Master's thesis

NTNU
Norwegian University of Science and Technology
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Department of Electric Power Engineering

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Price formation and market balancing in a local flexibility market using Model Predictive Control

Master's thesis in Energy and Environmental Engineering

Supervisor: Olav Bjarte Fosso

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Kunnskap for en bedre verden

Abstract

Flexibility is broadly defined as the willingness and ability to change production or consumption. By doing so, participants in the power system can adapt to the physical situation in the grid and contribute to more efficient grid operation. Theoretical tests and practical pilots unveil the potential for flexibility from various contributors. A general understanding is that flexibility can become valuable for several different applications in the power system. For example, balancing costs can decrease, and grid investments can be postponed.

A market solution is one of several means of accessing small-scale flexibility. The market is intended as a platform where those providing and requesting flexibility meet, facilitating balance in the power system. Whether a market platform for flexibility should be implemented, and the exact market design, is still a topic of discussion. There are many aspects to consider. For example, flexibility must be distinctly identified as a tradable commodity, and the framework for trades, agreements and price formation must be standardised. An important advantage of balancing through a market is the competitive aspect, creating socioeconomic and fair results for the participating parties.

To investigate flexibility markets further, an exemplified, local market model has been programmed using Python and the linear programming package Lpsolve. The proposed design is based on the methodology called Model Predictive Control (MPC). In the centre of this approach lies the ability to predict information based on system behaviour and historical data. This way, the market can arrive at optimal decisions for the present, based on anticipated system development. With different options within the exact algorithm design, the methodology can be tailored to systems with different qualities. An example is to change the prediction horizon, which is the interval over which the algorithm optimises.

The market platform determines the market balance by optimising the use of resources over time, thereby achieving an optimal flexibility dispatch and local electricity price in every time step. The market algorithm consists of an optimisation problem being executed every hour. Market analyses were performed in an assumed energy community, for a 24-hour day. Two different situations were chosen; normal operating conditions, and a day where there is reduced capacity in some hours due to an outage.

According to the analyses, the selection of prediction horizon strongly affects the timetable for flexibility activation, and thereby the balancing costs in different parts of the day. A market algorithm with a somewhat short prediction horizon has a limited overview of the upcoming load profile, hence less opportunity to schedule flexibility long-term. A market algorithm with a somewhat long prediction horizon produces a more evenly distributed flexibility dispatch, including preparation for anticipated capacity issues. These indications became even more visible when analysing a day where the grid faces an outage. When long-term preparation is possible, computed price sets show the least volatility, even when an unforeseen event occurs. On the contrary, when optimising for only a few hours at a time, the fault becomes difficult to handle, hence forcing the utilisation of any currently available resources. This can induce sudden and high price peaks, i.e. less predictable electricity bills for customers.

Even though the market algorithm produces the most socioeconomic results when it is scheduling flexibility for the longest set of hours, this might still not always be the optimal choice. For example, when distribution grid prices are difficult to predict, there is no use in making plans for a long period. Also, when unexpected events occur close to real-time, already performed computations are wasted and must be redone.

A general experience from the thesis work is how MPC can be a useful method in relation to flexibility market balancing. With for example Advanced Metering Systems (AMS) there will be more information on which to base predictions about future load curves. As for flexibility markets in general, there is definitely a potential to utilise flexibility for both balancing and grid purposes. Since the formation of an efficient market platform requires many participants to be active already from the beginning, the initial start-up phase might be the most challenging. However, the analyses performed in this thesis indicate a significant potential once a market-based flexibility platform is in operation.

Sammendrag

Fleksibilitet kan i bred forstand forstås som villigheten og evnen til å endre produksjon eller last. Slik tilpasningsdyktighet kan bidra til mer effektiv nettdrift. Teoretiske tester og pilotprosjekter har funnet potensial i å utnytte fleksibilitet fra flere forskjellige tilbydere. En generell erfaring er at fleksibilitet kan bli svært nyttig til flere formål. Blant annet kan balanseringskostnader reduseres, og nettinvesteringer kan utsettes.

En markedsløsning er en av flere muligheter til å aksessere småskala fleksibilitet. Markedet er ment som en plattform der de som tilbyr og etterspør fleksibilitet kan møtes, slik at det kan legges til rette for balansering. Hvorvidt en markedsløsning for fleksibilitet bør innføres, og det eksakte markedsdesignet, er et aktuelt diskusjonstema, der mange aspekter må tas i betraktning. For eksempel må produktet fleksibilitet tydelig defineres som en omsettelig vare, og rammeverk for utveksling, avtaler og prisbestemmelse må standardiseres. En viktig fordel ved balansering via et marked er også at konkurranseaspektet induserer samfunnsøkonomiske og rettferdige markedsresultater.

En eksemplifisert, lokal markedsmodell har blitt programmert ved å bruke Python og den lineære programmeringspakken Lpsolve, med mål om å studere fleksibilitetsmarkeder nærmere. Det foreslåtte designet er basert på Modell Prediktiv Kontroll (MPC), en responsbasert og dynamisk kontrollalgoritme. I kjernen av denne tilnærmingen ligger evnen til å forutse informasjon basert på systemets oppførsel og historiske data. Markedet kan dermed beregne optimale avgjørelser for nåtiden, basert på forespeilet systemutvikling. Parameteret kalt prediksjonshorisont er spesielt sentral for å kunne tilpasse algoritmen til spesifikke systemer.

Markedet finner markedsbalansen ved å optimere bruk av tilgjengelige ressurser over tid. Det beregnes en optimal timeplan for fleksibilitetsaktivering, samt en lokal strømpris, i hvert tidssteg. Markedsalgoritmen består av et optimeringsproblem som utføres hver time, for et sett av timer fremover. Testene gjennomføres for et antatt lokalt energisamfunn, og analysene blir gjort for ett døgn. To ulike situasjoner ble valgt; normale forhold, og en dag der det er redusert overføringskapasitet i noen timer, som følge av et utfall.

Ifølge analysene blir den optimale fleksibilitetstimeplanen og balanseringskostnader i ulike deler av dagen sterkt påvirket av valget av prediksjonshorisont. Et marked med en noe kort prediksjonshorisont har begrenset oversikt over den kommende lastprofilen, og dermed mindre mulighet til å planlegge bruk av fleksibilitet på sikt. Et marked med en noe lengre prediksjonshorisont genererer en mer jevnt distribuert fleksibilitetstimeplan, som inkluderer forberedelser til forutsette kapasitetsproblemer. Disse indikasjonene blir tydeligere når dagen med utfall analyseres. De beregnede priskurvene viser minst volatilitet når langsiktige forberedelser er mulige, selv når en uventet hendelse inntreffer. Derimot, når det kun optimeres for noen få timer av gangen, vil feilen kunne bli for stor til at markedet klarer å håndtere den. Dette kan indusere plutselige og høye pristopper, og følgelig mindre forutsigbare strømregninger.

Selv om det lokale markedet beregner de mest samfunnsøkonomiske resultatene når det planlegges for mange timer av gangen, kan det likevel være at en lang prediksjonshorisont ikke er det beste valget. Et eksempel er dersom prisene i distribusjonsnettet er vanskelige å forutsi. Da er det lite nytte i å legge planer for mobilisering av fleksible ressurser langt frem i tid. I tillegg vil beregninger kunne bli ubrukelige dersom det oppstår uforutsette hendelser nær sanntid, og det må optimeres på nytt.

En generell erfaring fra arbeidet med masteroppgaven er hvordan MPC kan være en nyttig metode å bruke i sammenheng med balansering i et fleksibilitetsmarked. Med for eksempel Avanserte Måle- og Styringssystemer (AMS) vil det for eksempel kunne bli mer informasjon å basere prediksjoner av lastkurver på. Når det gjelder fleksibilitetsmarkedet generelt er det definitivt et potensial i å utnytte fleksibilitet til både balansering og nettformål. Fordi etableringen av en effektiv markedsplattform avhenger av at mange deltakere er aktive allerede fra starten av, kan det tenkes at markedets oppstartsfase vil være den mest utfordrende. Likevel viser eksempelanalysene gjennomført i denne masteroppgaven at det finnes et betydelig potensial så snart en plattform for markedsbasert fleksibilitetsutveksling er i drift.

Preface

Through the submission of this thesis, I will have completed my five years of studying for a master's degree in Energy and Environmental Engineering at the Norwegian University of Science and Technology (NTNU), in Trondheim. The thesis work was performed during the spring semester 2020, represents 30 ECTS, and is being delivered to the Department of Electric Power Engineering.

This master's thesis is a continuation of my specialisation project, in which I studied the methodology behind Model Predictive Control and how it can be used to coordinate usage of stored energy over time. This was submitted in the autumn 2019. Insights from this project, as well as knowledge gained throughout my education, was further utilised and applied to discussions and balancing computations in a local market for flexibility.

Furthermore, the thesis is a contribution to the ongoing research project CINELDI, organised by SINTEF, with participants from many different levels of the Norwegian power system. The overall goal of the project is to be an interdisciplinary platform for research towards developing a green, robust, digitalised, efficient and flexible future distribution grid.

As I am completing this master's thesis, I would like to thank my supervisor, Olav Bjarte Fosso, for introducing me to an interesting topic, as well as guiding me through the thesis work with valuable advice, useful discussions and practical perspectives. In addition, I thank my proofreaders for their time and effort.

I am also grateful looking back at my years at NTNU, alongside my classmates and together with close friends. Many valuable experiences stand out, both educational and social, from a memorable time studying in Trondheim.

Trondheim, June 2020
Hannah Magnussen

List of Figures

List of Tables

Initiation

Indices

i = hour index
n = hour index within prediction horizon
c = customer index
b = battery index

Sets

S = dynamic set of length h, i.e. current optimisation horizon

Variables

$P_{up,nc}$ = load increase during hour n for customer c
$P_{down,nc}$ = load decrease during hour n for customer c
$x_{up,nb}$ = charging during hour n of battery b
$x_{down,nb}$ = discharging during hour n of battery b
x_{nb} = energy level at the end of hour n in battery b
G_n = energy purchased from main grid in hour n

Parameters

I = period of analysis
h = prediction horizon
C = number of customers
B = number of batteries
$p_c^{\downarrow}$ = customer c's price decrease requirement
$p_c^{\uparrow}$ = customer c's price increase requirement
$p_b^{\downarrow}$ = battery b's price decrease requirement
$p_b^{\uparrow}$ = battery b's price increase requirement
$v_{c,inc}$ = customer c's willingness to increase load, i.e. customer c's buy price
$v_{c,dec}$ = customer c's willingness to decrease load, i.e. customer c's selling price
$w_{b,inc}$ = battery b's willingness to charge, i.e. battery b's buy price
$w_{b,dec}$ = battery b's willingness to discharge, i.e. battery b's selling price

x_{0b} = initial energy level in battery b
$\overline{x}_b$ = maximum capacity for battery b
ϵ = required storage content, $0 \leq \epsilon \leq 1$
$\overline{x}_{up,b}$ = battery b's charging power
$\overline{x}_{down,b}$ = battery b's discharging power
ι_c = maximum allowed net regulation during S for customer c
ϑ_c = maximum allowed net regulation during I for customer c
χ_c = net regulation until hour $I - h$ for customer c
p_n = main grid electricity price in hour n
μ = main grid avg. electricity price during I
L_n = community load in hour n
$\overline{G}_n$ = transmission line capacity in hour n

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Table of contents

1 Introduction

1.1 Motivation

Main drivers such as environmental concerns, distributed generation and a growing energy demand require the traditional power system architecture to change fundamentally. Renewable generation depends on less predictable weather conditions, and it is not guaranteed that supply will be available at the same time as demand. Generation from wind and solar are often located in the distribution grid, where the infrastructure is not necessarily prepared for large scale electricity transport. Moreover, simultaneous energy demand is increasing due to a growing consumption and electrification of several aspects of our everyday life.

The combination of these trends causes capacity-related challenges, which further induces a need for grid expansions. Grid investments are, however, expensive for both grid operators and electricity customers. Also, the grid is only experiencing power scarcity in a few hours of peak load each year [1, 2]. The Norwegian Water Resources and Energy Directorate (NVE) is therefore currently in the process of redesigning the Norwegian grid tariff model. A capacity charge will be introduced such that grid costs are based on capacity demand rather than energy demand. Capacity issues are in fact a problem in several countries, and regulators are considering new standards for energy billing [3].

Flexibility is believed to be another key solution approach to the current capacity issues. Adaptable behaviour can be triggered both on the production and the demand side. As renewable resources comprise an increasingly large percentage of total energy conversion, consumption needs to adapt correspondingly. This is referred to as consumer flexibility. Customers must be able to ramp up their loads when availability is high and willing to ramp down in case of scarcity. Preferably, this flexibility can be activated in real-time based on the physical situation in the grid. Controllable production is also able to offer flexibility by adjusting its generation pattern. Another option could be to use storage. Either way, flexible resources can contribute to reduced stress on the power grid at times of high demand or unexpectedly large production. Existing infrastructure can also be utilised more efficiently, and consequently, grid investments can be postponed.

Surely, there are many advantages to utilising flexibility. Another application is for local communities with limited transmission capacity from the main grid. Local energy communities are part of the trend towards a decentralised and distributed energy system [4]. Instead of investing in grid expansions between the community and the main grid, available flexibility can be used to cover the non-steerable load. Local energy communities can, for example, consist of several consumers, prosumers and storage units. Here, flexibility could mean both local, small-scale production and adaptable consumer behaviour.

Flexibility should be activated in a way that is socially beneficial for the community. Therefore, flexible resources must be coordinated and matched against each other in order to decide which bids and offers to use first. This can be organised by establishing the local market balance, where the optimal flexibility dispatch can be determined. A remaining unresolved question is still how to design such a local power market optimally. There is not necessarily a straightforward solution, as it can be challenging to continuously balance incoming and outgoing flexibility for a number of customers.

As of today, local power markets for flexibility exchange is a topic mostly investigated theoretically. A functional market solution for flexibility trading, which is beneficial for both operation of the grid and for participating traders, is still to be determined. However, both grid operators and regulators in several European countries are engaged in studies considering roles, mechanisms and optimal market design for such an electricity market. In addition, the installation of Advanced Metering Systems (AMS) is an important step towards enabling flexible behaviour. Evidently, utilisation of flexibility is considered increasingly relevant in the progression towards a future, flexible power system [1]. Local markets can become a logical solution approach when facing both capacity challenges, integration of renewable energy conversion and implementation of flexibility.

1.2 Objectives

This master's thesis is about local flexibility markets, and a local market model based on linear programming is proposed. The goal with this flexibility market is to achieve utilisation and coordination of flexible resources over time, in a manner that is optimal for a flexible community. Activation of flexibility must be planned such that the community benefits from the adaptable behaviour of its market participants. Benefits include coverage of the community load, particularly in hours when the grid capacity is insufficient, as well as an overall low electricity price. The optimal flexibility dispatch will also contribute to smart and more efficient utilisation of existing grid capacity. At the same time, effective compensation mechanisms must be established.

By using a dynamic time horizon, the optimisation model comprising the market clearing process optimally allocates flexible resources over time. Model Predictive Control (MPC) is used to formulate the dynamic optimisation algorithm. It computes local electricity prices over a selected period of analysis based on several customised parameters. Price formation depends on coordination between willingness to offer flexibility and the benefits expected by flexibility traders. The rolling time horizon allows the model to make optimal decisions based only on currently available information. This enables the model to handle unforeseen events and still manage to obtain energy balance.

The market model is tested on an exemplified community consisting of flexible customers and storage units.

The objectives of this thesis are the following;

1. Develop a local flexibility market proposal by using the MPC methodology
2. Investigate the market model's performance through analysing example situations
3. Assess the model from the perspective of possible improvements and alternative extensions

2 Theoretical elements and methodology

In this section, relevant theoretical background and a description of the applied methodology will be presented.

2.1 Sensitivity analysis

Sensitivity analysis gives vast opportunities for interpreting changes in a linear programming problem. For example, the marginal worth of a resource and the profitability of an activity can be decided. In this thesis, shadow prices will become an important concept when analysing the performance of the local market model.

From linear programming, the shadow price of a constraint can be defined as the change in objective function value for a unit increase of the right-hand side of that particular constraint [5, Ch. 3]. Say, in the case of a resource allocation problem, maximising profits for a company, a constraint restricts the usage of a limited resource. The constraint's shadow price refers to how much profits would increase if the company had access to one more unit of this specific resource. For this reason, only binding constraints have non-zero shadow prices. If a constraint is satisfied at equality, all available units of the asset is being used. In this case, the optimiser detects improvement possibilities for the objective value, and the shadow price will hence be non-zero. On the contrary, if there is still some left of the limited resource in the optimal solution, there is no use in increasing the right-hand side of its corresponding constraint. The company from before will in this case not increase its profits by increasing the resource availability. Therefore, the shadow price would be zero.

Whether the shadow price has a positive or negative value will depend on how the objective value is affected by the right-hand side increase. For example, the shadow price of a binding constraint in a resource allocation problem would surely have a positive value. Increased resources would allow extended activities and further profits. On the other hand, the right-hand side of a constraint could represent a liability which must be satisfied. An example is demand which must be covered. In this case, the shadow price would take on a negative value because a right-hand side increase means added inconvenience. For a profit maximisation problem this means rising costs, as the objective value would decrease.

Shadow price can also be interpreted as willingness to pay for a limited resource. The company from the resource allocation problem is surely aware of the marginal cost of purchasing another unit of the emptied asset. As the shadow price indicates the marginal revenue from the unit increase, profitability of the trade can be determined. The company can then make a calculated decision to purchase another unit of the limited resource, if the corresponding shadow price is higher than the resource cost.

In a general optimisation problem there are usually non-negativity constraints on all variables. The shadow prices of these particular constraints are called reduced costs. If the right-hand side of such a constraint were to increase from 0 to 1, the respective decision variable would be forced to take on a positive value in the optimal solution. The reduced cost of a basic decision variable is therefore zero, because the objective value would not change if the non-negativity constraint's right-hand side increased. A basic variable already has a positive value in the optimal solution. On the contrary, the reduced cost of a non-basic variable is different from zero. Increasing the value of the variable with one unit could have positive or negative influence to the objective value, depending on the polarity of the reduced cost.

A reduced cost, $\overline{c}_j$, represents the net marginal revenue of an activity, j, represented by a decision variable, x_j [5, Ch. 4]. It can be calculated by means of the shadow prices by using the following expression.

$$\overline{c}_j = c_j - \sum_{i=1}^{m} a_{ij} y_i \quad , \quad j = 1, 2, ..., n \tag{2.1}$$

Here, c_j is the objective function coefficient of variable x_j, y_i indicates the shadow price of constraint i, and a_{ij} refers to the coefficient of variable x_j in constraint i. In Eq. (2.1), the coefficient c_j represents the marginal revenue of one unit of variable x_j, while the sum can be interpreted as the marginal cost of one unit of variable x_j. By subtracting the sum from the objective function coefficient, the *net* marginal income of one unit of activity j can be determined.

Reduced costs are valuable when deciding which variables should be included in the basis. Say the profit maximising company from before is considering including a new activity. To assist in this decision, the activity's reduced cost can be computed. By knowing the revenue of a unit increase of the corresponding decision variable, the marginal profit of the activity can be found. The outcome will give the company indications about the profitability of their choice.

2.2 Duality theory

Shadow prices have an important role in the context of duality theory. Duality explains the relationship between two linear problems, the primal and the dual. These are depicted in matrix form below. The maximisation problem (P) is the primal and the minimisation problem (D) is the dual. These are merely mirrored versions of each other, as solving one of the problems also means solving the other.

The equation sets show the relation between the problems. The dual will evidently have the same number of variables as the primal has constraints, and the primal will have the same number of variables as the dual has constraints. Since the two problems are complementary, their objective values, f and g, will be equal.

$$
\text{(P)} \qquad \begin{aligned} \max\ f(\boldsymbol{x}) &= \boldsymbol{c}^T\boldsymbol{x} \\ \text{subject to } \boldsymbol{A}\boldsymbol{x} &\le \boldsymbol{b} \\ \boldsymbol{x} &\ge \boldsymbol{0} \end{aligned} \qquad\qquad \text{(D)} \qquad \begin{aligned} \min\ g(\boldsymbol{y}) &= \boldsymbol{b}^T\boldsymbol{y} \\ \text{subject to } \boldsymbol{A}^T\boldsymbol{y} &\ge \boldsymbol{c} \\ \boldsymbol{y} &\ge \boldsymbol{0} \end{aligned}
$$

The relationship between the primal and the dual is neatly described by the complementary slackness condition. If a primal variable is positive, the corresponding dual constraint is satisfied at equally. The dual constraint thereby has no slack, since all of the limited resource belonging to the constraint is used. When there is no slack, the shadow price related to the dual constraint, i.e. the primal variable, takes on a positive value. Similarly, if a primal variable is zero, the corresponding dual constraint will hold at inequality [5]. In conclusion, the primal variables, $\mathbf{x}$, exactly correspond to the shadow prices in the dual, while the dual variables, $\mathbf{y}$, exactly correspond to the shadow prices in the primal.

Since solving one of the problems means solving the other, duality theory can give computational advantages. For example, the dual problem could be less time-consuming to solve than the primal. Solving either of the problems would produce the same, optimal results.

