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Optimizing and Evaluating Distributed Flexibility for Fast Frequency Reserve Provision and Demand Response: A Case Study of a Norwegian Prosumer

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Preface

This Master´s thesis concludes my Master of Science in Industrial Economics and Technology Management at the Norwegian University of Science and Technology, Department of Industrial Economics and Technology Management.

I would like to express my sincere gratitude to my supervisor Stian Backe and co-supervisors Sigurd Bjarghov and Kasper E. Thorvaldsen, for excelent guidance and valuable discussions. I would also like to thank the FME ZEN research center and Åse Lekang Sørensen for providing me with relevant data and valuable insight.

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Abstract

Buildings are responsible for considerable amounts of the total energy consumption in Europe, emphasizing the pivotal role that local energy systems and prosumers are positioned to play in the transition to a low-carbon energy system. With the increasing penetration of variable renewable energy sources and the growing complexity of load variations, there is a greater need for energy balancing services. In response, frequency reserve markets have emerged to enhance grid stability and address contingencies in energy systems. Local distributed flexibility resources (DFR) and demand side management by prosumers can contribute to these services while reducing their energy costs through adaptive demand response.

However, there is a lack of insight into the economic incentives and operational consequences for property owners to adopt prosumer qualities for provision of demand response and frequency reserve capacity. There is a need to quantify the economic value of optimally operating different flexible assets and to evaluate the consequences for local energy systems and communities. Facing recent variability of energy prices and supply in Europe, different potential scenarios should be evaluated along with the demand response signals that can enable effective operation of DFRs. This master's thesis aims to assess the cost-optimal flexibility responses from a Norwegian prosumer addressing various demand response mechanisms while participating in the Norwegian fast frequency reserve (FFR) market.

This master's thesis presents a case study of a Norwegian university campus, also participating as a pilot project in the Research Centre on Zero Emission Neighbourhoods in Smart Cities (FME ZEN). The local energy system of the prosumer has three different types of DFRs: a stationary lithium-ion battery, gird-to-vehicle (G2V) charging stations, and vehicle-to-grid (V2G) charging stations. Additionally, curtailment of thermostatic loads will be considered for FFR provision. Metered data from three distinct historical years are utilized to provide a comprehensive understanding of DFRs engaging in demand response. A deterministic and single-objective linear mathematical model is employed to minimize total electricity costs by optimizing the operation of DFRs, both with and without the opportunity to participate in FFR.

The findings of this study demonstrate that the optimized operation of DFRs offers significant potential for reducing prosumers' total energy costs through demand response. The analysis reveals the considerable potency of the demand response incentive linked to FFR market participation, leading to reduced consideration of alternative demand response mechanisms like the peak load grid tariff element. Importantly, the profits derived from FFR participation significantly outweigh the indirect cost impacts. Moreover, the study reveals that demand side flexibility enables load shifting and peak load reductions, aligning with the objectives of power system operators and regulatory policies. The case study provides valuable insights into the effective operation and interplay among various DFRs, emphasising the prominent capabilities of V2G technology in providing FFR reserves.

Sammendrag

Bygninger er ansvarlige for betydelige andeler av det totale energiforbruket i Europa, hvilket understreker den avgjørende rollen som lokale energisystemer og prosumenter er posisjonert til å ha i overgangen til et lavkarbonsamfunn. Med økende utnyttelse av variable fornybare energikilder og en voksende kompleksitet i lastvariasjoner, er det et økende behov for tjenester som bidrar til balanse i kraftmarkedet. Dette gir økt relevans av frekvensreservemarkedene, som har som hensikt å forbedre nettstabiliteten og håndtere nødsituasjoner som kan oppstå i kraftsystemer. Lokale distribuerte fleksibilitetsressurser (DFR) og forbrukerstyring fra prosumenter kan bidra til disse tjenestene samtidig som energikostnader kan reduseres gjennom tilpasningsdyktig etterspørselsrespons.

Imidlertid er det mangel på innsikt i de økonomiske insentivene og de operative konsekvensene som eiendomsforvaltere står ovenfor, når de skal påta seg prosumentrollen for å tilby etterspørselsrespons og frekvensreservekapasitet. Det er et behov for å kvantifisere den økonomiske verdien av optimal drift av ulike fleksible ressurser og evaluere konsekvensene for lokale energisystemer og samfunn. Med hensyn til den store variasjonen i energipriser og –forsyning i Europa de siste årene, bør forskjellige mulige scenarier vurderes sammen med etterspørselssignalene som muliggjør effektiv drift av DFR-er. Denne masteravhandlingen har som mål å vurdere kostnadsoptimale fleksibilitetshandlinger fra en norsk prosument som effektivt reagerer på ulike prissignaler for etterspørselsrespons samtidig som de deltar i det norske markedet for raske frekvensreserver (FFR).

I masteravhandlingen presenterers en casestudie med data fra et norsk universitetscampus, som også inngår som et pilotprosjekt under forskningssenteret for nullutslippsnabolag i smarte byer (FME ZEN). Prosumentens lokale energisystem innehar tre forskjellige typer DFR: et stasjonært litium-batteri, ladestasjoner for strøm til kjøretøy (G2V) og ladestasjoner med muligheten for å overføre strøm fra kjøretøy til nettet (V2G). I tillegg vil reduksjon av termostatiske laster for å bidra til FFR kapasitet bli vurdert. En deterministisk lineær matematisk modell benyttes for å minimere de totale elektrisitets kostnadene ved å optimalisere driften av DFR-er, både med og uten muligheten til å delta i FFR.

Resultatene i studien viser at optimal drift av DFR-er har et betydelig potensial for å redusere prosumenters totale energikostnader gjennom etterspørselsrespons. Analysen avslører at insentivene relatert til etterspørselsrespons og deltagelse i FFR-markedet er betydelige, noe som også medfører redusert hensyn til alternative mekanismer for etterspørselsrespons, spesielt for topplastelementet i nettleien. Et sentralt funn er at fortjenesten fra deltagelsen i FFR-markedet oppveier betydelig for de indirekte kostnadene som det medfører. Videre viser studien at fleksibilitet på etterspørselssiden muliggjør lastforskyvning og reduksjon av topplast, noe som er i tråd med målene til kraftsystemoperatører og norske regulatoriske retningslinjer for strømforbruk. Casestudien gir verdifull innsikt i den effektive driften og samspillet mellom de ulike DFR-ene, og fremhever særlig de fremtredende mulighetene for V2G teknologi for å levere FFR-reserver.

Table of Contents

Accronyms

RES	Renewable Energy Source
DFR	Distributed Flexibility Resource
FFR	Fast Frequency Reserve
TSO	Transmission System Operator
DSO	Distribution System Operator
EV	Electric Vehicle
BESS	Battery Energy Storage System
SoC	State of Charge
V2G	Vehicle to Grid
G2V	Grid to Vehicle
AC	Alternating Current
DC	Direct Current
PV	Photovoltaic
EDRP	Emergency Demand Response Programs
I/C	Interruptible/Curtailable
CMP	Capacity Market Programs
FCR	Frequency Containment Reserve
aFRR	automatic Frequency Restoration Reserve
mFRR	manual Frequency Restoration Reserve
ZEN	Zero Emission Neighborhood
CHP	Combined Heat and Power

List of Figures

List of Tables

1 Introduction

The energy sector is presently undergoing profound transformations as it shifts from a historically carbon-based energy reliance to a more sustainable system, utilizing renewable energy sources (RES) for energy generation. This shift is crucial to successfully mitigate climate changes and greenhouse gas emissions in a society that experience increasing electrification and dependency on energy. Buildings account for approximately 40% of energy consumption in the EU and considerable shares of greenhouse gas emissions[1]. Recognizing the critical role of the building sector in Europe's green transition, the European Commission consider the sector to play an essential part in reaching emission targets[19].

Higher shares of renewable energy is vital in achieving emission targets, but also introduces challenges which require innovative thinking across sectors. Renewable energy generation are often dependent on climatic parameters subject to uncertainty and variability such as wind and solar power. The integration of variable RES into the energy system introduces challenges in effectively balancing the supply and demand of power due to the fluctuating nature of its production patterns. Furthermore, the trend of transitioning from traditional mechanical and rotating generators that posses inertial capabilities to inverter-based RES, presents challenges of maintaining a healthy grid frequency and ensuring security of supply.

To overcome these challenges its crucial to ensure flexibility within power systems, which refers to the capacity to adjust electricity production or consumption in response to variability. A growing trend in enhancing flexibility within power systems involves the provision of demand-side flexibility from energy consumers. By property owners and/or neighborhoods adopting prosumer qualities, the traditional paradigm of supply following demand can be shifted towards demand adapting to supply of energy[24]. In this thesis, consumers who possess demand-side flexibility will be referred to as "prosumers," as they actively consume and produce energy services. By leveraging demand-side response and distributed flexibility resources (DFR), prosumers can not only reduce their energy costs but also contribute to the provision of essential balancing services.

Given the challenges posed by reduced inertia, the growing penetration of RES, and concerns regarding security of supply in power systems, the emergence of fast frequency reserve (FFR) markets has gained significance in recent years. In this context, the aggregation of local flexibility resources within neighborhoods can play a crucial role in supplying reserve capacity and provide grid stability.

1.1 Purpose of this Thesis

The purpose of this master's thesis is to asses the economic incentives and operational consequences for property owners to adopt prosumer qualities. Furthermore, this thesis aims to quantify the effect of addressing different demand response signals while also participating in a FFR market. Using a linear optimization problem framework that minimizes total electricity costs, this paper evaluates annual cost savings for a Norwegian university campus when value stacking the following flexibility services: responding to electricity spot prices, grid tariffs, and provision of FFR. Several flexibility resources are addressed in this study, including a stationary battery, electric vehicle charging stations and vehicle-to-grid charging stations. The operational characteristics of each of the flexible assets will be analysed with regard to providing demand response. Additionally, this thesis aims to investigate three distinct historical years characterized by significant variations in electricity spot prices. By doing so, it seeks to offer a comprehensive understanding of DFR engagement in demand response activities.

1.2 Structure of this Thesis

The remaining sections of this thesis are structured as follows. In Section 2, an overview of the Norwegian power system is provided, along with an exploration of demand-side flexibility.

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[1] https://ec.europa.eu/info/news/focus-energy-efficiency-buildings-2020-lut-17_en, last accessed: 9th June 2023

Additionally, the concepts of DFR, demand response, and frequency reserve markets are examined, while relevant literature is reviewed and discussed in the context of neighborhoods and local energy systems. Furthermore, a concise literature review is presented, focusing on the most pertinent studies related to this thesis. Finally, the research questions and contributions of this work are outlined. Section 3 provides a concise overview of the mathematical programming theory relevant to this thesis, and offers a reasoning for the selected modeling approach. Section 4 presents a description of the motivation behind the problem addressed in this thesis and provides a qualitative formulation of the problem. The mathematical model used for solving the problem is is introduced and described in Section 5. Section 6 presents the input data that is used- and implemented in the model and provides an overview of the conducted case study. Finally, results and discussion are presented in Section 7, while concluding remarks and future research opportunities can be found in section 8.

2 Distributed Flexibility - a comprehensive review of market application

2.1 Introduction to the Norwegian power system and its flexibility

The Norwegian power grid is a natural monopoly regulated by the Norwegian Water Resources and Energy Directorate (NVE), which supervises the transmission and production of electricity in Norway. The Norwegian power grid is composed of the transmission grid, the regional grid, and the distribution grid. The transmission grid is operated, developed, and maintained by Statnett (TSO), while there exist approximately 130 distribution system operators (DSOs)[51]. Norway produces 98% of its electricity from renewable energy, with hydropower accounting for 88% of the production capacity, followed by wind power (8%) and solar photovoltaic (160 MW in 2021)[2]. About 75% of Norway's production capacity is dispatchable, mainly due to hydro-power plants' capability to store water in reservoirs. Dispatchable energy refers to sources of power that can be generated or used on demand by request of the operators when needed[59]. There exist over 1000 water reservoirs with a collected storage capacity of over 87 TWh, which corresponds to approximately 62% of the Norwegian yearly power consumption[3]. The flexibility created by hydro power plants is highly valuable as the share of intermittent sources of energy production in Norway is growing, and non-dispatchable energy resources such as solar and wind power are in general not controllable by operators.

Flexibility refers to the ability of power systems to adapt to changes in demand and supply of power[18]. The energy exchange between producers and consumers needs to be balanced, which requires inherently flexible systems and ancillary services to do so. Power systems and grids are subject to variability and uncertainty as loads change over time, with consumption varying constantly throughout the day and with environmental and seasonal changes. The implementation and use of variable RES further complicates maintaining this balance as the efficiency of solar power, wind power, etc. fluctuate according to weather conditions. Introducing more RES generation in power systems creates a greater need for flexibility. RES generation might increase or decrease rapidly, while demand behaves indifferently, forcing power plants to ramp power generation up or down more quickly.

NVE projects that Norway's total gross electricity consumption will increase from 138 TWh in 2012 to 174 TWh by 2040, with population growth being the main instigator[13]. Statnett projects even higher growth in Norwegian electricity demand, potentially reaching 300 TWh in 2050[39]. Increasing power consumption, higher peak loads, and new intermittent sources of renewable energy generation entail greater requirements for operation and investment in the power grid. A flexible transmission grid with sufficient capacity to utilize and balance a wide range of intermittent power resources, connecting neighboring grids, and implementing smart grid technologies can better optimize transmission usage. Smart metering is an important part of increasing awareness related to electricity use, enabling the possibility for automatic metering of electricity consumption and higher frequency of information and communication with the DSO. All electricity customers in Norway have had smart-meters installed since 2019[4].

Incorporating high levels of RES generation into power systems can lead to the need for curtailment, where excess electricity production is wasted due to lack of demand. This requires dispatchable power plants to operate at lower output levels while remaining ready to match demand. Insufficient flexibility in power systems may result in the curtailment of solar and wind power generation. While some curtailment can be cost-effective for achieving flexibility, significant curtailment poses challenges in meeting emission targets and can reduce project revenues and contractor values [18]. As a result, the involvement of investors and stakeholders in current and future renewable energy projects may be discouraged.

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[2] https://energifaktanorge.no/, last accessed: 9th June 2023

[3] https://energifaktanorge.no/norsk-energiforsyning/kraftforsyningen/, last accessed: 9th June 2023

[4] https://www.nve.no/reguleringsmyndigheten/kunde/stroem/stromkunde/smarte-stroemmaalere-ams/, last accessed: 9th June 2023

2.2 Demand side management

Historically, sources of flexibility have been provided by the supply side of the energy system by controlling energy production to meet a varying demand and synchronize the grid frequency. This is predominantly achieved through the use of conventional and centralized dispatchable sources, which possess inertial capabilities. Inertia in traditional power systems refers to the energy that are stored in large rotating generators and industrial motors [48]. The grid consists of hundreds of generators, all uniformly synchronized to a grid frequency of 50Hz in Norway and Europe. The frequency of 50Hz is used as a baseline to measure the robustness of the grid. If one generator fail, energy from the rotational inertia of remaining generators are extracted to stabilize the supply of power. The mechanism entails a drop in frequency, notifying operators, while providing time to increase output of mechanical generators. Variable RES such as wind and solar PV does not inherently provide inertial response as they are inverter based. Increasing penetration of RES and inverter-based resources entails proportionally less inertia in the power-system, creating a demand for measures to tackle changes in frequency, supply and demand.

In recent years, demand-side management have become increasingly common and esteemed in regard to providing balancing services[52]. The European Commission's 2030 policy framework for climate and energy acknowledge the importance of providing end-user flexibility, through measures such as demand-side management, to proficiently tackle and promote higher shares of RES and to decarbonise the European energy system[64]. Demand-side management generally refers to electricity consumers ability to deviate from their consumption profile in response to market incentives or price signals. Prosumers can manipulate their consumption profile through home energy management systems, which can control certain loads and the operation of flexible assets in their home, building or neighborhood[38]. Smart meters was implemented at all Norwegian electricity customers in 2019[58], which, by automation and smart-control capabilities, have provided further accessibility to demand-side management. In addition to increasing power variability in the supply side of energy systems, increasing penetration of power-intensive applications such as electric vehicle (EV) chargers, induction ovens etc. on the demand side, can concentrate intensive power-consumption during short time-periods, straining local distribution grids[67]. Simultaneously, these power intensive applications, strengthens the prosumers influence in power systems and enhances the effect of acting flexibly.

Demand-side management can provide an active counter-measure to variation in power production, reduce peak-hour consumption and limit grid congestion through methods of temporal load flexibility. Strategies of providing demand-side management can be categorized into six different types, illustrated in Figure 1. The motivation behind these strategies essentially revolves around lowering peak consumption, redistributing loads to off-peak hours and smooth the operation of electrical systems[55]. The focus of this thesis find peak shaving, valley filling and load shifting to be most relevant in regard to managing daily consumption profiles of a prosumer. Demand-side management can serve the purpose of either providing a service to system operators or simply enabling more effective management of individual electricity needs and costs. The mechanisms and incentives that promote demand-side management will be further discussed in section 2.4.

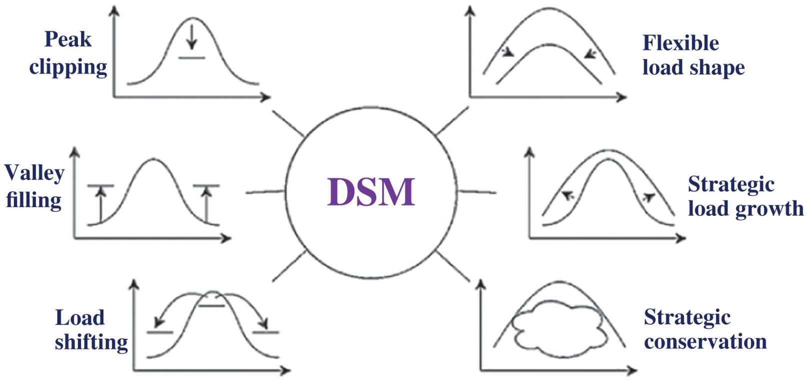

Figure 1: Demand side management categories [55]

In order for small prosumers to efficiently operate and provide flexibility services, it is crucial that they have access to sufficient information on market prices and drivers. Successful prosumer and demand-side management integration in the power system is dependent on customer engagement and calls for shifting the energy system towards presenting more opportunities for customers to provide valuable energy services. Illuminating prosumer benefits and providing knowledge and decision-making framework on societal, political, and regulatory planes will be important to achieve this, while aligning the interests of DSOs, consumers, electricity providers, political actors and societal welfare as a whole. Hubert and Grijalva [30] argue that dynamic pricing policies and access to real-time information at a residential level is crucial to engage end-users in actively managing energy consumption and providing DR, while lack there of will result in highly sub-optimal energy utilization. However, the authors emphasises the complexity of optimizing energy utilization on a residential level, and reasons that a level of centralized control or automation is likely to be necessary. Almeida et al. [4] quantifies the effects of aligning the utility of energy service providers and prosumer benefits (by minimization of expenses) in a two step multi-objective load scheduling problem. The proposed approach combines the pareto optimal solutions (optimal outcome where improving one party's situation requires worsening another's) of all prosumers while minimizing their aggregate demand profile. Compared to single-objective optimization models, the conducted multi-objective case study resulted in peak-to-average ratio being reduced by 11%, improving the energy service providers system-wide demand profile aggregation, while simultaneously reducing prosumer costs and discomfort (assosciated with the inconvinience of shifting, interrupting, and curtailing the operation of loads). In conclusion, engaging customers, providing market information, and aligning stakeholder interests are essential for efficient operation and flexibility services by prosumers in a progressively customer-centric energy system.

