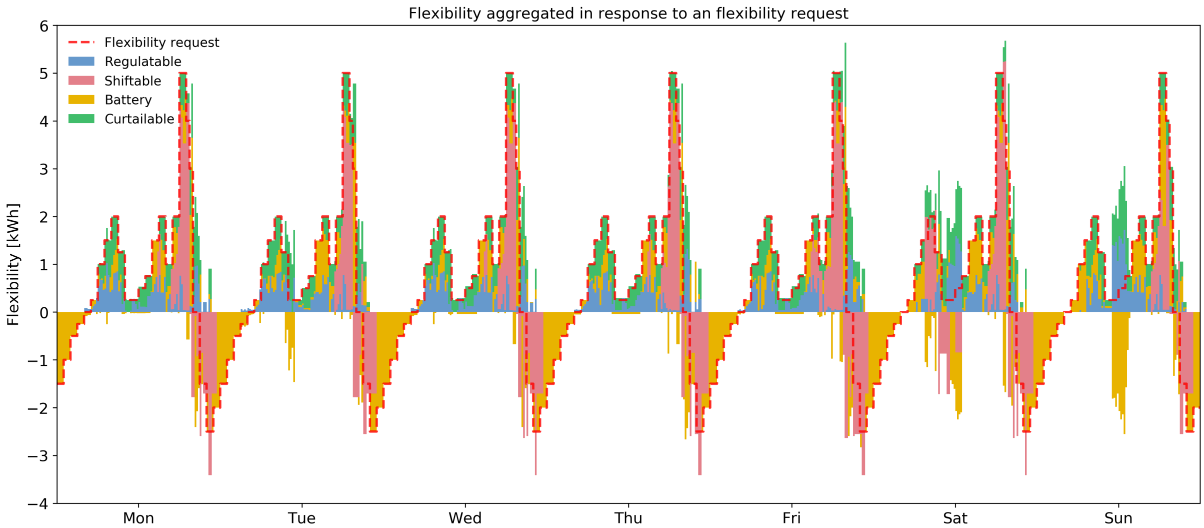


Figure 21: Optimal schedule for meeting the flexibility request from the BRP.

In some periods, more flexibility than requested is activated. This is particularly evident for Saturday and Sunday, as shown in Figure 21. Since the minimum price from the existing power markets is zero in many time periods for these two days, the cheapest schedule is achieved by activating more flexibility than requested. Activating flexibility during these periods does not incur any cost to the aggregator. The aggregator exploits this by charging the batteries during the periods when the price is zero in order to use them for discharging in later periods. This is feasible because the sum of up-regulation and down-regulation equals the requested flexibility. Since the activation and reservation price is zero in the quarters when no flexibility is requested, the same considerations arise for these periods. In both cases, the issue of fairness arises because the activation of sources results in potential inconvenience and degradation of sources, without payments to end-users.

4.2.1 Costs

The cost for the aggregator for providing a total of 128 kWh of flexibility everyday for seven days is 484.56 NOK. The activation and reservation costs constitute the total cost for the aggregator. The cost of the aggregator, the compensation received from the BRP, and the resulting profit for each day of the week are presented in Table 6.

Table 6: Activation costs, reservation costs and total costs for the aggregator, as well as the compensation the aggregator receives from the BRP and the profit for the aggregator for providing 128 kWh of flexibility everyday for seven days. All values are in NOK.

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Activation	63.63	54.33	66.35	106.68	106.86	37.71	38.99
Reservation	1.36	1.02	1.45	2.33	2.31	0.73	0.83
Total cost	64.99	55.35	67.80	109.01	109.17	38.43	39.82
Compensation	64.55	84.34	92.18	96.44	102.85	48.96	56.07
Profit	-0.44	28.99	24.38	-12.58	-6.31	10.53	16.25

The cost for the aggregator is higher than the payment from the BRP for Monday, Thursday and Friday, resulting in a negative profit for the aggregator, as shown in Table 6. One reason for this is the reservation price, which imposes an additional cost on the aggregator. In this thesis, the reservation price is defined as 1% of the activation price. The results presented in Table 6 shows that the aggregator's cost of activating the sources is less than the payment it received from the BRP on Monday, suggesting that a different definition of the reservation price could have made it profitable for the aggregator.

The reason why the aggregator is not profiting on Thursday and Friday is the user preferences and technical constraints that limit the optimal schedule. The price used as the activation price when determining the optimal schedule is the lower bound formed from the existing power markets, C^{lower}. This price is always less than or equal to the upper bound formed from the existing power market prices, C^{upper}. The aggregator would make a profit of $D_t \cdot (C^{upper} - C^{lower})$ if exactly the requested amount of flexibility is activated. However, if more flexibility than requested is activated, the aggregator's profit decreases. It is established that activating excess flexibility during periods when the price is zero does not impose a cost on the aggregator. However, surplus flexibility is also activated during periods when the activation price is not zero. This is particularly evident on Thursday and Friday, where this, combined with the additional reservation cost results in unprofitable flexibility provision for the aggregator.

4.2.2 Source and Profit Distribution

Figure 22 shows the percentage of activated flexibility [kWh] from each of the four source types. The fraction of activated flexibility from curtailable and regulatable sources is approximately 30% of the activated flexibility per day and is almost unchanged from day to day. The sum of these sources accounts for a smaller share of the activated flexibility because they cannot provide down regulation and generally have lower power ratings than shiftable sources and batteries. Batteries can provide both up-regulation and down-regulation and are not subject to any of the activation constraints (activation allowance, minimum rest duration and maximum activation duration). As a result, much of the flexibility is activated from the batteries. However, on most days, the majority of flexibility is activated from shiftable sources. From an aggregator's point of view, shiftable sources are the most favourable to activate because they are assumed to be recovered. As described in section 3.1.5, the aggregator pays for flexibility in the periods from which the load is shifted, rather than in the periods to which the load is shifted. Consequently, the aggregator's costs increase when the share of flexibility from shiftable sources decreases.

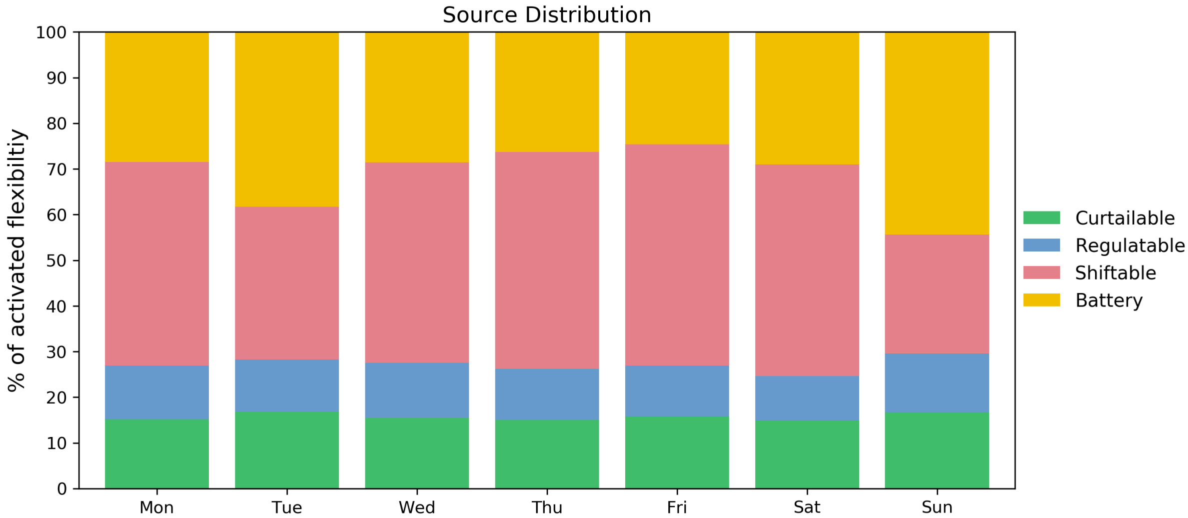


Figure 22: Source distribution of the activated flexibility [kWh] from each source type. The bars represent the share of the activated flexibility [kWh] from each of the source types.

