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Demand response potential modelling in buildings – development of a calculation tool and process

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Abstract

Ongoing climate change, push for energy transition, and evolving consumer behaviour are the driving efforts to replace fossil fuels with renewable energy sources to reduce emissions and achieve the decarbonisation of the energy supply. In this context, electricity plays a crucial role in the transition to cleaner energy. However, modern technology and the increasing demand for continuous power require a reliable and stable grid operation, necessitating a constant balance between supply and demand. As the share of renewable energy grows, and the supply becomes less controllable, there is a shift toward leveraging demand-side management for grid balancing. This approach is addressed by European Transmission System Operators which encourage consumers to engage in grid balancing by utilising various demand response mechanisms.

This thesis focuses on the development of a calculation tool for estimating the demand response potential and profits from the chosen case study building's electric loads. The potential and profit calculations are based on historical hourly market prices and demand data. The calculations are conducted through an estimation scheme in which Python scripts control an external energy simulation tool that simulates the loads' differentiated consumption patterns and eventually, the demand response potential and profits. The case study building's data is obtained from Granlund Oy. Values needed in the calculation are obtained from manual verifications, and previous literature and studies.

The results indicate that the most profitable marketplaces during the studied period (1.6. – 31.7.) were the manual frequency restoration reserve (mFRR) capacity market and the frequency containment reserve for disturbances (FCR-D) market. From the studied three scenarios, lighting had the highest potential and profits, consistently among each marketplace. Impacts on the calculation's execution and profits caused by external and internal factors were also investigated. The results indicate that execution speed was primarily influenced by computational capacity and memory usage, particularly when the Python script externally controlled the energy simulation tool, while the profits were mainly determined by magnitude factors, load activation time and recovery time.

Keywords demand response, reserve markets, calculation tool, profitability

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Tiivistelmä
Käynnissä oleva ilmastonmuutos, energiasiirtymä ja kuluttajakäyttäytymisen muutokset ohjaavat fossiilisten polttoaineiden korvaamista uusiutuvilla energialähteillä päästöjen vähentämiseksi. Tässä yhteydessä sähköllä on keskeinen rooli siirtymisessä puhtaampiin energianlähteisiin. Moderni teknologia ja kasvava kysyntä keskeytymättömästä sähköntoimituksesta edellyttävät luotettavaa ja vakaata sähköverkon toimintaa, mikä puolestaan vaatii jatkuvaa tasapainoa tarjonnan ja kysynnän välillä. Uusiutuvan energian osuuden kasvaessa ja tarjonnan muuttuessa vähemmän hallittavaksi, on siirrytty hyödyntämään kulutusjoustoa sähköverkon tasapainottamisessa. Tätä lähestymistapaa tukevat Euroopan kantaverkkoyhtiöt, jotka kannustavat kuluttajia osallistumaan verkon tasapainottamiseen erilaisten kulutusjoustomekanismien avulla.

Tämä diplomityö keskittyy laskentatyökalun kehittämiseen, joka arvioi kulutusjouston potentiaalin ja tuotot valitun esimerkkirakennuksen sähkökuormista. Potentiaali- ja tuottoarviot perustuvat historiallisiin tuntihintoihin ja kuormien kulutusdataan. Laskelmat suoritetaan prosessilla, jossa Python-koodi ajaa ulkoista energiasimulointityökalua, joka simuloi kuormien muuttuneita kulutusmalleja ja lopulta kulutusjouston potentiaalia sekä tuottoja. Esimerkkirakennuksen tiedot saadaan Granlund Oy:ltä, ja laskentaa varten tarvittavat tiedot kerätään manuaalisten tarkistusten sekä aiemman kirjallisuuden ja tutkimusten avulla.

Tulokset osoittavat, että tuottoisimpia markkinapaikkoja tarkastellulla ajanjaksolla (1.6. – 31.7.) olivat manuaalisen taajuuden palautusreservin (mFRR) kapasiteettimarkkinat sekä taajuusohjattu häiriöreservi (FCR-D). Kolmesta tutkitusta skenaariosta valaistus oli kaikissa markkinapaikoissa potentiaalisin ja tuottoisin. Myös ulkoisten ja sisäisten tekijöiden vaikutuksia laskentaan ja tuottoihin tutkittiin. Tulokset osoittavat, että laskentaan vaikuttivat ensisijaisesti laskentateho ja muistin käyttö, erityisesti kun Python-koodi ohjasi ulkoista energiasimulointityökalua, kun taas tuotot määräytyivät pääasiassa suuruuskertoimien sekä kuorman aktivointi- ja palautumisaikojen perusteella.

Avainsanat kulutusjousto, reservimarkkinat, laskentatyökalu, kannattavuus

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Preface and acknowledgements

This Master's thesis was conducted at Aalto University for Granlund Oy. I would like to begin by expressing my heartfelt gratitude to my colleagues and Granlund Oy for presenting this highly relevant and timely topic in the energy sector, and for entrusting me with the opportunity to contribute to it.

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Lastly, I am deeply grateful to my family for their support and encouragement throughout these years of study. Completing this Master's thesis marks the end of my master's studies in Aalto University – a journey filled with unforgettable memories, achievements, and countless hours dedicated to problem-solving.

Tapiola, 1 December 2024
Tuomas Lehto

Symbols and abbreviations

Symbols

°C	Degree Celsius
CO_2	Carbon Dioxide
Hz	Hertz
MW	Megawatt
m^2	Square Metre
m^3	Cubic Metre
kW	Kilowatt
kWh	Kilowatt-hour
kWp	Kilowatt-peak
ppm	Parts Per Million
T	Temperature

Abbreviations

AC	Air Conditioning
AHU	Air Heating Unit
API	Application Programming Interface
ATUS	American Time Use Survey
aFRR	Automatic Frequency Restoration Reserve
CBL	Customer Baseline Load
CET	Central European Time
CPP	Critical-Peak Pricing
DG	Distributed Generation
DHW	Domestic Hot Water
DLC	Direct Load Control
DSM	Demand Side Management
DR	Demand Response
DRP	Demand Response Program
ED	Economic Dispatch
EDRP	Emergency Demand Response Program
EEA	European Environment Agency
EEST	Eastern European Summer Time
EH	Electric Heater
ENTSO-E	European Network of Transmission System Operators for Electricity
ESM	Energy Service Management
EU	European Union
EV	Electric Vehicle
FCR	Frequency Containment Reserve

FCR-D	Frequency Containment Reserve Disturbance
FCR-N	Frequency Containment Reserve Normal
FFR	Fast Frequency Reserve
FRR	Frequency Restoration Reserve
GSHP	Ground Source Heat Pump
GUI	Graphical User Interface
HOMER	Hybrid Optimisation of Multiple Energy Resources
HP	Heat Pump
HVAC	Heating, Ventilation and Air Conditioning
ICE	Internal Combustion Engine
IEA	International Energy Agency
LSTM	Long Short-Term Memory
MD	Margin of Decision
MEF	Marginal Emission Factor
mFRR	Manual Frequency Restoration Reserve
MSP	Multi-Step-Price
MTU	Market Time Unit
PBDR	Price-Based Demand Response
PV	Photovoltaics
P2H	Power-to-Heat
RTP	Real-Time Pricing
RES	Renewable Energy Sources
SVR	Support Vector Regression
TOU	Time-of-Use
TSO	Transmission System Operator
UN	United Nations
VAT	Value-Added Tax
VPP	Virtual Power Plant
V2G	Vehicle-to-Grid

1 Introduction

1.1 Background

The share of fossil fuels – primarily coal, oil, and natural gas – in the global energy supply has remained stagnant at around 80% for decades (IEA, 2023a). Ongoing climate change, demand for energy transition and changes in consumer behaviour are the driving forces behind actions which aim to replace fossil fuels with renewable energy sources (RES) in order to reduce emissions and eventually, decarbonise the energy supply (UN, 2024; EEA, 2024; IEA, 2023b). Considering emission reduction, electricity has a significant role in transitioning to cleaner energy sources. Electricity is the foundation of modern economies around the world, and fully decarbonised electricity production is essential for reaching net zero emissions. Currently, unabated fossil fuels account for over 60% of total global electricity production (IEA, 2023c). In Finland, the situation is reversed. Renewables accounted for 54% of electricity production and the CO_2-neutrality level was 89% in 2022 (Statistics Finland, 2023).

While the share of renewables increases in the electricity production, it also raises concerns over stability and volatility. Renewables, such as solar and wind, are dependent on the weather conditions which implies that there will be times when neither one of these will produce electricity. This situation is not ideal for the power grid. Modern technology and increasing demand for continuous electricity supply require reliable operation of the grid, meaning that the demand and the supply need to be always in balance. If not, imbalance occurs and the frequency of the grid deviates from its nominal value (Fingrid, 2024a). Supply uncertainty from solar and wind power is already a challenge in the current market, and this will become more pronounced as their share in the electricity generation continues to grow.

In the past, meeting power demands involved producing and supplying all the required electricity to consumers, making the supply side the flexible component of the electricity production. However, as the share of renewables increases and the supply side becomes less controllable, there is a shift towards utilising the demand side for power grid balancing. Thus, supply uncertainty from integrating increasing amounts of RES into the grid can be addressed via demand response (DR). This can mean various things but generally it is referred to as shifting consumption away from peak hours when prices are high to times when it is more affordable. (Fingrid, 2024b) To help manage fluctuations in the electricity markets, Finland’s transmission system operator (TSO), Fingrid, operates reserve and balancing markets, which comprise on energy storages, power plants, and consumption resources (Fingrid, 2024c).

Demand response can present several advantages within the electricity markets, including financial gains for consumers, price reductions, enhanced market capacity, and improved grid reliability (Fingrid, 2024b). Achieving these benefits requires precise estimation of demand response. Buildings, in particular, are worth studying in this context because they represent a significant portion of the total energy consumption. The European Commission has stated that buildings, as energy end-users within the European Union (EU), account for 40% of energy consumption and 36% of greenhouse gas emissions. (European Commission, 2021). By identifying and controlling flexible loads within buildings, demand response can help unlock these advantages, optimising energy consumption patterns while contributing to emission reductions. Various methodologies exist to estimate, calculate, and schedule potential demand response capacities from different types of buildings. However, selecting the most suitable methodology for a specific building depends on many factors (Muthirayan *et al.*, 2018; Valentini *et al.*, 2022).

1.2 Research plan

The objective of this master's thesis is to investigate demand response potential and analyse the development and calculation processes of calculation tool, which will be separately implemented for demand response calculation by Granlund Oy. To demonstrate this, a raw model of the calculation tool will be developed. Potential profits and available demand response capacity are also calculated. The objectives of this thesis are attained through several steps. Firstly, a non-residential building is chosen for the case study, with energy data and other relevant building information provided by Granlund Oy. Suitable loads and marketplaces for demand response in the chosen building are identified. Secondly, load profiles are constructed using data provided by Granlund Oy, supplemented by general design data such as scheduling of loads, to generate inputs for the calculation process. Thirdly, the case study building is modelled with Granlund Oy's energy simulation tool and this model is semi-automatically simulated during the research using Python programming language. Several different demand response scenarios are generated for the simulation with the aim to represent the indicative demand response potential in the building. Lastly, the raw calculation model will be developed based on these findings. The model uses the energy simulation tool as its framework for all computations, while focusing on modelling the demand response in the building using Python. Simulation data is used whenever available, and when it is not, actual data and estimates from Granlund Oy and literature are used. Assumptions are made if no other data is found. Historical data of the markets are obtained from Fingrid and used in the calculations. Finally, the thesis evaluates main findings from the development and calculation process of the calculation tool. The research questions of this thesis are:

1. *What marketplaces are optimal for facilitating effective demand response?*
2. *What are the most important parameters for the functionality of a calculation tool?*
3. *How to modify a building energy simulation model to estimate DR capability?*
4. *How much the building's consumption can be increased or decreased for DR purposes?*

The markets that are in the scope of this thesis are day-ahead market, frequency containment reserves for normal and disturbance operation, automatic frequency restoration reserve, balancing energy market and balancing capacity market. The loads that are in the scope of this thesis are heating, ventilation, air-conditioning, lighting, and heat pumps. Building type included in the thesis is a non-residential building with relevant building information made available by Granlund Oy.

1.3 Thesis structure

This thesis includes a theory part, literature review, a calculation tool development process, a raw model of the calculation tool, results, sensitivity analysis, discussion, and conclusions. The first chapter introduces the thesis. In the second chapter, theoretical background relevant for the thesis is presented. The third chapter introduces the electricity markets, general demand response methods, benefits obtained from demand response and different calculation tools that have been developed earlier. In the fourth chapter, loads studied in this thesis are presented along with existing literature related to their application in demand response. In the fifth chapter, the calculation tool development process is presented. In the sixth chapter, results from the calculation tool development are presented. Finally, in the chapter seven, discussion on the results is provided alongside with future considerations. Chapter eight includes the conclusions of the thesis.

2 Demand response

Demand response is a resource that involves adjusting the electricity consumption habits of end-users, either in response to changes in electricity prices or through incentive programs designed to encourage lower usage during times of high wholesale prices or when the reliability of the system is under a threat (Albadi and El-Saadany, 2007). It is a concept that provides a resource to the utilities to influence the electricity markets through load profiles (Stanelyte, Radziukyniene and Radziukynas, 2022). Therefore, it is essential to understand the functionality of the electricity markets. The Finnish electricity markets have different marketplaces depending on the trade time and the duration of market participation. Fingrid, Finland's transmission system operator, is responsible for maintaining the real-time balance of the electricity system.

In the following subsections, the history and general characteristics of demand response are presented as the background information. Subsequently, Fingrid's role in the electricity markets and the overall market structure are explained. Lastly, demand response in Finland is discussed briefly from the perspective of different marketplaces.

2.1 History and characteristics

In the 1990s, the rise of distributed energy resources and distributed generation (DG) saw electricity consumers become active participants in power generation. This change, aligned with global electricity market liberalisation, has transitioned focus from supply to demand, emphasising consumers' role in the industry's demand side. The concepts of altering consumption patterns are basically associated with the ideas of Demand-Side Management (DSM) or Energy Service Management (ESM). DSM programs, originating in the 1970s, emerged in response to rising worries about reliance on foreign oil and environmental impacts from electricity generation, particularly nuclear energy. DSM can be further divided into three different subsets: 1) On-Site Backup and Storage, 2) Energy Efficiency and Conservation, and 3) Demand Response, from which the latter two are often confused with each other. (Lofti *et al.*, 2018; Honarmand *et al.*, 2021)

Demand response, as a part of DSM, plays a crucial role in modern energy systems, enabling them to manage different uncertainties existing in the power generation and load demand fluctuation. In principle, demand response is a mechanism in which power consumers dynamically adjust their electricity consumption behaviour, either in response to time-of-use electricity price or dispatching instructions. This flexibility helps in mitigating critical-peak demand, shifting power consumption more evenly across different time periods. (Huang *et al.*, 2019) On the supply side, demand response generally means actions taken to ensure that the electricity is produced and delivered with lower operating costs, reduced environmental impact and improved system reliability (Monyei and Adewumi, 2018).

Generally, the benefits offered by demand response vary depending on the perspective and can broadly be divided into three categories: economic efficiency, system reliability and environmental benefits. Economic advantages consist primarily of lower wholesale market prices, facilitated by demand response's ability to displace the costliest peak generation resources. In addition, it helps defer or avoid the need for producers to construct more capital-intensive new capacity by smoothing out the demand curve. Regarding system reliability, DR resources may also be urged by system operators to maintain the reliability of the electric system in the event of an emergency. In addition to reducing capacity constraints, certain demand resources can offer ancillary services like reserves or balancing by swiftly adjusting demand, either increasing or decreasing it as needed. The environmental benefits gained from demand response are various depending on the region. Generally, these benefits are mostly associated with the displacement of marginal fossil fuel resources or the capability to facilitate the integration of renewable resources. (Hurley, Peterson and Whited, 2013)

Although DR is usually discussed as changes in the electricity usage pattern of the consumers in relation to the market price, it can also be brought about using time-dependent tariffs. The tariffs can be divided into two branches which are also called demand response programs (DRP). (Vahid-Ghavidel *et al.*, 2020) These two branches are the main mechanisms of DR: price-based programs, also known as implicit demand response, use price signals and tariffs to encourage consumers to shift their consumption. In contrast, incentive-based programs, or explicit demand response, offer direct payments to consumers who adjust their demand as part of a demand-side response programme. (IEA, 2023d) The implicit and explicit demand response are illustrated in Figure 1 below.

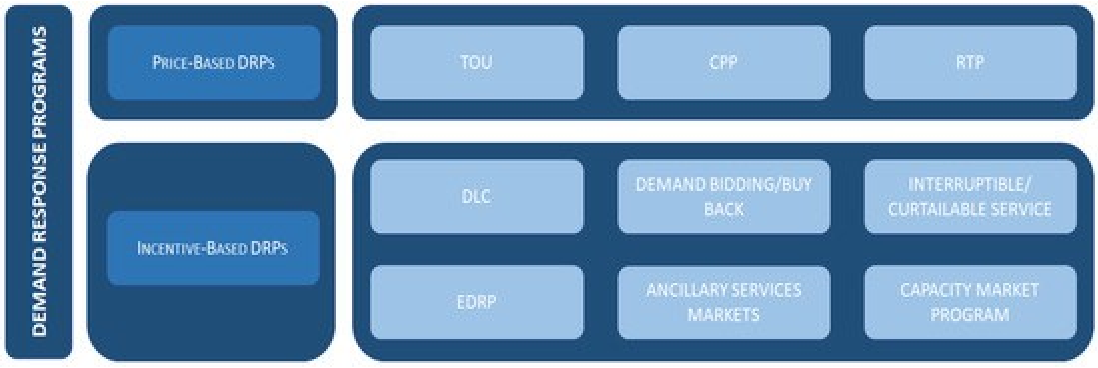


Figure 1. Two main branches of the demand response programs (Vahid-Ghavidel *et al.*, 2020).

Within the bounds of price-based DRPs, variations in electricity prices act as the primary mechanism for adjusting consumer energy consumption. This program involves three main programs which are Time-of-Use (TOU), Critical-Peak Pricing (CPP), and Real-Time Pricing (RTP). (Vahid-Ghavidel *et al.*, 2020) Huang *et al.* (2019) also recognised Multi-Step-Price (MSP) as a signal for the demand side.

TOU strategy uses different blocks of electricity prices corresponding to different periods of the day. Electricity prices are adjusted to encourage consumers to use less electricity during peak demand and more during off-peak hours, without significantly changing the amount of overall energy consumption. (Vahid-Ghavidel *et al.*, 2020) CPP involves a predetermined elevated electricity price that is added to TOU rates. These prices are activated during emergencies or periods of high wholesale electricity prices, typically occurring only for a limited number of days or hours annually. Lastly, RTP programs charge customers fluctuating hourly prices based on the actual cost of the electricity in the wholesale market. Customers receive pricing information either a day or an hour in advance. (Albadi and El-Saadany, 2007) In Finland, none of these are particularly used but the consumer can still participate in implicit demand response by using electricity market price signals. This is further discussed in chapter 2.3.

In incentive-based DRPs, the aim is to modify consumer energy demand with the help of incentives, as if by rewarding consumers. In this category, the most important tools used are Direct Load Control (DLC), interruptible services, emergency DRPs (EDRP), ancillary service markets, capacity markets and demand bidding/buyback programs. (Vahid-Ghavidel *et al.*, 2020)

In the DLC program, utilities can remotely shut down participant equipment on a short notice, typically targeting smaller loads such as air conditioners and water heaters. Participants in interruptible services are requested to decrease their load to predefined levels during the peak periods. Failure to respond may result in penalties, depending on the program's terms and conditions. In DLC and interruptible programs, participating customers will receive upfront incentives or discounted rates. These two programs are also known as classical programs. (Albadi and El-Saadany, 2007) Emergency DRPs are implemented during contingencies such as in the event of transmission line failure. In this scenario, customers receive incentives for measured load reductions. (Albadi and El-Saadany, 2008; Vahid-Ghavidel *et al.*, 2020) Demand bidding program, also known as buyback, entail consumers bidding to reduce electricity load in the wholesale market, with accepted bids being below market price. Upon acceptance, customers must comply with curtailment or face penalties. (Albadi and El-Saadany, 2007) Capacity market programs engage customers in committing to predefined load reductions during system contingencies. Ancillary service market programs allow customers to bid load curtailment for operational reserves, compensating the participants at spot market prices for standby commitment and spot market energy prices for load curtailment, if required. These four programs are known as market-based programs. (Albadi and El-Saadany, 2008) In Finland, the programs in use are a mix of classical and market-based approaches, where varying terms might be used across different segments. A selection of certain programs is further discussed in chapters 2.3 and 3.1.

In modern energy systems, various components including loads, distributed generation (DG), energy storage systems, and supply sources interact dynamically. Traditionally, the supply side has been the flexible component with the ability to curtail or ramp up production according to the demand. However, as highlighted earlier, the demand-side flexibility has evolved into an important element of power systems. Users and entities leveraging resources to facilitate flexibility on the demand side can broadly be categorised into commercial, industrial, and residential sectors (D'Ettorre *et al.*, 2022).

Demand response resources can be applied through these users in a variety of ways. These resources normally include flexible demand loads, electric vehicles (EVs), energy storages, DG, and their aggregation in Virtual Power Plants (VPPs). Flexible loads can be adjusted according to changes in electricity prices or incentives, and these mostly involve power-to-heat (P2H) appliances such as heat pumps (HPs) and electric heaters (EHs). (D'Ettorre *et al.*, 2022; Stanelyte, Radziukyniene and Radziukynas, 2022) On the other hand, O'Connell *et al.* (2014) argues that inflexible consumers may see their costs increase because of flexible consumers' behaviour, as the flexible consumers lower overall electricity prices by reducing their consumption during peak times. This reduction in peak demand benefits the system but shifts the financial burden to the inflexible consumers.

To further maximise the energy flexibility of P2H technologies, energy storages are essential. They decouple supply from demand, enabling effective load management strategies like load shifting while maintaining operationality. In addition, large-scale utilisation of EVs brings along new challenges with the power grid facing increased peak loads but this can also offer new opportunities: EVs can provide power to the grid in the vehicle-to-grid (V2G) mode. The last demand response resource, DG, has the potential to impact power system voltage levels and network losses. DG sources such as wind power and photovoltaics (PV) together with smart energy communities can exploit DR mechanisms to reduce their operating costs, while providing balancing services to the grid. (D'Ettorre *et al.*, 2022; Stanelyte, Radziukyniene and Radziukynas, 2022)

2.2 Fingrid in the volatile electricity markets

Over the past three decades, European electricity markets have evolved significantly to address emerging challenges regarding societal, political, and technological changes. Market designs remain dynamic, grappling with unresolved challenges posed by renewable energy, decentralised production, and increasing demand for demand response. Smart grid technologies facilitate the integration of distributed resources and bidirectional power flows, emphasising the importance of adhering to market fundamentals, effective governance, and proactive planning. Public discourse often focuses on price fluctuations, fostering mistrust during periods of high prices or excessive profits for renewable energy producers. This volatility strains electricity consumers financially and challenges conventional producers during extended periods of low prices. (Honkapuro, Jaanto and Annala, 2023) To mitigate these challenges experienced by consumers and producers, efficient demand response is one of the key solutions. The attractiveness of DR is rapidly increasing due to various technological advancements and in this matter, the Nordic countries have essential role as they have a well-operating and advanced wholesale electricity market, providing a solid foundation for a dynamic retail market. Finland, as one of the Nordic countries, possesses one of the most versatile power systems in this region and is thus in important role of enabling full-scale rollout of DR. (Rautiainen *et al.*, 2017; Söder *et al.*, 2018)

The current electricity market rules, adopted in 2019 as part of the 'Clean energy for all Europeans package', further enhance the previous round of EU energy market legislation, known as the 'Third energy package'. In the Third energy package, unbundling was implemented. The unbundling means that the energy supply and generation are separated from the operation of transmissions networks. Unbundling must take place depending on the preferences of individual EU country. (European Commission, 2024) In Finland, Fingrid operates as the transmission system operator, ensuring a separation between energy supply and generation, and the operation of the transmission system.

Fingrid is responsible for grid functionality and facilitating demand response through the existing marketplaces (Söder *et al.*, 2018). These marketplaces are further discussed in chapter three. Lagerroos (2023) discussed that the role of Fingrid as a system operator enables free competition in the electricity market, fostering a liberalised environment conducive to innovation and efficient energy utilisation. Therefore, Fingrid does not facilitate DR by generating electricity itself but procures it from various producers through different marketplaces, such as the day-ahead and reserve markets. The day-ahead markets serve the fundamental objective of efficiently supplying electricity to all participating regions, aligning with their demand requirements at minimal costs. However, the inherent fluctuations in both supply and demand often disrupt the balance, necessitating Fingrid's role in maintaining the real-time balance of the electricity system. Fingrid achieves this balance through the operation of reserve and balancing markets, ensuring stability and reliability of the electricity grid. (Fingrid, 2024d)

In the future, Fingrid will face crucial challenges concerning electricity market dynamics, primarily centered around increased volatility in the electricity supply. This volatility stems from multiple factors including rising demand levels, the growing presence of renewable energy sources in the power grid, and changes occurring in the market operations. The increased volatility in supply directly influences fluctuations in the electricity prices, thereby amplifying market uncertainties. If left unaddressed, these fluctuations have the potential to escalate into contingencies, highlighting the need for strategic interventions and robust market management strategies by Fingrid. Rintamäki, Siddiqui and Salo (2017) suggest that price spikes and dips become more frequent in the European electricity markets, which could mean additional investments in cross-border transmission capacity to decrease price volatility. As said, the volatility of the electricity supply depends on multiple factors, and there always exists some uncertainty in the electricity markets. In the future, the control of balance between supply and demand needs to be addressed more carefully while the supply should be the less flexible resource in the power system. Flexibility should be found on the demand side to tackle supply volatility and for this, demand response would be a key element.