2.3 Distributed flexibility resources

The provision of demand response and flexibility within a neighborhood can be facilitated through the operation of DFR such as battery energy storage systems (BESS) [5], EV charging [60], and the curtailment of non-essential loads to temporarily reduce consumption. DFRs offer the ability to adjust consumption and generation in response to market signals, thus enabling demand-side flexibility. Amid the growing trend of intelligent buildings and energy-efficient neighborhoods, various mechanisms and DFRs have emerged to facilitate demand-side management and promote energy production and sustainability. This section offers a succinct overview of selected DFRs, primarily focusing on load-shifting, which are of particular relevance to both this thesis and the forthcoming case study.

Battery Energy Storage System

A BESS is a stationary flexible asset consisting of electrochemical storage batteries capable of converting chemical energy into electrical energy. A BESS can be implemented in buildings or micro-grids for local energy storage, allowing for cheap off-peak energy or locally produced, excess energy to be stored and discharged at cost-optimal times. The chemical storage medium of the batteries may vary, but lithium-ion has established itself as the most viable and common option. Lithium-ion batteries stores energy in lithium ions and uses their reversible reduction properties to charge and discharge. The battery medium provides one of the highest energy densities of any battery technology available today[5]. In addition, lithium-ion batteries posses a high cell voltage, enabling large amounts of current for fast charging and discharging of power-intensive applications, while being relatively light compared to other mediums e.g. Ni-Cd or Ni-MH. Through appropriate operation of flexible capabilities, a BESS can provide peak-load shaving, valley-filling, and can contribute in frequency regulation[45]. As clarified by Thorvaldsen [67], a BESS does not constitute an additional, separate load in its local energy system, when disregarding losses, and does therefore not change the consumption pattern for demand, but rather influence the interaction with the electricity grid. A BESS can therefore be categorized as a "purely flexible" asset. Multiple studies have been conducted, assessing the flexible capabilities of BESS in local energy systems. Stephaniuk et al. [63] analyses the effect of BESS in local residential energy systems with solar PV and wind power generation, finding that the utilization of BESS in combination with RES reduced the total cost of energy as well as the energy import from the grid. The conducted case study

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[5] `http://www.cei.washington.edu/education/science-of-solar/battery-technology/`, last accessed: 9th June 2023

also provide evidence that increasing BESS capacity facilitates for more frequent opportunities of energy self-sufficiency and also grid balancing services when RES energy generation is high. As battery technology continues to improve and safety standards increase, BESS can be applied to many innovative technologies. With increasing RES creating variability in power supply, BESS are likely to play an increasingly important role in power systems.

Electric Vehicles
EVs are becoming increasingly more common in Norwegian households[6]. Much like BESS, EV charging can provide flexibility and demand-side management by temporal load-shifting, peak shaving and valley filling. The main objective of EV charging is to achieve a sufficient state of charge (SoC) for the specific, required utility. EV charging patterns are dependent on user-behavior, of which passive charging strategies may cause grid congestion, high peaks and high charging costs. Actively shifting charging patterns to off-peak hours when electricity cost is low can amount to large savings, while simultaneously freeing up grid capacity when loads usually are high. Grid tariff rates that vary temporally may also further enhance opportunities of EV charging arbitrage. For instance the Norwegian DSOs; Elvia (Innlandet) and Tensio (Trøndelag) prices their volumetric costs during night (10pm - 06am) about 72% and 78%, respectively, of the prices during the day (06am - 10pm)[7] [8]. EV charging technology are becoming increasingly smarter, with chargers enabling pre-specified charging periods, and smart control based on spot-price variation such as for Easee[9]. This thesis consider two categorical types of charging technology, namely vehicle-to-grid (V2G) and grid-to-vehicle (G2V).

V2G charging stations uses bidirectional charging properties to push and pull electric energy from connected vehicles. Bidirectional chargers inherit inverter capabilities, converting alternating current (AC) to direct current (DC) during charging and DC to AC during discharging. Bidirectional charging can be used to power a home or facility (vehicle-to-home) and/or provide backup power during blackouts and feed power back into the electricity grid (V2G). V2G chargers enables EV batteries to adopt the same qualities and potential yield as a BESS. V2G connected EVs can store cheap off-peak electricity or local RES production and export energy back into the electricity grid when demand and electricity prices are high, reducing total electricity costs. The technology present opportunities of arbitrage when presented with flexible EV demand profiles due to energy price fluctuation and dynamic grid tariffs. The charging stations are dependent on software that enables communication with the central grid to measure and asses the system demand at any given time[46].

In contrast to V2G, G2V charging stations are exclusively capable of transferring electric energy from the grid to EVs. Even though the charging technology is unidirectional, flexibility can be achieved by adaptability in charging patterns and predictive control[66]. Van et al. [68] presents a model predictive control approach to induce peak shaving and to minimize electricity costs for a local energy system, using four different EV charging strategies. The strategies involves V2G or G2V charging, where the objective function either exclusively consider minimization of the grid electricity cost or additionally includes minimization of power flow variability, thus inducing additional peak shaving and valley-filling. Comparative analysis against uncoordinated charging, based on typical user behavior, reveals that all four charging strategies successfully achieved peak shaving and reduced the peak-to-valley height. Notably, V2G charging outperformed G2V charging in all aspects, even demonstrating lower peak loads compared to scenarios without EVs within the local energy system.

Curtailable loads and space heating
Demand-side management can also be derived from curtailment of non-critical loads or space heating which under active control provide DFR capabilities. In the context of energy systems, the term 'curtailment' encompasses two distinct concepts. It can either denote the deliberate decrease in electricity generation from a specific asset, such as photovoltaic (PV) generation, or the restriction or complete cessation of electric consumption by an asset, such as for heating and cooling applications in buildings. With regard to DFRs in this thesis, 'curtailment' exclusively

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[6] https://www.ssb.no/en/transport-og-reiseliv/landtransport/statistikk/bilparken, last accessed: 9th June 2023

[7] https://www.elvia.no/nettleie/alt-om-nettleiepriser/nettleiepriser-for-bedrifter-og-naering/, last accessed: 9th June 2023

[8] https://ts.tensio.no/kunde/nettleie-priser-og-avtaler, last accessed: 9th June 2023

[9] https://easee.com/uk/home-charging/, last accessed: 9th June 2023

refers to the latter definition.

In Norway, space and water heating amount to 78% of the total residential energy consumption in 2020[43], where substantial portions of the residential heating demand is provided by electricity and/or heat pumps[67]. The high shares of energy consumption for heating in Norway, entails a substantial potential for space heating as a source of flexibility when heating applications are operated strategically. A building envelope has a thermal mass which can store either heat or coolness. The degree of thermal inertia in the buildings thermodynamics relies on the level of insulation and weather patterns[28]. Space heating flexibility pertains to the temporal control of heating and cooling in buildings, where demand-side management strategies can include load shifting and peak load shaving. These strategies involve deviating from the standard thermal demand profile by pre-heating or pre-cooling indoor spaces. By employing such approaches, effective regulation and optimization of energy usage in space heating systems can be achieved. The substantial thermal inertia exhibited by buildings offers potential opportunities for leveraging heating and cooling operations during periods of low energy prices, while ensuring the maintenance of thermal comfort for occupants when utilizing the indoor area later on. Taleghan et al. [65] conducted a comprehensive review of thermal comfort in buildings, taking into account various factors such as clothing, metabolism, humidity, and activity levels of occupants. The authors examined multiple studies that calculated acceptable temperature ranges for occupants in buildings and found that a deviation of approximately ±3°C is generally deemed acceptable. Klein et al. [35] evaluates and compares different types of flexibility and storage options in buildings, finding that thermal building mass can be effectively utilized for thermal storage and grid support, especially during heating seasons (vinter). However, the authors also conclude that leveraging thermal building masses for flexibility and storage purposes presents technical challenges. Accurate predictions of weather conditions, load patterns, occupancy, and usage are crucial to ensure the maintenance of thermal comfort while utilizing these thermal storage capabilities. Furthermore, considering the high and consistent space heating load required to maintain thermal comfort in buildings, especially in regions with cold or warm seasons, space heating systems may be better suited for providing fast frequency reserve capacity rather than shifting significant amounts of thermal loads. The thermal inertia of buildings means that short-duration load shutdowns are unlikely to have a significant impact on the temperature. The exploration of space heating systems and curtailable loads in fast frequency reserve markets will be further discussed in section 2.6.

DFR aggregation and ancillary services
Prosumer DFRs is suited to provide various types of ancillary services such as load balancing, grid load peak-shaving, grid frequency support and grid reserve flexibility[5]. Although active participation of prosumers in energy markets is promising, various barriers such as capacity constraints and consistent supply requirements are often imposed by these markets. In order to overcome these challenges, an effective solution is to aggregate multiple prosumers and their flexible qualities, assets and load profiles. Coordination of flexible assets on a neighbourhood-level presents opportunities for synergies and harmonization of individual energy needs and utility [8, 29]. Backe et al. [8] compare individual and coordinated demand response utilizing DFR, EV charging and curtailable loads when responding to a subscribed capacity tariff and spot-price variation in a neighborhood. The study found that combining assets and load profiles of two prosumers rather than responding to market signals individually reduced both total load and electricity costs. Brooks et al. [15] quantify the energy needs of both individual residences and aggregated microgrids through load variability, finding a variability reduction of 25% when aggregating a sample of just four residences. Aggregation of BESS capacity resulted in a 14% reduction of variability and decreased the necessary storage capacity by 10%. Flexibility markets where arguably designed for large industrial actors, and a revision of certain regulatory policies are warranted to lower market barriers for individual prosumers with limited loads and aggregated participation[20]. Nevertheless, there already exist several economic incentives to provide demand-side flexibility, which will be examined in the following section.

2.4 Demand Response and DFR incentives

Demand response encompasses targeted tariffs or programs designed to reduce or shift electricity loads during periods of peak consumption. Demand response can be categorized into two distinct types: price-based programs and incentive-based programs[55]. Price-based programs involve the utilization of dynamic price rates, such as time-of-use tariffs, critical peak pricing and real-time energy pricing. These programs incentivize consumers to adjust their electricity consumption based on fluctuating price signals, encouraging load reduction or shifting during peak demand hours. Incentive-based programs encompass various approaches, including participation in frequency reserve markets, direct load control, and the provision of curtailable and ancillary services. These programs offer incentives to consumers for actively participating in load management activities, such as temporarily reducing their electricity consumption or making their loads available for grid support when required. By employing a combination of price-based and incentive-based programs, demand response initiatives aim to achieve a more efficient utilization of electricity resources and mitigate the strain on the grid during periods of high demand.

Price-based programs
Price-based programs generally encompass costs that are imposed on all electricity consumers, designed to enforce penalties for inflexibility or high, static energy consumption. Price-based demand response signals include short-term fluctuations in electricity retail prices which can impact the utilization of DFR, similar to grid tariff components reflecting real-time market conditions. The effect of flexible capabilities are likely to be more prominent when electricity retail prices vary frequently, due to the resilience of DFR. Simmini et al.[57] substantiate this claim in a study that assesses prosumer response and cost savings in relation to price signals. The authors found that relative cost savings correlates to increasing daily variation of electricity purchase price analysing three cases with different degrees of price variability. The study also points to price variability enhancing end-user flexibility as an ancillary service for the DSO.

Research suggests that dynamic grid tariffs, in contrast to static tariffs, can offer greater incentives for residential and industrial customers to use the grid more efficiently [54]. Moreover, such tariffs can help establish a framework that recognizes and rewards the contributions of DFRs. Grid tariffs typically consist of a variety of cost components, including energy-based charges (which reflect the amount of energy consumed), capacity charges (which are based on the maximum power consumed during a specified time period), and fixed costs[69]. These cost elements are widely recognized within the industry and are often combined to create a comprehensive pricing structure. Askeland et al.[6] examines optimal operation of flexible EV charging loads in response to energy prices and different grid tariff elements, finding that time-dependent and capacity-based grid tariffs best incentivizes flexible utilization and load-shifting. A Danish case study investigating grid tariffs incentive for flexible energy systems, further substantiate the effectiveness of temporal cost variation, concluding that volumetric tariffs (cost proportional to consumption) are a barrier to flexibility in the energy sector as they limit cost effective market signals[11]. In summary, dynamic grid tariffs provide effective incentives for efficient grid utilization and promote the integration of flexible energy systems.

In addition, the adoption of prosumer attributes, such as the installation of PV arrays, has led to a growing utilization of feed-in-tariffs by consumers in Norway, commonly known as ”pluss customers”[50]. Chen et al. [17] conducts a cost-benefit analysis examining the impact of feed-in-tariff rates on PV system investment costs. Their findings indicate a decrease in the payback period and highlight the correlation between reduced carbon emissions and higher feed-in-tariff rates. Maldet et al. [42] conducted a study to examine the impact of grid tariff design on peer-to-peer trading in a local community. Their research highlights an increase in economic incentive for the use of local battery storage when the spread between retail price and feed-in tariff rates is higher. However, the study also brings attention to the conflicting interests of high feed-in tariff rates and engagement in peer-to-peer trading within the community examined. In addition, Selinger et al. [56] presents a study analyzing the economic incentive for locally generated electricity in the context of temporally variable feed-in tariffs. Their findings suggest that a two-step tariff, consisting of a high-priced period and a low-priced period, has the potential to replace highly variable time-of-use tariffs. This could reduce the need for complex communication and metering.

Traditionally, grid tariffs for residential consumers in Norway have comprised a fixed component and a volumetric component, with the latter being contingent on the marginal loss factor associated with power transmission to end-users [8]. Apart from the volumetric element, which primarily differentiates prices based on distance from the power supply and the quantity of power consumed, the tariff design has been characterized as static. However, a new and more dynamic tariff structure was implemented in Norway in 2022, incorporating energy and peak-capacity elements that vary seasonally[49]. Dynamic tariff designs have the potential to better reflect the costs of DSOs and promote flexible load shifting in response to price signals, as well as the utilization of prosumer DFRs [8]. The literature describes various principles for tariff design, highlighting the complexity of incentivizing efficient interactions among network users. These principles encompass efficiency, equity, simplicity, consistency, transparency, stability, and additivity [20, 25, 37]. It is important to acknowledge that dynamic tariffs may entail compromises in terms of both stability and transparency for residential users, potentially necessitating direct control or automation by aggregators to enhance the reliability of demand responsiveness. The Norwegian grid tariff, specific to the case study conducted in this thesis will be provided in section 6.

Incentive-based programs
In contrast to price-based programs, which often enforce participation requirements for electricity consumers and impose penalties for inflexibility, incentive-based programs take a different approach. These programs do not subject prosumers to additional economic penalties if they choose not to participate. Instead, they provide an opportunity for prosumers to generate additional value by actively offering demand response services. By engaging in incentive-based programs, prosumers can actively contribute to enhancing the grid's overall flexibility without being financially penalized for non-participation.

The majority of incentive-based programs operate under contract-based arrangements, wherein customers grant utilities or system operators the authority to remotely control appliances during periods of high demand or system emergencies[16]. This type of remotely controlled program is observed in direct load control. Alternatively, customers may opt to voluntarily curtail their electricity consumption when notified of system reliability-triggered events by system operators. This voluntary load reduction approach is often observed in Emergency Demand Response Programs (EDRP). Customers participating in ERDP may choose to not curtail when notified and thereby forgo payment[16]. Interuptible/Cutailable (I/C) service programs are commonly provided by load-serving entities, offering customers a rate discount or credit in exchange for their agreement to curtail or reduce their energy consumption during contingencies or high-demand situations. These programs involve a contractual agreement between the customer and the entity, wherein the customer commits to load reduction when requested. Failure to meet the load reduction requirements can result in penalties or additional charges imposed on the customer. Similarly, Capacity Market Programs (CMP) operate under contractual obligations for load reduction in the event of contingencies. However, CMP differs in regard to customers committing to a pre-specified capacity for load reduction. In CMP, customers are guaranteed payment for their commitment to load reduction, even during periods when curtailment is not necessary. This ensures that customers are financially compensated for their availability and readiness to curtail their energy consumption when called upon, regardless of whether actual curtailment is required. Aalami et al. [1] conducted an analysis of demand response considering the participation of customers in I/C and Capacity Market Programs (CMP), where customers allocate 10% of their total load to these programs. The study explored multiple case scenarios with varying levels of incentive and penalty costs. The findings of the study revealed that higher costs resulted in increased customer revenue and preferable load profiles while reducing revenue for suppliers. On the other hand, lower penalty and incentive costs led to minimal reductions in peak loads, energy consumption, and customer benefits. Additionally, the study identified that high elasticity of demand exacerbated the characteristics of the load. These findings shed light on the economic dynamics and implications of demand response programs, highlighting the importance of carefully balancing incentive and penalty costs to achieve optimal outcomes in terms of load reduction, energy consumption, and benefits for both customers and suppliers.

Categorically considered as a CMP, frequency reserve markets constitute a relatively novel yet undeniably significant concept, particularly in light of the growing penetration of RES. These markets play a crucial role in ensuring load capacity during contingencies when the energy system encounters frequency drops. Among the various incentive-based programs, this paper aims to underscore the impact of prosumer engagement in a fast frequency reserve market, warranting further investigation in the subsequent sections.

2.5 DFR in frequency reserve markets

Substantial shares of variable RES in future power systems creates opportunities for neighborhoods and prosumers to provide frequency restoration flexibility [52]. As discussed in Section 2.2, the increased integration of inverter-based RES in the power system leads to a proportional reduction in system inertia, traditionally provided by mechanical generators. Consequently, fast frequency reserve markets have emerged as a response to address this challenge, alongside the growing electrification of applications and the overall increase in electricity demand across the system. The demand for frequency regulation is particularly pronounced in scenarios characterized by considerable fluctuations in loads and power generation, as well as substantial disparities between projected and actual system load and consumption.

As TSO in Norway, Statnett is responsible for balancing the power system in which the reserve markets are an important tool. In the event of a frequency drop within the range of 49.7Hz to 49Hz, varying according to the specific reserve markets and options in Norway, the initial and fastest response is implemented through Fast Frequency Reserve (FFR) measures. These measures are designed to mitigate the rate of frequency decline[62]. The frequency drop is then completely stopped and ideally stabilized at a new level by the Frequency Containment Reserve (FCR). The frequency is brought back to normal levels (49.9Hz - 50Hz) by the automatic frequency restoration reserves (aFRR), thereby manual Frequency Restoration Reserves (mFRR) maintains the supply deficit until the power system achieves a new stable balance. The majority of these markets require participants capable of providing significant load reductions or capacities (MW), which often presents a barrier for prosumers with modest DFR capabilities from participating. However, Statnett does not object to aggregated loads partaking in FFR, FCR and aFRR.

The aggregator approach has been proven feasible for both participation in FCR [7], and in the frequency restoration markets (aFRR and mFRR) [31], but requires advanced bidding models [44]. Aggregation in theses markets are already being practiced in Norway. Aggregators such as Enfo, provide services to accumulate lesser loads of DFR into an overall portfolio that is submitted as a collected bid[22].

Of all the different reserve markets, FFR, has the shortest activation time and is therefore, arguably, the least invasive for participants in regard to daily operations. As this thesis consider the data of the FME ZEN pilot project at Campus Evenstad, FFR is found to be the most suitable reserve market to engage in, and will therefore be subject of further examination.