The distribution of sources does not correspond to the distribution of profits, as can be seen from Table 7 and Figure 22.

Table 7: Percentage of profits from each source type for each day of the simulated week.

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Curtailable	28.44	31.53	28.20	30.10	31.94	36.78	36.32
Regulatable	21.13	20.85	21.71	21.58	21.22	24.18	23.40
Shiftable	30.22	26.41	27.64	28.59	30.27	26.78	22.71
Batteries	20.21	21.16	22.45	19.73	16.57	12.27	17.57

Batteries account for the largest share of activated flexibility on Sunday, 44% in total. However, battery owners receive only 18% of the profits, making up the smallest share on this day. Similarly, shiftable sources account for 49% of activated flexibility on Friday, but receive only a 30% share of the profits. Correspondingly, curtailable and regulatable sources receive a large share of the profit compared to the small share of activated flexibility on that day. *These results suggest that pricing different types of sources differently may result in a more equitable distribution between the flexibility provided and the profit received.*

In summary, the aggregator exploits the quarters when the price is zero by activating more flexibility than requested, and it is found that shiftable sources and batteries are activated the most but profit the least. The minimum cost to achieve a feasible schedule is found by setting the activation price equal to the minimum price from the existing power markets. A feasible schedule is found for each day of the week. The next step is to determine whether there exist a price range for the schedule that guarantees a profit for both the aggregator and the end-users. In the following sections, only the activation price is presented. However, exactly the same trends can be found for the reservation price, since the reservation price is defined as a fraction of the activation price.

4.3 Price Strategy 1

In this section, the results with price Strategy 1 is presented. Price Strategy 1 presents a uniform price range for all sources. In each quarter of the day, the prices are constrained by the existing power market prices in the respective quarter, as previously shown in Figure 19. To determine the price range, two optimizations are performed. The first optimization forms the lower bound of the optimal price range and is found by maximizing the profit for the aggregator under the assumption that the aggregator is the price setter. The second optimization forms the upper bound of the price range and is found by maximizing the profit for the households, assuming that the households are the price setters. As previously presented, the optimizations can lead to two possible outcomes: either a feasible price range is found or not. Finding a feasible price range implies that all prices within the range guarantee a profit for both the aggregator and the households. If there is no feasible price range, the aggregator makes no profit or households do not profit.

4.3.1 Profits for Aggregator and End-users

A uniform price range that guarantees a profit to the aggregator as well as to the end-users is found for Tuesday, Wednesday, and Saturday. On these days, the spread between the minimum and maximum existing power market prices is the largest. These results suggest that greater profits can be made when there are large differences between spot prices, intraday prices, and balancing prices.

There is no feasible price range that guarantees a profit for both the aggregator and the end-user on Monday, Thursday, Friday, and Sunday. On Monday, Thursday and Friday, the aggregator does not profit. This means that the minimum price from the Nordic power market is too high to guarantee a profit for the aggregator. On Sunday there is no feasible price that guarantees a profit for all households. The households that do not make a profit on Sunday own batteries. As mentioned previously, batteries account for the largest share of activated flexibility on this day, but receive the smallest share of profits. As defined in section 3.1.6, baselines for the batteries are calculated by minimising the total cost of energy consumed by the household's water heaters, heat pumps, and electric vehicles. If the battery is instead used for flexibility services, battery charging and discharging are fully controlled by the aggregator. This can result in a large deviation from baseline consumption and potentially increase energy costs for battery owners. For Sunday, the increased costs exceed the compensation received for two of the batteries, resulting in two of the households not profiting.

The results from the feasible days will now be presented. Table 8 presents the range of feasible profits for the aggregator and end-users for Tuesday, Wednesday, and Saturday. Profits are given as a range in relation to the found price range. The range of profits for the aggregator, $\pi_{aggregator}$, represents the minimum guaranteed profit for the aggregator when the end-users are the price setters, to the maximum possible profit obtained when the aggregator is the price setter. The same explanation is given for the average profit range for the end-users, $\pi^{avg}_{households}$.

Table 8: Profits for aggregator and households for week 1 2021 in Trondheim, with price Strategy 1.

Day	Payment from BRP to aggregator [NOK]	$\pi_{aggregator}$ [NOK]	$\pi^{avg}_{households}$ [NOK]
Tuesday	84.34	0.001 - 28.99	1.91 - 2.49
Wednesday	92.18	0.001 - 24.37	2.00 - 2.48
Saturday	48.96	0.001 - 7.77	1.18 - 1.33

Table 8 shows that the aggregator's potential profit is significantly less than the payment received from BRP. The aggregator must pay a share of the payment from the BRP to the end-users to guarantee profits for them. The share of this payment for price Strategy 1 is presented in Table 9.

Table 9: Share of payment from BRP distributed between the aggregator and end-users for price Strategy 1 for Tuesday, Wednesday and Saturday. All values are gives as a percentage.

Strategy 1	Aggregator	End-users
Tuesday	0.002 - 33	67 - 99.998
Wednesday	0.002 - 26	74 - 99.998
Saturday	0.002 - 16	84 - 99.998

As can be seen in the table above, the aggregator must distribute a share of the payment from the BRP of at least 67% for Tuesday, 74% for Wednesday, and 84% for Saturday to end-users in order to guarantee profits for end-users. This result shows that the aggregator must pay more than half of the payment from the BRP to the end-users to make it profitable for them. In a worst case scenario, the aggregator would have to pay 99.998% of the payment to the end-users for Tuesday, Wednesday and Saturday. This means that the aggregator would only receive 0.002% of the payment for itself. The results indicate that approaching the highest price in the feasible range leads to an unfair distribution of profit. Furthermore, the results suggest that if the end-users are given a large amount of decision making power by being the price setters, this can significantly reduce the aggregator's profit.

4.3.2 Feasible Price Range

The lower bound formed from the existing power market prices guarantees a profit to both the aggregator and end-users for Tuesday and Wednesday. Since Saturday is the day when the aggregator profits the least and the feasible price range is more narrow than the defined bounds, this day is analyzed and presented in more detail. The feasible price range for Saturday is presented in Figure 23. The blue line represents the lowest feasible price of the range, and the red line represents the highest feasible price of the range. As can be seen in the figure, the two prices overlap during large parts of the day. In periods where only the blue line is visible, there is only one price that can be set to guarantee profit for the aggregator and the end-users. In the remaining periods, all prices in between the blue and red lines, represent feasible prices.

The minimum price from the existing power market is not sufficient to guarantee a profit for all households. Therefore, the aggregator increases the price for all sources between 7:30-7:45 and 7:45-8:00 to guarantee a profit for all participating households. Similarly, the maximum price from the existing power market is too high to guarantee a profit for the aggregator. Therefore, end-users lower the price for all