Honkapuro, Jaanto and Annala (2023) further discussed market evolution in a way that changes to bidding zone configurations and market designs are necessary. The EU, for instance, has been progressively implementing an internal market for electricity that emphasises zonal pricing and cross-border transmission capacity to enhance market efficiency and ensure supply security. While there will be challenges related to market reconfiguration and integration of variable renewable energies, the long-term outlook suggests that strategic market and infrastructure reforms will lead to more stable and potentially lower electricity prices.

2.3 Demand response in Finland

After 2022, Finland has almost entirely got rid of the energy imported from Russia. Coal, crude oil, wood and electricity from Russia have been successfully replaced by domestic production and imports from other countries such as Sweden and the Baltics. (Tilastokeskus, 2023) Regarding the increase of domestic production, renewables have been in an important role. Wind power capacity increased by 75% in 2022, and solar power capacity is also increasing annually (Energiavirasto, 2022; Finnish Wind Power Association, 2023). As the share of renewables, and thus, weather-dependent production increases, more consumption flexibility is needed. The consumption and the production of electricity need to be consistently balanced and as stated previously, demand response plays an important role in this.

In Finland, electricity consumption has traditionally been managed through reserve markets to maintain power balance, primarily targeting large-scale industries. However, there is still significantly unused potential in demand-side flexibility to increase supply in these reserve markets. (Fingrid, 2024b) The Finnish electricity demand is largely industrial-led, and the share of industrial use is 47% of all electricity (Söder *et al.*, 2018). According to Fingrid (2024b), industrial electricity consumption has increasingly showed more flexibility, responding more dynamically to prices on the day-ahead market, thereby indicating that demand response's potential is significantly increasing in Finland. However, industries may face a challenge with DR as their processes often require continuous operation (Söder *et al.*, 2018).

In addition to larger electricity consumers, smaller ones can also participate in demand-side flexibility. A new addition to the electricity market is the emergence of aggregators, companies that consolidate small consumption and production units into a larger entity capable of participating on various electricity markets. When a consumer's own small-scale production responds to market conditions, such as high electricity prices, it can be considered consumption flexible, aiding in lowering the electricity intake from the grid. (Fingrid, 2024b) Aggregation is currently permitted across all segments of the balance chain in the marketplace (Fingrid, 2024e). Aggregation plays a vital role in enabling the utilisation of a progressively expanding demand response potential across various marketplaces. Söder *et al.* (2018) discussed that Fingrid's market-based flexibility estimate, ranging from 2.7% to 8.0% of the peak demand, reflects a currently utilised portion of this potential.

Nonetheless, the technical capacity for demand response flexibility far exceeds these estimates, and with the integration of aggregators, this flexibility potential increases even more.

Typically, regular electricity consumers in Finland have the freedom to choose their own electricity contracts from the retail market. Most of the contracts are generally either fixed-term or open-ended, and the pricing is usually fixed or spot-priced. However, each electricity contract offered is entirely company-specific. With the increasing role of demand response in Finland, some electricity retail companies have started to offer the element of DR as a part of the electricity contracts, with so called hybrid contracts. In these contracts, the consumption impact affects the billing price. The electricity price can be partially, or entirely fixed but the fixed price changes upward or downward based on the consumer's timing of the electricity consumption. The consumption impact is calculated monthly by subtracting the arithmetic average spot price for the relevant calendar month from the consumer's usage-weighted average spot price. If most electricity is used during the cheapest hours of the month and less during the expensive ones, the consumption impact will be negative, leading to a reduced billing price. (Fortum, 2024; Omavoima, 2024) For smaller consumers, there may also be an option for automatic electric vehicle charging alongside the spot-priced electricity contract. This so-called 'smart charging' aims to automatically schedule the EV charging during hours with lower electricity prices, such as nighttime. (Nordic Green Energy, 2024).

In addition to the hybrid contracts and smart charging possibilities, Finnish Government has for few years prepared a proposal to amend the Electricity market Act. In this proposal, the regulations concerning electricity contracts and the retail electricity market are being updated. Regarding demand response, market-based end-user load control in the distribution network would be promoted. (Työ- ja elinkeinoministeriö, 2022) This proposal would allow both electricity companies and network operators to offer load control services, such as new electricity meters that enable households using spot-priced electricity to shift consumption to cheaper hours by using software or mobile application (Yle, 2024).

Demand-side flexibility has the capability to engage across all market segments. Engagement can occur through standard electricity contracts or by participating in reserves, which may involve either just brief reductions or increases in power consumption, or then longer interruptions once a year. The frequency of activations, compensation rates, and technical prerequisites differ across various marketplaces. (Fingrid, 2024b) These differences will be further discussed in the following chapter.

3 Demand response mechanisms

In this chapter, the different options to execute demand response, so-called demand response mechanisms are presented. These mechanisms are examined within the context of different marketplaces where demand response participation is feasible. The marketplaces in use are discussed below in the section 3.1. Demand response can be utilised through shifting, reducing, or increasing load consumption and the infrastructure of these strategies is elaborated upon in the section 3.2. Furthermore, a DR program is efficient only if it is possible to estimate the scheduling and the amount of available flexibility. Hence, the section 3.3 briefly addresses two estimation frameworks related to the electricity and heat consumption. DR is ultimately justified by the benefits gained and these are further discussed in section 3.3 as well. Lastly, in the section 3.4, different calculation tools that have been developed earlier to estimate demand response potential in different buildings are analysed.

3.1 Marketplaces

Electricity production must continuously match electricity consumption. This balance is indicated by the frequency of the electricity grid, typically set at 50.0 Hz. While market operators plan and balance consumption and production in advance, deviations inevitably occur each hour. To counterbalance these fluctuations, Fingrid acquires various reserves from the reserve markets. These reserves encompass power plants, consumption resources, and energy storage facilities, all of which dynamically adjust their electrical output to meet the demands of the power system. (Fingrid, 2024c) Demand-side flexibility can participate in all marketplaces and the distribution of demand response participation in Finnish electricity markets can be seen in Figure 2 below, with bubble size indicating the magnitude of DR.

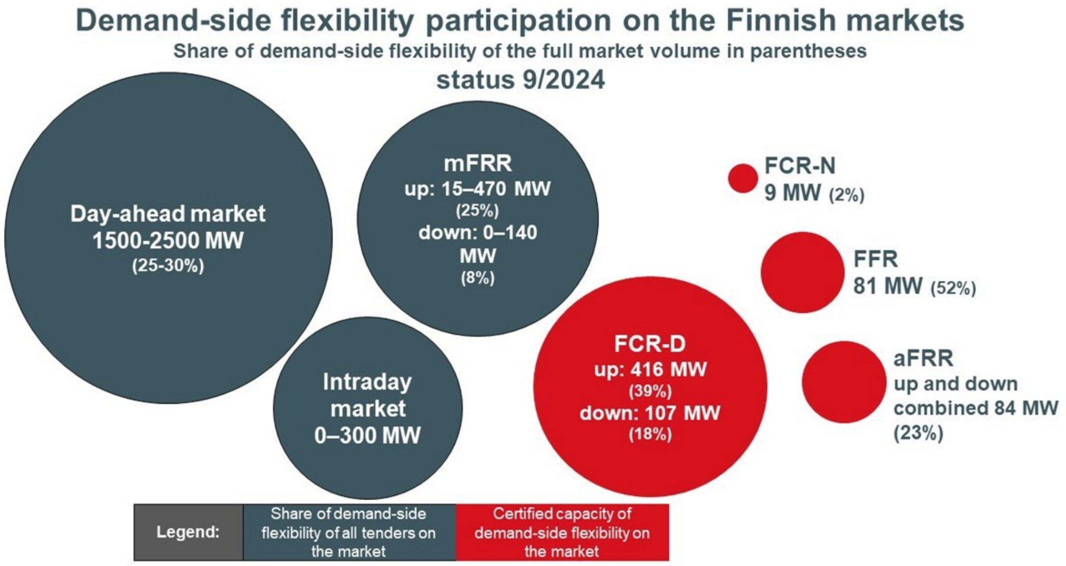


Figure 2. Demand-side flexibility participation in the Finnish markets in September 2024 (Fingrid, 2024b).

As can be seen from Figure 2, most markets have at least some activity with the DR. Quantitatively, reserve markets are the most prominent utilisers of DR. Depending on the market type, some DR resources need to respond to imbalances within seconds, minutes or hours, and the duration of response can be just few minutes or multiple hours (Nolan and O'Malley, 2015). The reserves are designed to be used for different purposes and consequently, they have different requirements and characteristics which are presented in subsection 3.1.2.

3.1.1 Day-ahead and intraday markets

Finland is part of the European electricity markets and Nord Pool. Nord Pool runs the leading power market in Europe, offering day-ahead and intraday markets to customers (Nord Pool, 2024a). These two markets are colloquially referred to as spot markets. The day-ahead market is a joint Nordic market, and it includes different bidding areas in the North-European market (Järventausta *et al.*, 2015; Rautiainen *et al.*, 2017). In the day-ahead market, customers have the opportunity to participate in a closed auction to either purchase or sell energy for the forthcoming 24-hour period (Nord Pool, 2024b). Within the intraday market, market participants are allowed to conclude trades that balance their electricity purchases and consumption up to one hour before the start of the delivery hour. After spot markets, electricity market participants buy/sell imbalance electricity through open delivery chains to cover the difference between the electricity consumption and purchases. In practice, a market participant buys or sells imbalance electricity in a quantity that balances the participant's actual purchases/production and consumption/sales. (Järventausta *et al.*, 2015)

In the day-ahead market, the aim is to establish balance between supply and demand. The daily process works in a way that at 10:00 CET the available capacities on interconnectors and in the grid are disclosed. Buyers and sellers then have until 12:00 CET to submit their final bids for delivery hours the following day. (Nord Pool, 2024b) The utilisation of DR resources in the day-ahead market has a few additional requirements. The capacity is required to be activated within 12 hours and the offered capacity needs to be at least 0.1 MW in size. Information about accepted trades and day-ahead prices are published around 13:00 CET. (Järventausta *et al.*, 2015)

In the intraday market, the daily process operates such that capacities are allocated by TSOs, determined based on the flow results from the day-ahead auction. The specific timing of the capacity allocation varies and is influenced by the operational protocols and bilateral agreements between TSOs on different borders. Intraday capacities are dynamically updated in response to the volume and direction of intraday trades. (Nord Pool, 2024c) For the market, bids on the capacities can be made right up until the delivery hour (D-0 min GCT). Cross-border trading is closed 30 minutes before the delivery (D-30 min GCT). Information on accepted trades is published as trades are executed. (Nord Pool, 2024d)

As part of the ongoing efforts to improve market efficiency and more effectively integrating renewable energy sources, the market time unit (MTU) will transition from 60 minutes to 15 minutes. In Finland, this change will take effect in March 2025 for both the intraday and day-ahead markets. (Nord Pool, 2024e)

3.1.2 Balancing and reserve markets

The balancing and reserve electricity markets are maintained by the Nordic TSOs, which in Finland is Fingrid. The Finnish Energy Authority supervises separate peak load capacity system (Järventausta *et al.*, 2015). Balancing and reserve markets are used to maintain power, and balance unexpected demand situations (Smart Energy Transition, 2017). Generally, the reserve products can be categorised into two groups based on their purpose as follows:

1. Frequency Containment Reserves (FCR) are active power reserves and used for continuous frequency control.
2. Frequency Restoration Reserves (FRR) aim to restore the frequency to the normal range (49.9-50.1 Hz) and release activated frequency

containment reserves back into operation. (Järventausta *et al.*, 2015; Fingrid, 2024c)

Additionally, since 2020, the Nordic countries have had Fast Frequency Reserve (FFR) in place. This reserve is used for the frequency control in situations with low inertia, alongside the frequency stability reserves. Fingrid procures FFR from a national hourly market. (Fingrid, 2024c; Fingrid, 2024g)

Frequency Containments Reserves can be divided by occurring situations: normal (N) and disturbed (D) operation. They activate automatically during frequency deviation. FCR-N is designed to maintain the frequency within the standard range of 49.9 Hz to 50.1 Hz, while FCR-D seeks to restrict the frequency deviation to 49.5 Hz or 50.5 Hz if it falls outside the standard range. (Fingrid, 2024f) FCR-N is a symmetrical product that must be able to perform both upregulation and downregulation. Upregulation involves either increasing power production or reducing consumption, while downregulation means either reducing power production or increasing consumption. In contrast, for the needs of FCR-D, adjustability in one direction alone (up or down) is sufficient. (Järventausta *et al.*, 2015; Fingrid, 2024f)

Frequency Restoration Reserves can be divided according to automatic and manual products. Automatic Frequency Restoration Reserve (aFRR) serves the purpose of returning the frequency to its nominal value of 50 Hz. aFRR operates as a centrally activated reserve that activates automatically. Its activation is initiated by a request signal sent from the TSO, calculated in response to the frequency deviation within the Nordic synchronous area, with signals dispatched every 10 seconds. (Fingrid, 2024h) Fingrid acquires aFRR reserve from both the hourly market and through inter-TSO trades with other Nordic countries. New reserve market, aFRR energy market, was launched in Finland in June 2024 and it allows for the pricing of aFRR energy bids 25 minutes before the utilisation (Fingrid, 2024h; Fingrid, 2024i) Balancing energy, balancing capacity markets and Fingrid's own or leased reserve power plants form the basis of the reserve product Manual Frequency Restoration Reserve (mFRR) (Lagerroos, 2023). A reserve provider participating in the balancing energy market needs contract with Fingrid and is obliged to offer a quantity of up- or downregulating bids equivalent to the accepted capacity bids to the balancing energy market, receiving financial compensation in return. A reserve provider can also voluntarily bid in the balancing energy market without first bidding to the balancing capacity market. (Fingrid, 2024j)

In the context of reserve markets, it must be noted that different reserves impose quite diverse requirements on the implementation of regulation. The main characteristics and requirements of the reserve products in Finland are collected in Table 1 below.

Table 1. Main characteristics of reserve products in Finland (Finlex, 2021; Fingrid, 2024c; Fingrid, 2024f; Fingrid, 2024g; Fingrid, 2024h; Fingrid, 2024j).

Reserve products in Finland				
Product	*Main procurement channel*	*Min. capacity of regulation*	*Activation performance*	*How often it is procured?*
FCR-N	Yearly and hourly markets	0.1 MW	3 min / 95% 1 min / 63% (activation after change of ± 0.1 Hz in frequency)	Maintained constantly
FCR-D	Yearly and hourly markets	1 MW	7.5 s / 86% (activation with fast frequency change from 49.9 Hz to 49.5 Hz)	Maintained to the extent of individual faults
aFRR	Hourly markets and inter-TSO trades	1 MW	Within 5 minutes	Procurement hours are informed in advance
mFRR	Nordic balancing capacity and energy markets	5 MW 1 MW if using electronic activation	Within 15 minutes	To the extent allowable by the operational situation of the power system
FFR	Hourly market	1 MW	49.7 Hz / 1.3 s 49.6 Hz / 1.0 s 49.5 Hz / 0.7 s	Procurement forecast published one week ahead
Peak load capacity system	Long-term contract (2 years)	1 MW	Within 12 hours	Rarely

3.2 DR infrastructure

As discussed in the previous chapter, different demand response marketplaces have different requirements for the minimum capacity of resources. In Finland, the minimum requirements range from 0.1 MW to 10 MW. Considering this, smaller consumers are not able to directly participate in these markets for now. Enabling this would mean that the requirements would have to be changed quite radically. Implementing these changes for thousands of small consumers would be highly challenging and expensive in practice. However, with an appropriate DR infrastructure in place, the business model for aggregating a large number of small resources could become reasonable and beneficial. (Rautiainen and Järventausta, 2020)

For demand response to operate efficiently, it requires controllable electrical loads, viable business models, and the appropriate infrastructure to integrate these elements into a functional system. The infrastructure controls and verifies the operation of the electrical loads used as DR resources. The DR resources are ultimately owned and controlled by the electricity consumers, but "smart" electricity consumption meters have the capability to control the loads for them. Electrical loads – electric heating, air conditioning (AC) devices, heat pumps and water heaters – are interesting DR resources because these loads typically consume significant amounts of electricity and have high nominal power ratings. Often, the timing of their electricity consumption is not critical, allowing for the load to be shifted in time. Besides shiftable loads, some loads, like lighting, can be curtailed temporarily. Additionally, electric vehicles represent a new type of DR resource that could become increasingly significant in the future. (Rautiainen and Järventausta, 2020) However, not all loads are suitable for DR purposes unless there is an electricity storage device available to shift the energy consumption of these loads to different times (Koskela, Rautiainen and Järventausta, 2017). Thus, electricity consumption and the controllability of the electric loads depend on various factors, all of which must be considered when designing the DR infrastructure (Rautiainen and Järventausta, 2020).

3.3 Benefits and estimation frameworks

The ultimate objective of the DR programs is to balance energy supply and demand more efficiently. By participating in the DR programs, consumers can expect various system-wide benefits. Apart from the potential economic gains, the adoption of the DR measures can also influence the carbon footprint at the end-user and system level. These possibilities are elaborated in section 3.3.1. To maximise the benefits gained, an estimation of demand response is needed. The estimation of demand response potential is possible by utilising multiple different frameworks. Section 3.3.2 introduces the two common methodologies, which solely require load data inputs, for such estimations.

3.3.1 Demand response benefits

In section 2.1, the benefits offered by demand response were divided into three general categories: economic efficiency, system reliability and environmental benefits. Albadi and El-Saadany (2008) discussed that the benefits associated with DR normally fall under the two first categories and can be more specifically divided into following categories: participant, market-wide, reliability and market performance benefits. The main benefits in each category are further divided in the following way (Albadi and El-Saadany, 2008):

Demand response benefits

- Participant
    - Compensation incentives
    - Expense reductions
- Market-wide
    - Price reduction
    - Capacity increases
    - Avoided/deferred infrastructure costs
- Reliability
    - Number of service interruptions decreases
    - Customer engagement
    - Diversified resources
- Market performance
    - Reduces market power
    - More options to customers
    - Reduction in price volatility

The benefits gained from demand response are related to economic efficiency and monetised benefits. However, DR can also offer CO_2 emissions reductions. DR can, for example, contribute to lowering forecasted peak demand and enhancing the integration of renewable generation into the system. Decreased reliance on peak power plants may contribute to the reduction of the system's carbon footprint. The reduced utilisation of peak power plants may contribute to the reduction of the carbon footprint of the system. Additionally, the electricity markets stand to gain from reduced and more consistent electricity prices. Even a slight decrease in demand during the periods of near-maximum electricity production can result in significant price reductions in the market, potentially leading to emission reductions. (Paterakis, Erdinç and Catalão, 2017)

On the other hand, Fleschutz *et al.* (2021) found that price-based load shifts indicated that carbon emissions increased for 8 out of the 20 European countries in their study. However, the marginal (power plant) emission factor (MEF) based load shifts led to carbon emission savings but at the same time, cost-saving potential decreased compared to price-based load shifts. So, using spot-market prices as an incentive signal for DR could increase operational carbon emissions, given the current carbon pricing.

While price-based demand response (PDBR) may have negative environmental impacts under certain conditions, it remains a highly promising method for reducing operating costs and carbon emissions when adequate carbon pricing is in place. To fully realise the environmental benefits of PBDR, there must be a strong correlation between carbon intensity and marginal cost in the merit order, achievable through proper carbon pricing or other market interventions. (Fleschutz *et al.*, 2021)

3.3.2 Estimation of demand response potential

Understanding the capacity value of demand response, which signifies its contribution to power system adequacy, can indicate its potential economic value and facilitate comparison with other resources (Nolan *et al.*, 2014). To realise economic value, demand response potential needs to be verified. Two primary data-driven estimation methods exist for determining the DR potential: customer baseline load (CBL) and load clustering. Typical dispatchable DR programs offer incentives to the customers based on the extent of their energy or power reduction. To verify the reduction amount, the CBL must be determined. CBL represents the electricity consumption that would have occurred if the DR event had not taken place. The difference between the actual load and the CBL is regarded as the load reduction, or the DR performance achieved by the customer. Therefore, accurately estimating the CBL is crucial for the success of the DR programs. (Park *et al.*, 2015; Xiang *et al.*, 2019) Figure 3 below illustrates an example of a DR event alongside its corresponding measured energy baseline.

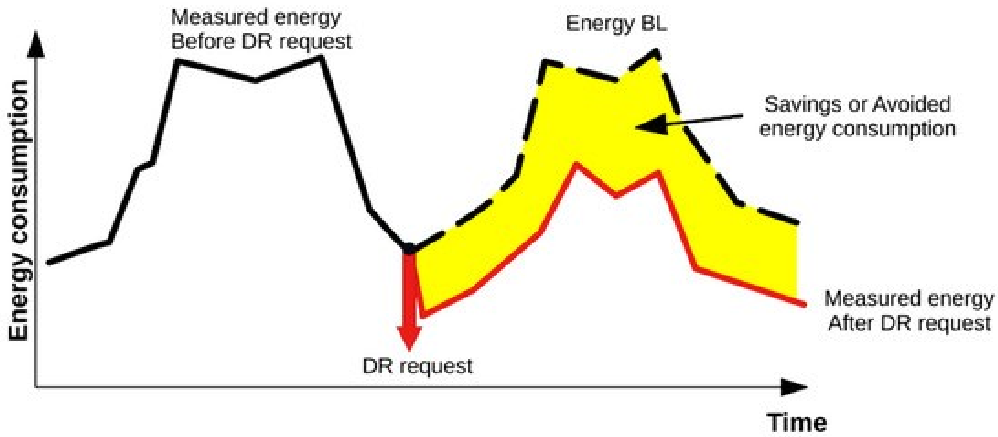


Figure 3. DR event in relation to CBL. Yellow area highlights the saved energy versus situation without DR. (Valentini *et al.*, 2022)

Considering the variability in a building's usage patterns throughout the year, the CBL estimation relies on identifying profile clusters. This allows for the determination of DR turndown opportunities by comparing variances between these profiles and selecting representative profiles from each cluster. (Park *et al.*, 2015) The calculation of CBL can be done using the so-called

HighXofY method shown in (1). The equation, where *High(X,Y,d)* involves determining the average load of the *X* highest consumption days within the *Y* non-DR days prior to the DR event day *d*. *B(d, t)* denotes the predicted baseline and *L(d, t)* the actual load, both on day *d* at the time *t*. (Wijaya, Vasirani and Aberer, 2014)

$$B(d,t) = \frac{1}{X} \sum_{d \in High(X,Y,d)} L(d,t) \tag{1}$$

By calculating CBL, the DR potential can be calculated knowing that the difference between the predicted baseline *B(d, t)* and the actual load *L(d, t)*, multiplied with the duration of it, is the potential *D(d, t)* during the days of DR participation on the day *d* at the time *t*, as in (2):

$$D(d,t) = \sum_{t \in T} [B(d,t) - L(d,t)] \times \Delta t \tag{2}$$

Additionally, load clustering among the CBL estimation is an important approach to the DR estimation. Data can be clustered using various methods. Curtis, Torriti and Smith (2018) discusses that by employing k-means clustering and subsequently linking the derived clusters to various timescales, usage profiles could be identified effectively. These clustering techniques indicate that building energy consumption generally follows a constrained set of consistent profiles. Roughly, K-means clustering method selects a number of groups and random centroid points. Values are assigned to the nearest centroid, means are calculated, and the centroids are adjusted accordingly. This equation, as shown in (3), repeats until a set number of iterations or a tolerance level is reached, thus minimising the objective function:

$$J_n = \sum_{j=1}^{K} \sum_{i=1}^{n} \left(x_i - c_j\right)^2 \tag{3}$$

where n represent the objects being clustered, with J_n denoting the cluster outcome for a given n value. The number of clusters is indicated by K. Each cluster j has a centroid c_j, and x_i represents an object i.

Profile clusters created by load clustering represent differences compared to the baseline usage. The differences are created by different levels of electrical loads utilised, and on the other hand, the baseline represents the periods when these electrical loads are not utilised. Thus, profiles form maximum and minimum boundaries of the electrical usage, and the difference between them and the baseline represents the DR potential. (Curtis, Torriti and Smith, 2018; Lagerroos, 2023)

3.4 Different DR calculation tools developed earlier

Many previously developed demand response calculation tools, which are openly available on the internet, focus on estimating the peak levelling savings and electricity energy shifts in buildings. These estimates are subsequently converted into economic evaluations which are deemed as the most important part of the estimation. Bel *et al.* (2009) discusses an example of a simple tool developed in the project of the International Energy Agency (IEA) task XIII. This tool assesses the market potential for demand response in electricity markets using benchmark data from Europe and America. It links flexibility strategies, for residential and small commercial consumers, to direct load control programs for air conditioners, water heaters, and space heating systems, using North American long-term participation rates. In this example, inputs include the number of hotels in Europe, the peak power (MW) in EU countries, the peak power (MW) for a typical hotel, and the average reducible power (MW) for a typical hotel. The result is the estimated DR potential (MW) in hotels, which is then used to draw a conclusion of the DR potentiality of deemed buildings.

Rodríguez-García *et al.* (2016) developed a dynamic simulation tool to perform a cost-benefit analysis concerning the participation of industrial consumers in the reserve energy markets. The tool's primary inputs include customer-specific load curves, DR action parameters, electricity contract details, historical reserve energy market prices, and CO_2 emission factors. The calculation process involves identifying interruptible power availability at quarter-hour intervals, considering technical constraints, followed by economic evaluation accounting for real benefits, economic balance, and variable costs. Participation in DR programs is determined by a margin of decision (MD). Technically, the tool assesses the energy balance by comparing energy reduction during DR events with additional consumption in preparatory and recovery phases. Evaluations encompass economic, technical, and environmental aspects, showing significant savings from the reduced energy consumption during DR events against the preparatory and recovery costs. (Rodríguez-García *et al.*, 2016)

Johnson *et al.* (2015) presented a tool that estimates demand response potential from residential loads using a bottom-up approach. The inputs include data on occupant behaviour from the American Time Use Survey (ATUS) and models of common residential loads. The calculation process employs the Markov chain models to simulate occupant behaviour and corresponding energy use. These behaviour models are combined with the dynamic load models of major residential appliances to predict power demand on a one-minute time scale. Various DR strategies, including direct load control and indirect load control, are implemented by sending signals to alter the consumption patterns of individual loads. The simulation results demonstrate the tool's ability to predict dynamic changes in residential power demand and assess the benefits and trade-offs of different demand response programs.