2.6 FFR Market

After two years of testing and tuning technical requirements, market conditions and operating routines, Statnett established a commercial market for the acquisition of FFR in 2022[61]. The need for FFR are greatest in situations where the power system experiences low loads and production, combined with high shares of wind- and solar power and import [61]. These situations are most prevalent during the summer months and especially when experiencing hydrological dry years, due to limited reservoir capacity in hydro-power plants and subsequently flexibility provision. The share of RES generation is more prominent during summer months, likely attributing to the need for FFR. Statnett requests two different kinds of contract types for FFR reserve capacity, FFR Profil and FFR Flex. The FFR 2023 season for Profil lasts from midnight May 27th until midnight September 3rd in entirety, while FFR Flex encompasses 400 hours delivered according to weekly orders during the season, from April 29th until October 30th. Delivery of FFR Profil applies to all hours of the day during Saturdays and Sundays, while solely from 10 pm until 7 am on weekdays. Statnett requests 50MW of FFR Profil and 100MW of FFR Flex for the 2023 FFR season. A uniform market price is set by Statnett for both Profil and Flex according to the bids admitted by suppliers. Statnett can slightly deviate from the initial request on volume and contract distribution, as they choose the combination of Flex and Profil that provide the lowest purchase cost, while still being operationally sound. The market results for 2022 was 45.2 MW FFR Profil at a market price of 150 NOK/MW/hour, which included a delivery of 1502 hours, and 109.5 MW of FFR Flex at a market price of 495 NOK/MW/hour[61]. The deadline for delivering FFR bids are set to February 27th in 2023.

FFR is intended to be a fast, active power support service, reacting to frequency drops. Statnett requests both long (30s) and short (5s) support duration and offers three different alternatives regarding activation level and maximum full activation time, presented in Table 1. The maximum acceptable over-delivery is 20% of the pre-qualified FFR capacity. After an activation and completion of the support duration, the FFR providing entity must be ready for a new activation cycle within 15 minutes. Statnett specifies terms for deactivation and recovery for both long and short support duration. For short support duration the deactivation is limited to a maximum of 20% of the pre-qualified FFR capacity per second, while there are no limitations on the rate of deactivation for long support duration. Neither can exceed a maximum recovery of 25% of the pre-qualified FFR capacity.

Alternative	Activation level [Hz]	Maximum full activation time [s]
A	49.7	1.30
B	49.6	1.00
C	49.5	0.70

Table 1: Alternatives for the activation of FFR

Contributions from DFR in the FFR market can be an important enabler for a sustainable energy transition. To comply with the requirements of the Norwegian FFR market, participants are expected to have a minimum delivery capacity of 1 MW [61]. Consequently, DFRs with lower capacity are required to be consolidated into a collective portfolio. In 2021, Enfo participated with aggregated loads ranging from 60kW to 5MW in the FFR market[22]. The limited research on provision of reserves from neighborhoods show that the participation in frequency restoration markets lower neighborhood costs [23]. However, there has been little research conducted on the FFR provision capabilities from a neighborhood with flexibility from batteries and EV charging.

FFR capacity can be sold by either reserving curtailable capacity through non-critical loads or by discharging flexible energy to the grid. Karbouj et al. [34] review different sources of frequency control in variable RES dominated systems and argue that demand response, distributed ESS and PV power plants has potential to actively participate in fast frequency support as long as fast performing control schemes are implemented.

Kushwaha et al.[36] assess aggregated scheduling of EVs potential for FFR support through both G2V and V2G charging stations in low inertia power systems, showing significant capacity for FFR support and reduction in system costs. The authors also consider the effect on renewable energy curtailment, of which the conducted case study revealed that the utilization of G2V + V2G resulted in lower curtailment of RES compared to scenarios without EV integration, as well as scenarios with only G2V implementation. Notably, the study does not consider FFR provision from V2G chargers individually.

Stationary batteries posses the same qualities as V2G connected EVs, but will in practical terms often differ in regard to SoC demand and practical constraints, when considering FFR participation. Despite the scarcity of research on DFR provision within the FFR context, a notable study evaluating the utilization of BESS for Frequency Containment Reserve (FCR) is discussed in Section 2.7.

Although the potential gain of DFR utilization in FFR markets might be significant, there also exists costs related to battery wear and tear. BESS and EV battery wear and aging is directly related to the absolute amount of energy transferred, and is negatively affected by high charge rates, battery temperature variation and high depth-of-discharge[26, 71]. Han et al. [26] provides an economic feasibility study of V2G connected EVs in frequency regulation markets, concluding that the economic gain exceeds costs of battery wear under current market situations (2013, USA). The authors emphasises that the cycle life of batteries will be significantly extended with well-designed aggregators and frequency regulation operation. Zhou et al. [71] similarly analyse the cost of utilizing EV batteries as energy storage in power grids in China and the UK, ascertaining a significantly greater DFR potential for lithium-ion powered EV batteries rather than Lead-acid or NiMH batteries due to longer cycle-life. Lead-acid and NiMH batteries was not found to be cost effective in V2G use with regard to the given grid tariff and battery costs at the time. Since the study was conducted in 2011, lithium-ion batteries have established itself as a standard in the EV market while experiencing a significant decrease in price and increase in recycling practices, strengthening the EV economic potential for providing FFR[3].

FFR is commonly also provided by curtailing capacity through non-critical loads. This method of providing FFR involves limiting or completely cutting off power to a load for a brief period, typically lasting from 5 to 30 seconds. The loads best suited for FFR reserves may vary depending on the specific case and prosumer, taking into account their energy needs, operation and routines. To minimize disruption to daily operations, it can be beneficial that the load has a certain level of inertia. Thermal heating systems in buildings inherently possess a high degree of inertia as heat can be conserved in buildings for substantial length of time, arguably making them well-suited for contributing to FFR reserves. Additionally, Lu et al. [40] expound on the benefits of using aggregated thermostatically controlled appliances for regulation services. They note that such appliances are often in frequent operation, allowing them to consistently provide frequency response. Furthermore, they possess a high capacity for response and typically offer a wide range of temperature settings, making them an advantageous choice for regulation services. The study, evaluating electric water heaters and residential heating, ventilation, and air-conditioning for intra-hour load balancing services, concludes that the appliances can become a major source of revenue for the prosumers, while recovering cost of implementing two-way communication and control network needed to participate in balancing markets. Further, Jimeno et al. [32] applies aggregated thermostatically controlled loads for flexibility markets in a case study based on an actual power system in Spain, finding that thermostatically controlled loads can contribute significantly in solving system balance.

2.7 Value stacking DFR applications for a Prosumer

This thesis aims to provide an comprehensive examination of the interplay between DFRs in a holistic perspective of a prosumer and/or neighboorhods, presented with demand response opportunities subject to pragmatic conditions. Special attention will be given to examining and analyzing participation in the newly established Norwegian FFR market and its impact on DFR operation and other demand response mechanisms. Much of the previously presented literature have provided valuable insight into facets or individual aspects of this research problem, providing different stakeholder perspectives. There exist limited research on prosumers utilizing DFRs to contribute reserves in FFR markets. However, this section will present a short literature review, focusing particularly on studies that closely align with the objectives and goals of this thesis.

Backe et al. [8] conducted a comparative analysis examining the effects of individual and coordinated demand response with dynamic and static subscribed capacity grid tariffs. Their study, similar to the scope of this thesis, incorporates decision-making regarding the operation of flexible assets. Additionally, the case study conducted over 25 weeks also assumes perfect foresight on loads and retail prices, but introduces stochastic elements between weeks. The findings of Backe et al. [8] indicate that coordinated demand response, when operating flexible assets, outperforms individual prosumer approaches in achieving total weekly load reductions and peak-shaving when subject to a capacity-based grid tariff. The analysis highlights that the cost-optimal operation of flexible assets is contingent upon the dynamics of the tariff scheme. Capacity subscription grid tariffs are, however, no longer in consideration by the Norwegian regulator due to several objections and concerns from different stakeholders according to NVE [27]. It is important to highlight that the case study conducted by Backe et al. [8] focuses on the same Norwegian prosumer, namely the FME ZEN pilot project of Campus Evenstad, as this thesis does. Consequently, both studies consider similar

DFRs and load profiles. However, this thesis builds on the analysis by incorporating broader range of practical considerations for DFR operations and shifts the focus towards value stacking demand response. Moreover, this thesis consider energy export through the "Plusskundeordning" [10], incorporates V2G technology and places a greater emphasis on examining the interplay and capacities of DFRs when subjected to frequency regulation reserve and other demand response mechanisms.

Ahčin et al. [2] provide a techno-economic analysis of different demand response applications of BESS in Norway. The study provides four cases of distinctive demand response mechanisms, which includes a power based tariff (case 1), power based tariff with an implemented PV system (case 2), frequency containment reserve (FCR) (case 3) and DSO grid support through a FCR-N (normal) market (case 4). Each of the resulting analyses, individually contributes to the context and scope of this thesis. However, the study does not concern the integration or synergies between multiple DFRs or demand response mechanisms.

The four cases regard internal rate of return of battery investment and analyses the economic feasibility of each case. The first two cases are deemed infeasible with regard to current tariff rates and battery prices (2019, Norway), even though the authors argue that the power based tariff structure incentives BESS flexibility utilization. Case 1 provided the most significant monthly peak shaving, while the inclusion of the PV-system and possibility of energy export in case 2 enhanced feasibility. In case 3 and 4, engagement in FCR market proved highly advantageous, decreasing total energy cost and providing BESS profitability at significantly higher battery prices than for the first two cases. It is important to note that the authors faced limited access to precise BESS prices and frequency reserve market data in 2019, necessitating the use of certain hypothetical assumptions. Ahčin et al. [2] provide valuable insight into economic battery investment feasibility by responding to demand response mechanisms. The authors concludes that value stacking demand response utilities can yield significant benefits and provide feasibility to battery investments.

Firoozi et al. [23] explores the optimized operation of a local energy community and its potential for enhancing grid stability through the provision of mFRR. The authors employ a two-stage scheduling model to investigate the optimal utilization of DFRs participating in FRR provision. In their case study, Firoozi et al. [23] presents a hypothetical local energy system consisting of a PV system, a BESS, EVs and several residential consumers. The results indicate that participation in FRR increases the profits of the local energy system while naturally contributing a valuable ancillary service to the TSO. It is important to note that FRR markets differ from FFR markets in terms of longer timeframes, extended response durations, and larger reserve capacity requirements, while allowing for slightly slower response times.

While the study provides valuable insights into the feasibility of aggregated DFR capacity provision in reserve markets, it primarily focuses on the aggregated operational characteristics of DFRs within an overall local energy system system. In contrast, this thesis intends to delve into the specific operational details and consequences of a single prosumer, which hypothetically could exist within such LEC. Moreover, while the research by Firoozi et al. [23] shares similarities in terms of flexible characteristics and DFRs, it places less emphasis on individual DFR operational aspects and the impact/concerns of reserve markets on other demand response mechanisms. Lastly, in contrast to Firoozi et al. [23], this thesis considers FFR, within the framework of frequency reserve markets.

This thesis aims to enhance the current body of research by offering a comprehensive analysis of the energy operation of individual prosumers, providing insights into specific operational intricacies and their implications. Additionally, it expands upon existing scientific literature by emphasizing the participation of prosumers in a FFR market.

2.8 Research questions

This thesis assesses the cost-optimal flexibility responses from a Norwegian prosumer participating in the Norwegian FFR market. To the authors knowledge, no study has explored how costs and

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[10] https://www.nve.no/reguleringsmyndigheten/regulering/nettvirksomhet/nettleie/tariffer-for-produksjon/plusskunder/, last accessed: 9th June 2023

operations of a prosumer with demand-side flexibility is impacted by the opportunity to participate in FFR. This thesis presents a case study of a Norwegian university campus that incorporates multiple flexibility resources to value stack demand response mechanisms. Metered data for three distinctly different historical years are utilized to provide a comprehensive understanding of DFR engaging in demand side management. The thesis provide an optimization model that minimizes prosumer costs by optimizing operation of the DFRs with and without the opportunity to participate in FFR. The research questions are the following:

- How are costs and operations of demand-side flexibility impacted by participation in FFR?
- How do economic characteristics of different years impact FFR participation?
- Which economic incentive (variable prices, grid tariff elements, exports, or FFR) provides the highest economic value from demand-side flexibility resources?
- Which flexible resource yields the most savings (per capacity) through its flexibility and demand response participation?

3 Mathematical programming

This section will provide an overview of some relevant optimization methods and mathematical programming with regard to literature and studies conducted that are considered relevant to this thesis.

The concept of mathematical programming pertains to the optimal allocation of limited resources among competing activities, taking into account sets of constraints imposed by the nature of the problem being investigated[14]. Mathematical programming is widely utilized in the field of optimization, enabling the ability to manipulate numerous variables and constraints to determine the optimal solution of a given problem[53]. Various problem domains are suitable to be solved using mathematical programming, including manufacturing problems, transportation problems, production problems and optimal allocation- or alignment problems. Distinct problems often requires a specific approach within the realm of mathematical programming, which includes; Linear, Mixed Integer, Nonlinear and Mixed Integer Nonlinear Programming.

For a problem to be classified as a linear program, both the objective function and the constraints must be linear. The objective function must consist of a linear combination of decision variables and constant coefficients. Similarly, the constraints need to be linear equalities or inequalities consisting of linear decision variables, constants and coefficients without any nonlinear function terms. The linearity of constraints and the objective function ensures that they are presented in a straight line or a flat hyperplane in the problem's mathematical space, allowing for efficient optimization algorithms to be applied to solve the problem.

Linear programs in its simplest, standard form can be expressed as in the following Formulation 1:

$$\begin{array}{cr} \text{Find the value of decision variable} & x \\ \text{that maximizes} & z = c^T x \\ \text{subject to} & Ax < b \\ \text{and} & x \geq 0 \end{array} \tag{1}$$

where, x is a decision variable, c and b are given vectors and A is a given matrix (referring to the mathematical properties of an object). z represents the objective value, which can either be maximized or minimized, and are constrained by $Ax \leq b$ and $x \geq 0$.

For some problem types and situations, decisions need to be discrete or presented as whole numbers. These types of problems are recognized as integer- or mixed-integer programs. The problem consist of integer decision variables which can be used to represent choices of binary options (0 or 1), selecting specific items to be utilized or determining the number of units produced or transferred. Relevant problems for integer programming include facility location, production planning or expansion planning.

The process of mathematical programming can be distinguished in to five key stages; formulating the model, gathering data, obtaining an optimal solution, applying sensitivity analysis and testing and implementing the solution[14]. When formulating the model various decisions has to be considered and applied. This includes determining the time horizon for applying the model, identifying and selecting decision variables that can be controlled by the decision-maker, and specifying parameters which are imposed by external environments. Additionally, the constraints should accurately reflect the intended relationship between decision variables and parameters, based on the problem's characteristics and nature. Precise and quantitative expression of the constraints and the interconnection that they describe is central in determining the models computational complexity of the model. An objective function can then be constructed, either minimizing or maximizing the function, measuring the profitability associated with various, feasible courses of action within the problem.

Once the mathematical model is implemented, the next stage involves gathering and formulating the necessary data to define the different parameters and coefficients relevant to the problem. Subsequently, the model can be solved using a computational solver, yielding an optimal objective value to be obtained. One notable convenient characteristic of linear-programming is its ability to conduct sensitivity analysis on the optimal solution, which is important when regarding uncertainty, but also dynamic considerations[14]. Typically, linear programming models assume a static environment where parameters remain constant and completely certain throughout the optimization process. However, by incorporating dynamic considerations in linear programming such as varying or time-dependent factors, the decision-makers can address optimized decisions that reflect the changing nature of the problem environment. Finally, the solution should undergo thorough testing to ensure that the model effectively represents the specified problem or intended situation. This testing phase aims to validate the model's accuracy and reliability.

In the context of the problem instances to be investigated and implemented in the mathematical model of this thesis, a deterministic and single-objective linear model is considered to be the most appropriate choice. While the inclusion of stochasticity and aspects of uncertainty might be beneficial in providing more realistic boundaries of the solution, given the specific data set and problem addressed in this case study, a deterministic model is deemed most efficient in providing a satisfactory solution. Stochastic programming presents a more complex method of solving problems, but a deterministic model is in some cases necessary to yield a feasible and eligible solution[33].

Furthermore, considering the nature of the problem and the available data, the incorporation of integer variables in this problem formulation is deemed unnecessary. The decision variables in this thesis do not inherently require discrete values, and the utilization of linear continuous optimization offers advantages in terms of model simplification and computational efficiency. However, it is worth noting that integer programming could be beneficial in future extensions of the current model. For instance, if the prosumer needs to determine the number and specific DFRs to deploy at certain times or make choices among mutually exclusive demand response markets or signals, integer programming may be applicable.

4 Problem Description

This thesis and the following case study aims to examine and estimate the value of implementing and operating DFRs for a prosumer, when value stacking several incentive-based and price-based demand response mechanisms. The thesis places significant emphasis on prosumer participation in a FFR market, with the objective of analyzing its impact on the interplay of DFRs while considering the influence of price signals related to other demand response mechanisms.

4.1 Motivating the problem

Increasing penetration of variable RES production, growing climatic concerns, global electrification, and the emergence of EVs presents energy systems with risk regarding unpredictable production- and consumption patterns. Furthermore, the integration RES implies lower inertia in power systems and subsequently, a need for innovative solutions for providing frequency reserve and grid stability. It is therefore important to investigate and analyse the different services that provides flexibility, providing balancing services and security of supply. Adapting prosumer qualities and contributing with demand response are likely to trigger significant cost savings.

Therefore, this thesis pursues to quantify the direct cost savings of Campus Evenstad when responding to price signals and operating flexible assets. Price signals include spot-price variation, dynamic grid tariffs, the possibility of energy export and FFR contracts. This thesis aims to study how different demand response signals impact the profitability of being a flexible prosumer in today's market, while simultaneously endeavouring to contribute a versatile modeling tool applicable to several prosumers.

4.2 The problem objective

The primary objective of this problem and the subsequent mathematical model is to minimize the energy costs incurred by a prosumer. This is accomplished by utilizing DFRs to respond to demand response price signals, while simultaneously contributing to the stability of the energy system through participation in the FFR market. The objective is to reduce prosumer costs and increase revenues associated with both price-based and incentive-based demand response.

The prosumer is subject to a monthly peak capacity cost, which is determined by multiplying the highest monthly peak load by the corresponding peak capacity cost. Additionally, the grid tariff imposes an energy-dependent cost that varies seasonally, and the prosumer must also pay an electricity import cost (retail cost) to the electricity provider, which fluctuates hourly.

Furthermore, the prosumer has the opportunity to generate revenue through energy exports to the grid, which vary hourly and are priced accordingly. Additionally, by providing capacity reserves in the FFR market, the prosumer can generate additional revenue. Since the objective function aims to minimize all cost-related elements, while the prosumer seeks to maximize revenues, these revenue elements are depicted as negative costs.

In summary, the proposed objective is to minimize costs for the prosumer, considering various cost elements such as peak capacity costs, grid tariff costs, and electricity import costs, while simultaneously maximizing revenues through energy exports and participation in the FFR market.

4.3 Decisions that impact the goal

Several operational decisions can be made to impact the achievement of the previously described problem objective.

To minimize the costs associated with monthly peak loads, the prosumer is incentivized to maintain the lowest peak level achievable throughout each month. Since the cost is solely determined by the highest load hour within each month, adopting peak-shaving strategies and valley-filling techniques can effectively reduce this cost.

The energy associated costs of both the DSO and the energy provider can be mitigated by minimizing the amount of electricity imported from the grid when the prices are high. As the prosumer needs to maintain its hourly load for operational purposes, the costs associated with energy import can only be reduced through storage capabilities, achieved by shifting loads to hours with lower energy costs. Subsequently, the energy export revenue can be increased by exporting energy during periods of high energy prices.

The prosumer possesses flexible assets capable of storing energy and being charged or discharged within specific timeframes, enabling them to provide demand response services. The extent of the demand response to each cost signal is contingent upon the state of charge (SoC) and capacities of these flexible assets.