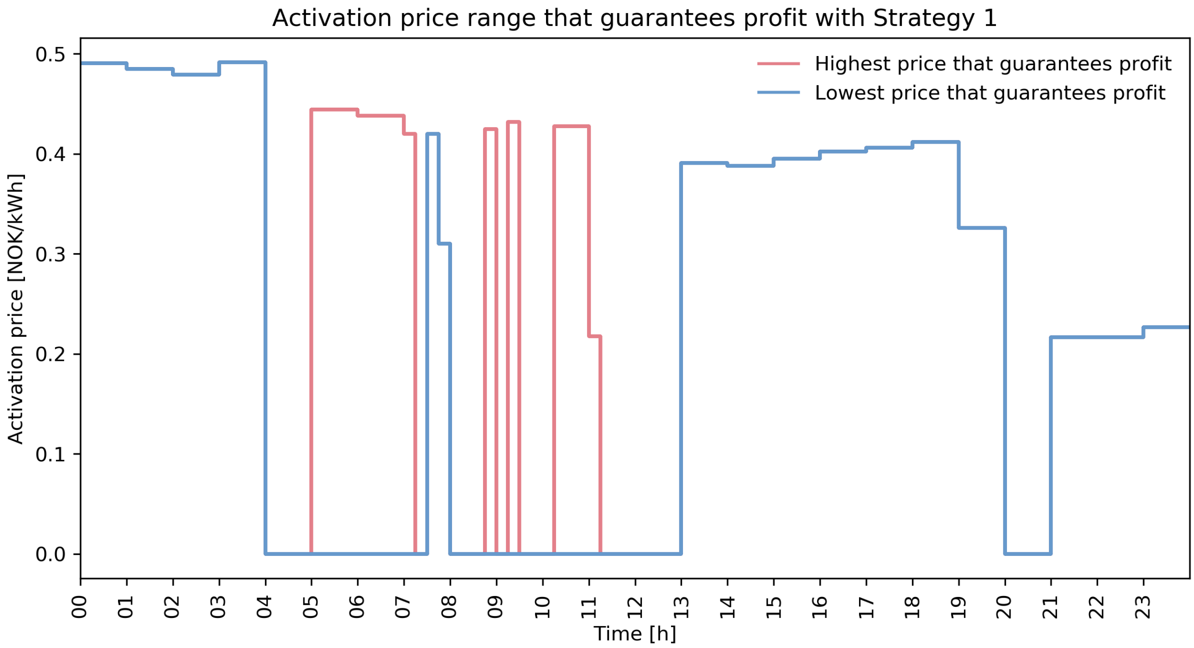


Figure 23: Feasible price range for ensuring profit for all participants for Saturday, for price Strategy 1.

sources in several time intervals of the day to guarantee a profit for the aggregator. In fact, the flexibility price can never reach the maximum power market price in all quarters of the day. This is explained by the profit requirement for the aggregator, which takes into account both activation and reservation costs. To summarize, the flexibility price is not equal to the maximum existing power market price in all quarters due to the aggregator's additional reservation costs.

4.4 Price Strategy 2

The results presented in the previous section demonstrate that a uniform price increase ensures profit for all participating households for Saturday. However, it reduces the aggregator's profit. It is conceivable that increasing the price only for the unprofitable sources is sufficient to ensure profit for the respective households. Therefore, another option is to allow the aggregator and end-users to set individual prices. This is defined by setting individual prices for each flexibility source and obtaining an individual price range for each flexibility source.

This section compares the feasibility and profitability of individual pricing with the results presented for Strategy 1. The same methodology as for Strategy 1 is repeated for individual pricing and repeated here for convenience: the first optimization forms the lower bound of the optimal price range for each source, which results from maximizing the aggregator's profit under the assumption that the aggregator is the price setter. The second optimization forms the corresponding upper bound, which results from maximizing the aggregator's profit for households under the assumption that the end-users are the price setters.

4.4.1 Profits for Aggregator and End-users

The days that yield feasible price ranges are the same days as shown in the results with Strategy 1. One might expect that individual prices would have given a feasible price range for more days than with uniform prices. While this is possible with the proposed model, the results presented in section 4.2 showed that the aggregator loses money when the price is equal to the lower bound formed from the existing power market prices, making it impossible to find feasible prices for these days with the same bounds as for uniform prices. Table 10 shows the range of possible profits for the aggregator and households for Strategy 2.

Table 10: Profits for aggregator and households for week 1 2021 in Trondheim, with price Strategy 2.

Day	Payment from BRP to aggregator [NOK]	$\pi_{aggregator}$ [NOK]	$\pi_{households}^{avg}$ [NOK]
Tuesday	84.34	0.001 - 28.99	1.91 - 2.49
Wednesday	92.18	0.001 - 24.37	2.00 - 2.48
Saturday	48.96	0.001 - 10.45	1.12 - 1.33

No changes are observed in the profit for Tuesday or Wednesday. This is explained by the fact that the minimum prices from the existing power market are sufficient to guarantee a profit for both parties. The profit range of the aggregator increases on Saturday when an individual pricing mechanism is used. For Saturday, the aggregator's maximum profit increases from NOK 7.77 to NOK 10.45, an increase of 26%. The corresponding average minimum profit for households decreases from NOK 1.18 to NOK 1.12, a decrease of 5%. This result suggests that individual pricing allows for a higher profit for the aggregator without significantly reducing the profit for the end-users. Another observation is that individual pricing distributes the payment from the BRP more evenly between the aggregator and the end-users. A comparison of the profit shares for price Strategies 1 and 2 is shown in Table 11.

Table 11: Comparison of the share of payment from BRP distributed between the aggregator and the end-users with price Strategies 1 and 2. All values are given as a percentage.

	Strategy 1		Strategy 2	
	Aggregator	End-users	Aggregator	End-users
Tuesday	0.001 - 34	66 - 99.999	0.001 - 34	66 - 99.999
Wednesday	0.001 - 26	74 - 99.999	0.001 - 26	74 - 99.999
Saturday	0.002 - 16	84 - 99.998	0.002 - 21	79 - 99.998

Table 11 shows that the aggregator's maximum share of the profits increases from 16% to 21% and the end-users' corresponding maximum share decreases from by 84% to 79%. Overall, 14 households profit more, while 28 households profit less with individual prices. The profit of the remaining households is unchanged. Moreover, the households that benefit the most from Strategy 1 benefit the most with Strategy 2. The same trend is observed for the households that benefit the least. While some might argue that individual prices are unfair, these results indicate otherwise. *These results suggest that individual prices distribute the share of payment from the BRP more equitably between the aggregator and end-users.*

4.4.2 Feasible Price Ranges

The feasible price ranges for Saturday are shown in Figure 24. The blue lines represent the lowest prices in the ranges and the red lines represent the highest prices in the ranges. All prices within the ranges for each quarter of the day for each source represent prices that secure profits for both the aggregator and the end-users.

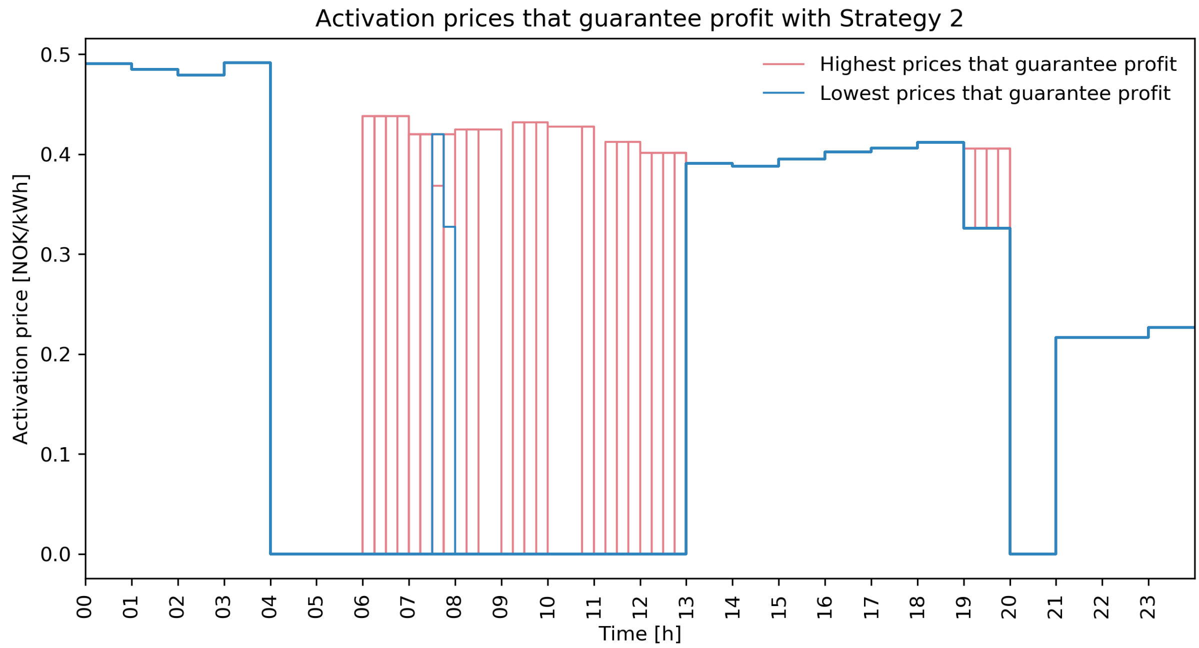


Figure 24: Feasible price range for ensuring profit for all participants for Saturday, for price Strategy 2.