Neves, Pina and Silva (2015) compared three different modelling tools with three different scenarios on implementation of DR. The first calculation tool, called Hybrid Optimisation of Multiple Energy Resources (HOMER) aims to economically optimise hybrid renewable energy systems (HRES). In this comparison, the inputs for HOMER included total load profile, predefined technology parameters including capacity and efficiency curve, and economic factors. Within the calculation process, HOMER used a daily time frame to model load following and cycle charging methods. It optimised system configurations to meet the load by rescheduling for hours with excess electricity and when generators operated above their nominal capacity. Results showed that HOMER tended to distribute demand evenly throughout the day, resulting in lower operational costs and diesel consumption compared to the baseline, with minimal savings when implementing DR.

Second tool, EnergyPLAN, is a grid modelling tool for planning energy supply (electricity and heat) strategies. In the study, EnergyPLAN used various inputs, including base load and flexible load profiles, additional energy inputs for specific technologies such as EVs or HPs, and predefined technology parameters. The tool rescheduled load primarily for off-peak hours or when there was excess electricity, considering both technical and economic factors. It operated on an hourly resolution over a year-horizon to simulate and optimise the energy system. The results indicated that EnergyPLAN effectively shifted demand to off-peak hours, yielding slight savings in operational costs and diesel consumption. While the tool was beneficial for studying larger systems and regional energy planning, it had limitations in modelling detailed DR strategies for isolated systems. (Neves, Pina and Silva, 2015)

The third and last tool, presented by Neves, Pina and Silva (2015), is a self-built economic dispatch (ED) model. It is a daily ED model that incorporates DR using an optimisation approach, reducing daily dispatch costs through optimised placement of solar thermal backup. In the scenarios, model utilised inputs such as base load and flexible load profiles, and economic factors. The calculation process employed genetic algorithms to optimise the daily dispatch by rescheduling flexible loads on a day-ahead basis. Operating on an hourly time step, the model was adaptable for various daily flexible loads. The results demonstrated that the ED model achieved the largest savings with DR by effectively rescheduling the domestic hot water (DHW) backup load.

Lagerroos (2023) researched in his thesis methods to estimate, forecast, and quantify DR potential in certain office building. For estimating the potential, load clustering through K-means clustering, and CBL method using *HighXofY*, which was presented in 3.3.2, and *LowXofY* calculations were used. The forecasting of DR potential was conducted with Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) methods. The quantification process was carried out in real time and day-ahead scales. Results of the research showed that the DR potential estimation and forecasting succeeded. However, accurate estimation was difficult because of the high variability in the results and the absence of reference data. The forecasting methods selected were not optimal because of the relatively high error (10-20%) in load forecasts. Thus, improving the estimation and forecasting methods to the level of actual deliverable capacity would be essential so that the DR participation would be reasonable and above all, profitable.

Savolainen, Einolander and Lahdelma (2024) researched and presented a novel linear programming optimisation model for managing implicit and explicit demand response in a building equipped with a hybrid energy system. The system included a ground source heat pump (GSHP), district heating, power storage, and heat storage, while also participating in the FCR market. The model was applied to the retrofit planning of an office building in subarctic Helsinki, Finland. The study evaluated four potential configurations, considering the scenarios with and without power storage, as well as with and without participation in FCR trading. The results showed that FCR trading reduced annual energy costs by approximately 3% for the target building. Additionally, the power storage was found to be cost-effective only when combined with FCR trading.

4 The case study building

This chapter introduces the building chosen as a case study for this thesis, along with its relevant parameters and consumption data. This building forms the basis for the development process of the demand response calculation and implementation of the raw calculation model, both of which will be presented in chapter 5. The loads from the building that are applicable for demand response, within the scope of this thesis, are identified and presented in section 4.2. Ultimately, the loads will determine the overall suitability of the DR in the building. The building data in its entirety was received from Granlund Oy and it will be treated anonymously due to confidentiality.

4.1 Building's parameters and modelled consumption

The construction of this case building was finished in 2021, and the building type in question is a combination of educational and office building, a so-called joint-use building, consisting of several teaching and research spaces, laboratories, and office spaces. It is large-sized, 7 floor building with heated gross floor area of approximately 23 000 m². In this thesis, and particularly in simulations that will be conducted to demonstrate the DR events, this building will be treated as an educational building. The key parameters regarding the electricity and the heating usage of the building are compiled in the Table 2 below.

Table 2. Key parameters of the case building used as the basis for developing a DR calculation tool.

Building type	Educational building
Location	Southern Finland
Heating supply	Ground Source Heat Pump, district heating and water circulating radiator heating
Heated gross floor area	22 879 m²
Gross air volume	90 174 m³
Heating demand	85.3 kWh/m²/a
Cooling demand	49.6 kWh/m²/a
Electric energy demand	70.1 kWh/m²/a
Peak demand	3287 kW

The building demonstrates high energy efficiency, evident from its E-value of 65 kWh/m². The building was chosen for a case study because it represents a modern educational building with automation, and heating, ventilation and air conditioning (HVAC) systems that could allow DR activities with a low threshold. Additionally, the building features a medium-sized PV system installed on its roof, with a peak capacity of 126 kWp. However, its influence on the annual electricity demand curve is minimal, primarily due to its electricity production occurring during the periods of lower consumption, such as summer months.

4.1.1 Heating and electricity consumption curves

Essential for estimating the magnitude of demand response are the demand curves. The building was modelled and simulated to establish baseline consumption, with the modelling process being discussed further in chapter 5. The baseline consumption serves as the foundation for assessing the potential for DR. Demand curves, shown in Figure 4 and Figure 5 below, represent the simulated heating and electrical demands of the case study building during a year.

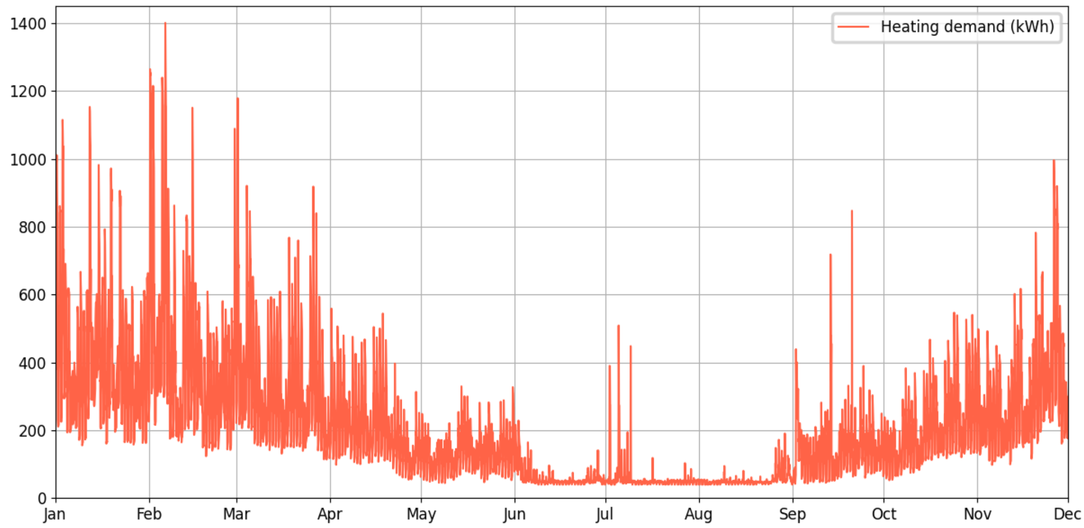


Figure 4. Annual heating demand curve (kWh) of the case study building. The heating demand includes space heating and domestic hot water (DHW).

On an annual scale, the heating consumption varies drastically thus indicating that potential for the demand response on the heating side exists on a theoretical level. The peaks observed in the heating consumption emerge as particularly significant focal points for the implementation of efficient DR measures.

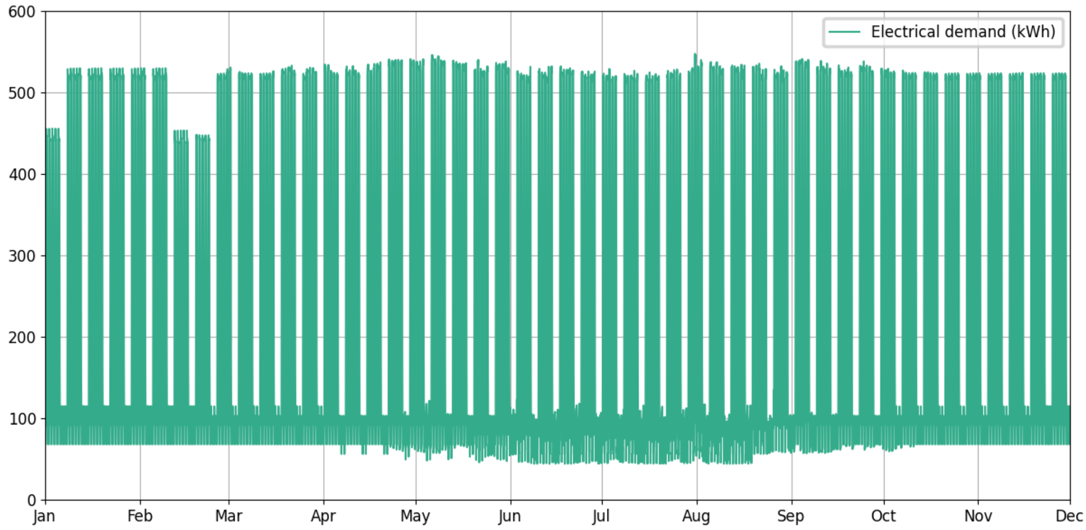
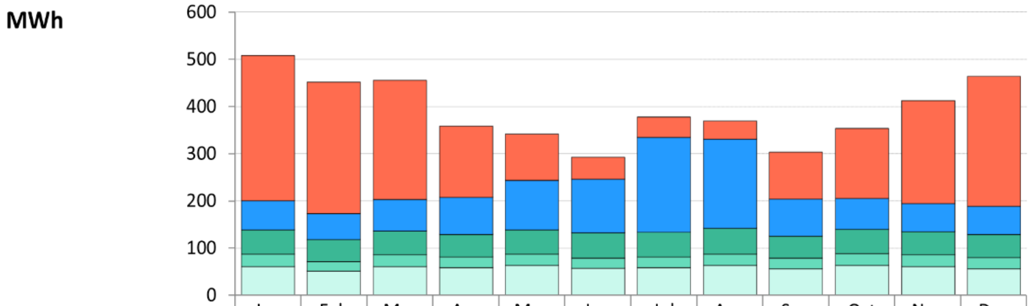


Figure 5. Annual electrical demand curve (kWh) of the case study building.

On the electrical consumption side, as seen in Figure 5 above, there exists certain base load constantly throughout the year, with fluctuations occurring in accordance with daily and weekly usage cycles. Despite these fluctuations, peaks in the electrical demand occur regularly without significant deviation, suggesting a recurring pattern in the consumption behaviour. The peak values are mainly caused by the HVAC and equipment electricity. Given the regularity of the peak demand occurrences, there exists an opportunity to deploy DR measures more uniformly across various time periods and usage cycles. The electrical demand curve shown in Figure 5 represents the electricity gross need which includes the user and building electricity usages, and the electricity needed for heating, cooling and ventilation. The electrical demand curve is derived from simulated values, which in itself causes distortions and makes the curve's shape more recurring compared to the actual values.

In the Figure 6 below, aggregated monthly energy needs of the building are shown. The demand is divided into three categories – heating, cooling and electricity – with the last one divided into three subcategories: HVAC and other electricity, lighting and equipment electricity. The heating demand, like the cooling demand, shows monthly variations in its profile in relation to different seasons. The electricity demand remains consistent throughout the year, independent of seasonal changes. The stability of the electricity demand primarily stems from its reduced reliance on outdoor temperature fluctuations, alongside the consistent occupancy rate.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Heating demand	307	278	251	151	98	46	43	39	99	148	217	275
Cooling demand	62	55	67	79	106	114	201	189	78	65	60	60
HVAC, other electricity	51	45	50	48	51	53	53	55	47	51	49	49
Lighting electricity	26	21	25	23	24	21	22	24	22	26	25	24
Equipment electricity	61	52	62	59	64	58	59	63	57	64	61	57

Figure 6. Monthly energy needs (MWh) of the building across different demand types. The graph does not include electricity used for heating and cooling.

4.2 Loads suitable for demand response

Estimating and implementing demand response in buildings typically involves a control scheme. Numerous control techniques for building loads exist, which can be classified by their approach or characteristics. The type of the building model and the demand response estimation technique used significantly influence the benefits obtained from the DR implementation. (Goy and Finn, 2015) On the other hand, equally important is to identify the DR capable loads inside the case study building and how their DR activation would affect the building's functionality, and the level of comfort experienced by the users.

The focus on this thesis will be on few chosen loads which are generally key components for the operationality of any building. These such loads are ventilation, lighting, and heat pump. The HVAC system is responsible for heating buildings, supplying fresh air, and transferring air from indoors to outdoors. Demand response in HVAC systems is possible because buildings possess high internal thermal mass, which acts as a natural thermal energy storage. Additionally, the oxygen buffer in the room air allows for temporary shutdowns of ventilation. Modern HVAC systems typically comprise one or more Air Handling Units (AHUs), each equipped with several Variable Air Volume (VAV) units and supply fans. The AHU regulates the air temperature by chilling or heating it to a specified set point, while the VAV units control the flow volume of the conditioned air. (Kalaimani *et al.*, 2018) The supply fans distribute air throughout the HVAC system. An important aspect in using the HVAC systems for the DR purposes is ensuring that the impact on the indoor air temperature is considered so that the comfort level remains satisfied throughout the demand response actions. The challenges with HVAC systems for the DR operation lie in the system energy efficiency. Wang, Wang and Tang (2019) conclude that HVAC systems can consume more energy when providing frequency regulation compared to normal operation. Additionally, the power consumption of the components involved in the frequency regulation can be significantly impacted, leading to efficiency losses. Therefore, activating DR in the HVAC systems implies that possible additional costs compared to the baseline operation may occur.

In a project carried out at Granlund Oy in 2019, it was discovered that the demand response potential of a ventilation is sensitive to changes in educational/office spaces. If indoor conditions are already poor, ventilation cannot be adjusted, especially when spaces are overcrowded. Adjusting ventilation units is more complex than adjusting radiator systems, and buildings should focus on large ventilation units. Reducing the ventilation decreases radiators' power needs but temporarily raises CO_2 levels, becoming noticeable for the users after the CO_2 concentration rises high enough. However, predicting the ventilation's demand response is straightforward, relying only on the air volume and the outdoor temperature. Regarding heating, it was discovered that the demand response with the radiator system may cause a draft feeling, even if the measured indoor conditions remain stable. A hot radiator prevents cold air from flowing downward in front of a window. Lowering the radiator temperature can exceed this critical temperature, causing the air to flow downward and create a draft feeling, even if the indoor temperature stays at normal level. Adjusting the radiator systems require less effort than ventilation units. The radiator system adjustments, implemented as reduction adjustments, lower the indoor temperature, while the ventilation adjustments, also part of the reduction measures, raise it. The operative temperature reacts more quickly to changed conditions than the indoor temperature. Therefore, to reduce the feeling of draft, utilising demand response for both the ventilation and radiator systems simultaneously would be the optimal option for indoor conditions.

Lighting is one of the easiest and fastest loads to use for demand response. Lighting is generally turned on during opening hours and off during closing hours. Lighting can respond within milliseconds and support demand response over extended durations. However, buildings participating in the reserve markets typically need dimmable lighting since completely turning off lights during opening hours is seldom feasible. Sectional control may also offer a solution for adjusting the lighting levels. (Kurkinen, 2018) The main challenge with the lighting is the effectivity of its use in demand response. Lighting itself does not consume too much electricity – except in cases like greenhouses – which means that the benefits of the demand response might stay low. However, if the gross floor area square metre is significantly high, the combined lighting consumption could present a relatively substantial demand response potential. Nevertheless, lighting generally represents a small proportion of overall consumption in relation to the floor area.

Heat pumps are used in buildings for energy efficient heating and cooling purposes. Heat pumps work in reverse compared to chillers as they extract heat from air, water or ground and transfer thermal energy using a refrigeration cycle. Heat pumps consume electricity to transfer energy rather than generate it, which makes them generally very energy efficient devices. Regarding the demand response, heat pumps have a very interesting role. DR with the heat pumps is typically managed according to the electricity prices and during these times, demand can be reduced manually or automatically, either by the property owner or an external party. Sometimes, demand reduction is preceded by increased power to pre-heat the building, charging its thermal mass and raising the internal air temperature. More commonly, automated third-party control is used. (Crawley *et al.*, 2023) However, utilising demand response has an impact on the electricity consumption of the heat pumps. The electricity consumption of the heat pumps increases significantly when they are utilised for demand response. Despite the notable increase in the electricity consumption, this approach still results in additional savings. Moreover, the increased electricity consumption by heat pumps corresponds to a decrease in district heating consumption, resulting in overall savings. (Nieminen, 2024)

4.3 The progress of the DR in the case building

In Figure 7 below, the flow chart regarding the impact of the loads participating in the demand response on the building's performance is presented. In Table 3 below, the comfort level limits set for the educational building in the case study are presented. Most of the limits are chosen according to the boundaries set by the Finnish Society of Indoor Air Quality.

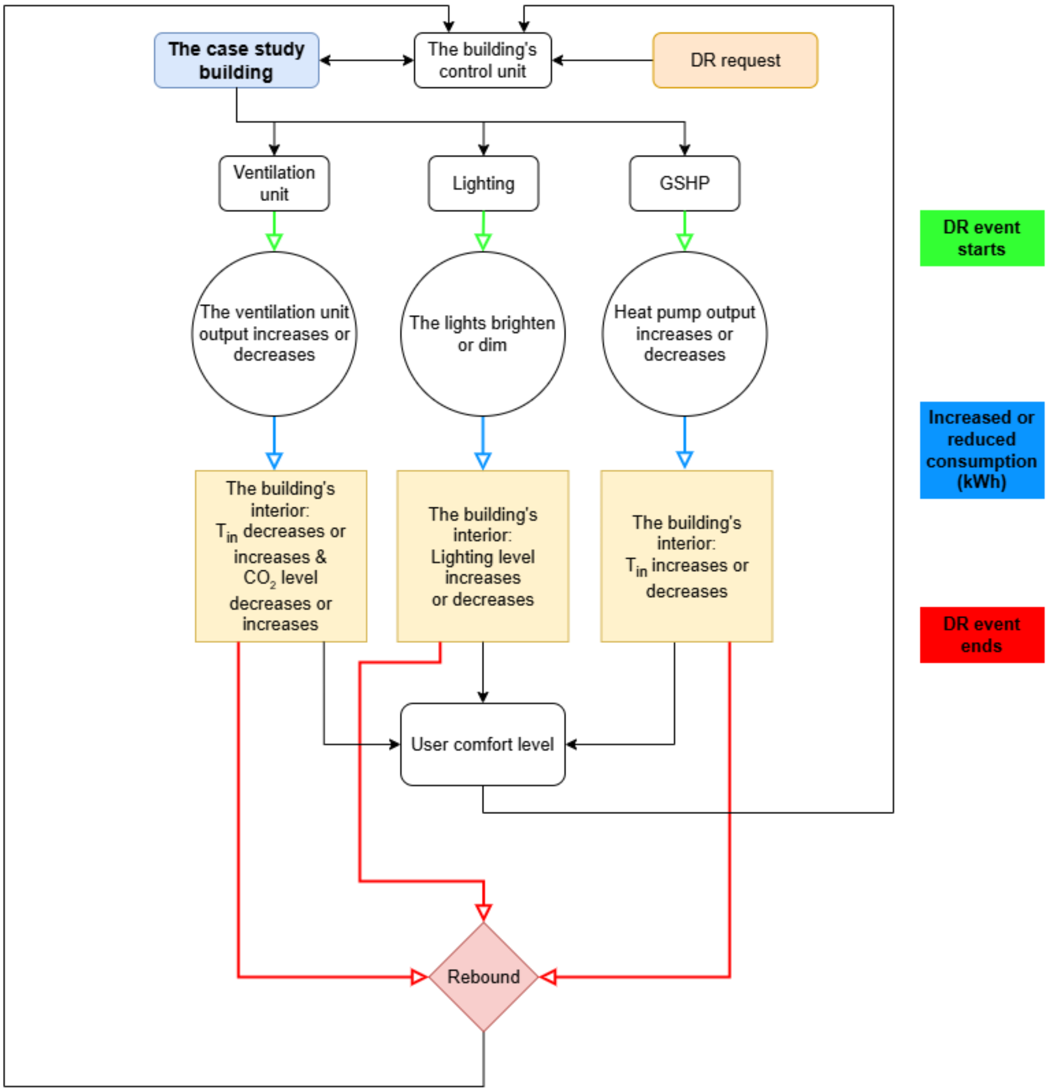


Figure 7. The flow chart representing the progress of demand response in the case study building during either downregulation or upregulation.

Table 3. The comfort level limits set for this case study. The first three limits are chosen according to Finnish Indoor Climate Classification S2 (Säteri, 2018; Suomen Ilmanvaihtosaneeraus, 2024).

User comfort level limits	
T_{in} (min.)	20 °C
T_{in} (max.)	27 °C
CO_2 (max.)	900 ppm
Lighting level (min.)	75% of the normal level

As can be seen from the flow chart above, the progress of demand response in the building is fundamentally straightforward process which affects the parameter levels introduced in Table 3. One of the key requirements for the DR is that the user comfort level limits from Table 3 should not be exceeded.

Up-directional demand response itself results in electricity savings, but it can also cause a so-called rebound effect which temporarily increases the electricity usage of a unit after the demand response event to compensate for the 'lost' energy. The cause of this rebound effect is that when the DR shifts peak demands to off-peak periods, it can potentially create a new peak. When determining the demand response schedule, it is essential to consider both the load profile and the voltage profile, as the required time for demand reduction and voltage regulation may differ. (Shi *et al.*, 2014). However, the voltage profile is not considered to be a limiting factor within this thesis. The demand response events in our case study building are divided into three options: the ventilation unit, the lighting and the GSHP. The DR request initiates the event and the building's control unit is the first to receive it and act upon it. The building's control unit is connected to the case building and its electrical systems. Via the control unit, different demand response adaptations can be implemented either individually or simultaneously. Demand response can be executed at varying magnitudes, ranging from completely turning off electrical units to turning them on to full power, or making just minor adjustments. Depending on the unit(s) chosen for the DR event, the effects can be observed within the building's interior, impacting the user comfort level. After the DR event ends, electrical appliances often experience a rebound effect.

A DR event can be initiated in the building if, for example, it is known that the electricity price is high within a certain time frame. However, if the time frame is in the middle of the day, as the highest occupancy rate usually is, it may not be possible to initiate a full demand response due to high demand for electricity or because the electrical units are already at full power. Usually, schedules and conditions are the simplest determinants of flexibility. Outside the busiest hours, for example, during the nighttime, DR could be implemented regularly as soon as the conditions are reasonable. The conditions normally include various factors like the weather, occupancy levels, and indoor temperature and CO_2 levels.

5 Calculation tool development process

In this chapter, the development process of the raw calculation model for identifying the demand response potential in buildings is presented. The first step is to introduce the modelled sub-assembly of the case study building which will be used for simulating different DR scenarios to provide insight into the behaviour of parameters associated for example with the rooms, air handling units, heat losses and energy consumption. In the second step, the scenarios for implementing DR are identified. This step will also require simplifications so that the comparison can be kept as linear as possible. The third step will consist of two phases: first, Python programming language will be integrated into the simulation to implement different DR scenarios. Secondly, the results file will be processed after the simulations using Python to visually and numerically present the obtained results from each scenario. In the fourth step, schedule deviations are generated based on the reserve and day-ahead market data. The deviations, combined with the user input values for the magnitude factor, will be integrated into the simulation to capture the quantity of demand response impact during each hour. The fifth and final stage of the development process presents the completed raw model, which can semi-automatically provide insights into the magnitude of different DR strategies within the modelled building, particularly in terms of energy impact (kWh). The model can demonstrate the demand response potential over an annual period or across shorter temporal intervals.

The calculations within the developed tool will utilise Granlund Oy's energy simulation tool, which is also employed to model the case study building. The raw model simply uses the energy simulation tool as its framework, with all the computations and the results achieved through it. However, in this initial version, the focus is on modelling the demand response in the building using Python programming. The long-term objective beyond this thesis is to further develop this into a comprehensive feature, potentially integrated into the energy simulation tool. The reason for choosing this tool is that it was specifically developed for situations where there is a desire to simulate only the performance of the building's energy systems based on the actual consumption. The tool is particularly well-suited for energy efficiency measures carried out in existing buildings or new developments, of which the demand response is one of the key measures to consider now and in the future. Other favourable aspect is that the tool can calculate several parallel energy-saving scenarios which can then be used for assessing the potentiality of different demand response strategies. Additionally, this energy simulation tool is computationally less demanding than, for example, IDA Indoor Climate and Energy simulation software and it could, in theory, enable automated analysis for a large number of buildings in the future.

The process demonstrated in this thesis represents a raw model of the calculation tool, which will conceivably require multiple development cycles to achieve a fully operational state with sufficient accuracy for detailed analysis. The main objective of this model is to demonstrate the building's DR potential and present indicative returns by utilising various marketplaces. This version of the model incorporates several simplifications, along with inherent shortcomings and limitations, not all of which can be addressed within the scope of this study. These aspects will be examined in greater detail in the following chapters.

5.1 The model of the case study building

As described in the chapter 4.1, the case study building comprises 7 floors (one of which serves as a basement) and approximately 23 000 m^2 of heated space. For this development process, the model itself is narrowed down to the third and fourth floors to reduce the complexity of the modelling and to better facilitate the integration of external programming. Thus, the obtained results represent roughly one-third of the case study building. The results are not multiplied by a factor of three because each floor has a different number of individual AHUs with varying schedules, and the same principle applies to lighting, for example. Consequently, obtaining reliable insights into the DR potential for the entire building would necessitate modelling the building in its entirety. However, the building's floors are highly interdependent and share significant similarities, so the building itself does not impose limitations on demonstrating the initial DR potential using only two floors as a basis. The basement was neglected entirely from consideration due to it being unimportant to be of concern. The modelling is conducted using Granlund Oy's own energy simulation tool and the result in 3D can be seen below in Figure 8.

