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Distributed Energy Resources in the Liberalized Electricity Markets

AALBORG UNIVERSITY
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Distributed Energy Resources in the Liberalized Electricity Markets
Ph.D. thesis

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Contents

Preface and Acknowledgments

This thesis is a part of the project *iPower* supported by the Danish government via the DSR-SPIR program. The thesis is completed at Aalborg University, Department of Electronic Systems, section for Control & Automation under supervision of Associate Professor Palle Andersen and Professor Jakob Stoustrup in the time period from August 2011 to August 2014 .

I would like to thank both my supervisors, Palle and Jakob, for great collaboration throughout the last years, for always having a positive attitude towards my ideas and my work, and for many valuable inputs. I am very thankful for many hours of brainstorming, guidance, and review, as well as helping me being able to attend conferences and visit top research institutions all over the world. I could not have hoped for better supervisors and am very thankful!

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Finally, I would like to thank Preben Nyeng and Henning Parbo from Energinet.dk for taking time to meet and discuss as well as reply to my numerous emails with questions concerning the Danish transmission system. This has been an irreplaceable help throughout my learning process of the Danish energy system.

Benjamin Biegel
May 2014, New York

Abstract

The Danish electricity system is currently undergoing major changes: the penetration of non-dispatchable renewables is increasing while the centralized coal power plants are being phased out. This is a part of reaching the Danish 2020 goal of 50 $\%$ wind in the electricity sector. The final goal is in 2050 where all energy sectors must be supplied entirely by renewables. As the most abundant renewable resource in Denmark is wind, an electrification of the heating and transport sector is encouraged and has already begun. For this reason, the electrical consumption is expected to increase over the coming years.

A number of issues are expected as the penetration of renewables increases and the electrical consumption grows. As the penetration of fluctuating and non-dispatchable renewables increases, the need for system stabilizing services also increases. However, the current providers of ancillary services are the centralized power plants which are being phased out. This calls for new alternative sources of stabilizing services such as flexible consumption and storage devices. Another related issue is that the current electricity markets are designed to handle large centralized dispatchable production plants and not to handle smaller devices such as consumers. Therefore, new market designs may be needed for better market integration of flexible consumers and storage devices.

Another issue is that an increase in the electrical load may cause congestion in the distribution system. In particular if consumption is optimized towards the electricity markets, the result may be that consumption will get a high concurrency causing large peaks that can overload the distribution cables. The conventional method for resolving grid congestion is to reinforce the gird. It may, however, be a better solution to utilize flexible consumption and production devices to avoid congestion and thereby avoid economically and environmentally expensive grid reinforcement.

The above issues are the main focus of this thesis, and a number of papers address each of the issues. Papers[1] 1 and 2 show the general concept of shifting flexible consumption in time according to the need, for example to outbalance system disturbances. This concept is made more concrete in Papers 3, 4, 5 where domestic heat pumps are the main focus and where it is illustrated how these pumps can be optimized towards the electricity markets and in that way help balance the system. The papers show that electricity price savings in the order of 20 $\%$ are achievable without violating the comfort of the inhabitants. Following in Paper 6 a real life demonstration is made where 54 heat pumps are aggregated to track an accumulated power reference. During the demonstration, the heat pump portfolio was able to track an hourly power reference for 7 days with satisfactory performance while maintaining a comfortable indoor temperature and sufficient hot water for the inhabitants. To the best of the author's knowledge, this is the world's first

[1]The list of papers is found in Sec. 1.5

real-life demonstration where a larger number of consumers are aggregated to follow a reference to the total consumption.

In Papers 7 and 8, we examine the concept of letting consumers deliver faster and more valuable ancillary services. In Paper 8, we show a method where a portfolio of ON/OFF devices are able to deliver a system stabilizing response that satisfies the current regulations for primary frequency control.

In Paper 9 and 10 we examine the current electricity markets in Denmark and identify the main barriers for flexible consumers to enter these markets. The papers show that consumers should have an energy capacity in the magnitude of 20 – 70 kWh to break-even in today's spot market, while a capacity of 70 – 230 kWh is required in the current regulating power market. In other words: the devices must be larger industrial devices to make revenue with today's regulations. Finally, in Paper 11 we propose a new method that allows flexible consumers to better participate in the fast regulating markets. Based on market data we simulate and show how this method allows flexible consumers to deliver significantly more fast reserves than under the current regulations.

Finally, in Paper 12 we illustrate the concept of utilizing flexible consumers to avoid grid congestion. In Paper 13 and 14, we expand this method such that grid constraints can be handled in a system operated by a number of competing players that are not willing to share their local information. This is done by using dual decomposition as a method to create distribution grid capacity markets. This method, however, has a number of limitations making real life implementation difficult. Therefore, in Paper 15, we take a much more practical approach. In collaboration with DONG Energy, we propose a concrete and implementable flexibility product that is able to resolve a certain type of congestion issues. Based on historical data from DONG Energy's grid, we show that the value of a flexibility product with an amount and a duration in the order of 100 – 200 kW and 1 – 4 hours, respectively, with an expected activation of 1 time per year has an annual value around $7,500$ Euro.

Synopsis

Det danske elsystem er under stor forandring, idet andelen af ikke-styrbar vedvarende energi øges kraftigt, mens de konventionelle kulkraftværker fases ud. Det sker som en del af den danske 2020 målsætning om 50 % vind i elsektoren. I 2050 er det målet, at samtlige energisekotorer skal forsynes udelukkende af vedvarende energi. Idet vindenergi er den primære kilde i Danmark til vedvarende energi, er det ønskeligt at elektrificere varme- og transportsektoren. Derfor forventes det, at elforbruget vil øges over de kommende år.

Den øgede mængde vedvarende energi og det øgede elforbrug udfordrer det nuværende danske elsystem. Større mængder produktion fx fra vindmøller og solanlæg vil øge mængden af fluktuationer i elnettet, hvilket vil forårsage et stigende behov for system-stabiliserende reserver. De nuværende leverandører af sådanne reserver er imidlertid de konventionelle kraftværker, som er ved at blive udfaset. Derfor er der behov for alternativer til at kunne levere disse system-stabiliserende reserver. Et af temaerne i denne afhandling er at undersøge, hvorvidt fleksible forbrugere og lager-enheder kan være en del af løsningen på denne udfordring. En relateret udfordring er, at de nuværende el-markeder er designede til udelukkende at facilitere store konventionelle produktionsenheder og ikke mindre fleksible forbrugere og lager-systemer. Det kan derfor være svært at få mindre fleksible forbrugere gjort aktive i disse markeder. Denne udfordring adresseres også i afhandlingen, og det undersøges desuden, hvordan det nuværende markedsdesign kan revideres til bedre at kunne håndtere reserver leveret af forbrugs- og lagerenheder.

En tredje udfordring i det fremtidige danske elnet er, at det øgede elforbrug kan forårsage overbelastninger i distributionsnettet. Specielt hvis fleksible enheders forbrug optimeres i forhold til el-markederne, kan der forekomme stor samtidighed i forbruget, hvilket kan lede til strøm-spidser, der kan overlaste distributionskablerne. I dag løses overbelastningsproblemer ved at forstærke nettet med større eller flere kabler. Men man kan forestille sig, at det i nogle tilfælde er en bedre økonomisk og miljømæssig løsning at udnytte fleksible forbrugs- og produktionsenheder til at reducere strøm-spidserne og derved undgå flaskehalse i distributionsnettet. Dette er også et tema, som denne afhandling arbejder med.

De ovenstående temaer og problemstillinger er hovedfokus i denne afhandling og de er blevet behandlet i en række artikler som beskrevet i det følgende. Artikel nummer[2] 1 og 2 gennemgår det overordnede koncept vedrørende brug af fleksibelt forbrug til udbalancering af fluktuationer i nettet. Konceptet konkretiseres i de følgende artikler, nummer 3, 4 og 5, hvor husstandsvarmepumper er i fokus. Her vises det, hvordan varmepumper kan optimeres i forhold til el-markedet og på den måde hjælpe med at balancere systemet. Artiklerne viser, at el-udgifterne til husstandsvarmepumper kan reduceres i omegnen af

[2] Der findes en artikelliste i Sektion 1.5

20 % ved at sælge sådanne balanceydelser i el-markederne uden at forårsage gener for beboerne. I artikel nummer 6 vises resultater fra et forsøg, hvor det samlede effektforbrug fra 54 varmepumper aggregeres og styres således, at det følger en reference. Over en 7 dages testperiode fulgte varmepumpernes samlede effektforbrug referencen med tilfredsstillende performance samtidigt med, at forbrugerens krav til temperatur og varmt vand blev overholdt. Efter forfatternes kendskab er det verdens første forsøg, hvor effektforbruget af en større mængde individuelle forbrugere aggregeres og styres til at følge en reference.

I artikel nummer 7 og 8 undersøges mulighederne for at lade forbrugsenheder levere hurtige og mere værdifulde systemydelser. I artikel nummer 8 præsenteres en metode for, hvordan en portefølje af tænd/sluk-enheder kan reguleres således at den kan levere primærreserve som overholder de danske systemydelses-regulativer.

Artiklerne nummer 9 og 10 undersøger el-markederne i Danmark og identificerer de største barrierer, der er for, at fleksible forbrugere kan komme ind på disse markeder. Artiklerne viser, at det er nødvendigt, at forbrugsenhederne er i størrelsesordenen 20 – 70 kWh, for at der er break-even mellem indtægter og udgifter ved deltagelse i spotmarkedet, mens enhederne skal være i størrelsesordenen 70 – 230 kWh for at opnå break-even i markederne for systemydelser. Det er med andre ord kun meget store industrielle forbrugsenheder, som på nuværende tidspunkt kan opnå et overskud ved at være aktive i el-markederne. I artikel nummer 11 foreslår vi en ny metode, som giver fleksible forbrugere bedre vilkår i markederne for hurtige reserver. Via simuleringer, baserede på markeds-data, viser vi, hvordan denne metode muliggør, at fleksible forbrugere kan levere væsentligt større mængder primærreserve end under de nuværende regulativer.

Endelig viser vi i artikel nummer 12 et koncept for at løse flaskehalsproblemer i distributionsnettet via fleksible forbrugere. I artiklerne nummer 13 og 14 udvider vi denne metode til at kunne løse flaskehalsproblemer, selv hvis de enkelte enheder, som hjælper med at aflaste flaskehalsene, ikke er villige til at samarbejde og derfor ikke vil dele deres lokale informationer med hinanden. Her benyttes kapacitetsmarkeder, som fremkommer ved at benytte dual dekompositions-metoden. Dual dekomposition har dog en række begrænsninger, som vanskeliggør en virkelig implementering. I artikel nummer 15 tages derfor en langt mere praktisk tilgang. Artiklen er baseret på et samarbejde med distributionsafdelingen i DONG Energy. Hovedresultatet er et konkret forslag til en fleksibilitetsydelse, som er i stand til at løse en bestemt type flaskehalsproblemer i distributionsnettet. Ved brug af historiske data viser vi i artiklen, at værdien af et fleksibilitetsprodukt med størrelsen ca. 200 kW leveret i $1-4$ timer med forventeligt 1 aktivering per år er ca. $7,500$ Euro.

Mandatory page

1) **Thesis title:** Distributed Energy Resources in the Liberalized Electricity Markets.
2) **Name of PhD student:** Benjamin Biegel.
3) **Name and title of supervisor and any other supervisors:** Associate professor Palle Andersen and Professor Jakob Stoustrup.
4) **List of published papers:**

a) *Title:* Information Modeling for Direct Control of Distributed Energy Resources. *Authors:* Benjamin Biegel, Palle Andersen, Jakob Stoustrup, Lars Henrik, Hansen David, and Victor Tackie. *Published in:* Proceedings of the American Control Conference Conference, Washington, District of Columbia, USA, June 2013. Published.

b) *Title:* Contracting Flexibility Services. *Authors:* Silas Harbo and Benjamin Biegel. *Published in:* Proceedings of the European Innovative Smart Grid Technologies Conference, Copenhagen, Denmark, October, 2013. Published.

c) *Title:* Electricity Market Optimization of Heat Pump Portfolio. *Authors:* Benjamin Biegel, Palle Andersen, Tom S. Pedersen, Kirsten Mølgaard Nielsen, Jakob Stoustrup, and Lars Henrik Hansen. *Published in:* Proceedings of the Multi-Conference on Systems and Control, Hyderabad, India, August 2013. Published.

d) *Title:* Lumped Thermal Household Model. *Authors:* Benjamin Biegel, Palle Andersen, Jakob Stoustrup, Mathias Bækdal Madsen, and Lars Henrik Hansen. *Published in:* Proceedings of the European Innovative Smart Grid Technologies Conference, Copenhagen, Denmark, October, 2013. Published.

e) *Title:* Smart Grid Dispatch Strategy for ON/OFF Demand-Side Devices. *Authors:* Benjamin Biegel, Palle Andersen, Tom S. Pedersen, Kirsten Mølgaard Nielsen, Jakob Stoustrup, and Lars Henrik Hansen. *Published in:* Proceedings of the European Control Conference, Zurich, Switzerland, July 2013. Published.

f) *Title:* Aggregation and Control of Flexible Consumers – A Real Life Demonstration. *Authors:* Benjamin Biegel, Palle Andersen, Jakob Stoustrup, Mathias Bækdal Madsen, Lars Henrik Hansen, and Lotte Holmberg Rasmussen. *Published in:* Proceedings of the 19th World Congress of the International Federation of Automatic Control, Cape Town, South Africa, August, 2014. Published.

g) *Title:* Predictive Control of Demand Side Units Participating in the Primary Frequency Reserve Market. *Authors:* Benjamin Biegel, Jakob Stoustrup, Palle Andersen, and Lars Henrik Hansen. *Published in:* Proceedings of the American Control Conference Conference, Washington, District of Columbia, USA, June 2013. Published.

h) *Title:* Primary Control by ON/OFF Demand-Side Devices. *Authors:* Benjamin Biegel, Lars Henrik Hansen, Palle Andersen, and Jakob Stoustrup. *Published in:* IEEE Transactions on Smart Grid (Issue: 99), April 2013. Published.

i) *Title:* Adjustable Consumption Participating in the Electricity Markets. *Authors:* Benjamin Biegel, Lars Henrik, Hansen Jakob Stoustrup, Palle Andersen, and Silas Harbo. *Published in:* Proceedings of the Conference on Decision and Control, Florence, Italy, December 2013. Published.

j) *Title:* Value of Flexible Consumption in the Electricity Markets. *Authors:* Benjamin Biegel, Lars Henrik Hansen, Jakob Stoustrup, Palle Andersen, and Silas Harbo. *Published in:* International Journal of Energy, March, 2014. Published.

k) *Title:* Integration of Flexible Consumers in the Ancillary Service Markets. *Authors:* Benjamin Biegel, Mikkel Westenholz, Lars Henrik Hansen, Jakob Stoustrup, Palle Andersen, and Silas Harbo. *Published in:* International Journal of Energy, April, 2014. Published.

l) *Title:* Model Predictive Control for Power Flows in Networks with Limited Capacity. *Authors:* Benjamin Biegel, Jakob Stoustrup, Jan Bendtsen, and Palle Andersen. *Published in:* Proceedings of the American Control Conference, Montreal, Canada , June 2012. Published.

m) *Title:* Congestion Management in a Smart Grid via Shadow Prices. *Authors:* Benjamin Biegel, Palle Andersen, Jakob Stoustrup, and Jan Bendtsen. *Published in:* Proceedings of the Power Plant and Power System Control Conference, Toulouse, France, September 2012. Published.

n) *Title:* Distributed Model Predictive Control via Dual Decomposition. *Authors:* Benjamin Biegel, Jakob Stoustrup, and Palle Andersen. *Published in:* Distributed Model Predictive Control Made Easy, Chapter 11, Springer, April 2013. Published.

o) *Title:* The Value of Flexibility in the Distribution Grid. *Authors:* Benjamin Biegel, Kåre Seest Rasmussen, Hans Knudsen, Sisse Merete Østberg, Peder Cajar, Lars Henrik Hansen, Palle Andersen, and Jakob Stoustrup. *Published in:* Proceedings of the 5th IEEE PES Innovative Smart Grid Technologies (ISGT) European 2014 Conference, Istanbul, Turkey, October, 2014. Published.

p) *Title:* Distributed Low-Complexity Controller for Wind Power Plant in Derated Operation. *Authors:* Benjamin Biegel, Daria Madjidian, Vedrana Spudicć, Anders Rantzer, and Jakob Stoustrup. *Published in:* Proceedings of the Multi-Conference on Systems and Control, Hyderabad, India, August 2013. Winner of The Best Student Paper Award. Published.

q) *Title:* Wind Turbine Pitch Optimization. *Authors:* Benjamin Biegel, Morten Juelsgaard, Matt Kraning, Stephen Boyd, and Jakob Stoustrup. *Published in:* Proceedings of the Multi-Conference on Systems and Control, Denver, CO, USA, September, 2011. Published.

r) *Title:* Indirect Control for Demand Side Management A Conceptual Introduction. *Authors:* Kai Heussen, Shi You, Benjamin Biegel, Lars Henrik Hansen, and Katrine Bech Andersen. *Published in:* Proceedings of the European Innovative Smart Grid Technologies Conference , Berlin, Germany, October, 2012. Published.

s) *Title:* Model Predictive Control of Domestic Heat Pump. *Authors:* Mikkel Urban Kajgaard, Jesper Mogensen, Anders Wittendorf, Attila Todor Veress, and Benjamin Biegel. *Published in:* Proceedings of the American Control Conference, Washington, District of Columbia, USA, June 2013. Published.

t) *Title:* Aggregation of Supermarkets as Demand Side Devices in a Smart Grid. *Authors:* Rasmus Pedersen, John Schwensen, Benjamin Biegel, Jakob Stoustrup, and Torben Green. *Published in:* Proceedings of the 19th World Congress of the International Federation of Automatic Control, Cape Town, South Africa, August, 2014. Published.

u) *Title:* Patent – A Method for Estimating and/or Controlling a Temperature of Foodstuff Stored in a Refrigerated Cavity. *Authors:* Rasmus Pedersen, John Schwensen, Benjamin Biegel, Jakob Stoustrup, and Torben Green (Danfoss A/S and Aalborg University). Patent accepted by the European Union in August 2014.

This thesis has been submitted for assessment in partial fulfillment of the PhD degree. The thesis is based on the submitted or published scientific papers which are listed above. Parts of the papers are used directly or indirectly in the extended summary of the thesis. As part of the assessment, co-author statements have been made available to the assessment committee and are also available at the Faculty. The thesis is not in its present form acceptable for open publication but only in limited and closed circulation as copyright may not be ensured.

1 | Introduction

1.1 Motivation

The Danish electrical system is currently undergoing a major transition. On the production side, distributed renewable energy sources such as wind, solar, and decentralized bio-power plants increase in numbers. Further, the conventional fossil fueled power plants which used to cover the consumption baseload, are being replaced with bio-fueled power plants which are only suitable to cover the peak load when the electricity prices are sufficiently large to cover the high prices of bio-fuel. Changes are also happening on the consumption side where new types of consumers have started to enter the market: heat pumps are currently an attractive alternative to oil-fired burners and electric cars are becoming a competitive alternative to combustion engine vehicles. These major electricity system changes are illustrated Figure 1.1.

These massive changes are challenging for the system. Traditionally, the centralized fossil-fueled power plants have been the main providers of system-stabilizing ancillary services. As these devices are being replaced with bio-fueled power plants that only operate during peak-hours, alternative sources of ancillary services are needed. In particular because fluctuating and non-dispatchable production such as wind and solar keep increasing, the system will become less predictable and consequently require greater volumes of stabilizing ancillary services. Further, the aforementioned electrification will challenge the existing grid infrastructure and potentially require widespread grid reinforcements

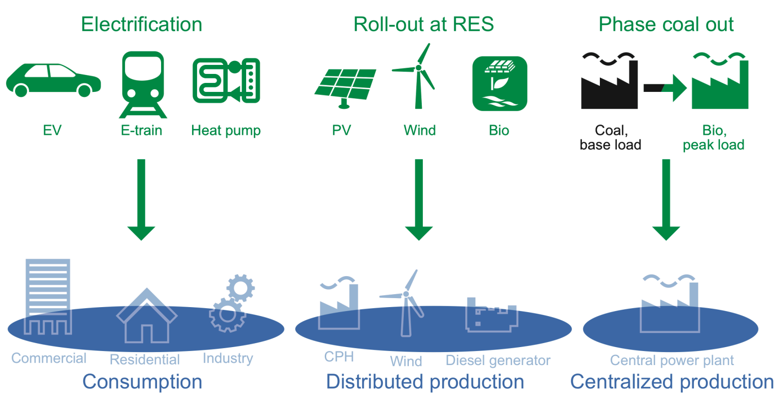

Figure 1.1: Large changes are happening in the electrical system.

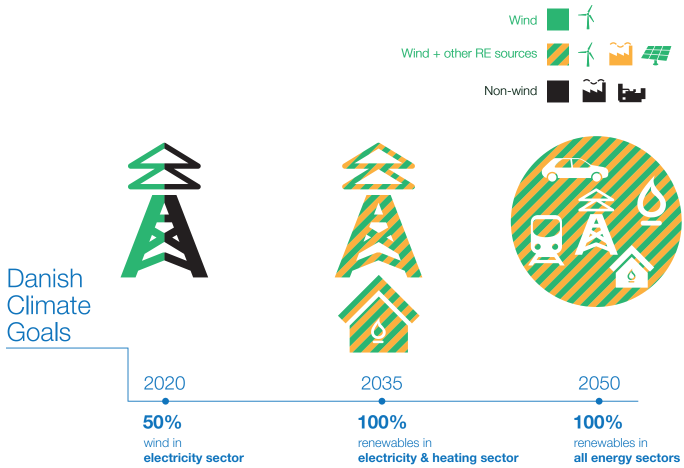

Figure 1.2: Illustration of three Danish climate goals.

which is both economically and environmentally costly.

Consequently, the future Danish electrical system calls for new innovative and smart solutions to ensure system stability and to avoid a need for massive costly grid reinforcement. This Danish *smart grid* is the topic of this thesis.

In the following we go more into the details of the brief motivation described above.

Growth in renewables in Denmark

The renewable energy sector is the fastest growing power generation sector and is expected to keep growing over the coming years [Dep08, Ass13]: the global share of non-hydro renewables has grown from 2 % in 2006 to 4 % in 2011 and is predicted to reach 8 % in 2018 [Ass13]. Many actions have been taken all over the world to increase the penetration of renewables: in the US, almost all states have renewable portfolio standards or goals that ensure a certain percentage of renewables [CS07]; similarly, the commission of the European Community has set a target of 20 % renewables by 2020 [Com06].

The Danish electricity system is a pioneer within integration of wind energy. In December 2013, Denmark made a world-record when more than 50 % of the consumption in the entire month was covered by wind. Throughout 2013 the wind penetration was 33 %. Further, Denmark has a number of very ambitions goals for renewables, see Figure 1.2. The first goal is that 50 % of the electricity consumption should be covered by wind in 2020. In 2035 the goal is that both the electricity and heating sector must be based on renewables, and finally in 2050, all energy sectors including gas and transport must be based on renewable energy [Dan12c].

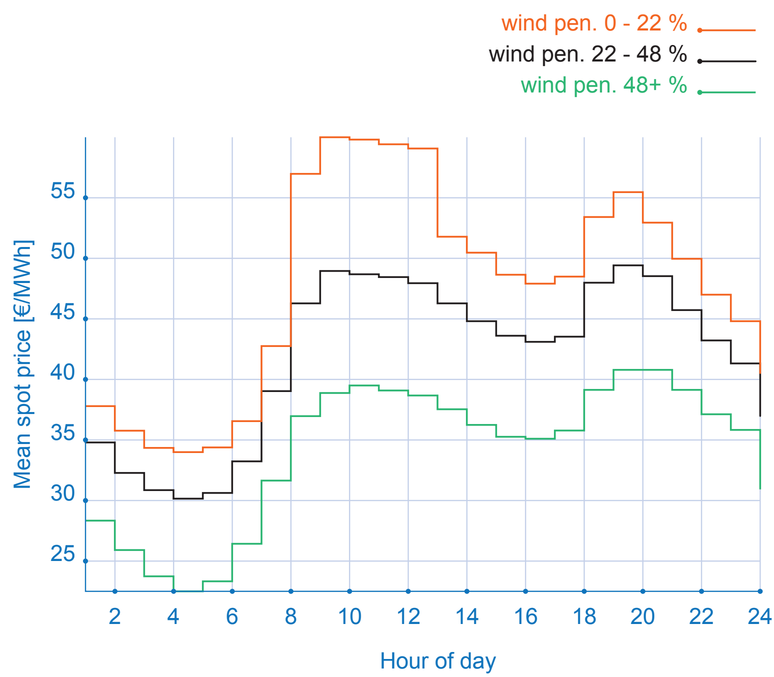

Figure 1.3: Average spot price profile for low-wind days (red), mean-wind days (black), and high-wind days (green).

Power plants shut down

As the penetration of renewables increases, the electricity prices will drop causing very difficult conditions for the conventional power plants to sell electricity [Dan12a]. This is illustrated in Figure 1.3 which shows the average electricity spot price profiles in 2013 in low-wind days, mean-wind days, and high-wind days [1]. The figure clearly illustrates the trend that the prices are dropping as the wind penetration is increasing. As the wind will continue to increase according to Figure 1.2, the prices are expected to drop further.

The decreasing electricity prices will push the conventional power plants out as they are not able to make sufficient revenue to stay in operation. Further, it is a government goal that all centralized fossil fueled power pants must be phased out by 2030 and a petition has been made for shutting down 8 central power plants [Ene11a].

[1] The figure is constructed by sorting all electricity spot price profiles from 2013 into three bins according to wind penetration. The wind penetration intervals of the bins are chosen so that there are the same number of days in each bin.

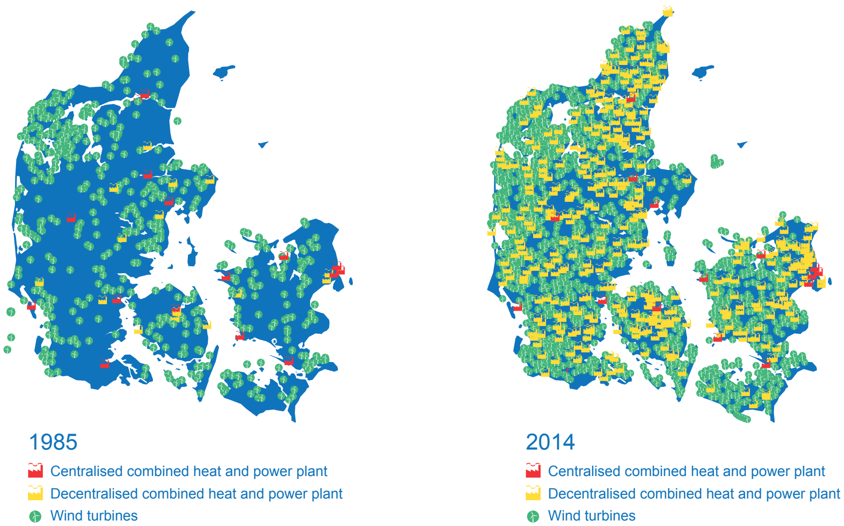

Figure 1.4: Transition of the Danish electrical system from a primarily centralized system based on conventional production in 1985 to a distributed system based on renewable generation. Figure based on data from the Danish Energy Agency [Dan14].

Decentralization

As a consequence of this increase of renewables, the power system is moving from a system base on a fewer centralized conventional power plants to a system driven by a large number of distributed smaller production units [JHH+12]. Denmark has moved from a situation with a total of 16 central power plants in 1985, to a system which today consists of 16 central power plants, more than 600 local combined heat and power plants and around 6,000 wind turbines [XGLO12]. This transformation is illustrated in Figure 1.4.

Electrification in transport and heating sector

A necessary step in reaching the Danish goal of 100 % renewables in all energy sectors is electrification of consumption from other energy forms [Dan13b]. This electrification has already begun: in recent years, $27,000$ heat pumps have been installed in Danish homes [Dan12b], and additionally $205,000$ households have the potential to benefit from replacing their oil-fired boilers with a heat pump [COW11]. Further, the Danish Government decided in 2012 to lower the taxes on electric heating to expedite electrification of the heating sector [SKA12]. Similarly, electrification of the transport sector is planned: the Danish Department of Transport decided in 2012 on electrification of the railroad in Denmark [Dep12] and a report from 2013 by the Danish Energy Association projects that electrical vehicles will become an attractive alternative to combustion engine vehicles in the following decades leading to an electrical vehicle (EV) population of $47,000$ in 2020 and $221,000$ in 2030 [Dan13a]. Interestingly, many of these newly introduced electricity consumers are *flexible electricity consumers*, meaning that although these consumers indeed require a certain amount of electricity, they possess some flexibility in exactly when

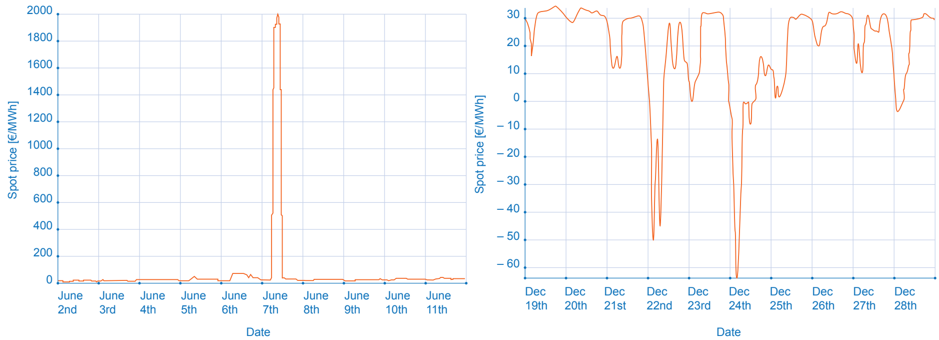

Figure 1.5: Extreme spot prices. Left: price reaching $2,000$ Euros/MWh due to low wind production and low capacity on transmission lines. Right: negative spot prices due to high wind and CHP production and low consumption.

the electricity is required. Two small examples are as follows. The inhabitants in a household heated with a heat pump will not experience discomfort if the indoor temperature varies a few degrees. Consequently there will be some flexibility in the operation of the heat pump. Similarly, an owner of an electric vehicle will need his vehicle fully charged at a certain time but will not specify the exact charging pattern, consequently there lies a flexibility in the charging of an EV.

In conclusion, the Danish electrical grid is moving towards a system with a large number of flexible electrical devices on the consumption side and a large number of distributed generators on the production side. The term *Distributed Energy Resources (DERs)* is used to encompass both flexible consumers and also smaller distributed generators throughout this thesis.

Challenge I: Alternative sources of balancing

The transition from centralized conventional power plants to non-dispatchable distributed renewable generation causes a number of difficulties. A major difficulty is that the system is harder to balance. Already today the effect of having 33 % wind in the system can be seen in the electricity market. In Figure 1.5 we examine two examples of this. Usually, the spot price is in the order of 30 Euros/MWh. However on the 7th of June 2013, the price cleared at a value of $2,000$ Euros/MWh for a number of hours, see the left graph. This happened because of very low wind (around 10 % of the installed capacity) at the same time as there was very little free capacity on the transmission lines to the neighboring countries. This represents a system where even the most expensive production assets are activated and thus a system close to its limits. The opposite situation occurred during Christmas in 2013 where a very high wind penetration collided with very high CHP production because of cold weather combined with low electricity consumption because of the Christmas holiday. This resulted in negative spot prices as seen in the right graph in Figure 1.5. Also, several wind turbines were requested to derate production for several hours on another occasion in 2012 due to a combination of circumstances. These instances are indicators of the increasing balancing issues due to the growth in non-dispatchable renewable energy sources. As a pioneer in utilizing fluctuating renewables such as wind power, Denmark is among the first places to experience these challenges; however, the rest of Europe can expect similar issues in the coming years [HMLH12]. It is therefore crucial to examine how flexibility can be mobilized to keep these types of situations from escalating such that it is possible to keep increasing renewables without jeopardizing system stability.

Another issue with non-dispatchable renewables is that they are characterized by highly fluctuating power generation and therefore suddenly can increase or decrease production depending on weather conditions. A recent example of this phenomenon took place Denmark on October 28, 2013 where a large number of wind turbines autonomously shut down because of too high wind speeds. This caused a drop from a situation where more than 100 % of the Danish electricity consumption was covered by wind to a situation where this number was less than 45 %. This happened in just 2 hours [Ene13b], see Figure 1.6. Such rapid production changes can imply severe consequences for grid stability due to the difficulty of accurately predicting the timing of the events [CS09].

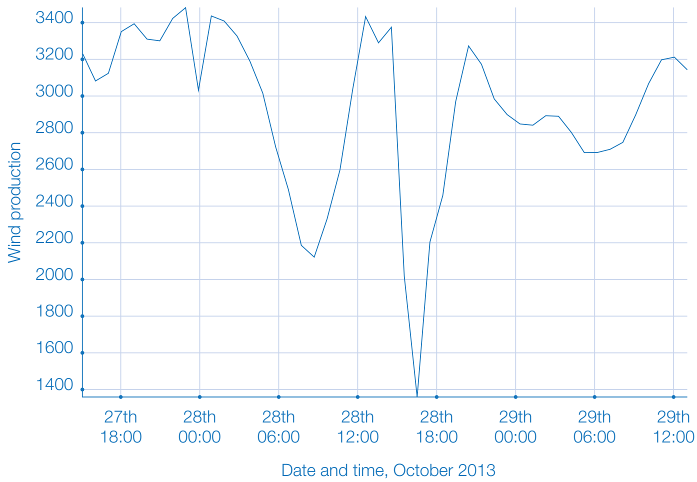

Figure 1.6: Wind production during 4 days in Denmark in end October, 2013. A storm hits Denmark in the afternoon on the 29th causing a large number of wind turbines to shut down resulting in a production drop of more than $2,000$ MW in just 2 hours.

Currently, the main providers of system stabilizing ancillary services are the fossil fueled centralized power plants. As these plants are replaced with renewables, the ability to provide ancillary services in the classical sense is lost. The fluctuating and non-dispatchable renewables such as wind and solar usually do not possess the ability to provide such system stabilizing reserves: First of all, keeping renewables in reserve will entail that free energy is wasted making this a very expensive solution. Second, the highly fluctuating nature of the renewables caused by weather conditions can make it difficult to deliver a well-defined power response. The dispatchable renewable sources such as bio power plants are indeed able to deliver ancillary services; however, they are expensive to keep in operation and will typically only cover the peak load and therefore not always be available to provide reserves.

The challenge is further increased by the fact that the conventional fossil fuel power

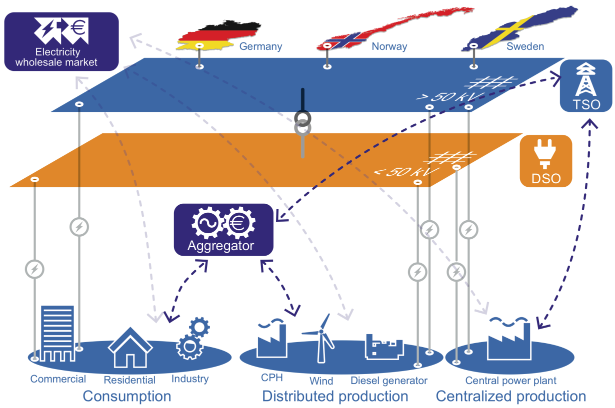

Figure 1.7: Aggregation of flexible consumption and distributed production to provide system stabilizing services to the TSO.

plants are synchronous with the grid and therefore provide rotating inertia that supports the system frequency against changes [Kun94]. As renewable energy sources typically interface with the grid via power electronics, they do not directly provide inertia to the grid as the conventional synchronous generators do [JOM+00], which further increases the balancing challenges. Although recent works suggest that wind turbines can provide synthetic and artificial inertia by regulating the active power output of the generator according to the system frequency [DBHL12, MCS11], this type of control is generally not implemented in the wind power plants of today.

It is therefore evident that alternative sources of ancillary services must be established as renewables replaces conventional generation. One approach to obtain ancillary services is to purchase reserves in neighboring countries; however, this requires that transmission line capacity is reserved for the reserve markets which will limit the capacity in the day-ahead spot markets and thereby possibly cause higher electricity prices [Ene11a]. Further, the European network of transmission system operators for electricity (ENTSO-E) grid code sets limits on the amount of reserves it is allowed to exchange internationally [ENT13]. Finally, the Danish neighbor Germany is also increasing the wind capacity. Consequently, it may be difficult to purchase ancillary services in Germany as they by then possibly will have similar issues.

An alternative approach to obtain alternative ancillary services when the centralized power plants are phased out, is a concept where flexible consumption and distributed production is utilized [His06, MK10]. The basic idea is to let an aggregator control a portfolio of flexible devices such as thermal devices, batteries, pumping systems etc. Hereby, the aggregator can utilize the accumulated flexibility by participating in the electricity markets for primary, secondary, and tertiary reserves, on equal terms with conventional generators [Ene12b, BAS+13]. This concept is illustrated in Figure 1.7 where an aggregator accesses flexibility from flexible consumers and distributed production, aggregates this flexibility and utilizes it to provide system stabilizing services to the transmission

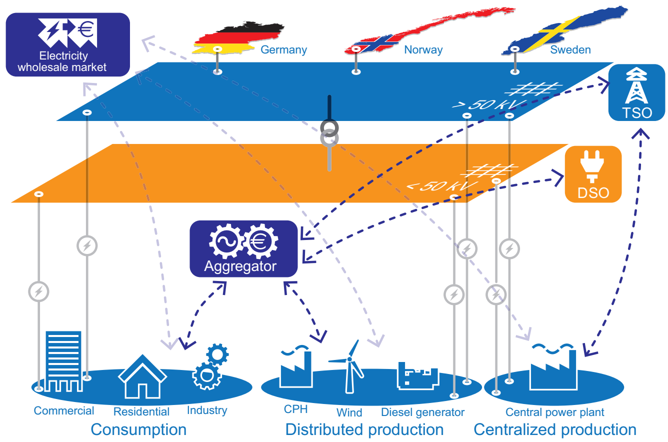

Figure 1.8: Aggregation of flexible consumption and distributed production to serve both the DSO with system stabilizing services but also to serve the DSO with grid congestion alleviation products.

system operator. This is the first part of the *smart grid* concept which is the focus of this thesis.

Challenge II: Congestion in the distribution grind

The previously mentioned planned electrification may cause congestion issues at the distribution level [IWA11, RBT12]. In particular, large consumption peaks can occur if the consumption of these devices is optimized towards the electricity markets causing a high level of concurrency [MMR10, BAP+13].

One of the proposed methods for solving distribution grid congestion issues is to utilize information and communication technology solutions to operate the grid more efficient, sustainable, and reliable. Again, the main idea in the concept is to utilize flexible consumers and distributed production to provide services, in this case to the distribution system operator. Currently, the DSOs do not utilize flexibility on either the production or consumption side in their operation of the grid. But with increased possibilities to remotely monitor and control flexible consumption or production assets, it may prove valuable that DSOs actively seek to utilize this flexibility to avoid congestion and thereby postpone conventional grid reinforcement. This concept is illustrated in Figure 1.8. This setup constitutes the second part of the *smart grid* concept this thesis is focused on.

1.2 State-of-the-art and background

This section seeks to illuminate the material that forms the background of this thesis. It is divided into four main categories, which are all important elements of this thesis. The first category, *demand response*, deals with experiences within the area of getting a response from demand side devices, which is a main element in the smart grid concept and a central part of this thesis. The next category, *Flexibility modeling* is concerned with building models to capture flexibility of different types of distributed energy resources. The following category, *aggregation and control of distributed energy resources*, deals with the studies where information and communication technology (ICT) solutions are utilized to aggregate and control larger numbers of demand-side devices, and possibly also distributed generators, to provide system stabilizing services or to shift load in time according to the system state. The third category is *market integration of distributed energy resources* and deals with analyzing how well the electricity markets are able to handle distributed energy resources, especially flexible consumption, and how the markets can be improved to better integrate these types of devices. These first three categories are all part of “Challenge I: Alternative sources of balancing” introduced in the previous section.

Finally, the last category is called *the smart distribution grid* and deals with the concept of utilizing smart solutions to allow the distribution grid to be operated closer to its limitations and thereby avoid or postpone conventional expensive grid reinforcements. This category refers to “Challenge II: Congestion on the distribution grind” which was also introduced in the previous section.

Demand-response

Management of DERs such as demand-side devices to provide system stability has been discussed for many years. The concept of controlling smaller appliances to support grid stability has for example been discussed as early as the 1980s [STK+80]. Since, the topic of management of DERs has received much attention from a research perspective. As a concrete and current example of research in this area, Figure 1.9 shows a demonstration conducted by DONG Energy where a water purifying plant is managed to deliver secondary reserve [J. 13]. The primary process of the water purifying plant is to clean water, however, the inherent flexibility of the plant is utilized to deliver system stabilizing secondary reserve. This demonstration is a good example of how demand side devices can be utilized to help stabilize the electrical grid while still performing its primary process.

Several programs of management of DERs are also currently in operation on a commercial basis. As an example, several demand-side programs are operational in the UK and the US systems [Ene12d, FER07, SE09]; moreover, a growth is seen in the volume of these programs: New England has experienced an increase in demand-side programs from contracts on 200 MW in 2003 to more than $2,000$ MW in 2009 [ISO09]. As of 2013, the largest demand response provider in the world is EnerNOC with a portfolio exceeding $8,600$ MW of demand response reserve [Ric13].

Many works describe methods of controlling *specific classes* of demand-side devices with focus of shifting load, integrating more renewables, delivering system-stabilizing services. In the following, we mention some of the main classes of flexible consumption devices addressed in the literature.

Commercial buildings One example of flexible devices are large commercial buildings. The consumption flexibility arises from heating or cooling devices due to the thermal mass of the building, as well as ventilation and dimming lighting.

Recent works have discussed how advanced control solutions can increase the performance of the climate control in large buildings and thereby provide significant savings [OJPM13]. Similarly, novel tools have been developed to model and design controllers

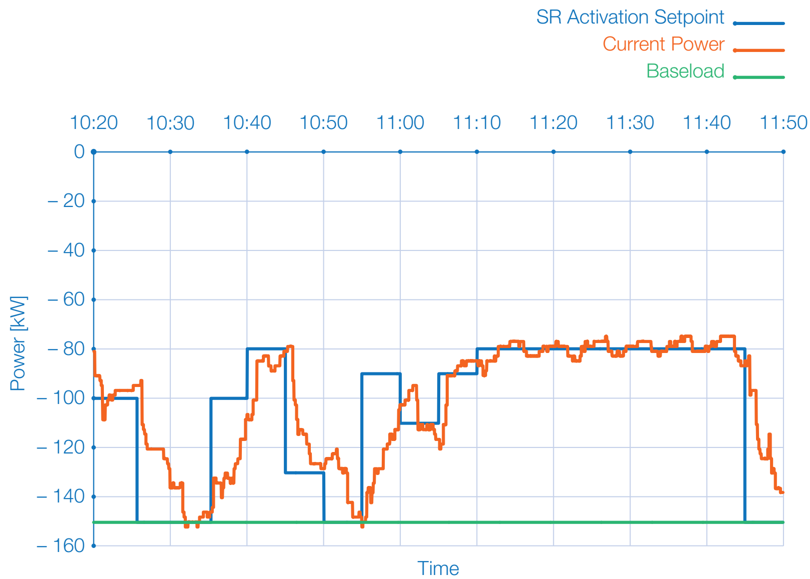

Figure 1.9: Example of water purifying plant delivering demand-response according to a virtual secondary reserve signal. Figure taken from [J. 13]

for climate systems in large commercial buildings [GQ14]. The smart grid concept extends these ideas of energy optimization by utilizing the consumption flexibility to shift loads temporally to the hours where the consumption does not stress the system. An academic example is found in [QGJ14], where simulations are conducted estimating the ability of a commercial building to participate in a New York demand response program. The simulation results show savings in the order of $23 - 33\ \%$. Another example of this is a demonstration made by the thermostat manufacturer Honeywell and the British utility SSE where the flexibility of thermal systems and the lighting in three large buildings were utilized to reduce the peak consumption by $20\ \%$ [Ale13].

Domestic heat pumps Several works specifically addresses aggregation and control of domestic electrical heating from heat pumps because of the inherent thermal mass of houses [AHP13], [MPM$^+$11]. In particular, this is interesting in a Danish context because it is expected that the number of domestic heat pumps in Denmark will increase: around 27.000 heat pumps are installed in Denmark [Dan12b], and potentially $205,000$ households can benefit from replacing oil-fired boilers with heat pumps in the coming years [COW11]. It is therefore most relevant to consider how to aggregate and control this flexibility towards the electricity markets. Some works in this area are [HMLH12, HPMJ12, PAN$^+$11, TSMR11, KMW$^+$13]. These works consider how the operation of heat pumps can be optimized to support grid stability and how to lower the operational electricity costs by performing spot price optimization of the consumption.

Supermarket refrigeration systems Another class of devices is supermarket systems. The foodstuff stored in supermarkets represents a thermal mass that can be utilized as a thermal storage of coldness — similarly to the households being used as a storage of heat. A few examples of recent works within the field of control of supermarkets with focus on storing energy as coldness in the foodstuff are [HLEJ12, PSS+13, HHLJ11, HLJ11].

Electric vehicles Another much discussed class of devices is EVs. As previously mentioned, recent studies project that the EV population in Denmark will be $221,000$ in 2030 which is significant compared to a population of 5.6 millions. Already today, a progress is seen in the introduction of EVs: In Norway, the most sold car was electric for two months in 2013 [Cle13]; another example is the Tesla Model S, which was the most sold car in the US in the first quarter of 2013 in the US, compared to other similar priced cars [CNN13]. Electric vehicles are interesting from a smart grid perspective due to the fact that a flexibility lies in the timing of battery charging which often can be postponed for some time with no discomfort for the car owner. Another interesting aspect is that appropriate configuration of the batteries may allow EVs to not only shift consumption but to provide actual deliveries to the grid. A few examples of recent work on utilization of EVs for system stabilizing services and load shifting are [PHO11, Juu12, KCM11, AHP+12].

Air conditioning systems The last example we mention here is air condition installations. Again, the air conditioned buildings will represent a certain capacity where coldness can be stored making load shifting possible. A few examples of recent works on aggregation and control of such systems can be found in [PKBW12, Cal09].

Real-life demonstrations The paragraphs above illustrate that there are numerous works on obtaining a response from different types of flexible demand side devices. A larger number of works further describe demonstrations and experiments on different types of devices to prove the feasibility of the smart grid concept. A few examples are: demonstration of obtaining demand response from heat pumps [PAN+11], bottle coolers [DGVN+11], refrigeration systems [PSS+13], and a water purifying plant [J. 13] (see also Figure 1.9).

Virtual power plant

The above paragraphs illustrate that much research is done within the field of obtaining a demand response from different types of devices which possess some type of flexibility.

Demand response can generate value in various ways, for example by shifting consumption from hours with high electricity prices to hours of lower prices, or by providing system stabilizing services which can be sold in the electricity markets. Also smaller generators, such as solar and wind, are discussed as providers of such system stabilizing services and reserves [DBHL12, MCS11, BMS+12, JSL12].

Common for both the demand-side devices and the distributed generators (DERs) is that they generally are too small to provide isolated bids into the electricity markets. Consequently, it is necessary to aggregate more of such devices to obtain a response that can generate value. This is the background for the concept of the virtual power plant (VPP), which is illustrated in Figure 1.10.

The basic idea is that a legal entity called an *aggregator* enters into contract with owners of the flexible devices which can be either demand-side devices or distributed generators. The contract specifies under what conditions the aggregator is allowed to uti-

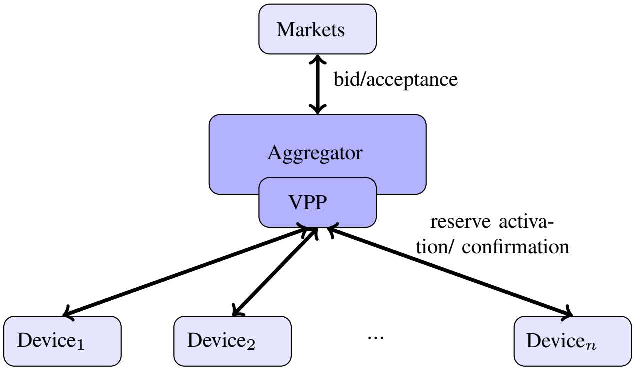

Figure 1.10: Aggregator bidding in the electricity markets by managing n flexible devices through a VPP.

lize the devices' flexibility. The aggregator is approved to trade in the electricity markets and accepted by the system operator as a provider of ancillary services and can thereby also trade in the ancillary service markets.

On this basis, the aggregator uses a technical unit often referred to as a virtual power plant to manage the devices. The VPP can monitor and control the flexible devices via a two-way communication link and is hereby able to mobilize the accumulated response of a portfolio of flexible consumption or production devices. This allows the aggregator to enter the electricity markets based on the flexible devices. Many existing works describe this kind of setup, where a VPP is utilized to aggregate several smaller devices to deliver an accumulated response, see e.g. [PHSSEE13, Pet11, SDD11, RSR13b, RSR13a, TPBS11a, PBS12], further, some works specifically describe how a VPP can enable a portfolio of devices to deliver electricity services, see [BM14, SDD11, AC10, YTP09].

An example which clearly illustrates the need for a VPP can be found in the regulations for delivery of system stabilizing services in the Danish electrical grid. In the current regulations, a minimum amount of 10 MW capacity is required to bid into the market for regulating power [Ene11b, Ene12a]. This demonstrates the necessity of a VPP to aggregate sufficient amounts of flexibility to pass this threshold. For example, a domestic heat pump has an electrical consumption in the order of a few kW meaning that thousands of such pumps must be aggregated to access the markets. Even a relatively large consumer as a water purifying plant only has in the order of $50 - 100$ kW of flexibility which is still relatively small compared to the 10 MW threshold of the regulating power market. Consequently, it is necessary to aggregate a large number of flexible devices to access the ancillary service markets.

Flexibility modeling

It is therefor evident that a main functionality of the VPP is to be able to monitor and harness the flexibility of a portfolio of DERs – potentially a really large number of DERs. A key element in the setup presented in Figure 1.10 is therefore the interface between the aggregator and the flexible consumption/distributed production devices (the double arrows between the devices and the VPP in Figure 1.10). It is desired that the VPP has an accurate overview of the flexibility of the entire portfolio, such that it is possible to utilize the portfolio flexibility to the largest extent possible.

Many works have discussed this area of flexibility modeling [HKA14]. In [PHM12], the concept of a virtual power plant is introduced and different types of flexible consumers and their constraints are discussed. In [PHB$^+$13] it is shown how a large class of flexible consumers can be modeled using a taxonomy known as bucket-battery-batch representing three classes of flexibility constraints. In this taxonomy, the bucket represents an ideal storage with power and energy constraints, the battery represents the same storage but where there are terminal constraints to the state of the energy level, while the batch represents a process that is flexible in its activation time but once the batch process is started, it must run to completion. In [TPBS12, TPBS11b], the focus is on the devices that can be modeled as buckets, i.e. ideal storage devices. The cited literature shows how a portfolio of this type of devices can be modeled altogether as one single device without loss of information.

Commercially, openADR (open automated demand response) is a standard for communication between a number of flexible consumers and a demand response automation server (DRAS). This standard is used by Honeywell [Tri11] to remotely control flexible consumers. The fact that such a standard has been developed illustrates that demand response has reached a maturity level where the industry is getting ready to adopt such solutions.

Ancillary services from VPP The setup illustrated in Figure 1.10 is sometimes referred to as *direct control* due to the fact that the devices are directly controlled through the two-way communication links. This is in contrast to *indirect control*, which refers to a setup where the devices are controlled indirectly by a signal broadcast by the VPP or aggregator [HYB$^+$12]. The signal could for example be an electricity price signal, an electricity price forecast signal, or other types of incentive signals. The concept of demand-response via prices are known from several larger projects. A few examples are the Dutch PowerMatching concept, which is an agent based method for demand response which was demonstrated on 25 households [BvdNR$^+$10]. Another example is the Danish EcoGrid EU demonstration, where demand response from a large number of customers was obtained via price mechanisms [JSBE11]. A third example is the Olympic Peninsula Project [Ham07] where the ability to affect consumer behavior through real time prices was demonstrated.

Direct and indirect control both have advantages and disadvantages, and it can be imagined that these two types of control will be used simultaneously to control different types of devices. The focus of this thesis is only on the direct control setup as illustrated in Figure 1.10. The reason is that direct control allows for both shifting load, delivering system stabilizing services with a high security of supply, and also deliver geographically constrained services on the distribution level.

In particular, this work is focused on providing ancillary services, as this is one of the key elements in the future smart grid where the conventional fossil fueled power plants will no longer be able to provide these services. In the literature, several works are found on this topic of aggregation of flexible loads or smaller production devices to deliver ancillary services. In [HSPV14] the focus is thermostatically controllable loads such as air conditioning systems. The paper is focused on California and concludes that in California the entire need for frequency regulating reserves can be more than covered by thermostatically controllable loads making this concept very interesting. Another recent example is [HLKM14] which describes a way to regulate fans to deliver system stability. Some works also show how fluctuating production devices can be used for system stability, which is an interesting concept as this allows the source of some of the instability to be part of the solution. An example here is [J. 13] where a small wind power plant with a capacity of 13.4 MW is utilized to provide a symmetric delivery of secondary reserve.

Other works show how demand can be used to deliver a very fast system stabilizing response, as fast as primary frequency control [SIF07]. One example of a real life implementation of this is described in [DGVN+11] where refrigerators were modified to adjust the thermostat level according to local grid frequency measurements and thereby deliver a frequency response.

Market integration of distributed energy resources

In a liberalized electricity system, the transmission system operators (TSOs) must assure system stability at all times which includes assuring balance between production and consumption. To accomplish this, TSOs purchase various system-stabilizing services, also known as *ancillary services*, from generators or flexible consumers. This allows each TSO to activate these reserves in the hour of operation to ensure balance.

In liberalized electricity markets, it is desired that flexibility from DERs is traded on equal market terms with the conventional service providers. This assures that the electricity services are delivered in the cheapest manner as the cheapest bidder will be accepted regardless if it is a virtual power plant or a conventional power plant.

In the Danish electricity system, it is already today possible to provide ancillary services based on demand-side devices [Ene11b, Ene12a]. The current regulations further directly describe that it is allowed to provide ancillary services based on a portfolio of devices as long as the aggregated response honors the requirements to the given ancillary service.

To the best of the authors' knowledge, the only type of demand-side devices that currently bid into the Danish ancillary service markets are heating elements at Combined Heat and Power (CHP) plants. These heating elements are able to provide a fast downward regulating power response which can be sold in the market for non-symmetric primary reserve.

The reason for the small uptake of DERs in the ancillary service markets may be that the regulations were defined at a time where generation primarily was based on centralized power plants. Consequently, the regulations are well-suited for large conventional power plants, but less suited for demand-side devices, storage devices, and non-dispatchable generation such as wind and solar.

A number of initiatives have been taken to better integrate flexible consumers and smaller producers. One example is the roll-out of smart meters making it easier for aggregators to mobilize demand-side flexibility [Dan13b]. Another example is the establishment of a Danish electricity market directory, the so-called *Data-hub*, which makes it easy for consumers to change electricity retailer and to access consumption data [Ene09]. The Data-hub is believed to increase competition between retailers, including competition on the flexibility side. Finally, the Danish TSO and the Danish Energy Association have together formed a *smart grid roadmap* that describes actions to better activate the untapped demand-side flexibility [Ene12c].

The smart distribution grid

The above subsections describe the concept of aggregation and control of flexible consumers to deliver system stabilizing services. This is one of the key elements in the envisioned future Danish smart grid. Another element in the Danish smart grid vision has to do with the actual *grid*. The expected electrification of the heating and transport sectors will cause a higher electrical load which may cause congestion in the existing distribution grids. Further, aggregated control of flexible devices may cause many consumers to start simultaneously which can cause very high peaks and thus aggravate the congestion issues.

The smart grid approach to resolving distribution grid congestion issues is two-fold: To monitor the grid to a higher extend and thereby allow grid operation close to the cable limits and to utilize distributed energy resources to shift load/production to shave peaks [Dan13b]. Increased sensing will make it possible to estimate the state of the distribution grid more accurately [VK09] while flexible consumption/production will allow peak shaving the most critical hours [BAHH12]. Both approaches will make it possible to operate the distribution grid closer to the system limits and consequently allow a more efficient use of the existing grid.

This thesis deals with the second element concerning the utilization of DER flexibility to allow a higher utilization of the existing distribution grid. This topic is touched upon in some works. The paper [NBM+13] examines the business case of using electrical storage to alleviate congestion issues. Another example is [IA09] which at an overall level describes the possibilities of using flexible consumers and demand response to shape the load and hereby avoid congestion on the distribution grid. Other works describe the concept of developing a *flexibility market* for services at the distribution grid making it possible for distribution grid operators to purchase peak shaving products [DHC+13, HBH+13].

Final remarks to the State-of-the-art

This section on state-of-the-art described ongoing works within the field of smart grid – both at the transmission level where the focus is ancillary services and the spot market, but also at the distribution level where the focus is to avoid overloading distribution cables. In the following section, the overall objectives for the thesis will be described. Following, these objectives and the state-of-the-art presented above will be used to form a number of hypotheses that this thesis seeks to answer.

1.3 Objectives

The Danish goal of becoming fossil free requires massive installations of non-dispatchable renewable generation over the coming years. The overall objective of this work is to support the integration of these renewable energy sources by activating existing untapped sources of flexibility to provide system-stabilizing services. Further, it is a goal to examine how these sources of flexibility can be utilized not only to provide global ancillary services, but also to deliver local distribution level services such that the existing grid can be utilized to the highest possible extend.

Activating flexibility to integrate renewables is a most interesting subject as it requires work in several widely different areas: From the technical point of view, methods for control and aggregation of flexibility must be developed. From an economical perspective, new types of contracts must be developed that legally allow an aggregator to act on behalf of the owner of the flexible resources. From a business-oriented perspective, a business case estimating the value of the flexibility compared to the operating expenses must be conducted. From a market perspective, the existing regulations may need to be adjusted to better accommodate the new type of flexible resources. Finally, from a distribution system operator (DSO) perspective, methods must be developed enabling DERs to provide services such that expensive grid reinforcements can be avoided. The objective of this thesis is to address these five areas.

In the following section we present four hypotheses that this thesis seeks to address. Each hypothesis represents an important piece in the smart grid puzzle that has not yet been addressed according to the state-of-the-art above.

1.4 Hypotheses

The objectives together with the state-of-the-art form the background for the following four hypotheses which are addressed in this thesis. For each hypothesis we describe how it corresponds to the state-of-the-art within that area. The hypotheses are arranged such that the first three hypotheses address "Challenge I: Alternative sources of balancing" while the fourth hypothesis addresses "Challenge II: Congestion in the distribution grid". Both of these challenges were presented in the thesis introduction.

Hypothesis 1. *A technical VPP can control the aggregated respnose of a portfolio of flexible consumption devices to deliver services in the current electricity markets without violating local consumer constraints.*

This hypothesis covers an important element in the smart grid concept, namely that a VPP can manage a portfolio of consumers which individually are not able to deliver a valuable power response; however, by aggregation it is possible to control the total consumption to follow a reference. This is valuable in the electricity markets as the portfolio thereby can function similarly to a power plant. The VPP must assure that the local constraints of the consumers are not violated, for example that certain temperature limits or runtime/stoptime constraints are honored. This ability can be used to participate in the electricity markets, for example by shifting consumption to hours where the electricity prices are low or by providing ancillary services.

While the topic of a VPP aggregating and controlling flexible load has been addressed in many works, two important elements are missing in the literature. The first is to clearly show that it is in fact possible to honor the actual market regulations. This is key because the flexibility *must* be utilized in the electricity markets on equal terms with other providers of system stabilizing services as we focus on the Danish liberalized electricity system. The second important element is that although many works show promising simulation results in the field of aggregation of load, no actual real-life demonstrations show the concept of aggregating a larger number of devices to provide a desired accumulated response. These two elements are part of the hypothesis described above and are addressed in this thesis.

Hypothesis 2. *An aggregator can generate significant profit in the current Nordic electricity markets based on a portfolio of flexible consumption devices.*

This hypothesis states that it actually is profitable for an aggregator to operate a number of flexible consumption devices through a VPP to participate in the electricity markets. Such operation is associated both with profit and expenses: selling ancillary services and making electricity price arbitrage can generate revenue while expenses to sensor and control equipment etc. will cause both an installation cost and an operating expense. The overall business case thus depends on whether the value of market participation is sufficiently high compared to the installation and operating expenses.

While several works illustrate how loads can be shifted depending on spot prices etc., no works complete the picture. First of all, the works found in the literature assume the electricity prices are known in advance which is not the case in the liberalized market where the spot prices are unknown before the spot market closes – and once the market is closed the spot prices only apply to the traded electricity. The second reason is that the works found in the literature do not assess the expenses that are associated with activating devices in the electricity markets. This hypothesis includes both these two important aspects and hereby provides a more complete picture.

Hypothesis 3. *By altering the current electricity market regulations, new types of flexible consumers and storage devices will be able to enter the electricity markets which consequently will increases the market uptake of distributed renewable energy resources.*

This hypothesis addresses the issue, that the electricity markets were built in a time where the electrical grid was based on conventional power plants and not distributed generation. Consequently, the electricity market regulations do not respect the limitations of DERs which cause a market barrier for these devices. The hypothesis above states that it is possible to increase the uptake of flexible consumers and storage devices by adequately modifying the existing regulations.

While the literature does indeed discuss that the current market setup may not be suitable for the new types of assets such as fluctuating production and flexible consumption, it does not provide any ideas or concrete suggestions for how to alter the market to better accommodate these assets. This is therefore a topic topic of this thesis.

Hypothesis 4. *DERs can generate significant value for DSOs by offering local flexibility services. It is possible to assess the amount and duration of flexibility required to resolve concrete grid issues and to assess the associated value of this flexibility.*

This hypothesis states that flexible consumers or distributed generation can generate value for the DSOs, who are responsible for the distribution grid. DERs offer an alternative to grid reinforcement, namely that the peak load is shifted to off-peak hours; alternatively, local production from distributed generation can produce during peak-hours and thereby reduce the peak load on the cables. Hereby, the DSOs will be able to postpone, or possibly avoid all together, expensive grid reinforcement. The result is economical and environmental savings. The hypothesis further states that it is possible to assess how large a portion of flexibility is required before it has value to the DSO and also what the DSO's value of this flexibility product is.

It is important to notice that these distribution level services are fundamentally different from the transmission level services. First of all, the distribution level services must be delivered at a given location in the grid. Second of all, the duration of a distribution level agreement/contract must be as long as a year or more. The reason is that the alternative to a flexibility service is conventional grid reinforcement, which is very time consuming as it includes replacing cables or constructing a new feeder. Consequently, services at the distribution level have very different characteristics than the electricity market services. A different type of analysis must therefore be made to evaluate whether it is economically beneficial to use DER flexibility at the distribution level.

While many works show concepts for providing services at the distribution level, they often have the nature of being very conceptual and far from implementable. The reason is that they often do not consider the actual physical and in particular also the practical limitations that a distribution grid is characterized by. An example of this is that it often is assumed that the aggregator will known the limitations of the grid and can use this knowledge to ensure that grid congestion is avoided. However, the grid topology and cable limitations are only known by the DSO and not the aggregator. An aggregator will consequently not know where in the grid the flexible consumers under its jurisdiction are, and not even know if two flexible consumers are on the same feeder. An aggregator can therefore not single-handed regulate flexible loads to ensure that the grid does not congest. Another example is that it is often assumed that distribution grid real-time measurements are available. The distribution grid is, however, often characterized by very few sensors and even fewer of the sensors operating in real-time. This hypothesis handles this by assuming that the interface between the aggregator and the DSO is that the aggregator delivers a well-defined *flexibility product* to the aggregator. The hypothesis describes that it is possible to assess the required amount and duration of such a flexibility product for this to be of value to the DSO, and further what DSO's value of such a product is.

1.5 Overview of contributions

In the following, we provide an overview of the main contributions of this thesis. The contributions are divided into four main categories. The first category *Utilizing DER flexibility to provide electricity services* consists of eight papers and addresses Hypothesis 1 and 2. The second category *Integration of DERs in the electricity markets* consists of three papers and addresses Hypothesis 3. The third category *Utilizing DER flexibility to resolve distribution grid congestion* consists of four papers and addresses Hypothesis 4. Finally, a fourth category is included to mention the research done during the PhD which, however, does not directly address any of the four hypotheses presented above, and where the papers are not enclosed in this thesis.

Each paper is associated with a small introduction to give an overview of the contributions of this work. A much more detailed summary of the actual content of the contributions is presented in Chapter 2. Finally, the actual papers associated with the first three categories are presented in full in the second part of the thesis.

In each of the three first categories, a star symbol ☆ is used to indicate the papers of most importance within that category.

Utilizing DER flexibility to provide electricity services

The following eight papers are concerned with the topic of aggregating DERs' flexibility to generate value in the electricity markets and thus address Hypothesis 1 and 2.

Paper 1

Title: Information Modeling for Direct Control of Distributed Energy Resources
Authors: Benjamin Biegel, Palle Andersen, Jakob Stoustrup, Lars Henrik, Hansen David, and Victor Tackie
Published in: Proceedings of the American Control Conference Conference, Washington, District of Columbia, USA, June 2013

Paper 1 describes the overall concept of utilizing DERs as a resource in the electricity markets and introduces the concept of an *aggregator* and a *VPP*. The focus is to construct an information model for the communication between an aggregator and a portfolio of DERs. The information model is constructed such that the aggregator is able to mobilize the DERs to provide a desired accumulated power response corresponding to the electricity markets.

Paper 2

Title: Contracting Flexibility Services
Authors: Silas Harbo and Benjamin Biegel
Published in: Proceedings of the European Innovative Smart Grid Technologies Conference, Copenhagen, Denmark, October, 2013

Paper 2 follows the concept presented in Paper 1 with focus on the legal relationship between the aggregator and the owners of the flexible resources. The paper introduces the concept of a *flexibility contract* that specifies the terms under which an aggregator is allowed to control a DER. Further, it is discussed how the aggregator can compensate the DER owner for the utilized DER-flexibility.

Paper 3

Title: Electricity Market Optimization of Heat Pump Portfolio
Authors: Benjamin Biegel, Palle Andersen, Tom S. Pedersen, Kirsten Mølgaard Nielsen, Jakob Stoustrup, and Lars Henrik Hansen
Published in: Proceedings of the Multi-Conference on Systems and Control, Hyderabad, India, August 2013

Paper 3 assumes the setup described in the two first papers, namely that an aggregator is legally and technically able to control a portfolio of DERs, namely a large number of heat pumps. The paper describes a method where the flexibility of the heat pump portfolio is optimized towards the electricity spot market to arbitrage the varying prices.

Paper 4

Title: Lumped Thermal Household Model
Authors: Benjamin Biegel, Palle Andersen, Jakob Stoustrup, Mathias Bækdal Madsen, and Lars Henrik Hansen
Published in: Proceedings of the European Innovative Smart Grid Technologies Conference, Copenhagen, Denmark, October, 2013

An underlying assumption in Paper 3 is that a portfolio of flexible consumers can be modeled as one unit of flexibility, i.e. a lumped flexibility model. Paper 4 addresses exactly this issue, and illustrates the benefits of using such a lumped model compared to using individual models for each devices in the portfolio. Again, heat pumps in domestic homes are the focus of the work.

Paper 5

Title: Smart Grid Dispatch Strategy for ON/OFF Demand-Side Devices
Authors: Benjamin Biegel, Palle Andersen, Tom S. Pedersen, Kirsten Mølgaard Nielsen, Jakob Stoustrup, and Lars Henrik Hansen
Published in: Proceedings of the European Control Conference, Zurich, Switzerland, July 2013

Paper 3 and 4 work with a lumped model of an entire portfolio of flexible consumers. Paper 5 shows how a *dispatcher* can transform an aggregated power reference to the entire portfolio to individual control signals to each device comprising the portfolio. The input to the dispatcher is thus a power reference to the total consumption of the portfolio of devices while the output is individual control signals to each individual device. The dispatcher takes local technical device constraints into account while an outer feedback loop ensures that the aggregated response follows the reference.

Paper 6 ☆

Title: Aggregation and Control of Flexible Consumers – A Real Life Demonstration
Authors: Benjamin Biegel, Palle Andersen, Jakob Stoustrup, Mathias Bækdal Madsen, Lars Henrik Hansen, and Lotte Holmberg Rasmussen
Published in: Proceedings of the 19th World Congress of the International Federation of Automatic Control, Cape Town, South Africa, August, 2014

Paper 6 implements the architecture first presented in papers 1 and 2 together with the dispatch strategy and feedback controller described in paper 5. Based on this, a real-life demonstration is conducted where a portfolio of 54 inhabited households is controlled such that the total consumption follows a power reference on a hourly basis while the individual local comfort constraints of the inhabitants are honored.

Paper 7

Title: Predictive Control of Demand Side Units Participating in the Primary Frequency Reserve Market
Authors: Benjamin Biegel, Jakob Stoustrup, Palle Andersen, and Lars Henrik Hansen
Published in: Proceedings of the American Control Conference Conference, Washington, District of Columbia, USA, June 2013

The papers 3, 4, and 5 primarily focus on spot price arbitrage and provisions of hourly regulating power based on a portfolio of flexible consumers. Paper 7 deals with the faster primary reserve, which is delivered on a basis of just seconds corresponding to system frequency deviations. The focus is to utilize closed-loop Model Predictive Control (MPC) to ensure that the flexible devices will prepare for unpredictable frequency deviations in an economically favorable manner.

Paper 8

Title: Primary Control by ON/OFF Demand-Side Devices
Authors: Benjamin Biegel, Lars Henrik Hansen, Palle Andersen, and Jakob Stoustrup
Published in: IEEE Transactions on Smart Grid (Issue: 99), April 2013

Similarly to Paper 7, Paper 8 deals with primary control delivered according to grid frequency deviations. The paper describes a method where a portfolio of ON/OFF consumers each are assigned with a trigger frequency which determines when the devices should be ON and OFF according to local system frequency measurements. The method distributes the trigger frequencies such that the aggregated response of the portfolio honors current regulations for primary reserve. Hereby, the method shows how ON/OFF consumers can be used in the liberalized electricity markets and participate on equal terms with the conventional power generators.

Integration of DERs in the electricity markets

The following three papers examine the current market regulations with focus on the possibility of utilizing DERs to provide various electricity services. Further, the main barriers for market entry are identified, and a change of the regulations is proposed which will make it easier for DERs to enter the ancillary service markets. These contributions thereby address Hypothesis 3.

Paper 9

Title: Adjustable Consumption Participating in the Electricity Markets
Authors: Benjamin Biegel, Lars Henrik, Hansen Jakob Stoustrup, Palle Andersen, and Silas Harbo
Published in: Proceedings of the Conference on Decision and Control, Florence, Italy, December 2013

Paper 9 examines the Nordic system and the regulations specifying how flexible consumers can be active in the spot market and the regulating power market. Further, the main barriers for entering these markets are identified.

Paper 10

Title: Value of Flexible Consumption in the Electricity Markets
Authors: Benjamin Biegel, Lars Henrik Hansen, Jakob Stoustrup, Palle Andersen, and Silas Harbo
Published in: International Journal of Energy, March, 2014

Paper 10 extends the findings of Paper 9 by estimating the costs of entering the spot market and the regulating power market, which are the two largest electricity markets. Further, the paper presents a method for examining how much flexibility a DER (or portfolio of DERs) should have before it is economically profitable to enter these markets.

Paper 11 ☆

Title: Integration of Flexible Consumers in the Ancillary Service Markets
Authors: Benjamin Biegel, Mikkel Westenholz, Lars Henrik Hansen, Jakob Stoustrup, Palle Andersen, and Silas Harbo
Published in: International Journal of Energy, April, 2014

Paper 11 addresses one of the barriers found in Paper 9 and 10 concerning electricity market participation of DERs. The barrier is that energy constrained DERs such as flexible consumers and storage systems risk reaching the energy limitations when providing fast ancillary services. This can happen for example if a long-duration energy-demanding delivery is requested. This paper proposes a method, where the aggregator managing the DERs is allowed to continuously purchase and utilize the slower ancillary services to restore the energy level of the DERs such that they avoid reaching the energy limits.

Utilizing DER flexibility to resolve distribution grid congestion

The following four papers are concerned with the issues that can arise at the distribution level as consumption increases potentially causing congestion issues. The papers examine how such distribution level congestion issues can be resolved via smart utilization of DERs. Hence, the following contributions address Hypothesis 4.

Paper 12

Title: Model Predictive Control for Power Flows in Networks with Limited Capacity
Authors: Benjamin Biegel, Jakob Stoustrup, Jan Bendtsen, and Palle Andersen
Published in: Proceedings of the American Control Conference, Montreal, Canada , June 2012

Paper 12 addresses the issue of resolving grid congestion by utilizing DER flexibility. It is assumed that the grid constraints are known and available to an entity controlling a portfolio of flexible consumers. The paper shows how this centralized entity can perform an economical dispatch of the flexible consumers while honoring the grid constraints. Hereby congestion can be avoided.

Paper 13

Title: Congestion Management in a Smart Grid via Shadow Prices
Authors: Benjamin Biegel, Palle Andersen, Jakob Stoustrup, and Jan Bendtsen
Published in: Proceedings of the Power Plant and Power System Control Conference, Toulouse, France, September 2012

Paper 12 assumes that all grid information is available to a centralized entity, who single-handed optimizes the operation of the flexible consumers. In Paper 13 the assumptions are tightened such that a number of operators each know part of the objective function while only a DSO knows the limitations of the grid. The paper shows how congestion issues can be resolved by introducing a capacity market on each line that potentially will be congested.

Paper 14

Title: Distributed Model Predictive Control via Dual Decomposition
Authors: Benjamin Biegel, Jakob Stoustrup, and Palle Andersen
Published in: Distributed Model Predictive Control Made Easy, Chapter 11, Springer, April 2013

Paper 14 follows the concept of Paper 13 but focus more on the method *dual decomposition* which enables the different operators to reach the global optimum via a capacity marketplace and price iterations.

Paper 15 ☆

Title: The Value of Flexibility in the Distribution Grid

Authors: Benjamin Biegel, Kåre Seest Rasmussen, Hans Knudsen, Sisse Merete Østberg, Peder Cajar, Lars Henrik Hansen, Palle Andersen, and Jakob Stoustrup
Published in: Proceedings of the 5th IEEE PES Innovative Smart Grid Technologies (ISGT) European 2014 Conference, Istanbul, Turkey, October, 2014

The final contribution in this category is Paper 15 which has a high focus on how the distribution grid is actually operated. It is based on data from the Danish distribution company DONG Energy, and proposes a concrete flexibility product that an aggregator can deliver to a DSO to resolve grid congestion. Further, the paper examines what the value of such a product is to the DSO.

Other contributions

The following contributions have been made or presented during the PhD, but do not directly address the four hypotheses that are the main focus of this thesis. They are therefore not included in the thesis.

Paper A

Title: Distributed Low-Complexity Controller for Wind Power Plant in Derated Operation
Authors: Benjamin Biegel, Daria Madjidian, Vedrana Spudicć, Anders Rantzer, and Jakob Stoustrup
Published in: Proceedings of the Multi-Conference on Systems and Control, Hyderabad, India, August 2013. Winner of The Best Student Paper Award.

Paper B

Title: Wind Turbine Pitch Optimization
Authors: Benjamin Biegel, Morten Juelsgaard, Matt Kraning, Stephen Boyd, and Jakob Stoustrup
Published in: Proceedings of the Multi-Conference on Systems and Control, Denver, CO, USA, September, 2011

Paper C

Title: Indirect Control for Demand Side Management A Conceptual Introduction
Authors: Kai Heussen, Shi You, Benjamin Biegel, Lars Henrik Hansen, and Katrine Bech Andersen
Published in: Proceedings of the European Innovative Smart Grid Technologies Conference , Berlin, Germany, October, 2012

Paper D

Title: Model Predictive Control of Domestic Heat Pump
Authors: Mikkel Urban Kajgaard, Jesper Mogensen, Anders Wittendorf, Attila Todor Veress, and Benjamin Biegel
Published in: Proceedings of the American Control Conference, Washington, District of Columbia, USA, June 2013

Paper E

Title: Aggregation of Supermarkets as Demand Side Devices in a Smart Grid
Authors: Rasmus Pedersen, John Schwensen, Benjamin Biegel, Jakob Stoustrup, and Torben Green
Published in: Proceedings of the 19th World Congress of the International Federation of Automatic Control, Cape Town, South Africa, August, 2014

Patent

Title: A Method for Estimating and/or Controlling a Temperature of Foodstuff Stored in a Refrigerated Cavity
Authors: Rasmus Pedersen, John Schwensen, Benjamin Biegel, Jakob Stoustrup, and Torben Green (Danfoss A/S and Aalborg University). Patent application accepted August 2014.

2 | Summary of Contributions

This chapter sums up the main contributions of the 15 papers included in this thesis. We encourage the reader to refer to the actual papers for further details.

2.1 Utilizing DER flexibility to provide electricity services

This section is concerned with aggregation and control of DERs making it possible to utilize their flexibility in the electricity markets and thereby generate value. The section covers Hypothesis 1 and 2, see Sec. 1.4, and is based on Paper 1 through Paper 8.

Motivation

In the following we motivate why some devices can be seen as flexible consumers and thereby as having a potential to generate revenue. We consider domestic households with electric heat pumps as an example of a flexible consumption devices.

Figure 2.1 from Paper 3 shows indoor temperature measurements from four inhabited houses over a one-month period. The houses are electrically heated from heat pumps using the default heat pump controller. The figure shows that the indoor temperature varies several degrees for all the houses over the period, which indicates the motivation of flexible consumption: people are used to and comfortable with indoor temperatures varying a couple of degrees, hence the indoor temperature in a house does not have to be accurately fixed at a given temperature setpoint. This motivates that certain consumers are flexible and allow consumption to be put forward or postponed a number of minutes or hours depending on the circumstances. The households with electrical heating represents one example of flexible consumers from the class of thermal devices. Other examples from this class of devices are air conditioning systems, refrigeration systems, cold rooms etc. Examples of other types of flexible consumers that allow a temporal shift of energy consumption are pumping systems, electrical battery systems, certain industry processes, etc. An example of flexible consumers that allow not only temporal load shifting, but to actually reduce consumption, is lighting which can be dimmed.

Now we have illustrated that consumption can be flexible and we want to motivate this can be a source to generating revenue, or savings on electricity (depending on the terminology). We therefore examine the spot market where electricity is traded every day for the 24 hours of the following day. Buyers and sellers provide their bids at noon where after the spot price is found as the intersection between demand and supply, see further details in Paper 9 and Paper 10. The spot prices, which we denote $\pi(k)$ for hour k, are

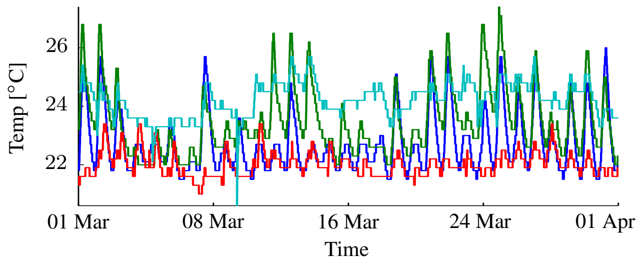

Figure 2.1: One month's indoor temperature measurements for four houses during March 2012.

published once the intersection is found but are only valid for the amounts of electricity traded before gate closure. It is, however, possible to make spot price predictions, denoted $\tilde{\pi}(k)$, before gate closure. This concept is illustrated in Figure 2.2 where we assume that the current time is between 11 a.m. and 12 noon (last hour before gate closure). At this time we know the spot prices for the current day $\pi(1), \ldots, \pi(24)$, but we do not know the spot prices the following day (the day-ahead) $\pi(25), \ldots, \pi(48)$, which are not announced until $k = 13$ (i.e. 1 p.m.). We do, however, have spot price predictions for the following day, $\tilde{\pi}(25), \ldots, \tilde{\pi}(48)$. The figure is taken from Paper 3 and represents real historical market data and predictions. The figure illustrates what is generally the case, namely that the predictions are able to capture the shape of the actual spot price realization.

This motivates that flexibility can be a source of value: by shifting consumption from hours with an expected high spot price to hours with an expected low spot price, it is possible to purchase cheaper electricity.

While the example presented here prepares the ground for arbitraging in the spot market, there are other ways of generating value in the electricity markets such as the ancillary service markets, see Paper 2 and Paper 11. Delivery of ancillary services are discussed in greater details later in this section.

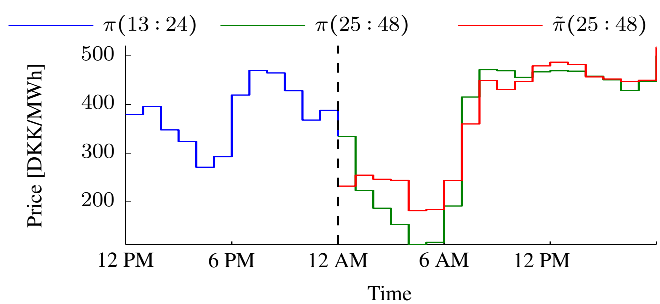

Figure 2.2: Spot prices π and predictions $\tilde{\pi}$ on January 9 and 10, 2011.

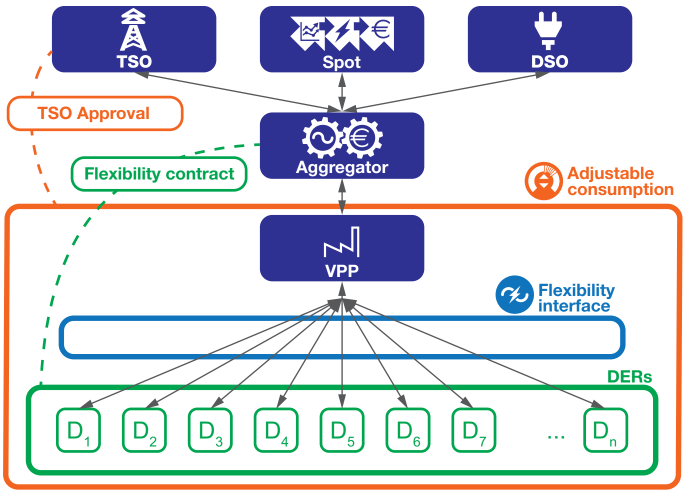

Figure 2.3: Overall architecture of DERs in the liberalized electricity markets.

Architecture

In the following we describe the overall architecture considered in this work. The basis of the architecture is that the DER flexibility should be utilized in the electricity markets.

Figure 2.3 illustrates the main elements of the architecture used in this work. The boxes D_1 through D_n illustrate n DERs which are connected to the technical VPP through a two-way communication link. This enables the VPP to monitor and control the flexibility of each individual device. The interface between the DERs and the VPP is denoted a *flexibility interface*, which is the focus of Paper 1. This interface specifies a unified way for different DERs to communicate their available flexibility to the VPP; similarly, it specifies what type of control signals the VPP can send to the DERs.

The technical VPP is under the jurisdiction of the aggregator. The aggregator is a legal entity that has entered into contract with the owners of the DERs which allows the aggregator to monitor and control the devices according to the contract specifications. These contracts are denoted *flexibility contracts*, and are the focus of Paper 2. The aggregator further has access to the existing electricity markets such as the ancillary service markets (TSO markets), the spot market, the regulating power market, and the intra-day market. It can further be imagined, that the aggregator in the future will have access to DSO markets.

Finally, the figure illustrates that the VPP and the portfolio of DERs together can be seen as a unit of *adjustable consumption* which is a term used in the regulations for the ancillary services. If the aggregator desires to participate in the ancillary service markets, the TSO must test and approve that the VPP together with the devices indeed are able to deliver the services according to the regulations. Details on the requirements for a *TSO approval* are presented in Paper 9 and Paper 10.