The minimum price from the existing power market is insufficient to guarantee a profit to all households, and so the aggregator increases the price of a water heater between 7:30-7:45 and 7:45-8:00 to guarantee a profit to all participating households. Under price Strategy 1, the aggregator must increase the price for all sources to guarantee a profit for all households. With the individual prices assumed in Strategy 2, the results show that it is sufficient to increase the price for only one source. As a result, the profit for the aggregator increases in Strategy 2 compared to Strategy 1. Similar to the first strategy, the highest price that guarantees a profit for both the aggregator and the end-users fluctuates. Compared to price Strategy 1, the individual prices fluctuate at different times because all sources have different price ranges.

The water heater that receives an increased price belongs to a household that also own an EV and a battery. That household's battery is the source responsible for the losses, and thus for raising the uniform price above the lower bound formed from the existing power markets with price Strategy 1. This shows that the price of the water heater is increased even though the non-profiting source is a battery. As the model constraint the profit on a household level, there are no requirements saying that the price needs to be increased for the non-profitable source and hence the battery is still not profitable with individual prices. However, the price increase for the water heater is sufficient to ensure the required profit of 0.001 NOK for the respective household.

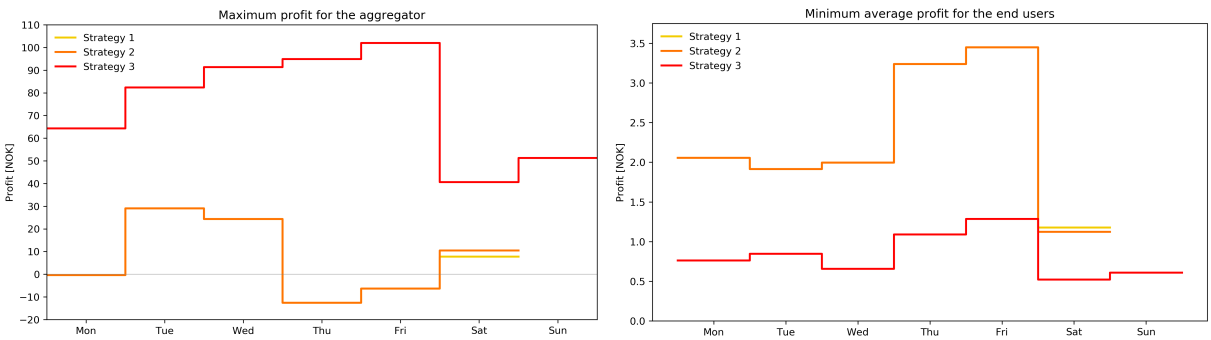
In summary, individual prices are found for the same days that a feasible uniform prices exist. Moreover, the results show that prices constrained by existing market prices in each quarter of the day limit the possible profits for the aggregator and do not realize the full profit potential for the aggregator. Since flexibility prices are constrained by existing prices in each quarter of the day, the feasible price ranges are very narrow for many time intervals of the day. This leads to an infeasible result for four of the days in the simulated week. Therefore, the next strategy aims to test whether constraining the flexibility price by setting fixed limits that exceed the existing power market prices for all quarters of the day, assuming the same payment from a BRP, could result in a feasible price range.

4.5 Price Strategy 3

Under this price strategy, the prices are no longer constrained by the existing power market prices in each quarter. Instead, the flexibility prices are constrained by some fixed boundaries outside the existing power market prices. This means that the aggregator is allowed to set prices below the existing market prices and the end-users are allowed to set prices above the existing market prices, with the same condition as in the previous price strategies that both parties make a profit for each day. It is further assumed that the flexibility buyer is a BRP, and the payment from the BRP to the aggregator is the same as previously shown in Table 5. To test whether feasible price ranges can be found by changing the bounds, the price optimizations are run again. The same schedules are taken as input, and the flexibility prices are constrained by some randomly chosen fixed limits set to 0 NOK/kWh and 100 NOK/kWh. The optimization is performed for uniform pricing.

4.5.1 Profits for Aggregator and End-users

For all days of the week, a feasible price range is found that guarantees a profit for both the aggregator and the end-users. Compared to the results of the two previously analyzed scenarios, which showed that profits are unfairly distributed when end-users set the price, these results show the opposite. Figure 25 compares the profit for the aggregator and end-user for all three price strategies. The yellow lines represent the maximum and minimum possible profit for the aggregator and end-users, respectively, with Strategy 1. The orange and red lines represent the same, but for Strategies 2 and 3.



(a) Maximum profit for the aggregator. **(b)** Minimum profit for the end-users.

Figure 25: Obtained profit when the activation price is the lowest price that ensures profit for both aggregator and end-users. The yellow line represent the profit obtained with price Strategy 1, the orange line represent the profit obtained with price Strategy 2 and the red line represent the profit obtained with price Strategy 3.

Figure 25(a) shows that the aggregator's maximum profit is increased on all days compared to Strategies 1 and 2. Figure 25(b) shows that the average minimum profit of the end-users decreases for Strategy 2 compared to Strategy 1 and further for Strategy 3. As can be seen from the figure, the distribution of profits is now altered. A comparison of the share of profits for the different price strategies are shown in Table 12.

Table 12: Comparison of the share of payment from BRP distributed between the aggregator and the end-users with uniform prices constrained by existing power market prices in each quarter and uniform prices constrained by fixed values.

	Strategy 1		Strategy 2		Strategy 3	
	Aggregator	End-users	Aggregator	End-users	Aggregator	End-users
Monday	-	-	0.001 - 34	66 - 99.999	0.002 - 99.6	0.4 - 99.998
Tuesday	0.001 - 34	66 - 99.999	-	-	0.001 - 97.7	2.3 - 99.999
Wednesday	0.001 - 26	74 - 99.999	0.001 - 26	74 - 99.999	0.001 - 99.1	0.9 - 99.999
Thursday	-	-	-	-	0.001 - 98.3	1.7 - 99.999
Friday	-	-	-	-	0.001 - 99.2	0.8 - 99.999
Saturday	0.002 - 16	84 - 99.998	0.002 - 21	79 - 99.998	0.002 - 82.9	17.1 - 99.998
Sunday	-	-	-	-	0.002 - 91.5	8.5 - 99.998

The table shows that the aggregator's maximum profit share increases for all days and the end-users' minimum profit share decreases with Strategy 3. Compared to the previously presented price strategies, this means that the aggregator's profit may increase, but at the same time the end-users risk earning less.

4.5.2 Feasible Price Range

The feasible price range when fixed bounds of 0 and 100 NOK/kWh are set for the whole week is shown in Figure 26. The blue line represents the lowest feasible price of the range and the red line represents the highest feasible prices of the range.