The provision of FFR and the associated revenue is accomplished by ensuring a constant reserve capacity throughout all active contract hours. The revenue generated is determined by the amount of FFR capacity supplied, which can be achieved by either discharging energy from the flexible assets or curtailing their charging. Consequently, the assets are motivated to prioritize charging activities that can be curtailed and restrict operational discharging during the hours when the contracts are in effect.

4.4 Considerations that limit decisions

Each of the different cost- and revenue elements presents varying levels of economic incentive, while the prosumer possesses limited resources to respond to these incentives. Therefore certain constraints and limitations must be considered when making the previously discussed decisions.

When minimizing the monthly peak load cost, feasibility requires the resulting grid import to be less than or equal to the highest monthly peak in every hour of the month. Additionally, both energy costs are contingent upon the operationally imported load across all hours. The hourly operational load is determined by the prosumer's energy demand, operational exports, and the charging, discharging states, quantities, and losses of all flexible assets. It is essential to maintain a balanced power exchange within the local system and with the grid at all times. The provision of energy exports is also dependent on this balance, as additional imported energy is required to achieve net equilibrium before exporting energy. Additionally, the production limit set by the DSO imposes constraints on quantity of exported energy.

Furthermore, it is crucial to ensure that the operational charging, discharging, and storage of each flexible asset do not exceed their inherent capacities at any given time. Some flexible assets may also have limited availability during certain periods, where their contribution to demand response is restricted. Moreover, the DFRs are required to provide charging to external inventory during specific periods, which further constrains the provision of demand response.

The capacity of the FFR is determined by the combined capabilities of discharging, charging, and curtailing exhibited by the flexible assets. However, the prosumer must adhere to certain limitations regarding FFR charging capacity. It cannot exceed the inherent charging capacity of the DFR resources. Similarly, the FFR discharging capacity should not surpass the available discharging capacities minus any operational discharging occurring at the specific time.

5 The Mathematical model

This section presents the mathematical modelling framework for the prosumer cost minimization problem. The model is a deterministic linear program that minimizes the prosumer costs subject to spot-price variation, FFR market contracts, different tariff elements and varying loads over the duration of a year. Decisions include operation of flexible assets, determination of FFR capacity participation and net consumption between the prosumer and the grid.

5.1 Sets, Indices, Parameters and Variables

Sets and Indices

$\mathscr{F}$ is defined as the set of different flexible assets and is indexed by f. Depending on the asset type (see Data analysis section 6), it can be flexibly charged (increasing a prosumers demand, e.g., by charging electric vehicle), flexibly discharged (decreasing a prosumers demand, e.g., by curtailing loads) or both (e.g. battery and V2G EV charger). The model considers a temporal scale with all operational periods defined in the ordered set $\mathscr{T} = \{1, 2, ..., t\}$. Every time-step includes operational decisions for flexible assets. The hourly time-steps is categorized in the set of months $\mathscr{M} = \{1, 2, ..., m\}$ as different tariffs entails varying cost elements, months and seasons. Storage of flexible assets are therefore operated with perfect foresight within an instance. The set of flexible assets contributing to FFR is defined by $\mathscr{F}^{\text{FFR}}$ and the active FFR operation is contained within the set $\mathscr{T}^{\text{FFR}} \subseteq \mathscr{T}$.

Set	Description
$\mathscr{F}$	Set of flexible asset types
$\mathscr{F}^{\text{FFR}}$	Set of flexible assets supporting FFR
$\mathscr{T}$	Set of market clearing time-steps
$\mathscr{T}^{\text{FFR}}$	Set of hours where FFR is active
$\mathscr{M}$	Set of months

Table 2: Sets

Index	Description
f	flexible asset
t	market clearing time-step
m	months in a year

Table 3: Indices

Parameters	Description
$\varepsilon_f^{\text{charge}}$	Charging losses of flexible asset $f \in \mathscr{F}$ [%]
$\varepsilon_f^{\text{diff}}$	Diffusion loss of flexible asset $f \in \mathscr{F}$ [%]
$\varepsilon_f^{\text{discharge}}$	Discharge loss of flexible asset $f \in \mathscr{F}$ [%]
η_f^{charge}	Charging capacity of $f \in \mathscr{F}$ [kWh/h]
η_f^{storage}	Storage capacity of $f \in \mathscr{F}$ [kWh]
$\eta_f^{\text{discharge}}$	Available discharging capacity of $f \in \mathscr{F}$ [kWh/h]
$\gamma_{f,t}^{\text{req}}$	Minimum required energy content of $f \in \mathscr{F}$ at time $t \in \mathscr{T}$ [kWh]
$\gamma_{f,t}^{\text{max}}$	Maximum energy content of $f \in \mathscr{F}$ at time $t \in \mathscr{T}$ [kWh]
$a_{f,t}^{\text{available}}$	Availability of flexible asset $f \in \mathscr{F}$ at time $t \in \mathscr{T}$
k_f	Energy initially available in $f \in \mathscr{F}$ at time $t \in \mathscr{T}$
ξ_t^{load}	Original demand for electricity at time $t \in \mathscr{T}$ [kWh/h]
β	Grid export limit during a year [kWh]
α^{curtail}	percentage of electricity consumption available for curtailment
c_t^{retail}	Electricity import cost (incl. taxes) at time $t \in \mathscr{T}$ [NOK/kWh]
c_t^{exp}	Revenue of electricity export (excl. surcharge) at time $t \in \mathscr{T}$ (wholesale price) [NOK/kWh]
c_t^{energy}	Energy dependent grid cost at time $t \in \mathscr{T}$ [NOK/kWh]
c_m^{peak}	Peak power dependent grid cost at month m [NOK/kWh/h]
c^{FFR}	the FFR market price [NOK/kW/h]
C^{FFR}	total FFR earings [NOK]
Υ^{FFR}	total number of hours where the FFR contract is active

Table 4: Parameters

Variable	Description
$w_{f,t}^{\text{charge}}$	Charging of flexible asset $f \in \mathscr{F}$ at time $t \in \mathscr{T}$
$w_{f,t}^{\text{discharge}}$	Discharging of flexible asset $f \in \mathscr{F}$ at time $t \in \mathscr{T}$
$w_{f,t}^{\text{storage}}$	Available energy of flexible asset $f \in \mathscr{F}$ at time $t \in \mathscr{T}$
p_m	Monthly measured peak load at time $t \in \mathscr{T}$ (per kWh/h)
y_t^{load}	Resulting grid import at time $t \in \mathscr{T}$
x_t^{load}	Resulting grid export at time $t \in \mathscr{T}$
$r_{f,t}^{\text{charge}}$	FFR capacity from charging asset $f \in \mathscr{F}$ at time $t \in \mathscr{T}$
$r_{f,t}^{\text{discharge}}$	FFR capacity from discharging asset $f \in \mathscr{F}$ at time $t \in \mathscr{T}$
z^{FFR}	The FFR capacity [kW]

Table 5: Variables

5.2 Objective function

The objective function quantifies the total electricity costs given a certain schedule for the flexible assets. This objective function is minimized:

$$\min z = \sum_{m \in \mathscr{M}} c_m^{peak} p_m + \sum_{t \in T} ((c_t^{energy} + c_t^{\text{retail}}) y_t^{\text{load}} - (c_t^{\text{exp}} x_t^{\text{load}})) - C^{FFR} \tag{2}$$

where p_m is a variable for the peak load during month m. The electricity import from the grid to cover the loads are identified by variable y_t^{load}, while variable x_t^{load} represent electricity export to the grid. The objective contains a time-varying load-dependent retail cost for import (c_t^{retail}) and for export (c_t^{exp}) and monthly peak load cost (c_m^{peak}). Finally, total FFR earnings is identified through C^{FFR} which is subtracted in the objective function and defined by equation (3):

$$C^{FFR} = c^{\text{FFR}} z^{\text{FFR}} \Upsilon^{\text{FFR}} \tag{3}$$

where c^{FFR} represents the FFR market price which is constant with regard to the pertinent FFR contract. The maximum, feasible FFR capacity that is submitted as a marked bid is defined by z^{FFR}. Note that an underlying assumption in the model is that the FFR bid is accepted at a deterministic price. The expression is then multiplied by the number of hours where the FFR contract is active, defined by Υ^{FFR}.

5.3 Constraints

The resulting import from the grid to the prosumer is defined by constraints (4). The resulting load after each time-step must be equal to the initial demand plus potential export to the grid as well as charged and discharged energy from the flexible assets:

$$y_t^{\text{load}} = \quad \xi_t^{\text{load}} + x_t^{\text{load}} + \sum_{f \in \mathscr{F}} (w_{f,t}^{\text{charge}} - \varepsilon_f^{\text{discharge}} w_{f,t,}^{\text{discharge}}) \qquad \forall \quad t \in \mathscr{T} \tag{4}$$

where ξ_t^{load} is the inflexible load, y_t^{load} and x_t^{load} are import and export of electricity, while $\omega_{f,t}^{\text{charge}}$ and $\omega_{f,t}^{\text{discharge}}$ are charging and discharging of flexible assets type f, respectively. Energy losses are only considered for discharging, represented by $\varepsilon_f^{\text{discharge}}$.

Constraint (5) ensure that flexible asset f start the operational horizon ($t = 1$) with an initial energy level stored equal to charging subject to losses, discharging and pre-defined energy in the first period (k_f).

$$k_f + \varepsilon_f^{\text{charge}} w_{f,1}^{\text{charge}} - w_{f,1}^{\text{discharge}} = w_{f,1}^{\text{storage}} \qquad \forall \quad f \in \mathscr{F} \tag{5}$$

Constraint (6) ensures that the flexible asset type f has an energy level stored equal to the previous period subject to diffusion losses plus charging subject to losses minus discharging.

$$\varepsilon_f^{\text{diff}} w_{f,t-1}^{\text{storage}} + \varepsilon_f^{\text{charge}} w_{f,t}^{\text{charge}} - w_{f,t}^{\text{discharge}} = w_{f,t}^{\text{storage}} \qquad \forall \quad f \in \mathscr{F}, t \in \{2, ..., |\mathscr{T}|\} \tag{6}$$

The losses with respect to charging ($\varepsilon_f^{\text{charge}}$), discharging ($\varepsilon_f^{\text{diff}}$) and diffusion ($\varepsilon_f^{\text{discharge}}$) are dependent on the characteristics of the flexible asset f. There are no losses related to discharging in constraints (5) and (6) as it is accounted for in constraint (4).

The maximum capacity for charging (η_f^{charge}), storage (η_f^{storage}) and discharging ($\eta_f^{\text{discharge}}$) of flexible asset f are defined as upper bounds for operational decisions in all time periods in constraints (7), (8) and (9).

$$w_{f,t}^{\text{charge}} \leq \eta_f^{\text{charge}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{7}$$

$$w_{f,t}^{\text{discharge}} \leq \eta_f^{\text{discharge}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{8}$$

$$w_{f,t}^{\text{storage}} \leq \eta_f^{\text{storage}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{9}$$

The constraints associated with FFR are given in (10), (11) and (12). FFR capacity can be acquired based on the curtailable charged quantity in (10) represented by variable $r_{f,t}^{\text{charge}}$, and by the remaining discharge capacity in (11) reperesented by variable $r_{f,t}^{\text{discharge}}$, for each flexible asset f at time t. The sum of the available FFR capacity from each flexible asset $f \in \mathscr{F}$ for each time-step of the year sets the upper limit of how much FFR capacity we can offer over the whole FFR season in (12). Notice that the expression for FFR capacity z^{FFR} does not contain a temporal index to ensure that the capacity is constant throughout the period. Energy use associated with FFR activation is disregarded in this formulation.

$$w_{f,t}^{\text{charge}} \geq r_{f,t}^{\text{charge}} \qquad \forall \quad f \in \mathscr{F}^{\text{FFR}}, t \in \mathscr{T} \tag{10}$$

$$w_{f,t}^{\text{discharge}} + r_{f,t}^{\text{discharge}} \leq \eta_f^{\text{discharge}} \qquad \forall \quad f \in \mathscr{F}^{\text{FFR}}, t \in \mathscr{T} \tag{11}$$

$$\sum_{f \in \mathscr{F}} (r_{f,t}^{\text{charge}} + r_{f,t}^{\text{discharge}}) + \alpha^{\text{curtail}} \xi_t^{\text{load}} \geq z^{\text{FFR}} \qquad \forall \quad t \in \mathscr{T}^{\text{FFR}} \tag{12}$$

Constraint (13) and (14) make sure that the energy level of of flexible asset f is at least at the required level $\gamma_{f,t}^{\text{req}}$ and does not exceed the maximum level $\gamma_{f,t}^{\max}$ for all time periods t.

$$\gamma_{f,t}^{\text{req}} \leq w_{f,t}^{\text{storage}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{13}$$

$$\gamma_{f,t}^{\max} \geq w_{f,t}^{\text{storage}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{14}$$

Constraint (15) make sure that the resulting grid export does not exceed the yearly ”plus-customer” surplus production limit:

$$\sum_{t \in \mathscr{T}} x_t^{\text{load}} \leq \beta \tag{15}$$

Constraint (16) determines the highest monthly peaks. The highest import quantity during each month p_m sets the threshold for the monthly demand charge grid tariff. As the objective function minimizes costs, and p_m is positive; the variables will be minimized, but can not achieve a value lower than the highest operational import during the specified periods.

$$y_t^{\text{load}} \leq p_m \qquad \forall \quad t \in \mathscr{T}(\text{m}), m \in \mathscr{M} \tag{16}$$

$$\tag{17}$$

Constraint (18) and (19) ensures that charging and discharging only are available when the flexible asset is connected. These constraints are necessary when considering flexible assets where availability fluctuates, such as for EV charging.

$$w_{f,t}^{\text{charge}} \leq a_{f,t}^{\text{available}} \qquad \forall \quad t \in \mathscr{T}, f \in \mathscr{F} \tag{18}$$

$$w_{f,t}^{\text{discharge}} \leq a_{f,t}^{\text{available}} \qquad \forall \quad t \in \mathscr{T}, f \in \mathscr{F} \tag{19}$$

Constraint (20) and (21) make sure that all decision variables are non-negative:

$$p_m, p_d, y_t^{\text{load}}, x_t^{\text{load}} \geq 0 \qquad \forall \quad t \in \mathscr{T} \tag{20}$$

$$w_{f,t}^{\text{charge}}, w_{f,t}^{\text{discharge}}, w_{f,t}^{\text{storage}}, r_{f,t} \geq 0 \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{21}$$

6 Input data and Case study

This section presents and discusses the data utilized to run the mathematical model described in the previous section 5. The data primarily relate to the selected prosumer and test case, namely the FME ZEN pilot project, Campus Evenstad. The FME ZEN Research Center and SINTEF have provided the data regarding Campus Evenstad. The Case study employs historical data related to Campus Evenstad's various energy characteristics and technologies, while making some general assumptions and simplifications. The subsequent sections outlines the input data and assumptions.

6.1 Campus Evenstad - electric energy system

Campus Evenstad is a Norwegian university located in Innlandet county and is one of the pilot projects in the FME ZEN initiative[11][10]. The FME ZEN project aims to achieve Zero Emission Neighborhoods (ZEN) with an ambition level of ZEB-COM, meaning that greenhouse gas emissions from operation, construction, and production will be compensated by renewable energy sources[9]. ZENs are designed to integrate multiple nearby buildings, logistics, and infrastructure into a cohesive system that optimizes energy, power, emissions, mobility, economy, spatial qualities, and innovation. This approach aims to achieve neighborhood-level energy cost savings and leverage synergies between energy demand profiles. Campus Evenstad comprises 22 buildings with a total area of 9000 m^2.

Between 2015 and 2021, Campus Evenstad's annual electricity consumption ranged from 650MWh to 1,100MWh. The Norwegian Directorate for Public Construction and Property Management (Statsbygg) owns, develops, and operates the campus plot and buildings. Electricity from the grid is supplied by the DSO Elvia, while the campus also generates electricity locally through RES, such as solar PV panels and a combined heat and power (CHP) plant.

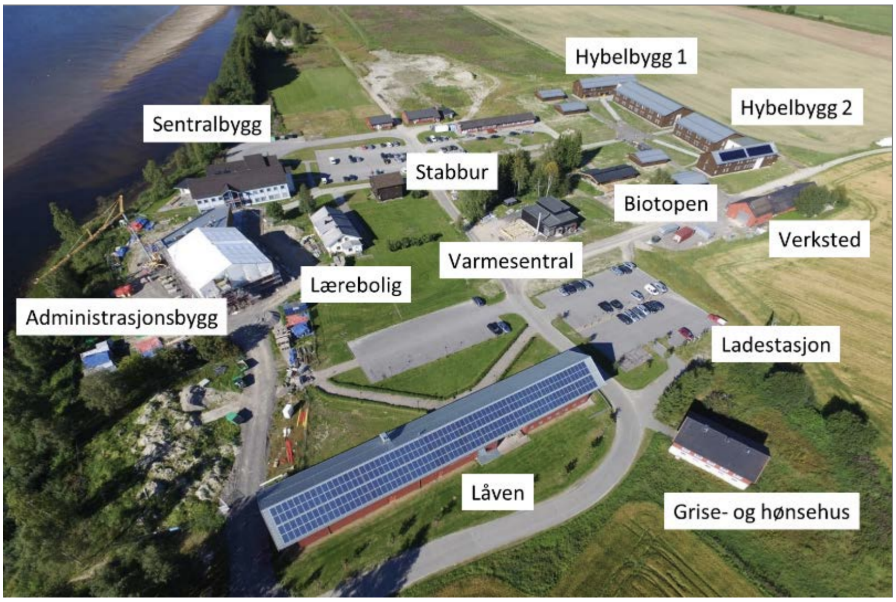

Figure 2: Campus Evenstad, Source: Statsbygg

Campus Evenstad has five G2V charging stations, including one fast charger from Fortum with a capacity of 50$\mathrm{kW_{el}}$, one E-route 71 charger delivering 20$\mathrm{kW_{el}}$, and three E-route 71 charging points capable of delivering 10$\mathrm{kW_{el}}$ each. In addition, two V2G charging stations have recently been installed, enabling two-way charging from electric vehicles. A stationary lithium-ion battery with a capacity of 204$\mathrm{kWh_{el}}$ and a charge/discharge rate of 120$\mathrm{kW_{el}}$ was Installed in 2018 [9]. Although currently used as a backup power source, the battery has the potential to store locally

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[11] https://fmezen.no

generated renewable energy and contribute as a DFR provider. Campus Evenstad receives hourly readings from their main meter, which also communicates with the DSO; Elvia. The total electric consumption are calculated by subtracting PV and CHP generation from the grid measurements.

6.2 Flexible assets

The three categorical flexible asset types that exists at Campus Evenstad are BESS, V2G charging, and G2V charging. The assets along with the cumulative capacities for charging, discharging and storage, are listed in Table 6. The capacities for the two categories of EV charging assets are simulated as two single aggregated charging points: One representing the five one-directional chargers and one representing the two V2G. No costs or losses are considered for any flexible asset in this case study.

Table 6: Operational characteristics of the flexible assets at Campus Evenstad.