In Paper 1, the mentioned flexibility interface is developed and presented. The key concept of this interface is that the aggregator must be able to overview the *total DER flexibility*; hereby, the aggregator has the best conditions for optimizing the aggregate flexibility towards the various electricity markets. The interface presented in Paper 1 is constructed in a modular manner making the interface suitable for a whole range of different DERs.

Figure 2.4 illustrates this modular flexibility interface concept. A DER in the portfolio is described by a number of *flexibility blocks*, which each describe a certain element of the device's flexibility. For example, a *DER Type* block describes the overall information such as name and type of the devices while the *Active power production* block describes the device's ability to have its consumption being remotely controlled. The reader is referred to Paper 1 for further details and a more elaborate description of the suggested flexibility blocks.

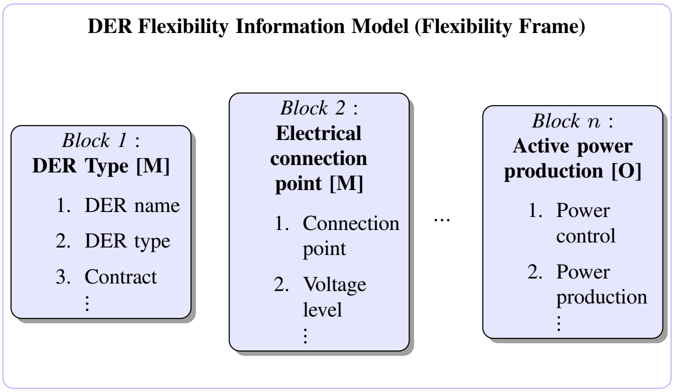

Figure 2.4: Illustration of a DER flexibility frame.

While the flexibility interface describes the communication interface between VPP and DERs, the flexibility contracts describe the contractual legal relationship between each DER owner and the aggregator. The flexibility contract specifies under what constraints and circumstances the aggregator is allowed to monitor and control the device and what the compensation to the DER owner is. Paper 2 deals exactly with this question and describes the elements a flexibility contract must contain in order to align the two contracting parties. Further, a flexibility contract template is developed and presented in this paper. This contract template serves as a powerful tool for manufacturers of devices with flexible consumption as it can be used to examine the possibilities of selling smart grid related services to an aggregating entity.

Figure 2.5 illustrates one of the main considerations of Paper 2. The figure illustrates that not all consumption is flexible: only parts of the DERs are technically capable of acting flexibly upon a signal to start, stop or adjust the power consumption. This could either be due to the fundamental DER technological specifications, or because a necessary hardware upgrade is considered unprofitable.

Flexibility model of distributed energy resource

The overall framework illustrated in Figure 2.3 and the concept of a flexibility interface and flexibility contracts are in principle valid for any DERs. However, the functionality

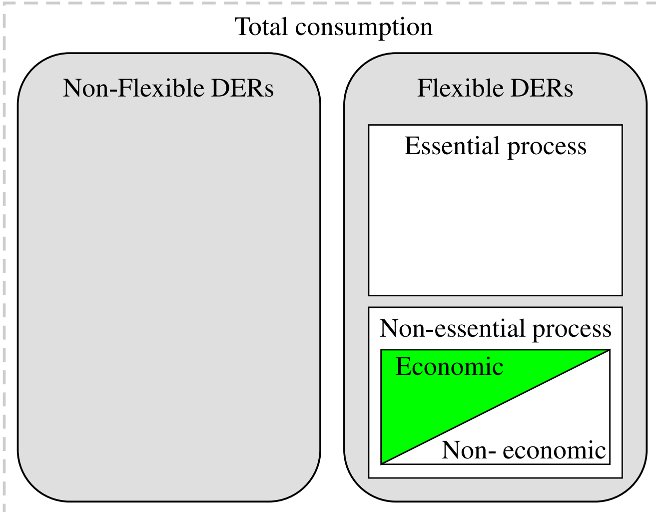

Figure 2.5: Flexible consumption vs. non-flexible consumption.

of the VPP and the aggregator will vary much depending on the type of DERs in the portfolio.

In this thesis, a main focus is on houses with electrical heating via heat pumps. The reason for this choice is that heat pumps are expected to widely replace oil-fired burners; further, it has been possible to do a real life demonstration on a portfolio of heat pumps. Therefore, heat pumps have a special focus although most of the control algorithms developed in this work can be used on a wider class of devices than just heat pumps. In the following, we present a simple DER model; following, we present a system architecture that allows the aggregator to optimize and control the lumped flexibility of the portfolio towards the electricity markets.

The portfolio is a collection of n flexible consumers (for simplicity, we use the term *consumer* to denote a *flexible consumption device* throughout the work) that can be remotely controlled within certain user-defined constraints. The control inputs are denoted $u(k) \in \mathbf{R}^n$, the power consumption of the devices are denoted $p(k) \in \mathbf{R}^n$, and the aggregate consumption is denoted $p_{\text{out}}(k) \in \mathbf{R}$ and given by $p_{\text{out}}(k) = \sum_{i=1}^{n} p_i(k)$ where k is the sample number.

The indoor temperature is used as an indicator of the comfort in the houses. Let $T_{\text{min}}, T_{\text{max}} \in \mathbf{R}^n$ denote the indoor temperature bounds specified in the flexibility contract by the individual heat pump owners and let $T(k) \in \mathbf{R}^n$ be the temperatures measured at time sample k across the portfolio.

The temperature will develop depending on outdoor temperature, wind and solar conditions, human behavior, use of electronics and wood stove, etc. A simple model for the behavior of the temperature is a first order model driven by the heat pump and an exogenous input describing the above mentioned disturbances

$$T_i(k+1) = a_i T_i(k) + (1 - a_i) T_{a,i} + b_i (p_i(k) + w_i(k)) \tag{2.1}$$

where $T_{a,i}$ is the ambient temperature and a_i, b_i describe the discrete dynamics of the

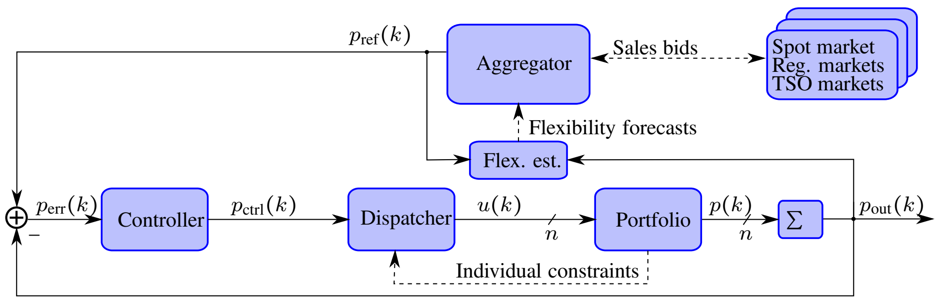

Figure 2.6: Overall system architecture. Solid arrows indicate signals while dashed arrows indicate information exchange.

household and $w_i(k)$ denotes the disturbance at house number i.

Overall system setup

With the simple model described above, we are ready to introduce the overall system setup, see Figure 2.6. The setup is comprised of several elements: a portfolio of the DERs (heat pumps in this example), a controller and dispatcher that control the total consumption of these devices, a flexibility estimator that estimates the lumped flexibility of the portfolio, and an aggregator that optimizes the flexibility towards the different electricity markets. In the following, the setup is described in greater detail. The full descriptions are found in Paper 5 and Paper 6.

Flexibility Estimator The flexibility estimator forecasts the consumption flexibility of the portfolio and makes this information available for the aggregator as indicated by the dashed arrow in Figure 2.6. This allows the aggregator to get an overview of the available flexibility and act accordingly in the markets. The flexibility can be estimated in various ways, for example by examining the power reference $p_{\mathrm{ref}}(k)$ and the actual consumption $p_{\mathrm{out}}(k)$ over time. Another option is that the individual devices report their temperature state to the flexibility estimator (not illustrated in this figure). Further, other relevant parameters such as weather forecasts can also be used by the flexibility estimator to make a more accurate estimate of the consumer flexibility.

Aggregator The aggregator has entered into flexibility contracts with the DER owners, allowing the aggregator to actively utilize the consumer flexibility. By using the flexibility estimator, the aggregator can optimize the lumped DER flexibility towards the different markets and following activate the portfolio accordingly via a portfolio consumption reference $p_{\mathrm{ref}}(k) \in \mathbf{R}$.

Controller The controller ensures that the aggregator-defined reference $p_{\mathrm{ref}}(k)$ is followed. The input to the controller is the tracing error $p_{\mathrm{err}}(k) = p_{\mathrm{ref}}(k) - p_{\mathrm{out}}(k)$ and the output is a control signal $p_{\mathrm{ctrl}}(k) \in \mathbf{R}$ which is fed to the dispatcher according to a given feedback control law.

Dispatcher The dispatcher distributes the scalar control signal $p_{\text{ctrl}}(k)$ to the n devices in the portfolio via the control vector $u(k)$. In doing this, the dispatcher takes the local constraints of the individual devices into consideration as indicated by the dashed arrow from portfolio to dispatcher in Figure 2.6. The dispatch strategy can for example be based on simple sorting algorithms, which makes the dispatcher very fast even for portfolios comprised of thousands of devices. Notice that the controller and dispatcher also can be seen as a VPP, as previously described and illustrate, see Figure 2.3.

It is important to notice that the architecture proposed in this work, and illustrated in Figure 2.6, divides the system into several separate modules, each with different tasks. The two main elements are on one hand the aggregator which is responsible for optimizing the lumped flexibility towards the markets, and on the other hand the VPP (controller and dispatcher) which has the task of executing the aggregator's plan. In the following two subsections, these two main elements are described in more detail.

Aggregator optimizing towards markets

The aggregator will optimize the flexibility of its portfolio towards the electricity markets. This can be done in various ways depending on the market and with different strategies.

In the following, we present one example describing how the lumped flexibility of a portfolio of heat pumps can be optimized towards the spot market which is the largest market in the Nordic electricity system. The basis for the control strategy is that the total flexibility over the entire portfolio can be seen as *one lumped portion of flexibility*; in other words, that the portfolio flexibility can be treated as one device. This is possible through the VPP (controller and dispatcher) which translates a reference to the entire portfolio into control signals to the individual devices. The concept of using such a lumped flexibility model is discussed in more detail in Paper 4.

In Paper 3 we examine how the lumped flexibility of a portfolio of heat pumps can be optimized towards the spot and regulating power markets and estimate the value that this generates based on current market conditions. In the following we present how optimization of flexibility towards the spot market can be done but refer the reader to Paper 3 for details on bidding into the regulating power market.

We use the same terms as previously, but now use an upper bar to denote that we are working with lumped parameters: $\overline{T}$, $\overline{u}$ are the lumped temperature and input power, respectively, while $\overline{a}$, $\overline{b}$ are lumped thermal parameters. Although it may seem restrictive to lump possibly very different DERs into one model which is used for flexibility optimization, this is found to be a good first step in the efforts to optimize flexibility (fore more details, refer to Paper 3 and Paper 4). Further, the simple lumped model approach presented here can be replaced with more complex and capturing models and replace the aggregator module in Figure 2.6 if this is desired.

The lumped parameters can be defined or found in different ways. An example of this is presented in Paper 3 where the lumped parameters are simply taken as averages of the actual parameters. Hereby, the lumped model represents an *average heat pump*, and this flexibility is optimized towards the markets.

Based on the above description of a lumped system together with the previously described spot price $\pi(k)$ and spot price predictions $\tilde{\pi}(k)$, the following simple day-ahead optimization problem can represent the core of the aggregator strategy:

$$
\begin{aligned}
\text{minimize} \quad & \sum_{\kappa \in \mathcal{K}} \left(\tilde{\pi}(\kappa) u(\kappa) + k_I x^2(\kappa) \right) \\
\text{subject to} \quad & T(\kappa+1) = aT(\kappa) + (1-a)\tilde{T}_{\text{a}}(\kappa) + \\
& \qquad\qquad b\left(u(\kappa) + v(\kappa)\right), \quad \kappa \in \mathcal{K} \\
& x(\kappa+1) = x(\kappa) + T(\kappa) - T_{\text{sp}}, \quad \kappa \in \mathcal{K} \\
& u(\kappa) \in \mathcal{U}, \quad T(\kappa) \in \mathcal{T}, \quad \kappa \in \mathcal{K} \\
& T(k+13) = \tilde{T}(k+13) \\
& x(k+13) = \tilde{x}(k+13)
\end{aligned}
\tag{2.2}
$$

where the set $\mathcal{K}$ represents the 24 hours of the next day, the variables are $u(\kappa)$, $T(\kappa)$, $x(\kappa)$, $\kappa \in \mathcal{K}$, and $k_{\text{I}} \in \mathbf{R}$ is a trade-off parameter. The data to the problem is the predicted spot prices and outdoor temperatures $\tilde{\pi}(\kappa), \tilde{T}_{\text{a}}(\kappa), \kappa \in \mathcal{K}$, the daily load profile $v(\kappa), \kappa \in \mathcal{K}$, and the predicted temperature and integrated error in the first hour of the following day $\tilde{T}(k+13), \tilde{x}(k+13)$. The sets $\mathcal{T}, \mathcal{U}$ represent given power and temperature limitations. The solution $u^{\star}_{\text{spot}}(\kappa), \kappa \in \mathcal{K}$ are the volumes of electricity that should be purchased in the spot market for the following day.

The presented algorithm can be extended in several ways. One natural extension is to include an optimization algorithm that not only looks day-ahead, but also performs intra-day optimization for example towards the regulating power market. This is done in Paper 3.

We illustrate the method of optimizing a lumped portion of flexibility towards the electricity markets with the following example which is presented in greater detail in Paper 3. A simulation case study of $10,000$ heat pumps with a heat capacity and a drain rate corresponding to Danish houses and a nominal power consumption of 4 kW; further, an allowable temperature band of $\pm\ 2$ °C around a setpoint of 21.5 °C is assumed. A sampling time of 5 minutes is used. The data utilized for the simulation is:

- Spot price data from Nord Pool,
- Spot price predictions,
- Outdoor temperature and daily loads from the Danish heat pump project “Styr din varmepumpe”,
- Outdoor temperature predictions from the Danish Meteorology Institute.

We perform simulations for a full year and assume a liquid market where we do not affect the market prices. The flexibility of the portfolio is optimized in a manner similar to the optimization problem (2.2) and it is assumed that the flexibility of the portfolio can be described as the simple lumped first order model. We compare the simulation result with real historical measurements taken from the heat pump project “Styr din varmepumpe” which is described in more detail in Paper 3.

In Figure 2.7 the operation over 5 days is presented to illustrate the behavior of this controller. The top subplot shows the spot price predictions (red) and realizations (blue). The second subplot shows the power consumption of the heat pumps in the “Styr din varmepumpe’ project (green) upscaled from the 130 available measurements to $10,000$ heat pumps. In the same subplot we show simulation results when the portfolio is operated by the controller developed in this work (purple). Finally, the lower subplot shows the resulting average indoor temperature with the spot price controller operating the portfolio (purple) compared to the observed data for that period (green).

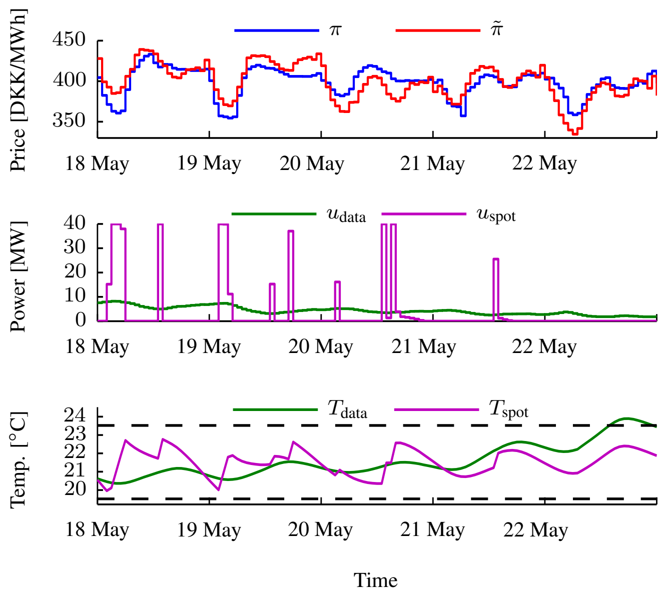

Figure 2.7: Simulated heat pump portfolio optimized towards spot prices (purple) compared to upscaled real measurements (green).

Together, the three subplots show the main result of the spot optimizing controller: that the developed controller is able to shift the main consumption to hours of low spot prices while keeping the temperature fluctuations in the same magnitude as the houses currently experience. It is important to notice that the aggregated portfolio is idealized as no delays, ramping constraints, etc. are included. This becomes evident in the bang-bang characterized power consumption of the portfolio as illustrated in Figure 2.7. Hence, the performance in the simulations is higher than what we can expect by implementing the strategy.

The resulting average temperature, power consumption, and costs over the course of the year of simulation are illustrated in Table 2.1. The column *Data* represents the values obtained by looking at real life heat pump data while the column *Spot* is the data obtained from the simulation described above. The last column, *Reg*, is obtained by extending the spot price optimization described above with also bidding in the regulating power markets. The first row shows that the average temperature based on measurements (data) is $21.5\,^{\circ}\mathrm{C}$, which therefore is used as a setpoint for the two simulations resulting in almost identical average temperature. The next row shows the average power consumption which is measured to be 732 W while the two control strategies require a slightly higher power consumption. The average spot price based on the data is 356 DKK/MWh which is close to the yearly average spot price of 357 DKK/MWh – this is a result of the smooth power consumption of the heat pumps. By comparison, the spot price optimizing controller is able to lower this around $18\,\%$ while the controller that also bids into the regulating power

		Data	Spot.	Reg.
Avg. temp.	[°C]	21.5	21.6	21.6
Avg. pwr.	[W]	732	737	744
Avg. spot.	[DKK/MWh]	356	282	270
Total cost per hp.	[DKK]	2.285	1.819	1.759
Savings	[%]	0	17.8	19.9

Table 2.1: Performance comparison of measurements and the two control strategies developed in this work.

market is able to save around 20 %. We observe that the annual savings per heat pump is in the magnitude of 470 DKK for spot price optimization but only additionally 60 DKK when also providing regulating power. We remind the reader that the simulated results are based on a somewhat idealized model; hence it should be expected that the savings when implementing this in real life will be lower.

Real life demonstration

In this subsection, we present results from a real life demonstration conducted on a portfolio consisting of 54 inhabited Danish households. The demonstration is conducted by implementing a dispatcher and a feedback controller as the one illustrated in Figure 2.6. The dispatch strategy is described in detail in Paper 5 while further details on the actual demonstration can be found in Paper 6. In the demonstration it was possible to remotely monitor the heat pump power consumption, the indoor temperature in the household, the consumption of hot water, and other values. Further, it was possible to allow the local heat pump controller to run (denoted the ON-state), and it was possible remotely to force the heat pump not to run (denoted the OFF-state). The objective was to control the total power consumption of the portfolio without violating local constraints such as comfortable indoor temperature, sufficient hot water, runtime and stoptime constraints on the heat pumps, etc. We believe this is the first real life demonstration where a power reference is followed based on the aggregate consumption of a larger number of devices – and consequently a significant step towards the smart grid vision.

An hourly power reference is generated each day at midnight for the 24 hours of the following day in the period 9th through 16th of October 2013. Due to the limitations in the setup, the power reference is kept close to the expected consumption of the portfolio.

In Figure 2.8 subplot (a), the reference is shown and compared with the measured aggregate consumption of the heat pump portfolio. Subplot (a) shows that the portfolio indeed is able to follow the reference with a reasonable performance. The reason for the deviation between reference and measured output is a combination of two things. First, it is because of the very fluctuating power consumption of the individual heat pumps, and second, it is because the controller is implemented with very small control gain due to a large non-deterministic communication delay in the system.

Subplot (b) shows the number of devices that at any given time are able to be switched OFF (deliver upward regulation) and ON (deliver downlard regulation) denoted $\mathcal{I}_{\text{up}}$ and $\mathcal{I}_{\text{dn}}$, respectively. These two numbers are compared to the total number of devices which is $n = 54$. We notice that throughout the whole week, there are always a number of devices

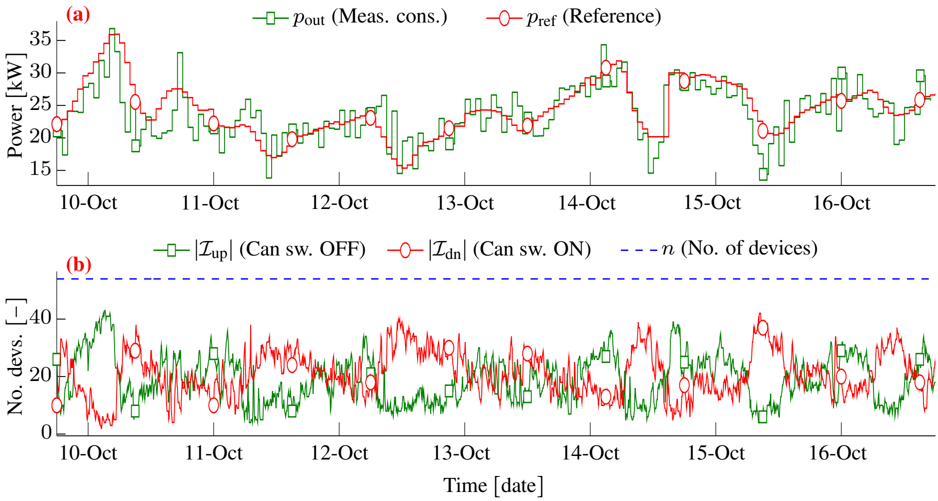

Figure 2.8: Experimental results. Subplot (a): Tracing ability. Subplot (b): Device available to be turned ON/OFF.

available for both upward and downward regulation, respectively, during the whole test. However, the slow controller is not able to exploit these available devices to follow the reference more accurately because of the low controller gain. As described previously, the gain had to be kept low due to a long non-deterministic communication delays in the setup.

To further examine the setup, we observe the operation of one of the 54 heat pumps in the portfolio during the first 48 hours of the demonstration, see Figure 2.9. Subplot (a) shows the ON/OFF state $u_i(k)$ of the device compared to the measured consumption of the device $p_i(k)$. This subplot shows what was previously described, namely that the OFF state forces a heat pump to shut down, while the ON state merely allows a heat pump to run. Also, the very stochastic nature of the consumption is evident.

Subplot (b) shows the measured indoor temperature $T_i(k)$ compared to the limits $T_{\text{min},i}, T_{\text{max},i}$ which are specified by the heat pump owner. The figure shows what is generally the case for all the houses, namely that the controller allows the heat pump to run such that the temperature does not go below the limit. The upper temperature bound is violated on one occasion, possibly caused by heating via solar irradiation. However notice that violations of the upper temperature bound is not caused by the aggregator since the aggregator cannot force the pump to run – it can only allow it to operate according to the local controller as described earlier.

Finally, subplot (c) show the accumulated water usage during periods where the heat pump is OFF. At one instance, the accumulated hot water usage exceeds 30 L which causes the aggregator to send the ON-command and thereby allow the heat pump to run, see subplot (a). This is a functionality implemented in the dispatcher to ensure that there always is sufficient hot water available to the inhabitants. See further details in Paper 6.

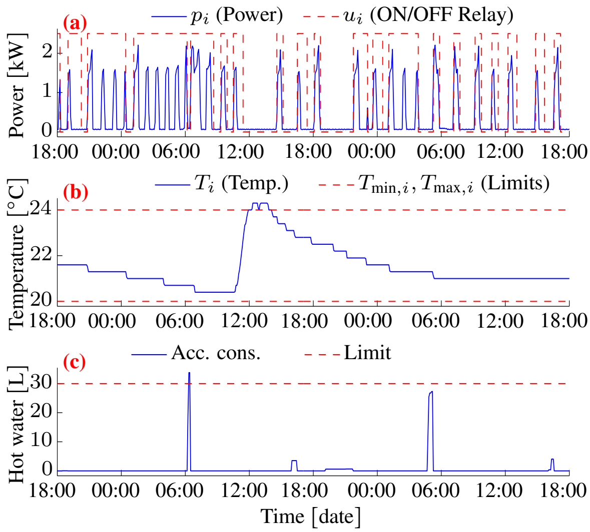

Figure 2.9: Measurements from a single heat pump. Subplot (a): ON/OFF relay and power consumption. Subplot (b): Indoor temperature and limits. Subplot (c): Accumulated hot water usage during OFF mode.

Primary frequency control

In this subsection we expand our focus to not just shift load according to the day-ahead market, but to provide actual ancillary services based on flexible consumers. The focus is on primary frequency reserve which is the most expensive ancillary service in the Nordic system, see Paper 11. The methods presented in this section is primarily based on Paper 8 but to some extend also Paper 7.

Providers of primary frequency reserve must keep a certain volume of flexibility in reserve and deliver power according to local measurements of the system frequency. Figure 2.10 illustrates this: an amount p_{prim} of symmetric primary reserve is sold which means that when the frequency deviation is given by Δf, the primary control action must be a delivery proportional with Δf however with a given allowable tolerance specified by f_{tol} and with an allowable dead band f_{db}.

It is allowed to deliver the service based on a portfolio of different devices as long as the aggregate response satisfy the regulations. In this work we propose a method where the VPP sends individual instructions to each single DER on how it should react to local frequency measurements such that a desired accumulated response is obtained. This will allow a portfolio of flexible ON/OFF consumers to together deliver primary reserve according to the current regulations which enables such devices to participate in the electricity markets which is desired.

Again, the choice of VPP strategy depends on what type of devices are in the portfolio and what the constraints are. In this work, we again consider energy-limited ON/OFF devices as described in (2.1). The key concept in the proposed method is to associate a subset of the devices in the portfolio with a *trigger frequency* t_i. These selected devices

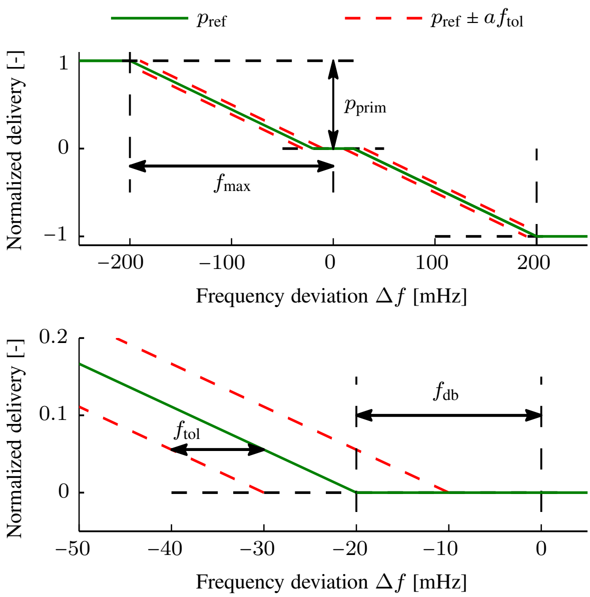

Figure 2.10: Primary frequency control droop curve with parameters from the ENTSO-E grid illustrating the power reference p_{ref} and the allowed tolerance bands for a normalized delivery.

must switch state according to the law

$$u_i(\Delta f(k)) = \begin{cases} p_i^{\text{nom}} & \text{if} \quad \Delta f(k) \geq t_i \quad \text{(device must turn ON)} \\ 0 & \text{if} \quad \Delta f(k) < t_i \quad \text{(device must turn OFF)} \end{cases} \tag{2.3}$$

where u_i is the consumption of device i and p_i^{nom} is the nominal consumption.

In Paper 8 a method is described how the trigger frequencies t_i can be assigned such that the aggregate DER response satisfies the droop curve specifications illustrated in Figure 2.10 while honoring the local energy-constraints of the consumers. As an example, Figure 2.11 from Paper 8 shows the result of an optimization of a diverse portfolio of 100 devices. The devices are associated with trigger frequencies enabling them to deliver the depicted droop curve. The details on how this allocation is done are found in Paper 8.

This is an illustration that flexible consumers can be used to not only shift consumption according to spot prices, but also to deliver more advanced high-value electricity services such as primary frequency control.

2.2 Integration of DERs in the electricity markets

This second part deals with the topic of integrating DER flexibility in the electricity markets. It thereby addresses Hypothesis 3 and is based on Paper 9 though Paper 11.

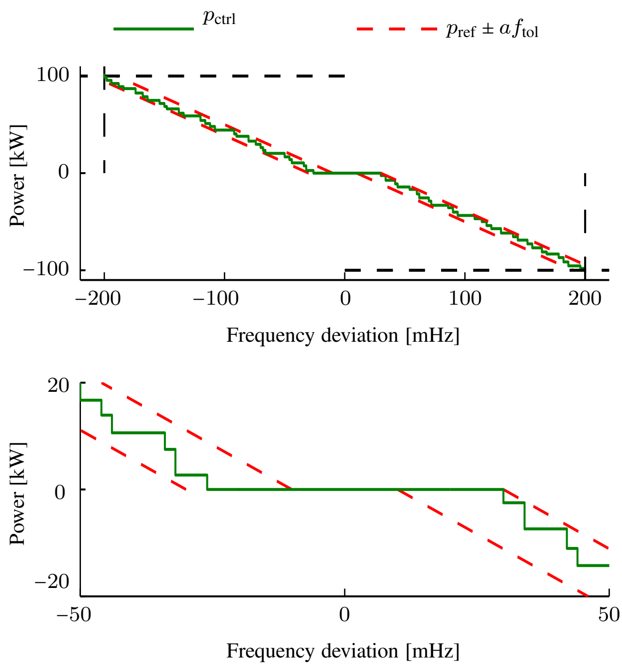

Figure 2.11: Allocation of ON/OFF devices that maximizes the delivery p_{prim}.

Motivation

Conventionally, the electricity markets have been designed to handle large centralized power plants. The centralized power plants are characterized by being dispatchable and able to reliably deliver large amounts of electricity. This is in contrast to many of the new distributed production units which typically only are able to deliver a smaller response and also often have a more non-dispatchable nature. The same is true for flexible consumption and storage devices, which typically are only able to deliver a limited amount of flexibility and also often have a more non-dispatchable consumption pattern.

It is therefore interesting to examine how DERs fit into the current electricity markets, examine the market barriers for these devices, and examine if improvements to the electricity markets can be made to better accommodate these new devices. In the following we first examine the value of DERs in the current electricity markets and identify the main market barriers for DERs. This is based on Paper 9 and Paper 10. Following; we propose a change in the electricity market structure to better integrate DERs as providers of flexibility. This part is based on Paper 11.

Market barriers and value of DERs in the electricity markets

The electricity markets are examined in great detail in Paper 9 and 10. The two largest markets, namely the electricity day-ahead spot market and the regulating power market, are examined and the main market barriers for storage devices and flexible consumers

	CAPEX		OPEX	
	Current	Future	Current	Future
Spot market	0	0[1]	$1 - 5,000$	$20 - 50$[1]
Regulating power market	$10 - 50,000$	0[2]	$2,000$	0[2]

Table 2.2: Marginal expenses per device active for spot optimization and regulating power provisions under current and future regulations.

are examined. The main barriers of enabling a device to be active in the day-ahead spot market are as follows.

1. The electricity consumption must be read on an hourly basis to allow spot market participation. The cost of being hourly metered is in the order of DKK $1,000$ – $5,000$ causing a large barrier.

2. It might be desired to have several electricity meters assigned with different electricity retailers within the same household or company. Such a setup will for example allow an aggregator to manage a portfolio solely consisting of flexible devices without managing the remaining inflexible consumption. It is, however, not currently possible to use an embedded electricity meter to allow a single device to receive separate settlement (for example an electricity meter embedded in a heat pump). Instead, a separate electricity meter must be installed which is significantly more costly (see the bullet above).

The main barriers of being active in the regulating power market are as follows.

1. Delivery of regulating power requires online measurements sent to the TSO. Consequently, this will be associated with both a CAPEX for installation of this equipment but also an OPEX for the ongoing expenses for the communication link.

2. The threshold for participating in the regulating power market is 10 MW which requires a large number of flexible consumption devices (for example in the order of 10,000 heat pumps).

3. A 5-minute operational schedule must be sent the day before operation showing the planned consumption for the following day of the flexible consumption device. The stochastic behavior of many consumers will make it difficult to make such schedules which consequently is another barrier.

To complete the conceptualization, we summarize the costs of making a single device able to honor the requirements of market participation in the current and future electricity markets. The costs for the future markets are based on planned market changes that are expected to take place over the coming years. The results are presented in Table 2.2 without further explanation; however, all details are found in the Papers 9 and 10.

[1]Expected costs in 2020 where the new market register DataHub is in place providing easy access to metered data, see [Ene13a].

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Now we can make the opposite analysis, namely examine the *value* that DERs can generate in these two markets. This allows us to examine which types of DERs are suitable to be utilized in the current electricity markets. The details for this analysis are found in Paper 10. We examine the revenue that a flexible consumer can generate over the course of a year by 1) participating in the spot market and 2) by participating both in the spot market but also the regulating power market. This is done for a flexible consumer with a normalized normalized energy capacity but varying power capacity (energy capacity represents the amount of kWh the consumer can "store", the power capacity represents how fast the stored energy can be charged and discharged). Historical spot and regulating power prices from 2011 are used and the work of [J1́0] is utilized to provide spot price forecasts. The chosen bidding strategies are found in Paper 10.

The results of a one-year simulation are shown in Figure 2.12 and should be interpreted as follows. The y-axis indicates the revenue per year in DKK per kWh of energy capacity available. We assume a liquid market where we do not influence the spot and regulating power prices, hereby the revenue will simply scale linearly with the energy capacity. The x-axis indicates the power capacity of the device ranging from $0-1$ kW/kWh. It is not required to examine higher power capacities than 1 kW/kWh: when the capacity is 1 kW/kWh we are able to fully fill/empty the energy storage in each hour.

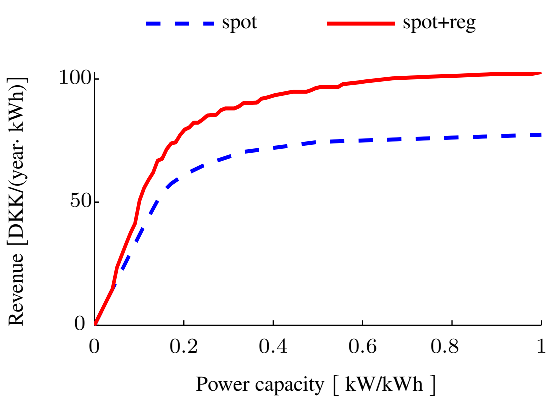

Figure 2.12: Revenue per kWh in 2011 for an energy storage when optimizing towards the spot market and when optimizing towards both the spot and regulating power market as a function of the consumer power capacity.

As the figure shows, the revenue curve is very steep from 0 up to around 0.3 kW/kWh, indicating that if the storage capacity for example is 1 MWh, then it is very profitable that the power capacity is at least around 300 kW. Higher power capacity will only slightly increase the possible revenue of the flexible consumer or storage device.

[2]The marginal cost can be 0 if the future market will allow the aggregator to utilize standardized equipment that already is embedded in the devices for other purposes and assuming we can communicate at no additional costs via the internet. This is, however, the most positive projections and may be far into the future.

We are now able to compare the revenue with the costs of being active in the market as specified Table 2.2. The following is observed.

1. *Spot price optimization.* An energy capacity of 20 – 70 kWh is required to break-even when considering the annual costs of hourly metering (assuming a power capacity of 0.3 kW/kWh).

2. *Spot and regulating power optimization.* An energy capacity of 70 – 230 kWh is required to break-even over a 5-year period when considering the investment costs and costs for the required equipment and communication (we assume a power capacity of 0.3 kW/kWh and an interest rate of 5 %).

3. *Future scenario.* If the revenue graph in Figure 2.12 is considered valid for the future scenario[1] and if the marginal expenses from Table 2.2 are used, an energy capacity as small as around 1 kWh is sufficient to break-even.

The general conclusion is therefore, that it is only economically reasonable to include relatively large devices in today's electricity markets, such as large industrial plants. However, the initiatives taken to mature the electricity markets may lower the expenses significantly allowing even small devices such as heat pumps to be utilized for market optimization.

Proposal for better integration of DERs in the electricity markets

The current electricity markets were defined in a time where dispatchable centralized power plants were the main providers of electricity. This, however, has the effect that non-dispatchable production devices and flexible consumption devices face several market barriers as described above, because the electricity markets are not designed for these devices.

In this subsection which is based on Paper 11, we examine how the current electricity market rules can be modified to better accommodate storage and flexible consumption devices. This work proposes a method for making better conditions for these types of devices to deliver ancillary services. The method is valid for the fast reserve markets such as primary reserve and secondary reserve (frequency control reserve and automatic generation control).

The method focus on the fast markets for two main reasons. The first reason is that flexible consumption devices and storage systems are well suited for fast reserves but less suited for slower reserves where large amounts of energy must be delivered. Many consumption devices are able to deliver a response fast enough even for primary reserve [XOT11, DGVN+11]; however, they are not able to provide actual energy deliveries as they only have a limited energy capacity. A battery system will for example only be able to deliver/consume a limited amount of energy before reaching the energy limitations; similarly, a consumption devices with a given thermal mass will only be able to shift a limited amount of energy before reaching the thermal comfort limits [BAS+13].

[1] It is difficult to predict how the market volatility will evolve: increasing penetration of renewables and increasing oil prices suggests higher and more fluctuating prices while increasing volumes of flexibility and new transmission cables suggest the opposite.

The second reason is that primary and secondary reserve are the most expensive reserves accounting for most of the turnover in the reserve markets, see details in Paper 11. The reason is that these reserves require fast actuation which is harder to deliver compared to regulating power (manual reserves).

The background for the proposal made in Paper 11 is as follows. A portfolio of flexible consumption devices and storage devices generally have two significant differences from conventional power generators when providing ancillary services. The first is that the portfolio will have a *limited energy capacity* whereas the conventional generator simply will be able to use more or less fuel. A heating system will for example have flexibility due to its thermal capacity; however, only a limited amount of energy can be stored depending on the temperature bounds that must be satisfied. This significantly limits the possibilities for flexible consumption devices to provide ancillary services. The reason is that the duration of services sold in the ancillary service markets are as long as one week and some markets one month. That means that the provider of the ancillary service should be able to deliver reserve throughout that period of time. In a worst case situation, the ancillary service provider may be required to provide large volumes of regulation in the same direction for long time periods, which will drive an energy storage to its capacity limit, i.e. it will exhaust the storage. For example, a thermal heating system will not be able to deliver large volumes of upward regulation (decreased consumption) for a long time period; eventually heating is needed.

The second difference is that a portfolio of flexible devices often not will have a well-defined *baseline*, i.e. the electricity consumption of the portfolio will not be exactly known many hours in advance as it depends on external parameters such as weather conditions or human behavior, which can be difficult to predict accurately. Many of the markets require an operational schedule the day before operation at noon for the 24 hours of the following day. The reason is that without a well-defined baseline, it is difficult to assess what services the portfolio actually has delivered; consequently, the lack of a baseline makes it difficult for flexible consumers to participate in the ancillary service markets under the current regulations.

In this work, we propose a method that resolves the issues of energy limitations and lack of accurate baselines *without* altering the existing ancillary service markets. In short, the method allows an aggregator via ICT to continuously adjust its operational schedule which is the baseline communicated to the TSO. This enables the aggregator to avoid violating the energy limitations of the consumption devices. The operational schedule adjustments must, however, be done under certain limitations ensuring that the TSO has sufficient time to activate slower reserves correspondingly.

The proposal is exactly in line with the general smart grid vision where a stable, reliable, and sustainable electricity system is ensured via ICT solutions [Ene12b, WDTD13, AADS13]. The proposal is as follows.

Proposal. *Operational schedules may be continuously adjusted throughout the delivery period. The TSO must be notified of the adjustment. The adjustment must satisfy the ramping and latency constraints of secondary or tertiary control. If the operational schedule is adjusted according to the secondary control constraints, the cost of secondary control shall apply for the difference between the original operational schedule and the adjusted operational schedule; similarly, if the operational schedule is adjusted according to the tertiary control constraints, the costs of tertiary control shall apply.*

Notice that although we propose a very specific method, this should merely be seen as an example. The main message of this work is not this exact proposed method; rather, that we in general can increase the possibilities for flexible consumers to participate in the ancillary service markets by having well-defined regulations that allow continuous adjustments of the operational schedule at a well-defined cost.

To illustrate the benefit of this method we present a small simulation example. The details of this example is found in Paper 11. We consider a portfolio of consumption devices with a constant baseline consumption of 1 MW which it is able to vary around with ± 1 MW however under strict energy limitations of 0.1 MWh, i.e. it can be considered an energy storage with capacity of 0.1 MWh and power limits ± 1 MW.

Now we use real frequency measurements from the ENTSO-E grid to simulate and compare the proposed method where we continuously adjust the operational schedule to a conventional situation where the operational schedule is not adjusted. The simulation is conducted as follows. The historical grid frequency deviation measurements Δf is translated to a certain required power consumption for the portfolio according to the ENTSO-E specifications for primary frequency control. For the conventional case, we simply let the portfolio consume the required electricity according to the reference dictated by the grid frequency deviations and examine the resulting energy level. This benchmark case is then compared to a case where the proposed method is utilized to restore the energy level via operational schedule adjustments. In this simulation, a simple controller is implemented that seeks to restore the portfolio energy level by continuously adjusting the operational schedule. This is further made clear in the following concrete simulation results.

In Figure 2.13, a four-hour period of operation is illustrated based on the historical frequency measurements presented in Subplot 1. Subplot 2 shows the resulting power consumption of the portfolio in the two situations illustrating that both strategies provide fast responses according to the demand. The consumption of the conventional strategy is directly dictated by the grid frequency deviation Δf; on the contrary, the consumption in the case where operational schedule adjustments are allowed is a function both of the grid frequency deviation but also of how the operational schedule is adjusted. Subplot 3 shows the energy level of the portfolio. This plot reveals that the conventional method with no operational schedule adjustments will require an energy delivery that is far outside the limits of the portfolio, while the presented method is able to stay within the limits. Subplot 4 shows the fixed operational schedule compared to the adjusted operational schedule. The operational schedule is adjusted under the latency and ramping constraints of secondary reserve which is the reason for the low frequency content in this signal.

The figure illustrates the method very well, namely that allowing the operational schedule to be adjusted can enable flexible consumption devices to deliver the expensive fast response while shifting the slow part of the response to other devices. The method proposed in this work consequently allows new providers of fast ancillary services to be able to enter the electricity markets and possibly replace the conventional fossil fuel based ancillary service providers.

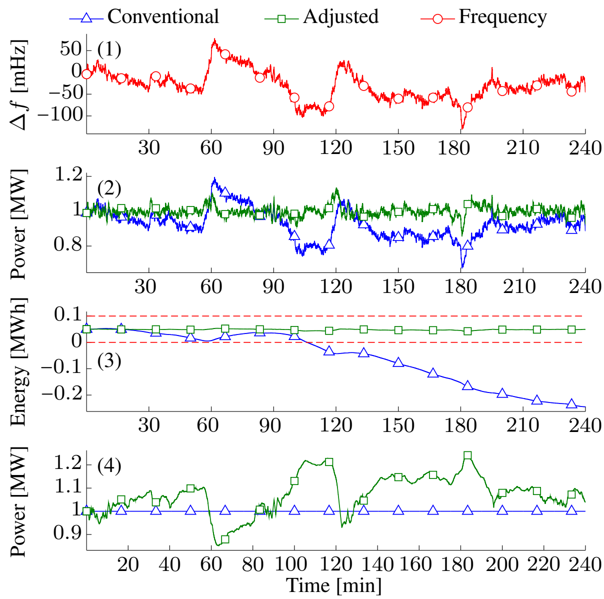

Figure 2.13: Comparison of the conventional case with no operational schedule adjustments and the proposed method where the operational schedule is adjusted. Subplot 1: System frequency deviation. Subplot 2: Portfolio power response. Subplot 3: Energy level of the portfolio. The dashed red lines indicate the energy limitations. Subplot 4: The adjusted operational schedule.

2.3 Utilizing DER flexibility to resolve distribution grid congestion

This section is concerned with utilizing flexibility from distributed energy resources as a means to resolve grid congestion. It addresses Hypothesis 4 and is based on Paper 12 through Paper 15.

Motivation

As previously mentioned, Denmark has an ambitious goal of 100 % renewables in all energy sectors by 2050. One of the necessary steps in reaching this goal is electrification of the transport and heating sectors such that these sectors can be supplied by green wind energy. An electrification via heat pumps or electric vehicles may cause congestion issues at the distribution level [IWA11]. Conventionally, congestion is resolved by reinforcing the grid; however, it is interesting to examine how flexibility on the production or consumption side can provide as an alternative solution to the issue of congestion.

Overall concept

In this section, we illustrate the concept of grid congestion at an overall level and show how dual decomposition can be utilized to resolve congestion in an idealized case. We examine a setup where we on the one hand desire to optimally utilize flexibility to achieve some given objective (e.g. reduce electricity costs) and at the same time want to avoid overloading the grid. This part is based on Paper 12, 13, and 14.

Consider a number of balancing responsible parties (BRPs) each responsible for a number of consumers under their jurisdiction. Each of these consumers belongs to exactly one BRP. The BRPs buy electricity at the day-ahead electricity market on behalf of the consumers. In the following, we illustrate how BRPs can utilize the flexibility of the consumers under their jurisdiction to minimize the imbalance between the purchased electricity and the consumed electricity thereby avoiding trading balancing energy at unfavorable prices.

Further, we show how the BRPs can be coordinated such that distribution grid congestion is avoided. Due to the competitiveness of the electricity markets, the BRPs are not willing to share local information such as objectives and states; therefore we use dual decomposition to resolve grid congestion. In this way, congestion management can be achieved without information sharing between the BRPs. Finally, we show how the dual decomposition method can be interpreted as a *distribution grid capacity market*.

Consider a star topology distribution grid (no loops) consisting of n_f distribution lines of limited capacity. A total of N BRPs are active in the distribution grid and BRP number i is responsible for $n_{x,i}$ consumers. The setup is illustrated in Figure 2.14 and discussed in detail in the sequel.

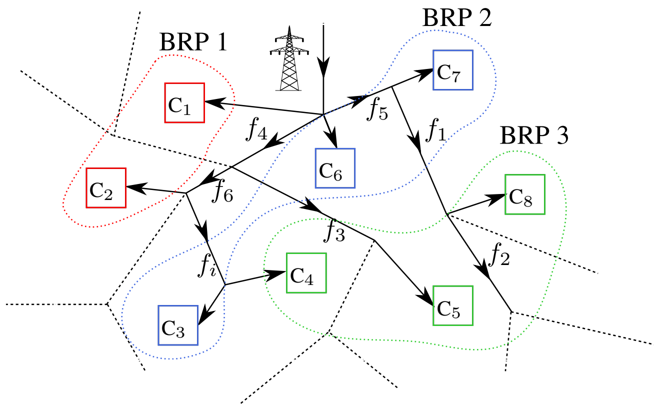

Figure 2.14: Interconnected consumers under the jurisdiction of different BRPs sharing the same distribution grid (dotted black lines indicate that only a small part of the total grid is shown).

The $n_{x,i}$ consumers under BRP i are characterized by an hourly electricity consumption given by $\mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k)$ where $\mathbf{u}_i(k) \in \mathbf{R}^{n_{x,i}}$ is the controllable (flexible) part of the consumption and $\tilde{\mathbf{u}}_i(k) \in \mathbf{R}^{n_{x,i}}$ is an uncontrollable base consumption. Due to the flexible consumption, the devices are able to *store* energy. We denote the amount of stored energy $\mathbf{x}_i(k) \in \mathbf{R}^{n_{x,i}}$ for the consumers under BRP i; this may be energy stored as either heat, cold, energy in a battery, or similar. The stored energy depends on the controllable power consumption

$$\mathbf{x}_i(k+1) = \mathbf{A}_i\mathbf{x}_i(k) + \mathbf{B}_i\mathbf{u}_i(k), \tag{2.4}$$

where $\mathbf{A}_i, \mathbf{B}_i \in \mathbf{R}^{n_{x,i}\times n_{x,i}}$ are diagonal with diagonal elements describing drain losses of each energy storage. The consumers are limited by power and energy constraints

$$0 \le \mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k) \le \mathbf{u}_i^{\max}, \qquad \mathbf{x}_i^{\min} \le \mathbf{x}_i(k) \le \mathbf{x}_i^{\max} \tag{2.5}$$

where $\mathbf{u}_i^{\max}$, $\mathbf{x}_i^{\min}$, $\mathbf{x}_i^{\max} \in \mathbf{R}^{n_{x,i}}$ describe these limits. Consumer models described this way can be found for example in [HKUA11].

The consumers are powered through the distribution grid, as illustrated in Figure 2.14. Each BRP will contribute to the loading of the distribution lines. Let $\mathbf{r}_i(k) \in \mathbf{R}_+^{n_f}$ denote the partial flow caused by BRP i to the n_f distribution lines; these partial flows can by flow conversation be described as

$$\mathbf{r}_i(k) = \mathbf{R}_i\left(\mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k)\right) \tag{2.6}$$

where $\mathbf{R}_i \in \mathbf{R}^{n_f\times n_{x,i}}$ is given by

$$(\mathbf{R}_i)_{pq} = \begin{cases} 1 & \text{if consumer } q \text{ under BRP } i \text{ is supplied through link } p, \\ 0 & \text{otherwise.} \end{cases}$$

This simply states that the power to each consumer under BRP i must flow through a unique path of distribution lines; these paths are indicated in the $\mathbf{R}_i$ matrix.

The distribution grid is protected from overcurrents by electrical fuses; hence, the distribution lines are subject to constraints. The total flows $\mathbf{f}(k) \in \mathbf{R}_+^{n_f}$ over the distribution lines and associated fuse limits can be expressed as

$$\mathbf{f}(k) = \sum_{i\in\mathcal{N}} \mathbf{r}_i(k), \qquad \mathbf{f}(k) \le \mathbf{f}^{\max} \tag{2.7}$$

where $\mathbf{f}^{\max}(k) \in \mathbf{R}_+^{n_f}$ denotes the limits of the fuses and $\mathcal{N}$ is the set of all BRPs.

The BRPs buy electricity at a day-ahead spot market for each hour of the following day. We denote the electricity bought by BRP i at the day-ahead spot market $\mathbf{p}_i(k) \in \mathbf{R}$; this means that BRP i has bought the electricity $\mathbf{p}_i(k)$ for the time interval from hour k to $k+1$. The objective of each BRP is to minimize the imbalance between the consumed electricity $\mathbf{1}^{\mathrm{T}}(\mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k))$ and the purchased electricity $\mathbf{p}_i(k)$, i.e.,

$$\ell_i(\mathbf{u}_i(k)) = \|\mathbf{1}^{\mathrm{T}}(\mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k)) - \mathbf{p}_i(k)\|_2^2, \tag{2.8}$$

where it is chosen to minimize the imbalance in the two-norm sense and where $\mathbf{1}$ denotes a vector of appropriate dimension with all entries equal to one. By keeping this imbalance small, the BPR minimizes the energy imbalances and thereby avoids trading balancing energy possibly at very unfavorable price.

The modeling reveals that the optimization problem is completely separable among the BRPs except for the coupling via the distribution line capacity constraints (2.7). We apply the dual decomposition algorithm presented in Paper 13 and Paper 14 to the presented application example and obtain Algorithm 1 when performing receding horizon control with a control horizon N_c and prediction horizon of $N_p = N_c$ samples.

Algorithm 1 Dual decomposition algorithm

1. Master initializes the prices $\boldsymbol{\Lambda}(k) \geq 0,\ \boldsymbol{\Lambda}(k) = \boldsymbol{\lambda}(k : k+N_c-1)$, where $\boldsymbol{\lambda}(k) \in \mathbf{R}^{n_f}$ and $\boldsymbol{\lambda}_j(k)$ is the price associated with the capacity limit of distribution line j at time sample k.

2. `repeat`

   a) Master broadcasts the current prices $\boldsymbol{\lambda}(\kappa), \forall \kappa \in \mathcal{K}$ to the subsystems.

   b) Each BRP locally solves the price dependent problem

$$\begin{array}{ll} \text{minimize} & \sum\limits_{\kappa \in \mathcal{K}} \left(\|\mathbf{1}^{\mathrm{T}}(\mathbf{u}_i(\kappa) + \tilde{\mathbf{u}}_i(\kappa)) - \mathbf{p}_i(\kappa)\|_2^2 + \boldsymbol{\lambda}(\kappa)^{\mathrm{T}} \mathbf{r}_i(\kappa) \right) \\ \text{subject to} & \mathbf{x}_i(\kappa+1) = \mathbf{A}_i \mathbf{x}_i(\kappa) + \mathbf{B}_i \mathbf{u}_i(\kappa), \quad \forall \kappa \in \mathcal{K} \\ & 0 \leq \mathbf{u}_i(\kappa) + \tilde{\mathbf{u}}_i(\kappa) \leq \mathbf{u}_i^{\max}, \quad \forall \in \mathcal{K} \\ & \mathbf{x}_i^{\min} \leq \mathbf{x}_i(\kappa) \leq \mathbf{x}_i^{\max}, \quad \forall \kappa \in \mathcal{K} \\ & \mathbf{r}_i(\kappa) = \mathbf{R}_i \left(\mathbf{u}_i(\kappa) + \tilde{\mathbf{u}}_i(\kappa) \right), \quad \forall \kappa \in \mathcal{K} \end{array} \tag{2.9}$$

   where the variables are $\mathbf{x}_i(k+1 : k+N_c), \mathbf{u}_i(k : k+N_c-1), \mathbf{r}_i(k : k+N_c-1)$. The solution is denoted $\overline{\mathbf{x}}_i(k+1 : k+N_c), \overline{\mathbf{u}}_i(k : k+N_c-1), \overline{\mathbf{r}}_i(k : k+N_c-1)$.

   c) Each BRP reports local partial flows $\overline{\mathbf{r}}_i(\kappa)$ to the master. The master centrally determines line capacity violations $\mathbf{s}(\kappa) = \sum_{i \in \mathcal{N}} \mathbf{r}_i(\kappa) - \mathbf{f}^{\max} \in \mathbf{R}^{n_f}, \forall \kappa \in \mathcal{K}$ where $\mathbf{s}_j$ is the capacity violation of line j and $\mathbf{S}(k) = \mathbf{s}(k : k + N_c - 1) \in \mathbf{R}^{N_c n_f}$.

   d) Master updates prices $\boldsymbol{\Lambda}(k)$ via projection: $\boldsymbol{\Lambda}(k) := \max\left(0, \boldsymbol{\Lambda}(k) + \alpha \mathbf{S}(k)\right)$. Notice that this corresponds to increasing the cost on congested lines and reducing the price on lines where there is free capacity; however, always assuring non-negative line prices.

   `until` $\max(\mathbf{S}(k)) \leq \epsilon$ or maximum number of iterations reached.

3. Master determines limits $\overline{\mathbf{c}}_i \in \mathbf{R}^{n_f}$ and communicates limits and final prices (shadow prices) to the BRPs.

4. Each subsystem locally solves Problem (2.9) with the additional constraint $\mathbf{r}_i(\kappa) \leq \overline{\mathbf{c}}_i$ and applies the first control input of the solution.

5. Increase k by one and repeat from 1.

The algorithm shows that the congestion management via dual decomposition can be interpreted as a new distribution grid market where each distribution line is associated with a time-varying cost per unit flow. If the lines are not congested, the BRPs are free to use the lines at no cost; however, if congestion occurs, the master will adjust the price on the lines until the congestion is resolved.

The sequence diagram in Figure 2.15 illustrates how this market can be imagined in an electrical power system setup. First, the individual loads communicate their flexibility (via states and predictions) to the individual consumers. Following, the consumers com-

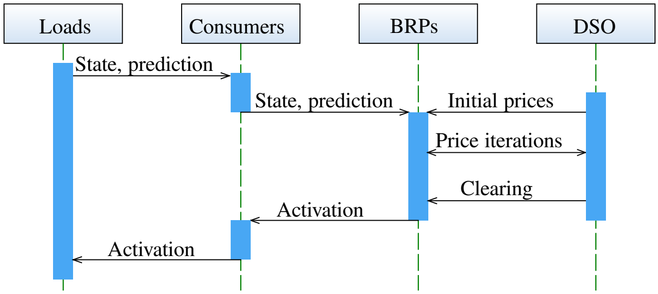

Figure 2.15: BRPs and DSO interaction resolving congestion.

municate the flexibility of all their respective loads to the corresponding BRP. Further, the BRPs are provided with initial prices on the distribution grid from the distribution grid operator (DSO) which has the role of the master. Based on this, a price iteration follows where the DSO adjusts the prices until all grid congestion issues are resolved. When the iteration is completed, the DSO clears the market by communicating final prices and line capacity limits for each BRP. Here it is important to note that the prices at the moment of the market clearing are *real prices* that will determine the economical settlement between the BRPs. From the perspective of a BRP, the prices on the distribution lines reveal the cost that the BRP will have to pay (or be paid) for using more (or less) of the line capacity.

Numeric examples on this method are found in both Paper 13 and Paper 14.

Concrete case study

The above subsection clearly shows the issue of grid congestion and the concept of using flexibility from distributed energy resources to resolve such issues. However, the approach presented above is idealized in many ways. Some of the main issues with utilizing the dual decomposition method in a real-world practical case are as follows. First of all, the method requires that the all balancing responsible parties know what connections (cables) their consumers are utilizing. This is, however, not known by BRPs in Denmark – only the DSOs know the topology of their respective grids. Second, the balancing entities must know the load of the individual consumers. This is also unknown to BRPs who might forecast the total load but not the load on consumer level. Third, a market must be established for *each* connection in the distribution grid which is also an issue as there are thousands of connections. Further, the method requires a possibly large number of price iterations at each time step making the method time consuming, complicated, and difficult to implement in practice. The method presented above using dual decomposition does illustrate the concept of resolving grid congestion. It is, however, difficult if not impossible to implement in reality.

For this reason we have made an investigation of this topic together with the Danish distribution company DONG Energy based on a concrete distribution grid and historical data. The focus of this work was to propose a concrete flexibility product that DERs can deliver, and to examine the value of such a product. In other words, to formulate a concrete flexibility product based on the DSO's actual needs and examine the expenses that a DSO can postpone by using a smart grid solution as an alternative to conventional grid reinforcement. The details of this work is found in Paper 15 and is summed up in the following.

As mentioned, the starting point of this case study is DONG Energy's distribution grid. DONG Energy serves around $980,000$ customers through its 50 kV and 30 kV high voltage (HV) grid, 10 kV medium voltage (MV) grid, and 0.4 kV low voltage (LV) grid. The MV grid which is the focus of this work, is a meshed grid operated as a radial (tree) grid. Each primary substation supplies a number of MV radial networks which are denoted *feeders*.

This distribution grid has a default topology defined by the DSO. If a feeder is in its default topology, it is said that the feeder is in *normal situation*. The grid topology can, however, be altered via switches to ensure supply during maintenance or grid faults. This is known as *reserve situation* and occurs on average around 1 time per year for each connection. The DSO regularly optimizes the grid based on historical data to find the optimal normal situation with the lowest losses and where consumers can be supplied by neighboring feeders in case of a worst case fault (also known as a $n-1$ situation).

Different issues can occur in the distribution grid if the consumption in Denmark gradually will increase due to the aforementioned electrification. The issue can be either power congestion or low voltage quality; further, it can either be an issue when the grid is in normal operation or in reserve situation. This gives a total of four different possible issues.

In this work, the focus is on the issue of power congestion in the reserve situation. There are two reasons for this choice. First, an analysis of DONG Energy's grid reveal that for 63 % of DONG Energy's feeders, the first issue that will occur as the load increases is reserve situation congestion. Second, distribution level services is a new and unproven concept. Therefore, using such services in the rare reserve situations seems like a natural first step instead of relying on these services in normal daily operation.

The distribution grid service considered in this work is designed specifically to support the grid if an unexpected reserve situation occurs, i.e. it addresses the issue of power congestion in reserve situation as discussed above. The concept is as follows. Once a failure in the gird occurs, the grid operators will examine how to reconfigure the grid to supply the faulty feeder. While doing so, the grid operators will have the possibility to activate the contracted distribution grid service. Upon activation, the flexible devices are obliged to reduce consumption or increase production according to the contract agreement. As mentioned previously, such flexibility contracts will allow the DSO to postpone grid reinforcement which is the DSO's incentive to purchase the proposed flexibility service. The distribution grid service can be defined using the following simple contract illustration.

Contract parameter	**Example**
Contract duration	1 year flexibility contract.
Seasonal constraint	All weekdays in Dec. – March.
Time-of-day constraint	From 4 pm to 8 pm.
Amount	300 kW.
Expected no. of activations	One per year.
Time from activation to delivery	At most 30 minutes.
Payment	$2,000$ €/year and 0 €/activation.

This represents a service that can be activated upon unexpected faults in the grid to avoid overload. It is important to notice that the flexibility product described above can be seen as an implementable flexibility product, as it is directly tailored to a concrete issue in the distribution grid.

Based on data from the distribution company DONG Energy, an analysis is made of the value of a product as the one described above. This gives insight into the feasibility of using DERs to provide flexibility at the DSO level. The following list describes at an overall level the method used to estimate the value of the proposed flexibility product. A more detailed description of the method is found in Paper 15.

1. The starting point is a feeder where historical data shows that the first issue that will occur as the load increases is *power congestion in reserve operation*.

2. The feeder is simulated as having a worst case fault causing a reserve situation.

3. The historical load is upscaled until at least one connection in the feeder reaches its current limit.

4. The load is further gradually increased. The amount and duration of flexibility that is required to resolve the congestion issues that arise according to the increased load is determined. Further, the corresponding cost of solving the issue via conventional reinforcement is also determined.

The last bullet allows us to compare the cost of grid reinforcement with the amount of flexibility required to solve the same issues.

Figure 2.16 shows the result based on 10 feeders in DONG Energy's distribution grid and compares the cost (top plot) of grid reinforcement with the power (middle plot) and duration (lower plot) of flexibility required to resolve the congestion that arises as the load is increased according to the value on the x-axis. Notice that there are two lines, a blue and a red which respectively describe the need for flexibility when a current and a temperature limit is used for the cables. Using a temperature limit instead of a current limit is less conservative and allows the grid to be utilized to a higher extend. This is, however, not discussed further here, but more details on this are found in Paper 15.

A number of interesting results from DONG Energy's grid are evident from Figure 2.16.

1. For the first few percent of up-scaling, the cost of grid reinforcement is in the order of M€ 0.15 and the required flexibility is in the range of $100 - 200$ kW for $1 - 4$ hours; however, with a large uncertainty (high standard deviation).

2. Consequently, the DSO's value of this flexibility product ($100 - 200$ kW for $1 - 4$ hours) with an expected value of 1 activation per year is in the order of € $7,500$/year[2].

[2]This value is found as the value of postponed investments. Using a cost of M€ 0.15 and assuming 5 % interest rate gives a value of € $7,500$/year in interest savings, see further details in Paper 15.

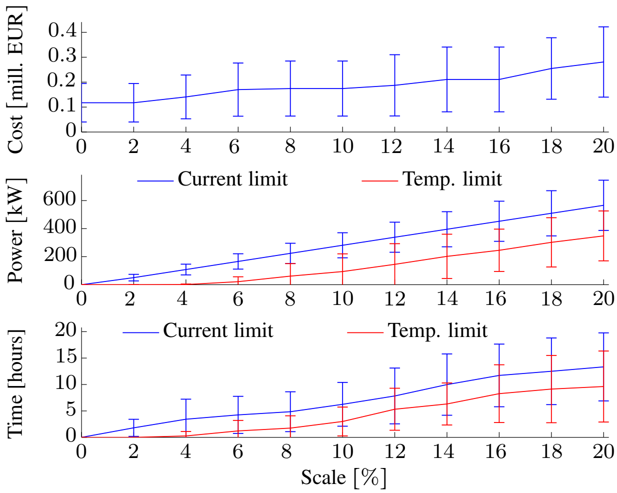

Figure 2.16: Top: Average cost of grid reinforcement. Middle and bottom: Average amount and duration of flexibility. Vertical bars indicate the standard deviation.

3. As the load increases above $15\ \%$, the flexibility service duration is in average above 12 hours which is an indicator that flexibility at this point may no longer be a solution[3].
4. Exploiting thermal dynamics of the cables allows for approximately $5\ \%$ extra load.

In conclusion, the DONG Energy case study reveals that the proposed flexibility product indeed is valuable to the DSO as savings in the order of € $7,500$ can be obtained.

[3]It is difficult for many flexible consumers to shift consumption for time periods longer than a few hours as this often will compromise the primary process of the device. If the flexibility is delivered by a production device it may, however, not be a problem.

3 | Conclusion

In this thesis we have examined the smart grid concept where flexible consumers and distributed production devices act as resources of flexibility. We examined both the transmission level and the distribution level. On the transmission level we examined how flexibility from flexible consumers and distributed production can be used to provide system stabilizing ancillary services to support the system operator. On the distribution level we showed how flexibility can be utilized to resolve congestion as an alternative to conventional grid reinforcement. In the following we conclude the thesis, first by examining the four hypotheses of the thesis from Sec. 1.4; following, we provide a more overall conclusion based on the experiences made throughout this PhD-study.

3.1 Conclusion on proposed hypotheses

The 15 papers included in this work go a long way in addressing the four hypotheses proposed in Sec. 1.4. We will discuss this in the following.

The first hypothesis deals with the question if it is possible to utilize a technical VPP to aggregate a number of flexible consumers to provide a response that can be sold in the electricity markets. At the same time, the consumers must not experience discomfort. This hypothesis is addressed from several perspectives. In Paper 1 the concept of aggregation of flexibility is addressed and methods for adequate communication between a VPP and consumption devices is proposed. Following, Paper 2 describes how contractual agreements can be made allowing a VPP to legally utilize the consumers' flexibility. Paper 4 and 5 describe VPP methods for monitoring the flexibility of a portfolio of consumers and further propose an algorithm for control of a large number of consumption devices while respecting local constraints. This enables the VPP to know the available flexibility and to control it according to the electricity markets and at the same time ensure comfort for the consumers. Finally, Paper 6 shows the results form a real life demonstration where 54 heat pumps in inhabited households were aggregated and controlled to track an hourly power reference while ensuring comfort for the inhabitants. We can therefore validate this hypothesis by concluding that it indeed is possible to model flexibility, to aggregate and control flexibility, and to deliver services in the current electricity markets without violating local consumer constraints.

The second hypothesis goes along the line of the first hypothesis and proposes that it is possible for an aggregator to generate profit in the current Nordic electricity markets based on a portfolio of flexible consumers. Paper 3 addresses this question by utilizing market data and meteorological data to simulate a portfolio of heat pumps being optimized based on forecasts of the electricity spot prices. The paper reveals that annual savings in the order of 20 % can be achieved. In Papers 7 and 8 the primary frequency control market is examined, as this is the most expensive of the Nordic markets. In Paper 8 an algorithm is proposed making it possible to aggregate ON/OFF consumers, such as thermal devices, such that they honor the current regulations for primary control reserve. Simulations verify the validity of this method. Based on these papers we can conclude that it is possible to aggregate flexible devices to deliver electricity services according to the current regulations and thereby generate value. We can hereby validate the second hypothesis.

The third hypothesis states that the market uptake of flexible consumers may be increased by appropriately altering the electricity markets. Paper 9 and 10 show that there indeed are a number of market barriers in the current electricity system. Following in Paper 11, the hypothesis is addressed directly and a concrete market change is proposed. The proposed market change makes it easier for storage devices and flexible consumers to enter the primary control market. Simulations are included that validate the proposed method. Thus, the paper proves the hypothesis, namely that new regulations can allow new types of devices to enter the electricity markets.

In the final fourth hypothesis, the focus is on the distribution grid, and whether flexible consumers can generate value for the distribution system operators. In Paper 12, 13, and 14 the general concept of utilizing flexibility to resolve grid congestion is proposed. Further, it is discussed how this can be done via a market approach. Following in Paper 15, a concrete case study is completed. A flexibility product is proposed that addresses a specific congestion issue that may occur in the distribution grid, and real life data from a distribution grid company is used to estimate the value that flexibility can have to a DSO. The conclusion is that a flexibility product in the order of $100 - 200$ kW and $1 - 4$ hours activated 1 time per year has a value around $7,500$ Euro per year. We can hereby validate this hypothesis and conclude that consumption/production flexibility in the distribution grid indeed has a significant value for distribution system operators.

3.2 Overall conclusion

In the following we make an overall conclusion of the thesis. The basis is the written papers included in this work, written iPower reports, participation in numerous smart grid workshops and conferences, discussions and collaboration with DSOs, the Danish TSO, companies producing flexible consumption devices, energy companies, the Danish Energy Association, several Danish universities, and visits to more than 20 international top-research institutions within the field of smart grid.

It is evident that huge changes will happen in the Danish electricity system. On the production side the conventional fossil fueled power plants will be replaced by distributed production such as wind, solar, and decentralized bio power plants. Large changes will also happen on the consumption side where electrification of the heating and transport sector is expected.

Similarly, large changes are expected in the electricity markets. The increase in renewables will generate a higher demand for ancillary services while the conventional providers of these services are phased out. Further, the electricity markets are merging with the neighboring countries such as the German electricity market.

These two perspectives are very interesting: On one side many new devices are entering the electricity system – on the other side the demand for services will increase and new market opportunities will arise as the European markets merge. Consequently, there will be room for players that are able to utilize the new consumption and production devices as sources of flexibility to meet the increasing demand and the new market opportunities. Smart grid solutions are very interesting in this context, as a means to harness flexibility among the new types of consumers and utilize it in the existing and arising electricity markets.

It is evident from the papers in this work that the business case in the current markets is very limited. Some of the papers show that only devices with an energy capacity in the order of hundreds of kWh can break even in the two largest markets today. This means that only very large industrial consumers will benefit from market participation. Elsewhere in the thesis we show that the electricity savings for a heat pump is in the order of $20\ \%$ of the electricity cost corresponding to approximately 50 Euro per year which is a very small number compared to potential expenses to equipment and additional communication. Finally, we estimate the value of hundreds of kW of flexibility at the distribution level accounts to around $7,500$ Euro annually. This value has to be split between the DSO, an aggregator, and the owner of the flexible device. Consequently, this accounts to a very small value especially in the light of the man-hours required to locate the source of flexibility, set up the contractual agreement, analyze if the flexibility source indeed is able to resolve congestion, etc.

The above statements may seem very negative from a smart grid perspective. However, on the contrary, the previous section just emphasizes that the solutions we are looking for are not simple and straightforward. They must really be *smart*. For example, aggregators must be able to utilize the same flexibility in several markets to generate sufficient value. Also, the aggregators must clearly examine what markets are most beneficial and aim at exactly these markets. As the Danish electricity system is very well interconnected to neighboring countries, the prices are not very volatile and Denmark may consequently not be the place where smart grid solutions have the most value. Finally, timing is key. As mentioned in several papers, many initiatives are ongoing in Denmark which seek to increase the market uptake of flexible resources. Energy companies must consequently pay close attention to the modifications of the market regulations and examine if the changes open opportunities for new business cases.

3.3 Perspectives

As a concluding remark, I want to share three concrete smart grid ideas/concepts I believe would be most interesting and valuable to investigate further – both from an academic and a commercial point of view.

The fist idea is to show that it is possible to remote control thermal loads that are equipped with intelligent thermostats. Such devices are off-the-shelf products available for example from Honeywell, Danfoss, LG, and NEST. This type of intelligence may be standard in average homes in a number of years. As such intelligent equipment inherently have embedded microprocessors and communication equipment, the equipment needed for smart remote control is already in place and paid for. Consequently, there should be a business case for doing aggregation and control of such assets.

The second idea is to examine the possibility of constructing a “micro grid” for a smaller population of EVs that are located in the same geographical area. This could for example be on a residential shared parking lot, at a company’s parking space, in the parking lot of a mall, etc. The micro grid will consist of the EV population (in the order of five to a few hundred EVs), solar panels, and a battery. The combination of these three elements allows a number of mutual benefits: the aggregate vehicle consumption can be managed to not violate the low voltage and medium voltage grid constraints. The local DSO might be willing to pay for this services as even a few EVs charging simultaneously may congest the low voltage grid. Further, the aggregator can assure that the cars primarily rely on electricity from the solar panes by storing the electricity in the micro grid battery. This is beneficial as it is free to use the electricity locally while it is expensive to purchase electricity from the grid because of taxes, and as the income for selling surplus electricity is low. Further, the aggregated vehicles and the battery will be able to provide fast system stabilizing services which can be sold to the TSO (when pooled with sufficiently many other sources of flexibility). Finally, the load pattern could be controlled to purchase electricity differently at the day-ahead and intra-day markets. This illustrates that there are at least four benefits that together may make a profitable business case that supports the transition to a green transport sector.

Finally, the third idea is to construct a “flexibility clearing house” that links the power markets with smaller and uncertain providers of flexibility such as flexible consumption and distributed production. This link is missing due to the electricity markets which often demand deliveries of long duration and high power. For example, the Danish market for primary reserve is merging with the German market, where the duration is 1 week and the minimum power threshold is 5 MW. Many of the flexible consumers and distributed producers are not able to guarantee a delivery for such a long duration. Further, the minimum power threshold is so high that even aggregators with many devices may not be able to meet this requirement. It is the job of the flexibility clearing house to resolve these issues. This can be done by dividing the long-duration and high minimum power threshold markets into deliveries of short duration and lower power limits. This will allow new sources flexibility to deliver system stabilizing services and replace conventional fossil fuel based providers.

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Contributions

Paper 1

Information Modeling for Direct Control of Distributed Energy Resources

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Abstract

We present an architecture for an unbundled liberalized electricity market system where a virtual power plant (VPP) is able to control a number of distributed energy resources (DERs) directly through a two-way communication link. The aggregator who operates the VPP utilizes the accumulated flexibility of the DERs to participate in the electricity market on equal terms with conventional power plants. The focus of this paper is the interface between the DERs and the VPP: this interface must enable the aggregator to overview the total DER flexibility and remote control the DERs to provide a desired accumulated response. In this paper, we design such an information model based on the markets that the aggregator participates in and based on the flexibility characteristics of the remote controlled DERs. The information model is constructed in a modular manner making the interface suitable for a whole range of different DERs. The devised information model can serve as input to the international standardization efforts on DERs.

1 Introduction

With an increasing focus on climate-related issues and rising fossil fuel prices, the penetration of renewable energy sources is likely to increase in the foreseeable future throughout the developed world [1]. Many actions are taken from a political point to increase the penetration of renewables: in the US almost all states have renewable portfolio standards or goals ensuring a certain percentage of renewables [2]. Similarly, the commission of the European Countries has set targets increasing the share of renewables in the final energy consumption to 20 % by 2020 [3] while China has doubled the wind power production every year since 2004 [4]. In Denmark, the 2020 goals 35 % sustainable energy and 50 % wind power in the electrical power consumption [5].

As a consequence of this increase in renewables, the power system is moving from a setup with few centralized conventional power plants to a setup with a large number of distributed, smaller production units [6]. As an example of this evolution, Denmark has moved from a situation with a total of 16 central power plants in 1980, to a system which today consists of 16 central power plants, 1000 local combined heat and power plants and around 6000 wind turbines [7].

The conventional power plants are currently the main providers of grid stabilizing services. As they are phased out gradually and replaced by distributed energy resources (DERs), alternative sources of ancillary services must be found. One of the approaches towards alternative ancillary services is the *smart grid* concept, where DERs such as smaller generation devices or flexible power consumers take part in the balancing effort [8], [9]. The basic idea is to let an *aggregator* manage the accumulated flexibility of the DERs to provide responses similar to those of the conventional power plants. This allows the aggregator to participate in the unbundled electricity markets using DER flexibility.

Control of DERs to support grid stability has been discussed as early as the 1980s [10]. Since, this topic has received much attention research perspective [11, 12, 13]. A few research examples in the area of smart grid DER control are: optimization of domestic heat pumps [14, 15], supermarket cooling systems [16, 17], domestic refrigerators [18, 19], and electrical vehicles [20, 21]. While these works, and many more, discuss methods for remote control of DERs, they do not discuss who the DERs should communicate their flexibility to the VPP.

It is, however, a crucial element in the aggregation and control of flexibility is that the DERs are able to represent their flexibility in a generic manner, such that the aggregator can obtain an overview of the available flexibility and control the DERs accordingly. This *flexibility interface* between DERs and VPP is the focus of this work. In the literature, standards exist defining protocols for control of substations such as wind turbines, combined heat and power plants etc. See, [22, 23]. Also, standards exist for remote control of various domestic appliances [24, 25]. However, these standards are not developed with the focus on flexibility aggregation for market participation and are thus not directly applicable in this setup.

In this paper, we show how a flexibility interface information model can be developed by identifying the flexibility characteristics of the DERs it is desired to be able to control, and by considering the markets that the aggregator should be able to participate in. We show this by identifying the flexibility characteristics of a number of key DERs and by examining the electricity markets. Based on this, we design and present an information model for the flexibility interface.

The structure of the paper is as follows. First, in Section 2, we describe the overall setup and architecture; following, in section 3, we describe a number of DERs and identify their flexibility characteristics. In Section 4, we describe the services that the aggregator should be able to provide, and in Section 5, we describe the role of the VPP. Finally, in Section 6, we present an overview of the developed flexibility interface information model and in Section 7, we conclude the work.

2 Overall Setup

This section briefly outlines the topic of this paper: the interplay between a number of DERs and an aggregator through a flexibility interface. Later, in sections 3, 4 and 5, more detailed descriptions of DERs, services and the aggregator are presented.

Distributed Energy Resources

DERs are smaller production units such as wind turbines or photovoltaics, or flexible consumption units such as heating and cooling systems or electric vehicles. Generally, the flexibility of each DER is smaller than the threshold for bidding into the electricity markets; it requires aggregation with other DERs to reach a volume large enough to enter the markets.

A DER is moreover characterized by being equipped with a local controller enabling the unit to operate autonomously. This local controller is assumed able to estimate the available flexibility of the DER, i.e. how flexible the DER is in the production/consumption of active/reactive power. Additionally, the DER is able to be remote controlled by receiving commands from an external controller; this allows for an aggregator to actuate the DER flexibility.

The purpose of the remote control is to utilize the flexibility of the DER without interfering in the primary process of the DER. We illustrate this ability to perform local control while allowing remote control with two examples. As an example from the demand side, we consider a supermarket freezer system. A freezer system is able to ensure correct cooling of goods, and within limits it is also able to offer flexibility in the active power consumption due to the large thermal time constants of the system. This flexibility can be remotely controlled by an aggregator.

This paper deals with aggregation and management of DERs via remote control of flexibility, enabling a portfolio of DERs to provide an accumulated response large enough for actual bids in the power and reserve markets.

Direct Control

Generally, two main approaches are envisioned when describing aggregation of DERs and in particular flexible consumption devices. These approaches are referred to as *direct control* and *indirect control* of the device [26, 27]. Direct control refers to a setup where two-way communication exists between VPP and DER: the DER reports its local flexibility to the VPP and the aggregator controls the DER through the VPP based on this information. The basis for direct control is an agreement/contract between each DER owner and the aggregator that uses the VPP. The contract describes to what extend and at which cost the aggregator is allowed to utilize the DER flexibility. In contrast, *indirect control* refers to a setup where a one-way signal is sent from aggregator to DER without any direct feedback from the DER (possibly the aggregator will get indirect feedback through grid measurements etc.).

This paper deals exclusively with a *direct control* setup between the DERs and the VPP. The flexibility interface information model developed in this work therefore only refers to the case where the DERs are directly controlled by an aggregator through a VPP.

Aggregator and VPP

The flexibility of a single DER is too small to make isolated bids into the electricity markets; for example, the threshold for primary frequency control reserves is 300 kW in Eastern Denmark [28]. For this reason, several DERs must be aggregated in order to achieve sufficient quantities of active or reactive power for bidding. Therefore, the role of the aggregator is to make contracts with the DERs, allowing the aggregator to utilize the DER flexibility through the VPP. Consequently, this enables the VPP to

- retrieve information of the flexibility limits of the DERs
- retrieve information of the cost of utilizing the flexibility
- manage the DERs within the given flexibility limits.

Flexibility Interface

We are now able to illustrate and describe the overall setup of this paper, see Figure 4.1. The figure illustrates an aggregator managing a total of n DERs through its VPP. This enables the aggregator to bid aggregated flexibility into the power markets. The flexibility interface, which is the topic of this work, is located between the local controllers of the DERs and the aggregator's VPP managing the DERs. The interface facilitates the two-way communication link making it possible for the DERs to report their flexibility to the VPP of the aggregator and making it possible for the aggregator to manage the DERs.

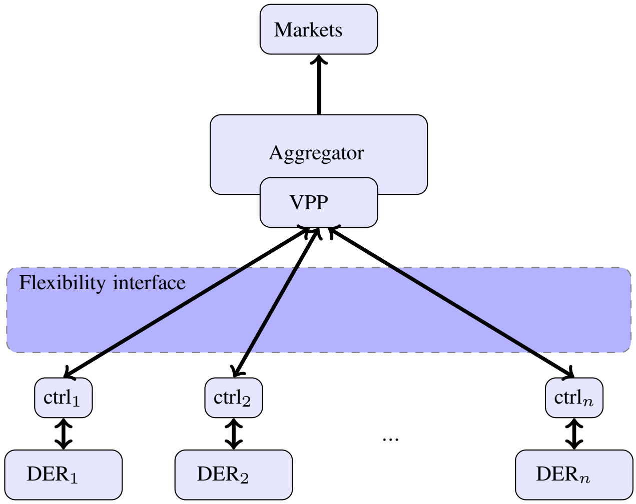

Figure 4.1: Aggregator manages n DERs through the VPP via a flexibility interface.

3 Distributed Energy Resources

The purpose of this section is to identify the various DER flexibility characteristics that the flexibility interface must be able to handle. These characteristics form a background for the actual flexibility interface presented later.

In [29], flexibility descriptions of a number of DERs are presented. In terms of power flexibility, the key DERs include:

- space heating systems
- electrical vehicles
- diesel generators
- hydro power plants
- domestic appliances
- combined heat and electricity generation
- photovoltaic systems.

By examining the functionality of these DERs, their flexibility characteristics can be identified [29] resulting in a list of various types of characteristics. These characteristics are presented in Table 4.1. The flexibility interface must be able to handle these different flexibility characteristics.

4 Supported Services

In this section we describe the services that the aggregator must be able to deliver and how this affects the requirements to the flexibility interface. The services are divided into three

Flexibility characteristic	Examples
Continuous/discrete active/reactive power limits	Electric vehicle able to consume power in the interval 1 kW to 6 kW.
Energy limitations	Refrigeration system able to store a total of 1 kWh.
Power reference tracking possible	Heat pump for space heating that can follow a remote power reference.
Power scheduling possible	Large scale chiller system able to perform 24 hour power scheduling.
Maximum/minimum runtime/stoptime	Heat pump must run for at least 15 minutes when started.
Minimum down-time	Heat pump must stay turned off for at least 15 minutes after turned off.
Fixed consumption, flexible activation time	Domestic appliances with flexible startup time (within certain time span).
Energy storage dynamics	Freezer system where the energy loss depends on temperature difference to ambience.
Coupled active/reactive power production/consumption	PQ-capabilities in inverter systems.
Energy storage with terminal energy constraint	Charging of an electric vehicle battery that must be fully charged at certain time.
Active/reactive power ramping limitations	Power ramping limits of wind turbine.
Flexibility costs	**Examples**
Energy level dependent cost	Discomfort cost for temperature deviations in heated houses.
Active/reactive power production dependent cost	Cost for derating the active production of a wind turbine.
Unit startup/shutdown costs	Cost for starting up a generator.
Activation time dependent cost	Cost related to the startup time of a flexible startup time appliance.

Table 4.1: Flexibility characteristics and costs.

main areas: distribution level services, transmission level services and day-ahead/intra-day services.

Distribution Level Services

The distribution level deals with the power lines from 0.4 kV up to 60 kV. Currently, distribution level markets do not exist but can be envisioned in the future electricity system as e.g., described in the Danish iPower project [30].

Distribution Grid Congestion Management

It is anticipated that congestion management on the distribution grid will become an issue in the future when larger quantities of for instance heat pumps and electric vehicles are introduced, significantly increasing the load. Therefore, distribution grid congestion management markets might be introduced in the future.