In this thesis, duality will be used to determine prices in a local flexibility market. This is not a new application for duality theory. Authors Bradley, Hax and Magnanti stated the following in their book *Applied Mathematical Programming*, already in 1977:

> The duality theory of linear programming has had a significant impact on mathematical economics through the interpretation of the dual as the price-setting mechanism in a perfectly competitive economy [5, Ch. 4].

The authors further present an example where the dual of a profit maximisation problem for a perfectly competitive company equals the clearing process in the market where the company is active. In this situation, the complementary slackness conditions indicate two essential features in a perfectly competitive market. Firstly, the market price of a resource may only be non-zero if all of the available resource is being used. If there is an unused amount of the resource left, the market price will be zero. Secondly, the market seeks to minimise any excess profits for the competitive company. Therefore, there is either no additional profits from engaging in an activity, or the competitive company is not engaging in the activity at all [5, Ch. 4]. Clearly, duality is a theory relevant for analysing market mechanisms and clearing processes.

2.3 Model Predictive Control

This methodology, also referred to as the abbreviation MPC, is a dynamic and feedback based control algorithm. By means of an optimiser and a model of the system being investigated, optimal control decisions are computed, aimed towards a predetermined target. The methodology uses predicted information about the future to find the optimal action to execute in real time [6]. A rolling time horizon enables the algorithm to handle disturbances or system changes as they occur. As control actions are executed, the system response is transmitted back to the model predictive controller. A chart illustrating the flow of information and control is shown in Figure 1.

The features of MPC were reviewed and accounted for in a previous work by the same author as this thesis, *Model predictive controller for charging of grid-connected battery*, 2019. The summary of characteristics in this section reuses some of the content from this report.

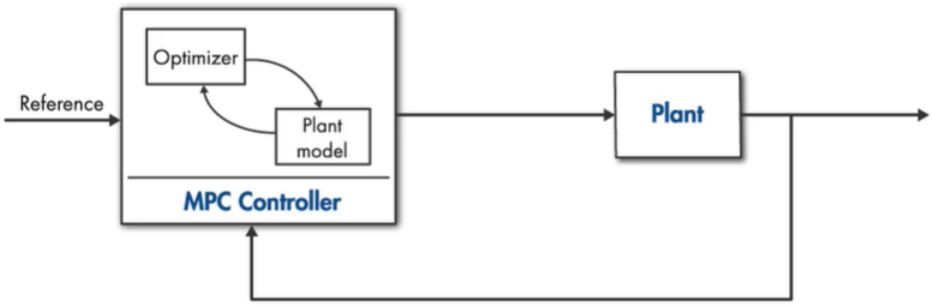

Figure 1: *Block diagram for MPC algorithm. Source: [7]*

The optimiser consists of an optimisation problem solving the system model over a given time interval. This interval is called the prediction horizon. The first hour of this interval is the present one. Since the algorithm produces assumed information based on the system model, it is able to compute decision for all hours currently being reviewed.

The selection of prediction horizon length strongly affects the characteristics of the controller. Iterating through the period of analysis, the horizon defines the model's field of view. A long horizon gives the algorithm opportunity to be prepared for system disturbances. Still, unexpected events can occur within the current horizon, causing wasted computations. A controller with a short horizon, on the other hand, can handle frequent interruptions close to real time. However, some disturbances might be too significant to handle without a few time steps of preparation. Also, computations are performed often, demanding powerful processing power. Consequently, short and long prediction horizon controllers each have their advantages and disadvantages.

Control actions are calculated for all hours of the prediction horizon based on anticipated data. However, only some of them are actually executed. The control horizon determines just how many. It is typical to set the control horizon to one hour. Then, only the first control action computed by the optimiser will be performed. New control decisions for the next set of hours are computed already in the consecutive hour.

A real model predictive controller would predict information on its own, based on previous knowledge about the system. It this thesis, however, this will be simulated by granting the market platform access for information in steps. This will be further explained in chapter 4.

3 Flexibility and activation approaches

Based on several definitions, flexibility can be widely understood as the ability and willingness to change demand or production [2, 8]. This chapter reviews the need for flexibility in the power system, and how it can be accessed. It will also initiate a discussion regarding local flexibility markets and how they can serve as an alternative to network tariffs and price signals.

3.1 Why flexibility is needed

Adjustable behaviour is highly valuable in balancing the power system, from both the supply and demand side. Price volatility in the electricity market reflects a power system regularly under pressure [9]. Both periods with very expensive and very cheap electricity indicate a significant gap between supply and demand. System imbalances are the reason behind these extremes. The market then faces complication in the process of determining the market equilibrium, because the amount of energy injected and withdrawn from the grid do not match. This leads to high balancing costs, as the market requires regulation and reserves in order to compensate.

Substitution of conventional and controllable power plants with unpredictable, renewable resources is one of the reasons behind great price differences. Electricity produced through renewable energy conversion is injected into the grid as it is being produced. This immediacy makes balancing difficult. For this reason, the Norwegian Transmission System Operator (TSO) expects higher price volatility in the future [9].

Flexibility is believed to be a suitable tool when bridging the gap between supply and demand. The market can then achieve smaller price differences and lower balancing costs. This is shown in Figure 2. The highest prices can become lower, and the lowest prices can become higher. Evidently, price volatility implies a demand for flexibility [10]. Utilisation of flexibility can also be vital in avoiding curtailment of electricity production from renewable resources.

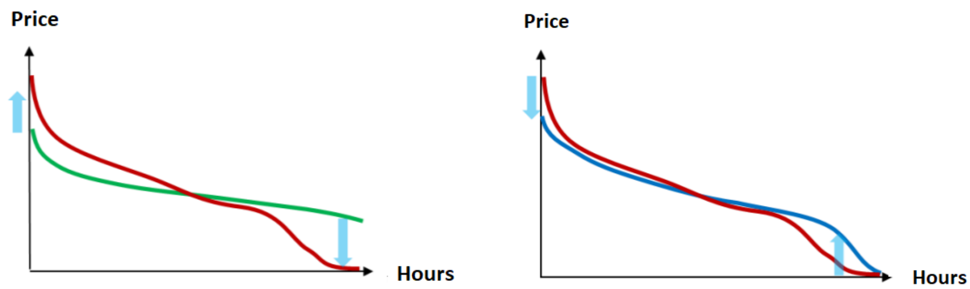

Figure 2: *Example duration curves for electricity prices. Left: Without flexibility, a development from low price volatility (green) towards high price volatility (red) will occur. Right: With flexibility, price differences can be limited. Price developments can be steered towards a situation with minimised volatility (blue). Source: [9]*

A goal among the Nordic TSOs is to enable electricity trading closer to real time than what the current intraday market can offer [11]. With more renewable energy conversion, the characteristics of the power system will change. As more rapid fluctuations in supply can be expected, the market design should adapt accordingly and enable trading closer to the hour of operation. This way, demand can match the available supply at all times.

Flexibility can further serve as a congestion management method [1]. Bottlenecks can occur when the distribution system is under pressure, as several consumer groups often contribute to the same power peaks. Besides, the energy demand is growing at a higher pace than the grid's transfer capacity. Flexible behaviour can operate as a reserve able to function both as a load and a generator. This way, flexibility can contribute to resolving local congestions. This mechanism can also relieve the tension on power electronic components such as transformers, in addition to power lines. Slowing down the technical ageing process of the infrastructure is an advantage that follows.

Utilising flexibility further enables new options with respect to energy flow scheduling. With reserves located all around the distribution grid in the form of flexible consumers, smarter and more efficient utilisation of the existing grid is possible. Power flow can be scheduled physically and in time according to where and when there is available transmission capacity. The need for expansions will thereby decrease.

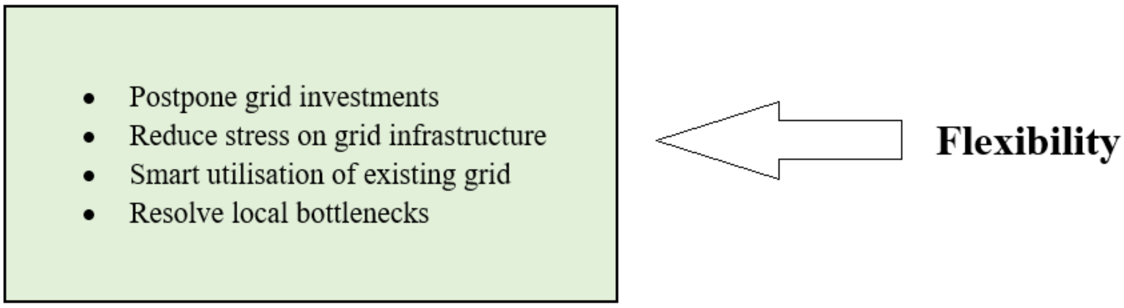

Figure 3: *Overview of important grid applications for flexibility. Source: [2, 1]*

Implementation of flexibility will require automation and more advanced control and measurement systems. Load patterns must be predicted with precision, and flexibility activation must occur automatically. As the hour of operation approaches, the energy flow schedule can change frequently due to redispatch and rebalancing. The sort of equipment required to perform these operations can be used to further improve grid performance. For example, optimisation of energy flow and automatic, smart charging can be achieved. Moreover, security of supply will enhance as flexibility can assist the grid operator during outages and faults.

3.2 Flexibility contributors

Various types of flexibility exist and can be offered by different providers. The production side can act flexibly by adjusting generation output according to demand and the physical situation in the grid [2]. Examples of power plants with control of their production output are hydro power and otherwise conventional power plants. Here, generation is decided by the amount of injected fuel. However, energy conversion from wind and solar cannot be monitored the same way.

The consumer side has other possibilities of being flexible. Prosumers can provide through the generation of renewable energy, for instance, by installing solar panels. Local production in general can serve as a flexible resource because most customers are connected to the distribution grid. Here, capacity issues can occur when the power requirement is high. Small-scale production units available at lower voltage levels can contribute to solving local bottlenecks and relieve both power lines and power transformers.

Adaptable consumer load is also a source of flexibility. Demand can shift in time and increase or reduce altogether. A typical example is to shift laundry or charging of electric vehicles to nighttime, for example through automatic load control. Figure 4 shows the anticipated development of available flexibility from the demand side. Among other sources, especially flexibility from charging of electric vehicles is expected to increase significantly towards 2045.

Other adjustable household loads are, for instance, ventilation and room- and water heating using electricity. These, and similar appliances such as heat pumps, are expected to provide a considerable combined potential for flexibility in the future. As more than 50% of the electricity consumed in Norwegian buildings is used for heating purposes, the flexibility potential from these loads is clearly present [12, 9]. This concerns both households, service and commercial buildings. Figure 4 also indicates an increase in demand-side flexibility from buildings and heat pumps.

Still, it is essential to ensure minimal to no influence on indoor comfort when electric heating appliances are used as flexible resources. Presumably, one can expect shifting of these loads to have little effect on resident convenience [14]. For this reason, offering electric heating devices as flexible loads can become increasingly attractive.

Load regulation can be useful in both directions. Flexible customers can reduce their load in case of capacity issues in the grid. The other way around, when renewable production is high and the grid suddenly experiences stress, consumer load can ramp up to maintain the energy balance. Another possibility is to change the energy source completely, hence decreasing the electricity consumption. In this case, the consumer does not need to be compensated at a later point in time, because another fuel source is covering the load. Concerning heating, this could mean switching to district heating or bio-fuelled heaters.

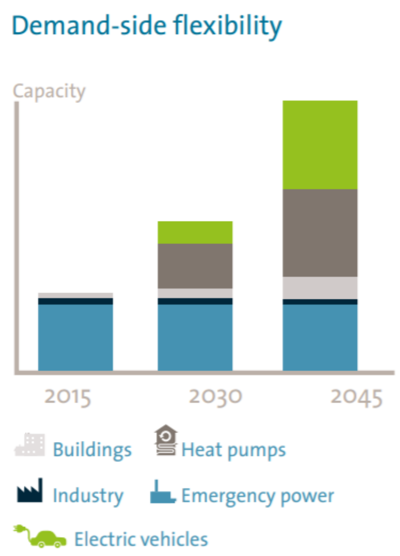

Figure 4: *Projected flexibility potential from different demand-side sources. Source: [13]*

Storage is another flexibility alternative, and a notable application is as green energy reserves. Weather conditions and seasonal differences determine when one can anticipate high production from renewable sources. However, generation patterns do not necessarily coincide with demand trajectories. Batteries can therefore become essential because of their unique ability to collect energy over time. Disabling the immediacy surrounding electricity as a commodity, implementing storage can contribute to a more flexible energy system. This way, environmentally friendly resources are taken advantage of, an energy reservoir is created and the grid is being assisted at times of high and unpredictable production rates.

Customers with electric vehicles could for example offer their car batteries as temporary storage while connected to a charger. Besides this option, an open question is still to whom batteries located in the distribution grid should belong. Some reports [1, 15] have arrived at a third-party owner, separated from customers and grid operators, to be the best solution.

3.3 Activation of flexibility

As described above, flexibility can originate from both the production and demand side, and has several applications. However, the focus from here on will be consumer flexibility.

For adaptable behaviour to become useful as a grid resource, it must be triggered effectively. This means that flexibility must be activated precisely when the grid is facing capacity issues and in the right amount, such that it can be used to achieve a particular goal. This could be managed through several different means.

A method commonly used for large scale industrial consumers in Norway today is a disconnect tariff (UKT). Both the TSO and DSOs can offer reduced tariff rates in exchange for the opportunity to disconnect large consumers on short notice [16].

Another option is to trigger flexibility through capacity tariffs. Customers are then billed for their simultaneous power consumption in addition to their energy use. The goal is to encourage consumers to evaluate their power needs, as the necessity for unlimited supply must be appreciated against the cost of capacity. Optimal capacity tariff design is challenging and often case dependent. Several approaches have been suggested for the Norwegian power system [2]. Today, an approach referred to as maximum capacity is being charged to several commercial buildings, among others. With maximum capacity, a consumer is billed for its highest power peak during a month, in order to motivate a capacity reduction during peak hours. To measure the maximum peak has been made possible by AMS. Another proposed arrangement is called subscribed capacity, where customers will be charged at expensive rates if they use more power than their subscribed amount [2].

Price signals is a third flexibility enabler as electricity prices reflect the physical situation in the grid. During capacity problems, prices can be set higher than under normal circumstances. This is an example of peak pricing, where consumers are charged extra during periods of high demand. It is a mean of regulation, to make sure demand does not exceed the levels of what can be supplied [17]. This way, the supplier can avoid congestions and brownouts.

A type of tariff using price signals is the time-of-use (TOU) tariff. Here, a price curve is set based on time of day and season [18]. Communicating these price signals to consumers will create an incentive to shift consumption from expensive peak hours to off-peak hours.

Another example of a price signal scheme is real-time-pricing (RTP), or spot pricing. RTP follows the actual electricity price curves computed by the central market clearing process. For the Nordic countries this is done by Nord Pool. This price scheme is thereby dynamic, in contrast to the static TOU model. Customers are then incentivised to reduce their consumption during power scarcity in real time. During winter time one could also expect higher overall prices than during summer time [19].

3.4 A market solution for flexibility

All the activation methods mentioned above are based on standardised agreements between a consumer and its grid operator. By means of capacity tariffs or price signals from the market clearing, implicit flexibility is triggered through demand response [9].

A quite different approach for flexibility initiation is to form a separate market platform for flexibility trades. Here, demand could be allowed to not only respond to incentives, but to participate in a flexibility exchange actively. This encourages activation of explicit flexibility [9]. Consumers can advance from their role as passive recipients, and become active participants in the power system [13]. Based on experience, a market clearing process will further provide more accurate signals for flexibility pricing and trades than tariffs [15].

A flexibility market has the potential to enable efficient trading of flexibility among customers, grid operators and the balance responsible party. The market serves as a common platform where bids and offers are matched, such that the power system balance is sustained. This is illustrated in Figure 5. An effective market will optimally evaluate flexibility according to offers and requests. Market mechanisms also decide the optimal flexibility volumes to be traded [20]. Moreover, an effective market would produce socioeconomic and fair results.

However, there are many decisions to be made before the formation of a flexibility market can take place. Systems and technology for automatic regulation and flow of information are also required in order for the market to become efficient. This subsection investigates the opportunities and barriers related to a market platform for flexibility.

Figure 5: *A market for flexibility can be a platform where those who offer and request flexibility can meet. The common goal is power system balance. Source: [1]*

3.4.1 Flexibility as a commodity

In order to make a flexibility market meaningful, flexibility must be explicitly identified as a commodity. During a transaction, both the buyer and the seller needs to be aware of the product which is being exchanged. A set of features can therefore define the product, and clarify the trade.

For example, capacity challenges can occur anywhere in the grid, and only flexible resources specifically at the critical location can be of help. Flexibility must therefore be defined according to the geographical location at which is it available. Further, flexibility providers will not have an infinite amount of energy to regulate. The amount of power linked to an offer must therefore be described. The flexibility's duration will naturally follow, because a consumer will only be able to ramp its load up or down during a specified period of time. Characteristics of flexibility as a commodity are summarised below [20].

- *Power.* How much capacity [kW] to count on from a flexible resource. This attribute is determined by the particular flexible load, and how much power it requires. The load can be activated during hours of excess supply, and deactivated during hours of scarcity. Its power demand describes the size of its flexible contribution.
- *Duration.* For how long one can expect the resource's capacity to be flexible and controllable. There will be limitations concerning the time interval a contributor can offer its resource, depending on convenience and the contributor's load pattern. How dependant the customer is of the particular flexible load also influences the flexibility's duration.
- *Timing.* At what time the flexibility can be utilised. A contributor's load pattern and daily routine affect the time at which the flexible resource is available, i.e. when it can be activated or deactivated. This attribute also depends on the possibility of automatic load control.
- *Grid location.* Where the flexibility is accessible. Flexibility contributors are based at different geographical locations. The one requesting flexibility, either a grid operator or a balance responsible, must have overview of where a flexible resource can be used. There might also be limitations concerning the distance a flexibility can be transmitted across.

3.4.2 Market design attributes

As of today, there is no standard market solution for flexibility in Norway. Whether or not it will be introduced depends on central decisions from the Norwegian energy regulator, NVE. The current opinion is to not change current regulation preventing the formation of such independent marketplaces, unless a market design fulfilling certain requirements has been established. Implementation of a flexibility market therefore depends on the particular market design [1]. For example, it should target socioeconomic efficiency, and the clearing results should affect the actions of market participants such that this is obtained.

The market must further create incentives such that it is beneficial for the demand to ramp up when there is excess supply, and beneficial for the demand to ramp down when there is power scarcity. In other words, consumption must increase when electricity is cheap and decrease when electricity is expensive [13].

The combination of several different attributes define the market design. Within each attribute there is a decision to be made. A selection of features which must be taken into account when describing a market for flexibility are listed and described below [1].

• *Physical location.* As mentioned in section 3.4.1, the geographical location of a flexible resource, and how it can be accessed through the local grid, restricts where it can be of use. This will limit the number of possible matches for the flexibility offered. A possible solution is to constrain the radius surrounding a flexibility provider. Then, only the local grid operator or the balance responsible party covering this particular area can accept the offer in the market. Also, if the flexibility market is local, then an entry barrier would be geographical location.

• *Impartiality.* A fair market requires no favouritism and equal evaluation of all offers. Different market roles and their subsequent tasks must therefore be defined. Impartiality is especially essential when deciding which party should operate the marketplace. Options include for example a grid operator, a retailer and an independent, third-party market participant.

• *Competitiveness and market power.* In order for the market to produce efficient results, there must be enough active traders present. If there are only a few trading parties, some of them might misuse their position and execute market power. Such manipulation can affect the market clearing process and the resulting electricity price [15]. The market can determine a price which is efficient for all participants only if there is sufficient competition present.

• *Feasibility.* The formation of a flexibility market depends on whether it is practically feasible to implement. The market should be designed such that the computed market actions are possible to carry out. Market operations should preferably be feasible with available technology, and with as little need for new and expensive equipment to be installed as possible.

For example, automatic and remote load control, as well as efficient flow of information between the flexibility provider and receiver, require robust and responsive communication systems. Measuring load patterns and validating actual regulation are further aspects which demand extensive metering and monitoring equipment. For a flexibility market to function effectively, these features, among others, need to be in place. On one hand, AMS enables new opportunities to track load in real-time. On the other hand, however, other characteristics are more difficult to realise.

• *Timing.* Flexibility can contribute to solving balancing challenges in the power system. In order to sustain an operative system, the amount of injected electricity must equal the amount of withdrawn electricity at all times. Hence, flexibility needs are time dependant. In a dynamic power system, however, it can be challenging to definitely know when balancing challenges will occur.

The market design must therefore, with respect to timing, include limitations regarding the interval before execution, in which bids and offers are accepted. This means the maximum and minimum allowed time which can pass between the finalisation of a trade and the physical transaction. If the interval is long, flexibility contributors have the opportunity to be well prepared for the future regulation schedule. However, imbalances must be handled instantaneously. This points in the direction of a short interval, and a need for the opportunity to trade close to real-time [11].

However, a market for flexibility can be designed similar to the day-ahead market, where the market closes 12 hours before the hour of operation. Flexible resources will then be allocated 12 hours before actual execution. Since imbalances are difficult to predict, this timing design might not be the most suitable for a flexibility market.