Flexible asset	η^{charge}[kWh/h]	$\eta^{discharge}$[kWh/h]	$\eta^{storage}$[kWh/h]	k_f[kWh]
1x li-ion battery	120	120	204	0
2x V2G	20.0	20.0	61.2	10
5x G2V	100.0	0.00	66.3	0

EV charging
Based on historical charging patterns at Campus Evenstad, a consistent cumulative daily demand of 66.3kWh for G2V charging and 26.5kWh for V2G charging is assumed. The mathematical procedure utilized to derive these values is presented in equations s (22 - 25). The calculation incorporates multiple data points and assumptions, including the annual average demand for all electric vehicles in the county of Evenstad (Innlandet), which is estimated to be 14,226 km by Statistics Norway[12]. Additionally, the calculation assumes an EV electricity demand of 0.2 kWh per km[41][12]. While this assumption is generally modest, it includes some margin to account for the significant impact on effect of cold Norwegian winters. Finally, based on the average 2022 data from campus Evenstad, the daily average charging performed by a single EV charger is assumed to be 13 kWh.

$$\textbf{EV demand:}\ \frac{14,266km(\text{avg. annual demand})}{365days}\cdot 0.2kWh/km \approx 7.8kWh/day \tag{22}$$

$$\textbf{Number of EVs charged per. charger daily:}\ \frac{13kWh}{7.8kWh/day} = 1.7\text{EVs} \tag{23}$$

$$\textbf{Daily demand for V2G:}\ 1.7\text{EVs}\cdot 7.8kWh/day\cdot 2\ (\text{chargers}) = 26.5kWh \tag{24}$$

$$\textbf{Daily demand for G2V:}\ 1.7\text{EVs}\cdot 7.8kWh/day\cdot 5\ (\text{chargers}) = 66.3kWh \tag{25}$$

Due to lack of data and complicity regarding accurately identifying the State of Charge (SoC) of each EV connecting to a charger, some assumptions and simplifications must be made to model the storage capacities. The average capacity of a EV battery storage capacity in Norway is between 50-60 kWh in 2021, and is estimated to increase to 70-80kWh in the following years[13]. The total storage capacity of EVs are therefore assumed to be 60kWh. According to Åse Sørensen Lekang, a researcher at Sintef Community and designated point of contact to the FME ZEN Campus Evenstad pilot project, the share of EV battery storage level that is appropriate to operate flexibly using V2G chargers is ranging in between 30-60% of the EV battery capacity to mitigate battery degradation. The cumulative battery capacity of the two V2G charging stations available for flexible operation is assumed to be 61.2kWh based on calculations in equation 26, while the cumulative storage capacity for the five G2V chargers is assumed to be $66.3kWh$, based on demand and as shown in previos equation 25. The storage capacities for each of the flexible assets are also presented in the above table 6.

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[12] https://www.ssb.no/en/statbank/table/12576/tableViewLayout1/, last accessed: 9th June 2023

[13] https://www.innovasjonnorge.no/no/om/tall-og-fakta/nytt-om-eksport--hpo/tall-om-batterier/, last accessed: 9th June 2023

$$60kWh \cdot 2\ \text{(chargers)} \cdot 1.7\ \text{(EVs)} \cdot 0.30\ \text{(flexible battery capacity)} = 61.2kWh \tag{26}$$

The EV charging demand is essentially an upper and lower bound for flexible operation of flexible asset f and time t implemented through input data $\gamma_{f,t}^{\text{req}}$ and $\gamma_{f,t}^{\text{max}}$ and constraint (13) and (14) in section 5. EV connective availability is assumed to be from 9am –3 pm for one-directional chargers ensuring that demand is met by the end of a typical Norwegian working day. V2G is mainly utilized by campus vehicles and employees, and the EVs are therefore assumed to be disconnected during working hours and connected from 3pm –9 am. Initial SoC for V2G is assumed to be 35%, to enable an initial possibility of discharging energy from the EVs at 3pm.

The required energy level for EVs connected to the V2G charger, as well as storage capacity available to operate flexible during a week is illustrated in Figure 3.

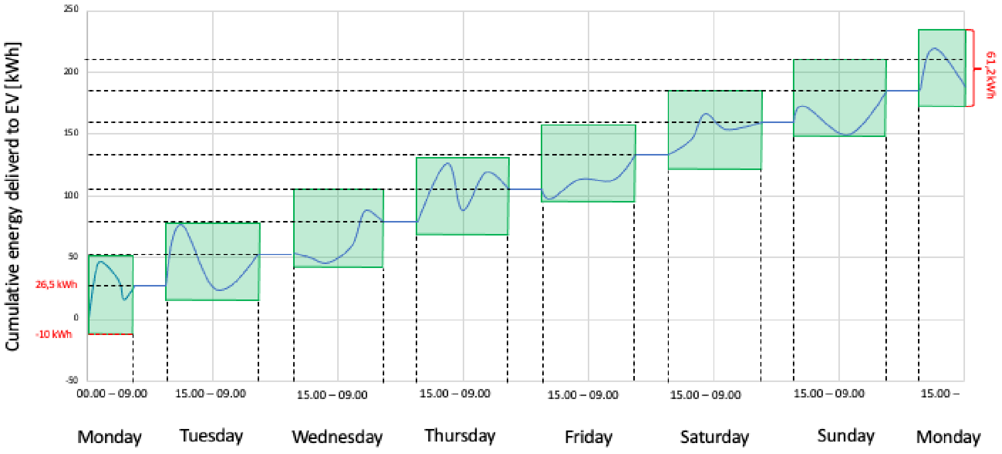

Figure 3: The required energy that must be charged to the EV batteries connected to V2G charging stations during the time interval from 9 AM to 3 PM each day. This offers flexible charging and discharging in every time-step within the interval. Examples of potential patterns of charging and discharging the EV batteries are drawn in blue.

The daily collective demand for vehicles connected to the one-directional chargers are, as previously calculated, $66.3kWh$. The demand has to be met within the interval from 9AM. to by 3PM. and is illustrated in Figure 4.

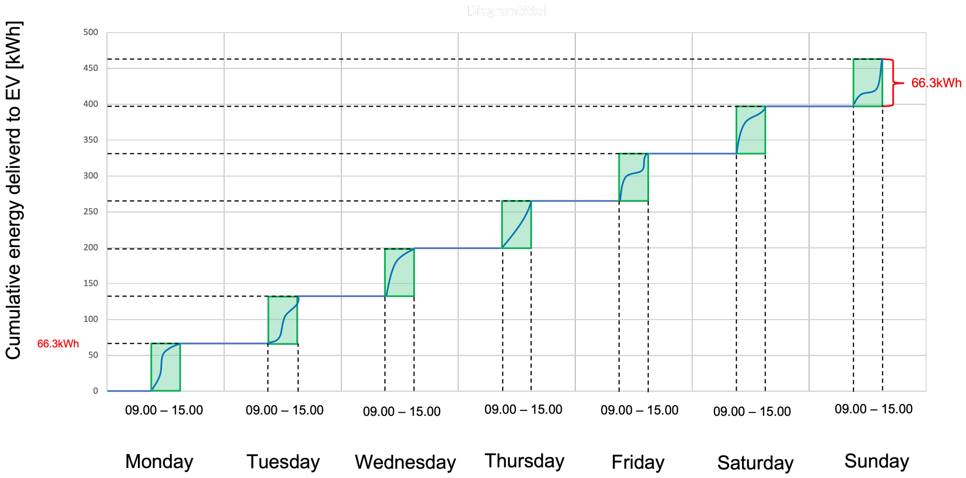

Figure 4: The required energy that must be charged to the EV batteries connected to one-directional charging stations during the time interval from 9 AM to 3 PM each day. This offers flexible charging in every time-step within the interval. Examples of potential patterns of charging the EV batteries are drawn in blue.

BESS

The lithium- ion battery is inherently flexible. At present, Campus Evenstad utilizes the battery as a backup power source and assigns it the responsibility of initiating the CHP system, which necessitates a low SoC. However, in the interest of further exploring its capabilities to provide flexibility, no temporal or capacity-limiting constraint will be provided in the model. The specific capacities are provided in table 6.

Note that the model formulation in Section 5, requires that any upper and lower limitations of the DFRs SoC must be taken into account when the data is implemented. This can either be done by limiting the DFRs capacity as seen in Equations 7, 8 and 9, or by limiting the minimum and maximum SoC in Equations 14 and 13. This is not considered for the BESS system, which will present the battery with possibility of supplying FFR reserve even if its SoC is zero. However, due to the short response time of FFR, activation will have limited effect on the SoC and we can assume the battery storage capacity to be 210kWh to account for this. Thus simulating that at 0kWh SoC the BESS will have 6kWh for FFR contingencies.

6.3 Fast Frequency Reserve market

For the FFR market, Statnett requests two different contracts for reserve capacity: ”Profil” and ”Flex”, which are described in section 2. The data is collected from 2023 and is congregated in table 7. According to correspondence with Statnett, the Flex orders are usually fairly scattered throughout the period. Therefore FFR orders assumed to be uniformly distributed, resulting in activation every 13th hour throughout the season. The FFR market price is assumed to be equal to the 2023 price of 150 NOK/MW-hour for Profil and 450 NOK/MW-hour for Flex. According to Statnett, FFR is generally only activated 0-3 times each season, and due to its infrequent use and short response time of either 5 or 30 seconds, the cost and logistics of FFR activation are not included in this case study. Nevertheless, it is crucial that the offered capacity is available for discharge into the grid at all times specified by the contract type. According to Statnett, information about unavailability must be given in advance. If the supplier fails to fulfill capacity obligations on multiple occasions, the supplier can ultimately be excluded from further participation in the FFR market[61]. The minimum capacity offered by a single supplier in the Norwegian FFR market is 1 MW. However, the prosumer featured in this study is unable to consistently provide this level of reserve capacity on its own, and therefore aggregated participation is assumed. Additionally, we assume that the aggregator will accept the maximum FFR capacity that the prosumer is capable of supplying (z^{FFR}) in its entirety.

FFR Contract	Starting day (h)	Ending day (h)	Total active hours [h]	Price [NOK/kW/h]
Profil	147 (3505)	246 (5905)	1350	0.150
Flex	88 (2089)	303 (7273)	400	0.450

Table 7: Characteristics of the two different FFR contracts

6.4 Grid Tariff

As presented in Section 2.4 a new power tariff was implemented in 01.07.2022 by Elvia in response to NVEs changes in tariff regulations. Tariff sheet 3.0 is valid for all business customers with annual consumption over 100.000 kWh[21]. Campus Evenstad has consistently consumed close to 1.000.000kWh in recent years, so it is valid to assume that the specified tariff in general would apply to Campus Evenstad. However, it is important to note that Campus Evenstad, being a pilot-project for the FME ZEN Resarch center, is likely to be offered a custom tariff from Elvia, which also has been implied by researchers related to the pilot. The information regarding the exact tariff is not publicly available and due to lack of insight, will not be taken into account. Furthermore, as this thesis aims to provide a general assessment of flexible assets and tariff designs effect on cost savings and load shifts, it is beneficial to assess indiscriminate tariff designs.

The power tariff differentiates between low- and high voltage outlets with regard to fixed costs. The fixed costs of low-voltage and high voltage outlets are 340 NOK and 1065 NOK, respectively. Elvia is not at liberty to disclose which type of outlet Campus Evenstad is connected to, but by examining grid maps provided by NVE, we can se that Campus Evenstad is connected to a low voltage outlet[14]. The tariff differentiates between summer (April-October) and winter (November-March). The seasonally varying energy- and peak capacity costs are presented in Table 8. Fixed costs are not included, as it does not affect the driving forces or decisions of the implemented model. It would however, affect the objective value marginally.

Table 8: Cost elements in Todays Tariff.

	Energy dependent cost	Capacity cost
Winter	0.085 NOK/kWh	90 NOK/kWh/h
Summer	0.060 NOK/kWh	40 NOK/kWh/h

The determination of peak costs in Elvias grid tariff relies on identifying the highest hourly peak consumption of the consumer within each month. This occurrence can transpire on any given day or hour, and is depicted in Figure 5.

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[14] `https://temakart.nve.no/link/?link=nettanlegg`, last accessed: 9th June 2023

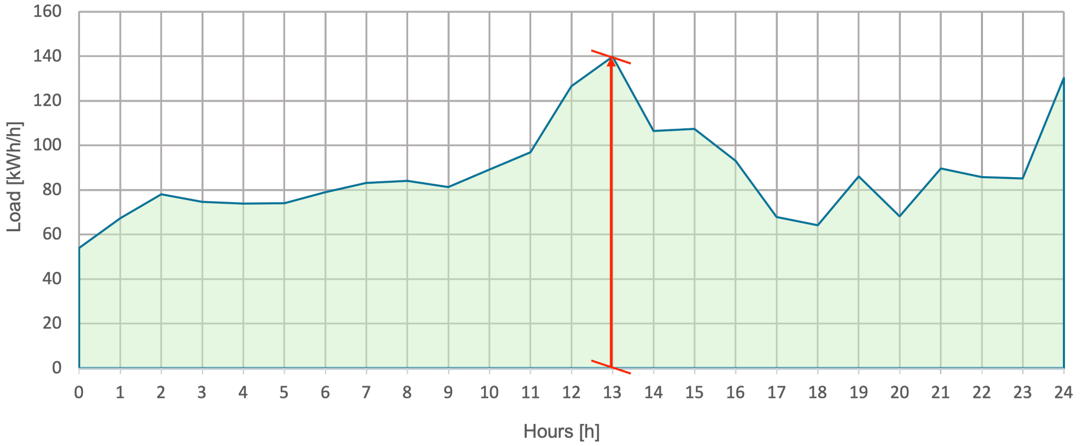

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Figure 5: Illustration of Elvias current tariff for customers with annual consumption above 100.000kWh - Monthly peak power

”Plusskunde”

The ”Plusskunde” arrangement dictates that if a prosumer delivers more input than 100 kW of surplus production, they are no longer exempted from paying the fixed joint for input which is 1,43 øre/kWh eksl MVA [15]. However, an organisation can deliver more that 100kW as long as production per customer does not exceed 1 GWh/year. For modeling simplicity, this serves as an upper bound to resulting grid export. In addition, the assets and prosumer characteristics of Campus Evenstad are very unlikely to enable energy export close to either of these limits.

6.5 Day-ahead prices

Day-ahead hourly prices are gathered from the ENTSO-E Transparency Platform for price zone nNO1 (Østlandet) in Norway. There exists five different price zones in Norway due to several infrastructural factors and variability in transmission capacity[16]. Price zone NO1 is chosen as the municipality of Evenstad is located within.

6.6 The investigated years

The case study will be conducted separately for three distinct years: 2019, 2020, and 2021. These selected years exhibit significant variations in prosumer loads and energy prices, providing an ideal context to investigate the resilience and effectiveness of DFRs in delivering demand response under diverse consumption patterns and price dynamics. The average spot-prices and hourly load along with their standard deviation are provided in Table 9. The total load for each year are 731.986MWh for 2019, 649.116MWh for 2020 and 772.895MWh for 2021. It is important to note that 2020 was a leap year, and to ensure modeling and comparative analysis simplicity, the data from January 31st has been excluded from the analysis.

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[15] https://www.nve.no/reguleringsmyndigheten/regulering/nettvirksomhet/nettleie/tariffer-for-produksjon/plusskunder/, last accessed: 9th June 2023

[16] https://www.statnett.no/om-statnett/bli-bedre-kjent-med-statnett/om-strompriser/fakta-om-prisomrader/, last accessed: 9th June 2023

Table 9: Characteristics of the analysed years

Year	2019	2020	2021
Avg. spot-price [NOK/kWh]	0.40	0.09	0.75
SD spot-price	0.8	0.8	0.48
Avg. hourly load [kWh]	83.56	74.10	88.23
SD load	49.37	44.75	62.30

6.7 Case study

The objective of this case study is to assess the impact of prosumer participation in a FFR market, with regard to limiting their electricity bill, particularly by leveraging different flexible capabilities. Four cases optimizing costs, revenues and flexible asset operation will be presented for each year; 2019, 2020 and 2021. The classes of cases analysed in this thesis are:

- **NoFlexNoFFR**: No flexible assets and no FFR market (no optimization).
- **FlexNoFFR**: All flexible assets available and no FFR market.
- **FlexFFR-P**: All flexible assets available and participation in FFR Profil.
- **FlexFFR-F**: All flexible assets available and participation in FFR Flex.

Additionally, the effect of including thermostatic loads and space heating for supplementary FFR provision will be discussed in the final part of Section 7. Thermostatic loads are modelled as a percentage value of the prosumers hourly, original load profile.

7 Results and discussion

This sections presents an evaluation of the model formulations proposed in this thesis and the following results from analyzing the problem instances presented in section 6. First, a description of the technical performance of the model for each problem instance.

7.1 Technical Performance

The model is implemented in the open-source optimization modeling language Pyomo [70] through Python version 3.10 and solved using the optimization software Gurobi version 9.5.2. The optimization was run on a computer with Intel Two-Core i5 processor with CPU at 2.9 GHz and 8 GB installed memory(RAM).

When considering the technical performance of the model, the run time and number of iterations for the different problem instances are presented in Table 10.

Problem Class	Run Time [sec]	Iterations
1. NoFlexNoFFR 2019	0.81	1570
2. NoFlexNoFFR 2020	0.68	1441
3. NoFlexNoFFR 2021	0.59	1538
4. FlexNoFFR 2019	2.55	21971
5. FlexNoFFR 2020	1.95	23497
6. FlexNoFFR 2021	2.14	24043
7. FlexFFR-P 2019	2.17	21854
8. FlexFFR-P 2020	2.23	23200
9. FlexFFR-P 2021	2.32	22813
10. FlexFFR-F 2019	2.33	3536
11. FlexFFR-F 2020	2.31	4322
12. FlexFFR-F 2021	2.04	8007

Table 10: Technical performance

The solver uses barrier algorithm with cross-over to dual simplex. The runtime for instances without the operation of flexibility assets is significantly lower, as expected, since there are fewer variables and iterations to consider. In fact, without flexibility options, the optimization problem simplifies to a calculation of costs based on the load, prices, and grid tariff. The runtime for instances with the operation of flexible assets is approximately 3 times longer than without flexibility. However, it is still relatively low considering that the proposed preliminary model in this report is a deterministic linear optimization problem that avoids binary decision variables and uncertainty.

7.2 Economical results

The overall resulting costs and revenues for each modelling instance are presented in Figure 6, highlighting the substantial variations among the three distinct historical years in terms of energy prices, whereas the differences between instances are comparatively much smaller. The stacked bar chart displayed in Figure 6 effectively differentiates various cost and revenue components, encompassing Grid Tariff Cost, Peak Capacity Cost, Energy Import Cost, Energy Export Revenue, and FFR Revenue. The representation presents revenues at the base of the bars as negative costs, signifying their deduction from the overall costs. The primary cost driver is observed to be the Energy Import Cost in both 2019 and 2021, followed by the Peak Capacity Cost and the Grid Tariff Cost. However, in 2020, the Energy Import Cost is significantly lower due to both the considerably low spot price and reduced load throughout the year. FlexFFR-P is consistently the most profitable, followed by FlexFFR-F, FlexNoFFR, and NoFlexNoFFR.

The consistent higher yield and cost savings provided by FFR Profil compared to FFR Flex can likely be attributed to two factors. Firstly, the total price signal of Flex (400 hours * 0.450NOK/kW/h) is approximately 89% of Profil (1351 hours * 0.150 NOK/kW/h), which provides stronger incentives for maintaining a high FFR capacity in Profil. This is supported by the percentage earnings difference between Flex and Profil, ranging from 0.81% to 0.86%, indicating a close correlation to the price signal. Secondly, Flex was required to be active every 13th hour over a longer period compared to Profil, which may have presented the congregated effort of DFRs with hours further limiting the provision of FFR reserves. This limitation arises because the capacity provided throughout the entire period is determined by the hour in which the prosumer is capable of providing the lowest FFR capacity. However, Flex dictates reserves in significantly fewer hours than Profil, while providing a stronger price signal pr. hour. Hence, indicating that DFRs reach an upper bound for providing FFR Flex capacity at lower volume than FFR Profil when also considering other price signals.