Local Voltage Control

It is anticipated that local voltage control will become an issue of increasing importance, as more DERs are put into operation. In cases where many DERs will be located on the same distribution line, this may affect the voltage quality, for example with many photovoltaics on the same line. It is possible to resolve voltage problems via grid codes by embedding voltage controllers at the DERs, but this method would mean that the producers of the DERs (and eventually the consumer) will be the ones paying for the grid voltage control. Another approach is to establish a market for local voltage control where voltage stabilizing services can be bought or sold.

Transmission Level Services

At the transmission grid level, the transmission system operators (TSOs) are responsible for secure and reliable system operation. This entails keeping balance between production and consumption as well as maintaining power quality and ensuring a stable transmission system. Generally, in an unbundled power market, TSOs do not own production units, they therefore have to procure ancillary services from suppliers.

Primary Frequency Reserve

The primary frequency reserve is an automatic control used in frequency control. A main target for the primary control is to stabilize the frequency in case of major outages of either loads or suppliers. The primary control reserve is required to sustain until relieved by the secondary control [31]. The time scale for activating primary frequency reserve is in the area of 10-30 seconds. The primary frequency reserve must be based on a local control loop using local system frequency measurements.

Secondary Frequency Reserve

The secondary frequency reserve, often referred to as the AGC (Automatic Generation Control) is activated by a TSO reference signal. The objective of the secondary control is to restore power balance in a control area, to take part in stabilizing the frequency, and to restore the primary reserve [32, 33]. The time scale for activation of secondary reserve is in the magnitude of 15 minutes.

Tertiary Frequency Reserve

Tertiary control is a reserve that can be activated manually by the TSO. Upon activation, the provider of the reserve will change the planned operation such that the necessary upward or downward regulation is achieved. The purpose of tertiary reserve is to resolve persistent balance or congestion problems and in this way restore the secondary and primary frequency reserve [31]. The time scale of activating tertiary reserve is in the time-frame from seconds up to 15 minutes [32].

Mvar-bands (Mega volt-ampere reactive bands)

The Mvar-bands are used in the Nordic system to represent certain limits on the flow of reactive power between the distribution and transmission grid. As an example, Denmark is divided into 15 Mvar regions. In each region, Mvar limits are given describing the maximum/minimum reactive power flow to/from the regions. The goal is to restrict the transport of reactive power in the transmission grid such that there is a high active power capacity. Because of these bands, the distribution system operators (DSOs) are required to control the exchange of reactive power in case the bands are in risk of being violated. The DSOs will typically perform this control by activation/deactivation of shunt capacitors, static var compensators, STATCOM generators or synchronous condensers. It would, however, also be possible for certain DERs to provide such reactive power services, e.g., wind turbines, combined heat and power plants. Therefore it might be possible to envision a future market for trading reactive power [34].

Day-ahead and Intra-day Services

In the day-ahead and intra-day markets, active power is sold and bought for one hour slots. The supply and demand will determine the market price for the active power.

Day-ahead Market

In the day-ahead market, power is bought and sold for the 24 hours of the following day. The Nordic day-ahead market Elspot, closes at 12:00 CET every day; by this time, bids for buying and selling power for the 24 hours of the following day must be submitted. At 13:00 CET, the resulting spot-prices and traded volumes are published.

Intra-day Market

In the intra-day markets, power is bought and sold for one-hour time slots closer to the operational hour. In the Nordic market, the intra-day market Elbas closes 45 minutes before the hour of operation.

Service Characteristics

Based on these descriptions, we sum up the characteristics relevant for the design of the flexibility interface information model.

- *Time scales:* from minutes in the faster ancillary services, up to 36 hours in the day-ahead spot market.
- *Geographical location*: the location of the DER in the grid is important in the case of distribution grid services.
- *Local control or remote control*: in the case of primary frequency reserve, the grid frequency must be measured locally and a local control loop determines the activation of the primary reserve. In contrast, secondary reserve provision must be activated based on remote signals.
- *Combined deliveries*: some services can only be provided by either only consumption units or only production units. Therefore it is necessary to distinguish between production and consumption units.
- *Active/reactive power*: both active and reactive power must be communicated through the flexibility interface.

5 Virtual Power Plant

The VPP must be able to overview the total flexibility of the DERs presented in Section 3 and manage this flexibility to participate in the markets described in Section 4. Several VPP control strategies can be imagined for managing the DERs to provide the contracted services. In, e.g. [35, 36, 37], a VPP control objective on the following form is used:

$$\begin{array}{ll} \text{minimize} & \sum_{i \in \mathcal{I}} \sum_{\tau \in \mathcal{T}} \ell_i(x_i(\tau), u_i(\tau)) \\ \text{subject to} & x_i(\tau) \in \mathcal{X}_i(\tau),\ u_i(\tau) \in \mathcal{U}_i(\tau), \quad \tau \in \mathcal{T}, i \in \mathcal{I} \end{array}$$

where $\mathcal{I}$ is the set of all DERs and $\mathcal{T}$ is the control time horizon; the optimization variables x_i, u_i represent states and inputs of DER i, respectively; the sets $\mathcal{X}_i(\tau)$,$\mathcal{U}_i(\tau)$ represent the dynamics and constraints of DER i while $\ell_i(x_i(\tau), u_i(\tau))$ is the control objective of DER i representing the costs of remote controlling the given DER.

This VPP control strategy is presented to illustrate an important requirement to the flexibility interface: the DERs should be able to communicate not only dynamics and constraints $\mathcal{X}_i$,$\mathcal{U}_i$ but also objective functions $\ell_i(x_i(\tau), u_i(\tau))$. This will allow the VPP to activate the DERs' flexibility in a cost effective manner, e.g., by activating the cheapest set of DERs that collectively are able to provide the contracted service.

Further, the VPP strategy presented above illustrates exactly how to apply the flexibility interface to manage DERs: the individual DERs will in a standardized way through the flexibility interface communicate the current state x_i, the objective function ℓ_i, the given constraints $\mathcal{X}_i$,$\mathcal{U}_i$, etc. With a well defined flexibility interface, different devices will be able to communicate objectives and constraints in a way that the VPP can interpret; hereby, the VPP is able to optimize over the entire portfolio. In a similar manner, the flexibility interface provides a standardized way for the VPP to control the individual DERs. By communicating the control signal, represented as u_i above, through the flexibility interface, the DERs will be able to interpret this control signal and alter the local operation accordingly.

6 Flexibility Interface

In this section we present a flexibility interface information model. This information model is constructed directly based on the identified flexibility characteristics (Section 3) and the markets the aggregator should be able to participate in (Section 4).

Flexibility Interface Information Model

The flexibility interface is constructed as follows. The identified DER flexibility characteristics (Table 4.1) relevant for the provision of services in the power markets are divided into a number of *flexibility blocks*. These flexibility blocks are presented in Table 4.2. Each flexibility block represents a certain flexibility aspect: a block denoted *active power* is able to describe active power flexibility of a DER; another block denoted *flexible startup time* is able to handle flexibility in the startup time of a DER, etc. The interface handles both production and consumption devices indicated with a generator sign. Based on these flexibility blocks, we can describe the flexibility of a given DER simply by selecting the appropriate blocks. We denote such a collection of flexibility blocks a *flexibility frame*; this concept is illustrated in Figure 4.2. In this manner, any DER can be described by selecting the set flexibility blocks relevant for the given device – if the DER is abel to store energy, the *energy storage* block is included; if the DER additionally is characterized by runtime limitations, the *runtime limitations* block should also be included, etc.

Note that while this work describes what information can be communicated over the flexibility interface via the flexibility blocks we do, however, not discuss where the data should be stored on either the VPP side or the DER side. The reason is that the main focus of this work is to model the necessary information required in a direct control setup, but not how the DERs and VPP should collect and store this data.

Block name	Explanation	Mandatory or Optional
Type	Nameplate information, consumer or producer	M
Electrical connection point	DER location in distribution grid	M
Status	Ability to be controlled by aggregator	M
Active power	Flexibility in the production/consumption of active power	O
Reactive power	Flexibility in the production/consumption of reactive power	O
Energy storage	Ability to store energy	O
Primary frequency control	Ability to react to local system frequency measurements	O
Flexible startup time	Ability to shift startup time of a fixed production	O
Runtime limitations	Limitations in minimum/maximum runtime and stoptime	O
Log	DER data to be stored at the aggregator for documentation purposes	O
Cost	Cost functions associated with utilization of DER flexibility	O

Table 4.2: Overview of flexibility blocks.

As illustrated in Table 4.2, the flexibility blocks are labeled as either mandatory [**M**] or optional [**O**], meaning that all DERs *must* use the mandatory blocks in the flexibility model but can *choose* to use the optional blocks. As an example, the *type* block is mandatory such that the aggregator knows the device type and name while the *energy storage* block is optional and should only be used if suitable. In a similar manner, the individual attributes are either mandatory or optional meaning that if a block is included, the mandatory attributes must be specified while the optional attributes should be chosen if relevant. The mandatory blocks are those that describe the device type, the point of connection, and the device status as shown in Table 4.2.

Structure

A single DER is associated with a single flexibility frame which consists of a number of flexibility blocks which again consist of a number of attributes. The attributes contain the actual information of the given DER. To give an overview of the attributes, we arrange them in the following categories.

- *Data:* static information provided by the DER, e.g., nameplate information.
- *Status:* DER status information provided by the DER, e.g., whether the device is turned on or off.
- *Local settings:* DER settings provided by the DER, e.g., whether the DER allows remote control or not.
- *Parameters:* local parameters provided by the DER, e.g., limitations in maximum/minimum power consumption/producion.
- *Commands:* commands provided by the aggregator to the DER, e.g., to enable remote control.
- *References:* reference signals provided by the aggregator to the DER, e.g., a reference for power tracking.

Also, each attribute is marked either as mandatory or optional analogous to the flexibility blocks. In Table 4.3, two of the flexibility blocks are presented showing examples of the attributes of a flexibility block.

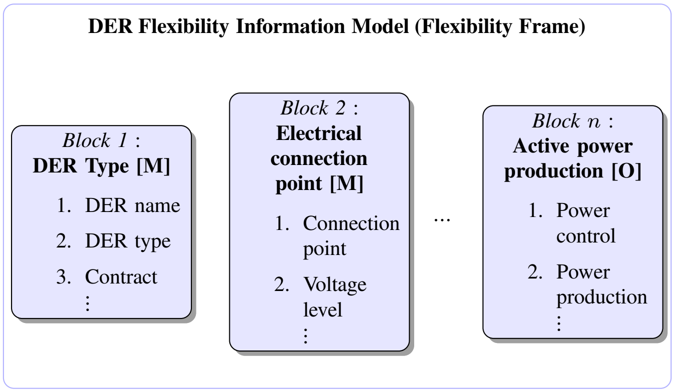

Figure 4.2: Illustration of a DER flexibility frame.

Modular Information Model

Constructing the flexibility interface in this modular manner allows us to easily extend the interface by constructing additional flexibility blocks. As an example, the presented blocks do not support voltage control, power factor control and delta-mode control. This could be included by specifying blocks relevant for these control types without altering the existing blocks.

It is important to note that the flexibility blocks are constructed such that they are able to express the flexibility of a *single* device. The flexibility interface does not provide a specific method of aggregating the flexibility of multiple devices into one frame. This means that if a set of devices (e.g., all flexible devices in one household) desire using the same flexibility frame, the devices (or a household level aggregator) must aggregate the flexibility such that it conforms with the flexibility blocks. The reason that this work does not support communication between nested VPPs is that this will require certain aggregation techniques, which is outside the scope of this work.

Examples

To clearly illustrate the design of the flexibility interface for direct control of DERs, Table 4.3 shows the *Power production, active power* block as an example of the flexibility blocks.

7 Conclusion

In this paper, we describe the need for a flexibility interface in order to allow an aggregator to directly control a portfolio of DERs to collectively provide actual power deliveries. We showed how an information model of such an interface can be constructed by identifying

<table>
<tr><th colspan="3">Power production, active power [O]</th></tr>
<tr><th>Attribute name</th><th>Explanation</th><th>M/O</th></tr>
<tr><td colspan="3">Status</td></tr>
<tr><td>Reference tracking status</td><td><table><tr><th>Value</th><th>Explanation</th></tr><tr><td>0</td><td>DER is not remotely controlled for reference tracking</td></tr><tr><td>1</td><td>DER is remotely controlled for reference tracking</td></tr></table></td><td>M</td></tr>
<tr><td>Schedule tracking status</td><td><table><tr><th>Value</th><th>Explanation</th></tr><tr><td>0</td><td>DER is not remotely controlled for schedule tracking</td></tr><tr><td>1</td><td>DER is remotely controlled for schedule tracking</td></tr></table></td><td>M</td></tr>
<tr><td colspan="3">Local settings</td></tr>
<tr><td>Reference tracking allowed</td><td><table><tr><th>Value</th><th>Explanation</th></tr><tr><td>0</td><td>DER does not allow remote control, reference tracking</td></tr><tr><td>1</td><td>DER allows remote control, reference tracking</td></tr></table></td><td>M</td></tr>
<tr><td>Schedule tracking allowed</td><td><table><tr><th>Value</th><th>Explanation</th></tr><tr><td>0</td><td>DER does not allow remote control, schedule tracking</td></tr><tr><td>1</td><td>DER allows remote control, schedule tracking</td></tr></table></td><td>M</td></tr>
<tr><td colspan="3">Parameters</td></tr>
<tr><td>Continuous power production/consumption intervals</td><td>Power production/consumption limits.
Example: power consumption between 0 and 1.000 W possible.</td><td>O</td></tr>
<tr><td>Continuous power production/consumption limits, time-varying</td><td>Example: power consumption between 0 and 1.000 W possible at day and between 0 and 500 W at night.</td><td>O</td></tr>
<tr><td>Discrete power production/consumption intervals</td><td>Example: power consumption of exactly 0 W or 1.000 W possible (on/off device).</td><td>O</td></tr>
<tr><td>Discrete power production/consumption intervals, time-varying</td><td>Example: power consumption of exactly 0 W or 1.000 W possible at day and only consumption of exactly 0 W possible at night.</td><td>O</td></tr>
<tr><td>Ramping limits</td><td>Upper and lower ramping limits.
Example: up-ramping 100 W/s and down-ramping 200 W/s possible.</td><td>O</td></tr>
<tr><td>PQ-capabilities</td><td>Specification of the relationship between active and reactive power</td><td>O</td></tr>
<tr><td colspan="3">Measurements</td></tr>
<tr><td>Current power production</td><td>Measured power production</td><td>O</td></tr>
<tr><td>Predicted future power production</td><td>Prediction of the future power production</td><td>O</td></tr>
<tr><td>Base power production</td><td>The power production of the DER if not remotely controlled (value can be used for economically settlement).</td><td>O</td></tr>
<tr><td colspan="3">Commands</td></tr>
<tr><td>Reference tracking, activation</td><td><table><tr><th>Value</th><th>Explanation</th></tr><tr><td>0</td><td>Aggregator deactivates remote control, reference tracking</td></tr><tr><td>1</td><td>Aggregator activates remote control, reference tracking</td></tr></table></td><td>M</td></tr>
<tr><td>Remote control, activation</td><td><table><tr><th>Value</th><th>Explanation</th></tr><tr><td>0</td><td>Aggregator deactivates remote control, schedule tracking</td></tr><tr><td>1</td><td>Aggregator activates remote control, schedule tracking</td></tr></table></td><td>M</td></tr>
<tr><td colspan="3">References</td></tr>
<tr><td>Power reference</td><td>Provided by the aggregator when operating in reference tracking.</td><td>O</td></tr>
<tr><td>Power schedule</td><td>Provided by the aggregator when operating in schedule tracking.</td><td>O</td></tr>
</table>

Table 4.3: Example of two flexibility blocks.

the flexibility characteristics of a number of key DERs and by examining the markets that the aggregator must be able to participate in. A modular approach was taken in the flexibility interface design phase, resulting in an interface where the flexibility of a DER is described by a range of various pre-defined flexibility blocks. Finally, we presented a list of flexibility blocks needed for basic DER operation and presented more detailed descriptions of two of the listed blocks.

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Paper 2

Contracting Flexibility Services

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Abstract

To substantiate and structure demand-side flexibility aggregation, a legally binding contract between aggregator and consumers is key. Flexibility contracts are the focus of this work. The work is elaborating on the experiences from US demand- response programs where flexibility contracts currently exist between aggregators and large-scale consumers. The main contribution of this work is to extend the American event-based flexibility contracts for larger-scale consumers, to the Danish case which is significantly different. The result is a contract template with the core contract elements that need to be determined to ensure an enforceable, reliable, and efficient relationship between aggregator and consumer.

1 Overview

The replacement of conventional power plants with intermittent renewable energy sources causes a major challenge for the electricity system: the central power plants do not only deliver power but also provide ancillary services ensuring a reliable and secure electric power system. It is therefore evident that in a grid with high penetration of renewables, alternative sources of ancillary services must be found ([1]). One solution is the *smart grid* concept where demand side devices with flexible power consumption take part in the balancing effort. The Danish TSO, Energinet.dk, has recently suggested a framework for smart grid in Denmark ([2]). A core element in this framework is to let an *aggregator* manage a portfolio of flexible demand side devices and utilize the accumulated flexibility in the liberalized electricity markets, including the ancillary service markets, on equal terms with conventional power plants.

Figure 5.1 illustrates the aggregators role in the Nordic electricity markets: by controlling a number of residential, commercial, and industrial consumers, the accumulated flexibility can be sold in the existing transmission system markets and possibly in future distribution system markets.

This architecture is interesting because the aggregator operates the portfolio of flexible consumers on market terms in competition with the conventional power plants and not just as a last resort. This is believed to improve the efficiency, economy and sustainability of the electrical grid.

We develop a flexibility contract template emphasizing the key elements in writing flexibility contracts between the aggregator and the consumer owing the flexible DERs. This contract template serves as a powerful tool for manufacturers of devices with flexible consumption as it can be used to examine the possibilities of selling smart grid related services to an aggregating entity. In cooperation with the industry, the template developed in this work has already been applied to two specific cases: a flexibility contract for supermarket cooling systems and a flexibility contract for a domestic heat pump. In both cases, the flexibility contracts are concerned with the inherent thermal flexibility of the DERs.

2 Methodology

The work is based on experiences from the US demand- response programs where flexibility contracts currently exist between aggregators and consumers ([3]). In the American

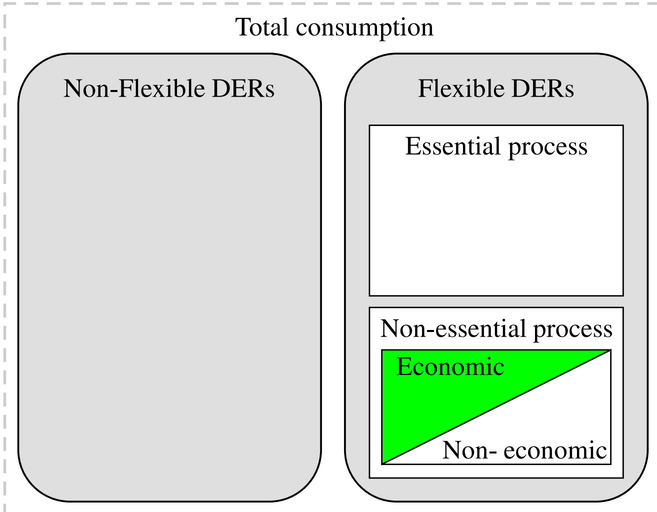

Figure 5.1: Flexibility in the liberalized electricity market.

electric power system, demand-response is mainly concerned about peak load reductions a few hours per year and primarily addresses larger power consumers with loads above 100 kW.

The main contribution of this work is to extend the American event-based flexibility contracts for larger-scale consumers, to the Danish case which is significantly different. In the Danish system, the goal is to utilize the flexible consumption, not only for load reduction in a few critical hours each year, but to aggregate and trade the flexibility in a more continuous manner through the electricity markets. Further, the goal in the Danish smart grid vision is to control not only large-scale consumers, but also smaller consumption devices such as domestic heat pumps and electric vehicles. This is the motivation behind this work which seeks to extend the American flexibility contracts to also include smaller consumption devices and to prepare the ground for more continuous flexibility operations.

An analysis of different flexible consumption devices and their characteristics combined with experiences drawn from the American demand response programs are used as a foundation for constructing the contract template. Further, two Danish companies, Dong Energys virtual power plant Power Hub and electric vehicle operator, Better Place, which currently operate flexible consumption, were interviewed to gain from their experiences.

3 Analysis

Electric Power System Services

By entering a flexibility contract a consumer allows remote control of its DERs. This enables an aggregator to control the DERs and create accumulated responses similar to those of conventional power plants. In this section, we briefly describe three different categories of such services.

Temporal power shifting

A balancing responsible party (BRP) for consumption holds responsibility for the power consumption of the loads under its jurisdiction. The BRP must buy power day-ahead on the energy exchange such that the demand is met. After the hour of operation, the BRP must buy or sell balancing power with the transmission system operator (TSO) in case the power bought day-ahead differs from the actual operating state. In this context, the BRP can utilize the flexibility of DERs for two purposes: (a) shift consumption temporally to avoid trading balancing power at an unfavorable price; (b) shift consumption temporally (e.g. from day to night) to achieve cheaper day-ahead power trades.

TSO services: The TSOs are responsible for secure and reliable system operation. This entails keeping balance between production and consumption as well as maintaining power quality and ensuring a stable transmission system. In general, the TSOs do not own production units and therefore procure ancillary services from suppliers. These services include up/down regulation and primary, secondary and tertiary reserves (possibly reactive reserves in the future electric power system) see, e.g., ([4]). The consumption used to provide such services must be separated from and independent of ordinary consumption; further, the consumption must be approved by the TSO as consumption that can be used as regulation reserves. Finally, TSO provided by consumption DERs require independent metering and settlement [5].

DSO services: The distribution system operators (DSOs) are responsible for the distribution grid and must ensure sufficient capacity and compliance with voltage boundaries. For aggregated consumers to provide congestion and voltage services they must be separated and independent from ordinary consumption. Further, the geographical grid location of consumers must be taken into account when providing services at the distribution grid level.

Distributed Energy Resources

Distributed energy resources are flexible consumption units (such as heating and cooling systems or electric vehicles) or smaller production units (such as wind turbines or photovoltaic). Generally, the flexibility of each DER is too small to provide a service to the electric power system; however, by aggregation it is possible to reach volumes large enough for actual power services (or bids into the power markets).

In terms contractual setup, we will refer to two different groups of demands-side DERs in this paper: power control assets and load control assets. This is elaborated in the following.

Power control assets: This type covers DERs where it is possible to control the power consumption directly and where a good power baseline estimate can be found. This typically covers DERs with a large load or a large group of small loads comprising one DER. The large scale of a DER justifies the investment in add-on equipment making it possible to determine power baselines and to respond to power references. Due to the large number of units, it will be possible to make good power baseline estimates.

Load control assets: This type covers DERs where the power consumption cannot be directly controlled and where it is not possible to make an accurate power baseline estimate. This typically covers smaller demand-side DERs such as domestic appliances, heat pumps, etc. In these cases, the aggregator can remotely control these types of loads, e.g., by turning a heat pump on/off or by choosing the startup time of domestic appliances; however, the aggregator is not able to control the power consumption directly. Such small devices are typically characterized by irregular power consumption that depends on user behavior it is therefore difficult to make good power baseline estimates. Note that the aggregator might be able to construct a good baseline estimate of a large portfolio of load control assets; however, not for a single load control asset.

Example: Consider an aggregator which is allowed to remotely turn the heat pump on/off within the comfort limits specified in the flexibility contract. The aggregator is able to perform direct control of the heat pump, but is only able to control the power consumption indirectly, as the power consumption of a heat pump is not constant over time and will depend on parameters such as outdoor temperature etc.

The Contracting Parties

To act as a competitive player on the electricity markets, the objective of the aggregator is to manage a portfolio with flexible consumers with low marginal flexibility costs. On the other hand, the consumers have insufficient market insight to enter the markets and tap their flexibility potential and are mainly concerned about reliable and affordable electricity.

In such a bilateral relationship between parties with different access to information and where one party is carrying out some task or effort on the behalf of another party, there is a risk that the objectives of the parties are misaligned. This information asymmetry generates a need for communication and transparency between consumer and aggregator, which must be assured through a legally binding flexibility contract. Further, this contract must assure sufficient incentive for both parties to participate in accordance with the contracted conditions while maintaining individual rationality [6].

4 Results

The result of this work is a flexibility contract template serving as an overview of the components that the aggregator and consumer must agree upon. The template can be used as a comprehensive check list to ensure that all relevant issues have been taken into account in the aggregator/consumer relationship. To provide an idea of the content of the flexibility contract, a short version template is shown in 5.1. The template is developed based on the core contract elements elaborated upon here.

Compensation and settlement

A main result of this work is the construction of two settlement regimes: flat rate and flex rate. We refer to the two regimes as poles to illustrate that a flexibility contract can vary from fully flat to fully flex or anywhere in between as a flat/flex-mix, reflecting the risk averseness of each consumer.

Flat Rate: In a flat rate regime, the aggregator pays the consumer the same amount of money per time period (monthly, quarterly, or annually) for signing up for a flexibility program and transferring some capacity of flexibility (kW) in a DER. Flexibility can be utilized according to the contractual agreement which lines out the capacity available as well as the frequency and duration of flexibility utilization. The periodic rate depends on the flexible capacity and will reflect the anticipated value for the aggregator and the consumers evaluation of the value of lost load and control. The flat rate compensation could come in the shape of a cash payment or percentage electricity bill reductions.

Flat rate regimes are especially applicable in situations where the contract involves (a) small DER units, (b) load control assets, (c) residential and small commercial consumers, and (d) risk-averse consumers.

A weakness in flat rate regimes is that consumers with low- value flexibility potential have an unfortunate incentive to subscribe under such regimes. In spite a negligible potential for flexibility in the contracted DERs and that actual utilization is expected to be limited, some flat payment will be paid.

This incentive structure issue can be managed in the contract by requiring a flexibility or eligibility assessment prior to the contract signing. Thereby, the aggregator is allowed to withdraw poorly performing DERs from the portfolio to minimize capacity costs and the exposure to this adverse selection problem. The adequate compensation regime is NOT determined by the specific services provided; rather, it is the correspondence with the control parameters, scale and preference dimensions that determine the appropriate regime.

For the aggregator, the flexibility contracted on a flat rate regime is free of charge within the limitations specified in the contract. This will incentivize the aggregator to use these DERs as much as possible. Market inefficiencies may occur if the least efficient resources end up being utilized the most. The contractual framework should associate an efficient compensational regime for each DER in its design.

Flex Rate: In a flex rate regime, the aggregator only pays the consumer for the utilized flexibility measured in terms of energy (kWh) or as a deviation from a pre-determined reference point or operational state (e.g. deviations from a temperature set-point or electric vehicle charging speed). The consumer is not certain of receiving any payments if the flexibility is never activated. However, once the consumer is activated, it will receive a much higher flexibility payment. The available capacity, the frequency and duration of utilization, are still determined in the contract. The consumers compensation will to a higher degree reflect the real market value of the flexibility.

Flex rate regimes are especially applicable in situations where the contract involves (a) larger DER units, (b) power control assets, (c) industrial and large commercial consumers and (d) risk-willing consumers.

Depending on whether the DER compensation reflects the market value of the utilization, the flex regime will require more settlement issues than the flat rate regime. While measurement and verification of the utilized flexibility is uniform, the aggregator has to justify the compensation by referring to real time market value of each activated units. This will incur additional settlement and transparency efforts under a flex rate regime. Flex-rate programs are thus more expensive to manage, and it sets higher requirements for scale and flexibility automation in order to justify the investment in making the flexibility available.

The aggregator can use the flex rate regimes to attract more valuable flexibility to its portfolio because consumers signing such flex-rate contract generally will possess large DERs. In spite of the higher management efforts and costs, these sources are most attractive for the aggregators portfolio. In the case of Dong Energys Power Hub, a number of valuation criteria determine how the generated revenues on various markets are allocated among units or consumers in their portfolio.

Control Parameters

To assure a fair and transparent compensation for the utilized flexibility, the compensation must depend on how the aggregator controls the DER: if the control is based on a price signal, the price signal should be used for compensation settlement if the control is based on an active power reference, the power reference should be used for compensation settlement, etc. This will ensure that it is clear to the customer how the compensation is settled.

Communication and transparency

A necessity for flex-rate program settlement is to have a baseline, which simply means: how would the DER behave if its flexibility were not utilized? Comparing the baseline with the observed behavior of the DER will reveal the delivery of the DER for verification and settlement purposes hence good baseline estimates are necessary for flex-rate settlements. It is, however, not always trivial to obtain such a consumption baseline.

No further details on the construction of a power baseline will be dealt with here. Reliable and transparent methods exist for assessing power baselines for certain devices but primarily for down-regulation purposes. In these cases where such baselines can be constructed, it makes sense to compensate the DER based on the actual power consumption compared with the calculated baseline.

For devices, with highly volatile power consumption, smaller devices etc., it may not be possible to make a good power baseline estimate. Alternative compensation methods must be used in these cases, e.g., flat-rate settlement.

Determination of compensation

The aggregators compensation to the consumer for utilized DER flexibility should be fair and the settlement should be calculated in a transparent manner. It is therefore reasonable to base the compensation upon the control parameter used by the aggregator to control the DER, as it is possible for both aggregator and consumer to access and verify this information.

Price-based control: Settlement is simply that consumed power at the price provided by the aggregator which is lower than peak prices [7]. This type of settlement is highly transparent, as both aggregator and consumer will know the prices and the consumed power. Using the electric vehicle example, this would correspond to allowing the aggregator to shift battery charging into hours with lower wholesale prices.

Active power control: Settlement for this type of control is based on the power response which equals the difference between the actual power consumption and the power baseline. The settlement of the power response can be done in a number of different ways. (a) Controlling the DER only for curtailment of active power in certain time intervals, a fixed payment per kWh can be used for settlement, see [8]. (b) The DER is also used in up-regulation, other compensation methods should be used, e.g., fixed prices for up- and down regulation. (c) Alternatively, compensation can be based on the market prices for up- and down regulation as for conventional consumers with adjustable consumption, see, e.g., -([9]).

State control: In state control, we control the power consumption of the DERs indirectly by controlling certain DER states such as the on/off state, a temperature reference for a thermal system, a process activation time, etc. As the control does not directly relate to the power consumption, it is undesired to base the compensation on the DER power response. We present two different approaches to settlement in the case where we do not control the power consumption directly but rather control a certain DER state.

Flat-rate payment is an obvious solution for compensation in the case of state-control. Using the heat pump example, this would correspond to a fixed payment for the heat pump owner to allow a certain amount of flexibility. Alternative measures can be used to ensure a transparent settlement. Using the heat pump example, another option for settlement is to use temperature measurements as a basis for compensation: the larger deviations in temperature, the higher compensation.

Ancillary service control: If the ancillary service delivered is up-regulation, compensation settlement can be done via a fixed amount per kWh. An alternative compensation method is necessary in case the deliveries are not solely up-regulation, e.g., deliveries of primary reserve, voltage control, reactive reserve, etc. One example of compensation in this case is that the aggregator pays a certain fraction of the aggregators income for the ancillary service delivery. This is possible as ancillary service deliveries in a market setting will correspond directly to a payment, e.g., in the Nord Pool market [10].

Availability and constraints

Not all consumption is flexible and even consumers with flexible consumption may only offer flexibility in limited time periods to ensure essential performance and cost-efficient operation. In this section we try to conceptualize the delineation of the available flexibility based on the most significant constraints, illustrated in Figure 5.2.

Technical: Naturally, only parts of the DERs are technically capable of acting flexibly upon a signal to start, stop or adjust the power consumption. This could either be due to the fundamental DER technological specifications, or because the required hardware upgrade is considered uneconomic.

Process: Essential processes are considered part of the main functionality for the consumers and cannot be considered flexible at a reasonable price. At industrial facilities, this could be the main production line. For commercial entities, IT- systems or data warehouses that are not available for curtailment under any circumstances. Residential consumers may find television and cooking patterns relatively inflexible. Some processes are considered essential under certain circumstances depending on the time of the day, week, or year.

Economic: In cases where flexibility is a technical possibility and not interfering with any essential processes, the availability depends on the consumers preferences over the trade-off between the expected value from offering flexibility versus the value of lost service. While the technical and process based constraints are hard constraints, the economic evaluation is characterized by a more dynamic nature. Preferences are highly correlated with behavioural differences between consumers and also depending on seasonal changes.

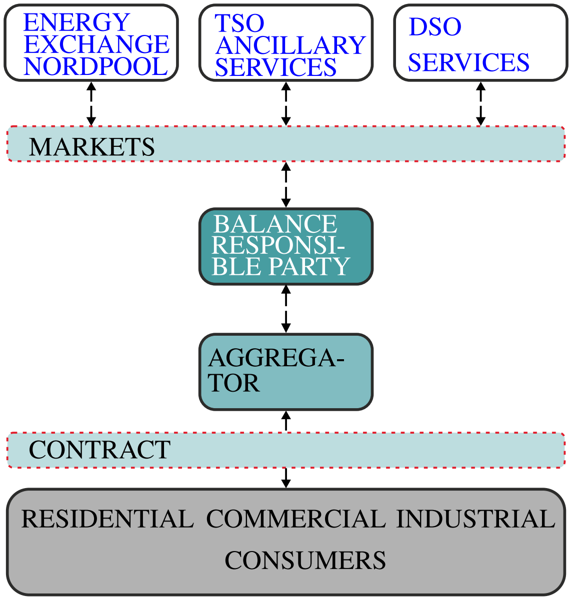

Figure 5.2: Delineated Flexibility

Allocation of Risk

An aggregator adds significant value to each of the flexible DERs in a portfolio. The most obvious and vital lever is the sole inclusion in the aggregators portfolio. In this case, the value added corresponds to the whole value of the flexibility operation. With increasing capacity of the DER, the added value from inclusion diminishes. At some point the consumer is better off without the aggregator, because it is eligible and capable of individual market operations.

The aggregator is superior at managing the risk exposure. Based on its technical insight and market knowledge, and through a diversified portfolio of flexible units, the aggregator holds a clear value proposition. The allocation of risk affects the associated compensation as the party assuming the risk must be compensated accordingly. In this section we highlight the key risks, which must be incorporated into the flexibility contract.

Operational Risk: The risk related to the technical operation of the flexible DERs involves being responsible for managing the technical devices; specifically to (a) ensure that DERs are online and in a technically flexible state, (b) activating the contracted DERs according to the protocol, (c) respect contracted restrictions and avoid causing wear on the DERs, and (d) measuring, verifying, and communicating the utilized flexibility.

Market Risk: Market risk concerns the risk related to market operations, which are subject to competition among the supplying parties. The return from market operations are encumbered by uncertainty and some consumers, depending on their aversion towards risk, are unlikely to take part facing the risk at hand.

5 Conclusion

We have presented a framework for the legal bindings, where a number of consumers enter into a contract with an aggregator, who is able to utilize the consumers flexible devices to bid into the various electricity markets. Flexible devices were divided into two categories: power control assets, where the power consumption can be directly controlled, and load control assets, where the load is controllable but the power consumption cannot be directly controlled.

Based on the studies of market needs and the nature of the contractual relationship, an aggregator/consumer contract template was developed to illustrate how such contracts can be formulated. The core elements are shown in 5.1.

The framework works as a guideline for assessing the potential value in the contracts from the aggregators perspective. Thereby it creates the ground for valuing the contracts and determining an adequate level of compensation. The aggregator is provided a delineated capacity, the expected hours of flexible operations and based on that determines what value a DER or a costumer can provide.

1. **Legal Contracting Parties**	
Consumer and aggregator data. Contract terms, scope of services	Aggregator and consumer company name, address etc. Contract start and end date. Description of flexibility service that the consumer allows the aggregator to utilize in the electricity market.
2. **Specifications of the flexible consumption device**	
Device type, available capacity, reaction time, technical duration.	Type of device, control parameters, minimum capacity available. Response time and maximum time duration that the device can sustain flexible operation.
3. **Available Constraints**	
Time specific constraints, comfort constraints, overrule rights.	Daily, weekly, seasonal constraints. Maximum allowable number of activations per day. List of specific overrule rights and potential cost associated. User comfort settings, for example temerature bands.
4. **Financial Data**	
Compensetional regime, determination of compensetaion	Flat rate or flex rate: payment per month, fixed payment per utilized kWh, specific share of aggregator market revanue. Specifications of baseline determination
5. **Consumer and Aggregator Obligations**	
Required hardware on-site, consumer liabilities	Responsibility and payment for installment of additional communication, control, and censoring equipment. Responsibility and payment for underperformance. Allocation of financional risks.

Table 5.1: Core Contract Elements

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Paper 3

Electricity Market Optimization of Heat Pump Portfolio

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Abstract

We consider a portfolio of domestic heat pumps controlled by an aggregator. The aggregator is able to adjust the consumption of the heat pumps without affecting the comfort in the houses and uses this ability to shift the main consumption to hours with low electricity prices. Further, the aggregator is able to place upward and downward regulating bids in the regulating power market based on the consumption flexibility. A simulation is carried out based on data from a Danish domestic heat pump project, historical spot prices, regulating power prices, and spot price predictions. The simulations show that electricity price reductions of $\mathbf{18}$ – $\mathbf{20}$ % can be achieved compared to the heat pumps currently in operation.

1 Introduction

With an increasing focus on climate-related issues and rising fossil fuel prices, the penetration of renewable energy sources is likely to increase in the foreseeable future throughout the developed world [1]. The Danish electric power system, which is the focus of this work, is a particularly interesting case with a wind energy penetration of 30 % today and an expected 2020 penetration of 49.5 % [2]. When conventional power plants are outdone with renewables such as wind turbines and photovoltaics, the ability to provide balancing services in the classical sense disappears, as the renewable energy sources often will fully utilize the available power. It is therefore evident that in a grid with high penetration of renewables, alternative sources of balancing services must be established. One of the approaches to obtaining such services is the *smart grid* concept, where demand-side devices with flexible power consumption take part in the balancing effort [3]. The basic idea is to let an *aggregator* manage and optimize a portfolio of flexible demand-side devices on behalf of the balancing responsible party (BRP) for this consumption. This allows the balancing responsible to utilize the accumulated flexibility in the unbundled electricity markets on equal terms with conventional generators [4]. In the future Danish electricity system it is expected that domestic heat pumps will play an important role as flexible consumption: already now, around 27.000 heat pumps are installed in Denmark [5], and potentially 205,000 households can benefit from replacing oil-fired boilers with heat pumps in the coming years [6]. It is therefore most relevant to consider how to aggregate and control this flexibility towards the electricity markets.

Control of smaller flexible consumers to support grid stability has been discussed as early as the 1980s [7]. Since, the topic of demand-side management has received much attention from a research perspective including control of heat pumps [8, 9]. In particular, optimization of heat pumps has received much attention in Denmark the last few years. See, e.g., [10, 11, 12, 13, 14]. These works consider how the operation of heat pumps can be optimized to support grid stability and how to lower the operational electricity costs by performing spot price optimization of the consumption. None of the works do, however, account for the structure of the Nordic system, which consists of a day-ahead spot market and an intra day balancing market. As an example of this, several works use the electricity spot price as a *price signal* that the aggregator will face without any planning phase. In this work we move closer to the real electricity market by including both a day-ahead planning phase and an intra-day balancing market. The aggregator will purchase electricity based on spot price *predictions* at the day-ahead market and will intra-hour adjust the operation of the portfolio according to the experienced load and possibly place bids of upward and downward regulation in the intra-day market. Finally, the intra-day imbalances will be settled as balancing power according to the regulations.

The structure of the paper is as follows. First in Sec. 2 we model the heat pump portfolio and in Sec. 3 we describe the electricity markets. In Sec. 4 we develop a control strategy that takes the spot prices into account and a control strategy that further is able to bid into the regulating power market. Following in Sec. 5 we show two simulation examples of the developed control strategies and finally in Sec. 6 we conclude the work.

2 Lumped Portfolio Model

The Heat Pump Project "Styr Din Varmepumpe"

Several large projects dealing with flexible consumption are currently ongoing in Denmark. The project "Styr din varmepumpe" (meaning: *control your heat pump*) deals specifically with understanding domestic heat pumps and how they can be operated depending on the electricity markets [15]. In this project, around 200 heat pumps installed in Danish homes have been subsequently equipped with various measurement devices such that power consumption, flows, temperatures etc. can be measured. The data is collected via Internet connections and can be used for modeling and analysis. This data forms the background for this work.

System Architecture

The starting point of this work is the Nordic unbundled liberalized electricity system architecture. In this setup, the Transmission System Operators (TSOs) are responsible for secure and reliable system operation and must consequently ensure balance between production and consumption. Generally, in an unbundled electricity system, TSOs do not own production units and must therefore procure ancillary services in the electricity markets to ensure system stability.

The aggregator is a legal entity able to enter into flexibility contracts with consumers allowing the aggregator to manage the consumers' flexible consumption; in return, the consumers will achieve some type of compensation. This enables the aggregator to utilize the accumulated flexibility to participate in the electricity markets through the consumers' BRP. The flexible devices are managed by the aggregator through a technical unit often referred to as a Virtual Power Plant (VPP).

Aggregated House Model

It is desired to have a simple model that describes the accumulated flexibility of all the houses in the portfolio rather than a model for each of the houses. There are two reasons for this. The first reason is that it can be computationally difficulty to perform optimization across thousands of heat pumps each described by its own model. The second reason is that it is difficult to predict the future behavior of a single house due to the many unpredictable disturbances affecting a house: fluctuating sunshine, opening/closing of doors and windows, the use of wood stove etc. For a lumped heat pump model, however, these local disturbances will, however, smooth out as the number of houses in the portfolio increases.

Several works have suggested the use of a first order model to describe the energy level, or temperature, in a house; see, e.g., [12, 14, 16]. Such a model can be formulated as

$$\dot{T}_i(t) = \frac{1}{R_i C_i} \left(T_{\mathrm{a},i}(t) - T_i(t)\right) + \frac{1}{C_i} \left(u_i(t) + v_i(t) + w_i(t)\right) \tag{6.1}$$

for house number i where the constants $R_i, C_i \in \mathbf{R}_+$ are the thermal resistance and the heat capacity of the house, respectively, while $T_i(t) \in \mathbf{R}$ is the indoor temperature and $T_{\mathrm{a},i} \in \mathbf{R}$ is the outdoor (ambient) temperature affecting the house. The input $u_i(t)$ is the electrical equivalent of the stored thermal energy, $v_i(t) \in \mathbf{R}$ represents a deterministic daily load pattern on the house, i.e. $v_i(t) = v_i(t + 24 \text{ hours})$ while $w_i(t) \in \mathbf{R}$ is an exogenous disturbance. Note that this model covers houses with electrical heating, but also with a transformation of parameters a house with a heat pump with a given COP by letting $C_i = C_{\text{house}}/\text{COP}$, $R_i = R_{\text{house}}\text{COP}$.

In this work we assume that we can describe the entire heat pump portfolio by a first order model. This is clearly a rough assumption: if the individual houses are described by first order models as (6.1), the order of the lumped model will be the total number of houses unless some houses have identical parameters C_i, R_i. It may seem crude to make a lumped first order model, as the houses definitely will have different thermal resistance and heat capacity; however, the parameters will be in the same order of magnitude as all the houses are standard-sized Danish houses. Further, it must be stressed that the purpose of the aggregated model is not to accurately describe the houses' states; rather, the purpose is to have a model suitable for rough planning of the future electricity consumption. The benefit of actually having a very accurate model will also be very limited as the flexibility optimization depends on several parameters that we do not know accurately such as future temperatures and spot prices. Finally, attempts on individual household modeling on inhabited houses show that the disturbances often are so great that the actual house dynamics cannot be observed. Further argumentation and real life demonstrations motivating the use of a lumped heat pump model can be found in [17].

This leads us to the following model description of the entire portfolio. Let $T(t) \in \mathbf{R}$ be the average indoor temperature, $T_{\mathrm{a}}(t) \in \mathbf{R}$ the average outdoor temperature, $u(t) \in \mathbf{R}$ the average heat pump power input, $v(t) \in \mathbf{R}$ the average daily load profile, and $w(t) \in \mathbf{R}$ the average disturbance. The aggregated model can then be described as

$$\dot{T}(t) = \frac{1}{RC} \left(T_{\mathrm{a}}(t) - T(t)\right) + \frac{1}{C} \left(u(t) + v(t) + w(t)\right) \tag{6.2}$$

where the constants $R, C \in \mathbf{R}_+$ are the parameters of the aggregated model. As mentioned, a benefit of this model is that the outdoor temperature $T_{\mathrm{a}}(t)$, the daily load profile $v(t)$, and the exogenous input $w(t)$ to an extend will smooth out as the number of houses increase. Note that we in this work only consider scheduling of the operation of the accumulated system represented by (6.2); we do not discuss how to control the individual devices but assume that an underlying dispatch algorithm distributes power to the individual houses in order to be able to let local control loops reject individual disturbance patterns. For details on how this can be achieved, see for example [18, 19].

Thermal Flexibility for House Heating

Figure 6.1 shows indoor temperature measurements from four of the houses that are at part of the heat pump project over a one-month period. The heat pumps operate using the default heat pump controller. The figure shows that the indoor temperature varies several degrees for all the houses over the period, which indicates the foundation for this work: that people are used to and comfortable with indoor temperatures varying a couple of degrees, hence the indoor temperature in a house does not have to be fixed at a given temperature setpoint. This motivates a formulation where the indoor temperature is allowed to vary within a given interval for each house $\underline{T}_i \leq T_i \leq \overline{T}_i$. This gives the following requirement to the aggregated model:

$$\underline{T} \leq T(t) \leq \overline{T} \tag{6.3}$$

where $\underline{T}, \overline{T} \in \mathbf{R}$ describe the average temperature limits. Finally, the power consumption

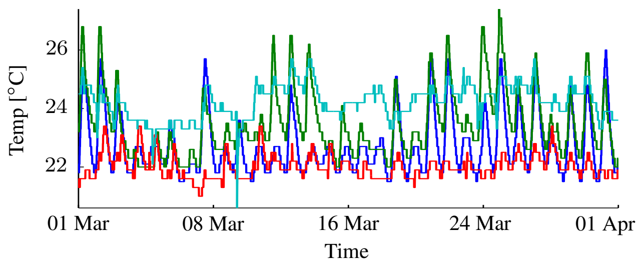

Figure 6.1: One month's indoor temperature measurements for four houses during March 2012.

of a heat pump is limited $\underline{u}_i \leq u_i \leq \overline{u}_i$ which for the aggregated model implies that

$$\underline{u} \leq u(t) \leq \overline{u} \tag{6.4}$$

where $\underline{u}, \overline{u} \in \mathbf{R}$ describe the average power limits.

Further note that honoring the temperature and power limits on the aggregated system as described by (6.3) and (6.4) will not guarantee that the individual device constraints are honored; this is the task of the dispatcher which is not described in this work.

Model Estimation

The purpose of the heat pump portfolio is to optimize the flexibility towards spot prices and the intra-day markets. As these are hourly markets in the Nordic system we discretize the portfolio model with a sampling time of 1 hour and obtain

$$T(k+1) = aT(k) + (1-a)T_{\mathrm{a}}(k) + b\left(u(k) + v(k) + w(k)\right) \tag{6.5}$$

where $a, b \in \mathbf{R}$, which depend on R, C and are found by discretization, and k is used to indicate the sample number.

One year's data from 130 heat pump heated houses is used to identify the parameters a, b via quadratic fitting. For details on such parameter estimation, see for example [14].

Figure 6.2 shows the power added to the portfolio of houses from the heat pump u, the daily load profile v, the exogenous input w, and the energy that drains out due to the lower ambient temperature, which we denote d for *drain*. The figure shows averages for the entire portfolio over a two-month period. The figure illustrates that the average heat pump power u throughout the period is in the order of $1.0 - 2.5$ kW. Further it can be seen that the load v varies daily between 500 and 700 W describing the average profile of heat added by people in the house, electronics, wood stove, etc. Finally, the unpredictable load w has a contribution in the magnitude ±500 W caused by the disturbances that cannot be captured by the daily load profile. The parameters of the model reveal a time constant of 33 hours.

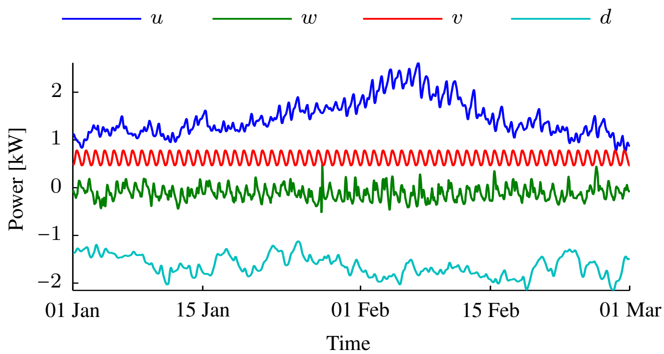

Figure 6.2: Energy transfer to portfolio of houses from heat pump u, daily load v, exogenous load w, and drain d.

3 Electricity Markets

In this section we briefly describe the electricity markets that the aggregator faces.

Electricity Spot Market

In the Nordic system, electricity is bought and sold at the electricity spot market. Every day before 12 p.m. (noon), buyers and sellers of electricity can place bids into the electricity spot market specifying what volume they will buy/sell depending on the price of electricity for each hour of the following day. The hourly spot prices for the following day will be set to the intersection between the aggregated supply and demand curves. All electricity traded in each hour will be settled at this spot price; further, the spot price determines the volumes of traded electricity. As the spot prices are unknown at the time when electricity is purchased, the aggregator must rely on a spot price prognosis when purchasing electricity day-ahead.

Let the spot prices at hour k be denote $\pi(k)$ and let $\tilde{\pi}(k)$ denote the prediction of $\pi(k)$ available day-ahead before gate closure. To illustrate this, assume that the current time is between 11 a.m. and 12 p.m. (last hour before gate closure); further, let this correspond to sample $k = 12$. At this time we know the spot prices for the current day $\pi(1), \ldots, \pi(24)$, but we do not know the spot prices the following day (the day-ahead) $\pi(25), \ldots, \pi(48)$, which are not announced until $k = 13$ (i.e. 1 p.m.). We do, however, have spot price predictions for the following day, $\tilde{\pi}(25), \ldots, \tilde{\pi}(48)$. This is illustrated in Figure 6.3. The figure further illustrates what is generally the case, namely that the predictions are able to capture the shape of the actual spot price realization.

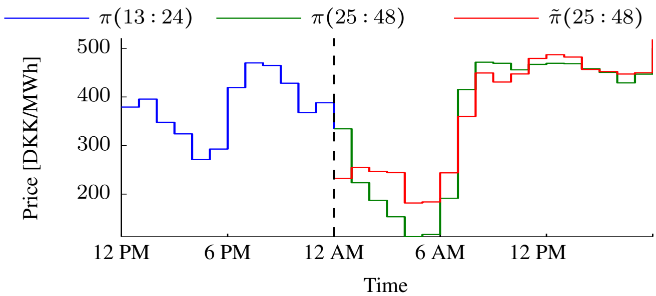

Figure 6.3: Spot prices π and predictions $\tilde{\pi}$ on January 9 and 10, 2011.

Balancing Power and Regulating Power

During the day, the portfolio of consumers will consume a given volume of power $u(k)$ for each of the hours of the day. If the actual consumption $u(k)$ deviates from the electricity purchased day-ahead in the spot market, the aggregator will by definition trade the difference as *balancing power* with the TSO. The price of balancing power is the regulating power price (RP price) which we denote $\pi_{\text{RP}}(k)$. The total cost $J_{\text{el}}(k)$ of electricity in hour k thus depends on the electricity purchased at the spot market, denoted $u_{\text{spot}}(k)$, and the electricity actually consumed $u(k)$:

$$J_{\text{el}}(k) = u_{\text{spot}}(k)\pi(k) + (u(k) - u_{\text{spot}}(k))\pi_{\text{RP}}(k) \tag{6.6}$$

assuming that all consumers contributing to $u(k)$ are hourly metered and settled.

To counteract for the imbalances caused by electricity traders, the TSO activates regulating power from the regulating power market. Providers of regulating power can place bids in the regulating power market up to 45 minutes before the hour of operation, specifying the price at which they are willing to increase or decrease production or consumption. The TSO will activate the required volume of regulating power and will select the bids in merit order after price. The RP price will be set as (defined by) the bidding price of the most expensive regulating power bid activated in a delivery hour. If the direction of regulation is upward, the RP price will be greater than or equal to the spot price; similarly, if the direction of regulation is downward, the RP price will be less than or equal to the spot price. The RP price will be used to settle all the provisions of regulating power in that given hour. Further, it will be used to settle all imbalances according to the power balancing settlement procedures. Note that the RP price is not published until after the hour in question.

An example of the regulating power price is illustrated in Figure 6.4 where we compare the hourly spot price π with the regulating power price π_{RP}. The figure illustrates

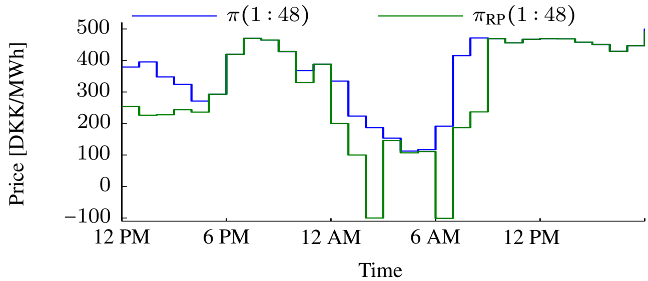

Figure 6.4: An example with relatively large differences between the spot prices π and regulating power prices π_{RP}. January 9 and 10, 2011.

that the regulating power price is lower than the spot price in the first hours of the figure indicating that the system is in downward regulation. If we have a higher consumption in these hours than the purchased electricity at the spot market, we will buy this additional electricity (balancing power) from the TSO at RP price which is beneficial as the RP price is low; on the contrary, if we have a lower consumption in these hours, we will sell the excess electricity to the TSO at RP price which is disadvantageous as the RP price is low. As the RP price is not published until after the hour in question, it is not possible to adjust the consumption corresponding to the RP price.

4 Controller Synthesis

In this section we describe two strategies of operating the flexibility of the heat pumps: a strategy that optimizes the flexibility according to spot prices and a strategy that also bids into the regulating power market.

Spot Price Optimization

The overall idea in the spot price optimization control is that the aggregator achieves a lower operational cost of the portfolio of heat pumps by shifting consumption into hours of low electricity prices. This optimization is non-trivial due to the fact that the spot prices only apply for the electricity purchased at the spot market – if the consumption of the portfolio deviates from the purchased volumes, the difference will be settled using the regulating power price according to (6.6). For this reason, the optimization is divided into a day-ahead optimization that determines the volumes that will be bought at the electricity markets and an intra-day optimization that operates the portfolio hour by hour. This is elaborated in the following.

Day-ahead Optimization

The key idea in the day-ahead optimization is to purchase the electricity needed for the following day based on spot price and outdoor temperature predictions such that the cost of operating the portfolio is minimized. To formally describe this, we assume that the current hour k corresponds to the last hour before gate closure, i.e., the hour between 11 a.m. and 12 p.m. Define $\mathcal{K} = \{k+13, \ldots, k+36\}$; hence $\mathcal{K}$ will correspond to a set of the 24 hours of the following day which we have to purchase electricity for. The overall objective is to minimize the electricity cost for operation the following day which is given by $\sum_{\kappa\in\mathcal{K}}\pi(\kappa)u(\kappa)$ where $\pi(\kappa)$ is the hourly spot price and $u(\kappa)$ is the hourly consumption. Again we remind that the spot prices $\pi(\kappa)$ are not available day-ahead; hence, spot price predictions $\tilde{\pi}(k)$ must be utilized to minimize the objective.

Further, we want the portfolio to be at a temperature setpoint T_{sp} in steady state instead of converging to either of the temperature limits $\overline{T},\underline{T}$. This is achieved by minimizing the norm of a state $x(k)\in\mathbf{R}$ that corresponds to the integrated temperature error as described by:

$$x(k+1) = x(k) + T(k) - T_{\text{sp}} \tag{6.7}$$

In this work it is chosen to minimize the integrated temperature error in a two-norm sense as described in the following.

To perform this optimization, it is necessary to collect predictions of both the temperature and integrated temperature tracking error for the first hour of the following day $\tilde{T}(k+13),\tilde{x}(k+13)$ which are 12 hours into the future; besides, spot price and outdoor temperature predictions for each hour of the following day $\tilde{\pi}(\kappa),\tilde{T}_{\text{a}}(\kappa),\kappa\in\mathcal{K}$ must be collected. Based on this data we can formulate the optimization as follows:

$$\begin{array}{ll}
\text{minimize} & \displaystyle\sum_{\kappa\in\mathcal{K}}\left(\tilde{\pi}(\kappa)u(\kappa) + k_I x^2(\kappa)\right) \\
\text{subject to} & T(\kappa+1) = aT(\kappa) + (1-a)\tilde{T}_{\text{a}}(\kappa) + \\
& \qquad\qquad b\left(u(\kappa)+v(\kappa)\right), \quad \kappa\in\mathcal{K} \\
& x(\kappa+1) = x(\kappa) + T(\kappa) - T_{\text{sp}}, \quad \kappa\in\mathcal{K} \\
& u(\kappa)\in\mathcal{U}, \quad T(\kappa)\in\mathcal{T}, \quad \kappa\in\mathcal{K} \\
& T(k+13) = \tilde{T}(k+13) \\
& x(k+13) = \tilde{x}(k+13)
\end{array} \tag{6.8}$$

where the variables are $u(\kappa),T(\kappa),x(\kappa),\kappa\in\mathcal{K}$ and $k_{\text{I}}\in\mathbf{R}$ is a trade-off parameter. The data to the problem is the predicted spot prices and outdoor temperatures $\tilde{\pi}(\kappa),\tilde{T}_{\text{a}}(\kappa),\kappa\in\mathcal{K}$, the daily load profile $v(\kappa),\kappa\in\mathcal{K}$, and the predicted temperature and integrated error in the first hour of the following day $\tilde{T}(k+13),\tilde{x}(k+13)$. The sets $\mathcal{T},\mathcal{U}$ represent the power and temperature limitations as described by (6.3) and (6.4). The solution $u^{\star}_{\text{spot}}(\kappa),\kappa\in\mathcal{K}$ are the volumes of electricity we will purchase for the following day.

The reason for choosing a horizon of 24 hours is that 24 hour forecasts of the following day's spot prices is a standard product that can be purchased from forecasting providers. As the time constant of the aggregated houses is in the magnitude of 33 hours, a longer horizon could be beneficial; however, such long spot price predictions are not available.

Intra-Day Optimization

Day-ahead we purchase electricity at the spot market based on predictions of load on the heat pump as described above. Intra-day we decide how to actually operate the portfolio. This intra-day operation may differ from the plan made day-ahead, as the houses will experience loads that differ from the predictions. Different strategies can be chosen for the intra-day operation. One strategy is to track the electricity we have purchased day-ahead as closely as possible to avoid trading balancing power with the TSO at possibly unfavorable prices. Another option, which we choose in this work, is to simply consider the known spot prices as predictions of the regulating power price. The reason for choosing this approach is that the upward and downward regulating power prices on average only differs around 10 % from the spot price; further, we are only penalized when our imbalance is in the same direction as the overall imbalance – else we are rewarded according to the (6.6). This indicates that deviations from the purchased electricity typically are not associated with a large penalty.

Assume that we are at hour k and let H describe the number of hours into the future that the spot prices are known. Further let $\mathcal{H} = \{k, \dots, k + H - 1\}$ denote the set of future hours where the spot price is known. To perform intra-day optimization we must collect the current temperature and current integrated error $T(k), x(k)$; further, outdoor temperature predictions and known spot prices must be collected $\tilde{T}_{\text{a}}(\kappa), \pi(\kappa), \kappa \in \mathcal{H}$. The object of this problem is again to minimize the cost of operating the portfolio and the integrated error subject to the temperature bands. By using the known spot prices as predictions of the regulating power price, the intra-day optimization problem becomes:

$$\begin{array}{ll} \text{minimize} & \sum_{\kappa \in \mathcal{H}} \left(\pi(\kappa) u(\kappa) + k_I x^2(\kappa) \right) \\ \text{subject to} & T(\kappa + 1) = aT(\kappa) + (1 - a)\tilde{T}_{\text{a}}(\kappa) + \\ & \qquad\qquad b\left(u(\kappa) + v(\kappa)\right), \quad \kappa \in \mathcal{H} \\ & x(\kappa + 1) = x(\kappa) + T(\kappa) - T_{\text{sp}}, \quad \kappa \in \mathcal{H} \\ & u(\kappa) \in \mathcal{U}, \quad T(\kappa) \in \mathcal{T}, \quad \kappa \in \mathcal{H} \end{array} \tag{6.9}$$

where the variables are $u(\kappa), T(\kappa), x(\kappa), \kappa \in \mathcal{H}$. The data to the problem is the known spot prices and outdoor temperature predictions $\pi(\kappa), \tilde{T}_{\text{a}}(\kappa), \kappa \in \mathcal{H}$, the daily load profile $v(\kappa), \kappa \in \mathcal{H}$, and the current temperature and integrated error $T(k), x(k)$. We denote the solution $u^{\star}_{\text{intra}}(\kappa)$.

The first element of the solution $u^{\star}_{\text{intra}}(k)$ is now applied meaning that the VPP will regulate the portfolio to collectively consume the electricity $u^{\star}_{\text{intra}}(k)$ within the current hour. In this work we do not discuss how the power $u^{\star}_{\text{intra}}(k)$ is dispatched among the individual heat pumps – we only state that the heat pump portfolio collectively should consume $u^{\star}_{\text{intra}}(k)$ within hour k.

Note that other strategies could be implemented instead; for example, the day-ahead optimization could be merged with the intra-day optimization when planning how to purchase electricity day-ahead.

Algorithm

We are now able to describe the algorithm for spot price optimization. This is presented in Algorithm 1.

Spot Price and Regulating Power Optimization

In this section we present an extension to the spot price optimization strategy by letting the aggregator place bids of regulating power via the BRP into the regulating power market.

Consumer as Provider of Regulating Power

A BRP for flexible consumption participating in the regulating power market must submit operational schedules for the portfolio's planned consumption and is allowed to update

Algorithm 1 Spot Price Optimization Algorithm

for $k = 1, 2, \dots$ **do**

Collect the published spot prices $\pi(\kappa)$ and temperature predictions $\tilde{T}_{\mathrm{a}}(\kappa)$ for the horizon $\kappa \in \mathcal{H}$ and collect current state of the heat pump portfolio $T(k), x(k)$ Optimize intra-day operation of the portfolio by solving Problem 6.9 to obtain $u^{\star}_{\mathrm{intra}}(\kappa), \kappa \in \mathcal{H}$ Let VPP steer portfolio's consumption to $u^{\star}_{\mathrm{intra}}(k)$

if *Current hour is between 11 a.m. and 12 p.m.* **then**

Collect predictions of spot prices and temperatures for the following day $\tilde{\pi}(\kappa), \tilde{T}_{\mathrm{a}}(\kappa), \kappa \in \mathcal{K}$ Collect state predictions $\tilde{T}(k+13), \tilde{x}(k+13)$ (available from the latest solution of (6.9)) Optimize spot trades by solving Problem 6.8 to achieve $u^{\star}_{\mathrm{spot}}(\kappa), \kappa \in \mathcal{K}$ Purchase electricity $u^{\star}_{\mathrm{spot}}(\kappa), \kappa \in \mathcal{K}$ for the following day.

end

end

this schedule if it is discovered that the schedule cannot be followed [20]. The regulations do not specify the deadline for updating the operational schedules. In this work we assume that the aggregator is allowed to update the operational schedule for consumption up to 45 minutes before the hour of operation; hereafter, the aggregator must commit to the planned consumption for the given hour.

Bidding in the Regulating Power Market

We enable the aggregator via the BRP to bid in the regulating power market by expanding Algorithm 1. Let $u_{\mathrm{sch}}(k)$ denote the scheduled power consumption at hour k. The aggregator cannot update this volume after hour $k-1$, i.e., the hour before operation. Further, let $u_{\mathrm{act}}(k)$ denote the volume of regulating power the aggregator is activated to deliver in hour k; hence, the portfolio *must* consume the power $u_{\mathrm{reg}}(k) = u_{\mathrm{sch}}(k) + u_{\mathrm{act}}(k)$ in hour k. Note that we use the convention that $u_{\mathrm{act}}(k) < 0$ corresponds to upward regulation and $u_{\mathrm{act}}(k) > 0$ corresponds to downward regulation.

The bidding strategy must ensure that we only deviate from the scheduled consumption $u_{\mathrm{sch}}(k)$ if this is economically favorable for the aggregator. A number of different bidding strategies can be imagined. In this work we do not seek to predict the future RP prices, which is a very difficult task, but instead implement a simple strategy that examines the marginal cost associated with being activated in the following hour for a given delivery of regulating power. This marginal cost is then used as our bid in the regulating power market. As the Nordic regulating power market has a minimum bid size of 10 MW, we simply examine the marginal cost of delivering any feasible multiple of 10 MW. As an example, for a portfolio with limits $\underline{u} = 0$ MW, $\overline{u} = 40$ MW with a scheduled consumption of $u_{\mathrm{sch}}(k) = 10$ MW for the next hour, we will examine the marginal cost of delivering 10 MW upward regulation and $10, 20$, and 30 MW downward regulation. Following, we use these marginal costs as bids for the four regulating power deliveries.

Described more formally, we determine the cost of activating a regulating power activation of $u_{\text{act}}(k)$ by solving

$$\begin{array}{ll} \text{minimize} & \sum_{\kappa\in\mathcal{H}} \left(\pi(\kappa)u(\kappa) + k_I x^2(\kappa)\right) - T(H)\frac{\tilde{\pi}_{\text{avg}}}{b} \\ \text{subject to} & T(\kappa+1) = aT(\kappa) + (1-a)\tilde{T}_{\text{a}}(\kappa) + \\ & \qquad b\left(u(\kappa) + v(\kappa)\right), \quad \kappa \in \mathcal{H} \\ & x(\kappa+1) = x(\kappa) + T(\kappa) - T_{\text{sp}}, \quad \kappa \in \mathcal{H} \\ & u(\kappa) \in \mathcal{U}, \quad T(\kappa) \in \mathcal{T}, \quad \kappa \in \mathcal{H} \\ & u(k) = u_{\text{sch}}(k) + u_{\text{act}}(k). \end{array} \tag{6.10}$$

The variables and the data to the problem have all been previously described (see Problem 6.8) except $\tilde{\pi}_{\text{avg}}$ which is the predicted average spot price for the following day; hence the term $T(H)\frac{\tilde{\pi}_{\text{avg}}}{b}$ is a way to appraise the energy stored in the portfolio at the end of the horizon. The optimal value is denoted $J^\star(u_{\text{act}}(k))$ and describes the cost if we choose to bid and are activated for regulating power of volume $u_{\text{act}}(k)$.

The regulating power bid $\pi_{\text{bid}}(u_{\text{act}}(k))$ for providing the regulating power delivery $u_{\text{act}}(k)$ can be found as the RP price where the cost of not providing regulating power $J^\star(0)$ equals the cost of being activated for a delivery $u_{\text{act}}(k)$ given by $J^\star(u_{\text{act}}(k))$ plus the portfolio's imbalance cost $u_{\text{act}}(k)(\pi_{\text{RP}}(k) - \pi(k))$. We can therefore find the regulating power bid $\pi_{\text{bid}}(u_{\text{act}}(k))$ associated with a regulation power delivery $u_{\text{act}}(k)$ by solving

$$J^\star(0) = J^\star(u_{\text{act}}) + u_{\text{act}}(\pi_{\text{bid}}(u_{\text{act}}(k)) - \pi(k)). \tag{6.11}$$

We illustrate the equation with a small example: assume the cost of operating the portfolio with no activation is $J^\star(0) = 1000$ DKK while the cost of delivering 10 MW of downward regulation ($u_{\text{act}} = 10$ MW) is $J^\star(10) = 1.200$ DKK and assume a spot price of 200 DKK/MW. In this case, our downward regulating power bid is $\pi_{\text{bid}}(10) = 180$ DKK/MW according to (6.11) as we will break even at this price while we will profit if the regulating power price becomes even lower. If the cost of operating the portfolio to provide 10 MW of upward regulation ($u_{\text{act}} = -10$ MW) is $J^\star(-10) = 1.200$ DKK, the regulating power bid will be $\pi_{\text{bid}}(-10) = 220$ DKK/MW according to (6.11).

Algorithm

We can now describe the algorithm of operating the portfolio to both perform spot price optimization and also bid into the regulating power market. This is presented in Algorithm 2.

5 Numerical Simulations

We perform two simulations to examine the presented control algorithms and use data from the "Styr din varmepumpe" project as a benchmark. Hereby we get a benchmark that corresponds to heat pumps operating using their default controllers which are only concerned with honoring a temperature setpoint and do not take spot prices into account. In both cases we consider a portfolio of $10,000$ heat pumps with heat capacity and drain rate as estimated in Sec. 2 and a nominal power consumption of 4 kW; further, an allowable temperature band of $\pm$ 2 °C around a setpoint of 21.5 °C is assumed. A sampling time of 5 minutes is used. The utilized data are:

Algorithm 2 Regulating Power Algorithm

for $k = 1, 2, \ldots$ **do**
  Collect data and perform intra-day optimization similar to Algorithm 1 Determine regulating power bids $\pi_{\text{bid}}(u_{\text{act}}(k))$ for all feasible multiples of 10 MW based on Problem (6.10) and (6.11) and place bids in market
  if *Current hour is between 11 a.m. and 12 p.m.* **then**
    Purchase electricity similar to Algorithm 1
  end
  if *Activated for delivery* $u_{\text{act}}(k)$ **then**
    Let VPP steer portfolio's consumption to $u(k) = u_{\text{sch}} + u_{\text{act}}(k)$
  else
    Let VPP steer portfolio's consumption to $u(k) = u_{\text{sch}}(k)$
  end
  update scheduled consumption for next hour $u_{\text{sch}}(k+1)$
end

- Spot price data from Nord Pool,
- Spot price predictions provided by [21],
- Outdoor temperature and daily loads from the "Styr din varmepumpe" project,
- Outdoor temperature predictions from the Danish Meteorology Institute.

We perform simulations for a full year and assume a liquid market where we do not affect the market prices[1].

Simulation 1: Spot Price Optimization

Algorithm 1 is utilized to operate the portfolio for spot price optimization for a full year. The resulting average temperature, power consumption, and costs are illustrated in Table 6.1. In Figure 6.5 the operation over 5 days is presented to illustrate the behavior of this controller. The top subplot shows the spot price predictions (red) and realizations (blue). The second subplot shows the power consumption of the heat pumps in the "Styr din varmepumpe' project (green) upscaled from the 130 available measurements to 10,000 heat pumps. In the same subplot we show the power consumption when the portfolio is operated by the controller developed in this work (purple). Finally, the lower subplot shows the resulting average indoor temperature with the spot price controller operating the portfolio (purple) compared to the observed data for that period (green).

Together, the three subplots show the main result of the spot optimizing controller: that the developed controller is able to shift the main consumption to hours of low spot prices while keeping the temperature fluctuations in the same magnitude as the houses currently experience. It is important to notice that the aggregated portfolio is idealized

[1] It is difficult to predict how the market volatility will evolve the following years: increasing penetration of renewables and increasing oil prices suggests higher and more fluctuating prices while increasing volumes of flexibility and new transmission cables suggest the opposite.

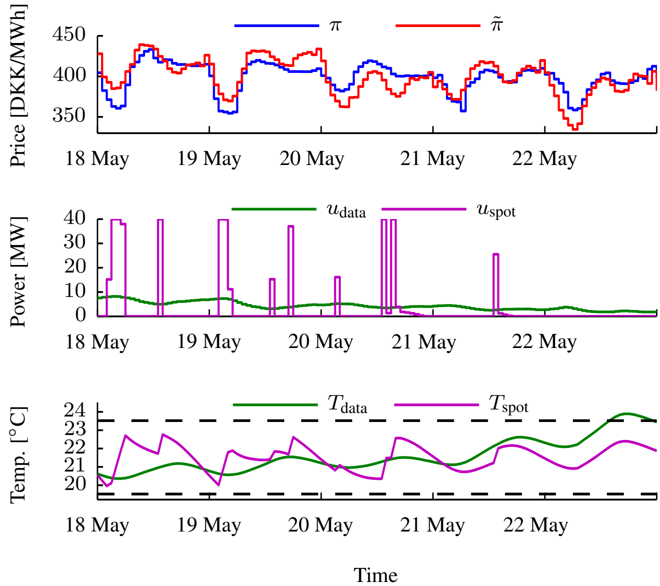

Figure 6.5: Simulated heat pump portfolio optimized towards spot prices (purple) compared to upscaled real measurements (green).

		Data	Spot.	Reg.
Avg. temp.	[°C]	21.5	21.6	21.6
Avg. pwr.	[W]	732	737	744
Avg. spot.	[DKK/MWh]	356	282	270
Total cost per hp.	[DKK]	2.285	1.819	1.759
Savings	[%]	0	17.8	19.9

Table 6.1: Performance comparison of measurements and the two control strategies developed in this work.

as no delays, ramping constraints, etc. are included. This becomes evident in the idealized on/off characterized power consumption of the portfolio as illustrated in Figure 6.5. Hence, the performance in the simulations will be higher than what we can expect by implementing the strategy.

Finally, notice that the spot price optimization will cause the natural smoothing of the heat pump portfolio consumption to disappear which may distribution grid congestion issues. This problem is, however, outside the scope of this work.

Simulation 2: Regulating Power Optimization

Algorithm 2 is utilized to operate the portfolio both for spot price optimization and for providing regulating power. Again, the end results are presented in Table 6.1 while a 5-

day closeup is presented in Figure 6.6. The top subplot shows the spot price realizations (blue) and the regulating power realizations (red). Following in the second subplot, the activations of regulating power is shown (yellow) along with the resulting consumption (purple) for the regulating power controller. It is observed, that the portfolio is activated for upward regulation in the cases where the RP price is significantly high; similarly the portfolio is activated for downward regulation when the RP price is significantly low. Note the portfolio is not able to perform upward regulation (decrease consumption) in the start of May 21st where the highest regulating power price is observed as the consumption already is scheduled to be zero and cannot be decreased further. Finally, the third plot again shows the resulting temperatures indicating that the fluctuations in the case of the regulating power controller is in the same order of magnitude as the observed indoor temperatures in the same period.

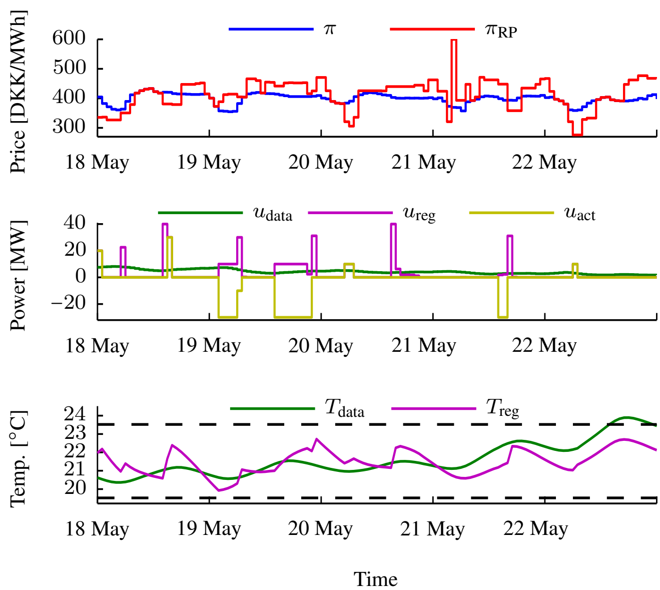

Figure 6.6: Simulated heat pump portfolio optimized towards spot prices and the regulating power market (purple) compared to upscaled real measurements (green).

Comparison

In Table 6.1 we compare the two controllers with the data observed the same year. The first row shows that the average temperature based on measurements (data) is 21.5 °C, which therefore is used as a setpoint for the two controllers resulting in almost identical average temperature. The next row shows the average power consumption which is measured to be 732 W while the two control strategies require a slightly higher power consumption. The average spot price based on the data is 356 DKK/MWh which is close to the yearly average spot price of 357 DKK/MWh – this is a result of the smooth power consumption of the heat pumps. By comparison, the spot price optimizing controller is able to lower this around 18 % while the controller that also bids into the regulating power market is able to save around 20 %. We observe that the annual savings per heat pump is in the magnitude of 470 DKK for spot price optimization but only additionally 60 DKK when also providing regulating power. We remind the reader that the simulated results are based on a somewhat idealized model; hence it should be expected that the savings when implementing this in real life will be lower. As described, actual spot price predictions are utilized for the simulation. By applying the actual spot prices, i.e. perfect predictions, we gain additionally 5 percentage points illustrating that the spot price predictions are of reasonable quality.

6 Conclusion

In this work we showed how the consumption of a portfolio of heat pumps could be optimized towards spot price predictions day-ahead and adjusted intra-day to ensure comfort. Simulations were presented showing that savings in terms of reduced electricity costs in the magnitude of 18 % could be achieved compared to conventional heat pump operation. The controller was further extended to also bid into the regulating power market increasing the savings up to around 20 %. The savings 18 – 20 % correspond to around 500 DKK/year indicating that the equipment and installation costs must be very small to justify this type of optimization. Both controllers were designed based on the current regulations in the Nordic electricity market.

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Paper 4

Lumped Thermal Household Model

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Abstract

In this paper we discuss two different approaches to model the flexible power consumption of heat pump heated households: individual household modeling and lumped modeling. We illustrate that a benefit of individual modeling is that we can overview and optimize the complete flexibility of a heat pump portfolio. Following, we illustrate two disadvantages of individual models, namely that it requires much computational effort to optimize over a large portfolio, and second that it is difficult to accurately model the houses in certain time periods due to local disturbances. Finally, we propose a lumped model approach as an alternative to the individual models. In the lumped model, the portfolio is seen as baseline consumption superimposed with an ideal storage of limited power and energy capacity. The benefit of such a lumped model is that the computational effort of flexibility optimization is significantly reduced. Further, the individual disturbances will smooth out as the number of houses in the portfolio increases.

1 Introduction

The use of heat pumps is expected to increase in the foreseeable future throughout the developed world, due to its high efficiency and ability to utilize the inexhaustible and renewable ambient ground or air heat. In the future Danish electricity system it is expected that domestic heat pumps will play an important role as flexible consumption: already now, around $27,000$ heat pumps are installed in Denmark [1], and potentially $205,000$ households can benefit from replacing oil-fired boilers with heat pumps in the coming years [2]. It is therefore most relevant to consider how to aggregate and control this flexibility towards the electricity markets.

Control of smaller flexible consumers to support grid stability has been discussed as early as the 1980s [3]. Since, the topic of demand-side management has received much attention from a research perspective including control of heat pumps [4, 5]. In particular, optimization of heat pumps has received much attention in Denmark the last few years, see [6, 7, 8, 9, 10].

Adequate flexibility models are a crucial element in the control of flexible devices. In many works, such flexibility models are used to design appropriate control strategies for controlling heat pumps, see e.g. [11, 7, 9, 12]. Several studies demonstrate how to construct such household models: In [13], an individual heat pump model is successfully constructed based on real life experiments conducted in a laboratory setting. In [14], a custom built house is modeled successfully with a linear model for an inhabited household. Other works construct household models based on inhabited households, see [8, 15].

In this work, we argue that an alternative to such individual household models is to utilize a lumped model that represents an *entire portfolio* of households. Two main arguments for proposing this lumped model are as follows. The first reason is that a lumped flexibility model has the clear advantage that the computational efforts of flexibility optimization decreases drastically by comparison with individual models. The second reason is that the many disturbances to some extent will cancel out as the number of households in the portfolio increases, reducing the disturbances seen in the lumped model. Such a lumped model approach is described for example in [16, 17, 18], but is only dealt with via simulations. In this work we use real life data to motivate the use of such a lumped model.

First, we use data from inhabited Danish houses heated with heat pumps to illustrate that local disturbances at the households can be large and that this may result in poor modeling results at certain times. Following, we present the lumped model as an alternative approach. The basic concept is to consider a portfolio of households as an ideal storage of a given volume. Combined with the baseline consumption of the portfolio, this model can be utilized for flexibility optimization.

The paper is structured as follows. First in Sec. 2 we describe the heat pump platform where the data is taken from; following in Sec. 3, we introduce the concept of flexibility modeling and optimization. In Sec. 4 we present the individual modeling approach and show the benefits and limitations associated with this method, similarly in Sec. 5, a lumped model is presented and the benefits and limitations of this method is illustrated. Finally in Sec. 6, a discussion of the two methods is presented and in Sec. 7 we conclude the work.

2 Real Life Heat Pump Demonstration Setup

In this section, we describe the platform of households with heat pumps used as data source in this study.

Heterogeneous Households Portfolio

The platform called *Styr din varmepumpe* (meaning: Control your heat pump) consists of 300 households with heat pump heating [8]. The houses are all real life inhabited houses located in different locations in Denmark. The houses vary from smaller houses with a total area of 100 m^2 to larger houses with an area of 400 m^2. Further, the houses vary in type: some are old houses constructed in the 1850s while other houses are newly constructed.

Also the heat pumps are different; more than 50 different heat pump designs are present. Moreover, the heating systems vary much in the different houses: all the houses have a heat pump but some of the houses use underfloor heating while other have radiators. Additionally, some of the houses are equipped with other heating sources than the heat pump, for example a wood stove or solar heating. Consequently, we are dealing with a realistic real life heterogeneous household portfolio representative of typical Danish households.

Controlling and Monitoring the Households

The households included in this platform have all installed the heat pumps before being a part of this project. Various sensor equipment has therefore been subsequently installed. These sensors include power measurements of the heat pump, a single indoor thermometer, and an outdoor thermometer. In this project it has not been possible to remotely control the heat pumps.

The sensor data is transmitted over an Internet connection to a server. The sampling time of the communication link between heat pump and the server is 5 minutes.

3 Modeling and Optimization of Flexible Consumption

In this section, we briefly describe the purpose of a heat pump flexibility model, how such a model can be utilized, and motivate why it is interesting to examine a lumped flexibility model approach.

Flexibility Optimization

Heat pumps are flexible consumption devices due to the inherent thermal capacity of the houses. Consequently, it is possible to aggregate and optimize the consumption of a portfolio of heat pumps towards some given objective. Examples could be to optimize the consumption based on a price signal or based on predictions of the spot price, or it could be to provide ancillary services.

Flexibility Model

A flexibility model is required to perform flexibility optimization, i.e. we must know to what extent the consumption can be shifted without violating the comfort limits of the inhabitants. Such flexibility models are constructed on household level in many works, meaning that a flexibility model of each house is constructed, see e.g. [11, 7, 9, 12].

In this work we are argue that when dealing with real life households equipped with a single indoor thermometer, disturbances can in certain time periods be so severe and the available sensing is so limited, that individual flexibility modeling is difficult. Therefore we propose an alternative approach: Instead of modeling each house separately, we consider the portfolio as one entity and construct a model of the combined flexibility, i.e., we consider a lumped model. The benefit of such a lumped model is that the many disturbances will cancel out as the number of houses comprising the portfolio increases.

4 Individual Modeling of Households

In this section, we show the concept of an individual household model and how such a model can be used for flexibility optimization. Further, we illustrate the difficulties in utilizing such a flexibility model.

Individual Model and Flexibility Optimization

Let i index the households, let I be the total number of houses in the portfolio, and let $\mathcal{I} = \{1, \ldots, I\}$ represent the entire portfolio. A linear nth-order individual household model can be expressed as

$$x_i(k+1) = A_i x_i(k) + B_i u_i(k) + C_i v_i(k) \tag{7.1}$$

where $x_i(k) \in \mathbf{R}^n$ is the state vector, $u_i(k) \in \mathbf{R}$ is the power input from the heat pump, and $v_i(k) \in \mathbf{R}^m$ is the disturbance inputs such as outdoor temperature, solar irradiation, wind, etc. The matrices $A_i \in \mathbf{R}^{n\times n}, B_i \in \mathbf{R}^{n\times 1}, C_i \in \mathbf{R}^{n\times m}$ represent the household dynamics. Further, the state and input limitations are modeled as follows

$$x_i(k) \in \mathcal{X}_i, \quad u_i(k) \in \mathcal{U}_i, \quad i \in \mathcal{I} \tag{7.2}$$

where sets $\mathcal{X}_i, \mathcal{U}_i, i \in \mathcal{I}$ describe the system limitations such as the power limitations of the heat pump and the thermal comfort limitations. Many of the works using individual heat pump models rely on such linear models.