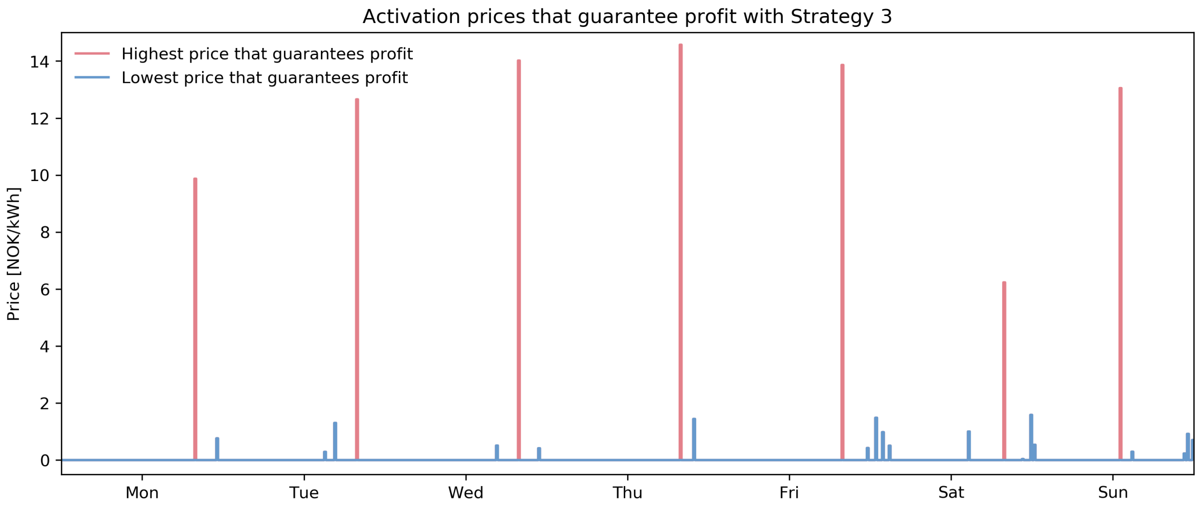


Figure 26: Feasible price range for ensuring profit for all participants for week 1, for Strategy 3 assuming uniform prices constrained between 0 and 100 NOK/kWh in every quarter of the day.

The aggregator desires to set the price to zero in as many quarters as possible, as this gives the aggregator itself the highest profits. However, the price of 0 NOK/kWh is not sufficient to guarantee a profit to all households. Therefore, the aggregator increases the price for all sources for at least one interval every day of the week. This proves sufficient to guarantee a profit for all participating households, as most households earn sufficiently from the additional cost savings from the adjusted consumption. Similarly, the maximum price of NOK 100/kWh is not sufficient to guarantee a profit for the aggregator. Therefore, end-users set the price to zero in most time intervals and increase the price as much as possible for a single interval of the day in addition to the time intervals in which the aggregator also increases the price.

4.6 Summary of Results

In the Section 4.2, the optimal schedule for each day of the week is determined. It is shown that more flexibility is activated than requested in quarters where the activation cost is zero. Moreover, the aggregator's cost of obtaining the optimal schedule on three days exceeds the payment received from the BRP. This means that the aggregator is not always able to provide the requested flexibility without losing money. Furthermore, the distribution of flexibility provision by each source type does not correspond to the profit achieved per source type. This suggests that it may be fairer to differentiate flexibility prices for each source type.

Furthermore, three price strategies are analyzed and presented. Strategy 1 assumes uniform prices bounded by existing power market prices in each quarter of the day. The results show that there is a feasible price range that guarantees a profit for both the aggregator and the end-users for three of the seven simulated days. Strategy 2 assumes individual prices bounded by existing power market prices in each quarter of the day. Feasible price ranges are obtained for the same days as for Strategy 1, and for one of these three days the maximum possible profit of the aggregator is increased without significantly reducing the minimum possible profit of end-users. For Strategy 3, uniform prices limited by fixed values of 0 NOK/kWh and 100 NOK/kWh are assumed. This significantly increases the aggregator's profit and results in a feasible price range that guarantees profit for both participants for each day of the simulated week.

5 Discussion and Further Work

The results led to several findings on the profitability of different pricing strategies. This chapter further discusses the results and their implications together with model limitations and suggestions for further work.

5.1 Discussion

In this section, the main results from the optimal allocation program are first discussed. This includes a discussion of the exploitation of flexibility sources when the price of flexibility is zero, as well as the potential losses resulting from a zero or negative price for flexibility. Second, a comparison of the three pricing strategies and the value of the results is discussed. Finally, the importance of fairness is discussed.

5.1.1 Optimal Allocation

The results from running the optimal scheduling program showed that more flexibility than requested is activated when the activation price for flexibility is zero. The aggregator exploits this by charging the batteries when the price for flexibility is zero. This means that the end-users do not get paid even though the aggregator activates their flexibility assets. Another aspect that was not observed in the results, but is related to the same discussion, is the possibility that the price for flexibility becomes negative. Spot prices in Norway are relatively stable due to the production and regulation of hydro power but in countries dominated by renewable energy sources such as wind power, market prices become more volatile. Furthermore, prices often become negative during production periods with oversupply.

Since the allocation program uses the minimum price from the spot, intraday, and balancing markets, there could have been a negative price for flexibility in another week or region was simulated. This would result in the aggregator being paid by end-users for activating their sources. This is an issue of fairness as activating sources leads to potential inconvenience and degradation of sources without payments to end-users. It can be argued that the lowest possible price paid to end-users should be greater than zero, as this is considered fairest to end-users. On the other hand, it can be argued that negative prices should be allowed as long as end-users make a profit at the end of the chosen optimization horizon.

Another aspect to consider when negative prices are allowed in the scheduling program is the potential losses that may occur for the end-users. In the results, the curtailable, regulatable, and shiftable sources always benefit. If negative prices are allowed, the owners of flexibility sources that provide up-regulation risk losing money. For the owners of curtailable and regulatable loads, the potential energy savings come from reducing consumption because only up-regulation is considered and the load is assumed to be non-recovered. If consumption is reduced during a period when the spot price is negative, the household would make money on increasing the energy consumption and thus lose money on reducing the consumption. For the owners of shiftable loads, the energy savings become a cost when the load is shifted from a period with a low price to a period with a higher price. This may be a problem in the Danish or German market. However, it is unlikely that the aggregator will receive a request for upward regulation when prices are negative, as this represents an abundance of energy in the network rather than a scarcity.

5.1.2 Comparison of the three Pricing Strategies

By comparing the potential profits resulting from the price ranges identified for the three strategies, it is found that the aggregator receives the lowest share of payments from the BRP in Strategy 1 and the highest in Strategy 3. The results also show that end-users gain more profit than the aggregator when they are given a high degree of decision-making power. However, it is well known that aggregation of multiple sources is necessary to provide a sufficient degree of flexibility. If the aggregator has no incentive to participate, end-users will have no intermediary to provide flexibility services on their behalf. This may ultimately result in household flexibility not being implemented. However, the model presented assumes that both participants are satisfied as long as both benefit, and the results show that this is possible. Furthermore, whether the distribution of benefits should be weighted more in favor of the aggregator or the end-users is an open question that needs further research.

From an aggregator's perspective, one could say that price Strategy 2 is preferable to price Strategy 1 because individual pricing lowers the aggregator's costs compared to uniform pricing. However, comparing all three strategies, one could say that Strategy 3 is the best option as it gives the aggregator the highest possible profits. On top of that, since Strategy 2 proves to be more cost-effective than Strategy 1, and Strategy 3 proves to be more cost-effective than Strategy 2, it is likely that a strategy that combines the price limits from Strategy 3 and the individual pricing from Strategy 2 is a desirable choice for the aggregator. From the end-users' perspective, one might conclude that price Strategies 1 or 2 is preferable to Strategy 3 due to its higher risk of loss. Nevertheless, there will always be a trade-off between the profits of the aggregator and the end-users because it is a zero-sum game, and it is therefore difficult to say whether the estimated prices would actually be sufficient to satisfy the participants.

The maximum profit the aggregator can make in a day from each of the three strategies while guaranteeing a profit of at least 0.001 NOK for the 50 participating households, is 100 NOK if the payment from the BRP is 102.85 NOK. These values need to be seen in line with the low flexibility request and the size of the portfolio. The magnitude of the request is about one thousandth of the energy requested in the balancing market. Moreover, the flexibility request is only a fraction of the flexibility capacity of the portfolio and nor does it reflect the market situation. A realistic demand request, that reflects the market situation may give more insight into the presented profitability of these figures. Therefore, the focus should not be on the exact values, as the key finding is that a profit can be made. Similarly, the minimum average profit that a household could possibly make while guaranteeing the aggregator a profit of at least 0.001 NOK is 0.5 NOK. If this household participates in the program for one year, it would have earned 182.5 NOK. Whether this value represents a fair compensation for the inconvenience of participating in a flexibility program is an open question that needs to be discussed.