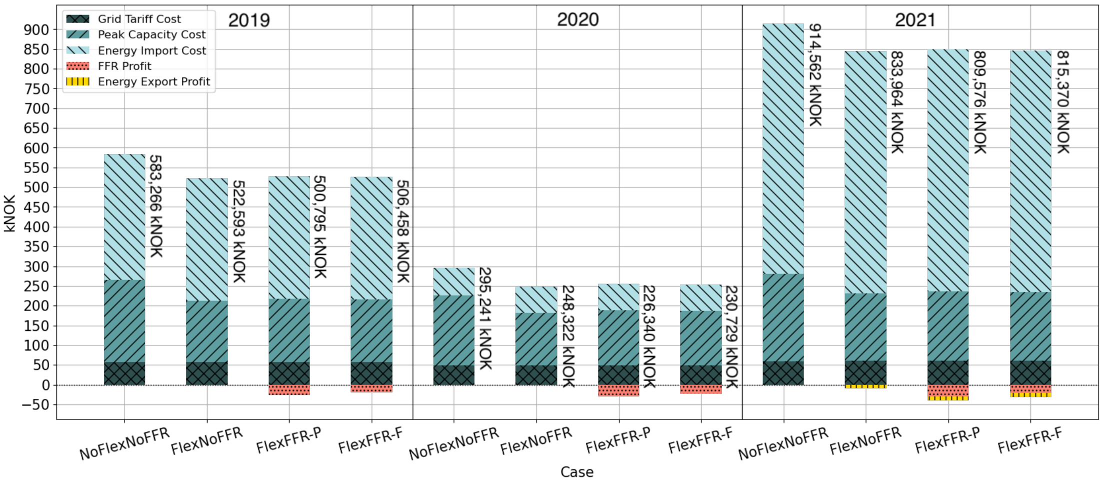


Figure 6: Overview of costs and revenues of each case for 2019, 2020 and 2021.

Figure 7 provides an annual analysis of the changes in costs and revenues for each case in relation to the NoFlexNoFFR scenario. The positive values assigned to the revenue and cost components indicate a reduction in prosumer costs. However, it is worth noting that the Grid Tariff Cost exhibited a marginal increase in each flexible operation case, represented by negative costs at the base of the bars. This increase in Grid Tariff Cost can be attributed to the augmented electricity trade between the prosumer and the grid, aimed at enabling a broader range of flexibility options. Nonetheless, these changes are barely noticeable in Figure 7 and can be considered negligible in each respective case.

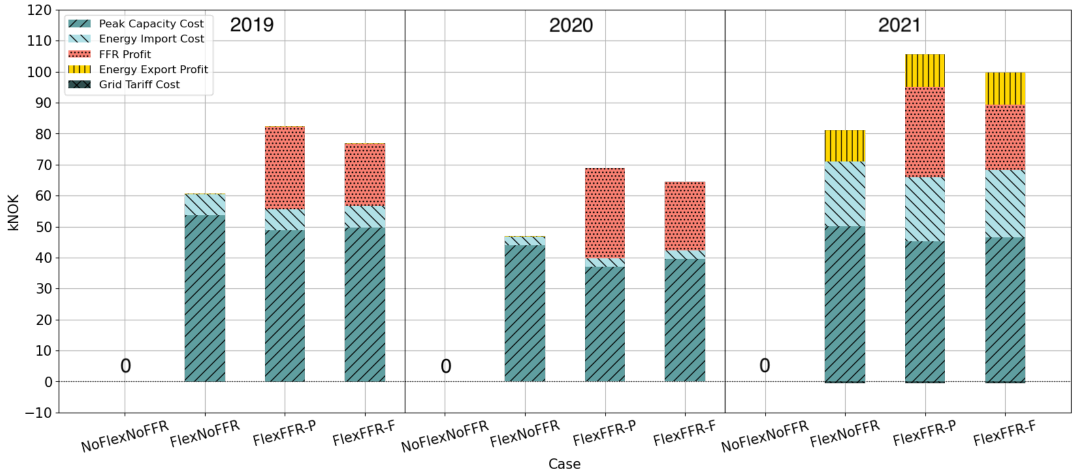


Figure 7: Overview of the cost reduction and yield compared to the base case of no flexible operation (NoFlexNoFFR) for each case in 2019, 2020 and 2021.

As seen in Figure 7, optimal operation of flexible assets and FFR Contracts led to the greatest cost savings in 2021, followed by 2019 and 2020. However, the assessment of relative cost savings by comparing the most profitable case (FlexFFR-P) to the base case (NoFlexNoFFR) reveals a contrasting order, with participation in FFR Profil resulting in total cost reductions of 23.34% for 2020, 14.14% for 2019, and 11.48% for 2021. This outcome is primarily attributed to the prosumer's ability to provide a rather consistent supply of FFR capacity (standard deviation ≈ 12.443) across the diverse price-years. The analysis depicted in Figure 7 reveals that, when employing flexible operations for DFRs, the most significant contributor to cost reduction is the reduction in Peak Capacity costs. This is followed by the gains obtained from participation in the FFR market and the revenue generated from energy exports.

Table 11 provides a quantification and presentation of the FFR earnings, the overall indirect increase in other cost elements, and the seasonal FFR capacity. It is evident that the prosumer consistently maintains FFR capacity above 110 kW in all instances, thereby establishing the substantial influence of FFR yield on relative energy cost savings. This effect is particularly pronounced during years marked by low energy prices and high spot-price variability.

Table 11: FFR earnings, indirect FFR losses in other cost elements (compared to FlexNoFFR) and reserved FFR capacity for all instances.

Contract Year	FFR Earnings [kNOK]	Indirect FFR Costs [kNOK]	FFR Capacity [kW]
Profil 2019	26.6	4.8	131.4
Profil 2020	29.1	7.1	143.6
Profil 2021	29.1	4.7	143.6
Flex 2019	19.9	3.8	110.7
Flex 2020	22.2	4.6	123.1
Flex 2021	21.2	2.6	117.7

Over the three years, implementation of FFR contracts resulted in an average reduction of total costs by 6.8% for Profil and 5.1% for Flex. The highest total cost reduction of 12% was achieved with the Profil contract in 2020. FFR volume and profits for both Flex and Profil contracts peaked in 2020, closely followed by in 2021 with 2019 showing approximately 9% less FFR volume for both contracts.

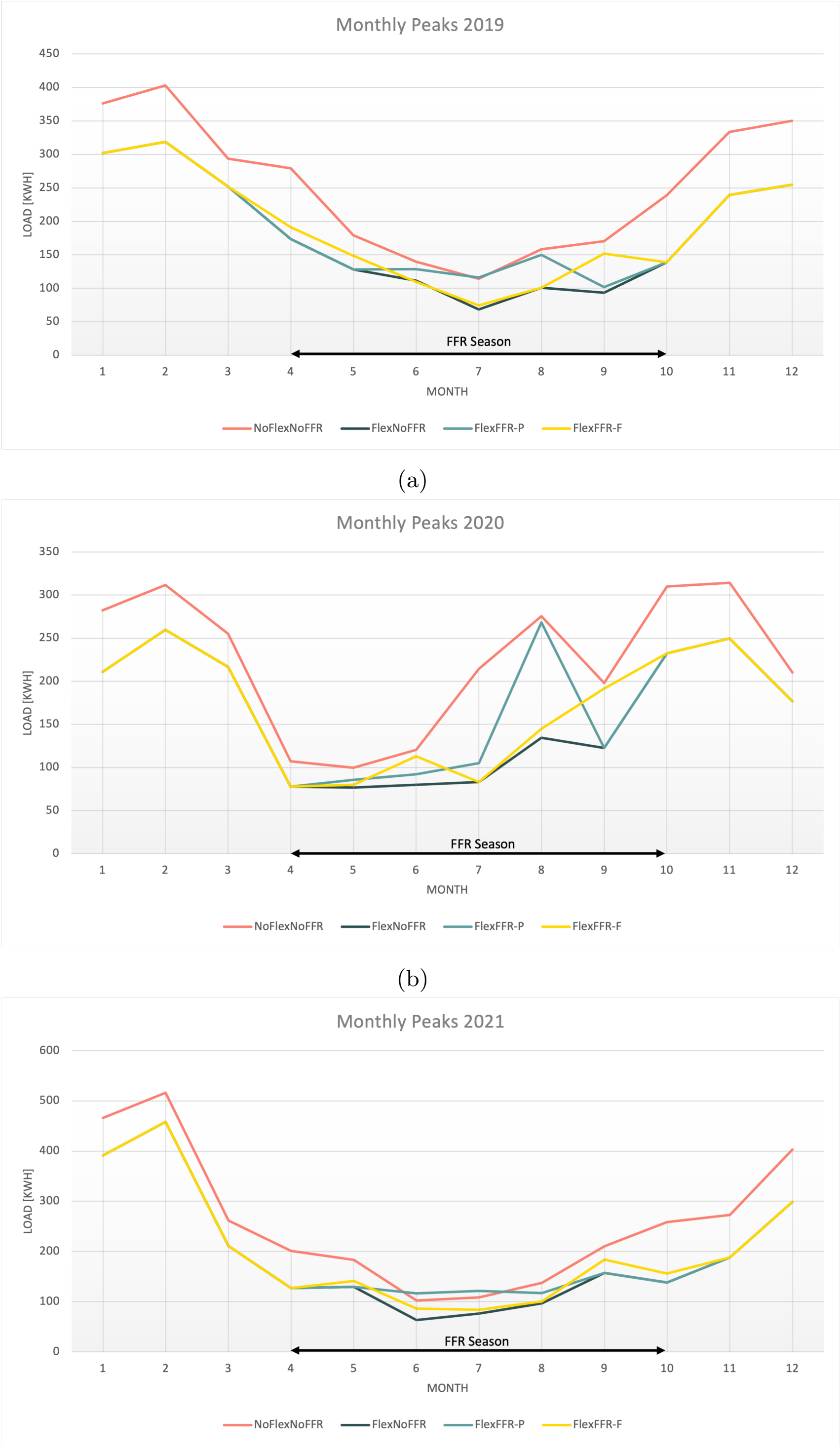
The Profil contract yielded the highest FFR earnings, reaching 29.1 kNOK in both 2020 and 2021 as depicted in Table 11. The consistent results over both years indicate that the FFR capacity has reached its limit relative to the case's flexibility.

In 2019, the decline in FFR capacity can be attributed to a combination of factors: a high average spot-price of 0.40 NOK/kWh, a low standard deviation of 0.08, and a high average load of 83.56 kWh. These conditions incentivized prioritizing cost limitations for energy and peak capacity, thereby compromising the maintenance of a high FFR capacity. It is important to note that, aside from fluctuating loads and price signals unrelated to FFR, the DFRs were subjected to consistent demands in the form of EV charging patterns. Thus, the ability of DFRs to provide reserves cannot solely be attributed to variations in supply and SoC.

Participating in the FFR market resulted in increase in other cost components as can be seen in Figure 7 and quantified in Table 11. The average losses across the three years are 19.65% and 17.31% of the FFR profits for Profil and Flex contracts, respectively. Almost all of the indirect losses are attributed to the peak capacity cost (approximately 90%). FFR seems to have little effect on the other cost elements, but interestingly, resulted in an increase in energy export profits by an average of 8.1% for Flex and 2.4% for Profil. The export profits reached a significant high in 2021 due to the remarkable spot-price standard deviation of 0.48, in contrast to 0.08 observed in 2020 and 2019. Energy export exclusively takes place when flexibility is present, driven by the model's encouragement of load-shifting to align with temporal fluctuations in price signals. Consequently, instead of introducing additional loads for self-consumption, surplus energy is exported, which is particularly beneficial when it can be obtained at a low cost.

7.3 Peak load performance

The monthly peak loads for each case and year is presented in Figure 8. Utilization of flexible asset without FFR participation (FlexNoFFR) induces significant peak load shaving, reducing the monthly average by 25.2% in 2021, 28.8% in 2020 and 28.1% in 2019. Thus substantiating the potential demand response impact of optimizing DFR utilization for a prosumer as well as for energy systems.



(a)

(b)

(c)

Figure 8: Monthly highest peak loads for all cases in 2019 (a), 2020 (b) and 2021 (c).

The monthly highest peak either increased or remained constant in every month where FFR capacity was reserved for FlexFFR-P and FlexFFR-F. The monthly peaks increased on average with 20.41% for Profil and 14.12% for Flex compared to FlexNoFFR. Engagement in FFR Profil seems to completely negate the price signals of the grid tariffs monthly capacity costs in certain months, as very prominently seen in August of 2020 and throughout the entire FFR Profil season of 2019 and 2020. In 2021, the highest peaks of June and July also surpasses that of NoFlexNoFFR, which somewhat contradicts the fundamental concepts of which grid tariff policy makers are striving for when enticing demand response. This also constitutes that additional energy is imported and coherently exported on the basis of providing a high FFR capacity, which is observed for both Profil and Flex during some of the months. However, the increase in energy import are consistently less than 1% and are also observed for flexible operation without participation in FFR markets, though slightly less. The Norwegian power system is renowned for its low loads and high production capacity due to significant reservoir inflow to hydro-power plants in spring and summer [47]. Consequently, increasing loads during the summer months may not be as detrimental. Moreover, the grid tariff offered by Elvia (see Table 8) presents a noteworthy 56% reduction in peak capacity costs during summer, aligning with the objective of accommodating higher loads in this season. While the increase in consumer load during summer months may not inherently provide utility, it might be unfortunate that the tariffs in Norway present peak capacity price signals during this season.

7.4 Load duration

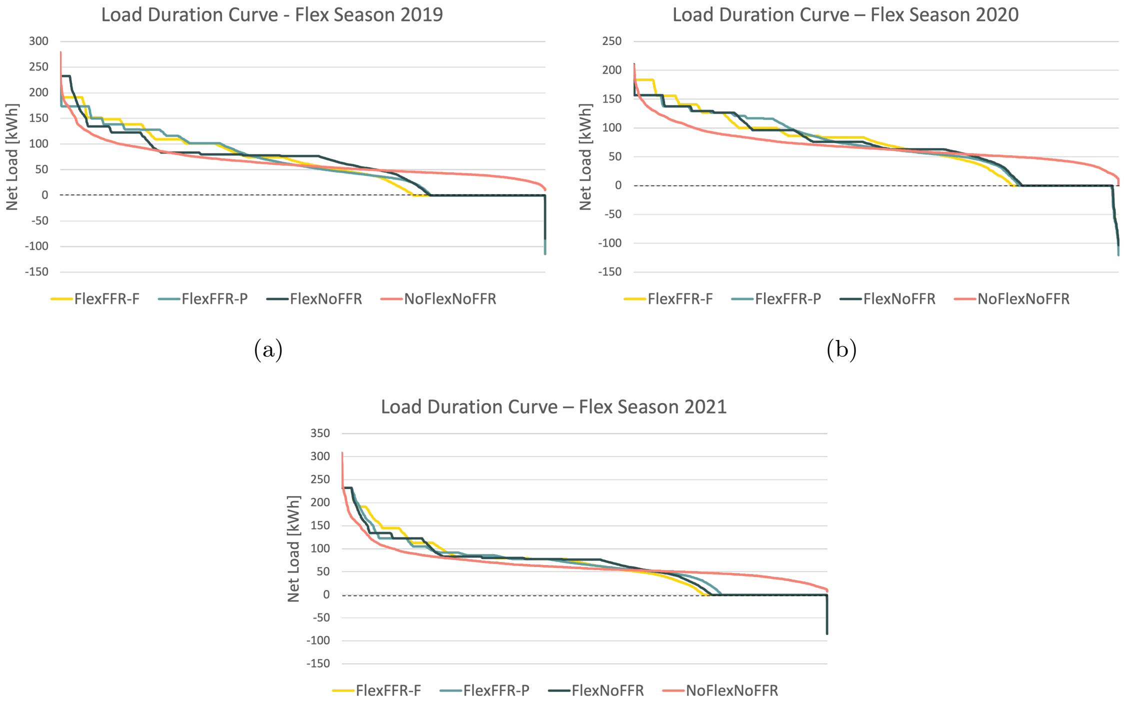
The load duration curve for the FFR season of 2019, 2020, and 2021 is depicted in Figure 9. The NoFlexNoFFR case exhibits a smooth load trajectory and demonstrates the highest peak consumption hours. In contrast, the cases utilizing DFRs exhibit a step-wise curve pattern, attributed to their ability to consider the price signals associated with monthly peak capacity costs. As previously presented, flexible asset operation facilitates prosumer electricity export, which applies to all years. However, the export hours are significantly higher and more frequent in 2021 due to the heightened energy price variability.

Interestingly, FlexFFR-F displays more hours with zero net load compared to FlexNoFFR across all yearly seasons. This finding is somewhat surprising since maintaining consistent consumption would provide a stronger foundation for offering high FFR capacity. However, this phenomenon is likely attributed to FFRFlex being active only every 13th hour, leading the model to prioritize load shifting from adjacent hours, resulting in high consumption during active periods. The cases considering FFR capacity generally exhibit more hours with reasonably high consumption (located in the left one-third section of the graphs) compared to FlexNoFFR. This can also be attributed to FFR's load-shifting capabilities, contributing to increased consumption during periods of FFR activation.

The effectiveness of load-shifting for FFR demand response becomes even more evident when analyzing the load duration curves specifically for the FFR Profil season, as depicted in Figure 10. As previously established, the Profil contract offers a stronger incentive for maintaining high FFR capacity compared to the Flex contract, and it is characterized by more frequent and periodic activity.

In the case of FlexFFR-P, the net load exhibits striking similarities to the scenario where no flexible operation is considered, as observed in NoFlexNoFFR. FlexFFR-P displays a considerably smoother curve, showing little emphasis on maintaining temporally constant loads to mitigate peak capacity costs and permitting substantial peaks. This is particularly prominent in 2020 (see Figure 10b), coinciding with the year with the lowest spot-price (see Table 8).

It is important to note that loads and electricity costs generally are low during the periods where FFR is required to be active, which facilitate for increased FFR engagement without entailing excessive consequences in relation to other demand response signals.



(a) (b)

(c)

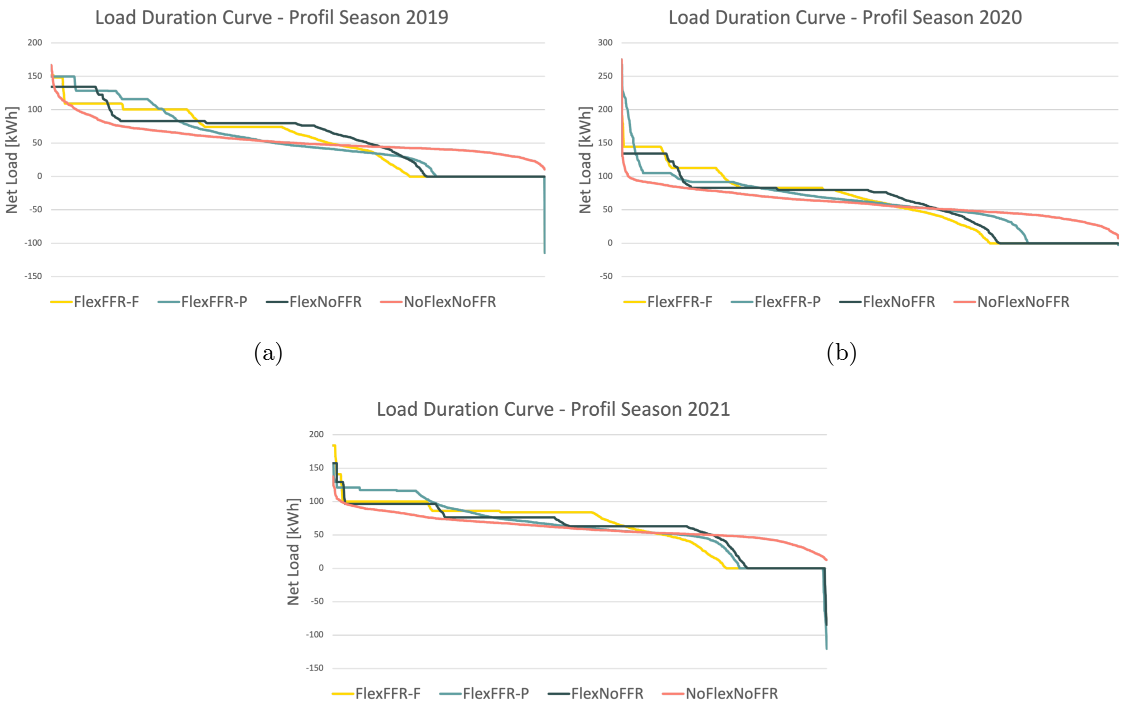
Figure 9: Load duration curve for FFR seasons in 2019 (a), 2020 (b), and 2021 (c), sorted from highest to lowest hourly load. The graph includes the 5184-hour FFR Flex season, containing the entire 2400-hour FFR Profil season.