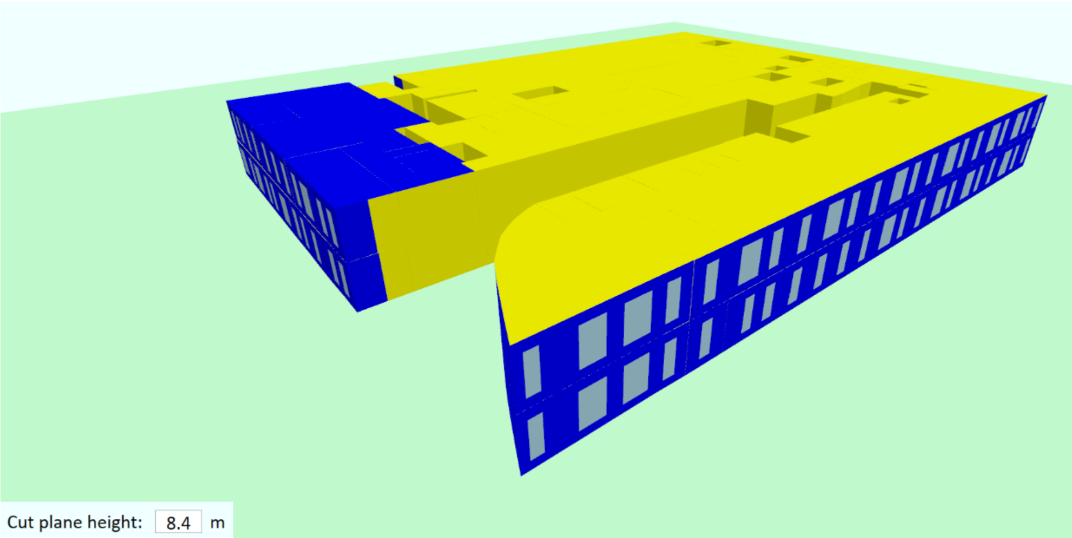


Figure 8. The model of the case study building showing the floors three and four. The yellow colour indicates that the structure is in contact with indoor air, while the blue colour shows that the structure is in contact with outdoor air.

The two floors in this model include a total of 185 spaces with majority being offices, laboratories or teaching spaces. The gaps between the structures, as shown in Figure 8, represent various unheated spaces, such as elevator shafts, which are excluded from the simulation to avoid unnecessary distortion of the calculation. The height of each floor is 4.2 meters with 0.5 meters belonging to the midsole. Each room is associated with a specific AHU. There are 12 AHUs across these two floors. The heating system of the building is designed to efficiently harness multiple energy sources and comprises three key components: a district heating, a brine source heat pump utilising boreholes, and solar panels. Similarly, the building's cooling system incorporates ground and district cooling.

Table 4 and Table 5 provide a detailed overview of all the room types within the case study building, including their set-point temperatures, airflows, air handling unit types, and lighting and equipment loads. The values presented here are indicative of the baseline situation, serving as a reference point. The case study building primarily comprises basic offices, teaching rooms, and laboratories, each with distinct occupancy schedules. The spaces distributed across these two floors are organised into seven distinct room types, each categorised based on its intended function and designed to accommodate unique patterns of use. For each room type, a specific occupancy profile has been developed.

Table 4. The simulation model data related to the heating and cooling of different room types in the case study building. Room types arranged by their count in the dataset.

Detailed overview of all the room types					
Room type	*Min. T set-point (°C)*	*Max. T set-point (°C)*	*Supply air flow (l/s, m²), average*	*Return air flow (l/s, m²), average*	*AHU type*
Office	20	27	1.9	1.9	CAV
Laboratory	20	27	2.0	2.0	CAV
Toilet	20	27	4.9	4.9	CAV
Other	20	27	85.4	85.4	CAV
Corridor	20	27	1.9	1.9	CAV
Storage	20	27	1.7	1.7	CAV
Stairwell	20	27	0.4	0.4	CAV

Table 5. The simulation model data related to the occupancy, lighting and equipment loads of different room types in the case study building. Room types arranged by their count in the dataset.

Detailed overview of all the room types			
Room type	*Occupancy (persons/room), average*	*Lighting (W/m²), average*	*Equipment (W/m²), average*
Office	6.5	6.2	14.4
Laboratory	2.9	5.9	13.9
Toilet	-	6.0	-
Other	-	65.8	84.9
Corridor	7.3	6.2	3.0
Storage	0.2	3.2	3.6
Stairwell	-	6.1	-

Figure 9 below shows all seven occupancy, lighting, and equipment schedules used, with the specific schedules applied to each room type detailed in Table 6 below. Some room types use two different schedules, with one of them consistently being the 'Always off' schedule. This schedule signifies that the loads remain at zero continuously in certain rooms. It is important to note that all the schedules presented apply exclusively to weekdays. On weekends, when the building is not in use, most loads are assumed to be zero, with only a few rooms as exceptions.

Figure 9. The schedules used for occupancy, lighting and equipment during the weekdays. The height of the blue shape represents the magnitude of the profile for a single hour, while the width of the blue shape represents the duration.

Table 6. The occupancy, lighting and equipment schedules used by each room type during the weekdays. Room types arranged by their count in the dataset.

Load schedules by the room type			
Room type	*Occupancy*	*Lighting (W/m^2)*	*Equipment (W/m^2)*
Office	Office	Office	Office
Laboratory	Laboratory	Laboratory	Laboratory
Toilet	Always off	Toilet	Always off
Other	Always off	Always off and Other	Always off and Other
Corridor	Always off and Corridor	Corridor	Always off and Corridor
Storage	Always off and Storage	Always off and Storage	Always off and Storage
Stairwell	Always off	Stairwell	Always off

Additionally, this case study building has five distinct schedules for the AHUs and one for the GSHP. One of the AHU schedules controls toilet ventilation, making it an unsuitable target for the DR due to potential odor issues, and is therefore excluded from the study. Also, the case study building contains a significant number of specialised laboratories, classified as unique spaces, which are unsuitable for the DR schemes involving ventilation adjustments. As a result, the AHUs in these rooms are excluded from the study, which considerably reduces the number of available rooms where the AHUs can be adjusted. In general, the AHU names are less descriptive than the room types, and the schedules are quite similar, so they are not further detailed in this chapter. The same reasoning applies to the heat pump schedule.

5.2 Demand response scenarios

Several demand response scenarios are explored to understand the potential flexibility of the case study building under different conditions. The aim is to assess how the building's energy systems can be adjusted to participate in demand response while maintaining operational efficiency and user comfort. The scenarios are selected based on the building's load types and the potential for shifting or shedding these loads when the electricity and reserve market prices are high enough to make a response profitable.

1. **AHUs:** The operation schedules for AHUs are carefully adjusted to provide substantial flexibility in managing energy consumption during demand response events. Manual verifications with the energy simulation tool for the case study building revealed that the AHU output could be temporarily lowered to 90% of its standard level without

breaching indoor comfort level limits. This value is used for the remainder of this thesis. As evidenced, the AHUs are crucial for maintaining indoor air quality and comfort by regulating air temperature, humidity, and ventilation within the building. For DR events, the AHUs can have their output reduced, or alternatively, their output can be increased. Adjusting the AHUs not only provides an opportunity to reduce energy consumption and respond to high electricity prices, but it also enables participation in reserve markets. By decreasing or increasing the AHU output during specific periods, the building can take advantage of the reserve market prices and generate additional profits, provided the energy cost increase is less than the compensation received from the reserve market.

Reducing the output of the AHUs lowers energy consumption and addresses high electricity prices. Increasing their output, however, increases energy consumption and operating costs, which may offset some of the potential profits achieved through the DR. To ensure that the adjustments do not compromise indoor air quality or occupant comfort, specific conditions must be met. Firstly, the indoor CO_2 levels must remain below a maximum threshold to ensure adequate ventilation and air quality. High CO_2 levels can lead to discomfort and reduced cognitive function for occupants, so maintaining these levels within safe limits is essential. Secondly, indoor temperatures must also stay within a defined range, typically between 20 °C and 27 °C, as outlined in Table 3 in chapter 4.3. By monitoring these parameters closely, the AHUs can be operated more flexibly without negatively impacting the building's indoor environment. The ability to adjust AHU operation provides a significant opportunity for demand response, as it allows the building not only to reduce its energy consumption but also to increase it when the reserve market conditions are optimal, without sacrificing indoor air quality or comfort. This dual approach enables the building to participate in DR more efficiently.

2. **Lighting:** In this scenario, the lighting in selected rooms is reduced to 75% of normal levels during DR events. By lowering lighting in these areas, the building can achieve substantial energy savings while ensuring that the occupant comfort and safety are maintained. The factor of 75% is chosen as studies have shown that the human eye perceives light on a logarithmic scale. For example, when a light source is dimmed to 75%, the human eye perceives about 85% of the original light level. (Lee *et al.*, 2020) Thus, the impact on visibility in these spaces is minimal, as 75% lighting is typically sufficient for safe navigation and basic tasks. Newsham and Birt (2010) discussed that in

prior studies, 80% of participants found a 20-30% reduction in lighting to be acceptable in a room without daylight.

Lighting adjustments can also be used to increase energy consumption when advantageous conditions in the reserve market arise. By temporarily decreasing or increasing the lighting output, the building can respond to the reserve market signals and generate additional revenue. Increasing the output is only justified if the compensation received exceeds the cost of additional energy consumption. These approaches enable the building to participate in DR events by reducing or increasing energy use based on the reserve market conditions, achieving cost savings and profits without compromising operationality or occupant comfort.

3. **Heat pump:** With this configuration, the operation schedule of the GSHP is adjusted during the DR events. Manual verifications with the energy simulation tool for the case study building revealed that the GSHP's output could be temporarily lowered to 50% of its standard level without breaching indoor comfort level limits. This value is used for the remainder of this thesis. The heat pump's output can be increased as well but in the case study building's baseline simulations, the heat pump was configured to operate at maximum power continuously. Thus, the case study building's heat pump cannot participate in downregulation, and it can only be operated at a reduced capacity to capitalise on favorable reserve market conditions. Generally, while reducing the output of the GSHP directly lowers energy consumption, increasing its capacity would allow the building to store thermal energy, which can be, for example, utilised during subsequent DR events to reduce or avoid energy usage when electricity prices are high. Additionally, by decreasing or increasing the GSHP's output during favorable reserve market conditions, the building can generate additional profits from providing capacity. Regarding the increase in output, this only applies if the compensation received outweighs the cost of increased energy consumption. These methods offer considerable flexibility, as they allow the building to leverage one of its most electricity-intensive systems to either reduce consumption or increase it strategically. Coordinating the GSHP adjustments allows the building to optimise DR participation, balancing cost savings and profits while keeping indoor temperatures reasonable.

To simplify the analysis, several assumptions were made regarding the operation of the energy systems during demand response events. These simplifications allow for a more straightforward comparison between different scenarios and facilitate the modeling process. Key simplifications are explained in the subchapter 5.2.1.

5.2.1 Simplifications

A key consideration in this study is whether the specific hours of DR participation for the building can be predetermined, as opposed to employing dynamic optimisation techniques. This alternative approach, which involves implementing a fixed schedule through analysing the past reserve market data, offers a more simplified framework for analysis. For the purposes of this thesis, adopting such a simplification is justified, as it allows for a more streamlined investigation without the complexity of real-time optimisation. Real-time optimisation would also require a more advanced software environment with the possibility of iterating the calculation again as the real-time data is received. At present, the software performs a single calculation that provides results for a one-year period, with each iteration requiring manual re-execution. Given the current software framework, performing multiple iterations would be prohibitively time-consuming, and implementing such functionality would require significant additional development to accommodate the increased computational demand and automation. Therefore, for instance, the authentication of rebound effect was excluded from the calculation process. The integration of the reserve market data into the schedules is detailed in subsection 5.4.

Another simplification in the approach arises from the variability in procurement channels, minimum capacity requirements, and the activation performance across different marketplaces, as illustrated in Table 1. Each marketplace imposes distinct constraints, including specific requirements for capacity thresholds and activation standards, which can influence participation in demand response programs. In this thesis, it is assumed that the capacity thresholds are met with the use of independent aggregation, which is already possible for FCR-D, FCR-N and FFR products. In aFRR and mFRR markets, independent aggregation is estimated to be allowed during 2025 and 2026, respectively. (Fingrid, 2024e) Also, the mFRR market permanence factors or any penalty fees from unprovided capacity are not considered (Fingrid, 2024k). Other constraints are excluded from the analysis, as the primary focus lies on evaluating the demand response potential and its profitability. By abstracting away marketplace-specific limitations, a broader assessment is enabled, highlighting generalisable insights into the DR feasibility.

These simplified approaches provide a clear and manageable starting point for developing the raw model of the calculation tool. However, it also leaves room for future development, where more sophisticated methods, such as DR potential forecasting and real-time optimisation, could be explored to achieve more accurate and responsive potential identification. Each demand response scenario incorporates simplifications to facilitate a more straightforward calculation process. Additionally, the number of individual DR events per day in each scenario is limited to four; however, on the majority of days, only one or two events are observed per day.

In scenario 1, the DR events initialised usually account for multiple AHUs at once as a single schedule may be in use for several different AHUs. The number of AHUs affected by certain schedule can be either one or three. Also, the number of rooms connected to a single AHU varies considerably. To further improve the accuracy of potential calculation, each AHU should be allocated with its own schedule, making calculation at this stage unnecessarily complex and time-consuming. By accounting for multiple AHUs in a single DR event, the results are likely to be more favorable, as participation with only one AHU would arguably have minimal energy-impact in a building of this scale.

Scenario 2 has very similar circumstances as described previously. The lighting schedules are organised based on the room types, with each category typically comprising several dozen individual rooms. As a result, adjusting one lighting schedule during the DR event can impact a significant portion of the building. Although lighting would typically function independently for each room, the schedules were grouped by room categories to simplify the calculations. Additionally, the lighting of a single room does not significantly impact the building's overall electricity consumption. This approach not only simplifies the calculation process, but it also makes it easier to have all rooms participating in the DR event, resulting in higher potential and savings.

Scenario 3 shares many similarities with the previously described scenarios. In this case, however, the focus shifts to the space and AHU heating. Adjusting the GSHP usage schedule will substantially impact the whole building's overall energy consumption. The heat pump is connected to the room and AHU heating systems, so any adjustments in the heat pump schedule will affect all the rooms and the AHUs. This occurs solely due to limitations in the energy simulation tool, which does not allow for specifying which individual room or AHU would be impacted by the adjustments to the heat pump; therefore, it affects all of them. This simplification allows for easier participation of the heat pump during the DR event, enhancing the overall energy-saving potential of the building.

In prior studies by Sihvonen (2017) and Kurkinen (2019) on applying demand response in office and school loads, specific durations were established for demand response events and recovery periods, particularly for the lighting and ventilation systems. In the office environment, the lighting was estimated to participate in demand response for up to two consecutive hours, followed by a one-hour recovery period. The ventilation systems, in contrast, could participate in DR for three consecutive hours, requiring a two-hour recovery period afterward. In the school environment, the lighting could engage in DR for up to four consecutive hours, followed by a one-hour recovery period, while the ventilation was limited to 15 minutes of demand response, followed by a one-hour recovery period. The case study building is a combination of educational and office features and thus, for the purposes of this thesis, it is estimated that lighting can participate in demand response for three consecutive hours, followed by a one-hour recovery period. For ventilation, the estimated duration is two consecutive hours of demand response, followed by a two-hour recovery period. These values are only applied during upregulation.

In prior studies by Sihvonen (2017), Kurkinen (2019) and Nieminen (2024) on utilising heat pump in demand response, three-hour period for consecutive participation was used, followed by one-hour recovery period. Crawley *et al.* (2023) focused on reducing heat pump electricity demand in three-hour periods. The recovery period was not specified. Thus, for the remainder of this thesis, it is estimated that the heat pump can participate in demand response for three hours, followed by a one-hour recovery period. These values are only applied during upregulation.

5.3 Implementation of Python

For simulating the scenarios within the framework of the energy simulation tool, Python programming language is implemented. The external code scripts would parametrically execute the simulations and execute the analysis of the results, to replicate and analyse the DR event as accurately as possible. Python offers a powerful and efficient approach to automate the extraction and processing of the schedule deviation data – which will be discussed later in subsection 5.4.2 – and subsequently interacting with the external energy simulation tool. By leveraging Python libraries such as *pandas* and *openpyxl*, the implementation reads and manipulates input data from Excel dynamically, allowing for the updating of the schedules based on the calculated deviations. To interface with the energy simulation tool, *pywinauto* is employed to automate graphical user interface (GUI). This allows the script to control the application programmatically, simulating user actions. It reduces efficiently the potential for manual errors and significantly speeds up the process of updating software configurations. Additionally, the implementation of the Python-based approach ensures that the process is scalable, meaning that it can handle a large and varying number of deviations.

Figure 10 below displays all the necessary Python libraries, along with the implemented function names and their inputs for the automated simulation process script. Additionally, Appendix A contains the Python libraries, function names, and their inputs used in a script for setting up the schedules for the process. Appendix B contains the Python libraries, function names, and their inputs used in two separate scripts for processing and generating the results.

```
import time
import pandas as pd
import Deviations_testing
from Choice_of_reserve import open_single_select_popup
from Choice_of_reserve import open_schedule_select_popup

from tkinter import messagebox
from subprocess import Popen
from pywinauto import application
from datetime import datetime
from pywinauto.keyboard import send_keys

# Definition of a new class named "application"
class application():

# Setting up the application and the model
def __init__(self):
def open_application(self):
def open_file(self):

# Parametric run of the DR
def set_value_range(self, value_range_window, from_hour, to_hour, value):
def select_date(self, deviation_window, date_str, calendar_button_index):
def open_manage_schedules_window(self, case_number):
def modify_schedule(self, case_number, schedule_name, add_deviation,
deviations):
def case(self, case_number, schedule_name,
add_deviation, start_date=None, end_date=None,
normal_hours_from_1=None, normal_hours_to_1=None, normal_value_1=None,
normal_hours_from_2=None, normal_hours_to_2=None, normal_value_2=None,
normal_hours_from_3=None, normal_hours_to_3=None, normal_value_3=None,
hours_from_1=None, hours_to_1=None, first_value=None,
hours_from_2=None, hours_to_2=None, second_value=None,
hours_from_3=None, hours_to_3=None, third_value=None,
hours_from_4=None, hours_to_4=None, fourth_value=None):

# Execution of the simulation and closing the application
def simulation(self):
def close_application(self):
```

Figure 10. The implemented Python libraries, function names and inputs in the automated simulation process. The syntax *self* refers to the current instance of the class.

5.4 Integration of the market data

For the integration of the market data, real data from the Finnish reserve markets and the day-ahead market for the period of January 1, 2023, to December 31, 2023, is utilised. Notably, data for the aFRR energy market is included only from its launch in June 2024 until August 2024. The aFRR capacity market data is from January 1, 2024, to August 31, 2024, to ensure alignment of both markets over the same time period in the simulations. In the development of the calculation tool, each scenario is validated using data from a three-month period, which is sufficient to demonstrate the functionality of the raw model. The period from June 1 to August 31 was selected to enable an analysis of both heating and cooling dynamics within the simulations, despite the predominance of the cooling requirements during the summer months. This approach also ensures unbiased utilisation of the aFRR energy market data, as it avoids the need for extrapolation that would otherwise be required for a full-year simulation. The reserve market data is obtained from Fingrid Open Data platform (Fingrid Open Data, 2024). The day-ahead market data is obtained directly from the European Network of Transmission System Operators for Electricity (ENTSO-E) through an application programming interface (API) connection created by Granlund Oy.

5.4.1 Day-ahead market data

The day-ahead market data is the only electricity price data that is integrated into the calculation tool. The day-ahead market data originally excludes taxes, electricity distribution fees, basic fees for electricity and demand charges. Some of these costs are incorporated into the model to provide a more accurate and realistic representation from a cost perspective.

In Finland, the total price of electricity consists of three components: the price of electricity, the price of network services, and the electricity and value added taxes. The price of electricity is a consumption-based component, and the price of network services consists of the electricity distribution fee and various taxes. (Energiateollisuus, 2024) The average consumer also pays various monthly basic fees for electricity, which vary significantly depending on the contract type and the specific electricity retail and distribution companies. In the calculation tool, the most common fees are added to the day-ahead market prices to offer a more realistic approach to demand response calculations, as these fees would need to be accounted for regardless. Monthly fees are excluded because they vary significantly based on the contract type and they are not impacted by demand response activations. Additionally, the electricity supplier's margin per kWh, i.e., the commission fee, is not included in the calculations, as it varies significantly between different electricity suppliers. The general Value Added Tax (VAT), 25.5%, is not included. The fees included are the electricity tax (tax bracket 1), 2.253 c/kWh (incl. security of supply charge) and the power distribution 1 LV, 3.52 c/kWh (VAT 0%) (Finnish Tax Administration, 2022; Caruna, 2024a). The low-voltage network power transmission product 1 is suitable for larger buildings, as the case study building, which have main fuses rated at over 63 A and the electricity consumption is over 80 MWh in a year (Caruna, 2024b). For example, during 26th of June 2023 at 19:00 (EEST) the day-ahead price for electricity was 100 €/MWh. After adding the fees, the actual electricity price can be calculated using the equation (4):

$$\left[\left(100\frac{€}{MWh}\right)+\left(2.253\frac{c}{kWh}\times 10\frac{\frac{c}{€}}{\frac{kWh}{MWh}}\right)+\left(3.52\frac{c}{kWh}\times 10\frac{\frac{c}{€}}{\frac{kWh}{MWh}}\right)\right]= 157.73\frac{€}{MWh} \tag{4}$$

The day-ahead prices affect directly the result of whether buildings will profit from participating in the downregulation within the reserve markets. During the downregulation, which requires an increase in consumption (notation Q), participation in the reserve market becomes unprofitable if the marginal price (notation C) offered by the market is lower than the day-ahead price (including additional fees) at hour h, as the operational costs would exceed the compensation received. This relationship can be mathematically expressed using the equation presented in (5).

$$C_{h,reserve}\times Q_{increased} < \left(C_{h,day-ahead}+C_{h,fees}\right)\times Q_{increased} \tag{5}$$

Thus, the day-ahead market prices not only influence the operational decisions but also determine the attractiveness of engaging in the reserve market activities, directly impacting the economic outcomes for participating entities. In some cases, it may be possible that providing DR for aFRR and mFRR energy markets incurs costs only for balancing energy, rather than incorporating the day-ahead price as well, with the balancing energy procured from Fingrid. Consequently, increasing consumption would result in charges solely for balancing energy rather than both balancing and day-ahead prices. However, this is entirely a contractual matter and highly dependent on the specific circumstances.

5.4.2 Reserve market procurement and price data

The reserve markets that are integrated into the calculation tool are aFRR, FCR-N, FCR-D, FFR and mFRR. Among these markets, the aFRR and the mFRR include separate capacity and energy markets; however, when evaluating the capacity market, the energy market must be considered concurrently. In contrast, when focusing solely on the energy market, the capacity market can be considered optionally. Also, every market, except for the FFR, is divided into upregulation and downregulation. The FFR market only requires a decrease in consumption, which is considered upregulation from the consumer's perspective. This increases the total number of marketplaces to 12, allowing the simulation to be conducted on each of them.

The reserve markets are integrated into the model, utilising procurement and price data to produce deviations for each specific schedule and reserve marketplace. The deviations represent individual DR events, and the number of them is limited to four during a single day. These deviations reflect the optimal behaviour of a participant actively engaging in the markets by placing offers to provide demand response. This idealised behaviour is then applied to the scenarios within the energy simulation tool, which models differentiated energy consumption patterns. These patterns reveal the theoretical maximum impact on consumption when participating in demand response under optimal conditions. A key element in determining these deviations is the magnitude factor of the demand response, which quantifies the amount of electricity and/or heat adjusted during the DR event. This factor is determined by the user input, with distinct values assigned for each three-month period. The periods align with the seasons, and they are December-February, March-May, June-August and September-November. Additionally, the values are categorised into two groups: weekdays and weekends. Since each season comprises three months, the user is required to input a total of eight values to account for both seasonal and weekly variations. The values also affect directly the indoor conditions of the building as they – depending on the scenario – control the ventilation, heating and cooling. The conditions cannot exceed the user comfort level limits, so the user is required to manually iterate the eight input values to ensure that the conditions remain feasible throughout each season. This estimation scheme is presented in Figure 11 below.