From a game theory perspective, it can be argued that all customers will participate as long as there is a profit, no matter how small. This thesis focuses on the economics of flexibility provision and assumes that the households' comfort is guaranteed by the contract and that all households will choose to participate as long as there is a profit of 0.001 NOK/day. However, in reality, there will be large differences in what different end-users consider a fair price and profit. Some will see the common good as good enough to participate, while others will need a bigger incentive. This makes it difficult to estimate the value of flexibility. The same is true for the aggregator, as it needs to make enough profit to make the business worthwhile. Therefore, it should be considered whether the profit requirement of 0.001

NOK/day should instead be a different amount required at the end of the week or month. Changing this requirement would have changed the results. Whether the profit requirement should be defined per day, week, or month and whether 0.001 NOK/day is a fair value is something that needs to be considered.

In addition to differences in what is considered a fair value for flexibility, there are other factors that affect the true value of flexibility. Feasible price ranges are defined by the lowest and the highest possible price that guarantees a profit for both the aggregator and the end-users. However, it is not certain that the price ranges found represents the true price range that guarantees a profit, as it exists additional hidden costs. When the price is set at the lowest feasible price, end-users receive a minimum profit. When this profit is evaluated relative to other additional costs, it is not certain that this price is sufficient to guarantee a profit for households. These additional costs may include software installation and degradation costs. On the other hand, if the price is set at the highest feasible price, the aggregator will receive a minimum profit. Again, the same principle applies as there are also hidden costs to the aggregator. Hidden costs for the aggregator that need to be considered are related to risk, machine learning and investment. In summary, hidden costs are difficult to estimate but will provide a more accurate range for the optimal price.

5.1.3 Fairness

The optimal distribution and pricing of flexibility services is in many ways a discussion of fairness. For this reason, an exact optimal price cannot be determined without further investigation of the fairness aspect. The results suggest that flexibility pricing should be based on additional factors than just profits, as flexibility pricing is as much a matter of fairness and social aspects as it is of economic efficiency.

The prices obtained fluctuate, which means that some households risk getting a low price for flexibility, while others get a high price. This can lead to large differences in profits for each of the participating households. It can be argued that this is unfair as two sources can provide the same amount of flexibility but receive different payments. On the other hand, it can be argued that households should be allowed to receive different payments because the sources that contribute the most to, for example, reducing imbalances in the grid, deserve the most.

There are many suggestions as to how the price of flexibility should be defined. Flexibility is supposed to provide all kinds of services, including balancing supply and demand in wholesale power markets and various ancillary services. For some buyers of flexibility, flexibility is worth more when the grid is in a critical state, so the buyer would be willing to pay more for flexibility. Therefore, the price for flexibility could be set based on various parameters. These include setting the price based on deviation from baseline consumption, duration of activations, number of activations, grid savings, or utilization rates. In general, it can be concluded that prices should be constrained by parameters other than profit alone. Further work in the area of residential flexibility pricing should therefore incorporate additional parameters such as load factor, discomfort, and fairness. The next section summarizes the limitations of the model presented and the topics that need to be addressed in future research.

5.2 Further Work

This chapter addresses model improvements and proposals for further work within the research area of flexibility pricing.

Model Improvements

The model is divided into two parts, since the aim of this thesis is two-fold. The first part is to determine the optimal allocation from a portfolio and to show that there is a feasible schedule. The optimal schedule results from minimizing the cost to the aggregator when the activation price is equal to the lowest price from the existing power markets, but does not guarantee a profit for either the aggregator or the end-users. The profit is ensured in the second part of the model, where a price range is determined for the obtained schedule with three different pricing strategies. When a feasible price range is found, it means that the profit for the BRP, the aggregator and the end-users is guaranteed for all prices within the range. Since both parts of the model have proven successful, a further development would be to combine the two models into a joint optimization model where an optimal schedule with an associated price that guarantees a profit for both parties is determined simultaneously.

In addition to developing a joint optimization model, there are some improvements that should be made to each of the two models. The allocation model presented assumes that the aggregator can provide the required flexibility. However, there are two cases where this may not be the case. The first case is when the portfolio does not contain enough capacity to meet demand. The second case is when, despite sufficient capacity, technical constraints and-user preferences prevent a solution. In future models, the first step should be to estimate the amount of available flexibility in the portfolio, before the aggregator accepts the request.

Furthermore, it should be determined whether the aggregator is allowed to activate more flexibility than requested, as long as the sum of upward and downward regulation equals the requested flexibility. In this thesis, the requested upward and downward flexibility is ensured as a combined constraint. This means that a request of 10 kWh upward regulation can be achieved either by activating exactly 10 kWh of upward regulation or, for example, by activating 20 kWh upward regulation and 10 kWh downward regulation. The second option should be avoided as this will lead to unnecessary wear of sources. Splitting this into two constraints could result in less surplus flexibility being activated, which would benefit both the aggregator and the end-users. Unnecessary activations lead to more inconvenience and wear and tear on sources, which can have a negative impact on end-users. It also creates additional costs for the aggregator, which reduces the profitability of the aggregator.

Another limitation in our model is the assumption of deterministic baselines, since in reality these would not be available to the aggregator in advance. An improvement that would make the model more realistic is to develop a predictive and stochastic model. Machine learning and advanced predictive software can allow the aggregator to estimate baselines. A stochastic model can discard the assumptions that end-users will not violate the contract. In addition, the model presented is built for an optimization horizon of 24 hours. This limits the use of shiftable sources since load profiles cannot be shifted to the next day. Implementing a stochastic dynamic model with a rolling horizon will allow load profiles to be shifted from peak hours to the next morning, allowing better utilization of shiftable loads.

Moreover, the baselines for batteries are not available in the dataset and are therefore found by optimizing the battery usage to minimize the household energy cost. For simplicity and due to lack of data, only the energy consumptions of the household's flexibility sources were included in the calculation. This is a limitation of our model. In future modeling, the entire household's energy consumption should be included in the optimization of battery use, as the battery baseline could look very different if the entire energy consumption is included.

In addition, there are some improvements that should be implemented for the different source types in the optimal allocation model. The batteries are not limited by the number of activations or the minimum rest duration, as is the case for the curtailable and regulatable sources. The lifetime of the batteries is sufficiently shortened if they are activated as frequently as this optimization program allows. However, how to count the activations for a battery is a challenging problem that must be considered in future modeling. Another limitation is the assumption of non-recovered consumption of curtailable and regulatable loads. This is not realistic and recovered energy from each source type should be accounted for in future models. The assumption that end-users can only reserve their flexibility assets for one of the intervals available in the contract is another limitation. It is conceivable that end-users may reserve their sources for multiple time intervals of the day and accordingly this should be considered in future modeling.

There are also some improvements and important factors that should be considered with respect to the pricing model and the assumptions made. As mentioned earlier, the reservation price affects the price range that ensures profitability for the aggregator. Setting a high reservation price is one way to mitigate the potential losses to end-users and therefore ensure a profit for all households. While this ensures that end-users earn higher profits, it reduces the aggregator's profit. As explained earlier, when the reservation price is of the same order of magnitude as the activation price, the cheapest schedule is obtained by activating as much flexibility as possible, as it becomes cheaper to activate a source than to reserve it. This ultimately leads to an unprofitable solution for the aggregator and an unnecessary demolition of flexibility sources, which means that setting a reservation price that is too high is not desirable for either the aggregator or the end-users. For this reason, the reservation price should be significantly lower than the activation price, but exactly how much lower the reservation price should be needs further investigation.