7.5 DFR operation

The FFR capacity and volume distribution of the DFR types for each year is provided in Table 12. On a yearly average, the li-ion battery provides approximately 86% of the total FFR capacity in both Profil and Flex, whereas V2G and G2V on average contributes 13% and 2%, respectively. The data does not display considerable variation in the DFR distribution for providing FFR, which is to be expected as the different flexible assets are imposed the same operational constraints in every year. It is important to note that operation of G2V assets and FFR Profil activation only coincides during Saturdays and Sundays, limiting G2V provision to Profil.

Due to the flexible assets' different characteristics in capacity for charging and discharging, hourly availability and EV charging constraints, the average distribution was somewhat as expected. However, when adjusting for operational hours of the flexible assets and charge/discharge capacity for each flexible asset type, V2G contributes with approximately 9% and 1% more FFR capacity than the electric battery and 42% and 40% more than G2V for Profil and Flex, respectively. This highlights the remarkable capabilities of V2G technology in delivering FFR capacity and demand response, particularly when compared to G2V technology. Furthermore, after accounting for hourly availability and operational characteristics (see Table 6), V2G also outperforms BESS, which may come as a surprise considering that BESS is not subject to any specific operational requirements. However, the explanation is actually quite the opposite. V2G assets are required to charge the campus EVs daily between 3 pm and 9 am, which aligns with all FFR Profil hours on weekdays from 10 pm to 7 am. As a result, this charging requirement imposes a mandatory load on V2G during this specific period, providing the asset with a notable operational advantage. The ability to suspend charging during any given hour allows V2G to effectively contribute to providing high FFR capacity.

The results in Table 12 also reveals that discharging capabilities are highly valuable in regard to providing FFR capacity. For Profil, discharging of V2G and the li-ion battery in turn contributed, on average, with 55.6% and 22.6% more FFR capacity than curtailment of charging. These results



(a) (b)

(c)

Figure 10: Load duration curve for the FFR Profil season in 2019 (a), 2020 (b) and 2021 (c). The duration of the hours displayed includes the FFR Profil season, which spans 2400 hours. The graph is sorted from highest to the lowest hourly load.

can be attributed to the consistent accessibility of discharging capacity, which remains available in most instances, even during battery charging operations.

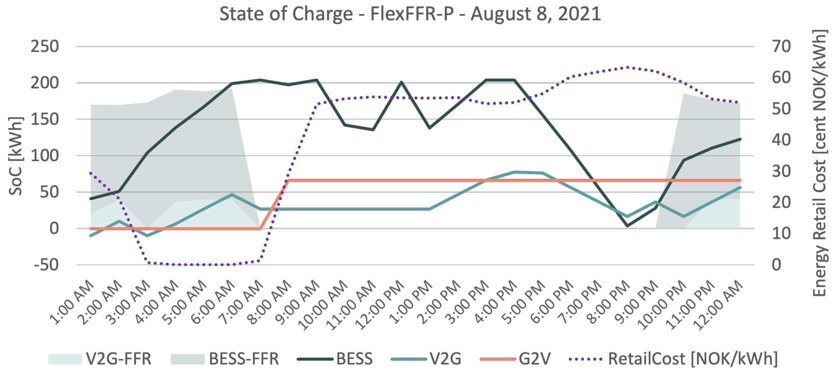
Table 12: FFR-volume distribution in contribution percentage for each year and asset.

Contract Year\ FFR	FFR Volume [kW]	FFR Battery charge [%]	FFR Battery discharge [%]	FFR EV charge [%]	FFR V2G discharge [%]	FFR G2V charge [%]
Flex 2019	110.74	32.22	54.69	3.80	6.90	2.39
Flex 2020	123.10	28.65	57.35	3.96	7.41	2.64
Flex 2021	117.70	32.13	54.30	3.76	6.95	2.87
Profil 2019	131.41	35.18	50.41	4.85	8.58	0.98
Profil 2020	143.61	40.74	46.63	4.75	7.01	0.86
Profil 2021	143.61	40.00	45.44	5.55	8.03	0.97

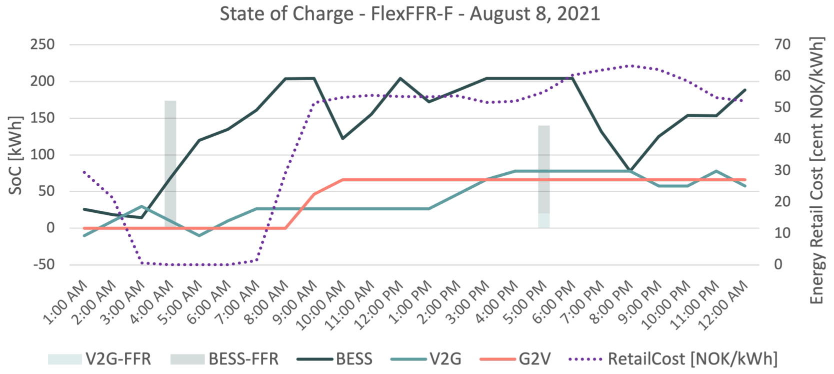
To gain further insights into the operational dynamics of DFRs, an analysis of an operational activity of DFRs during a 24-hour day will be presented. Figure 11 provides a representation of the hourly SoC of the DFRs during August 8, 2021, which corresponds to a Wednesday and is encompassed within both the Flex and Profil seasons. The cases depicted in the figure include FlexFFR-P (11a), FlexFFR-F (11b) and FlexNoFFR (11c). The hourly spot-price (Retail Cost [NOK/kWh]) is also included for the second axis to demonstrate the effect of energy price variation enticing demand response.

During weekdays, FFR Profil is active from 10 PM to 7 AM, as evidenced by the stacked area diagram that represents the FFR reserve capacity (see Figure 11a). Moreover, on this particular day, FFR Flex is active at 4 AM and 5 PM, visually presented through stacked bars that signify the FFR capacity (see Figure 11b). Notably, the provision of FFR reserves during this particular day is solely attributed to the BESS and V2G assets as none of the contracts require reserves during the hours where the G2V assets are active. This finding provides a deeper understanding of the constrained delivery of FFR by G2V charging in the context of this particular case study. The reduced availability of active hours for a flexible asset diminishes its reliability and capacity to fulfill reserve requirements.

This particular day exhibits highly variable spot prices, ranging from 0.04 to 0.63 NOK/kWh. The response of the DFR to spot price signals is clearly illustrated in the FlexNoFFR graph (see Figure 11c). Both the BESS and V2G assets reliably respond to price signals by increasing storage during periods of low retail costs and discharging energy during high peaks in retail price. The curves of both assets demonstrate an inverse correlation to the retail cost curve. Although G2V charging appears to occur during sub-optimal periods in Figure 11c compared to the graphs with FFR provision, the corresponding dip in BESS SoC indicates that the G2V connected EVs are being aided in charging by the BESS. This demonstrates that battery flexibility can facilitate affordable EV charging during periods of higher prices by temporally shifting and transferring loads.



(a)



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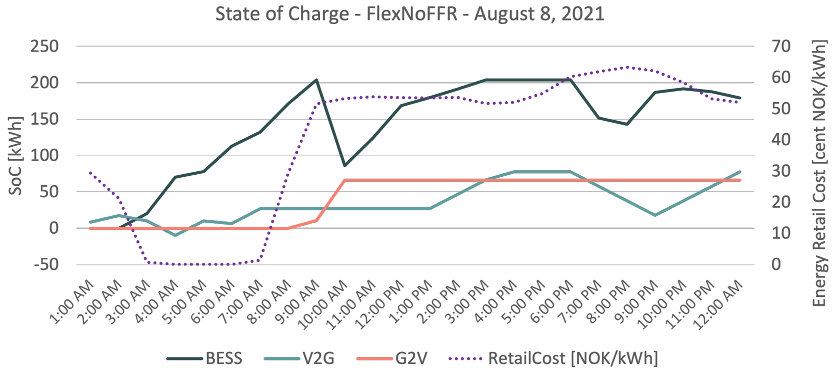

(c)

Figure 11: August 8, 2021: State of Charge and FFR contribution for each DFR. The energy retail cost (spot-price) is included in the second axis. The Figures shows the operational day in the cases of FFR profil (a), FFR Flex (b) and no FFR (c).

In the case where the prosumer participate in FFR Profil (see Figure 11a), the assets show relatively less responsiveness to spot price signals. Both the V2G and BESS assets exhibit increased storage during hours of active FFR Profil contracts to provide curtailing reserve capacity, both from charging and potential discharging. This is also evident in the first active hour for the Flex contract in Figure 11b, while for the second bar, the assets rely solely on discharging capacity. The FFR volume in 2021 is recorded as 143.61 kW for Profil and 117.70 kW for Flex. This value represents the minimum provision of FFR capacity throughout the entire season, and it is adequately met on this particular day, with satisfactory margins. Conclusively, the results showcases the potential interplay and synergies between the DFRs when optimally responding to FFR contracts and demand response signals.

7.6 Curtailing thermostatic loads

To estimate the prosumers potential for supplying additional provision of FFR capacity by curtailing thermostatic loads, six supplementary cases are provided and presented in Table 14. The inclusion of thermostatic loads is modeled as a percentage of the prosumers original demand as seen in Equation (12) in Section 5. To ensure the comfort of residents and avoid any discomfort, a conservative approach is taken in selecting the percentage value of 10% of the prosumers' original demand. This deliberate choice ensures that the capacity chosen for curtailment is manageable and does not impose any inconvenience. To provide context for the subsequent results, Table 13 presents the characteristics of the prosumer's original load during hours when the FFR contracts are active. Figure 14 depicts the FFR yield, FFR volume and percentage increase of FFR provision in relation to their equivalent cases without thermostatic curtailment.

Table 13: Characteristics of the prosumer's load profile during active hours of the two FFR contracts for each year.

Contract Year	Avg. Load [kWh]	SD Load	Lowest Load [kWh]
Profil 2019	52.7	18.6	14.1
Profil 2020	59.9	19.6	3.6
Profil 2021	59.9	15.6	15.3
Flex 2019	62.9	30.9	4.2
Flex 2020	62.3	34.2	3.6
Flex 2021	65.1	26.9	3.0

Table 14: The effects of including thermostatic loads for FFR provision: FFR earnings, supplied volume, volume increase, and impact on other costs. The percentage values in the two adjacent columns are computed relative to the corresponding values of the previously presented cases.

Contract Year	FFREarning[kNOK]	FFRVolume[kW]	FFR increase[%]	Cost impact[%]
TProfil 2019	29.4	145.1	10.4	10.9
TProfil 2020	29.8	147.2	2.5	-21.1
TProfil 2021	29.9	147.6	2.8	-17.9
TFlex 2019	22.1	122.6	10.7	-17.4
TFlex 2020	23.8	132.3	7.5	-14.6
TFlex 2021	23.4	130.0	10.4	-8.0

The annual increase in FFR for Flex surpasses that of Profil, which is somewhat unexpected considering that the Flex contract consistently involves hours with the lowest curtailable load and highest standard deviation compared to Profil. This observation is intriguing because FFR delivery necessitates a consistent contribution of capacity. However, the noticable FFR capacity increase shown in Table 14 in comparison to only 10% of the lowest load values provided in Table 13 provides evidence that additional FFR contributions are not solely dependent on adding the lowest curtailable load capacity to the total FFR contribution for a specific year. Instead, these contributions enable the DFRs to alleviate FFR scarcity during hours of high loads, allowing for load-shifting through DFRs and increased FFR capacity in subsequent or previous hours. The higher FFR yield observed in Flex can be attributed to its composition of fewer hours and longer temporal intervals between each active FFR hour. This configuration allows for more time and provides stronger incentives to engage in demand response activities.

In five out of the six cases analyzed, the collected costs of other demand response signals exhibited a substantial reduction, as seen in Table 14. This reduction was primarily observed in the peak capacity cost component, while the other cost components deviated to a negligible extent. The decrease in costs can be attributed to the liberation of DFRs, enabling them to allocate their capacity to attend to other demand response signals. It is likely that the FFR capacity for this particular prosumer is approaching its upper limit in relation to the available resources and the time-series of FFR activation. Consequently, the additional FFR support from thermostatic loads serves to redistribute the workload of DFRs, enabling them to respond to other signals more effectively. This is exemplified through the FFR Profil contract displayed in Figure 12, which depicts the same operational day as Figure 11, but with the inclusion of curtailable loads. The figure illustrates a minor decrease in overall FFR provision from DFRs and reallocates the V2G assets from FFR provision to address other signals during certain hours. It is noteworthy that the seasonal FFR capacity bid is not constrained by this specific day.

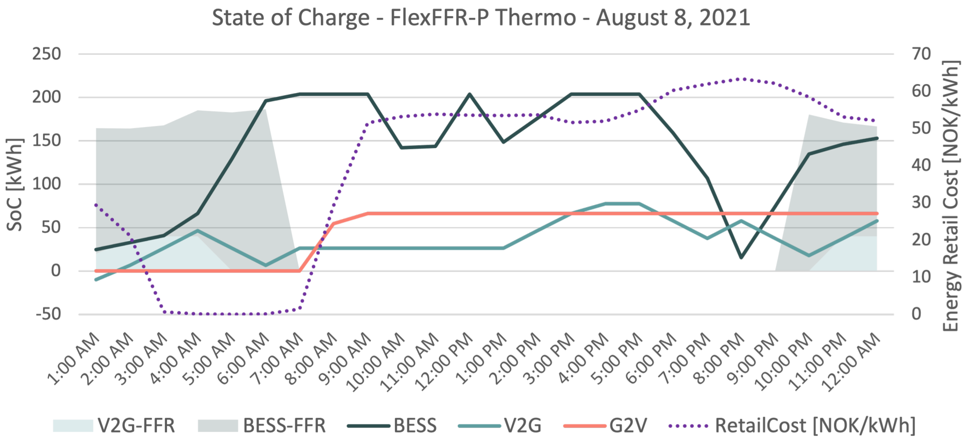

Figure 12: August 8, 2021: State of Charge and FFR contribution for each DFR when including thermostatic loads for FFR. The energy retail cost (spot-price) is included in the second axis.

As observed in Table 14, the introduction of thermostatic curtailment in the ”TProfil 2019” case resulted in an increase of 10.9% in other cost components, consequently leading to a substantial rise in its FFR capacity. This outcome can be attributed to the comparatively lower FFR capacity in the original FlexFFR-P case of 2019, as well as the alleviation of the triggering factors described earlier. The comparative limitation in FFR capacity likely provided a greater potential and incentive for the DFRs to expand their FFR contribution, shifting the focus from peak reductions to overall FFR capacity enhancement.

These results, which manly rely on the original load data of the prosumer, provide valuable insights into the potential magnitude of FFR provision through thermostatic load curtailment. Moreover, they demonstrate the prosumer’s capacity to alleviate the burden on other DFRs. The findings also suggest that implementing load-shifting techniques such as pre-heating or pre-cooling indoor areas of the prosumer can effectively facilitate curtailable loads during active and scarce FFR periods, potentially making it a highly beneficial strategy. However, it is important to highlight the substantial variability observed in the resulting FFR provision through load curtailment among the different cases. This variability underscores the limited reliability of prosumers when making decisions regarding the offering of additional FFR capacity through thermostatic curtailment.

8 Concluding remarks

8.1 Conclusion

This thesis provides a tangible analysis of how different flexible assets are optimally utilized when value stacking flexible qualities for a prosumer. Furthermore, it contributes with a generalizable modeling framework applicable to a wide array of scenarios and data.

The case study underscores the potential benefits of involving distributed flexibility resources (DFR) in fast frequency reserve (FFR) markets. It evaluates the interplay between FFR participation and various market drivers, such as dynamic grid tariffs, spot prices, and electricity export opportunities, across disparate years. This analysis sheds light on how DFR participation in FFR markets interacts with these market dynamics, providing valuable insights into their combined impact. The results implies that the profits of FFR participation is significantly predominant to the indirect losses of reserving security capacity, reducing the prosumers three year average total costs by 6.8% and 5.1% for Profil and Flex contracts, respectively. By incorporating three distinct price-years into the analysis, this study reveals the substantial motivation and resilience of prosumers in delivering FFR capacity. Simultaneously, it also highlights the importance of spot prices and their variability in evaluating the incentives for FFR provision in comparison to other demand response mechanisms. A notable example is the relatively lower FFR participation in 2019, primarily influenced by elevated electricity spot prices coupled with limited variability and high loads. These conditions constrained the arbitrage opportunities for DFRs to adjust loads to consider FFR participation.

The study also provides key indicators that FFR market participation can effectively complement electricity exports. This is achieved through active trading with the grid, which enhances the capacity of DFRs to provide FFR reserve. Simultaneously, this approach has a negative impact on limiting monthly peak loads compared to flexible operation without contributing to FFR. The results demonstrate that the demand response incentive associated with the FFR market is stronger than for the peak capacity cost imposed by tariffs, albeit having a limited impact on other cost elements. Thus providing valuable insights for energy market stakeholders and policy makers.

The results provides support for the notion that the discharging capabilities of flexible assets can be highly effective in providing reserve capacity, while emphasizing the versatility and potency of vehicle-to-grid (V2G) technology when contributing to FFR. Despite the battery energy storage system in the conducted case study being unconstrained and classified as purely flexible, the imposed daily electric vehicle (EV) charging from the V2Gs grants the asset a significant advantage in FFR markets. This advantage arises from the inherent requirement of the asset to provide charging, allowing it to effectively curtail charging for FFR provison. This capability further enhances its potential contribution to FFR and reinforces the value of integrating V2G technology. While Grid-to-vehicle (G2V) EV charging show-cased limited potential for FFR provision, the timing and charging trends of EVs in relation to FFR activation play a crucial role in supplying reserve capacity.

Optimized operation of flexible assets effectively reduces peak loads and thereby the peak capacity costs for the prosumer. Furthermore, it leads to a decrease in energy import costs while simultaneously increasing export revenue. This is achieved by leveraging the arbitrage opportunities provided by DFRs for energy trading.

8.2 Future research opportunities

During the course of this thesis, various aspects and potential avenues for further research have come to light. Building upon the findings and insights obtained, future investigations could explore the following directions:

- Participation in multiple frequency reserve markets; exploring the benefits of concurrent engagement in FCR and/or mFFR in addition to FFR. Investigating the implications, benefits, and challenges associated with such multi-market participation can shed light on the potential synergies and trade-offs in optimizing reserve capacity provision.