A simple version of this thermal model is a first order model where the state x_i is the indoor temperature and where $\mathcal{X}_i$ represent the lower and upper allowable temperature and where u_i is the electrical power and $\mathcal{U}_i$ describe the power limitations for house number i. This simple model can be extended for example to include a state for the floor temperature or for separate rooms, etc.

We construct a small example to illustrate how such a model can be utilized for flexibility optimization. Assume we have purchased electricity at the spot market for example for the following day. We denote the purchased electricity $p_{\text{spot}}(k), k \in \mathcal{K}$ where $\mathcal{K} = \{k_1, \dots, k_2\}$ represent our horizon. Further, assume our objective is to consume what we have purchased at the spot market to avoid imbalance and thus avoid trading balancing power at possibly unfavorable prices. We can formulate this as an optimization problem

$$\begin{array}{ll} \text{min.} & \sum_{k \in \mathcal{K}} \left| p_{\text{spot}}(k) - \sum_{i \in \mathcal{I}} u_i(k) \right| \\ \text{s.t.} & x_i(k+1) = A_i x_i(k) + B_i u_i(k) + C_i \hat{v}_i(k) \\ & x_i(k+1) \in \mathcal{X}_i, \quad u_i(k) \in \mathcal{U}_i \\ & k \in \mathcal{K}, i \in \mathcal{I} \end{array} \tag{7.3}$$

where the variables are $u_i(k), x_i(k+1), i \in \mathcal{I}, k \in \mathcal{K}$ and the data is current state $x(k)$, the purchased electricity and predictions of the disturbance inputs $p_{\text{spot}}(k), \hat{v}_i(k), k \in \mathcal{K}$.

We notice two things in Problem 7.3: First we see that this method is able to deal with each household individually and therefore will handle the energy optimization optimally within the horizon provided the models are true and the disturbance predictions are perfect. Second, we observe that the computationally complexity grows rapidly with the number of houses I indicating that this method might not be suitable when dealing with thousands of heat pumps.

Individual Modeling of Inhabited Household

In the above subsection, we illustrated how household models can be utilized to optimize the flexibility towards some objective. In this subsection, we illustrate some of the difficulties of making individual flexibility models.

We use data from 40 of the houses in the available platform and attempt to fit different models including 1st and 2nd order linear models. The heat pump power is taken as input and the indoor temperature as output. Different disturbance inputs are included in the model: the outdoor temperature, the solar irradiation, and a daily consumer load pattern. As presented in [15, 8], it is possible to capture the main dynamics of the households. However in this study we also conclude, that in certain time periods, it is difficult to capture the house dynamics presumably because of local disturbances. We illustrate this with a concrete example where we fit a first order model that takes power and outdoor temperature as inputs and the indoor temperature as output. The prediction error method is utilized based on observations of the last 7 days to predict the behavior the 24 hours of the following day; this is repeated each day. The result is illustrated in Figure 7.1 showing both the predicted indoor temperature when the future temperature and future power consumption is known and the actual indoor temperature realization. As the figure shows, it is in this case not possible to make a good model fit. Similar results are obtained also when including other inputs such as solar irradiation and also for higher order models.

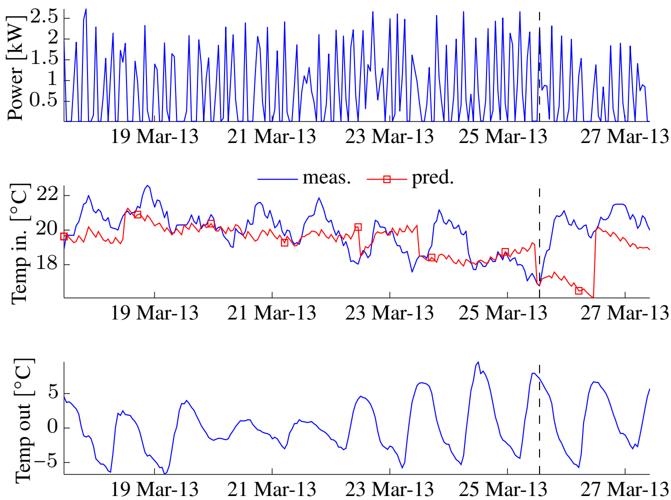

Figure 7.1: Data from 10 days in March 2013 showing the heat pump power consumption, the indoor temperature and predicted indoor temperature, and finally the outdoor temperature. The jumps in the predicted indoor temperature every 24 hours occur because we predict for one full day at a time. The vertical black dashed line represents a time instance where the behavior of the household is particularly inexplicable: the indoor temperature is rising although the outdoor temperature is decreasing and the power is constant.

To illustrate the difficulties that the individual modeling of inhabited households can have we observe the figure more closely. In the afternoon of the 25th of March (indicated with a vertical dashed black line) the outdoor temperature is dropping, the sun is setting (not visible from plot) and the heat pump power is approximately constant; however, surprisingly the indoor temperature is rising. The reason could be the use of a wood-stove; however, we do not have access to this kind of information. Consequently, we cannot capture this in the system identification resulting in poor modeling for this particular example.

Sub-conclusion on Individual Household Modeling

In this section we have showed that flexibility optimization of heat pump flexibility based on individual models can be computationally heavy. Further we have showed that individual modeling of real inhabited households can be done, see for example [15, 8]; however, large disturbances makes it difficult to capture the house dynamics in certain time periods. These disturbances are believed to be the effect of opening/closing of windows and doors, wood stove or other alternative heating sources, use of electronic devices generating heat such as oven, computers, etc.

We conclude that it is reasonable to consider if there are alternatives to the individual modeling approach.

5 Lumped Modeling of Households

In this section, we show the concept of a lumped model of a portfolio of heat pump heated houses and show how such a model can be utilized for flexibility optimization. We are not able to conduct the necessary experiments to verify the proposed flexibility model altogether, instead we illustrate the benefit of such a model by examining some historical heat pump data.

Lumped Model and Flexibility Optimization

In the previous section it was concluded that it makes sense to examine alternatives to the individual modeling approach. Therefore, we propose to consider a much simpler approach: namely to model an entire heat pump portfolio using a lumped model. Obviously such a model will have its limitations as it is not able to capture the different dynamics and constraints of the individual heat pumps in the portfolio; on the contrary, it will capture the main flexibility and make it possible to optimize this flexibility towards a given objective. The advantage of such a lumped model is the simplicity and the low computational effort of optimizing the portfolio flexibility; further, the many disturbances affecting the individual heat pumps will to a large extend cancel out as the number of houses increases.

The main idea is to consider the heat pump portfolio as two parts: a baseline consumption (consumption when heat pumps operate in default mode) superimposed with an ideal storage. Let $p(k)$ be the accumulated consumption of the heat pump portfolio at time k, i.e. $p(k) = \sum_{i\in\mathcal{I}} u_i(k)$. Now assume that the accumulated consumption $p(k)$ consists of a baseline consumption $\overline{p}(k)$ and a flexible consumption part $\tilde{p}(k)$; finally, let $x(k)$ denote the energy stored in the ideal storage. We can write this flexibility model as

$$p(k) = \overline{p}(k) + \tilde{p}(k), \quad p_{\text{min}} \le p(k) \le p_{\text{max}} \tag{7.4}$$

$$x(k+1) = x(k) + T_s\alpha\tilde{p}(k), \quad x_{\text{min}} \le x(k) \le x_{\text{max}} \tag{7.5}$$

where $p_{\text{min}}, p_{\text{max}}$ and $x_{\text{min}}, x_{\text{max}}$ are power and energy limitations, T_s is the sampling time, and α is a parameter that performs a desired scaling of the power to energy. One method of implementing this is to use the individual indoor temperatures as a measure of $x(k)$ and the individual temperature comfort limits to find x_{min} and x_{max}, see [19]. In this case, the parameter α will describe the households' thermal parameters and the heat pumps' COP. The power limitations $p_{\text{min}}, p_{\text{max}}$ can be set to the minimum and maximum power consumption of the entire portfolio, possibly adjusted by some margin.

Obviously, the simple model presented in (7.4), (7.5) have many limitations. An example is that the ideal storage model will predict that the energy loss to the ambient is independent of the indoor temperature. This obviously conflicts with the physics, as the energy loss will increase with increasing indoor temperature. It is, however, the authors' opinion that the presented model is a solid starting point when performing real life optimization of the flexibility of inhabited houses. The reason is that when dealing with real life inhabited households, the local disturbances are so severe that what is needed is a rough estimation of the available flexibility and not a high fidelity model. For example, the disturbances illustrated in Figure 7.1 will be much larger than the increased loss to the ambient that will occur if we increase the indoor temperature one or two degrees from the set-point.

We consider the same small problem as presented in the previous section to illustrate how this model can be used for flexibility optimization. With the lumped model, we can formulate the power tracking optimization problem as follows

$$\begin{array}{ll} \text{min.} & \sum_{k\in\mathcal{K}} \left|p_{\text{spot}}(k) - \tilde{p}(k) - \hat{\overline{p}}(k)\right| \\ \text{s.t.} & p_{\min} \le \hat{\overline{p}}(k) + \tilde{p}(k) \le p_{\max}, \quad k \in \mathcal{K} \\ & x(k+1) = x(k) + T_s\tilde{p}(k), \quad k \in \mathcal{K} \\ & x_{\min} \le x(k) \le x_{\max}, \quad k \in \mathcal{K} \end{array} \tag{7.6}$$

where the variables are $x(k+1), \tilde{p}(k), k \in \mathcal{K}$ while the data is the current storage level $x(k)$ and the purchased electricity and the baseline consumption predictions $p_{\text{spot}}(k)$, $\hat{\overline{p}}(k)$.

Notice that solving Problem (7.6) can be done with low computational effort independent on the number of households due to the lumped model, i.e. we can easily optimize over thousands of heat pumps. Further notice, that the solution $\tilde{p}^\star(k), k \in \mathcal{K}$ will show the *accumulated* flexible consumption over time. Therefore a so-called *dispatcher* must dispatch the total consumption among the individual heat pumps, i.e. the dispatcher must translate $\overline{p}(k) + \tilde{p}^\star(k)$ into $u_1(k), \dots, u_I(k)$. Such dispatch strategies can be implemented based on sorting algorithms and thus require low computational effort and easily handle thousands of units. For details on how this can be achieved, see for example [19, 20].

Further notice that this optimization problem clearly illustrates some of the limitations of the lumped model: The fixed limits on the power consumption assumes that none of the heat pumps are saturated such that they all are available for regulation. This is obviously a simplification and may cause a performance loss. A solution is to reduce the limits $p_{\min}, p_{\max}$ with a given margin. Again we remind the reader that we do not seek a high fidelity model; rather, we seek the most simple model that can be used for flexibility optimization.

Lumped Modeling of Inhabited Households

In the subsection above we presented a lumped model of a heat pump portfolio consisting of a baseline consumption combined with an ideal storage. In the following, we show how the power baseline $\overline{p}(k)$ can be estimated for a 24 hour horizon. In this study we do, however, not estimate the energy and power limits $x_{\min}, x_{\max}$ as it requires active control of the heat pumps, which is not possible in this study.

The baseline prediction is constructed as follows: The hourly energy consumption of the heat pump portfolio and the hourly outdoor temperature is collected for the previous 7 days and an affine transformation is made relating the observed outdoor temperature and energy consumption. Other parameters such as solar irradiation could be included, but for simplicity this is left out in this study. Now, meteorological predictions of the outdoor temperature the following day can be converted to predicted energy consumption based on the affine transformation.

This simple method is one out of many: higher order models could have been used, additional inputs could have been included, etc. However, we have implemented this very simple model to emphasize how easily such baseline estimation can be made. We test this method on data from 40 households from 1st of January until end of May 2013. The result is an average prediction error of 140 W per heat pump corresponding to an average prediction error of less than 11 % as the average heat pump consumption is 1.3 kW. Again, 10 days data are presented showing this predictor's ability to capture the hourly consumption of the portfolio, see Figure 7.2.

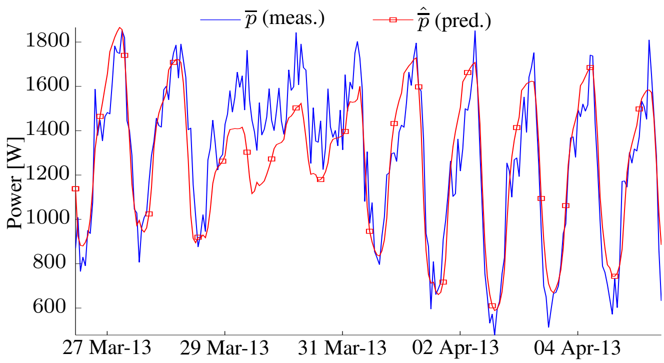

Figure 7.2: Predictions made every midnight for the 24 hours of the following day for a total of 10 days for a portfolio of 40 heat pumps. The power is scaled with a factor 40 and thus represents and "average" heat pump.

Notice that the fit in Figure 7.2 only shows the ability to predict the hourly portfolio consumption; hence, it does not show any dynamics of the portfolio and therefore does not validate the proposed flexibility model an and can therefore not be compared to the individual model fig in Figure 7.1. For this reason, Figure 7.2 does not validate the proposed lumped model; rather, it validates that we can predict the portfolio baseline consumption and motivates our argument that the disturbances will cancel out as number of households increases.

Sub-conclusion on Lumped Household Modeling

We illustrated that the lumped modeling approach reduced the computational effort of flexibility optimization radically. We were, however, not able to verify the proposed model altogether as this would require extensive experiments. Instead, we used historical data to illustrate the benefit of the lumped modeling approach: that the disturbances on the individual houses to a large extend will cancel out which enables us to predict the baseline consumption with acceptable performance.

6 Discussion

A much debated issue within the smart grid community is the use of flexible consumers to resolve grid congestion issues. Here we notice that we cannot use a lumped model to resolve local grid congestion issues: we do not know the geographical location of the individual heat pumps as they are all lumped into one model. One way to extend the presented method to cover this is to construct a lumped model for each feeder with issues; consequently we will have a number of lumped models for example with hundreds of heat pumps in each. Another approach is to incorporate the congestion alleviation mechanism in the dispatcher.

7 Conclusion

In this paper we discussed two different approaches of modeling a heat pump portfolio: individual modeling and lumped modeling. We proposed a simple lumped model approach where an entire heat pump portfolio was modeled all together. This lumped model consisted of a baseline consumption superimposed with an ideal storage of limited energy capacity and with given power constraints. A clear benefit of the lumped model was that low computational effort required for flexibility optimization. Another advantage of the lumped model was the smoothing of individual household disturbances. We were not able to verify the mode altogether but motivated the benefit of the approach by showing that the portfolio baseline consumption could be predicted 24 hours ahead with an acceptable accuracy.

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Paper 5

Smart Grid Dispatch Strategy for ON/OFF Demand-Side Devices

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Abstract

We consider an aggregator managing a portfolio of runtime and downtime constrained ON/OFF demand-side devices. The devices are able to shift consumption in time within certain energy limitations. We show how the aggregator can manage the portfolio of devices to collectively provide upward and downward regulation. Two control strategies are presented enabling the portfolio to provide regulating power while respecting the runtime, downtime, and energy constraints of the devices. The first strategy is a predictive controller requiring complete device information; this controller is able to utilize the full flexibility of the portfolio but can only handle a small number of devices. The second strategy is an agile controller requiring less device information; this controller is able to handle a large number of devices but not able to utilize the full flexibility of the portfolio.

1 Introduction

With an increasing focus on climate-related issues and rising fossil fuel prices, the penetration of renewable energy sources is likely to increase in the foreseeable future throughout the developed world [1]. Many actions have been taken from a political point to increase the penetration of renewables: in the US, almost all states have renewable portfolio standards or goals that ensure a certain percentage of renewables [2]. Similarly, the commission of the European Community has set a target of 20 % renewables by 2020 [3], while China has doubled its wind power production every year since 2004 [4]. In Denmark, the 2020 goals are 35 % sustainable energy over all energy sectors and 50 % wind power in electrical energy sector [5].

A major challenge arises when replacing central power plants with renewable energy sources: the central power plants do not only deliver power but also provide ancillary services to ensure a reliable and secure electrical power system. This includes frequency stability support, power balancing, voltage control, etc. When the conventional power plants are replaced with renewables such as wind turbines and photovoltaics, the ability to provide ancillary services in the classical sense disappears; the renewable energy sources will often fully utilize the available power and thus not be able to provide balancing ancillary services. Moreover, many renewable sources are characterized by highly fluctuating power generation: they can suddenly increase or decrease production depending on weather conditions. These rapid production changes are not always predictable and can therefore have severe consequences for grid stability [6].

It is therefore evident that in a grid with high penetration of renewables, the need for balancing ancillary services will increase [7], [8]. As conventional power plants are pushed out gradually, alternative sources of ancillary services must be found. One of the approaches to obtaining alternative ancillary services is the *smart grid* concept, where demand-side devices with flexible power consumption take part in the balancing effort [9], [10]. The basic idea is to let an *aggregator* manage a portfolio of flexible demand-side devices and utilize the accumulated flexibility in the unbundled electricity markets on equal terms with conventional generators [11].

In this work, we consider the class of flexible consumption devices that only can be switched either ON or OFF possibly with minimum runtime and minimum downtime constraints. This covers a large range of different devices, for example thermal devices such as heat pumps, refrigeration and freezer systems, etc. We present two different direct load control strategies for enabling these devices to provide ancillary services: a predictive and an agile controller. The predictive controller requires full knowledge of all device parameters and provides an upper performance bound. This controller is, however, only able to handle a limited number of devices due to the computational burden. On the other hand, the agile controller is able to handle many devices and requires only little knowledge of the device parameters at the expense of not being able to utilize the full flexibility.

The paper structure is as follows. In Sec. 2, the system architecture is presented. Following, in Sec. 3, it is described how flexible ON/OFF consumers are able to deliver regulating reserves. In Sec. 4 and Sec. 5, the predictive and agile control strategies are presented. Numerical examples demonstrating these strategies are presented in Sec. 6. Finally, Sec. 7 concludes the work.

2 System Architecture

In this section, we describe the overall relation between consumers, the aggregator, and the electricity markets.

The Aggregator as a Player in the Electricity Markets

We consider an unbundled liberalized electricity market system architecture. In this setup, the Transmission System Operators (TSOs) are responsible for secure and reliable system operation and must consequently ensure balance between production and consumption. Generally speaking, in an unbundled electricity market, TSOs do not own production units and must therefore procure ancillary services in the electricity markets to ensure system stability [12].

The aggregator is a legal entity able to enter into flexibility contracts with consumers. These contracts allow the aggregator to manage the consumers' flexible consumption; hereby, the aggregator is able to utilize the accumulated consumer flexibility to participate in the electricity markets. The flexible devices are managed by the aggregator through a technical unit often referred to as a virtual power plant (VPP). This setup is illustrated in Figure 8.1 and inspired by [11]. In this work, we consider an aggregator utilizing the consumer flexibility to participate in the regulating power markets.

The Regulating Power Market

The suppliers can submit bids for upward regulation (increased production or reduced consumption) or downward regulation (decreased production or increased consumption) in the regulating power market. In the delivery hour, the TSO will activate the submitted bids if needs for upward or downward regulation occur.

The focus of this work is a dispatch strategy for a portfolio of devices activated for a given regulating power delivery. This means that we do not consider flexibility estimation, bidding strategies or similar in this work; rather, we describe how the portfolio should be managed to deliver regulating power once activated.

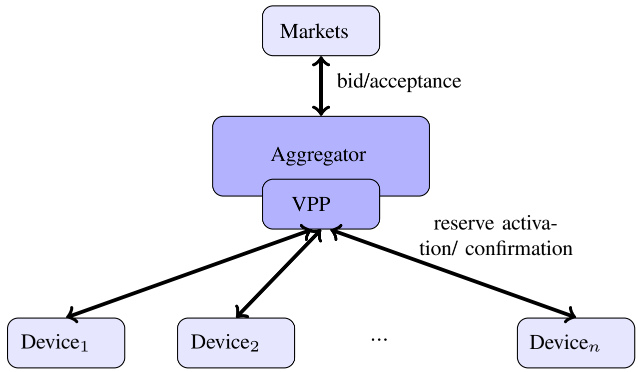

Figure 8.1: Aggregator bidding in the electricity markets by managing n flexible ON/OFF devices through a VPP.

Demand-Side Devices as Power Reserves

Through a VPP, the aggregator manages a portfolio of runtime/downtime constrained ON/OFF devices with flexible power consumption. This covers a large class of devices; for example, thermal devices with large time constants such as electrically heated houses, refrigerations systems, water heaters, etc. [13]. The power consumption of these devices is not continuously adjustable; rather, the devices are either turned ON or OFF.

In order for consumption devices to provide ancillary services, they must be separated from and independent of ordinary consumption and must be approved by a TSO as consumption that can be used as regulation reserves [14]. The hourly energy consumption of the portfolio must equal the energy bought at the spot-markets as long as the portfolio is not activated for power reserves. Upon activation, the hourly energy consumption of the portfolio must be adjusted accordingly.

In this work, we assume that the portfolio of devices under the jurisdiction of the aggregator indeed is approved by a TSO. Moreover, we assume that the necessary two-way communication between the aggregator's VPP and the ON/OFF devices exists as illustrated in Figure 8.1.

3 Regulating Reserves via ON/OFF Devices

In this section we describe how a portfolio of ON/OFF devices collectively can deliver regulating power.

ON/OFF Consumption Devices

The VPP manages a portfolio of n flexible ON/OFF consumption devices. We assume that these devices can be modeled as energy storages with a time-varying drain. Denote the energy levels of the devices $x(k) \in \mathbf{R}^n$, the nominal device power ratings $p(k) \in \mathbf{R}^n$, and the drain rates $v(k) \in \mathbf{R}^n$, where k is the sample number using a sampling time T_s.

We model device i is as

$$x_i(k+1) = x_i(k) + T_\mathrm{s}\left(p_i u_i(k) - v_i(k)\right) \tag{8.1}$$

$$x_i(1) = x_i^0 \tag{8.2}$$

where $x^0 \in \mathbf{R}^n$ represents the initial states of the devices and

$$u(k) \in \{0,1\}^n \tag{8.3}$$

describes the state of each device: $u_i(k) = 1$ if device i is ON and $u_i(k) = 0$ if device i is OFF. The storage capacities are limited in size, thus we have

$$0 \le x(k) \le \overline{x} \tag{8.4}$$

where $\overline{x} \in \mathbf{R}^n$ describes the devices' energy limits and $\le$ represents componentwise inequality. The interpretation of these limitations depends on the type of device. For space heating systems, space cooling systems, water heating systems, etc., the limits could represent an allowable temperature band [13].

The ON/OFF devices are furthermore characterized by *minimum runtime constraints* and *minimum downtime constraints* describing that once a device is turned ON, it must remain ON for a certain amount of time; similarly, that once a devices is turned OFF, it must remain OFF for a certain amount of time. We use $\overline{r}, \underline{r} \in \mathbf{Z}_+^n$ to describe the runtime and downtime limits by letting $\overline{r}_i$ be the minimum number of samples device i must remain ON once turned ON and by letting $\underline{r}_i$ be the minimum number of samples device i must remain OFF once turned OFF:

$$\begin{aligned} u_i(k) - u_i(k-1) = 1 \implies& \\ u_i(k+1) = 1, \dots, u_i(k+\overline{r}_i - 1) = 1& \end{aligned} \tag{8.5}$$

$$\begin{aligned} u_i(k) - u_i(k-1) = -1 \implies& \\ u_i(k+1) = 0, \dots, u_i(k+\underline{r}_i - 1) = 0& \end{aligned} \tag{8.6}$$

where (8.5) describes the runtime constraint while (8.6) describes the downtime constraint. This type of constraints occur in many ON/OFF devices such as thermal systems where rapid switching of the compressor can damage the device or reduce lifetime significantly; likewise, rapid switching of for example heat pumps, will deteriorate performance.

Provisions of Regulating Reserves

The portfolio of ON/OFF devices is separated from and independent of regular consumption and is approved by the TSO as being able to deliver regulating reserves. The portfolio must therefore consume the electricity purchased at the spot-markets for each hour of the day. If the portfolio is activated for upward regulation, the consumption must be decreased accordingly the given hour; similarly, if activated for downward regulation, the consumption must be increased accordingly the given hour.

For simplicity, we make two assumptions that do not correspond to the regulating power markets. First, we assume that regulating power deliveries always are activated for exactly one delivery hour. In reality, however, the activation can be done for a shorter period and also within a delivery hour. Second, we assume that regulating power can be delivered in any manner, as long as the correct volume of energy is provided within the delivery hour. In reality, however, the regulating power must be provided at constant power.

Let l be the index of the operation hour and let the electricity purchased in the electricity markets for hour l be denoted $e_{\text{spot}}(l) \in \mathbf{R}$. Further, let $e_{\text{reg}}(l) \in \mathbf{R}$ denote the activated regulating power delivery in time period l and define $e_{\text{reg}}(l)$ as positive for upward regulation and negative for downward regulation in production terms. The energy reference $e_{\text{ref}}(l) \in \mathbf{R}$ for the portfolio is hereby given by

$$e_{\text{ref}}(l) = e_{\text{spot}}(l) - e_{\text{reg}}(l) \tag{8.7}$$

meaning that the portfolio of ON/OFF devices must consume the energy $e_{\text{ref}}(l)$ in hour l.

Regulating Power via ON/OFF Devices

As described, it is assumed that the power consumption within hour l can be chosen in any way as long as the energy reference $e_{\text{ref}}(l)$ is tracked according to the requirements. The portfolio is operated at a sampling rate T_{s} which is in the magnitude of minutes and thereby faster than the one-hour energy periods. The total power consumption of the portfolio at time sample k is denoted $p_{\text{out}}(k) \in \mathbf{R}$ and given by

$$p_{\text{out}}(k) = \mathbf{1}^T p(k) \tag{8.8}$$

where $\mathbf{1}$ is a vector with all components one. The hourly energy consumption $e_{\text{out}}(l) \in \mathbf{R}$ of the portfolio is found by integrating the portfolio power consumption $p_{\text{out}}(k)$ over each hour l:

$$e_{\text{out}}(l) = T_{\text{s}} \sum_{k=k_1(l)}^{k_2(l)} p_{\text{out}}(k) \tag{8.9}$$

where $k_1(l)$ and $k_2(l)$ indicate the first and last sample of the power consumption within hour l:

$$k_1(l) = \tfrac{3600}{T_{\text{s}}}(l-1) + 1, \quad k_2(l) = \tfrac{3600}{T_{\text{s}}} l \tag{8.10}$$

as $\frac{3600}{T_{\text{s}}}$ corresponds to the number of samples within one delivery hour. As the portfolio operates as a regulating reserve provider, it must be assured that the difference between the hourly energy consumption reference $e_{\text{ref}}(l)$ and the hourly energy consumption $e_{\text{out}}(l)$ is sufficiently small, hence we must minimize the tracking error $e_{\text{error}}(l) \in \mathbf{R}$ given by

$$e_{\text{error}}(l) = |e_{\text{ref}}(l) - e_{\text{out}}(l)| \,. \tag{8.11}$$

Summary of ON/OFF Device Characteristics

To visualize some of the concepts introduced in this section, we conclude with a small example. Consider a portfolio of 20 ON/OFF devices. The parameters of the portfolio are not important for this example but can be found later in (8.21). We assume that each device is operated by a local hysteresis controller on the form

$$u_i(k) = \begin{cases} 1 & \text{if } x_i(k) \le 0 \\ 0 & \text{if } x_i(k) \ge \overline{x}_i \\ u_i(k-1) & \text{otherwise.} \end{cases} \tag{8.12}$$

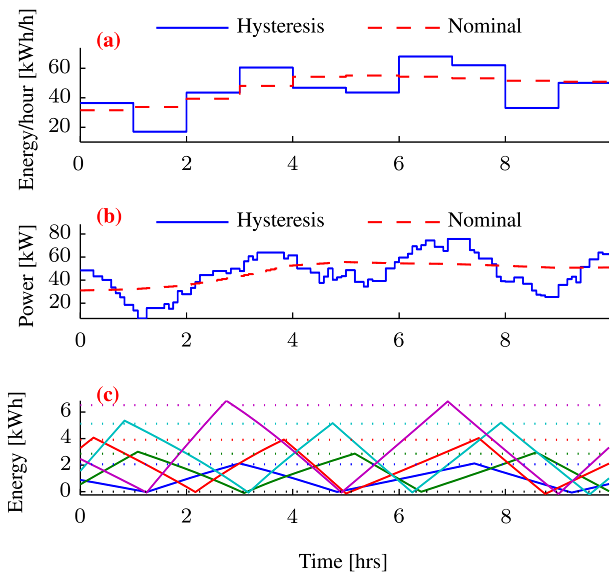

Figure 8.2: Behavior of portfolio controlled with local hysteresis controllers compared to the nominal (predictable) behavior. Subplot (a): hourly energy consumption; subplot (b): power consumption; subplot (c): energy levels $x(k)$ for 5 of the 20 devices and corresponding energy limitations $\overline{x}$.

The hourly power consumption $p_{\text{ref}}(k)$ and the energy consumption $e_{\text{out}}(l)$ are presented in Figure 8.2 along with the energy levels of 5 of the devices, for a 10 hour period. For comparison, the figure also shows the nominal power consumption, given directly by summation of the drain rates $v(k)$, and the nominal energy consumption, given by the accumulated drain per hour. The nominal energy consumption could correspond to the expected energy consumption and therefore the electricity we have purchased at the spot-market.

An important point can be made from the energy delivery plot: large deviations between purchased electricity and actual consumption can occur due to the stochastic behavior of the ON/OFF devices. This is, however, not acceptable as a provider of regulating reserves. Therefore, a controller must manage the switching of the ON/OFF devices to assure that we indeed consume the purchased electricity. Further, this controller must adjust the consumption when activated for upward or downward regulation. Such controllers are developed in the following two sections.

4 Predictive Controller Synthesis

In this section, we design a predictive controller to manage the portfolio of runtime/-downtime constrained ON/OFF devices. The controller relies on perfect information of the future load $v_i(k)$, the power rating p_i, and the capacity $\overline{x}_i$ of all devices for a given horizon of L hours.

The predictive controller is not to be seen as an implementable strategy as it is not realistic to achieve such perfect information several hours ahead; further, the algorithm will show to be computationally heavy and thus only applicable for a limited number of devices. On the contrary, the predictive controller serves as an *upper performance bound*: it uses perfect information of the future conditions and finds a control strategy for the portfolio within the control horizon of L hours if feasible. This upper bound allows us to evaluate the performance of the agile controller which is presented in next section.

Optimization of ON/OFF Devices

The objective of the predictive control strategy is to determine the ON/OFF pattern of each device in the portfolio such that the hourly energy consumption of the portfolio tracks the energy reference while the devices honor runtime, downtime, and energy constraints. Define $\mathcal{I}$ as the set of all devices, $\mathcal{L}$ as the set of the L delivery hours, and $\mathcal{K}$ as the set of time samples from the beginning of the first delivery hour to the end of the last delivery hour:

$$\mathcal{I} = \{1, \ldots, n\}, \quad \mathcal{L} = \{1, \ldots, L\}, \quad \mathcal{K} = \{1, \ldots, K\}, \tag{8.13}$$

where $K = 3600L/T_\mathrm{s}$ is the number of time samples within the horizon of L delivery hours.

Based on the previously introduced model, we can summarize the constraints and roughly formulate the predictive controller as follows.

$$\begin{array}{ll} \text{minimize} & \sum_{l \in \mathcal{L}} e_\text{error}(l) \\ \text{subject to} & \text{Eqs. } 8.1\text{–}8.3, 8.5\text{–}8.6, \quad i \in \mathcal{I}, k \in \mathcal{K} \\ & \text{Eqs. } 8.4, 8.8, \quad k \in \mathcal{K} \\ & \text{Eqs. } 8.9, \quad l \in \mathcal{L} \end{array} \tag{8.14}$$

where the variables are $u(k), k \in \mathcal{K}$. Denote a solution to the optimization problem $u^\star(k), k \in \mathcal{K}$. Note that $v(k), k \in \mathcal{K}$ is data to the problem meaning that perfect drain rate predictions are required to solve the problem. The solution $u^\star(1), \ldots, u^\star(K)$ will describe how the devices can be switched ON and OFF such that the energy reference $e_\text{ref}(1), \ldots, e_\text{ref}(L)$ is tracked within the smallest average deviation, while runtime, downtime, and energy constraints are honored.

Notice that in this work we simply use Problem (8.14) in a static manner, i.e. we perform an open loop optimization over the whole horizon. This is done as the solution only is used as an upper performance bound based on perfect portfolio knowledge as previously described. The optimization problem could, however, be implemented in a receding horizon fashion where we optimize over a given horizon, apply the first element of the solution $u^\star(1)$ to the plant, and then reoptimize the following sample after new information is obtained [15].

Binary Linear Optimization Problem

Problem (8.14) is a mixed integer linear optimization problem: dynamics (8.1), (8.2), state limitations (8.4), and conversion from power to energy (8.8), (8.9) are linear constraints.

Further, the runtime and downtime constraints (8.5), (8.6) can be rewritten into linear constraints, see for example [16, 17]; similarly, the energy constraint (8.11) can be rewritten into linear constraints, see for example [18]. Finally, the ON/OFF constraint (8.3) makes the optimization problem binary (mixed integer). This mixed integer linear optimization problem resembles a unit commitment problem [19]. Generally speaking, this type of program is hard and can only be solved for a smaller number of devices and for shorter time horizons when using commercial optimization tools. For a larger number of devices, alternative methods are needed. As it is desired to be able to aggregate and control thousands of devices, alternative control strategies are needed. Therefore, an agile strategy is presented in the following section, relying on fast sorting algorithms rather than mixed integer optimization.

5 Agile Controller Synthesis

In this section, we present an agile controller that is able to overcome some of the limitations of the predictive strategy. By agile is meant a controller that seeks to maximize the agility of the portfolio by utilizing the least agile devices first [20]. In this context, an agile device corresponds to a device that is able to change state but does not demand a state change within a short horizon. Three major advantages are that the agile controller is able to:

1. handle a portfolio with a large numbers of devices
2. operate with little knowledge of the device parameters
3. handle devices that autonomously switch state.

These three features are necessary in a real life scenario where it is desired to aggregate thousands of small devices and where specific knowledge of each single device is difficult to assess and expensive to communicate. In the following, we describe an agile controller that satisfies the above three features.

Agile Controller Structure

The agile controller consists of two parts: a feedback controller and a dispatcher, see Figure 8.3. Each device in the portfolio operates by hysteresis control corresponding to (8.12) such that each device autonomously switches state if it reaches its energy limits. The feedback controller and dispatcher work on top of this: the power consumption of the portfolio p_{out} is measured and subtracted from a power reference p_{ref} resulting in a power error p_{error} which is the input to the feedback controller. The controller determines the control signal p_{ctrl} and feeds this signal to the dispatcher which translates p_{ctrl} to ON/OFF signals as described by u.

To emphasize the simplicity and robustness of the agile controller, we assume that the available information is very limited as described by the following:

1. the individual drain rates $v_i(k)$ are unknown,
2. the individual power ratings p_i are unknown; only the mean power rating $\tilde{p} = \frac{1}{n}\mathbf{1}^T p$ and the real-time total power consumption $p_{\text{out}}(k)$ are known,

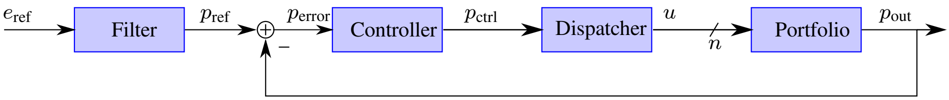

Figure 8.3: Illustration of the agile strategy: a controller integrates the power error p_{error} between the power reference p_{ref} and the measured power consumption p_{out} to determine a control signal p_{ctrl} to the dispatcher. The dispatcher translates the control signal p_{ctrl} to ON/OFF signals u.

3. the individual device states $x(k)$ and energy limits $\overline{x}_i$ are unknown; only the real-time *state of charge* $s_i(k) = x_i(k)/\overline{x}_i$ is known.

Hereby, each device is only required to communicate the state of charge $s_i(k) \in \mathbf{R}$ to the VPP, which significantly reduces the communication flow. Further, the VPP tasks are simplified as it is sufficient to estimate the mean power rating $\tilde{p} \in \mathbf{R}$ instead of individual power ratings and drain rates. Note, however, that this relaxation requires that the power ratings, drain rates, and energy limits of the devices in the portfolio are within the same order of magnitude, i.e., this is not intended for a portfolio mixing for example large-scale CHP heating elements and small domestic heat pumps.

Energy Reference and Power Reference

The controller must ensure that the energy reference $e_{\text{ref}}(l)$ is tracked for each delivery hour l. This is done by translating the energy reference $e_{\text{ref}}(l)$ to a power reference $p_{\text{ref}}(k)$. The sampling rate of the power reference is in the magnitude of minutes and thus faster than the hourly sampling time of the energy reference. A freedom lies in the translation from energy reference to power reference. In this work, this freedom is utilized to make the power reference smooth over time such that fast power reference jumps are avoided. In this work we construct a filter that minimizes the two-norm of the change in power from sample to sample; however, other methods can be chosen. Later, in Figure 8.5, this smoothing is seen when comparing the energy reference in subplot (a) with the power reference in subplot (b).

Feedback Controller

The feedback controller measures the power consumption of the portfolio $p_{\text{out}}(k)$ and compares this with the power reference $p_{\text{ref}}(k)$ to determine the power error $p_{\text{error}}(k) \in \mathbf{R}$:

$$p_{\text{error}}(k) = p_{\text{ref}}(k) - p_{\text{out}}(k). \tag{8.15}$$

The feedback controller is implemented as a pure integral controller as our main objective is to follow the hourly energy reference $e_{\text{ref}}(l)$ which is exactly the integrated power. Further, the integral action will provide the necessary robustness to cope with the incomplete knowledge of the portfolio. The control signal $p_{\text{ctrl}}(k)$ is therefore simply found as

$$p_{\text{ctrl}}(k) = p_{\text{ctrl}}(k-1) + k_I p_{\text{error}}(k) \tag{8.16}$$

where $k_I \in \mathbf{R}$ is the integral gain.

Agile Dispatcher

The dispatcher translates the control signal $p_{\text{ctrl}}(k)$ into an ON/OFF signal $u(k)$ to the devices. The basic idea in the dispatcher is to *maximize the agility of the portfolio* meaning that the least agile devices should be activated first.

Feasible Devices

First, it is necessary to examine the subset of devices $\mathcal{I}_{\text{up}}(k) \subseteq \mathcal{I}$ able to provide upward regulation at time k and the subset of devices $\mathcal{I}_{\text{down}}(k) \subseteq \mathcal{I}$ able to provide downward regulation at time k. For a device to provide upward regulation at sample k, it must currently be in state ON and be able to switch to state OFF which requires that it has been ON for at least $\overline{r}_i$ samples. Similar argumentation can be made for a device to be able to provide downward regulation. Define the counters $c(k) \in \mathbf{Z}_+^n$ as

$$c_i(k) = \begin{cases} c_i(k-1)+1 & \text{if } u_i(k) = u_i(k-1) \\ 1 & \text{otherwise} \end{cases} \tag{8.17}$$

such that $c_i(k)$ is the number of samples that device i has been in its current state $u_i(k)$. Then the sets

$$\mathcal{I}_{\text{up}}(k) = \{i \in \mathcal{I} | u_i(k-1) = 1, c_i(k-1) \geq \overline{r}\} \tag{8.18}$$

$$\mathcal{I}_{\text{down}}(k) = \{i \in \mathcal{I} | u_i(k-1) = 0, c_i(k-1) \geq \underline{r}\} \tag{8.19}$$

will describe the devices feasible for upward and downward regulation, respectively.

Least Agile Device First

The dispatcher is given the control signal p_{ctrl} and must determine if some of the devices in the portfolio must be switched from ON to OFF or vice versa. The agile dispatch strategy is to choose among the devices available for upward (downward) regulation the device closets to its upper (lower) bound. This strategy can be interpreted in different ways. One interpretation is that this is the strategy that will operate the devices as close as possible to the nominal hysteresis control strategy previously presented. Another interpretation is that this strategy maximizes the agility of the portfolio by always selecting the least agile device, see for example [20]. Finally, this strategy can be interpreted as resembling the scheduling algorithm known as "least laxity first", where the process with the smallest process slack time is activated first [21].

Dispatch Algorithm

Under the assumption that each device has a nominal power consumption given by $\tilde{p}$, the dispatcher expects the power output of the portfolio to equal $\tilde{p}\mathbf{1}^T u(k)$. Therefore, the dispatcher will choose to switch the state of $|n_{\text{sw}}(k)|$ devices at time k:

$$n_{\text{sw}}(k) = \text{round}\left(p_{\text{ctrl}}(k)/\tilde{p} - \mathbf{1}^T u_{\text{meas}}(k)\right) \tag{8.20}$$

where $u_{\text{meas}}(k) \in \mathbf{R}^n$ is the measured ON/OFF-state of the n devices at time k and $\text{round}(\cdot)$ is the "round to nearest integer" function. Note that it is necessary to measure the ON/OFF-states of the devices at time k as some devices may have reached the limitations and autonomously switched state according to the local hysteresis control. The dispatcher will switch $\max(0, n_{\text{sw}}(k))$ devices from OFF to ON and $\max(0, -n_{\text{sw}}(k))$ devices from ON to OFF at time k. Hereby the expected power output $\tilde{p}\mathbf{1}^T u(k)$ will get as close as possible to the control signal $p_{\text{ctrl}}(k)$.

In order to maximize the agility of the portfolio, we simply activate the device closest to its limit first. When $n_{\text{sw}}(k) < 0$, we need to decrease consumption and switch the $-n_{\text{sw}}(k)$ devices with the highest state of charge from ON to OFF; similarly, when $n_{\text{sw}}(k) > 0$, we need to increase consumption and therefore switch the $n_{\text{sw}}(k)$ devices with the lowest state of charge from OFF to ON. This way of finding $u(k)$ is described in Algorithm 1. The algorithm simply states that if $n_{\text{sw}}(k) < 0$, upward regulation is provided by selecting the $-n_{\text{sw}}(k)$ devices with highest state of charge from $\mathcal{I}_{\text{up}}$ (if non-empty) and switching the state of these devices from ON to OFF, and vice versa for downward regulation.

Algorithm 1 Agile Dispatch Algorithm.

Initialize $u(k) := u_{\text{meas}}(k)$ collect control signal $p_{\text{ctrl}}(k)$ and find $n_{\text{sw}}(k)$ by (8.20)
for $j = 1, \ldots, |n_{\text{sw}}(k)|$ **do**
  update $\mathcal{I}_{\text{up}}(k), \mathcal{I}_{\text{down}}(k)$ based on (8.18) and (8.19)
  if $n_{\text{sw}}(k) > 0$ ***and*** $\mathcal{I}_{\text{down}} \neq \varnothing$ **then**
    find the least agile device that can provide downward regulation: $i := \text{argmin}_{i \in \mathcal{I}_{\text{down}}} s_i$ switch device ON: $u_i(k) := 1$
  else if $n_{\text{sw}}(k) < 0$ ***and*** $\mathcal{I}_{\text{up}} \neq \varnothing$ **then**
    find the least agile device that can provide upward regulation: $i := \text{argmax}_{i \in \mathcal{I}_{\text{up}}} s_i$
    switch device OFF: $u_i(k) := 0$
  end
end
apply $u(k)$ to the portfolio

Agile Controller Algorithm

We are now ready to describe the full algorithm of the agile controller, see Algorithm 2. As mentioned, the algorithm can be visualized as in Figure 8.3.

Algorithm 2 Agile Controller Algorithm.

Initialize Determine the energy reference $e_{\text{ref}}(l)$ by (8.7) and convert to a smooth power reference $p_{\text{ref}}(k)$
for $k = 1, \ldots, 3600L/T_{\text{s}}$ **do**
  if $e_{\text{reg}}(l)$ *is changed by system operator* **then**
    Update energy reference $e_{\text{ref}}(l)$ by (8.7) and convert to a smooth power reference $p_{\text{ref}}(k)$
  end
  Measure current power consumption $p_{\text{out}}(k)$ and determine $p_{\text{error}}(k)$ according to (8.15) Obtain $p_{\text{ctrl}}(k)$ by integration according to (8.16) Translate $p_{\text{ctrl}}(k)$ to $u(k)$ according to Algorithm 1 Dispatch the ON/OFF signals $u(k)$ to the portfolio
end

6 Numerical Examples

In this section, two numerical examples are considered: a small-scale example where the predictive strategy and the agile strategy are compared and a large-scale example that only the agile controller is able to handle. A sampling time $T_s = 5$ minutes is used.

Small-Scale Example

In this example, the portfolio consists $n = 20$ ON/OFF devices with parameters

$$\begin{aligned} &p_i \in [2,9], && v_i(k) \in [0, p_i], && [\text{kW}], \\ &\overline{x}_i \in [1,7], && x_i^0 \in [1, \overline{x}_i], && [\text{kWh}], \\ &\overline{r}_i = 6, && \underline{r}_i = 6, && [\text{samples}]. \end{aligned} \tag{8.21}$$

The parameters are selected such that the time to fully charge a device and to fully discharge a device are uniformly distributed in the interval 1 to 4 hours. Further, the load vectors $v(k)$ are chosen such that the total load curve $\mathbf{1}^T v(k)$ has the typical consumption shape with a morning and an evening peak as is visible in subplot (a) of Figure 8.5. The runtime and downtime constraints are identical and equal to 6 samples corresponding to 30 minutes. These parameters are the same as used in the hysteresis controller case presented in Figure 8.2.

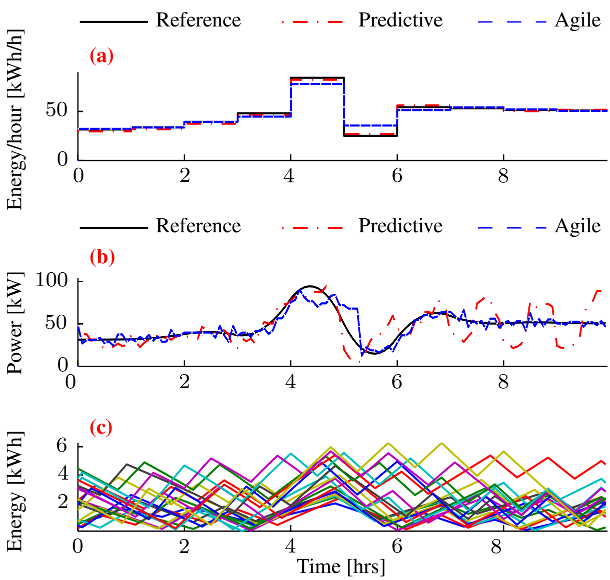

Figure 8.4: Comparison of the behavior of the predictive controller and the agile controller tracking the hourly energy reference $e_{\text{ref}}(l)$. Subplot (c) shows the energy levels of the devices in the predictive controller case.

A horizon of 10 hours is considered. The energy reference $e_{\text{ref}}(l)$ is set equal to the nominal energy consumption in the first and last 4 hours of the horizon. In hour 5 and

6, the energy consumption is set such that the maximum possible energy consumption is moved from hour 6 to hour 5; the volume of energy we can move is found via the predictive controller. The reference and the behavior of both the predictive and the agile controller are illustrated in Figure 8.4.

This numerical example shows a number of interesting results. In subplot (a) we notice, that the agile controller is able to track the same reference as the predictive controller except for the two hours where load is shifted. In these two hours, the predictive controller is able to move at most 30 kWh while the agile controller is able to move at most 19 kWh corresponding to 63 $\%$ of the maximum possible.

Subplot (b) of Figure 8.4 shows the power reference found by smoothing the energy reference; further, this plot shows the power consumption in case of the agile controller and in case of the predictive controller. This plot shows an important difference between the two control strategies: the agile controller seeks to track this power reference, while the predictive controller does not consider the power reference; instead it directly considers the energy reference which in this case causes a fluctuating power consumption.

Finally, subplot (c) of Figure 8.4 shows the energy levels of the 20 devices in the case of the predictive method. This plot illustrates the fundamental idea of moving consumption in time: almost all devices are ON in hour 5 to increase consumption lifting the energy levels of all devices; following, in hour 6, many of the devices are switched OFF again.

Large-Scale Example

We consider a portfolio of $n = 10,000$ ON/OFF devices with parameter distributions and runtime/downtime limitations similar to the previous example. A horizon of 24 hours is used. The predictive controller is not able to handle a portfolio of this size, therefore we only consider the agile controller. We consider an energy reference equal to the nominal power consumption; however, we shift a total of 14 MWh of consumption from the afternoon peak hours to the off-peak hours in the evening as depicted in subplot (a) of Figure 8.5. The agile controller is able to track the reference with an error less than 0.5 MWh/h throughout all 24 hours.

In subplot (b) of Figure 8.5, the nominal power consumption and the power reference are showed. Subplot (c) show the energy levels of 100 of the $10,000$ devices in the portfolio. This figure shows the behavior of the controller: the overall energy levels in the devices are reduced in the afternoon peak hours to assure that the consumption is decreased as required; following, the energy levels are restored when the energy consumption reference is increased in the evening.

Finally, subplot (d) shows the number of devices n_{avail} able to perform upward regulation and downward regulation:

$$n_{\text{avail}}(k) = \mathbf{card}(\mathcal{I}_{\text{up}}(k)) + \mathbf{card}(\mathcal{I}_{\text{down}}(k)) \tag{8.22}$$

where $\mathbf{card}(\mathcal{X})$ denotes the cardinality of $\mathcal{X}$, i.e., the number of elements in $\mathcal{X}$. The plot shows that throughout the delivery period, there are between 2,000 and 7,500 available devices. Further, the plot shows that after the consumption of the devices is reduced at hour $l = 14$, the number of available devices decreases as the overall energy level must be kept low until the consumption of the devices is increased at hour $l = 19$.

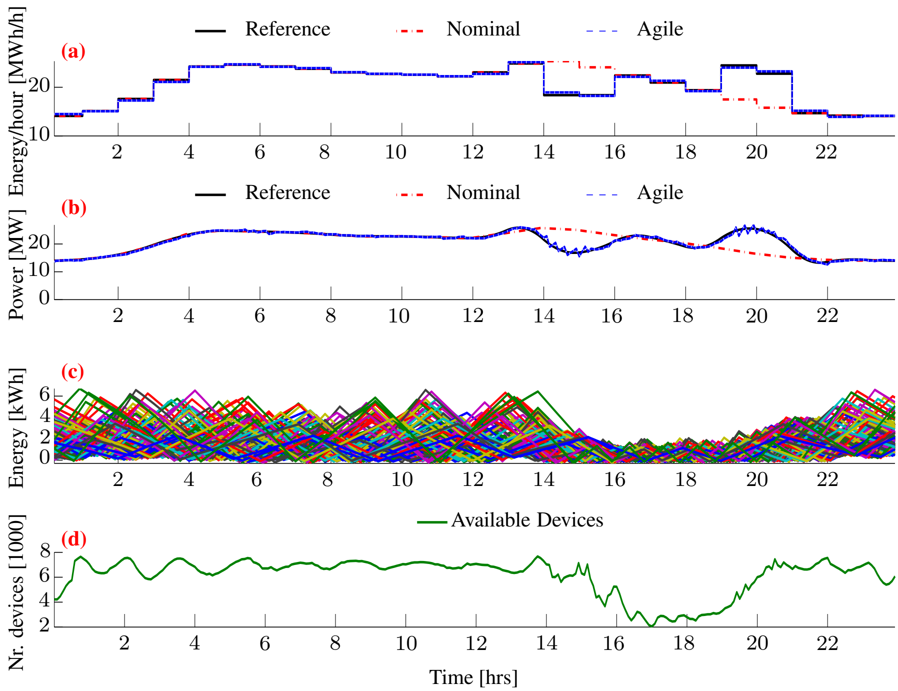

Figure 8.5: 24 hour simulation of a portfolio of $10,000$ ON/OFF devices. Subplot (a) show the energy reference, the nominal consumption, and the response of the agile controller; similarly for the power in the subplot (b). Subplot (c) show the energy levels of 100 of the devices. Finally, subplot (d) shows the number of devices n_{avail} available for either upward or downward regulation.

7 Conclusion

In this work we showed how a portfolio of runtime and downtime constrained ON/OFF devices with flexible power consumption can be managed to collectively provide a delivery of regulating power. We described how to track a regulating power reference based on a predictive controller requiring perfect information of the device parameters. The predictive strategy was able to fully utilize the flexibility of the devices and thereby provide the largest possible amount of regulating reserves. Following, we described how to track the regulating power reference based on an agile control strategy relying only on estimates of the device parameters. The agile controller was able to track an energy reference even for a large number of devices and with very limited knowledge of the portfolio parameters; however, it was not able to utilize the flexibility to the limits as the predictive controller.

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Paper 6

Aggregation and Control of Flexible Consumers – A Real Life Demonstration

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Abstract

In this paper, we present an architecture for aggregation and control of a portfolio of flexible consumers. The architecture makes it possible to control the aggregated consumption of the portfolio to follow a power reference while honoring local consumer constraints. Hereby, an aggregator is able to utilize a portfolio of consumers as a virtual power plant to deliver services in the electricity markets. The architecture is implemented and demonstrated in a field test on a portfolio consisting of 54 heat pumps each located in an inhabited household. In this demonstration, a power reference varying between 15 kW and 35 kW is followed over a 7 day period. The field test showed satisfactory performance in terms of following the power reference and assuring comfort for the inhabitants. To the best knowledge of the authors, this is the first real life demonstration where a power reference is followed based on the aggregated consumption of a larger number of devices – and consequently a significant step towards the smart grid vision.

1 Introduction

Many actions have been taken from a political point of view to increase the penetration of renewables throughout the world. A few examples are renewable portfolio standards or goals that ensure a certain percentage of renewables in almost all states in the US and a European Union energy target of 20 % energy consumption from renewables by 2020.

As the renewable penetration increases, the conventional generators are phased out. This, however, causes a major challenge: the central power plants do not only deliver electricity but also provide stabilizing ancillary services to ensure a reliable and secure electrical power system. The ability to provide such services in the classical sense disappears as the conventional power plants are replaced by renewable energy resources. The reason is that keeping renewables in reserve will entail that free energy is wasted making this a very expensive solution. Further, many renewable sources are characterized by highly fluctuating electricity generation and can suddenly increase or decrease production depending on weather conditions, making it difficult to deliver such services.

It is therefore evident that alternative sources of stabilizing services must be established as renewables replace conventional generation. One of the approaches to obtain such services is the *smart grid* concept, where demand-side devices with flexible power consumption take part in the balancing effort. The basic idea is to let an aggregator control a portfolio of flexible devices such as heating and cooling devices. Hereby, the aggregator can act as a *virtual power plant* and utilize the accumulated flexibility in the electricity markets on equal terms with conventional generators ([1, 2]).

A most important aspect in enabling an aggregator to participate in the electricity markets is the ability to control a number of devices such that the sum of the devices' consumption follows a power reference. Therefore it is also the topic of many recent works. A few examples are: aggregation and control of thermostatic loads ([3]), control of heating systems such as heat pumps ([4, 5], refrigeration systems ([6, 7]), etc. However, while these works describe a virtual power plant setup where demand side devices are used to deliver system-stabilizing services, they are all purely based on simulations and no field demonstration.

Demonstrations showing the concept of demand response do exist. The Dutch PowerMatching concept is an agent based method for demand response which was demon-

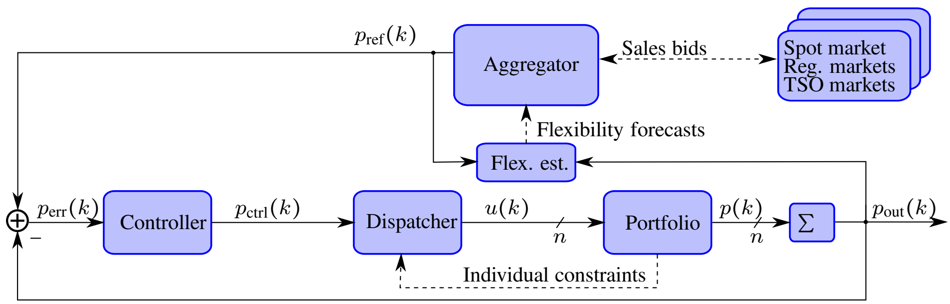

Figure 9.1: Overall system architecture. Solid arrows indicate signals while dashed arrows indicate information exchange.

strated on 25 households ([8]). Another example is the Danish EcoGrid EU demonstration, where demand response from a large number of customers was obtained via price mechanisms ([9]). A third example is the Olympic Peninsula Project ([10]) where the ability to affect consumer behavior through real time prices was demonstrated. Common for these demonstrations is the use of price mechanisms causing a demand response. If implemented with an outer control loop, such price incentive mechanisms could be used to control consumers to follow a power reference; however, this is not done any of the above demonstrations.

Other examples of demonstrations within the smart grid field focus on control of individual consumers. In [11], a direct control method was used on heat pumps to perform optimization towards the electricity spot prices. The focus of [12] was a demonstration of how refrigeration systems can respond to local grid measurements and thereby provide a system-stabilizing service. In [13], a controller for a single refrigeration system was developed and it was demonstrated that is was possible to store and release energy. The class of demonstrations of control of individual devices is large – but does not show how a portfolio of devices can deliver a desired *aggregated* response.

To the best knowledge of the authors of this paper, no demonstration has been made where a power reference is followed by the aggregated consumption of a portfolio of flexible consumers. In this work, such a demonstration is completed: The consumption of 54 heat pumps located in different households is controlled to follow a power reference over a 7-day period while local consumer comfort constraints are honored.

First, in Sec. 2, an architecture for aggregation and control of a large portfolio of flexible consumers is presented. Following in Sec. 3, the architecture is applied to a real life portfolio of 54 households equipped with heat pumps, and finally in Sec. 4 and Sec. 5 we show the demonstration results and conclude the work.

2 System architecture

This section describes an architecture for aggregation and control of flexible consumers. The overall criteria for the system architecture are as follows:

1. Enable the portfolio to follow a power reference.

2. Handle a large number of devices (up to thousands).

3. Be simple and transparent.

4. Ensure that local consumer constraints are honored.

The ability to follow a power reference will enable the consumer portfolio to deliver most electricity services (if implemented with the right sampling time) which is an important element in the smart grid vision. The ability to be able to manage many devices is likewise a most important smart grid aspect. The simplicity constraint is chosen to allow a setup simple enough to implement and demonstrate in a field test. Finally, the bullet assuring that local constraints are honored is vital, as the consumers in the portfolio are mainly concerned about their local primary process – and not about their ability to deliver electricity services.

The system architecture illustrated in Figure 9.1 satisfies these criteria. In the following, the architecture is presented at an overall level and next, in Sec. 3, the architecture is applied to a real life setup.

Components in the system architecture

Portfolio

The portfolio is a collection of n flexible consumers[1] that can be remotely controlled within certain user-defined constraints. The control inputs are denoted $u(k) \in \mathbf{R}^n$, the power consumption of the devices are denoted $p(k) \in \mathbf{R}^n$, and the aggregated consumption is denoted $p_{\text{out}}(k) \in \mathbf{R}$ and given by $p_{\text{out}}(k) = \sum_{i=1}^{n} p_i(k)$ where k is the sample number.

Flexibility Estimator

The flexibility estimator forecasts the consumption flexibility of the portfolio and makes this information available for the aggregator as indicated by the dashed arrow in Figure 9.1. This allows the aggregator to get an overview of the available flexibility and act accordingly in the markets. The flexibility can be estimated in various ways, for example by examining the power reference $p_{\text{ref}}(k)$ and the actual consumption $p_{\text{out}}(k)$ over time. Other relevant parameters such as weather forecasts can also be used by the flexibility estimator to make a more accurate estimate of the consumer flexibility.

Aggregator

The aggregator is an entity that has entered into contracts with owners of the flexible devices allowing the aggregator to actively utilize the aggregated consumer flexibility. This ability can be used to participate in the electricity markets, as indicated in Figure 9.1. By using the knowledge from the flexibility estimator, the aggregator can optimize the available flexibility towards the different markets and actuate the portfolio accordingly via the portfolio consumption reference $p_{\text{ref}}(k) \in \mathbf{R}$.

[1] For simplicity, we use the term *consumer* to denote a *flexible consumption device* throughout the work.

Controller

The input to the controller is the tracing error $p_{\text{err}}(k) = p_{\text{ref}}(k) - p_{\text{out}}(k)$ and the output is a control signal $p_{\text{ctrl}}(k) \in \mathbf{R}$ which is fed to the dispatcher according to a given feedback control law.

Dispatcher

The dispatcher distributes the scalar control signal $p_{\text{ctrl}}(k)$ to the n devices in the portfolio via the control vector $u(k)$. In doing this, the dispatcher takes the local constraints of the individual devices into consideration as indicated by the dashed arrow from portfolio to dispatcher in Figure 9.1. The dispatch strategy can for example be based on simple sorting algorithms, which makes the dispatcher very fast even for portfolios comprised of thousands of devices ([14]).

3 Real life demonstration

A portfolio consisting of real life inhabited households heated with heat pumps is used to demonstrate the proposed system architecture. In the following, we first describe the actual demonstration setup and what the limitations are, and following how the control architecture presented in Sec. 2 is implemented. The actual demonstration results are presented in Sec. 4.

Portfolio of households heated with heat pumps

The platform *Styr din varmepumpe* (meaning: Control your heat pump) consisting of 300 households with heat pump heating is used to demonstrate the presented architecture. This platform is briefly described in the following.

Overall setup

The houses are all real life inhabited houses in different locations in Denmark. The houses vary from smaller houses with a total area of 100 m^2 to larger houses with an area of 400 m^2. Further, the houses vary in type: some are old houses built in the 1850s while other houses are newly built.

Also the heat pumps are different; more than 50 different heat pump designs are present in the platform with some pumps being water-to-water while others are air-to-water based. Moreover, the heating systems vary much in the individual houses: all the houses have a heat pump but some of the houses use underfloor heating while other have radiators. Additionally, some of the houses are equipped with other heating sources than the heat pump, for example a wood stove or solar heating. *Consequently, we are dealing with a realistic real life heterogeneous household portfolio representative of typical Danish households.*

Sensors and actuator

The households included in this platform have all installed the heat pumps before being a part of the platform. The communication- and sensor equipment has therefore been sub-

Figure 9.2: One of the 54 domestic heat pumps subsequently installed with sensors and actuator that can be accessed over an Internet connection.

sequently installed as shown in Figure 9.2. These sensors include a power measurement of the heat pump, a single indoor thermometer, and various flow meters.

The heat pumps are equipped with a relay that can be switched between ON and OFF. In the ON-mode, the heat pump will act according to the local embedded control strategy that assures the desired indoor temperature, sufficient hot water, etc. In other words: the ON-mode allows the heat pump to operate, but it *does not* force the heat pump to start. On the contrary, the OFF-mode *will* force the heat pump to shut down.

The sensor data and the ON/OFF control commands are transmitted over an Internet connection to a server via a Linux-in-a-Box system (the box seen in the top on Figure 9.2). The sampling time of the communication link between heat pump and the server is 5 minutes.

Setup limitations

A number of system restrictions limit the abilities to apply the presented control architecture. First, only 54 of the houses are suitable to be remotely controlled due to various issues on the remaining heat pumps. The demonstration therefore relies on aggregation and control of these 54 households. Another limitation is a non-deterministic delay of up to 25 minutes in the communication link. For this reason, a power reference with a resolution of one hour is chosen (which could alternatively be denoted an energy per hour reference).

Implementation of proposed architecture

In the following, the implementation of the blocks in Figure 9.1 on the heat pump platform is described. Notice that a 5 minute sampling time is used in the control; however, the power reference $p_{\text{ref}}(k)$ is kept constant within each hour due to the slow communication link.

Portfolio

The control signal to the $n = 54$ heat pumps is $u(k) \in \{0,1\}^n$, where $u_i(k) = 1$ corresponds to ON while $u_i(k) = 0$ corresponds to OFF for pump i. The power consumption of the individual houses is measured and communicated such that $p_{\text{out}}(k)$ is available to the controller as illustrated in Figure 9.1.

The heat pumps have a number of local constraints that must be honored. These are:

1. Runtime and stoptime constraints. To protect the heat pump equipment, the pump must remain ON for at least 30 minutes when switched from OFF to ON. Similarly when turned OFF.

2. Temperature constraints. The indoor temperature in the houses must be kept within certain user-defined temperature bounds.

3. Hot water constraint. There must always be hot water available in the hot water tank.

These constraints must be honored to ensure customer satisfaction. As illustrated in Figure 9.1, the devices are able to communicate these individual constraints to the dispatcher which is responsible that they are honored.

Dispatcher

The dispatcher must distribute the control signal $p_{\text{ctrl}}(k)$ among the n heat pumps without violating the three local constraints described above. This is done by implementing a method close to the one presented in [14] as described in the following.

First, the dispatcher examines if more than 30 L of hot water has been used during an OFF period for any heat pump that is still OFF. If this is the case, the aggregator registers that these pumps should be turned ON such that water can be heated. Let $n_{\text{hw}}(k) \in \mathbf{Z}_+$ denote the number of pumps that must be turned ON for this reason.

Following, the dispatcher determines the number of heat pumps $n_{\text{sw}}(k) \in \mathbf{Z}$ that should be switched from OFF to ON (or vice versa if $n_{\text{sw}}(k)$ is negative) such that the expected heat pump consumption equals the control signal $p_{\text{ctrl}}(k)$ at time sample k. By assuming that each heat pump has a constant power consumption given by $\overline{p} \in \mathbf{R}$, the number $n_{\text{sw}}(k)$ can be determined as

$$n_{\text{sw}}(k) = \text{round}\left(p_{\text{ctrl}}(k)/\overline{p} - \mathbf{1}^T u(k-1) - n_{\text{hw}}(k)\right) \tag{9.1}$$

where $u(k-1) \in \mathbf{R}^n$ is the ON/OFF-state at the previous sample and $\text{round}(\cdot)$ is the "round to nearest integer" function.

The temperature and runtime constraints are honored as described in the following. Let the set $\mathcal{I} = \{1, \dots, n\}$ represent the entire heat pump portfolio and let the subset $\mathcal{I}_{\text{up}}(k) \subseteq \mathcal{I}$ denote the heat pumps that are able to provide upward regulation[2] by being able to be switched from ON to OFF at time sample k; similarly, let $\mathcal{I}_{\text{dn}}(k) \subseteq \mathcal{I}$ denote the heat pumps that are able to be switched from OFF to ON. The dispatcher forms the set $\mathcal{I}_{\text{up}}(k)$ by identifying the heat pumps that currently are ON and have been ON longer time than the stoptime constraint. The set $\mathcal{I}_{\text{dn}}(k)$ is determined in a similar manner.

The temperature constraints are incorporated by looking at the temperature of each single device relative to the temperature bounds set by the device owner. Let $T_{\text{min}}, T_{\text{max}} \in \mathbf{R}^n$ denote the indoor temperature bounds specified by the individual heat pump owners and let $T(k) \in \mathbf{R}^n$ be the temperatures measured at time sample k across the portfolio. Finally, let $s(k) \in \mathbf{R}^n$ be the *state of charge* of the devices defined as

$$s_i(k) = (T_i(k) - T_{\text{min},i})/(T_{\text{max},i} - T_{\text{min},i}). \tag{9.2}$$

If $n_{\text{sw}} > 0$, which means that devices must be switched from OFF to ON, the dispatcher will choose the devices with the lowest state of charge and vice versa if $n_{\text{sw}} < 0$. The following pseudo code describes this algorithm.

Initialize $u(k) := u(k-1)$ Assign $u_i(k) := 1$ for the $n_{\text{hw}}(k)$ devices that have consumed 30 L hot water or more while pump is OFF Collect control signal $p_{\text{ctrl}}(k)$ and find $n_{\text{sw}}(k)$ by (9.1) **for** $j = 1, \dots, |n_{\text{sw}}(k)|$ **do**

Update $\mathcal{I}_{\text{up}}(k), \mathcal{I}_{\text{dn}}(k)$ **if** $n_{\text{sw}}(k) > 0$ ***and*** $\mathcal{I}_{\text{dn}} \neq \emptyset$ **then**

Find the least agile device that can provide downward regulation: $i := \text{argmin}_{i \in \mathcal{I}_{\text{dn}}} s_i$ Switch device ON: $u_i(k) := 1$

else if $n_{\text{sw}}(k) < 0$ ***and*** $\mathcal{I}_{\text{up}} \neq \emptyset$ **then**

Find the least agile device that can provide upward regulation: $i := \text{argmax}_{i \in \mathcal{I}_{\text{up}}} s_i$

Switch device OFF: $u_i(k) := 0$

end

end

Apply $u(k)$ to the portfolio

Controller

The power consumption patterns of the individual heat pumps are not identical and will also vary over time depending on local circumstances as illustrated later in Figure 9.4 subplot (a). The role of the controller is to apply feedback control to the entire portfolio, such that the local disturbances are canceled out and the overall reference $p_{\text{ref}}(k)$ is followed.

In this work we construct a controller that seeks to follow a 1-hour power reference (or energy/hour reference). Such a controller is desired for example if the aggregator trades in hourly electricity markets. The reason for this choice is the practical limitations in the setup: the sampling time of 5 minutes and in particular the non-deterministic delay up to 25 minutes makes it impossible to follow a power reference with higher resolution.

[2] Notice that production terms are used such that upward regulation corresponds to increased production or reduced consumption.

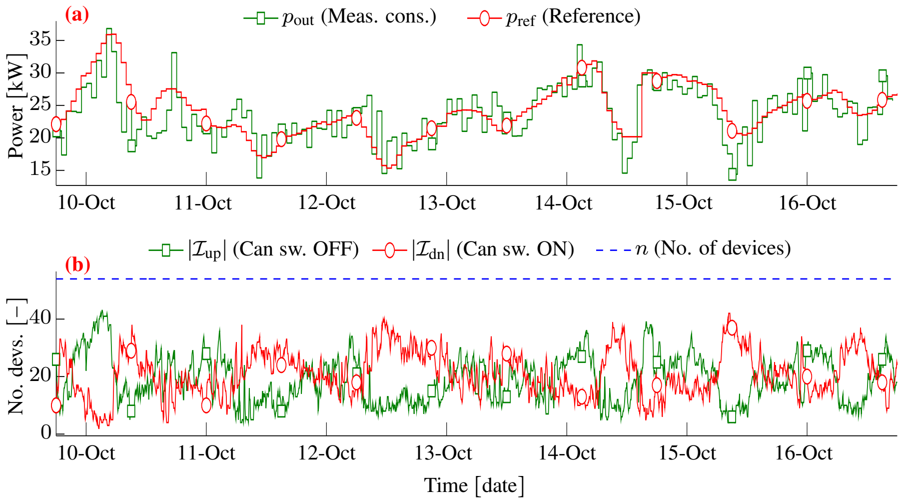

Figure 9.3: Experimental results. Subplot (a): Tracing ability. Subplot (b): Device available to be turned ON/OFF.

The controller is implemented as a discrete PI-controller where the integral term is reset at the start of each hour. The controller operates with a sampling time of 5 minutes according to the following law:

$$p_{\text{err}}(k) = p_{\text{ref}}(k) - p_{\text{out}}(k) \tag{9.3}$$

$$p_{\text{err,I}}(k) = \begin{cases} p_{\text{err,I}}(k-1) + p_{\text{err}}(k) & \text{if } \mathrm{mod}(k,12) \neq 1 \\ p_{\text{err}}(k) & \text{if } \mathrm{mod}(k,12) = 1 \end{cases} \tag{9.4}$$

$$p_{\text{ctrl}}(k) = p_{\text{ref}}(k) + K_{\text{P}} p_{\text{err}}(k) + K_{\text{I}} p_{\text{err,I}}(k) \tag{9.5}$$

where $K_{\text{P}}, K_{\text{I}} \in \mathbf{R}$ are the controller gains. The modulus function $\mathrm{mod}(\cdot)$ assures that the integrated error is reset every time a new hour has begun, i.e. every 12th sample. Hereby the controller will compensate for a reference tracing error inside each hour – but an error in one hour will not affect the following hour.

Scope and limitations

As the goal of this work is to show that it is possible to follow a power reference based on a larger portfolio of flexible devices, the main focus has been put on the dispatcher and controller. The implementation of a flexibility estimator and aggregator is outside the scope of this work. Ideally, the portfolio flexibility would be estimated and optimized towards electricity spot price predictions and possibly regulating power prices to generate a power reference $p_{\text{ref}}(k)$. Instead, we simply construct a varying power reference every day at midnight for the 24 hours of the following day and just assure that the amplitude of the reference is sufficiently low such that it can be followed with satisfactory performance.

4 Results

The setup described in the previous section has been implemented on 54 individual inhabited households and tested in a real life demonstration from 9th to 16th of October 2013. In the following, the demonstration results are presented.

Overall reference following ability

An hourly power reference is generated each day at midnight for the 24 hours of the following day. Due to the limitations in the setup, the power reference is kept close to the expected consumption of the portfolio.

In Figure 9.3 subplot (a), the reference is shown and compared with the measured aggregated consumption of the heat pump portfolio. Subplot (a) shows that the portfolio indeed is able to follow the reference with a reasonable performance. The reason for the deviation between reference and measured output is a combination of two things. First, it is because of the very fluctuating power consumption of the individual heat pumps, and second, it is because the controller is implemented with very small control gain due to the large non-deterministic communication delay in the system, as previously described.

Subplot (b) shows the cardinality of $\mathcal{I}_{\text{up}}$ and $\mathcal{I}_{\text{dn}}$, i.e. it shows how many devices are able to provide upward and downward regulation, respectively, and compares this to the total number of devices which is $n = 54$. We notice that throughout the whole week, there are always some devices available for both upward and downward regulation, respectively, i.e. $\mathcal{I}_{\text{up}}(k), \mathcal{I}_{\text{dn}}(k) \neq \emptyset$ during the whole test. However, the slow PI controller is not able to exploit these available devices to follow the reference more accurately because of the low controller gain. As described previously, the gain is chosen this low due to the long non-deterministic communication delays in the setup.

Closeup on one heat pump

To further examine the setup, we observe the operation of one of the 54 heat pumps in the portfolio during the first 48 hours of the demonstration, see Figure 9.4.

Subplot (a) shows the ON/OFF state $u_i(k)$ of the device compared to the measured consumption of the device $p_i(k)$. This figure shows what was previously described, namely that the OFF state forces a heat pump to shut down, while the ON state merely allows a heat pump to run. Also, the very stochastic nature of the consumption is evident.

Subplot (b) shows the measured indoor temperature $T_i(k)$ compared to the limits $T_{\text{min},i}, T_{\text{max},i}$ which are specified by the heat pump owner. The figure shows what is generally the case for all the houses, namely that the controller allows the heat pump to run such that the temperature does not go below the limit.

The upper temperature bound is violated on one occasion, possibly caused by heating via solar irradiation. However notice that violations of the upper temperature bound is not caused by the aggregator since the aggregator cannot force the pump to run – it can only allow it to operate according to the local controller through the ON-command.

Finally, subplot (c) show the accumulated water usage during periods where the heat pump is OFF. At one instance, the accumulated water usage exceeds 30 L which causes the aggregator to send the ON-command and thereby allow the heat pump to run, see subplot (a).

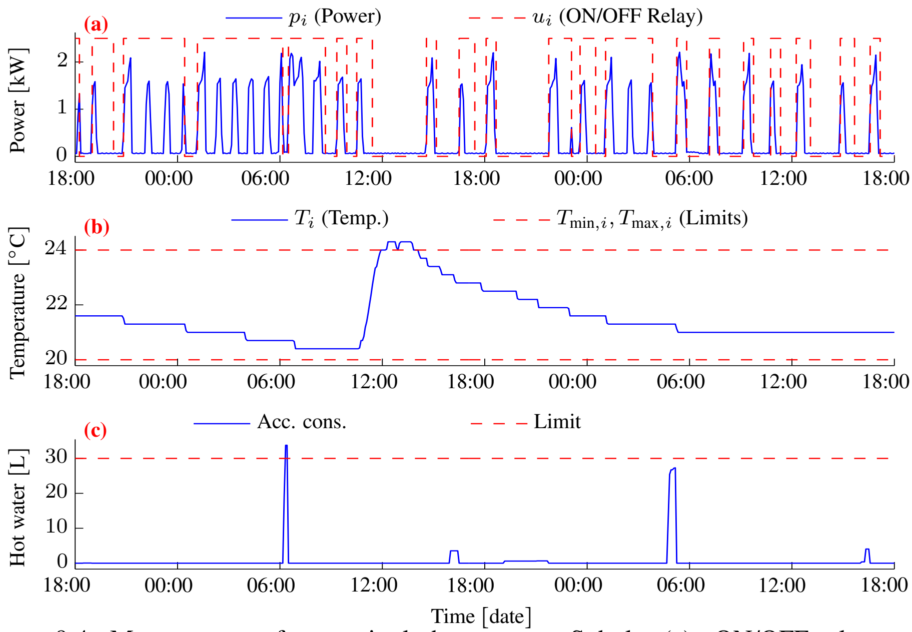

Figure 9.4: Measurements from a single heat pump. Subplot (a): ON/OFF relay and power consumption. Subplot (b): Indoor temperature and limits. Subplot (c): Accumulated hot water in OFF mode.

Comfort of consumers

The main purpose of this work is to shift consumption in time to follow a power reference without violating the comfort of the inhabitants. In the data, we can see that the temperature and hot water constraints generally are honored as desired. However, it is important to notice that these constraints merely are mathematical representations of the real constraint, which is comfort for the inhabitants.

The inhabitants knew that the demonstration was ongoing and had the opportunity to make inquiries if they felt that the heat pump did not perform as desired. However, no inquiries were made during the test, whereby we can conclude that comfort was assured.

5 Conclusion

In this work, we presented an architecture for aggregation and control of flexible consumers. The basis for the architecture was a feedback controller regulating the aggregated power consumption of the portfolio towards a reference. The architecture was demonstrated on a portfolio of 54 heat pumps and a total power consumption reference to the devices was followed over a period of 7 days with satisfactory performance and no discomfort for the inhabitants.

We claim that this is the first demonstration of its kind but we do not claim that the setup itself is the best that can be imagined; rather, it is a simple and transparent setup that is very suitable for a first field test in this area. Obvious improvements lie in reducing the communication delays to allow a higher controller gain and the implementation of a flexibility estimation and optimization algorithm.

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Paper 7

Predictive Control of Demand Side Units Participating in the Primary Frequency Reserve Market

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Abstract

We consider an aggregator controlling a mixed portfolio of conventional power generators and demand side units. The generators are controllable within certain power and ramp limitations while the demand side units are characterized by flexible consumptions and therefore can be treated as energy storages of limited capacity. We address the problem of reducing the load on the conventional generators by letting the flexible consumers participate in the provision of primary frequency reserve. In particular, it is desired that the flexible consumers compensate for rapid grid frequency changes. In this work, we design an aggregator control strategy based on closed-loop model predictive control. The controller is able to mobilize the flexible consumers ahead of time such that we are able to reduce the load on the conventional generators by more extensive use of the demand side units.

1 Introduction

With an increasing focus on climate-related issues and rising fossil fuel prices, the penetration of renewable energy sources is likely to increase in the foreseeable future throughout the developed world [1]. Indeed many actions are taken from a political point to increase the penetration of renewables: in the US almost all states have renewable portfolio standards or goals ensuring a certain percentage of renewables [2]. Similarly, the commission of the European Countries has set targets of 20 % renewables by 2020 [3] while China has doubled the wind power production every year since 2004 [4].

As a consequence of this increase of renewables, the power system is moving from a system with fewer centralized conventional power plants to a system with a large number of distributed smaller production units [5]. As an example of this evolution, Denmark has moved from a situation with a total of 16 central power plants in 1980, to a system which today consists of 16 central power plants, 1000 local combined heat and power plants and around 6000 wind turbines [6].

A number of challenges are associated when replacing central power plants with distributed generating units: the central power plants not only deliver power but also provide ancillary services to ensure reliable delivery of electricity and secure operation of the transmission system. This includes frequency stability support, power balancing, voltage control etc. When these power plants are replaced with renewables such as wind turbines and photovoltaics, the ability to provide ancillary services in the classical sense disappears; the renewable energy sources will typically maximize the power production thus not provide ancillary services. Though recent works suggest that renewable production units can take part in the balancing effort in certain conditions (see, e.g., [7, 8]), it remains impossible for wind power plants and photovoltaics to provide ancillary services when there is no or little wind or solar irradiation.

Another benefit of conventional fossil fuel power plant generators is that they are synchronous with the grid and therefore provide rotating inertia supporting the grid frequency against changes [9]. As renewable energy sources typically interface with the grid via power electronics, they will not be able to provide this inertia [10].

Moreover, renewables are often times intermittent sources characterized by highly fluctuating power generation: they can suddenly increase or decrease the production depending on the weather conditions. These sudden production changes are not always predictable and can therefore be severe for the grid stability [11].

It is therefore evident, that in a grid of high penetration of renewables, the need for balancing ancillary services will increase [12], [13]. As the conventional power plants are phased out, alternative sources of ancillary services must be found. One of the approaches towards alternative ancillary services is the *smart grid* concept, where consumers take part in the balancing effort [14], [15]. The idea is to utilize the demand side in a way beneficial for the grid stability by moving loads in time, e.g. by allowing local devices with large time constants to store more or less energy at convenient times, thereby adjusting the momentary consumption. One obvious method to do so is by exploiting large thermal time constants in deep freezers, refrigerators, local heat pumps etc. See, e.g., [16].

A lot of effort is put into research in the context of demand side flexibility utilization to support the electrical grid. In [17], a hierarchical MPC design is introduced to utilize flexible consumers to counteract quickly fluctuating imbalances. This idea is extended in [18] and [19], where the ability to handle grid congestion is included in the controller design. But while the works [17, 18, 19] illustrate that flexible consumers are able to contribute to the balancing effort, they do not describe how this can be accomplished in a liberalized market setting. Further, the cases are idealized such that the controller possesses almost perfect predictions of the future fluctuations.

In this work, we examine the possibilities of using a mixed portfolio of demand side units and productions units to participate in the ancillary service market by providing primary frequency reserve. Following, we design a controller that is able to mobilize the portfolio of generators and consumers to provide primary frequency reserve at minimum cost. The controller achieves this by utilizing the demand side units with hardly any ramp constraints to compensate for the fast frequency changes while using the slow and inexpensive conventional power generators to release the demand side units. Hereby the load on the conventional generators is kept at a minimum. This control behavior is achieved based on a closed-loop model predictive control strategy, which is able to prepare the storages and generators ahead of time for the future unknown frequency changes.

The outline of the rest of the paper is as follows. First, in Sec. 2, we briefly describe the various forms of balancing services. Next, in Sec. 3, we present a general model for the generators and consumers. In Sec. 4, we design a closed-loop predictive controller that utilizes the portfolio of production and consumption units to provide primary frequency reserve at minimum operational cost. Sec. 5 illustrates the methods with a numerical example and finally, Sec. 6 sums up the work.

2 Primary Frequency Reserves

In the following, we briefly describe primary frequency reserve and how a mixed portfolio of consumers and generators are able to provide this ancillary service.

Primary Frequency Reserve Specifications

In the electrical grid, TSOs are responsible for enabling a secure and reliable power system by keeping balance between production and consumption as well as maintaining power quality and ensuring a stable transmission system. In general, the TSOs do not possess production units, and therefore procure ancillary services from suppliers [20].

To ensure balance, the TSOs must maintain the system frequency at its target value. In order to do this, a certain amount of active power must be kept in reserve and available for control such that frequency deviations can be restored. For this purpose, three types of frequency reserve services exist: primary, secondary and tertiary frequency reserves [9], where we concentrate about the fastest reserve, namely the primary frequency reserve.