Another alternative is to match trades close to real-time, from at most a couple of hours to only a few minutes before the hour of physical delivery. Current tendencies in the power system, such as for example integration of unpredictable supply, points in this direction [11].

A third option is to form the flexibility market similar to the balancing market. Here, the balance responsible party organises the settlement after activating resources in order to sustain the energy balance. This indicates immediate activation of customer flexibility, perhaps without time for notification at all. For this kind of operation, standardised agreements between the flexibility contributor and the grid operator or balance responsible party are especially important.

• *Agreements.* Market players requesting flexibility often have limited knowledge in advance about when regulation is required. It is therefore difficult to anticipate when to activate flexibility. This complicates the formation of standards and predictable contracts because a need for flexibility can arrive abruptly. As a consequence, there are narrow opportunities to alert a consumer before activation. Agreements must reflect this unpredictability.

Agreement for flexibility exchange

- Contract duration
- Definition of flexible load
- Power contribution from flexibility
- Time interval for remote regulation
- Notification before activation, if any
- Compensation scheme and post-delivery settlement
- Penalise not delivered flexibility

A way to accommodate this issue is to let a customer offer a few of its flexible loads which are available for remote regulation. Then, the customer sets an interval within which it is willing to let its load be regulated. It should also be a possibility for the customer to be notified prior to regulation. Example loads are electric heating devices, such as heat pumps, hot water tanks and other room heating appliances.

Following the activation, a flexible customer must somehow be compensated for its service. The agreement must contain information concerning how flexible behaviour is beneficial for the one being flexible. Here, there are several different possibilities. The grid operator can use flexibility to resolve congestions in the grid, and thereby avoid investments and component damage. The two parties could then split the total benefits. Another option is to provide the customer with reduced network tariffs in exchange for flexibility.

In the settlement process, there must also be routines in place for handling flexibility not delivered. Due to an unexpected energy requirement, a customer might need to override the remote regulation. In this case, the customer is not upholding its side of the agreement. Since the receiving end is counting on flexibility being available, it is entitled to penalise the flexibility provider.

The text box summarises important points which should be considered when designing an agreement for flexibility exchange [15].

• *Price formation.* The market clearing process decides how the price is settled. As mentioned above, there should be enough competition present such that the resulting asset price becomes efficient, the asset here being flexibility. When the price is efficient, it reflects all relevant information in the system. This information must be available to all market participants. The reason behind this, according to price efficiency theory, is how all data which can influence the value of an asset should be taken into account in the price formation process [21].

In Nord Pool's market clearing process, the optimal electricity price is found when supply and demand in every hour is balanced. This method is called marginal price setting [22]. The calculation process should produce economically efficient results. This means, resources are divided based on needs and usefulness, while minimising waste and inconvenience. If adjustments are made in any direction, benefiting a participant, another participant would be worse off than in the optimal, and economically efficient, solution [23]. The electricity price should reflect producers' and consumers' opposite requirements. Electricity will be valued somewhere in between, preferably as low as possible according to the quote below.

> A well-functioning and competitive power market produces electricity at the lowest possible price for every hour of the day [22].

Several different price formation methods exist. For example, the authors of [24] propose a market clearing mechanism for flexibility in two steps, resembling the traditional day-ahead and intraday market. A general selection of other possible choices is presented in Figure 6.

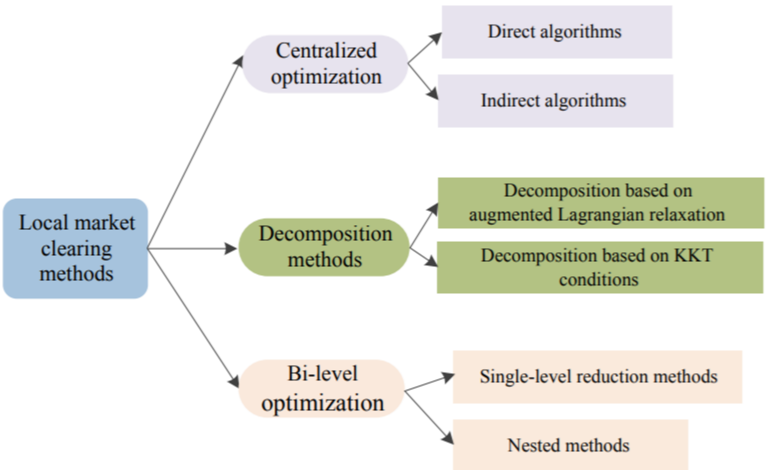

Figure 6: *Categorisation of different market clearing processes for a local flexibility market. Source: [20]*

Centralised optimisation methods represent the market clearing processes where all trades are made through a central instance. An optimisation problem determines the price and optimal traded volumes. The terms direct and indirect algorithms are used to differentiate between problems which can and cannot be solved with commercial solvers. Optimisation problems which are difficult to solve can be redefined and then indirectly solved using a commercial solver. The original AC Optimal Power Flow problem is an example of such a system [20].

Decomposition methods are decentralised clearing approaches. If an optimisation problem is better solved in parts than all at once, sub-problems can be defined and solved decentralised. Bi-level optimisation might seem to resemble decomposition methods in the sense that they both refer to the main problem being split into difference pieces. Separate levels, however, indicate a certain order in which the problems must be solved, and not just requiring the problems to be solved separately. In a bi-level optimisation problem, the local market operator's decisions depend on the decisions made by the market participants. Therefore, the lower level problem comprises a constraint in the upper level problem. A reasonable example could be a grid operator as the leader, and electricity consumers as followers [20]. In a decomposition method, however, the order in which the problems are solved is not important.

3.4.3 Barriers could hinder future development

Even though there are many advantages to a market solution for flexibility, significant barriers could stand in the way of future development. Firstly, it is more difficult for grid operators to handle dynamic market results than predictable tariff rates. When flexibility is needed to solve capacity issues in the grid, the grid operator is not necessarily aware of the market results for the specific hour. The market clearing will determine which flexible customers to use and the flexibility price. The grid operator has no say in this process and must have agreements in place, which allows them to trade with whoever the chosen flexible customer in the area is. This is a far less predictable procedure than having customers on standardised disconnect or capacity tariffs.

Another difficulty seen from the grid operator's perspective is the relation between a flexibility trade and the actual regulation. This issue originates from how retailers predict the future consumption of their customers. The data comprises the demand curve for the following day, and the market computes day-ahead prices by matching the demand and supply curve. This procedure causes problems when agreeing on a suitable compensation for flexibility. Since there is uncertainty concerning future consumption, it is challenging to determine if regulation was actually performed.

To illustrate with an example; say a customer submits a flexibility offer in the market for the following day. The offer states the customer's willingness to reduce load at a given hour. When the hour of operation arrives, the grid experiences no capacity problems, presumably because the flexibility was activated. Still, the grid operator has limited opportunity to determine if the customer actually did decrease its load, or if the customer just happened to consume a lower amount of energy than predicted by the retailer. In case of the former scenario, the customer deserves payment from the grid operator for its flexibility. In case of the latter scenario, the customer in reality did nothing [1].

The functionality of flexibility markets depends on more active participation from the consumer side. This is both a strength and a weakness. Current developments in the power system require demand to become more responsive to supply. This has to do with renewable generation as well as grid constraints. Demand response is therefore vital. Still, participation in a flexibility market sets even higher expectations to consumer commitment. For example, consumers must decide on flexibility volumes to offer and request in the market, perhaps regularly. At what time they are flexible and for which duration is also necessary to choose. Further, consumers must have a clear understanding of what compensation they request. In general, flexibility providers must define their offers according to the attributes described in section 3.4.1.

To expect this engagement rate from regular electricity customers would be completely new. Too comprehensive participation barriers could turn customers uninterested in a flexibility market altogether.

Since flexibility markets as a concept is not currently present in the system, customers will have little knowledge about which benefits they can expect. Questions related to compensation could form obstacles keeping them from possibly taking part in the market. If they still participate, risk aversion can cause them to value their flexibility at a high price. This will affect the market results and could make flexibility trades expensive.

3.4.4 Possible flexibility market designs

A market solution for flexibility is still a quite immature idea. As of today, it is mainly a subject of investigation on a theoretical basis. Still, some market projects and tests have been implemented.

In [20], a flow chart for a suggested local flexibility market is presented. The authors have collected and reviewed existing literature and suggested market designs for flexibility. The scheme is shown in Figure 7.

In the presented scheme, flexibility is exchanged between flexibility providers and buyers through an aggregator. An aggregator collects flexibility from its associated customers. These customers could be all types of flexibility providers, ranging from production plants with adjustable generation to household consumers. The aggregator then submits accumulated offers on the local flexibility market (LFM) platform. This competitive marketplace is managed by the LFM operator.

DSOs and balance responsible parties are the buyers of flexibility. They submit flexibility bids, and the LFM operator matches the offers and requests. Optimal trading volumes and flexibility prices are calculated. Then, flexibility is activated and transfers are executed. Finally, flexibility receivers are billed.

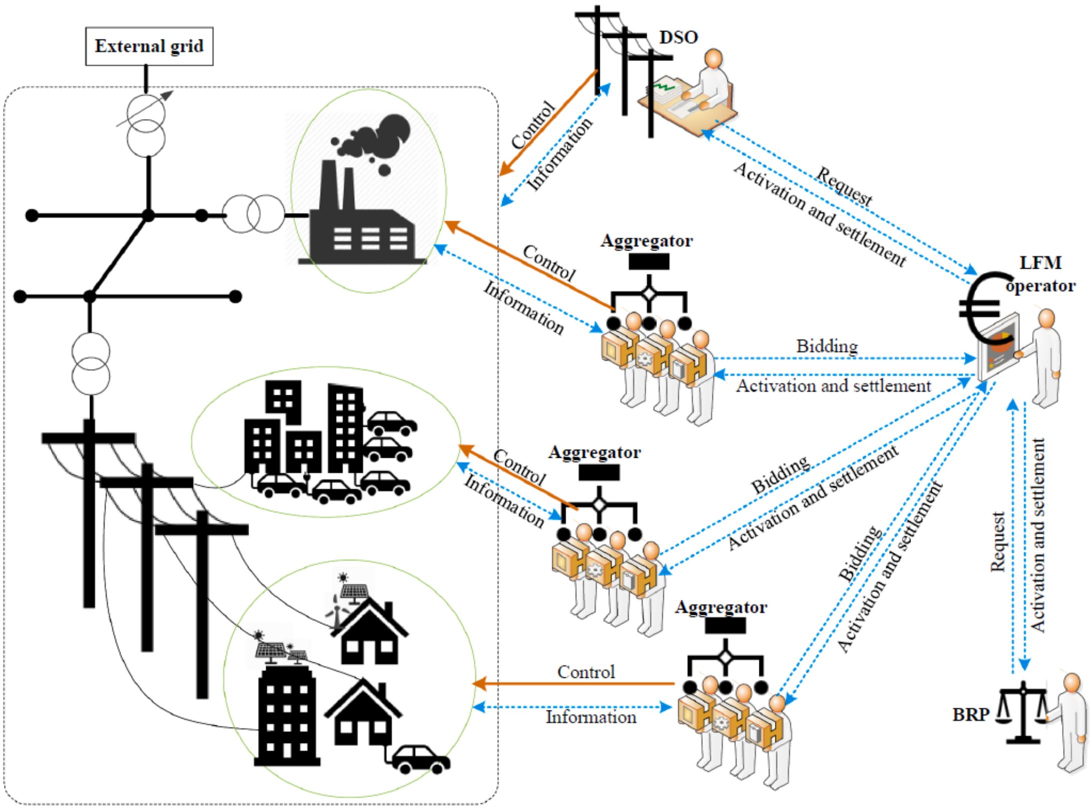

Figure 7: *A generic local flexibility market where flexibility aggregators, DSOs and the balance responsible party exchange energy on a competitive market platform. Source: [20]*

Another example is the Nordic market initiative NODES. Its goal is to become an independent market platform for flexibility trading, connecting flexibility providers to the existing day-ahead and intraday markets. NODES points out the current absence of a platform on which flexibility can be traded and used for grid purposes. The initiative further emphasises the need for a market with a higher resolution than the existing ones [25].

Their market design, shown in Figure 8, resembles the one presented in [20]. Aggregators assemble flexibility offers from their customers and submit bids in the market. Here, microgrids and the balance responsible party are also possible flexibility providers. The NODES platform is not necessarily meant for a local community, but rather aims at opening up for the European electricity market.

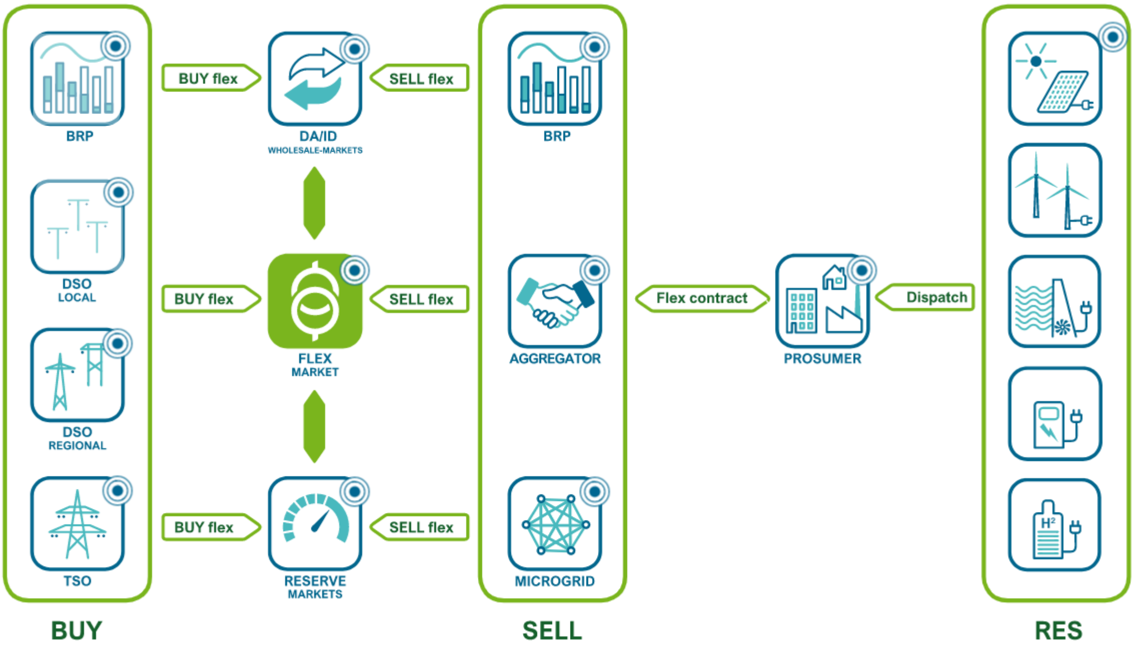

Figure 8: *Nodes marketplace design. Source: [26]*

An important difference between the market design in Figure 7 and Figure 8 is the connection to the existing electricity markets. NODES proposes full integration of their flexibility platform with the other markets. In addition, they suggest BRPs and microgrid also being among the flexibility sellers.

In [20], the roles of buyers and sellers are more strictly divided. Furthermore, there is no mention of the communication between the LFM and the day-ahead and intraday market.

3.5 Regulatory concerns

In the end, whether a market platform for flexibility can be realised or not, lies with the regulator. It is the regulator who decides whether current regulation should allow, or even appoint, market participants to assemble a flexibility market.

However, regulatory concerns comprise barriers. According to a report studying flexibility markets from a theoretical point of view [1], the most important indicator of functionality is whether the market contributes to more efficient grid expansions than a situation without a flexibility market. A power system with a market platform should therefore produce more economically efficient results than a system without a market platform. It is in the regulator's interest to execute what is best for society. Therefore, a crucial evaluation criterion is whether the market serves as a more efficient option than regular grid investments.

In the local market model proposed in chapter 4, this relates to the balancing costs the local market operator is facing. This cost must be compared with the opportunity cost of expanding the line's transmission power. For the market to induce more efficient grid expansions in the system, the market must solve the same problems as a grid expansion would, but at a lower cost.

As mentioned in section 3.1, flexibility is useful for several grid applications. However, the argument surrounding reduced balancing costs and price volatility does not seem to be as important to the regulator. Regulation monitors grid operators, as these are natural monopolies. Electricity producers, on the other hand, are independent participants acting in competitive electricity markets. Since the regulation does not control the electricity markets, arguments involving efficiency in these processes are not included in the regulator's analyses.

4 Proposed local market model

The aim of this thesis is to further study and understand how a marketplace for flexibility can be designed, and how the most efficient price can be determined. On this note, an exemplified, local flexibility market has been built using Python. The market model is intended for a local community facing challenges related to capacity, where flexible participants trade flexibility with a central operator in order to solve congestions.

The remaining part of this thesis consists of planning, programming and testing of this local market model. This chapter in particular will display the system on which the model is based, explain how flexibility is evaluated and present the mathematical representation of the optimisation problem behind the market clearing. There will also be emphasis on price formation.

4.1 Model objective

The goal is to use the market model as a method for effective price calculation in a general local community with capacity issues, through coordination of loads and flexible resources over time. This is done at a local market platform, where flexibility bids and offers are matched. By iterating forward through a selected period of analysis, the optimal flexibility schedule in each time step can be determined. The market will also compute a balanced electricity price, which takes all relevant and available information into account.

The intention with the proposed model, and thereby this thesis, is to be a contribution to the ongoing discussion concerning flexibility market design and optimal price formation methods in such markets.

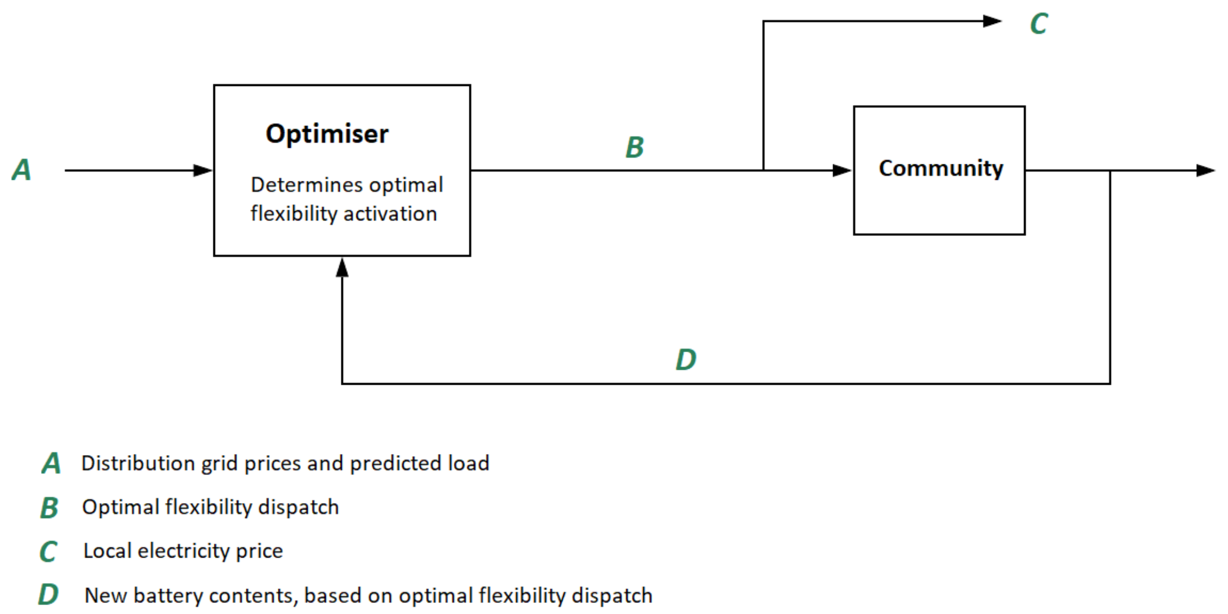

Figure 9: *Flow chart illustrating the iterative market process, where the optimal flexibility schedule and a local electricity price in each time step are computed.*

Figure 9 presents a schematic representation of the iterative market process, where the community consists of flexible customers and storage units. An optimisation problem constitute the foundation for how the market balance is computed. It is executed in every time step, and takes price and load data as input (A). Market results, i.e. the optimal flexibility dispatch (B) is communicated to the community, where the schedule will be executed. The optimisation problem also calculates the most effective local electricity price (C).

After activating flexibility according to the schedule set by the market, the community submits the consequences of these actions back to the market through the feedback loop (D). In this case, this means the new storage contents after performing the suggested charging and discharging. This comprises the new situation for which the market must perform optimisation.

4.2 A local market operator

In order to ensure impartiality, a third-party operator is chosen to manage the local market platform [15]. The local operator monitors the energy flows and flexibility trades in the energy community. Its main responsibility is to manage the local market platform by means of the optimisation model. The model computes the market balance by optimising the activation of available flexibility, subject to the local system load and transmission capacity from the main grid. How much flexibility is worth to each individual participant also influences the market outcome. The local operator's tasks are summarised below;

1. Have overview of **total energy demand** in the community.
2. Request and process data for **price expectations** from customers and batteries.
3. Manage the local market, thereby **executing the optimisation problem** in each time step.
4. **Purchase energy** from the main grid on behalf of the community.

The optimisation problem is formulated from the operator's point of view. The operator seeks to maximise profits by selling flexibility to customers and storage units. This implies that customers are ramping up their load, or batteries are charging.