Further Work

The results shows that there is a profit to be made for both the aggregator and end-users when flexibility prices are based on existing power market prices and the buyer is a BRP. Further, the results also show that there could be greater profits for the aggregator if prices are bounded outside of existing market prices. As addressed in the literature review, there are other buyers of flexibility, such as a DSO, who may be willing to pay more for flexibility than a BRP. Future research should therefore consider flexibility requests from multiple buyers, such as DSOs, TSOs, and BRPs. As there are large research gaps on how to set such limits independently of existing prices, this is a topic for further research.

Further work should also aim to identify an optimal price, not just a feasible price range. As discussed earlier, the issue of flexibility pricing is as much a matter of social factors and fairness as it is a matter of economics. Further research into residential flexibility pricing should therefore consider social factors. Future research should incorporate measures of fairness and explore how profits can be distributed based on parameters such as discomfort or deviation from baseline consumption.

6 Conclusion

The aim of this thesis is to investigate the allocation feasibility and economic viability of residential flexibility. To this end, an optimal allocation algorithm and a pricing mechanism are constructed. The objective is to study the profitability of residential flexibility services under the assumption that the buyer of flexibility is a BRP. Furthermore, this thesis compares three different pricing strategies to analyze the profitability of aggregators and end-users.

For all days of the simulated week, a schedule is determined that minimizes the aggregator's cost. The allocation algorithm optimally allocates sources from an aggregator's portfolio of batteries, curtailable, regulatable, and shiftable loads in response to a flexibility request, taking into account user preferences and technical constraints. The results show that shiftable sources and batteries provide the most flexibility but benefit the least. This suggests that it is fairer to differentiate flexibility prices for each source type.

The developed pricing mechanism determines a price range for the optimal schedule that guarantees a profit for both the aggregator and the end-users. The pricing mechanism consists of three different pricing strategies. Strategy 1 assumes uniform prices for all sources bounded by existing power market prices in each quarter of the day. The same is assumed for Strategy 2, but with individual prices for each source. Strategy 3 assumes uniform prices for all sources, bounded by fixed values of 0 NOK/kWh and 100 NOK/kWh in each quarter of the day. A feasible price range is found to exist only for three days of the simulated week with Strategies 1 and 2, but found to exist for all seven days with Strategy 3. Strategy 2 increases the maximum possible profit for the aggregator without significantly reducing the minimum possible profit for the end-users compared to Strategy 1. Using price Strategy 3 further increases the aggregator's profit on each day of the week while maintaining a profit for all households.

A comparison of the three pricing strategies shows that the distribution of the payment from the BRP to the aggregator and the end-users differs significantly depending on the pricing strategy chosen. From the aggregator's point of view, the results show that Strategy 3 is the best pricing strategy as it significantly increases the potential profit for the aggregator, which follows from the significant increase in the defined bounds. On the other hand, Strategy 1 guarantees the highest share of payment from the BRP to the end-users. In summary, there will always be a trade-off between the profits of the aggregator and the end-users.

This work has shown that the profit can be distributed differently depending on the pricing strategy chosen. However, whether the distribution of profit should be weighted more in favor of the aggregator or the end-users is an open question that needs further research. Fairness and social factors need to be included to determine how the share of profit should be weighted between them to set an accurate price for residential flexibility. In conclusion, this thesis shows that bounding the flexibility prices based on the existing power market prices is profitable for both the aggregator and end-users. Future research should incorporate measures of fairness and explore how prices can be set based on additional parameters, taking into account social and behavioural aspects.

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Appendices

Appendix A. Sets, Parameters and Variables for Optimal Allocation and Battery Baseline Programs

Table 13: Sets

T	Set of periods, indexed by t
C	Set of curtailable loads, indexed by c
R	Set of regulatable loads, indexed by r
S	Set of shiftable loads, indexed by s
B	Set of batteries, indexed by b
H	Set of households, indexed by h

Table 14: Price parameters

$C_{c,t}^{act}$	Price defined for curtailing the curtailable source $c \in C$ in time t [NOK/kWh]
$C_{r,t}^{act}$	Price defined for regulating the regulatable source $r \in R$ in time t [NOK/kWh]
$C_{s,t}^{act}$	Price defined for shifting the shiftable source $s \in S$ in time t [NOK/kWh]
$C_{b,t}^{ch}$	Price defined for charging battery $b \in B$ in time t [NOK/kWh]
$C_{b,t}^{dis}$	Price defined for discharging battery $b \in B$ in time $t \in T$ in [NOK/kWh]
$C_{c,t}^{res}$	Price defined for reserving the curtailable source $c \in C$ in time $t \in T$ in [NOK/hour]
$C_{r,t}^{res}$	Price defined for reserving the regulatable source $r \in R$ in time $t \in T$ in [NOK/hour]
$C_{s,t}^{res}$	Price defined for reserving the shiftable source $s \in S$ in time $t \in T$ in [NOK/hour]
$C_{b,t}^{res}$	Price defined for reserving battery $b \in B$ in time $t \in T$ in [NOK/hour]
$C_{b,t}^{spot}$	Spot price in time $t \in T$ in [NOK/time]

Table 15: Flexibility request and time step parameters

D_t	Requested flexibility in terms of upward or downward regulation for time t [kWh/hour]
α	Describing the length of the time step [hours]

Table 16: Curtailable load parameters

P_c	Rated power of the curtailable source $c \in C$ in [kW]
$\delta^{res}_{c,t}$	Binary parameter = 1 if curtailable source $c \in C$ is reserved in time t, else 0
$\lambda^{state}_{c,t}$	Binary parameter = 1 if curtailable source $c \in C$ is normally on in time t, else 0
N_c	Maximum number of curtailments allowed for the curtailable source $c \in C$
R^{min}_c	Minimum duration between two curtailments for the curtailable source $c \in C$ in [#/hour]
A^{max}_c	Maximum curtailment duration allowed for the curtailable source $c \in C$ in [#/hour]

Table 17: Regulatable load parameters

P_r	Rated power of the curtailable source $r \in R$ in [kW]
$\delta^{res}_{r,t}$	Binary parameter = 1 if the regulatable source $r \in R$ is reserved in time t, else 0
$\delta^{state}_{r,t}$	Parameter between 0 and 1 representing the normal state of the regulatable source $r \in R$ in time t
N_r	Maximum number of regulations allowed for the regulatable source $r \in R$
R^{min}_r	Minimum duration between two regulations for the regulatable source $r \in R$ in [#/hour]
A^{max}_r	Maximum regulation duration allowed for the regulatable source $r \in R$ in [#/hour]

Table 18: Shiftable load parameters

P_s	Rated power of the shiftable source $s \in S$ in [kW]
$P^{ch,max}_s$	Maximum charging power of shiftable source $s \in S$ in [kW]
T^{start}_s	The first hour in the reservation period of the shiftable source $s \in S$
T^{stop}_s	The latest possible end hour for load shifting of the shiftable source $s \in S$
V^{start}_s	The first hour in the baseline consumption of the shiftable source $s \in S$
V^{stop}_s	The last hour in the baseline consumption of the shiftable source $s \in S$
$W_{s,t}$	The baseline consumption of the shiftable source $s \in S$ in time t in [kWh/hour]
$State^{init}_s$	The initial state of the shiftable source $s \in S$ in [%]
η_s	Charging efficiency of the shiftable source $s \in S$ in [%]

Table 19: Battery parameters

$P_b^{ch,max}$	Maximum charging power of battery $b \in B$ in [kW]
$P_b^{dis,max}$	Maximum discharging power of battery $b \in B$ in [kW]
E_b	Battery capacity for battery $b \in B$ in [kWh]
$\delta_{b,t}^{res}$	Binary parameter = 1 if battery $b \in B$ is reserved in time t, else 0
$\eta_{b,t}^{ch}$	Charging efficiency for battery $b \in B$ in time t in [%]
$\eta_{b,t}^{dis}$	Discharging efficiency for battery $b \in B$ in time t in [%]
$\eta_{b,t}^{self-dis}$	Discharging efficiency for battery $b \in B$ in time t in [%]
SoC_b^{min}	Minimum allowed storage power in battery $b \in B$ in [%]
SoC_b^{max}	Maximum allowed storage power in battery $b \in B$ in [%]
ϵ_b	Tolerance to account for self-discharge for battery $b \in B$ in [%]