The primary frequency reserve is an automatic control which is used in frequency control. A main target for the primary control is to stabilize the frequency in the case of major outages of either loads or suppliers. The primary control reserve is required to sustain at least a certain amount of time, as it is then relieved by the secondary control [21]. The time scale for activation primary frequency reserve is in the area of 10-30 seconds.

Consumers Providing Primary Frequency Reserve

In the context of ancillary services, two main consumer properties are important. The fist property is that the consumers will have very high ramp limits as they are determined by the time it takes to switch the devices on/off, which is very fast compared to adjusting the power production of e.g. a combined heat and power plant. The second property is that flexible consumers only are able to store a limited amount of energy. This is evident from the fact that the flexible consumers in general only are able to move consumption in time, not actually use more or less energy. If we as an example consider an electrically heated house, a cold storage, or an electric vehicle battery, we observe that they indeed are flexible and thus able to store energy, but that they over time will use the same amount of energy.

Due to the high ramp limits of the demand side units, they are well suited for primary frequency control where a fast response is needed. But as they are limited in energy capacity, we can not rely solely on demand side units; we will therefore consider a portfolio consisting of both demand side units and conventional generators. The idea is to use the demand side units to compensate for the fast changes in frequency while using slow and inexpensive generators to relieve the demand side units. The consumers will then allow us to reduce the actuation of the conventional power plants, in particular the fast generators which are also most expensive to operate. In the following, we consider such a mixed portfolio.

3 Modeling

We consider a portfolio of a total of n power production and demand side units interconnected in a star topology consisting of n_l lines, see Fig. 10.1. We limit the work to star topology girds as this corresponds to the topology of low voltage grids; however, the methods in the paper can easily be extended to meshed grids.

The n units are under the jurisdiction of an aggregator who is able to control their power consumption/production within given limits. The aggregator utilizes the portfolio to participate in the primary frequency reserve market and must control the units accordingly depending on their characteristics and on the amount frequency reserve sold to the TSO. Throughout the modeling of the system, we describe the dynamics with discrete time equations and use subscript t to indicate the sample number.

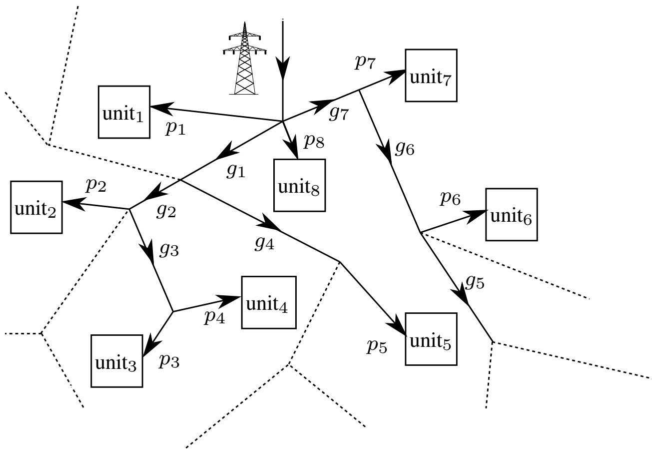

Figure 10.1: Interconnected producers and consumers in a grid of limited capacity (figure adapted from [22]).

Generators and Demand Side Units

We describe both the generators and the demand side units using the same model. The n units in the portfolio are characterized by power consumptions/productions $u \in \mathbf{R}^n$ subject to power constraints

$$u^{\min} \leq u_t \leq u^{\max} \tag{10.1}$$

where $u^{\min}, u^{\max} \in \mathbf{R}^n$ are lower and upper limits, respectively. Here $\leq$ represents componentwise inequality. Note that the power consumption/production u is a small signal value; hence the lower power limits $u^{\min}$ can be negative. For a power producer, the power constraints represent the maximum and minimum deviation from the nominal production, while for a consumer it describes the maximum and minimum deviation in power consumption. We define u in consumption terms such that $(u_t)_i < 0$ corresponds to a decrease in consumption compared to the nominal consumption for device i and vice versa for $(u_t)_i > 0$. Further, the units are subject to ramp limit given by

$$\Delta u^{\min} \leq \Delta u_t \leq \Delta u^{\max} \tag{10.2}$$

where $\Delta u_t = u_t - u_{t-1}$ and where $\Delta u^{\min}, \Delta u^{\max} \in \mathbf{R}^n$ describe the ramp limits.

With each unit, we associate an amount of stored energy $x \in \mathbf{R}^n$. The relation between the power consumption u and the stored energy x is described by the difference equation (see, e.g., [23])

$$x_{t+1} = Ax_t - Bu_t \tag{10.3}$$

where $A, B \in \mathbf{R}^{n \times n}$ are diagonal matrices where the diagonal elements of A and B describe the first order dynamics of the energy storages. The model only represents the flexible part of the units and therefore does not contain any base load. The storage limits are given by

$$x^{\min} \leq x_t \leq x^{\max}, \tag{10.4}$$

where $x^{\min}, x^{\max} \in \mathbf{R}^n$ describe the lower and upper limits, respectively. These power constraints could be extended to be time-varying which for example would allow us to specify a specific time where a battery must be fully charged etc., but in this work we keep the limits time-invariant for simplicity. For a house with electrical heating, the limits could represent the lowest and highest allowed temperature in the house. Similarly for an electrical vehicle, the limits could represent an empty and a full battery. Note that for generators, we simply let the corresponding entries in the matrices A, B equal zero, as they do not possess the ability to store energy.

The consumed or produced power of the units flow through the links of the grid, as illustrated in Fig. 10.1. The partial flows $g \in \mathbf{R}^{n_l}$ through the links caused by the generators and consumers are given by

$$g_t = Gu_t \tag{10.5}$$

where $G \in \mathbf{R}^{n_l \times n}$ has the structure

$$G_{ij} = \begin{cases} 1 & \text{if unit } j \text{ is supplied through link } i, \\ 0 & \text{otherwise.} \end{cases}$$

In Fig. 10.1 this is illustrated: the different consumers with power consumption $p_1, \dots, p_8$ will load the different lines with loads $g_1, \dots, g_7$ depending on the grid structure, which is described by G.

The grid is protected from overcurrents by electrical fuses; hence, the partial line flows are subject to given partial flow constraints

$$g_t \le g^{\max} \tag{10.6}$$

where $g^{\max} \in \mathbf{R}^{n_l}$ describes the limits. Note that such limits are not currently an issue, but it is expected to be an issue in the future when large numbers of heat pumps and electrical vehicles will be put into operation. Therefore it is possible that legislations or markets will enforce such partial flow limits. See, e.g., [19]. Further note that voltage issues also are expected in the coming years on long thin distribution lines that are subject to large loads. By including a more sophisticated model, voltage limits could also be included as constraints to the problem but this is not done in this work.

Finally note, that the total power delivery of the portfolio is given by $\mathbf{1}^T u_t$, where $\mathbf{1}$ is a vector of all ones. The total power $\mathbf{1}^T u_t$ is positive for a net production and negative for a net consumption.

Primary Frequency Reserve

The aggregated generators and consumers participate in the primary frequency reserve market by placing a symmetric bid of p MW for a certain time span (for instance 4 hours in some systems [24]). If the bid is accepted, the aggregator must provide the sold primary frequency reserve. The specifications of the delivery of primary frequency control depend on the system. Typical specifications are that primary control must be provided linearly with the frequency deviation in the frequency deviation interval ±200 mHz; further, the activation time of the full reserve must be no more than 30 seconds.

Let $\Delta f_t \in \mathbf{R}$ describe the frequency deviation from the nominal frequency at sample t. Then the aggregator must track the reference r_t at sample t given by

$$r_t = \max\left(\min\left(p\Delta f_{t-t_0}/\Delta\overline{f}, p\right), -p\right). \tag{10.7}$$

Here $\Delta\overline{f}$ is the frequency deviation at which the full bid must be activated, e.g., $\Delta\overline{f}$ = 200 mHz as described above. The scalar t_0 is the number of samples before the full reserve should be activated, e.g., $t_0 = 3$ if the activation time is 30 seconds as described above and the sampling time is 10 seconds.

We model the grid frequency as a first order system

$$\Delta f_{t+1} = a\Delta f_t + w_t \tag{10.8}$$

where $w_t \in \mathcal{W} = [\underline{w},\ \overline{w}]$ is the change in frequency at every sample which is assumed bounded, white and zero mean. The reason for this model is that we assume a large system where we do not affect the system frequency; however, the accumulated primary control will drive the frequency towards the nominal frequency. The bounds reflect that the frequency in the grid can not jump arbitrarily from sample to sample. The parameter $a \in \mathbf{R}$ describes how fast the grid restores to the nominal frequency. Note that a linear model of any order can be chosen, but for the sake of simplicity it is chosen to use a first order model.

4 Controller Synthesis

The basis of the controller is that the n generators and consumers are aggregated and utilized to bid into the primary frequency reserve market with a bid of p MW. The goal of the controller is to provide primary frequency reserve according to the given specifications at the lowest possible price while honoring the limits of the generators, consumers, and the links in the grid. We emphasize that the provision of primary frequency reserve is based on a portfolio of units with various characteristics, ranging from storages to small and large generators – this is in contrast to conventional reserve provision done by a single power plant. In order to optimize cost, the controller must exploit this diversity of the units, especially the fast ramp limits of the demand side units.

Problem Formulation

Based on the overall model of generators, consumers, and the the grid, we construct a problem formulation which is later used to design a controller.

Constraints

The aggregator must provide a certain amount of frequency reserve depending on the deviation from the nominal grid frequency Δf and on the amount of sold primary reserve p. The amount of primary reserve, that the aggregator must provide, is described by (10.7) and gives the following constraint to the aggregator

$$\mathbf{1}^T u_\tau = r_\tau \tag{10.9}$$

for $\tau \geq 0$. Further, the aggregator must honor the rate-, power- and energy storage limitations of grid, generators, and consumers, which can be described as follows:

$$x_\tau \in \mathcal{X}, \quad u_\tau \in \mathcal{U}, \quad \Delta u_\tau \in \Delta\mathcal{U} \tag{10.10}$$

for $\tau \geq 0$ where

$$\mathcal{U} = \{u | u^{\min} \leq u \leq u^{\max},\ Gu \leq g^{\max}\}$$
$$\mathcal{X} = \{x | x^{\min} \leq x \leq x^{\max}\}$$
$$\Delta\mathcal{U} = \{\Delta u | \Delta u^{\min} \leq \Delta u \leq \Delta u^{\max}\}.$$

Objective

The objective of the aggregator is to minimize the average production cost of delivering the sold frequency reserve.

The cost of operating the portfolio is a function of u and x. We assume a convex stage cost function $\ell : \mathbf{R}^n \times \mathbf{R}^n \to \mathbf{R}$ and define the average cost J_∞ as

$$J_T(x,u) = \frac{1}{T}\sum_{\tau=0}^{T-1} \ell(x_{\tau+1}, u_\tau) \tag{10.11}$$

$$J_\infty(x,u) = \limsup_{T\to\infty} J_T(x,u). \tag{10.12}$$

If we consider an operating production unit, the cost of providing frequency reserve will reflect the cost of deviating from the nominal operation point and is thus a function of u. For a flexible consumer, the cost of providing frequency reserve will reflect the discomfort associated with storing energy and is therefore a function of x. For a house with electrical heating, the discomfort cost would represent the cost of deviating from the desired temperature set-point.

Closed-loop Model Predictive Control

The problem formulation states that the controller must ensure the provision of the required primary frequency reserve while minimizing the average production cost. In other words: the objective J_∞ is to be minimized under the constraints (10.9) and (10.10). In the following, we design a receding horizon control strategy which approximately solves this problem. The receding horizon controller minimizes J_T over a the finite horizon of T samples and applies first control input; at next sample this optimization is redone (hence the name *receding horizon*). This results in an economic finite horizon model predictive controller, as the objective is a minimization of an economical cost and not a distance to a certain reference, as is the case in stabilization problems.

A main question in the controller design concerns tracking the reference r_t, as this reference is driven by the unpredictable disturbance w, see (10.7). One obvious way to deal with the disturbance is to use the expected value, i.e., let $w_{\tau|t} = \mathbf{E}(w) = 0, \tau \geq t$ at sample t. The benefit of this strategy is that it leads to the design of a simple certainty equivalent MPC strategy but on the other hand, such simple disturbance model may lead to poor performance [25]. In particular, a certainty equivalent strategy will not prepare the storages in the power portfolio for possible future up- and down-regulation needs as it assumes no future disturbance.

Another way to handle the unpredictable disturbance is to design a robust model predictive controller that optimizes a single control signal to minimize the worst case cost under all possible disturbance realizations. While this formulation takes the future disturbances into account in the optimization, it suffers from often being conservative [26].

The reason for this conservatism is that this strategy is open-loop within the horizon, in the sense that the controller does not take into account that at the next time sample, more information will be available and the optimization will be redone including this new information.

The above described certainty equivalent controller and robust MPC controller are both open-loop MPC strategies, where the next sample of the control signal is chosen from optimization of a *single* control sequence. In order to design a controller that is able to prepare the power portfolio for future frequency changes in a non-conservative fashion, we instead consider closed-loop MPC. In contrast to open-loop MPC where we optimize a single control sequence, closed-loop MPC optimizes a sequence of *control policies*. This means that we do not commit to a certain control input sequence for the whole control horizon; instead we choose a control policy which will allow different control sequences depending on the realizations of the future disturbances. Hereby the controller will achieve a closed-loop behavior, where we allow recourse as more information becomes available (see, e.g., [26, 22, 27]). Note that the terminology of open-loop MPC vs. closed-loop MPC is adopted from the literature, e.g., the references above. Further, note that *both* open-loop and closed-loop MPC strategies indeed are receding horizon control strategies where reoptimization is performed at each sample when new measurements are available; however, only the closed-loop control strategy considers the various possible disturbance outcomes within each optimization.

Such closed-loop MPC strategy is considered in the following. The motivation is that this strategy will enable us to act preemptively against future disturbance realizations, even though they are unpredictable. By considering all possible disturbance realizations, instead of just the expected value of the disturbance, we obtain a controller that is able to mobilize the storages such that they are ready to provide both up- and down-regulation, depending on the future unpredicted frequency behavior. In a sense, closed-loop MPC is a systematic way of implementing a mid-ranging strategy on the energy storages [28], however where we avoid being conservative due to the closed-loop fashion where recourse is allowed.

Min-Max Feedback Predictive Control

One way to implement closed-loop MPC is a min-max approach. In this approach, all possible disturbance realizations within a finite horizon are considered and the maximum cost is minimized over a sequence of control policies. As the disturbance w is bounded in a polytope $\mathcal{W}$ and as the model of the dynamics is linear and the objective is convex, we know that such min-max optimization can be performed by considering the vertices of the disturbance polytope alone [22].

The min-max method is chosen as this method clearly illustrates the main message of this paper: that performance is increased when our control strategy takes the possible future frequency deviation realizations into account and hereby plan for the future unknown events. Other strategies could have been chosen instead such as scenario based strategies. See, e.g., [29, 30].

For a finite horizon T, the controller must therefore consider the 2^T extreme disturbance realizations based on the vertices $\underline{w}$, $\overline{w}$ of $\mathcal{W}$. Following the notation of [22], we denote the extreme disturbance sequences and associated reference sequences

$$\{w_t^i, \ldots, w_{t+T-1}^i\},\ i \in \mathcal{I} \tag{10.13}$$

$$\{r_t^i, \ldots, r_{t+T-1}^i\},\ i \in \mathcal{I}, \tag{10.14}$$

respectively, where $i \in \mathcal{I} = \{1, 2, \ldots, 2^T\}$; i.e., $\mathcal{I}$ describes the number of extreme disturbance realizations. The reference sequences can be found based on previous frequency measurements and the disturbance sequence by (10.7). Similarly, we denote the control and state sequences

$$\{u_t^i, \ldots, u_{t+T-1}^i\},\ i \in \mathcal{I} \tag{10.15}$$

$$\{x_t^i, \ldots, x_{t+T}^i\},\ i \in \mathcal{I}, \tag{10.16}$$

respectively. The objective of the controller is to optimize the control sequences $\{u_t^i, \ldots, u_{t+T-1}^i\}$ such that the maximum cost of $\sum_{\tau=t}^{\tau+T} \ell(x_\tau^i, u_\tau^i)$ for $i \in \mathcal{I}$ is minimized. Based on the dynamics and constraints of the system and on the cost function, we are able to formulate this as a finite horizon optimization problem. At sample t the optimization problem is given as follows:

$$\begin{array}{ll} \text{minimize} & \displaystyle\max_{i \in \mathcal{I}} \sum_{\tau=t}^{t+T-1} \ell(x_{\tau+1}^i, u_\tau^i) \\ \text{subject to} & x_{\tau+1}^i = A x_\tau^i + B u_\tau^i \\ & x_{\tau+1}^i \in \mathcal{X},\ u_\tau^i \in \mathcal{U},\ \Delta u_\tau^i \in \Delta\mathcal{U} \\ & \mathbf{1}^T u_\tau^i = r_\tau^i \\ & x_\tau^{i_1} = x_\tau^{i_2} \Rightarrow u_\tau^{i_1} = u_\tau^{i_2} \end{array} \tag{10.17}$$

for $\tau = t, \ldots, t+T-1$; $i, i_1, i_2 \in \mathcal{I}$ and where the variables are the control sequences $\{u_t^i, \ldots, u_{t+T-1}^i\}$ and associated states $\{x_{t+1}^i, \ldots, x_{t+T}^i\}$. The data is the reference sequences $\{r_t^i, \ldots, r_{t+T-1}\}$, the previous input $u_{t-1}^i = u_{t-1}$ and the current state $x_t^i = x_t$. Note that the grid frequency dynamics (10.8) are indirectly included in the optimization problem as the reference sequences r_τ^i are generated based on the possible extreme disturbance realization. This means that we must construct the reference sequences r_τ^i at each iteration as described in the algorithm later in this section.

The first two constraints in (10.17) regard the system dynamics and the input and state constraints. The third constraint assures that the controller indeed provides the required primary reserve. The last constraint, $x_\tau^{i_1} = x_\tau^{i_2} \Rightarrow u_\tau^{i_1} = u_\tau^{i_2}$, is a causality constraint (see [22], [26]) which is described in the following.

The closed-loop min-max model predictive controller is illustrated in Figure 10.2. The figure illustrates the extreme disturbance realizations with a horizon $T = 3$ when we are at time sample t; further, the figure shows the control- and state sequences for the given horizon. We can use the figure to describe the behavior of the controller: at sample t we observe the state x_t and determine the control sequences and associated state sequences $\{u_t^i, u_{t+1}^i, u_{t+2}^i\}$, $\{x_t^i, x_{t+1}^i, x_{t+2}^i, x_{t+3}^i\}$ such that the objective is minimized. Due to the causality constraint, we have that $u_t^i = u_t$ as $x_t^i = x_t$ which means that we settle on a single control signal u_t which is applied to the plant. We, however, do not settle on single future control signals u_{t+1}, u_{t+2}; instead we design a control sequence for each possible extreme disturbance realization and do not choose which control signal to

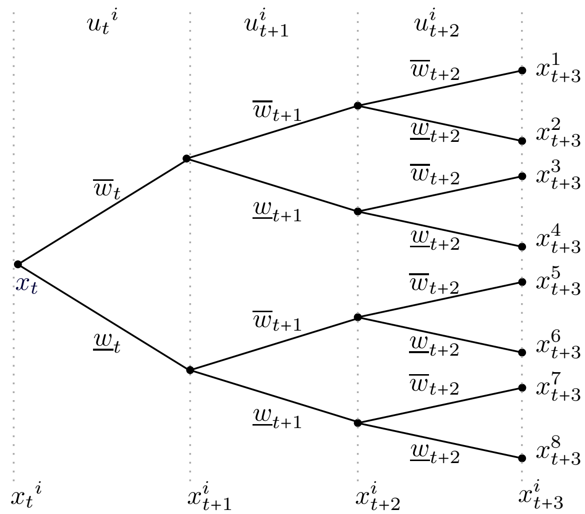

Figure 10.2: The 8 different extreme disturbance realizations with a horizon $T = 3$.

apply until next sample when w_t is known. In this way, the controller takes into account our ability to perform recourse as more information becomes available.

Finally we note that Problem (10.17) is a convex optimization problem as the causality constraint can be reformulated to linear equality constraints. This means that the problem can be solved globally and efficiently [31].

The Control Algorithm

Based on the above description of the closed-loop optimization, we are able to formulate the controller algorithm:

At sample t

1. Collect the current storage levels of the consumers x_t, the previously applied control input u_{t-1} and the current grid frequency f_t.

2. Construct the extreme disturbance sequences $\{w_t^i, \dots, w_{t+T-1}^i\}$, $i \in \mathcal{I}$ based on the disturbance vertices $\underline{w}, \overline{w}$.

3. Construct the extreme reference sequences $\{r_t^i, \dots, r_{t+T-1}^i\} \in \mathcal{I}$ based on the previous references $r_{t-t_0}, \dots, r_{t-1}$, the disturbance sequences and the amount of sold primary reserve p using (10.7).

4. Solve Problem (10.17) and denote the optimal control sequences $\{u_t^{i\star}, \dots, u_{t+T-1}^{i\star}\}$, $i \in \mathcal{I}$.

5. Apply the fist control input $u_t^\star = u_t^{i\star}$ to the generators and consumers.

6. Increase t by one and repeat from 1.

Scalability and Implementation

A major difficulty with the presented method is the scalability as the min-max MPC method scales exponentially with the control horizon. For larger number of devices and in particular for large horizons, the presented method therefore has its limitations. For practical implementation, it might therefore be necessary to alter the method for example to scenario based methods, see [29, 30], or methods that assume a certain class of policies, for example causal affine functions of the uncertainty as in [32], instead of dealing with each of the 2^T extreme disturbance realizations.

5 Numerical Example

We perform a number of numerical examples that illustrate the behavior of the closed-loop MPC algorithm. The examples are kept at a conceptual level with a small number of units to clearly visualize the behavior of the controller. We consider a portfolio of four units: two consumers and two generators. They have the following characteristics.

- unit_1 and unit_2: ideal storages with no ramp limits but limited storage capacity; unit_1 is on line close to congestion.
- unit_3: slow generator with low operational cost.
- unit_4: fast generator with high operational cost.

Throughout the examples, we will use an open-loop certainty equivalent MPC controller as reference. This reference controller is implemented with same objective and constraints but use the expected value of the disturbance as prediction, i.e., $w_{t|\tau} = \mathbf{E}(w) = 0,\ \tau \geq 0$.

A cost function on the form

$$\ell(x_t, u_t) = x_t^T Q x_t + \|R u_t\|_1 \tag{10.18}$$

is used. The cost of utilizing the storages is assumed quadratic; this could reflect temperature comfort limits of an electrically heated house where a small deviation has close to no cost, while larger deviations are expensive. The cost of the generating is are chosen to be a weighted one-norm; this illustrates that even small changes in the operation of the generators have a significant cost. Note that we are operating with small-scale values and that u_t corresponds to deviations from the nominal power consumption/generation.

The aggregator managing the portfolio has sold $p = 5$ MW primary frequency reserve and we assume that the power reference must be met in 15 s and use a sampling rate of 15 s for simplicity. Finally, we assume that the frequency never changes faster than 40 mHz/sample and we use a prediction horizon of $T = 8$ samples. We can specify the properties of the optimization problem as follows:

$$\begin{aligned}
&x^{\min} = (0,\ 0,\ -,\ -)^T,\ x^{\max} = (80,\ 80,\ -,\ -)^T \ \text{kWh} \\
&\Delta u^{\max} = -\Delta u^{\min} = (100,\ 100,\ 25,\ 100)^T \ \text{kW/s} \\
&Q = \mathbf{diag}(1,\ 1,\ 0,\ 0),\ R = (0,\ 0,\ 10,\ 1)^T,
\end{aligned}$$

which simply state two consumers with limited capacity but no ramp limits, a slow inexpensive generator and a fast and expensive generator. We do not consider power limits. Further, $unit_1$, $unit_3$, $unit_4$ are on lines with no congestion while $unit_2$ is on a line which allows only 0.3 MW.

The desired behavior of the controller is to use the storages $unit_1$, $unit_2$ to provide fast regulation then use the slow inexpensive generator $unit_3$ to relieve the storages hereby avoiding using the expensive generator $unit_4$. But as utilizing the storages is also associated with a cost, the controller must ensure that the storage level in $unit_1$ and $unit_2$ are minimized while still being able to provide both up- and down-regulation.

In the following, we will look at two examples. The first example is constructed such that the ability of the closed-loop MPC controller to take preemptive action against future frequency changes is made obvious. The second example is meant to be an example of normal operation for the controller.

Preemptive Action

In this example we consider an example where the frequency suddenly drops more than 0.2 Hz, see top plot of Fig. 10.3. The frequency drop causes the aggregator to provide the full 5 MW of up-regulation. The behavior of the closed-loop MPC controller is seen in

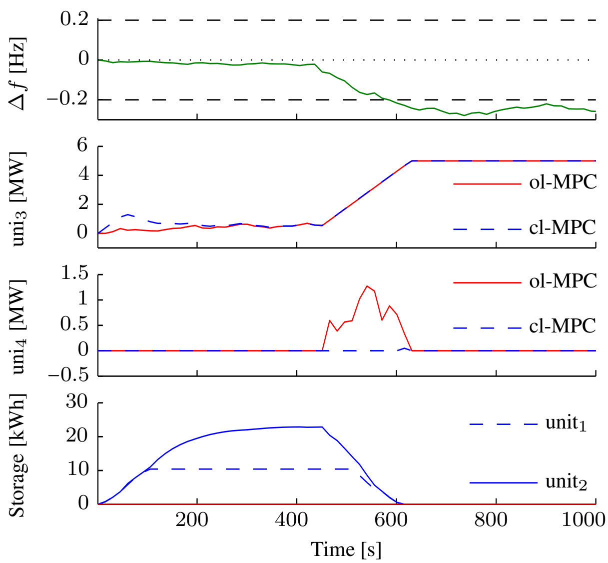

Figure 10.3: Plot 1: grid frequency deviation Δf and limits $\pm\Delta\overline{f}$. Plot 2,3: power productions of $unit_3$ (slow, inexpensive) and $unit_4$ (fast, expensive) for the open-loop (red, solid) and the closed-loop controller (blue, dashed). Plot 4: energy levels of $unit_1$ on congested line (blue, dashed) and $unit_2$ on the non-congested line (blue, solid) in the closed-loop case; the open-loop storage levels are not visible as they remain zero.

Fig. 10.3. In the first minutes where the frequency is stable, the controller uses the slow and inexpensive generator to fill up the energy storages of $unit_1$ and $unit_2$, mainly the

storage of $unit_2$ where there is no congestion problem. The controller fills up the storages as it knows this will be beneficial in case of a sudden frequency drop.

Exactly because of this preemptive action, the closed-loop MPC algorithm is able to provide the necessary up-regulation at the time of the frequency drop without utilizing the expensive generator $unit_4$; instead the storages compensate for the fast frequency drop while the slow generator $unit_3$ relieves the storages (see Figure 10.3). This is exactly the desired behavior for the controller and is achieved as the controller minimizes the worst case future cost in a closed-loop manner.

Further we note, that the closed-loop MPC algorithm does not refill the storages $unit_1$ and $unit_2$ after they have been relieved; the controller knows that the reference never will exceed 5 MW even if the frequency drops further. Thereby no unnecessary storage actuation is performed.

As comparison we observe the behavior of the open-loop MPC reference controller. This controller does not consider the effects of future frequency changes and therefore minimizes its cost function by keeping all storages empty. When the frequency drops, it is forced to use the expensive generator to provide up-regulation at a high cost. The comparison is presented in Fig. 10.3.

Note that we start the simulation with the storages empty, hereby the action of the closed-loop control becomes clear as it can be seen that it fills the storages. If we had started with the storages filled up, we would see the closed-loop control decrease the storage level to the same levels as in the presented example; on the contrary, the open-loop control would decrease the storage levels to zero as it does not expect future disturbances and therefore does not expect to benefit from non-empty storages.

Normal Operation

We now consider an example of what could be normal operation for the controller. It is assumed that the change in frequency is band-limited Gaussian noise with standard deviation 40 mHz per sample and limits ±40 mHz per sample. An example of this is illustrated in Fig. 10.4 for a 50 minute sequence. The performance of the open-loop and the closed-loop MPC strategy is presented, illustrating that the closed-loop controller is able to almost completely avoid using the fast and expensive generator by more extensive and intelligent utilization of the storages. The example shows that the closed-loop MPC controller is able to let the storages act as a fast generator, thereby reducing the operational costs significantly.

To enhance the reliability of the results, 5 such 50 minute simulations are completed with different system frequency realizations, all revealing similar results: a significantly lower cost when utilizing the closed-loop MPC control law. The normalized costs for the 5 simulations are presented in Table 10.1.

As previously mentioned, and ad-hoc control strategy could be to implement mid-ranging on the energy storages. This was done on the example presented here and by extensive tuning it was possible to achieve a performance that indeed was better than the certainty equivalent scheme, however still significantly worse than the closed-loop MPC control strategy. These results are not presented here.

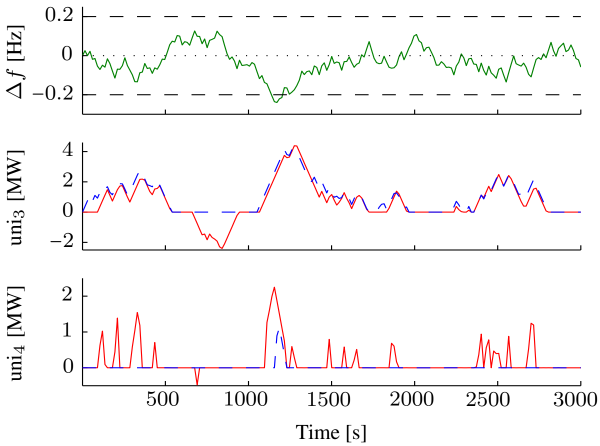

Figure 10.4: Plot 1: grid frequency f and limits $\pm\Delta\overline{f}$. Plot 2,3: power productions of unit$_3$ (slow, inexpensive) and unit$_4$ (fast, expensive) for the open-loop (red, solid) and the closed-loop controller (blue, dashed).

Disturbance sequence	1	2	3	4	5
$J_{\text{ol-MPC}}$	0.79	0.70	1.00	0.34	0.56
$J_{\text{cl-MPC}}$	0.32	0.30	0.49	0.04	0.16

Table 10.1: Performance comparison.

6 Conclusion

In this paper we have described how a mixed portfolio of power generators and flexible demand side units can be aggregated and used to provide primary frequency reserve. Hereby we are able to reduce the load on conventional generators. Further, we have shown how a simple model of the grid frequency and bounds on the change in frequency can be used in the design of a closed-loop model predictive controller. The controller assures that the frequency reserve obligation is met and that the grid constraints are honored, while minimizing the operational cost of the portfolio. Further, the closed-loop controller enables the energy storages to act preemptively against future rapid grid frequency changes, which significantly reduces the load on the conventional generators in the portfolio.

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Paper 8

Primary Control by ON/OFF Demand-Side Devices

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Abstract

We consider an aggregator managing a portfolio of ON/OFF demand-side devices. The devices are able to shift consumption in time within certain energy limitations; moreover, the devices are able to measure the system frequency and switch ON and OFF accordingly. We show how the aggregator can manage the portfolio of devices to collectively provide a primary reserve delivery in an unbundled liberalized electricity market setting under current regulations. Furthermore, we formulate a binary linear optimization problem that minimizes the aggregator's cost of providing a primary reserve delivery of a given volume, and demonstrate this method on numerical examples.

1 Nomenclature

Indices	
i	Index of devices
j	Index of frequency deviation
k	Index of time sample number

Parameters		
a	[W/Hz]	Droop curve slope
J_{prim}	[-]	Cost of act. devices $\mathcal{I}_{\text{prim}}$
$f_{\text{db}}, f_{\text{max}}, f_{\text{tol}}$	[Hz]	Droop curve parameters
f_{nom}	[Hz]	Nominal system frequency
$f_{\text{sys}}(k)$	[Hz]	System frequency
K	[-]	Samples in a delivery period
m	[-]	Number of frequency intervals
n	[-]	Number of devices
p	[W]	Nominal power consumptions
$p_{\text{ctrl}}(k)$	[W]	Primary control reference
$p_{\text{prim}}(k)$	[W]	Primary reserve volume
$p_{\text{prim}}^{\text{max}}, p_{\text{prim}}^{\text{min}}$	[W]	Up./lower primary res. limit
T	[s]	Duration of delivery period
t_i	[Hz]	Trigger frequency of device i
$t_i^{\text{min}}, t_i^{\text{max}}$	[Hz]	Min/max trig. freq. for dev. i
$\bar{t}, \underline{t}$	[Hz]	Frequency interval vectors
T_s	[s]	Sampling time
$u(k)$	[W]	Device power consumptions
v	[W]	Device drain rates
$x(k)$	[J]	Device energy storage levels
$x^{\text{min}}, x^{\text{max}}$	[J]	Up./lower energy limits
$x_0(k)$	[J]	Initial device energy levels
$\Delta f(k)$	[Hz]	Frequency deviation
π	[-]	Device activation costs

Sets	
$\mathcal{I}$	Devices index set
$\mathcal{I}_{\text{prim}}$	Devices activated for primary reserve
$\mathcal{I}_{\text{up}}, \mathcal{I}_{\text{up}}$	Upward/downward regulation devices
$\mathcal{J}$	Frequency deviation index set
$\mathcal{K}$	Sample number index set

Variables	
$\overline{X}$	Frequency allocation matrix for upward reg.
$\underline{X}$	Frequency allocation matrix for downward reg.

Throughout the nomenclature, the notation [-] is used to denote a dimensionless parameter. Notice that the costs are assumed normalized and hence described as dimensionless.

2 Introduction

With an increasing focus on climate-related issues and rising fossil fuel prices, the penetration of renewable energy sources is likely to increase in the foreseeable future throughout the developed world [1]. Many actions have been taken from a political point to increase the penetration of renewables: in the US, almost all states have renewable portfolio standards or goals that ensure a certain percentage of renewables [2]. Similarly, the commission of the European Community has set a target of 20 % renewables by 2020 [3], while China has doubled its wind power production every year since 2004 [4]. In Denmark, the 2020 goals are 35 % sustainable energy over all energy sectors and 50 % wind power in the electrical energy sector [5].

A major challenge arises when replacing central power plants with renewable energy sources: the central power plants do not only deliver power but also provide ancillary services to ensure a reliable and secure electrical power system. This includes frequency stability support, power balancing, voltage control, etc. When the conventional power plants are replaced with renewables such as wind turbines and photovoltaics, the ability to provide ancillary services in the classical sense disappears; the renewable energy sources will often fully utilize the available power and thus not be able to provide balancing ancillary services. Furthermore, conventional fossil fuel power plant generators are synchronous with the grid and therefore provide rotating inertia that supports the system frequency against changes [6]. As renewable energy sources typically interface with the grid via power electronics, they do not directly provide inertia to the grid as the conventional synchronous generators [7], which further increases the balancing challenges. Although recent works suggest that wind turbines can provide synthetic and artificial inertia by regulating the active power output of the generator according to the system frequency [8, 9], this type of control is generally not implemented in the wind power plants of today. Moreover, many renewable sources are characterized by highly fluctuating power generation: they can suddenly increase or decrease production depending on weather conditions. These rapid production changes are not always predictable and can therefore imply severe consequences for grid stability [10].

It is therefore evident that in a grid with high penetration of renewables, the need for balancing ancillary services will increase [11], [12]. As conventional power plants are phased out gradually, alternative sources of ancillary services must be established. One of the approaches to obtaining alternative ancillary services is the *smart grid* concept, where demand-side devices with flexible power consumption take part in the balancing effort [13], [14]. The basic idea is to let an *aggregator* manage a portfolio of flexible demand-side devices and utilize the accumulated flexibility in the unbundled electricity markets on equal terms with conventional generators [15].

Flexible demand-side devices have significantly different characteristics than conventional generators: while conventional generators are able to provide more or less energy by adjusting the fuel consumption, demand-side devices will on average roughly consume the same amount of energy. An electrical vehicle may for example be able to consume energy in one hour and deliver the energy back in the following hour; however, over the course of a year, the net energy consumption will roughly be the same independent of how the flexibility is utilized. On the other hand, many demand-side devices can be switched ON and OFF almost instantaneously enabling them to react faster than most conventional generators. These characteristics make demand-side devices ideal for primary frequency control, as this type of reserve demands rapid up and down power regulation abilities but generally does not require actual energy deliveries.

Another benefit of primary frequency control in this context is that the delivery of reserves depends on local system frequency measurements; hence, no expensive near real-time communication from aggregator to devices is necessary. Furthermore, primary reserves are generally the most expensive deliveries, as they require fast control action. This increases the attractiveness of enabling demand-side devices to participate in the primary reserve market.

Demand-side management by controlling smaller appliances to support grid stability has been discussed as early as the 1980s [16]. Since, the topic of demand-side management has received much attention from a research perspective. See, e.g., [17, 18, 19]. Currently, demand-side programs are in operation in many systems, for example in the UK and the US systems [20, 21, 22]; moreover, a growth is seen in the volume of these programs. As an example of this growth, New England has experienced an increase in demand-side programs from contracts on 200 MW in 2003 to more than $2,000$ MW in 2009 [23].

Recent works have discussed the use of demand-side management to provide primary reserve. A few examples are: refrigeration systems that adjust the power consumption according to the system frequency deviation [24, 25], thermal systems that respond when the system frequency drops below a certain value [26], and primary frequency control of flexible domestic consumption devices activated through a local smart meter [27]. While these works discuss methods for providing primary reserves, they do not consider these services sold through the current liberalized market system. In other words: the cited works show how to deliver primary reserve for grid support but do, however, not design the control strategies such that the accumulated response of the demand-side devices satisfy the regulatory requirements for primary reserve deliveries.

The main contribution of this work is to show how an aggregator can manage a portfolio of ON/OFF demand-side devices to collectively provide a delivery of primary reserve that comply with the current regulations in the European electric power system. This allows the aggregator to enter the primary frequency control market and thus compete with the conventional generators as is desired in a liberalized market setting [15].

The paper is structured as follows. In Sec. 3, we present a system architecture where an aggregator manages a portfolio of ON/OFF device. Following, in Sec. 4, we describe how these ON/OFF devices can be managed to provide frequency reserves complying with current regulations. In Sec. 5, we present a method for minimizing the cost of a reserve delivery, and in Sec. 6 this method is applied to a numerical example. Finally, in Sec. 7, we conclude the work.

3 System Architecture

In this section, we describe the overall relation between consumers, aggregator and the primary reserve market.

Aggregator as Player in the Electricity Markets

We consider an unbundled liberalized electricity system architecture. In this setup, the Transmission System Operators (TSOs) are responsible for secure and reliable system operation and must consequently ensure balance between production and consumption. Generally, in an unbundled electricity system, TSOs do not own production units and must therefore procure ancillary services in the electricity markets to ensure system stability.

The aggregator is a legal entity able to enter into flexibility contracts with consumers. These contracts allow the aggregator to manage the consumers' flexible consumption; hereby the aggregator is able to utilize the accumulated consumer flexibility to participate in the electricity markets. The flexible devices are managed by the aggregator through a technical unit often referred to as a Virtual Power Plant (VPP) as illustrated in Figure 11.1. In this work, the aggregator utilizes the consumer flexibility to participate in the primary reserve market.

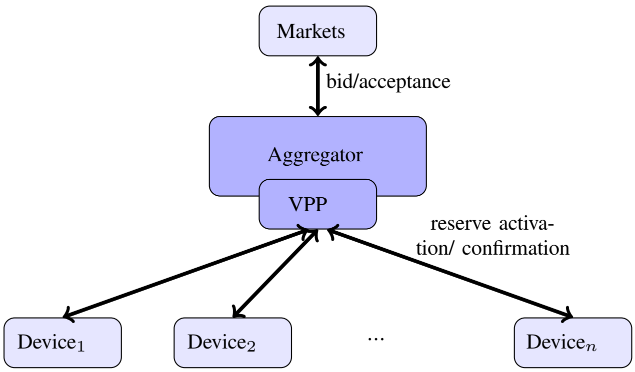

Figure 11.1: Aggregator bidding in the electricity markets by managing n devices through a VPP.

Primary Reserve

Primary reserve is an automatic control used in frequency control. A main target for the primary control is to stabilize the system frequency in case of major outages of either loads or suppliers until the primary control reserve is relieved by secondary control [28]. The activation time for primary control is in the magnitude of 1-180 seconds depending on the system [29].

Primary frequency control must be provided according to the deviation from the nominal system frequency. Basically, a local control loop must assure that upward regulation is provided at frequencies below the nominal frequency, and similarly, downward regulation is provided at frequencies above the nominal frequency. For the sake of consistency we only consider *symmetric* primary reserve deliveries where equal volumes of upward and downward regulation must be delivered. It is, however, straightforward to extend the methods presented in this work to asymmetric deliveries.

Primary reserve is critical to grid stability. Therefore, the local control loop must rely on a *local* system frequency measurement. This makes the primary reserve delivery independent from communication links etc.

In the liberalized electricity market, the TSOs will ensure grid stability by procuring sufficient volumes of primary reserve from the suppliers. Typically, each day is divided into a number of primary reserve delivery periods, for example 24 one-hour periods. The suppliers can place sales offers for primary reserves in each delivery period of the day. Following, the TSOs will purchase the cheapest of these bids according to the need for primary reserve. We assume that each bid is either full accepted or not accepted at all as is the case in for example the Nordic electricity system [29].

Demand-Side Devices as Primary Reserve

The aggregator manages a portfolio of ON/OFF devices with flexible power consumption: the power consumption of each device is not continuously adjustable; rather, it is either turned ON or OFF. This covers large class of devices, for example thermal devices such as heat pumps, refrigeration systems, water heaters, etc.

In order for such consumption devices to provide ancillary services, they must be separated from and independent of ordinary consumption and must be approved by a TSO as consumption that can be used as regulation reserves [30]. In this work, we assume that the portfolio of devices under the jurisdiction of the aggregator indeed is approved by a TSO. Moreover, we assume that the devices are able to measure the system frequency with the required accuracy, typically in the range of few mHz, and that they can apply the control action as fast as required, typically in the range of few seconds.

Note that this setup requires very little communication between devices and VPP: the devices respond to local system frequency measurements and therefore do not need external control signals. The only communication needed is before the start of each reserve delivery period where each device will send state information to the VPP after which the VPP will send primary reserve activation commands to the devices. Hence, no near real-time communication link is needed. This is an attractive feature of the presented architecture and greatly lowers the overall communication costs.

4 Primary Reserve via ON/OFF Devices

In this section we examine the primary frequency control requirements and describe how ON/OFF devices collectively can fulfill these requirements.

ON/OFF Consumers

The VPP manages a portfolio of n flexible consumption devices represented by the index set $\mathcal{I} = \{1, \ldots, n\}$. We assume that these devices can be modeled as energy storages with a certain drain rate. Further, we assume that the drain rates can be assumed constant within each primary reserve delivery period. This assumption allows us to clearly show the main message of this work: that an aggregator can manage a portfolio of small ON/OFF devices to collectively provide primary frequency reserve on market terms. Note, however, that modeling consumers as having a constant drain rate may be a crude assumption: in many cases, the drain rate will be characterized by stochastic behavior depending on user behavior, weather conditions, etc. An extenuating circumstance is that the assumption only has to hold for the delivery period which is in the order of an hour – hereafter the model can be updated.

Let the energy storage levels of the flexible consumers be denoted $x(k) \in \mathbf{R}^n$, the power consumptions $u(k) \in \mathbf{R}^n$, and the drain rates $v \in \mathbf{R}^n$, where k is the sample number. We model device i is as

$$x_i(k+1) = x_i(k) + T_s\left(u_i(k) - v_i\right), \quad i \in \mathcal{I} \tag{11.1}$$

$$x_i(0) = x_i^0, \quad i \in \mathcal{I} \tag{11.2}$$

where $x^0 \in \mathbf{R}^n$ is the initial energy storage level and T_s is the chosen sampling time. The notation x_i is used to denote element number i of the vector x, i.e. $x = [x_1, \ldots, x_n]^T$; this notation is used throughout the work. Let $p \in \mathbf{R}^n$ denote the nominal power consumptions of the n ON/OFF devices, hence

$$u_i(k) = \begin{cases} p_i & \text{if device } i \text{ is ON} \\ 0 & \text{if device } i \text{ is OFF} \end{cases}, \quad i \in \mathcal{I} \tag{11.3}$$

as each device is only able to be turned ON or OFF. In this work, we do not include any penalty for the number of switches per device. It might, however, be a useful extension to include switching costs as rapid switching may cause damage or reduce lifetime depending on the type of device.

Each energy storage is limited in size which we describe by the limit vectors $x^{\text{min}}, x^{\text{max}} \in \mathbf{R}^n$; hence we have the requirement that

$$x_i^{\text{min}} \le x_i(k) \le x_i^{\text{max}}, \quad i \in \mathcal{I}. \tag{11.4}$$

The interpretation of these limitations depends on the type of device. For space heating systems, space cooling systems, water heating systems, etc., the limits could represent a desired temperature band [31]. Therefore, we refer to the constraints (11.4) as *comfort constraints* in the sequel.

A *flexibility contract* between aggregator and consumer will specify the payment the consumer must receive for being activated by the aggregator for a primary frequency reserve delivery. The payment could for example be *flex rate* with a certain payment each time the device is activated or it could be *flat rate* with an annual payment or electricity discount independent of how often the device is activated. The type of contract will depend on the aggregator/consumer setup [32]. For example, a heating system could be sold with a given discount; in return an aggregator is allowed to utilize the device for primary reserve provisions as long as the comfort limits are honored. This is an example of a flat rate contract, where the consumer does not get any activation payment but instead a one-off payment (in the form of a discount). Such a contract will be relevant if the aggregator is willing to take all the risk. If the consumer is willing to take more risk, a flex rate contract can be established with a given payment per activation which may generate higher profit for the consumer in the long run. The consumer's willingness to take risks will therefore affect what type of contract is signed. Further, the flat rate or flex rate payment will depend on a number of parameters including the energy and power capacity of the consumer and how often the consumer allows activations for primary reserve deliveries.

In this work, we represent the costs by a vector $\pi \in \mathbf{R}_+^n$ where π_i is the payment the aggregator must pay consumer i for activation of a primary frequency reserve delivery. This means that if the aggregator constructs a primary reserve bid based on the devices $\mathcal{I}_{\text{prim}} \subseteq \mathcal{I}$, he will face an expense given by

$$J_{\text{prim}} = \sum_{i \in \mathcal{I}_{\text{prim}}} \pi_i \tag{11.5}$$

if the bid is accepted for that given delivery period. Later, these costs will be further elaborated.

Notice that a number of other constraints and conditions can be included in the flexibility contracts such as constraints on when the devices will allow activations [32]. Certain devices may only allow activation during certain hours of the day, certain days in the week, only certain seasons, etc. Such constraints are not included in this work. Further, the flexibility contract must describe the penalty for non-compliance. In this case where we deal with primary reserve which is crucial for grid stability, non-compliance should be associated with a large penalty such as financial penalty and termination of the contract. The regulations in the Nordic electricity systems specify that in case the sold delivery of primary reserve cannot be delivered, the reserve must be re-esablished within 30 minutes after the incident [29]. If the aggregator detects that a device does not deliver as required, the aggregator must then exclude this device and redistribute his portfolio to re-establish the sold delivery.

Frequency Control Specifications

Frequency control depends on the system frequency deviation $\Delta f(k) \in \mathbf{R}$ which is the difference between the system frequency $f_{\text{sys}}(k) \in \mathbf{R}$ and the nominal system frequency $f_{\text{nom}} \in \mathbf{R}$:

$$\Delta f(k) = f_{\text{sys}}(k) - f_{\text{nom}}. \tag{11.6}$$

Let $p_{\text{prim}} \in \mathbf{R}$ denote a symmetric delivery of primary reserve. An entity activated for a delivery p_{prim} must deliver power according to the measured frequency deviation $\Delta f(k)$: between the frequency deviations $\pm f_{\text{max}}$, the sold reserve p_{prim} must be provided proportionally with $\Delta f(k)$ except for a dead band of $\pm f_{\text{db}}$; moreover, a controller tolerance of $\pm f_{\text{tol}}$ is allowed. In the ENTSO-E grid, the parameters of this droop curve are $f_{\text{max}} = 200$ mHz, $f_{\text{db}} = 20$ mHz, and $f_{\text{tol}} = 10$ mHz [33] resulting in a primary frequency control droop curve as illustrated in Figure 11.2.

Let $p_{\text{ctrl}}(\Delta f(k))$ denote the primary reserve that must be delivered at sample number k when the system frequency deviation is $\Delta f(k)$ and the delivery is p_{prim}. Then we have (sample number k is omitted to ease the notation):

$$p_{\text{ref}}(\Delta f) = \begin{cases} p_{\text{prim}} & \text{if} \quad \Delta f < -f_{\text{max}} \\ a(\Delta f + f_{\text{db}}) & \text{if} \quad -f_{\text{max}} \le \Delta f < -f_{\text{db}} \\ 0 & \text{if} \quad -f_{\text{db}} \le \Delta f \le f_{\text{db}} \\ a(\Delta f - f_{\text{db}}) & \text{if} \quad f_{\text{db}} < \Delta f \le f_{\text{max}} \\ -p_{\text{prim}} & \text{if} \quad \Delta f > f_{\text{max}} \end{cases} \tag{11.7}$$

$$p_{\text{ctrl}}(\Delta f) \in [p_{\text{ref}}(\Delta f) + a f_{\text{tol}},\ p_{\text{ref}}(\Delta f) - a f_{\text{tol}}] \tag{11.8}$$

where $p_{\text{ref}}(\Delta f) \in \mathbf{R}$ is the reference that the primary frequency control should track, $a = p_{\text{prim}}/(f_{\text{db}} - f_{\text{max}})$ is the slope of the primary reserve droop curve, and $\pm a f_{\text{tol}}$ specifies the control tolerance band.

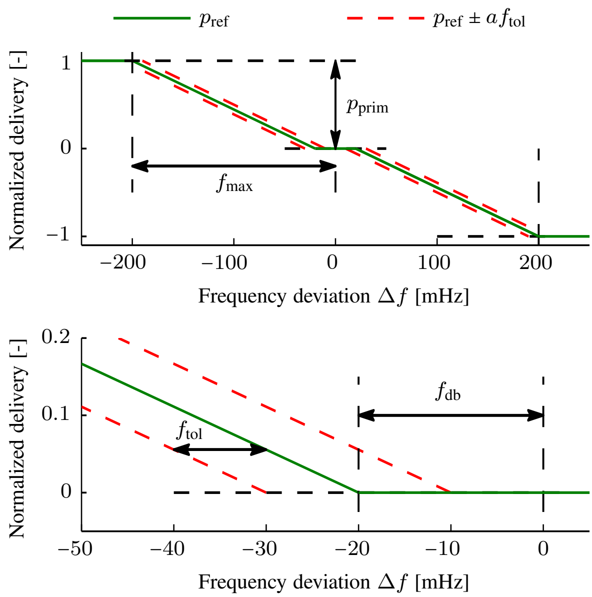

Figure 11.2: Primary frequency control droop curve with parameters from the ENTSO-E grid illustrating the power reference p_{ref} and the allowed tolerance bands for a normalized delivery.

Delivery of Primary Reserves

In this section we illustrate how the accumulated response of a portfolio of ON/OFF consumption devices can comprise a primary reserve delivery.

Local Frequency Measurements and Local Control

Primary frequency control must be provided based on local frequency measurements. As each device is only able to be either ON or OFF, the local control law of each device is on the form

$$u_i(\Delta f(k)) = \begin{cases} p_i & \text{if} \quad \Delta f(k) \geq t_i \quad \text{(device ON)} \\ 0 & \text{if} \quad \Delta f(k) < t_i \quad \text{(device OFF)} \end{cases} \tag{11.9}$$

for $i \in \mathcal{I}_{\text{prim}} \subseteq \mathcal{I}$ where $\mathcal{I}_{\text{prim}}$ is an index set of the ON/OFF devices activated for a primary reserve delivery. Here $t_i \in \mathbf{R}, i \in \mathcal{I}_{\text{prim}}$ are predefined frequency deviation thresholds for each of the devices that comprise the delivery. In the following, we refer to the threshold t_i as the *trigger frequency* of device i.

Combined Delivery

The basic idea in this work is as follows: to assign trigger frequencies t_i to a subset of devices $\mathcal{I}_{\text{prim}}$ such that they collectively can provide a delivery of p_{prim} at the lowest possible cost J_{prim}. This means that the activated devices $\mathcal{I}_{\text{prim}}$ must satisfy

$$p_{\text{ctrl}}(\Delta f(k)) = p_{\text{base}} - \sum_{i \in \mathcal{I}_{\text{prim}}} u_i(\Delta f(k)) \tag{11.10}$$

where $p_{\text{base}} \in \mathbf{R}$ is a chosen baseline consumption of the devices $\mathcal{I}_{\text{prim}}$ and where $p_{\text{ctrl}}(\Delta f(k))$ satisfy the primary frequency requirements as specified by (11.8). We comment further on the baseline p_{base} in the following section. Graphically, (11.10) corresponds to fitting the staircase shaped combined response of the devices $i \in \mathcal{I}_{\text{prim}}$ between the primary frequency control droop curve tolerance bands shown in Figure 11.2.

Symmetric Delivery

As described, we consider a symmetric delivery where we provide equal volumes of upward and downward reserve according to Figure 11.2. This can be expressed as follows: the set of devices $\mathcal{I}_{\text{prim}}$ that comprise the symmetric delivery consists of devices that provide upward regulation $\mathcal{I}_{\text{up}}$ and devices that provide downward regulation $\mathcal{I}_{\text{down}}$ where $\mathcal{I}_{\text{prim}} = \mathcal{I}_{\text{up}} \cup \mathcal{I}_{\text{down}}$, $\mathcal{I}_{\text{up}} \cap \mathcal{I}_{\text{down}} = \emptyset$. The devices $i \in \mathcal{I}_{\text{up}}$ that provide upward regulation have trigger frequencies $t_i < 0$ and comprise the left half of the droop curve in Figure 11.2 while the devices $i \in \mathcal{I}_{\text{down}}$ that provide downward regulation have trigger frequencies $t_i > 0$ and comprise the right half of the droop curve. This means that at zero frequency deviation $\Delta f(k) = 0$, no frequency reserve is to be delivered; consequently, all upward regulation devices $i \in \mathcal{I}_{\text{up}}$ will be ON while all downward regulation devices $i \in \mathcal{I}_{\text{down}}$ will be OFF, hence the baseline consumption is $p_{\text{base}} = \sum_{i \in \mathcal{I}_{\text{up}}} p_i$.

To further illustrate the concept, we can describe the setup as follows. If the frequency deviation gradually decreases from 0 to $-f_{\text{max}}$, the devices $i \in \mathcal{I}_{\text{up}}$ will gradually switch from ON to OFF as the frequency deviation becomes lower than the individual trigger frequencies. Hereby the portfolio will provide upward regulation. A similar argument can be made when the frequency deviation increases from 0 to f_{max} for the devices $i \in \mathcal{I}_{\text{up}}$; hence, the combined response will comprise a symmetric primary reserve delivery. Note that we assume that the aggregator is free to choose any baseline p_{base} for the devices activated for primary reserve.

Primary Reserve Volume

In the following we consider an upper and a lower bound on the volume of primary frequency control that the portfolio can deliver and neglect the activation costs π.

Optimistic Case Consider an optimistic case where we completely ignore the comfort constraints (11.4) and regardless of the activation costs π activate the whole portfolio for primary reserve. The smallest consumption of the portfolio is 0 while the maximum consumption of the total portfolio is $\mathbf{1}^T p$, where $\mathbf{1}$ is a vector with all components one; hence, we are able to deliver at most a symmetric primary reserve bid of

$$p_{\text{prim}}^{\text{max}} = \mathbf{1}^T p/2. \tag{11.11}$$

This optimistic example is not meant as an implementable method as the comfort constraints are ignored, but provides an upper bound on the volume we can bid as primary reserve.

Conservative Case Now consider a conservative strategy where we only utilize the devices that are fully flexible, again independent of the costs π. The fully flexible devices are those that will not violate the comfort constraints (11.4), no matter if they are turned ON or OFF for the whole primary reserve delivery period. In this case we are able to deliver at most a symmetric primary reserve bid of

$$p_{\text{prim}}^{\min} = \sum_{i \in \mathcal{I}^{\min}} p_i/2, \tag{11.12}$$

$$\mathcal{I}^{\min} = \{i \in \mathcal{I} | x_i^0 - Tv_i \geq x_i^{\min}, x_i^0 + T(p_i - v_i) \leq x^{\max}\}. \tag{11.13}$$

Here T is the duration of a delivery period such that $x_i^0 - Tv_i$ is the end state of device i if it is turned OFF the whole period T; similarly, $x_i^0 + T(p_i - v_i)$ is the end state of device i if it is turned ON the whole period T – hereby $\mathcal{I}^{\min}$ corresponds to the devices that do not violate the comfort constraints for any input sequence $u_i(k)$ throughout the whole period T. This delivery $p_{\text{prim}}^{\min}$ serves as a lower bound on the volume we can bid as primary reserve.

Probabilistic Approach In this work, we propose an alternative to the optimistic and the conservative methods. In our method we require that the comfort constraints (11.4) should be honored with probability α:

$$\mathbf{Prob}(x_i^{\min} \leq x_i(k) \leq x_i^{\max}, \forall k = 1, \ldots, K) \geq \alpha, \quad i \in \mathcal{I}_{\text{prim}} \tag{11.14}$$

where $K = T/T_s$ is the total number of samples in a delivery period. Hereby we will be able to utilize the portfolio to a far greater extent than the conservative case as illustrated in the numerical example in the end of this work.

This setup requires that the flexibility contract states that the comfort constraints might be violated when the consumer is activated for reserve deliveries; in return, the consumer achieves the activation payment specified by π_i. By choosing the parameter α sufficiently high, the aggregator will ensure that the consumer rarely will experience discomfort thereby making it attractive for consumers to be part of the portfolio.

5 Controller Synthesis

In this section we describe how to construct bids for the primary frequency reserve market based on the portfolio of ON/OFF devices. The basic idea is simple: we find the set of devices $\mathcal{I}_{\text{prim}}$ with the lowest total cost J_{prim} that collectively can provide a symmetric reserve p_{prim} that is kept within the tolerance bands $p_{\text{ref}} \pm a f_{\text{tol}}$ while honoring the comfort constraints with a desired certainty.

Problem Variables and Parameters

In the following, we define the variables and parameters needed to formulate the problem of minimizing the cost J_{prim} of providing a primary reserve bid of volume p_{prim}. Due to the discontinuity of the primary control droop curve caused by the dead band, we separate the problem formulation into an upward regulation part and a downward regulation part. Consequently, we will distinguish between the parameters associated with upward regulation and the parameters associated with downward regulation. We indicate upward regulation parameters with an upper bar and downward regulation parameters with a lower bar.

First, let us define two vectors describing the frequency ranges associated with upward and downward regulation denoted $\overline{t}$ and $\underline{t}$, respectively. Each range is divided into m equidistant intervals:

$$\overline{t} = (-f_{\text{db}}, \dots, -f_{\text{max}}) \in \mathbf{R}^m$$
$$\underline{t} = (f_{\text{db}}, \dots, f_{\text{max}}) \in \mathbf{R}^m$$

where $(f_{\text{max}} - f_{\text{db}})/(m-1)$ is the quantization of the two frequency vectors. This quantization can for example be chosen as the accuracy of the frequency measurement equipment. Furthermore, we define two binary matrices $\overline{X}, \underline{X} \in \mathbf{R}^{m \times n}$ where

$$\overline{X}_{ji} = \begin{cases} 1 & \text{if device } i \text{ has threshold } \overline{t}_j \\ 0 & \text{else,} \end{cases} \tag{11.15}$$

$$\underline{X}_{ji} = \begin{cases} 1 & \text{if device } i \text{ has threshold } \underline{t}_j \\ 0 & \text{else.} \end{cases} \tag{11.16}$$

for $i \in \mathcal{I}$ and $j \in \mathcal{J} = \{1, \dots, m\}$. These matrices describe the trigger frequencies of the devices activated for upward regulation $i \in \mathcal{I}_{\text{up}}$ and downward regulation $i \in \mathcal{I}_{\text{down}}$. The sets $\mathcal{I}_{\text{up}}$ and $\mathcal{I}_{\text{down}}$ can be expressed in terms of $\overline{X}$ and $\underline{X}$ as:

$$\mathcal{I}_{\text{up}} = \{i \in \mathcal{I} | (\overline{X}^T \mathbf{1})_i = 1\}, \quad \mathcal{I}_{\text{down}} = \{i \in \mathcal{I} | (\underline{X}^T \mathbf{1})_i = 1\}. \tag{11.17}$$

Problem Objective and Constraints

Objective

The objective is to minimize the total cost J_{prim} of providing a primary reserve bid of volume p_{prim} for a delivery period T, as specified by (11.5). We can express J_{prim} in terms of $\overline{X}, \underline{X}$ as

$$J_{\text{prim}} = \mathbf{1}^T (\overline{X} + \underline{X}) \pi \tag{11.18}$$

as $\left(\mathbf{1}^T (\overline{X} + \underline{X})\right)_i = 1$ if and only if device i is activated for upward or downward regulation and as the associated cost is π_i.

Reference Tracking

The devices comprising a bid of primary reserve $i \in \mathcal{I}_{\text{prim}}$ must collectively track the power reference p_{ref} within the given control tolerance bands as described by (11.8). This is equivalent to allocating the trigger frequencies of the devices $i \in \mathcal{I}_{\text{prim}}$ such that the combined upward and downward regulation lie within the tolerance bands. In the following we describe how to constrain $\overline{X}, \underline{X}$ such that this is achieved. We illustrate this first for upward regulation.

Let $R \in \mathbf{R}^{m \times m}$ serve as a cumulative sum operator by having zeros on all elements above the diagonal and ones in all elements on and below the diagonal. The power provision between a frequency deviation $\overline{t}_j$ to $\overline{t}_{j+1}$ can thus be described as $(R\overline{X}p)_j$. To honor the control tolerance bands it is necessary that

$$a(\bar{t}_{j+1} + f_{\text{db}} + f_{\text{tol}}) \leq (R\overline{X}p)_j \leq a(\bar{t}_j + f_{\text{db}} - f_{\text{tol}}) \tag{11.19}$$

for $j \in \mathcal{J}\backslash m$ due to the allowed control tolerance $\pm f_{\text{tol}}$. Further we must assure that we deliver the required reserve p_{prim} when the system frequency deviation reaches $\bar{t}_m = -f_{\max}$ which can be described as

$$(R\overline{X}p)_m \geq p_{\text{prim}}. \tag{11.20}$$

The requirements (11.19) and (11.20) can be rearranged and written in compact form as a constraint to the allocation matrix $\overline{X}$ as follows

$$\begin{aligned}\overline{X} \in \overline{\mathcal{X}}_{\text{ref}} = \{X \in \mathbf{R}^{m\times n} | \bar{t}_j - f_{\text{tol}} \leq \frac{(RXp)_j}{a} - f_{\text{db}} \\ \leq \bar{t}_{j+1} + f_{\text{tol}}, (RXp)_m \geq p_{\text{prim}}, \forall j \in \mathcal{J}\backslash m\}.\end{aligned} \tag{11.21}$$

By a similar set of arguments, we can make a compact formulation of the requirements for the downward regulation to honor the tolerance bands and deliver the full reserve $-p_{\text{prim}}$ at frequency deviation $\underline{t}_m = f_{\max}$. Hereby we obtain

$$\begin{aligned}\underline{X} \in \underline{\mathcal{X}}_{\text{ref}} = \{X \in \mathbf{R}^{m\times n} | \underline{t}_j + f_{\text{tol}} \leq \frac{(RXp)_j}{a} + f_{\text{db}} \\ \leq \underline{t}_{j+1} - f_{\text{tol}}, (RXp)_m \leq -p_{\text{prim}}, \forall j \in \mathcal{J}\backslash m\}\end{aligned} \tag{11.22}$$

Assure Comfort

As described in (11.14), we must assure that comfort is maintained for the devices activated for upward and downward regulation with probability α or greater. The key idea in assuring this comfort is to use historical system frequency measurements to determine probabilities for how long time a device will be ON and OFF respectively when assigned with a given trigger frequency. Hereby we can determine the trigger frequencies that with a given probability will not cause violations of the comfort constraints.

In Appendix 8, we present a method for mapping the device parameters $\{x_i^0, p_i, v_i, x_i^{\min}, x_i^{\max}\}$ into upper and lower limits $\{t_i^{\min}, t_i^{\max}\}$ on the trigger frequency of device i for $i \in \mathcal{I}$. The mapping is based on historical system frequency measurements and is constructed such that if device i is activated for upward or downward regulation according to the control law (11.9) with trigger frequency t_i, then the largest allowable trigger frequency band that assures comfort with probability at least α is $t_i^{\min} \leq t_i \leq t_i^{\max}$. Hence, sufficient comfort is assured if

$$t_i^{\min} \leq t_i \leq t_i^{\max}, \quad i \in \mathcal{I}_{\text{prim}} \tag{11.23}$$

which can be expressed in terms of $\overline{X}, \underline{X}$ as

$$\mathbf{diag}(t^{\min})\overline{X}^T\mathbf{1} \leq \overline{X}^T\bar{t} \leq \mathbf{diag}(t^{\max})\overline{X}^T\mathbf{1} \tag{11.24}$$

$$\mathbf{diag}(t^{\min})\underline{X}^T\mathbf{1} \leq \underline{X}^T\underline{t} \leq \mathbf{diag}(t^{\max})\underline{X}^T\mathbf{1}, \tag{11.25}$$

where $\mathbf{diag}(x)$ denotes a diagonal matrix with diagonal entries $x_1, \ldots, x_n$ and where $\leq$ represents componentwise inequality. Constraint (11.24) can be explained as follows:

$(\mathbf{diag}(t^{\min})\overline{X}^T\mathbf{1})_i$ and $(\mathbf{diag}(t^{\max})\overline{X}^T\mathbf{1})_i$ are the minimum and maximum allowable trigger frequencies for device i if activated for upward regulation $i \in \mathcal{I}_{\text{up}}$; otherwise it is zero. Similarly, $(\overline{X}^T\overline{t})_i$ is the trigger frequency of device i if activated for upward regulation $i \in \mathcal{I}_{\text{up}}$; otherwise it is zero. Hereby, constraint (11.24) ensures that device i will have a trigger frequency within the allowable range $[t_i^{\min},\ t_i^{\max}]$ if it is activated for upward regulation. Similarly for the downward regulation inequality (11.25).

ON/OFF Behavior

The devices are only able to be turned ON or OFF which can be formulated as

$$\overline{X}, \underline{X} \in \mathcal{X}_{\text{bin}} \tag{11.26}$$

$$\mathcal{X}_{\text{bin}} = \{X \in \mathbf{R}^{m\times n} | X_{ji} \in \{0,1\}, \forall i \in \mathcal{I}, \forall j \in \mathcal{J}\}. \tag{11.27}$$

Furthermore, we must construct $\overline{X}, \underline{X}$ such that each device is associated with at most one trigger frequency. This requirement can be expressed as

$$(\overline{X} + \underline{X})^T\mathbf{1} \le \mathbf{1}. \tag{11.28}$$

Optimization Problem

Based on the objective and constraints, we can formulate the problem that minimizes the cost of providing a delivery p_{prim} of primary reserve:

$$\begin{array}{ll} \text{minimize} & J_{\text{prim}} = \mathbf{1}^T(\overline{X} + \underline{X})\pi \\ \text{subject to} & \overline{X} \in \overline{\mathcal{X}}_{\text{ref}}, \quad \underline{X} \in \underline{\mathcal{X}}_{\text{ref}}, \quad \overline{X}, \underline{X} \in \mathcal{X}_{\text{bin}} \\ & (\overline{X} + \underline{X})^T\mathbf{1} \le \mathbf{1} \\ & \mathbf{diag}(t^{\min})\overline{X}^T\mathbf{1} \le \overline{X}^T\overline{t} \le \mathbf{diag}(t^{\max})\overline{X}^T\mathbf{1} \\ & \mathbf{diag}(t^{\min})\underline{X}^T\mathbf{1} \le \underline{X}^T\underline{t} \le \mathbf{diag}(t^{\max})\underline{X}^T\mathbf{1} \end{array} \tag{11.29}$$

where the variables are $\overline{X}, \underline{X} \in \mathbf{R}^{m\times n}$. The data to the problem is the activation costs $\pi \in \mathbf{R}^n_+$, the primary frequency delivery specification described by the sets $\overline{\mathcal{X}}_{\text{ref}}, \underline{\mathcal{X}}_{\text{ref}}$, the ON/OFF behavior set $\mathcal{X}_{\text{bin}}$, the upward and downward frequency ranges $\overline{t}, \underline{t} \in \mathbf{R}^m$, and the upper and lower trigger frequency limits $t^{\min}, t^{\max} \in \mathbf{R}^n$. The optimal value $J^\star_{\text{prim}}$ of the optimization problem (11.29) is the minimum cost associated with a delivery p_{prim} of primary reserve under the specified comfort constraints throughout the delivery period T. The optimal solution $\overline{X}^\star, \underline{X}^\star$ specifies which devices should be activated for this delivery and the associated trigger frequencies according to (11.15) and (11.16).

Problem 11.29 is a linear mixed integer optimization problem and resembles a unit commitment problem. See, e.g., [34]. Generally, this type of program is hard and can only be solved for a smaller number of devices (up to hundreds) using commercial optimization tools. For a larger number of devices, alternative methods are needed such as decomposition techniques [35, 36] or heuristics [37, 38]. In Appendix 9, we present a very simple and straightforward heuristic method that is able to handle large numbers of devices and approximately solve the binary optimization problem. Note that the heuristic method is presented mainly to illustrate that Problem 11.29 can be approximately solved with reasonable performance via heuristic methods, which is useful when the number of devices is large; it is, however, beyond the scope of this work to develop more sophisticated heuristics or to conclude proofs of the performance of the presented heuristic.

Algorithm

Based on the previous sections, we present an algorithm for utilizing a portfolio of ON/OFF devices to provide primary reserve. The algorithm must be executed before the bidding deadline of each primary reserve delivery period.

1. Collect state information of the portfolio of ON/OFF devices $\{x_i^0, p_i, v_i, x_i^{\text{min}}, x_i^{\text{max}}\}$, $i \in \mathcal{I}$.

2. Map the state information into upper and lower allowable trigger frequency limits $\{t_i^{\text{min}}, t_i^{\text{max}}\}, i \in \mathcal{I}$ according to Appendix 8.

3. Solve the binary linear program (11.29) or approximately solve it using the heuristic method presented in Appendix 9 based on a desired delivery volume p_{prim}. If feasible, denote the resulting values of the binary matrices $\overline{X}^+, \underline{X}^+$ and the associated cost J_{prim}^+.

4. Place a bid of p_{prim} in the primary reserve market at price J_{prim}^+.

5. If the bid is accepted, find $\mathcal{I}_{\text{up}}, \mathcal{I}_{\text{down}}$ according to (11.17) and activate by assign trigger frequencies $(\bar{t}^T \overline{X}^+)_i$ to devices $i \in \mathcal{I}_{\text{up}}$ and trigger frequencies $(\underline{t}^T \underline{X}^+)_i$ to devices $i \in \mathcal{I}_{\text{down}}$.

A natural extension to the above algorithm is to repeat step 3 with varying primary reserve volumes to find the associated costs. This information can be used to place several bids into the reserve market allowing the aggregator to become a more competitive player. Note that bidding the marginal cost as in step 4 is just meant as an example of a bidding strategy – alternative strategies can be applied as well.

6 Numerical Examples

We consider two numerical examples: a small-scale example with 100 ON/OFF devices and a large scale example with $10,000$ ON/OFF devices. We assume a primary reserve delivery period of 1 hour, a sampling time of 10 s, a frequency resolution of 2 mHz, and a comfort constraint certainty of $\alpha = 0.99$. The following parameters are used:

$$\begin{aligned} &x_i^{\text{min}} = 0, \quad x_i^{\text{max}} \in [0, 6], \quad x_i^0 \in [0, x_i^{\text{max}}] \quad [\text{kWh}], \\ &p_i \in [2, 5], \quad v_i \in [0, p_i] \qquad\qquad\qquad\quad [\text{kW}] \end{aligned} \tag{11.30}$$

for $i \in \mathcal{I}$. The parameters are uniformly distributed within the given intervals. An interpretation of this portfolio could be water heaters with tanks between 0 and 250 L where each heater allows the water temperature to vary within a band of 50 ± 10 °C. The nominal power consumption of each water heater lies in the interval from 2 kW to 5 kW. It is assumed that one quarter of the consumers have signed flat rate contracts and receive no additional payment per activation while the remaining three quarters of the consumers have flex rate contracts causing a cost per activation:

$$\begin{aligned} \pi_i &= 0, & i &= 1, \ldots, n/4 \\ \pi_i &\in [0,1], & i &= n/4+1, \ldots, n, \end{aligned} \tag{11.31}$$

where the flex rate costs are assumed uniform in the given interval.

Small-Scale Example

In this example, the portfolio consists of $n = 100$ ON/OFF devices. The maximum power consumption of the entire portfolio is 360 kW. The upper and lower bounds on the primary reserve volume are

$$p_{\text{prim}}^{\max} = 180\ \text{kW}, \quad p_{\text{prim}}^{\min} = 17\ \text{kW}, \tag{11.32}$$

remembering that the upper bound corresponds to completely ignoring the comfort constraints while the lower bound corresponds to guaranteeing no violated comfort constraints.

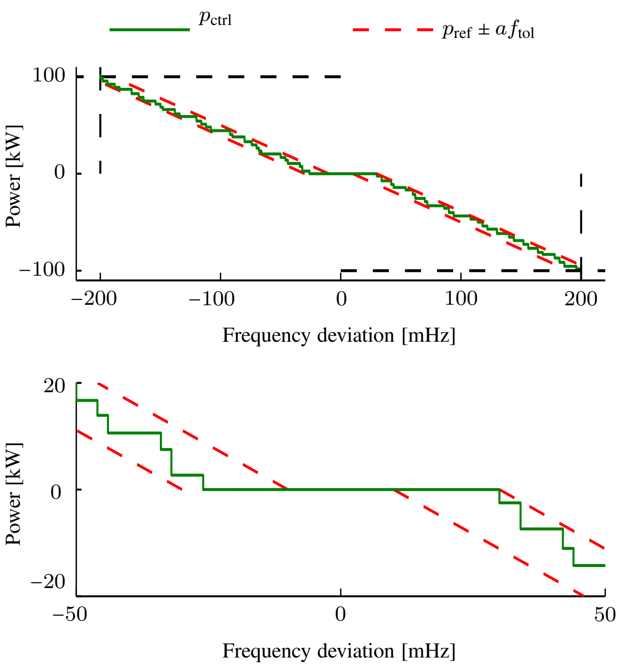

Figure 11.3: Allocation of ON/OFF devices that maximizes the delivery p_{prim}.

We use the algorithm presented in Sec. 5 to find the minimum cost of providing a primary frequency delivery of respectively 50 kW and 100 kW. The binary optimization problem (11.29) is used whereby we obtain

$$J^{\star}_{\text{prim, 50 kW}} = 2.1, \quad J^{\star}_{\text{prim, 100 kW}} = 15.0. \tag{11.33}$$

This shows that we are able to construct a bid of 50 kW almost solely relying on the flat rate consumers while we are able to construct a bid of additionally 50 kW at an additional cost of 12.9. The maximum volume of primary reserve we are able to construct using the binary optimization is 117 kW corresponding to 65 % of the maximum possible $p_{\text{prim}}^{\max}$ and 6.7 times as much as the conservative bid $p_{\text{prim}}^{\min}$. The resulting droop curve for p_{prim} = 100 kW is presented in Figure 11.3.

The performance of the portfolio is examined by evaluating 300 sequences of duration 1 hour based on frequency measurements from the ENTSO-E grid. The first 30 minutes of one such sequence is illustrated in Figure 11.4 to show the behavior of the portfolio. Through these 300 simulations, less than 1 % of the devices experience comfort constraint violations as expected.

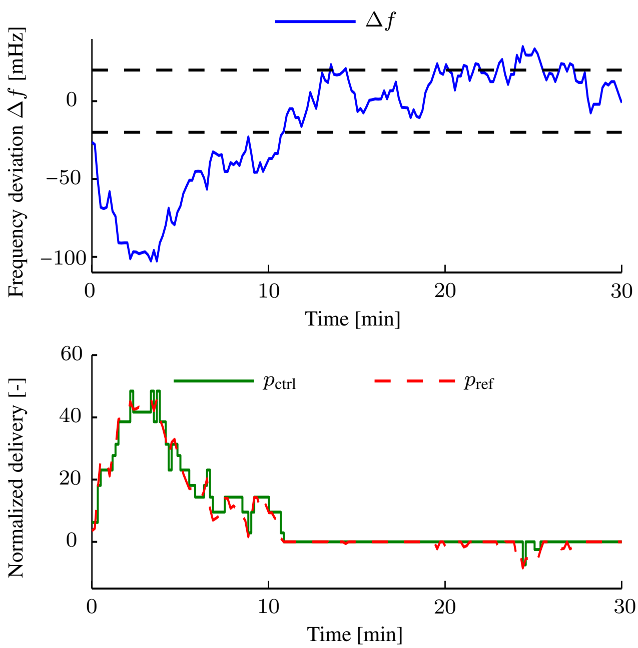

Figure 11.4: Transient response of the portfolio of ON/OFF devices to a given sequence of frequency deviations $\Delta f(k)$.

For comparison, the optimization problem is approximately solved using the heuristic method yielding

$$J^{+}_{\text{prim, 50 kW}} = 2.3 \quad J^{+}_{\text{prim, 100 kW}} = 18.4. \tag{11.34}$$

This shows that the heuristic method also is able to deliver 50 kW of primary reserve relying almost solely on the flat rate consumers while the delivery of 100 kW is 23 % more expensive than the optimal cost. The maximum volume of primary reserve we are able to deliver using the heuristic method is 103 kW corresponding to 12 % less than when solved using the binary optimization.

Large Scale Example

We consider a portfolio of $n = 10,000$ ON/OFF devices with the same distribution as in the previous example. The maximum power consumption of the entire portfolio is 35.1 MW and the upper and lower bounds on the primary reserve volume are

$$p_{\text{prim}}^{\max} = 17.5 \text{ MW}, \quad p_{\text{prim}}^{\min} = 1.8 \text{ MW}. \tag{11.35}$$

We cannot solve the binary optimization problem using commercial solvers due to the high number of devices. Therefore we use the heuristic method described in Appendix 9 to approximately solve the problem. This is illustrated by Figure 11.5 where the cost J_{prim} at different primary reserve volumes p_{prim} is illustrated. Four of these bids and associated costs are

$$\begin{aligned} J^{+}_{\text{prim},3\text{ MW}} &= 0, & J^{+}_{\text{prim},6\text{ MW}} &= 297 \\ J^{+}_{\text{prim},9\text{ MW}} &= 1.183, & J^{+}_{\text{prim},11.1\text{ MW}} &= 2.354 \end{aligned} \tag{11.36}$$

illustrating that the flat rate consumers allow the aggregator to construct regulating power reserve bids associated with very low costs; however, as the volume increases, the associated costs increase drastically. The pairs of different volumes of primary reserve and associated costs allow the aggregator to place multiple bids with different costs and hereby increase the competition with the conventional generators.

The maximum volume of primary reserve we are able to construct using the heuristic method is 11.1 MW corresponding to 63 % of the upper bound $p_{\text{prim}}^{\max}$ and 6.2 times as much as the conservative bid $p_{\text{prim}}^{\min}$. Note that 11.1 MW corresponds to more than 40 % of the entire need for primary reserve in Western Denmark.

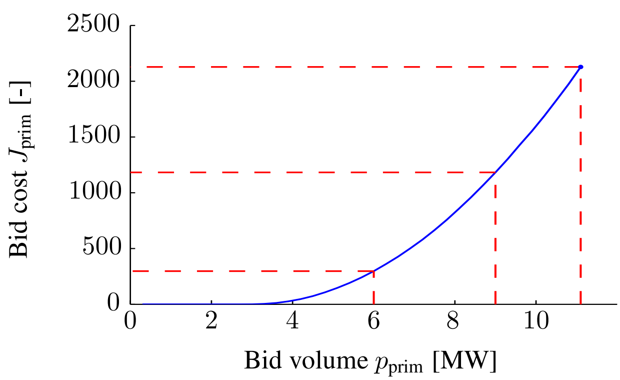

Figure 11.5: Bid costs J_{prim} as a function of the bid volume p_{prim}.

7 Conclusion

In this work we showed how a portfolio of ON/OFF devices with flexible power consumption is able to collectively provide a delivery of primary reserve. We described how to minimize the cost of a given primary reserve delivery while honoring device comfort constraints with a given certainty. Through numerical examples, we illustrated the ability of this method to mobilize a large fraction of a portfolio for primary reserve even when only a small fraction of the portfolio possessed full flexibility throughout the delivery period.

8 Appendix A: Map

This appendix describes how we can perform a mapping from device characteristics $\{x_i^0, p_i, v_i, x_i^{\min}, x_i^{\max}\}$ to upper and lower limits $\{t_i^{\min}, t_i^{\max}\}$ on the trigger frequency for device i. The mapping is constructed as follows: $t_i^{\min} \leq t_i \leq t_i^{\max}$ is the largest trigger frequency interval where the comfort constraints are honored at least with probability α. We determine this mapping based on a large set of system frequency measurement sequences taken from the ENTSO-E grid and assume that these sequences are representative for the system frequency characteristics.

Denote the system frequency deviation measurement sequences $\Delta f_l(k)$ for $k \in \mathcal{K} = \{1, \ldots, K\}$ and $l \in \mathcal{L} = \{1, \ldots, L\}$, where K is the total number of samples in a delivery period (in this example, $K = 360$ corresponding to a primary reserve delivery period of 1 hour $= 3,600$ s and a sampling time $T_s = 10$ s) and L is the number of examined sequences. Let $\overline{e}_{lj}(k)$ denote the *accumulated duty cycle* of a device with trigger frequency $\overline{t}_j$ when system frequency deviation measurement sequence l is applied:

$$\overline{e}_{lj}(k) = \frac{1}{k} \sum_{\kappa=1}^{k} I(\Delta f_l(\kappa), \overline{t}_j) \tag{11.37}$$

where

$$I(a,b) = \begin{cases} 1 & \text{if } a \geq b \\ 0 & \text{else.} \end{cases} \tag{11.38}$$

Hereby, $\overline{e}_{lj}(k)$ will be the accumulated duty cycle, or average duty cycle, of a device with trigger frequency $\overline{t}_j$ at time k in the case of the specific frequency realization Δf_l. By having a large set of such frequency realizations (large L), we can use the accumulated duty cycles $\overline{e}_{lj}(k)$ to examine the expected duty cycle of devices with a trigger frequency given by $\overline{t}_j$. By removing the number of outliers corresponding to the value of $1 - \alpha$, we can select the realization with the highest and lowest accumulated duty cycle among the remaining accumulated duty cycle realization. If a given device is able to be turned ON/OFF according to both these two extreme realizations, it will also be able to handle all realizations within these two extreme realizations and thus able to handle the fraction α of all the given realizations. Hence, it will be able to be associated with trigger frequency $\overline{t}_j$ given that the observed data is representable. This is described in more detail in the following.

The α-envelopes (the two extreme realizations) for the accumulated duty cycle can be found as

$$\overline{e}_j^{\max}(k) = \max_{l \in \mathcal{L} \setminus \overline{\mathcal{L}}} \overline{e}_{lj}(k), \quad \overline{e}_j^{\min}(k) = \min_{l \in \mathcal{L} \setminus \overline{\mathcal{L}}} \overline{e}_{lj}(k), \quad j \in \mathcal{J} \tag{11.39}$$

where $\overline{\mathcal{L}}$ is a set consisting of the $\lfloor L(1-\alpha) \rfloor$ largest outliers of $\overline{e}_{lj}(k)$; hereby we remove the accumulated duty cycle sequences that deviate the most from the remaining sequences. The removed duty cycle sequences correspond to the most extreme frequency deviations where we are allowed to violate the comfort constraints in concordance with the parameter α. In a similar manner, we can determine the accumulated duty cycle envelopes $\underline{e}_j^{\max}, \underline{e}_j^{\min}$ for the trigger frequencies $\underline{t}_j$.