Simultaneously, the community's original load can in some hours demand more energy than the transmission line from the main grid is able to transmit. This requires congestion management, hence initiation of flexibility in order to avoid overloading the line. Customers must then ramp down their load and batteries must discharge, such that the total demand can meet the available supply. In this case, the operator must purchase energy from system participants. This corresponds to costs for the operator, as flexibility providers must be compensated for their services. Still, in order to maximise profits, the operator seeks to minimise the need for consumers to decrease their load.

Alternatively, the local operator could decide to upgrade the transmission line between the local community and the distribution grid. Then there would be no capacity problems. The local load would always be covered, hence no need to initiate local flexibility. However, this option is rather expensive [27]. Instead, the operator is choosing to solve the capacity issues by utilising flexible behaviour among its customers. This solution will also produce costs for the operator. Compensating customers, however, could be cheaper than to expand the transmission volume altogether. Moreover, grid replacements are the exact expenses preferably avoided on a system wide basis. Utilising local flexibility is one of many solution approaches to the current challenges in the power system.

4.3 System outlines

An example community is used to test the market model, and consists of flexible customers and storage units. The market design is based on the local platform being the centre for energy trades in the system. All participants are therefore exchanging energy with the local operator, and not with each other.

Figure 10 illustrates the system setup. The variables P_{up} and P_{down} indicate flexibility trades between a customer and the platform. These variable names are defined from the customer's standpoint, i.e. when it is ramping *up* its load and when it is ramping *down* its load. Variables x_{up} and x_{down} indicate flexibility trades between a storage unit and the platform. These names are defined in the same manner as customer regulation. The variable x signals the energy level of the storage unit.

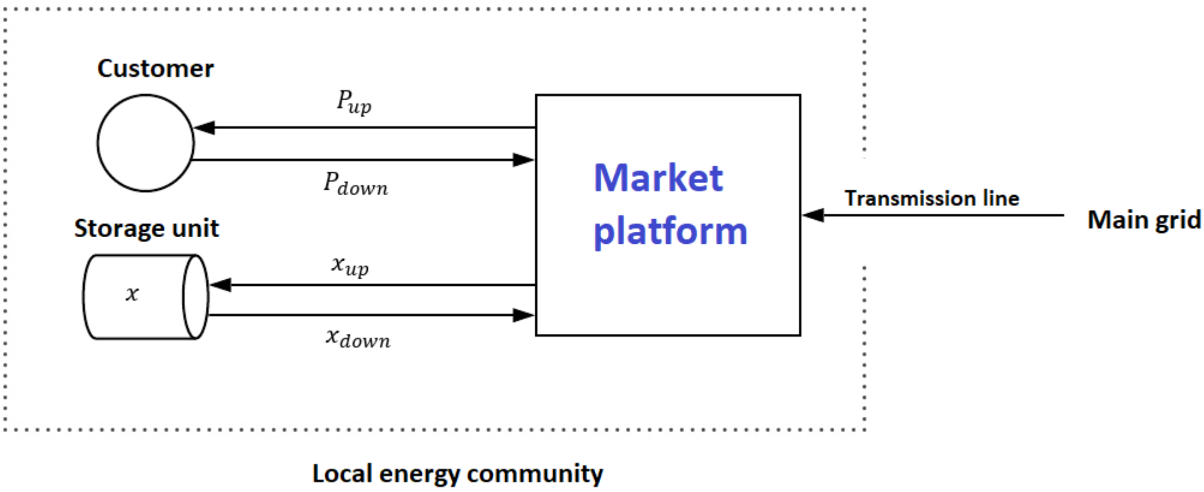

Figure 10: *Example system with only a single customer and a single storage unit. Both participants are exchanging flexibility with the market platform.*

For the optimisation model and market clearing process, all arrows in Figure 10 represent energy flows. Seen from the market platform's perspective, entering arrows represent supply and exiting arrows indicate demand. Therefore, P_{up} and x_{up} signal additional demand, while P_{down} and x_{down}, together with the transmission line, signal supply. Customers additionally receive energy to cover their load. Arrows indicating these energy flows have not been included.

Increased demand represented by P_{up} and x_{up} are actual energy flows which will occur if a consumer increases its load. Even though P_{down} and x_{down} indicate supply in the optimisation problem, these are not physical energy flows entering the market platform. On the contrary, P_{down} and x_{down} imply amounts of energy never transmitted to the customer or storage unit, respectively. The market participant and the operator agrees on a flexibility trade involving decreasing load. This means the consumer will be consuming less energy, and not transmitting electricity back to the operator.

The transmission line between the community and the main grid has limited transfer capacity.

4.4 The value of flexibility

In order to determine the exact balancing costs in the system, and thereby the market price, the worth of flexibility must be assessed.

Flexibility, seen from the consumer side, means the ability to change demand. A consumer will expect something in return for changing its original load profile. For example, the consumer can require compensation to make up for the inconvenience of changing its consumption pattern. A reward in some form is expected both when a consumer is required to increase and decrease its total load.

In this market design, benefit expectations set by each flexible consumer in the local community decide the value of flexibility. This way, the worth of each participant's flexibility is selected by the participant itself. Profit expectations are quantified in price change requirements. Price changes are always defined based on the average day-ahead electricity price in the main grid.

In order to *ramp up* its original load, a consumer will require a specific price *reduction*. This means that the consumer is only willing to increase its load if the present electricity price is lower than the average day-ahead price in the main grid. In other words, the consumer will increase its load only if there are benefit opportunities. A low price could mean cost savings for the consumer, if this was energy it was going to use either way. When increasing load, the consumer would be purchasing additional energy. The consumer's buy price for flexibility will therefore always be lower than the daily price average.

A consumer's required price reduction before it is willing to increase load equals the consumer's benefit expectation. This expectation reflects the size of the reward the consumers requires when ramping up load. In conclusion, the buy price at which a consumer is willing to trade flexibility reflects the consumer's willingness to increase its consumption. The buy price is calculated according to the equation below.

$$\begin{aligned} &\text{buy price} = \text{daily price average - benefit expectation when increasing load} \\ &v_{inc} = \mu - p^{\downarrow} \end{aligned} \tag{4.1}$$

If a consumer's benefit expectation is valued at 20%, the current electricity price must be 20% lower than the daily average before the consumer increases its demand. If the price never reaches this low during the day, the consumer's flexibility will not be activated. The flexibility will hence not be activated unless the price reaches 80% of its daily average.

The other way around, a consumer requires the electricity price to *increase* before it would be willing to *ramp down* its load. To reduce load is inconvenient, and the consumer would only consider this is the price became particularly high. The consumer would further expect to be compensated for its regulation. This compensation is reflected in the consumer's benefit expectation, which equals the requested price increase. In this case, the consumer would be selling flexibility because it is renouncing energy it otherwise would have consumed. The consumer's selling price will therefore always be higher than the daily price average in the main grid, in order for it to be beneficial for the consumer. The selling price at which the consumer is willing to trade flexibility thereby reflects the consumer's willingness to reduce its consumption. The equation is shown below.

$$\begin{aligned} &\text{selling price} = \text{daily price average + benefit expectation when decreasing load} \\ &v_{dec} = \mu + p^{\uparrow} \end{aligned} \tag{4.2}$$

A consumer could for example require a benefit of 40% for lowering its load. This consumer's flexibility would therefore only be activated if the electricity price became 40% higher than the daily average. A price as high as 140% of the daily average may not occur during the entire day, leaving this flexibility unused.

The market platform will activate flexibility based on how the resources are priced. In hours when there is no congestion on the transmission line from the main grid, consumer flexibility will not be activated. It is cheaper for the market platform to buy electricity from the main grid than to initiate expensive, local flexibility. In hours when the grid constraint is binding, however, the situation is quite different. Now, the system depends on flexibility from local contributors. The local price will then be set based on flexibility activation among consumers with higher benefit expectations than the main market.

It is reasonable to assume that the local operator charges a fee for its services. The work of data collection, optimising and control of energy flows in the community require the users of the service to pay. The profit expectations submitted by market participants are assumed to account for the operator fee. This means, consumers select profit rates equal to the sum of their required benefit *and* the service fee.

4.5 Assumptions and limitations

To define the scope of the proposed market model, the assumptions listed below have been applied. To many and broad assumptions *can* create questionable output. However, limitations can also enable clear investigation of a specific topic or field of study. In this case, results can still pose new and valuable insights.

The primary intention with the market analyses is to exemplify realistic situations, and describe how the market model computes decisions and influences energy flows. Simplifications have therefore been made in order to mainly focus on principles. In several cases, certain data or considerations are not required when simply explaining the core of an event, and how this event affects market decisions.

Other assumptions, on the other hand, have been applied because work load and time prioritisation limit the opportunities to explore all possible discussion topics concerning a flexibility market.

- **Example load data**. All load data used for customers in the community has been chosen, and is not based on real consumers. However, selected data is based on behaviour expected from the respective customer group. Realistic load data is not necessary to show how the model in principle responds to different physical situations.
- **Full overview of load data**. It is assumed the local operator has enough historical load data for the community to also be sure of future load curves. This is necessary in order for the local operator to determine whether a customer actually changed its original load according to the flexibility dispatch decided by the market results. This issue was considered in section 3.4.3.
- **No bidirectional energy flows**. To sell excess flexibility back into the main grid has not been considered in this market design. This simplification was made for scope limitation purposes.
- **System for data submission**. A functional interface for submission of price expectations from customers and batteries is assumed to be in place. The market model depends on benefit expectations from system participants in order to evaluate flexibility.
- **Automatic activation and obedience**. Flexibility will be automatically activated according to the market outcome from the optimisation problem. That is, all participants are expected to execute the flexibility schedule set by the market results. This enables demonstration of how the market platform makes new decisions through a dynamic time horizon based on its previous decisions, by means of MPC. This might not be completely realistic, as consumers could have the opportunity to override the flexibility dispatch.
- **Disregarding physical grid**. The physical grid topology in the local grid has not been accounted for, nor has internal grid constraints. These simplifications has been applied for scope limitation purposes. The constraints set by the local grid topology could however be interesting to investigate alongside the flexibility constraints.
- **Disregarding the electricity bill**. The local market operator is not necessarily the one who bills community participants for their total consumption. This is because the exact role of the operator is up for discussion. In this market it has tasks similar to that of a retailer and a grid operator. Still, the issue concerning a definite role has not been addressed, as the focus in this thesis lies with the performance of the local market.

- **Battery efficiencies are disregarded.** Since the emphasis in the discussions concerning the market model is with the calculations of a flexibility dispatch and a local price, battery efficiencies have been left out of the analyses.
- **Perfect competition**. When using duality theory as a price-setting mechanism, one must assume all participants are acting under perfectly competitive conditions.
- **All regulation correspond to trades for the local operator.** The operator is the only one trading with the flexibility providers in the system, and it is also obligated to do so. For example, the operator must purchase any energy which becomes available when consumers decrease their load or batteries discharge. Similarly, when a consumer increases load or a battery charges, the operator must be the one to cover this extra demand. This assumption is added in order to keep model complexity at a manageable level. However, it is possible to implement for example load shedding or the opportunity to trade with other parties than the local operator.

4.6 Mathematical formulation

In this section, the mathematical formulation of the optimisation problem is presented. It is based on the general form of a maximisation problem, formulated as the primal in section 2.2.

The mathematical aim of the optimisation problem is to maximise profits for the local operator through management of the local market platform. In reality this means minimising costs of balancing demand and supply by activating flexibility. Referring to section 4.2, the operator has selected a market solution for flexibility instead of investing in grid expansions in order to solve local congestion issues. Either way, the goal is to minimise operational costs through monitoring energy flows in the community.

The market executes the optimisation problem in every hour. In each optimisation the market uses day-ahead electricity prices from the main grid and anticipates community load for a given number of hours into the future. How far into the future the market will forecast information is decided by the prediction horizon. The market determines the optimal flexibility dispatch based on this data, subject to constraints.

In the following, the problem variables, parameters, constraints and variable bounds will be presented and explained. All indices, sets, variables and parameters introduced in this section are also summarised in section Initiation, on page VII.

4.6.1 Indices and parameters

Parameters must be defined for the period of analysis, the number of customers and the number of batteries. Indices are needed to systematically iterate through them. These are given below.

Table 1: *Indices and main parameters for outlining the dynamic optimisation.*

	Indices		**Parameters**
i	hour index	I	period of analysis
n	hour index within prediction horizon	h	prediction horizon
c	customer index	C	number of customers
b	battery index	B	number of batteries

The rolling time horizon is implemented by defining the dynamic set S. It denotes the set of hours over which the optimisation problem is executed in each iteration. S always has the length h, but will dynamically shift one hour forward for each iteration. The index n iterates through the set S, i.e. $n \in S$. Visualising the relationship between i, S and h, examples for $h = 3$ are shown below.

$$\text{Hour 1} \;,\;\; i = 1 \qquad \Rightarrow \qquad S = [1, 2, 3]$$

$$\text{Hour 2} \;,\;\; i = 2 \qquad \Rightarrow \qquad S = [2, 3, 4]$$

$$\text{Hour 3} \;,\;\; i = 3 \qquad \Rightarrow \qquad S = [3, 4, 5]$$

$$\text{Hour i} \qquad \Rightarrow \qquad S = [i, ..., (i + h - 1)]$$

4.6.2 Variables

In each hour, or iteration, the optimisation problem determines optimal regulation for all traders involved. This means up- and down-regulation for customers, and input to and output from storage. The operator must also decide on how much energy to purchase from the main grid. All of these decisions are based on the obligation of covering the community load. Variable definitions are presented in the following.

$$\begin{aligned}
P_{up,nc} &= \text{ load increase, or up-regulation, during hour } n \text{ for customer } c \\
P_{down,nc} &= \text{ load decrease, or down-regulation, during hour } n \text{ for customer } c \\
x_{up,nb} &= \text{ charging during hour } n \text{ of battery } b \\
x_{down,nb} &= \text{ decharging during hour } n \text{ of battery } b \\
x_{nb} &= \text{ energy level at the end of hour } n \text{ in battery } b \\
G_n &= \text{ energy purchased from the main grid during hour } n
\end{aligned}$$

The variables representing flexibility flows are opposites, and therefore cannot be non-zero at the same time. This means that either $P_{up,nc}$, $P_{down,nc}$ or both are equal to zero in the optimal solution for a particular hour. A customer is thereby offering flexibility by either increasing its load or by decreasing its load. Both actions cannot be performed in the same hour. The same requirement holds for the batteries. Either $x_{up,nb}$, $x_{down,nb}$ or both are equal to zero.

4.6.3 Objective function

The local operator trades energy with customers, storage and the main grid. As explained in section 4.2, profit is made when customers increase load or batteries charge, i.e. when the operator sells flexibility. On the other hand, costs are generated when customers decrease their load and batteries discharge, i.e. when the operator purchases flexibility. Purchasing energy from the main grid is also an expense. Based on this, the objective function is divided into five elements, shown in Table 2.

Each of the five elements are equal to a sum of products. The products are always on the form

$$p \cdot Q \;\; [NOK], \tag{4.3}$$

where Q is the energy volume purchased. The marginal value of electricity, p, is given in NOK per energy volume. For energy purchased from the grid, p is equal to the main grid electricity price. For customers and batteries, p is equal to the marginal willingness to change load. The willingness parameters are given in Table 3, and are defined based on the relations given in Eq. (4.1) and Eq. (4.2). The first four parameters indicate customers' and batteries' willingness to purchase or sell energy by increasing or reducing load, respectively.

Table 2: *Elements of the objective function.*

Type	**Element name**	**Description**
Revenue	*CI* - Customer Increase	Flexibility sold to customers increasing their load
Cost	*CD* - Customer Decrease	Flexibility purchased from customers reducing their load
Revenue	*BI* - Battery Increase	Flexibility sold to charging storage units
Cost	*BD* - Battery Decrease	Flexibility purchased from discharging storage units
Cost	*GR* - Grid	Energy purchased from the main grid

Table 3: *Parameters in the cost coefficient vector of the objective function.*

Parameter	**Type**	**Description**
$v_{c,inc}$	buy price	customer c's willingness to increase load
$v_{c,dec}$	selling price	customer c's willingness to decrease load
$w_{b,inc}$	buy price	battery b's willingness to charge
$w_{b,dec}$	selling price	battery b's willingness to discharge
p_n	buy price	electricity price in the main grid

The elements of the objective function in their general form are presented in the following. The first element, *CI*, is the revenue for flexibility sold to customers ramping up their load, given in Eq. (4.4). Each customer's willingness to consume more energy is multiplied with the customer's increased load, according to Eq. (4.3). This product is calculated for every hour in the current prediction horizon. Since a customer's willingness to increase load is constant, the sum of load increases across the current prediction horizon is multiplied with the marginal willingness, for each respective customer. This way, there will be one product per flexible customer; willingness times total increased load. The sum of these products add up to the element *CI*.

$$CI = v_{c,inc} \sum_{n \in S} P_{up,nc} + v_{(c+1),inc} \sum_{n \in S} P_{up,n(c+1)} + ... + v_{C,inc} \sum_{n \in S} P_{up,nC} \tag{4.4}$$

Element *CD* is determined similarly. Each customer's willingness to ramp down load is multiplied with the sum of load reductions during the current prediction horizon for this particular customer. This element has a negative impact on the objective value because the local operator will see decreasing load as an expense. Reduced load equals flexibility the operator has to purchase.

$$CD = -\Big(v_{c,dec} \sum_{n \in S} P_{down,nc} + v_{(c+1),dec} \sum_{n \in S} P_{down,n(c+1)} + ... + v_{C,dec} \sum_{n \in S} P_{down,nC}\Big) \tag{4.5}$$

The objective function elements for batteries are found in a similar manner below.

$$BI = w_{b,inc} \sum_{n \in S} x_{up,nb} + w_{(b+1),inc} \sum_{n \in S} x_{up,n(b+1)} + ... + w_{B,inc} \sum_{n \in S} x_{up,nB} \tag{4.6}$$

$$BD = -\Big(w_{b,dec}\sum_{n\in S} x_{down,nb} + w_{(b+1),dec}\sum_{n\in S} x_{down,n(b+1)} + ... + w_{B,dec}\sum_{n\in S} x_{down,nB}\Big) \tag{4.7}$$

Finally, energy purchased from the main grid needs its own element in the objective function. Iterating through all hours in the current prediction horizon, i.e. the set S, the energy volumes are multiplied with the electricity price in the main grid. The element GR therefore always consists of a sum of h products, as S has length h.

$$GR = -\Big(\sum_{n\in S} p_n G_n\Big) \tag{4.8}$$

Eq. (4.9) shows the total objective function of the optimisation problem.

$$z = CI + CD + BI + BD + GR \tag{4.9}$$

Illustrative objective function example
The objective function can be illustrated in more detail through an example. For a system managing $C = 4$ customers and $B = 5$ batteries over the course of a prediction horizon of $h = 3$ hours, the objective function is equal to Eq. (4.10).

$$\begin{aligned}
\max \quad & \left.\begin{aligned} & v_{1,inc}(P_{up11} + P_{up21} + P_{up31}) \\ & +v_{2,inc}(P_{up12} + P_{up22} + P_{up32}) \\ & +v_{3,inc}(P_{up13} + P_{up23} + P_{up33}) \\ & +v_{4,inc}(P_{up14} + P_{up24} + P_{up34}) \end{aligned}\right\} CI \\
& \left.\begin{aligned} & -\Big(v_{1,dec}(P_{down11} + P_{down21} + P_{down31}) \\ & +v_{2,dec}(P_{down12} + P_{down22} + P_{down32}) \\ & +v_{3,dec}(P_{down13} + P_{down23} + P_{down33}) \\ & +v_{4,dec}(P_{down14} + P_{down24} + P_{down34})\Big) \end{aligned}\right\} CD \\
& \left.\begin{aligned} & +w_{1,inc}(x_{up11} + x_{up21} + x_{up31}) \\ & +w_{2,inc}(x_{up12} + x_{up22} + x_{up32}) \\ & +w_{3,inc}(x_{up13} + x_{up23} + x_{up33}) \\ & +w_{4,inc}(x_{up14} + x_{up24} + x_{up34}) \\ & +w_{5,inc}(x_{up15} + x_{up25} + x_{up35}) \end{aligned}\right\} BI \\
& \left.\begin{aligned} & -\Big(w_{1,dec}(x_{down11} + x_{down21} + x_{down31}) \\ & +w_{2,dec}(x_{down12} + x_{down22} + x_{down32}) \\ & +w_{3,dec}(x_{down13} + x_{down23} + x_{down33}) \\ & +w_{4,dec}(x_{down14} + x_{down24} + x_{down34}) \\ & +w_{5,dec}(x_{down15} + x_{down25} + x_{down35})\Big) \end{aligned}\right\} BD \\
& \left. -\Big(p_1G_1 + p_2G_2 + p_3G_3\Big)\right\} GR
\end{aligned} \tag{4.10a}$$

4.6.4 Constraints

The maximisation problem is limited by four groups of constraints; hourly energy balance, maximum load change per customer, relation between storage content over time, and memory of the selected storage content from the previous hour.