- The deterministic mathematical model presented in this thesis can be extended to consider uncertainty regarding loads and energy prices to enable real-time employment.
- Utilizing empirical data for EV Charging scheduling and uncertainty analysis in real-world applications.
- Perform an investment costs analysis associated with the different flexible assets compared to their relative economic savings when optimally operated.
- Include operational costs of each of the flexible assets, such as degradation- disadvantage costs.

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9 Appendix A

The paper presented in this Appendix entitled **"Value stacking flexibility services in neighborhoods participating in fast frequency reserve markets"** is peer-reviewed and accepted ("subject to minor revisions") for publication in a CISBAT special issue of Journal of Physics Conference Series at the time of submission of this Master's thesis.

Value stacking flexibility services in neighborhoods participating in fast frequency reserve markets

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Abstract. Neighborhoods are responsible for considerable amounts of the total energy demand in Europe, and increased shares of variable renewable energy sources will require energy balancing services. Local flexibility resources in neighborhoods can help provide this. However, there is a lack of insight into the economic incentives and operational consequences for property owners to adopt prosumer qualities. Using a linear program that minimizes total electricity costs, this paper evaluates annual cost savings for a Norwegian university campus when value stacking the following flexibility services: responding to electricity spot prices, grid tariffs, and provision of fast frequency reserve (FFR). Several flexibility resources are addressed in this study, including a stationary battery, electric vehicle charging stations, and a vehicle-to-grid charging station. The results found an average 6.8% yearly cost decrease by FFR participation, supporting the notion that there is a significant economic potential in applying flexible resources from prosumers in fast frequency reserve markets, without significant conflicts with other flexibility services.

1. Introduction

Substantial shares of variable renewable energy sources (VRES) in future power systems creates opportunities for neighborhoods to provide frequency restoration flexibility [1]. Historically, sources of flexibility have been provided by the supply side of the energy system by controlling energy production to meet a varying demand and synchronize the grid frequency. In recent years, demand-side flexibility and distributed flexibility resources (DFR) have become increasingly common and esteemed in regard to providing balancing services [1].

The Fast Frequency Reserve (FFR) market emerged in Norway and the Nordics in 2022 due to the general decline in power systems' inherent synchronous inertia. The FFR reserves are the fastest measure to decelerate frequency drops in the power system and have been implemented in a variety of countries worldwide [2]. FFR markets present prosumers a new market opportunity to prosumers with DFRs. FFR capacity can be sold by either reserving curtailable capacity through non-essential loads or by discharging flexible energy to the grid.

For a neighborhood, demand-side flexibility can be provided by energy storage systems [3] and electric vehicles (EVs) [4]. Economic incentives for demand-side flexibility include short-term variability of electricity prices, dynamic grid tariff designs, and net exports. In addition, DFRs can also participate in reserve markets. Yet, there are still market barriers related to the participation of neighborhood flexibility in reserve markets [5]. The Norwegian FFR market currently requests participants capable of delivering at least 1 MW [6], acting as a barrier for modest resources to enter the market. However, Statnett does not object to aggregated loads partaking as as singular bidder, enabling aggregators for participation in FFR. The aggregator approach has been proven feasible for both participation in frequency containment reserve markets (FCR) [7], and in the frequency restoration markets (aFRR and mFRR) [8], but requires advanced bidding models [9]. Although the potential gain of DFR utilization might be significant in multiple aspects and markets, there also exist costs of providing demand-side flexibility, e.g., battery wear and tear as well as purchase and integration costs [10].

Contributions from DFR in the FFR market can be an important enabler for the sustainable energy transition. Batteries have proven to be more valuable when providing FFR in addition to FCR services due to value stacking [11]. Kushwaha et al. [12] assess aggregated scheduling of EVs potential for FFR support through both Grid-to-vehicle (G2V) and Vehicle-to-grid (V2G) charging stations, showing significant capacity for FFR support and reduction in system costs. The limited research on provision of reserves from neighborhoods show that the participation in frequency restoration markets lower neighborhood costs [13]. However, there has been little research conducted on the FFR provision capabilities from a neighborhood with flexibility from batteries and EV charging, while also responding to spot price and grid tariff price signals.

This paper assesses the cost-optimal flexibility responses from a Norwegian prosumer participating in an FFR market. To the authors knowledge, no study has explored how costs and operations of demand-side flexibility are impacted by the opportunity to participate in FFR. This paper presents a case study of a Norwegian university campus with several flexibility resources. Using metered data for three historical years, we provide an optimization model that minimizes neighborhood costs by optimizing operation of the DFRs with and without the opportunity to participate in FFR. The research questions are the following:

- How are costs and operations of demand-side flexibility impacted by participation in FFR?
- How do economic characteristics of different years impact FFR participation?

The remaining paper is structured as follows: Section 2 presents the linear programming model used to simulate cost-optimal prosumer responses to price signals, including the FFR market. Section 3 presents input data and the case study setup, while Section 4 presents and discusses the results. Concluding remarks can be found in Section 5.

2. Methodology

In this section, we present the mathematical modelling framework for the prosumer cost minimization problem. The model is a deterministic linear program that computes the cost optimal responses to spot-price variation, FFR market contracts, different tariff factors and varying loads over the duration of a year. Decisions include operation of flexible assets, determination of FFR capacity participation and net consumption between the prosumer and the grid. All decision variables are non-negative.

The objective function quantifies the total electricity costs given a certain schedule for the flexible assets. This objective function is minimized:

$$\min \quad z = \sum_{m \in \mathscr{M}} c_m^{peak} p_m + \sum_{t \in T} \big((c_t^{energy} + c_t^{\mathrm{retail}}) y_t^{\mathrm{load}} - (c_t^{\exp} x_t^{\mathrm{load}}) \big) - c^{\mathrm{FFR}} z^{\mathrm{FFR}} \tag{1}$$

where p_m are variables for the peak load during month m. The electricity import from the grid to cover the loads are identified by variable y_t^{load}, while variable x_t^{load} represent electricity export to the grid. The total FFR capacity during $t \in \mathscr{T}^{\mathrm{FFR}}$ is represented by variable z^{FFR}. The objective contains a time-varying load-dependent retail cost for import (c_t^{retail}) and for export ($c_t^{\exp}$), a monthly peak load cost (c_m^{peak}), and the FFR market price (c^{FFR}) which is constant with regard to the pertinent FFR contract.

The resulting import from the grid to the prosumer is defined by constraint (2). The resulting load at each time-step must be equal to the initial demand plus potential export to the grid as well as charged and discharged energy from the flexible assets:

$$y_t^{\text{load}} = \quad \xi_t^{\text{load}} + x_t^{\text{load}} + \sum_{f \in \mathscr{F}} (w_{f,t}^{\text{charge}} - \varepsilon_f^{\text{discharge}} w_{f,t,}^{\text{discharge}}) \qquad \forall \quad t \in \mathscr{T} \tag{2}$$

where ξ_t^{load} is the inflexible load, y_t^{load} and x_t^{load} are import and export of electricity, while $\omega_{f,t}^{\text{charge}}$ and $\omega_{f,t}^{\text{discharge}}$ are charging and discharging of flexible assets type f, respectively. Energy losses are only considered for discharging, represented by $\varepsilon_f^{\text{discharge}}$.

Constraint (3) ensures that the flexible asset type f has an energy level stored equal to the previous period subject to diffusion losses plus charging subject to losses minus discharging. This constraint has an initial condition version ($t = 1$) with an initial storage value k_f.

$$\varepsilon_f^{\text{diff}} w_{f,t-1}^{\text{storage}} + \varepsilon_f^{\text{charge}} w_{f,t}^{\text{charge}} - w_{f,t}^{\text{discharge}} = w_{f,t}^{\text{storage}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{3}$$

The losses with respect to charging ($\varepsilon_f^{\text{charge}}$), discharging ($\varepsilon_f^{\text{diff}}$) and diffusion ($\varepsilon_f^{\text{discharge}}$) are dependent on the characteristics of the flexible asset f. There are no losses related to discharging in constraint (3) as it is accounted for in constraint (2).

The maximum capacity for charging ($\eta_{f,t}^{\text{charge}}$), storage ($\eta_{f,t}^{\text{storage}}$) and discharging ($\eta_{f,t}^{\text{discharge}}$) of flexible asset f are defined as upper bounds for operational decisions in all time periods in constraints (4), (5) and (6). Constraint (6) makes sure that the energy level of of flexible asset f is within the required boundaries of ($\gamma_{f,t}^{\text{req}}$) and ($\gamma_{f,t}^{\max}$) for all time periods t. The time-dependency of ($\eta_{f,t}^{\text{charge}}$) and ($\eta_{f,t}^{\text{discharge}}$) are necessary to consider flexible assets where availability fluctuates, such as for EV charging.

$$w_{f,t}^{\text{charge}} \leq \eta_{f,t}^{\text{charge}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{4}$$

$$w_{f,t}^{\text{discharge}} \leq \eta_{f,t}^{\text{discharge}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{5}$$

$$\gamma_{f,t}^{\text{req}} \leq w_{f,t}^{\text{storage}} \leq \gamma_{f,t}^{\max} \leq \eta_{f,t}^{\text{storage}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{6}$$

The constraints associated with FFR are given in (7), (8) and (9). FFR capacity can be acquired based on the curtailable charged quantity in (7), and by the remaining discharge capacity in (8), for each flexible asset f at time t. The sum of the available FFR capacity from each flexible asset $f \in \mathscr{F}$ for each time step of the year sets the upper limit of how much FFR we can offer over the whole year in (9). Energy use associated with FFR activation is disregarded in this formulation.

$$w_{f,t}^{\text{charge}} \geq r_{f,t}^{\text{charge}} \qquad \forall \quad f \in \mathscr{F}, t \in \mathscr{T} \tag{7}$$

$$w_{f,t}^{\text{discharge}} + r_{f,t}^{\text{discharge}} \leq \eta_f^{\text{discharge}} \qquad \forall \quad \in \mathscr{F}, t \in \mathscr{T} \tag{8}$$

$$\sum_{f \in \mathscr{F}^{FFR}} r_{f,t}^{\text{charge}} + r_{f,t}^{\text{discharge}} \geq z^{\text{FFR}} \qquad \forall \quad t \in \mathscr{T}^{\text{FFR}} \tag{9}$$

Constraint (10) determines the highest monthly peaks of import. The highest import quantity during each month $p_m^{monthly}$ sets the threshold for the monthly demand charge grid tariff.

$$y_t^{\text{load}} \leq p_m \qquad \forall \quad t \in \mathscr{T}(m), m \in \mathscr{M} \tag{10}$$

3. Case study

Campus Evenstad is a Norwegian university campus located in Innlandet county, and it is participating as one of the FME ZEN[1] pilots[14]. From 2015 to 2021, Campus Evenstad consumed between 650MWh to 1,100MWh electricity per year. We use historical hourly load profiles from Campus Evenstad. Characteristics of the flexible assets at Campus Evenstad are provided via the FME ZEN Research Center and summarized in Table 1.

Based on historical charging patterns at campus Evenstad, we have assumed a consistent cumulative daily demand of 66.3kWh for G2V charging and 26.5kWh for V2G charging. EV connective availability is assumed to be from 9–3 pm for one-directional chargers ensuring that demand is met by the end of a typical Norwegian working day. V2G is mainly utilized by campus employees and assumed to be connected from 3–9 pm. EV battery storage level is allowed to operate between 30–60%, and initial storage level for V2G is assumed to be 35%. No costs or losses are considered for any flexible asset in this case study.

Day-ahead hourly prices are gathered from the ENTSO-E Transparency Platform for price zone NO1 (South-East) in Norway. The Elvia grid tariff includes a seasonal volumetric cost, at 0.085 NOK/kWh during winter and 0.065 NOK/kWh during summer. In addition, there is a monthly demand charge cost of 90 NOK/kWh/h for the highest hourly import during a month in winter, and 40 NOK/kWh/h for summer [15]. Export of electricity is priced as the spot price minus 0.02 NOK/kWh. Fixed costs are disregarded in this analysis.

For the FFR market, Statnett requests two different contracts for reserve capacity: "Profil" and "Flex". All FFR data is collected from 2023. For Profil, capacity is sold on weekends and from 10 pm until 7 am on weekdays during the period of 27.May–3.Sep. For Flex, capacity is sold for 400 hours according to weekly orders during the period 29.Apr–30.Oct. According to correspondence with Statnett, the Flex orders are usually fairly scattered throughout the period, so we assume FFR orders every 13th hour. The FFR market price is assumed to be equal to the 2023 price of 150 NOK/MW-hour for Profil and 450 NOK/MW-hour for Flex. According to Statnett, FFR is generally only activated 0-3 times each season, and due to the short response time, the cost and logistics of FFR activation is not considered in this case study.

Table 1: Operational characteristics of the flexible assets at Campus Evenstad.

Flexible asset	η^{charge}[kWh/h]	$\eta^{discharge}$[kWh/h]	$\eta^{storage}$[kWh/h]	k_f[kWh]
1x li-ion battery	120	120	204	0
2x V2G	20.0	20.0	61.2	10
5x G2V	100.0	0.00	66.3	0

The objective of this case study is to assess the impact of prosumer participation in a FFR market, with regard to limiting their electricity bill, particularly by leveraging different flexible capabilities. Four cases optimizing costs, revenues and flexible asset operation will be presented for each year; 2019, 2020 and 2021. The classes of cases analysed in this paper are:

- **NoFlexNoFFR**: No flexible assets and no FFR market (no optimization).
- **FlexNoFFR**: All flexible assets available and no FFR market.
- **FlexFFR-P**: All flexible assets available and participation in FFR Profil.
- **FlexFFR-F**: All flexible assets available and participation in FFR Flex.

4. Results and discussion

Figure 1 shows resulting costs and revenues for each modelling instance, and it shows larger differences between years than between instances. Among the four instances considered within each year, FlexFFR-P is consistently the most profitable, followed by FlexFFR-F, FlexNoFFR, and NoFlexNoFFR. Optimal operation of flexible assets led to the greatest cost savings in 2021,

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[1] `https://fmezen.no`

followed by 2019 and 2020, although the results show the opposite order in terms of relative cost savings (23.34% for 2020, 14.14% for 2019, and 11.48% for 2021).

Over the three years, implementation of FFR contracts resulted in an average reduction of total costs by 6.8% for Profil and 5.1% for Flex. The highest total cost reduction of 12% was achieved with the Profil contract in 2020. FFR volume and profits for both Flex and Profil contracts peaked in 2020, with 2019 showing approximately 9% less FFR volume for both contracts. The authors attribute this to a high average spot-price of 0.40 NOK/kWh and a low standard deviation of 0.08, in relation to a high average load of 83.56 kWh for 2019, which incentivized limiting energy costs and peak capacity costs at the expense of maintaining a high FFR capacity. The Profil contract yielded the highest FFR earnings, reaching 29.1 kNOK in both 2020 and 2021. The consistent results over both years indicate that the FFR capacity has reached its limit relative to the case's flexibility. Participating in the FFR market resulted in losses in other cost components, which represented an average of 19.65% and 17.31% of the FFR profits for Profil and Flex contracts, respectively. Almost all of the indirect losses are attributed to the peak capacity cost (90%), where the monthly highest peak either increased or remained constant in every month where FFR was available. The monthly peaks increased on average with 20.41% for Profil and 14.12% for Flex. FFR seems to have little effect on the other cost elements, but interestingly, resulted in an increase in energy export profits by an average of 8.1% for Flex and 2.4% for Profil. The export profits reached a significant high in 2021 due to the remarkable spot-price standard deviation of 0.48, in contrast to 0.08 observed in 2020 and 2019. Electricity is only exported in the cases when flexibility is available.

The FFR capacity and volume distribution for each year is provided in Table 2. On a yearly average, the li-ion battery provides approximately 86% of the total FFR capacity in both Profil and Flex, whereas V2G and G2V on average contributes 13% and 2%, respectively. Profil had a higher contract quantity than Flex, mainly due to a total reduced availability of V2G and G2V participation, during periods of reserve need. Due to the flexible assets' different characteristics in capacity for charging and discharging, hourly availability and EV charging constraints, the distribution was somewhat as expected. However, when adjusting for active hours and charge/discharge capacity for each flexible asset type, V2G contributes with approximately 9% and 1% more FFR capacity than the electric battery and 42% and 40% more than G2V for Profil and Flex, respectively. The case study also revealed that discharging capabilities are highly valuable in regard to providing FFR capacity. For Profil, discharging of V2G and the li-ion battery in turn contributed, on average, with 55.6% and 22.6% more FFR capacity than curtailment of charging.

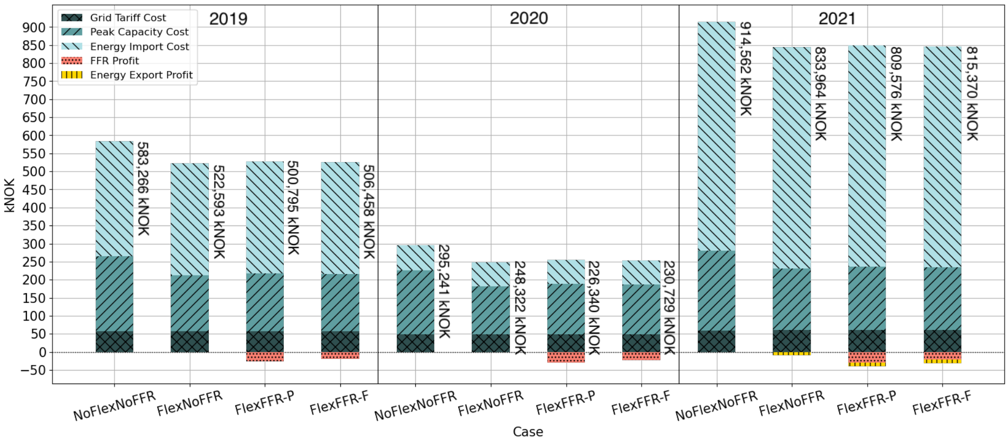

Figure 1: Overview of costs and revenues of each case for 2019, 2020 and 2021.

Table 2: FFR-volume distribution in contribution percentage for each year and asset.

Contract Year\ FFR	FFR Volume [kW]	FFR Battery charge [%]	FFR Battery discharge [%]	FFR EV charge [%]	FFR V2G discharge [%]	FFR G2V charge [%]
Flex 2019	110.74	32.22	54.69	3.80	6.90	2.39
Flex 2020	123.10	28.65	57.35	3.96	7.41	2.64
Flex 2021	117.70	32.13	54.30	3.76	6.95	2.87
Profil 2019	131.41	35.18	50.41	4.85	8.58	0.98
Profil 2020	143.61	40.74	46.63	4.75	7.01	0.86
Profil 2021	143.61	40.00	45.44	5.55	8.03	0.97

5. Conclusion

This paper provides a tangible analysis of how different flexible assets are optimally utilized when value stacking flexible qualities for a prosumer, and we contribute with a generalizable modeling framework applicable to a wide array of scenarios and data. The case study highlights the potential gain of distributed flexibility resources participation in fast frequency reserve (FFR) markets and assesses how reserved FFR capacity interacts with several market drivers across contrasting years. The case implies that the profits of FFR participation is predominant to the indirect losses of reserving security capacity, reducing the three year average total costs by 6.8% and 5.1% for Profil and Flex contracts, respectively. The study also provides key indicators that FFR market participation can effectively complement electricity exports, while simultaneously having a negative effect on limiting monthly peaks, thus providing valuable insights for energy market stakeholders. The paper provides support for the notion that the discharging capabilities of flexible assets can be highly effective in providing reserve capacity, while emphasizing the versatility and potency of vehicle-to-grid technology.

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