An illustration of the accumulated duty cycle is seen in Figure 11.6 for a trigger frequency of 20 mHz. The figure is built according to the description above: a large number of system frequency measurements are compared to a trigger frequency $\bar{t} = 20$ mHz and a number of accumulated duty cycle sequences are generated according to (11.37). The outliers are removed and the envelopes (extreme realizations) are found according to (11.39), these extreme realizations are plotted in the figure (black dash-dotted). For comparison, the overall mean and standard deviation of the accumulated duty cycle sequences are also presented.

A number of observations can be made from the figure. The overall mean of the observed sequences illustrates that the system frequency is above 20 mHz approximately $10\ \%$ of the time. The figure further shows the accumulated duty cycle envelopes. A device with trigger frequency 20 mHz must be able to handle any duty cycle sequence within these envelopes to ensure comfort with the required probability. This means that a device with trigger frequency of 20 mHz must be fully flexible the first 40 minutes whereafter the duty cycle requirement decreases.

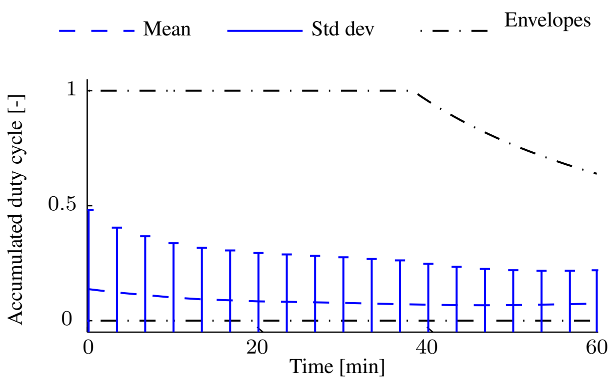

Figure 11.6: Accumulated duty cycle mean, standard deviation and $\alpha = 0.99$ envelopes $\overline{e}_j^{\max}(k), \underline{e}_j^{\max}(k)$ for trigger frequency $\bar{t}_j = 20$ mHz.

If instead of a trigger frequency of $\bar{t} = 20$ mHz we had taken a higher value, for example $\bar{t} = 100$ mHz, we would see different envelopes: the lower envelope would still be at 0, but the higher envelope would decrease drastically. The reason is that a device with such a high trigger frequency only rarely will be ON, as the system frequency deviation only rarely increases above 100 mHz.

Based on envelopes $\overline{e}_j^{\max}(k), \overline{e}_j^{\min}(k), j \in \mathcal{J}$, we can perform the desired mapping from device characteristics to a trigger frequency interval. Let the set $\mathcal{T}_i$ denote all feasible trigger frequencies for device i. Then we have

$$\bar{t}_j \in \mathcal{T}_i \tag{11.40}$$

if and only if the comfort constraints (11.4) holds in two cases:

1. for the upper envelope $u_i(k) = \overline{e}_j^{\max}(k),\ k \in \mathcal{K}$,
2. for the lower envelope $u_i(k) = \overline{e}_j^{\min}(k),\ k \in \mathcal{K}$.

If the comfort constraints hold for the accumulated duty cycle envelopes, the constraint will also hold for any realizations between the envelopes and consequently hold with probability α. Similarly, we can determine the necessary conditions for having $\underline{t}_j \in \mathcal{T}_i$. The resulting trigger frequency limitations are given as

$$t_i^{\max} = \max \mathcal{T}_i, \quad t_i^{\min} = \min \mathcal{T}_i. \tag{11.41}$$

9 Appendix B: Heuristic Method

In this appendix we present a simple heuristic method that approximately solves the mixed integer problem (11.29) for large n. The following steps describe the method at an overall level.

1. **Initialize** $\overline{X}_{ji}, \underline{X}_{ji} = 0, i \in \mathcal{I}, j \in \mathcal{J}$ and $\mathcal{I}_{\text{up}}, \mathcal{I}_{\text{down}} = \varnothing$.
2. **Loop** through all upward regulation trigger frequencies $\overline{t}_j, \quad j = 1, \ldots, m$.
3. **Repeat**
4. Determine the feasible devices for trigger frequency $\overline{t}_j$:
   $\mathcal{I}_{\text{feas}} := \{i \in \mathcal{I} \backslash \mathcal{I}_{\text{prim}} | t_i^{\min} \leq \overline{t}_j \leq t_i^{\max}\}$.
5. If $\mathcal{I}_{\text{feas}} \neq \varnothing$, assign trigger frequency $\overline{t}_j$ to the device with the lowest cost by $\overline{X}_{ji} :=$ 1 where $i = \text{argmin}_{i \in \mathcal{I}_{\text{feas}}} \pi_i$. Update $\mathcal{I}_{\text{up}}$ according to (11.17).
6. **Until** the error between the delivery $\overline{p}_j$ and the reference $p_{\text{ref}}(\overline{t}_j)$ increases.
7. Repeat for down-regulating frequencies.
8. Denote the final allocation matrices $\overline{X}^+, \underline{X}^+$.

This illustrates the basic idea in the method: to start from the innermost trigger frequency $\overline{t}_1$ and assign trigger frequencies to devices until we are as close as possible to the power reference, always selecting the device with the lowest activation cost. After allocating devices for the first trigger frequency $\overline{t}_1$, move outwards to the following trigger frequency $\overline{t}_2$, etc. When the algorithm has run to completion we can test that the final allocation as defined by $\overline{X}^+, \underline{X}^+$ indeed satisfy the constraints as specified in (11.29).

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Paper 9

Adjustable Consumption Participating in the Electricity Markets

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Abstract

We consider a player managing a portfolio of flexible demand-side devices and examine the requirements for such a player to become an active player in the Nordic electricity system. In particular, we examine the regulatory requirements that must be satisfied to perform spot price optimization and to participate in the regulating power market. To conceptualize these requirements, we estimate the costs per consumer for honoring the given requirements, both under the current regulations but also under the planned future regulations. Finally, we consider a specific case study where domestic appliances are aggregated and utilized for spot price optimization and to participate in the regulating power market. In this case study we examine in detail the implications of the given regulatory requirements for market participation in the Nordic system and compare this with estimates of the revenue that can be generated via market participation. The case study shows that the profit in the current system is very limited but that planned regulatory changes will make market participation significantly more attractive.

1 Introduction

With an increasing focus on climate-related issues and rising fossil fuel prices, the penetration of renewable energy sources is likely to increase in the foreseeable future throughout the developed world. As the conventional power plants are outdone by renewables such as wind turbines and photovoltaics, the ability to provide balancing services in the classical sense disappears. One of the approaches to obtaining such balancing is the *smart grid* concept, where demand-side devices with flexible power consumption take part in the balancing effort. The basic idea is to let an *aggregator* manage and optimize a portfolio of flexible demand-side devices on behalf of the balancing responsible party (BRP) for this consumption. This allows the BRP to utilize the accumulated flexibility in the unbundled electricity markets on equal terms with conventional generators [1].

The topic of demand-side management has received much attention from a research perspective. In particular, optimization of flexible consumption has received much attention in Denmark due to the high penetration of wind. A few examples from Denmark are: optimization of domestic heat pumps [2, 3], supermarket cooling systems [4, 5], domestic refrigerators [6, 7], and electrical vehicles [8, 9].

The focus of these existing works is to use the demand-side devices for power balancing by performing spot price optimization or providing ancillary services. These works and many more describe the revenue that can be generated via market participation but do not discuss the requirements for entering these markets. This is, however, a most relevant topic as these requirements must be honored before any revenue can be generated. Further, it will have a certain cost to enable each individual demand-side device to honor the requirements, which must be taken into consideration when developing such smart grid strategies.

In this work we examine the requirements for market participation in the Nordic system based on the current regulations and the planned future regulations. Further, we estimate the costs of utilizing the accumulated flexibility of a portfolio of flexible devices towards the spot price and in the regulating power market. With these cost estimates it is possible to examine whether different smart grid strategies for spot price and regulating power optimization have economic grounds in the Nordic electric power system under current and planned future regulations.

This work hereby serves as a survey and reality check of the regulatory framework for flexible consumers to participate in the current and future Nordic market. The basis is the existing regulatory documents, technical reports describing details for market participation, and interviews with the Danish transmission system operator (TSO) Energinet.dk. The end result is a thorough description of the requirements for flexible consumers to perform spot price optimization and for participation in the regulating power market. Further, we present a specific case study to conceptualize the implications of these requirements for flexible demand-side devices.

The structure of the paper is as follows. First, in Sec. 2, we discuss the requirements for enabling flexible demand-side devices for spot price settlement; following, in Sec. 3, we discuss the requirements for participation in the regulating power market. In Sec. 4, a case study on household devices is presented discussing in detail the requirements, costs, and possible revenue associated with enabling market participation. Finally, in Sec. 5, we conclude the work.

2 Spot Price Optimization

This section describes the requirements for flexible demand-side devices to optimize the electricity consumption towards the spot market prices. It is based on the following TSO regulations and technical reports: [10, 11, 12, 13]. First we describe how the spot prices are found, then how the prices are settled, and finally how spot price settlement can be achieved via hourly sampled electricity meters. It is important to notice that these are the requirements that determine to what extend it is possible to construct controllers that optimize the flexibility towards the electricity spot prices.

Spot Prices

Each day before gate closure at noon (12.00 pm), the BRPs for both consumption and production place purchase bids in the Elspot market for each hour of the following day specifying the volumes they are willing to trade given the hourly electricity prices. The spot prices for each hour of the following day are found as the intersection between the accumulated bids for supply and demand. At 1 pm, all BRPs are informed of the traded volumes and hourly prices for the following day.

Settlement Methods

Two different methods are used for consumption settlement in Denmark: load-profile settlement and hourly settlement. Further, Energinet.dk and the Danish Energy Association have proposed a third settlement method that is planned to be implemented in the Nordic system. These three methods are described in the following.

Load Profile Settlement

All consumers with an annual consumption lower than a threshold of $100,000$ kWh will be settled using load profile settlement; however, hourly settlement can voluntarily be chosen for smaller consumers. For load profile settlement, the accumulated consumption is read typically once a year. As a result of this infrequent metering, the hourly consumption is unknown and identical consumption profiles are used for all consumers within the same grid area for settlement purposes. It is therefore clear that spot price optimization of flexible consumers is not possible for load profile customers, which today account for almost all private consumers in Denmark.

Hourly Settlement

Hourly settlement is mandatory for consumers with a consumption exceeding $100,000$ kWh/year but can voluntarily be chosen. This settlement method requires daily collection and validation of hourly-metered values. The hourly-metered values will be used in the balancing settlement of the consumers' BRP. Consumers with hourly settlement are hereby able to be used for spot price optimization, as their hourly electricity consumption is recorded and communicated. The subscription fee varies for different distribution companies as illustrated by the following two examples: Dong Energy Distribution with a subscription of 180 €/year and TREFOR with 660 €/year [1]. The subscription fee covers both the electricity meter and the extra data handling associated with collecting data on a daily basis instead of a yearly basis.

3rd Settlement Method

Energinet.dk and the Danish Energy Association have suggested the implementation of a third settlement method denoted "3. afregningsgruppe" (meaning: 3rd settlement group). The concept of this group is that the consumption is metered hourly but only read and communicated once every month. This has the advantage that hourly consumption settlement is possible while the communication costs are kept small. Many households already have smart meters installed and therefore are able to perform this hourly metering. Distribution companies estimate that the additional subscription fee for this monthly metering would be in the order of 2.5 to 7.0 €/year additional to the fee in load profile settlement [14]. Hereby, the 3rd settlement method allows for spot price optimization of flexible consumers at a low annual fee.

Regulating Power

The TSO is responsible for maintaining balance between production and consumption in the delivery hour. If BRPs for consumption or production cause imbalances in the system, the TSO will compensate by activating regulating power. The TSO will procure this regulating power from the regulating power market where generators or consumers with adjustable consumption are able to place bids. The regulating power bids are sorted in merit order after price such that the cheapest bids that fulfill the requested regulating power demand are activated first. This merit order list of regulating power is often referred to as the Nordic Operational Information System list (NOIS list) [15].

The price paid to the providers of regulating power is denoted the "RP price" and is found as the bidding price of the most expensive regulating power bid activated in a

[1] Prices available online, `www.dongenergy-distribution.dk`, and `www.trefor.dk`.

delivery hour. The RP price will be used to settle all the provisions of regulating power in that given hour.

Balancing Power

After the delivery-hour, the consumption of each BRP can be calculated by adding the metered electricity consumption of the hourly metered customers with the electricity consumption determined for the load profile customers as described in Sec. 2. Any difference between the calculated hourly consumption of a BRP and the electricity this BRP has purchased at the spot market is by definition traded with the TSO as *balancing power* and settled as such. If the imbalance of a given BRP is in the same direction as the overall system imbalance, the BRP will trade balancing power with the TSO at a price equal to or worse than the spot price[2]. On the contrary, if the imbalance of a given BRP is in the opposite direction of the overall system imbalance, BRP will trade the balancing power with the TSO at a price equal to or better than the spot price.

Let us describe this more formally. If a BPR has purchased the electricity volumes $u_{\text{spot}}(k), k = 1, \dots, 24$ at the spot market for the 24 hours of the day and if the sum of the hourly metered consumption and the load profile consumption is given by $u(k), k = 1, \dots, 24$, then the total cost J on this day will be

$$J = \sum_{k=1}^{24} \left(u_{\text{spot}}(k)\pi_{\text{spot}}(k) + \left(u(k) - u_{\text{spot}}(k) \right) \pi_{\text{RP}}(k) \right) \tag{12.1}$$

where $\pi_{\text{spot}}(k)$ and $\pi_{\text{RP}}(k)$ are the electricity spot price and regulating power price, respectively, in hour k. This price model is denoted the one-price model.

Based on this, it is important to understand that the spot prices *cannot be seen as a price signal*, as the spot prices only apply to the electricity traded day-ahead.

Multiple Electricity Meters

It might be desired to have several electricity meters assigned with different electricity retailers within the same household or company. Such a setup will allow an aggregator to manage a portfolio solely consisting of flexible demand-side devices without managing the remaining inflexible consumption. Currently, such a setup is only possible by installing a separate meter and having a separate subscription plan for this meter, which will cause a subscription fee in the magnitude of 180 to 660 €/year as described in Sec. 2.

3 Regulating Power Market Participation

This section describes the requirements for flexible demand-side devices to optimize the electricity consumption towards the regulating power markets. It is based on the following TSO regulations and technical reports: [16, 17, 18, 19, 12, 20, 21]. First we briefly describe regulating power and manual reserves and then how demand-side devices can provide these services.

[2] By *worse* we mean a price higher than the spot price when we purchase from the TSO and a price lower than the spot price when we sell to the TSO.

Regulating Power and Manual Reserves

Players can place bids for upward and downward regulation in the regulating power market up to 45 minutes before the delivery hour. If upward or downward regulation is needed, the TSO will activate the required regulating power by selecting the cheapest bids first (the merit order) from the NOIS list. To ensure that sufficient reserve capacity is available on the regulating power market, the TSO can conclude manual regulation reserve agreements with suppliers (reserve capacity) day-ahead. This takes place on a daily auction that closes at 9 am. The suppliers who win these auctions will receive an availability payment for having reserves available in the given hours of the following day.

Requirements for Demand-Side Participation

In the following, the requirements in terms of balance responsibility and volumes are discussed.

Balance Responsibility

Regulating reserve bids are made through a BRP. Consumers must therefore rest with the same BPR in order to collectively provide regulating reserves; further, this BRP must be approved by the TSO and conclude an agreement on balance responsibility.

Combined Delivery

It is allowed to make a regulating reserve bid by aggregating a portfolio of consumption units as long as the aggregated (combined) portfolio response satisfies the requirements to upward and downward regulation. It is, however, not allowed to include both production and demand-side devices in a combined delivery.

Volumes, Durations, and Response Time

Regulating power is bought and sold day-ahead on the manual reserve market and intraday in the regulating power market for each hour of the day. The minimum volume of a regulating power bid is 10 MW and the maximum is 50 MW for both upward and downward regulation. Bids greater than 10 MW can be activated in part. Regulating power bids can be placed until 45 minutes before the delivery hour and it must be possible to activate the full delivery within at most 15 minutes from receipt of the activation order. Notice that the presented volumes etc. are taken from the Danish system but may vary from country to country in the Nordic system.

Communication Requirements

In the following, the requirements in terms of day-ahead, intra-day, and real time communication are discussed. Three main elements that must be communicated are notifications, operational schedules, and adjusted operational schedules. This is elaborated in the following and illustrated in Figure 12.1.

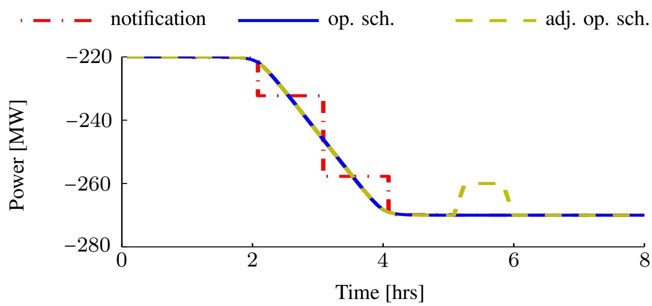

Figure 12.1: Illustration of the hourly notification (red, dash-dot) and a 5-minute operational schedule (blue, solid). Finally, an activation order of 10 MW upward regulation is illustrated in form of an adjusted operational schedule (yellow, dashed). The adjusted operational schedule is identical to the original operational schedule except for the activation in hour 5 to 6.

Day-ahead Communication

In the following we describe the type of information the BRP must provide to the TSO day-ahead (the day before operation).

Notification A BRP for consumption must submit a notification for trade in MWh/h prepared for the 24 hours of the following day with an accuracy of one decimal. The deadline for notifications is 3 pm the day before the day of operation.

Operational Schedule A BRP for adjustable consumption must in addition to the notifications also submit a 24-hour operational schedule with a 5-minute resolution for the planned consumption the following day. The operational schedules are specified with the unit MW and the accuracy is one decimal. The deadline for these operational schedules is at 5 pm the day before operation. For adjustable demand-side devices with a capacity less than 10 MW it is sufficient to provide an operational schedule with the total consumption for the entire portfolio of devices. Notice that the time resolution of 5 minutes applies in the Danish system but may vary from country to country in the Nordic system.

Regulating Power Bids If the BRP has entered into agreement with the TSO on keeping manual reserves available, the BRP must place the first regulating power bids by 5 pm the day before operation with volumes at least equal to the volume agreed upon. New regulating power bids can be placed up to 45 minutes before the delivery hour.

Intra-hour Communication

In the following it is described what type of information the BRP must provide to the TSO during the day of operation.

Notification A BRP for consumption can send an adjusted notification to the TSO if intra-day bilateral trades or trades on the intra-day market Elbas are made. The adjusted notification is the original notification with changed time series for consumption and trade. The deadline for the adjusted notification is 45 minutes before each delivery hour.

Operational Schedule A BRP for adjustable consumption must be prepared at any time to provide the TSO with information about the anticipated operation of the devices in the form of a 5-minute operational schedule. The BRP must submit an adjusted operational schedule if deviations occur exceeding 10 % of the installed capacity and is above a threshold of 10 MW. Such an adjusted operational schedule must be submitted as soon as possible after the deviation is detected.

The current regulations do not specify any penalty for updating the operational schedules. This gives adjustable consumption the large benefit, that updates of the operational schedule can be made if needed without penalty. This is a clear advantage for aggregation and control of flexible consumers with stochastic loads where it may be very difficult or even impossible to produce perfect day-ahead operational schedules.

Regulating Power Bids A BRP for adjustable consumption can place and alter bids for upward or downward regulation up to 45 minutes before the delivery hour. Upon activation of regulating power, the TSO will send a 5-minute power schedule to the BRP in question. The BRP will then plan the regulation and submit an adjusted operational schedule that includes the activated regulating power, see Figure 12.1.

Real Time Communications

Using adjustable consumption for regulating power deliveries requires independent metering. The metered data collector must acquire active power measurements for *each device* in the portfolio comprising the adjustable consumption [21]. The equipment and installation costs depends on how difficult the installation is, but typically the costs are in the order of $1,300 - 6,700$ € per device in installation costs and a running expense of 270 €/year for communication and maintenance which must be paid by the BRP [3].

It is important to notice that the strict regulations for real time measurements were composed in a system where regulating services from smaller units were of no interest. Currently, it is discussed whether these requirements should be made more favorable towards smaller flexible demand-side devices to increase the volume of available balancing services. Some suggestions are: that the metered data collectors will accept standardized equipment installed by aggregators, that real time measurements on portfolio level instead of individual device level can be accepted, and that real time communication can replaced with ex-post communication. In a future scenario, the high costs might therefore be significantly reduced – possibly even to a marginal cost of zero if it eventually will be possible to use the same equipment as is required between the aggregator and the devices for control purposes. Note that such regulatory changes are currently not planned only discussed.

[3] Numbers are based on a private interview on the 4th of March 2012 with a Danish BRP for adjustable consumption with experience in this field.

4 Case Study: Aggregation of Flexible Demand-Side Devices

To conceptualize the implications of the described regulations, we consider a concrete case study where smaller flexible consumers are aggregated and utilized in the markets. First, we examine the requirements for such aggregation, and second, we estimate the costs associated with enabling devices to be active in the markets.

Balancing Responsibility, Hourly Settlement, and Real Time Measurements

As different households in Denmark will have different electricity retailers, they will by default rest with different BRPs. However with the current legislations it is necessary that the flexible household devices in the portfolio rest with the same BRP to enable spot price optimization and provisions of regulating power. One way to accommodate this requirement is to install an additional electricity meter. The additional meter only measures the consumption of the flexible devices in the household and is assigned with a separate electricity retailer belonging to a specific BRP.

This additional electricity meter also serves another purpose than assigning the household devices to a certain BRP. Many consumers are still load profile customers, which does not allow hourly settlement. But by installing a new hourly read electricity meter, it is possible to obtain hourly settlement as desired. Such a meter is, however, associated with a higher monthly fee. In a future setup it will be possible to obtain inexpensive hourly settlement based on the 3rd settlement method as previously described.

In order for an aggregator/BRP to not only perform spot price optimization, but also provide regulating power, it is necessary that the metered data collector installs and operates certain required real time measurement equipment for each household. The expense for this equipment is by far the largest barrier for small consumers to participate as regulating reserves. As previously described, it may be possible to use inexpensive ex-post settlement equipment in a future setup.

Market Threshold

The portfolio must exceed the regulating power participation threshold of 10 MW to be able to deliver TSO service. Household devices such as domestic heat pumps and electrical vehicles have nominal power consumption in the magnitude of 1 kW to 10 kW and the devices are not always available as flexible resources; hence, a portfolio in the magnitude of $10,000$ household devices is needed in order to reach a volume that exceeds the regulating power threshold. Notice that this huge number constitutes a real barrier for market participation of flexible consumption as this means that an aggregator is required to contract with thousands of households before a bid can be placed in the regulating power market.

Consumption forecast

In order to optimize for spot prices, the aggregator must forecast the BRP consumption of the portfolio at noon (12.00 pm) the day before operation and procure electricity accordingly; hence, a 36-hour load forecast must be made. If the actual consumption deviates from the procured electricity, the deviation will by definition be traded with the TSO as balancing power at the RP price.

In order to enable provisions of regulating power reserve, 5-minute operational schedules must be provided to the TSO at 5 pm day-ahead. During operation, the BRP must ensure that the aggregated consumption of the portfolio tracks the operational schedule. The aggregator must therefore steer the domestic appliances to collectively track the operational schedule. In case of activation for upward or downward regulation, the aggregator must update the operational schedule and ensure tracking of the updated schedule. If it is not possible to follow the operational schedule, the BRP must submit an adjusted operational schedule to the TSO. Notice that this option to adjust the operational schedules with no charges is a big advantage for the BRP, as it allows correction of prediction errors.

Estimation of Expenses

To complete the conceptualization, Table 12.1 shows the costs for enabling demand-side devices within the same household to be activated for spot price optimization and to provide regulating power. The table only shows the costs associated with the TSO regulations – not the costs for enabling the device itself to be flexible.

Exp./dev. [€]	Investment costs		Running costs per year	
	Cur. reg.	Fut. reg.	Cur. reg.	Fut. reg.
Spot opt.	0	0[1]	130 – 670	2.5 – 7.0[1]
Reg. opt.	1,300 – 6,700	0[2]	270	0[2]

Table 12.1: Expenses per device for market participation.

Estimation of Possible Profit

To illustrate how Table 12.1 can be used, we construct a control strategy that optimizes the electricity consumption of a house with electric heating towards the electricity spot prices. We perform this optimization for a single house to examine the possible profit per household; however, in reality this optimization would be done by an aggregator on an entire portfolio.

Spot price optimization can be done in a simple way, as illustrate in the following. Participation in the regulating power market is, however, more complicated and requires certain bidding strategies and possibly predictions of regulating power prices; hence, it is outside the scope of this work.

The control strategy developed in this work is very simple and should not be seen as directly implementable, but rather as an example of how revenue can be generated based on flexible consumption and how this profit compares to the expenses of participating in the electricity markets.

[1] Expected costs when the 3rd settlement group will be implemented, see Sec. 2.

[2] The marginal cost is 0 if the future market will allow the aggregator to utilize standardized equipment, see Sec. 3.

Household Flexibility Model

We assume that the household is electrically heated and acts as a thermal storage. It is assumed that the average consumption of the heating system is 1 kW; further, the house has concrete floors which serve as a thermal storage with a capacity of 3 kWh. The maximum power consumption of the heater is 4 kW. These parameters are chosen as they correspond to typical values of Danish households, see [3]. For simplicity, we describe the flexibility of the house as an ideal energy storage limited in power and capacity and describe this with a discrete time model.

Let k index the hours of the day and define $x(k) \in \mathbf{R}$ as the electrical equivalent of the stored thermal energy (i.e., we scale with the COP to obtain a simpler formulation). Further, let $v(k) \in \mathbf{R}$ be the load and let $p(k) \in \mathbf{R}$ be the power that we store or collect from the house's thermal energy storage. Then we have

$$x(k+1) = x(k) + T_{\mathrm{s}}\left(p(k) - v(k)\right) \tag{12.2}$$

where we assume the time constant is $T_{\mathrm{s}} = 1$ hour and use kW and kWh as units. The heat pump power limits and energy limits can be described as

$$0 \le p(k) \le \overline{p}, \quad \underline{x} \le x(k) \le \overline{x} \tag{12.3}$$

where $\overline{p} = 4$ and $\underline{x} = 0, \overline{x} = 3$ according to the assumed parameters of the house. Note that these parameters depend much on the type of house including the construction and the insulation. For larger houses with concrete floors, the thermal capacity can be significantly larger than the 3 kWh used in this example. Further, we assume a constant load of 1 kW, hence $v(k) = 1$. Notice that this thermal model is very simplified: disturbances and prediction errors etc. are not taken into account as we only seek a rough estimate of the value of consumption flexibility.

Spot Price Optimization

The flexibility in power consumption is utilized to optimize the consumption of the household towards the electricity spot prices. It is assumed that the electricity needed to meet the daily load of 1 kW is purchased day-ahead at the spot market. By utilizing the flexibility, the household will deviate from the electricity purchased day-ahead and cause imbalances which are settled with the TSO as balancing power at the RP prices according to Sec. 2. The control strategy developed in this work utilizes the spot prices as predictions of the RP price.

As described in Sec. 2, the spot prices for the following day are published each day at noon; hereby we always know the spot prices at least 12 hours ahead which we use as prediction of the future RP prices. This allows us to design a receding horizon controller with a horizon of 12 hours, see Algorithm 1.

We simulate this controller using the spot prices from 2011 and use the RP prices from the same year for settlement according to (12.1). As a benchmark we consider a strategy where we do not shift the load but simply purchase and consume 1 kW for each hour of the year.

This simulation reveals that an annual saving in the order of 360 € is achievable using this method. Simulating the previous years reveals similar results. By comparison with the values presented in Table 12.1 it is evident that an annual profit can be made in the

Algorithm 1 Spot Price Optimization

for $k = 1, 2, \ldots$ **do**

Collect current state $x(k)$ and spot prices $\pi(\kappa), \kappa \in \mathcal{K} = \{k, \ldots, k + 11\}$ Solve the optimization problem

$$\begin{array}{ll} \text{minimize} & \sum_{\kappa \in \mathcal{K}} p(\kappa)\pi(\kappa) \\ \text{subject to} & x(\kappa + 1) = x(\kappa) + p(\kappa) - v(\kappa), \ \kappa \in \mathcal{K} \\ & \underline{p} \leq p(\kappa) \leq \overline{p}, \quad \underline{x} \leq x(\kappa) \leq \overline{x}, \ \kappa \in \mathcal{K} \end{array}$$

with variables $x(\kappa + 1), p(\kappa), \kappa \in \mathcal{K}$ and where we denote the solution $x^\star(\kappa + 1), p^\star(\kappa), \kappa \in \mathcal{K}$ Consume power $p^\star(k)$

end

grid areas where the cost of hourly metering is as low as around 130 €/year; however, in some regions these costs are around 670 €/year ruining the business case. However in a future setup with hourly metering costs in the magnitude of $2,5 - 7,0$ €/year, spot price optimization could prove as a desirable business case. The annual profit of participating in the regulating power market is not calculated; however, the high market participation expenses reveal that it is impossible to generate profit based on household devices in the current setup. Depending on the development in the regulations, regulating power participation might become attractive in a future setup even for small demand-side devices.

5 Conclusion

In this work we made a survey of the possibilities for flexible consumers to participate in the Nordic electricity markets. The regulatory requirements for optimization of the electricity consumption towards the spot prices were examined and the costs to achieve this were estimated. Likewise, the requirements for participation in the regulating power market were examined and the costs to honor these requirements were estimated. Further, the planned changes in the regulations were presented and the implications on the costs of market participation were discussed. Finally, a case study was presented illustrating the requirements for aggregation and market participation of a portfolio of households with flexible consumption. The study showed that the possible consumer revenue was very low compared to the expenses of market participation under the current regulations but that the future regulations might make it possible to generate profit.

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Paper 10

Value of Flexible Consumption in the Electricity Markets

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Abstract

A transition from an oil and coal based energy system to a systems based on renewable and sustainable energy sources has begun in many countries throughout the developed world. As a pioneer, Denmark currently has a wind energy penetration of 30 % in the electricity sector and an end goal of 100 % renewables in all energy sectors by 2050. The main elements in this transition are an increase in the wind energy production and electrification of main energy sectors such as transport and heating. Activation of flexible consumption in the electricity markets is believed to be one of the means to compensate for the growth of fluctuating renewables and the decrease of conventional power plants providing system-stabilizing services. In this work, we examine the requirements for flexible consumption to be active in the spot market and the regulating power market in the Nordic system and estimate the costs of entering these markets; further, we briefly describe the debated and planned changes in the electricity market to better accommodate flexible consumers. Based on recent market data, we estimate the revenue that flexible consumers can generate by market entry depending on the capacity of the consumers. The results show that consumers should have an energy capacity in the magnitude of 20 – 70 kWh to break-even in the spot market, while a capacity of 70 – 230 kWh is required in the regulating power market under current regulations. Upon implementation of the debated and planned market changes, the break-even capacity will decrease significantly, possibly to an energy capacity as low as 1 kWh.

1 Introduction

Many actions have been taken from a political point of view to increase the penetration of renewables throughout the world. A few examples are: renewable portfolio standards or goals that ensure a certain percentage of renewables in almost all states in the US [1], an energy target of 20 % renewables by 2020 in the European Union [2], and an increase in wind power capacity in China from 1,260 MW in 2005 to 62,000 MW in 2011 [3]. The Danish electric power system, which is the focus of this work, is a particularly interesting case with a wind energy penetration of 30 % in 2012 and an expected 2020 penetration of 49.5 % [4, 5]. The end goal in Denmark is to phase coal out by 2030 and become 100 % renewable in *all energy sectors* by 2050 [4].

The implementation of the Danish 100 % renewable goal requires actions from the entire energy supply system [6, 7, 8]. One of the necessary steps is electrification of consumption from other energy forms [9]. This electrification has already begun: in recent years, 27,000 heat pumps have been installed in Danish homes [10], and additionally 205,000 households have the potential to benefit from replacing their oil-fired boilers with a heat pump [11]. Further, the Danish Government decided in 2012 to lower the taxes on electric heating to expedite electrification of the heating sector [12]. Similarly, electrification of the transport sector is planned: the Danish Department of Transport decided in 2012 on electrification of the railroad in Denmark [13] and a report from 2013 by the Danish Energy Association projects that electrical vehicles will become an attractive alternative to combustion engine vehicles in the following decades leading to an electric vehicle population of 47,000 in 2020 and 221,000 in 2030 [14].

This planned electrification and replacement of conventional power plants with renewables are crucial elements in the future 100 % renewable energy system in Denmark.

However, when conventional power plants are replaced with renewables such as wind turbines and photovoltaics, the ability to provide power balancing services in the classical sense disappears: the renewable energy sources will often fully utilize the available power and thus not be able to provide balancing ancillary services. Furthermore, conventional fossil fuel power plant generators are synchronous with the grid and therefore provide rotating inertia that supports the system frequency against changes [15]. As renewable energy sources typically interface with the grid via power electronics, they do not directly provide inertia to the grid as the conventional synchronous generators [16], which further increase the balancing challenges. Although recent works suggest that wind turbines can provide artificial inertia by regulating the active power output of the generator according to the system frequency [17, 18], this type of control is generally not implemented in the wind power plants of today. Moreover, many renewable sources are characterized by highly fluctuating power generation: they can suddenly increase or decrease production depending on weather conditions. These rapid production changes are not always predictable and can therefore imply severe consequences for grid stability [19].

It is therefore evident that the transition towards a Danish 100 % renewable energy system will lead to challenges of balancing the electricity supply and demand [7]. Already now, indications of balancing issues are seen in Denmark as evident from the following examples. Negative spot prices occurred in 24 hours in 2012 at the electricity day-ahead spot market [20] even reaching the minimum limit of -200 €/MWh. Notice that the negative spot prices occurred in spite of Denmark being well interconnected with Germany ($950 + 600$ MW), Norway ($1,040$ MW), and Sweden ($1,900 + 740$ MW) [21]. Also, several wind turbines were requested to derate production for several hours on one occasion in December 2012 due to a combination of circumstances where high wind and CHP production collided with a holiday with low consumption[1]. These instances are indicators of the increasing balancing issues due to the growth in renewables. As a pioneer in utilizing fluctuating renewables such as wind power, Denmark is among the first places to experience these challenges; however, the rest of Europe can expect similar issues in the coming years [22].

2 Scope and structure of the article

As the wind penetration from fluctuating renewables increases, the need for balancing services will consequently also increase [23], [24]. Alternative sources of balancing services must therefore be established as the conventional power plants are pushed out. One of the approaches to obtaining alternative balancing services is the *smart grid* concept, where flexible consumption takes part in the balancing effort [25], [26]. This approach is supported by the European Network of Transmission System Operators for Electricity (ENTSO-E), who in a resent paper stated that demand side response is acknowledged as "a main contributor to more effective markets and to system security with a high penetration of fluctuating generation" [27]. Therefore, demand side response is included in the 2012 ENTSO-E network code [28]. In Denmark, the smart grid approach is supported by the Danish TSO and the Danish Energy Association, who have concluded that it is economically attractive to implement the smart grid concept in Denmark as a means

[1] Information based on e-mail correspondence with the Danish transmission system operator (TSO), Energinet.dk on March 22, 2013

to reach the 100 % renewable goal. The main stakeholders have recommended a smart grid roadmap with the ultimate goal of having flexible consumption traded on a market place on equal terms with conventional production according to the deliberated electricity market setup in Denmark [29, 30].

Control of flexible consumers to support grid stability has been discussed as early as the 1980s [31]. Since, the topic of demand-side management has received much attention from a research perspective [32, 33, 34]. Within the deliberated electricity markets, the *aggregator* or *virtual power plant (VPP)* concept has likewise been much discussed. The functionality of the aggregator or VPP is to aggregate and control flexible consumption devices whereby the accumulated flexibility can be sold in the electricity markets, as described e.g. in [35, 36, 37, 38]. Examples of flexible consumption devices examined as power balancing resources are: domestic heat pumps [22, 39, 40, 41, 42], supermarket cooling systems [43, 44, 45, 46], domestic refrigerators [47, 48], electrical heating elements at CHPs [49, 50], and electrical vehicles [51, 52, 53, 54]. These existing works describe the effects of including flexible consumers in electric power balancing. Some of the works describe how utilizing flexible consumers will allow larger penetration of renewables, while the focus of other works are the possible electricity savings that can be achieved by selling balancing services. The works do, however, not discuss the requirements for such devices to enter the electricity markets, which is a crucial element in the Nordic liberalized system. Further, these works do not consider the costs associated with being active in the electricity markets.

In this work, we take the aggregator's point of view and examine the Nordic electricity markets and describe the requirements for market participation of flexible consumption. In particular, we describe the requirements and identify the barriers for participation in the two largest markets: the day-ahead spot market and the regulating power market. Moreover, we estimate the costs of making devices able to participate in these markets. The main contribution of this part of the work is a short overview intended for potential aggregators and smart grid researchers in the Nordic countries, describing the core regulations that apply for market participation of flexible consumers. The background for this market overview is the existing regulations, technical documents, reports, and interviews with the Danish TSO.

Following, we describe how an aggregator can generate revenue via the flexibility of consumers by participating in the two examined markets, namely the spot market and the regulating power market. We present concrete methods for utilizing flexibility in the markets and estimate the revenue that can be generated depending on the power and energy capacities of the consumers. This revenue is compared to the previously found costs of enabling devices to be active in the markets. Hereby we are able to examine the capacity of a consumer required to make market participation attractive. To complete the conceptualization, we briefly describe the potential of some specific flexible devices: domestic heat pumps, supermarket refrigeration systems, and water purifying plants.

Notice, that this paper does not analyze the social benefit of utilizing demand response or examine how flexibility is best utilized. This while social benefit analysis is a most important topic [55, 56, 57, 58], we instead take the aggregator's point of view and examine the costs and potential benefits an aggregator can expect when entering the main electricity markets. This aspect gives an indicator of the state of the current markets with regards to the ability to accommodate aggregated flexible consumers. Also, it provides an easy overview to potential aggregators of the barriers and costs that can be expected upon market entry.

The structure of this work is as follows. First, in Sec. 3, a brief overview of the considered markets is presented; following in Sec. 4 and Sec. 5, we describe the requirements for participating in the day-ahead spot market and the regulating power market, respectively. In Sec. 6, we describe the main barriers for market entry and show the estimated costs of market participation. Following, in Sec. 7, we estimate the revenue flexible devices can obtain by being active in the spot market and the regulating power market and complete the comparison between expenses and revenue of market participation. Finally in Sec. 8, we conclude the work.

3 Market overview

Three electricity markets exist at an overall level: a day-ahead market, an intra-day market and an ancillary service market. In the day-ahead market, electricity is traded for each hour of the following day. If the market players are not able to realize the volumes traded day-ahead, bids can be placed in the intra-day market which closes an hour before the delivery hour. In the delivery hour, ancillary services are activated to accommodate for any system imbalances [59].

The largest turnovers in the Nordic system are in the day-ahead market and the ancillary service market for regulating power; only very small volumes of electricity are traded in the intra-day market. This work therefore focuses on the day-ahead and regulating power market.

4 The day-ahead spot market

This section describes the requirements for flexible consumption devices to optimize the electricity consumption towards the spot market prices. First we describe how the hourly spot prices are derived, then how the prices are settled, and finally how devices can achieve settlement at the spot prices via hourly sampled electricity meters.

Spot prices

Each day before gate closure at noon (12.00 p.m.), the balancing responsible parties (BRPs) for both consumption and production place bids in the day-ahead market for each hour of the following day specifying the volumes they are willing to trade given the hourly electricity prices [60]. The spot prices for each hour of the following day are found as the intersection between the accumulated bids for supply and demand. At 1 p.m., all BRPs are informed of the traded volumes and hourly prices for the following day [59].

Settlement methods

Two different methods are used for consumption settlement in Denmark: load-profile settlement and hourly settlement. Further, the Danish TSO and the Danish Energy Association have proposed a third settlement method that is planned to be implemented in the Nordic system. These three methods are described in the following.

Load profile settlement All consumers with an annual consumption lower than a threshold of $100,000$ kWh will by default be settled using load profile settlement. By comparison, the average annual energy consumption of a Danish household is in the order of $4,500$ kWh [61]; consequently, all private consumers and smaller industrial consumers will fall into the load profile settlement category. For load profile settlement, the accumulated consumption is read typically once a year. As a result of this infrequent metering, the hourly consumption is *unknown* and identical consumption profiles are used for all consumers within the same grid area for settlement purposes [62, 63]. Spot price optimization is thus *not possible* for load profile customers, which today account for almost all private consumers in Denmark.

Hourly settlement Hourly settlement is mandatory for consumers with a consumption exceeding $100,000$ kWh/year but can voluntarily be chosen for smaller consumers. This settlement method requires daily collection and validation of hourly-metered values [63, 64]. The subscription fee varies for different distribution companies as illustrated by the following two examples: Dong Energy Distribution with a subscription of $1,368$ DKK/year[2] and TREFOR with $4,940$ DKK/year[3]. The subscription fee covers both the installation of the hourly sampled electricity meter (smart meter) and the extra data handling associated with collecting data on a daily basis instead of a yearly basis.

3rd settlement method The Danish TSO Energinet.dk and the Danish Energy Association have suggested the implementation of a third settlement method. The concept of this method is that the consumption is metered hourly but only read and communicated once every month [65]. This has the advantage that hourly consumption settlement is possible while the communication costs are kept small. Distribution companies estimate that the subscription fee for this monthly metering will be in the order of 20 to 50 DKK/year additional to the load profile settlement fee [66]. The Danish Government has made a plan to roll out hourly sampled electricity meters to all consumers by 2020 making it possible to fully enable this settlement method [9].

Balancing power

After the delivery hour, the balance of the BRPs is found. This is done by adding the hourly-metered electricity consumption of the hourly-metered customers with the electricity consumption determined for the load profile customers. The difference between these hourly values and the purchased electricity is by definition traded with the TSO as *balancing power* at the *regulating power price* (RP price) [67]. The origin of the RP price will be described in detail in the next section.

It is important to notice that the spot prices therefore *cannot be seen as a price signal* that all consumption will be traded at, as done in many works describing control of flexible consumers. This is evident as the spot prices only apply to the electricity purchased day-ahead.

[2] 1 DKK approximately equals 0.13 €.

[3] Prices available online, `www.trefor.dk` and `www.dongenergy.dk`

Multiple electricity meters

It might be desired to have several electricity meters assigned with different electricity retailers within the same household or company. Such a setup will for example allow an aggregator to manage a portfolio solely consisting of flexible devices without managing the remaining inflexible consumption. Currently, such a setup is only possible by installing a separate meter and having a separate subscription plan for this meter, which will cause a subscription fee in the magnitude of 1,368 to 4,940 DKK/year, as described in Sec. 4 [65]. The Danish Energy Association and the Danish TSO are, however, currently in the process of developing methods to handle separate electricity measurements with separate billing from within the same household [9].

5 Regulating power market participation

This section describes the requirements for consumers to optimize their flexibility towards the regulating power markets. First we briefly describe the regulating power market, then how demand-side devices can participate.

Regulating power

The TSO is responsible for maintaining balance between production and consumption in the delivery hour. If BRPs for consumption or production cause imbalances in the system, the TSO will compensate by activating regulating power. The TSO will procure this regulating power from the regulating power market where generators or consumers with flexible consumption are able to place bids. Players can place bids for upward and downward regulation in the regulating power market up to 45 minutes before the delivery hour [67]. The TSO's expenses for regulating power are financed via the balancing power traded with the BRPs that caused the imbalances.

The regulating power bids are sorted in merit order after price in a list often referred to as the Nordic operational information system list (NOIS list) [68]. If upward or downward regulation is needed, the TSO will activate the required regulating power by selecting the cheapest bids first (the merit order) [67]. The price paid to the providers of regulating power is the RP price which is found as the bidding price of the most expensive regulating power bid activated in the delivery hour [59, 67].

Requirements for demand-side participation

In the following, the requirements in terms of balance responsibility and volumes are discussed.

Balance responsibility Regulating reserve bids are made through a BRP. Consumers must therefore rest with the same BPR in order to collectively provide regulating reserves; further, this BRP must be approved by the TSO and conclude an agreement on balance responsibility [69, 70, 59].

Volumes, duration, and response time Regulating power is bought and sold in the regulating power market for each hour of the day. The minimum volume of a regulating power bid is 10 MW and the maximum is 50 MW for both upward and downward regulation in Denmark (values may vary in the Nordic countries). Bids greater than 10 MW can be activated in part. Regulating power bids can be placed until 45 minutes before the delivery hour and it must be possible to activate the full delivery within at most 15 minutes from receipt of the activation order [67, 71].

Combined delivery It is allowed to make a regulating reserve bid by aggregating a portfolio of consumption units as long as the aggregated (combined) portfolio response satisfies the requirements. It is, however, not allowed to include both production and consumption devices in a combined delivery [71].

Day-ahead communication requirements

In this subsection, the required day-ahead communication is described; following, in the next two subsections, the requirements to intra-day and online communication are described. Three main elements that will be described in the following are: notifications, operational schedules, and adjusted operational schedules, see Figure 13.1.

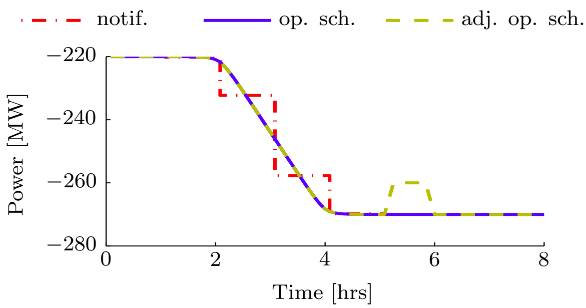

Figure 13.1: Illustration of the hourly notification (red, dash-dot) and a 5-minute operational schedule (blue, solid). Finally, an activation order of 10 MW upward regulation is illustrated in form of an adjusted operational schedule (yellow, dashed). The adjusted operational schedule is identical to the original operational schedule except for the activation in hour 5 to 6.

Notification A BRP for consumption must submit a notification for trade in MWh per hour prepared for the 24 hours of the following day with an accuracy of one decimal. The deadline for notifications is 3 p.m. the day before the day of operation [59, 67, 72].

Operational schedule A BRP for flexible consumption must in addition to the notifications also submit a 24-hour operational schedule with a 5-minute resolution for the planned consumption the following day. The operational schedules are specified with the unit MW and the accuracy is one decimal. The deadline for these operational schedules is at 5 p.m. the day before operation. For flexible consumption devices with a capacity less than 10 MW it is sufficient to provide an operational schedule with the total consumption for the entire portfolio of devices [73, 72]. Notice that the time resolution of 5 minutes applies in the Danish system but may vary from country to country in the Nordic system.

Intra-day communication

In the following it is described what type of information the BRP must provide to the TSO during the day of operation.

Regulating power bids and activation A BRP for flexible consumption can place and alter bids for upward or downward regulation up to 45 minutes before the delivery hour. Upon activation of regulating power, the TSO will send a 5-minute power schedule to the BRP in question; this schedule will describe how the regulating power should be delivered. Following, the BRP must submit an adjusted operational schedule that includes the activated regulating power (see Figure 13.1) and finally, the TSO will confirm the adjusted schedule [72].

Notification A BRP for consumption can send an adjusted notification to the TSO if intra-day trades are made. The adjusted notification is the original notification with changed time series for consumption and trade. The deadline for the adjusted notification is 45 minutes before each delivery hour [73].

Operational schedule A BRP for flexible consumption must be prepared at any time to provide the TSO with information about the anticipated operation of the devices in the form of a 5-minute operational schedule. Further, the BRP must submit an adjusted operational schedule if deviations occur exceeding 10 % of the installed capacity and is above a threshold of 10 MW. Such an adjusted operational schedule must be submitted as soon as possible after the deviation is detected [73]. The regulations do not specify any cost for updating the operational schedules.

Real time communications Using flexible consumption for regulating power deliveries requires independent metering. The metered data collector must acquire active power measurements from *each device* in the portfolio comprising the flexible consumption except if the devices are behind the same point of connection and have a total capacity below 1.5 MW. The real time data must be communicated via certain protocols to the TSO [74]. It is the responsibility of the BRP to make the necessary metering data easily accessible for the metered data collector. Further, the BRP must finance the establishment and operation of the metering equipment. The metered data collector is responsible for the physical metering task and for the data communication to Energinet.dk [74]. The equipment and installation costs will vary depending on the consumption device. The typical costs are in the order of $10,000$ – $50,000$ DKK per device in installation costs and a running expense of $2,000$ DKK/year for communication and maintenance[4].

It is important to notice that the strict regulations for real time measurements were composed in a system where regulating services from smaller units were of no interest. Currently, it is debated whether these requirements should be made more favorable towards smaller flexible consumption devices to increase the volume of available balancing services. Some suggestions are: that the metered data collectors will accept standardized

[4]Numbers are based on a private interview with a Danish BRP for flexible consumption with experience in this field, 4th of March 2012.

equipment installed by aggregators, that real time measurements on portfolio level instead of individual device level can be accepted, and that real time communication can be replaced with ex-post communication. In a future scenario, the high costs might therefore be significantly reduced – possibly even to a marginal cost of zero if it eventually will be possible to use the same equipment as is required between the aggregator and the devices for control purposes. Note that such regulatory changes are currently not planned.

6 Market barriers

In this section we summarize the barriers for market entry of flexible consumers and present estimates of the costs per device to enter these markets.

The main barriers of enabling a device to be active in the day-ahead spot market are as follows.

1. The high annual costs of being read on an hourly basis. This will, however, be resolved with the planned 3rd settlement group possibly in 2020.
2. The requirement of a separate new electricity meter to enable a single device to receive separate settlement. The Danish Energy Association and the Danish TSO are working on resolving this issue.

The main barriers of being active in the regulating power market are as follows.

1. The high annual and one-off costs of real time equipment. Although it is debated to loosen this requirement, no plans are currently made.
2. The threshold of 10 MW requires a large number of flexible devices. Currently, there are no plans to reduce this value.
3. The requirement of 5-minute operational schedules sent the day before operation. The stochastic behavior of many consumers will make it difficult to make such schedules. The current regulations, however, allow the schedules to be updated at no costs.

To complete the conceptualization, we summarize the costs of making a single device able to honor the requirements of market participation in the current and future electricity markets. This is presented in Table 13.1. A number of comments to this table are necessary. First, notice that we do not include the costs of making the devices themselves controllable, we only consider the costs of honoring the regulations. Second, notice that since we take the aggregator's view, and not a socioeconomic view, we only consider the costs that the consumers will face and not the global society costs. For example, we consider the cost the consumer will have pay to the distribution company for being hourly-metered instead of considering the actual costs the distribution company will have to pay for installation of a smart meter, etc.

[1] Expected costs when the 3rd settlement group will be implemented around 2020, see Sec. 4.

[2] The marginal cost can be 0 if the future market will allow the aggregator to utilize standardized equipment that already is embedded in the devices for other purposes and assuming we can communicate at no additional costs via the internet, see Sec. 5. This is, however, the most positive projections and may be far into the future.

	Investment costs		Running costs per year	
	Cur.	Fut.	Cur.	Fut.
Spot.	0	0^1	$1-5,000$	$20-50^1$
Reg.	$10-50,000$	0^2	$2,000$	0^2

Table 13.1: Marginal expenses per device active for spot optimization (Spot.) and regulating power provisions (Reg.) under current (Cur.) and future (Fut.) regulations.

7 Market participation of flexible consumers

In this section, we examine the profit a flexible consumption device can obtain by being part of a portfolio that is optimized towards the day-ahead spot market and regulating power markets. Hereby we can determine the possible profit per device and compare this value with the cost of market entry presented in Table 13.1. Notice that we consider the devices individually to find the profit per consumer; however, in practice the devices' flexibility would be aggregated before market entry. The reason we examine the cost per consumer is that the aggregator should be able to cover the cost of each device included in the portfolio.

We assume that each flexible consumption device is able to shift consumption in time at no additional cost and with no additional energy loss; further, we assume that the load on each device is constant over time. This model is presented in more detail in 10.

Obviously, this model is very simplified: flexible devices such as thermal storage, electrical batteries, etc., are all associated with losses that depend on how the device flexibility is utilized. Further, the load will vary over the day, often with a stochastic behavior depending on user behavior, weather conditions etc. Finally, shifting consumption in time may for some devices be associated with a given cost such as a *disutility* or a *discomfort* cost. Some consumers will require an economical compensation for utilizing their devices' flexibility while other consumers will not experience any loss of quality or comfort and consequently not necessarily require compensation. These issues are, however, neglected as our objective is to illustrate how revenue can be generated and what the magnitude of this revenue is – the objective is not to accurately model consumers or design implementable control strategies.

Strategies for flexibility optimization towards the day-ahead spot market and the regulating power market are found in 11 and 12, respectively. To obtain an estimate of the revenue that can be generated based on participation in the spot market and in both the spot market and the regulating power market, we simulate market participation over one year. We do this for a storage with normalized energy capacity but varying power capacity. Historical spot and regulating power prices from 2011 are used and the work of [75] is utilized to provide spot price forecasts.

Results The results of a one-year simulation are shown in Figure 13.2 and should be interpreted as follows. The y-axis indicates the revenue per year in DKK per kWh of energy capacity available. We assume a liquid market where we do not influence the spot and regulating power prices, hereby the revenue will simply scale linearly with the energy capacity. The x-axis indicates the power capacity of the device ranging from $0-1$ kW/kWh. It is not required to examine higher power capacities than 1 kW/kWh:

when the capacity is 1 kW/kWh we are able to fully fill/empty the energy storage in each hour.

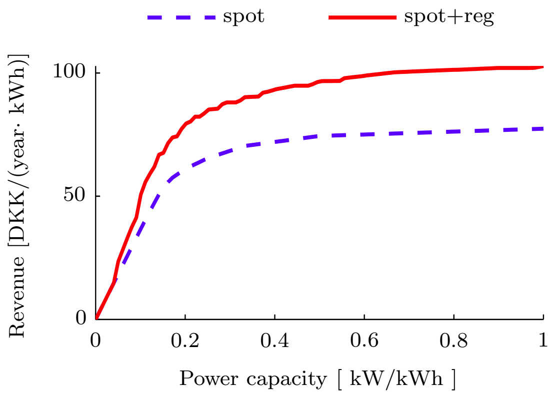

Figure 13.2: Revenue per kWh in 2011 for an energy storage when optimizing towards the spot market and when optimizing to both spot and regulating power market as a function of the consumer power capacity.

As the figure shows, the revenue curve is very steep from 0 up to around 0.3 kW/kWh, indicating that if the storage capacity for example is 1 MWh, then it is very profitable to increase the power capacity up to around 300 kW. Increasing the power capacity further will only slightly increase the possible revenue.

We are now able to compare the revenue with the costs of being active in the market as specified Table 13.1. The following is observed.

1. *Spot price optimization.* An energy capacity of 20 – 70 kWh is required to break-even when considering the annual costs of for hourly metering and assume a power capacity of 0.3 kW/kWh.

2. *Spot and regulating power optimization.* An energy capacity of 70 – 230 kWh is required to break-even over a 5-year period when considering the investment costs and costs for the required equipment and communication. We assume a power capacity of 0.3 kW/kWh and an interest rate of 5 %.

3. *Future scenario.* If the revenue graph in Figure 13.2 is considered valid for the future scenario[5] and if the marginal expenses from Table 13.1 are used, an energy capacity in the magnitude of 1 kWh is required to break-even.

Notice that the revenue-graph and the estimates above are made for the Nordic electricity system and for a specific year; however, the methods for making the graph are general and can readily be implemented to other electricity markets to form the background for similar analysis. Alternatively, the revenue-graph can be generated based on data from several years to examine how stable the revenue is over time.

[5]It is difficult to predict how the market volatility will evolve: increasing penetration of renewables and increasing oil prices suggests higher and more fluctuating prices while increasing volumes of flexibility and new transmission cables suggest the opposite.

	Device capacity		Annual revenue	
	Energy [kWh]	Power [kW]	Spot [DKK]	Spot+reg [DKK]
Heat pump	60	2	900	1,200
Supermarket	200	10	5,100	6,700
Water plant	1,000	300	67,900	88,000

Table 13.2: Marginal expenses per device active for spot optimization (Spot.) and regulating power provisions (Reg.) under current (Cur.) and future (Fut.) regulations.

Further, notice that the electricity system of today is rapidly changing, possibly affecting the spot and regulating power prices. For example, the rapid growth of renewables in Denmark will likely give rise to more fluctuating electricity prices. On the other hand, new interconnectors from Denmark to Norway are being constructed which possibly will compensate this effect to some extend. Likewise, integration of demand response might smooth out fluctuating electricity prices. As these effects point in different directions for the market prices, it is difficult to say anything definite about the future electricity prices and consequently difficult to find better estimates than looking at today's prices which are the basis of the analysis in this work.

Finally, let us examine the results presented in Figure 13.2 further by considering a number of specific flexible devices. We examine three consumption devices: an electric heat pump, a supermarket system, and a water purifying plant, see Table 13.2. The power and energy capacities for the heat pump are based on [22], for the supermarket they are based on [76] (idealized and scaled up to a larger supermarket), while the capacity for the water plant is based on DONG Energy's experiences in flexibility optimization of water plants. Again, we remind the reader that we consider these consumers as ideal storage with constant load, which clearly is a simplification as such devices will be characterized by stochastic consumption and possibly a consumption coupled with the storage level. However, the presented values will reflect the magnitude of the revenue that can be generated base on the devices' consumption flexibility. The table shows that both heat pumps and supermarket refrigeration systems will generate a profit that is too low compared to the costs of enabling spot market and regulating power market participation in the current market; however, it may prove as a desirable business case in the future system that is better at accommodating flexible consumers. The water plant generates sufficient profit to perform spot price optimization. The revenue increase of DKK $20,100$ for activating regulating power will cover the running costs and allow a payback period of $1-3$ years for the installed equipment making such investments very attractive.

Notice, that the business case presented in Table 13.2 is only concerned with selling services in the regulating power market and the spot market. However, some works emphasize that the real value of flexible consumers might lie in the distributed nature of these devices [56] making it possible to deliver services on the distribution level such as voltage control [77] or congestion alleviation [78]. Other works further mention energy efficiency and ancillary services participation as possibilities to generate revenue . These services are not included in the business case presented here, but might be able to further increase the value of the flexible devices.

8 Conclusion

In this work we made a thorough survey of the Nordic regulations for flexible consumers to participate in the current and future day-ahead market and the regulating power market. Based on this, a list of main barriers for market entry was presented and estimates of the costs for enabling flexible consumers to enter the considered markets were made. Following, the possible revenue of participating in these markets was estimated based on the consumer energy and power capacity limitations. The market entry costs were compared with the possible profit of market participation, which resulted in an estimate of the capacities required to make market participation profitable. The estimates showed that market entry for flexible consumers had a break-even capacity in the magnitude of 20 – 70 kWh and 70 – 230 kWh, respectively, for day-ahead and regulating power market entry under the current regulations. Further, the results showed that the future regulations (around 2020) will remove many of the market barriers; possibly reducing the break-even capacity to a magnitude of around 1 kWh.

9 Acknowledgments

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10 Appendix A:Ideal flexible consumer model

The idealized consumption device is modeled as a consumer with constant load which the overall consumption can be varied around. As both the spot market and the regulating power market are based on hourly bids, we use a discrete time model with a sampling time of 1 hour. Let k index the hours and let $x(k)$ denote the energy level; further let $\overline{p}$ be the constant load. Finally, let $p(k)$ be the total consumption of the device. By using units kWh for $x(k)$ and kWh for $\overline{p}$ and $p(k)$ (energy delivered over an hour) we obtain

$$x(k+1) = x(k) + p(k) - \overline{p}. \tag{13.1}$$

This simply expresses that if the total consumption equals the constant load $p(k) = \overline{p}$, no energy is stored; however, if the consumption increases above the constant load, energy is stored accordingly and vice versa. The storage is limited in energy capacity and power capacity which can be expressed as

$$0 \le x(k) \le \overline{x}, \quad 0 \le p(k) \le 2\overline{p} \tag{13.2}$$

where $\overline{x}$ is the energy capacity in kWh and where we assume the device is able to vary its total power consumption with $\pm\overline{p}$ around the constant load of $\overline{p}$. This model is a much simplified version the consumer model presented in [79].

11 Appendix B:Spot market optimization

Various strategies can be envisioned when participating in the spot market. In this work we utilize the following strategy: before gate closure at noon, we collect spot price forecasts by using data from the work in [75]. Based on the storage energy level just before midnight (which is known from the optimization done the previous day), the flexibility is optimized towards the spot price forecasts and electricity is purchased accordingly. During the day, the purchased electricity is consumed such that we avoid trading balancing power with the TSO at possibly unfavorable prices.

Formally, this can be formulated as shown in Algorithm 2. We use k to indicate the hour number. Further, we use $\mathcal{K} = \{k+12, \ldots, k+35\}$ to describe the 24 hours of the following day at the point in time just *before* gate closure which is at 12 noon (the first hour of the following day is 12 hours ahead).

Algorithm 2 Spot Optimization

for hour $k = 1, 2, \ldots$ **do**
  if Current hour is 12 p.m. (just before gate closure) **then**
    Collect spot prices forecasts $\tilde{\pi}(\kappa), \kappa \in \mathcal{K}$;
    Collect the predicted storage level at midnight $x(k+12)$;
    Solve the optimization problem

$$\begin{array}{ll} \text{minimize} & \sum_{\kappa \in \mathcal{K}} p(\kappa)\tilde{\pi}(\kappa) \\ \text{subject to} & x(\kappa+1) = x(\kappa) - \overline{p} + p(\kappa) \\ & 0 \le p(\kappa) \le 2\overline{p}, \quad \underline{x} \le x(\kappa) \le \overline{x} \\ & \kappa \in \mathcal{K} \end{array} \tag{13.3}$$

    where the variables are $p(\kappa), x(\kappa+1), \kappa \in \mathcal{K}$ and the data is $x(k+13), \overline{p}, \overline{x}, \tilde{\pi}(\kappa), \kappa \in \mathcal{K}$;
    Denote the solution $p^\star(\kappa), \kappa \in \mathcal{K}$ and purchase these volumes for following day;
  end if
  Consume electricity $p^\star(k)$;
end for

12 Appendix C:Regulating power optimization

Optimization towards the regulating power market is a delicate task and many strategies can be imagined: regulating power price forecasts can be utilized, alternative day-ahead purchase strategies can be used to allow more flexibility in bidding in the regulating power market, etc. In this work we utilize the following simple strategy. After gate closure at 1 p.m., the spot price realizations will be published. Based on these spot price realizations, we reoptimize the consumption of the portfolio. Following, for each hour of the day, we bid the difference between the purchased electricity and the volume gained from the reoptimization, if feasible, with a bidding price equal to the spot price. If activated, we will get a regulating power price equal to or better than the spot price (our bid). Hereby we still avoid trading balancing power with the TSO, but enable ourselves to get access to regulating power prices when they are favorable.

Formally, this is presented in Algorithm 3. Again, we use k to indicate the hour number but now let $\mathcal{K} = \{k+11, \ldots, k+34\}$ describe the 24 hours of the following day just *after* gate closure which is 11 hours ahead in time.

Algorithm 3 Spot and Reg. Power Optimization

for hour $k = 1, 2, \ldots$ **do**
  if Current hour is 12 p.m. **then**
    Purchase electricity $p^\star(\kappa)$ as in Alg. 2;
  end if
  if Current hour is 1 p.m. (first hour after gate closure) **then**
    Collect spot price realizations $\pi(\kappa), \kappa \in \mathcal{K}$ and storage level $x(k+11)$;
    Reoptimize by solving (13.3) using $\pi(\kappa)$ instead of $\tilde{\pi}(\kappa)$;
    Denote solution $p^+(\kappa), \kappa \in \mathcal{K}$;
  end if
  Bid $\mathbf{f}eas(p^\star(k) - p^+(k))$ as regulating power at price $\pi(k)$ where $\mathbf{f}eas(y)$ returns the value closest to y that does not violate the energy constraints (13.2) throughout the rest of the day;
  Consume electricity $p^\star(k) - p^\dagger(k)$ where $p^\dagger(k)$ is the activated regulating power;
end for

Notice that more advanced strategies can be utilized to further increase the value of the available flexibility. An example is to withhold flexibility in the electricity spot market if forecasts indicate that it might be more profitable to trade on the regulating power market. This requires forecasts of the regulating power prices as well as sophisticated optimization algorithms and is consequently outside the scope of this work.

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Paper 11

Integration of Flexible Consumers in the Ancillary Service Markets

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Abstract

Flexible consumption devices are often able to quickly adjust the power consumption making these devices very well suited as providers of fast ancillary services such as primary and secondary reserves. As these reserves are among the most well-paid ancillary services, it is an interesting idea to let an aggregator control a portfolio of flexible consumption devices and sell the accumulated flexibility in the primary and secondary reserve markets. However, two issues make it difficult for a portfolio of consumption devices to provide ancillary services: First, flexible consumption devices only have a limited energy capacity and are therefore not able to provide actual energy deliveries. Second, it is often difficult to make an accurate consumption baseline estimate for a portfolio of flexible consumption devices. These two issues do not fit the current regulations for providing ancillary services. In this work we present a simple method based on the existing ancillary service markets that resolves these issues via increased information and communication technology. The method allows an aggregator to continuously utilize the markets for slower ancillary service to ensure that its portfolio is not driven towards the energy limitations resolving both the baseline issue and the energy limitation issue.

1 Introduction

The renewable energy sector is the fastest growing power generation sector and is expected to keep growing over the coming years [1, 2]: the global share of non-hydro renewables has grown from $2\ \%$ in 2006 to $4\ \%$ in 2011 and is predicted to reach $8\ \%$ in 2018 [2]. Many actions have been taken all over the world to increase the penetration of renewables: in the US, almost all states have renewable portfolio standards or goals that ensure a certain percentage of renewables [3]; similarly, the commission of the European Community has set a target of $20\ \%$ renewables by 2020 [4].

A number of challenges arise as the penetration of renewables increases. Many renewable sources are characterized by highly fluctuating power generation and can suddenly increase or decrease production depending on weather conditions. A recent example of this phenomenon took place Denmark on October 28, 2013 where a large number of wind turbines were shut down because of a storm. This caused a decrease from a level where more than $100\ \%$ of the Danish electricity consumption was covered by wind to a level less than $45\ \%$ in just 2 hours[1], see Figure 14.1. Such rapid production changes can imply severe consequences for grid stability due to the difficulty of accurately predicting the timing of the events [6].

Further, as more renewables are installed, the conventional generators are phased out: in Denmark, the increase of renewables during the last years has caused a petition for shutting down 8 central power plants [7]. This, however, causes another major challenge because the central power plants currently are the providers of system stabilizing ancillary services. As the conventional power plants are replaced with renewables, the ability to provide ancillary services in the classical sense is lost as the renewables usually do not possess the ability to provide such system stabilizing reserves: First of all, keeping renewables in reserve will entail that free energy is wasted making this a very expensive solution. Second, the highly fluctuating nature of the renewables caused by weather conditions can make it difficult to deliver a well-defined power response.

[1] Data taken from the website of the Danish transmission system operator: [5]

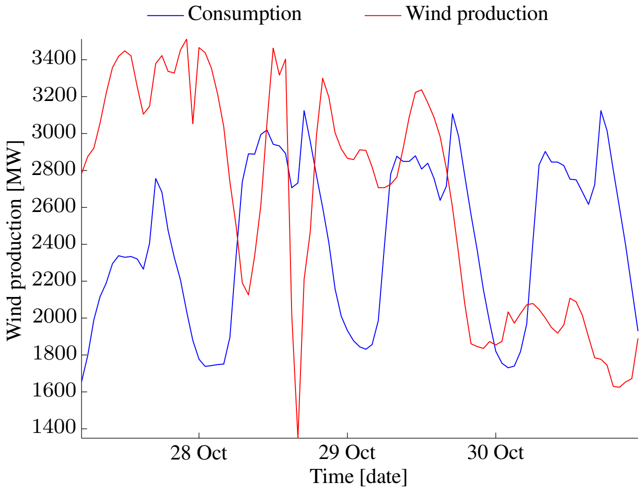

Figure 14.1: Hourly consumption and wind production during 4 days in Denmark in end October, 2013. A storm hits Denmark in the afternoon on the 29th causing a large number of wind turbines to shut down resulting in a production drop of more than $2,000$ MW in just 2 hours.

It is therefore evident that alternative sources of ancillary services must be established as renewables replace conventional generation. One approach to obtain ancillary services is to purchase reserves in neighboring countries; however, this requires that transmission line capacity is reserved for the reserve markets which will limit the capacity in the day-ahead spot markets and thereby possibly cause higher electricity prices [7]. Further, the ENTSO-E grid code sets limits on the amount of reserves it is allowed to exchange internationally [8].

An alternative approach to obtain alternative ancillary services is the *smart grid* concept, where local generation and demand-side devices with flexible power consumption take part in the balancing effort [9, 10]. The basic idea is to let an aggregator control a portfolio of flexible devices such as thermal devices, batteries, pumping systems etc. Hereby, the aggregator can utilize the accumulated flexibility in the unbundled electricity markets for primary, secondary, and tertiary reserves, on equal terms with conventional generators [11, 12].

In this work, we identify the difficulties of including flexible consumption devices in the existing ancillary service markets and propose a method for better integration of this type of devices.

2 Scope and structure of the article

The increase of renewables and shutdown of central power plants call for alternative sources of primary, secondary, and tertiary reserves. This work proposes a method for making better conditions for flexible consumption devices to deliver these services. The method is valid for both the primary and secondary reserve, but not for the tertiary reserve, as will be come evident later. For the following reasons, we still believe the method is most relevant.

The first reason is that flexible consumption devices and storage systems are well suited for fast reserves but less suited for slower reserves where large amounts of energy must be delivered. Many consumption devices are able to deliver a response fast enough even for primary reserve [13, 14]; however, they are not able to provide actual energy deliveries as they only have a limited energy capacity. A battery system will for example only be able to deliver/consume a limited amount of energy before reaching the energy limitations; similarly, a consumption devices with a given thermal mass will only be able to shift a limited amount of energy before reaching the thermal comfort limits [12].

The second reason is that although the amounts of required tertiary reserves is significantly higher than the required amount of primary and secondary reserves, the expenditure on primary and secondary reserve exceeds that of tertiary reserve by far. This is illustrated in Figure 14.2 where 2011 and 2012 data for Western Denmark is analyzed[2]. The figure shows that the amount of tertiary reserve in 2011 and 2012 indeed is the highest of the tree comprising more than 50 % and 55 %, respectively, of the combined primary, secondary and tertiary reserve those years. However, as illustrated in the same figure, the expenditure for the tertiary reserve in these two years accounted for below 12 % and 11 %, respectively. The reason is the fast delivery requirements for primary and secondary reserves making it more difficult, and thus more costly, to provide these reserves.

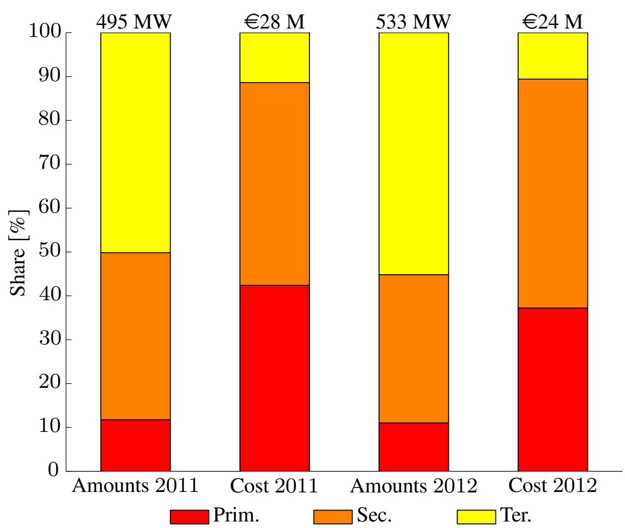

Figure 14.2: Amounts and prices of traded primary, secondary, and tertiary reserves in Western Denmark in 2011 and 2012.

Based on the observation that flexible consumers are well suited for fast reserves and

[2]Data for primary and tertiary reserve taken from [5] while data for secondary reserve is from [15, 16]. Only the reservation prices are included, not the activation prices which only apply for secondary and tertiary reserves.

because the value of these services is far greater than of tertiary reserve, it is chosen to limit the scope exclusively to primary and secondary reserves.

A portfolio of flexible consumption devices generally has two significant differences from conventional power generators when providing ancillary services. The first is that the portfolio will have a *limited energy capacity* whereas the conventional generator simply will be able to use more or less fuel. A heating system will for example have flexibility due to its thermal capacity; however, only a limited amount of energy can be stored depending on the temperature bounds that must be satisfied. Similarly, a factory may be able to expedite or postpone a batch production, but will in the long run have the same average consumption. This significantly limits the possibilities for flexible consumption devices to provide ancillary services. The second difference is that a portfolio of flexible devices often not will have a well-defined *baseline*, i.e. the aggregator will not exactly know the electricity consumption of the portfolio many hours in advance as it depends on external parameters such as weather conditions or human behavior, which can be difficult to predict accurately. Without a well-defined baseline it is difficult to assess what services the portfolio actually has delivered; consequently, the lack of a baseline makes it difficult for flexible consumers to participate in the ancillary service markets under the current regulations. These two issues therefore constitute a barrier for the roll out of the smart grid concept in the liberalized electricity markets.

In this work, we propose a method that resolves the issues of energy limitations and lack of accurate baselines *without* altering the existing ancillary service markets. In short, the method allows an aggregator via ICT to continuously adjust its operational schedule which is the baseline communicated to the TSO. This enables the aggregator to avoid violating the energy limitations of the consumption devices. The operational schedule adjustments must, however, be done under certain limitations ensuring that the TSO has sufficient time to activate slower reserves correspondingly.

The proposal is exactly in line with the general smart grid vision where a stable, reliable, and sustainable electricity system is ensured via ICT solutions [11, 17, 18].

The paper is organized as follows. First in Sec. 3 we describe the overall system architecture. Following in Sec. 4 and Sec. 5 we present overall models of flexible consumption devices and of the ancillary service markets, respectively. In Sec. 6 we discuss the issues of delivering ancillary service via flexible consumers and following in Sec. 7 we present our proposal of resolving these issues. The proposed method is illustrated with numerical examples in Sec. 8 and finally in Sec. 9 we conclude the work.

3 Architecture

For many consumption devices, the flexibility is too small to make isolated bids into the electricity markets; for example, the threshold for primary frequency control reserves is 300 kW in Western Denmark [19] while the capacity of a domestic flexible consumption device is in the magnitude of a few kW at most. Only certain very large consumers such as large pumping facilities, heating elements for combined heat and power plants, etc. will be able to reach the minimum threshold. For this reason, aggregation is required in order to achieve sufficient quantities of active power for bidding.

The basic idea is to let an *aggregator* enter into contract with the owners of the flexible devices. The contract specifies under what conditions the aggregator is allowed to utilize

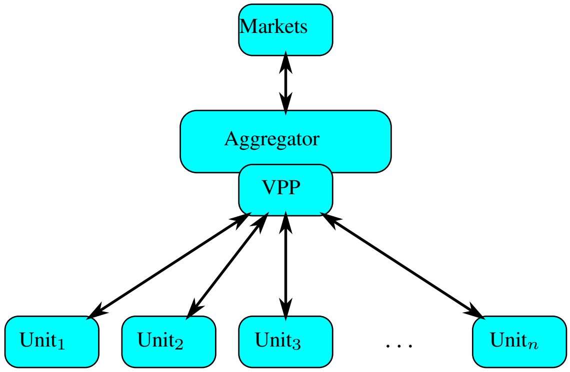

Figure 14.3: Aggregator participating in the electricity markets based on the flexibility of n consumption devices (units) managed through a technical VPP.

the flexibility [20]. On this basis, the aggregator uses a technical unit often referred to as a *VPP* to manage the devices [12]. The VPP can monitor and control the flexible devices and is thereby able to mobilize the accumulated response of a portfolio of flexible consumption devices, see [21, 22, 23, 24] for a few examples of VPP strategies. This allows an aggregator to enter the ancillary service markets based on the flexible devices. This architecture is illustrated in Figure 14.3.

4 Flexible consumption devices and storage devices

In this section, we present a model that describes a portfolio of flexible consumption devices managed by an aggregator. The model is very simple but captures characteristics in focus in this work: power and energy limitations and inaccurate knowledge of the consumption baseline.

Nomenclature

Table 14.1 gives an overview of the parameters used in the following modeling section. Later, each parameter is described in more detail; further, some of the parameters are illustrated in Figure 14.4.

Model

A flexible consumption device portfolio model can be described as follows. Let $E(t)$ denote an energy level and define its derivative as

$$\dot{E}(t) = P^{\text{cons}}(t) - P^{\text{base}}(t) \tag{14.1}$$

where $P^{\text{cons}}(t)$ is the portfolio electricity consumption, $P^{\text{base}}(t)$ is the baseline consumption of the portfolio, i.e., how much the portfolio of devices would consume if not activated for ancillary services, and $E(t)$ is the energy stored in the flexible consumption

$E(t)$	[J]	Energy level in portfolio.
$E^{\text{min}}, E^{\text{max}}$	[J]	Portfolio min/max energy levels.
$P^{\text{cons}}(t)$	[W]	Portfolio power consumption.
$P^{\text{min}}, P^{\text{max}}$	[W]	Portfolio min/max power consumption.
$P^{\text{base}}(t)$	[W]	Portfolio baseline consumption.
P^{cap}	[W]	Portfolio power capacity (largest possible symmetric power bid).
E^{cap}	[J]	Portfolio energy capacity (maximum amount of energy that can be stored).
$\hat{P}^{\text{base}}(t)$	[W]	Prediction of the baseline consumption $P^{\text{base}}(t)$.
P^{acc}	[W]	Accuracy of baseline prediction within horizon.
P^{del}	[W]	Amount of symmetric reserve.
P^{os}	[W]	Operational schedule reported to the TSO.

Table 14.1: Description and units of the parameters used throughout the work.

devices[3]. In other words: by deviating from the nominal portfolio baseline consumption $P^{\text{base}}(t)$, energy is stored or released from the portfolio. Notice that the baseline consumption always will be non-negative $P^{\text{base}}(t) \geq 0$ as the portfolio does not include power generators.

The model (14.1) can also be utilized for a battery storage. In this case the baseline consumption will simply be zero $P^{\text{base}}(t) = 0$ whereby $\dot{E}_{\text{batt}}(t) = P^{\text{cons}}(t)$, given the battery is not used for other purposes and does not have any drain/loss. Now, as the battery charges we will have $P^{\text{cons}}(t) \geq 0$ and the battery level $E_{\text{batt}}(t)$ will increase and vice versa for discharge.

The consumption of the portfolio is limited in power and energy, which can be represented as

$$P^{\text{min}} \leq P^{\text{cons}}(t) \leq P^{\text{max}}, \quad E^{\text{min}} \leq E(t) \leq E^{\text{max}} \tag{14.2}$$

where $P^{\text{min}}, P^{\text{max}}$ represent the limits of the portfolio's accumulated consumption. For a portfolio of consumption devices, P^{min} could be 0 if it is allowed to turn all devices OFF; similarly, P^{max} could be the total consumption with all devices ON, provided this is allowed. For a battery system, $P^{\text{min}}, P^{\text{max}}$ will correspond to the maximum rate of charge and discharge. The parameters $E^{\text{min}}, E^{\text{max}}$ are the minimum and maximum amount of stored energy and can for example represent an allowable temperature band for thermal devices; similarly, it can represent the limits of a battery. Notice that for consumption devices we will have $P^{\text{min}} \geq 0$ as the devices cannot *generate* electricity.

Note that modeling a portfolio of many individual devices with a single *lumped* model as the one presented above in many case is a vast simplification of reality [25]. Further note that the model does not account for state dependent losses, i.e. it can for example not capture that the energy loss of a thermal device will increase with increasing temperature difference to the ambient. Consequently, the presented model is a rough estimation of reality. However, the focus of this work is not modeling but rather the proposal for a market change that can increase the market uptake of flexible consumers. As the presented

[3]Notice that *storing* electricity for consumption devices refer to the device's ability to shift consumption in time within certain limits.

model is able to capture the main characteristics of flexible consumers, namely energy limitations and inaccurate baseline predictions, the model is found suitable for this work.

Based on (14.1) and (14.2) we define the power capacity P^{cap} of the portfolio within a specific delivery time T as

$$P^{\text{cap}} = \min(P^{\max} - \max_{t \in \mathcal{T}}(P^{\text{base}}(t)), \min_{t \in \mathcal{T}}(P^{\text{base}}(t)) - P^{\min}). \tag{14.3}$$

Hereby, the power capacity describes the maximum possible deviation in either direction away from the power baseline within the horizon $\mathcal{T} = \{t \in \mathbf{R} | 0 \le t \le T\}$. The basis of this definition is the underlying assumption that the portfolio as default will consume the baseline consumption and deviate from this baseline upon ancillary service activation. In this case, P^{cap} is the highest *symmetric* power bid we can make. By symmetric, we mean that when a reserve capacity of size P^{cap} is sold, the provider should be able to deliver power within the symmetric interval $[-P^{\text{cap}}, P^{\text{cap}}]$. This illustrates that flexibility of a portfolio is highest when the baseline consumption is constant and given by $P^{\text{base}}_{\text{opt}}(t) = (P^{\max} - P^{\min})/2$ whereby $P^{\text{cap}}_{\text{opt}} = (P^{\max} - P^{\min})/2$. For the energy part, we define the capacity E^{cap} as the size of the energy storage:

$$E^{\text{cap}} = E^{\max} - E^{\min}. \tag{14.4}$$

The baseline consumption $P^{\text{base}}(t)$ can be predicted with a given accuracy for a given horizon. Let $\hat{P}^{\text{base}}(t)$ denote the prediction of $P^{\text{base}}(t)$ and let the accuracy of the prediction be described as

$$|P^{\text{base}}(t) - \hat{P}^{\text{base}}(t)| \le P^{\text{acc}}, \quad \forall t \in \mathcal{T} \tag{14.5}$$

where P^{acc} represents the accuracy. The parameter P^{acc} can for example describe the ability to predict the outdoor temperature which is relevant when dealing with a portfolio of heating or cooling devices, or it can describe disturbances such as human behavior which is relevant for heating systems of households.

It is necessary for the aggregator to report an *operational schedule* $P^{\text{os}}(t)$ to the TSO describing the scheduled portfolio consumption. The operational schedule must be submitted day-ahead and describes the consumption of the portfolio the following day with a given resolution. As an example, the deadline for the operational schedule is 17.00 in the Danish market and the resolution is 5 minutes [26]. The aggregator can for example choose to assign the predicted baseline consumption as the operational schedule $P^{\text{os}}(t) := \hat{P}^{\text{base}}(t)$ as this is the best possible prediction of the actual baseline consumption $P^{\text{base}}(t)$.

By definition, ancillary services are delivered by letting consumption deviate from the operational schedule. If we let $P^{\text{del}}(t)$ denote the delivered ancillary service, we have

$$P^{\text{del}}(t) = P^{\text{os}}(t) - P^{\text{cons}}(t) \tag{14.6}$$

where $P^{\text{del}}(t)$ is in production terms, i.e., $P^{\text{del}}(t) > 0$ corresponds to increased production or reduced consumption while we use consumption terms for $P^{\text{cons}}(t), P^{\text{os}}(t), P^{\text{base}}(t)$, i.e., $P^{\text{cons}}(t) > 0$ corresponds to consuming power. The complete setup is illustrated in Figure 14.4.