Firstly, the model must ensure **energy balance** in each hour of the prediction horizon. The sum of the total community load, customers' load increases and battery charging must be covered by the combination of energy from outside the community, customers' load decreases and battery discharging. This is ensured by Eq. (4.11). By moving $P_{up,nc}$ and $x_{up,nb}$ to the right side of the equation, supply will be assembled on the left side and demand on the right. In the general constraint, L_n represents aggregated community load and G_n represents line capacity. Eq. (4.11) will generate h constraints in each problem.

$$\sum_{c=1}^{C}\Big(P_{down,nc} - P_{up,nc}\Big) + \sum_{b=1}^{B}\Big(x_{down,nb} - x_{down,nb}\Big) + G_n = L_n \quad , \quad n \in S \tag{4.11}$$

Secondly, the model contains constraints **limiting the net regulation per customer**. This limitation applies in both directions, both when increasing and decreasing load. However, different constraints apply for each separate prediction horizon h and within the total period of analysis I. As previously mentioned, activation of customer flexibility should preferably not induce any inconvenience for a flexible consumer. The constraints are therefore added in order to preserve a customer's total electricity demand over time.

The set of constraints limiting net customer regulation within a prediction horizon is present in every optimisation problem. The general form of the constraint is shown in Eq. (4.12). Here, customer c is restricted from either increasing or decreasing its load with more than ι_c during h hours. This upper limit can be customised to each individual customer, or set centrally by the market platform operator.

For example, ι_c could be set to zero. In this case, all performed regulation must be cancelled out within the same prediction horizon. The sum of load increased must equal the sum of load reduced. This corresponds to load only being shifted in time, and not changed altogether.

$$\left|\sum_{n\in S}\Big(P_{down,nc} - P_{up,nc}\Big)\right| \leq \iota_c \quad , \quad c = 1, 2, ..., C \tag{4.12}$$

A different set of constraints is needed to restrict total net customer regulation over the course of the whole period of analysis, I. This limitation is denoted ϑ_c for customer c, and is set independently of ι_c. These constraints are only added once $i \geq I - h$, as the last hour of the period is in sight.

In order to restrict regulation within the period of analysis, the model must be aware of the regulation performed by each customer up to this point in time. By tracking regulation in each iteration, the model can detect whether there is a need for further regulation in the final hours of the period.

Constraints to cancel out regulation within a prediction horizon is already in place. However, the model uses MPC and therefore only executes the first decision computed in each horizon. This might lead to a net increase or net decrease in load over time, despite the stepwise cancellation constraints. Therefore, χ_c denotes the total net regulation for customer c in the interval from hour 1 to hour I - h. Net regulation could be either upward or downward, resulting in either a net increase or a net decrease from the original load. Load decrease is defined to be positive, while load increase is defined as negative.

$$\begin{aligned}
\chi_c > \iota_c \quad &\Rightarrow \quad \text{customer } c \text{ has decreased load during the interval } \{1, ..., I - h\} \\
\chi_c < \iota_c \quad &\Rightarrow \quad \text{customer } c \text{ has increased load during the interval } \{1, ..., I - h\}
\end{aligned}$$

The right-hand sides of the constraints limiting total load change performed by customers depend on previous regulation. In order to explain this in more detail, an example will be used.

Say customer c has already decreased its load with $\chi_c > \iota_c$. Hence, there is less space for further decreasing the load in the final h hours. The remaining allowed load decrease cannot exceed, i.e. must be less than, $\vartheta_c - \chi_c$, since ϑ_c constrains the total load change. The remaining allowed load increase, however, has increased, since the customer had already performed downward regulation. In the final h hours, the customer can increase its load with no more than $|-\vartheta_c - \chi_c|$, i.e. the extra consumption must be greater than, $-\vartheta_c - \chi_c$. There is more space for a load increase as $|-\vartheta_c - \chi_c| > |-\vartheta_c|$.

The form of the right-hand sides will be the same even though the situation is reversed. Say customer c has already increased its load, meaning $\chi_c < \iota_c$. The customer now has less opportunity to increase its load further, but more opportunity to reduce its load. If the customer wishes to consume more electricity, this increase cannot exceed $|-\vartheta_c - \chi_c|$, meaning it must be greater than $-\vartheta_c - \chi_c$. On the other hand, a load decrease still cannot exceed, i.e. must be less than, $\vartheta_c - \chi_c$.

The constraints in the their general forms are shown below. Their purpose is to cancel out customer regulation beyond predetermined limits.

$$\begin{aligned} &\text{Remaining load decrease} : \sum_{n=i,...,I} \Big(P_{down,nc} - P_{up,nc}\Big) \leq \vartheta_c - \chi_c \quad , \quad c = 1,2,...,C \\ &\text{Remaining load increase} : \sum_{n=i,...,I} \Big(P_{down,nc} - P_{up,nc}\Big) \geq -\vartheta_c - \chi_c \quad , \quad c = 1,2,...,C \end{aligned} \tag{4.13}$$

Illustrative example: Constraints for net customer regulation

Case I:
Previously decreased load, $\chi_c = \mathbf{2}$, $\vartheta_c = 5$.

net load decrease $\leq \vartheta_c - \chi_c = 5 - \mathbf{2} = 3$

net load increase $\leq -\vartheta_c - \chi_c = -5 - \mathbf{2} = -7$

$\Rightarrow$ Remaining load decrease can be 3, while remaining load increase can be 7.

Case II:
Previously increased load, $\chi_c = \mathbf{-2}$, $\vartheta_c = 5$.

net load decrease $\leq \vartheta_c - \chi_c = 5 - (\mathbf{-2}) = 7$

net load increase $\leq -\vartheta_c - \chi_c = -5 - (\mathbf{-2}) = -3$

$\Rightarrow$ Remaining load decrease can be 7, while remaining load increase can be 3.

Energy storage is the only system feature which is bounded over time, hence by actions outside of the current prediction horizon. Present battery contents will always depend on charging decisions in the past. Eq. (4.14) depicts the general **relation between two consecutive hours for a battery $\boldsymbol{b}$**, which is the third constraint group. The battery content at the end of hour j is a result of the content at the end of hour *j-1*, as well as the (dis)charging decisions made during the course of hour *j-1*. The index j here indicates hour.

$$\begin{gathered} x_{jb} = x_{(j-1)b} + x_{up,jb} - x_{down,jb} \\ \text{current content} = \text{previous content + charge - discharge} \end{gathered} \tag{4.14}$$

The format of which the constraint is added to the optimisation problem is shown in Eq. (4.15). Here, all variables are assembled on the left-hand side. Since each iteration optimises across h hours for all batteries, the below constraint is inserted $h \cdot B$ times in each problem. The first constraint for each battery includes the content from the hour prior to the first hour in the current iteration. Hence, in every iteration there are $h + 1$ x-variables, signalling storage content.

$$x_{nb} - x_{(n-1)b} - x_{up,nb} + x_{down,nb} = 0 \quad , \quad n \in S \tag{4.15}$$

The model chooses input and output values to each battery in every hour inside the current prediction horizon. Decisions from only the first hour in the prediction horizon will be executed. This must be saved, and forms the basis for the consecutive optimisation problem. This enables the presence of $h+1$ x-variables signalling battery content in each optimisation. The energy level of a battery prior to the current hour is always required, and the model must therefore have **memory of previous battery contents**. This is the fourth and final constraint group.

As an example, consider optimisation for a single battery for hours 1, 2 and 3. This is iteration number $i = 1$. There are constraints corresponding to Eq. (4.15) for each hour, and for the first hour $x_i = x_1$. The value of x_1, i.e. the energy level at the end of hour 1, is to be determined. In order to initialise this constraint, the content from the hour before is required, that is, x_0. The situation is therefore;

$$x_{i-1} = x_0$$

The optimisation problem will compute optimal energy levels in the battery for the three hours. Execution of only the first decision, in hour 1, means that only the value of x_1 is saved. In the following iteration, when $i = 2$, the constraint calculating the energy level at the end of hour 2, x_2, needs the content from hour 1. Now the situation is $x_i = x_2$, implying that $x_{i-1} = x_1$. The value of x_{i-1} is therefore set equal to the energy level decision from the hour prior to the one currently under consideration.

The variable x_{i-1} takes the value of the optimisation problem's choosing. The general constraint is therefore formulated as such.

$$x_{(i-1)b} = x_{choice,b} \tag{4.16}$$

4.6.5 Variable bounds

There will be added no upper variable bounds on the variables representing customer regulation, $P_{up,nc}$ and $P_{down,nc}$. It will be up to the market to optimise customer regulation over time, based on available information. Only the constraints restricting total net regulation through period h and period I, Eq. (4.12) and Eq. (4.13), implicitly limit customer regulation in each hour.

With respect to storage units, physical conditions are considered the limiting factor. Chemical properties influence the peak power, and therefore speed, at which a battery can (dis)charge. The market must be prevented from obtaining input and output values that signal overcharging, exceeding the batteries' physical limitations. These upper and lower limits for charging and discharging during an hour are therefore vital. These correspond to the batteries' transfer power. Ageing effects are assumed to not affect the performance. Therefore, charging and discharging power is assumed to be equal and constant during the period of analysis.

$$\begin{aligned} x_{up,nc} &\leq \overline{x}_{up,b} \\ x_{down,nc} &\leq \overline{x}_{down,b} \end{aligned} \tag{4.17}$$

Physical characteristics also determine the maximum battery capacity. Maximum storage space is entirely battery specific, and must be ensured in every hour.

$$x_{ib} \leq \overline{x}_b \tag{4.18}$$

In addition to the variable bounds reflecting the batteries' maximum capacity, the market allows lower variable bounds on storage contents in two selected hours. This functionality is optional, and the user can choose to activate one, both or none of these requirements.

For each of the two conditions, the user can enter an hour, t, in which a certain storage content in all the batteries are required. The desired storage content will be given as a percentage, ϵ, of the maximum storage capacity, $\overline{x}_b$. The lower variable bounds will therefore take the following form;

$$x_{tb} \geq \underline{x}_{tb} = \epsilon \cdot \overline{x}_b \quad , \quad 0 \leq \epsilon \leq 1 \tag{4.19}$$

These variable bounds are only considered in the optimisation problems where the content variable in the selected hour is present. For example, for a selected hour t, lower variable bounds equal to Eq. (4.19) must be included in all iterations where the variable x_{tb} is present. This means all iterations where $i \geq t-h$. In the optimisation problem for the hour $t-h$, the variable x_{tb} will be the last storage content variable included in the problem.

Assuming the local energy community is located in the distribution grid, there will be limited capacity from the main grid. This needs to be considered in all analysed hours. The market model can handle different limitations on maximum transfer capacity from hour to hour. The analyses can then become more realistic as available grid capacity might vary in time. Faults and planned disconnections might also influence the transmission capacity.

$$G_n \leq \overline{G}_n \tag{4.20}$$

4.7 Price formation

The local electricity price in hour i will be given by the negative shadow price related to the energy balance constraint for this particular hour. This means, the shadow price of constraint number i corresponding to Eq. (4.11).

An increase of the right-hand side in this constraint corresponds to an increase in aggregated community load. Demand is a liability for the local market operator, and an increase means more resources are required to cover it. This was introduced in section 2.1. Here, mobilising more resources means purchasing electricity from the distribution grid, and if necessary, also purchasing flexibility from customers or batteries. When congestions occur between the community and the grid, the market operator is forced to assemble resources locally, inducing higher costs.

Since the market performs a maximisation problem, the objective value would decrease in the case of a demand increase. For this reason, the shadow price will be negative, as a demand increase causes a profit reduction. The exact value of the decrease corresponds to the loss the market operator is suffering due to the increase in liability. In other words, the decrease represents the worth of the extra unit demanded. This is interpreted as the marginal price of electricity in the community, i.e. the local electricity price.

$$-y_i = \text{local electricity price in hour } i$$

Similarly as for the computed variable values, only the shadow price for the first energy balance constraint in each optimisation will be considered the current local price. This will then be stored and included in the local price curve, which will be further investigated in chapter 5. The reason why only the shadow price for energy balance constraint number i will be stored as the price in hour i is that the control horizon has been set to one hour. As explained in section 2.1, this is common when performing the MPC methodology.

4.8 The model in programming

The optimisation programme is written in Python with the linear programming package Lpsolve. This is a mixed integer programming solver which can be used both in a stand-alone version and in combination with several different programming languages. Other programming packages needed to run the market model in Python is NumPy, pandas and matplotlib.

The local market programme consists of three separate Python files. The set of functions performing different operations in every step of computing the optimal flexibility dispatch is collected in one file, functions. All functions are written by the author, except the function lp_solve, solving a linear programming problem, which is taken from [28]. Several functions have also been defined for specific results, prints and visualised output.

All input data is gathered in another file, data. This is the only file where the user should make changes, and insert information about its own system. Parameters and variables have been thoroughly named in order to describe their purposes.

Finally, functions and data are assembled in the file called local market. This is where the market algorithm is performed. Input data and functions are imported from the two other files in the proper order. Following the principles of MPC, the optimisation algorithm iterates through the period of analysis, accessing available information in steps of h hours at a time.

4.8.1 Input data

Parameters and vectors requiring input values are listed and described in Table 4. In order to calculate a decision for all hours of the prediction horizon, forecasted information about the next h hours is required. Therefore, the length of each vector has also been specified, as the submitted data must satisfy these in order for the market to execute its tasks.

It is worth mentioning that the vector called previous is somewhat different from the other parameters in Table 4. The vector first indicates the initial battery contents, before period I begins. These values are only set at the beginning of the analysis. After optimising for the first h hours, the market algorithm will be updating the entries of this vector. In the second iteration, the vector will contain the optimal battery contents selected by the previous optimisation problem. To sum up, the vector previous will first contain given input values, and then become a vector containing variables. This transition only occurs for this particular vector, as the other parameters are constants throughout the whole market optimisation.

4.8.2 Functions

The two following tables present all functions used in the local market file. Table 5 contains the functions used to execute the actual dynamic optimisation algorithm, while Table 6 introduces the functions used to present market results, that is, prints and plots.

Table 4: *Input data required to execute the Python programme.*

Name	**Variable type**	**Description**
h	Parameter	Prediction horizon
I	Parameter	Period of analysis
$cust$	Parameter	C, number of customers
$batt$	Parameter	B, number of batteries
price_down	$\lvert\text{Vector}\rvert = cust$	Price reduction requirements for increasing load
price_up	$\lvert\text{Vector}\rvert = cust$	Price increase requirements for reducing load
load_change_start	$\lvert\text{Vector}\rvert = cust$	Maximum change in load during h
load_change_end	$\lvert\text{Vector}\rvert = cust$	Maximum change in load during I
batt_down	$\lvert\text{Vector}\rvert = batt$	Price reduction requirements for charging
batt_up	$\lvert\text{Vector}\rvert = batt$	Price increase requirements for discharging
previous	$\lvert\text{Vector}\rvert = batt$	Initial battery levels before period of analysis starts
power	$\lvert\text{Vector}\rvert = batt$	(Dis)Charging power
max_content	$\lvert\text{Vector}\rvert = batt$	Maximum energy content of each battery
grid_max	$\lvert\text{Vector}\rvert = I + h$	Transmission capacity
prices	$\lvert\text{Vector}\rvert = I + h$	Electricity prices in the main grid

Table 5: *Functions for initialising and solving the optimisation problem in the Python programme.*

Name	**Description**
make_variables	Creates vector with all variable names present in current optimisation problem, hence sets the variable order for the problem
c_vector	Creates vector of coefficients in the objective function, in the same order as make_variables
cons_energy_balance	Initiates A-matrix, adds rows corresponding to the energy balance constraints for all hours h, i.e. Eq. (4.11)
cons_load_change	Adds rows for max load change for all customers during a period h to the A-matrix, i.e. Eq. (4.12)
cons_batt_relation	Adds relation constraints between hours for all batteries to the A-matrix, i.e. Eq. (4.15)
cons_previous_content	Adds constraints ensuring memory of previous battery content to the A-matrix, i.e. Eq. (4.16)
inequalities	Creates vector of inequality signs
b_vector	Creates vector of right-hand sides
ub_batt_charge	Adds upper bounds for battery charge and discharge in a single hour, i.e. Eq. (4.17)
ub_batt_level	Adds upper bounds for maximum battery level, i.e. Eq. (4.18)
ub_gridmax	Adds upper bounds for maximum power outtake from the main grid, i.e. Eq. (4.20)
lb_batt_level_final	Initiates vector of lower bounds. Adds lower bounds for final battery contents at the end of the period of analysis, corresponding to Eq. (4.19)
lp_solve	Solves a mixed integer linear programming problem [28]
previous_battery_level	Saves current battery energy levels for the consecutive optimisation problem in a vector of length b
LECprice	Appends currently computed price in the local energy community to a vector where all prices during the period of analysis is collected
resulting_load	Computes the current resulting system load, taking customer regulation and battery charging into account
hourly_storage_input	Saves total storage input in the current iteration
cons_cancel_out_regulation	Creates constraint rows for cancelling out customer regulation within the end of I, i.e. Eq. (4.13)

Table 6: Functions for prints and plots in the Python programmed market model.

Name	Description
print_input_customers	Prints overview of input data concerning customers
print_customer_prices	Prints overview of buy and sell prices for consumer flexibility, resulting from the input data
print_input_battery	Prints overview of input data concerning batteries
print_battery_prices	Prints overview of buy (charge) and selling (discharge) prices for batteries, resulting from the input data
print_eb_constraints	Prints current energy balance constraints
print_lc_constraints	Prints current constraints for maximum load change for customers within h hours
print_br_constraints	Prints current constraints for relations between battery levels during h hours
print_pc_constraints	Prints current constraints ensuring memory of battery contents from the previous hour
print_all_constraints	Prints out all constraints
print_all_variables	Prints all variable names and the their optimal value in the current optimisation problem
print_customer_regulation	Prints overview of regulation activities for all customers in the current hour
print_battery_charge	Prints overview of charging and discharging activities for all batteries in the current hour
print_battery_levels	Prints battery levels in the current hour
print_LECprice	Prints the local electricity price in the current hour
plot_load	Plots load curves of all flexible customers, as well as a curve representing their joint load
plot_resulting_load	Plots the resulting system load, flexibility taken into account, alongside the original load curve
print_cancellation_constraint	Prints constraints related to cancellation of customer regulation within I hours

5 Market analysis examples

To illustrate how the model operates, this chapter will present analyses examples showing how the market platform schedules available flexible resources over time under different operating conditions. The examples will include testing of model functionality, and the effects of different computational decisions will be investigated.

5.1 Assumed input data

This section will present the data comprising the foundation for the following analyses. All input data has been chosen for demonstration purposes, and the context behind the selection of data will be explained.

Often, simulation data is chosen to resemble reality, such that a realistic situation can be simulated. However, input information can also be selected with the intention to prove a point, or to simply investigate the consequences following a particular decision. Here, data has been chosen in order to simulate a practical situation, but most importantly to achieve clear feedback and results from the market. The market output can give indications as to which decisions are the most decisive, and the effect from assumed input data.

The text box below contains the initialising parameters for the analyses in this chapter. The market model will compute optimal decisions for a full, 24-hour day, from 00:00 to 00:00. The community consists of four flexible customers and five batteries. The prediction horizon, h, will be a subject of variation during the analyses.

$$\boxed{I = 24 \quad , \quad C = 4 \quad , \quad B = 5} \tag{5.1}$$

5.1.1 General data for market participants

Customer and battery specific data for regulation is presented in Table 7 and Table 8. The top row of each table displays the variable names in both the mathematical optimisation problem and the Python programme.

Values not given as a percentage are given in MWh. This is a large unit to be representing daily household consumption. However, since the price data used in the analyses is given in NOK/MWh, it was chosen to keep this unit for community load. The selection of load unit will not affect the interpretation of market results, as the main focus is to discuss principles.

Data has been selected in order to encourage regulation in the community, such that the market's functionality is revealed. The market participants' price change expectations will determine at which buy and selling prices the participants are willing to trade flexibility at. The compensation requirements following the price change expectations will be more thoroughly explained in section 5.1.5. Customers' and batteries' price expectations are given in the columns price_down, price_up, batt_down and batt_up.

Table 7: *Assumed input data for four flexible customers.*

Customer	price_down $p_c^{\downarrow}$	price_up $p_c^{\uparrow}$	load_change_start ι_c	load_change_end ϑ_c
1	8%	15%		
2	5%	20%	0	10
3	2%	13%		
4	4%	12%		

Table 8: *Assumed input data for five flexible storage units.*

Battery	batt_down $p_b^{\downarrow}$	batt_up $p_b^{\uparrow}$	previous x_0	maximum $\overline{x}_b$	power $\overline{x}_{up,b}$, $\overline{x}_{down,b}$
1	4%	9%			
2	6%	8%			
3	8%	10%	15	30	10
4	10%	12%			
5	12%	14%			

The constraints given by Eq. (4.12) and Eq. (4.13) limit customer regulation. Firstly, it has been chosen to set $\iota_c = 0$ for all customers c. All initiated customer regulation must therefore be cancelled out within the same prediction horizon as it was performed. This way, long-term influence on customers' load profiles will be minimal. Any customer participation in the market might in fact rely on minimal effect on everyday routines and planned load schedules.