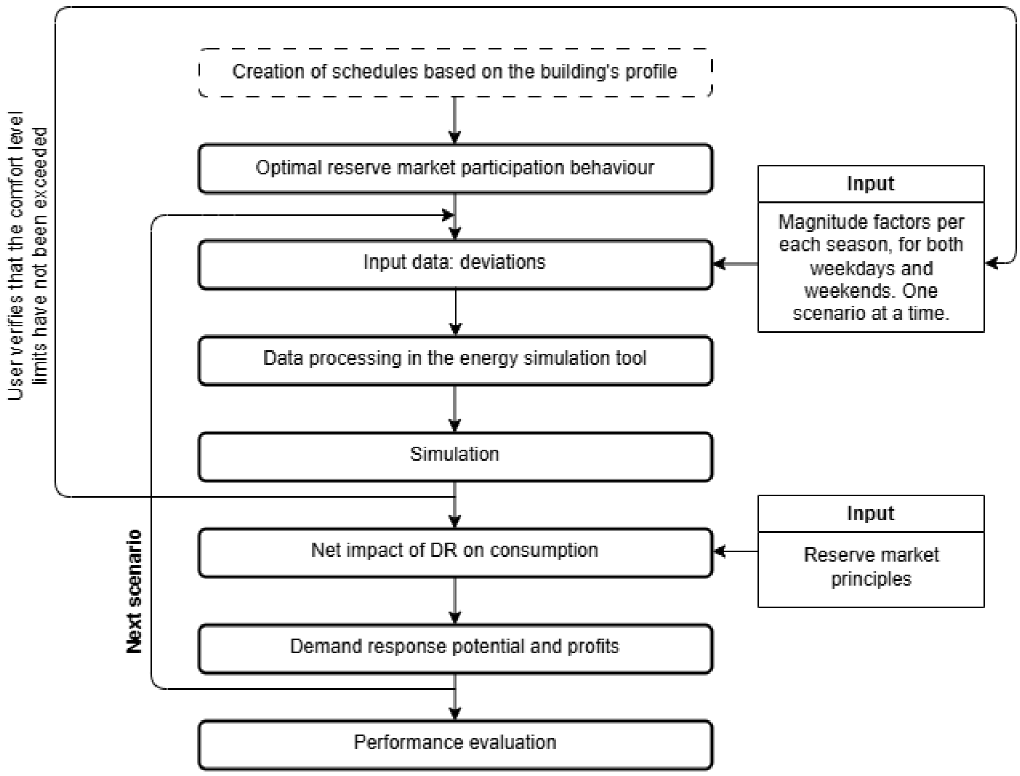


Figure 11. Process chart of the estimation scheme of the demand response potential within one chosen reserve market.

The estimation scheme, as shown in Figure 11, outlines the process steps required to generate the final results from the raw model. The results are produced one scenario at a time, meaning it takes three estimation cycles to obtain the final results for a single marketplace. Process element with dashed outline indicates that this step is neither scenario- nor marketplace-dependent, meaning its data remains unchanged between the simulations for different reserve markets. Deviations serve as the primary input for the energy simulation tool and are dependent on both the scenario and the marketplace. As a result, the data may need to be iterated multiple times to ensure the results meet the specified comfort level limits. Appendix C shows the different external data sources and tools used in relation to the estimation scheme.

The results obtained from the simulation based on the deviations capture the net impact of DR during each hour. These results do not represent the final results on the demand response potential. The net impact, based on the specific reserve market, predominantly dictates only the hours during which offers can be submitted but also how the consumption behaves around the deviations. However, the available capacity varies each hour. Thus, a critical consideration in the offer placement is the energy impact. In the markets that necessitate only short-term activations, participation can occur more frequently with minimal operational disruption. Conversely, the markets requiring long-term activations impose a greater influence on the building's overall operational performance, thus reducing the number of hours for feasible participation. The results obtained from the simulation are further refined by applying the different reserve market principles and the conditions for reserve market product providers, along with insights into the energy impacts, yielding the final outcomes derived from the raw model. This will be discussed in chapter 5.5.3.

The idealised participation behaviour is calculated in Excel for each reserve market, utilising the procurement and price data from the markets alongside the time series of schedules for each scenario. The results consist of one-year time series of values (notation *Y*) ranging from 0 to 1, from which the deviations are generated for each schedule i in every scenario (notation {1,2,3}). The simplifications outlined in chapter 5.2.1 are incorporated into the participation behaviour. The day-ahead price referenced in the equations includes the fees detailed in chapter 5.4.1. The following Table 7 includes the parameters used in the equations between (6) and (24).

Table 7. The parameters used in the equations (6) to (24).

Parameters	
$\boldsymbol{A_{h,reserve\ market}}$	The procurement quantity of the reserve market for hour h.
$\boldsymbol{C_h}$	The marginal price compensated by the reserve market, the price for purchasing the mFRR or aFRR energy from Fingrid, or the day-ahead electricity price (incl. fees) at hour h. The second subscript indicates the context.
$\boldsymbol{E_{h,act.}}$	The energy activation percentage at hour h. Further discussed in section 5.4.3.
$\boldsymbol{S_{h,i}}$	The schedule's (notation i) value at hour h. S belongs to the closed interval [0, 1], representing the operating level of the schedule's electrical unit, where 1 indicates full power and 0 indicates an off state.
$\boldsymbol{Y_{h,i}}$	The value in the schedule's (notation i) participation behaviour time series at hour h. Y is a binary variable that can only take the value 0 (inactive) or 1 (active).
$\boldsymbol{IF(Parameter = 0; 0; 1)}$	The formula checks if the value of the parameter is equal to 0. If true, it returns 0. If false, it returns 1.
$\boldsymbol{AND(Parameter_1 = 0; Parameter_2 = 1)}$	The formula checks if multiple conditions inside it are true at the same time. If true, it returns True, otherwise it returns False.
$\boldsymbol{OR(Parameter_1 = 0; Parameter_2 = 1)}$	The formula checks if at least one of the conditions inside it is true. If true, it returns True, otherwise it returns False.
$\boldsymbol{\{1, 2, 3\}}$	The notation for scenario 1, 2 and 3.

The mathematical logic behind the generation of participation behaviour for each marketplace can be expressed in Excel followingly:

$$FFR_{\{1,2,3\}}: IF(A_{h,FFR} = 0; 0; 1) \tag{6}$$

$$FCR - D_{down,\{1,2,3\}}: IF\left(S_{h,i} = 1; 0; IF\left(A_{h,FCR-D_{down}} = 0; 0; IF\left(C_{h,FCR-D_{down}} < C_{h,day-ahead} \times E_{h,act.}; 0; 1\right)\right)\right) \tag{7}$$

$$FCR - D_{up,\{1\}}: IF\left(A_{h,FCR-D_{up}} = 0; 0; IF\left(S_{h,i} > 0; IF\left(OR\left(AND\left(Y_{h-1,i} = 0; Y_{h-2,i} = 1\right); AND\left(Y_{h-1,i} = 1; Y_{h-2,i} = 1\right)\right); 0; 1\right); 0\right)\right) \tag{8}$$

$$FCR - D_{up,\{2,3\}}: IF\left(A_{h,FCR-D_{up}} = 0; 0; IF\left(AND\left(S_{h,i} > 0; OR\left(Y_{h-1,i} \neq 1; Y_{h-2,i} \neq 1; Y_{h-3,i} \neq 1\right)\right); 1; 0\right)\right) \tag{9}$$

$$FCR - N_{down,\{1,2,3\}}: IF\left(S_{h,i} = 1; 0; IF\left(A_{h,FCR-N_{down}} = 0; 0; IF\left(C_{h,FCR-N_{down}} < C_{h,day-ahead} \times E_{h,act.}; 0; 1\right)\right)\right) \tag{10}$$

$$FCR - N_{up,\{1\}}: IF\left(A_{h,FCR-N_{up}} = 0; 0; IF\left(S_{h,i} > 0; IF\left(OR\left(AND\left(Y_{h-1,i} = 0; Y_{h-2,i} = 1\right); AND\left(Y_{h-1,i} = 1; Y_{h-2,i} = 1\right)\right); 0; 1\right); 0\right)\right) \tag{11}$$

$$FCR - N_{up,\{2,3\}}: IF\left(A_{h,FCR-N_{up}} = 0; 0; IF\left(AND\left(S_{h,i} > 0; OR\left(Y_{h-1,i} \neq 1; Y_{h-2,i} \neq 1; Y_{h-3,i} \neq 1\right)\right); 1; 0\right)\right) \tag{12}$$

The following equations apply to mFRR and aFRR capacity markets, both of which also require energy bids to be submitted to the energy market:

$$mFRR_{down,\{1,2,3\}}: IF\left(S_{h,i} = 1; 0; IF\left(A_{h,mFRR_{down,capacity}} = 0; 0; IF\left(A_{h,mFRR_{down,energy}} = 0; 1; IF\left(C_{h,mFRR_{down,capacity}} - C_{h,mFRR_{down,energy}} < C_{h,day-ahead}; 0; 1\right)\right)\right)\right) \tag{13}$$

$$mFRR_{up,\{1\}}: IF\left(A_{h,mFRR_{up,capacity}} = 0; 0; IF\left(S_{h,i} > 0; IF\left(OR\left(AND(Y_{h-1,i} = 0; Y_{h-2,i} = 1); AND(Y_{h-1,i} = 1; Y_{h-2,i} = 1)\right); 0; 1\right); 0\right)\right) \tag{14}$$

$$mFRR_{up,\{2,3\}}: IF\left(A_{h,mFRR_{up,capacity}} = 0; 0; IF\left(AND\left(S_{h,i} > 0; OR(Y_{h-1,i} \neq 1; Y_{h-2,i} \neq 1; Y_{h-3,i} \neq 1)\right); 1; 0\right)\right) \tag{15}$$

$$aFRR_{down,\{1,2,3\}}: IF\left(S_{h,i} = 1; 0; IF\left(A_{h,aFRR_{down,capacity}} = 0; 0; IF\left(A_{h,aFRR_{down,energy}} = 0; 1; IF\left(C_{h,aFRR_{down,capacity}} - C_{h,aFRR_{down,energy}} < C_{h,day-ahead}; 0; 1\right)\right)\right)\right) \tag{16}$$

$$aFRR_{up,\{1\}}: IF\left(A_{h,mFRR_{up,capacity}} = 0; 0; IF\left(S_{h,i} > 0; IF\left(OR\left(AND(Y_{h-1,i} = 0; Y_{h-2,i} = 1); AND(Y_{h-1,i} = 1; Y_{h-2,i} = 1)\right); 0; 1\right); 0\right)\right) \tag{17}$$

$$aFRR_{up,\{2,3\}}: IF\left(A_{h,aFRR_{up,capacity}} = 0; 0; IF\left(AND\left(S_{h,i} > 0; OR(Y_{h-1,i} \neq 1; Y_{h-2,i} \neq 1; Y_{h-3,i} \neq 1)\right); 1; 0\right)\right) \tag{18}$$

The following equations apply to mFRR and aFRR energy markets, which do not require capacity bids to be submitted to the capacity market:

$$mFRR_{down,\{1,2,3\}}: IF\left(S_{h,i} = 1; 0; IF\left(A_{h,mFRR_{down,energy}} = 0; 0; IF\left(C_{h,mFRR_{down,energy}} < -C_{h,day-ahead}; 1; 0\right)\right)\right) \tag{19}$$

$$mFRR_{up,\{1\}}: IF\left(A_{h,mFRR_{up,energy}} = 0; 0; IF\left(S_{h,i} > 0; IF\left(OR\left(AND(Y_{h-1,i} = 0; Y_{h-2,i} = 1); AND(Y_{h-1,i} = 1; Y_{h-2,i} = 1)\right); 0; 1\right); 0\right)\right) \tag{20}$$

$$mFRR_{up,\{2,3\}}: IF\left(A_{h,mFRR_{up,energy}} = 0; 0; IF\left(AND\left(S_{h,i} > 0; OR(Y_{h-1,i} \neq 1; Y_{h-2,i} \neq 1; Y_{h-3,i} \neq 1)\right); 1; 0\right)\right) \tag{21}$$

$$aFRR_{down,\{1,2,3\}}: IF\left(S_{h,i} = 1; 0; IF\left(A_{h,aFRR_{down,energy}} = 0; 0; IF\left(C_{h,aFRR_{down,energy}} < -C_{h,day-ahead}; 1; 0\right)\right)\right) \tag{22}$$

$$aFRR_{up,\{1\}}: IF\left(A_{h,aFRR_{up,energy}} = 0; 0; IF\left(S_{h,i} > 0; IF\left(OR\left(AND(Y_{h-1,i} = 0; Y_{h-2,i} = 1); AND(Y_{h-1,i} = 1; Y_{h-2,i} = 1)\right); 0; 1\right); 0\right)\right) \tag{23}$$

$$aFRR_{up,\{2,3\}}: IF\left(A_{h,aFRR_{up,energy}} = 0; 0; IF\left(AND\left(S_{h,i} > 0; OR(Y_{h-1,i} \neq 1; Y_{h-2,i} \neq 1; Y_{h-3,i} \neq 1)\right); 1; 0\right)\right) \tag{24}$$

5.4.3 Activation of energy

The reserve market FFR is used for frequency control in situations with low inertia and as mentioned in Table 1 in chapter 3.1.2, the energy activation performance in this reserve market is very rapid but also brief. Consequently, the energy impact associated with this reserve market can be regarded as minimal, allowing for the continuous availability of up-directional demand response capacity, except during the hours there is no procurement. This logic is shown in equation (6). Furthermore, due to the limitations of the energy simulation tool, the FFR market is not simulated, as it is not possible to model short and rapid energy impacts. As a result, no deviations are generated for this reserve market. The final results concerning approximate demand response potential can be directly derived from the baseline scenario, supplemented by reserve market procurement and price data.

The reserve market FCR-D is used for frequency control during disturbances. The energy activation in this reserve market, as shown in Table 1, is quite rapid. The amount of energy required for balancing during disturbances is linearly dependent on the frequency deviation, as shown in Figure 12 and Figure 13 below. In 2023, the average energy activation percentage in downregulation was -0.99% and 1.09% in upregulation, respectively. Figure 14 shows the energy activation percentages during year 2023. The average energy activation percentage was calculated from the frequency of the Nordic synchronous system with a 10 Hz sample rate (Fingrid Open Data, 2024). Based on the average energy activation percentages, the energy impact can be deemed as minimal, allowing for the continuous availability of demand response capacity if other constraints are neglected. However, this only applies during upregulation, similarly as with the FFR, and the available capacity during downregulation is determined for each hour. For downregulation, the market's marginal price must exceed the day-ahead electricity price, multiplied by the energy activation percentage, for the activated energy to be profitable. Otherwise, the increase in consumption results in additional costs. This logic for FCR-D down is shown in equation (7). The logic for FCR-D up is shown in equations (8) and (9).

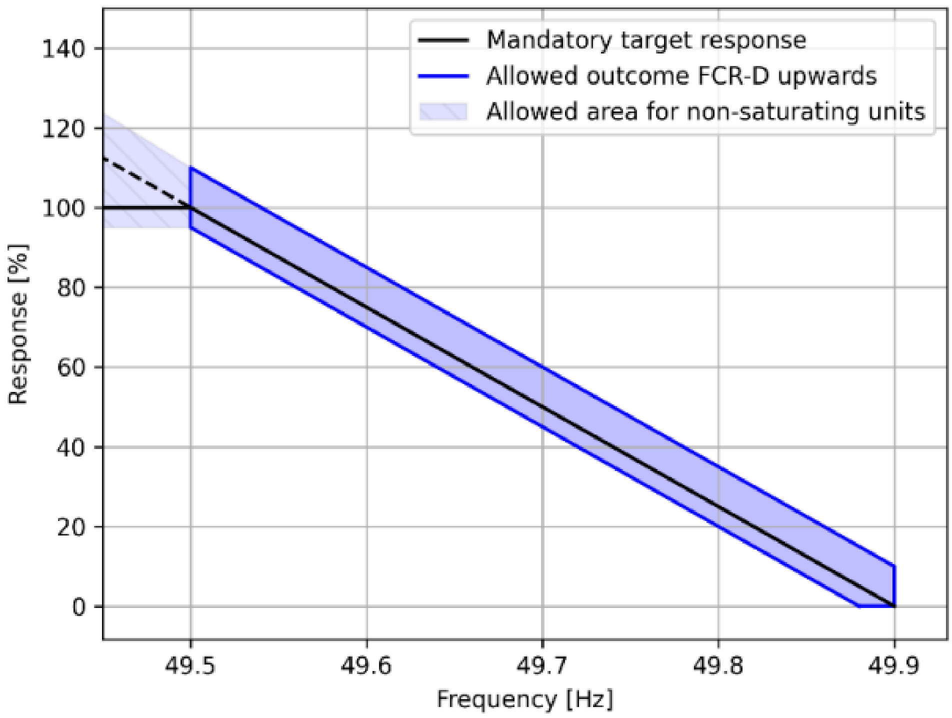


Figure 12. Activation of FCR-D up resources with a piecewise linear approach (Fingrid, 2023).

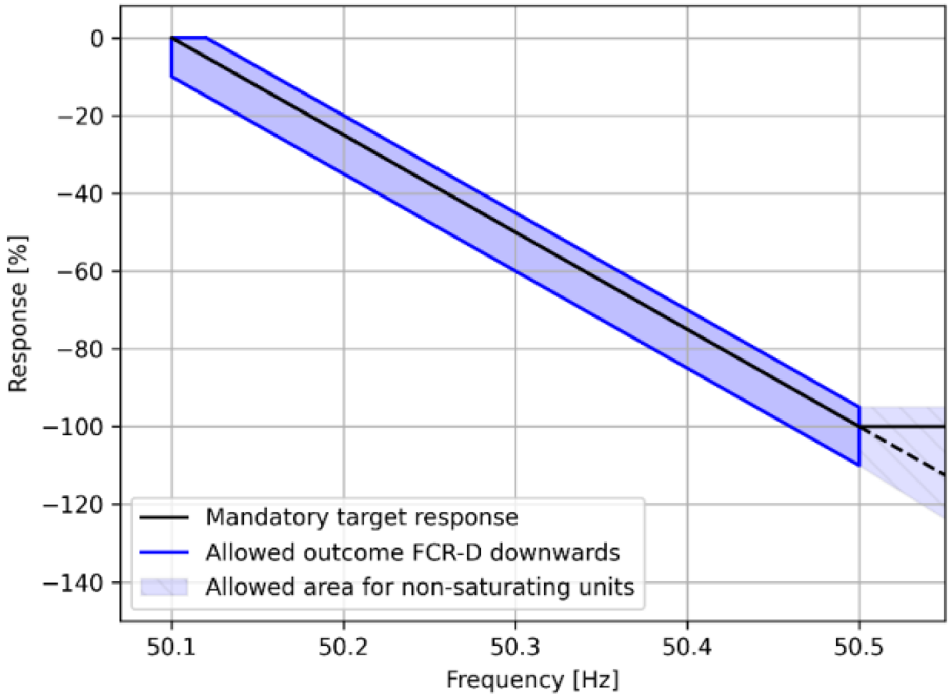


Figure 13. Activation of FCR-D down resources with a piecewise linear approach (Fingrid, 2023).

Figure 14. Energy activation percentages in the FCR-D market based on frequency data from Fingrid, year 2023 (Fingrid Open Data, 2024).

The reserve market FCR-N is used for frequency control during normal operation. The energy activation in this market is not as rapid as in the FFR or the FCR-D but the energy impact is greater. The amount of energy required for balancing during normal operation is linearly dependent on the frequency deviation. In 2023, the average net energy activation percentage in FCR-N market was 15.8%. During upregulation, the available capacity is constrained by recovery periods and the schedules, similarly as with the FCR-D up. The available capacity during downregulation is determined for each hour. For downregulation, the market's marginal price must exceed the day-ahead electricity price, multiplied by the energy activation percentage, for the activated energy to be profitable. Otherwise, the potential increase in consumption results in additional costs. This logic for FCR-N is shown in equations (10), (11) and (12).

5.5 Methodology to estimate demand response potential

To fully assess the demand response potential, it is essential to apply the reserve market principles to the simulated data. This simulated data is derived from the integration of Python programming and the market data, as discussed in chapters 5.3 and 5.4. The generation of this simulated data necessitates the generation of deviations within the energy simulation tool. Consequently, estimating the demand response potential involves a multi-step process that requires various inputs. The full estimation scheme of the DR potential is presented in Figure 11 above.

5.5.1 Reserve market deviations

Schedule deviations refer to the differences between the planned operation schedules and the actual performance, primarily caused by fluctuating conditions in the reserve market. These deviations are crucial for introducing variability into the building's energy consumption model, as the initial model lacks the ability to anticipate changes in the future market dynamics and thus cannot adjust its energy consumption in real time. The data for the deviations is sourced from the creation of schedules based on the building's profile and the optimal reserve market participation behaviour. The deviations allow the model to simulate more realistic consumption patterns.

The creation of deviations is conducted by identifying scenarios where deviations can occur. Generally, most scenarios exhibit deviations as the normal operating schedules do not impose restrictions related to reserve market requirements. Regarding the case study building, the heat pump is modelled to have 100% operational level 24 hours a day, 7 days a week but it is still affected by external conditions such as the weather and occupation variability. However, since the heat pump is already at full capacity, there is no possibility of increasing consumption within the energy simulation tool, thereby making downregulation unachievable, which in reality, should be possible. Similarly, when the schedule is set to zero during certain hours, such as for lighting at night, there is no potential for upregulation, as energy consumption cannot drop below zero.

In the future development stages, it is essential for deviations to be implemented in a manner that better aligns with the dynamic nature of real-world conditions, allowing for variations that occur at different times of the day based on the actual energy consumption and real-time reserve market activity. Integrating an energy storage system would be an ideal addition, as it can help optimise engagement in reserve markets by providing flexibility in response to price signals and demand fluctuations. Additionally, temperature setpoints should be capable of dynamic adjustment, as they are currently maintained at a constant level. This would enable the system to more accurately capture the complexities of energy consumption and reserve market interactions. However, the current energy simulation model lacks the capacity to incorporate such dynamic behaviour due to its more simplified structure, which limits the ability to reflect nuanced operational changes. As a result, deviations in the current model must align with these simplifications, such as the aforementioned heat pump operation, resulting in a more rigid and predictable pattern. This rigidity prevents the model from representing the most realistic variations, making it less suitable for simulating complex scenarios where demand response occurs more dynamically.

5.5.2 Prioritisation and constraints

Prior to obtaining the final simulation results, the user must ensure that all predefined constraints have been met, mostly related to preserving appropriate indoor conditions. Once compliance with these restrictions has been confirmed, the reserve market principles are applied in the final stage of the process to generate conclusive outcomes, as discussed later in chapter 5.5.3. Prioritisation and restrictions for demand response actions are governed by several key parameters, including CO_2 levels, temperature constraints, lighting conditions and room types. Each of these parameters plays a critical role in ensuring that the DR events are executed without compromising the operational efficiency or occupant comfort within the building. When considering CO_2 levels, it is important to maintain indoor air quality standards to prevent adverse effects on occupant health and productivity. Therefore, any reduction in ventilation during a DR event must ensure that CO_2 concentration remains within acceptable limits. The calculation tool addresses this constraint by requiring the user to perform a manual check, as demonstrated in Figure 11 above. Similarly, temperature regulation is subject to predefined boundaries that ensure the indoor environments remain comfortable. The main prioritisation for CO_2 and temperature levels are subject to the deviations created that control the demand response recurrence.

Lighting restrictions are more straightforward. The lighting in non-essential areas can be reduced or turned off completely. For essential areas, dimming the lights to 75% of the normal level is the recommended approach to balance energy savings with adequate visibility and occupant comfort. Room types present more stringent constraints on AHU operations, particularly in spaces such as toilets and laboratories. Adjusting ventilation in these areas is undesirable due to inherent challenges, such as managing odors in toilets and maintaining the controlled environments required in laboratories. Consequently, these spaces are considered the least prioritised for applying DR.

5.5.3 Reserve market principles

To fully assess the demand response potential and consider the profitability of a certain marketplace, the energy activation based on the available demand response capacity must be calculated. The initial results, which show the theoretical maximum impact on consumption from participating in demand response, need to be refined using reserve market principles. The reserve market principles define the final results for each marketplace. The principles outline: 1) Available capacity for DR offer 2) How the activated energy is calculated from the available capacity, and this is directly linked to the profits of demand response. The results on profitability are presented later in chapter 6. Generally, the available capacity for DR offer is determined as follows: the optimal participation behaviour from each scenario is compared to the hourly consumption. For each hour, if any of the schedules are active in the scenario, the difference in consumption compared to baseline during that hour determines the available capacity for demand response.

The reserve market principles for the FCR-D market are:

$$Available\ capacity\ for\ demand\ response\ offer: P_{h,j} = Q_{h,j,FCR-D\ down\ or\ FCR-D\ up} - Q_{h,baseline} \tag{25}$$

$$Activated\ energy\ during\ demand\ response: E_{h,j} = P_{h,j} \times E_{h,act.} \tag{26}$$

The reserve market principles for the FCR-N market are:

$$Available\ capacity\ for\ demand\ response\ offer: P_{h,j} = MIN(Q_{h,j,FCR-N\ down} - Q_{h,baseline}; Q_{h,j,FCR-N\ up} - Q_{h,baseline}) \tag{27}$$

$$Activated\ energy\ during\ demand\ response\ event: E_{h,j} = P_{h,j} \times E_{h,act.} \tag{28}$$

The reserve market principles for the mFRR and aFRR capacity and energy markets are:

$$\boldsymbol{A}vailable\ capacity\ for\ demand\ response\ offer: P_{h,j} = Q_{h,j,reserve\ capacity\ or\ energy\ down\ or\ up} - Q_{h,baseline} \tag{29}$$

$$Activated\ energy\ during\ demand\ response\ event: E_{h,j} = P_{h,j} \tag{30}$$

where $P_{h,j}$ stands for power to be offered to the reserve market at hour h in scenario j. $Q_{h,j}$ denotes the consumption at hour h in scenario j and $E_{h,j}$ denotes the activated energy at hour h in scenario j. $E_{h,act.}$ represents the energy activation percentage at hour h, as discussed in chapter 5.4.3. The summation for the demand response potential in all marketplaces for scenario j can be determined using the following equation (31):

$$DR_{potential} = \sum_{h=1}^{8760} P_{h,j} \tag{31}$$

The summation for the profit from the offered capacity across all marketplaces for scenario j can be calculated using equation (32):

$$Profit_{capacity} = \sum_{h=1}^{8760} P_{h,j} \times C_{h,reserve} \tag{32}$$

The summation for the profit from activated energy (downregulation) within a certain marketplace (FCR-D and FCR-N) for scenario j can be calculated using the following equation (33):

$$Profit_{energy} = \sum_{h=1}^{8760} -E_{h,j} \times (C_{h,day-ahead} + C_{h,fees}) \tag{33}$$

For the mFRR and aFRR capacity and energy markets, the summation for the profit from activated energy (downregulation) for scenario j can be calculated using the following equation (34):

$$Profit_{energy} = \sum_{h=1}^{8760} E_{h,j} \times -C_{h,reserve} - E_{h,j} \times (C_{h,day-ahead} + C_{h,fees}) \tag{34}$$

In equation (34), the activated energy in downregulation is bought directly from Fingrid, which means that it is cost rather than compensation as it is in equation (33). However, if the price for purchasing mFRR or aFRR energy from Fingrid is sufficiently negative compared to the day-ahead price, increasing consumption consistently results in a profit. It is assumed that both equations (33) and (34) are only used with downregulation. In upregulation, the equations for determining the profit from decreasing consumption in all marketplaces are presented in Appendix D. Same notation principles apply.