In this work we propose that an aggregator is allowed to adjust its operational schedule as long it is done sufficiently slowly, such that the TSO is able to activate slower reserves

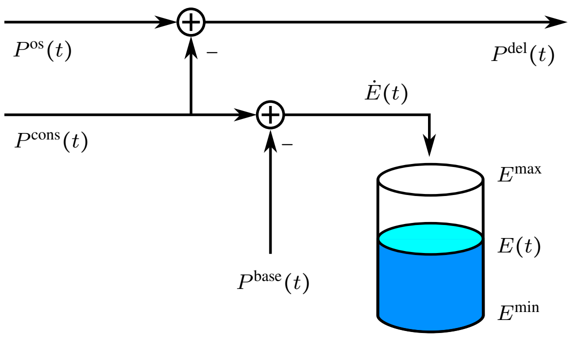

Figure 14.4: Illustration of the simple model of a portfolio of flexible consumers and how it is able to make a power delivery $P^{\text{del}}(t)$ by deviating from the operational schedule $P^{\text{os}}(t)$.

accordingly. This allows the aggregator to keep the energy level of its portfolio close to a certain desired level, for example the energy midpoint $E^{\min} + E^{\text{cap}}/2$, and hereby avoid violating the energy limits.

Examples

Let us consider a few concrete examples of flexible consumption devices that are considered potential providers of ancillary services in the smart grid literature.

The first example is a household heated with a heat pump which can be seen as a flexible consumption device due to the thermal mass of the house [27, 28, 29]. The energy/power parameters will vary much from house to house. To give an example, a set of parameters for a smaller house where we are allowed to vary the temperature a few degrees around the temperature set-point is presented in Table 14.2 inspired by the papers cited above.

The second device is a supermarket refrigeration system where energy can be stored in the refrigerated foodstuff [30, 31, 32]. A set of parameters for a smaller supermarket system where we are allowed to lower the foodstuff temperature a few degrees is presented in Table 14.2 inspired by [33].

Finally we also consider an EV battery. Typical values for an EV battery are presented in Table 14.2 [34, 35]. We assume a fast DC charging station and that the battery is not in use, which would be the case for example if the battery is located at a charging station.

These examples are presented to illustrate the types of devices that go under the category *flexible consumption devices* in this work and to give an idea of the energy and power capacities of such devices.

We notice, as previously mentioned, that all these devices are too small for individual participation in the ancillary service markets where the threshold is 300 kW or more; consequently, aggregation is a requirement.

	Energy limits [kWh]		Power limits [kW]	
	$E^{\min}$	$E^{\max}$	$P^{\min}$	$P^{\max}$
Heat pump	−4	4	0	6
Supermarket	0	50	0	20
EV battery	0	24	−70	50

Table 14.2: Energy and power capacity for two types of flexible consumption devices and a storage device.

5 Ancillary service markets

We limit our focus to the active power ancillary services although other ancillary services exist. The active power services are denoted primary, secondary, and tertiary reserve as previously mentioned. In ENTSO-E's network code on load-frequency control and reserves, the terminology used for these services are frequency containment reserve, frequency restoration reserve, and replacement reserves [8, 36]. These terms describe the functionality of the reserves in case the system frequency deviates from the nominal value: namely that the fast primary reserve ensures that the frequency is contained, the secondary reserve restores the frequency, while finally, the tertiary reserve replaces the secondary reserve.

We assume these services are distinguished by how fast they are with primary as the fastest and tertiary as the slowest reserve. In this work we describe a method that allows an aggregator providing fast reserves, for example primary reserve, to utilize the slower reserves, for example secondary reserve, to ensure that the energy limitations of the portfolio are not violated.

Throughout the examples, we examine providing primary reserve and utilizing the markets for secondary or tertiary reserve to restore the portfolio energy level; however, the method would also apply to a case where we provide secondary reserve and utilize the market for tertiary reserve to restore the portfolio energy level.

Generic market description

In the following we construct a simple description of the active power reserves seen from an ancillary service provider's point of view.

A provider has contracted a capacity given by P_i^{res} for a duration given by T_i where the subscript i denotes the market, i.e. $i = 1$ is the primary, $i = 2$ is the secondary, and $i = 3$ is the tertiary reserve market. This notation is used throughout this work. For simplicity we only consider symmetric deliveries.

We use the following simple model to describe the ancillary service markets: each market i is described by two parameters: a *ramping time* t_i^{ramp} and a *latency time* t_i^{lat}. These parameters should be understood as follows. If a reserve is fully activated, either via local grid frequency measurements for primary reserve or by activation from a TSO for secondary and tertiary reserve, the provider should start providing the reserve at the latest after the latency time of t_i^{lat} seconds; hereafter the full reserve should be ramped up within an additional t_i^{ramp} seconds.

Generally, primary control needs faster response than secondary control which needs faster response than tertiary control. This can be described in terms of the ramping and latency parameters:

$$
\begin{aligned}
t_1^{\text{ramp}} &\le t_2^{\text{ramp}} &&\le t_3^{\text{ramp}} \\
t_1^{\text{lat}} &\le t_2^{\text{lat}} &&\le t_3^{\text{lat}}.
\end{aligned}
\tag{14.7}
$$

The faster reserves are in average more expensive than the slower, as they are more difficult to deliver. This is the reason it is interesting to examine how flexible consumption devices can be managed to deliver the fast expensive reserves by restoring the energy level via the inexpensive slower reserves.

Example: European grid

We consider a concrete example by examining the control performance specifications of the ENTSO-E. Based on [37, 38] as well as the newly published grid code [8], typical parameters for the three ancillary services are

$$
\begin{aligned}
t_1^{\text{ramp}} &= 30 \text{ s}, & t_1^{\text{lat}} &= 0 \text{ s} \\
t_2^{\text{ramp}} &= 6 \text{ min}, & t_2^{\text{lat}} &= 30 \text{ s} \\
t_3^{\text{ramp}} &= 10 \text{ min}, & t_3^{\text{lat}} &= 5 \text{ min}.
\end{aligned}
\tag{14.8}
$$

The parameters stated in (14.8) should not be seen as definite values as they can vary from country to country, but they are chosen to mimic the parameters presented in [38, p. 3].

An illustration of primary, secondary and tertiary reserve can be seen in Figure 14.5 with the parameters from (14.8) and assuming an instance of 1 MW at time 0. Further, it is assumed that the fault is corrected by three providers of each 1 MW reserve, i.e. $P_1^{\text{res}} = P_2^{\text{res}} = P_3^{\text{res}} = 1$ MW. The figure shows that the primary response within 30 seconds fully provides the 1 MW of power where after the secondary reserve starts ramping up followed by the tertiary reserve after another 4.5 minutes. The secondary reserve thus restores the primary reserve and is itself eventually restored by the tertiary reserve.

Further we notice that the figure illustrates what was discussed in Sec. 2, namely that the required amount of tertiary reserve is larger than that of primary and secondary reserve because the tertiary control will replace the primary and secondary control action and provide an actual energy delivery. The figure also illustrates the higher timing requirements to the primary and secondary control action, which is the reason for the higher absolute costs of these reserves although the volumes are smaller, as was illustrated previously in Figure 14.2.

Finally we comment on the delivery duration T_i of the reserves which is the duration that the contracted reserve P_i^{res} should be available. The delivery duration vary from market to market, however we use the Danish system an example [39]

$$
T_1 = 1 \text{ week}^4, \quad T_2 = 1 \text{ month}, \quad T_3 = 1 \text{ hour}. \tag{14.9}
$$

[4] The Western Danish system is currently merging with the German system where primary reserve is delivered in blocks of 1 week.

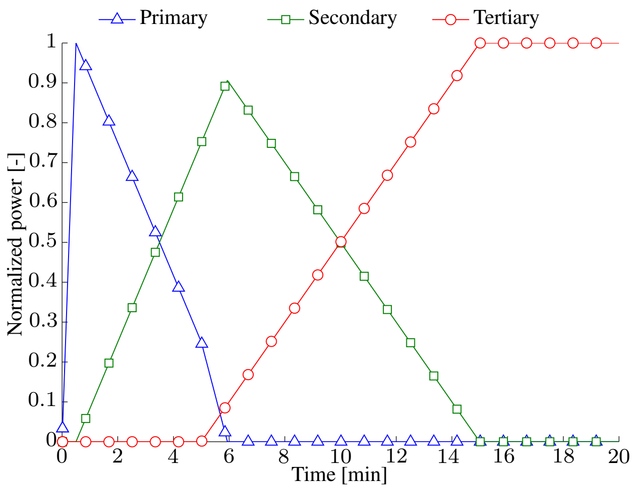

Figure 14.5: A 1 MW instance is restored by the primary reserve which is relieved by the secondary reserve which again is relieved by the tertiary reserve.

This means that the reserves are sold in blocks of 1 week, 1 month, and 1 hour, respectively.

Finally, we look at the ancillary service prices in Denmark to illustrate that the faster reserves are more expensive than the slower reserve. Let π_i denote the average cost per MW of reserve, then

$$\pi_1 \approx 30 \text{ €/MW}, \quad \pi_2 \approx 11 \text{ €/MW}, \quad T_3 \approx 5 \text{ €/MW}. \tag{14.10}$$

where these prices are taken from [19] for the secondary reserve and based on prices from the first 6 months of 2013 for the primary and tertiary reserve[5].

6 Ancillary services by flexible consumers

The limiting factors for conventional generators to provide ancillary services are their power limitations, the startup time, and ramping limitations. Generally, the energy capacity of a conventional generator is a non-issue: the generator will be able to continuously produce both minimum and maximum power simply by using more or less fuel.

For flexible consumers the situation is completely different. Consumption devices will typically hardly have any rampling limitations and have a very low startup (or shutdown) time. The reason is that the consumption devices often rapidly can change the process to consume more or less power or it can simply be turned ON/OFF and thus instantaneously change the power consumption. This makes flexible consumption devices ideal for providing fast reserves such as primary reserve. This further illustrates why it

[5]Data taken from DK West from [5]

is very interesting to improve the possibility for these devices to participate in the fast ancillary service markets.

As previously described, two main differences from conventional generators make it difficult for flexible consumption devices to provide ancillary services: First, the flexible consumption devices are energy-limited and they will therefore on average have to consume the same energy and consequently not be able to provide actual energy deliveries. Second, the flexible consumption devices generally do not have an exact baseline for the future consumption. In the following we will describe why this becomes a limiting factor for the flexible consumption devices as providers of ancillary services in the current markets.

Energy limitations

It is easy to illustrate how the energy limitations can limit the power delivery P_i^{res} we are able to offer as an aggregator. An aggregator providing ancillary services in market i should in principle be able to deliver the reserve within the power limitations $\pm P_i^{\text{res}}$ continuously throughout the delivery period[6] T_i. For the primary reserve market with a duration of one week, this means that the worst case energy deliver in principle is ± 168 hours$\cdot P_1^{\text{res}}$. As an example, a portfolio of 100 EV batteries with an energy capacity of $E^{\text{cap}} = 2.4$ MWh can at most bid a symmetric power reserve of $P_1^{\text{res}} = 2.4/(2 \cdot 168)$ MW $= 0.007$ MW which is *very* restrictive compared to the power capacity of $P^{\text{cap}} = 5.0$ MW. It can be argued that in practice, an extreme energy delivery of ± 168 hours$\cdot P_1^{\text{res}}$ will not occur. However, by examining historical grid frequency measurements[7], weeks can be found where an energy delivery in the magnitude of ± 10 hours$\cdot P_1^{\text{res}}$ is required. This yields $P_1^{\text{res}} = 2.4/(2 \cdot 10)$ MW $= 0.12$ MW which is still very low compared to the 5.0 MW power capacity available.

Notice that the restriction depends on how the energy and power capacity relates: the problem increases for a portfolio with a relatively high power capacity compared to energy capacity. For a portfolio of heat pumps or supermarket refrigeration systems, the issue is smaller than the example presented above, however it will be worse for other types of devices with even smaller energy capacities, for example thermal devices with very tight allowable temperature bands. Finally, the situation will be even worse for the secondary reserve where the duration is longer, namely $T_2 = 1$ month.

Uncertain baseline

It is also easy to illustrate how the uncertain baseline can be a limiting factor for how large a power delivery P_i^{res} we are able to offer based on a portfolio of flexible consumption devices. The provided reserve is defined as the difference between the operational schedule and the actual consumption as stated in (14.6). The operational schedule is sent to the TSO the day before operation. As the actual baseline of the portfolio is unknown before operation, the aggregator will have to use the best available baseline prediction instead, i.e. $P^{\text{os}}(t) := \hat{P}^{\text{base}}(t)$. If the baseline prediction equals the actual baseline we have no issues; however, if the actual baseline consumption deviates from the baseline

[6] Some markets allow restoration time but we ignore this for simplicity.
[7] System frequency data from the ENTSO-E grid from 2012 is used.

prediction, the aggregator will have to use the portfolio's energy capacity to compensate for the inaccurate operational schedule. Consequently, the energy capacity will be limited based on the accuracy of the baseline prediction.

The operational schedule is reported every day. Using the simple uncertainty model in (14.5) it is evident that over a day, the worst case energy delivery due to an uncertain energy prediction will be ±24 hours$\cdot P^{\mathrm{acc}}$. As an example, consider a portfolio of $1,000$ heat pumps with $P^{\mathrm{acc}} = 0.2$ MW (this inaccuracy is based on [40], see Sec. 8). Then the worst case situation for the portfolio is that the prediction error over the course of 24 hours accumulates to 24 hours$\cdot 0.4$ MW = 9.6 MWh which is more than the total energy capacity $E^{\mathrm{cap}} = 8.0$ MW of the portfolio of houses under consideration. Consequently, we cannot guarantee to follow the submitted operational schedule during the day and will thus not be able to participate in the ancillary service markets at all. This clearly illustrates how the uncertain baseline predictions can influence the possibilities to participate in the ancillary service markets.

Suboptimal market operation

One way to overcome the energy limitations of the flexible consumers is to provide ancillary services as *combined deliveries*, where the portfolio of flexible consumption devices is combined with conventional generators. This can be done for example if a market player owns a portfolio of flexible devices with high ramping limits and low startup time and also owns a slower conventional generator. Depending on the devices' properties, it may be possible for the market player to design a control strategy that allows the fast portfolio and the slow generator unit to collectively provide primary reserve. Hereby, the player can gain from the flexible consumers to increase the value of the slower generator, which else would only be able to participate in the less attractive markets for secondary or tertiary reserve.

However, now consider the case where a second player has a generator able to provide secondary reserve at a lower cost than the first player. Seen from a global perspective, it would be optimal if the cheaper secondary reserve generator of the second player was used together with the flexible consumer portfolio of the first player to provide a combined delivery. However, as these two devices are owned or operated by different players, such combined delivery cannot be handled under current market regulations. Consequently, suboptimal market operation can occur when players combine local devices to provide faster reserves. The method we propose in this paper exactly solves this issue by coupling the ancillary service markets.

7 Proposal of market interaction

In the previous section we have illustrated three major issues of using a portfolio of flexible consumption devices as providers of ancillary services. The first two issues deal with the energy limitation and the uncertain baseline. The third issue illustrates how combined deliveries can lead to suboptimal market operation.

In this work we propose the following approach to improve the possibility for flexible consumers to participate in the fast ancillary service markets.

Proposal. *Operational schedules can be continuously adjusted throughout the delivery* *period. The adjustment must satisfy the ramping and latency constraints of secondary or tertiary control. If the operational schedule is adjusted according to the secondary control constraints, the cost of secondary control shall apply for the difference between the original operational schedule and the adjusted operational schedule; similarly, if the operational schedule is adjusted according to the tertiary control constraints, the costs of tertiary control shall apply.*

Notice that although we propose a very specific method, this should merely be seen as an example. The main message of this paper is not this exact proposed method; rather, that we in general can increase the possibilities for flexible consumers to participate in the ancillary service markets by having well-defined regulations that allow continuous adjustments of the operational schedule at a well-defined cost.

Illustration of proposed method

The sequence diagram in Figure 14.6 illustrates the proposed method in the market context. The first actor in the sequence diagram is the aggregator who utilizes a portfolio of flexible consumption devices in the ancillary service markets, and uses the proposed method to restore the portfolio energy level. The second actor is the TSO, who is the buyer of ancillary service, and finally, the third actor is the remaining providers of ancillary services.

As the figure illustrates, the aggregator will submit an operational schedule day-ahead describing the following day's consumption with a given resolution according to current regulations (see also Sec. 4). Intra-day, the proposed method allows the aggregator to adjust the operational schedule continuously. This means that the aggregator at any time intra-day can submit an adjusted operational schedule according to the limitations described in Sec. 7; following, the TSO will confirm the adjusted operational schedule provided the adjustment satisfies the regulation. Next, the TSO will compensate for the adjustment of the operational schedule by activating the necessary reserves from the other ancillary service providers. One such an adjustment is illustrated in Figure 14.6.

Comparison with existing regulations

Denmark is among the most active smart grid countries in Europe, therefore it is interesting to compare the method proposed above to the current Danish ancillary service regulations.

The Danish regulations describe that market players already now indeed *are* allowed to adjust a previously submitted operational schedule [19, 41]. The regulations do, however, differ significantly from the method proposed in this work as elaborated in the following.

- The regulations specify that the operational schedule can be adjusted in case a difference between actual operation and the submitted operational schedule larger than 10 MW is detected. Consequently, the possibility to adjust the operational schedules is a way for the TSO to be aware of larger outages. Hence, it is different from the method proposed in this work where the operational schedule is adjusted in a continuous manner to restore the energy level of the flexible consumers. The proposal in this work is not only meant as a way for the TSO to be aware if an ancillary

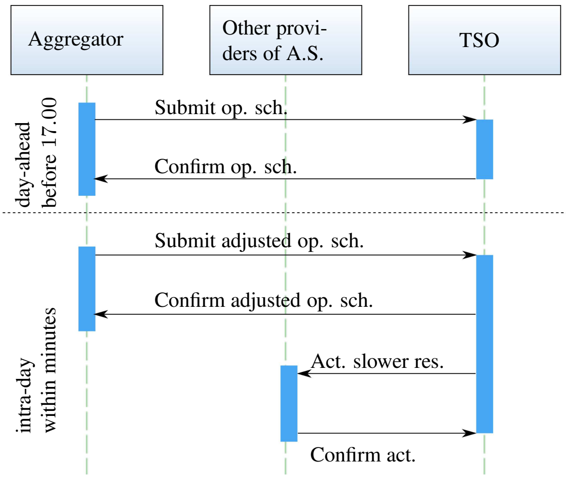

Figure 14.6: Sequence diagram illustrating an aggregator submitting an operational schedule (op. sch) day-ahead and following, an aggregator adjusting the submitted schedule using the proposed method.

service provider has a larger outage; rather, we propose to deliberately couple the markets by allowing market players to actively and continuously adjust operational schedules. This allows the TSO to continuously utilize the slower reserves to compensate for operational schedule adjustments.

- The regulations do not state under what constraints the operational schedule can be adjusted, only that a latency time of 5 minutes must be honored. Consequently, a market player making a rapid change in the operational schedule can cause activation of faster reserves at no cost causing a loss for the TSO. This is therefore not a sustainable solution if a large number of market players will perform continuous operational schedule adjustments, as this potentially can generate a large economical deficit for the TSO. In the proposed method, the TSO covers its expenses by charging the aggregator according to the operational schedule adjustments.

Also in the ENTSO-E handbook [37, 38], no specifications of operational schedule adjustments are mentioned.

8 Numerical results

In this section, we present a number of numerical results that illustrate the benefit of allowing continuous operational schedule adjustments according to the proposal in Sec. 7. First, we illustrate the overall concept; following, we illustrate how the method is able to handle both energy limitations and inaccurate baseline predictions.

Illustration of the overall concept

We illustrate the overall concept using the following example. Consider a portfolio of flexible consumers with parameters

$$\begin{aligned} &P^{\min} = 0 \text{ MW}, \quad P^{\max} = 2 \text{ MW}, \qquad\qquad P^{\text{base}}(t) = 1 \text{ MW} \\ &P^{\text{cap}} = 1 \text{ MW}, \quad E^{\max} = -E^{\min} = 0.1 \text{ MWh}, \quad P_1^{\text{res}} = 0.5 \text{ MW} \end{aligned} \tag{14.11}$$

i.e. the aggregator has offered a symmetric primary reserve equal to half of its capacity $P_1^{\text{res}} = 0.5$ MW. The aggregator has further submitted a constant operational schedule $P^{\text{os}}(t) = P^{\text{base}}(t) = 1$ MW to the TSO. This could correspond to a portfolio of battery systems with a low energy capacity or a portfolio of thermal devices with very tight temperature bounds (see Table 14.2). The relatively small energy capacity is chosen deliberately to illustrate the presented method's ability to use such devices in the ancillary service markets.

We consider the extreme power reference illustrated in subplot 1 of Figure 14.7 (purple dashed line): after 5 minutes the reference changes from 0 MW to the maximum delivery of 0.5 MW and following, after 25 minutes, the reference changes to the other extreme of −0.5 MW. For primary reserve, the reference depends on the system frequency and we notice that the presented reference is highly unlikely; however, we have deliberately constructed it to illustrate the overall concept. Later, real life frequency measurements will be used to construct realistic power references.

Two scenarios are considered: a case where the aggregator *is not* allowed to adjust the operational schedule and a case where the aggregator *is* allowed to adjust the operational schedule as proposed in this work. Both cases are illustrated in Figure 14.7 and show that the aggregator is able to track the power reference when allowed to adjust the operational schedule while it is not able to track the reference when adjustments are not allowed. Let us examine this further to gain insight in the presented method.

First, we examine the behavior of the conventional method where the operational schedule is not adjusted. At the first instance at time 5 minutes, the portfolio reduce its consumption to 0.5 MW as seen in subplot 2; however, the energy storage is empty after 12 minutes as shown in subplot 3 and the portfolio fails to track the reference as seen in subplot 1. The conventional method also fails at time 50 minutes, this time because the storage is full.

Now let us examine how the proposed operational schedule adjustment method works. First as the reference changes from 0 MW to 0.5 MW at time 5 minutes, the portfolio delivers the full response as evident from subplot 2, however, the aggregator starts adjusting the operational schedule as seen in subplot 4. The adjustments are made under the constraints of secondary reserve such that the TSO is able to activate secondary reserve accordingly as illustrated previously in Figure 14.6. After the latency time of 30 seconds and the ramping time of 6 minutes, the aggregator has adjusted the operational schedule from 1 MW to 1.5 MW and restored the consumption to the nominal 1 MW as seen in subplot 2. Hereby, the reference of 0.5 MW is still tracked $P^{\text{del}}(t) = P^{\text{os}}(t) - P^{\text{cons}}(t) = 1.5 - 1$ MW $= 0.5$ MW as requested while the portfolio consumes the desired 1 MW; consequently, the energy storage does not saturate, as shown in subplot 3. As the power reference changes from 0.5 MW to −0.5 MW at time

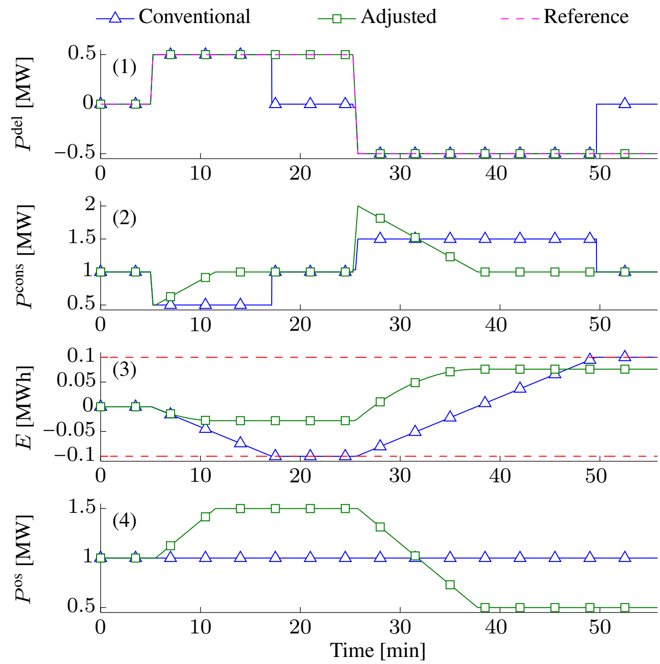

Figure 14.7: Comparison of the conventional strategy with *no* operational schedule adjustments (legend: *Conventional*) and the proposed method *with* operational schedule adjustments (*legend: Adjusted*). Subplot 1: The extreme power reference and the corresponding power delivery. The reference is only tracked when the aggregator *is* allowed to adjust the operational schedule. Subplot 2: Power consumption of the portfolio. Subplot 3: Energy level of the portfolio; the red dashed lines illustrate the energy storage limits. Subplot 4: The operational schedule.

25 minutes, the portfolio must deliver the full change of 1 MW causing the consumption to be 2 MW; following, the operational schedule is adjusted such that the consumption can be restored to the desired 1 MW ensuring that the energy storage does not saturate. The figure further illustrates that in this worst case scenario, the aggregator will not be able to place higher bids than half of its capacity $P_1^{\text{res}} = P^{\max}/2$ as seen in subplot 2.

Finally, Figure 14.7 can be used to determine the energy storage E^{worst} required to handle this worst case situation. The worst case energy is given by

$$E^{\text{worst}} = 2P_1^{\text{res}}(t_2^{\text{ramp}} + t_2^{\text{lat}} - t_1^{\text{ramp}}) \tag{14.12}$$

as this is the required energy deliver if the reference changes from one extreme to the other. In Figure 14.7 subplot 2, E^{worst} corresponds to the area between the baseline of 1 MW and the triangular shaped power consumption at the time of the worst case situation at time 25 minutes until it is restored at time 37 minutes.

The correlation (14.12) can be used to determine how much power an aggregator at most is able to bid into the primary reserve market. Again we consider the energy storage described above with $P^{\text{cap}} = 1$ MW. The curve in Figure 14.8 shows the maximum power bid we are able to place in the primary reserve market depending on the available energy capacity E^{cap} by utilizing the secondary or tertiary reserve to restore the storage energy level. As the figure shows, using the secondary reserve makes it possible to offer a reserve of $P_1^{\text{res}} = P^{\text{cap}}/2 = 0.5$ MW with an energy capacity $E^{\text{cap}} \geq 0.11$ MWh while an energy capacity $E^{\text{cap}} \geq 0.25$ MWh is required when relying on the slower tertiary reserve to restore the energy storage. This is clearly much more favorable for the aggregator compared to a worst case energy capacity requirement of 84 MWh if we are not allowed to adjust the operational schedule, see Sec. 6. This reveals how the presented method allows an aggregator to participate in the primary reserve market on much better terms.

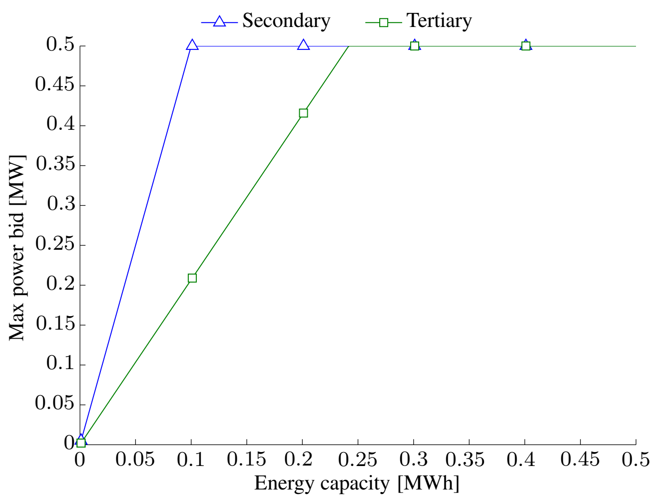

Figure 14.8: The maximum power we are able to bid into the primary reserve depending on the energy capacity E^{cap} when utilizing either the secondary or tertiary reserve to restore the energy level.

Simulation example I: limited energy storage

In this subsection we consider how the proposed method resolves the first issue, namely the limited energy storage. We consider a portfolio with the same parameters as the previous example, see (14.11), i.e we have a portfolio of flexible consumption device with a constant baseline consumption 1 MW which it is able to vary around with ± 1 MW however under strict energy limitations of 0.1 MWh.

Based on the worst case consideration presented in (14.12) it can be seen that by relying on the secondary reserve, we are able to provide $P_1^{\text{res}} = 0.5$ MW of primary reserve. By comparison, a worst case situation without operational schedule adjustments would limit the bid to $P_1^{\text{res}} = 0.1/(2 \cdot 168)$ MW $= 0.0003$ MW which in practice means this device would not be suitable for primary reserve. Again this shows the benefit of the presented method.

Now we use real frequency measurements from the ENTSO-E grid to compare the proposed method where we continuously adjust the operational schedule to a conventional situation where the operational schedule is not adjusted. We do this via simulations based on the model presented in Sec. 4. The simulation is conducted as follows. The historical grid frequency deviation measurements Δf is translated to a certain required power consumption for the portfolio according to the ENTSO-E specifications for primary frequency control, see Sec. 5. The sampling time is 1 second, as required by the regulations. For the conventional case, we simply let the portfolio consume the required electricity according to the reference dictated by the grid frequency deviations and examine the resulting energy level. This benchmark case is then compared to a case where the proposed method is utilized to restore the energy level via operational schedule adjustments. In this simulation, a simple controller is implemented that seeks to restore the portfolio energy level by continuously adjusting the operational schedule. This is further made clear in the following concrete simulation results.

In Figure 14.9, a four-hour period of operation is illustrated based on the real life frequency measurements presented in subplot 1. Subplot 2 shows the resulting power consumption of the portfolio in the two situations illustrating that both strategies provide fast responses according to the demand. The consumption of the conventional strategy is directly dictated by the grid frequency deviation Δf; on the contrary, the consumption in the case where operational schedule adjustments are allowed is a function both of the grid frequency deviation but also of how the operational schedule is adjusted, see Figure 14.4. Subplot 3 shows the energy level of the portfolio. This plot reveals that the conventional method with no operational schedule adjustments will require an energy delivery that is far outside the limits of the portfolio, while the presented method is able to stay within the limits. Subplot 4 shows the fixed operational schedule compared to the adjusted operational schedule. The operational schedule is adjusted under the latency and ramping constraints of secondary reserve which is the reason for the low frequency content in this signal.

The figure shows the important result that the continuous operational schedule adjustment method allows an energy limited portfolio of flexible consumption devices to utilize its strength of being able to provide fast regulation without being driven away from the energy midpoint.

To further investigate the method, we perform a number of 1-week long simulations using real ENTSO-E frequency measurements. The simulations show that the operational schedule adjustments during the course of a week sum up to around 6 MWh of both upward and downward regulation when providing a symmetric delivery of $P_1^{\text{res}} = 0.5$ MW. The adjustments are made according to the constraints of secondary reserve and consequently the price of secondary reserve applies. The price is $\pi_2 \approx 13$ €/MWh in the Western Danish market which yields an expense around 150 € for a week. By comparison, the income per symmetric MW of primary reserve capacity is $\pi_1 \approx 30$ €/MW yielding a total income in the order of $2,500$ € for the delivery of $P_1^{\text{res}} = 0.5$ MW for one full week. This illustrates that the fast regulation of the flexible consumption devices is very valuable compared to the small amounts of secondary reserve that must be purchased to continuously restore the energy level. In other words: the method allows the flexible consumers to deliver the expensive fast reserve while while the inexpensive slow responses are shifted to the slower reserve providers.

By simulating over several weeks we further discover that when the contracted deliv-

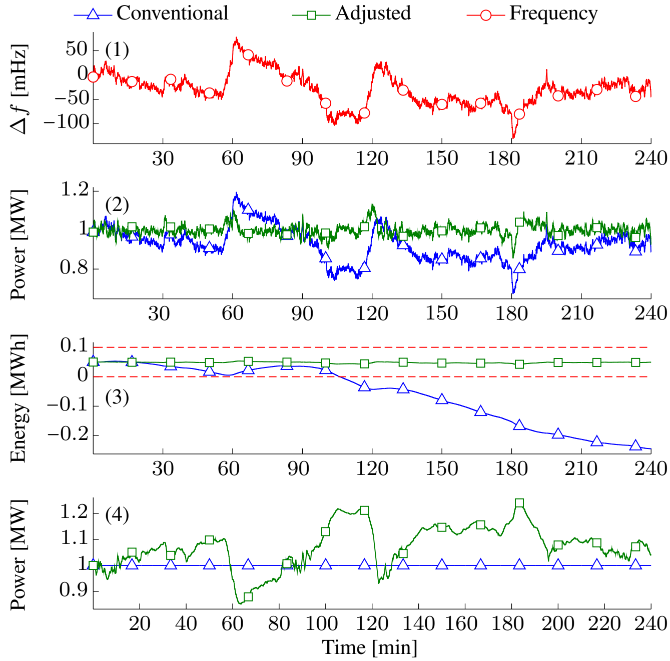

Figure 14.9: Comparison of the conventional case with no operational schedule adjustments and the proposed method where the operational schedule is adjusted. Subplot 1: system frequency deviation. Subplot 2: Portfolio power response. Subplot 3: Energy level of the portfolio. The dashed red lines indicate the energy limitations. Subplot 4: The adjusted operational schedule.

ery is $P_1^{\text{res}} = 0.5$ MW, the highest consumption of the portfolio is in the order of 1.3 MW while the smallest consumption is in the order of 0.7 MW which is very conservative compared to the limits $P^{\max} = 2$ MW and $P^{\min} = 0$ MW. The reason is that we have dimensioned the bid P_1^{res} after the worst case situation as described in Sec. 8; however, these simulations indicate that it might be possible to find a way to be less conservative such that bids close to the total capacity can be made, i.e. that we in this example would be able to offer $P_1^{\text{res}} = 1$ MW. This study is, however, outside the scope of this work.

Simulation example II: uncertain baseline

In this second example we illustrate how the proposed method resolves the issue of uncertain baseline predictions. We consider the real life case presented in [40] where the baseline consumption of a portfolio of heat pumps is examined. The uncertainty arises from the fact that the outdoor temperature, the solar irradiation, and the human behavior cannot be predicted accurately. In Figure 14.10 we show the real life power consumption of a heat pump portfolio along with a prediction of the consumption made the day before. The results are taken from [40] and scaled from a portfolio of 40 heat pumps to a portfolio of $1,000$ heat pumps revealing an inaccuracy in the order of $P^{\text{acc}} = 0.2$ MW for the entire portfolio. The energy parameter is set to $E^{\text{cap}} = 8$ MWh for the portfolio (see Table 14.2).

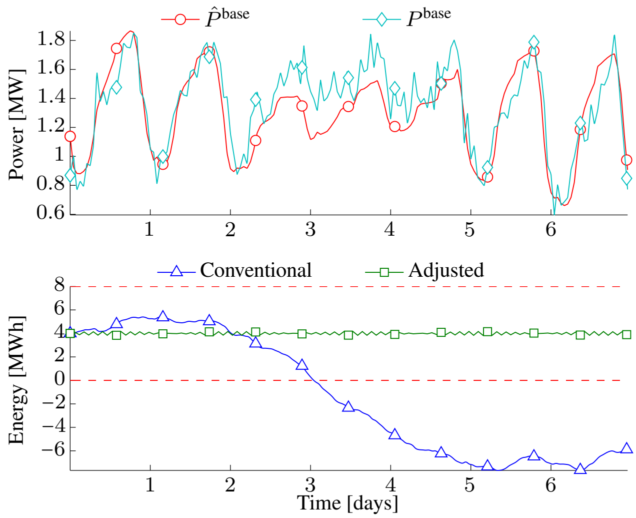

Figure 14.10: Comparison of strategies with and without adjustable operational schedules. Top: predicted baseline consumption $\hat{P}^{\text{base}}$ and actual baseline consumption P^{base}. Bottom: Energy level if no adjustments are made vs. the case where the operational schedule indeed is adjusted. The red dashed lines are the energy limitations.

We compare the two strategies: continuous baseline adjustments versus no baseline adjustments for the course of one week. The contracted reserve is $P_1^{\text{res}} = P^{\text{cap}}/2 = 0.3$ MW. To clearly show the effect of uncertain baseline predictions, we assume that no energy delivery is required during the week; consequently, the heat pump portfolio must simply assure that no power delivery is made, which corresponds to tracking the submitted operational schedule. The second subplot of Figure 14.10 clearly shows that if the operational schedule is not adjusted, the energy limitations will be violated due to the inaccurate baseline predictions; however, by allowing the operational schedule to be adjusted the energy level can be kept close to the energy midpoint.

Again, we consider the economic aspects. Over the course of a week, the amount of purchased upward and downward secondary reserve is each in the order of 3 MWh yielding a total expense of 78 € while the value of a symmetric primary reserve delivery of 0.3 MW is in the order of $1,500$ €. This clearly shows that the presented method is able to let the portfolio deliver the valuable fast responses while the slower and cheaper responses are shifted to the providers of secondary reserve.

9 Conclusion

In this paper we considered an aggregator that provided ancillary services based on a portfolio of flexible consumption devices. We proposed a method where the aggregator was allowed to continuously adjust its operational schedule and hereby restore the energy level of the flexible consumption devices. This made it possible to utilize flexible consumption devices with energy limitations and with inaccurate baseline predictions to participate in the ancillary service markets to a much larger extent than under the current regulations.

The proposed method was illustrated through two numerical examples, one example where an aggregator of flexible consumption devices was characterized with a very low energy capacity, and another example where only an inaccurate consumption baseline was available. In both examples, the proposed method was able to radically increase the feasible reserve bids compared to a situation where the aggregator was not allowed to adjust the operational schedule.

Consequently, the method proposed in this work allows new providers of fast ancillary services to be able to enter the electricity markets and possibly replace the conventional fossil fuel based ancillary service providers.

Acknowledgements

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Paper 12

Model Predictive Control for Power Flows in Networks with Limited Capacity

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Abstract

We consider an interconnected network of consumers powered through an electrical grid of limited capacity. A subset of the consumers are *intelligent consumers* and have the ability to store energy in a controllable fashion; they can be filled and emptied as desired under power and capacity limitations. We address the problem of maintaining power balance between production and consumption using the intelligent consumers to ensure smooth power consumption from the grid. Further, certain capacity limitations to the links interconnecting the consumers must be honored. In this paper, we show how this problem can be formulated as an optimization problem, leading directly to the design of a model predictive controller. Using this scheme, we are able to incorporate predictions of future consumption and exploit knowledge of link limitations such that the intelligent consumers are utilized ahead of time ensuring high performance.

1 Introduction

With an increasing focus on climate-related issues and rising fossil fuel prices, the penetration of renewable energy sources is likely to increase in the foreseeable future throughout the developed world [1]. Since many of these renewable sources of energy are difficult to control, base load units (e.g., fossil fuel-fired co-generation plants) must be kept in reserve to compensate for temporary shortages. The higher the percentage of renewable sources and the more fluctuating the power production, the harder the regulation task becomes for the base load units (see e.g. [2]). This *balancing problem* is typically solved centrally by a Balance Responsible Entity for a given power grid region, by activating or de-activating controllable reserves via an Automatic Generation Control system (see e.g. [3]).

Traditionally, control of large, networked systems is achieved by designing local, subsystem-based controllers that ignore the interactions between the different subsystems [4]. However, it is well known that such designs can lead to poor performance and coordinated solutions have thus been pursued in recent years. [3] and [5] present distributed model-based predictive control (MPC) schemes to solve the Automated Generation Control problem, albeit without taking uncontrollable energy sources into account. [6] uses distributed MPC to solve the balancing problem by actively controlling a portfolio of fossil fuel fired power plants in order to counteract fluctuations induced by renewable sources such as wind farms. However, most existing solutions have so far only considered the production side.

A *smart grid* is an electric power system, where both producers and consumers are equipped with control capabilities that allow them to participate in these balancing efforts, for instance by allowing local devices with large time constants to store more or less energy at convenient times and thereby adjusting the momentary consumption, see e.g. [7] and [8]. One obvious method to do so is by exploiting large thermal time constants in deep freezers, refrigerators, local heat pumps etc.; extra energy can be stored during off-peak hours, and the accumulated extra cooling or heating can then be used by turning compressors and similar devices on less frequently during peak hours, see e.g. [9]. Implementing such capabilities requires local measurement and feedback of current energy and power demands [10]. Consumers equipped with such measurement and feedback capabilities will be referred to as *intelligent consumers* in the following. Such an intelligent consumer could also represent a large number of units aggregated into one consumer.

Recently, [11] introduced a hierarchical MPC design to distribute resources to intelligent consumers that makes active use of the consumers to counteract quickly fluctuating imbalances. Since the consumers do require a certain amount of energy over time in order to satisfy local performance requirements, e.g. quality of foodstuff kept in cold storage, constraints on both instantaneous power and energy consumed over a specific time horizon had to be considered for each consumer. However, the setup considered in [11] was idealized in many ways; for example, the grid topology was completely ignored. That is, it was not taken into account that the power grid itself has limits to how much power it can convey at any given point in time from one node to another and that these constraints may be different from one part of the grid to another.

In this paper, we extend the design in [11]. We consider a number of both intelligent consumers and uncontrollable consumers interconnected in a network. The uncontrollable consumers are characterized by power consumptions that cannot be controlled but that we have good predictions of due to the very competitive energy market, where such predictions are most valuable. The intelligent consumers, on the other hand, are characterized by the ability to store energy in a controllable fashion.

A controller is responsible for ensuring balance between power consumption and production. The controller can balance the uncontrollable consumption by assigning power directly from the supplier, but at a significant cost; it is therefore advantageous for the controller to utilize the storage possibilities in the intelligent consumers. Further, the controller must ensure that the grid capacity limitations are honored.

Based on the structure of the problem, it follows naturally to design a model predictive controller. Based on two simulation examples, we show that the developed MPC controller indeed is able to utilize the intelligent consumers such that high performance is achieved. We use the examples to show that the MPC controller uses the predictive abilities to ensure balance without stressing the supplier; based on consumption predictions, the controller is able to fill or empty the energy storages ahead of time, to compensate for future known events. Further, the examples show that the MPC controller is able to exploit knowledge of grid capacities and thereby reduce congestion problems by preemptive action.

The outline of the rest of the paper is as follows. First, in Section 2 we describe the system setup under consideration. Next, in Section 3 we present the main result of the work: a predictive control strategy that takes simple grid constraints into account in the distribution of power to intelligent consumers. Section 4 presents simulation examples that illustrate the feasibility of the design, and finally Section 5 describes future work, while 6 sums up the work.

2 Modeling

We consider a setup as depicted in Figure 15.1. The figure illustrates two types of consumers; a set of m uncontrollable consumers and a set of n intelligent consumers.

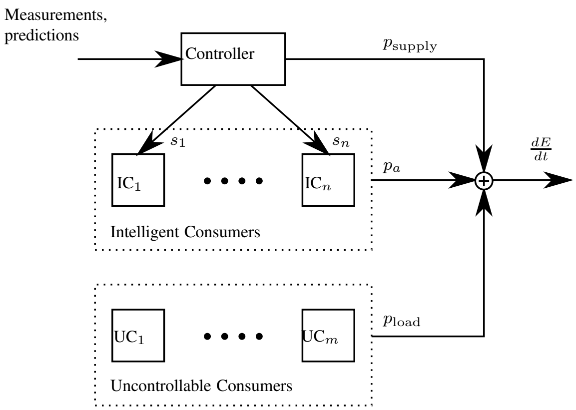

Figure 15.1: The signal flow in the network. The controller must reduce the power imbalance E by appropriate utilization of the ICs without stressing the power supplier.

The n intelligent consumers are characterized by power consumptions $p = (p_1, \ldots, p_n) \in \mathbf{R}^n$, and a total consumption $p_a = \mathbf{1}^T p$, where $\mathbf{1}$ is a vector of ones, i.e. $\mathbf{1} = (1, \ldots, 1) \in \mathbf{R}^n$. The consumption p_i of an intelligent consumer consists of a drain rate and a storage rate

$$p_i(t) = s_i(t) + r_i(t) \tag{15.1}$$

$$\frac{dE_i(t)}{dt} = s_i(t) \tag{15.2}$$

where r_i is the drain rate while s_i is the storage rate and $E_i(t)$ is the stored energy, as illustrated in Figure 15.2. As an example, consider a house with electrical heating as an intelligent consumer. Some energy is lost due to heat exchange with the outside world corresponding to the drain rate r_i. If the supplied power is larger than this drain rate, i.e. $s_i(t) > 0$, thermal energy is stored in the house and E_i increases. This allows us to supply little or zero power to the house at a later time such that $s_i(t) < 0$ whereby we will use the stored energy and E_i will decrease. With this understanding we note, that a negative s_i does not necessarily mean that we supply electrical power to the grid, but simply that we use less than the natural drain rate r_i. Finally note, that for simplicity we assume that the drain rate is independent on the amount of stored energy.

The stored energy E can take various forms; if the intelligent consumer i is a house with electrical heating, E_i would be thermal energy, while E_i would be electrical energy if consumer i was an electric vehicle. The amount of energy stored in intelligent consumer i can be freely regulated via storage rate s_i under limitations regarding rate and capacity:

$$\underline{s}_i \le s_i(t) \le \overline{s}_i \tag{15.3}$$

$$\underline{E}_i \le E_i(t) \le \overline{E}_i, \tag{15.4}$$

where the constants $\underline{s}_i$, $\overline{s}_i$, $\underline{E}_i$, $\overline{E}_i \in \mathbf{R}$ describe these limits. For a house with electrical heating, the energy levels $\underline{E}_i$, $\overline{E}_i$ would describe the lowest and highest allowed temperature in the house (comfort limits). The rate limits $\underline{s}_i$, $\overline{s}_i$ would describe lower and upper bounds on the power we can put into or avoid putting into the house.

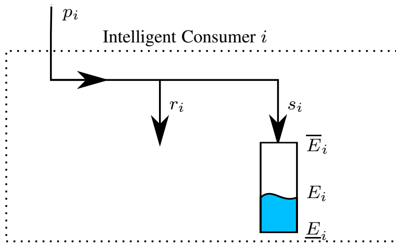

Figure 15.2: Model of an intelligent consumer consisting of a drain rate r_i and a storage rate s_i, thus with a total consumption p_i. The stored energy is denoted E_i.

The m uncontrollable consumers are characterized by power consumptions $q = (q_1, \ldots, q_m) \in \mathbf{R}^m$, yielding a total consumption $p_{\text{load}} = \mathbf{1}^T q$.

We define the system imbalance E as the integrated mismatch between production and consumption

$$\frac{dE(t)}{dt} = p_{\text{supply}}(t) - p_{\text{load}}(t) - p_a(t), \tag{15.5}$$

where p_{supply} denotes the power requested from the power supplier, see Figure 15.1. The interpretation of this imbalance depends on the system under consideration, but could e.g. represent deviation from planned operation. In this case, the imbalance would be penalized economically according to up- and down regulation prices.

The requested power p_{supply} is subject to power limits

$$\underline{p}_{\text{sup}} \leq p_{\text{supply}}(t) \leq \overline{p}_{\text{sup}}, \tag{15.6}$$

due to physical constraints of the power supplier. Further, it is desired to keep p_{supply} smooth to avoid stressing the power plant.

Next, we consider the power flows in the network. The $n+m$ consumers are connected to the grid through a network of links, as illustrated in Figure 15.3. Let l and v denote the number of links and nodes, respectively, and let $f = (f_1, \ldots, f_l) \in \mathbf{R}^l$ denote the flows through the links. We can then represent the coupling between flows and power consumptions as

$$Ff(t) = Pp(t) + Qq(t), \tag{15.7}$$

where $F \in \mathbf{R}^{v \times l}$, $P \in \mathbf{R}^{v \times n}$, $Q \in \mathbf{R}^{v \times m}$. The entries in F, P, Q describe the network interconnections:

$$(F)_{ij} = \begin{cases} 1 & \text{if flow } j \text{ enters node } i \\ -1 & \text{if flow } j \text{ leaves node } i \\ 0 & \text{if flow } j \text{ is not connected to node } i \end{cases}$$

$$(P)_{ij} = \begin{cases} 1 & \text{if IC}_j \text{ is connected to node } i \\ 0 & \text{if IC}_j \text{ is not connected to node } i \end{cases}$$

$$(Q)_{ij} = \begin{cases} 1 & \text{if UC}_j \text{ is connected to node } i \\ 0 & \text{if UC}_j \text{ is not connected to node } i, \end{cases}$$

where $(X)_{ij}$ denotes the (i, j)th entry in X.

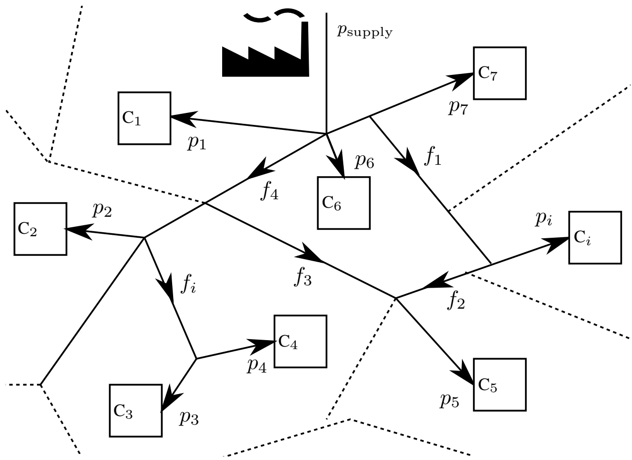

Figure 15.3: A number of intelligent consumers (ICs) and uncontrollable consumers (UCs) powered through a network of links.

$$-\overline{f}_j \leq f_j(t) \leq \overline{f}_j, \tag{15.8}$$

where $\overline{f}_j$ represents the capacity limitation of link j.

3 Controller Synthesis

The objective of the controller is twofold. The controller must

- maintain system balance (between consumption and production),
- avoid stressing the power supplier.

This means that the imbalance E must be driven to zero by the controller. As it is costly to assign power from the power supplier p_{supply} for fast regulation, it is attractive for the controller to involve the intelligent consumers in the balancing; the intelligent consumers will provide this regulation freely under the given power and capacity limitations.

In the following we formulate the task of the controller as an optimization problem based on the models presented above. As the dynamics of the intelligent consumers are pure integration, we can easily formulate discrete approximations. In the rest of the paper, we use discrete time models where k is used to indicate sample number and a sample time of 1 s is used to ease the notation.

Objectives

Based on a finite horizon N, we formulate the following three objectives of the controller at time k.

Imbalance Reduction The main task of the controller is to minimize the imbalance E between production and consumption. We can describe the imbalance to be minimized as

$$J_e(k) = \sum_{\kappa=k+1}^{k+N} \|E(\kappa)\|^2.$$

Low Stress on Power Supplier It is further desired to avoid stressing the power supplier, which is accomplished by assigning power from the power plant smoothly. We formulate this as a minimization of the change in p_{supply}

$$J_p(k) = \sum_{\kappa=k}^{k+N-1} \|p_{\text{supply}}(\kappa) - p_{\text{supply}}(\kappa-1)\|^2.$$

Energy Storage Mid-Ranging Finally, it is desirable to keep the energy storages close to their respective mid-points, hereby allowing large freedom for preemptive action. By using $(\overline{E}_i - \underline{E}_i)/2$ as the energy mid-point, we can formulate this storage mid-ranging as

$$J_m(k) = \sum_{\kappa=k+1}^{k+N} \sum_{i=1}^{n} \|E_i(\kappa) - (\overline{E}_i - \underline{E}_i)/2\|^2.$$

Optimization Problem

At time k we look N steps into the future and minimize the cost $J(k) = (J_e(k), J_p(k), J_m(k)) \in \mathbf{R}^3_+$ subject to the dynamics and the given constraints. This can be expressed as the following optimization problem.

$$\begin{array}{ll}
\text{minimize} & \lambda^T J(k) \\
\text{subject to} & E(\kappa+1) = \\
& \quad E(\kappa) + p_{\text{supply}}(\kappa) - \mathbf{1}^T q(\kappa) - \mathbf{1}^T p(\kappa) \\
& E_i(\kappa+1) = E_i(\kappa) + s_i(\kappa) \\
& p_i(\kappa) = s_i(\kappa) + r_i(\kappa) \\
& \underline{s}_i \le s_i(\kappa) \le \overline{s}_i \\
& \underline{E}_i \le E_i(\kappa) \le \overline{E}_i \\
& \underline{p}_{\text{sup}} \le p_{\text{supply}}(\kappa) \le \overline{p}_{\text{sup}} \\
& Ff(\kappa) = Pp(\kappa) + Qq(\kappa) \\
& -\overline{f}_j \le f_j(\kappa) \le \overline{f}_j
\end{array}$$

where $\kappa = k, \ldots, k+N-1$ and where $i = 1, \ldots, n$ and $j = 1, \ldots, l$. The variables are $p_i(\kappa),\ E(\kappa+1),\ E_i(\kappa+1),\ s_i(\kappa),\ p_{\text{supply}}(\kappa),\ f_j(\kappa) \in \mathbf{R}$, while $\lambda \in \mathbf{R}^3_+$ is a vector valued parameter providing a weighting between the three objectives. The data to the optimization problem is $r_i(\kappa),\ q_i(\kappa),\ E_i(k),\ E(k) \in \mathbf{R}$. Discrete time equivalents of Equations (15.1) – (15.8) are used.

Note that this is a standard MPC problem, see e.g. [12].

Controller Algorithm

Based on the optimization presented above, we formulate an algorithm for controlling the intelligent consumers as follows. The controller algorithm implements the above optimization in a receding horizon fashion.

1. Gather estimates of the future drain rates of the intelligent consumers $[r_i(k), \ldots, r_i(k+N-1)]$ and power consumptions of the uncontrollable consumers $[q_i(k), \ldots, q_i(k+N-1)]$. Further, gather the current energy levels $E_i(k)$ and the imbalance $E(k)$.
2. Solve the MPC optimization problem presented in Section 3. Let the solution be denoted $[s_i^\star(k), \ldots, s_i^\star(k+N-1)]$ for the storage rates and $[p_{\text{supply}}^\star(k), \ldots, p_{\text{supply}}^\star(k+N-1)]$ for power of the supplier.
3. Apply the power $s_i^\star(k)$ to intelligent consumer i for $i = 1, \ldots, n$ and assign the power $p_{\text{supply}}^\star(k)$ from the power supplier.
4. Increase k by one and repeat from step 1.

Hereby we have a controller that is able to react preemptive to future known events, while taking given physical constraints of the system into account.

4 Simulation Example

The examples presented in this section show the benefits of utilizing the storage capacities of intelligent consumers, and illustrate that MPC is an attractive control scheme to accomplish this task.

In order to keep the methods of this paper generic to both the transmission level and the distribution level, we do not include any units on the consumers. Hereby we do not specify whether the intelligent consumers represent a single electrical unit or a large number of aggregated units. Further, the simulation example is kept at a conceptual level with only $n = 4$ intelligent consumers and $l = 4$ links, such that the behavior of the controller is clear (see Figure 15.4). We impose capacity and power constraints for the storages

$$\begin{aligned} \underline{s}_i &\le s_i(k) \le \overline{s}_i \\ 0 &\le E_i(k) \le \overline{E}_i, \end{aligned}$$

i.e. we let $\underline{E}_i = 0$ for simplicity. Further we have constraints on the link capacities and power limits on the production

$$\begin{aligned} -\overline{f}_j &\le f_j(k) \le \overline{f}_j \\ \underline{p}_{\text{sup}} &\le p_{\text{supply}}(k) \le \overline{p}_{\text{sup}}. \end{aligned}$$

The limits on energy storages and on link capacities are presented in Table 15.1 while $\underline{p}_{\text{sup}}$, $\overline{p}_{\text{sup}}$ are chosen to be -10.0 and 10.0, respectively. We assume that the drain rates are constant $r_i(k) = r_i$ and use the values presented in Table 15.1.

$$Ff(k) = p(k) + q(k)$$

where

$$F = \begin{bmatrix} 1 & -1 & -1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

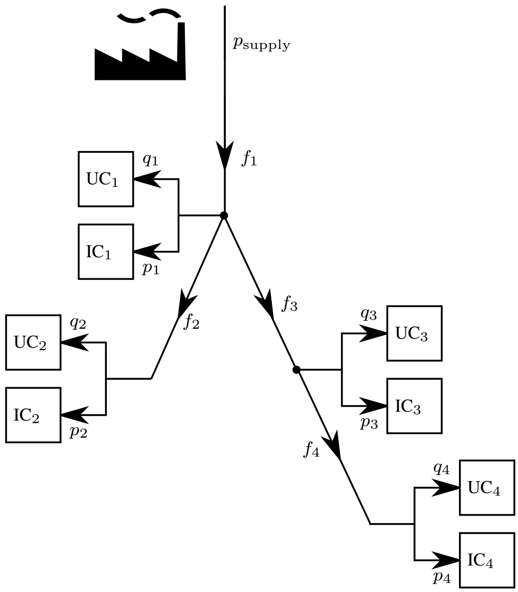

Figure 15.4: Simulation example setup. Four intelligent consumers and four uncontrollable consumers are interconnected by four links.

$\overline{E}_1 = 4.0$	$\underline{s}_i = -4.7$	$\overline{s}_i = 3.4$	$r_1 = 4.0$	$\overline{f}_1 = 40.0$
$\overline{E}_2 = 5.0$	$\underline{s}_i = -3.3$	$\overline{s}_i = 3.5$	$r_2 = 1.0$	$\overline{f}_2 = 10.0$
$\overline{E}_3 = 4.0$	$\underline{s}_i = -4.2$	$\overline{s}_i = 4.0$	$r_3 = 2.0$	$\overline{f}_3 = 25.0$
$\overline{E}_4 = 5.0$	$\underline{s}_i = -2.8$	$\overline{s}_i = 5.5$	$r_4 = 3.0$	$\overline{f}_4 = 15.0$

Table 15.1: Key parameters used in the simulation example.

In the following we present simulation results using a prediction horizon of $N = 10$ and an appropriate weight vector λ.

Overall Performance

The behavior of the controller is illustrated in the following. We compare two cases, one where the controller is allowed to utilize the storage facilities in the intelligent consumers and one where this is not allowed. In both cases we observe the imbalance E and utilization of the power p_{supply}. In the case where it is not allowed to utilize the intelligent consumers, the controller will simply choose p_{supply} such that the optimal trade-off between imbalance and power supply stress is found.

Figure 15.5 (top) illustrates the four uncontrollable consumptions q_1 to q_4. The four consumptions constitute p_{load} as $p_{\text{load}} = \mathbf{1}^T q$. The resulting accumulated imbalance E and utilization of power from the power supplier p_{supply} are also shown in Figure 15.5.

We compare the case where the MPC controller regulates the intelligent consumers (red, dashed) with the case where the intelligent consumers are not utilized (blue, solid). We note a significant reduction of the imbalance E and a smoothing of p_{supply}.

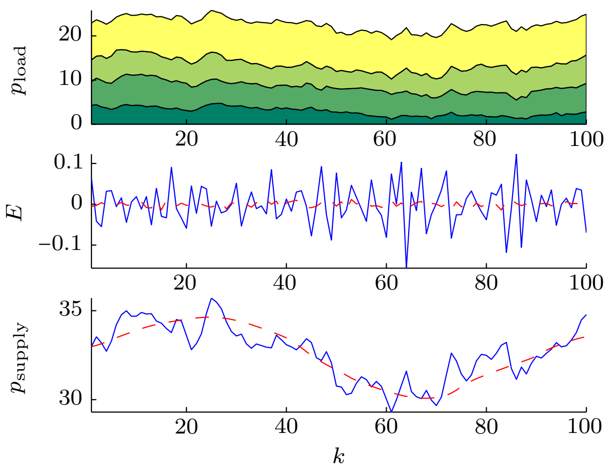

Figure 15.5: Top: the uncontrollable consumptions from q_1 (yellow, top) to q_4 (dark green, bottom). Middle and bottom: responses E and p_{supply}, respectively, with MPC control of the intelligent consumers (red, dashed) and with no active intelligent consumers (blue, solid).

Next, we examine how the MPC controller is able to handle constraints and benefit from consumption predictions. We illustrate this by considering a case where consumer 1 suddenly increases the power consumption, q_1, while the remaining consumers have constant consumptions. This results in a power consumption as illustrated in Figure 15.6 (top). The controller is assumed to be able to make a good prediction of this step (this could reflect a factory starting production at a known time of the day). Figure 15.6 illustrates that by utilizing the storage facilities of the intelligent consumers, the MPC is able to keep the imbalance close to zero, while only smoothly utilizing the power supplier p_{supply} (red, dashed curves). For comparison, the response to the same load without prediction results in an undesired abrupt change in p_{supply} and a significant imbalance (blue, solid curves).

Figure 15.7 shows the corresponding energy levels of the intelligent consumers. In the case of prediction (red, dashed curves), the intelligent consumers contribute to the smooth transition of p_{supply}; all four intelligent consumers use the external power p_{supply} to fill their reservoirs before the step in the load occurs, and start unloading once the step occurs. This action ahead of time, allows the external power p_{supply} to increase smoothly over 40 samples, instead of an undesired rapid change causing congestion. With no prediction (blue, solid curves), the intelligent consumers are not able to fill their reservoirs ahead of time and are therefore incapable of allowing a smooth transition.

Figure 15.8 shows the corresponding link flows f along with the link capacities. In the predictive case (red, dashed curves), the four reservoirs start filling up the reservoirs ahead of time, saturating f_4. This is the reason that reservoir 4 is only partially filled prior

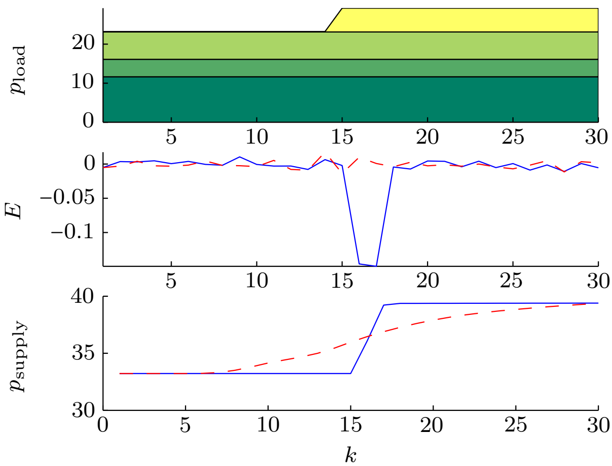

Figure 15.6: Response to a step in the load q_1 of consumer 1 (upper plot) where we observe the resulting imbalance E and power from the supplier p_{supply} (bottom two plots). A comparison is presented with a controller utilizing predictions of the step (red, dashed) and a controller not utilizing this prediction (blue, solid).

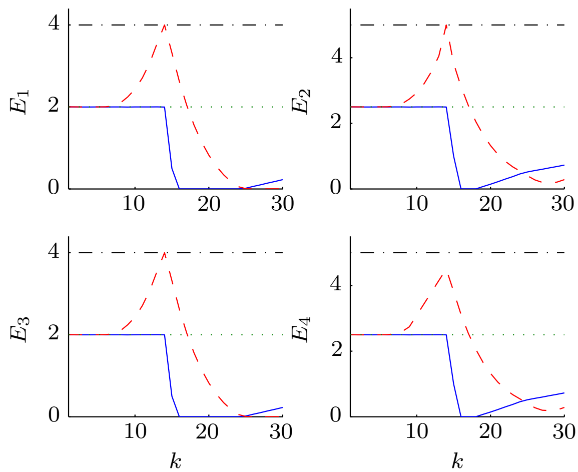

Figure 15.7: The four energy levels E_i in the case of predictive control (red, dashed) and no prediction (blue, solid) when applying a load as presented in Figure 15.6. Further, the upper energy levels $\overline{E}_i$ (black dash-dotted) and the energy mid-points $(\overline{E}_i - \underline{E}_i)/2$ (green dotted) are depicted.

to the step in load, see Figure 15.7. This is in contrast to the case with no prediction (blue, solid curves), where the controller does not act ahead of time, and therefore does not use the full capacity of link 4.

We sum up and conclude on the results in Section 6.

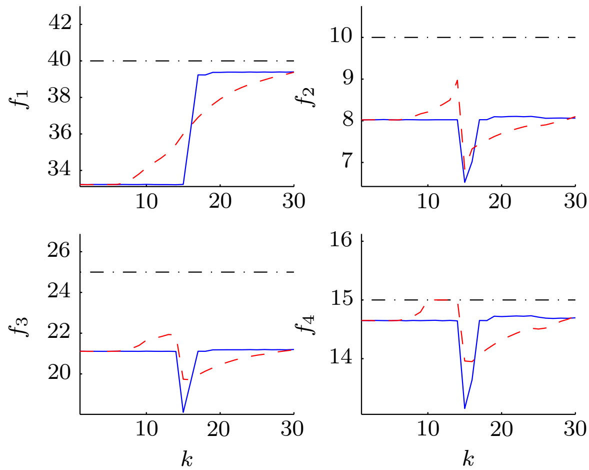

Figure 15.8: The four link flows corresponding to the step in p_{load} presented in Figure 15.6 in the predictive case (red, dashed) and with no prediction (blue, solid). The capacity limits $\overline{f}_j$ are black dashed.

5 Discussion

In the presented method, two rough assumptions are used. The first is that the intelligent consumers are seen as ideal storages and the second is that only the predictable noise is considered. A natural extension of this work is therefore to extend the MPC algorithm to handle storages, that are not ideal, as presented in e.g. [13], and further to handle unpredictable noise. We intend to address this in our future research.

Another important issue is that we have assumed that all consumers in the network are under the jurisdiction of the same balancing responsible. In our future research, we will consider the questions that arise when there are several balancing responsible companies in the network, as is the case in a liberalized energy market.

Finally we note that the presented method is only suitable for a relatively small number of consumers, as the computational burden scales poorly with the number of states ($O(n^3)$), see [14]. This calls for alternative methods when the system is large e.g. in the case of control on a national level. One approach to remedy this problem is to use a hierarchical approach, where a high-level controller controls a number of so called *aggregators*. Each aggregator then controls a small number of consumers, such that the computational burden is reduced and distributed among the aggregators. This concept is presented in [11] and would be a natural extension of the controller design presented in this work.

6 Conclusion

In this paper, an MPC approach was proposed for the control of intelligent consumers connected to the power grid through a network of limited capacity. The MPC strategy is well suited for this problem, as it directly incorporates consumption predictions and system limitations; given good predictions within the control horizon, we are able to handle the trade-off between the objectives optimally, while honoring all constraints.

The presented simulation examples illustrate the advantages of using MPC to control the intelligent consumers where we are able to exploit consumption predictions and handle system constraints. The result is that the controller is able to act ahead of time, ensuring balance without stressing the power supplier.

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Paper 13

Congestion Management in a Smart Grid via Shadow Prices

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Abstract

We consider a distribution grid interconnecting a number of consumers with flexible power consumption. Each consumer is under the jurisdiction of exactly one balancing responsible party (BRP), who buys energy at a day-ahead electricity market on behalf of the consumer. We illustrate how BRPs can utilize the flexibility of the consumers to minimize the imbalance between the consumed and the purchased energy thereby avoiding trading balancing energy at unfavorable prices. Further we show how shadow prices on the distribution lines can be used to resolve grid congestion without information sharing between the BRPs.

1 Introduction

Due to the increasing focus on renewable energy and the rising fossil fuel prices, the penetration of renewable energy is likely to increase in the foreseeable future throughout the developed world ([1]). In Denmark, the wind penetration has increased from close to zero in the 1980s to around 20 % in 2009 ([2]), while the Danish Government Platform states that the wind penetration should be 50 % by 2020 ([3]). This increase of renewable non-dispatchable production causes a balancing problem between production and demand ([4]) which is typically solved at the production side ([5, 6, 7])

In a *smart grid*, not only the production side is active; both producers and consumers participate in the balancing efforts. The consumer side can contribute by *moving loads* in time, e.g. by allowing local devices with large time constants to store more or less energy at convenient times, thereby adjusting the momentary consumption, see e.g. ([8], [9] and [10]). One obvious method to do so is by exploiting large thermal time constants in deep freezers, refrigerators, local heat pumps etc. ([11]). Consumers with this ability to move load in time will be referred to as *flexible consumers* in the sequel.

The control of such flexible consumers in a grid of limited capacity is described in ([12]). That work treats the problem at an overall level where the energy market is not taken into consideration: both optimization and congestion management relies on all information being centrally available. However, due to the deregulation of the European power market ([13]), the congestion management should be handled via markets and not by regulations. In this paper we therefore take the current electricity market as starting point: energy is bought and sold at a day-ahead market while balancing energy is traded after the hour of operation to ensure financial balance. We show how balancing responsible parties (BRPs) can utilize flexible consumers to move load in time, thereby minimizing imbalance between the energy purchased at the day-ahead market and the actual consumption. This allows the BRPs to buy energy at the day-ahead market in the hours where the energy is cheap, e.g. in the hours of high renewable energy generation or at night. It also minimizes the amount of balancing energy the BRP has to trade at unfavorable prices. We further show how the distribution grid constraints can be honored based on the shadow prices at distribution line capacities; in this way grid congestion can be resolved via a market and not by regulations.

The outline of the rest of the paper is as follows. First, in Sec. 2 we describe the congestion management problem under consideration. Next, in Sec. 3 we design a distributed receding horizon controller for imbalance reduction using shadow prices. Section 4 describes how to implement this structure with the current players in the electrical market, while Sec. 5 illustrates the methods with a numerical example. Finally, Sec. 6 sums up the work.

2 Modeling

We consider a number of consumers and a number of BRPs: each consumer has entered an agreement with exactly one BRP who buys energy at the energy market on behalf of the consumer. In this work we consider the future scenario where each BRP is allowed to control some flexible consumption of the consumers under their jurisdiction based on a contract between the consumer and the BRP. This flexible consumption might be a refrigerated warehouse allowing BRP to control the refrigerator temperature within some band or it could be a private household, allowing the BRP to control the exact charging pattern of the batteries of an electric vehicle. Each BRP will benefit from this by utilizing the flexibility to optimize the energy purchase while the consumer will benefit from the contract by some payment from the BRP.

The active control of the consumers is likely to cause congestion on the distribution grid as the BRPs often will activate the flexible consumption at the same hours of operation, namely when favorable energy prices occur. It is therefore necessary for the BRPs to consult the distribution grid operator (DSO) before activating flexible consumption, such that congestion is avoided. In the following we show how this congestion management can be settled through shadow prices.

In the following we consider a star topology distribution grid (no loops) consisting of n_L distribution lines of limited capacity. A total of n_B BRPs are active in the distribution grid and BRP number i is responsible for m_i consumers. The setup is illustrated in Fig. 16.1 and discussed in detail in the sequel.

In the following modeling of the system, we describe the dynamics by discrete time equations. We use k to indicate sample number and use a sample time of 1 hour to ease the notation.

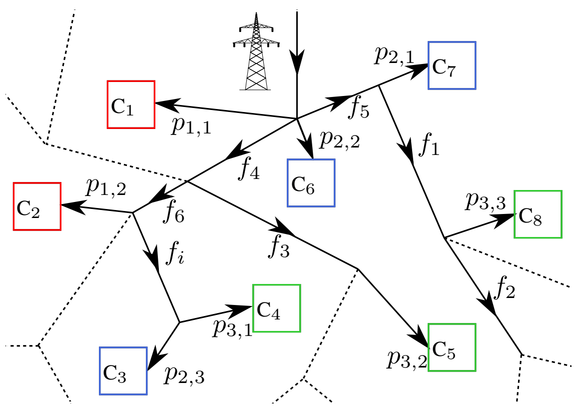

Figure 16.1: Interconnected consumers under the jurisdiction of different BRPs sharing the same distribution grid (dotted lines indicate that only a small part of the total grid is shown). Note that the consumers are connected in a star-like topology, i.e., there are no loops in the grid structure.

Dynamics and Constraints

The m_i consumers under BRP i are characterized by hourly energy consumptions $p_i = (p_{i,1}, \ldots, p_{i,m_i}) \in \mathbf{R}^{m_i}$ consisting of a controllable part $\tilde{p}_i \in \mathbf{R}^{m_i}$ and an uncontrollable part $\overline{p}_i \in \mathbf{R}^{m_i}$:

$$p_i(k) = \overline{p}_i(k) + \tilde{p}_i(k) \tag{16.1}$$

subject to hourly energy constraints

$$p_i^{\min} \le \tilde{p}_i(k) \le p_i^{\max} \tag{16.2}$$

where $p_i^{\min}, p_i^{\max} \in \mathbf{R}^{m_i}$ are the lower and upper limits, respectively and where $\le$ represents componentwise inequality. Note that with this notation, non-dispatchable producers (such as wind and solar) can be included in the model as negative consumers.

The stored energy is denoted $e_i = (e_{i,1}, \ldots, e_{i,m_i}) \in \mathbf{R}^{m_i}$; this may be energy stored as either heat, cold, energy in a battery, or similar. It depends on the controllable consumption

$$e_i(k+1) = D_i e_i(k) + \tilde{p}_i(k) \tag{16.3}$$

where $D_i \in \mathbf{R}^{m_i \times m_i}$ is diagonal with diagonal elements describing the proportional drain loss of each energy storage. The storages are limited in size as described by

$$0 \le e_i(k) \le e_i^{\max} \tag{16.4}$$

where $e_i^{\max} \in \mathbf{R}^{m_i}$ is the capacity limit of the storages under BRP i.

This setup is presented in Fig. 16.2 for the consumers under BRP i: the uncontrollable consumption (load) $\overline{p}_i$ is independent on the energy storage while the drainage depends on the energy level e_i.

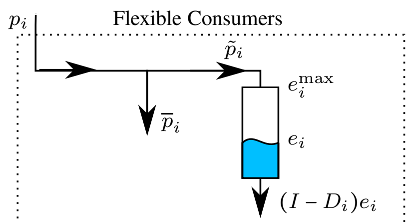

Figure 16.2: Model of the intelligent consumers under BRP i (see e.g. [14]).

The consumers are powered through the distribution grid, as illustrated in Fig. 16.1. Each BRP will contribute to the loading of the distribution lines. Let $t_i \in \mathbf{R}_+^{n_L}$ denote the partial flow caused by BRP i to the n_L distribution lines. By flow conservation, i.e. no transmission losses, and by assuming a star topology, the partial flow caused by the consumers under BRP i is given by

$$t_i(k) = R_i p_i(k) \tag{16.5}$$

where $R_i \in \mathbf{R}^{n_L \times m_i}$ is given by

$$(R_i)_{mn} = \begin{cases} 1 & \text{if consumer } n \text{ is supplied through link } m, \\ 0 & \text{otherwise.} \end{cases}$$

A meshed grid topology can be modeled by reformulating (16.5), see [12].

The total flows $f = (f_1, \ldots, f_{n_L}) \in \mathbf{R}_+^{n_L}$ over the distribution lines are therefore given by

$$f(k) = \sum_{i=1}^{n_B} t_i(k) \tag{16.6}$$

where f_j is the flow through line j. The distribution grid is protected from overcurrents by electrical fuses; hence, the distribution line flows are subject to constraints

$$f(k) \le f^{\max} \tag{16.7}$$

where $f^{\max} \in \mathbf{R}_+^{n_L}$ denotes the limits of the fuses.

Objectives

The BRPs buy energy at a day-ahead spot market for each hour of the following day. We denote the energy bought by BRP i at the day-ahead spot market $q_{\mathrm{spot},i} \in \mathbf{R}$: this means that BRP i has bought the energy $q_{\mathrm{spot},i}(k)$ for the time interval from hour k to $k+1$.

During operation, the consumers under BRP i will consume the energy they need leading to a total hourly energy consumption $\mathbf{1}^T p_i(k)$ for the consumers under BRP i, where $\mathbf{1}$ is a vector of all ones. If this energy consumption does not match the energy bought at the day-ahead market, the BRP must settle the economic imbalance between the bought and consumed energy. This *balancing energy* is by definition traded with the transmission system operator (TSO): if the BRP has bought more energy than is consumed, he has per definition sold the excess energy to the TSO and vice versa. We denote the balancing energy $q_{\mathrm{bal},i}$ and use the sign convention

$$q_{\mathrm{bal},i}(k) = \mathbf{1}^T p_i(k) - q_{\mathrm{spot},i}(k) \tag{16.8}$$

meaning that the regulating energy $q_{\mathrm{bal},i}$ is positive when BRP i buys energy from the TSO and negative when the BRP sells energy to the TSO.

Trading balancing energy with the TSO is often disadvantageous for a BRP due to the prices on balancing energy. One strategy for the BRPs is therefore to minimize q_{bal} thereby avoiding trading balancing energy. This minimization of q_{bal} is currently done by estimating the future energy consumption and buying accordingly at the day-ahead spot market. Introducing flexible consumers, however, allows the BRPs to actively minimize the balancing energy during the hour of operation by utilizing the flexible consumers accordingly.

3 Controller Synthesis

In this section, a controller is designed to utilize the flexible consumers under each BRP such that the imbalance is minimized. It is natural to design a receding horizon controller, as this allows us handle the constraints of the flexible consumers and to incorporate predictions of the future energy consumption ([15]) which are available due to the very competitive nature of the energy market. We assume that good predictions exist $K-1$ hours into the future, and use this as a basis for the controller design in the following.

We assume that the strategy of each BRP is to minimize the balancing energy. Based on this, we describe the objective function of BRP i as a convex function of the balancing energy which we denote $\ell_i(q_{\mathrm{bal},i}(k)) : \mathbf{R} \to \mathbf{R}_+$.

Compact Representation

To ease the notation when deriving the controller, we stack the variables introduced in the previous section: upper case variables denote the stacked version of the lower case variables, e.g. for $P_i(k)$ we have

$$P_i(k) = \left(p_i^T(k), \ldots, p_i^T(k+K-1)\right)^T \in \mathbf{R}^{n_B K}$$

and similarly for $E_i, \tilde{P}_i, \overline{P}_i, T_i, F, F^{\max}, Q_{\text{bal},i}$ and $Q_{\text{spot},i}$.

Using this notation, we can describe the dynamics of the consumers under the jurisdiction of BRP i for time $k, \ldots, k+K-1$ as follows.

$$\begin{array}{lcl} E_i(k+1) & = & \Omega_i E_i(k) + \tilde{P}_i(k) \\ Q_{\text{bal},i}(k) & = & \Upsilon_i(\overline{P}_i(k) + \tilde{P}_i(k)) - Q_{\text{spot},i}(k) \\ T_i(k) & = & \Psi_i(\overline{P}_i(k) + \tilde{P}_i(k)) \end{array} \tag{16.9}$$

where

$$\begin{aligned} \Omega_i &= \mathbf{diag}\left(D_i, \ldots, D_i\right) \in \mathbf{R}^{m_i K \times m_i K} \\ \Upsilon_i &= \mathbf{diag}\left(\mathbf{1}^T, \ldots, \mathbf{1}^T\right) \in \mathbf{R}^{K \times m_i K} \\ \Psi_i &= \mathbf{diag}\left(R_i, \ldots, R_i\right) \in \mathbf{R}^{n_L K \times m_i K} \end{aligned}$$

where $\mathbf{diag}(X, Y, \ldots)$ denotes a block diagonal matrix with diagonal blocks $X, Y, \ldots$. We express the energy capacity constraint and rate constraints as

$$\begin{array}{lcl} \mathcal{E}_i & = & \{x \in \mathbf{R}^{m_i K} | 0 \le x \le E_i^{\max}\} \\ \mathcal{P}_i & = & \{x \in \mathbf{R}^{m_i K} | P_i^{\min} \le x \le P_i^{\max}\}. \end{array}$$

Further, we describe the distribution line constraints as

$$F(k) = \sum_{i=1}^{n_B} T_i(k) \le F^{\max}. \tag{16.10}$$

We stack the variables

$$\begin{aligned} \eta(k) &= (\eta_1(k)^T, \ldots, \eta_{n_B}(k)^T, F^T)^T \in \mathbf{R}^v \\ \eta_i(k) &= (\tilde{P}_i^T(k), E_i^T(k+1), Q_{\text{bal},i}^T(k), T_i^T(k))^T \in \mathbf{R}^{v_i} \end{aligned}$$

where $v_i = K(2m_i + n_L)$, $v = n_L + \sum_{i=1}^{n_B} v_i$ such that η_i describes the variables local to BRP i while η describes all variables. Based on this, we represent the cost of BRP i as

$$\Phi_i(\eta_i(k)) = \sum_{\kappa=k}^{k+K-1} \ell_i(q_{\text{bal},i}(\kappa))$$

and the total cost as

$$\Phi(\eta(k)) = \sum_{i=1}^{n_B} \Phi_i(\eta_i(k)).$$

Centralized Controller

Using the compact representation presented above, we can design a receding horizon controller. At time k we look $K-1$ steps ahead and solve the optimization problem

$$\begin{array}{ll} \text{minimize} & \Phi(\eta(k)) \\ \text{subject to} & E_i(k) \in \mathcal{E}_i,\ \tilde{P}_i(k) \in \mathcal{P}_i \\ & F(k) \le F^{\max} \end{array} \tag{16.11}$$

for $i = 1, \ldots, n_B$ where the optimization variables are $\eta(k)$. The solution $\tilde{P}_i^\star(k)$ is the planned action for the following K steps. In a receding horizon manner, we apply the first of the planned actions $\tilde{p}_i^\star(k)$ and then redo the optimization at next time step.

Problem (16.11) is a convex optimization problem and thus readily solvable ([16]). But this centralized controller has a huge disadvantage: all data must be centralized to solve the problem. In practice this means that each BRP would have to provide their cost functions, the states of all their flexible consumers, their consumption predictions, etc., to the central unit solving the problem. Due to the competitive nature of the energy market such information sharing is highly unlikely and we therefore decompose the optimization.

Distributed Controller

In the following we show how we can distribute the controller problem (16.11) to avoid sharing of local information among the BRPs. The centralized problem is coupled by the distribution line capacity constraints $F(k) \le F^{\max}$. As these are affine constraints, the problem is separable by dual decomposition (see, e.g., [17], [18]). By introducing Lagrange multipliers for the coupling inequality constraints we obtain the partial Lagrangian of problem (16.11)

$$L(\eta(k), \Lambda(k)) = \Phi(\eta(k)) + \Lambda^T(k)(F(k) - F^{\max})$$

where $\Lambda(k) \in \mathbf{R}_+^{n_L K}$ is the Lagrange multiplier, or shadow price, associated with the inequality $F(k) \le F^{\max}$ (see, e.g., [16], [19]). The dual function is given by

$$g(\Lambda(k)) = \inf_{\eta(k)} \left(\Phi(\eta(k)) + \Lambda^T(k)(F(k) - F^{\max})\right).$$

A subgradient of the negative dual is given by

$$S(k) \in \partial(-g)(\Lambda(k))$$

where $\partial(-g)(\Lambda(k))$ is the subdifferential of $-g$ at $\Lambda(k)$ and where $S(k) = \overline{F}(k) - F^{\max} \in \mathbf{R}^{n_L K}$ with $\overline{F}(k)$ being the solution to the optimization problem

$$\begin{array}{ll} \text{minimize} & \Phi(\eta(k)) + \Lambda^T(k)F(k) \\ \text{subject to} & E_i(k) \in \mathcal{E}_i,\ \tilde{P}_i(k) \in \mathcal{P}_i \end{array} \tag{16.12}$$

for $i = 1, \ldots n_B$ ([18]) where the optimization variables are $\eta(k)$. This optimization is completely separable between the n_B BRPs, and can therefore be solved distributedly. For BRP i the optimization problem becomes

$$\begin{array}{ll} \text{minimize} & \Phi_i(\eta_i(k)) + \Lambda^T(k)T_i(k) \\ \text{subject to} & E_i(k) \in \mathcal{E}_i,\ \tilde{P}_i(k) \in \mathcal{P}_i \end{array} \tag{16.13}$$

where the optimization variables are $\eta_i(k)$. Solving problem (16.13) for $i = 1, \ldots, n_B$ gives flows $\overline{T}_i(k)$ that can be used to find a subgradient

$$S(k) = \sum_{i=1}^{n_B} \overline{T}_i(k) - F^{\max}. \tag{16.14}$$

Subgradient Algorithm

The centralized problem (16.11) is solved distributedly by the following algorithm where we use the subgradient method.

1. Initialize dual variable $\Lambda(k) := \Lambda_0(k) \geq 0$, e.g. using $\Lambda_0(k) = 0$ or $\Lambda_0(k) = \Lambda(k-1)$.
2. **loop**
   - Optimize flows using the dual variable $\Lambda(k)$ by locally solving problem (16.13).
   - Determine capacity margins $S(k)$ based on the solutions $\overline{T}_i(k)$ to the subproblems using (16.14).
   - Update dual variables $\Lambda(k) := (\Lambda(k) + \alpha_k S(k))_+$.
3. Terminate by providing flows limits $T_i^{\max}(k)$ to each BRP base on the final solutions $\overline{T}_i(k)$.
4. Increase k by one and go to step 1.