Still, customers in the community are considered flexible nevertheless. Constraints represented by Eq. (4.13) enable non-zero net regulation for all customers over the course of period I. Maximum load change during I (ϑ_c) has been set to 10 MWh in this simulation. This value was chosen in order to give the dynamic optimisation problem space to actually utilise customer regulation. If the limitation was set lower, the market might not suggest to use this flexibility at all, because the constraint is too rigid.

As for the batteries, the intention with the chosen data is to urge the model to frequently use flexibility from storage. The maximum battery capacity and power was therefore chosen to be quite limited, such that small charging and discharging decisions would be performed often, and spread out across a longer time span. If the capacity and power was chosen to be large, the model would have the opportunity to fully charge each battery during a single hour. In a realistic case, this could lead to capacity problems in an off-peak hour. The model would then also not be coordinating flexible resources over time, which is an important goal of these analyses.

The initial energy level (parameter name: previous) was set to half of the total capacity in all batteries. Again, the choice was made with the optimisation problem's flexibility in mind. With some energy storage to go on, the model will have more slack during balancing.

5.1.2 Load data

Load data for the four customers have been assumed for demonstration purposes. The customer selection consists of two households, one essential load (for example a hospital), and a commercial customer (for example a shop). Referring to Table 7, customer 1 is household 1, customer 2 is household 2, customer 3 is the essential load and customer 4 is the commercial load.

The load curves for each customer, and their aggregated load curve, are presented in Figure 11. Expected usage patterns based on the respective customer group comprise the basis for the load data. The households both have power peaks during the morning, around 07-10, and late afternoon, around 16-20. Still, household 2 has a somewhat higher consumption during night and midday, for example directed at heating purposes. The minima of household 2's load profile are therefore higher than the minima of household 1's load profile. A hospital presumably has a quite evenly distributed consumption during a day compared to residential buildings, although higher than an average household. This expectation is projected onto the assumed essential load. Lastly, the commercial consumer's load profile is anticipated to follow the opening hours, approximately 10-20. Otherwise, its demand is low.

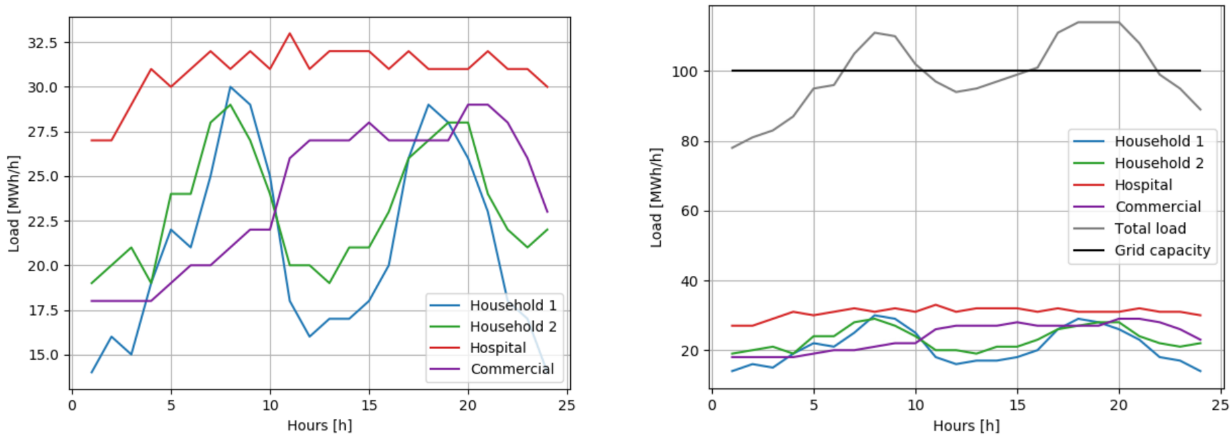

Figure 11: *Left: Load curves for example customers. Right. Their combined load curve compared with the grid constraint.*

5.1.3 Line capacity

The transmission line capacity is also depicted in Figure 11. The transmission capacity is chosen in order to encourage regulation in the system. To achieve this, the accumulated load curve should be oscillating around the transmission line constraint. In some hours the capacity would be sufficient, while in others the total load would exceed the capacity.

To select the transmission line capacity equal to the average of the accumulated load curve therefore seems like a valid choice. However, the optimisation problem in the hours of insufficient transmission capacity would become quite rigid. There would be little opportunity to study the influence of parameter variations, because the optimisation problems would barely be feasible. Preferably, the model's task is to compute the optimal choice among a set of possible choices. If the problem description is too rigid, the model will instead end up determining the *only* possible choice.

For this reason, the line capacity is chosen to be slightly higher than the average of the accumulated load curve. This way, there can be room for parameter alterations. Further, the market platform will have several decision options to choose from, and the optimal one can be determined.

For the selected data, the community load is exceeding the line constraint in hours 07-10 and 16-21. This can be seen on the right side of Figure 11, where the aggregated community load profile (grey) is plotted against the line capacity (black).

5.1.4 Main grid prices

Day-ahead price curves from the dates 20.02.19 and 21.02.19 in Trondheim, Norway, have been used [29]. Prices are given in NOK/MWh. These price curves were chosen due to their clear variations between morning and afternoon, and midday and nighttime. In addition, these differences are usually more visible during wintertime. The trajectories represent the day-ahead electricity prices in the distribution grid to which the community is connected. They will become important later on when the market platform's electricity price computations are discussed.

Price curves were chosen from winter 2019 because electricity prices during winter 2020 were unusually low. The difference between the highest and lowest price during most dates was quite small. Reasons for the low electricity prices this winter are for example quite warm weather, a large amount of inflow to hydropower reservoirs and high production from wind power [30].

As mentioned in section 4.4, the benefit expectations of customers and batteries are based on the average day-ahead price in the main grid. In order to simplify the comparison between local prices and distribution grid prices, all distribution grid prices are divided by the average price calculated for the period of analysis, I. This way, all distribution grid prices oscillate around an average price of $\mu = 1$.

5.1.5 Compensation requirements

Benefit expectations are based on the percentage rates in Tables 7 and Table 8. Individual willingness to buy and sell flexibility has been determined by using Eq. (4.1), Eq. (4.2) and μ. The resulting flexibility prices are shown in Table 9.

The best prices as seen from the local operator's perspective are the highest buy prices and the lowest selling prices. When a consumer's buy price is high, the operator can make the most by selling flexibility to this customer. Similarly, when a consumer's selling price is low, the operator can save the most by purchasing flexibility from this consumer.

Table 9: *Buy and selling prices set by the benefit requirements of customers and batteries.*

Customer	**Buy price** $v_{c,inc}$	**Sell price** $v_{c,dec}$
1	0.92	1.15
2	0.95	1.2
3	0.98	1.13
4	0.96	1.12

Battery	**Buy price** $w_{b,inc}$	**Sell price** $w_{b,dec}$
1	0.96	1.09
2	0.94	1.08
3	0.92	1.1
4	0.9	1.12
5	0.88	1.14

What is worth noticing is that customer 4 possesses the cheapest flexibility compared to its peers. Since the selling price is 1.12, the customer is willing to reduce load and sell flexibility when the price increases with 12%. The same customer is also one out of two customers with the highest willingness to pay for flexibility. The local operator can sell flexibility to customer 4 for a price of 0.96. Hence, the customer has a price change requirement of 4% when increasing load.

The market platform will, however, benefit the most by selling electricity to customer 3. It is therefore reasonable to assume usage of this customer's flexibility before the others.

Still, customer regulation does not possess the same properties as storage. That is, when the market platform chooses a customer to sell flexibility to, it can not expect to purchase the same flexibility back at a later point in time. The buy price/selling price ratio for customers is thereby meaningless for the market platform to consider when selecting a customer to sell flexibility to. Purchasing flexibility from and selling flexibility to customers are two independent trades, and are not connected in time in the same way as for storage. Therefore, the market platform is expected to utilise the flexibility for which it can profit the most, no matter the customer's selling price.

The remaining customers have far higher reward expectations. For example, customer 1 is the least favourable one. It demands to save 8% from a flexibility purchase, and to earn 15% from a flexibility sale.

Among the batteries, battery 1 and 2 seem to stand out from the other with respect to willingness to trade. Battery 2 offers the cheapest flexibility for the market platform to purchase, while it can profit the most by selling flexibility to battery 1.

Still, a flexibility trade with battery 1 will generate least losses. If the market platform sells a single unit of flexibility to battery 2, wishing to purchase it back later, it will first gain a revenue of 0.96 and then purchase the unit back for 1.09. This creates a loss of 0.14. A similar trade with battery 1, however, will only generate a loss of 0.13, hence making battery 1 the more favourable storage unit to trade with.

The least favourable storage unit is battery 5, which has the lowest willingness to charge. The market platform is therefore expected to sell electricity to this battery last, because it can profit more from selling to the other storage units first.

5.1.6 Regulation requirements and limitations

Making use of the functionality enabled by Eq. (4.19), both of the two possible storage level requirements are activated in this demonstration.

The first condition is set for hour 07, stipulating a storage content of 60% in all five batteries. This requirement was chosen based on assuming the flexible storage units to be car batteries in electric vehicles. For example, it is reasonable to anticipate the cars to be in use driving to work or school during the morning hours. In order for the car battery to be charged enough to travel these distances, the demanded energy level was set as high as 60% of the total capacity.

The second condition is set for hour 24. This requirement is set in order to prevent the batteries from completely emptying during nighttime. The energy level in the batteries must be at least 33% of the total capacity. Moreover it is preferable to have stored energy available for optimisation during the consecutive day. Indeed, stored energy can be essential in order to cover load the following day.

The two battery conditions are expressed as variable bounds below.

$$\begin{aligned} x_{7b} &\geq \underline{x}_{7b} = 0.60 \cdot \overline{x}_b \\ x_{24b} &\geq \underline{x}_{24b} = 0.33 \cdot \overline{x}_b \end{aligned} \tag{5.2}$$

5.2 Simulation example: Normal operating conditions

Firstly, a simulation will be conducted to show the market model's functionality under normal operational conditions. The focus of the analysis will be on price calculation and utilisation of flexible resources from different market participants. How the model adapts to limitations concerning participant regulation will also be discussed. The input data is as described in section 5.1.

5.2.1 Computing local prices

The market's goal is to optimise the activation of flexible resources over time. By doing so, the optimal electricity price can be determined in hours when there are capacity problems between the grid and the community. Flexibility offered by community participants enables coverage of the community load even when it demands more than the grid can allow.

From the simulations, results show that the local price is always higher than or equal to the main grid price. This is not surprising because there is limited transmission capacity between the two zones. When the demand for a commodity is exceeding the capacity, the price should be set higher than the marginal cost of production [1]. Precisely, bottlenecks in the grid cause different prices to occur in different geographical areas. In order to minimise price differences between zones, the market will have energy flowing from the area with low price to the area with a high price [31]. In this example system the community has no power generation of its own, and is not in a position to feed energy back into the grid. Therefore, energy will always be flowing *towards* the community. Hence, this will always be the area with high price and the distribution grid is the area with the low price.

The exact optimal electricity price in the community is further connected with the participants' compensation concerns. The community has a challenge the moment their accumulated load exceeds the transmission capacity. As seen on the right side of Figure 11, this is the case in quite a few of the hours during this particular day. In order to solve this problem, flexibility reserves must be activated. These services are not free of charge, and flexibility prices are set by customers' and batteries' compensation requirements. As mentioned in section 3.1, balancing will become more expensive as demand more frequently is exceeding existing transfer capacity.

In conclusion, the local electricity prices will never pass the distribution grid prices in this example system. This could potentially change if the community installed internal electricity production. The energy flow between the community and the distribution grid could then become bidirectional.

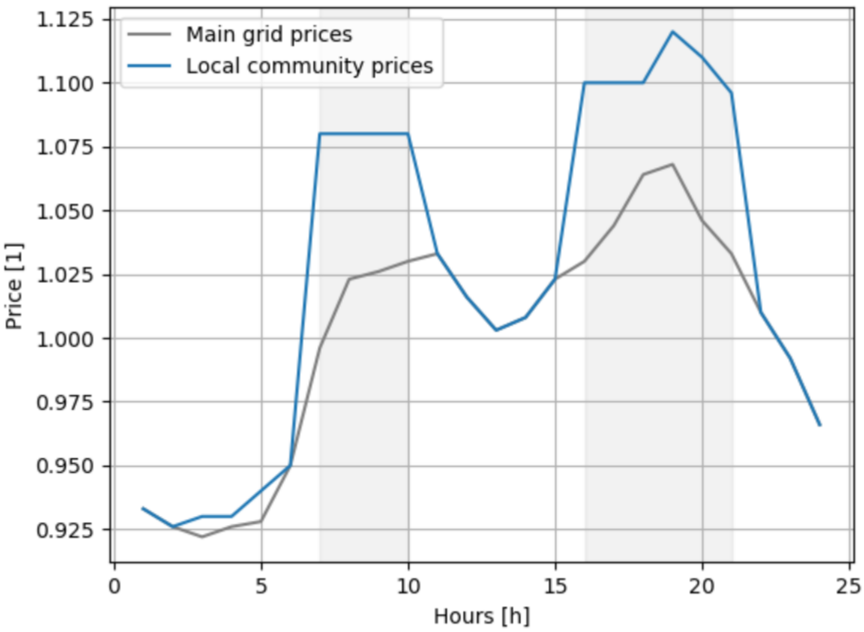

Figure 12: *Prices in the local community (blue) compared to prices in the main grid (grey) during normal operational conditions, and $h = 6$. The shaded areas indicate the intervals with capacity problems.*

For the set of selected input data, the price curve shown in Figure 12 was calculated for the community under normal operational conditions. Here, the selected prediction horizon length is $h = 6$. The intention here is to elucidate the characteristics of a typical local price curve, and how it differs from the distribution grid price curve.

The shaded areas represent the intervals where the community faces capacity challenges, i.e. hours 07-10 and 16-21. The local price curve mostly follows the main grid trajectory, except from these two deviation periods. Here, the local price is higher than the main grid price.

However, there are also small differences during the first six hours of I. In this interval, the distribution grid prices are at their lowest. This indicates opportunity for the batteries to charge at a low cost. Moreover, the model results suggest that some customers should buy flexibility and ramp up their load in these hours. In addition to low grid prices, the model also observes a steadily rising load. It thereby identifies a need for customers to reduce load later. In order to satisfy the load change constraints, given by Eq. (4.12), customers must therefore increase load in these hours during early morning.

Since both batteries and customers are purchasing flexibility, the community's aggregated capacity request is closing in on the maximum available transmission capacity. This happens even though the original community load is below the grid constraint. This can be seen on the right side of Figure 11, as the grey load curve is below the black line representing grid capacity. When the full capacity is maxed out, the next unit of energy demanded in the community must be covered by internal flexibility. Since flexibility costs more than purchasing energy from the main grid, the local price becomes slightly higher than the distribution grid prices during the first six hours of I.

In hours 07-10, the community faces significant capacity problems. The aggregated load is exceeding the transmission capacity, and there are requirements for certain storage levels to be obtained in hour 07. The market operator is therefore forced to purchase flexibility back from the market participants in order to cover the peak demand. This means customers are selling flexibility corresponding to their load decreases, and batteries are selling flexibility corresponding to their energy discharge. By means of flexibility trades, the market platform manages to reduce the aggregated community load such that the line constraint is satisfied. This is expensive for the market operator. Additionally, the next unit of energy demanded in the community must be covered by local flexibility. This causes the next unit of energy demanded in the community to be worth far more than the next unit of energy demanded in the distribution grid. The local prices in the interval 07-10 therefore become significantly higher than the distribution grid prices.

The other deviation period, 16-21, also shows high local prices. Similar arguments as for the first interval can be used here. During the day's first demand peak, the model is using energy stored in the batteries with the cheapest flexibility to cover load instead of purchasing expensive electricity from the grid. However, with a prediction horizon of six hours, the model is unaware of the second demand peak arising during the evening. It is thereby unable to prepare for events occurring outside of its current field of view.

As well as in the first deviation period, flexibility must be used in order to match community load to the line constraint. Since most of the cheap storage flexibility was used during the first interval with capacity issues, the market operator must now utilise flexibility stored in the more expensive batteries. It must also exploit customer regulation. Even though the operator starts with the cheapest flexibility, a high enough load will force it to eventually buy more expensive resources. The local price will therefore be affected by the market participants' compensation requirements, since the next unit of energy demanded must be covered by flexibility. Again, the dependence on flexibility will cause the next unit demanded to be appreciated at a high value, inducing a high local price.

5.2.2 Flexibility dispatch decisions

In the following two sections, discussions will centre around market decisions for different prediction horizons, h. First, flexibility dispatches computed by the market using two different prediction horizons, $h = 6$ and $h = 12$, will be presented. In the next section, their respective price curves will be analysed and compared.

The timetables for flexibility activation are shown in Table 10. Some contributors of flexibility seem to be more favourable than others. Looking at the customers, customer 3 and 4 are the ones who's flexibility is used in both cases. As expected in section 5.1.5, that is because of their low profit requirements when trading flexibility. In both cases, the market platform is only trading energy with these two customers.

The customers' net regulation within period I further satisfies the upper regulation limit of 10 MWh. This can be seen in the bottom row of Table 10.

The use of batteries are more diverse than customers. In the beginning, all batteries are being charged in some hours in both cases, because the main grid price is low. Later on, however, the algorithm with $h = 6$ is discharging all the batteries, except battery 5. The algorithm with $h = 12$, on the other hand, is avoiding the costly flexibility in battery 4 and 5. These differences will become important when reviewing the resulting price curves later on.

The batteries' net regulation during I satisfies the requirement for a certain storage level in hour 24. All storage units began with an energy level of 15, seen in Table 8, and had to contain at least 33% of its total capacity in the final hour. Therefore, the absolute value of net regulation for batteries can be no more than $15 - 0.33 \cdot 30 = 5.1$.

No regulation activities are suggested in hours 11-15. There is little pressure on the system in these hours, as the aggregated community load is below the line constraint. These hours have therefore been excluded from Table 10.

Table 10: *Flexibility schedule computed by the market algorithm, with two different prediction horizons, $h = 6, 12$. There is no regulation in hours 11-15.*

	h = 6									**h = 12**								
Hour	**Customer**				**Battery**					**Customer**				**Battery**				
	1	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*5*
1																		
2			5		5		3	3	1			14		5				
3			3		2	10			2					2	10	3	2	
5			4		8							1		8	4			
5						5									1		1	3
6																		
7			-2			-3						-5						
8			-11									-10		-1				
9						-10									-3	-7		
10						-2										-2		
...																		
16							-1					-1						
17					-1		-10					-5.1	-5.9					
18					-8		-6					-3.9		-10	-0.1			
19				-6.3				-7,7						-10	-4			
20			-3.7		-10	-0.3								-9	-5			
21					-3.2	-4.8									-8			
22																		
23																		
24					2.1		8.9							9.9		0.9		
NET	0	0	-3.7	-6.3	-5.1	-5.1	-5.1	-4.7	3	0	0	-10	-5.9	-5.1	-5.1	-5.1	3	3

5.2.3 Prediction horizon (h) selection

The market optimises the community's flexibility dispatch over h hours at a time. The interval over which the market model has information about future development will influence its recommendations for optimal flexibility activation. For this reason, computed local electricity price curves will also differ.

This section will look closer at price computations using three different prediction horizons, $h = 2$, $h = 6$ and $h = 12$. The goal is to investigate how and why the different optimisation designs produce different price curves. This way, the influence from the selection of prediction horizon on the market model's characteristics can be unveiled.

A. Price curve differences

In Figure 13, the three different price curves are plotted against each other, and compared with the price curve in the main grid. For simplicity, the price curves will from here on be referred to as h2, h6 and h12, based on their respective prediction horizons. The price curve in the distribution grid will be referred to as the main curve. The line of reasoning will focus on price curve differences and the degree of price volatility.

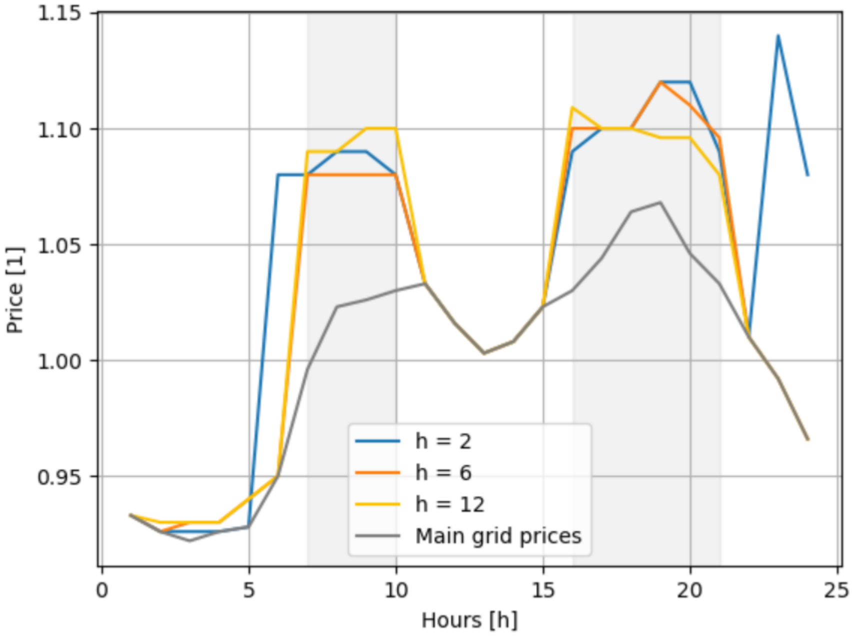

Figure 13: *Computed price curves for different prediction horizons,* $h = 2, 6, 12$.