The total profit from providing both demand response capacity and energy in the marketplace can be calculated by adding equations (32) and (33), or (32) and (34), or (32) and one of the equations from Appendix D.

5.6 Framework of the raw model

As shown in Figure 11, the raw model – as a proof of concept – for estimating demand response potential performs three functions: data processing, integrated simulation of the processed data and performance evaluation of predicted results. In the processing stage, the input data is processed to produce clean data for the simulation. The input data consists of three elements of which two are, from the start, preprocessed by creating schedules and generating the optimal reserve market participation behaviour by using equations shown in chapter 5.4.2. The third element, magnitude factors, are manually fed by the user. Then, the integrated simulation is completed with the processed input data, while the user ensures that the simulation's indicative results on the DR potential do not compromise the boundaries of the physical comfort levels. Given that different rooms are sensitive to different features, the user may need to readjust the magnitude factors several times. In the future, manual adjustment of the magnitude factors should be replaced by automated iteration and automatic verification of the indoor conditions within the tool. Lastly, the results are performance-evaluated after applying the reserve market principles to the initial results. The framework of the raw model is entirely deterministic as the outcomes are precisely determined by initial conditions, inputs and predefined formulas.

The performance evaluation of the demand response potential is challenging due to the absence of absolute reference values. Therefore, the following approach is recommended to draw cautious conclusions regarding the accuracy of the estimation results.

1. The magnitude of demand response potential can exceed the current load.
2. The highest demand response potential can be found during the closing hours for the DR *down* and during the opening hours for the DR *up*. This derives directly from the calculation, meaning that when the electrical units are off, the power can be increased the most. For the

symmetrical product, the highest demand response potential can be found based on the availability of simultaneous DR *down/up*.

However, without the ability to execute the modelling over shorter intervals using linear optimisation, the accuracy of the estimation results is only directional. Even though the demand response activations are based on real data and the adjustments during the activations are carefully calibrated, the analysis of the raw model performance is entirely based on the quantitative significance of the profits. Therefore, optimising the magnitude factors over a shorter time index could lead to more precise metrics. This issue should be prioritised for resolution in the future development stages. In the next chapter, the results and sensitivity analysis from the current operation of the raw model are presented, providing further insights into the restrictions and potential improvements.

6 Results and analysis

In this chapter, the results obtained from the raw model are presented. The results are divided into the initial results and the final results. The initial results are presented in chapter 6.1 and the final results in chapter 6.2, respectively. The initial results are directly obtained from the energy simulation tool, and they represent the net theoretical maximum of the demand response impact on consumption. The final results represent the initial results which are further refined by using different reserve market principles. The final results are intended to highlight the profitability and economic viability of the marketplace. The process for acquiring the initial results is thoroughly explained in chapter 5.4.2. The reserve market principles for refining the initial results are clarified in chapter 5.5.3. The results cover the third and fourth floors of the case study building, and the time period from June 1 to August 31.

After presenting the results, sensitivity analysis of different factors influencing the results is provided. The calculation process includes various simplification, restrictions and assumptions which subjectively affect the results at different stages of the calculation. The sensitivity analysis is covered in chapter 6.4. Lastly, the raw model of the calculation tool is further analysed, and the results are summarised in chapter 6.4.5.

6.1 Initial results

The following results in Table 8 are directly obtained from the energy simulation tool. The results are presented for each marketplace and scenario. As described in section 5.2, scenario 1, in which the operation schedules of AHUs were adjusted during demand response events, allowed their output to be temporarily reduced to 90% of the standard level during upregulation, or increased to 100% during downregulation. Similarly, scenario 2 involved dimming the lighting in the selected rooms to 75% of the normal levels during the up-directional demand response. In the down-directional DR, the lighting was increased to 100%. In scenario 3, the GSHP output was reduced to 50% during the up-directional DR events, with limited scope for increasing its output due to its configuration for continuous maximum operation. All the scenarios involved certain activation and recovery times, which were further discussed in section 5.2.1.

In the initial results, six different metrics are showing the achieved net theoretical maximum impact on consumption when participating in demand response in each scenario. The metrics do not represent the whole energy consumption of the building. The metrics are as follows:

1. Space heating consumption
2. AHU heating consumption
3. Space cooling consumption
4. AHU cooling consumption
5. Electrical energy consumption
6. Heat pump purchased energy

In scenario 3, in which the case study building's heat pump was adjusted, only upregulation was possible as the heat pump was set to operate on maximum power in baseline simulations, as discussed in chapter 5.2. As a result, results for the third scenario in the marketplaces with downregulation are unavailable. The FCR-N market is split into downregulation and upregulation segments, as the simulation was conducted separately for each. Therefore, the net demand response impact is presented for both segments. For the final results, these two are combined according to the reserve market principles.

Table 8. The initial results obtained from the energy simulation tool. The values in each cell show the overall difference – the net demand response impact – compared to the baseline in MWh. The results cover the time period from June 1 to August 31.

Marketplace	**Scenario**	**Metrics (MWh)**					
		1	2	3	4	5	6
Baseline	-	15.35	20.04	62.48	45.31	119.45	16.05
aFRR capacity market (down)	1	+1.47	+0.93	-4.13	+3.4	+6.99	+0.54
	2	-0.83	≈0	+9.89	0	+13.83	-0.18
	3	-	-	-	-	-	-
aFRR capacity market (up)	1	-0.4	-0.56	+1.01	-1.21	-1.01	0
	2	+0.3	≈0	-3.42	0	-3.99	-0.21
	3	-	-	-	-	-	-0.11
aFRR energy market (down)	1	+0.01	≈0	-0.03	≈0	+0.04	≈0
	2	-0.02	0	+0.1	≈0	+0.16	≈0
	3	-	-	-	-	-	-
aFRR energy market (up)	1	-0.39	-0.44	-1.06	-1.32	-0.99	-0.18
	2	+0.25	≈0	-2.87	0	-3.35	+0.05
	3	-	-	-	-	-	-0.07
FFR	1	≈0	≈0	≈0	≈0	≈0	≈0
	2	≈0	≈0	≈0	≈0	≈0	≈0
	3	≈0	≈0	≈0	≈0	≈0	≈0
FCR-D (down)	1	+9.31	+2.8	-10.37	+19.43	+30.16	+2.68
	2	-2.26	-0.01	+52.68	0	+63.64	-0.5
	3	-	-	-	-	-	-
FCR-D (up)	1	-0.44	-0.64	1.37	-1.31	-1.27	-0.24

	2	+0.38	≈0	-4.14	≈0	-4.87	+0.08
	3	-	-	-	-	-	-0.17
FCR-N (down)	1	+8.01	+2.59	-10.08	+17.47	+27.18	+2.35
	2	-2.12	-0.01	+47.23	0	+57.25	-0.47
	3	-	-	-	-	-	-
FCR-N (up)	1	-0.48	-0.7	+1.28	-1.28	-1.26	-0.26
	2	+0.38	≈0	-4.26	≈0	-4.98	+0.08
	3	-	-	-	-	-	-0.1
mFRR capacity market (down)	1	+7.07	+2.17	-9.82	+15.45	+24.78	+2.04
	2	-2.01	-0.01	+42.33	0	+52.27	-0.44
	3	-	-	-	-	-	-
mFRR capacity market (up)	1	-0.49	-0.64	+1.41	-1.45	-1.32	-0.25
	2	+0.38	≈0	-4.24	≈0	-4.96	+0.08
	3	-	-	-	-	-	-0.14
mFRR energy market (down)	1	+0.15	+0.09	-0.68	+0.13	+0.81	+0.05
	2	-0.14	≈0	+0.97	0	+1.47	-0.03
	3	-	-	-	-	-	-
mFRR energy market (up)	1	-0.23	-0.27	+0.56	-0.65	-0.55	0
	2	+0.11	≈0	-1.48	0	-1.67	-0.11
	3	-	-	-	-	-	-0.05

The initial results show that adjusting one electrical element within a scenario affects multiple metrics, either positively or negatively. Thus, the total impact on consumption of an individual demand response event extends far beyond the event's duration, both in scale and scope. Figure 15 shows an example of the net DR impact from four individual down-directional DR events, per each scenario, measured over the course of the entire day. The DR events occur between 2:00-4:00, 5:00-6:00, 17:00-21:00 (scenario 2), 18:00-21:00 (scenario 1) and 22:00-24:00 (both scenarios). During these DR events, for scenario 1, the operation of AHUs was adjusted to increase their output. For scenario 2, the lighting levels were increased.

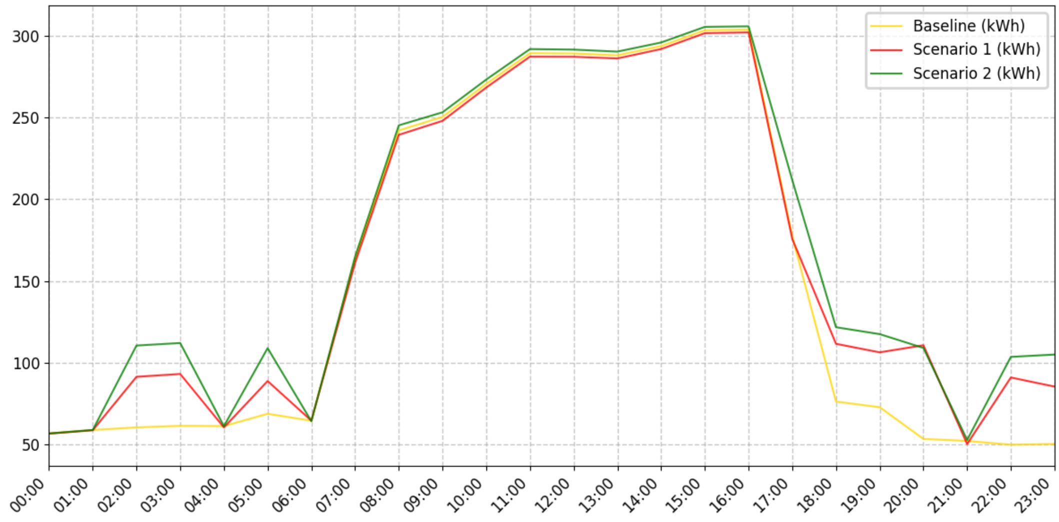


Figure 15. The net impact of four individual demand response events, measured across the entire day (10th of June 2023). The reserve market presented in the figure is mFRR energy market (downregulation).

During the DR events, both scenarios 1 and 2 show a noticeable difference in the consumption compared to the baseline. The energy simulation tool models the DR events in a way that causes the consumption to slightly increase or decrease some tens or hundreds of watthours just before the event begins, depending on the scale of upcoming demand response. After the DR event ends, the consumption does not immediately return to the baseline. Instead, the consumption lags for several hours, as can be seen during hours 08:00-16:00. Two main reasons behind this can be assumed: if the lighting participates in down-directional control, a small heat load will be generated into the space, leading to an increase in the cooling demand after the DR event. Additionally, increasing the ventilation through the AHUs causes a slight rebound effect after the DR event, resulting in a temporary decrease in consumption in scenario 1 compared to the baseline following the event. However, the duration of the lagging is uncertain as short DR events are followed by long rebound effects, as seen with scenario 1. This is likely due to certain unknown distortions in the calculations and limitations within the energy simulation tool.

Figure 16 below shows an example of the net DR impacts from multiple down-directional DR events across one week. As previously, in scenario 1, the AHUs were adjusted to increase their output and in scenario 2, the lighting was increased.

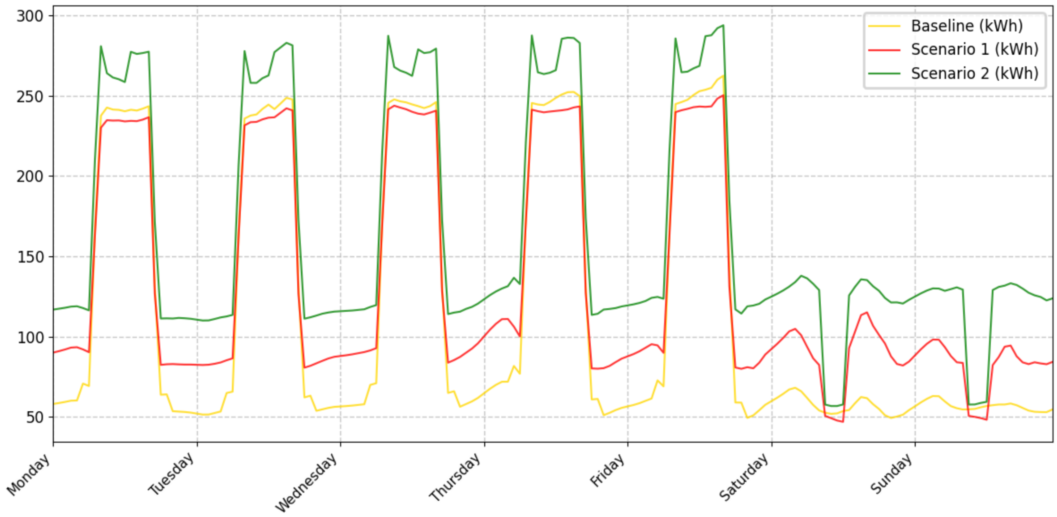


Figure 16. The net impacts of multiple demand response events, measured across the entire week (3rd to 9th of June 2023). The reserve market presented in the figure is aFRR capacity market (downregulation).

During each DR event, both scenarios 1 and 2 show a significant difference in the consumption compared to the baseline. During these events, the energy simulation models the DR events as in Figure 15, leading to a similar behaviour of the consumption throughout the week. In both scenarios, the DR events occur outside the normal opening hours 07:00-17:00. However, during the opening hours, the consumption does not follow the baseline levels, particularly with the lighting. Thus, variation in the consumption during opening hours likely arises from the same factors discussed previously. The magnitude of the variation is now greater, and this is reflected in the consumption following the DR events.

Scenario 3 was not included in Figure 15 and Figure 16 as the case study building's heat pump is not able to participate in downregulation. Additionally, unlike scenarios 1 and 2, the only metric affected in scenario 3 is the heat pump's purchased energy. As a result, comparing it on the same chart would not be feasible. Figure 17 below shows an example of the net DR impact on the heat pump's purchased energy from two individual up-directional DR events, measured over the course of the entire day. The DR events occur between 7:00-10:00 and 11:00-14:00.

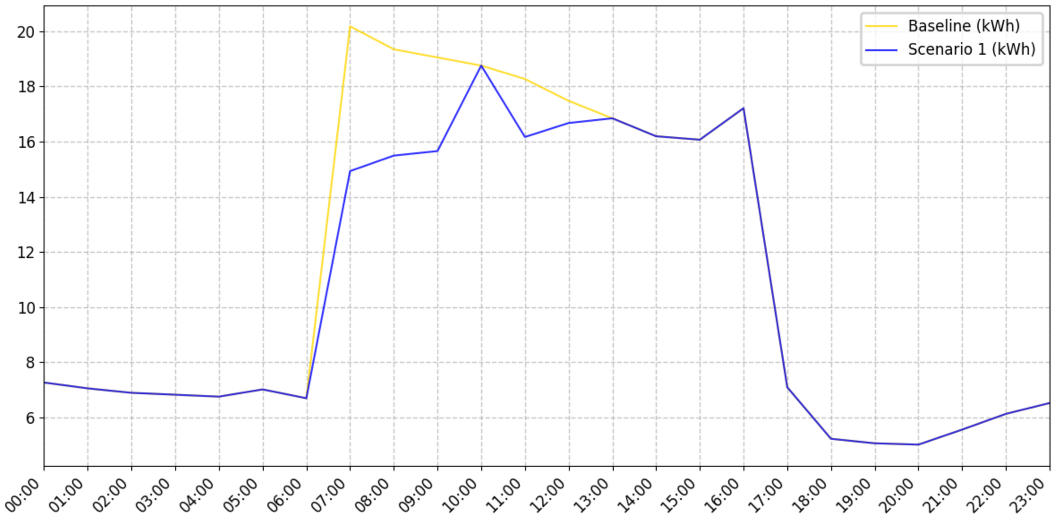


Figure 17. The net impact of multiple demand response events on heat pump's purchased energy, measured across one day (30th of June 2023). The reserve market presented in the figure is FCR-D (upregulation).

Additionally, Appendix E shows the net impact on the consumption of demand response events (upregulation) for one day and one week. The markets used are the same as in Figure 15 and Figure 16.

6.2 Final results

Table 9 presents the average demand response potential that could be offered to the market during the period of June 1 to August 31 and the total activated energy during the same period if the whole offered potential would be accepted. The values are either power or energy. Positive values present the potential for increasing the consumption and negative values present the potential for decreasing the consumption. In the FCR-N market, the values representing the demand response potential show the total absolute value, as the potential can change between positive and negative. Similarly, the activated energy values show the absolute sum of all the activations in the FCR-N market. Generally, with the case study building, the largest demand response potentials are found in the FCR-D and the mFRR capacity markets (both downregulation).

Table 9. The final results on the demand response potential. The results cover the time period from June 1 to August 31.

Marketplace	Scenario	Average demand response potential (kW)	Total activated energy during DR events (kWh)
aFRR capacity market (down)	1	2.11	214.64
	2	4.98	441.50

	3	-	-
aFRR capacity market (up)	1	-1.05	-1611.72
	2	-3.03	-4496.64
	3	-0.05	-62.89
aFRR energy market (down)	1	≈0	≈0
	2	≈0	≈0
	3	-	-
aFRR energy market (up)	1	-0.55	-1214.73
	2	-1.83	-4050.67
	3	-0.03	-59.04
FFR	1	4.50	≈0
	2	0.84	≈0
	3	1.96	≈0
FCR-D (down)	1	21.62	364.34
	2	47.78	777.85
	3	-	-
FCR-D (up)	1	-1.02	24.00
	2	-3.84	104.38
	3	-0.07	2.5
FCR-N	1	0.47	155.67
	2	2.98	716.36
	3	0	0
mFRR capacity market (down)	1	14.76	1167.50
	2	32.39	2956.53
	3	-	-
mFRR capacity market (up)	1	-1.20	-614.95
	2	-3.79	-2258.31
	3	-0.06	-49.94
mFRR energy market (down)	1	0.04	94.11
	2	0.07	158.16
	3	-	-
mFRR energy market (up)	1	-0.15	-330.38
	2	-0.45	-1003.55
	3	-0.01	-15.86

Table 10 represents the actual profits gained from the markets during the period of June 1 to August 31. The values indicate the profits that could have been achieved if all available demand response capacity had been offered into a single market and energy was activated as required. Additionally, the energy activated during upregulation considers savings from the reduced spot-priced electricity consumption. The highest total profits with the case study building can be attained from the mFRR capacity market (down).

Table 10. The final results on the demand response profitability. The results cover the time period from June 1 to August 31.

Marketplace	Scenario	Offered DR capacity profits (€)	Activated energy profits (€)	*Total profits (€)*
aFRR capacity market (down)	1	98	-9	*89*
	2	228	-11	*217*
	3	-	-	-
aFRR capacity market (up)	1	38	237	*275*
	2	108	712	*820*
	3	2	12	*14*
aFRR energy market (down)	1	-	≈0	*≈0*
	2	-	≈0	*≈0*
	3	-	-	-
aFRR energy market (up)	1	-	169	*169*
	2	-	646	*646*
	3	-	12	*12*
FFR	1	831	≈0	*831*
	2	322	≈0	*322*
	3	180	≈0	*180*
FCR-D (down)	1	851	-31	*820*
	2	1964	-69	*1896*
	3	-	-	-
FCR-D (up)	1	104	2	*106*
	2	435	11	*446*
	3	6	≈0	*6*
FCR-N	1	83	-3	*80*
	2	337	9	*346*
	3	0	0	*0*
mFRR capacity market (down)	1	796	133	*929*
	2	1767	262	*2029*
	3	-	-	-
mFRR capacity market (up)	1	79	112	*191*
	2	285	429	*714*
	3	7	14	*21*
mFRR energy market (down)	1	-	36	*36*
	2	-	62	*62*
	3	-	-	-
mFRR energy market (up)	1	-	53	*53*
	2	-	186	*186*
	3	-	6	*6*

Figure 18 below shows the combined marketplace profits from the table above. The results are obtained by summing all scenarios' profits from the market. Left columns show the profits from the offered DR capacity and right columns show the profits from the activated energy during the DR events.

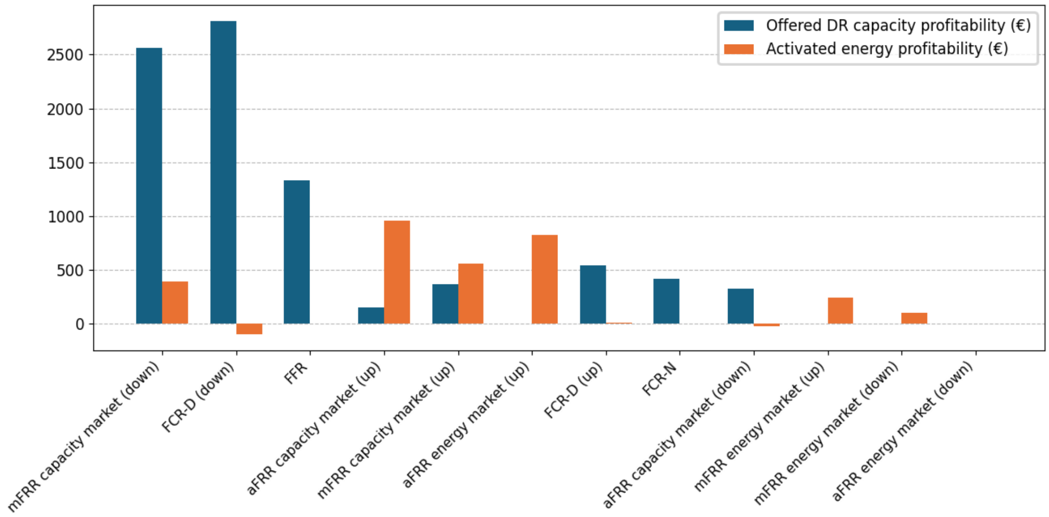


Figure 18. Combined marketplace profits from all three scenarios. The markets are in descending order by total net profits.

As Figure 18 shows, the highest combined marketplace profits are obtained from the mFRR capacity market (down), the FCR-D (down) and the FFR markets. A clear pattern emerges from the data: the markets with high profits from the DR capacity tend to exhibit lower profits from the activated energy, while the markets that generate higher profits from the activated energy are typically associated with lower profits from the offered DR capacity. This inverse relationship highlights a trade-off between the two income sources in these markets. Markets, such as the FCR-D and the FFR yield minimal energy impact as the energy activation is based on frequency deviations, and these deviations generally last only fractions of seconds. In 2023, using sample rate of 10 Hz, the frequency dropped below 49.9 Hz 2 751 359 times (0.9% of the annual count). Similarly, the frequency increased above 51.1 Hz 3 264 461 times (1.0% of the annual count). The activated energy profits directly correlate with the amount of frequency deviations and their magnitude, which was presented in Figure 14 for the FCR-D market. Thus, these markets' profits are gained directly from the flexibility of loads.

Figure 19 shows the profits from all the marketplaces across all three scenarios. The results are obtained by summing profits from every marketplace. Left columns show the profits from the offered DR capacity and right columns show the profits from the activated energy.

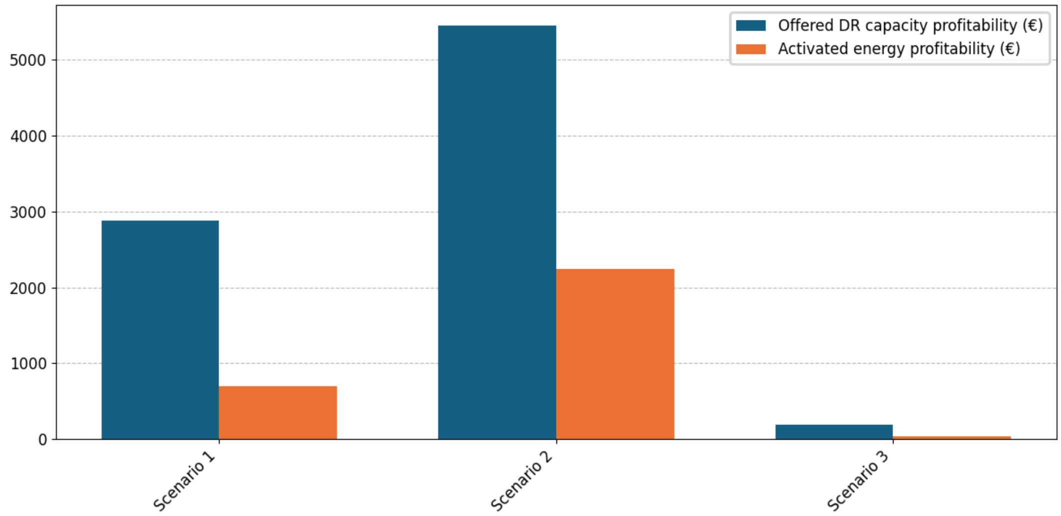


Figure 19. Profits from all the marketplaces per each scenario.

Scenario 2 (lighting) yields the highest profits in both categories. In scenario 2, seven schedules were implemented, in contrast to the four schedules in scenario 1 and a single schedule in scenario 3. Notably, two of the seven schedules in scenario 2 were set to operate on levels between 0-55%, thereby increasing the likelihood of more frequent engagement in downregulation. Conversely, in scenario 1, two out of the four schedules were set to operate at a constant level of 100%, effectively excluding them from downregulation opportunities. This also applies to scenario 1's heat pump schedule. This scheduling arrangement emphasises the increased flexibility on the load side in scenario 2, which explains why it consistently delivers higher profits across all market segments. Also, in scenario 2, the seven schedules covered 100% of the modelled spaces, compared to 69% coverage by the four schedules in scenario 1, partially explaining the profit difference. The lighting can also be increased or decreased more flexibly without significant changes to indoor conditions, unlike the AHUs.