Table 20: Household parameters

$D_{h,t}$	The baseline consumption of households $h \in H$ in time $t \in T$ in [kWh]
$W_{h,t}^{curt}$	The baseline consumption of the curtailable sources in household $h \in H$ in time $t \in T$ in [kWh]
$W_{h,t}^{reg}$	The baseline consumption of the regulatable sources in household $h \in H$ in time $t \in T$ in [kWh]
$W_{h,t}^{shift}$	The baseline consumption of the shiftable sources in household $h \in H$ in time $t \in T$ in [kWh]
$E_{h,t}^{import}$	The energy purchased from the grid by household $h \in H$ in time $t \in T$ in [kWh]

Table 21: Variables

$F_{c,t}$	Activated flexibility from curtailing the curtailable source $c \in C$ in time t [kWh]
$F_{r,t}$	Activated flexibility from regulating the regulatable source $r \in R$ in time t [kWh]
$F_{s,t}$	Activated flexibility from shifting the shiftable source $s \in S$ in time t [kWh]
$F^{ch}_{b,t}$	Activated flexibility from charging battery $b \in B$ in time t [kWh]
$F^{dis}_{b,t}$	Activated flexibility from discharging battery $b \in B$ in time t [kWh]
$\delta^{act}_{c,t}$	Binary variable = 1 if curtailable source $c \in C$ is curtailed in time t, else 0
$\delta^{act}_{r,t}$	Binary variable = 1 if regulatable source $c \in C$ is regulated in time t, else 0
$\delta^{act}_{s,t}$	Binary variable = 1 if shiftable source $s \in S$ is shifted from time t, else 0
$\delta^{ch}_{b,t}$	Binary variable = 1 if battery $b \in B$ is charging in time t, else 0
$\delta^{dis}_{b,t}$	Binary variable = 1 if battery $b \in B$ is discharging in hour t, else 0
$\delta^{start}_{c,t}$	Binary variable = 1 if curtailment of the curtailable source $c \in C$ starts in hour t, else 0
$\delta^{start}_{r,t}$	Binary variable = 1 if regulation of the regulatable source $r \in R$ starts in time t, else 0
$\delta^{stop}_{c,t}$	Binary variable = 1 if curtailment of the curtailable source $c \in C$ stops in hour t, else 0
$\delta^{stop}_{r,t}$	Binary variable = 1 if regulation of the regulatable source $r \in R$ stops in hour t, else 0
$\gamma_{s,t}$	Binary variable = 1 if the shiftable load $s \in S$ starts consuming in hour t, else 0
$\omega_{s,t}$	Delivered energy to the shiftable load $s \in S$ in time t
$SoC_{b,t}$	State of charge of battery $b \in B$ in time t
$SoC^{self-dis}_{b,t}$	Self-discharge rate of battery $b \in B$ in time t [%]
$E^{dis}_{b,t}$	The energy discharged from battery $b \in B$ in time $t \in T$ [kWh]

Appendix B. Battery Data

Table 22: The obtained data for batteries including charging power in kW, capacity of the batteries in kWh and the associated reference.

Battery model	Charging power [kW]	Capacity [kWh]	Reference
Tesla Powerwall	7	13.5	[98]
xStorage Home (worst case)	3.6	4.2	[99]
xStorage Home (best case)	6	10.08	[99]

Appendix C. Activation Parameters

Table 23: The most important activation parameters for operational criteria and user preferences used as a basis for the optimal allocation model. The parameters must be agreed upon in a flexibility contract. The reservation duration for EVs are the 25 different baselines from the data set + two hours.

Source type	Parameter	Symbol	Description	Options
Curtailable	Reservation duration	T_c^{start}, T_c^{stop}	The hours the source is reserved, i.e. the hours when the aggregator can activate the source. Only one period can be selected.	06:00 - 09:00 06:00 - 11:00 07:00 - 10:00 10:00 - 14:00 15:00 - 17:00 15:00 - 19:00 18:00 - 21:00 19:00 - 23:00 20:00 - 24:00
	Activation allowance	N_c	The maximum number of allowed activations during one day.	Between 1 and 3 times
	Minimum rest duration	R_c^{min}	Minimum allowed duration between two activations.	Between 1 and 2 hours
	Maximum activation duration	A_c^{max}	Maximum allowed duration of an activations.	Between 1 and 3 hours
Regulatable	Reservation duration	T_r^{start}, T_r^{stop}	The hours the source is reserved, i.e. the hours when the aggregator can activate the source. Only one period can be selected.	00:00 - 07:00 07:00 - 13:00 12:00 - 16:00 15:00 - 18:00 17:00 - 21:00 20:00 - 24:00
	Activation allowance	N_r	The maximum number of allowed activations during one day.	Between 1 and 3 times
	Minimum rest duration	R_r^{min}	Minimum allowed duration between two activations.	Between 1 and 4 hours
	Maximum activation duration	A_r^{max}	Maximum allowed duration of an activations.	Between 2 and 5 hours
Shiftable	Reservation duration	T_s^{start}, T_s^{stop}	The hours the source is reserved, i.e. the hours when the aggregator can activate the source.	Read caption
	Activation allowance	N_s	The maximum number of allowed activations during one day.	1 time
Battery	Reservation duration	T_b^{start}, T_b^{stop}	The hours the source is reserved, i.e. the hours when the aggregator can activate the source. Only one period can be selected.	07:00 - 15:00 15:00 - 23:00 23:00 - 07:00 All day
	Minimum state of charge	SoC_b^{min}	The minimum allowed SoC within the reservation period.	15%
	Maximum state of charge	SoC_b^{max}	The maximum allowed SoC within the reservation period.	90%
	Final state of charge	$\text{SoC}_b^{T_b^{stop}}$	The minimum allowed SoC at the end of the reservation period, at T_b^{stop}.	Same as start of period

Appendix D. Portfolio

Table 24: Portfolio showing which households owns which sources. The rated power of each source in kW is included.

Household	Water heater	Heat pump	EV	Battery
1	0.49	0,2	7	-
2	0.41	0,2	7	-
3	0.5	0,2	3,9	-
4	0.51	0,2	-	-
5	0.42	1,4	-	-
6	0.51	-	1,5	-
7	0.4	2,1	6,8	-
8	0.5	0,3	-	3,6
9	0.52	-	-	-
10	0.49	0,2	-	6
11	0,5	0,2	7	-
12	0,55	0,2	-	-
13	0,51	-	-	-
14	0,43	-	6,8	3,6
15	0,5	0,2	7	-
16	0,5	0,3	-	-
17	0,42	2,3	-	3,6
18	0,4	0,2	7	-
19	0,42	0,2	3,4	-
20	0,4	-	-	-
21	2,66	0,2	-	-
22	0,4	0,3	3,4	-
23	0,51	0,2	-	-
24	0,4	2,5	1,5	-
25	0,4	1,5	-	-
26	4,31	3,8	3,8	3,6
27	0,5	0,3	-	-
28	0,4	3	1,6	3,6
29	0,49	-	6,9	-
30	0,42	2,7	-	-
31	0,4	-	-	-
32	0,51	0,2	6,8	-
33	0,51	0,2	1,5	7
34	0,41	3,1	3,4	-
35	0,42	0,2	6,8	-
36	0,42	2,1	3,4	-
37	0,4	3,1	-	6

38	0,51	0,2	-	-
39	0,51	0,2	1,5	-
40	0,41	2,7	-	-
41	0,51	2,2	3,8	7
42	0,49	0,2	-	-
43	0,54	-	-	-
44	0,51	0,2	-	-
45	0,49	2,1	-	-
46	0,5	-	3,8	-
47	0,49	2,3	3,4	7
48	0,49	2,1	3,8	-
49	0,51	-	-	-
50	0,51	2,2	-	-

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