In the algorithm, $\alpha_k \in \mathbf{R}_+$ denotes the step size and can be chosen any standard way, e.g. square summable but not summable

$$\sum_{k=1}^{\infty} \alpha_k^2 \leq \infty, \quad \sum_{k=1}^{\infty} \alpha_k = \infty$$

such that convergence is guaranteed ([18]).

To ensure feasibility when the loop (step 2) is terminated, maximum partial flow limits $T_i^{\max}$ are provided to the BRPs (step 3) based on the final solutions $\overline{T}_i(k)$:

$$T_i^{\max}(k) = A\overline{T}_i(k)$$

where $A \in \mathbf{R}^{n_L K \times n_L K}$ is diagonal with entries $A_{jj} = F_j^{\max} / \left(\sum_{i=1}^{n_B} \overline{T}_i\right)_j$. This assures feasibility using backtracking. Each BRP must then ensure that their partial flow honor $T_i(k) \leq T_i^{\max}(k)$.

It is important to notice that the problem of finding dual variables is a simple summation and therefore is scalable even to a large number of BRPs.

4 Market Implementation

In this section, we describe how the distributed algorithm can be understood in an electrical market setting.

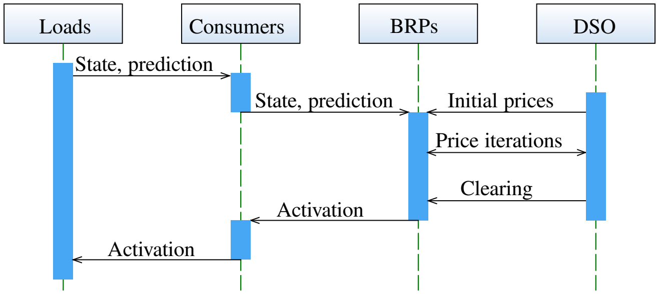

Figure 16.3: BRPs and DSO interaction resolving congestion.

Interplay between BRPs and DSO

The interacting players are the BRPs, who utilize the distribution grid, and the distribution system operator (DSO), who is responsible for safe grid. At hour k, each distribution line is initially associated with non-negative prices $\Lambda_0(k)$. Based on these prices and based on state information aggregated from the loads of the consumers, each BRP locally optimizes their own portfolio, see Fig. 16.3. The BRPs then inform the DSO of their partial flows $\overline{T}_i(k)$ under the initial prices.

By summing all the partial flows, the DSO determines if the distribution grid is overloaded or underloaded; for an overloaded line the price is increased, for an underloaded line the price is decreased, according to the presented algorithm (illustrated by the price iteration double-arrow in Fig. 16.3). The prices will eventually converge to the shadow prices of the centralized problem (16.11): the distribution line prices will equal the marginal prices that a BRP is willing to pay for an additional unit flow in each distribution line and the BRPs will reach the global optimum (within the horizon) without information sharing.

When the duality gap is sufficiently small, or after a fixed number of iterations, the DSO stops the iterations by sending final partial flow constraints $T_i^{\max}$ to BRP i and by publishing the final distribution line prices $\Lambda^*(k)$. The BRPs can now activate the flexible consumption as desired under the constraint $T_i \le T_i^{\max}$, see Fig. (16.3).

Settlement

The BRPs pay tariffs to the DSO for utilizing the distribution grid. Let $t_i^{\text{tariff}} \in \mathbf{R}^{n_L}$ denote the capacity of each line in the distribution grid, which BRP i has paid for through the tariffs, e.g. based on yearly tariff averages. Further, let $\sum_{i=1}^{n_B} t_i^{\text{tariff}} = f^{\max}$, such that the total capacity is divided among the BRPs. Based on this, the additional cost $c_i(k)$ of BRP i at time k is given by

$$c_i(k) = \lambda^{*T}(k)\left(t_i^{\max}(k) - t_i^{\text{tariff}}\right) \tag{16.15}$$

where $\lambda^*(k)$ are the final distribution line prices at time k.

The interpretation of the suggested settlement is straightforward: if $c_i(k) > 0$, BRP i has utilized the distribution grid more than paid for via tariffs in an hour of congestion and will have to pay the amount $c_i(k)$. If $c_i(k) < 0$, BRP i used less capacity than paid for

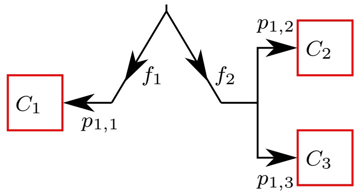

Figure 16.4: Three interconnected consumers sharing the same distribution grid.

through tariffs in an hour of congestion to the advantage of other BRPs and will be paid the amount $-c_i(k)$. Finally, if $c_i(k) = 0$, there is no congestion on the grid or BRP i has used the exact grid capacity paid for through tariffs. Note that $\sum_{i=1}^{n_B} c_i(k) = 0$, meaning that this settlement is internally between the BRPs; the DSO will only earn money through the tariffs, not the shadow prices.

5 Numerical Examples

In this section we first illustrate how the BRPs can benefit from utilizing the flexible consumers and secondly how grid congestion can be alleviated via shadow prices. We keep the examples at a conceptual level with a low number of consumers to make examples easy to follow.

Utilization of Flexible Consumers

We consider a simple case with a single BRP with three consumers $C_1,\ C_2,\ C_3$ under its jurisdiction, see Fig. 16.4. The characteristics of the consumers and the grid are

$$p_1^{\max} = -p_1^{\min} = (0,\ 30,\ 30)^T, \quad f_1^{\max} = (200,\ 90)^T$$
$$e_1^{\max} = (0,\ 200,\ 200)^T, \quad D_1 = \mathbf{diag}(0,\ 0.80,\ 0.99)$$

while the cost function is chosen to be

$$\ell_1(q_{\mathrm{bal},1}(k)) = \|q_{\mathrm{bal},1}(k)\|_2^2.$$

The characteristics show that C_1 is not controllable while C_2, C_3 are controllable with identical capacity and rate limits, but with higher storage quality in C_3 than C_2. The line capacity constraints lead to congestion on distribution line 2, but no congestion on line 1.

The top of Fig. 16.5 shows the predicted consumptions of C_1, C_2 and C_3; the total area thus corresponds to $\overline{p}_1(k)$. The red dashed line illustrates the energy bought at the day-ahead spot market $q_{\mathrm{spot},1}(k)$. As is seen from the plot, not enough energy is bought in the hours of high consumption, while excess energy is bought in the hours of low consumption. This could represent a BRP buying cheap energy at night thereby being able to buy less energy in the expensive peak hours.

The lower plot of Fig. 16.5 shows how the controller uses the flexible consumption of C_2 and C_3 to alter the consumption pattern by solving problem (16.11). The corresponding utilization of the storages e_1 is illustrated in the top plot of Fig. 16.6 where the solid green line shows the storage utilization of C_3 and the blue dashed line shows that of C_2.

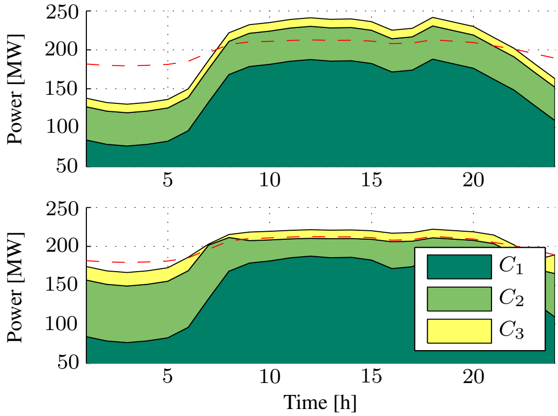

Figure 16.5: Power consumption predictions of the three consumers (shaded areas) compared to the energy bought at the day-ahead spot market (red, dashed)

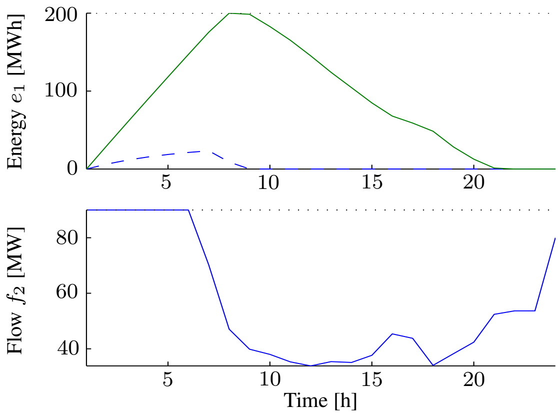

Figure 16.6: Top: Energy levels of the flexible consumers C_2 (blue, dashed) and C_3 (green, solid). Bottom: Power flow in distribution line 2. The capacity constraints are shown in both plots (black, dotted).

The figure shows that the flexible consumers fill their energy reserves in the first hours, where excess energy is bought at the day-ahead market, and empty their storages in the hours of missing energy. This utilization of the flexible consumers causes congestion on distribution line 2, which is illustrated in the lower plot of Fig. 16.6. Due to the congestion, the flexible consumers cannot both be fully utilized: as seen from the top plot, only the good storage of C_3 is fully utilized reaching both the capacity limit and the rate limit, while the storage capacity C_2 is only slightly utilized. Finally we note that the storage of C_2 discharges as soon as energy is needed (around $k = 7$), while the storage of C_3 does not discharge until later, again due to the fact that storage 3 is of higher quality than storage 2.

Distribution Grid Prices

We consider the case where C_1 and C_2 is under the jurisdiction of BRP 1 while C_3 is under the jurisdiction of BRP 2. Conflicting objectives cause congestion on the shared distribution line 2, see Fig. 16.7. Both BRP 1 and 2 desire to increase the controllable

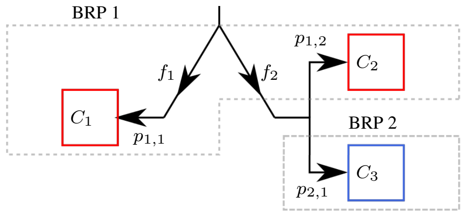

Figure 16.7: Three consumers under the jurisdiction of two different BRPs sharing the same distribution grid.

consumption in the first hours, and decrease the consumption in the later hours, as in the previous example. If no action is taken, this will violate the capacity constraint $f_2 \leq f_2^{\max}$.

To remedy the problem without information sharing, shadow prices are introduced by following the suggested algorithm. The DSO starts by publishing the initial prices $\Lambda(1) = 0$ where after the two BRPs report back to the DSO how they then plan to utilize the distribution grid, by respectively sending $T_1(1)$ and $T_2(1)$, to the DSO. The DSO discovers that congestion will occur with the initial prices and therefore updates the prices $\Lambda(1) := \Lambda(1) + \alpha S(1)$. The top plot of Fig. 16.8 shows the price adjustments, converging to the shadow prices $\Lambda^\star(k)$, optimally resolving the congestion (within the given horizon).

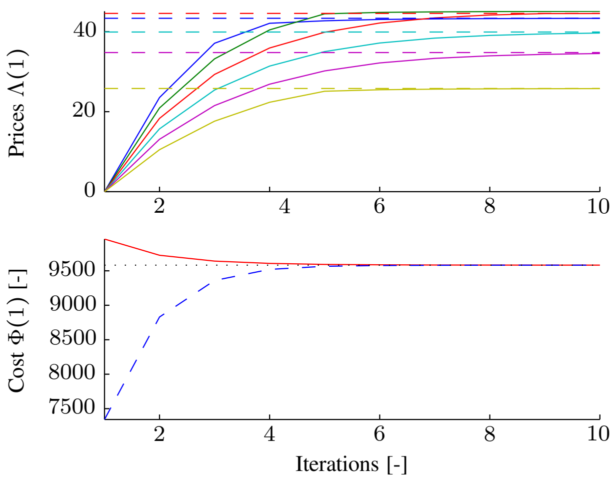

Figure 16.8: Top: Convergence of $\lambda_2(1), \ldots, \lambda_2(6)$ (solid) towards the shadow prices (dashed). Bottom: Primal (red, solid) and dual (blue, dashed) objective.

Further, we observe the convergence of the optimization by looking at the primal and dual objective at each iteration. This is illustrated in the lower plot of Fig. 16.8. The solid red line shows the primal objective when using feasible flows while the blue dashed line is the dual objective and the black dotted line is the optimal value within the control horizon.

6 Conclusion

In this paper, a receding horizon control approach was proposed for the control of flexible consumers under the jurisdiction of a BRP allowing the net consumption to be moved in time. We further showed how different BRPs sharing the same distribution grid could obtain the global optimum via the shadow prices at the distribution grid capacities thereby avoiding sharing local information. Finally we suggested how this approach could be implemented in an energy market by an appropriate communication pattern between the BRPs and the DSO.

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Paper 14

Distributed Model Predictive Control via Dual Decomposition

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Abstract

This chapter presents dual decomposition as a means to coordinate a number of subsystems coupled by state and input constraints. Each subsystem is equipped with a local model predictive controller while a centralized entity manages the subsystems via prices associated with the coupling constraints. This allows coordination of all the subsystems without the need of sharing local dynamics, objectives and constraints. To illustrate this, an example is included where dual decomposition is used to resolve power grid congestion in a distributed manner among a number of players coupled by distribution grid constraints.

1 Short introduction

In this chapter we consider a number of dynamical subsystems; each subsystem has local inputs and states, a local objective function, and local state and input constraints. Moreover, global state and input constraints make the subsystems mutually dependent. The subsystems are not able (or willing) to share the local information; hence optimization of the operation of the subsystems cannot be performed centrally and a distributed approach is necessary.

We consider two small figurative examples to illustrate such global constraints causing coupling of the subsystems. As a first example, consider a number of subsystems that are dependent on the same shared limited resource: this could correspond to coupling input inequality constraints. In the second example, consider a number of producing and consuming subsystems in a setup where balance must exist: this could correspond to coupling state equality constraints. In both cases the optimization problem is to minimize the total objective while honoring both local and global constraints – without sharing local information.

This chapter presents an approach to solve this problem via dual decomposition: by associating each coupling constraint with a price, the subsystems can be managed by a central entity to reach the solution. This allows coordination of the individual subsystems without sharing local dynamics, constraints or objectives. Further, the final prices of the coupling constraints, the so-called *shadow prices*, will reveal the marginal cost that each agent is willing to pay for the shared resources. This allows the shadow prices to be used for economical settlement purposes between the subsystems.

Dual decomposition is a huge area of research and there exists a large amount of literature on the topic. Dual decomposition appeared already in 1960s where it was used for solving large-scale optimization problems [1, 2]. Also within the area of coordination of dynamic systems via dual decomposition, which is the topic of this chapter, large amounts of literature exists; some references for this are [3, 4, 5, 6]. In this chapter, we show the basic idea in using dual decomposition in the coordination of coupled dynamic subsystems.

2 Boundary conditions

We consider N subsystems each described by a discrete linear time-invariant state space model. The states and inputs of subsystem i are denoted $\mathbf{x}_i(k) \in \mathbf{R}^{n_{x,i}}$ and $\mathbf{u}_i(k) \in \mathbf{R}^{n_{u,i}}$, respectively. The state space model is formulated as

$$\mathbf{x}_i(k+1) = \mathbf{A}_i\mathbf{x}_i(k) + \mathbf{B}_i\mathbf{u}_i(k) \tag{17.1}$$

where $\mathbf{A}_i \in \mathbf{R}^{n_{x,i}\times n_{x,i}}$ is the state matrix and $\mathbf{B}_i \in \mathbf{R}^{n_{x,i}\times n_{u,i}}$ is the input matrix. Each subsystem is subject to state and input constraints:

$$\mathbf{x}_i(k) \in \mathcal{X}_i, \qquad \mathbf{u}_i(k) \in \mathcal{U}_i \tag{17.2}$$

where $\mathcal{X}_i$ and $\mathcal{U}_i$ are convex constraint sets with $0 \in \mathcal{X}_i, 0 \in \mathcal{U}_i$. The stage cost function of subsystem i is convex and denoted $\ell_i(\mathbf{x}_i(k), \mathbf{u}_i(k))$ and $\ell_i(0,0) = 0$.

Taking a receding horizon control approach with a finite control horizon of N_c time samples and a prediction horizon of $N_p = N_c$ time samples, a local control strategy at subsystem i can be formulated as follows. Let $\mathcal{K}$ be a set containing the current time sample k and the following $N_c - 1$ time samples: $\mathcal{K} = \{k, \ldots, k + N_c - 1\}$, and let $\mathcal{N}$ denote the set of all N subsystems: $\mathcal{N} = \{1, \ldots, N\}$. Then we can formulate a decentralized model predictive control algorithm as follows for subsystem i.

Algorithm 1*:* ***Decentralized Model Predictive Control***

1. *Observe the current state* $\mathbf{x}_i(k)$ *and solve the optimization problem*

$$\begin{array}{ll} \textit{minimize} & \sum_{\kappa\in\mathcal{K}} \ell_i(\mathbf{x}_i(\kappa+1), \mathbf{u}_i(\kappa)) \\ \textit{subject to} & \mathbf{x}_i(\kappa+1) = \mathbf{A}_i\mathbf{x}_i(\kappa) + \mathbf{B}_i\mathbf{u}_i(\kappa), \quad \forall\kappa\in\mathcal{K} \\ & \mathbf{x}_i(\kappa+1) \in \mathcal{X}_i,\ \mathbf{u}_i(\kappa) \in \mathcal{U}_i, \quad \forall\kappa\in\mathcal{K} \end{array} \tag{17.3}$$

   where the variables are $\mathbf{x}_i(k+1:k+N_c), \mathbf{u}_i(k:k+N_c-1)$ *and* $\mathbf{x}_i(k)$ *is data. The solution is denoted* $\mathbf{x}_i^\star(k+1:k+N_c), \mathbf{u}_i^\star(k:k+N_c-1)$.

2. *Apply the first control input solution* $\mathbf{u}_i^\star(k)$ *to subsystem* i.
3. *Increase* k *by one and repeat from 1.*

This algorithm is presented to illustrate the concept of receding horizon control as this control strategy forms the background for the method presented in this chapter. However, this algorithm is not applicable to the subsystems we have in scope: the N subsystems are not only subject to the local constraints (17.2), but also to global state and input constraints. Consider the following compact notation for inputs and states:

$$\mathbf{x}(k) = \left[\mathbf{x}_1(k)^{\mathrm{T}}, \ldots, \mathbf{x}_N(k)^{\mathrm{T}}\right]^{\mathrm{T}} \tag{17.4}$$

$$\mathbf{u}(k) = \left[\mathbf{u}_1(k)^{\mathrm{T}}, \ldots, \mathbf{u}_N(k)^{\mathrm{T}}\right]^{\mathrm{T}} \tag{17.5}$$

where $\mathbf{x}(k) \in \mathbf{R}^{n_x}$, $n_x = \sum_{i=1}^N n_{x,i}$, and $\mathbf{u}(k) \in \mathbf{R}^{n_u}$, $n_u = \sum_{i=1}^N n_{u,i}$. With this notation we can express the coupling constraints as

$$\mathbf{C}\mathbf{u}(k) \le \mathbf{c}, \qquad \mathbf{D}\mathbf{u}(k) = \mathbf{d}, \tag{17.6}$$

$$\mathbf{E}\mathbf{x}(k) \le \mathbf{e}, \qquad \mathbf{F}\mathbf{x}(k) = \mathbf{f}, \tag{17.7}$$

where $\le$ denotes componentwise inequality; $\mathbf{C} \in \mathbf{R}^{n_c\times n_u}, \mathbf{c} \in \mathbf{R}^{n_c}$, and $\mathbf{D} \in \mathbf{R}^{n_d\times n_u}$, $\mathbf{d} \in \mathbf{R}^{n_d}$ describe n_c input inequality constraints and n_d input equality constraints, respectively, while $\mathbf{E} \in \mathbf{R}^{n_e\times n_x}, \mathbf{e} \in \mathbf{R}^{n_e}$ and $\mathbf{F} \in \mathbf{R}^{n_f\times n_x}, \mathbf{f} \in \mathbf{R}^{n_f}$ describe n_e state inequality

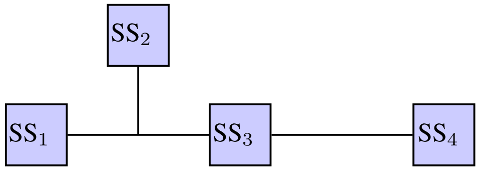

Figure 17.1: Illustration of coupled subsystems: subsystems 1, 2, and 3 are coupled and subsystems 3 and 4 are coupled.

constraints and n_f state equality constraints, respectively. These types of constraints can for example express the previously described resource couplings or balancing couplings.

We illustrate this idea of coupled subsystems with a small figurative example. Consider $N = 4$ subsystems where subsystems 1, 2, and 3 share a limited resource while a production/consumption balance must exist between subsystems 3 and 4. This example can be visualized as in Figure 17.1: subsystems 1, 2 and 3 are interconnected by a net of lines and subsystems 3 and 4 are interconnected by a single line representing the coupling constraints. In dual decomposition, each coupling constraint (each interconnection) will be associated with a price. These prices will be used to coordinate the subsystems to collectively honor the coupling constraints. Hereby the subsystems avoid sharing local information such as dynamics, objective and constraints. Two prices exist in the small example presented in Figure 17.1: one for the coupling of subsystems 1, 2 and 3 and one for the coupling of subsystems 3 and 4.

Due to the coupling constraints (17.6) and (17.7), the subsystems depend on each other and must coordinate their actions to reach feasibility. In the following sections it will be shown that the subsystems can be coordinated via prices associated with the coupled resources by letting an external agent that adjust these prices. It is therefore necessary to assume that each subsystems is able to establish a two-way communication link with such an external agent.

3 Description of the approach

We only consider coupling constraints on the form $\mathbf{C}\mathbf{u}(k) \leq \mathbf{c}$, $\mathbf{C} \in \mathbf{R}^{n_c \times n_x}, \mathbf{c} \in \mathbf{R}^{n_c}$ in the following and neglect the three other constraints presented in (17.6) and (17.7). This simplification is made to ease the notation. It is, however, straightforward to follow the method presented in the following to include all four of the presented constraints.

Let

$$\ell(\mathbf{x}(k), \mathbf{u}(k)) = \sum_{i \in \mathcal{N}} \ell_i(\mathbf{x}_i(k), \mathbf{u}_i(k)) \tag{17.8}$$

be the sum of the N convex objective functions of the subsystems and thereby itself a convex function. Based on this, we formulate a control algorithm using the receding horizon approach with a finite control and prediction horizon of $N_c = N_p$ time samples. This algorithm can be applied if all information is available centrally (which is not the case in our setup).

Algorithm 2: ***Centralized Model Predictive Control***

1. *Observe the current states* $\mathbf{x}_i(k)$ *for all subsystems* $i \in \mathcal{N}$ *and solve the centralized optimization problem*

$$\begin{array}{ll} \textit{minimize} & \sum_{\kappa\in\mathcal{K}} \ell(\mathbf{x}(\kappa+1),\mathbf{u}(\kappa)) \\ \textit{subject to} & \mathbf{x}_i(\kappa+1) = \mathbf{A}_i\mathbf{x}_i(\kappa) + \mathbf{B}_i\mathbf{u}_i(\kappa), \quad \forall\kappa\in\mathcal{K},\ i\in\mathcal{N} \\ & \mathbf{x}_i(\kappa+1)\in\mathcal{X}_i,\ \mathbf{u}_i(\kappa)\in\mathcal{U}_i, \quad \forall\kappa\in\mathcal{K},\ i\in\mathcal{N} \\ & \mathbf{C}\mathbf{u}(\kappa)\le\mathbf{c}, \quad \forall\kappa\in\mathcal{K} \end{array} \tag{17.9}$$

   where the variables are

$$\boldsymbol{\eta}(k) = \left[\mathbf{x}(k+1:k+N_c)^{\mathrm{T}}, \mathbf{u}(k:k+N_c-1)^{\mathrm{T}}\right]^{\mathrm{T}}$$

   and $\boldsymbol{\eta}(k) \in \boldsymbol{R}^{N_c(n_x+n_u)}$ *is used as a compact representation of states and inputs in the following.*

2. *Apply the first control input solution* $\mathbf{u}_i^\star(k), \forall i\in\mathcal{N}$ *to the* N *subsystems.*

3. *Increase* k *by one and repeat from 1.*

The centralized optimization problem (17.9) is completely separable except for the last coupling constraint $\mathbf{C}\mathbf{u}(\kappa)\le\mathbf{c}$. As the coupling constraints are affine, we are able to apply dual decomposition to eliminate the coupling (see, e.g., [7], [8]). This is exactly what we will do in the following.

First, we relax the coupling constraints by introducing the associated Lagrange multipliers; hereby the partial Lagrangian of Problem (17.9) becomes

$$L(\boldsymbol{\eta}(k),\boldsymbol{\Lambda}(k)) = \sum_{\kappa\in\mathcal{K}} \left(\ell(\mathbf{x}(\kappa+1),\mathbf{u}(\kappa)) + \boldsymbol{\lambda}(\kappa)^{\mathrm{T}}\left(\mathbf{C}\mathbf{u}(\kappa)-\mathbf{c}\right)\right) \tag{17.10}$$

where $\boldsymbol{\lambda}(\kappa)\in\mathbf{R}^{n_c}$ are the Lagrange multipliers associated with the inequality constraint $\mathbf{C}\mathbf{u}(\kappa)\le\mathbf{c}$ and $\boldsymbol{\Lambda}(k)\in\mathbf{R}^{N_c n_c}$ is a compact representation of the Lagrange multipliers: $\boldsymbol{\Lambda}(k) = \boldsymbol{\lambda}(k:k+N_c-1)$.

Define $g(\boldsymbol{\Lambda}(k))$ as the optimal value of the problem

$$\begin{array}{ll} \text{minimize} & \sum_{\kappa\in\mathcal{K}} \left(\ell(\mathbf{x}(\kappa+1),\mathbf{u}(\kappa)) + \boldsymbol{\lambda}(\kappa)^{\mathrm{T}}\left(\mathbf{C}\mathbf{u}(\kappa)-\mathbf{c}\right)\right) \\ \text{subject to} & \mathbf{x}_i(\kappa+1) = \mathbf{A}_i\mathbf{x}_i(\kappa) + \mathbf{B}_i\mathbf{u}_i(\kappa), \quad \kappa\in\mathcal{K},\ i\in\mathcal{N} \\ & \mathbf{x}_i(\kappa+1)\in\mathcal{X}_i,\ \mathbf{u}_i(\kappa)\in\mathcal{U}_i, \quad \kappa\in\mathcal{K},\ i\in\mathcal{N} \end{array} \tag{17.11}$$

where the variables are $\boldsymbol{\eta}(k)$. This problem is completely separable as both objective and constraints can be separated among the i subsystems. We see this clearly by separating the matrix $\mathbf{C}$ into blocks

$$\mathbf{C} = [\mathbf{C}_1,\ldots,\mathbf{C}_N] \tag{17.12}$$

where $\mathbf{C}_i\in\mathbf{R}^{n_c\times n_{u,i}}$ such that

$$\mathbf{C}\mathbf{u}(k) = \sum_{i\in\mathcal{N}} \mathbf{C}_i\mathbf{u}_i(k). \tag{17.13}$$

Evaluating a subgradient of $g(\boldsymbol{\Lambda}(k))$ can be done as follows. Solve Problem (17.11) and let $\overline{\mathbf{u}}(\kappa)$ denote the optimal $\mathbf{u}(\kappa)$, $\forall\kappa\in\mathcal{K}$ for a given realization of $\boldsymbol{\Lambda}(k)$. By differentiation of the objective of Problem 17.11 with respect to $\mathbf{\Lambda}(k)$ it is evident that a subgradient of $g(\mathbf{\Lambda}(k))$ can be described as

$$\left[(\mathbf{C}\overline{\mathbf{u}}(k)-\mathbf{c})^{\mathrm{T}},\ldots,(\mathbf{C}\overline{\mathbf{u}}(k+N_c-1)-\mathbf{c})^{\mathrm{T}}\right]^{\mathrm{T}} \in \partial(g)(\mathbf{\Lambda}(k)), \tag{17.14}$$

where $\partial(g)(\mathbf{\Lambda}(k))$ denotes the subdifferential of g at $\mathbf{\Lambda}(k)$.

We can formulate the dual of the original centralized problem (17.9) as

$$\begin{array}{ll} \text{maximize} & g(\mathbf{\Lambda}(k)) \\ \text{subject to} & \mathbf{\Lambda}(k) \geq 0 \end{array} \tag{17.15}$$

with variables $\mathbf{\Lambda}(k)$. Based on the above, we are able to solve the original problem (17.9) in a distributed manner. The key idea is to solve the primal problem (17.9) by solving its dual problem (17.15) using a projected subgradient method. In the subgradient method, steps of appropriate length are taken in the direction of a subgradient of the dual problem which corresponds to iteratively updating the Lagrange multipliers $\mathbf{\Lambda}(k)$. We can do this in a distributed manner as a subgradient of the dual problem (17.15) is given by (17.14) which is separable among the subsystems as $\mathbf{C}\overline{\mathbf{u}}(\kappa) = \sum_{i\in\mathcal{N}} \mathbf{C}_i\overline{\mathbf{u}}_i(\kappa)$. The following algorithm illustrates this. Note that we use the term *Master* to denote a centralized entity able to perform two-way communication with all subsystems (an interpretation of this master entity is presented in the example in the end of this chapter).

Algorithm 3: ***Distributed Model Predictive Control***

1. *Master initializes the prices (Lagrange multipliers)* $\mathbf{\Lambda}(k) \geq 0$.
2. `repeat`
   a) *Master broadcasts the current prices* $\mathbf{\Lambda}(k)$ *to all subsystems.*
   b) *Problem (17.11) is solved under the current* $\mathbf{\Lambda}(k)$ *distributedly by letting each subsystem* $i \in \mathcal{N}$ locally *solve the optimization problem*

   $$\begin{array}{ll} \textit{minimize} & \sum_{\kappa\in\mathcal{K}} \left(\ell_i(\mathbf{x}_i(\kappa+1),\mathbf{u}_i(\kappa)) + \boldsymbol{\lambda}(\kappa)^{\mathrm{T}}\mathbf{C}_i\mathbf{u}_i(\kappa)\right) \\ \textit{subject to} & \mathbf{x}_i(\kappa+1) = \mathbf{A}_i\mathbf{x}_i(\kappa) + \mathbf{B}_i\mathbf{u}_i(\kappa), \quad \forall\kappa\in\mathcal{K} \\ & \mathbf{x}_i(\kappa+1)\in\mathcal{X}_i,\ \mathbf{u}_i(\kappa)\in\mathcal{U}_i, \quad \forall\kappa\in\mathcal{K} \end{array} \tag{17.16}$$

   where the variables are $\mathbf{x}_i(\kappa+1), \mathbf{u}_i(\kappa), \forall\kappa\in\mathcal{K}$. *The solution is denoted* $\overline{\mathbf{x}}_i(k+1:k+N_c), \overline{\mathbf{u}}_i(k:k+N_c-1)$ *and the vectors* $\mathbf{C}_i\overline{\mathbf{u}}_i(\kappa) \in \boldsymbol{R}^{n_c}, \forall\kappa\in\mathcal{K}$ *are determined locally at each subsystem and communicated to the master.*
   c) *Master determines the violations* $\mathbf{s}(\kappa)\in\boldsymbol{R}^{n_c}$ *of the coupling inequality constraints:* $\mathbf{s}(\kappa) = \sum_{i=1}\mathbf{C}_i\overline{\mathbf{u}}_i(\kappa) - \mathbf{c}, \forall\kappa\in\mathcal{K}$*;* $\mathbf{S}(k) = \mathbf{s}(k:k+N_c-1)\in\boldsymbol{R}^{N_cn_c}$ *and assigns new prices via projection:* $\mathbf{\Lambda}(k) := \max(0, \mathbf{\Lambda}(k) + \alpha\mathbf{S}(k))$.

   `until` $\max(\mathbf{S}(k)) \leq \epsilon$ *or maximum number of iterations reached.*
3. *Based on the final utilization of the input* $\mathbf{u}(\kappa), \forall\kappa\in\mathcal{K}$*, the master determines limits* $\overline{\mathbf{c}}_i$ *assuring feasibility of the overall problem and communicates the limits to all subsystems.*
4. *Each subsystem locally solves Problem (17.3) with the additional constraint* $\mathbf{C}_i\mathbf{u}_i(\kappa) \leq \overline{\mathbf{c}}_i, \forall\kappa\in\mathcal{K}$ *and applies the first control input solution.*
5. *Increase* k *by one and repeat from 1.*

Figure 17.2 illustrates this algorithm: each interconnection of solid lines represents a coupling constraint while the dashed lines illustrate the necessary communication. This shows that the master needs information form each subsystem in order to update the prices and communicate these prices to the subsystems. It is important to note that the master needs no information of local subsystem constraints, objectives or dynamics; it is sufficient that the master knows how much the limited resources will be used at each subsystem under a sequence of different price realizations. Finally we note that the resulting algorithm using dual decomposition has a straightforward interpretation: in step 2c the master observes if the shared resources $\mathbf{u}(k : k + N_c - 1)$ are overutilized or underutilized. If the subsystems overutilize a limited resource, the associated price is increased; if the subsystems underutilize a shared resource, the associated price is decreased (while keeping it non-negative).

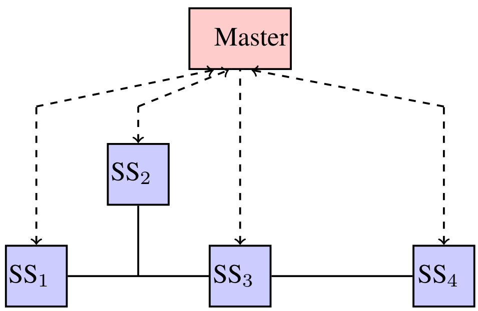

Figure 17.2: Coupled subsystems interact with master: master broadcasts prices $\mathbf{\Lambda}(k)$ and subsystems respond by reporting how much they utilize the limited resources $\mathbf{C}_i\mathbf{x}_i(\kappa), \forall\kappa \in \mathcal{K}$. The dashed lines indicate the necessary two-way communication links between subsystems and master.

4 Theoretical results availability

In this section we briefly comment on the computational burden of the optimization algorithm and describe under what circumstances the algorithm will converge.

First, we note that the optimization problem of each subsystem in the distributed algorithm (Problem 17.16) is only slightly more complex than if the subsystem couplings were neglected (Problem 17.3). However, the complexity increases significantly as we are required to solve the distributed optimization problem (17.16) a number of times until convergence. Further we note that the update law of the master (Algorithm 3 step 2c) requires only a single addition and multiplication operation. The computational burden of the master therefore scales well with the number of subsystems N.

A requirement for Algorithm 3 to converge is that we have no duality gap, i.e., the value of the primal and the dual solutions are identical. If the primal problem is convex, it often holds that the primal and dual solutions are identical but additional conditions are necessary to guarantee this. One such condition is Slater's condition [9, p. 226] which states that the primal and dual solutions are identical if the primal problem is convex and there exists a solution to the primal problem that is strictly feasible. In the formulation of Problem 17.3, Slater's condition requires that a solution exists such that

$$\mathbf{x}_i(\kappa+1) \in \mathbf{relint}\,\mathcal{X}_i, \qquad \mathbf{u}_i(\kappa) \in \mathbf{relint}\,\mathcal{U}_i, \quad \forall\kappa \in \mathcal{K} \tag{17.17}$$

where $\mathbf{relint}\,\mathcal{X}_i$ denotes the relative interior of $\mathcal{X}_i$ and is a set that contains all points which are not on the edge of $\mathcal{X}_i$, relative to the smallest set in which $\mathcal{X}_i$ lies [10, p. 448]. Under this assumption, convergence can be guaranteed depending on the choice of step size in the subgradient method, which will be discussed in the following.

In the presented algorithm, a projected subgradient method is used to solve the constrained convex optimization problem (17.15). The subgradient method updates $\mathbf{\Lambda}(k)$ according to

$$\mathbf{\Lambda}(k) := \mathbf{P}(\mathbf{\Lambda}(k) - \alpha\mathbf{g}) \tag{17.18}$$

where $\mathbf{P}$ is a projection of $\mathbf{\Lambda}(k)$ onto the feasible set $\{\mathbf{\Lambda}(k) \in \mathbf{R}^{N_c n_c} | \mathbf{\Lambda}(k) \geq 0\}$ and $\mathbf{g}$ is any subgradient to the dual problem and α is a (constant) step size. Using such constant step size assures that we will converge to a value that lies within some range of the optimum value. If the objective of Problem 17.11 is differentiable, i.e., $\ell(\mathbf{x}(\kappa+1), \mathbf{u}(\kappa)), \kappa \in \mathcal{K}$ is differentiable, the subgradient method will indeed converge to the optimum for sufficiently small α [11].

Another option is to let the step size vary with the iteration number j, hereby convergence to the optimal value can be guaranteed also for the case of a non-differentiable objective. One example is a non-summable diminishing step size

$$\lim_{j\to\infty} \alpha_j = 0, \qquad \sum_{j=1}^{\infty} \alpha_j = +\infty \tag{17.19}$$

where α_j is the step size at iteration i; this will guarantee that the subgradient method converges to the optimum [12, p. 215]. Other step size rules with same convergence result exist.

It is important to note that the subgradient method is chosen due to the fact that this allows us to decouple the problem. Other methods (such as second order methods) can provide much faster convergence than the subgradient method presented here. They are, however, not suitable for the type of decoupling presented in this chapter.

A final note concerns the convergence proofs of dual decomposition algorithms. Dual decomposition algorithms rely on subgradient methods as presented above. Generally, convergence proofs for gradient methods are based on the function value decreasing at each iteration; however, for subgradient methods this is not the case. In subgradient methods, the convergence proofs are generally based on the Euclidian distance to the optimal set by showing under what circumstances this distance will decrease at each iteration [11]. Therefore, the objective value can increase during the iterates in the subgradient method used in the algorithm; however, the distance to the optimal set will decrease at each iteration.

5 Application results availability

In this section, an application of distributed model predictive control via dual decomposition is presented. The example is taken from a *smart grid* setup where the basic idea is to increase the sustainability and stability of the electrical grid by utilizing the flexibility of the demand side (consumers) in the balancing efforts. Two main ideas of the smart grid concept are

- balancing of production and consumption by moving load temporally,
- avoiding distribution grid congestion by moving load temporally or spatially.

In this example, we address these two topics at an overall level.

Consider a number of balancing responsible parties (BRPs) each responsible for a number of consumers under their jurisdiction; each consumer belongs to exactly one BRP. The BRPs buy energy at the day-ahead electricity market on behalf of the consumers. In the following, we illustrate how BRPs can utilize the flexibility of the consumers under their jurisdiction to minimize the imbalance between the purchased energy and the consumed energy thereby avoiding trading compensating balancing energy at unfavorable prices. Further, we show how the BRPs can be coordinated such that distribution grid congestion is avoided. Due to the very competitive electricity market, the BRPs are not willing to share local information such as objectives and states; therefore we use the dual decomposition approach presented in this chapter to resolve grid congestion. In this way, congestion management can be achieved without information sharing between the BRPs. Finally, we show how the dual decomposition method can be interpreted as a *distribution grid capacity market*. Throughout the following, the notation from the previous section will be used to the extent possible.

Consider a star topology distribution grid (no loops) consisting of n_f distribution lines of limited capacity. A total of N BRPs are active in the distribution grid and BRP number i is responsible for $n_{x,i}$ consumers. The setup is illustrated in Figure 17.3 and discussed in detail in the sequel.

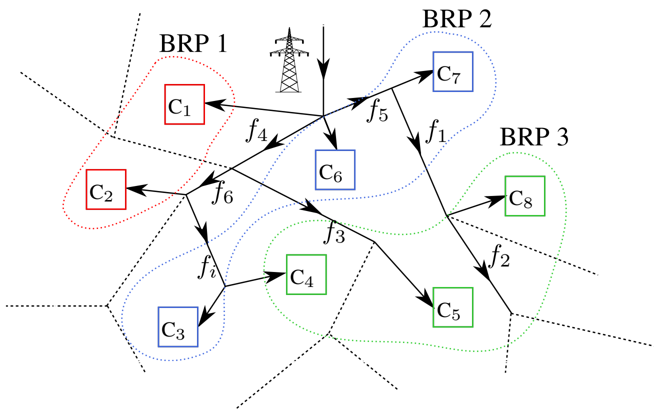

Figure 17.3: Interconnected consumers under the jurisdiction of different BRPs sharing the same distribution grid (dotted lines indicate that only a small part of the total grid is shown).

The $n_{x,i}$ consumers under BRP i are characterized by hourly energy consumptions $\mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k)$ where $\mathbf{u}_i(k) \in \mathbf{R}^{n_{x,i}}$ is the controllable (flexible) part of the consumption and $\tilde{\mathbf{u}}_i(k) \in \mathbf{R}^{n_{x,i}}$ is an uncontrollable base consumption assuming a sampling time of 1 hour. Due to the flexible consumption, the devices are able to *store* energy. We denote the amount of stored energy $\mathbf{x}_i(k) \in \mathbf{R}^{n_{x,i}}$ for the consumers under BRP i; this may be energy stored as either heat, cold, energy in a battery, or similar. The stored energy depends on the controllable power consumption

$$\mathbf{x}_i(k+1) = \mathbf{A}_i \mathbf{x}_i(k) + \mathbf{B}_i \mathbf{u}_i(k), \tag{17.20}$$

where $\mathbf{A}_i, \mathbf{B}_i \in \mathbf{R}^{n_{x,i} \times n_{x,i}}$ are diagonal with diagonal elements describing drain losses of each energy storage. The consumers are limited by power and energy constraints

$$0 \leq \mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k) \leq \mathbf{u}_i^{\max}, \qquad \mathbf{x}_i^{\min} \leq \mathbf{x}_i(k) \leq \mathbf{x}_i^{\max} \tag{17.21}$$

where $\mathbf{u}_i^{\max}$, $\mathbf{x}_i^{\min}$, $\mathbf{x}_i^{\max} \in \mathbf{R}^{n_{x,i}}$ describe these limits. Consumer models described this way can be found for example in [13].

The consumers are powered through the distribution grid, as illustrated in Figure 17.3. Each BRP will contribute to the loading of the distribution lines. Let $\mathbf{r}_i(k) \in \mathbf{R}_+^{n_f}$ denote the partial flow caused by BRP i to the n_f distribution lines; these partial flows can by flow conversation be described as

$$\mathbf{r}_i(k) = \mathbf{R}_i \left(\mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k)\right) \tag{17.22}$$

where $\mathbf{R}_i \in \mathbf{R}^{n_f \times n_{x,i}}$ is given by

$$(\mathbf{R}_i)_{pq} = \begin{cases} 1 & \text{if consumer } q \text{ under BRP } i \text{ is supplied through link } p, \\ 0 & \text{otherwise.} \end{cases}$$

This simply states that the power to each consumer under BRP i must flow through a unique path of distribution lines; these paths are indicated in the $\mathbf{R}_i$ matrix.

The distribution grid is protected from overcurrents by electrical fuses; hence, the distribution lines are subject to constraints. The total flows $\mathbf{f}(k) \in \mathbf{R}_+^{n_f}$ over the distribution lines and associated fuse limits can be expressed as

$$\mathbf{f}(k) = \sum_{i \in \mathcal{N}} \mathbf{r}_i(k), \qquad \mathbf{f}(k) \leq \mathbf{f}^{\max} \tag{17.23}$$

where $\mathbf{f}^{\max}(k) \in \mathbf{R}_+^{n_f}$ denotes the limits of the fuses and $\mathcal{N}$ is the set of all BRPs.

The BRPs buy energy at a day-ahead spot market for each hour of the following day. We denote the energy bought by BRP i at the day-ahead spot market $\mathbf{p}_i(k) \in \mathbf{R}$; this means that BRP i has bought the energy $\mathbf{p}_i(k)$ for the time interval from hour k to $k+1$. The objective of each BRP is to minimize the imbalance between the consumed energy $\mathbf{1}^{\mathrm{T}}(\mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k))$ and the purchased energy $\mathbf{p}_i(k)$, i.e.,

$$\ell_i(\mathbf{u}_i(k)) = \|\mathbf{1}^{\mathrm{T}}(\mathbf{u}_i(k) + \tilde{\mathbf{u}}_i(k)) - \mathbf{p}_i(k)\|_2^2, \tag{17.24}$$

where it is chosen to minimize the imbalance in the two-norm sense and where $\mathbf{1}$ denotes a vector of appropriate dimension with all entries equal to one. By keeping this imbalance small, the BPR minimizes the energy imbalances and thereby avoids trading balancing energy possibly at very unfavorable price.

The modeling reveals that the optimization problem is completely separable among the BRPs except for the coupling via the distribution line capacity constraints (17.23). We apply Algorithm 3 to the presented application example and obtain the following algorithm when performing receding horizon control with a control horizon N_c and prediction horizon of $N_p = N_c$ samples.

Algorithm 4: ***4 – Congestion Management Example***

1. *Master initializes the prices* $\mathbf{\Lambda}(k) \geq 0,\ \mathbf{\Lambda}(k) = \mathbf{\lambda}(k : k + N_c - 1)$, *where* $\mathbf{\lambda}(k) \in \boldsymbol{R}^{n_f}$ *and* $\mathbf{\lambda}_j(k)$ *is the price associated with the capacity limit of distribution line* j *at time sample* k.
2. `repeat`
   a) *Master broadcasts the current prices* $\mathbf{\lambda}(\kappa), \forall \kappa \in \mathcal{K}$ *to the subsystems.*
   b) *Each BRP locally solves the price dependent problem*

$$\begin{array}{ll} \textit{minimize} & \sum_{\kappa \in \mathcal{K}} \left(\|\mathbf{1}^{\mathrm{T}}(\mathbf{u}_i(\kappa) + \tilde{\mathbf{u}}_i(\kappa)) - \mathbf{p}_i(\kappa)\|_2^2 + \mathbf{\lambda}(\kappa)^{\mathrm{T}} \mathbf{r}_i(\kappa) \right) \\ \textit{subject to} & \mathbf{x}_i(\kappa + 1) = \mathbf{A}_i \mathbf{x}_i(\kappa) + \mathbf{B}_i \mathbf{u}_i(\kappa), \quad \forall \kappa \in \mathcal{K} \\ & 0 \leq \mathbf{u}_i(\kappa) + \tilde{\mathbf{u}}_i(\kappa) \leq \mathbf{u}_i^{\max}, \quad \forall \in \mathcal{K} \\ & \mathbf{x}_i^{\min} \leq \mathbf{x}_i(\kappa) \leq \mathbf{x}_i^{\max}, \quad \forall \kappa \in \mathcal{K} \\ & \mathbf{r}_i(\kappa) = \mathbf{R}_i \left(\mathbf{u}_i(\kappa) + \tilde{\mathbf{u}}_i(\kappa) \right), \quad \forall \kappa \in \mathcal{K} \end{array} \tag{17.25}$$

   where the variables are $\mathbf{x}_i(k+1 : k+N_c), \mathbf{u}_i(k : k+N_c-1), \mathbf{r}_i(k : k+N_c-1)$. *The solution is denoted* $\overline{\mathbf{x}}_i(k+1 : k+N_c), \overline{\mathbf{u}}_i(k : k+N_c-1), \overline{\mathbf{r}}_i(k : k+N_c-1)$.
   c) *Each BRP reports local partial flows* $\overline{\mathbf{r}}_i(\kappa)$ *to the master. The master centrally determines line capacity violations* $\mathbf{s}(\kappa) = \sum_{i \in \mathcal{N}} \mathbf{r}_i(\kappa) - \mathbf{f}^{\max} \in \boldsymbol{R}^{n_f}, \forall \kappa \in \mathcal{K}$ *where* $\mathbf{s}_j$ *is the capacity violation of line* j *and* $\mathbf{S}(k) = \mathbf{s}(k : k + N_c - 1) \in \boldsymbol{R}^{N_c n_f}$.
   d) *Master updates prices* $\mathbf{\Lambda}(k)$ *via projection:* $\mathbf{\Lambda}(k) := \max\left(0, \mathbf{\Lambda}(k) + \alpha \mathbf{S}(k)\right)$. *Again notice that this corresponds to increasing the cost on congested lines and reducing the price on lines where there is free capacity; however, always assuring non-negative line prices.*

   `until` $\max(\mathbf{S}(k)) \leq \epsilon$ *or maximum number of iterations reached.*
3. *Master determines limits* $\overline{\mathbf{c}}_i \in \boldsymbol{R}^{n_f}$ *and communicates limits and final prices (shadow prices) to the BRPs.*
4. *Each subsystem locally solves Problem (17.25) with the additional constraint* $\mathbf{r}_i(\kappa) \leq \overline{\mathbf{c}}_i$ *and applies the first control input of the solution.*
5. *Increase* k *by one and repeat from 1.*

The algorithm shows that the congestion management via dual decomposition can be interpreted as a new distribution grid market where each distribution line is associated with a time-varying cost per unit flow. If the lines are not congested, the BRPs are free to use the lines at no cost; however, if congestion occurs, the master will adjust the price on the lines until the congestion is resolved.

The sequence diagram in Figure 17.4 illustrates how this market can be imagined in an electrical power system setup. First, the individual loads communicate their flexibility (via states and predictions) to the individual consumers. Following, the consumers communicate the flexibility of all their respective loads to the corresponding BRP. Further, the

BRPs are provided with initial prices on the distribution grid from the distribution grid operator (DSO) which has the role of the master. Based on this, a price iteration follows where the DSO adjusts the prices until all grid congestions are resolved. When the iteration is completed, the DSO clears the market by communicating final prices and line capacity limits for each BRP. Here it is important to note that the prices at the moment of the market clearing are *real prices* that will determine the economical settlement between the BRPs. From the perspective of a BRP, the prices on the distribution lines reveal the cost that the BRP will have to pay (or be paid) for using more (or less) of the line capacity.

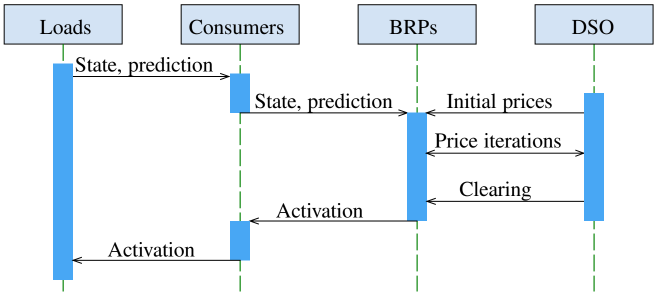

Figure 17.4: Market interpretation of congestion alleviation via dual decomposition.

Finally, we consider a small numerical example to illustrate the price iteration. The example is kept at a conceptual level to clearly illustrate the concept. The details of the simulation are not presented here but can be found in [14]. Consider two BRPs responsible for one and two consumers, respectively, as presented in Figure 17.5. The example is constructed with dynamics and objectives fitting the structure of Algorithm 4; we assume we are at time sample $k = 1$ and use a control horizon and prediction horizon of $N_c = N_p = 10$. Both BRP 1 and 2 desire to increase the controllable consumption in the first hours, and decrease the consumption in the later hours. If no action is taken, this will violate the capacity constraint on line 2: $\mathbf{f}_2 \leq \mathbf{f}_2^{\max}$. To remedy the problem without information sharing, Algorithm 4 is used. The DSO starts by publishing the initial prices $\boldsymbol{\Lambda}(1) = 0$ where after the two BRPs report back to the DSO how they will utilize the distribution grid under this price, by respectively sending $\overline{\mathbf{r}}_1$ and $\overline{\mathbf{r}}_2$ to the DSO. The DSO discovers that congestion will occur under the initial prices and therefore updates the prices according to $\boldsymbol{\Lambda}(1) := \boldsymbol{\Lambda}(1) + \alpha \mathbf{S}(1)$. The top plot of Figure 17.6 shows the price adjustments, converging to the shadow prices $\boldsymbol{\Lambda}^\star(1)$, optimally resolving the congestion (within the given horizon). The solid line shows the primal objective when using feasible flows, the dashed line is the dual objective, and the dotted line is the optimal value within the control horizon. The lower plot shows the iteration of the prices associated with capacity constraint at line 2 from time sample $k = 1$ to $k = 6$; the prices at time $k = 7$ to $k = 10$ remain at zero as there is no congestion at these hours.

The large benefit of resolving congestion management by prices is that the global economical optimum is reached within the control horizon N_c without the need of a centralized optimization. In the presented example, consumer 3 under PRB 2 is a storage of high quality (low drainage) while consumer 2 under BRP 1 is a storage of low quality (high drainage). In this market approach, this results in consumer 3 being the main user of the shared distribution line because BRP 2 is willing to pay a higher price for the line

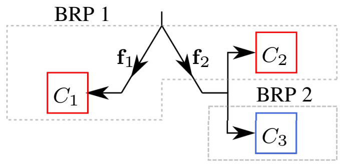

Figure 17.5: Three consumers under the jurisdiction of two different BRPs sharing the same distribution grid.

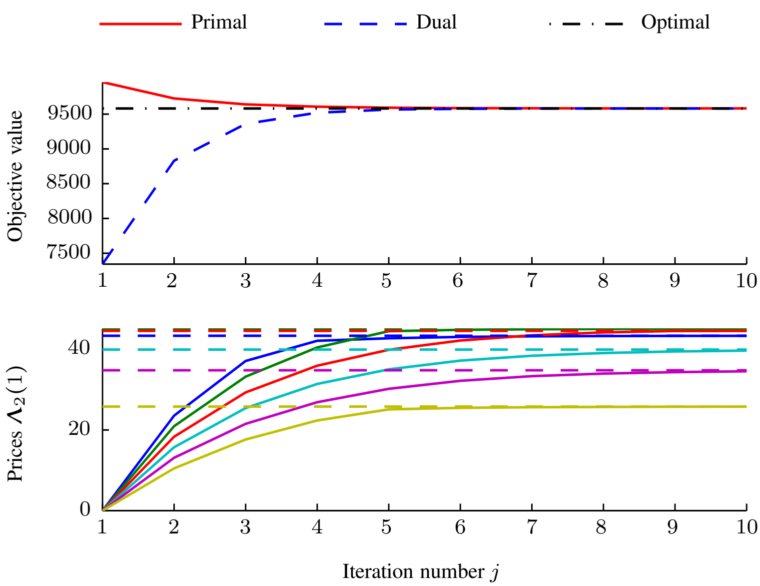

Figure 17.6: Top: objective value progress. Bottom: convergence of $\boldsymbol{\lambda}_2(1), \ldots, \boldsymbol{\lambda}_2(6)$ (solid lines) towards the shadow prices (dashed lines).

utilization due to the fact that he can profit much from this high quality storage. BRP 1, on the other hand, is willing to decrease the use of his low quality storage by receiving a payment from BRP 2 as he is not able to profit much from his poor storage.

To illustrate the benefit of using the distribution grid market approach to resolve grid congestion, consider an alternative very simple strategy: congestion is simply resolved by splitting the capacity of the shared line equally among the players sharing the line. In this case, the high quality storage would be used less and the low quality storage would be used more. As a result, a larger amount of energy would be lost due to the higher utilization of the low quality storage; hence, we would not have reached the global economical optimum.

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Paper 15

The Value of Flexibility in the Distribution Grid

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Abstract

In this paper we introduce four issues that can occur in a distribution grid as an effect of an increase in the electrical load. These four issues are: Poor voltage quality and power congestion in either normal or reserve situation. We focus on power congestion in reserve situation and show how a flexibility product delivered by production or consumption devices is able to solve this type of congestion and consequently allow grid reinforcements to be postponed. Following, we present a method that is able to compare the value of postponed grid reinforcement with the required amount and duration of the flexibility product. Finally, this method is used to conduct an analysis of a Danish 10 kV grid. The analysis shows that on average, solving the first congestion issues that will occur as the load increases has a cost around M€ 0.15. The method further shows that these issues alternatively can be solved by a flexibility product with an amount and a duration in the order of 100 – 200 kW and 1 – 4 hours, respectively, and an expected value of one activation per year.

1 Introduction

Denmark has an ambitious goal of 100 % renewables in all energy sectors by 2050. The implementation of the Danish 100 % renewable goal requires actions from the entire energy supply system [1, 2]. One of the necessary steps in reaching this goal is electrification of the transport and heating sectors [3]. This electrification has already begun: in recent years, $27,000$ heat pumps have been installed in Danish homes [4], and additionally $205,000$ households have the potential to benefit from replacing their oil-fired boilers with a heat pump [5]. Further, the Danish Government decided in 2012 to lower the taxes on electric heating to expedite electrification of the heating sector [6]. Similarly, electrification of the transport sector is planned: the Danish Department of Transport decided in 2012 on electrification of the railroad in Denmark and a report from 2013 by the Danish Energy Association projects that electrical vehicles will become an attractive alternative to combustion engine vehicles in the following decades leading to an electric vehicle population of 47.000 in 2020 and 221.000 in 2030 [7].

An electrification caused by for example heat pumps or electric vehicles may cause congestion issues at the distribution level [8]. In particular, large consumption peaks can occur if the consumption of these devices is optimized towards the electricity markets causing a high level of concurrency [9, 10]. Conventionally, congestion is resolved by reinforcing the grid; however, it is interesting to examine how flexibility on the production or consumption side can serve as an alternative solution to the issue of congestion. In this work, we conduct an analysis of a Danish distribution grid and examine the value that flexibility can have when used to resolve distribution grid congestion.

2 The 10 kV distribution grid

This section provides a brief introduction to the DSO DONG Energy's 10 kV distribution grid.

DONG Energy's 10 kV grid

DONG Energy serves around 980,000 customers through its 50 kV and 30 kV high voltage (HV) grid, 10 kV medium voltage (MV) grid, and 0.4 kV low voltage (LV) grid. The MV grid is a meshed grid mainly operated as a radial (tree) grid. Hereby, most consumers can be supplied through at least two distinct MV connections which assures a high level of security of supply. In this work, we focus on the part of DONG Energy's MV grid that is operated as a radial grid.

Nomenclature

Figure 18.1 which shows one feeder in DONG Energy's grid is used to introduce a number of terms used throughout this paper.

Substations

The MV grid is supplied from the HV grid through *primary substations*; similarly, the LV grid is supplied from the MV grid through *secondary substations*. DONG Energy's grid consists of around 100 primary substations and around 10,000 secondary substations.

Feeder

Each primary substation supplies a number of MV radial networks which are denoted *feeders*. As an example, the primary substation MDR supplies several feeders, one of which is denoted MDR10. This feeder is illustrated in Figure 18.1: the square represents the primary substation and the triangles represent secondary substations. Finally, the solid red lines indicate connections. The black text next to each substation is the substation name.

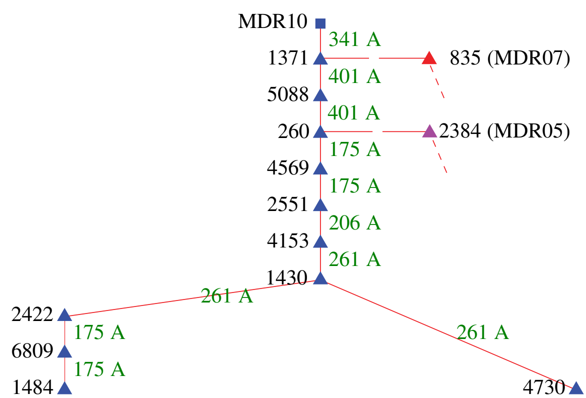

Figure 18.1: Feeder MDR10 in normal situation with open connections to the neighboring feeders MDR07 and MDR05. The dashed lines from 835 and 2384 indicate that these substations each are part of other feeders.

Connections

The substations are interconnected with 10 kV cables denoted *connections*. These connections are named using the two substations they connect, for example MDR10-1371 denotes the first connection. The connection from the primary substation to the first secondary substation is denoted the *feeder head*, i.e. MDR10-1371 is the feeder head of feeder MDR10.

Grid limitations

Each connection is able to carry a limited current depending on the cable and on the characteristics of the soil it is buried in. These limitations are described in the following.

Current and temperature limitations

Each cable has a nominated current capacity. For the feeder MDR10 in Figure 18.1, the current ratings are listed to the right of each connection in green text. For example, the current limit of the feeder head is 341 A. The current limit is the current that can flow continuously in each connection without damaging the cables under certain assumptions on the cable surroundings [11]. Overloading the cable will cause the temperature to increase to a level that damages the insulation and consequently deteriorates the cable.

Due to the thermal mass of the cable, the isolation, and the surrounding soil, the temperature of the cable will be a low pass filtered version of the current. It is, however, difficult to obtain an accurate thermal distribution grid model due to a large number of uncertainties. Some of these unknowns are whether the soil is dry or wet, whether multiple cables are buried next to each other, whether district heating pipes are in the vicinity of the cables, whether the cable is buried under a road which will have a higher temperature during sunshine, etc.

Temporary cable overloading

In addition to the nominal current limit, the cable manufacturer specifies that the cable can withstand a current overload of +17 % for a time period of 50 hours; however, such overloading *will* deteriorate lifetime and should be kept at a minimum [11] [1].

Normal and reserve situation

The entire distribution grid has a default topology defined by the DSO. If a feeder is in its default topology, it is said that the feeder is in *normal situation*. The grid topology can, however, be altered via switches to ensure supply during maintenance or grid faults. This is known as *reserve situation*.

Grid limitations in normal and reserve situation

The DSO regularly optimizes the grid based on historical data to find the optimal normal situation with the lowest losses and where consumers can be supplied by neighboring

[1] Notice that these extra 17 % for 50 hours are *not* a result of the thermal capacity of the cables; on the contrary, the cables *will* overheat and the cables will be damaged if this occurs many times.

feeders in case of a worst case fault (also known as a $n-1$ situation). The design criteria for the grid is a current limit specified by the cable manufacturer when the grid is in normal operation while a current limit of 117 % of the nominal value is used for the reserve situation. The reason is that reserve situations only occur on average one time per year per feeder and usually can be resolved within a 50 hour time frame. Hereby, the allowed temporary cable overloading possibility described in Sec. 2 can be exploited.

Example of $n-1$ situation

We use a concrete example to illustrate the concept of normal and reserve situation. In Figure 18.1, the feeder MDR10 is illustrated in normal situation. The worst case situation ($n-1$) for this feeder is if a failure occurs on the feeder head MDR10-1371. If this occurs, the two neighboring feeders MDR05 and MDR07 will be used to supply this feeder as illustrated in Figure 18.2 and Figure 18.3. This is done by performing a number of switches: the faulty connection MDR10-1371 is disconnected in both ends while the connection 5088-260 is disconnected in one end; further a connection is established from the secondary substation 835 in feeder MDR07 to the secondary substation 1371; similarly, a connection is established from 2384 in feeder MDR05 to 260.

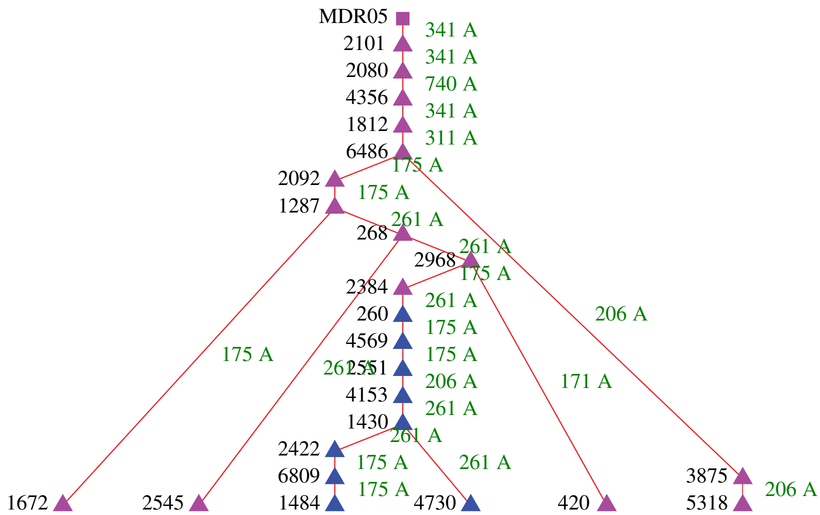

Figure 18.2: Feeder MDR05 in reserve situation to supply a part of feeder MDR10. The purple triangles represent the secondary substations in the original feeder MDR05 while blue triangles represent substations that originally were part of the feeder MDR10.

Congestion and voltage issues

Different issues can occur in the distribution grid when the consumption in Denmark gradually increases due to the aforementioned electrification. The issue can either be power congestion or low voltage quality; further, it can either be an issue when the grid

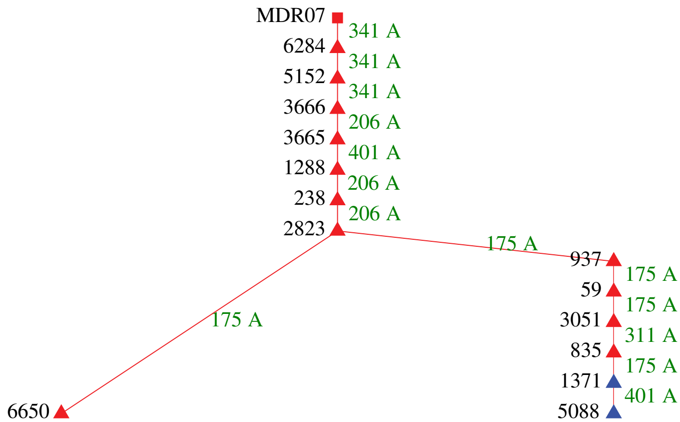

Figure 18.3: Feeder MDR07 in reserve situation to supply a part of feeder MDR10, see caption of Figure 18.2

is in normal operation or in reserve situation. This gives a total of four different possible issues. In this work, the focus is on the issue of power congestion in the reserve situation. The reason for this choice is described later in Sec. 3.

3 Flexibility services for the distribution grid

In this section, we motivate and propose a service that can be sold to the DSO by units having flexible consumption or production capabilities. The service allows the DSO to activate local production or reduce consumption if a reserve situation occurs.

Contracting flexibility services

The basic concept in the flexibility services is that a legal entity, which we denote *an aggregator*, enters into contract with a number of flexible production or consumption device owners to manage their flexibility. This allows the aggregator to utilize the flexibility in the traditional electricity markets, but also to sell the flexibility to a DSO either directly or through some flexibility clearing house [12, 13].

Overall service description and motivation

The distribution grid service considered in this work is designed specifically to support the grid if an unexpected reserve situation occurs, i.e. it addresses the issue of power congestion in reserve situation as discussed in Sec. 2. The concept is as follows. Once a failure in the grid occurs, the grid operators will examine how to reconfigure the grid to supply the faulty feeder. While doing so, the grid operators will have the possibility to activate the contracted distribution grid service. Upon activation, the flexible devices are obliged to reduce consumption or increase production according to the contract agreement. As mentioned previously in Sec. 2, such flexibility contracts will allow the DSO to postpone grid reinforcement which is the DSO's incentive to purchase the proposed flexibility service.

There are two reasons why this work focuses on the issue of power congestion in reserve situations, rather than the three other possible issues. First, an analysis of DONG Energy's grid reveals that in 63 % of the feeders, the first issue that will occur as the load increases is reserve situation congestion. Second, distribution level flexibility products are a new and unproven concept. Therefore, using such services in the rare reserve situations seems like a natural first step instead of relying on these services in normal daily operation.

Reserve description

The distribution grid service can be defined using the following simple contract illustration.

Contract parameter	Example
Contract duration	1 year flexibility contract.
Seasonal constraint	All weekdays in Dec. – March.
Time-of-day constraint	From 4 pm to 8 pm.
Amount[2]	300 kW
Expected no. of activations	One per year.
Time from activation to delivery	At most 30 minutes.
Payment	2,000 €/year and 0 €/activation.

This represents a service that can be activated upon unexpected faults in the grid to avoid overload.

4 Method for appraisal of flexibility services

In the following, we present the main contribution of this paper: a method for estimating the value of the flexibility service proposed in Sec. 3.

Overall description of the appraisal method

At an overall level, the method for estimating the value of flexibility is as follows.

1. The starting point is a feeder where historical data shows the issue that will occur as the load increases is *power congestion in reserve operation* (see Sec. 2).

2. The feeder is simulated as having a worst case fault causing a reserve situation.

3. The historical load is upscaled until at least one connection reaches its current limit.

4. The load is further gradually increased. The amount and duration of flexibility that is required to resolve the congestion issues that arise according to the increased load is determined. Further, the corresponding cost of conventional reinforcement is also determined.

The last two items allows us to compare the cost of grid reinforcement with the amount of flexibility required to solve the same issue.

[2]The amount can also be specified hour by hour, for example: 12 noon to 6 pm: 100 kW; 6 pm to 7 pm: 200 kW; 7 pm to 8 pm: 300 kW.

Savings due to postponed investments

The method described above examines the cost of grid reinforcement which can be postponed when using a flexibility solution. In this work the annual value of postponing investments is calculated as the interest the investment could have made. A $5\ \%$ interest rate is used throughout these calculations corresponding to a generic WACC (weighted average cost of capital) used in distribution grids for low-risk investments such as infrastructure. Notice that depreciation allowance should not be included as a cost saving because it is also postponed when the grid reinforcement investments are postponed.

Detailed description of the appraisal method

In the following, we elaborate the method presented in Sec. 4. Let m be the total number of secondary substations and n be the total number of connections in the feeder under consideration and its neighboring feeders. We index the secondary substations and the connections by the sets $\mathcal{I} = \{1, \ldots, m\}$ and $\mathcal{J} = \{1, \ldots, n\}$.

Finding historical load

The first step in the appraisal method is to collect the historical load at the worst case times during the last year where "worst case" refers to the time where the smallest load increase would have resulted in a situation with congestion. Let $S(t) \in \mathbf{C}^m$ denote the historical complex load over the m secondary substations. Further, let $I(t) \in \mathbf{C}^n$ be the resulting complex currents over the n connections under the load $S(t)$. We let the worst case time be denoted t_{worst} and collect the historical load for at time period $\mathcal{T}$ of four days centered around t_{worst}, i.e. $\mathcal{T} = \{t \in \mathbf{R} | t_{\text{worst}} - 2 \text{ days} \leq t \leq t_{\text{worst}} + 2 \text{ days}\}$. As previously mentioned, grid faults are typically resolved within 50 hours. By choosing a time span of four days, we ensure to capture the load over a time period at least equal to the expected time it takes to return from reserve to normal situation.

Flexibility service description

The flexibility service delivered by the aggregator described in Sec. 3 is characterized by two parameters, namely the reserve duration (hours) and the amount (MW) which we denote $\Delta T, \Delta P \in \mathbf{R}_{++}$, respectively. In the following, we use the parameter $\theta = (\Delta T, \Delta P)$ to describe a given service.

Upon activation, the aggregator's power response $P_\theta(t) \in \mathbf{R}_+$ is given by

$$P_\theta(t) = \begin{cases} \Delta P & \text{if } t \text{ is witin hours } t_{\text{worst}} \pm \Delta T \\ 0 & \text{else} \end{cases} \tag{18.1}$$

where $P_\theta(t) > 0$ corresponds to an increased production or the absolute value of a reduced consumption.

Current and temperature limits

Let the current limits defined by the cable manufacturer be denoted $\overline{I}_{\text{nom}} \in \mathbf{R}^n$. As we only deal with the grid in reserve situation where a $17\ \%$ overload is allowed (see Sec. 2), the resulting current constraint can be described as

$$I(t) \preceq \overline{I}_{\text{res}} = 1.17 \cdot \overline{I}_{\text{nom}}, \tag{18.2}$$

where $\preceq$ represents componentwise inequality. As mentioned in Sec. 2, the actual limitation is not the current but the cable temperature. This phenomenon can be roughly captured with a simple first order model on the form

$$\dot{T}_j(t) = a(T_{\text{amb},j}(t) - T_j(t)) + b_j P_j(t), \quad \forall j \in \mathcal{J} \tag{18.3}$$

where $T_j(t) \in \mathbf{R}$ is the cable temperature, $T_{\text{amb},j}(t) \in \mathbf{R}$ is the ambient temperature, and $a, b_j \in \mathbf{R}$ are cable parameters. Finally, $P_j(t) \in \mathbf{R}_+$ is the power consumed by the cable (per unit length) which is given by

$$P_j(t) = |I_j^2| R_0(1 + \rho(T_j(t) - T_0)), \quad \forall j \in \mathcal{J} \tag{18.4}$$

where ρ is the temperature coefficient of resistance for aluminum and (T_0, R_0) is an operating point. Notice that the above model assumes that the cable has the same temperature along the whole length.

As previously mentioned, the limiting factor for cables is temperature and not current. In reserve situations, the temperature constraint is given by

$$T(t) \preceq \overline{T}_{\text{res}} \tag{18.5}$$

where $\overline{T}_{\text{res}} \in \mathbf{R}^n$ are the steady state temperatures corresponding to a 17 % current overloading.

Upscaling of load

As previously described, the first step in the appraisal method is to upscale consumption with a factor denoted $\alpha_0 \in \mathbf{R}_{++}$ until at least one connection reaches its current limit. Following this pre-scaling, the historical load is further scaled up by factor greater than 1, which causes congestion on at least one connection in the feeder. More formally, let $S^x(t) = xS(t) \in \mathbf{C}^m$ be an upscaled version of the historical load and let $I^x(t) \in \mathbf{C}^n$ and $T^x(t) \in \mathbf{R}^n$ describe the resulting currents and temperatures, respectively. The prescaling factor α_0 can now be defined as

$$\alpha_0 = \underset{x \in \mathbf{R}}{\text{argmax}}(x | I^x \preceq \overline{I}_{\text{res}}), \tag{18.6}$$

i.e., scaling with α_0 will adjust the load on the feeder such that it is on the point of congestion on at least one of the connections if it is in a reserve situation. Now we can upscale the consumption further to a value $S^x(t)$ with $x > \alpha_0$ to simulate a future scenario where congestion will occur.

Effect of flexibility service

Upon activation of a flexibility service with parameter θ, the aggregator will provide a total power delivery amount ΔP with duration ΔT at the time agreed upon as described in (18.1). The service can be delivered by activating one or several devices that are located "behind" the congested connection. To simplify notation, we assume the entire service is delivered at one single substation $\bar{i}$, although it could be delivered at several substations. Upon delivery of the flexibility service θ, the resulting loads are denoted $S^x_\theta(t) \in \mathbf{C}^m$ and given by[3]

$$S^{\alpha}_{\theta,i}(t) = \begin{cases} S^x_i(t) - P_\theta(t) & \text{if } i = \bar{i} \\ S^x_i(t) & \text{else} \end{cases}, \forall i \in \mathcal{I}, t \in \mathcal{T}. \tag{18.7}$$

Similarly, we let $I^x_\theta(t) \in \mathbf{C}^n$ denote the complex currents and $T^x_\theta(t) \in \mathbf{R}^n$ denote the cable temperatures when the loads on the substations are given by $S^x_\theta(t)$, i.e. when the load is upscaled with a factor x and a flexibility service $\theta = (\Delta T, \Delta P)$ is delivered.

Congestion alleviation via flexibility service

As the load is upscaled above α_0, congestion will occur at different connections in the grid. These congestion issues can be resolved either by a number of conventional grid reinforcements or alternatively by a flexibility service of a given amount and duration $\theta = (\Delta T, \Delta P)$. It is desired to compare these two quantities: cost of reinforcement and the size of the required flexibility service. This is done as follows.

Upon an upscaling $x > \alpha_0$ we find the smallest service θ^x_I that is able to ensure the current constraints (18.5) are honored (subscript I is chosen because we examine the current limit). This can be described as

$$\theta^x_I = \underset{\theta \in \mathbf{R}^2}{\text{argmin}}(\lambda^T \theta | I^x_\theta(t) \leq \bar{I}_{\text{res}}) \tag{18.8}$$

where $\theta^x_I = (\Delta T^x_I, \Delta P^x_I)$ represents the smallest service that will ensure the current limits (18.2) are honored when the consumption is upscaled with a factor $x > \alpha_0$. The parameter $\lambda \in \mathbf{R}^2$ is a trade-off parameter between minimizing duration and amount of flexibility.

Similarly, we can find the required service θ^x_T that ensures that the temperature limits are honored (see Sec. 4)

$$\theta^x_T = \underset{\theta \in \mathbf{R}^2}{\text{argmin}}(\lambda^T \theta | T^x_\theta(t) \leq \bar{T}_{\text{res}}). \tag{18.9}$$

where $\theta^x_T = (\Delta T^x_T, \Delta P^x_T)$ represents the smallest service that can ensure the temperature limits (18.5) when the consumption is upscaled with a factor $x > \alpha_0$.

Congestion alleviation via grid reinforcement

The classical way of dealing with congestion issues is to replace the congested connections with larger cables or alternatively construct a new feeder to supply a part of the load to bypass the congestion. In this work we assume that the congestion issues are resolved by replacing the congested cables with new cables of higher capacity. The cost is C_{length} per installed meter of new cable plus a startup cost of C_{start} per cable that must be replaced. The cost $C^x \in \mathbf{R}$ associated with grid reinforcement when the consumption is

[3]Notice that $S^x_i(t) > 0$ corresponds to a load while $P_\theta(t) > 0$ corresponds to production, a minus sign is therefore required to calculate the resulting load.

upscaled with a factor $x > \alpha_0$ is consequently given by

$$C^x = \sum_{j \in \mathcal{J} | I_j^x(t) > \overline{I}_{\text{res},j}} \left(C_{\text{start}} + l_j C_{\text{length}} \right) \tag{18.10}$$

where l_j is the length of connection j.

Case study from DONG Energy's grid

The method described at an overall level in Sec. 4 and in detail in Sec. 4 is used on a number of feeders in DONG Energy's distribution grid.

An example of this is shown in Figure 18.4 where the original feeder MDR10 in reserve situation (see Fig. 18.1, Fig. 18.2, and Fig. 18.3.) is examined with a scaling of $x = 1.10 \cdot \alpha_0$, i.e. we have increased the consumption 10 % above the level where the first congestion occurs. With this scaling, connection 2092 – 6486 and connection 1287 – 2092 are congested. In Figure 18.4 we examine the connection 2092 – 6486. The two plots to the left are in the case where we use the temperature limits (18.5) as a basis for dimensioning. In this case with $x = 1.10 \cdot \alpha_0$, the temperature plot (lower plot) shows that no congestion will occur as the temperature is lower than the limit over the four day period although the current limit is violated. In other words, the required flexibility service when using the thermal limit is $\Delta T_T = 0$ hours and $\Delta P_T = 0$ kW. The two plots to the right show the case where the current limits (18.2) are used as dimensioning. Here, a flexibility service $\Delta T_I = 2.5$ hours and $\Delta P_I = 210$ kW is required to resolve congestion.

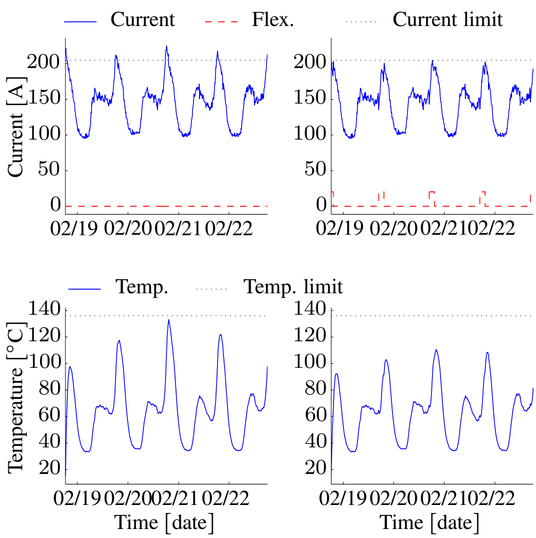

Figure 18.4: Historical load on connection 2092 – 6486 at the time with the highest load upscaled with a factor $1.10 \cdot \alpha_0$. Left: Without flexibility delivery. Right: With flexibility delivery.

Figure 18.5 is also based on feeder MDR10 in reserve situation where the load is upscaled above α_0, i.e. to a level where congestion occurs. The top plot of Figure 18.5

shows the cost of grid reinforcement and the two lower plots show the required flexibility in terms of power and duration as a function of how much the load is upscaled. As seen, the initial cost of grid reinforcement is M€ 0.05 which will correspond to the cost of replacing the first congested connection. As the scaling reaches $5\ \%$ above α_0, the cost increases to M€ 0.18 because the feeder now has two congested connections that must be reinforced. The middle and bottom plots show the required flexibility θ_I^x, θ_T^x (current limit or temperature limit) to resolve the overload in terms of power and duration. It is interesting to notice that the thermal limit allows a $10\ \%$ increase of the load before flexibility is required. This is due to the shape of the overload peak (see Figure 18.4) which is very "narrow" causing the temperature to not increase greatly.

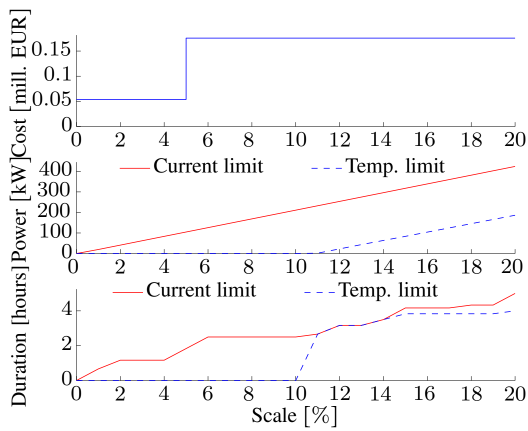

Figure 18.5: Top: Cost of grid reinforcement. Middle and bottom: Required flexibility to solve grid reinforcement in power and duration, respectively, when using current (red solid curves) and temperature (blue dashed) as limit. The x-axis describes the upscaling above α_0 in percent.

5 Results

We now perform the same analysis as presented in Sec. 4 on 10 feeders in DONG Energy's distribution grid to get a more representative picture of grid reinforcement costs and to compare these costs to flexibility. The result is seen in Figure 18.6 which is similar to Figure 18.5 except that the figure now shows mean values and the associated standard deviations based on analysis of 10 feeders.

A number of interesting results from DONG Energy's grid are evident from Figure 18.6.

1. For the first few percent above α_0, the cost of grid reinforcement is in the order of M€ 0.15 and the required flexibility in range $100-200$ kW for $1-4$ hours, however with a large uncertainty (high std. deviation).

2. Consequently, the DSO's value of this flexibility product ($100-200$ kW for $1-4$ hours) with an expected value of 1 activation per year is in the order of € $7,500$/year corresponding to a $5\ \%$ interest rate (see Sec. 4).

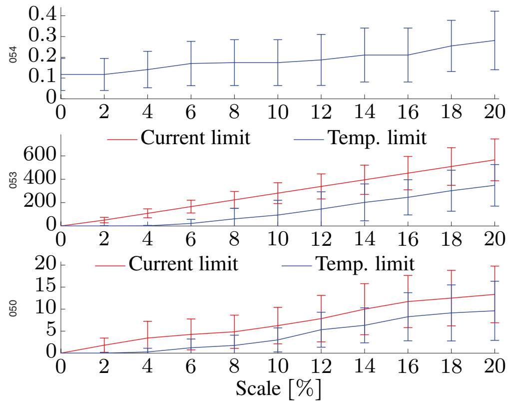

Figure 18.6: Top: Average cost of grid reinforcement. Middle and bottom: Average amount and duration of flexibility. Vertical bars indicate the standard deviation.

3. As the load increases above 15 %, the flexibility service duration is in average above 12 hours which is an indicator that flexibility at this point no longer is a desired solution[4].

4. Exploiting thermal dynamics of cables yields approximately 5 % extra load in average.

6 Conclusion

In this work we examined the issue of power congestion in reserve situations, which will occur if the load in the grid increases. We presented a method that was able to compare the value of postponing grid reinforcement with the duration and amount of flexibility required to avoid congestion in a worst case reserve situation. A concrete case study was conducted on DONG Energy's 10 kV grid revealing that the first power congestion issues to occur if the load increases can be resolved with flexibility in the order of 100 – 200 kW for 1 – 4 hours with an expected number of activations per year equal to 1. On average, this saves the DSO a total of € 7,500 annually because grid reinforcement investments can be postponed; however, the savings will vary greatly from feeder to feeder. This gives an indication of the magnitude of flexibility required to actually postpone grid reinforcement and also roughly estimates the value of this flexibility.

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