6.3 Separate study on district heating

District heating, among GSHP, is one of the heating supply methods in the case study building. It was excluded from the calculation tool development process as the energy simulation tool did not allow temporarily altering the consumption of district heating. In the future development stages, implementing district heating into the calculation tool is one of the key considerations and therefore, at this stage, separate study on district heating was concluded to gain insight how total consumption among the six metrics presented in chapter 6.1 would be affected on annual level by increasing and decreasing the maximum and minimum indoor temperature setpoints by one degree.

Table 11. Consumption behaviour, presented in MWh, among the six metrics presented in chapter 6.1, in response to changes in indoor temperature setpoints.

Temperature setpoint	**Metrics (MWh)**						***Total (MWh)***
	1	2	3	4	5	6	
Min. T setpoint decreased by 1 °C	-18.96	+1.26	-0.02	0	0	-3.74	-21.46
Min. T setpoint increased by 1 °C	+35.51	-1.68	+0.02	0	0	+6.81	*+40.65*
Max. T setpoint decreased by 1 °C	0	+0.17	+17.59	0	0	0	*+17.76*
Max. T setpoint increased 1 °C	0	-0.13	-14.71	0	0	0	*-14.84*

As Table 11 shows, consumption, especially of space heating and cooling, and heat pump are greatly affected by the varying levels of indoor temperature setpoints. Increasing the minimum temperature setpoint raises the demand for space heating and increases the energy consumption of the heat pump. Conversely, decreasing the minimum temperature setpoint decreases the need for space cooling, reduces space heating demand, and decreases the heat pump's energy consumption. However, the total net impacts from increasing and decreasing the minimum indoor temperature setpoints are significantly different. Raising the minimum indoor temperature setpoint by one degree leads to an increase in consumption of nearly 41 MWh, while lowering the setpoint by one degree reduces total consumption by only about 22 MWh. On the other hand, increasing the maximum indoor temperature setpoint only affects the demand for AHU heating and space cooling. Allowing the temperature to increase beyond the usual range reduces the need for cooling. Consequently, lowering the maximum temperature setpoint significantly increases the demand for space cooling, as the need for enhancing cooling arises more frequently than usual. The total net impact in both situations is similar. Decreasing the maximum temperature setpoint, however, leads to a bit higher overall impact.

There is clear potential for demand response regarding the district heating. This can be achieved by adjusting the temperature setpoints, particularly by raising the minimum and lowering the maximum setpoints. For example, during winter, when the price for district heating is generally higher as the outdoor temperatures are lower, it would be sensible to optimise the peak power consumption by lowering the minimum indoor temperature setpoint during peak times. This optimisation would lead to lower indoor temperatures as heating demand decreases, and this would reduce the power fee and the energy fee. The power fee is based on the property's power needs and the energy fee is based on how much energy is used (Tampereen Energia, 2024). Therefore, lowering the indoor temperature during peak times decreases the water flow as the temperature difference between district heating's supply and return water stays high, therefore resulting in lower power fee. As consumption decreases, the energy fee also decreases.

6.4 Sensitivity analysis

6.4.1 Magnitude factor

The impact on the demand response profits was studied further by changing the magnitude factors by five percent in the FCR-D market and the mFRR capacity market. These markets were chosen as they yielded some of the highest profits, as shown in Table 10. The results presented in chapters 6.1 and 6.2 were obtained by using values 100% (all scenarios) in downregulation, and 90% (scenario 1), 75% (scenario 2) and 50% (scenario 3) in upregulation. In downregulation, the new percentage used was 95%. In upregulation, the new percentages used were 95%, 80% and 55%, respectively. In downregulation, the percentage could only be decreased as the maximum DR level was already used during the development process. In upregulation, the percentages could not be decreased as the indoor conditions would have breached the given user comfort level limits. The changes in total profits are presented in percentages in the Figure 20 below.

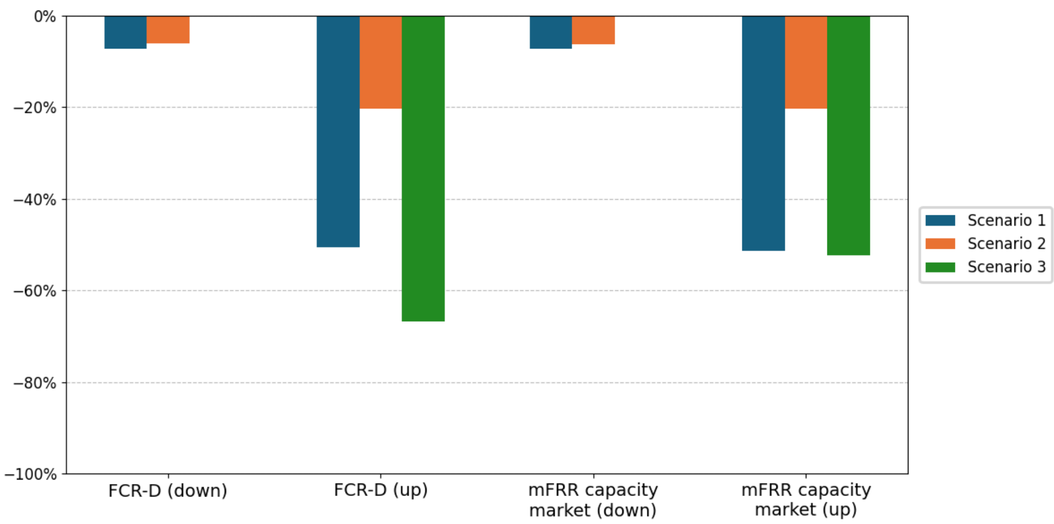


Figure 20. Changes in total profits from demand response, resulting from adjustments to magnitude factors by five percent.

Figure 20 presents the changes in scenarios' total profits from four markets during the same period used in the calculation tool development process. The changes were caused by altering the magnitude factors by five percent. The changes vary drastically between downregulation and upregulation. Across the different markets, whether participating in upregulation or downregulation, the magnitude of the changes tends to exhibit remarkable consistency across the two or three scenarios being analysed. This alignment suggests a uniformity in the response patterns, regardless of the specific market dynamics at play. For instance, if the mFRR capacity market were to be changed into the mFRR energy market, the results would likely remain very similar. This is because the magnitude factors do not influence the number of DR events or the occurrence of participation; rather, they directly control the potential energy available from the DR events.

During the calculation process, for downregulation events, a magnitude factor of 100% was used. For this sensitivity analysis, a factor of 95% was used. Consequently, the total profits in both scenarios decreased by approximately 7%. Thus, reducing the utilisation during the DR events essentially establishes a linear relationship with the resulting profits, directly influencing the amount of capacity available.

On the other hand, for upregulation events, different magnitude factors were used for each scenario. The percentages were determined by identifying the minimum values that maintain comfort levels within acceptable boundaries during DR events. Thus, the percentages could only be increased for this sensitivity analysis. In scenario 1, the percentage was increased from 90% to 95%, effectively halving the magnitude of demand response, as the available DR capacity decreased from 10% to 5%. Therefore, the total profits also decreased by approximately 50%. In scenario 2, the percentage was increased from 75% to 80%, resulting in the loss of approximately one-fifth of the original DR capacity. This change is also clearly depicted in the figure. Lastly, in scenario 3, the percentage was adjusted from 50% to 55%, resulting in a loss of only 10% of the original DR capacity. However, the findings reveal a significant deviation from this initial expectation, suggesting that the observed outcomes differ substantially from what was anticipated. The total profits decreased by nearly 60% on average, highlighting that scenario 3 is particularly sensitive to the changes in the magnitude factor. This discrepancy highlights potential uncertainties in the energy simulation tool's calculations, as the impact of changing the DR magnitude factor appeared in the results at a magnitude six times greater than observed in the other scenarios and markets. Additionally, as demonstrated in Table 10, the total profits obtained in scenario 3, regardless of the market, were consistently low, suggesting that even a small absolute change in the profits leads to a significant relative change.

6.4.2 Electricity price

Electricity prices were used in the development process for defining the optimal participation behaviour schedules, in addition to the reserve market data. The electricity price affects directly the obtained demand response potential but also the profits gained from each marketplace. Thus, the electricity prices were increased and decreased five percent in each marketplace to capture the changes in profits gained from activating energy. Table 12 below shows the monetary and relative changes in each marketplace. Relative changes are shown if the monetary changes are above or below zero.

Table 12. Monetary and relative changes in profits gained from activating energy in each marketplace after electricity price increases or decreases 5%.

Marketplace	Scenario	Electricity prices increase by 5% (€/%)	Electricity prices decrease by 5% (€/%)
aFRR capacity market (down)	1	0	0
	2	0	0
	3	-	-
aFRR capacity market (up)	1	8 / 3.4%	-9 / -3.8%
	2	26 / 3.7%	-27 / -3.8%
	3	0	-1 / -8.3%
aFRR energy market (down)	1	0	0
	2	0	0
	3	-	-
aFRR energy market (up)	1	6 / 3.6%	-6 / -3.6%
	2	25 / 3.9%	-24 / -3.7%
	3	1 / 8.3%	0
FFR	1	0	0
	2	0	0
	3	0	0
FCR-D (down)	1	0	1 / 3.2%
	2	-1 / -1.4%	3 / 4.3%
	3	-	-
FCR-D (up)	1	0	0
	2	1 / 9.1%	0
	3	0	0
FCR-N	1	0	0
	2	1 / 11.1%	-1 / -11.1%
	3	0	0
mFRR capacity market (down)	1	-4 / -3.0%	3 / 2.3%
	2	-4 / -1.5%	7 / 2.7%
	3	-	-
mFRR capacity market (up)	1	3 / 2.7%	-3 / -2.7%
	2	13 / 3.0%	-12 / -2.8%

	3	0	0
mFRR energy market (down)	1	0	0
	2	-1 / -1.6%	0
	3	-	-
mFRR energy market (up)	1	1 / 1.9%	-2 / 3.8%
	2	5 / 2.7%	-6 / -3.2%
	3	0	0

As presented in Table 12, the monetary changes are generally small or non-existent as many of the marketplaces, depending on the scenario, are not affected by minor changes in the electricity price. The average relative change after the electricity price increased is 1.6%, and -1.2% when the electricity price decreased. In some marketplaces, a change of only one euro can result in moderate relative change, as in the FCR-N and FCR-D (up) markets. This is primarily because the energy impact in these markets is minimal, resulting in small monetary gains from the activated energy. Notably, the largest monetary changes occur consistently in upregulation markets, where the electricity prices directly determine the savings achieved by reducing the electricity consumption. Conversely, in downregulation markets, the electricity prices are viewed as a direct expense, and when these prices decline, profits from these markets tend to increase. Moreover, implementing these changes throughout the entire calculation process would substantially alter the optimal participation schedules, influencing both the initial and final results of the analysis. Performing a sensitivity check in this manner is unnecessary, as the effect of varying electricity prices is already evident in any of the results obtained from the process. Only the magnitude of the changes would differ.

6.4.3 Factors influencing the accuracy of the calculation process and its execution speed

The calculation process for assessing the profitability of demand response in the case study building involves multiple different steps. This multistep approach inherently adds complexity and contributes to slower computation times. Various factors influence either the calculation outcomes or the execution speed of the programming. Key elements affecting the calculation outcomes include the energy simulation tool, simplifications applied to the modelling of the building, scheduling parameters, and weather data. These aspects collectively shape the accuracy and efficiency of the overall process.

The energy simulation tool calculates the differentiated energy consumption patterns according to the deviations. As discussed in chapter 6.1, the energy simulation tool's calculations are significantly influenced by even a short DR event, as even several hours after the conclusion of the DR event, the energy consumption fails to return to baseline levels. This is particularly evident in the case of lighting – in which the consumption should return to the baseline level – where the tool's calculation algorithms appear to be disrupted by these deviations, causing the energy consumption to remain deviated from the baseline until the next DR event occurs. This behavior is likely attributable to the inaccuracies in the simulation of indoor conditions, as these deviations directly impact the indoor conditions. Followingly, the simplifications regarding the modelling influence the calculation. Firstly, the entire case study building would need to be modeled to encompass both the whole structure and each individual floor. To reduce complexity arising from the large number of rooms, adjacent smaller rooms were combined. Additionally, the building contained several laboratories, which were excluded from participating in demand response. Accurately modeling these spaces would have significantly increased the complexity of the calculation and likely introduced greater uncertainty in the differentiated consumption, a challenge that already exists with simpler, more typical spaces.

The scheduling parameters impact the calculation by providing the framework for the energy consumption behavior. The calculation becomes more straightforward when the number of schedules and their contents are minimised. Regarding the case study building, there were 12 schedules across all three scenarios. Doubling this number would not only increase the time required for the calculation but also enhance its accuracy, as some spaces that are highly similar and follow the same schedule may, in reality, exhibit subtle differences. Additionally, the calculation generates simulations based on the weather data from Helsinki Airport for the year 2020. Updating the location and year to more closely reflect the specific conditions of the case study building would enhance the accuracy of the calculation.

Factors influencing the calculation speed of the simulations are mostly related to the number of deviations per each schedule and the programming. Depending on the marketplace, scenario and schedule, the maximum number of deviations for one schedule during the period of June 1 to August 31 was 92. This would mean that every day of this period would have at least one individual DR event. The maximum number of DR events for one day is four, so in the most complex situation, the same period would have 368 DR events for one schedule. During the simulations, the impact of the number of deviations on the execution speed of the programming was analysed. Initially, when simulating a particular schedule, the first deviations took approximately between 62 and 78 seconds to implement. The first value corresponds to a scenario where there was only one DR event during the day, while the second reflects a situation if there would have been four DR events during that day. As the simulation of the same schedule progressed, the values for one and four DR events increased to 117 seconds and 172 seconds, respectively, after 30 deviations. After 60 deviations, the implementation of the deviations took 198 seconds for one DR event and 265 seconds for four DR events. As the simulation neared its end, the execution time had increased significantly, reaching approximately 269 seconds and 350 seconds, respectively, for one and four DR events per day. The deviations between each threshold incorporated random variations, including between one to four DR events per deviation. Consequently, the results may vary slightly if only deviations involving one or four DR events were studied. However, the current representation more accurately reflects a realistic scenario.

Figure 21 illustrates the slowdown as the number of deviations rises. This increasing delay is a significant limitation for scaling up the calculation process, as the issue would be exacerbated if the simulation were extended to cover an entire year. In an ideal scenario, where the regression line is flat, scaling the process for one year would increase the required execution time by a factor of four. However, based on the regression line, the time would increase by approximately 15 times.

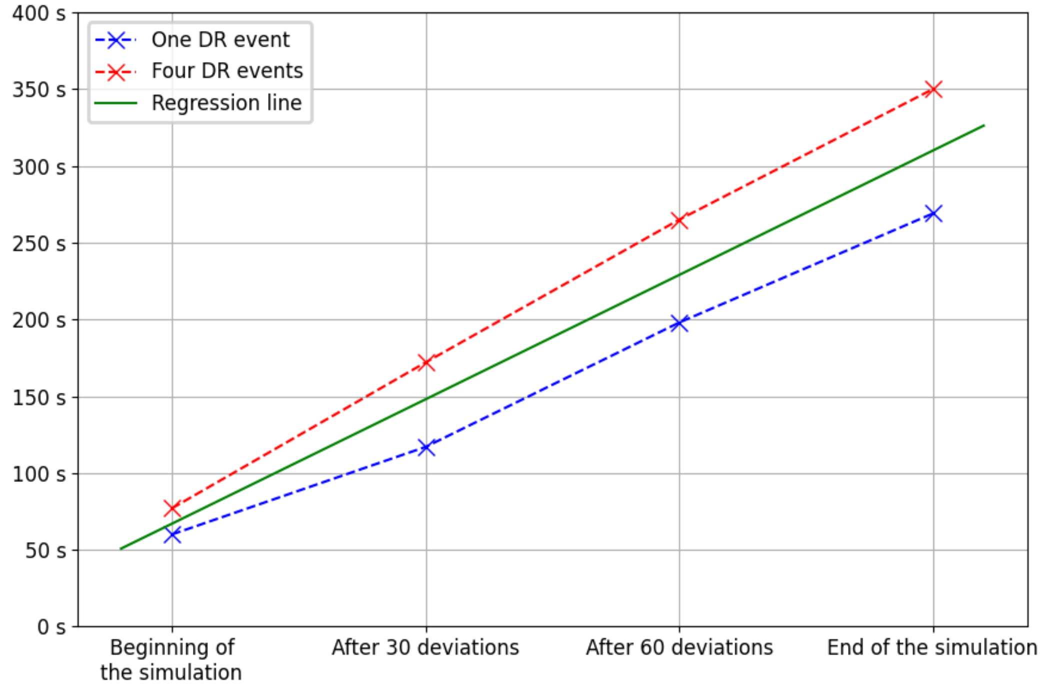


Figure 21. The slowdown of the simulation as the simulation progresses. The simulation covered the time period from June 1 to August 31. During this period, under ideal conditions, 92 deviations would occur. The time taken to implement one deviation (including either one or four DR events) into the energy simulation tool increased approximately 4.5 times between the beginning and end of the simulation.

In addition to the number of deviations, the number of schedules or scenarios linearly increases the execution speed. The number of scenarios can be effectively reduced if the systems participating in demand response can be limited. Similarly, the number of schedules can be minimised by simplifying the model, such as by grouping similar rooms and reducing the consideration of their individual differences. This, however, can lead to inaccuracies in the final results.

In the current calculation tool, the deviations are collected from an input Excel file, and its size also impacts the simulations' execution speed. However, the file size itself is not a major constraint, as Python's Pandas DataFrame enables efficient data handling by loading the file into memory, eliminating the need to repeatedly open and close the file. This means that, even with large files, the Excel file needs to be opened only once. Once the file is read, its contents are imported into memory as a DataFrame, allowing for direct manipulation and analysis without further interaction with the file. All subsequent operations are performed in memory, which significantly reduces computational overhead and improves efficiency by avoiding the time-consuming process of reopening the file. (Auden, 2024) However, the available memory on the executing computer limits the execution speed, as insufficient memory may slow down processing. The increasing slowness of the simulations is likely attributed to the fact that the code is executed externally, separate from the source code, rather than being caused by large Excel file sizes, for example. With the limited available memory, the processing time increases as the number of deviations grows. For the future development, it would be crucial to integrate the calculation tool's Python script directly into the source code, allowing all deviations to be set at once and greatly improving the efficiency of the process.

6.4.4 Factors influencing the demand response potential

The factors influencing the demand response potential can be divided into external and internal factors. Within the boundaries of this thesis, certain decisions regarding the internal factors were made. Some of these are entirely building-specific. The external factors which directly influence the demand response potential are the reserve market data and the day-ahead market data.

The reserve market data was entirely received from Fingrid. The reserve market data was mostly used for the year 2023 and the idealised participation behaviour followed directly the markets' behaviour. From the perspective of the case study building, more favourable market data would generally lead to improved outcomes. However, even with more favourable market conditions, the same constraints related to prioritisation and indoor conditions would still apply. As a result, better market data may not directly translate to better results, as the impact is influenced by a complex interplay of internal and external factors, such as the electricity price and the timing of the demand response. Further analysis and verification with updated market data would be required to fully understand the potential effects and scale of the results. Similarly, the day-ahead market data influences the participation behaviour as it defines the optimal moments when demand response could be the most beneficial. These external factors, namely the reserve and the day-ahead market data, significantly influence the initial and final results derived from the calculation tool. However, consumers have limited control over these factors. Consequently, while these factors define the direction for the results, the extent of their impact depends on the specific circumstances and various other factors.

The natural differences among the different reserve markets also influence directly the DR potential. The differences were accounted for when applying the reserve market principles outlined in section 5.5.3 to the initial results. The primary differences are related to the available capacity for DR offers and the energy activation. For instance, the FCR-N market requires participants to be capable of providing either up- or downregulation during given periods. This requirement significantly restricts the available hours during which participation is feasible, resulting in a lower DR potential compared to certain other reserve markets. Additionally, the energy activation percentage plays a crucial role in defining the optimal participation behaviour in specific markets, which directly influences the DR potential. In general, a higher average energy activation percentage leads to a lower DR potential.

The internal factors influencing the DR potential are mostly related to the predefined boundaries for the indoor comfort level limits, assumptions made in the scenarios and the limitations in the energy simulation tool. These internal factors could be modified, changed or generally improved to gain better and more accurate results on the DR potential. Often these factors would negatively impact the DR potential, meaning that there exist certain distortions in the calculation. Predefined boundaries for the comfort level limits greatly influence the DR potential by setting limitations to the magnitude factors. In upregulation markets, systems such as the lighting and the AHUs could theoretically offer much greater demand response potential. In downregulation markets, the maximum magnitude factor has already been fully utilised, meaning there is no further potential for increase under the current market principles. Adjusting the magnitude factors to leverage the extra potential in upregulation markets further would risk exceeding the comfort level boundaries. Such modifications would impact user comfort, which cannot be compromised. Therefore, without sacrificing comfort, enhancing demand response potential is only possible through improved optimisation of space usage and more efficient scheduling of the demand response events. This would also require improving the overall calculation accuracy to better represent the ongoing indoor conditions. For example, the calculation encounters difficulties in buildings with numerous small spaces, such as the case study building, because the energy simulation tool does not account for air exchanging between rooms, leading to less accurate CO_2 level calculations. In contrast, for enclosed spaces where air typically does not circulate between rooms, the tool provides a more accurate estimation of CO_2 levels.

In addition, the energy simulation tool encounters minor difficulties when considering the duration of the rebound effect originating from the DR events. For example, following a DR event where consumption of a system was temporarily increased, the system would compensate for it by decreasing the consumption after the DR event ends. However, the duration of the rebound effect was multiple times longer than the preceding DR event which seems illogical. Consequently, the calculation would need to be performed iteratively for each hour of the period to realistically simulate the hours following the DR events. However, due to limitations within the current framework of the energy simulation tool, simulating the rebound effect was deemed unfeasible. As a result, the authentication of the rebound effect was excluded from the development of the calculation tool. This exclusion implies that the estimated DR potentials are partially overestimated, as the rebound effect would either reduce the magnitude or duration of DR events to prevent significant changes in consumption after the DR event ends. Additionally, the distortions observed in the calculation, such as the significantly strong rebound effect, as shown in Figure 16, further suggest that the DR potentials were overestimated at the outset.

The loads are characterised by an active period, during which they can provide demand response without interruption, as well as a recovery period, during which they rest. The recovery period corresponds to the duration required for the load to rest after delivering demand response throughout the entire active period. These periods were outlined for each scenario in chapter 5.2.1. For the purpose of studying the factors influencing the demand response potential and profits, each scenario in the FCR-D (up) market had its active and recovery times extended by one hour. The results in the offered DR capacity profitability and the activated energy profitability for the FCR-D (up) market are presented in Table 13 below.

Table 13. The total profits acquired from the FCR-D (up) market after the active and recovery periods were extended by one hour in each scenario.

The percentage values represent relative changes in profits compared to the original results.

Market-place	Sce-nario	Offered DR capacity profits (€/%)	Activated energy profits (€/%)	*Total profits (€/%)*
FCR-D (up)	1	169 / 62.1%	4 / 60.5%	*173 / 62.1%*
	2	483 / 10.9%	11 / -1.5%	*494 / 10.6%*
	3	6 / -1.4%	≈0 / 20.6%	*6 / -0.2%*

The primary factor influencing the results lies in how the adjusted active and recovery periods align with the schedules, as well as the price-driven conditions of both the electricity and the reserve markets. For instance, in scenario 1, the initial active and recovery periods are two hours each. Within an ideal eight-hour timeframe, this equates to four hours of active operation and four hours of recovery. After the adjustments, the same eight-hour period would comprise either five active hours and three recovery hours or three active hours and five recovery hours. Consequently, extending both periods could lead to either increased or decreased profits, heavily dependent on the timing and synchronisation of the related factors. In the case study building, the period extensions result in increased total profits from the FCR-D (up) market in scenarios 1 and 2. In scenario 3, the total profits experienced a slight decrease, resulting in a negligible negative change. Also, the monetary difference was so small that it was effectively rounded to zero.

6.4.5 Summary

Several distinct elements can significantly impact the total profits, each influencing them in different ways. The summary of the total profits after the changes in different elements is presented in Table 14 below. Missing values indicate that these markets were not included in the analysis. The values represent the combined profits across all scenarios. The metrics used in the table are as follows:

1. Electricity prices increase by 5%
2. Electricity prices decrease by 5%
3. Magnitude factors increase by 5%
4. Magnitude factors decrease by 5%
5. Active and recovery periods extend by one hour

Table 14. The summary of the total profits in each marketplace after the changes on loads were implied.

Marketplace	**Total profits (€/%) among the metrics**				
	1	**2**	**3**	**4**	**5**

aFRR capacity market (down)	306 / 0%	306 / 0%	-	-	-
aFRR capacity market (up)	1143 / 3.1%	1072 / -3.3%	-	-	-
aFRR energy market (down)	≈0	≈0	-	-	-
aFRR energy market (up)	859 / 3.9%	797 / -3.6%	-	-	-
FFR	1333 / 0%	1333 / 0%	-	-	-
FCR-D (down)	2714 / 0%	2719 / 0.1%	-	2542 / -6.4%	-
FCR-D (up)	559 / 0.2%	558 / 0%	411 / -26.6%	-	673 / 20.3%
FCR-N	427 / 0.2%	425 / -0.2%	-	-	-
mFRR capacity market (down)	2950 / -0.3%	2968 / 0.3%	-	2764 / -6.6%	-
mFRR capacity market (up)	942 / 1.7%	911 / -1.6%	672 / -27.4%	-	-
mFRR energy market (down)	97 / -1.0%	98 / 0%	-	-	-
mFRR energy market (up)	251 / 2.4%	237 / -3.3%	-	-	-

Table 14 shows the aggregated impacts of the changes in each market. The most impactful changes are the magnitude factor changes, which alter the capacity that can be offered to the markets and the load demand level. Extending the active and recovery periods by one hour could significantly influence market profitability, although this analysis was limited to a single market. The electricity price changes affect the upregulation markets more than the downregulation markets. The FFR, the FCR-D and the FCR-N are not impacted by the changes in the electricity price. In the balancing energy markets, the electricity price changes are more impactful. However, the electricity prices influence the participation schedules, which directly determine the demand response potential and, consequently, the total profits. Therefore, changes in the electricity prices must be analysed throughout the entire estimation scheme to fully assess their impact on different stages of the process.