A common factor among the local price curves is having price peaks around the same time as there are capacity challenges between the community and the distribution grid, which are the intervals 07-10 and 16-21. These intervals have been shaded in Figure 13. They naturally coincide with the hours where the distribution grid experiences price peaks.

Looking closer at each individual price curve, and how they differ from each other, the following observations stand out;

<u>Observation 5.2.3.A 1:</u> Curve h2 increases to a high price (in hour 06) one hour before the other two curves.

During early morning, h2 almost coincides with the main curve. Then, h2 increases to a high price one hour before the other two curves. This difference occurs because of the market model's limited scope. The market operator suggests battery charging in the first hours of I, as this is a source of income when main grid prices are low.

Until hour 05, the market observes no capacity challenges as the community load is well below the grid constraint. There is also no indication of this changing in the foreseeable future. However, the market's foreseeable future in this scenario is only two hours. In hour 06, the market model suddenly discovers the upcoming need for activation of flexibility in hour 07, as the community load will be higher than the transmission line capacity. Additionally, there is the storage level requirement of 60% in all batteries in the same hour. In abrupt preparation, the market decides to spend the remaining transmission capacity on charging storage units in hour 06. The community will then be utilising all available capacity, which leads to a higher local price than in the main grid, as the next unit demanded must be covered by local flexibility. The price continues to be high during the interval 07-10.

Still, one could argue that h2 will produce the most accurate and representative price signals to consumers. Since the market is frequently reoptimising the situation, the physical situation in the grid will always be represented in the calculated price.

*Observation 5.2.3.A **2**: The global price peak of h2 during the evening (hour 23) exceeds the price in all other hours.*

In hour 23 the market algorithm with $h = 2$ suddenly notices the storage requirement of energy levels of 33% in all batteries in hour 24. Instead of preparing for this, the batteries have rather been discharging to cover the community load in the second interval of capacity challenges, 16-21. When the storage condition is detected in hour 23, several batteries are empty. When forced to charge its batteries, the community is now using all available capacity, inducing a very high local price in this hour. Since the required storage volume must be assembled by any available flexibility, the market operator might also be forced to purchase expensive resources.

*Observation 5.2.3.A **3**: Customer regulation will not be used, until the final hour of I, when $h = 2$.*

The use of customer regulation when $h = 2$ is peculiar. If the system needs a customer to increase or decrease its load, the market is obligated to compensate the customer with the same energy volume which was changed within h hours. When the prediction horizon is only two hours, customer regulation will never be used.

Again, the optimisation range is of importance. The assumed load curve in this simulation example has a clear demand peak during morning and afternoon. Looking at a general hour with capacity issues, it is likely to also assume similar challenges in the two adjacent hours. This means, when customer regulation is needed, the market assumes it will also be needed in the consecutive hour. Since the market operator is unable to require a customer to only decrease its load within a prediction horizon, it will never activate customer regulation. That is, except from in the final hours of I. Customer regulation is in fact utilised in the final two hours, when the constraints related to net regulation during I (Eq. (4.13)) become active. Without this opportunity, the market would be unable to satisfy the lower bounds for storage.

*Observation 5.2.3.A **4**: Curves h6 and h12 often overlap and have more similar qualities compared to h2.*

During the first hours of I, both h6 and h12 recognize the prediction of a forthcoming rising load and the storage level condition for hour 07. Therefore, preparations include battery charging, leading to slightly higher prices than the main curve. Due to energy storage, the price does not rise to a high level until the first hour of capacity challenges. However, there are price differences between curves h6 and h12 during the intervals of capacity problems. This is a result of the market model having different time perspectives, which is affecting the selection of which flexibilities to use.

*Observation 5.2.3.A **5**: Curve h6 has lower prices during the first interval with capacity problems (07-10) compared to h12.*

As seen from Table 9, battery 1 and 2 are the two most favourable choices when it comes to stored flexibility. The market platform can profit the most when selling flexibility and saving the most by purchasing flexibility from these two batteries. During the first interval with capacity issues, 07-10, h6 is using energy only from battery 2 to cover the peak demand, since this is the absolute cheapest flexibility. This can be seen in Table 10. This leads to quite low prices in this interval for h6.

With $h = 12$, on the other hand, the market model is observing variations in the load profile long ahead of their occurrence. During the first interval with congestions, it is already aware of the second demand peak in the afternoon. Instead of using only a single battery, h12 is utilising both battery 1, 2 and 3 during hours 07-10. This is shown in Table 10. Since the flexibility stored in battery 1 and 3 is more expensive than in battery 2, the prices end up being higher for h12 than for h6 in this interval.

Observation 5.2.3.A ***6:*** *Curve h6 has higher prices during the second interval with capacity problems (16-21) compared to h12.*

With $h = 6$, the model's field of view is somewhat limited. When planning flexibility activation during the first demand peak, the market is using cheap energy stored in battery 2. At this point in time, the market model is unaware of the second demand peak. When this peak is discovered, however, battery 2 has the lowest energy level among all the storage units. The model's next move is then to save the remaining cheap energy contained in battery 2 until it is absolutely necessary. This will be done as long as the model observes a rising load curve. Battery 2 is therefore not being used until the end of the second demand peak. Instead, the model is forced to utilise the more expensive energy stored in battery 3 and 4. This leads to high prices during the interval 16-21. The described flexibility activation is shown in Table 10.

On the contrary, h12 can now benefit from its previous decisions. Since the market model observed the second demand peak already when it was making decision for the first demand peak, it can divide available resources on the two intervals. Battery 2 has not been emptied because battery 1 and 3 was also used to cover the high demand in hours 07-10. Later on, during the second demand peak, there is enough energy stored in battery 1 and 2 combined to cover the high load. It is therefore not necessary to use the costly flexibility stored in battery 3 and 4. This leads to h12 having lower prices than h6 in the interval 16-21.

Observation 5.2.3.A ***7:*** *The market model utilises customer flexibility more when the prediction horizon is long.*

Customer regulation opportunities is another factor influencing the differences between h6 and h12. When $h = 12$ there is more time to compensate a load change than when $h = 6$. The market model is therefore utilising flexible customers more when the prediction horizon is longer. This is the other reason why h12 does not use the expensive energy stored in battery 3 and 4 during the second demand peak. The market is rather obliging customers to decrease their load. Some of the customers' flexibility is cheaper than the stored flexibility.

B. Price volatility

The purpose of the local market optimisation is to determine the most efficient electricity price in the community in the hours when the accumulated load exceeds the transmission capacity. The most efficient price is formed when all relevant information is considered. From a socioeconomic point of view, the price should preferably be as low and stable as possible. The selection of h will influence the calculation of electricity prices, as the model will have access to different ranges of information when performing computations. The prediction horizon will thereby affect volatility in local prices.

Based on experiences from the observations above, a *short* prediction horizon indicates limited time for preparations. An occurring disturbance must be handled right away, with existing resources. For example, the algorithm observes the community load exceeding the line constraint in the hour following the present one. To cover the load, the market must perform regulation or initiate battery discharge in the present hour.

Generally, when the market discovers significant future capacity challenges close to their occurrence, extreme measures might be necessary on short notice. Any available flexibility must then be bought to satisfy the load. This leads to peak electricity prices.

Selecting a *long* prediction horizon, on the other hand, enables the market model to schedule the flexibility dispatch long-term. A disturbance in the form of a high community load can be dealt with by planning charging and regulation activities based on information from a broad set of hours. When a disturbance is discovered, storage units can charge during cheap hours in preparation for the hours with capacity issues. The same can be done for customer regulation. If the market requires customers to decrease their load in some hours, it must make sure to let them increase their load close by in time. With a long prediction horizon, the market has time to make these adjustments ahead of the disturbance. The market can then make trade-offs between hours with peak and off-peak demand. In exchange for a higher price during hours of low demand, the price during hours of high demand can be reduced. This arrangement leads to a more stable, i.e. less volatile, price curve.

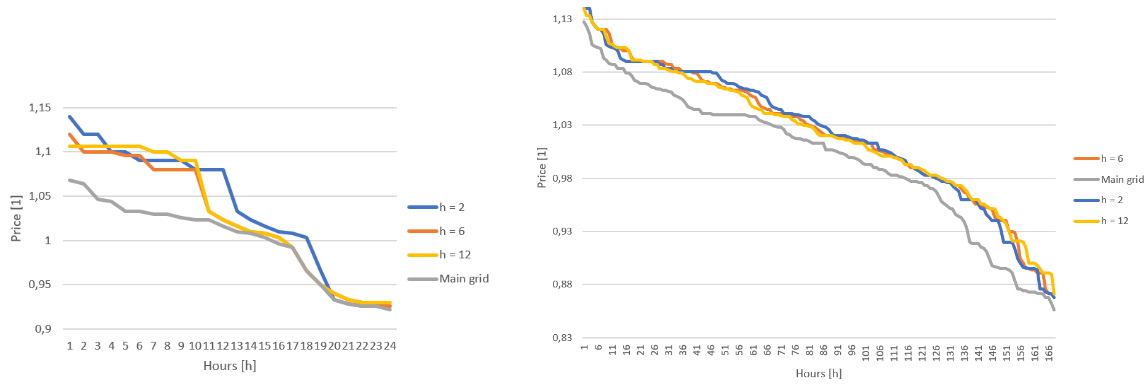

Figure 14: *Duration curves for electricity prices for a day, i.e.* $I = 24$. *(left), and for a week, i.e.* $I = 168$ *(right).*

The points described above are visualised by the duration curve of electricity prices for different values of h. The left side of Figure 14 shows three different duration curves compared with the main grid price curve for $I = 24$. The right side of Figure 14, on the other hand, shows price curves computed for a full week, $I = 168$, for the same set of prediction horizons. All curves show higher local prices than distribution grid prices. As explained in section 5.2.1, the community prices will never drop below the distribution grid prices as long as there is no local production installed.

Certain observations stand out with respect to price volatility;

Observation 5.2.3.B ***1:*** *The longer the prediction horizon, the more stable the price curve.*

This is clear from the comparison of duration curves, both on a daily and weekly basis. When $h = 2$, the duration curve is the most volatile. This can be seen from the slope of its duration profile, as the curve for $h = 2$ has the steepest slope. It is when $h = 12$ the market achieves the least volatile price curve, out of the performed analyses.

Observation 5.2.3.B ***2:*** *Computed, local price data has a smaller standard deviation when h is long.*

Price volatility can also be determined by computing the standard deviation within the data-sets for each h. The standard deviation represents the dispersion within a set of data. Calculations has been done for the weekly price curves. Here, the main curve actually has the highest standard deviation among the curves. Using this as a basis, the volatility of the other price curves can be compared. When $h = 6$, the standard deviation is about 3% less, and when $h = 12$, it is about 7% less than the main grid prices. The price curve for $h = 2$ has around the same volatility as the main grid prices. This further supports the observations from Figure 14. An optimisation algorithm with $h = 12$ will produce the least volatile set of local prices among the cases analysed.

Observations 5.2.3.B 1 and 5.2.3.B 2 indicate a long prediction horizon to be the best choice when designing the market's optimisation algorithm. Even though this results in the most stable community price curve, it still might not be the optimal design decision. If h is large, market decisions rely on the accuracy of predicted data, for example demand profiles. In a situation with perfect information, anticipated data is exactly right, and optimal flexibility decisions can be made. In reality, however, unforeseen events might occur and cause deviations from the expected load profile. In this case, a model with a long prediction horizon will have calculated optimal actions based on old information. Since the load profile has changed, computations are wasted and must be redone.

Another example of when a long prediction horizon might not be the best solution is when distribution grid prices have been difficult to predict. The day-ahead electricity price curve might vary a lot, making it challenging to perform market optimisation. In this case, there is also no point in executing optimisations for a long prediction horizon. The distribution grid prices might change before the hour of operation arrives, making the calculations useless.

5.3 Simulation example: Limited transmission capacity

The above simulation illustrates the model's features through a numeric example under normal physical conditions. This demonstration, however, will describe how the market model handles a more stressed situation.

Assuming the community is receiving electricity through two parallel transmission lines, they will have a combined transfer capacity of 100%. Line 1 has 90% of the capacity, while line 2 has 10%. The objective is to investigate market results in a situation where there is a fault on line 2. The fault occurs in hour 09 during a 24-hour day, and the grid operator's repair team spends four hours correcting the fault. The transmission capacity to the community is thereby reduced to 90% during the time interval 09-12. Figure 15 illustrates the physical situation in these hours. The outage is assumed to be sudden and unexpected, and is therefore first detectable for the market model in the hour where it occurs.

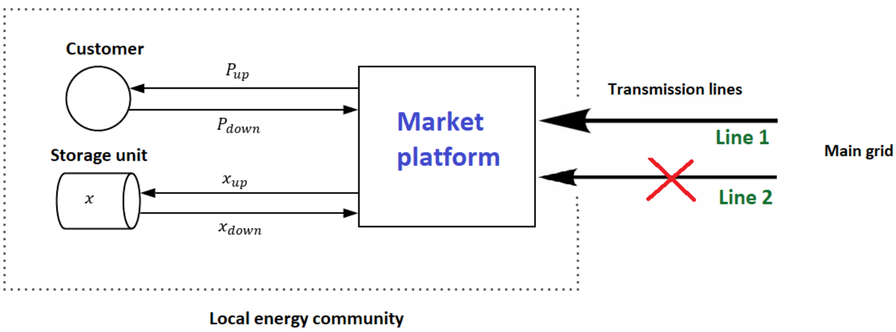

Figure 15: *Example system with a fault on line 2.*

It was considered useful to simulate how a partial capacity outage would affect optimal market decisions. A demonstration of this type could provide information about how similar faults will influence consumers and the local price appearing on their electricity bills. It can also be valuable when scheduling planned maintenance, where some lines need to be disconnected or even replaced. Being aware of the effect on a local market, one can achieve minimal effect on electricity prices on the deficit side of a bottleneck.

5.3.1 Expectations

Ahead of analysing a situation with reduced capacity, the following points can already be anticipated.

- Less transmission capacity leads to a higher flexibility demand. The flexibility schedule is therefore expected to show more regulation being performed. As the transmission capacity is reduced for four hours from 09 to 12, the intervals with capacity issues have expanded. Now, the market optimisation algorithm must optimise flexible resources during the intervals 07-12 (previously 07-10) and 16-21.
- Local electricity prices will be higher during the periods of capacity challenges. The transient outage on line 2 limits the power flow from the distribution grid. The flow in line 1 will therefore equal its capacity limit, at least in the hours where the community is demanding more power than the line can carry. A grid constraint satisfied at equality indicates a transmission line under pressure. The next unit of energy demanded will therefore have a high value, as it will be costly to deliver. This corresponds to a high shadow price value related to the grid constraint, and thereby a high local electricity price.

5.3.2 Flexibility dispatch decisions

There is visibly being performed more flexibility activation in this simulation than in section 5.2. This can be seen in Table 11, showing the flexibility dispatches for $h = 6$ and $h = 12$. Regulation is further centred either in the two periods with capacity challenges, or in the first hours of I, where electricity prices are low in the distribution grid. There is also clearly a turning point in hour 09, when the outage occurs. From this hour on, the market platform is more dependant on flexibility to manage its tasks.

There are also internal differences between flexibility decisions for the market model with $h = 6$ and $h = 12$ in Table 11. The battery columns for $h = 6$ show battery 1 and 2 being used the most, while the battery columns for $h = 12$ show battery activities are more evenly distributed over all units.

In addition, the table shows the net regulation, or energy change, for each customer and battery. Customers can maximally change their load during a 24-hour day with 10 MWh, while the energy level in each battery it set to be 33% of its total capacity. These are all within their limitations.

The contrast between the columns for $h = 6$ and $h = 12$ will be further discussed and analysed in the following section.

5.3.3 Prediction horizon (h) selection

In section 5.2.3, differences in price curves and price volatility for a set of prediction horizons were subjects of investigation for a system under normal operating conditions. These analyses pointed at the advantages with a long prediction horizon, with respect to price stability and scheduling.

However, as seen from Table 11, the optimisation model is obtaining quite different market results for this new situation. Therefore, similar features will be studied for the case with limited transmission capacity in a specified set of hours.

Table 11: *Flexibility schedule computed by the market optimisation, with two different prediction horizons, when there is reduced transmission capacity in hours 09-12.*

	h = 6									**h = 12**									
Hour	**Customer**				**Battery**					**Customer**				**Battery**					
	1	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*1*	*2*	*3*	*4*	*5*
1																		
2			5		5		3	3	1			14		5				
3			3		2	10			2					2	10	3	2	
4			5		8							1		8	4			
5							5								1		1	3
6																		
7			-2				-3					5						
8			-11									-10		-1				
9					-10	-10								-10			-10	
10					-6	-6									-5		-7	
11					-1	-6										-6	-1	
12					-1	-3									-2			-2
13														5				
14														3				
15																		
16									-1									-1
17					-1				-10					-8,4				-2,6
18							-4	-10					-10	-2,9	-1,1			
19	-6,5		-2	-5,5								-10			-1,9	-2,1		
20			-8	-4,5	-1,5									-10	-4			
21					-3,9		-4,1							-1,9	-6,1			
22						1												
23						0,2		1,9	2,9								5	
24					4,3	6,7								6,1			4,9	
NET	-6,5	0	-10	-10	-5,1	-5,1	-5,1	-5,1	-5,1	0	0	0	-10	-5,1	-5,1	-5,1	-5,1	-2,6

A. Price curve differences

Price trajectories for $h = 6$ and $h = 12$ are plotted against the main grid prices in Figure 16. The area shaded red indicates the hours where line 2 is out of operation. The areas shaded grey still represent the hours where the original community load was exceeding the combined line capacity of line 1 and 2.

In a similar manner as for the simulation under normal operational conditions, this section will elaborate on particular remarks concerning the price curves for different values of h.

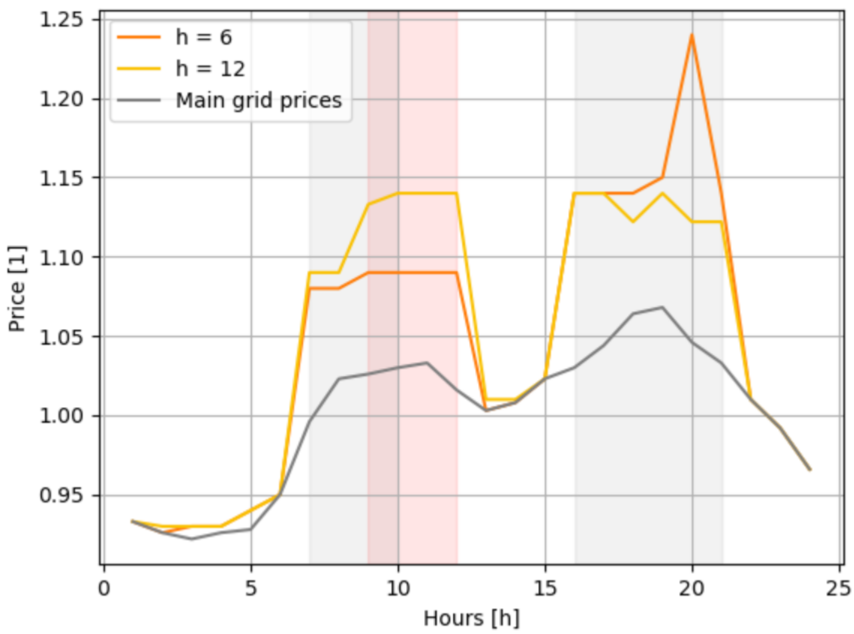

Figure 16: *Computed price curves for different prediction horizons, $h = 6, 12$. There is reduced transmission capacity in hours 09-12. The areas shaded in grey mark the hours with capacity issues based on the original load, and the area shaded in red marks the interval with reduced capacity.*

Observation 5.3.3.A ***1****: There is no price curve for $h = 2$ in Figure 16.*

The market model is unable to find a feasible solution when $h = 2$. This is underlined by the absence of a blue curve representing prices for h2.

Since the transmission capacity is reduced to only 90% in hour 09, the capacity challenges become too significant, too fast. An optimisation model with a short prediction horizon has not prepared for such large changes. When a change is too critical, the optimisation problem is simply incapable of finding a solution where the load is being covered. Since there is no feasible solution for $h = 2$, the market algorithm was unable to complete a full price curve for h2.

Observation 5.3.3.A ***2****: Both h6 and h12 jumps to a higher price in hour 09.*

When calculating optimal decisions for hour 09, the market model suddenly observes stricter limitations than usual. In hour 09, and for four hours ahead, the power supply from the distribution grid is reduced to 90% of its original capacity. The operator must now utilise more local flexibility in order to cover the load. In addition, the remaining transmission line is under even more pressure than before. Since the community depends on local flexibility to cover their aggregated load, it will become more costly for the market platform to perform balancing. Therefore, when the transmission capacity suddenly reduces, the local electricity prices jump to a higher level accordingly.

Observation 5.3.3.A ***3****: Curve h6 has lower prices during the first interval with capacity problems (07-12) compared to h12.*

Both h6 and h12 is mostly utilising stored energy to resolve their capacity challenges during this interval. Nevertheless, they are choosing quite different strategies.