7 Discussion

7.1 Main findings

The main findings related to the goal of this thesis, developing a raw model of the calculation tool which would estimate the potential of demand response and its profits, are manifold. Key factors for the tool's functionality included sufficient computational power, effective management of the demand response events (magnitude factors, activation and recovery times, and optimal market participation behaviour), and accurate modelling of the building. The primary limitation was the execution speed of the script controlling the tool. Performance notably slowed down due to the high number of system operation schedules, which resulted from the increased number of demand response events and the building's complexity. Additionally, the tool showed few uncertainties and inaccuracies, especially in scenario 3 with the heat pump adjustment, highlighting areas for improvement in the future versions.

Based on the simulations done with the calculation tool in this thesis, the highest average demand response potential is obtained from the FCR-D (down) and the mFRR capacity (down) markets. The conducted calculations show that the most profitable markets are the balancing capacity markets, the FCR-D (down) and the FFR markets for the period of June 1 to August 31 when all the scenarios are combined. Among the scenarios, scenario 2 proved consistently to have the largest profits. Scenario 1 gained approximately 820€ during the studied period from FCR-D (down) hourly markets. In the same market, scenario 2 gained approximately 1900€ and scenario 3, 0€. In the FCR-D (up) market, profits were approximately 110€ in scenario 1, 447€ in scenario 2, and in scenario 3, only 6€. This highlights the significant contrast in profits between downregulation and upregulation markets when utilising the case study building's loads.

The heat pump's profits were consistently lower than first anticipated. The magnitude factor used in this scenario was high, 50%, but the heat pump provided very low potential and profits. This is likely related to the energy simulation tool, which appeared to incorrectly adjust the heat pump's electrical consumption based on the magnitude factor. However, this adjustment worked correctly in scenarios 1 and 2, where it resulted in significantly higher potential and profits. The AHUs generated 50% lower profits when the magnitude factors were increased by 5%, while the lighting's profits decreased by approximately 20% with the same 5% increase in magnitude factors. This reduction and sensitivity analysis suggest that the magnitude factors optimisation is of high importance for demand response profits. Other important factors are the electricity prices, the duration of possible load activation and recovery time. One of the most surprising findings from the sensitivity analysis is that extending the activation and recovery times by one hour led to a 20% increase in profits in the studied FCR-D (up) market.

7.2 Accuracy of the results and implications

This thesis uses simulated input data from an existing building and an energy simulation tool for the calculations. The magnitude factors, activation, and recovery times – key determinants of the average demand response potential – were selected based on literature sources and manual verifications with the energy simulation tool. These values have a significant impact on the results. However, the values are specific to each experimental simulation in every scenario, making them building-specific. The ideal values would be derived from real-world experiments that examine the building's and the loads' extreme conditions. These extreme values for demand response capability would not only enhance DR potential but also enable more accurate scenario profit calculations. Additionally, it was deemed unattainable to obtain precise values for certain parameters, such as activation and recovery times, which had to be estimated based on previous studies, as acquiring the limits would require manually simulating indoor conditions separately for each hour, leading to thousands of manual iterations. To mitigate the uncertainty associated with these values regarding this thesis, it would be paramount to achieve sufficiently accurate energy and building performance model, develop a dynamic simulation that iterates the model and indoor conditions hourly, and integrates the demand response events to determine the boundary limits for the activation and recovery times. The dynamic simulation should test the available demand response times across various markets with distinct requirements, magnitude factors, and response times.

A major constraint regarding the accuracy of the results is in the calculation algorithms of the energy simulation tool. For example, the energy simulation tool models the CO_2 and differentiated consumption patterns quite rigidly. This results in some uncertainties and gaps in proving the results' accuracy. The author had no control over the calculation logic of the energy simulation tool. Therefore, scaling and implementing the developed raw model should involve specific improvements, particularly when applied to other buildings. An additional improvement in accuracy could be attained by incorporating dynamic demand response values for response times and capacities. While this thesis uses semi-dynamic values that change seasonally, they do not fully capture real-world variations. For instance, extreme temperatures significantly influence how long a heat pump can remain offline. Implementing this approach would require linear optimisation to identify the optimal moments for response, a task beyond the scope of this thesis. However, the weather data captures most of the variations in outdoor temperatures, which are generally reflected in the demand profiles in the energy simulation tool. Optimising the participation schedule more rigorously would be beneficial, allowing for the DR bidding process to be refined dynamically over the course of an entire year. Also, historical data is used throughout the process. The markets are undergoing various changes, making it increasingly difficult to estimate future market prices; however, doing so would help assess the potential profits from the markets in the future.

The developed raw model employs a semi-automatic calculation process to determine the average demand response potential, activated energy, and total profits. Before the model can be applied to calculate these parameters for different buildings, it requires the building to be modelled, and the relevant data inputted into the energy simulation tool before calculations can begin. Additionally, optimal market participation behaviour, based on the building's load data, must be determined. All these factors must be carefully considered and completed before the demand response potential can be obtained and analysed.

This thesis does not account for the permanence factors of the balancing capacity market; these are subject to the balancing capacity agreements and, therefore, are of limited relevance to the development of the calculation tool. In this thesis, it is also assumed that all relevant information is available, and capacity can be accurately bid into markets whenever it is profitable. It is presumed that the required reserve can be aggregated effectively, ensuring compliance with all market requirements – such as capacity thresholds and demand response duration – without incurring penalties. Another key assumption is that all submitted bids are accepted into the market. While this is not always the case, as acceptance depends on bid prices and competing offers, the assumption is reasonable in many instances. This is particularly true for demand response in a building like the case study building, where the costs associated with demand response are minimal. For example, reducing lighting levels in educational spaces incurs negligible costs, provided the necessary controls are already installed.

7.3 Suggestions for further research and development

The future development stages of the raw model should see numerous different implications of which majority are discussed throughout this thesis. The suggestions for further research and development can be divided into primary and secondary. The primary development aspects are those that have the most significant impact on the calculation process and results. The secondary aspects, on the other hand, primarily address nuances and are intended for fine-tuning. However, they too can influence the outcomes, often in ways comparable to the primary factors.

The most critical primary development aspect concerns the memory usage of the energy simulation tool and the Python script when incorporating deviations into the model's schedules. As shown in Figure 21, the simulation time slowed down radically as the simulation progressed. This poses a significant limitation for extending the study period of demand response or scaling the calculations to include additional systems participating in demand response. To address this issue, it would be essential to integrate the Python script of the raw model directly into the simulation tool's source code. This integration would enable aggregating deviations from the input Excel file and applying them collectively, instead of iterating through each day or week, thereby considerably optimising the workflow. The ideal option would be to eliminate the use of Excel altogether. Under the current raw model, studying more than one reserve market is impractical due to time constraints. However, expanding the model to assess potential and profitability from multiple markets at once is crucial for gaining a comprehensive understanding of demand response opportunities.

The primary improvements should also focus on implementing deviations in a manner that more accurately reflects the dynamic nature of real-world conditions, as they are currently constrained by static schedules, electricity prices, and reserve market conditions. Under normal circumstances, loads operate with greater flexibility, which suggests that increased potential and profits could be achieved. Furthermore, the energy simulation tool's calculations should be slightly refined to better reflect realistic and dynamic indoor condition patterns, yielding more accurate results. At present, the tool still exhibits uncertainties and inaccuracies in its simulations, highlighting the need for further enhancement.

The secondary improvements should prioritise optimising the magnitude factors, simplifying the estimation process for these and other parameters, and incorporating additional electrical and heating systems into the energy simulation tool to enable broader participation in demand response. Optimising the magnitude factors to operate over shorter time intervals – currently set seasonally – could result in more precise metrics. For example, magnitude factors could be dynamically adjusted using indoor conditions from the previous iteration, which would then determine the conditions for the next iteration and set the boundaries for the magnitude factors. Similarly, the energy simulation tool should allow simulations to be conducted over shorter intervals, such as 15 minutes instead of one hour, to better align with the operational timeframes of fast-acting reserves. Parameters such as activation and recovery times should be more accessible and grounded in the dynamic simulation rather than estimations from literature. Accurate and location-specific weather data should also be integrated to allow for more site-specific simulations.

Furthermore, the energy simulation tool should incorporate additional electrical and heating systems, such as district heating, to broaden its scope. Currently, the simulations are limited to AHUs, lighting and heat pumps, the latter of which presented some uncertainties in the results. As demand response methods advance, it will become increasingly important to include as many flexible loads as possible to maximise the DR potential and, ultimately, total profits. Finally, as demand response forecasting and real-time optimisation grow in importance, the calculation process should proactively account for these developments to ensure it remains relevant and effective in the evolving energy markets.

8 Conclusion

The objective of this master's thesis was to investigate demand response (DR) potential of a case study building and analyse the development and calculation processes of a calculation tool, which will be separately implemented for demand response calculation by Granlund Oy. The research questions of this thesis were:

1. *What marketplaces are optimal for facilitating effective demand response?*
2. *What are the most important parameters for the functionality of a calculation tool?*
3. *How to modify a building energy simulation model to estimate DR capability?*
4. *How much the building's consumption can be increased or decreased for DR purposes?*

The calculations conducted in this thesis indicate that the optimal marketplaces for facilitating effective demand response are the balancing capacity markets (mFRR), the frequency containment reserves for disturbances (FCR-D) and the automatic frequency restoration reserve (aFRR) capacity markets. The market offering the highest profits can vary annually due to shifting market dynamics and the specific demand response resource involved. However, these four marketplaces account for the highest profits in the calculation scenarios. The FCR-D market, in down-directional control, presents the largest total potential for demand response but the mFRR capacity market, also in down-directional control, dominates the total profits. Out of the three scenarios, scenario 2, in which lighting is adjusted, yields the best results in terms of potential and profits, regardless of the marketplace. Scenario 2 covered 100% of the modelled spaces and the lighting can be adjusted up or down more frequently without significant changes to indoor conditions. The mFRR capacity market totals to over 2900€, which is achieved through down-directional control within the study period of June 1 to August 31 if all scenarios are combined. The FCR-D totals to over 2700€ under the same conditions. Third largest profits are found in the fast frequency reserves (FFR) market but due to its fast-paced nature, it is not regarded optimal for facilitating effective demand response with the case study building. Thus, the next largest profits are found in the aFRR capacity market in up-directional control. In this marketplace, the profits total to approximately 1100€ per the study period. The majority of the other marketplaces analysed fall significantly short of achieving similar figures. Marketplaces with up-directional control present generally slightly better potential and profits, but down-directional control yields significantly higher profits in certain marketplaces.

The calculations conducted in this thesis were based on the data from 2023 (and 2024, for the aFRR capacity and energy markets). The calculations utilise data only from a single year, as using data from multiple years would not alter the process. Therefore, using a single year's data was deemed sufficient to validate the development process of the calculation tool. The market data used was the most recent whole year data (except for the aFRR capacity and energy markets), ensuring maximum relevance considering the constantly evolving nature of the markets. Thus, given the ongoing and implemented changes in the reserve markets, each year presents unique conditions, making it challenging for the calculations to reliably forecast the future DR potential and profits. Also, in 2025, the Finnish electricity markets are transitioning into the 15-minute market time unit (MTU), which will further change the dynamics in the electricity markets. In Finland, with the upcoming amendment to the Electricity market Act, the electricity companies and the network operators are allowed to offer load control services, meaning that the demand response will occur more and more on the demand-side in the near future. Speculatively, this could attract numerous newcomers to the reserve markets, complicating the bidding process and consequently reducing the potential profits attainable from offering demand response capabilities.

To compare the available potential and profit levels from different marketplaces and resource types, a raw model of the calculation tool was developed. The raw model's simulation calculations were conducted by using an external energy simulation tool obtained from Granlund Oy. The most important parameters for the functionality of the calculation tool were found to be sufficient computational power and memory usage, the comprehensive management of demand response events (magnitude factors, activation and recovery times, and optimal market participation behaviour), and the adequate modelling of the building. The most important constraints regarding the operation of the calculation tool were found to be within the execution of the script which controls the external energy simulation tool and sets the demand response events in a given time period. As the simulation progressed, slowdown of the execution stood out as both notable and significant. The slowdown was, especially, related to the number of individual demand response events and the complexity of the case study building, resulting in an increased number of system operation schedules. It was considered that in future development stages, the controlling of the energy simulation tool and the handling of demand response events should primarily take place within the source code rather than in external script, to further improve the calculation speed. In addition to the computational slowness, the energy simulation tool displayed some unknown uncertainties and inaccuracies, particularly in scenario 3, where the heat pump was adjusted. These issues were identified as the key areas for improvement in the future developments.

The thesis involved an analysis of the net impacts that changes in the power level have on the expected consumption from the baseline calculations. Magnitude factors, which directly control the power level between 0-100%, were found to be the primary source of modifying the building energy simulation model in order to estimate the DR capability. The impacts were measured by comparing the overall change to the absolute values in the baseline scenario. The magnitude factors used in the development of the calculation tool were estimated based on manual verifications and literature. The building energy simulation model can also be further modified by partitioning the model into smaller parts, which leads to more accurate differences among spaces and scheduling. A more accurate building model, on the other hand, directly leads to more realistic results concerning the DR capability.

Based on the calculations conducted in this thesis, the building's consumption can be temporarily increased or decreased for DR purposes. The results indicate that on average, in scenario 1 where the air heating units (AHUs) are adjusted, and in the best-case marketplaces, consumption could increase by nearly 22 kW, while it could only decrease by just over 1 kW. In relation, during the same time period, the average power consumption was approximately 130 kW. Adjusting the AHUs would, on average, lead to either a 17% increase or a 0.8% decrease in consumption. In scenario 2, on average, the consumption can be temporarily increased by 48 kW or decreased by 4 kW, respectively. Similarly to scenario 1, adjustments in the lighting would correspond to a 37% increase or a 3% decrease relative to the average power consumption. In both scenarios 1 and 2, changes in consumption – whether increased or decreased – significantly impacted several interconnected systems. As a result, the comparison focused on average power consumption. Lastly, scenario 3 consistently resulted in the lowest potential, meaning that consumption could, on average, only be increased by 2 kW and decreased by 0.1 kW. The average power consumption of the heat pump was, during the same time period, approximately 7 kW. Hence, the relative increase in relation to the average power consumption would amount to 29%, while the relative decrease would be 1.5%. Therefore, as the percentages indicate, when designing demand response strategies, it is crucial to carefully manage the scheduling of demand response bids to marketplaces to maximise the potential. Equally important is optimising the duration for which demand response can be made available to the markets, while minimising the recovery period.

It is recommended that further analysis regarding the magnitude factors, the energy simulation tool's calculation principles and the reserve markets' requirements is conducted. Refining participation schedules, along with the calculation principles, to better account for the dynamic nature of reserve markets is crucial, as these factors significantly influence both the available potential and the resulting profits. Realistic market activations and load operations should be incorporated to accurately reflect the building's behaviour and its loads. Additionally, future changes in the energy markets can present certain limitations to the implementation of the calculation tool. Achieving this would necessitate further enhancements and simulations at both the building and load levels. Additionally, shorter timescales should be considered – shorter than the hourly scale used in this thesis – since market dynamics are increasingly shifting in that direction. This presents a challenge, as there is currently insufficient data at the shorter time scales, and simulations could only be performed at the hourly level. The introduction of more international markets adds another layer of uncertainty to the implementation of the calculations. Therefore, studying the application of demand response in electricity markets is crucial for ensuring its profitability and efficiency. The significance of this lies in the ability of demand response to improve the flexibility of the power system, enabling it to better accommodate the fluctuations in supply and demand. By actively responding to these changes, demand response helps stabilise the grid, reducing the need for additional generation capacity and promoting a more efficient use of energy resources. This, ultimately, plays a key role in transitioning toward a more sustainable and resilient power system. Beyond its environmental and societal advantages, further exploration of the demand response also opens new opportunities for various stakeholders – such as businesses and consumers – to leverage underutilised resources, turning previously dormant potential into valuable assets that can generate additional savings or profits.

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Appendix A

```
import tkinter as tk
import openpyxl
import pandas as pd
from tkinter import simpledialog, messagebox, Toplevel, BooleanVar
from tkinter import ttk

# Function to initialize a multi-choice selection popup
def multi_choice_popup(options):
def get_selected_schedules():

# Function to create a matrix selection popup to store values
def create_schedule_matrix_popup():
def select_cell(event):
def fill_all_cells():
def fill_selected_cells():
def save_schedule_values():

# Generation of time series for each entered schedule
def generate_time_series(selected_schedules):
```

Appendix A. The Python libraries, function names and input values of the schedule generation script.

Appendix B

```
import pandas as pd
from openpyxl import load_workbook
from openpyxl.styles import Font
from openpyxl.utils import get_column_letter

# Function to process the calculations for a single reserve market
def adjust_column_width_based_on_header(ws, column, row=1):
def process_results(file_path, result_file):

# Function to save differences into the xlsx file and calculate sums
def save_to_reserves_excel(df, df_case3, difference_data, result_file):

# Saving the updated workbook
wb.save(reservit_file_path)
```

Appendix B1. The Python libraries, function names and input values of the results processing script.

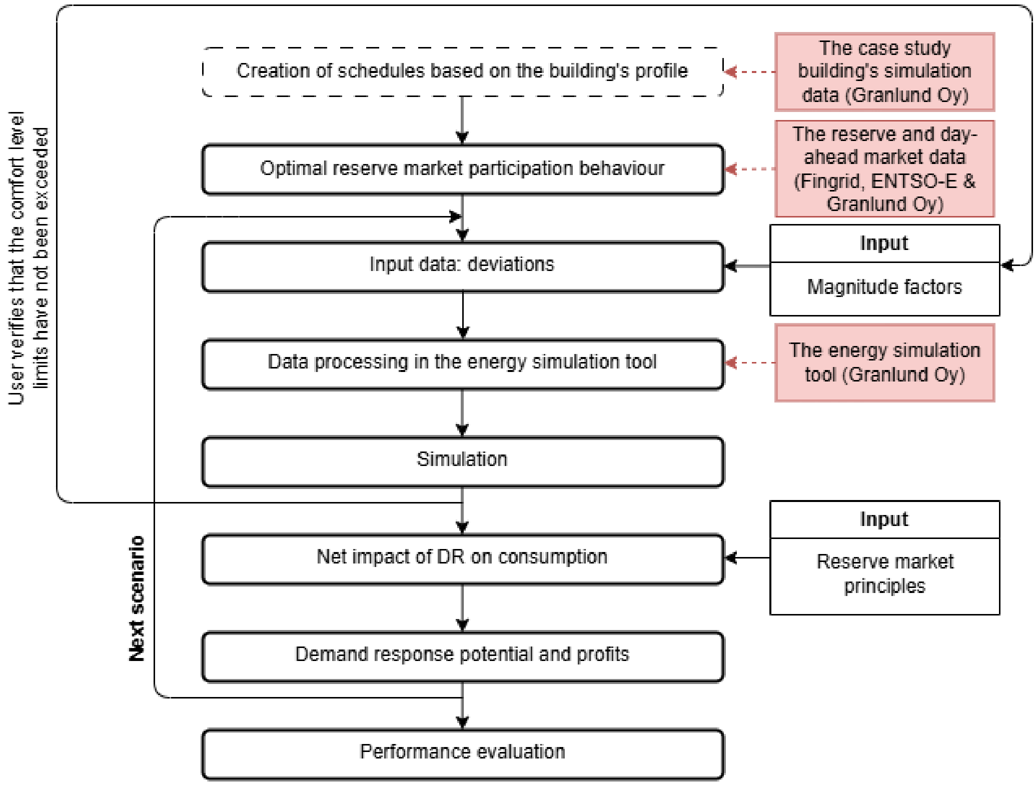
```
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.dates import DateFormatter
import tkinter as tk
from tkinter import messagebox

# Function to initialize a multi-choice selection popup
def open_multichoice_popup():
def on_ok():
def on_cancel():

# Execute the processing results function
from Processing_of_the_results import process_results
process_results(file_path, result_file)
```

Appendix B2. The Python libraries, function names, and input values used in the result-generating script.

Appendix C



Appendix C. Process chart of the estimation scheme of the demand response potential within one chosen reserve market. The red boxes show the external data sources or tools used during the estimation scheme.

Appendix D

The profits from upregulation in the FCR-D market can be calculated followingly. The value for the activated in this market was formulated to be positive during upregulation:

$$Profit_{energy} = \sum_{h=1}^{8760} E_{h,j} \times (C_{h,day-ahead} + C_{h,fees}) \tag{35}$$

The profits from upregulation in the FCR-N market can be calculated followingly. The value for the activated energy in this market was formulated to be negative during upregulation:

$$Profit_{energy} = \sum_{h=1}^{8760} E_{h,j} \times -(C_{h,day-ahead} + C_{h,fees}) \tag{36}$$

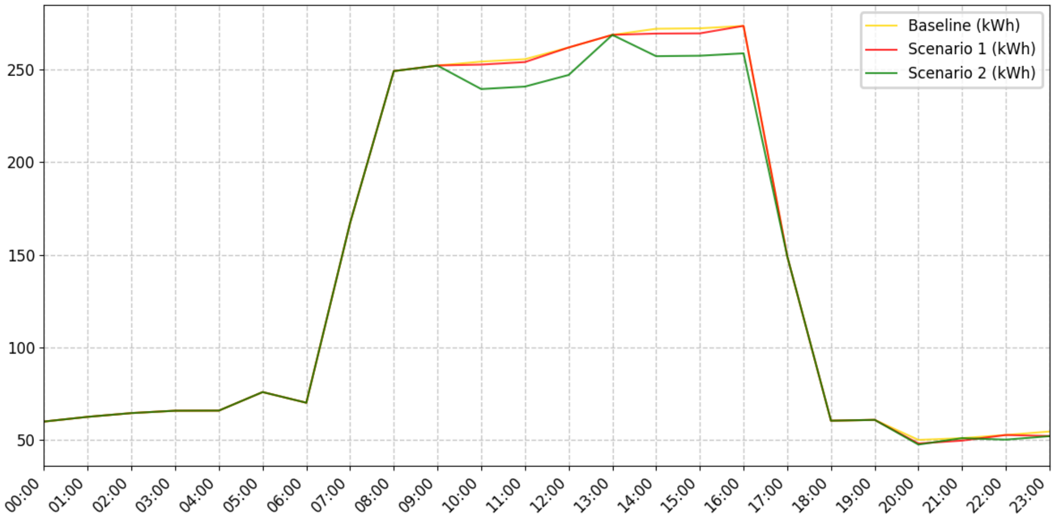
The profits from upregulation in the mFRR and aFRR capacity markets can be calculated followingly. The value for the activated energy in this market was formulated to be negative during upregulation:

$$\begin{aligned} Profit_{energy} = \sum_{h=1}^{8760} -E_{h,j} \times C_{h,reserve} \\ + \left(-E_{h,j} \times \left(C_{h,day-ahead} + C_{h,fees}\right)\right) \end{aligned} \tag{37}$$

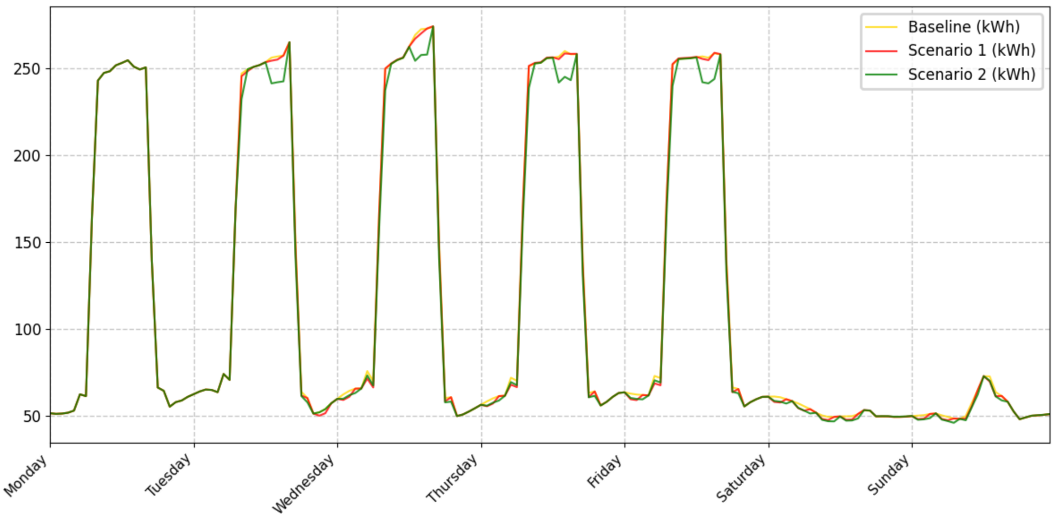
The profits from upregulation in the mFRR and aFRR energy markets can be calculated followingly. The value for the activated energy in this market was formulated to be negative during upregulation:

$$\begin{aligned} Profit_{energy} = \sum_{h=1}^{8760} -E_{h,j} \times C_{h,reserve} \\ + \left(-E_{h,j} \times \left(C_{h,day-ahead} + C_{h,fees}\right)\right) \end{aligned} \tag{38}$$

Appendix E



Appendix E1. The net impact of four individual demand response events, measured across the entire day (26th of June 2023). The DR events occur between 10:00-13:00, 14:00-17:00, 20:00-21:00 and 23:00-24:00. The reserve market presented in the figure is mFRR energy market (upregulation).



Appendix E2. The net impact of multiple demand response events, measured across the entire week (24th to 30th of June 2023). The DR events occur during open-ing hours (Tuesday-Friday) and 01:00-03:00, 05:00-07:00, 09:00-11:00 and 13:00-15:00 (Saturday-Sunday). The reserve market presented in the figure is aFRR capacity market (upregulation).