The fault on line 2 occurs unexpectedly, and the market model must quickly find a way to allocate resources in a way which satisfies the problem constraints. From Table 11, h6 is only using flexibility from battery 1 and 2 throughout this entire interval. These are the batteries with the cheapest flexibility. The model is thereby minimising its balancing costs by purchasing electricity from the participants who are requesting the least compensation for being flexible. When balancing costs are low, there is less need to send price signals to customers, signalling they should reduce their consumption. The corresponding local electricity price therefore becomes (quite) low.

On the contrary, h12 is utilising a wider selection of flexibility contributors in this phase. Starting from hour 09 and throughout the first interval with capacity issues, h12 suggests all the batteries should discharge to some extent. In hour 09 the model is already observing the rest of the day in its entirety, as it can view information for the next 12 hours. Knowing about the upcoming capacity challenges, flexibility activation is spread out across all flexible storage units.

Since h12 is using flexibility from some of the more expensive batteries, the model's balancing costs are higher than for h6. For example, in hour 09 when the fault takes place, h6 is discharging battery 1 and 2. On the other hand, h12 is discharging battery 1 and 4, hence inducing higher expenses since battery 4 sells its flexibility at a higher price than battery 2. Hence, the optimisation problem related to h12 chooses to pay more to cover the load in hour 09. The corresponding local electricity price then becomes high.

Observation 5.3.3.A 4: Curve h6 has considerably higher prices during the second interval with capacity problems (16-21) compared to h12.

Both curves have high prices deviating from the main curve only in the shaded hours. Yet, optimal prices are far higher when $h = 6$ than when $h = 12$ in the second shaded interval, and with a price peak in hour 20. The consequences of previous decisions will now become evident.

Unable to see far enough ahead, h6 has no incentive to retain any flexibility in the interval 07-12. Consequently, a large portion of cheap, stored resources is spent during this period. For this reason, the batteries generally have lower energy levels in hour 15 when following directions given by a market model with $h = 6$ than by a market model with $h = 12$. This can be seen in Table 12, which shows the battery contents in hour 15, i.e. available stored energy to use in hour 16.

To accommodate the power gap, h6 must therefore use flexibility from the more expensive batteries, as well as customer regulation. This can be seen in Table 11. As a result, the sum of net customer regulation is much higher for h6 than for h12. Even the most flexible and willing customers require a compensation price which is almost as high as the most expensive batteries. This leads to high prices for h6 during the interval 16-21.

Table 12: *Energy level in each battery in hour 15, for $h = 6, 12$.*

Battery	$h = 6$	$h = 12$
1	12	27
2	2	23
3	18	12
4	18	0
5	18	16
NET	68	78

Since h12 observes the second shaded area when scheduling flexibility for the first shaded area, it makes sure to not exhaust any flexibility sources. The market model is hence performing resource allocation planning for a longer time perspective. When undergoing decision-making for hour 16, there is still energy left in the batteries with the lowest selling prices, battery 1 and 2. While h6 must utilise what is available, h12 can now concentrate on the cheapest resources, and places emphasis on these two batteries. Additionally, h12 can benefit from the decision to charge battery 1 during the low-price interval in the distribution grid, i.e. in hours 13-14. For this reason, h12 has local prices higher than the main curve, but still lower than h6.

As a result of the observations above, the price curve h12 computes prices which are on about the same level during the two demand peaks, around 1.14. To avoid unexpectedly peaking prices, the market performs a trade-off between two intervals in which congestion management is required. In exchange for avoiding a significant price extreme during one period, the market computes a slightly higher price in another period, where the capacity problems are smaller. This is done differently when $h = 6$. Oblivious of any other need for balancing using flexibility outside the current optimisation horizon, a trade-off is not being considered. Consequently, a price peak of almost 1.25 occurs in hour 20.

The price differences in this interval are explicit and direct consequences of choices made in the market model design process. A model will compute the lowest optimal prices when it has as much information about the future as possible. However, letting the optimisation problem access predicted data for too many hours ahead might cause problems when sudden and unexpected events occur.

6 Model remarks and discussion

This chapter will summarise the most important findings and indications from the previously performed analyses. Recommendations for further improving or expanding the local market model will also be presented.

6.1 Experiences from the model simulations

The central aspect under investigation was the market model's performance with respect to flexibility dispatch decisions and price formation. In this section, a summary of important simulation results and general experiences from the analyses will be discussed.

6.1.1 General observations

Considering existing research, pilots and interest from regulators, there is presumably a need to further investigate market solutions for flexibility trading. How such markets can be expediently designed in a manner which is useful for the future power grid is an ongoing topic of discussion.

The proposed method for establishing a fair electricity price is effective in the sense that the price is being calculated based on all relevant information. The physical situation in the grid is being considered, hence generating suitable price signals. Consumers will then be encouraged to adapt their consumption patterns to the physical circumstances in the grid through which they are being supplied. Furthermore, both customers and storage units have a clear understanding of their compensation requirements. These are also taken into account, as they set the price of flexibility.

Even though this price formation method can be effective, it might not be efficient. As the assumed community only consists of a few customers and storage units, the market platform was able to perform calculations rather quickly. However, this might change when trying to solve optimisation problems iteratively for a normal size community. The amounts of data will increase as there are more market participants, and the market must coordinate hourly load data for each consumer. This could already be an issue in the existing power system, where AMS will give access to comprehensive amounts of data.

Another aspect to evaluate is the model's feasibility. To achieve power balance, the market is dependant on correct price and load data. This seems viable. Electricity prices for the following day are calculated in the day-ahead market, and retailers are already submitting predicted load profiles on behalf of their customers. Unforeseen events might occur, of course, and influence the price or demand curve. Furthermore, the market model is only optimising for a set of h hours at a time. This way, it is assuming less predicted data to be correct in each time step. The optimisation problem is thereby computing effective market results to the best of its ability, based on the information it has access to.

6.1.2 Prediction horizon selection

The presented market model is meant to be a tool for testing how system features and decisions in the market design process affect market results. For example, the model reveals how using MPC to coordinate resources will influence market balance calculations, and thereby the electricity price. A more specific example within MPC is the prediction horizon, the interval over which the market operator optimises in each time step.

Generally, the market computes the overall lowest, and thereby the most economically efficient, electricity prices when scheduling flexible resources over a longer period. That is, overall balancing costs will also become the lowest when the market is coordinating resources over the longest set of hours at a time. The cheapest flexibility from customers and storage will be divided across the entire period of analysis and prioritised to the most critical grid challenges. This way, the market is utilising available resources in the community's best interest. This is an implication from simulations in both section 5.2 and 5.3.

One could say, the selection of either a relatively long or short prediction horizon is a trade-off between two options. On the one hand, at worst, computing power is wasted when unforeseen events occur close to real-time, while otherwise, the market is obtaining the most socially beneficial results. This is typical for a long prediction horizon. On the other hand, new optimisations are frequently taking current system development into account, at the same time as the market is not prepared for large system changes, and is at worst not at all capable of solving a complication with existing resources. This is typical for a short prediction horizon. The main advantages and disadvantages by choosing a prediction horizon at each end of the scale, based on experiences from the performed simulations, are summarised in Table 13 and Table 14.

Table 13: *Advantages and disadvantages with a long prediction horizon in relation to the presented market simulations.*

Long prediction horizon

Pros	*Cons*
• Computes the overall most economically efficient results	• Relies on predicted information for many time steps into the future
• Prepares storage units for upcoming and anticipated market development	• Small, unforeseen events can occur within a period which has already been optimised, requiring reoptimisation

Table 14: *Advantages and disadvantages with a short prediction horizon in relation to the presented market simulations.*

Short prediction horizon

Pros	*Cons*
• Frequently handles the newest system development. Can therefore sufficiently handle small, unforeseen changes	• A too short time span can lead to insufficient preparation in relation to significant, unexpected events
• Can produce economically efficient results short-term, because market results are based on instant events	• Might require an unnecessary amount of processing capacity for a system which from experience faces few disturbances

6.1.3 Irrational storage decisions

A noticeable characteristic concerning the market results is occasional illogical decisions for use of stored energy. Storage decisions are calculated optimally within each separate prediction horizon, through separate optimisation problems. The possibility of storing electricity can help solve capacity issues by simulating the presence of extended supply when the demand is requiring more energy than the grid can transmit. Storage decisions calculated by the market platform will presumably depend on the electricity price development in the main grid. Still, the charging schedules might not always follow the path one would expect.

In an interval where the price is strictly decreasing, one would expect the model to suggest charging of the storage units as late in the interval as possible. This way, the batteries could charge at the lowest cost in the current optimisation problem. Cheap energy could then be saved for later when electricity from the main grid is more expensive. However, this is not necessarily always the case.

Using MPC, the market model will only have an overview of a certain number of hours in each optimisation. In each interval, the model will determine and execute decisions to prepare the system for future developments, such as the future main grid price trajectory and load curve. For preparatory reasons, the market can compute storage decisions which seem unreasonable.

To visualise this effect, take for example a set of consecutive hours where the main grid price is strictly dropping. The system under consideration consists of a load and a storage unit, where the storage helps cover the load during capacity issues. Intuitively, available storage should be charging when the price is at its lowest. Here, this corresponds to the latest hours of the interval. The load curve, however, is strictly rising during the same interval. In fact, the load is exceeding the available transmission capacity in these final hours. This situation is illustrated in the left side of Figure 17. In the first eight hours or so, the blue load curve is strictly increasing, while the grey price curve is strictly decreasing.

In this interval, the storage unit needs to prepare for the hours where the load is exceeding the grid constraint. Therefore, the market's recommendation will be to charge at the beginning of the interval, when the price is at its highest. This is shown in the right side of Figure 17. The red curve signals storage input to the battery when the demand is low, and when the electricity price is high.

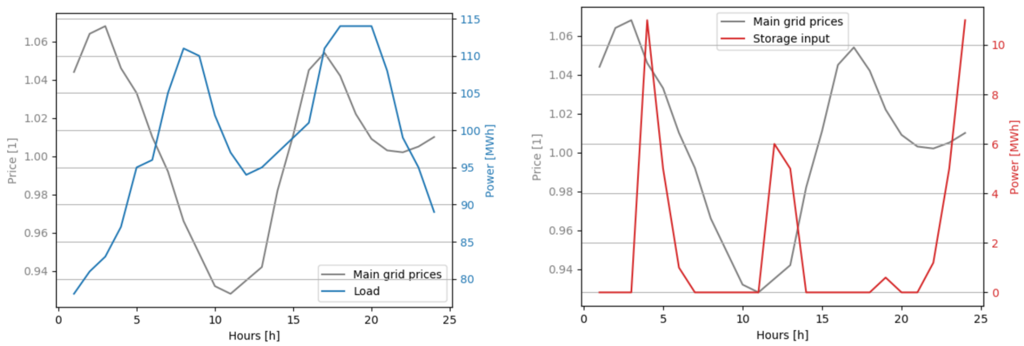

Figure 17: *Example of irrational storage decisions. Left: load plotted against main grid prices. Right: storage input plotted against main grid prices.*

This decision might seem irrational at first. Yet, it is essential to ensure coverage of the load. As mentioned, the principle of the MPC algorithm is to enable preparation for only a few hours into the future. This way, new developments and observations can be handled as they occur. When the load is strictly increasing, as in the above example, the market will schedule charging such that future electricity needs are met. The storage unit will therefore charge at the beginning of the current time interval. This way, there will be available energy ready to cover the rising load towards the end of the interval, when the transmission capacity is insufficient. These actions induce high costs, but are still highly necessary.

In summary, the explanation behind the somewhat counter-intuitive storage decisions has to do with preparation opportunities and evaluation of system needs. Since the storage unit will charge when the grid price is at a local maximum, the system will face higher expenses. Unnecessary, some might say. The alternative, however, is to not be able to cover the system load at all. The market model is therefore instructed to let demand coverage take precedence over cost minimisation. In this situation, the optimisation problem might suggest decisions which create higher costs. In exchange, the system participants can consume electricity according to their regular load patterns.

The length of the time interval under consideration will also significantly influence the market results.

The mechanism described above is most likely to occur for a short prediction horizon. When only a few hours are being considered at a time, the model will have limited time to prepare for upcoming events. A strictly increasing slope of the load curve might be invisible to the market model before it must be dealt with in real-time. In such a stressed situation, the optimisation problem must do whatever is required to cover the demand in the following hours. If the prediction horizon is somewhat longer, however, the model has both more time and a better overview of future developments. Then, charging at high electricity prices can be avoided.

6.2 Model alternatives and extensions

The market model is designed with the intention to illustrate examples. Therefore, it has potential to expand, such that it can handle increased complexity and additional features. This section takes note of some extension alternatives.

6.2.1 Reallocation of benefits

The market operator in the analysed system purchases flexibility from customers at the price of each individual seller. The price per unit is the same regardless of the total energy volume being exchanged. This compensation mechanism might not be the most socioeconomic solution, as some customers or batteries could be contributing more than others.

The flexibility providers contributing the most would accordingly receive the most payment for flexibility, since they are performing the most regulation. Still, the question is whether they are receiving benefits *corresponding* to the worth they are giving up by offering their flexibility. The profits from offering flexibility should be weighted against the total volume and inconvenience the regulation comprises.

An example can illustrate this issue. Say there is limited grid capacity between a community and the main grid. A flexible customer, say, customer A, can be obliged to reduce its load in order to not overload the transmission line. This means other customers can consume at their original load patterns, because customer A takes one for the team. Still, customer A are now worse off by participating in the community compared to acting on its own. If it was not part of the community market, it would not have been required to reduce its load. The other customers are then enjoying benefits at the expense of customer A. In this type of situation, compensation mechanisms must ensure customer A receives a reward for its flexible behaviour. The form and size of this reward must be determined based on the benefit increase all the other customers experienced.

The sacrifice made by customer A benefits the entire community. It ensures coverage of the remaining community load, and induces a lower electricity price altogether. However, in order to make this happen, customer A is the only one being affected. A more fair solution might therefore be to redirect parts of the profits the community is gaining as a whole. A compensation mechanism in the local market should reallocate some of the benefits from the entire customer base to the consumers actually contributing to the benefits.

6.2.2 Participant compensation

A flexible consumer should be compensated with its marginal willingness to pay for the energy consumption it is renouncing when its flexibility is activated [32]. Each consumer must therefore decide on how much their original consumption pattern is worth. Organisation of participant compensation can take several forms.

In the proposed model, flexibility contributors are being rewarded only when their resource is activated. Otherwise, there are no benefits for simply offering flexibility. An alternative option is to compensate contributors for being standby. Consumers will then receive profits according to a flexibility agreement, regardless of actual activation. They are then benefiting from simply being available if needed. This could make participation in a flexibility market more attractive by lowering the participation threshold.

Long-term contracts between consumers and grid operators in need of flexibility to resolve congestion is suggested in [1]. This is advantageous in the sense that both parties are benefiting from the agreement. Compensation for being standby motivates consumers, and the long-term availability of flexibility appeals to grid operators.

According to [1], only rewarding activation is discouraged. Operational complexity and market power comprise the foundation of this recommendation. Based on this, the proposed market model could be expanded to also reward customers and batteries for being standby.

6.2.3 Aggregated flexibility

The presented market model for flexibility utilises small household consumers and storage units to solve a community's capacity issues. Market results, in Table 10 and Table 11, show only small contributions from each individual participant. This is a considerable barrier to the actual implementation of a market solution for flexibility. Household consumers might not be willing to continuously submit bids and offers directly on the market platform. Acting on agreements directly with the market is indeed far more demanding than reacting to price signals or following predefined price agreements with a utility.

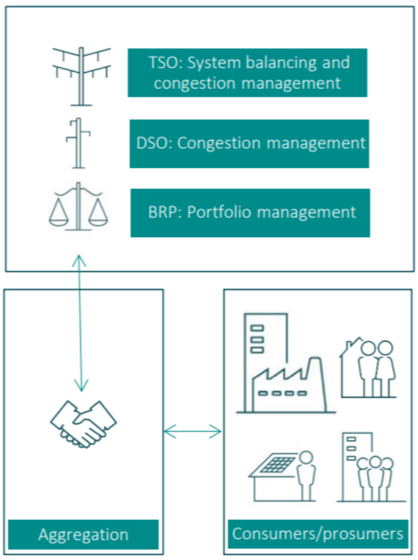

Figure 18: *Aggregation is the commercial process of assembling small-scale and decentralised generation and consumption, such that it is valuable for other market participants. Source: [33]*

To accumulate many small flexibility contributions through an aggregator is proposed as a solution to this concern. An aggregator is a market player both willing and able to collect many small flexibility volumes from decentralised customers in their portfolio [13, 34]. The contributions must be defined in time and volume, and customers may provide flexibility in the form of both generation and consumption. The aggregator can then transform the pooled volume into energy services, which can be offered on the central electricity market [33]. Here, it may be of use to both grid operators and the balance responsible party. This is visualised in Figure 18.

An important advantage of aggregation is the ability to offer large-scale flexibility. A diversified portfolio consisting of many consumers increases the possibility of always having available flexibility [13]. Different contributors have different load patterns and different loads which can act flexibly. This affects both the time and the volume at which each customer can provide flexibility. Assembling enough consumers will enable an aggregator to enter agreements with other market participants, where it can ensure a reliable flexibility supply. Aggregated to a sufficient volume, this supply can help grid operators solve congestions, and the balance responsible party to bridge imbalances.

On the consumer side, trading flexibility through an aggregator can simplify participation in a flexibility market for regular household customers [15]. By entering agreements with an aggregator, a consumer's flexibility can be utilised with little action required from the individual consumer. The aggregator then functions as an intermediate party between the consumer and the electricity market [34]. To maximise the potential for flexibility, the agreement should be tailored to each customer's power requirement level and consumption pattern. Which type of loads are considered flexible is also important to clarify.

For example, an aggregator can offer energy schedule optimisations free of charge, in exchange for the opportunity to occasionally control a customer's flexible loads. This agreement should preferable not influence the customer's comfort or create inconvenience [15]. Another option is to let the aggregator be the main intermediate party between a consumer and the electricity market. It can then offer package deals to the consumer, including both heating, electricity transport and schedule optimisation [13].

Aggregators are necessary because existing market players have not developed profitable agreements to translate demand-side flexibility into viable energy products [33]. However, it is not clarified who should take on this role of accumulating small-scale flexibility. The Danish TSO, Energinet, has together with several other companies and organisations developed suggestions for the future development of aggregators in the electricity system [33]. The alternatives span from the aggregator being an individual, third-party market player, to an electricity retailer or a balance responsible party assuming the tasks of aggregation. In the first case, the aggregator can offer different types of services to the grid. In one of the proposed future models, the aggregator role was taken on by a retailer, now both being responsible for electricity supply and flexibility management. Another suggestion was to let the aggregator be an independent player offering both flexibility and electricity for frequency control.

In addition to issues related to the division of roles in the market, other challenges also form barriers for the establishment of functional aggregators. Firstly, it is difficult for an aggregator to get started. Current regulation prevents individual, commercial market players to perform the suggested tasks [33]. Furthermore, it must land agreements with a vast number of flexible customers already in the initial phase, in order for its business to be profitable. Arrangements must satisfy both the parties providing flexibility and the parties requesting flexibility [13].

Moreover, metering and monitoring of demand-side flexibility might require additional metering equipment [13]. As previously mentioned, to verify activation of flexibility before the hour of actual consumption is challenging. Flexibility trades are finalised in advance, and future load patterns are only based on predictions and historical data. This leads to increased system complexity and requires an effective flow of information between customers, the aggregator and its trading partners.

Viewing the proposed market model in this context, aggregation might be able to remove entry barriers for flexibility providers. If the agreements are well thought out and customised to each individual consumer, the flexibility potential can be maximised. In this case, the community could even be able to deliver flexibility back to the distribution grid through their aggregator.

7 Conclusion

To utilise small-scale flexibility through a market platform clearly has potential. The market simulations show useful resource allocation over time, and the computed prices reflect the stressed situation the community is in. After studying a market solution for flexibility through exemplified simulations, a general experience is how such a marketplace requires the involvement of and cooperation between many different participants in the power system. Also, many different aspects of the market design process require attention before a flexibility exchange can be realised.

Using MPC added a new aspect to the market balancing. The performed analyses showed how different prediction horizons, i.e. different optimisation perspectives, influence the price calculations. The suggested type of price formation, through the shadow price of the energy balance in a dynamic optimisation problem, proved to be a potential method to use in flexibility markets.

The appropriate market design must compute fair and socioeconomic prices and electricity volumes. As the regulator is the one enabling the market realisation, a potential market must satisfy the regulator's requirements in order to be approved. Further, flexibility must be accessed effectively through agreements between the ones providing and requesting flexibility. A retailer or an aggregator could collect flexibility, while grid operators and the balance responsible party would demand flexibility. Since an efficient market platform requires so many participants to be active already from the start, the market's initialisation phase might be the most challenging. However, the analyses performed in this thesis indicate functional market results once a local flexibility market is in operation.

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9 Appendix

The Python programme for the proposed local flexibility market design is available upon request. The source code can be distributed to interested readers by contacting Olav Bjarte Fosso per email, at olav.fosso@ntnu.no.

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